ESTIMATION OF PAN EVAPORATION USING ANN – A CASE STUDY

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PROJECT REPORT

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DECLARATION

We hereby declare that this project report entitled **"Estimation of pan evaporation using ANN – a case study"** is a bonafide record of project work done by us during the course of project and that the report has not previously formed the basis for the award to us of any degree, diploma, associate ship, fellowship or other similar title of any other university or society.

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CERTIFICATE

Certified that this project report entitled **"Estimation of pan evaporation using ANN – a case study"** is a record of project work done jointly by **Amrutha Gayathry. V and Sharmina. V. K** under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associate ship to them.

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Amrutha Gayathry. V.

Sharmina. V. K

Dedicated to

God Almighty,

Loving Parents

and Teachers

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SYMBOLS AND ABBREVIATIONS

º	Degree
’	Minute
”	Second
/	Per
ANFIS	Adaptive neuro fuzzy inference system
ANN	Artificial Neural Network
Appl.	Applied
cm	Centi meter (s)
DLS	Damped Least Squares
Engng.	Engineering
ET	Evapotranspiration
FFNN	Feed Forward propagation Neural Networks
GA	Genetic Algorithm
GM	General Model
GRNN	Generalised Regression Neural Network
GRNNM	Generalised Regression Neural Network Model
GUI	Graphical User Interface
Hydol.	Hydrology
J.	Journal
K. C. A. E. T.	Kelappaji College of Agricultural Engineering and Technology

LLR	Linear Local Regression
LMA	Levenberg - Marquardt Algorithm
LN	Linear neural
LR	Local Regression
MAE	Mean absolute error
MARE	Mean absolute Relative error
MATLAB	MATrix LABoratory
MLP	Multi layer perception
Mm	Milli meter(s)
MSE	Mean Square Error
nctool	Neural Clustering Tool
NE	North East
NF	Neuro-Fuzzy
nftool	Neural Fitting Tool
NMD	Nagpur model development
nntool	Neural Network Tool
nntraintool	Neural Network Training display
nprtool	Neural Network Pattern Recognition Tool
PE	Pan Evaporation
PM	Penman Monteith
R^2	Regression coefficient
RBF	Radial basis function
RBNN	Radial basis neural network
Res.	Research
Resour.	Resource
Rev.	Review
RMSE	Root Mean Square Error

s	Second(s)
Sci.	Science
SOM	Self-Organizing Map
SPIDA	Simulation program interactive drainage analysis
SVM	Support vector machines
SVR	Support vector regression
SW	South West
Trans.	Transactions
trinlm	Levenberg-Marquardt Training algorithm
U. S. E.P.A	United States Environmental protection agency
U. S. G. S	United States Geological Survey

Introduction

1. INTRODUCTION

Water is one of vital natural resource required for very survival of living beings. Sustenance of life on earth depends on the way water resource is conserved and managed. For the efficient water conservation suitable watershed management measures has to be adopted, so that the resources are utilized in the most judicious and sustainable way. In the total earth surface oceans occupy about 70.8 percent and only 29.2 percent is occupied land. About 97.5 percent of the world water resource is in the oceans and is saline. Of the remaining, 2.5 percent of the global water resource, about 2 percent is entrapped in the icecaps and glaciers and is generally not available for the requirements of mankind. The amount of water available for development activities is mainly the water in the streams, rivers, fresh water lakes and the water can be taken from the ground water. The use of water has increased more than 35 folds over the past three centuries. Globally 3240 km^3 of fresh water are withdrawn and used annually. In the present scenario the water availability is depends on climate change and the timing of precipitation. The availability also varies from season to season and year to year, resulting in distinct dry and wet periods.

The hydrologic cycle is defined as a water transfer cycle, in which water is transferred from the oceans or sea to the atmosphere, then from atmosphere to the earth and ultimately again return back to the sea. It always maintains a balance between the water present on the ground surface and in atmosphere. Precipitation, runoff, evaporation and transpiration are the major phases of the hydrologic cycle. Precipitation is the total amount of water falling from the atmosphere in the form of rain, snow, mist etc. on the earth. It takes place due to lifting of evaporated water moisture into the atmosphere and the subsequent cloud formation. The water from these clouds will falls on the earth surface in a form which can be used by the human being. Precipitation in the form of rainfall is the source of water for the runoff generation over the earth surface. During occurrence of rainfall, a part of it is intercepted by the vegetations, buildings and several other objects, lying over the earth surface and some portion infiltrates into the soil. The rest of the water will tend to move from one place to another under the effect of land gradient and ultimately it meets the streams, channels etc.

Evaporation and transpiration are the processes by virtue of which water or moisture from water body or soil surface is removed continuously, mainly under the effect of temperature. The total water lost due to evaporation and transpiration in combined form is referred as evapo-transpiration loss. The transpiration loss is only from the plants through respiration process. These two processes are mainly responsible for contributing the moisture to the atmosphere.

Evaporation is a major component of hydrologic cycle. It plays an important role in water resources development and management in arid and semi-arid climatic regions. Evaporation takes place whenever there is a vapour pressure gradient between a water surface and the overlying atmosphere with an energy source. The process of evaporation is influenced by a number of factors, the most common and important meteorological parameters affecting evaporation are solar radiation, temperature, relative humidity, wind speed and atmospheric pressure.

Evaporation has wide range of application in the field of hydrology, agronomy, forestry and land use planning such as water balance computation, irrigation management, crop yield forecasting model, river flow forecasting, ecosystem modelling etc. There are number of models for the estimation of evaporation developed by investigators in different fields of study. The interrelated factors are incorporated into various formulae for estimating evaporation. A large number of experimental formulae exist for estimation of evaporation. There are direct and indirect methods available for estimating potential evaporation. Due to complex interactions between the components of the land-plant-atmospheric systems the reliable estimation of evaporation are extremely difficult.

The limitation in measuring the pan evaporation leads to development of pan evaporation models using various meteorological variables. Since the evaporation is a non-linear process, models gives better results for evaporation measurement. Over the past two decades, 'Artificial Neural Networks (ANNs)' have been increasingly employed in modelling of hydrological process because of their ability to model non-linear systems. According to Dr. Robert Hecht-Nielsen (1989), a neural network can be defined as; "*a computing system made up of a number of simple, highly interconnected processing elements, which information by their dynamic state response to external input".* An Artificial Neural Network (ANN) is a method of computation and information processes that mimics the process of biological neurons found in the human brain. ANN's have been successfully applied across an extraordinary range of problem domains in areas as diverse as Finance, Medicine, Physics, Engineering, Geology and Hydrology (ASCE task committee on application of Artificial Neural Networks in hydrology 2000). Artificial Neural Networks are one of the most popular and promising areas of artificial intelligence research and they are abstract computational models, roughly based on the organizational structure of the human brain. There are a wide variety of network architectures and learning methods that can be combined to produce neural networks with different computational abilities. ANNs are most robust than any computational methods or modelling techniques in hydrology because of their ability to handle large variations of parameters.

The ANN modelling and evaluation use the software, MATLAB (ver. 7.6.0.324 (R2008a)) as the source code program. MATLAB is a high-level language and interactive environment for numerical computation, visualization and programming; it is used extensively by control engineers for analysis of design. MATLAB can be used to analyze data, develop algorithms and to create models and applications. An application of MATLAB includes signal processing, control systems, test and measurement, computational finance and computational biology. Initially, it was simply a MATrix LABoratory. However, today it is much more powerful. It was designed to group large amounts of data in arrays and to perform mathematical operations on this data as individual arrays rather than as groups of data. This makes it very easy to apply complicated operations to the data, and it makes it very difficult to do it wrong.

1.1 Objectives of the present study are

1. To analyze the possibility of application of Artificial Neural Network in the field of hydrology.

2. To develop, test and evaluate a daily pan evaporation model for KCAET campus using Artificial Neural Network (ANN).

Review of Literature

2. REVIEW OF LITERATURE

The chapter reviews the concepts and literatures available on evaporation modelling and Artificial Neural Network (ANN).

2.1 Estimation of evaporation from water surface

Conservation of water from its liquid phase to vapour phase under effect of atmospheric temperature is called as evaporation. In hydro-meteorological study, the evaporation is considered only from free water surface and soil.

The following methods can be used to estimate evaporation from large water surfaces such as rivers, ponds, reservoirs etc.

2.1.1 Storage equation

This equation is based on the concept that, there is a balance between the amount of water lost and additional water supplied to the storage body by different sources. The storage equation is given below (Suresh, 1997),

$$\mathbf{P + I \pm Q_g = E + O \pm S} \qquad \text{(Eq.2.1)}$$

Where,

P = Total amount of water added by the precipitation

I = Surface inflow quantity

Q_g= Amount of water, +ve sign is used for inflow condition and –ve sign is for outflow condition of the ground water

E = Evaporation loss from the water surface

O = Surface outflow

S = Change in storage of water surface, the +ve and –ve signs are used for increasing and decreasing conditions of storage, respectively

2.1.2 Pan- Measurement method

In this method the depth of water lost from a standard size of pan in which, water is filled to a fixed depth, is allowed for evaporation is measured within a given time period. From this direct measurement, evaporation rate per unit surface area of the pan is calculated by dividing with the time. The evaporation value obtained so is not authentic for use, since it varies with the extend of surface area of water body. That is why, a factor known as 'pan coefficient' is multiplied to the obtained evaporation rate for getting the accurate evaporation value.

The pan coefficient is defined as the, ratio of lake evaporation to the pan evaporation (Suresh, 1997) and it can be represented as,

$$\mathbf{P_C = \frac{E_L}{E_P}} \qquad \text{(Eq.2.2)}$$

Where,

P_C= Pan Coefficient

E_L= Lake evaporation

E_P= pan evaporation

2.1.3 Empirical formulae

Empirical formulae developed on the basis of weather parameters such as temperature, solar radiation, saturation vapour pressure, wind velocity etc. One of the important empirical formulae for evaporation estimation is given by Rohwer (Suresh, 1997),

$$\mathbf{E = 1.958\ (1.465 - 0.00732\ p)\ (0.44 - 0.00737\ V)\ (e_s - e_a)} \qquad \text{(Eq. 2.3)}$$

Where,

E= Evaporation rate, cm/day

P= Mean barometric pressure, cm at 0ºC

e_a= Average vapour pressure of air, measured in cm of mercury

e_s= Saturation vapour pressure at mean water temperature in terms of cm of mercury

V= Wind velocity (km/h) at the height of 15 cm from the ground surface

$V_Z = V_1 (1+\log_{10} z)$

V_Z= Wind speed at height z from the ground surface

V_1= Wind velocity at 1 feet height from the ground surface

2.1.4 Energy budget method

This method is based on the principle of conservation of heat energy and cooling produced by the evaporation. Various energy based-equations are as follows (Suresh, 1997),

Penman's formula (1948): $\mathbf{E = 0.89\,(1-0.15U_2)\,(e_s-e_a)}$ (Eq.2.4)

Meyer's formula (1915): $\mathbf{E = C\,(1 + \frac{U_S}{16})\,(e_s-e_a)}$ (Eq.2.5)

USSR formula: $\mathbf{E = 4.57\,T+43.3}$ (Eq.2.6)

Harbeck formula (1954): $\mathbf{E = 0.1156U_4\,(e_s-e_2)}$ (Eq.2.7)

Shahtin formula $\mathbf{E = 0.35\,(e_s-e_a)\,(1+0.15\,U_2)}$ (Eq.2.8)

Where,

E = Evaporation (cm/day)

e_s = Saturation vapour pressure at water surface temperature, (mb)

e_a = Saturation vapour pressure of air, (mb)

U_2= Wind velocity at 2m height, (cm/s)

U_8= Wind velocity at 8m height, (cm/s)

T= Mean annual temperature ºC

U_4= Wind velocity at 4m height, (cm/s)

e_2= Vapour pressure at 2m height, (mb)

2.2 Application of ANN Technique on hydrological processes

The ANN technique can be adopted for model generation of various hydrologic processes. ANN is widely used in the problems of runoff modelling of a watershed. Determination of relationship between rainfall and runoff for a watershed is one of the most important problems faced by the hydrologists and engineers. Information about rainfall and runoff is needed for hydrologic engineering design and management purposes. A number of researchers have investigated the potential of neural networks in modelling watershed runoff based on the rainfall inputs.

Halff *et al* (1993) investigated the potential of neural networks in modelling watershed runoff based on rainfall inputs. They developed a three-layer feed forward ANN using the observed rainfall hyetographs as inputs and hydrographs recorded by the U.S. Geological Survey (USGS) at Bellvue, Washington, as outputs. Five storm events were considered with five nodes in the hidden layer. On a rotation basis, data from four storms were used for training, while data from the fifth storm were used for testing network performance. A sequence of 25 normalized 5 min rainfalls was applied as inputs to predict the runoff.

Zhu *et al.* (1994) predicted upper and lower bounds on the flood hydrograph in Butter Creek, New York. Off-line predictions were made when present flood data were not available and estimates had to be based on rainfall data alone. On-line predictions were based on both rainfall and previous flood data. Using a nonlinear storage model data for ANN testing and validation were generated. Model performance was strongly influenced by the training data set. The ANN did well during interpolation; predictions made by ANNs outside the range of the training data set were not encouraging. The process of trying to make ANNs adaptive was computationally very demanding, because the entire training process needed to be repeated with each new data pair. As the lead time for forecasting increased, ANN performance deteriorated. By comparison, ANNs were found to be marginally better than fuzzy inference-based techniques.

Smith and Eli (1995) applied a back-propagation neural network model to predict peak discharge and time to peak over a hypothetical watershed. Training and validation data sets were generated by either a linear or a nonlinear reservoir model. The watershed is represented as a grid of cells, so that it was possible to incorporate the spatial and temporal distribution information of rainfall into the ANN model. A synthetic watershed which is composed of 5 × 5 cells was used. A tree-type drainage pattern was superimposed on the grid to concentrate runoff towards a single watershed outlet. Each cell was treated as a reservoir and water was routed in a cascading fashion. A rainfall depth of one unit was applied instantaneously at several cells on a random basis. Each rainfall pattern in the training set was presented to the network as an input image in which 1 representing a wet cell and 0 a dry cell. The peak discharge and the time to peak corresponding to each rainfall pattern were computed using a linear and nonlinear reservoir model and served as target outputs for the ANN model. The output was either the watershed runoff alone or the runoff and the time to peak. For single-storm events, the peak discharge and the time to peak were predicted well by the neural network, both during training and testing. Due to insufficient number of nodes in the output layer the authors were less successful for multiple- storm events.

Mason *et al.* (1996) used RBF networks for accelerating the training procedure as compared with regular back-propagation techniques. Using the Simulation Program for Interactive Drainage Analysis (SPIDA) model data were generated. The network output was runoff based on inputs consisting of time, rainfall intensity, cumulative rainfall, and derivative of rainfall intensity. Sixty data sets were utilized for network training, and 39 were used for validation of the model. From the study RBF networks provide faster training, such networks require the solution of a linear system of equations that may become ill conditioned, especially if a large number of cluster centers are chosen.

Shamseldin (1997) compared ANNs with a simple linear model, a season-based linear perturbation model, and a nearest neighbour linear perturbation model. From six different watersheds around the world daily average values of rainfall and runoff were collected for this study. Four different scenarios based on combinations of some or all of input information was examined. Training uses conjugate gradient method and three-layer neural network. A two-parameter gamma function representation was chosen as the impulse response of the rainfall series. The network output consisted of the runoff time series. The results suggested that the neural networks generally performed better than the other models during training and testing.

Dawson and Wilby (1998) conducted a study on the rainfall runoff modelling using ANN technique to flow forecasting in two flood-prone UK catchments using real hydrometric data. Comparisons were made between the performance of the ANN and those of conventional flood forecasting systems. The results obtained for validation forecasts were of comparable quality to those obtained from operational systems for the River Amber. The ability of the ANN to cope with missing data and to “learn” from the event currently being forecast in real time makes it an appealing alternative to conventional lumped or semi-distributed flood forecasting models.

Kuligowski and Barros (1998) present an ANN approach for short-term precipitation prediction. Upper atmospheric wind direction and antecedent precipitation data from a rain gauge network to generate a 0–6 hour precipitation forecast for a target location. Architecture used for model was feed forward method. Compared with a persistence model, the proposed ANN model showed significant improvement for short-term precipitation prediction.

Jain *et al.* (1999) conducted a study on the application of ANNs for reservoir inflow prediction and operation. The Upper Indravati multipurpose project, in the state of Orissa, India, has been selected as the focus area. The project has primarily two objectives: To provide irrigation to 128,000,000 ha of agricultural land and to generate 600 MW of electric power. An autoregressive integrated moving average time-series model and ANN-based model performances were compared. The ANN was found to model the high flows better, whereas low flows were better predicted through the autoregressive integrated moving average model. Reservoir operation policies were formulated through dynamic programming. The optimal release was related with storage, inflow, and demand through linear and nonlinear regression and the ANN. The results of inter comparison indicate that the ANN is a powerful tool for input-output mapping and can be effectively used for reservoir inflow forecasting and operation.

Tokar and Johnson (1999) conducted a study to forecast daily runoff for the Little Patuxent River, Maryland. Daily precipitation, temperature, and snowmelt equivalent were serves as inputs. Study reported that ANN models provided higher training and testing accuracy when compared with regression and simple conceptual models. Also the selection of training data has a large impact on accuracy of prediction. They trained and tested the ANN with wet, dry, and average-year data, respectively, as well as combinations of these, in order to illustrate the impact of the training series on network performance. The ANN that was trained on wet and dry data had the highest prediction accuracy. The length of training record had a much smaller impact on network performance than the types of training data.

Akbarpour (2002) studied simulation of the rainfall-runoff process by Artificial Neural Networks (ANNs) and HEC-HMS model. The ANN models of, Multi Layer Perceptron (MLP) with two structures of one and two hidden layer, and Radial Basis Function (RBF), was used for simulation of this process. It has been applied to the Zard river basin in Khuzestan province using daily rainfall and runoff data, during the period of 1991-2000.In this period, 14 flood events were selected for simulation of the HEC-

HMS model. The obtained results of the above models were compared with the observed data from Zard river basin. This comparison shows that RBF model has much more power than MLP and HEC-HMS.

Jain *et al*. (2004) conducted study in order to examine whether or not the physical processes in a watershed are inherent in a trained ANN rainfall-runoff model. The investigation is based on analyzing definite statistical measures of strength of relationship between the disintegrated hidden neuron responses of an ANN model and its input variables, as well as various deterministic components of a conceptual rainfall-runoff model. The approach is illustrated by presenting a case study for the Kentucky River watershed. The results suggest that the distributed structure of the ANN is able to capture certain physical behaviour of the rainfall-runoff process. The results demonstrate that the hidden neurons in the ANN rainfall-runoff model approximate various components of the hydrologic system, such as infiltration, base flow, and delayed and quick surface flow, etc., and represent the rising limb and different portions of the falling limb of a flow hydrograph.

