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ESTIMATION OF REFERENCE EVAPOTRANSPIRATION USING SUPPORT VECTOR MACHINES: A CASE STUDY OF ADANA, TURKEY

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ABSTRACT. Evapotranspiration is an important parameter in hydrological and meteorological studies. Evapotranspiration forecasting plays an important role in irrigation management and hydraulic designs, especially during dry periods. In this study, average temperature (T), relative humidity (RH), wind speed (U), solar radiation (SR) parameters were used to estimate the daily evapotranspiration amount. Daily evapotranspiration estimation (ET0) was made according to the Penman-Monteith method recommended by FAO (Food and Agriculture Organization) as a standard method. The Penman-Monteith method was considered as the reference equation. Support Vector Machines (SVM) methods with four different input combinations were used to estimate the daily evapotranspiration of Adana province. SVM models were compared with each other and the reference equations' results. According to the results obtained from SVM models, SVM3 model giave slightly better results according to the higher determination coefficient and lowest error data.

Keywords (4-6): Evapotranspiration, Prediction, Penman-Monteith FAO, Support Vector Machines,

1. INTRODUCTION

Accurate estimation of evapotranspiration is important for various purposes such as the development, control, and management of water resources. However, the evapotranspiration process is a nonlinear physical process involving many variables in nature. Many researchers have emphasized the need for accurate evaporation estimates in hydrological modeling studies. In recent years, researchers have used some artificial intelligence techniques to deal with nonlinear hydrological problems such as evapotranspiration. Chen (2011), used support vector machines to estimate

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daily reference evapotranspiration and compared it with the Penman-Monteith equation and artificial neural network models. Kaya et al. (2016), estimated evapotranspiration using the M5T method and the Turc empirical formula. In their study, they used meteorological data readings of 1543 days of solar radiation, air temperature, relative humidity, and wind speed. They stated that the methods and empirical equations developed for ET estimation may have variable outputs with different characteristics of hydrological regions. Kaya et al. (2021), estimated the daily evapotranspiration in Košice City (Slovakia) using several soft computing techniques. Tasar et al. (2018), used Artificial Neural Networks (ANN) method to estimate the amount of evaporation, using the data from the Cambridge reservoir and basin of Massachusetts, U.S.A. Shiri and Kisi (2011) used the fuzzy logic (BM) method for short-term operational water level estimation. Unes et al. (2019), estimated daily dam reservoir level changes using artificial intelligence methods. Demirci et al. (2018), estimated dam reservoir volume using the fuzzy logic method. Arslan et al. (2020), Fuzzy Logic (FL), and Multiple Linear Regression methods were used to estimate the daily water level of the Keban Dam Lake and the results were evaluated with real observation data. Traore et al. (2010), used an artificial neural network to model the reference ET in the Sudano-Sahelian region. In addition, many researchers have used different artificial intelligence techniques to solve hydrological problems ((Gavili et al. (2018); Gocić et al. (2015); Bakır et al. (2019); MirásAvalos et al. (2019); Yihdego and Webb (2018))

The aim of this study is to investigate the applicability and validity of Support Vector Machines (SVM) is one of the soft computing methods in the estimating evapotranspiration. In the SVM model estimation, four different models were created by applying different input combinations. And the model results were compared with each other. In SVM 1 model, the daily average temperature (T), relative humidity (U), solar radiation (SR), in SVM 2 model, the daily average temperature (T), relative humidity (RH), wind speed (U), in SVM 3 model, the daily average temperature (T), wind speed (U), solar radiation (SR), SVM 4 model, relative humidity (RH), wind speed (U), solar radiation (SR) were used as inputs. The Penman-Monteith FAO 56 equation was accepted as the reference equation, and SVM results were compared with PM FAO 56

2. DATA AND METHODS

2.1. Data used

In this study, 3 years (2016-2019) meteorological data of the Adana station, which is 23 m above sea level, located south of Turkey and which is managed by the Turkish Meteorology Directorate, is used in this study. 75% of the 910 data obtained from the station was used for training and the remaining 25% was used for testing. Adana has a typical Mediterranean climate. Winters are warm and rainy, and summers are hot and dry. Most of the region of Adana is a wide and flat land that is very suitable for agriculture. Evapotranspiration in this region; It is important to form a guide in the management and planning of water resources, and to control, determine and operate the water level of water resources. In addition, since it is an arid region, estimation of evapotranspiration plays an important role in irrigation management and hydraulic designs. The daily average temperature (T), relative humidity (RH), wind speed (U), and solar radiation (SR) of this station were arranged as input parameters with different combinations to see the effect of each parameter on evapotranspiration of Adana region.

Fig. 1. Location of Study Area

2.2. Methods

In this study, Support Vector Machine (SVM) methods were used to estimate the evapotranspiration of the Adana region. In the estimation, the Penman-Monteith FAO 56 equation was accepted as the reference equation.

