Application of Artificial Neural Networks for Estimating Reference Evapotranspiration in Western Himalayan Region

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Abstract: This paper aims to examine the utility of artificial neural networks (ANN) for estimating reference evapotranspiration (ET_0) in western Himalayan region. The study considered meteorological data of 3 sub-regions (Jammu-Kashmir, Uttarakhand and Himachal Pradesh) comprising 47 stations for the period 1979-2011. Two ANN models with different input data combinations were used in the study. Model A1 was comprised of 5 input variables (minimum temperature, maximum temperature, relative humidity, solar radiation and wind speed) and model A2 was comprised of 2 input variables (maximum and minimum temperature). The ANN modelling was performed using MATLAB, wherein two-third of the dataset was used for training the network and remaining dataset for testing the developed network. The ET_0 predicted using ANN models were compared with the ET_0 computed using FAO-56 Penman-Monteith method. The performance of the ANN models was evaluated using sum of squared errors (SSE), root mean squared error (RMSE) and R^2 values. Model A1 performed relatively better than A2 for all the sub-regions, however, model A2 performed better than A1 during testing stage for most locations. The error statistics indicate that the performance of A2 is comparable to A1 and can be effectively utilized to estimate ET_0 in absence of sufficient climatic data. A comparison was also conducted among the three sub-regions in the study area. Study validated the performing capability of ANN in estimating ET_0 with sufficient as well as limited set of climatic data.

Keywords: Irrigation; CROPWAT; Soft computing; Meteorological parameters; India.

1. Introduction

Reference evapotranspiration (ET_0) is a major component in hydrologic studies. ET_0 modelling finds applications in various areas such as irrigation scheduling, crop yield simulation, hydrologic water balance factor and variability analysis (Poddar et al. 2018). Owing to unavailability of lysimeters in most locations, direct measurements of ET_0 is unlikely to be available and mostly unfeasible (Kumar et al. 2012). Hence, it is usually estimated from indirect methods which include use of theoretical and empirical equations requiring meteorological variables (Nandagiri and Kovoor 2006). Most of these methods do not effectively represent the complex nonlinear dynamics in the ET_0 measurement process (Adeloye et al. 2012).

FAO-56 Penman-Monteith (*hereinafter referred as PM*) (Allen et al. 1998) method is considered as the best indirect method to estimate ET_0 under various agroclimatic conditions using meteorological data as input variables (Irmak et al. 2003; Cai et al. 2007; Garg et al. 2016). Due to the superiority of the method, it is mostly used by researchers and practitioners to estimate the ET_0, however, the routine use of this method is constrained due to non-availability of humidity, wind speed and radiation data at all locations. To overcome this, researchers have evaluated other empirical methods requiring limited climatic data for estimating ET_0 in various agroclimatic conditions (Nandagiri and Kovoor, 2006; Trajkovic and Kolakovic, 2009; Tabari, 2010; Pandey et al. 2016; Poddar et al., 2018).

In last few years, soft computing has emerged as a reliable technique to solve such complex problems. One such technique, artificial neural networks (ANN) modelling has a great significance in modelling nonlinear systems because it requires lesser inputs, negligible computational efforts and a very short real-time control (ASCE 2000). Kumar et al. (2002)

stated that local ANN models can be trained to predict lysimeter ET_0 values better than the PM method. Zanetti et al. (2007) and Khoob (2008) tested the ANN to estimate ET_0 as a function of maximum and minimum temperature using pan evaporation data in semi-arid conditions and recommended further studies to evaluate ANN method in other climate regions. Kisi (2008) evaluated the potential of three different ANN techniques for comparing the performance of Penman, Hargreaves and Ritchie ET_0 estimation techniques and calibrated with PM equation using various climatic data and found Hargreaves method to perform better than other ET_0 estimation models.

However, most of the previous studies were confined to a single location or a small study area. This study aims to explore the potential of ANN modelling in estimating ET_0 for the whole of the Western Himalayan region using sufficient as well as limited climate data.

