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Article

Application of Machine Learning Technique for Rainfall-Run-off Modelling of Highly Dynamic Watersheds

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Abstract: Nowadays, great attention has been attributed to the study of runoff and its fluctuation over space and time. There is a crucial need for a good soil and water management system to overcome the challenges of water scarcity and other natural adverse events like floods and landslides, among others. Rainfall-runoff modeling is an appropriate approach for runoff prediction, making it possible to take preventive measures to avoid damage caused by natural hazards such as floods. In the present study, several data driven models, namely: Multiple linear regression (MLR), Multiple adaptive regression splines (MARS), Support vector machine (SVM), and Random Forest (RF), were used for rainfall-runoff prediction of the Gola watershed, located in the south-eastern part of the Uttarakhand. The performance of the models was evaluated based on the coefficient of determination (R^2), root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), and percent bias (PBAIS) indices. In addition to the numerical comparison, the models were evaluated and their performances were evaluated base on graphical plotting, i.e., line diagram, scatter plot, Violin plot, relative error plot and Taylor diagram (TD). The comparison results revealed that the four heuristic methods gave higher accuracy than the MLR model. Among the machine learning models, the RF (RMSE (m^3/s), R^2, NSE, and PBIAS (%) = 6.31, 0.96, 0.94, and -0.20 during the training period, respectively, and 5.53, 0.95, 0.92, and -0.20 during the testing period, respectively) surpassed the MARS, SVM, and the MLR models in forecasting daily runoff for all cases studies. Among all four models, the RF model outperformed in the training and testing periods. It can be summarized that the RF model is best-in-class and delivers a strong potential for runoff prediction of the Gola watershed.

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Keywords: MARS; SVM; RF; rainfall; runoff; rainfall-runoff modelling

1. Introduction

Forecasting heavy precipitation is an important function in estimating the runoff and flooding in the short to medium term [1–4], flood warning [5], real-time flood forecasting [6], and flood mitigation [7,8]. Nonetheless, rainfall directly affects runoff generation in streams, rivers, and even floods, making it one of the most specific hydrological phenomena [2]. The socio-economic impacts resulting from rainfall are significant, from physical damage in floods to disruptions in transport networks [3,9]. Simultaneously, India is challenged with increasing population and climate change which has created a threat to present freshwater need for irrigation and drinking purpose [10–13]. To overcome from challenges of water scarcity and deterioration of cultivable land, the modelling of rainfall-runoff plays important role. Many aspects of our daily lives depend on the amount of rain we receive [14,15]. Rainfall remains one of the most influential meteorological variables [16]. The rainfall-runoff modelling in water resource management which attracts a lot of researchers and practitioners worldwide. Planning and managing water properly is the only way to prevent water stress and to balance the supply and demand [17–19]. In addition to natural disasters such as floods caused by runoff from precipitation and river flow and droughts caused by shorten of rainfall for long duration, we can also determine the occurrence of these natural disasters by assessing the rainfall–runoff relationship [20].

The major role of several nonlinear variables as well as nonstationary variables in conversion of rainfall into runoff are difficult to comprehend [21]. The response to the catchment precipitation become more complex due to the Moreover, the spatiotemporal variability in rainfall intensity and its uniformity [22]. However, the direct contribution of rainfall in runoff generation and runoff in streams, rivers, and even floods are one of the most focused hydrological phenomena. To understand the accurate relationship between two hydrological variables, the concept of rainfall-runoff (*R-R*) plays a critical role if the area of hydrological science [23]. However, the remaining inconsistency in rainfall–runoff relation, the application of machine learning is promising. These computational techniques either reduce the requirement of modelling parameters or improve modelling accuracy, or even applicable for both purposes [24]. The main aim of this modelling is to improve our understandings of the major's hydrological phenomenon's which influence all watershed system. It also helps to develop a simulation tool to help decision-makers optimize and plan operational rules of the water resource system [25].

In rainfall–runoff modelling [2,26] and rainfall forecasting [27,28], the use of artificial intelligence (AI) and machine learning (ML) established modelling in water resource to a new direction. Several research attempts the application of AI and ML whether for *R-R* or for rainfall forecasting [4,9,29,30], streamflow [31–36], suspended sediment load prediction [36–42], flood forecasting [5,6,43], stage discharge modeling [44–48], soil temperature estimation [49–56], pan evaporation [57–68], reference evapotranspiration [69–78], soil parameter estimation such as infiltration, permeability and saturated hydraulic conductivity [79–88], groundwater quality index [89–92], drought- and stress-tolerance in maize crop [93], water footprint [94,95], rice yield estimation [96] crop coefficients [97]. Artificial neural networks (ANN) gained immense popularity in rainfall–runoff modelling [22,23,28,98] as well as rainfall forecasting [99–101]. Although, there is no requirement for deep knowledge of hydrological processes in AI-based rainfall-runoff modelling [102]. The MLR linear mode is the most common statistical tool to predict the output-input variables and develops a linear relationship between multiple variables [12,103,104]. A quantitative relationship is formed between dependent and independent variables in MLR [105]. The values of the independent variable in MLR are affiliated with the values of dependent variables [106]. The dependent variable, independent variables,

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and intercept are local behavior that is calculated by the least-square rule or different other rules of regression [45].

For *R-R* modelling, AI and ML have been extensively used for many decades [28]. These models have been compared to traditional statistical methods, and conceptual models. the nonlinear MARS is a non-linear and non-parametric regression [107,108]. MARS built several MLR models in the range of the dataset [109]. It is done by creating knots based on splitting strategy and running of suite of linear model for each subset, the nonlinear responses between input and output of a dataset are divided into piecewise linear segments (splines) of different gradients [110]. The SVM is a generalized nonlinear model for both classification and regression analysis, and it was introduced by Vapnik [111]. The basic concept of SVM is to minimize the structural risk, and the algorithm converts the patterns that are not linearly separable to higher-dimensional features space using kernel functions. It attempts to reduce the upper limit of the generalization error. For its advantages over another general algorithm such as ANN, it is a better method in the hydrological field for simulation and forecasting hydrological events. The RF is a supervised ML algorithm based on bagging or bootstrap aggregation, a part of ensemble learning [112].

Al-Sudani et al. [113] hybridized the MARS model using the differential evolution algorithm (DE) and they compared its performances, i.e., MARS-DE, with those of the single MARS and the least square support vector machine model (LSSVM). They reported the superiority of the hybrid MARS-DE. Adnan et al. [114] compared the performance of four ML models, i.e., the optimal pruning extreme learning machine (OPELM), MARS, M5Tree, and MARS- K_{means}. It was found that MARS- K_{means} surpassed all other models for multi-step ahead forecasting, i.e., one, six and twelve hours in advance. In another study, Li et al. [115] evaluated the performances of extreme learning machine (ELM), RF, SVM for forecasting daily, low and peak streamflow, and they reported the superiority of the ELM model.

Therefore, the aim of the present paper is the comparison between the MLR, the SVM, MARS and the RF models for forecasting daily runoff at Gola watershed, located in Southeastern part of Uttarakhand. The study was conducted with major's objectives of selecting the most relevant inputs variables for R-R forecasting and the comparisons of models performances across the studied stations.

2. Materials and Methods

2.1. General Description of Study Area

The Gola watershed is located in the South-Eastern part of Uttarakhand state shown in Figure 1. Gola river is originated in Bhirapani valley near Paharpani village of Uttarakhand state in lesser Himalayas. The river's major tributaries are Kanchi, Kharkai, and Karkari. The watershed lies between 29°16'18" to 29°27'33" N latitudes and 79°46'5" to 79°32'51" E longitudes in Northern India. The total catchment area of the Gola watershed is about 611 km^2. The climatic condition of the Gola watershed is mild and generally warm. The minimum and maximum elevation of the watershed are 252 m and 2302 m, respectively, above mean sea level. Gola watershed comes under a sub-tropical climate with predominant seasonal rainfall. The average annual rainfall is 1699 mm, heavily influenced by monsoon rainfall. As the watershed lies on the Eastern edge of the Himalayan ranges, it is subjected to heavy rainfall. The monsoon season extends from July to September and produces 90% of annual rainfall. The months of July and August receive heavy rainfall in the watershed. Due to this, the mainstream of rainfed rivers like the Gola River has subsequently had high discharge in these months of the year.

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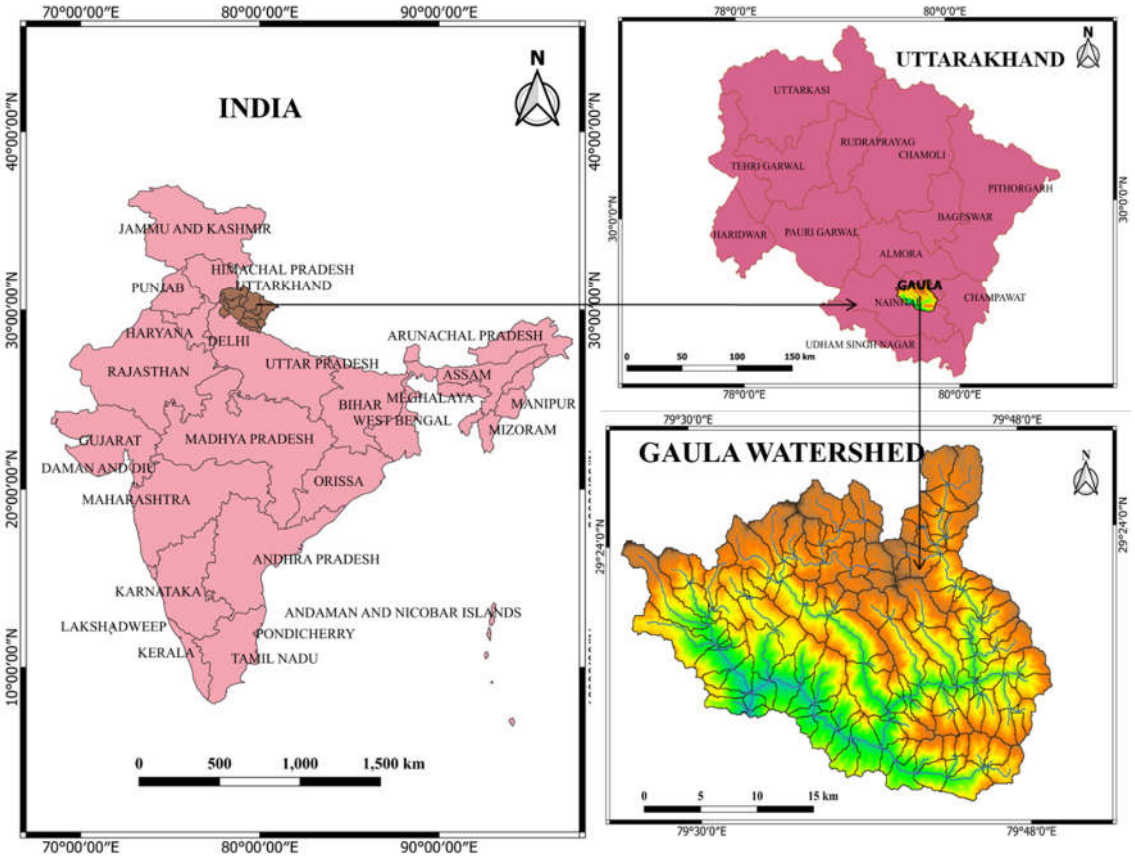

Figure 1. Location map of the study area.

2.2. Data Acquisition and input data preparation

The daily data of rainfall and runoff for 12 years (2009 to 2020) of the study location (Gola watershed) were used to analyze rainfall-runoff modeling. The runoff data of the Gola River was taken from an observation station located at Kathgodam barrage. The rainfall data of three rain-gauge stations, namely- Nainital, Bhimtal, and Kathgodam, was taken from respective irrigation departments (Figure 2a). Thiessen polygon method was used to calculate the mean areal rainfall of the Gola watershed. The plot of rainfall and runoff time series data is shown in Figure 2b and Figure 2c, respectively. The daily data of rainfall and runoff for twelve years were used to develop and validate models.

Table 1. The basic statistics of training, testing, and total rainfall and runoff datasets at study stations.

Statistical Parameters	Mean	Median	Minimum	Maximum	Standard Deviation	C.V. (%)	Skewness
Total Dataset							
Rainfall (mm)	6.45	0	0	172.38	15.60	24.18	3.87
Runoff (m^3/s)	17.22	6.06	1.88	250.03	27.51	15.97	3.80
Training data							
Rainfall (mm)	6.45	0	0	172.38	15.87	24.60	4.02
Runoff (m^3/s)	17.35	5.66	1.38	250.03	28.69	16.54	3.76
Testing data							
Rainfall (mm)	6.89	0	0	111.69	14.47	21.00	3.07
Runoff (m^3/s)	16.83	7.5	1.61	197.08	22.16	13.16	3.59

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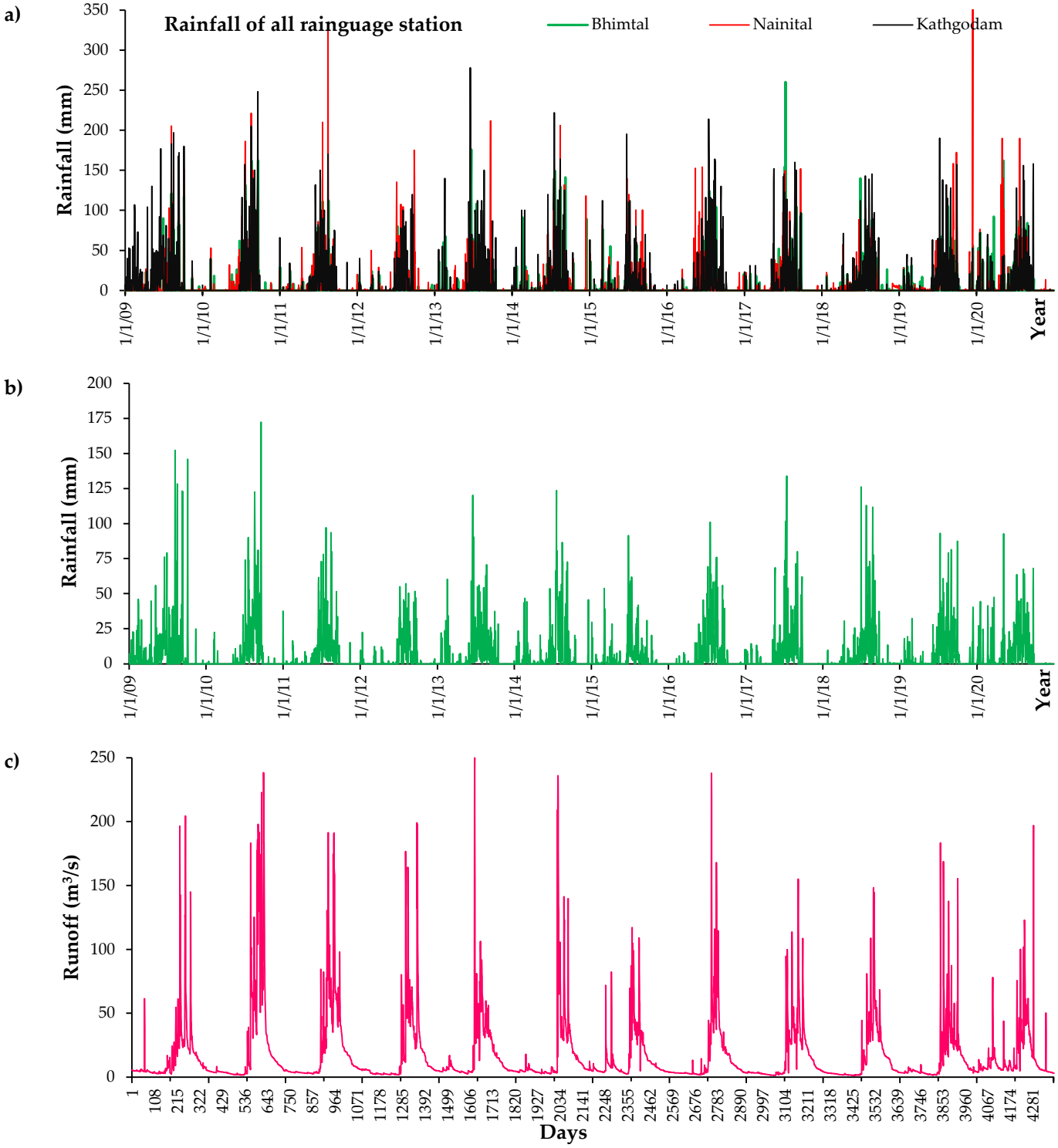

Figure 2. (a) Rainfall data of three rain-gauge stations, namely- Nainital, Bhimtal, and Kathgodam; (b) Mean areal rainfall time-series data of Gola watershed and (c) Runoff time-series data of Gola watershed.

