Artificial Neural Network Models of Daily Pan Evaporation

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Abstract: Artificial neural network (ANN) models are proposed as an alternative approach of evaporation estimation for Lake Eğirdir. This study has three objectives: (1) to develop ANN models to estimate daily pan evaporation from measured meteorological data; (2) to compare the ANN models to the Penman model; and (3) to evaluate the potential of ANN models. Meteorological data from Lake Eğirdir consisting of 490 daily records from 2001 to 2002 are used to develop the model for daily pan evaporation estimation. The measured meteorological variables include daily observations of air and water temperature, sunshine hours, solar radiation, air pressure, relative humidity, and wind speed. The results of the Penman method and ANN models are compared to pan evaporation values. The comparison shows that there is better agreement between the ANN estimations and measurements of daily pan evaporation than for other model.

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Introduction

Although there is always continuous exchange of water molecules to and from the atmosphere, the definition of evaporation is limited to the net transfer of water molecules to the atmosphere. This change in state requires an exchange of approximately 600 cal for each gram of water evaporated. If the temperature of the surface is to be maintained, these large quantities of heat must be supplied by radiation and conduction from the overlying air or at the expense of energy stored below the surface (Linsley et al. 1982).

In hydrological practice, the estimation can be achieved by direct or indirect methods. Indirect methods based on meteorological data have been used to estimate evaporation on a water body by many researchers. Stewart and Rouse (1976) determined the summertime evaporation from a shallow lake using energy budget and equilibrium models. They showed that the actual evaporation could be determined within 10% over periods of 2 weeks using these models. Warnaka and Pochop (1988) compared six equations—the Kohler–Nordenson–Fox, Kohler–Parmele, Linacre, Priestley–Taylor, Stewart–Rouse, and deBruin equations—to estimate evaporation using climatologic data. They showed that the equations vary greatly in their ability to define the magnitude and variability of evaporation. On the other hand, de Bruin (1978) used a simplified model by combining the Priestley–Taylor and Penman equations to estimate evaporation. He indicated that the model would produce good results for periods of 10 days or more. Andersen and Jobson (1982) estimated evaporation using Morton's model and the evaporation map by Linsley et al. (1982) They determined that this map was slightly better to estimate annual lake evaporation in the United States than Morton's model. A modified model was used to estimate annual evaporation from a lake, based on monthly observations of temperature, humidity, and sunshine duration by Morton (1979). The results of the model are compared with those of the water budget for lakes. The comparison showed that there was a good agreement between the results of the model and the water budget approach. On the other hand, direct methods such as evaporation pan have also been used and compared to estimate evaporation by researchers (Choudhury 1999; McKenzie and Craig 2001; Vallet-Coulomb et al. 2001; Abtew 2001).

Many researchers have investigated the applicability of artificial neural networks (ANN) to problems in the hydrological and meteorological areas. Solar radiation has been estimated using a radial basis function and multilayer perceptron ANN (Dorvlo et al. 2002). They used latitude, longitude, altitude, sunshine hours, and the month of the year as inputs. The results of these methods are compared with the observed values, and the radial basis function is found to be a reasonable model. Also, ANN models have been used to estimate river flow, rainfall-runoff, short-term streamflow, rainfall, etc. (Imrie et al. 2000; Zealand et al. 1999; Luk et al. 2000; Tokar and Johnson 1999).

This study has three objectives: (1) to develop ANN models to estimate daily pan evaporation from measured climatic data; (2) to compare the ANN models with the Penman model; and (3) to evaluate the potential of ANN for estimating daily pan evaporation. It may be noted that Penman method agrees most closely with the pan evaporation values (Xu and Singh 1998).

