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Comparison of Rainfall-Runoff Relationship Modeling using Different Methods in a Forested Watershed

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Abstract The daily rainfall-runoff relationship in an experimental watershed was modeled using a statistical method and an artificial neural network method. The estimations were examined and a performance evaluation was done. It was seen that the ANN method, FFBP (Feed Forward Back Propagation), provided closer flow estimations reproducing the shape of the observed hydrograph more realistic. The superiority of FFBP was reflected in the performance evaluation criteria. The extreme flows, i.e., high and low flows, were relatively better approximated by FFBP indicating its promise as a useful tool for hydrologic studies such as flood modeling. The Rational Method was also used, as a conventional tool, to predict the maximum discharge for selected return periods. It was found to be realistic for the forested watershed under consideration when the *C* coefficient was taken as 0.20 for the 10-year period.

Keywords ANN · FFBP · Rational method · Rainfall-runoff model · Runoff coefficient

1 Introduction

Due to huge spatial and temporal variability of watershed characteristics and precipitation patterns, and the large number of variables involved in the modeling of the physical processes, the rainfall-runoff relationship is one of the most complex hydrologic phenomena to comprehend. Over the last 70 years, numerous rainfall-runoff (R-R) models have been developed to forecast streamflow. Conceptual models provide daily, monthly, or seasonal estimates of streamflow for long-term forecasting on a continuous basis. The essential elements in the

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physical process in the hydrologic cycle are mathematically formulated in conceptual models that involve a large number of parameters. Due to several model parameters being dominant and highly complicated interactions of these parameters, the optimization of model parameters is usually accomplished by a trial-error procedure or, more generally, by automatic optimization. The perceived accuracy of model predictions is very subjective and highly dependent on the user's ability, knowledge, and understanding of the model and the watershed characteristics.

The artificial neural network (ANN) approach, which is a non-linear black box model, is extensively used in the water resources literature. The major ANN application domains can be summarized as river flow forecasting (Dawson and Wilby 2001; Khalil et al. 2001; Brikundavyi et al. 2002; Cigizoglu 2003a, b; Cigizoglu and Kisi 2005), various groundwater problems (Ranjithan et al. 1993), and estimation of suspended sediment (Cigizoglu 2004; Alp and Cigizoglu 2007; Cigizoglu and Kisi 2006; Partal and Cigizoglu 2008). The neural network application in hydrology was summarized by ASCE Task Committee (2000b) and Maier and Dandy (2000).

There are also many ANN studies for modeling the rainfall-runoff relationship (Hsu et al. 1995; Minns and Hall 1996; Fernando and Jayawardena 1998; Tokar and Johnson 1999). In most of these studies, either the conventional feed-forward error back-propagation method (FFBP) or the radial basis function was employed to train the neural networks. In the broader literature, the employment of another ANN algorithm, namely, the Generalized Regression Neural Network (GRNN), can be found (Cigizoglu 2005a, b). A problem frequently faced during the application of FFBP is the 'local minima' issue. In their work, Maier and Dandy (2000) summarized the methods used in the literature to overcome the local minima problem, such as training a number of networks starting with different initial weights, the on-line training mode to help the network to escape the local minima, including the addition of random noise, the employment of second order (Newton algorithm, Levenberg-Marquardt algorithm) or global methods (stochastic gradient algorithms, simulated annealing). The Levenberg-Marquardt algorithm was employed for FFBP applications in the present study. Other ANN methods such as conjugate gradient algorithms, the radial basis function, the cascade correlation algorithm and recurrent neural networks were described by ASCE Task Committee (2000a) and Thirumalaiah and Deo (1998, 2000).

