Original Research Article

PAN EVAPORATION ESTIMATION USING ARTIFICIAL NEURAL NETWORK (ANN) AND FUZZY LOGIC MODELS FOR RAICHUR REGION, KARNATAKA – A CASE STUDY

Abstract:

Aims: Accurate estimates of evaporation by employing efficient and proven soft computing techniques that involve least number of influencing variables are important to tackle present water crisis.

Place and Duration of Study: In the present study, Artificial Neural Network (ANN) and fuzzy logic models were developed to predict the pan evaporation (Ep) in Raichur, Karnataka, using six input parameters *viz.,* maximum and minimum temperatures, maximum and minimum relative humidity, sunshine hours and wind speed. for the period of 30 years (1990-2019).

Methodology: Comparison between models was done to select best suitable model to predict pan evaporation. The ANN models were trained withthree training algorithms. Gaussian membership function was used in fuzzy logic (FL) model.

Results: The results revealed that, the ANN-GDX model performed better over ANN-LM, ANN-BR and fuzzy logic models during validation period. The correlation coefficient (r), coefficient of efficiency (CE), mean absolute error (MAE) and root mean square error (RMSE) were observed to be 0.7637, 0.5831, 1.3880 and 1.8541 respectively during validation period between actual and predicted pan evaporation (Ep) with 1.3880 mm root mean square error. Therefore, ANN-GDX model was chosen for predicting pan evaporation in the study area.

CONCLUSION: ANN-GDX model was chosen for predicting pan evaporation in the study area.

Keywords*: Pan evaporation, artificial neural network, fuzzy logic, feed forward neural network, Bayesian regularization*.

1. INTRODUCTION

Evaporation play a vital role in integrated water resource management and modelling studies related to hydrology, agronomy, forestry, irrigation, flood and lake ecosystem [7]. Evaporation is one of the major processes in the hydrologic cycle. It is the process by which water is changed from the liquid into vapour through the transfer of heat energy. Considerable energy is needed to evaporate liquid water. This energy, the latent heat of vaporization is six times larger than the energy needed to warm the same amount water from 0 to 100°C. The water vapour is further diffused into the atmosphere.

The process of evaporation, however, is influenced by number of factors. Meteorological parameters such as sunshine hours, temperature, relative humidity and wind speed are the major parameters affecting evaporation. These parameters also depend upon factors such as geographical location, season and time of the day. Meteorological parameters, therefore, induce an evaporative demand of the atmosphere, but the actual evaporation resulting will be influenced by nature of the evaporating surfaces as well as the availability of water.

Pan evaporation is a complex and non-linear phenomenon. The Artificial Neural Networks (ANNs) are effective tools to model non-linear systems [8]. A neural network model is a mathematical construct whose architecture is essentially analogous to the human brain. Basically, the highly interconnected processing elements, arranged in layers are similar to the arrangement of neurons in the brain.

Fuzzy logic programming is flexible and allows the incorporation of expert opinion, which could make it more acceptable to operators. This technique is applicable to number of water resources applications. Because, general optimization techniques have usual 'crisp' objective function and some or all constraints and these are replaced by fuzzy constraints. The study was carried out to develop the fuzzy logic model with combination of inputs to compute pan evaporation. In recent years, many applications using fuzzy logic theory appeared, since it is an alternative and effective tool for studying complex phenomena. Fuzzy logic models can give answers to practical problems, without being time consuming.

In order to account for any uncertainty component in the evaporation measurements, the fuzzy logic concept and its rule-based system design are suggested for the evaporation modelling and estimation in this study. Though there are studies on estimation of evaporation for the semi-arid region of Raichur using different methods, none of the studies used data driven models like ANN and fuzzy logic. In this study, an attempt was made to find the best ANN and fuzzy logic model architecture for prediction of pan evaporation in Raichur region of Karnataka.

2. MATERIAL AND METHODS

2.1 STUDY AREA AND DATA ACQUISITION

The study was conducted at Raichur.It is situated in North-Eastern Dry zone (Zone 2) of Karnataka state at 16° 15′ N latitude and 77° 20′ E longitude with an average elevation of 407 meters above the mean sea level and it lies in semi-arid climatic condition. The district has a total geographical area of 8,383 sqkms. Climatically major part of the year remains dry and hot. In the month of May, it recors the highest temperature while lowest temperature experiences in December. The average annual rainfall of the area is 655 mm.The daily meteorological data including maximum and minimum temperature (Tmax and Tmin), maximum and minimum relative humidity (RH I and RH II), wind speed (WS), sun shine hours (SS) and pan evaporation (Ep) were collected from the Main agricultural research station, University of Agricultural Sciences, Raichur, Karnataka, India (Fig. 1) for the period of 30 years (1990-2019). The total available meteorological data set of 10956 was considered for the development of the models.The daily data were used for analysis and were used as input parameters in ANN and fuzzy logic modelling to predict daily pan evaporation and also it is used to compare and select best suitable model for Raichur region.

