Content list available at http://epubs.icar.org.in, www.kiran.nic.in; ISSN: 0970-6429

Indian Journal of Hill Farming

June 2018, Volume 31, Issue 1, Page 166-176

Modelling of Daily Rainfall - Runoff Using Multi-Layer Perceptron Based Artificial Neural Network and Multi-Linear Regression Techniques in A Himalayan Watershed

Sanjarambam Nirupama Chanu* • Pravendra Kumar

Department of Soil & Water Conservation Engineering, College of Technology, G. B. Pant University of Agriculture and Technology, Pantnagar - 263145 (U. S. Nagar) Uttarakhand

ARTICLE INFO

Article history:
Received 18 August 2017
Revision Received 25 February 2018
Accepted 9 April 2018

Key words:
Hydrological processes; Gamma test; Rainfall; Runoff ; Watershed

ABSTRACT

Modelling of rainfall-runoff is considered one of the prerequisite of hydrological processes for various applications involving conservation and management of water resources. In this study, two techniques that is Multi-Layer Perceptron (MLP) neural network, which is well known efficient Artificial Neural Network (ANN), and Multi-Linear Regression (MLR) were applied for modelling daily rainfall-runoff and results obtained were compared. In order to simulate the processes, time series monsoon data of ten years (2000-2009) of rainfall and runoff at Bino watershed in Almora and Pauri Garhwal districts of Uttarakhand, India were used. In addition, Gamma Test (GT) was used for identifying the best input combinations for rainfall-runoff modelling. Performance of models was evaluated qualitatively as well as quantitatively employing statistical indices *viz.* correlation coefficient (r), root mean square error (RMSE) and coefficient of efficiency (CE), both for training as well as testing. Different MLP based ANN models were developed with the change of number of neurons and hidden layers and best model among them was selected based on performance indices. The same inputs were used to develop MLR model. The r, RMSE and CE values of best performing MLP model were found to be 0.95, 1.27 (mm) and 0.88, respectively during training while their corresponding values during testing were determined to be 0.92, 0.96 (mm) and 0.80. The comparison of both MLP and MLR models reveals that MLP based ANN is superior in performance for rainfall-runoff modelling and able to predict the daily runoff with good accuracy for the study area.

1. Introduction

The accurate estimation of hydrological phenomena such as rainfall–runoff processes is one of the primary requirements for water resource planning and land use management like designing of dams, reservoir management, prediction of risks, potential losses caused by flooding and drought on water resources systems. Because of its non-linear, multi-dimensional and inter-relationships nature of underlying climatic and physiographic factors, modelling of rainfall-runoff is extremely complex and it exhibits both temporal and spatial variability. Therefore, different hydrological models have been developed for simulating such a hydrological process such as conceptual, physically based distributed models and black box models. Physically based distributed models attempt to provide all the processes through the application of physical laws within the desired hydrological system. In a rigorous theoretical sense, these models can be considered a better choice.

2. Materials and Methodologies

However, the significant data requirements of such models, coupled with longer time taken in model development, calibration and validation compared to other

*Corresponding author: linthoich@gmail.com

model categories, make them an unfavourable choice in operational hydrology (Gautam *et al.,* 2000). Conceptual models are developed based on confined studies of the existed processes in basin hydrology unlike the physically-based models whose development is based on all physical processes (Lafdani *et al.,* 2013a). These models are applicable where there is limited data requirements and inclusion of a conceptual framework, but require a lengthy calibration, rigorous parameterization process (Duan *et al.,* 1992) and sophisticated mathematical tools (Sorooshian *et al.,* 1993). While in case of black box models, they do not clearly consider the physical laws of the processes and only convert inputs to output values through the conversion function in ways that have nothing to do with what happening in reality (Leavesley *et al.,* 2002). In such cases, with high degree of complexity and uncertainty where it is difficult to consider every effective physical parameter, it is not a surprising fact that black box models may produce more accurate results than physical based models (Nourani and Komasi 2013). Artificial Neural Network (ANN) which is such a black box modelling tool that have been found applicable frequently in last few decades in a variety of areas due to its great flexibility and adaptive nature in modelling and predicting the non-linear processes such as rainfall–runoff processes overcoming the limitations associated with conceptual and physical based approaches. ANN is a self-learning and self-adaptive universal approximator that has been applied as a successful tool to solve various problems concerned with hydrology and water resources engineering (ASCE 2000a, b). Extensive review on concepts and applications of ANN in hydrologic simulation and forecasting have been reported in ASCE (2000a, b), Govindaraju and Rao (2000), Dawson and Wilby (2001). Numerous studies have been conducted by many researchers around the world so far for modelling hydrological phenomena using ANN (French *et al.,* 1992; Karunanithi *et al.,* 1994; Fernando and Jayawardena 1998; Minns and Hall 1996; Tokar and Johnson 1999; Tingsanchali and Gautam 2000; Sarangi and Bhattacharya 2005; Chen *et al.,* 2006; Nourani *et al.,* 2009a, b; Kisi *et al.,* 2013). Above studies explained the capability of ANN superior than the conventional models without requiring an explicit description of the complex nature of the underlying process in a mathematical form. This is one of the main advantages of the ANN approach over traditional methods (Sudheer *et al.,* 2002). Rajurka (2004) stated that the application of an ANN for rainfall-runoff modelling started with a preliminary study by Halff *et al.* (1993) using a three layer feed forward ANN for the hydrographs prediction. Since then, many studies have been carried out in the field of rainfall-runoff modelling using ANN. Raman and Sunil kumar (1995) conducted a study for modelling multivariate monthly hydrologic time series using ANNs and the results were compared with those obtained from a statistical model. Tokar and Johnson (1999) and Tokar and Markus (2000) have used ANN for rainfall- runoff modelling and demonstrated the impact of the training data selection on the accuracy of runoff prediction. Coulibaly *et al*. 2000; Coulibaly *et al.* 2001a, b reported that the use of recurrent neural network (RNN) for inflow forecasting with precipitation, snowmelt and temperature as input parameters. Zhang and Govindaraju (2003) developed a geomorphology-based ANN (GANN) that explicitly accounts for the geomorphologic characteristics of the watershed within its architecture for estimation runoff hydrographs from several storms over two Indiana watersheds. Sarangi *et al.* (2005) developed ANN and regression models using watershed-scale geomorphologic parameters to predict surface runoff and sediment losses of the St. Esprit watershed, Quebec, Canada. Kalteh (2008) developed a rainfall-runoff model using an ANN approach, and described different approaches including Neural Interpretation Diagram, Garson's algorithm, and randomization approach to understand the relationship learned by the ANN model. Kisi *et al.* (2013) modelled rainfall-runoff process using three Artificial Intelligence (AI) approaches *viz.* ANNs), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Gene Expression Programming (GEP) for a small catchment in Turkey and the results were compared with the traditional Multi Linear Regression (MLR) model. Patil and Valunjkar (2014) applied multi-layer perceptron (MLP) for Gunjwani water in lower Bhima sub-basin (Maharashra, India) to forecast next-day runoff and compared results with MLR.

