Evapotranspiration modeling using different Heuristic neural network Approaches

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Sirisha Adamala and Monisha Perli

Abstract
To schedule irrigation properly, a grower must know the environmental demand for surface water. For the grower, this surface water loss occurs primarily through evapotranspiration (ET_o), which is simply the amount of water returned to the atmosphere through evaporation (moisture loss from the soil, standing water, etc.) and transpiration (biological use and release of water by vegetation). In this study, the potentiality of different ANN models: multi-layer perceptrons (MLPs), radial basis neural networks (RBNNs) and generalized regression neural networks (GRNNs) were tested for different climatic locations in India. The performance indices used for comparing the above models include root mean squared error (RMSE), coefficient of determination (R^2), mean absolute error (MAE), and the ratio of average output to the average target ET_o values (R). The results revealed that though all models performed well in estimating or modelling ET_o, the performance of GRNN models was superior with respect to low RMSE and MAE errors and high R^2 values as compared to MLP and RBNN models.

Keywords: Neural networks; multi-layer perceptron; generalized regression; evapotranspiration

Introduction
Modeling of evapotranspiration (ET) is the major priority of researchers, working in various fields of water resources as it plays a significant role in the hydrological cycle. Reference evapotranspiration (ET_o) is the basis for estimating crop evapotranspiration (ET_c) and computing crop irrigation water requirements (Dai *et al*., 2009) [11]. Smith *et al*. (1997) [14] defined the ET_o as "the rate of ET from a hypothetical crop with an assumed crop height of 12 cm, a fixed canopy resistance of 70 s m^{-1} and albedo of 0.23, closely resembling the ET from an extensive surface of the green grass of uniform height, actively growing, completely shading the ground and not short of water." The Food and Agricultural Organization (FAO) accepted it as a standard definition (Allen *et al*., 1998) [9].

Estimation of ET_o is an extremely complex non-linear phenomenon because several interacting climatic parameters, such as temperature (T_{avg}), relative humidity (RH_{avg}), wind speed (W_s), and solar radiation (S_{ra}) are driving this process (Jackson, 1985) [13]. Despite its complexity, it is one of the least measured components of the hydrologic cycle, probably because of the expensive and cumbersome requirements for its direct measurement methods (Brutsaert, 1982) [10]. As a result, indirect methods varying from empirical such as radiation, temperature, and evaporation based equations to complex combined equations such as Penman and FAO-56 Penman-Monteith (FAO-56 PM) are developed for estimating ET_o. Though researchers have a number of methods for estimating ET_o indirectly, most of them require all or subsets of climate data (T_{avg}, RH_{avg}, W_s, and S_{ra}) depending on the selected method. In all of the indirect methods, the complex and non-linear relations exist between climatic variables and hydrological variables such as ET_o are difficult to describe analytically.

The above limitations lead to the need of developing some techniques that can not only estimate the complex non-linear ET_o accurately but also to model it without requiring the explicit formulation of the possible relationships that may exist between variables. The artificial neural networks (ANNs), which can provide a model to predict and investigate the complex non-linear process without having a complete understanding of it, can be a useful tool for the above purpose (Adamala *et al*., 2014a; 2014b; 2015a; 2015b; 2015c; 2016; 2017a; 2017b) [1-8]. The potential of three different artificial neural network (ANN) techniques, the multi-layer perceptrons (MLPs), radial basis neural networks (RBNNs) and generalized regression neural networks (GRNNs), in modelling of reference evapotranspiration (ET_o) was done in this study. More details about these techniques can be accessed from references.

Study Area

For the purpose of this study, 25 different climatic locations distributed over four climates or agro-ecological regions (AER) are selected (Fig. 1). The selected locations are Parbhani, Kovilpatti, Bangalore, Solapur, Udaipur, Kanpur, Anand, Akola, Anantapur, Hissar, Bijapur, Raipur, Faizabad, Ludhiana, Ranichauri, Jabalpur, Samastipur, Bhubaneswar, Ranchi, Rakh Dhiansar, Palampur, Jorhat, Mohanpur, Thrissur, and Dapoli. Table1 shows the details of 25 climatic stations of India along with location characteristics (altitude, latitude and longitude) and duration of available data.

Daily climate data of minimum temperature (T_{min}), maximum temperature (T_{max}), minimum relative humidity (RH_{min}), maximum relative humidity (RH_{max}), wind speed (W_s), and solar radiation (S_{ra}) for the period of five years (Jan 01, 2001 to Dec 31, 2005) were collected from All India Coordinated Research Project on Agrometeorology (AICRPAM), Central Research Institute for Dryland Agriculture (CRIDA), Hyderabad, Telangana, India. These data were used for development and testing of various ANN based ET_o models. Due to the unavailability of lysimeter measured ET_o values for these stations, it is estimated by the FAO-56 PM method which has been adopted as a standard method for the computation of ET_o and calibrating other equations (Allen *et al*., 1998) [9].

