Journal of Scientific & Industrial Research
Vol. 81, March 2022, pp. 319-328

Neural Network based Predictors for Evaporation Estimation at Jabalpur in Central India

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Received 12 December 2021; revised 13 February 2022; accepted 17 February 2022

Free water evaporation is an imperative parameter for estimation of crop water requirement, and irrigation scheduling. This study aims to evaluate different techniques to estimate evaporation with weather parameters inputs. Multilayer Perception (MLR), Radial Basis Function (RBF) based neural network, traditional statistical Linear Regression (LR) approach and conventional empirical methods of Linacre and Christianson were used to estimate the evaporation at Jabalpur station situated under Kymore Plateau and Satpura Hills Agro-climatic Zone of Madhya Pradesh in the Central India. The weather parameters considered for estimation of evaporation are temperature, humidity, sunshine hours and wind speed. Results indicate that MLP and RBF based models with input of all selected weather parameters is able to estimate evaporation much precisely than LR and empirical approaches. It was found that higher accuracy may be obtained with multiple weather data input and low accuracy with only temperature input. It was observed that with temperature used as input the performance accuracy reduces in estimating evaporation with the selected models. However, neural network approach seems to produce better results as compared to statistical and empirical approach. The neural network based model RBF found more efficient in estimation of evaporation as compared to MLP. This study suggests that evaporation can be estimated by RBF model of a station, where there is no standard instrument available for its observation.

Keywords: Empirical methods, Linear regression, Machine learning, RMSE, Weather parameters

Introduction

Evaporation is an important weather factor and influences the irrigation scheduling, crop water requirement and water management. Though weather parameters are recorded routinely at many stations in India, but still some of the stations have not instruments for measurements of evaporation. The recording or estimation of evaporation is of vital importance for crop water demand, and irrigation scheduling. Evaporation is recorded by using the instrument called USWB Class-A open pan instrument as recommended by World Meteorological Organization (WMO). However, due to upkeep and other difficulties (non availability of trained human resources) continuous record of evaporation is still lacking at few stations. Hence, estimation of evaporation is carried out indirectly using different weather parameters with empirical methods. The main weather parameters affecting evaporation are temperature, rainfall, relative humidity, wind speed and solar radiation. Evaporation process is very complex and its estimation using empirical formulas for a given location is not very much accurate.[1] Many methods are available for its measurement and estimation across the world. Evaporation (E_p) were estimated by several methods and techniques such as pan evaporation, mass transfer, energy balance and water balance methods.[2] Class A pan is a typical method for measurement of evaporation in different regions of the globe.[3] In recent decade, machine learning techniques including Artificial Neural Network (ANN), fuzzy logic, genetic algorithm, support vector machine etc., have emerged as an alternate method for estimation and prediction of evaporation using the weather factors. During the past two decades ANNs have been widely used for estimation and prediction of meteorological parameters and show ability of pattern recognition.[4]

Guven and Kisi[5] have showed the performance of different empirical methods and machine learning techniques in estimating total evaporation losses at various locations and found that different variant of linear genetic programming models have performed

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better than fuzzy logic, ANN and Stephens and Stewart empirical model. Wang *et al.*[6,7] have also modeled pan evaporation and examine the performance of different heuristic soft computing techniques (MLR, Generalized Regress Neural Network, support vector machine, fuzzy genetics) and regression methods and found that soft computing techniques showed better results as compared to regression model. Ghorbani *et al.*[8] have estimated the pan evaporation using nuro computing model. Kutlu *et al.*[9] applied three machine learning techniques namely, Support Vector Machines (SVM), Common Vector Approach (CVA) and K-Nearest Neighbor (KNN) for classification of wheat genotypes in Turkey. They reported that SVM model performed well in comparison to others for wheat genotypes classification. Ayaz *et al.*[10] indicated that methods likewise incorporate SVR and RF were applied for estimation of evapotraspiration. The hybrid models like back propagation neural network and dynamic factor were used for estimation of the pan evaporation. But these models were not working efficiently in all conditions and thus not proved to be a robust model, and estimated results were not close to reality. The results of evaporation estimations by hybrid models are just a generalization and involve more error in estimation.[11] Therefore, hybrid models were not considered in the present study.

In this study evaporation was modeled and estimated to validate the ability of MLP and RBF in estimation of weekly evaporation at Jabalpur station using various weather parameters as compared to traditional statistical LR approach and conventional empirical methods of Linacre and Christianson. Through this study, it was observed that the best performance of the models with all selected weather parameters used as input variables, however, the models showed low accuracy with single weather parameter (temperature) as input.

Materials and Methods

Meteorological Data Used

Recent long term (2001 to 2020) day by day weather data of maximum and minimum temperature (Tmax & Tmin), relative humidity morning (RH_I), relative humidity afternoon (RH_{II}), Bright Sunshine hours (BSS), Wind Speed (WS) and pan evaporation (E_p) were collected from the IMD certified observatory located at College of Agricultural Engineering, Jawaharlal Nehru Krishi Vishwavidyalaya, Jabalpur, Madhya Pradesh (India). The daily weather data was converted in weekly as per Standard Meteorological Week (SMW) used in this study. The descriptive statistics of the weekly averages of weather parameters at Jabalpur are given in Table 1.

