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ORIGINAL PAPER

Neural networks with artificial bee colony algorithm for modeling daily reference evapotranspiration

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Abstract The study investigates the ability of artificial neural networks (ANN) with artificial bee colony (ABC) algorithm in daily reference evapotranspiration (ET_0) modeling. The daily climatic data, solar radiation, air temperature, relative humidity, and wind speed from two stations, Pomona and Santa Monica, in Los Angeles, USA, are used as inputs to the ANN–ABC model so as to estimate ET_0 obtained using the FAO-56 Penman–Monteith (PM) equation. In the first part of the study, the accuracy of ANN–ABC models is compared with those of the ANN models trained with Levenberg–Marquardt (LM) and standard back-propagation (SBP) algorithms and those of the following empirical models: The California Irrigation Management System (CIMIS) Penman, Hargreaves, and Ritchie methods. The mean square error (MSE), mean absolute error (MAE) and determination coefficient (R^2) statistics are used for evaluating the accuracy of the models. Based on the comparison results, the ANN–ABC and ANN–LM models are found to be superior alternative to the ANN–SBP models. In the second part of the study, the potential of the ANN–ABC, ANN–LM, and ANN–SBP models in estimation ET_0 using nearby station data is investigated.

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Introduction

Accurate estimation of evapotranspiration (ET) is needed to compute irrigation water requirement and to determine the water budget, especially under arid conditions where water resources are scarce and fresh water is a limited resource. As described by Brutsaert (1982) and Jensen et al. (1990), various methods have been proposed for estimating ET. The energy balance/aerodynamic combination equations generally "provides the most accurate results as a result of their foundation in physics and basis on rational relationships" (Jensen et al. 1990). The Food and Agricultural Organization of the United Nations (FAO) accepted the FAO Penman–Monteith as the standard equation for estimation of ET (Allen et al. 1998; Naoum and Tsanis 2003).

A number of researchers have attempted to model ET_0 using artificial neural network (Kumar et al. 2002; Sudheer et al. 2003; Trajkovic 2005, 2009, 2010; Kisi and Yildirim 2005a, b; Kisi 2006a, b, 2007; Kisi 2008; Kim and Kim 2008; Jain et al. 2008; Khoob 2008a, b; Landeras et al. 2009; Kumar et al. 2009; Marti et al. 2010; Kumar et al. 2010). Kumar et al. (2002) used a artificial neural network (ANN) for estimation of ET_0. They tried various ANN architectures and obtained accurate ET_0 estimates. Sudheer et al. (2003) established radial basis ANN in modeling ET_0 using limited climatic data. Trajkovic et al. (2003) forecasted ET_0 by a radial basis type ANN. Trajkovic (2005) used temperature-based radial basis neural network (RBNN) for modeling FAO-56 PM ET_0. He compared the RBNN results with empirical methods and reported that the RBNN generally performed better than the other models in estimation of ET_0. Kisi (2006a) estimated ET_0 using ANN method, and he compared the ANN estimates with those of the Penman and Hargreaves empirical models. He concluded that the ANN model performed better than the empirical models. Kisi (2006b) developed generalized regression neural network (GRNN) models for estimating ET_0. Kisi (2008) investigated the accuracy of feed-forward neural network, radial basis neural network, and GRNN techniques in modeling ET_0. Kim and Kim (2008) estimated the alfalfa ET_0 using GRNN model with genetic algorithm. Jain et al. (2008) modeled the ET_0 using ANN and gave a procedure to evaluate the effects of input variables on the output variable using the weight connections of ANN models. Khoob (2008a) used ANN for estimating ET_0 from pan evaporation in a semi-arid environment. Khoob (2008b) compared the accuracy of ANN models with Hargreaves method in a semi-arid environment and found that the ANN method predicted the ET_0 better than the Hargreaves method. Landeras et al. (2009) compared ANN and ARIMA models in forecasting weekly evapotranspirations. Kumar et al. (2009) evaluated the ANN models in prediction of ET_0 under the arid conditions. They compared the ANN estimates with those of the FAO-24 Radiation, Turc, and FAO-24 Blaney-Criddle empirical methods and found that the ANN model performed better than the other models. Marti et al. (2010) proposed a data scanning procedures for the ANN modeling of ET_0. Kumar et al. (2010) have reviewed and discussed the ANN studies related to application of ANN in estimation ET_0. All these studies used conventional ANN models with Levenberg–Marquardt (LM) and/or standard back-propagation (SBP) algorithms for modeling ET_0. In this study, an ANN model with a novel algorithm, that is the artificial bee colony (ABC) algorithm, is used for modeling ET_0. To the best knowledge of the authors, there is no published work indicating the input–output mapping capability of ANN–ABC technique in modeling of ET_0.

This study is concerned with the application of ANN–ABC technique for modeling daily ET_0. The ability of ANN–ABC is compared with those of the ANN–LM and the ANN–SBP, CIMIS Penman, Hargreaves, and Ritchie methods employed in the previous work of Kisi and Ozturk (2007). For this aim, two stations in Los Angeles, USA, are used as case studies. In the hydrological context, the presented study is the first study that investigates the accuracy of ANN–ABC in modeling.

Artificial neural networks (ANN)

Artificial neural networks (ANNs) are based on the present understanding of biological nervous system, though neglecting much of the biological details. ANNs are parallel systems composed of many processing elements connected by weights. Of the many ANN paradigms, the back-propagation network is by far the most popular (Haykin 1998). The network composed of layers of parallel processing elements, called neurons. Each layer is fully connected to the next layer by interconnection weights. Initial weight values are corrected during a training (learning) process that compares estimated outputs to known outputs and back propagates any errors to obtain the appropriate weight adjustments necessary to minimize the errors. Detailed information about ANN can be found in the study of Kisi and Ozturk (2007).

