Estimating daily pan evaporation from climatic data of the State of Illinois, USA using adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN)

J. Shiri, W. Dierickx, A. Pour-Ali Baba, S. Neamati and M. A. Ghorbani

ABSTRACT

Evaporation is a major component of the hydrological cycle. It is an important aspect of water resource engineering and management, and in estimating the water budget of irrigation schemes. The current work presents the application of adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) approaches for modeling daily pan evaporation using daily climatic parameters. The neuro-fuzzy and neural network models are trained and tested using the data of three weather stations from different geographical positions in the U.S. State of Illinois. Daily meteorological variables such as air temperature, solar radiation, wind speed, relative humidity, surface soil temperature and total rainfall for three years (August 2005 to September 2008) were used for training and testing the employed models. Statistic parameters such as the coefficient of determination (R^2), the root mean squared error (RMSE), the variance accounted for (VAF), the adjusted coefficient of efficiency (E_1) and the adjusted index of agreement (d_1) are used to evaluate the performance of the applied techniques. The results obtained show the feasibility of the ANFIS and ANN evaporation modeling from the available climatic parameters, especially when limited climatic parameters are used.

Key words | cross-station application, evaluation, station modeling, testing, training

J. Shiri (corresponding author)
S. Neamati
M. A. Ghorbani
Department of Water Engineering,
Faculty of Agriculture,
University of Tabriz,
Tabriz,
Iran
E-mail: *j_shiri2005@yahoo.com*

W. Dierickx
Geraardsbergsesteenweg 18,
9860 Oosterzele,
Belgium

A. Pour-Ali Baba
MSc Student of Agronomy,
Islamic Azad University,
Myaneh Branch,
Iran

INTRODUCTION

Estimation of evaporation is an important issue in the management of water resource systems, climatology, hydrology research and irrigation scheduling. Estimating reservoir evaporation using a pan has long been popular. The most widely used pan in the USA is the class A pan, which is 10 cm in diameter and 25 cm deep, mounted on a timber grid about 15 cm above the soil surface (Jensen 1974; Frevert *et al.* 1983). There are several pan methods, such as direct measurements of the class A pan, as used by Salih & Sendil (1984); an adjusted form of those measurements according to the recommendation of Doorenbos & Pruitt (1977); or as suggested by Christiansen's model (Jensen 1974). Evaporation is given by the change in the water level inside the pan, after allowance is made for precipitation (Feddes & Lenselink 1994). Because of the absorption of radiation through the pan wall and the transfer of sensible heat between the air and the pan wall, the above-ground pan receives an additional amount of energy, resulting in higher evaporation rates than those calculated from meteorological data. Sunken pans perhaps give more reliable values for evaporation, but the accuracy of their results are limited by the heat exchange between the pan wall and the surrounding soil, as well as by surface roughness effects (Feddes & Lenselink 1994). It is neither practical nor possible to place evaporation pans everywhere (i.e. at every reservoir or irrigation field). Of course, because

doi: 10.2166/nh.2011.020

of the importance of pan evaporation in hydrology and related subjects (Kişi 2006a), pans have been placed in many areas. Likewise, a number of attempts has been made to relate evaporation to climatic variables (Stephen & Stewart 1963; Linarce 1967; Burman 1976; Gavin & Agnew 2004; Jabloun & Sahli 2008). Over the years, several linear relationships have been proposed (Stephen & Stewart 1963), but the process of evaporation is highly non-linear because of the interdependence of climatic variables.

The use of artificial intelligence has recently received more attention in evaporation modeling. Kumar *et al.* (2002) applied a multi-layer neural network using a back-propagation training algorithm for the estimation of reference evapotranspiration (ET_0). Sudheer *et al.* (2003) applied a radial basis neural network with limited climate data to model ET_0. Trajkovic (2005) modeled ET_0 according to FAO 56 (Allen *et al.* 1998) using a temperature-based radial basis neural network. Kişi (2006b, 2006c) applied generalized regression neural networks and feed-forward neural networks to estimate ET_0. Kişi (2007) modeled evapotranspiration from climatic data using a neural computing technique. Guven *et al.* (2008) reported a new genetic-programming-based approach for the formulation of reference evapotranspiration. Landeras *et al.* (2008) compared neural network models and semi-empirical equations for estimating daily reference evapotranspiration in Spain.

Due to its advantages, effective data driving neuro-fuzzy models have received more attention in the recent past. The adaptive neuro-fuzzy inference system (ANFIS) was first introduced by Jang (1993), Jang & Sun (1995), Jin *et al.* (1995), and later widely applied in engineering problems. Palit & Popovic (1999, 2000, 2005) applied a neuro-fuzzy network for time series forecasts. Deka & Chandramouli (2003) derived the river stage-discharge relationship using a fuzzy neural network model. Kişi (2005) estimated suspended sediment using neuro-fuzzy and neural network approaches. Neamati (2009) applied the neuro-fuzzy technique for estimating the suspended sediment load in the Ligovan River, Iran. Shiri & Kişi (2010) applied a wavelet-neuro-fuzzy conjunction model for predicting short-term and long-term streamflows.

Only a few studies related to the application of the neuro-fuzzy technique for evaporation modeling exist. Kişi (2006a) proposed a neuro-fuzzy computing technique for daily pan evaporation modeling. Kişi & Öztürk (2007) used the adaptive neuro-fuzzy computing technique for evapotranspiration estimation. Aytek (2009) modeled evapotranspiration using a co-active neuro-fuzzy inference system. Moghaddamnia *et al.* (2009) applied neural networks and ANFIS techniques for evaporation estimation in a hot and dry climate in Iran. The objective of this paper is to demonstrate the feasibility of the neuro-fuzzy and neural network techniques to daily pan evaporation modeling using climatic parameters.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