Moreover, one of the major phases in modelling using artificial intelligence techniques is identifying the best input combination of the network (Lafdani *et al.,* 2013 a, b, c). There are different methods for reducing the number of input variables such as principal component analysis (PCA) (Zhang *et al.,* 2006; Zhang 2007), Gamma test (GT) (Corcoran *et al.,* 2003; Moghaddamnia *et al.,* 2008), forward selection (FS) (Chen *et al.,* 2004; Eksioglu *et al.,* 2005; Wang *et al.,* 2006; Khan *et al.,* 2007; Noori *et al.,* 2010a), and other techniques. The GT was firstly reported by Stefansson *et al.* (1997), Koncar (1997) and Agalbjörn *et al.* (1997) and later it was discussed and utilized by many experts and scientists (Durrant 2001; Tsui *et al.,* 2002; Jones *et al.,* 2002; Jamalizadeh *et al.,* 2008; Ramesan *et al.,* 2009). Ahmadi *et al.* (2009) reviewed the capability of GT technique and entropy theory to determine effective variables on solar radiation in Brue Basin, England and showed that the number of required variables for modelling had reduced significantly using GT. Noori *et al.* (2010b) applied PCA and GT techniques for selecting the inputs of ANN for weekly solid waste generation in Tehran, Iran.

Noori *et al.* (2011) explored the role of pre-processing of input parameters using Principal Component Analysis (PCA) techniques, GT and Forward Selection (FS) techniques to assess the performance of the support vector machine (SVM) model for monthly stream flow prediction and authors recommended to use the PCA and GT techniques for increasing the SVM model performance especially in cases where lack of knowledge about the input variables exists. Lafdani *et al.* (2013a) used GT technique for identifying the best input combination of variables to predict rainfall as predicted using ANN and ANFIS and daily runoff was simulated using hydrological model of MIKE11/NAM in Eskandari Basin, Iran. Lafdani *et al.* (2013b) have also applied GT technique for rainfall prediction using ANFIS in Qaleh Shahrokh basin, Iran. The use of the GT in input variable pre-processing is new and there are only a few studies involving the application of this method to water resources management (Noori *et al.,* 2011). Maier and Dandy (2000) mentioned that determining of adequate model inputs and development of suitable network architecture are key aspects requiring further attention. In development of nonlinear simulation models the proper selection of input variables is a challenging task because a false combination of input variables could prevent the model from achieving the optimal solution. Keeping above points in view, in the present study GT technique was used for selection of best input combination for modeling of daily runoff using Multi-Layer Perceptron (MLP) neural network and Multi Linear Regression (MLR) techniques in Bino watershed, India.

2. Materials and Methods

2.1 Gamma Test (GT)

Gamma test is one of the non-linear modeling and analysis tools that can investigate an underlying input-output relationship in a numerical data set as well as establishing a smooth model. GT estimates the minimum mean square error (MSE) that can be achieved when modeling the unseen data using any continuous non-linear models (Moghaddamnia *et al.,* 2009). Suppose there exists a set of data observations as $\{(x_i, y_i), 1 \leq i \leq M\}$ where the input vectors $x_i \in R^m$ are m dimensional vectors (with a record length of M) confined to some closed bounded set $C \in R^m$ and $y_i \in R$ is corresponding outputs scalar. If the underlying relationship between input-output can be expressed as:

$$y = f(x_1 \dots x_m) + r \qquad (1)$$

where f is a smooth unknown function and r is a random variable representing noise. GT allows the variance of the noise variable r (Var(r)) to be estimated, despite the fact that f is unknown. GT calculates model output variance that cannot be accounted by a smooth data model called Gamma statistic (Γ). GT is based on the kth ($1 \leq k \leq p$) nearest neighbors $x_{N[i,k]}$ for each vector x_i ($1 \leq i \leq M$) and p is the number of near neighbors, typically p = 10 (Jamalizadeh *et al.,* 2008). It can be derived from Delta function of the input vectors which calculates the mean squared distance of the k^{th} neighbor:

$$\delta_M(k) = \frac{1}{M}\sum_i^M \left|x_{N\,[i,k]} - x_i\right|^2 ;(1 \leq k \leq p)$$

(2)

where |…| denotes Euclidean distance, and corresponding Gamma function output is given as:

$$\gamma_M(k) = \frac{1}{2M}\sum_i^M \left|y_{N\,[i,k]} - y_i\right|^2 ; (1 \leq k \leq p)$$

(3)

where $y_{N[i,k]}$ is the corresponding y-value for the k^{th} nearest neighbor of x_i in Eq. (2).To compute Γ, a least squares regression line which is fitted for p points (δ_M(k), γ_M (k)) as:

$$\gamma = A\delta + \Gamma$$

The intercept on the vertical this axis (δ= 0) is the Γ value as $\gamma_M(k) \rightarrow Var(r)$ in probability as $\gamma_M(k) \rightarrow 0$.Selecting the most important and influencing parameters of a nonlinear and unknown function is one of the most difficult steps in model development. If *n* number of the input variables exists, the combination of 2*n* -1 would be among them and analysing all these combinations consumes lots of time. One of the main advantages of GT technique is its speed in large databases which consist thousands of points for data sets, while a single run of the GT takes a few seconds (Jones 2004). It reduces volume of model development work and creates guidance for proper needed input data and the most important variables before actually developing model. Input selection by trial and error procedure is huge time taking process and this can be one of the major weaknesses in modeling studies. In this context, GT is such a good mathematical algorithm. Therefore, GT was used in this study for selecting the best combination of the input variables and it was achieved through win Gamma™ software implementation (Durrant 2001).