Study Domain

Jabalpur (23.16 N, 79.97E, 412 m msl) station of Madhya Pradesh in Central India was used for the present study (Fig. 1). The Jabalpur is one of the district of Kymore Plateau and Satpura Hills Agro-climatic Zone of Madhya Pradesh. It received around 1370 mm normal rainfall and having sub humid climate. Jabalpur district is covering an area around 5918 km^2 and suitable for cultivation of oilseed, pulses, cereals and horticultural crops. The major crops grown are Wheat, Soybean, Chickpea, Mustard, Peas etc.

Table 1 — Descriptive statistics of the weekly averages of climatic parameters at Jabalpur

Parameters	Mean	High	Low	Range	SD	CV	CC
			Jabalpur				
			Training period (2001–2016)				
T_{max} (°C)	31.7	45.5	19.8	25.7	5.5	0.17	0.90
T_{min} (°C)	18.1	31.0	3.1	27.9	6.8	0.37	0.59
RH_I (%)	79	97	25	72	18	0.23	−0.92
RH_{II} (%)	43	94	5	89	22	0.52	−0.52
WS ($kmph$)	4.0	12.0	0.5	11.5	2.2	0.54	0.51
BSS ($hours$)	7.0	10.8	0.0	10.8	2.4	0.34	0.29
E_p ($mm\ d^{-1}$)	4.5	15.3	0.9	14.4	2.7	0.61	1.00
			Testing period (2017-2020)				
T_{max} (°C)	31.6	44.4	19.6	24.8	5.4	0.17	0.90
T_{min} (°C)	17.7	28.6	3.1	25.6	6.8	0.38	0.55
RH_I (%)	79	97	34	63	16	0.20	−0.80
RH_{II} (%)	47	93	9	84	21	0.44	−0.38
WS ($kmph$)	3.8	8.5	0.6	7.9	1.7	0.45	0.50
BSS ($hours$)	6.6	10.6	0.0	10.6	2.7	0.41	0.40
E_p ($mm\ d^{-1}$)	4.0	10.3	1.2	9.1	2.1	0.53	1.00

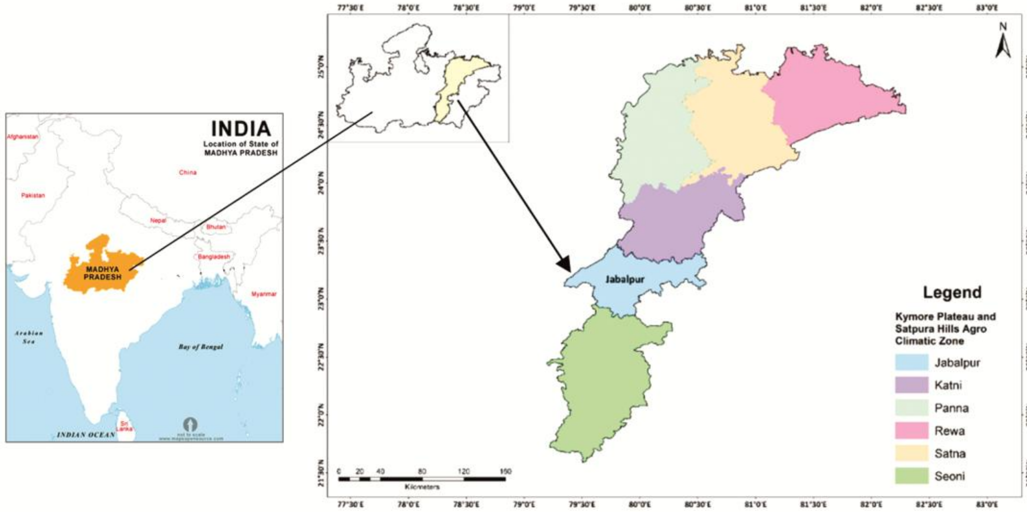

Fig. 1 — Location map of Jabalpur district in Kymore Plateau and Satpura Hills Agroclimatic Zones of Eastern Madhya Pradesh

Four models namely, MLP, RBF, LR and empirical method were used for estimation of weekly evaporation at Jabalpur. The comparison between these models for estimating weekly mean evaporation values at Jabalpur region was performed.

Two types of modeling approaches were adopted for E_p estimation. In first approach only temperature (Maximum, Minimum) data was used as input and in second approach all collected weather parameters were used as input. The collected weather parameters were used for training and testing of the selected models. The models' performance was assessed by utilizing standard statistical measures (RMSE, R^2, CC and EF). The performance of models was ranked to have a superior accuracy model for evaporation estimation. The weekly normals and correlation coefficients of weather parameters with evaporation Correlation Coefficient (CC) between evaporation and other weather parameters were calculated and shown in Table 1. It was found the normal values of maximum, minimum, WS, BSS and evaporation are 31.7, 17.9, 3.5, 6.8 and 4.2 respectively. The relative humidity values were much more variable (coefficient of variability range from 20 to 52%) as compared to other weather variables. The maximum, minimum temperature, WS, and BSS were positively related with evaporation, while relative humidity is negatively related.

