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Comparative Performance of Multiple Linear Regression and Artificial Neural Network Based Models in Estimation of Evaporation

Neeraj Kumar[1*], Ganesh Upadhyay[1] and Pankaj Kumar[1]

[1]Department of Soil and Water Conservation Engineering, College of Technology, GBPUA&T, Pantnagar, Uttarakhand, 263145, India.

Authors' contributions

This work was carried out in collaboration between all authors. Author NK conducted the study and wrote the first draft of the manuscript. Author PK helped in analyzing the results of study. Author GU assisted in final draft of manuscript. All authors read and approved the final manuscript.

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ABSTRACT

Evaporation is an integral part of water cycle. The measurement of evaporation plays a significant role in water management planning, irrigation requirement and to know the water availability in storage system. Considering the complexity in estimation of evaporation by empirical formulas, this study was undertaken to develop regression and neural network based models for estimation of evaporation from climatic variables. The parameters viz. average temperature (T_{avg}), wind speed (W), average relative humidity (Rh_{avg}) and sunshine hours (S) were used as predictors and evaporation was considered as response variable. Mean squared error (MSE) and correlation coefficient (r) were used to judge the performance of developed models. The multiple linear regression (MLR) model exhibited MSE 1.12 and 0.92 whereas with artificial neural network (ANN) model, MSE was found to be 0.56 and 0.68 in training and testing phase, respectively. In training period, correlation coefficient was 0.92 for MLR model as compared to 0.96 with ANN model. The correlation coefficient in testing phase was found to be 0.95 and 0.97 for MLR and ANN model, respectively. The developed ANN model outperformed MLR model in estimation of evaporation from climatic variables.

**Corresponding author: E-mail: neerajkumarsaini.126@gmail.com;*

Keywords: Evaporation; climatic variables; gamma test; multiple linear regression; artificial neural network; performance.

NOMENCLATURES

E_{est}	:	*Estimated evaporation (mm),*
Rh_{max}	:	*Maximum relative humidity (%),*
Rh_{min}	:	*Minimum relative humidity (%),*
T_{max}	:	*Maximum temperature (°C),*
T_{min}	:	*Minimum temperature (°C),*
W	:	*Wind speed (kmh^{-1}),*
S	:	*Sunshine hours (h).*

1. INTRODUCTION

In evaporation process, the particles in liquid phase are transformed into a gaseous phase at any temperature below its boiling point. It is the process which transfers water from the ground back to atmosphere. Molecules near the surface of liquid with enough heat energy to overcome the cohesion of their neighbours escape from liquid and evaporation takes place. At higher temperatures, evaporation is more rapid because of large number of energetic particles. In evaporation process, vapour pressure difference between water and adjacent air plays a role of driving force. John Dalton indicated that evaporation is proportional to the difference between vapour pressure of air at the water surface and that of overlying air.

Evaporation has wide application in hydrological processes and it plays a significant role in planning, operation and monitoring of water resources. From design aspect of view also, it can't be ignored particularly in water storage reservoir and conveyance structure. Therefore, evaporation is considered as one of the important hydrological processes. The major factors affecting evaporation are vapour pressure difference, solar radiation, temperature, wind speed and relative humidity. Although there are different empirical formulas available for indirect measurement of evaporation but nowadays modeling technique is being more popular to overcome the complexity of empirical formulas. Many researchers applied mass transfer method for evaporation models [1,2,3]. The statistical techniques like time series, regression, and nonparametric regression have been used to develop models for prediction of evaporation [4,5]. However, these techniques require long time series data for model development and its validation. Murthy and Gawande [6] conducted a study on evaporation and established a linear relationship between meteorological parameters and evaporation using multiple linear regression (MLR) technique. Goel [7] used support vector machine (SVM) technique to predict the reservoir evaporation on daily basis by using solar radiation, relative humidity, wind speed, and temperature as input variables. It was reported that RBF based SVM technique was found to be superior in estimation of evaporation as compared to polynomial based SVM and linear regression technique. Shrivastava et al. [8] used linear regression method to explore the relationship between evaporation and meteorological parameters for Jabalpur. In statistical analysis it was found that morning time relative humidity have more influence on evaporation followed by temperature. The developed model was verified by comparing predicted and actual evaporation and relative error was found from -0.45 to 1.45 mmd^{-1} and -0.35 to 1.55 mmd^{-1} for the year 1994 and 1995, respectively. Kumar et al. [9] applied local linear regression technique for evaporation modeling and explored linear dependency between evaporation and climatic variables.

