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Daily river flow forecasting in a semi-arid region using twodata-driven

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Abstract

Rainfall-runoff relationship is very important in many fields of hydrology such as water supply and water resource management and there are many models in this field. Among these models, the Artificial Neural Network (ANN) was found suitable for processing rainfall-runoff and opened various approaches in hydrological modeling. In addition, ANNs are quick and flexible approaches which provide very promising results, and are cheaper and simpler to implement than their physically based models. Therefore, this study evaluated the use of ANN models to forecast daily flows in Bar watershed, a semi-arid region in the northwest Razavi Khorasan Province of Iran. Two different neural network models, the multilayer perceptron (MLP) and the radial basis neural network (RBF), were developed and their abilities to predict run off were compared for a period of fifty-five years from 1951 to 2006. The best performance was achieved based on statistical criteria such as RMSE, RE and SSE. It was found that MLP showed a good generalization of the rainfall-runoff relationship and is better than RBF. In addition, 1-day antecedent runoff affected river flow, such that the statistical criteria decreased but the 5-day antecedent rainfall remained unaffected. Furthermore, considering MLP, RE and RMSE, the best model produced the values 46.21 and 0.75 while the RBF model recorded 177.60 and 0.82, respectively.

Keywords: Artificial Neural Network; Bar watershed; MLP; Rainfall-Runoff; RBF

1. Introduction

Since the nineteenth century, the rainfall-runoff process has been explained quantitatively (Dawson and Wilby, 2001). Rainfall-runoff models are much researched in the area of hydrological engineering and play a key role in water resource management planning, hydropower generation, irrigation and water supply. Hence, different types of models with various degrees of complexity have been developed for this purpose (Dooge, 1977; Harun *et al*., 2002; Solaimani, 2009; Fernando *et al*., 2011). Indeed, the relationship between rainfall-runoff is known to be highly non-linear and complex. The rainfall-runoff relationship is one of the most complex hydrological events to comprehend, due to the tremendous spatial and temporal variability of watershed characteristics, precipitation patterns, and the number of variables involved in the modeling of the physical processes (Tokar and Johnson, 1999; Buch *et al*., 1993). Hydrologists are often confronted with problems of prediction and estimation of runoff, precipitation, water stages, and so on (Harun *et al*., 2002).

Although many watersheds have been gauged to provide continuous records of stream flow, hydrologists are often faced with situations where little or no information is

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available. In such situation, simulation models are often used. The available rainfall-runoff models are HEC-HMS, MIKE-11, etc. These models are useful for hydrologic and hydraulic engineering planning and designing, as well as water resources management; e.g., flood protection and irrigation. The existing popular model is considered as not flexible and require many parameters. Obviously, the models have their own weaknesses (Harun *et al*., 2002). However, system theoretic models do not consider the physical characteristics of the parameters; they illustrate the data from input to output using transferred functions. Artificial neural network (ANN) models are examples of system theoretic models that have gained considerable popularity in recent years, for describing rainfall–runoff processes (Abrahart and See, 2007; Mutlu *et al*., 2008).

Nowadays, artificial neural networks (ANNs) have become one of the most promising tools in the modeling of complex hydrological processes, such as the rainfall-runoff process. In many fields, ANNs have been proven to be good in simulating complex, non-linear systems (Campolo *et al*., 1999; Cannon and Whitfield, 2002). For this reason, ANNs have been used for forecasting in many areas of science and engineering and are applied in many fields like financial management, manufacturing, control systems, design, environmental science and pattern recognition in, for instance, remote sensing (Dawson and Wilby, 2001). The main advantage of this approach over traditional methods is that, it does not require the complex nature of the underlying process under consideration to be explicitly described, in a mathematical form. This makes ANN an attractive tool for modeling water table fluctuations (Minns and Hall, 1996).

Some scientists have worked on ANNs specifically on rainfall–runoff modeling (Halff *et al*., 1993; Hjemfelt and Wang, 1993; Karunanithi et al., 1994; Hsu *et al*., 1995; Smith and Eli, 1995; Minns and Hall, 1996; Dawson, 1996; Jain and Chalisgaonkar, 2000; Rajurkar *et al.*, 2002; Wilby *et al*., 2003; Giustolisi and Laucelli, 2005; Jain and Srinivasulu, 2006; Abrahart and See, 2007; Mutlu *et al*., 2008; Solaimani, 2009; Fernando *et al*., 2011). The interest of applying ANNs for rainfall-runoff modeling grew greatly in the 1990s (Hsu *et al*., 1995; Zhang and Govindaraju, 2003; Solaimani, 2009). ANNs were usually assumed to be powerful tools for functional relationship establishment or nonlinear mapping in various applications and perhaps, the ANN could be regarded as the ultimate black-box model (Amorocho and Hart, 1964; Kalteh, 2008; Solaimani, 2009).

Additionally, there are no strict rules for governing the design of a neural network. More complex problems generally require a more complex solution. When there are many free parameters, the network will be slower to train and more susceptible to over fitting. Factors such as number of inputs, number of hidden nodes, and their arrangement into layers are often determined by using systematic “trial and error” (Fischer and Gopal, 1994) or based on reasonable but subjective opinion (Cheng and Noguchi, 1996).

Testing optimum inputs and architectures can be a time-consuming process, and the end result may be neither informative nor convincing. The particular advantage of the ANN is that, even if the exact relationship between sets of input and output data is unknown but is acknowledged to exist, the network can be trained to learn that relationship, without requiring prior knowledge of the catchment's characteristics (Minns and Hall, 1996; Dawson, 1996). Furthermore, they are also well suited to dynamic problems and are parsimonious in terms of information storage within the trained model (Thirumalaiah and Deo, 1998). Therefore, in accordance to the importance of the relationship between rainfall-runoff, the present study was undertaken in order to develop rainfall-runoff models that can be used to provide reliable and accurate estimates of runoff.

1.1. About artificial neural network

The human brain has more than one hundred billion neurons and each is connected to ten thousand others and is therefore a dense and highly complex structure (Minns and Hall, 1996). Every biological neuron has three parts: 1) the cell body, 2) the axon and 3) the dendrites. The axon is usually highly branched and attached to the cell body. Synapses are the termination points for the axons and play the role of interfaces, connecting some axons to the spines of the dendrites, which input that information can be transferred through axon to dendrite in synapse (Varoonchotikul, 2003).

