Distributed Long-Term Hourly Runoff Predictions Using Deep Learning – A Case Study for State of Iowa

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Highlights:

- Developed Neural Runoff Model (NRM) using deep learning for 120 hours streamflow forecasts.
- NRM on 125 USGS stations in Iowa outperforms other machine learning methods.
- NRM shows effectiveness in integrating stage level data for runoff forecasts.

Key Words:

Rainfall-Runoff modeling; deep learning; distributed model; streamflow forecasting; data integration modeling

Abstract

This study presents a rainfall-runoff model using precipitation, evapotranspiration, stream runoff observation data on each USGS streamflow gage with a new deep recurrent neural network, Neural Runoff Model (NRM). Proposed model, NRM, has been applied on 125 available USGS streamflow gages in the State of Iowa for predicting the next 120 hours in the water year 2018. Based on river network structure, upstream observation and forecast are used as additional inputs for the distributed version of the model, NRM-Distributed and improved the median NSE from 0.68 to 0.74 for the 120-hour ahead predictions. Proposed NRM models have shown strong predictive power and overcome the bottleneck limitation of encoder-decoder model for long-term runoff predictions. NRM results outperform the runoff persistence, ridge regression and random forest regression on majority of the gages. Results also show the streamflow predictions can be improved by integrating water level gauges from sensor networks.

1 Introduction

Extensive precipitation and surface runoff are the main reasons causing flash flooding. In Iowa, flooding is an ongoing concern after the record-setting 2008 floods devastated Eastern Iowa. Many modeling frameworks, information systems and applications such as the Iowa Hydrologic Model and Iowa Flood Information System (Krajewski et al., 2017) has been developed and widely used in hydrological studies in Iowa for the communication of flooding (Demir et al., 2018; Demir and Szczepanek, 2017; Sermet and Demir, 2018) and water quality (Weber et al., 2018). The Iowa Flood Center (IFC) deployed a statewide network of stream stage sensors to measure the stream height every 15 mins (Kruger et al., 2016). These extensive data collection and sensor networks (Sermet et al., 2019; Weber et al., 2018) can be used for the rainfall-runoff modeling (Agliamzanov et al., 2019) and provide more accurate runoff forecasts which are helpful to local governments and watershed management authorities and reduce the loss of life and property from flooding (Sit et al., 2019; Yildirim and Demir, 2019).

Recent studies have shown strong abilities to use machine learning methods for runoff predictions. Support vector machines (SVMs) have been used for runoff predictions and have faster runtime with better accuracy than physical models such as MIKE Flood (Yan et al., 2018) and Storm Water Management Model (SWMM) (Granata et al., 2016). Random Forest is another type of machine learning model that can be used for water resources classification and regression tasks such as the water level (Li et al., 2016), rainfall downscaling (Q. Pham et al., 2019), and streamflow simulation (Shortridge et al., 2016). RF shows strong potential on these tasks and outperforms both physically-based models such as SWAT (Shortridge et al., 2016) and machine learning models such as ANN and SVM (Li et al., 2016). Studies (Mosavi et al., 2018; Q. B. Pham et al., 2019; Riad et al., 2004) using Artificial neural networks (ANNs) shown that ANNs can provide higher accuracy than the classical regression models in rainfall and runoff predictions. Studies (Chang et al., 2015; Ömer Faruk, 2010) also show that ANNs can provide comparable results to physical models. In the past decade, deep learning models have shown strong abilities and achieved significant improvements in many fields, including the language translation (Cho et al., 2014a), speech recognition (LeCun et al., 2015), social media data analysis (Sit et al., 2019) and intelligent systems (Sermet & Demir, 2018). These successful applications are based on many new neural networks, structures, functions and, technologies. Some of them have been used in earth science and water resources studies.

Recurrent Neural Networks (RNNs) are a new type of neural networks that can deal with input sequences. Currently, the most common RNNs are Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), which can be used in natural language processing, speech recognition, and other time-series earth science studies including rainfall-runoff modeling (Kumar et al., 2016; Sit and Demir, 2019; Wen et al., 2015). Recent studies have applied the LSTM model to soil moisture modeling (Fang et al., 2017), water table predictions (Zhang et al., 2018), and rainfall-runoff modeling (Hu et al., 2018; Kratzert et al., 2018).

However, one of the limitations in recent machine learning and deep learning models is that they can predict single timestep with a short leading time. For example, a multiple additive regression trees model proposed by Fu et al., (2019) can forecast the river stages with a three-hour lead-time. An LSTM model proposed by Kratzert et al., (2018) can forecast the daily runoff with a one-day lead-time. An LSTM model that proposed by Hu et al., (2018) can forecast the hourly runoff from 1- to 6- hour lead-time with 6 different models. Xiang et al., (2020) applied the sequence learning in rainfall-runoff modeling with an Encoder-Decoder structure and the model outperforms multiple benchmarks including linear regressions, SVMs, and LSTM for predictions of the following 24 hours on several USGS streamflow gages on two watersheds. Although 24 hours of continuous prediction is an improvement, bottleneck effect in the model may reduce the efficiency for applications longer than 24 hours (Xiang et al., 2020).

In this paper, a station-based rainfall-runoff model is proposed with inspiration from a classical sequence-based model, Google's Neural Machine Translation (GNMT), that was used for language translation by Google (Luong et al., 2017). The new neural runoff model (NRM) is a continuous hourly rainfall-runoff model for the next 120 hours that uses the latest deep learning techniques including GRU, seq2seq learning, ReLU activation function, dropout regularization, mini-batch training, and GPU acceleration. Other machine learning methods, including Ridge regressions and Random Forest regression (RFR) are used to evaluate the proposed model performance.

The following section introduces the details of NRM and NRM-Distributed model architectures, settings and parameterization, and benchmark methods. Section 3 describes the results and discussions. The conclusion provides a summary of the work and recommendations for future research.

2 Methods

2.1 Neural Rainfall-Runoff Model Architecture

Luong et al (2017) proposed a full sequence-based neural network that can be used for machine translation tasks. Different to the previous encoder-decoder neural networks (Cho et al., 2014b; Sutskever et al., 2014), this neural machine translation (NMT) model has deep RNNs with stacking layers for all timesteps, rather than using a single vector as intermediation between input and output. Thus, the bottleneck between encoder and decoder was removed and the NMT shows better results than previous encoder-decoder models in language translation. This paper proposes a new sequence-based neural network for the rainfall-runoff modeling using the idea of the neural machine translation to test if it is effective to make rainfall prediction in high temporal resolution for the long-term studies.

