Cprecip Parameter for Checking Snow Entry for Forecasting Weekly Discharge of the Haraz River Flow by Artificial Neural Network[1]

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Abstract—Prediction of river flows requires the use of computer facilities and the latest innovations in this field. Artificial Neural Networks (ANNs), as a data-driven approach, are widely and successfully used in the management of water resources, which includes river flow forecasts. However, not using a number of parameters that influence the flow of streams as an input to the network will significantly reduce the performance of the model. One of these parameters, especially in snow basins, is snow. Snow Water Equivalent (SWE) is a common parameter in river flow modeling and is used to effect the snow in the models. This study attempts to introduce cumulative precipitation parameters (Cprecip) instead of SWE. Some basins lack the required SWE; therefore, the Cprecips are applied in order to cope with the changes in these basins. The results show that the Cprecip can be used to replace the SWE when the suitable changes occur according to the conditions of the studied basin.

Keywords: weekly discharge prediction, snow, cumulative precipitation parameters (Cprecip), Artificial Neural Network, Haraz River

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INTRODUCTION

Water is an economic and social commodity and is one of our primary needs. Due to the importance of water resources, management of these resources is highly needed. As far as river engineering is concerned, especially in cases of floods and water harvesting, it is important to have knowledge about the quantity of water [3]. In order to predict river flows, it is essential to use computers and the latest innovations in this field. Statistical, hydraulic and hydrological models are used widely in the prediction of stream flows. However, since the mid-1990s, the use of artificial intelligence models, such as Artificial Neural Networks (ANN$_s$), has been considered [7, 28].

Furthermore, hydraulic and hydrological conceptual models may have practical problems, and are sensitive to errors (small though) of input parameters. While some empirical and statistical models lack the required generalizability power, artificial intelligence models are found to be the right tools for making a relationship between the input and output values, particularly while dealing with non-linear and complex relationships without any necessity to know the physical relationships. Black box methods, such as the ANNs, are data-driven approaches that have been extensively used in water resources management [5, 8, 16, 20], which includes rainfall-runoff modeling [10, 39, 40], water quality modeling [17, 31], groundwater modeling [24], flood prediction [12], sediment forecasts [19], and flow prediction [26, 35, 41, 42].

River flow modeling is one of the most complex hydrological challenges and its values are affected by a large number of different variables [33, 44]. ANNs are able to understand these complexities, but they usually require a large number of input parameters in a long time interval as data in order to improve their model efficiency [11]. Issues involving river flow modeling include errors in data, corrupted data and in some cases, insufficient data (including lack of information on a special input parameter or insufficiency of time intervals for that parameter) [2, 4]. According to the previous researches, one of the parameters for prediction, especially in snow basins, is the snow parameter. Researchers have shown that snowmelt water stored in the river basin has a significant impact on river discharge [1, 14, 25, 30].

