



Simulation of rainfall-runoff process using geomorphology-based adaptive neuro-fuzzy inference system (ANFIS)

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ABSTRACT

This research was conducted to present an integrated rainfall-runoff model based on the physical characteristics of the watershed, and to predict discharge not only in the outlet, but also at any desired point within the basin. To achieve this goal, a matrix of hydro-climatic variables (i.e. daily rainfall and daily discharge) and geomorphologic characteristics such as upstream drainage area (A), mean slope of watershed (S) and curve number (CN) was designed and simulated using artificial intelligence techniques. Integrated Geomorphology-based Artificial Neural Network (IGANN) model with Root Mean Squared Error (RMSE) of $0.02786 \text{ m}^3 \text{ s}^{-1}$ and Nash-Sutcliffe Efficiency (NSE) of 0.9403 and Integrated Geomorphology-based Adaptive Neuro-Fuzzy Inference System (IGANFIS) model with RMSE of $0.02795 \text{ m}^3 \text{ s}^{-1}$ and NSE of 0.94467 were able to predict the discharge values of all hydrometric stations of the Chalus River watershed with a very low error and high accuracy. The results of cross validation stage confirmed the efficiency of models. Hydro-climatic variables and geomorphologic parameters selected in the study were: discharge of one day ago, discharge of two days ago, rainfall of current day and rainfall of one day ago and S, CN and A, respectively. In addition, the IGANN model shows superiority compared with the IGANFIS model.

Key words: Physical characteristics of watershed, Rainfall-runoff modeling, Black box modeling, Artificial intelligence, Geomorphologic unit hydrograph.

INTRODUCTION

Accurate prediction of hydrological phenomena such as rainfall-runoff process can provide effective information for urban planning and water resources management, which plays an important role in reducing flood and drought impacts on the water resources systems. Understanding the Rainfall-Runoff (RR) model of a catchment is one of the most complicated of hydrologic activities because it involves temporal and spatial variations. It is very difficult to determine uncertainty for all of the physical parameters of watersheds. It is not surprising that black box models can convert input to output data and have more accurate results than physical models. The artificial intelligence (AI) methods are black box modeling tools that have recently been applied in several sectors including RR modeling (Nayak *et al.* 2007; Nourani *et al.* 2011; Talei & Chua 2012; Nourani & Komasi 2013). The success of artificial neural network (ANN) in any hydrological modeling process depends on the quantity and quality of data used to train model. The model used to simulate the rainfall-runoff process is usually uncertainties. For example, the average amount of rainfall was measured by point rainfall stations in whole of watershed, that it has been usually attributed to the entire basin. Using such a method for calculating rainfall in the watershed as an input layer of ANN can be a source of uncertainty. In such a situation, fuzzy theory is used to solve the uncertainties involved in real-world issues (Nash & Sutcliffe 1970; Nourani & Komasi 2013). From this point of view, the ANN compound and the fuzzy system are the focal points of the research focus. The Adaptive Neuro-Fuzzy

Inference (ANFIS) uses the advantages of both ANN and fuzzy systems. A review article on the application of a comparative neuro-fuzzy inference system in river flow prediction by Jacquin and Shamseldin (2009) has/ been published. In this paper, the comparative Neuro-Fuzzy Inference System is introduced as an effective tool for predicting flow and its application is relatively limited in comparing with the Artificial Neural Network models. Several studies have been conducted on the use of ANFIS in rainfall-runoff modeling (Wang *et al.* 2009; Kurtulus & Razack 2010; Talei *et al.* 2010; Vafakhah 2012; Lohani *et al.* 2012; Asadi *et al.* 2013; Ghose *et al.* 2013; Kisi *et al.* 2013; Jayawardena *et al.* 2014). Nourani & Komasi (2013) applied Integrated Geomorphology-based ANFIS (IGANFIS) model in multi-station modeling of rainfall-runoff process. They approved usage of IGANFIS model. Accordingly, the purposed model by Nourani & Komasi (2013) was applied in this study. They used rainfall and discharge variables and geomorphologic characteristics such as upstream drainage area (A), mean slope of watershed (S) and Curve Number (CN) as inputs in an integrated matrix of available stations within the basin. The distinction between the current research and the above research is used the Subtractive Clustering instead of Fuzzy C-means (FCM) Clustering. The Chalus catchment is included wide part of south of Noushahr and Chalus cities in north of Iran. In the past years, these areas have been affected by devastating and destructive floods (floods in 1994 & 2003 years).

The study area characteristics

The Chalus River basin with longitude 51° 00' to 51° 35' East and Latitude 36° 08' to 36° 43' North is located on the northern slopes of central Alborz and in the south of the Chalus city, draining to the Caspian Sea after cross short distances from the Khazari plain (Fig. 1). The Chalus River basin is limited from west to the Sardabrood basin and from east to the Korcorsar basin and from south to the Karaj basin and north to the Caspian Sea (Moghimi *et al.* 2009). The maximum and minimum heights of studied area are 4260 and 158 m above sea level, respectively. It is a mountainous region and extremely steep and also has a general northern direction. In terms of climate, it has different climates. According to Emberger's climatic classification, the most dominant climate conditions are recognized in most of regions semi-humid cold to cold and in some places are semi-arid cold. The average annual rainfall and average discharge is 836 mm 8.13 m³ s⁻¹ and it has an average fresh water annually 44.38 MCM, some amount of that consume for agricultural (rice fields), and the remainder deployed to the Caspian Sea (Eshagh Teimori *et al.* 2012).

METHODOLOGY

Daily discharge data from seven hydrometric stations and daily rainfall data from three weather stations within the watershed were collected in Iran Water Resources Management Company (IWRM). Location of these stations is shown in Fig.1. Table 1 illustrates characteristics of weather stations within the watershed.

Table 1. Characteristics of weather stations within the watershed.