Methods

Artificial Neural Networks

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. Commonly, neural networks are adjusted, or trained, so that a particular input

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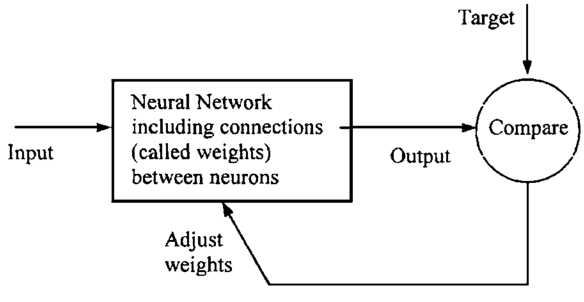

Fig. 1. Basic principle of artificial neural networks

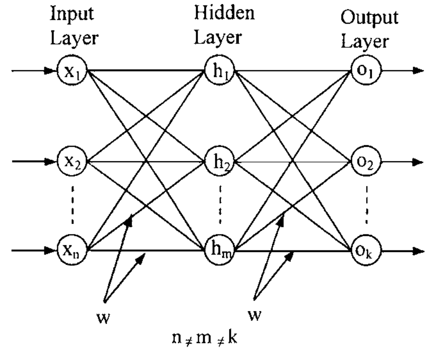

Fig. 2. Typical three-layer feed-forward ANN

leads to a specific target output. Such a situation is shown in Fig. 1. Here, the network is adjusted, based on a comparison of the output and the target, until the sum of square differences between the target and output values becomes the minimum. Typically, many such input/target output pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after the presentation of each individual input vector. Neural networks have been trained to perform complex functions in various fields of application, including pattern recognition, identification, classification, speech, vision, and control systems. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings (Demuth and Beale 2001).

Feed-forward ANNs comprise a system of neurons that are arranged in layers. Between the input and output layers, there may be one or more hidden layers. The neurons in each layer are connected to the neurons in a subsequent layer by a weight w, which may be adjusted during training. A data pattern comprising the values x_i presented at the input layer i is propagated forward through the network toward the first hidden layer j. Each hidden neuron receives the weighted outputs $w_{ij}x_{ij}$ from the neurons in the previous layer. These are summed to produce a net value, which is then transformed to an output value upon the application of an activation function (Imrie et al. 2000). A typical three-layer feed-forward ANN is shown in Fig. 2.

In Fig. 2, a typical ANN consists of three layers, namely, the input, hidden, and output layers. The input layer neurons are $x_o, x_1, x_2 \ldots x_n$; the hidden layer neurons are $h_1, h_2 \ldots h_m$; and the output layer neurons are $o_1, o_2 \ldots o_k$.

A neuron consists of multiple inputs and a single output. The sum of the inputs and their weights lead to a summation operation of

$$\mathrm{NET}_j = \sum_{i=1}^{n} w_{ij} x_{ij} \tag{1}$$

in which w_{ij}=established weight; x_{ij}=input value; and NET_j=input to a node in layer j.

The output of a neuron is decided by an activation function. There are a number of activation functions that can be used in ANNs, such as step, sigmoid, threshold, linear, etc. The sigmoid activation function, $f(x)$, commonly used, can be formulated mathematically as

$$f(x) = 1/[1 + \exp(-x)] \tag{2}$$

$$\mathrm{OUTPUT}_j = f(\mathrm{NET}_j) = 1/[1 + \exp(-\mathrm{NET}_j)] \tag{3}$$

The back-propagation learning algorithm is one of the most important historical developments in neural networks. It has re-awakened the scientific and engineering community to the

