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Using Intelligence Models to Estimate Evapotranspiration

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Abstract
Exact estimation of evapotranspiration is an important parameter in water cycle, study, design and management of irrigation systems. In this study, the efficiency of intelligent models such as fuzzy rule base, fuzzy regression and Artificial Neural Networks for estimating daily evapotranspiration has been examined and the results are compared to real data measured by lysimeter on the basis of a grass reference crop. Using daily climatic data from Ekbatan station in Hamadan in western Iran, including maximum and minimum temperatures, maximum and minimum relative humidities, wind speed and sunny hours, evapotranspiration was estimated by the aforementioned intelligent models. The predicted evapotranspiration values from fuzzy rule base, fuzzy linear regression and artificial neural network provided root mean square error (RMSE) of 0.72, 0.86 and 0.74 mm/day and determination coefficient (R^2) of 0.88, 0.86 and 0.84, respectively. The fuzzy rule base was hence found to be the most appropriate method employed for estimating evapotranspiration.

Keywords: Evapotranspiration, Fuzzy rule base, Fuzzy regression, Artificial neural network.

بررسی کارایی مدل‌های هوشمند در برآورد تبخیر و تعرق پتانسیل

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چکیده
تعیین تبخیر تعرق واقعی یکی از مهم‌ترین اجزاء مطالعه سیکل هیـدرولوژی و طراحی و مدیریت سیستم‌هـای آبیـاری کشـاورزی اسـت. درایـن تحقیـق کارایی مدل‌های هوشمند مثل منطق فازی، رگرسیون فازی و شبکه عصـبی مصنوعی برای تخمین تبخیر و تعرق روزانه را بررسی و بـا مقـادیر واقعـی و مشاهده اندازه‌گیری شده در سیستم بر اسـاس گیـاه مرجـع چمـن در منطقـه اکباتان همدان در غرب ایران مقایسه گردیده است. داده‌های مـورد اسـتفاده در مدل‌های هوشمند عبـارت اسـت از حـداکثر و حـداقل درجـه حـرارت، حداکثر و حداقل رطوبت‌نسـبی، سـرعت بـاد و سـاعت آفتـابی در ایسـتگاه هواشناسی همدان. مقدار Rmse در سه روش منطق فازی، رگرسیون فازی و روش شبکه عصبی مصنوعی به ترتیب برابر با ۰/۷۲، ۰/۸۶ و ۰/۷۴ میلی‌متر در روز و هم‌چنین مقدار R^2 به ترتیب برابر ۰/۸۸، ۰/۸۶ و ۰/۸۴ می‌باشد. بر اساس نتایج بدست آمده روش منطق فازی بهترین روش در بـین مـدل‌هـای هوشمند استفاده شده برای برآورد تبخیر و تعرق روزانه می‌باشد.

کلمات کلیدی: تبخیر و تعرق روزانه، منطق فازی، رگرسیون فـازی، شـبکه عصبی مصنوعی.

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Introduction

The process of evapotranspiration (ET) is an important part of the water cycle and as such, its exact estimation is required for designing irrigation systems and managing water resources. Accurate estimation of ET is crucial in agriculture since over-estimation causes the waste of valuable water resources while its underestimation leads to the plant moisture stress and decrease in the crop yield. Estimation methods developed over the past few decades ranges from simple ones such as Blany-Criddle and complex ones which use physical processes like the Penman compound method (Najafi, 2004). Penman used parameters such as the dynamic of evaporation, intensity of net radiations and surface aerodynamic characteristics. Montieth later improved this by considering plant daily resistance and presented Penman-Montieth equation (1965). Several researchers studied the validation of these equations (Alen *et al.,* 1986, 1998). Jenson *et al.,* (1990) compared twenty such methods with the results of lysimeters in 11 stations at different parts of the world with various climates and concluded that in all climates the Penman-Montieth method gave the best results. In recent years, intelligent models such as fuzzy rule base model (FRBM) and Artificial Neural Networks (ANN) or a combination of them have been employed for estimating ET (Teshnehlab *et al.,* 2006).

