ESTIMATION OF REFERENCE EVAPOTRANSPIRATION USING ARTIFICIAL NEURAL NETWORK FOR MOHANPUR, NADIA DISTRICT, WEST BENGAL: A CASE STUDY

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Abstract

Estimation of evapotranspiration plays a key role in various water management studies including irrigation scheduling and water budgeting. Being an extremely complex and non-linear phenomena, precise estimation of evapotranspiration requires large number of climatological data as well as vast time. In recent past, artificial neural network has emerged as a successful tool to model complex non-linear relationships including evapotranspiration process. The current study investigates the potential of artificial neural network models to estimate reference evapotranspiration (ET_0) for Mohanpur area and compares the performance of ANN models with reference ET estimated by FAO-Penman method. Different combinations of six weather parameters namely maximum air temperature, minimum air temperature, maximum relative humidity, minimum relative humidity, wind velocity and actual sunshine hours were used as inputs to train the 12 multilayer feed forward perceptron ANN models selected for the study. The FAO-56 Penman estimated ET_0 was used as output for all the models. The models were trained with back propagation learning algorithm. The analysis is carried out in MATLAB software. For each combination of input parameters, the best ANN model was selected with least SEE and highest R^2. The result of the study inferred that ANN performed very well with all the input parameters which were used in reference ET estimation by FAO-Penman method but the ANN models with less input variables also yielded very good estimation of ET_0. Therefore, it can be suggested that ANN method can be used for ET_0 estimation for the study area with high degree of accuracy in limited data condition also.

***Keywords**: Evapotranspiration, artificial neural network, Penman-Monteith method, Mohanpur*

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1. INTRODUCTION

Evapotranspiration (ET) represents one of the major contributor of hydrologic cycle which combinedly represents two hydrological process namely evaporation and transpiration. This parameter of hydrologic cycle plays a key role in various water resources management studies and therefore, its precise estimation has paramount importance on efficient water resources planning and budgeting. Actual evapotranspiration can directly be measured from the field, but field measurement of ET demands precision and time. Reference evapotranspiration (ET_0) is one of the very common terms used to define ET as theoretical evapotranspiration from an extensive surface of green grass of uniform height, actively growing, completely shading the ground, and not short of water [1]. In the past few decades, numerous studies were carried out in developing various empirical and semi-empirical models for precise estimation of ET_0 using various climatological data [2, 3, 4, 5, 1]. Some of these models depend on a variety of weather parameters whereas, some models give good results with less climatological data. Among the various reference ET estimation methods, the Penman-Monteith method is widely accepted [6] and it is proved to be the most accurate method of estimating evapotranspiration. But the requirements of large input parameters have limited the use of this method. In recent past, artificial neural network (ANN) approach has been successfully employed in evapotranspiration estimation studies [7, 6, 8, 9]. According to Sudheer et al., (2003) [10], ANN methods lead over conventional methods in their ability to solve the complex nonlinear relationships through flexible mathematical configurations. Evapotranspiration process is a complex and nonlinear phenomenon and depends on several interacting climatological factors, such as temperature, humidity, wind speed, radiation, type, and growth stage of the crop etc. The unique feature of ANN of solving complex nonlinear problems has made this technique a huge success in evapotranspiration estimation and modeling studies. Bai and Sinha (2015) [11] used artificial neural networks (ANNs) model for estimating reference crop evapotranspiration with limited climatic data and compared the performance of ANNs with P-M method for Ambikapur regions. The result depicted a satisfactory performance of ANN in the ET_0 estimation as compared to Penman Montieth method and inferred that these ANN models may therefore be adopted for estimating ET_0 in the study area with reasonable degree of accuracy. With this background, the present study has aimed to model evapotranspiration using artificial neural network for Mohanpur area, West Bengal.

2. MATERIALS AND METHODS

2.1 Study Area Description

The present study was conducted at Bidhan Chandra Krishi Viswavidyalaya, Mohanpur, Nadia, West Bengal at latitude $23°30'$N, longitude $89°E$ and at an elevation of 9.75m above the mean sea level (MSL). It has humid climate with an average rainfall of 1400 mm, approximately 75% of which occurs during the month of June to September due to onset of southwest monsoon. The mean temperature, relative humidity and bright sunshine hours of the study area vary from 8 to 40^0C, 30 to 95% and 6.94 to 6.97, respectively.

