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Prediction of reference evapotranspiration using artificial intelligence technique

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Abstract
Evapotranspiration requirement is a principal component in planning any crop and precise prediction of this component would reduce the squandering of huge quantities of water. The aim of this study was to develop an Artificial Neural Network (ANN) model for prediction of daily reference evapotranspiration (ET_0) in the sub-tropical regions of India. Feed-forward Back-propagation Neural Network model is employed in this study to evaluate the performance of Artificial Neural Networks in comparison with Empirical FAO Penman-Monteith (FAO-56) equation in predicting reference evapotranspiration. Daily climatic data were collected and used for analysis of best fit ANN model. After the network structure and parameters were determined reasonably, the network was trained with daily climatic data (maximum and minimum temperature, relative humidity, solar radiation and wind speed) as input and the FAO-56 estimated ET_0 as output. The ANN learning model recognized the evapotranspiration patterns with acceptable accuracy, with RMSE of 0.211 in comparison to the results of FAO-56, coefficient of determination of 0.910, and Linear Correlation Coefficient (r) of 0.948 demonstrating the best approximation for the 5-4-1 network architecture, with multilayers, back-propagation learning algorithm and learning rate of 0.01. The Mean Absolute Error (MAE) between ET_0 by ANN and FAO-56 equation was 0.308 mm. The result shows that the predictions of ET_0 using the developed ANN model were strongly correlated with the results of FAO-56 equation.

Keywords: Artificial intelligence, artificial neural network (ANN), evapotranspiration, temperature, relative humidity

Introduction
A common practice for estimating crop evapotranspiration (ET_C) from a well irrigated agricultural crop is to estimate reference evapotranspiration (ET_0) from a standard surface and multiply it with crop coefficient. In the past few decades, several studies (Allen *et al*. 1989; Allen *et al*. 1998) [1, 2] have focused on the development of accurate methods for ET_0 estimation and improving the performance of existing methods due to wide application of ET_0 data. ET_0 can either be estimated using lysimeter or water balance approach or estimated indirectly using the meteorological data. Accurate estimation of reference evapotranspiration (ET_0) has a vital importance for many studies such as hydrologic water balance, the design and management of irrigation system and water resources planning and management. Reference evapotranspiration rate is "the rate of evapotranspiration from an extensive surface of 0.08-0.15 m tall, green grass cover of uniform height, actively growing, completely shading the ground, and not short of water" [Doorenbos and Pruitt (1977)] [15]. The Penman-Monteith FAO 56 (PM FAO-56) model is recommended as the sole method for calculation of ET_0 and it has been reported to be able to provide consistent ET_0 values in many regions and climates. The main shortcoming of the PM FAO-56 method is, however, that it needs large number of climatic data and variables which are unavailable in many regions.

Therefore, there is a need for developing an appropriate method using Artificial Intelligence (AI) techniques for estimating ET_0 on a daily scale, using simpler and fewer input data for subtropical region. Artificial neural network (ANN) is an AI technique that allows easier translation between human and computers for decision making and better way to handle imprecise and uncertain information.

Artificial Neural Networks
ANN was first introduced as a mathematical tool by McCulloch *et al*. (1943) [10]. They were inspired by the neural network structure of the human brain. Most of the ANN architecture has

three layers or more: an input layer, which is used to provide data to the network; an output layer, which is used to present an appropriate response to the given input and one or more intermediate layers, which are used to act as a collection of feature detectors. The ability of a neural network to process information is obtained through a learning process, which is the adaptation of link weights so that the network can produce an approximate output(s). In general, the learning process of an ANN will reward a correct response of the system to an input by increasing the strength of the current matrix of nodal weights. Various application of ANN in estimation of evapotranspiration has been implemented by many researchers.

Kumar *et al*. (2002) [9] developed MLFF NN models for the estimation of daily ET_0, using six basic climatic parameters as inputs, and compared the results with the FAO-56 PM method and with the lysimeter measured ET_0. Kisi (2007a,b) investigated the potential of various MLFF NN models such as multi-layer perceptrons (MLPs), radial basis neural networks (RBNNs), and generalized regression neural networks (GRNNs) to estimate ET_0 using different combinations of climatic input data. Zanetti *et al*. (2007) [14] developed MLFF NN models for estimating ET_0 as a function of the maximum and minimum air temperatures and compared their performance with the conventional temperature-based methods. Aytek *et al*. (2008) [3] developed MLFF NN models for estimating daily ET_0 and compared the results with five conventional ET_0 models and with the multiple linear regression (MLR) models. Jain *et al*. (2008) [6] developed MLFF NN models to estimate ET_0 from limited climatic data and analyzed sensitivity of the input variables on ET_0, using the connection weights of the developed models.