Chetan and Sudheer (2006) present a novel hybrid linear-neural (LN) model formulation to effectively model rainfall-runoff processes. A training algorithm for the proposed model is designed based on minimum description length criteria. The advantage of the algorithm is that the final architecture of the LN model is arrived at during the training process, thus avoiding selection from a class of models. The proposed model has been developed and evaluated for its performance for forecasting the river flow of Kolar basin, in India. The values of three performance evaluation criteria, namely, the coefficient of efficiency, the root-mean-square error, and the coefficient of correlation, were found to be very good and consistent for flows forecasted 1 hour in advance by the LN model. The value of the relative error in peak flow prediction was within reasonable limits for the model. The forecasts by the LN model at higher lead times (up to 6 hours) are found to be good. A relative evaluation of LN model performance with that of an ANN model and of a multiple linear regression model indicates that the LN model effectively combines the strength of the other two, implying that the LN model seems to be well suited to exploit the information to model the nonlinear dynamics of the rainfall-runoff process.

Kalteh (2008) developed a rainfall-runoff model using an ANN approach, and described different approaches including Neural Interpretation Diagram, Garson's algorithm, and randomization approach to understand the relationship learned by the ANN model. The results indicate that ANNs are promising tools not only in accurate modelling of complex processes but also in providing insight from the learned relationship, which would assist the modeler in understanding of the process under investigation as well as in evaluation of the model.

Landeras *et al* (2009) studied forecasting weekly evapotranspiration with ARIMA and artificial network models. The main objective of their study was to compare weekly evapotranspiration ARIMA with ANN based forecasting. The ARIMA and ANN models reduced the prediction RMS differences with respect to the mean year model by 6 to 8 percent and reduced the standard deviation differences by 9 to 16 percentages.

Kalteh (2013) studied the relative accuracy of artificial neural network (ANN) and support vector regression (SVR) models coupled with wavelet transform in monthly river flow forecasting and compared to regular ANN and SVR models, respectively. The relative performance of regular ANN and SVR models is also compared to each other. Monthly river flow data of Kharjegil and Ponel stations in Northern Iran are used for the study. The comparison of the results reveals that both ANN and SVR models coupled with wavelet transform, are able to provide more accurate forecasting results than the regular ANN and SVR models. Also SVR models coupled with wavelet transform provide better forecasting results than ANN models coupled with wavelet transform. The results also indicate that regular SVR models perform slightly better than regular ANN models.

2.3 Evaporation estimation using ANN

Based on the limitations in measuring the pan evaporation, research has been performed to model pan evaporation using various meteorological variables. It is therefore necessary to develop approaches to estimate the evaporation rates from other available meteorology variables, which are comparatively easier for measurements. The class A pan evaporation is direct method. Indirect method includes those that use meteorological data to estimate evaporation from other weather variables through empirically developed methodologies or artificial neural network and statistical approaches.

Bruton *et al.* (2000) developed an ANN models to estimate daily pan evaporation using measured weather variables as input. Data were taken from Rome, Plains and Watkinsville, Georgia. Records from 1992 to 1996 were considered to develop the models of daily pan evaporation. Records from 1997 to 1998 were served as an independent evaluation data set for the models. The weather data includes daily observation of rainfall, temperature, relative humidity, solar radiation and wind speed. The developed ANN model is compared with the values of estimated daily pan evaporation using multiple linear regression. The pan evaporation estimated with ANN models was slightly more accurate than the pan evaporation estimated with a multiple linear regression.

Sudheer *et al*. (2002) conducted an investigation on the prediction of class A pan evaporation using the artificial neural network (ANN) technique. The ANN back propagation algorithm was used for the prediction of evaporation from minimum climatic data. By considering four combinations of input data, the evaporation models were created and models are evaluated and compared with those of existing models. The study indicated that the temperature data only can be used for evaporation estimation through the ANN technique.

Taher (2003) estimated potential evaporation especially in arid regions. In this study a four three-layer back propagation neural networks were developed to forecast monthly potential evaporation in arid regions such as Riyadh, Soudhi- Arabia. The four main climatic factors considered for the study includes relative humidity, solar radiation, temperature and evaporation for the past 22 years. The result obtained that the networks developed were able to well learn the events they were train to recognize.

Ozlem *et al.* (2005) estimated daily pan evaporation are achieved by a suitable ANN model for the meteorological recorded from the Automated grow weather meteorological station near lake Egirdir, Turkey. The meteorological variables considered for the study are air temperature, water temperature, solar radiation, air pressure, wind speed and relative humidity. They developed an ANN model four input neurons in the input layer with one at the output layer and the model consist of 3 neurons in the hidden layer and the result revealed that the developed ANN model provides good estimate with the least mean square error.

Martinez*et al*. (2006) developed and validate a simulation model of the evaporation rate of a class A evaporimeter. The model was calibrated and validated using hourly averaged measurements of the evaporation rate and water temperature. The study area was Cartagena (southeast Spain). In this study multilayer model appears to be more appropriate for research purposes and simulated outputs of both water temperature and pan evaporation proved to be realistic when compared to the observed values.

Keskin and Terzi (2006) studied the ANN models and proposed as an alternative approach of evaporation estimation for lake, Eirdir. They aim to develop ANN model to estimate daily pan evaporation from measured meteorological data and to compare this ANN model with penman model and to evaluate potential of the ANN model. The meteorological data from 2001 to 2002 are used to develop the model. The meteorological parameters considered for the study includes daily observation of Air and water temperature, sunshine hours, solar radiation, air pressure, relative humidity and wind speed. The result of penman method and ANN model are compared and shows that ANN model is better than any other model.

Kisi (2006) developed a daily pan evaporation model using a neuro-fuzzy computing technique. This paper investigates the abilities of neuro-fuzzy (NF) technique to improve accuracy of daily evaporation estimation. The study consist of five different combinations of daily climatic variables such as air temperature, solar radiation, wind speed, pressure and humidity for the development of five different NF model and to evaluate degree of effect of each of these variables on evaporation. The developed model is compared with the ANNs. Various static measures are used for the evaluation of performance of the model. The result obtained indicates that the NF method is also applicable for model generation with better result.

Kim and Kim (2008) developed a model a neural network and genetic algorithm approach for nonlinear evaporation and evapotranspiration modelling. The purpose of the study is to develop and apply the generalized regression neural networks model(GRNNM) embedding the genetic algorithm(GA) in order to estimate and calculate pan evaporation(PE) and the Alfalfa reference evapotranspiration(ET), Republic of Korea. Penman-monteith (PM) method was used to estimate the observed Alfalfa ETr. According to the result of training, testing and the reproduction performances, the results of the statistical analysis for the PE and the Alfalfa ETr were found to be outstanding using the standard statistical indexes.

Eslamian *et al* (2008) estimates monthly pan evaporation using artificial neural networks and support vector machines. The meteorological parameters considered for the study are monthly observations of air temperature, solar radiation, wind speed, relative humidity and precipitation. They obtained a result that the ANN technique and SVM works well for the selected set of data and SVM gives a better result than the ANN technique.

Kisi *et al.* (2009) made studies on the abilities of artificial neural networks (ANNs) techniques to estimate daily pan evaporation through multi-layer perceptions (MLP), radial basis neural networks (GRNN). An MLP model comprises combinations of meteorological data such as air temperature, solar radiation, wind speed, pressure and humidity. The daily climatic data of two automated weather stations, Arcata-Eureka station and Daggett station operated by the US Environmental Protection Agency (US EPA) were used in this study. The MLP estimates are compared with those of RBNN and GRNN techniques. Root mean square errors (RMSE), mean absolute error (MAE) and determination coefficient (R^2) statistics are the methods used to evaluate the performance of model. It was observed that the MLP and RBN computing technique can be successfully employed to model the evaporation process using the climatic data. By comparing the GRNN was found to be performing better than Stephen- Stewart method.

Piri *et al.* (2009) made an attempt on daily pan evaporation modelling in a hot and dry climate using artificial neural network (ANN) technique. Weather factors considered in the model inputs are wind speed, saturation vapor pressure deficit and relative humidity. This paper explores evaporation estimation method based on artificial neural networks and (ANN) and adaptive neuro-fuzzy inference system (ANFIS) techniques. A new data analysis tool called the gamma test were used for obtain a best combination of input data for the study. It has been found that the ANN and ANFIS techniques have much better performance than the empirical formulas. Between ANN and ANFIS techniques, ANN model is slightly better.

Moghaddamnia *et al.* (2009) estimated evaporation using ANNs and adaptive neuro-fuzzy inference system techniques (ANFIS).It has been found that ANN and ANFIS technique have much better performance than the empirical formulas. By the comparison between ANN and ANFIS model, ANN model is found to be slightly better.

Shirgure and Rajput (2012) Investigated to develop and test the daily pan evaporation prediction models using various weather parameters as input variables with artificial neural network (ANN) and validated with the independent subset of data for five different locations in India. The measured variables included daily observations of maximum and minimum temperature, maximum and minimum relative humidity, wind speed, sunshine hours, rainfall and pan evaporation. In this general model (GM) model development and evaluation has been done for the five locations viz. NRCC, Nagpur (M.S.); JNKVV, Jabalpur (M.P.); PDKV, Akola (M.S.); ICRISAT, Hyderabad (A.P.) and MPUAT, Udaipur (Raj.). The daily data of pan evaporation and other inputs for two years was considered for model development and subsequent 1-2 years data for validation. Weather data consisting of 3305 daily records from 2002 to 2006 were used to develop the GM models of daily pan evaporation. Additional weather of Nagpur station, which included 2139 daily records from 1996 - 2004, served as an independent evaluation data set for the performance of the models. The model plan strategy with all inputs has shown better performance than the reduced number of inputs. The General ANN models of daily pan evaporation with all available variables as a inputs was the most accurate model delivering an R2 of 0.84 and a root mean square error 1.44 mm for the model development data set. The GM evaluation with Nagpur model development (NMD) data shown lowest RMSE (1.961 mm), MAE (0.038 mm) and MARE (2.30 %) and highest r (0.848), R2 (0.719) and d (0.919) with ANN GM M-1with all input variables.

Kumar *et al.* (2013) conducted a study on evaporation modelling using weather data. Evaporation values are estimated by using adaptive neuro- fuzzy inference system (ANFIS) and local regression (LR) models. The meteorological input parameters used for this study are relative humidity, solar radiation, temperature, wind speed. Weather data input selection process is done by the Gamma test. The performances of the models are evaluated using root mean square error and correlation coefficient statistics method. The obtained result shows that the higher values of correlation coefficients and lower values of root mean square error suggests better applicability of ANFIS model for evaporation estimation over the LLR model.

Materials and Methods

3. MATERIALS AND METHODS

The section demonstrates the methods and materials adopted for evaporation estimation using Artificial Neural Network.

3. 1. Study area

3. 1. 1 Location

The experiment was conducted in K.C.A.E.T. campus at Tavanur in Malappuram district (Fig.1) which is situated at 10^0 51’23” North latitude and 75^0 59’13” East longitudes and lie adjoining to the Bharathappuzha river. The total geographical area of the region is about 40.25ha.

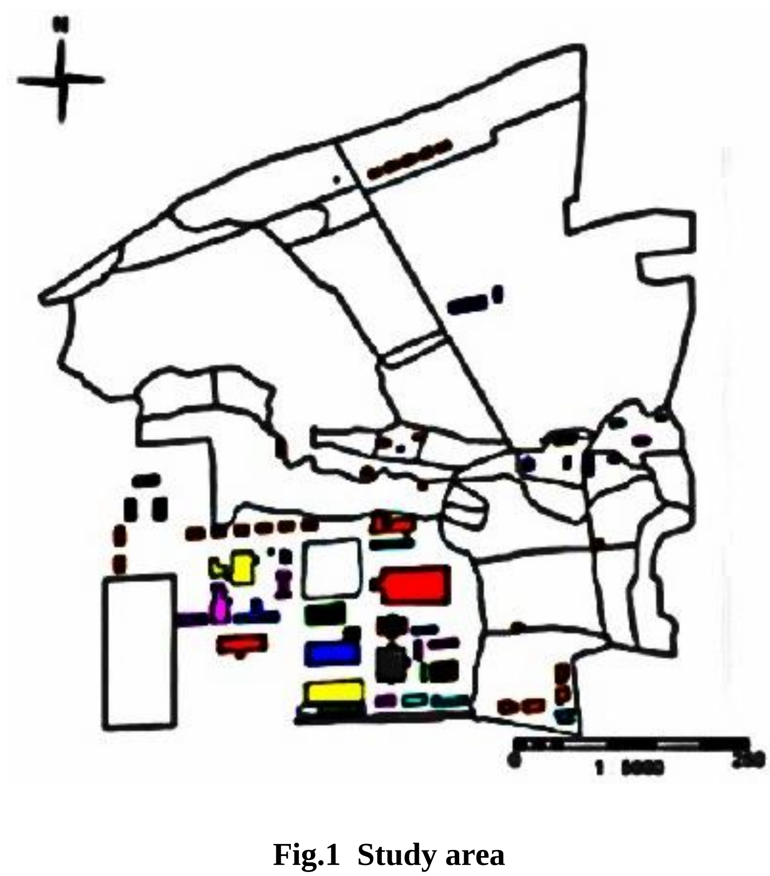

Fig.1 Study area

3. 1. 2. Climate and rainfall

The study area has more or less the same climatic conditions viz. dry season from December to February and hot season from March to May, the South-West monsoon from June to September and the North- East monsoon from October to December. Climatologically the area is in the high rainfall zone (2500mm to 3000mm). The area receives the rainfall mainly from south west (SW) monsoon and certain extend from north east (NE) monsoon.

The normal rainfall is 2793.3 mm. SW monsoon is usually very heavy and nearly 73.5% of the rainfall is received during this season. NE monsoon contributes nearly 9.9% and the balance 0.2% is accounted for January and February months.

The climate is generally hot and humid. The average relative humidity of the area is 83%. The maximum temperature ranges from 28.9 to 36.2^{o}C and the minimum temperature ranges from 17 to 23.3^{o}C. The mean evaporation of the study area is 6 mm/day. The temperature starts rising from January and March shows peak temperature. April onwards temperature decreases and again rising from September onwards.

3. 1. 3. Hydrology of the study area

The principal formation of KCAET campus includes lateritic rock, lateritic soil and sandy soil. The thicknesses of the various layers vary spatially in the campus. The lateritic rock is present in the high elevation part of the area only. And sandy soil is the top layer in the low lying paddy fields in the north.

3.2. Artificial Neural Network

The Artificial Neural Network technique is used in this study for developing the evaporation model of K.C.A.E.T campus.

An Artificial Neural Network (ANN) is a method of computation and information processing that mimics the process of biological neurons found in the human brain. The simplest definition of a neural network is provided by the inventor of one of the first neurocomputers, Dr. Robert Hecht-Nielsen (1989). He defines a neural network as: *"...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs".* ANN was first introduced as a mathematical aid by McCulloch and Pitts. They were inspired by the neural structure of the human brain. Although ANN's have been around since the late 1930's it was not until the mid 1980's that algorithms became sophisticated enough for general application. The advantage of ANN lies in their resilience against distortions in the input data and their capability of learning. They are often good at solving problems that are too complex for conventional technologies. Over the last few years, ANNs have been successfully applied across an extra ordinary range of problem domains, in areas as diverse as finance, medicine, physics, engineering, geology and hydrology. Indeed ANNs can be employed in problems of prediction, classification or control. During the last two decades, interest in ANNs has grown significantly because of their ability to represent nonlinear relationships that are difficult to model by means of other computational methods. ANNs are most robust than other modelling techniques in hydrology because of their ability to handle large variation of parameters. Owing to the complex and dynamic nature of various hydrologic processes, the ANN technique has become increasingly popular for hydrologic modelling in recent years.

The Artificial Neural Network (ANN) approach is extensively used in the water resource literature. ANN is a flexible mathematical structure, which is capable of identifying complex nonlinear relationships between input and output data sets. The ANN models have been found useful and efficient, particularly in problems for which the characteristics of the processes are difficult to describe using physical equations. An ANN model can compute complex nonlinear problems, which may be too difficult to represent by conventional mathematical equations. These models are well suited to situations where the relationship between the input variable and the output is not explicit. While the evaporation is a complex and nonlinear phenomenon, which depends on several interacting climatological factors, such as temperature, humidity, winds speed, bright sunshine hours, etc, Artificial Neural Networks (ANN) are effective tools to model the evaporation.

3.2.1 Analogies between nervous system and ANNs

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.

Biological neural networks like nervous systems can receive information from the senses at different location in the network. This information travels from neuron to neuron through the network, after which proper response to the information is generated. Biological neurons pass information to each other by releasing chemicals, which causes a synapse (a connection between neurons) to conduct an electric current. The receiving neuron can either pass this information to other neurons in the network or neglect its input, which causes damping of the impact of the information. This is an important characteristic of neurons and the artificial counterparts of biological neurons replicate it to a certain degree. There are many variations on the basic type of neuron, but all biological neurons have the same four basic components as shown in Fig. 2.

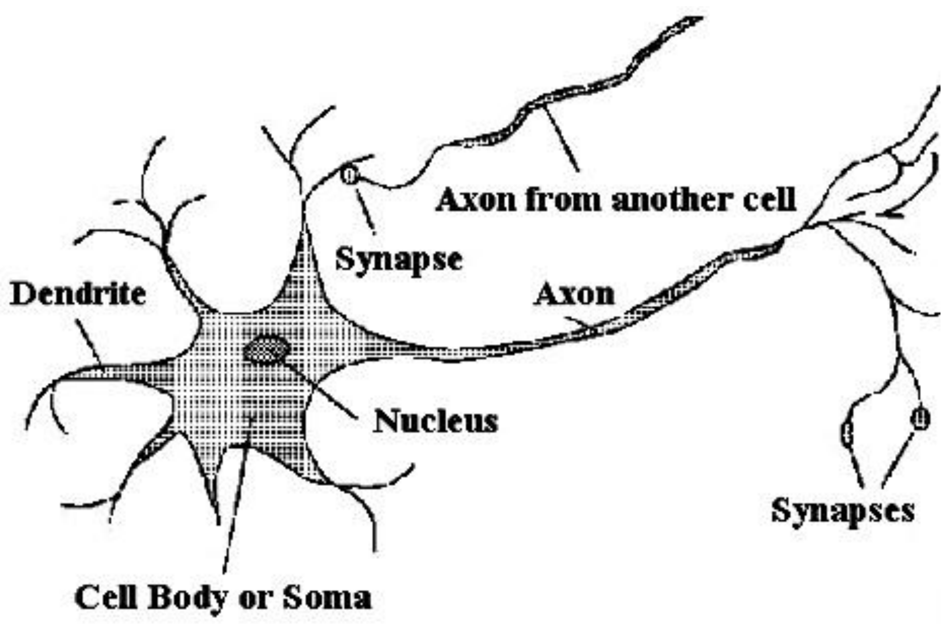

Fig.2 Biological neuron

Dendrite accept the input signal and the cell body or soma will process the input signal. The signals travelling along the axon of the pre-synaptic neuron trigger the release of neurotransmitter substances at the synapse.The neurotransmitters cause excitation or inhibition in the dendrite of the post-synaptic neuron. The integration of the excitatory and inhibitory signals may produce spikes in the post-synaptic neuron. The contribution of the signals depends on the strength of the synaptic connection.

3.2.2 Artificial neuron

Artificial Neurons are the building units or basic components of every Artifial Neural Network. An artificial neuron is a mathematical function conceived as a model of biological neurons. Each network has been formed from one input layer, one output layer and one or more hidden layer. The artificial neuron receives one or more inputs (representing dendrites) and sums them to produce an output (representing a neuron's axon). Usually the sums of each node are weighted and the sum is passed through a non-linear function known as an activation function or transfer function. The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions, step wise linear functions, or step functions.