There are a number of studies that compared different hydrological models in the modeling relationship between rainfall and runoff. For instance, Seckin et al. (2013) used the Neural Network and L-moments methods to compare flood flow at ungauged watersheds whereas Singh et al. (2010) used the Backpropagation Neural Network and M5 Models methods to compare annual flooding in a catchment. However, there is no study available comparing the Feed Forward Back Propagation method, Multiple Regression Model, and the Rational Method in a rainfall-runoff modeling based on daily runoff and precipitation records from a well-protected forested watershed in a subhumid climatic region. Furthermore, compared to this study, most of the studies examined hydrological modeling in larger river basins consisting of different land use types (Agarwal and Singh 2004; Mutlu et al. 2008; Sohail et al. 2008; Johnston and Smakhtin 2014). In this study, the rainfall-runoff modeling in a small watershed within the boundaries of Istanbul, Turkey was accomplished using the conventional multi linear regression (MLR) method and the artificial neural network (FFBP) method. Before considering the application of the method, the description of the flow measurement system was presented in detail. The rainfall-runoff modeling study was accomplished using the daily total rainfall and the daily mean flow records. The performance of the two estimation methods for the peak and low flows was investigated. In the final part of the study, concentration was focused on

modeling the maximum discharges on the same watershed. For this purpose, the Rational Method was employed and the appropriate flow coefficient (C) value was determined.

2 Description of the Methods Used

2.1 Feed Forward Back Propagation (FFBP) Method

Given a training set of input–output data, the most common learning rule for the multi-layer perceptrons defining the network is the feed forward back propagation algorithm (FFBP). A neural network with such type of learning algorithms is usually referred to as a back-propagation network (BPN). Back propagation involves two phases: a feed forward phase in which the external input information presented to the input nodes is propagated forward to compute the output information signal at the output unit and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and observed information signals at the output units (Eberhart and Dobbins 1990).

The neural network employed in this study possessed a three-layer learning network consisting of an input layer, a hidden layer and an output layer. The average system error or mean square error (MSE), E, for all input patterns is:

$$E = \frac{1}{2N}\sum_{p=1}^{N}\sum_{n=1}^{m}\left(T_{pn}-O_{pn}\right)^2$$

where;

T_{pn} is the target value for the for the p^{th} pattern and O_{pn} is the neural network output value for the p^{th} pattern.

The aim of the back propagation algorithm is to minimize iteratively the averaged square error. During the training procedure, two quantities, called the momentum rate, α, and the learning rate, η, were used to improve convergence and to provide the step size, respectively. In this study, adaptive momentum- and learning rate values were employed.

2.2 Multiple Regression Model

If y is a dependent variable and $x_1, x_2, \ldots x_i$ are independent variables, then the basic linear regression model is given by (Metcalfe 1997):

$$y = a + b_1x_1 + b_2x_2 + \ldots + b_ix_i$$

where;

a and the b_i are constants

2.3 The Rational Method

The Rational equation is the oldest and simplest method to determine peak discharge from drainage basin runoff. It is still the most common method used for the sizing of sewer systems. The Rational equation is,

$$Q = CIA$$

where;

Q is the peak discharge (m^3/s), C represents the Rational method runoff coefficient, I is the rainfall intensity (m/s) and A corresponds to the drainage area (m^2).

The Rational method runoff coefficient (c) is a function of the soil type and drainage basin slope. The Rainfall intensity (i) is typically found from Intensity/Duration/Frequency curves for rainfall events in the geographical region of interest. The duration is usually equivalent to the time of concentration of the drainage area. The storm frequency is typically stated by local authorities depending on the impact of the development. A 10-yr, 25-yr, 50-yr, or even 100-yr storm frequency may be specified.

3 Data Analysis

3.1 Description of the Study Watershed and Data Collection

The study watershed was selected as a representative of Belgrad Forest (41° 13′ 00″–41° 14′ 13″ N and 28° 54′ 25″–28° 56′ 37″E), which is the only preserved natural oak-beech forest ecosystem in Istanbul, Turkey. It has several watersheds draining into old small dams built in 17, 18, and 19th centuries. The watershed is typical of Belgrad Forest in terms of deciduous forest cover, soil type, parent materials, and topography. It covers an area of 77.50 ha with a slope of 14 % and a drainage density of 3.8 km/km^2. The study site is about 3–4 km far away from the Black Sea and has a humid, mesothermal and oceanic climate with a moderate water deficit in the summer months (Özhan et al. 2005). Annual precipitation averages around 1091 mm and most of it falls between October and March. The Mean annual temperature is 12.8 °C.