Keeping the above aspects in mind this study was conducted to investigate the potential of ANN model to predict reference evapotranspiration as affected by climatic factors and to evaluate the performance of ANN model in predicting daily reference evapotranspiration.

Materials and Methods

Estimation of Reference Evapotranspiration (ET_0)

Reference evapotranspiration (ET_0) was estimated using the method suggested by American Society of Civil Engineers and the FAO-56 (Allen *et al*., 1998) [2]. The equation used to estimate ET_0 is described below:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1+0.34u_2)} \quad \ldots (1)$$

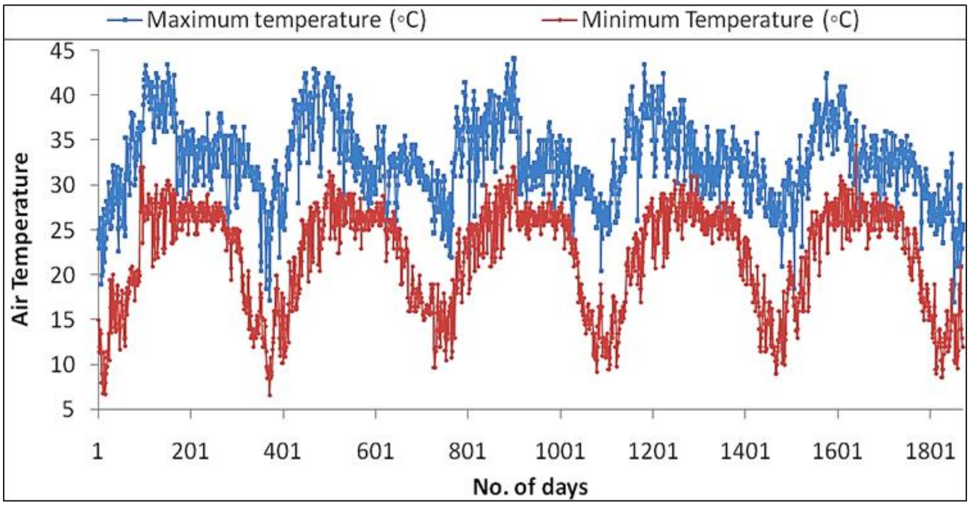
Where,

ET_0-Reference evapotranspiration [mm day^{-1}], R_n-Net radiation at the crop surface [MJ m^{-2} day^{-1}], G - Soil heat flux density [MJ m^{-2} day^{-1}], T-Mean daily air temperature at 2 m height [°C], u_2-Wind speed at 2 m height [m s^{-1}], e_s-Saturation vapour pressure [kPa], e_a-Actual vapour pressure [kPa], e_s-e_a-Saturation vapour pressure deficit [kPa], Δ-Slope vapour pressure curve [kPa °C^{-1}], γ-Psychrometric constant [kPa °C^{-1}].

The meteorological observations of six years (2014 to 2020) collected from automatic weather stations, Varanasi, UP were used to estimate daily ET_0 using FAO Penman-Monteith equation and the results are shown in Table 1.

Application of ANN

In this study, the daily climatic data for the years 2014- 2020 were used to train and test the model for prediction of ET_0. The inputs for model were maximum and minimum temperature (T) and relative humidity (RH), average wind speed (WS) and solar radiation (RS). After normalizing and pre-processing of data set in desired time lag format, three different data sets were extracted from the input and target data for training, validation and test phase. Training set consists of 60% of data to build the model and determine the parameters such as weights and activation function, validation data set includes 15% to measure the performance of network by holding constant parameters. Finally, 25% of data is used to increase the robustness of model in the test phase. Analysis of daily meteorological observations and reference evapotranspiration in presented as Fig 1. It can be seen from Fig 1, the maximum and minimum temperature varies from 43.5 °C to 7 °C and daily relative humidity varies from 94% to 31%. Average monthly meteorological observations and reference evapotranspiration is presented in Table 1.



