Real-Time Streamflow Forecasting Framework, Implementation and Post-Analysis Using Deep Learning

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Abstract

Rainfall-runoff modeling and streamflow prediction using deep learning algorithms have been studied significantly in the last few years. The majority of these studies focus on the simulation and testing of historical datasets. Deployment and operation of a real-time streamflow forecast model using deep learning will face additional data and computational challenges such as inaccurate rainfall forecast data and real-time data assimilation with limited studies guiding on these difficulties. We proposed a real-time streamflow forecast framework that includes pre-event model training using deep learning, real-time data acquisition, and post-event analysis. We implemented the framework for 124 USGS gauged watersheds across Iowa to forecast 120-hour streamflow rates since April 2021. This is the first time deep learning models have been used to predict streamflow in real-time operational settings at a large scale, and we anticipate seeing more real-time implementations of deep learning models in the future.

Key Points

- We proposed a real-time streamflow forecast framework using the pre-event trained deep learning models.
- We implemented the framework for 124 USGS gauged watersheds across Iowa to forecast 120-hour streamflow since April 2021.
- Our results showed that the implemented framework work well for real-time operation, with high computational speed and accuracy.

Key Words

Streamflow forecast; deep learning; real-time forecast; flood forecast; data assimilation

1. Introduction

Floods are the most harmful natural disasters in the world, causing massive human and property losses every year. Floods can be divided into riverine floods, coastal floods, and lake floods according to their sources, with the main cause being weather and meteorological events. While we don't have much control over meteorological events, scientists and engineers are using the tools and methods to inform the public with more accurate weather forecast models, river forecast models, disaster planning (Teague et al., 2021), flood mitigation (Carson et al., 2018; Yildirim and Demir, 2021), and advanced early warning platforms to reduce losses and help the people who may be affected by floods (Alabbad et al., 2022). It's important to use accurate flood forecasting models to figure out how much land will be flooded (Li et al., 2022; Hu and Demir, 2021), as well as how floods will affect transportation networks (Alabbad et al., 2021) and agriculture fields (Yildirim and Demir, 2022).

With the increase of computing power and the development of novel algorithms, deep learning models have become powerful tools that have been widely utilized in hydrology studies (Fang et al., 2017; Orland et al., 2020; Liu et al., 2021; Feng et al., 2021a) in the past few years. The majority of studies focus on daily rainfall-runoff modeling and streamflow forecasting (Kratzert et al., 2018; Kratzert et al., 2019; Feng et al., 2020; Qian et al., 2020; Sarkar et al., 2020; Van et al., 2020; Lees et al., 2021). Most recent research has focused on improving neural network model accuracy with physical information (Feng et al. 2020; Fang et al. 2020; Rahmani et al. 2021; Gauch et al. 2021; Klotz et al. 2021). Although various studies (Li et al., 2020; Xiang et al., 2020; Xiang et al., 2020; Sit et al., 2021; Lin et al., 2021) have been conducted on hourly streamflow forecast data, studies on the real-time operation of deep learning forecast models in hydrology are limited.

Nonetheless, several studies have proposed attempts at real-time operation. Klocek et al. (2021) implemented operational precipitation nowcasting with deep learning at Microsoft Weather and improved precipitation forecasts by at most six hours after post-processing the HRRR model output. Other precipitation forecast models integrating the HRRR results were summarized in the review by Hussain & Zoremsanga (2021). For the hydrology modeling, Bowes et al. (2019) simulated the real-time conditions to forecast the groundwater tables for three storm events from 2016 to 2018, and used the HRRR precipitation forecast data as the rainfall input. Frame et al., (2021) post-processed the daily NWM streamflow model output with deep learning for the years from 1994 to 2014. The above deep learning studies simulated real-time conditions on historical datasets (Demir et al., 2022), but no deep learning-based streamflow forecast model has been deployed for real-time operation.

The current official operational streamflow and flood forecast model in the United States is the Advanced Hydrologic Prediction Service (AHPS) model from the National Oceanic and Atmospheric Administration (NOAA). Other operational streamflow forecast models include the ones from the National Water Center (NWC) and the Iowa Flood Center (IFC, Krajewski et al., 2017). These traditional hydrologic models were designed by state or federal agencies, and they are physical process-based models that are computationally intensive and rely on high-performance computations. Recently, a blueprint for real-time flood forecasting was developed by Ivanov et al. (2021). The blueprint suggests that pre-event training surrogate models should be developed and that real-time data such as the forecasted rainfall data and flood stage should be used for real-time forecasting with surrogate models. It is also proposed that the models be highly adaptive to include additional data, which consists mainly of the strengths of the deep learning models.

