Monthly pan evaporation modelling using multiple linear regression and artificial neural network techniques

G. T. Patle, M. Chettri and D. Jhajharia

ABSTRACT

Accurate estimation of evaporation from agricultural fields and water bodies is needed for the efficient utilisation and management of water resources at the watershed and regional scale. In this study, multiple linear regression (MLR) and artificial neural network (ANN) techniques are used for the estimation of monthly pan evaporation. The modelling approach includes the various combination of six measured climate parameters consisting of maximum and minimum air temperature, maximum and minimum relative humidity, sunshine hours and wind speed of two stations, namely Gangtok in Sikkim and Imphal in the Manipur states of the northeast hill region of India. Average monthly evaporation varies from 0.62 to 2.68 mm/day for Gangtok, whereas it varies from 1.4 to 4.3 mm/day for Imphal during January and June, respectively. Performance of the developed MLR and ANN models was compared using statistical indices such as coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) with measured pan evaporation values. Correlation analysis revealed that temperature, wind speed and sunshine hour had positive correlation, whereas relative humidity had a negative correlation with pan evaporation. Results showed a slightly better performance of the ANN models over the MLR models for the prediction of monthly pan evaporation in the study area.

Key words | ANN, evaporimeter, meteorological parameters, MLR, modelling, pan evaporation

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INTRODUCTION

Evaporation is the primary process of water transfer in the hydrologic cycle and plays a significant role in water balance assessment (Liu *et al.* 2004). It is an indicator of potential evaporation or potential evapotranspiration which indicates the evaporation plus transpiration from a vegetated surface with unlimited water supply (Shirgure & Rajput 2012). Globally, evapotranspiration or evaporation is the primary cause of soil moisture depletion in agricultural fields and the volume of reduction in water bodies. Evaporation being a complicated process, it is influenced by the many weather parameters which are involved in the hydrological process (Tabari *et al.* 2010). Major meteorological parameters which influence the process of evaporation are air temperature, relative humidity, solar radiation, wind speed, and vapour pressure deficit (Jhajharia *et al.* 2009). Long-term time series of pan evaporation have shown decreasing trends in evaporation in many parts of the world under arid, semiarid, and humid climatic conditions in spite of increase in surface air temperature globally (Roderick & Farquhar 2002). Knowledge and accurate estimation of evaporation are necessary for different water resources planning, design, operation and management studies including hydrology, agronomy, horticulture, forestry, land resources, irrigation management, flood forecasting, investigation of agro-ecosystem and modelling etc. (Malik *et al.* 2017, 2018). In many parts of the world,

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where availability of water resources is scarce, the estimation of evaporation is very important in the planning and management of irrigation practices, and these quantities should be considered in the design of various water resources and irrigation systems (Tabari *et al.* 2010).

Direct and indirect methods are used for the estimation of evaporation. Direct measurement of evaporation mainly includes use of pan evaporimeters. The United States Weather Bureau (USWB) Class A pan evaporimeter is widely used in meteorological observatories throughout the world (Allen *et al.* 1998). Several location-specific empirical formulae have been developed using one or more meteorological parameters and are used for the estimation of evaporation. Although evaporation measurement using pan evaporimeter is the most accurate and realistic technique, its installation and maintenance involves more expenditure and requires the skills to interpret pan evaporation readings. Therefore, modelling of pan evaporation from readily available weather parameters is an alternative (Shirsath & Singh 2010). The different indirect methods used in the estimation of evaporation include temperature-based formulae (e.g. Blaney–Criddle process), temperature- and radiation-based formulae (e.g. Priestley–Taylor method), and combination formulae which also include the variation of evaporation with wind velocity and humidity. A regression analysis approach was also used to model the relationship between dependent (evaporation) and independent variables (temperature, humidity, wind speed and sunshine hours). In traditional regression analysis, residuals are assumed to be due to random errors (Sriram & Rashmi 2014). Artificial neural networks (ANNs) and genetic programming (GP) are well-known machine-learning techniques which apply artificial intelligence for the modelling of complex hydrological systems. The features of these techniques provide neural networks with the potential to model complex non-linear phenomenon like the prediction of daily pan evaporation using measured meteorological variables. Recent experiments have reported that ANN may offer a promising alternative in the hydrological context (Tabari *et al.* 2010; Abudu *et al.* 2011; Guven & Kişi 2011, 2013; Sanikhani *et al.* 2012; Shirgure & Rajput 2012; Malik *et al.* 2017, 2018).

