Original Research Article https://doi.org/10.20546/ijcmas.2018.701.111

Estimation of Evaporation in Hilly Area by Using Ann and Canfis System Based Models

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A B S T R A C T

The water is an essential component of human life and survival of plants and animals. Estimation of evaporation is very important in arid and semi-arid region where the shortage of water occurs. It plays an important role for planning and management of water resources projects, necessary for scheduling of irrigation and in planning farm irrigation systems. It is a very important component of hydrologic cycle and water resources problems. In the present study the Artificial Neural Network (ANN) and Co-Active Neuro Fuzzy Inference System (CANFIS) models were developed for estimating evaporation. The data set consisted of four years of daily records from 2010 to 2013. The daily data consist of temperature, relative humidity, wind speed, sunshine hour and evaporation. The daily data of temperature, relative humidity, wind speed, sunshine hour were used as input and the evaporation was used as the output. For estimation of evaporation 70% data was used for training and 30% for testing of models. ANN and CANFIS were used for designing of models based on activation function; Tanh Axon and learning rule; Levenberg Marquardt with 1000 number of epochs, two hidden layers with 2, 3...8 neuron in each hidden layers. Gaussian membership function was used in CANFIS. The performance of ANN and CANFIS models was compared on the basis of statistical functions such as RMSE, R^2, and CE. The results indicate that the ANN performed superior to the CANFIS. It was concluded that the ANN model can be successfully employed for the estimate on of daily evaporation at Hawalbagh, Almora.

Introduction

Evaporation is the process in which a liquid changes to the gaseous state at the free surface, below the boiling point through the transfer of heat energy. The rate of evaporation is depend on the vapour pressure at the water surface and air above, air and water temperature, wind speed, atmospheric pressure, quality of water and size of water body. Evaporation is the primary process of water transfer in the hydrogical cycle. Evaporation estimates are necessary for integrated water resources management and modelling studies related to hydrology, agronomy, forestry, irrigation, food and lake ecosystems (Terzi and Keskin, 2005). Evaporation losses can represent a significant part of the water budget for a lake or reservoir and may contribute significantly to the

lowering of the water surface elevation where water scarcity problem present (McCuen, 1998).

Evaporation is the most difficult and complicated parameter to estimate among all the components of the hydrological cycle because of the complexity between the components of land, plant, water surface, and atmosphere system (Singh and Xu, 1997). In the direct method of measurement, the observation from United States Weather Bureau (USWB) Class A Pan evaporimeter and eddy correlation techniques were used (Ikebuchi *et al.,* 1988) the evaporation pans and associated automated measurement devices are relatively expensive, whereas in indirect method use meteorological data like rainfall, temperature, relative humidity, solar radiation, wind speed etc. to estimate evaporation by empirical based methods or statistical and stochastic approaches (Gupta, 1992). The indirect methods are used temperature based formulae, radiation method, humidity based relation, Penman formulae, energy balance approach and etc. Although all these approaches are based on Penman formula, they are sensitive to site-specific evaporation parameters, which can vary from one place to other.

Artificial Neural Network (ANN) was most frequently used by researchers with different network topology and weather variables combinations (Sudheer *et al.,* 2002). Neural network approaches have been successfully applied in a number of diverse fields, including water resources. ANN method is used where no pans are available to estimate the evaporation in hydrological, agricultural and meteorological sector (Kisi, 2009).

In recent times, fuzzy-logic based modelling has been significantly utilized in various fields of science and technology including reservoir operation and management, river flow

forecasting, evaporation estimation and rainfall runoff modelling (Kisi, 2006). The concept of fuzzy-logic was introduced by Zadeh (1965).

In this study, an attempt has been made to estimate daily evaporation at Hawalbagh, Almora. The techniques, namely artificial neural network (ANN) and co-active neuro-fuzzy inference system (CANFIS) are used. The main purpose of this study is to analyse the performance of ANN and CANFIS techniques in daily evaporation estimation. The accuracy of ANN, MLR and CANFIS model is compared on the basis of statistics indices such as root mean square error (RMSE), coefficient of determination (R^2) and coefficient of efficiency (CE).

Materials and Methods

General description of study area

Location

Hawalbagh is located in Almora district of Uttarakhand, India. Geographically it is located at 29^0 36' N latitude and 79^0 40' E longitudes at an elevation of 1250 m from the mean sea level. The location of Hawalbagh is shown in figure 1. The climate of the study area is cool temperate with annual maximum, minimum and average temperatures in the area stands at 25.77°C, 13.50°C and 19.635°C respectively. Maximum rain is received from south-west monsoon during four months rainy season from June to September. The monthly temperature data reveal that May is the hottest month when the mean maximum temperature rises up to 31.50°C and January is the coldest month when the mean minimum temperature drops down to 5.04°C. The maximum and minimum temperatures gradually decrease between July and October. The soil of this region is good for agriculture and holds enough moisture to produce good crops.