Based on the blueprint by Ivanov et al. (2021), we proposed a framework for real-time operational streamflow forecasting using deep learning algorithms. We also implemented the framework with the deep learning models in April 2021 in the state of Iowa. In this study, we evaluated the framework using forecast results from April to September 2021. Model performance comparison and post-event analysis are also presented as part of the analysis.

2. Methods

2.1. Real-time Forecast Framework

The proposed real-time forecast workflow is shown in Figure 1. The framework consisted of three phases: pre-event training, real-time forecast, and post-event analysis. Pre-event training is the first phase, which is also known as the model development phase. As is discussed in the introduction, models from most machine learning and deep learning studies working on historical datasets can be used in this phase. We need a historical dataset that contains the input data (*X*) and output data (*Y*) in the pre-event training step. Since our model needs to be implemented in real-time, the input features should be available in real-time as well. In our work, we used three types of input parameters, which are the watershed parameters (i.e., watershed size and soil type), historical monitoring data (i.e., streamflow and rainfall observations), and forecast data (i.e., rainfall). And the output Y in our study represents the streamflow observation in the future. With abundant data and appropriate integration methods, deep learning models can be developed with high model accuracy. Since this study is not focusing on the development of new deep learning models, the details of the methods and approaches used in this phase can be found in our previous studies (Xiang et al., 2020).

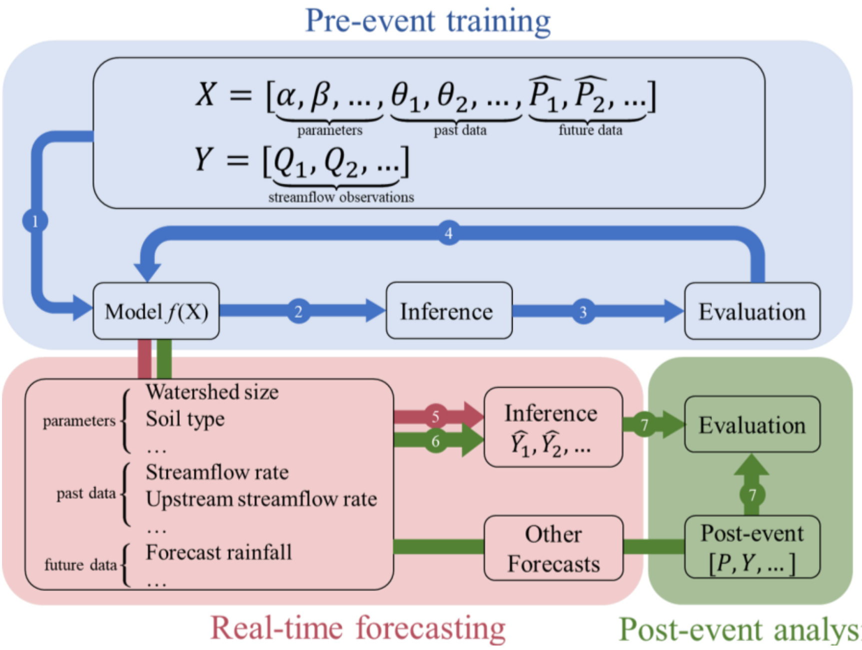

Figure 1. The real-time forecasting framework with deep learning models including three phases as pre-event training operations (in blue), real-time forecasting operations (in red), and post-event analysis operations (in green)

The real-time forecast is the second phase of the framework. This includes real-time data acquisition, data integration, model inference, and forecast output. Data acquisition is the step to obtain all the input data needed in the model developed in the pre-event training phase. This step includes obtaining and integrating the real-time data for input and output. The watershed parameters are considered fixed values, so the same values used in the model training will be utilized in this step. Historical data such as streamflow and rainfall observations can be obtained from the federal agencies. Since these are observed data, different radar rainfall products (Seo et al., 2019) would not make a big difference as studied by Ghimire et al. (2022). The main data component in this phase is the future data for rainfall since different forecast products may provide different forecast performances and they may further affect our final streamflow output. In our model, we have the input of future rainfall, and this may be a source of uncertainty due to the difficulty of rainfall predictions. After the data acquisition, we processed the data as needed by the model and integrated it into the framework. For example, since the pre-trained models used a moving average to smooth the hourly rainfall data, we applied the same moving average to the real-time rainfall data as well. Then, for each watershed, we feed the real-time rainfall predictions into the model, and this is called model inference. As is used in many studies in other domains such as face recognition and autopilot, the deep learning models with millions of parameters only take a millisecond to run for each inference (Feng et al., 2021b). This suggests the model inference does not require high performance computing or HPC systems.

