ISSN 2345 - 5012

Available online at: www.waterdevelop.com

Vol. (II)– No. (04)- S.N. (07)- Autumn 2014
20th Article– P. XLI-LIII

IBWRD
International Bulletin of Water Resources & Development

A Comparative Study of the Efficiency of Artificial Neural Network and Multivariate Regression in Prioritizing Climate Factors Affecting Runoff Generation in Research Plots: A Case Study of Sangane Station, Khorasan Razavi

Marzieh Qaderi[1], Mohammad Taqi Dastorani[2], Mohammad Reza Khaleqi[3], Kazem Saber Chenari[4*]

[1] *Young Researchers and Elite Club, Torbat-e-Jam Branch, Islamic Azad University, Torbat-e-Jam, Iran (marzie.ghaderi65@gmail.com)*
[2] *Associate Professor, Faculty of Natural Resources and Environment, Ferdowsi University of Mashhad, Mashhad, Iran (Mtdastorani@gmail.com)*
[3] *Assistant Professor, Department of Range and Watershed Management, Faculty of Natural Resources and Environment, Ferdowsi University of Mashhad, Mashhad, Iran (Drmrkhaleghi@gmail.com)*
[4] *Young Researchers and Elite Club, Rasht Branch, Islamic Azad University, Rasht, Iran*

* Corresponding Author (k.saberchenari@gmail.com)

Article History	Received: Apr. 10, 2014	Reviewed: Apr. 30, 2014
Revised: May, 12, 2014	Accepted: Jun. 16, 2014	Published: Dec. 16, 2014

Abstract

Estimating runoff in watersheds is of great importance in water resources management.The aim of this study was to compare the efficiency of Artificial Neural Network and Multivariate regression in prioritizing climate factors affecting runoff generation in research plots (areas of 10, 20, 30 and 40 m^2) of Soil Conservation Research Database of Sanganeh. Sanganeh has an area of 50 hectares and is located in Khorasan Razavi province. For this purpose, the data of rainfall – runoff of 72 events was used in 32 plots. The multivariate regression relationships were created between the input variables (rainfall amount and intensity) and the height of the surface runoff collected in the selected output plot (10, 20, 30 and 40 m^2), plots with the same conditions on a slope, plots on different slopes and finally, the total plots existing in the area. The results were indicative of a significant and positive effect of climate variables on output runoff volume. The study showed a greater impact of rainfall variables than rainfall intensity in the spatial scales under study. In addition, according to the parameter coefficient and Root Mean Square Error (R^2, RMSE), it can be concluded that multi-layer perceptron artificial neural network models are more accurate than multivariate regression models.

Keywords: Regression Model, Rainfall-Runoff Relationship, Sanganeh Research Base, Artificial Neural Network

1. Introduction

Understanding and prediction of runoff processes and transferring the runoff to the watershed outlet is one of the most fundamental issues in the science of hydrology. Due to the interaction of various factors, the behavior of hydrological cycle of watershed changes into a relatively complex process. Therefore, hydrological models are often used to evaluate it. Estimation of runoff in the watersheds is of great importance in water resources management. A great deal of effort has been made in investigating the methods that can support or alternate tools of estimating runoff. Accurate data on rainfall is essential for planning and management of water resources (Hung et al., 2009). Due to the complexity of the atmospheric processes that generate rainfall and the great variations in the time series of scales both in space and time, understanding and modelling rainfall and its relationship with runoff is very complex and difficult in the hydrological cycle (Hung et al., 2009; French et al., 1992).The relationship between rainfall and runoff is one of the most important and complex hydrological processes that plays a very important role in understanding hydrology and water resources. For this reason, many studies have been carried out in this area. In recent years, artificial neural networks (ANNs), systematic theoretic/black-box methods, have become one of the most promising tools to model complex hydrological processes such as the rainfall-runoff process. In many studies, ANNs have demonstrated superior results compared to alternative methods. According to Wechmongkhonkon et al., (2012), ANNs are able to map the underlying relationship between input and output data without prior understanding of the process under investigation. The results indicated that ANNs are promising tools not only in modelling complex processes in an

accurate way, but also in providing insights from the learned relationship which would assist the modeler in understanding the process under investigation as well as in evaluating the model. According to Mutlu et al. (2008), the ANN model does not require detailed knowledge of internal functions of a system in order to recognize relationships between inputs and outputs. Artificial Neural Networks (ANNs) have been widely applied to model many of nonlinear hydrologic processes such as rainfall-runoff (Hsu et al., 1995; Shamseldin, 1997; Lorrai and Sechi, 1995; Minns and Hall, 1996; Dawson and Wilby, 1998; Sajikumar and Thandaveswara, 1999; Tokar and Johnson, 1999; Rajurkaret al., 2002; Wilbyet al., 2003; Giustolisi and Laucelli, 2005; Jain and Srinivasulu, 2006;Adamowski et al., 2012; Shrivastava et al., 2012; Asadi et al., 2013; Mokhtari et al., 2013), rainfall forecasting (French et al., 1992; Hung et al., 2009), stream flow (Campolo and Soldati, 1999; Abrahart and See, 2000; Dawson et al., 2002; Lauzon et al., 2006), groundwater management (Rogers and Dowla, 1994) and water quality simulation (Maier and Dandy, 1996; Maier and Dandy, 1999) and shown to be one of the most promising tools in hydrology (ASCE Task Committee, 2000a,b; Maier & Dandy, 2000; Dawson & Wilby, 2001). Previous studies have obviously argued that ANN is a good approach and has a high potential to forecast rainfall. The ANN is able to model without prescribing hydrological processes, catching the complex nonlinear relation of input and output, and to solve without useing differential equations (Luk et al., 2000; Hsu et al., 1995; French et al., 1992). Dawson et al. (2002) evaluated two neural networks: the popular multilayer perceptron (MLP) and the radial basis function network (RBF).The results showed that both neural network types can simulate river flows better in the time series of the training set. Dasturani et al. (2007) investigated the performance of ANNs inference system and neural-fuzzy adaptive modeling of rainfall-runoff in the river basin of Zayanderuddam.The results of this study showed that ANN and Fuzzy– Neural system produced different results in different situations and with different combinations of input variables, but all these methods are acceptable to estimate runoff resulted from rainfall using appropriate variables and the use of Neural- Fuzzy network structures and ANNs. Nasri et al. (2010) estimated daily runoff from daily rainfall in Pola Sobhan watershed using multilayer Perceptron Neural Network. Their findings showed that Perceptron neural network with four hidden layer is more reliable in estimating runoff than other networks.ZareAbiane and Bayat Varkeshi (2011), using observed data, investigated the applicability of experimental models, ANNs (ANN) and Fuzzy Neural Network (CANFIS), in estimating runoff. The results showed that intelligent neural models have a high level of accuracy in estimating runoff.Sarvi et al., (2010), investigated the effects of climate change on the rainfall– runoff model, using methods which are based on mathematical logic and using climate scenarios based on different climatic conditions in Golestan dam watershed. A comparison of precipitation and runoff from each scenario was indicative of the effects of climate change on precipitation and temperature, an increase in temperature and a decrease in precipitation and runoff from rainfall and occurrence of drought conditions.Keskin et al. (2003) used Fuzzy Logic for predicting runoff using rainfall data in River Dim which is located in the central Mediterranean. The results suggested that the predictions made by fuzzy logic has a good correlation with historical data and in general, the results were appropriate and satisfactory. Vieux et al. (2003) presented a distributed hydrological model to simulate rainfall-runoff through drainage. Their goal was to investigate regional and local water management and emergency response agencies. The results showed that the model was effective. Parametric Multivariate Regression (MR) is a widely used statistical data analysis technique that can also be viewed as a supervised learning algorithm. Assad et al. (2001) used a non-linear Auto-Regressive Exogenous-input model (NARXM) river flow forecasting output-updating procedure and compared its performance with that of the linear Auto-Regressive Exogenous-input (ARXM) model updating procedure, the latter being a generalization of the widely used Auto-Regressive (AR) model forecast error updating procedure. The results of the comparison indicated that the NARXM procedure performs better than the ARXM procedure. Lauzon et al. (2006) used a clustering algorithm based on the Kohonen neural network for discriminating daily precipitation fields in a watershed into coherent groups. The results demonstrated the relevance of the proposed clustering method, which produces groups of precipitation fields that are in agreement with the global climatological features affecting the region, with the topographic constraints of the watershed (i.e., orography). Although many studies have applied different ANNs and Multivariate Regression procedures to predict various water resource aspects, few investigations have utilized these two procedures to achieve runoff from experimental plots of Sanganeresearch base. Hence, further investigations are needed to achieve the rate of runoff in various places. These methods proved to be efficient for solving a number of various problems. In this paper, this method was applied to estimate runoff.

