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Effect of Snow Water Equal Consideration in Runoff Prediction by Using RBF and ANFIS Models

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Abstract. Flood is one of devastating natural disasters prediction of which is significantly important. Rainfall-runoff process and flood are physical phenomena with very difficult investigation due to effectiveness of different parameters. Various methods have so far introduced to analyze these phenomena. Current study was aimed to investigate the performance of RBF and ANFIS models in simulation of rainfall-runoff process involved with Snow Water Equivalent (SWE) height in Latian watershed, Tehran province, Iran. Toward this attempt, 92 MODIS images were provided by NASA website during three water years 2003-2005, snow cover surface area in all images was extracted and finally SWE values were calculated for mentioned period. Also, precipitation height, temperature and discharge data of the study period were used for modeling. The results performance comparison of RBF and ANFIS models showed that the latter with rainfall-temperature-SWE inputs, 1-day delay, RMSE of 0.059 and R^2 of 0.656 and RBF model with rainfall-temperature-SWE inputs, 1-day delay, RMSE of 0.054 and R^2 of 0.35 had more accurate predictions than other models. It can be concluded from the results that involving SWE in the models improved their performance and increased their accuracy. Also, by comparing the results of ANFIS and RBF models, it can be concluded that ANFIS model with rainfall-temperature-SWE inputs, 1-day delay, RMSE of 0.059 and R^2 of 0.656 had better and more accurate prediction.

Keywords: Neural-fuzzy model, RBF model, rainfall-runoff model, SWE height, Latian watershed

1. INTRODUCTION

Snow is one of the main water resources in most areas over the world. Snow water equivalent (SWE) provides about one third required water for agricultural and irrigation activities all over the world (Raygani et al., 2008).According to the literature, about 60% of surface waters and 57% of groundwater are fed by snowmelt (Mashayekhi, 2011). Latian watershed is one of the most important watersheds in the Tehran and a considerable portion of the water requirements of its inhabitants is relied upon this watershed. The snow is one of the most important precipitation forms in the Latian watershed that plays significant role as delayed currents in high water seasons and minimum currents in low water seasons, water required for agricultural and drinking water and energy production. On the other hand, the runoff resulted from melted snow is the main resource to feed water tables because of its dilatory role and in some cases, leads to devastating floods with currents more than river capacity. Rainfall-runoff process is very important in water resources management so that various models with different levels of complexity have been developed to model this relationship. Many researches have been done in water resources planning and hydrology using neural-fuzzy model (Shamseldin, 1997; Dawson and Wilby, 2001; Tokar and Johnson,1999; Vafakhah et al, 2011; Bhattacharya and Solomatine, 2000; Baratti et al., 2003; Matreata, 2006; Nilsson and Berndtsson, 2006; Anctil and Rat, 2005; Khan and Coulibaly, 2006; Baareh et al, 2006; Wang et al, 2006; Firat