The last phase in the framework is the post-event analysis. We included this phase to demonstrate how this study was conducted. This is an important phase for both the data and model lifecycles. In this phase, we collected actual rainfall and streamflow observations for the days we made the forecast. We evaluated the streamflow forecast accuracy of our deep learning models and those of other agencies by comparing them to USGS observations. In addition, we evaluated the accuracy of the future data we used in the real-time forecast phase by comparing the forecasted rainfall to the observed rainfall. As a retrospective, we applied the post-event data back to the model and evaluated the sources of errors by checking the model output, assuming we had accurate rainfall forecast data. After the post event analysis, the new data could be merged into the historical dataset and help with next-generation model training and updating in the future.

2.2. Framework Implementation in the State of Iowa

In previous studies, we have trained deep learning models using the data from water year 2011 to 2018 on 124 USGS gauges in the State of Iowa. In this study, we implemented the real-time forecast framework in the state of Iowa by executing the pre-trained models on the real-time data every 6 hours from April 1, 2021, to September 30, 2021. Specifically, the deep learning model can be described by the following equation (Eq. 1):

$$streamflow(t, t+1, \ldots, t+120) = f(area, slope, Tc, soil(1, 2, \ldots, 12), ET, past\ precipitation(t-72, t-71, \ldots, t-1), future\ precipitation(t, t+1, \ldots, t+120), past\ streamflow(t-72, t-71, \ldots, t-1), past\ upstream\ flow(t-72, t-71, \ldots, t-1), future\ upstream\ flow(t, t+1, \ldots, t+120)) \quad \text{(Eq. 1)}$$

When designing the neural network model, we took into account all types of data that may be obtained when operating in real time. For data assimilation, we can use the real-time streamflow observations of the gauge and its upstream gages. For longer predictions, future rainfall data from weather forecasts can be used as an extra input.

Table 1 shows all the datasets we acquired and used for the model training, forecasting, and analysis. In our implementation, the watershed scale parameters include the watershed area, watershed average slope, time of concentration (Tc), and the fraction of each of the 12 soil orders. We considered these parameters to be constant over time. We also include historical monthly average evapotranspiration (ET) data representing the month of the events. We used this data in all three phases.

Other than these constant parameters, for each streamflow prediction, we also input the past precipitation, and future precipitation. If there is an upstream USGS gauge, the past and future upstream streamflow of its upstream will be used as additional input. In each phase, the input data is different. In the model training phase, the past and future rainfall are both based on the StageIV precipitation observations because we assume we know the exact rainfall information. In addition, we also assumed that we know the exact streamflow information from the upstream, therefore, the past and future upstream flow are from the USGS gauge observations. All of the data used in the training period ranges from 2012 to 2018.In the real-time forecast phase, we kept using the StageIV precipitation observations for the past rainfall, and the USGS gauge observations for the past streamflow and past upstream flow. However, it is obvious that, we cannot know the exact future rainfall and the future upstream flow rate at the time we make predictions. Therefore, we used several data scenarios for these inputs. For the future rainfall, we looked at scenarios where the rainfall data is all zeros (no rainfall), and the HRRRv4 precipitation forecast product. HRRRv4 is the latest implementation since Dec 2020 (Alexander et al., 2020). Since the HRRRv4 provides the hourly precipitation forecast for at most 48 hours every 6 hours or 12 hours, we used the former one in our implementation. For the future upstream flow, we ran our deep learning models from upstream to downstream sequentially and we used the model forecast for the upstream as the input for the downstream because this method has worked better in the past studies (Xiang & Demir, 2020).

Table 1. The dataset used in the real-time streamflow forecast framework.