Data acquisition

The weather data used to develop the ANN models were acquired from the Meteorological observatory of Vivekananda Parvatiya Krishi Anusandhan Sansthan (VPKAS) Almora, Uttarakhand. The daily weather data of maximum and minimum temperature, wind velocity, relative humidity (Rh_1 was recorded in the morning at 7 am and relative humidity (Rh_2) was recorded in afternoon at 2 pm at Indian Standard Time), sunshine hour and evaporation. The data set consisted of four years of daily records from 2010 to 2013.

Development of models for study area

The data set formulation was carried out with standard meteorological weather data of, mean of maximum and minimum temperature, mean of relative humidity, sunshine hours and wind velocity as input and remaining evaporation data was used for output. Total number of data for each year's period comes out to be 365. Then the whole numbers of data of 4 year were 1461. The 70% of daily data was used for training of the models and remaining 30% was used for testing of the models.

Artificial Neural Networks (ANNs)

ANN's are a type of artificial intelligence that attempts to initiate the way a human brain works. Rather than using a digital model, in which all computational manipulate zeros and ones, a neural network works by creating connections between processing elements, the computer equivalent of neurons. The organization and weight of the connections determine the output.

A neural network is a massively parallel-distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects: (i) knowledge is acquired by the network through a learning process and (ii) Inter- neuron connection strengths known as synaptic weights are used to store the knowledge.

ANN thus is an information- processing system. In this information- processing system, the elements called as neurons, process the information.

The signals are transmitted by means of connection links. The links possess an associated weight, which is multiplied along with the incoming signal (net input) for any typical neural network. The output signal is obtained by applying activations to the net input.

ANN was used for designing of models based on activation function; Tanh Axon and learning rule; Levenberg Marquardt.

Co-Active Neuro Fuzzy Inference System (CANFIS)

CANFIS stands semantically for Co-Active Neuro Fuzzy Inference Systems which is an extended form of Adaptive Neuro Fuzzy Inference Systems (ANFIS) (Jang *et al.,* 1997). The extension emphasizes the characteristics of a more fused neuro-fuzzy system which can integrate advantages of the Artificial Neural Networks (ANN) and the linguistic interpretability of the fuzzy inference system (FIS) in the same topology.

CANFIS design

The CANFIS design is based on the first-order Sugeno fuzzy model because of its transparency and efficiency. For example, if the fuzzy inference system with two inputs x_1 and x_2 and one output z is used then for the first-order Sugeno fuzzy model, a typical rule set with two fuzzy IF-THEN rules for

CANFIS architecture can be expressed as follows (Saemi and Ahmadi, 2008):

Rule 1: IF x_1 is A_1 AND x_2 is B_1 THEN z = p_1 x_1 + q_1 x_2 + r_1...3.13

Rule 2: IF x_1 is A_2 AND x_2 is B_2 THEN z = p_2 x_1 + q_2 x_2 + r_2...3.14

Where A_1, A_2 and B_1, B_2 are the membership functions for inputs x_1 and x_2 respectively and p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function.

The major building blocks of a CANFIS are the architecture, membership function, fuzzy operator, activation function and training algorithm.

Architecture of CANFIS

The architecture of CANFIS with two inputs and single output is shown in Figure 2. It is a five layer feed-forward network consisting of two parts.

An FS model (upper part) that computes the normalized weights of antecedent part of the rules.

ANN model (lower part) that computes the consequent outputs using the weights from the FS model.

The function of each layer is described below:

In this present study Gaussian membership function was used in CANFIS.

Performance evaluation of developed models

The performance of ANN and CANFIS models was compared on the basis of statistical functions such as RMSE, R2, and CE.

Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}(Y_j - Y_{ej})^2}{n}}$$

Where,

Y_j =observed values, Y_{ej} = Estimated values and n =number of observation

Coefficient of determination (R^2)

$$R^2 = \frac{\sum_{i=1}^{n}(E_{io}-E_{mo})(E_{ie}-E_{me})}{\sqrt{\sum_{i=1}^{n}(E_{io}-E_{mo})^2 \sum_{i=1}^{n}(E_{ie}-E_{me})^2}}$$

Where,

E_{io} = observed value at the Ith time step, E_{ie} = corresponding simulated value, N = number of time steps, E_{mo} = mean of observational values and E_{me} = mean value of the simulations.

Coefficient of efficiency (CE)

$$CE = 1 - \frac{\sum_{i=1}^{n}(Y_j - Y_{ej})^2}{\sum_{i=1}^{n}(Y_j - \bar{Y})}$$

Where,

Y_j =observed values, Y_{ej} = estimated values and Ȳ=mean of observed values.

