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Neural computation technique for estimating of hydrologic cycle

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Abstract
An artificial neural network (ANN) methodology was employed to estimate the values of crop evapotranspiration (ET) and evaporation from daily values of air temperature. The study investigated two ANN architectures, a radial basis function network and a multi layer feed forward back propagation network for mapping an input output relationship. The ANN models compared favorably with observed values of the processes. At the same time, it represents an improvement upon the prediction accuracy and flexibility over current methods. A statistical analysis of the results suggested that the ANN model could be employed in estimating ET and evaporation using limited weather data with reasonable accuracy.

INTRODUCTION

The process of evapotranspiration (ET) from vegetated surface, and evaporation from water bodies are two major, complex hydrological phenomena to comprehend, due to spatial and temporal variability of the climatic characteristics of the watershed. However, past research has provided sound theoretical knowledge and practical applications that have been verified through field measurements. Many different approaches have been used; however, when primary concepts and standard definitions are accepted, it is possible to find a reasonable agreement among methods.

Detailed measurement of ET or collecting data for estimating ET are time consuming and expensive. Some of these measurement methods are soil water depletion (Robins et. al., 1954; Jensen, 1967; Jensen and Wright, 1978), tanks and lysimeters (Harrold, 1966; Aboukhaled et. al., 1982). However these methods are not employed in common owing to their requirement of intensive experimental work. Similarly, the direct measurement of evaporation under field condition is not feasible at least in the sense that one is able to measure river stage, rainfall etc. As a consequence, a variety of techniques have been derived for determining or estimating vapor transport from water surface as well as from plants (Kohler et. al, 1955; Penman, 1948; Christiansen, 1966; Blaney and Criddle, 1966). These estimation techniques have been modified for better approximation by various researchers (Doorenbos and Pruitt, 1977; Hargreaves and Samani, 1985; Jensen et. al, 1990; Frevert et. al., 1983; Allen and Pruitt, 1991). Though these methods have been tested for various regions (de Souza and Yoder, 1994; Jensen et. al., 1990), most of them require climatic data that are not widely available.

However, there are situations where estimates of these processes are needed, when only a limited meteorological data are available. This requirement could be addressed through system theoretic modeling approaches. Linear time series models such as ARMA (Box and Jenkins, 1976), or regression analysis may be employed in such situations. However, both these approaches fail to represent the internal nonlinear complexities inherent in the processes.

Recently, significant improvement in the fields of nonlinear pattern recognition and system control theory have been made possible through advances in a branch of nonlinear system theoretic modeling called artificial neural networks (ANN). Previous works demonstrate that ANNs are adequate to model complex hydrological processes (Zhu et. al., 1994; Minns and Hall, 1996; Shamseldin, 1997). A comparison between ANN models and traditional models has been made by Hsu et. al. (1995), who concluded that the ANN approach is more effective and more efficient whenever explicit knowledge of the hydrologic sub-process is not required. The ANN methodology has been reported to provide reasonably good solutions for circumstances where there are complex systems that may be poorly defined or understood using simple mathematical equations (Tokar et. al., 1999; Takahashi, 1993; Vemuri and Rogers, 1994).

This paper demonstrates the capability of system theoretic ANN approach in estimating the evapotranspiration and evaporation from widely available climatic data. While such a model is not intended as a substitute for physically based theoretical equations for estimation, it can provide a viable alternative when the hydrologic application requires that an accurate estimate of these processes be provided from limited meteorological observations.

Artificial Neural Networks

The architectures of ANNs are motivated by models of biological neural networks, which can recognize patterns and learn from their interactions with the environment. Since the 1950's many ANN structures have been proposed and explored. However, the main function of all ANN paradigms is to map a set of inputs to a set of outputs. This mapping is achieved through an automated learning process. The most widely researched and used structures are multi layer feed forward networks (Rumelhart et. al., 1986), self-organizing feature maps (Kohonen, 1982), Hopfield networks (Hopfield, 1982), counter propagation networks (Hect-Nielsen, 1987) and radial basis function networks (Moody and Darken, 1989). Of these, multi layer feed forward networks and radial basis function networks have been employed in the present study.