Sudheer *et al.* (2002) used a feed-forward ANN to estimate evaporation and found that the ANN compared favourably with regression methods. Keskin & Terzi (2006) developed feed-forward ANN for modelling daily evaporation and found that the ANN model performed better than the traditional way. Tan *et al.* (2007) used an ANN technique for modelling hourly and daily open-water evaporation rates. Kisi (2009) modelled daily pan evaporations using three different neural network techniques, multilayer perceptrons (MLPs), radial basis neural networks (RBNNs) and generalised regression neural networks (GRNNs) and he found that the MLP and RBNN can be employed successfully to model the evaporation process using the available climatic data. Tabari *et al.* (2010) compared ANN and multivariate non-linear regression techniques for modelling daily pan evaporation and found that the ANN performed better than the non-linear regression.

The above-mentioned studies have shown the effectiveness of the multiple linear regression (MLR) and ANN techniques in the estimation of evaporation and also show the superiority of the neural network approach over the MLR using limited weather parameters. The northeastern region of India shares about 8% of the total geographical area of the country and consists of almost mountainous topography. The availability of climatic data is very scarce in the region due to the limited weather stations and this makes it difficult to estimate the evaporation. Therefore, considering the importance of pan evaporation in water resources management and planning, this study investigates the comparative superiority among the MLR and ANN techniques for the estimation of monthly pan evaporation for the study area.

MATERIALS AND METHODS

Study area and data used

The study area includes two meteorological stations, namely Gangtok in Sikkim and Imphal in the Manipur states of India. Sikkim State of India is characterised by mountainous terrain. Crops are grown organically without using chemical fertilisers and pesticides in the entire state. It is bounded approximately between 27°05′ to 27°09′ north latitudes and 87°59′ to 88°56′ east longitudes, covering a total geographical area of 7,096 km^2. The altitude ranges from 280 m to 8,585 m above mean sea level. The climate of Sikkim State varies from subtropical to temperate.

The average annual rainfall of the eastern district of Sikkim is about 3,067 mm. The minimum and maximum air temperatures range from 13 °C to 28 °C and 0 °C to 13 °C in summer and winter months, respectively. Daily mean relative humidity ranges between 64% and 85%. The highest and lowest wind speeds are 3 and 1 km/h, with an annual average of 2 km/h. Imphal is located at 24°80′N 93°93′E in extreme eastern India with an average elevation of 786 metres. It has a humid subtropical climate with mild, dry winters and a hot monsoon season. The city receives about 1,320 mm of rain, with June the wettest month (Figure 1).

Monthly meteorological data values were collected from the India meteorological department (IMD), Pune, for Imphal and Gangtok stations and used for the analysis. Meteorological data consisting of maximum air temperature (Tmax), minimum air temperature (Tmin), maximum relative humidity (RHmax), minimum relative humidity (RHmin) and solar sunshine hours (SSH) for the duration of 2007–2014 were used for Imphal (Manipur) and from 2009 to 2014 were used for Gangtok.

Development of evaporation estimation models

For model development, monthly data of temperature (T), wind speed (W), relative humidity (Rh) and sunshine hours (S) were taken as inputs to the models, and monthly average evaporation was considered as the output of the models. The entire data were divided into the ratio of 70:30 for both the stations, out of which 70% of the data were used for model development (training of the network), and 30% of the data were used for verification of the models (testing of the network). Different combinations of weather parameters were considered for model development using the MLR and ANN approaches in the present study. The performance of models was verified through selected performance evaluation criteria.

