Fuzzy Genetic Approach for Estimating Reference Evapotranspiration of Turkey: Mediterranean Region

Ozgur Kisi · Taner Mustafa Cengiz

Abstract The applicability of fuzzy genetic (FG) approach in modeling reference evapotranspiration (ET_0) is investigated in this study. Daily solar radiation, air temperature, relative humidity and wind speed data of two stations, Isparta and Antalya, in Mediterranean region of Turkey, are used as inputs to the FG models to estimate ET_0 obtained using the FAO-56 Penman–Monteith equation. The FG estimates are compared with those of the artificial neural networks (ANN). Root mean-squared error, mean absolute error and determination coefficient statistics were used as comparison criteria for the evaluation of the models' accuracies. It was found that the FG models generally performed better than the ANN models in modeling ET_0 of Mediterranean region of Turkey.

Keywords Reference evapotranspiration · Penman-Monteith · Fuzzy genetic · Neural networks

1 Introduction

Accurately estimation of evapotranspiration is crucial for the calculation of irrigation water requirement, water resources management, and determination of the water budget, especially under arid conditions where water resources are rare and fresh water is a restricted resource. As described by Brutsaert (1982) and Jensen et al. (1990), a number of methods have been proposed for estimating evapotranspiration. 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) approved the evapotranspiration definition of Smith et al. (1997) and accepted the FAO Penman-Monteith as the standard equation for evapotranspiration estimation (Abghari et al. 2012; Allen et al. 1998; Demirtas et al. 2007; Dinpashoh et al. 2011; Gavilan et al. 2008; Jhajharia et al. 2009, 2012; McVicar et al. 2012; Naoum and Tsanis 2003; Perugu et al. 2013).

The application of artificial neural networks (ANN) in modeling reference evapotranspiration (ET_0) has received much attention recently (Cobaner 2011; Jain et al. 2008; Khoob 2008a,

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2008b; Kim and Kim 2008; Kim et al. 2012, 2013; Kisi 2006a, b, 2007a, 2008; Kisi and Cimen 2009; Kisi and Ozturk 2007; Kisi and Yildirim 2005a, b; Kumar et al. 2008, 2009, 2011; Landeras et al. 2009; Marti et al. 2011a, b; Sanikhani et al. 2012; Sudheer et al. 2003; Trajkovic et al. 2003; Trajkovic 2005). Sudheer et al. (2003) used radial basis function ANN (RBNN) for estimating ET_0 using limited climatic data. Trajkovic et al. (2003) developed a RBNN in forecasting ET_0. Trajkovic (2005) employed temperature-based RBNN for modeling FAO-56 PM ET_0. Kisi (2006a) modeled ET_0 using ANN method and he compared ANN results with those of the Penman and Hargreaves empirical models. Kisi (2006b) developed generalized regression neural network (GRNN) models for estimating ET_0. Kisi (2007a) examined the modeling ET_0 using ANN method and he compared ANN results with those of the Penman, Hargreaves and Turc empirical models. He found MLP to be superior to the empirical models. Kisi and Ozturk (2007) used the neuro-fuzzy and ANN models in estimating daily ET_0 using the observed climatic variables. Kisi (2008) examined and compared the potential of different ANN techniques in modeling ET_0. Kim and Kim (2008) used GRNN model trained with genetic algorithm in order to model alfalfa ET_0. Khoob (2008a) used ANN model for modeling monthly ET_0 of Khuzestan plain, Iran and compared with Hargreaves method. The results showed that the Hargreaves method underestimated and overestimated the monthly FAO-56 PM ET_0 values by maximum of 20 and 37 %, respectively. Khoob (2008b) modeled ET_0 from pan evaporation using ANN in a semi-arid environment and indicated that the Hargreaves method was poor for regional estimation of ET_0. Jain et al. (2008) modeled ET_0 with ANN and outlined a procedure to evaluate the effects of input variables on the output variable using the weight connections of ANN models. Kumar et al. (2008) used different ANN models for modeling daily ET_0 and compared with conventional methods. They found that the ANN models gave better FAO-56 PM ET_0 estimates than the respective conventional methods. Kumar et al. (2009) investigated the accuracy of the ANN models in modeling ET_0 under arid conditions. Landeras et al. (2009) compared ANN and ARIMA models in forecasting weekly FAO-56 PM ET_0. Kisi and Cimen (2009) compared the ability of support vector machines (SVM) and ANN models with those of the Penman, Hargreaves, Ritchie and Turc models for estimating ET_0 and demonstrated the superiority of SVR and ANN to the empirical models. Marti et al. (2011a) investigated the accuracy of four-input ANN model for ET_0 estimation through data set scanning procedures. Marti et al. (2011b) modeled daily FAO-56 PM ET_0 using ANN without local climatic data. Cobaner (2011) used two different neuro-fuzzy methods for modeling daily ET_0. Kumar et al. (2011) reviewed the studies related with application of ANN in modeling ET_0. All these studies revealed that the ANN models performed better than the conventional methods in estimating ET_0. In the present study, fuzzy genetic approach is proposed as an alternative to ANN model for estimating daily FAO-56 PM ET_0 of Mediterranean region of Turkey.