2. Material and Methods

Study Area and Meteorological Data

The study area considered is the western Himalayan agro-climatic region of India. The region lies in northern part of India and is divided into three sub-regions: Jammu and Kashmir (SR-1), Himachal Pradesh (SR-2) and Uttarakhand (SR-3). The climatic conditions in the region varies from sub-tropical to temperate to cold arid. Daily meteorological data comprising air temperature, humidity, solar radiation and wind speed, of all the districts falling in the study area (47 stations in total) was collected from Indian Meteorological Department Pune (India) for the period 1979-2011 (33 years). Apart from meteorological data, the latitude, longitude and elevation of each station was considered. Reference evapotranspiration (ET_0) at each station was estimated using the meteorological and spatial data mentioned above.

ET_0 Estimation using FAO-56 Penman-Monteith Method

Considering the number of data points, daily meteorological parameters were converted into monthly mean values. The ET_0 of each station was calculated using CROPWAT software (Smith 1992). CROPWAT requires the meteorological and spatial variables mentioned above and follows the methodology described in FAO-56 (Allen et al. 1998). A detailed guidance on using the CROPWAT software is given in CROPWAT manual (Clarke et al. 2001). The software uses PM equation for computing the ET_0 given by:

$$ET_0 = \frac{0.408\,\Delta\,(R_n - G) + \gamma\left(\frac{900}{T+273}\right)u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34\,u_2)} \tag{1}$$

Where, T = mean air temperature (^{0}C); u_2 = wind speed at 2 m height (m s^{-1}); e_s = saturation vapour pressure (kPa); e_a = actual vapour pressure (kPa); G = soil heat flux density (MJ m^{-2} d^{-1}); Rn = net radiation at crop surface (MJ m^{-2} d^{-1}); γ = psychrometric constant (kPa °C^{-1}); and Δ = slope of vapor pressure versus temperature curve at mean temperature (kPa °C^{-1}).

CROPWAT has been successfully used in many studies for estimating the crop water requirements (Kuo et al. 2001; Feng et al. 2007; Bouraima et al. 2015; Surendran et al. 2015). The software also allows water management and irrigation schedule development under rainfed and irrigated conditions (Cavero et al. 2000; Smith et al. 2002; Muhammad 2009).

ET_0 Estimation using Artificial Neural Network Modelling

ANN models

Two ANN models were used in this study named as A1 (5-5-1) and A2 (2-10-1). A1 model was the sufficient data model and consists of 5 inputs variables (minimum and maximum temperature, relative humidity, solar radiation and wind speed), 5 nodes in hidden layer and 1 output node as ET_0. Whereas, A2 model was the limited data model and consists of 2 inputs only (minimum and maximum temperature), 10 nodes in hidden layer and 1 output node as ET_0. The purpose of using A2 model was to determine whether, only temperature data is sufficient to determine ET_0.

ANN modelling architecture

For ANN modelling, data from each station of the sub-region was divided into training phase (70%) and testing phase (30%). The network-type used was feed-forward backpropagation and was trained using Levenberg-Marquardt algorithm. A gradient descent with momentum weight and bias learning was used as the adaptive function. All neural networks were created, trained and tested in MATLAB. Activation transfer function used was log-sigmoidal function. The architecture was based on trial and error approach.

Once the network was trained and tested, a regression plot was generated between output and target data for the overall dataset. After this, the trained network was validated for a new set of input variables, in which, it will predict the output from the hidden deduced complex relationship. Fig. 1 shows the step by step procedure followed in ANN modelling.