Multiple linear regression (MLR) models

Statistical methods, such as regression models, are the most suitable tools for investigating any relation between small sample sizes of dependent and independent variables

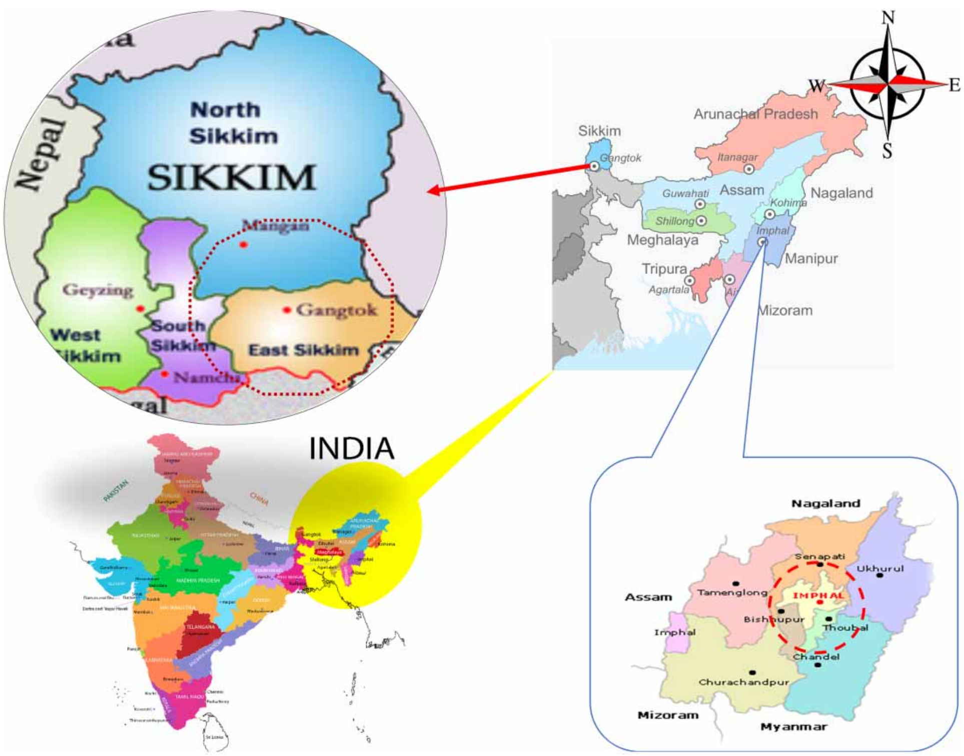

Figure 1 | Study area showing the synoptic station for which data were retrieved.

(Razi & Athappilly 2005). Multiple linear regression techniques can be used to model the evaporation data in terms of the local climatological parameters of temperature, relative humidity and wind speed (Almedeij 2012). For a multiple linear regression model, the dependent variable y is assumed to be a function of k independent variables x_1, x_2, x_3, …, x_k.

The model is expressed in the form of Equation (1):

$$y_i = b_0 + b_1x_{1,i} + \cdots + b_kx_{k,i} + e_i \tag{1}$$

where b_0, b_1, …, and b_k are fitting constants; y_i, $x_{1,i}$, …, $x_{k,i}$ represent the ith observations of each of the variables y, x_1, …, x_k, respectively; and e_i is a random error term representing the remaining effects on y of variables not explicitly included in the model. For simple regression models, e_{i} can be assumed to be an uncorrelated variable with zero mean.