The main purpose of this study is to investigate the accuracy of fuzzy genetic approach in modeling ET_0 of Mediterranean region of Turkey. The ET_0 values were obtained using the standard FAO-56 Penman-Monteith (FAO-56 PM) equation. The accuracy of the FG models was compared with those of the ANN method.

2 Methodology

2.1 Fuzzy Logic Approach

Fuzzy logic, first introduced by Zadeh (1965), has been applied in different areas of engineering, business and many other sciences. Figure 1 illustrates a general fuzzy system
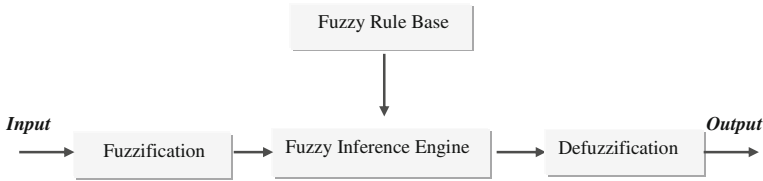
Fig. 1 A typical fuzzy inference system

composed of four components, fuzzification, fuzzy rule base, fuzzy inference engine and diffuzzification. The basic idea of fuzzy logic is that it allows for something to be partly this and partly that, rather than having to be either all this or all that. The belongingness degree to a set can be defined numerically by a membership number between 0 and 1.

In the fuzzy inference method, a set of input and output data is introduced to the fuzzy system. Fuzzy system can "learn" how to transform a set of inputs to the corresponding set of outputs by using a fuzzy associative map, sometimes called fuzzy associative memory (Kosko 1993). While the ANNs can also perform the same function such as regression, these tend to be "black box" methods. A fuzzy logic system is more flexible and transparent than the ANNs. It is possible to see how it works, and adjust it by using the black-box analogy (Russel and Campbell 1996). The fuzzy logic approach used for the estimation of ET_0 in this study is explained as below:

First, the input and output parameters are divided into a number of subsets with Gaussian membership functions. There are c^k fuzzy rules where c and k respectively indicate the numbers of subsets and input parameters. As the number of subsets increase so does the possible efficiency but the rule base gets larger, that is harder to construct (Şen 1998). In the case of one input, x, with k subsets, the rule base takes the form of an output y_n ($n=1, 2, \ldots, k^2$). If there is one input variable as x with "low", "medium", "high" and "very high" fuzzy subsets then consequently there will be four rules as follows.

R1: IF x has low THEN y_1
R2: IF x has medium THEN y_2
R3: IF x has high THEN y_3
R4: IF x has very high THEN y_4

Thus the weighted average of the outputs from these four rules results a single weighted output, y, as:

$$y = \frac{\sum\limits_{n=1}^{4} w_n \cdot y_n}{\sum\limits_{n=1}^{4} w_n} \tag{1}$$

where w_n, membership degree, for x is computed to be assigned to the corresponding output y_n for each rule triggered.

Thus, the output values (y) can be calculated by Eq. (1) for any combination of input parameter fuzzy subsets after designating the rule base (Şen 1998). A fuzzy rule base used in the current study can be incrementally obtained from sets of input and output data as follows:

1. Use minimum number of input parameters.

2. Specify membership functions for each input.
3. Calculate the membership value (w_n) for x in each of the fuzzy subsets.
4. Keep the output y_n along with the complete set of rule weights w_n.
5. Renew for all the other data points.
6. Compute the weighted average similar to Eq. (1) (Kiszka et al. 1985a, b).

