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Evaluation of combination methods for garlic evapotranspiration estimation

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ABSTRACT- Different evapotranspiration (ET) estimation equations having different accuracy with different conditions have been developed for ET estimation. This study will firstly focus on the estimation of 13 climatic equations of daily garlic ET estimation whose ET is measured by lysimeter to provide information which can be helpful in selecting an appropriate ET equation. The paper aims at showing the potential for combining the result of the best equation to improve the overall accuracy. The findings showed that the five equations of FAO 56 Penman–Monteith, ASCE Penman–Monteith, Kimberly Penman, Penman, and FAO-24 Blaney-Criddle were the most accurateequations for estimating garlic ET. The results of these five equations were combined using the three combination methods of Simple Average Method (C-SAM), multiple linear regression (C-MLR) and Adaptive Neuro-Fuzzy Interface System (C-ANFIS).The comparison of combination methods at the test stage showed that although C-SAM used simpler equations than C-MLR but its results were more reasonable than C-MLR. Overall, the results of these two combination methods did not significantly surpass those of the best ET estimation equations (FAO 56 PM); however,C-ANFIS combination method estimated ET better than the other techniques. Based on the results of this study, the C-ANFIS combination method is recommended for estimating garlic ET.

INTRODUCTION

Evapotranspiration (ET) is the process of water loss from thesurface of soil and plant to the atmosphere through evaporation and transpiration. ET is an important factor in the calculation of water budget, estimation of water demand and supply, and management of irrigation plans. Since more than half the world's populations are dependent on products from irrigated agriculture, it is very important to determine the exact amount of ET (Kim and Kim, 2008).

Garlic (*Allium sativum* L.) is the 14th most important vegetable in worldwide crop (FAO, 2011). Despite the widespread use of garlic, there is not much information about its water consumptive use. Garlic is susceptible to drought and requires enough soil moisture for its growth. Water stress can influence garlic's early stages of growth and reproduction, and consequently, garlic bulbs may become very small and finish with small bulb sat harvest time. Because of the importance and the effect of soil moisture on the quality and quantity of garlic product, it is very essential to evaluate water requirements for irrigation management plans and for efficient use of water in irrigation duration.

Lysimeter is a measuring device which can be used to measure the amount of actual ET which is released by plants. The level of ET can be directly obtained through measuring water balance parameters using lysimeter(Allen et al., 1998). Due to difficulties in its application, it is not possible to utilize lysimeter everywhere; therefore, mathematical, empirical, and semi-empirical equations can take an advantage to apply meteorological parameters in order to estimate the crop ET. Temperature data are the most commonlyrecorded meteorological data in the world and are simple to measure accurately. Therefore, some researchers have proposed temperature-based evapotranspiration equations (Doorenbos and Pruitt, 1977; Hargreaves and Samani, 1985). In some equations, humidity (Papadakis, 1975) and sunshine (Makkink, 1957; Turc, 1961) were also included.

As mentioned above, there are several equations to estimate reference crop ET (ET_o), but their performance in different weather conditions vary since all of them have different empirical backgrounds. The Most empirical equations do not show unanimous results regarding the climatic conditions (Traore et al., 2010). After Allen et al. (1998), the FAO Penman–Monteith equation (FAO PM) is recommended as the sole equation for determining ET_o, even considering that it can lead to errors as high as 30% in special weather conditions (Widmoser, 2009). The FAO PM equation estimates ET_o considering a full weather data set. This is normally the main restriction on its use in the locations where weather data are limited (Popova et al., 2006;

Jabloun and Sahli, 2008; Gocic and Trajkovic, 2010;Pereira et al., 2010;Sentelhas et al., 2010). Besides, with missing data, some equations such as Priestley-Taylor, Hargreaves-Samani, and Thornthwaitewhich use calibration and modification parametersmay provide acceptable resultscompared to FAO PM (Sentelhas et al., 2010).

Regardless of complexity and sophistication, however, no single equation has been found to work satisfactorily for simulation and forecasting ET in all climatic conditions. Inexperienced engineers or hydrologistsmay get perplexed with the selection of an appropriate equation (Mohan and Arumugam, 1995).Suppose each individual (single) equation can provide acceptable results in one or more weather conditions;it may be that the results obtained from a combination of individual (single) equations lead to more accurate and comprehensive outcomes than any of those single equations. More details are available in Shamseldinet al.'s study (Shamseldin et al., 1997).

Mathematically,if there are n relations for calculating ET, the combination process is generally expressed as follows (Shamseldin et al., 1997):

$$ETc_{c,i} = F\left(ETc_{1,i}, ETc_{2,i}, ..., ETc_{j-1,i}, ETc_{j,i} \right) \quad (1)$$

Where $Etc_{1i,}$ is the result of jth relation in ith time interval, and $Etc_{2,1}$ is the result of the combination of j ET equation in ith time period.

