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Multi Criteria Decision Making Results Integration with Borda, Copeland, and Averaging Methods in Precise ET_0 Method Determination

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Abstract: Demand control in agriculture enhances water efficiency by optimizing resource utilization. Among the primary causes of water loss are evaporation and transpiration, making their accurate estimation crucial for effective water management. This study aims to determine the most precise potential evaporation and transpiration (ET_0) estimation method using data from 18 synoptic stations. The methods evaluated include Ivanov, Thornthwaite, Blaney-Criddle (BC), Priestley-Taylor, Makkink, Turc, and Hargreaves-Samani (HS). Two analytical approaches were employed: evaluation criteria and multi-criteria decision-making (MCDM) techniques, incorporating the Analytic Hierarchy Process (AHP), VIKOR, and Shannon entropy methods. The rankings derived from these methods were further refined through integration techniques such as averaging, Copeland, and Borda methods. Among the evaluated methods, HS and BC performed best based on evaluation criteria. The relative root mean square error (RMSE) reduction from HS to other methods was 82.92% for Ivanov, 72.45% for Thornthwaite, 39.16% for BC, 37.39% for Priestley-Taylor, 26.64% for Makkink, and 68.54% for Turc. Notably, the Shannon entropy and AHP rankings aligned, consistently placing BC and HS at the top. In integrated ranking approaches, the Copeland and Borda methods yielded identical results, with BC, HS, Makkink, and Turc achieving high rankings. Priestley-Taylor and Ivanov were ranked equally in the averaging method, whereas Thornthwaite ranked lowest. The Ivanov method consistently placed last in Copeland and Borda rankings. Considering similarity criteria values exceeding 0.8, the BC method is particularly effective in wet and semi-arid climates, while the HS method demonstrates reliability across all three climate zones studied.

Key words: Climate, evaporation and transpiration, Integration, Multi-criteria decision-making.

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Water policy is a critical global concern aimed at regulating water consumption and developing strategies to prevent the overuse and wastage of freshwater resources (Sharma *et al*., 2022). Accurate estimation of crop water consumption is essential for efficient water resource management, allowing for reduced water use, increased irrigation efficiency, and improved irrigation planning. Evapotranspiration (ET) plays a crucial role in the water cycle, significantly influencing water management strategies and crop production (Shirmohammadi-Aliakbarkhani and Saberali, 2020). ET is affected by various factors, including plant canopy characteristics, soil properties, climate conditions, and management practices. Key meteorological parameters influencing ET include solar radiation, air temperature, vapor pressure deficit, and wind speed (Allen *et al*., 1998). In semi-arid regions, where freshwater availability is often insufficient to meet evaporative demand, supplementary irrigation is necessary. ET integrates evaporation (water loss from the soil) and transpiration (water loss through plant stomata) and serves as a critical parameter for determining crop water requirements. Due to its complexity, ET estimation requires robust modeling techniques that account for climatic variables, crop characteristics, and environmental conditions (Sharma *et al*., 2022). To assess reference evapotranspiration (ET_0) - a standardized measure for irrigation planning - two broad approaches exist: direct and indirect methods. Direct methods, such as water balance approaches and lysimeters, provide high-precision measurements but are costly and impractical for large-scale applications. Indirect methods rely on empirical models based on meteorological data and are preferred due to their lower cost, shorter processing time, and ease of use (Allen *et al*., 1998). Among indirect methods, the FAO Penman-Monteith model is the most widely accepted standard for ET_0 estimation, recommended by the Food and Agriculture Organization (FAO) and the World Meteorological Organization (Allen *et al*., 2005). However, this method requires extensive meteorological data, making alternative approaches necessary in data-scarce environments. Alternative ET_0 estimation methods include empirical models and machine learning approaches. Empirical models use simplified equations based on limited meteorological parameters. Common models include Blaney-Criddle, Hargreaves-Samani, Priestley-Taylor, and Turc (Shu *et al*., 2022). Temperature-based models (e.g., Blaney-Criddle, Hargreaves-Samani) are useful when only temperature data is available, while radiation-based models (e.g., Jensen-Haise, Priestley-Taylor) are suitable when wind speed data is missing. Machine learning approaches leverage artificial intelligence to estimate ET_0 using limited meteorological data, improving accuracy through calibration and optimization (Shu *et al*., 2022). Comparative studies have evaluated the accuracy of various ET_0 models across different climatic regions. Mahdavi and ZareAbyaneh (2014) compared 12 methods in Isfahan Province and identified Penman and Kimberley-Penman as the most reliable. Almorox *et al*. (2015) evaluated 11 temperature-based models globally, concluding that Hargreaves-Samani performed best in arid, semi-arid, and temperate climates. Jarchi Eterabad and Khashei (2015) determined that the Priestley-Taylor method was the most suitable across all stations. Feng *et al*. (2017) demonstrated that calibrating the Hargreaves-Samani model significantly improved its accuracy. Hadria *et al*. (2021) assessed ET_0 estimation across 22 stations in Morocco, highlighting the need for model calibration in dry and semi-arid climates. Dai *et al*. (2022) found that the Bowen ratio energy balance method performed best among 14 reference ET models in Tibet. Given the variability in model performance across different climates, selecting an effective ET_0 estimation method is crucial. Multi-Criteria Decision-Making (MCDM) techniques facilitate optimal model selection by considering multiple performance criteria. MCDM methods have been widely applied in water resource management, including site selection for dams using Analytic Hierarchy Process (AHP) and GIS (Dai, 2016) and optimization of water distribution systems (Narayanamoorthy *et al*., 2020). A study in semi-arid Central Delhi, India, evaluated 12 temperature-based, 10 radiation-based, and 7 mass-transfer-based models using 31 years of meteorological data, ranking them using MCDM methods such as TOPSIS and entropy. The results identified Priestley-Taylor and Blaney-Criddle as the best alternatives to FAO Penman-Monteith (Rajput *et al*., 2024). Despite the potential of MCDM in ET_0 model selection, its application remains limited, and previous studies have primarily relied on a single MCDM method, which may not fully capture the complexity of model evaluation. This study aims to identify the most suitable ET_0 estimation method using Shannon entropy, VIKOR, and AHP while enhancing ranking accuracy by integrating multiple ranking techniques, including averaging, Copeland, and Borda methods. The study evaluates the performance of key empirical models, including Ivanov, Thornthwaite, Blaney-Criddle, Priestley-Taylor, Makkink, Turc, and Hargreaves-Samani, under different climatic conditions. By refining ET_0 model selection, this research contributes to more precise irrigation planning, efficient water resource management, and sustainable agricultural practices in water-limited regions.