Snow Water Equivalent (SWE) is the most common parameter in modeling stream flow, which is used for inserting the snow effect. In this regard, either SWE statistical information is not available in a considerable percent number of basins, or its time interval is not adequate for modeling. Therefore, it seems nec-
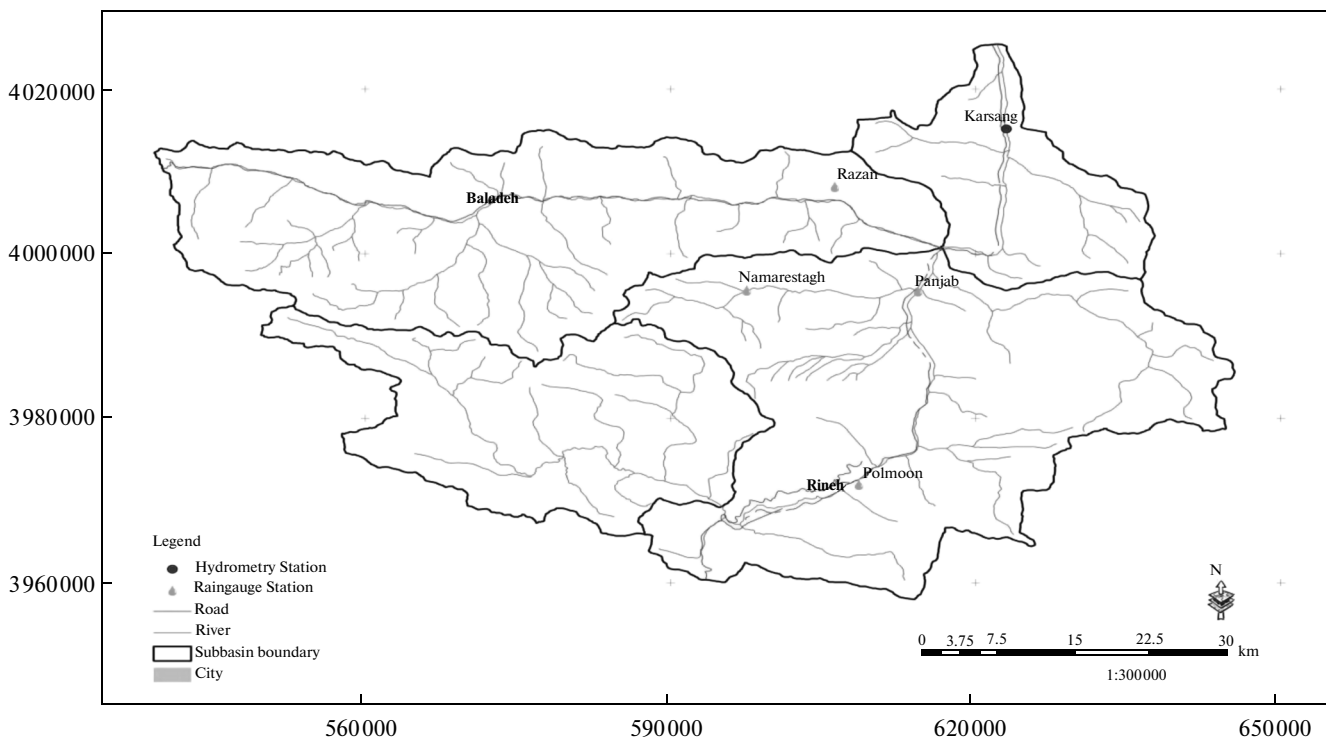
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Fig. 1. The Haraz River and its watershed.

essary to use alternative parameters that are available. Zeland et al. (1999) first used Cprecip parameter, which represents the accumulated snow in winter as an input to the model in order to predict the weekly discharge of the Winnipeg basin in Canada. Moreover, Amiri et al. (2012) applied Cprecip parameter in the Tajan River for daily flow forecasts. He showed that applying changes in Cprecip parameter, in order to adapt it with the studied basin, had a positive impact on model performance.

The main goal of this research was to compare Cprecip parameter with SWE common parameter, and explain how they adapt to changes in the basin. In the next section, we further describe the studied area and examine the statistical parameters. In Section 3, a brief introduction of ANN performance metrics is stated. Also, the Cprecip parameter and the results of the modeling process are explained in Section 4. In addition, we further discuss how to adapt to changes in the Cprecip parameter of the basin. Finally, in Section 5, the overall results obtained from this research are provided.

STUDY AREA AND DATA SETS

The Haraz River is located in Mazandaran province of Iran. It originates in the Lar Valley to the south of Mount Damavand and it flows north into the Caspian Sea. The Haraz River supplies the water required for agriculture in the adjacent cities. Also, the river has a large mountainous drainage basin. Since snow is

responsible for more than half of the precipitations in this basin, the river water is mainly supplied by the slow-melting winter snow. In addition, many rivers are created by annual rainfall, especially in the highlands, which helps the regular discharge. The Haraz River drainage area is more than 1100 km². Karsang Hydrometric Station is located 20 km south of Amol City on the Haraz River, and its rate of weekly discharge was considered as the output of this research. The geographical coordinates of Karsang Hydrometric Station lies between the longitudes of 52°22′05″, latitudes of 36°16′25″, and its height above the sea level is 375 m. The Haraz River basin is shown in Fig. 1.

