ESTIMATION OF RAINFALL-RUNOFF RELATIONSHIP USING SOFT COMPUTING TECHNIQUES

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Abstract. The estimation of rainfall-runoff data is crucial for managing basins, preventing or mitigating flood disasters, making better use of water resources, and designing hydraulic structures. In this work, 1802 days of precipitation, runoff, and temperature data from the Quinapoxet River, which supplies the Wachusett Reservoir in the state of Massachusetts, USA, were used to develop models. The rainfall-runoff relationship was predicted using this data as input for Multiple Linear Regression (MLR), Artificial Neural Network (ANN), Support Vector Machines (SVM), and M5 Decision Tree (M5T) techniques. The results of each model were compared with the site measurement data separately. The models are compared with each other according to the three criteria, namely, the root-mean-squared error (RMSE), mean absolute error (MAE), and the correlation coefficient (R). It has been found that Artificial Neural Network (ANN) models perform better in runoff prediction compared to the other models.
Keywords: *prediction, flow, hydrological parameters, neural network, statistical approach*

Introduction

In hydrology, flow and precipitation are the most crucial variables. When it comes to designing and implementing projects for flood control, water supply, and building water structures like hydroelectric power plants for energy production, engineers must accurately analyze the amount of precipitation that falls in a basin, moving through specific stages and finally turning into runoff. It is significiant to understand the translation of rainfall to runoff to estimate streamflow properly for the objectives of various water resource projects. These analyses can be carried out using precipitation data on a daily, monthly, and annual basis. The results are consistent when the data is steady and has a large recording range. The link between rainfall and runoff can be found using two methods in general. These Black Box models fall under the categories of systems and parametric methods. In great detail, parametric models address the process of converting precipitation into flow, evaluate the hydrological parameters such as infiltration, evaporation, surface and subsurface flow in terms of basin scale. Black Box models do not account for physical events that take place in the basin. It is believed that the basin just converts precipitation into runoff, acting as a mathematical function. In recent years, planning for hydraulic and water infrastructure has made extensive use of artificial intelligence techniques, commonly known as black box models (Tasar et al., 2017; Kaya et al., 2018; Unes et al., 2020; Unes et al., 2021). Because of their generalization qualities, Artificial Neural Networks (ANN) derived from black box models show excellent learning and problem-solving capabilities (Grosan and Abraham, 2011). An essay written by McCulloch and Pitts (1943) set the groundwork for the first Artificial Neural Network models. They studied electrical circuits with rudimentary artificial neurons. The use of ANN for various issues commonly found in water resources is the subject of numerous studies conducted nowadays. According to several studies (Hsu et al., 1995; Mason et al., 1996; Minns and Hall, 1996; Fernando and Jayawardena, 1998; Guzel et al., 2023) the rainfall-runoff connection is accurately represented by the ANN technique.

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Vapnik (1995) and colleagues (Cortes and Vapnik, 1995) created machine learning techniques known as Support Vector Machines (SVMs). This two-layer structure technique was first created as a mean of interpreting sensor data. A weighted sum of the kernel outputs makes up the second layer, while an unweighted nonlinear kernel on support vectors holding the series of input variables makes up the first. Once support vectors and suitable kernel filters are identified, SVMs can frequently outperform ANN techniques in terms of efficiency. Numerous academics have looked into the idea of employing SVMs to solve hydrological challenges such as rainfall-runoff and stage-discharge relation modeling (Dibike et al., 2001; Pal and Goel, 2006). The challenges of choosing an appropriate model structure and pertinent parameters for precipitation modeling were highlighted (Bray and Han, 2004). SVMs were employed to estimate the daily precipitation of the Hanjiang basin (Chen et al., 2010). The SVM technique was promising in solving forestry-related problems recently, including calculating daily precipitation flow and determining solar radiation (Nieto et al., 2012). SVMs have become popular in recent years, particularly for forecasting water reservoirs (Asefa et al., 2005; Khan and Coulibaly, 2006; Khalil et al., 2006; Hosseini and Mahjouri, 2016).

One artificial intelligence technique, the M5 decision tree method (M5T), is a powerful, computationally demanding, non-parametric approach that can be used for both regression and classification issues. In their investigations, numerous researchers have employed M5T to estimate rainfall-runoff (Solomatine and Xue, 2004; Bhattacharya and Solomatine, 2005; Rao et al., 2007). Using the M5T decision tree method, Sattari et al. (2013) examined the daily stream flow potential in the Sohu River, Ankara, Turkey. The M5T results were compared with support vector machines (SVM).

This study used data from observation station 01095375, which is situated in the Quinapoxet River in the United States. The data included 1802 days of rainfall, temperature, and runoff measurements. Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), Support Vector Machines (SVMs), and M5 Decision Tree (M5T) were used to try and determine new flow values, and the outcomes were compared with each other. This study aims to add new data to the literature for hydrologists by using different models in rainfall-runoff estimation.