Data / Feature	Data Type	Sources	Spatial Resolution	Temporal Resolution	Unit
Area	GIS shapefile	IFC (Krajewski et al., 2017)	Station based	constant	km^2
Slope	GIS shapefile		Hillslope based	constant	%
Time of concentration	Array		Station based	constant	hour
Evapotranspiration	Array		State based	monthly	mm
Soil order fraction	GIS shapefile	NASA (Post et al., 2000)	0.5-degree grid	constant	%
StageIV precipitation observation	GRIB2	NOAA (Lin, 2011)	4km grid	hourly	mm
HRRRv4 precipitation forecast	GRIB	NOAA (Alexander et al., 2020)	3km grid	hourly, every 6hrs up to 48hrs	mm
USGS streamflow observation	Array	USGS (Miller et al., 2022)	Station based	15-60 mins	ft^3/s
National Water Model v2.1	NetCDF	NOAA (Cosgrove et al., 2019)	Stream based	hourly	m3/s
AHPS forecast	XML	NOAA (McEnery et al., 2005)	Station based	every 3hrs	m3/s

In the post-event analysis phase, we obtained the streamflow forecast products, AHPS and NWM, from federal agencies such as NOAA and NWC. We considered the USGS streamflow observation as the ground truth to evaluate the model’s forecast accuracy. We also re-ran our models to test the model accuracy assuming the exact rainfall amount is known by replacing the HRRRv4 data with the StageIV precipitation, and this helps us to understand how much error propagated from the meteorological rainfall forecast model to the streamflow forecast model.

2.3. Evaluation Metrics

We conducted the post-event analysis on our streamflow forecast models as well as the collected rainfall forecast data. Selected evaluation metrics were used for post-event analysis. In this study, we used the following three metrics: Kling-Gupta efficiency (KGE), root mean squared errors (RMSE), and percentage bias (BIAS). KGE evaluates the forecast model performance, and the closer to one, the better. RMSE evaluates the errors between forecast and real values, and the closer to zero, the better. The percentage difference between the forecast and observed values is evaluated by BIAS, and the closer to zero the better.The equations are shown below:

$$\mathrm{KGE} = 1 - \sqrt{(\mathrm{r}-1)^2 + (\frac{\sigma_{\hat{\mathrm{Y}}_i}}{\sigma_{\mathrm{Y}_i}} - 1)^2 + (\frac{\mu_{\hat{\mathrm{Y}}_i}}{\bar{\mathrm{Y}}} - 1)^2} \qquad \text{(Eq. 2)}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_1^n (\mathrm{Y}_i - \hat{\mathrm{Y}}_i)^2}{n}} \qquad \text{(Eq. 3)}$$

$$\mathrm{BIAS} = \frac{\mu_{\hat{\mathrm{Y}}_i}}{\bar{\mathrm{Y}}} \times 100\% \qquad \text{(Eq. 4)}$$

where: Y_i is the observation at the time *I*; $\hat{\mathrm{Y}}_i$ is the model result at the time *i*; $\bar{\mathrm{Y}}_i$ is the mean of all observations; *n* is the total number of observations; *r* is the Pearson correlation coefficient; σ is the standard deviation; and μ is the mean.

We conducted the evaluations on two approaches. The first approach is the event-wise evaluation, which calculates the model accuracy for each of the forecasted events. This helps to understand how the model performs in a flood event. The second approach is the lead time-level evaluation, where we calculated the model accuracy based on all forecasts during the last six months and grouped by the prediction hours. This evaluates the overall model performance at different lead times.

3. Results and Discussions

In this study, we presented and discussed the results from real-time and post-event analysis of pre-trained deep learning models name Neural Runoff Models (NRM) for operational streamflow forecasting applications. The detailed results and discussions of the pre-trained NRM models are shared in previous studies (Xiang & Ibrahim, 2020; Xiang et al., 2021). The real-time forecast using HRRRv4 rainfall forecast is named NRM-HRRR, and the real-time forecast using zero rainfall forecast is named NRM-NoRain. The post-analysis using the StageIV rainfall observations is named NRM-StageIV.

3.1. Real-time Streamflow Forecast

Figure 2a shows the time-series plots of the prediction made on July 14, 12:00 at the USGS 05449500 Iowa River near Rowan, IA, and the model input features that were available at the time of the real-time prediction. As is shown from the figure, the rainfall data consists of three parts, which are the historical rainfall observation from StageIV (blue), the future 48-hour rainfall prediction from HRRRv4 (green), and no rain assumption for the rest of the hours (red). Other than the HRRRv4 model, we also developed a model with the assumption that there would be no rainfall for the forecast period. Two model results were named NRM-HRRR (green) and NRM-NoRain (red). Since a small amount of rainfall is predicted by HRRR, as shown in Figure 2a, the predictions of NRM models using HRRR rainfall or no rainfall do not show a significant difference. During operation, most of the time is spent on data integration and preprocessing, since the model inference of deep learning models is fast. While model prediction based on deep learning models takes less than one second for each prediction cycle on a single GPU, physical forecast models often require a powerful workstation or high performance computing environment.