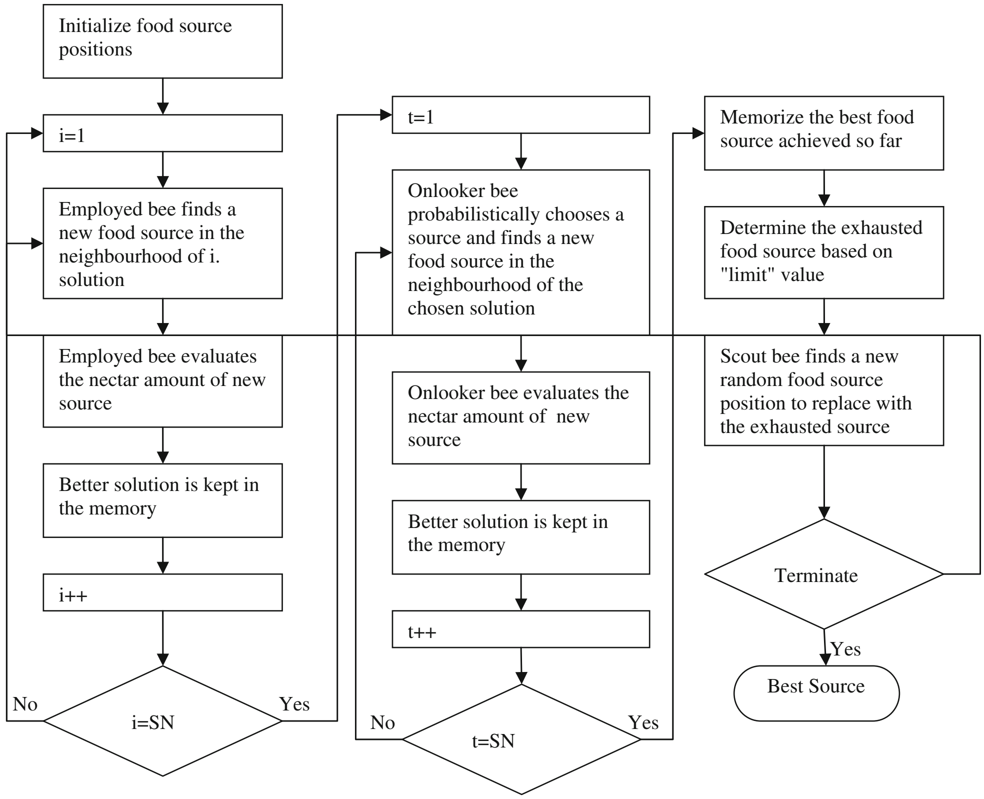
In the present study, novel algorithms, that is the artificial bee colony (ABC) algorithm and Levenberg–Marquardt (LM), were used for the ANN training. The standard back-propagation (SBP) algorithm was used by Kisi and Ozturk (2007) before. Next, the ABC, LM, and SBP algorithms are introduced.

Artificial bee colony (ABC) algorithm

In nature, there are some species living as social groups without supervision in order to defense themselves, enhance foraging success, find a mate etc., which correspond to collective intelligence. One of these species, honey bees, lives as big colonies and manifests several collective intelligent behaviors such as communicating, task selection nest site selection, foraging. In all of tasks performed by honey bees, foraging is one of the most crucial tasks to keep the colony alive. Forager bees perform foraging behavior to meet the requirements of the colony. Foraging behavior includes finding profitable food sources around the hive, recruiting the other bees in the hive to the rich sources by dancing, and abandoning the exhausted sources and finding the new potentially rich ones. Therefore, there are three kinds of bees allocated for the foraging task: employed bees search the neighborhood of the sources discovered by them; onlooker bees recruited by the employed bees depending on the dances of employed foragers; and scout bees search the environment randomly depending on some internal motivation external clues. When an employed bee finds a rich source, she communicates onlooker bees in the hive to share information about the profitability, distance, and direction of the source from the nest by dancing. The richness of a source depends on several factors including its proximity to the nest, amount or concentration of nectar, and the ease of extracting this nectar. Employed bee of an exhausted source becomes a scout and tries to find a new source.

Artificial bee colony (ABC) algorithm introduced by Karaboga (2005) is a recent optimization algorithm that mimics the foraging behavior of honey bees. In the ABC algorithm, each food source corresponds to a solution in the space and ABC tries to find the position of the most

Fig. 1 The schematic diagram of the ABC algorithm



profitable source by searching the food source space, which is conducted by employed bees, onlooker bees, and scout bees. The schematic diagram of the ABC algorithm is given in Fig. 1.

The main steps of the algorithm are given below:

Initialize.

REPEAT.

(a) Employed bees are sent to find food source sites in the neighborhood of their sources
(b) Employed bees share information about their sources to recruit the other bees
(c) Onlooker bees are sent to find food source sites in the neighborhood of the sources they choose depending on the information shared by employed bees
(d) Memorize the best source achieved so far
(e) Send the scouts to the search area for discovering new food sources.

UNTIL (requirements are met).

In the initialization phase of the algorithm, a food source population is generated and then the ABC algorithm starts to optimize the predefined cost function. Initial solutions that correspond to food source positions are produced randomly by Eq. (1)

$$x_{ij} = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min}) \quad (1)$$

where $i = 1.\mathrm{SN}$, $j = 1.\mathrm{D}$, SN is the number of food sources, D is the number of variables to be optimized. $x_j^{\min}$ and $x_j^{\max}$ are Llower and upper bounds of the jth parameter, respectively.