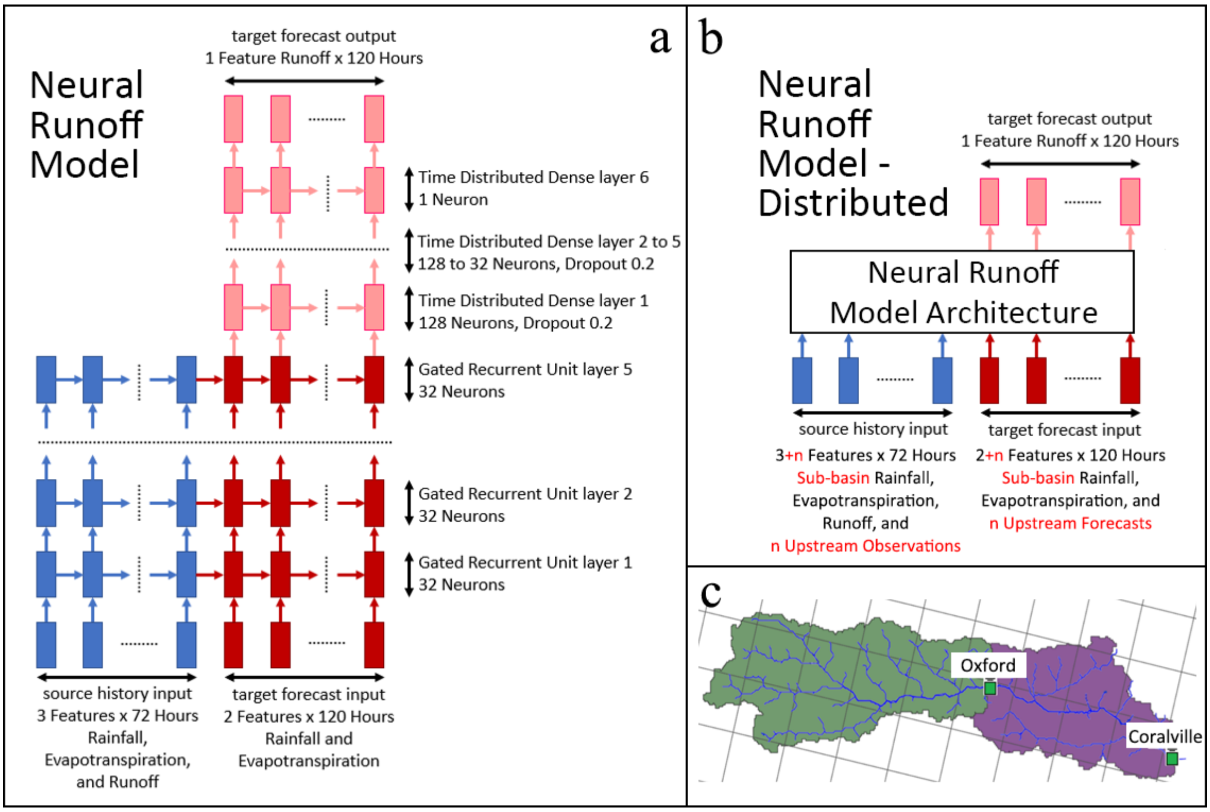

Figure 1. Neural Runoff Model (NRM) and NRM-Distributed proposed in this study for runoff forecasting. NRM (figure *a*) requires the input of rainfall for the history and forecast periods, history runoff observation, and evapotranspiration. For the NRM-Distributed (figure *b*), additional upstream observations and forecast data can be included, and the rainfall data only use the represented sub-basin area after the upstream station. An example of downstream relationship is shown in figure *c*.

The proposed neural runoff model (NRM) structure is shown in Figure 1. Target forecast output is the runoff. Source history input has multiple features such as rainfall observation, runoff observations, and evapotranspiration. Target forecast input includes the rainfall forecast data and evapotranspiration. As shown in Figure 1, for stations such as Coralville that has an upstream measuring gage at Oxford, Oxford observations and forecasts can be used as additional input for the forecasting Coralville. The distributed model based on NRM is called NRM-Distributed.

Since deeper networks can perform better in general than the shallower networks (He and Sun, 2015), this paper proposed a structure stacking 5 RNN layers for history and forecast input data. The stacking of 5 RNN layers has shown the best model performance in previous studies (Sak et al., 2014). The RNN layer used in this study is Gated Recurrent Units (GRU), which is a well-performed recurrent layer that is more efficient than traditional Long-Short Term Memory (LSTM) (Cho et al., 2015). This study aims to provide 5-days hourly prediction, which is 120 timesteps for the target forecast input and output. The source history input used in this project contains 72 hours, which is determined in previous work that can provide sufficient information for runoff predictions (Xiang et al., 2020). Thus, each GRU layer contains 192 timesteps in the proposed architecture.

In Figure 1, each blue or red block in the GRU layer is a GRU cell. The detailed algorithms of GRU are shown in Equations 1 to 4. The first step for each GRU cell is the updating gate for parameter z_t, which is a rate range from 0 to 1 determined by the information of the last state and the current input. It applies a sigmoid function after linear transformations of the current input x_t and the previous result h_{t-1} with weight parameters W_z and U_z. The second step is the reset gate for parameter r_t, which is another rate used for the candidate of new cell values h'_t. In the third step, the candidate h'_t determined by the *tanh* function after the linear transformations of the current input parameter x_t and a reset cell value $r_t \cdot h_{t-1}$. In the end, the current timestep cell state h_t get updated with the linear transformation of the parameter z_t, the previous state h_{t-1}, and the candidate state h'_t. The final cell state h_t will pass to the next timestep in the same layer and the next layer in the same timestep.

$$z_t = \sigma(W_z \cdot x_t + U_z \cdot h_{t-1}) \quad (1)$$

$$r_t = \sigma(W_r \cdot x_t + U_r \cdot h_{t-1}) \quad (2)$$

$$h'_t = \tanh(W_h \cdot x_t + U_h \cdot (r_t \times h_{t-1})) \quad (3)$$

$$h_t = z_t \times h_{t-1} + (1 - z_t) \times h'_t \quad (4)$$

The GRU layer is a standard package embedded in many modern machine learning packages. This project used the build-in GRU layer directly from the Tensorflow and Keras.

2.2 Model Settings and Evaluating

The goal of this project is to develop a standard rainfall-runoff model structure that can be applied to any watershed stream gage. In this study, proposed models are trained and then applied to each available USGS gage in Iowa for evaluation.

This model applied a min-max normalization to all the input values. Then, it applies 32 neurons in each GRU layer. After five GRU layers, there are six time-series dense layers with neurons ranging from 128 neurons to 1 to project the results to final output. The first five dense layers used the activation of *tanh* after the linear transformation. And the last layer used the *ReLU* activation function (LeCun et al., 2015) to set the negative values to zero due to a negative runoff is meaningless. A dropout rate of 0.2 is used that can randomly delete 20% of neural connections between dense layers in the training processes. The dropout method helps to reduce the overfitting issue and can provide better results. The optimizer used in this model for the minimum loss is *RMSprop*, which is a good working gradient descent-based algorithm for time-series models. Mini-batch method is used in the training process in this study. The batch size of 64 has been discovered to be effective in rainfall-runoff modeling in a previous study (Xiang et al., 2020). This model used the residual sum of squares divides the total sum of squares, which is also named the variance unexplained (FVU, Equation 5) as the loss function. The lower loss function, the higher Nash–Sutcliffe Efficiency (NSE, Equation 6), which is a widely used statistic for evaluating the water resources modeling performance (Arnold et al., 2012).

$$\text{Loss Function} = \frac{\sum_{i=1}^{n}\left(\mathrm{Y}_i - \hat{\mathrm{Y}}_i\right)^2}{\sum_{i=1}^{n}(\mathrm{Y}_i - \bar{\mathrm{Y}})^2} \quad (5)$$

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{\mathrm{Y}}_i\right)^2}{\sum_{i=1}^{n}(Y_i - \bar{\mathrm{Y}})^2} \quad (6)$$

where: Y_i is the observation at the time <u>*i*</u>; $\hat{\mathrm{Y}}_i$ is the model result at the time <u>*i*</u>; $\bar{\mathrm{Y}}$ is the mean of all observations, and *n* is the total number of observations.