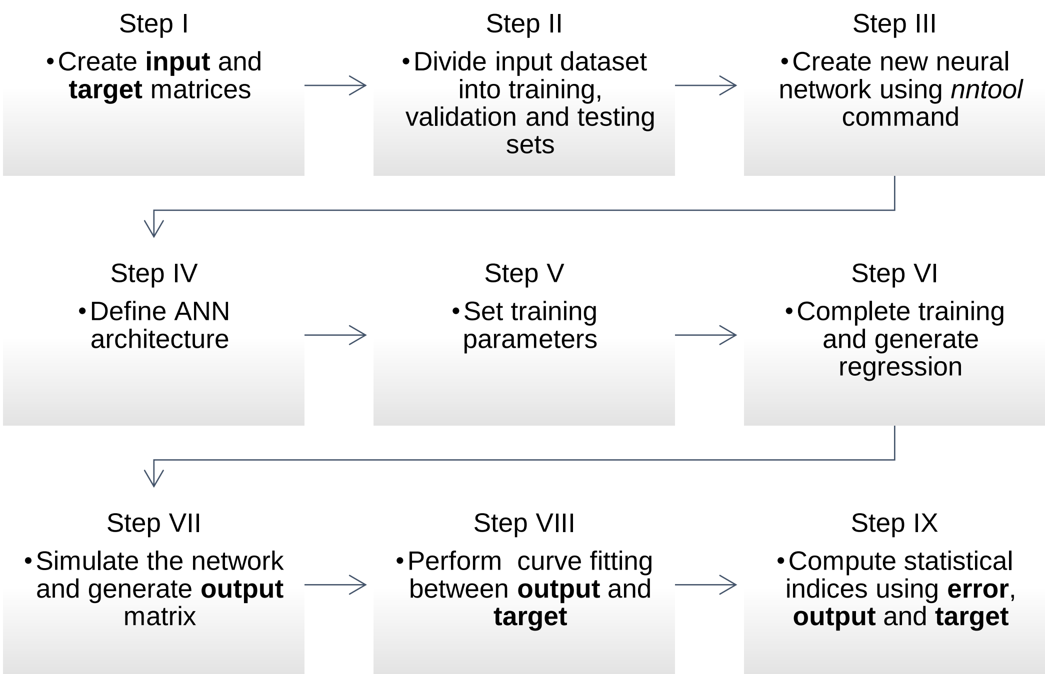

Fig. 1 Flow chart for ANN based ET_0 modelling

Performance Evaluation Indicators

The performance of ANN modelling was evaluated using statistical indices coefficient of correlation (R), root mean square error (RMSE) and mean absolute error (MAE). The equations are given by:

$$r = \frac{\sum_{i=1}^{n}(T_i - \bar{T})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(T_i - \bar{T})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2}} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - O_i)^2} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|T_i - O_i| \quad (4)$$

Where, T_i = Target ET_0 (mm day^{-1}); O_i = Output ET_0 (mm day^{-1}); $\bar{T}$ = Mean target ET_0 (mm day^{-1}); $\bar{O}$ = Mean target ET_0 (mm day^{-1}); n = number of data points.

3. Results and Discussion

FAO-56 Penman-Monteith ET_0 results

Monthly mean ET_0 for each station in the study area was computed using FAO-56 PM method in the CROPWAT software. A time series plot of monthly mean ET_0 averaged over the study period (1971-2011) is shown in Fig. 2.

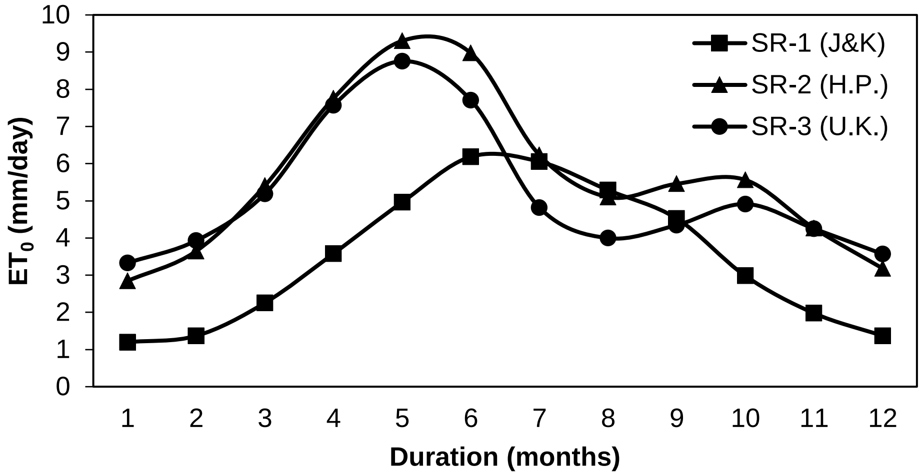

Fig. 2 Monthly mean ET_0 for the three regions estimated using FAO-56 P-M method

As expected, it was observed that the peak ET_0 occurred in summers and lowest ET_0 occurred in winters. It was found that the maximum ET_0 occurred in the month of May for sub-regions SR-2 and SR-3. But for the sub-region SR-1, maximum ET_0 occurred during the month of June. During the post-monsoon period in sub-regions SR-2 and SR-3, ET_0 exhibited a slight increase followed by the final decrease. But for sub-region SR-1, ET_0 variation for post-monsoon periods showed a gradual descent. From Fig.1, it was also observed that the ET_0 in SR-2 and SR-3 remained higher than ET_0 in SR-1 for most part of the year, except during monsoon season, when ET_0 in SR-1 was higher than SR-2 and SR-3.