The ability of the human brain to perform difficult and complex operations to recognize patterns, has captivated scientists for centuries. The particular capability of the brain to learn from experience without a predefined knowledge of the underlying physical relationships, makes it an exceptional and powerful calculating device. Therefore, scientists have been attempting to produce or model these physical phenomena, using electronic computational machines. This can prove useful in solving ever complex partial differential equations as well as empirical relationships by rapidly increasing the computational capacity of modern computers and recognition of emerging advantages of parallel computationcapable of performing the required calculations with ever-increasing speed (Minns and Hall, 1996). ANNs are based on the highly interconnected structure of brain cells. This approach is fast and robust in noisy environments, flexible in different range of problems solving, and highly adaptive to new environments (Jain *et al*., 1999; Jeong and Kim, 2005).

For the first time, McCulloch and Pitts in the 1940s have had modern look to artificial neural network. Actually, they showed that the network of neurons have the calculation capability of every mathematical and logical function. Therefore, their activity can be considered as the birth and start of the artificial neural network. However, the first application of a neural network was at the end of the 1950s, by Frank Rosenblatt. He and his colleague built a perceptron network and proved these networks have the capability of pattern recognition and therefore, various relatively successful neural computers were built during the following two decades. After a period of little development, interest in ANNs increased significantly in the late 1980s, due to improvements on existing techniques in combination with the increase of computational resources. By achieving these successes in neural network, numerous investigations were done all over the world, for neural network improvement. Since that time, the fields of ANNs have rapidly developed, and the numerous applications of ANNs show that their potentials have been recognized in many fields such as the earth sciences, economics, health sciences etc.

Every ANN is an interconnected network of many processing units called neuron. Neurons are the smallest unit in the artificial neural network. These neurons are very similar to the biological neuron and cells of the human brain. Despite the fact that these neurons function at a higher speed, compared to biological neurons, they possess lower ability and capacity. Neurons in every layer are connected through weights to neurons in the next layer. The parameters associated with each of these connections are called weights. These weights represent information which is used by the net to solve a problem (Varoonchotikul, 2003). During the training network these weights, constant amount of that assemble with them, and bias changed consecutively, until the target function reached a favorite amount. We used activation functions (sometimes called a transfer function or threshold function) to transfer output from every layer to the next layer (Varoonchotikul, 2003).

These activation functions may be logistic sigmoid, linear, threshold, Gaussian or hyperbolic tangent functions, depending on the type of network employed during the training algorithm (Norgaard *et al*., 2000; Dawson and Wilby, 2001; Jeong and Kim, 2005). On the other hand, the method used for achieving weights and biases are learning to rule for favorite and terminal amounts. In fact, this rule is a complex mathematical algorithm. Every network needs to create two groups of data and be acceptable: 1) training series and 2) testing series. About 80% of the data belonged to the training series and the rest of it was used for testing. The duration of learning time, and amount of network learning were evaluated continually by target function. The optimal network was selected through the least error and highest correlation. The other evaluation criteria such as RE, RMSE and SSE are explained in the next section of this paper.

Normally, the ANNs formed three layers with many nodes in each layer. Input data are fed into the first layer called the input layer, while the outputs are taken from the last layer, which is called the output layer, and the layers in between are hidden layers. Every layer has many nodes that are neurons. There are two connections or weighted connection: 1) the forward and 2) the backward connection (recurrent connection). In the forward connection, signals are fed only in the forward direction from the input to output layer. However, in the backward connection (recurrent connection) information is fed from the top layer to the bottom layer and therefore, the output layer is used as input in the same layer (Hertz *et al*., 1991; Imrie *et al*., 2000; Varoonchotikul, 2003; Solaimani, 2009). Forward selection is the most commonly used approach and begins by finding the best single input and selecting it for the final model. In each subsequent step, given a set of selected inputs, the input improves the performance ofmodels added mostly to the final model. Backward elimination starts with a set of inputs, and sequentially deletes the input that reduces the least performance (Bowden *et al*., 2002). In addition, there are two models in ANN, the multi-layer perceptron (MLP) and the radial basis function (RBF). In all cases, a multi-layer perceptron (MLP) ANN was employed for rainfall–runoff modeling, and the weights were determined by error back-propagation. Sigmoid activation functions were used at all nodes in the hidden and output layers. Before presentation to the networks, all series of events were converted into time series (Hettiarachchi *et al*., 2005). The objectives of this study were to develop and evaluate the ability of MLP and RBF models to predict rainfall-runoff relationship. Multi-layer perceptron (MLP) is used in many complicated mathematical problems which result to nonlinear equations. Indeed, this method is the most commonly used artificial neural network in hydrological application. Training in this network is back propagation. Figure 1 shows the structure of a three layer forward connection in multi-layer perceptron.

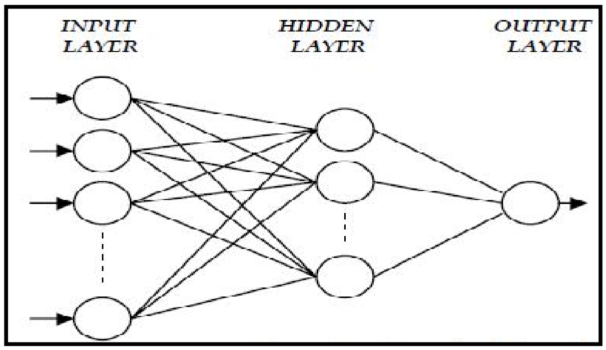

Fig. 1. Structure of a three layer forward connection in multi-layer perceptron

Today MLP networks have special importance in many fields and are a quick and safe way to solve different categories of problems. The main difference between MLP and RBF is that RBF has a middle layer and neurons activation functions that are radial (for example Gaussian function) along with center and special width. In addition, MLP is the distance every pattern from vector of center in middle layer of every neuron is computed to as entrance of radial activation function. Another difference is that the exit neurons activation function in this network is a simple linear function and for this reason, this study can use linear optimization algorithm which has high speed processing and preventing from falling in local pits that exist in almost MLP (Poggio and Girosi, 1990). Activation functions in MLP and RBF is shown in Figure 2.