One of the basic problems in designing any fuzzy system is building fuzzy subsets because all changes in the subsets will directly affect the performance of the fuzzy model. Hence, the optimum determination of the membership functions is crucial for the successful optimum modeling. In current study, the genetic algorithm is used to determine optimum membership functions. Next section provides information about genetic algorithm.

2.2 Genetic Algorithm

Genetic algorithms (GAs) are heuristic combinatorial search methods based on the mechanics of natural genetic and selection. The top idea is to simulate the natural evolution mechanisms of chromosomes, involving the main factors of natural genetics such as reproduction, crossover, and mutation. Three main processes are included in a typical form of a genetic algorithm (Preis and Ostfeld 2008):

– Generation of initial population: GA generates a set of strings (or population), with each string (chromosome) which composed of a set of values of the parameters to be optimized.
– Computing strings fitness: GA evaluates the objective function of each string.
– Production of next generation: the GA produces the new generation by performing: selection, crossover and mutation. Selection is used for choosing chromosomes from the current population for reproduction according to their fitness values. Crossover is used for producing new parameter sets by changing pairs of strings. Mutation is used for changing one of the strings locations.

GA is a powerful method which can search the optimum solution to complex problems such as the selection of the membership functions where it is hard or almost impossible to test for optimality (Ahmed and Sarma 2005). The main differences between GAs and traditional optimization methods are (Goldberg 1989):

– The sets of parameters are coded in GAs instead of parameters.
– Local optimum is searched from a population in GAs instead of a single point.
– The objective function information is used in GAs instead of derivatives or other adjutant knowledge.
– Probabilistic evolution rule is used in GAs instead of deterministic rules.

The GAs seek for the best possible solutions of a problem from available solution sets. The problem is turned into binary form and the solutions are allowed to crossover and mate with a given criterion to generate the optimal. The basics of the GA are explained by many authors like Wang (1991), Ahmed and Sarma (2005). Therefore, the current study is not focused on the details of the basic procedures of GA.

2.3 Artificial Neural Network

Artificial neural network (ANN) is a massively parallel system which is composed of many processing units connected by links of weights. Of the many ANN paradigms, feed-forward

back-propagation network (FFBP) is one of the most popular and it has been intensively studied and widely used at different engineering fields (Haykin 1998). FFBP network is composed of layers of parallel processing elements, called neurons, with each layer being fully connected to the proceeding layer by interconnection weights. During a training process, initial assigned weight values are progressively corrected at each iteration. Network compares predicted outputs with target outputs, and back-propagates any errors to determine the proper weight adjustments which are necessary to minimize errors. Detailed theoretical information for FFBP can be found in Haykin (1998).

The trained ANN can estimate behavior of any process even with incomplete information whereas the mathematical models need precise knowledge of all the contributing variables. It is indicated that the FFBP has a robust generalization ability, which means that once it has been correctly trained, it is able to provide accurate results even for cases it has never seen before (Haykin 1998; Hecht-Nielsen 1991). The ANN was trained using conjugate gradient algorithm in this study because this technique is more powerful and faster than the conventional gradient descent algorithm (Kisi 2007b).

2.4 Analysis of Variance (ANOVA)

One way ANOVA is used for testing significant differences among two sample means. ANOVA test is summarized as below (Scheffé 1959):

1. There are two hypothesis

H_0 Means of the two samples are equal to each other.
H_1 Means of the two samples are different from each other.

2. Obtain the critical value from F table. Tables are for one-tailed test because ANOVA is always one-tailed.
3. Calculate the F test value as

$$F = \frac{S_B^2}{S_W^2} = \frac{\dfrac{\sum n_i \left(\overline{X}_i - \overline{X}_{GM} \right)^2}{k-1}}{\dfrac{\sum (n_i-1)s_i^2}{\sum (n_i-1)}} \tag{2}$$

where S_B^2 and S_W^2 indicate the variance between and variance within, respectively. Here, $\overline{X}_i$ is the mean of group i, $\overline{X}_{GM}$ is the grand mean, S_i^2 is the variance in group i, n_i is the number of data in group i and k is the number of groups. k-1 indicates the degree of freedom.

4. Make a decision; if F > critical F value, reject H_0
5. Summarize the results in a table. Means of the two samples are the same or come from the same population or means of the two samples are significantly different from each other.

