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Estimating daily pan evaporation using data mining process

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Abstract. This study investigates the applicability of the data mining process in estimation of daily pan evaporation, a fundamental element in the hydrological cycle. Firstly, the models were developed using autoregressive modeling, frequently preferred in hydrological studies, for Lake Eğirdir in the southern part of Turkey, and the suitability of the AR(3) model was shown. Hence, the previous 1-, 2- and 3- day, daily pan evaporation values of Lake Eğirdir were used to develop the other DM models. The correlation coefficient and root mean square error criteria were used for evaluating the accuracy of the developed models. When the results of the developed models were compared to observed pan evaporation according to these criteria, it was determined that the AR(3) model is a little more appropriate in estimation of daily pan evaporation. Consequently, it was shown that DM models are useful, as they are based on only daily pan evaporation data and do not include meteorological parameters.

1. Introduction

Evaporation is the process by which water that has accumulated on land surfaces (including that held in surface depressions and water bodies, such as lakes and reservoirs) is converted into a vapor state and returned to the atmosphere. Evaporation occurs at the evaporating surface; contact between the water body and overlying air. At the evaporation surface, there is a continuous exchange of liquid water molecules into water vapor, and vice versa. Evaporation refers to the net rate of water transfer (loss) into a vapor state. Evaporation rate is a function of several meteorological and environmental factors. Those that are important, from an engineering standpoint, are net solar radiation, saturation vapor pressure, vapor pressure of the air, air and water surface temperatures, wind velocity, and atmospheric pressure. Unlike other phases of the hydrologic cycle, lake evaporation cannot be measured directly. Therefore, several approaches have been developed to calculate evaporation. These vary in nature and are based on a water budget, an energy budget, or mass-transfer techniques. Uncertainty in the applicability of various evaporation formulas has led to the indirect measurement of evaporation using evaporation pans. An evaporation pan is a device designed to measure evaporation by monitoring the loss of water in the pan during a given time period, usually one day. It provides a measurement of the integrated effect of net radiation, wind, temperature and humidity on evaporation from an open surface [1].

Many scientists have tried to estimate evaporation from climatic variables. Stewart and Rouse (1976) determined summertime evaporation from shallow lakes using the energy budget and equilibrium models. They showed that actual evaporation could be determined within 10% over periods of two weeks using these models [2]. de Bruin (1978) used the simplified model by combining Priestley-Taylor and Penman equations to estimate evaporation. He indicated that the model

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could produce good results for periods of 10 days or more [3]. Morton (1979) modified a model to estimate annual evaporation from lakes based on monthly observations of temperature, humidity and sunshine duration. The results of the model were compared with those of the water budget for lakes, and showed that there was good agreement between them [4]. Singh and Xu (1997a) evaluated and compared 13 evaporation equations that belonged to the category of the mass transfer method, and a generalized model form for that category was also developed [5]. Singh and Xu (1997b) further examined the sensitivity of mass transfer based evaporation equations to errors in daily and monthly input data [6]. Xu and Singh (2001) evaluated and generalized temperature based methods for evaporation calculations. Pan evaporation values have been widely used for estimating lake and reservoir evaporation [7-14].

