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Mid- to Long-Term Runoff Forecasting in the Huaihe River Basin Using a Spatiotemporal Graph Neural Network Coupled with LSTM

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Abstract

To address the difficulty of simultaneously characterizing runoff temporal variation and spatial connectivity among stations under the complex river network conditions of the Huaihe River Basin, a spatiotemporal graph neural network model integrating temporal feature extraction and graph-based spatial modeling was developed for mid- to long-term runoff forecasting. Based on multi-station daily precipitation, air temperature, and runoff data from 2011 to 2020 in the Huaihe River Basin, data preprocessing was conducted, including missing-value imputation, outlier detection, standardization, and basin graph construction, and an adjacency matrix was established according to the upstream–downstream hydrological connectivity among stations. The model employed LSTM to extract dynamic features from historical sequences and graph convolution to capture spatial dependencies within the basin. Compared with LSTM, K-nearest neighbor, support vector regression, decision tree, and AdaBoost models, the proposed model achieved better overall predictive performance on the basin-wide test set, with an average R^2 of 0.915, average MAE of 30.019, and average RMSE of 50.243, demonstrating strong runoff process fitting ability and good error control at the basin scale. The results indicate that incorporating basin spatial connectivity can effectively improve the accuracy of mid- to long-term runoff forecasting and provide methodological support for water resources regulation and flood-control decision-making in complex river basins.

Keywords

spatiotemporal graph neural network, Huaihe River Basin, mid- to long-term runoff forecasting, spatial connectivity, complex river-network basin

1. Introduction

Runoff forecasting serves as a critical foundation for water resources allocation, flood control scheduling, and integrated basin management. Among these, mid- to long-term runoff forecasting holds significant importance for basin operation decision-making, water supply security, and the formulation of risk response plans. Influenced by multiple factors such as meteorological drivers, underlying surface conditions, and human activities, runoff processes typically exhibit pronounced nonlinearity, non-stationarity, and time-varying characteristics, which increase the complexity of predictive modeling.

Therefore, improving the accuracy of mid- to long-term runoff forecasting under complex conditions has become an important research issue in the field of hydrology and water resources [1-2].

Regarding runoff forecasting, domestic and international research has followed a developmental path from traditional statistical models and machine learning models to deep learning models [2-3]. Traditional statistical models and shallow machine learning models have certain application foundations in runoff forecasting, but their ability to characterize complex nonlinear hydrological processes is limited. Although traditional machine learning methods such as Random Forest (RF) and Support Vector Regression (SVR) can improve prediction accuracy to some extent, they usually rely on manual feature engineering and struggle to adequately capture the long-term temporal dependencies and dynamic cumulative effects in runoff evolution. Shallow models such as Back Propagation Neural Networks also tend to be limited by insufficient feature representation capability when addressing mid- to long-term runoff problems [3-6]. In contrast, Long Short-Term Memory (LSTM) networks and related deep learning models demonstrate stronger advantages in time series modeling and have been widely applied in runoff forecasting research [7-9].

Although existing studies have made some progress in improving runoff prediction accuracy, most methods still primarily focus on mining temporal sequence features while paying insufficient attention to spatial dependency relationships in complex river-network basins, such as upstream–downstream transmission, tributary inflows, and multi-station coordinated responses [1-2]. For basin systems like the Huaihe River Basin, which feature dense river networks and significant spatial connectivity, modeling based solely on single stations or purely temporal dimensions makes it difficult to fully reflect the spatiotemporal interaction characteristics during runoff evolution. In recent years, Graph Neural Networks (GNN) have provided new approaches for modeling the spatial topological relationships of basins. Combining them with Long Short-Term Memory networks is expected to more comprehensively characterize both the temporal dependency features and spatial propagation features of runoff changes in complex river-network basins, thereby enhancing mid- to long-term runoff forecasting capability [10-13].

