Bilecik Şeyh Edebali Üniversitesi Fen Bilimleri Dergisi
Bilecik Seyh Edebali University Journal of Science

11(1), 26-36, 2024

DOİ: 10.35193/bseufbd.1209924
e-ISSN: 2458-7575 (https://dergipark.org.tr/tr/pub/bseufbd)

Araştırma Makalesi - Research Article

Priestly-Taylor Coefficient Evaluation for Konya Closed Basin

Konya Kapalı Havzası için Priestly-Taylor Katsayısı Değerlendirmesi

Alara Cicibıyık[1], Nermin Şarlak[2*], Deniz Üstün[3]

Geliş / Received: 25/11/2022 ***Revize / Revised: 16/05/2023*** ***Kabul / Accepted: 22/08/2023***

ABSTRACT

Measurement of evaporation in the field is difficult and expensive; thus, the empirical evaporation estimation methods have been developed. However, these estimation methods have both advantages and disadvantages. The main disadvantage is that their coefficients were determined by the climatic conditions of the study areas. One of these methods is Penman. The Penman method, accepted as a reference, has reached the closest estimations to the measurement of evaporation in the field of the different parts of the world. However, it needs lots of measured climatic data. The Priestley-Taylor method was derived to reduce the measured data needs of the Penman method. Priestly and Taylor represented the variables such as saturated and actual vapor pressures and wind speed with α coefficient of 1.26. The researchers have continued to study on the calibration of the α coefficient for their studies' area since this method has been known to underestimate evaporation value in areas where advection is effective. The present study consists of two stages. First, evaporation was tried to be estimated with these two methods by using the measured climatic data of five meteorological stations in the Konya Closed Basin. Estimated values were evaluated making comparison with the pan measurements. Although slightly higher values were estimated from the pan measurements with each method, the Penman method was found to be relatively more consistent on the basis of statistical indicators. Second, α coefficient was obtained as 1.28 for the study area by using three artificial intelligence-based optimization algorithms. The Penman method was used for comparison in this stage. It was concluded that there was no need for any calibration of the α coefficient and the original one was found to be valid for the study area as well.

Keywords- Penman, Priestly-Taylor, Evaporation

ÖZ

Arazide buharlaşma ölçümü zor ve pahalıdır; bu sebepten ampirik buharlaşma tahmin yöntemleri geliştirilmektedir. Ancak bu tahmin yöntemlerinin avantaj ve dezavantajları vardır. Başlıca dezavantaj, katsayılarının çalışma alanlarının iklim koşullarına göre elde edilmiş olmasıdır. Ampirik yöntemlerden biri Penman'dır. Referans kabul edilen bu yöntem, dünyanın farklı yerlerinde arazide ölçülen verilere en yakın

[1]Contact: alarabolgenn@gmail.com (https://orcid.org/0000-0003-3225-6070)
Civil Engineering Department, Engineering Faculty, Karamanoğlu Mehmetbey University, Karaman, Turkey
[2*]Corresponding Author Contact: nsarlak@ktun.edu.tr (https://orcid.org/0000-0003-3632-2725)
Civil Engineering Department, Engineering Faculty, Konya Technical University, Konya, Turkey
[3]Contact: denizustun@tarsus.edu.tr (https://orcid.org/0000-0002-5229-4018)
Computer Engineering Department, Engineering Faculty, Tarsus University, Tarsus-Mersin, Turkey

tahminlere ulaşmaktadır. Ancak, çok sayıda ölçülen iklimsel veriye ihtiyaç duymaktadır. Penman yönteminin ölçülen veri ihtiyaçlarını azaltmak için Priestley-Taylor yöntemi geliştirilmiştir. Priestly ve Taylor, doymuş ve gerçek buhar basınçları ve rüzgâr hızı gibi değişkenleri değeri 1,26 olan α katsayısı ile temsil etmişlerdir. Bu yöntemin adveksiyonun etkili olduğu yerlerde daha az buharlaşma değeri tahmin ettiği bilindiğinden, araştırmacılar hala α katsayısının kalibrasyonu üzerinde çalışmaktadırlar. Sunulan çalışma iki aşamadan oluşmaktadır. İlk olarak Konya Kapalı Havzası'ndaki beş meteoroloji istasyonunun ölçülen iklimsel verileri kullanılarak bu iki yöntemle buharlaşma tahmin edilmeye çalışılmıştır. Tahmini değerler buharlaşma tavası ölçümleri ile karşılaştırılmıştır. Her bir yöntemle tava ölçümlerinden biraz yüksek değerler tahmin edilse de Penman yöntemi istatistiksel göstergeler temelinde nispeten daha uyumlu bulunmuştur. İkinci olarak, yapay zekâ tabanlı üç optimizasyon algoritması kullanılarak çalışma alanı için α katsayısı 1,28 olarak elde edildi. Bu aşamada karşılaştırma için Penman yöntemi kullanılmıştır. α katsayısı için herhangi bir kalibrasyona gerek olmadığı ve orijinal halinin çalışma alanı için de geçerli olduğu sonucuna varılmıştır.