2.2 Artificial Neural Network (ANN)

McCulloch and Pitts (1943) are generally recognized as the first to design the neural network (NN). ANN is a method that is inspired by the studies of the brain and nerve systems in biological organisms. NNs have the capability of self-learning and automatic abstracting and are flexible computing frameworks for modeling a broad range of non linear problems. Most of the NNs possess three or more layers. First layer is the input layer in which data are fed to the network, one or more intermediate layers, which act as an interface between the inputs and outputs and used to act as a collection of feature detectors , and another last layer is the output layer in which the network response of the given input is produced. Their power comes from the parallel data processing of the information from the data which is accomplished through training of data and the correlation between input data are weighted in order to estimate the output appropriately. The main advantage of ANN paradigms is to map a set of inputs to a set of outputs with minimum basic or initial assumption on which the process that would be obtained from. One more significant advantage of the ANN models over other classes of non linear model is that ANNs are universal approximators which can approximate a large class of functions with a high degree of accuracy. Because of these special features, neural networks are less vulnerable to adverse modeling compared with other parametric non-linear techniques and applying this technique may reduce modeling time of complex systems. Thus, ANNs are important alternatives technique to the traditional methods of data analysis and modeling.

2.3 ANN architecture

A neural network will be characterized by its architecture that presents the pattern of connection between nodes. ANNs are massively parallel systems composed of many processing elements called artificial neurons, or simply neurons or node and arranged in form of layers of these parallel neurons, with each layer being fully connected to the proceeding layer by interconnection weights. The architecture of an ANN is designed by weights between neurons, a transfer function that controls the generation of output from a neuron and learning laws that define the relative importance of weights for input to a neuron. During a training process randomly assigned initial weight values are corrected progressively and compares calculated outputs with the observed outputs and the errors are back-propagated to determine the appropriate weight adjustments necessary to minimize the errors (Kisi 2005). Thus, the learning capability of an artificial neuron is being achieved by adjusting the weights in accordance to the chosen learning algorithm. In the present study, Multi- Layer Perceptron (MLP) neural network which is the one most popular ANN architecture was used for rainfall-run off modeling. MLPs are layered feed forward networks typically trained with static back propagation. A typical three layer MLP structure is shown in Fig 1. These networks have found their way into countless applications requiring static pattern classification. Two main characteristics of the MLP are its non-linear processing elements which have a non-linear activation function that must be smooth (most widely used being the logistic function with ranges from 0 to 1 and the hyperbolic tangent with ranges from –1 to 1) and its massive interconnectivity (*i.e.* any element of a given layer feeds all the elements of the next layer) (Memarian and Balasundram 2012). Their main advantage is that they are easy to use, and that they can approximate any input/output map. The transfer functions that are most commonly employed in ANN are sigmoidal type functions, such as the logistic and hyperbolic tangent functions (Maier and Dandy 2000).

2.4 Selection of network architecture

Choosing the most appropriate architecture of a layered neural network design is one of the most important attributes in ANN modeling. The number of input nodes is simply determined by the dimension of the input vector to be generalized or associated with a certain output quality. The dimension of the input vector corresponds to the number of distinct feature of the input pattern. Similarly, the number of neurons in output layer can be made equal to the dimensions of vectors to be associated. The size of the hidden layer(s) is

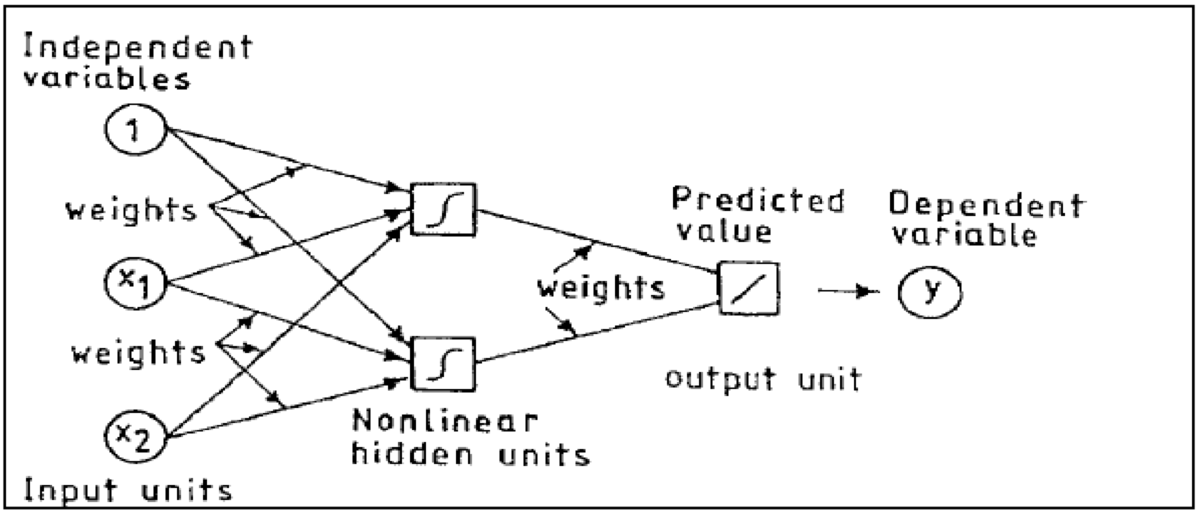


Figure 1. A typical three- layer MLP.

the most important consideration when solving the actual problems using multilayer feed-forward neural networks. The most popular and effective strategy for selecting the appropriate number and size(s) of the hidden layer(s) is trial-and-error procedure.

Multiple Linear Regressions (MLR)

A multiple linear regression method is a multivariate statistical technique used to model the linear correlations between a single dependent variable, Y, and two or other several independent variables $X_1, X_2,.....,X_k$. Linear relationship between dependent variable Y is affected by n independent variables $X_1, X_2,.....,X_k$ and a linear mathematical relationship (model) assumed is (Berk 2004):

$$Y= a+ b_1X_1+ b_2X_2+ ... +b_kX_n \quad (5)$$

where $a, b_1,.....,b_k$ are multiple regression coefficients and $X_1, X_2.....,X_k$ are independent variables. Thus, it is assumed that Y is linearly related to each of the independent variables and that each independent variable has an additive effect on Y. Therefore, at this stage, we are assuming that $X_1, X_2,.....,X_k$ do not interact amongst themselves in their effect on Y.

