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Monthly Evaporation Modelling Using ANN and WANN Model

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Abstract As the basic component of hydrologic cycle evaporation is extensively used in various fields of water resources management, hydrology, irrigation management, drainage designing and many more. In the recent era of water scarcity the need for precise monitoring of evaporation is getting more popular. Evaporation estimation is also more important from the point of planning the conjunctive use of water in any basin. In this paper, monthly evaporation was modeled with the help of an Artificial Neural Network (ANN) based model and a model combining the wavelet with ANN (WANN). The input data used here was obtained from NIH observatory. The results obtained during the study were revealed that the wavelet-ANN model was more significant than the ANN model. The estimation accuracy of WANN was increases over ANN model due to use of multi-scale time series input data.The RMSE valve of ANN model during calibration and validation was (0.210 and 0.364), whereas for WANN model, RMSE value during calibration and validation was (0.147 and 0.154) respectively. The model efficiency of ANN during calibration and validation was (0.816 and 0.872) whereas the model efficiency of WANN during calibration and validation was (0.922 and 0.930). These indicate a substantial improvement in the WANN model performance. In addition to this, the comparison of the between observed evaporation, ANN, WANN indicate that the values of evaporation estimated by the WANN model were more precise than those found by the ANN model.

Keywords WANN, ANN, Evaporation, Calibration, Validation.

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Introduction

Evaporation losses estimation are needed in a wide ranges of problems in hydrology, agronomy, forestry and land resources planning for water balance computation, irrigation management, crop yield forecasting model, river flow forecasting, ecosystem modeling. Irrigation scheduling is one of the most important areas where appropriate estimation of evaporation losses is necessary (Shirgure and Rajput 2011). The evaporation estimation is also useful for climatological application. Evaporation process is complex and non-linear hydrological process which can be modeled through the soft computing techniques such as Artificial Neural Networks (ANN), Fuzzy-neuro technique, WANN and many more.

The Artificial Neural Network (ANN) is a modeling tool which greatly satisfied the modeling of dynamic non-linear system. As universal approximators tool the ANN is greatly used for mapping and modeling of non-linear system data. It is capable to extracts the non-linear behavior between input and output of a process without having sufficient knowledge of the underlying principles. The other main feature of ANN is that it does not require any explicit characterization and quantification of physical properties and conditions. ANN can learn the system behavior of its interest from representative data that consist of easily measurable variables. French et al. (1992) described the advantages of ANN models over physically based models. To modeled hydrological time series ANN proved to be a flexible and efficient tool but it has some drawbacks when it handled a high non-stationary hydrologic process that involves seasonalities which vary from 1 day to several decades. To overcome this drawbacks a pre-processing of time and space may prove an effective approach.

The effectiveness of the wavelet transform to disintegrate the non-stationary time series into sub-series at different scales is helpful for better understanding of the hydrological process. So, ANN with wavelet transform as a hybrid wavelet-ANN (WANN) model simultaneously explain the spectral and temporal information of the signal which creates an effective implement for estimation of hydrological processes (Vahid and Masoumeh 2013). Wavelet analysis grabs attention towards it because of its ability to analyze rapidly changing transient signals. Wavelet transform of a function is the improved version of Fourier transform. Wavelet analysis is an exciting new method for solving difficult problems in mathematics, physics, and engineering, with modern applications as diverse as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics, the detection of aircraft and submarines and other medical image technology. The analyzing function in the wavelet transformation is called as wavelet. It will adjust the time width of the frequencies in such a way that high frequency once will be broader. Wavelet transform is one of a best tool to determine low frequency area and high frequency area.

In the present analysis, ANN based model with feed forward neural architecture have been employed to estimate the evaporation with monthly data of antecedent rainfall, maximum temperature, minimum temperature and relative humidity as input vector and evaporation as output vector. The data of maximum monthly temperature, minimum monthly temperature, monthly rainfall and monthly humidity from June 2009 to January 2014 (56 Months) were obtained from NIH observatory. These climatic data were fed to ANN model as inputs to estimate the monthly evaporation. The different discrete time wavelet transformations were used to decompose the input data to estimate the monthly evaporation and the performance of ANN model with wavelet transformed input (WANN) was compared.