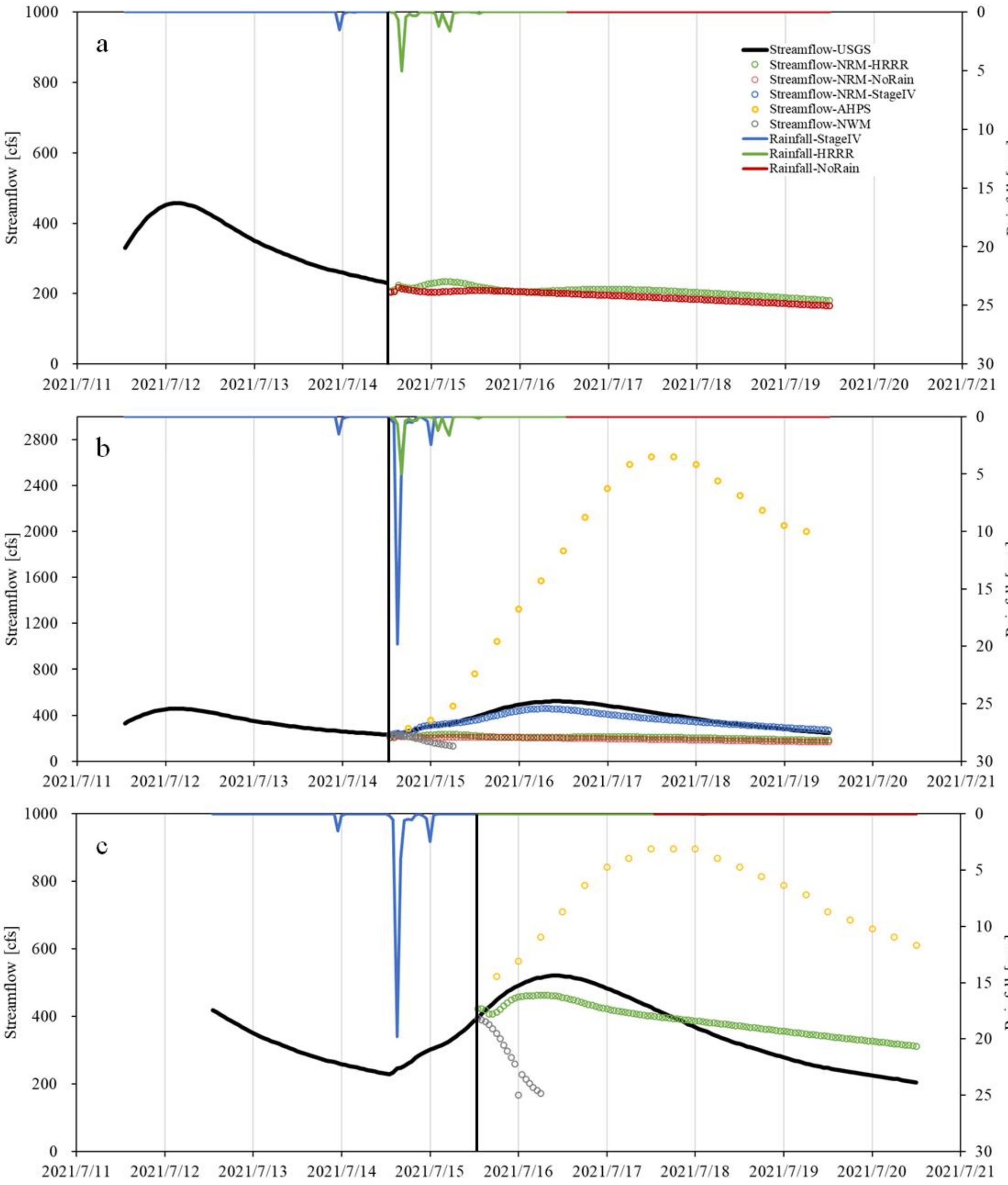

Figure 2. Streamflow forecast model at a) Real-time on July 14, noon, 2021, b) Post-analysis on July 14, noon, 2021, c) Post-analysis on July 15, noon, at the USGS 05449500 Iowa River near Rowan, IA

3.2. Post-event Analysis

Figure 2b shows the post analysis of the sample event in Figure 2a. The actual rainfall measured from StageIV (blue) was much more than HRRR predictions (green). This is the reason that our NRM-HRRR and NRM-NoRain were underpredicted when compared to the

USGS streamflow measurements (black). We also reran the prediction model NRM with the actual rainfall from StageIV, and the results showed that NRM-StageIV is more consistent with the USGS measurement, which highlights the importance of accurate rainfall prediction products for streamflow forecast modeling. We also included the real-time streamflow forecast results at that time from NOAA's AHPS and NWMv2.1, and our prediction models have shown the best performance compared to these federal products.