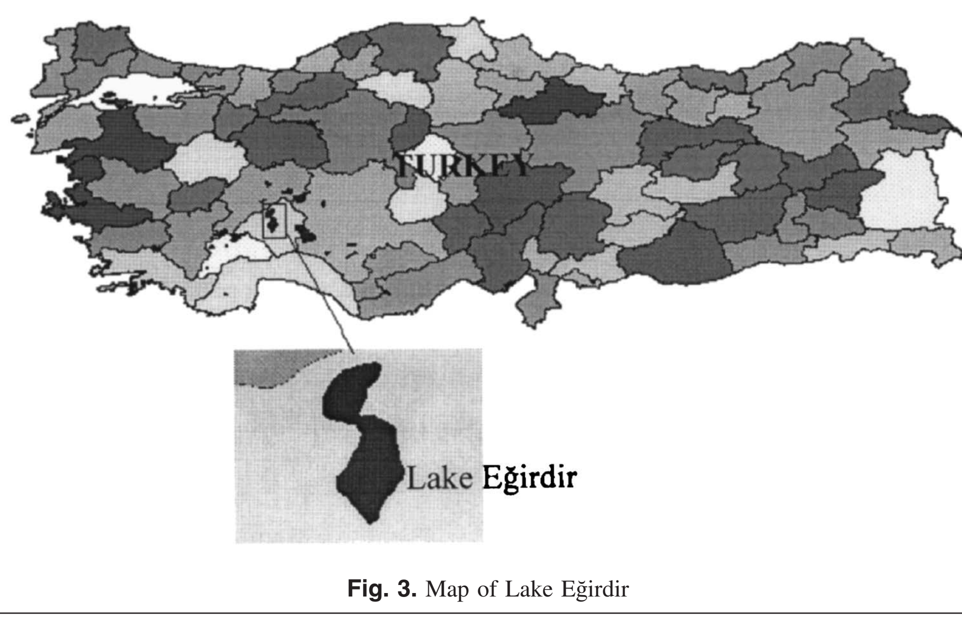

Fig. 3. Map of Lake Eğirdir

Table 1. Values of Cross-Validation Errors of Different ANN Architectures

Network structure	Number of hidden neurons	Average cross-validation MSE	Network structure	Number of hidden neurons	Average cross-validation MSE
Two inputs (T_a, T_w)	2	0.012943	Five inputs (T_a, T_w, R_c, P_a, n)	2	0.008282
	3	0.012334		3	0.009679
	4	0.011423		4	0.009235
	5	0.010157		5	0.009933
	6	0.012197		6	0.010927
	7	0.010376		7	0.012640
	8	0.010872		8	0.015955
	9	0.011785		9	0.012123
	10	0.012552		10	0.018392
	11	0.012968		11	0.018741
	12	0.011745		12	0.025287
Three inputs (T_a, T_w, R_c)	2	0.010999	Six inputs ($T_a, T_w, R_c, P_a, n, R_h$)	2	0.010259
	3	0.010968		3	0.011238
	4	0.010485		4	0.011184
	5	0.010765		5	0.014222
	6	0.009803		6	0.020503
	7	0.011908		7	0.015718
	8	0.011669		8	0.015373
	9	0.011533		9	0.024594
	10	0.012603		10	0.01885
	11	0.01564		11	0.037630
	12	0.021028		12	0.027854
Four inputs (T_a, T_w, R_c, P_a)	2	0.01334	Seven inputs ($T_a, T_w, R_c, P_a, n, R_h, U_2$)	2	0.009821
	3	0.010715		3	0.012123
	4	0.011631		4	0.011959
	5	0.019477		5	0.011016
	6	0.013970		6	0.018849
	7	0.014646		7	0.015697
	8	0.013387		8	0.026724
	9	0.016585		9	0.017987
	10	0.016227		10	0.025477
	11	0.020929		11	0.021583
	12	0.019538		12	0.026325

Note: T_a=air temperature; T_w=water temperature; R_c=solar radiation; P_a=air pressure; n=sunshine hours, R_h=relative humidity; and U_2=wind speed.

modeling and processing of many quantitative phenomena using neural networks. This learning algorithm is applied to multilayer feed-forward networks consisting of processing elements with continuous and differentiable activation functions. Such networks associated with the back-propagation learning algorithm are also called back-propagation networks. Given a training set of input–output pairs, the algorithm provides a procedure for changing the weights in a back-propagation network to classify the given input patterns correctly. The basis for this weight update algorithm is simply the gradient-descent method as used for simple perceptrons with differentiable neurons.

For a given input-output pair, the back-propagation algorithm performs two phases of data flow. First, the input pattern is propagated from the input layer to the output layer, and as a result of this forward flow it produces an output pattern with minimum sum of square differences between the output and target data. Then, the error signals resulting from the difference between the output pattern and an actual output are back-propagated from the output layer to the previous layers for them to update their weights (Lin and Lee 1995).