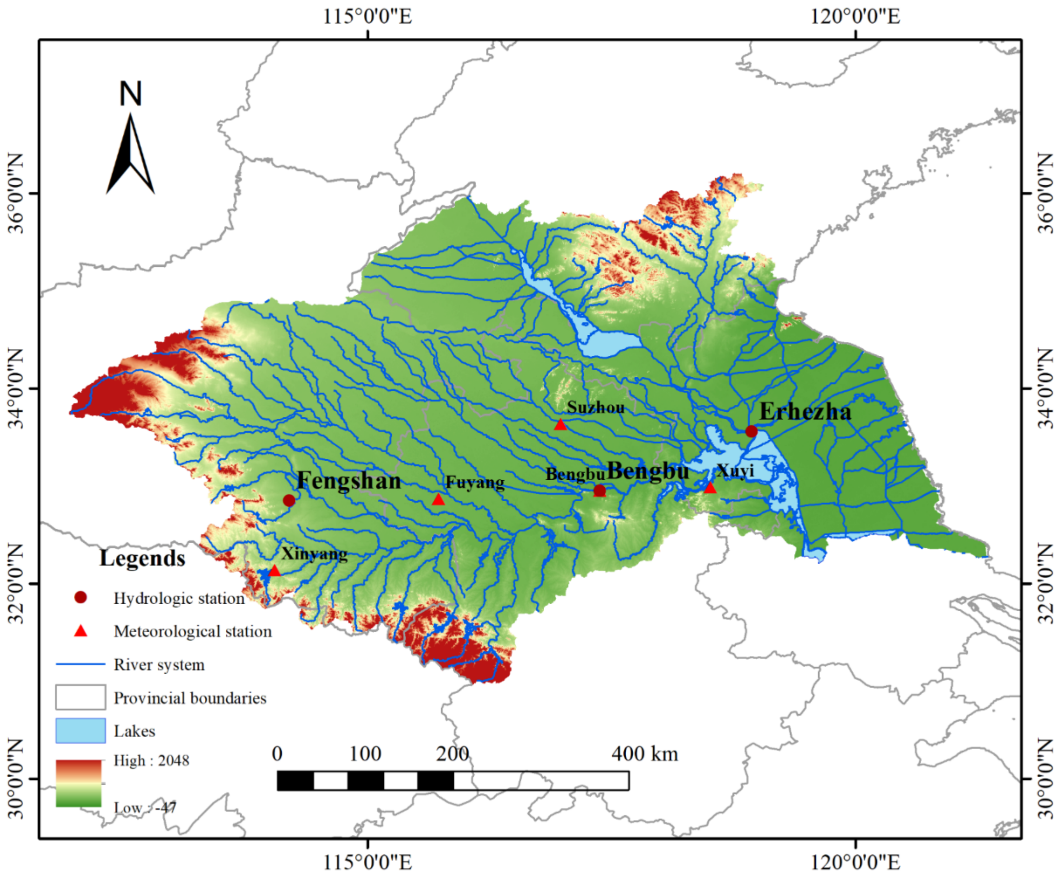
Based on the above considerations, this paper takes the Huaihe River Basin as the study area and constructs a spatiotemporal joint runoff forecasting model that integrates LSTM and GNN. By incorporating basin spatial connectivity information, the model jointly extracts temporal dependency features and spatial propagation features in the runoff evolution process. The proposed model is compared with LSTM, K-nearest neighbor, support vector regression, decision tree, and AdaBoost models [14-17] to evaluate its applicability and accuracy advantages in mid- to long-term runoff forecasting, with the aim of providing new modeling ideas for runoff prediction in complex river-network basins.

2. Study Area and Data Preprocessing

2.1 Overview of the Study Area

The Huaihe River Basin is located in the north-south transitional zone of eastern China and serves as a key region for water resources allocation and flood control scheduling (Figure 1). Affected by the monsoon climate, precipitation within the basin is unevenly distributed throughout the year, with concentrated inflow during the flood season and pronounced fluctuations in the runoff process. According to multi-station daily-scale data from 2011 to 2020, the multi-year average temperature in the study area ranges from 15.6 to 15.8 °C, and the multi-year average annual precipitation ranges from 919 to 981 mm, of which precipitation from June to September accounts for 58%–65% of the annual total. The maximum daily precipitation can reach 92.4–112.03 mm, and the maximum daily discharge at representative hydrological stations can reach 7340.0 m^3/s, indicating significant runoff fluctuations under extreme weather conditions. Meanwhile, the Huaihe River Basin has numerous tributaries and a dense river network, with close hydrological connections between upstream and downstream areas. Runoff changes are simultaneously influenced by local meteorological conditions, upstream inflow transmission, and tributary confluence processes, exhibiting typical spatiotemporal evolution characteristics of a complex river-network basin. Therefore, selecting this basin for mid- to long-term runoff forecasting research is highly representative and practically necessary.

Figure 1: Distribution map of meteorological and hydrological stations in the Huaihe River Basin



2.2 Data Sources and Dataset Construction

2.2.1 Data Sources

The raw data used in this study include meteorological and hydrological data, covering the period from 2011 to 2020 at a daily scale, for a total of 3653 days. Meteorological data were obtained from observations at multiple meteorological stations within the basin, with main variables including sunshine duration, average temperature, daily maximum temperature, daily minimum temperature, relative humidity, average wind speed, and precipitation. Hydrological data were derived from observations at major hydrological stations in the basin, with the indicator being daily runoff discharge.

To facilitate regional-scale analysis, the study area was divided into three regions—upstream, midstream, and downstream—based on the spatial distribution of stations and basin sectional characteristics, and corresponding datasets were constructed. The specific grouping is as follows: For the upstream region, meteorological data from Xinyang and Fuyang stations were selected and matched with runoff data from Fengshan station. For the midstream region, meteorological data from Bengbu and Fuyang stations were selected and matched with runoff data from Bengbu station. For the downstream region, meteorological data from Bengbu, Suzhou, and Xuyi stations were selected and matched with runoff data from Erhezha station. This grouping method takes into account both basin sectional division and data availability, and can better characterize the meteorological–runoff response relationships in different river reaches.

2.2.2 Data Cleaning and Preprocessing

To ensure the integrity and reliability of the modeling data, the raw meteorological and hydrological data were cleaned and preprocessed [1, 14]. For meteorological data, the time format was first unified and arranged in ascending chronological order. Outliers were then handled using a quantile-based method: values below the 1% quantile and above the 99% quantile were regarded as outliers and corrected using linear interpolation to reduce noise interference while preserving the characteristics of extreme hydrometeorological events as much as possible. For hydrological data, missing values in the runoff discharge series were primarily addressed.