Burten *et al.,* (2000) used ANN and estimated daily evaporation from pan evaporation by 2044 data gathered from various places all over the world from 1992 to 1996. Input data included precipitation, temperature, relative humidity, solar irradiance and wind speed. Compared with multiple linear regression methods such as the one proposed by Priestley-Taylor (1972), ANN provided the least error of 1.11 mm/day in ET estimation. Odhiambo *et al.,* (2001) compared the results from FRBM with those of Penman-Montieth and Hargreaves-Samani methods (1994 & 1985) and used two fuzzy rule based models, in which solar irradiance and relative humidity were the input data in the first model (FRBM-1) and wind speed was also added in the second (FRBM-2). Comparison with the lysimeter data, the standard error for FRBM-1, FRBM-2, Penman-Montieth and Hargreaves- Samani was found to be 0.73, 0.54, 0.50 and 0.66 mm per day, respectively. It can be seen that FRBM-2 and Penman-Montieth yield a similar error despite the fact that the number of input parameters was less in FRBM-2. Shayannejad *et al,* (2007) used Fuzzy Linear Regression (FLR) for ET estimation in Hamadan (Iran) and demonstrated that FLR gave a higher determination coefficient (R^2) with less error than Penman-Montieth method.

Materials and Methods

Meteorological Station

The necessary climatic data for this research was provided from Ekbatan meteorological station, near Hamadan, West of Iran. This station has a longitude 48° and 32″ North, and a latitude 34° and 52″ East, and an elevation of 1730m above sea level. The climate can be described as semi-arid and cold according to Kopen's classification. Maximum and minimum daily air temperature is 40°C and -34°C respectively. The average annual rainfall during the period of 1983-2003 has been 312.3mm. A 1m∗2.25m∗1.2m lysimeter equipped with drainage was used to measure ETP with a grass reference crop. The soil characteristics could be described as: alkaline, deep, medium to heavy texture, electric conductivity of 0.35 to 0.65 deci siemens per metre and specific gravity of 1.74-1.91 gram per cm^3. A layer of 20cm thickness gravel consisting of various sizes covered the slopped bottom of the lysimeter at the station and soil was added in separate horizontal layers. Daily ET was obtained using water balance model measuring water input and output and soil humidity.

Models Employed

In this study three intelligent models FRBM, FLR and ANN were used to estimate the potential evapotranspiration and they were evaluated using the lysimeter data.

Fuzzy Rule Base

Fuzzy rule-based models developed by Lotfizadeh (1965) for handling imprecise information, have found important applications in various fields, including water based systems, over the last five decades. Introduction of Linguistic Terms (LT) by Fontane *et al.,* (1997) and application of complex mathematical models by Bárdossy *et al.* (1995), Pesti *et al.* (1996) and Abebe *et al.* (2000) have established this methodology as a reliable tool for predicting water resource parameters. An FRBM contains membership functions of fuzzy sets constructed on the range of all the inputs to the model. The model matches the input and output, which also contains membership functions, with fuzzy rules (Abebe *et al.,* 2000). In this study, as suggested by Bárdossy and Duckstein (1995), following a local search on the four available membership functions of triangular, bell-shaped, dome-shaped and inverted cycloid, the triangular input membership function was selected based on the lowest root square mean error (RSME) of 0.72 and highest R^2 of 0.88 as shown in Table 1.

FRBM Design

In the design of the FRBM, six inputs containing minimum and maximum daily temperature (T_{min}, T_{max}), minimum and maximum daily relative air humidity (Rh_{min}, Rh_{max}), daily wind speed (U), as well as daily sunny hours (N) were considered and ET was the model output. In order to establish the rule-bases, 40 lines of the data containing inputs and outputs were selected randomly.

Five FRBM models (FRBM-1 to FRBM-5) were defined based on the quantity of linguistic terms and also, the type and number of input parameters mentioned above (see Table 2). Using six similar input parameters, FRBM-1, FRBM-2 and FRBM-3 have been defined with 2, 3 and 5 LT respectively, and as suggested by Figures 1 to 6, FRBM-1 with 2 LT showed the least RMSE of 0.733. FRBM-4 and FRBM-5 were thus defined using 2 LT but different types and number of input parameters. Based on the results demonstrated in Table 2, FRBM-1 with the lowest RMSE, with a triangular input membership function and 2 LT was selected as the best FRBM for this study.

