The viability of co-active fuzzy inference system model for monthly reference evapotranspiration estimation: case study of Uttarakhand State
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ABSTRACT
Reference evapotranspiration (ET₀) is a major component of the hydrological cycle linking the irrigation water requirement and planning and management of water resources. In this research, the potential of co-active neuro-fuzzy inference system (CANFIS) was investigated against the multilayer perceptron neural network (MLPNN), radial basis neural network (RBNN), self-organizing map neural network (SOMNN) and multiple linear regression (MLR) to estimate the monthly ET₀ at Pantnagar and Ranichauri stations, located in the foothills of Indian central Himalayas of Uttarakhand State, India. The significant combination of input variables for implemented techniques was decided by the Gamma test (GT). The results obtained by CANFIS models were compared with MLPNN, RBNN, SOMNN and MLR models based on performance evaluation indicators and visual inspection using line, scatter and Taylor plots for both the stations. The results of comparison revealed that CANFIS-5/ CANFIS-9 models (RMSE = 0.0978/0.1394, SI = 0.0261/0.0475, COE = 0.9963/0.9846, PCC = 0.9982/ 0.9942 and WI = 0.9991/0.9959) with three and five input variables provide superior results for estimating monthly ET₀ at Pantnagar and Ranichauri stations, respectively. Also, the adopted modelling strategy can build a truthful expert intelligent system for estimating the monthly ET₀ at the study stations.

Key words | CANFIS, estimation, gamma test, reference evapotranspiration, Uttarakhand

INTRODUCTION
Estimation of reference evapotranspiration (ET₀) is essential for hydrologic water balance, irrigation system design and management, crop yield simulation, and planning and management of water resources (Sentelhas et al. 2010). Normally, ET₀ is measured directly using lysimeters or also by eddy covariance, while indirectly calculated using the meteorological data. However, measurement of ET₀ by lysimeters is more time-consuming and needs precise and accurate planned experiments (Lopez-Urrea et al. 2006). The Food and Agriculture Organization (FAO-56) standardized Penman–Monteith (PM) equation was developed for estimating ET₀ by referring a hypothetical crop with an assumed height of 0.12 m, surface resistance of 70 s·m⁻¹ and an albedo of 0.23 (Allen et al. 1998). FAO-56 PM equation requires numerous meteorological variables for effective application which may be unavailable or missing in some locations, especially in developing countries. Therefore, alternative approaches that require less meteorological inputs are needed (Kumar et al. 2002; Yassin et al. 2016; Kisi & Alizamir 2018).
In recent years, soft computing techniques have been successfully applied for modelling reference evapotranspiration using various available meteorological variables (Sudheer et al. 2003; Kisi 2007; Zanetti et al. 2007; Kim & Kim 2008; Kumar et al. 2008; Rahimikhoob 2010; Tabbari & Talaei 2012; Shiri et al. 2013, 2019; Falamarzi et al. 2014; Patil & Deka 2015; Kisi & Demir 2016; Banda et al. 2017; Gavili et al. 2018; Karbasi 2018; Kisi & Alizamir 2018; Tao et al. 2018; Shiri 2018, 2019a, 2019b; Granata 2019). Kisi et al. (2015) examined the comparative potential of multi-layer perceptron artificial neural networks (MLP-ANN), adaptive neuro-fuzzy inference system (ANFIS) with grid partition (ANFIS-GP), ANFIS with subtractive clustering (ANFIS-SC) and genetic expression programming (GEP) in predicting monthly reference evapotranspiration from 50 stations located in Iran. They concluded that the ANFIS-GP models performed better than the other models. Mattar & Alazba (2018) employed GEP and MLR techniques in modelling monthly reference evapotranspiration from 27 stations located in Egypt and found that the GEP models are more powerful models. Pour et al. (2018) used support vector machine (SVM), ANFIS and GEP approaches for modelling monthly potential evapotranspiration in Iran and found that the SVM models performed better than the ANFIS and GEP models. Sanikhani et al. (2018a) investigated the comparative potential of MLP, generalized regression neural network (GRNN), RBNN, ANFIS-GP, ANFIS-SC, GEP and Hargreaves–Samani (HS) techniques in modelling monthly reference evapotranspiration at Antalya and Isparta stations located in Turkey. The results of comparison showed that the GEP and GRNN models estimated successfully at Antalya station, while the RBNN and ANFIS-SC models performed better than the other models at Isparta station. Granata (2019) estimated daily ET₀ in central Florida, USA, using M5P regression tree, bagging, random forest (RF) and support vector regression (SVR) models. He found that the M5P regression tree model with inputs net solar radiation, sensible heat flux, moisture content of the soil, wind speed, mean relative humidity and mean temperature performed superior to the other models for daily ET₀ estimation. Shiri (2019a, 2019b) compared the performance of gene expression programming (GEP), against temperature-based (HS), radiation/humidity-based (Priestley–Taylor, Makkink and Turc), and mass-transfer based (Dalton, Trabert and Penman) equations in modelling monthly ET₀ at five meteorological locations of Iran. The results of analysis revealed that the GEP models (mass transfer-based) performed better than the other models.

Furthermore, the number of relevant applications of soft computing and time series methods have been found in modelling various hydrological processes, such as river flow forecasting (Yaseen et al. 2015a, 2018a, 2019; Papacharalampous et al. 2019); forecasting air temperature (Sanikhani et al. 2018a); soil temperature estimation (Sanikhani et al. 2018b); stream-flow forecasting (Yaseen et al. 2015b, 2016a, 2016b, 2017; Granata et al. 2018); suspended sediment load estimation (Khosravi et al. 2018; Kisi & Yaseen 2019); rainfall pattern forecasting (Yaseen et al. 2018b); flood forecasting (Solomatine & Xue 2004; Singh et al. 2010); soil moisture estimation (Ahmad et al. 2010); rainfall–runoff modelling (Granata et al. 2016); and predicting monthly temperature and precipitation using stochastic models (Papacharalampous et al. 2018).

This research utilized the Gamma test (GT) for selecting the significant combination of input variables in modelling monthly ET₀ at study stations. In the recent decade, on global scale, several studies have been conducted using GT in diverse fields such as modelling daily pan-evaporation (Moghaddamnia et al. 2008; Piri et al. 2009; Goyal et al. 2014; Malik et al. 2017b, 2018; Ashrafzadeh et al. 2018); rainfall–runoff and river flow modelling (Remesan et al. 2009; Malik & Kumar 2018; Singh et al. 2018); and suspended sediment load (SSL) modelling (Kakaei-Lafdani et al. 2013; Malik et al. 2017a). Moghaddamnia et al. (2008) decided on an optimal input variables combination for ANN and ANFIS approaches using GT for modelling daily evaporation in an arid and semi-arid region of Iran. They reported the high ability of the ANN and ANFIS models in daily evaporation estimation. Kakaei-Lafdani et al. (2013) utilized the GT to select the most influential inputs for ANN and SVM for SSL estimation in Doiraj River, Iran and found that the ANN and SVM models perform better with the selected inputs using GT. Malik et al. (2017a) applied GT for selecting the appropriate input variables combination for CANFIS, MLPNN, MLR and multiple non-linear regression (MNLR) techniques in simulating daily SSL in Pranhita river basin, India. They found that the CANFIS model performs better than the other models.
models using its selected input combination by the GT. Malik et al. (2018) applied RBNN, SOMNN, MLR, Penman, Stephens-Stewart, Griffiths, Christiansen, Priestley-Taylor and Jensen–Burman–Allen approaches for estimation of daily evaporation at Pantnagar, India. The significant combination of input variables for RBNN, SOMNN and MLR was selected using the GT. They found the RBNN model performed better than the other models.

So far, no literature has been found that utilized the GT for identifying the optimal input combination for CANFIS, MLPNN, RBNN, SOMNN and MLR in monthly reference evapotranspiration estimation. In view of the above-mentioned literature, this study was conducted with the following specific objectives: (i) to decide the significant input variable combination for CANFIS, MLPNN, RBNN, SOMNN and MLR approaches by utilizing the GT; (ii) to compare the accuracy of CANFIS, models with MLPNN, RBNN, SOMNN and MLR models based on various performance indicators and visual inspection for ET₀ estimation at Pantnagar and Ranichauri stations.

