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Performance Evaluation of Artificial Neural Networks in Estimating Reference Evapotranspiration

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Abstract

The present study examines the applicability of an artificial neural network (ANN) models for estimating daily reference evapotranspiration (ET_0) from climatological data. The various climatic parameters mostly influencing the ET_0 in the study region have been identified through multiple and partial correlation analysis using observed climatic data and ET_0 estimated by FAO-56 Penman-Monteith (PM) method. The ANN models with these mostly influencing climatic parameters (temperature, sunshine hours, wind velocity and relative humidity) as input nodes and ET_0 estimated by PM method as output node by varying the number of nodes in the hidden layer have been tried to obtain optimal architectures. A part of the data was used for the purpose of train the models and the rest for test the models developed. The performance of the models was assessed by the performance indicators such as regression coefficients (slope and intercept of scatter plots), Root Mean Square Error (RMSE), Coefficient of Determination (R^2) and Efficiency Coefficient (EC). The study shows that the best model for estimation of daily ET0 is ANN (4-3-1). This ANN model may therefore be recommended for estimating daily ET_0 in the study region.

Keywords: Reference evapotranspiration, Multiple and Partial correlation coefficients,

Artificial Neural Network, Climatic parameters.

1.0 INTRODUCTION

In any country, effective use of water resources in agriculture is becoming an important issue because of the rapid depletion of freshwater resources due to the fast growth of population and industries. Reliable and consistent forecast of reference evapotranspiration is main element of managing water resources efficiently. There are number of methods to forecast reference evapotranspiration (ET_0). Allen et al. (1998) recommend the application of the FAO-56 Penman-Monteith (PM) method as the sole standard method for ET_0 estimation and it gives more accurate ET_0 estimates in different environs. However, under limited climatic data availability conditions, the simple empirical methods yielding results similar to that of PM method may be selected at local level for reasonable estimation of ET_0.

Majority of the ET_0 estimation methods are not properly represent the nonlinear dynamics presented in the ET_0 process. Artificial Neural Networks (ANNs) are capable to capture the nonlinear dynamics of the hydrologic data, which may not be always possible with the application of other traditional statistical techniques. The success with which ANNs have been used to model dynamic systems suggests that the ANNs approach may prove to be an effective and efficient way to model the ET_0

process. ANNs also identify the underlying rule, even if the data are noisy and contaminated with errors (ASCE Task committee, 2000a and 2000b) and which may not be always possible with the application of traditional statistical techniques. In recent times, ANNs are used as a successful soft computing tool in ET_0 modelling. Although ANNs belong to the class of data driven approaches, it is important to determine the governing network model inputs as this not only reduces the training time, but also increases the generalization ability of the network for a given data set. The present study inspects several aspects associated with the use of ANN structure, including the type of input data, number of hidden layers and nodes in each hidden layer to be included in the network in the ET_0 estimation.

Armin et al. (2014) considered two data-driven models ANN and M5model tree to estimate ET_0 values and results were compared with calculated ET_0 by FAO-Penman-Monteith equation using climatic data of five weather stations in Khuzestan province, southeastern Iran. Found that both models are properly estimating ET_0. Kale et al. (2013) checked the performance of ANN model, FAO-56 Penman–Monteith and Hargreaves-Samani model with FAO-24 Pan evaporation model for ET_0 estimation. ANN (2-2-1) model recommended for estimating fairly accurate ET_0 when data relating to climatic parameters is insufficient to apply standard ET_0 estimation methods.

The present study reports the identification of most influencing climatic parameters in ET_0 estimation and development of ANN models for estimation of daily ET_0 for Anakapalli region of Andhra Pradesh.

2.0 MATERIAL AND METHODS

The study area selected is Anakapalli, Visakhapatnam district of Andhra Pradesh, India. Geographically it is located at 17^0 38′ N latitude and 83^0 01′ E longitude and an altitude of 25 m above mean sea level. In this area the main agricultural crops are Rice, Corn, Sugarcane, and all types of vegetables. The chief crop this region is sugarcane. It is well known for Jaggery imports/exports and it is the second biggest Jaggery market in India. The weather data recorded by Regional Agricultural Research Station, Anakapalli for the period 1980-2001 were collected from India Meteorological Department (Ministry of Earth Sciences, Government of India), Pune. Data from 1980-1994 is used for training the model and 1995-2001 for testing the model. A brief description of study area is given in Table 1.