One of the first studies about the combination approach was conducted by Bates and Granger (1969). They showed that the linear combination of forecasts had a smaller amount of error variance than any individual model (Batchelor and Dua, 1995). Then, much research was conducted which most often concluded that the combinations of forecasts are more accurate than a single forecast (Granger and Terasvirta, 1992; Lebaron, 1992; Lisboa, 1992; Thiesing andVornberger, 1997;Yip et al., 1997).

Clemen (1989) reported several studies about the advantages and superiority of combination methods in various fields. See and Openshaw (2000) used four combination methods to forecast the river level. Shamseldin et al. (1997) used the combination methods of simple average (SAM), weighted average (WAM), and neural network (NNM) to forecast flood.

Various methods including the calculation of averages, regressions, and intelligent systems methods (neural networks, fuzzy inference, and adaptive neuro-fuzzy method) can be used to combine different relations. Due to the interaction between climatic variables, the simple analysis methods may not be appropriate for evaluating ET (Nandagiri and Kovoor, 2006). Additionally, according to Kumar et al. (2002), ET phenomenon is non-linear and complex.

Recently, there has been a rise of interest in using soft computing methodologies especially neural network, fuzzy logic and neuro-Fuzzy (ANFIS) to find nonlinear relations between variables. Nessabian (2009) showed that the artificial neural network (ANN) model of agricultural sectors is more appropriate than the other techniques applied for forecasting. In recent years, adaptive neuro-fuzzy inference systems (ANFIS) have evolved as a powerful tool for modeling complex non-linear systems and have been widely adopted for forecasting various parameters. Kisi (2006) and Kisi and Ozturk (2007) utilized ANFIS to investigate pan evaporation and ET, respectively. Moghaddamnia et al. (2009) used ANFIS and ANN to estimate evaporation in arid and semi-arid areas in Iran. Shiri and Kisi (2001a, 2011b) compared ANFIS and ANN and concluded that ANFIS can estimate pan evaporation better. Terziet al. (2006) declared that the ANFIS can estimate ET of reference crop with a high-precision.

So far, many studies have used ANFIS to forecast ET; however, the literature review shows that the combination methods have received less attention. This study aimed at assessing the utilization of the combination methods for estimating ET. Accordingly, the combination of five relations of FAO 56 PM, ASCE PM, Kimberly Penman, Penman, and FAO-24 Blaney-Criddle were assessed using the combination methods of simple average method (C-SAM), regression method (C-REG) and adaptive neuro-Fuzzy Inference System (C-ANFIS); then, the results were compared with the actual values obtained from the lysimeters.

MATERIALS AND METHODS

Study area

This study was carried out in an experimental farm in Hamadan University, located in western part of Iran (48° 34' North latitude and 48° 28' longitude, at an altitude of 1800 m) during the two years of 2007 and 2008. Under the Koppen climate classification, Hamadan is considered as a cold semi-arid region. Fig. 1 shows the location of the study area.

Fig. 1. location of the studied area

A system of four drainage lysimeters was used to determine daily actual garlic ET. The lysimeter was located at the Bu Ali Sina University. The dimension of each lysimeter was 2m × 2m to a side and 2m depth. In order to represent field soil property, the box was filled in by cutting original soil. Each year in mid-November, clove (variety Hamedani) was planted on the rows 10 cm apart from each other to a depth of 10 cm with a spacing of 20 cm between rows. After germination, irrigation was applied on March 21st and the amount of irrigation water was controlled by a gypsum block in which the soil moisture potentials reached to 50% of field capacity soil moisture content. The volume of drain water obtained from the lysimeter output was measured daily. To minimize the effect of the boundary layer, the rim was maintained close to the ground.

The daily meteorological data including maximum temperature (T_{max}), minimum temperature (T_{min}), maximum relative humidity (RH_{max}), minimum relative humidity (RH_{min}), sunshine hours (SH) and wind speed (W) were obtained from the Meteorological station located next to the lysimeter. Meteorological statistical parameters during the growing period are presented in Table 1.

Table 1. Statistical meteorological parameters

Data set	Unit	x_{min}	x_{mean}	x_{max}	Sx	Cv (Sx/x_{mean})	Csx
T_{max}	°C	5.70	24.0	37.4	6.4	0.26	-0.20
T_{min}	°C	-6.0	7.0	17.3	4.4	0.62	-0.40
RH_{max}	%	24.0	60.9	99.0	18.0	0.30	0.31
RH_{min}	%	10.2	25.6	88.0	12.3	0.48	2.31
SH	hour	0.0	9.1	13.6	3.5	0.39	-0.97
W	m/s	0.0	4.7	22.7	3.9	0.83	2.01
ET_c	mm/day	0.1	4.8	11.2	2.9	0.61	0.08

x_{mean}, S_x, C_v, C_{sx}, x_{max}, and x_{min} denote the mean, standard deviation, variation coefficient, skewness, maximum, and minimum, respectively

Table 1 shows that the skewed values for RH_{min} and W are high. Other statistical parameters show that changes in meteorological data are normal.