Study area and data

The Bino watershed, a sub-watershed of Ramganga catchment in Uttarakhand, India, was selected for this study. The Bino watershed with a drainage area 296.178 Km^2 is situated in North-Eastern part of Ramganga catchment in middle and outer ranges of Himalayas between 79^o 6' 14.4" to 79^o 17' 16.8" E longitude and 29^o 47' 6" to 30^o 02'9.6" N latitude in Almora and Pauri Garhwal district of Uttarakhand, India. River Ramganga is one of major tributary of river Ganga and originates in outer Himalayas in Chamoli district of Uttarakhand, India and drains into river Bino (a tributary of Ramganga River) through its outlet located at 79^o 14' 13.2" E longitude and 29^o 47' 6" N latitude. Fig. 2 shows the location map of the study area. The watershed has very undulating topography with mean length of 28.46 Km and 17.27 Km and irregular slopes varying from moderate to steep in valley areas on either sides of the Bino River. The climate of the watershed varies from Himalayan sub-tropical to sub-temperate with mean annual maximum and minimum air temperature of 30 ^{o} C to 18 ^{o} C, respectively. The daily mean temperature remains higher during the months of May and June and minimum in December and January. The mean annual rainfall of the area is 931.3 mm. The maximum and minimum elevations in the watershed are 2884 m and 802 m above the mean sea level respectively. Based on slope, land in the watershed may be categorized into valley, moderate and steep hill areas. More than 75.31 % of the watershed area falls under slope class of more than 25 % with an average slope of 37.43 %. Soils in the watershed are coarse texture varying with sandy loam, loam, sandy clay loam, stony and are highly erodible. 49.7 % of the watershed area is under forest and 29.4 % is under agricultural land. Daily rainfall, runoff data of 10 years (2000-2009) were collected from Divisional Forest and Soil Conservation Office, Ranikhet, Uttarakhand, India. Table 1 shows the statistical analysis of the rainfall (mm) and runoff (mm) data.

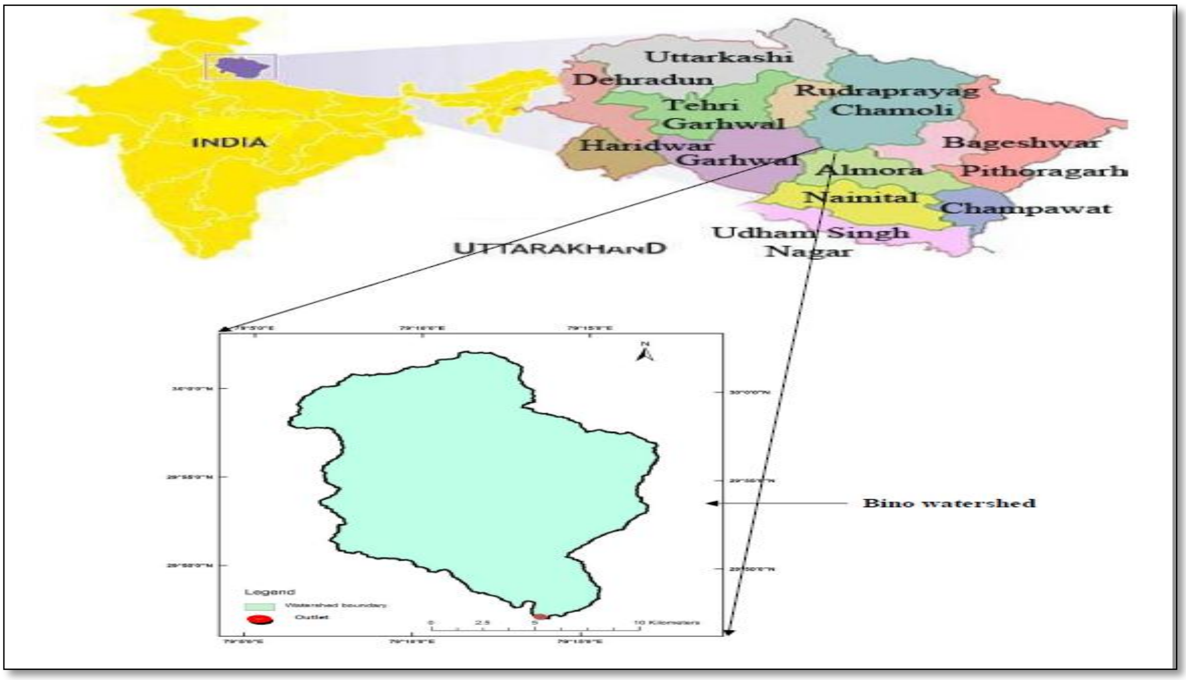


Figure 2. Location map of Bino watershed, Uttarakhand.

Table 1. Statistical analysis of observed data at Bino watershed

Data	Training data					Testing data				
	Mean	Min	Max	Standard deviation	Skewness coefficient	Mean	Min	Max	Standard deviation	Skewness Coefficient
Rainfall (mm)	3.55	0.00	133.00	10.92	6.24	3.69	0.00	63.50	8.91	3.47
Runoff (mm)	2.29	0.04	72.27	3.68	10.03	2.15	0.15	15.97	2.15	2.94

Model Development

In the present study, daily rainfall and runoff data of monsoon period (1st June to 30th September) for the period 2000-2009 were used for training and testing of MLP and MLR models. Out of this, 70 % of data (2000 to 2006) were used for training or calibration and remaining 30 % of data (2007 to 2009) were used for validation or testing of developed models. Best input combination was selected using GT technique and these inputs were used to train MLP and MLR for simulating current day runoff. Here, the MLP with both single and double hidden layers were trained using Levenberg–Marquardt as learning rule (which is an improved second order method for gradient) and hyperbolic tangent as transfer function using software Nuero Solutions 5.0 designed and written by Curt Lefebvre & Jose Principe. The network training was stopped as soon as the maximum number of epochs, which was predetermined at 1000, and training threshold of 0.001 were reached. Different combinations of hidden neurons were tried and a network that yields the minimum root mean square error (RMSE), maximum correlation coefficient (r) and coefficient of efficiency (CE) was selected.

Performance evaluation of models

Three criteria, the root mean square error *(RMSE)*, the correlation coefficient (r) and Coefficient of efficiency (CE) or Nash-Sutcliffe efficiency have been used to assess the goodness of fit performance of the models:

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} (O_j - P_j)^2}{n}} \tag{6}$$

$$r = \frac{\sum_{j=1}^{n} \{(O_j - \bar{O})(P_j - \bar{P})\}}{\sqrt{\sum_{j=1}^{n} (O_j - \bar{O})^2 \sum_{j=1}^{n} (P_j - \bar{P})^2}} \tag{7}$$

$$CE = \left(1 - \frac{residual\ variance}{initial\ variance}\right) = \left(1 - \frac{\sum_{j=1}^{n} (O_j - P_j)^2}{\sum_{j=1}^{n} (O_j - \bar{O}_j)^2}\right) \tag{8}$$

where, j is an integer varying from 1 to n, O_j, P_j, $\bar{O}$, $\bar{P}$ and n are observed value, predicted value, mean of observed value, mean of predicted value and the number of observations respectively. The RMSE was used to measure prediction accuracy which produces a positive value by squaring the errors. The RMSE is zero for perfect fit and increased values indicate higher discrepancies between predicted and observed values. r is used as an indicator of degree of closeness between observed and predicted values. If observed and predicted values are completely independent, the r will be zero. The coefficient of efficiency can be used to compare the relative performance of two approaches effectively and is commonly used to assess the predictive power of hydrological models (Nash and Sutcliffe 1970). Theoretically it varies from $-\infty$ and 1, with 1 being corresponding to perfect model. For zero agreement, all the predicted values must be equal to the observed mean. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the predicted value, which indicates unacceptable performance. Therefore, closer this ratio is to unity, the better is the regression relation.