2.2 Data Collection

Daily data of maximum temperature (T_{max}), minimum temperature (T_{min}), wind speed (u), sunshine hour (n), maximum RH (%) (RH_1), and minimum RH (%) (RH_2) for 10 years period (1^{st} January 2006-31^{st} December 2015) for the study site was collected from "Department of Agricultural Meteorology and Physics", Bidhan Chandra Krishi Viswavidyalaya, Mohanpur, Nadia, West Bengal.

2.3 Estimation of Reference Evapotranspiration (ET_0) using FAO-56 Penman-Monteith (P-M) Method

FAO-56 Penman-Monteith method is considered as a sole standard method for the computation of ET_0 from meteorological data. This model contains energy balance term, aerodynamic term, and surface resistance. It is expressed as [1]:

$$ET_o = \frac{0.408\,\Delta(R_n - G) + \frac{900}{T+273}\gamma(e_s - e_a)u_2}{\Delta + \gamma(1 + 0.34u_2)} \qquad ....1$$

where, ET_o = reference evapotranspiration (mm/day); R_n= net radiation at the crop surface (MJ/m^2/day); G = soil heat flux density (MJ/m^2/day); T = mean daily air temperature at 2 meter height (^{0}c); u_2 = wind speed at 2 meter height (m/sec); e_s= saturation vapour pressure (kPa); e_a= actual vapour pressure (kPa); Δ = slope of vapour pressure curve (kPa/^{0}c); γ = psychometric constant (kPa/^{0}c).

2.4 Construction of Artificial Neural Network Models

Artificial Neural Network (ANN) structures are simplified mathematical models similar to biological neural network system and are capable of handling complex interrelationships between various input and output datasets of various natural processes. The commonly used network in hydrological applications consists of three layers namely: input layer, hidden layer/s and output layer. The input layer provides information to the network. The hidden layers enhance the network's ability to represent the complex interrelationships between the input and output as well as the various input parameters. The numbers of hidden layers and the numbers of nodes in each hidden layer are usually determined by trial and error procedure. The output layer consists of values predicted by the network and thus represents model output. Each node in a layer receives and processes weighted input from previous layer and transmits its output to nodes in the following layer through links. The weighted summation of inputs to a node is converted to an output according to a transfer function. The type of network, where data flow is in one direction, is known as feed-forward network.

In the present study, multilayer perceptron (MLP) models with one input layer, hidden layer and output layer were used to simulate the reference evapotranspiration for the study site. Different combinations of six weather parameters namely maximum air temperature, minimum air temperature, maximum relative humidity, minimum relative humidity, wind velocity and actual sunshine hours were used as inputs to the various ANN models tested for the study. Daily reference ET estimated from FAO-56-Penman-Monteith method was considered as the output for all the ANN models. In order to understand the relative importance of different input variables on the reference ET value, a correlation matrix between different input parameters and FAO estimated reference ET was constructed. Based on the correlation between selected variables and the output and on the physical laws that expresses the evapotranspiration process (Temperature based law, radiation based law, combined law), twelve different ANN architectures were selected with different combinations of input nodes in the input layer. The models were trained by back propagation algorithm. During training, the networks first assumes random initial values of wights and then computes a one-pass back propagation algorithm at each time step, which consists of a forward pass propagating the input vector through the network layer by layer and a backward pass to update the wights of the gradient decent rule. The models were trained using 80% of the data i.e. 2922 patterns (1^{st} January 2006 to 31^{st} December 2013) of maximum temperature (T_{max}), minimum temperature (T_{min}), wind speed (u), sunshine hour (n), maximum relative humidity (RH_1), minimum relative humidity (RH_2). After optimizing the number of nodes in the hidden layer and the network structure, the models were tested with rest 20% i.e. 730 data (1^{st} January 2014 to 31^{st} December 2015). The networks were trained and tested for all 12 ANN architectures. The networks were designed in MATLAB environment using neural network tool box of MATLAB-2013a. After selection of appropriate ANN architectures with different input parameters, the performances of the models were assessed.