The present paper deals with the application of the neural network technique as an updating procedure for estimating runoff and assessing its performance in comparison with Multivariate Regression procedures. The objectives of the present study are: (i) to develop suitable regression and ANN models based on minimum ground truth data for fast, cost-effective and accurate assessment of watershed management and (ii) to compare the two models and their performance

reliability as a decision support tools with reasonable accuracy towards livelihood security assessment.

2. The Study Area

The study area is Soil Conservation Research Center of Sanganeh, established in the Shekarkalat Rangeland located about 100 km northeast of Mashhad. This area represents the dominant type of arid parts of Khorasan Razavi in the ranglands. It is also of great importance in terms of animal husbandry.Sanganeh research base area is more than 50 hectares. Sanganeh average annual rainfall is less than 180 mm.A total of 92 experimental plots to measure runoff and sediment, with a fixed width of 2 m and lengths 5, 10, 15 and 20 yards in different conditions of vegetation, slope and soil depth were established and at the end of each plot, a metal tank was installed to collect runoff. For more information about intensity, duration and amount of each rainfall event, two rain gauges were installed in Sanganeh research base. Fig. 1 shows the location of the study area. Fig. 2 shows examples of installed plots in different situations.

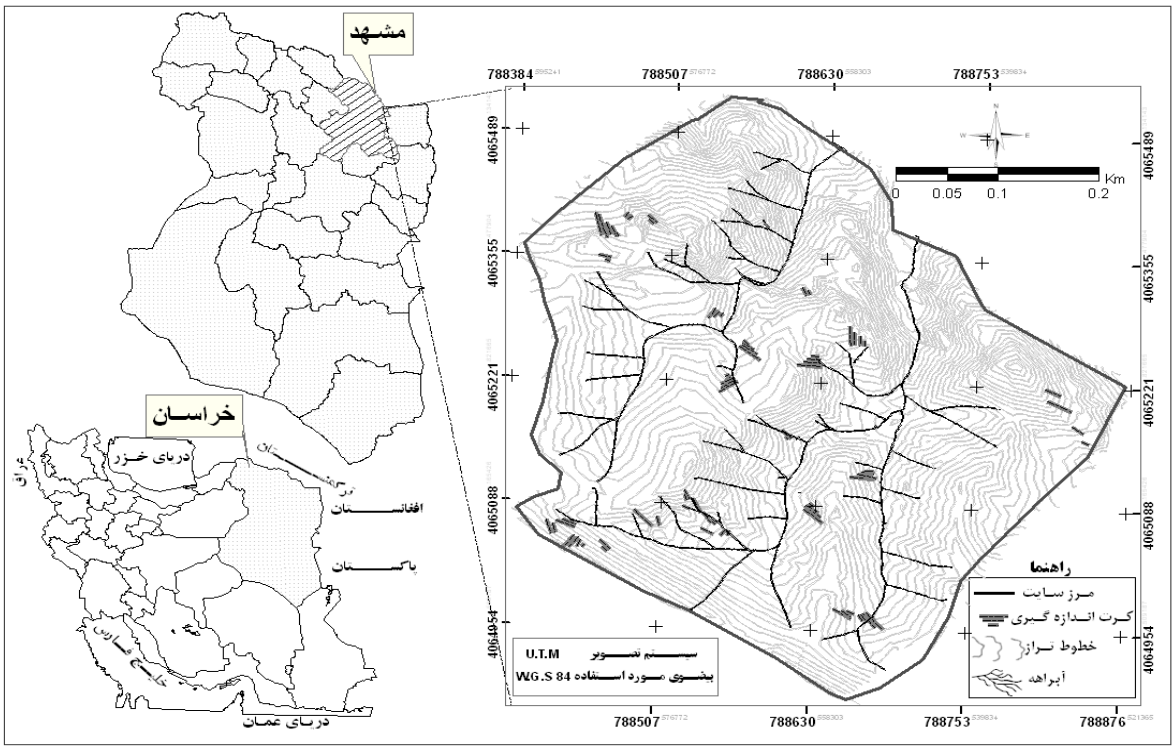


Fig. 1. Location of the study area.

Fig. 2. Examples of installed plots in different situations.

3. Materials and Methods

To establish the relationships between area rainfall-runoff and prioritizing climatic factors influencing the production of plots runoff, the data on rainfall- runoff from 72 rainfall events in 32 experimental plots that were obtainrd through the installation of tanks were used to collect rain runoff and sediment. First, to select the appropriate plot for this study, bivariate regression relationships between the input variables (rainfall amount and intensity) and the output parameter (runoff height) were investigated in 72 plots. Then, the validation of generated regression relationships in the selected plots was measured by rainfall– runoff relationships from the control plots. In the next step, multivariate regression relationship was generated the

input variables (rainfall amount, intensity and duration) and the height of runoff was collected in the output plots (the control plots, A few examples of the same plot, located on a slope, plots on different slopes and finally, the entire study area) and according to the results of the correlation matrix tables and analysis of variance, in turn, the credit of the generated regression models and input variables affecting runoff height in the time series span(from 1996-2000 and 2006-2009) in same area plots and in the whole area was determined.In the next step, to determine the important variables affecting runoff height, various neural network models were generated using NeuroSolution software in plots with different areas,a few sample plots are located on a slope and finally the whole study plots. For verification and comparison of different neural networks, the actual amount of runoff (measured) at the output of the study plots were calculated. Moreover, the models which had the highest and lowest amount of RMSE and R2 were selected. Finally, a comparison between the results of both methods (multiple regression and ANN) was conducted to estimatethe output runoff.

3.1. Feed-forward Multilayer Perceptron (MLP)

The feed-forward Multilayer Perceptron (MLP) is the most commonly used ANN in hydrological applications. The structure of a three-layer MLP consists of three layers; an input layer, a hidden layer, and an output layer. The configurations of the ANN model (the number of neurons in the hidden layer(s), in this study a single hidden layer with six neurons, is usually defined via a trial-and-error procedure with different selections of inputs and different numbers of hidden nodes. In order to obtain the optimal values of these connection weights, ANNs must be trained. The MLP is usually trained using the error back-propagation algorithm (Mutlu et al., 2008). For this reason, we used a back-propagation algorithm (Sudheer et al., 2002; Kalteh, 2008; Adamowski et al., 2012; Asadi et al., 2013) for training the network, in which the inputs are presented to the network and the outputs obtained from the network are compared with the real output values (target values) of the system under investigation in order to compute error and then, the computed error is back-propagated through the network and the connection weights are updated. This procedure, called training procedure, continues until an acceptable level of convergence is reached.