Station no.	Name	Station type	Organization	Lat. (m)	Long. (m)	Elevation (m a.s.l.)
1	Pol-e-Zoghal	Evaporator	Ministry of Energy (Iran)	529649	4040537	360
2	Vaspol	Raingauge	Ministry of Energy (Iran)	520647	4018419	1000
3	Siah Bisheh	Synoptic	Iran Meteorological Organization	526952	4011719	1855

The data during 2002-2003 to 2006-2007 (1 Nov. 2002 to 31 Sept. 2007) were selected for modeling due to the construction of the Siyah Bisheh Dam in 2012 and its effect on discharge data recorded by hydrometric stations and, the availability land use map in 2006. Daily rainfall data from Pol-e-Zoghal, Vaspol and Siah Bisheh stations were used for Pol-e-Zoghal and Doab catchments, Abshar and Vaspol catchments and Harijan, Valiabad and Polemargan catchments, respectively. Table 2 presents characteristics of hydrometric stations within the watershed. The slope map of Chalus watershed was derived from digital elevation model with 1:25000 scale by ArcGIS9.3 software. Maps of land use and hydrologic soil groups with 1:50,000 scale were collected from Sari Natural Resources and Watershed Management Administration, Iran and then Curve Number (CN) of the sub-basins was prepared by combining land use and soil hydrologic groups layers through Soil Conservation Service (SCS) method. To determine appropriate input variables (rainfall and discharge) to the IGANFIS models, the autocorrelation, partial autocorrelation and cross correlation between rainfall and discharge were used (Vafakhah 2012). Fig. 2 illustrates IGANFIS modeling flowchart. In Fig. 2, numbers of 1 to 6 displays Pol-e-Zoghal, Doab,

Abshar, Valiabab, Harijan and Pol-e-Mergen sub-basins, respectively and V symbol exhibits Vaspol sub-basin. I, Q, A, S and CN respectively are rainfall, discharge, area, slope and curve number.

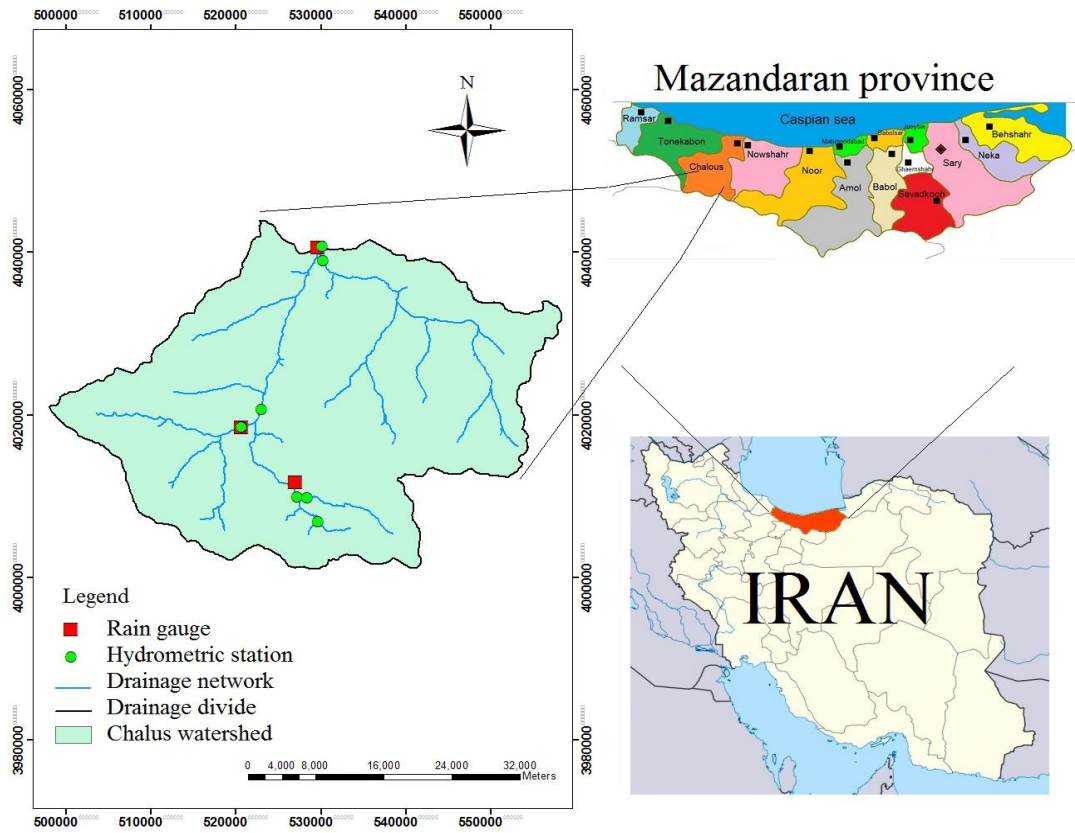


Fig.1. Location Chalus Watershed in Mazandaran, Iran.

Table 2. Characteristics of hydrometric stations within the watershed.

Station no.	Name	River	Lat. (m)	Long. (m)	Elevation m a.s.l.
1	Pol-e-Zoghal	Chalus	530171	4040631	351
2	Abshar	Chalus	522961	4020643	823
3	Vaspol	Anguran	520672	4018449	963
4	Pol-e-Mergan	Zangule	529664	4006798	2170
5	Harijan	Harijan	528356	4009782	1814
6	Valiabab	Chalus	527208	4009871	1749
7	Doab	Hanisk	530202	4038875	390

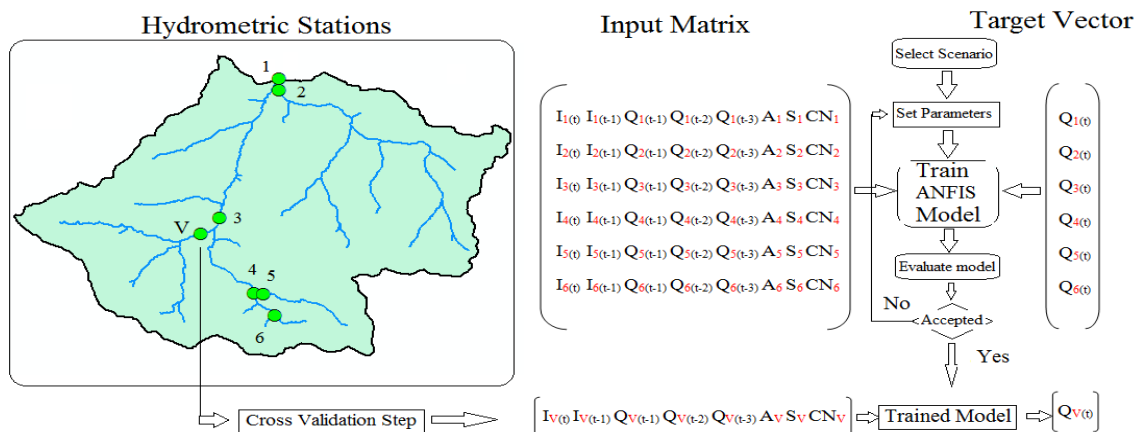


Fig. 2. IGANFIS Modeling Flowchart.