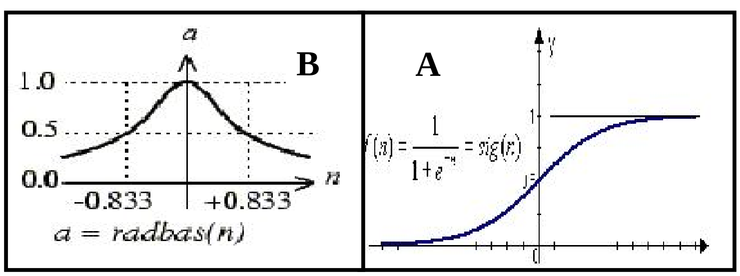

Fig. 2. Sigmoid Function in Gaussian Function in RBF (A) and MLP (B) are as activation function (Varoonchotikul, 2003)

2. Material and methods

2.1. Study area

Measured data from Bar-Arieh watershed were used to develop and compare the ability of both MLP and RBF models to predict stream flow. Bar-Arieh watershed is located in Neyshabur district in Razavi Khorasan province. The area of this watershed is 113 km^2 and located between 36º 27´ 38´´ and 36º 36´ 32´´ N-latitude and 58º 40´ 46´´ and 58º 49´ 31´´E-longitude (Jafari *et al*., 2012). Elevation ranges in the watershed is from approximately 2861 to 1580 m in watershed outlet as well as in stream–gauging station. Annual average of total precipitation is approximately 330.4m. The value of evaporation is about 2035 mm because of very high temperature. Moreover, every year this area has faced to many flood events because of its physical characters. The length of Bar seasonal river is 22.5 km and average slope is 4.2 percent and in the end it reaches to Neyshabur plain. Bar-Arieh stream–gauging station is located in the outlet of this watershed and Marusk and Neyshabur ghand recording stations are outside of Bar-Arieh watershed (Sadeghi *et al*., 2010). It is noticeable that in this article the data used was from Bar-Arieh station. Figure 3 shows general view of this watershed in Neyshabur and Iran respectively.

