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Estimating the Hourly Reference Evapotranspiration with Fuzzy Inference Systems and Limited Weather Data

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ABSTRACT

Evapotranspiration is the most important part of the hydrological cycle, which plays a key role in water resource management, crop yield simulation, and irrigation scheduling. Therefore, developing a cost-effective and precise model is essential for estimating hourly grass crop reference evapotranspiration (ETo). In this study the potential of the fuzzy inference system (FIS) is investigated as a simple technique for modeling hourly ETo obtained using the FAO-56 Penman-Monteith and ASCE equations. Then, combinations of efficient hourly climatic data namely temperature, wind speed, relative humidity and solar radiation were used as inputs to the fuzzy model. Four fuzzy models were developed based on different combinations of inputs. Common statistics such as Mean square error, average absolute relative error and determination coefficient and two more statistics of Jacovides (t) and R2/t are used as comparison criteria for evaluation of the model performance. Here, Training and testing fuzzy models were done with Fariman meteorological data – an arid region in the northeast of Iran. The fuzzy model whose inputs are solar radiation, air temperature, relative humidity and wind speed, yield the highest correlation and compatibility to reference models of FAO-56 PM and ASCE, based on common statistics. Whereas, the fuzzy model whose inputs are solar radiation, air temperature and relative humidity, are selected as the best model based on combination of common and additional statistics. The fuzzy model with two inputs namely solar radiation and relative humidity has acceptable results, too. The results show that solar radiation is the most effective parameter on hourly reference evapotranspiration and temperature, relative humidity and wind speed were other effective parameters, respectively. These results for training and testing phase are alike. It was found that the developed fuzzy models could be successfully employed in estimating the hourly ETo with a limited weather data.

1. Introduction

Evapotranspiration is one of the most important components of the hydrological cycle. Therefore, its accurate estimation is essential for many studies, such as water hydrologic balance, designing and management of irrigation, planning and management of water resources and crop production simulation (Vaziri *et al*., 2008). This subject is encountered with two facts: 1) The multiplicity of required parameters for calculating evapotranspiration and, 2) The lack of recording some influential parameters that make difficult its correct estimation (Kuchakzadeh and Bahmani, 2005). Since evapotranspiration is complicated, developing a mathematical model considering all effective climatic factors is hard. Also, the existence of uncertainty in efficient parameters causes unavoidable errors. Moreover, most of these models require much data that preparing all of them is difficult, time-consuming and costly. Furthermore, any developed mathematical model in a particular climate is just valid for that climate (Shayannezhad, 2006). With due attention to suitability of fuzzy technique to model high-uncertainty parameters and nonlinear systems without any complex equation, the fuzzy model can be a useful tool to consider the nature of evapotranspiration. Thus, we think fuzzy model can be a useful tool considering the nature of evapotranspiration. In contrast to conventional methods that needs advanced and complex math for designing and modeling a system, Fuzzy models use linguistic values and conditions or knowledge of experts with simplifying and improving the efficiency (Ghasemnezhad Moghadam *et al*. 1999; Kurehpazan Dezfuli, 2006). During the past years, researchers were continuously seeking to model evapotranspiration. So, in the last five decades, the most of studies have concentrated on developing mathematical estimation methods of evapotranspiration and improving

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the performance of available methods. Also, many researches have conducted fuzzy systems in many engineering fields like drought monitoring, reservoir management, deposits estimation, weather prediction, and river flow and runoff prediction. However, some studies focused on modeling daily reference crop evapotranspiration (Aytek, 2009; Hasheminajafi *et al*., 2007; Doğan, 2009; Jia Bing *et al*., 2004; Kisi and Öztürk, 2007; Kisi, 2010; Odhiambo *et al*., 2001; Shayannezhad, 2007), but modeling hourly reference evapotranspiration with fuzzy inference system hasn't been performed, yet. The mentioned studies shows that fuzzy model can apply different input data for daily estimation and finally, and their comparisons to other methods are representing its capabilities for estimating daily reference evapotranspiration. Some researchers used artificial neural networks to estimate evapotranspiration and introduced them as a useful tool for estimating these parameters besides fuzzy model. It is necessary to mention when wind speed, temperature of dew point or cloudiness level during day vary, it is better to output be hourly. As value of energy to evaporate varies during a day, then its effects cannot be generalized by simply averaging hourly values to daily (Allen *et al*., 1998). This causes large errors in calculation of daily evapotranspiration.