Statistical parameters were used to analyze the time-series dataset for rainfall-runoff modeling of the Gola watershed presented in Table 1. The complete dataset has been divided into training and testing datasets. The first 80% of the complete data was used in training, and the rest 20% was used for the testing period. During the division of datasets in training and testing subsets, cross-validation of the dataset is necessary to have the

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same statistical population. The skewness value of the dataset showed that the distribution was highly skewed. Figure 3 shows the flow chart of the proposed methodology.

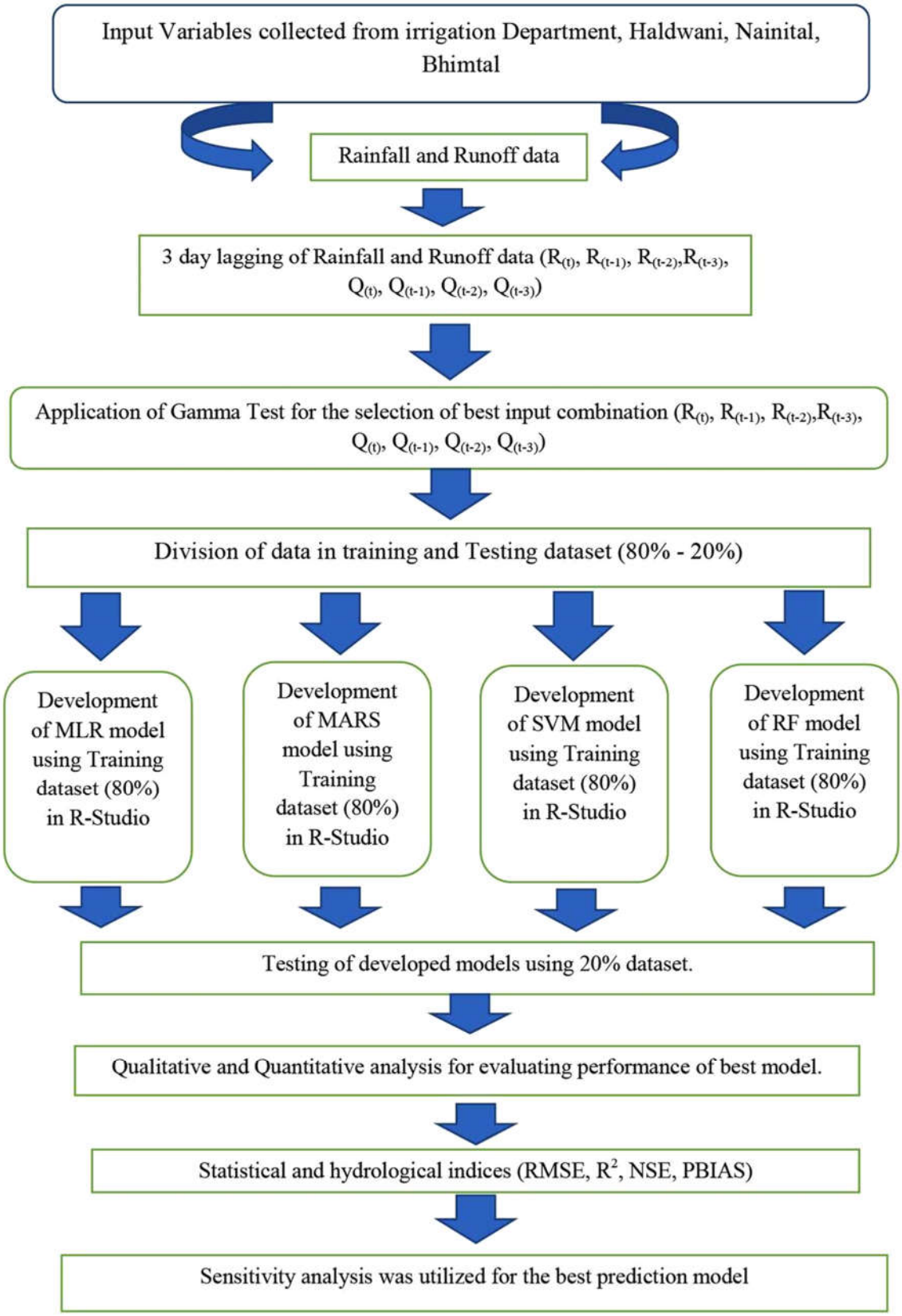

Figure 3. Flowchart of methodology.

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2.3. Gamma test

The Gamma test selects the best input variables in modeling a dataset [47,116–119]. It is a flexible and unbiased tool for evaluating the potential of each input parameter. Traditionally, trial and error methods were used to select the best input variable, making it a very time-consuming and tedious job that includes training and testing of every possible input combination to select the best suitable input vector. It also fails to provide information about the number of data points necessary for calibration to achieve the accuracy of the optimum model. The Gamma test plays a significant role by guiding the selection of various input parameters to develop reliable and smooth models. Non-linear correlation between random variables is evaluated by gamma tests, like the non-linear correlation between input and output pairs. The idea of the Gamma test was first discovered by Stefansson et al. [120] for simulation; it was then another researcher further adapted it for research activity [38,47,121–123]. It was used for estimating the minimum standard error for non-linear models for any input variables [121].

The mathematical gamma test is represented as:

$$\{X_1(i), \ldots \ldots \ldots X_n(i), Y_i\} = \{(X_i, Y_i) | 1 \leq i \leq N\} \quad (1)$$

where X is the $X_1,\ldots, X_n$ correspond to the predictors variables, i. e, m variables for a total of N data points , , scalar Y_i is the output variable, Gamma (Γ) is calculated by building up a linear regression between input (X) and output (Y) as:

$$Y = f(X_i, . \ldots \ldots \ldots X_n) + \Gamma \quad (2)$$

Where f is a smooth function and Γ corresponds to the noise. The overall model complexity is evaluated according to the output of the Eq. 2. More suitable input variables were reflected by a low value of Γ, i.e., close to zero. In addition, based on the obtained gradient value a complicated model is obtained and based on the standard error (SE) of Γ, more reliable gamma value is obtained. In addition, V_{ratio} given by Eq. 3 indicates the predictability of the output variables. A model's complexity can be determined from the output Y of Eq. 2. A value of Γ close to zero indicates a suitable input variables. We has a complicated model when the gradient is high; we have a simple model if the gradient is low. Gamma value is more reliable if the standard error (SE) of Γ is smaller. $V_{ratio,}$ given in Eq. 3, measures the predictability of a variable.

$$V_{ratio} = \frac{\Gamma}{\sigma^2(Y)} \quad (3)$$

Here $\sigma^2(y)$ is the output variance of Y, and Γ is the gamma function. When Vratio is near 0, predictability is higher. We can build a more qualitative mathematical model with smaller values for gamma (Γ), gradient, SE, and V_{ratio}.

3. Multiple linear regression and machine learning techniques for rainfall-runoff modeling

The machine learning techniques, namely, MLR, MARS, SVM, and RF, were used in rainfall-runoff modeling of the Gola watershed. The description of these models is as follows:

3.1. Multiple linear regression

Multiple linear regression is the simplest statistical technique to predict the output from several input variables. The linear relationship is developed between multiple vari-

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ables. In this regression, a quantitative relationship is made by independent and dependent variables. The values of independent variables are related to dependent variables [106].

MLR predicts runoff from input rainfall by taking the dataset into training and testing data periods. The expression for MLR is defined as follows:

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 \dots\dots\dots + \alpha_n X_n \quad (4)$$

where, Y = the output or he modelled variable; X_1, X_2……. X_n = the inputs variables variables; α_0 = intercept, and α_1, α_2…… α_n= Regression coefficients.

3.2. Multivariate adaptive regression splines (MARS)

Multivariate adaptive regression splines (MARS) is a non-linear and non-parametric regression method that built several MLR models across the range of predictor values. It is done by splitting data and running a linear model on each different partition. The non-linear responses between input and output of a dataset are divided into piecewise linear segments (splines) of different gradients [124]. The extensible regression models proposed by mars have the solution space for each model divided into intervals, and splines fit every interval space [125]. There is the creation of a bias function and finding a potential knot location to improve the model's performance result and over-fit. The backstage of the MARS model is done by pruning the ineffective term [126]. The comparison of different subsets of the model is done by the less expansive technique of generalized cross-validation [127]. It is expressed as follows:

$$GCV = \frac{MSE}{\left[1 - \frac{(f+1) + pf}{n}\right]^2} \quad (5)$$

where, MSE= mean square error; f = number of bias functions; p = bias function penalty and n= number of observations.

The MARS model performs under two types of forwarding and backward functions [126]. In the forward stage of function, the model develops a huge quantity of bias functions introduced by the MARS model. The generalized form of the MARS model is given below [128]:

$$Y = \beta_o + \sum_{i=1}^{m} \beta_i H_{ei}\left(X_v(e, I)\right) \quad (6)$$

where, Y = output parameter; β_o = constant value; I= number of bias functions; $H_{ei}\left(X_v(e, I)\right)$ = i^{th} bias function, β_i = the corresponding coefficient of $H_{ei}\left(X_v(e, I)\right)$.

The model has a collection of bias functions. In the second stage, it can estimate the least square model. MARS model is defined as follows [129]:

$$Y = \partial_o + \sum_{i=1}^{n} \partial_i h_i(X) \quad (7)$$

where, $h_i(X)$= splines function; δ= coefficient of the spline function; I = total number of functions in model.

3.3. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a supervised ML model that uses a nonlinear generalization algorithm used to classify two groups and regression problems, The foundation of the SVM was made by Vapnik [111,130]. It was introduced by Bray and Han [131]; Vapnik [111]. SVM are generalized linear classifiers, supervised learning methods

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used for regression and data classification. The kernel allows SVMs to form non-linear boundaries. Different kernel functions like Linear kernel, Polynomial kernel, Radial basis, and Sigmoid kernel. The expression of the algorithm by the inner products of the dataset is called the Dual problem. Support vector regression (SVR) was developed by Vladimir Vapnik [111]. It is characterized by using kernels, sparse solution, and Vapnik-Chervonenkis (VC) controls of margin and many support vectors.

SVR is a powerful tool in real value function estimation. It estimates continuous value multivariate function. It uses a supervised learning approach; SVR trains by taking symmetrical loss functions, reducing high and low misestimation [132]. Support vector regression (SVR) attempts to minimize the upper limit of the generalization error instead of fixing the empirical error. The first formulation of SVR is a hard-margin solution that contributes to overfitting. Soft margin appears to generalize in the presence of outliers and noise. It prevents overfitting, which makes it favorable for forecasting research work. It has high generalization capability and great prediction accuracy. SVM formulate binary classification problems to convex optimization problems [111]. The ε-intense region around the function does SVM generalization to SVR, also called ε-tube. It helps reformulate the optimization problem in continuous-valued function, which helps to balance model complexity and prediction error. Considering the training dataset, T, represented as:

$$T = \{(x_1, y_1), (x_2, y_2) \dots \dots (x_m, y_m)\} \quad (8)$$

$x \in X\ R^n$ are the training inputs and $y \in Y \subset R^n$ are the training outputs. Assume a non-linear function y is given by:

$$f(x)=wT\Phi(xi)+b \quad (9)$$

where, *f(x)* = Non-linear function; T = Training data; W = Weight vector, b = Bias, $\boldsymbol{\Phi}(x_i)$ = higher dimensional feature space by linear mapping function of input space x. The main objective is to fit dataset T with the help of function f(x), having the highest deviation ε from training dataset T. The equation is now transformed into a constrained complex problem as follows:

$$\min.\left(\frac{1}{2}w^T w\right) \quad (10)$$

$$\text{subject to: } \begin{cases} yi - (\mathbf{w^T \Phi(x_i)} + b) \leq \varepsilon \\ yi - (\mathbf{w^T \Phi(x_i)} + b) \geq \varepsilon \end{cases}$$

Where, ε (≥0) is the maximum acceptable deviation. The equation (7) can be written as:

$$\min.\left(\frac{1}{2}w^T w\right) \quad (11)$$

$$\text{subject to: } \begin{cases} yi - \mathbf{w^T \Phi(x_i)} - b \leq \varepsilon \\ \mathbf{w^T \Phi(x_i)} + b - y_i \leq \varepsilon \end{cases}$$

Further, the final expression for SVM becomes:

$$f(x) = \sum_{i=1}^{m} (\alpha_i^+ - \alpha_i^-) K(x_i, x_j) + b \quad (12)$$

where, α_i^+ and α_i^- are the Langrangian multipliers, $K(x_i, x_j)$ is the kernel function. [133].

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3.4. Random Forest (RF)

Random Forest is supervised ML that uses ensemble learning techniques for classification and regression problems. It is a technique that predicts from different machine learning algorithms or the same algorithm several times for more accurate prediction. RF uses the bagging technique or bootstrap aggregation, part of ensemble learning. It is used to create several subsets of data from training samples chosen randomly with replacement. Each subset of data is used to train its decision tree.

The bootstrap aggregation technique reduces the variance of an estimated prediction function. Bagging works excellent for high variance and low bias, such as decision trees. Random forest constructs multiple decision trees at training time. It combines the prediction results from each decision tree to give the final output. Decision trees are computationally expansive; these are very sensitive to data on which they are trained and may get deviation in prediction the underlying data gets changed. Several decision trees are constructed by the algorithm that operates the model. RF is the aggression of tree predictors. The trees are estimated by the values of a random vector computed from the same distribution for each forest tree [134]. In the RF model, every tree is grown with a random subset of variables [135]. It ensures that the bagged trees are in the way that a single tree reduces the correlation and variance between trees of the model. Each decision tree picks a random sample from the dataset while generating its split adds a further element of randomness to minimize the problem of overfitting. The random forest chooses nodes from a random subset of available features that breaks variables at each node to reduce the association between trees. The mean square error (MSE) can be calculated as [127]:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{m}(Z_i - i)^2 \quad (13)$$

Z_i = measured variable value and i= mean of all out-of-bag (OOB) predictions.