Soils of the study site are developed mainly from neocene deposits and Carboniferous clay schists. The soils, formed from Carboniferous clay schists are generally shallow to moderately deep, consisting of gravely, loamy clay with good permeability rates greater than 30 cm/h while the soils derived from Neocene deposits consist of deep loamy clay in the surface horizons and clay in the subsoil with medium permeability rates (Balcı et al. 1986). Soils have high erodibility potentials with no carbonate reaction. Deep topsoil of the study area has a saturation capacity over 40 % while subsoil has over 25 % (Özhan 1977). The area has forest floor with an average depth of 5 cm. Elevation of the watershed ranges from 97 to 187 m. The vegetation mainly consists of completely deciduous trees of the *Quercus* species and *Fagus orientalis* L., mixed with varying amount of *Carpinus betulus* L., having a crown closure of around 75–100 %.

The experimental watershed was monitored from October 1979 to June 1996 inclusive for the streamflow measurements. Stream discharge was recorded with an Elliott round chart recording system in a 120° concrete sharp-crested, V-shaped notch weir. The precipitation data were obtained from the nearby Bahçeköy Meteorological Station of the State Meteorological Works.

Graphical analyses were performed on the hydrographs of charts from the water-level recorder and mean daily flows were computed as cubic meters per second by using the following formula:

$$Q = C.H^n$$

where;

Q is the discharge (m^3/s^{-1}), H is the stage (m), C is a constant taken as 2.35 dependent on the angle of the weir opening and units of measurement and n is an empirical coefficient taken as 2.48 (King and Brater 1954). Then, the discharge values were converted from cubic meter per second to liter per second for statistical analysis.

3.2 Statistical Analysis of the data

The daily total rainfall and the daily mean flow data covered the time period between 1 October 1979 and 30 June 1996. In total both time series consisted of 6155 daily values. The basic statistical parameters of the flow and rainfall data were presented in Table 1. The unit of the flow was liter per second (l/s) and the rainfall was measured in mm. Both flow and rainfall series have quite high skewness values (c_{sx}=11.19 for the flow, c_{sx}=6 .62 for the rainfall). It was shown that the ANN estimation performance was negatively affected if the hydrologic series were highly skewed (Altun et al. 2007). The X_{max}/ X_{mean} ratios for the flow and rainfall data had extremely high values (111.61 and 74.86, Table 1). The effect of the cross- and autocorrelations on the determination of the number of nodes in the ANN input layer was analyzed in detail by Sudheer et al. (2002). The first and second order autocorrelations of the flow series were equal to 0.51 and 0.24, respectively (Table 1). The first and second order cross correlations between rainfall and flow were equal to 0.29 and 0.19, respectively (Table 1).

4 Application of the Estimation Methods

The observed data were divided into two time periods, i.e., by split-sampling, for the training and testing stages. The training data consisted of the first 4992 daily flow and rainfall series for the time period between 1 October 1979 and 22 May 1993. The remaining 1133 daily values, corresponding to the time period of 23 May 1993 to 30 June 1996, constituted the testing data. In the present study, the "Early stopping" technique was employed. In this method, the training set was splited in two subsets: the estimation and the validation. Accordingly, the 75 % of the first 5000 values in the training set (3750 values) was considered for estimation and the last 1250 values for the validation. The mean square error (MSE) was computed at each training step by means of the validation subset, while the search direction was computed by means of estimation subset. The training was stopped as soon as the validation error rate started to go up. The number of iterations required was found using this method. The statistics for the training and testing flow data were presented in Table 1. Accordingly, the skewness values for both data sets were seen to be similar although the period maximum values differed from each other (X_{max}=838.2 l/s and 413.3 l/s) for the training and testing periods, respectively (Table 1). For the flow estimation two methods were employed: the feed forward back propagation (FFBP) and the multi-linear regression (MLR).