In last decades, hydrological processes simulated by different non-linear models using ANN, ANFIS and Bayesian networks [10,11,12,13]. Among these methods, neural network has been widely used for modeling of hydrological processes. Bruton et al. [14] used five years weather data (1992 to 1996) to develop ANN and MLR model for estimation of daily pan evaporation using weather variables and two years data (1997-1998) for validation of developed model. During validation, ANN model explained 71.7% variation in evaporation with root mean square error of 1.11 mm. ANN model was found to be slightly more accurate than MLR model for estimation of pan evaporation. Sudheer et al. [15] suggested that a properly trained ANN model can reasonably estimate the evaporation values for a temperate region. Piri et al. [3] used artificial neural network for evaporation estimation in a study of hot and dry region and reported that neural network worked very well in estimation of evaporation from climatic parameters. Taher [16] used 22 years weather data to train and test the four three-layer back propagation neural networks to predict evaporation from climatic variables for Riyadh, Saudi Arabia. With developed ANN models, values of coefficient of correlation and mean square error were found in the range of 0.98 and 0.00015, respectively. Ozlem et al. [17] developed ANN model to estimate daily pan evaporation of Lake Egirdir in Turkey using air and water temperature, solar radiation and air pressure. The model performed well and estimated the evaporation with least mean square error. Martínez et al. [18] simulated the evaporation rate of Class A evaporimeter pan using multilayer neural network and found estimated evaporation close to actual evaporation. Dogan and Demir [19] applied genetic algorithm (GA) and feed forward neural network technique to estimate daily pan evaporation for Lake Sapanca using wind speed, relative humidity, minimum and maximum temperature, real and maximum solar period. The performance of feed forward neural network was found to be more realistic as compared to GA technique. Terzi and Keskin [20] also applied ANN technique for prediction of daily pan evaporation. Moghaddamnia et al. [21] investigated the ability of ANN and ANFIS models for prediction of evaporation from reservoirs. Shirgure and Rajput [22] developed general ANN model with 3305 daily records (2002-2006) of min and max temperature, min and max relative humidity, wind speed, sunshine hours, rainfall and pan evaporation for estimation of evaporation in Udaipur, Jabalpur, Nagpur, Akola and Hyderabad. The weather data from these five location was used to validate the model. The general ANN model involving all input parameters was found the most accurate having R^2 value 0.84 and RMSE value 1.44 mm for training phase. The general ANN model evaluated with 2139 daily records (1996-2004) from Nagpur station indicated lowest RMSE value 1.961 mm and highest R^2 value 0.719. Goyal et al. [23] used 3801 daily records of meteorological data to improve the accuracy of daily pan evaporation for Karso watershed in India by applying ANN, least squares – support vector regression (LS-SVR), fuzzy logic, and ANFIS techniques. The fuzzy logic and LS-SVR machine learning methods outperformed the traditional Stephens–Stewart and Hargreaves and Samani empirical methods in estimation of evaporation for sub-tropical region. Kim et al. [24] used soft computing models namely gene expression programming (GEP), multilayer perceptron-neural networks model (MLP-NNM) and Kohonen self-organizing feature maps-neural networks model (KSOFM-NNM) to predict daily pan evaporation with temperature-based, radiation-based, and sunshine duration based input combinations for two stations of south-western Iran. It was reported that temperature-based model produced the best results for both stations. All three soft computing models demonstrated the superiority over multiple linear regression model in prediction of evaporation. Allawi and El-Shafie [25] used RBF-NN and ANFIS based models to predict daily evaporation at Layang reservoir, Malaysia. RBF-NN model was found to be superior over ANFIS which showed minimum mean absolute error (MAE) 0.0471, MSE 0.0032, and maximum R^2 0.963. Antonopoulos et al. [26] applied ANN method to estimate daily evaporation for Lake Vegoritis, Greece and compared its results with empirical methods of Penman, Priestley-Taylor and the mass transfer method. The neural network based evaporation model (4-4-1) showed RMSE from 0.69 to 1.35 mmd^{-1} and correlation coefficient from 0.79 to 0.92. Wang et al. [27] used six different soft computing methods namely Stephens and Stewart model (SS), multiple linear regression (MLR), least square support vector machine (LSSVM), multi-layer perceptron (MLP), fuzzy genetic (FG) and multivariate adaptive regression spline (MARS) for estimation of monthly pan evaporation. The MLP model showed superiority over other models in predicting monthly evaporation. With MLP model, MAE, RMSE and coefficient of determination (R^2) were found to be 0.314 mmd^{-1}, 0.405 mmd^{-1} and 0.988, respectively for HEB station. The GRNN model performed better for Tibetan Plateau having MAE, RMSE and R^2 values 0.459 mmd^{-1}, 0.592 mmd^{-1} and 0.932, respectively. They reported the accuracy of these models in the order as: MLP, GRNN, LSSVM, FG, ANFIS-GP, MARS and MLR.

