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Applicability of Mamdani and Sugeno fuzzy genetic approaches for modeling reference evapotranspiration

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SUMMARY

This study investigates the applicability of Mamdani and Sugeno fuzzy genetic approaches in modeling reference evapotranspiration (ET_0). The daily air temperature, solar radiation, relative humidity and wind speed data from Adana and Antalya stations, Turkey, were used as inputs to the fuzzy genetic models for estimating ET_0 obtained using the standard FAO-56 Penman–Monteith equation. Comparison of two different fuzzy genetic methods indicated that the Sugeno fuzzy genetic (SFG) method was faster and had a better accuracy than the Mamdani fuzzy genetic (MFG) method in modeling daily ET_0. SGF and MFG models were also compared with the recently proposed Valiantzas's equations and following empirical models: Hargreaves–Samani and Priestley–Taylor methods. Root mean-squared errors (*RMSE*), mean-absolute errors (*MAE*) and determination coefficient (R^2) were used for the evaluation of the models' performances. Results revealed that the SFG and MFG models were performed better than the empirical models in modeling daily ET_0 process. Comparison of the two different fuzzy genetic approaches indicated that the SFG had a better accuracy than the MFG. For the Adana and Antalya stations, the SFG1 model with *RMSE* = 0.219 and 111 mm/day, *MAE* = 0.097 and 0.080 mm/day and R^2 = 0.983 and 0.998 in validation period was found to be superior in modeling daily ET_0 than the other models, respectively.

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1. Introduction

Evapotranspiration is a process composed of combination of two different processes whereby water is lost on the one hand from the soil surface (evaporation) and on the other hand from the crop (transpiration) (Allen et al., 1998). Evapotranspiration is crucial for optimization of the irrigation water use in arid and semi-arid regions where there is a water shortage problem. Estimation of evapotranspiration is very important for agricultural, hydrological and climatic studies, as it composes a major part of the hydrological cycle (Sobrino et al., 2005).

Various methods have been proposed for estimating evapotranspiration as reported by Brutsaert (1982) and Jensen et al. (1990). The combination of energy balance/aerodynamic equations generally provides the most accurate results because they are based on physics and rational relationships (Jensen and Burman, 1990). The Food and Agricultural Organization of the United Nations (FAO) accepted the FAO Penman-Monteith as the standard equation for estimation of ET (Allen et al., 1998; Naoum and Tsanis, 2003).

The application of artificial intelligence (AI) techniques (e.g., artificial neural networks, neuro-fuzzy) for reference evapotranspiration (ET_0) modeling has received much attention in recent years (Cobaner, 2011; Hamid et al., 2011; Jain et al., 2008; Kim and Kim, 2008; Kisi, 2006a,b, 2007a, 2008, 2011; Kisi and Cimen, 2009; Kisi and Yildirim, 2005a,b; Kumar et al., 2009; Ozkan et al., 2011; Sudheer et al., 2003; Tabari et al., 2012; Trajkovic et al., 2000, 2003; Trajkovic, 2005, 2010). Cobaner (2011) compared two different neuro-fuzzy systems in ET_0 estimation and he found that that the subtractive clustering based neuro-fuzzy models yield plausible accuracy with fewer amounts of computations as compared to the grid partition based neuro-fuzzy models in estimating the ET_0 process. Hamid et al. (2011) compared the accuracy of artificial neural networks (ANN) and neuro-fuzzy models in estimating ET_0. Jain et al. (2008) used ANN for estimating ET_0 and introduced a procedure to evaluate the effects of input variables on the output using the ANN weight connections. Kim and Kim (2008) examined the accuracy of generalized regression neural networks (GRNN) model with genetic algorithm for estimating the alfalfa ET_0. Kisi (2006a) examined the ET_0 modeling using ANN method and he compared ANN results with the Penman and Hargreaves models. He reported that the ANN model performed better than the empirical models. Kisi (2006b) modeled ET_0 by using generalized regression ANN models. Kisi (2007b) estimated ET_0 using multi-layer perceptron (MLP) method and compared test results with the Penman, Hargreaves and Turc models. He showed the superiority of the MLP to the empirical models. Kisi (2008) compared the accuracy of dif-

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ferent ANN techniques in ET_0 estimation. Kumar et al. (2009) applied different ANN models for prediction of ET_0 under the arid conditions and compared the ANN results with the FAO-24 Radiation, Turc, and FAO-24 Blaney–Criddle methods. They found ANN model to be better than the empirical models. Sudheer et al. (2003) employed radial basis neural networks (RBNN) in estimating ET_0 by limited climatic data. Tabari et al. (2012) compared different AI methods with climate based models for ET_0 modeling using limited climatic data in a semi-arid highland environment. Trajkovic et al. (2003) illustrated the applicability of RBNN in forecasting ET_0. Trajkovic (2005) developed temperature-based RBNN models for estimating FAO-56 PM ET_0. In his study, the ANN results were compared with the Hargreaves, Thornthwaite and reduced Penman Monteith (PM) methods and RBNN was found to be better than the empirical models. Detailed situation of modeling ET_0 using ANN models can be found in review of Kumar et al. (2011). It is proved from the related literature, the ANN method is more popular than the fuzzy approach. The main reason of ANN becoming so popular that it has an ability to learn complex and nonlinear relationships which are difficult to map with conventional approaches. Fuzzy logic approach is, however, more transparent and more flexible than the ANN approach (Russel and Campbell, 1996). To the best knowledge of the author, there isn't any published work comparing the input–output mapping capability of Mamdani and Sugeno fuzzy genetic techniques in ET_0 modeling.