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and Güngo, 2007; Alvisi, 2006; Aqil et al., 2007; Tabari et al, 2008; Banihabib, 2010; Farahmand et al, 2011; Zare Abyaneh, 2011). Deshmukh (2010) compared a temporary method using the periodic neural network with time delay and the general periodic neural network in modeling rainfall-runoff in the upper part of Wordha River in India. They found that the periodic neural network with time delay gives satisfactory predications three hours earlier. They also showed that the periodic neural network with time delay is more diverse than the general period neural network and can be used as a secondary practical tool in order to predict short-term floods. Kurtulus (2010) used ANN and ANFIS models to predict daily discharge of the lime watersheds and compared their abilities with each other. They included the daily data of watershed for seven years in a MATLAB code and implemented an automatic instruction in order to select the best calibrated models. Through comparing the predictions, they concluded that both models (ANN and ANFIS) accurately predict daily discharge of the lime watersheds. In addition, they improved the performance of both models by increasing inputs from one to two and minimized the root mean square error (RMSE). Their results also showed that ANFIS model predicts the peak flow better than ANN model. ANFIS method had better generalization capability and to some extent, better performance than ANN model, particularly for peak discharges. Vafakhah (2011) simulated runoff resulted from the snowmelt by ANN and neural-fuzzy methods in the Taleghan watershed, Albroz province, Iran and found that the ANN has better efficiency in predicting the flow than the neural-fuzzy. They also found that involving SWE height in two stations increased the performance of the network structure and increase of the number of inputs from one to three return periods in two stations declined the performance of the models. Dastorani et al. (2011) evaluated the performance of the ANN and ANFIS models in predicting rainfall-runoff process in Zaiandeh-rood dam. Their results showed that the ANN and ANFIS models had different results in different conditions and combinations of input parameters. However, both models gave acceptable estimation of the runoff resulted from rainfalls, if appropriate input parameters and network structures are used. Moreover, when the number of the input parameters was less than 4, the results of ANFIS were better than those obtained from ANN and vice versa, if the number of input parameters was higher than 4. Pustizadeh (2011) also used the same models to predict Zaiandeh-rood River flow and found that the ANFIS model gives better results than the ANN model. Also, many researches have been done on hydrology and water resources planning by using of Radial Basis Function (RBF) neural network. Dawson and Wilby (2001)used 15min period precipitation in neural network model in the Mole river, Times river upstream, England, in order to produce rainfall-runoff relationship. They used both MLP and RBF models. Suhaimi and Bustami (2009) in their study modeled the runoff in the Sungei watershed in Sarawak and they compared its results with multilayer Perceptron model. The results showed that distributed RBF network has successfully modeled watershed runoff with more than 98.3% accuracy. Sarvary et al. (2011) in their study modeled rainfall-runoff process in a river by fuzzy ANFIS system and compared the results with that of RBF. The results showed that fuzzy ANFIS system has better results than RBF but in the latter, more neurons are required when input variables are increased and the more the network inputs, the weaker the results and the performance. Also, Moharrampour et al. (2011) predicted daily runoff by using RBF neural network. The results showed that the latter has a good performance to predict daily runoff. Moharrampour and Mohsenabadi (2011) also in a study collected statistic data for 14 weather and hydrometric stations of a watershed by means of RBF neural network in order to predict daily runoff for 18 statistical years (1989-2007). Seventy five percent of data was used in order to train and the rest of data (25 percent) was used for testing. The results showed that RBF neural network has a good property to predict daily runoff.

In this paper, snow-influenced Latian watershed has been studied by using RBF and ANFIS. According to the literature, SWE which has not been considered in researches done so far is taken into account in this paper. It has been tried to develop applications of this method to more accurately predict output runoff from a watershed. The results of current study can be used in water resources management projects and by the related organizations.

2. METHODOLOGY

2.1. Study area

Roodak watershed, 25’-51” to 46’-51” at longitude and 50’-35” to 36” at latitude, with an area of 436km^2 includes Garmabdar, Meigoon, Ahar, Amame, Roodak sub-watersheds in Tehran. This watershed is mountainous with elevations of 1700 m to 4212 m above the sea level (a.s.l.), average elevation of 2830 m a.s.l. and an average slope of 45.6% increasing northward or on the other hand, its general slope is southward (Fig. 1).