Considering the ability of regression and non-linear model in prediction of different hydrological process, this study was undertaken to investigate the comparative performance of multiple linear regression and artificial neural network model in estimation of weekly evaporation for Pantnagar. The climatic variables viz. temperature, wind speed, sunshine hours and relative humidity were used as independent parameters and evaporation was considered as dependent parameter.

1.1 Study Area

The weekly weather data considered for this study were collected from meteorological observatory of G.B. Pant University of Agriculture and Technology, Pantnagar (Fig. 1). It falls in sub-humid and subtropical climatic zone and situated in Tarai belt of Shivalik range, of foot hills of Himalayas. Geographically it is located at 29°N latitude and 79.29°E longitude and an altitude of 243.84 m above mean sea level.

2. MATERIALS AND METHODS

The weekly meteorological data from 2002-11 used in this study were collected from meteorological observatory, G.B. Pant university of agriculture and technology, Pantnagar. Out of 520 meteorological dataset, 349 datasets were used for training and remaining 171 datasets were used for testing in both MLR and ANN model.

2.1 Multiple Linear Regression

Regression analysis is a statistical analysis technique which explores the relationship between response variable and predictors. Regression model using time series data is widely used in the field of economics, business and engineering. In linear modeling, simplicity and ease of use makes linear regression more advantageous over other methods. The ability of achieving the reliable statistical modeling even with a small data set is another advantage with linear regression technique.

Multiple linear regression involves a dependent variable and two or more explanatory variables. Basically, it is an extension of simple linear regression. A multiple linear regression model can be represented by following equation.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_n x_{in} + \varepsilon_i \quad (1)$$

$$\varepsilon_i = y_i - \hat{y_i} \quad (2)$$

Where,

$x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}$ are explanatory variables

y_i is actual output corresponding to $x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}$

$\hat{y_i}$ is predicted output corresponding to $x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}$

and ε_i is error.

2.2 Artificial Neural Network

The famous neurophysiologist Warren McCulloch and logician Walter Pits discovered first artificial neuron in 1943. An artificial neural network (ANN) is an information processing paradigm that simulates biological nervous systems, such as brain processes the information in human body. Artificial neural networks process the information received at input layer and sends the signal to hidden layers where these signals pass through activation function to produce an output. There may be one or more hidden layers with same or different number of neurons. The neurons present in hidden layer are typically treated as black boxes. Hidden layers are used to act as a collection of feature detectors.