Materials and Methods

Case study: The stations which were used to evaluate ET_0 methods performance include Ramsar (Mazandaran province), Rasht (Gilanprovince), Kerman (Kerman province), Yazd (Yazd province), Urmia, Maku, Khoy, Mahabad and Salmas (West Azerbaijan province), Tabriz, Jolfa, Ahar, Tabriz airport, Kalibar, Maragheh, Marand, Miyaneh, Sarab and Bonab (East Azerbaijan province), which their location (provinces and cities) are shown in figures 1-a and 1-b. Based on the De Martonne climate classification, the governing climate of Ramsar and Rasht is very humid (I_D>45), Kerman and Yazd are arid (I_D<10), Urmia, Tabriz, Maku, Khoy, Salmas, Mahabad, Sarab, Kalibar, Maragheh, Marand, Bonab, Tabriz-airport, Ahar, Miyaneh and Jolfa are located in semi-arid climates. The chart of effective precipitation index (PEI) in Fig. 1-c,

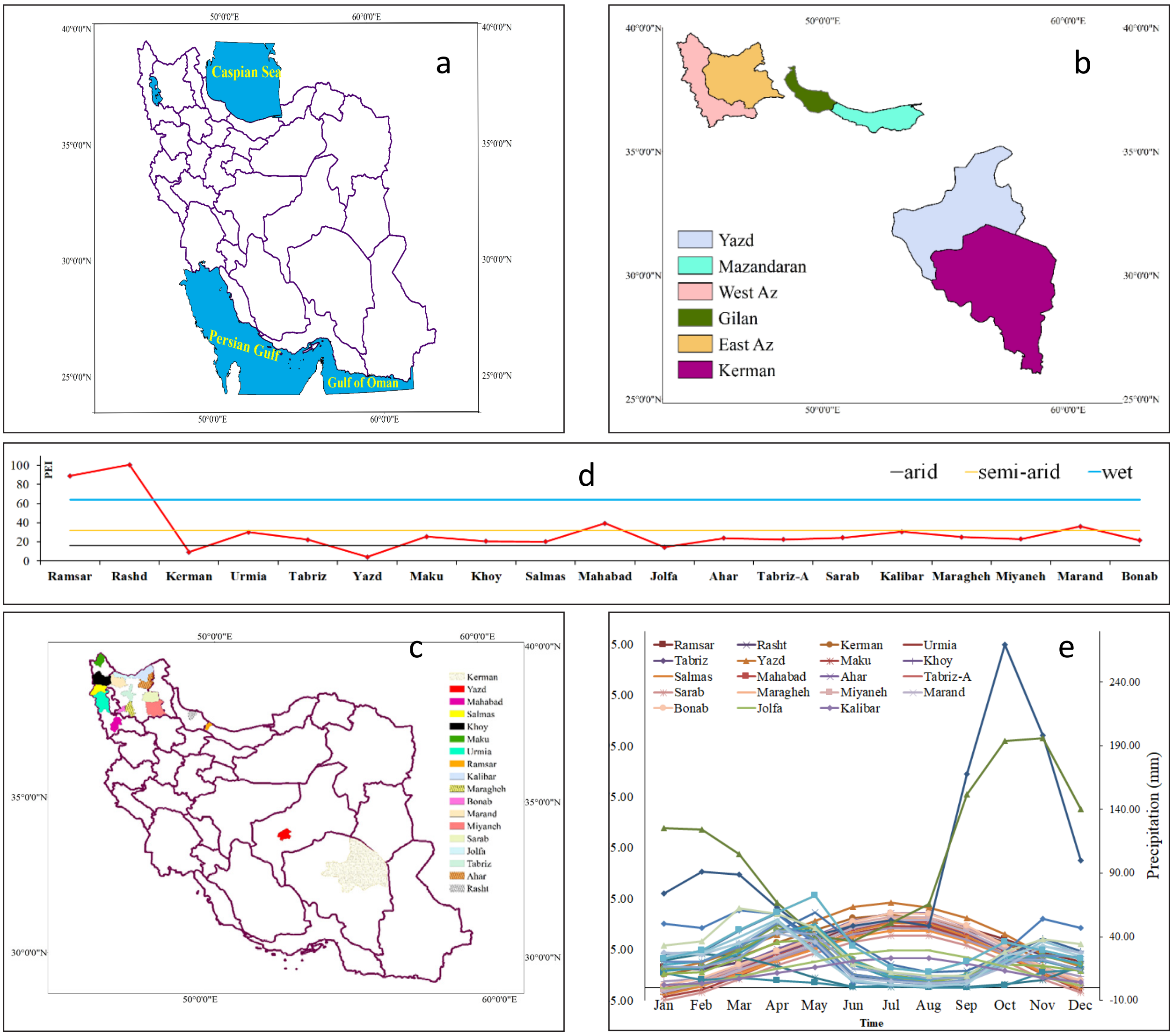

Fig. 1. The map of Iran (a), provinces (b) and cities of studied stations (c), the climate of stations based on of effective precipitation index (PEI) method (d), and Embrotermic diagram (e).

also confirms the climate of the stations based on De Martonne climate classification. In the Embrotermic diagram of Fig. 1-d, this issue is also observed in the climate of the stations, so that in the Embrotermic diagram of Rasht and Ramsar, the number of months when precipitation has increased over temperature is higher and in the stations of Yazd and Kerman, this is inverse, and in the rest of the stations, this number has an interstitial state.

ET_0 equations: ET_0 is the maximum amount of water that can be removed by soil and plant levels if not limited. There are different methods for ET_0 determining, each of which requires different data and methods. In 1948, Penman proposed a formula for ET_0, which was later used and modified by a large number of experts who took different