Research Article

Deep Learning Approaches for Stream Flow and Peak Flow Prediction: A Comparative Study

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Abstract

Stream flow prediction is crucial for effective water resource management, flood prevention, and environmental planning. This study investigates the performance of various deep neural network architectures, including LSTM, biLSTM, GRU, and biGRU models, in stream flow and peak stream flow predictions. Traditional methods for stream flow forecasting have relied on hydrological models and statistical techniques, but recent advancements in machine learning and deep learning have shown promising results in improving prediction accuracy. The study compares the performance of the models using comprehensive evaluations with 1-6 input steps for both general stream flow and peak stream flow predictions. Additionally, a detailed analysis is conducted specifically for the biLSTM model, which demonstrated high performance results. The biLSTM model is evaluated for 1-4 ahead forecasting, providing insights into its specific strengths and capabilities in capturing the dynamics of stream flow. Results show that the biLSTM model outperforms other models in terms of prediction accuracy, especially for peak stream flow forecasting. Scatter plots illustrating the forecasting performances of the models further demonstrate the effectiveness of the biLSTM model in capturing temporal dependencies and nonlinear patterns in stream flow data. This study contributes to the literature by evaluating and comparing the performance of deep neural network models for general and peak stream flow prediction, highlighting the effectiveness of the biLSTM model in improving the accuracy and reliability of stream flow forecasts.

Keywords: *Stream flow prediction, Peak flow forecasting, LSTM, biLSTM, GRU, biGRU, Deep learning, Hydrological modeling.*

1. Introduction

Stream flow prediction plays an important role in water resource management, flood prevention, and environmental planning. Accurate forecasts are crucial for applications like reservoir planning, agricultural water management, and catchment water balance estimation. The stream flow is influenced by various factors such as watershed characteristics, wetland presence, and hyporheic zone interactions [1]. Both physical and data-driven models are used in stream flow forecasting. Physical models rely on an understanding of hydrological processes, while data-driven models, such as Artificial Neural Networks (ANN) and hybrid models rely on leverage historical data. Data-driven models, have been shown to improve the accuracy of stream flow forecasting and can handle complex non-linear relationships and patterns in the data, making them effective in capturing the dynamics of stream flow [2], [3], [4]. Traditional methods of streamflow forecasting have been based on hydrological models and statistical techniques. However, recent advancements in machine learning (ML) and deep learning (DL) methods have shown promise results in improving the accuracy and reliability of streamflow predictions [2], [3], [5]. Several studies have demonstrated the effectiveness of machine learning models, such as support vector regression, extreme learning machine, and Gaussian processes, in stream flow forecasting [6], [7], [8], [9], [10]. Additionally, the application of deep learning techniques, including recurrent neural networks (RNN) and long short-term memory (LSTM), has shown accurate results in capturing the temporal dependencies and nonlinear patterns in stream flow data [11], [12], [13], [14]. Furthermore, the integration of machine learning algorithms with optimization techniques, such as genetic algorithms and gravitational search algorithms has been explored to enhance the accuracy of river flow forecasting model [15], [16]. The use of ensemble learning methods, such as hybrid tree based and instance-based learning, has been investigated to improve the robustness and generalization of stream flow forecasting models [17], [18]. These approaches aim to address the inherent uncertainties and complexities associated with hydrological systems, thereby providing more reliable predictions of stream flow dynamics. Stream flow forecasting has traditionally focused on overall stream flow patterns, but there is a growing recognition of the importance of peak flow forecasting. Peak flow forecasting is crucial for determining the severity of potential floods. In particular, the ability to predict the magnitude and timing of peak flows is essential for effective flood risk management [19]. One approach involves the use of k-means clustering to identify regions with similar mean annual runoff, followed by Random Forest to map climate and catchment features to flow quantiles in each cluster [20]. Another study compared different machine learning algorithms for streamflow forecasting and found that categorical-based streamflow forecast outperformed regression-based forecast, with forest-based algorithms showing superior performance in forecasting high streamflow fluctuations [21]. Additionally, a comparison between a stacked model based on Random Forest and Multilayer Perceptron algorithms and a bi-directional LSTM network model showed comparable forecasting capabilities, with the stacked model performing better in predicting peak flow rates [22]. Ensemble machine-learning regression frameworks have also been developed to predict missing monthly streamflow data, achieving high accuracy using models such as gradient boosting regression and random forest regression [23]. The performance of three data-driven models (ANN, ANFIS, and SVM) was evaluated for streamflow prediction, with the SVM model outperforming the other two models [24]. Li and Yuan developed a cascade LSTM model to forecast daily streamflow, achieving skillful predictions with high Kling-Gupta efficiency (KGE) values at different lead times [25]. Taormina et al. compared LSTM models trained with local and global datasets, finding that training with global meteorological forcing resulted in higher model performance for streamflow predictions in ungauged basins [26]. Granata compared a simpler model based on stacked Random Forest and Multilayer Perceptron algorithms with a more complex bi-directional LSTM network model, finding comparable forecasting capabilities but with shorter computation times for the stacked model [27]. Majumder and Reich proposed a non-stationary process mixture model (NPMM) for extreme streamflow forecasts, incorporating downscaled climate model precipitation projections and neural networks to address intractable likelihoods [22].

In the presented study, deep neural network architectures incorporating LSTM, biLSTM, GRU, and biGRU layers were developed to perform stream flow and peak stream flow predictions. Through this, the performance of the four models was compared, and an evaluation of the peak and overall stream flow predictions was conducted. The motivation of the study is listed as:

The study involves evaluating used models for general peak current prediction, namely LSTM, GRU, and biLSTM. The aim is to compare the performance of these models to identify their strengths and weaknesses.

There is no existing study in the literature that utilizes a biGRU model for peak current prediction. By incorporating the biGRU model, this study aims to contribute to the literature by evaluating and comparing the performance of this model against others.

In addition to the comparative analysis of LSTM, biLSTM, GRU, and biGRU models in terms of general stream flow and peak stream flow predictions, this study employs a comprehensive evaluation approach using 1-6 input steps.

Beyond this, a detailed analysis is conducted specifically for the biLSTM model, which demonstrated high performance results. For the 1-input case, the study delves into the model's ability to make accurate 1-4 steps ahead predictions for both general stream flow and peak stream flow.

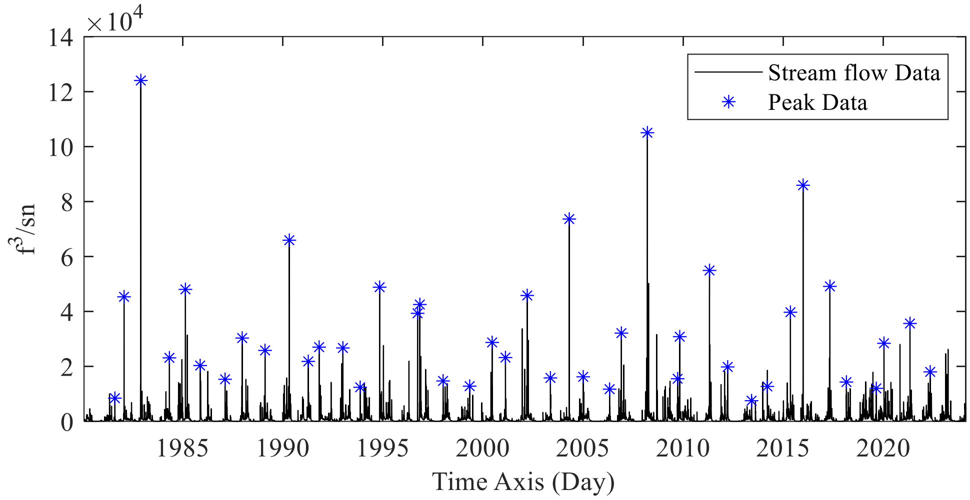
This detailed examination aims to provide insights into the specific strengths and capabilities of the biLSTM model in capturing the dynamics of stream flow, contributing to a more nuanced understanding of its predictive abilities.