Nash-Sutcliffe efficiencies can range from -∞ to 1

Results and Discussion

This chapter deals with development and application of ANN, and CANFIS based models to estimate the daily evaporation of Hawalbagh, Almora. The daily meteorological data i.e. temperature (T), wind velocity (W), relative humidity (Rh) and sunshine hours (S) were taken as inputs for models and evaporation (Ep) considered as output of the

models. The 70% of daily data was used for training of the models and remaining 30% was used for testing of the models.

Artificial Neural Networks (ANN) based evaporation estimation models

In the present study, learning algorithm (i.e. Levenberg–Marquardt) was applied in order to identify the one which best train the network. The activation function (i.e. TanhAxon) was used for identify one which best train network of artificial neural networks. Various networks of two hidden layers were trained for a maximum iteration of 1000.

The quantitative performance of this model was evaluated by using various statistical and hydrologic indices viz. root mean square error, coefficient of determination and coefficient of efficiency. The value of RMSE were calculated by using equation, to select the best network for training and testing periods RMSE varies from 0.409 to 0.425 for best network(4-5-5-1). The value of R^2 was calculated by equation, during testing and training periods R^2 varies from 0.921 to 0.912 for the same network. The value of CE was calculated by using equation; CE varies from 90.96% to 90.22% during training and testing periods for the same network were showed in Table 1. The performance of the Levenberg-Marquardt and activation function TanhAxon was evaluated by the comparing ordinates of observed and estimated graphs. The observed and estimated values of evaporation for training and testing periods were shown in Figure 4 and 5.

CANFIS based evaporation estimation models

The CANFIS models have been developed using the daily data of temperature (T), wind velocity (W), relative humidity (Rh), and sunshine hours (S), as a set of input and daily evaporation (Ep) as the output for the model.

In the present study, learning algorithms (Levenberg–Marquardt) was applied in order to identify the one which best train the network. The activation functions (TanhAxon) was used for identify one which best train network of CANFIS. Various models of different membership function were trained for a maximum iteration of 1000 (Table 2).

Table.1 Comparison of various ANN models for the Levenberg-Marquardt and TanhAxon combination during training and testing periods

Network	Training			Testing		
	RMSE	CE (%)	R^2	RMSE	CE (%)	R^2
4-2-2-1	0.429	89.40	0.879	0.415	88.45	0.893
4-3-3-1	0.431	89.67	0.896	0.435	88.78	0.902
4-4-4-1	0.414	91.28	0.915	0.439	90.14	0.910
4-5-5-1	**0.409**	**90.96**	**0.921**	**0.425**	**90.22**	**0.912**
4-6-6-1	0.417	90.33	0.904	0.463	88.60	0.893
4-7-7-1	0.421	90.14	0.902	0.450	82.07	0.896

Table.2 Different combination of learning algorithm and activation function in CANFIS model for evaporation estimation

Model	Membership function	Membership function per input	Combination of learning algorithms and activation functions
CANFIS	Gaussian	2	Levenberg-Marquardt and TanhAxon
	Gaussian	3	Levenberg-Marquardt and TanhAxon

Table.3 Comparison of various CANFIS models for the Gaussian membership function during training and testing periods

MODEL	MFs per input	TRAINING			TESTING		
		RMSE	CE	R^2	RMSE	CE	R^2
CANFIS	Gauss-2	0.441	89.99	0.901	0.455	88.09	0.891
	Gauss-3	0.431	89.22	0.892	0.447	85.11	0.860

Fig.1 Location of the study area
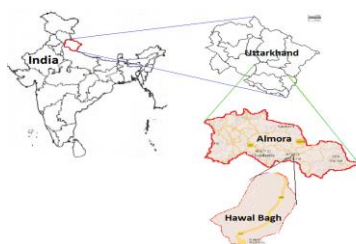
Fig.2 Artificial neural network
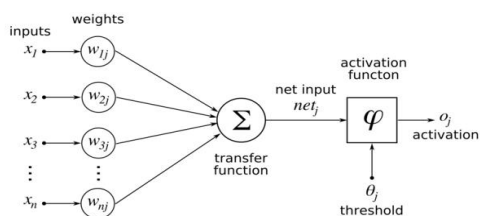

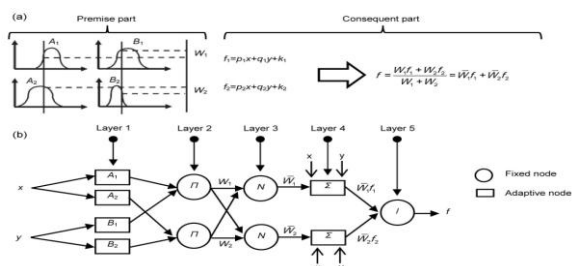**Fig.3** (a) First order Surgeno fuzzy model; and (b) Equivalent CANFIS architecture