The meteorological data were used to calculate the reference evapotranspiration (ET_o) values for each equation using reference crop evapotranspiration calculator (REF-ET) which was developed by Allen et al. (1989). Reference evapotranspiration calculator (REF-ET) Manual (Allen, 2000) provides details about the methods which use net radiation, soil heat flux, aerodynamic and bulk resistances, and other coefficients needed in each equation.

In order to evaluate the accuracy of each ET equation, daily ET_c values obtained from lysimeters were compared using various climatic methods. In climatic methods, ET_c was determined as $ET_c=ET_o \times K_c$. REF-ET was used to calculate ET_o, and Crop coefficient (K_c) was determined based on FAO's Irrigation and Drainage Paper No. 56 (Allen et al., 1998). Values of Kc for most agricultural crops increase from a minimum value at planting until maximum Kc is reached at about full canopy cover. The K_c tends to decline at a point after a full cover is reached in the crop season. The K_c value in the initial stage of garlic plant growth is 0.83, and increases to 1.14 by increasing cropping ground cover until the third stage. Then, it decreases at the end of the fourth stage to 1.07. The comparison was based on 206 observations during the two years of plant's growth period.

Theoretical basis of combination methods

An important motive for combining forecasts from different models is the fundamental assumption that one cannot identify the true process exactly, but different models may play a complementary role in the approximation of the data generating process (Terui and Van Dijk, 2002).

Suppose there are n forecasts as $f1$, $f2$, $f3$, ...,fn. There are various methods to combine these forecasts and merge them into a single forecast (fc).

The general form of the model for such combined forecast can be written as:

$$fc = \sum_{i=1}^{n} w_i f_i \tag{2}$$

where w_i is the assigned weight of f_i. There are several methods for estimating w_i.

Simple average method (SAM)

Because the weights in the combination are so unstable, a simple average may be the best technique to use in practice (Kang, 1986). Simple average method (SAM) is the simplest technique for combining the results of different equations. According to this method, using n ET_c estimates, the combined result is expressed as:

$$ETc_c = \frac{1}{n}\sum_{i=1}^{n} ET_{C_i} \tag{3}$$

This equation shows that it is very simple to obtain the result of this combination method, and it does not require much effort or any curve fitting.

Multiple linear regression (MLR)

A multiple linear regression analysis is carried out to predict the values of a dependent variable, ET_{cc}, given a set of n explanatory variables (ET_{c1}, ET_{c2},….,ET_{cn}). In multiple linear regression, there are n explanatory variables, and the relationship between the dependent variable and the explanatory variables is represented by the following equation:

$$ETc_c = \beta_0 + \beta_1 ETc_1 + ... + \beta_n ETc_n \tag{4}$$

where:

β_0 is the constant term, and β_1 to β_n are the coefficients relating the n explanatory variables to the variables of interest. Using SPSS software (version 14), β_0 to β_n was determined, and regression combination method (C-REG) was used to combine the results.

Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a multi-layer adaptive network-based fuzzy inference system proposed by Jang (1993). An adaptive neural network is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a function with fixed or adjustable parameters. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. The basic learning rule is the well-known back-propagation method which seeks to minimize some measure of error, usually sum of squared differences between network's outputs and desired outputs (Drake, 2000). ANFIS can be constructed as a five-layer MLP network, illustrated in Fig. 2, with the following five-layer operations:

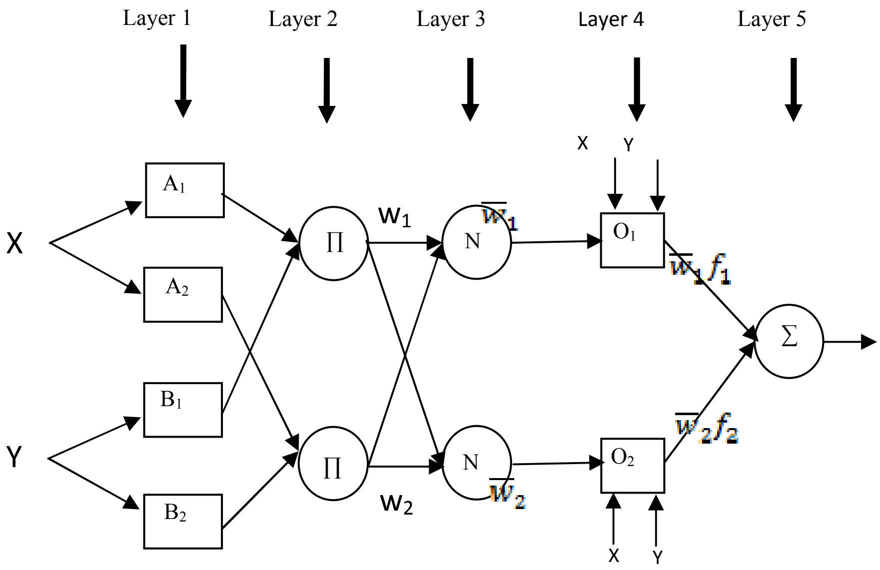

Fig. 2. A typical structure of ANFIS

Layer (1): Let X and Y be the two typical input values fed at the two input nodes, which will then transform those values to the membership functions.

$$O_i^1 = \mu_{A_i}(X) i = 1, 2$$
$$O_i^1 = \mu_{B_{i-2}}(Y) i = 3, 4 \quad (5)$$

Where X (or Y) is input, and μ_{A_i} (or $\mu_{B_{i-2}}$) is the fuzzy set associated with this node.