3 Case Study

The daily climatic data of two automated weather stations, Isparta Station (latitude 37° 47′ 00″N, longitude 30° 34′ 00″ E) and Antalya Station (latitude 36° 42′ 00″ N, longitude 30° 44′ 00″ E), operated by the Turkish Meteorological Organization (TMO) in Turkey were

used in the study. The locations of the Isparta and Antalya stations in Mediterranean region of Turkey are shown in Fig. 2. The elevations are 997 and 64 m for the Isparta and Antalya stations, respectively. The Mediterranean Region has a Mediterranean climate characterized by warm to hot (dry) summers and mild to cool (wet) winters. The temperature may reach the maximum value of 24 °C in winter, and it may be as high as 40 °C in summer.

The data sample consisted of 20 years (1982–2006) of monthly records of air temperature (T), solar radiation (R_s), wind speed (U_2) and relative humidity (RH). For each station, the first 12 years data (50 % of the whole data) were used to train the models, the second 6 years data (25 % of the whole data) were used for testing and the remaining 6 years data (25 % of the whole data) were used for validation. The monthly statistical parameters of the climatic data are given in Table 1. In the table, the x_{mean}, Sx, Cv, Csx, x_{min} and x_{max} denote the mean, standard deviation, variation coefficient, skewness, minimum and maximum, respectively. The relative humidity shows significantly low variation for the both stations (see Cv values in Table 1). For the both stations, solar radiation and temperature data show low skewed distribution and have high correlations between ET_0. Wind speed data have the lowest correlations between ET_0. For the Isparta station, however, climatic data do not show skewness as low as Antalya. The mean relative humidity is more than 55 % for both stations. Solar radiation and temperature data seem to be the most effective parameters on ET_0 with respect to correlation values.

4 Application and Results

Fuzzy genetic (FG) models were compared with those of the ANN models. First, the ET_0 values of the Isparta and Antalya stations were calculated using the FAO-56 PM method as described in Allen et al. (1998)

$$ET_0 = \frac{0.408\,\Delta(R_n - G) + \gamma\,\dfrac{900}{T+273}\,U_2(e_a - e_d)}{\Delta + \gamma(1 + 0.34 U_2)} \tag{3}$$

where ET_0 = reference evapotranspiration (mm day^{-1}); Δ = slope of the saturation vapour pressure function (kPa °C^{-1}); R_n = net radiation (MJ m^{-2} day^{-1}); G = soil heat flux density (MJ m^{-2} day^{-1}); γ = psychometric constant (kPa °C^{-1}); T = mean air temperature (°C); U_2 =

Fig. 2 The location of the Isparta and Antalya stations in Mediterranean Region of Turkey

Table 1 The monthly statistical parameters of each data set for the entire time series

Station	Variable	x_{mean}	x_{min}	x_{max}	S_x	C_v (S_x/x_{mean})	C_{sx}	Correlation with ET_0
Isparta	R_s (langley)	325	112.3	657	123	0.38	0.13	0.940
	T (°C)	13.3	−2.3	25	7.77	0.58	−0.35	0.759
	RH (%)	60.7	46	72.5	4.88	0.08	−0.51	−0.684
	U_2 (m/s)	1.76	0.6	3.6	0.51	0.29	0.45	0.001
	ET_0 (mm)	3.52	0.69	6.80	1.52	0.43	0.01	1.000
Antalya	R_s (langley)	401	120	679	153	0.38	−0.07	0.924
	T (°C)	19.6	7.3	32.3	7.32	0.37	0.05	0.842
	RH (%)	56.2	45.5	68.5	4.20	0.08	0.18	−0.379
	U_2 (m/s)	2.64	0.9	4.9	0.66	0.25	0.17	0.002
	ET_0 (mm)	5.62	1.16	10.4	2.05	0.37	0.17	1.000

average 24 h wind speed at 2 m height (m s^{-1}), e_a is the saturation vapour pressure (kPa), e_d is the actual vapour pressure (kPa).