Considering the results of the previous studies about fuzzy logic potentiality, this study aims at using fuzzy inference system to estimate hourly reference evapotranspiration. Additionally, the absence of meteorological data and costly recording hourly data, made us suggest a model with minimum inputs. Clearly, if it is possible to provide such a model, it could be as the expected model with high accuracy because of reduced measuring error using fewer data.

2. Method and materials

2.1. The Study area

The study area, Fariman County, is located in the Khorasan Razavi state, Iran. The climate of study area is similar to the climate of Khorasan Razavi state based on climatically aggregations. Based on average annual temperature of 12.4° C and annual average rainfall of 150 mm, study area is classified as arid and semi-arid climate. The study area is over 4132 km2 which consists of 2.5 percent of Khorasan Razavi province area. The study county is located in latitude 35° 42′ north and longitude 59° 51′ east, and its height is 1411m above sea level. Hourly values of inputs were gathered and evaluated for calculating hourly reference evapotranspiration. The online private weather station has the ability to collect simultaneously the primary parameters such as temperature, relative humidity, wind speed and direction, radiation rate, soil moisture in different layers and soil temperature. Soil moisture depletion rate of root zone gathered from soil sensors in every 10 minutes. Also, evapotranspiration and plant's water requirement calculation using Penman-Montith formula does at the same time. Station data informs farm manager via SMS every three hours after receiving and logical analyzing data and save them on server computer. Recorded data in surveyed station was used for training and testing models during 2008 and 2009. Discarding faraway and lost points, the number of remaining data in the statistical period was 6000, that 70 percent of data (4200 data) used for training and 30 percent (1800) for testing.

2.2. Hourly reference evapotranspiration models

Penman-Montith-FAO and the America Society of Civil Engineers (ASCE) methods were used to calculate hourly reference evapotranspiration. Four fuzzy models were used to combine different input parameters in this study (table 1).

Table 1. Fuzzy models and inputs

Model No.	Inputs
Model I	Temperature(T) Relative Humidity(RH) Solar Radiation(Rs) Wind Speed(U2)
Model II	Temperature(T) Relative Humidity(RH) Solar Radiation(Rs)
Model III	Relative Humidity(RH) Solar Radiation(Rs)
Model IV	Temperature(T) Relative Humidity(RH)

Penman-Montith-FAO 56 (FAO-56 PM) model:

General equation for calculating reference evapotranspiration in hourly time step is as follows (Allen *et al*., 1998):

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{37U_2}{T+273}(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (1)$$

Where, ETo is hourly reference evapotranspiration (mm), Δ is the slope of saturated vapor pressure curve in air temperature (kPa °C^{-1}), Rn is the net radiation in grass surface (MJ/m^2/h), and G is density of heat flux of soil (MJ/m^2/h) determined as:

If Rn> 0, or daytime G = 0.1 Rn
If 0 ≥ Rn or nighttime G = 0.5 Rn

Where, T is the mean air temperature (hourly) at 1.5 - 2.0 m height from the ground (°C), U_2 is hourly mean wind speed (ms^{-1}) at 2.0 m height, e_s is mean saturated vapor pressure at 1.5 - 2 m height (kPa), e_a is mean vapor pressure of air in 1.5-2 m height (kPa), and γ is psychometric constant (kPa^{o}C^{-1}). The instructions provided in the FAO paper No. 56 can be used for calculating components of the FAO Penman-Montith.