After unifying the time format and sorting, linear interpolation was applied to fill missing discharge values, forming a cleaned hydrological station dataset. This approach maintains temporal continuity while mitigating the impact of missing data on prediction results.

2.2.3 Construction of Regional Datasets

After completing data cleaning for meteorological and hydrological stations, an overall dataset covering the upstream, midstream, and downstream areas of the Huaihe River Basin was constructed. The dataset contains 9 variables and 3653 daily-scale samples, with complete temporal coverage and a unified structure, making it suitable for subsequent statistical analysis, correlation analysis, and prediction model construction.

As shown in Table 1, the main meteorological variables in the Huaihe River Basin are generally stable, with a mean temperature of 15.7 °C and a mean precipitation of 2.6 mm. In contrast, the mean runoff discharge is 379.8 m^3/s, with a standard deviation of 716.0 m^3/s, indicating more significant fluctuations. This suggests that the runoff process has greater complexity and uncertainty. These findings demonstrate objective differences in inflow conditions and hydrological response characteristics across different river reaches, further validating the necessity of partitioned modeling and regional comparative analysis.

Table 1: Statistical table of meteorological and hydrological characteristics in the Huaihe River Basin

Feature	Unit	Mean	Standard Deviation	Minimum	Median	Maximum
Sunshine duration	h	5.0	3.8	0.0	5.3	12.6
Temperature	℃	15.7	9.5	-8.1	17.0	33.7
Humidity	%	71.2	14.2	18.0	72.5	99.5
Wind speed	m/s	2.2	0.9	0.4	2.1	7.2
Precipitation	mm	2.6	8.2	0.0	0.0	112.0
Evaporation	mm	2.7	1.5	0.4	2.5	7.2
Runoff discharge	m^3/s	379.8	716.0	-65.6	190.0	7340.0

2.2.4 Dataset Division and Standardization

Given the strong temporal correlation of runoff time series, samples were not randomly divided to ensure the prediction process aligns with real-world application scenarios. Instead, they were divided chronologically, with the first 70% of samples used as the training set and the remaining 30% as the test set [1, 14]. For models sensitive to data scale, the Z-score standardization method was applied to both input features and the target variable, converting the data to a standardized form with a mean of 0 and a standard deviation of 1 using the sample mean and standard deviation. For models insensitive to feature magnitude, the original data were used for modeling and comparison [14].

2.3 Model Evaluation Metrics

To quantitatively evaluate the fitting performance and prediction accuracy of different models on the runoff process, this study selected Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2) as model evaluation indicators [1, 16-17]. These indicators have been widely used in runoff forecasting and hydrological time series simulation research. Among them, RMSE and MAE reflect the magnitude of deviation between predicted and observed values; smaller values indicate better model prediction performance. R^2 is used to measure the model's ability to explain the variation characteristics of the observed series; values closer to 1 indicate better model fitting [1, 16-17].

Let the observed runoff value be y_i, the predicted runoff value be $\hat{y}_i$, the number of samples be n, and the mean of the observed values be $\bar{y}$. The calculation formulas for each evaluation indicator are as follows:

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{1}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \tag{2}$$

$$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right| \tag{3}$$

By integrating the above indicators, the predictive performance of different models can be compared from the perspectives of error level and fitting degree.

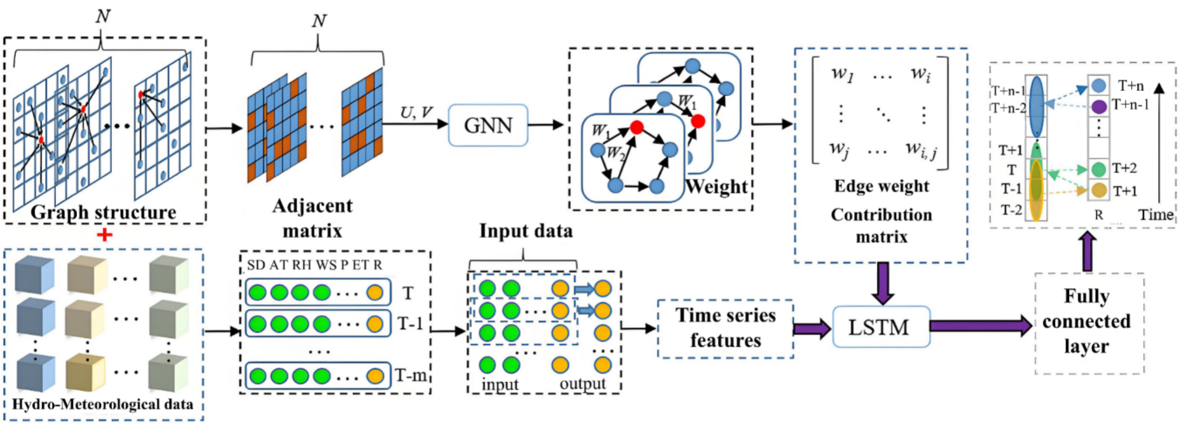
3. Construction of the Spatiotemporal Graph Neural Network Runoff Forecasting Model

To fully characterize the temporal dependency features and spatial connectivity features in the runoff evolution process of the Huaihe River Basin, this study constructs a spatiotemporal joint forecasting model that integrates Long Short-Term Memory (LSTM) and Graph Neural Network (GNN) [9-13]. The model is based on a multi-station meteorological–runoff joint dataset and the basin graph structure. It extracts dynamic features from historical sequences in the temporal dimension and learns propagation relationships between upstream and downstream nodes in the spatial dimension, thereby achieving joint modeling of mid- to long-term runoff processes in complex river-network basins (Figure 2).