Material and methods

Study area

The Quinapoxet River, which feeds the Wachusett Reservoir (latitude 42°22'22" and longitude 71°49'43") at Canada Mills Near Holden, in the state of Massachusetts USA, was chosen as the study area. In northern Massachusetts, the Quinapoxet River is a member of the Nashua River basin. It is a component of the water system run by the Massachusetts Water Resources Authority, which provides drinking water to the greater Boston area. In this study, data from the Quinapoxet River station of the Wachusett Reservoir, which has a drainage area of 140 km^2 was used. The elevation of river is 244 m. Station data numbered 01095375 was received from the United States Geological Survey (USGS). The location of the study area is shown in *Fig. 1*.

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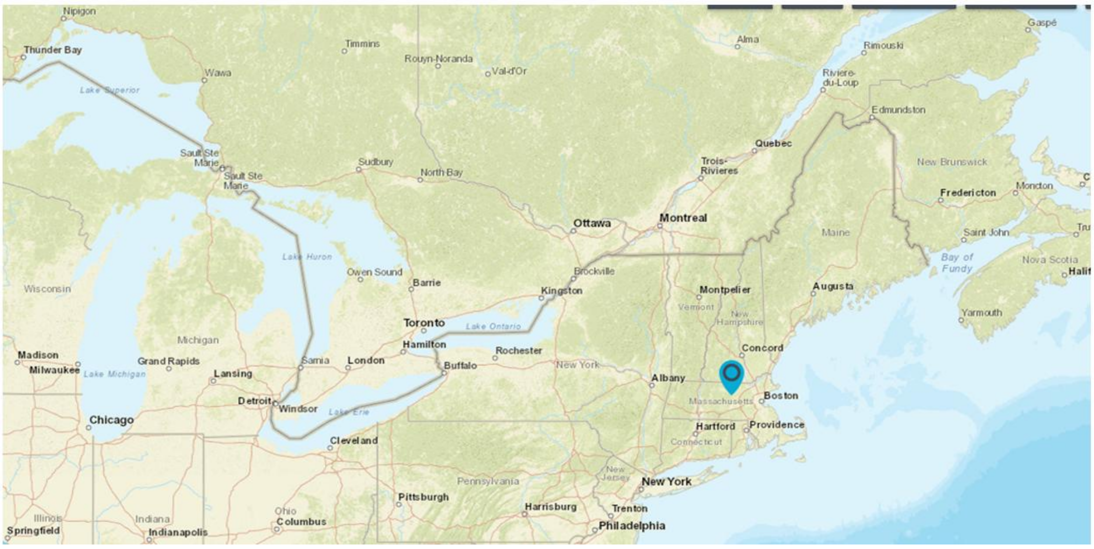

Figure 1. *Study area*

Methods

In this study, the data taken from the aforementioned station which includes 1802-day rainfall, runoff and temperature information between 2019 and 2024 were used to predict runoff. Four different models, namely, Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), Support Vector Machines (SVMs) and M5 Decision Tree Method (M5T) were used to obtain the results. The following sections detail the models employed in this study.

Multiple linear regression (MLR)

In events encountered in nature, there are many variables that affect the event. These variables are classified as dependent and independent variables according to the way the event occurs. Predictions were made by trying to determine the relationship between these variables using the Multiple Linear Regression (MLR) method. Good estimation results show that the relationship between the variables is linear. Below is the *Equation (1)* created to establish this relationship. In equation (1), $X_1, X_2 \ldots\ldots\ldots X_j$ is defined as the independent variables, Y as the dependent variable , and ε as the error term.

$$Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \ldots \ldots + \beta_j X_j + \varepsilon \qquad \text{(Eq.1)}$$

As seen in the *Equation (1)*, the β_j regression coefficient corresponds to the unit change in Y depending on each X_j value.

Artificial neural networks (ANNs)

Many traditional mathematical methods make certain assumptions and focus on linear problems, however fail to represent and solve the non-linear dynamic problems of the rainfall-runoff relationship. The transformation of rainfall into runoff over basin is a very complex, highly nonlinear, and variable in both temporal and spatial scales. The Artificial Neural Network (ANN), which mimics the functioning of neurons in the human brain, is a black box model that gives successful results in this sense. The ANN technique for

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modeling the inherently non-linear problem of rainfall-runoff has added a new dimension and has been applied in recent years, as a successful prediction tool, to solve many problems related to hydrology and water resources issues. It has the features of learning, generalization, error tolerance, working with incomplete data, trial and error, and using a large number of variables and parameters.