The Random Forest model comes under the classification of regression tree (CART) tools and is used for classification and regression problems. Many trees of RF models are key parameters; the model performance can be evaluated by Out-of-bag (OOB). Random Forest can help over-fitting the model for the training dataset, which can be evaded by selecting input data during the training cycle and establishing variation in weak learners [136]. The RF model makes multiple decision trees, and the output of models can be estimated by taking the mean output of every tree. The predicted values are calculated as:

$$Y = \frac{1}{N}\sum_{i=1}^{N} R(x) \quad (14)$$

where, Y = predicted output by RF model, N = number of trees (n-tree) utilized in RF model, and R(x) = results of every random tree.

4. Performance Evaluation of Models

The performances of the MLR, MARS, SVM, and RF models were evaluated based on the coefficient of determination (R^2), root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), and percent bias (PBAIS), and visual interpretation using line diagram, scatter diagram, Violin plot, relative and Taylor diagram. The R^2, RMSE [47,117,137–139], NSE [140], and BIAS [119,141,142] are described as:

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$$R^2 = \left[\frac{[\sum Q_o Q_p] - \left[\frac{\sum Q_o \sum Q_p}{N}\right]}{\sqrt{\left[\sum {Q_p}^2 - \frac{(\sum Q_p)^2}{N}\right]\left[\sum {Q_o}^2 - \frac{(\sum Q_o)^2}{N}\right]}} \right]^2 \quad (15)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_o - Q_p)^2} \quad (16)$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{N}(Q_o - Q_p)^2}{\sum_{i=1}^{N}(Q_o - \overline{Q_o})^2}\right] \quad (17)$$

$$\text{PBIAS} = \left[\frac{\sum_{i=1}^{N}(Q_o - Q_p)}{\sum_{i=1}^{N}(Q_o)}\right] 100 \quad (18)$$

where, Q_o = observed runoff value; Q_p = predicted runoff value; N = total number of values of the variable in the dataset; $\overline{Q_o}$ = mean of observed discharge data.

The coefficient of determination describes the statical relationship (collinearity) between variables and helps to show the nature of association among predicted and observed data. R^2 is the ratio of explained variation compared to the total variation [143]. The coefficient of multiple determination measures the percentage of various independent variables, which could be explained by variation in independent variables when taken together [144]. It ranges from 0 to 1; its higher value indicates less error variance; generally, a value greater than (0.5) is considered acceptable [145,146]. It is famously used in model evaluation. This statistical tool is highly sensitive to outliers and insensitive to additive and proportional differences between observed and predicted data [147]. The square root of the average square of all the errors is called root mean square error (RMSE) [104]. It is an excellent general-purpose error matrix commonly used for the numerical prediction model. RMSE has a good measure of accuracy, but it can only compare the prediction error of models or configure only a particular variable and not between two different variables, making it scalar-dependent. RMSE lies between 0 to ∞ [47]. NSE is a normalized statistical tool that determines the relative magnitude of residual variance or noise. NSE lies between -∞ to 1, and it is less sensitive to high extreme values [140]. Percent bias measures the relationship between observed data and its predicted data; it measures the average tendency of observed data to be larger or smaller than predicted data [148]. Percent bias describes whether the simulated model is over-estimated or under-estimated. A low value or the value that tends to zero of PBIAS indicates the optimal model. A low value or the value that tends to zero of PBIAS indicates the optimal model. The negative value indicates the overestimation of the model. In contrast, the positive value of PBIAS indicates an underestimation of the model [119,141,142,148]. When data is evaluated, PBIAS reveals a deviation of data in percent [149].

The model had higher R^2 and NSE values and lower RMSE and PBAIS values decreed a relatively better model for the simulation of Q_t.

5. Results and discussion

This section deals with developing runoff prediction models using ML techniques for the Gola watershed. Multiple linear regression (MLR), Multivariate adaptive regression splines (MARS), Support vector machine (SVM), and random forest (RF) models were applied to develop rainfall-runoff models for the Gola watershed in Uttarakhand. In the present study total of twelve years of data from 2009-to 2020 (4380 data points) were used, from which 80% of the total dataset was used in training. The remaining 20% were used in the testing period. The use of more data length than the data above length would lead to an overfitting problem due to increased complexity of the learning process, whereas using fewer data compared to standard length would reduce the efficiency of the models

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significantly, as the model would not be able to learn the entire data patterns (Singh et al., 2018). Thus, using length data other than the standard length would hinder developing a potential model. The qualitative performance evaluation of models was done by visual observation, and quantitative evaluation was carried out using different statistical and hydrological performance indices; namely, root mean square error (RMSE), coefficient of determination (R^2), Nash-Sutcliffe coefficient of efficiency (NSE), percent bias (PBIAS).

5.1. Selection of Best input combination

The selection of the most appropriate input variables is a vital part of model development [79]. In the present investigation, the GT algorithm was used for selecting the relevant inputs variables combination for runoff prediction. In this study, various combinations of present-day runoff ($Q_{(t)}$), previous day runoff ($Q_{(t-1)}$), two-day previous runoff ($Q_{(t-2)}$), three-day previous runoff ($Q_{(t-3)}$), present-day rainfall ($R_{(t)}$), previous day rainfall ($R_{(t-1)}$), two days previous rainfall ($R_{(t-2)}$) and three days previous rainfall ($R_{(t-3)}$) were used for testing by Gamma test (Table 2). The models having low Gamma (Γ) and low V_{ratio} values were considered most appropriate for developing models [150]. It could be noticed that the gamma value and V_{ratio} decreased with an increase in the number of predictors. However, after a certain point, the gamma value again started increasing. It might be due to the following two reasons: i) the inclusion of high number of inputs variables may be the cause of overfitting, and ii) inclusion of less number of input variables results in incapacity of the model to correctly provide an explanation of the total variance of the forecasted subset. . The minimum gamma (Γ) and V_{ratio} values were 0.407 and 0.191, respectively, for the M19 predictor set. Hence, the M19 predictor combination was employed for further analysis. It could be stated that using rainfall till two-day lag and the discharge from one to three days lag as a predictor would produce an optimum rainfall-runoff model. It was also noticed that the gamma value and V_{ratio} increased when rainfall of three-day lag was included in the predictors. It might be due to the low correlation of the predictor variable with the predictand.

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Table 2. Gamma statistics for different input combinations.

Model No.	Model input combination	Mask	Gamma	V-Ratio
M1	$Q_{(t-1)}$	0000001	0.082	0.329
M2	$R_{(t)}$, $Q_{(t-1)}$	1000001	0.061	0.244
M3	$R_{(t)}$, $R_{(t-1)}$, $Q_{(t-1)}$	1100001	0.064	0.256
M4	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $Q_{(t-1)}$	1110001	0.056	0.225
M5	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $R_{(t-3)}$, $Q_{(t-1)}$	1111001	0.051	0.207
M6	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $R_{(t-3)}$, $Q_{(t-3)}$, $Q_{(t-1)}$	1111101	0.054	0.217
M7	$Q_{(t-1)}$, $Q_{(t-2)}$	0000011	0.081	0.320
M8	$R_{(t)}$, $Q_{(t-1)}$, $Q_{(t-2)}$	1000011	0.063	0.254
M9	$R_{(t)}$, $R_{(t-1)}$, $Q_{(t-1)}$, $Q_{(t-2)}$	1100011	0.051	0.212
M10	$Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	0000111	0.076	0.307
M11	$R_{(t)}$, $R_{(t-1)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1000111	0.053	0.213
M12	$R_{(t)}$, $R_{(t-2)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1100111	0.048	0.194
M13	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $R_{(t-3)}$	1111000	0.107	0.430
M14	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $R_{(t-3)}$, $Q_{(t-1)}$	1111001	0.061	0.207
M15	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1110111	0.050	0.200
M16	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$	1110000	0.114	0.459
M17	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $Q_{(t-1)}$	1110001	0.056	0.225
M18	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $Q_{(t-1)}$, $Q_{(t-2)}$	1110011	0.052	0.209
M19	**$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$**	1110111	0.047	0.191
M20	$R_{(t)}$, $R_{(t-1)}$	1100000	0.124	0.498
M21	$R_{(t)}$, $R_{(t-1)}$, $Q_{(t-1)}$	1100001	0.064	0.256
M22	$R_{(t)}$, $R_{(t-1)}$, $Q_{(t-1)}$, $Q_{(t-2)}$	1100011	0.053	0.212
M23	$R_{(t)}$, $R_{(t-1)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1100111	0.073	0.194
M24	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-3)}$ $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1101111	0.050	0.203
M25	$R_{(t)}$, $Q_{(t-1)}$	1000001	0.061	0.244
M26	$R_{(t)}$, $Q_{(t-1)}$, $Q_{(t-2)}$	1000011	0.063	0.254
M27	$R_{(t)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1000111	0.053	0.213
M28	$R_{(t)}$, $R_{(t-1)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1100111	0.048	0.194
M29	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $R_{(t-3)}$	1111000	0.107	0.430
M30	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $R_{(t-3)}$, $Q_{(t-1)}$	1111001	0.051	0.207
M31	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$, $Q_{(t-1)}$, $Q_{(t-2)}$	1110011	0.052	0.209
M32	$R_{(t)}$ $R_{(t-1)}$ $R_{(t-2)}$ $R_{(t-3)}$ $Q_{(t-1)}$ $Q_{(t-2)}$	1111011	0.050	0.200
M33	$R_{(t)}$, $R_{(t-1)}$, $R_{(t-2)}$ $R_{(t-3)}$, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$	1111111	0.048	0.194

5.2. Application of Machine Learning Techniques for Rainfall-Runoff Modelling

As per the GT result, the best-input combination for the development of MLR, MARS, SVM, and RF models was made based on the following equation:

$$Q_{(t)} = f\left(R_{(t)}, R_{(t-1)}, R_{(t-2)}, Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)}\right) \quad (20)$$

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5.2.1. MLR model for runoff prediction

The MLR technique was used to predict runoff of the Gola watershed using the best input combination based on Gamma test results in the R-Studio environment. The developed MLR model with training dataset can be formulated as follows:

$$Q_{(t)} = 1.11 + 0.55R_{(t)} + 0.01R_{(t-1)} - 0.03R_{(t-2)} + 0.48Q_{(t-1)} + 0.21Q_{(t-2)} + 0.03Q_{(t-3)} \quad (21)$$

The qualitative performance assessment of the MLR model for predicting runoff of the Gola watershed was done by graphical comparison between ordinates of observed and predicted runoff values (Figures 4 & 5). It was revealed from the visual observation that there was a large variation in observed and predicted peak values of runoff. It was also observed that the MLR model underpredicts larger values and overpredicts small values of runoff in the training and testing periods. The MLR, being a linear model, could not capture the nonlinearity in the predictor-predictand relationship. Hence, the MLR model explained the medium range of variance in the predictand variable better than the extreme values. In other words, these models simulated the average runoff values more effectively than extreme events.

The values of RMSE, R^2, NSE, and PBIAS were 13.44 m^3/s, 0.78, 0.72, 0.00%, respectively during training and 12.67 m^3/s, 0.67, 0.51 and 0.80%, respectively during testing period for the MLR model (Table 3). It revealed that the model has a low bias in training and under-estimation of runoff values in the testing period. It was seen that the MLR model lacked in mapping runoff of the Gola watershed satisfactorily.

Table 4. Comparison of different machine learning models for daily runoff prediction.

Model	Training				Testing			
	RMSE (m^3/s)	R^2	NSE	PBIAS (%)	RMSE (m^3/s)	R^2	NSE	PBIAS (%)
MLR	13.44	0.78	0.72	0	12.67	0.67	0.51	0.80
MARS	12.55	0.81	0.76	0	10.07	0.79	0.74	0.20
SVM	12.61	0.83	0.81	-3.90	14.02	0.60	0.60	0.40
RF	6.31	0.96	0.94	-0.20	5.53	0.95	0.92	-0.20

5.2.2. MARS model for runoff prediction

In the case of MARS modeling, the backward pass was used to prune the model by deleting unnecessary bias functions at every stage until the supermodel has been found and for good generalization ability. The value of the GCV parameter for best models was 159.80 and 107.05 for the training and testing set, respectively. RMSE, R^2, NSE, and PBIAS were 12.55 m^3/s, 0.81, 0.76, and 0.00%, respectively, during training, and 10.07 m^3/s, 0.79, 0.74, and 0.20%, respectively during the testing period for the MARS model (Table 3). Temporal variations and scatter plot of observed and predicted runoff during the testing period is displayed in Figure 6 & 7, respectively. The trend of predicting runoff was satisfactory for observed runoff of the Gola watershed. The peak values of runoff were not predicted with great accuracy. Low values of PBIAS were found in the MARS model during the training period, which indicates an accurate model simulation. It was revealed by (0.00%) PBIAS value, and the positive value (0.20%) of PBIAS indicated slight under-estimation during the testing period.

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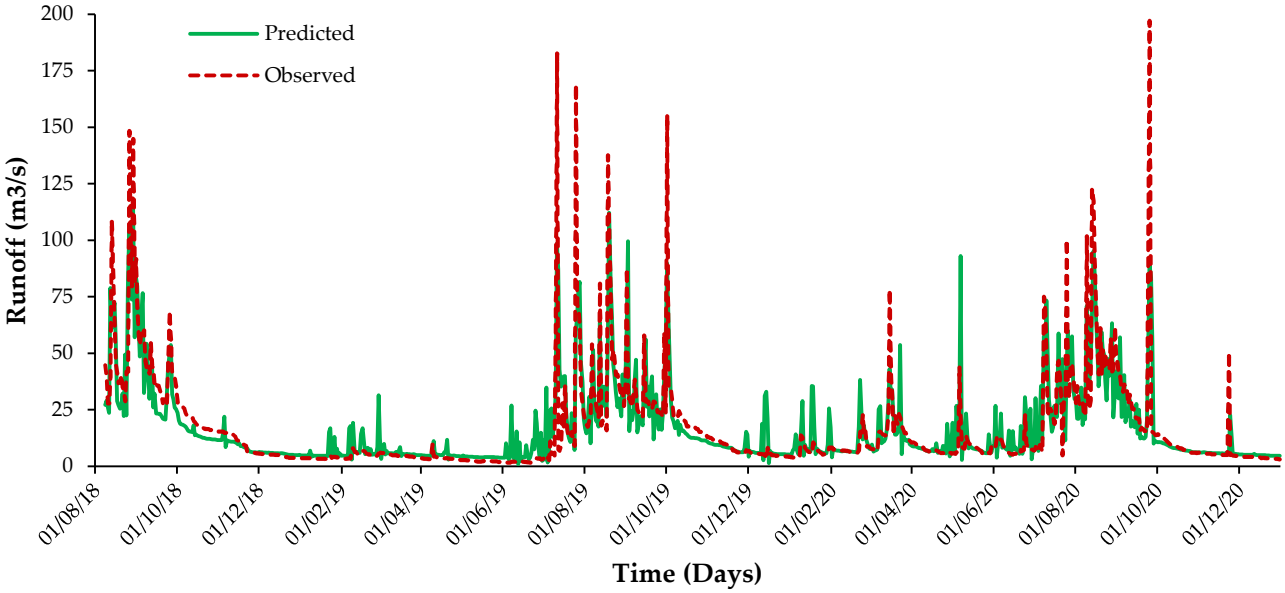

Figure 4. Observed and predicted runoff using the MLR model during the testing set.