An ANFIS is a combination of an adaptive neural network (ANN) and a fuzzy inference system. The parameters of the fuzzy inference system are determined by the neural network learning algorithms. As this system is based on the fuzzy inference system, reflecting amazing knowledge, an important aspect is that the system should be always interpretable in terms of fuzzy IF-THEN rules. ANFIS is capable of approximating any real continuous function of a compact set of parameters to any degree of accuracy (Jang *et al.* 1997). ANFIS identifies a set of parameters through a hybrid learning rule combining a back-propagation gradient descent error digestion and a least squared error method. There are mainly two approaches for fuzzy inference systems, namely the approach of Mamdani (Mamdani & Assilian 1975) and the approach of Sugeno (Takagi & Sugeno 1985). The difference between the two approaches arises from the fact that Mamdani's approach uses fuzzy membership functions, while linear or constant functions are used in Sugeno's approach. In this study the Sugeno method was applied for modeling the evaporation. As a simple example a fuzzy inference system with two inputs x_1 and x_2 and one output y is assumed. Here, x_1 and x_2 might be considered as air temperature T_A and wind speed S_W, while the output y would represent the pan evaporation E. Suppose that the rule base contains two fuzzy IF–THEN rules:

$$\text{Rule 1: IF } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1, \text{THEN } y = p_1 x_1 + q_1 x_2 + r_1 \quad (1)$$

$$\text{Rule 2 : IF } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2, \text{THEN} \quad y = p_2x_1 + q_2x_2 + r_2 \tag{2}$$

in which the IF (antecedent) part is fuzzy in nature, while the THEN (consequent) part is a crisp function of an antecedent variable (as a rule, a linear equation). Applied on the above example for pan evaporation, Equations (1) and (2) read:

$$\text{Rule 1 : IF } T_A \text{ is LOW and } S_W \text{ is LOW, THEN} \quad E = p_1T_A + q_1S_W + r_1$$

$$\text{Rule 2 : IF } T_A \text{ is HIGH and } S_W \text{ is MEDIUM, THEN} \quad E = p_2T_A + q_2S_R + r_2$$

A common rule set may have n inputs and m IF–THEN rules and can be expressed as

$$y = k_ix_1 + l_ix_2 + \ldots + p_ix_{n-1} + q_ix_n + r_i \tag{3}$$

where k_i, l_i,…, p_i, q_i and r_i are parameters with $i = 1, 2, 3, \ldots, m$ corresponding to Rule 1, Rule 2, Rule 3, …, Rule m. The node function in the same layer of the same function family, is described as follows (Jang 1993).

Layer 1

Every node i in this layer is an adaptive node with node function O_i^1 given by

$$O_i^1 = \mu_{A_i}(T_A) \tag{4}$$

where T_A is the input to the ith node and μ is the membership function of A_i which is a linguistic label (such as HIGH, or LOW) associated with this node function. A similar equation to Equation (4) may be considered for the input S_W.

The node function O_i^1 is the membership function of A_i and specifies the degree to which the given input T_A (or S_W) satisfies the quantifier A_i. The membership function for A is usually described by bell-functions, such as

$$\mu_{A_i}(T_A) = \frac{1}{1 + [(T_A - c_i)/a_i]^{2b_i}} \tag{5}$$

or

$$\mu_{A_i}(T_A) = \exp\left\{-\left(\frac{T_A - c_i}{a_i}\right)^2\right\} \tag{6}$$

where $\{a_i, b_i, c_i\}$ is the parameter set and μ is the membership function of A_i. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership functions depending on the linguistic label A_i. In fact, any continuous and piecewise differentiable functions, such as commonly used triangular or trapezoidal membership functions, are also qualified candidates for the node function in this layer. Parameters in this layer are referred to as *premise parameters*.

Layer 2

This layer consists of circle nodes labeled TT which multiply incoming signals and sending the product out. For instance

$$O_i^2 = w_i = \mu_{A_i}(T_A)\mu_{B_i}(S_W), \quad i = 1, 2. \tag{7}$$

Each node output represents the firing strength of a rule.

Layer 3

In this layer, the circle nodes labeled N, calculate the ratio of the ith rule firing strength to the sum of all rule firing strengths

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad \text{for } i = 1, 2. \tag{8}$$

The outputs of this layer are referred to as *normalized firing strengths*.

Layer 4

All of the nodes in this layer are adaptive with a node function

$$O_i^4 = \bar{w}_iy_i = \bar{w}_i(p_iT_A + q_iS_W + r_i) \tag{9}$$

where $\bar{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are called *consequence parameters*.

Layer 5

The single circle node of this layer, labeled Σ, computes the overall outputs as the summation of all incoming signals:

$$O_i^5 = \sum_{i=1}^{i} \bar{w}_i y_i = \frac{\sum_{i=1}^{i} w_i y_i}{\sum_{i=1}^{i} w_i} \tag{10}$$

Thus, an adaptive network which is functionally equivalent to a Type 3 fuzzy inference system has been constructed. Further details about ANFIS can be found in Jang (1993).

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are basically parallel information-processing systems. The internal architecture of ANNs is similar to the structure of a biological brain with a number of layers of fully interconnected nodes or neurons. Each neuron is connected to other neurons by means of direct communication links, each with an associated weight. The neural network usually has two or more layers of neurons in order to process non-linear signals.

The input layer admits the incoming information, which is processed by the hidden layer(s), and the output layer presents the network result. During the learning process, the weights of the interconnections and the neural biases are adjusted in trial and error procedures, to minimize the errors. Two-layer feed-forward networks were employed in this study, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The hidden-layer-node numbers of each model were determined after an iterative process, because there is not yet a definite theoretical background for determining the interconnections of neurons. The basic details and concepts of the working of an ANN can be found in Bishop (1995) or Haykin (1999).

APPLICATION

Data used

The daily climatic data of three weather stations, Freeport (latitude 42°28′N, longitude 89°67′W, altitude 265 m); Spring field (latitude 39°68′N, longitude 89°62′W, altitude 177 m) and Carbondale (latitude 37°70′N, longitude 89°23′W, altitude 137 m) operated by the Illinois State Water Survey were used in this study (www.isws.illinois.edu/data.asp). The climatic data consisted of three years (August 2005 to November 2008) of daily records of air temperature (T_A), solar radiation (R_S), wind speed (S_W), relative humidity (H_R), total precipitation (P_T), soil temperature at 10 cm depth (T_S), and pan evaporation (E). For each station the last 365 days (December 1, 2007 to November 30, 2008) were reserved for the test set and the remaining data were used for training. The daily statistical parameters of the applied climatic variables are presented in Table 1. In the table, the symbols X_{mean}, X_{max}, X_{min}, S_x, C_v and C_{sx} denote mean, maximum, minimum, standard deviation, coefficient of variation and skewness, respectively. The average evaporation losses in the three stations are almost the same and rather limited, while the relative humidity shows high values of more than 95% during some days. Wind speed and total precipitation data show a high skewness and, moreover, the total precipitation shows high variation for all three stations. Table 1 clearly illustrates that the climatic variables of the three studied stations have similar statistical trends.