Evaporation is negatively associated with rainfall but generally it is not considered for E_p estimation either in empirical, conventional or machine learning techniques. Therefore, it was not considered in the present analysis as an input parameter for E_p estimation. The humidity data indirectly provides the supplementary information about rainfall and this was considered as an input in this model.

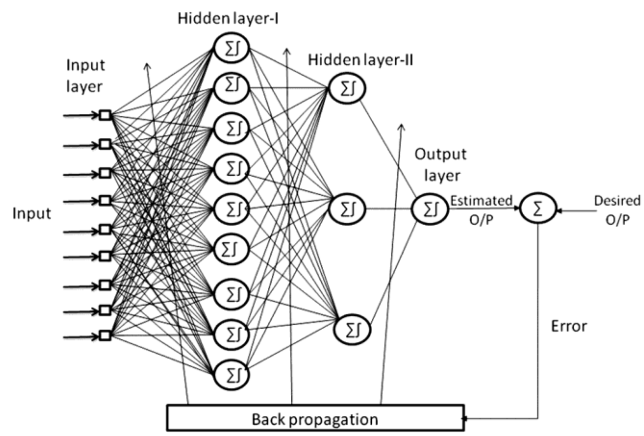

Fig. 2 — Block diagram of MLP based estimator

Design of Neural Network Structures

Multilayer Perception (MLP) based Artificial Neural Network

The MLP model has input, output and one or more hidden layers with feed forward neutral network.[12] The each layer neurons were initialized using hyperbolic tangent transfer function between the vales from −1 to 1. Testing of different combination of hidden layer of neurons was carried out for the data used for this study. MLP of N-9-1 structure was used for different input combinations (N = 2.6) (Fig. 2). The weights and biases of each layer neuron were uploaded using back-propagation algorithms.

Radial Basis Function (RBF) Neural Network

The RBF model has one output, hidden layer and a feed forward network and was formulated by

Broomhead and Lowe.[13] The block diagram of the RBF is given in Fig. 3. Each hidden layer neuron has centers $c = c_1, c_2, c_3 \ldots\ldots c_h$, and width $\sigma = \sigma_1, \sigma_2, \sigma_3 \ldots\ldots \sigma_h$, where h is the number of neuron in the hidden layer. Each and every hidden layer neuron receives the identical data set of input data ($x = x_1, x_2, x_3 \ldots\ldots x_n$). Each centers of every hidden neuron have the same dimension as that of the input data, *i.e.* $c_i \in R^n, x \in R^n$. The output of each hidden layer neurons ($\emptyset_1, \emptyset_2, \emptyset_3 \ldots\ldots \emptyset_h$) is associated with synaptic weight ($w_1, w_2, w_3 \ldots\ldots w_h$). Output $\emptyset_i$ of i^{th} hidden layer neuron represented by:

$$\emptyset_i(z) = e^{\frac{-z^2}{2\sigma_i{}^2}} \quad \ldots (1)$$

where, $z = ||x - c_i||$, represents the Euclidian distance between input data of the corresponding centers and $\emptyset_i = \emptyset(||x - c_i||$. The weights of RBF are computed by the given formula:

$$y = \sum_{i=1}^{h} w_i \, \emptyset_i \quad \ldots (2)$$

RBF calibration for input and output i was done in recursive by following function.

$$e = \frac{1}{2}\left(y^d - y\right)^2 \quad \ldots (3)$$

The weight update rules to optimize the network parameters $\{w_i, c_i, \sigma_i\}$ at time t is given given below:

$$w_i(t+1) = w_i(t) + \eta_1\left(y^d - y\right)\emptyset_i \quad \ldots (4)$$

$$c_{ij}(t+1) = c_{ij}(t) + \frac{\eta_2}{\sigma_i^2}\left(y^d - y\right)w_i\emptyset_i(x_j - c_{ij}) \quad \ldots (5)$$

$$\sigma_i(t+1) = \sigma_i(t) + \frac{\eta_3}{\sigma_i^3}\left(y^d - y\right)w_i\emptyset_i z_i{}^2 \ldots (6)$$

where, y^d = desired outputor target value

c_{ij} = j^{th} element of i^{th} center

η_1, η_2, η_3 = learning rate for network parameters $\{w_i, c_i, \sigma_i\}$ respectively.

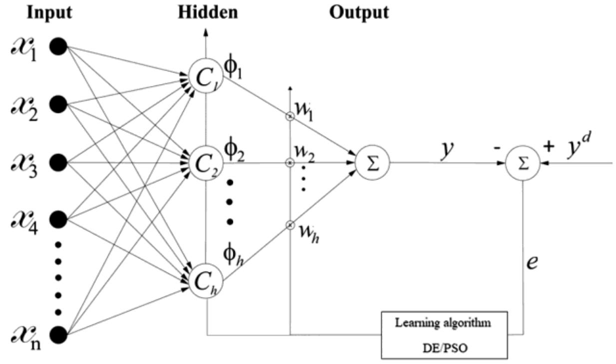

Fig. 3 — Block diagram of RBF based estimator

Linear Regression (LR) Analysis

It is a regression between the E_p and weather parameters. The E_p (target variable) is considered as dependent variable and weather parameters (predictor variable) referred as independent variable. A linear relationship between target and predictor variables is established and the basic regression equation is given below:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots \beta_n x_n \quad \ldots (7)$$

where y = target variable (E_p)

x_1 to x_n = predictor variables (Tmax, Tmin, RH1, RH2, WS, SSH)

β's = regression coefficients or weights (β_0 is intercept and $\beta_1, \beta_2 \ldots\ldots \beta_n$ are slopes of the regression plain in the direction of x). These coefficients are obtained through least squares method in this study.