Table 1 Statistical parameters of the observed flow and rainfall series

	X_{mean}	S_x	C_{sx}	X_{max}	X_{min}	X_{max}/ X_{mean}
Flow (whole Series)	7.51 l/s	33.75 l/s	11.19	838.2 l/s	0	111.61
Flow (training period)	7.93 l/s	35.69 l/s	10.88	838.2 l/s	0	105.70
Flow (testing period)	5.64 l/s	23.28 l/s	11.21	413.3 l/s	0	73.28
Rainfall (whole series)	2.84 mm	8.25 mm	6.62	212.6 mm	0	74.86
Cross Correlations (Rainfall-Flow)			Autocorrelations (Flow)			
$r_{P(t)-Q\ (t)}$	$r_{P(t-1)-Q(t)}$		r_1	r_2		
0.29	0.19		0.51	0.24		

For the application of the ANN method, the structure of the ANN input layer must be determined. The analysis of the cross- and autocorrelations indicated that the flows of two previous days (Q_{t-1}, Q_{t-2}) and the daily rainfall values at days 't' and 't-1' (R_t, R_{t-1}) can sensibly be employed as input nodes in order to estimate the daily flow value Q_t (Table 1). Hence the FFBP configuration took the form FFBP (4, x, 1) where 4, x and 1 represented the number of nodes in the consecutive input, hidden and output layers, respectively. The number of nodes in the hidden layer, on the other hand, was found simply by trial and error. The performance evaluation criteria values (R^2 and MSE) for the testing period, obtained by the FFBP for different numbers of nodes in the hidden layer, were presented in Table 2. Accordingly, the highest R^2 and the lowest MSE values were obtained for 6 hidden layer nodes (R^2=0.63 and MSE=202.03 l^2/s^2). The FFBP estimation results for the testing period were plotted in the form of the hydrograph (Fig. 1a) and scatter plot (Fig. 1b). The hydrograph was plotted in the semi-logarithmic scale in order to distinguish between the FFBP performance for the low-, medium- and high flows (Fig. 1a). The scatter plot was double-logarithmic (a log-log plot), illustrating the estimated flows plotted against the observed measurements (Fig. 1b). The low flows were seen to be slightly over-estimated whereas the medium flows were closely approximated. Some over-and under approximations can be seen for the high flows although the majority of peak flows were closely approximated (Fig. 1).

The multi linear regression (MLR) method was employed for the purpose of comparison. The independent variables of the MLR relation were Q_{t-1}, Q_{t-2}, R_t, and R_{t-1}. The dependent variable was Q_t. Accordingly the MLR relation had the following equation:

$$Q_t = aQ_{t-1} + bQ_{t-2} + c\,R_t + dR_{t-1} + e$$

where;

a, b, c, d and e were the regression coefficients. For consistency, the training period of the FFBP method was also employed for the calibration of the regression equation. The relation so obtained was thereafter applied to the testing data. The coefficients of the regression were presented in Table 3. The MLR estimations for the testing flow series were illustrated in the form of hydrograph (Fig. 1c) and scatter plot (Fig. 1d). The performance evaluation criteria results obtained with the MLR for the testing period were relatively weaker (R^2=0.56 and MSE=249.26 l^2/s^2) compared with the corresponding FFBP values (R^2=0.63 and MSE= 202.03 l^2/s^2). Figure 1c showed that the MLR hydrograph deviated from the observed one for most of the time.