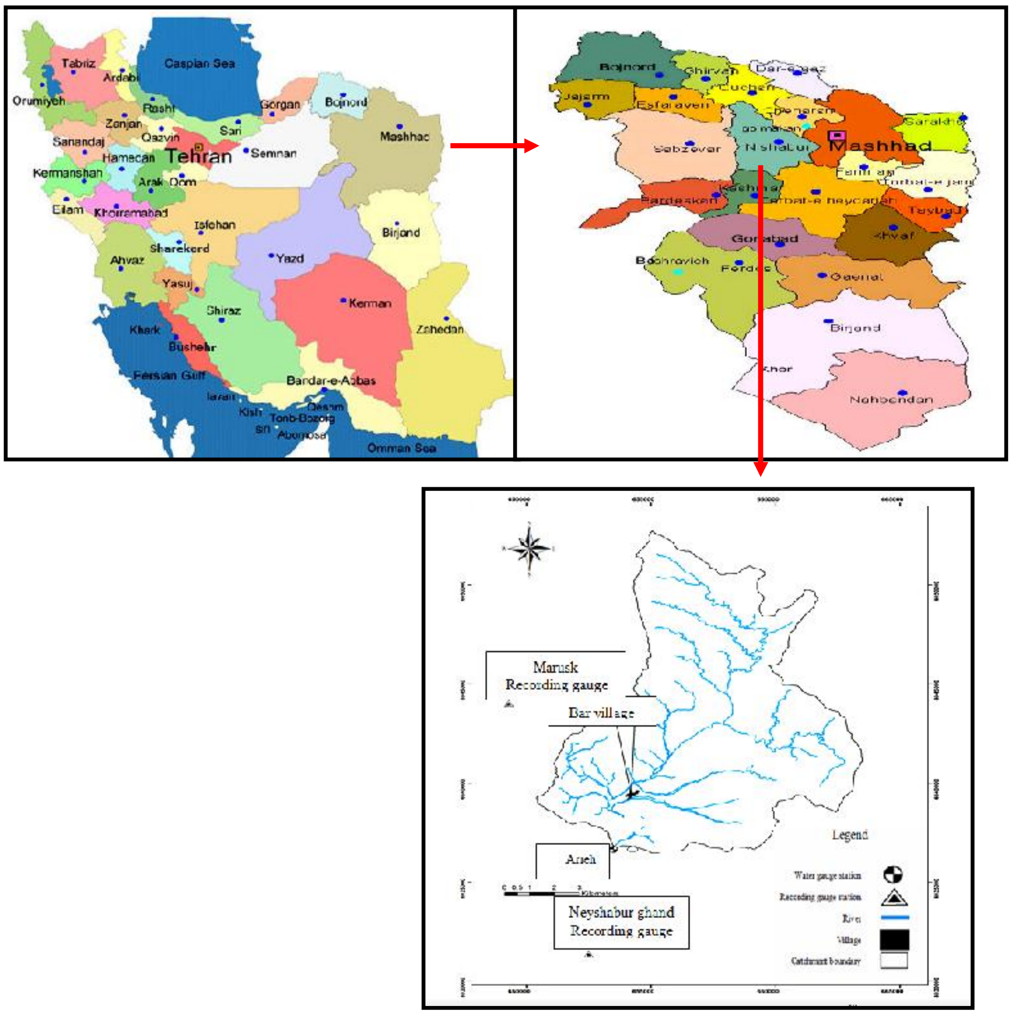

Fig. 3. General view of Bar-Arieh watershed in Iran and Neyshabur plain

2.2. Artificial network methods

In this study, daily runoff in conjunction with rainfall data was observed and measured for a period of fifty- five years from 1951 to 2006. One of the most important steps in the model development process is the determination of significant input variables. Usually, not all of the potential input variables will be equally informative since some may be correlated, noisy or have no significant relationship with the output variable that are being modeled (Maier and Dandy, 2000; Nayak *et al*., 2006). Accordingly, some solutions such as cross-auto and partial autocorrelation analysis of data are often used (Sudheer *et al*., 2002; Srinivasulu and Jain, 2006; Wu *et al*., 2009; Huo *et al*., 2012). In this study Cross-autocorrelation analysis between rainfall and runoff in different lag time series were informed to get the important factors for stream flow estimation. According to the results obtained, five and one lag time of rainfall and runoff were significant respectively. In addition, the concept of the time marching scheme is to keep the lag structure among the input constant data. In the case of the Bar-Arieh Watershed, the inputs for predicting one time step ahead (QP_{t+i}) were composed of twelve inputs: (i) the concurrent rainfall and runoff (QP), (ii) the concurrent rainfall and runoff and one antecedent rainfall (QPP_1), (iii) the concurrent rainfall and runoff, one and two antecedent rainfall (QPP_1P_2), (iv) the concurrent rainfall and runoff, one to three antecedent rainfall ($QPP_1P_2P_3$), (v) the concurrent rainfall and runoff, one to four antecedent rainfall ($QPP_1P_2P_3P_4$), (vi) the concurrent rainfall and runoff, one to five antecedent rainfall ($QPP_1P_2P_3P_4P_5$), (vii) the concurrent rainfall and runoff and one antecedent runoff (QPQ_1), (viii) the concurrent rainfall and runoff and one antecedent rainfall and runoff (QPP_1Q_1), (ix) the concurrent rainfall and runoff, one and two antecedent rainfall and antecedent runoff ($QPP_1P_2Q_1$), (x) the concurrent rainfall and runoff, one to three antecedent rainfall antecedent runoff ($QPP_1P_2P_3$), (xi) the concurrent rainfall and runoff, (xii) one to four antecedent rainfall antecedent runoff ($QPP_1P_2P_3P_4Q_1$), the concurrent rainfall and runoff, one to five antecedent rainfall antecedent runoff ($QPP_1P_2P_3P_4P_5Q_1$). The training and testing patterns had better be representative of similar physical system for development of ANN models (Sudheer *et al*., 2002; Srinivasulu and Jain, 2006; Huo *et al*., 2012). In this research 70% of available data had separated for training and 30% for testing. Furthermore, ANNs with one hidden layer are commonly used in hydrologic modeling (Dawson and Wilby, 2001; Varoonchotikul, 2003; Wu *et al*., 2009). However, a three-layer ANN is considered to provide enough complexity to accurately simulate nonlinear behaviors process in a watershed models developed. Nevertheless the number of hidden layer and its nodes is selected through trial and error (Hettiarachchi *et al*., 2005). The Levernberg-Marquardt (lm) training algorithm is a modification of Back propagation (BP) and is used in this study for adjusting the weight and base. Furthermore, to increase network speed and network accuracy, data presented to the network normalized values between 0 and1 by equation 1 (Sarangi and Bhattacharya, 2005).

$$X_N = \frac{X\max - Xi}{X\max - X\min} \qquad (1)$$

where X_N is the normalized data, Xmax is the maximum data, Xi is the raw data and Xmin is the minimized data.

For comparison, both multi-layer perceptron (MLP) and radial basis function (RBF) is used. Three parameters for criteria evaluation (RE, RMSE and SSE) were used in this study.

2.3. Model evaluation criteria

There are many performance criteria which have been used worldwide to evaluate rainfall-runoff relationship models. But there is not any standard measurement (Dawson and Wilby, 2001). Since there are various conditions in a catchment such as climate, topography, and soil, there exist a complicated relationships between rainfall and runoff, and this should be used from evaluation criteria (Legates and McCabe, 1999; Dawson and Wilby, 2001; Huo *et al*. 2012). Therefore, the performance of all models in this article was evaluated by using a wide variety of standard statistical performance evaluation measures. Three different statistical performance indexes were employed (Srinivasulu and Jain, 2006): root-mean-square error (RMSE), Relative error (RE %) and sum squared error (SSE) and is used to assess the predictive power of models. These statistical parameters can be calculated using the following expressions.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Q_O - Q_e)^2}{N}} \qquad (2)$$

$$RE(\%) = \frac{|Q_o - Q_e|}{Q_o} * 100 \qquad (3)$$

$$SSE = \sum_{i=1}^{n}(Q_O - Q_e)^2 \qquad (4)$$

where Q_O is the measured and observed amount of variable, Q_e is the estimated value and N is the number of data. Relative error (RE) is expressed in percent.

3. Results

Daily rainfall and runoff data in Bar watershed was used for this study. For this aim about 10634 data (80%) and 4588 data for training and (20%) for testing were used. In this research two models of artificial neural network MLP and RBF was considered and then compared with evaluation criteria such as RE, RMSE, SSE and CR. Sigmoid activation function was used as transfer function at both hidden layer and output layers. Also, the number of neurons in the hidden layers was determined using a trial and error procedure which was between 1 to 15. In this method independent variables were P, P_1, P_2, P_3, P_4, P_5 and $Q_1$and Q was dependent. The results are shown in Table 1.

Table 1. The Value of evaluation criteria in artificial neuron networks (MLP and RBF)