The main aim of the present study is to examine the applicability of two different fuzzy genetic (FG) approaches in modeling of ET_0 obtained using the standard FAO-56 Penman-Monteith (FAO-56 PM) equation. The performance of the FG models is also compared with those of the ANN and recently proposed Valiantzas's equation and following empirical models: Hargreaves–Samani and Priestley–Taylor methods.

2. Methodology

2.1. Fuzzy logic

Fuzzy logic, first introduced by Zadeh (1965), is used different scientific researches. The fuzzy concepts and operational algorithms are given in many textbooks (Kosko, 1993; Ross, 1995).

Fuzzy logic makes possible for something to be partly this and partly that, rather than having to be either all this or all that. The level of "belongingness" to a set or category can be numerically described by a membership degree between 0 and 1.0. There are different types of fuzzy membership functions (triangular, Gaussian, etc.), but Gaussian functions are generally preferred (Russel and Campbell, 1996).

Sets of input and output data are provided to the fuzzy system, commonly known as fuzzy inference system (FIS), in the fuzzy inference method. FIS, shown in Fig. 1, is a rule-based system and consists of three conceptual components: (1) a rule base comprising fuzzy IF-THEN rules; (2) a database composed of membership functions used in fuzzy rules; (3) an inference mechanism that combines these rules to relate a set of outputs to a set of inputs and to derive a reasonable output. In the fuzzification, input and/or output data are partitioned into subsets defined by linguistic terms (e.g., small, medium, big) and membership degrees are determined. In the defuzzification, a crisp numerical value is calculated from the fuzzy outputs derived from the inference mechanism (Nayak et al., 2005). Fuzzy rule base composed of IF-THEN rules. The part between IF and THEN is called antecedent, while the consequent part exists after THEN.

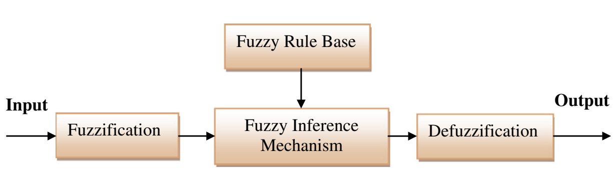

Fig. 1. A fuzzy inference system.

Let assume that the input and output variables are divided into a number of subsets with Gaussian fuzzy membership functions. If there are two input variables comprising three membership functions in the antecedent part, there should be 3^2 fuzzy rules in the rule base. If the subsets' number increases, better accuracy may be obtained. In this case, however, the rule base gets larger, which is more difficult to construct (Şen, 1998). In the case of Mamdani fuzzy system, assume that we have two inputs with two fuzzy subsets or membership functions labeled as "low" and "high" and one output with three fuzzy subsets labeled as "low", "medium" and "high" then there should be four rules as follows:

R_1 : IF x_1 is low and x_2 is low THEN y_1 is low

R_2 : IF x_1 is low and x_2 is high THEN y_2 is medium

R_3 : IF x_1 is high and x_2 is low THEN y_3 is medium

R_4 : IF x_1 is high and x_2 is high THEN y_4 is high

where x_1, x_2 and y are input1, input2 and output variables, respectively.

In the Sugeno fuzzy system, the consequent part of the fuzzy IF-THEN rules is different from the Mamdani fuzzy system. In the case of Sugeno fuzzy system, the rule base can be shown as:

R_1 : IF x_1 is low and x_2 is low THEN y_1

R_2 : IF x_1 is low and x_2 is high THEN $y2$

R_3 : IF x_1 is high and x_2 is low THEN y_3

R_4 : IF x_1 is high and x_2 is high THEN y_4

where y_1, y_2, y_3 and y_4 are linear equations.

In the Mamdani and Sugeno fuzzy methods, membership degrees, w_n, for x_1 and x_2 are computed to be assigned to the corresponding output y_n for each rule triggered. Hence a single weighted output, y, is obtained by weighting average of the outputs from four rules as:

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

Thus, the output values, y, can be computed from Eq. (1) for any combination of input variable fuzzy subsets after setting up the rule base (Şen, 1998).

In the present study, the optimal parameters (e.g. membership functions) of the fuzzy genetic models were determined using genetic algorithms (GA). The flowchart of the fuzzy genetic model is illustrated in Fig. 2. GA optimization is done by minimizing the error (objective function) between model results and observed values. In this study, mean square error used as objective function in GA can be expressed as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(yi_{observed} - yi_{model})^2 \tag{2}$$

where N denotes the number of training data. Here, the objective function (Eq. (2)) was minimized by tuning the membership function parameters of the input and outputs. Although the optimization of the membership functions is a complex problem for the supervised learning scheme, GA having a non-supervised learning scheme can be successfully applied to solve this problem (Goldberg,

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