In the employed bee phase, neighborhood of each food source is searched by an employed bee. The neighbor solution ($\vec{\upsilon i}$) of the current solution ($\vec{x}_i$) is produced by Eq. (2)

$$\upsilon_{ij} = x_{ij} + \varphi_{ij}(x_{kj} - x_{ij}) \quad (2)$$

where i = { 1, 2, ...SN} , j is a randomly chosen parameter index in the range [1, D], k ∈ { 1, 2, ...SN} is a randomly chosen solution different from i, and $\varphi_{ij}$is a uniform random real number in the range [−1,1]. After a neighbor solution is produced, its fitness is calculated by substituting the solution in the cost function. If the neighbor is better, it is inserted to the population by removing the old one. If the current solution cannot be improved by the neighbor solution, current solution is kept in the population and the trial number of current solution $\vec{x}_i$ is incremented by one in order to be used in abandonment process.

After all the food sources are exploited by employed bees, the information about these sources is shared in the hive to recruit the onlooker bees to potentially rich sources probabilistically. In order to make the profitable sources favorable to onlookers and give chance to less profitable sources to be selected, a roulette wheel selection mechanism is used in ABC algorithm. Probabilities of the solutions to be selected by an onlooker bee to make a local search are calculated by Eq. (3)

$$p_i = \frac{fitness_i}{\sum_{j=1}^{n} fitness_j} \tag{3}$$

If a uniform random number is less than the probability value (p_i) associated with the source, $\vec{x}_i$, an onlooker bee finds a food source site in the neighborhood of the source, $\vec{x}_i$, by Eq. (2). As in employed bee phase, if the neighbor is better, it is inserted to the population; otherwise, the current solution is kept in the population and the trial number of current solution $\vec{x}_i$ is incremented by one.

After onlookers and employed bees search the food source sites, the exhausted sources are determined by checking their trial numbers. If the trial number of a source exceeds the predefined control parameter of ABC algorithm, called "limit", it is assumed to be exhausted or not worth to exploiting. In each cycle, one of the exhausted sources is removed from population and a scout bee generates a new solution for it by (Eq. 1).

Levenberg–Marquardt algorithm

Levenberg–Marquardt (LM) algorithm (Levenberg 1944; Marquardt 1963) incorporates the advantages of gradient descent and the Gauss–Newton method and iteratively optimizes a cost function (Eq. 4) that is sum of squares of nonlinear functions.

$$F(x) = \frac{1}{2}\sum_{i=1}^{m} [f_i(x)]^2. \tag{4}$$

LM algorithm is initialized at a starting point ($\vec{x}_0$) and produces a new solution by Eq. (5)

$$\vec{x}_{\hat{i}+1} = \vec{x}_i - (H + \lambda I)^{-1}\nabla f(\vec{x}_i) \tag{5}$$

where I is identity matrix, H is the Hessian matrix evaluated at $\vec{x}_i$, and λ determines the behavior of the algorithm between steepest descent and the Gauss–Newton method. If λ is large, LM algorithm behaves as steepest descent method; if λ gets small, the LM algorithm behaves as Gauss–Newton method.

If the error value increases by the modification by Eq. (5), $\vec{x}_{i+1}$ is copied from $\vec{x}_i$ and λ is increased. Otherwise, if the error values decreases by the modification by Eq. (5), $\vec{x}_{i+1}$ is taken and λ is decreased, and so on.

Standard back-propagation algorithm

Standard back-propagation (SBP) algorithm (Rumelhart et al. 1986) is used to train neural networks and has two phases: propagation and weight update. In propagation phase, first network output is calculated by feed-forward computation and the error values are back-propagated to the neurons. In the second phase, weights are updated by the back-propagation of error values (Rojas 1996).

Assuming the back-propagated error at the j-th node is δ_j, the partial derivative of Edefined by Eq. (6) with respect to w is given by Eq. (7):

$$E = \frac{1}{2}\sum_{i=1}^{p} \|o_i - d_i\|^2 \tag{6}$$

where E is the error calculated based on weight values, d_i is the desired output, o_i is the actual output, and p is the number of patterns.

$$\frac{\partial E}{\partial w_{ij}} = o_i \delta_j \tag{7}$$

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The weights in the network are updated by the amount of Δw_{ij} given by Eq. (8):

$$\Delta w_{ij} = -\gamma o_i \delta_j \tag{8}$$

Empirical methods

CIMIS Penman method

The CIMIS Penman equation employs the modified Penman equation (Pruitt and Doorenbos 1977) with a wind function that was developed at the University of California, Davis. The method uses hourly average weather data as an input to calculate hourly ET_0. The 24 h ET_0 values for the day (midnight–midnight) are then summed to produce estimates of daily ET_0. The hourly PM equation that CIMIS uses to estimate hourly PM ET_0 is the Food and Agricultural Organization's version that is described in Irrigation and Drainage Paper No. 56 (Allen et al. 1998). The CIMIS Penman equation is also described in detail in Hidalgo et al. (2005), (see CIMIS website: http://wwwcimis.water.ca.gov/cimis/infoEtoCimisEquation.jsp);

$$ET_0 = \left(\frac{\Delta}{\Delta + \gamma}\right)R_n + \left(1 - \frac{\Delta}{\Delta + \gamma}\right)(e_a - e_d)f_U \tag{9}$$

where ET_0 = mean hourly reference evapotranspiration (mm day^{-1}); Δ = slope of the saturation vapor pressure function (kPa°C^{-1}); R_n = mean hourly net radiation (Wm^{-2}); γ = psychometric constant (kPa °C^{-1}); e_a is the saturation vapor pressure (kPa); e_d is the actual vapor pressure (kPa); and the f_U = wind function (m s^{-1}). Daily ET_0 equals to the sum of 24 h ET_0 (mm).