Many researchers have also investigated the applicability of the time series analysis, firstly proposed by Box and Jenkins [15], to hydrology studies, such as rainfall [16], flow [17,18], wind speed [19,20], and radiation [21,22]. Kişi (2004) used Artificial Neural Networks (ANN) to predict monthly flow and compared the results with autoregressive models. He stated that ANN predictions, in general, are better than those found with AR(4) [23]. Yurekli and Özturk (2003) determined alternative autoregressive moving average process (ARMA) models using the graphs of autocorrelation (ACF) and partial autocorrelation functions (PACF). The plots of the ACF showed that ARMA (1,0) with a constant was the best model by considering Schwarz Bayesian Criterion (SBC) and error estimates [24]. Torres et al. (2005) used ARMA and persistence models to predict the hourly average wind speed up to 10 h in advance. They showed that the use of ARMA models significantly improved wind speed forecasts compared to those obtained with persistence models [25]. Wu and Chau (2010) investigated ARMA, K-Nearest-Neighbors (KNN), ANN and Phase Space Reconstruction-based Artificial Neural Network (ANN-PSR) models to determine the optimal approach of predicting the monthly stream flow time series. They compared these models by a one-month-ahead forecast. They determined that the KNN model gives the best performance among the four models, but only exhibits weak superiority to ARMA [26]. Alhassoun et al. (1997) generated annual and monthly evaporation sequences using the first order Markov model for ten stations in Saudi Arabia. They evaluated the performance of the developed models using the methods of fragments, Thomas-Fiering and Two-Tier, and defined their suitability [27]. Knapp et al. (1984) generated a weekly evaporation time series using the mass transfer method for Milford Lake. They also developed a mathematical model for the time series. The model consists of a mean weekly component represented by a Fourier approximation and a stationary random residue represented by an autoregressive model. They obtained frequency distribution from the synthetic evaporation series, and defined that the estimated evaporation was most sensitive to changes in water temperature [28].

Knowledge discovery uses data mining and machine learning techniques that have evolved through a synergy in artificial intelligence, computer science, statistics, and other related fields. Although there are technical differences, the terms 'machine learning', 'data mining', and 'knowledge discovery and data mining (KDD)' are often used interchangeably [29].

Data mining is often defined as the process of extracting valid, previously unknown, comprehensible information from large databases in order to improve and optimize decisions [30]. In another words, data mining is defined as the identification of interesting structures, where a structure designates the patterns, and statistical or predictive models of the data, and the relationships between their parts [31]. Data mining has been applied to a wide variety of fields for prediction. In addition, data mining has also been applied to other types of scientific data, such as bioinformatical, astronomical, and medical [32]. Keskin et al. (2009) developed pan evaporation models using the data mining process for Lake Eğirdir, Lake Kovada, and the Karacaören Dam, and formed an integrated evaporation model by aggregation of their daily pan evaporation for the Lake District in the southern part of Turkey. They showed that the REP tree model has better agreement with measured daily pan evaporation than other models [33]. Terzi (2012) used the data-mining process to develop rainfall estimation models in Isparta, and tried different input combinations using the rainfall values of Senirkent, Uluborlu, Eğirdir, and Yalvaç stations in Isparta. The most appropriate model was determined as the multilinear regression model (relative error; 0.7%), having monthly rainfall values of Senirkent, Uluborlu and Eğirdir stations among the developed models [34].

The objective of the present study is to evaluate the applicability of the data mining process for daily pan evaporation estimation. This task is intended to be accomplished for Lake Eğirdir, which is the second largest freshwater lake in the southern part of Turkey.

2. Data mining process

The Data Mining (DM) process generally involves phases of data understanding, data preparation, modeling, evaluation and knowledge. The DM process is a hybrid discipline that integrates technologies of databases, statistics, machine learning, signal processing, and high performance computing. This rapidly emerging technology is motivated by the need for new techniques to help analyze, understand or even visualize the huge amounts of stored data gathered from scientific applications. The major data mining functions developed in research communities include summarization, association, classification, prediction and clustering [35].

Data understanding starts with an initial data collection and proceeds with activities to get familiar with the data, to identify data quality problems and to discover first insights into the data. Data preparation covers all activities that construct the final dataset to be modeled from the initial raw data. The tasks of this phase may include data cleaning for removing noise and inconsistent data, and data transformation for extracting embedded features [32]. Successful mining of data relies on refining tools and techniques capable of rendering large quantities of data understandable and meaningful [36]. The modeling phase applies various modeling techniques, determines the optimal values for parameters in models, and finds the one most suited to meeting the objectives. The evaluation phase evaluates the model found at the last stage to confirm its validity to fit problem requirements. No matter to which areas data mining is applied, most efforts are directed towards the data preparation phase [32].

A good relational database management system will form the core of the data repository, and adequately reflect both the data structure and the process flow. The database design will anticipate the kind of analysis and data mining to be performed. The data repository should also support access to existing databases, allowing retrieval of supporting information that can be used at various levels in the decision making process [37].