Materials and Mathods

Study area

Roorkee is located in Haridwar district at 29^0 51´ N and 77^0 53´E on Solani river bank. The upper ganga canal is the most important feature which add beauty to city and separates it two distinct part. The city is located 274 meters above mean sea level. The average annual rainfall of city is 1068 mm with average monsoon rainfall of 878 mm. The average maximum temperature is about 40 ^{0}C with average minimum temperature 2 ^{0}C. The other information regarding city are maximum humidity (100%), average minimum humidity (30%), and average annual wind speed (4.9 m/s)

Artificial neural network

An ANN consist various processing elements called nodes, similar to human brain neurons, interconnected to each other (Azhar et al. 2007). A neural network represents connection pattern between nodes, its method to determine the connection weights and activation function (Fausett 1994). Weight values are stored in synapses of neural network. Feed forward neural networks (FFNN) with BR algorithms were used in the present study to model the monthly evaporation.

The model development process in ANN is the preliminary step in the selection of significant input variables. In this input vectors are selected 0 the basis of correlation analysis between various input vectors and monthly evaporation. The auto-correlation coefficient is calculated as per equation 1.

The auto-correlation coefficient (Salas et al. 1980) is defined as :

$$r_k = \frac{\sum_{t=l}^{N-k} (X_t - \overline{X_t})\ (X_{t+k} - \overline{X_{t+k}})}{\left[\sum_{t=1}^{N-k} \left(X_t - \overline{X_l}\right)^2 \sum_{t=1}^{N-k} \left(X_{t+k} - \overline{X_{t+k}}\right)^2 \right]^{1/2}} \qquad (1)$$

Where r_k is called the *lag-k* correlation coefficient, the serial correlation coefficient or the auto-correlation function (ACF), X_t is the time series for $t = l,...N$, X_{t+k} is the lagged time series for $t = l, ...N-k$, $\overline{X_t}$ is the sample mean for $t = l, ...N$, $\overline{X_{t+k}}$ is the sample mean for $t = l,....,N-k$, N is the sample size.

The second step in ANN modelling is normalization of input values between 0 and 1 before passing to a neural network because the output of sigmoidal function is bound between 0 and 1. The output from the ANN should be denormalized to provide meaningful results (Dawson and Wilby 1998). Normalization of data can be done with the equation 2.

$$Ni = \frac{Ri - Mini}{Maxi - Mini} \qquad (2)$$

Where, R_i is the real value applied to neuron *i; N_i* is the subsequent normalized value calculated for neuron *i; Min_i* is the minimum value of all values applied to neuron *i; Max_i* is the maximum value of all values applied to neuron *i.*

In feed-forward networks, the data flow through the network in one direction from the input layer to the output layer through the hidden layer (s). Each output value is based solely on the current set of inputs. The input layer receives an input from the external environment and sends the weighted values to immediately adjacent node usually hidden layer. The hidden layer receives the transferred weighted inputs from the input layer, perform transformations on it and then pass the output to the next adjacent layer may be hidden layer or the output layer. The output layer receives the hidden layer output and send to the user. The net input x_i to node i is the weighted sun of all the incoming signals as per equation 3.

$$\text{Net\_input} = \Sigma\, W_{ij}\, x_i \qquad (3)$$

Where, w_{ij} = Weight between node i and node j, xi = Input to node i, y_i = Activation function at node i.

The activation function, yi, which is a non-linear function of its net-input, is described by the sigmoid logistic function as in equation 4.

$$y_i = \frac{1}{1 + \exp(-\text{net\_input})} \qquad (4)$$

Determining the best values of of all the weights is called training the ANN. The main objective of training (calibrating) a neural network is to produce an output vector $Y = (y_i, y_2,...y_p)$ that is as close as possible to the target vector (variable of interest or forecast variable) $T = (t_i, t_2,....., t_p)$ when an input vector $X = (x_i, x_2,...., x_p)$ is fed to the ANN. In this process, weight matrices W and bias vectors V are determined by minimizing a pre-determined error function as explained in equation 5.

$$E = \sum_p \sum_p (y_i - t_i)^2 \qquad (5)$$

Where, t_i is a component of the desired output T; y_i is the corresponding ANN output; p is the number of output nodes ; and P is the number of training patterns. Bayesian regularization algorithm is used to train the network more efficiently. The Bayesian regularization is an algorithm that automatically sets optimum values for the parameters of the objective function (Anctil and Tape 2004, Coulibaly et al. 2001).