Figure 2c shows the post analysis results of the event that was one day later than the data in Figure 2b. It is shown that at 12pm on July 15, 2021, there is actually no rainfall in the next 120 hours, and this is why the real-time forecast results (NRM-HRRR, NRM-NoRain) and post-analysis model results (NRM-StageIV) are the same. Compared to either the NRM-HRRR or AHPS model, the forecast results both perform much better than they did one day ago in Figure 2b. This is because the rain event has already occurred and there will be no prediction errors from the rainfall forecast.

Figure 3 shows the model results from two sample watersheds with date ranges from April 1, 2021 to September 30, 2021 in Iowa. Since the AHPS prediction models are event-based in most watersheds, we collected the operational NWMv2.1 short-term predictions as a reference. We compared the model results at a lead time of 18 hours, which is the longest forecast of the NWMv2.1 short-term prediction product.

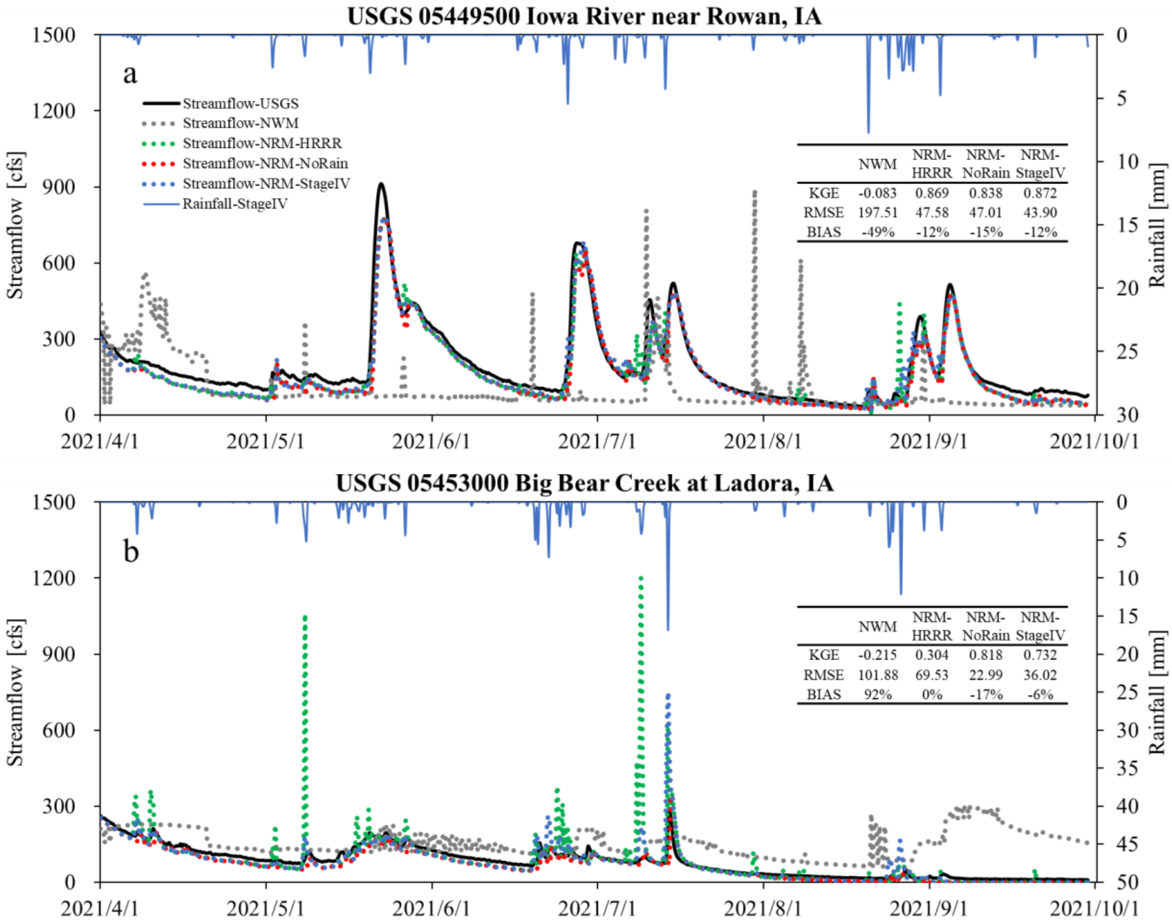

Figure 3. Two sample watershed streamflow forecast model results at the lead time of 18 hours from April 1, 2021 to Sep 30, 2021.