3. Results and Discussion

3.1 Gamma test

Selecting an appropriate combination from input parameters is one of the most important steps while designing every mathematical and intelligent modeling. If *n* is assumed to be the affecting parameter on occurrence of a phenomenon, 2^n-1 significant combinations of inputs are possible. The GT is able to provide the best mean square error (MSE) that can possibly be achieved using any non-linear smooth models and can greatly reduce the model development workload providing best selection of input parameters before a model is actually developed (*i.e.* its result is independent of the models to be developed). In order to predict current day runoff (Q_t), the current day rainfall (R_t) and previous days rainfall (R_{t-1}, R_{t-2} .... R_{t-n}) as well as previous days runoff (Q_{t-1}, Q_{t-2} .... Q_{t-n}), were used, where n is number of lags and here from one to three lags were used since lags after three were hardly affected as mentioned in literatures. The results for different combinations obtained from Gamma test are shown in Table 2. According to the principals of the GT, the combination with the minimum gamma value would be the best combination for modeling and show that the data with the provided combination has the possibility to achieve a better result in modeling. Therefore, R_t, R_{t-1},R_{t-2},Q_{t-1},Q_{t-2} are selected as the best input combination and optimum variables for developing MLP and MLR models for predicting daily runoff in Bino watershed.

Table 2. Results of GT for determining the best combination out of the input variables for runoff modelling

Sl No.	Model input	Gamma value
1	R_t	0.160395
2	R_t,Q_{t-1}	0.226494
3	R_t,Q_{t-1},Q_{t-2}	0.097237
4	R_t,R_{t-1},Q_{t-1}	0.231138
5	R_t, R_{t-1},Q_{t-1},Q_{t-2}	0.074221
6	R_t,Q_{t-1},Q_{t-2},Q_{t-3}	0.121361
7	R_t, R_{t-1},R_{t-2}, Q_{t-1}	0.201045
8	R_t, R_{t-1},R_{t-2}, Q_{t-1},Q_{t-2}	0.064161
9	R_t, R_{t-1},Q_{t-1},Q_{t-2} ,Q_{t-3}	0.128235
10	R_t, R_{t-1},R_{t-2}, R_{t-3}, Q_{t-1},Q_{t-2}	0.126393
11	R_t, R_{t-1},R_{t-2},Q_{t-1},Q_{t-2} ,Q_{t-3}	0.155590
12	R_t, R_{t-1},R_{t-2}, R_{t-3}, Q_{t-1},Q_{t-2},Q_{t-3}	0.119028

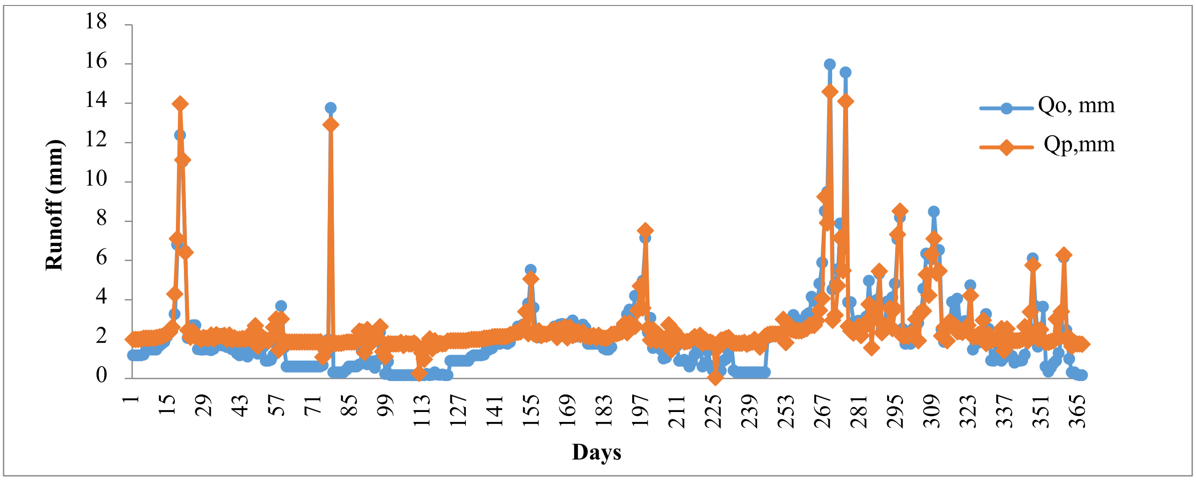
3.2 MLP based ANN and MLR runoff models

For modeling of daily runoff in Bino watershed, different models with the varying hidden neurons and hidden layer of both single and double have been trained and tested with MLP neural network to select the optimal architecture of the network. A trial and error procedure based on the minimum RMSE maximum r and CE criterion has been used to select the best network architecture. If the ANN architecture is I - N -1, the output layer has one neuron corresponding to the predicted runoff at time t with inputs I and hidden neurons of N. ANN architecture I-N-N-1 indicates for double hidden layer case. The optimal number of neurons (N) in the hidden layers has been identified using a trial and error procedure by varying the number of hidden neurons 2 to 11 for single hidden layer. All together 20 models *i.e.* MLP1 to MLP 20 has been developed and out of these, 10 are single hidden layer neural networks *i.e.* MLP1 to MLP10 and rest are double hidden layer neural networks. Out of the 20 models developed MLP7 (5-8-1) with 5 inputs and one hidden layer with 8 neurons and one output was best as compared to other networks based on the performance criteria r, RMSE and CE values 0.95, 1.27 (mm) and 0.88, respectively during training while their corresponding values during testing are found to be 0.92, 0.96 (mm) and 0.80, respectively. Among the double hidden neuron networks developed, MLP19 (5-10-11-1) having hidden neurons 10 for first hidden layer and 11 second hidden layer with 5 inputs and one output. The r, RMSE and CE for MLP19 model during training are found to be 0.93, 1.48 and 0.84, respectively and 0.90, 1.16 (mm), 0.70 are their respective values during testing. The MLR technique was also applied to predict the current day runoff (Q_t) using the same inputs as used in ANN and the result obtained are being compared with ANN. The developed model of MLR is shown below:

$$Q_t = 1.1758 + 0.0496R_t + 0.0249R_{t-1} - 0.0054R_{t-2} + 0.2642Q_{t-1} + 0.1141Q_{t-2} \quad (9)$$

The performance indices values of r, RMSE and CE for MLR model are found to be 0.71, 1.59 (mm) and 0.45, respectively.