The network geometry is generally highly problem oriented in order to get optimal network geometry trial and error procedure is adopted. The numbers of nodes in the input layer were decided based on the inputs to the model. The number of hidden neurons in the network, which is responsible for capturing the dynamic and complex relationship between various input and output variables, was identified by various trials. For each set of hidden neurons, the network was trained with input data sets in batch mode to minimize the mean square error at the output layer. Various internal parameters used in the ANN model like learning rate, momentum coefficient, scalar μ, and combination of transfer functions for hidden and output layer were also found out by trial and error. MATLAB 2010a software was used for analysis.

Wavelet transformation

Wavelet analysis appears to be a more effective tool than the Fourier Transform in analyzing non-stationary time series. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. Wavelet analysis can be used to decompose an observed time series (such as rainfall, evaporation, evapotranspiration and groundwater levels) into various components so that the new time series can be used as inputs for a WANN model. In wavelet analysis, the use of a fully scalable modulated window solves the signal-cutting problem (Rao et al. 2014). In the present study Discrete Wavelet Transformation is used. The Discrete Wavelet Transform (DWT) allows one to reduce the computation time and it is considerably simpler to implement than CWT. In one-dimensional DWT the signal is split into two parts, usually the high frequency and the low frequency part. This splitting is called decomposition. The signal is passed through a series of high pass filters to analyze the high frequencies, and it is passed through a series of low pass filters to analyze the low frequencies as per equation 6.

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} X[k]\, g[n-k] \quad (6)$$

The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two as in equation 7 and 8.

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]\, g[2n-k] \quad (7)$$

$$y \,\square\, ig \,\square\, [n] = \sum_{k=-\infty}^{\infty} x[k]\, \square\, [2n-k] \quad (8)$$

The time series after wavelet decomposition allows one to have a look at the signal frequency at different scales. The discrete wavelet transform allows reducing computation time than CWT. High pass and low pass filters of different cut off frequencies are used to separate the signal at different scales. The scale is changed by up scaling and down scaling operations (Cannas et al.2006).

Performance evaluation of ANN and WANN model

The whole data length are divided into two sets based on statistical properties of the time series such as mean and standard deviation, in that one is used for calibration (training) and another for validation of ANN model and the same data set with de-noised values are used as an input for WANN model. The performance during calibration and validation is evaluated by using statistical parameters. They are Coefficient of Efficiency (CE), Root Mean Square Error (RMSE) and Explained Variance (EV) given by following equations.

Coefficient of efficiency (CE)

Based on the standardization of residual variance with initial variance, the coefficient of efficiency can be used to compare the relative performance of the two approaches effectively. It is expressed as equation 9.

$$CE = \left\{ 1 - \frac{\textit{Residual variance}}{\textit{Initial variance}} \right\} = \left\{ 1 - \frac{\sum_{j=t1}^{n} (Y_j - X_j)^2}{\sum_{j=1}^{n} (Y_j - \bar{Y}_j)^2} \right\} \quad (9)$$

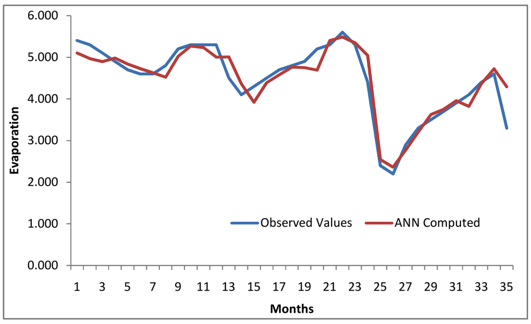

Fig. 1. Observed and computed monthly evaporation during calibration in ANN model.