2. Materials and Methods

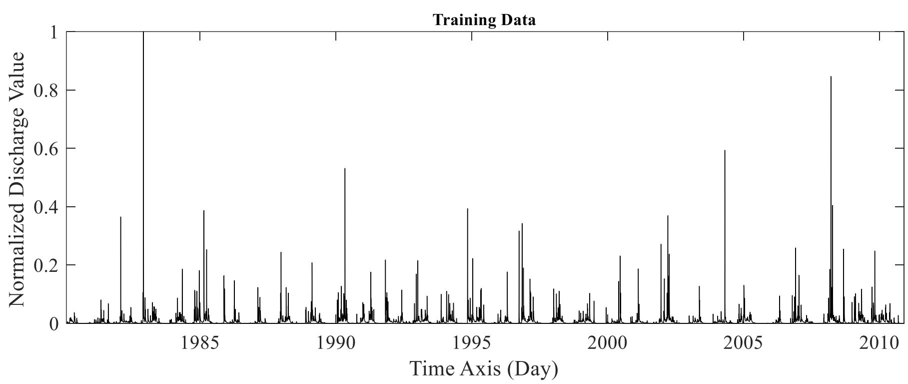
2.1. Daily Stream Flow Data Used for Forecasting Study

In this study, the stream flow data have been collected from the Buffalo River near St. Joe, AR. This region, nestled in the Arkansas, experiences a temperate climate characterized by distinct seasons. Summers are typically warm and humid, with average temperatures ranging from 70°F to 90°F (21°C to 32°C). Winters are relatively mild, with temperatures averaging between 30°F and 50°F (−1°C to 10°C). The location associated with the recorded daily stream flow data can be described as follows: The data pertains to a specific area within Searcy County, Arkansas, identified by the Hydrologic Unit Code (HUC) 11010005. The geographical coordinates of this location are approximately 35°58'59" North latitude and 92°44'50" West longitude in the NAD83 coordinate system. The drainage area of this location, indicating the total land area that contributes water flow to a specific point, is measured to be 829 square miles.

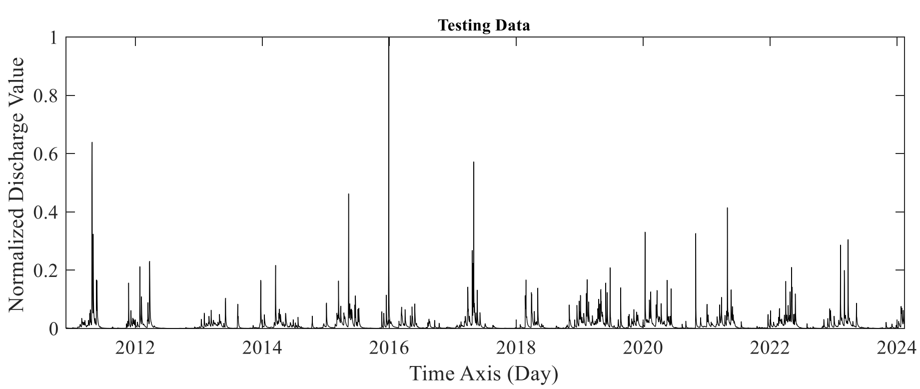
The stream flow data has been recorded from USGS Water Data for USA [28], covering the period from 1980 to 2024, with daily granularity. The utilized datasets and the defined peak data in the database are presented in Figure 1. Seventy percent (70%) of the data has been allocated for training purposes, while the remaining thirty percent (30%) has been reserved for testing purposes.


×10^4
Stream flow Data
Peak Data
f^3/sn
Time Axis (Day)

a)


Training Data
Normalized Discharge Value
Time Axis (Day)

b)


Testing Data
Normalized Discharge Value
Time Axis (Day)

c)

Figure 1. a) Daily stream flow data and peak flow data recorded from Buffalo River near St. Joe, AR b) Normalized stream flow training data c) Normalized stream flow testing data

Table 1. Statistical values of the streamflow data used in this study.

	Maximum (f^3/sn)	Minimum (f3/sn)	Mean (f3/sn)	Variance	Skewness	Kurtosis
Training Data	124000	11	1.0847e+03	9.7819e+06	15.4538	415.2162
Testing Data	85900	12.4000	1.2468e+03	8.1589e+06	11.4995	237.3822

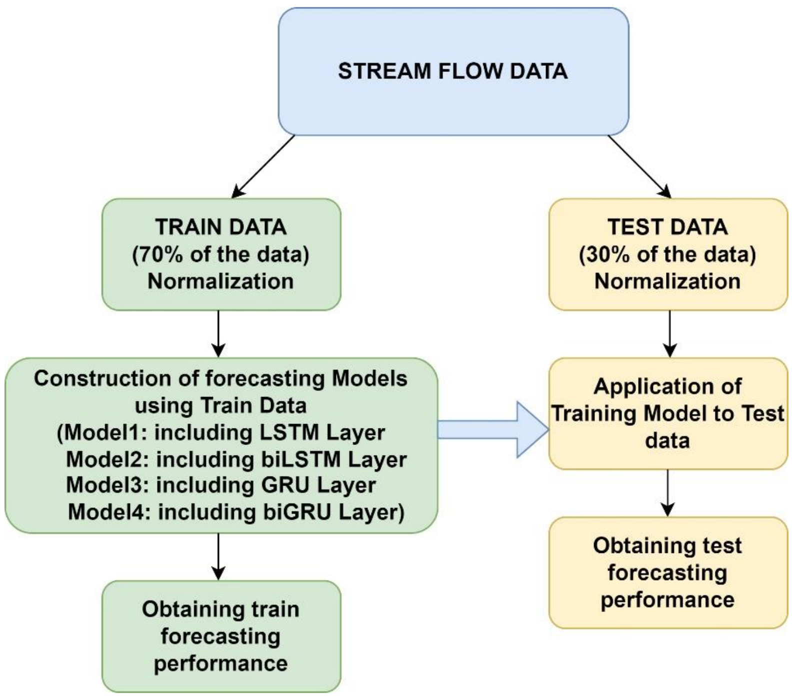


Figure 2. Flow chart of the study

In the conducted study, predictions were performed for 1-3 steps ahead using input data from the previous 1–5-time lags. The variables corresponding to the input and output data used in the prediction study are provided in Table 2.

Table 2. Input and output variables used for forecasting study.

	Input Variables	Output Variable		Input Variables	Output Variable

One Input-One ahead forecasting	Q(t-1)	Q(t)	**Four Input-One ahead forecasting**	Q(t-4), Q(t-3), Q(t-2), Q(t-1)	Q(t)
One Input-two ahead forecasting	Q(t-2)	Q(t)	**Four Input-two ahead forecasting**	Q(t-5), Q(t-4), Q(t-3), Q(t-2)	Q(t)
One Input-Three ahead forecasting	Q(t-3)	Q(t)	**Four Input-three ahead forecasting**	Q(t-6), Q(t-5), Q(t-4), Q(t-3)	Q(t)
Two Input-One ahead forecasting	Q(t-2), Q(t-1)	Q(t)	**Five Input-One ahead forecasting**	Q(t-5), Q(t-4), Q(t-3), Q(t-2), Q(t-1)	Q(t)
Two Input-two ahead forecasting	Q(t-3), Q(t-2)	Q(t)	**Five Input-two ahead forecasting**	Q(t-6), Q(t-5), Q(t-4), Q(t-3), Q(t-2)	Q(t)
Two Input-three ahead forecasting	Q(t-4), Q(t-3)	Q(t)	**Five Input-three ahead forecasting**	Q(t-7), Q(t-6), Q(t-5), Q(t-4), Q(t-3)	Q(t)
Three Input-One ahead forecasting	Q(t-3), Q(t-2), Q(t-1)	Q(t)	**Six Input-One ahead forecasting**	Q(t-6), Q(t-5), Q(t-4), Q(t-3), Q(t-2), Q(t-1)	Q(t)
Three Input-two ahead forecasting	Q(t-4), Q(t-3), Q(t-2)	Q(t)	**Six Input-two ahead forecasting**	Q(t-7), Q(t-6), Q(t-5), Q(t-4), Q(t-3), Q(t-2)	Q(t)
Three Input-three ahead forecasting	Q(t-5), Q(t-4), Q(t-3)	Q(t)	**Six Input-three ahead forecasting**	Q(t-8), Q(t-7), Q(t-6), Q(t-5), Q(t-4), Q(t-3)	Q(t)

2.2. Deep Learning Algorithm

Deep learning, a subset of machine learning, has gained significant attention due to its ability to process large datasets, identify hidden patterns, and make accurate predictions [29]. It is characterized by its capacity to generalize to new users, making it suitable for real-world applications [30]. The existence of LSTM, biLSTM, GRU, and biGRU models is well established in the field of deep learning algorithms for prediction work. These models have been widely used and compared in various studies. In this study, predictions were made using deep learning algorithms, including LSTM, biLSTM, GRU, and biGRU models.