Development of any ANN model consists of the following steps: selection of input-output data set suitable for calibration (training) and validation, selection of a model structure and estimation of its parameters, and the validation of the identified model. Though there are a multitude of neural networks, the main function of all paradigms is similar. They try to map a set of inputs to a set of outputs, through the use of connection strengths (network weights). The weight distribution in every ANN is unique and will determine the specific response to any given input vector. In order to perform a required process task, these weights must be determined in advance through a learning process. The learning process of ANNs (also referred to as training of ANNs) encompasses the adjustment of weights and this process makes use of a learning algorithm and a training set of examples. The learning process in ANN can be seen as teaching the network to yield a particular response to a specific input. This often consists of an iterative process, whereby the network tries to match the output vectors to desired ones and uses any deviations to adjust some or all of its weights. The rules that determine the magnitude of these adjustments are contained in the learning algorithm. After numerous training cycles, once the ANN has learned the examples with considerable accuracy, test data is presented to the network, which it has never encountered before. The resulting outputs are validated and the network performance is tested using multiple statistical criteria. The General structure of a three layer neural network is presented in Fig 1.

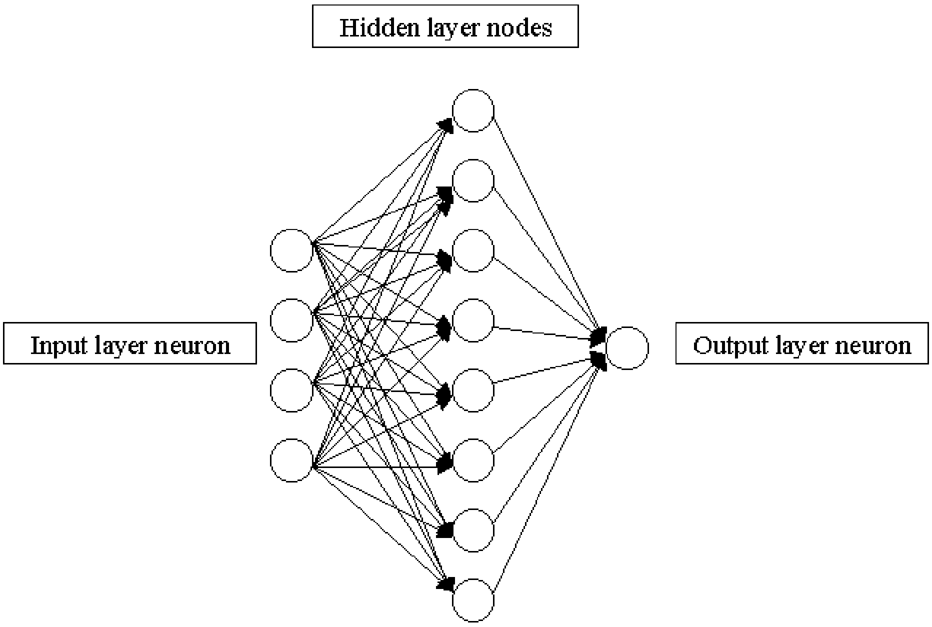

Figure 1. General structure of a three layer neural network.

METHODOLOGY

Evapotranspiration Estimation using ANN

One of the commonly employed neural networks, the radial basis function network (see Dayhoff, 1990; Judith, 1990 for details of this network), has been employed in this study to estimate the daily evapotranspiration for rice crop. As stated earlier, the main task in developing any ANN model is identifying the input vector (dependant variables) to the network so as to produce the output. Since the main objective of the present study was to estimate ET using widely available climatic variables, average temperature alone was considered as the input to the model. This input structure could be considered as an alternative to the temperature based methods (Thronthwaite, 1948; Blaney and Criddle, 1962;

Pochop et. al., 1984) for estimating ET that relate the ET to air temperature. In addition to it, the temperature data is mostly available with all stations, and an attempt is being made to have a better estimate of ET from air temperature data alone, in comparison to other temperature-based methods. However, an indirect index of growing stage of the crop has been presented in the input by adding normalized day of growth of the crop.

The climatic data as well as the actual measurements of ET used in this part of the study were obtained from the agricultural research farm of Kerala Agricultural University, Tavanur (India). Actual evapotranspiration data for rice crop was found from a lysimeter study performed in that area. The station is located at 100 53' 30" North latitude and 760 East longitude. The data was available for a period from October 1989 to January 1990 and has been used in this study.