Artificial neural network (ANN) model

An ANN consists of a network of neurons (i.e. simple processing elements) operating on their local data and communicating with other elements (Svozil *et al.* 1997). An ANN functions as a replica of the human brain, having the capability for handling complex non-linear relationships between input and output datasets. The main processor of artificial-intelligence-based models is the neuron. They are arranged in groups called layers. The basic structure of a network usually consists of three layers: the input layer, the hidden layer and the output layer (Kharat & Shetkar 2016). Several types of neural network exist but the basic principles are the same. We used multilayer perceptron (MLP), which is a widely used ANN configuration. MLP-ANN has been used frequently in the field of hydrological modelling (Leahy *et al.* 2008). The MLP is the simplest neural network model and also known as a supervised network because it knows the desired output and the adjusting of weight coefficients is done in such way that the calculated and desired outputs are as close as possible (Svozil *et al.* 1997). In this study, an adaptive momentum technique of Levenberg–Marquardt based on the generalised delta rule was adopted. Each node is a simple processing element that responds to the weighted inputs it receives from other nodes. The receiving node sums the weighted signals from all nodes to which it was connected in the preceding layer. The net input x_j to node j is the weighted sum of all the incoming signals, as shown in Equation (2):

$$\text{Net\_input} = x_j = \sum w_{ij}y_i \tag{2}$$

where x_j is the net input coming to node j; w_{ij} is the weight between node i and node j; and y_i is the activation function at node i.

The activation function y_j, which is a nonlinear function of its net input, is described by the sigmoid logistic function expressed by Equation (3):

$$y_j = \frac{1}{1 + \exp(-x_j)} \tag{3}$$

Levenberg–Marquardt (LM) algorithm

The Levenberg–Marquardt method is a modification of the classic Newton algorithm for finding an optimum solution to a minimisation problem. It uses the following Equation (4) for weight updating:

$$X_{k+1} = X_k - [J^{\mathrm{T}}J + \mu I]^{-1}J^{\mathrm{T}}e \tag{4}$$

where X is the weights of the neural network, J the Jacobian matrix of the performance criteria to be minimised, μ a scalar that controls the learning process and e the residual error vector (Ali & Saraf 2015).

In this study, various combinations of the meteorological parameters used as inputs to the multilinear regression and artificial neural network models to evaluate the degree of effectiveness for pan evaporation are shown in Table 1.

Table 1 | The various input combinations of the meteorological parameters

Model developed	T_{max}	T_{min}	Rh_{max}	Rh_{min}	SSH	WS
1	Y	–	–	–	–	–
2	Y	Y	–	–	–	–
3	Y	Y	Y	–	–	–
4	Y	Y	Y	Y	–	–
5	Y	Y	Y	Y	Y	–
6	Y	Y	Y	Y	Y	Y

Y: indicates inclusion of the variable in the model.

The dataset was divided into two sets, namely training and testing sets consisting of 70% and 30% of the data values. Epan estimated by the USWB class 'A' pan evaporimeter was used as an output to the multiple linear regression and artificial neural network models. The number of hidden nodes in the artificial neural network was determined empirically by trial and error, considering the need to derive consistent results. The inputs and outputs of the datasets were normalised to improve the performance of the network.

Performance evaluation criteria

The performances of the models developed in this study were evaluated using statistical tests, namely the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE).

Coefficient of determination (R^2)

R^2 is the square of the correlation coefficient (R) and ranges from 0 to 1. R^2 closer to 1 indicates goodness of fit between observed and predicted dataset. R^2 is expressed by Equation (5):

$$R^2 = \frac{\sum_{i=1}^{n}(Xi - Xi')(Yi - Yi')}{\sqrt{\sum_{i=1}^{n}(Xi - Xi')^2 (Yi - Yi')^2}} \tag{5}$$

Root mean square error (RMSE)

RMSE yields the residual error in terms of the mean square error. The RMSE is zero for perfect fit and increased values indicate higher discrepancies between predicted and observed values. A low value (<0.3) is considered as a good predictive model. RMSE is expressed as shown in Equation (6):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Xi - Yi)^2}{n}} \tag{6}$$

Mean absolute error (MAE)

MAE is the average of the absolute difference between the predicted values and observed value. The least value of MAE is acceptable. MAE was calculated using Equation (7) as given below:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|Xi - Yi|}{n} \tag{7}$$

where, $Xi = i$th observed value, $Yi = i$th predicted value, $XI =$ mean of Xi, $YI =$ mean of Yi, and $n =$ total number of data.