The ANN model consists of cells as shown in *Figure 2*. These are divided into five stages: input, weight, transfer function, activation function and output. Levenberg-Marquardt, Gradient Discent, Resilient Back-Propagation Learning Algorithms, and Gradient Descent with Momentum training algorithms were employed in the study, while ANN models were developed using MATLAB software. Purelin, tagsig, and logarithmic-sig were employed as transfer functions for the output layer and hidden layer during the model-building process. The correlation coefficient (R), mean absolute error (MAE) and root-mean-squared error (RMSE) were used to identify which of these models performed the best. The weight creates the learning ability of the model by establishing the relationship between the input and output defined in the model, and can be adjusted during the calibration or training process until it approaches the correct result (Lu et al., 2012). The weight, which is of great importance in this respect, is multiplied by the inputs and added to the bias value, and the transfer function is obtained by adding the results for each input together. The transfer function is given in *Equation (2)*.

$$net = f(\sum_{i=1}^{N} x_i . w_i + bias_i) \quad \text{(Eq.2)}$$

It is very important to choose the appropriate activation function so that the net output obtained from the transfer function gives the most accurate result. Some Activation functions are; Piecewise linear function, Hyperbolic tangent activation function, and Stepwise activation.

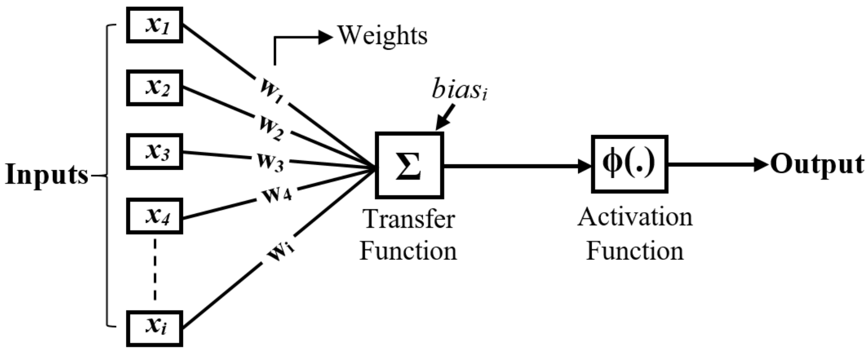

Figure 2. *Artificial neural network system*

Support vector machines (SVMs)

The support vector machines (SVMs) are a machine learning technique used in data-driven research domains (Vapnik, 1995). The foundation of SVMs is statistical learning theory. Basically, SVMs are used to determine which two classes of data can be distinguished from each other the best. Decision boundaries, or hyperplanes, are established for this reason. SVMs are unable to create a linear hyperplane in a nonlinear dataset. Core numbers are utilized for this reason. Machine learning on nonlinear data is

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substantially enhanced by the kernel approach. The SVM estimator (y) procedure in the kernel technique can be written as follows:

$$y = \left(Kx_i . W_{jk}\right) + b \quad \text{(Eq.3)}$$

where W_{jk} is referred to as the weight vector, b is the bias term of the SVM network. Kx_i is a non-linear function that is used for mapping input vectors to a high-dimensional property field.

Figure 3 shows the structure of the three-layer SVM model that was employed in this investigation. The framework consists of three layers: inputs, kernel functions, and outputs. There are several common types of kernels, namely linear, polykernel, and functions with a radial basis. In this analysis, the polykernel function was selected as the most suitable kernel function. The output value of this SVM model example is equal to the product of the three input products and independent combinations of Lagrange multipliers.

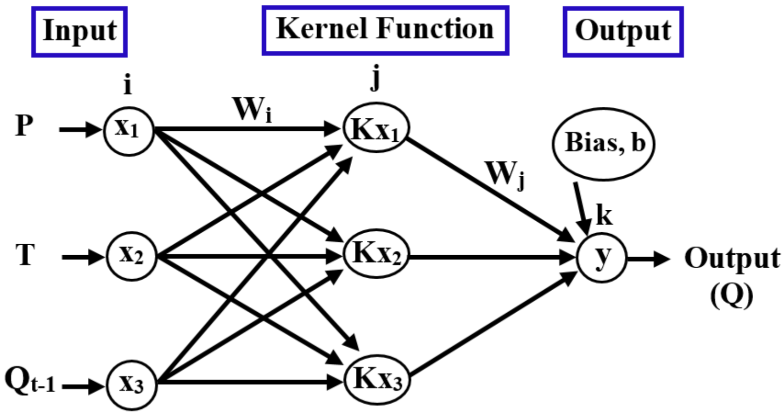

Figure 3. *Structure of the SVM model used in the study*

M5 Decision tree method (M5T)

A decision tree is a binary (two-way split) logical model that illustrates how the values of a set of independent variables can be used to estimate the value of a dependent variable. Essentially, decision trees come in two types: (1) Classification trees are the most commonly used symbolic class for predicting the value of a numerical quantity (2) utilized to predict regression trees. A tree is referred to as a model tree if each leaf has a linear regression model that is used to predict the target variable at that leaf (Quinlan, 1992; Witten and Frank, 2005). This method is described in brief below. Using tests on a single variable that maximizes the variance in the target space, the M5 method iteratively splits the sample space to produce a regression sequence. The standard deviation reduction (SDR) can be calculated using the following formula:

$$SDR(T) = sd(T) - \sum \left(\frac{T_i}{T}\right) * sd\ (T_i) \quad \text{(Eq.4)}$$

In *Equation (4),* the subset of samples that come from the potential set is denoted by T_i, the standard deviation is represented by sd, and T stands for the set of samples that

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reach the node. After the tree has developed, each data of the internal node and all attributes that took part in the tests in that node's subtest are used to generate a linear multiple regression. After that, to solve the oversized tree issue, each subtree is considered during the pruning process. When the expected error for a subtree is equal to or less than the estimated error for a linear model at its root, the subtree is pruned. Therefore, the final version of the created tree exists based on the error reduction procedure and the pruning stages.