Then, the inputs, R_s, T, RH and U_2 and output ET_0 values calculated using the FAO-56 PM method were used for the calibration of FG and ANN models. Root mean square error (RMSE), mean absolute error (MAE) and determination coefficient (R^2) statistics were used for the evaluation of the models. The RMSE, MAE and R^2 are defined as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-y_i)^2} \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i-y_i| \tag{5}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)\left(y_i-\overline{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2\sum_{i=1}^{n}\left(y_i-\overline{y}\right)^2}}\right)^2 \tag{6}$$

in which N and bar respectively denote the number of data and mean of the variable, x and y are the predicted and FAO-56 PM ET_0 values.

Two different FG models were developed. First, Gaussian membership functions with equal base widths were selected for each FG model. Then, the parameters of the membership functions were found using GA as shown in Fig. 3. A program code was prepared in MATLAB language using Fuzzy Logic and GA toolboxes for the applications of FG models. Different FG architectures were employed using this code and the optimal models' structures were determined. Optimum parameters of the membership functions were determined by minimizing the objective function (RMSE error between estimated and FAO-56 PM ET_0 values). Two membership functions were found to be sufficient for the FG models. The small numbers of membership functions were used because the model becomes
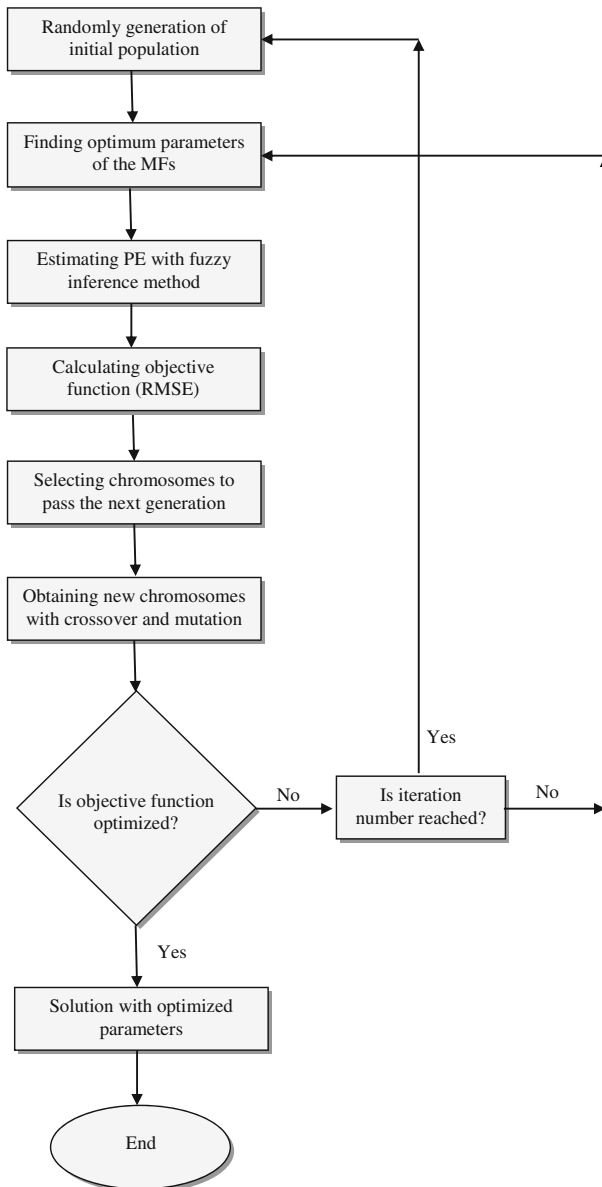
Fig. 3 The flowchart of the FG model

exponentially more complex as the number of variables or membership functions increases (Keskin et al. 2004).

   The daily ET_0 estimation was also carried out by conventional ANN model. The conjugate gradient algorithm was used for adjusting the weights of the ANN model. The sigmoid and linear activation functions were used for the hidden and output nodes, respectively. The optimal hidden layer node numbers of each model were obtained after trying various network structures since there is no theory yet to tell how many hidden units are

Table 2 The performance statistics of the models in validation period

Models	Model inputs	RMSE (mm day^{-1})	MAE (mm day^{-1})	R^2
Isparta Station				
FG1(2,50000,100)	R_s, T, RH and U_2	0.549	0.422	0.933
ANN1(4,4,1)	R_s, T, RH and U_2	0.685	0.492	0.851
FG2(6,500000,40)	R_s and T	0.772	0.708	0.961
ANN2(2,10,1)	R_s and T	0.760	0.770	0.942
Antalya Station				
FG1(2,20000,100)	R_s, T, RH and U_2	0.251	0.198	0.988
ANN1(4,3,1)	R_s, T, RH and U_2	0.285	0.221	0.978
FG2(2,20000,40)	R_s and T	0.533	0.418	0.928
ANN2(2,3,1)	R_s and T	0.648	0.509	0.908

needed to approximate any given function. The ANN networks training were stopped after 250 epochs following the suggestion of Kisi and Uncuoglu (2005) and Kisi (2007a).