Goodness of fit of model performance

Three statistical evaluation criteria were used to assess the model performance: (i) the coefficient of determination (R^2) of the linear relationship between measured and estimated evaporation; (ii) the root mean square error (*RMSE*) defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_{io} - E_{ie})^2} \tag{11}$$

Table 1 | Statistic parameters of daily climatic data

Station	Climatic variable	S_W (m/h)	R_S (MJ/m^2)	T_A (°C)	H_R (%)	P_T (mm)	T_S (°C)	E (mm)
Freeport	X_{mean}	6.15	15.21	10.22	69.70	2.41	12.43	2.96
	X_{max}	19	32.71	29.5	97.00	94.48	28.22	7.36
	X_{min}	1.7	0.50	−22.11	39.85	0.00	−1.11	0.00
	S_x	2.64	8.58	4.24	10.04	2.51	1.69	1.25
	C_v	0.43	0.56	0.41	0.15	1.04	0.135	0.42
	C_{sx}	0.92	0.16	−0.49	0.09	5.36	−0.04	0.39
	C_c^a	−0.33	0.96	0.75	−0.57	−0.14	0.75	1.00
Springfield	X_{mean}	6.19	14.84	13.20	67.02	2.35	14.73	3.06
	X_{max}	20.40	30.86	30.27	98.15	70.35	29.77	7.62
	X_{min}	1.30	0.62	−14.61	39.80	0.00	-0.80	0.00
	S_x	2.73	8.16	10.21	10.70	7.05	8.97	2.01
	C_v	0.44	0.55	0.77	0.16	2.99	0.61	0.66
	C_{sx}	0.86	0.06	−0.39	0.20	4.53	−0.14	0.26
	C_c	−0.33	0.97	0.76	−0.51	−0.18	0.75	1.00
Carbondale	X_{mean}	5.65	15.93	14.58	71.16	3.1	17.01	3.34
	X_{max}	18.1	31.12	31.27	98.45	183.13	31.88	7.36
	X_{min}	0.00	0.00	−10.61	33.05	0.00	0.00	0.00
	S_x	2.93	8.40	9.48	10.17	11.5	8.95	2.06
	C_v	0.52	0.52	0.65	0.14	3.70	0.52	0.62
	C_{sx}	1.01	−0.07	−0.42	−0.13	7.99	−0.16	0.15
	C_c	−0.37	0.97	0.73	−0.21	−0.22	0.73	1.00

[a]C_c is the correlation coefficient of the linear regression of each climatic variable with E.

where E_{io} and E_{ie} denote the observed and estimated evaporation, and (iii) the variance accounted for (VAF) defined as

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{Var}(E_{io} - E_{ie})}{\mathrm{Var}(E_{io})}\right] * 100. \tag{12}$$

If the VAF is 100, it represents a perfect fit.

Also, other evaluation measures, such as the adjusted coefficient of efficiency E_1 and the adjusted index of agreement d_1, should supplement model assessment as discussed by Legates & McCabe (1999). These two measures are defined as

$$E_1 = 1 - \frac{\sum_{i=1}^{n} |E_{io} - E_{ie}|}{\sum_{i=1}^{n} |E_{io} - E_{m}|} \tag{13}$$

$$d_1 = 1 - \frac{\sum_{i=1}^{n} |E_{io} - E_{ie}|}{\sum_{i=1}^{n} (|E_{ie} - E_{m}| + |E_{io} - E_{m}|)} \tag{14}$$

where E_m denotes the mean (observed) evaporation.

RESULTS AND DISCUSSION

Various combinations of climatic variables were analyzed to estimate daily pan evaporation and examine the effect of each variable. It is relevant to note that the present paper consisted of two parts in which: (1) the individual weather variables are introduced as input parameters to ANFIS and ANN; and (2) the ANFIS and ANN models were built up with multi-variable input combinations.

Table 2 | Error statistics of single-input ANFIS and ANN models during the test period

	ANFIS model			ANN model		
Input parameter	**Number of Membership functions**	***R***	**RMSE (mm)**	**ANN structure**	***R***	**RMSE (mm)**
T_A	3	0.777	1.271	1-10-1	0.776	1.273
S_W	3	0.368	1.912	1-5-1	0.379	1.886
P_T	2	0.188	2.011	1-4-1	0.400	1.861
H_R	4	0.472	1.79	1-10-1	0.471	1.782
T_S	3	0.758	1.316	1-5-1	0.762	1.306
R_S	2	0.967	0.515	1-8-1	0.968	0.508

Single-input ANFIS and ANN models

In this section the weather variables of three studied stations were pooled and the effect of each variable on estimating evaporation through application of ANFIS and ANN models was investigated. As mentioned earlier, the last 365 days data were applied for testing the developed models and the remaining data were used for training. Table 2 represents the statistical analysis of the obtained results through the application of coefficient of correlation (R) and RMSE. From the table it is clear that introducing the solar radiation (R_S) as single input for both the ANFIS and ANN models produces good results among others and the single-input models with T_A and T_S as unique input parameters can be ranked as the second and third models, respectively. A reason behind this conclusion may be the high linear correlation between these parameters and evaporation in all of the studied stations (see Table 1). The final architecture (number of membership functions) of the single-input ANFIS models are also given in Table 2. Two, three or four membership functions are sufficient for the evaporation estimation. For instance, with application of R_S-based single-input ANFIS model, there are two Gaussian membership functions for the input, parameter, R_S. In the implementation of fuzzy logic, several types of membership functions can be used. However, recent studies have shown that the type of membership function does not affect the results fundamentally (Vernieuwe *et al.* 2005). In the present study, the Gaussian membership functions were used. The number of membership functions was determined by trial and error. The fifth column of Table 2 gives the final architecture of each single-input ANN model. This column represents the number of input, hidden and output nodes in each of the ANN models. Table 3 gives the consequent parameters of the R_S-based single-input ANFIS model.