Qualitative performance of developed model was evaluated by comparing observed and predicted values of daily runoff graphically in the form of time series and scatter plot as shown in Fig. 3 and 4 for MLP7 and MLR, respectively during testing. It can be observed from time series that the observed and predicted runoffs are in close agreement in most of the points although there are under and over predictions in some points. In general, both models MLP7 and MLR underestimate the observed runoff. This is clear from scatter plots as the best line of models are close to the ideal line (1:1) with R^2 values 0.85 for MLP7 and 0.50 for MLR.



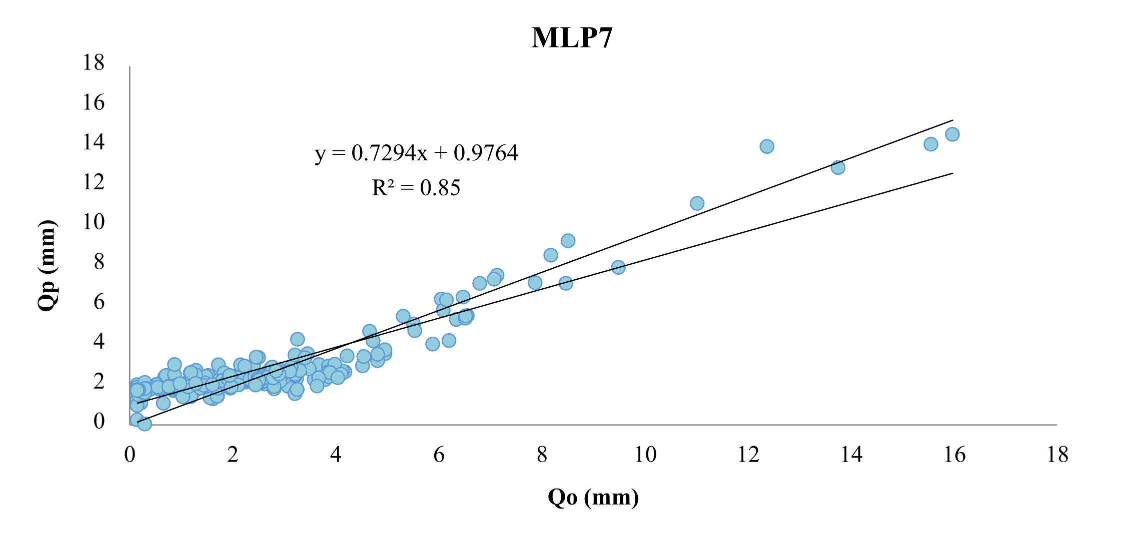
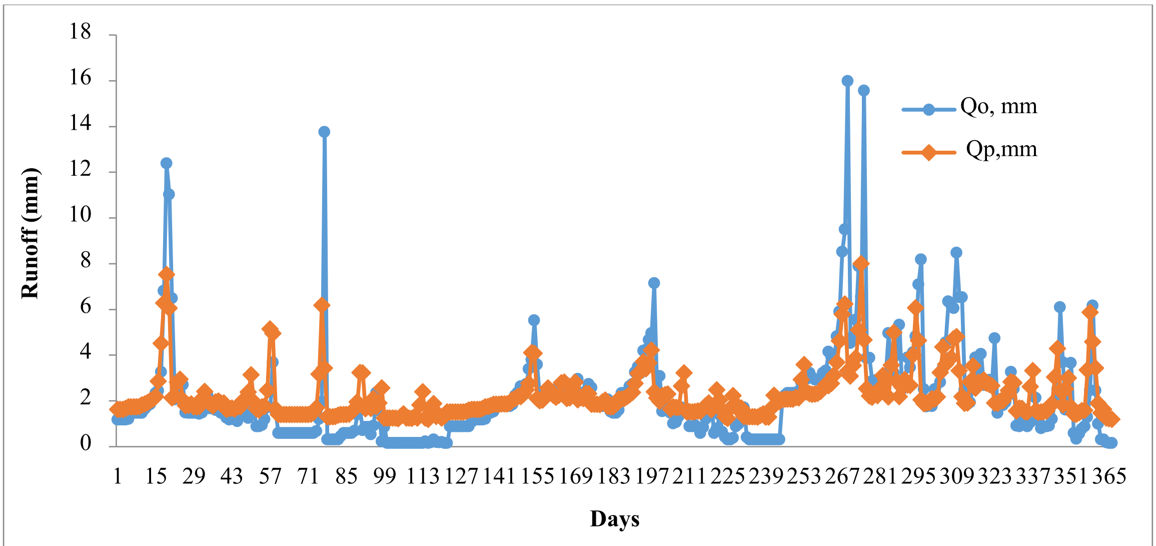


Figure 3. Time series and scatter plot of observed (Qo, mm) and predicted runoff (Qp, mm) during testing period for MLP7 (5-8-1) model.



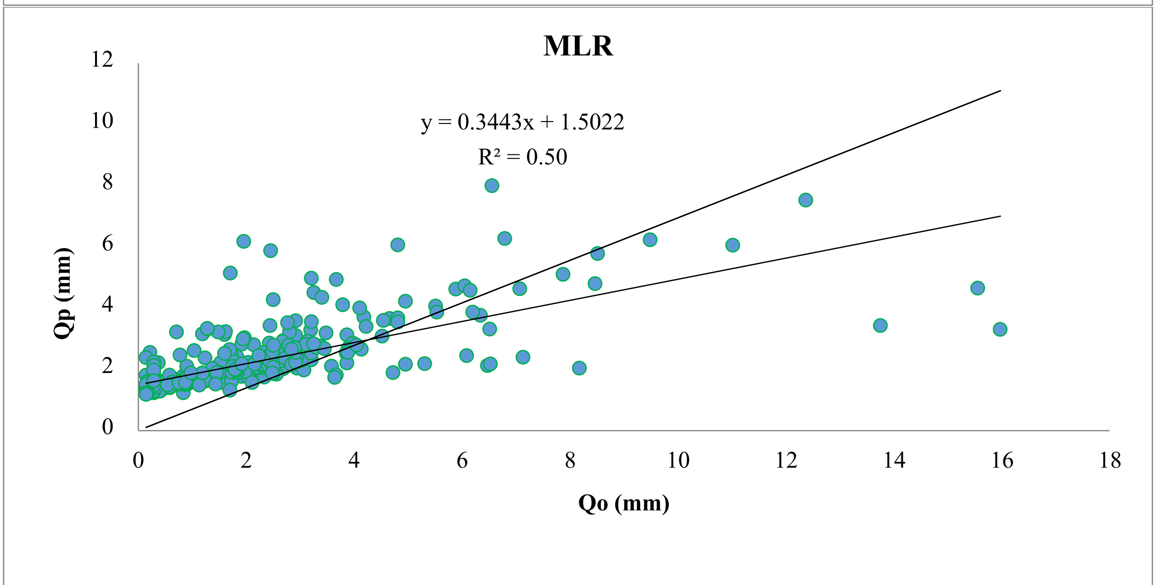


Figure 4. Time series and scatter plot of observed (Qo, mm) and predicted runoff (Qp, mm) during testing period for MLR model.