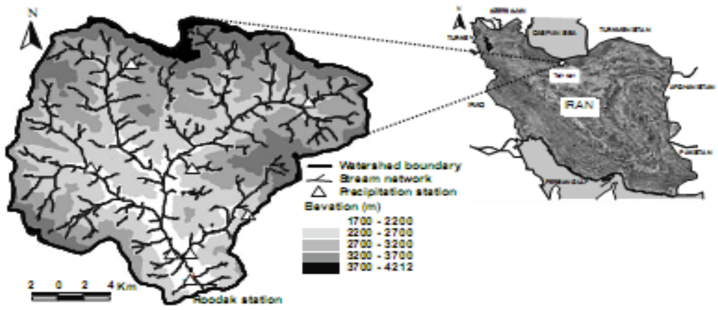

Figure 1. Location of Roodak watershed in Iran

Initially, MODIS images of the site were received and saved from NASA website (http://ladsweb.nascom.nasa.gov) in HDF format and were entered, read and displayed in ENVI processor environment(Reference for ENVI). Processing the satellite digital images with computer includes data preprocess, preparation, categorization, extraction and final process. Geo-referencing of the images was done automatically by using the ENVI software toolbox. Atmospheric modifications were applied to the images by means of the amount of wave reflexed from the Latian dam lake. It has been tried to use the images with no cloud coverage on the study area. An algorithm has been presented by (Hall et al, 2001) by using bands with ground resolution of 500 to differentiate snow from cloud in order to provide the snow cover map. The algorithm employed for preparing the snow cover map is based on the fact that snow has high reflection in the visible wavelengths (05-0.7 micrometers) and has low reflection in short infrared wavelengths (1-4 micrometers) (Hall et al, 2001). Bands 4 and 6 were used to automatically extract and calculate normalized difference snow index (NDSI) based on Eq. (1) as follows:

$$NDSI = \frac{MODIS_{band\ 4} - MODIS_{Band\ 6}}{MODIS_{Band\ 4} + MODIS_{Band\ 6}} \tag{1}$$

where NDSI represents the normalized difference snow index, $MODIS_{Band4}$ is MODIS 4-band image after radiometric modifications and $MODIS_{Band6}$ is MODIS 6-band image after radiometric modifications. This index could be used to differentiate snow from ice, also snow from clouds of above atmosphere like cumulonimbus clouds. In fact, this index is a criterion to calculate the relative amount of differential properties which are achieved from the snow reflections between visible and infrared bands with short wavelength. The mentioned index is insensitive to exposure conditions and could be adjustable relative to the atmospheric effects. In other words, this index is dependent on not only the reflection amounts in a specific band, but also on the digital value of reflections from the pixels. Hall et al. (2001) proved that the algorithm acts the best to prepare the snow map of places with sparse vegetation such as meadows, farms and tundra. In these cases, MODIS 2-band would be basically processed to differentiate the snow and NDSI components of the snow map in the algorithm will effectively filter the clouds (except the high-elevation clouds). These clouds contain ice pieces and may cause to incorrect categorization of snow cover. According to this criterion, the results from NDSI index could be accepted only if the amount of reflection from 2-band would be more than 11%. The second criterion called dark-targets has been discussed by Klein et al (1998). In this case, a 10% reflection in 4-band is known as the lower bound for differentiation of vegetation cover from snow. For the pixels categorized as snow, the reflection in 4-band should be more or equal to 10%. Despite the high value of the NDSI index, in some cases the dark-targets impede a correct categorization. Therefore, according to the two above-mentioned criteria, the snow cover algorithm would consider a pixel as snow only if the following conditions would be satisfied:

2-band has a reflection more than 11%.

4-band has a reflection more than or equal to 10 %.

NDSI amount should be totally estimated more than 0.4.

It should be considered that final snow map is in binary format and follows Boolean logic and in this model, the image as a whole is divided into two (snow and snowless) areas.

2.2. Extracting snow coverage surface area in the days with no satellite images

Having extracted the snow coverage area at different times by using MODIS images, snow cover surface area in days without any images was obtained using the cumulative snowmelt depth (ΔM). ΔM is a function of degree-day factor (α) and number of the degree-days over the critical degree-day (T+) and is obtained between t_1 and t_2 from Eq. (2):

$$\Delta M(t_1, t_2) = \sum_{t_1}^{t_2}(aT^4)\, t_1 < t_x \tag{2}$$

$$\alpha = 1.1\, \frac{\rho_s}{\rho_w} \tag{3}$$

where, ρ_s is the snow density, ρ_w is the water density and if it falls new snow, the degree-day factor would be modified and introduced to the model. Assume that there are two satellite images at times t_1 and t_2 and snow cover surface areas extracted by these two images are SCA(t_1) and SCA(t_2), respectively. If the temperature falls below the critical temperature between times t_A and t_E, snowmelt stops in which the snow cover surface area in time t_k will be obtained from Eq. (4):