Table 3 | The consequent parameters of the single-input ANFIS model (with R_S as input variable)

Rules	***p***	***q***	***R***
Rule 1	0.18	0.0	0.08
Rule 2	0.25	0.0	−0.98
Rule 3	0.18	0.0	1.067

Multiple-input ANFIS and ANN models using the recorded weather data

In the first step, the weather variables are introduced as input parameters to ANFIS and ANN models to see the degree of the effect of each variable on the evaporation estimation. In this way, the following input combinations were studied: (i) T_A; (ii) T_A, S_W; (iii) T_A, S_W, P_T; (iv) T_A, S_W, P_T, H_R; (v) T_A, S_W, P_T, H_R, T_S; (vi) T_A, S_W, P_T, H_R, T_S, R_S as ANFIS 1 to ANFIS 6, and ANN 1 to ANN 6, respectively. It should be noted that in many weather stations worldwide, there are no advanced instruments for detecting all of the weather variables, so it would be of great utility if some artificial intelligence based models could be developed for estimating evaporation values from limited climatic data. Therefore, the model with air temperature as the unique input parameter would be of interest to be studied. In this way, the single-input ANFIS and ANN models with T_A may be developed for each station. Though the results of such investigation at individual station scale may be not so surprising, the application of this variable with pooled data set over the state, showed some promising results, as can be seen from Table 2.

Application of ANFIS model

The resulting statistic values of the ANFIS test for the Freeport, Springfield and Carbondale stations are given in Table 4. From the table it can be seen that introducing the air temperature as a model input solely cannot produce acceptable results at Freeport station, yet applying air temperature and wind speed and/or the combination of these two parameters with the total daily precipitation does not give better results. The model with the air temperature as the only input variable, yielded some better results at Springfield station ($R^2 = 0.533$, RMSE = 1.346 mm/d, VAF = 52.44%, $E_1 = 0.367$ and $d_1 = 0.657$) than the same input combination for the Freeport station (R^2=0.368, RMSE = 1.700 mm/d, VAF = 28.28%, $E_1 =$ 0.0327 and $d_1 = 0.641$). This is most likely due to the higher temperature at the Springfield than at the Freeport station. For Springfield station, introducing air temperature and wind speed gives less accurate results, and unsatisfactory results are also obtained by adding the daily total precipitation, which was not the same as for Freeport station. For Carbondale station, introducing air temperature, wind speed and daily total precipitation as inputs cannot learn the non-linear relationship between input variables and evaporation. It seems that adding the relative humidity to the input combinations improves the results to a great extent in all of the studied stations and, consequently, they are more effective in estimating evaporation

Table 4 | Error statistics of the ANFIS models for each station during the test period

Input combinations	R^2	RMSE (mm/d)	VAF (%)	E_1	d_1
	Freeport station				
(i) T_A	0.368	1.700	28.28	0.0327	0.641
(ii) T_A, S_W	0.060	5.181	18.24	−0.009	0.548
(iii) T_A, S_W, P_T	0.226	0.304	68.58	0.277	0.660
(iv) T_A, S_W, P_T, H_R	0.794	0.914	79.27	0.608	0.799
(v) T_A, S_W, P_T, H_R, T_S	0.854	0.025	85.37	0.659	0.977
(vi) T_A, S_W, P_T, H_R, T_S, R_S	0.994	0.000	99.46	0.934	0.977
	Springfield station				
(i) T_A	0.533	1.346	52.44	0.367	0.657
(ii) T_A, S_W	0.024	1.092	10.23	0.044	0.558
(iii) T_A, S_W, P_T	0.039	2.489	9.57	−0.197	0.534
(iv) T_A, S_W, P_T, H_R	0.761	0.025	76.01	0.556	0.769
(v) T_A, S_W, P_T, H_R, T_S	0.802	0.025	79.87	0.583	0.777
(vi) T_A, S_W, P_T, H_R, T_S, R_S	0.991	0.000	99.16	0.918	0.959
	Carbondale station				
(i) T_A	0.414	1.651	34.75	0.318	0.627
(ii) T_A, S_W	0.011	6.705	9.58	−0.185	0.501
(iii) T_A, S_W, P_T	0.047	8.813	7.64	−0.178	0.535
(iv) T_A, S_W, P_T, H_R	0.364	2.286	26.01	0.455	0.728
(v) T_A, S_W, P_T, H_R, T_S	0.807	0.036	80.55	0.609	0.790
(vi) T_A, S_W, P_T, H_R, T_S, R_S	0.993	0.006	99.39	0.930	0.965

Table 5 | Error statistics of the ANN models for each station during the test period

Input combination	R^2	RMSE (mm/d)	VAF (%)	E_1	d_1
	Freeport station				
(i) T_A	0.554	0.054	45.20	0.457	0.548
(ii) T_A, S_W	0.671	0.047	67.13	0.483	0.717
(iii) T_A, S_W, P_T	0.631	0.048	63.16	0.451	0.451
(iv) T_A, S_W, P_T, H_R	0.631	0.048	63.14	0.452	0.521
(v) T_A, S_W, P_T, H_R, T_S	0.631	0.050	67.17	0.452	0.703
(vi) T_A, S_W, P_T, H_R, T_S, R_S	0.632	0.050	67.25	0.350	0.703
	Springfield station				
(i) T_A	0.568	0.049	46.10	0.432	0.612
(ii) T_A, S_W	0.624	0.047	62.63	0.441	0.693
(iii) T_A, S_W, P_T	0.624	0.048	62.40	0.438	0.438
(iv) T_A, S_W, P_T, H_R	0.623	0.047	62.62	0.441	0.692
(v) T_A, S_W, P_T, H_R, T_S	0.653	0.048	65.32	0.441	0.692
(vi) T_A, S_W, P_T, H_R, T_S, R_S	0.653	0.048	65.33	0.444	0.694
	Carbondale station				
(i) T_A	0.609	0.067	44.23	0.398	0.589
(ii) T_A, S_W	0.614	0.049	61.47	0.443	0.689
(iii) T_A, S_W, P_T	0.609	0.051	60.96	0.44	0.687
(iv) T_A, S_W, P_T, H_R	0.610	0.051	61.04	0.439	0.687
(v) T_A, S_W, P_T, H_R, T_S	0.606	0.050	60.64	0.439	0.686
(vi) T_A, S_W, P_T, H_R, T_S, R_S	0.612	0.050	60.89	0.440	0.687

(obviously, in combination with aforementioned parameters). However, there is still a weak agreement between the observed and estimated evaporation values. Input combination (v) which additionally considers the soil temperature as variable, gives more accurate estimates than those obtained with the input combinations (i) to (iv). Finally, the input combination (vi) which employs all selected climatic variables gives the best performance, as the ANFIS 6 model has the smallest RMSE as well as the highest R^2, VAF, E_1 and d_1 values in all of the studied stations.