The data available for the present investigation was only for a single season. This has restricted the training data set to a part of the available data. The data for about two months were used for training the network, and the rest of the data was used for validation. The radial basis function (RBF) network uses a hybrid learning procedure (Moody and Darken 1989). The most common idea in a hybrid learning procedure is to have one layer that learns in an unsupervised way, followed by one (or more) layers trained by back propagation. After experimenting with various values for the network spread constant (a RBF network parameter, see Moody and Darken, 1989), an optimal network structure was finalized. The value of spread constant affects the converging speed of the model. The Mean square error criterion was used to identify the best-fit model while training. The mean square error (MSE) is defined as,

$$MSE = \frac{1}{p}\sum_{j=1}^{p}[y_j^d - y_j^o]^2 \tag{1}$$

in which y^d = desired response; y^o = output response from ANN; p = number of patterns presented. The input data were normalized prior to training, using the procedure suggested by Romesburg, 1984.

Modeling evaporation using ANN

A 'three layer feed forward back propagation network' was employed to estimate the pan evaporation values from climatological data as input (see Dayhoff, 1990; Judith, 1990 for details of the network). As stated earlier, the identification of a model involves selection of input-output data, model structure and training of network and its evaluation.

The data for this part of the investigation came from the daily climatological record of the meteorological observatory in the study area (Agricultural Research Farm, Samalkot). The data sample consisted of 4 years daily record of minimum temperature, maximum temperature. The period of data used in the study is 1990-1993. The data for the year 1991 was used to train the network. The testing of the model was done using the data for the years 1990,1992 and 1993. The input was standardized using the procedure suggested by Romesburg (1984).

In this investigation too, the attempt was to relate the air temperature to evaporation using ANN approach. As a result, the input vector to the model considered only 2 input nodes representing Maximum and Minimum temperatures. The architecture of the network is finalized after a trial and error procedure. If the architecture is too small, the network may not have sufficient degrees of freedom to learn the process correctly. On the other hand, if the network is too large, it may not converge during training or it may over fit the data (Karunanithi et. al., 1994). The trial and error procedure started with only one neuron in the hidden layer. Then the trial is carried out with more neurons (2, 3, 4, etc.). The values of mean square error are used here as the indices to check the ability of a particular architecture in matching the target output.

In the optimal model structure identification stage, training is done for 15000 sweeps. Fig 2 shows the values of MSE for the ANN model with different number of hidden neurons. The Fig 2 indicates that a network with 5 neurons provided a better mapping than a network with 3 neurons, for MSE values. The performance is found deteriorating after the number of neurons increased to six or more (Fig 2). The number of hidden layers selected after the trials were only one, and the number of hidden nodes in this layer were 5. The structures is represented by ANN(2,5,1) in this paper.

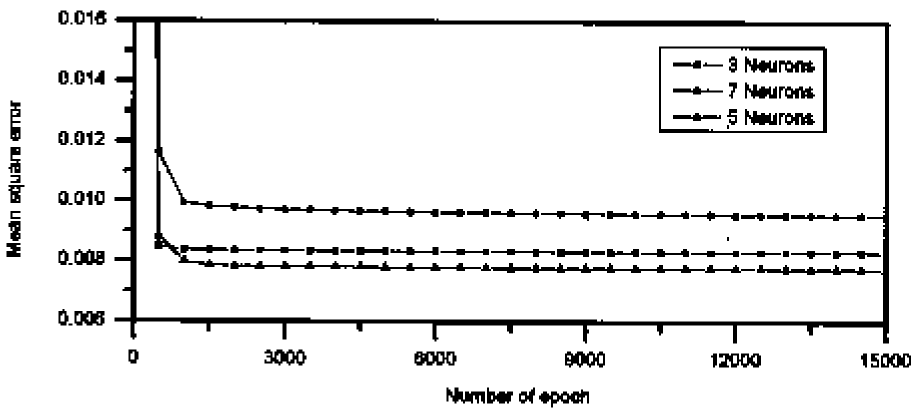

Figure 2. The MSE graph during optimization of network architecture.

For identification of the optimal network structure, the data for the year 1991 was presented to the network for training. After experimenting with different transfer functions, learning and momentum rates, the following parameters were selected: a learning rate of 0.019 and a momentum rate of 0.013. The transfer function selected was the sigmoidal function. The threshold error was set at 0.0075 (normalized units). The network training stopped after approximately 50000 epochs (an epoch is one complete pass through a set of inputs and target patterns while training the network.

The trained network was used to run a set of test data (data for the year 1990, 1992 and 1993, untrained, normalized input vectors). The outputs were compared with the measured values of evaporation. Statistical analysis were carried out for comparing the network output and measured value.