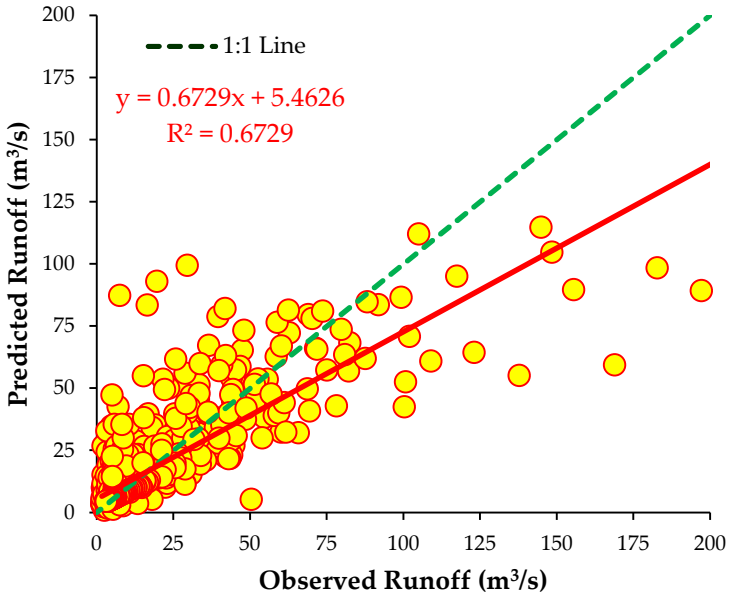

Figure 5. Scatter plot of runoff using MLR model during the testing set.

5.2.3. SVM model for runoff prediction

The present study uses the radial basis and linear kernel functions for SVM-based runoff modeling. The radial basis function performed better than the linear function; that is why selected for the current study. Variations in three parameters, namely, cost (*C*), gamma (γ), and epsilon (ε), were done to conduct a trial-and-error method for the selection of an optimum performing SVM model. The variation in the C parameter was made from (C=1 to C=10), and it was found that there was negligible variation in the results. The ε parameter was varied too (0.1, 0.01, 0.001), and it was revealed that there was a significant change in results for every model. It was observed that there was an increase in RMSE value when the value of ε decreased from (0.1 to 0.001). After comparing the results, it was concluded that the SVM model having (C = 10, γ = 0.1667, ε = 0.1) outperformed in mapping the rainfall-runoff relationship for the Gola watershed. The time-series plot revealed the fact that the model was underpredicting large values in the training period as well as in the testing period.

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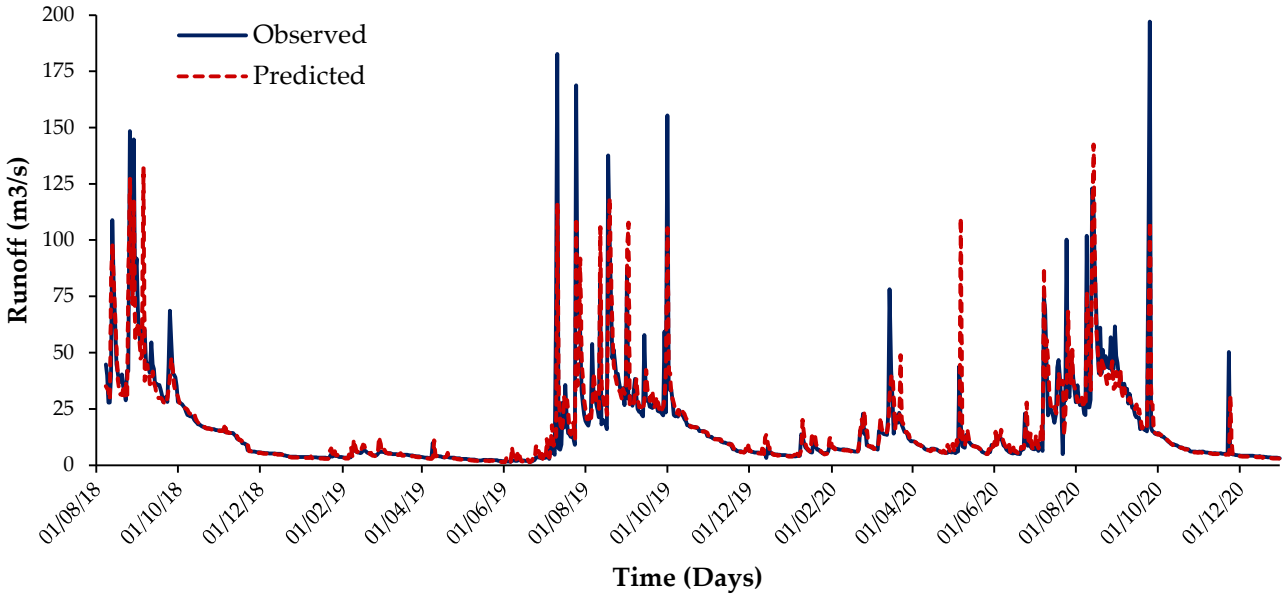

Figure 6. Observed and predicted runoff using MARS mode during the testing set.

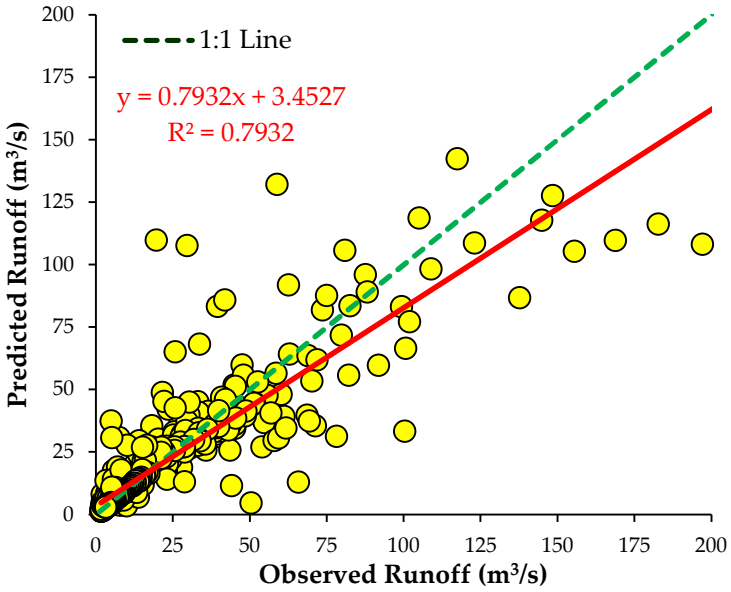

Figure 7. Scatter plot of runoff using MARS model during the testing set.

The values of RMSE, R^2, NSE, and PBIAS for the SVM model were 12.614 m3/s, 0.83, 0.81, and -3.90% for the training period 14.02 m^3/s, 0.60, 0.60, and 0.40% for the testing period respectively (Table 3). Temporal variations and scatter plot of observed and predicted runoff during the testing period is displayed in Figure 8 & 9, respectively. The R^2 value (0.83) shows the strong linear relationship between observed and predicted variables in the training period. It was found satisfactory (0.60) during the testing period. The NSE value (0.81) revealed good model predictive skills during the training period. The 0.60 value in the testing period shows satisfactory predictive skills during the testing period. The PBIAS value was found to be (-3.90%) during the training period, which shows the model was over-predicting runoff values during the training period and the testing period (0.40%) reveals that the model was under-predicting runoff values.

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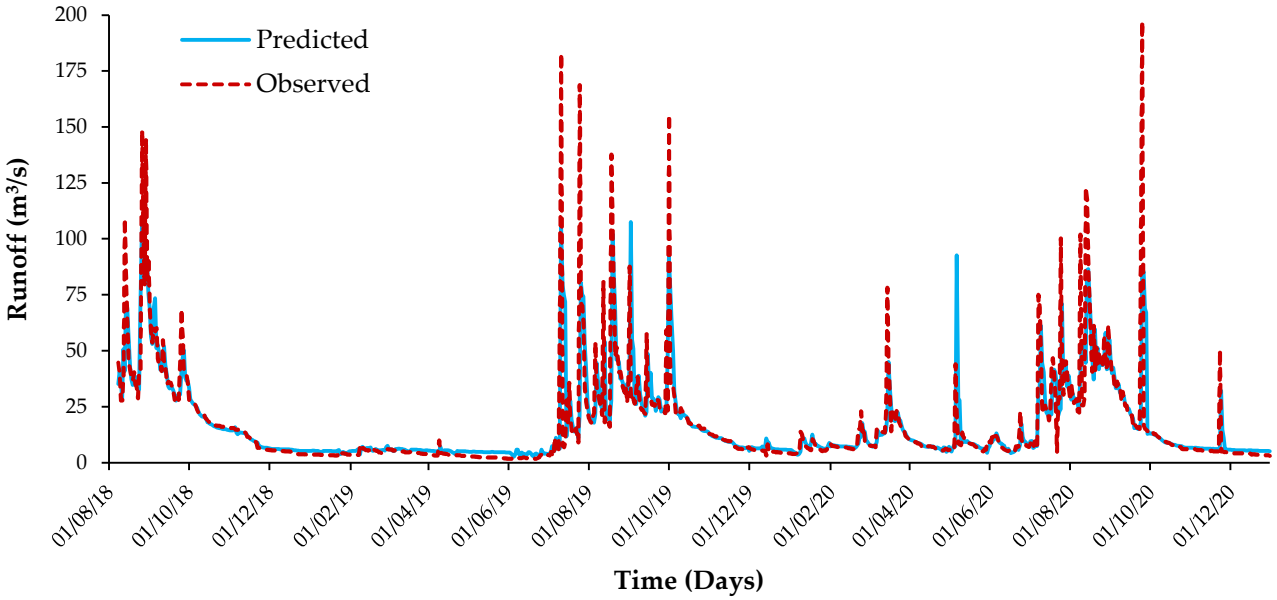

Figure 8. Observed and predicted runoff using the SVM model during the training set.

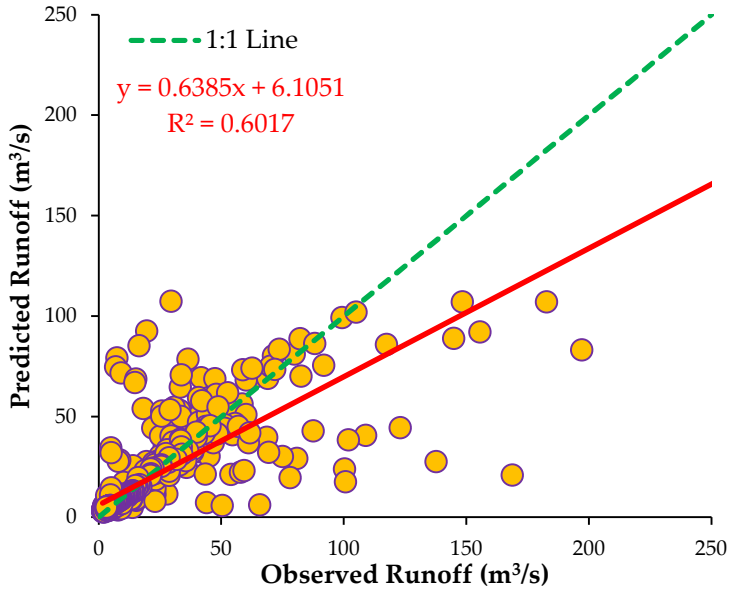

Figure 9. Scatter plot of runoff using SVM model during the testing set.

5.2.4. Random Forest model for runoff prediction

Two parameters were used in tuning the Random Forest model *ntree* (number of trees) and *mtry* (number of variables) (Naghibi *et al.*, 2017). In the present study, a trial-and-error technique was used in which *n-trees* values were varied from 200 to 600, and the *m-try* values were varied from 2 to 6 to find the best performing Random Forest model. It was found that 400 decision trees (*n-tree*) and seven variables (*m-try*) were optimal for the best fit model. It was apparent from Table 4 that RMSE values were in the range of 6.318 m^3/s to 6.480 m^3/s and R^2 values were in the range of 0.95 to 0.96 during the training period. The values of RMSE lie in the range of 5.430 m^3/s to 5.677 m^3/s, and R^2 values lie in a range of 0.94 to 95 during the testing period. From the evaluation of all the results, it was observed that the RF-28 model was superior to other RF models.

The value of RMSE, R^2, NSE, and PBIAS of the RF-28 model was 6.318 m^3/s, 0.96, 0.94, and -0.20% for the training period and 5.565 m^3/s, 0.95, 0.92, -0.10% for the testing period (Table 3). Low values of RMSE show a concentration of data around the best fit line. The

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R^2 value (0.96 & 0.95) during the training and testing period revealed a strong linear relationship between observed and predicted runoff values. The value of NSE was found to be 0.94 and 0.95 during the training and testing period, respectively, which shows the good predictive ability of the model. The PBIAS values revealed that the model slightly overpredicts runoff values during training and testing. Temporal variations and scatter plot of observed and predicted runoff during the testing period is displayed in Figure 10 & 11, respectively.

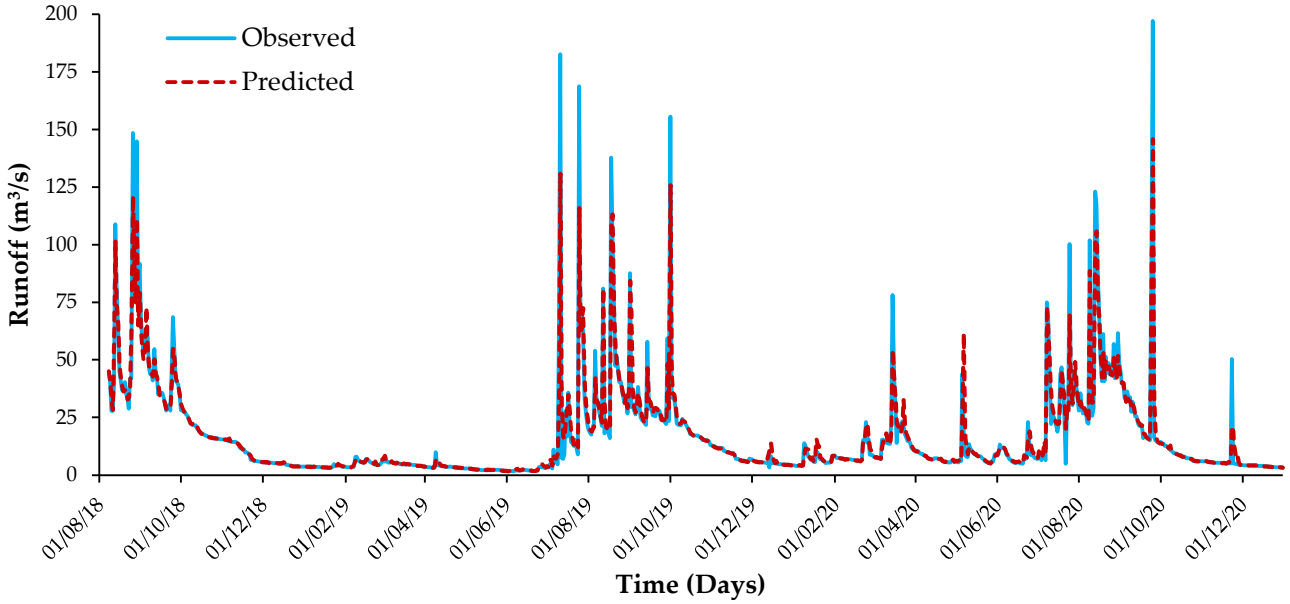

Figure 10. Observed and predicted runoff using RF during the testing set.