RESULTS AND DISCUSSION

Estimation of monthly pan evaporation (Epan)

Daily pan evaporation was estimated using a USWB Class A pan evaporimeter. The daily Epan values were converted into monthly pan evaporation. The variation in the average monthly pan evaporation for the period 2009–2014 for Gangtok and Imphal station is shown in Figure 2(a) and 2(b). It was observed that the lowest and highest evaporation rate was 0.615 mm/day and 2.68 mm/day for Gangtok whereas it was 1.4 mm/day and 4.3 mm/day for Imphal station in January and June, respectively.

ANN architectural parameters were optimised by performing several runs with different architectural configurations. In this study, the networks were trained and tested for each combination of meteorological parameters. Training and testing of the networks were accomplished on SPSS software. Although several tests were carried out using one and two hidden layers, it was observed that a single hidden layer with ten neurons was the best architecture and predicted closer values to the observed Epan values. The simulations showed that an increase in the hidden layer and the number of neurons in the hidden layer had brought almost no significant improvement to the Epan estimates. For the best architecture, the activation function was set to be a sigmoid function as this proved by trial and error to be the best in depicting the nonlinearity of the model natural system. The results showed that an increase in iteration value had brought almost no significant improvement to the prediction of Epan.

The statistical performance evaluation criteria of the MLR and ANN models for Gangtok are presented in Table 2. The analysis revealed that model performance

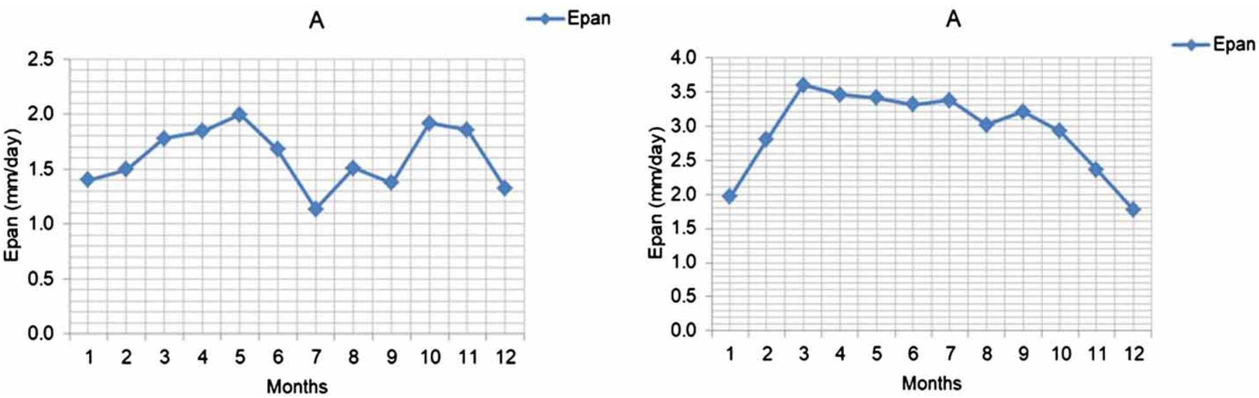

Figure 2 | Average monthly Epan for (a) Gangtok (2009–2014) and (b) Imphal (2007–2014).