Other performance statistics including Pearson's correlation coefficient (r, Equation 7), percent bias (bias, Equation 8), and normalized root mean square error (NRMSE, Equation 9) are used for model evaluation. The defining equations are shown below.

$$r = \frac{\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{7}$$

$$\text{bias} = \frac{\sum_{i=1}^{n}\hat{Y}_i - \sum_{i=1}^{n}Y_i}{\sum_{i=1}^{n}Y_i} \times 100\% \tag{8}$$

$$\text{NRMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{n}}}{\bar{Y}} \tag{9}$$

The rainfall-runoff modeling in the NRM has three phases – training, validation, and testing. Available data are separated into three independent datasets. The training and validation datasets are used to calibrate the model. The loss function was calculated in both training and validation datasets and the early-stopping technology is used to avoid over-fitting. When the loss of the training dataset keeps decreasing, the model will be considered as overfitting if the validation dataset loss function cannot decrease. The early-stopping technology helps to monitor the model accuracy on the validation dataset and save the model with the best validation accuracy as the final model. In the end, the best model will be tested on the independent test dataset for the final evaluation.

The whole work was conducted by the Keras library in Python3 with the Tensorflow backend. NVIDIA GPU Quadro M5000 was used for training and testing.

2.3 Study Area and Datasets

There are nearly 200 historical and real-time USGS stations in the State of Iowa, which can provide stream runoff data for the evaluation of the proposed models. However, many stations are not capable to be used for the modeling because some old stations stopped operation in recent years, some new stations just built recently which do not have enough data, and some do not measure the streamflow. Overall, totally 125 stations in Iowa are available for the use of rainfall-runoff modeling in this paper. These stations are deployed on different watersheds with varieties of land use and topographies. The models are calibrated on the station-specific data for each sensor.

The Iowa Flood Center (IFC) has installed stream stage level sensors that collect stage data for over 250 locations in Iowa (Kruger et al., 2016), and some of them located in the upstream of the USGS gages have been used in this study. The watershed of the sensors and stage level data were obtained from the IFC (Krajewski et al., 2017).

Rainfall is the key driving force of the runoff process. The data from the NOAA Climate Prediction Center 4km gridded data Stage IV was used as the rainfall input (Lin, 2011). This rainfall data was used in both the source for historical and forecast input in this paper. Simple moving average with 6 hours (Xiang et al., 2020) was used to reduce the noise for a smoother rainfall data.

For, evapotranspiration, due to the lack of high temporal resolution data, estimated monthly evapotranspiration from history for the entire State of Iowa were used (Krajewski et al., 2017). The monthly evapotranspiration values were then repeated on each hour. The evapotranspiration values used in this study are 19, 18, 30, 32, 48, 77, 121, 112, 52, 20, 15, and 13 mm per month from January to December.

Some USGS gages have monitoring intervals for the streamflow data every 15 minutes and some are hourly, thus, a pretreatment to aggregate all data to hourly is the first step. In winter, the frozen rivers have no runoff data, and the frozen hours were not considered in this paper. In addition, there are issues of heavy snow and ice melt in Iowa in

February and March on some years for several watersheds. Since there is no accurate hourly snow cover monitoring data in Iowa, February and March data are not considered in this paper as well. The runoff data were used as the target output for model evaluation, and as the past observation in the source input part in Figure 1.

2.4 Model Tests

This project carried out four tests for achieving the best runoff predictions on gaged watersheds in Iowa. In the first test, the proposed NRM for predictions of 120 hours and 24 hours was applied to the Clear Creek Watershed, and the results are compared to the Encoder-Decoder LSTM-seq2seq model with the prediction of 120 hours and 24 hours (Xiang et al., 2020). The data from Oct 2011 to Sep 2016 were used for training and validation, and Water year (WY) 2018 was used as the test year.

In the second test, the proposed NRM was applied to 125 USGS stations in Iowa for forecasts of up to 120 hours. In this test, NRM used the data from Oct 2011 to Sep 2018. WY 2012 to 2017 (6 years) were used for calibration and WY 2018 for the final evaluation. In the calibration, WY 2014 to 2017 were used for training and WY 2012 to 2013 were used for the validation. For each station, we calibrated the model with training data and stop the calibration to save the best model with the best performance of the validation data. In the end, the model performance was evaluated with the test dataset of WY 2018.

In the third test, a distributed structure was applied to the NRM, which is called NRM-Distributed. All the datasets are the same as the first test besides using the upstream model forecast generated in the first test as an additional data source for predicting the downstream watersheds. NRM-Distributed was applied to 63 stations located on the downstream of USGS gages.

In the last test, IFC stream stage sensors located at the upstream of the USGS gages were used for forecasting using model NRM-Distributed. The stage level data were suffering from many uncertainties due to insufficient observations, inadequate rating curve, rating curve extrapolation, and temporal river geometry changes (Hulsman et al., 2018). This test used data from stage level sensors located at the upstream of USGS gages as input directly to verify if the data-driven model can integrate stage level data to improve the model performance. Since many stream stage sensors were built in the past few years, this part used 4 years of data from WY 2014 to 2017 for the calibration. In detail, the last 2.5 years of data were used for training and the first 1.5 years of data were used for validation. Same as previous tests, WY 2018 was used for the test. In this test, the results of NRM and NRM-Distributed with 4 years of training and validation data will be compared and then compared to the NRM with 6 years of training and validation data.

2.5 Model Benchmarks

Several model benchmarks were used in this study. In the first test of comparing NRM to the LSTM-seq2seq model, the results of LSTM-seq2seq on 24-hr predictions (Xiang et al., 2020) and the revised LSTM-seq2seq on 120-hr predictions were used in the benchmark. NRM models for predicting the next 24 and 120 hours were tested using the same data periods as LSTM-seq2seq models for comparison. Three different benchmarks were used in the rest of the tests on 125 USGS gages and additional stage level sensors.

To evaluate the change of runoff, the hourly persistence of runoff for at most 120 hours was used as a benchmark. A high NSE for the persistence represents a stable runoff and fewer changes over the past hours. In this paper, the persistence of the runoff is using the model of $Runoff_t=Runoff_{t-T}$, where the T represents the lead time. Thus, for 120-hr ahead prediction, the 120^{th}-hour persistence is the results of $Runoff_t=Runoff_{t-120}$.

The linear regression model Ridge regression was used as the linear model benchmark. It has shown better results than the least square regression and Lasso regression for rainfall-runoff modeling (Xiang et al., 2020). For each station, the same input variables in NRM were used. As shown in Figure 1, there are 456 input variables and 120 output variables. This paper used Python package Sklearn, with the module SGDRegressor in Sklearn for each output variable, and the module MultiOutputRegressor was used to predict 120 outputs together. This strategy creates 120 Ridge regression models without considering the linkages among output variables.