Table 1: Brief description of the Anakapalli region

Mean daily relative humidity	Mean daily temperature	Mean daily wind velocity	Mean daily sunshine hours	Mean daily vapour pressure	Mean annual rainfall
(%)	(^{0}C)	(kmph)	(hr)	(mm of Hg)	(mm)
71.9	27.9	4.6	7.1	20.6	1190

2.1 Multiple Correlation Analysis

In the present study, Penman-Monteith ET_0 was correlated linearly with climatic parameters such as temperature(T), wind velocity(W), sunshine hours(S), relative humidity(RH), vapor pressure(VP) and rainfall(R) in the study area.

However, implementation of multiple least-squares regression considering all the predictor variables may lead to over fit and consequent reduction in the predictive capability. To overcome this and to have parsimony in terms of input data requirements, partial correlation analysis is carried out to arrive at the final form of regression model involving only those predictor variables that influence more the response variable. The objective of the analysis is to develop an optimal prediction equation eliminating superfluous predictor variables.

2.2 Artificial Neural Network (ANN) model

A standard multilayer feed forward ANN with logistic sigmoid function was adopted in the present study. The input data were standardized in the range of (0.1, 0.9) to avoid any saturation effect in the ET_0 estimation process. Error feedback propagation which is an iterative nonlinear optimization approach based on the gradient descent search method (Rumelhart, 1996) was used in calibration. The calibration set was used to minimize the error and validation set was used to ensure proper training of the neural network model such that it does not get over-trained. The performance of the model was checked for its improvement on every iteration to avoid over-learning. The optimal network corresponding to the minimum mean squared error was obtained through trial and error process. Care was taken to avoid too few and too many neurons, which can cause difficulties in mapping each input and output in the training set and increase training time unnecessarily, in the process of determination of optimal number of hidden layers and nodes in each hidden layer to arrive at the optimal neural network. The entire process was carried out with MATLAB routines.

2.3 PERFORMANCE EVALUATION CRITERIA

The performance evaluation criteria used in the present study are, namely, the coefficient of determination, the root mean square error, systematic RMSE, unsystematic RMSE and the efficiency coefficient.

2.3.1 Coefficient of Determination (R^2)

It is equivalent to the square of the correlation coefficient (R). Mathematical formula of ‘R’ is

$$R = \frac{\sum_{i=1}^{n} (o_i - \bar{o})(p_i - \bar{p})}{\left[\sum_{i=1}^{n}(o_i - \bar{o})^2 \sum_{i=1}^{n}(p_i - \bar{p})^2\right]^{1/2}}$$

Where, O and P are observed and estimated values, $\overline{O}$ and $\overline{P}$ are the means of observed and estimated values and n is the number of observations. It indicates the strength of the linear association between O and P. It evaluates performance of the model.

2.3.2 Root Mean Square Error (RMSE)

It measures the residuals between observed and estimated values and is expressed as

(Yu et al., 1994)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (p_i - o_i)^2}{n}}$$

2.3.3 Efficiency Coefficient (EC)

It is used to assess the predictive power of hydrological models (Nash and Sutcliffe, 1970). When the calibration and verification periods have different lengths, EC is better choice than RMSE statistic (Liang et al., 1994). It measures directly the ability of the model to reproduce the observed values and is expressed as

$$EC = 1 - \frac{\sum_{i=1}^{n} (o_i - p_i)^2}{\sum_{i=1}^{n} (o_i - \overline{o})^2}$$

A value of EC of 90% generally indicates a very satisfactory model performance. EC value in the range 80-90% indicates a fairly good model. A value of EC in the range 60-80% indicates an unsatisfactory model.

3.0 RESULTS AND DISCUSSION

The analysis of multiple linear correlation between $PMET_0$ and the climatic parameters was carried out by omitting one of the climatic parameter each time. In the process of analysis, the data period was divided into training and testing periods. The training period data was used to identify the parameters influencing the study area and to develop linear ET_0 models in terms of these climatic parameters. The verification of the applicability of the models developed was checked using the testing period data. The multiple linear correlation coefficients and partial correlation coefficients between ET_0 estimated by PM method and climatic parameters of the region were computed for both training and testing periods are presented in Table 2 and 3.