$$SCA(t_x) = SCA(t_{x-1}) - \frac{SCA(t_1) - SCA(t_2)}{\Delta M(t_1, t_A) + \Delta M(t_E, t_2)} \Delta M(t_{x-1}, t_x) \tag{4}$$

where: SCA(t_x) is snow cover surface area at time t_x; SCA(t_{x-1}) is snow cover surface area attime t_{x-1}; SCA(t_1) is snow cover surface area at time t_1; SCA(t_2) is snow cover surface area at time t_2; ΔM(t_1, t_A) is cumulative snowmelt depth between t_1 and t_A; ΔM(t_g, t_2) is cumulative snowmelt depth between t_g and t_2; and ΔM(t_{x-1}, t_x) is cumulative snowmelt depth between t_{x-1} and t_x.

2.3. SWE

Referring to the research company of water resources, SWE data for the Amame snow sensing station were gathered for years 2003 to 2005. In order to determine SWE height in the days without sensing, a regression relation between SWE and the snow cover surface area was used.

2.4. Meteorological and water sensing data

Referring to the research company of water resources, the data for precipitation in weather stations (Roodak, Amame, Galookan (Kamarkhani), Rahat Abad, Ahar, Garmabdar, Shemshak, Roodbar Ghasran), the daily temperature in weather stations (Amame, Rahat Abad, Galookan) and the daily flow in Roodak water sensing station were obtained for the years of 2003-2005. Also, in order to determine the average daily precipitation and the watershed temperature, Thiessen method were used.

2.5. Determination of input parameters

Data selection is the first step in building the neural network appropriate to estimate the rainfall-runoff equations. Generally, two types of data could be used as the input data for the neural network which include statistics just related to the daily precipitation, daily temperature and SWE height. To select the input values to the network, an appropriate solution could be hydrological observations in different delay times. Toward this attempt, the number of delays required for modeling the input variables to the network was obtained by using partial autocorrelation diagram in STATISTICA software (Table 1).

Table 1. Information obtained from the partial autocorrelation plot

Lag	1	2	3	4	5
Rainfall(mm)	0.41	-0.04	0.08	0.014	0.011
Temperature (̊C)	0.98	0.12	0.07	0.025	0.028
SWE (mm)	0.98	-0.05	-0.02	-0.02	-0.01

2.6. Data normalization

In order to prevent underestimation of RBF weights, its inputs need to be normalized. In this study, following equation was used (Banihabib et al., 2010):

$$N_i = 0.8\times\left(\frac{x_i - x_{min}}{x_{max} - x_{min}}\right) + 0.1 \tag{5}$$

where, N_i is the normalized value; x_i shows real value; x_{min} and x_{max} are the minimum and maximum values, respectively. The above equation normalizes the inputs between 0.1 and 0.9.

2.7. Adaptive neural fuzzy inference system (ANFIS)

In recent years, ANFIS network has been produced by combination of fuzzy logic and artificial neural networks (ANNs) that is known as one of the most common neural-fuzzy systems. This model implements a Sugeno fuzzy system in a neural structure and takes advantage of combination of back-propagation training methods and root mean square error (RMSE). It is assumed that a fuzzy system has two inputs; X and Y, one output, Z, then from Takagi-Sugeno system following IF-THEN rules are the case:

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$ (6)

Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$ (7)

Rules are constant in ANFIS and what optimized are parameters of membership functions. In order to determine parameters (or forms) of membership functions, training neural networks algorithms are taken advantage. The types of membership functions (e. g. triangular, Gaussian and etc.) and the number of membership functions are determined by trial and error method for inputs and outputs. It is required in ANFIS that the type of membership functions and their number are identified in first layer.