RFR is another type of machine learning model that was used as a machine learning model benchmark. For each station, 456 input variables were used to predict 120 output variables, which is the same as Ridge. This paper used Python package Sklearn, and the build-in module *RandomForestRegressor* in Sklearn can be used to make regression models for 120 output predictions at the same time. Default methods of allowance of all features and 100 estimators were used for the RFR.

3 Results

Results of the comparison of the NRM to the LSTM-seq2seq in the selected watershed are shown in section 3.1. Results of proposed models and benchmark including persistence, ridge regression, and random forest regression on 125 USGS gages are summarized for upstream gages in section 3.2 and downstream gages in 3.3. Experimental results of integrating stage level sensors are shown in section 3.4.

3.1 NRM and LSTM Encoder-Decoder Models

Xiang et al., (2020) proposed the first multi-timestep rainfall-runoff prediction model LSTM-seq2seq using the encoder-decoder LSTM method. LSTM-seq2seq shows successful applications on several USGS streamflow gages and outperforms popular machine learning models such as SVMs and LSTM in the rainfall-runoff predictions for up to 24 hours. Here are results comparing the proposed NRM to the encoder-decoder based model named LSTM-seq2seq on the Clear Creek Watershed using the same settings and data. As is shown in Figure 2, the LSTM-seq2seq has the NSE values of 0.82 at 24-hour ahead predictions for at most 24-hour predictions. However, when the prediction timesteps increased from 24 to 120 hours, the model accuracy statistics NSE at 24-hour ahead predictions decreased from 0.82 to 0.58. This decreasing behavior is consistent with the language translation studies that the increase of input length will cause the performance degrading quickly (Cho et al., 2015). The main limitation of the encoder-decoder sequence model is the bottleneck links the encoder and decoder. The model performance may decrease significantly in long-term predictions for runoff modeling.

When applying the NRM to the Clear Creek Watershed with the same training methodology and training and testing data from Xiang et al., (2020), the NSE for 120 hours ahead predictions is 0.79, which is significantly improved. There is also no decreasing trend for the last few hours, which indicates that the 120 timesteps may not reach the limitation and this model has the potential to forecast further future. This result confirmed that, although both are sequence models, the proposed NRM is a significant improvement compared to encoder-decoder models in long-term rainfall-runoff modeling on the Clear Creek Watershed.

In addition to solving the bottleneck limitation for long-term predictions, proposed NRM also has a huge benefit on simplified architecture and training speed. LSTM-seq2seq

(Xiang et al., 2020) used a layer of encoder LSTM with 256 neurons, and a layer of decoder LSTM with 512 neurons, which has 3,134,721 trainable parameters for the task of 120 hours forecast. Although proposed NRM has five GRU recurrent layers, each layer has only 32 neurons. NRM contains only 77,505 trainable parameters for the same task, which is 40 times smaller. The proposed NRM model has fewer parameters, which can speed up the training and testing processes and be more stable.

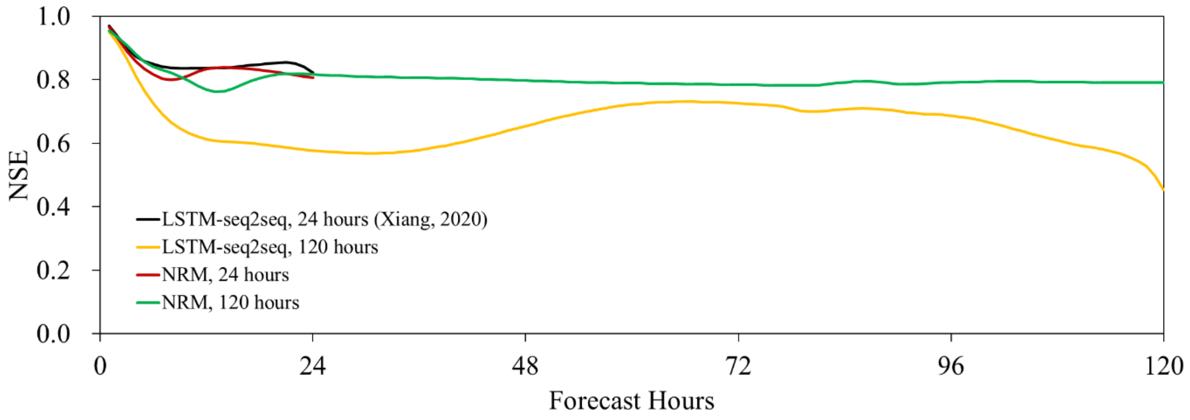

Figure 2. NSE values for LSTM-seq2seq and NRM models for 24- and 120-hrs predictions.

3.2 NRM on USGS Upstream Watersheds

Within 125 USGS gages, 62 gages are measuring the most upstream watersheds. These watersheds are relatively small, with an average drainage area of 384 square miles. They have less baseflow, and their runoff is significantly affected by the rainfall events. The persistence NSEs of these stations are mostly negative over 48 hours, which shows weak self-autocorrelation, and relatively hard modeling potential.

For these 62 stations, NRM was calibrated for each station with its training data from WY2014-2017 and validation data from WY2012-2013. Final test results of 120-hour predictions based on WY2018 were calculated for each station. The results were aggregated into 24 hours periods and shown in Table 1. The most upstream stations show a median NSE among 62 stations ranges from 0.67 to -0.41 for the first day to the fifth day for the persistence. Ridge regression model results have a median NSE of 0.66 for the first 24-hour, and it drops to 0.38 for the fifth 24-hour predictions. RFR model results have a higher median NSE of 0.76 for the first 24-hour predictions and it drops to 0.27 for the fifth 24-hour predictions. RFR shows better results than Ridge regression for the first 96 hours. NRM shows median NSEs ranges from 0.82 to 0.71 for the first and fifth 24-hour predictions, which outperforms all other models. The persistence decreases significantly from the second 24 hours, which indicates the rainfall dominants the stream runoff and the NRM model shows a strong and effective prediction ability for predictions up to 120 hours. Since our test is based on the historical events and the observed rainfall data were used, this study does not consider the rainfall prediction errors.

The distribution of NSE values of stream persistence and model forecast at the 120-hr ahead is shown in Figure 3. The median NSE values of the 120-hr ahead predictions are -0.44, 0.41 and 0.48 among 62 upstream USGS stations for the persistence, ridge regression, and RFR. The proposed NRM has the median NSE of 0.69, which outperforms other models. There are 15 stations with 120-hr ahead NRM prediction NSE higher than 0.8, while there is only 2 for ridge regression achieve that high accuracy, and no station for persistence and RFR. Comparing each station, NRM at the 120-hr ahead prediction outperforms persistence on all 62 stations, it also performs better than 55 stations than ridge regression and RFR.

Table 1. Median NSEs among 62 most upstream stations for five-day predictions in different models.