2.5 Performance Evaluation of the Models

A model's performance was evaluated using two standard statistical indices including the coefficient of determination (R^2) and the root mean square error (RMSE). A high R^2 and a low RMSE imply good model performance and vice versa.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \qquad ....2$$

$$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(x_i - \bar{x})^2}} \quad ....3$$

Where, y_i and x_i are ANN predicted reference ET and actual reference ET, respectively; whereas $\bar{y}$ and $\bar{x}$ represent the average values of corresponding variables.

3. RESULTS AND DISCUSSIONS

In the present study, 12 ANN models were tested with different input parameters namely maximum and minimum air temperature, maximum and minimum relative humidity, wind speed and actual sunshine hours. The single output considered in the present study was the FAO-PM estimated ET_0. Based on the correlation between selected variables and the output and on the physical laws that describes the evapotranspiration phenomena (Temperature based law, radiation based law, combined law), 12 different combinations of input parameters in the input layer were selected. The numbers of nodes in the hidden layer was optimized after training each model with 80% of the patterns (2922). The selected models were then tested with rest 20% (730) of the patterns. The architecture of the selected models along with R^2 value and RMSE values are presented in the Table 1.

3.1 Comparison of Different Models

The performances of all the models were tested with FAO-56 PM method. The ANN architecture M-6-25-1(6 nodes in input layer, 25 nodes in hidden layer and one node in output layer) (Table 1) gives highest R^2 and lowest RMSE. But this model has used all the input parameters which were used in reference ET estimation by FAO-Penman method. So, the good result is quite obvious for this model. The M-4-5-1 model also gives very high performance with R^2 0.9875 and RMSE 0.1534. The other models which perform very good with lesser input parameters are M-3-35-1 with R^2 0.9784 and RMSE 0.1937, M-4-10-1 with R^2 0.9779 and RMSE 0.0.1767 and M-2-50-1 with R^2 0.9774 and RMSE 0.1963 (Table 1). The regression analysis between FAO-56 PM estimated ET_0 vs. ET_0 obtained by different ANN models are shown in the following scatter diagrams (Fig 1 a-l).

Table 1 Summary of model statistics

Model No.	Input parameters	Model	R^2	RMSE
M-1	T_{max}, n	M-2-50-1	0.9774	0.1963
M-2	T_{max},T_{min}, n	M-3-35-1	0.9784	0.1937
M-3	T_{max},T_{min}, n, u	M-4-10-1	0.9779	0.1767
M-4	T_{max},RH_1,RH_2	M-3-10-1	0.699	0.6906
M-5	T_{max},T_{min},RH_1,RH_2	M-4-5-1	0.6864	0.6925
M-6	T_{max},T_{min},RH_1,RH_2,n	M-5-30-1	0.9875	0.1534
M-7	T_{max},T_{min},RH_1,RH_2,n,u	M-6-25-1	0.9929	0.1064
M-8	T_{min},RH_1,RH_2	M-3-10-1	0.6159	0.7560
M-9	RH_1,RH_2,n	M-3-10-1	0.8789	0.4163
M-10	RH_1,RH_2,n,u	M-4-15-1	0.9021	0.3722
M-11	RH_1,RH_2,u	M-3-30-1	0.5218	0.8647
M-12	n, u	M-2-5-1	0.8846	0.4021

