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-RESEARCH ARTICLE-

The Evaluation and Comparison of Daily Reference Evapotranspiration with ANN and Empirical Methods

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Abstract

Evapotranspiration is an important parameter in hydrological and meteorological studies, and accurate estimation of evaporation is important for various purposes such as the development and management of water resources. In this study, daily reference evapotranspiration (ET_0) is calculated by using Penman-Monteith equation, which is accepted as standard equation by FAO (Food and Agriculture Organization). ET0 is tried to be estimated by using Hargreaves-Samani and Turc traditional equations and results are compared with Artificial Neural Network (ANN) model performance. A station which is stated near to the Hartwell Lake (South Carolina, USA) was chosen as the study area. Average daily air temperature (T), highest (T_{max}) and lowest daily air temperatures (T_{min}), wind speed (U), solar radiation (SR) and relative humidity (RH) were used for daily average evapotranspiration estimation. Feed forward-back-propagation ANN method is used for model creation. Comparison between empirical equations and ANN model shows that ANN model performance for daily ET0 estimation is better than others.

Keywords:
Evapotranspiration, Penman-Monteith equation, Hargreaves-Samani equation, Turc equation, Artificial Neural Network

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Introduction

Evapotranspiration is defined as the return of liquid or solid water as gaseous to the atmosphere by the effect of meteorological factors. The majority of the rain falling on the earth returns to the atmosphere by evaporation and transpiration before direct runoff. Determination of these losses is of great importance especially in the dry season. ET0 is an important component of the hydrological cycle and knowledge of water losses due to ET0 under the hydrological cycle is an important consideration in terms of water management and planning. Accurate estimation of ET0 is required for good planning and management of water resources. It is also important to determine the ET0 in many hydrological problems such as water budget and irrigation. Direct or indirect methods may be used to determine ET0 on free water surfaces. As the direct method, the most widely used method in the world is the evaporation pan. Indirect methods, in terms of complexity and data requirements, are temperature-based formulas (Thornthwaite, 1948); radiation-based approaches (Turc, 1961); formulas based on humidity (Romanenko, 1961); formulas that combine temperature, humidity and wind speed (Penman, 1948). These and similar methods have been used and estimated by many researchers for ET0 estimation (Gümüş,V., et. all; Warnaka and Pochop, 1988; Choudhury, 1999; Abtew, 1996; McKenzie and Craig, 2001). Generally, these formulas also contradict each other and therefore it is very difficult to determine the best solution. The complexity, and uncertainty of the problem do not allow the casual modeling of classical methods. There are other methods that can be used more appropriately in these situations.

In recent years, many researchers have used artificial intelligence methods as an alternative to classical methods in hydrology and water resources studies. (Üneş et al., 2013, 2015, 2017; Demirci et al., 2015,2016; Taşar et al., 2017) Nowadays, artificial neural networks (ANN) are being used widely because they can easily resolve complex and difficult relationships. ANN is applied to many fields of science. This approach is also used in hydraulics and hydrology as other fields of science to achieve good results. In the past years, researchers have estimated the use of artificial intelligence methods in predicting hydrological events such as evaporation or ET0 (Aytek et al., 2008; Fenga et al., 2016; Partal 2016). Doğan et al. (2007) was estimated the daily evaporation amount for Sapanca Lake by using feed-forward back-propagation (FFBP) and radial-based artificial neural network (RBNN) model and compared with the Penman-Monteith (PM) model.

Kaya et al., (2016), studied to estimate the amount of evaporation. They used M5T and Turc methods to predict. They observed that the M5T method, which is one of the data mining methods, gave better estimation results than the Turc empirical method. Taşar et al. (2018) selected the study area as Massachusett, USA (Cambridge Reservoir and Basin) to determine the average daily ET0, by using wind speed (U), duration of sunshine (DS), relative humidity (RH) and then they compared the results of traditional Hargreaves-Samani, Ritchie and Turc methods. When the empirical methods and ANN model results were compared, it was observed that ANN model gave better results than empirical methods.