names, such as Penman-Write, Penman-FAO, *Penman-Monteith*. The used equations (*FAO Penman-Monteith* equation 1 as the standard method, Ivanov equation 2, Thornthwaite equation 3, Hargreaves-Samani equation 4, Blaney-Criddle equation 5, Priestley-Taylor equation 6, Makkink equation 7, Turc equation 8,) of different ET_0 methods in this study, are given in equations 1-8.

$$ET_0 = \frac{0.408\Delta\,(R_n - G) + \gamma\left[\frac{890}{T+273}\right]U_2(e_a - e_d)}{\Delta + \gamma(1 + 0.34U_2)} \quad \text{... 1}$$

$$ET_0 = 0.0018(2.5 + T^2)(100 - r) \quad \text{... 2}$$

$$ET_0 = 16N_m\left(\frac{10T_m}{I}\right)^a \qquad {}_m = \left(\frac{T_m}{5}\right)^{1.51}, I = \sum_{m=1}^{12} i_m,$$
$$a = 675\times10^{-9}I^3 - 771\times10^{-7}I^2 + 675\times10^{-4}I + 0.492 \quad \text{... 3}$$

$$ET_0 = 0.0023.(T_{mean} + 17.8).(T_{max} - T_{min})^{0.5}.R_a \quad \text{... 4}$$

$$ET_0 = a + b[p(0.46T + 8.13)] \quad \text{... 5}$$
$$a = 0.0043(RH_{min}) - \frac{n}{N} - 1.41$$
$$b = 0.82 - 0.0041(RH_{min}) + 1.07\left(\frac{n}{N}\right) + 0.066(U_{day}) - 0.006(RH_{min})(U_{day})$$

$$ET_0 = 1.26\frac{\Delta}{\Delta + \gamma}\frac{R_n - G}{\lambda} \quad \text{... 6}$$

$$ET_0 = 0.611\frac{\Delta}{\Delta + \gamma}\frac{R_s}{2.45} - 0.12 \quad \text{... 7}$$

$$ET_0 = 0.013\frac{23.89R_s + 50}{T + 15} \quad \text{... 8}$$

where, T is the average monthly temperature, i_m is the monthly heat index, I is the annual heat index, N_m is the correction factor, T_{max} is the maximum daily temperature, T_{min} is the minimum daily temperature, R_a is the amount of incoming radiation at the top of the atmosphere, P it the coefficient related to the length of the day or the annual percentage of sunshine per month, RH_{min} is the minimum relative humidity, U_{day} is the wind speed, n is the sun hours, N is the maximum sun hours (Shu *et al.,* 2022; Djaman *et al.,* 2015).