All input parameters were standardized with their values varying from 0 to 1 before using as input parameters into an ANN and fuzzy logic models, as the log-sigmoidal and pure linearactivation function of ANN deals with the binary numbers. The final output was again reverse-standardized to get real values of the output signals.

2.2 DESCRIPTION OF ARTIFICIAL NEURAL NETWORK MODELS

The ANN is capable of representing arbitrarily complex non-linear processes that relate the inputs and outputs of any system. The fundamental processing element of a neural network is a neuron. The most commonly used ANN for hydrological modelling is a feed forward network with the back propagation (BP) training algorithm which is also capable of nonlinear pattern recognition and memory association [12]. This architecture was considered and used in this study. The model was trained using three training algorithms, Levenberg–Marquardt (LM),Bayesian Regularization (BR) and Gradient Descent with Momentum and Adaptive Learning Rate Back propagation (GDX) algorithms. Finally, selection of proper and optimized model was done by statistical parameters [1].

2.2.1 FEED FORWARD NEURAL NETWORK (FNN)

The feed forward neural networks (FNN) otherwise known as multilayer perceptrons (MLP). This study evaluates the utility of MLP neural networks for estimating evaporation (Fig.2) provides an overview of the structure of this network. The FNN consists of three layers of neurons: (i) an input layer,(ii) intermediate (hidden) layer and (iii)an output layer. Each neuron has a number of inputs (from outside the network or the previous layer) and a number of outputs (leading to the subsequent layer or out of the network). A neuron computes its output response based on the weighted sum of all its inputs according to an activation function [4]. The net input xj to node j is the weighted sum of all incoming signals as shown in the following equation [3]:

$$\text{Net input} = xj = \sum wijyi \ldots(1)$$

Where,

xj = Net input coming to node j,

wij = Weight between node i and node j, and

yi = Activation function at node i.

The activation function, y_j, which was a nonlinear function of its net-input, is described by the sigmoid logistic function as shown in the following equation [3]:

$$y_j = \frac{1}{1+\exp(-x_j)} \ldots(2)$$

<u>2.2.2</u> BAYESIAN REGULARIZATION (BR) ALGORITHM

The Bayesian regularization (BR) is an algorithm that automatically sets optimum values for the parameters of the objective function. One feature of this algorithm is that it provides a measure of how many network parameters (weights and biases) are being effectively used by the network, so that the function will not be over-fitted irrespective of the size of the network. BR has been effectively used in the past studies for social data [6] and for groundwater data [2].

<u>2.2.3</u> LEVENBERG–MARQUARDT (LM)ALGORITHM

The Levenberg Marquardt method is a modification of the classic Newton algorithm for finding an optimum solution to a minimization problem. It was used as an approximation to the Hessian matrix following Newton-like weight updated method. LM has great computational and memory requirements and thus it can only be used in small networks. Nevertheless, many researchers have been successfully using it [10].

<u>2.2.4</u> GRADIENT DESCENT ALGORITHM (GDX)

This method uses back propagation to calculate derivatives of performance cost function with respect to the weight and bias variables of the network. This is probably the simplest and most common way to train a network [5]. Basic difference between BR and GDX algorithms is that, BR algorithm updates the weights and bias value according to LM optimization and GDX algorithm updates the weights and bias values according to gradient descent momentum and an adaptive learning rate.

2.2.5 NETWORK ARCHITECTURE

The network geometry is generally highly problem oriented in order to get optimal network geometry trial and error procedure. The trial and error procedure started with one hidden neuron initially and it has been increased up to 20 neurons based on the performance criteria of the models. The optimized number of neurons in the hidden layer is decided based on the statistical parameter results.For this study, an ANN architecture with six input neurons, one hidden layer with one output neuron was selected as most favourable architecture. For each set of hidden neurons, the network was trained with input datasets in batch mode to minimize the mean square error at the output layer.The transfer functions of hidden and output layers have been considered as log sigmoid and pure linear respectively in the both training and validation period of the different ANN models.MATLAB R2017B software was used for the analysis.

2.3 DESCRIPTION OF FUZZY LOGIC MODEL

Fuzzy logic representations found on fuzzy set theory try to capture the way humans represent and reason with real world knowledge in the face of uncertainty. A fuzzy set can be defined mathematically by assigning to each possible individual in the universe of discourse, a value representing its grade of membership in the fuzzy set. This grade corresponds to the degree to which that individual is similar or compatible with the concept represented by the fuzzy set [11].

2.3.1 FUZZY INFERENCE SYSTEM

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The basic structure of fuzzy inference system followed for the development of model is presented in Fig 3.In the present study,Mamdani typeof fuzzy inference system was used, which is the most commonly seen fuzzy methodology and as defined for the toolbox, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification.