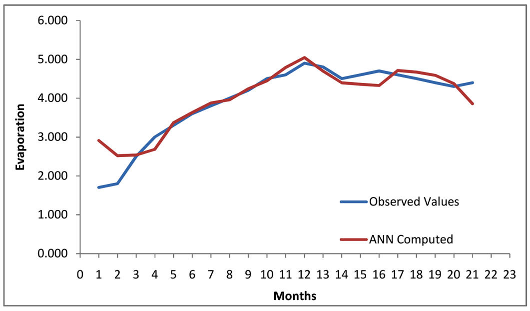

Fig. 2. Observed and estimated monthly evaporation during validation in ANN model.

Chiew et al. (1993) classified the coefficient of efficiency into three categories viz. perfectly acceptable simulation (CE > 0.90), acceptable simulation (CE between 0.60 and 0.90) and unacceptable simulation (CE < 0.60).

Root mean square error (RMSE)

RMSE indicates the discrepancy between the observed and calculated values. The lowest the RMSE, the more accurate the prediction. It is expressed as equation 10.

$$\text{RMSE} = \sqrt{\frac{\textit{Residual variance}}{n}} = \sqrt{\sum_{j=1}^{n} \frac{(Y_j - X_j)^2}{n}} \tag{10}$$

Explained variance (EV)

Explained variation measures the proportion to which a mathermatical model accounts for the variation (dispersion) of a given data set. It is given by equation 11.

$$EV = \sqrt{\left(\frac{\Sigma\,(X_j - \overline{Y}_j)^2}{\Sigma\,(Y_j - \overline{X}_j)^2}\right)} \tag{11}$$

Where, Yj = Observed monthly evaporation, Xj = Predicted monthly evaporation, n = Number of observations, $\overline{Y}j$ = Mean of observed monthly evaporation, $\overline{X}j$ = Mean of predicted monthly evaporation.

In this study an attempt has been made to estimate the monthly evaporation at NIH campus. An ANN model developed with the monthly historical data of rainfall, maximum temperature, minimum temperature and relative humidity of Roorkee. The best ANN model trained with the input data derived from statistical analysis. The input data time series are decomposed using different wavelets at different decomposition level and these decomposed signals were used as input to the WANN model. The performance of both the models is evaluated by using statistical parameters.

Results and Discussion

The ANN models have been trained using Bayesian regularization algorithm. The whole data set has been divided into two sets for the training and validation of the ANN model. The data from June 2009 to January 2014 (56 Months) have been considered for the training of the model. Out of 36 month data sets 35 sets (62.50%) of data were used for calibration

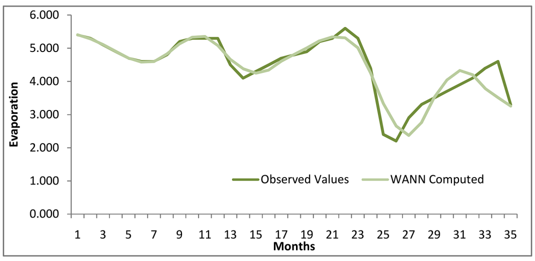

Fig. 3. Observed and computed monthly evaporation during calibration in WANN model.

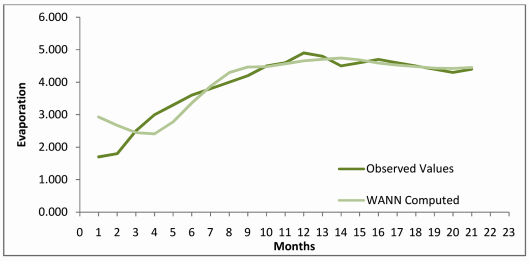

Fig. 4. Observed and computed monthly evaporation during validation in WANN model.

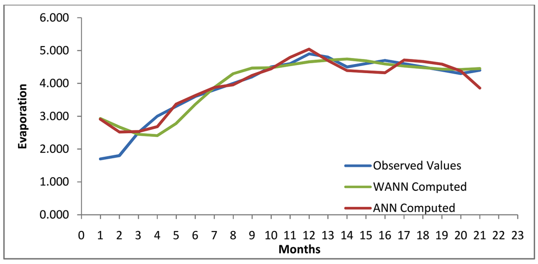

Fig. 6. Observed and computed monthly evaporation during calibration in ANN and WANN model.