Anahtar Kelimeler- Penman, Priestly-Taylor, Buharlaşma

I. INTRODUCTION

Evaporation, accurate measurement of which is difficult and time-consuming, is the amount of water lost from open water surfaces. The main reason for the difficulty is the lack of instrumentation to reliably measure evaporation. One of the direct methods to measure evaporation is the eddy-covariance. The eddy-covariance method is based on determination of the rate of upward movement of water vapor near the surface by vertical air movement and absolute humidity. The required data are obtained with the help of the mechanic sensors. This method has strong theoretical background and requires no making assumptions about parameters; thus, the evaporation values were accepted as correct. However, it is expensive and generally used for relatively small areas [1]. Another direct and relatively inexpensive measurement technique is evaporation pan. Evaporation is measured directly using the metal container in all around the world. However, operation of it is difficult, labor-intensive and readings are often complicated on rainy days. Class A evaporation pan, which is the most used type in many countries including Turkey, has an area of 1 m^2 and a depth of 25 cm. The pan is filled with water to a depth of 20 cm and then amount of evaporation is determined by measuring the decrease in water level. One of the problems in pan measurement is that it gives overestimation in arid regions since the surrounding air of pan tends it to be drier and hotter. However, it is known that it often gives realistic estimations in humid regions because of the insignificant advective heat transfer. A pan coefficient is applied to consider these effects. It is taken as 0.70 in Turkey. Another problem in evaporation pans is that they are often located at meteorological stations which are near dams or natural lakes. Floating pans are also available, but they are not preferred because there are some difficulties in their positioning and operation on the lake surface.

Evaporation is often estimated by measured meteorological data because of the mentioned difficulties in obtaining accurate direct measurement of it under field conditions. These methods, called for indirect methods, can be broadly grouped into several categories: empirical, water budget, energy budget and mass transfer. Input requirements of these methods vary in complexity, ranging from single input (temperature only) to multiple inputs (temperature, wind speed, humidity and solar radiation data). There is no universally accepted objective criteria for selection of the most appropriate indirect methods. The selection of method is depended on the meteorological data that are available. Although the methods derived with multiple inputs are usually considered as accurate, long-term records of wind speed, humidity, and solar radiation data are often limited in many regions. One of these indirect methods based on the combination of energy budget and aerodynamic equations was developed by Penman [2]. Studies conducted in many parts of the world have shown that the Penman equation gives very successful results in the estimation of open surface evaporation. Priestley and Taylor tried to simplify the Penman equation with the coefficient α (1.26) which includes the effect of some of its variables [3]. However, there are some studies reported less evaporation estimation with this equation in cases where advection, the horizontal movement of energy, is effective [4].

Some recent studies on evaporation can be mentioned into three groups. The first group of studies were concerned about suggesting the empirical methods with needing less input variables that makes the best estimation for their study areas [5-14]. The second group compares the performance of artificial intelligence models, such as artificial neural networks and fuzzy logic with that of empirical equations, highlighting the potential of these models [15-20]. Third group studies were interested in calibration of Priestly-Taylor coefficient to improve the accuracy of estimating open water evaporation [21-26].

In this study, the Konya Closed Basin was chosen as the application area. Although the groundwater reserve of the basin is considered to be relatively good, it is known to have limited surface water resources. In recent years, the increasing water demands due to drinking and irrigation water needs, excessive groundwater consumption for agricultural activities etc. is tried to be met by transferring water from the neighboring basin. Therefore, accurately estimating the evaporation amount has become increasingly important for this basin. In this context, potential evaporation amounts were estimated using the Penman method and the Priestley-Taylor method. These estimated values were then compared to evaporation pan measurements. The coefficient (α) in the Priestley-Taylor method, which represents variables such as saturated and actual vapor pressures and wind speed, was evaluated for the study area by using Particle Swarm, Artificial Bee Colony, and Differential Evolution optimization algorithms. The Penman method was used for comparison in this stage. The results showed that there is no need for calibration of the α coefficient and the original value is valid for the study area as well.

II. MATERIAL AND METHODS

A. Material

The daily measurement data of air temperature, relative humidity, wind speed, solar radiation and pan open water evaporation (E_{Pan}) from 2000 to 2019 were obtained from the five meteorological stations established and operated by Turkish State Meteorological Service. Location of the selected stations in the Konya Closed Basin are illustrated in Fig.1. Metadata and moment values of E_{pan} for utilized stations are given in Table 1.

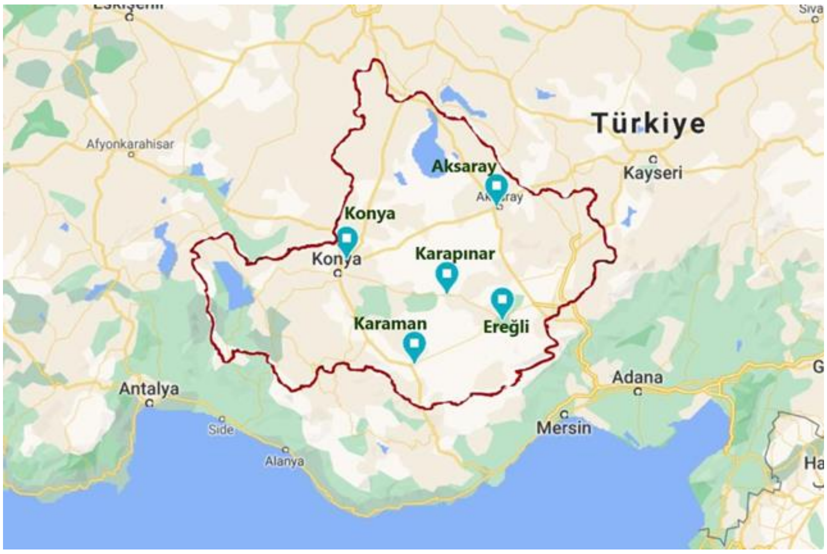

Figure 1. Locations of selected stations in the Konya closed basin.

Table 1. Metada and First, Second and Third Moment values for E_{Pan} for utilized stations.