The generalised feed forward networks with back propagation algorithm are widely used as these networks have capability of solving complex problems in different area. In forward phase, network is initiated with random values of

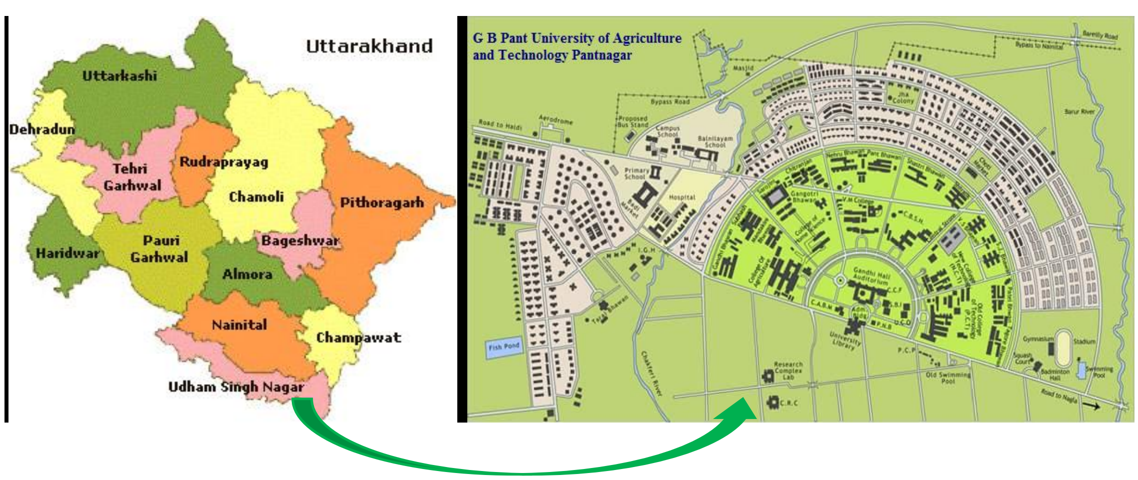

Fig. 1. Map showing the location of study area

weights and input signals transmit through different layers. The error is computed at output layer of network. The signals of computed error are sent in the backward direction. In this process, the previously assigned weights are adjusted to minimize the computed error. The architecture of a multilayer feed forward network is shown in Fig. 2. A single artificial neuron (perceptron) is shown in Fig. 3. Being a non-parametric and data-driven technique and flexible nonlinear function mapping in neural network makes it less susceptible to model misspecification than other parametric nonlinear methods [10,28]. ANN has been used as a powerful tool to build up linear and nonlinear relationships in complex engineering problems.

The network can be trained with different learning algorithm.The delta rule and back-propagation algorithm is widely used for supervised learning [29]. Kisi and Unchoglu [30] investigated the effect of learning algorithm on the performance of ANN model and reported that Levenberg-Marquardt technique is more powerful than conventional gradient descent techniques in minimizing the error function during training of ANN. In this study, the network was trained by Levenberg–Marquardt technique based on back-propagation rule.