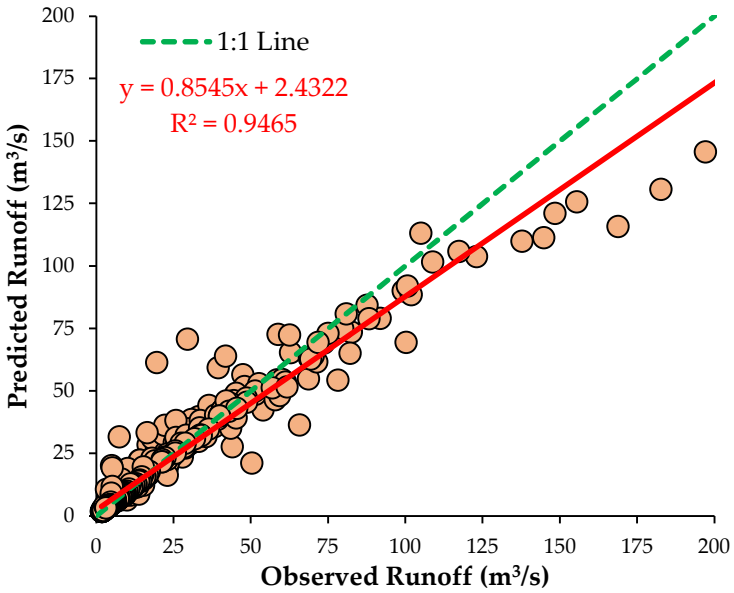

Figure 11. Scatter plot of runoff using RF model during the testing set.

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Table 4. Results of different performance indicators for RF models during training and testing sets.

Models	Training		Testing	
	RMSE	R^2	RMSE	R^2
RF-1	6.443	0.95	5.553	0.95
RF-2	6.388	0.95	5.576	0.95
RF-3	6.351	0.96	5.572	0.94
RF-4	6.423	0.95	5.550	0.95
RF-5	6.442	0.95	5.621	0.94
RF-6	6.480	0.95	5.459	0.95
RF-7	6.415	0.95	5.609	0.95
RF-8	6.371	0.95	5.677	0.94
RF-9	6.404	0.95	5.598	0.95
RF-10	6.378	0.95	5.521	0.95
RF-11	6.403	0.95	5.430	0.95
RF-12	6.445	0.95	5.481	0.95
RF-13	6.373	0.95	5.563	0.95
RF-14	6.449	0.95	5.500	0.95
RF-15	6.447	0.95	5.468	0.95
RF-16	6.435	0.96	5.571	0.94
RF-17	6.386	0.95	5.580	0.95
RF-18	6.395	0.95	5.539	0.95
RF-19	6.481	0.95	5.451	0.95
RF-20	6.408	0.95	5.575	0.95
RF-21	6.375	0.95	5.626	0.94
RF-22	6.389	0.95	5.529	0.95
RF-23	6.451	0.95	5.467	0.95
RF-24	6.446	0.95	5.613	0.94
RF-25	6.369	0.95	5.453	0.95
RF-26	6.427	0.95	5.536	0.95
RF-27	6.322	0.95	5.547	0.95
RF-28	6.318	0.96	5.565	0.95
RF-29	6.375	0.95	5.480	0.95

5.3. Model comparison

It was noticed that the MLR model showed the least accuracy among all models (Table 3). As reported by Panda et al. (2022), the poor performance of the MLR model might be attributed to the following two reasons, (1) the inability of the MLR to address predictor-predictand nonlinearity and (2) reduced efficiency of the model due to the presence of outliers and serially correlation. The hydrological model developed by the RF was a significant improvement over the rest of the models. The superior performance of the RF model could be due to the following reasons, (1) superior ability of the model to address nonlinearity compared to the rest of the models (Zhang et al., 2019), (2) capability to handle noisy data efficiently (Reis et al., 2018), and (3) ability to reduce the overfitting problem (Kim et al., 2022). It was also found that the MARS model outperformed the SVM model

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during the testing period. It indicated that the MARS could handle the predictor-predictand nonlinearity better than the SVM model.

The Violin plot distribution of observed and simulated runoff during the training and testing periods was depicted in Figure 12. The MARS model captured the extreme values better during the training period than the other models. However, the RF model demonstrated a greater ability to capture the high runoff values during the testing period. It indicated that the RF model could learn the hidden processes better than other models. The performance of the MARS model was similar to that of the RF. Although the MLR performed better in capturing extreme events during the calibration period, it could not perform similarly during the validation period. The SVM model showed the least efficacy in simulating the high values during calibration and validation periods.

The relative error plot further validated the above results (Figure 13). Finally, the model efficiencies were compared using a Taylor diagram (Figure 14). It was concluded that the RF model showed the highest accuracy, followed by the MARS model. In contrast, the SVM model showed the lowest efficacy, followed by the MLR model.

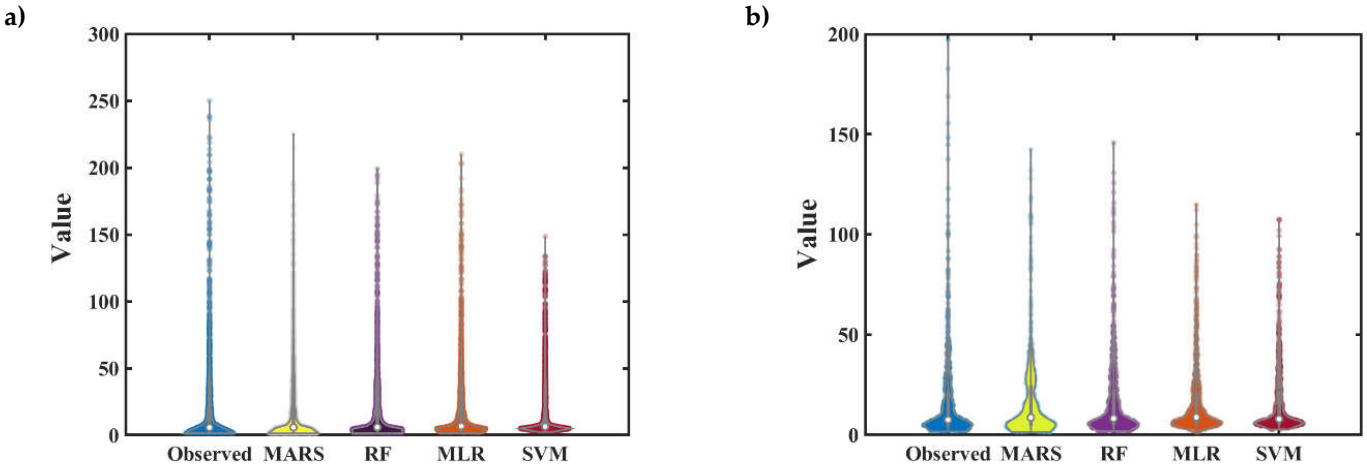
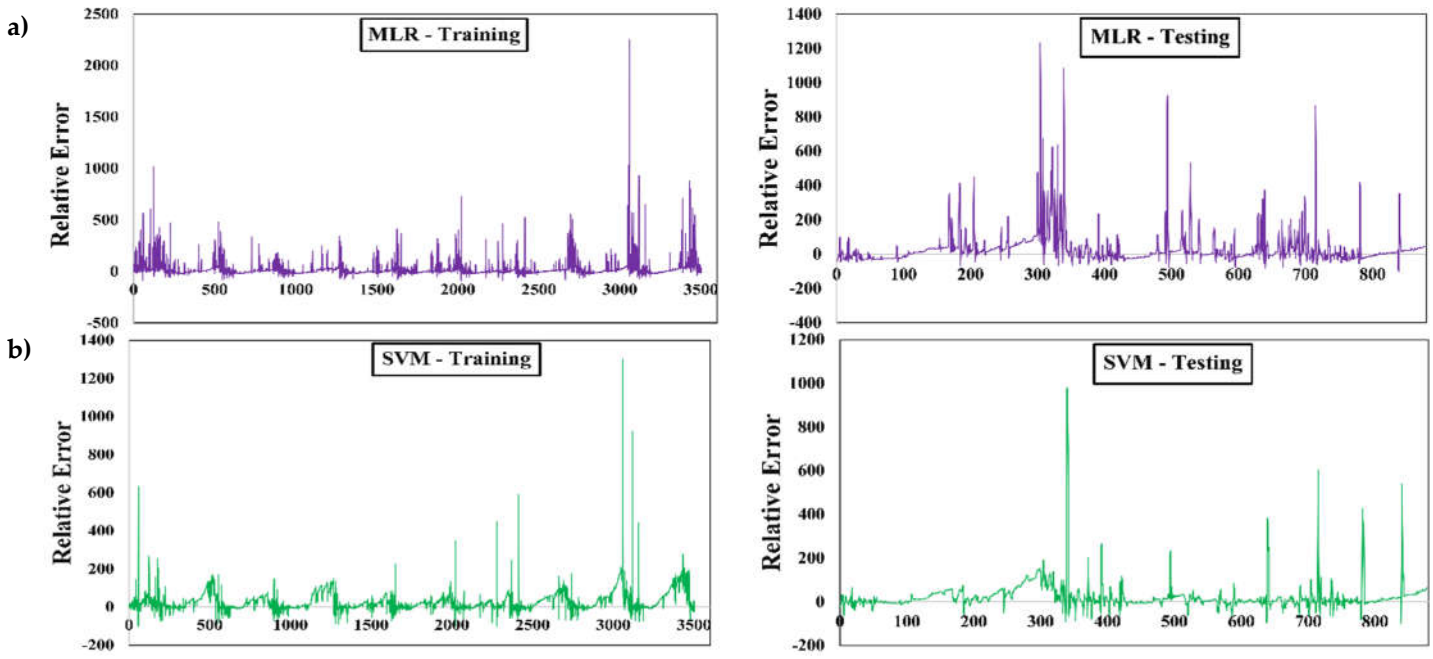


Figure 12. The Violin plot displays the observed and predicted runoff distribution for the four models during the a) training and b) testing phase at the Gola watershed.



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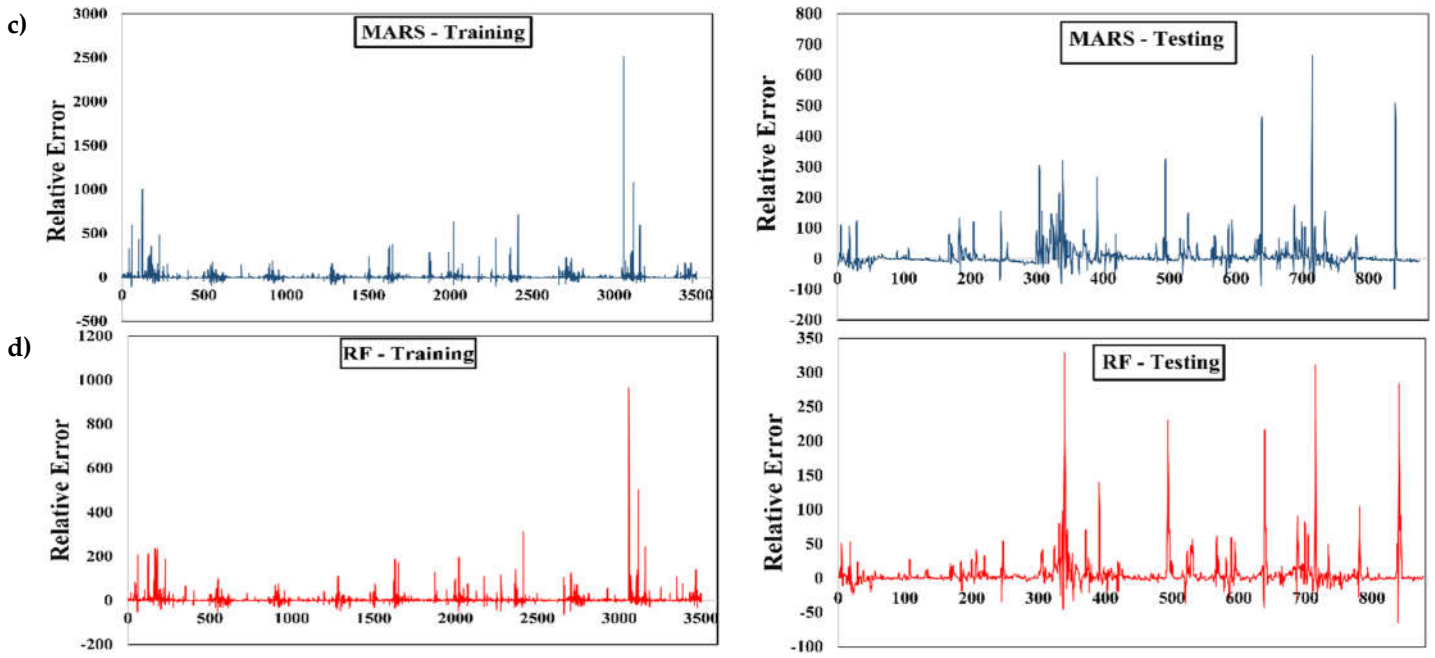

Figure 13. Relative error distribution over the training and testing phase for the daily time scale river flow for the Gola watershed, (a) MLR, (b) SVM and (c) MARS, and (d) Random Forest.

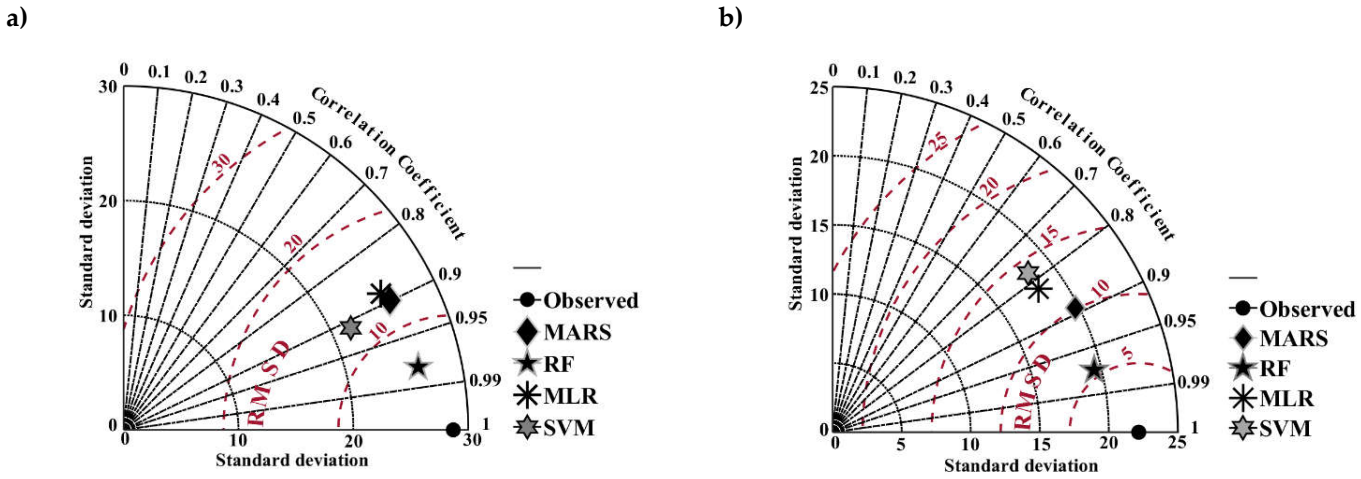

Figure 14. Taylor diagram of SVM, Random Forest, MARS, and MLR models during the a) training and b) testing period at the Gola watershed.