Data normalization

Data normalization, as one of the data processes in the development of IGANFIS models data is performed due to problems caused by large amounts of descriptive. It recommended each amounts placed as a linear scale range (1.0, 9.0), (+1, -1) or (0, 1). In the modeling process, all data of rainfall and discharge are normalized between 0.1 and 0.9 according to equation 1:

$$N_i = 0.8 \times \left(\frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \right) + 0.1 \quad (1)$$

where, N_i is the normalized amount, X_i is original data and X_{\min} and X_{\max} are the minimum and maximum of rainfall and discharge, respectively (Rashidi *et al.* 2016).

As input variables of geomorphology have different units, they were also normalized as $\left(\frac{A_i}{A_T}, \frac{S_i}{\bar{S}} \text{ and } \frac{CN_i}{\bar{CN}} \right)$, where A_i and A_T are area of each sub-basin and Chalus Watershed, S_i and \bar{S} are average slope of each sub-basin and Chalus watershed and CN_i and \bar{CN} are curve number each sub-basin and Chalus Watershed, respectively.

Compiling the ANFIS model

For run of ANFIS was used ANFIS code through MATLAB software. Inputs were divided into three categories: training (60%), testing (20%) and validation (20%). For compiling ANFIS, a fuzzy inference model in Sugeno type with grid partitioning and subtractive clustering methods were used (Jang 1993). Type of membership functions (triangular, trapezoidal, generalized bell-shaped, Gaussian, Gaussian type II, II-shaped and circular) was then designated (Jacquin & Shamseldin 2006). Type of output membership function was selected linear. In the optimization procedure, it used a hybrid learning rule combining the back propagation gradient descent and a least-squares method. Optimal error was considered zero. Then the model was trained with these characteristics (Aalami & Hosseinzadeh 2010). ANFIS training parameters used in the study are presented in Table 3.

Table 3. Learning parameters in ANFIS model.

Type	Sugeno
AND method	Product
OR method	Probabilistic
Implication method	Product
Aggregation method	Sum
Defuzzification method	Weighted Average

First scenario of IGANFIS

In the first scenario, discharge as an input of model was not considered, for checking in the absence of the pervious discharge as an input, therefore rainfall, A, S and CN were used as inputs to predict current day discharge according to equation 2:

$$Q_i(t) = f\left(I_i(t), I_i(t-1), \frac{A_i}{A_T}, \frac{S_i}{\bar{S}}, \frac{CN_i}{\bar{CN}}\right) \quad (2)$$

where i shows number of the sub-basin and $I_i(t)$, $I_i(t-1)$ and $Q_i(t)$, are subsequently pervious and current day rainfall and current day discharge as output of the model. A_i and A_T are area of each sub-basin and Chalus Watershed, S_i and \bar{S} are average slope of each sub-basin and Chalus watershed, while CN_i and \bar{CN} are curve numbers of each sub-basin and Chalus watershed, respectively.

Second scenario of IGANFIS

In the second scenario, one day ago discharge was applied in the model as an input to select the best ANFIS model.

$$Q_i(t) = f\left(I_i(t), I_i(t-1), Q_i(t-1), Q_i(t-2), Q_i(t-3), \frac{A_i}{A_T}, \frac{S_i}{\bar{S}}, \frac{CN_i}{\bar{CN}}\right) \quad (3)$$

Cross validation

Capability of IGANFIS model was measured for spatiotemporal RR modeling process through the cross validation method for a station. To achieve this goal, Since Vaspoul station is close to Abshar station. Vaspoul station was not used in training model, but in the playoff validation process, Vaspoul station statistics was modeled into the matrix

instead of the Abshar station. Recreation and interaction of data stations, which through the training phase of model is learned, the model helps to predict for cross validation (Vaspol station).

Criteria efficiency

To evaluate the efficiency of different models and components used in this study, the following performance criteria were used.

Root Mean Squared Error (RMSE) values vary from zero (for perfectly accurate predictions) to high positive values (when the difference between observed and computed values is greater).

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Q_{obs_i} - Q_{com_i})^2}{N}} \quad (4)$$

The higher the Nash-Sutcliffe Efficiency (NSE) (at most 1), the model is more efficient (Nash & Sutcliffe 1970).

$$NSE = 1 - \frac{\sum_{i=1}^N (Q_{obs_i} - Q_{com_i})^2}{\sum_{i=1}^N (Q_{obs_i} - \bar{Q}_{com})^2} \quad (5)$$

Pearson's correlation coefficient (R) is one of the important coefficients to determine the correlation between two variables and varies between -1 and +1.

$$R = \frac{\sum_{i=1}^N [(Q_{obs_i} - \bar{Q}_{obs})(Q_{com_i} - \bar{Q}_{com})]}{\sqrt{\sum_{i=1}^N (Q_{obs_i} - \bar{Q}_{obs})^2 \sum_{i=1}^N (Q_{com_i} - \bar{Q}_{com})^2}} \quad (6)$$

The relative error of peak discharge (REp) shows the near-peak computed and observed values. Due to the importance of peak values in a hydrological process, this performance criterion was also used to fully evaluate the model's performance (Green & Stephenson 1986).

$$RE_P(\%) = \frac{1}{M} \sum_{j=1}^M \frac{|QP_{obs_j} - QP_{com_j}|}{QP_{obs_j}} \quad (7)$$

where N , number of observations, Q_{obs_i} , observed discharge, Q_{com_i} , computed discharge, \bar{Q}_{obs} , mean of the observed discharge, \bar{Q}_{com} , the mean of computed discharges, M , number of peak values, QP_{obs_j} , the observed peak discharge value, QP_{com_j} , the computed peak discharge.

RESULTS

Descriptive statistics characteristics of variables such as rainfall, temperature and discharge are presented in Table 4. To determine the number of the lag times, autocorrelation, partial autocorrelation and cross correlation between rainfall and discharge for 10 lag times were calculated for all meteorological and hydrometric stations, and the results are presented in Tables 5 - 7.

As shown in Table 5, autocorrelation coefficients and partial autocorrelation coefficients of rainfall in the first lag time for all three meteorological stations were significant at 5% confidence level.

The results of the cross correlation between rainfall and discharge (Table 7) for five out of seven stations (except for Pol-e-Zoghal and Doab) were significant. Consequently, rainfall was selected with one day ago, as an input the model.