Empirical Methods

Linacre Method

Linacre[14] gave a simplified formula after modifying the Penman equation to compute E_p using temperature data and is given below:

$$E_p = \frac{\frac{700T_m}{(100-A)} + 15(T - T_d)}{(80 - T)} \quad \ldots (8)$$

where, $(T - T_d) = 0.0023h + 0.37T + 0.53R + 0.35R_{ann} - 10.9$

$and\ T_m = T + 0.006h$

$T = \frac{T_{max} + T_{min}}{2}$ = mean temperature °C, h = elevation in meters, A = latitude in degree, R = mean daily range of temperature in °C and R_{ann} = difference between the mean temperature of hottest and coldest months in °C.

Christiansen Method

Christiansen[15] used different coefficients values of temperature, wind speed, relative humidity and sunshine data.

Evaporation Estimation

Evaporation E_p was estimated by the formulae given below:

$$E_P = 0.473 R_a C_T C_W C_H C_S C_E C_M \quad \ldots (9)$$

where,

$R_a = $ extraterrestrial radiation $(mm\ d^{-1})$

$C_T = 0.393 + 0.5592\left(\frac{T}{20}\right) + 0.04756\left(\frac{T}{20}\right)^2,$

$T\ is\ mean\ air\ temperature\ °C$

$$C_W = 0.708 + 0.3276\left(\frac{W}{96.6}\right) - 0.036\left(\frac{W}{20}\right)^2,$$

W $is\ mean\ daily\ wind\ speed\ (km\ d^{-1})$

$$C_H = 1.250 - 0.212\left(\frac{H}{57.4}\right) - 0.038\left(\frac{H}{57.4}\right)^2,$$

H $is\ mean\ daily\ relative\ huidity$ (%)

$$C_S = 0.542 + 0.64\left(\frac{S}{80}\right) - 0.4992\left(\frac{S}{80}\right)^2 + 0.3174\left(\frac{S}{80}\right)^3, S\ is\ sunshine\ (\%)$$

$$C_E = 0.970 + 0.030\left(\frac{E}{305}\right), E\ is\ elevation\ (m)$$

$$T = \frac{T_{max} + T_{min}}{2}\ and\ H = \frac{RH_I + RH_{II}}{2}$$

Training and Testing of the Neural Network based Predictors (RBF and MLP)

Out of 20 years of meteorological data (2001 to 2020) of Jabalpur only sixteen years of data (from 2001–2016) were used to train the model and four years of data (from 2017 to 2020) used for testing purpose. Input patterns were normalized to lie between −1.0 to 1.0. Weights and biases were also initialized to random values lying between −1.0 to 1.0 for different layers. For the training of model the first pattern was fed into the input layer of the MLP and RBF and after the forward pass though intermediate hidden and output layer neurons, an estimated output was obtained. The data set used for training and testing are from 2001 to 2016 and 2017 to 2020 respectively. Total numbers of pattern (weekly) used were 1112, in which 884 patterns were used for training and remaining 208 pattern for testing. The estimated output was compared with corresponding values of the input pattern and an error value was computed. During the backward pass, the updated values of weight and biases were applied to each layer. This process was repeated and all the remaining input patterns were sequentially fed in to the neural network model. In each case, error values were obtained after each forward pass as well as weights and biases were updated in each backward pass. Thus through the above iteration process completes an epoch or iteration. The training process was continued for 10000 epochs or iterations. The training process was complete and after that the values of convergence coefficient (μ) were fixed at 0.01. In order to understand the learning characteristic of the predictor, after each epoch, RMSE values were computed and plotted against iterations. The training process was stopped when the RMSE values reached a desired minimum value. The test patterns were fed sequentially for each layer of the neuron network and their weights and biases values were fixed for the test model parameters. The estimated and input values were compared and thus an error was computed after each test pattern. The errors values and RMSE values were used to evaluate model performance.

Two types of MLP, RBF and LR models were developed with different input features combination and shown in Table 2. Christiansen and Linacre models were compared with other models and shown below.

The proposed models were developed in MATLAB to estimate daily E_p. All the meteorological parameters were normalized using the following equation.

$$\frac{x_k - x_{min}}{x_{min} - x_{max}} \quad \ldots (10)$$

where, x_k = k^{th} sample of input parameters
x_{min} = Minimum of the input parameter
x_{max} = Maximum of the input parameter

Datasets were normalized to lie between −1 to 1 for MLP with hyperbolic tangent activation function and between 0 to 1 for RBF, the biases and weights were initialized for the transfer functions.