Table 2: Multiple correlation coefficients

Multiple correlation coefficient													
Independent variable omitted													
----		T		S		W		RH		VP		R	
Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period
0.9656	0.9763	0.7836	0.8154	0.7981	0.8165	0.9082	0.9623	0.9614	0.9735	0.9645	0.9760	0.9654	0.9762

Table 3: Partial correlation coefficients

Partial correlation coefficient											
T		S		W		RH		VP		R	
Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period
0.9082	0.9275	0.9021	0.9271	0.7836	0.6057	0.3270	0.3231	0.1745	0.1111	0.0754	0.0644

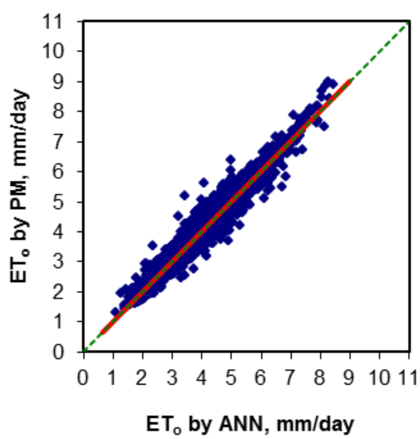
From Tables 2 and 3, it may be observed that the influence of Temperature(T), Sunshine hours(S), Wind velocity(W) and Relative humidity(RH) is relatively more on ET_0 in the region of the study area. It is found that, no significant effect of Vapour Pressure(VP) and Rainfall(R) on ET_0 in the study area. It is due to the fact that the region lies in the semi-arid zone and experienced by high temperature and radiation.

The ANN models with these mostly influenced parameters (T, S, W and RH) as input nodes varying the number of nodes in the hidden layer have been tried to obtain best architectures. The statistical evaluations of these ANN models are presented in Table.4.

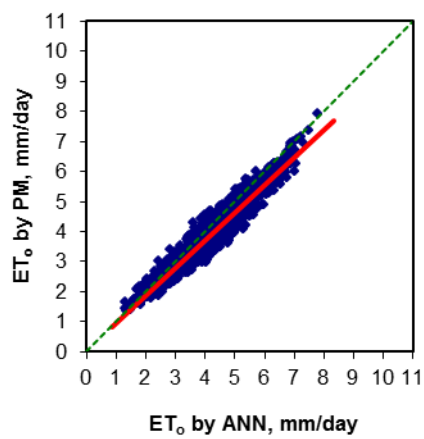
Table 4: Performance indices of Artificial Neural Network (ANN) models

ANN Architecture	Slope of the scatter plot		Intercept of the scatter plot		R^2		RMSE (mm)		EC (%)	
	Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period	Training period	Testing period
4-3-1	1.0009	0.9208	-0.0028	0.0257	0.9614	0.9499	0.24	0.27	96.14	94.99
3-4-1	1.0000	0.8292	0.0000	0.5244	0.6959	0.6798	0.67	0.67	69.59	67.98
2-5-1	1.0010	1.0488	-0.0039	-0.0773	0.6112	0.6685	0.76	0.68	61.12	66.85
1-5-1	1.0002	1.0095	-0.0006	0.3436	0.1992	0.2428	1.09	1.03	19.92	24.28

The low values of RMSE and high values of EC represent the reasonable performance of ANN (4-3-1) models for the study area. The scatter plots of ET_0 values estimated using ANN models with those estimated by FAO-56 PM method shown in Fig.1 also represent similar results.



A) Training period



B) Testing period

Fig.1 Scatter plots of ET_0 values estimated using Artificial Neural Network (ANN) models with those estimated by FAO-56 Penman-Monteith (PM) method.

The models proposed may therefore be used for ET_0 estimation in the selected region of the study area with a reasonable degree of accuracy.

4.0 CONCLUSIONS

The effect of climatic parameters on ET_0 at Anakapalli region is brought out through multiple and partial correlation analysis. It is found that Temperature(T), sunshine hours(S), wind velocity(W) and relative humidity(RH) are mostly influencing ET_0 in the study region. The Artificial Neural Network models comparable with PM method for the region have been developed in terms of the mostly influencing climatic parameters to estimate ET_0. The performance of ANN models developed was verified based on the statistical criteria. The high values of R^2 and EC and low values of RMSE indicate satisfactory performance of the ANN models. The ANN(4-3-1) model showed better performance in ET_0 estimation. Therefore, the model may be recommended for estimating ET_0 in the study region and also the other regions of similar climatic conditions with a reasonable degree of accuracy.

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