A specific comparison between FFBP and MLR performances in terms of the high and low flows in particular was presented in Fig. 2. The majority of the FFBP peak flow estimates were seen to be in harmony with the observations (Fig. 2a) whereas it was the opposite for the MLR (Fig. 2c). The result was similar for the low flows (Figs. 2b and d). Thus, if we consider the modeling of the rainfall-runoff relation for the extreme flow time periods, i.e., low and high

Table 2 The performance evaluation criteria (R^2 and MSE) values for the testing period obtained by the FFBP for different hidden layer node numbers

Performance Evaluation Criteria	Hidden Layer Node Number				
	5	7	8	6	4
R^2	0.41	0.51	0.39	0.63	0.51
MSE (l^2/s^2)	244.00	225.38	240.81	202.03	266.00

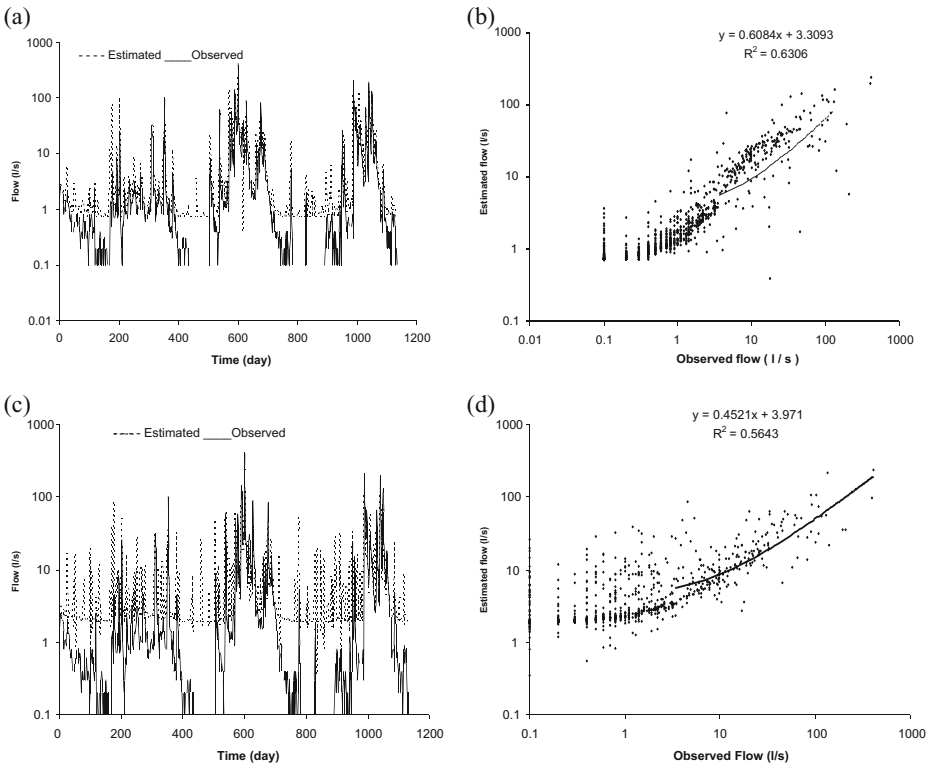


Fig. 1 Estimated flows in the form of hydrograph (**a**) and scatter plot (**b**) by FFBP and in the form of hydrograph (**c**) and scatter plot (**d**) by MLR

flows, then the employment of the ANN method provides closer estimations, capturing better the general behavior of the observed hydrograph. The comparison of the statistics obtained by the different methods for the testing period was presented in Table 4. The standard deviation, S_x, and the X_{max} values of the FFBP estimations were closer to the observed values compared with those of the MLR. Both methods provided nearly identical mean values (Table 4). The skewness of the MLR estimations was, however, closer to that of the observed series. For the zero flow observation (X_{min}) in the testing period, the MLR provided a negative estimate whereas the FFBP estimate was slightly above zero (Table 4).