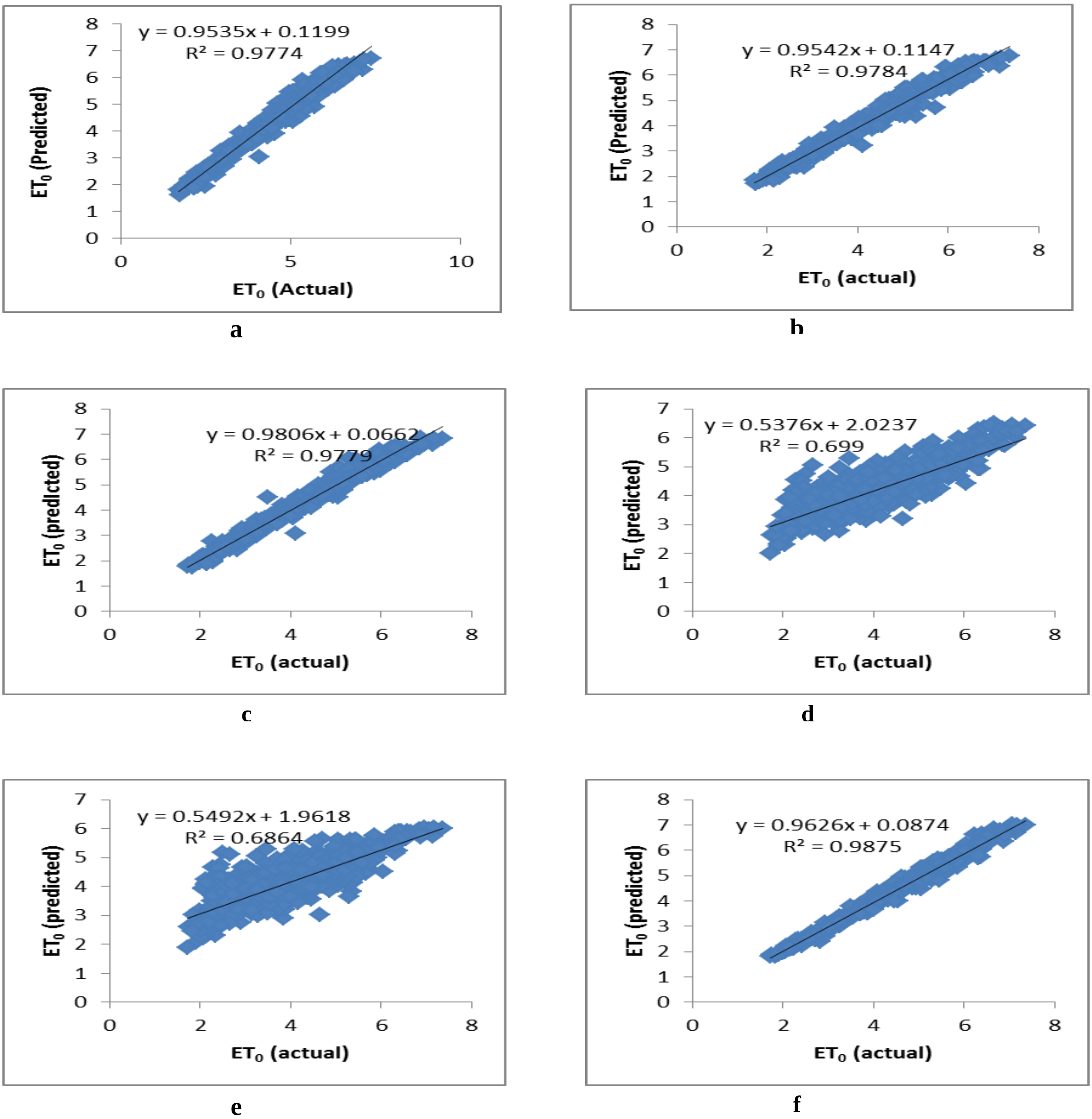

Fig 5.3 [a-f] The distribution diagram of the predicted and observed ET_0 for models M-1, M-2, M-3, M-4, M-5 and M-6, respectively.