To determine the appropriate method of ET_0 estimation, two approaches, including evaluation criteria and MCDM were used and the flowchart of the research is presented in Fig. 2.

***Evaluation criteria*:** To evaluate the performance of different ET_0 methods, some evaluation criteria such as Table 1, were used and the base method for comparison is the *FAO Penman-Monteith* method (Phan and Nguyen, 2020; Park *et al.,* 2017).

***Multi-criteria decision making*:** Multiple criteria decision-making (MCDM) can be generally used as the process of selecting one among a finite set of options or ranking options, based on a set of multiple criteria. In these cases, we use normalization to convert the various dimensions of the criteria into non-dimensional criteria. MCDM methods have recently been used by researchers in various fields of study such as finance, business, science, and engineering. These methods are used to evaluate, sort, rank, and select between different options. One of the main objectives of the MCDM method is to help the decision-maker understand the multiple criteria involved in the decision-making process and to manage them to select a viable option. Calculating priorities and weights based on a set of component criteria is essential. Various MCDM methods have been proposed that can address a variety of multi-criteria problems, some of which are: Elimination ET Choice Translating Reality (ELECTRE), AHP, and Analytical Network Process (ANP). Each MCDM method has advantages and limitations that make it suitable for certain situations and unsuitable for others (De Brito and Evers, 2016).

Table 1. The evaluation criteria for ET_0 methods comparison

Kling-Gupta Efficiency (KGE)	$KGE = 1 - \sqrt{(\rho - 1)^2 + (\frac{\sigma_S}{\sigma_O} - 1)^2 + (\frac{M_S}{M_O} - 1)^2}$
Similarity (SIM)	$Sim(O,S) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{1+\frac{\lvert O_i - S_i \rvert}{\max(o)-\min(o)}}$
Relative Root Mean Square Error (RRMSE)	$RRMSE = \frac{\frac{\sum_{i=1}^{N}(O_i - P_i)}{N}}{\bar{O}}$
Theil's coefficient, UII	$UII = \frac{(\sum (S_i - O_i)^2)^{0.5}}{(\sum O_i^2)^{0.5}}$
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert \frac{S_i - O_i}{O_i} \right\rvert$

O: observed values, S: simulated values, N: number of data, M: mean of data, σ:standard deviation values

***AHP (Analytic Hierarchy Process)*:** The AHP method divides the complex problems of an unstructured position into variables. Variables are organized in a hierarchical order form, providing numerical values for subjective assessment of the relative importance of variables. In addition, the evaluation is combined with the variable with the highest impact priority for the solution. AHP has been developed independently in the use of alternative comparisons regarding various criteria and weight criteria estimated using the theory of Saaty (2001). The AHP algorithm is defined as 1. Creating a pair comparison