The optimal FG and ANN models for the Isparta and Antalya stations are given in Table 2. In this table, the FG1(2,50000,100) model indicates a fuzzy genetic model having 2, 2, 2 and 2 Gaussian membership functions for the inputs, T, R_s, U_2 and RH with 50,000 generations and 100 populations. In Table 2, the ANN1(4,4,1) denotes an ANN model comprising 4 inputs, 4 hidden and 1 output nodes.
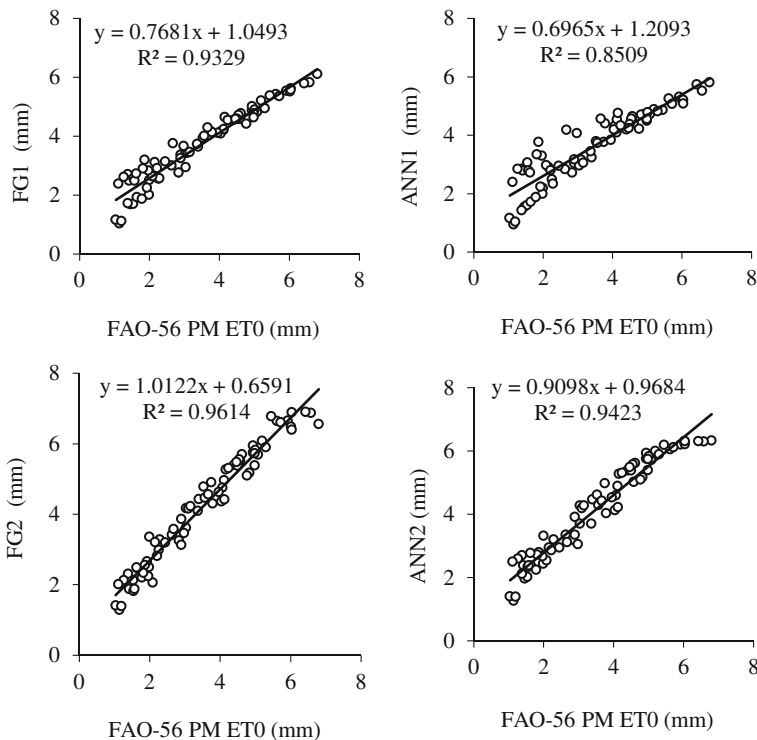

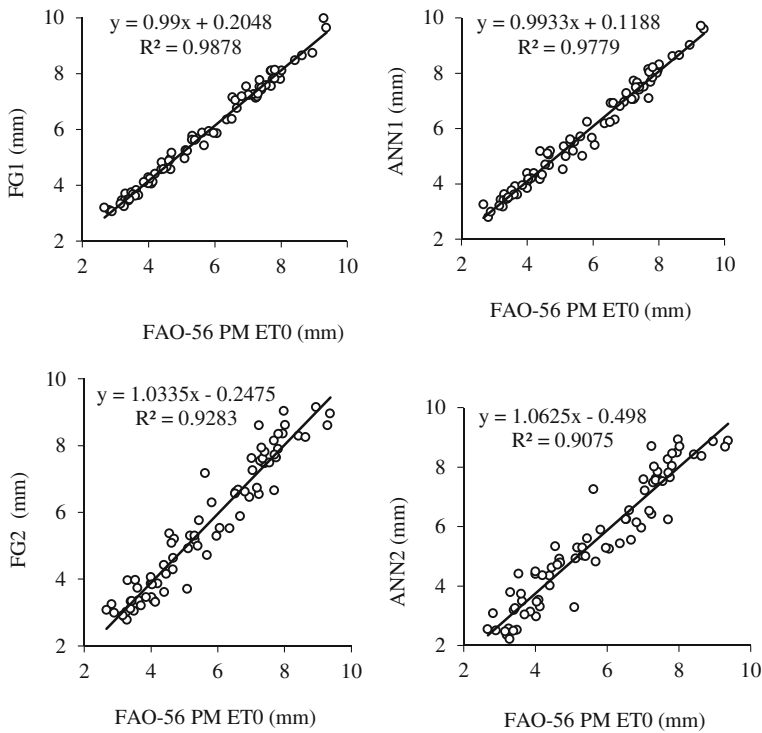**Fig. 4** The FAO-56 PM and estimated ET_0 values of the Isparta station in validation period