2.2.1. Long Short-Term Memory Networks

LSTM is a type of recurrent neural network (RNN) that has gained significant attention due to its ability to handle long-term dependencies and process sequential data effectively. It was first proposed by Schmidhuber et al. in 1997 and designed to address the vanishing and exploding gradient problems encountered in traditional RNNs [31]. The architecture of LSTM includes specialized units called cells, which have the unique ability to maintain and update a cell state, allowing them to retain information over long sequences and selectively forget or remember information as needed. LSTM cells consist of three main components:

Cell State: The part that stores and carries long-term information.

Input Gate: A gate that determines which information will be added to the cell state.

Output Gate: A gate that determines how much information will be output from the cell state.

These components regulate the flow of information during the learning process of LSTM. The input gate controls the addition of new information to the cell state, while the output gate determines which information will be output [31].

2.2.2. Bidirectional Long Short Term Memory Networks

Bidirectional Long Short-Term Memory (BiLSTM) refers to a variant of LSTM, standing for "Bidirectional Long Short-Term Memory." The key feature of BiLSTM is its ability to provide a bidirectional flow of information [32]. This involves processing input data both in a regular manner (from backward to forward) and in a reversed manner (from forward to backward), resulting in the generation of two distinct cell states. Consequently, biLSTM offers greater flexibility in understanding both directions of dependencies in a time series and capturing long-term contexts more effectively. The components of biLSTM are similar to traditional LSTM and consist of the Cell State, Input Gate, and Output Gate. However, BiLSTM, by integrating bidirectional processing, assists in obtaining a more comprehensive context compared to traditional LSTM [32]. This feature proves particularly beneficial in applications such as natural language processing, time series prediction, and similar tasks.

2.2.3. Gated Recurrent Units

The Gated Recurrent Unit (GRU) is a deep learning model proposed for various applications, including time series classification and disease prediction. GRU is a type of RNN cell, similar to another popular RNN type called LSTM. The primary goal of GRU is to effectively model long-term dependencies and sequential data sets.

The GRU, introduced by Cho et al. in 2014, was designed to allow each recurrent unit to adaptively capture dependencies of different time scales [33]. Much like the LSTM unit, the GRU incorporates gating units that modulate the flow of information within the unit. However, unlike LSTM, GRU does not have separate memory cells. The distinctive features of GRU include the Update Gate, which controls how much old information to retain, with a higher value preserving more old information, and the Reset Gate, which determines which information to forget, with a higher value leading to more past information being discarded. Additionally, GRU maintains a Cell State, similar to the cell state in LSTM, to store long-term information.

GRU effectively manages long-term dependencies akin to LSTM but uses fewer parameters. Consequently, GRU demonstrates comparable performance to LSTM while potentially achieving faster training times and reduced computational costs [34].

2.2.4. Bidirectional Gated Recurrent Units

Bidirectional Gated Recurrent Units consist of two sets of Gated Recurrent Units that process input data in both the forward direction (from backward to foward) and the backward direction (from forward to backward). BiGRUs provide the capability to model dependencies in both directions of the input data more effectively by enabling bidirectional information flow. GRU cells operating in both directions are utilized to gain a more comprehensive understanding of relationships in time series or sequential data.

The fundamental components of biGRUs are as follows:
Forward GRU: A GRU cell that processes input data from past to future.
Backward GRU: A GRU cell that processes input data from future to past.

2.2.5. Proposed Deep Neural Network Architectures

In the proposed study, deep neural network architectures were developed for the 1-3 step ahead prediction of daily stream flow data using LSTM, biLSTM, GRU, and biGRU layers. In the first model, an LSTM layer was utilized, followed by a biLSTM layer in the second model, a GRU layer in the third model, and a biGRU layer in the fourth model. During the development of the architecture, prediction tasks were performed using LSTM, biLSTM, GRU, and biGRU layers consisting of different numbers of cells ranging from 32 to 256. Additionally, fully connected layers with varying numbers and sequences were incorporated into the architecture. The final network structure was determined based on the achieved best prediction performance and is illustrated in Figure 3.

The options are used in this study as follows: The optimization algorithm employed for training is 'adam', which is an adaptive optimization algorithm widely used in deep learning models. The training process is set to run for a maximum of 100 epochs. The 'Gradient Threshold' parameter is set to 1, limiting the gradient value to prevent exploding gradients during training. The 'Initial Learn Rate' is set to 0.01, defining the initial learning rate for the model. Additionally, a piecewise learning rate schedule is implemented using 'Learn Rate Schedule', which allows the learning rate to adapt at different stages of training. The 'Learn Rate Drop Factor' of 0.1 and 'Learn Rate Drop Period' of 50 indicate that the learning rate will drop by a factor of 0.1 every 50 epochs.

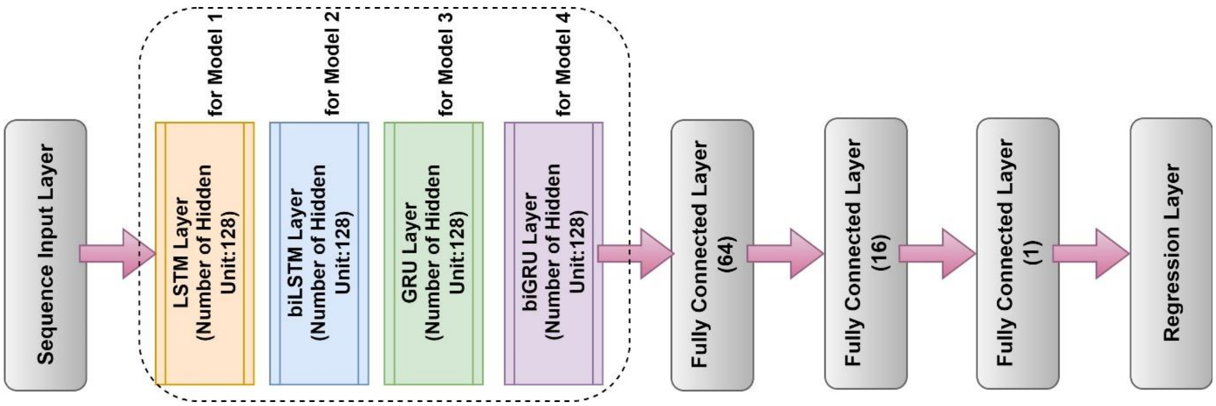


Figure 3. Deep network structure used in forecasting study.

2.3. Performance Parameters Used in the Study

In the conducted prediction study, the performance of the models was evaluated based on several performance parameters for stream flow prediction, including the Correlation Coefficient (R), Mean Squared Error (MSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE).

Mean Absolute Error (MAE) represents the average absolute difference between the observed and predicted values in the dataset and is calculated using the formula in Equation 1:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|X_{observed,i} - X_{forecasted,i}\right| \quad (1)$$

Mean Squared Error (MSE) is computed by averaging the squared differences between observed and predicted values in the dataset, as shown in Equation 2:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_{observed,i} - X_{forecasted,i})^2 \quad (2)$$

Correlation Coefficient (R) indicates the degree, direction, and significance of the relationship between observed and predicted values and is represented by Equation 3:

$$R = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{X_{observed,i}-\mu_x}{\sigma_x}\right)\left(\frac{X_{forecasted,i}-\mu_{xfor}}{\sigma_{xfor}}\right) \quad (3)$$

In this equation, μ_x and μ_xfor are the means of the observed and predicted time series, while σ_x and σ_xfor are their standard deviations, respectively.

Coefficient of Determination (R^2) is commonly used to measure the prediction capability of models. As R^2 approaches 1, it indicates an increased relationship between observed and predicted values. R^2 is calculated using Equation 4:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(X_{observed,i} - X_{forecasted,i})^2}{\sum_{i=1}^{N}(X_{observed,i} - \mu_x)^2} \quad (4)$$

3. Results

In the conducted study, the prediction performance of LSTM, biLSTM, GRU, and biGRU models was initially obtained for 1-6 input steps and one-ahead forecasting from normalized stream flow data. The prediction study includes the illustration of one-input one-ahead forecasting graphs, as an example in Figure 4. The overall stream flow prediction performances obtained from all models are presented in Table 3, and the peak stream flow prediction performances are provided in Table 4. Additionally, scatter plot graphs illustrating the prediction performances are presented for general stream flow in Figure 5 and for peak stream flow in Figure 6.