The input and output relationships are defined in terms of IF-THEN rules and the outputs are also fuzzy set which can be made “crisp” using defuzzification techniques. First the crisp values of system variables are fuzzified to express them in linguistic terms. Fuzzification is a process of translating a crisp set to a fuzzy set or increase the fuzziness of a fuzzy set. Actually, this process involves the models of selected membership function. This is determined by evaluating the membership function of the fuzzy set for a particular value.

2.3.2 MEMBERSHIP FUNCTIONS

In this study, the Gaussian membership function has been used and is defined as a probability distribution function (PDF) that creates a smooth boundary transition depending on the function parameters $\sigma$and *c* in the Gaussian MF formula, where *c* is the centre of the MF and $\sigma$is a constant related to the width of the function. The membership value μ(x) is the degree to which a given input x belongs to that membership function and 0 < μ(x) < 1. The membership value for the Gaussian membership function is defined as:

$$\mu_A(x) = e^{-\left(\frac{(x-c)}{\sigma}\right)^2} \qquad \ldots(3)$$

The neural networks were trained with 1-20 nodes in the hidden layer (or layers), with activation function, training function and adaption learning function. Fuzzy logic was trained with Gaussian membership function. After each training statistical parameters *viz.,* correlation coefficient (r), correlation efficiency (CE), mean absolute error (MAE) and root mean square error (RMSE) were calculated for calibration and validation periods to find the optimal number of hidden nodes using trial and error method.

2.4 COMPARISON OF ANN AND FUZZY LOGIC MODELS

The whole dataset was divided into two divisions; with 60% data used for model training (calibration) and the rest 40% data used for testing (validation) a model. The performances of both the models during calibration and validation were evaluated by using statistical parameters,viz., Correlation Coefficient (r), Coefficient of Efficiency (CE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) [13].The model with least RMSE and MAE value, and highest correlation coefficient (r) and coefficient of efficiency (CE) were selected as the best-fit model.

3. RESULTS AND DISCUSSION

3.1 Artificial neural network (ANN) model

In the current study, to determine the best suitable model for estimation of pan evaporation (Ep) for the study area, different ANN models were developed. Three models *viz.,*FNN-BR, FNN-LM and FNN-GDX were developed for pan evaporation (Ep) estimation. To get more accurate ANN model, the performance of three predictive training algorithms were evaluated (Table. 1) while developing the model itself. The most promising training algorithm in the hidden layer of ANN model was determined by trial and error, at which a model performs better.

To select the best ANN model, the key parameters were the correlation coefficient between actual and predicted pan evaporation (Ep) during the calibration and validation period. The comparison of actual and predicted pan evaporation (Ep) computed by the different ANN models during the calibration and validation periods are represented in Fig 4 (a) to Fig 6 (b).For the study area at Raichur, FNN-GDX model used more number of neurons for training the model. An optimal ANN architecture for FNN-GDX considered for Raichur region was found to be6-7-1 architecture.

The comparison of actual and predicted pan evaporation computed by the FNN-LM model during the calibration and validation period for study area at Raichur (Fig. 5a and b) was observed that, the values of predicted pan evaporation (Ep) followed the actual pan evaporation (Ep) pattern both in calibration and validation period. But in case of FNN-BR model (Fig. 4b), the prediction was little matching at few events during validation period. Quite similar correlation was observed for prediction of Ep was shown in FNN-GDX model (Fig 6b).For Raichur region FNN-GDX with 6-7-1 architecture was observed to be best fit model to predict pan evaporation.

3.2 Fuzzy logic (FL) models

For pan evaporation (Ep) estimation by FIS system 10956 datasets were used. Among total data set, 6026 datasets were used for its calibration and about 4930 datasets for its validation period. This clearly shows that, the model developed for the study area requires more training to yield good performance.The comparison of actual and predicted pan evaporation (Ep) computed by FL-GaussMF model for study location at Raichur was observed that, the prediction trend was moderately correlated with observed values (Fig 7a) during calibration and poorly correlated with actual values (Fig 7b) during validation.

3.3 Comparison of artificial neural network and fuzzy logic models

Performance of the developed ANN models has been assessed by comparing with the Fuzzy logic model. The performance of different ANN and FL models, derived from statistical procedure with the input combinations during calibration and validation for the study area is shown in Table 2. It was observed that, the "r" evaluating the linear correlation between the computed and observed pan evaporation (Ep) was high (0.7637) for FNN-GDX and low (0.6940) for FL model with GaussMF during validation period. The CE evaluating how far the network would explain the total variance of data, was high (0.5831) for the FNN-GDX model and was low (0.4767) for FL model with GaussMF during validation period. The MAE was low (0.8640) during calibration period for the FNN-LM model and high (1.5399) for FL model with GaussMF during validation period. The variation of RMSE statistics, a measure of residual variance illustrating the global goodness of fit between the computed and observed pan evaporation (Ep) was low (1.1587) during calibration period for FNN network with LM algorithm and was high (2.0338) during validation period for FL model with GaussMF.