Models	MLP					
	RE (%)		RMSE		SSE	
	Training	Testing	Training	Testing	Training	Testing
QP	758.89	526.03	2.53	1.20	5233.25	2304.37
QPP_1	850.36	602.63	2.50	1.20	4304.86	2076.55
QPP_1P_2	710.39	452.61	1.98	1.19	3503.64	1075.07
$QPP_1P_2P_3$	711.25	453.83	2.53	1.20	2954.84	973.46
$QPP_1P_2P_3P_4$	718.58	456.80	2.53	1.21	2008.62	691.09
$QPP_1P_2P_3P_4P_5$	800.14	531.92	3.90	1.28	2458.79	1138.17
QPQ_1	123.56	86.85	0.89	0.79	2119.19	1388.18
QPP_1Q_1	115.89	74.64	0.84	0.77	1818.41	696.96
$QPP_1P_2Q_1$	<u>90.01</u>	<u>46.21</u>	<u>0.80</u>	<u>0.75</u>	<u>1450.91</u>	<u>459.29</u>
$QPP_1P_2P_3Q_1$	90.59	47.80	0.85	0.77	1271.42	422.35
$QPP_1P_2P_3P_4Q_1$	92.58	48.08	0.89	0.78	1004.11	348.29
$QPP_1P_2P_3P_4P_5Q_1$	100.71	65.85	0.99	0.94	1095.37	599.44
	RBF					
QP	717.30	527.50	2.80	1.19	5219.34	2294.68
QPP_1	692.70	508.34	2.75	1.19	4234.92	2067.65
QPP_1P_2	719.98	519.98	2.80	1.19	3458.29	941.46
$QPP_1P_2P_3$	700.01	510.34	2.80	1.20	2880.36	1189.42
$QPP_1P_2P_3P_4$	555.98	495.38	2.72	1.18	2015.94	767.45
$QPP_1P_2P_3P_4P_5$	698.60	511.65	2.85	1.27	2371.68	822.86
QPQ_1	324.10	224.92	0.95	0.88	2831.81	1218.51
QPP_1Q_1	301.98	224.49	0.92	0.84	1968.29	999.75
$QPP_1P_2Q_1$	275.29	178.14	1.09	0.92	1778.73	446.18
$QPP_1P_2P_3Q_1$	295.02	188.82	1.00	0.91	1657.01	699.96
$QPP_1P_2P_3P_4Q_1$	270.00	177.60	0.90	0.82	1340.60	359.85
$QPP_1P_2P_3P_4P_5Q_1$	359.78	283.89	1.99	1.09	1407.44	1223.39

rainfall (P), 1-day antecedent rainfall (P_1), 2-day antecedent rainfall (P_2), 3-day antecedent rainfall (P_3), 4-day antecedent rainfall (P_4), 5-day antecedent rainfall (P_5), runoff (Q) and 1-day antecedent runoff (Q_1) were inputs and runoff (daily discharge) was output.

From Table 1 the least values of RE (%) in MLP for training and testing data were 90.01 and 46.21% respectively for some inputs such as Q_1, P, P_1, and P_2 and the most values of training and testing data, were 850.36 and 602.63% for the inputs such as P and P_1. However, RMSE was very low (0.80 and 0.75%) for some inputs like Q_1, P, $P_1$and P_2 whereas the highest values were 3.90 and 1.28 for P, P_1, P_2, P_3, P_4 and P_5. While in RBF the least values of RE (%) variables for training and testing data were 270.00 and 177.60 repectively for inputs like Q_1, P, $P_{1,}$ $P_{2,}$ P_3 and $P_{4.}$ Minor difference in errors was 275.29 and 178.14 for training and testing data in inputs such as Q_1, P, P_1 and P_2. In addition the worst structure in RBF was model with one input (P). The values of this structure were 717.30 and 527.50 for training and testing data respectively. The ranges of values in RMSE were the least, between 0.90 and0.82 and 2.85 and 1.27 in RBF model. As shown in Figures 4 and 5, when rainfall is used errors are high and errors declined when other variables are used so that the least errors are in variables such as P, P_1, P_2, P_3 and P_4. However when variable P_5 was used, errors increased. The best architectures in this article were 4-6-1 and 6-9-1 in Multi-layer perceptron (MLP) and Radial basis function (RBF) respectively. Furthermore, from Table 1 it is observed that the most range of data is related to SSE criteria while the least range of data belongs to RMSE because of the form of statistical criteria. SSE criteria is the sum of the squared differences between observed and computing river flow while RMSE is a frequently used measure of the root differences between values observed and computing flow and therefore the range of data error is naturally lower than SSE criteria.

The relationship between output observation (Q_o) and output calculated (Q_e) is shown in Figures 4 and 5.

4. Discussion and Conclusion

This article considers predicting stream flow in a semi-arid region in Neyshabur region by using two data driven models (MLP and RBF) and comparing each other. These results show that five antecedent rainfalls does not have any effect on output and runoff. Since this watershed is situated in semi-arid region and solar radiant is very high, therefore the rainfalls does not affect soil moisture. These results are in agreement with the findings of Sadeghi *et al*. (2010) and Jafari *et al*. (2012), who worked in Bar-Arieh and emphasized that five antecedent rainfalls do not have any effect on stream flow.