	Persistence	Ridge	RFR	NRM
1st day (1-24 hrs)	0.67	0.66	0.76	0.82
2nd day (25-48 hrs)	0.15	0.46	0.58	0.75
3rd day (49-72 hrs)	-0.10	0.39	0.46	0.72
4th day (73-96 hrs)	-0.31	0.39	0.40	0.72
5th day (97-120 hrs)	-0.41	0.38	0.27	0.71

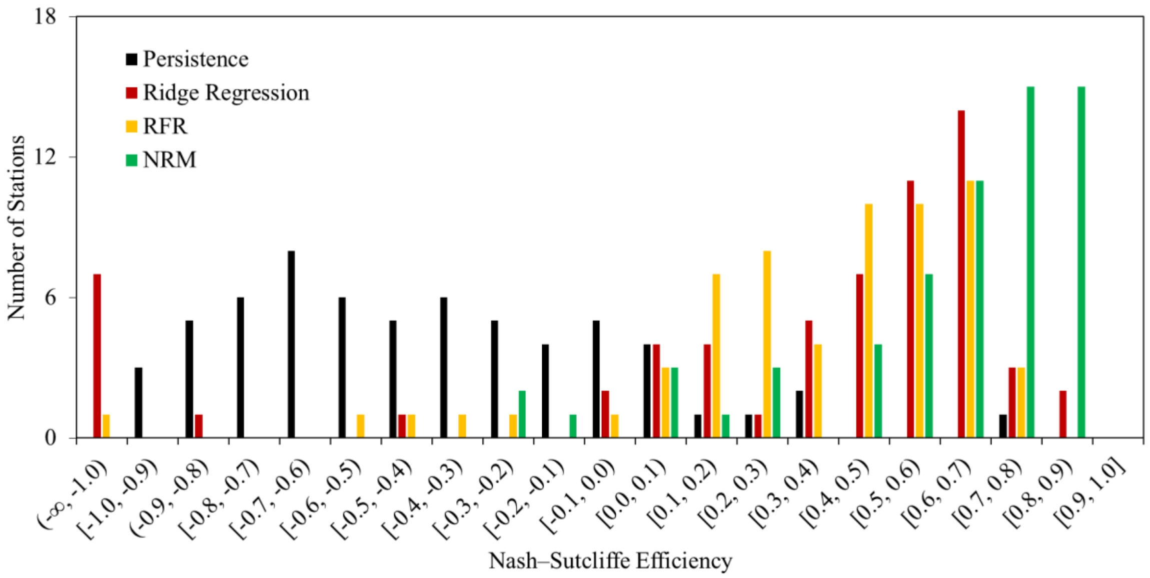

Figure 3. Distribution of the 120-hr ahead NSE for the 62 most upstream USGS stations.

3.3 NRM and NRM-Distributed on USGS Downstream Watersheds

63 downstream gages show a different picture because they are relatively large watersheds with an average drainage area of 3,765 square miles. They have a relatively high stream runoff and long recession period, and the runoff is less affected by the rainfall events. It is shown in Table 2 that these downstream stations have the median NSE of 0.66 for the third 24-hours, which is even higher than the NSE of the first 24 hours for the most upstream stations. The median NSE of the 97-120 hours, persistence for downstream stations is 0.34, which indicates these stations are relatively easier to predict than small watersheds.

Proposed NRM shows that the median NSE of the first 24-hour predictions is 0.96, and it outperforms the results from Ridge and RFR. The median NSE of the persistence for the first 24 hours is also 0.96, which indicates a high auto-correlation of stream runoff and stable recession period in the first 24 hours. Although Ridge and RFR cannot beat the persistence model at the beginning, they start to outperform the persistence after 48 hours.

The distribution of NSE values of stream persistence and 120-hr forecast results are shown in Figure 4. The median NSE values of the 120-hr predictions are 0.38, 0.71, 0.63 and 0.68 among 63 downstream USGS stations for the persistence, ridge regression, RFR, and

NRM. There are 18 stations with 120-hr ahead NRM prediction NSE higher than 0.8, while there are only 7, 13 and 9 stations with high for the persistence, ridge regression, and RFR.

The station-based watershed prediction used the total rainfall among the watershed as a single value ignored the rainfall inequality. And using upstream forecast data as an additional input to represent the upstream rainfall may help to reduce the error caused by the rainfall inequality for larger watersheds represented by downstream stations.

Table 2. Median NSEs among 63 downstream stations for five-day predictions in different models.

	Persistence	Ridge	RFR	NRM	NRM-Distributed
1st day (1-24 hrs)	0.96	0.94	0.94	0.95	0.97
2nd day (25-48 hrs)	0.83	0.81	0.82	0.87	0.92
3rd day (49-72 hrs)	0.66	0.73	0.73	0.81	0.90
4th day (73-96 hrs)	0.51	0.68	0.65	0.79	0.88
5th day (97-120 hrs)	0.34	0.66	0.52	0.76	0.85

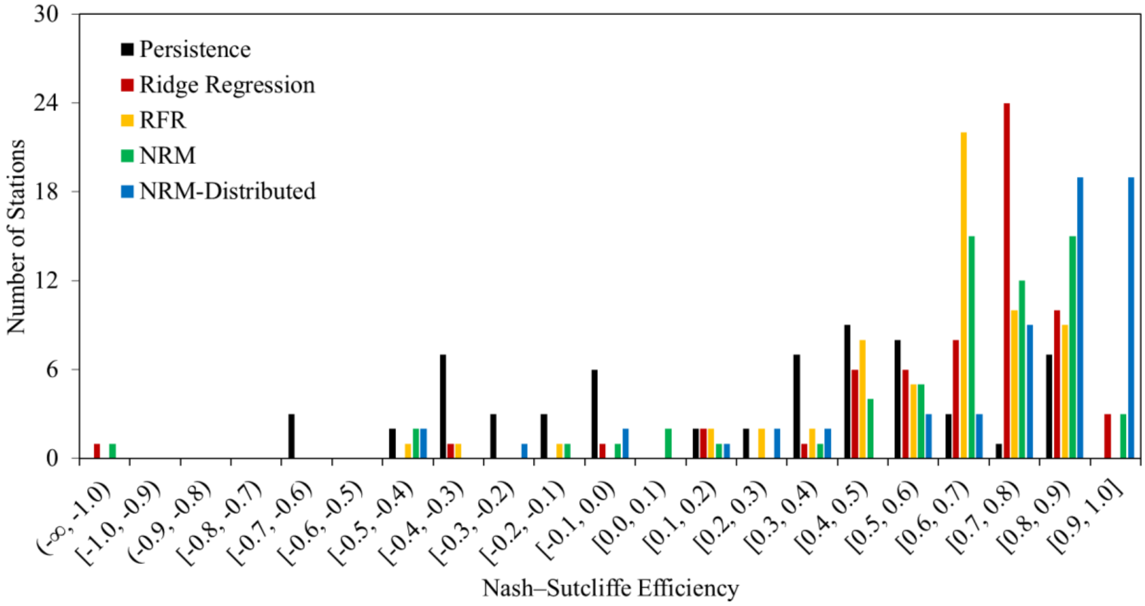

Figure 4. Distribution of the 120-hr ahead prediction NSE for the 63 downstream USGS gages.