All the results of r, CE, MAE and RMSE (indicators of performance of different ANN and fuzzy logic model) are presented in Fig 8. This indicates performance of the different ANN and FL models during calibration and validation with the input combination derived from statistical procedure for the study area of Raichur.

From the Table 2, it revealed that, model with training algorithm LM (trainlm) resulted good value of “r” and CE as 0.8851 and 0.7834, respectively during calibration. Model with training algorithm GDX (traingdx) resulted good value of “r” and CE as 0.7637 and 0.5831, respectively during validation; which represents the best performing indices (Fig 8). The model performance indices; MAE and RMSE with scaled estimate and target is moderate as 0.8640 and 1.1587 during calibration, respectively for FNN-LM and 1.3880 and 1.8541 during validation periods for FNN-GDX. However, there is no much difference in performance among neural network with three different algorithms but FL model showed least performance with least “r” (0.8072 and 0.6940), CE (0.6474 and 0.4767) and highest MAE (1.1290 and 1.5399) and RMSE (1.4797 and 2.0338) during calibration and validation.

The MAE and RMSE was found highest in case of FL model with Gaussian membershipfunctions (GaussMF) and the MAE was observed to be 1.1290 and 1.5399 during calibration and validation, respectively and finally the RMSE was observed to be 1.4797 and 2.0338 during calibration and validation, respectively. Because of highest MAE and RMSE values, the FL model with GaussMF was not considered as the best model; because during validation periods (Fig 7b) it is clearly observed that, the actual and predicted values were poorly correlated but in case of FNN-GDX algorithm it was observed that, the predicted values of Ep followed the actual values (Fig 6b) with good correlation. Based on the performance of correlation indices the FNN-GDX model was chosen as the best model for the present study area.

Table 1. Optimal ANN architecture and dataset division for calibration and validation for the different ANN models for Raichur (1990-2019)

ANN Model	Optimal ANN architecture	Data set for calibration	Data set for validation
FNN-BR	6-2-1	1-6574 (6574)	6575-10956 (4382)

FNN-LM	6-4-1	1-6683 (6683)	6684-10956 (4273)
FNN-GDX	6-7-1	1-6793 (6793)	6794-10956 (4163)

FNN-BR: Feed forward neural network with bayesian regularization algorithm; FNN-LM: Feed forward neural network with levenberg-marquardt algorithm; FNN-GDX: Feed forward neural network with gradient descent with momentum and adaptive learning rate back propagation algorithm.

Table 2. Performance of different ANN and Fuzzy Logic models for Raichur (1990-2019)

Model	Architecture	Calibration				Validation			
		r	CE	MAE	RMSE	r	CE	MAE	RMSE
FNN-BR	6-2-1	0.8830	0.7798	0.8761	1.1733	0.7561	0.5710	1.3934	1.8645
FNN-LM	6-4-1	0.8851	0.7834	0.8640	1.1587	0.7548	0.5687	1.4025	1.8847
FNN-GDX	6-7-1	0.8761	0.7675	0.9012	1.2025	0.7637	0.5831	1.3880	1.8541
FL-GaussMF	N.A.	0.8072	0.6474	1.1290	1.4797	0.6940	0.4767	1.5399	2.0338

FNN-BR: Feed forward neural network with bayesian regularization algorithm; FNN-LM: Feed forward neural network with levenberg-marquardt algorithm; FNN-GDX: Feed forward neural network with gradient descent with momentum and adaptive learning rate back propagation algorithm; FL-GaussMF: Fuzzy logic model with Gaussian membership function; N.A: Not assigned; r: Correlation coefficient; CE: Coefficient of efficiency; MAE: Mean absolute error;RMSE: Root mean square error.

