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Convolutional Neural Networks (CNN)-Signal Processing Combination for Daily Runoff Forecasting

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ABSTRACT

Aims: The main aim of this study was to assess the efficacy of two important signal processing approaches i.e., wavelet transform and ensemble empirical mode decomposition (EEMD) on the performance of the convolutional neural network (CNN).
Materials & Methods: The study was performed in two watersheds i.e., the Kasilian and Bar-Erieh Watersheds. In the first step, the CNN-based runoff modeling was done in its single form i.e., using the original data as input. In the next step, the input data was decomposed into several different sub-components i.e., approximation and details using Wavelet transform and Intrinsic Mode Functions (IMFs) using EEMD. Then the decomposed data were imported to the CNN model as input and combined Wavelet-CNN and EEMD-CNN models were provided.
Findings: The results showed that CNN in its single form could not estimate the one-day-ahead runoff with acceptable accuracy. CNN in its original form had a moderate performance (with NRMSE of 83 and 66%). However, the application of Wavelet transform and EEMD in combination with CNN produced acceptable results. It was shown that Wavelet transform had a higher impact (with NRMSE of 48 and 26%) on the performance of CNN in comparison to EEMD (with NRMSE of 52 and 61%).
Conclusion: This study showed that signal processing approaches can enhance the ability of deep learning methods such as CNN in predicting runoff values for one-day-ahead. However, the impact of signal processing methods on the performance of deep learning methods is not equal.

Keywords: Deep Learning; Empirical mode decomposition; Rainfall-runoff modeling; Wavelet transform.

CITATION LINKS

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Introduction

Runoff forecasting is of paramount importance in water resource management, flood mitigation, drought mitigation, and ecosystem service assessment [1, 2, 3, 4, 5]. Accurate streamflow forecasting can help regional authorities to take appropriate strategies. Three main types of modeling approaches can be used for runoff forecasting i.e., empirical, conceptual, and physically based models [6, 7, 8, 9, 10]. Conceptual and physically based models usually consider the process of the phenomenon that is being modeled. They are robust models and generally produce acceptable results. However, these types of models are relatively complex and require a great deal of data [11]. Also, they encompass several parameters in their structure that should be calibrated. The huge number of variables and parameters can sometimes meaningfully increase the uncertainty in the modeling results. Empirical models are acceptable alternatives, especially in data-scarce conditions. These models which are also known as data-driven models such as regression artificial neural networks, support vector regression, and adaptive neuro-fuzzy inference systems explore the relation between runoff and some independent variables. These models are relatively simply applicable. Artificial intelligence methods are the most robust data-driven models. With the advent of strong computer processors, deep learning methods have been widely used in different fields, especially in hydrology [12, 13]. The main advantage of deep learning over traditional neural networks is related to its high level of complexity and higher depth of hidden layers. One of the most widely used deep learning methods is the convolutional neural network (CNN) which is developed based on the local connectivity idea.

The main problem with runoff modeling with artificial intelligence models is related to the non-stationarity of data. Artificial intelligence models usually cannot deal with highly non-stationary signals (time series) [14, 15, 16]. Signal processing approaches can be used to cope with this problem [17, 18]. Wavelet transform (WT) and Ensemble Empirical Mode Decomposition (EEMD) are the most widely used signal processing methods that can be used in conjunction with artificial intelligence methods. Different studies have assessed the effect of wavelet transform and EEMD on the performance of artificial intelligence models to forecast runoff. Shoaib et al. (2014) [19] investigated the efficacy of some mother wavelets on the performance of the artificial neural network in runoff prediction. In this study, the hybrid MLP and SVR models have been processed using both continuous and discrete wavelet transformations. The performance of 92 hybrid models was assessed in comparison with single and simple neural network models without any pre-processing. Their results showed that wavelet has a significant effect on the performance of neural network models. Wang et al. (2015) [20] proposed a combined artificial neural network (ANN) -Ensemble Empirical Mode Decomposition (EEMD) model for predicting medium and long-term runoff time series. In this study, first of all, the time series of runoff was decomposed into a limited and often small number of the IMFs and the remaining series were analyzed using the EEMD technique to gain deeper insights into data properties. In the next step, all IMFs and residuals were predicted by ANN models. Finally, the IMF prediction results were modeled and the remaining series were collected to provide an ensemble prediction for the main annual runoff series. The results showed that EEMD can effectively increase the forecast accuracy and the proposed EEMD-ANN model can achieve a significant improvement over the ANN approach in predicting