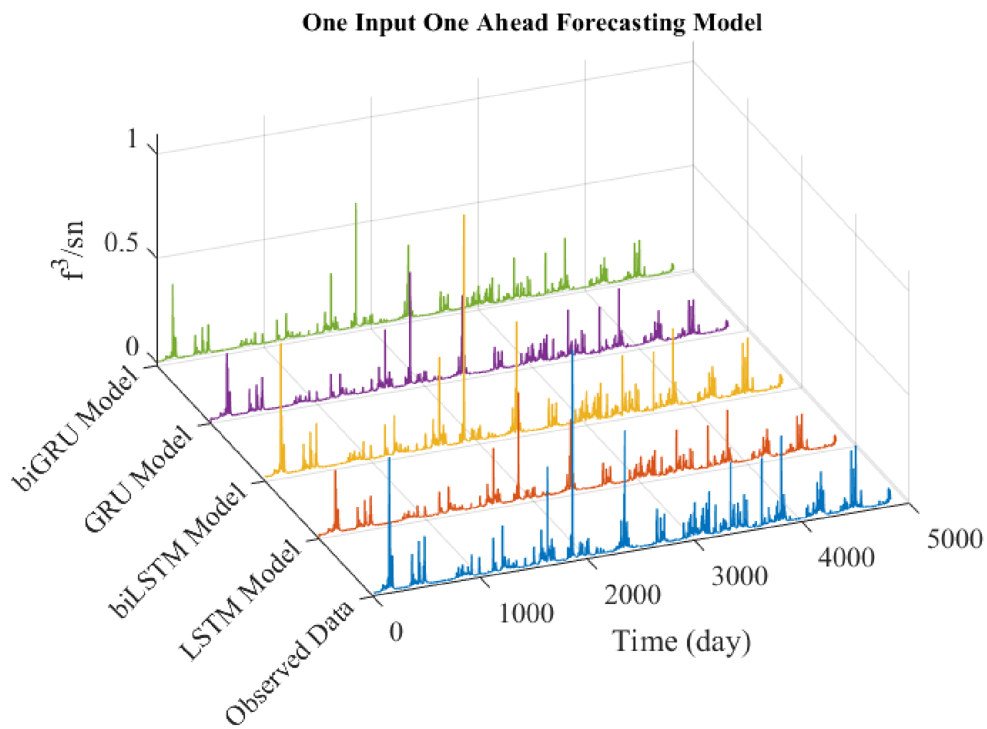


Figure4. One Input One ahead forecasting data using LSTM, biLSTM, GRU, biGRU Models

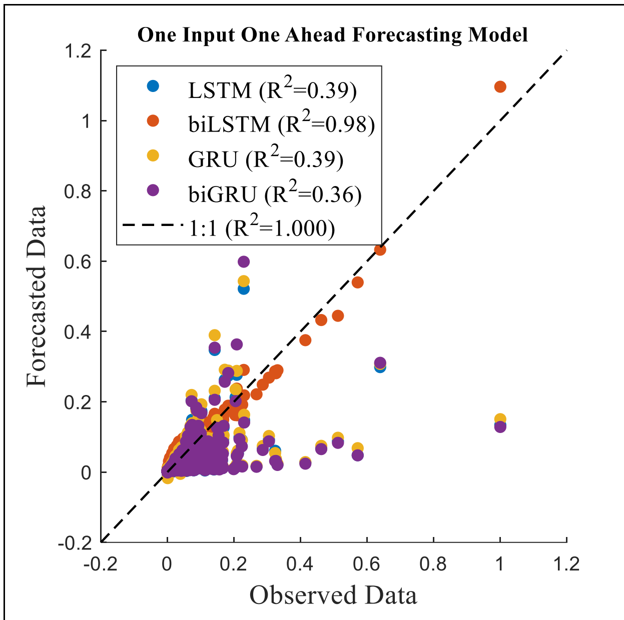
Table 3. One-six input one ahead streamflow forecasting performances using proposed models.

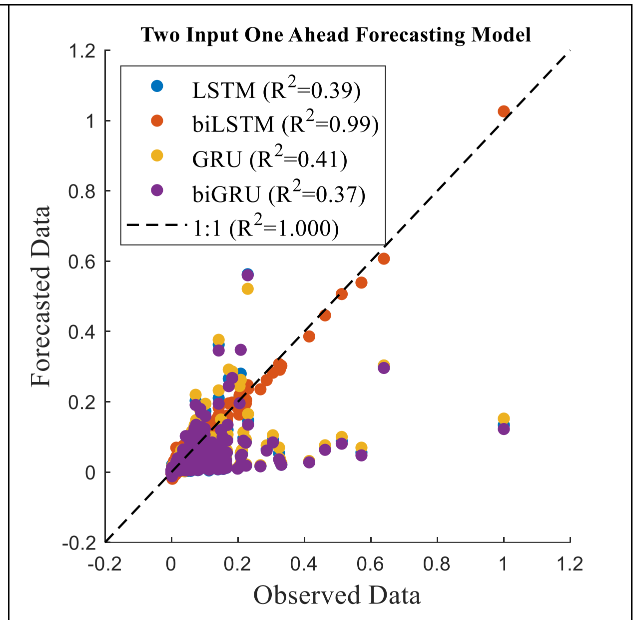
Model	MSE	MAE	R	R^2
One Input One Ahead Forecasting				
LSTM	0.0007	0.0059	0.6240	0.3894
biLSTM	0.0000	0.0033	0.9891	0.9784
GRU	0.0007	0.0067	0.6278	0.3941
biGRU	0.0007	0.0066	0.6035	0.3642
Two Input One Ahead Forecasting				
LSTM	0.0007	0.0061	0.6219	0.3868
biLSTM	0.0000	0.0023	0.9929	0.9859
GRU	0.0007	0.0076	0.6365	0.4052
biGRU	0.0007	0.0069	0.6055	0.3667
Three Input One Ahead Forecasting				
LSTM	0.0007	0.0061	0.6041	0.3650
biLSTM	0.0001	0.0025	0.9746	0.9499
GRU	0.0007	0.0078	0.6383	0.4075
biGRU	0.0007	0.0064	0.6068	0.3682
Four Input One Ahead Forecasting				
LSTM	0.0007	0.0074	0.6150	0.3783
biLSTM	0.0000	0.0021	0.9833	0.9669
GRU	0.0007	0.0063	0.6355	0.4039
biGRU	0.0007	0.0061	0.6210	0.3857
Five Input One Ahead Forecasting				
LSTM	0.0007	0.0070	0.6294	0.3962
biLSTM	0.0000	0.0038	0.9809	0.9622
GRU	0.0007	0.0064	0.6387	0.4080
biGRU	0.0007	0.0060	0.6325	0.4001
Six Input One Ahead Forecasting				
LSTM	0.0007	0.0073	0.6293	0.3960
biLSTM	0.0001	0.0047	0.9783	0.9571
GRU	0.0007	0.0062	0.6241	0.3895
biGRU	0.0007	0.0059	0.6127	0.3754

Table 4. One-six in.put one ahead peak streamflow forecasting performances using proposed models.

Model	MSE	MAE	R	R^2
One Input One Ahead Forecasting				
LSTM	0.1592	0.3073	0.5497	0.3022
biLSTM	0.1446	0.2825	0.9947	0.9895
GRU	0.1556	0.3021	0.5769	0.3328
biGRU	0.1603	0.3092	0.5385	0.2899
Two Input One Ahead Forecasting				
LSTM	0.1585	0.3062	0.5530	0.3058
biLSTM	0.1341	0.2745	0.9976	0.9953
GRU	0.1545	0.3003	0.5780	0.3341
biGRU	0.1604	0.3092	0.5364	0.2877
Three Input One Ahead Forecasting				
LSTM	0.1645	0.3150	0.5354	0.2867
biLSTM	0.1347	0.2787	0.9904	0.9809
GRU	0.1541	0.2997	0.5842	0.3413
biGRU	0.1599	0.3085	0.5493	0.3017
Four Input One Ahead Forecasting				
LSTM	0.1601	0.3087	0.5386	0.2901
biLSTM	0.1246	0.2659	0.9918	0.9837
GRU	0.1553	0.3014	0.5818	0.3385
biGRU	0.1584	0.3062	0.5544	0.3073
Five Input One Ahead Forecasting				
LSTM	0.1576	0.3049	0.5570	0.3103
biLSTM	0.1266	0.2682	0.9888	0.9778
GRU	0.1546	0.3006	0.5864	0.3439
biGRU	0.1565	0.3031	0.5771	0.3331
Six Input One Ahead Forecasting				
LSTM	0.1567	0.3036	0.5597	0.3133
biLSTM	0.1279	0.2698	0.9848	0.9699
GRU	0.1569	0.3039	0.5718	0.3270