MATERIALS AND METHODS

Study area and data acquisition

The study was conducted at Pantnagar (29°0'0"N latitude, 79°38'0"E longitude) with an altitude of 245.8 m above mean sea level (msl) and Ranichauri (30°18'40"N latitude, 78°24'35"E longitude) with an altitude of 2,000 m above msl (Figure 1). Both stations are located in the foothills of Indian central Himalayan region of Uttarakhand State, India. The average annual rainfall at Pantnagar station is approximately 1,400 mm, while at Ranichauri station it is approximately 1,176 mm. The monthly meteorological data of minimum and maximum air temperatures (Tmin and Tmax), wind speed (U₀), relative humidity (RH), and solar radiation (Rs), were collected from Crop Research Centre (CRC) of Pantnagar and Ranichauri stations located in Uttarakhand State, India. The available data of 32 years (January, 1985–December, 2016) for Pantnagar station and 19 years (January, 1994–December, 2012) for Ranichauri station are presented graphically in Figure 2 using a box and whisker plot. The box and whisker plot provides the information about minimum, first quartile, median, third quartile and maximum values (start interpretation from bottom to top) of meteorological variables.

FAO-56 Penman–Monteith equation

The Cropwat 8.0 software was used to calculate ET₀ values using available meteorological data for Pantnagar and Ranichauri stations. In Cropwat 8.0 software, the FAO-56 Penman–Monteith (FAO-56 PM) equation is programmed and described as (Allen et al. 1998):

\[ ET₀ = \frac{0.408 \Delta (Rₐ - G) + \gamma (900/(T + 273)) U₂ (eₛ - eₐ)}{\Delta + \gamma (1 + 0.34 U₂)} \]  

(1)

where ET₀ is reference evapotranspiration (mm/month), Δ is slope of saturation vapour pressure curve (kPa °C⁻¹), Rₐ is net radiation (MJ/m²/month), G is soil heat flux (MJ/m²/month), γ is psychrometric constant (kPa °C⁻¹), eₛ and eₐ are saturated and actual vapour pressures (kPa), T is average monthly air temperature (°C) and U₂ is mean monthly wind speed at 2 m (m s⁻¹).

Gamma test

Stefansson et al. (1997) introduced the concept of GT to reduce the problem of selection of appropriate input variables for modelling non-linear processes. Gamma test computes the minimum standard error (SE) of each input–output model by constructing the least-square linear regression line as (Piri et al. 2009; Rashidi et al. 2016):

\[ y = G \delta + \Gamma \]  

(2)

where, y is output vector, G is gradient and gamma (Γ) is intercept (δ = 0). The smaller value of the Γ (closer to zero) indicates the more appropriate input variables. The gradient is taken into account as a complexity indicator of the applied model and high gradient reveals complicated model fitting. The standard error (SE) of Γ shows the gamma value’s reliability (i.e., small SE indicates reliable gamma value). The V_ratio indicates the model’s predictability.
for given input and output variables:

\[ V_{\text{ratio}} = \frac{\Gamma}{\sigma^2(y)} \]  

(3)

where, \( \sigma^2(y) \) is the variance of the output y and \( \Gamma \) is the gamma function. If the value of \( V_{\text{ratio}} \) is close to zero it represents the high predictability of the model. In general, a good model (input variable combination) is selected based on minimum value of \( \Gamma \), SE, G, and \( V_{\text{ratio}} \) (Remesan et al. 2008; Moghaddamnia et al. 2009; Piri et al. 2009; Malik et al. 2017a, 2018; Ashrafzadeh et al. 2018).

In this study, the significant combination of input variables for CANFIS, MLPNN, RBNN, SOMNN and MLR approaches was selected based on the minimum value of
Г, SE, G and V_{ratio} for reference evapotranspiration estimation at Pantnagar and Ranichauri stations.

**Co-active neuro-fuzzy inference system**

Jang *et al.* (1997) introduced the concept of co-active neuro-fuzzy inference system (CANFIS). The architecture of CANFIS is composed of five layers, fuzzification layer (fuzzy membership), rule layer (and multiplication), normalization layer, defuzzification layer (consequent) and summation layer (fuzzy association), and each input is processed through these five layers (Figure 3). The functioning of each layer and detailed information is given by Aytek (2009) and Tabari *et al.* (2012a).

For two inputs (x and y) and one output (C), set with fuzzy IF-THEN rules for CANFIS architecture is as follows (Jang *et al.* 1997):

**Rule 1:** IF $x$ is $A_1$ AND $y$ is $B_1$, THEN $C_1 = p_1 x + q_1 y + r_1$  \hspace{1cm} (4)

**Rule 2:** IF $x$ is $A_2$ AND $y$ is $B_2$, THEN $C_2 = p_2 x + q_2 y + r_2$  \hspace{1cm} (5)

where, $A_1$, $A_2$ and $B_1$, $B_2$ are the MFs for inputs $x$ and $y$, respectively, $p_1$, $q_1$, $r_1$ and $p_2$, $q_2$, $r_2$ are the parameters in...
the consequent part (THEN-part) as illustrated in Figure 4.

Layer 1 (Fuzzification layer or fuzzy membership): Every node $i$ in this layer is a square node with a node function as:

$$O_1^i = \mu_{A_i}(x) \quad \text{for, } i = 1, 2, \ldots ,$$

$$O_1^i = \mu_{B_i}(y) \quad \text{for, } i = 1, 2, \ldots .$$

where, $x$ (or $y$) is the input to node $i$, and $A_i$, (or $B_i$) is a linguistic label (small, large, etc.) associated with this node function. In other words, $O_1^i$ is the membership function of $A_i$, (or $B_i$) and it specifies the degree to which the given $x$ (or $y$) satisfies the quantifier. Usually, we choose $\mu_{A_i}(x)$ or $\mu_{B_i}(y)$ to bell-shaped with maximum equal to one and minimum equal to zero, such as:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[ \frac{(x - c_i)}{a_i} \right]^2 b_i}$$

or the Gaussian function is written as:

$$\mu_{A_i}(x) = \exp \left\{ - \left( \frac{x - c_i}{a_i} \right)^2 \right\}$$

where, $a_i$, $b_i$, $c_i$ are the parameter set. As the values of these parameters change, the bell-shaped or Gaussian functions vary accordingly, thus exhibiting various forms of membership functions on the linguistic label ($A_i$). The parameters in this layer are referred to as premise parameters.

Layer 2 (Rule layer or AND multiplication): Every node in this layer is a circle node (Π) which multiplies the incoming signals and sends the product out as:

$$O_2^i = \mu_{A_i}(x) \mu_{B_i}(y) \quad i = 1, 2,$$

Each node output represents the firing strength (weights) of a rule. T-norm operators that perform generalized AND can be used as the node function in this layer.

Layer 3 (Normalization layer): Every node in this layer is a circle node (N). The $i$th node calculates the ratio of the

Figure 3 | Architecture of CANFIS.
ith rule’s firing strength to the sum of all rules’ firing strengths as:

\[ O_i^3 = \frac{w_j}{w_1 + w_2} \quad i = 1, 2, \]  

(11)

For convenience, the outputs of this layer are called normalized firing strengths.

Layer 4 (Defuzzification layer or consequent): Every node \( i \) in this layer is a square node with a node function as:

\[ O_i^4 = \overline{w_i} C_i = \overline{w_i} (p_i x + q_i y + r_i) \]  

(12)

where, \( \overline{w_i} \) is the output of layer 3, and \( p_i, q_i, r_i \) are the parameter set. The parameters of this layer are referred to as consequent parameters.

Layer 5 (Summation layer or fuzzy association): The single node in this layer is a circle node (\( \Sigma \)) that computes the overall output as the summation of all incoming signals:

\[ O_i^5 = \text{overall output} = \sum_i \overline{w_i} C_i = \frac{\sum_i \overline{w_i} C_i}{\sum_i \overline{w_i}} \]  

(13)

In this research, the network of CANFIS was constructed using two to three Gaussian membership functions (MFs), Sugeno fuzzy model (Takagi & Sugeno 1985), hyperbolic tangent activation function (ranges from \(-1 \) to \(1 \)) for data normalization, and delta-bar-delta (DBD) learning algorithm with the threshold of 0.001 and 1,000 iterations in NeuroSolutions software.

Multilayer perceptron neural network

Haykin (1998) first introduced multilayer perceptron neural network (MLPNN), which consists of layers of parallel processing elements (called neurons), with each layer being fully connected to the preceding layer by interconnection strengths or weights (W). Figure 4 illustrates a feed-forward MLPNN, consisting of an input layer (\( i \)), hidden layer (\( j \)) and output layer (\( k \)), with the inter-connection weights (\( W_{ij} \) and \( W_{jk} \)) between layers of neurons. One or more than one hidden layer exists between an input and an output layer. The number of hidden layers and neurons are specified by the problem to which the network is applied (i.e., the number of predictors and predictands, respectively). The hydrologist must specify the number of hidden layers and neurons for accurate mapping of all the training dataset. Initial estimated weight values are progressively corrected during a training process that compares predicted outputs
to known outputs and backpropagates any errors (from right to left in Figure 4) to determine the appropriate weight adjustments necessary to minimize the errors (Dawson & Wilby 2001).