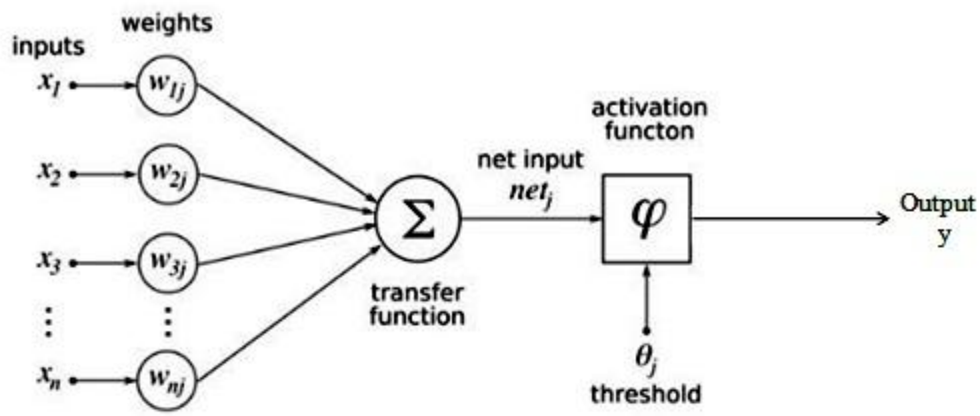

Fig.3 Schematic diagram of a Artificial Neural Network

Where $x_{1,}$ $x_{2,}$ .... x_n are the input signals, $w_{1j,}$ $w_{2j,}$ ……..w_{nj} are the synaptic weight, y is the output signal of the neuron and φ is the activation function.

The first step in a processing element's operation is the summation function, to compute the weighted sum of all the inputs. Mathematically, the inputs and the corresponding weights are vectors which can be represented ($x_{1,}$ $x_{2,}$ .... x_n) and ($w_{1j,}$ $w_{2j,}$ ……..w_{nj}). The total input signal is the dot product of these two vectors. The result of the summation function, usually the weighted sum, is transformed to a working output through an algorithmic process known as the transfer function. In the transfer function the summation total can be compared with some threshold to determine the neural output. The difference between the current output and the desired output is calculated through error function. The artificial neuron's error is then typically propagated into the learning function of another processing element. This error term is sometime called the current error.

3.3 Neural network methods

3.4.1 Multi layer perceptions (MLP) neural network

The MLP is the most popular network architecture in use today. A typical MLP has neurons arranged in a distinct layered topology, as shown in Fig.4. The input layer simply serves to introduce the values of the input variables. The hidden and output-layer neurons are each connected to all of the units in the preceding layer. Each hidden neuron in an ANN receives a number of inputs (either from original data or from the output of other neurons in the neural network). Each input comes via a connection that has a strength (or weight). Each neuron also has a single threshold value. The weighted sum of the inputs is formed, to compose the activation of the neuron (also known as the post-synaptic potential of the neuron). The activation signal is passed through an activation function (also known as a transfer function) to produce the output (or response) of the neuron.

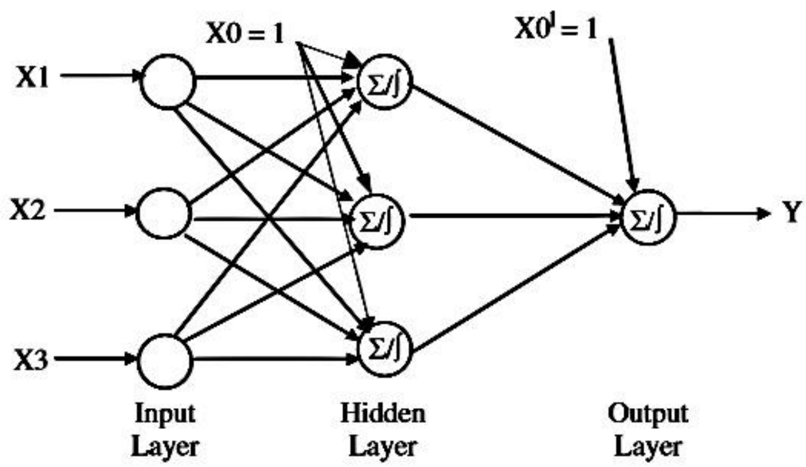

Fig.4 Structure of a typical MLP

3.3.2 Feed forward propagation neural networks (FFNN)

In this type of neural network architecture, there are layers and nodes at each layer. Each node at input and inner layers receives input values, processes and passes to the next layer. This process is conducted by weights. Weight is the connection strength between two nodes. The numbers of input layer and the output layer are determined by the numbers of input and output parameters, respectively.

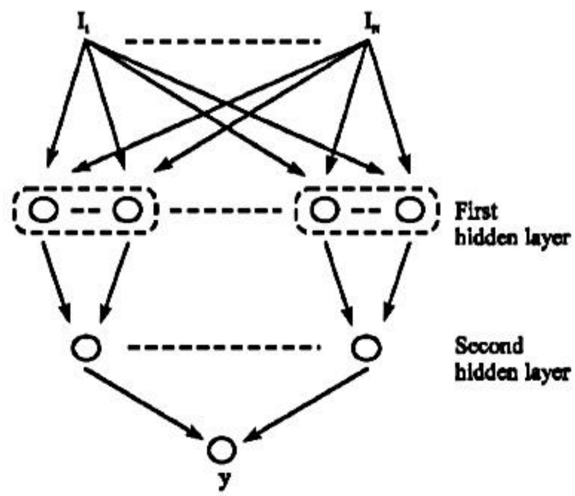

Fig.5 Feed forward propagation neural networks with two layers

3.3.3 Feed forward back propagation (FFBP)

Feed forward back propagation (FFBP) is the most commonly used ANN approach in hydrological predictions and in approximating nonlinear functions The FFBP is a supervised learning technique used for training ANN. Basically, it is a gradient descent technique to minimize some error criteria because of the method used in its training. Training is a process of adjusting the connection weights in the network so that the network's response best matches the desired response. Although this can be treated as an optimization method, the FFBP avoids this costly exercise by using an approximation to a gradient descent method. In this method during forward pass the outputs are calculated and the error at the output units calculated. In backward pass, the output unit error is used to alter weights on the output units. Then the error at the hidden nodes is calculated (by back-propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values.

3.3.4 Radial basis function (RBF) neural network

The theoretical basis of the RBF approach lies in the field of interpolation of multivariate functions. Radial basis function network consists of three layers. The input layer has neurons with a linear function that simply feed the input signals to the hidden layer. Moreover, the connections between the input and hidden layer are not weighted. The hidden neurons are processing units that perform the radial basis function. Radial basis functions have been applied in the area of neural networks where they may be used as a replacement for the sigmoidal hidden layer transfer characteristic in multi-layer perceptrons.

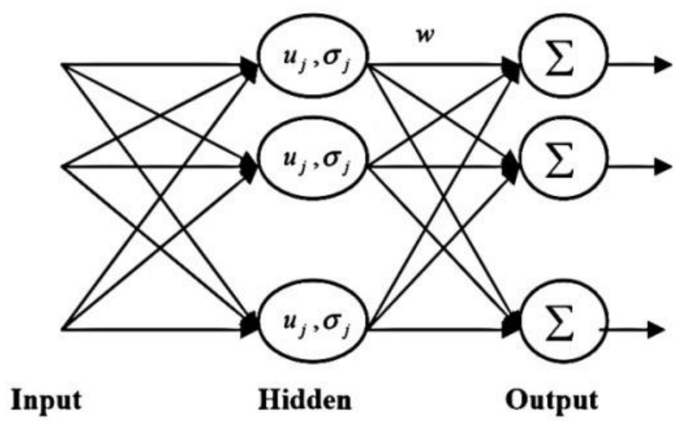

Fig.6 Radial basis function neural network structure

3.3.5 Generalized regression neural networks model (GRNNM)

Generalized regression neural networks model (GRNNM) is a modified form of radial basis function neural networks model (RBFNNM). GRNNM is composed of four layers, that is, the input layer, the hidden layer, the summation layer and the output layer. The input layer, the hidden layer, and the summation layer nodes are completely connected, whereas the output layer node is connected only with some of the summation layer nodes.

3.4 Back propagation training algorithm

Out of different methods for ANN technique back propagation method is used for this study.

Back propagation training algorithm is a supervised learning algorithm for multilayer feed forward neural network. Since it is a supervised learning algorithm, both input and target output vectors are provided for training the network. The error data at the output layer is calculated using network output and target output. Then the error is back propagated to intermediate layers, allowing incoming weights to these layers to be updated. This algorithm is based on the error- correction learning rule.

Basically, the error back-propagation process consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, input vector is applied to the network and its effect propagates through the network, layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with the error- correction rule. The actual response of the network is subtracted from a desired target response to produce an error signal. This error signal is then propagated backward through the network, against direction of synaptic connections - hence the name “error back-propagation”. The synaptic weights are adjusted so as to make the actual response of the network move closer the desired response. The back propagation algorithm calculates how the error depends on the output, inputs and weights. After which the weights and biases are updated.

3.5 Neural network architecture

Feed-forward networks have the following characteristics:

1. Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world and hence are called hidden layers.
2. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "feed forward" from one layer to the next, and this explains why these networks are called feed-forward networks.
3. There is no connection among perceptrons in the same layer.
4. The number of nodes in the input, hidden and output layer follows a pyramidal rule i.e, if you have 5 nodes in the input layer and 1 node in the output layer, then the hidden layer shall have 4 or 3 or 2 nodes. (5-4-1 or 5-3-1 or 5-2-1, see the hierarchy or pyramid structure here) However, this is just a general rule and need not be followed strictly.

3.6 Learning of a neural network

Learning is a fundamental component to a neural system, although a precise definition of learning is hard to make. In terms of an artificial neural network, learning typically happens during a specific training phase. Once the network has been trained, it enters a production phase where it produces results independently. Training can take on many different forms, using a combination of learning paradigms, learning rules and learning algorithms. A system which has distinct learning and production phases is known as a static network. Networks which are able to continue learning during production use are known as dynamical systems.

A learning paradigm is supervised, unsupervised or a hybrid of the two, and reflects the method in which training data is presented to the neural network. A method that combines supervised and unsupervised training is known as a hybrid method. A learning rule is a model for the types of methods to be used to train the system, and also a goal for what types of results are to be produced. The learning algorithm is the specific mathematical method that is used to update the inter-neuronal synaptic weights during each training iteration. Under each learning rule, there are a variety of possible learning algorithms for use. Most algorithms can only be used with a single learning rule. Learning rules and learning algorithms can typically be used with either supervised or unsupervised learning paradigms, however and each will produce a different effect.

Overtraining is a problem that arises when too many training examples are provided and the system becomes incapable of useful generalization. This can also occur when there are too many neurons in the network and the capacity for computation exceeds the dimensionality of the input space. During training, care must be taken not to provide too many input examples and different numbers of training examples could produce very different results in the quality and robustness of the network.

3.7 MATLAB

The software used for the development of the evaporation model of K.C.A.E.T campus, using ANN technique is MATLAB version 7.6.0.324 (R2008a).MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, we can analyze data, develop algorithms, and create models and applications. The language, tools, and built- in math functions enable to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java. MATLAB can be used for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing.

3.7.1 Key features

- High-level language for numerical computation, visualization and application development
- Interactive environment for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration and solving ordinary differential equations
- Built-in graphics for visualizing data and tools for creating custom plots
- Development tools for improving code quality and maintainability and maximizing performance • Tools for building applications with custom graphical interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages such as C, Java, .NET and Microsoft Excel

3.7.2 MATLAB work environment

When you start MATLAB, the desktop appears in its default layout.

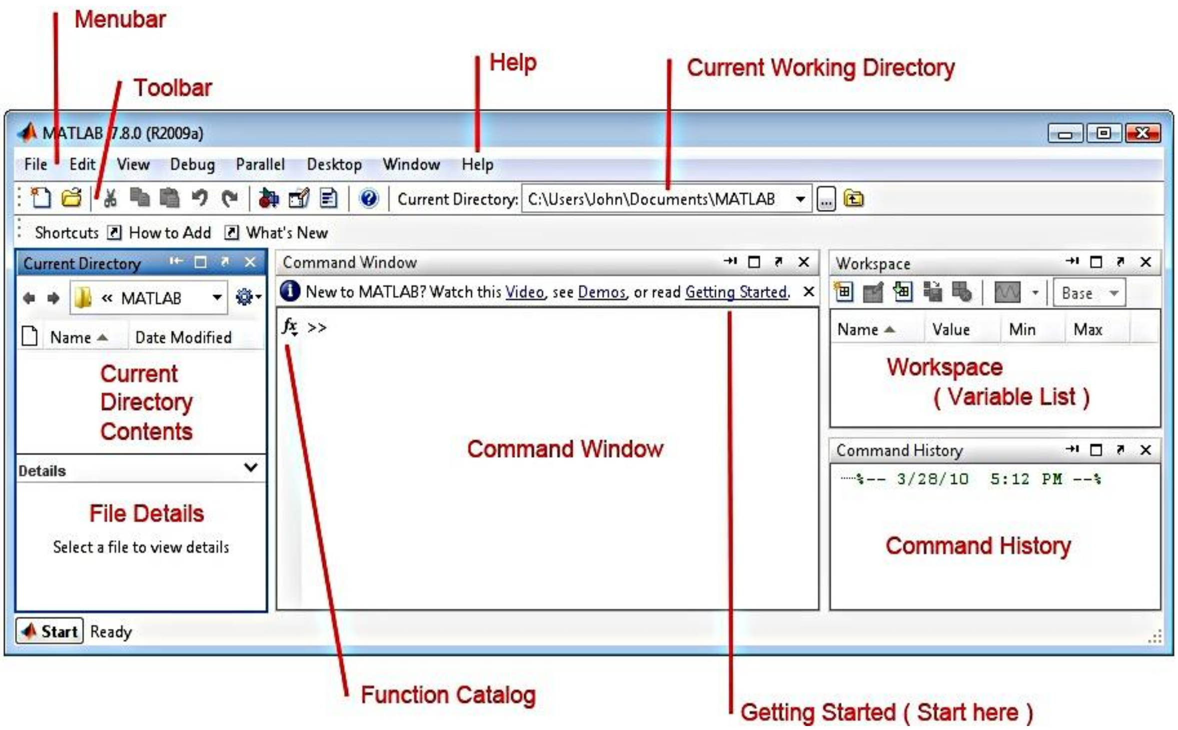

Fig.7 Working environment of MATLAB

The desktop includes these panels:

- Current Folder — Access files.
- Command Window — Enter commands at the command line, indicated by the prompt (>>).
- Workspace — Explore data that you create or import from files.

3.7.3 Neural network tools

Neural Network Toolbox™ provides functions and apps for modelling complex nonlinear systems that are not easily modelled with a closed-form equation. Neural network tool box supports supervised learning with feed forward, radial basis, and dynamic networks. It also supports unsupervised learning with self-organizing maps and competitive layers. With the tool box you can design, train, visualize and simulate neural networks. Neural network toolbox can be used for applications such as data fitting, pattern recognition, clustering, time-series prediction, and dynamic system modelling and control.

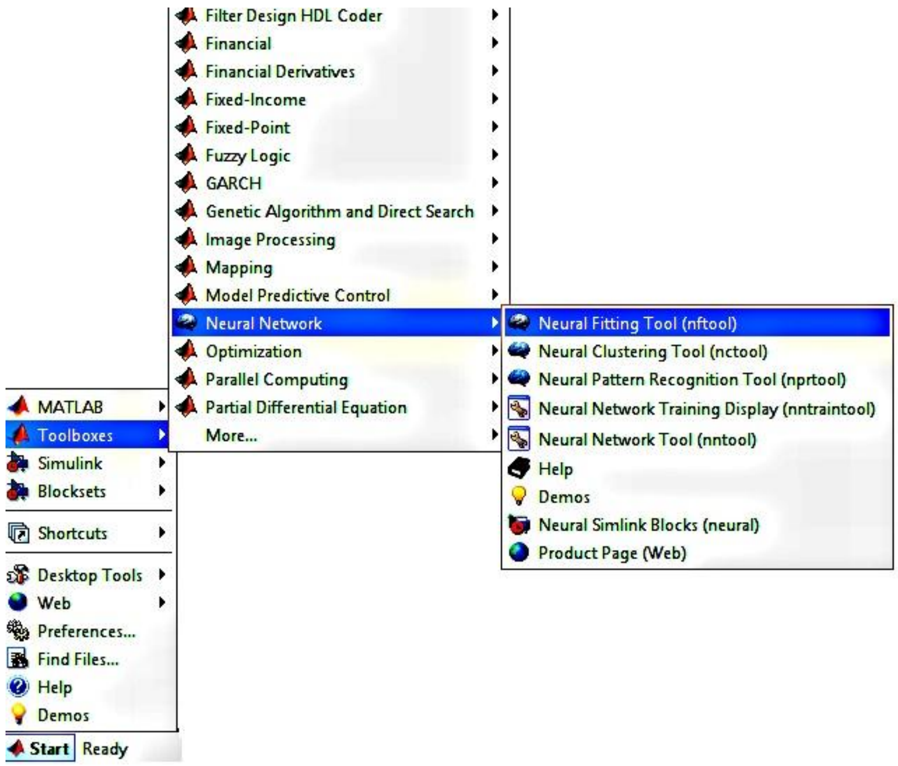

Fig.8 Neural network tool box of MATLAB

3.7.3.1 Neural fitting tool (nftool)

The neural network tool used for this study is neural fitting tool (nftool).

Neural fitting tool can solve an input-output fitting problem with two layer feed-forward neural network. The neural network is used to map between a data set of numeric inputs and a set of numeric targets. The neural network fitting tool will help to select data, create and train a network and evaluate the performance using mean square error and regression analysis.

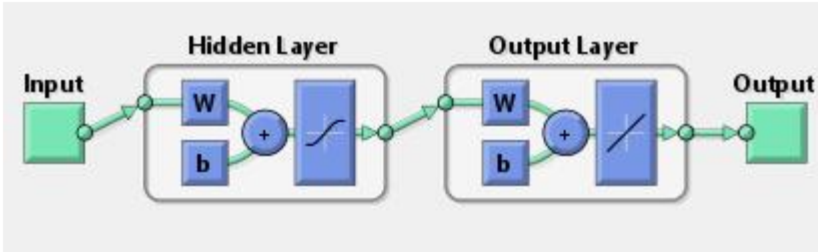

Fig.9 Representation of neural fitting tool

3.7.3.2 Neural clustering tool (nctool)

Neural clustering tool solve a clustering problem with a self- organizing map (SOM) network. In clustering problems a neural network is needed to group data by similarity. The nctool will help to select data and train network and evaluate its performance using a variety of visualization tools. A self- organizing map consists of a competitive layer which can clarify a dataset of vectors with any number of dimensions into as many classes as the layer has neurons. The network is trained with the SOM batch algorithm (trainubwb, learnsomb).