The performances of the created soft computing models were tested using statistical approaches. The correlation coefficient (R), root-mean-squared error (RMSE), and mean absolute error (MAE) criteria were determined to compare and evaluate the predictions of each model (MLR, ANN, SWM and M5T) and measurement data. The root-mean-squared error (RMSE), mean absolute error (MAE), and the correlation coefficient (R) were calculated for each model using *Equation (5)*, *Equation (6) and Equation (7)* respectively,

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Q_{i_m} - Q_{i_p}\right)^2} \tag{Eq.5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Q_{i_m} - Q_{i_p}\right| \tag{Eq.6}$$

$$R = \frac{\sum_{i=1}^{N}(Q_{i_m} - \bar{Q}_m).\left(Q_{i_p} - \bar{Q}_p\right)}{\sqrt{\sum_{i=1}^{N}(Q_{i_m} - \bar{Q}_m)^2 .\ \sum_{i=1}^{N}\left(Q_{i_p} - \bar{Q}_p\right)^2}} \tag{Eq.7}$$

where N is the total number of data samples, Qi_m and Qi_p are the values of measured and predicted runoff at ith time interval, respectively.

Results and discussion

A total of 1802 days of station data were gathered for this study, which aimed to evaluate the link between rainfall and runoff. Out of these, 1442 (or 75%) were utilized for training, and the remaining 360 (or 25%) were used for testing. Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), Support Vector Machines (SVM), and M5 Decision Tree (M5T) were used to make the predictions. In this study, average air temperature (T), runoff (Q_t), the time-lagged runoff (Q_{t-1}), Precipitation (P_t), and the time-lagged Precipitation (P_{t-1}) were used as inputs to estimate runoff. Three different input scenarios were created to assess the performances of the models (see *Table 1*). For MLR1, ANN1, SVM1, and M5T1 models, the average temperature (T), precipitation (P), and runoff (Q_{t-1} one-day lagged) were used as inputs. In the second group, average temperature (T), Precipitation (P), one-day lagged Precipitation (P_{t-1}) and one-day lagged runoff (Q_{t-1}) were used as inputs for the models MLR2, ANN2, SVM2 and M5T2. Lastly, in the MLR3, ANN3, SVM3 and M5T3 models, the average temperature (T), Precipitation (P), and one-day lagged Precipitation (P_{t-1}), one-day lagged runoff (Q_{t-1}), and two-day lagged runoff (Q_{t-2}) were used to estimate runoff. *Table 1* displays compatibility and the effectiveness of the developed models based on the statistical assessments.

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Table 1. *Compatibility and statistical error values of the results for all the models*

Models	Model Inputs	RMSE (m^3/s)	MAE (m^3/s)	R
MLR1	T, P, Q_{t-1}	2.16	0.85	0.797
ANN1	T, P, Q_{t-1}	**2.07**	**0.90**	**0.818**
SVM1	T, P, Q_{t-1}	2.28	0.84	0.781
M5T1	T, P, Q_{t-1}	2.08	0.87	0.815
MLR2	T, P, P_{t-1}, Q_{t-1}	1.90	0.76	0.847
ANN2	T, P, P_{t-1}, Q_{t-1}	**1.58**	**0.63**	**0.914**
SVM2	T, P, P_{t-1}, Q_{t-1}	2.11	0.80	0.813
M5T2	T, P, P_{t-1}, Q_{t-1}	1.67	0.64	0.890
MLR3	T, P, P_{t-1}, Q_{t-1}, Q_{t-2}	1.86	0.74	0.853
ANN3	T, P, P_{t-1}, Q_{t-1}, Q_{t-2}	**1.47**	**0.62**	**0.916**
SVM3	T, P, P_{t-1}, Q_{t-1}, Q_{t-2}	1.81	0.64	0.885
M5T3	T, P, P_{t-1}, Q_{t-1}, Q_{t-2}	1.55	0.62	0.909

T: Average Temperature; P: Precipitation; Q: Runoff; R: Correlation coefficient

The performances of all models were assessed using the root-mean-squared error (RMSE), mean absolute error (MAE), and coefficient of correlation (R). *Table 1* displays the comparison parameters for RMSE, MAE, and R that were derived from the test results which were used to compare the prediction performance of the models with observation data. When the results in *Table 1* were analyzed, the developed MLR3, ANN3, SVM3, and M5T3 models gave the best outputs amongst all the models.

