ARTIFICIAL NEURAL NETWORK MODELING FOR ESTIMATION OF REFERENCE EVAPOTRANSPIRATION AT NAGPUR

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Abstract

Precise estimation of reference crop evapotranspiration (ET_o) is of paramount importance in water resources planning. ET_o depends on several interacting climatological factors. Artificial Neural Networks (ANN) is effective tool and universal approximators to model complex and nonlinear process like ET_o.

The multilayer back propagation feed forward neural networks were developed for estimating ET_o at Nagpur having hot dry sub-humid climate, using different ANN model strategies with different input combinations, as ANN1 (Tmax, Tmin), ANN2 (Tmax, Tmin, SH), ANN3 (Tmax, Tmin, RHmax, RHmin), ANN4 (Tmax, Tmin, RHmax, RHmin, SH), and ANN5 (Tmax, Tmin, RHmax, RHmin, SH, WS).

In ANN model validation, using independent evaluation data set of the same location, mean absolute error (MAE), mean absolute relative error (MARE), root mean square error (RMSE), correlation coefficient (r), determination coefficient (R^2), index of agreement (D) and model efficiency (E) were found to be good enough for all network models and showed that ANN1 to ANN5 models are suitable and can be used for estimation of ET_o, according to the availability of data. However, Nagpur ANN5 model emerged as best model and ranked first followed by ANN2, ANN4, ANN1 and ANN3 models. Nagpur ANN5 model provided accurate estimation of ET_o with 0.2200 mm day^{-1} RMSE and 0.9777 model efficiency and followed by Nagpur ANN2 model with 0.4147 mm day^{-1} RMSE and 0.9207 model efficiency.

Keywords: *Reference evapotranspiration, Artificial neural networks, Climatological factors*

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1. INTRODUCTION

Evapotranspiration is an important component of the hydrologic cycle, which continues to be of foremost importance in water resources planning and management. Thus, its accurate estimation is of paramount importance in a wide array of problems in hydrology, agronomy, forestry and land resources planning.

For estimating crop evapotranspiration (ET_c), a common practice is to first estimate reference crop evapotranspiration i.e. grass reference evapotranspiration (ET_o), from a standard surface and to then apply an appropriate empirical crop coefficient. ET_o can be either measured with a lysimeter or water balance approach, or estimated from climatological data. However, it is not always possible to measure ET_o. Thus, indirect methods based on climatological data are used for ET_o estimation. Numerous researchers have analyzed the performance of various calculation methods for different locations. The FAO Penman-Monteith method is now recommended as the sole standard method for the definition and computation of the reference evapotranspiration, as the method provides consistent ETo values in all regions and climates (Allen *et al.*, 1998; Jensen *et al.*, 1990; Kashyap and Panda, 2001).

ET_o calculated using Penman-Monteith equation is used as reference values to develop different models and also to evaluate the performance of different models (Kisi, 2006a; Landeras, *et al.*, 2008).

The main difficulty in ET_o estimation with this method is the requirement of large number of meteorological parameters that are not easily available and this is the most important drawback of this equation. In many places, limited meteorological information is available. Hence, other methods though less accurate and location specific, continue to remain popular among researchers either because of traditional usage or due to shortage of input data. However, ET_o is a complex and nonlinear phenomenon because it depends on several interacting climatological factors.

To overcome such difficulty, Artificial Neural Networks (ANN) can be used. ANN is a mathematical construct whose architecture is essentially analogous to the human brain. Basically, the highly interconnected processing elements, arranged in layers are similar to the arrangement of neurons in the brain. Recently, artificial neural networks have been applied in meteorological and agro ecological modelling. ANNs are effective tools to model nonlinear systems, pattern recognition and classification problems. One significant advantage of the ANN models over other classes of nonlinear model is that ANNs are universal approximators, which can approximate a large class of functions with a high degree of accuracy (Kumar *et al.*, 2002; Sudheer *et al.*, 2003; Trajkovic, 2005; Zanetti *et al.*, 2007; Landeras, *et al.*, 2008). The model may require significantly less input data than a similar conventional mathematical model. Thus ANN approach may prove to be an effective and efficient way to model the reference evapotranspiration under the conditions of availability of data on limited weather parameters.