The study includes 236 weekly data series which were gathered for testing, dating from 11/01/2002 to 04/05/2007. It also includes 70 weekly data series used for testing the network, from 05/11/2007 to 05/09/2008. The data includes variables, such as discharge, rainfall, temperature, evaporation and snow water equivalent, as demonstrated in Table 1. The data characteristics, such as minimum, maximum, mean, variance, and skewness are shown separately in two phases of training and testing [22]. In order to avoid any surprises at the testing phase of the model, testing should be included in the largest quantities of discharge. Also, the output range must be a subset of the test period in the training phase, which is carefully considered in the present study.

Table 1. Statistical characteristics of the data in training and testing stages

Variable	Training					Testing				
	variance	skewness	average	max	min	variance	skewness	average	max	min
Q, m³/s	485.31	1.00	39.85	96.16	16.8	161.14	2.03	31.94	84.76	17.53
P, mm	46.07	2.31	4.35	40.65	0	28.17	2.10	3.49	24.4	0
SWE, mm	48.99	2.99	3.36	43.33	0	49.47	4.81	2.00	43	0
Tab, mm	196.84	0.36	16.41	49.2	0	293.48	−0.05	25.53	60.4	0
T, c	41.95	−0.02	9.79	21.88	−1.39	62.22	−1.20	12.50	22.12	−8.61

MATERIAL AND METHODS

ANNs are an idea for information processing that is inspired by human brain. Therefore, the key element of this idea is the new structure of the information processing system. This system is composed by a large number of highly interconnected processing elements (neurons) and acts coordinately to solve a problem. Also, same as humans, it learns by examples. ANNs are set to perform a specific task, such as identifying patterns and classified information during the learning process [15, 21]. A learning algorithm sets the parameters of an ANN. ANNs have the remarkable ability to derive meaning from complicated or imprecise data, derive relationships, and identify ways in which information is very complex and difficult to be applied for humans and other computer techniques. A trained ANN can be considered as a specialist in the analysis of data items. Finally, the key point in multi-objective methods, such as ANN is minimizing the number of neurons in the hidden layer and at the same time maximizing precision of validation in the rest of data [13].

Multi-Layer Perceptron (MLP) is a type of back-propagation feed-forward neural network and its algorithm is an oversight. This is the most practical neural network in modeling, particularly in predicting river flows [18]. Furthermore, a MLP with a hidden layer is capable of approximating a complex nonlinear function with sufficient accuracy by selecting the optimal architecture and learning function techniques. However, this selection depends on several factors requiring the user experience and trial and error, and is not an easy task [27, 38]. A typical MLP with one hidden layer is shown in Fig. 2.

Input layer neurons only receive input values and can distribute them among all hidden neuron layer. Each neuron receives input weight added values in the hidden layer and adds them up together. Then, the output value is calculated based on the activation function applied on the neurons. Also, the output value of the output layer is computed in a similar manner.

The mathematical form of a three-layer MLP is given as below:

$$Y_k = f_0\left[\sum_{j=1}^{M'} W_{kj} f_h\left(\sum_{i=1}^{M} W_{ji} X_i + B_j\right) + B_k\right]. \quad (1)$$

Moreover, X_i is the ith input variable for the input layer and Y_k is the output variable at the kth neuron of the output layer, B_j and B_k are the biases for the jth hidden neuron and the kth output neuron, W_{ji} and W_{kj} are weights in the hidden and output layers, M and M' are the number of neurons in the input and hidden layers, and f_h and f_0 are the activation functions for the hidden and output layers, respectively.

In order to predict the Haraz River flowing in this study, a three-layer MLP was used with Levenberg–Marquardt algorithm. Levenberg–Marquardt is the quickest method in training [32]. Furthermore, logistic and hyperbolic functions are usually used in the activation function of the hidden layer while the linear activation function is used in the activation function of the output layer [21]. Therefore, in this study Tan Sigmoid activation function is used for the hidden layer, and the linear activation function is applied to the output layer.