Table 2 | Comparison of MLR and ANN models for Gangtok, Sikkim

	Development dataset						**Evaluation of dataset**					
	MLR			**ANN**			**MLR**			**ANN**		
Model	R^2	**RMSE**	**MAE**	R^2	**RMSE**	**MAE**	R^2	**RMSE**	**MAE**	R^2	**RMSE**	**MAE**
1	0.15	0.37	0.30	0.20	0.43	0.35	0.27	0.33	0.25	0.28	0.33	0.25
2	0.51	0.30	0.24	0.52	0.30	0.23	0.84	0.28	0.23	0.84	0.27	0.22
3	0.51	0.28	0.22	0.52	0.27	0.20	0.87	0.28	0.22	0.88	0.27	0.20
4	0.60	0.25	0.21	0.61	0.24	0.18	0.88	0.28	0.22	0.89	0.26	0.20
5	0.62	0.26	0.20	0.63	0.23	0.17	0.88	0.28	0.22	0.90	0.25	0.19
6	0.62	0.25	0.20	0.65	0.21	0.17	0.90	0.27	0.21	0.91	0.24	0.18

was higher for the combination of weather parameters having more input variables. MLR model 6 whose inputs are Tmax, Tmin, RHmax, RHmin, SSH and WS has the smallest RMSE (0.25 and 0.27 mm day^{-1}), MAE (0.20 and 0.21 mm day^{-1}) and the highest R^2 (0.62 and 0.90) for training and testing phases, respectively. Similarly, ANN model 6 has the smallest RMSE (0.21 and 0.24 mm day^{-1}), MAE (0.17 and 0.18 mm day^{-1}), and the highest R^2 (0.65 and 0.91) for training and testing phases, respectively. This emphasises the factors influencing the predicted Epan since the model considered all the variables. Therefore, it is appropriate to consider the combined influence of all the meteorological parameters on Epan. The result was very satisfactory and indicates that the relationship between the two series is very high. Thus, using only the air temperature input (i.e. Tmax) provided a poor prediction of Epan for the MLR and ANN techniques.

The statistical performance evaluation criteria of MLR and ANN for Imphal station is presented in Table 3. Similar results were obtained as for Gangtok station. The increased number of independent variables during model development increased the prediction accuracy of Epan. MLR model 6 whose inputs are Tmax, Tmin, RHmax, RHmin, SSH and WS has the smallest RMSE (0.25 and 0.30 mm day^{-1}), MAE (0.19 and 0.24 mm day^{-1}), and the highest R^2 (0.88 and 0.85) for training and testing phases, respectively. The R^2, RMSE and MAE statistics of each ANN model in testing and training phases for Imphal station are presented in Table 3. ANN model 6 whose inputs are Tmax, Tmin, RHmax, RHmin, SSH and WS has the smallest RMSE (0.24 and 0.29 mm day^{-1}), MAE (0.18 and 0.23 mm day^{-1}), and the highest R^2 (0.89 and 0.86) for training and testing phases, respectively. This emphasises the factors influencing the predicted Epan since the model considered all the

Table 3 | Comparison of MLR and ANN models for Imphal, Manipur

	Training dataset						Testing of dataset					
	MLR			ANN			MLR			ANN		
Model	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
1	0.62	0.44	0.38	0.63	0.44	0.37	0.67	0.35	0.28	0.67	0.35	0.29
2	0.63	0.44	0.37	0.68	0.41	0.35	0.77	0.32	0.26	0.78	0.32	0.26
3	0.76	0.35	0.28	0.77	0.35	0.28	0.78	0.32	0.26	0.78	0.33	0.25
4	0.78	0.35	0.28	0.79	0.33	0.26	0.78	0.32	0.26	0.79	0.30	0.25
5	0.79	0.33	0.26	0.80	0.32	0.26	0.83	0.30	0.25	0.84	0.30	0.24
6	0.88	0.25	0.19	0.89	0.24	0.18	0.85	0.30	0.24	0.86	0.29	0.23

variables. Therefore, it is appropriate to consider the combined influence of all the meteorological parameters on Epan.

In general, the study confirmed the capabilities of ANN as a useful tool for modelling Epan. ANN models showed a slight superiority for the estimation of evaporation over the MLR models. Many researchers also reported that evaporation estimation done through ANN was better compared with estimation through MLR (Deswal & Pal 2008; Shirsath & Singh 2010; Ali & Saraf 2015; Malik *et al.* 2018).