American Society of Civil Engineers (ASCE) model:

Standard equation suggested by the American Society of Civil Engineers (ASCE) in order to calculate hourly reference evapotranspiration of grass is as follows (Snyder and Pruitt, 1992):

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{37U_2}{T + 273}(e_s - e_a)}{\Delta + \gamma(1 + C_d U_2)} \quad (2)$$

Where, C_d is constant from time steps of plant resistance (rs) and the aerodynamic resistance (ra) which varies with the reference plant and time period of day or night. For hourly time period, C_d is 0.24 and 0.96 and rs is 50 (sm^{-1}) and 200 (sm^{-1}) during day and night, respectively. Other parts of the equation and their units are the same as FAO-56 Penman-Monteith equation.

2.3. Fuzzy models

Each Fuzzy model includes three parts of inputs, fuzzy rules as inference engine, and outputs. Fuzzy models use different methods to describe inputs and outputs and how to combine rules to get results. In fuzzy models, the inputs and outputs are fuzzified variables, usually relates with fuzzy rules (IF_THEN). Since in most applications, inputs and outputs in a fuzzy system are natural numbers, we have to create intermediaries between fuzzy inference engine and environment. These intermediaries allow crisp numbers to become fuzzy numbers and conversely. One of the most important parts of each fuzzy model is fuzzy inference system. Fuzzy inference system is a non-linear model based on IF_THEN rules that with respective rules relates input and output variables of a real system together (Kerre, 1992). Some indices of selecting inference engine are intuitive meaning, computational efficiency and special features. Definition of fuzzy rules and combination of functions mentioned like:

$$\begin{aligned} &If\,(x_1 is A_{1,m}) And\,(x_2 is A_{2,m}) And\,(x_k is A_{k,m}) \\ &\quad Then \qquad y is B_{j,m} \end{aligned} \quad (3)$$

In other words, a fuzzy rule expresses the relationship k input variables x_1, x_2.... x_k, and output y. Where x_k (input) and y(output) are defined fuzzy sets and $A_{k,m}$ and $B_{j,m}$ (j=1,…k) are linguistic variables (Ansari *et al*., 2010).

In order to develop a fuzzy model, at first input parameter were determined and fuzzified (with finding out membership functions), then by describing inference rules to estimate evapotranspiration, fuzzy outputs were connected to fuzzy inputs and defuzzification of fuzzy outputs accomplished. Producing fuzzy input and output parameters were investigated according to the range of available data and proper number of levels was considered for them. So, in this research based on researchers' suggestions especially FAO-56, we used 8, 9, 6 and 7 ranges for temperature, relative humidity, solar radiation and wind, respectively. The model output with 10 levels was considered proportional to input variation in training (figure 1-5). Membership function variables and the degree of overlapping fuzzy functions determined to physical characteristics of the mentioned subject and expert opinions (Coa and Kandel, 1989). Considering the extensive use of triangular and trapezoidal membership functions in practical problems and the investigations results, this functions also used to fuzzification of variables, in this study.