Layer (2): Every node in this layer multiplies the incoming signals. The output O_i^2 of the node i can be computed as:

$$O_i^2 = W_i = \mu_{A_i}(X) * \mu_{B_i}(Y) i = 1, 2 \quad (6)$$

Layer (3): Such products or firing strengths are then averaged:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} i = 1, 2 \quad (7)$$

Layer (4): The node i in this layer calculates the contribution of i[th] rule in the model output function which is defined based on the first-order Takagi and Sugeno's (1985) method as:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i X + q_i Y + r_i) i = 1, 2 \quad (8)$$

where $\overline{W}$ is the output of layer 3, and p_i, q_i, and $r_i$are the parameter sets.

Layer (5): The single node of this layer calculates the weighted global output of the system as:

$$O_i^5 = \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (9)$$

Further details about ANFIS and hybrid algorithm can be found in Jang and Sun (1995).

In ANFIS model, 80% of daily ET_c data was randomly selected to train the model (164 days),and the remaining 20% (42 days) was dedicated to the verification of the model. The maximum/minimum values of each parameter were used in the training stage. The ET_c values in the training and test phases are presented in Fig. 3.

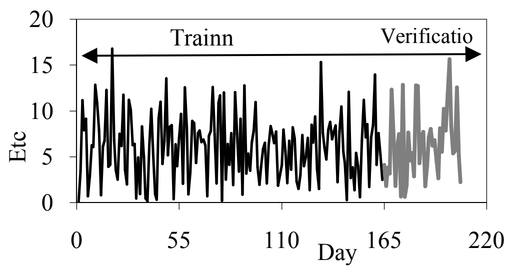

Fig. 3. Variation of evapotranspiration (ETc) for the training and verification stages

A code programed in Matlab software was used (version 7.4) to run the ANFIS model. The membership functions including Triangular, Trapezoidal, Gaussian, Π shape, difference between two sigmoidal and generalized bell-shaped, linear and constant Output membership function (MF), and MF's number of input including 2, 3 and 4 were studied to determine the best ANFIS structure. Finally, Gaussian membership function, constant Output MF, 3 numbers of input MF and 40 numbers of rulewere selected as the best structure.

Evaluation Criteria

In this research,the statistical tests were applied to determine the error rate for each ET equation and also for combination methods. Root mean square error (RMSE) and mean bias error (MBE) were used as evaluation criteria.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{i=n} (A_i - B_i)^2}{n}} \quad (10)$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(A_i - B_i) \quad (11)$$

In all of the above-mentioned tests, A_i is the calculatedET_c, and B_i is the ET_c obtained from lysimeters, and n is the number of observations.

RESULTS AND DISCUSSION

Evaluation of the performance of single models

Table 2 shows the results of the comparison. The table presents the MBE, RMSE, and R^2 values obtained from 13 equations.

Table 2. The R2, RMSE and MBE of single models in estimating ETc

Estimatiom method	R^2	RMSE	MBE
FAO 56 PM (Allen et al. 1989)	0.67	1.90	0.15
ASCE PM (Allen et al. 1989)	0.67	1.90	0.25
Kimberly Penman (Wright, 1996)	0.60	2.02	0.06
Penman (1948;1963)	0.62	2.09	0.66
FAO-24 Blaney-Criddle (Doorenbos and Pruitt, 1975,1977)	0.55	2.15	-0.17
FAO-24 Radiation Method (Doorenbos and Pruitt, 1975,1977)	0.42	2.53	0.73
FAO-PPP-17 Penman (Frere and Popov, 1979)	0.60	2.61	1.57
FAO-24 Corrected Penman (Doorenbos and Pruitt, 1975,1977)	0.39	2.62	0.83
Kimberly Penman (Wright and Jensen, 1972)	0.53	2.80	1.29
Hargereaves (Hargereaves and samani, 1985)	0.26	2.84	-0.77
Turc (1961)	0.36	2.95	-1.43
Priestly-Taylor (1972)	0.25	3.14	-1.48
Makkink (1957)	0.28	3.44	-2.05