Data mining is a powerful technique for extracting predictive information from large databases. The automated analysis offered by data mining goes beyond the retrospective analysis of data. Data mining tools can answer questions that are too time-consuming to resolve with methods based on first principles. In data mining, databases are searched for hidden patterns to reveal predictive information in patterns that are too complicated for human experts to identify [38]. Detailed explanations of the used algorithms in modeling are given in the following.

2.1. Autoregressive modeling

Since the early 1960's, time series models have been extensively used in hydrology and water resources for modeling annual and periodic hydrologic time series. The application of these models has been attractive in hydrology, mainly because the autoregressive form has an intuitive type of time dependence (the values of variable at the present time depend on the values at previous times), and they are the simplest models to use. The autoregressive model (AR) may be generally written as:

$$y_t = \mu + \varphi_1(y_{t-1} - \mu) + \cdots + \varphi_p(y_{t-p} - \mu) + \varepsilon_t, \tag{1}$$

where y_t is the time dependent series (variable) and ε_t is the time independent (uncorrelated) series, which is independent of y_t, and normally distributed with mean zero and variance, σ_ε^2. Coefficients $\varphi_1, \cdots, \varphi_p$, are called autoregression coefficients. The parameter set of the model of Eq. (1) is $\{\mu, \sigma^2, \varphi_1, \cdots, \varphi_p, \sigma_\varepsilon^2\}$, which must be specified or estimated from data.

Autoregressive models with periodic parameters are those in which part or all of their parameters vary within the year or are periodic. These models are often referred to as periodic AR models. The time series used in hydrological studies are generally annual or monthly [39].

2.2. Multilayer perceptron

The back-propagation learning algorithm is one of the most important historical developments in neural networks. It has reawakened the scientific and engineering community to the modeling and processing of many quantitative phenomena using neural networks. This learning algorithm is applied to multilayer feed-forward networks consisting of processing elements with continuous and differentiable activation functions. Such networks associated with the back-propagation learning algorithm are also called back-propagation networks. Given a training set of input-output pairs, the algorithm provides a procedure for changing the weights in a back-propagation network to classify the given input patterns correctly. For a given input-output pair, the back-propagation algorithm performs two phases of data flow. First, the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow of data, produces an actual output. Then, the error signals resulting from the difference between the output pattern and the actual output are back-propagated from the output layer to previous layers for them to update their weights [40].

2.3. Radial basis function network

A radial basis function network is a two-layer network, whose output neurons form a linear combination of the basis functions computed by the hidden neurons. The basis functions in the hidden layer produce a localized response to the input. That is, each hidden neuron has a localized receptive field. The basis function can be viewed as the activation function in the hidden layer, and the basis function used is a Gaussian function [41].

2.4. Decision table

The decision table summarizes the data set with a "decision table." In its simplest state, a decision table contains the same number of attributes as the original data set, and a new data item is assigned a category by finding the line in the decision table that matches the nonclass values of the data item. This implementation employs the wrapper method to find a good subset of attributes for inclusion in the table. By eliminating attributes that contribute little or nothing to a model of a data set, the algorithm reduces the likelihood of overfitting and creates a smaller, more condensed decision table [42].

2.5. REP tree

The decision tree tool of the REP tree in Weka was employed to formulate resource access patterns for considered applications that are common in the target execution environment. The REP tree procedure builds a decision tree using information gain as the splitting criterion, and uses reduced-error pruning for pruning. This procedure is also characterized by lower computational overhead compared to other decision-tree-based classification methods, due to its efficient pruning mechanism [43].

2.6. KStar

As a nearest-neighbor classifier, this algorithm is highly effective in situations with noisy training data, provided it is supplied with a large enough training set. An important note to consider is that the algorithm calculates the distance between instances on all attributes, unlike some other methods. If only a few features of the given vector are relevant, then two instances with two identical values for the relevant features may find themselves spaced far apart by this algorithm [44].