Station Name	Station No.	Altitude (m)	Latitude	Longitude	Moment values of E_{Pan} Mean (mm)	Standard Deviation (mm)	Skewness coefficient
Aksaray	17192	970	33.59	38.22	6.69	2.71	0.04
Ereğli	17248	1046	34.02	37.31	6.05	2.42	-0.28
Karapınar	17902	996	33.31	37.42	6.12	2.42	-0.14
Karaman	17246	1026	33.13	37.11	7.06	2.76	-0.09
Konya	17244	1018	32.34	37.59	5.98	2.69	0.20

1)Data Imputation: Missing data was detected in the measurement of E_{Pan} and solar radiation at each meteorological station. The daily measurements of E_{Pan} were not consistently available for each station from November to April. Moreover, there were also some missing data in the existing data set. The percentages of missing E_{Pan} (solar radiation) data are 14(6) %, 8(46) %, 4(3) %, 47(45) % and 1(65) % at Aksaray, Ereğli, Karaman, Karapınar and Konya stations, respectively. Since the empirical evaporation estimation methods were applied to the stations separately and both utilized empirical methods require solar radiation data, the Radial Based Function (RBF) surrogate interpolation method was used to complete the missing solar radiation data. This method was chosen because it can accurately model the curvature of multidimensional data. The thin-plate-spline (TPS) function was selected as the non-linear function, as it is known to provide the most accurate results for scattered data approximations [27]. Before proceeding to the statistical analysis, the homogeneity of the data was tested using Pettitt, Buishand, Standard Normal Homogeneity, and Von-Neumann tests [28].

B. Methods

1) Penman: Energy budget and mass transfer methods were combined as [29]:

$$\lambda E = \frac{\Delta\,(R_{ns} - G) + \gamma . E_a}{(\Delta + \gamma)\,\rho_w} \quad (1)$$

$$E_a = 6.43(a_w + b_w * u_2)(e_s - e_a) \quad (2)$$

(2)

where E: evaporation rate from open water surface in $mmday^{-1}$; Δ: gradient of saturation vapor pressure at air temperature in $kPa°C^{-1}$; λ: is the latent heat of vaporization ($MJkg^{-1}$); G: soil heat flux in $MJm^{-2}day^{-1}$; γ: psychometric constant in $kPa°C^{-1}$; u_2: wind velocity at 2 m height in m/s; R_{ns}: net radiation in $MJm^{-2}day^{-1}$; e_s: saturation vapor pressure of air in kPa; e_a: actual vapor pressure of air in kPa; E_a: evaporation due to mass transfer of vapor in $mmday^{-1}$; a_w and b_w: constants; ρ_w: water density in kg/m^3.

2) Priestly-Taylor: Priestley and Taylor derived an equation with temperature and solar radiation variables. The formula is intended to be used in the areas where the meteorological parameters measurements required in the Penman method are not available. By reducing the vapor pressure difference and convection terms to an empirical coefficient α, they developed the following relation:

$$E = \alpha \frac{\Delta}{\Delta + \gamma}\left(\frac{R_{ns} - G}{\lambda}\right) \quad (3)$$

Priestley and Taylor determined the α coefficient as 1.26 [3]. This method generally gives accurate estimates of potential evaporation under minimum advection condition.

3) Artificial Intelligence Optimization Algorithms: The optimization is simply the process of finding the best solutions for the problems under the given constraints. The solutions for optimization problems are achieved through the use of algorithms that rely on mathematical expressions in a way that were provided certain constraints. Optimization problems can be represented as:

$$\text{minimize} \quad f\,(X) \quad (4)$$

$$\text{constraints} \quad g_k\,(X) \leq 0 \quad (5)$$

$$x_j^{min} \leq x_j \leq x_j^{max} \quad j = 1, ..., n \quad (6)$$

f(*X*) is the objective or cost function; $g_k(X)$ is a set of constraints and $X=\{x_1, x_2, x_3, ..., x_n\}$is a set of real-valued variables. The aim is to find the best solution that meets all the limitations of the problem [30].

3.1) Particle Swarm Optimization (PSO): Particle swarm optimization is an optimization method based on swarm intelligence, developed by Kennedy and Eberhart [31]. The algorithm is established on routing information obtained from the interactions between each bird in the swarm. Each individual is referred to as a particle, and the population of particles is called a swarm. The goal of the PSO is to bring the positions of particles in the swarm closer to the best position. This is achieved by calculating the positions and velocities of particles using equations Eqs. 7-8:

$$v_i^{k+1} = w.v_i^k + c_1.rand_1^k.\left(pbest_i^k - x_i^k\right) + c_2.rand_2^k.(gbest^k - x_i^k) \quad (7)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (8)$$

where k is iteration number; x_j is j^{th} particle position, and the velocity of the particle x_j can be represented by v_j; w is the inertia weight. c_1 and c_2 are the scale factors that used to adjust the step length in each iteration. pbest is the best position vector of each particle and gbest is the best position vector of the swarm.

3.2) Artificial Bee Colony (ABC) Algorithm: The Artificial Bee Colony (ABC) algorithm is modelled by basing the search food behavior of the honey bees [32]. It tries to find the most appropriate value of the result that gives the minimum or maximum of the problem from the solution space while searching the location of the food resource having the most nectar [33]. The algorithm consists of the three phases: employed, onlooker, and scout bees. There are certain assumptions made in this optimization model, including assigning an equal number of bees to each food resource and having an equal number of employed and onlooker bees. When a food resource's nectar is exhausted, the bee responsible for it becomes a scout bee. The basic steps of the ABC algorithm are given below:

- ✓ Randomly generating the positions of food resources having nectar within the specified solution space for the given optimization problem;
- ✓ Directing the employed bees to the available food resources;
- ✓ Calculating probability values for each food resources based on information from the attendant employed bees;
- ✓ Onlooker bees choose food resources based on the computed probability values;
- ✓ Checking the limit values for each food resources if the limit is exceeded, a scout bee is generated and the scout bee randomly selects a new food resource;
- ✓ Stopping the algorithm if the termination criteria are met [33].