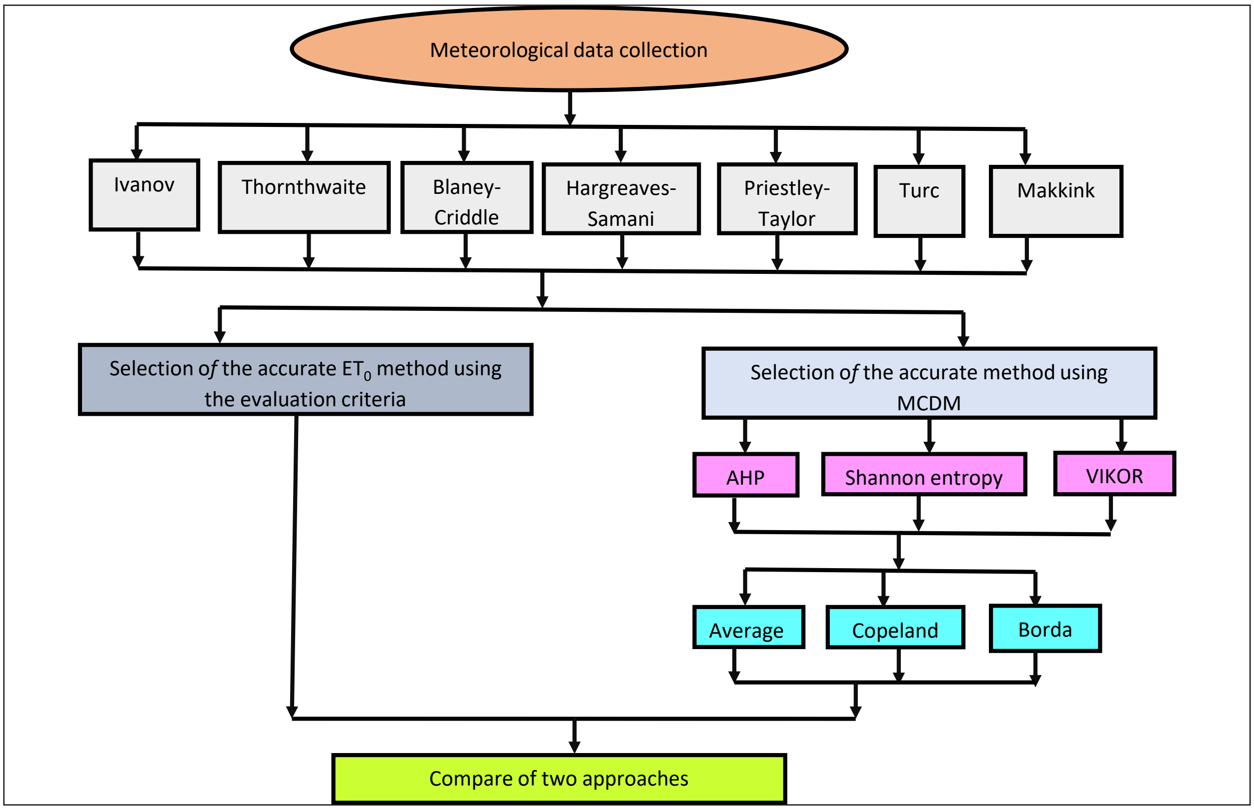

Fig. 2. The study flowchart for ET_0 methods comparison is based on two approaches.

matrix by comparing the degree of importance between criteria using the Saaty comparison scale 2. Calculating the sum of each criterion in a column of pair comparison matrix 3.Divide each column by the number of columns to create the normalized matrix, 4. Total each column in the normalized matrix calculation and divide by the number of criteria, 5. Determination of the consistency index (CI) 5- If the CI value is smaller or equal to 0.1, the process ends otherwise the dedicated weights in the decision matrix should be changed (Wibawa *et al.,* 2019).

***VIKOR*: **This method was developed in the 1990s and then published thanks to research by Opric and Tzeng 20004, a comparative analysis of VIKOR and TOPSIS methods. Similar to TOPSIS, the VIKOR method allows the evaluation of decision-making options based on their position relative to the defined reference points. The computing steps of the VIKOR algorithm are that in the first stage, the best and worst scores are determined based on the given criteria, which are so-called ideal and anti-ideal points. Then for individual decision types, the sum of weighted and normalized intervals is calculated from the ideal solution (indicators) and the maximum weighted normalized assessment distance (indicators R). The less the value of these criteria the better. In the next step, the comprehensive Q index is obtained from equation 9.

$$Q_i = \nu \frac{S_i - S^+}{S^- - S^+} + (1-\nu)\frac{R_i - R^+}{R^- - R^+} \quad \text{... 9}$$

where υ is the strong weight of most criteria, S is the S index (sum of weighted normalized distances from the ideal solution, and R_i is the R index (Maximum normalized weight distance).

In a variety of circumstances, VIKOR aims to extract an alternative to ranking results as an ideal approximate solution by providing a compromise solution. This method has advantages in compromising existing options and can solve discrete decision-making based on inconsistent and incomparable criteria (Wibawa *et al.,* 2019).

***Shannon entropy*: **Shannon entropy is a well-known method of gaining weight for a multi-attribute decision-making (MADM) problem. The steps involved normalizing the decision matrix equation 10, calculating entropy equation 11, degree of diversification calculation equation 12, and weight determination equation 13.

$$P_{ij} = \frac{x_j}{\sum_{j=1}^{m} x_j}, \; j = 1,...,m \quad i = 1,...,n \quad \text{... 10}$$

$$h_i = -h_0 \sum_{j=1}^{m} p_j \,.\mathrm{h}\; p_j \quad \text{... 11}$$

$$d_i = 1 - h_i \quad \text{... 12}$$

$$w_i = \frac{d_i}{\sum_{s=1}^{n} d_s} \quad \text{... 13}$$

where, x_{ij} is a matrix where the columns are the criteria and the rows are the options, h is the entropy, d is the degree of deviation, w is the weight criterion.

***Rank merging method*: **In a multi-criteria decision-making problem, several related methods may be used, which are not always the same. In fact, in such cases, when the results of different multi-criteria decision-making methods are not the same, the question that arises is, which option should be chosen. It is at such times that integration methods should be used above. However, three methods of averaging, Borda and Copeland are used, which are explained in an example in Table 2. In the averaging method for each option, the arithmetic average of the obtained ratings is determined using different decision-making methods.

In this method of decision-making, a couple comparison matrix is created between options. If, based on different criteria decision-making methods, the number of option preferences over the other option exceeds the number of recesses of that option over the other option in the couple comparison matrix, the number 1 is placed, and if there is no majority vote or the votes are equal, in the couple comparison matrix the number is zero. The number 1 means that the row is preferred over the column, and the number zero is the number that the column is preferred over the row. The Copland method calculates not only the number of wins but also

Table 2. Description of ranking integration methods

Mean	Method 1	Method 2	Method 3	Mean	Ranking
A_1	b_1	b_2	b_3	$(b_1+b_2+b_3)/3$	
A_2	c_1	c_2	c_3	$(c_1+c_2+c_3)/3$	
A_3	d_1	d_2	d_3	$(d_1+d_2+d_3)/3$	
A_4	k_1	k_2	k_3	$(k_1+k_2+k_3)/3$	

Copeland	A_1	A_2	A_3	A_4	Sum	Ranking
A_1	0	1	1	1	3	
A_2	0	0	1	1	2	
A_3	0	0	0	1	1	
A_4	0	0	0	0	0	

Borda	A_1	A_2	A_3	A_4	Sum		Ranking
A_1	0	1	1	1	3	3-0=3	
A_2	0	0	1	1	2	2-1=1	
A_3	0	0	0	1	1	1-2=-1	
A_4	0	0	0	0	0	0-3=-3	
Sum	0	1	2	3			

A is an alternative b, c, d, k is the ranking of some methods

the number of losses for each option. The score that Copland gives to each option is calculated by reducing the number of losses from the number of wins.