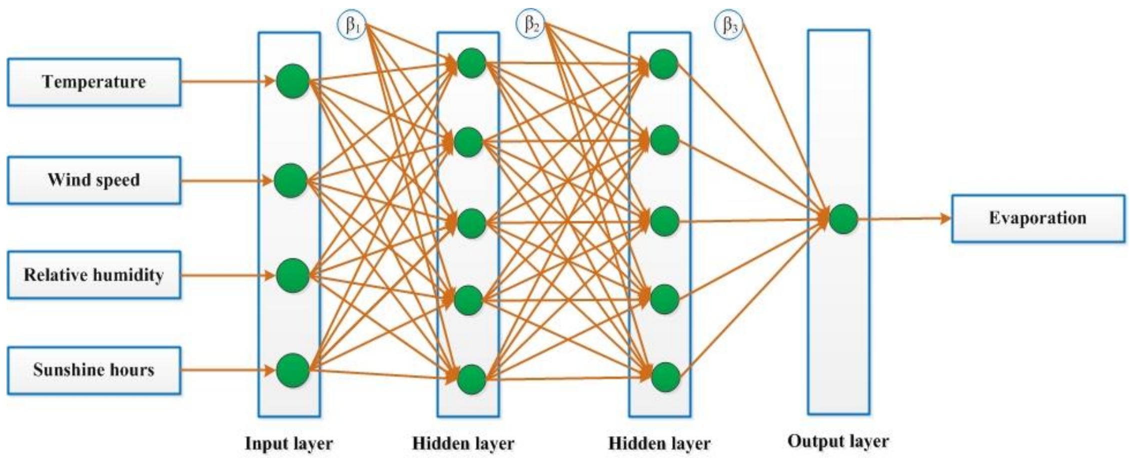

Fig. 2. Architecture of a multilayer feed forward network

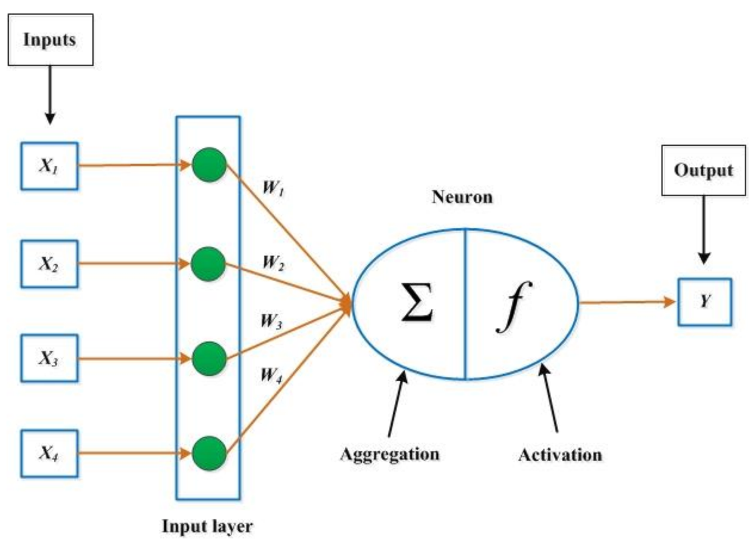

Fig. 3. A single artificial neuron (perceptron)

The number of hidden layers and neurons were varied to achieve the good results. The processing of information in neural network can be understood with the following equations.

Let consider X_i (i = 1,2, ... n) as inputs in neural network with their respective weights W_i (i = 1,2, … n). The net input to the node can be expressed as

$$net = \sum_{i=1}^{i=n} X_i W_i \quad (3)$$

The signal from node is then passed through an activation function $f(.)$ and the output Y from the node can be computed by following equation.

$$Y = f(net) \quad (4)$$

Sigmoid function is one of the commonly used nonlinear activation function which can be expressed as in eqn. (5).

$$Y = f(net) = \frac{1}{1+e^{-net}} \quad (5)$$

2.3 Selection of Model Input Parameters Using Gamma Test

Selection of effective variables is one of the most important part in modeling. Gamma test is a modeling tool widely used in non-parametric methods to select effective input variables resulting in least gamma value. The main function of gamma test is to estimate the minimum mean square error which can be attained in a nonlinear continuous modeling with unseen dataset [31]. Suppose we have dataset in the form of $\{(x_i, y_i),\ 1 \le i \le m\}$, where x_i represents input vectors which are confined on a closed bounded set $S \in R^m$ and y_i is the corresponding output belonging to R. In this method, the relationship between output and input variables is assumed in the following form.

$$y = f(x) + r \quad (6)$$

Where f and r are continuous function and random variable, respectively. The term r is nonresponsive to input data in the model and generally it is called noise. The gamma test estimates the variance of noise Var(r). The gamma test is based on the k^{th}($1 \le k \le p$) nearest neighbors $x_{N[i,k]}$for each vector x_i ($1 \le i \le m$) which is derived from Dirac's delta function of input vectors and gamma function of output values as given in eqns. (7) and (8), respectively [21].

$$\delta_M(k) = \frac{1}{2M} \sum_{i=1}^{M} \left| x_{N[i,k]} - x_i \right|^2 \quad (7)$$

$$\gamma_M(k) = \frac{1}{2M} \sum_{i=1}^{M} \left| y_{N[i,k]} - y_i \right|^2 \quad (8)$$

where k varies from 1 to p, M represents number of input-output training pairs and |…| represents Euclidean distance.

