NEURO-FUZZY SYSTEMS TO ESTIMATE REFERENCE EVAPOTRANSPIRATION.

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Abstract

This paper deals with an application of two Neuro-Fuzzy (ANFIS) systems for modeling the Evapotranspiration of a catchment located in Algeria. The two neuro-fuzzy systems are: (1) Fuzzy c-means clustering (FCM) based fuzzy inference system, named F-ANFIS, and (2) subtractive clustering based fuzzy inference system, named S-ANFIS. Various daily climatic data, that is, solar durationtion, air temperature, relative humidity and wind speed from Dar El Beida station, in Algiers, Algeria, are used as inputs to the FIS models so as to estimate ET0 obtained using the FAO-56 Penman–Monteith equation. Based on the comparisons, it is found that the S-ANFIS model yields plausible accuracy with fewer amounts of computations as compared to the G-ANFIS and MLP models in modeling the ET0 process.

Keywords: Modeling, FAO-56 PM Evapotranspiration, S-ANFIS, F-ANFIS, MLR, Algeria.

1. INTRODUCTION

Evapotranspiration is a significant component of the hydrological cycle, the combination of water loss from the soil surface by evaporation and that from crops by transpiration is referred to as evapotranspiration (ET_0) [1]. Routine and rapid estimation of ET (evapotranspiration) at regional scale is of great significance for agricultural, hydrological and climatic studies. A large number of empirical or semi-empirical equations have been developed for assessing ET from meteorological data. The FAO-56 PM is a physically based method, Comparative studies strongly suggest that the PM formula is preferred to other empirical models [2], but the use of The FAO-56 PM, which requires data for large number of climatic parameters. However, records for such weather variables are often incomplete or not always available for many locations and it is the short comings of the FAO-56 PM model [3]. In this context, the potential of two different adaptive network-based fuzzy inference systems (ANFIS) (i) Fuzzy c-means clustering (FCM) based fuzzy inference system, named F-ANFIS, and (ii) subtractive clustering based fuzzy inference system, named S-ANFIS in modeling of reference evapotranspiration (ET_0) are investigated in this paper. Various daily climatic data, that is, temperature (T), relative humidity (RH), wind speed (U) and the insolation duration (ID) from Dar El Beida, in Algiers, Algeria, are used as inputs to the FIS models so as to estimate ET_0 obtained using the FAO-56 Penman–Monteith equation.

2. Adaptive network-based fuzzy inference system (ANFIS)

The Neuro-fuzzy systems are fuzzy systems formed by a learning algorithm inspired by the theory of neural networks. The learning technique operates according to local information and a unique production of local changes in the original fuzzy system. So the interest is to establish a predictive system based on the integration of neural networks and fuzzy inference systems (FIS) because of their complementarity. FIS fit linguistic rules of the type (IF-THEN) translate knowledge on the dynamics system [4]. ANFIS is a fuzzy inference (FIS) 'Sugeno' type supervised learning 'Takagi', implemented in the framework of adaptive neural networks, the first introduction of this system was by Jang [5, 6].

3. Data clustering overview

As mentioned earlier, data clustering is concerned with the partitioning of a data set into several groups such that the similarity within a group is larger than that among groups.

3.1. Subtractive clustering

The idea is to find regions in the feature space with high densities of data points. The point with the highest number of neighbours is selected as center of the cluster. The data points within a prespecified fuzzy radius are then removed, and the algorithm looks for a new point with the highest number of neighbours [7].

3.2. Fuzzy C-Means clustering

Bezdek [8] introduced Fuzzy C-Means clustering method in1981, with the development of the fuzzy theory. This algorithm is used for analysis based on distance between various input data points.

4. Performance criteria

The statistical parameters used in this work are: The mean absolute relative error (MARE), the mean square error (MSE), the mean error (ME) and the Nash-Sutcliffe efficiency coefficient (EC) [9].

5. Case study

In the present study, the afore mentioned fuzzy inference systems are applied to the daily climatic data of Dar El Beida automated weather Station (36°43 N; 03°15 E) in the north-center of (Algiers) Algerian County (Fig. 3). Dar El Beida weather station is located 24 m above sea level. The climate in Algiers is classified as a Mediterranean Sea climate.

6. Results and discussions

The S_ANFIS, F_ANFIS and MLR approaches proposed in this paper, the results obtained are presented in Table (1). The three models are evaluated based on the indices described. The NASH criterion (EC) provides overall assessment of the quality of estimation. Models with NASH values close to 0.9 are generally a good quality, while models with NASH values close to 1 are deemed to produce near perfect estimation. The NASH values for the S_ANFIS and F_ANFIS models are all over 90 % which indicates that both types of models achieved a good quality results. the overall quality of estimation of the S_ANFIS model is better than the F_ANFIS and multiple linear regression (MLR) models, which indicate that the NASH values of the S-ANFIS model are higher than those of the F_ANFIS and MLR models. The estimation of total FAO-56 PM ET0 obtained from the estimated ET0 values is also considered for comparison due to its importance in irrigation systems (in determining the irrigation channel and/or tube, and total required irrigation water demand and its storage capacity etc.). The total estimated ET0 amounts in test period are given in Table (2). The S-ANFIS, F-ANFIS and MLR models whose input parameters are T, RH, U and ID, estimate the total FAO-56 PM ET0 value of 770.80 mm as 706.52 mm and 693.25 mm, with an underestimation of 8.34 %, 10.06 % and 10.69 %, respectively.

		S_ANFIS	**F_ANFIS**	**MLR**
Training	MARE %	16.27	16.98	29.54
	MSE mm^2	0.233	0.240	0.512
	ME mm	$-2 .10^{-9}$	$-5 .10^{-9}$	-0.0306
	EC %	94.73	94.58	88.43
Validation	MARE %	21.52	21.96	34.97
	MSE mm^2	0.415	0.417	0.626
	ME mm	0,12	0,11	0.01
	EC %	89.01	88.98	83.44
Testing	MARE %	16.43	17.50	29.30
	MSE mm^2	0.316	0.370	0.416
	ME mm	0,30	0,36	0.39
	EC %	94.01	93.00	92.12

Table (2). Parameters performance indicators of models S_ANFIS and F_ANFIS.

	S_ANFIS	**F_ANFIS**	**MLR**
ET_0 sim (mm)	706.52	693.25	688.37
ET_0 obs (mm)	770.80	770.80	770.80
ARE (%)	8.34	10.06	10.69

Table (3). Total estimated ET0 amounts in test period.

Conclusion

The results obtained in this study showed the effectiveness of clustering algorithms based fuzzy inference systems for to estimate of FAO-56 PM ET_0. The use of this hybrid method is an alternative fully justified for good water management. These encouraging results open a number of perspectives; it would be interesting to try hybrid models by coupling wavelet transform with neuro-fuzzy systems, and simultaneously optimizing by genetic algorithm: membership functions, scaling factors, and conclusions of fuzzy rules.

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