6. Conclusions

Rainfall is an essential hydrological phenomenon to maintain the balance of freshwater availability for the survival and growth of life. This study was conducted to evaluate the runoff pattern of the Gola watershed. The comparative results of training and testing dataset sets between the MLR, MARS, SVM, and RF model's potential in predicting runoff of the Gola watershed were investigated. Among the developed models, for root mean square error (RMSE), the ranking of models was RF, MARS, SVM, and MLR for the training period and RF, MARS, MLR, and SVM for the testing period, respectively. Based on the coefficient of determination (R^2) statistics, the models were ranked as RF, SVM, MARS, and MLR for the training dataset and RF, MARS, MLR, and SVM for the testing dataset. The models were ranked as RF, SVM, MARS, and MLR for training and RF, MARS, SVM, and MLR for testing in the case of NSE statistics, respectively. Based on the quantitative analysis and indices, the ranking of models was RF, MARS, SVM & MLR for the training period. It was RF, MARS, MLR & SVM for the testing period. Perhaps these uncertainties

in results were due to data division, input uncertainties, and model parameter optimization. In order to determine the consistency of models, these should be tested by varying data length and training-testing split. The obtained results suggested that the accuracy of MLR, MARS, SVM and RF techniques were adequate using rainfall and runoff parameter for modeling. It was found that there was variation in the results of different machine learning models. The evaluation of performances revealed that the RF model outperformed other regression models for predicting runoff of the Gola watershed.

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References

1. Alizadeh, Z.; Yazdi, J.; Najafi, M.S. Improving the outputs of regional heavy rainfall forecasting models using an adaptive real-time approach. *Hydrol. Sci. J.* **2022**, *67*, 550–563, doi:10.1080/02626667.2022.2027951.
2. Khan, M.T.; Shoaib, M.; Hammad, M.; Salahudin, H.; Ahmad, F.; Ahmad, S. Application of machine learning techniques in rainfall–runoff modelling of the soan river basin, Pakistan. *Water (Switzerland)* **2021**, *13*, 3528, doi:10.3390/w13243528.
3. Barrera-Animas, A.Y.; Oyedele, L.O.; Bilal, M.; Akinosho, T.D.; Delgado, J.M.D.; Akanbi, L.A. Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting. *Mach. Learn. with Appl.* **2022**, *7*, 100204, doi:https://doi.org/10.1016/j.mlwa.2021.100204.
4. Basha, C.Z.; Bhavana, N.; Bhavya, P.; S., V. Rainfall Prediction using Machine Learning & Deep Learning Techniques. In Proceedings of the 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC); 2020; pp. 92–97.
5. Yang, T.-H.; Yang, S.-C.; Ho, J.-Y.; Lin, G.-F.; Hwang, G.-D.; Lee, C.-S. Flash flood warnings using the ensemble precipitation forecasting technique: A case study on forecasting floods in Taiwan caused by typhoons. *J. Hydrol.* **2015**, *520*, 367–378, doi:https://doi.org/10.1016/j.jhydrol.2014.11.028.
6. Liu, J.; Wang, J.; Pan, S.; Tang, K.; Li, C.; Han, D. A real-time flood forecasting system with dual updating of the NWP rainfall and the river flow. *Nat. Hazards* **2015**, *77*, 1161–1182, doi:10.1007/s11069-015-1643-8.
7. Mosavi, A.; Ozturk, P.; Chau, K. Flood Prediction Using Machine Learning Models: Literature Review. *Water* 2018, *10*, 1536.
8. You, G.J.-Y.; Thum, B.-H.; Lin, F.-H. The examination of reproducibility in hydro-ecological characteristics by daily synthetic flow models. *J. Hydrol.* **2014**, *511*, 904–919, doi:https://doi.org/10.1016/j.jhydrol.2014.02.047.
9. Le, T.-T.; Pham, B.T.; Ly, H.-B.; Shirzadi, A.; Le, L.M. Development of 48-hour Precipitation Forecasting Model using Nonlinear Autoregressive Neural Network. In *Innovation for Sustainable Infrastructure. Lecture Notes in Civil Engineering, vol 54. Springer*; Ha-Minh, C., Dao, D. Van, Benboudjema, F., Derrible, S., Huynh, D.V.K., Tang, A.M., Eds.; Springer Singapore: Singapore, 2020; pp. 1191–1196 ISBN 978-981-15-0802-8.
10. Amin, I.; Kumar, R.; Jhajharia, D.; Sherring, A. Estimation and validation of runoff and sediment model for Dachigam watershed of Kashmir Valley . Indian Journal of Soil Conservation Estimation and validation of runoff and sediment models for Dachigam watershed of Kashmir valley (India). **2015**.

11. Kumar, R.; Manzoor, S.; Vishwakarma, D.K.; Al-Ansari, N.; Kushwaha, N.L.; Elbeltagi, A.; Sushanth, K.; Prasad, V.; Kuriqi, A. Assessment of Climate Change Impact on Snowmelt Runoff in Himalayan Region. *Sustainability* **2022**, *14*, 1–23, doi:10.3390/su14031150.
12. Vishwakarma, D.K.; Kumar, R.; Pandey, K.; Singh, V.; Kushwaha, K.S. Modeling of Rainfall and Ground Water Fluctuation of Gonda District Uttar Pradesh, India. *Int. J. Curr. Microbiol. Appl. Sci.* **2018**, *7*, 2613–2618, doi:10.20546/ijcmas.2018.705.302.
13. Kumar, M.; Kumar, R.; Rajput, T.B.S.; Patel, N. Efficient Design of Drip Irrigation System using Water and Fertilizer Application Uniformity at Different Operating Pressures in a Semi-Arid Region of India. *Irrig. Drain.* **2017**, *66*, 316–326, doi:https://doi.org/10.1002/ird.2108.
14. Thomas, D.S.G.; Twyman, C.; Osbahr, H.; Hewitson, B. Adaptation to climate change and variability: farmer responses to intra-seasonal precipitation trends in South Africa. *Clim. Change* **2007**, *83*, 301–322, doi:10.1007/s10584-006-9205-4.
15. Kramer, K.L.; Hackman, J. Scaling climate change to human behavior predicting good and bad years for Maya farmers. *Am. J. Hum. Biol.* **2021**, *33*, e23524, doi:https://doi.org/10.1002/ajhb.23524.
16. Zhao, Q.; Ma, X.; Liang, L.; Yao, W. Spatial–Temporal Variation Characteristics of Multiple Meteorological Variables and Vegetation over the Loess Plateau Region. *Appl. Sci.* 2020, *10*, 1000.
17. Turgut, M.S.; Turgut, O.E.; Afan, H.A.; El-Shafie, A. A novel Master–Slave optimization algorithm for generating an optimal release policy in case of reservoir operation. *J. Hydrol.* **2019**, *577*, 123959, doi:https://doi.org/10.1016/j.jhydrol.2019.123959.
18. Tikhamarine, Y.; Souag-Gamane, D.; Ahmed, A.N.; Sammen, S.S.; Kisi, O.; Huang, Y.F.; El-Shafie, A. Rainfall-runoff modelling using improved machine learning methods: Harris hawks optimizer vs. particle swarm optimization. *J. Hydrol.* **2020**, *589*, 125133, doi:https://doi.org/10.1016/j.jhydrol.2020.125133.
19. Banadkooki, F.B.; Ehteram, M.; Ahmed, A.N.; Fai, C.M.; Afan, H.A.; Ridwam, W.M.; Sefelnasr, A.; El-Shafie, A. Precipitation Forecasting Using Multilayer Neural Network and Support Vector Machine Optimization Based on Flow Regime Algorithm Taking into Account Uncertainties of Soft Computing Models. *Sustainability* 2019, *11*, 6681.
20. Tikhamarine, Y.; Malik, A.; Kumar, A.; Souag-Gamane, D.; Kisi, O. Estimation of monthly reference evapotranspiration using novel hybrid machine learning approaches. *Hydrol. Sci. J.* **2019**, *64*, 1824–1842, doi:10.1080/02626667.2019.1678750.
21. Chang, T.K.; Talei, A.; Alaghmand, S.; Ooi, M.P.-L. Choice of rainfall inputs for event-based rainfall-runoff modeling in a catchment with multiple rainfall stations using data-driven techniques. *J. Hydrol.* **2017**, *545*, 100–108, doi:https://doi.org/10.1016/j.jhydrol.2016.12.024.
22. Tokar, A.S.; Johnson, P.A. Rainfall-runoff modeling using artificial neural networks. *J. Hydrol. Eng.* **1999**, *4*, 232–239, doi:https://doi.org/10.1061/(ASCE)1084-0699(1999)4:3(232).
23. Sawaf, M.B. Al; Kawanisi, K.; Jlilati, M.N.; Xiao, C.; Bahreinimotlagh, M. Extent of detection of hidden relationships among different hydrological variables during floods using data-driven models. *Environ. Monit. Assess.* **2021**, *193*, 692, doi:10.1007/s10661-021-09499-9.
24. Peel, M.C.; McMahon, T.A. Historical development of rainfall-runoff modeling. *WIREs Water* **2020**, *7*, e1471, doi:https://doi.org/10.1002/wat2.1471.
25. Moradkhani, H.; Sorooshian, S. General Review of Rainfall-Runoff Modeling: Model Calibration, Data Assimilation, and Uncertainty Analysis. In *Hydrological Modelling and the Water Cycle. Water Science and Technology Library, vol 63.*; Sorooshian, S., Hsu, K.-L., Coppola, E., Tomassetti, B., Verdecchia, M., Visconti, G., Eds.; Springer Berlin Heidelberg: Berlin, Heidelberg, 2008; pp. 1–24 ISBN 978-3-540-77843-1.
26. Daniell, T.M. Neural networks. Applications in hydrology and water resources engineering. In Proceedings of the National Conference Publication- Institute of Engineers. Australia; 1991.
27. French, M.N.; Krajewski, W.F.; Cuykendall, R.R. Rainfall forecasting in space and time using a neural network. *J. Hydrol.* **1992**, *137*, 1–31, doi:https://doi.org/10.1016/0022-1694(92)90046-X.
28. Asadi, H.; Shahedi, K.; Jarihani, B.; Sidle, R.C. Rainfall-Runoff Modelling Using Hydrological Connectivity Index and Artificial Neural Network Approach. *Water* 2019, *11*, 212.
29. Dash, Y.; Mishra, S.K.; Panigrahi, B.K. Rainfall prediction for the Kerala state of India using artificial intelligence approaches. *Comput. Electr. Eng.* **2018**, *70*, 66–73, doi:https://doi.org/10.1016/j.compeleceng.2018.06.004.
30. Chau, K.W.; Wu, C.L. A hybrid model coupled with singular spectrum analysis for daily rainfall prediction. *J. Hydroinformatics* **2010**, *12*, 458–473, doi:10.2166/hydro.2010.032.
31. Zounemat-kermani, M.; Kisi, O.; Rajaee, T. Performance of radial basis and LM-feed forward artificial neural networks for predicting daily watershed runoff. *Appl. Soft Comput.* **2013**, *13*, 4633–4644, doi:https://doi.org/10.1016/j.asoc.2013.07.007.
32. Harshburger, B.J.; Walden, V.P.; Humes, K.S.; Moore, B.C.; Blandford, T.R.; Rango, A. Generation of Ensemble Streamflow Forecasts Using an Enhanced Version of the Snowmelt Runoff Model1. *JAWRA J. Am. Water Resour. Assoc.* **2012**, *48*, 643–655, doi:https://doi.org/10.1111/j.1752-1688.2012.00642.x.
33. Humphrey, G.B.; Gibbs, M.S.; Dandy, G.C.; Maier, H.R. A hybrid approach to monthly streamflow forecasting: Integrating hydrological model outputs into a Bayesian artificial neural network. *J. Hydrol.* **2016**, *540*, 623–640, doi:https://doi.org/10.1016/j.jhydrol.2016.06.026.
34. Kisi, O.; Cimen, M. A wavelet-support vector machine conjunction model for monthly streamflow forecasting. *J. Hydrol.* **2011**, *399*, 132–140, doi:https://doi.org/10.1016/j.jhydrol.2010.12.041.
35. Thapa, S.; Zhao, Z.; Li, B.; Lu, L.; Fu, D.; Shi, X.; Tang, B.; Qi, H. Snowmelt-Driven Streamflow Prediction Using Machine Learning Techniques (LSTM, NARX, GPR, and SVR). *Water* 2020, *12*, 1734.