3.1 Construction of the Basin Graph Structure

To represent the spatial connectivity relationships among different sections of the Huaihe River Basin, a basin graph structure was constructed based on the regional datasets [10-13]. In this graph structure, river sections and their corresponding control stations are treated as nodes, and the upstream–downstream relationships of rivers are abstracted as edges to describe the spatial transmission paths of the runoff process [10-13]. In accordance with the data organization method used in this study, the upstream, midstream, and downstream regions are regarded as three primary nodes, corresponding respectively to the control areas of Fengshan station, Bengbu station, and Erhezha station. Node features are composed of multidimensional meteorological elements and runoff information from the corresponding region at previous time steps. Based on the natural flow direction in the river network, directed connections are established from upstream to midstream and from midstream to downstream. Self-loops are introduced to retain each node's own information, thereby forming the basin adjacency matrix.

Figure 2: Architecture diagram of the GNN-LSTM model



3.2 Temporal Feature Extraction Module

The runoff process is jointly influenced by multiple factors such as antecedent precipitation, temperature, evaporation, and historical discharge, exhibiting significant temporal correlation and hysteresis. Although traditional regression models or shallow machine learning methods can characterize some nonlinear relationships, they are insufficient in capturing cumulative effects and long-term dependency information in long time series [7-9]. To address this, the Long Short-Term Memory (LSTM) network is introduced in the temporal dimension to extract features from the input sequences [7-9].

As shown in Figure 3, LSTM realizes selective retention and updating of historical information through the forget gate, input gate, and output gate. It can retain key temporal information while suppressing irrelevant disturbances, thereby effectively overcoming the gradient vanishing problem that commonly occurs in ordinary recurrent neural networks during long-sequence training [8-9]. Let x_t be the input vector at time t, and h_{t-1} and C_{t-1} be the hidden state and cell state of the previous time step, respectively. The computation process of LSTM is as follows:

$$f_t=\sigma(W_f[h_{t-1},x_t]+b_f) \tag{4}$$

$$i_t=\sigma(W_i[h_{t-1},x_t]+b_i) \tag{5}$$

$$\widetilde{C}_t=\tanh(W_c[h_{t-1},x_t]+b_c) \tag{6}$$

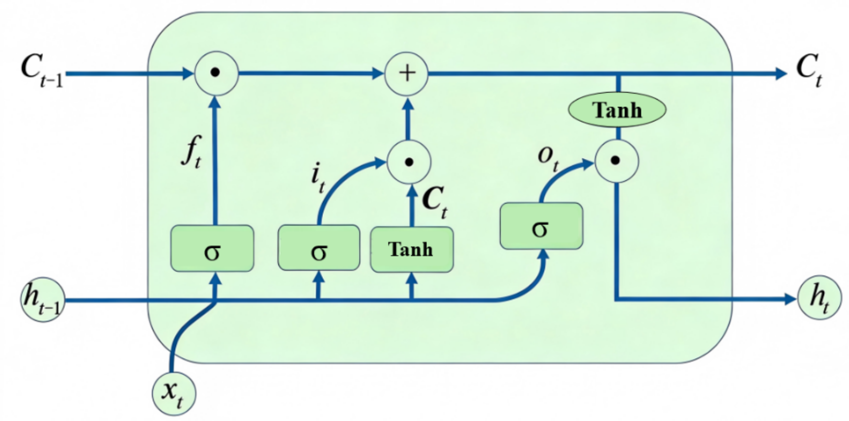
$$C_t=f_t\odot C_{t-1}+i_t\odot\widetilde{C}_t \tag{7}$$

$$o_t=\sigma(W_o[h_{t-1},x_t]+b_o) \tag{8}$$

$$h_t=o_t\odot\tanh(C_t) \tag{9}$$

where f_t, i_t, and o_t represent the forget gate, input gate, and output gate, respectively; σ denotes the Sigmoid activation function; and $\odot$ represents the Hadamard product. Through its gating mechanism, LSTM retains historical information useful for current prediction while suppressing irrelevant disturbances, enabling it to effectively capture the long-term temporal dependencies among precipitation, temperature, evaporation, and runoff [8-9].