Food resources positions (solutions) are assigned randomly for the initial scout bees by using Eq. 9:

$$x_{ij} = x_j^{min} + rand(0,1) * (x_j^{max} - x_j^{min}) \qquad i=1,...,RN \qquad j=1,...M \tag{9}$$

here, x_j^{min} and x_j^{max} are lower and upper bound. x_{ij} is the first food resource positions that represented to the possible solutions for the initial bee population. RN is the number of solution and M is the number of parameters to be optimize. New food resources are defined by Eq. 10:

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) \tag{10}$$

here, k≠i and x_{ij} is old food resource position. x_{kj} is other food resource position in the search space. v_{ij} is a new food resource position and $\emptyset_{ij}$ is a random number between (-1,1). The boundary conditions of new generated food resource positions are controlled via Eq. 11:

$$v_{ij} = \begin{bmatrix} x_j^{min}, & v_{ij} < x_j^{min} \\ v_{ij}, & x_j^{min} \le v_{ij} \le x_j^{max} \\ x_j^{maks}, & v_{ij} > x_j^{min} \end{bmatrix} \tag{11}$$

The fitness values of each food resource are calculated by substituting the f_i in the Eq. 12. The greedy selection process is applied to select better one between v_i (new food resource position) and x_i (old food resource position).

$$fitness_i = \begin{bmatrix} 1/(1+f_i) & f_i \ge 0 \\ 1/|(f_i)| & f_i < 0 \end{bmatrix} \tag{12}$$

where f_i is the cost function value of the v_i. The cost function changes from one problem to another. The scout bees perform the selection of food area by using the probability values calculated by Eq. 13. SN is the number of attendant bees.

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \tag{13}$$

If the value of p_i is greater than the randomly generated value between 0 and 1, a new food resource is generated by Eq.10 and the best one from v_i and x_i is selected. This procedure is repeated until all onlooker bees have spread out to food resources. The best solution is kept in mind.

3.3) Differential Evolution (DE) Algorithm: The differential evolution (DE) algorithm is a biological based optimization method that works on the basis of the population. DE algorithm gives effective results for problems with the solution spaces that has the intervals of continuous or discrete data [34]. The initial population and control parameters are defined to satisfy following conditions: NP is the size of population (chromosome number) NP ≥4 (1, 2, 3, …, i); D is the dimension of problem (gene number) (1, 2, 3, …, j); CR is the crossover rate [0.1, 1]; G_k is k^{th} generation (1, 2, 3, …, G_{kmax}); F is the scale factor [0, 2]; $x_{j,i,G}$ is j^{th} parameter (gene) of the i^{th} chromosome at the G generation; $n_{j,i,G+1}$ is the intermediate chromosome that the mutation and crossover operators were applied to; $u_{j,i,G+1}$ generated for the next generation from the $x_{j,i,G}$ is the chromosome (child-trial); r_1, r_2 and r_3 are the random numbers to be used for generating new chromosome. x_j^l and x_j^u are lower and upper boundary for the variables. Because the next generation will be produced by using the current population, the initial population is created by selecting randomly elements having the uniform distribution from research space that has a well-defined constraint:

$$i \le \text{NP and } j \le \text{D:} \qquad x_{j,i,G=0} = x_j^{(l)} + rand_j[0,1].(x_j^u - x_j^l) \tag{14}$$

In the DE algorithm, three chromosomes (r_1, r_2, r_3) different from chromosome to be mutated are selected. The mutation operation is performed for the difference of the first two of the selected chromosomes. This difference is multiplied by scale factor, F and added to the selected third chromosome. Thus, the chromosome to be used in crossover is obtained from mutation ($n_{j,i,G+1}$):

$$n_{j,i,G+1} = x_{j,r3,G} + F.(x_{j,r_1,G} - x_{j,r_2,G}) \tag{15}$$

In the crossover step, a trial chromosome ($u_{j,i,G+1}$) is produced by using the difference chromosome obtained after the mutation step and $x_{j,i,G}$ chromosome for a crossover rate (CR) providing crossover probability.

$$u_{j,i,G+1} = \begin{Bmatrix} n_{j,i,G+1} & \text{if } (\text{randbj} \leq CR) \text{ or } j = rnbr(i) \\ x_{j,i,G} & \text{otherwise} \end{Bmatrix} \quad j=1,2,\ldots,D \tag{16}$$

where randb(j) is the jth evaluation of a uniform random number generator [0,1]; rnbr(i) is a randomly chosen index from 1 to D which ensures that $u_{j,i,G+1}$ gets at least one parameter from $n_{j,i,G+1}$. The criteria used in the determination of new chromosome that will be pass to the next generation (G=G+1) is the fitness value of target chromosome calculated from cost function ($f(x_{j,i,G})$). The fitness value of $u_{j,j,G+1}$ is compared to fitness value of target chromosome and then the best chromosome is chosen for that generation with respect to fitness values.

$$x_{j,i,G+1} = \begin{cases} u_{j,i,G+1} & \text{if } f(u_{j,i,G+1}) \leq f(x_{j,i,,G}) \\ x_{j,i,,G} & \text{otherwise} \end{cases} \tag{17}$$