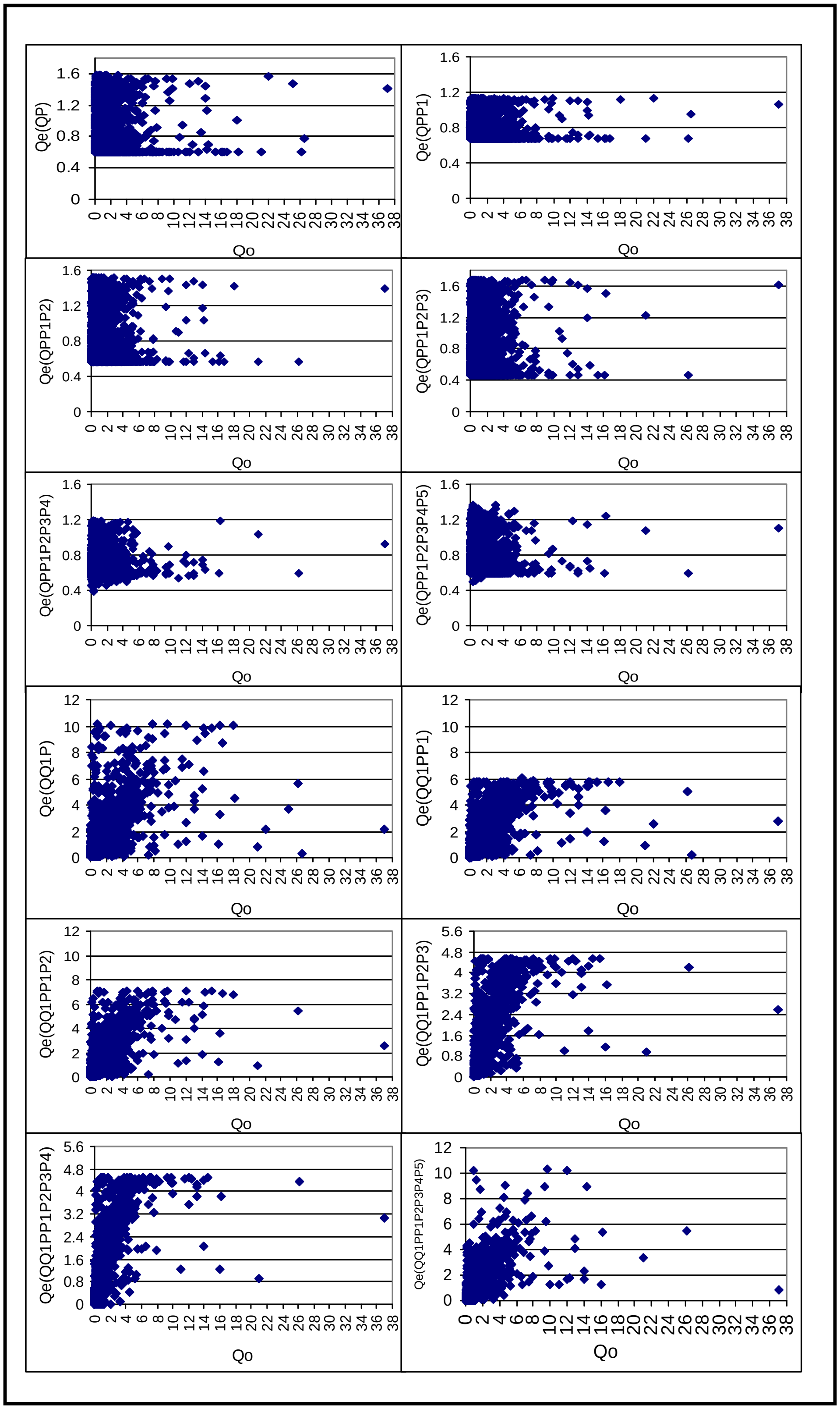

Fig. 4. Relationship between discharge observation (Q_o) and calculation (Q_e) in MLP

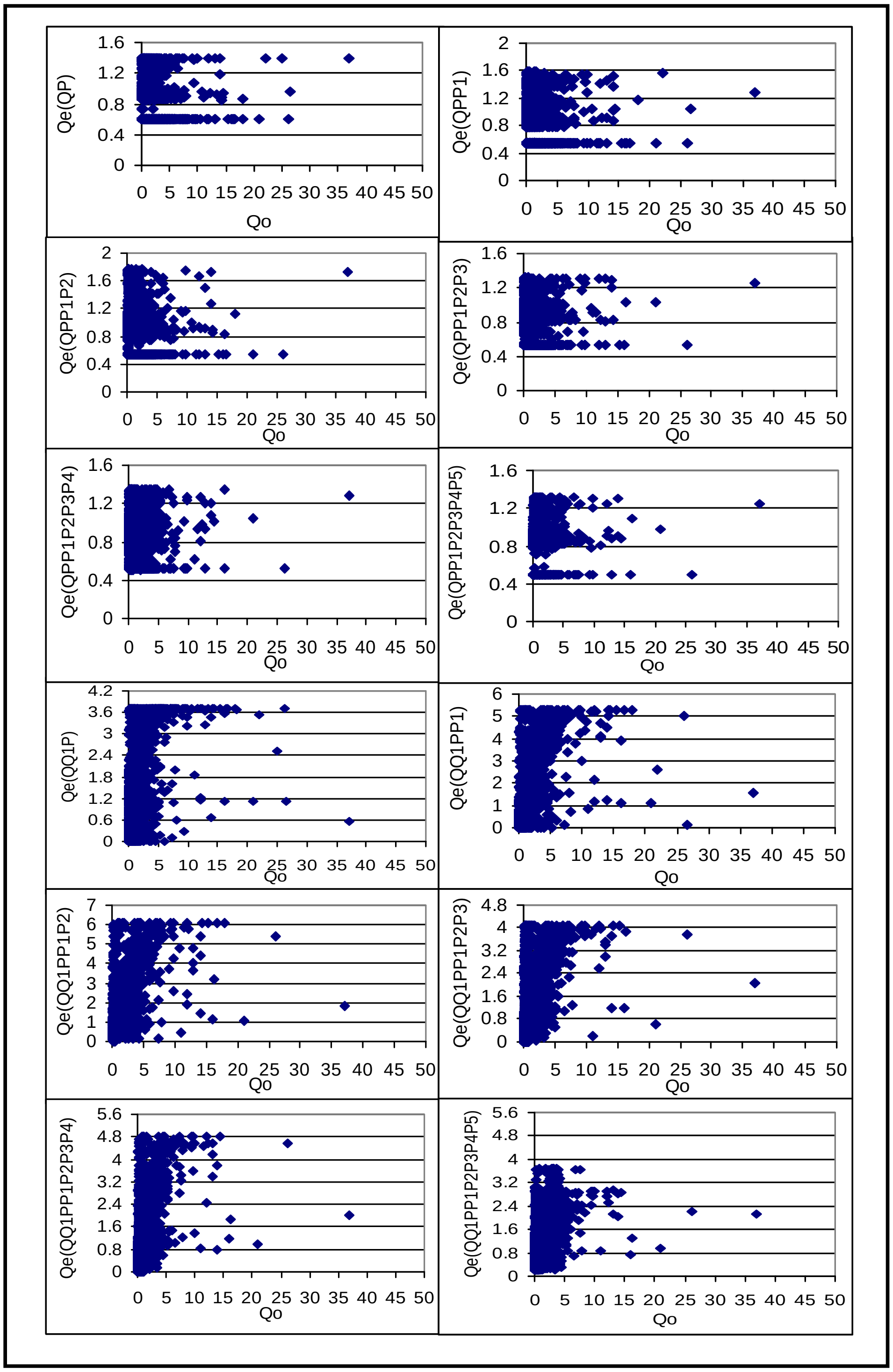

Fig. 5. Relationship between discharge observation (Q_o) and calculation (Q_e) in RBF