Figure 3: Structure diagram of the Long Short-Term Memory network model



3.3 Spatial Feature Extraction Module

After constructing the basin graph structure, Graph Neural Network (GNN) is introduced in the spatial dimension for feature extraction [10-13]. Let the basin graph structure be G=(V,E,A), where V is the set of nodes, E is the set of edges, and A is the adjacency matrix. To retain node self-information, self-loops are added to the adjacency matrix:

$$\widetilde{A}=A+I \tag{10}$$

The corresponding degree matrix is:

$$\widetilde{D}_{ii}=\sum_j\widetilde{A}_{ij} \tag{11}$$

The graph convolution layer can be expressed as:

$$H^{(l+1)}=\sigma\left(\widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{12}$$

where $H^{(l)}$ and $H^{(l+1)}$ are the node representations at the 1-th and (l+1)-th layers, respectively, and $W^{(l)}$ is the trainable weight matrix. This process propagates neighborhood information across the graph structure, allowing the model to capture not only the historical variation patterns at individual stations but also the spatial influences brought by upstream inflow, tributary confluence, and coordinated responses from adjacent regions.

3.4 Model Hyperparameter Settings

To ensure model stability and predictive performance, hyperparameters of the constructed spatiotemporal model were set and optimized. The main hyperparameters include the number of graph convolution layers, hidden layer dimension, time step length, learning rate, and number of training epochs. In the spatial modeling component, the number of graph convolutional network layers is set to 2 to balance feature representation capability and overfitting risk; the hidden layer dimension is set to 64 to extract basin spatial correlation features. In the temporal modeling component, the number of LSTM layers is set to 1–2, with 64 hidden units, to capture the temporal dependencies in the runoff sequence. The time window length is set to 7 days to characterize short-term hydrological response processes. During model training, the Adam optimizer is used for parameter updating, with an initial learning rate of 0.001 that is dynamically adjusted according to validation set performance. The batch size is set to 32, the number of training epochs is set to 100, and an early stopping strategy is introduced to prevent overfitting.

3.5 Settings of Comparison Models

To verify the effectiveness of the proposed GNN-LSTM model, LSTM, K-nearest neighbor, support vector regression, decision tree, and AdaBoost models are selected as baseline models for comparative analysis [3-6, 15-17]. Among them, LSTM is primarily used to characterize time series modeling capability, while K-nearest neighbor, support vector regression, decision tree, and AdaBoost represent different types of machine learning methods [3-6, 15-17]. By comparing with the above models, the applicability and accuracy advantages of GNN-LSTM in mid- to long-term runoff forecasting for complex river-network basins can be further evaluated.

In the comparative experiments, all models use the same input variables, identical training set and test set division methods, and a unified evaluation indicator system to ensure fairness and consistency in result comparison [1, 16-17]. The predictive performance of different models is analyzed by comparing their results on RMSE, MAE, and R^2, thereby assessing the accuracy advantages and applicability in mid- to long-term runoff forecasting for complex river-network basins.

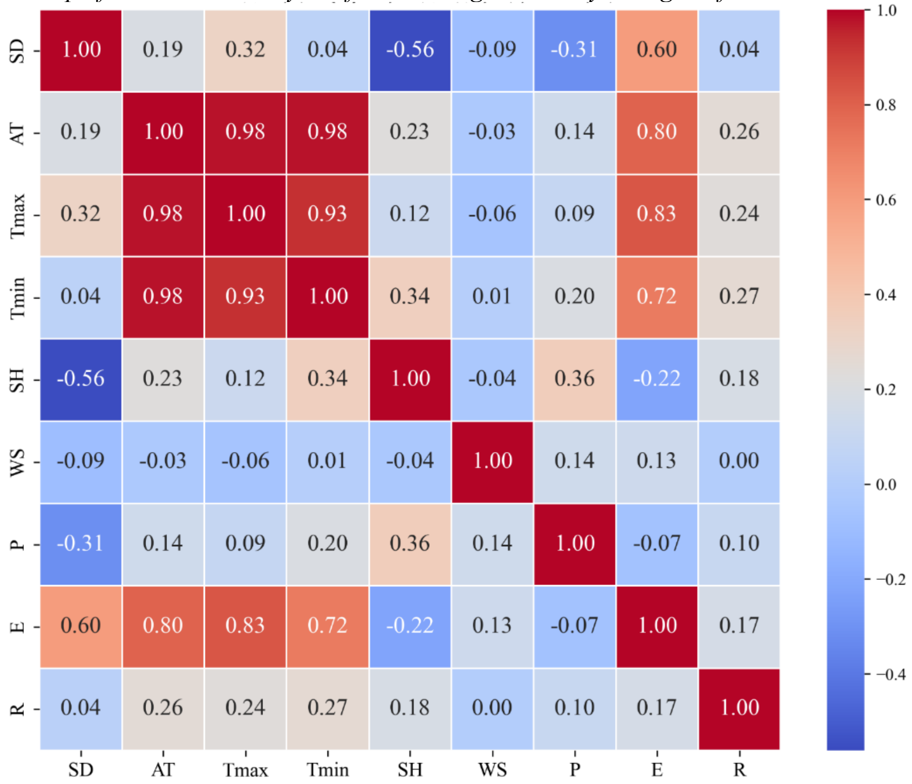
4. Results and Discussion

4.1 Correlation Analysis Between Meteorological Variables and Runoff

To identify the statistical relationships between meteorological elements and runoff in the Huaihe River Basin, a correlation analysis was conducted based on the overall basin data, with results shown in Figure 4. Overall, temperature-related variables exhibited strong correlations with each other; air temperature showed significant positive correlations with both maximum and minimum temperatures. Evaporation also had a high correlation with temperature-related variables ($r=0.72–0.83$). Sunshine duration and humidity displayed a clear negative correlation ($r=-0.56$). In comparison, wind speed showed generally weaker correlations with other variables.