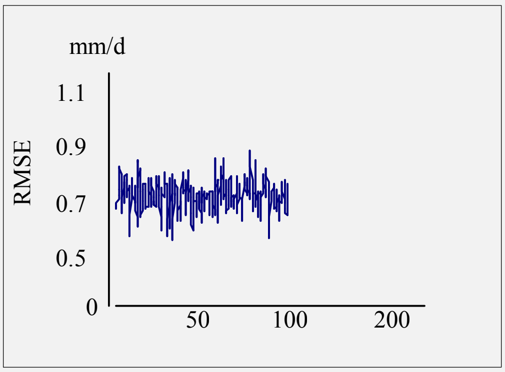
Table 1 - Comparison of membership functions type used in FRBM.

Number	*Membership Function Type*	*RMSE*	*R^2*
1	TRI-MF	0.72	0.88
2	TRAP-MF	1.21	0.751
3	GBELL-MF	1.43	0.786
4	GAUSS1-MF	2.01	0.735
5	GAUSS2-MF	1.74	0.794

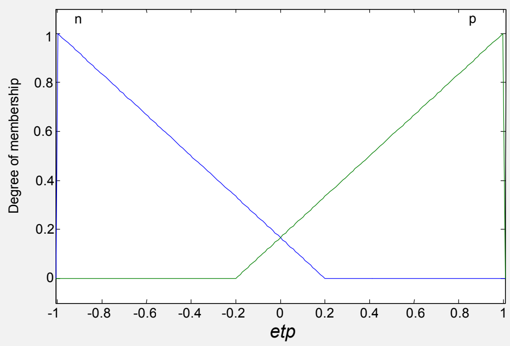
Membership Function Type: TRI: triangular, TRAP: Trapezoid, GBELL: generalized bell, GAUSS, GAUSS2-MF: Gaussian

Table 2 - Characteristics of various FRBM's defined for this study.

parameters	FRBM-1	FRBM-2	FRBM-3	FRBM-4	FRBM-5
Minimum temperature	*	*	*		*
Maximum temperature	*	*	*		*
Minimum humidity	*	*	*	*	
Maximum humidity	*	*	*	*	
Wind speed	*	*	*	*	*
Sunny hour	*	*	*	*	*
Mean relative humidity				*	
Mean temperature					*
RMSE mm/day	0.733	0.874	0.92	0.98	1.02



(B)



(A)

Figure 1 - (A): Membership function, model FRBM-1, with two linguistic terms.

Figure 2- (B): RMSE for model FRBM-1, with two linguistic terms.

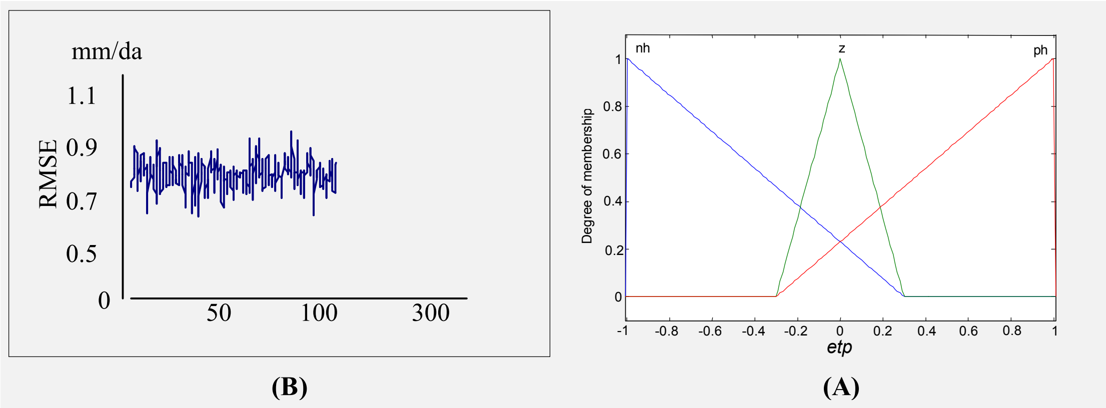


Figure 3- (A): Membership function, model FRBM-1, with three linguistic terms.