Discharge autocorrelation coefficients calculated for 10 lag times for each seven hydrometric stations were significant at 95% confidence level, but since in the 4th lag time, the auto correlation coefficient was only significant for one station (Abshar station).

Consequently, discharge was selected with three days ago as inputs of the model. The cross correlation between rainfall and discharge was also significant, from first up to third lag times at least four stations.

Table 4. Descriptive statistics characteristics of data used in the study.

Station	Step	Mean	Minimum	Maximum	Standard deviation	Skewness
Pol-e-Zoghal	Training	17.326	4.6	79.2	11.504	1.358
Doab	Discharge (m ³ s ⁻¹)	3.344	1.28	18.2	1.437	2.445
Abshar		12.504	2.93	60	9.377	1.245
Valiabad		4.207	0.118	29.2	4.551	1.832
Harijan		1.551	0.033	11/9	1.691	1.948
Polemergan		1.972	0.294	11.3	1.975	1.401
Vaspol		8.042	1.99	40.5	6.124	1.391
Pol-e-Zoghal	Training	0.967	0	40	3.438	6.027
Siah Bisheh	Rainfall (mm)	1.595	0	40	4.315	4.315
Vaspol		1.538	0	95	5.205	8.114
Pol-e-Zoghal	Training	15.055	-1	29.5	7.16	-0.167
Siah Bisheh	Temperature (°C)	10.299	-8.9	27	7.748	-0.298
Pol-e-Zoghal	Testing	12.154	4.39	41.5	7.216	1.296
Doab	Discharge (m ³ s ⁻¹)	2.332	1.32	3.46	0.549	0.293
Abshar		10.217	4.32	31.5	6.640	1.446
Valiabad		2.911	0.303	15.3	3.307	1.664
Harijan		1.366	0.161	8.88	1.777	2.049
Polemergan		1.386	0.269	5.91	1.596	1.650
Vaspol		5.405	2.53	17.9	2.780	1.571
Pol-e-Zoghal	Testing	0.568	0	14	1.867	4.791
Siah Bisheh	Rainfall (mm)	1.446	0	30	4.101	4.029
Vaspol		1.036	0	50	3.789	7.696
Pol-e-Zoghal	Validation	16.607	5.17	91	16.267	2.015
Doab	Discharge (m ³ s ⁻¹)	3.231	1.51	10.2	1.478	1.925
Abshar		12.381	4.54	45.9	9.583	1.447
Valiabad		3.332	0.979	21.1	3.268	2.816
Harijan		1.841	0.248	16	2.578	2.555
Polemergan		1.596	0.368	7	1.587	1.515
Vaspol		7.392	2.75	27	5.217	1.336
Pol-e-Zoghal	Validation	1.026	0	36	2.990	5.965
Siah Bisheh	Rainfall (mm)	1.908	0	37	4.524	3.925
Vaspol		1.345	0	20	3.303	3.037

Table 5. Autocorrelation and partial autocorrelation coefficients of the daily rainfall from lag-1 (r1) to lag-10 (r10).

Station	Autocorrelation coefficients									
	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10
Pol-e-Zoghal	0.107	-0.02	-0.017	0.038	0.022	-0.025	0.008	0.023	0.031	0.004
Vaspol	0.205	0.197	0.127	0.061	0.033	0	0.007	0.014	0.004	0.003
Siah Bisheh	0.286	0.039	0.039	0.039	0.071	0.021	0.028	-0.005	0.024	0.005
Station	Partial autocorrelation coefficients									
	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10
Pol-e-Zoghal	0.107	-0.032	-0.11	0.041	0.012	-0.027	0	0.022	0.024	0
Vaspol	0.205	0.162	0.064	-0.002	-0.009	-0.032	0.003	0.016	0.001	-0.002
Siah Bisheh	0.286	-0.047	0.045	0.019	0.06	-0.019	0.031	-0.028	0.034	-0.02

* Values that are significant at a confidence level of 95% are highlighted.

Selection of different input combinations

Based on the results of autocorrelation and partial autocorrelation coefficients, and cross correlation between

rainfall and discharge, eight various combinations of rainfall and discharge were selected as inputs of the initial RR model for ANFIS model (Table 8).

Table 6. Autocorrelation and partial autocorrelation coefficients of the daily discharge from lag-1 (r1) to lag-10 (r10).

Station	Autocorrelation coefficients									
	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10
Pol-e-Zoghal	0.968	0.932	0.905	0.88	0.858	0.841	0.826	0.815	0.807	0.802
Station	Partial autocorrelation coefficients									
	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10
Pol-e-Zoghal	0.968	-0.076	0.143	-0.032	0.079	0.05	0.046	0.075	0.038	0.078

* Values that are significant at a confidence level of 95% are highlighted.

Table 7. Cross correlation coefficients of the rainfall and discharge from lag-0 (r0) to lag-10 (r10).

Station	Cross correlation between rainfall and discharge										
	r0	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10
Pol-e-Zoghal	0.07	0.032	0.008	0.008	0.006	0.009	0.007	0.012	0.011	0.009	0.02
Doab	0.057	0.04	0.018	0.008	0.01	0	0.008	0.014	0.011	0.006	0.002
Abshar	0.109	0.087	0.069	0.06	0.051	0.045	0.05	0.061	0.059	0.068	0.069
Valiabad	0.189	0.173	0.145	.111	0.096	0.091	0.096	0.104	0.099	0.093	0.093
Harijan	0.143	0.142	0.116	0.094	0.08	0.089	0.087	0.083	0.085	0.081	0.088
Polemergan	0.123	0.137	0.132	0.12	0.113	0.104	0.105	0.116	0.115	0.11	0.109
Vaspol	0.085	0.063	0.044	0.031	0.023	0.018	0.03	0.041	0.039	0.041	0.06

Table 8. Different combinations of rainfall and discharge for initial modeling of ANFIS

No.	Combination	
1	R_t	rainfall of current day
2	R_t, Q_{t-1}	rainfall of current day, discharge of one day ago
3	R_t, Q_{t-1}, Q_{t-2}	rainfall of current day, discharge of one day ago, discharge of two days ago
4	$R_t, Q_{t-1}, Q_{t-2}, Q_{t-3}$	rainfall of current day, discharge of one day ago, discharge of two days ago, discharge of three days ago
5	R_t, R_{t-1}	rainfall of current day, rainfall of one day ago
6	R_t, R_{t-1}, Q_{t-1}	rainfall of current day, rainfall of one day ago, discharge of one day ago
7	$R_t, R_{t-1}, Q_{t-1}, Q_{t-2}$	rainfall of current day, rainfall of one day ago, discharge of one day ago, discharge of two days ago
8	$R_t, R_{t-1}, Q_{t-1}, Q_{t-2}, Q_{t-3}$	rainfall of current day, rainfall of one day ago, discharge of one day ago, discharge of two days ago, discharge of three days ago

RR model results of ANFIS

Eight different combinations were implemented with eight fuzzy sets and two membership functions. The best result is shown in Table 9. According to the results of the validation stage, the composition (R_t, R_{t-1}, Q_{t-1} i.e. current day rainfall, one day ago rainfall, one day ago discharge) were selected with the lowest RMSE (0.029693) and the highest Nash-Sutcliffe coefficient (0.94658) as the best combination of ANFIS. In the combinations considered only rainfall is as inputs of the model, the R_t, R_{t-1} model had a better performance than R_t .