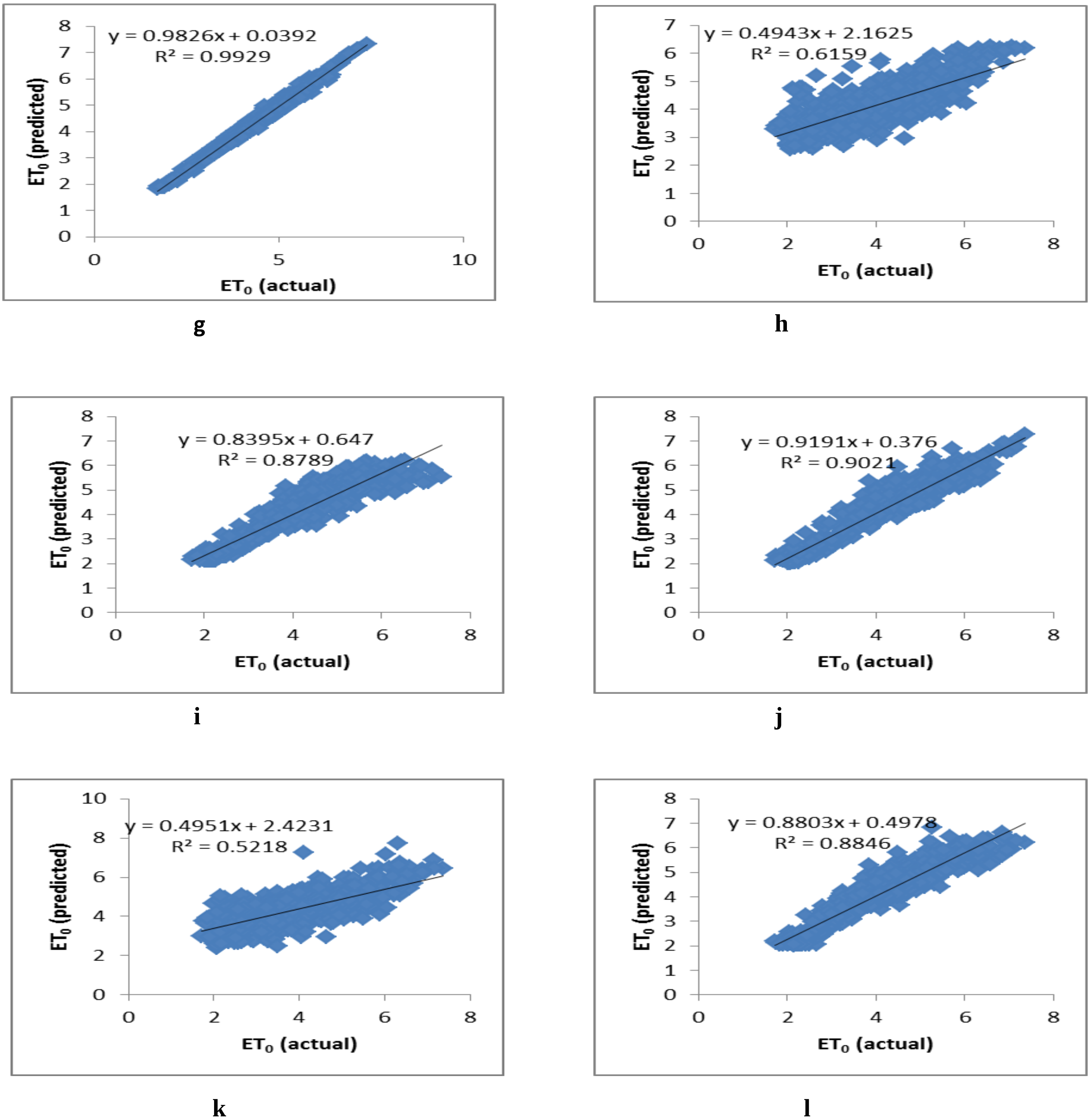

Fig 5.3 [g-l] The distribution diagram of the predicted and observed ET_0 for models M-7, M-8, M-9, M-10, M-11 and M-12, respectively.

4. CONCLUSION

In the current study, an attempt was made to test the performance of artificial neural network models to estimate the reference evapotranspiration for Mohanpur area, West Bengal with limited data condition. Six climatic parameters which affect the evapotranspiration process were used in different combinations in 12 different artificial neural network models as input parameters. FAO-56 PM estimated ET_0 was used as output parameter. The results of the study revealed that maximum and minimum temperature and sunshine hour have maximum effect on evapotranspiration process. The M-6-25-1 model yields the best result, but this model does not provide any added advantage in ET_0 estimation as it requires all the parameters that are required in FAO-56 PM method. The models M-3-35-1 with R^2 0.9784 and RMSE 0.1937, M-4-10-1 with R^2 0.9779 and RMSE 0.0.1767 and M-2-50-1 with R^2 0.9774 and RMSE

0.1963 yield very good results with lesser climatic parameters. Therefore, it can be inferred that artificial neural network can be successfully used for estimation of evapotranspiration with limited availability of data for the study area.

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