The gamma value (Γ) is calculated from the intercept on the vertical axis by line $\gamma = A\delta + \Gamma$ plotted with least square method for p points $(\delta_M(k), \gamma_M(k))$.

In past, Moghaddamnia et al. [21] applied gamma test to select best combination of independent parameters in ANN and ANFIS model for prediction of evaporation. Niknia *et al*. [32] applied gamma test for selection of effective parameters in prediction of pipe line scouring depth. In this study, gamma test was performed to find the best combination of predictors so that a model having good accuracy can be developed.

3. RESULTS AND DISCUSSION

3.1 Gamma Test

All combination of input parameters viz. temperature, wind speed, sunshine hours and relative humidity were put on gamma test to know the most effective combination and thereby reducing the mean squared error in model. The gamma values for some combination of input parameters are presented in Table 1. From the Table 1, it is clear that the combination of W, S, T_{avg} and Rh_{avg} showed minimum gamma value. So this combination was used for modeling of evaporation by MLR and ANN technique.

3.2 Multiple Linear Regression Model

3.2.1 Model training

The model was trained with 349 meteorological datasets. The relation between response variable and predictors is given in eqn. (9). The performance of model was checked in terms of root mean square error and correlation coefficient. In training phase, values of mean squared error and correlation coefficient were found to be 1.12 and 0.92, respectively. A good linear dependency between estimated and actual evaporation can be observed in Fig. 4.

$$E_{est} = 6.5074 - 0.1009S + 0.1585W + 0.2391T_{avg} - 0.1139\ Rh_{avg} \quad (9)$$

3.2.2 Model testing

A model cannot be said well unless its performance checked with a different data. The developed model was tested with 171 observations. For testing period, values of mean square error and correlation coefficient were found to be 0.96 and 0.95, respectively. The comparison between estimated and actual values of evaporation can be seen in Fig. 5.

3.3 Artificial Neural Network Model

3.3.1 Model training

Levenberg–Marquardt technique was used for training of ANN model. Out of total data, 349 observations were considered to train the network. The number of hidden layers and number of neurons in each hidden were varied upto 3 and 10, respectively. The network with three hidden layers did not show any significant improvement in mean squared error and correlation coefficient over the network having two hidden layers and it also required comparatively more computational time. The network having two hidden layers with five neurons in each hidden layer was found to be the most effective. The network 4-5-5-1 demonstrated good results for which mean squared error and correlation coefficient were 0.56 and 0.96, respectively. The qualitative performance of developed model can be seen in Fig. 6. It is clear from Fig. 6 that estimated values of evaporation are very close to those of actual values of evaporation.

3.3.2 Model testing

The developed model was tested with different data (171 datasets) in order to check its accuracy. The model performed well in qualitative and quantitative evaluation. The model showed mean squared error and correlation coefficient as 0.68 and 0.97, respectively. The qualitative performance of model can be seen in Fig. 7.

From the above results, it is clear that both MLR and ANN model performed well in estimation of evaporation using climatic variables. The overall comparative performance of both models is shown in Table 2. In terms of mean squared error and correlation coefficient, it can be understand that ANN model outperformed MLR model in estimation of evaporation. So like other hydrological processes, ANN model can estimate evaporation as well with a good accuracy.