3.2. Model Performance Comparison

The performance of different models may be assessed in terms of goodness of fit. In this research, two commonly used performance indices were used to evaluate the accuracy of the models: correlation coefficient (r) and the Root Mean Squared Error (RMSE). The RMSE evaluates the variance of errors independently of the sample size via the following formula (Eq. 1):

$$\mathrm{RMSE}=\left[\frac{\sum_{i=1}^{n}\left(Q_{(i)}-\hat{Q}_{(i)}\right)^{2}}{n}\right]^{0.5} \quad (1)$$

The correlation coefficient shows the discrepancy between the observed and forecasted data and indicates how close the points are to the bisector in the scatter plot of the two variables. The correlation coefficient (r) is calculated via the following formula (Eq. 2):

$$r=\frac{\sum_{i=1}^{n}\left(Q_{(i)}-\bar{Q}\right)\left(\hat{Q}_{(i)}-\breve{Q}\right)}{\sqrt{\sum_{i=1}^{n}\left(Q_{(i)}-\bar{Q}\right)^{2}\sum_{i=1}^{n}\left(\hat{Q}_{(i)}-\breve{Q}\right)^{2}}} \quad (2)$$

Where $\hat{Q}_{(i)}$ is the estimated runoff value, $Q_{(i)}$ is theobserved runoff value, $\bar{Q}$ is the mean of the observed runoff values, and $\breve{Q}$ is the mean of the estimated runoff values.

In order to compare the performance of MLR and ANN, we divided the data sets randomly into 75 percent of the total data used to train the process and 25 percent of data used to test the process. Both MLR and ANN were applied to the training data. Then, the correlation between the observed runoff related to the considered plot number and its estimated runoff was computed by both methods using log-transformed data. The correlation coefficients were interpreted as a measure of prediction accuracy.

4. Findings and Discussion

4.1. Runoff Estimation

In this study, a three-layer feed-forward MLP model was developed in order to estimate the monthly runoff in a watershed in east northern Iran. As mentioned in the study area and data section, the feed-forward MLP model was developed using 5 input variables and 1 output variable which are defined based on the problem at hand. However, we have chosen 3 neurons in the hidden layer based on a trialanderror procedure. It was observed that runoff can be reasonably well simulated by using the developed feed-forward MLP model. The results of the simple linear relations of the variables of precipitation (rainfall intensity and amount) and runoff in the study plots in the time series d in 72 storm event showed that in all plots, there is a significant relationship between the amount of rainfall and runoff height (P-value<0.05). Moreover, despite the linear relationship between variables of the amount of rainfall and runoff height, values of the determination coefficient (R2) of regression equations showed that as the area of plot increases, the effect of rainfall on runoff production variables will decrease per unit area. Figs. 3-a, 3-b, 3-c and 3-d show the relationship between the amount of rainfall and runoff height at various areas. Tables 1, 2, 3 and 4show the significant effect of input variables related to the amount of rainfall on the output runoff in plots with different areas.

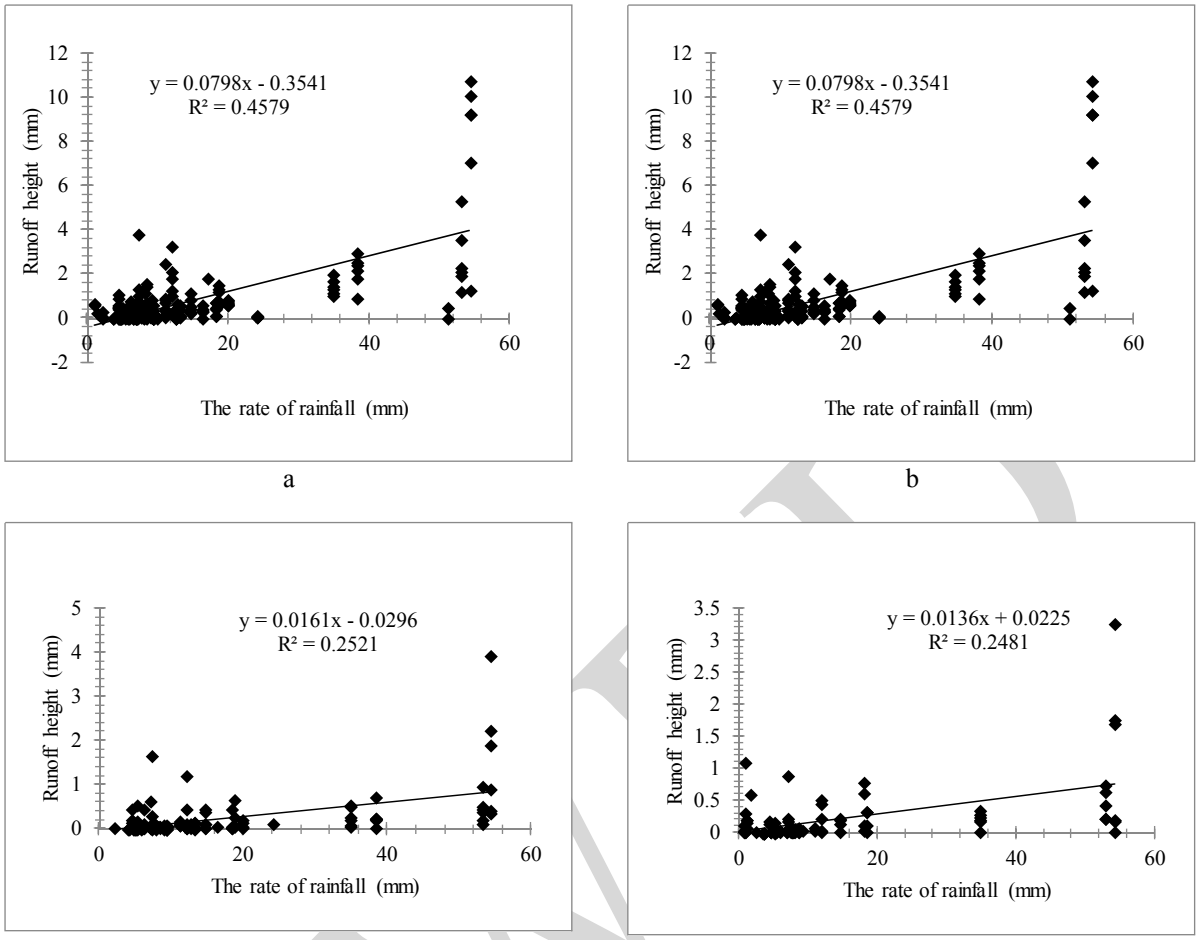


Fig.3. Simple linear relationship between the amount of rainfall and runoff height in plots of a) 10 m^2, b) 20 m^2, c) 30 m^2 and d) 40 m^2.

Table 1. Analysis of variance in plots of 10 m^2.

Input variable	Constant coefficient	Standard deviation	T parameter	p-value	95% lower	95% upper
Intercept	-0.35	0.1	-3.37	0.0009	-0.56	-0.14
the amount of rainfall (mm)	0.08	0.005	13.96	0.00	0.06	0.09

Table 2. Analysis of variance in plots of 20 m^2.