916

Fig.4 and 5 Observed and estimated evaporation for Levenberg-Marquardt TanhAxon and combination of ANN model during training period for network 4-5-5-1
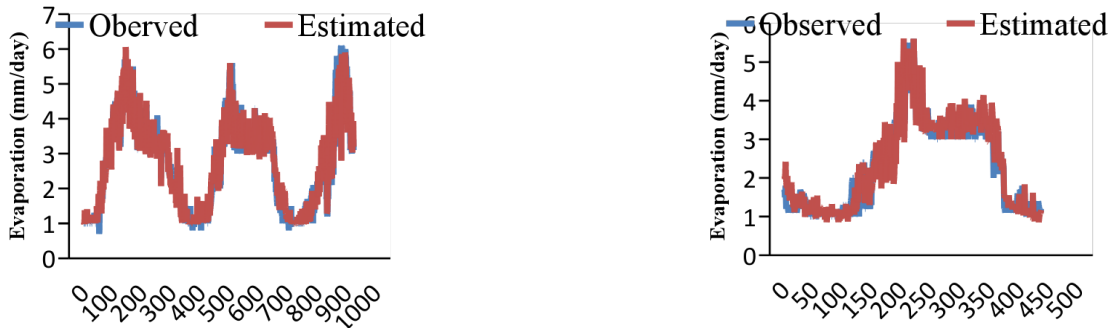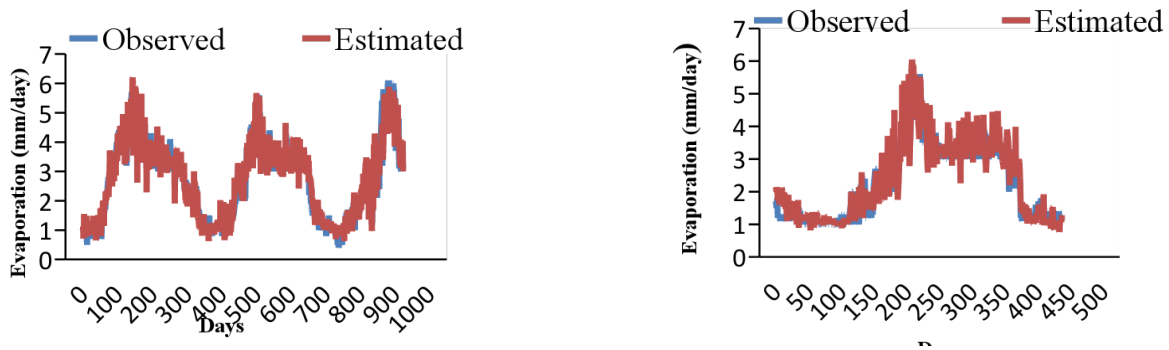

Fig.6 and 7 Observed and estimated evaporation for CANFIS (Gauss-2) model using Gaussian membership function during training period

Performance evaluation of CANFIS model using Gaussian membership function developed model

The quantitative performance of this model was evaluated by using various statistical and hydrologic indices viz. root mean square error, coefficient of determination and coefficient of efficiency. The value of RMSE were calculated by using equation, to select the best model during training and testing periods RMSE varies from 0.441 to 0.455 for the CANFIS model with Gauss-2 membership function. The value of R^2 was calculated by equation, during testing and training periods R^2 varies from 0.901 to 0.891. The value of CE was calculated by using equation; CE varies from 89.22% to 85.11% during training and testing periods for the same model were showed in Table 3.

The performance of the CANFIS models with Gaussian membership function were evaluated by the comparing ordinates of observed and estimated graphs. The observed and estimated values of evaporation for training and testing periods were shown in Figure 6 and 7. It was observed from Figs. that there were a closed agreement between observed and predicted evaporation and over all shape of the plot of estimated evaporation was similar to that of the observed evaporation.

In the present study ANN and CANFIS based models have been developed for evaporation estimation. In the ANN based models, the combinations of activation functions and learning rules are used and the model were trained and tested for maximum iterations of 1000 for two hidden layers network for

estimation of evaporation and same procedure was also applied for CANFIS with Gaussian membership functions. Since there is no specific rule to determine the best structure of the network, a trial and error method was used for the selection of the best network among various structures of the networks.

The results indicate that the ANN performed superior to the CANFIS model (R^2 value for, ANN=0.912 and CANFIS=0.891). It was concluded that the ANN model can be successfully employed for estimate on of daily evaporation at Hawalbagh, Almora.

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