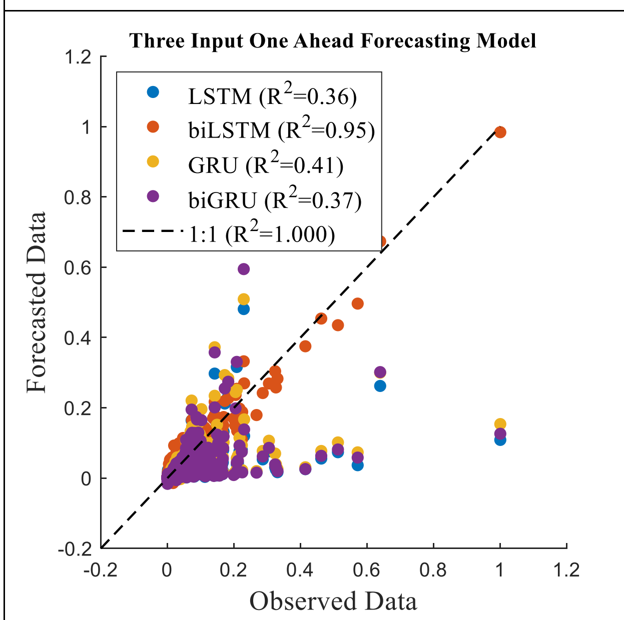
biGRU	0.1596	0.3080	0.5532	0.3060

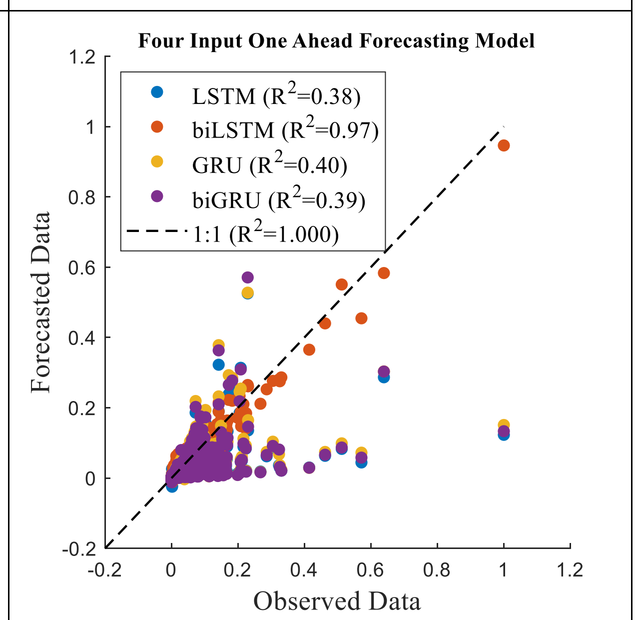




a

b





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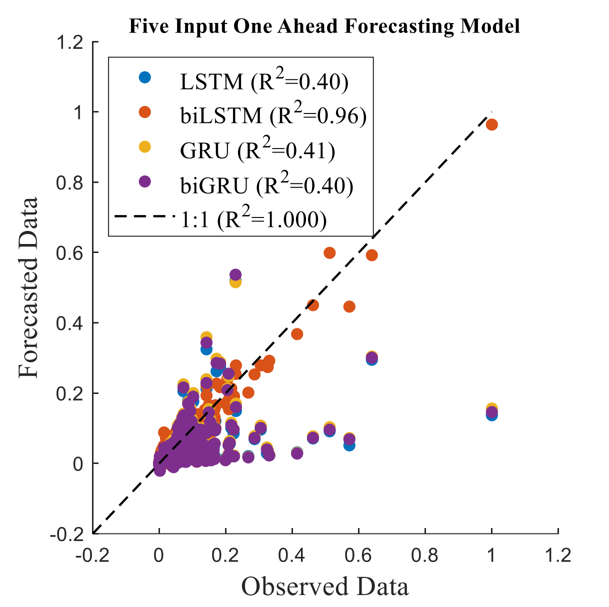

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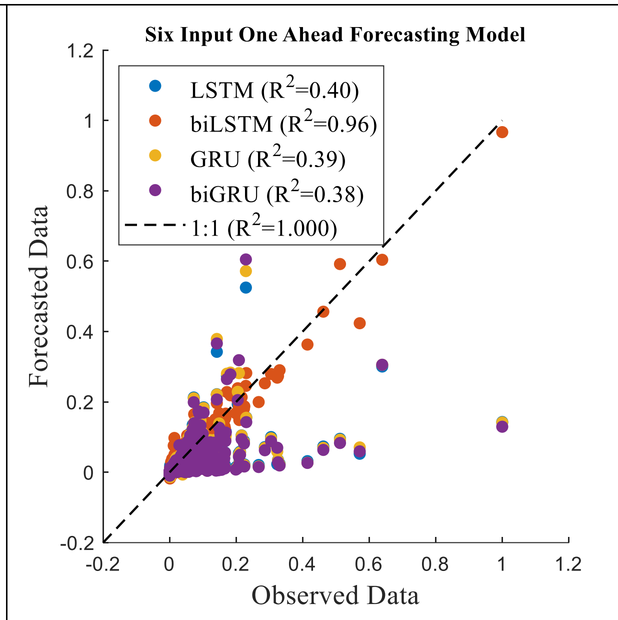
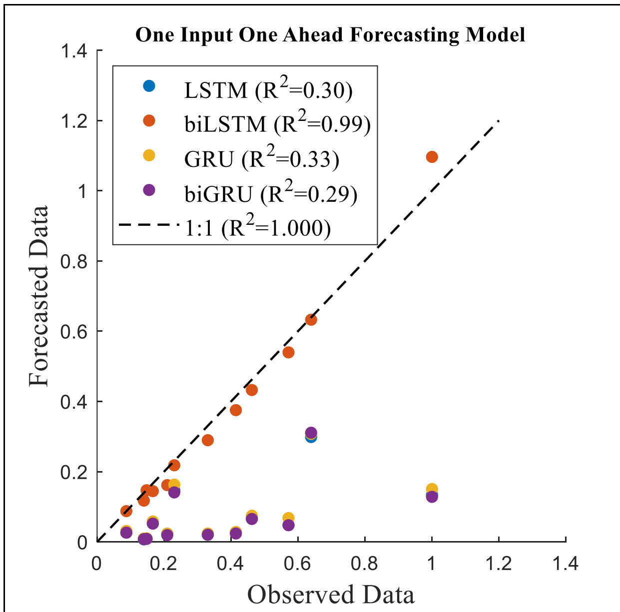


f

Figure5. Scatter plots for a-f) one-six input one ahead forecasting data using LSTM, biLSTM, GRU, biGRU models.



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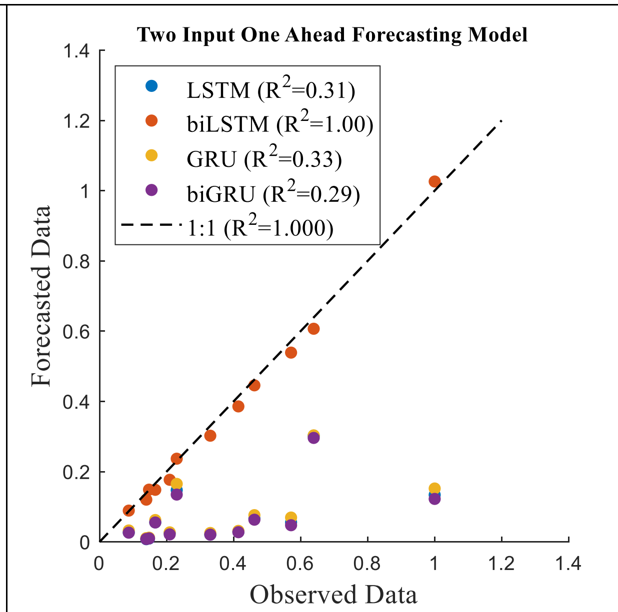