Performance Evaluation Criteria

Comparative analysis between estimated evaporation obtained with different neural network, statistical and empirical methods were carried out with help of their Root Mean Square Error (RMSE), efficiency factor (NSE/EF) proposed by Nash and Sutcliffe[16] and determination coefficient (R^2). The mathematical expression of evaluation measures are given below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Out_{est} - Out_{obs})^2} \quad \ldots (11)$$

Table 2 — Input features combination used in different models

Type	Machine learning and Regression Models			Empirical method	The input features combination
I	MLP-1	RBF-1	LR-1	Linacre	T_{max}, T_{min}
II	MLP-2	RBF-2	LR-2	Christiansen	$T_{max}, T_{min}, RH_I, RH_{II}, W, S$

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(Out_{obs} - \overline{Out_{obs}}\right)\left(Out_{est} - \overline{Out_{est}}\right)\right)^2}{\sum_{i=1}^{n}\left(Out_{obs} - \overline{Out_{obs}}\right)^2 \sum_{i=1}^{n}\left(Out_{est} - \overline{Out_{est}}\right)^2} \quad \ldots (12)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Out_{est} - Out_{obs}\right)^2}{\sum_{i=1}^{n}\left(Out_{obs} - \overline{Out_{obs}}\right)^2} \quad (-\infty \leq EF \leq 1) \ldots (13)$$

where, Out_{obs} = the target vales of evaporation Out_{est} = estimated evaporation values.

n = the number of testing patterns.

Model accuracy were evaluated based on the values of R^2 and efficiency factor (NSE/EF). Higher values close to 1 or 1 indicates more accuracy of the models.

Results and Discussion

It was found and also reported that the temperature is the most important weather parameter associated with evaporation, hence in first attempt (type I model) RBF, MLP, LR and Linacre models were used for estimation of weekly E_p. Performance evaluation was performed between observed and estimated E_p for Jabalpur and are shown in Table 3. It was inferred that RBF-1 and MLP-1 performance was better than for type-I models. The low RMSE values of 1.02 and 1.05 and high EF of 0.76 and 0.75 were obtained with RBF-1 and MLP-1 respectively at Jabalpur, whereas, RMSE and EF for LR-1 and Linacre models were comparatively higher. Abed *et al.*[17] were applied different models to estimate of the monthly evaporation and concluded that the machine learning models performed better than empirical models for identical input data. The performance of the Linacre model is comparatively poor as compared to RBF-1 and MLP-1 models at Jabalpur because of the high RMSE (1.31) and low EF (0.60). The type–I models performance were low because the input data were only maximum and minimum temperature values. A comparison of observed and estimated values of daily E_p for type-I models (MLP-1, RBF-1, LR-1 and Linacre) with maximum and minimum temperatures as input data for testing data set period (2017-2020) at Jabalpur are shown in Fig. 4. The above discussion indicates that during the testing phase both observed and estimated values of E_p through MLP-1 and RBF-1 were in close agreement with each other. The estimated value of E_p by Linacre model was underestimated and its peak E_p values are not in agreement with corresponding observed values. The Linacre model underestimates evaporation values and was very much mismatch in estimation of peak observations of evaporation. Kumar *et al.*[18] have examined the ability of multilayer perception model with back propagation technique for different input combinations at different stations to evaluate the sensitivity of the models for ranking of input combinations in estimation of weekly evaporation. They reported that the temperature was the most influential weather parameter for estimation of evaporation. Majhi and Naidu[19] used artificial neural network to estimate daily pan evaporation in Chhattisgarh state and reported that estimated evaporation were better as compared with multi-layer artificial neural networks and empirical methods of Linacre and Christiansen. A closer view of Figs 4 and 5 indicates that estimated values of E_p for type I models with T_{max} *and* T_{min} as input are in close agreement with each other for RBF and MLP at Jabalpur, but large deviations was evident with the Linacre model. Majhi *et al.*[20] compared the performance of Deep-LSTM models with multilayer artificial neural network and Hargreaves and Blaney–Criddle methods with minimum input weather

Table 3 — R^2, CC, EF and RMSE of MLP, RBF, LR and empirical models (Linacre & Christiansen) for weekly E_p estimation with training and testing datasets at Jabalpur

Type	Models	R^2	Rank	CC	Rank	EF	Rank	RMSE	Rank
				Testing period (2017-2020)					
I	MLP-1	0.85	2	0.92	2	0.75	2	1.05	2
	RBF-1	0.85	1	0.92	1	0.76	1	1.02	1
	LR-1	0.83	3	0.91	3	0.70	3	1.15	3
	Linacre	0.76	4	0.87	4	0.61	4	1.31	4
II	MLP-2	0.87	2	0.93	2	0.80	2	0.94	2
	RBF-2	0.88	1	0.94	1	0.83	1	0.85	1
	LR-2	0.84	3	0.92	3	0.78	3	0.97	3
	Christiansen	0.78	4	0.89	4	0.76	4	1.03	4

parameters and revealed that Deep-LSTM model projected the evaporation with high precision than the other models.