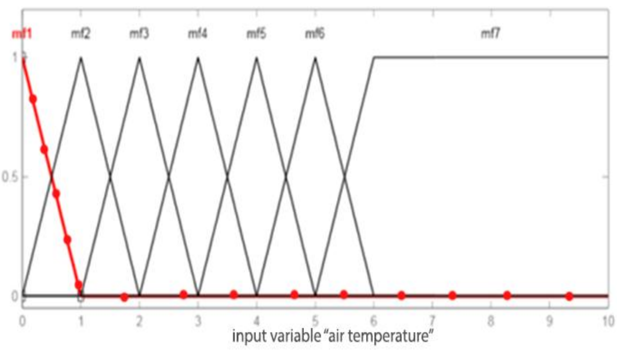

Figure 1. Membership functions of wind speed

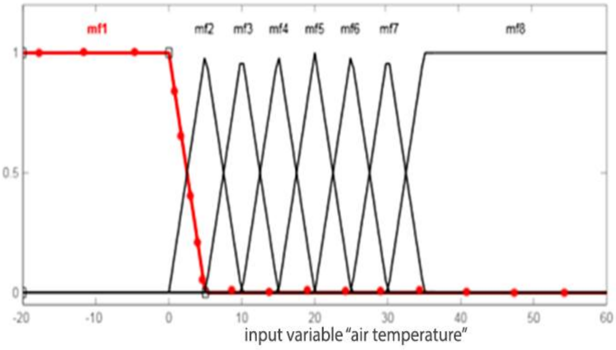

Figure 2. Membership functions of air temperature

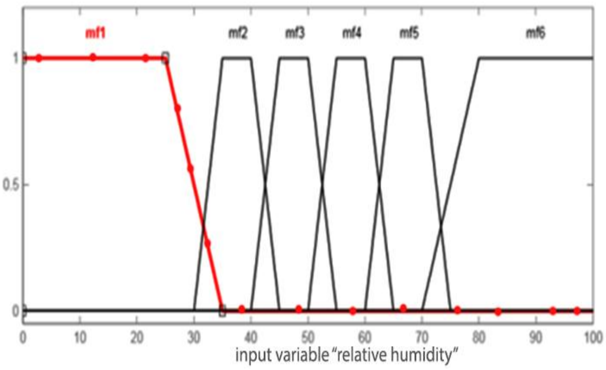

Figure 3. Membership functions of relative humidity

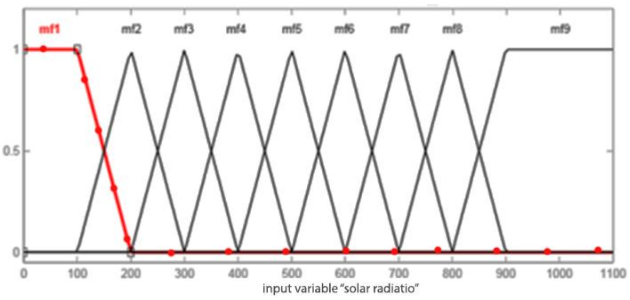

Figure 4. Membership functions of solar radiation

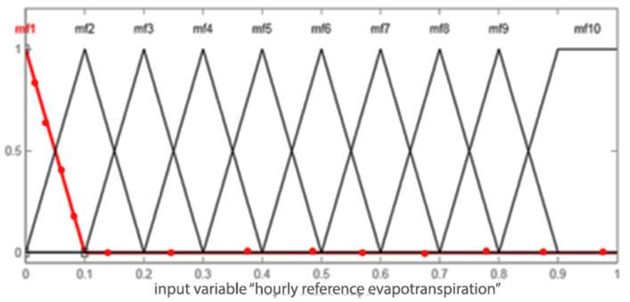

Figure 5. Membership functions hourly reference evapotranspiration

As referred in fuzzy rule's definition-one of the most important steps of developing a fuzzy model-we considered different rules, membership functions, and various degree of overlapping in training. It is notable; rules with different weights for each set of input variables were mentioned. These weights were calculated by the ratio of observed output of basic model in a given level to predict output in the same level. To complete modeling, Mamdani method for fuzzy inference, minimum method for implication, and maximum method for aggregation were used (Coa and Kandel, 1989, Bardossy *et al*., 1990; Lee, 1990). As final inference leads to a fuzzy result, achieving to a real and crisp number is satisfied with many defuzzification methods suggested by researchers. The most common methods presented in figure 6 are centroid of area (center of gravity), bisector of area (crossing bisectors), mean of maximum (mom), smallest of maximums (som) and largest of maximums (lom). The center of gravity method was applied for defuzzification because it is a comprehensive method suggested in many studies and yielded good results here.