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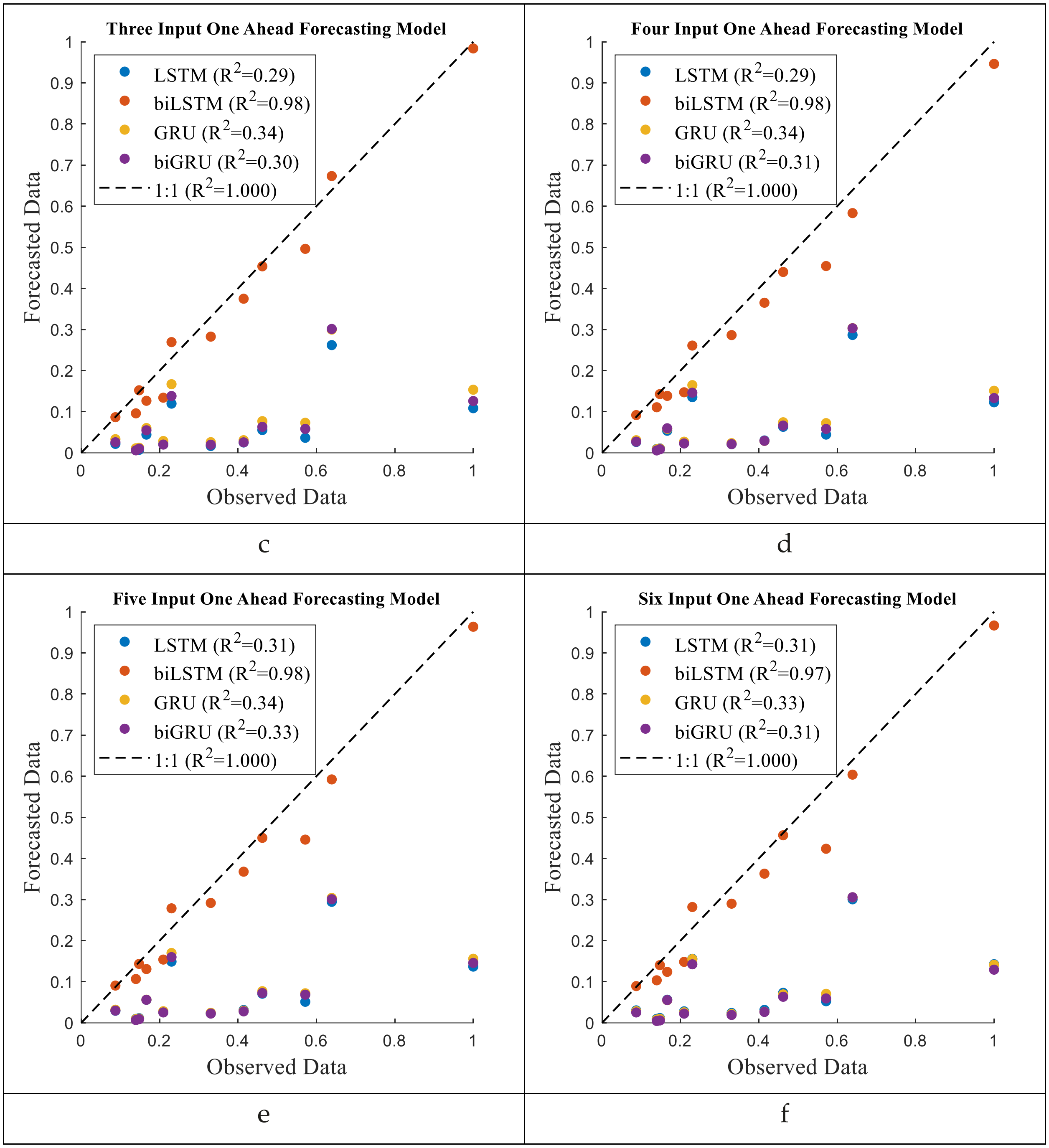


Figure 6. Scatter plots for a-f) one-six input one ahead forecasting peak data using LSTM, biLSTM, GRU, biGRU models.

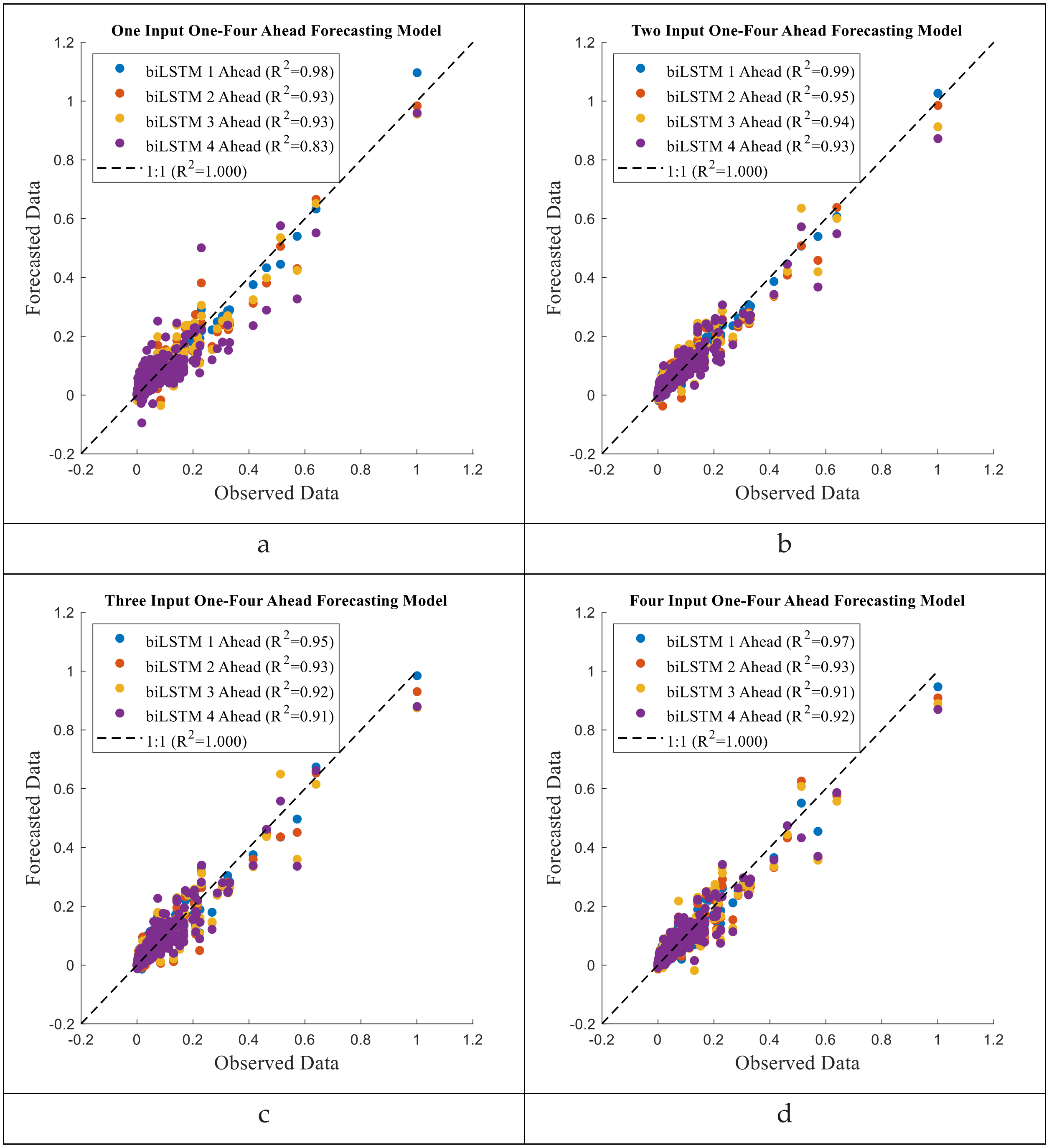
In the second phase of this study, the biLSTM model, which exhibited high prediction performance, was analyzed for 1-6 input steps and 1-4 ahead forecasting. The overall and peak stream flow performances are provided in Table 5 and Table 6, respectively. Additionally, scatter plots illustrating the ahead forecasting performances of the biLSTM model for both general stream flow and peak stream flow are presented in Figure 7 and Figure 8, respectively.