In second attempt (type II model) evaporation were estimated by RBF, MLP, LR and Christiansen with selected weather parameters as input. The estimation of E_p values and model performance was also done. It is eminent that the type II model was used to estimate the E_p values and the performance was improved as compared to type-I model (Table 3). This is due to the inclusion of temperature, sunshine, wind speed and humidity as input. Thus the input of weather parameters influenced the estimated E_p values. Hence, evaporation is influenced not only by temperature alone but also other weather parameters like sunshine hours, wind speed and humidity also. In type–II modeling the Linacre was excluded because it estimates E_p based only on temperature. At Jabalpur, low RMSE (0.85) and high EF (0.83) was obtained with RBF-2 model, whereas MLP-2 resulted slightly high RMSE of 0.94 and low EF values of 0.80. With same combination of weather parameters LR-2 model also resulted in improved RMSE and EF factor of 0.97 and 0.78, which were similar to MLR-2 performance. The Christiansen model was used to estimate the E_p values and its performance was also evaluated having a higher RMSE (1.03) and low EF (0.76) which was not better than other model of type – II. The observed and estimated daily E_p values comparison for type-II models (RBF-2, MLP-2, LR-2 and Christiansen) with maximum, minimum temperature, relative humidity, wind speed and bright sunshine hours as input parameters with the test datasets (2017–2020) at Jabalpur was shown in Fig. 5. It was inferred that during the testing phase both estimated and observed E_p values were in close agreement for the proposed RBF-2 models. RBF-2 and MLP-2 appear more efficient in estimating the variability in E_p value was more accurately estimated as compared to other LR-2 and Christianson model. Much more fluctuation was seen between observed and estimated E_p with the LR-2 and Christianson model at Jabalpur. It was visible in the figure that Christiansen model usually under estimate weekly E_p.

To evaluate the model performance further, R^2 and Correlation Coefficient (CC) were also computed and shown in Table 3. The marginally higher values of R^2

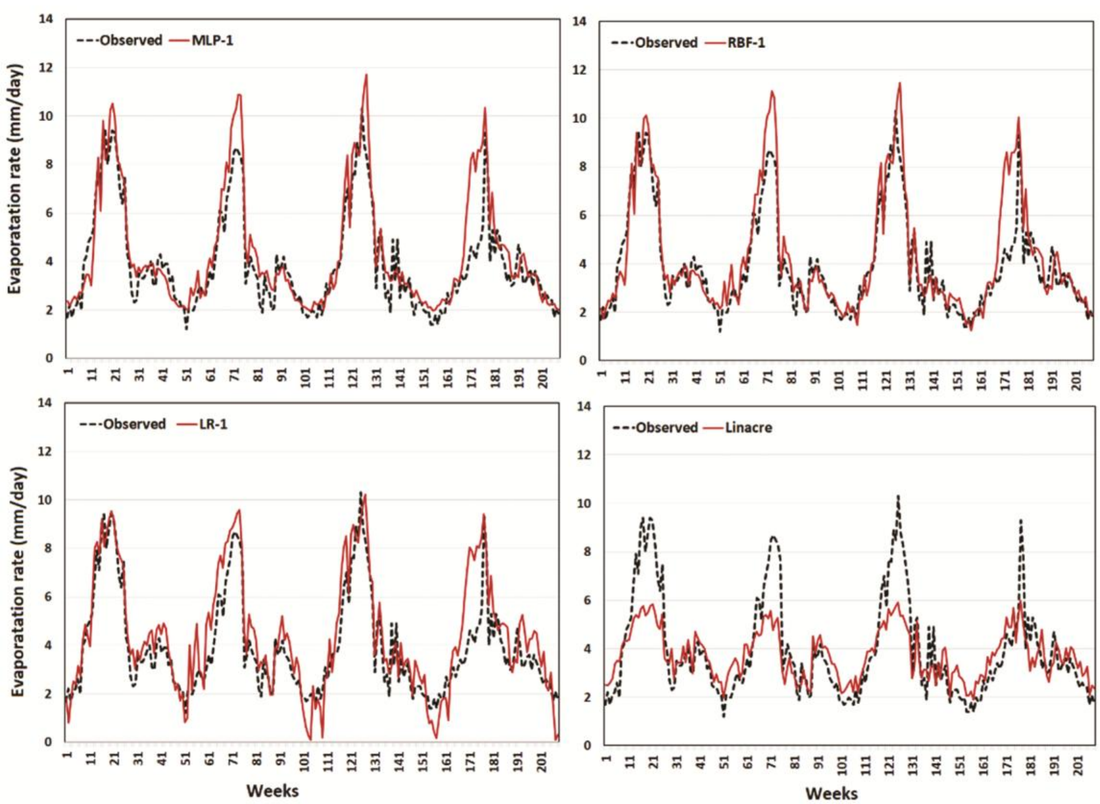

Fig. 4 — Observed and estimated values of evaporation for MLP-1, RBF-1, LR-1 and Linacre models during testing dataset period (2017-2020) in Jabalpur.