III. RESULTS AND DISCUSSION

A. *Evaporation Estimation by Penman and Priestley-Taylor Methods*

The performance of the Penman and Priestley-Taylor methods was evaluated by comparing their estimations to daily observed pan evaporation values (E_{Pan}). The available daily E_{Pan} measurements from April to November over a period of ten years were used as independent indicators of potential evaporation. While there are inherent differences between open water areas and evaporation pans, this comparison allows us to demonstrate the accuracy of the estimations. The methods were assessed using the coefficient of determination (R^2), the Mean Square Error (MSE), the ratio between estimated evaporation and observed E_{Pan} (r=estimated value/observation value) and the Nash-Sutcliffe efficiency (NSE) as shown in Table 2. The model performance is accepted as optimum for high R^2, for low MSE. A value of 1.0 for r and NSE indicates a perfect match between estimated and observed data.

Table 2. The performance of methods for each station with R^2, MSE, r (ratio) and NSE

Methods/ Stations	Penman				Priestly-Taylor			
	R^2	MSE	r	NSE	R^2	MSE	r	NSE
Aksaray	0.4708	5.26	1.17	0.29	0.5244	5.37	1.12	0.27
Ereğli	0.6190	4.31	1.23	0.26	0.5769	4.78	1.24	0.18
Karapınar	0.6394	4.24	1.24	0.27	0.6222	4.01	1.22	0.31
Karaman	0.5245	3.96	1.07	0.48	0.4684	4.44	1.05	0.42
Konya	0.5526	8.18	1.35	-0.13	0.5157	5.37	1.22	0.26

The correlation between estimated and E_{Pan} values resulted in a low coefficient of determination. The highest R^2 value obtained from the Karapınar station was 0.6394. These results suggest that the performance of the considered method was very close to each other; albeit, the Penman method was obtained in relatively good agreement with pan evaporation based on MSE and NSE, except for the Karapınar and Konya stations. The E_{Pan} measurements were slightly overestimated by the methods, as indicated by the r values. All r values are greater than 1 (one). The closest values to E_{Pan} were estimated from the Karaman station. The r (NSE) values for the Penman and Priestly-Taylor methods were 1.07 (0.48) and 1.05 (0.42), respectively. These results are consistent with those of [12], who also used these methods on measured data at the Samsun station. They noted that the Penman method tends to overestimate E_{pan} compared to the Priestly-Taylor method. They concluded that while the Penman method performed better overall, it was not accurate in estimating very high or very low values of E_{pan}.

E_{Pan} values which were greater (lower) than 4 mm were extracted from total data set to find first (second) data group since it was detected that each method tended to underestimate (overestimate) the high (low) E_{Pan}. The methods' performances for each data group were also investigated and given in Table 3.

Table 3. The performance of methods for each group data with R^2, MSE, r and NSE

Methods/ Stations		Penman				Priestly-Taylor			
		R^2	MSE	r	NSE	R^2	MSE	r	NSE
Aksaray	First data group (E_{Pan}<4mm)	0.8303	9.80	1.99	-0.786	0.8092	9.70	1.94	-0.768
	Second data group (E_{Pan} >4mm)	0.7997	4.15	1.09	0.300	0.7639	4.37	1.05	0.275
Ereğli	First data group (E_{Pan} <4mm)	0.8233	7.40	1.88	-0.512	0.8009	8.01	1.88	-0.636
	Second data group (E_{Pan} >4mm)	0.8823	3.39	1.16	0.282	0.8682	3.82	1.17	0.194
Karapınar	First data group (E_{Pan} <4mm)	0.8669	7.26	1.84	-0.366	0.8471	7.07	1.79	-0.330
	Second data group (E_{Pan} >4mm)	0.8842	3.32	1.00	0.425	0.8805	3.07	0.99	0.468
Karaman	First data group (E_{Pan} <4mm)	0.8286	6.86	1.75	-0.130	0.8071	7.39	1.75	-0.218
	Second data group (E_{Pan} >4mm)	0.7808	3.42	1.00	0.441	0.7514	3.88	0.99	0.365
Konya	First data group (E_{Pan} <4mm)	0.8403	9.40	1.99	-1.057	0.8242	8.09	1.88	-0.771
	Second data group (E_{Pan} >4mm)	0.8301	7.69	1.00	-0.065	0.8805	4.37	0.89	0.385

The coefficients of determination for each data group were higher than those for the entire data set. Additionally, the methods did a good job of estimating E_{Pan} values higher than 4 mm, as evidenced by the MSE and NSE values. However, the r values indicate that the methods tended to overestimate the first data group of E_{Pan}. The smallest r value for the first data group was 1.75. It was found that the estimated evaporation values from the Penman and Priestly-Taylor methods were generally close to or slightly higher than the E_{Pan} values for the second data group, with the exception of the Konya station. At the Konya station, the Priestly-Taylor method underestimated E_{Pan}, with an r value of 0.89. The comparison between E_{Pan} <4mm (E_{Pan} >4mm) and the estimated evaporation values from the Penman and Priestly-Taylor methods for the Aksaray station can be seen in Fig. 2 (Fig. 3). In general, the estimated evaporation values from each method were higher than the E_{Pan} values for the majority of the data set, as shown in Fig. 2.