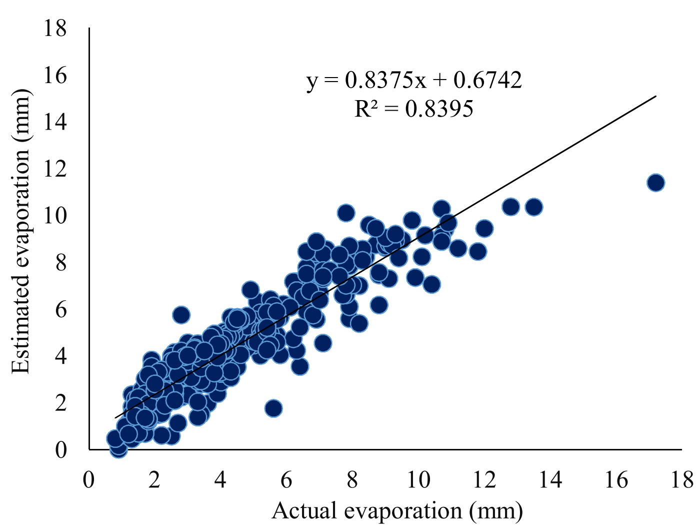

Fig. 4. Actual vs. estimated evaporation for training period of MLR model

Table 1. Gamma value for different combination of input parameters

Parameters	W, S, T_{max}, Rh_{max}	W, S, T_{min}, Rh_{min}	W, S, T_{min}, Rh_{max}	W, S, T_{max}, Rh_{min}	W, S, T_{avg}, Rh_{avg}	W, T_{max}, Rh_{max}	W, T_{min}, Rh_{min}	W, T_{max}, Rh_{min}	W, T_{min}, Rh_{max}
Gamma value	0.49749	0.62135	0.51206	0.54896	0.48819	0.60521	0.69357	0.58066	0.67437

Table 2. Comparative performance of MLR and ANN model

Parameter	Model	Phase	
		Training	Testing
Mean squared error	MLR	1.12	0.96
	ANN	0.56	0.68
Correlation coefficient	MLR	0.92	0.95
	ANN	0.96	0.97