Input variable	Constant coefficient	Standard deviation	T parameter	p-value	95% lower	95% upper
Intercept	-0.11	0.06	-1.68	0.09	-0.24	0.01
the amount of rainfall (mm)	0.03	0.003	11.73	0.00	0.03	0.04

Table 3. Analysis of variance in plots of 30 m^2.

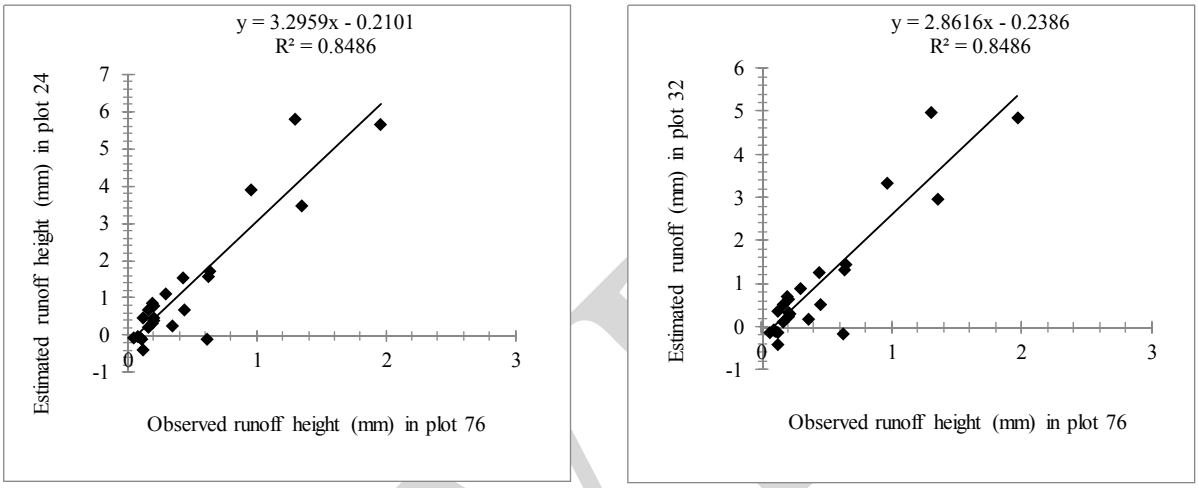
Input variable	Constant coefficient	Standard deviation	T parameter	p-value	95% lower	95% upper
Intercept	-0.03	0.05	-0.53	0.59	-0.14	0.08
the amount of rainfall (mm)	0.01	0.002	6.44	0.00	0.01	0.02

Table 4. Analysis of variance in plots of 40 m^2.

Input variable	Constant coefficient	Standard deviation	T parameter	p-value	95% lower	95% upper
Intercept	0.02	0.05	0.42	0.67	-0.08	0.12
the amount of rainfall (mm)	0.01	0.002	5.57	0.00	0.08	0.01

The results of validation and calibration of the bivariate regression model between the rainfall characteristics (amount and intensity of rainfall) and runoff height showed that the best regression equations generated parameter is related to the amount of rainfall and runoff height. Accordingly, validation of regression models in the study plots was used by relationships between the amount of rainfall and runoff height. In other words, rainfall amounts of each plot number were placed in the linear equation between the amount of rainfall and runoff height

related to the plot which had the same length and the runoff values were estimated. Then, the correlation between the observed runoff related to the considered plot number and its estimated runoff in excel software was measured. The results of the validation in plots of the same length in the time series of 72 storm eventsshowed that between plots of 5 m length, the best regression equations was observed in plots 26 and 76 with by replacing the amount of their rainfall in the equations between the amount of rainfall and runoff height (plots 24 and 32). In plots of 10 m length, the best equations with higher coefficient of determination and higher significance levels resulting from rainfall in each plot was generated in rainfall-runoff equation related to plot 16. In the plots of 15 m length, the best regression equations was obtained in the plot 35 by replacing the amount of rainfall which is related to the plot 35 in rainfall-runoff equations in the plots of 15 m length, in the plots 38 and 71. In the plots of 20 m length, the best regression equation was obtained in plot 31 by replacing the amount of rainfall related to plot 31 in rainfall-runoff equations of plots 28 and 72.

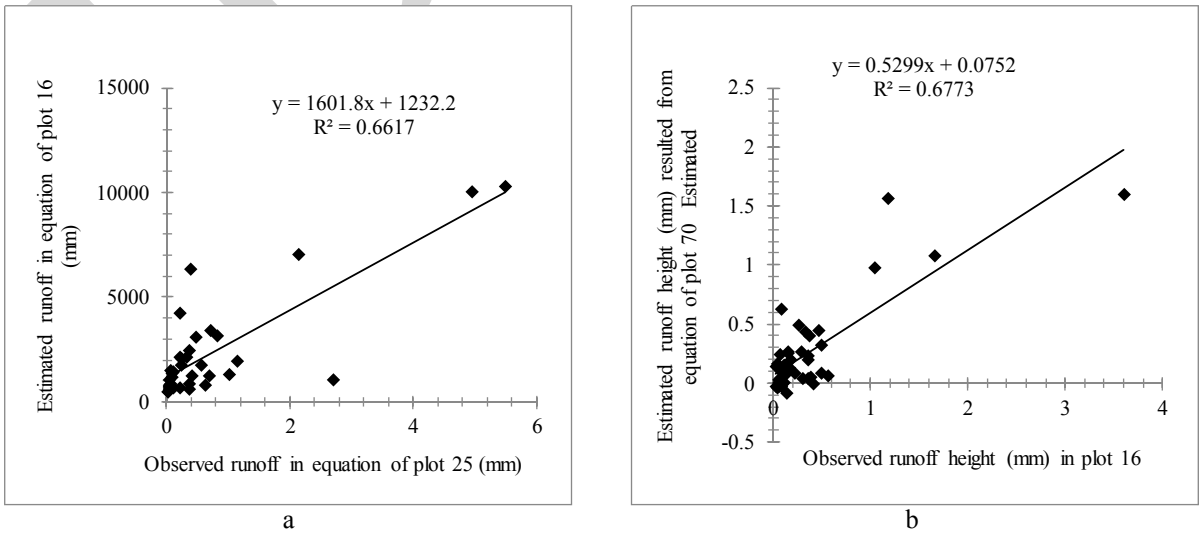


a b

Fig. 4. The relationship between the observed and predicted runoff in plot 76: a) According to equation 24 and b) According to equation 32.

Tables 5, 6 and 7 show the results of the validation and the best regression equations in the plots with the same length in the period1996-2000 and 2006-2009. In all plots, the observed runoff resulted from each plot was compared with the estimated runoff of the same plot. The estimated runoff is sometimes negative; this is due to the insufficiency of the observational data and incompatibility of other plots equations in the plots. Fig. 4 shows the results of the validation and the best generated models in the plots of 5 m length.