Regarding the relationship between runoff and various meteorological factors, the linear correlations between each variable and runoff were generally weak, showing only a certain degree of weak or low correlation. This indicates that runoff variation is not directly controlled by a single meteorological factor but is jointly influenced by multiple factors and possesses a certain degree of complexity. Considering the high correlation between evaporation and temperature-related variables, as well as its relatively weak correlation with runoff, evaporation was excluded from the final input variables. Ultimately, variables such as temperature, precipitation, lagged precipitation terms, and lagged runoff terms were selected for model construction.

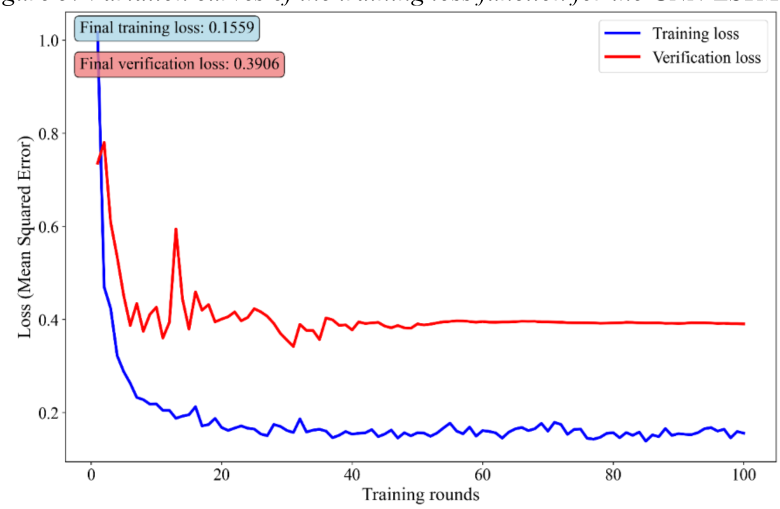
Figure 4: Heatmap of correlation analysis of meteorological and hydrological factors in the Huaihe River Basin



4.2 Comparison of Prediction Accuracy Among Different Models

To compare the performance differences of various models in runoff forecasting for the Huaihe River Basin, this study adopted a unified data division method and evaluation indicator system to analyze the GNN-LSTM, LSTM, K-nearest neighbor, support vector regression, decision tree, and AdaBoost models. The results are presented in Tables 2–4. Overall, the GNN-LSTM model achieved the highest coefficient of determination (R^2) on the test sets across all three regions, reaching 0.915, 0.952, and 0.878 for the upstream, midstream, and downstream regions, respectively. This demonstrates that the model has a strong advantage in fitting the overall variation trend of the runoff process. In addition, Figure 5 shows that both the training loss and validation loss of the GNN-LSTM model decreased steadily and gradually stabilized during training, indicating good convergence and training stability.

Figure 5: Variation curves of the training loss function for the GNN-LSTM model



From the comprehensive results on the overall basin test set, the GNN-LSTM model achieved average R^2, MAE, and RMSE values of 0.915, 30.019, and 50.243, respectively. Compared with the other models, its average R^2 improved by 3.62%–24.49%, the average MAE decreased by 3.62%–42.74%, and the average RMSE was also superior to most comparison models. These results indicate that the model exhibits good comprehensive performance in overall trend fitting and error control. In summary, the LSTM and K-nearest neighbor models produced relatively stable prediction results, though their overall accuracy remained slightly lower than that of GNN-LSTM. Support vector regression and AdaBoost showed relatively weaker performance on the test sets across regions. Although the decision tree model fitted the training set well, its test set metrics declined noticeably, reflecting a certain tendency toward overfitting. Overall, the GNN-LSTM model demonstrates good applicability in mid- to long-term runoff forecasting for the Huaihe River Basin. This suggests that combining temporal feature extraction with spatial topology modeling helps improve the accuracy of runoff prediction in complex river-network basins.

Table 2: Performance comparison of models in the upstream region during training and testing periods

Model	Training Set			Test Set		
	R^2	MAE	RMSE	R^2	MAE	RMSE
GNN-LSTM	0.985	15.321	28.654	0.915	13.842	22.104
LSTM	0.978	8.545	11.923	0.911	15.205	22.621
K-nearest neighbor	0.983	13.336	25.931	0.913	14.152	22.297
Support vector regression	0.972	21.536	51.499	0.78	24.031	35.459
Decision tree	0.989	7.436	10.827	0.866	16.662	27.661
AdaBoost	0.982	28.017	40.918	0.764	28.517	36.795

Table 3: Performance comparison of models in the midstream region during training and testing periods