Figure 4- (B): RMSE for model FRBM-1, with three linguistic terms.

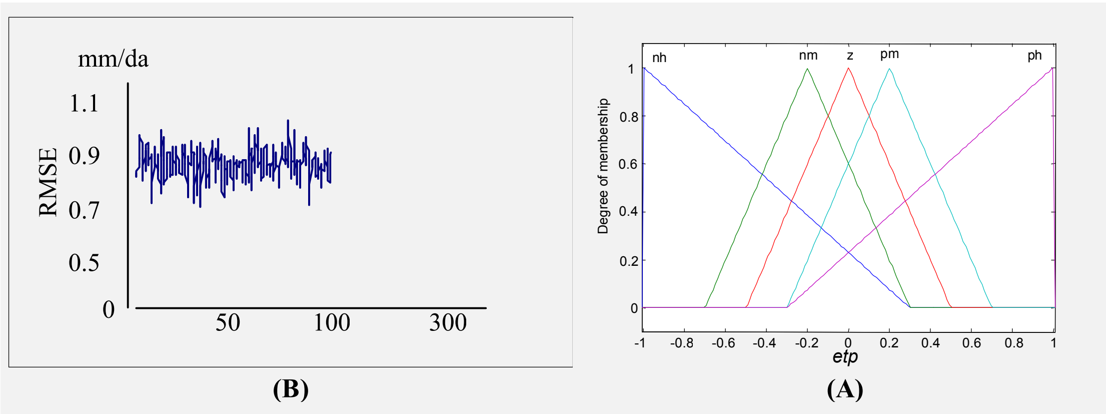


Figure 5 - (A): Membership function, model FRBM-1, with five linguistic terms.

Figure 6 - (B): RMSE for model FRBM-1, with five linguistic terms.

Artificial Neural Network Method

The modern thinking about ANNs began in the 1940s with the work of McCulloch and Pitts. ANNs are mathematical models consisting of highly interconnected processing nodes or elements (artificial neurons) under a pre-specified topology (sequence of layers or slabs with full or random connections between the layers). In the 1950s Rosenblatt built many variations of a specific type of early neural computational models called perceptron networks and developed associated learning rules which led to the introduction of first practical application of ANN. They have been used extensively since 1980's in a variety of diverse real world applications (Benardos and Kaliampakos, 2004). In this work, the multi-layer perceptron network has one input layer (with three processing elements), one hidden layer (with two processing elements) and one output layer (with one processing element).

Fuzzy Linear Regression

In regression analysis, the best mathematical expression describing the functional relationship between one response and one or more independent variables is obtained. Following the introduction of the fuzzy theory by Lotfizadeh, the fuzzy regression model (FLR) was developed by Tanaka *et al.* (1982) in which the fuzzy uncertainties of dependent variables with the fuzziness of response functions were explained. Based on the conditions of variables, there are three categories of FLR: a) input and output data are both non-fuzzy numbers, b) input data is non-fuzzy number but output data is fuzzy number, and c) input and output are both non-fuzzy numbers (Buckley, 2007). Estimation of FLR, although it has been the subject of continuous research, is often carried out by two techniques, namely fuzziness minimization by numerical method using linear programming (as suggested by Tanaka, 1982) and deviation minimization between the estimated and observed outputs, sometimes referred to as the fuzzy least square method (Diamond, 1988).