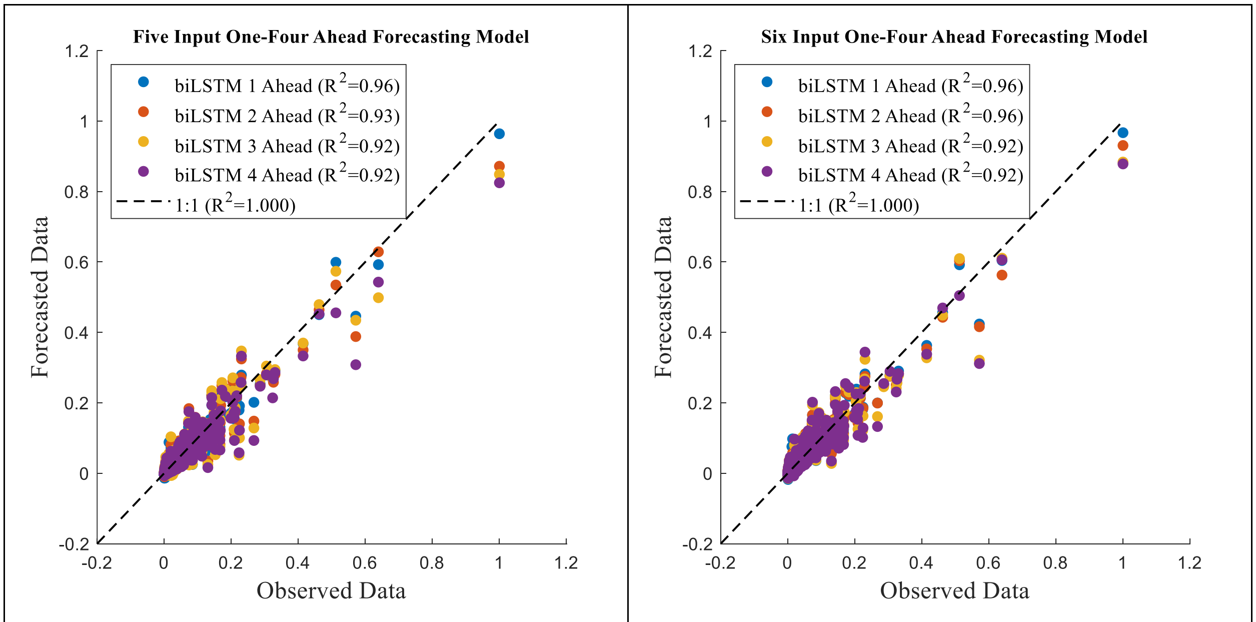
Table 5. One-six input one-four ahead streamflow forecasting performances using biLSTM model.

Model	MSE	MAE	R	R^2
One Ahead Forecasting				
One Input biLSTM Model	0.0000	0.0033	0.9891	0.9784
Two Input biLSTM Model	0.0000	0.0023	0.9929	0.9859
Three Input biLSTM Model	0.0001	0.0025	0.9746	0.9499
Four Input biLSTM Model	0.0000	0.0021	0.9833	0.9669
Five Input biLSTM Model	0.0000	0.0038	0.9809	0.9622
Six Input biLSTM Model	0.0001	0.0047	0.9783	0.9571
Two Ahead Forecasting				
One Input biLSTM Model	0.0001	0.0029	0.9662	0.9336
Two Input biLSTM Model	0.0001	0.0033	0.9760	0.9525
Three Input biLSTM Model	0.0001	0.0029	0.9668	0.9347
Four Input biLSTM Model	0.0001	0.0029	0.9659	0.9330
Five Input biLSTM Model	0.0001	0.0032	0.9645	0.9303
Six Input biLSTM Model	0.0001	0.0027	0.9775	0.9555
Three Ahead Forecasting				
One Input biLSTM Model	0.0001	0.0034	0.9650	0.9312
Two Input biLSTM Model	0.0001	0.0034	0.9713	0.9435
Three Input biLSTM Model	0.0001	0.0031	0.9605	0.9225
Four Input biLSTM Model	0.0001	0.0035	0.9536	0.9093
Five Input biLSTM Model	0.0001	0.0033	0.9584	0.9185
Six Input biLSTM Model	0.0001	0.0030	0.9614	0.9242
Four Ahead Forecasting				
One Input biLSTM Model	0.0002	0.0049	0.9106	0.8293
Two Input biLSTM Model	0.0001	0.0032	0.9658	0.9328
Three Input biLSTM Model	0.0001	0.0045	0.9548	0.9117
Four Input biLSTM Model	0.0001	0.0030	0.9618	0.9250
Five Input biLSTM Model	0.0001	0.0036	0.9581	0.9180
Six Input biLSTM Model	0.0001	0.0034	0.9582	0.9182

Table 6. One-six input one-four ahead peak streamflow forecasting performances using biLSTM model.

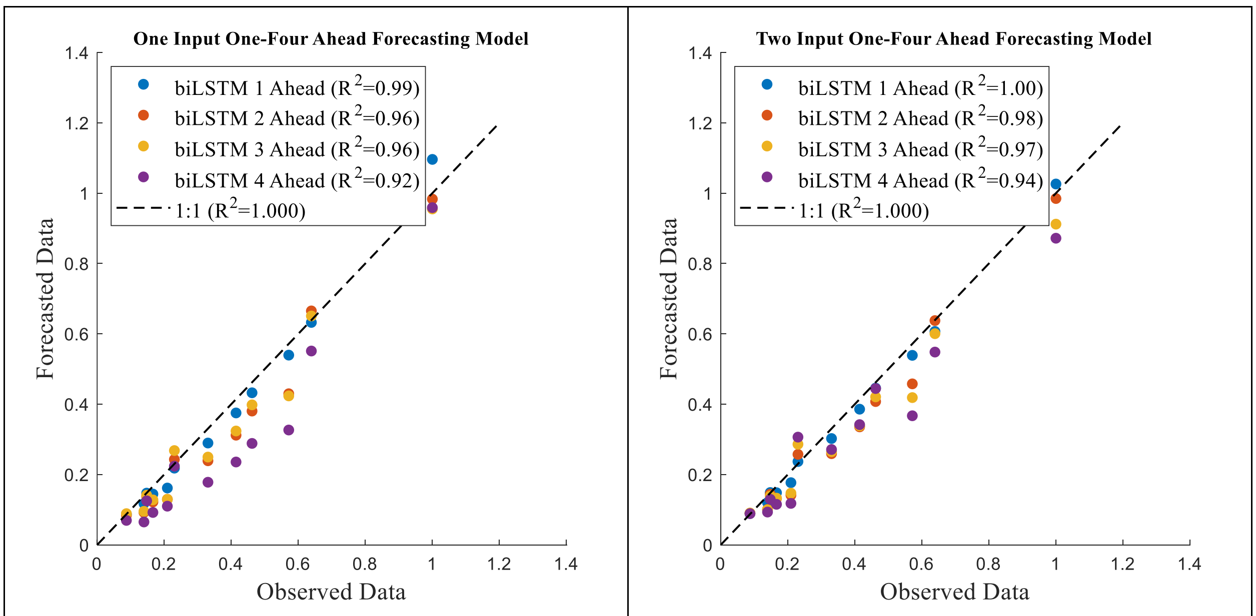
Model	MSE	MAE	R	R^2
One Ahead Forecasting				
One Input biLSTM Model	0.1446	0.2825	0.9947	0.9895
Two Input biLSTM Model	0.1341	0.2745	0.9976	0.9953
Three Input biLSTM Model	0.1347	0.2787	0.9904	0.9809
Four Input biLSTM Model	0.1246	0.2659	0.9918	0.9837
Five Input biLSTM Model	0.1266	0.2682	0.9888	0.9778
Six Input biLSTM Model	0.1279	0.2698	0.9848	0.9699
Two Ahead Forecasting				
One Input biLSTM Model	0.1352	0.2754	0.9816	0.9635
Two Input biLSTM Model	0.1320	0.2720	0.9882	0.9765
Three Input biLSTM Model	0.1299	0.2748	0.9850	0.9702
Four Input biLSTM Model	0.1234	0.2659	0.9727	0.9461
Five Input biLSTM Model	0.1230	0.2692	0.9663	0.9337
Six Input biLSTM Model	0.1227	0.2641	0.9853	0.9708
Three Ahead Forecasting				
One Input biLSTM Model	0.1302	0.2714	0.9814	0.9631
Two Input biLSTM Model	0.1224	0.2641	0.9843	0.9689
Three Input biLSTM Model	0.1214	0.2653	0.9662	0.9335
Four Input biLSTM Model	0.1211	0.2645	0.9662	0.9336
Five Input biLSTM Model	0.1173	0.2638	0.9626	0.9266
Six Input biLSTM Model	0.1223	0.2660	0.9538	0.9098
Four Ahead Forecasting				
One Input biLSTM Model	0.1362	0.2740	0.9602	0.9219
Two Input biLSTM Model	0.1193	0.2630	0.9706	0.9421
Three Input biLSTM Model	0.1254	0.2714	0.9487	0.9001
Four Input biLSTM Model	0.1209	0.2671	0.9590	0.9196
Five Input biLSTM Model	0.1176	0.2628	0.9446	0.8924
Six Input biLSTM Model	0.1231	0.2685	0.9443	0.8916