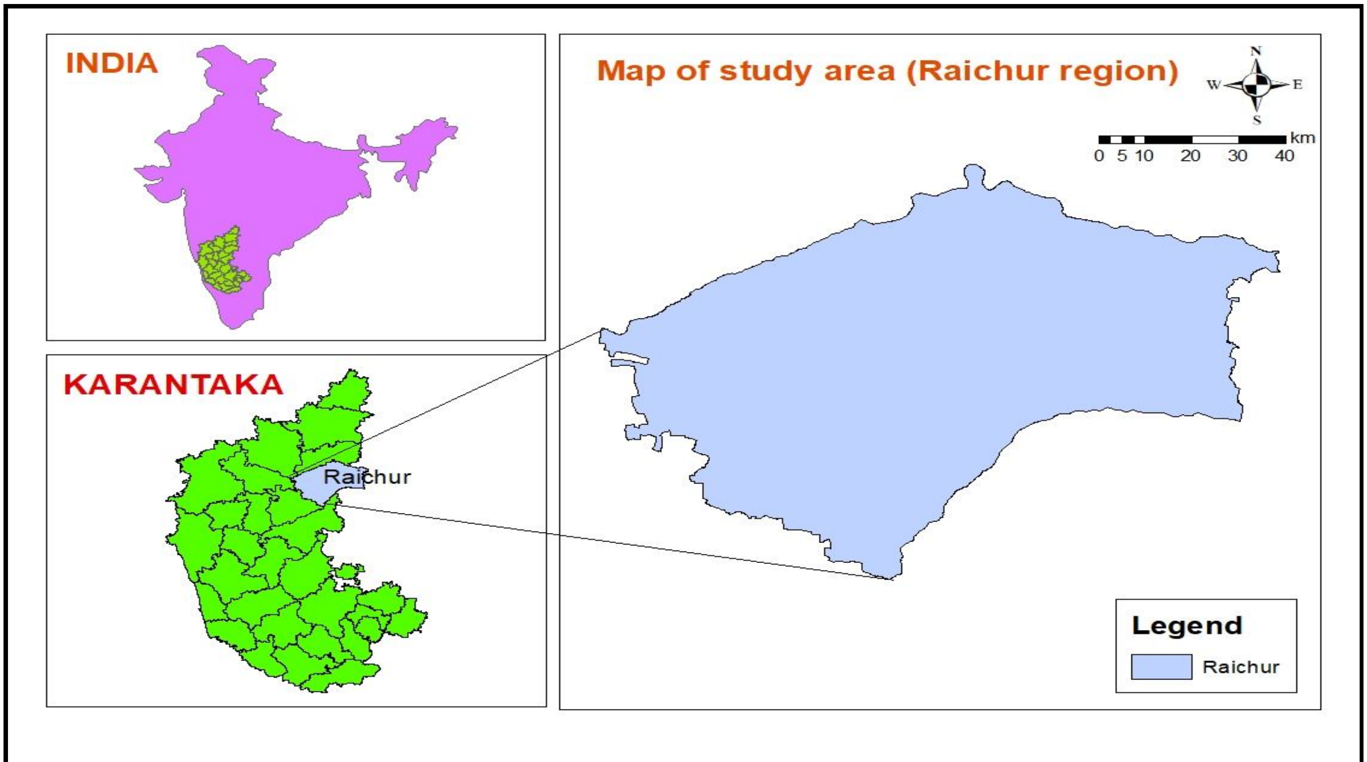

Fig. 1. Location map of study area (Raichur region)