The modified Copeland method is the Borda method with the difference that in prioritizing in addition to the number of dominating (total elements of each row). The number of recesses (total elements of each column) is also used. For this purpose, options are prioritized based on the difference in the number of dominance and the number of defeats.

Results and Discussion

In this study, a variety of methods for determining ET_0 methods were used, which required a comprehensive data set including maximum temperature, minimum relative humidity. The length of the used statistical period includes 1991-2023. The Hurst coefficient was used to check the adequacy of the statistical period, which was obtained, and as a sample the Hurst coefficient for the annual temperature data is 0.72 and the wind speed of Yazd is 0.78. The value of the Hurst coefficient is greater than 0.5, which shows the adequacy of the statistical period of time series. The performance of different methods varies according to the governing structure of the equations, so the average values of ET_0 are presented in Fig. 3a. The results of comparing the performance of different methods with different statistics are presented in Fig. 3b.

Based on Fig. 3a, the maximum and minimum amount of ET_0 is related to Ivanov and Thornthwaite methods, respectively. Ivanov and Turc's methods are over-estimated compared to the Penman method, and the rest of the methods are of smaller amounts than the Penman method. In the case of comparing the performance of different methods of ET_0, the optimal states of statistics are first examined. Based on Fig.2b, a less common form of UII is related to the Hargreaves-Samani , Blaney-Criddle methods, and Makkink.The highest amount of KGE is related to Blaney-Criddle and Hargreaves-Samani , which are very similar to each other. The highest amount of SIM and the lowest value of MAP, RRMSE related to the methods of Hargreaves-Samani, Blaney-Criddle, and Makkink. In the case that the status of the statistics is not appropriate, the position of the methods is the maximum value of RRMSE, MAPE, and UIIis initially related to Ivanov and then Thornthwaite. Also, the lowest amount of KGE is related to Ivanov andThornthwaite. The lowest value of SIM is related to Ivanov, Turc, and Thornthwaite. RRMSE reduction rate from the Hargreaves-Samani method to Ivanov, Thornthwaite, Blaney-Criddle, Priestley-Taylor, Makkink, and Turc equals 82.92%, 72.45%, 39.16%, 37.39%,

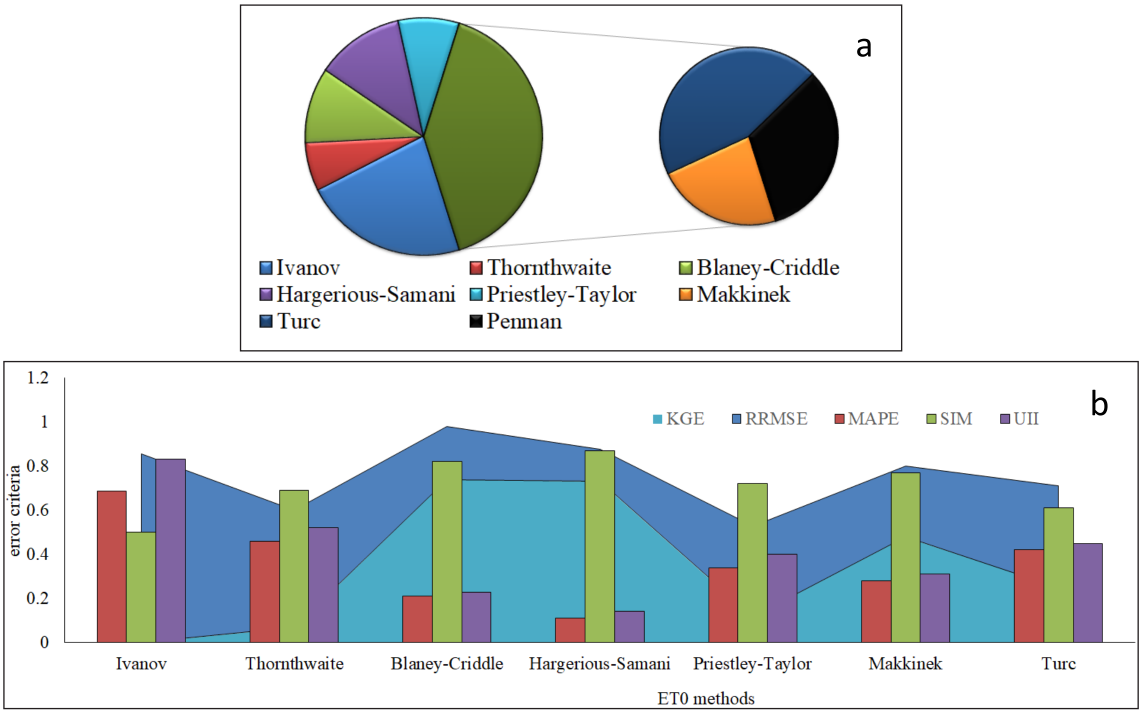

Fig. 3. The average values of ET_0 with different methods (a), comparing the performance of different methods (b).