ANN predicted ET_0 results

In ANN modelling, network training regressions were plotted after the training was completed. During testing phase, an output vector file was generated, and both the vectors were subjected to curve fitting and performance evaluation indices (R, RMSE, MAE) were calculated. Polynomial-type fit was used along with degree 1 for getting the best fit line. Whole procedure was performed for all the three sub-regions for both the models A1 and A2.

Model A1 results

Model A1 with 5 climatic parameters as input presented exemplary results. The model estimated ET_0 showed strong agreement with the FAO-56 Penman-Monteith ET_0 estimates. A comparison between ET_0 estimates for all three sub-regions is shown in Fig. 3-5. It was observed that the performance of model A1 was relatively better in SR-1 and SR-2 as compared to SR-3. The performance was further analysed by the statistical error indices given in Table 1. The values of statistical indices indicate that model A1 performed better during validation stage. The R value was close to 0.99 in most of the cases, indicating, a strong correlation between model A1 predicted ET_0 estimates and FAO-56 Penman-Monteith ET_0 estimates.

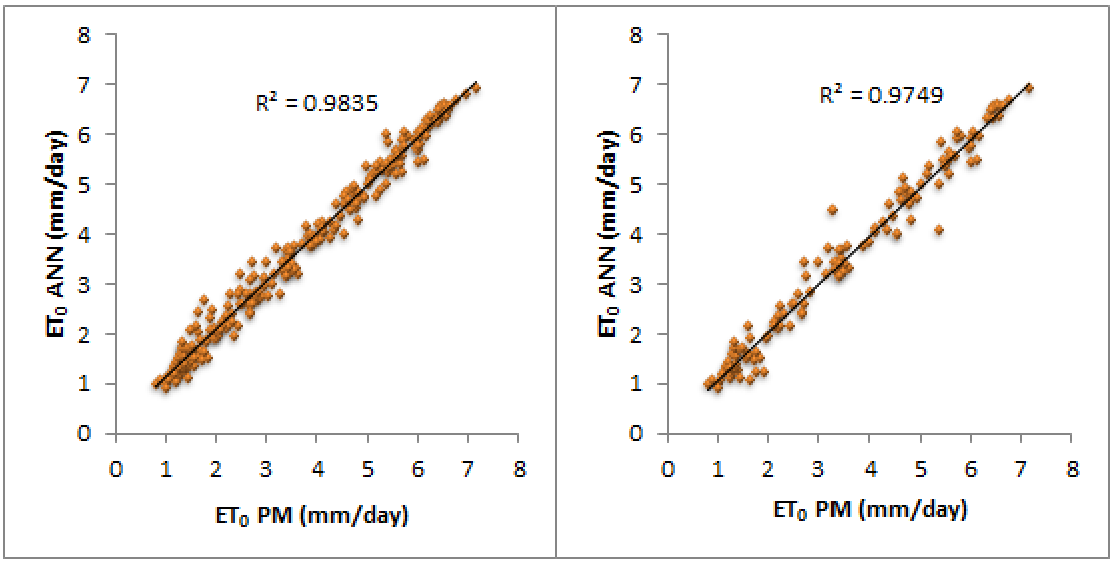

Fig. 3 Relationship between ET_0 (ANN) and ET_0 (PM) during calibration and validation stage for model A1 for sub-region SR-1

