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EVAPOTRANSPIRATION CALCULATION FOR SOUTH CAROLINA, USA AND CREATION DIFFERENT ANFIS MODELS FOR ET ESTIMATION

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ABSTRACT. Evapotranspiration (ET) is a significant parameter of hydrologic cycle. Accurate calculation or estimation of ET is an important issue for water management engineers and irrigation engineers. However, it is not always so simple to calculate ET because of the direct and indirect effects. In this study, Daily ET is calculated by using Penman FAO 56 standard equation which is developed by U.S. Food and Agricultural Organization-FAO. 1416 daily meteorological data is taken from USGS (United States of Geological Survey) South Carolina observation station. Data set is divided as training and test set randomly and test set is existed from 233 daily data. Daily Air Temperature, Wind Speed, Relative Humidity and Solar Radiation meteorological variables are used in adaptive neuro fuzzy inference system (ANFIS) model creation process. Three different models are created and results are compared with each other.

Keywords: Evapotranspiration, Estimation, ANFIS, Empirical Equation

1. INTRODUCTION

Evapotranspiration (ET) is defined as the combination of transpiration and evaporation. It is one of the main part of hydrological cycle. Understanding hydrological cycle has critical importance for hydraulic and irrigation engineers especially in dry sessions. It is important to calculate or estimate evapotranspiration loss to make future projections based on water use planning. However, it is not so clear and easy to estimate ET directly because of the effects of direct and indirect variables. In the past decade, scientists used different methods to estimate ET such as calibration of empirical equations and soft computing techniques (Chen, 2012; Dogan, 2009; Kaya et al., 2017, 2016b, 2016a; Kisi, 2008; Kişi, 2006; Kumar et al., 2011; Mamak et al., 2017; Pal and Deswal, 2009; Ünès et al., 2017).

These soft computing techniques are also in use for further hydrological cases because of the their abilities on making estimations on nonlinear cases (Demirci et

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al., 2018a; Demirci et al., 2018b; Demirci and Baltacı, 2013; Demirci et al., 2015a; Kaya et al., 2018; Kim and Kim, 2008; Kutylowska, 2016; Talei et al., 2013; Taşar et al., 2017; Taşar et al., 2018; Üneş F., 2010a; Üneş F., 2010b; Unes and Demirci, 2015; Üneş et al., 2015a, 2015b; Üneş et al., 2018a; Üneş et al., 2018b; Üneş et al., 2018c; Yu et al., 2006; Üneş et al., 2013; Üneş et al., 2017; Demirci et al., 2015b; Demirci et al., 2016; Demirci et al., 2016).

In this paper, authors used Adaptive Neuro-Fuzzy Inference System (ANFIS) soft computing technique to estimate daily ET values of South Carolina, USA. Data set contains Wind Speed (U), Relative Humidity (RH), Air Temperature (T) and Solar Radiation (SR) meteorological records. Data set is belonging to United States of Geological Survey (USGS) and it has 1416 daily measurements. Data set is divided 1183 days as training and 233 days as test set randomly.

Three different ANFIS models are created to make estimations on ET and results are compared with each other by using correlation coefficient, Mean Square Error (MSE), and Mean Absolute Error statistics.

2. METHODOLOGY

2.1. Adaptive neuro-fuzzy inference system

Adaptive neuro-fuzzy inference system (ANFIS) uses the learning ability and parallel calculation of neural networks and benefits of fuzzy logic together so it is a hybrid artificial intelligence method.

ANFIS model is built up by Jang (Jang, 1993) and this model uses Sugeno&Kank type (Takagi and Sugeno, 1985) fuzzification system and hybrid learning algorithm. Adaptive networks occur from directly connected nodes and each node represents a transaction unit. The structure of an ANFIS model consists of 5 different layers. For further information about ANFIS readers are referred to (Jang, 1993).

ANFIS model 1 is created by using all four SR, T, RH, U parameters as input and ET is coded as output. ANFIS model 2 is creating by using SR, T, RH parameters as input and ET is coded as output. And for the ANFIS model number 3 only SR and T parameters are chosen as inputs and ET as output.

2.2. Penman FAO 56 Equation

SR, AT, RH, U daily meteorological parameters are needed to calculate daily ET using Penman FAO 56 equation. Equation is given as below (Jensen et al., 1990);

$$ET = \left(\frac{\Delta}{\Delta + \gamma} \right) R_n + \frac{\gamma}{\Delta + \gamma} [15.36(1 + 0.0062u_2)(e_w - e_a)] \frac{1}{\lambda} \quad (1)$$

where γ is the psychrometric constant,
 Δ is the slope of the vapour pressure curve,
 R_n is the net radiation,
 u_2 is the wind speed at 2 m height,
 e_w is the saturation vapour pressure,
 e_a is the actual vapour pressure and
 λ is the latent heat of vaporization in equation.

This equation is approved as standard equation by U.S. Food and Agricultural Organization-FAO. Therefore, it is used to calculate ET for mentioned area and ANFIS model's results are compared with these calculated values

3. RESULTS

Three different ANFIS model distribution graphs and scatter charts are given separately to see the performance of the models.

Fig. 1. Distribution graph of Model 1

Fig. 2. Scatter chart of Model 1

Distribution graph and scatter chart belonging to model 1 are given with Figure 1 and Figure 2 respectively. This model uses SR, T, RH, U parameters as input and as it is seen it gives super close results with Penman FAO 56 empirical equation.

Fig. 3. Distribution graph of Model 2

Fig. 4. Scatter chart of Model 2

Figure 3 is drawn to show the distribution of model 2 against Penman FAO 56 results and Figure 4 is the scatter chart of this model. It is possible to see the high relation between calculated and estimated results.

Model 3 is created by using air temperature and solar radiation meteorological variables as input. As it is seen from the figure 5 and figure 6 model results has less

relation with Penman FAO 56 equation then the other two models results. Statistics belonging to models' results are given with Table 1.

Fig. 5. Distribution graph of Model 3

Fig. 6. Scatter chart of Model 3

4. CONCLUSIONS

In this study, three different adaptive neuro fuzzy inference system models are generated by using SR, T, U, RH meteorological variables. Models performances' are compared with each other by using MSE, MAE and correlation coefficient statistics. ET calculations are done by using Penman FAO 56 standard equation but, this equation needs all four meteorological daily parameters for

calculation. However, it is not always possible to have all parameters recorded for a study area. Therefore, some other methods must be tried to estimate ET accurately as much as possible. In this study authors focused on using ANFIS on ET estimation for mentioned area.

Table 1. Comparison Statistics

ANFIS Model No	Parameters Used	Correlation Coefficient	MSE	MAE
1	T,SR,RH,U	0.993	0.023	0.101
2	T, SR, RH	0.909	0.251	0.391
3	T,SR	0.791	0.551	0.576

Model 1 estimation results are super close to Penman FAO 56 formula as it is expected. Model 2 performance shows that it gives quite close results to Model 1 performance and Penman FAO 56 equation even it is generated without wind speed parameter. Also, it is understood that, if only SR and T meteorological parameters are recorded for a studied area, results are still acceptable according to the Model 3 performance statistics.

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