IGANFIS results

At first scenario, discharge was not applied as the input of the model and three geomorphologic parameters including A, S and CN along with the best combination of ANFIS model i.e. R_t, R_{t-1} was performed (Table 10). According to the results of validation stage, it was observed that, S and A have been able to reduce the amount of error combination of R_t, R_{t-1} (0.117525) and combination of R_t, R_{t-1}, S has been performed with the best result (0.116538). In the second scenario, discharge was also applied as the input of the model and three geomorphologic parameters including A, S and CN along with the best combination of ANFIS model i.e. R_t, R_{t-1}, Q_{t-1} was performed (Table 11). According to the results of validation stage, It was observed that, only S has been able to reduce the amount of combination error of R_t, R_{t-1}, Q_{t-1} (0.0796) and combination of R_t, R_{t-1}, S has been performed with the best result (0.03795). The slope combination (S) with other inputs has not helped to increase the performance of the model. The results of second scenario of the IGANFIS model were implemented with subtractive clustering method in the various combinations of three geomorphologic parameters with R_t, R_{t-1}, Q_{t-1} combination using generalized bell-shaped membership function that are presented in Table 12. As can be observed, all compounds except combinations of (R_t, R_{t-1}, Q_{t-1}, S) had better results than their corresponding

combinations in the subtractive clustering, but none of them could have reduced the best ANFIS combination error namely R_t, R_{t-1}, Q_{t-1} combination. Due to the above results, the IGANFIS model with grid partitioning method and generalized bell-shaped membership function and R_t, R_{t-1}, Q_{t-1}, S combination was selected as the best model. Fig. 3 illustrates the comparison of computed and observed data of the IGANFIS model in five years from six stations.

Table 9. RMSE and NSE of the ANFIS models.

No.	Combination	Membership Function	Criteria	Training	Testing	Validation
1	R_t	Pimf	RMSE	0.113	0.0931	0.1183
			NSE	0.0124	-0.1650	0.0088
2	R_t, Q_{t-1}	gbellmf	RMSE	0.0291	0.0139	0.0281
			NSE	0.9349	0.9740	0.9439
3	R_t, Q_{t-1}, Q_{t-2}	Trimf	RMSE	0.0282	0.0141	0.0293
			NSE	0.9389	0.9732	0.9389
4	$R_t, Q_{t-1}, Q_{t-2}, Q_{t-3}$	trapmf	RMSE	0.0267	0.0142	0.0325
			NSE	0.9453	0.9726	0.9250
5	R_t, R_{t-1}	gaussmf	RMSE	0.1129	0.0932	0.1175
			NSE	0.0251	-0.1670	0.0224
6	R_t, R_{t-1}, Q_{t-1}	gbellmf	RMSE	0.0282	0.0141	0.0279
			NSE	0.9389	0.9729	0.9446
7	$R_t, R_{t-1}, Q_{t-1}, Q_{t-2}$	gbellmf	RMSE	0.0226	0.0146	0.0295
			NSE	0.9459	0.9711	0.9380
8	$R_t, R_{t-1}, Q_{t-1}, Q_{t-2}, Q_{t-3}$	Pimf	RMSE	0.0260	0.146	0.0371
			NSE	0.9482	0.9712	0.9024

*Since all data are normalized, the RMSE has no dimension.

Table 10. RMSE of the IGANFIS models with grid partitioning method in the first scenario.

No	combination	training	testing	validation
1	R_t, R_{t-1}, A	0.1119	0.0932	0.1167
2	R_t, R_{t-1}, S	0.1119	0.0926	0.1165
3	R_t, R_{t-1}, CN	0.1114	0.0927	0.1175
4	R_t, R_{t-1}, CNS	0.1094	0.0946	0.1168
5	R_t, R_{t-1}, AS	0.1105	0.0962	0.1178
6	R_t, R_{t-1}, ACN	0.1094	0.0951	0.1168
7	$R_t, R_{t-1}, ASCN$	0.1087	0.1153	0.1172

*Since all data are normalized, the RMSE has no dimension.

Table 11. RMSE and NSE of the IGANFIS models with grid partitioning method in the second scenario.

No.	Combination	Criteria	Training	Testing	Validation
1	R_t, R_{t-1}, Q_{t-1}, A	RMSE	0.0266	0.0148	0.0320
		NSE	0.9459	0.9702	0.9350
2	R_t, R_{t-1}, Q_{t-1}, S	RMSE	0.0273	0.0146	0.0279
		NSE	0.9427	0.9710	0.9446
3	$R_t, R_{t-1}, Q_{t-1}, CN$	RMSE	0.0268	0.0159	0.0296
		NSE	0.9451	0.9658	0.9377
4	$R_t, R_{t-1}, Q_{t-1}, CNS$	RMSE	0.0255	0.0167	0.0315
		NSE	0.9498	0.9620	0.9296
5	$R_t, R_{t-1}, Q_{t-1}, AS$	RMSE	0.0257	0.0187	0.0322
		NSE	0.9490	0.9527	0.9262
6	$R_t, R_{t-1}, Q_{t-1}, ACN$	RMSE	0.0252	0.174	0.0335
		NSE	0.9514	0.9589	0.9204
7	$R_t, R_{t-1}, Q_{t-1}, ASCN$	RMSE	0.0241	0.0280	0.0341
		NSE	0.9554	0.8940	0.9176

*Since all data are normalized, the RMSE has no dimension.

From 6576 days of training, every 1096 days are related to one station (respectively, Pol-e-Zoghal, Dawab, Abshar, Validabad, Harjian, Pol-e-Morgen), and from 2190 days of test (from 6576 to 8766) and validation (from 8766 up to 10956), each 365 days are related to base station in order to list each one, respectively. Fig. 4 exhibits

the comparison of computed and observed data of the IGANFIS model in the last year (validation period) for the six stations separately.