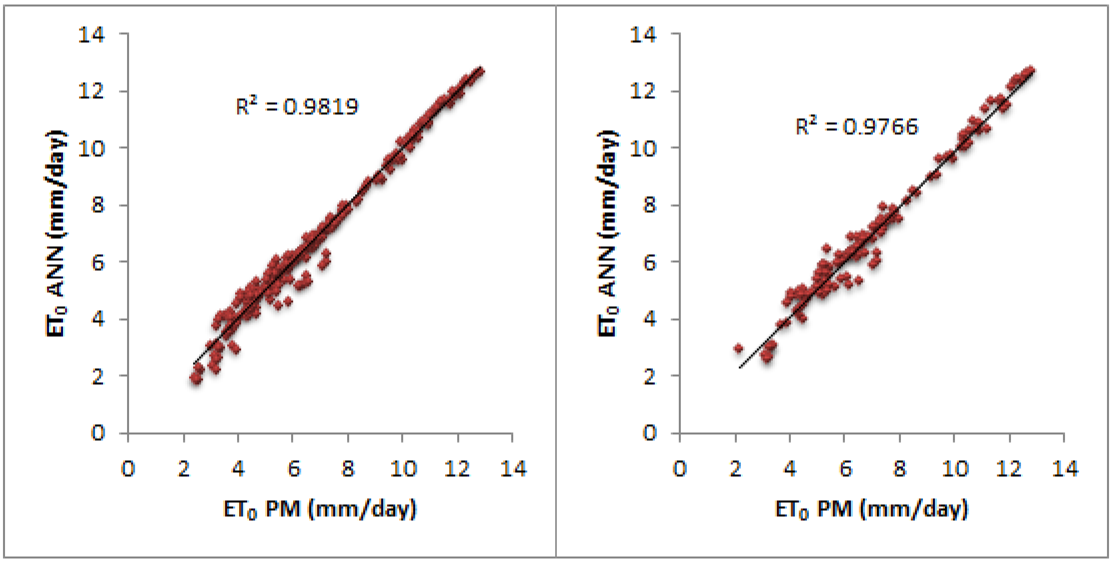

Fig. 4 Relationship between ET_0 (ANN) and ET_0 (PM) during calibration and validation stage for model A1 for sub-region SR-2

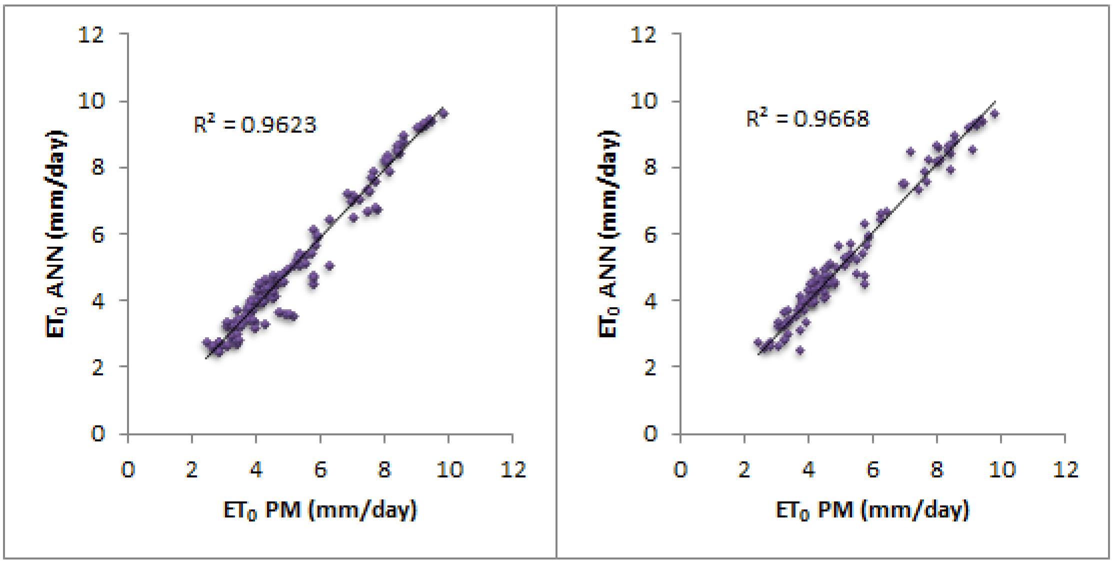

Fig. 5 Relationship between ET_0 (ANN) and ET_0 (PM) during calibration and validation stage for model A1 for sub-region SR-3

Model A2 results

The performance of model A2 with only 2 input parameters was commendable considering the data requirement of the model. The results were not as good as model A2 but were still reliable. The model predictions were better for SR-1 and SR-2 as compared to SR-3. The performance of model was better during calibration stage as indicated by the statistical error indices (Table 1).