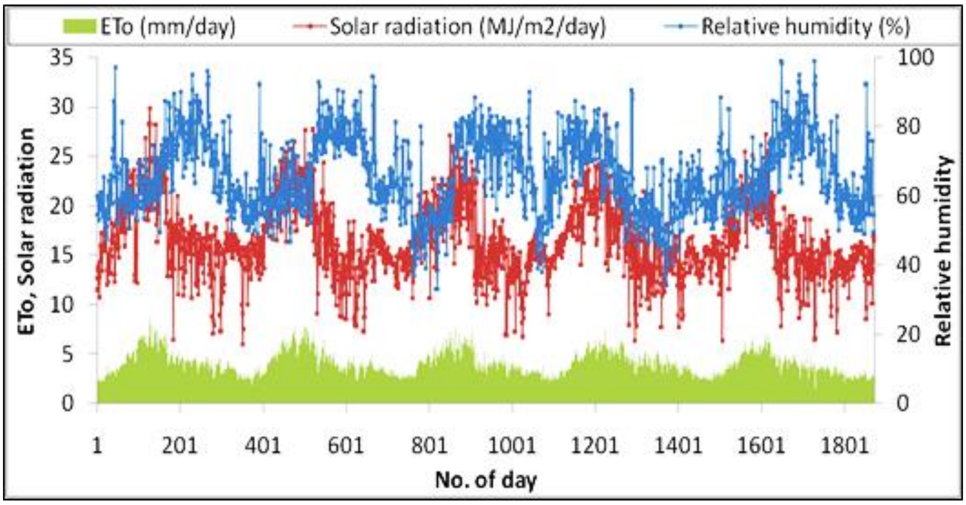


Fig 1: Climatic data used in this study for prediction of ET_0

Determination of neural network structure

Experimental data were used to determine the optimal ANN structure and simulations were carried out using Neuro-solutions software developed by Neuro Dimensions Inc. of Florida. In order to determine the optimal network architecture, various network architectures were designed; the number of neurons in the hidden layer and transfer functions in hidden/output layer was changed. Based on the Kosmogorov approaching theory, the BP neural network with a single hidden layer including a sufficient number of neurons can approximate any function with the desired accuracy; the neural network with only one hidden layer was chosen (He *et al*., 2007; Said, 1992; Imran *et al*., 2002) [4, 12, 5]. According to the factors affecting the meteorological observations, the network input layer neuron was set as 5. The output layer neuron was 1. For the determination of number of neurons in the hidden layer, we chosen different number of neurons of hidden layer to try after inputting the same training and validating data. For each network RMSE, MAE, R^2 and R_{ratio} values of the outputs were calculated and compared. When the number of neurons in hidden layer was 4, the network output error was smallest, which showed the network structure was better. A typical architecture of ANN model showing inputs and output of this study is presented in Figure 2. The learning rate η is taken to be 0.01.

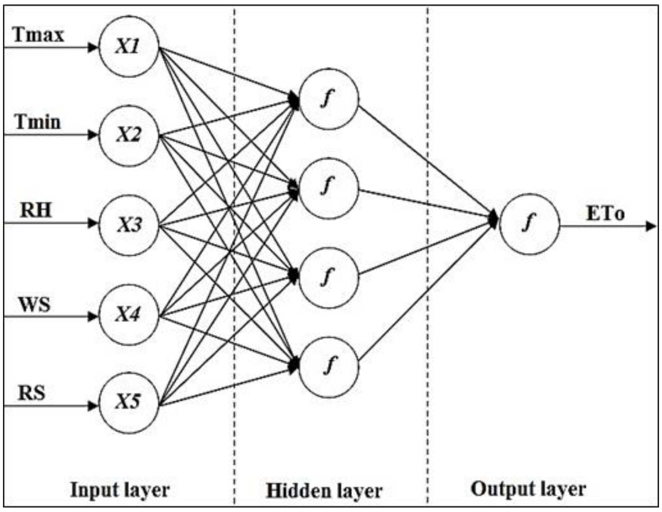


Fig 2: The architecture of ANN model

Training of the network

Training of the network was performed using Levenberg-Marquardt feed-forward back propagation algorithms. It is the fastest and ensures the best convergence to a minimum of mean square error (MSE) for function approximation problems (Sahai *et al*., 2000) [11]. Then, the ANN models were tested and the results were compared by means of correlation coefficient and root mean square error (RMSE) statistics. The best suited network was selected based on the minimized values of root mean square error (RMSE), and the maximum value of correlation coefficient (CC).

Let x_i (i = 1, 2, ... n) are inputs and w_i (i = 1, 2, … n) are respective weights. The net input to the node can be expressed as:

$$\text{net} = \sum_{i=1}^{n} x_i w_i$$

The net input is then passed through an activation function $f(.)$ and the output y of the node is computed as $y = f(net)$

A three-layer structure was selected with hyperbolic tangent (tanh) transfer function for hidden layer and linear transfer function for output layer. Therefore, an ANN with 5 inputs, *h* hidden neurons and one output units defines a nonlinear parameterized mapping from an input *x* to an output *y* given by the following relationship:

$$y = y(x, w) = \sum_{j=0}^{h} \left[w_j . f\left(\sum_{i=0}^{6} w_{ji} x_i \right) \right]$$

There are two main steps to obtain the ANN optimal model: The learning phase and the generalization phase. During the learning phase, the ANN is trained using a training dataset of N inputs and output.