Furthermore, 1-day antecedent runoff affected run off in the way that the least values of RE are equal to 90.01 and 46.21 and 270.00 and 177.60 for training and testing data in multi-layer perceptron and radial basis function respectively while this was much lower than when 1-day antecedent runoff was not used so that the least error in MLP and RBF without 1-day run off are 710.39, 452.61 and 555.98 and 495.38 in training and testing data respectively. Finally with regards to the entire statistical criteria, Multi-layer perceptron (MLP) is more skillful than the radial basis function (RBF) and this finding are in agreement with studies such as Braddock *et al*. (1998), Dawson and Wilby (2001), Varoonchotikul (2003), Solaimani (2009), and Wu and Chau (2011) who showed that the ability of Multi-layer perceptron in comparison to Radial Basis Function is very high and significant. But this finding is not in agreement with the study of Takor and Markus (2000) and Srinivasulu *et al*. (2006). That showed that the ANN rainfall-runoff model trained using BPA and Multi-layer perceptron through statistical criteria do not perform well. The ANN performance is influenced by the selection of training data. A large number of training data sets are required to perform successful training (Dawson and Wilby, 2001; Varoonchotikul, 2003). The number of hidden layer neurons significantly influences the performance of a network. If this number is small, the network can suffer from under fit data and may not achieve the desired level of accuracy, while with too many nodes it will take a long time to be adequately trained and may sometimes over fit the data. In this study, two model of ANN are compared. The results show that multi-layer perceptron is better than radial basis function for the estimation of rainfall-runoff relationship in the arid and semiarid regions in spite of varying rainfall and runoff. However, according to the evaluation criteria, the high values of those criteria show that the trained ANN models using BPA are not efficient in learning processes especially in low flow event. Thus, it is suggested to improve ANN's performance such as particle swarm optimization (PSO), or singular spectrum analysis (SSA) for ANN's training (Srinivasulu and Jain, 2006; Wu et al., 2009; Huo et al., 2012). Since this study is developed with just two types of ANN models, it is necessary to perform other ANNs and compare the result in more than one watershed and in different climate.

In addition, the performances of all the models developed in this study were evaluated by using a wide variety of standard statistical performance evaluation measures. It is therefore recommended to apply an error analysis of the result for varying ranges of flow such as low flow, medium and high because of properly examining the robustness and predictive capability of the ANN models. In addition, the performance of various ANN models should be evaluated using a wide variety of standard statistical performance evaluation measures instead of relying on a few global errors statistical such as correlation coefficient and efficiency, as well as Nash-Sutcliff efficiency that are similar in nature to the global errors which are minimized at output layer of an ANN model.

Reference

Abrahart, R.J., L.M. See, 2007. Neural network emulation of a rainfall-runoff model. Journal of Hydrology and Earth System Sciences, 4; 287–326.

Amorocho, J., W.E. Hart, 1964. A critique of current methods in hydrology systems investigation. Transactions, American Geophysical Union, 45; 307-321.

Braddock, R.D., M.L. Kremmer. L. Sanzogni, 1998. Feed forward artificial neural network model for forecasting rainfall-runoff. Environmental Sciences, 9; 419-432.

Bowden, G.J., H.R. Maier, G.C. Dandy, 2002. Optimal division of data for neural network models in water resources applications. Journal of Water manage, 38; 1-11.

Buch, A.M., H.S. Mazumdar, P.C. Pandey, 1993. A case study of runoff simulation of a himalayan glacier basin.Proceeding of International Joint Conference on Neural Networks, Nagoya, Japan. pp. 971-974.

Campolo, M., P. Andreussi, A. Soldati, 1999. River flood forecasting with a neural network model. Water Resources Research 35; 1191–97.

Cannon, A.J., P.H., Whitfield, 2002. Downscaling recent stream-flow conditions in British Columbia. Canada Using Ensemble Neural Networks. Journal of Hydrology, 259; 136-151.

Cheng, X., M., Noguchi, 1996. Rainfall–Runoff modeling by a neural network approach. Proceedings of the 4th International Conference on Water Resources and Environmental Research, Adelaide, Australia, pp. 143–50.

Dawson, C.W., 1996. A neural network approach to software project effort estimation. Applications of Artificial Intelligence in Engineering, 1; 229–237.

Dawson, C.W., R.L. Wilby, 2001. Hydrological modeling using artificial neural networks. Progress in Physical Geography, p. 80–108.

Dooge, J.C.I., 1977. Problems and methods of rainfall-runoff modeling. In: Ciriani, T.A., U. Maione and J.R. Wallis (Eds.). Mathematical Models for Surface Water Hydrology: The Workshop Held at the IBM Scientific Center, Pisa. Wiley, London, pp: 71-108.

Fernandoa, A.K., A.Y. Shamseldinb, R.J. Abrahart, 2011. Comparison of two data-driven approaches for daily river flow forecasting, Proceedings of 19th International Congress on Modeling and Simulation, Perth, Australia, pp.1077-1083.

Fischer, M.M., S. Gopal, 1994. Artificial neural networks: a new approach to modeling interregional telecommunication Flows. Journal of regional Science, 34; 503–527.

Giustolisi, O., D. Laucelli, 2005. Improving generalization of artificial neural networks in rainfall-runoff modeling. Journal of hydrology Science, 50; 439-457.

Halff, A.H., H.M. Halff, M. Azmoodeh, 1993. Predicting from rainfall using neural networks, process engineering, Journal of Hydrology, 18; 760–765.