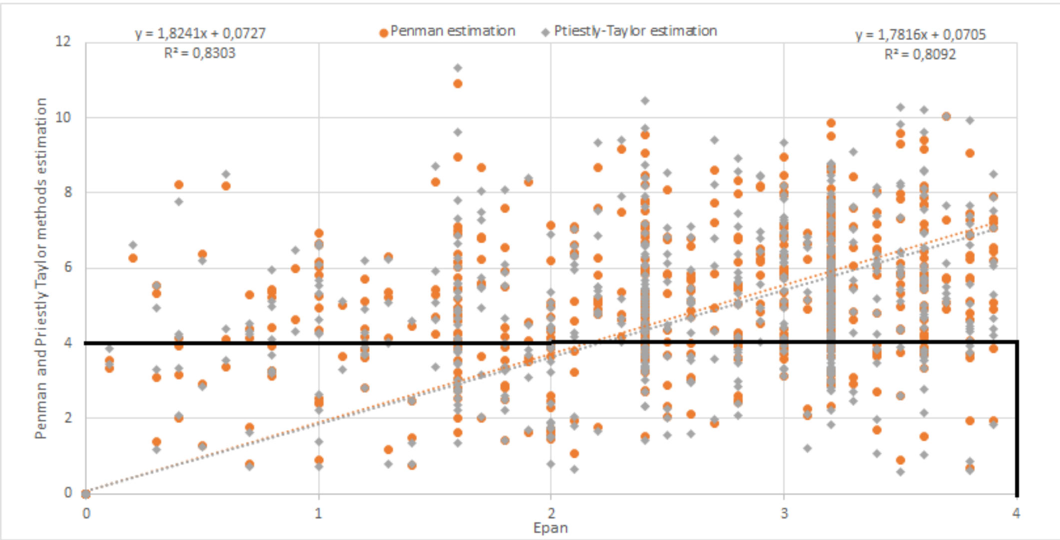

Figure 2. Comparison between E_{Pan} and estimated evaporation by Penman and Priestly-Taylor methods for Aksaray station (E_{Pan} <4mm) (The equation given in upper-left of the figure belongs to Penman method).

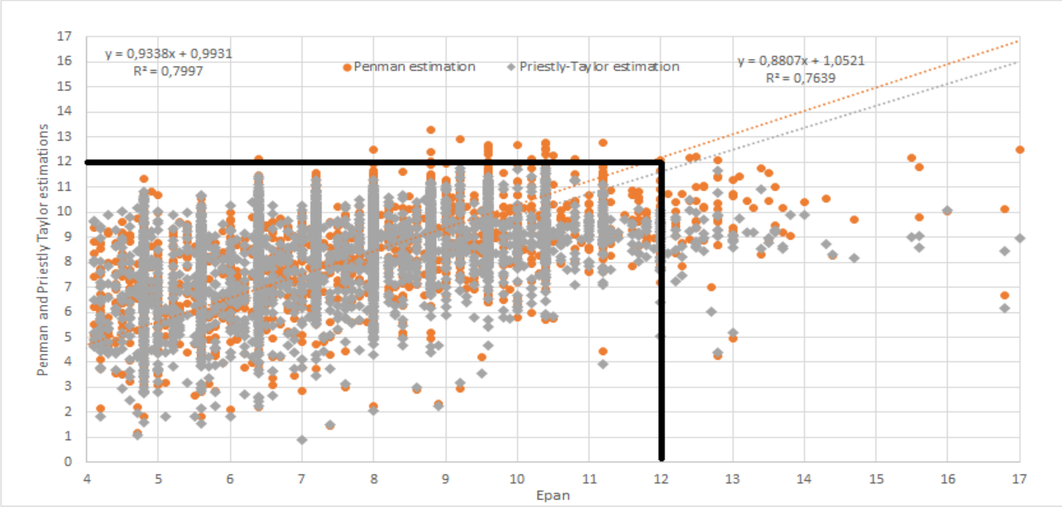

Figure 3. Comparison between E_{Pan} and estimated evaporation by Penman and Priestly-Taylor methods for Aksaray station (E_{Pan} >4mm) (The equation given in upper-left of the figure belongs to Penman method).

Fig. 3 showed that the methods followed the pattern of the measured E_{Pan} relatively well, though they either over- or under-estimate evaporation rates. As it can be seen in Fig.3, both methods failed to estimate greater than 12 mm of E_{Pan} values.

B. Determination of α Coefficient in Priestly-Taylor Method for Study Area

The performance of Priestly-Taylor method comparing with the Penman method were provided with R^2, MSE, r and NSE values for each station in Table 4.

Table 4. The performance of Priestly-Taylor method comparing with the Penman method

Stations/Performance Criteria	R^2	MSE	r	NSE
Aksaray	0.9163	0.49	0.962	0.896
Ereğli	0.9498	0.26	1.005	0.946
Karapınar	0.9439	0.26	0.984	0.940
Karaman	0.9550	0.25	0.988	0.951
Konya	0.9022	1.42	0.902	0.809

In fact, the evaporation values estimated by the Priestly-Taylor method were found to be in good agreement with Penman estimates. However, it was observed that the Priestly-Taylor method tended to underestimate the evaporation compared to the Penman method at the selected stations, with the exception of the Ereğli station (r=1.005). As a result, it was decided to determine the α coefficient for the study basin. The estimated evaporation values using the Penman method were considered as the “true” values. The data from each station were combined into one dataset in order to determine a single coefficient for the entire basin. The α coefficient was determined using three artificial intelligence optimization algorithms.