Fig. 5 The FAO-56 PM and estimated ET_0 values of the Antalya station in validation period

The four-input FG1 and double-input FG2 models are compared with the ANN models with respect to RMSE, MAE and R^2 statistics in Table 2. The input variables used for each model are also given in this table. The FG2 and ANN2 models use the same input variables. It is clear from the Table 2 that the FG1 model comprising four inputs performed better than the other models in terms of RMSE, MAE and R^2 performance criteria. The FG2, ANN2 models are rather simple and consider only T and R_s data. Compared with the ANN2 model, the FG2 model performed better in Antalya station.

The ET_0 estimates of each model for the Isparta and Antalya stations are shown in Figs. 4 and 5 in the scatterplot form. It is clear from the scatterplots that the FG1

Table 3 Total estimated evapotranspirations in validation period

Models	Total evapotranspiration (mm)		Relative error (%)	
	Isparta	Antalya	Isparta	Antalya
Observed	267	437	–	–
FG1	268	448	0.3	2.6
ANN1	279	443	4.5	1.4
FG2	321	432	20	−1.0
ANN2	318	425	19	−2.5

Table 4 ANOVA of the FG, ANN and empirical models in the validation period

Method	Isparta		Antalya	
	F-statistic	Resultant significance level	*F*-statistic	Resultant significance level
FG1	0.003	0.958	0.249	0.619
ANN1	0.471	0.493	0.073	0.787
FG2	7.216	0.008	0.035	0.851
ANN2	6.931	0.009	0.208	0.649

estimates are closer to the corresponding FAO-56 PM ET_0 values than those of the other models especially for the Antalya station. For the Antalya station, the superiority of FG2 model to ANN2 model can be obviously seen from the scatterplots. It can be seen from the fit line equations (assume that the equation is y=ax+b) that a and b coefficients of the FG1 and FG2 models are closer to the 1 and 0 with higher R^2 values than those of the ANN1 and ANN2 models, respectively. These are confirmed by the RMSE, MAE and R^2 values given in Table 2.

The total ET_0 estimation of each model was also compared with each other since it is important in irrigation management (see Table 3). For the Isparta station, the FG1 model gave an estimate closest to the total FAO-56 PM ET_0 value. The ANN1 was ranked as the second best. For the Antalya station, double-input FG2 model provided the closer total ET_0 estimate than the ANN2 model.

The results were also tested by ANOVA for verifying the robustness (the significance of differences between the FAO-56 PM ET_0 values and model estimates) of the models. The statistics of the tests are given in Table 4. The FG1 and FG2 models give the smallest testing values with highest significance levels than the corresponding ANN models for the Isparta and Antalya stations, respectively.

5 Conclusion

The ability of fuzzy genetic approach for the estimation of reference evapotranspiration using climatic variables was investigated in this study. Fuzzy genetic models were tested and validated by applying monthly climatic data of two stations, Isparta and Antalya, in Mediterranean region of Turkey to estimate ET_0 obtained using the FAO-56 Penman–Monteith equation. The accuracy of the fuzzy genetic models was compared with those of the ANN method. The fuzzy genetic model whose inputs are the R_s, T, RH and U_2 were found to perform better than the other models in estimation of FAO-56 PM ET_0. However, in some areas (e.g., developing countries) the available data may be the solar radiation and air temperature due to the difficulty in obtaining the data of other two parameters, relative humidity and wind speed. Therefore, fuzzy genetic and ANN models containing only two inputs, R_s and T, were also developed and compared with each other. The comparison results indicated that, double-input fuzzy genetic model was generally superior to the double-input ANN2 model in both stations. The results were also compared according to the ANOVA test. The FG1 and FG2 models were found to be more robust than the corresponding ANN models for the Isparta and Antalya stations, respectively.

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