2.2.1. Penman-Monteith FAO Equation

Jensen, et al. (1990), the FAO Penman-Monteith equation is given with equation (1). The Penman-Monteith FAO 56 equation was accepted as the reference equation

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

In this equation;

ET0; Reference evapotranspiration (mm day^{-1}), Rn; Net radiation on the plant surface (MJ $m^{-2}day^{-1}$, G; Soil heat flux density (MJ $m^{-2}day^{-1}$), T; Average daily air temperature at 2m altitude [°C], u_2; Wind speed at 2m height [m s-1], e_s; Saturated vapor pressure [kPa], ea; Current vapor pressure [kPa], es – ea; Saturated vapor pressure gap [kPa], Δ; It represents the slope of the vapor pressure curve [kPa °C-1], γ : the psychrometric constant [kPa °C-1].

2.2.2. Support Vector Machine (SVM) Method

SVM is a method of learning found by Cortes and Vapnik (1995) for solving classification and regression problems. It is likely that classification of variables on a plane by drawing a boundary between them. The boundary which is drawn between variables must be as far as possible to each variable. SVM provides to define how to draw this boundary between variables group. In SVM, the Kernel method greatly increases machine learning in nonlinear data. The process of an SVM estimator (y) can be expressed in equation (2).

$$y = (K_{xi} \cdot W_{jk}) + b \tag{2}$$

where the Kernel function is K_{xi}, b is bias term of SVM network and W_{jk} is called as the weight vector. K_x and W show Lagrange multipliers. K_{xi} is a nonlinear function that maps the input vectors into a high-dimensional feature space. The inner product of the inputs is calculated by using kernel functions. Lagrange multipliers show the weights The non-linear Poly Kernel functions are used in this study. Details about SVM can be found in Vapnik (1999) and Haykin (1999).

For each model root of mean error squares (RMSE), mean absolute error (MAE), and determination coefficient (R^2) between observed values were calculated. The results are also used to compare the performances of model prediction and observation data.

In order to determine the success of the models used to estimate the evapotranspiration amount, mean absolute error (MAE), the root mean square error (RMSE), and correlation coefficient (R^2) given in equations (3) and (4), respectively, were used. . From here, n is the number of data and ET is the evapotranspiration amount value;

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|ET_{meauserement} - ET_{predicted}\right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(ET_{measurement} - ET_{predicted}\right)^2} \tag{4}$$

3. RESULTS AND DISCUSSIONS

In this study, the daily evapotranspiration was estimated by using Support Vector Machines (SVM) and the performances of the obtained results were compared. 3 years (2016-2019) meteorological data of 17351-Adana station, which is managed by the Turkish Meteorology Directorate, were used. 75% of the 910 data obtained from the station was used for training purposes and the remaining 25% was used for testing. 685 days of data were used for training and 225 days of measurement data for testing. Obtained test results were compared with actual evaporation results. The results according to these comparisons are given in Table 1.

In this study, the average daily evapotranspiration amount, temperature, wind speed, solar radiation, and relative humidity data obtained and edited from DSI in all model applications were used to estimate the daily evapotranspiration amount. The Penman-Monteith FAO 56 equation was accepted as the reference equation, and SVM model results were compared with PM FAO 56. In the SVM model estimation, 4 different models were created by trying different input combinations.

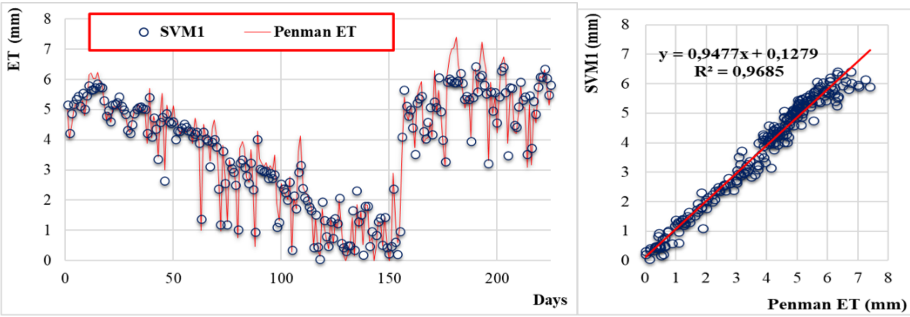

Fig. 2. Penman ET and SVM1 a) distribution graph b) sctatter graph daily evapotranspiration estimate data

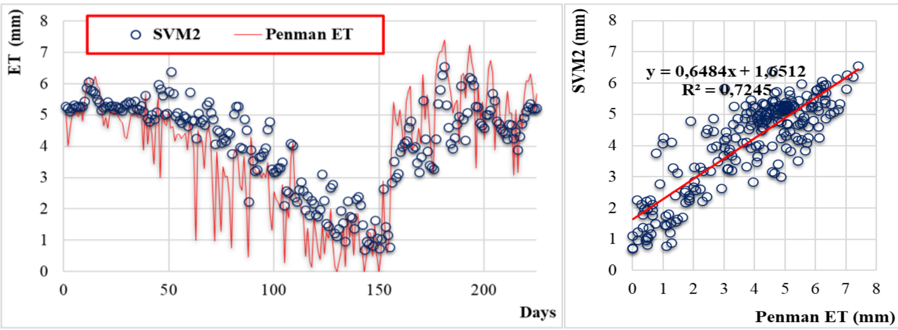

Fig. 3. Penman ET and SVM2 a) distribution graph b) scatter graph daily evapotranspiration estimate data