Among all equations, FAO 56 PM with a coefficient of determination (R^2) of 0.67, the RMSE value of 1.90 mm/day, and MBE value of 0.15 provided the best result. The R^2 and RMSE values of ASCE PM equation were similar to FAO 56 PM values, but its MBE value was 1.5 times as more as that of FAO 56 PM equation. As shown in table 2, although the MBE value in Kimberly Penman is very low, the R^2 and RMSE values obtained from this equation gave poorer results than the two previous methods; hence, Kimberly Penman equation is ranked the third. Comparing the R^2 and RMSE values obtained from Kimberly Penman and Penman equations showed that there was no significant difference between the two equations; however, the MBE value in the Kimberly Penman was much less than that of Penman. In FAO-24 Blaney-Criddle, the R^2 was 0.55 which was small, but its MBE value was -0.17 which was approximately equal to the result of the best method (FAO 56 PM); the FAO 56 PM overestimated the value while the FAO-24 Blaney-Criddle underestimated it. The results of our study are not in line with those obtained byJensen et al. (17) and Lopez-Urrea et al. (25) because they reported overestimation in FAO-24 Blaney-Criddle. Compared with FAO-24 Blaney-Criddle, the FAO-24 Radiation method provided the worst results in terms of R^2, RMSE and MBE parameters. In FAO-PPP-17 Penman equation,R^2 value was 0.60 which showed a significant increase in R^2 compared with the FAO-24 Radiation equation; however, its MBE value was 2.5 times as more as that of FAO-24 Radiation Method, and its RMSE value increased slightly as well. The R^2 value of FAO-24 Corrected Penman equation was 0.39 which was very small and its MBE value was 0.83 which was very high compared with the previous equations. Allen et al.(1989), Jensen et al. (1990) and Lopez-Urreaet al. (2006) also reported that MBE values in FAO-24 Corrected Penmansignificantly overestimated ET_C.

In comparison with the aforementioned equations, Kimberly Penman method had the highest RMSE values, and its MBE was 1.29 which was only less than that of FAO-PPP-17 Penman. Hargereaves, Turk, Priestly-Taylor (Priestly and Taylor, 1972) and Makkink methods had very low R^2 values (about 0.3), and their RMSE values ranged from 2.84 to 3.44 which are high values. Their MBE values were negative which indicated that these methods underestimate ET_c. Among the above-mentioned methods, only FAO-24 Blaney-Criddle underestimated ET_C, while the others overestimated it.

Comparison of different equations showed that FAO 56 PM was the best model, and Makkink model, with the highest RMSE and MBE values, was the worst in estimating garlic ET in the studied area.

In order to avoid the complexity in combination methods, it is essential to select and utilize only those methods which had the best results. Therefore, RMSE criterion was used to select the best models. Fig. 4 shows the RMSE of each method. As shown in this figure, in both FAO 56 PM and ASCE PM methods, RMSE was less than 2.0 and in three equations of Kimberly Penman, Penman, and FAO-24 Blaney-Criddle, RMSE was slightly higher than 2.0. In addition, these five methods had the lowest MBE values. As a result, they were selected as the best five methods for estimating garlic ET in the studied area.

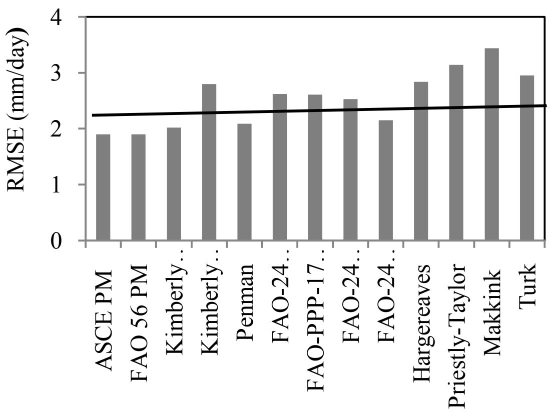

Fig. 4. Selecting the best methods for estimating garlic ET

Fig. 5 demonstrates the comparison between the real ET_c with the results of the ANFIS combination methods. Figs. 5a and b, which show FAO 56 PM and ASCE PM equations, respectively, are very similar to each other in terms of the fitted line coefficients and R^2 values. As shown in these two figures, these two equations had overestimation for values less than 4 mm/day and underestimation for values higher than 8 mm/day.

Fig. 5c shows Kimberly Penman results that was approximately similar to the two previous equations; however, it was more scattered and consequently tend to lower R^2 values. Penman equation (Figure 5d) overestimated values less than 7 mm/day and underestimated values between 7-12 mm/day. Unlike others, in this equation, for values higher than 12 mm/day the points were uniformly scattered. Figure5e shows that FAO-24 Blaney-Criddle equation overestimated values less than 4 mm/day and underestimated values more than 7 mm/day.