Model	Training Set			Test Set		
	R^2	MAE	RMSE	R^2	MAE	RMSE
GNN-LSTM	0.962	85.214	70.338	0.952	38.563	65.742
LSTM	0.96	24.609	35.525	0.871	39.181	60.778
K-nearest neighbor	0.963	37.148	67.299	0.853	42.585	64.89
Support vector regression	0.923	42.132	97.307	0.835	44.991	68.731
Decision tree	0.988	25.287	39.019	0.805	48.217	74.802
AdaBoost	0.928	71.662	94.09	0.74	61.802	86.356

Table 4: Performance comparison of models in the downstream region during training and testing periods

Model	Training Set			Test Set		
	R^2	MAE	RMSE	R^2	MAE	RMSE
GNN-LSTM	0.935	48.215	82.441	0.878	37.652	62.883
LSTM	0.939	24.979	36.743	0.868	39.057	61.55
K-nearest neighbor	0.964	36.659	67.057	0.854	41.461	64.619
Support vector regression	0.923	43.422	97.579	0.853	39.729	64.992
Decision tree	0.986	27.275	41.821	0.812	46.609	73.329
AdaBoost	0.915	79.501	102.455	0.701	66.962	92.576

4.3 Mid- to Long-Term Runoff Forecasting Based on the GNN-LSTM Model

To further verify the applicability and accuracy advantages of the GNN-LSTM model in mid- to long-term runoff forecasting for the Huaihe River Basin, Fengshan station, Bengbu station, and Erhezha station were selected as representative stations, and prediction analysis was performed on the runoff process during the test period. The results show that the predicted values and observed values maintained good consistency in overall variation trend and could accurately reflect the phased fluctuation characteristics of the runoff process in different sections. This indicates that the constructed model has good applicability to the runoff evolution process in complex river-network basins. The relevant results are shown in Figures 6–8.

From the prediction results at different stations, the predicted curves for Fengshan station, Bengbu station, and Erhezha station were generally consistent with the observed curves and effectively reflected the phased fluctuation characteristics of the runoff process. The model demonstrated good responsiveness to major flood peak processes, accurately capturing the timing and variation trends of peak values. During the dry season, the predicted values also maintained good consistency with the observed values, indicating strong simulation capability for low-flow processes as well. Overall, the GNN-LSTM model can effectively extract temporal dependency features from runoff sequences and, by incorporating basin spatial topological relationships, enhance its ability to represent the runoff variation process in complex river-network systems.

Figure 6: Rainfall-runoff prediction results at Fengshan station during the test period based on GNN-LSTM