Table 12. RMSE and NSE of the IGANFIS models with subtractive clustering method in the second scenario.

No	Combination	Criteria	Training	Testing	Validation
1	R _t R _{t-1} Q _{t-1} A	RMSE	0.0298	0.0141	0.0285
		NSE	0.9322	0.9732	0.9421
2	R _t R _{t-1} Q _{t-1} S	RMSE	0.0291	0.0138	0.0283
		NSE	0.9350	0.9743	0.9429
3	R _t R _{t-1} Q _{t-1} CN	RMSE	0.0297	0.0146	0.0284
		NSE	0.9321	0.9712	0.9428
4	R _t R _{t-1} Q _{t-1} CNS	RMSE	0.0298	0.0143	0.0284
		NSE	0.9318	0.9722	0.9425
5	R _t R _{t-1} Q _{t-1} AS	RMSE	0.0293	0.0139	0.0284
		NSE	0.9338	0.9738	0.9428
6	R _t R _{t-1} Q _{t-1} ACN	RMSE	0.0295	0.0138	0.0285
		NSE	0.9332	0.9743	0.9422
7	R _t R _{t-1} Q _{t-1} ASCN	RMSE	0.0292	0.0138	0.0284

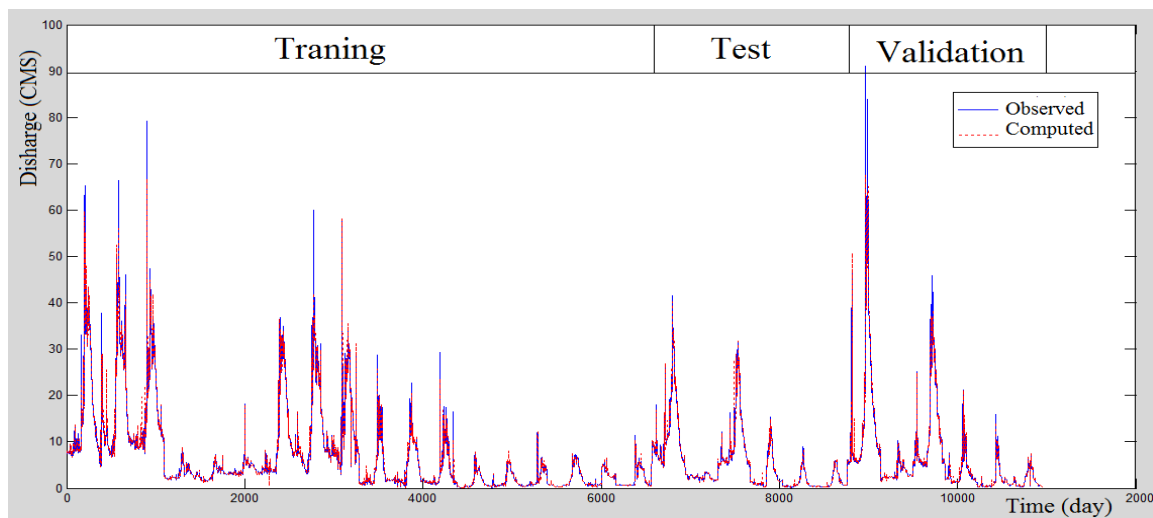


Fig. 3. Comparison of computed and observed of the IGANFIS model in five years for six stations.

Cross Validation of IGANFIS model

At this stage, in order to check validity of the model at each station that did not have data in the training of model (Vaspol), this was done as follows: instead of data of Abshar station, which is the adjacent to Vaspol station, data of the current day and one day ago rainfall and one day ago discharge of Vaspol station were entered into the input matrix of the model and again the IGANFIS model was executed by combining the R_t , R_{t-1} , Q_{t-1} , S and the subtractive clustering. Results are displayed in Table 14. RMSE of the whole model was obtained at validation stage (0.0291) and RMSE of Vaspol station (0.0346). Coefficient of performance (0.98941) and correlation coefficient (0.9496) for Vaspol station indicate high accuracy of the model in cross validation stage.

Fig. 5 exhibits the comparison of computed and observed data of IGANFIS model in the last year (validation period) as well as separately for the Vaspol station.

Table 13. Cross validation results of the best combination IGANFIS model (R_tR_{t-1}Q_{t-1}S)

Combination	Criteria	Training	Testing	Validation
All stations	RMSE	0.0268	0.0139	0.0291
	RMSE	0.0271	0.0146	0.0346
Vaspol	NSE	0.9544	0.9358	0.8491
	R	0.977	0.9676	0.9469

The best results of the models are given in Table 14. As shown in Table 14, IGANFIS has been able to increase performance of ANFIS. Finally, the IGANFIS with grid partitioning method was selected as the best model.