Results considering the station relationships are shown in Table 2. The distributed model for these 63 stations using their upstream forecast results increased the NSE for all prediction hours. 51 stations show a positive increment when using their upstream forecast data, and the 5th day NSE was increased from 0.76 to 0.85 for the median. For the longest prediction ability, the median NSE of the 120-hr ahead prediction was increased from 0.68 to 0.86. The distributed model shows huge improvement not only because of less error from rainfall inequality from accurate sub-watersheds, but also integrating upstream gages for past observation and future predictions. The higher prediction accuracy of upstream gages from NRM is also important to make NRM-Distributed predict better.

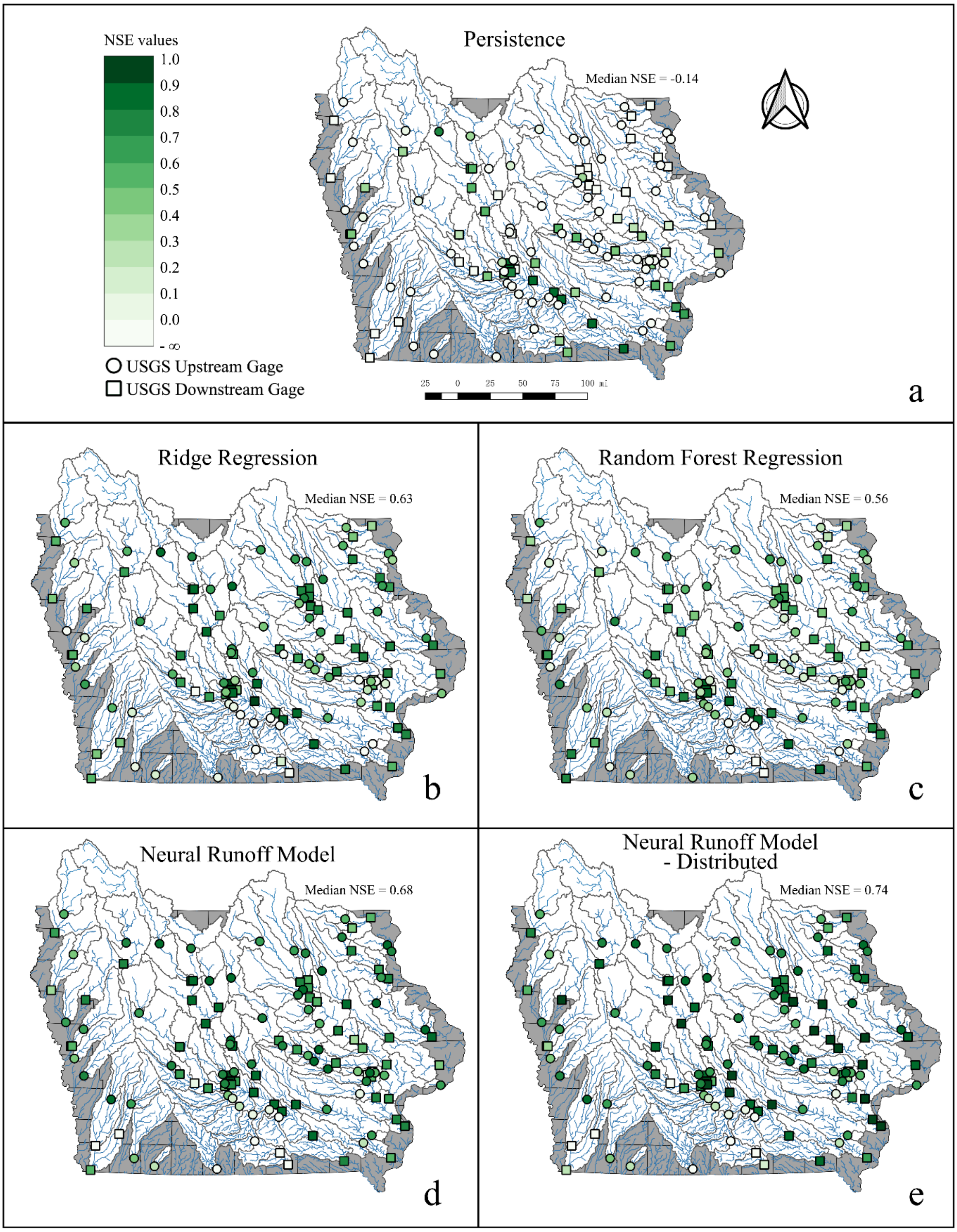

Figure 5. NSE values for proposed NRM models with benchmarks at the 120-hr ahead predictions in WY2018 on 62 USGS upstream gages in circles and 63 downstream gages in squares in the State of Iowa. Figure *a* for the result of 120 hours persistence, figure *b* for the

ridge regression, figure *c* for random forest model, figure *d* for proposed neural runoff model, figure *e* for distributed neural runoff model on downstream gages.

Figure 5 presents the NSE values for the 120-hr ahead predictions for 125 USGS gages in Iowa. The color palette for NSE has 11 ranges from 1 to negative infinity, which is another way of representing the data in Figures 3 and 4. Upstream gages values in Figure 5e are the same in Figure 5d since they do not have an upstream gage. Proposed NRM-Distributed and NRM models have the 120-hour ahead predictions outperform runoff persistence, Ridge regression and RFR on 118, 107, and 109 out of 125 gages.

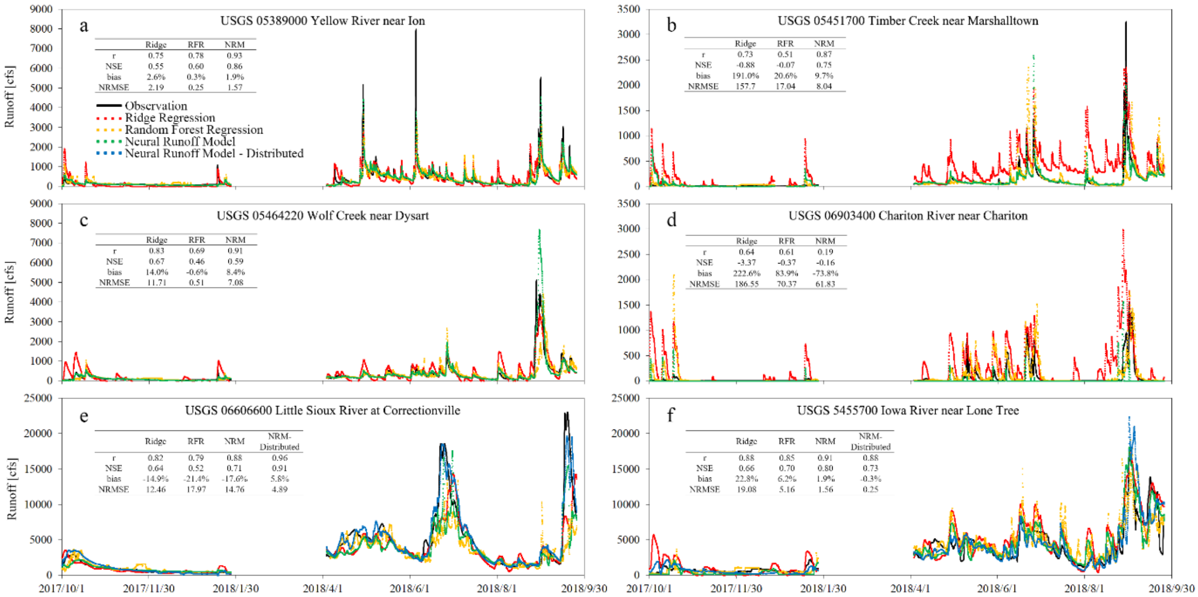

Figure 6. Example USGS streamflow gages in time-series with the observations and model predictions of 120-hr ahead predictions in WY2018. Figure *a*, *b*, *c*, and *d* are example results of upstream gages; figure *e* and *f* are example results of the downstream gages.