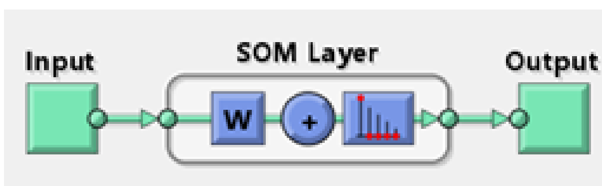

Fig.10. Representation of a neural clustering tool

3.7.3.3 Neural network pattern recognition tool (nprtool)

Network pattern recognition tool solve a pattern recognition problem with a two-layer feed- forward network. It requires a neural network to classify inputs into a set of target categories. This tool will help you to select data, create and train a network and evaluate its performance using mean square error and confusion matrices. A two-layer feed-forward network, with sigmoid hidden and output neurons (newpr), can classify vectors arbitrarily well, given enough neurons in its hidden layer. The network will be trained with scaled conjugate gradient backpropagation (trainscg).

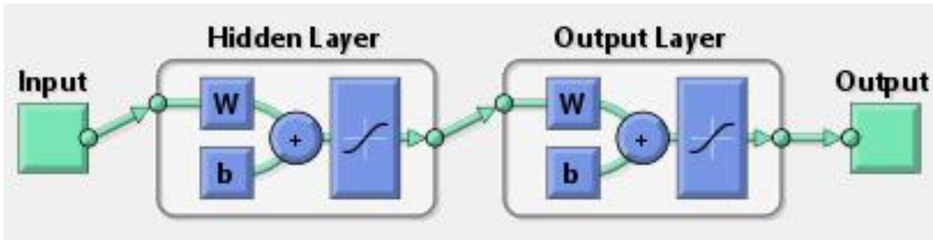

Fig.11 Representation of neural network pattern recognition tool

3.7.3.4 Neural network training display (nntraintool)

This function can be called to make the training GUI visible before training has occurred, after training if the window has been closed, or just to bring the training GUI to the front. Network training functions will handle all activity within the training window. To access additional useful plots, related to the current or last network trained, during or after training, click their respective buttons in the training window.

3.7.3.5 Neural network tool (nntool)

The nntool opens the Network/Data Manager window, which allows you to import, create, use, and export neural networks and data.

3.8 Development of neural network

3.8.1 Selection of data

Data were taken from meteorological observatory of K.C.A.E.T campus. The parameters considered are; monthly observation of wind speed (m/s), dry bulb temperature (^{o}C), wet bulb temperature (^{o}C), maximum temperature (^{o}C), minimum temperature (^{o}C) and evaporation (mm). For purpose of the study monthly observations from February 2003 to January 2009 is considered. The entire data is divided into three categories as pre-monsoon observations, monsoon observations and post monsoon observations. So each category consists of 24 observations of each parameter. The model development data set was further divided by randomly placing 75% of the observations in a training data set, 15% in a testing data set and the remaining 15% for validation of developed model. The training data set was used to develop the neural network models. The testing set was used to evaluate the accuracy of the ANN models during training in order to determine when to stop the training.

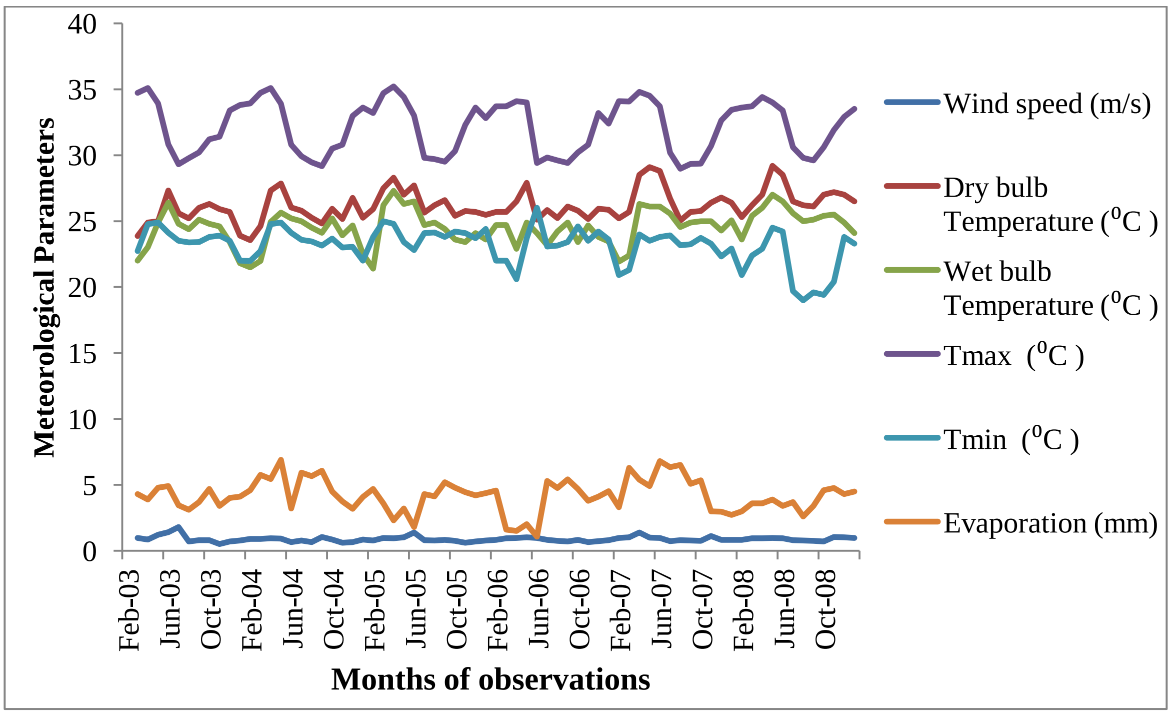

Fig.12 Graphical representation of meteorological parameters considered for the study

3.8.2 Uploading of input data

- The meteorological data is imported to the MATLAB workspace
- The input is a 24 x n matrix, which includes 24 observations of n variables, where n is the number of inputs considered in the particular strategy.
- Five different combinations of input parameters are considered for this study. The input parameters are the monthly observation of wind speed (m/s), dry bulb temperature (^{o}C), wet bulb temperature (^{o}C) and maximum and minimum temperature (^{o}C). The combinations selected for the study is given in the table below. The strategies selected for this study are;

Table.1 The strategies selected for the study

Input parameters	**Strategy M- 1**	**Strategy M-2**	**Strategy M-3**	**Strategy M-4**	**Strategy M-5**
Wind speed	✓		✓		
Dry bulb Temperature	✓	✓	✓	✓	
Wet bulb Temperature	✓	✓	✓	✓	
Maximum Temperature	✓	✓			✓
Minimum Temperature	✓	✓			✓

3.8.2.1 Classification of data

1. Pre-monsoon data – Monthly observations of parameters from February 2003 to May 2008. It includes total 24 observations.
2. Monsoon data – Monthly observations of parameters from June 2003 to September 2008. It includes total 24 observations.
3. Post monsoon data – Monthly observations of parameters from October 2003 to January 2009. It includes total 24 observations.

3.8.3 Selection of target

- Monthly observed Evaporation data corresponding to each season is selected as target.
- The target is a 24 x 1 matrix, which includes 24 observations of 1 variable

3.8.4 Network size selected

No.of hidden layer selected as 10 for the development of the neural network.

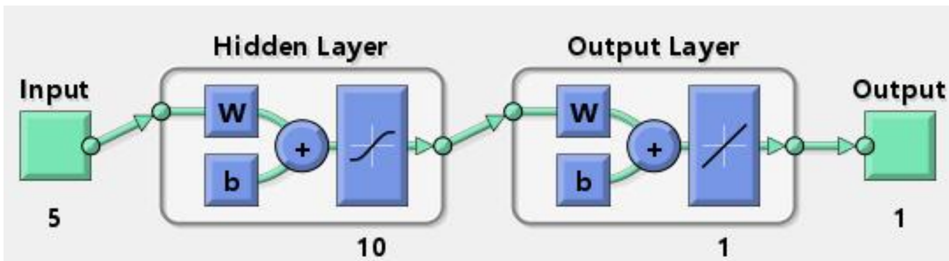

Fig.13 Representation of neural network for this study

The number of input will vary according to the strategy selected for developing the neural network. The number of hidden layer is considered as same for all the strategy.

3.8.5 Validation and Testing of data

Randomly divide up the 24 samples for training, validation and testing.

3.8.5.1 Training

- 16 samples were taken for training (about 70 % of total sample) procedure
- Train the network to fit the input and output.
- These samples were presented to the network during the training and network was adjusted according to its error.

- The network will be trained with Levenberg-Marquardt backpropagation algorithm (trainlm).
- Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.
- Training multiple times will generate different results due to different initial conditions and sampling.

3.8.5.2 Validation

- 4 samples were taken (15%)
- These samples were used to measure network generalization, and to halt training when generalization stops improving

3.8.5.3 Testing

- 4 samples were taken (15%)
- These samples have no effect on training and so provide an independent measure of network performance during and after training.

3.9 Levenberg-Marquardt (trainlm)

For the training of the created network, Levenberg-Marquardt (trainlm) network training function is used in this study.

Levenberg-Marquardt (trainlm) is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. trainlm is often the fastest backpropagation algorithm in the tool box, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms

In mathematics and computing, the Levenberg–Marquardt algorithm (LMA), also known as the damped least-squares (DLS) method, is used to solve non-linear least squares problems. These minimization problems arise especially in least squares curve fitting.

3.10 Mean squared error (MSE)

Mean Squared Error (MSE) is used for calculating the error which is obtained from the average squared difference between outputs and targets. Lower values are better. Zero means no error.

MSE is a network performance function. It measures the network's performance according to the mean of squared errors. In statistics, the mean squared error (MSE) of an estimator measures the average of the squares of the "errors", that is, the difference between the estimator and what is estimated.

3.12 Regression analysis

Regression is the process of fitting models to data. The process depends on the model. If a model is parametric, regression estimates the parameters from the data. If a model is linear in the parameters, estimation is based on methods from linear algebra that minimize the norm of a residual vector. If a model is nonlinear in the parameters, estimation is based on search methods from optimization that minimize the norm of a residual vector.

In statistical modelling, regression analysis is a statistical process for estimating the relationships among variables. It includes many techniques for modelling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables (or 'predictors'). More specifically, regression analysis helps one understand how the typical value of the dependent variable (or 'criterion variable') changes when any one of the independent variables is varied, while the other independent variables are held fixed.

Result and Discussion

4. RESULT AND DISCUSSION

The estimation of pan evaporation was carried out using ANN technique and MATLAB software and the results are discussed in this chapter.

4.1 Model development

The meteorological parameters of K.C.A.E.T campus had been examined and a corresponding evaporation model was developed. The entire meteorological data were divided into three different categories based on the rainfall season viz. pre-monsoon, monsoon and post monsoon and corresponding evaporation models were developed.

4.1.1 Pre-monsoon season

Pre-monsoon meteorological data included monthly observations of parameters from February 2003 to May 2008, total 24 observations. Five different combinations of input data were studied and the results are given below:

4.1.1.1 Observed evaporation v/s estimated evaporation

The plot between the observed evaporation and estimated evaporation showed the linear relationship with observed evaporation in x-axis and estimated evaporation in y-axis. The coefficient or regression (R^2) value was obtained from this plot, which defines the relation between the combination of the inputs selected for each strategy and the corresponding estimated evaporation. The plot between observed and estimated evaporation are shown in Fig. 14 to Fig. 18 and the R^2 value obtained from this figures indicated the correlation between estimated or observed evaporation.

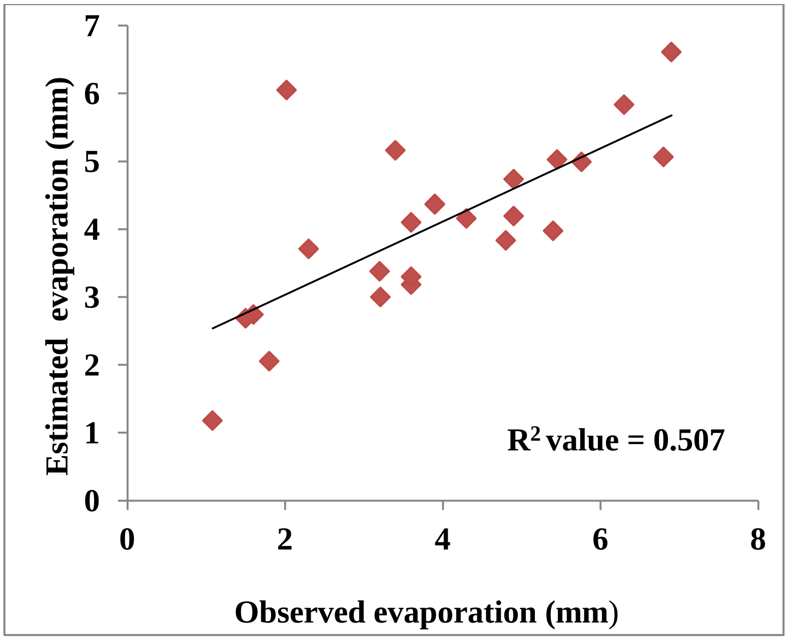

Fig. 14 Observed and estimated evaporation using ANN for strategy M- 1

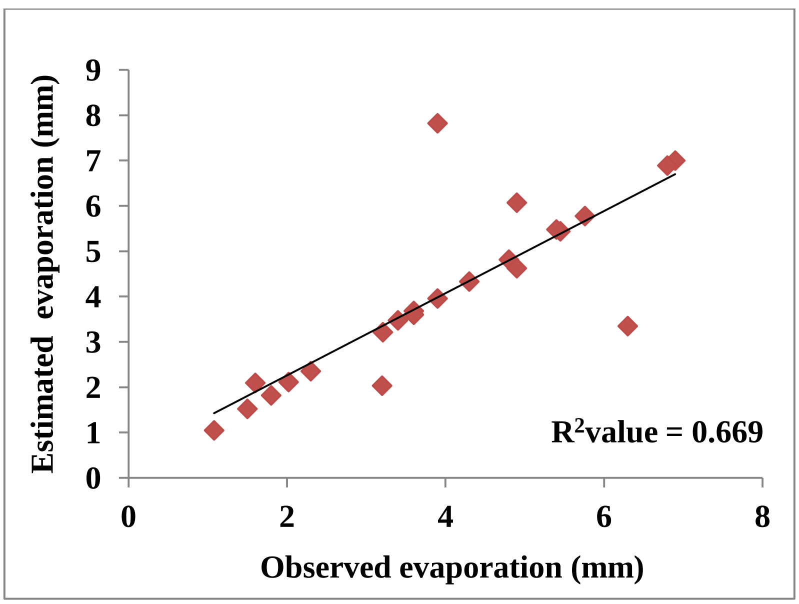

Fig. 15 Observed and estimated evaporation using ANN for strategy M- 2

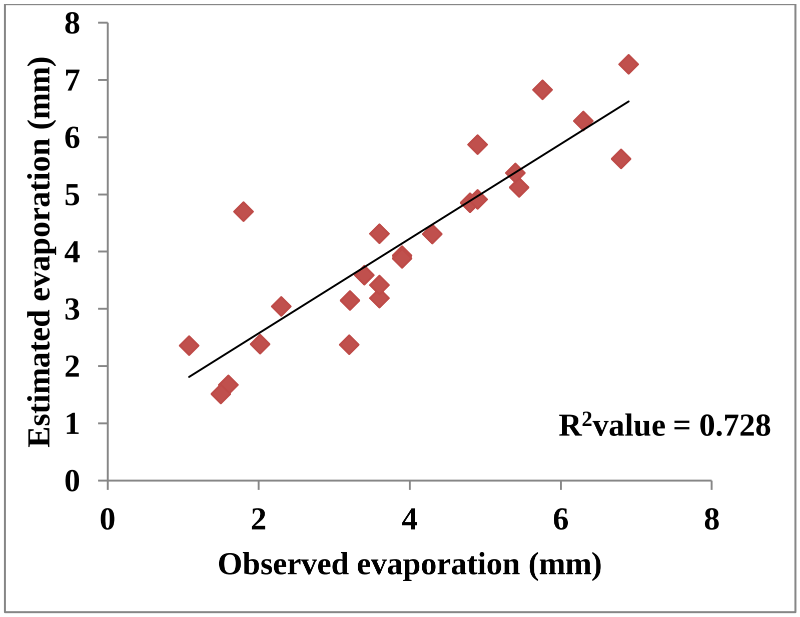

Fig. 16 Observed and estimated evaporation using ANN for strategy M- 3

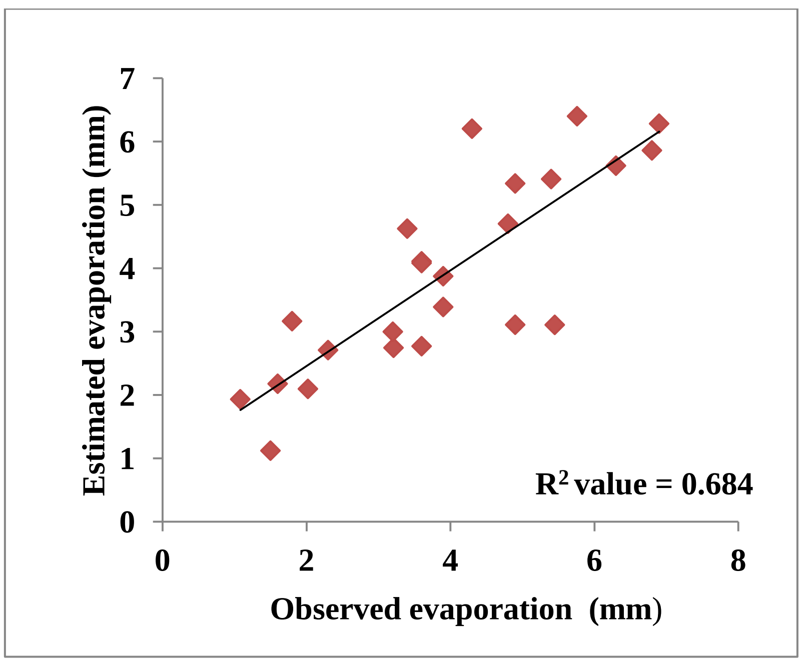

Fig. 17 Observed and estimated evaporation using ANN for strategy M- 4

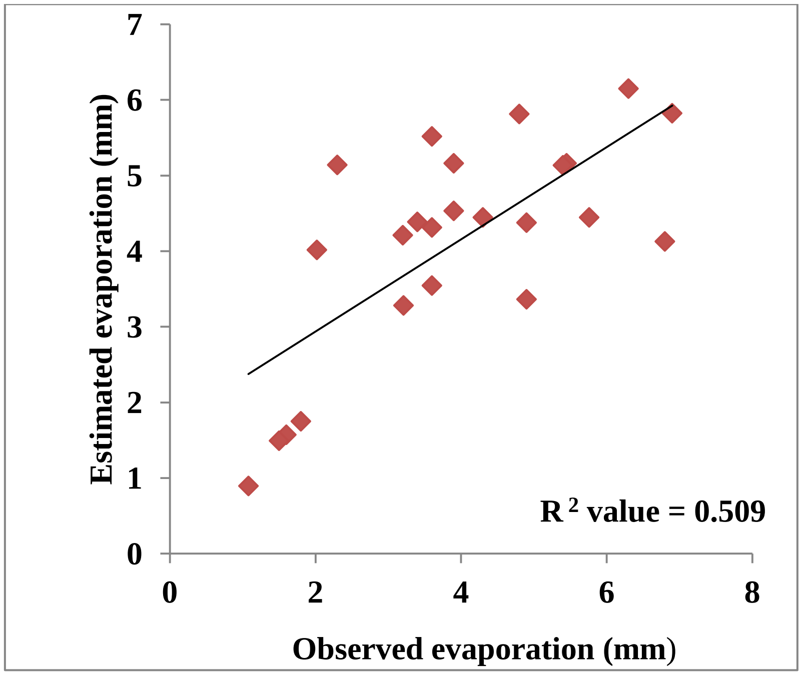

Fig. 18 Observed and estimated evaporation using ANN for strategy M- 5

4.1.1.2 Variation between observed and estimated data

The variation between the observed and estimated evaporation data can be obtained as mean squared error (MSE). The error can be represented graphically through a plot between the evaporation with time (months) in x-axis and evaporation in y-axis. This graph showed the accuracy of the field observation of the evaporation. The green line indicates the measured value or observed value from the meteorological observatory in the study area. The red line indicates the estimated value of the evaporation which was obtained through the ANN technique with the help of Matlab. Fig. 19 to Fig.23 showed the variation of observed and estimated evaporation with time for five strategies selected for the study respectively.