According to the wide range of data used in this study, the following equation was used to normalize the data:

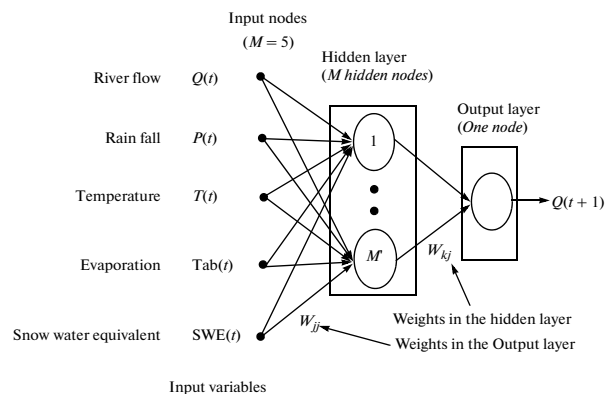$$X_n = \left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) \times 2 - 1, \quad (2)$$

Fig. 2. Multilayer Perceptron with one hidden layer.

where X and X_n are the original and normalized data, and $X_{\min}$ and $X_{\max}$ are the minimum and maximum amounts of original data, respectively.

Accuracy of prediction is studied by performance criteria. Performance criteria used in this study is consisted of the five following criteria:

$$R^2 = 1 - \frac{\sum\limits_{i=l}^{n}(\text{obs} - \text{forc})^2}{\sum\limits_{i=1}^{n}(\text{obs} - \overline{\text{obs}})^2}, \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{\sum\limits_{i=l}^{N}(\text{obs} - \text{forc})^2}{N}}, \tag{4}$$

$$\text{SDE} = \sqrt{\frac{\sum\limits_{i=l}^{N}\left[\frac{|\text{obs} - \text{forc}|}{\overline{\text{obs}}} - \frac{\text{MAPE}}{100}\right]^2}{N}}, \tag{5}$$

$$\text{MAPE} = \frac{100}{N} \times \sum \frac{|\text{obs} - \text{forc}|}{\text{obs}}, \tag{6}$$

$$\text{MSDE} = \frac{1}{N} \tag{7}$$

$$\times \sum_{N=1}^{N} \left(\left[\text{forc}_{(N)} - \text{forc}_{(N-1)}\right] - \left[\text{obs}_{(N)} - \text{obs}_{(N-1)}\right]\right)^2,$$

where obs is the flow rate of observing and forc is flow rate predicted by the model. Also, $\overline{\text{obs}}$ is mean and N equals the number of data in the testing phase.

Performance criteria Coefficient of Determination (R^2) is independent from the scale and if it is more and closer to one, shows the observed and predicted values are close to each other. If R^2 value of the model is greater than 0.9, the result will be desirable [23, 34]. In performance criteria of Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Standard Deviation Error (SDE) and Mean Squared Derivative Error (MSDE), the lower and closer the value is to zero, the better the performance

of the model. MSDE is an appropriate measure for comparing observed and predicted discharge hydrographs, but cannot be used in isolation as a measure of model performance [9].

RESULTS AND DISCUSSION

Melting snow provides most of the base discharge of a snowy river. Moreover, accumulation and melting of snow plays an important role in rivers' flood behavior. In these situations, snow water equivalent is considered the most common variable for hydrological predictions. The snow water equivalent is the height of water calculated as a result of snow melting [29, 36, 37].

To improve the performance of neural networks, Zeland et al. (1999) used Cprecip for the prediction of input discharge in the Winnipeg basin in Canada. Cprecip parameter is the cumulative precipitation from the months of November to April. In fact, that is the accumulated snow until now, and is stored during winter and melts in spring. Cprecip parameter, according to atmospheric conditions, is especially designed for the Winnipeg Basin in Canada. Therefore, necessary changes were made in order to apply for the Mazandaran basin. While snow occurs during the entire year in the Winnipeg basin in Canada, in the Mazandaran basin snow melts by the end of spring, except in certain areas. Therefore, in Cprecip−MAZ, after the cumulative rainfall was calculated from the first of November to the beginning of April, this value was linearly reduced to zero by the first of June [6].