36. Nourani, V.; Andalib, G. Wavelet Based Artificial Intelligence Approaches for Prediction of Hydrological Time Series BT - Artificial Life and Computational Intelligence.; Chalup, S.K., Blair, A.D., Randall, M., Eds.; Springer International Publishing: Cham, 2015; pp. 422–435.
37. Idrees, M.B.; Jehanzaib, M.; Kim, D.; Kim, T.-W. Comprehensive evaluation of machine learning models for suspended sediment load inflow prediction in a reservoir. *Stoch. Environ. Res. Risk Assess.* **2021**, *35*, 1805–1823, doi:10.1007/s00477-021-01982-6.
38. Kakaei Lafdani, E.; Moghaddam Nia, A.; Ahmadi, A. Daily suspended sediment load prediction using artificial neural networks and support vector machines. *J. Hydrol.* **2013**, *478*, 50–62, doi:https://doi.org/10.1016/j.jhydrol.2012.11.048.
39. Rajaee, T.; Mirbagheri, S.A.; Zounemat-Kermani, M.; Nourani, V. Daily suspended sediment concentration simulation using ANN and neuro-fuzzy models. *Sci. Total Environ.* **2009**, *407*, 4916–4927, doi:https://doi.org/10.1016/j.scitotenv.2009.05.016.
40. Melesse, A.M.; Ahmad, S.; McClain, M.E.; Wang, X.; Lim, Y.H. Suspended sediment load prediction of river systems: An artificial neural network approach. *Agric. Water Manag.* **2011**, *98*, 855–866, doi:https://doi.org/10.1016/j.agwat.2010.12.012.
41. Gupta, D.; Hazarika, B.B.; Berlin, M.; Sharma, U.M.; Mishra, K. Artificial intelligence for suspended sediment load prediction: a review. *Environ. Earth Sci.* **2021**, *80*, 346, doi:10.1007/s12665-021-09625-3.
42. Azamathulla, H.M.; Cuan, Y.C.; Ghani, A.A.; Chang, C.K. Suspended sediment load prediction of river systems: GEP approach. *Arab. J. Geosci.* **2013**, *6*, 3469–3480, doi:10.1007/s12517-012-0608-4.
43. Nguyen, D.T.; Chen, S.-T. Real-Time Probabilistic Flood Forecasting Using Multiple Machine Learning Methods. *Water* **2020**, *12*, 787, doi:10.3390/w12030787.
44. Al-Abadi, A.M. Modeling of stage–discharge relationship for Gharraf River, southern Iraq using backpropagation artificial neural networks, M5 decision trees, and Takagi–Sugeno inference system technique: a comparative study. *Appl. Water Sci.* **2016**, *6*, 407–420, doi:10.1007/s13201-014-0258-7.
45. Kisi, Ö.; Çobaner, M. Modeling River Stage-Discharge Relationships Using Different Neural Network Computing Techniques. *CLEAN – Soil, Air, Water* **2009**, *37*, 160–169, doi:https://doi.org/10.1002/clen.200800010.
46. Lohani, A.K.; Goel, N.K.; Bhatia, K.K.S. Takagi–Sugeno fuzzy inference system for modeling stage–discharge relationship. *J. Hydrol.* **2006**, *331*, 146–160, doi:https://doi.org/10.1016/j.jhydrol.2006.05.007.
47. Shukla, R.; Kumar, P.; Vishwakarma, D.K.; Ali, R.; Kumar, R.; Kuriqi, A. Modeling of stage-discharge using back propagation ANN-, ANFIS-, and WANN-based computing techniques. *Theor. Appl. Climatol.* **2021**, doi:10.1007/s00704-021-03863-y.
48. Ajmera, T.K.; Goyal, M.K. Development of stage–discharge rating curve using model tree and neural networks: An application to Peachtree Creek in Atlanta. *Expert Syst. Appl.* **2012**, *39*, 5702–5710, doi:https://doi.org/10.1016/j.eswa.2011.11.101.
49. Araghi, A.; Mousavi-Baygi, M.; Adamowski, J.; Martinez, C.; van der Ploeg, M. Forecasting soil temperature based on surface air temperature using a wavelet artificial neural network. *Meteorol. Appl.* **2017**, *24*, 603–611, doi:https://doi.org/10.1002/met.1661.
50. Feng, Y.; Cui, N.; Hao, W.; Gao, L.; Gong, D. Estimation of soil temperature from meteorological data using different machine learning models. *Geoderma* **2019**, *338*, 67–77, doi:https://doi.org/10.1016/j.geoderma.2018.11.044.
51. Bilgili, M. Prediction of soil temperature using regression and artificial neural network models. *Meteorol. Atmos. Phys.* **2010**, *110*, 59–70, doi:10.1007/s00703-010-0104-x.
52. Hariharan, G.; Kannan, K.; Sharma, K.R. Haar wavelet in estimating depth profile of soil temperature. *Appl. Math. Comput.* **2009**, *210*, 119–125, doi:https://doi.org/10.1016/j.amc.2008.12.036.
53. Singh, V.K.; Singh, B.P.; Kisi, O.; Kushwaha, D.P. Spatial and multi-depth temporal soil temperature assessment by assimilating satellite imagery, artificial intelligence and regression based models in arid area. *Comput. Electron. Agric.* **2018**, *150*, 205–219, doi:https://doi.org/10.1016/j.compag.2018.04.019.
54. Mehdizadeh, S.; Fathian, F.; Safari, M.J.S.; Khosravi, A. Developing novel hybrid models for estimation of daily soil temperature at various depths. *Soil Tillage Res.* **2020**, *197*, 104513, doi:https://doi.org/10.1016/j.still.2019.104513.
55. Wu, W.; Tang, X.-P.; Guo, N.-J.; Yang, C.; Liu, H.-B.; Shang, Y.-F. Spatiotemporal modeling of monthly soil temperature using artificial neural networks. *Theor. Appl. Climatol.* **2013**, *113*, 481–494, doi:10.1007/s00704-012-0807-7.
56. Seifi, A.; Ehteram, M.; Nayebloei, F.; Soroush, F.; Gharabaghi, B.; Torabi Haghighi, A. GLUE uncertainty analysis of hybrid models for predicting hourly soil temperature and application wavelet coherence analysis for correlation with meteorological variables. *Soft Comput.* **2021**, *25*, 10723–10748, doi:10.1007/s00500-021-06009-4.
57. Ali Ghorbani, M.; Kazempour, R.; Chau, K.-W.; Shamshirband, S.; Taherei Ghazvinei, P. Forecasting pan evaporation with an integrated artificial neural network quantum-behaved particle swarm optimization model: a case study in Talesh, Northern Iran. *Eng. Appl. Comput. Fluid Mech.* **2018**, *12*, 724–737, doi:10.1080/19942060.2018.1517052.
58. Terzi, Ö. Daily pan evaporation estimation using gene expression programming and adaptive neural-based fuzzy inference system. *Neural Comput. Appl.* **2013**, *23*, 1035–1044, doi:10.1007/s00521-012-1027-x.
59. Guven, A.; Kişi, Ö. Daily pan evaporation modeling using linear genetic programming technique. *Irrig. Sci.* **2011**, *29*, 135–145, doi:10.1007/s00271-010-0225-5.
60. Kushwaha, N.L.; Rajput, J.; Elbeltagi, A.; Elnaggar, A.Y.; Sena, D.R.; Vishwakarma, D.K.; Mani, I.; Hussein, E.E. Data Intelligence Model and Meta-Heuristic Algorithms-Based Pan Evaporation Modelling in Two Different Agro-Climatic Zones: A Case Study from Northern India. *Atmosphere (Basel).* 2021, *12*, 1654.
61. Piri, J.; Amin, S.; Moghaddamnia, A.; Keshavarz, A.; Han, D.; Remesan, R. Daily Pan Evaporation Modeling in a Hot and Dry Climate. *J. Hydrol. Eng.* **2009**, *14*, 803–811, doi:10.1061/(ASCE)HE.1943-5584.0000056.
62. Shabani, S.; Samadianfard, S.; Sattari, M.T.; Shamshirband, S.; Mosavi, A.; Kmet, T.; Várkonyi-Kóczy, A.R. Modeling daily pan evaporation in humid climates using Gaussian Process Regression. *Atmos. Ocean. Phys.* **2019**, arXiv:1908.04267, doi:10.48550/arXiv.1908.04267.

63. Kim, S.; Shiri, J.; Singh, V.P.; Kisi, O.; Landeras, G. Predicting daily pan evaporation by soft computing models with limited climatic data. *Hydrol. Sci. J.* **2015**, *60*, 1120–1136, doi:10.1080/02626667.2014.945937.
64. Keshtegar, B.; Piri, J.; Kisi, O. A nonlinear mathematical modeling of daily pan evaporation based on conjugate gradient method. *Comput. Electron. Agric.* **2016**, *127*, 120–130, doi:https://doi.org/10.1016/j.compag.2016.05.018.
65. Kumar, M.; Kumari, A.; Kumar, D.; Al-Ansari, N.; Ali, R.; Kumar, R.; Kumar, A.; Elbeltagi, A.; Kuriqi, A. The superiority of data-driven techniques for estimation of daily pan evaporation. *Atmosphere (Basel).* **2021**, *12*, 1–23, doi:10.3390/atmos12060701.
66. Malik, A.; Tikhamarine, Y.; Al-Ansari, N.; Shahid, S.; Sekhon, H.S.; Pal, R.K.; Rai, P.; Pandey, K.; Singh, P.; Elbeltagi, A.; et al. Daily pan-evaporation estimation in different agro-climatic zones using novel hybrid support vector regression optimized by Salp swarm algorithm in conjunction with gamma test. *Eng. Appl. Comput. Fluid Mech.* **2021**, *15*, 1075–1094, doi:10.1080/19942060.2021.1942990.
67. Tabari, H.; Marofi, S.; Sabziparvar, A.-A. Estimation of daily pan evaporation using artificial neural network and multivariate non-linear regression. *Irrig. Sci.* **2010**, *28*, 399–406, doi:10.1007/s00271-009-0201-0.
68. Bhagwat, S.; Kashyap, P.S.; Singh, B.P.; Singh, V.K. Daily pan evaporation modeling in hilly region of Uttarakhand using artificial neural network. *Indian J. Ecol.* **2017**, *44*, 467–473.
69. Huang, G.; Wu, L.; Ma, X.; Zhang, W.; Fan, J.; Yu, X.; Zeng, W.; Zhou, H. Evaluation of CatBoost method for prediction of reference evapotranspiration in humid regions. *J. Hydrol.* **2019**, *574*, 1029–1041, doi:https://doi.org/10.1016/j.jhydrol.2019.04.085.
70. Nourani, V.; Elkiran, G.; Abdullahi, J. Multi-step ahead modeling of reference evapotranspiration using a multi-model approach. *J. Hydrol.* **2020**, *581*, 124434, doi:https://doi.org/10.1016/j.jhydrol.2019.124434.
71. Wen, X.; Si, J.; He, Z.; Wu, J.; Shao, H.; Yu, H. Support-Vector-Machine-Based Models for Modeling Daily Reference Evapotranspiration With Limited Climatic Data in Extreme Arid Regions. *Water Resour. Manag.* **2015**, *29*, 3195–3209, doi:10.1007/s11269-015-0990-2.
72. Mor, N.; Jhajharia, D. Time series modelling of monthly reference evapotranspiration for Bikaner, Rajasthan (India). *Indian J. soil Conserv.* **2018**, *46*, 42–51.
73. Feng, Y.; Peng, Y.; Cui, N.; Gong, D.; Zhang, K. Modeling reference evapotranspiration using extreme learning machine and generalized regression neural network only with temperature data. *Comput. Electron. Agric.* **2017**, *136*, 71–78, doi:https://doi.org/10.1016/j.compag.2017.01.027.
74. Dong, L.; Zeng, W.; Wu, L.; Lei, G.; Chen, H.; Srivastava, A.K.; Gaiser, T. Estimating the Pan Evaporation in Northwest China by Coupling CatBoost with Bat Algorithm. *Water* 2021, *13*, 256.
75. Fan, J.; Yue, W.; Wu, L.; Zhang, F.; Cai, H.; Wang, X.; Lu, X.; Xiang, Y. Evaluation of SVM, ELM and four tree-based ensemble models for predicting daily reference evapotranspiration using limited meteorological data in different climates of China. *Agric. For. Meteorol.* **2018**, *263*, 225–241, doi:https://doi.org/10.1016/j.agrformet.2018.08.019.
76. Kim, S.; Kim, H.S. Neural networks and genetic algorithm approach for nonlinear evaporation and evapotranspiration modeling. *J. Hydrol.* **2008**, *351*, 299–317, doi:https://doi.org/10.1016/j.jhydrol.2007.12.014.
77. Elbeltagi, A.; Raza, A.; Hu, Y.; Al-Ansari, N.; Kushwaha, N.L.; Srivastava, A.; Kumar Vishwakarma, D.; Zubair, M. Data intelligence and hybrid metaheuristic algorithms-based estimation of reference evapotranspiration. *Appl. Water Sci.* **2022**, *12*, 152, doi:10.1007/s13201-022-01667-7.
78. Elbeltagi, A.; Kushwaha, N.L.; Rajput, J.; Vishwakarma, D.K.; Kulimushi, L.C.; Kumar, M.; Zhang, J.; Pande, C.B.; Choudhari, P.; Meshram, S.G.; et al. Modelling daily reference evapotranspiration based on stacking hybridization of ANN with meta-heuristic algorithms under diverse agro-climatic conditions. *Stoch. Environ. Res. Risk Assess.* **2022**, doi:10.1007/s00477-022-02196-0.
79. Singh, V.K.; Panda, K.C.; Sagar, A.; Al-Ansari, N.; Duan, H.-F.; Paramaguru, P.K.; Vishwakarma, D.K.; Kumar, A.; Kumar, D.; Kashyap, P.S.; et al. Novel Genetic Algorithm (GA) based hybrid machine learning-pedotransfer Function (ML-PTF) for prediction of spatial pattern of saturated hydraulic conductivity. *Eng. Appl. Comput. Fluid Mech.* **2022**, *16*, 1082–1099, doi:10.1080/19942060.2022.2071994.
80. Sihag, P.; Tiwari, N.K.; Ranjan, S. Modelling of infiltration of sandy soil using gaussian process regression. *Model. Earth Syst. Environ.* **2017**, *3*, 1091–1100, doi:10.1007/s40808-017-0357-1.
81. Sihag, P.; Tiwari, N.K.; Ranjan, S. Prediction of unsaturated hydraulic conductivity using adaptive neuro- fuzzy inference system (ANFIS). *ISH J. Hydraul. Eng.* **2019**, *25*, 132–142, doi:10.1080/09715010.2017.1381861.
82. Sihag, P.; Tiwari, N.K.; Ranjan, S. Estimation and inter-comparison of infiltration models. *Water Sci.* **2017**, *31*, 34–43, doi:https://doi.org/10.1016/j.wsj.2017.03.001.
83. Singh, B.; Sihag, P.; Parsaie, A.; Angelaki, A. Comparative analysis of artificial intelligence techniques for the prediction of infiltration process. *Geol. Ecol. Landscapes* **2021**, *5*, 109–118, doi:10.1080/24749508.2020.1833641.
84. Sihag, P.; Singh, B.; Sepah Vand, A.; Mehdipour, V. Modeling the infiltration process with soft computing techniques. *ISH J. Hydraul. Eng.* **2020**, *26*, 138–152, doi:10.1080/09715010.2018.1464408.
85. Singh, B.; Sihag, P.; Pandhiani, S.M.; Debnath, S.; Gautam, S. Estimation of permeability of soil using easy measured soil parameters: assessing the artificial intelligence-based models. *ISH J. Hydraul. Eng.* **2021**, *27*, 38–48, doi:10.1080/09715010.2019.1574615.
86. Sihag, P.; Kumar, M.; Singh, B. Assessment of infiltration models developed using soft computing techniques. *Geol. Ecol. Landscapes* **2021**, *5*, 241–251, doi:10.1080/24749508.2020.1720475.
87. Sihag, P.; Singh, V.P.; Angelaki, A.; Kumar, V.; Sepahvand, A.; Golia, E. Modelling of infiltration using artificial intelligence techniques in semi-arid Iran. *Hydrol. Sci. J.* **2019**, *64*, 1647–1658, doi:10.1080/02626667.2019.1659965.