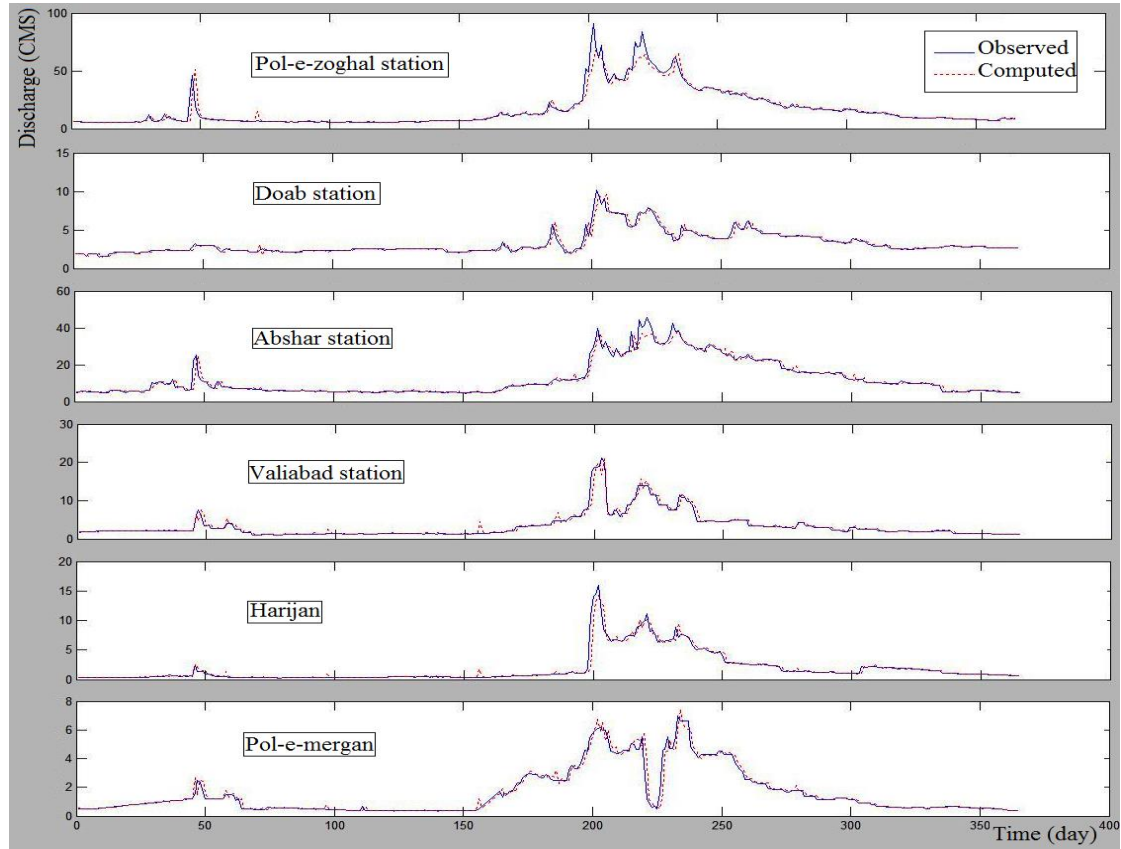


Fig. 4. Comparison of computed and observed of the last year (validation period) of the IGANFIS model.

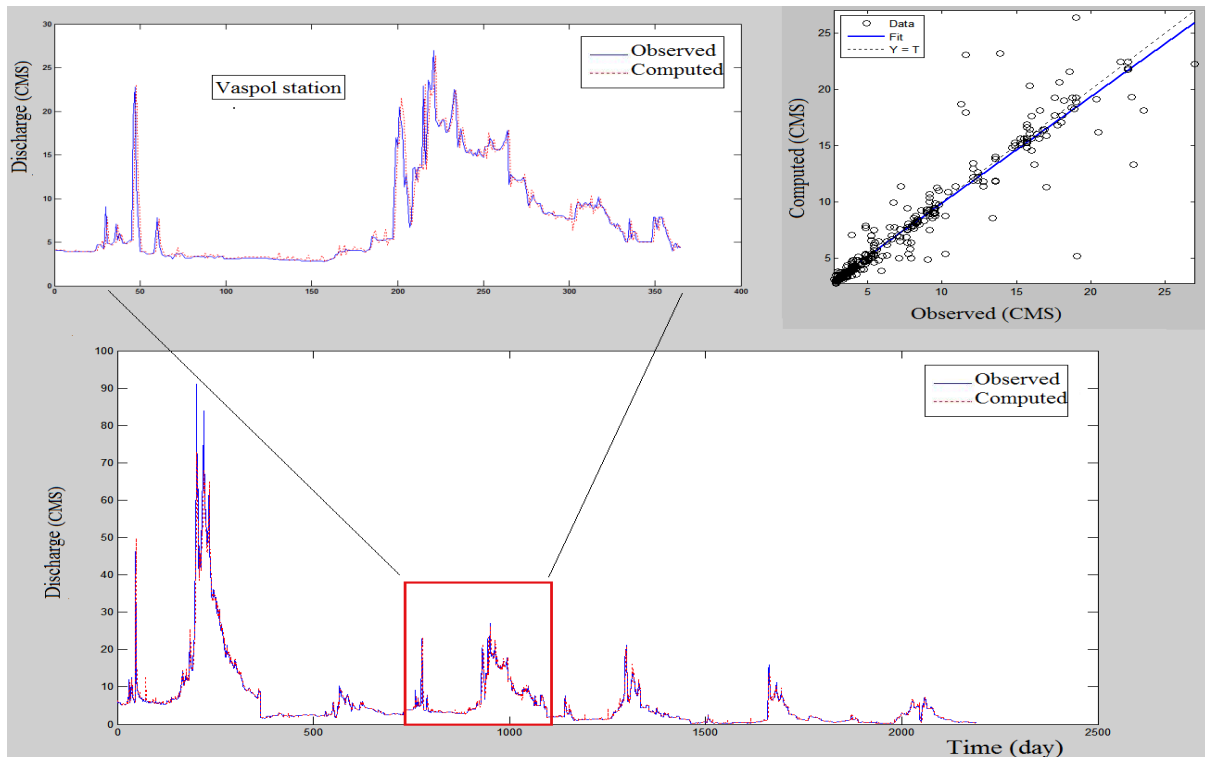


Fig. 5. Comparison of computed and observed discharge data of the last year (validation period) of the IGANFIS model during the omit validation stage in the whole station and Vaspoul station.

Table 14. Final comparison of models using RMSE and NSE.

No	Combination	Criteria	Training	Testing	Validation
1	ANFIS	RMSE	0.0282	0.0141	0.02796
		NSE	0.9389	0.9729	0.94465
2	IGANFIS with grid partitioning method	RMSE	0.0273	0.146	0.02795
		NSE	0.9427	0.9710	0.94467
3	IGANFIS with subtractive clustering method	RMSE	0.0291	0.0138	0.0283
		NSE	0.9350	0.9743	0.9429

Since all data are normalized, the RMSE has no dimension.

Amount of peak discharge error have been obtained based on five peak discharge in the fifth year (validation period, Table 15). All models were underestimated. However, the ANFIS model exhibited a better estimation of the peak discharge than the others.

Table 15. Comparing the maximum values of forecasted peak discharge.

No.	Model	Relative error %
1	ANFIS	19.16
2	IGANFIS with grid partitioning method	20.26
3	IGANFIS with subtractive clustering method	23.43

DISCUSSION

RR modeling using ANFIS

It can be concluded that the ANFIS model with RMSE (0.0279) and NSE (0.9466) with low error and high accuracy can predict the RR process (Table 9). It is confirmed by the results of Nayak *et al.* (2004), Firat & Güngör (2007) and Nourani & Kalantari (2010). In 3 out of 8 combinations used in the ANFIS models (Table 9) and also in the best ANFIS composition, the generalized bell-shaped membership function was the best fuzzer.

