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Predicting Runoff with Pre-Processing Approaches in Ardabil Plain

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1-Introduction

Nowadays water resources management is a vitally important task and is the optimum planning of irrigation projects, and the development and exploitation of water resources especially during drought and flood events are strictly dependent on the accuracy of the used rainfall-runoff modeling tool. Therefore, different models have been already developed and employed for modeling rainfall-runoff processes of the watersheds (Partovian et al., 2017).
The wavelet-based pre-processing approach in the present study was used in the modeling of runoff time series via ANN. Furthermore, the impacts of denoising (smoothing) and wavelet transform have been simultaneously investigated in the accuracy of runoff prediction for one month ahead at the outlet of Ardabil plain.

2-Methodology

2-1-Case of the Study

The plain of Ardabil (38°03′– 38°27′N and 47°55′– 48°20′E), located in north-western Iran, covers an area of about 990 km^2 (see Fig. 1). In the present study, the trend analysis was carried out on the rainfall (P) and runoff (R) parameters for three stations including Samian (P_S, R_S), Gilandeh (P_G, R_G), and Kozatopraghi (P_K, R_K)) located in the Ardabil plain from 1977 to 2019. The data sampling has been reported in the one-month interval at all of the stations. Figure 2 shows the locations of the rainfall and runoff stations. In this study, five combinations of input data were consumed for runoff prediction as to the following:
Comb. 1: $R_S(t)$, $R_S(t-1)$, $P_S(t)$; Comb. 2: $R_S(t)$, $R_S(t-12)$, $R_S(t-24)$, $P_S(t)$; Comb. 3: $R_K(t)$, $R_G(t)$, $R_G(t-1)$, $P_G(t-12)$, $R_K(t-12)$

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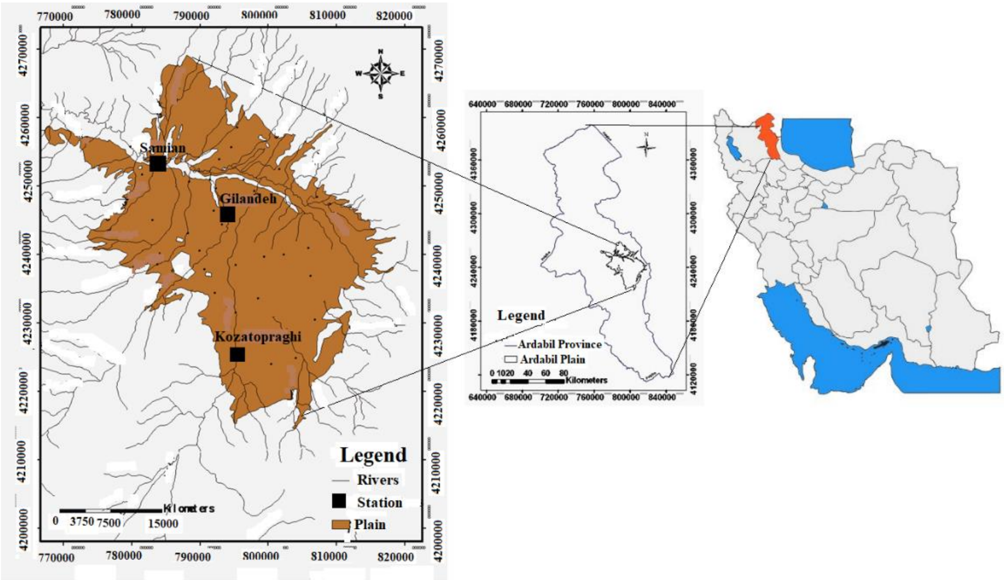

Fig. (1): Case of the study and the position of rainfall and runoff stations.

2-2-Artificial Neural Network (ANN)

Three-layered feed-forward backpropagation, which is usually used in forecasting hydrologic time series, provides a general framework for representing the nonlinear functional mapping between a set of input and output variables.

2-3-Wavelet transform (WT)

In hydrological problems, the time series are usually in the discrete but continuous format; therefore, the discrete WT was used in the following form (Mallat, 1998):

(2) $$g_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} g^*\left(\frac{t - nb_0 a_0^m}{a_0^m}\right)$$

2-4-Wavelet based de-noising

Wavelet de-noising technique is operated as follows: (1) an applicable mother wavelet and several resolution level methods are selected. An approximation subseries at the resolution level L and detailed sub-series at different resolution levels are decomposed from main time series xi (2) The absolute amounts of detailed-sub-series, which exceed the values of the fixed threshold are changed by the difference between the values of threshold and detailed sub-series.