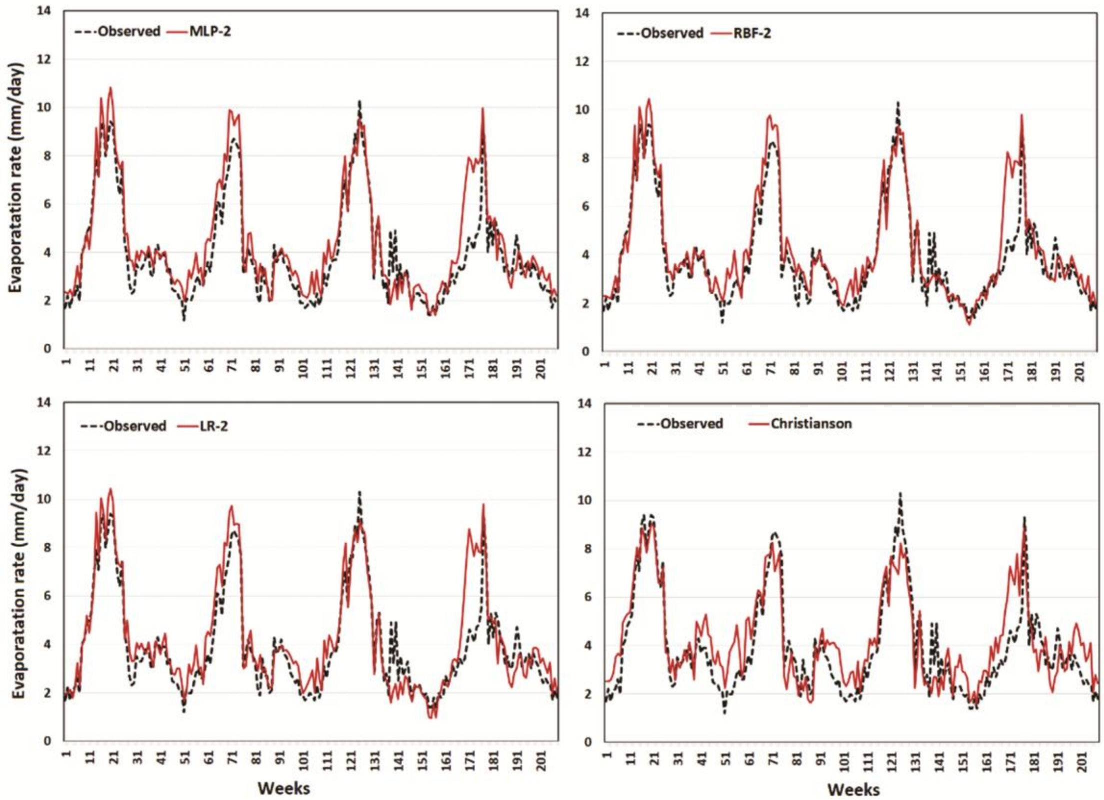

Fig. 5 — Observed and estimated values of evaporation for MLP-2, RBF-2, LR-2 and Christianson models during testing dataset period (2017–2020) in Jabalpur

and CC was obtained in type II models, and thus it was found that multiple weather parameters were contributing towards E_p estimation. Singh *et al.*[21] reported the temperature, air pressure, wind speed and relative humidity are the controlling factors of evaporations. To categorize these models, the models ranking were done based on their efficiency values and shown in Table 3. Ranking of models acquired with efficiency (EF) and RMSE remains same, hence the model performance interpretation based on EF relics the same. The ranking of the model was done on the basis of EF and RMSE values. The RMSE and EF values were used to rank the model performance.

Further, the model performance only based on the value of R^2 is very much challenging, and it was observed that R^2 values stay comparatively same for RBF and MLP models in most of the cases. But based on the EF values the model effectiveness of different models was clearly done. In present study, the RMSE and EF values were found much steady as compared to R^2 and CC for model performance selection. Adan *et al.*[22] conducted study on evapotranspiration estimation using different Machine Learning (ML) models with weather parameters as input variable and compared with FAO-Penman-Monteith model. They reported that 99 per cent accuracy was accomplished with all weather as input, whereas precision decreased to 86 per cent with less weather data.

Association between E_p of observed and estimated for type-I as well as for type-II models are given away in Figs 6 and 7 respectively. The RBF models appear to be much consistent E_p estimator with the test dataset in comparison to other models. It was again found that the RBF model produce consistent E_p estimate. In another study performed by Deo *et al.*[23] for estimation of monthly evaporation by using machine learning (Support Vector Machine (SVM), Extreme Learning Machine, and Multivariate Adaptive Regression Spline). They concluded that RVM was resulted to be the best out of three approaches for evaporation prediction. Kumar *et al*.[4] have estimated evaporation using local linear regression (LLR) with feed forward neural network model with different weather parameters as input and their combinations. They compared the LLR performance with ANN and recommended LLR over ANN in evaporation estimation.