Application of ANN model

The ANFIS estimates are compared with the ANN estimates in order to assess the ANFIS performance. The results of this comparison are given in Table 5. The ANN models use the same input combinations as the ANFIS models, but the results did not show visible changes between different input combinations, and overall, the performances of the ANN models are less accurate in all three stations. As the performance of the input combinations (i) to (iv) are quite weak, the comparison between ANFIS and ANN models deals with the comparison of ANFIS 5, 6 and ANN 5, 6 for all the studied stations. The total evaporation estimates of the ANFIS 5 and 6, and the ANN 5 and 6 models for Freeport station are respectively 5.9, 0.1, 0.8 and 0.7% lower than the observed value (1002.5 mm/yr) in the test period. It is clear that ANFIS 6 is the best model to estimate the total evaporation. Though ANFIS 5 has the highest overestimation, a review of the statistical

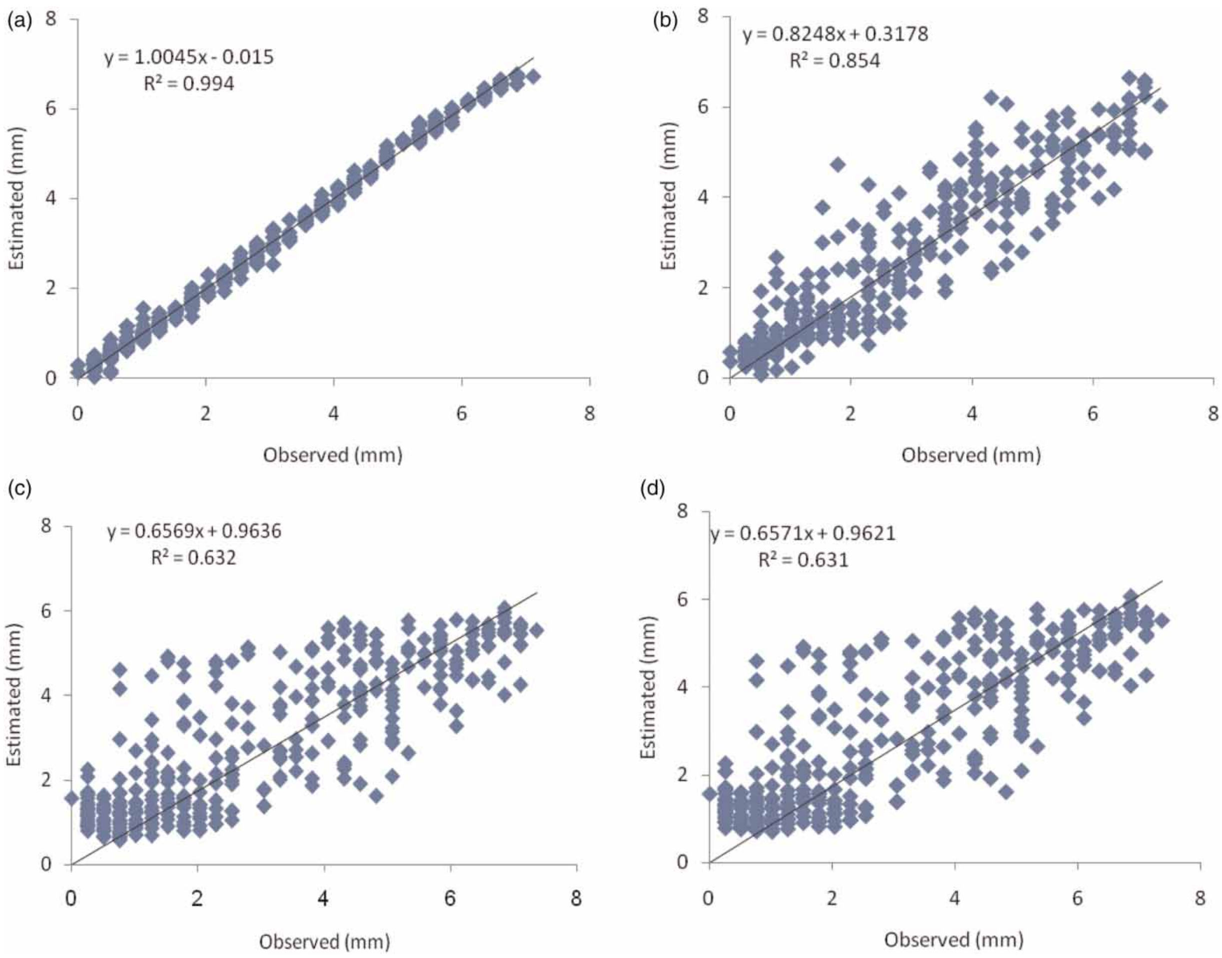

Figure 1 | Estimated and observed evaporation for Freeport station in the test period: (a) ANFIS 6, (b) ANFIS 5, (c) ANN 6 and (d) ANN 5.