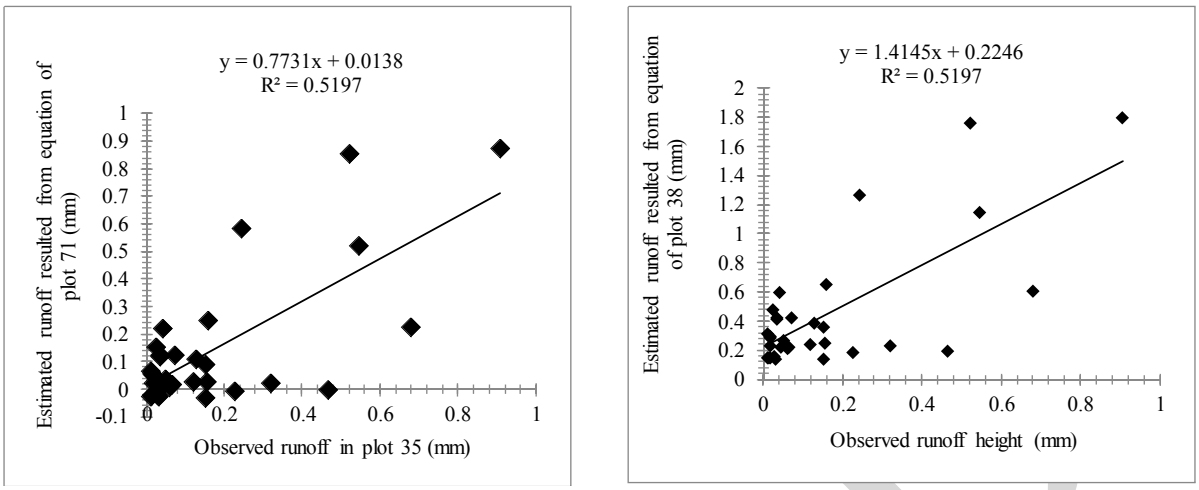
Fig. 5 shows the results of validation in plots of 10 m length that were obtained by replacing the amount of rainfall related to plots 25 and 16 (which have the same area as the aforementioned plots) in rainfall-runoff equations in plots 16 and 70.



a b

Fig. 5. The relationship between the observed and predicted runoff: a) in plot 25, according to equation 16 and b) in plot 16, according to equation 70.

Fig. 6 shows the best generated equations in plot 35 of 15 m length that its runoff has generated with replacing the amount of rainfall related to plot 35 in the rainfall-runoff equations related to plots 38 and 71.



a b

Fig. 6. The relationship between the observed and predicted runoff in plot 35: a) According to equation 71 and b) According to equation 38.

Table 5. A few examples of the observed and estimated runoff values in plots of 10 m length, equation 16.

Estimated runoff related to plot 16 in the equations of plot 30	Estimated runoff related to plot 16 in the equations of plot 27	Estimated runoff related to plot 16 in the equations of plot 25	Observed runoff related to plot 16
-	-0.051	-0.007	0.391
0.076	0.134	0.245	0.0658
-0.214	-0.085	-0.055	0.065
0.034	0.102	0.201	0.092
-0.155	-0.041	0.005	0.087
0.084	0.139	0.253	0.138
2.16	1.708	0.396	1.026
0.046	0.11	0.213	0.482
0.138	0.18	0.308	0.087
0.413	0.388	0.593	0.343
0.337	0.33	0.514	0.162
-0.045	0.041	0.118	0.06
3.646	3.832	3.931	3.59
0.613	0.539	0.798	0.477
-0.168	-0.051	-0.007	0.391
0.076	0.134	-0.245	0.065
-0.214	-0.085	-0.05	0.06
0.034	0.102	0.201	0.092
-0.155	-0.041	0.005	0.087

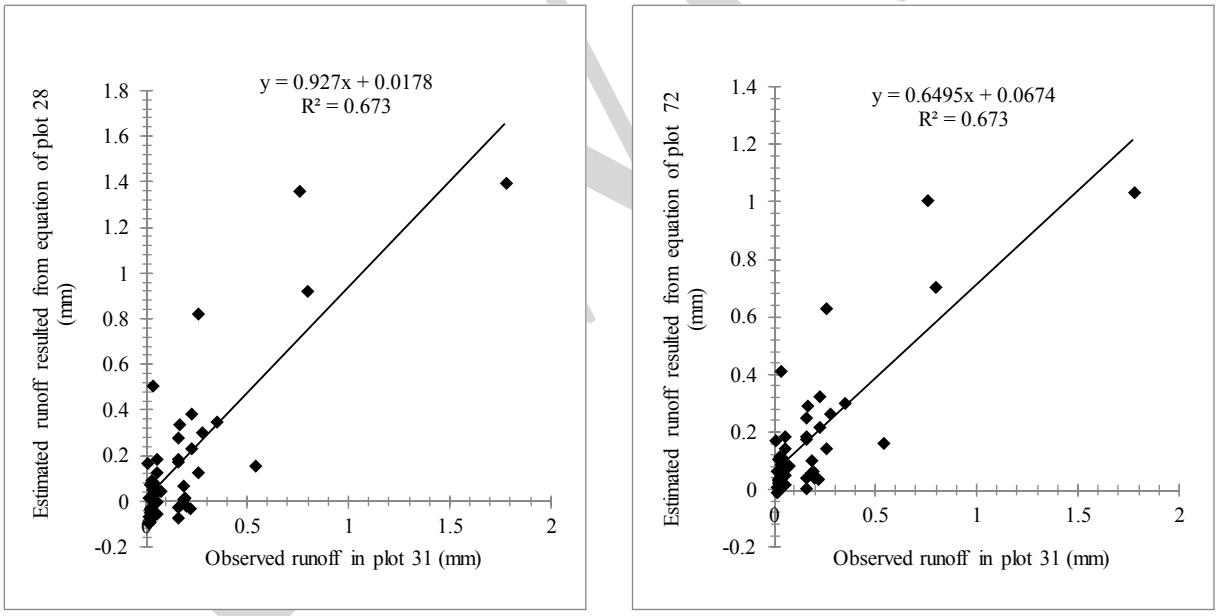
Table 6. An example of the observed and estimated runoff values in plots of 15 m length, equation 35.

Estimated runoff related to plot 16 in the equations of plot 27	Estimated runoff related to plot 16 in the equations of plot 25	Observed runoff related to plot 16	The amount of rainfall (mm) related to plot 16
-0.027	0.062	0.151	4.4
0.031	0.118	0.118	7.6
0.021	0.108	0.042	7.05
-0.024	0.065	0.031	4.57
0.033	0.119	0.154	7.7
0.526	0.695	0.545	34.8
0.023	0.11	0.318	7.2
0.111	0.201	0.0126	12
0.879	1.165	0.905	54.2
0.158	0.252	0.024	14.6
0.052	0.14	0.017	8.8
0.857	1.135	0.52	53
0.231	0.335	0.678	18.6
0.253	0.36	0.157	19.8
0.588	0.775	0.242	38.2
0.224	0.326	0.041	18.2
0.093	0.181	0.151	11

Table 7. An example of the observed and estimated runoff values in plots of 20 m length, equation 31.

Estimated runoff related to plot 31 in the equations of plot 72	Estimated runoff related to plot 31 in the equations of plot 28	Observed runoff related to plot 31	The amount of rainfall (mm) related to plot 31
0.022	-0.062	0.152	4.4
0.049	0.031	0.031	7.6
0.017	-0.079	0.009	3.8
0.044	0.015	0.032	7.05
0.023	-0.057	0.024	4.57
0.05	0.034	0.025	7.7
0.487	0.83	0.0249	34.8
0.049	0.02	0.18	7.2
0.058	0.055	0.024	8.4
0.099	0.161	0.532	12
0.086	0.132	0.043	11
0.035	-0.015	0.021	6
0.946	1.402	1.77	54.2
0.132	0.237	0.213	14.6
0.062	0.067	0.031	8.8
0.915	1.366	0.748	53
0.19	0.355	0.344	18.6
0.056	0.049	0.065	8.2
0.029	-0.032	0.028	5.4
0.016	-0.085	0.004	3.6
0.053	0.043	0.03	8

Fig. 7 shows the best generated equations in the plot 31 of 20 m length whose runoff was generated by replacing the amount of rainfall related to plot 31 in the rainfall-runoff equations related to plots 28 and 72.



a b

Fig. 7.The relationship between the observed and predicted runoff in plot 31: a) According to equation 28 and b) According to equation 72.