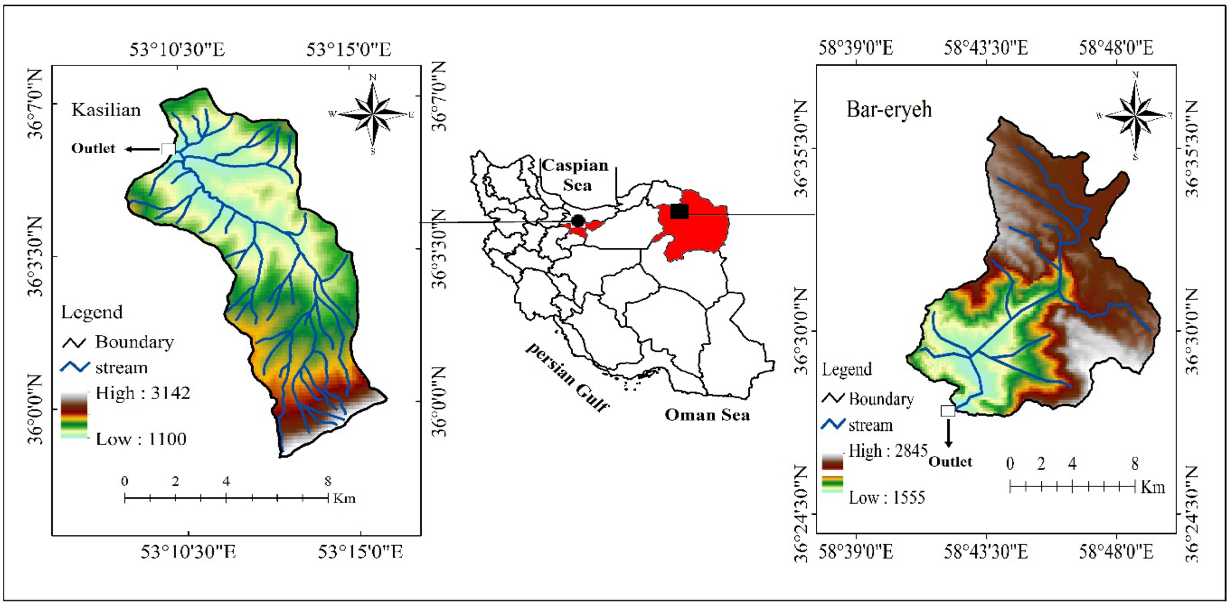

Figure 1) Location of the Kasilian and Bar-Erieh Watersheds in Iran.

runoff time series. Shoaib et al. (2016) [21] investigated the effect of wavelet transform on the performance of Lagged Recurrent Neural Network (TLRNN) model in runoff forecasting. Single and hybrid models were then compared. The results showed that TLRNN models with wavelet transform can be used as a good alternative for static wavelet MLPNN models. Tan et al. (2018) [22] investigated the effect of the EEMD signal processing method on the performance of ANN models in runoff prediction. The results demonstrated that the hybrid EEMD-ANN model outperformed the single ANN model. Mao et al. (2021) [12] examined the performance of artificial intelligence and common hydrological models in runoff modeling. The results showed that the artificial neural network model and LSTM had higher accuracies for monthly and daily time scales, respectively.

Both WT and EEMD decompose the main variables into their sub-components. This decomposition can enhance the performance of data-driven models. In this regard two different watersheds i.e., the Kasilian Watershed and the Bar-Erieh Watershed were selected to assess the efficacy of the signal processing approaches on the performance of deep learning methods for runoff forecasting. The selection of two different watersheds helps the generalizability of the results. To the best of our knowledge, no research has been performed on the combination of WT and EEMD with a convolutional neural network for runoff forecasting. The main goal of this study was to compare the performance of the convolutional neural network in its simple form with the combined signal processing-CNN models.

Materials & Methods

Study area and data

Two physically and climatologically different watersheds i.e., the Kasilian Watershed, and the Bar-Erieh Watershed were used to perform this study to increase the generalizability of the results. Figure 1 shows the study area. Part A of Figure 1 shows the Kasilian Watershed with an area, precipitation, slope, and elevation of 68km2, 809mm, 15.8%, and 1691m, respectively [23]. Part B of Figure 1 shows the Bar-Erieh Watershed which covers an area of 113 km2. The precipitation, slope, and elevation

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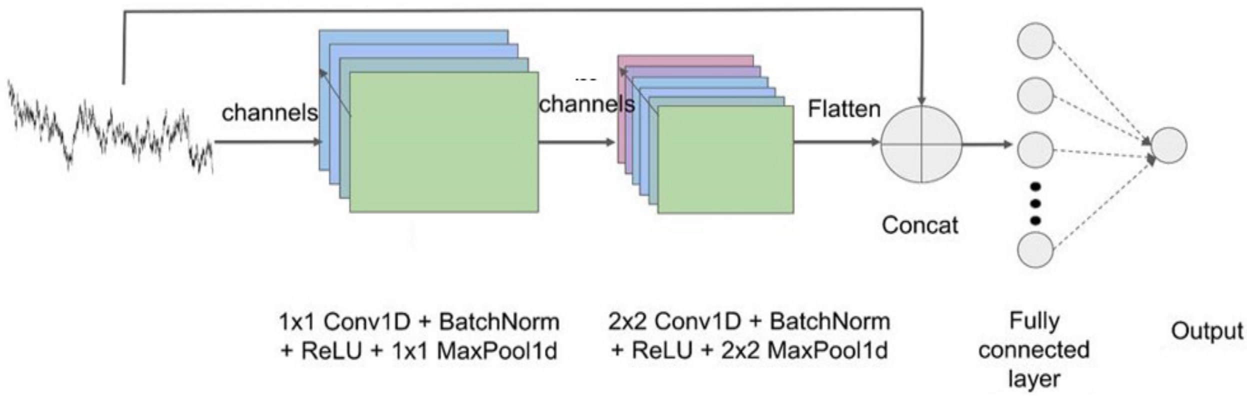