Table 2. Coefficient of Determination (R^2) and Mean Square Error (MSE) of ANN Models

Number of input neurons	Training data set		Testing data set	
	MSE	R^2	MSE	R^2
2	0.011516	0.684	0.011874	0.629
3	0.009693	0.734	0.007359	0.770
4	0.008991	0.753	0.008667	0.729
5	0.008825	0.758	0.007451	0.767
6	0.008521	0.766	0.006795	0.787
7	0.008296	0.772	0.006789	0.788

Penman Method

In 1948, Penman presented a theory and formulas for the estimation of evaporation from weather data. The theory is based on two requirements, which must be met provided that continuous evaporation occurs. These requirements are that: (1) there must be a supply of energy to provide latent heat of vaporization; and (2) there must be some mechanism for removing the vapor, once produced. The formula has been checked in many parts of the world and gives good results. Being based on physical principles, it is of general application and gives values that should serve for most project studies until supplemented by actual evaporation measurements. The Penman formulas can be given as follows:

$$E = [\Delta/(\Delta+\gamma)]R_n + [\gamma/(\Delta+\gamma)]\{[6.43(1+0.536U_2)(e_w - e_a)]/\lambda\} \tag{4}$$

in which E=evaporation (mm/day); Δ=slope of the vapor pressure versus temperature curve (kPa/°C); γ=psychometric constant (kPa/°C); λ=latent heat of vaporization (°C); U_2=wind speed at 2 m height (m/s); R_n=net radiation (cal/cm^2/day); e_w=saturation vapor pressure of air at temperature T_a (kPa); and e_a=actual vapor pressure of air at temperature T_a (kPa); (Wilson 1990).

Application

Lake Eğirdir is a freshwater lake located in the Lakes District of Turkey; it is the second largest lake in the country with a 47,000 hm^2 surface area and a volume of $4{,}360\times10^9$ dm^3 (see Fig. 3). It is used as a drinking and irrigation water source. Lake Eğirdir is of tectonic origin and geographically lies on a 50 km stretch in the northern part of Eğirdir County. The altitude of the lake is 916 m with a depth of around 1.8 m. The mean depth of the lake is 9 m and the deepest point is 15 m. In the southern part, the width of the lake reaches a maximum of 16 km.

Meteorological data to develop the ANN model are obtained from the Automated GroWeather Meteorological Station set up near Lake Eğirdir. Meteorological parameters include air and water temperature, relative humidity, solar radiation, wind speed, air pressure, and sunshine hours, which are logged every 2 h. Two hourly data are integrated subsequently to obtain daily data, because the pan evaporation values used as output in the ANN models are daily measurements obtained from the Directorate of State

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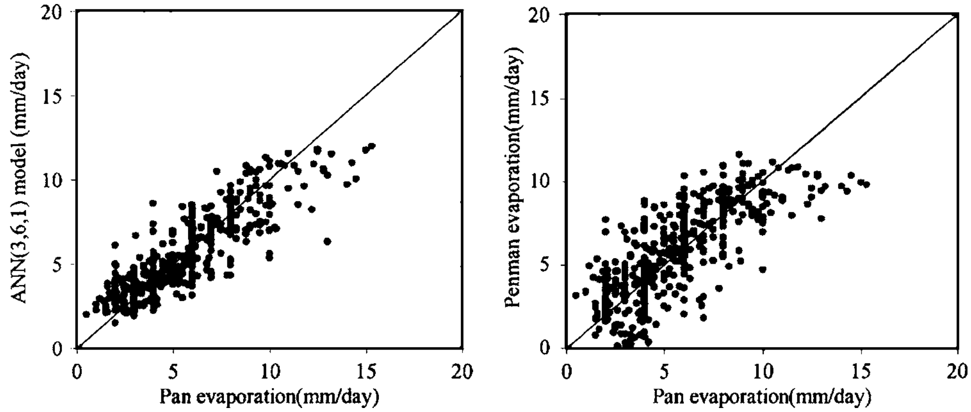

Fig. 4. Comparison of daily pan evaporation with ANN(3,6,1) model and Penman method

Hydraulic Works, Turkey. The data to develop the ANN models includes 490 daily observations from March 1 to October 31 in the years 2001 and 2002.