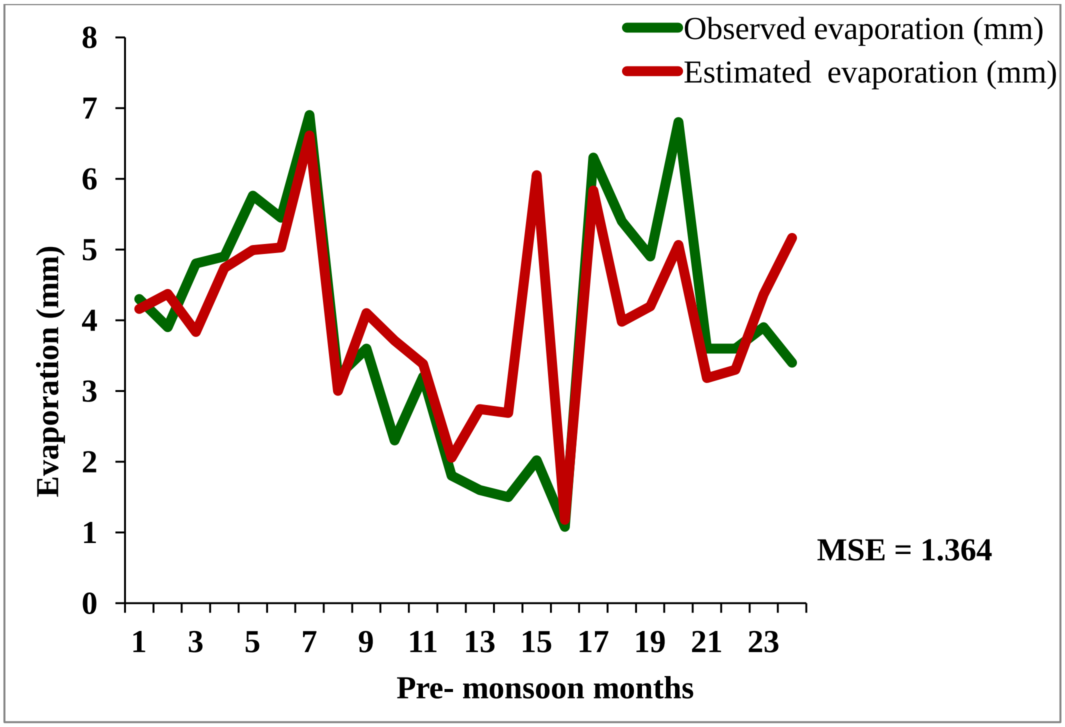

Fig. 19 Variation between observed and estimated evaporation for strategy M-1

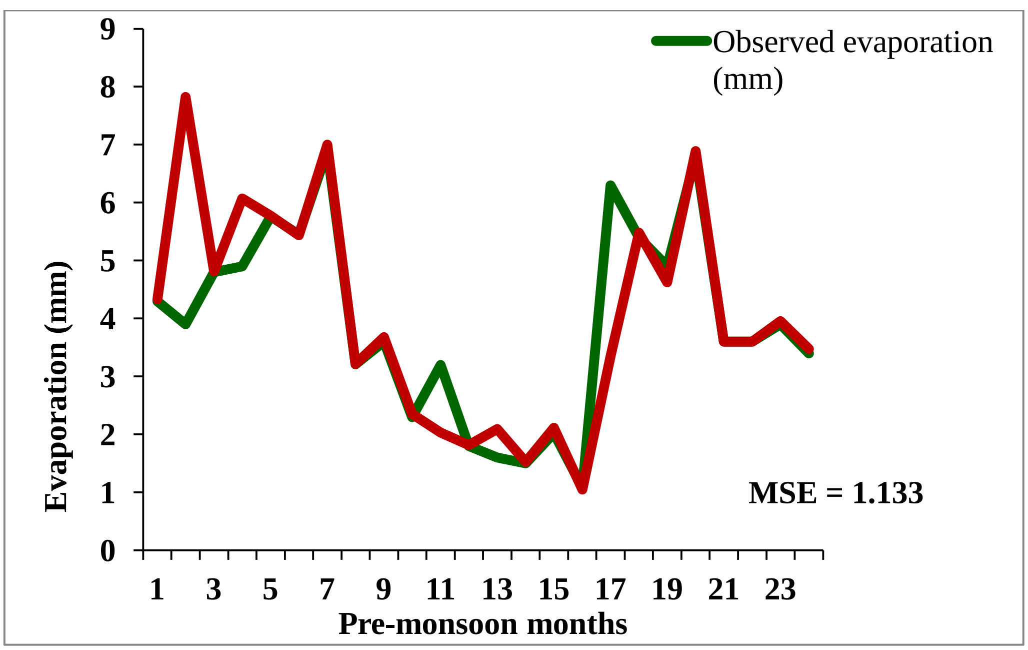

Fig. 20 Variation between observed and estimated evaporation for strategy M-2

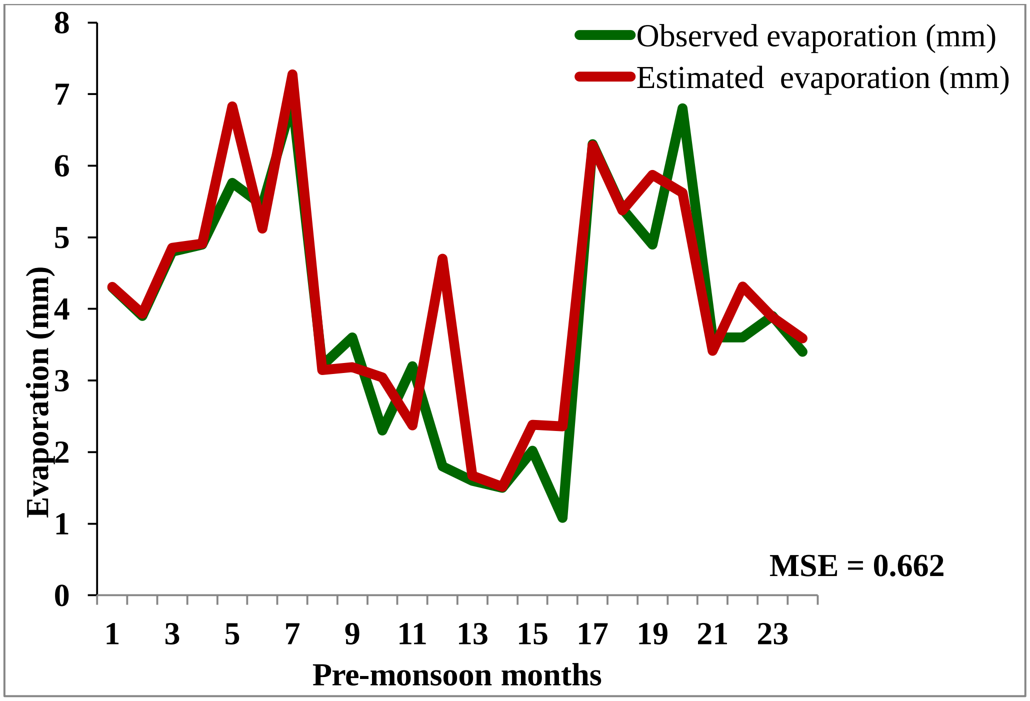

Fig. 21 Variation between observed and estimated evaporation for strategy M-3

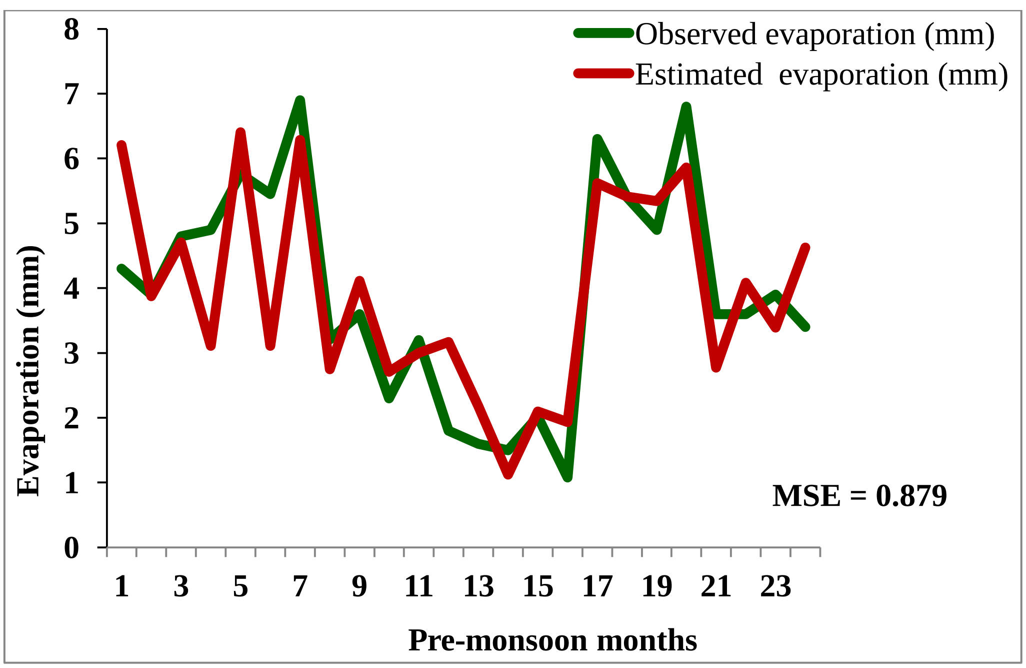

Fig. 22 Variation between observed and estimated evaporation for strategy M-4

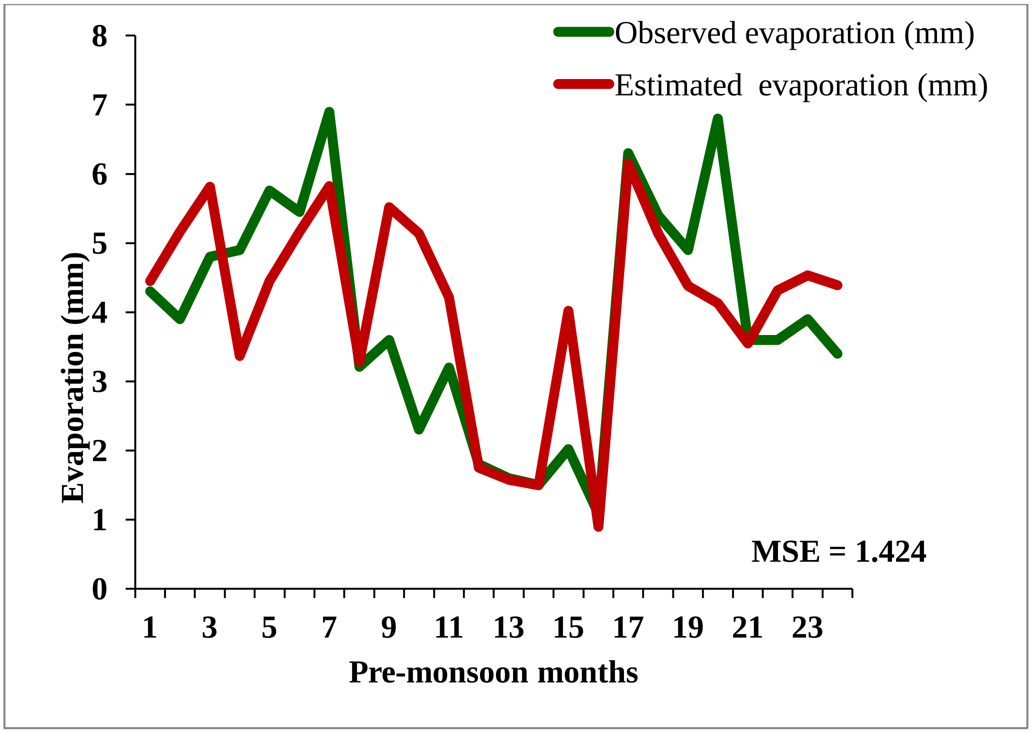

Fig. 23 Variation between observed and estimated evaporation for strategy M-5

The result obtained from this figures showed that, for strategy M- 3 which include wind speed, dry bulb and wet bulb temperature as the input parameters have least error and high R^2value as compared to other strategies. The MSE obtained for this strategy was 0.662 and the corresponding R^2 value was 0.728 which showed that the observed evaporation of strategy M-3 was most accurate as compared to other observed values of evaporation. The MSE value was increased to 0.879 and the corresponding R^2 value decreased to 0.684 for the strategy M-4 in which the input parameters considered were the dry bulb and wet bulb temperature. This result showed that the wind speed along with the dry bulb temperature and wet bulb temperature has greater influence on the evaporation of the area. The highest R^2 value indicated that the evaporation is mainly depend on the combination of independent variables such as wind speed, dry bulb and wet bulb temperature. The strategy M-1 has least R^2 value and this includes all the five parameters as the input. Individually all the parameters has influence on the evaporation in different way. But the combination of all the input has least influence as well as the combination with lesser parameters has good influence on the evaporation. The strategy M-5 has the highest MSE which was 1.424. This indicated that the observed evaporation corresponding to the combination of input variables of maximum temperature and minimum temperature has a high variation with the estimated evaporation through ANN technique. So this combination was least accurate for the evaporation modelling during pre-monsoon season. The obtained result is tabulated below.

Table. 2 MSE and R^2 value obtained for pre-monsoon season

Strategy	MSE	R^2 value
M- 1	1.364	0.507
M- 2	1.133	0.669
M- 3	0.662	0.728
M- 4	0.879	0.684
M- 5	1.424	0.509

4.1.2 Monsoon season

Monsoon meteorological data included monthly observations of parameters from June 2003 to September 2008, total 24 observations. The results obtained are given below;

4.1.2.1 Observed evaporation v/s estimated evaporation

The plot between the observed evaporation and estimated evaporation showed the linear relationship between the observed and estimated evaporation with observed evaporation in x-axis and estimated evaporation in y-axis. The R^2 value obtained from the Fig. 24 to Fig. 28 showed the correlation between the estimated and observed evaporation.