The results of binary regression between climatic variables and runoff height in plot 32 according to the plot area shows that in all plots with the same area, the amount of rainfall had a greater impact on output runoff from plots and according to the analysis of variance tables, both variables were significant only in plots of 20 m length; the effect of rainfall intensity on runoff generation was not significant.

Tables 8 and 9 show the results of multivariate analysis of variance in plots of 5 and 15 m length. Table 10 shows the regression equations generated at different levels.

Table 8. Multivariate analysis of variance by Forward technique in plots 5 m length.

Variable name	Standard coefficient		T Parameter	P-VALUE
	Constant coefficient	BETA		
The amount of rainfall	-0.354	0.67	-3.37 13.96	0.001 0.00
The amount of rainfall Rainfall intensity	-0.57	0.7 0.16	-4.72 14.28 -3.4	0.00 0.00 0.001
Coefficient of determination	0.69			

Table 9. Multivariate analysis of variance by Forward technique in plots 15 m length.

Variable name	Constant coefficient	The estimated coefficients of equation	BETA	P-VALUE
The amount of rainfall	0.02	0.15	0.46	0.69 0.00
The amount of rainfall Rainfall intensity	0.06	0.016 0.019	0.49 0.2	0.31 0.000 0.009
Coefficient of determination	0.49			

Table 10. The regression equations generated at different levels in the entire period of data.

Regression equation	The Plot area (m^2)	Equation Number
R=-0/57+0/08P+0/05P.I	10	3
R=-0/25+0/04P+0/02P.I	20	4
R=-0.06+0.01P+0/01P.I	30	5
R=0/03+0/01P-0/003V	40	6

The overall results obtained from the above tables show that with increasing the area of plot, the effect of rainfall input variables on plots runoff is reduced, and it is quite reasonable. It should be noted that in all cases studied, Pearson correlation matrix table was studied between input variables. In most cases, there was no significant relationship between variables that entered the model (P-value>0.05). In a few cases, due to the large volume of data, despite a very low correlation between the input variable, a significant relationship was found. The results of the bivariate regression in plots of 10 m length and numbers 16 and 27 constructed in the south face of a concave slope and with 60 percent steepness (two plots in the same conditions mentioned), in the time series of 1996-2000 and 2006-2009 showed that only the amount of rainfall has a significant effect on the plots runoff. Plots 25 and 37 are located in the west of the concave slope with 30-40 percent steepness. The results of the analysis of variance table in the two plots shows that the amount of rainfall and rainfall intensity has the most significant effect on runoff output. In the regression equation developed, given the constant rainfall intensity, with the increase of 1mm in rainfall, runoff output will increase by 0.8. The correlation coefficient of the regression equation is equal to 0.74. In plots of 10 m length, plots 25 and 37 are located in the west of the concave slope with 60 percent steepness. The results indicated that the amount of rainfall is more important than plots runoff (16 and 27). Tables 11 and 12 show the multivariate analysis of variance in a few samples of the mentioned plots. In the equations generated, P is the amount of rainfall and R is the runoff height. Table 13 shows the generated regression equations.

Table 11. Multivariate analysis of variance using Forward technique in plots 10 m length related to numbers 16 and 27, constructed in the south face of concave slope.

Parameter Name	Constant Coefficient	The estimated coefficients of equation	BETA	T Parameter	P-VALUE
The amount of Rainfall	-0.16	0.38	0.64	-1.83 7.78	0.07 0.00
Coefficient of determination	0.64				

Table 12. Multivariate analysis of variance using Forward technique in plots of 5 m length related to plots 26 and 17, constructed in the southern of concave slope.

Parameter Name	Constant Coefficient	The estimated coefficients of equation	BETA	T Parameter	P-VALUE
The amount of Rainfall	-0.26	0.07	0.64	-1.52 7.62	0.13 0.00
Coefficient of determination	0.64				

Table 13. The regression equations developed in plots with the same environmental conditions.

Regression Equation	The Number of plots	Equation Number
R= -0.16+ 0.38P	27&16	12
R= -0.59+ 0.08P + 0.06P.I	37&25	13
R= -0.26+ 0.07P	17&26	14

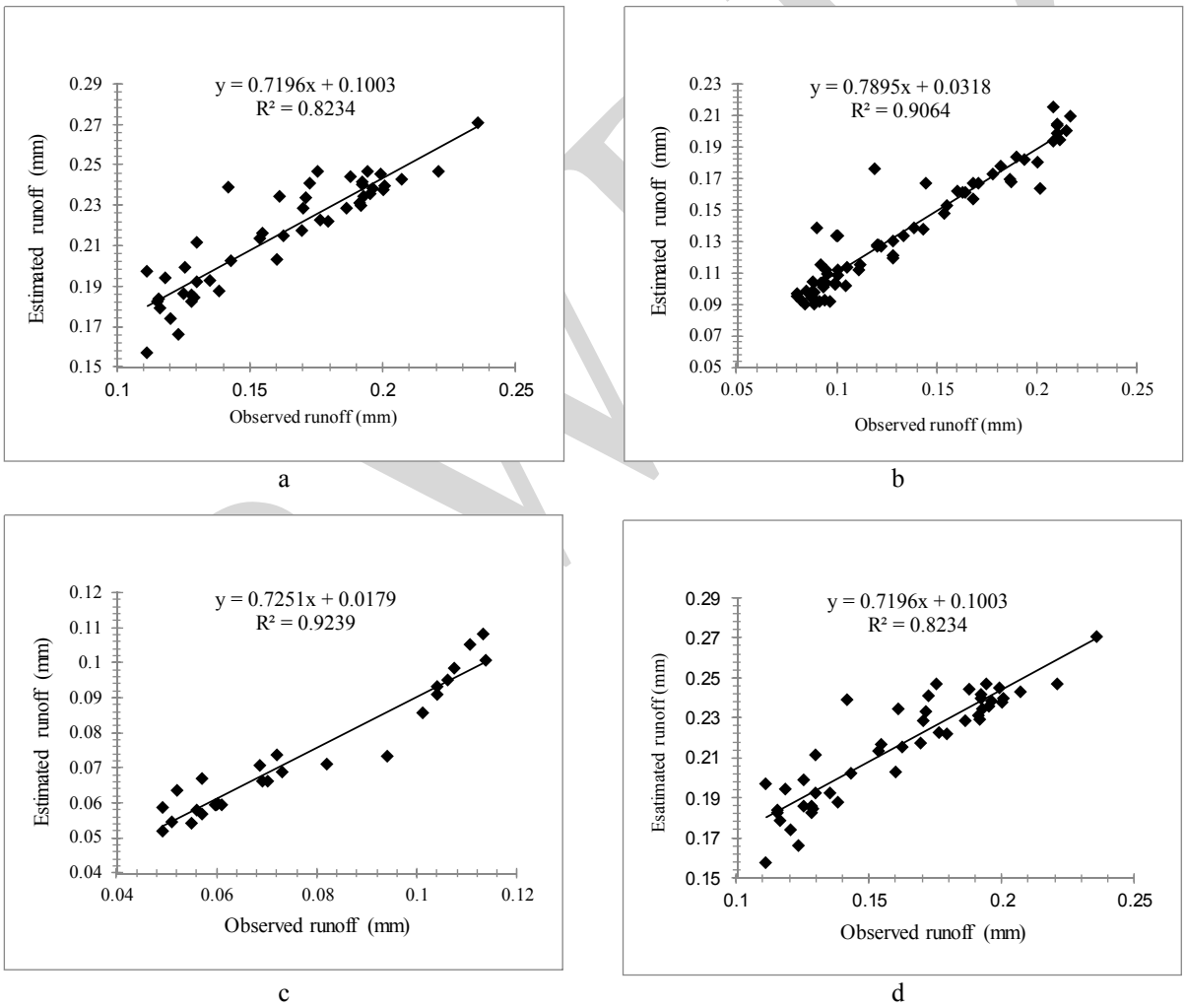


Fig. 8. Correlation relationship between estimated and observed runoff in plots of; a) 5 m length, b) 10 m length c) 15 m length and d) 20 m length.