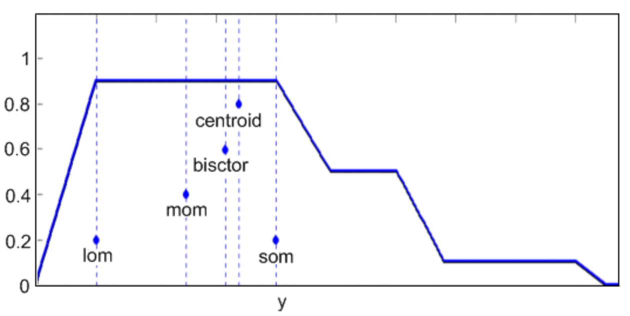

Figure 6. Defuzzification methods

Output value of center of gravity is estimated with following equation:

$$Y = \frac{\int y\mu(y)dy}{\int \mu(y)dy} \tag{4}$$

Where, y is fuzzy output value, μ (y) is output membership of y, and Y is the real value of output index.

2.4. Model's performance criteria

Statistical difference measurements are all arisen from the fundamental quality of outputs (P_i - O_i), although each measurement is scaled in a different way to describe particular features of its magnitude. The MBE and RMSE statistics estimate the average error, but none of them provide information about, 1) the relative size of the average difference or 2) the nature of the differences comprising MBE or RMSE. Relative difference statistics such as RMSE/Ō occasionally appear in the literature, but the general utility of such indices is questionable because they are unbounded. Therefore, Statistical tests proposed by Jacovides (1998) contribute to evaluate models precision and comparing the results of fuzzy models to Penman-Montith-FAO and ASCE models. According to his recommendation besides two criteria generally used to compare evapotranspiration models, a third criterion called t statistic should be used which is a combination of the two mentioned criteria.

$$RMSE = \sqrt{\frac{\sum(ET_{model} - ET_{obs})^2}{n}} \tag{5}$$

$$MBE = \frac{\sum(ET_{model} - ET_{obs})}{n} \tag{6}$$

$$t = \sqrt{\frac{(n-1)(MBE^2)}{(RMSE^2 - MBE^2)}} \tag{7}$$

Where, t is Jacovides criterion and n is the number of observations. The less t, the more accuracy the model is. Sometimes it might be followed the results of a model show high R^2 but acceptable value of RMSE, MBE and t; it makes it difficult to select the best model. Thus, in this study as well as the criteria introduced by Jacovides, new combined criterion which is the ratio of R^2/t (Sabziparvar *et al*., 2008), was also used; its higher value indicate higher compatibility of the model to reality.

3. Results and Discussion

As stated before, values of hourly evapotranspiration calculated by FAO-56 Penman-Monteith methods as outputs and different combinations of effective parameters in penman equation (table 2) as inputs were considered to develop fuzzy models.

Table 2. Statistic tests of different meteorological parameters affecting evapotranspiration

Data set	x_{Mean}	x_{min}	x_{max}	S_x	Correlation whit ET_O
Solar radiation (w/m^2) (Rs)	196	0	1055	276.6	0.62
Temperature (°C) (T)	11	-13	35	9	0.47
Wind Speed (m/s) (U2)	2.16	0	10	1.33	0.24
Relative Humidity (%) (RH)	59	8	100	25.8	0.42
Evapotranspiration (ETo(mm/hr))	0.08	0	0.92	0.167	1

According to table 2, solar radiation and wind speed have the highest and lowest correlation coefficient with hourly reference evapotranspiration, respectively. After data analyzing, different combinations of suitable inputs were selected for fuzzy models. Then, output of fuzzy models with ASCE and both of them were compared with FAO-56 Penman-Monteith as a reference model in training and testing.

As we expected, comparing the outputs of FAO-56 PM and ASCE models in the training and testing present high correlation and low MBE and RMSE (table 3), because theoretical basis of ASCE and FAO-56 PM equations are the same. Meanwhile, the value of statistics in both of training and testing are approximately alike.