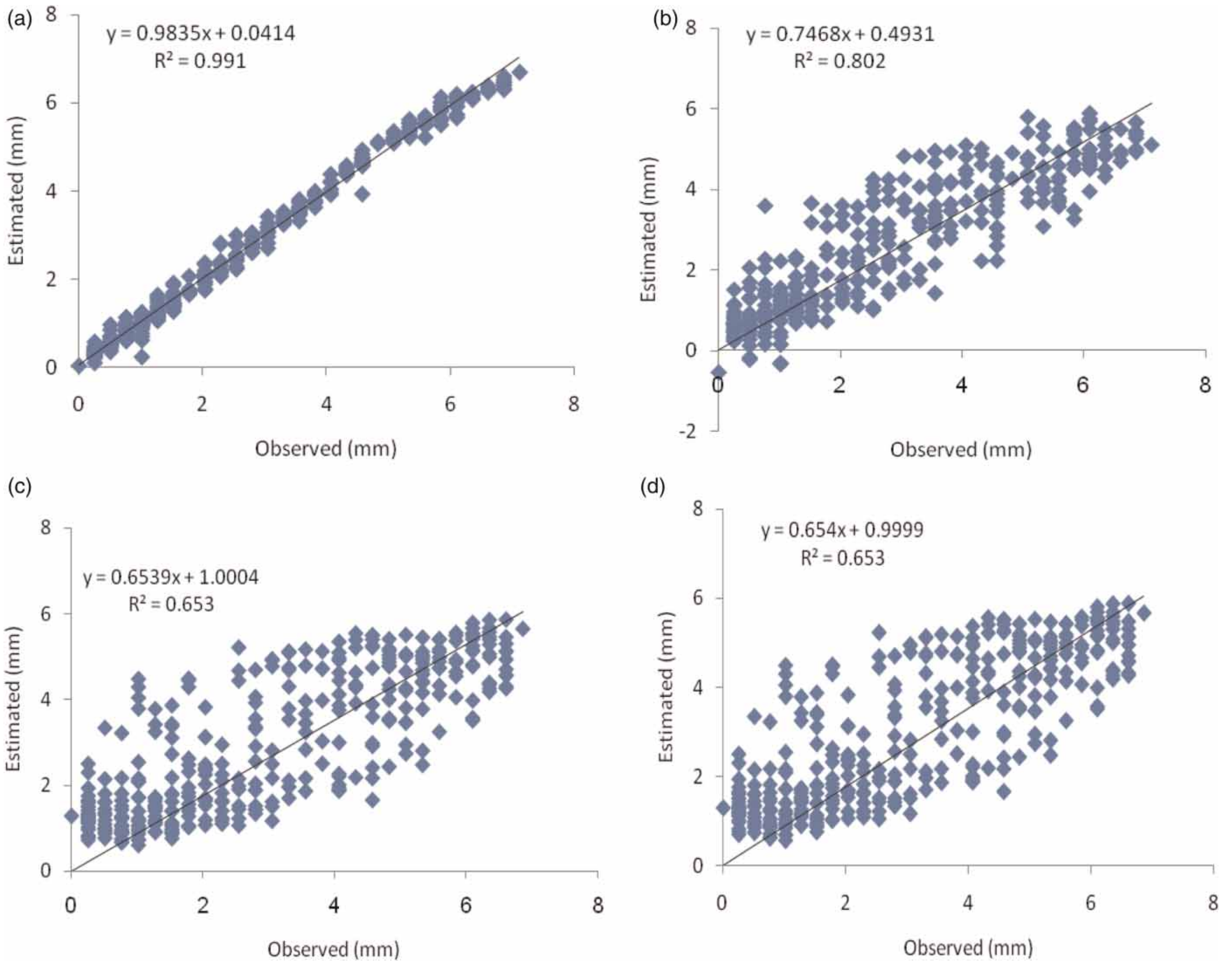

Figure 2 | Estimated and observed evaporation for Springfield station in the test period: (a) ANFIS 6, (b) ANFIS 5, (c) ANN 6 and (d) ANN 5.

parameters presented in Table 4 shows that ANFIS 5 also gives a rather good accuracy and ranked as the second best model for estimating evaporation. For Springfield station, the total evaporation of the ANFIS 5 and 6 models are 7.5 and 0.1% lower than the observed value during the test period (1012.4 mm/yr), while ANN 5 and 6 models overestimates the observed value with 1 and 2%, respectively. Therefore, ANFIS 6 is again superior in estimating the total evaporation amount in the test period. Regarding ANFIS 5, for which R^2 (0.802) is higher than for ANN 5 (0.653) and ANN 6 (0.653), confirmed by the greater E_1 and d_1 indices, the ANN 5 and 6 models cannot model the total evaporation in the test period well. The total evaporation estimated by ANFIS 6, ANN 5 and ANN 6 in Carbondale station during the test period is 0.03, 2.12 and 2.20% higher and the ANFIS 5 estimation is 6.9% lower than the observed value. Alike for the Freeport and Springfield stations, the ANFIS 6 model surpasses the others with relatively high accuracy. Figures 1–3 display the observed and estimated evaporation values for Freeport, Springfield and Carbondale stations, respectively, through scatter plots, for the ANFIS 5 and 6, and the ANN 5 and 6 models. The scatter plots reveal that ANFIS 6 is quite successful in modeling the evaporation process. It is clear from the scatter plots that the regression coefficients of the linear fit equations for ANFIS 5 and ANFIS 6 are closer to 1 and the intercepts closer to 0, than those of the ANN models. Therefore, ANFIS 6 is considered the best model for modeling