The results of climatic variables affecting runoff output using artificial neural network (ANN) in plots with different area showed that in plot of 5 m length, MLP neural network, having one profile hidden layer, 3 neurons and a sigmoid transfer function, estimates the runoff with higher reliability and accuracy (RMSE=0.05, R2=0.82). The amount of rainfall parameter has had the greatest influence on the model output. In plot of 10 m length, ANN after back-propagation, with 2 hidden layers, 4 neurons and sigmoid function, estimates the runoff values with high accuracy of 90%. RMSE of the created model is equal to 0.01. Moreover, the input variables affecting

L

runoff are the amount of rainfall and rainfall intensity, respectively. The results of the different networks, studied in plot of 15 m length, showed that MLP neural network, having one profile hidden layer, 3 neurons and a sigmoid transfer function, estimates the runoff with higher reliability and accuracy compared to other neural networks (RMSE=0.008, R^2=0.92). The amount of rainfall parameter has the highest correlation with output runoff and is discussed as the most influential variable on runoff output in plots of 15 m length. MLP neural network, having 3 profile hidden layers, 1 neuron and a sigmoid transfer function, estimates the runoff with higher reliability and accuracy compared to other neural networks in plots of 20 m length (RMSE=0.007, R2=0.57). In plots of 20 m length, the importance of the amount of rainfall parameter in selected MLP neural network on output runoff is much more than other input variables. Fig. 8 shows the relationships between different neural network models in plots with different lengths.

Table14. Neural network characteristics and runoff variables in the time series (1996-2000 and 2006-2009).

The plot area (m^2)	Characteristics of the selected neural network	Variables affecting runoff	ValueR^2	RMSE value
10	MLP neural network having one profile hidden layer, 3 neurons and a sigmoid transfer function	The amount of rainfall	0.82	0.05
20	back-propagation, MLP neural network having 2 profile hidden layer, 4 neurons and a sigmoid transfer function	The amount of rainfall and rainfall intensity	0.9	0.01
30	MLP neural network having one profile hidden layer, 3 neurons and a sigmoid transfer function	The amount of rainfall	0.92	0.008
40	MLP neural network having 3 profile hidden layer, 1 neurons and a sigmoid transfer function	The amount of rainfall	0.57	0.007

Overall, the results of several neural networks are in accordance with those of the aforementioned methods in the experimental plot of Sanganeh base.Moreover, they are indicative of the good performance and acceptability of ANNs to determine the most influential variables affecting the amounts of collected runoff in the plots output.

5. Conclusion

We presented an ANN model to estimate monthly runoff in a watershed in the east north of Iran. The ANN model was proven to be reasonably accurate. However, in order to provide some explanations for those who criticize ANN as a black-box model, we considered the Multivariate Regression in order to understand the mechanisms of being modelled and the results showed the utility. Consequently, ANN gained greater acceptability among hydrologists by combining their interpretation and predictive abilities. The adoption of this approach is, therefore, recommended for those areas in which procedures are established for the estimation of runoff from the experimental plots. Climatic variables (the amount of rainfall and rainfall intensity) have a significant and positive effect on runoff production and also the effect of the amount of rainfall on the plot runoff output and in all cases (the whole plot of the studied plots, the plots of 10, 20, 30 and 40 m^2, plots with the same range of slopes) is more than other parameters. Using systematic methods, it is also possible to say that the accuracy of the generated ANN in estimating runoff is high, considering 20% of the average amount of data available for testing of the generated ANN. After studying the two methods, it was found out that there was no difference in prioritizing of the examined variables in the time series of this study. In both methods, the amount of rainfall parameter is more effective, but in prioritizing the effective parameters, the accuracy of ANN is higher than regression models.

Acknowledgment

The authors wish to acknowledge the kind cooperation of Dr Ali Talebi and Hamid Sodaeizade and DrAbdolsalehRangavar for providing the data from the Soil Conservation Research Database of Sanganeh that was used in this study.

References

Abrahart, R. J. & See, L. (2000) Comparing neural network and autoregressive moving average techniques for the provision of continuous river flow forecast in two contrasting catchments. *Hydrological Processes.* [online] 14(11-12), 2157–2172. Available from: doi:10.1002/1099-1085(20000815/30).

ZareAbianeh, H. & BayatVarkeshy, M. (2011) Evaluation of intelligent neural models and experimental estimates of annual runoff. *Soil and Water Journal*, 25(2), 379-365.

Adamowski, J., Chan, H. F., Prasher, S. O. & Sharda, V. N. (2012) Comparison of multivariate adaptive regression splines with coupled wavelet transform artificial neural networks for runoff forecasting in Himalayan micro-watersheds with limited data. *Journal of Hydroinformatics.* [online] 14(3), 731–744. Available from: doi:10.2166/hydro.2011.044.

Asaad, Y. Sh. & O'Connor, K. M. (2001) A non-linear neural network technique for updating of river flow forecasts. A non-linear neural network technique for updating of river flow forecasts. *Hydrology and Earth System Sciences*, 5(4), 577–597.

Asadi, A., Shahrabi, J. & Tabanmehr, S. (2013) A new hybrid artificial neural network for rainfall–runoff process modeling. *Neurocomputing.*[online] 121(9), 470–480. Available from: doi:10.1016/j.neucom.2013.05.023.

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000a) Artificial neural networks in hydrology, I: preliminary concepts. *Journal of Hydrologic Engineering*, 5(2), 115-123.

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000b) Artificial neural networks in hydrology, II: hydrologic applications. *Journal of Hydrologic Engineering,*5(2), 124-137.

Campolo, M. & Soldati, A. (1999) Forecasting river flow rate during low-flow periods using neural networks.*Water Resources Research*. [online] 35(11), 3547–3552. Available from: doi:10.1029/1999WR900205.

Dastorani, M. T. (2007) Evaluation of the application of artificial intelligence models on simulation and real-time prediction of peak flaw. *Journal of Science and Technology of Agriculture and Natural Resources (Water and Soil Science)* 40(1/2), 27-36.

Dawson, C. W., Harpham, C., Wilby, R. L. & Chen, Y. (2002) Evaluation of artificial neural network techniques for flow forecasting in the River Yangtze, China. *Hydrology and Earth System Sciences.* [online] 6(4), 619-626. Available from: doi:10.5194/hess-6-619-2002.

Dawson, C. W. & Wilby, R. L. (1998) An artificial neural network approach to rainfall-runoff modeling. *Hydrological Sciences Journal*. [online] 43(1), 47-65. Available from: doi:10.1080/02626669809492102.