Six representative USGS gage results in time-series are shown in Figure 6. Figure 6a shows a typical upstream gage that is easy to forecast with Ridge, RFR, and NRM have the NSE of 0.55, 0.60, and 0.86. NRM outperforms Ridge regression and RFR, with significantly higher r and NSE with its best forecasts for the top three stormwater events. Figure 6b shows a typical station that Ridge regression and RFR cannot forecast well with NSE of -0.88 and -0.07. However, NRM works well with NSE of 0.75 and r of 0.87. Although Ridge regression forecasts the top two stormwater events better than NRM, it has poor accuracy for normal rainfall events and has a lower correlation coefficient of 0.73 than NRM. Figure 6c shows the gage results with NRM that performs lower than Ridge on NSE. Although Ridge has the issue of overprediction on many rainfall events, it predicts the strongest stormwater event better than other models and has the highest annual NSE value. Figure 6d shows a station that all three models have negative NSE. The storm hydrograph of this station indicates a very short lag time and narrow storm peak. In addition, at over half of the time, the Chariton River near Chariton is almost dry up with streamflow below 5 cfs. It is still limited to make long-term predictions for stations in this situation.

Figure 6e shows a typical downstream gage that Ridge, RFR, and NRM have the NSE of 0.64, 0.52, and 0.71. NRM has the best forecast with the highest NSE value and correlation coefficient. NRM predicts the top two stormwater events better among three models. With the integration of its upstream gage (USGS 6605850 Little Sioux River at Linn Grove - Linn Station), the NRM-Distributed improved the strongest stormwater event's streamflow prediction and the second strongest stormwater event's streamflow distribution. Statistically, NRM-Distributed improved the NSE from 0.71 to 0.91. It also has the best metric scores on r, bias, and NRMSE. For Linn Station, Ridge, RFR, NRM, and NRM-Distributed have the NSE of 0.64 and 0.44, 0.80, and 0.86 respectively. In this study, the distributed structure of Ridge regression and RFR was not tested because it requires accurate predictions on their upstream gages. A high model accuracy of upstream gages is important to make the distributed model more accurate for downstream gages. An opposite example is shown in Figure 5f that the NRM-Distributed model gets poor prediction results than NRM. The station is located downstream of three gages. At this station, NRM outperforms Ridge and RFR with high NSE and correlation coefficient, and low bias and NRMSE. However, the distributed model integrating its three upstream gages caused the 120-hr ahead prediction NSE decreased from 0.80 to 0.73, and the top two stormwater events get overpredicted or underpredicted. Its three upstream gages have the NRM-Distributed model of 120-hr ahead prediction NSE of 0.74, 0.60, and 0.04 respectively. A test of removing the relationship of the third gage station increased the 120-hr ahead prediction NSE from 0.73 to 0.77. This direct impact proved that low model accuracy of upstream may decrease the downstream gages predictions in the NRM-Distributed model. Only 7 out of 63 USGS downstream gages have the 120-hr ahead prediction NSE decreased over 0.05. All of them have a significant low forecast accuracy on their upstream. These results indicate that the inaccuracy of upstream gages forecasts would cause an extra error introduced to the distributed model for downstream forecasts, although in most cases the distributed structure helps to increase the model accuracy. The upstream gages with poor accuracy can be removed from the upstream-downstream relationships in NRM-Distributed because they did not help to improve the modeling accuracy when a station is always underperformed. This also indicates high model accuracies on upstream gages are a necessary reason why the NRM-Distributed model can succeed.

3.4 Integration of Stage Level Sensors

Since applications of the NRM-Distributed significantly improved the forecast accuracy of USGS downstream gages, the distributed structure could possibly improve the forecast of upstream gages if there are more measurements located at their upstream. However, since the most of stage level sensors located at the upstream of USGS gages were established by the year 2013, when applying the NRM-Distributed model on both stage level and streamflow gages, only the data from WY2014 to 2017 were available. There are 60 stage level sensors located at the upstream of 29 USGS upstream gages. The locations and model results for stage level and streamflow gages are shown in Figure 7. The results in Figure 7b used the NRM calibrated with only 4 years of data rather than 6 years of data in Figure 5d.

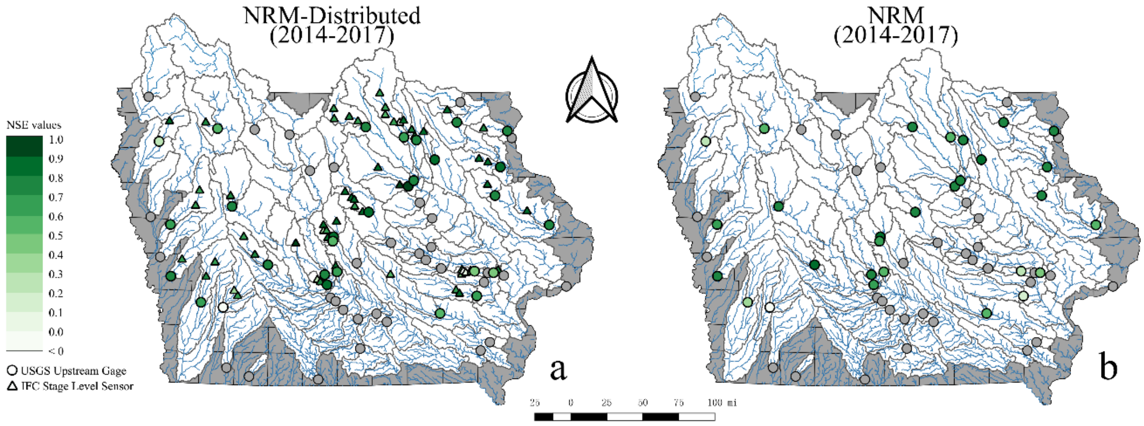

Figure 7. NSE values for proposed NRM-Distributed and NRM models on USGS upstream gages for WY2018 with training and validation data from WY2014 to 2017. 33 gray circles are USGS upstream gages without stage level stages at their upstream. 29 colored circles are USGS upstream gages that have available NRM-Distributed results. Figure *a* shows the NRM-Distributed model results on USGS gages and the stage level sensors. Figure *b* shows the NRM model results on USGS gages.