The aim of this study is to investigate the feasibility and validity of artificial neural network (ANN) method and classical methods for a different study area. Daily data were taken from the meteorological station near the Hartwell lake in the Anderson region, South Carolina, USA.

Materials and Methods

In this study, Hargreaves-Samani, Turc equations which are two of the empirical (classical) methods, and Artificial Neural Networks (ANN) method which is one of the artificial intelligence methods were used for prediction of daily ET0.

Hargreaves-Samani Equation

Necessary parameters for calculation of daily ET0 with Hargreaves-Samani equation are daily maximum temperature (Tmax), daily minimum temperature (Tmin) and extraterrestrial solar radiation (Rs) (Hargreaves & Samani, 1985). The equation which is used for calculation is given below;

$$ET0=0.0135\times0.408\ Rs\ (T+17.8) \quad \textbf{(1)}$$

$$R_S=0.16 R_a.\sqrt{T_{max}+T_{min}}) \quad \textbf{(2)}$$

where, “T” represents daily mean temperature and “Rs” extraterrestrial solar radiation in Hargreaves-Samani equation.

Penman FAO Equation

SR, AT, RH, U daily meteorological parameters are needed to calculate daily ET0 using Penman FAO 56 equation. Equation is given as below (Jensen et al., 1990),

$$ET_0=\frac{0.408\,\Delta\,(Rn-G)+\gamma\frac{900}{T+273}.u_2\,(e_s-e_a)}{\Delta+\gamma(1+0.34u_2)} \quad \textbf{(3)}$$

where γ is the psychometric 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.

Turc Equation

In the Turc method, the amount of evaporation depends on the parameters such as air temperature, relative humidity and amount of sunbathing. The Turc equation is given below (Turc, 1961).

$$\text{If RH} > \%50\ ;\ ET0 = 0.0133\times\frac{Tm}{Tm+15}\times(SR+50) \quad \textbf{(4)}$$

$$\text{If RH} < \%50;\ ET0 = 0.0133\times\frac{Tm}{Tm+15}\times(SR+50)\times\left(1+\frac{(50-RH)}{70}\right) \quad \textbf{(5)}$$

Where,ET is the daily evapotranspiration (mm day-1), SR is the solar radiation (MJ m-2 day-1), Tm is the mean air temperature (^{0}C) and RH is the relative humidity (%).

Artificial neural networks

The concept of artificial neural networks first emerged with the idea of making computer simulations based on the working principle of the brain. According to Yurtoğlu (2005); ANN defines the relationship between input variables and target variables of previous examples by weight assignment method. In other words, they are trained. Once these relationships have been determined, the ANN can now run estimates with new data. The performance of a trained network is measured by the intended signal and error criterion. The output of the network is compared with the intended output to obtain a margin of error. An algorithm called Back Propagation is used to adjust the weights to reduce the margin of error. This process is repeated several times and the training of the network is completed. With this training process, it is tried to obtain the most suitable solution based on performance measurements.

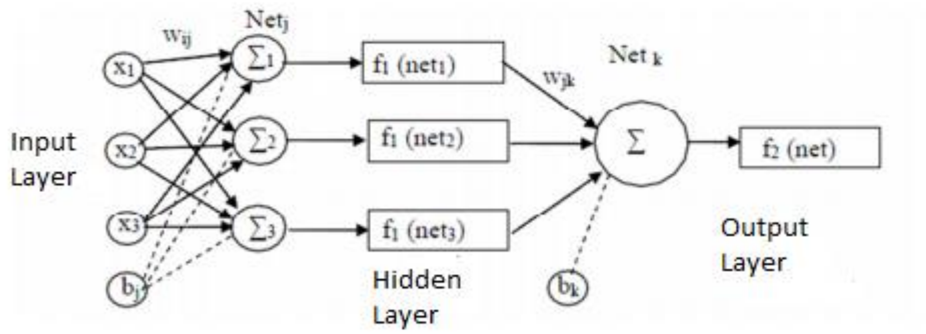

Figure 1. Artificial Neural Network Layers used in this study

ANN consists input layer, hidden layer and output layer as it is shown in Figure 1. W_{ij} and W_{jk} are weights of connections between layers.