Figure 4, *Figure 5*, *Figure 6* and *Figure 7* for MLR. ANN, SVM and M5T, respectively, display the distribution and scatter plots that illustrate the correlations between the three assembled models and the corresponding observed values.

The MLR models in *Figure 4* showed a strong correlation coefficient and rainfall-runoff estimations that were reasonably close to the actual values. In comparing all MLR models, the MLR3 model performed better and showed low error and good correlation based on the RMSE, MAE, and R (01.86, 0.74, 0.853) criteria listed in *Table 1*.

When the distribution and scatter plots for the SVM models in *Figure 6* were examined, it appeared that there was consistency between the measured values and the predicted values. Among the SVM models, the SVM3 model showed the best performance with low error values and a high correlation coefficient (RMSE: 1.81, MAE: 0.64, and R:0.885) given in *Table 1*. Compared to all other models, the SVM model gave the worst result.

The evaluation for M5T models yielded the following results, as shown in *Figure 7* which displays the distribution and scatter plots of the M5T models. The estimated values were close to the real values when the distribution and scattering patterns were analyzed, and the M5T3 model performed better than the other M5T models according to the RMSE, MAE, and R (1.55, 0.62, 0.909) criteria values displayed in *Table 1*.

In *Figure 5,* when the ANN model results were examined, it was seen that computed runoff values produced by the ANN model compared well with their corresponding observed values. The ANN model results provided the highest coefficient of correlation. When it was compared to all MLR, SVM, and M5T models and with all other ANN results according to RMSE, MAE, and R (1.47, 0.62, 0.916) criteria, the ANN3 model showed the best results amongst all models.

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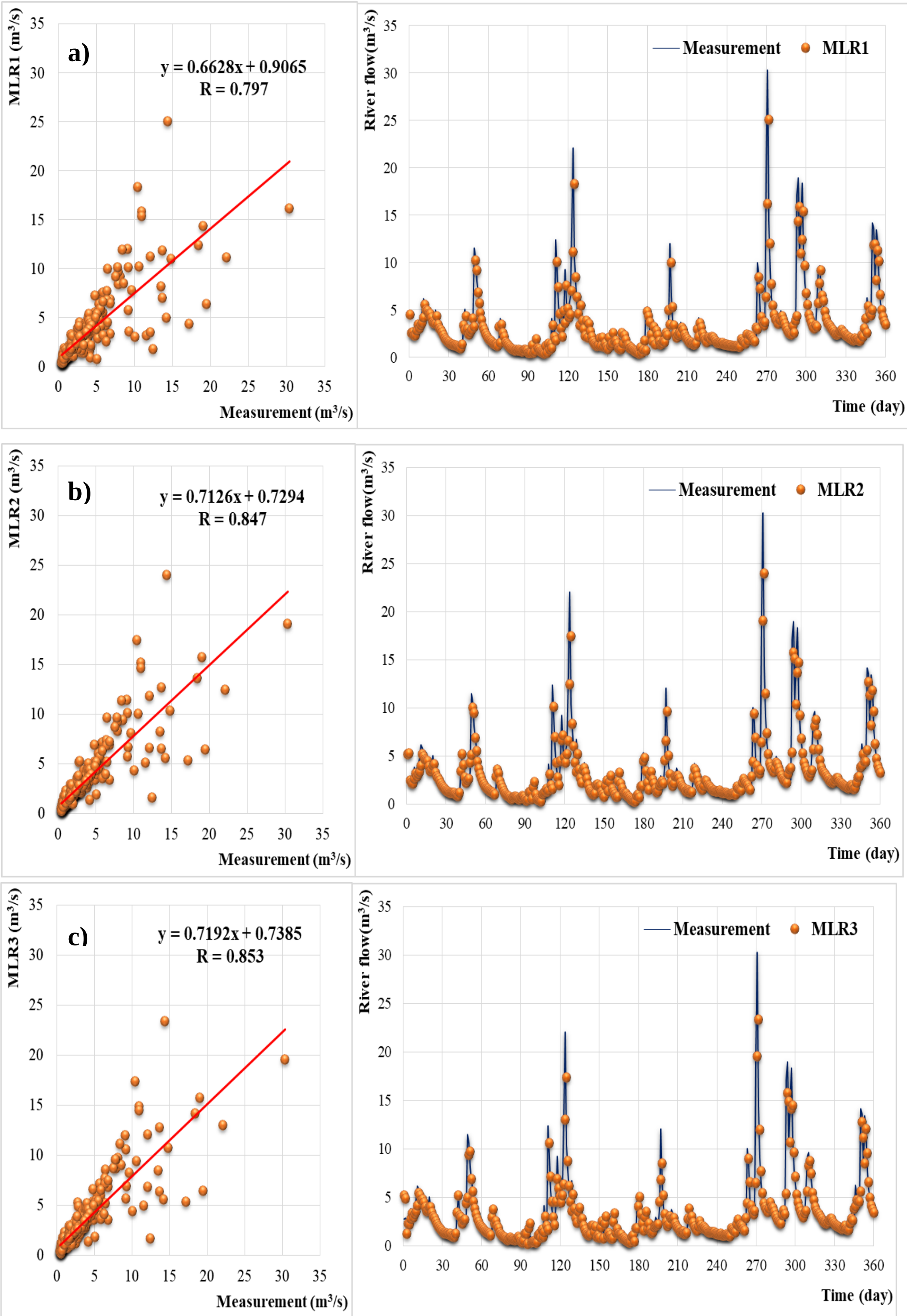