The performance measure is usually given by the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE) and R_{ratio} (Singh and Tiwari 2017) [13]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n}\left[\frac{(\hat{y}_i - y_i{}^2)}{n}\right]}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Y_{sim} - Y_{obs})^2}{\sum_{i=1}^{n}(Y_{sim} - \bar{Y}_{obs})^2} \quad \ldots (3.7)$$

$$R_{ratio} = \frac{\hat{y}}{y} \quad \ldots (3.8)$$

Where, $\hat{y}$ is predicted value, y is estimated value, $\bar{y}$ is the mean of estimated variables and n is the number of samples.

Results and Discussion

Estimation of ET_0 using FAO-56 method

The meteorological observations of six years (2014 to 2022) collected from automatic weather stations were used to estimate daily ET_0 using FAO Penman-Monteith equation and the results are shown in Table 1. Based on the observations, it was found that average monthly ET_0 values were relatively of greater magnitude from March to September as compared to that of from October to March. ET_0 values were directly related with solar radiation and day light hours. ET_0 gradually increases with the increase of sunshine hours and the intensity of solar radiation (Allen *et al*. 1998) [2]. The estimated peak value of the ET_0 was found as 6.39 mm/day in the month of May and the lowest value as 2.34 mm/day is estimated for the month of December. The average daily ET_0 values were found to reduce from June month onward till September due to incidence of rainfall, low solar radiation and high humidity especially during monsoon months (Allen *et al*. 1989) [1]. Further due to reduction in temperature from October to March, daily ET_0 values also reduced and attained to lowest in the month of December.

Table 1: Average monthly meteorological observations and reference evapotranspiration

Month	Air temperature (°C)		Relative humidity (%)	Solar radiation (MJ/m²/day)	Wind speed (m/s)	ET_0 (mm/day)
	Maximum	Minimum				
Jan	19.5	14.6	36.0	19.8	0.9	2.40
Feb	23.0	18.7	40.8	21.5	0.8	3.12
Mar	26.5	23.9	44.5	25.0	1.0	4.18
Apr	35.0	32.2	56.6	26.5	1.3	4.99
May	41.3	36.9	63.9	28.5	1.5	6.39
Jun	38.6	35.6	75.0	24.0	1.3	5.59
July	34.3	31.7	80.3	22.4	1.2	5.05
Aug	33.0	29.8	73.0	23.5	1.3	5.11
Sept	33.5	28.5	70.0	23.9	0.8	4.02
Oct	30.3	22.4	67.2	23.4	0.6	3.96
Nov	26.8	20.3	61.8	20.1	0.6	2.96
Dec	21.5	15.7	50.1	19.1	0.8	2.34

Prediction of ET_0 using ANN

The ANN model was trained using the daily climatic data of the years 2014–2019, and the trained model was then tested with the daily climatic data of the year 2020. This process was begun with a network which had 3 neurons in its hidden layer, and repeated, increasing the number of neurons up to 10. The calculated statistical parameter (R^2, MAE, RMSE, Nash-Sutcliffe efficiency and R_{ratio}) of different ANN architectures are listed in Table 2, for each network. The LM algorithm with 4 neurons in the hidden layer for network (5-4-1) has produced the best results, and it is used for generating the graphical outputs.

From the comparison curve presented in Fig. 3 and 4 it is observed that the predicted values are in good agreement with the estimated values and the predicted error is very less. The predictions of ET_0 values simulated using the developed ANN model was strongly correlated with the estimated values of ET_0 (Kumar *et al*., 2002) [9]. Therefore, the proposed MLP Back Propagation Neural Network model with the developed structure can perform good prediction with least error, which illuminated the neural network model had the ability to predict the inside mean temperature. Similar results, while predicting ET_0 values using ANN models and comparing it with FAO-56 ET_0 values were also reported by Kumar *et al*. (2002) [9], Kisi (2007a,b) [7], Zanetti *et al*. (2007) [14] and Aytek *et al*. (2008) [3].