Study Area

The station which is used in this study given in Figure 2, is located in South Carolina State in the southeastern part of the USA, where it is located in temperate subtropical climate zone and the summers are very hot and humid, while winters are mild and soft. The station is located on 34 ° 30'30 "latitude and 82 ° 51'19" longitude and is managed by the South Atlantic WSC Clemson Field Office. Data set which is taken from station contains 4 years daily records (2013-2017).

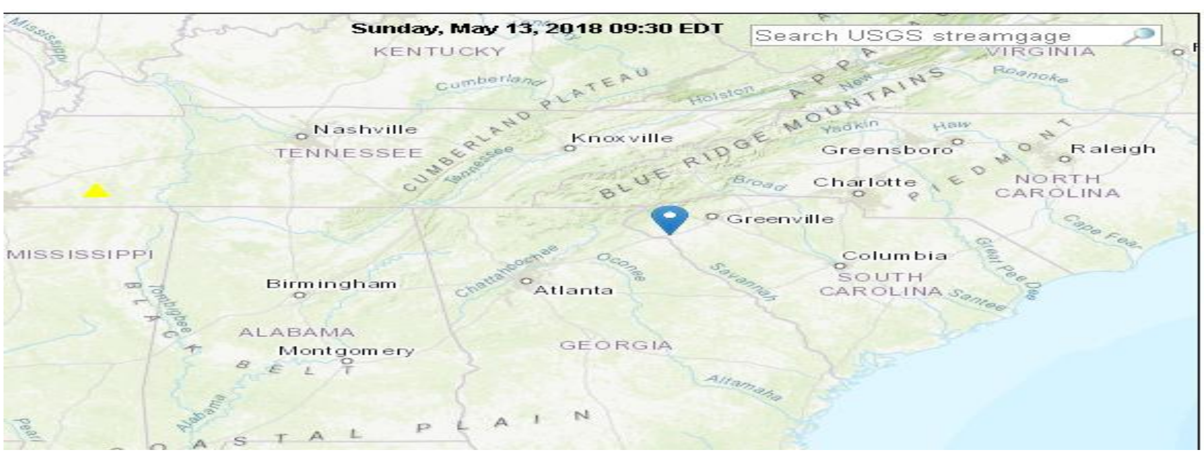

Figure 2. Location of station in South Carolina (USGS)

Results and Discussions

In this study, ET0 is estimated by using artificial neural networks (ANN), Hargreaves-Samani (HS) and Turc (T) equations. Obtained results are compared with each other. 1416 total daily meteorological data were used which include 2013-2017 time period. In the study, 80% of all data is reserved for training, 20% for testing. 1133 daily data was used for the training and 283 day measurement data were used for the testing. The data used was taken from the USGS. At first, ET0 values are calculated by using standard PM FAO 56 equation. Necessary parameters for this calculations are daily air temperature, daily maximum air temperature, daily minimum temperature, wind speed, relative humidity and sunshine duration. In the second part of the study ET is calculated by Hargreaves-Samani and Turc equations and ET estimations belonging to test set are done with ANN method.

Mean square error (MSE), mean absolute error (MAE) and correlation coefficient (R) statistics were used to determine the success of the models used to estimate the daily ET0 value.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|ET_{i_{observed}} - ET_{i_{estimate}}\right| \quad (6)$$

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(ET_{i_{observed}} - ET_{i_{estimate}}\right)^2} \quad (7)$$

where, N represents data numbers and ET_i daily evapotranspiration data.

All calculated MSE, MAE and correlation coefficient statistics for test set are given with Table 1.

Table 1. Test set statistics

	Hargreaves-Samani	Turc	ANN
INPUTS	T,SR	T,SR, RH	T, SR, RH,U
MSE	1.524	1.077	**0.119**
MAE	1.061	0.878	**0.290**
R	0.686	0.613	**0.976**

Distribution and scatter graphs of Hargreaves-Samani equation are shown in Figure 3 and 4 below, respectively.