Harun, S., N.I. Ahmat Nor, M.A.H. Kassim, 2002. Artificial neural network model for rainfall-Runoff Relationship. Journal of technology, 37; 1-12.
Hertz, J., A. Krogh, R.G. Palmer, 1991. Introduction to the theory of neural computation.Journal of Hydrology, 14; 630-645.
Hettiarachchi, P.M., J. Hall, A.W. Minns, 2005.The extrapolation of artificial neural networks for the modeling of rainfall–runoff relationships. Journal of Hydro informatics, 7; 291-296.
Hjemfelt, A.T., M. Wang, 1993. Artificial neural networks as unit hydrograph applications, process engineering. Journal of hydrology, 10; 754–759.
Hsu, K.l., H.V. Gupta, S. Sorooshian, 1995. Artificial neural network modeling of the rainfall-runoff process. Journal of water resource manage, 31; 2517-2530.
Huo, Z., S. Feng, S. Kang, G. Huang, F. Wang, P. Guo, 2012. Integrated neural networks for monthly river flow estimation in arid inland basin of northwest China. Journal of hydrology, 420–421; 159–170.
Jafari, M., M. Vafakhah, H. Abghari, A. Tavasoli, 2012. Runoff coefficient forecasting usingartificial neuralnetworkin Neyshabur Bar-Arieh watershed, Iran Natural Ecosystem Journal, 2; 85-97.
Jain, S.K, D. Das, D.K. Srivastava, 1999. Application of ANN for reservoir inflow prediction and operation. Journal of Water Resources Planning and Management, 125; 263–271.
Jain, S.K., D. Chalisgaonkar, 2000. Setting up stage-discharge relations using ANN. Journal of Hydrologic Engineering, 5; 428-433.
Jain, A., S. Srinivasulu, 2006. Integrated approach to model decomposed flow hydrograph using artificial neural network and conceptual techniques. Journal of Hydrology, 317; 291-306.
Jeong, D.I., Y-O. Kim, 2005. Rainfall-Runoff models using artificial neural networks for ensemble stream flow prediction, hydrological processes. Journal of Hydrology, Published online in Wiley Inter Science (www.interscience.wiley.com). DOI: 10.1002/hyp.5983.Process. 19; 3819–3835.
Kalteh, A.M., 2008. Rainfall-Runoff modeling using artificial neural networks (ANNs): modeling and understanding. Caspian Journal of Environmental Sciences (CJES), 2008, 6; 53-58.
Karunanithi, N., W.J. Grenney, D. Whitley, K. Bovee, 1994. Neural network for river flow pre15 Diction. Journal of Computing Civil Engineering, 8; 201–220.
Imrie, C.E., S. Dumcan, A. Korre, 2000. River flow prediction using artificial neural networks: generalization beyond the calibration range. Journal of Hydrology, 233; 138-153.
Legates, D.R., G.J. McCabe, 1999. Evaluating the use of 'goodness-of-fit' measures in hydrologic and hydro climatic model validation. Water Resources Research, 35; 233–241.
Maier, H.R., G.C. Dandy, 2000, Neural networks for the prediction and forecasting of water resources variables: A review of modeling issues and application, Environmental Modeling and Software, 15; 101–124.
Minns, A.W., M.J. Hall, 1996, Artificial neural networks as rainfall–runoff models. Hydrological Sciences Journal, 41; 399– 417.
Mutlu, E., I. Chaubey, H. Hexmoor, S.G. Bajwa, 2008. Comparison of artificial neural network models for hydrologic predictions at multiple gauging stations in an agricultural Watershed. Hydrological processes, 22; 5097–5106.
Nayak, P.C., Y.R. Satyajirao, K.P. Sudheer, 2006. Groundwater level forecasting in a shallow aquifer using artificial neural network. Water Resources Management, 20; 77-90.
Norgaard, M., O. Ravn, N.K. Poulsen, L.K. Hansen, 2000. Neural networks for modelling and control of dynamic systems, Springer, UK. 3; 246.
Poggio, T., F. Girosi, 1990. Networks for approximation and learning proceedings of the IEEE, vol 78, pp. 1481-1497.
Rajurkar, M.P. U.C. Kothyari, U.C. Chaube, 2002. Artificial neural networks for daily Rainfall-Runoff modeling. Journal of Hydrology, 47; 865-877.
Sadeghi S.H.R., A. Tavasoli, H.R. Moradi, 2010. Simulation intra-change storm of runoff coefficient with use in factors rain for Neyshabur Bar watershed, Iran. Journal of Science and Watershed Management Engineering, 4; 21-33.
Sarangi, A., A.K. Bhattacharya, 2005, Comparison of artificial neural network and regression models for sediment loss prediction from Banha watershed in India. Agricultural Water Management, 78; 195–208.
Smith, J., R.B. Eli, 1995. Neuralnetwork models of rainfall-runoff process. Journal of water Resource Planning and Management, 4; 232-239.
Solaimani, K., 2009. Rainfall-Runoff prediction based on artificial neural network (A case study: Jarahi Watershed). American-Eurasian Journal of Agriculture and Environment Science, 5; 856-865.
Srinivasulu, S., A. Jain, 2006. A comparative analysis of training methods for artificial neural network rainfall–runoff models. Apply Soft Computing, 6; 295–306.
Sudheer, K.P., A.K. Gosain, K.S. Ramasastri, 2002. A data-driven algorithm for constructing artificial neural network rainfall–runoff models. Hydrological Process, 16; 1325–1330.
Thirumalaiah, K., M.C. Deo, 1998. Real-Time flood forecasting using neural networks. Computer-Aided Civil and Infrastructure Engineering, 13; 101–11.
Tokar, A.S. and P.A. Johnson, 1999. Rainfall-Runoff modeling using artificial neural networks. Journal of Hydrology Engineering, 4; 232-239.
Varoonchotikul, P., 2003. Flood forecasting using artificial neural networks, vrijeuniversiteit unesco-ihe Institute for Water Education Press.
Wilby, R.L., R.J. Abrahart, C.W. Dawson, 2003. Detection of conceptual model rainfall-runoff processes inside an artificial neural network. Journal of Hydrology, 48; 163-181.
Wu, C.L., K.W. Chau, Y.S. Li, 2009. Methods to improve neural network performance in daily flow prediction. Journal of Hydrology, 372; 80–93.
Wu, C.L., K.W, Chau, 2011. Rainfall–Runoff modeling using artificial neural network coupled with singular spectrum analysis, Journal of Hydrology, 399 (3-4), pp. 394–409.
Zhang, B., R.S. Govindaraju, 2003. Geomorphology-Based artificial neural networks (GANNs) for estimation of direct runoff over watersheds. Journal of Hydrology, 273; 18-34.