In the forward mode, the input pattern vector \( I_p \) is presented to the input layer of neurons \( i \) and simply passed through unchanged output \( O_p \), to be distributed to the second layer \( j \). Each neuron in layers \( j \) and \( k \) receives the weighted sum of outputs \( NET \) from the previous layer as input. Mathematically, the \( NET \) for layer \( j \) is written as:

\[
NET_{pi} = \sum_{i=1}^{N} W_{ij}O_{pi} + b_j
\]

(14)

where \( W_{ij} \) is the weight between the input layer and hidden layer, \( O_{pi} \) is the output of the input layer, \( b_j \) is a bias for neuron \( j \). Each neuron in layers \( j \) and \( k \) produces its output \( f(NET) \) by passing its value of \( NET \) through a non-linear activation function. A commonly used functional form is the logistic activation function:

\[
f(NET) = \frac{1}{1 + e^{-NET}}
\]

(15)

The overall output of the \( k \)th layer is obtained as:

\[
y_k = f(NET)
\]

(16)

where \( f \) is the activation function. All input and output values used in training and testing are scaled through the activation function. In this study, the architecture of MLPNN was designed by supervised learning with one input layer, one hidden layer and one output layer with a single output. The hyperbolic tangent activation function (range \(-1 \) to \( 1 \)) was used for data normalization with DBD learning algorithm because this technique is more powerful and faster than the conventional gradient descent. The optimal number of neurons in the hidden layer were determined using \( 2n + 1 \) concept given by Mishra & Desai (2006), where \( n \) is the number of inputs. The MLPNN training was stopped after 1,000 epochs with a threshold value of 0.001 in NeuroSolutions 5.0 software.

Radial basis neural network

The radial basis neural network (RBNN) is a branch of ANN, and the concept of RBNN was given by Bishop (1995). The radial basis functions (RBF) of the RBNN serve as the activation function. The architecture of RBNN is composed of three layers (input layer, hidden layer and output layer). The functioning of the hidden layer is to create clusters and then outputs are multiplied by the weights; these multiplied weights are incorporated into the hidden layer using the multivariate interpolation functions. In this study, different quantities of hidden layer neurons and spread constants were analysed using a trial-and-error method in NeuroSolutions software. The functioning of each layer and more insightful details of RBNN are given by Bishop (1995), Kisi (2009) and Banda et al. (2017).

Self-organizing map neural network

Kohonen (1982) discovered the self-organizing map neural network (SOMNN) algorithm for effective and clustering analysis. The structure of SOMNN is composed of three steps, (i) initialization: in this step, any random value of initial weights is chosen; (ii) winner finding: this step involves finding the optimal weight vectors with the neuron (winner weights); (iii) weight updating: this step involves adjustment of the winner weights and neighbourhood neurons towards the input vectors. More detailed and theoretical insightful information about SOMNN is given by Chang et al. (2007, 2010). In this study, the size of SOMNN, i.e., rows \( \times \) columns matrix, neighbourhood shape, hidden layer, processing elements, activation function and learning algorithm were decided using a trial-and-error procedure in NeuroSolutions software, to train and test the obtained networks based on training and testing datasets, respectively.

Multiple linear regression

Multiple linear regression (MLR) is utilized to model the colinearity between a dependent variable and more than one independent variables. The regression equation can be
expressed as (Malik & Kumar 2015):

\[
ET_o = \beta_0 + \beta_1 T_{\text{min}} + \beta_2 T_{\text{max}} + \beta_3 RH + \beta_4 U_s + \beta_5 R_s
\]  

(17)

where \( ET_o \) is the dependent variable (output); \( T_{\text{min}}, T_{\text{max}}, RH, U_s \) and \( R_s \) are the independent variables; \( \beta_0 \) is the intercept; and \( \beta_1, \beta_2, \beta_3, \beta_4 \) and \( \beta_5 \) are the regression coefficients.

Model performance evaluation indicators

In this study, the performances of CANFIS, MLPNN, RBNN, SOMNN and MLR models were evaluated using root mean squared error (RMSE), scatter index (SI), coefficient of efficiency (COE), Pearson correlation coefficient (PCC), Willmott index (WI), relative error (RE) and Taylor diagram (Taylor 2001). The RMSE (Malik & Kumar 2015), SI (Shiri 2018; Tao et al. 2018), COE (Nash & Sutcliffe 1970), PCC (Malik et al. 2018; Singh et al. 2018), WI (Willmott 1981) and RE (Tao et al. 2018; Yaseen et al. 2018a) are described as:

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (ET_{o,\text{obs},i} - ET_{o,\text{pre},i})^2} \quad (0 < \text{RMSE} < \infty)
\]  

(18)

\[
\text{SI} = \frac{\text{RMSE}}{ET_{o,\text{obs}}}
\]  

(19)

\[
\text{COE} = 1 - \frac{\sum_{i=1}^{N} (ET_{o,\text{obs},i} - ET_{o,\text{pre},i})^2}{\sum_{i=1}^{N} (ET_{o,\text{obs},i} - \overline{ET}_{o,\text{obs}})^2} \quad (-\infty < \text{NSE} < 1)
\]  

(20)

\[
\text{PCC} = \frac{\sum_{i=1}^{N} (ET_{o,\text{obs},i} - \overline{ET}_{o,\text{obs}})(ET_{o,\text{pre},i} - \overline{ET}_{o,\text{pre}})}{\sqrt{\sum_{i=1}^{N} (ET_{o,\text{obs},i} - \overline{ET}_{o,\text{obs}})^2} \sum_{i=1}^{N} (ET_{o,\text{pre},i} - \overline{ET}_{o,\text{pre}})^2} \quad (-1 < \text{PCC} < 1)
\]  

(21)

\[
\text{WI} = 1 - \frac{\sum_{i=1}^{N} (ET_{o,\text{pre},i} - ET_{o,\text{obs},i})^2}{\sum_{i=1}^{N} (ET_{o,\text{pre},i} - ET_{o,\text{obs}})^2 + \|ET_{o,\text{obs},i} - ET_{o,\text{obs}}\|^2} \quad (0 < \text{WI} < 1)
\]  

(22)

\[
\text{RE} = \frac{(ET_{o,\text{obs},i} - ET_{o,\text{pre},i})}{ET_{o,\text{obs},i}} \times 100
\]  

(23)

where, \( ET_{o,\text{obs}} \) and \( ET_{o,\text{pre}} \) are observed and estimated monthly \( ET_o \) values for the \( i \)th dataset, \( N \) is total number of observations in a dataset, \( ET_{o,\text{obs}} \) and \( ET_{o,\text{pre}} \) are mean of observed and estimated monthly \( ET_o \) values, respectively, \( |ET_{o,\text{pre},i} - ET_{o,\text{obs},i}| \) is absolute difference between estimated and observed mean, and \( |ET_{o,\text{obs},i} - ET_{o,\text{obs}}| \) is absolute difference between observed values and their mean. The model that had higher value of COE, PCC and WI, and lower RMSE and SI values was adjudged relatively the better model for monthly \( ET_o \) estimation at study stations.

RESULTS

Deciding optimal input variables using GT

The descriptive statistics of training and testing datasets are provided in Table 1 for the Pantnagar and Ranichauri stations. From Table 1, it was observed that the Pantnagar station has higher temperatures compared to Ranichauri station. \( T_{\text{min}}, T_{\text{max}} \) and RH have negative skewness while \( U_s, R_s \) and \( ETo \) show positive skewness in training and testing datasets of both stations. The solar radiation has the least skewness at Pantnagar station and it follows a normal distribution. The kurtosis was generally found to be platykurtic (−) except the \( U_s \) data which are leptokurtic (+) in nature in training datasets for both the stations. The cross-correlation between input and output variables are given in Table 2 for Pantnagar and Ranichauri stations. As observed from Table 2 for Pantnagar and Ranichauri stations, significant correlation was found between \( T_{\text{min}} \) and \( T_{\text{max}}, U_s, R_s \) and \( ETo \); \( T_{\text{max}} \) and RH, \( U_s \) and \( ETo \), RH and \( U_s \), \( R_s \) and \( ETo \), \( U_s \) and \( R_s \) and \( ETo \) at 5% significance level, respectively.