In modeling the Haraz River flow, the following four input patterns were first used in order to predict the following week's discharge:

$$Q(t + 1) = f\{P(t), Q(t), \text{Tab}(t), T(t)\}, \tag{8}$$

$$Q(t + 1) = f\{\text{SWE}(t), P(t), Q(t), \text{Tab}(t), T(t)\}, \tag{9}$$

$$\begin{aligned} Q(t + 1) \\ = f\{\text{Cprecip}(t), P(t), Q(t), \text{Tab}(t), T(t)\}, \end{aligned} \tag{10}$$

$$Q(t + 1) = f\{\text{MAZ} - \text{Cprecip}(t), P(t), Q(t), \text{Tab}(t), T(t)\}, \tag{11}$$

where Q is the average weekly rate, P is the weekly rainfall, T is the average weekly temperature, Tab is the weekly evaporation, SWE is the weekly snow water equivalent, Cprecip is the average weekly cumulative precipitation, MAZ−Cprecip is the average weekly cumulative precipitation of the Mazandaran zone, and t is the computational time per week. For example, in the last input pattern, the average discharge value of the following week depended on the cumulative precipitation in the Mazandaran zone, as well as rainfall, evaporation and discharge during that week.

In order to predict next week's Haraz River flow, using MLP and the obtained data from the river, the first step was to train and then examine the models. Table 2 shows the performance criteria for different input patterns. The highest numbers for every period and every performance measured are indicated in bold. Also, the diagrams resulted from modeling with the input pattern of Eq. (9) in the testing stage are given as an example in Fig. 3.

By comparing the input pattern of Eq. (8) with the input pattern of Eq. (9), it could be observed that, at the total test time and at all seasons of testing, the

Table 2. Performance metrics for different input patterns

Performance criteria	Input pattern	General	Spring	Summer	Fall	Winter
R^2	INPUT 1	0.9169	0.8970	0.8999	−0.1756	0.5467
	INPUT 2	**0.9504**	**0.9429**	**0.9235**	**0.4878**	0.7652
	INPUT 3	0.9295	0.9056	0.9209	0.2040	0.6225
	INPUT 4	0.9427	0.9329	0.9078	0.1082	**0.8811**
RMSE	INPUT 1	3.1678	4.2271	2.7889	2.2673	2.6424
	INPUT 2	**2.4473**	**3.1478**	**2.4379**	**1.4966**	1.9016
	INPUT 3	2.9182	4.0460	2.4794	1.8657	2.4111
	INPUT 4	2.6314	3.4122	2.6770	1.9748	**1.3534**
SDE	INPUT 1	0.0688	0.0705	0.0688	0.0463	0.0614
	INPUT 2	0.0514	0.0500	0.0530	**0.0379**	0.0370
	INPUT 3	0.0652	0.0728	0.0524	0.0433	0.0556
	INPUT 4	**0.0493**	**0.0467**	**0.0463**	0.0437	**0.0265**
MSDE	INPUT 1	14.1845	23.1145	16.1871	5.7446	5.0166
	INPUT 2	**9.5245**	18.5932	**7.8765**	4.6905	3.8361
	INPUT 3	12.5659	24.9183	11.1801	5.8204	**3.2027**
	INPUT 4	9.5604	**16.6212**	9.7146	**4.2709**	3.7897
MAPE	INPUT 1	8.1540	7.6333	8.2751	7.2227	9.7787
	INPUT 2	**6.1559**	**6.0070**	6.9980	**4.0954**	6.8822
	INPUT 3	7.0442	6.8414	7.1252	5.5324	8.8511
	INPUT 4	7.2406	7.2426	9.1215	5.6894	**4.9994**

model with the input pattern of Eq. (8) had lower accuracy than the model with input pattern of Eq. (9). Moreover, the lack of a SWE parameter (representing snow variable) in the input pattern of the model had a negative impact on model predictions. For this reason, a parameter was needed to enter snow effect on the model for the snow zones where there are no SWE parameters.