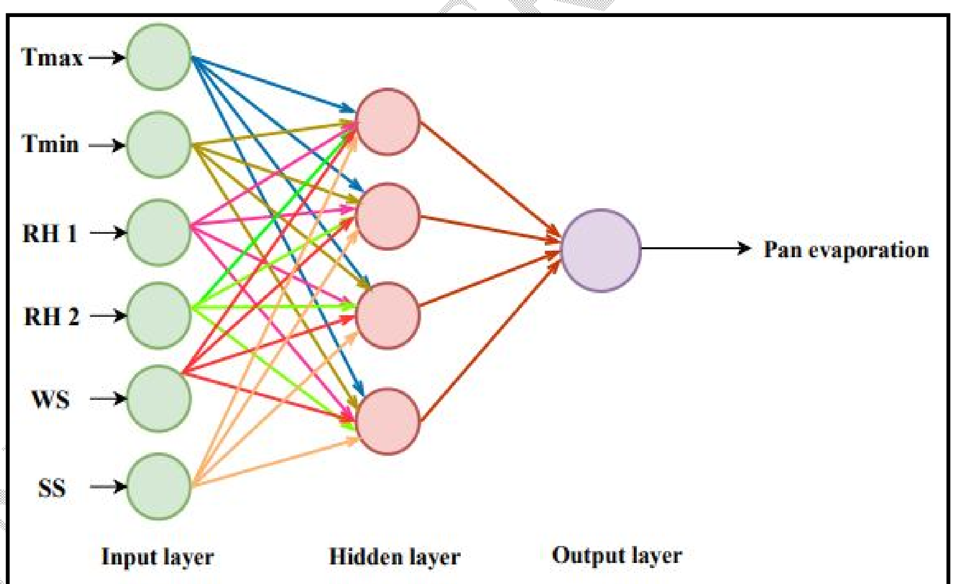

Fig. 2. The architecture of an artificial neural network

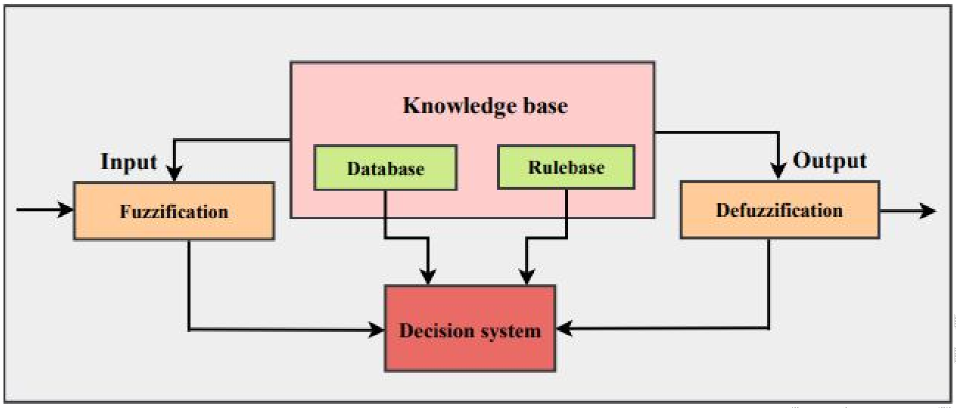

Fig. 3. Basic structure of a fuzzy inference system

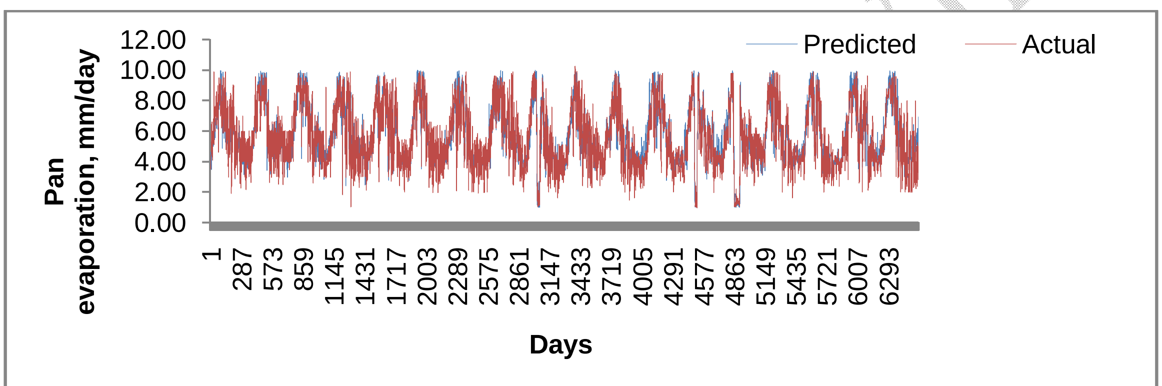

Fig. 4a. Comparison of pan evaporation (Ep) computed by FNN-BR model (Calibration)

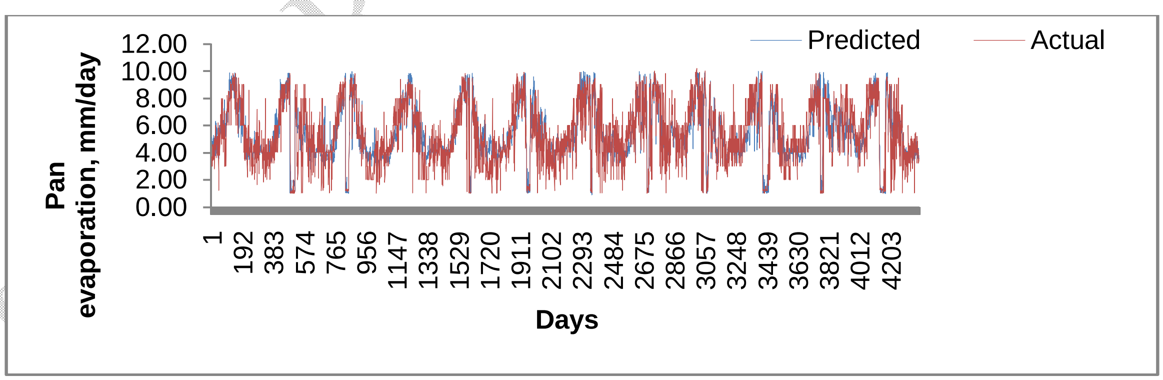

Fig. 4b. Comparison of pan evaporation (Ep) computed by FNN-BR model (Validation)

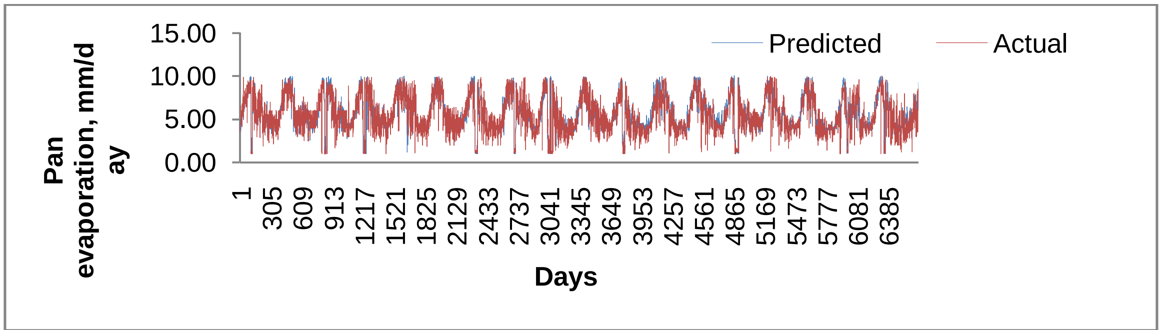

Fig. 5a. Comparison of pan evaporation (Ep) computed by FNN-LM model (Calibration)