Deciding significant model inputs is a tedious procedure, especially for the non-linear hydrological processes. In this study, the nine combinations of available inputs were considered to evaluate their effects on monthly \( ET_o \) (Table 3). The GT test was applied to the full dataset for identifying the significant combination of input variable for CANFIS, MLPNN, RBNN, SOMNN and MLR approaches. The test statistics of the GT were reported in Table 4, which revealed minimum value of \( \Gamma = 0.0240 \), \( G = 0.0062 \), \( SE = 0.0044 \), \( V_{\text{ratio}} = 0.0084 \) with the mask 01011 for Pantnagar station.
(Figure 5(a)), and \( \Gamma = -0.0022 \), \( G = 0.0039 \), \( SE = 0.0011 \), \( V_{\text{ratio}} = -0.0018 \) with the mask 11111 for Ranichauri station (Figure 5(b)). The term mask defines the number of effective input variables used, for instance, the mask 01011 and 11111 indicates three and five input variables are used at a time to give an output, i.e., \( E_{T_0} \) at Pantnagar and Ranichauri stations, respectively. Therefore, the appropriate input combination of three variables \( (T_{\text{max}}, U_s, R_s) \) was used for the CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models at Pantnagar station, while five variables \( (T_{\text{min}}, T_{\text{max}}, RH, U_s, R_s) \) were used for CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models at Ranichauri station to estimate monthly \( E_{T_0} \).

### Monthly \( E_{T_0} \) estimation at Pantnagar station

The selected CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models were trained (January, 1985–December, 2010) and tested (January, 2011–December, 2016) to estimate the monthly \( E_{T_0} \) at Pantnagar station. The performance of CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models were evaluated statistically using RMSE, SI, COE, PCC and WI, and visually inspected using line, scatter, relative error and Taylor plots. The values of RMSE, SI, COE, PCC and WI of the applied models during the testing period are reported in Table 5. As clearly seen from Table 5, the CANFIS-5 model had the best performance (RMSE = 0.0978 mm/month, \( SI = 0.0261, \) \( COE = 0.9963, \) \( PCC = 0.9982 \) and \( WI = 0.9991 \)) with two Gaussian MFs for each input, activation function of hyperbolic tangent. Increasing MFs’ number did not improve the model performance. The various tests were made with MLPNN-5 using one, two and three hidden layers with varying numbers of neurons in hidden layer. The MLPNN-5 with 3-5-1 architecture (three inputs, five neurons and one output, respectively) was found to be optimal for \( E_{T_0} \) estimation with \( RMSE = 0.1082 \) mm/month, \( SI = 0.0289, \) \( COE = 0.9958, \) \( PCC = 0.9980 \) and \( WI = 0.9989 \). The RBNN-5, SOMNN-5, and MLR-5 models have \( RMSE = 0.1972 \), 0.1487 and 0.2445 mm/month; \( SI = 0.0527, \) 0.0397 and 0.0653; \( COE = 0.9850, \) 0.9915 and 0.9770; \( PCC = 0.9925, \) 0.9960 and 0.9892; and \( WI = 0.9962, \) 0.9978 and 0.9943, respectively. Table 5 clearly showed that the CANFIS-5 model has lower RMSE and SI, and higher COE, PCC and WI than the MLPNN-5, SOMNN-5, RBNN-5 and MLR-5 models, respectively. The regression equation for the MLR-5 model with their intercepts and regression coefficients obtained from the training phase are written as:

\[
MLR-5 = -3.697 + 0.126 T_{\text{max}} + 0.759 U_s + 0.159 R_s \quad (24)
\]

### Table 1 | Descriptive statistics of the meteorological variables for training and testing periods

| Statistical parameters | \( T_{\text{min}} \) (°C) | \( T_{\text{max}} \) (°C) | RH (%) | \( U_s \) (m/s) | \( R_s \) (MJ/m²) | \( E_{T_0} \) (mm) |
|------------------------|--------------------------|--------------------------|--------|--------------|-----------------|-----------------|
| Pantnagar (Training dataset: January 1, 1985–December 31, 2010) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) |
| Minimum | 4.30 | 14.50 | 36.00 | 0.20 | 8.60 | 31.14 |
| Maximum | 26.70 | 40.00 | 89.00 | 4.00 | 25.60 | 8.26 |
| Mean | 16.82 | 29.70 | 67.38 | 1.40 | 17.62 | 3.90 |
| SD | 7.10 | 5.59 | 12.19 | 0.70 | 4.08 | 1.71 |
| Skewness | -0.15 | -0.39 | -0.61 | 0.78 | 0.02 | 0.53 |
| Kurtosis | -1.55 | -0.71 | -0.39 | 0.37 | -0.77 | -0.57 |
| Pantnagar (Testing dataset: January 1, 2011–December 31, 2016) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) |
| Minimum | 5.80 | 17.00 | 42.00 | 0.60 | 8.20 | 1.23 |
| Maximum | 26.30 | 40.10 | 87.00 | 2.80 | 24.70 | 7.63 |
| Mean | 17.27 | 29.77 | 68.71 | 1.38 | 16.38 | 3.74 |
| SD | 7.08 | 5.80 | 10.91 | 0.49 | 4.40 | 1.62 |
| Skewness | -0.13 | -0.51 | -0.78 | 0.36 | -0.05 | 0.43 |
| Kurtosis | -1.57 | -0.54 | -0.29 | -0.03 | -0.82 | -0.55 |
| Ranichauri (Training dataset: January 1, 1994–December 31, 2008) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) |
| Minimum | 0.50 | 8.50 | 29.00 | 1.00 | 9.60 | 1.23 |
| Maximum | 17.80 | 28.50 | 94.00 | 1.80 | 25.40 | 5.33 |
| Mean | 9.87 | 19.55 | 70.43 | 1.42 | 16.37 | 2.93 |
| SD | 5.32 | 4.83 | 14.04 | 0.15 | 4.15 | 1.06 |
| Skewness | -0.16 | -0.50 | -0.15 | 0.13 | 0.44 | 0.42 |
| Kurtosis | -1.37 | -0.90 | -0.69 | 0.11 | -0.73 | -0.70 |
| Ranichauri (Testing dataset: January 1, 2009–December 31, 2012) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) | \( \quad \) |
| Minimum | 0.50 | 9.30 | 37.00 | 0.40 | 10.50 | 1.13 |
| Maximum | 16.70 | 29.10 | 93.00 | 1.60 | 24.60 | 5.42 |
| Mean | 9.83 | 20.16 | 67.38 | 1.05 | 16.38 | 2.93 |
| SD | 5.34 | 4.67 | 15.41 | 0.40 | 4.09 | 1.13 |
| Skewness | -0.20 | -0.36 | 0.16 | -0.37 | 0.57 | 0.59 |
| Kurtosis | -1.43 | -0.54 | -0.89 | -1.28 | -0.74 | -0.48 |

Notes: \( T_{\text{min}} \) and \( T_{\text{max}} \) minimum and maximum air temperatures (°C); RH, relative humidity (%); \( U_s \), wind speed (m/s); \( R_s \), solar radiation (MJ/m²); \( E_{T_0} \), reference evapotranspiration (mm); SD, standard deviation.
The temporal variation between the observed and estimated monthly ET₀ values of CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models during the testing period are plotted using line plot (left side) and scatter plot (right side) in Figure 6(a)–6(e), respectively. As observed from Figure 6(a)–6(e), the regression line and best fit line (1:1) for all the models were perfectly close to each other; however, these lines were closer to each other for CANFIS-5 (Figure 6(a)) and MLPNN-5 (Figure 6(b)) models, respectively. It can be concluded that based on the statistical and visual comparisons, the ranks of the model (from the best to worst) can be classified as the CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models for Pantnagar station, respectively.

Using Equation (23), the relative error percentage between observed and estimated monthly ET₀ values of CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models during the testing period was calculated and presented graphically in Figure 7. As Figure 7 demonstrates, the RE percentage concentrated around the ±10% upper band (UB) and lower band (LB) for 100% (CANFIS-5), 98.61% (MLPNN-5), 81.94% (RBNN-5), 97.22% (SOMNN-5) and 81.94% (MLR-5) of testing dataset. Here, the CANFIS-5 model shows less percentage of RE as compared to the MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models in the testing dataset. It was also noticed that the maximum distribution of RE for all given models appeared in the peak value of monthly ET₀.

The spatial pattern of estimated and observed values’ monthly ET₀ by CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models during the testing period was also evaluated by using the Taylor diagram (TD). Taylor (2001) provided a polar plot for acquiring a visual judgement of model performance. It has the ability to emphasize the accuracy and efficiency of models based on the observed values. The Taylor diagram exhibits three specific statistics (i.e., correlation coefficient, normalized standard deviation and RMSE). Figure 8 provides the Taylor diagram for observed and estimated values using

### Table 2 | Cross-correlation between the meteorological variables

| Station/Variables | Tmin (°C) | Tmax (°C) | RH (%) | Uₜ (m/s) | Rs (MJ/m²) | ET₀ (mm) |
|-------------------|----------|----------|--------|----------|------------|----------|
| Pantnagar         |          |          |        |          |            |          |
| Tmin (°C)         | 1.0      |          |        |          |            |          |
| Tmax (°C)         | 0.834*   | 1.0      | 0.041  | -0.468*  | -0.396*    | 0.719*   |
| RH (%)            |          |          |        | 0.476*   | 0.544*     | 0.919*   |
| Uₜ (m/s)          | 0.621*   | 0.883*   | -0.648*| 0.606*   | 0.764*     | 0.933*   |
| Rs (MJ/m²)        |          |          |        |          |            |          |
| ET₀ (mm)          | 0.918*   | 0.934*   | -0.610*| 0.507*   | 0.921*     | 1.0      |

*Rstatistically significant correlation at 5% level of significance.