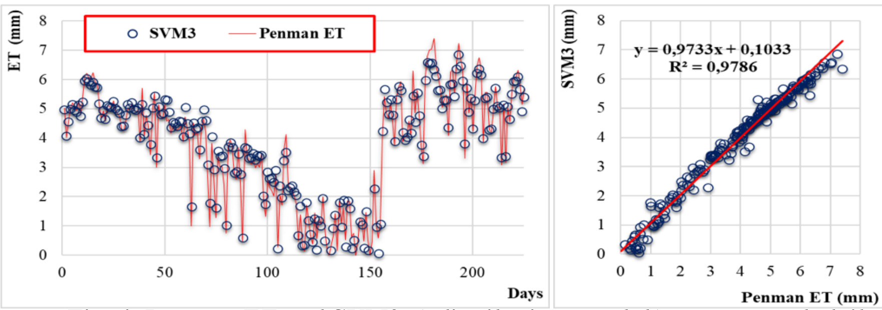

Fig. 4. Penman ET and SVM3 a) distribution graph b) scatter graph daily evapotranspiration estimate data

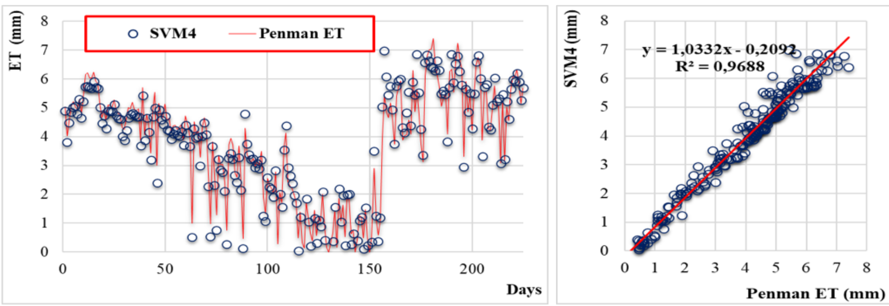

Fig. 5. Penman ET and SVM4 a) distribution graph b) scatter graph daily evapotranspiration estimate data

Table 1. Performance of Models

MODELS	***SVM1***	***SVM2***	***SVM3***	***SVM4***
INPUTS	T,U,SR	T,U,RH	T,SR,RH	U,SR,RH
MAE (mm)	0,275	0,910	0,230	0,299
RMSE (mm)	0,378	1,081	0,293	0,401
$\mathbf{R^2}$	0,968	0,724	0,979	0,969

In SVM 1 model, the daily average temperature (T), relative humidity (RH), solar radiation (SR), in SVM 2 model, the daily average temperature (T), relative humidity (RH), wind speed (U), in SVM 3 model, the daily average temperature (T), wind speed (U), solar radiation (SR), SVM 4 model, relative humidity (RH), wind speed (U), solar radiation (SR) were used as inputs. The distribution and scatter chart of the SVM1 model with PM FAO 56 equation is shown in Figure 2. As can be seen from Figure 2, when the SVM1 model is applied to the test data, the model results are close to the PM FAO 56 equation results and the determination coefficient is 0.968. The distribution and scatter graphs of the SVM2 model are shown in Figure 3. When Figure 3 is examined, it is seen that SVM2 model results are close to the PM FAO 56 equation results, and the determination coefficient is 0.724. Distributions and scatter graphs of the SVM3 model with PM FAO 56 equation are presented in Figure 4. It is seen in Figure 4 that, the SVM3 model results are also close to the PM FAO 56 equation results, and the determination coefficient is the highest as 0.979 in all models. In Figure 5, results of the SVM4 model with the PM FAO 56 equation results are seen. When Figure5 is examined, it is seen that the SVM4 model results are close to the PM FAO 56 equation results, and correlation coefficient is as 0.969. As can be also seen from Table 1, SVM3 model gave better results than the other SVM models according to the a little bit higher determination coefficient and lowest error data. (MAE: 0.230 mm. RMSE: 0.293, R^2:0,979)

4. **CONCLUSIONS**

In the study, the daily evapotranspiration amount was estimated by using the meteorological data from Adana station (2016-2019), which is managed by the Turkish Meteorology Directorate. Support Vector Machines (SVM) models with four different combinations were used to estimate the amount of evapotranspiration and the models. SVM model results were compared with the reference PM FAO 56 equation.

It has been observed that the SVM model results gave close results to each other in estimating the amount of evapotranspiration. When the graphs of the SVM models are examined, it is seen that the SVM3 model gives slightly better results according to the higher determination coefficient and lowest error data. (MAE: 0.230 mm. RMSE: 0.293, R^2: 0,979). The reason for this is that evapotranspiration, which is the dependent variable, has a good correlation between the independent variables (the daily average temperature, wind speed, solar radiation). It has been understood that the SVM method can be used in many studies as an alternative to classical methods for the science of hydrology. It is important to make the modeling for regions with different climatic conditions in order to generalize the modeling success.

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