4.1 Determination of the Peak Discharge using the Rational Method

The sudden peak discharges for different return periods were quite significant for the determination of the flood protection strategies. Although the daily mean flow estimation study with FFBP provided successful approximation for the peak daily mean flows, for the modeling

Table 3 The coefficients of the regression equation

a	b	c	d	e
0.475	−0.008	0.227	−0.020	0.002

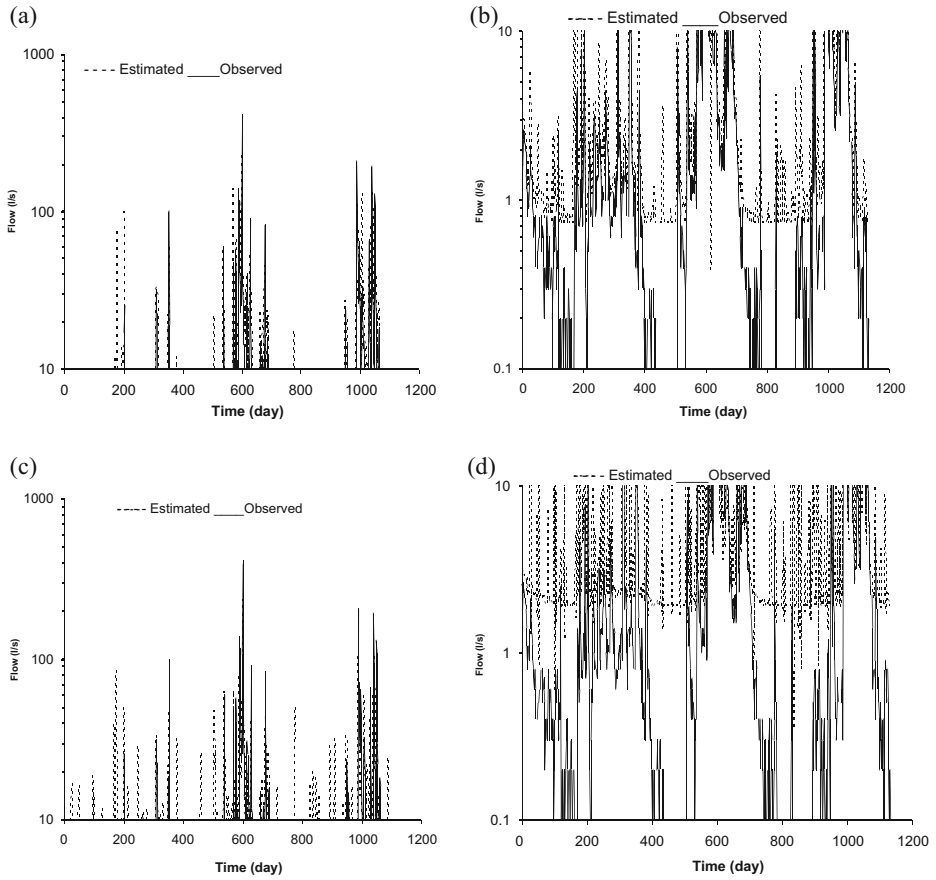


Fig. 2 Estimated flows for the testing period: high (**a**) and low flows (**b**) by FFBP and high (**c**) and low flows (**d**) by MLR

of the sudden peak discharges it was decided to employ another well known method, i.e., the 'Rational Method'. The rational method is a conventional, frequently used method in hydrology for determining peak discharge. It is given, in the SI system, as

$$Q = C.I.A \Big/ 360$$

where;

Q is the peak discharge (m^3/s), C is the runoff coefficient (dimensionless), I is the rainfall intensity (m/s), and A is the drainage area (m^2) (Balcı and Özyuvacı 1989).

Table 4 Statistical parameters of the observed and estimated series for the testing period

	X_{mean} (l/s)	S_x (l/s)	C_{sx}	X_{max} (l/s)	X_{min} (l/s)
Observed	5.64	23.28	11.21	413.30	0
MLR	6.53	14.03	8.75	234.29	−0.24
FFBP	6.75	17.85	6.43	243.03	0.39