### Table 3 | Input combinations for CANFIS, MLPNN, RBNN, SOMNN and MLR at study station

| Climatic variables | CANFIS | MLPNN | RBNN | SOMNN | MLR |
|--------------------|--------|-------|------|-------|-----|
| Tmin               | ✓✓✓✓✓✓✓✓✓ |
| Tmax               | ✓✓✓✓✓✓✓✓✓ |
| RH (%)             | ✓✓✓✓✓✓✓✓✓ |
| Uₜ (m/s)           | ✓✓✓✓✓✓✓✓✓ |
| Rs (MJ/m²)         | ✓✓✓✓✓✓✓✓✓ |
| ET₀ (mm)           | ✓✓✓✓✓✓✓✓✓ |

The temporal variation between the observed and estimated monthly ET₀ values of CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models during the testing period are plotted using line plot (left side) and scatter plot (right side) in Figure 6(a)–6(e), respectively. As observed from Figure 6(a)–6(e), the regression line and best fit line (1:1) for all the models were perfectly close to each other; however, these lines were closer to each other for CANFIS-5 (Figure 6(a)) and MLPNN-5 (Figure 6(b)) models, respectively. It can be concluded that based on the statistical and visual comparisons, the ranks of the model (from the best to worst) can be classified as the CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models for Pantnagar station, respectively.
the applied models at Pantnagar station. Figure 8 demonstrated that the CANFIS-5 and MLPNN-5 models provided the lower RMSE, lower standard deviation and higher correlation coefficient than the SOMNN-5, RBNN-5 and MLR-5 models. Hence, the CANFIS-5 model with selected inputs (Tmax, Us, Rs) can be used for modelling monthly ETo at Pantnagar station.

**Monthly ETo estimation at Ranichauri station**

The selected CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models were trained (January, 1994–December, 2008) and tested (January, 2009–December, 2012) to estimate the monthly ETo at Ranichauri station. The performance of CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models was evaluated using RMSE, SI, COE, PCC and WI, and visually inspected using line, scatter, relative error and Taylor plots. The value of RMSE, SI, COE, PCC and WI of the applied models during the testing period is reported in Table 5. As observed from Table 5, the lowest RMSE = 0.1394 mm/month and SI = 0.0475, and the highest COE = 0.9846, PCC = 0.9942 and WI = 0.9959 were found for the CANFIS-9 model with two Gaussian MFs for each input. Table 5 clearly indicates that the CANFIS-9 model has a lower value of RMSE and SI, and higher COE, PCC and WI than the MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models, respectively. The RBNN-9, SOMNN-9 and MLR-9 models have RMSE = 0.3179, 0.4616 and 0.1967 mm/month; SI = 0.1085, 0.1575 and 0.0671; COE = 0.9198, 0.8310 and 0.9693; PCC = 0.9665, 0.9151 and 0.9887; and WI = 0.9790, 0.9495 and 0.9918, respectively. It should be noted that the MLPNN-9 model closely follows the CANFIS-9 model. The regression equation for the MLR-9 model with its intercepts and regression coefficients obtained from the training phase is written as:

\[ \text{MLR}_9 = C_0 + C_1 \times T_{\text{min}} + C_2 \times T_{\text{max}} + C_3 \times R_H + C_4 \times U_s + C_5 \times R_s \]

The temporal variation between observed and estimated monthly ETo values of CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models during the testing period is plotted using line plot (left side) and scatter plot (right side) in Figure 9(a)–9(e), respectively. As observed from the time variation graphs (line and scatter), the estimates of the CANFIS-9 were closer to the observed monthly ETo values (PM FAO-56) compared to other models. It is clear from the scatterplots that the CANFIS-9 has less scattered estimates than the other models. It should be noted that all the models underestimated the peak ETo values. This may be due to the fact that there is insufficient number of peak values in the training and applied methods cannot learn the process. The ranks of the models were the CANFIS-9, MLPNN-9, MLR-9, RBNN-9 and SOMNN-9 for Ranichauri station based on the statistical and visual comparisons, respectively.

The relative error percentage (Equation (23)) between observed and estimated monthly ETo values of CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models during the testing period is presented in Figure 10. As
Figure 10 demonstrates, the RE percentage was between ±10% upper band (UB) and lower band (LB) for 95.83% (CANFIS-9), 95.75% (MLPNN-9), 72.91% (RBNN-9), 75% (SOMNN-9) and 87.5% (MLR-9) of testing dataset. Here, the CANFIS-9 model shows lesser percentage of RE as compared to the MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models in the testing dataset. It also indicated that the maximum distribution of RE for all prescribed models appeared in the peak value of monthly ETo.

The spatial pattern of observed and estimated values of monthly ETo by CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models during the testing period was also evaluated by using the Taylor diagram (TD). Figure 11 provides the TD for observed and estimated values using the applied models at Ranichauri station. Figure 11 illustrates that the CANFIS-9 model provided lower RMSE and higher correlation coefficient than the MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models. Hence, the CANFIS-9 model with selected inputs (Tmin, Tmax, RH, Us, Rs) can be successfully used for monthly ETo estimation at Ranichauri station.

DISCUSSION

In this study, the feasibility of a hybrid model, i.e., co-active fuzzy inference system was evaluated for estimating monthly
reference evapotranspiration at Pantnagar and Ranichauri stations. The CANFIS model is the integration of an artificial neural network and fuzzy inference system in a single topology. The significant combination of input variables was decided using a non-linear modelling tool, i.e., Gamma test. The estimates yielded by the CANFIS model were compared to the multilayer perceptron neural network, radial basis neural network, self-organizing map neural network and multiple linear regression models using statistical indicators such as root mean squared error, scatter index, COE, PCC, Willmott index, relative error, and visual basis using line plot, scatter plot, relative error plot and Taylor diagram for both the stations under study. The CANFIS model with Gaussian membership functions, Takagi-Sugeno-Kang fuzzy inference system, hyperbolic tangent activation function, and DBD learning algorithm improved substantially the performance of modelling by increasing the COE, PCC and WI and reducing the RMSE, SI and RE measurements at both the stations. The estimation accuracy of the MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models with respect to RMSE was decreased by 2%, 56%, 70% and 29% by applying the CANFIS-9 model, respectively. The applied modelling strategy builds a standard and reliable intelligent system that can be used for Pantnagar and Ranichauri stations and is extremely valuable for water resources managers, agriculture and irrigation engineers and agronomists.

Over the past decade, throughout the world, studies have been conducted by researchers on reference evapotranspiration or pan-evaporation estimation using numerous artificial intelligence techniques (hybrid or simple) (Aytek 2009; Cobaner 2011; Karimaldini & Shui 2012; Tabari et al. 2012b; Shiri et al. 2014; Marti et al. 2015; Shrestha & Shukla 2015; Kumar et al. 2016; Ghorbani et al. 2017; Shiri 2017, 2019b; Landeras et al. 2018; Pour et al. 2018; Saggi & Jain 2018). Aytek (2009) applied the CANFIS for modelling daily reference evapotranspiration from three meteorological stations located in the USA. The performance of CANFIS model was compared to the California Irrigation Management Information System (CIMIS) Penman equation, Penman–Monteith equation, the HS equation and the Turc equation based on root mean square error, coefficient of efficiency, adjusted coefficient of efficiency and determination coefficient. The results of analysis revealed that the performance of CANFIS model with four inputs (solar radiation, mean temperature, relative humidity and wind speed) was superior to the other models. Tabari et al. (2012a) utilized the CANFIS and MLP model to predict the daily pan-evaporation in the semi-arid region of Iran. They reported that the CANFIS model outperformed the MLP model for daily pan-evaporation prediction in the study region. Ghorbani et al. (2017) estimated pan-evaporation using hybrid multilayer perceptron-firefly algorithm (MLP-FFA) in the north of Iran. The estimates of MLP-FFA model were compared to the traditional MLP and support vector machine (SVM) models using statistical indicators. They found that the hybrid model (MLP-FFA) performed better than the traditional models (MLP and SVM). Saggi & Jain (2018) examined the performance of deep learning-multilayer perceptrons (DL), generalized linear model (GLM), random forest (RF) and gradient-boosting machine (GBM) in H2O environment in estimating the daily ET₀ at Hoshiarpur and Patiala districts of Punjab, India. They reported that the DL models outperformed the other models for daily ET₀ estimation in the study region.