Hargreaves method

The Hargreaves empirical formula is one of the simplest equations used to estimate ET_0. It is expressed as (Hargreaves and Samani 1985):

$$ET_0 = 0.0023R_a\left(\frac{T_{\max} + T_{\min}}{2} + 17.8\right)\sqrt{T_{\max} - T_{\min}} \quad (10)$$

where ET_0 = reference evapotranspiration (mm day^{-1}); T_{max} and T_{min} = maximum and minimum temperature (°C) and R_a = extraterrestrial radiation (mm day^{-1}).

Ritchie method

The Ritchie method, as described by Jones and Ritchie (1990)

$$ET_0 = \alpha_1.\left[3.87 \times 10^{-3}.R_s.(0.6T_{\max} + 0.4T_{\min} + 29)\right] \quad (11)$$

where ET_0 = reference evapotranspiration (mm day^{-1}); T_{max} and T_{min} = maximum and minimum temperature (°C) and R_s = solar radiation (MJ m^{-2} day^{-1}). When

$$\left.\begin{array}{ll} 5 < T_{\max} \le 35°C & \alpha_1 = 1.1 \\ T_{\max} > 35°C & \alpha_1 = 1.1 + 0.05(T_{\max} - 35) \\ T_{\max} < 5°C & \alpha_1 = 0.01.\exp[0.18(T_{\max} + 20)] \end{array}\right\}. \quad (12)$$

Data

The daily climatic data from two automated weather stations, Pomona Station (Latitude 34° 03′N, Longitude 117°48′W) and Santa Monica Station (Latitude 34°02′N, Longitude 118°28′W) operated by the California Irrigation Management Information System (CIMIS) are used in the current study. The elevations are 222 and 104 m for the Pomona and Santa Monica stations, respectively. The location of the stations was illustrated by Kisi and Ozturk (2007). The Santa Monica Station is located in a coastal area. The data sample consists of daily records of 4 years (2001–2004) of solar radiation, air temperature, relative humidity, and wind speed. For each station, the first 3 years (2001–2003) data were used to train the ANN models, and the remaining data were used for testing. The detailed information about the climatic data of Pomona and Santa Monica stations can be obtained from the study of Kisi and Ozturk (2007).

Application and results

Kisi and Ozturk (2007) developed two different ANN–SBP models for the estimation of ET_0 of Pomona and Santa Monica stations before. They compared four-parameter ANN1 model comprising R_s, T, RH, and U_2 inputs and two-parameter ANN2 model whose inputs are the R_s and T with the four-parameter CIMIS Penman and two-parameter Hargreaves and Ritchie empirical methods, respectively. They used mean square error (MSE), mean absolute error (MAE), and determination coefficient (R^2) statistics for the evaluation of ANN–SBP models in test period, and they found that the ANN–SBP models performed better than the empirical methods. In this study, four- and two-parameter ANN–ABC and ANN–LM models were developed using the same data, and the results were compared with those of the ANN–SBP, CIMIS Penman, Hargreaves, and Ritchie models employed in Kisi and Ozturk (2007). The MSE and MAE statistics can be given as

$$MSE = \frac{\sum_{i=1}^{N}\left(ET_{FAO-56PM,i} - ET_{estimated,i}\right)^2}{N} \quad (13)$$

$$MAE = \left(\sum_{i=1}^{N}\left|\frac{ET_{FAO-56PM,i} - ET_{estimated,i}}{ET_{FAO-56PM,i}}\right|\right)/N \quad (14)$$

where $ET_{FAO\text{-}56\ PM,\ i}$ is the ET_0 values obtained by FAO-56 PM method, $ET_{estimated,i}$ is the estimated ET_0 values, N is the data number.

Next, the accuracy of the ANN–ABC and ANN–LM techniques is tested for two different applications. In the first application, the ET_0 data of two stations are estimated, separately, and the ANN–ABC and ANN–LM estimates are compared with those of the ANN–SBP and empirical models employed in the study of Kisi and Ozturk (2007). In the second application, the ET_0 data of one station are estimated using the climatic data from the other station, and the test results of the ANN–ABC and ANN–LM models are compared with those of the ANN–SBP and multi-linear regression (MLR) models.

Estimation of ET_0 data of Pomona Station

For the Pomona Station, the ANN–ABC1, ANN–ABC2, ANN–LM1, ANN–LM2, ANN–SBP1, ANN–SBP2, and the empirical models are compared in Table 1. In this table, ANN–ABC1 (4,5,1) denotes an ANN model comprising 4 inputs, 5 hidden nodes, and 1 output node. As seen from this table that the ANN–ABC, ANN–LM, and ANN–SBP models have the same structure. The input variables used for each model are also given in Table 1. The temperature-based methods mostly underestimate or overestimate ET_0 obtained by the FAO-56 PM method. In those cases, Allen et al. (1994) recommended that empirical methods be calibrated using the standard PM method. ET_0 is calculated as