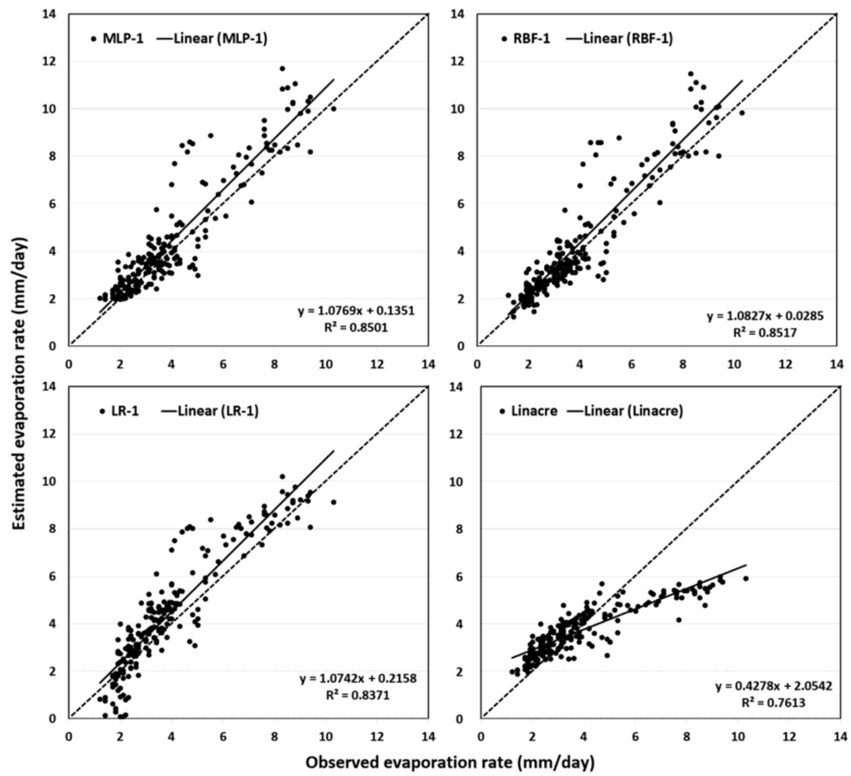

Fig. 6 — Relational diagram between observed and estimated values of evaporation for MLP-1, RBF-1, LR-1 and Linacre models with test dataset period (2017-2021) of Jabalpur

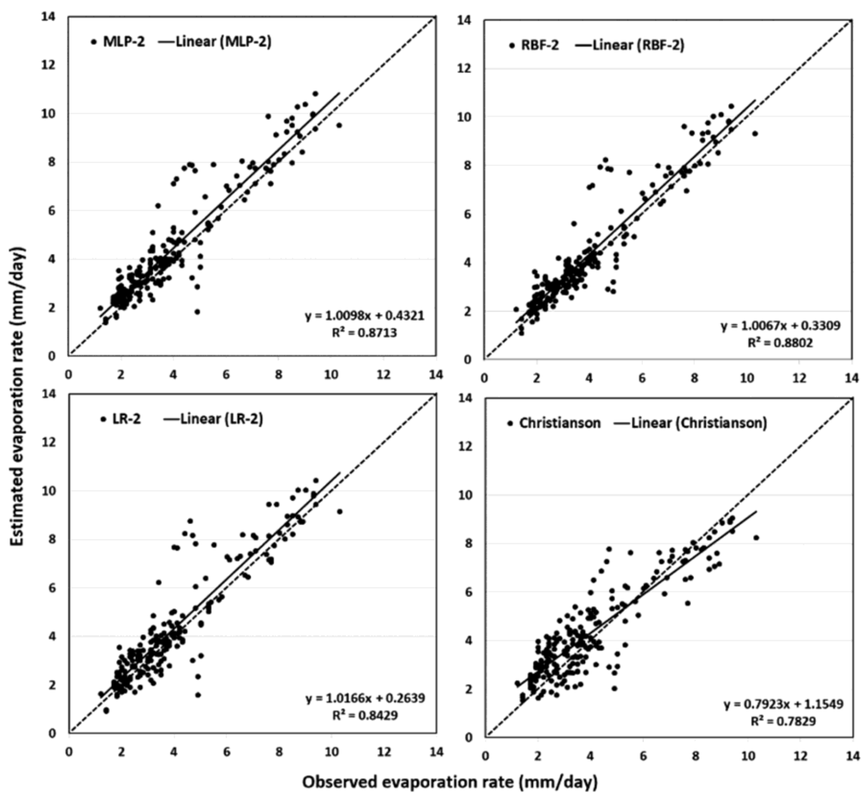

Fig. 7 — Relational diagram between observed and estimated values of evaporation for MLP-2, RBF-2, LR-2 and Christianson models with test dataset (2017–2021) of Jabalpur

Conclusions

Weekly evaporation at Jabalpur was estimated using RBF, MLP, LR and Christiansen and Linacre with temperature input and with all selected weather parameters. It was observed that RBF and MLP models are more efficient in estimation of E_p losses as contrary to LR and empirical models. It was observed that the RBF-2 model estimates weekly E_p values with low RMSE values of 0.85 mm/day at Jabalpur with input data combinations *viz.* temperature, sunshine, wind speed, and humidity. R^2 and EF are higher with the RBF models as compared to other models. Besides this, the RBF-1 model may also be used if only temperature (maximum, minimum) data is available for E_p estimation. Hence, RBF is more efficient in the estimation of E_p value and used for weekly E_p estimation at any place in Central India, where it is not measured directly. The outcomes of this study specified that the two machine learning models be better than empirical models and improve the E_p estimate precision with same weather inputs.

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