26.64% and 68.54%, respectively.The rate of SIMincrease from Ivanov, Thornthwaite, Blaney-Criddle, Priestley-Taylor, Makkink, and Turc to Hargreaves-Samani methodsequals 74%, 26.08%, 6.09%, 20.83% 12.98%, 42.62%, respectively. In the following, to rank different methods of ET_0determining, a multi-criteria decision-making approach was used with the methods of VIKOR, AHP, and Shannon entropy, and the ratings of the methods are shown in Fig. 4. The used criteria in this approach include MAP, SIM, UII, and KGE for weighting.

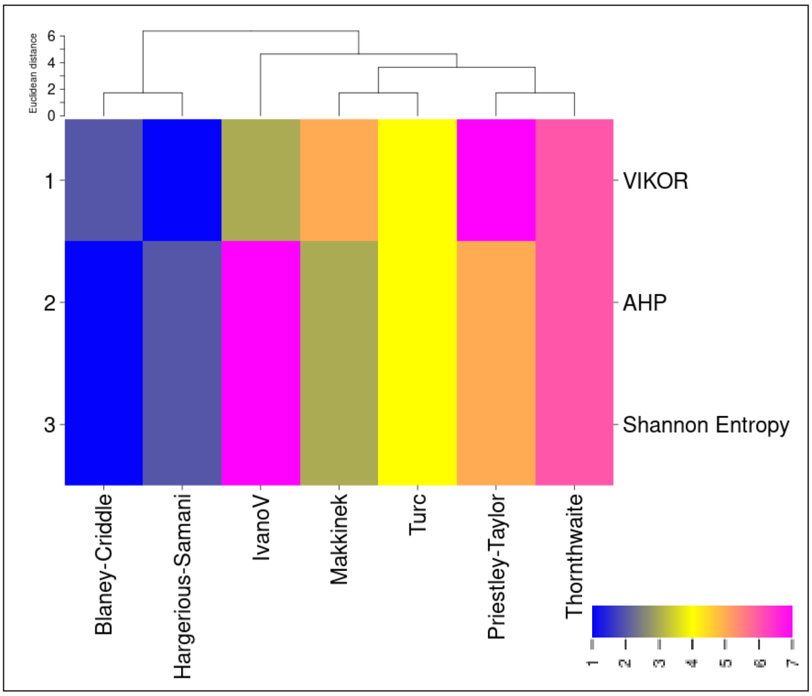

Fig. 4. The heat map for ranking the ET_0 methods based on MCDM methods.

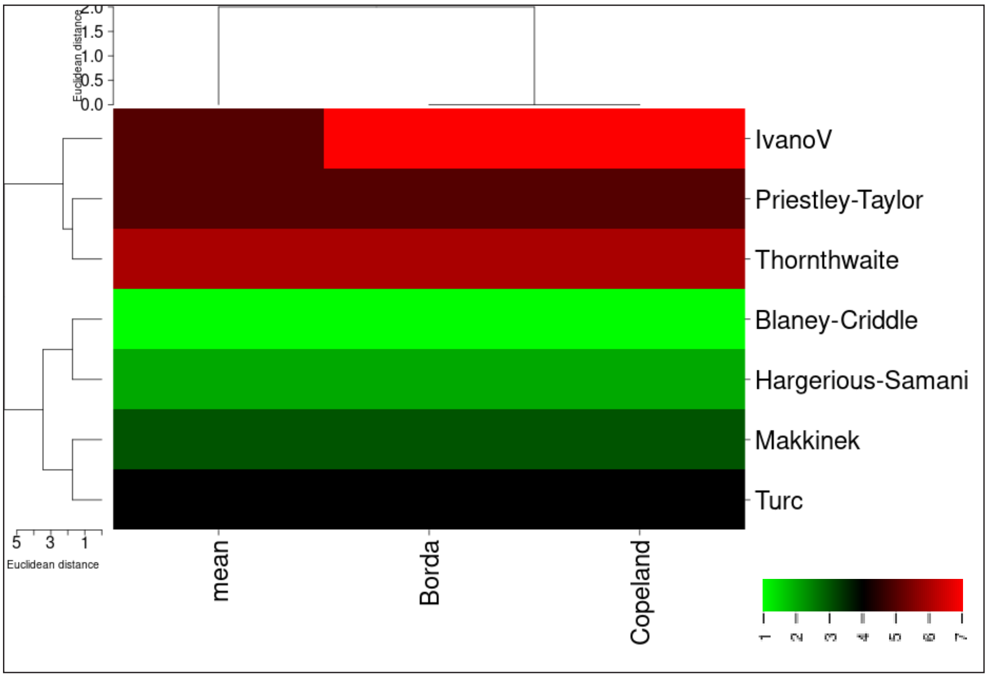

Fig. 5.The heat map for ranking the ET_0 methods based on the rank integration methods.