Results in Figure 3 have shown that NRM-HRRR has better model performance compared to the NWM model. However, NRM-HRRR does not always show better performance compared to NRM-NoRain. This indicates that the errors from the HRRRv4 rainfall forecast may propagate significant bias to the streamflow forecast and reduce the performance of the prediction below the no rain scenario. NRM-StageIV has shown better performance than NRM-HRRR, which reveals the ceiling of model accuracy assuming we know the actual rainfall.

As expected, the streamflow forecast accuracy will decrease when we have a longer lead time. The detailed statistics of the streamflow model accuracy and HRRR rainfall accuracy are in Appendix A.

3.3. Discussions

In this study, we worked towards realizing Ivanov et al. (2021) design in operational forecasting using deep learning and implemented a framework for real-time predictions. Our results from real-time operations reveal that our framework is capable of effectively leveraging all available real-time data. Integration of data is relatively simple, and the forecasting process is quick (1sn). Additionally, as deep learning models are data-driven, it is possible to incorporate additional data where available.

In addition, our analysis showed that pre-trained deep learning models may be utilized to anticipate real-time streamflow with a high degree of efficiency and accuracy when compared to existing operational streamflow forecast products. For the first time, deep learning models are shown to be successful not only in historical simulation data but also in real-time prediction of streamflow for large-scale implementations.

Our models have strong data integration capabilities, which is both a benefit and a challenge. The integration of the streamflow observation helps the data assimilation and increases the forecast accuracy for the first several lead time hours. As seen in the post-event analysis, the addition of 48 hours of HRRRv4 rainfall data had no short-term benefit on streamflow model accuracy. Additionally, the median value of streamflow forecasts in 124 Iowa watersheds is less accurate than the assumption of no additional precipitation. This is due to the prediction accuracy limitations of HRRRv4. Assuming accurate rainfall data from StageIV is available in advance for post-event analysis, the median KGE increases from 0.33 to 0.62 with a 48-hour lead time. This indicates that forecast errors in rainfall can account for a significant number of streamflow forecast errors, which is consistent with other studies (Ghimire et al., 2022). As a result, streamflow projections are significantly constrained by the accuracy of rainfall forecasts.

There are still several constraints that are not addressed in this study. On the one hand, only observational data from federal agencies (i.e., USGS) is included, and no other supplementary sensor networks, such as the IFC stage sensors, are used, despite the benefit of additional data as shown in early studies (Xiang et al., 2020). Integrating data collected from actual observations of river stages would be extremely beneficial for prediction accuracy improvement. On the other hand, our framework and models were developed for forecasting at the watershed level, and we neglected the geographical distribution of rainfall. Several simulation experiments involving graph neural networks have been conducted (Jia et al., 2021; Xiang et al., 2022), and that could be addressed in future studies. We recommended updating the deep learning model continuously with the most recent data in our framework as a potential improvement step for prediction. However, we have not implemented or tested this step yet. We will update the model using the collected data in 2021 for the next year's prediction.

4. Conclusion

In this study, we proposed an operational and real-time framework for deep learning-based forecasting and analysis of streamflow for the USGS gauges in the State of Iowa. Based on successful deep-learning studies carried out over the past few years, we implemented a state-wide real-time forecasting system for the first time. The real-time acquisition, processing, and integration of input data depends on timely and reliable data interfaces from federal and state agencies, including USGS, NOAA, and IFC. The results showed that the implemented model and framework work well for real-time operation, with high computational speed and accuracy. In addition, no high-performance computing is required during the operation, which greatly reduces the cost and required resources for real-time forecasting. However, we must be aware of the fact that our model has some limitations. For example, our forecasts are site-specific and thus predictable only for USGS gauged sites. Furthermore, as a streamflow forecasting product, our model was shown to be highly reliant on and limited by rainfall data accuracy. To obtain more accurate streamflow forecasts, our framework is expected to be compatible with next-generation rainfall measurements or forecast products.

5. Acknowledgments

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Appendix A

It is worth noting that, as shown in Figure 4a, the streamflow forecast of NRM-HRRR is better than the NRM-NoRain on the median KGE among 124 watersheds in Iowa. This indicates that the HRRRv4 rainfall forecast product may be worse than assuming no rainfall. Our further analysis of the HRRRv4 rainfall forecast error in Figure 4d verified it as well. These results are in good agreement with published studies. For example, Grim et al. (2022) showed that HRRRv4 underpredicted the rapid increase in storm during the initiation period. Another study from Yue & Gebremichael (2020) showed that the bias estimated at the spatial scale of several thousand km^2 mostly ranges from -100% to 100%.