One Input One-Four Ahead Forecasting Model
biLSTM 1 Ahead (R^2=0.98)
biLSTM 2 Ahead (R^2=0.93)
biLSTM 3 Ahead (R^2=0.93)
biLSTM 4 Ahead (R^2=0.83)
1:1 (R^2=1.000)
Forecasted Data
Observed Data
a
Two Input One-Four Ahead Forecasting Model
biLSTM 1 Ahead (R^2=0.99)
biLSTM 2 Ahead (R^2=0.95)
biLSTM 3 Ahead (R^2=0.94)
biLSTM 4 Ahead (R^2=0.93)
1:1 (R^2=1.000)
Forecasted Data
Observed Data
b
Three Input One-Four Ahead Forecasting Model
biLSTM 1 Ahead (R^2=0.95)
biLSTM 2 Ahead (R^2=0.93)
biLSTM 3 Ahead (R^2=0.92)
biLSTM 4 Ahead (R^2=0.91)
1:1 (R^2=1.000)
Forecasted Data
Observed Data
c
Four Input One-Four Ahead Forecasting Model
biLSTM 1 Ahead (R^2=0.97)
biLSTM 2 Ahead (R^2=0.93)
biLSTM 3 Ahead (R^2=0.91)
biLSTM 4 Ahead (R^2=0.92)
1:1 (R^2=1.000)
Forecasted Data
Observed Data
d

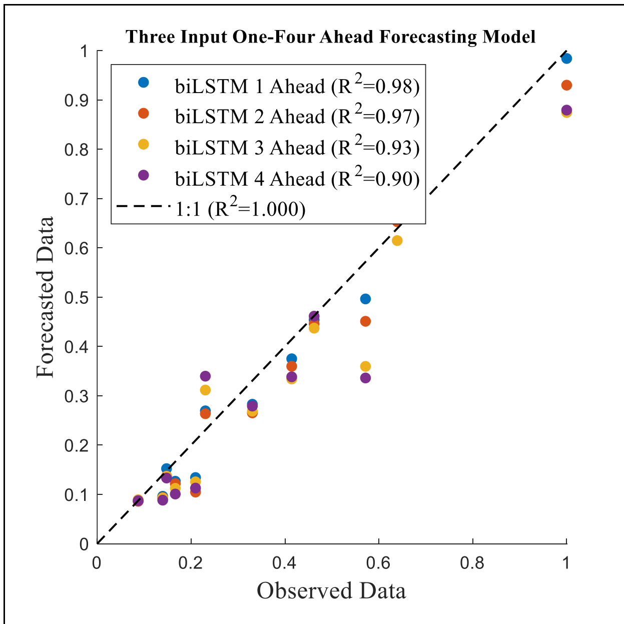


e	f

Figure 7. Scatter plots for a-f) one-six input one-four ahead forecasting data using biLSTM model.



a	b



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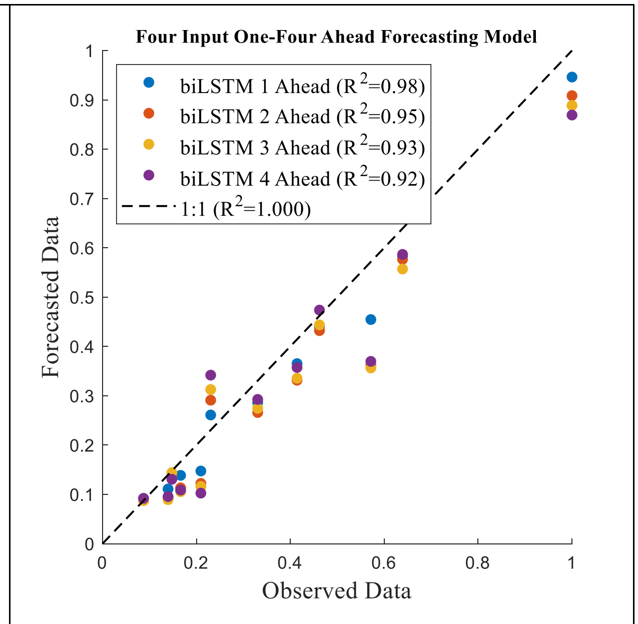
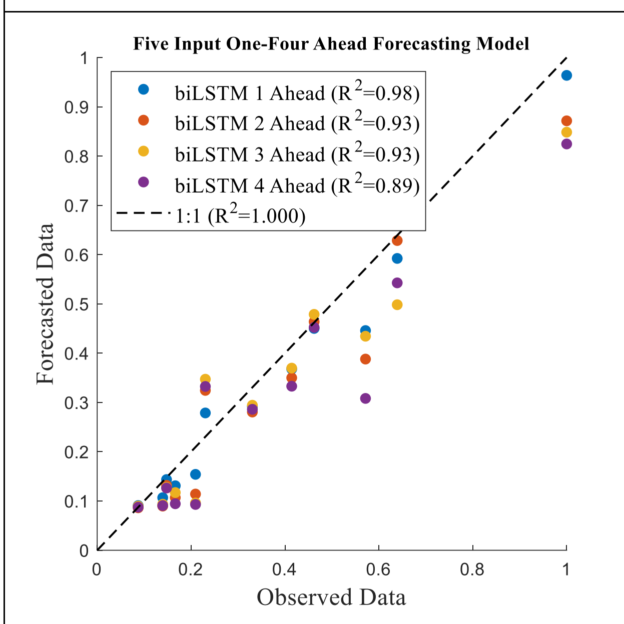
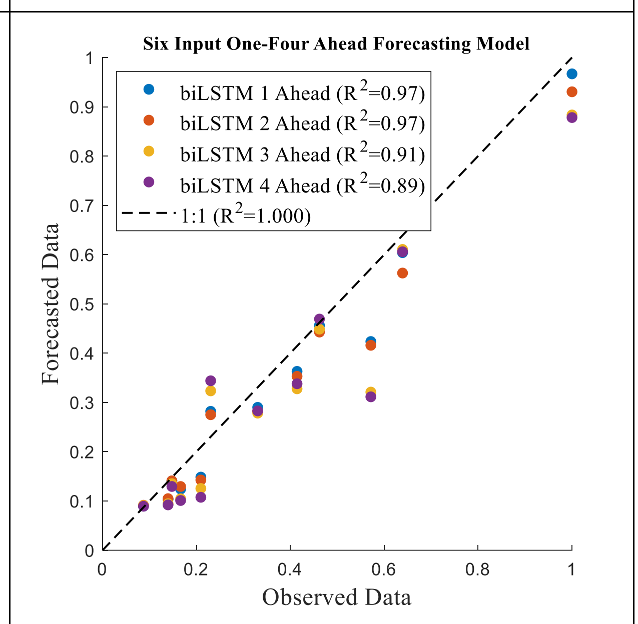


d



e



f

Figure 8. Scatter plots for a-f) one-six Input one-four ahead forecasting peak data using biLSTM model.

4. Discussion and Conclusion

The results of the study indicate significant variations in the performance of different deep neural network architectures for stream flow and peak stream flow predictions. The models evaluated include LSTM, biLSTM, GRU, and biGRU, with a comprehensive analysis conducted using 1-6 input steps. For one-ahead streamflow forecasting, the biLSTM model consistently outperforms the other models, achieving a remarkably low MSE and MAE, as well as high values for R and R^2. This suggests that the biLSTM model excels in capturing the complex dynamics of stream flow and demonstrates superior predictive abilities compared to LSTM, GRU, and biGRU models.

Similar trends are observed in one-ahead peak streamflow forecasting, where the biLSTM model consistently exhibits superior performance across various input steps. The model achieves low MSE and MAE values, while obtaining high R and R^2 values, indicating its effectiveness in predicting peak stream flows accurately.

The detailed analysis for the biLSTM model further highlights its strengths. In one-ahead forecasting, the biLSTM model showcases exceptional accuracy across different input steps, providing robust predictions for both general stream flow and peak stream flow. Additionally, the model's ability to make accurate one-four ahead predictions is demonstrated, contributing valuable insights into its predictive capabilities.

The superiority of the biLSTM model in stream flow and peak stream flow predictions suggests that its architecture, incorporating bidirectional long short-term memory, effectively captures the temporal dependencies and intricate patterns present in the data. The bidirectional aspect allows the model to consider both past and future information, enabling more accurate predictions.

The incorporation of the biGRU model in the study adds a novel dimension, as there is a lack of existing literature on its application for peak stream current prediction. However, the results indicate that, while the biGRU model performs reasonably well, it falls short of the accuracy achieved by the biLSTM model. This emphasizes the importance of model selection in achieving optimal performance for specific prediction tasks.

In conclusion, this study contributes valuable insights to the field of stream flow prediction by comparing and evaluating LSTM, biLSTM, GRU, and biGRU models. The biLSTM model emerges as a powerful choice for accurate and reliable stream flow and peak stream flow predictions, showcasing its potential for practical applications in hydrological forecasting. The study also highlights the importance of considering bidirectional architectures and comprehensive evaluation approaches for achieving optimal results in stream flow prediction tasks.

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