3. Application

3.1. Data understanding

The DM process was applied to Lake Eğirdir in the southwestern part of Turkey to estimate daily evaporation. Lake Eğirdir has a surface area and volume of 470 km^2 and 4360 hm^3, respectively, and is used as a source of drinking and irrigation water (Figure 1).

The daily pan evaporation data were obtained from the State Hydraulic Works for 1998-2005. The training dataset consisted of the years 1998-2003, and the trained models were used to run a set of test data for the year 2004-2005.

3.2. Data preparation

This step investigates whether or not there are any missing data. For substitution of missing data, mean values were used. The previous 1-, 2- and 3- day pan evaporation values of Lake Eğirdir were used to estimate daily pan evaporation in the data mining process.

3.3. Modeling

In order to estimate daily pan evaporation for Lake Eğirdir, autoregressive modeling, multilayer perceptron, a radial basis function network, a decision table, a REP tree and KStar algorithms in the data mining process were used. A detailed explanation of these algorithms is given above.

3.4. Evaluation

In this study, class A pan evaporation measurement values were used in the data mining modeling. The major difficulty in using a class A pan for direct measurements is due to the subsequent application of coefficients based on the measurements from a small

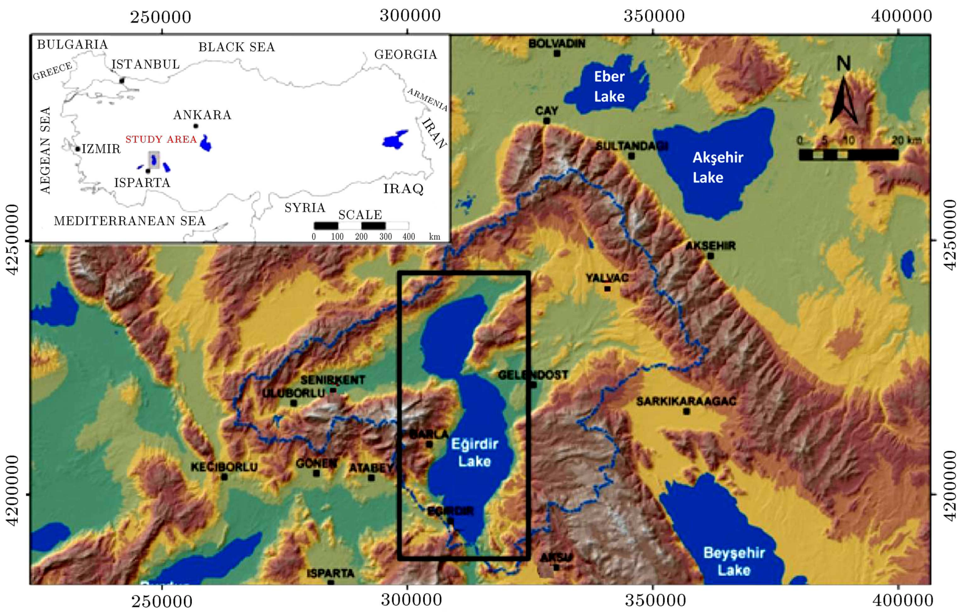


Figure 1. The map of Lake Eğirdir.

tank to large bodies of open water. Such difficulties can be accommodated by the data mining process.

Two criteria were used to evaluate the adequacy of each model: The correlation coefficient (R) and the Root Mean Square Error (RMSE). The R, based on evaporation estimation errors, is calculated as:

$$R=\frac{\sum_{i=1}^{n}(E_i-E_{\text{mean}})(E_{i(m)}-E_{(m)\text{mean}})}{\sqrt{\sum_{i=1}^{n}(E_i-E_{\text{mean}})^2}\sqrt{\sum_{i=1}^{n}(E_{i(m)}-E_{(m)\text{mean}})^2}}, \quad (2)$$