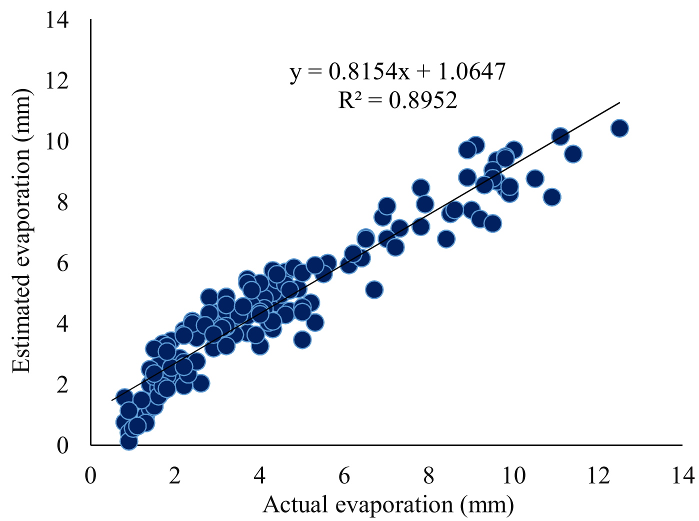

Fig. 5. Actual vs. estimated evaporation for testing period of MLR model

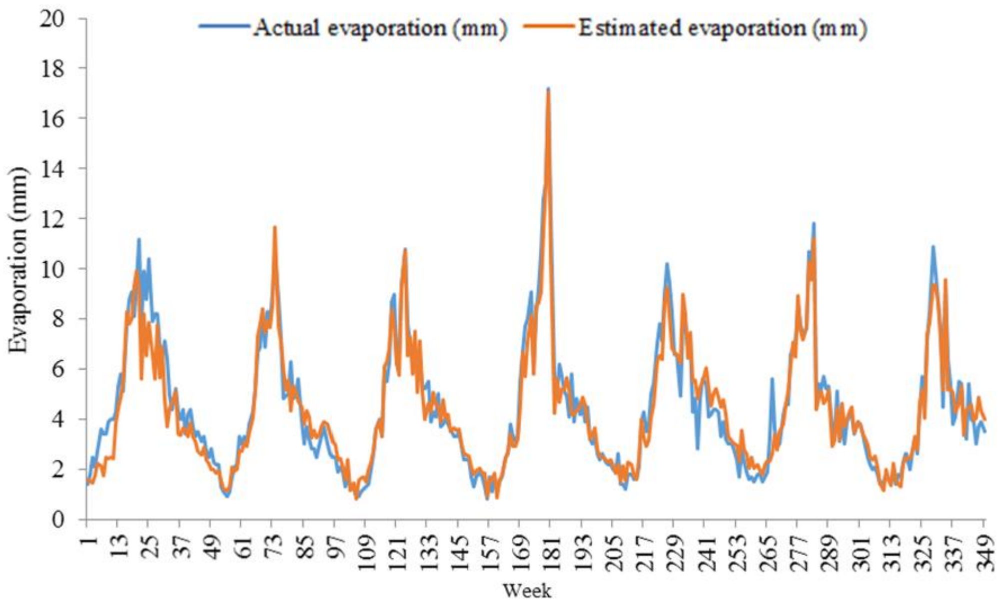

Fig. 6. Actual and estimated evaporation for different week in training period of ANN model

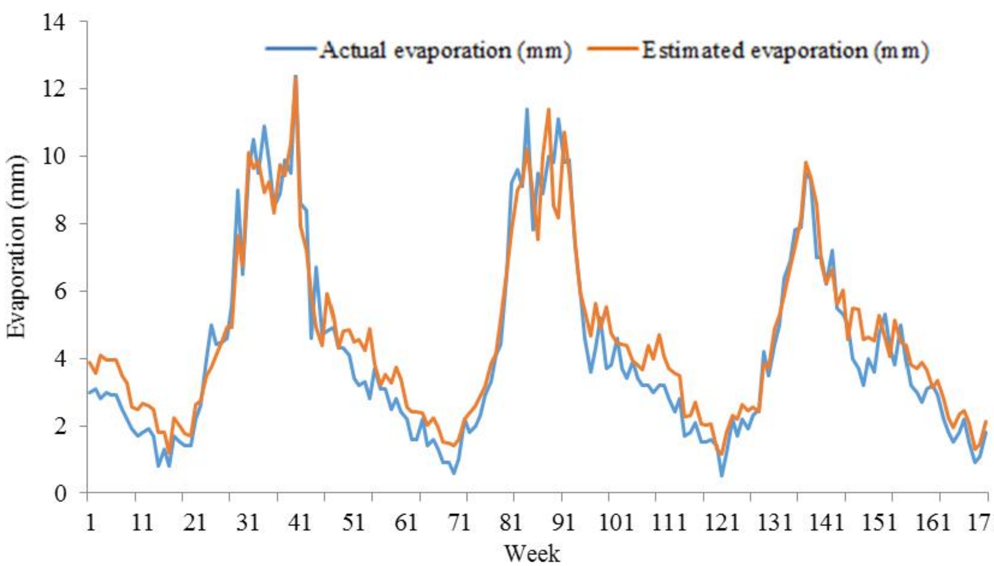

Fig. 7. Actual and estimated evaporation for different week in testing period of ANN model

4. CONCLUSIONS

Based on the results obtained in this study, following concluding remarks can be made.

1) The input parameters viz. average temperature (T_{avg}), wind speed (W), sunshine hours (S), and average relative humidity (Rh_{avg}) were found the most effective input parameters affecting the evaporation.
2) The developed MLR model showed mean squared error and correlation coefficient respectively as 1.12 and 0.92 in training phase. In testing phase mean squared error and correlation coefficient was found to be 0.96 and 0.95, respectively.

3) The mean squared error and correlation coefficient in neural network based model was found to be 0.56 and 0.96, respectively during training phase. In testing period, the developed ANN model exhibited mean squared error and correlation coefficient 0.68 and 0.97, respectively.
4) The ANN model outperformed MLR model in estimation of evaporation from climatic variables.

From the results obtained in this study, it can be understood that gamma test helped in the selection of best combination of climatic parameters affecting the evaporation. Although both MLR and ANN models estimated evaporation with a good accuracy. But with ANN model values of estimated evaporation were found very close to actual values of evaporation. So, ANN model can estimate the evaporation easily as compared to other complex and time consuming methods for evaporation estimation. A neural network based modeling can also be helpful in other complex hydrological processes.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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