| Station/Model | RMSE (mm/month) | SI | COE | PCC | WI |
|---------------|-----------------|----|-----|-----|----|
| Pantnagar     |                 |    |     |     |    |
| CANFIS-5      | 0.0978          | 0.0261 | 0.9963 | 0.9982 | 0.9991 |
| MLPNN-5       | 0.1082          | 0.0289 | 0.9955 | 0.9980 | 0.9989 |
| RBNN-5        | 0.1972          | 0.0527 | 0.9850 | 0.9925 | 0.9962 |
| SOMNN-5       | 0.1487          | 0.0397 | 0.9915 | 0.9960 | 0.9978 |
| MLR-5         | 0.2445          | 0.0653 | 0.9770 | 0.9892 | 0.9943 |
| Ranichauri    |                 |    |     |     |    |
| CANFIS-9      | 0.1394          | 0.0475 | 0.9846 | 0.9942 | 0.9959 |
| MLPNN-9       | 0.1428          | 0.0487 | 0.9838 | 0.9936 | 0.9958 |
| RBNN-9        | 0.3179          | 0.1085 | 0.9198 | 0.9665 | 0.9790 |
| SOMNN-9       | 0.4616          | 0.1575 | 0.8310 | 0.9151 | 0.9495 |
| MLR-9         | 0.1967          | 0.0671 | 0.9693 | 0.9887 | 0.9918 |
Figure 6 | Graphical representation of temporal variation between observed and estimated monthly reference evapotranspiration values by (a) CANFIS-5; (b) MLPNN-5; (c) RBNN-5; (d) SOMNN-5; and (e) MLR-5 models during testing period at Pantnagar station.
Figure 7 | The RE (%) distribution of CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models during testing period at Pantnagar station.

Figure 8 | Taylor diagram of observed and estimated monthly reference evapotranspiration by CANFIS-5, MLPNN-5, RBNN-5, SOMNN-5 and MLR-5 models during testing period at Pantnagar station.
Figure 9 | Graphical representation of temporal variation between observed and estimated monthly reference evapotranspiration values by (a) CANFIS-9, (b) MLPNN-9, (c) RBNN-9, (d) SOMNN-9, and (e) MLR-9 models during testing period at Ranichauri station.
Figure 10 | The RE (%) distribution of CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models during testing period at Ranichauri station.

Figure 11 | Taylor diagram of observed and estimated monthly reference evapotranspiration by CANFIS-9, MLPNN-9, RBNN-9, SOMNN-9 and MLR-9 models during testing period at Ranichauri station.
Shiri et al. (2019) applied the data splitting strategy to GEP for estimating the daily $E_{TO}$ from five meteorological locations in northwestern Iran, and they found good results of GEP under different scenarios.

The above-reported studies also confirmed the supremacy of hybrid models in the estimation of reference evapotranspiration or pan-evaporation. Thus, this study provided conclusive evidence that the estimation of monthly reference evapotranspiration can be done effectively in order of accuracy by CANFIS-5 > MLPNN-5 > SOMNN-5 > RBNN-5 > MLR-5 models at Pantnagar station, and by CANFIS-9 > MLPNN-9 > MLR-9 > RBNN-9 > SOMNN-9 models at Ranichauri station.

CONCLUSIONS

This study was conducted to examine the potential of CANFIS model against the MLPNN, RBNN, SOMNN and MLR models for estimating the monthly reference evapotranspiration at Pantnagar and Ranichauri stations, situated in foothills of Indian central Himalayan region of Uttarakhand State, India. For estimating monthly reference evapotranspiration at both the stations, the significant combination of input variables for CANFIS, MLPNN, RBNN, SOMNN and MLR models were decided based on the minimum value of gamma statistics (i.e., gamma, gradient, standard error and $V_{ratio}$) obtained by applying the Gamma test. The following specific conclusions were derived from this study:

- The three input variable combination (maximum air temperature, wind speed and solar radiation) was selected as the most appropriate combination based on the GT for estimating monthly reference evapotranspiration at Pantnagar station.
- The five input variable combination (minimum and maximum air temperatures, relative humidity, wind speed and solar radiation) was selected as the most appropriate combination based on the GT for estimating monthly reference evapotranspiration at Ranichauri station.
- Based on performance indicators and a visual inspection, the performance of CANFIS model was found superior to the MLPNN, RBNN, SOMNN and MLR models for estimation of monthly reference evapotranspiration at Pantnagar and Ranichauri stations.
- The performance of the MLR model was found to be worst at Pantnagar station, while at Ranichauri station, the performance of MLR model was better than the RBNN and SOMNN models.
- Due to the changing climatic environment, this study confirmed that at low altitude (Pantnagar) only three climatic variables (i.e., $T_{max}$, $U_s$ and $R_s$) are required for estimating the monthly $E_{TO}$, while at high altitude (Ranichauri), five climatic variables (i.e., $T_{min}$, $T_{max}$, RH, $U_s$, and $R_s$) are required for estimating the monthly $E_{TO}$.
- The proposed CANFIS models guide irrigation engineers and agriculturists towards better estimation of monthly reference evapotranspiration at study stations in light of data availability.
- The results of CANFIS models would help local stakeholders in terms of irrigation scheduling, and planning and management of water resources.

Since this study focuses on a specific area of India (i.e., Pantnagar and Ranichauri stations), the results from this research cannot generalize the capability and accuracy of applied models for other climatic zones in the world. Thus, it is recommended that areal extension (e.g., multi-case study including other climatic conditions) can confirm the generalization of applied models. Therefore, these approaches can be accomplished based on spatial-temporal scales including different climatic zones. Furthermore, the various percentages of training and testing datasets for different years should be considered for better predictability of data-driven models for future studies. The obtained results of this study may be compared with other machine learning (e.g., simple and hybrid approaches) and empirical models.

REFERENCES

Ahmad, S., Kalra, A. & Stephen, H. 2010 Estimating soil moisture using remote sensing data: a machine learning approach. Advances in Water Resources 33, 69–80.
Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. 1998 Crop evapotranspiration guidelines for computing crop water requirements. In: FAO Irrigation and Drainage. Paper no. 56. Food and Agriculture Organization of the United Nations, Rome, Italy.
Ashrafzadeh, A., Malik, A., Jothiprakash, V., Ghorbani, M. A. & Biazar, S. M. 2018 Estimation of daily pan evaporation using neural networks and meta-heuristic approaches. ISH Journal of Hydraulic Engineering. doi:10.1080/09715010.2018.1498754.

Aytek, A. 2009 Co-active neuro fuzzy inference system for evapotranspiration modelling. Soft Computing 13 (7), 691–700.

Banda, P., Cemek, B. & Küçüktopcu, E. 2007 Estimation of daily reference evapotranspiration by neuro computing techniques using limited data in a semi-arid environment. Archives of Agronomy and Soil Science 64 (7), 916–929.

Bishop, C. M. 1995 Neural networks for pattern recognition. Journal of the American Statistical Association 92 (440), 16–42.

Chang, F. J., Chang, L. C. & Wang, Y. S. 2007 Enforced self-organizing map neural networks for river flood forecasting. Hydrological Processes 21 (6), 741–749.

Chang, F. G., Chang, L. C., Kao, H. S. & Wu, G. R. 2010 Assessing the effort of meteorological variables for evaporation estimation by self-organizing map neural network. Journal of Hydrology 384, 118–129.

Cobaner, M. 2011 Evapotranspiration estimation by two different neuro-fuzzy inference systems. Journal of Hydrology 398, 292–302.

Dawson, C. W. & Wilby, R. L. 2001 Hydrological modelling using artificial neural networks. Progress in Physical Geography 25 (1), 80–108.

Falamarzi, Y., Palizdan, N., Huang, Y. H. & Lee, T. S. 2014 Estimating evapotranspiration from data temperature and wind speed using artificial and wavelet neural networks (WNNs). Agricultural Water Management 140, 26–36.

Gavili, S., Sanikhani, H., Kisi, O. & Mahmoudi, M. H. 2018 Evaluation of several soft computing methods in monthly evapotranspiration modelling. Meteorological Applications 25, 128–138.

Ghorbani, M. A., Deo, R. C., Yaseen, Z. M., Kashani, M. H. & Mohammadi, B. 2017 Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (MLP-FFA) model: case study in North Iran. Theoretical and Applied Climatology 133 (3–4), 1119–1131.