Figure 2) Schematic illustration of convolutional neural network (27).

of this watershed are 330mm, 11.9%, and 2226m, respectively. Important data i.e., rainfall, air temperature, evaporation, air humidity, wind speed, and discharge data were obtained in the first step. Climatic data as well as discharge with appropriate time lags (i.e., discharge for previous days) were used as input and the discharge for one-day-ahead was used as the target in the modeling process. The modeling process is performed on a daily time scale and for 20 years.

Deep learning model

The convolutional neural network was used in this study for daily runoff forecasting [24, 25 26, 27]. Convolutional Neural Network (CNN) has been used in different fields. [28] proposed the convolutional neural network and developed the LeNet-5 model for the first time. This method consists of three main layers namely convolutional, pooling, and fully-connected layers [15]. As Figure 2 shows the CNN includes a series of 1D convolutional blocks, a Batch norm layer, ReLU activation functions, a max pooling 1D layer, and finally fully connected layers. In the next step, the input variables and the result of convolutional blocks are concatenated and imported to the fully connected layer and the output is calculated [29, 11]. The convolution layer performs some mathematical operations by using filters on the data. The pooling layer performs a down-sampling process. Max and average are two main pooling methods. The results of the pooling layer will pass the fully connected layer. The data were divided into two subsets i.e., train and test with a 70/30% ratio. 70% of the data were used for training or calibration processes. The training process was performed in two steps consisting of a forward stage in which the input is passed completely through the network and the backward stage in which gradients are back-propagated and weights are updated.

The combined signal processing-deep learning model

To provide combined signal processing-deep learning models, the original datasets i.e., climatic and hydrometric data were decomposed using wavelet transform and EEMD signal processing methods. There are two main types of wavelet transforms i.e., continuous (CWT) and discrete (DWT) transforms. As the continuous wavelet transform provides a great deal of data, discrete wavelet transform was used in this study. Wavelet transforms as a linear transformation uses some base functions that are known as mother wavelets. The mother wavelets are used to extract different coefficients from the original signal (that are meteorological and hydrometric data here). DWT provides a high-frequency component namely detail and a low-frequency component namely approximation. Several different mother wavelets such as Daubechies (db2, db3, db4, db5, db6, db7,

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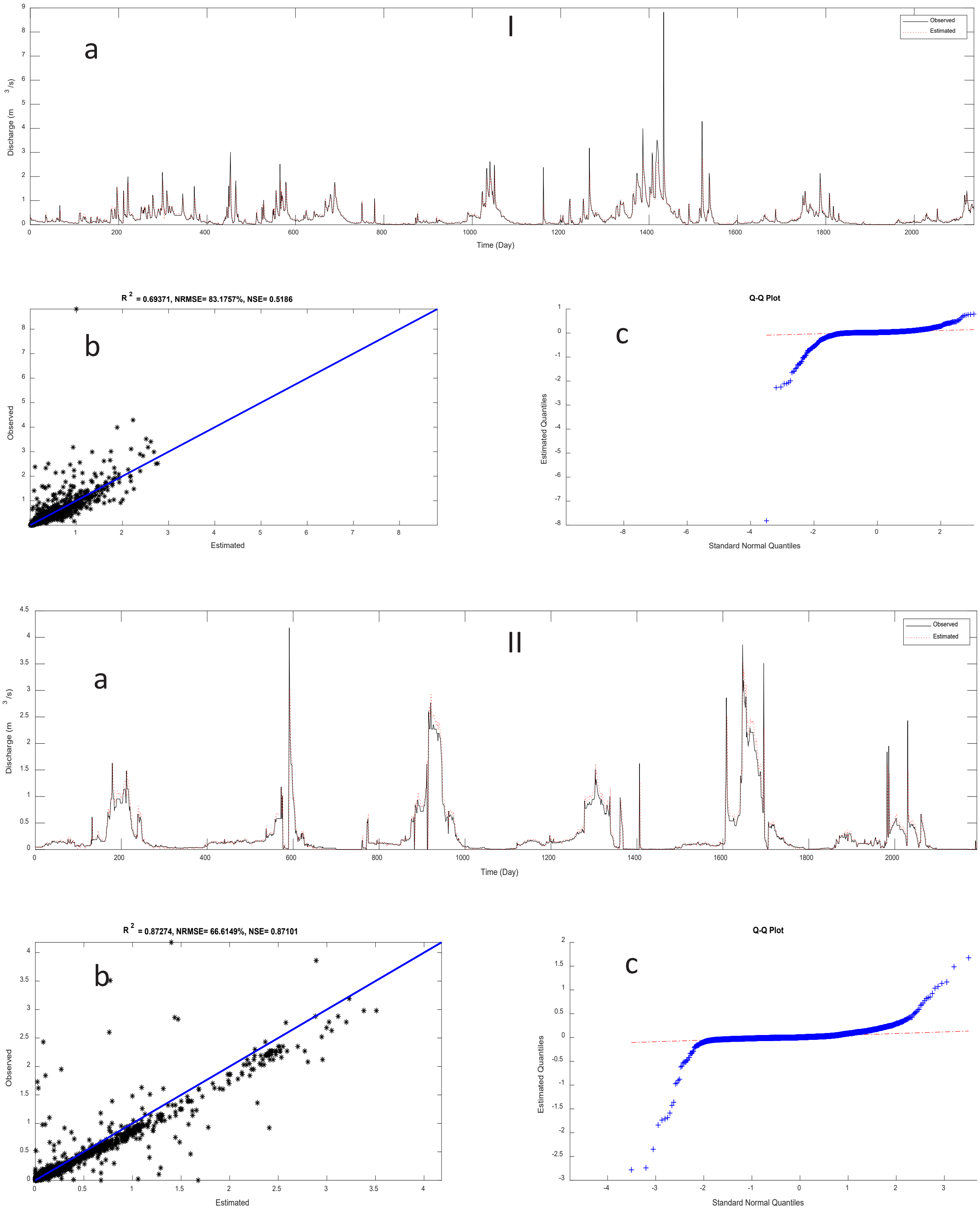