RESULTS AND DISCUSSION

Evaluation of ANN ET estimation model

To have a visual comparison of lysimeter-measured rice evapotranspiration and ANN model estimates, the results are plotted in Fig. 3. The figure depicts ET values computed as well as lysimeter recorded for the whole season (October-January, 1989-1990). The evaluation of the results suggests that the ANN was able to relate air temperature to ET satisfactorily.

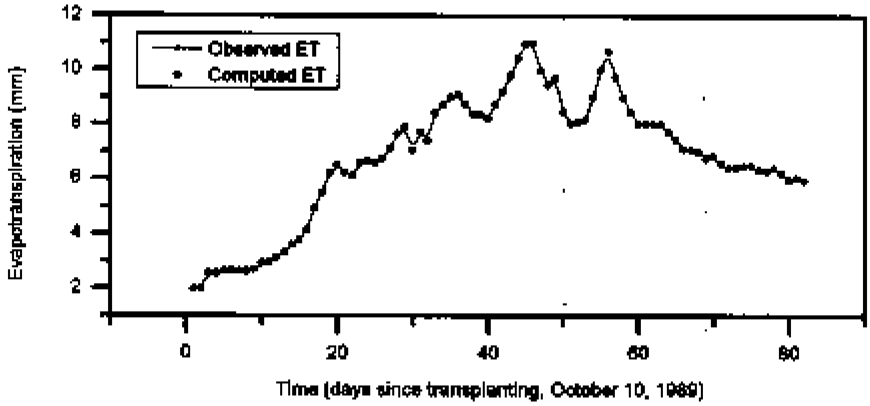

Figure 3. ANN computed ET and lysimeter observed ET.

Though a visual inspection of the observed and computed evapotranspiration values explains the capability of ANN to represent the ET process in a reasonably accurate manner, the effectiveness of the model is to be understood through statistical analysis of the results. Linear regression analysis was used to test the agreement and variations of neural network estimated evapotranspiration with lysimeter measurements. Two regression equations were evaluated. The first model was of the form:

$$ET_a = a + b(ET_{ann}) \tag{2}$$

where ET_a is lysimeter measured evapotranspiration; and ET_{ann} is the particular evapotranspiration estimated from ANN models.

The second regression model was of the form:

$$ET_a = b(ET_{ann}) \tag{3}$$

where, the zero intercept was forced through the origin. The value of coefficient ‘b’ in equation 2 could be used to indicate relative conversion ratios. The hypothesis that the coefficient ‘a’ in equation 1 is significantly different from zero was tested according to the procedures defined by Steele and Torrie (1960). The values of ‘a’ was not found significantly different from zero. Therefore equation 2 was used to compare the fit of the ANN model.

The results of the regression analysis using equation 2 are presented in Table 1. Each set of columns in Table 1 are regression coefficient ‘b’, correlation coefficient ‘r’, standard error of estimates (SEE), and raw standard error of estimates (RSEE). The standard error of estimates is an estimate of the mean deviation of the regression from observed data. It is defined as:

$$SEE = \sqrt{\frac{\sum (Y - \hat{Y})^2}{(n-2)}} \tag{4}$$

where Y is observed (lysimeter-measured) evapotranspiration; and $\hat{Y}$ is the regression estimated lysimeter evapotranspiration using equation 2. The square of the standard error of estimate is an unbiased estimate of the true variance about regression with (n-2) degrees of freedom (Steele and Torrie, 1960). The fourth row in Table 1 is the raw standard error of estimate (RSEE) of the direct comparisons of lysimeter-measured evapotranspiration to ANN estimated evapotranspiration. The RSEE term (Allen, 1987) is an indicative of how well each method estimated with no local or statistical correction (a=0 and b=1). The RSEE is calculated using the equation 4, in which $\hat{Y}$ is replaced by the computed value of ET.

Table 1. Performance indices of the ANN ET model.

Regression coeffcient, b	0.99
Correlation coeffcient, r	0.99
Standard Error of Estimate (mm)	0.03
Raw Standard Error of Estimate (mm)	0.03
Nash-Sutcliffe Efficiency (%)	99.0

The evaluation criterion proposed by Nash and Sutcliffe (1970) was also employed to evaluate the performance of the model. The values of efficiency of computation for each model are also presented in Table 1. From the Table 1, it is clear that the ANN model performance was extremely good and all the evaluation factors agree to this conclusion. The high value of the regression coefficient clearly suggests that the ANN model was able to match the ET data effectively. According to Shemseldin (1997), efficiency of 80% and above can be considered as a good fit to the data in ANN models, and in the present study the observed efficiency is 99%. The low value of the RSEE term depicts the closeness of prediction of ET with the actual measured data. The analysis of the results clearly demonstrates the capability of ANN in ET estimation from limited meteorological data.