It is shown that the proposed model NRM and NRM-Distributed can work well not only on the USGS streamflow data predictions but also on the stage level sensors. The median NSE of 29 USGS streamflow gages for 120-hr ahead runoff prediction is 0.71. With the data from 60 stage level sensors, the NRM-Distributed model shows significantly better results with a median NSE of 0.72 (Figure 8b), which is higher than the models without stage level data. The station-to-station comparison of two model results in Figure 8a shows that 21 out of 29 stations have a better model performance. Especially, looking at the under-performed gages with NRM NSE less than 0.75 only, 19 out of 21 underperformed gages get improved. The results indicate that the distributed model is effective by integrating the stage level sensor data for the predictions of USGS gages. However, it also shows that the improvement of the distributed model has been limited since the systematic error and random error in stage level sensors and their forecast model results are introduced in the distributed model and may affect the predictions on stations that are already well performed.

Comparing the model results to the test in section 3.2, both model results with 4 years (WY2014-2017) data of training and validation perform worse than the NRM results using 6 years (WY2012-2017). The median NSE of these 29 USGS streamflow gages for 120-hr ahead runoff predictions is 0.73 as shown in Figure 8b, higher than 0.72 and 0.71 in NRM and NRM-Distributed with 4 years data for training and validation. This indicated that data quantity is also important since longer data normally have more stormwater event data which are scarce and are important for rainfall-runoff modeling. Integrating more measuring stations (e.g., stage level sensors) helps to improve the predictions on underperformed gages, but still performs worse than the USGS stations only with a longer data period. As a result, more data with more stations and more temporal data periods help to improve the artificial neural runoff model. For runoff predictions at USGS gage level, more temporal data can improve the model accuracy more than integrating more stage level stations in this test. However, the models with these new stations would be more effective in the near future with more measurement.

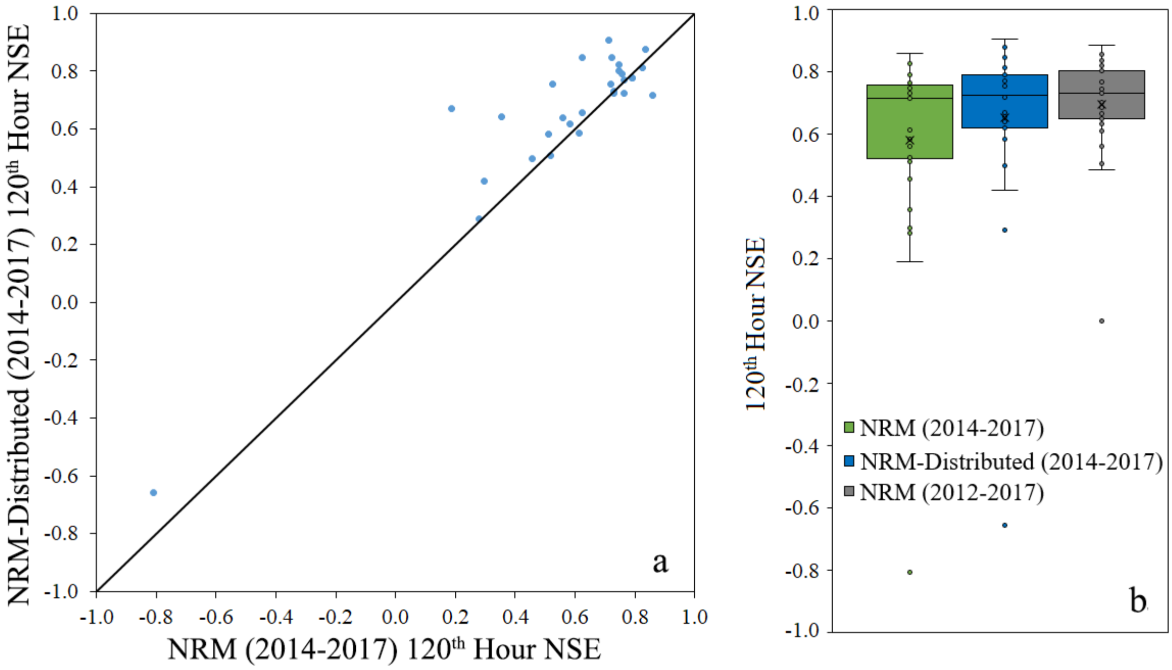

Figure 8. NSE values from the NRM and NRM-Distributed with stage level sensors on the 29 USGS upstream gages.

4 Conclusion

This study developed a deep learning based rainfall-runoff model named Neural Runoff Model (NRM) using the recurrent neural network and sequence learning. This model can predict hourly runoff for up to 120 hours using the rainfall observation, rainfall forecast, runoff observation, and evapotranspiration data.

In the first test, the proposed NRM and previous model LSTM-seq2seq on the Clear Creek Watershed showed a 120-hr ahead model prediction NSE of 0.79 and 0.58. The significant improvement shows that the proposed model NRM overcome the bottleneck problem of the encoder-decoder based model in long-term predictions.

In the second test, applying NRM on 62 upstream streamflow gages, the median NSE values of the 120-hr ahead predictions are -0.44, 0.41, 0.48 and 0.69 for the persistence, ridge regression, random forest regression, and NRM. The proposed NRM outperforms all other models on the median NSE.

In the third test, applying the NRM and NRM-Distributed on 63 downstream streamflow gages, the median NSE values of the 120-hr ahead predictions are 0.38, 0.71, 0.63, 0.68, and 0.86 for the persistence, ridge regression, RFR, NRM, and NRM-Distributed. Proposed NRM-Distributed on downstream gages and NRM on upstream gages have the 120-hour ahead predictions outperform runoff persistence, Ridge regression and RFR on 118, 107, and 109 out of 125 gages. The proposed distributed model can work well on most of the USGS streamflow gauges. This indicates that high accuracy predictions of upstream gages can be integrated into the distributed model and used for improving the predictions of the downstream in neural networks.

In the last test, with 4 years of training and validation data, 21 out of 29 USGS upstream gages have a better model performance on the 120-hr ahead predictions when integrating the stage level data using NRM-Distributed. The results indicate the integration of different measurements located at the upstream of USGS gages can help to improve the runoff prediction with the NRM-Distributed model. Although these results are not as good as the ones in the second test with 6 years of training and validation data, it indicates that more temporal data and more stations are both important.

NRM showed great success with a strong prediction ability on long-term rainfall-runoff modeling. It overcomes the bottleneck effect caused in the encoder-decoder based sequence model. The large-scale application on 60 stage level sensors from IFC and 125 streamflow gages from USGS in Iowa shows the robustness of the proposed NRM and NRM-Distributed models. The NRM-Distributed model also shows the potential improvements in the prediction accuracy by integrating observation data from multiple sources. However, as a data-driven model, it is highly dependent on historical data. As shown in the final test, considering the limited data by using 4 years rather than 6 years of data, the model accuracy will decrease significantly. Some issues such as the winter snow season predictions are not considered in this study since the lack of accurate snow cover data in Iowa. The model can be considered as a successful attempt at integrating multiple measurements and model results in one model for long-term rainfall-runoff modeling. Real-time forecast applications with data-driven techniques like deep learning can possibly be a complement or substitute for physically-based models, especially for underperforming watersheds.

Acknowledgment

The work reported in this study was possible with the support and work of members of the Iowa Flood Center and Civil and Environmental Engineering at the University of Iowa.

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