Table 2. The training parameters of the ANFIS

Parameters	Roodak station
Membership function	gbellmf
AND method	Prod
Or method	Maximum
Imp. method	Prod
Aggr. method	Maximum
Defuzzification method	wtaver

2.8. Radial Basis Function (RBF) neural network

RBF is one of the most powerful neural networks that have been used in function estimation problems. This network has some advantages relative to multi layer feed-forward perceptron (MLP) neural networks. Unlike MLP networks with many successive layers, RBF network is composed of three layers. Input layer feeds input signals to the network, middle layer or RBF stratum includes RBF functions and output layer is linear combination of all outputs of the RBF stratum. In most cases, Gauss functions are used in RBF layer and are identified with two parameters, Gauss center and variance or Gauss extensiveness. A RBF structure is observed in Fig. 2. All operations conducted in this network are in the matrix form:

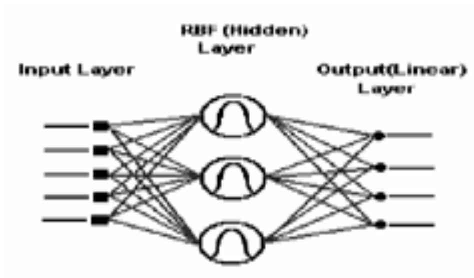

Figure 2. RBF neural network structure

$$d_i(P) = \sum_{j=1}^{N} \varphi_J(P).w_{ij} \quad (8)$$

$$\varphi_j = Exp\left(\frac{-1}{2\sigma_j^2}\left\|P - C_j\right\|^2\right) \quad (9)$$

2.9. Data classification

In this study, the data for average daily precipitation (P/mm), average daily temperature (t/°C), the daily SWE height (SWE/mm) and average daily discharge (Q/m^3/s) all gathered over three water years of 2003-2005 in Roodak hydrometric station. Totally 1096 data points were used from this station. Seventy percent (768) of data points were used as the training set and the remaining (thirty percent, 330) as the test set.

2.10. Network performance evaluation criteria

In order to compare the results of RBF and ANFIS models with the observed data in the test stage, threshold values were used to compare different networks and choose the best model. The coefficient of determinations (R^2) for the observed and estimated values is the most common comparison index. However, this coefficient is a general index and could not be an appropriate index (Khan and Coulibaly, 2006). Therefore, here, two more indices beside R^2 were used:

$$Coefficient\ of\ determination:\quad R^2 = \frac{\sum_{i=1}^{N}\left(Q_{ci}-\overline{Q}_{oi}\right)^2}{\sum_{i=1}^{N}\left(Q_{oi}-\overline{Q_{oi}}\right)^2} \tag{10}$$

$$\text{Root mean square error:}\quad \mathrm{RMS}E = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{Q_{ci}}-\mathrm{Q_{oi}})^2}{\mathrm{n}}} \tag{11}$$

$$Coefficient\ of\ efficiency:\quad CE = 1 - \frac{\sum_{i=1}^{N}(Q_{ci}-Q_{oi})^2}{\sum_{i=1}^{N}\left(Q_{oi}-\overline{Q}_{oi}\right)^2} \tag{12}$$

3. RESULTS

Prediction models were obtained based on the methodology. Table (3) shows the descriptions for input data and output results. The results obtained from the RBF models are shown in Table 4.

Table 3. Descriptive data for input and output.

Variable	Data set	Numbers of data	Average	Standard deviation	Maximum	Minimum
Rainfall (mm)	Training	768	2.08	5.47	68.90	0
	Test	328	2.01	5.21	31.67	0
	Entire	1096	2.06	5.39	68.90	0
Temperature (°C)	Training	768	10.94	8.46	29.26	-5.45
	Test	328	11.32	9.88	26.92	-9.32
	Entire	1096	11.06	9.03	29.26	-9.32
SWE (mm)	Training	768	80.87	113	292.68	0
	Test	328	79.42	112.01	292.23	0
	Entire	1096	80.43	112.66	292.68	0
Streamflow ($m^3\ s^{-1}$)	Training	768	8.99	10.21	119	2.32
	Test	328	9.98	9.36	38.7	2.17
	Entire	1096	9.28	9.97	119	2.17

Table 4. The results for the best RBF structures with different inputs.