Table 3. Statistic tests to compare FAO-56 PM and ASCE outputs

Phase	R^2	RMSE	MBE	t	R^2/t
Training	0.93	0.038	0.005	10.6	0.091
Testing	0.94	0.038	-0.005	8	0.122

3.1. Fuzzy models vs. FAO-56 PM model

The results of fuzzy models show proper correlation with FAO-56 PM and ASCE in training step. Matching the results of fuzzy models to FAO-56 PM points out fuzzy models I (whose inputs are T, RH, U_2 and R_s) and IV (whose inputs are T and RH) has the highest and lowest correlations, respectively (table 4). Besides, Mean Biased Error was about -0.014 to -0.042 mm/hour. These small values represent high accuracy of developed fuzzy models. Since the MBE values are negative, clearly the estimated values of fuzzy models are more than FAO-56 PM model.

Table 4. Statistic tests to compare fuzzy models with FAO-56 PM model outputs

Fuzzy Model	Training					Testing				
	R^2	RMSE	MBE	t	R^2/t	R	RMSE	MBE	t	R^2/t
Model I (T, U2, Rh, Rs)	0.98	0.031	-0.019	59.6	0.017	0.98	0.033	-0.020	39.0	0.025
Model II (T, Rh, Rs)	0.97	0.035	-0.014	33.2	0.0292	0.97	0.034	-0.013	23.5	0.042
Model III (Rh, Rs)	0.94	0.048	-0.018	32	0.0295	0.94	0.049	-0.020	20.9	0.046
Model IV (T, Rh)	0.56	0.128	-0.042	26.8	0.021	0.59	0.132	-0.044	25.4	0.030

Also, the Fuzzy models RMSE in training are calculated between 0.31 to 0.128 mm/hour with the lowest value for Model I. Considering R^2, RMSE and MBE statistics point out, selecting proper model is not simple; because there isn't a significant difference among models I to III. Moreover, t and R^2/t values do not justify the results of general statistics. Therefore, it is better to use t and R^2/t as additional statistics. Jacovides statistic (t) shows that

Minimum and maximum values equal to 26.8 and 59.6 for Fuzzy models IV and I, respectively but R^2/t is not maximum for model IV. However, this statistic is almost the same for model II with three variables (temperature, relative humidity, and solar radiation) and model III with two variables (relative humidity, solar radiation). Simultaneous evaluations of all statistics show that

Estimating ET_O with fuzzy model II (temperature, relative humidity and solar radiation) yields the best result in training. But it is notable that there isn't much difference between models II and III.

Matching outputs of fuzzy models and FAO-56 PM model in the testing revealed the results are almost similar to what earned in training (table 4). Based on general statistics (R^2, MBE and MRSE) the best results are for fuzzy model II. Figure 7 marks results of the fuzzy model with three inputs against FAO-56 PM in testing. The linear relationship is determined as $ET_{O\ (Fuzzy)} = 0.9986ET_{O\ (FAO\text{-}56\ PM)}$ (R^2=0.97). The slope of the line is close to 1 and its intercept is zero. This result shows a good alignment along the 1:1 line and demonstrates that simulated values by Fuzzy model are close to those found by FAO-56 PM model.

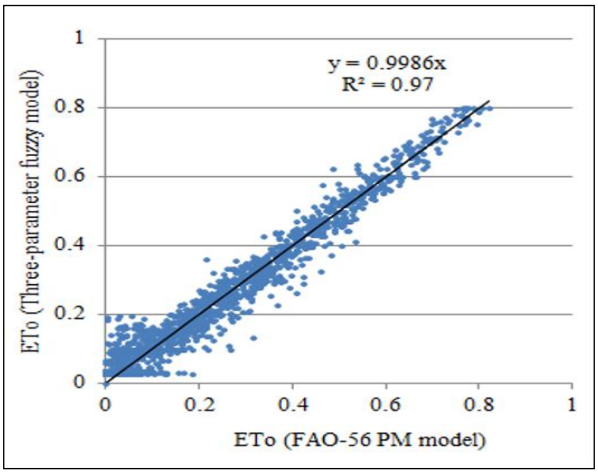

Figure 7. Hourly reference evapotranspiration obtained from three-parameter fuzzy model compared with FAO-56 PM model in testing