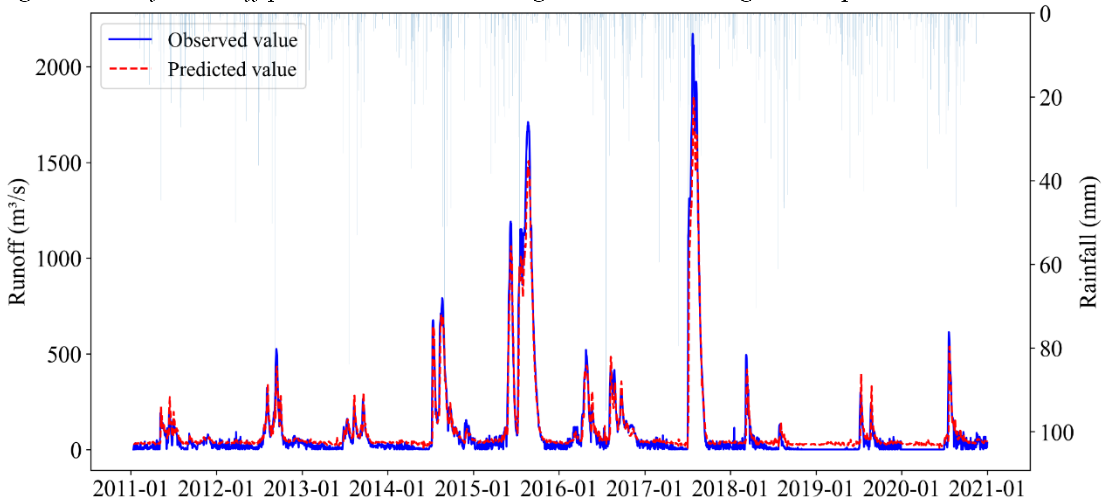


Figure 7: Rainfall-runoff prediction results at Bengbu station based on GNN-LSTM

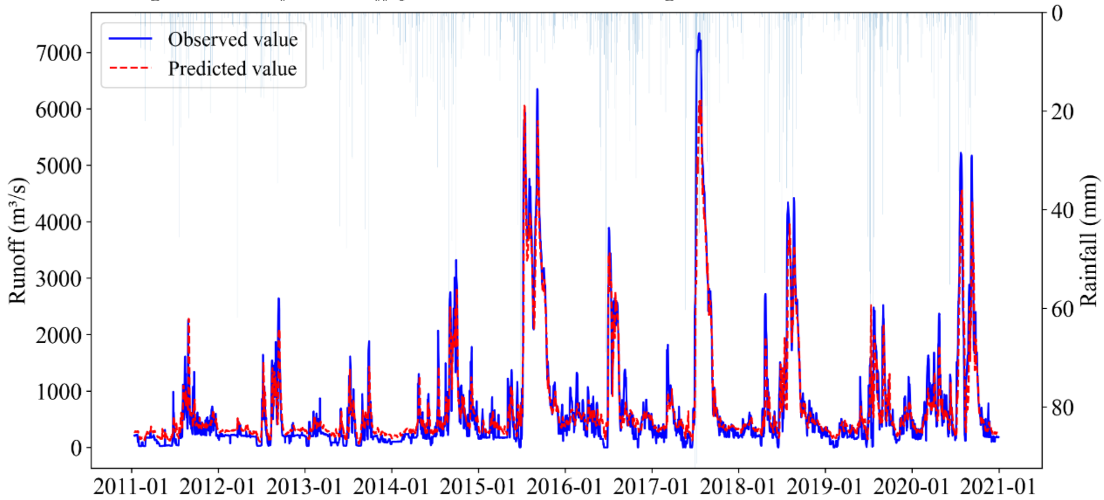
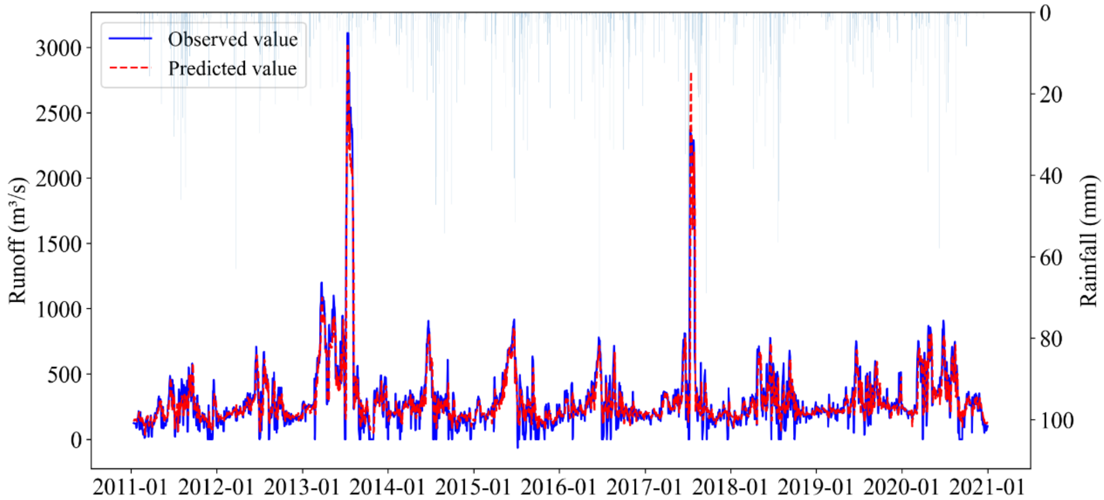


Figure 8: Rainfall-runoff prediction results at Erhezha station based on GNN-LSTM



5. Conclusion

Aiming to address the challenge that temporal dependency features and spatial connectivity relationships in the runoff evolution process under complex river-network conditions in the Huaihe River Basin are difficult to characterize simultaneously, this study constructed a GNN-LSTM mid- to long-term runoff forecasting model integrating LSTM and Graph Neural Network, based on multi-station daily meteorological and runoff data from 2011 to 2020. Through data preprocessing, basin graph structure construction, and multi-model comparative analysis, the applicability and accuracy of the model for runoff forecasting in complex river-network basins were examined. The main conclusions are as follows:

(1) Runoff variation in the Huaihe River Basin is jointly influenced by multiple meteorological factors and underlying surface conditions, exhibiting pronounced nonlinearity and complexity. Correlation analysis shows that the linear correlation between various meteorological elements and runoff is generally weak. This indicates that relying solely on a single factor or purely time-series methods is insufficient to fully characterize the runoff evolution patterns in complex river-network basins.

(2) Compared with LSTM, K-nearest neighbor, support vector regression, decision tree, and AdaBoost models, the GNN-LSTM model demonstrates superior comprehensive performance in mid- to long-term runoff forecasting for the Huaihe River Basin. Test results show that the coefficient of determination on the three regional test sets reached 0.915, 0.952, and 0.878, respectively. The model exhibits stronger fitting capability for the overall runoff variation trend, indicating that the introduction of temporal feature extraction and spatial topology modeling helps improve the accuracy of runoff prediction in complex river-network basins.

(3) From the prediction results at typical stations, the predicted values of the GNN-LSTM model are generally consistent with the observed values. The model not only reflects the phased fluctuation characteristics of the runoff process well but also demonstrates good simulation performance for the timing of flood peaks, trends in peak value changes, and low-flow processes during the dry season. This indicates that the model can effectively capture the spatiotemporal variation characteristics of runoff processes in complex river-network basins and possesses certain engineering application potential.

(4) The model constructed in this study provides a new modeling approach for mid- to long-term runoff forecasting in complex river-network basins, but there remains room for further optimization. Future research can incorporate more hydrometeorological influencing factors, more refined river network topological structures, and longer time-scale data to further improve the model's ability to characterize extreme hydrological events and regional differences in runoff response, thereby enhancing the model's generalization capability and practical application value.

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Conflicts of Interest

The authors declare no conflict of interest.

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