Figure 3) The results of convolutional neural network runoff modeling. I) Kasilian Watershed, and II) Bar-Erieh Watershed.

db8, db9, db10), Coiflet (coif1, coif2, coif3, coif4, coif5), Symlet (sym2, sym3, sym4, sym5, sym6, sym7, sym8) and Biorthogonal (bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8) were tested in order

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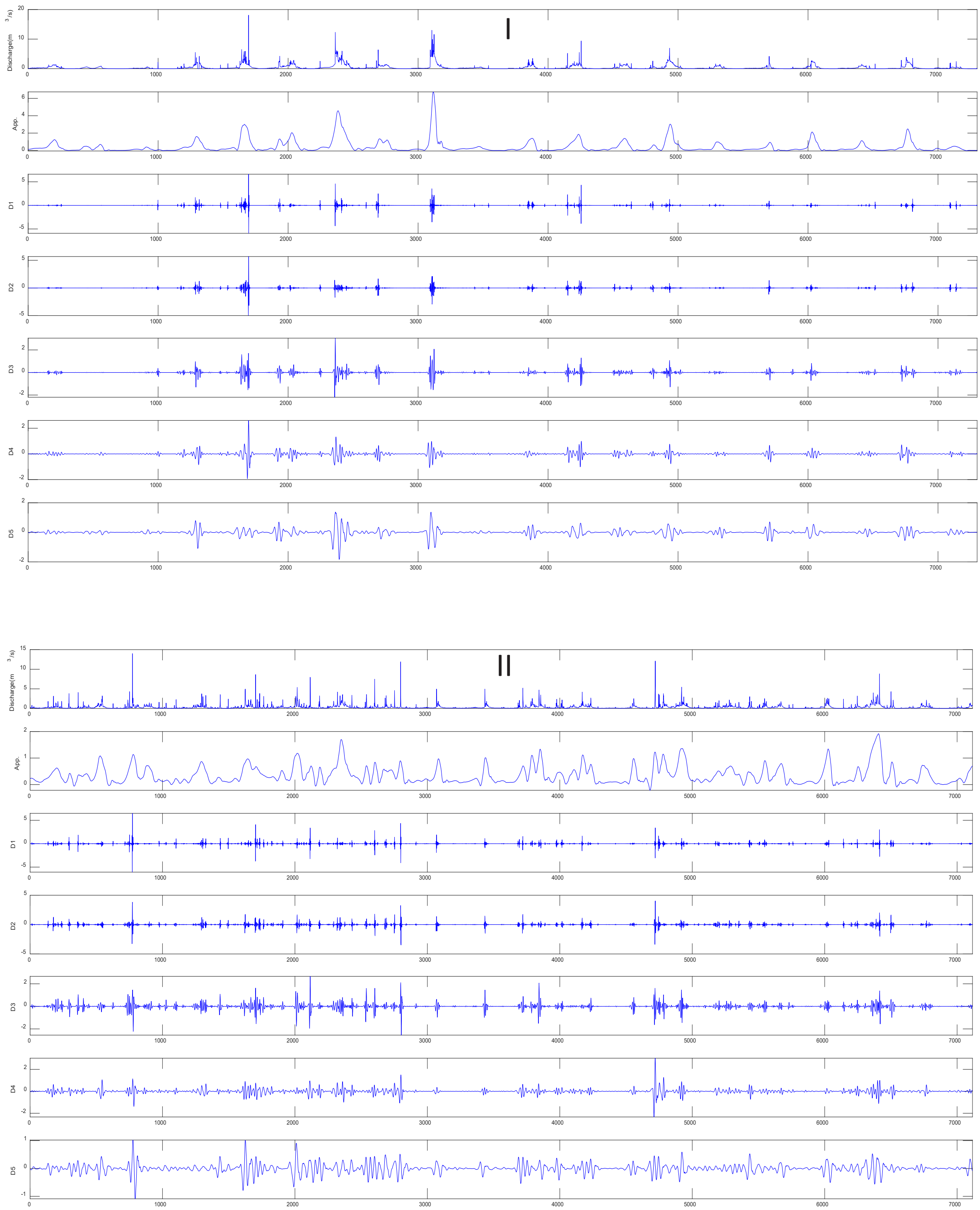