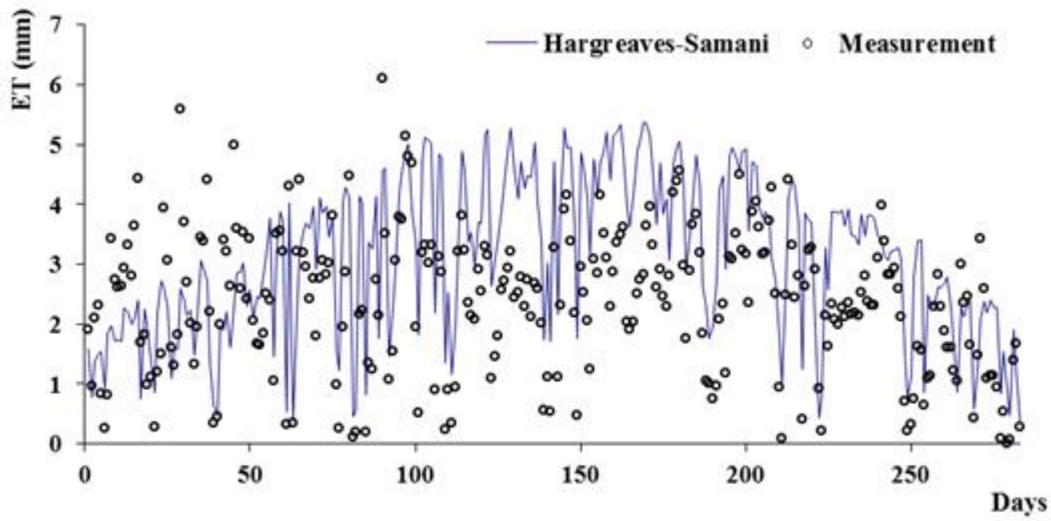

Figure 3. Hargreaves-Samani equation distrubition graph for test set

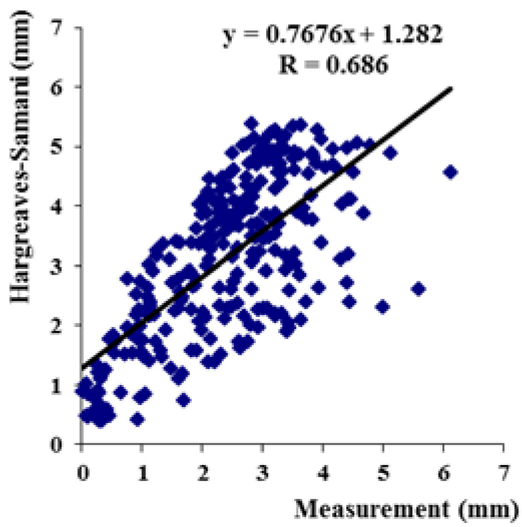

Figure 4. Hargreaves-Samani equation scatter chart for test set

Figure 3 and Figure 4 show the performance of Hargreaves-Samani equation against PM FAO 56 equation. Correlation coefficient for Hargreaves-Samani is calculated as 0.686. Distribution and scatter graphs of Turc equation are shown in Figure 5 and 6 below, respectively.