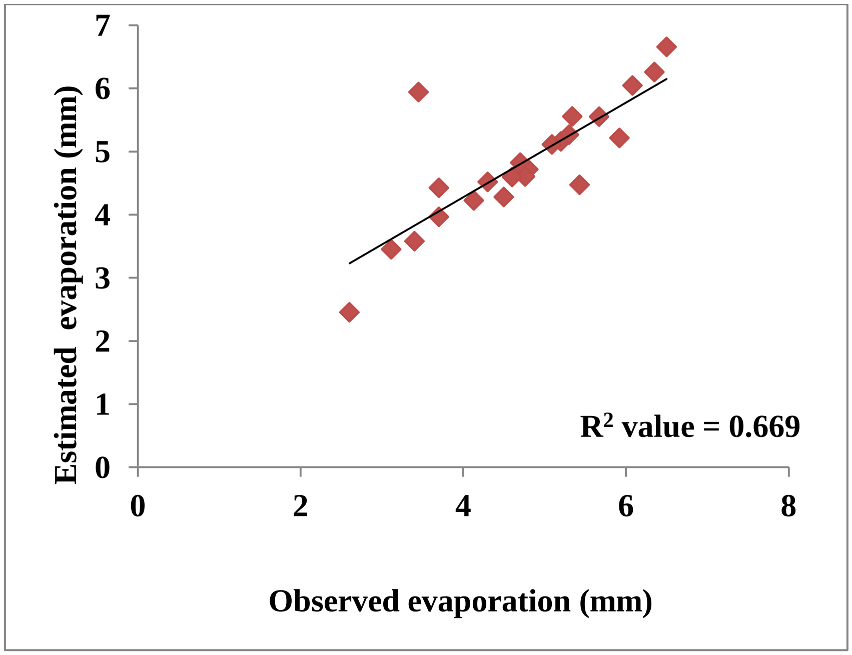

Fig. 24 Observed and estimated evaporation using ANN for strategy M-1

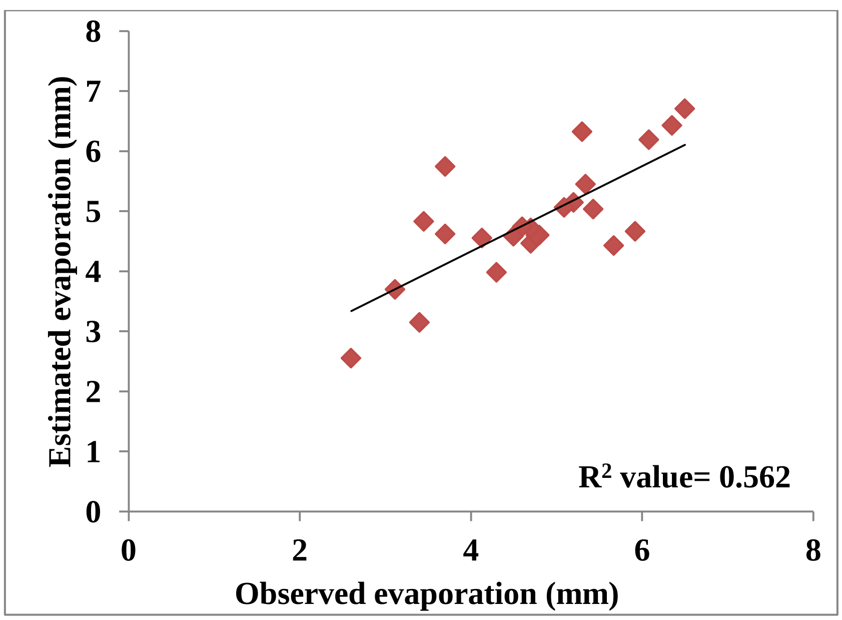

Fig. 25 Observed and estimated evaporation using ANN for strategy M-2

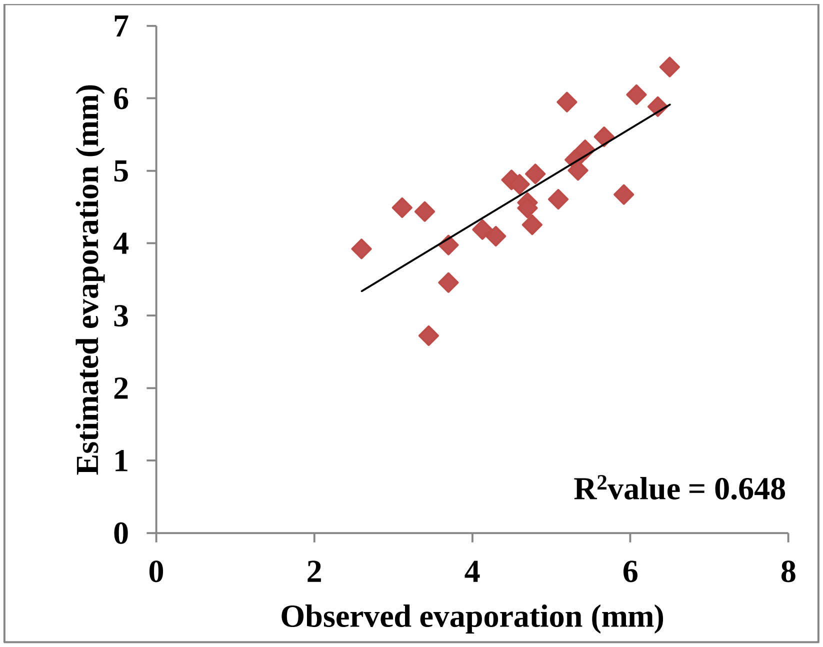

Fig. 26 Observed and estimated evaporation using ANN for strategy M- 3

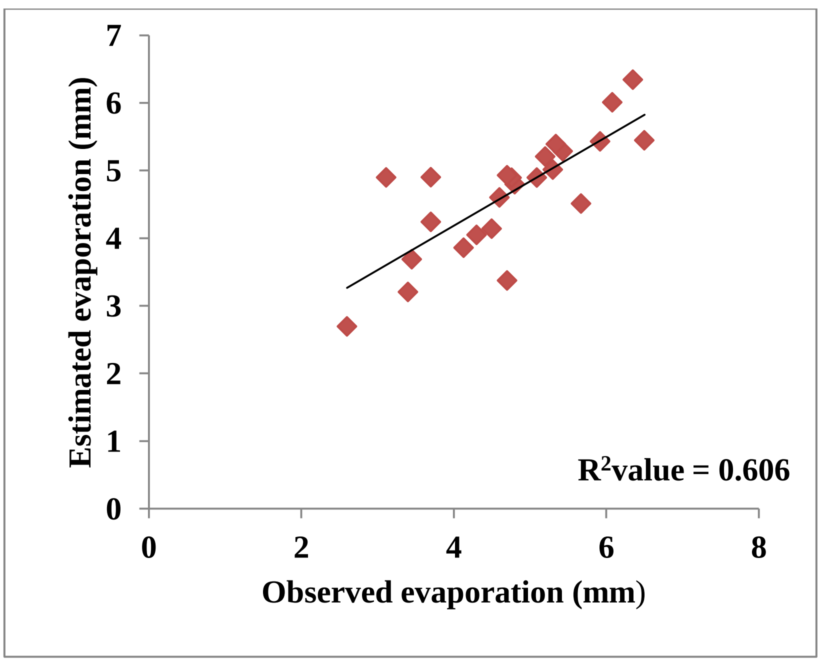

Fig. 27 Observed and estimated evaporation using ANN for strategy M- 4

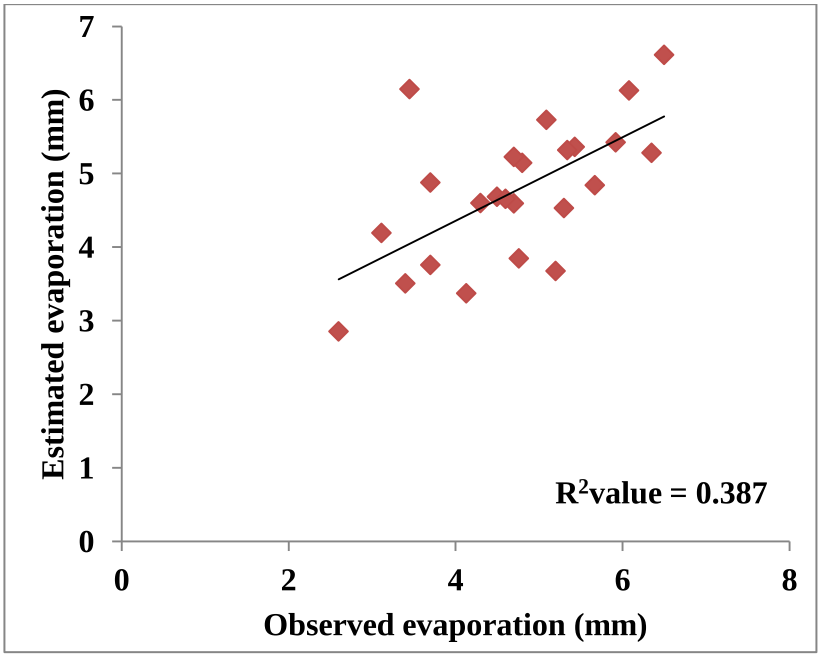

Fig. 28 Observed and estimated evaporation using ANN for strategy M-5

4.1.2.2 Variation between observed and estimated data

The variation between the observed and estimated evaporation data can be obtained as mean squared error (MSE). The error can be represented graphically through a plot between the observed and estimated data with time. In x-axis time of observation is taken which is denoted as monsoon months. In y-axis the values of observed and estimated evaporation is taken. Fig. 29 to Fig. 33 showed the variation of observed and estimated evaporation with time for five strategies selected for the study respectively.

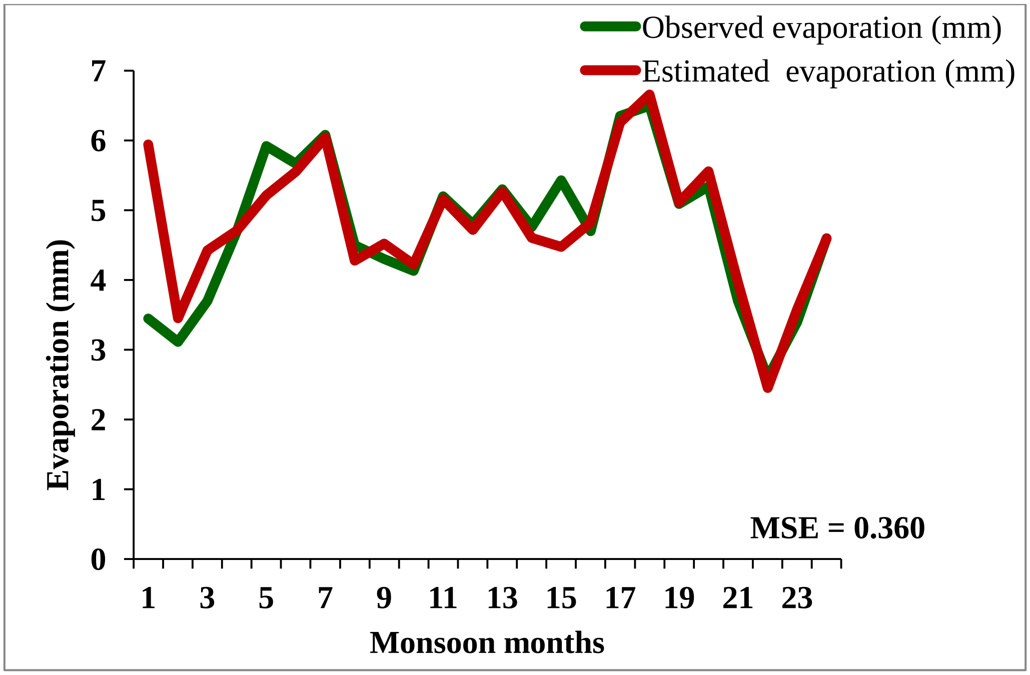

Fig. 29 Variation between observed and estimated evaporation for strategy M-1

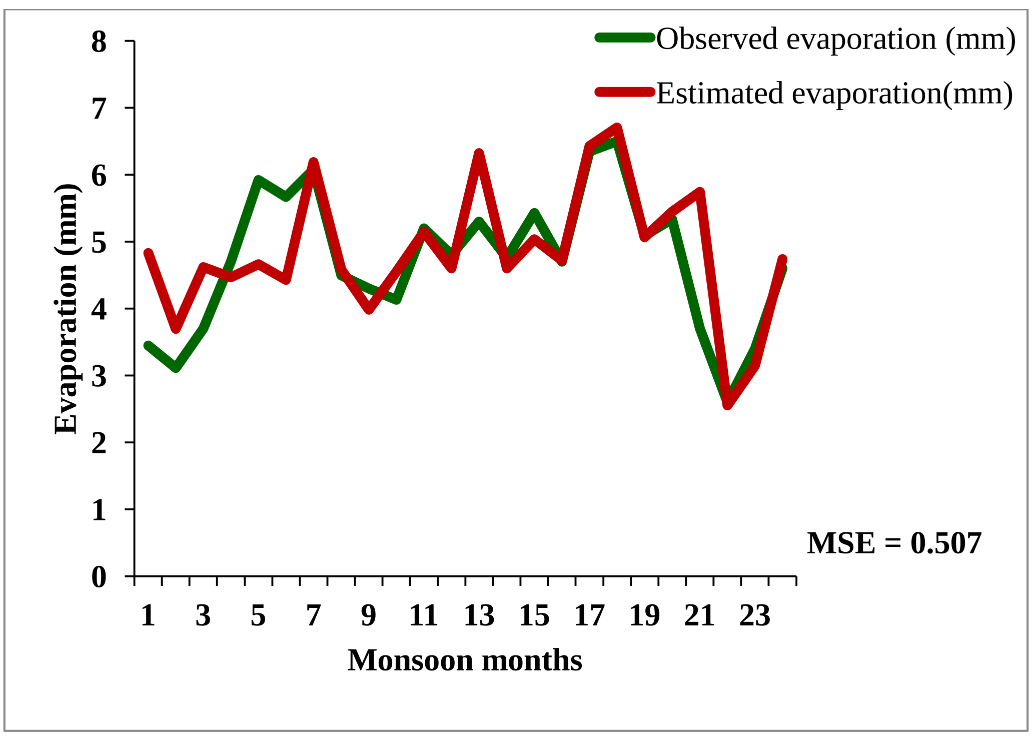

Fig. 30 Variation between observed and estimated evaporation for strategy M-2

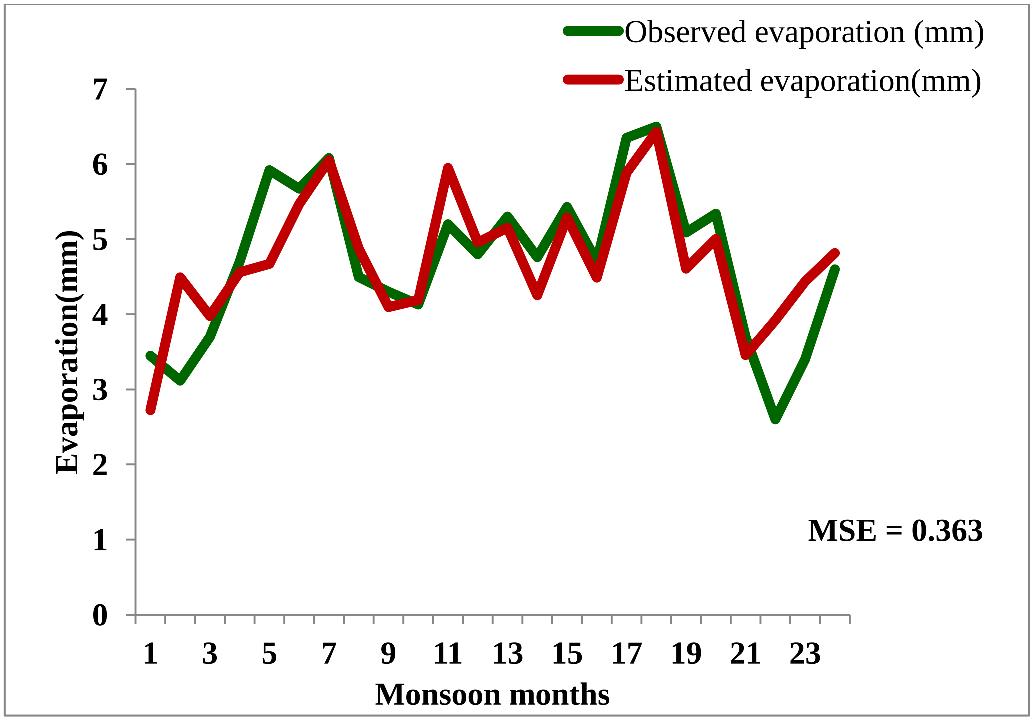

Fig. 31 Variation between observed and estimated evaporation for strategy M-3

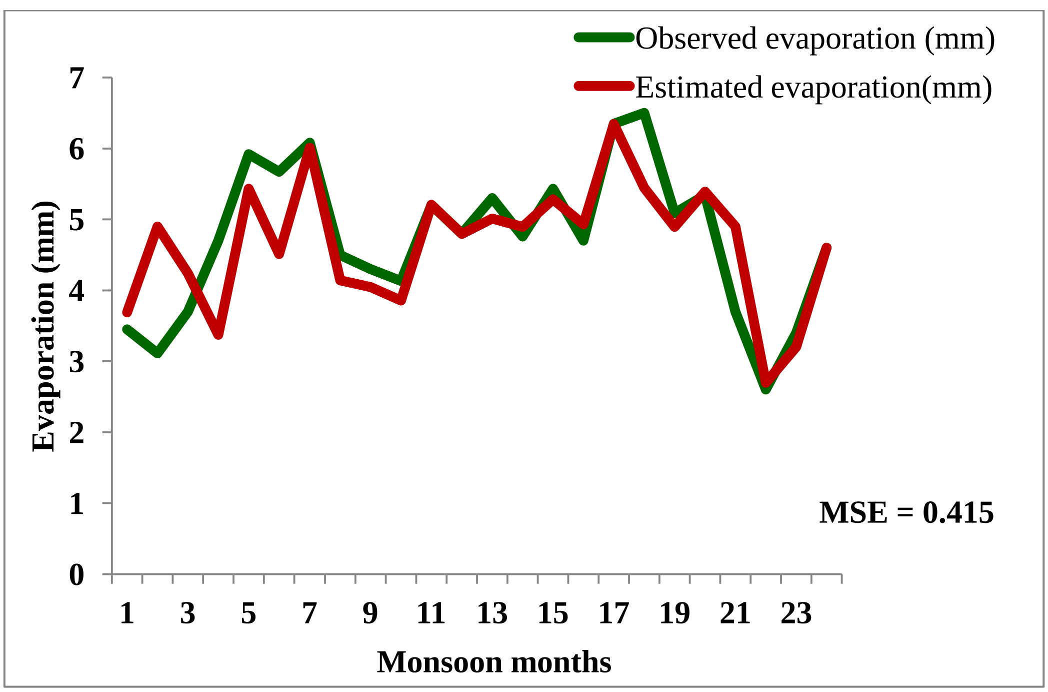

Fig. 32 Variation between observed and estimated evaporation for strategy M-4

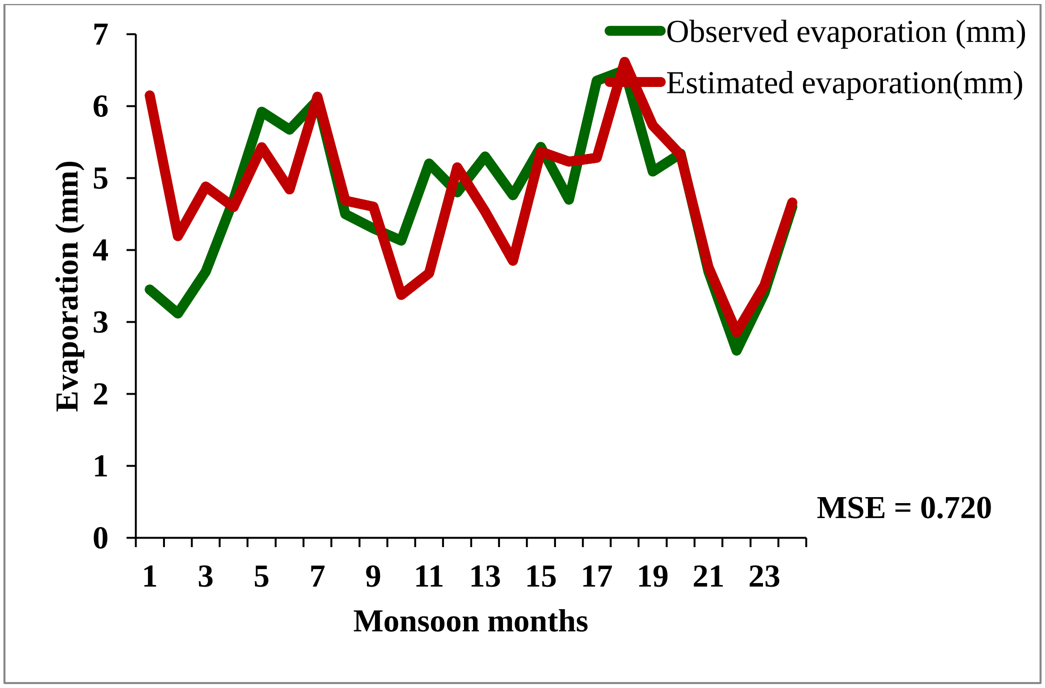

Fig. 33 Variation between observed and estimated evaporation for strategy M-5

The strategy M-1 which includes all the parameters as input variables has least MSE and highest R^2 value as compared to other strategies. It has the MSE value as 0.360 and has R^2 value is 0.669. In strategy M-3 which has the combination of wind speed, dry bulb temperature and wet bulb temperature as input parameters the MSE is increased to 0.363 as well as the strategy M-5 having maximum temperature and minimum temperature as the input variables have highest MSE of 0.720 which shows that the observed evaporation of strategy M-5 was least accurate as compared to other observed values of evaporation. In strategy M-5 the R^2value is decreased to0.387, it shows that the during monsoon seasons the maximum and minimum temperature has least significant role in the evaporation rate. As in the case of pre-monsoon season the evaporation rate is greatly influenced by the wind speed along with the dry bulb temperature and wet bulb temperature. Strategy M- 4, in which the dry bulb and wet bulb temperatures are the input variable has MSE of 0.415 and R^2value of 0.606 and the R^2 value for the strategy M-3 which has wind speed, dry bulb and wet bulb temperature as input parameters is 0.648. From this it was clear that the best combination for estimating evaporation rate was strategy M- 3 and these parameters has greater influence on the evaporation rate during monsoon .The result obtained is tabulated below;

Table. 3 MSE and R^2 value obtained for monsoon season

Strategy	**MSE**	**R^2 value**
M-1	0.360	0.669
M-2	0.507	0.562
M-3	0.363	0.648
M-4	0.415	0.606
M-5	0.720	0.387

4.1.3 Post monsoon season

Post monsoon data consists of monthly observations of parameters from October 2003 to January 2009, total 24 observations. Five different combinations of input data were studied and the results are given below;

4.1.3.1 Observed evaporation v/s estimated evaporation

The plot between the observed evaporation and estimated evaporation showed the linear relationship between the observed and estimated evaporation with observed evaporation in x-axis and estimated evaporation in y-axis. The coefficient or regression (R^2) value was obtained from this plot, which defines the relation between the combination of the inputs selected for each strategy and the corresponding estimated evaporation. The plot between observed and estimated evaporation are shown in Fig. 34to Fig. 38 and the R^2 value obtained from this figures indicated the correlation between estimated or observed evaporation.