2. MATERIAL AND METHODS

Mean weekly meteorological data, viz. maximum temperature (Tmax), minimum temperature (Tmin), maximum relative humidity (RHmax), minimum relative humidity (RHmin), bright sunshine duration (SH) and wind speed (WS) were obtained for Nagpur from Agricultural Meteorological Observatory (Nagpur), Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola for a period of 30 years (1978-2007). Nagpur comes under hot dry sub-humid climate with monsoon rains, hot summer and moderate winter.

The mean weekly ET_o was estimated using Penman-Monteith (FAO-56) method, as measured data on ET_o was not available at the station. The methodology suggested in FAO-56 was used for estimation of each parameter of equation (Allen *et al.*, 1998). The FAO-56 Penman-Monteith (PM) model is expressed as:

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

2.1. Modelling using Artificial Neural Networks

The multilayer back propagation feed forward neural networks were trained to estimate the ET_o based on various combinations of climatological parameters as input, to evaluate the degree of dependence of these parameters. Thus number of neurons in input layer corresponded to number of input climatological parameters considered in the respective combination, whereas output layer node corresponded to ET_o estimated by Penman-Monteith equation. Summary of the inputs used for implementation of each ANN model strategy for estimation of ET_o is as given in Table 1.

Table 1. Summary of inputs used for the implementation of ANNs

ANN1	**ANN2**	**ANN3**	**ANN4**	**ANN5**
Tmax	Tmax	Tmax	Tmax	Tmax
Tmin	Tmin	Tmin	Tmin	Tmin
	SH	RHmax	RHmax	RHmax
		RHmin	RHmin	RHmin
			SH	SH
				WS

2.2. Performance Evaluation of ANN Models

Each developed model was evaluated for estimation of ET_o using independent evaluation data set of Nagpur. The estimated values from each model were compared to the target values. The variation of the ANN predicted and target data was presented graphically. Statistical analysis of data has been carried out. For scientific sound model evaluation a combination of different efficiency criteria complemented by the assessment of the squared, absolute or relative error was used. Finally the comparisons have been made between different ANNs developed under study using performance criteria and error statistics.

3. RESULTS AND DISCUSSION

3.1 Model Development

For each of input combination (i.e. ANN1, ANN2, ANN3, ANN4, and ANN5 model strategies) the best architecture of network was selected on the basis of mean square error of training data set obtained during training phase of different architectures. The data in respect of mean square error for training set, correlation coefficient for test set, number of epochs required; for different architectures tried in each model strategy are presented in Tables 2 to 6.

Table 2. Architectures of Neural Networks with their performance indices obtained during training phase of ANN1

Sr. No.	Architecture	Number of epochs	Training set Mean Square Error	Correlation coefficient for test set
1	2-1-1	49	0.177187	0.8987
2	2-2-1	25	0.150374	0.9193
3	2-3-1	25	0.150498	0.9194
4	2-4-1	53	0.149486	0.9199
5	2-5-1	84	0.149476	0.9200
6	2-6-1	13	0.149515	0.9199

Table 3. Architectures of Neural Networks with their performance indices obtained during training phase of ANN2

Sr. No.	Architecture	Number of epochs	Training set Mean Square Error	Correlation coefficient for test set
1	3-1-1	29	0.109826	0.9466
2	3-2-1	22	0.129759	0.9205
3	3-3-1	23	0.109525	0.9471
4	3-4-1	20	0.110014	0.9471
5	3-5-1	20	0.109353	0.9461
6	3-6-1	10	0.107035	0.9469
7	3-7-1	22	0.108782	0.9473
8	3-8-1	17	0.109204	0.9465
9	3-9-1	21	0.099947	0.9447

Table 4. Architectures of Neural Networks with their performance indices obtained during training phase of ANN3

