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Short Communication

Estimation of evapotranspiration using neural network approach

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Reference evapotranspiration (ET_o) is the basis for estimating crop evapotranspiration and computing crop water requirements. ET_o is a complex and non-linear phenomenon depending on several interacting meteorological variable, such as temperature, humidity, radiation and wind speed (Singh *et al.,* 2016). Artificial Neural Networks (ANNs) are effective tools to model nonlinear system and have been increasingly employed in modelling of hydrological processes because of their ability in mapping the input-output relationship without any understanding of physical process. Kumar *et al.*, (2002) investigated the utility of ANNs for the estimation of ET_o and found that the ANNs can predict ET_o better than the conventional method. Recently, the multi-layer perceptron (MLP) neural network ssuccessfully applied in ET_o estimation. Kisi (2007) investigated the accuracy of the MLP with Levenberg-Marquardt training algorithm and reported that MLP can be successfully employed in modeling ET_o from available climate data. MLP models were compared with some empirical models and found to have better accuracy in estimating ET_o. Considering potential applicability of ANN in ET_o modeling, it was planned to apply neural network approach for estimation of ET_o under limited and full data condition for Padegaon, Satara region, Maharashtra, India.

Padegaon station lies with latitude of 16°42'18"N, longitude of 74°14'36"E and 567 m above mean sea level. The climate data for Padegaon station was collected from IMD, Pune and SAU, Rahuri, Maharashtra, India The data sample is composed of 1300 weekly (1990-2014) records of maximum temperature (Tmax), minimum temperature (Tmin), maximum relative humidity (RHmax), minimum relative humidity (RHmin), bright sun shine hours (BSS), wind speed (WS) and pan evaporation (Epan). First 1040 data sets (80% of the whole data) were used to train the MLP models, remaining 260 data sets (20% of the whole data)data were used for validation of models.

Model architecture

In this study feed forward back propagation type of network with single hidden layer was selected for development of architecture. The various selected variables were discussed and presented in Table 1. In this study Levenberg-Marquardt algorithms with '*trainlm'* training function was chosen for ET_o modelling application with *Learngdm* (gradient descent with momentum weight and Bias learning function) adaption learning function for this application. The most widely used non-linear activation function i.e., a log sigmoid for the hidden layer and linear transfer function in output layer were selected.The number of nodes in the input layer depends on the number of meteorological parameters used in estimating ET_o. The different combinations of input variables were selected for limited data condition, while all six parameters required for estimation of ET_o in Penman Monteith was used for full data condition (Bhatt *et al.*, 2007) (Table 1). The number of nodes in hidden layer was varied alternatively from 3 to 19. The number of nodes in the output layer depends on the number of target variables, so the output layer will be single node corresponding to ET_o estimated using sole standard Penman-Monteith method (Allen, *et al.,* 1998). ET_o estimation performance of developed networks were compared statistically with estimated values of ET_o by Penman-Monteith method to select best network architecture. The best fit architecture was identified with statistical criteria *viz.,* coefficient of correlation (R), index of agreement d(IA), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and coefficient efficiency (CE) (Singh *et al.,* 2018). The best fit network architecture was simulated with unseen data and evaluates the performance with same statistical measures for validation of the model.

Identification of models

The best fit ANN models were identified by influence of number of hidden neurons on statistical performance measures for all models for Padegaon station under limited and full data condition. For identification of ANN1 (as input: Epan) model (Table 2), network architecture 1-7-1 trained with *trainlm* training function has the best values of all six performance criteria as R(0.900), d(IA) (0.945), RMSE (0.454), MAE (0.280), MAPE (9.885) and CE (0.809) among

Table 1: Selected variables for the development of ANN architecture in ET_o modelling.

Particulars	ANN Models				
	ANN1	ANN2	ANN3	ANN4	ANN5
Network type	Feed Forword back propogation				
Inputs	Epan	Tmax, Tmin	Tmax, Tmin and SSH	Tmax, Tmin, RHmax, RHmin and SSH	Tmax, Tmin, RHmax, RHmin, WS and SSH
No. of nodes in input layer	1	2	3	5	6
No. of hidden layers	1	1	1	1	1
No. of nodes in hidden layer	3 to 19 (alternatively)				
No. of nodes in output layer	1	1	1	1	1
Training algorithm	Levenberg-Marquardt algorithms, *(trainlm)*.				
Transfer function	Log sigmoid in hidden layer and Linear function in output layer				

Table 2: Performance evaluation of best fit ANN models with limited and full data for Padegaon Station

Model	Training function	Network	Statistical Criteria					
			R	d(IA)	RMSE	MAE	MAPE	CE
Training period (1990-2009)								
ANN1	trainlm	1-7-1	0.900	0.945	0.454	0.280	9.885	0.809
ANN2	trainlm	2-15-1	0.938	0.967	0.359	0.224	7.881	0.880
ANN3	trainlm	3-19-1	0.969	0.984	0.257	0.165	5.752	0.939
ANN4	trainlm	5-17-1	0.976	0.988	0.227	0.139	4.827	0.952
ANN5	trainlm	6-13-1	0.996	0.998	0.096	0.057	2.191	0.991
Validation period (2010-2014)								
ANN1	trainlm	1-7-1	0.909	0.934	0.431	0.291	11.761	0.730
ANN2	trainlm	2-15-1	0.884	0.890	0.609	0.383	14.932	0.461
ANN3	trainlm	3-19-1	0.925	0.943	0.418	0.261	9.977	0.745
ANN4	trainlm	5-17-1	0.950	0.952	0.394	0.244	9.256	0.775
ANN5	trainlm	6-13-1	0.969	0.984	0.214	0.135	5.522	0.933