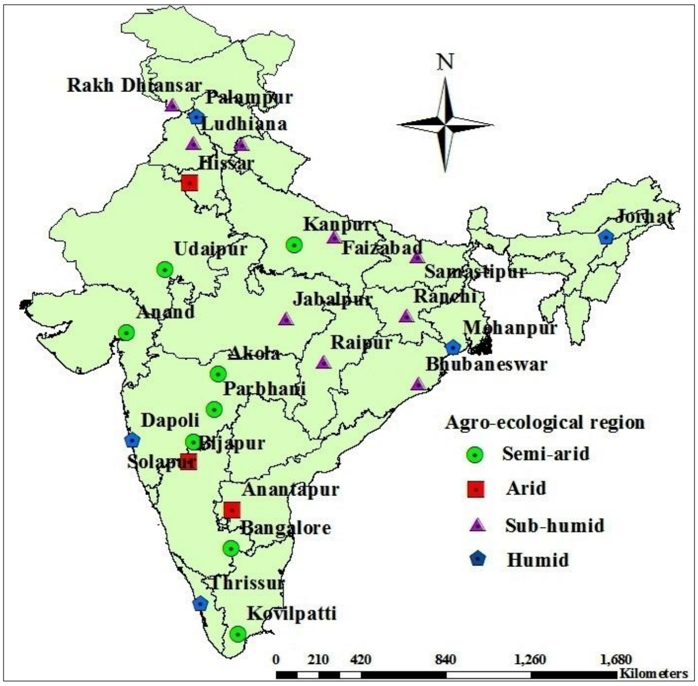

Fig 1: Study area (25 climatic stations and four agro-ecological regions)

Table 1: Data pertaining to selected climatic locations and period of records

S. No.	Station	Code	Lat. (ºN)	Lon. (ºE)	Alt. (m)	Period
1	Ludhiana	LD	30°56'	75°52'	247	2001-2005
2	Hissar	HS	29°10'	75°44'	215	2001-2005
3	Jorhat	JR	26°47'	94°12'	86	2001-2005
4	Mohanpur	MH	21°52'	87°26'	10	2001-2005
5	Raipur	RP	21°14'	81°39'	298	2001-2005
6	Parbhani	PR	19°08'	76°50'	423	2001-2005
7	Solapur	SL	17°41'	75°56'	25	2001-2005
8	Anantapur	AN	14°41'	77°37'	350	2001-2005
9	Bangalore	BN	12°58'	77°35'	930	2001-2005
10	Kovilpatti	KL	9°10'	77°52'	90	2001-2005
11	Udaipur	UD	25°21'	74°38'	433	2001-2005
12	Thrissur	TR	10°31'	76°13'	26	2001-2005
13	Bijapur	BJ	16°49'	75°43'	594	2001-05
14	Dapoli	DP	17°46'	73°12'	250	2001-05
15	Faizabad	FZ	26°47'	82°08'	133	2001-05
16	Palampur	PL	32°06'	76°03'	1291	2001-05
17	Ranichauri	RN	30°52'	78°02'	1600	2001-05
18	Kanpur	KN	26°26'	80°22'	126	2004-05
19	Anand	AN	22°33'	72°58'	45	2003-05
20	Jabalpur	JB	23°09'	79°58'	393	2002-05
21	Samastipur	SM	25°53'	85°48'	52	2004-05
22	Akola	AK	20°42'	77°02'	282	2001-03
23	Bhubaneswar	BB	20°15'	85°50'	25	2002-05
24	Ranchi	RN	23°17'	85°19'	625	2005
25	Rakh Dhiansar	RD	32°39'	74°58'	332	2005

Materials and Methods

The main objective of this study is to develop daily ET_o models using different supervised ANNs (Multi-layer perceptrons (MLPs), Radial basis neural networks (RBNNs) and Generalized regression neural networks (GRNNs)). The developed ANN models consisting 6 variables (T_{min}, T_{max}, RH_{min}, RH_{max}, W_s, and S_{ra}) as input, one variable ET_o (The ET_o values are calculated from DSS_ET software using the standard FAO-56 PM equation) as target. Levenberg-Marquardt (LM) algorithm was used to train the ANN models. Number of hidden layers is selected as one and hidden neurons are varying. The transfer function used is log-sigmoid. Program codes, including ANN toolboxes, are written in MATLAB language for the MLP, RBNN and GRNN simulations.