The cost function was defined as the calculation of the difference between the Penman estimations and the Priestly-Taylor estimations calibrated with new α coefficients for each algorithm:

$$\text{cost function} = \text{f(x)} = \left(\frac{\sum_{i=1}^{N}\left|E_{Penman_i} - E_{CalibratedPriestlyTaylor_i}\right|}{N}\right) \tag{18}$$

In the PSO algorithm, the number of populations and iteration number were taken as 20; the values of the c_1 and c_2 were chosen as 2 [35]. In the ABC algorithm, the both size of bee swarm and iteration number that are used in the process of the optimization are set of 20 [36]. In the DE algorithm, the size of population is set of 50; the number of iterations is equal to 20; the values of upper and lower limits are 0.8 and 0.2; the rate of crossover (CR) is 0.2 [37]. The problem solution was investigated with the written Matlab code for the selected parameters and the procedures of three optimization algorithms described in the methodology section.

All three algorithms found α value as 1.28; although the initial positions and values of the algorithms in the solution of the problem are different from each other. It was obtained that each algorithm converged to the same solution for dataset.

1) The Evaluation of Determined α Coefficient: In order to see the effect of the α coefficient determined from three artificial intelligence optimization techniques, the calibrated Priestley-Taylor (α=1,28) evaporation estimations were statistically compared with the Penman estimates. The same performance criteria were used and presented in Table 5.

Table 5. The performance of calibrated Priestly-Taylor method comparing with the Penman method

Stations/Performance Criteria	R^2	MSE	r	NSE
Aksaray	0.9163	0.44	0.977	0.908
Ereğli	0.9498	0.30	1.021	0.938
Karapınar	0.9439	0.25	1.000	0.943
Karaman	0.9550	0.26	1.003	0.950
Konya	0.9022	1.23	0.917	0.834

A significant improvement in Priestly-Taylor evaporation estimates could not be detected when comparing Tables 4 and 5. Therefore, it was concluded that the original Priestly-Taylor α coefficient can be utilized to estimate evaporation for the Konya Closed Basin. The seasonal and diurnal variability of α value was examined over a large ephemeral lake in China. At a daily scale, α was found to be 1.25 and 1.28 on average during high-water and low-water periods, respectively. The researchers also concluded that the original α value is generally applicable at daily scales [26].

IV. CONCLUSION

Daily evaporation values were estimated by using the Penman and Priestley-Taylor methods from 2000 to 2019. Although slightly higher values were estimated from the pan measurements with each method, the Penman method was found to be more consistent based on statistical indicators. The Priestley-Taylor method tended to underestimate evaporation comparing to the Penman method except for Ereğli station. This situation revealed that the coefficient obtained empirically in the Priestley-Taylor method may need to be calibrated for the study area. The α coefficient was determined to be 1.28 by PSO, ABC, and DG algorithms. The calibrated Priestley-Taylor estimations were then compared to the Penman estimations. The results showed that the α coefficient should be increased due to an increase in advected sensible heat. However, any remarkable improvement was not detected in the estimations based on the statistical evaluation. Therefore, it was concluded that the original Priestley-Taylor coefficient can be used for evaporation estimation in the Konya Closed Basin, as there are lots of unexplained mechanisms involved in the evaporation process. Further studies utilizing other methods, such as mass transfer, are highly recommended to reach a final conclusion about the α coefficient.

REFERENCES

[1] Dingman, S.L. (2008). Physical Hydrology. Long Grove, Illinois, Waveland Press, Inc., 646.
[2] Penman, H.L. (1948). Natural evaporation from open water, bare soil and grass. *Proceedings, Royal Society of London Ser. A, 193,* 120–145.
[3] Priestley, C. H. B. & Taylor, R. J. (1972). On the assessment of surface heat flux and evaporation using large-scale parameters. *Monthly Weather Review, 100 (2),* 81–92.
[4] Subedi, A. & Chavez, J.L. (2015). Crop evapotranspiration (ET) estimation models: A review and discussion of the applicability and limitations of ET methods. *Journal of Agricultural Science, 7 (6),* 50-68.
[5] Sene, K.J., Gash, J.H.C. & McNeil, D.D. (1991). Evaporation from a tropical lake: comparison of theory with direct measurements. *Journal of Hydrology, 127,* 193-217.
[6] Singh, V. P. & Xu, C.Y. (1997). Evaluation and generalization of 13 mass-transfer equations for determining free water evaporation. *Hydrological Process, 11,* 311-323.
[7] Öztürk, F. & Apaydin, H. (1998). Estimating pan evaporation from limited meteorological observations from Turkey. *Water International, 23 (3),* 184-189.
[8] Abtew, W. (2001). Evaporation estimation for lake Okeechobee in South Florida. *Journal of Irrigation and Drainage Engineering, 127 (3),* 140-147.