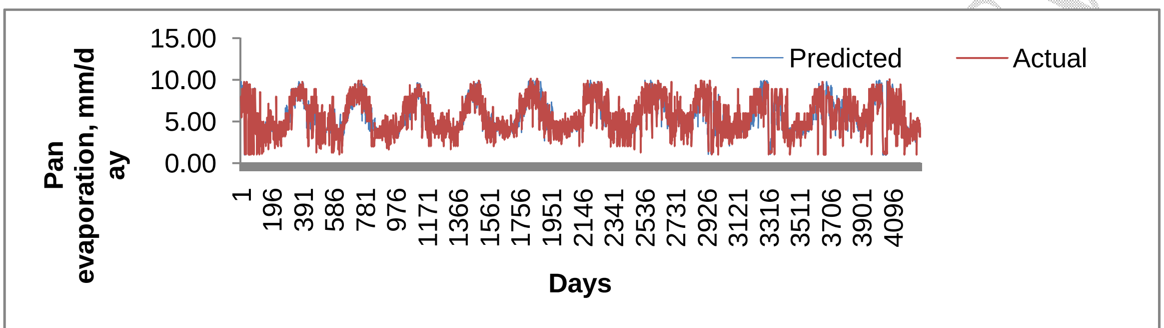

Fig. 5b. Comparison of pan evaporation (Ep) computed by FNN-LM model (Validation)

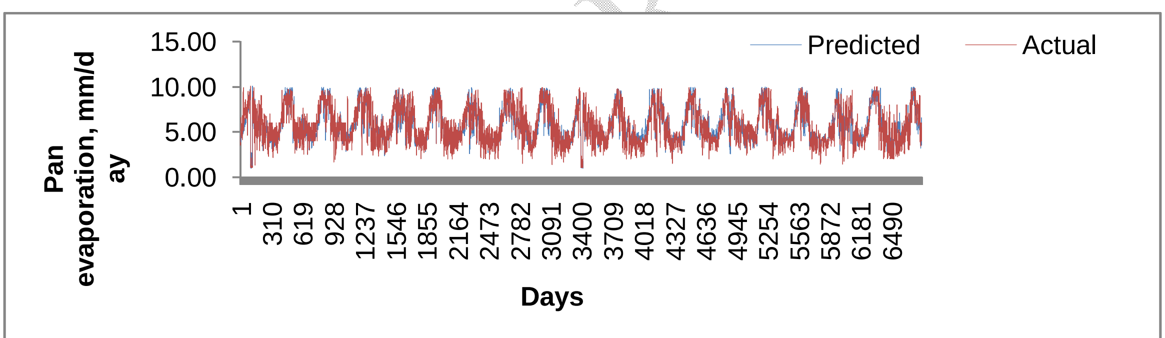

Fig. 6a. Comparison of pan evaporation (Ep) computed by FNN-GDX model (Calibration)

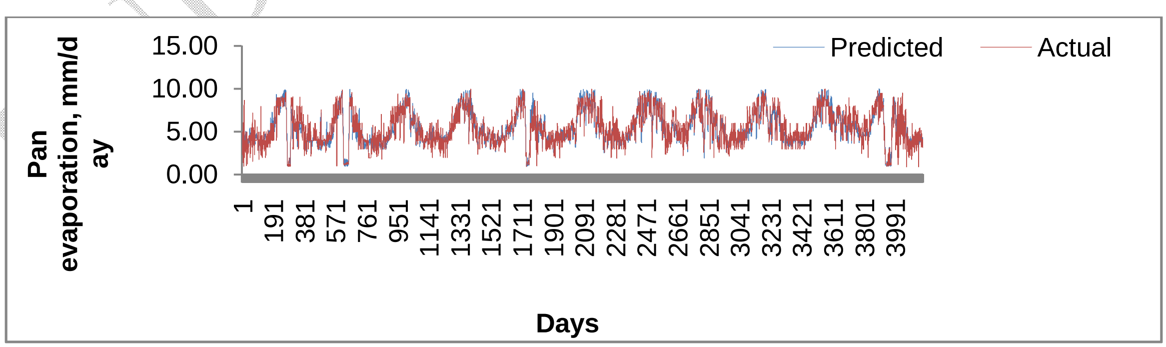

Fig. 6b. Comparison of pan evaporation (Ep) computed by FNN-GDX model (Validation)