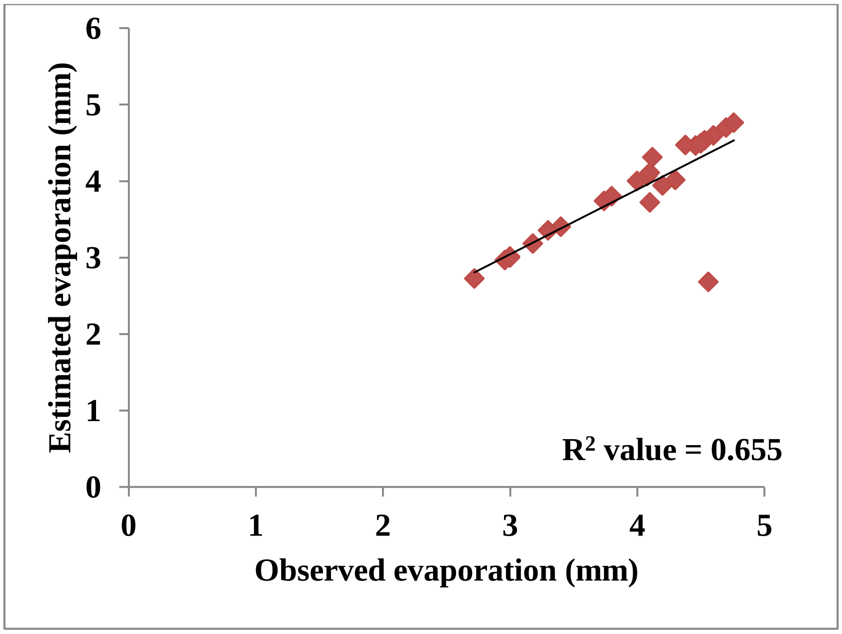

Fig. 34 Observed and estimated evaporation using ANN for strategy M- 1

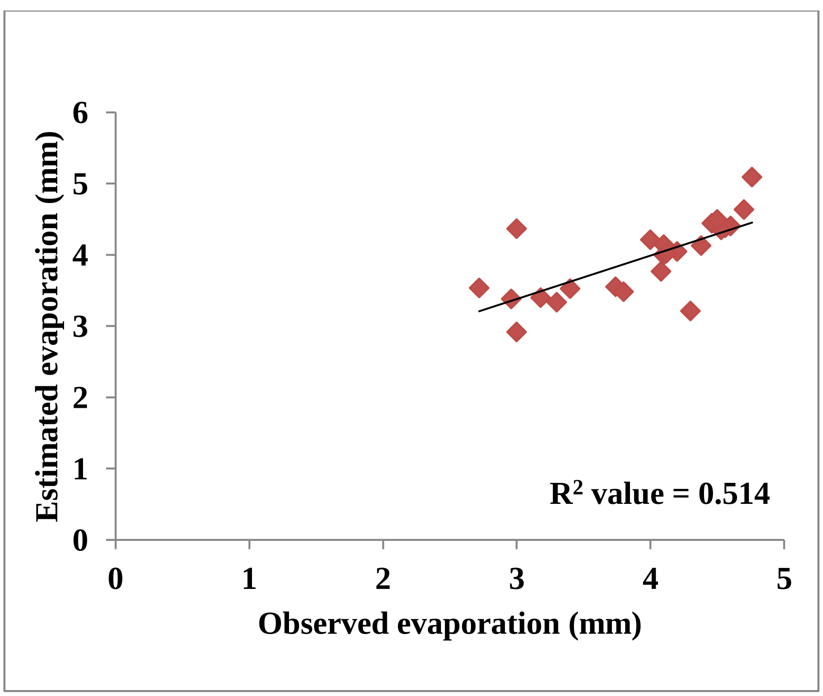

Fig. 35 Observed and estimated evaporation using ANN for strategy M- 2

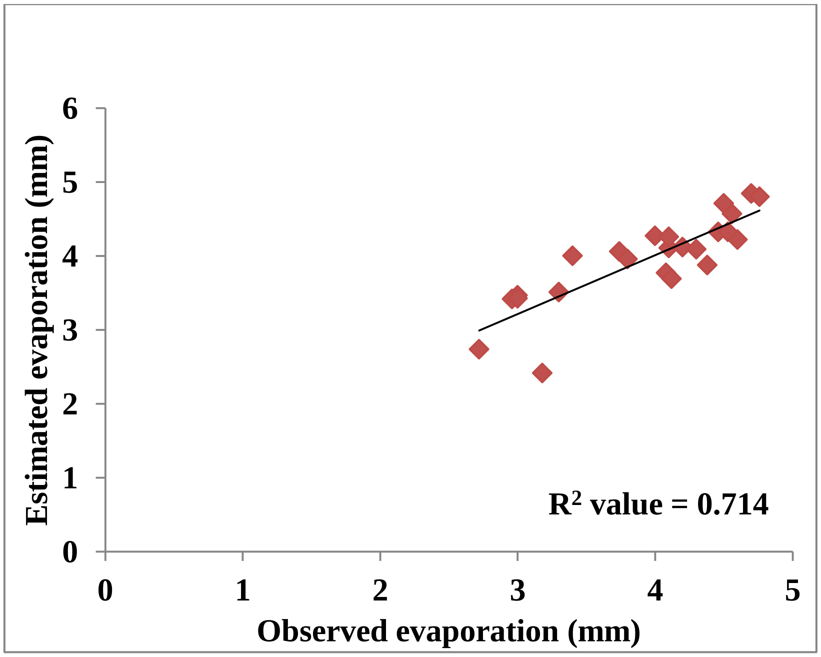

Fig. 36 Observed and estimated evaporation using ANN for strategy M-3

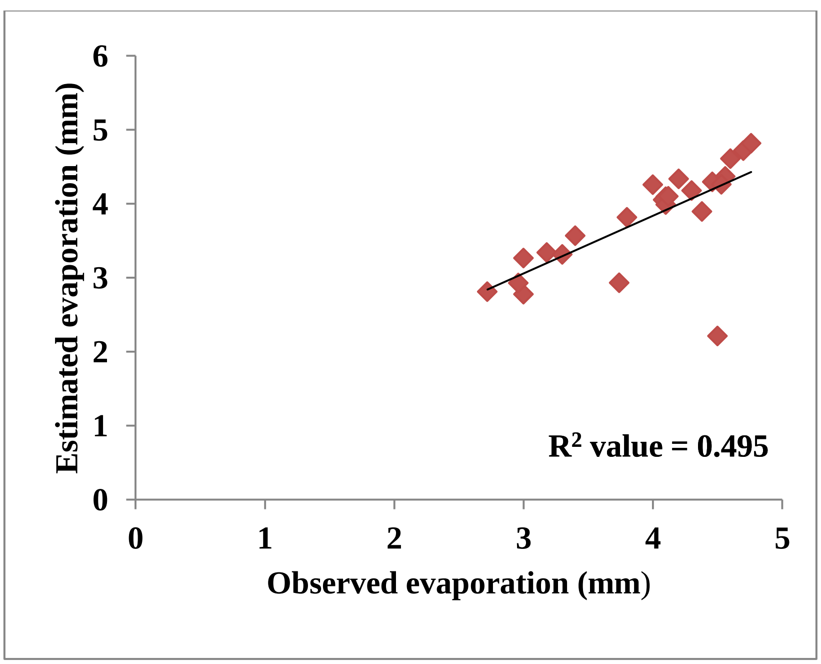

Fig. 37 Observed and estimated evaporation using ANN for strategy M-4

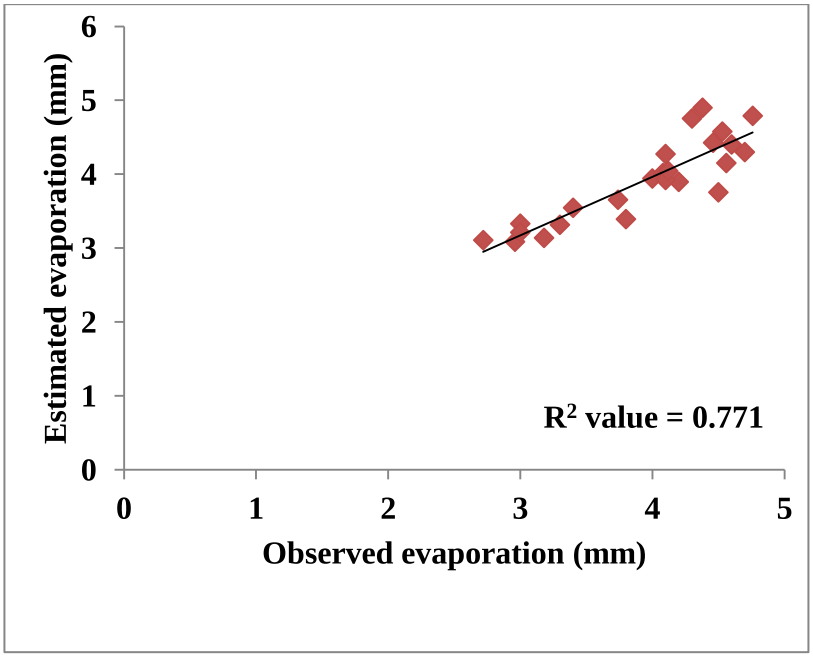

Fig. 38 Observed and estimated evaporation using ANN for strategy M- 5

4.1.3.2 Variation between observed and estimated data

The variation between the observed and estimated evaporation data can be obtained as mean squared error (MSE). The error can be represented graphically through a plot between the observed and estimated data with time (months) in x-axis and evaporation in y-axis. Fig. 39 to Fig. 43 showed the variation of observed and estimated evaporation with time for five strategies selected for the study respectively.