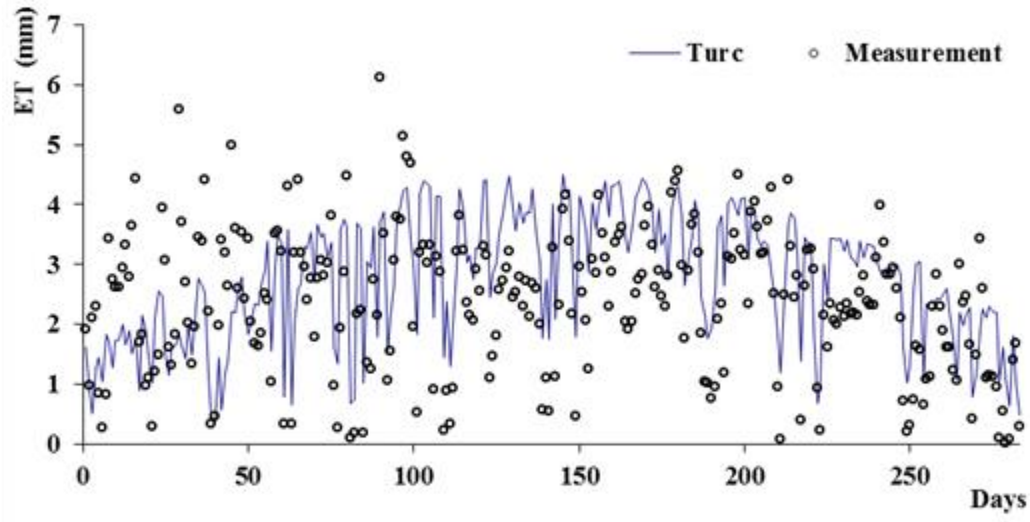

Figure 5. Turc equation distribution graph for test set

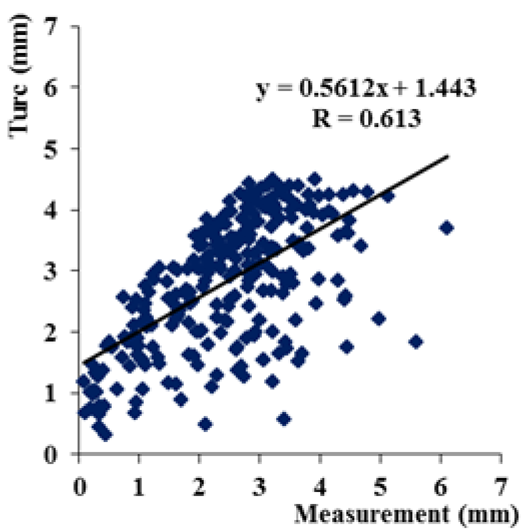

Figure 6. Turc equation scatter chart for test set

Figure 5 and Figure 6 show the performance of Turc equation against PM FAO 56 equation. Correlation coefficient for Turc is calculated as 0.613. Turc and Hargreaves-Samani equation gave close results. Distribution and scatter graphs of ANN method are shown in Figure 7 and 8 below, respectively.