88. Singh, V.K.; Kumar, D.; Kashyap, P.S.; Singh, P.K.; Kumar, A.; Singh, S.K. Modelling of soil permeability using different data driven algorithms based on physical properties of soil. *J. Hydrol.* **2020**, *580*, 124223, doi:https://doi.org/10.1016/j.jhydrol.2019.124223.
89. Elbeltagi, A.; Pande, C.B.; Kouadri, S.; Islam, A.R.M.T. Applications of various data-driven models for the prediction of groundwater quality index in the Akot basin, Maharashtra, India. *Environ. Sci. Pollut. Res.* **2021**, doi:10.1007/s11356-021-17064-7.
90. Gholami, V.; Khaleghi, M.R.; Pirasteh, S.; Booij, M.J. Comparison of Self-Organizing Map, Artificial Neural Network, and Co-Active Neuro-Fuzzy Inference System Methods in Simulating Groundwater Quality: Geospatial Artificial Intelligence. *Water Resour. Manag.* **2021**, doi:10.1007/s11269-021-02969-2.
91. El Bilali, A.; Taleb, A.; Brouziyne, Y. Groundwater quality forecasting using machine learning algorithms for irrigation purposes. *Agric. Water Manag.* **2021**, *245*, 106625, doi:https://doi.org/10.1016/j.agwat.2020.106625.
92. Singha, S.; Pasupuleti, S.; Singha, S.S.; Singh, R.; Kumar, S. Prediction of groundwater quality using efficient machine learning technique. *Chemosphere* **2021**, *276*, 130265, doi:https://doi.org/10.1016/j.chemosphere.2021.130265.
93. Kumar, A.; Singh, V.K.; Saran, B.; Al-Ansari, N.; Singh, V.P.; Adhikari, S.; Joshi, A.; Singh, N.K.; Vishwakarma, D.K. Development of Novel Hybrid Models for Prediction of Drought-and Stress-Tolerance Indices in Teosinte Introgressed Maize Lines Using Artificial Intelligence Techniques. *Sustainability* **2022**, *14*, 2287, doi:https://doi.org/10.3390/su14042287.
94. Elbeltagi, A.; Azad, N.; Arshad, A.; Mohammed, S.; Mokhtar, A.; Pande, C.; Ramezani, H.; Ahmad, S.; Reza, A.; Islam, T.; et al. Applications of Gaussian process regression for predicting blue water footprint : Case study in Ad Daqahliyah , Egypt. *Agric. Water Manag.* **2021**, *255*, 107052, doi:10.1016/j.agwat.2021.107052.
95. Elbeltagi, A.; Deng, J.; Wang, K.; Hong, Y. Crop Water footprint estimation and modeling using an artificial neural network approach in the Nile Delta, Egypt. *Agric. Water Manag.* **2020**, *235*, 106080, doi:10.1016/j.agwat.2020.106080.
96. Babaee, M.; Maroufpoor, S.; Jalali, M.; Zarei, M.; Elbeltagi, A. Artificial intelligence approach to estimating rice yield*. *Irrig. Drain.* **2021**, 1–11, doi:10.1002/ird.2566.
97. Elbeltagi, A.; Zhang, L.; Deng, J.; Juma, A.; Wang, K. Modeling monthly crop coefficients of maize based on limited meteorological data : A case study in Nile Delta , Egypt. *Comput. Electron. Agric.* **2020**, *173*, 105368, doi:10.1016/j.compag.2020.105368.
98. Kumar, S.; Roshni, T.; Himayoun, D. A Comparison of Emotional Neural Network (ENN) and Artificial Neural Network (ANN) Approach for Rainfall-Runoff Modelling. *Civ. Eng. J.* **2019**, *5*, 0–10, doi:10.28991/cej-2019-03091398.
99. Abbot, J.; Marohasy, J. Application of artificial neural networks to rainfall forecasting in Queensland, Australia. *Adv. Atmos. Sci.* **2012**, *29*, 717–730, doi:10.1007/s00376-012-1259-9.
100. Shoaib, M.; Shamseldin, A.Y.; Melville, B.W.; Khan, M.M. A comparison between wavelet based static and dynamic neural network approaches for runoff prediction. *J. Hydrol.* **2016**, *535*, 211–225, doi:https://doi.org/10.1016/j.jhydrol.2016.01.076.
101. Ghumman, A.R.; Ghazaw, Y.M.; Sohail, A.R.; Watanabe, K. Runoff forecasting by artificial neural network and conventional model. *Alexandria Eng. J.* **2011**, *50*, 345–350, doi:https://doi.org/10.1016/j.aej.2012.01.005.
102. Nayak, P.C.; Sudheer, K.P.; Jain, S.K. Rainfall-runoff modeling through hybrid intelligent system. *Water Resour. Res.* **2007**, *43*, W07415, doi:https://doi.org/10.1029/2006WR004930.
103. Sinharay, S. An Overview of Statistics in Education. In *International Encyclopedia of Education (Third Edition)*; Peterson, P., Baker, E., McGaw, B.B.T.-I.E. of E. (Third E., Eds.; Elsevier: Oxford, 2010; pp. 1–11 ISBN 978-0-08-044894-7.
104. Vishwakarma, D.K.; Pandey, K.; Kaur, A.; Kushwaha, N.L.; Kumar, R.; Ali, R.; Elbeltagi, A.; Kuriqi, A. Methods to estimate evapotranspiration in humid and subtropical climate conditions. *Agric. Water Manag.* **2022**, *261*, 107378, doi:https://doi.org/10.1016/j.agwat.2021.107378.
105. Chenini, I.; Khemiri, S. Evaluation of ground water quality using multiple linear regression and structural equation modeling. *Int. J. Environ. Sci. Technol.* **2009**, *6*, 509–519, doi:10.1007/BF03326090.
106. Snedecor, G.W.; Cochran, W.G.; Fuller, J.A.R. *Métodos estadísticos*; Continental México, 1971;
107. Sekhar Roy, S.; Roy, R.; Balas, V.E. Estimating heating load in buildings using multivariate adaptive regression splines, extreme learning machine, a hybrid model of MARS and ELM. *Renew. Sustain. Energy Rev.* **2018**, *82*, 4256–4268, doi:https://doi.org/10.1016/j.rser.2017.05.249.
108. Akin, M.; Eyduran, S.P.; Eyduran, E.; Reed, B.M. Analysis of macro nutrient related growth responses using multivariate adaptive regression splines. *Plant Cell, Tissue Organ Cult.* **2020**, *140*, 661–670, doi:10.1007/s11240-019-01763-8.
109. Mirabbasi, R.; Kisi, O.; Sanikhani, H.; Gajbhiye Meshram, S. Monthly long-term rainfall estimation in Central India using M5Tree, MARS, LSSVR, ANN and GEP models. *Neural Comput. Appl.* **2019**, *31*, 6843–6862, doi:10.1007/s00521-018-3519-9.
110. Zhang, J.; Zhang, H.; Xiao, H.; Fang, H.; Han, Y.; Yu, L. Effects of rainfall and runoff-yield conditions on runoff. *Ain Shams Eng. J.* **2021**, *12*, 2111–2116, doi:https://doi.org/10.1016/j.asej.2020.10.010.
111. Vapnik, V. *Statistical learning theory.*; John Wiley & Sons, Inc. Oxford, UK, 1998; Vol. 1;.
112. Li, M.; Zhang, Y.; Wallace, J.; Campbell, E. Estimating annual runoff in response to forest change: A statistical method based on random forest. *J. Hydrol.* **2020**, *589*, 125168, doi:https://doi.org/10.1016/j.jhydrol.2020.125168.
113. Abdulelah Al-Sudani, Z.; Salih, S.Q.; sharafati, A.; Yaseen, Z.M. Development of multivariate adaptive regression spline integrated with differential evolution model for streamflow simulation. *J. Hydrol.* **2019**, *573*, 1–12, doi:https://doi.org/10.1016/j.jhydrol.2019.03.004.
114. Adnan, R.M.; Petroselli, A.; Heddam, S.; Santos, C.A.G.; Kisi, O. Comparison of different methodologies for rainfall–runoff modeling: machine learning vs conceptual approach. *Nat. Hazards* **2021**, *105*, 2987–3011, doi:10.1007/s11069-020-04438-2.

115. Li, X.; Sha, J.; Wang, Z.-L. Comparison of daily streamflow forecasts using extreme learning machines and the random forest method. *Hydrol. Sci. J.* **2019**, *64*, 1857–1866, doi:10.1080/02626667.2019.1680846.
116. Goyal, M.K.; Bharti, B.; Quilty, J.; Adamowski, J.; Pandey, A. Modeling of daily pan evaporation in sub tropical climates using ANN, LS-SVR, Fuzzy Logic, and ANFIS. *Expert Syst. Appl.* **2014**, *41*, 5267–5276, doi:https://doi.org/10.1016/j.eswa.2014.02.047.
117. Malik, A.; Kumar, A.; Piri, J. Daily suspended sediment concentration simulation using hydrological data of Pranhita River Basin, India. *Comput. Electron. Agric.* **2017**, *138*, 20–28, doi:https://doi.org/10.1016/j.compag.2017.04.005.
118. Malik, A.; Kumar, A.; Kim, S.; Kashani, M.H.; Karimi, V.; Sharafati, A.; Ghorbani, M.A.; Al-Ansari, N.; Salih, S.Q.; Yaseen, Z.M.; et al. Modeling monthly pan evaporation process over the Indian central Himalayas: application of multiple learning artificial intelligence model. *Eng. Appl. Comput. Fluid Mech.* **2020**, *14*, 323–338, doi:10.1080/19942060.2020.1715845.
119. Singh, A.; Malik, A.; Kumar, A.; Kisi, O. Rainfall-runoff modeling in hilly watershed using heuristic approaches with gamma test. *Arab. J. Geosci.* **2018**, *11*, 261, doi:10.1007/s12517-018-3614-3.
120. Stefánsson, A.; Končar, N.; Jones, A.J. A note on the Gamma test. *Neural Comput. Appl.* **1997**, *5*, 131–133, doi:10.1007/BF01413858.
121. Noori, R.; Karbassi, A.R.; Moghaddamnia, A.; Han, D.; Zokaei-Ashtiani, M.H.; Farokhnia, A.; Gousheh, M.G. Assessment of input variables determination on the SVM model performance using PCA, Gamma test, and forward selection techniques for monthly stream flow prediction. *J. Hydrol.* **2011**, *401*, 177–189, doi:https://doi.org/10.1016/j.jhydrol.2011.02.021.
122. Singh, V.K.; Kumar, D.; Kashyap, P.S.; Kisi, O. Simulation of suspended sediment based on gamma test, heuristic, and regression-based techniques. *Environ. Earth Sci.* **2018**, *77*, 708, doi:10.1007/s12665-018-7892-6.
123. Singh, V.; Kumar, D.; Kashyap, P.S.; Singh, P. *Predicting Unsaturated Hydraulic Conductivity of Soil Based on Machine Learning Algorithms*; 2019;
124. Zhang, W.; Goh, A.T.C.; Zhang, Y.; Chen, Y.; Xiao, Y. Assessment of soil liquefaction based on capacity energy concept and multivariate adaptive regression splines. *Eng. Geol.* **2015**, *188*, 29–37, doi:https://doi.org/10.1016/j.enggeo.2015.01.009.
125. Friedman, J.H. Multivariate adaptive regression splines. *Ann. Stat.* **1991**, *19*, 1–67.
126. Kisi, O.; Parmar, K.S. Application of least square support vector machine and multivariate adaptive regression spline models in long term prediction of river water pollution. *J. Hydrol.* **2016**, *534*, 104–112, doi:https://doi.org/10.1016/j.jhydrol.2015.12.014.
127. Zhang, X. *Matrix analysis and applications*; Cambridge University Press, 2017; ISBN 1108417418.
128. Rezaie-Balf, M.; Zahmatkesh, Z.; Kim, S. Soft Computing Techniques for Rainfall-Runoff Simulation: Local Non–Parametric Paradigm vs. Model Classification Methods. *Water Resour. Manag.* **2017**, *31*, 3843–3865, doi:10.1007/s11269-017-1711-9.
129. Adnan, R.M.; Liang, Z.; Trajkovic, S.; Zounemat-Kermani, M.; Li, B.; Kisi, O. Daily streamflow prediction using optimally pruned extreme learning machine. *J. Hydrol.* **2019**, *577*, 123981, doi:https://doi.org/10.1016/j.jhydrol.2019.123981.
130. Vapnik, V. *The nature of statistical learning theory*; Springer science & business media, 1999; ISBN 0387987800.
131. Bray, M.; Han, D. Identification of support vector machines for runoff modelling. *J. Hydroinformatics* **2004**, *6*, 265–280, doi:10.2166/hydro.2004.0020.
132. Awad, M.; Khanna, R. Support Vector Regression. In *Efficient Learning Machines*; Awad, M., Khanna, R., Eds.; Apress, Berkeley, CA: Berkeley, CA, 2015; pp. 67–80 ISBN 978-1-4302-5990-9.
133. Kumar, M.; Kumari, A.; Kushwaha, D.P.; Kumar, P.; Malik, A.; Ali, R.; Kuriqi, A. Estimation of Daily Stage–Discharge Relationship by Using Data-Driven Techniques of a Perennial River, India. *Sustainability* 2020, *12*, 7877.
134. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32, doi:10.1023/A:1010933404324.
135. Prasad, A.M.; Iverson, L.R.; Liaw, A. Newer Classification and Regression Tree Techniques: Bagging and Random Forests for Ecological Prediction. *Ecosystems* **2006**, *9*, 181–199, doi:10.1007/s10021-005-0054-1.
136. Sadler, J.M.; Goodall, J.L.; Morsy, M.M.; Spencer, K. Modeling urban coastal flood severity from crowd-sourced flood reports using Poisson regression and Random Forest. *J. Hydrol.* **2018**, *559*, 43–55, doi:https://doi.org/10.1016/j.jhydrol.2018.01.044.
137. Malik, A.; Kumar, A. Pan Evaporation Simulation Based on Daily Meteorological Data Using Soft Computing Techniques and Multiple Linear Regression. *Water Resour. Manag.* **2015**, *29*, 1859–1872, doi:10.1007/s11269-015-0915-0.
138. Kumar, R.; Kumar, A.; Shankhwar, A.K.; Vishkarma, D.K.; Sachan, A.; Singh, P. V; Jahangeer, J.; Verma, A.; Kumar, V. Modelling of meteorological drought in the foothills of Central Himalayas: A case study in Uttarakhand State, India. *Ain Shams Eng. J.* **2022**, *13*, 101595, doi:https://doi.org/10.1016/j.asej.2021.09.022.
139. Vishwakarma, D.K.; Rohitashw, K.; Kusum, P.; Vikash, S.; Kushwaha, K.S. Modelling of Rainfall and Ground Water Fluctuation of Gonda District Uttar Pradesh, In. *Orig. Res. Artic. Int.J.Curr.Microbiol.App.Sci* **2018**, *7*, 2613–2618, doi:https://doi.org/10.20546/ijcmas.2018.705.302.
140. Nash, J.E.; Sutcliffe, J. V River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290, doi:https://doi.org/10.1016/0022-1694(70)90255-6.
141. Malik, A.; Kumar, A.; Kisi, O. Daily pan evaporation estimation using heuristic methods with gamma test. *J. Irrig. Drain. Eng.* **2018**, *144*, doi:10.1061/(ASCE)IR.1943-4774.0001336.
142. Nury, A.H.; Hasan, K.; Alam, M.J. Bin Comparative study of wavelet-ARIMA and wavelet-ANN models for temperature time series data in northeastern Bangladesh. *J. King Saud Univ. - Sci.* **2017**, *29*, 47–61, doi:https://doi.org/10.1016/j.jksus.2015.12.002.
143. Wooldridge, M. *An introduction to multiagent systems*; John wiley & sons, 2009; ISBN 0470519460.
144. Schroeder, R.; Van de Ven, A.; Scudder, G.; Polley, D. Managing innovation and change processes: Findings from the Minnesota innovation research program. *Agribusiness* **1986**, *2*, 501–523, doi:https://doi.org/10.1002/1520-6297(198624)2:4<501::AID-AGR2720020412>3.0.CO;2-G.

145. Santhi, C.; Arnold, J.G.; Williams, J.R.; Dugas, W.A.; Srinivasan, R.; Hauck, L.M. Validation of the swat model on a large rwer basin with point and nonpoint sources. *JAWRA J. Am. Water Resour. Assoc.* **2001**, *37*, 1169–1188, doi:https://doi.org/10.1111/j.1752-1688.2001.tb03630.x.
146. Van Liew, M.W.; Arnold, J.G.; Garbrecht, J.D. Hydrologic simulation on agricultural watersheds: Choosing between two models. *Trans. ASAE* **2003**, *46*, 1539, doi:doi:10.13031/2013.15643.
147. Legates, D.R.; McCabe Jr., G.J. Evaluating the use of "goodness-of-fit" Measures in hydrologic and hydroclimatic model validation. *Water Resour. Res.* **1999**, *35*, 233–241, doi:https://doi.org/10.1029/1998WR900018.
148. Gupta, H.V.; Soroosh, S.; Yapo, P.O. Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration. *J. Hydrol. Eng.* **1999**, *4*, 135–143, doi:10.1061/(ASCE)1084-0699(1999)4:2(135).
149. Moriasi, D.N.; Arnold, J.G.; Van Liew, M.W.; Bingner, R.L.; Harmel, R.D.; Veith, T.L. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. ASABE* **2007**, *50*, 885–900, doi:10.13031/2013.23153.
150. Kheirfam, H.; Mokarram-Kashtiban, S. A regional suspended load yield estimation model for ungauged watersheds. *Water Sci. Eng.* **2018**, *11*, 328–337.