Dawson, C. W. & Wilby, R. L. (2001) Hydrological modelling using artificial neural networks. *Physical Geography Journal*. [online] 25(1), 80-108. Available from: doi:10.1177/030913330102500104.

French, M. N., Krajewski, W. F. & Cuykendall, R. R. (1992) Rainfall forecasting in space and time using neural network. *Journal of Hydrology.*[online] 137(1-4), 1–31. Available from: doi:10.1016/0022-1694(92)90046-X.

Giustolisi, O. & Laucelli, D. (2005) Improving generalization of artificial neural networks in rainfall-runoff modelling. *Hydrological Sciences Journal*. [online] 50(3), 439-457. Available from: doi:10.1623/hysj.50.3.439.65025.

Hsu, K. L., Gupta, H. V. & Sorooshian, S. (1995) Artificial neural network modelling of the rainfall-runoff process. *Water Resources Research*. [online] 31(10), 2517–2530. Available from: doi :10.1029/95WR01955.

Hung, N. Q., Babel, M. S., Weesakul, S. & Tripathi, N. K. (2009) An artificial neural network model for rainfall forecasting in Bangkok, Thailand.*Hydrology and Earth System Sciences*. [online] 13(8), 1413–1425. Available from: doi:10.5194/hess-13-1413-2009.

Jain, A. & Srinivasulu, S. (2006) Integrated approach to model decomposed flow hydrograph using artificial neural network and conceptual techniques. *Journal of Hydrology*. [online] 317(3-4), 291-306. Available from: doi:10.1016/j.jhydrology.2005.05.022.

Kalteh, A. M. (2008) Rainfall-runoff modelling using artificial neural networks (ANNs): modelling and understanding. *Caspian Journal of Environmental Sciences*. 6(1), 53-58.

Keskin, M. E., Taylan, E. D., & Yilmaz, A. G. (2003) Flow prediction with fuzzy logic appriaches: Dimstream. *International Congress on River Basin Management*, Antalya, Turkey.

Lauzon, N., Anctil, F. & Baxter, C. W. (2006) Clustering of heterogeneous precipitation fields for the assessment and possible improvement of lumped neural network models for stream flow forecasts.*Hydrology and Earth SystemSciences*, 10(4), 485–494 Available from: www.hydrol-earth-syst-sci.net/10/485/2006.

Lorrai, M. & Sechi, G. M. (1995) Neural nets for modelling rainfall-runoff transformations.*Journal ofWater Resource Management.* [online] 9(4), 299-313. Available from: doi:10.1007/BF00872489.

Luk, K. C., Ball, J. E. &Sharma, A. (2000) A study of optimal model lag and spatial inputs to artificial neural network for rainfall forecasting.*Journal of Hydrology.*[online] 227(1), 56–65.Available from: doi:10.1016/S0022-1694(99)00165-1.

Maier, R. H. & Dandy, G. C. (2000) Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications.*Environmental Modelling and Software.*[online] 15(1), 101–124. Available from: doi:10.1016/S1364-8152(99)00007-9.

Maier, R. H. & Dandy, G. C. (1999) Empirical Comparison of various methods for training feed-forward neural network for salinity forecasting.*Water Resources Research.*[online] 35(8), 2591–2596. Available from: doi:10.1029/1999WR900150.

Maier, R. H. & Dandy, G. C. (1996) The use of artificial neural network for the prediction of water quality parameters.*Water Resources Research.*[online] 32(4), 1013–1022, Available from: doi:10.1029/96WR03529.

Minns, A. W. & Hall, M. J. (1996) Artificial neural networks as rainfall runoff models. *Hydrological ScienceJournal.* [online] 41(3): 399-417. Available from: doi:10.1080/02626669609491511.

Mokhtari, M. H., Busu, I., Mokhtari, H., Zahedi, G., Sheikhattar, L. & Movahed, M. A. (2013) Neural network and multiple linear regressions for estimating surface albedo from aster visible and near-infrared spectral bands.*Earth Interact.* [online] 17(3), 1–20. Available from: doi:10.1175/2011EI000424.1.

Mutlu, E., Chaubey, I., Hexmoor, H. & Bajwa, S. G. (2008) Comparison of artificial neural network models for hydrologic predictions at multiple gauging stations in an agricultural watershed. *Hydrological Processes*. Available from: doi:10.1002/hyp.7136.

Nasri, M., Modarres, R. & Dastorani, M. D. (2010) Validation of neural network model relating rainfall- runoff in the watershed of the river dam. *Watershed Research*, No. 88.

Rajurkar, M. P., Kothyari, U. C. & Chaube, U. C. (2002) Artificial neural networks for daily rainfall-runoff modeling.*HydrologicalScience Journal*. [online] 47(6), 865-877. Available from: doi:10.1080/02626660209492996.

Rogers, L. L. & Dowla, F. U. (1994) Optimization of groundwater remediation using artificial neural networks with parallel solute transport modeling.*Water Resource Research*. [online] 30(2), 457–481. Available from: doi:10.1029/93WR01494.

Sajikumar, N. & Thandaveswara, B. S. (1999) A non-linear rainfall–runoff model using an artificial neural network.*Journal of Hydrology*. [online] 216(1–2), 32–55. Available from: doi:10.1016/S0022-1694(98)00273-X.

Sarvi, A. & Motie, H. (2010) Assess the effects of climate change on the model of rainfall- runoff using scenarios of climate in watershed Golestan dam. *Sixth National Conference on Science and Engineering Watershed and the Fourth National Conference of erosion and deposition*, 8 and 9 May.

Shamseldin, A. Y. (1997) Application of a neural network technique to rainfall-runoff modeling. *Journal of Hydrology*. [online] 199(3-4), 272–294. Available from: doi:10.1016/S0022-1694(96)03330-6.

Shrivastava, G., Karmakar, S. & Kowar, M. K. (2012) Application of artificial neural networks in weather forecasting: a comprehensive literature review. *International Journal of Computer Applications* (0975–8887). [online] 51(18), 17-29. Available from:doi:10.5120/8142-1867.

Sudheer, K. P., Gosain, A. K. & Ramasastri, K. S. (2002) A data-driven algorithm for constructing artificial neural network rainfall-runoff models. *Hydrological Processes*. [online] 16(6), 1325–1330. Available from: doi:10.1002/hyp.554.

Thirumalaiah, K. & Deo, M. C. (1998) River stage forecasting using artificial neural networks. *Journal of Hydrologic Engineering*. [online] 3(1), 26–32. Available from: doi:10.1061/ (ASCE) 1084-0699(1998)3:1(26).

Tokar, A. S. & Johnson, P. A. (1999) Rainfall-runoff modeling using artificial neural networks.*Journal ofHydrologic Engineering*. ASCE. [online] 4(3), 232-239. Available from: doi:10.1061/ (ASCE) 1084-0699(1999)4:3(232).

Vieux, J., Vieux, E., & Baxter, E. (2003) Operational deployment of a physics- based distributed rainfall-runoff model for flood forecasting in Taiwan. HSo3: In: *International Symposium on Information from Weather Radar and Distributed Hydrological Modeling*, July 7-8.

Wechmongkhonkon, S., Poomtong, N. & Areerachakul, S. (2012) Application of artificial neural network to classification surface water quality, world academy of science. *Engineering and Technology*, 69, 228-232.

Wilby, R. L., Abrahart, R. J. & Dawson, C. W. (2003) Detection of conceptual model rainfall-runoff processes inside an artificial neural network. *Hydrological Science Journal*. [online] 48(2), 163-181. Available from: doi:10.1623/hysj.48.2.163.44699.