Results of the model with input pattern of Eq. (10) show that the entire range of input Cprecip in the test model, in all seasons except for spring, had a positive impact on network accuracy. However, its precision for
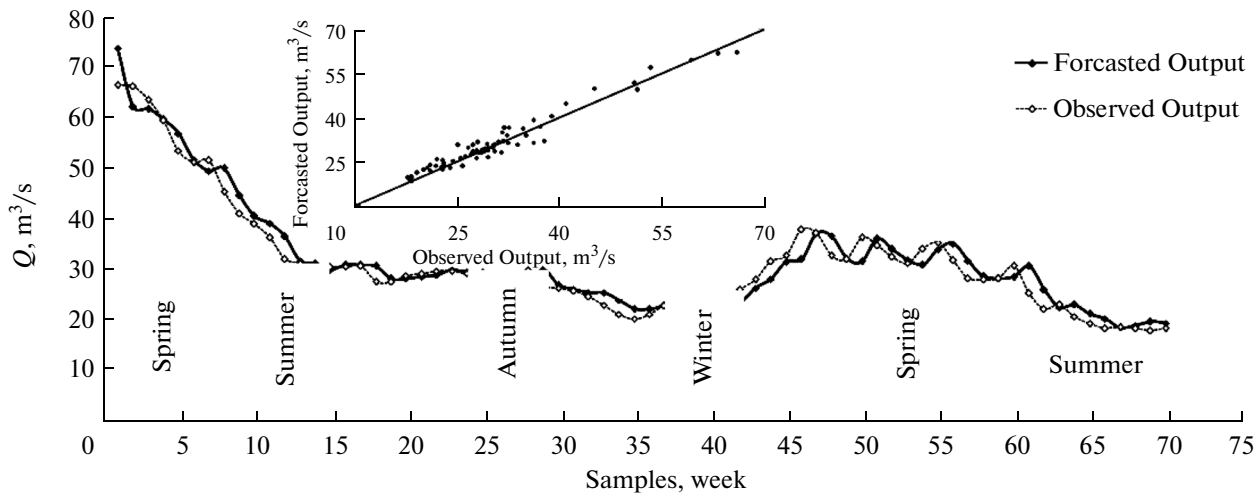

Fig. 3. Rating curve and scatter plot, observed versus predicted discharge for input pattern of Eq. (9) in testing period.
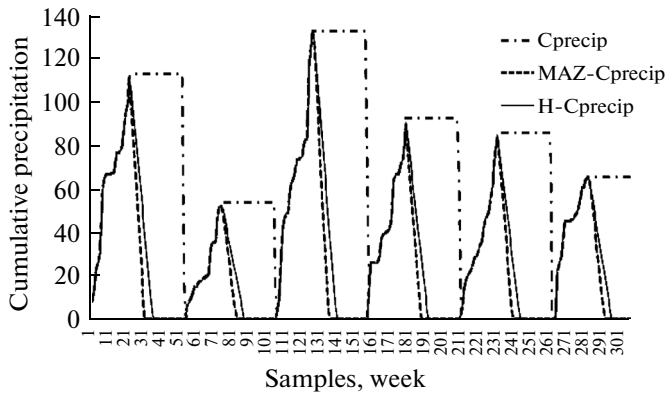
Fig. 4. Time series of weekly Cprecip, MAZ−Cprecip and H−Cprecip for the Haraz River.

the entire model test, during all seasons, was still far from the network accuracy with input pattern of Eq. (9). Therefore, several changes are required for Cprecip in order to adjust to the zone of interest (Haraz zone).

Moreover, MAZ−Cprecip model was used as an input in the input pattern of Eq. (11) by Amiri et al. [6], and was further introduced as the adapted Cprecip with Mazandaran Province of Iran. The results indicated the positive impact of changes in the input pattern of MAZ−Cprecip with the accuracy of the prediction model. The comparison of the performance metrics with the input pattern and the input pattern of Eq. (10) indicated that MAZ−Cprecip was markedly superior to Cprecip in the entire test, during winter and spring. Also, these two variables were observed to have the same effect in the fall. However, during the summer Cprecip had a better effect on the performance of model prediction than the MAZ−Cprecip. Furthermore, the comparison results of the model with input pattern of Eq. (11) with the model with input pattern of Eq. (9) demonstrated that the accuracy of these two models are very close; however, there was still a difference in the accuracy of predictions.