Sr. No.	Architecture	Number of epochs	Training set Mean Square Error	Correlation coefficient for test set
1	4-1-1	47	0.0936879	0.9482
2	4-2-1	67	0.0860380	0.9500
3	4-3-1	22	0.0839290	0.9480
4	4-4-1	15	0.0842973	0.9455
5	4-5-1	69	0.0826151	0.9502
6	4-6-1	49	0.0914242	0.9492
7	4-7-1	22	0.0837848	0.9458
8	4-8-1	51	0.0805914	0.9503
9	4-9-1	41	0.0787619	0.9499
10	4-10-1	36	0.0848330	0.9513
11	4-11-1	27	0.0823619	0.9489
12	4-12-1	29	0.0874258	0.9478

Table 5. Architectures of Neural Networks with their performance indices obtained during training phase of ANN4

Sr. No.	Architecture	Number of epochs	Training set Mean Square Error	Correlation coefficient for test set
1	5-1-1	47	0.1295690	0.9284
2	5-2-1	34	0.0615922	0.9615
3	5-3-1	24	0.0667978	0.9621
4	5-4-1	37	0.0668516	0.9616
5	5-5-1	41	0.0643454	0.9632
6	5-6-1	30	0.0638848	0.9626
7	5-7-1	19	0.0685059	0.9612
8	5-8-1	32	0.0625859	0.9599
9	5-9-1	34	0.0604108	0.9626
10	5-10-1	23	0.0676469	0.9641
11	5-11-1	13	0.0635806	0.9626
12	5-12-1	38	0.0637425	0.9610
13	5-13-1	38	0.0599700	0.9613
14	5-14-1	19	0.0635439	0.9621
15	5-15-1	22	0.0607552	0.9613

Table 6. Architectures of Neural Networks with their performance indices obtained during training phase of ANN5

Sr. No.	Architecture	Number of epochs	Training set Mean Square Error	Correlation coefficient for test set
1	6-1-1	61	0.0060578	0.9967
2	6-2-1	43	0.0056025	0.9969
3	6-3-1	20	0.0063049	0.9961
4	6-4-1	32	0.0052308	0.9969
5	6-5-1	41	0.0054556	0.9970
6	6-6-1	36	0.0056364	0.9967
7	6-7-1	48	0.0046072	0.9971
8	6-8-1	71	0.0046984	0.9972
9	6-9-1	49	0.0047785	0.9973
10	6-10-1	36	0.0093053	0.9944
11	6-11-1	75	0.0043222	0.9971
12	6-12-1	51	0.0046327	0.9970
13	6-13-1	82	0.0036835	0.9973
14	6-14-1	56	0.0044509	0.9973
15	6-15-1	38	0.0049873	0.9970
16	6-16-1	31	0.0048165	0.9972
17	6-17-1	48	0.0044818	0.9972
18	6-18-1	58	0.0048038	0.9974

Similarly for the best architecture, the scatter plot between target and ANN predicted values for test data set obtained during training phase is presented in Fig. 1 for each model strategy.

It is observed from the Table 2 for ANN1 model having only two input parameters (Tmax, Tmin), that the 2-5-1 architecture (2, 5 and 1 nodes in input, hidden and output layer respectively) was enough for training the network as it gave lowest error and highest correlation coefficient. It is also observed that lowest mean square error was obtained when number of neurons in hidden layer was five. Hence scatter plot of test data set for this architecture was obtained (Fig. 1 ANN1), representing that the regression line was close to 1:1 line, which indicates the closeness of the target and predicted values. It is seen that network somewhat underestimated the ETo at higher rates, as line is slightly deviated from 1:1 line at higher rates of ETo. The standard error of estimate was 0.74 mm day^{-1} and significant correlation (0.9200) was observed between target and predicted values of test set. Therefore for ANN1 model strategy, the model with 2-5-1 architecture was selected for evaluating its performance using independent evaluation data set i.e. for validation.