$$ET_0 = a + bET_{eq} \quad (15)$$

where ET_0 = grass reference ET defined by the FAO-56 PM equation; ET_{eq} = ET estimated by the temperature-based methods; and a and b = calibration factors, respectively. The data used for the training of ANN models were used for calibration of temperature-based methods. The CIMIS Penman method was also calibrated. C_CIMIS Penman denotes the calibrated version of CIMIS Penman model. It is clear from Table 1 that the ANN–ABC2, ANN–LM2, ANN–SBP2, Hargreaves, and Ritchie models use the same input variables. It can be seen from the table that the ANN–ABC1 and ANN–LM models give almost similar estimates and they perform better than the four-parameter ANN–SBP1 and CIMIS Penman models. Among the two-parameter models, the ANN–ABC2 seems to be superior to the others. The ANN–LM models are slightly worse than the ANN–ABC models. The ET_0 estimates of each model for the Pomona Station are shown in Fig. 2 in the form of scatter plot. It is seen from the scatter plots that the ANN–ABC1 and ANN–LM1 estimates are closer to the corresponding FAO-56 PM ET_0 values than those of the other models. Among the two-parameter models, the ANN–ABC2 and ANN–LM2 are similar to the each other, and they perform better than the ANN–SBP2, Hargreaves, Ritchie, C_Hargreaves, and C_Ritchie models. As seen from the fit line equations (assume that the equation is $y = a_o x + a_1$) in the scatter plots, the a_o and a_1 coefficients for the ANN–ABC1 and ANN–LM1 model are closer to the 1 and 0 with a higher R^2 value than those of the other models. This is also confirmed by the MSE, MAE, and R^2 values in Table 1. The total ET_0 estimates of the ANN–ABC and ANN–LM models were compared with those of the ANN–SBP, CIMIS Penman, Hargreaves, and Ritchie because it is important for irrigation management. The total ET_0 values were calculated by integrating the ET_0 estimates of each model in the test period. The ANN–ABC2, ANN–LM2, ANN–SBP2, C_Hargreaves, and C_Ritchie computed the total FAO-56 PM ET_0 of 1,288.8 mm as 1,271, 1,274, 1,272, 1,273, and 1,283 mm with underestimations of 1.4, 1.2, 1.3, 1.2, and 0.4%, while the ANN–ABC1, ANN–LM1, ANN–SBP1, CIMIS Penman, Hargreaves, Ritchie, and C_CIMIS Penman methods resulted in 1,303, 1,305, 1,291, 1,411, 1,405, 1,377, and 1,295 mm, with overestimations of 1.1, 1.3, 0.2, 9.5, 9, 6.8, and 0.5, respectively. Among the four-parameter models, the ANN–SBP1 had the closest estimate. However, calibrated Ritchie model gave better estimate than the other two-parameter models. For the Pomona Station, while four-parameter models overestimates the ET_0, two-parameter models underestimates. This implies that the relative humidity (RH) and wind speed (U_2) data lead the four-parameter models to overestimate the total ET_0 value.

Estimation of ET_0 data of Santa Monica Station

For the Santa Monica Station, the estimates of the ANN–ABC, ANN–LM, ANN–SBP, and the empirical models are compared in Table 2. Here, the ANN–ABC1 and ANN–LM1 models give almost similar estimates, and these two models perform much better than the others. The ANN–ABC2 and ANN–LM2 seem to be better than the two-parameter ANN–SBP2, Hargreaves, C_Hargreaves, Ritchie, and C_Ritchie models. The superiority of ABC and LM algorithms to the SBP algorithm can be obviously seen from the Table 2. The ET_0 estimates of each model are illustrated in Fig. 3 in the form of scatter plot. The R^2 coefficients of the ANN–ABC1 and ANN–LM1 equal to each other, and they are higher than those of the other models. The a_o and a_1 coefficients of the ANN–ABC1 model are closer to the 1 and 0 than those of the other ANN and empirical models. Out of the two-parameter models,

Table 1 The performance statistics of the models in test period—Pomona Station

Models	Model inputs	MSE ($mm^2\ day^{-2}$)	MAE ($mm\ day^{-1}$)	R^2
ANN–ABC1(4,5,1)	R_s, T, RH and U_2	0.035	0.137	0.991
ANN–LM1(4,5,1)	Rs, T, RH and U2	0.036	0.141	0.991
ANN–SBP1(4,5,1)*	R_s, T, RH and U_2	0.098	0.225	0.976
CIMIS Penman*	R_s, T, RH and U_2	0.439	0.361	0.970
C_CIMIS Penman*	R_s, T, RH and U_2	0.109	0.253	0.970
ANN–ABC2(2,4,1)	R_s and T	0.066	0.192	0.984
ANN–LM2(2,4,1)	R_s and T	0.067	0.194	0.983
ANN–SBP2(2,4,1)*	R_s and T	0.124	0.255	0.970
Hargreaves	R_s and T	0.296	0.405	0.978
Ritchie*	R_s and T	1.381	0.756	0.985
C_Hargreaves	R_s and T	0.078	0.215	0.978
C_Ritchie*	R_s and T	0.071	0.205	0.985

* The test results of the model were obtained from the previous study, Kisi and Ozturk (2007)