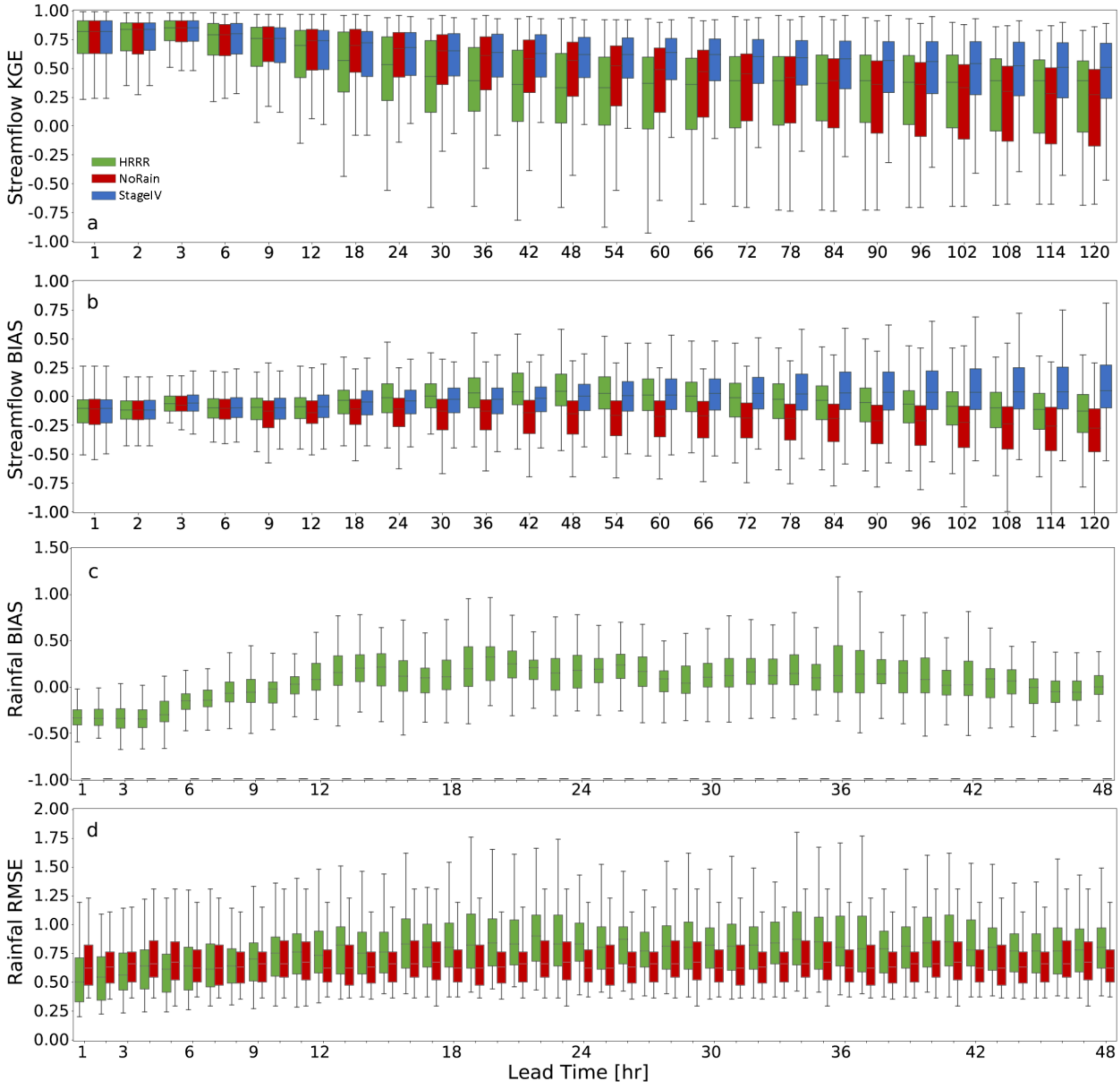

Figure 4. The model performance statistics for streamflow forecasting at 124 watersheds in the State of Iowa for the KGE (a), streamflow forecast BIAS (b), and rainfall forecast BIAS (c), and rainfall forecast RMSE (d) at the lead time from hour 1 to hour 120.

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