2-5- Efficiency criteria in runoff prediction

Two different criteria were used to measure the efficiency of the proposed forecasting methods; the root means square error *(RMSE)* and the determination coefficient *(DC)*.

3-Results and Discussion

Some temporal features may also exist in the runoff time series due to their highly non-stationary fluctuations. To handle such features, wavelet-based temporal pre-processed data were entered into the ANNs to improve the accuracy of runoff modeling. WT and wavelet-based de-noising approaches were used for modeling the rainfall-runoff process via the ANN model. The Daubechies-4(db4) mother wavelet, which is almost similar to the runoff signal could capture the features of the signal, especially peak values, thus, it was selected as the mother wavelet for the decomposition of the runoff time series in this study. The decomposition of runoff time series at level L yields $L+1$ sub-signals (one approximation sub-signal, $Pa(t)$ and L detailed sub-signals, $Pdi(t)$ $(i=1, 2, ..., L)$). Decomposition level 3 was considered as the optimum decomposition level. Each of the decomposed sub-series of the runoff demonstrated a specific seasonal feature of the process. In WT-ANN (WANN) model, decomposed sub-series accompanied by the rainfall and runoff data of each compound were used in the FFNN to predict one-month-ahead runoff values at the outlet of Ardabil plain (Samian station). In the second stage, the runoff time series were denoised via WT, and the denoised runoff data were used to predict the runoff at Samian station for one month ahead. Finally, the ANN model was compared with ANN models using pre-processing inputs.

The results of three models for one-step-ahead runoff forecasting at Samian station have been presented in Table 1. Results indicated that better accuracy was comprised with another model via the WANN model in the comb. 3. WANN models via comb. 3 used the runoff data of Gilandeh and Kozatopragi that lied in the upstream and showed accurate performance. These demonstrated Gilandeh and Kozatopragi runoff time series played an important role in Samian runoff modeling. Accuracy improvement in the WANN model was 17%, 3.5%, and 35% combs. 1, 2, and 3 of inputs. The ANN model with denoised inputs showed little improvement (1, 6, and 6.2 percent in combs. 1, 2, and 3 of data) in runoff modeling at the outlet of the plain.

Table (1): The results of ANN and SVM models for one-step-ahead predictions

Input combination	Output variable	Model Type	DC		RMSE (Normalized)	
			Calibration	Verification	Calibration	Verification
1	Rs(t+1)	ANN	0.592	0.434	0.065	0.051
		ANN with denoised data	0.594	0.438	0.065	0.052
		WANN	0.791	0.587	0.047	0.044
2	Rs(t+1)	ANN	0.795	0.567	0.043	0.0434
		ANN with denoised data	0.813	0.601	0.039	0.042
		WANN	0.791	0.587	0.047	0.044
3	Rs(t+1)	ANN	0.907	0.730	0.029	0.035
		ANN with denoised data	0.831	0.775	0.040	0.032
		WANN	0.880	0.854	0.032	0.026

4-Conclusions

In this study, the wavelet-based denoised data and WT were employed in ANN for rainfall-runoff modeling at the outlet of Ardabil plain using data pre-processing techniques. Accordingly, first, it was sought to smooth the hydrological time series by eliminating the outliers and large noises of raw observed time series, which may be due to human or tool measurement error or systematic error. Then, different sub-series were generated by decomposing runoff time series and used to train the ANN model for rainfall-runoff modeling. Using processed and unprocessed data, the obtained results were compared; this comparison indicated the merit of applied data pre-processing approaches due to robust identification of hidden patterns in data so that the developed models could simulate and predict runoff values with lower margin of error and higher confidence and the best results were achieved by employing the decomposed runoff data via WT having different training time series with the same components of original time series. For future study, it is recommended to examine the efficiency of the proposed data pre-processing method in the rainfall-runoff modeling of other watersheds since it is expected that the merit of the method is more highlighted where the quality of the collected data is blurred due to the technical limitations. Furthermore, it is suggested to evaluate the efficiency of the proposed method in modeling the process at other time scales and for modeling other hydrological processes which may involve distinct noise levels and patterns regarding the type of process.

Keywords: Runoff modeling, Wavelet Transform, Wavelet-based de-noising, Artificial Neural Network (ANN), Ardabil plain

5-References

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