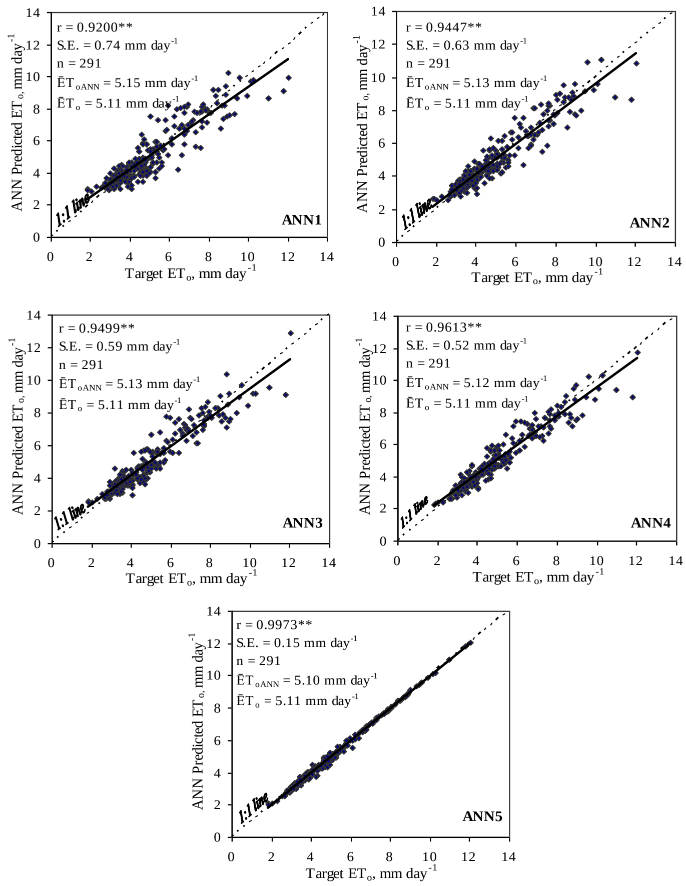

Fig. 1. Scatter plot between target and ANN predicted ET_o values for test data set obtained during training phase of different ANNs

Similarly it is observed from the Table 3 for ANN2 model, which was having three input parameters (i.e. Tmax, Tmin, SH), that the 3-9-1 architecture was enough for training the network as it gave lowest error. The scatter plot of test data set for this architecture was obtained (Fig.1 ANN2), representing the closeness of the target and predicted values. Hence, in ANN2 model strategy, the model with 3-9-1 architecture was selected for validation.

In case of ANN3 model strategy, which was composed of four input parameters (i.e. Tmax, Tmin, RHmax, Rhmin), architecture of 4-9-1 was found best (Table 4). The lowest mean square error was obtained when number of neurons in hidden layer was nine. It is also seen from Fig. 1 (ANN3) that regression line was close to 1:1 line, which indicates the closeness of the target and predicted values for test set. The standard error of estimate was low (0.59 mm day^{-1}). Therefore in ANN3 model strategy, the model with 4-9-1 architecture was selected for further evaluation.

In case of ANN4 model strategy, having five input parameters (i.e. Tmax, Tmin, RHmax, Rhmin, SH), the lowest mean square error was obtained in respect of 5-13-1 architecture (Table 5), with high the correlation coefficient between network output and target for test set data. Results indicate that lowest mean square error was observed when number of neurons in hidden layer was thirteen. Similarly regression line was more close to 1:1 line, which indicates the closeness of the target and predicted values (Fig. 1 ANN4). Therefore in ANN4 model strategy, the model with 5-13-1 architecture was selected for further evaluation.

However, in respect of ANN5 model strategy, having input vector of all six input parameters (i.e. Tmax, Tmin, RHmax, Rhmin, SH, WS), the lowest mean square error was obtained for 6-13-1 architecture (Table 6). The scatter plot of test data set for this architecture was obtained and it indicates that regression line coincides with 1:1 line, i.e. exact fit of the target and predicted values (Fig. 1 ANN5)). Therefore for ANN5 model strategy, the model with 6-13-1 architecture was selected for evaluation using independent evaluation data set.