[9] Mosner, M.S. & Aulenbach, B.T. (2003). Comparison of methods used to estimate lake evaporation for a water budget of lake Seminole, Southwestern Georgia and Northwestern Florida. *Proceedings of the 2003 Georgia Water Resources Conference. The University of Georgia, Athens, Georgia, USA.*
[10] Sezer, Ç.Ö. & Öztekin, T. (2016). A sınıfı buharlaşma kabından olan günlük buharlaşmanın Penman ve Linacre modelleri ile tahmini. *Journal of Agricultural Faculty of Gaziosmanpasa University, 33 (3),* 137-147.
[11] Irmak, S. & Haman, D. Z. (2003). Evaluation of five methods for estimating class A pan evaporation in a humid climate. *HortTechnology, 13(3),* 500–508.
[12] Sezer, Ç.Ö., Öztekin, T. & Sezer, E.K. (2018). A-sınıfı buharlaşma kabından olan buharlaşma miktarının Penman ve Priestley-Taylor (PT) modelleri ile tahmini. *Journal of Agriculture Faculty of Ege University, 55 (4),* 379-388.
[13] Althoff, D., Rodrigues, L. N. & Silva, D. D. (2019). Evaluating evaporation methods for estimating small reservoir water surface evaporation in the Brazilian savannah. *Water, 11(9),* 1942.
[14] Jansen, F.A. & Teuling, A.J. (2020). Evaporation from a large lowland reservoir-(dis)agreement between evaporation models from hourly to decadal timescales. *Hydrology and Earth System Sciences, 24,* 1055-1072.
[15] Terzi, Ö. (2004). *Eğirdir gölü'ne ait buharlaşma modellerinin geliştirilmesi ve uygulanması.* Ph.D. thesis, University of Süleyman Demirel, Isparta, Turkey.
[16] Doğan, E., Isik, S. & Sandalci, M. (2007). Estimation of daily evaporation using Artificial Neural Networks. *Technical Journal of Turkish Chamber of Civil Engineers, 18,* 4119-4131.
[17] Dalkilic, Y., Okkan, U. & Baykan, N. (2014). Comparison of different Ann approaches in daily pan evaporation prediction. *Journal of water Resource and Protection, 6,* 319-326.
[18] Alsumaiei, A.A. (2020). Utility of artificial neural networks in modeling pan evaporation in hyper-arid climates. *Water, 12,* 1508.
[19] Jasmine, M. (2020). *A comparative study on prediction of evaporation in arid area based on artificial intelligence techniques*. Master Thesis, University of Ottowa, Canada.
[20] Üçler N. & Kutlu, F. (2021). Estimating daily pan evaporation data using adaptive neuro fuzzy inference system: Case study within Van local station-Turkey. *Journal of Polytechnics, 24(1),* 195-204.
[21] Castellvi, F., Stockle, C.O., Perez, P.J. & Ibanez, M. (2001). Comparison of methods for applying the Priestly-Taylor equation at a regional scale. *Hydrological Processes, 15,* 1609-1620.
[22] Ali, S., Ghosh, N. C. & Singh, R. (2008). Evaluating best evaporation estimate model for water surface evaporation in semi-arid region, India. *Hydrological Processes, 22,* 1093-1106.
[23] Arasteh, P. D. & Tajrishy, M. (2008). Calibrating Priestly-Taylor model to estimate open water evaporation under regional advection using volume balance method-case study: Chahnimeh reservoir, Iran. *Journal of Applied Sciences, 8 (22),* 4097-4104.
[24] Ai, Z. & Yang, Y. (2016). Modification and validation of Priestly-Taylor model for estimating cotton evapotranspiration under plastic mulch condition. *American Meteorological Society, 17,* 1281-1293.
[25] Seleshi, Y. (2018). Calibration of the Priestly-Taylor evaporation model for Ethiopia. *Journal of EEA, 36 (July),* 28-40.
[26] Gan, G., Liu, Y., Pan, X., Zhao, X., Li, M. & Wang, S. (2020). Seasonal and diurnal variations in the Priestly-Taylor coefficient for a large Ephemeral Lake. *Water, 12,* 849.
[27] Cicibiyik, A. Şarlak, N. & Üstün, D. (2020). Karaman ili hava kirliliği durumu. *KMÜ Mühendislik ve Doğa Bilimleri Dergisi, 1(1),* 59-69.
[28] Cicibiyik, A. Şarlak, N. & Üstün, D. (2022). Adjustment of the Evaporation Pan Coefficient: Case Study of Konya Closed Basin. In: Gökçekuş, H., Kassem, Y. (eds) Climate Change, Natural Resources and Sustainable Environmental Management. NRSEM 2021. Environmental Earth Sciences. 110-118, Springer, Cham.
[29] Jensen, M.E. & Allen, R.G. (2016). Evaporation, evapotranspiration and irrigation water requirements. ASCE Manuals and Reports on Engineering Practice No.70, Reston-Virginia, USA.
[30] Coşkun, A. (2007). Yapay zeka optimizasyon teknikleri: Literatür değerlendirmesi. *Fırat Üniversitesi Doğu Araştırmaları Dergisi, 5(2),* 142-146.
[31] Kennedy, J. & Eberhart, R. (1995). Particle swarm optimization. *Proceedings of ICNN'95 - International Conference on Neural Network.* 1942-1948, Perth, WA, Australia.
[32] Karaboğa, D. & Basturk, B. (2007). Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems. *IFSA 2007: Foundations of Fuzzy Logic and Soft Computing*. 789-798, Cancun.
[33] Kaya, B. & Eke, İ. (2020). Yapay arı kolonisi algoritması ile yapılan geliştirmeler ve sonuçları. *Journal of Productivity, Republic of Turkey Ministry of Industry and Technology, 1,* 99-115.
[34] Storn, R. & Price, K. (1997). Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization, 11,* 341–359.

[35] Shi, Y., & Eberhart, R.C. (1998). Parameter Selection in Particle Swarm Optimization. Lecture Notes in Computer Science, vol 1447. Springer, Berlin, Heidelberg.
[36] Fındıklı, M. A. & Kocamaz, A.F. (2018). Yapay arı koloni algoritmalarının sürü robot hedef bulma problemine uygulanması. *SETSCI Conference Indexing System, 3,* 1034-1039.
[37] Karaboğa, N. & Koyuncu, C.A. (2005). Diferansiyel gelişim algoritması kullanılarak adaptif lineer toplayıcı tasarımı. *EMO, III. Automation Symposium*. 216-220, Denizli, Turkey.