Table 4 shows the correlation between pan evaporation and independent parameters, namely maximum temperature (Tmax), minimum temperature (Tmin), wind speed, sunshine hour, minimum relative humidity (Rhmin) and maximum relative humidity (Rhmax). It was observed that the Tmax, Tmin, wind speed and sunshine hour had a positive correlation with pan evaporation of 0.80, 0.60, 0.68 and 0.005, respectively, whereas minimum relative humidity (Rhmin) and maximum relative humidity (Rhmax) had a negative correlation with pan evaporation. Among all, the maximum temperature had a strong positive correlation followed by wind speed and minimum temperature. This means an increase in these parameters will increase the rate of evaporation, whereas maximum relative humidity (Rhmax) has a significant negative correlation, which is responsible for decreasing the rate of evaporation. Sunshine duration does not have any vital role in evaporation.

Evaporation is influenced by the number of meteorological parameters and estimates of evaporation are required for irrigation planning and scheduling as well as water balance computation. Evaporation data are not always available for a climatic region. In hill states like Sikkim and Manipur, the meteorological observatories with the facility of a pan evaporimeter are very few. Weather data can be retrieved from the automatic weather stations. Therefore, in the absence of measured evaporation rates, developed models using ANN and MLR techniques would be very useful for the estimation of evaporation rate in the study area.

Table 4 | Correlation between dependent and independent variables for Imphal

	Epan (mm)	Tmax (°C)	Tmin (°C)	WS (km/h)	Sunshine (h)	Rhmin (%)	Rhmax (%)
Epan	1						
Tmax	0.80	1					
Tmin	0.60	0.84	1				
WS	0.68	0.36	0.28	1			
Sunshine	0.005	−0.25	−0.56	0.02	1		
Rhmin	−0.10	0.27	0.61	−0.41	−0.56	1	
Rhmax	−0.40	−0.08	0.33	−0.50	−0.51	0.86	1

CONCLUSIONS

Monthly evaporation was modelled using MLR and ANN and the developed models were compared in terms of predictive accuracy and to identify the most suitable model for the study area. The ANN models were compared with the MLR models. The ANN models gave slightly better performance than the MLR models. The statistical performance evaluation criteria of MLR and ANN showed that increasing the numbers of independent variables in the model improved the accuracy of predicted evaporation for Gangtok and Imphal station. A comparison of the model performance between the MLR and ANN models indicated that ANN was more accurate to predict monthly evaporation in the study area. Correlation analysis revealed that Tmax, Tmin, wind speed and sunshine hour had a positive correlation with pan evaporation of 0.80, 0.60, 0.68 and 0.005, respectively, whereas, minimum relative humidity (Rhmin) and maximum relative humidity (Rhmax) had a negative correlation with pan evaporation. Among all, the maximum temperature had a strong positive correlation followed by wind speed and minimum temperature.

REFERENCES

Abudu, S., Cui, C. L., King, J. P., Moreno, J. & Bawazir, A. S. 2011 Modeling of daily pan evaporation using partial least squares regression. *Science China Technological Sciences* **54** (1), 163–174.

Ali, J. & Saraf, S. 2015 Evaporation modelling by using artificial neural network and multiple linear regression technique. *International Journal of Agricultural and Food Science* **5** (4), 125–133.

Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. 1998 *Crop Evapotranspiration: Guidelines for Computing Irrigation Crop Water Requirements*. Irrigation and Drainage Paper No. 56, Food and Agriculture Organization, Rome, Italy.

Almedeij, J. 2012 Modeling pan evaporation for Kuwait by multiple linear regression. *The Scientific World Journal* **2012**, 574742.

Deswal, S. & Pal, M. 2008 Artificial neural network based modeling of evaporation losses in reservoirs. *International Journal of Civil and Environmental Engineering* **2** (3), 18–22.