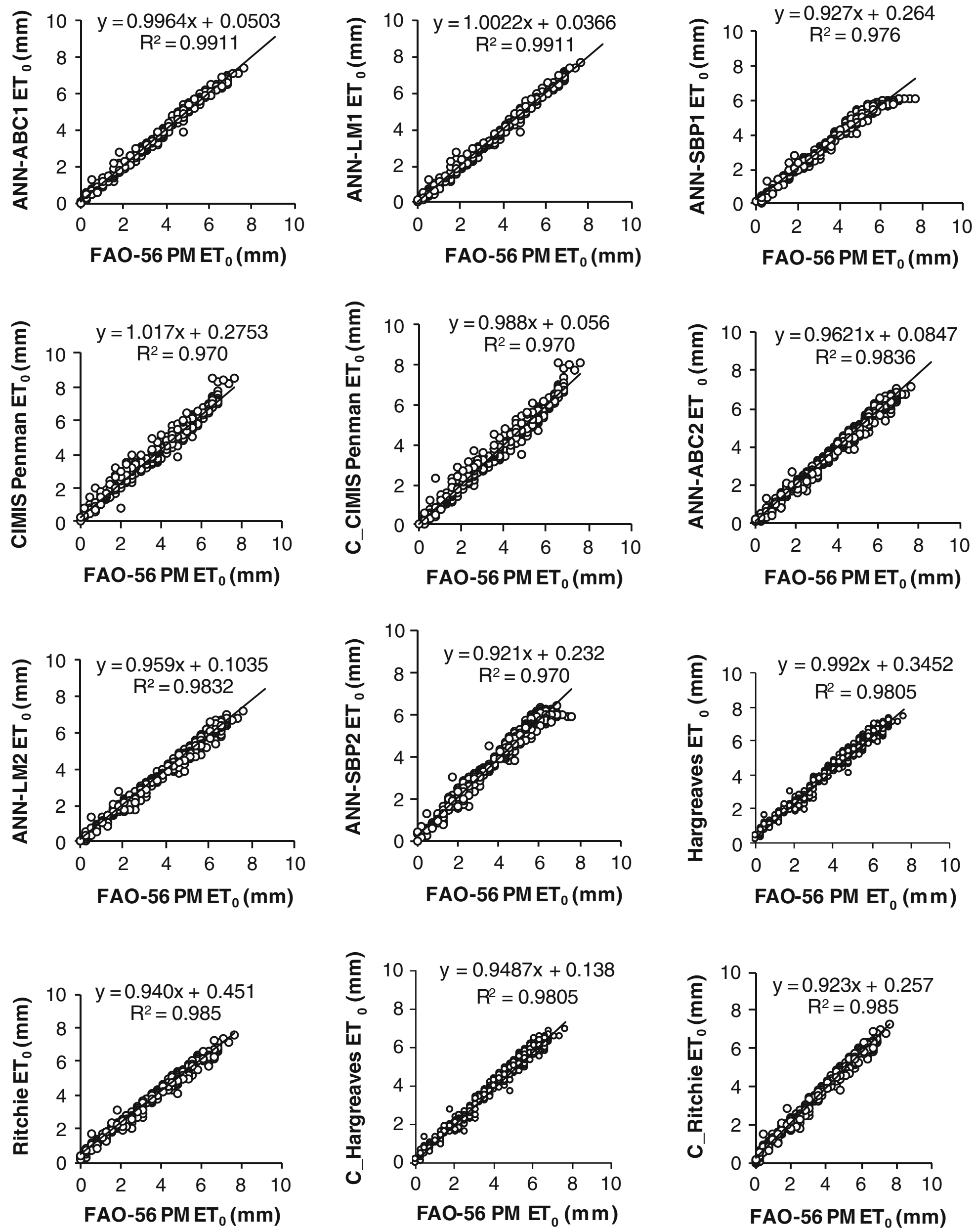

Fig. 2 The FAO-56 PM and estimated ET_0 values of the Pomona Station in test period

Table 2 The performance statistics of the models in test period—Santa Monica Station

Models	Model inputs	MSE ($mm^2\ day^{-2}$)	MAE ($mm\ day^{-1}$)	R^2
ANN–ABC1(4,5,1)	R_s, T, RH and U_2	0.005	0.053	0.997
ANN–LM1(4,5,1)	Rs, T, RH and U2	0.005	0.048	0.997
ANN–SBP1(4,5,1)*	R_s, T, RH and U_2	0.066	0.179	0.969
CIMIS Penman*	R_s, T, RH and U_2	0.410	0.392	0.830
C_CIMIS Penman*	R_s, T, RH and U_2	0.371	0.415	0.830
ANN–ABC2(2,4,1)	R_s and T	0.297	0.399	0.856
ANN–LM2(2,4,1)	R_s and T	0.291	0.385	0.859
ANN–SBP2(2,4,1)*	R_s and T	0.400	0.432	0.814
Hargreaves	R_s and T	0.399	0.414	0.818
Ritchie*	R_s and T	0.641	0.650	0.780
C_Hargreaves	R_s and T	0.381	0.471	0.818
C_Ritchie*	R_s and T	0.456	0.474	0.780

* The test results of the model were obtained from the previous study, Kisi and Ozturk (2007)