Figure 4) Wavelet-based decomposition of discharge data using "db" mother wavelet in 5 levels, I) Kasilian Watershed, and II) Bar-Erieh Watershed.

to find the best mother wavelet. The original data were also decomposed at different levels to find the optimal decomposition level. The wavelet base function is shown in equations 1 and 2.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t\text{-}b}{a}) \qquad \text{Eq. (1)}$$

$$c = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})\,\mathrm{dt} \qquad \text{Eq. (2)}$$

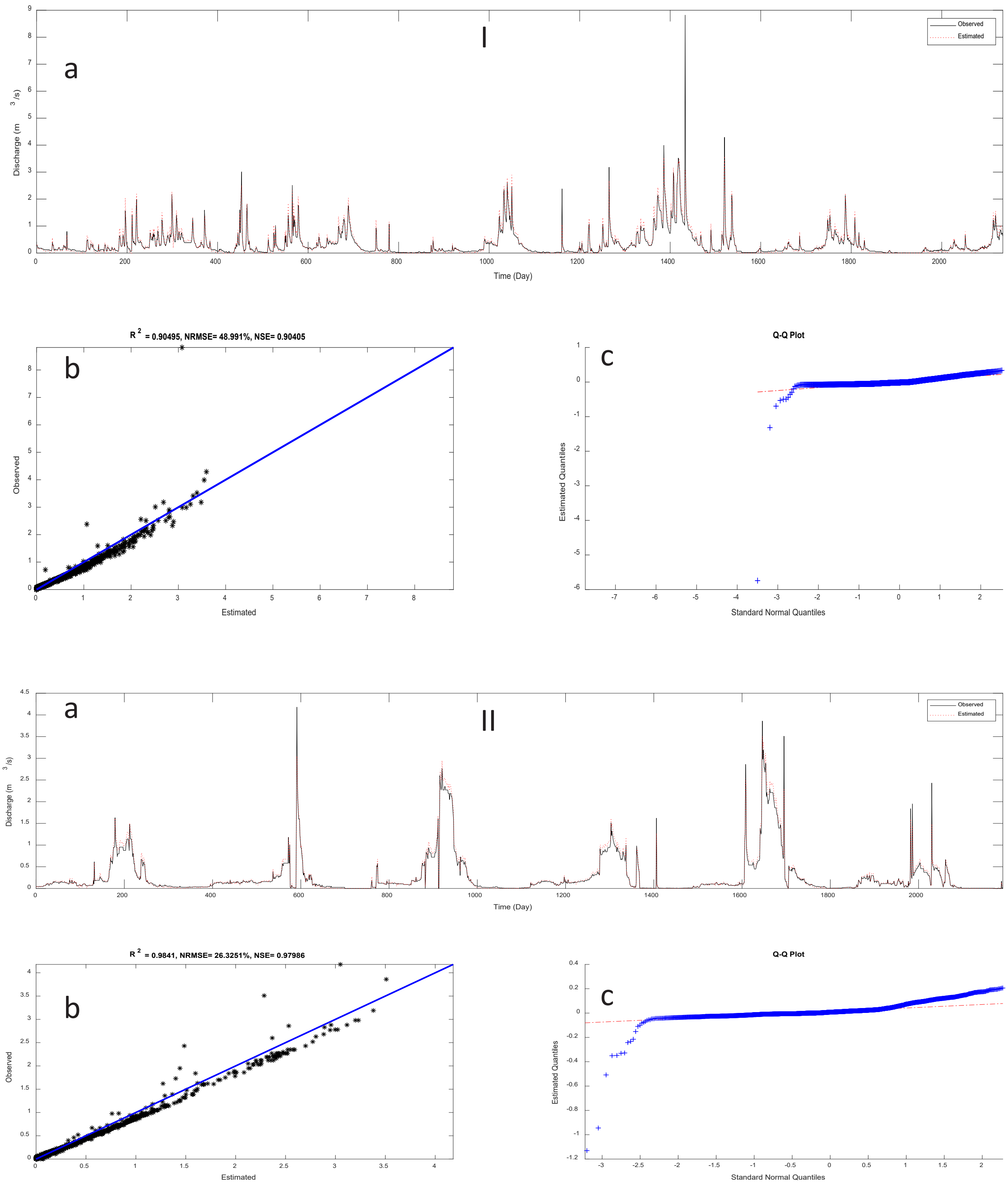

Figure 5) The results of wavelet-CNN runoff modeling, I) Kasilian Watershed, and II) Bar-Erieh Watershed.

in which is the mother wavelet, *b* is shifting and *a* is the scaling factor.