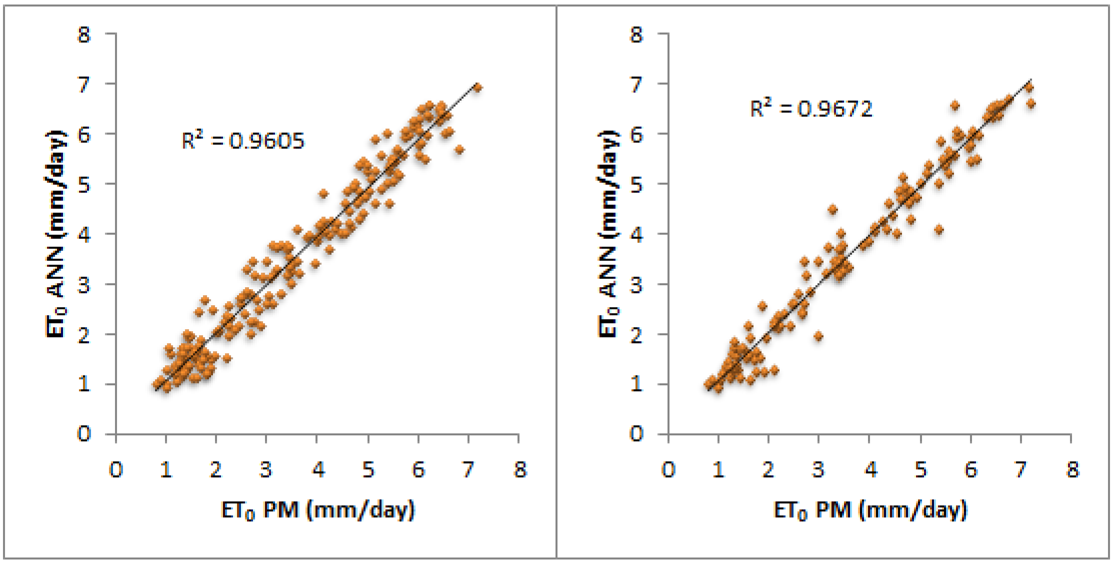

Fig. 6 Relationship between ET_0 (ANN) and ET_0 (PM) during calibration and validation stage for model A2 for sub-region SR-1

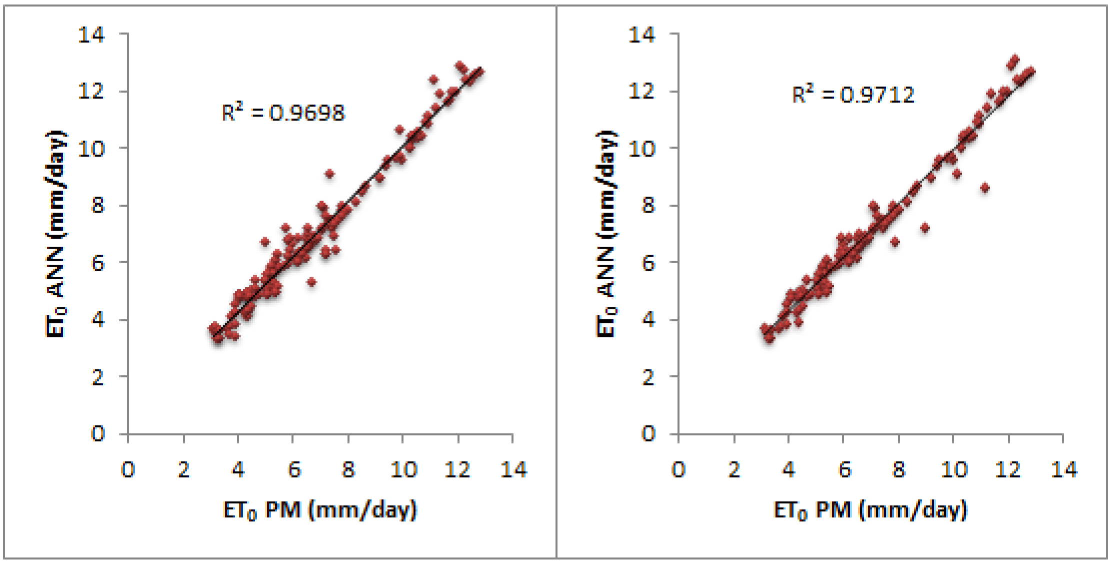

Fig. 7 Relationship between ET_0 (ANN) and ET_0 (PM) during calibration and validation stage for model A2 for sub-region SR-2