In this method, the basic problem is the estimation of runoff coefficient. Various coefficients were proposed for the forest ecosystems in literature ranging between 0.05 and 0.25 (Randolph 2004; Brikovski 2007). In this wide range, 2 values were tested (C=0.1, C=0.2) in computations because reliable information was not available the forest ecosystem in consideration. The first C coefficient value, 0.1, was suggested according to the hydrologic soil group of the watershed, which was symbolized as B. The second C coefficient value, 0.2, was also used according to results of our 17 years of long term paired experimental watershed study (Özhan et al. 2008). The rainfall intensity (I) values were obtained from The Frequency Atlas of Maximum Rainfalls in Turkey (D.S.I 1970) as 23, 28, 31, 36, 40, and 43 mm/hr for the following 6 different return periods T=2.33, 5, 10, 25, 50 and 100 years, respectively. The corresponding peak discharge values, Q, were computed subsequently for those two selected C values (Table 5). As seen in Table 5, the Q values proportionally increased when the C value was doubled. This showed clearly that the determination of the C value was very important in the prediction of the peak discharge. The maximum Q value was predicted as 1330 l/s when C was taken as 0.2 for the ten-year return period. In our experimental watershed, the maximum measured discharge was 1332 l/s on 30 November of 1981. Thus, whereas the maximum Q in the 17—year monitoring period was measured as 1332 l/s, the peak discharge predicted by using the Rational formula (for the ten-year return period) was found to have virtually the same value, i.e., 1330 l/s. This near-equality suggests that a C value of 0.20 for Rational Method may be reasonable for other similarly-sized areas in the region having conditions similar to those of our study watershed.

Even though different models were compared in our study and others, results of this study were consistent with the results of some other studies that FFBP model showed a better performance than the others (Agarwal and Singh 2004; Rai and Mathur 2008; Sohail et al. 2008; Seckin et al. 2013). Contrary to our results, Singh et al. (2010) found that performance of M5 model tree was better than ANN model for the estimation of mean annual flood in Indian catchments. These differences can be due to differences in the watershed characteristics, variability in the precipitation and runoff data, and length of the study periods. Therefore, further studies are still needed under different conditions to find a reliable modeling method.

5 Conclusions

The presented study dealt with the performance analysis of two different methods for the rainfall-runoff modeling of a small watershed in Istanbul Turkey, i.e., the multi linear regression (MLR) and the ANN method feed-forward back-propagation (FFBP) method. The results showed that the FFBP network captured the general shape of the observed flow hydrograph better than the MLR, although admittedly neither could be considered as being really ‘good’. This conclusion was supported by the relatively better performance of the FFBP network

Table 5 Peak discharges computed using rational method for two different runoff coefficient values

Return periods (years)	2.33	5	10	25	50	100
I (mm/hr)	23	28	31	36	40	43
C=0.1	495 l/s	603 l/s	665 l/s	775 l/s	861 l/s	926 l/s
C=0.2	990 l/s	1206 l/s	1330 l/s	1550 l/s	1722 l/s	1851 l/s

according to the mathematical model evaluation criteria applied. The extreme flows (high and low values) are also found to be better approximated by the FFBP network. This result was quite significant from the point of flood modeling studies on this watershed.

The estimation of sudden peak discharges with the Rational Method resulted in higher peak discharge values compared with the daily maximum mean runoff. Therefore, peak discharge estimated by the rational method was higher than the daily high flows produced by the MLR and FFBP methods. The runoff coefficient C=0.2 provided a peak runoff estimation for the 10 year return period that was quite close to the experimental studies.

The study suggests that the ANN method can provide quite reasonable estimation of daily mean flow peaks. In order to obtain such close approximations for a time interval such as 1 h the ANN method would have to be trained for the hourly data. Clearly the ANN estimations for shorter time intervals can provide more sensitive information concerning the floods. In the absence of hourly (or other short time intervals) data, however, the employment of the Conventional Rational Method may provide useful information on sudden peak discharges corresponding to various return periods. For the flood protection, the river cross-sections are designed so that the computed peak discharges are transported safely. The distance between the flood protection zone and the nearby settlement area can be controlled in the light of such flood estimation studies.

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