A comparison is made between the estimates provided by the developed daily ET_o ANN models such as MLP, RBNN and GRNN and the empirical FAO-56 PM model (i.e. observed ET_o). The statistical indices used for the evaluation of the models' performance are: (i) Root Mean Squared Error (RMSE), (ii) Coefficient of Determination (R^2), and (iii) Ratio of average observed value to average predicted value (R).

i) Root Mean Squared Error (RMSE)

RMSE is the square root of the average value of the squares of the differences between the target and the output values. It is a measure of the residual variance and it indicates the overall discrepancy between the target and the output values. A low RMSE indicates good model performance, and vice-versa. A perfect match between the target and the output values would yield RMSE = 0.0. It is expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - O_i)^2} \quad (1)$$

Where T_i and O_i = target (FAO-56 PM ET_o) and output (ET_o resulted from ANN models) values at the i^{th} step, respectively; n = number of data points.

ii) Coefficient of Determination (R^2)

The R^2 measures the degree to which two variables are linearly related. It is the square of the Pearson's correlation coefficient (r) and describes the proportion of the total variance in the observed data that can be explained by the model. The value of R^2 ranges from 0 to 1, with higher value indicating better agreement between the target and the output values. For example, R^2 of 0.80 indicates that the model explains 80% of the variability in the observed data. It is expressed as:

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O}\right)\left(T_i - \overline{T}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2 \sum_{i=1}^{n}\left(T_i - \overline{T}\right)^2} \quad (2)$$

Where $\overline{T}$ and $\overline{O}$ = average of target (FAO-56 PM ET_o) and output (ET_o resulted from ANN models) values, respectively.

iii) Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|T_i - O_i\right| \quad (3)$$

It should be optimally zero.

iv) Ratio of Average Output to Average Target ET_o Values (R)

Generally, the R is used only to know whether the models overestimated or underestimated output values. The R > 1 indicates the over-estimation, R < 1 indicates the under-estimation, and R = 1 indicates neither over- nor under-estimations.

$$R = \frac{\overline{O}}{\overline{T}} \quad (4)$$

Results and Discussion

The data sample for the training consists of daily pooled data of 1 year (2001) from 12 stations (6 input variables and 1 target variable). So that the no. of patterns include for training are 4380. The developed ANN models have tested with a pooled data of 12 locations for 2002, 2003, 2004 and 2005 years. For evaluating generalization capability of developed ANN models, these models have also tested for not only the pooled data of 12 locations which were used in training but also the pooled data of 13 locations for the years 2001 to 2005 which were not used for training. Firstly, MLP models are trained with LM training algorithm for the pooled 12 climatic stations of 2001 year. Table 2 shows the results of MLP trained network for 2001 year. From this, the minimum training RMSE observed at 12^{th} hidden node. Therefore, an optimum network for MLP model considered was 6 input-12 nodes -1 output. By using this optimum network, MLP models were tested for the 12 locations which were used in training and 13 locations which were not used in training.

Table 2: Training of MLP with LM training algorithm (Pooled data 12 stations for 2001 year: No. of Patterns = 4380).

No. of hidden nodes (NH)	Training			
	RMSE	R^2	R	MAE
1	0.3002	0.9738	1.0025	0.2132
2	0.2137	0.9867	1.0009	0.1619
3	0.1274	0.9953	1.0015	0.0999
4	0.1224	0.9957	1.0018	0.0948
5	0.1267	0.9953	1.0012	0.0994
6	0.1089	0.9965	1.0006	0.0839
7	0.1098	0.9965	0.9996	0.0842
8	0.1053	0.9968	1.0016	0.0805
9	0.0981	0.9972	1.0002	0.0735
10	0.1013	0.997	1.0007	0.0764
11	0.0982	0.9972	1.0002	0.0734
12	0.0977	0.9972	1.0003	0.0731
13	0.0989	0.9972	1.0002	0.0745

Table 3 shows that the testing results of developed MLP models for different locations with varying years (2001, 2002, 2003, 2004 and 2005). MLP models gave RMSE values nearly same for all years except 2003 year, where the models overestimated ET_o values during training and testing.

Table 3: Testing of MLP with LM training algorithm for 13 and 12 locations

Year	NH	Testing				No. of patterns
		RMSE	R^2	R	MAE	
For locations which were not used for training (pooled data of 13 locations)						
2001	12	0.2639	0.9849	0.9778	0.1921	2190
2002	12	0.311	0.9815	0.9779	0.1949	2920
2003	12	0.7411	0.8283	0.9722	0.5051	3285
2004	12	0.3022	0.9773	0.9651	0.2424	3660
2005	12	0.3558	0.9706	0.9579	0.2752	4380
For locations which were used for training (pooled data of 12 locations)						
2002	12	0.199	0.989	0.996	0.122	4380
2003	12	0.126	0.996	0.998	0.094	4380
2004	12	0.123	0.996	0.996	0.095	4392
2005	12	0.144	0.995	0.993	0.114	4380

Similarly, RBF and GRNN models were developed as shown in Tables 4-7, and compared their performance with the MLP models. From the Table 4 the optimum results observed at a spread of 5.5. Therefore, this RLB network at 5.5 spread was used for testing. Table 6 shows the results of developed GRNN model with ANN technique. The results from this procedure were totally different than other models. Based on the comparisons, it is found that the MLP and RBNN techniques could be employed successfully in modeling the ET_o process.