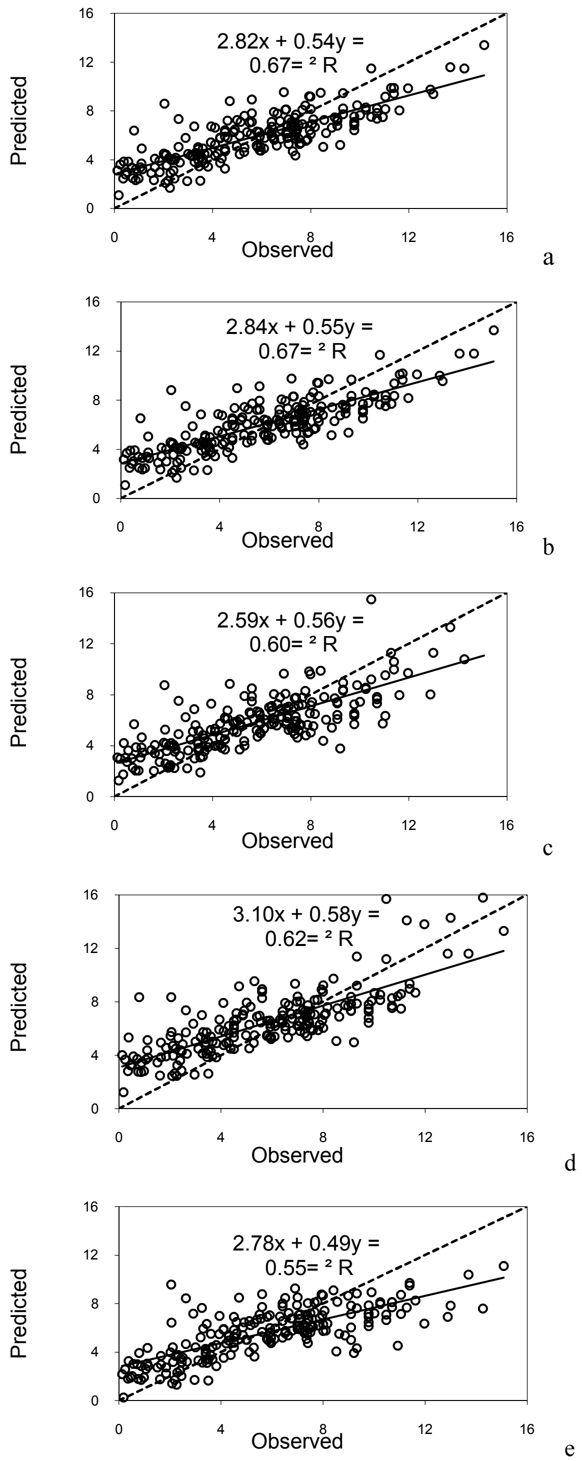

Fig. 5. Comparison of lysimeter measured daily ETc (as observed) with: (a) FAO 56 PM; (b) ASCE PM; (c) Kimberly Penman; (d) Penman; (e) FAO-24 Blaney-Criddle

The combination methods

As mentioned,the combination method used in this study included C-SAM, C-REG, and C-ANFIS. The ET_c values estimated by thefive methods of FAO 56 PM, ASCE PM, Kimberly Penman, Penman, and FAO-24 Blaney-Criddle,which were more consistent with the results obtained from lysimeters, were considered as independent variables(or input)of combination methods, and the lysimeters' ET_c values were considered as the outputs of the combination methods.

In order to facilitate the comparison of combination and climatic methods like ANFIS model, 80% of data were used for calibration,and the 20% remaining were used for verification. Table 3 presents the correlation coefficients and error functions of RMSE, R^2, and MBE for combination methods and climatic ET methods.

Comparing the results of the two equations of ASCE PM and FAO 56 PM in the training and test stages showed that their results are almost similar; however, since in the majority of studies,FAO 56 PM equation is considered as a benchmark, in this study, this equation was used to compare the combination methods.In climatic ET equations, R^2 and RMSE values in the training and test stages were slightly different.

Comparing the simplest combination method (C-SAM) with FAO 56 PM showed that, in the training stage, R^2, RMSE, and MBE values did not significantly change; however, in the test stage, C-SAM slightly improved these values so that R^2 changed from 0.74 to 0.77, RMSE changed from 2.08 to 1.95, and MBE changed from -0.20 to -0.14. Compared with FAO 56 PM equation, C-REG had a better estimation of ET_c in the training stage so that its MBE value was 0.0; however, in the test stage,R^2, RMSE, and MBE did not have significant changes. Comparing C-SAM and C-REG in the test stage showed that although C-REG is more complex, C-SAM had better ET_c estimates.

Table 3. Comparison of Individual and combination methods in estimating ETc

	Train			Test		
	R^2	RMSE	MBE	R^2	RMSE	MBE
FAO 56 PM	0.72	1.93	0.18	0.74	2.08	-0.20
ASCE PM	0.72	1.93	0.28	0.74	2.06	-0.18
Kimberly Penman	0.66	2.09	0.12	0.74	1.96	-0.28
Penman	0.67	2.15	0.66	0.71	2.07	0.43
FAO 24 BC	0.61	2.22	-0.10	0.72	2.15	-0.55
C-SAM	0.71	1.96	0.23	0.77	1.95	-0.14
C-REG	0.74	1.82	0.00	0.74	1.99	-0.38
C-ANFIS	0.82	1.50	0.00	0.83	1.56	-0.19

Compared with FAO 56 PM equation, C-ANFIS provided significantly better ET_c estimates so that in the test stage R^2 value increased from 0.74 to 0.83 and RMSE decreased from 2.08to 1.56. C-ANFIS Method properly combined climatic ET_c equations. Fig. 6 shows the comparison of the results obtained from FAO 56 PM with those obtained from lysimeters in the test stage.