Conclusions

In this study, GT technique was applied for best input selection for smooth daily rainfall-runoff modeling using MLP based ANN and MLR techniques. The results of the study showed that GT technique can be effectively used prior to actual hydrological modeling thereby saving huge time while selecting the best inputs to fed in models. Out the twenty developed models by MLP based models ANN, single hidden layer was found better than double hidden layer. The results showed that MLP based ANN has better performance than and MLR. Therefore, MLP based ANN model can be successfully applied for daily rainfall-runoff modeling in Bino watershed, Uttarakhand.

Acknowledgements

The authors are thankful to Divisional Forest and Soil Conservation Office, Ranikhet, Uttarakhand, India for providing required data for the study and the first author is thankful to the Department of Science and Technology (DST), Ministry of Science and Technology, New Delhi for the financial support in the form of INSPIRE Fellowship rendered for pursuing her doctoral degree.

References

Agalbjörn S, Koncar N, AJ Jones (1997). A note on the gamma test. *Neural Computing and Applicatios.* 5: 131–133

Ahmadi A, Han D, Karamouz M, R Remesan (2009). Input data selection for solar radiation estimation. *Hydrological processes.* 23: 2754-2764

ASCE Task Committee on the application of ANNs in hydrology (2000a). Artificial neural networks in hydrology, I: Preliminary concepts. *J Hydrologic Eng.*5(2): 115–123

ASCE Task Committee on the application of ANNs in hydrology. 2000b. Artificial neural networks in hydrology, II: Hydrologic applications. *J Hydrologic Eng* 5(2): 124–137

Berk RA (2004). Regression Analysis: A Constructive Critique. Sage Publications, Thousand Oaks.

Chen S, Hong X, Harris CJ Sharkey, PM (2004). Sparse modeling using orthogonal forward regression with PRESS statistic and regularization. Transactions on Systems, Man and Cybernetics-Part B 34, pp. 898–911.

Chen SH, Lin YH, Chang LC Chang FJ (2006). The strategy of building a flood forecast model by neuro-fuzzy network. *Hydrological processes.* 20: 1525–1540

Corcoran J, Wilson I Ware J (2003). Predicting the geo-temporal variation of crime and disorder. *International J Forecasting.* 19: 623–634

Coulibaly P, Anetil F Bob'ee B (2000). Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. *J Hydrology*. 230: 244–257

Coulibaly P, Anetil F Bob'ee B (2001a). Multivariate reservoir inflow forecasting using temporal neural networks. *ASCE J Hydrologic Eng.* 6(5): 367–376

Coulibaly P, Bob'ee B Anetil, F (2001b). Improving extreme hydrologic events forecasting using a new criterion for ANN selection. *Hydrological processes*. 15(8): 1533–1536

Dawson CW Wilby RL (2001). Hydrological modelling using artificial neural networks. *Progress in Physical Geography* 25(1): 80–108

Duan Q, Sorooshian S Gupta VK (1992). Effective and efficient global optimization for conceptual rainfall–runoff models. *Water Resources Research.* 28(4): 1015–1031

Durrant PJ (2001) wingamma: A Non-linear Data Analysis and Modeling Tool with Applications to Flood Prediction. PhD thesis, Department of Computer Science, Cardiff University, Wales, UK.

Eksioglu B, Demirer R Capar I (2005). Subset selection in multiple linear regression: a new mathematical programming approach. *Computers & Industrial Engineering.* 49: 155–167

Fernando DA, Jayawardena AW (1998). Runoff forecasting using RBF networks with OLS algorithm. *J Hydrologic Eng.* 3: 203–209

French M, Krajewsi WF, Cuykendall RR (1992). Rainfall forecasting in space and time using a neural network. *J Hydrol*ogy .137 (1–4): 1–31

Gautam MR., Watanabe K, Saegusa H (2000). Runoff analysis in humid forest catchment with artificial neural network*. J Hydrol*ogy 235: 117–136

Govindaraju RS, Rao AR (Eds.) (2000). Artificial Neural Networks in Hydrology. Kluwer Academic Publisher, Amsterdam.

Halff AH, Halff HM, Azmoodeh M (1993). Predicting runoff from rainfall using neural networks, Proceeding on Engineering Hydrolology ASCE, New York, pp. 768–775

Jamalizadeh MR, Moghaddamnia AR, Piri J, Arabi V, Homayounfar M Shahryari A (2008). Dust storm prediction using ANNs technique (A case study: Zabol city). *World Academy of Science, Engineering and Tech*nology. 43: 512-520

Jones AJ, Tsui A, deOliveira AG (2002). Neural models of arbitrary chaotic systems: construction and the role of time delayed feedback in control and synchronization. *Complexity International* 9: 1-9.

Kalteh AM (2008). Rainfall-runoff modelling using artificial neural networks (ANNs): modelling and understanding. *Caspian J Environ Sci*.6(1): 53-58

Karunanithi N, Grenney WJ, Whitley D, Bovee K (1994). Neural networks for river flow prediction. *Journal of Computing in Civil Engineering,, ASCE* 8(2): 201–220

Khan JA, Aelst SV Zamar RH (2007). Building a robust linear model with forward selection and stepwise procedures. *Computational Statistics & Data Analysis*.52: 239–248

Kisi O (2005). Suspended sediment estimation using neuro-fuzzy and neural network approaches. *Hydrological Sci J*.50(4): 683–696

Kisi O, Shiri J, Tombul, M (2013). Modelling rainfall-runoff process using soft computing technique. *Computers & Geoscience* 51: 108-177

Koncar N (1997). Optimisation Methodologies for Direct Inverse Neurocontrol. PhD thesis, Department of Computing, Imperial College of Science, Technology and Medicine, University of London.