3.2. Model Evaluation

ANN1, ANN2, ANN3, ANN4, ANN5 models developed were used for prediction of ET_o, using only inputs from independent evaluation data set of Nagpur. The predicted rates of ET_o were then compared with the target values of ET_o. The variation and scatter plot between target and predicted ET_o using ANN models are presented in Fig. 2 and 3. Different performance indices are presented in Table 7.

Table 7. Performance of different ANN models developed using evaluation data set of Nagpur

Performance indicators	*ANN1*	*ANN2*	*ANN3*	*ANN4*	*ANN5*
MAE, mm day^{-1}	0.3670	0.3055	0.3243	0.2901	0.1935
MARE	0.0964	0.0785	0.0832	0.0720	0.0494
RMSE, mm day^{-1}	0.4674	0.3990	0.4092	0.3986	0.2458
Correlation coefficient	0.9502	0.9668	0.9623	0.9701	0.9875
Coefficient of determination	0.9028	0.9347	0.9260	0.9410	0.9751
Index of agreement	0.9713	0.9794	0.9787	0.9787	0.9926
Model efficiency	0.8992	0.9266	0.9228	0.9267	0.9721

Performance of ANN1 model is shown in Fig. 2 & 3 (ANN1). The errors statistics were obtained to be low enough with good performance indices. Results of ANN1 model suggest that it can approximate the function of temperatures to estimate ET_o and is suitable for fairly accurate estimation of ET_o (Zanetti, 2007; Sudheer *et al.*, 2003) under the conditions of availability of temperature data only, which can easily be obtained in any class of meteorological observatory.