Figure 4. *Distribution and scatter diagrams for MLR models a) MLR1, b) MLR2, c) MLR3*

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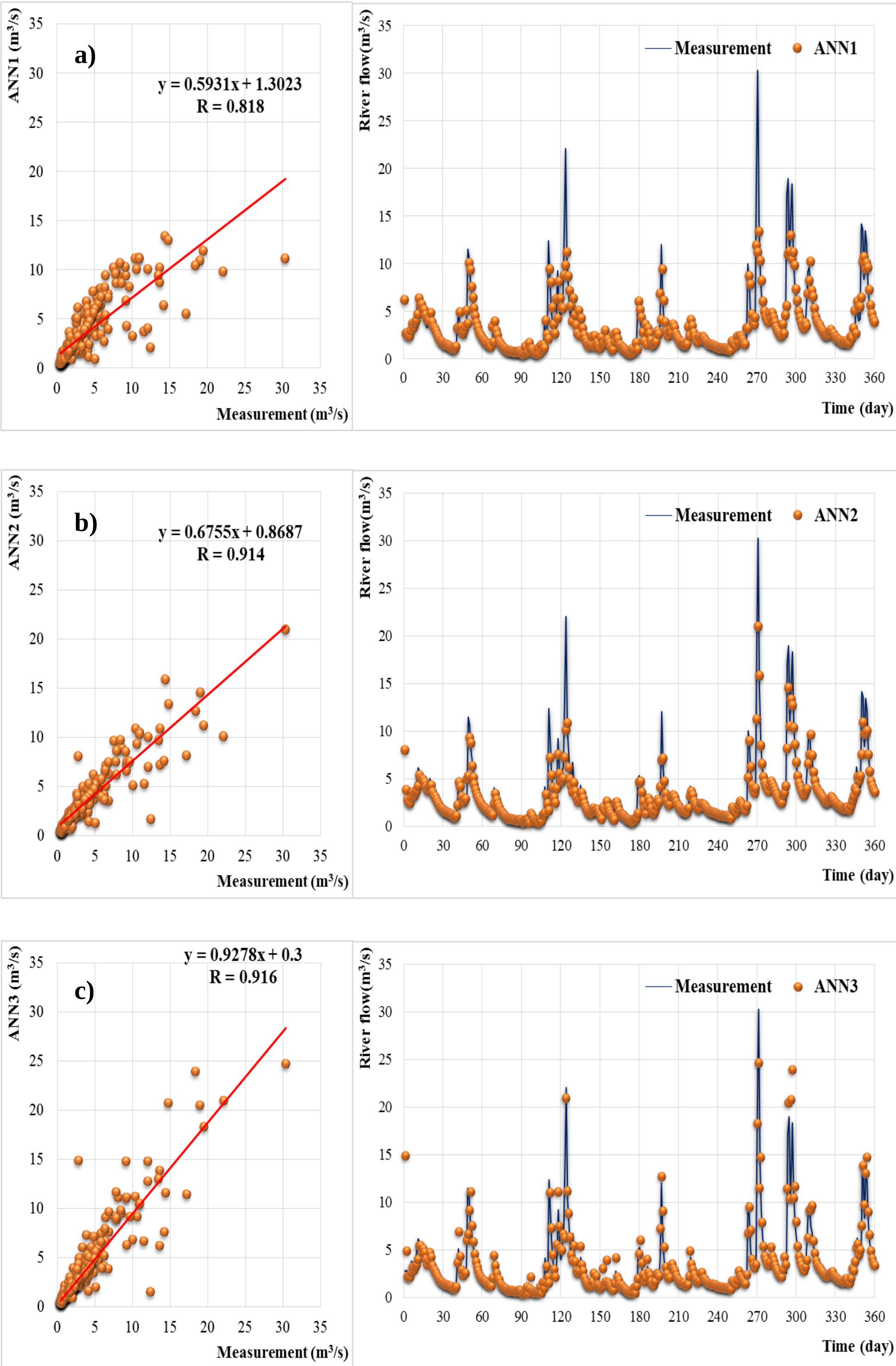

Figure 5. *Distribution and scatter diagrams for ANN models a) ANN1, b) ANN2, c) ANN3*