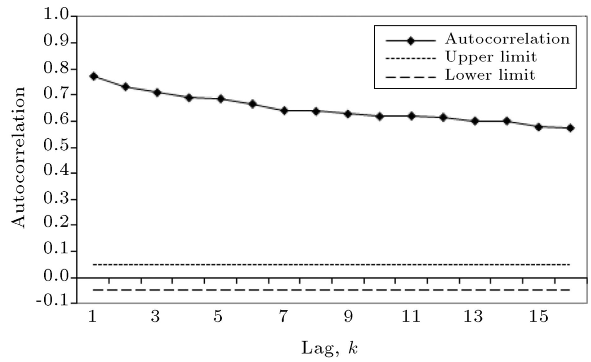
where n is the number of observed data, E_i, $E_{i(m)}$, E_{mean} and $E_{(m)\text{mean}}$ are daily pan evaporation measurements, the result of the developed evaporation model, the mean evaporation measurement and mean model result, respectively. The root mean square error represents the error of the model and is defined as:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i-E_{i(m)})^2}, \quad (3)$$

whose parameters have been defined above.

3.5. Knowledge

The daily pan evaporation data set is a periodic series due to shorter time intervals than the annual data set. Internal dependence increases because statistical characteristics in periodic series are different for another day of the same process. Firstly, the series must be fitted to normal distribution and then standardized for removing the periodicity of the daily pan evaporation data set. It was controlled, according to skewness, whether or not pan evaporation values fit to normal distribution, and it was seen that they do. Then, moment values (mean, standard deviation and skewness) of pan evaporation data were determined. The standard normal series was obtained by applying a standardization process to the historical time series. The autocorrelation and partial autocorrelation values of a standard normal series were obtained. The upper and lower limits were determined for a 95% confidence interval (Figure 2). It was shown that the y_t series was a dependent series, according to autocorrelation values. Then, the autocorrelation coefficient (δk) was calculated and the residual series was determined according to this value. The AR(1), AR(2) and AR(3) models were tested for Lake Eğirdir and it was concluded that the AR(3) model was the most appropriate for autocorrelation values. A correlogram of the models is given in Figure 3, and it can be seen that there is agreement between the AR(3) model and the correlogram of the historical series. The parameters of developed AR models were given Table 1. It was shown that the AR(3) model provided a stationarity



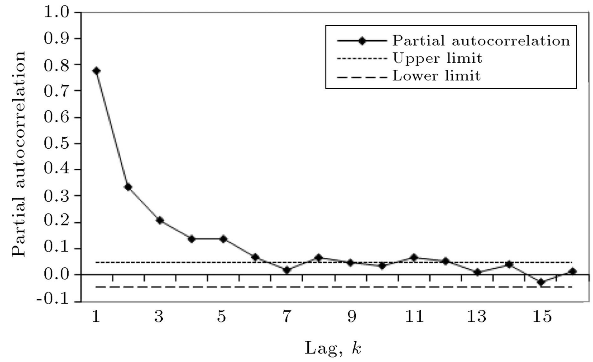


Figure 2. The 95% confidence interval, autocorrelation and partial autocorrelation values.

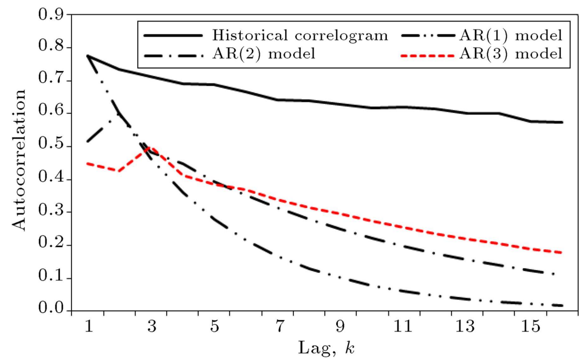


Figure 3. Correlogram of historical and AR(1), AR(2) and AR(3) models.

condition when using Eq. (4):

$$u^p-\varphi_1u^{p-1}-\varphi_2u^{p-2}-\cdots-\varphi_p=0. \quad (4)$$

According to Eq. (5), variance of residual series (σ_ϵ^2) was obtained:

$$\sigma_\epsilon^2=\frac{N\sigma^2}{(N-p)}\left(1-\sum_{j=1}^{p}\varphi_j r_j\right), \quad (5)$$

where N is number of data, p is model parameter, and φ is autoregression coefficient. The Akaike Information Criterion (AIC) was used to investigate the fitness of the selected model degree. The AICs of AR (1), AR(2) and AR(3) models were calculated to be

Table 1. The autocorrelation coefficients of AR models.