Table 4: Training of RBF ANN (Pooled data 12 stations for 2001 year: No. of Patterns = 4380)

Spread	Training			
	RMSE	R^2	R	MAE
1	0.5386	0.9075	1	0.3801
1.5	0.2990	0.9715	1	0.2175
2	0.2164	0.9851	1	0.1578
2.5	0.1980	0.9875	1	0.1487
3	0.1553	0.9923	1	0.1182
3.5	0.1610	0.9917	1	0.1236
4	0.1562	0.9922	1	0.1203
4.5	0.1485	0.9930	1	0.1162
5	0.1479	0.9930	1	0.1151
5.5	0.1256	0.9950	1	0.0985
6	0.1292	0.9947	1	0.1018
6.5	0.1270	0.9949	1	0.0992
7	0.1282	0.9948	1	0.0995
7.5	0.1235	0.9951	1	0.0966
8	0.1236	0.9951	1	0.0972

Table 5: Testing of RLB network with 13 and 12 locations

Year	Spread	Testing				No. of Patterns
		RMSE	R^2	R	MAE	
For locations which were not used for training (13 stations)						
2001	5.5	0.2915	0.9820	0.9741	0.2125	2190
2002	5.5	0.3527	0.9765	0.9762	0.2193	2920
2003	5.5	0.6746	0.8588	0.9630	0.4863	3285
2004	5.5	0.3236	0.9748	0.9635	0.2561	3660
2005	5.5	0.3846	0.9641	0.9574	0.2967	4380
For locations which were used for training (12 stations)						
2002	5.5	0.2139	0.9869	0.9981	0.1354	4380
2003	5.5	0.1489	0.9938	1.0016	0.1100	4380
2004	5.5	0.1438	0.9941	0.9982	0.1088	4392
2005	5.5	0.1610	0.9931	0.9939	0.1253	4380

Table 6: Training of GRNN algorithm (Pooled data 12 stations for 2001 year: No. of Patterns = 4380)

Spread	Training			
	RMSE	R^2	R	MAE
0.01	0.0138	1	1	0.0582
0.02	0.0243	1	1	0.0103
0.03	0.0311	1	1	0.0164
0.04	0.0512	1	1	0.0138
0.05	0.0881	1	1	0.0657
0.06	0.0130	1	1	0.0117
0.07	0.0180	1	1	0.0203
0.08	0.0240	1	1	0.0346
0.09	0.0310	1	1	0.0576
0.1	0.0390	1	1	0.0931
0.2	0.0293	0.9997	0.9999	0.0182
0.3	0.0753	0.9983	0.9993	0.0561

Table 7: Testing of GRNN model at 13 and 12 Locations

Year	Spread	Testing				No. of Patterns
		RMSE	R^2	R	MAE	
For locations which were not used for training (13 stations)						
2001	0.01	0.0192	1	1	0.0646	2190
2002	0.01	0.0146	1	1	0.0531	2920
2003	0.01	0.0487	1	1	0.0120	3285
2004	0.01	0.0210	1	1	0.0637	3660
2005	0.01	0.0131	1	1	0.0322	4380
For locations which were used for training (12 stations)						
2001	0.01	0.0138	1	1	0.0582	4380
2002	0.01	0.0144	1	1	0.0413	4380
2003	0.01	0.0839	1	1	0.0179	4380
2004	0.01	0.0116	1	1	0.0252	4392
2005	0.01	0.0256	1	1	0.0905	4380

Conclusions

The potential of different ANN models corresponding to the FAO-56 PM method for the estimation of ET_o has been studied in this paper by considering daily climate data for a period of five years from 25 stations distributed over the India. Variants of ANNs, MLP, RBF and GRNN models were trained and tested for a pooled data of 12 and 13 locations, respectively during 2001, 2002, 2003, 2004 and 2005 years. The optimum ANN architecture for MLP models was obtained at 12 hidden neurons with a trial run of 1 to 15 hidden nodes. RBF neural network gave best results at a spread of 5.5 and GRNN models gave best results at spread of 0.01. All the models were tested with known and unknown locations data at optimum conditions. Overall, comparisons suggested the greater potential of GRNN models in estimating ET_o with low RMSE and MAE and high R^2 and R values as compared to MLP and RBF neural networks. However, further research is required to evaluate the MLP, RBF and GRNN models corresponding to different ET_o estimation methods and under different climatic regions of other countries.

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