Lafdani EK, Nia AM, Pahlavanravi A, Ahmadi A, Jajarmizadeh, M (2013a). Daily Rainfall-Runoff Prediction and Simulation Using ANN, ANFIS and Conceptual Hydrological MIKE11/NAM Models. *International J Eng & Technol Sci.* 1(1): 32-50

Lafdani EK, Nia AM, Pahlavanravi A, Ahmadi A (2013b). Rainfall-Runoff Simulation using MIKE11/NAM and ANFIS Models (A Case Study: Qleh Shahrokh Basin in Iran). *World Sci J.* 4 (1): 53-61

Lafdani EK, Nia AM, Ahmadi A (2013c). Daily suspended sediment load prediction using artificial neural networks and support vector machines. *J Hydro*logy. 478: 50-62

Leavesley GH, Markstrom SL, Restrepo PJ, Viger RJ (2002). A modular approach to addressing model design, scale, and parameter estimation issue in distributed hydrological modeling. *Hydrological Processes*. 16(2): 173-187

Maier H, Dandy GC (2000). Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications. *Environmental Modeling and Software* 15: 101–124

McCulloch WS Pitts WH (1943). A logical calculus of the ideas immanent in neural nets. Bulletin of Mathematical Biophysics. 5: 115–133

Memarian H, Balasundram SK (2012). Comparison between Multi-Layer Perceptron and Radial Basis Function Networks for Sediment Load Estimation in a Tropical Watershed. Journal of *Water Resource and Protect*ion 4: 870-876

Minns AW, Hall MJ (1996). Artificial neural networks as rainfall runoff models. *Hydrological Sci J*. 41(3): 399–417

Moghaddamnia A, Ghafari-Gousheh M, Piri J, Amini S, Han D (2008). Evaporation estimation using artificial neural networks and adaptive neurofuzzy inference system techniques. Advances in Water Resources. doi: 10.1016/ j.advwatres.2008.10.005.

Moghaddamnia A, Ghafari M, Piri J, Han D (2009). Evaporation estimation using support vector machines technique. *International J Eng Appl Sci.* 5(7): 415-423

Nash JE, Sutcliffe JV (1970). River flow forecasting through conceptual models: Part I. A discussion of principles. *J Hydrology*. 10: 282–290

Noori R, Hoshyaripour G, Ashrafi K, Nadjar-Araabi B (2010a). Uncertainty analysis of developed ANN and ANFIS models in prediction of carbon monoxide daily concentration. *Atmospheric Environment.*. 44: 476–482

Noori R, Karbassi AR, Sabahi MS (2010b). Evaluation of PCA and Gamma test techniques on ANN operation for weekly solid waste predicting. *J Environ Manag.* 91: 767–771

Noori R, Karbassi AR, Moghaddamnia A, Han D, Zokaei-Ashtiani MH, Farokhnia A, Ghafari Gousheh M (2011). Assessment of input variables determination on the SVM model performance using PCA, Gamma test and forward selection techniques for monthly stream flow prediction. *J Hydrology*. 401: 177-189

Nourani V, Komasi M, Mano A (2009a). A multivariate ANN-wavelet approach for rainfall–runoff modeling. *Water Resources Manage*ment. 23: 2877–2894.

Nourani V, Alami, MT, Aminfar MH (2009b). A combined neural-wavelet model for prediction of Ligvanchai watershed precipitation. *Engineering Applications of Artificial. Intelligence*. 22: 466–472

Nourani V, Komasi M (2013). A geomorphology-based ANFIS model for multi-station modeling of rainfall–runoff process. *J Hydro*logy 490: 41–55

Patil S, Valunjkar S (2014). Forecasting of daily runoff using artificial neural networks. *International J Civil Eng Technol.* 5(1): 13-20

Rajurkara MP, Kothyari UC, Chaubec UC (2004). Modeling of the daily rainfall-runoff relationship with artificial neural network. *J Hydrol*ogy 285: 96–113

Raman H, Sunilkumar N (1995). Multivariate modelling of water resources time series using artificial neural networks. *Hydrological Sci J.* 40 (2): 145–163

Remesan R, Shamim MA, Han D, Mathew J (2009). Runoff prediction using an integrated hybrid modelling scheme. *J Hydrology*.. 372: 48-60

Sarangi A, Bhattacharya AK (2005). Comparison of Artificial Neural Network and regression models for sediment loss prediction from Banha watershed in India. *Agricultural Water Management* 78: 195–208

Sarangi A, Madramootoo CA, Enright P, Prasher SO, Patel RM (2005). Performance evaluation of ANN and geomorphology-based models for runoff and sediment yield prediction for a Canadian watershed. *Current Sci*ence 89: 12- 25

Sorooshian S, Duan Q, Gupta VK (1993). Calibration of the SMA-NWSRFS conceptual rainfall–runoff model using global optimization. *Water Resources Research.*29(4): 1185–1194

Stefansson A, Koncar N, Jones AJ (1997). A note on the gamma test. *Neural Computing & Application* 5: 131-133

Sudheer KP, Gosain AK, Ramasastri KS (2002). A data-driven algorithm for constructing artificial neural network rainfall-runoff models. *Hydrological Processes*. 16: 1325–1330

Tingsanchali T, Gautam MR (2000). Application of tank, NAM, ARMA and neural network to flood forecasting. *Hydrological Processes* 14: 2473–2487

Tokar AS, Johnson PA (1999). Rainfall runoff modeling using artificial neural networks. *J Hydrologic Eng ASCE* 4(3): 232–239

Tokar AS, Markus M (2000). Precipitation runoff modeling using artificial neural networks and conceptual models. *J Hydrologic Eng. ASCE* 5(2): 156–161

Tsui APM, Jones AJ, deOliveira AG (2002). The construction of smooth models using irregular embeddings determined by a gamma test analysis. *Neural Computing & Applications.* 10: 318–329.

Wang XX, Chen S, Lowe D, Harris CJ (2006). Sparse support vector regression based on orthogonal forward selection for the generalised kernel model. *Neurocomputing* 70: 462–474

Zhang B, Govindaraju RS (2003). Geomorphology-based artificial neural networks (GANNs for estimation of direct runoff over watersheds. *J Hydrology.*273(1): 18–34

Zhang Y, Li H, Hou A, Havel J (2006). Artificial neural networks based on principal component analysis input selection for quantification in overlapped capillary electrophoresis peaks. *Chemom. Intell. Lab. Syst.* 82: 165–175

Zhang YX (2007). Artificial neural networks based on principal component analysis input selection for clinical pattern recognition analysis. *Talanta* 73: 68–75.