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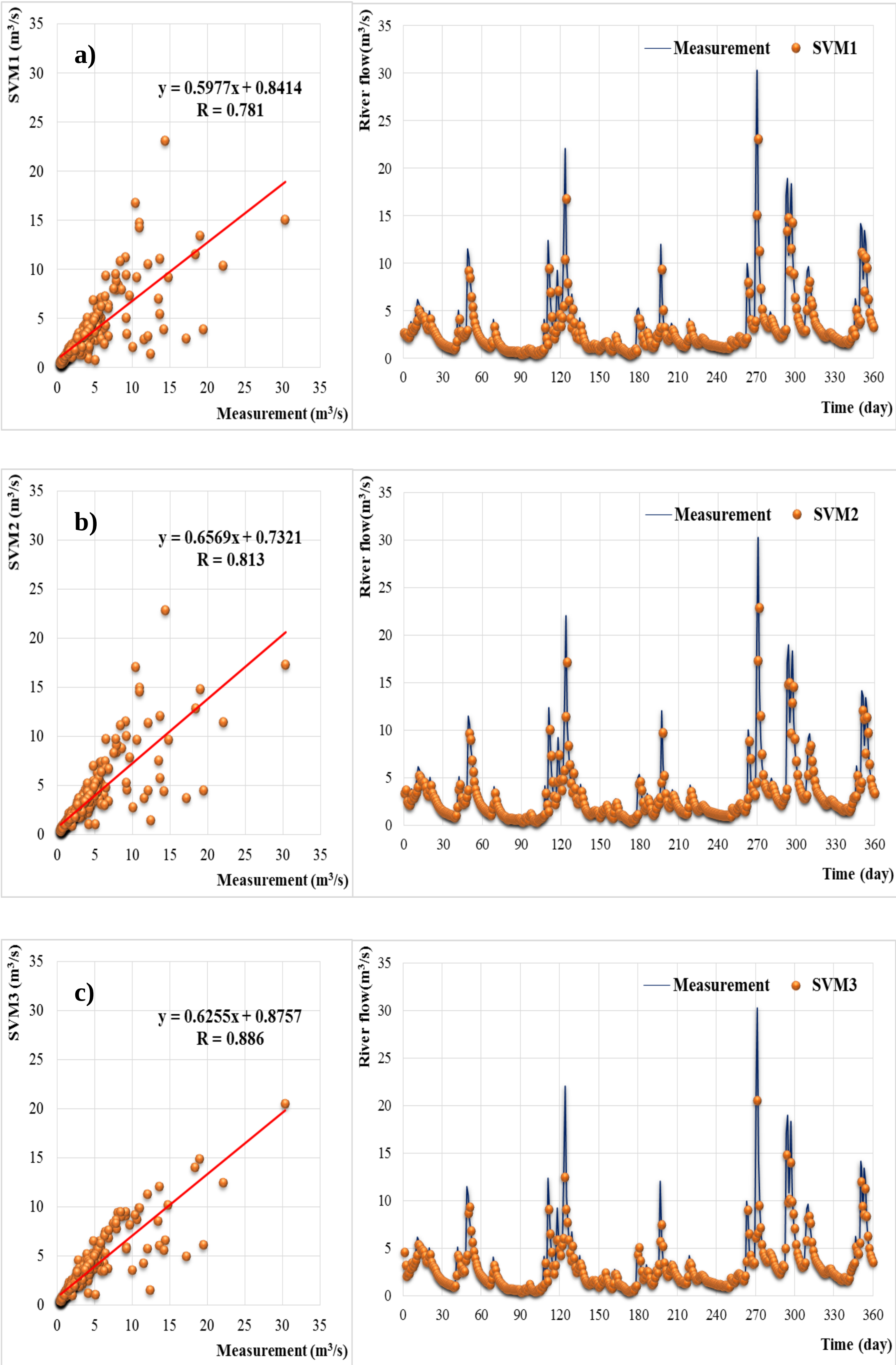

Figure 6. *Distribution and scatter diagrams for SVM models a) SVM1, b)SVM2, c) SVM3*