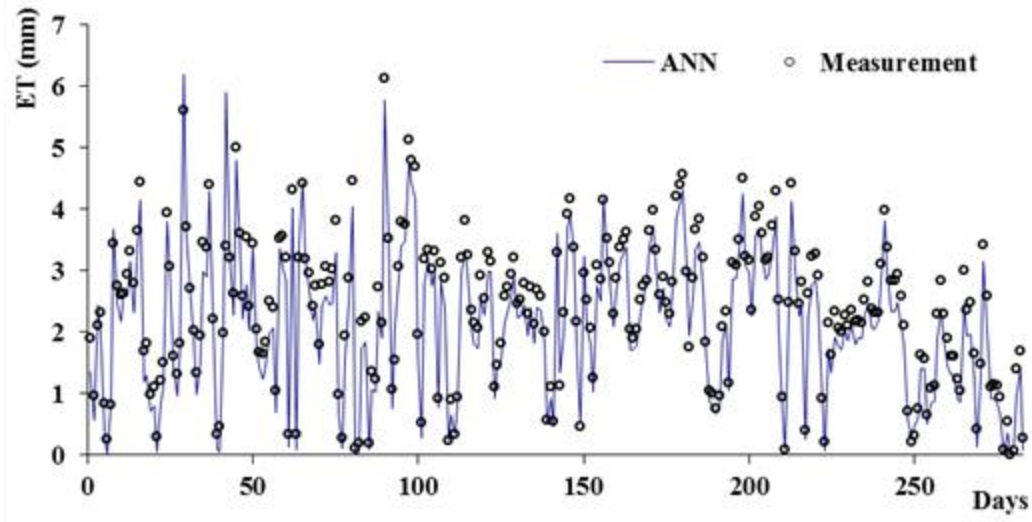

Figure 7. ANN method distribution graph for test set

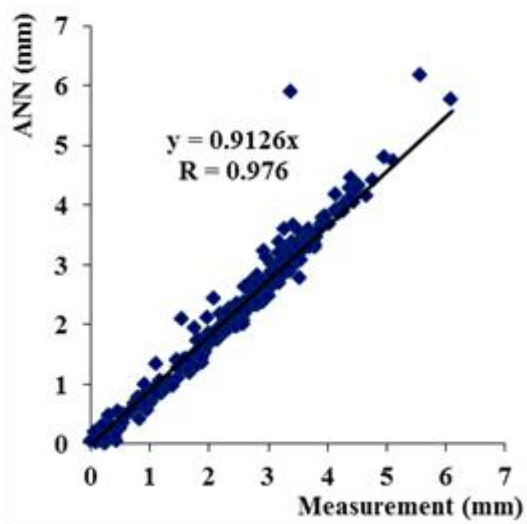

Figure 8. ANN method scatter chart for test set

Figure 7 and Figure 8 show the performance of ANN method. Correlation coefficient for ANN is calculated as 0.976 which is the highest correlation value of this study. The purpose of these graphs is to determine how the ET0 values calculated by conventional methods and ANN are different from actual ET0 observations. It is possible to see high performance of ANN method against conventional methods from drawn graphs and charts.

As a result, it is seen that estimation of daily ET0 by using daily meteorological parameters can be done by empirical equations and ANN method both. But, as the results show that empirical equations errors values are higher than ANN method and also correlation between ANN method and PM FAO 56 equation is much more acceptable for the study area. Authors suggest that similar solutions must be done with ANN by using less input meteorological parameters to understand ANN performance better.

Conclusion

In this paper, ET0 is tried to be estimated by using Hargreaves-Samani and Turc traditional equations and results are compared with Artificial Neural Network (ANN) model performance. A station which is stated near to the Hartwell Lake (South Carolina, USA) was chosen as the study area. Applicability of ANN models was investigated using meteorological variables such as mean daily air temperature, wind speed, solar radiation and, relative humidity for ET estimation.

As a result of the present study, ANN methods give correct results in solving the problem. This method could provide low mean square error (MSE) and mean absolute error (MAE) values for estimating the amount of daily ET0. Hargreaves-Samani, and Turc methods have the worst results in all criteria. Nevertheless, ANN's performance has been better than empirical methods in ET predictions.

The presented work has shown that daily evaporation modeling is determined with the ANN method. As an alternative to the empirical methods of Hargreaves-Samani, and Turc, the ANN model of artificial intelligence methods can be presented in estimating the amount of daily ET0.

In estimating the amount of evapotranspiration, ANN is more advantageous than the traditional methods because of the ANN structure’s nonlinear dynamics to the solution problem.

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References

Abtew, W. (1996). Evapotranspiration measurement and modeling for three wetland systems in South Florida. *Water Resour. Bull*. 32, 465–473.

Aytek, A., Güven, A.,Yüce, M.İ., & Aksoy, H. (2008). An explicit neural network formulation for evapotranspiration. *Hydrological Sciences Journal*, 53, 4, 893-904, DOI: 10.1623/ hysj.53.4.893.

Choudhury, B.J. (1999). Evaluation of an empirical equation for annual evaporation using field observations and results from a biophysical model. *Journal ofHydrology*, 216 (12), 99–110. doi:10.1016/S0022-1694(98)00293-5.

Demirci, M., & Baltaci, A. (2013). Prediction of suspended sediment in river using fuzzy logic and multilinear regression approaches. *Neural Computing Applications*, 23, 145-151.

Demirci, M., Üneş, F., & Aköz, M.S. (2015). Prediction of cross-shore sandbar volumes using neural network approach. *Journal of Marine Science and Technology* 20(1), 171-179.

Demirci, M., Unes, F., & Akoz, M. S. (2016). Determination of nearshore sandbar crest depth using neural network approach. *International Journal of Advanced Engineering Research and Science*, 3(12).