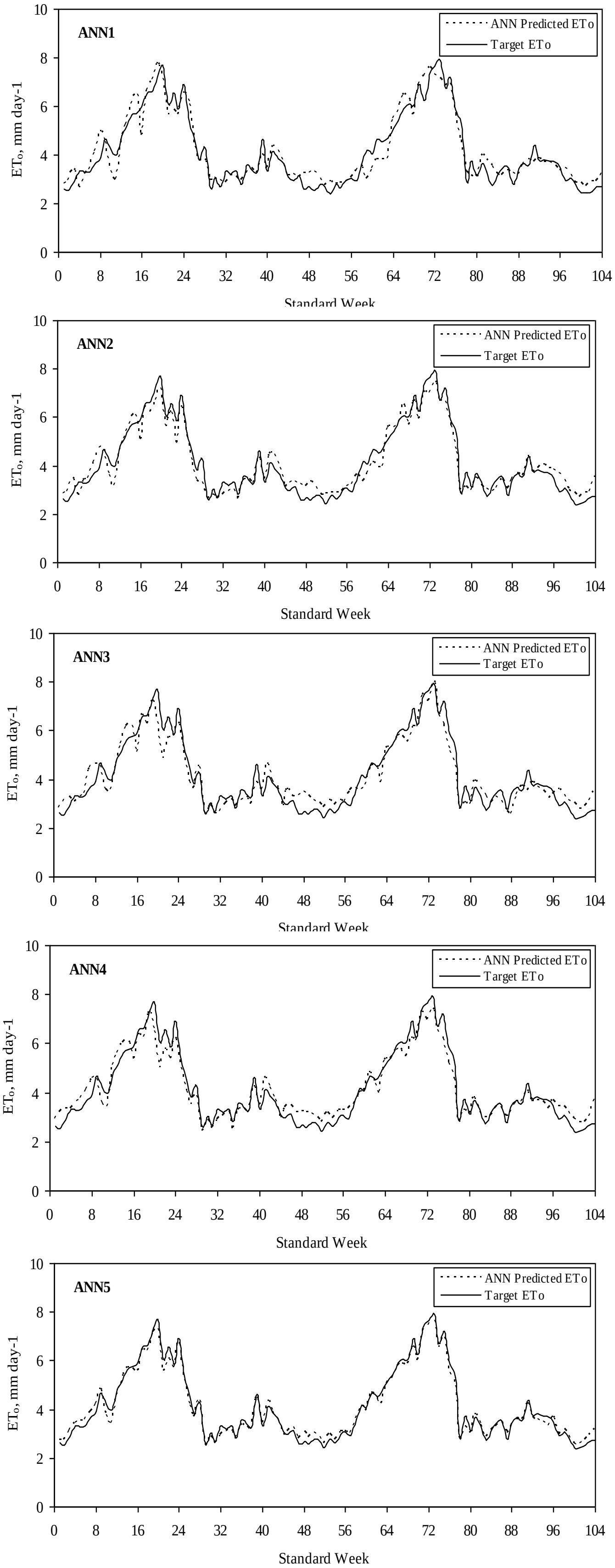

Fig. 2. Variation between target and ANN predicted ET_o using different ANN models for the independent evaluation data set of Nagpur

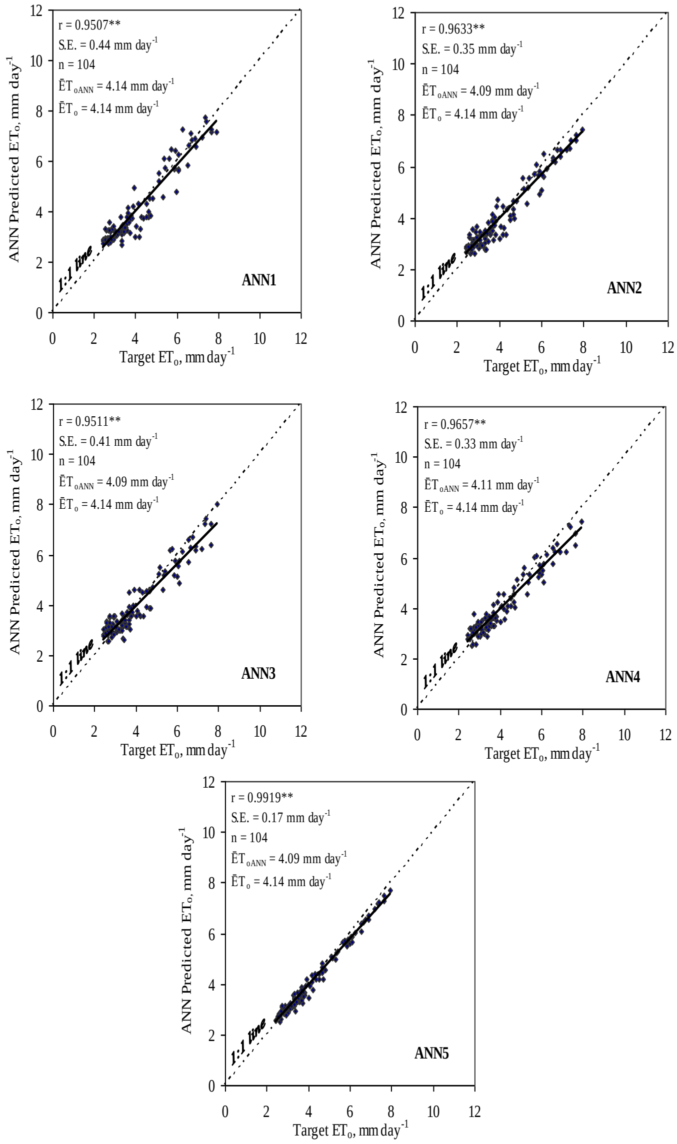

Fig. 3. Scatter plot between target and ANN predicted ET_o using different ANN models for the independent evaluation data set of Nagpur

Similarly the performance of ANN2 is represented in Fig. 2 & 3 (ANN2). ANN2 model has accurately estimated ET_o. The regression line almost coincide the 1:1 line, with low standard error of estimate. The errors statistics were found to be very low with high efficiency indices. It can be inferred from results that ANN2 model is suitable for estimation of ET_o at Nagpur having dry sub-humid climates; even data only on air temperatures and sunshine duration are available (Kisi, 2007).