Goyal, M. K., Bharti, B., Quilty, J., Adamowski, J. & Pandey, A. 2014 Modeling of daily pan evaporation in sub-tropical climates using ANN, LS-SVR, Fuzzy Logic, and ANFIS. Expert Systems with Applications 41 (11), 5267–5276.

Granata, F. 2019 Evapotranspiration evaluation models based on machine learning algorithms – a comparative study. Agricultural Water Management 217, 303–315.

Granata, F., Gargano, R. & Marinis, G. D. 2016 Support vector regression for rainfall-runoff modeling in urban drainage: a comparison with the EPA’s storm water management model. Water 8, 1–13. doi:10.3390/w8030069.

Granata, F., Saroli, M., Marinis, G. D. & Gargano, R. 2018 Machine learning models for spring discharge forecasting. Geofluids. doi:10.1155/2018/8328167.

Haykin, S. 1998 Neural Networks – A Comprehensive Foundation, 2nd edn. Prentice-Hall, Upper Saddle River, NJ, USA, pp. 26–32.

Jang, J. R., Sun, C. T. & Mizutani, E. 1997 Neuro Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice-Hall, Upper Saddle River, NJ, USA, p. 607.

Kakaei-Lafdani, E., Moghaddam, N. A. A. & Ahmadi, A. 2013 Daily suspended sediment load prediction using artificial neural networks and support vector machines. Journal of Hydrology 478, 50–62.

Karbas, M. 2018 Forecasting of multi-step ahead reference evapotranspiration using wavelet-Gaussian process regression model. Water Resources Management 32, 1035–1052.

Karimaldini, F. & Shui, L. 2012 Daily evapotranspiration modeling from limited weather data by using neuro-fuzzy computing technique. Journal of Irrigation and Drainage Engineering 138, 21–34.

Khosravi, K., Mao, L., Kisi, O., Yaseen, Z. M. & Shahid, S. 2018 Quantifying hourly suspended sediment load using data mining models: case study of a glacierized Andean catchment in Chile. Journal of Hydrology 567, 165–179.

Kim, S. & Kim, H. S. 2008 Neural networks and genetic algorithm approach for nonlinear evaporation and evapotranspiration modeling. Journal of Hydrology 351 (5–4), 299–317.

Kisi, O. 2007 Evapotranspiration modelling from climatic data using a neural computing technique. Hydrological Processes 21, 1925–1934.

Kisi, O. 2009 Modeling monthly evaporation using two different neural computing techniques. Irrigation Science 27, 417–430.

Kisi, O. & Alizamir, M. 2018 Modelling reference evapotranspiration using a new wavelet conjunction heuristic method: wavelet extreme learning machine vs wavelet neural networks. Agricultural and Forest Meteorology 263, 41–48.

Kisi, O. & Demir, V. 2016 Evapotranspiration estimation using six different multi-layer perceptron algorithms. Irrigation and Drainage Systems Engineering 5 (2), 1–6.

Kisi, O. & Yaseen, Z. M. 2019 The potential of hybrid evolutionary fuzzy intelligence model for suspended sediment concentration prediction. Catena 174, 11–23.

Kisi, O., Sanikhani, H., Zounemat-Kermani, M. & Niazi, F. 2015 Long-term monthly evapotranspiration modeling by several data-driven methods without climatic data. Computers and Electronics in Agriculture 115, 66–77.

Kohonen, T. 1982 Self-organized formation of topologically correct feature maps. Biological Cybernetics 45 (1), 59–69.

Kumar, M., Raghuwanshi, N. S., Singh, R., Wallender, W. W. & Pruitt, W. O. 2002 Estimating evapotranspiration using artificial neural network. Journal of Irrigation and Drainage Engineering 128 (4), 224–233.

Kumar, M., Bandypadhyay, A., Raghuwanshi, N. S. & Singh, R. 2008 Comparative study of conventional and artificial neural network based ETo estimation models. Irrigation Science 26 (6), 531–545.

Kumar, D., Adamowski, J., Suresh, R. & Ozga-Zielinski, B. 2016 Estimating evapotranspiration using an extreme learning machine model: case study in north Bihar, India. Journal of Irrigation and Drainage Engineering 142 (9). doi:10.1061/(ASCE)IR.1943-4774.0001044.
Landeras, G., Bekoe, E., Ampofo, J., Logah, F., Diop, M., Cisse, M. & Shiri, J. 2018 New alternatives for reference evapotranspiration estimation in West Africa using limited weather data and ancillary data supply strategies. *Theoretical and Applied Climatology* 132, 701–716.

Lopez-Urrea, R., Martin de Santa Olalla, F., Fabeiro, C. & Moratalla, A. 2006 Testing evapotranspiration equations using lysimeter observations in a semi-arid climate. *Agricultural Water Management* 85, 15–26.

Malik, A. & Kumar, A. 2015 Pan evaporation simulation using daily meteorological by soft computing techniques and multiple linear regression. *Water Resources Management* 29 (6), 1859–1872.

Malik, A. & Kumar, A. 2018 Comparison of soft-computing and statistical techniques in simulating daily river flow: a case study in India. *Journal of Soil and Water Conservation* 17 (2), 192–199.

Malik, A., Kumar, A. & Pirj, J. 2017a Daily suspended sediment concentration simulation using hydrological data of Pranhita river basin, India. *Computers and Electronics in Agriculture* 138, 20–28.

Malik, A., Kumar, A. & Kisi, O. 2017b Monthly pan-evaporation estimation in Indian central Himalayas using different heuristic approaches and climate based models. *Computers and Electronics in Agriculture* 143, 302–313.

Malik, A., Kumar, A. & Kisi, O. 2018 Daily pan evaporation estimation using heuristic methods with gamma test. *Journal of Irrigation and Drainage Engineering* 144 (9). doi:10.1061/(ASCE)IR.1943-4774.0001336.

Martí, P., González-Altozano, P., López-Urrea, R., Mancha, L. A. & Shiri, J. 2015 Modeling reference evapotranspiration with calculated targets: assessment and implications. *Agricultural Water Management* 149, 81–90.

Matar, M. A. & Alazba, A. A. 2018 GEP and MLR approaches for the prediction of reference evapotranspiration. *Neural Computing and Applications* doi:10.1007/s00521-018-3410-8.

Mishra, A. K. & Desai, V. R. 2006 Drought forecasting using feed-forward recursive neural network. *Ecological Modelling* 198, 127–138.

Moghaddamnia, A., Ghaferi, G. M., Pirj, J., Amin, S. & Han, D. 2008 Evaporation estimation using artificial neural networks and adaptive neuro-fuzzy inference system techniques. *Advances in Water Resources* 32, 88–97.

Moghaddamnia, A., Remesan, R., Kashani, M. H., Mohammadi, M., Han, D. & Pirj, J. 2009 Comparison of LRR, MLP, Elman, NNARX and ANFIS Models with a case study in solar radiation estimation. *Journal of Atmospheric and Solar-Terrestrial Physics* 71, 975–982.

Nash, J. E. & Sutcliffe, J. V. 1970 River flow forecasting through conceptual models: Part I. A discussion of principles. *Journal of Hydrology* 10 (3), 282–290.

Papacharalampous, G., Tyralis, H. & Koutsoyiannis, D. 2018 Predictability of monthly temperature and precipitation using automatic time series forecasting methods. *Acta Geophysica* 66 (4), 807–831. https://doi.org/10.1007/s11600-018-0120-7

Papacharalampous, G., Tyralis, H. & Koutsoyiannis, D. 2019 Comparison of stochastic and machine learning methods for multi-step ahead forecasting of hydrological processes. *Stochastic Environmental Research and Risk Assessment* 33 (2), 481–514. https://doi.org/10.1007/s00477-018-1638-6

Patil, A. P. & Deka, P. C. 2015 Performance evaluation of hybrid Wavelet-ANN and Wavelet-ANFIS models for estimating evapotranspiration in arid regions of India. *Neural Computing and Applications*. doi 10.1007/s00521-015-2055-0.

Piri, J., Amin, S., Moghaddamnia, A., Keshavarz, A., Han, D. & Remesan, R. 2009 Daily pan evaporation modeling in a hot and dry climate. *Journal of Hydrologic Engineering* 14, 803–812.

Pour, O. M. R., Piri, J. & Kisi, O. 2018 Comparison of SVM, ANFIS and GEP in modeling monthly potential evapotranspiration in arid region (Case study: Sistan and Baluchestan province, Iran). *Water Science and Technology* 19 (2), 392–403. doi:10.2166/ws.2018.084.

Rahimikhooob, A. 2010 Estimation of evapotranspiration based on only air temperature data using artificial neural networks for a subtropical climate in Iran. *Theoretical and Applied Climatology* 101, 83–91.