AR models	Φ_1	Φ_2	Φ_3
AR(1)	0.775	-	-
AR(2)	0.516	0.334	-
AR(3)	0.447	0.227	0.207

0.954, 0.881 and 0.846, respectively. It was confirmed that the AR(3) model having the smallest AIC was appropriate.

The synthetic series was generated for the AR(3) model. The mean and standard deviations of the series were calculated and compared with the historical series (Figures 4 and 5). As shown in Figures 4 and 5, there was agreement between the historical and synthetic series.

Hence, previous 1-, 2- and 3-day daily pan evaporation values of Lake Eğirdir were used to develop the models with multilayer perceptron, a radial basis function network, a decision table, a REP tree and KStar algorithms in the process, after the compatibility of AR(3) was shown. The best-fit DM algorithm was determined according to R and RMSE values for the testing data set. The results of statistical analyses of the developed models were given in Table 2. As seen from Table 2, comparing these models, it is shown that the AR(3) model has the lowest RMSE (0.899) and the highest R (0.805) for the testing set. The results of the AR(3) model were plotted against measured daily pan evaporation for training and testing sets in Figure 6.

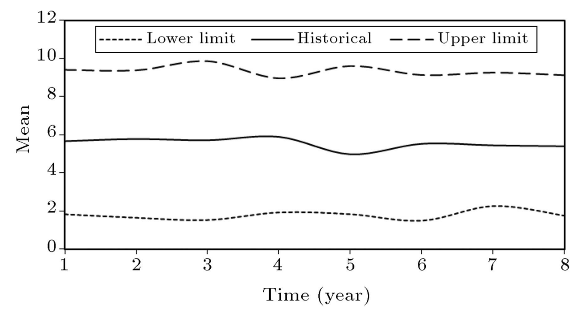


Figure 4. The mean values for synthetic series.

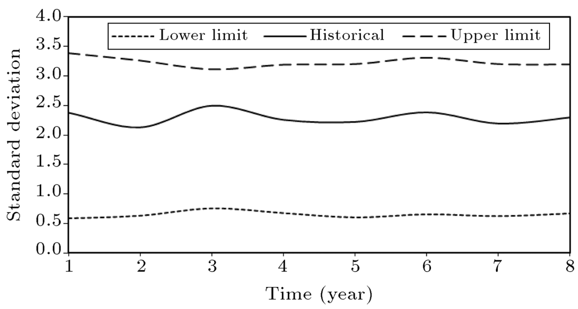


Figure 5. Standard deviations for synthetic series.

As shown in Figure 6, the AR(3) model comparison plot is around 45° straight lines, which imply that there are no bias effects in the models for all sets. The results of the AR(3) model, together with the daily pan evaporation measurements, were presented in Figure 7. It shows that the AR(3) model matches daily pan evaporation closely, although it has variations during high and low evaporation periods. It shows that the developed AR(3) model gives the best result to estimate evaporation for Lake Eğirdir. In the future, when more data are obtained, the developed models need to be revised. Also, the other developed models can give better results than AR(3) when adding more data or when developing models for different regions. Suitable results cannot be always obtained from the AR(3) model when estimating evaporation in another region, because the AR(3) model was developed only for Lake Eğirdir. The models need to be reestablished