The other time-frequency analysis which was used in this study was Ensemble Empirical Mode Decomposition (EEMD) which is the modified version of Empirical Mode Decomposition (EMD). In signal processing, time-frequency analysis includes all techniques that assess a signal in both the time and frequency domains at the same time, using various time-frequency representations. A time-frequency representation (TFR) can

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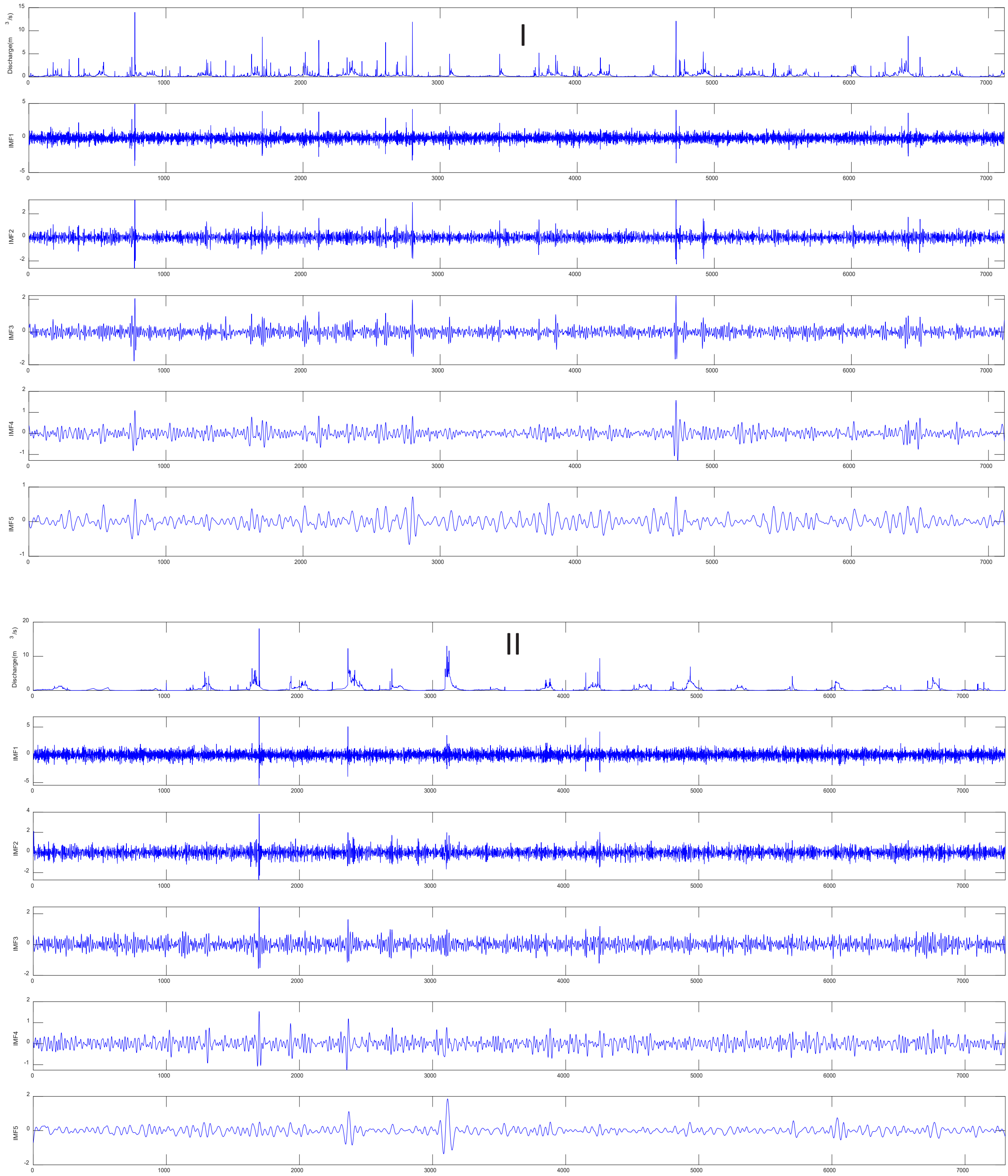

Figure 6) EEMD-based decomposition of discharge data, I) Kasilian Watershed, and II) Bar-Erieh Watershed.

be defined as the view of a signal *characterized by both time and* frequency. EMD can be used to treat nonstationary data. EMD decomposes the original signals into some intrinsic mode functions (IMFs). One of the main advantages of EMD in comparison with the wavelet transform is its self-adaptability which makes it very user-friendly. However, the core disadvantage of EMD is a mode-mixing problem that is a result of signal intermittency. EEMD has solved the mode-mixing problem. This method is known as a noise–assisted method which adds white noise to the signals.

In this study, two parallel paths were

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followed. In the first path, the original data were imported to the deep learning model and in the second path, the decomposed data using wavelet transform and EEMD were imported to the deep learning model. The results were then compared to identify the effect of signal processing approaches on the performance of the deep learning model.