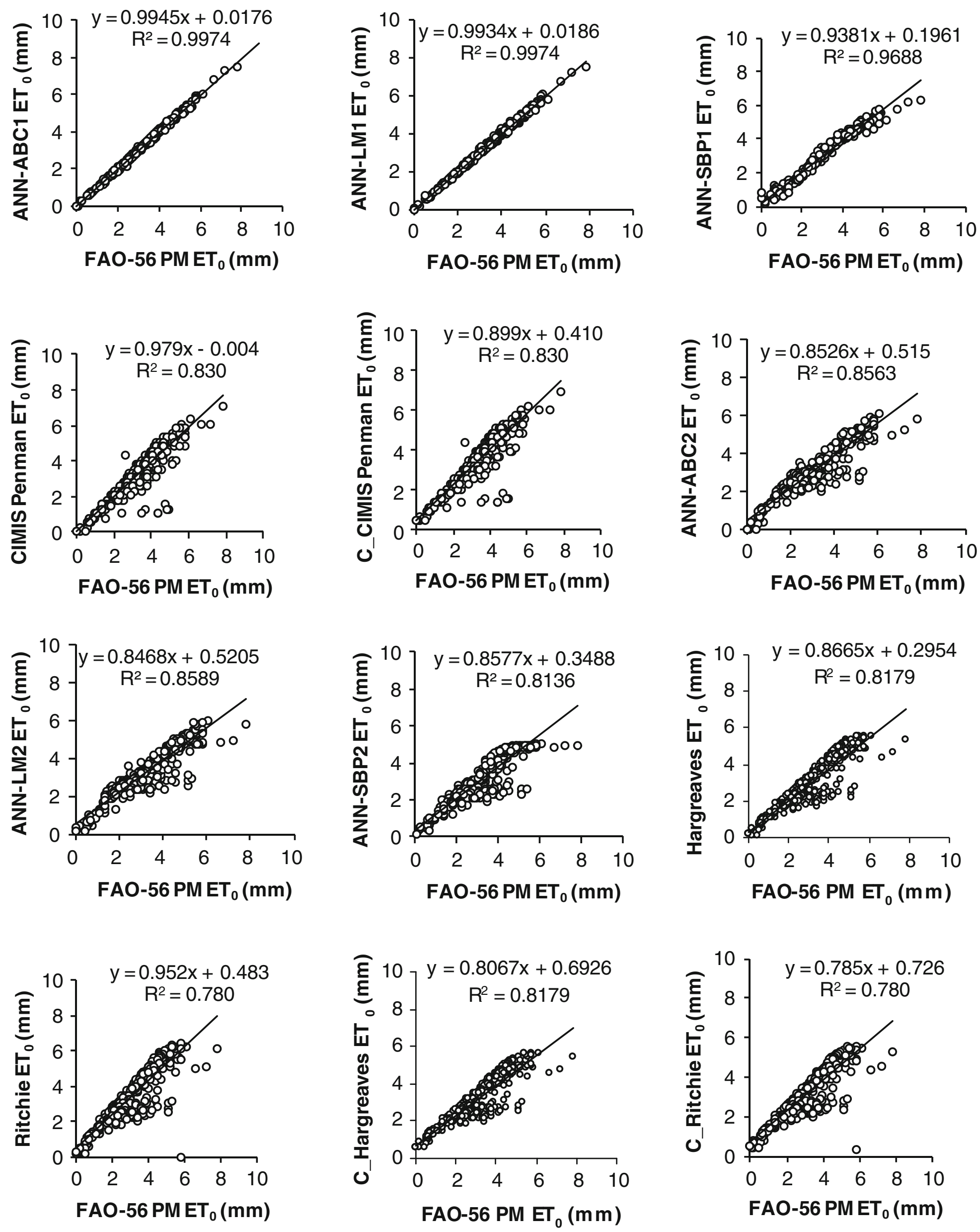

Fig. 3 The FAO-56 PM and estimated ET_0 values of the Santa Monica Station in test period

the ANN–LM2 model is slightly better than the ANN–ABC2 model and these two models outperform the ANN–SBP2, Hargreaves, C_Hargreaves, Ritchie, and C_Ritchie models. For this station, the performance differences between the two- and four-parameter ANN models are much more than those of the Pomona Station. This implies that the relative humidity (RH) and wind speed (U_2) data are more effective on ET_0 for the Santa Monica Station than those of the Pomona Station. This may be due to the fact that the Santa Monica Station is located in a coastal area. While the ANN–ABC1, ANN–LM1, ANN–SBP1, ANN–SBP2, CIMIS Penman, and Hargreaves estimated the total FAO-56 PM ET_0 as 1,180.7, 1,179.6, 1,179.4, 1,140, 1,155, and 1,131 mm, compared to the computed FAO-56 PM ET_0 value of 1,181 mm, with underestimations of 0.001, 0.09, 0.11, 3.4, 2.1, and 4.2%, the ANN–ABC2, ANN–LM2, Ritchie, C_CIMIS Penman, C_ Hargreaves, and C_Ritchie models resulted in 1,195, 1,190, 1,301, 1,213, 1,206, and 1,194 mm, with overestimations of 1.2, 0.8, 0.9, 10, 2.7, 2.1, and 1.1%, respectively. The ANN–ABC1 estimate is almost equal to the total FAO-56 PM ET_0 value. Out of two-parameter models, the ANN–LM2 performed the best in total ET_0 estimation. In contrast to Pomona, while four-parameter models generally underestimates the ET_0, two-parameter models overestimates the ET_0 in this station. This implies that the relative humidity (RH) and wind speed (U_2) data lead the four-parameter models to underestimate the total ET_0 value. It can be said that the Pomona and Santa Monica stations have different climatic conditions.