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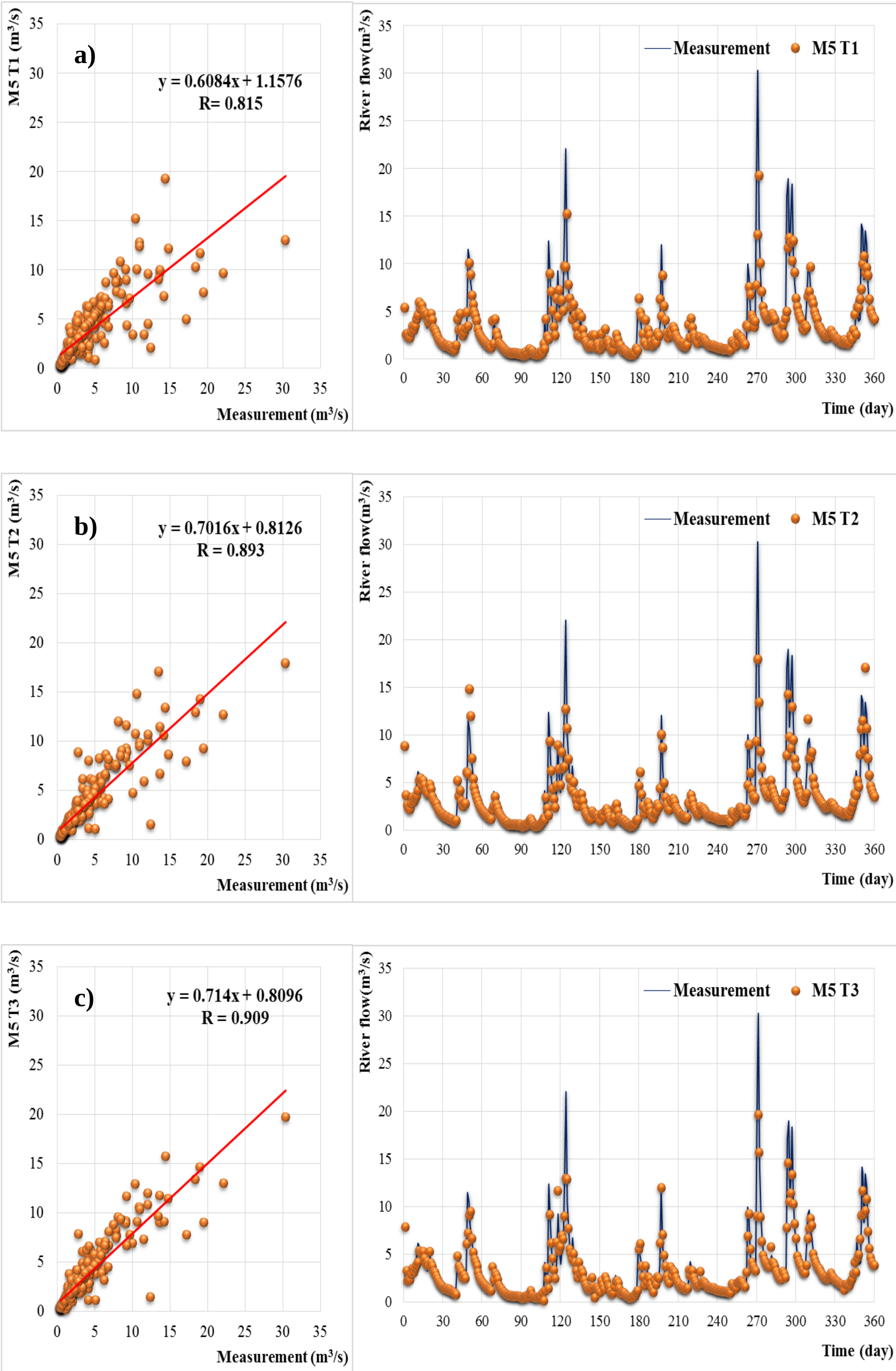

Figure 7. *Distribution and scatter diagrams for M5T models a) M5T1, b) M5T2, c) M5T3*

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Because of its benefits over ANN, a novel alternative kernel-based method known as a support vector machine (SVM) has gained popularity in modeling studies over the last ten years (Okkan and Serbes, 2012). Sharma et al. (2015) used RMSE and R values criteria and sediment estimations. As a result of the modeling, it was determined that the ANN model was summarized and predicted with high correlation results.

Conclusion

The relationship between rainfall and runoff is one of the main concerns of hydrologists and irrigation managers in terms of efficient water use of a basin or sub-basin. Due to the complexity of the phenomenon it is not easy to define this relationship. To overcome these difficulties, applications of the soft computing techniques can be very helpful. Using Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), Support Vector Machines (SVM),s and M5 Decision Tree (M5T) methods, 1802 days of rainfall, runoff and temperature data from the Quinapoxet River basin observation station with the number 01095375 were entered as input and new runoff values were estimated. The link between the models was investigated by contrasting the predicted results with the observed findings. Of the 1802 data utilized in the modeling process, 75% were used in the training phase, and the remaining 25% in the testing phase.

The SVM model had the worst results when evaluated using the MSE, MAE, and R criteria. Research has also indicated that the M5T and MLR model results are more accurate and have fewer error outcomes than the SVM method. Even though it is stated that the SVM model was found to have the worst performance, and the M5T and the MLR are the better models, it is seen that the results of the SVM, MLR, and M5T models are close to each other.

Based on the evaluation and comparison of all models, the ANN models outperformed all the other models in predicting the rainfall-runoff relationship. When it comes to all ANN models, it has been noted that the ANN3 model performs the best in terms of high correlation coefficient (R) and low error (RMSE, MAE) rates.

It has been shown that all of the estimation models developed for this study are highly helpful in predicting the rainfall-runoff, despite the comparison parameters used in the models having pros and cons when compared to one another.

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