Doğan, E., Işık, S., & Sandalci, M. (2007). Estimation of daily evaporation using artificial neural networks. *Teknik Dergi*, *18*(2), 4119-4131.

Fenga, Y., Cuib, N., Zhaob, L., Hud, X., & Gonga, D. (2016). Comparison of ELM, GANN, WNN and empirical models for estimating reference evapotranspiration in humid region of

Southwest China. *Journal of Hydrology*, 536, 376–383.

Gümüş,V., Yenigün, K., Toprak, F., & Baçi, N. (2018). Şanlıurfa ve Diyarbakır istasyonlarında sıcaklık tabanlı buharlaşma tahmininde YSA, ANFIS ve GEP yöntemlerinin karşılaştırılması, *DÜMF Mühendislik Dergisi* 9, 553 – 562 (in Turkish).

Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. *Appl. Engng. Agric*. 1(2), 96–99.

Jensen, M. E., Burman, R. D., & Allen, R. G. (1990). Evapotranspiration and Irrigation Water Requirements. *ASCE Manuals and Reports on Engineering Practices* no. 70., ASCE, New York, USA.

Kaya, Y. Z., Mamak, M., & Unes, F. (2016). Evapotranspiration Prediction Using M5T Data Mining Method. *International Journal of Advanced Engineering Research and Science (IJAERS)*, 3(12), 225-229.

McKenzie RS., & Craig AR. (2001). Evaluation of river losses from the Orange River using hydraulic modelling. *J Hydrol*. 241, (12), 62–9.

Partal, T. (2016). Comparison of wavelet based hybrid models for daily evapotranspiration estimation using meteorological data. *KSCE Journal of Civil Engineering*, 20(5), 2050–2058

Penman, H.L. (1948). Natural evaporation from open water, bare soil and grass. *Proc R Soc Lond* 193:120–146

Romanenko, V.A. (1961). Computation of the Autumn Soil Moisture Using a Universal Relationship for a Large Area. *Ukrainian Hydrometeorological Research Institute*, Kiev, No. 3.

Taşar, B., Kaya, Y. Z., Varçin, H., Üneş, F., & Demirci, M. (2017). Forecasting of suspended sediment in rivers using artificial neural networks approach. *International Journal of Advanced Engineering Research and Science*, 4(12).

Taşar, B., Üneş, F., Demirci, M., & Kaya, Y. Z. Yapay sinir ağları yöntemi kullanılarak buharlaşma miktarı tahmini. *DÜMF Mühendislik Dergisi*, *9*(1), 543-551 (in Turkish).

Thornthwaite, C.W. (1948) An approach toward a rational classification of climate. *Geograph. Rev.*, 38, 55-94

Turc, L. (1961). Evaluation des besoins en eau d'irrigation, évapotranspiration potentielle, formulation simplifié et mise à jour. *Ann. Agronomiques* 12, 13–49.

USGS.gov | Science for a changing world [WWW Document], n.d. URL https://www.usgs.gov/

Warnaka & Pochop. (1988). Analysis of Equations for Free Water Evaporation Estimates. *Water Resources Research* 24(7), 979-984. DOI: 10.1029/WR024i007p00979

Yurtoğlu, (2005). Yapay sinir ağlari metodolojisi ile öngörü modellemesi: bazı makroekonomik değişkenler için Türkiye örneği, *DPT* (in Turkish).

Ünes, F., Yildirim, S., Cigizoglu, H.K., & Coskun, H. (2013). Estimation of dam reservoir volume fluctuations using artificial neural network and support vector regression. *Journal of Engineering Research*, 1(3), 53-74.

Üneş, F., Demirci, M., & Kişi, Ö. (2015). Prediction of millers ferry dam reservoir level in usa using artificial neural network. *Periodica Polytechnica Civil Engineering*, 59(3), 309–318.

Ünes, F., Gumuscan, F.G., &Demirci, M. (2017). Prediction of Dam Reservoir Volume Fluctuations Using Adaptive Neuro Fuzzy Approach. *EJENS*, 2 (1), 144-148.