Evaluation of ANN model for estimation of evaporation

The results of all ANN models are presented in Fig 4 for calibration year 1991, along with the observed evaporation. A visual inspection of the figure clearly demonstrates the capability of the ANN approach in modeling evaporation. However, there is clearly room for improvement. These results are further analyzed using numerical indices that are reported to evaluate the performance of a model. The analysis used the correlation between the observed and computed evaporation and the efficiency of the model (Nash and Sutcliffe, 1970) as indices for comparison of the performance of the model. Other statistical indices such as root mean square error (RMSE), percentage error of estimate of annual evaporation, and the standard deviation of ratio of observed to computed evaporation are also employed for performance analysis. The values of all these indices are presented in Table 2 for training as well as testing.

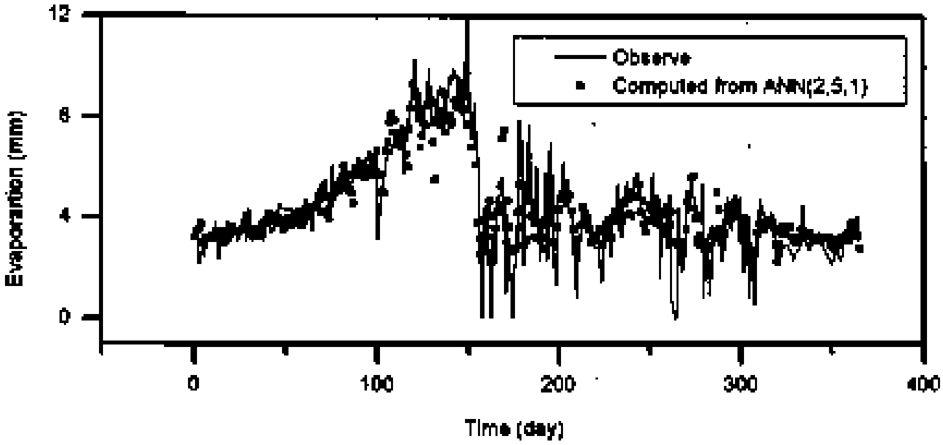

Figure 4. ANN computed evaporation alongwith observed during training year 1991.

Table 2. The values of performance indices for evaporation estimation from ANN model.

	1990	1991	1992	1993
RMSE (mm)	1.22	1.07	1.56	2.07
Efficiency	12.23	73.35	41.24	45.41
% Error in Total Annual Evaporation (estimated)	10.97	-0.30	11.49	-7.25
Correlation coefficient	0.56	0.86	0.70	0.69
Standard deviation of ratio of observed to computed evaporation	0.33	0.28	0.39	0.44

The RMSE statistics measure the residual variance; optimal value is 0.0. The models tend to have small RMSE during training as well as calibration. From Table 2, it is clear that the model estimated the total annual evaporation with minimum error during calibration. However, the performance was found to deteriorate during validation. The correlation between the computed and observed evaporation values were satisfactory throughout, except for the year 1990. The standard deviation of the ratio of observed to computed evaporation measures the deviation of the regression line from 1:1 line, and is found minimum during calibration as well as training.

From the Table 2, it may be seen that all the indices show a good performance of ANN model during training. However, the performance was found deteriorating during validation. A significant observation may be that the model showed drastic deterioration in performance during the year 1990 (as is evident from the low efficiency and correlation), while the performance was satisfactory during other validation years. This may be due to an inconsistent data during the year 1990. At the same time, the investigation demonstrated the potential of ANN approach in estimating evaporation from limited meteorological data.

SUMMARY AND CONCLUSIONS

A research study has been conducted to explore the capabilities of system theoretic ANN approach in modeling complex hydrological processes. The foregoing discussions clearly illustrate the faculty of ANN techniques to extract patterns from the input output data set, irrespective of the complexity associated with the relationships. The testing accuracy, which is favorably compared with training accuracy in each application, based on standard performance evaluation indices, supports this conclusion. The investigation indicated that because of its power and flexibility, ANN approach could even employed in estimating evapotranspiration and evaporation using widely available meteorological data. However, in the case of modeling evapotranspiration, only a single season data was only employed, and further research may be required to reinforce this conclusion.

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