Findings

Figure 3 shows the results of the CNN model using the original data without any preprocessing of the data. Part I shows the results for the Kasilian Watershed and part II shows the results for the Bar-Erieh Watershed. In each part, there are three sections. Section "*a*" demonstrates the variations of estimated and observed discharges, section "*b*" shows the scatter plot of estimated and observed discharges, and section "*c*" denotes the q-q plot. As this figure shows, CNN in its single form produces moderate results. The NSEs for Kasilian and Bar-Erieh are about 0.51 and 0.87, respectively. The coefficients of determination for Kasilian and Bar-Erieh are about 0.69 and 0.87, respectively.

Figure 4 shows the results of wavelet decomposition on discharge data using the "*db*" mother wavelet in 5 levels for Kasilian (I) and Bar-Erieh (II) watersheds. As this Figure shows there are one approximation component and 5 detail components. Approximation shows the low-frequency variations and detail components show the high-frequency variations in the discharge data. Figure 5 shows the results of the combined wavelet-CNN model for the Kasilian (I) and Bar-Erieh (II) watersheds. As this figure shows, the coefficients of determination for Kasilian and Bar-Erieh are about 0.9 and 0.98, respectively. The NSEs for Kasilian and Bar-Erieh are also about 0.9 and 0.97, respectively. It is shown that wavelet transform could significantly enhance the performance of deep learning methods such as CNN. As we can understand from Figures 3 and 5, wavelet transform increased the coefficients of determination by 30% and 12% for Kasilian (I) and Bar-Erieh (II) watersheds, respectively. It also increased the NSE by 76% and 11% for Kasilian (I) and Bar-Erieh (II) watersheds, respectively. The NRMEs were enhanced by 41% and 60%, for Kasilian (I) and Bar-Erieh (II) watersheds, respectively. The better results of modeling in the Bar-Erieh Watershed may be related to the more regular and symmetrical variations of discharge in this watershed.

Figure 6 shows the EEMD-based decomposition of discharge data. As this figure shows, the main signal is decomposed to several IMFs. The first IMF shows the component with the highest frequency and the other IMFs show the components with lower frequencies. Figure 7 shows the results of combined EEMD-CNN runoff modeling for Kasilian (I) and Bar-Erieh (II) watersheds. As this figure shows, the coefficients of determination for Kasilian and Bar-Erieh are about 0.9 and 0.88, respectively. The NSEs for Kasilian and Bar-Erieh are also about 0.81 and 0.88, respectively. It is shown that the EEMD transform could enhance the performance of deep learning methods such as CNN to some extent. As we can understand from Figures 3 and 7, EEMD increased the coefficients of determination by 30% and 1% for Kasilian (I) and Bar-Erieh (II) watersheds, respectively. It also enhanced the NSE by 58% and 1% for Kasilian (I) and Bar-Erieh (II) watersheds, respectively. The NRMEs were also enhanced by 37% and 7%, for Kasilian (I) and Bar-Erieh (II) watersheds, respectively.

Discussion

The results of all models are shown in Table 1 for an easier conclusion. The main advantage of a convolutional neural network in comparison with other neural networks is the ability to detect some important features from the

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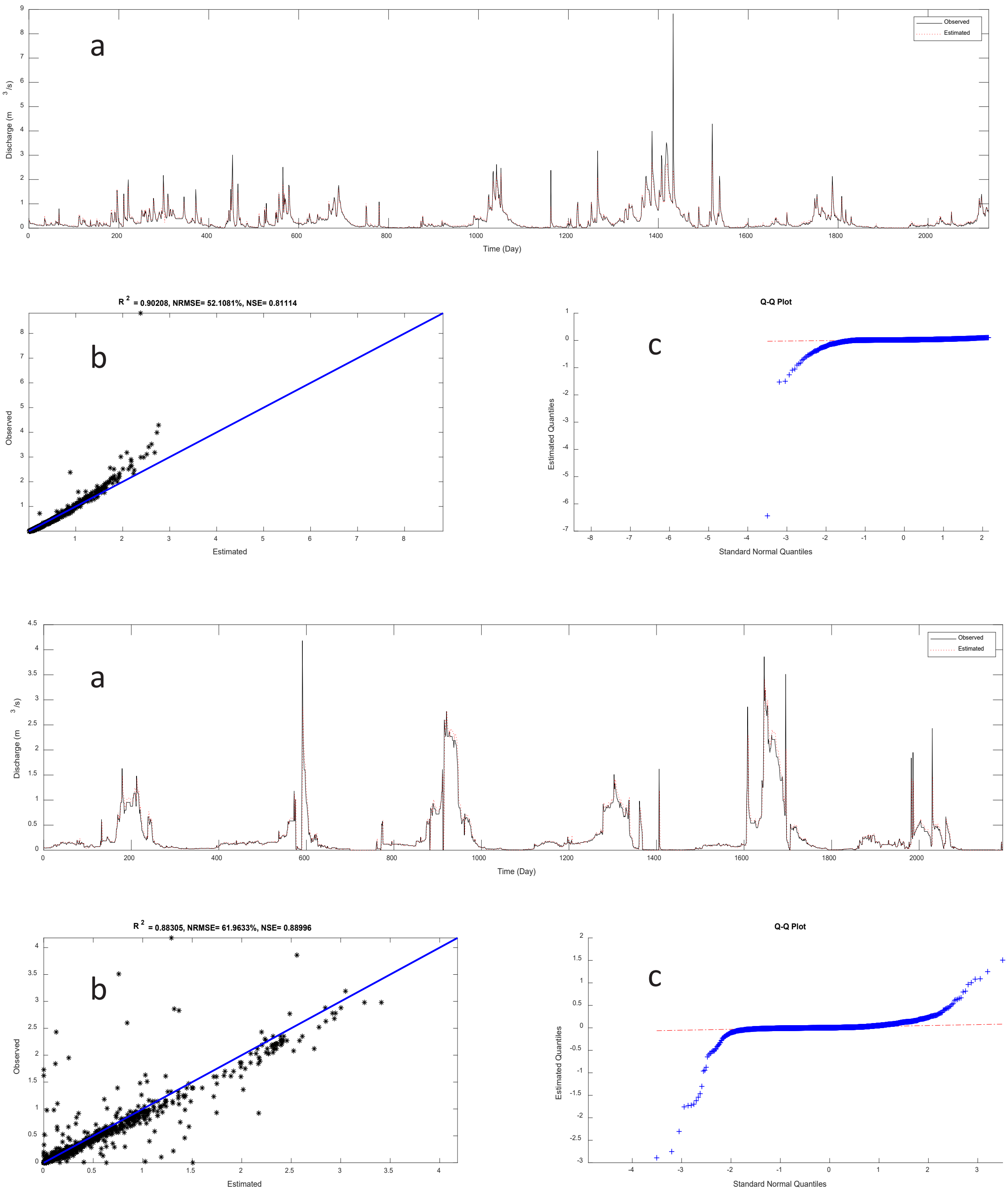