The performance of ANN3 model is depicted in Fig. 2 & 3 (ANN3). ANN3 model predicts fairly accurate estimates of ET_o for the most of periods of year. Model underestimated ET_o during summer only for 20th and 21st weeks of 2006 when ET_o rates were high. Rest of period it has predicted well. Hence the regression line slightly deviated from 1:1 line at higher rates. The errors statistics indicate that ANN3 network model could approximated the function of ET_o estimation fairly. It also indicates that ANN3 model is suitable for prediction of ET_o

with fair accuracy. Hence, ANN3 model can be used for estimation of ET_o in the situations, where weather data only on air temperatures and relative humidity are available.

Fig. 2 & 3 (ANN4) shows the performance of ANN4 model. The results of ANN4 model indicate that it can approximate the prediction function of ET_o without wind speed as input, in relation to full set of inputs of Penman-Monteith model. It is possible to predict ET_o accurately without wind speed. It can be inferred that ANN4 model is suitable for estimation of ET_o at Nagpur, whenever wind speed data is not available.

The performance of ANN5 model is represented in Fig. 2 & 3 (ANN5). Results indicate that ANN5 model having all six weather parameters in input vector similar to input set of Penman-Monteith model, has predicted ET_o with high degree of accuracy. All the errors statistics were found to be very low and other performance indices were found to be very high. It means that artificial neural networks can precisely approximate the physical laws considered in relating the ET_o with weather parameters without actual involving these laws in the network development process.

3.3. Comparative Performance of various ANNs

From the comparison, it may become easy to identify or choose the best combination of input meteorological parameters for precise estimation of ET_o. Comparison may also give an idea about the selection of alternative ANN models in the situations whenever data on limited meteorological parameters are available and the precision that can be achieved with the selected model in estimation of ET_o.

It is seen from Table 7 that all indices viz. mean absolute error (MAE), mean absolute relative error (MARE), root mean square error (RMSE), correlation coefficient (r), determination coefficient (R^2), index of agreement (D) and model efficiency (E) were found to be good enough for all network models. Hence ANN1 to ANN5 models are feasible and can be used for estimation of ET_o according to the availability of data. When comparing their performance, among ANN1 to ANN5, lowest MAE, MARE, RMSE and highest r, R^2, D, E were obtained for ANN5 model. It may be due to that its input vector consists of all six meteorological parameters similar to that of Penman-Monteith model. This result also confirms the fact that air temperatures, relative humidity, wind speed and sunshine duration, all are influencing and necessary parameters for exact or highly accurate estimation of ET_o. Hence ANN5 model emerged as best model and ranked first followed by ANN2, ANN4, ANN1 and ANN3 models. Next to ANN5 model, ANN2 has produced second lowest MAE, MARE, RMSE and second highest E, D and third highest r, R^2. Here also advantage of ANN2 model is that it has input vector of only minimum and maximum air temperatures, and sunshine duration. It reflects that in situations whenever all six weather parameters are not available, ANN2 model may be used to estimate ET_o. Next to ANN2 model, ANN4 has performed better which requires inputs of minimum and maximum air temperatures, minimum and maximum relative humidity, and sunshine duration. In case of ANN4, MAE, MARE and RMSE were third lowest and E, D were third highest; but r, R^2 were second highest. ANN4 model was followed by ANN1 and ANN3. ANN1 model showed fourth lowest MAE, MARE, RMSE and fourth highest r, R^2, D, E; which has input vector of minimum and maximum air temperatures only. Comparatively highest MAE, MARE, RMSE and lowest r, R^2, D, E were obtained for ANN3 model, which has input vector of minimum and maximum air temperatures, and minimum and maximum relative humidity.

It can be inferred from comparison that ANN5 model performs best, whereas under the situations of availability of data on limited weather parameters ANN2 model may be preferred for estimation of ET_o at Nagpur over other models, because of its minimal requirement of input parameters. It can be used even in the absence of maximum and minimum relative humidity and wind speed data.

4. CONCLUSION

When all weather parameters are available artificial neural network models developed at Nagpur using input combination of all six parameters can be used for estimating reference evapotranspiration. But under the situations of availability of limited weather parameters, ANN model developed using maximum air temperature, minimum air temperature and sunshine duration can be used for estimating reference evapotranspiration.

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