In combinations which only rainfall is considered as the input of the model, in ANFIS models, the combination (R_t, R_{t-1}) has a better performance than R_t combination, which indicates the effect of rainfall in the one day ago on increasing saturation, reducing soil permeability and increasing runoff. However, in the combinations which rainfall and discharge of previous days were considered, the best rainfall and discharge combinations were R_t, R_{t-1}, Q_{t-1} and $R_t, R_{t-1}, Q_{t-1}, Q_{t-2}$ respectively.

RR modeling using IGANFIS model

Modeling in this method was carried out with two different scenarios. At the first scenario, rainfall was only considered as input, and in the second one, in addition to rainfall, discharge were also considered as an input. Furthermore, we examined in the first scenario, different geomorphologic combinations with the best rainfall composition (R_t, R_{t-1}) and in the second one with the best combination of rainfall and runoff (R_t, R_{t-1}, Q_{t-1}). The results of the first scenario exhibit that R_t, R_{t-1}, S has been able to reduce the error of the ANFIS model with the combination (R_t, R_{t-1}) (RMSE = 0.116538). This result reveals that the slope is a determinant factor in outflow runoff, consistent with results of Nourani & Komasi (2013). The area and CN were not affected. The reason why the slope combination with other factors did not exhibit better results may be due to weak nature of ANFIS in estimating models with inputs greater than number 4 (Dastorani *et al.* 2012). The results of second scenario (Table 11) also indicate that the geomorphology model (R_t, R_{t-1}, Q_{t-1}, S) has been able to reduce the error of the ANFIS model with the combination (R_t, R_{t-1}, Q_{t-1}). In this case, slope as the determining factor in output runoff, is in accordance with the first scenario of the present study, as well as with the results of Nourani & Komasi (2013).

Clearly, the model has been able to predict the output of all stations with high precision. This model is based on geomorphology in cross validation stage that can predict discharge of Vaspoul station in the current day which it was not involved initial training (Table 13) with high accuracy and these results also in line with results of Nourani & Komasi (2013).

IGANFIS with subtractive clustering method

To investigate the effect of data clustering on modeling, IGANFIS with subtractive clustering method was implemented. According to the results (Table 12), the data cluster segregation has been clearly able to increase the efficiency of 6 out of 7 combinations, due to the efficiency of ANFIS with the large inputs and complexity of

the structure. The clustering decreases the complexity of the structure of the model by decreasing the number of rules

Integrated modeling of RR

Typical rainfall-runoff models, such as ANN and ANFIS ones which is used in various papers, generally consider a single hydrometric station in the watershed output as a model output, but in the models used in this study, an integrated matrix was used to include total existing stations in the basin to model the rainfall-runoff process of Chalus River basin. Given the fact that they have been trained by the data of six hydrometric stations (instead of an outlet station), they are very promising and highly accurate, and the results of the cross validation stage can be pointed out as the witness that the Vaspol station has no role in the initial training of the model, but by placing the station in the input matrix.

CONCLUSIONS

The purpose of this study was to predict runoff, not only at the basin outlet but also at any desired point within the catchment area. In order to achieve this goal, a matrix of hydro-climatic variables (rainfall and discharge) and physical properties (area, slope and CN) of the catchment area were created and highly desirable results with high accuracy by ANFIS model. So that the geomorphologic-adaptive fuzzy inference system (IGANFIS) with RMSE value equal to 0.02795 and the amount of NSE coefficient equal to 0.94467, as well as the models exhibited the predicted discharge value in the outlet of all Chalus basin stations with very low error and high precision. The results of cross validation phase at the Vaspol Station also verified this issue. The effective hydro-climatic factors were respectively selected discharge at the outlet of basin (the current and one-day ago rainfalls, the one, two and three days ago discharges) as well as the effective geomorphologic factors (average slope, curve number and upstream basin area) respectively. Meanwhile, the results of IGANFIS exhibited superior to the ANFIS model. Support Vector Machine (SVM) may also be used for modeling RR and their accuracies may be compared with each other.

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شبیه‌سازی فرآیند بارش-رواناب با استفاده از روش استنتاج عصبی-فازی تطبیقی مبتنی بر ژئومورفولوژی در حوزه آبخیز چالوس

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چکیده

پیش‌بینی دقیق دبی رودخانه یکی از ضروریات مدیریت منابع آب حوزه آبخیز برای برنامه‌ریزی و کنترل اثرات سیل و خشکسالی به حساب می‌آید. در این راستا مدل‌سازی فرآیند بارش رواناب به منظور درک بهتر آن و پیش‌بینی دقیق‌تر دبی در کانون توجه قرار گرفته است. این تحقیق به منظور ارائه یک مدل بارش رواناب یکپارچه که مبتنی بر خصوصیات فیزیکی حوزه آبخیز باشد، انجام شده است. هدف از این تحقیق این بود که پیش‌بینی رواناب نه فقط در خروجی حوضه، بلکه در هر نقطه دلخواه در داخل حوضه قابل انجام باشد. برای وصول به این هدف، ماتریسی از پارامترهای هیدروکلیماتیک (بارش روزانه و دبی روزانه) و خصوصیات ژئومورفولوژیک (مساحت، شیب و CN) طراحی شد و با استفاده از روش‌های هوش مصنوعی اجرا شد. مدل شبکه عصبی مصنوعی یکپارچه مبتنی بر ژئومورفولوژی (IGANN) با مقدار RMSE برابر ۰/۰۲۷۸۶ و ضریب کارایی برابر ۰/۹۴۵۰۳ و سیستم استنتاج عصبی فازی تطبیقی یکپارچه مبتنی بر ژئومورفولوژی (IGANFIS) با مقدار RMSE برابر ۰/۰۲۷۹۵ و ضریب کارایی برابر ۰/۹۴۴۶۷ توانستند با خطای بسیار کم و دقت بسیار بالا، دبی خروجی همه ایستگاه‌های هیدرومتری حوزه آبخیز چالوس را پیش‌بینی کنند. نتایج مرحله اعتبارسنجی حذفی در ایستگاه واسپول نیز این مسئله را تایید کرد. عوامل هیدروکلیماتیک موثر در خروجی دبی به ترتیب (دبی روز قبل، دبی دو روز قبل، بارش روز جاری و بارش روز قبل) و عوامل ژئومورفولوژیک موثر به ترتیب (شیب متوسط، شماره منحنی و مساحت حوضه بالادست) انتخاب شد. در ضمن نتایج مدل IGANN نسبت به IGANFIS برتری نشان داد.

* مؤلف مسئول

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