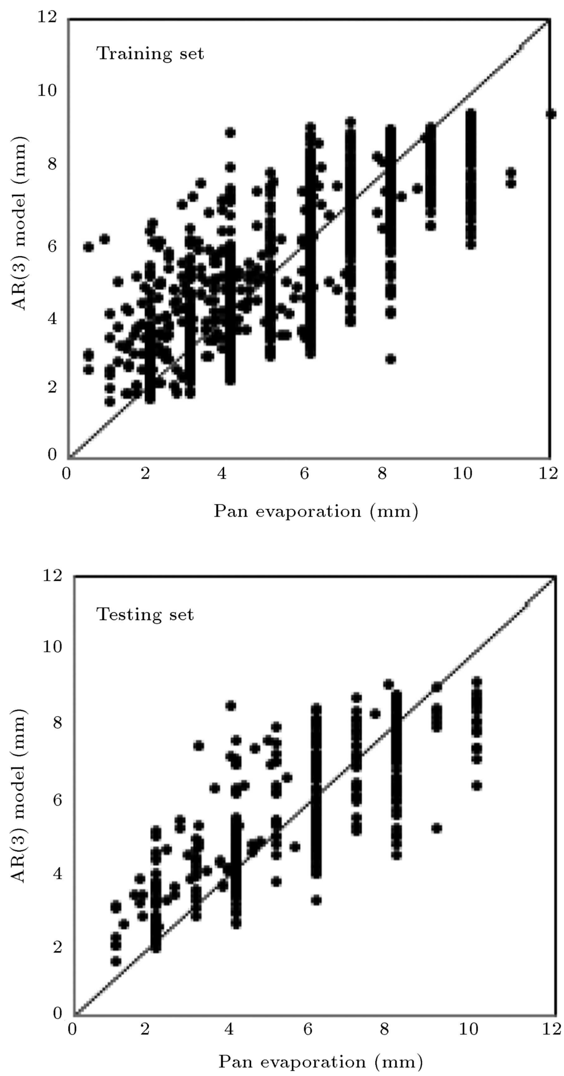


Figure 6. Scatter diagrams between the AR(3) model versus daily pan evaporation.

Table 2. The descriptive statistics of developed models.

Models	Mean (mm)	Std. Dev.	Skewness	Kurtosis	RMSE (mm)	*R*
Measured evaporation	5.43	2.24	0.038	-0.827	-	-
Multilayer perceptron	5.49	1.70	-0.176	-1.142	1.158	0.787
RBF network	5.52	1.76	0.186	-1.904	1.435	0.643
Decision table	5.48	1.78	0.100	-1.082	1.227	0.756
REP tree	5.46	1.83	0.174	-1.134	1.215	0.762
KStar	5.45	1.72	0.097	-1.195	1.175	0.779
AR(3)	5.59	1.84	-0.022	-1.035	0.899	0.805

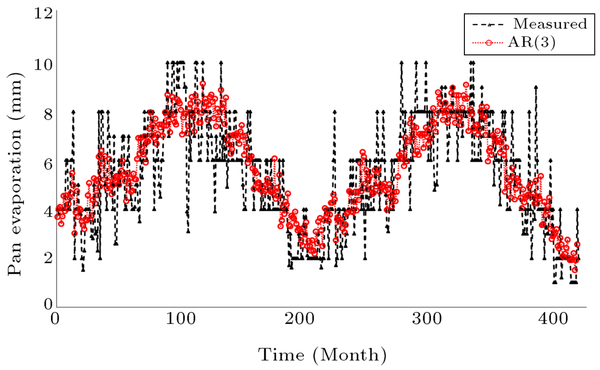


Figure 7. Time series of estimated and observed daily evaporation values for testing set.

or calibrated according to the data of the different region.

4. Conclusions

For the purpose of comparing data mining techniques, in this study, various models were developed to estimate daily pan evaporation. The proposed techniques were applied to Lake Eğirdir, which meets vital requirements, such as irrigation and drinking water. Firstly, AR(1), AR(2) and AR(3) models were developed, and it was shown that the AR(3) model was the most appropriate, according to autocorrelation values. Then, the previous 1-, 2- and 3- day pan evaporation values of Lake Eğirdir were used to develop the models, using the other algorithms in the DM process. Comparing the developed models, it was demonstrated that the AR(3) model had higher R than other DM algorithms. Also, the performance of the developed models suggested that daily pan evaporation could be successfully estimated using DM approaches, without needing meteorological parameters in water resources planning and management. Finally, the models can be used for estimating evaporation, when the measurement system has failed, or to estimate missing daily pan evaporation data in hydrological modeling studies.

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Biography

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