Inputs	Training		Testing	
	R^2	RMSE	R^2	RMSE
Rt, SWEt	0.521	0.048	0.304	0.056
Rt, SWEt	0.499	0.049	0.192	0.058
Rt, Tt	0.430	0.052	0.206	0.058
Rt	0.270	0.059	0.024	0.064
Rt,Rt-1,Tt,Tt-1,SWEt,SWEt-1	0.504	0.048	0.355	0.054
Rt,Rt-1,SWEt,SWEt-1	0.469	0.050	0.185	0.0600
Rt,Rt-1,Tt,Tt-1	0.442	0.0522	0.219	0.060
Rt,Rt-1	0.312	0.057	0.012	0.068
Rt,Rt-1,Rt-2,Tt,Tt-1,Tt-2	0.484	0.050	0.242	0.059
Rt,Rt-1,Rt-2	0.375	0.055	0.006	0.068

Rt,Rt-1,Rt-2,Rt-3,Tt,Tt-1,Tt-2,Tt-3	0.499	0.049	0.299	0.056
Rt,Rt-1,Rt-2,Rt-3	0.389	0.054	0.001	0.071

According to the Table 4, RBF network with precipitation input, RMSE of0.064 and R^2 of 0.024 had more appropriate performance than input precipitation with 3-days and no delay. Also, neural network with rainfall-temperature inputs, without delay and up to 2-days delay had more appropriate performance. In rainfall-temperature-SWE with 1-day delay, RMSE of 0.054 and R^2 of 0.355, there is higher performance than rainfall-temperature-SWE model without delay. The results obtained from the ANFIS models are shown in Table 5.

Table 5. The results for the best ANFIS structures with different inputs.

Inputs	Training		Testing	
	CE(m^3/s)	RMSE	CE(m^3/s)	RMSE
Rt	0.4675	0.0768	0.4478	0.0817
Rt,Rt-1	0.5606	0/0698	0/4657	0/0815
Rt,Rt-1,Rt-2	0.6106	0.0657	0.185	0.0976
Rt,Rt-1,Rt-2,Rt-3	0.633	0.0638	-0.0753	0.1104
Rt,Tt	0.6295	0.0641	0.5565	0.0773
Rt,Rt-1,Tt,Tt-1	0.7293	0.0548	0.5623	0.076
Rt,Rt-1,Rt-2	0.791	0.0481	0.4374	0.0849
Rt,Rt-1,Rt-2,Rt-3	0.858	0.0397	0.1489	0.1035
Rt,Tt,SWEt	0.7481	0.0528	0.6068	0.0687
Rt,Rt-1,Tt,Tt-1,SWEt,SWEt-1	0.8999	0.0333	0.6564	0.0592
Rt,SWEt	0.6571	0.0616	0.5294	0.0748
Rt,Rt-1,SWEt,SWEt-1	0.7399	0.0537	0.4646	0.0797

According to the Table 5, ANFIS model with rainfall input, 1-day delay, RMSE of 0.0815 and R^2 of 0.465 had better performance than neural-fuzzy model with no-delay rainfall input and 3-days delay at the testing stage. Also, neural-fuzzy model with rainfall-temperature inputs, 1-day delay, RMSE of 0.076 and R^2 of 0.56 had better predictions than neural-fuzzy model with rainfall-temperature inputs and no delay. Neural-fuzzy model with rainfall-temperature-SWE inputs, 1-day delay, RMSE of 0.592 and R^2 of 0.65 had better performance than neural-fuzzy model with rainfall-temperature-SWE inputs without any delay.

Table 6. Best RBF and ANFIS structures.

Inputs	Training			Testing		
	CE(m^3/s)	R^2	RMSE	RMSE	R^2	CE(m^3/s)
Rt,Rt-1,Tt,Tt-1,SWEt,SWEt-1	0.51	0.504	0.048	0.054	0.355	0.27
Rt,Rt-1,Tt,Tt-1,SWEt,SWEt-1	0.89	0.77	0.033	0.059	0.62	0.65

Table 6 provides best RBF and ANFIS structures. Also, as can be seen in Fig. (8), first maximum observed discharge (38.7m^3/s) in testing stage attributed to the best RBF model and ANFIS model were estimated 13.32 m^3/s (65.58% underestimation) and 36.37 m^3/s (6.02% underestimation), respectively. This indicated that ANFIS model had more accurate prediction than RBF model. In addition, second maximum observed discharge (38.1m^3/s) attributed to the best RBF model and ANFIS model were estimated 16.24 m^3/s (57.37% underestimation) and 36.76 m^3/s (3.51% underestimation), respectively which is consistent with and confirms previous result.