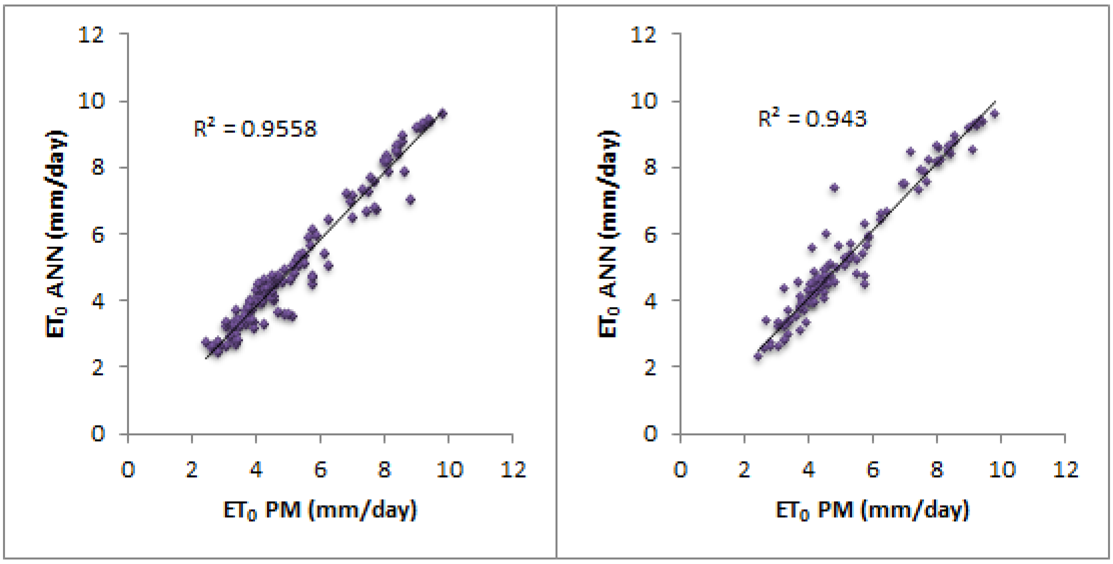

Fig. 8 Relationship between ET_0 (ANN) and ET_0 (PM) during calibration and validation stage for model A3 for sub-region SR-3

Table 1: Performance evaluation indices for ANN modelling (Calibration and Validation stage) for each region and model

Sub-region	**ANN model**	**Statistical Index**					
		Calibration			**Validation**		
		R (%)	*RMSE* (mm/day)	*MAE* (mm/day)	*R* (%)	*RMSE* (mm/day)	*MAE* (mm/day)
A1	M1	97.36	0.32	0.22	99.17	0.21	0.11
	M2	98.34	0.28	0.16	98.00	0.35	0.23
A2	M1	98.82	0.19	0.11	99.09	0.12	0.05
	M2	98.54	0.21	0.12	98.47	0.27	0.19
A3	M1	98.32	0.25	0.18	98.09	0.24	0.13
	M2	97.10	0.33	0.24	97.76	0.29	0.20

Cross-comparison of models A1 and A2

From Fig.3 to Fig.8, it can be observed that both models A1 (5-5-1) and A2 (2-10-1) provided best results for SR-2 and least accurate results for SR-3. Statistical error indices R, RMSE and MAE were also found to be in resonance with the above results (Table-1). The results of the models postulate that ANN performs exceptionally well in the western Himalayan region for estimating ET_0. Though, a comparison with other empirical methods was not conducted in the study, it was observed that, ANN presented better results when compared with the findings of Poddar et al. (2018), who also evaluated ET_0 in the same region.

4. Conclusions and Recommendations

This study was undertaken to estimate the reference evapotranspiration (ET_0) using artificial neural networking (ANN) and evaluate its performance with FAO-56 Penman-Monteith ET_0 estimates. Two ANN models were considered in the study, model A1 with 5 input variables and model A2 with 2 input variables. ANN modelling was done in three stages: calibration, validation and performance evaluation. The results prove the potential of ANN for modelling ET_0 using sufficient (A1 model) and limited (A2 model) climate variables. Both models performed better during validation stage than calibration stage. The ANN modelling results of sub-region 2 (Himachal Pradesh) were relatively better than other sub-regions. Though A2 performed slightly poor than A1, still it presented reliable performance and can be used for estimating ET_0 with limited climatic data through ANN approach with a reasonable level of accuracy.

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