FLR has been used where the response variable is in intervals. By taking the mean or mode, the interval value can be changed to crisp values but at a cost of losing useful information about the spread. Hence, no proper interpretation of the fuzzy regression interval can be made (Wang and Tsaur, 2000) Tanaka's approach, referred to as a possibilitic regression has also been criticized both for not being based on sound statistical principles (Prajneshu, 2008) as well as creating computational difficulties when large number of data points is encountered (Chang and Ayyub, 2001; D'Urso, 2003). Peters (1994) complains about Tanaka's model being extremely sensitive to the outliers. Kim *et al.,* (1996) reported that fuzzy linear regression (FLR) may tend to become multicollinear as more independent variables are collected. The drawback with the fuzzy least square method, on the other hand, is the spread of estimated response increases as the magnitude of explanatory response increases, even though the spread of observed responses is roughly constant or decreasing. To overcome this, Kao and Chyu (2002) proposed a "two-stage" approach for fitting fuzzy linear regression (FLR) through the fuzzy least square approach and showed superiority over Diamond's procedure. This approach is discussed by Singh *et al.* (2007) and relevant nonlinear computer programs, such as LINGO, have been developed to solve such cases. As far as fuzzy nonlinear regression is concerned, Buckley and Feuring (2000) proposed "evolutionary algorithm solutions" in which, for given fuzzy data, algorithm searches from a library of fuzzy functions (including linear, polynomial, exponential and logarithmic) one which would fit the data. In this study, using HYDROGENERATOR and LINGO software, a fuzzy possibilistic model was employed in which coefficients are fuzzy, while inputs and outputs are non-fuzzy observational. The model used may be represented by the following equation:

$$\widetilde{y} = \widetilde{A}_0 + \widetilde{A}_1 x_1 + \widetilde{A}_2 x_2 + \widetilde{A}_3 x_3 + \dots\dots\dots + \widetilde{A}_n x_n$$

where, $\widetilde{A}_0, \widetilde{A}_1, \dots, \widetilde{A}_n$ are fuzzy coefficients and $x_1, x_2, x_3, \dots, x_n$ are observational input variables which are normal numbers and ỹ is the fuzzy output for each variable n. Table 3 shows the object function and the restrictions used for the FLR in this work.

Table 3 - Linear programming model for solving linear regression with non-fuzzy observations.

Fuzzy regression:	$\widetilde{y} = \widetilde{A}_0 + \widetilde{A}_1 x_1 + \widetilde{A}_2 x_2 + \dots + \widetilde{A}_n x_n$
function:	$\text{Minimize : mc}_0 + \sum_{j=1}^{m} \sum_{i=1}^{n} c_i \lvert x_{ij} \rvert$
Limits:	$p_0 + \sum p_i x_{ij} - (1-h)\left[c_0 + \sum c_i x_{ij}\right] \le y_j$
	$p_0 + \sum p_i x_i + (1-h)\left[c_0 + \sum c_i x_{ij}\right] \ge y_j$

Results

For calculating ET in the Penman-Mantis method and Fuzzy regression, Excel and MATLAB software are used, respectively. RMSE and R2 were used for validation and approval of the results.

Sensitivity Analysis

A sensitivity analysis was required to indicate which one of the input parameters plays a more important role in defining the ET in the models. This is carried out in the two following methods: addition of input parameters and removal of input parameters. Accordingly, whichever parameter whose addition or removal would cause the most reduction in RMSE would be identified as the most sensitive parameter. In this work, using the latter approach, one of the six input parameters was removed at a time and the corresponding RMSE was calculated as shown in Table 4. Maximum temperature was therefore found to be the most sensitive parameter in all methods used while, the sunny hour showed the least sensitivity in FRBM, and maximum relative humidity was the least sensitive for ANN and FLR.

Discussion

RMSE and R2 were used to select the best method to determine ET amongst FRBM, ANN and FLR. As can be seen from Table 4, the results indicate that R2 does not vary much (0.83 to 0.88), while RMSE alters more so that the least RMSE relates to the FRBM model with two linguistic terms (FRBM-1), followed by ANN, FLR, FRBM-2, FRBM-3, FRBM-4 and FRBM-5, which showed a higher RMSE (RMSE altered in the range of 0.72 to 1.02).

Table 4 - Sensitivity analysis.