Although the Haraz River basin is one of the major basins of Mazandaran, it is colder and more mountainous than the basin used by Amiri et al. [6] as a representative region of Mazandaran. Considering the lower prediction accuracy of the models with MAZ−

Cprecip input in summer, as well as the conditions of the Haraz River basin, it can be said that accumulated winter snow requires more time to be completely melted. As a result, some changes were applied on MAZ−Cprecip parameter and a new parameter was designed for the Amol basin, which was called H−Cprecip. In MAZ−Cprecip parameter, the cumulative precipitation linearly decreased from the beginning of April and became zero at the beginning of June. This is while in the H−Cprecip parameter, the amount of cumulative precipitation with the lower slope was reduced so that it became zero at the beginning of July. Time series of weekly Cprecip, MAZ−Cprecip and H−Cprecip in the Haraz River can be observed in Fig. 4.

Input model of Eq. (12) was then used to model the weekly discharge of the Haraz River:

$$Q(t+1) = f\{H - \text{Cprecip}(t), P(t), Q(t), \text{Tab}(t), T(t)\}. \quad (12)$$

Performance coefficient results of neural networks of input pattern in Eq. (12) are given in Table 3 for weekly Haraz River flow model. The numbers depicted in bold indicate the input pattern of Eq. (12) for each period, and each performance criteria has the best results among the five input pattern. The diagram simulating the testing phase of input model of Eq. (12) is given in Fig. 5. For a better comparison of the two input patterns of Eqs. (12) and (9), absolute error plot is shown in Fig. 6. Moreover, the results on the charts indicate that the effect of H−Cprecip parameters on the performance of the model was approximately equal to SWE parameters over the entire range of test in all seasons.

CONCLUSIONS

One of the important issues in the field of planning and developing water resources is providing accurate and consistent models with the structure of the problem for predicting river flows. This paper analyzes the efficiency of artificial neural network in predicting weekly discharge of the Haraz River and the results proved that ANN had a good performance in this area. We also found out that using different combinations of input parameters in the model had a significant impact on the accuracy of model predictions. On the other

Table 3. Performance criteria for input pattern of Eq. (12)

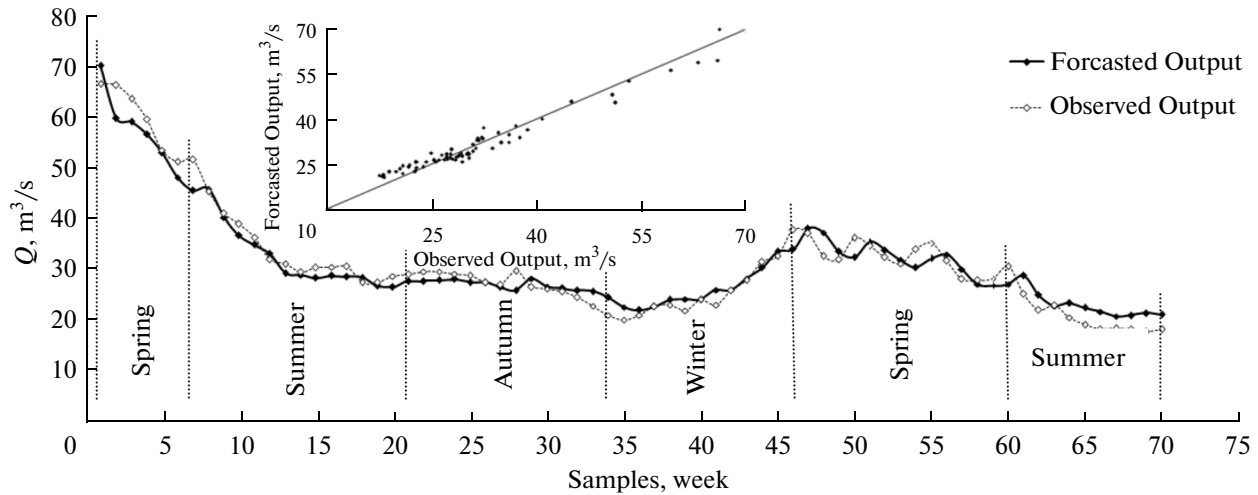| Performance criteria	Input pattern	General	Spring	Summer	Fall	Winter
R^2	INPUT 5	0.9503	**0.9478**	0.9147	0.3303	0.8069
RMSE	INPUT 5	2.4510	**3.0085**	2.5747	1.7113	1.7247
SDE	INPUT 5	**0.0460**	**0.0400**	0.0478	**0.0350**	0.0465
MSDE	INPUT 5	**7.6875**	15.0642	**6.5660**	**3.5332**	**2.8446**
MAPE	INPUT 5	6.9087	6.1487	8.9099	5.2613	5.7907