all combinations of ANN1 model, so network architecture 1-7-1 trained with *trainlm* training function defined as the best architecture for ANN1 model. The results for identification of ANN2 (as inputs: Tmax and Tmin); ANN3 (as inputs: Tmax, Tmin and SSH; ANN4 (as inputs: Tmax, Tmin, RHmax, RHmin, and SSH) ; ANN5 (all inputs: Tmax, Tmin, RHmax, RHmin, WS and SSH) models were presented in Table 2, It was also observed that various network architectures with varying hidden neurons in light of statistical performance measures showed satisfactory performance. However, network architecture 2-15-1 has the best values of all six performance criteria as R (0.938), d(IA) (0.967), RMSE (0.359), MAE (0.224), MAPE (7.881) and CE (0.880) among all combinations of ANN2 model; network architecture 3-19-1 has the best values of all six performance criteria as R (0.969), d(IA) (0.984), RMSE (0.257) MAE (0.165), MAPE (5.752) and CE (0.939) among all combinations of ANN3 model; network architecture 5-17-1 has the best values of four performance criteria as R (0.976), d(IA) (0.988), RMSE (0.227) and CE (0.952) among all combinations of ANN4 model; network architecture 6-13-1 has the best values of all six performance criteria as R (0.996), d(IA) (0.998), RMSE (0.096), MAE (0.057), MAPE (2.191) and CE (0.991) among all combinations of ANN5 model. Hence network architecture 2-15-1, 3-19-1, 5-17-1 and 6-13-1 trained with *trainlm* training function defined as the best architectures for ANN2, AANN3, ANN4 and ANN5 models respectively.

Performance evaluation of models

Table 2 shows the statistical performance of best fit ANN models of limited (ANN1 to ANN4) and full (ANN5) data conditions during training and validation period for Padegaon Station. During training mode, it was observed that ANN5 model showed best values of all performance measures as higher values of R (0.996), d(IA) (0.998), CE (0.991) and lower values of RMSE (0.096), MAE (0.057), MAPE (2.191) while ANN1 model shows lower performance among them as R (0.900), d(IA) (0.945), CE (0.809), RMSE (0.454), MAE (0.280) and MAPE (9.885). It was observed that the values of R, d(IA) and CE shows increasing trend while the values of RMSE, MAE and MAPE shows decreasing trend with respect to increasing number of input parameters for all ANN models. It reveals that ANN5 model shows best performance followed by ANN4, ANN3, ANN2 and ANN1 model. The reason is that ANN5 requires all six inputs (Tmax, Tmin, RHmax, RHmin, WS and SSH) while remaining limited data ANN models require less parameter in decreasing order as ANN4 (Tmax, Tmin, RHmax, RHmin, and SSH), ANN3 (Tmax, Tmin, and SSH), ANN2 (Tmax and Tmin) and it was agrees with the findings of Huo *et al.* (2012) that ANNs with five inputs were more accurate than those with four or three for prediction of ET_o in arid and semiarid areas of northwest China. Considering limited data condition, it was observed that the results of all performance measures for all limited data (ANN1 to ANN4) models varies in the range as R (0.900 to 0.976), d(IA) (0.945 to 0.988), RMSE (0.227 to 0.454), MAE (0.139 to 0.280), MAPE (4.827 to 9.885) and CE (0.809 to 0.952). It can be seen that all limited data models demonstrate relatively very close performances for statistical criteria; hence it reveals that all limited data models can be used for prediction of ET_o

The results for the validation of all ANN models are shown in Table 2. In ANN1 model, the value of the R in training stage is 0.900 and it increases to 0.909 in validation stage, similar kind of enhancement also occurred in MAE (0.280 to 0.291), MAPE (9.885 to 11.761) for ANN1 model. It was also observed that there was reduction in the values of d(IA), RMSE and CE during validation of ANN1 model as 0.945 to 0.934, 0.454 to 0.431 and 0.809 to 0.730 respectively. It indicates that ANN1 model showed slightly increase in performance in training stage than validation stage, however it shows close difference in enhancement and reduction of each performance measures during training and validation of ANN1 model. Similar kind of close difference for each performance measures were occurred during training and validation stage of remaining ANN models. It indicates that all ANN models were validated satisfactorily and generalized for prediction of ET_o values. Overall, the performance suggests that all ANN models can be an acceptable approach for accurate prediction ET_o values for Padegaon station as per data availability.

Thus it can be concluded that the network architecture 1-7-1, 2-15-1, 3-19-1, 5-17-1 and 6-13-1 trained with *trainlm* training function found the best architectures for ANN1 (as input: Pan evaporation); ANN2 (as inputs: Tmax and Tmin); ANN3 (as inputs: Tmax, Tmin and SSH; ANN4 (as inputs: Tmax, Tmin, RHmax, RHmin, and SSH) ; ANN5 (all inputs: Tmax, Tmin, RHmax, RHmin, WS and SSH) models respectively. Overall performance suggest that all ANN models can be an acceptable approach for accurate prediction ET_o values for Padegaon region under limited and full data availability.

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