Input Parameters	FRBM RMSE(mm/day)	ANN RMSE(mm/day)	FLR RMSE(mm/day)
Tmin, Tmax, RHmin, RHmax, U, n	0.72	0.74	0.86
Tmin, Tmax, RHmin, RHmax, n	0.93	0.77	0.95
Tmin, Tmax, RHmin, RHmax, U	0.83	0.84	0.89
Tmin, Tmax, RHmin, U, n	0.96	0.75	0.87
Tmin, Tmax, RHmax, U, n	1.16	0.76	0.94
Tmin, RHmin, RHmax, U, n	1.47	1.1	1.2
Tmax, RHmin, RHmax, U, n	1.39	0.94	0.96

Table 5- Comparison of RMSE and R^2 for ANN, FRM and FRBM.

parameter	FRBM-1	FRBM-2	FRBM-3	FRBM-4	FRBM-5	ANN	FLR
RMSE(mm/day)	0.72	0.87	0.92	0.98	1.02	0.74	0.86
R^2	0.88	0.86	0.83	0.84	0.83	0.84	0.86

Considering Figures 7, 8 and 9 in which the observed and estimated ET are demonstrated using the three models FLR, FRBM and ANN, the fuzzy rule-based model proved to be the best method and is proposed to be used for ET estimation of the region.

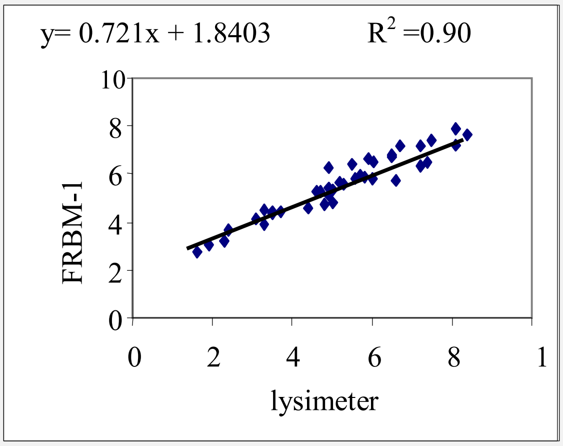


Figure 7 – Comparing observed and estimated ET using the FRBM–1 model.

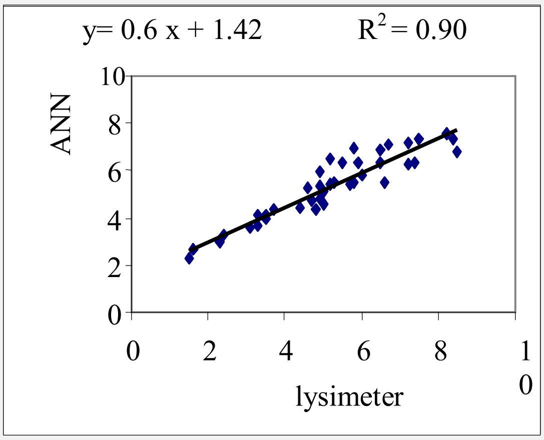


Figure 8 - Comparing observed and estimated ET using the ANN model.

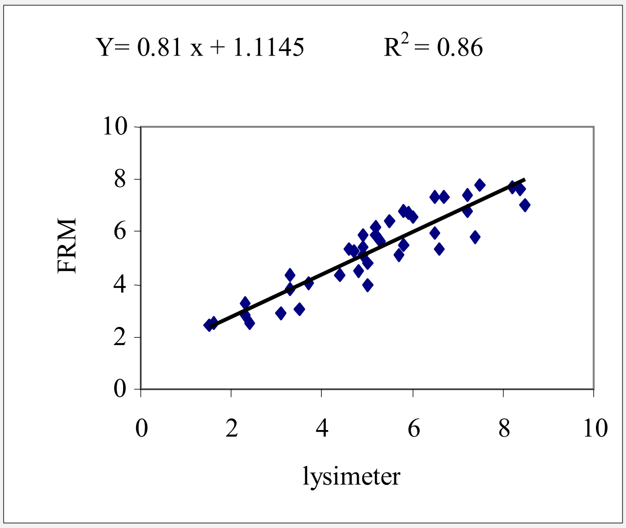


Figure 9 - Comparing observed and estimated ET using the FRM model.

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