Fig. 5. Rating curve and scatter plot, observed versus predicted discharge for input pattern of Eq. (12) in testing period.
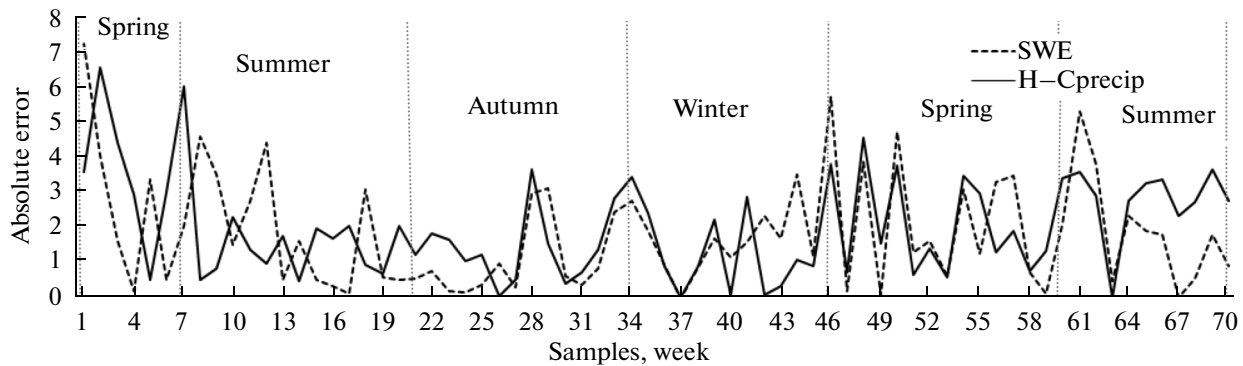

Fig. 6. Absolute error model with input patterns of Eqs. (12) and (9).

hand, the lack of one of the parameters affecting the rivers flow in the model's input parameters had a negative impact on the accuracy of model prediction.

Furthermore, this study demonstrated that lack of snow parameter in the input pattern led to reduce model performance, especially in snow basins. Since SWE was almost the only parameter used for entering the snow effect on snow basins, a parameter should be found to replace it in basins with unavailable SWE statistical information. Following the use of Cprecip parameter, we found out that although this parameter had a positive effect on the model prediction by being added to the input pattern, its impact was far less than the SWE. The reason is that Cprecip was designed for the Winnipeg basin in Canada and the condition of this basin was different from the one studied. Therefore, MAZ−Cprecip parameter was applied, which was designed according to Mazandaran zone conditions.

The results showed that MAZ−Cprecip had a positive effect on the model when compared to Cprecip, and its impact, although slightly different, was close to the SWE effect. To eliminate the slight difference, H−Cprecip parameter was designed according to the Haraz River basin. After adding H−Cprecip to the input pattern, the results indicated almost identical effect of H−Cprecip parameter and SWE parameter on the performance model. In sum, we can conclude that in order to insert a snow variable effect in the model when SWE is unavailable, it may be helpful to design a Cprecip parameter according to the atmospheric conditions of the basin being studied.

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