3.2. Fuzzy models vs. ASCE model

The performance of the FIS models is compared with ASCE model for training and testing. The results show that fuzzy model I (R_s, T, RH, and U_2) has the highest and fuzzy model IV (T and RH) has the lowest correlation among fuzzy models in training. Also, presented fuzzy models have low RMSEs; their values are 0.045 to 0.136 mm /hr. Considering MBE changes -0.037 to -0.009 mm/hr, in conclusion fuzzy models estimates hourly evapotranspiration values slightly more than ASCE model. According to above statistics, model IV has the highest accuracy in training. But, this result is not justified with t and R^2/t statistics. Based on these two statistics, fuzzy model II (R_s, T and RH) is the best (table 5). These results have been justified in testing however the statistics values are fairly different. But on the whole, results affirmed that model II is the best in both of training and testing phases and results presented in table 5 approve it, too.

Table 5. Statistic tests to compare fuzzy models with combined ASCE model outputs

Fuzzy Model	Training					Testing				
	R^2	RMSE	MBE	t	R^2/t	R^2	RMSE	MBE	t	R^2/t
Model I (T, U2, Rh, Rs)	0.96	0.045	-0.014	25.0	0.039	0.96	0.047	-0.014	17.3	0.056
Model II (T, Rh, Rs)	0.95	0.050	-0.009	13.9	0.068	0.95	0.050	-0.008	9.5	0.100
Model III (Rh, Rs)	0.93	0.059	-0.013	17.9	0.052	0.92	0.061	-0.012	10.9	0.085
Model IV (T, Rh)	0.57	0.136	-0.037	21.7	0.026	0.60	0.135	-0.034	20.4	0.030

4. Conclusion

This paper suggests simple fuzzy models for estimating hourly reference evapotranspiration with limited weather data. The ability of fuzzy inference system (FIS) has been investigated as a simple technique. The FIS models performance is compared with ET_o obtained with the FAO-56 Penman-Monteith and ASCE equations. The FAO-56 PM equation is recommended as the standard for computing reference evapotranspiration, but using these equations is limited due to data availability in areas where meteorological information is scarce. At first, the common climatic variables namely solar radiation, temperature, and relative humidity and wind speed have been selected as inputs for FIS models. Also, the correlation between these climatic data with values of the hourly ET_o estimated with FAO-56 PM equation were considered. The results showed that solar radiation (R_s) was found to be more effective in ET_o estimation than the other three parameters. Other effective parameters were determined as air temperature, relative humidity and wind speed, respectively. The basic cause is possibly that solar radiation acts as an energy resource. As short-term changes of meteorological parameters influence each other, therefore the estimation of hourly ET_o can be carried out with selecting more efficient parameters and removing some of them. Four fuzzy models were developed based on different combinations of these inputs. According to the results obtained, FIS models appear to be a useful tool and these models have high compliance and enough ability for predicting the hourly reference ET_o. The fuzzy models whose inputs are the solar radiation, temperature, and relative humidity have the best performance criteria among the input combinations tried in the study. Moreover, fuzzy models whose inputs are the solar radiation, temperature, relative humidity and wind speed, and fuzzy models whose inputs are the solar radiation and relative humidity have high correlations and low RMSEs, too. The fuzzy models whose inputs are temperature and relative humidity have the lowest precision. Based on the comparison results, fuzzy models can be developed based on data availability or data precision in any region. But, initially the fuzzy models which are supposed to use, must be evaluated and validated, again.

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