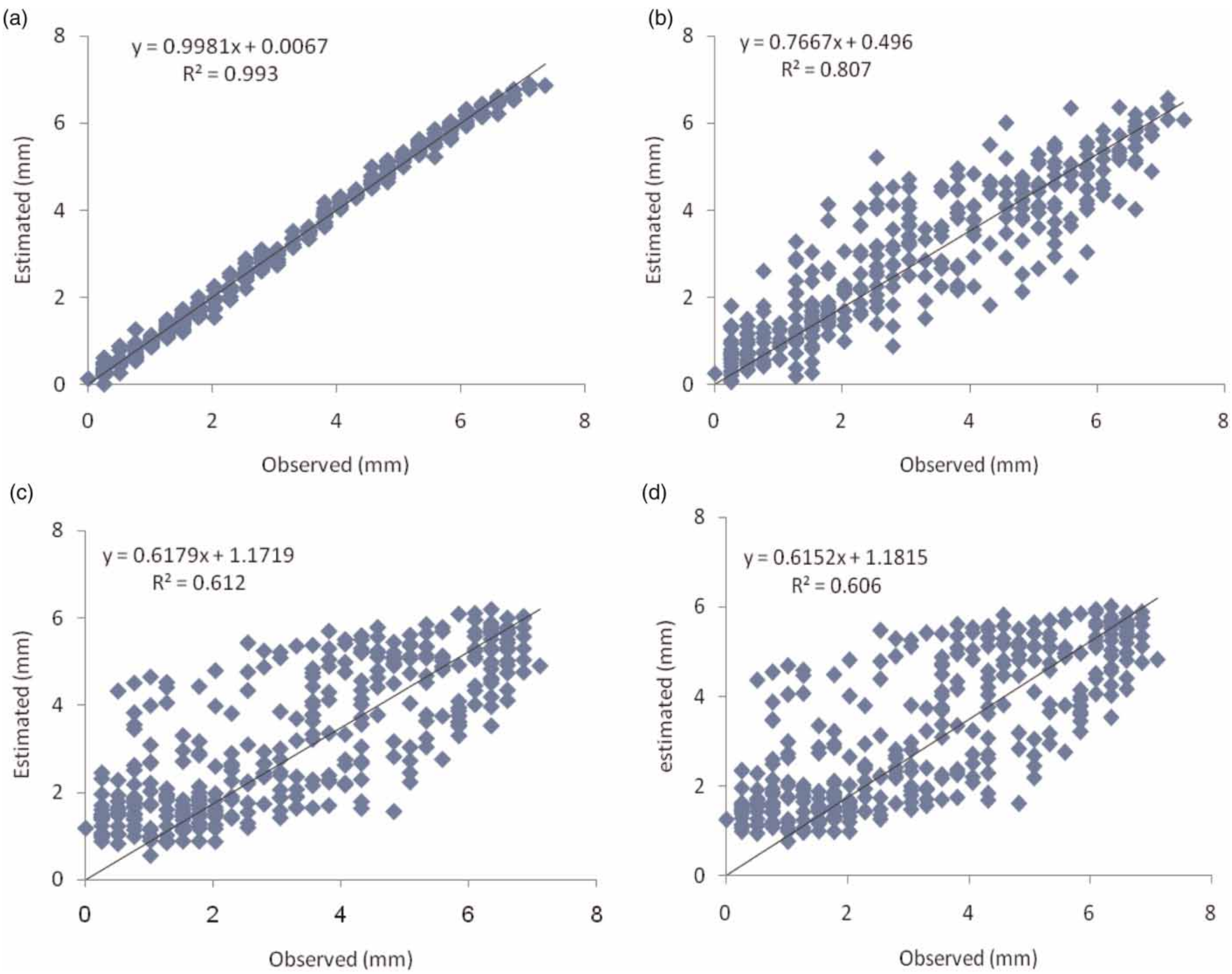

Figure 3 | Estimated and observed evaporation for Carbondale station in the test period: (a) ANFIS 6, (b) ANFIS 5, (c) ANN 6 and (d) ANN 5.

evaporation in all three stations and ANFIS 5 is the second best model.

Cross-station application of ANFIS and ANN models

Estimation of evaporation values of a specified weather station by using the weather data from a nearby weather station is an important issue in water resources, since the weather data of some stations are sometimes missing. Therefore, this section deals with the application of ANFIS and ANN techniques to solve this problem. As demonstrated in the former section, the performances of ANFIS and ANN models with input combinations (v) and (vi) (ANFIS 5, 6; ANN 5, 6) are superior to the other input combinations, so the cross-station application of ANFIS and ANN models will be achieved through these models. In the first application, the weather data from Freeport station will be used to estimate the evaporation values of Carbondale station. In the second application, the evaporation values of Carbondale station will be estimated through the simultaneous use of Freeport and Springfield stations data. Table 6 represents the statistical analysis of the obtained results. From the table it is clear that the ANFIS 6 model surpasses the other studied models in estimating the evaporation values. The results clearly demonstrate that the ANN produces better results than ANFIS model, with the quintuple-input in both applications. but for input combination (vi) the ANFIS is the best model. Therefore, it may be concluded that the ANFIS and ANN models can be

Table 6 | Statistical analysis of the cross-station application of ANFIS and ANN models

	Model inputs	R^2	RMSE (mm/d)	VAF (%)	E_1	d_1
		Application I[a]				
ANFIS 5	T_A, S_W, P_T, H_R, T_S	0.512	1.48	47.72	0.449	0.706
ANFIS 6	T_A, S_W, P_T, H_R, T_S, R_S	0.701	1.19	70.1	0.518	0.738
ANN 5	T_A, S_W, P_T, H_R, T_S	0.638	1.23	63.76	0.466	0.715
ANN 6	T_A, S_W, P_T, H_R, T_S, R_S	0.697	1.28	68.30	0.502	0.704
		Application II[b]				
ANFIS 5	T_A, S_W, P_T, H_R, T_S	0.507	1.48	47.97	0.352	0.647
ANFIS 6	T_A, S_W, P_T, H_R, T_S, R_S	0.726	1.07	72.37	0.551	0.766
ANN 5	T_A, S_W, P_T, H_R, T_S	0.648	1.21	64.74	0.472	0.707
ANN 6	T_A, S_W, P_T, H_R, T_S, R_S	0.718	1.08	71.70	0.535	0.751

[a]Estimating Carbondale evaporation values from Freeport weather data.
[b]Estimating Carbondale evaporation values from Freeport and Springfield weather data.

employed in cross-station application for evaporation estimation.

CONCLUSION

The current work aims to demonstrate the capability of ANFIS and ANN theories to map the non-linear behavior of evaporation. Various combinations of daily climatic variables of three weather stations in Illinois, USA as well as single-inputs were used for training and testing the applied ANFIS and ANN models. The results obtained showed the capability of ANFIS for modeling the daily pan evaporation. The ANN model can be ranked as the second best model. In all the studied stations, the ANFIS 6 model with air temperature, wind speed, daily total precipitation, relative humidity, soil temperature and solar radiation as inputs is the best model for estimating evaporation, and the ANFIS 5 model, which does not consider solar radiation, ranked next as the second best. Though ANN models estimate the accumulate evaporation with acceptable accuracy, the statistical model parameters strongly confirm the superiority of the ANFIS models. Also the application of pooled data from these three stations reveals that whenever single-input ANFIS and ANN models are developed by using the air temperature as unique input variable, some acceptable results may be reached, which emphasizes the applicability of these techniques for estimating evaporation values by using limited weather data. The cross-station application of the applied models showed the feasibility of these techniques for estimating the evaporation values by using the weather data from other (nearby) weather stations.

ACKNOWLEDGEMENTS

W. Dierickx is retired from Ministry of the Flemish Community, Institute for Agriculture and Fisheries Research, Technology and Food, Agricultural Engineering, Van Gansberghelaan 115, B-9820 Merelbeke, Belgium.

REFERENCES

Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. 1998 Crop Evapotranspiration – Guidelines for Computing Crop Water Requirements. FAO Irrigation and Drainage Paper 56.

Aytek, A. 2008 Co-active neurofuzzy inference system for evapotranspiration modeling. *Soft Comput.* **13**, 691–700.

Bishop, C. M. 1995 *Neural Networks for Pattern Recognition*. Oxford University Press, New York, 504 pp.

Burman, R. D. 1976 Intercontinental comparison of evaporation estimates. *J. Irrig. Drain. Engng* **102** (IR1), 109–118.

Deka, P. & Chandramouli, V. 2003 A fuzzy neural network model for deriving the river stage-discharge relationship. *Hydrol. Sci. J.* **48** (2), 197–209.

Doorenbos, J. & Pruitt, W. O. 1977 Crop Water Requirements. FAO Irrigation and Drainage Paper No. 24. FAO, Rome.

Feddes, R. A. & Lenselink, K. J. 1994 Evapotranspiration. In: *Drainage Principles and Applications* (H. P. Ritzema, ed.), 2nd edition. International Institute for Land Reclamation and Improvement (ILRI), Wageningen, The Netherlands, pp. 145–173.