Rashidi, S., Vafakhah, M., Kakaeei Ladjfani, E. & Javadi, M. R. 2016 Evaluating the support vector machine for suspended sediment load forecasting based on gamma test. *Arabian Journal of Geosciences* 9, 2–15.

Remesan, R., Shamim, M. A. & Han, D. 2008 Model data selection using gamma test for daily solar radiation estimation. *Hydrological Processes* 22, 4301–4309.

Remesan, R., Shamim, M. A., Han, D. & Mathew, J. 2009 Runoff prediction using an integrated hybrid modelling scheme. *Journal of Hydrology* 372, 48–60.

Saggi, M. K. & Jain, S. 2018 Reference evapotranspiration estimation and modeling of the Punjab northern India using deep learning. *Computers and Electronics in Agriculture* 156, 387–398.

Sanikhani, H., Kisi, O., Maroufpour, E. & Yaseen, Z. M. 2018a Temperature-based modeling of reference evapotranspiration using several artificial intelligence models: application of different modeling scenarios. *Theoretical and Applied Climatology* 135, 449–462.

Sanikhani, H., Deo, R. C., Yaseen, Z. M., Eray, O. & Kisi, O. 2018b Non-tuned data intelligent model for soil temperature estimation: a new approach. *Geoderma* 330, 52–64.

Sanikhani, H., Deo, R. C., Samui, P., Kisi, O., Mert, C., Mirabbasi, R., Gavili, S. & Yaseen, Z. M. 2018c Survey of different data-intelligent modeling strategies for forecasting air temperature using geographic information as model predictors. *Computers and Electronics in Agriculture* 152, 242–260.

Sentelhas, P. C., Gillespie, T. J. & Santos, E. A. 2010 Evaluation of FAO Penman-Monteith and alternative for estimating reference evapotranspiration with missing data in southern Ontario, Canada. *Agricultural Water Management* 97, 635–644.

Shiri, J. 2017 Evaluation of FAO56–PM, empirical, semi-empirical and gene expression programming approaches for estimating daily reference evapotranspiration in hyper-arid regions of Iran. *Agricultural Water Management* 188, 101–114.

Shiri, J. 2018 Improving the performance of the mass transfer-based reference evapotranspiration estimation approaches
through a coupled wavelet-random forest methodology. *Journal of Hydrology* **561**, 737–750.

Shiri, J. 2019a Modeling reference evapotranspiration in island environments: assessing the practical implications. *Journal of Hydrology* **570**, 265–280.

Shiri, J. 2019b Evaluation of a neuro-fuzzy technique in estimating pan evaporation values in low-altitude locations. *Meteorological Applications* **26** (2), 204–212.

Shiri, J., Nazemi, A. H., Sadraddini, A. A. & Marti, P. 2015 Global cross-station assessment of neuro-fuzzy models for estimating daily reference evapotranspiration. *Journal of Hydrology* **480**, 46–57.

Shiri, J., Nazemi, A. H., Fard, A. F., Sadraddini, A. A., Landera, G., Kisi, O. & Marti, P. 2014 Comparison of heuristic and empirical approaches for estimating reference evapotranspiration from limited inputs in Iran. *Computers and Electronics in Agriculture* **108**, 230–241.

Shiri, J., Marti, P., Karimi, S. & Landera, G. 2019 Data splitting strategies for improving data driven models for reference evapotranspiration estimation among similar stations. *Computers and Electronics in Agriculture* **162**, 70–81.

Shrestha, N. K. & Shukla, S. 2015 Support vector machine based modeling hydro-climatic of evapotranspiration using variables in a sub-tropical environment. *Agricultural and Forest Meteorology* **200**, 172–184.

Singh, K. K., Pal, M. & Singh, V. P. 2010 Estimation of mean annual flood in Indian catchments using backpropagation neural network and M5 model tree. *Water Resources Management* **24**, 2007–2019.

Singh, A., Malik, A., Kumar, A. & Kisi, O. 2018 Rainfall-runoff modelling in hilly watershed using heuristic approaches with gamma test. *Arabian Journal of Geosciences* **11** (11), 1–12. doi:10.1007/s12517-018-3614-3.

Solomatine, D. P. & Xue, Y. 2003 M5 model trees and neural networks: application to flood forecasting in the upper reach of the Huai river in China. *Journal of Hydrologic Engineering* **9** (6), 491–501.

Stefansson, A., Koncar, N. & Jones, A. J. 1997 A note on the gamma test. *Neural Computing and Applications* **5**, 131–133.

Sudheer, K. P., Gosain, A. K. & Ramanastri, K. S. 2005 Estimating actual evapotranspiration from limited climatic data using neural computing technique. *Journal of Irrigation and Drainage Engineering* **129** (3), 214–218.

Tabari, H. & Talea, P. H. 2012 Multilayer perceptron for reference evapotranspiration estimation in a semi-arid region. *Neural Computing and Applications* **23**, 341–348.

Tabari, H., Talea, P. H. & Abghari, H. 2012a Utility of cooperative neuro-fuzzy inference system for pan evaporation modeling in comparison with multilayer perceptron. *Meteorology and Atmospheric Physics* **116**, 147–154.

Tabari, H., Kisi, O., Ezani, A. & Talea, P. H. 2012b SVM, ANFIS, regression and climate based models for reference evapotranspiration modeling using limited climatic data in a semi-arid highland environment. *Journal of Hydrology* **444-445**, 78–89.

Takagi, T. & Sugeno, M. 1985 Fuzzy identification of systems and its application to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics* **15** (1), 116–132.

Tao, H., Diop, L., Bodian, A., Djamal, K., Ndiaye, P. M. & Yaseen, Z. M. 2018 Reference evapotranspiration prediction using hybridized fuzzy model with firefly algorithm: regional case study in Burkina Faso. *Agricultural Water Management* **208**, 140–151.

Taylor, K. E. 2001 Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research* **106** (D7), 7183–7192.

Willmott, C. J. 1981 On the validation of models. *Physical Geography* **2** (2), 184–194.

Yaseen, Z. M., El-Shafie, A., Afan, H. A., Hameed, M., Mohtar, W. H. M. W. & Hussain, A. 2015a RBFNN versus FFNN for daily river flow forecasting at Johor River, Malaysia. *Neural Computing Applications* **27**, 1533–1542. doi:10.1007/s00521-015-1952-6.

Yaseen, Z. M., El-shafie, A., Jaafar, O., Afan, H. A. & Sayl, K. N. 2015b Artificial intelligence based models for stream-flow forecasting: 2000–2015. *Journal of Hydrology* **530**, 829–844.

Yaseen, Z. M., Jaafar, O., Deo, R. C., Kisi, O., Adamowski, J., Quilty, J. & El-Shafie, A. 2016a Stream-flow forecasting using extreme learning machines: a case study in a semi-arid region in Iraq. *Journal of Hydrology* **542**, 603–614.

Yaseen, Z. M., Kisi, O. & Demir, V. 2016b Enhancing long-term streamflow forecasting and predicting using periodicity data component: application of artificial intelligence. *Water Resources Management* **30**, 4125–4151.

Yaseen, Z. M., Ebtehaj, I., Bonakdari, H., Deo, R. C., Mehr, A. D., Mohtar, W. H. M. W., Diop, L., El-shafie, A. & Singh, V. P. 2017 Novel approach for streamflow forecasting using a hybrid ANFIS-FFA model. *Journal of Hydrology* **554**, 263–276.

Yaseen, Z. M., Awadh, S. M., Sharafati, A. & Shahid, S. 2016a Complementary data-intelligence model for river flow simulation. *Journal of Hydrology* **567**, 180–190.

Yaseen, Z. M., Ghareb, M. I., Ebtehaj, I., Bonakdari, H., Siddique, R., Heddam, S., Yusif, A. A. & Deo, R. C. 2018 Rainfall pattern forecasting using novel hybrid intelligent model based ANFIS-FFA. *Water Resources Management* **32**, 105–122.

Yaseen, Z. M., Sulaiman, S. O., Deo, R. C. & Chau, K.-W. 2019 An enhanced extreme learning machine model for river flow forecasting: state-of-the-art, practical applications in water resource engineering area and future research direction. *Journal of Hydrology* **569**, 387–408.

Yassin, M. A., Alazba, A. A. & Mattar, M. A. 2016 Artificial neural networks versus gene expression programming for estimating reference evapotranspiration in arid climate. *Agricultural Water Management* **163**, 110–124.

Zanetti, S. S., Sousa, E. F., Oliveira, V. P., Almeida, F. T. & Bernardo, S. 2007 Estimating evapotranspiration using artificial neural network and minimum climatological data. *Journal of Irrigation and Drainage Engineering* **133**, 83–89.

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