(training), 21 sets (37.50%) of data were used for validation. These data sets were selected by trial and error method. The number of the neurons in the hidden layer is found by a trial and error based, the trial and error procedure started with one hidden neuron initially, and it has been increased up to ten based on the performance criteria of the model. The transfer functions of hidden and output layers have been considered as log sigmoid and pure linear respectively in the training of the ANN model. The performance of the ANN model during calibration and validation with the input combination derived from statistical procedure given by Sudheer et al. (2002).

Analysis of results of ANN and WANN models

The performance of ANN model with observed evaporation was presented in Figs. 1 and 2 whereas the performance of WANN models for evaporation estimation at Roorkee during calibration and validation was presented in Figs. 3 and 4. The combined graphical comparison was made between ANN model, WAPP model and observed evaporation in Figs. 5 and 6, which demonstrates the potentiality of WANN models over ANN model in the evaporation estimation. The results of the calibration and validation of the ANN and WANN models in terms of various statistical indices are presented in the Table 1.

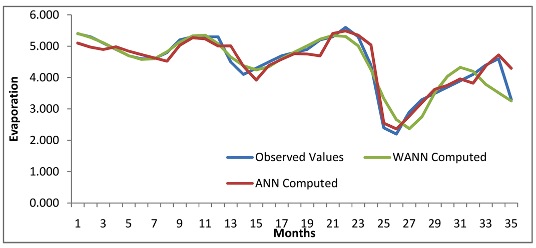

Fig. 5. Combined observed and computed monthly evaporation during calibration in ANN and WANN model.

Conclusion

ANN model has been developed to estimate evaporation at NIH observatory Roorkee. The antecedent rainfall, maximum, minimum and RH data were collected from June 2009 to April 2014 (56 Months). The correlation analysis was carried for selection of the input vector and based on the results of correlation analysis the monthly rainfall (R) with one month lag (t-l), monthly RH with one month lag (t-l), monthly maximum temperature at t and monthly minimum temperature at t have been used as the input. The feed forward neural network architecture trained with Bayesian regularization algorithm having 4 input

Table 1. Comparison of results between best ANN and WANN models.

Model	Calibration CORR (CE)	Calibration RMSE	Calibration EFF% (EV)	Validation CORR (CE)	Validation RMSE	Validation EFF% (EV)
ANN_EVAP (4-5-1)	0.811	0.210	0.816	0.829	0.364	0.872
WANN_EVAP (4-5-1)	0.910	0.147	0.922	0.921	0.154	0.930

nodes and the l hidden and output node, the number of neurons in the hidden layer is optimized to 10 by trial and error, network parameters is also optimized by trial and error. Out of 56 months data sets, 35 sets (62.5%) of data is used for training, 21 sets (37.5%) of data is used for calibration. Similarly, WANN model is developed by using decomposed signals monthly rainfall, RH, maxt and mint as input data. The statistical indices such as coefficient of correlation, root mean squared error (RMSE) and model efficiency have been used to evaluate the performance of the both the models.

The analysis of the performance of the both ANN and WANN models clearly indicate that the application of ANN helps in the better prediction of evaporation. Moreover wavelet transform when combined with ANN was able to substantially enhance the performance of the model. A comparison of results obtained by the ANN model without any data pre-processing with those of the WANN model that employs wavelet transform to pre-process the input signals revealed the true value of wavelet transform.

The RMSE of ANN model during calibration and validation was found to be 0.210 and 0.364 respectively, whereas for the WANN model, RMSE value during calibration and validation was 0.147 and 0.154 respectively and also the ANN model efficiency during calibration and validation was 0.816 and 0.872 respectively, whereas the WANN model efficiency during calibration and validation was 0.922 and 0.930 respectively, indicates a substantial improvement in the model performance. In addition, comparison of time series plots and the scatter plots showed that the water level depth values estimated by the WANN model are more precise than those found by the ANN.

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