The relationships between meteorological variables and pan evaporation were investigated first using statistical analyses. The effective variables on pan evaporation are arranged in the order of air temperature, water temperature, solar radiation, air pressure, sunshine hours, relative humidity, and wind speed according to degree of effectiveness. ANN models with two, three, four, five, six, and seven inputs were developed according to the statistical analyses results. For example, the model with two inputs included air and water temperature variables, whereas the model with three inputs consisted of air and water temperature and solar radiation. In this paper, ANN(i,j,k) indicates a network architecture with i, j, and k neurons in the input, hidden, and output layers, respectively. Herein, i runs from 2 to 7, j assumes values of 2–12, and $k=1$ is adopted in order to decide the best ANN model alternative.

Prior to execution of the model, standardization is done according to the following expression such that all data values fall between 0 and 1:

$$X=(X_i-X_{\min})/(X_{\max}-X_{\min}) \tag{5}$$

where X=standardized value of X_i; and $X_{\max}$ and $X_{\min}$=maximum and minimum values in the all observation sequence. The main reason for standardizing the data is that the variables are usually measured in different units. By standardizing the variables and recasting them into dimensionless units, the arbitrary effect of similarity between objects is also removed (Sudheer et al. 2002).

An alternative model selection method often referred to in the neural networks literature is cross-validation. It may be noted that uncertainty is not completely removed by cross-validation. The motivation for this model selection is similar to the line of arguments leading to information criteria. Model complexity does not necessarily result in a better description of the underlying function, due to increasing estimation error. In order to find an appropriate degree of complexity, it is appealing to compare the mean squared errors (MSE) of different model specifications in standardized data units. Such prediction errors are obtained by sampling the data into M subsets with n observations each. The simplest case is $M=3$, but for a better approach in this paper $M=5$ is adopted. In practice, odd numbers of data sets are selected. From the M available sets of observed data, (M-1) are used to train the ANN. The training is finished when the least sum of error squares is reached and the result is compared to the observed data. This procedure is repeated M times, once for each training data set. The average MSE on the M subsets that have been left out defines the cross-validation error. If, for instance, a large value of this error is obtained, the point excluded during the training process is important and its absence will produce an ANN with poor estimation and generalization capabilities. On the other hand, if the associated error is small, it means that the data set has enough support from its neighbors that its presence is not very important. (Anders and Korn 1999; Sudheer et al. 2002). The average cross-validation errors for various model structures are given in Table 1. The model with the lowest cross-validation error is finally chosen.

The number of hidden layers considered after trial and cross-validation is only 1 in all the structures proposed, and the numbers of hidden neurons are five, six, three, two, two, and two. These structures are represented by ANN(2,5,1), ANN(3,6,1), ANN(4,3,1), ANN(5,2,1), ANN(6,2,1), and ANN(7,2,1), respectively. The values of the cross-validation errors are least for the selected models as compared with other structures (Table 1). The learning rate and momentum are the parameters that affect the speed of convergence of the back-propagation algorithm. A stopping criteria is employed at 10,000 for training. A learning rate of 0.001 and a momentum of 0.1 are fixed for the selected network after training and model selection is completed for year 2001. The trained networks are used to run a set of test data for the year 2002.