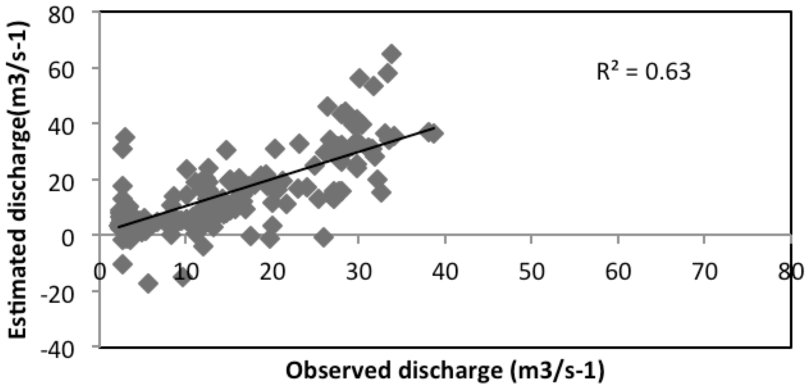

Figure 3. Observed versus estimated discharge diagram for neural-fuzzy model with rainfall-temperature-SWE inputs, 1-day delay at testing stage.

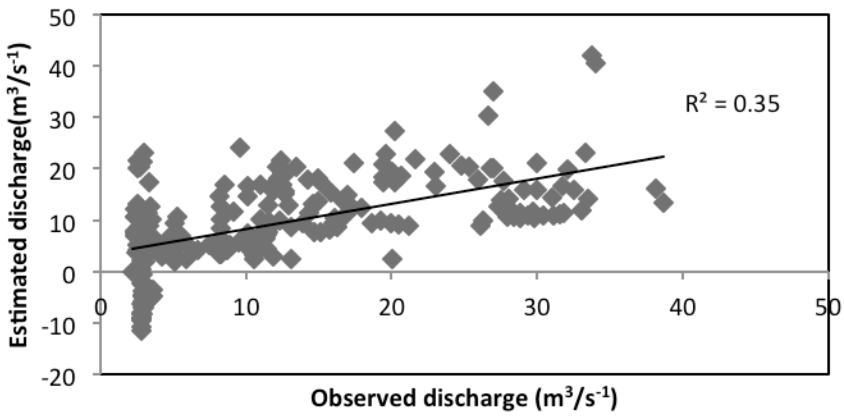

Figure 4. Observed versus estimated discharge diagram for RBF model with rainfall-temperature-SWE inputs, 1-day delay at testing stage.

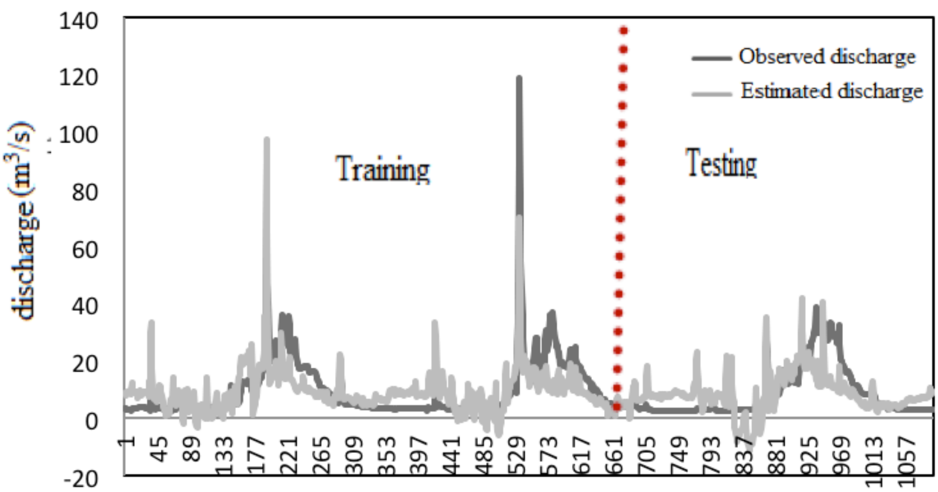

Figure 5. Comparison of observed and estimated discharges for RBF model with rainfall-temperature-SWE inputs, 1-day delay at testing stage.