Estimation of ET_0 data of Pomona Station using data of Santa Monica

Estimating ET_0 using nearby station data is very important, since the data of some stations are missing. In this case, the missing ET_0 values can be estimated using the meteorological data from the nearby station. To solve such a problem, the regression techniques are generally used. This part of study focused on the investigation of ANN–ABC1 and ANN–LM1 techniques' performances to solve this problem. The FAO-56 PM ET_0 of Pomona Station was estimated using the climatic data of Santa Monica Station. In this application also, 3 years (2001–2003) data were used for the calibration of ANN–ABC1 and ANN–LM1 models and remaining 1-year data were used for testing. The test results of the ANN–ABC and ANN–LM models were compared with those of the ANN–SBP and MLR models employed by Kisi and Ozturk (2007) before. The performance statistics of each model in test period are given in Table 3. It is clear from this table that the ANN–ABC performs better than the other ANN and MLR models from the MSE viewpoint. The FAO-56 PM ET_0 and estimated ET_0 of the Pomona Station using the data of Santa Monica Station are illustrated in Fig. 4. From the figure, it is obvious that the ANN–ABC and ANN–LM performs better than the ANN–SBP model. The ANN–ABC, ANN–LM, ANN–SBP, and MLR estimated the total FAO-56 PM ET_0 value of 1,289 mm as 1,172, 1,145, 1,210, and 1,099 mm, with underestimations of 9.1, 11.2, 6.1, and 14.7%, respectively. The ANN–SBP model has a better estimate than the other models in estimation of total ET_0 value of the Pomona using the data of nearby station. Here, four-parameter models underestimated the total ET_0 value of the Pomona Station in contrast to the preceding application (see Sect. 4.1). The reason behind this may be the fact that the climatic data of Santa Monica Station were used in this application. This also implies that the relative humidity (RH) and wind speed (U_2) data of Santa Monica lead the four-parameter models to underestimate the total ET_0 value.

Conclusions

The estimation of FAO-56 PM *ET_0* using climatic variables by ANN–ABC and ANN–LM technique has been investigated in the present study. The accuracy of ANN–ABC and ANN–LM models is compared with those of the ANN–SBP, CIMIS Penman, Hargreaves, and Ritchie methods

Table 3 The performance statistics of the models in ET_0 estimation of Pomona Station using data of nearby Santa Monica Station

Models	Model inputs	MSE ($mm^2\ day^{-2}$)	MAE ($mm\ day^{-1}$)	R^2
ANN–ABC(4,8,1)	R_s, T, RH and U_2	0.650	0.621	0.860
ANN–LM(4,8,1)	R_s, T, RH and U_2	0.661	0.619	0.870
ANN–SBP(4,8,1)*	R_s, T, RH and U_2	0.682	0.643	0.847
MLR*	R_s, T, RH and U_2	1.051	0.826	0.828

* The test results of the model were obtained from the previous study, Kisi and Ozturk (2007)

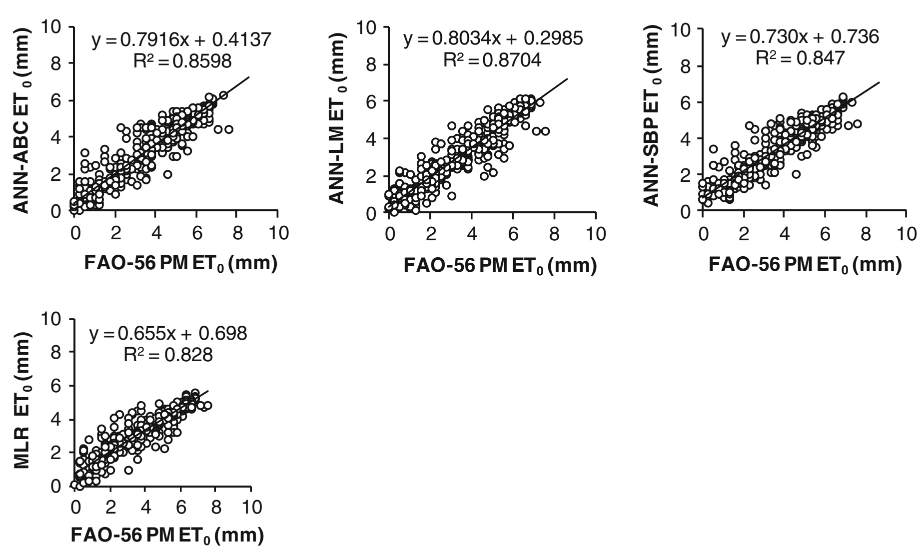

Fig. 4 The FAO-56 PM and estimated ET_0 values of Pomona Station using data of Santa Monica Station in test period

obtained from the previous study (Kisi and Ozturk 2007). In the first part of the study, the accuracy of ANN–ABC models was compared with those of the ANN models trained with Levenberg–Marquardt (LM) and standard back-propagation (SBP) algorithms and CIMIS Penman, Hargreaves, and Ritchie empirical methods. The daily climatic data of two stations, Pomona and Santa Monica, in Los Angeles, USA, were used for the model simulations. The comparison results indicated that the ANN–ABC1 and ANN–LM1 models whose inputs are the R_s, T, RH, and U_2 gave similar results to each other, and they performed better than the ANN–SBP and empirical models in estimation of FAO-56 PM ET_0. Out of the two-parameter models, the ANN–ABC2 and ANN–LM2 models were found to be better than the ANN–SBP2, Hargreaves, Ritchie, C_Hargreaves, and C_Ritchie models. This part of study indicated that the ANN–ABC2 models can be successfully used in estimation of FAO-56 PM ET_0 where there exist only the R_s and T data. The total ET_0 estimate of the ANN–ABC and ANN–LM models were compared with those of the ANN–SBP, CIMIS Penman, Hargreaves, and Ritchie. The comparison results showed that the ANN–ABC and ANN–SBP models generally performed better than the ANN–LM models in estimation of total ET_0. The estimates obtained using ANN–ABC model were found to be almost equal to the total FAO-56 PM ET_0 value in one station. In the second part of the study, the accuracy of the ANN–ABC, ANN–LM, and ANN–SBP models in estimation ET_0 using nearby station data was investigated. The results of the cross-station applications indicated that the ANN–ABC and ANN–LM could be more adequate than the ANN–SBP and MLR models in estimation of ET_0 using nearby station data.

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