As shown in Figure 6a, FAO 56 PM overestimated ET_cvalues less than 4 mm/day and underestimated values more than 9 mm/day. The hydrograph plots also show that this equation could better estimate ET_c between 4-9 mm/day. Figure 6b shows thehydrograph and scatter plotof C-SAMwhich are similar to FAO 56 PM. C-SAM is the average of the results of the five equations of FAO 56 PM, ASCE PM, Kimberly Penman, Penman, and FAO-24 Blaney-Criddle. As it was described for Figure 5,all these equations overestimate small values of ET_c and underestimate the large values. As expected, C-SAM could not accurately estimate the small and large amounts of ET_c. Although C-REG (Figure 6c) is a much more complex equation than C-SAM, while it just slightly improved ET_c estimates for values less than 4 mm/day, it has been shown to underestimate ET_cat higher values (>9mm/day) like C-SAM. Figure of C-ANFIS (Figure 6d) is different from the figures for the two other combination methods. As it is clear in the scatterplot, the fitted line is very close to the 1:1 line, and it has good estimates for the full range of ET_c. The hydrograph plot also shows that C-ANFIS properly followed the real ET_c values. Using intelligent system and having high simulationcapability,C-ANFIS could adequately solve the problem of underestimate and overestimate values in single methods.

The weight of each attribute inC-ANFIS is set to the gain ratio of the attribute relative to the average gain ratio acrosseach single equation allowing for accurate simulations and, therefore, can properly forecast ET_c values obtained from the lysimeters.

Considering the hydrograph plot, it is clear that the estimated values of C-ANFIS methodare closer to the real values when compared with the results obtained from others. C-ANFIS can estimate almost correct values, close to the real values, over different ranges of ET_c. The scatter plot also verifies the fairly good estimation power of C-ANFIS in all ranges of ET_c.