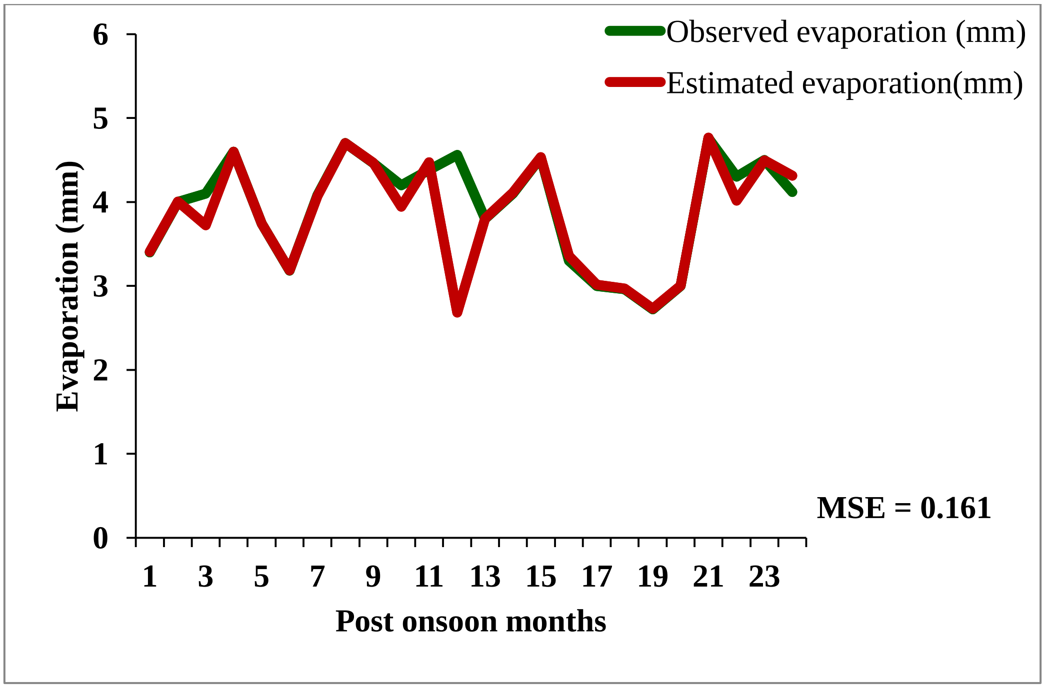

Fig. 39 Variation between observed and estimated evaporation for strategy M-1

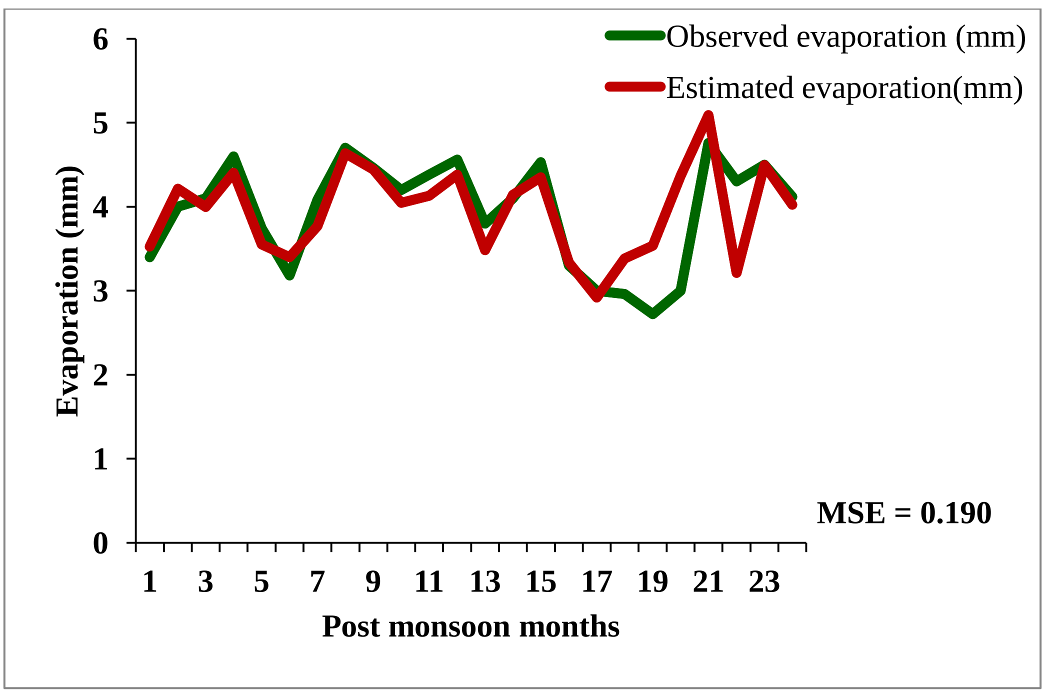

Fig. 40 Variation between observed and estimated evaporation for strategy M-2

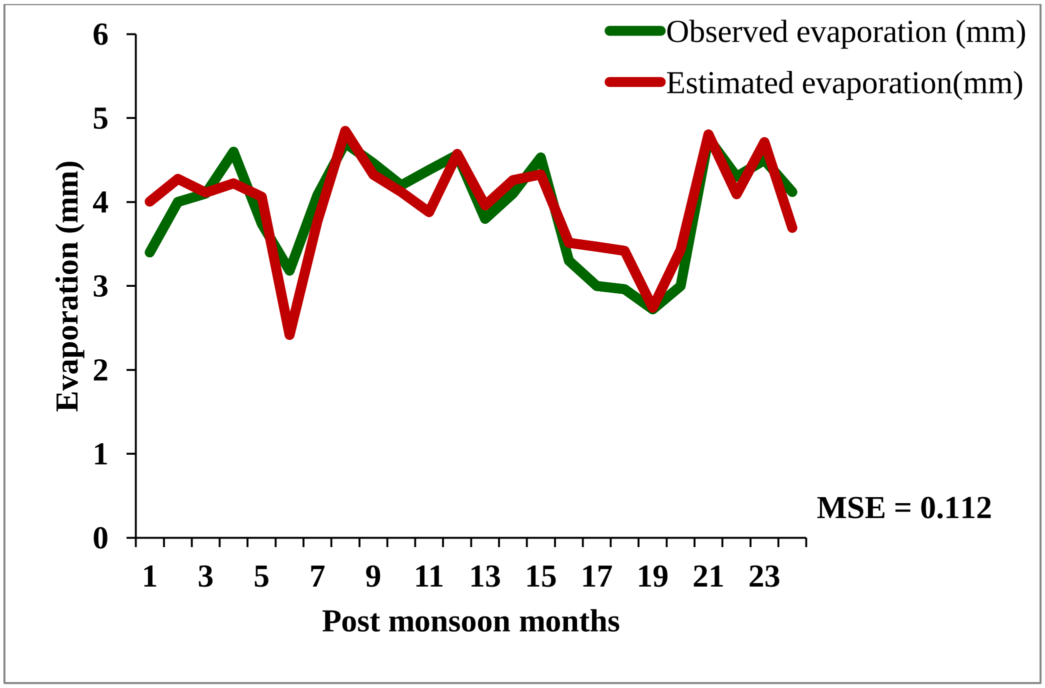

Fig. 41 Variation between observed and estimated evaporation for strategy M-3

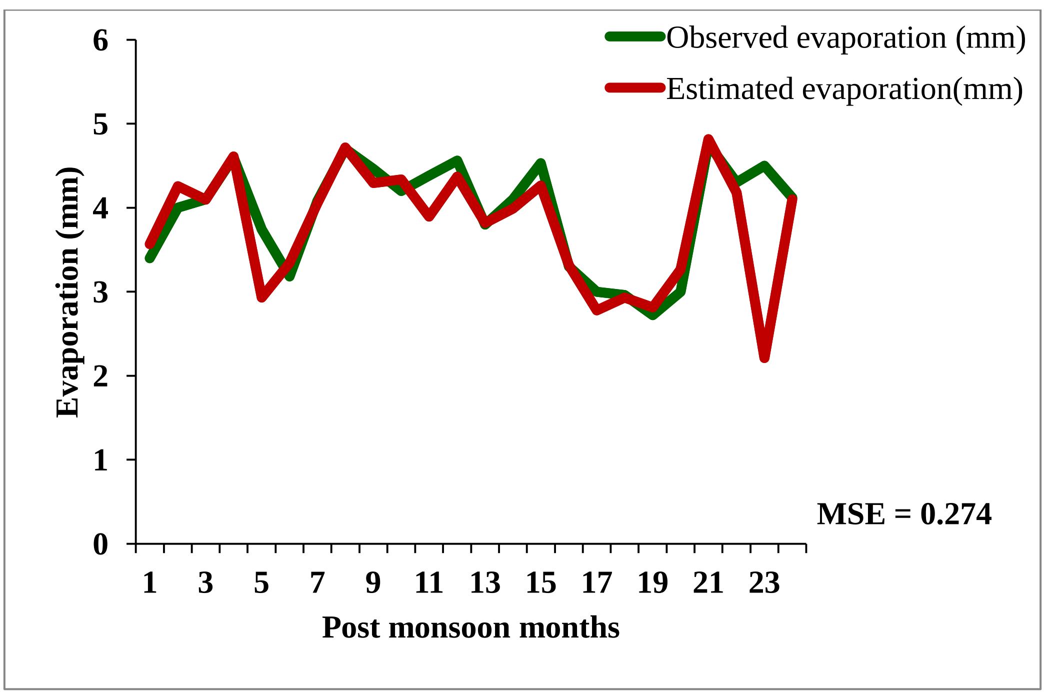

Fig. 42 Variation between observed and estimated evaporation for strategy M-4

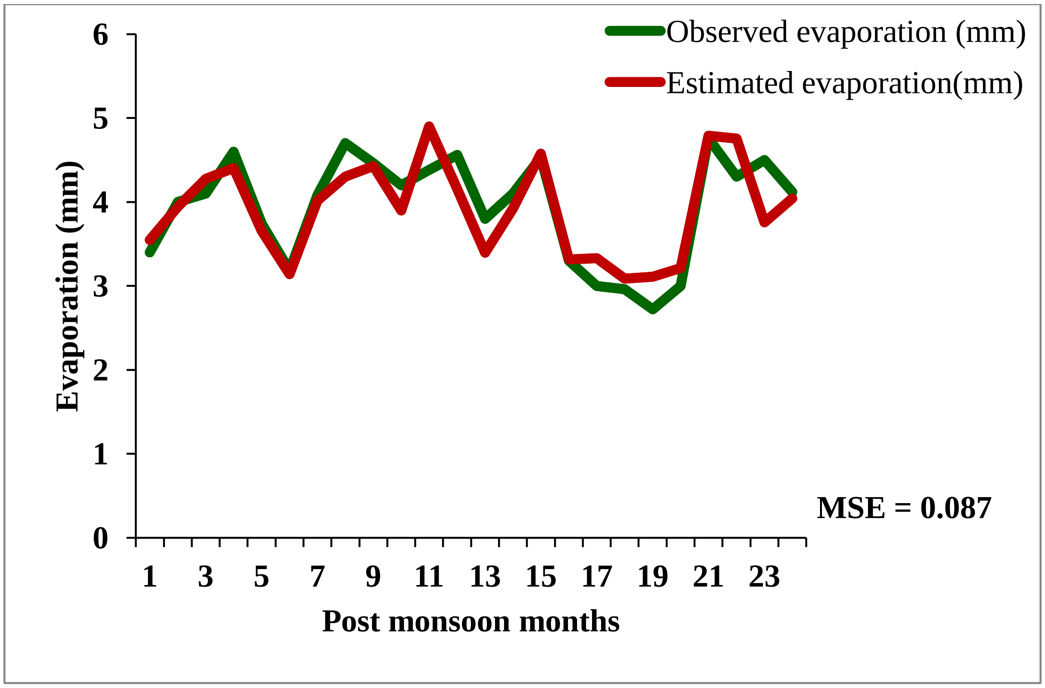

Fig. 43 Variation between observed and estimated evaporation for strategy M-5

The strategy M-5 has least MSE value as well as the strategy M-4 has highest MSE value. M-5th strategy has MSE as 0.0869 which has the combination of minimum and maximum temperatures as the input variables as well as the M-4th strategy has dry bulb and wet bulb were the input parameters and the obtained MSE was 0.273. The result showed that the observed evaporation of strategy M-5was most accurate as compared to other observed values of evaporation during post-monsoon season. The strategy M-5 has highest R^2value as well as the strategy M-4 has highest R^2value.

The R^2value of strategy M-5 is 0.771and it showed that the combination of maximum and minimum temperature has greater influence on the evaporation rate during post monsoon. The R^2value was reduced to 0.714 for the strategy M- 3 in which the wind speed, dry bulb temperature and wet bulb temperature was considered as the input variables. But in the case of M-4 strategy, in which the input variables considered were the dry bulb and wet bulb temperatures, has the R^2 value of 0.495 only. From this result it was clear that the wind speed along with the dry bulb temperature and wet bulb temperature has a significant role in the post monsoon evaporation rate. The results obtained are tabulated below;

Table. 4 MSE and R^2 value obtained for post monsoon season

Strategy	MSE	R^2 value
M-1	0.161	0.655
M-2	0.190	0.514
M-3	0.112	0.714
M-4	0.274	0.495
M-5	0.087	0.771

Summary and Conclusion

5. SUMMARY AND CONCLUSION

The objective of this study was to develop an evaporation model for the K.C.A.E.T. campus, Tavanur using Artificial Neural Network (ANN) technique and MATLAB software.

Monthly observations of meteorological parameters during the period February 2003 to January 2009 collected from meteorological observatory, K. C. A. E. T, Tavanur were used for the model development. The process of evaporation is complex and non-linear in nature with respect to the meteorological parameter which influences the evaporation. The neural network is a new tool which can solve the more complex modelling problems of estimating evaporation from pan, which may be difficult to solve by conventional mathematical equations and multiple linear regression.

Models were developed for three different seasons and the evaporation rate was estimated according to the various combinations of the inputs variables selected for the study. Meteorological parameters considered for the study were wind speed (m/s), dry bulb temperature (^{0}C), wet bulb temperature (^{0}C), maximum temperature (^{0}C) and minimum temperature. MATLAB software (ver. 7.6.0.324 (R2008a)) source code program was used for the ANN generation. The entire data was divided into three according to the seasons, pre-monsoon, monsoon and post monsoon and five different combinations of input parameters were used for model generation. The variables were imported to the MATLAB works space in the form of matrices. The neural fitting tool (nftool) was used for the model generation and the Levenberg- Marquardt (trainlm) network function was used for the training of created network. Mean squared error (MSE) obtained from the average squared difference between input and output, indicated the comparison of observed and estimated values of evaporation. Regression analysis was carried out to find out the relation between the observed and estimated evaporation data.

From this study, it could be seen that the wind speed had greater influence on the evaporation rate during all seasons. During pre-monsoon season the combination of wind speed, dry bulb temperature and wet bulb temperature highly influenced the evaporation rate. The MSE and R^2 value obtained for this combination is 0.662 and 0.728 respectively.

During monsoon season the combination of all input variable (strategy M-1) highly influenced the evaporation rate with least MSE and R^2 value and strategy M-3 with wind speed, dry bulb temperature and wet bulb temperature closely followed with MSE of 0.363 and R^2 value of 0.648. In the pre-monsoon season the combination of wind speed, dry bulb temperature and wet bulb temperature (strategy M- 3) has greater influence on the evaporation rate.

During post monsoon season the combination of maximum and minimum temperature (strategy M-5) highly influenced on evaporation with least MSE and high R^2 value of 0.087 and 0.771 respectively. The combination of the wind speed, dry bulb temperature and wet bulb temperature (strategy M-3) has also greater influence on evaporation with MSE value of 0.112 and R^2 value of 0.714. This inferred that during post monsoon season the wind speed along with the dry bulb temperature and wet bulb temperature has greater influence on the evaporation rate.

Out of the five strategies considered for the study, the strategy with wind speed, dry bulb temperature and wet bulb temperature (strategy M- 3) was found to be the accurate combination for the estimation of evaporation during all the seasons with comparatively least MSE and high R^2 value when compared with other strategies. Hence, it can be concluded that the combination of wind speed, dry bulb temperature and wet bulb temperature has great influence on the evaporation during all seasons.

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APPENDICES

APPENDIX I

Meteorological data for pre-monsoon months (February 2003 to May 2008)

Sl.No.	Months	Wind speed (mm)	Dry bulb Temperature (^oC)	Wet bulb Temperature (^oC)	Tmax (^oC)	Tmin (^oC)	Evaporation (mm)
1	Feb 03	0.98	23.87	22	34.72	22.72	4.3
2	March 03	0.85	24.88	23.03	35.1	24.77	3.9
3	April 03	1.21	25	24.89	33.92	24.9	4.8
4	May 03	1.41	27.33	26.4	30.81	24.12	4.9
5	Feb 04	0.9	24.62	21.97	34.72	22.72	5.76
6	March 04	0.96	27.32	24.94	35.1	24.77	5.45
7	April 04	0.92	27.85	25.65	33.9	24.9	6.9
8	May 04	0.65	26.04	25.2	30.8	24.12	3.21
9	Feb 05	0.98	27.5	26.2	34.7	25	3.6
10	March 05	0.96	28.3	27.3	35.2	24.8	2.3
11	April 05	1.03	27	26.3	34.4	23.4	3.2
12	May 05	1.4	27.7	26.5	33	22.8	1.8
13	Feb 06	0.96	25.7	24.7	33.7	22	1.6
14	March 06	0.98	26.5	22.9	34.1	20.6	1.5
15	April 06	1.03	27.9	24.9	34	23.7	2.02
16	May 06	0.97	25.1	24.1	29.4	26	1.08
17	Feb 07	1.02	25.7	22.4	34.07	21.3	6.3
18	March 07	1.4	28.5	26.3	34.8	24	5.4
19	April 07	0.99	29.1	26.1	34.5	23.5	4.9
20	May 07	0.98	28.8	26.1	33.7	23.8	6.8
21	Feb 08	0.96	26.2	25.4	33.7	22.4	3.6
22	March 08	0.94	27	26	34.4	22.9	3.6
23	April 08	0.97	29.2	27	34	24.5	3.9
24	May 08	0.96	28.5	26.5	33.4	24.2	3.4

APPENDIX II

Meteorological data for monsoon months (June 2003 to September 2008)

Sl.No.	Months	Wind speed (m/s)	Dry bulb Temperature (^oC)	Wet bulb Temperature (^oC)	Tmax (^oC)	Tmin (^oC)	Evaporation (mm)
1	June 03	1.79	25.6	24.8	29.3	23.5	3.45
2	July 03	0.71	25.2	24.37	29.78	23.375	3.114
3	August 03	0.81	26	25.1	30.2	23.4	3.7
4	September 03	0.8	26.3	24.8	31.2	23.8	4.7
5	June 04	0.78	25.8	25	29.91	23.58	5.92
6	July 04	0.654	25.25	24.5	29.45	23.45	5.67
7	August 04	1.06	24.83	24.12	29.16	23.15	6.08
8	September 04	0.857	25.93	25.21	30.51	23.67	4.498
9	June 05	0.81	25.65	24.7	29.8	24.1	4.3
10	July 05	0.78	26.2	24.9	29.7	24.13	4.13
11	August 05	0.82	26.6	24.4	29.5	23.8	5.2
12	September 05	0.76	25.4	23.6	30.3	24.2	4.8
13	June 06	0.83	25.83	23.16	29.83	23.08	5.3
14	July 06	0.75	25.24	24.2	29.6	23.14	4.76
15	August 06	0.72	26.1	24.9	29.4	23.42	5.43
16	September 06	0.84	25.8	23.4	30.2	24.6	4.7
17	June 07	0.73	26.7	25.57	30.18	23.91	6.35
18	July 07	0.81	25.03	24.54	28.96	23.16	6.5
19	August 07	0.78	25.68	24.88	29.34	23.24	5.09
20	September 07	0.76	25.77	25	29.37	23.73	5.34
21	June 08	0.8	26.5	25.6	30.6	19.7	3.7
22	July 08	0.78	26.2	25	29.8	19	2.6
23	August 08	0.75	26.1	25.1	29.6	19.6	3.4
24	September 08	0.72	27	25.4	30.6	19.4	4.6

APPENDIX III

Meteorological data for post monsoon months (October 2003 to January 2009)

Sl.No.	Months	Wind speed (m/s)	Dry bulb Temperature (^oC)	Wet bulb Temperature (^oC)	Tmax (^oC)	Tmin (^oC)	Evaporation (mm)
1	October 03	0.52	25.9	24.6	31.4	23.9	3.4
2	November 03	0.7	25.7	23.4	33.4	23.5	4
3	December 03	0.79	23.9	21.8	33.8	22	4.1
4	January 04	0.91	23.56	21.5	33.92	21.98	4.6
5	October 04	0.62	25.17	23.92	30.8	23.007	3.74
6	November 04	0.66	26.77	24.68	32.97	23.05	3.18
7	December 04	0.85	25.26	22.51	33.61	22.01	4.08
8	January 05	0.78	25.9	21.4	33.2	23.8	4.7
9	October 05	0.6	25.76	23.4	32.3	24.1	4.46
10	November 05	0.72	25.7	24.1	33.6	23.7	4.2
11	December 05	0.78	25.48	23.6	32.8	24.4	4.38
12	January 06	0.82	25.7	24.7	33.7	22	4.56
13	October 06	0.67	25.17	24.68	30.8	23.5	3.8
14	November 06	0.73	25.94	23.8	33.2	24.2	4.1
15	December 06	0.81	25.86	23.47	32.4	23.6	4.53
16	January 07	0.98	25.2	21.94	34.1	20.9	3.3
17	October 07	1.12	26.4	25	30.7	23.3	3
18	November 07	0.82	26.78	24.29	32.63	22.31	2.96
19	December 07	0.83	26.4	25.05	33.44	22.92	2.72
20	January 08	0.84	25.3	23.6	33.6	20.9	3
21	October 08	1.05	27.2	25.5	31.9	20.4	4.76
22	November 08	1.02	27	24.9	32.9	23.8	4.3
23	December 08	0.98	26.5	24.1	33.5	23.3	4.5
24	January 09	1.12	25.5	23	33.8	22.3	4.12

APPENDIX IV

Estimated evaporation rate (mm) for pre-monsoon months (February 2003 to May 2008)

Sl.No.	Months	Strategy M-1	Strategy M-2	Strategy M-3	Strategy M-4	Strategy M-5
1	February 03	4.159	4.330	4.308	6.205	4.447
2	March 03	4.373	7.821	3.930	3.876	5.163
3	April 03	3.835	4.814	4.854	4.705	5.815
4	May 03	4.737	6.069	4.913	3.110	3.365
5	February 04	4.992	5.775	6.829	6.402	4.447
6	March 04	5.027	5.438	5.122	3.108	5.163
7	April 04	6.611	6.999	7.274	6.284	5.825
8	May 04	3.001	3.213	3.147	2.746	3.283
9	February 05	4.101	3.681	3.188	4.111	5.519
10	March 05	3.710	2.353	3.043	2.710	5.141
11	April 05	3.380	2.033	2.373	3.000	4.212
12	May 05	2.055	1.819	4.700	3.167	1.751
13	February 06	2.743	2.094	1.672	2.178	1.573
14	March 06	2.687	1.522	1.512	1.122	1.494
15	April 06	6.051	2.113	2.383	2.098	4.017
16	May 06	1.179	1.047	-2.358	1.934	0.896
17	February 07	5.835	3.347	6.284	5.621	6.151
18	March 07	3.976	5.478	5.375	5.410	5.136
19	April 07	4.194	4.623	5.871	5.340	4.378
20	May 07	5.065	6.888	5.621	5.862	4.129
21	February 08	3.184	3.600	3.416	2.771	3.546
22	March 08	3.299	3.600	4.314	4.084	4.314
23	April 08	4.365	3.956	3.882	3.390	4.534
24	May 08	5.162	3.474	3.589	4.627	4.388

APPENDIX V

Estimated evaporation rate (mm) for monsoon months (June 2003 to September 2008)

Sl.No.	Months	Strategy M-1	Strategy M-2	Strategy M-3	Strategy M-4	Strategy M-5
1	June 03	5.942	4.830	2.724	3.687	6.148
2	July 03	3.452	3.698	4.491	4.898	4.194
3	August 03	4.426	4.621	3.975	4.240	4.878
4	September 03	4.709	4.466	4.561	3.374	4.595
5	June 04	5.215	4.665	4.672	5.430	5.425
6	July 04	5.553	4.428	5.469	4.511	4.842
7	August 04	6.046	6.191	6.051	6.008	6.130
8	September 04	4.280	4.583	4.874	4.140	4.685
9	June 05	4.519	3.983	4.097	4.048	4.600
10	July 05	4.225	4.554	4.189	3.858	3.373
11	August 05	5.160	5.147	5.949	5.206	3.676
12	September 05	4.718	4.602	4.957	4.797	5.146
13	June 06	5.267	6.325	5.152	5.013	4.531
14	July 06	4.605	4.599	4.254	4.893	3.847
15	August 06	4.474	5.036	5.289	5.285	5.363
16	September 06	4.824	4.722	4.486	4.929	5.227
17	June 07	6.259	6.429	5.885	6.343	5.282
18	July 07	6.657	6.707	6.432	5.446	6.614
19	August 07	5.112	5.064	4.607	4.896	5.731
20	September 07	5.556	5.450	5.005	5.390	5.320
21	June 08	3.966	5.745	3.457	4.901	3.759
22	July 08	2.455	2.553	3.921	2.695	2.855
23	August 08	3.580	3.149	4.437	3.204	3.508
24	September 08	4.596	4.741	4.814	4.602	4.657

APPENDIX VI

Estimated evaporation rate (mm) for post monsoon months (October 2003 to January2008)

Sl.No.	Months	Strategy M-1	Strategy M-2	Strategy M-3	Strategy M-4	Strategy M-5
1	October 03	3.405	3.525	4.003	3.567	3.546
2	November 03	4.003	4.212	4.273	4.257	3.942
3	December 03	3.723	3.998	4.110	4.094	4.273
4	January 04	4.598	4.405	4.222	4.609	4.402
5	October 04	3.742	3.552	4.061	2.931	3.654
6	November 04	3.184	3.399	2.417	3.340	3.138
7	December 04	4.068	3.768	3.772	4.052	4.015
8	January 05	4.701	4.635	4.846	4.717	4.300
9	October 05	4.467	4.443	4.326	4.295	4.426
10	November 05	3.944	4.047	4.120	4.336	3.896
11	December 05	4.473	4.129	3.877	3.894	4.900
12	January 06	2.682	4.380	4.572	4.369	4.151
13	October 06	3.803	3.483	3.959	3.816	3.393
14	November 06	4.112	4.143	4.259	3.988	3.922
15	December 06	4.535	4.350	4.327	4.262	4.577
16	January 07	3.356	3.335	3.512	3.314	3.316
17	October 07	3.015	2.917	3.468	2.776	3.331
18	November 07	2.968	3.381	3.419	2.928	3.087
19	December 07	2.727	3.535	2.738	2.811	3.108
20	January 08	3.000	4.367	3.428	3.265	3.213
21	October 08	4.766	5.091	4.802	4.817	4.790
22	November 08	4.016	3.212	4.092	4.178	4.754
23	December 08	4.496	4.497	4.712	2.211	3.755
24	January 09	4.313	4.022	3.693	4.100	4.044

ESTIMATION OF PAN EVAPORATION USING ANN – A CASE STUDY

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ABSTRACT

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ABSTRACT

A study on ‘Estimation of pan evaporation using Artificial Neural Network’ was carried out in K. C. A. E. T, campus, Tavanur. The meteorological parameters considered were monthly data of wind speed, dry bulb temperature, wet bulb temperature, maximum temperature, minimum temperature and evaporation for six years (February 2003 to January 2009) for the model development. The entire data was divided in to three based on the season, as pre- monsoon, monsoon and post monsoon. The five different strategies were considered for the study viz. M-1, M-2, M-3, M-4, and M-5. Strategy M-1 included all the input parameters. M-2 included all the input parameters except wind speed and M-3 included wind speed, dry bulb temperature and wet bulb temperature. Dry bulb temperature and wet bulb temperature were only considered in strategy M-4 where as strategy M-5 included only maximum temperature and minimum temperature. From the available data 70% data were taken for training and 15% each for testing and validation. From the results of the study, it can be seen that the strategy M- 3, combination of wind speed, dry bulb and wet bulb temperature has greater influence on evaporation rate the least MSE value and high R^2 value.