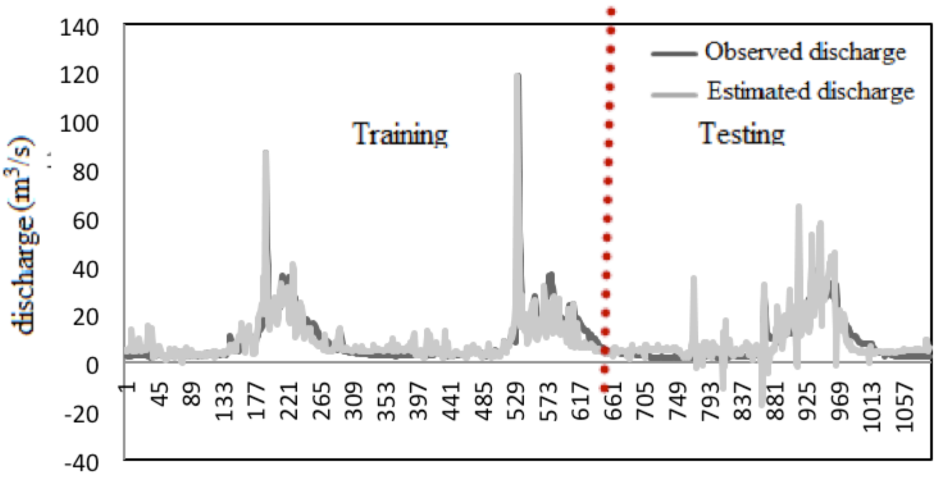

Figure 6. Comparison of observed and estimated discharges for ANFIS model with rainfall-temperature-SWE inputs, 1-day delay at testing stage.

3.1. Extracting snow cover surface area from MODIS Images

4. DISCUSSIONS AND CONCLUSIONS

The rainfall-runoff relationship depends upon climatic and physical parameters such as temporal variations in precipitation, slope, height, plant cover, soil humidity, underground water and etc. This dependency on many variables makes the rainfall-runoff relationship deviate from linear form and convert it to a nonlinear complicate relationship. Many physical models have so far been proposed for this relationship, but they have not high applicability due to lack of some required parameters and some simplifications. Owing to capability of modeling complicate nonlinear relations without any need for a high number of parameters, ANNs have recently attracted a lot of attentions to investigate the rainfall-runoff relationship. From Table 6, the best structures for RBF and ANFIS models were provided with RMSE, R^2 and performance measure as well as different inputs. From Table 6, RBF with the rain-temperature input, 3-days delay, RMSE of 0.056 and R^2 of 0.29 had better performance than the model with rainfall input, do delay, RMSE of 0.064 and R^2 of 0.024, while ANFIS network with rainfall-temperature inputs, 1-day delay, RMSE of 0.076 and R^2 of 0.562 had better performance than the model with rainfall inputs, 1-day delay, RMSE of 0.0815 and R^2 of 0.465 at the testing stage. As a result, temperature involvement improved the performance of RBF and neural-fuzzy networks. Also, comparing the performance of RBF and ANFIS models, the latter with rainfall-temperature-SWE inputs, 1-day delay, RMSE of 0.059 and R^2 of 0.656 and RBF model with rainfall-temperature-SWE inputs, 1-day delay, RMSE of 0.054 and R^2 of 0.35 had more accurate predictions than other models. It can be concluded that SWE involvement in the models improved their performance and increased their accuracy. Also, by comparing the results of ANFIS and RBF models, it can be concluded that ANFIS model with rainfall-temperature-SWE inputs, 1-day delay, RMSE of 0.059 and R^2 of 0.656 had better and more accurate predictions.

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