Frevert, D. K., Hill, R. W. & Braaten, B. C. 1983 Estimation of FAO evapotranspiration coefficients. *J. Irrig. Drain. Engng* **109** (2), 265–270.

Gavin, H. & Agnew, C. A. 2004 Modeling actual, reference and equilibrium evaporation from a temperate wet grassland. *Hydrol. Process.* **18**, 229–246.

Guven, A., Aytek, A., Yuce, M. I. & Aksoy, H. 2008 Genetic programming-based empirical model for daily reference evapotranspiration estimation. *Clean* **36** (10–11), 905–912.
Haykin, S. 1999 *Neural Networks: A Comprehensive Foundation*. Prentice-Hall, Upper Saddle River, NJ.
Jabloun, M. & Sahli, A. 2008 Evaluation of FAO 56 methodology for estimating reference evapotranspiration using limited climatic data application to Tunisia. *Agric. Water Manage.* **95**, 707–715.
Jang, J. S. R. 1993 ANFIS: adaptive-network-based fuzzy inference system. *IEEE Trans. Syst. Manage. Cyber.* **23** (3), 665–685.
Jang, J. S. R. & Sun, C. T. 1995 Neuro fuzzy modeling and control. *Proc. IEEE* **83**, 378–405.
Jang, J. S. R., Sun, C. T. & Mizutani, E. 1997 *Neurofuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*. Prentice-Hall, Englewood Cliffs, NJ.
Jensen, M. E. 1974 *Consumptive Use of Water and Irrigation Water Requirements*. ASCE, New York.
Jin, Y., Jiang, J. & Zhu, J. 1995 Neural network based fuzzy identification and its applications to modeling and control of complex systems. *IEEE Trans. Syst. Manage. Cybern.* **25** (6), 990–997.
Kişi, Ö. 2005 Suspended sediment estimation using neuro-fuzzy and neural network approaches. *Hydrol. Sci. J.* **50** (4), 683–696.
Kişi, Ö. 2006a Daily pan evaporation modeling using a neuro-fuzzy computing technique. *J. Hydrol.* **329**, 636–646.
Kişi, Ö. 2006b Generalized regression neural networks for evapotranspiration modeling. *Hydrol. Sci. J.* **51** (6), 1092–1105.
Kişi, Ö. 2006c Evapotranspiration estimation using feed forward neural networks. *Nord. Hydrol.* **37** (3), 247–260.
Kişi, Ö. 2007 Evapotranspiration modeling from climate data using a neural computing technique. *Hydrol. Process.* **21** (6), 1925–1934.
Kişi, Ö. & Öztürk, Ö. 2007 Adaptive neurofuzzy computing technique for evapotranspiration estimation. *J. Irrig. Drain. Engng* **133** (4), 368–379.
Kumar, M., Raghuwanshi, N. S., Singh, R., Wallender, W. W. & Pruitt, W. O. 2002 Estimating evapotranspiration using artificial neural networks. *J. Irrig. Drain. Engng* **128** (4), 224–233.
Landeras, G., Ortiz-Barredo, A. & Lopez, J. J. 2008 Comparison of artificial neural network models and empirical and semi-empirical equations for daily reference evapotranspiration estimation in the Basque County (Northern Spain). *Agric. Water Manage.* **95**, 553–565.
Legates, D. R. & McCabe, G. J. 1999 Evaluating the use of 'goodness-of-fit' measures in hydrologic and hydroclimatic validation. *Water Resour. Res.* **35** (1), 233–241.
Linarce, E. T. 1967 Climate and evaporation from crops. *J. Irrig. Drain. Engng* **93**, 61–79.
Mamdani, E. H. & Assilian, S. 1975 An experiment in linguistic synthesis with a fuzzy logic controller. *Int. J. Man Mach. Stud.* **7** (1), 1–13.
Moghaddamnia, A., Ghafari Gousheh, M., Piri, J., Amin, S. & Han, D. 2009 Evaporatin estimation using artificial neural networks and adaptive neurofuzzy inference system techniques. *Adv. Water Resources* **32**, 88–97.
Neamati, S. 2009 *Suspended sediment estimating in Ligovan river, using ANFIS theory technique and time series analysis.* M.Sc. Thesis, Faculty of Agriculture, University of Tabriz, Iran.
Palit, A. K. & Popovic, D. 1999 Forecasting chaotic time series using neuro fuzzy approach. In: *Proceedings of the IEEE IJCNN*. Washington, DC, vol. 3, pp. 1538–1543.
Palit, A. K. & Popovic, D. 2000 Intelligent processing of time series using neuro fuzzy genetic approach. In: *Proceedings of the IEEE-ICIT Conference*. Goa, India, vol. 1, pp. 141–146.
Palit, A. K. & Popovic, D. 2005 *Computational Intelligence in Time Series Forecasting; Theory and Engineering Applications*. Springer, Heidelberg.
Salih, A. M. A. & Sendil, U. 1984 Evapotranspiration under extremely arid climates. *ASCE J. Irrig. Drain. Engng* **110** (3), 289–303.
Shiri, J. & Kişi, Ö. 2010 Short term and long term streamflow forecasting using a wavelet and neuro-fuzzy conjunction model. *J. Hydrol.* **394**, 486–493.
Stephen, J. C. & Stewart, E. H. 1963 *A Comparison of Procedures for Computing Evaporation and Evapotranspiration*. Publication 62, International Association of Scientific Hydrology. International Union of Geodynamics and Geophysics, Berkeley, CA, pp. 123–133.
Sudheer, K. P., Goasin, A. K. & Ramasastri, K. S. 2003 Estimating actual evapotranspiration from limited climate data using neural computing technique. *ASCE J. Irrig. Drain. Engng* **129** (3), 214–218.
Takagi, T. & Sugeno, M. 1985 Fuzzy identification of systems and its application to modeling and control. *IEEE Trans. Syst. Man. Cybern.* **15** (1), 116–132.
Trajkovic, S. 2005 Temperature-based approaches for estimating reference evapotranspiration. *J. Irrig. Drain. Engng* **131** (4), 316–323.
Vernieuwe, H., Georgieva, O., De Baets, B., Pauwels, V. R. N., Verhoest, N. E. C. & De Troch, F. P. 2005 Comparison of data-driven Takagi–Sugeno models of rainfall–discharge dynamics. *J. Hydrol.* **302** (1–4), 173–186.

First received 18 February 2010; accepted in revised form 13 December 2010. Available online July 2011