Figure 7) The results of EEMD-CNN runoff modeling, I) Kasilian Watershed, and II) Bar-Erieh Watershed.

original data without any human control. In a simple neural network, the original data are imported to the hidden layers and the weights are computed. When the size of data increases, the number of weights and parameters in the structure of the neural network that should be tuned increases dramatically. In this situation, overfitting can easily occur. A convolutional neural network by extracting important features and using convolution and pooling functions provides a very robust structure to deal with a huge number of data and to find very complex relations between dependent and independent variables. As the relations

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Table 1) The final results of CNN, WT-CNN, and EEMD-CNN models.

Model	Kasilian Watershed			Bar-Erieh Watershed		
	R^2	NRMSE (%)	NSE	R^2	NRMSE (%)	NSE
CNN	0.69	83.1	0.51	0.87	66.6	0.87
WT-CNN	0.9	48.9	0.9	0.98	26.3	0.97
EEMD-CNN	0.9	52.1	0.81	0.88	61.9	0.88

in natural processes are usually intricate, the simple neural networks sometimes fail to determine the relations appropriately. In these cases, deep learning methods are good approaches to cope with these problems. Deep learning as a machine learning approach imitates the behavior of the human brain to detect the relations between different variables in a specific process. In this type of neural network, several hidden layers are used despite the simple neural network that usually includes a handful of hidden layers. The other advantage of the deep learning method is its ability to work with unstructured data and its better self-learning capabilities. Having several hidden layers make deep learning models able to efficiently learn the behavior of the process applying more complicated computations. Using these advantages, deep learning methods usually outperform other machine learning approaches. The next advantage of deep learning methods against traditional approaches is their high scalability. This approach performs a lot of computations on a huge number of data effectively. It significantly increases the generalizability of the results obtained using deep learning models.

Conclusion

The study revealed that the Wavelet transform and EEMD had a significant effect on the performance of deep learning methods in runoff modeling and prediction. The single form of CNN had a moderate performance in estimating runoff values for one-day-ahead. The results showed that both Wavelet transform and EEMD enhanced the performance of CNN. However, Wavelet transform had a higher impact on the CNN rather than EEMD. The results are following many previous studies such as [19, 20, 21, 22]. There are some limitations related to the deep learning method. Like other empirical methods, deep learning algorithms cannot consider the process and just determine a relation between input and output variables. These methods need a rather huge amount of data for the training step. In addition, these models have a local performance and can only be used for the area for which the model is developed. The other main point that should be taken into account is the higher computational cost of Wavelet transform compared to EEMD. Finding the optimum mother Wavelet and decomposition level is a time-consuming task. It should be done using a trial-and-error method (which was done in this study) or by combining the modeling approaches with optimization methods such as genetic algorithm or particle swarm optimization method. EEMD doesn't need any pre-conception. Therefore, if the results with higher accuracies are needed, Wavelet transform can be a better option. Otherwise, EEMD can be used to enhance the performance of CNN to some

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extent. Other signal processing methods such as singular spectrum analysis (SSA) can be used in conjunction with CNN. Also, performing other deep learning methods such as Long short-term memory (LSTM) or auto-encoders can be suggested for future studies.

Declaration of competing interest

The authors declare no conflict of interest.

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