Guven, A. & Kişi, Ö. 2011 Daily pan evaporation modelling using linear genetic programming technique. *Irrigation Science* **29**, 135–145.

Guven, A. & Kisi, O. 2013 Monthly pan evaporation modelling using linear genetic programming. *Journal of Hydrology* **503**, 178–185.

Jhajharia, D., Shrivastava, S. K., Sarkar, D. & Sarkar, S. 2009 Temporal characteristics of pan evaporation trends under the humid conditions of northeast India. *Agricultural and Forest Meteorology* **149**, 763–770.

Keskin, M. E. & Terzi, Ö. 2006 Artificial neural network models of daily pan evaporation. *Journal of Hydrology* **11** (1), 65–70.

Kharat, P. & Shetkar, R. 2016 Predicting reservoir evaporation using artificial neural network. *International Journal of Innovative Research in Science, Engineering and Technology* **5** (4), 5851–5857.

Kişi, Ö. 2009 Modeling monthly evaporation using two different neural computing techniques. *Irrigation Science* **27** (5), 417–430.

Leahy, P., Kiely, G. & Corcoran, G. 2008 Structural optimisation and input selection of an artificial neural network for river level prediction. *Journal of Hydrology* **355**, 192–201.

Liu, B., Xu, M., Henderson, M. & Gong, W. 2004 A spatial analysis of pan evaporation trends in China, 1955–2000. *Journal of Geophysical Research* **109**, D15102.

Malik, A., Kumar, A. & Kisi, O. 2017 Monthly pan-evaporation estimation in Indian central Himalayas using different heuristic approaches and climate based models. *Computers and Electronics in Agriculture* **143**, 302–313.

Malik, A., Kumar, A. & Rai, P. 2018 Weekly pan-evaporation simulation using MLP, CANFIS, MLR and climate-based models at Pantnagar. *Indian Journal of Ecology* **45** (2), 292–298.

Razi, M. A. & Athappilly, K. 2005 A comparative predictive analysis of neural networks (NNs), nonlinear regression and classification and regression tree (CART) models. *Expert Systems with Applications* **29**, 65–74.

Roderick, M. L. & Farquhar, G. D. 2002 The cause of decreased pan evaporation over the past 50 years. *Science* **298**, 1410–1411.

Sanikhani, H., Kisi, O., Nikpour, M. R. & Dinpashoh, Y. 2012 Estimation of daily pan evaporation using two different adaptive neuro-fuzzy computing techniques. *Water Resources Management* **26**, 4347–4365.

Shirgure, P. S. & Rajput, G. S. 2012 Prediction of daily pan evaporation using neural networks models. *Scientific Journal of Agricultural* **1** (5), 126–137.

Shirsath, P. B. & Singh, A. K. 2010 A comparative study of daily pan evaporation estimation using ANN, regression and climate based models. *Water Resources Management* **24**, 1571–1581.

Sriram, A. V. & Rashmi, C. N. 2014 Estimation of potential evapotranspiration by multiple linear regression method. *IOSR Journal of Mechanical and Civil Engineering* **11** (2), 65–70.

Sudheer, K. P., Gosain, A. K., Rangan, D. M. & Saheb, S. M. 2002 Modeling evaporation using an artificial neural network algorithm. *Hydrology Processes* **16**, 3189–3202.

Svozil, D., Kvasnika, V. & Pospichal, J. 1997 Introduction to multi-layer feed-forward neural networks. *Chemometrics and Intelligent Laboratory Systems* **39**, 43–62.

Tabari, H., Marofi, S. & Sabziparvar, A. A. 2010 Estimation of daily pan evaporation using artificial neural network and multivariate non-linear regression. *Irrigation Science* **28**, 399–406.

Tan, S. B. K., Shuy, E. B. & Chua, L. H. C. 2007 Modelling hourly and daily open-water evaporation rates in areas with an equatorial climate. *Hydrological Processes* **21** (4), 486–499.

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