Table 2: Variation of R^2, MAE, RMSE, Nash-Sutcliffe efficiency and R_{ratio} with different number of hidden neurons in test phase

ANN structure	R^2	MAE	RMSE	Nash-Sutcliffe efficiency (NSE)	R_{ratio}
5-3-1	0.868	0.673	0.519	0.87	1.013
5-4-1	0.910	0.308	0.211	0.98	1.007
5-5-1	0.873	0.564	0.415	0.87	1.018
5-6-1	0.778	0.512	0.323	0.78	1.016
5-7-1	0.876	0.476	0.621	0.88	1.003
5-8-1	0.695	0.668	0.412	0.70	0.957
5-9-1	0.773	0.397	0.521	0.77	0.961
5-10-1	0.871	0.599	0.729	0.87	0.978

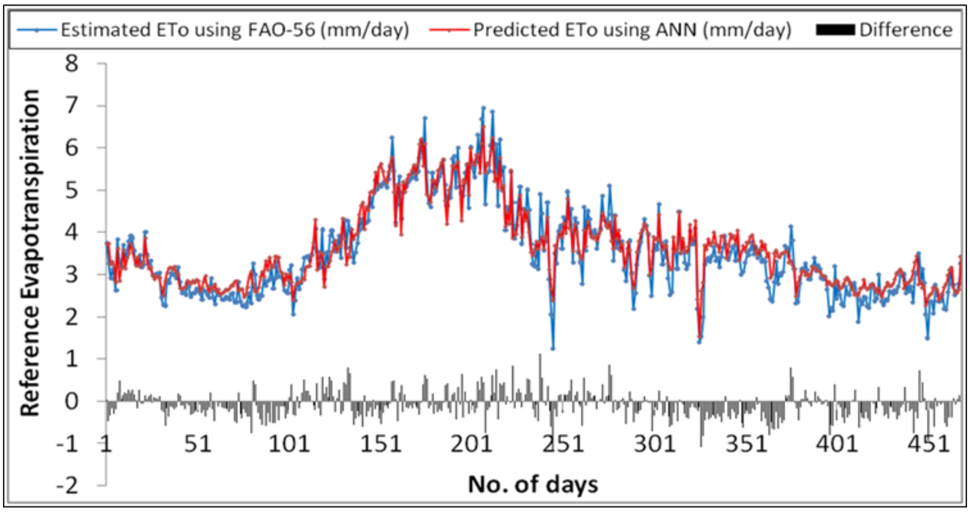


Fig 3: Comparison between estimated and predicted daily evapotranspiration

The ANN learning model recognized the evapotranspiration patterns with acceptable accuracy, with RMSE of 0.211 in comparison to the results of FAO-56, coefficient of determination of 0.910, and Linear Correlation Coefficient (r) of 0.948 demonstrating the best approximation for the 5-4-1 network architecture, with multilayers, back-propagation learning algorithm. The results demonstrated the neural network model can predict the change of ET_0 values with respect to climatic parameters accurately. It is clear from test result that the higher values of correlation coefficients and lower values of root mean square error suggests the applicability of ANN model for prediction of ET_0.

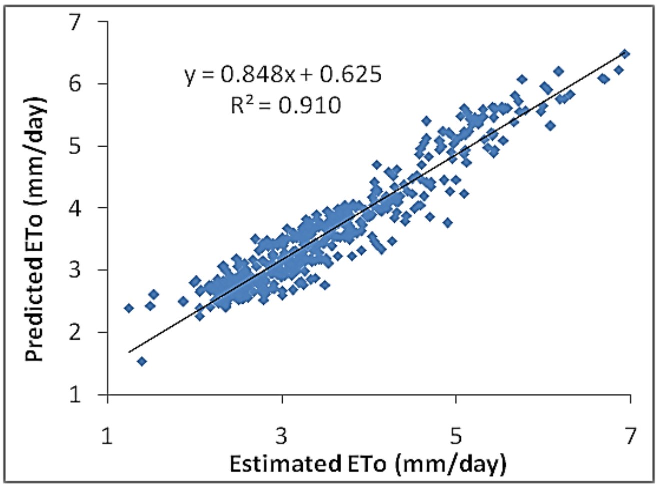


Fig 4: The relationship between estimated and predicted daily reference evapotranspiration

Conclusions

The present study discusses the application and usefulness of artificial neural network-based modeling approach in predicting the reference evapotranspiration. This approach is able to determine the nonlinear relationship that exists between the climatic data supplied to the system during the training phase and on that basis, make a prediction of what the reference evapotranspiration would be in future. RMSE and MAE statistical indicators showed small values that demonstrates the correct behavior of the developed forecasting models. The study, therefore, establishes that the NN structure with 4 hidden neurons in single layer is the best predictive model over the other structures.

This study also concludes that a combination of minimum and maximum air temperature, relative humidity, wind speed and solar radiation provides better performance in predicting the reference evapotranspiration. The results are quite encouraging and suggest the usefulness of artificial neural network-based modeling technique in accurate prediction of the reference evapotranspiration.

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