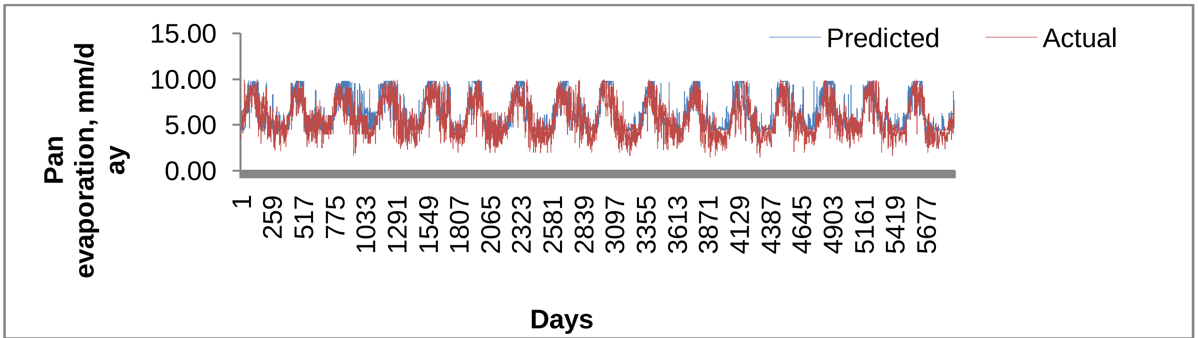

Fig. 7a. Comparison of pan evaporation (Ep) computed by FL-GaussMF model for Raichur(Calibration)

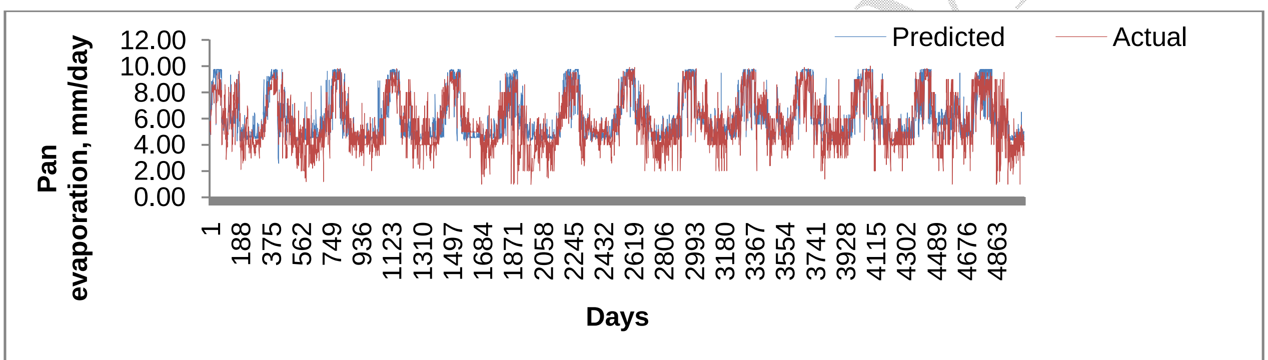

Fig. 7b. Comparison of pan evaporation (Ep) computed by FL-GaussMF model for Raichur (Validation)

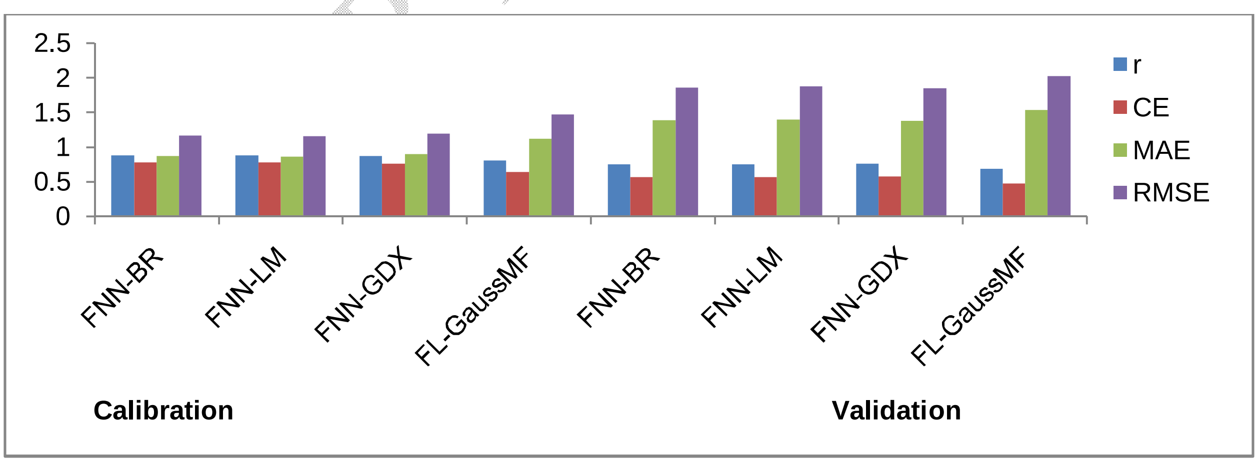

Fig. 8. Performance of different ANN and Fuzzy Logic models for Raichur (1990-2019)

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