The results of the statistical analyses are given in Table 2. As seen from Table 2, comparison of ANN(3,6,1), ANN(6,2,1), and

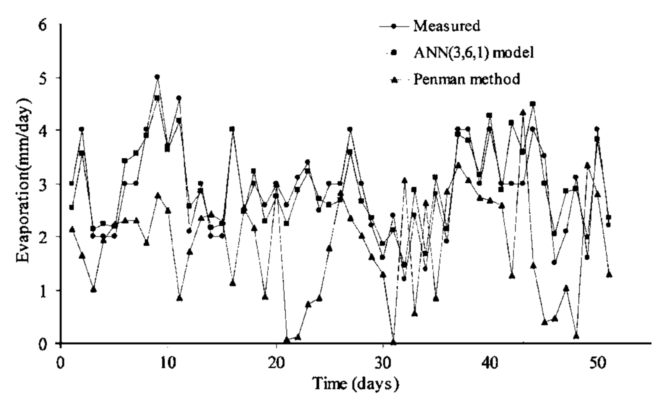

Fig. 5. Modeled and measured evaporation

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ANN(7,2,1) model performances indicates that these models have more or less similar performances. The R^2 values of the ANN(3,6,1), ANN(6,2,1), and ANN(7,2,1) models are 0.770, 0.787, and 0.788 for the testing set, respectively. The difference between these three models is only in the input variables. The ANN(3,6,1) model depends on daily mean values of air temperature, water temperature, and solar radiation, but ANN(6,2,1) is based on air pressure, sunshine hours, and relative humidity, and ANN(7,2,1) depends on wind speed and six parameters. This could lead to the conclusion that using daily values of air temperature, water temperature, and solar radiation for estimating evaporation would not significantly reduce the performance. This observation may help to reduce drastically the data requirement for estimating evaporation from meteorological variables. The performance of the ANN(3,6,1) model suggests that the evaporation could be estimated easily from available data using the ANN approach. This result is of significance in a situation where a hydrological model is to be developed with limited data.

In order to expose the performance of ANN(3,6,1), the ANN(3,6,1) model and the Penman method are plotted versus daily pan evaporation in Fig. 4 for the whole data values. As seen in Fig. 4, the Penman method underestimates evaporation values. R^2 and MSE values of the Penman method are obtained as 0.548 and 0.0161, respectively. Also, the ANN(3,6,1) model comparison plot is around a 45° straight line, which implies that there are no bias effects. The results of ANN(3,6,1) and the Penman method and daily pan evaporation are presented in Fig. 5, where ANN(3,6,1) matches daily pan evaporation more closely than the Penman method.

Conclusions

The aim of this research is to develop an ANN model to estimate daily pan evaporation for Lake Eğirdir when the measurement system has failed or to estimate missing daily pan evaporation data. Convenient models with various inputs are developed and compared to the Penman method. In the analyses, ANN models have higher R^2 and lower MSE values for both the training and testing data sets than the Penman method. It was shown that the ANN(6,2,1) and ANN(7,2,1) models are superior among the ANN models. Comparing the performance of the ANN(6,2,1), ANN(7,2,1), and ANN(3,6,1) models, it can be observed that they are performed in a similar way. The difference between them is only in the input variables considered. The performance of the ANN(3,6,1) model with air and water temperature and solar radiation inputs suggests that the evaporation could be estimated from easily available data using the ANN approach. Finally, ANN models can be put into place with existing methods for estimating daily pan evaporation in hydrological modeling studies.

Notation

The following symbols are used in this paper:

E = evaporation;
e_a = actual vapor pressure of air at temperature T_a;
e_w = saturation vapor pressure of air at temperature T_a;
$f(x)$ = sigmoid function;
h_i = hidden layer neuron;
i = neurons in input layer;
j = neurons in hidden layer;
k = neurons in output layer;
M = subsets with n observations each;
NET_j = input to neuron in hidden layer j;
n = sunshine hours;
OUTPUT_j = output to neuron in hidden layer j;
o_i = output layer neuron;
P_a = air pressure;
R_c = solar radiation;
R_h = relative humidity;
R_n = net radiation;
T_a = air temperature;
T_w = water temperature;
U_2 = wind speed at 2 m height;
w = weight;
w_{ij} = established weight;
X = standardized value of X_i;
X_i = measured values;
$X_{\max}$ = maximum value in all observation sequence;
$X_{\min}$ = minimum value in all observation sequence;
x_i = input layer neuron;
x_{ij} = input value;
γ = psychometric constant;
Δ = slope of vapor pressure versus temperature curve; and
λ = latent heat of vaporization.

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