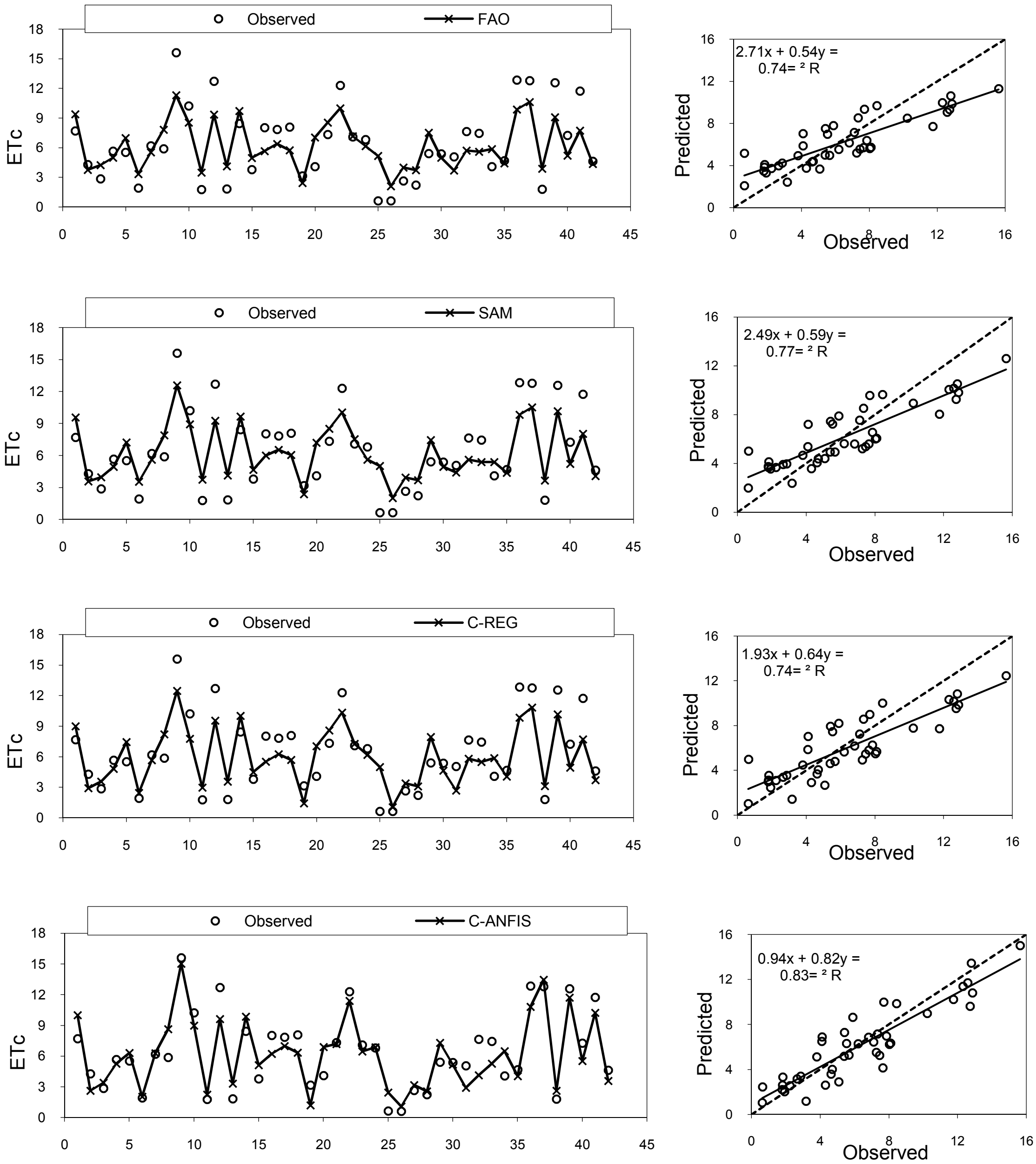

Fig. 6. Comparison of lysimeter measured daily ET_c with: (a) FAO 56 PM; (b) C-SAM; (c) C-REG; (d) C-ANFIS

CONCLUSIONS

The accuracy of the comparison of the single climatic methods and combination methods for estimating garlic ET was studied. First, the data from a drainage lysimeter was used to assess the accuracy of 13 climatic methods for estimating garlic ET. Meteorological data utilized in this study included maximum and minimum temperatures, maximum and minimum relative humidity, wind speed and sunshine hours. The results showed that FAO 56 PM equation could accurately estimate ET_c compared with other equations. Other equations of ASCE PM, Kimberly Penman, Penman, and FAO-24 Blaney-Criddle were respectively ranked next. The first four equations over estimated ET_c and only Blaney-Criddle equation underestimated it. Then, in order to obtain better results, a combination of the three methods of C-SAM, C-MLR, and C-ANFIS were used.

The ensemble forecast combinations techniques weighted the results obtained from each of the five mentioned equations to combine the individual model forecasts into a single new forecast thatis at least as good as any of the individual forecasts. Compared with C-SAM, C-MLR methods, the results of C-ANFIS were more consistent with ET_c values obtained from lysimeters. Using intelligence systems and because of high flexibility, C-ANFIS provided good results in all ranges of garlic ET. The outcomes of this research can provide basic information for specialists about the utilization of combination methods for estimating ET.

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ارزیابی و مقایسه روش های ترکیبی به منظور پیش بینی تبخیر-تعرق گیاه سیر

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واژه های کلیدی:
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چکیده- روش‌های زیادی برای تخمین تبخیر-تعرق وجود دارد که نتایج آن‌ها در مناطق مختلف، متفاوت است. در این تحقیق ابتدا تبخیر-تعرق گیاه سیر توسط لایسیمتر اندازه‌گیری شد و با ۱۳ روش مختلف مقایسه گردید تا بهترین روابط تعیین گردد. هدف اصلی این تحقیق بررسی توانایی روش‌های ترکیبی به منظور بهبود دقت تخمین می‌باشد. نتایج نشان داد ۵ روش پنمن فائو، پنمنASCE ، پنمن کیمبرلی، پنمن و بلانی کریدل دارای بیشترین دقت در تخمین تبخیر-تعرق می‌باشند. نتایج این ۵ روش توسط ۳ روش ترکیبی میانگین حسابی (C-SAM)، رگرسیون خطی و فازی-عصبی (C-ANFIS) با یکدیگر ترکیب شدند.نتایج این ۵ روش با استفاده از سه روش ترکیبی میانگین حسابی، رگرسیون خطی(C-MLR) و فازی-عصبی با یکدیگر ترکیب شدند. مقایسه نتایج در مرحله صحت‌سنجی نشان داد اگرچه روش میانگین حسابی از رابطه‌ی ساده‌تری نسبت به رگرسیون خطی استفاده می‌نماید اما نتایج آن از رگرسیون خطی بهتر می‌باشد. به طور کلی دو روش ترکیبی میانگین حسابی و رگرسیون خطی نتایج را نسبت به بهترین روش تخمین تبخیر-تعرق (پنمن فائو) به مقدار قابل توجهی بهبود نمی‌دهد اما روش ترکیبی فازی-عصبی تبخیر-تعرق را بهتر از روش‌های دیگر تخمین می‌زند. بر مبنای نتایج این تحقیق روش ترکیبی عصبی-فازی به منظور پیش‌بینی تبخیر-تعرق پیشنهاد می‌گردد.