Based on Fig. 4, the order ratings from better to final method in Shannon entropy and AHP method is Blaney-Criddle, Hargreaves-Samani, Makkinek, Turc, Priestley-Taylor, Thornthwaite and Ivanov in VIKOR is Hargreaves-Samani, Blaney-Criddle, Ivanov, Turc, Makkink, Thornthwaite and Priestley-Taylor. In general, Blaney-Criddle and Hargreaves-Samani are in first place. According to the results of multi-criteria decision-making approaches, the results of all methods are not the same, so the rank integration mode is used, and their results are in Fig. 5.

The results of the Copland and Borda method are the same. In all methods, Blaney-Criddle, Hargreaves-Samani, Makkinek, and Turc have high ratings. In the averaging method, Priestley, Taylor, and Ivanov have the same ratings, and the Thornthwaite method is the last. In the Copland and Borda methods, the Ivanov is in the final rank. Now, based on two methods with better performance ratings, the performance of different methods in different climates is investigated and shown in Fig. 6.

Based on Fig. 6, in the Blaney-Criddle method, the ideal state of the statistics is

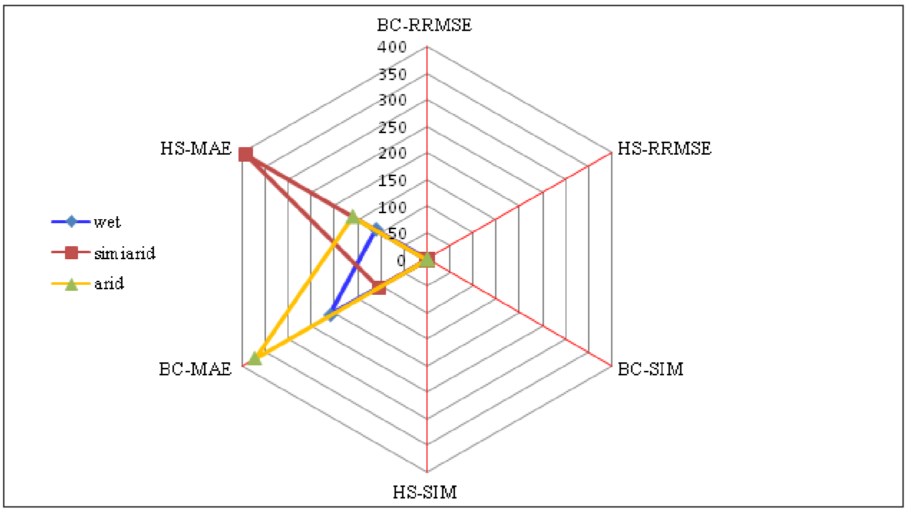

Fig. 6. Evaluation of the performance of high-efficiency ET_0 methods in different climates.

related to the semi-arid climate, so the amount of RRMSE from wet and arid to semi-arid climate is 72.6% and 78.76%, respectively, and the SIM rate increased by 5% and 38.8%, respectively. SIM values in three climates with the Hargreaves-Samani method is above 0.8, which indicates better performance of the Hargreaves-Samani method in three climates, but the closer examination of the statistics indicates that the minimum amount of RRMSE is in arid (reduction rate of RRMSE from wet climate and semi-arid to arid equals 20% and 36.84%), and minimum values of MAE is in wet (MAE reduction rate from arid and semi-arid to wet climate equals 31.17%and 71.7%), and the maximum amount of SIM is in wet climate(the rate of SIM increase from arid and semi-arid to wet climate is equal to 13.41% and 5.68%).

Considering the importance of evaporation and transpiration, the determination of the exact ET method has a dominant pattern. In ET_0 determining with mathematical equations, two factors, namely meteorological data and the type of mathematical equation, play an important role. The type of weather data in the equations can affect the results of evaporation and transpiration, for example, the reduction of correlation coefficient between temperature and ET_0 method, from Thornthwaite to Ivanov, Blaney-Criddle, Hargreaves-Samani, Priestley-Taylor, Makkink, Turc equal 51.04%, 44.79%, 75%, 26.04%, 95.83% and 98%, respectively. In addition, the correlation coefficient between wind speed and the ET_0 method in Ivanov, Blaney-Criddle, Hargreaves-Samani is equal to 0.12, 0.34, and 0.28, respectively. The type of mathematical structure is the second factor that plays an important role in the values of ET_0, which has led to the determination of different amounts of ET_0. The rate of increase in evapotranspiration values from Penman to Ivanov and Turc is 71.23%, 37.28% and the reduction rate from Penman to Thornthwaite, Blaney-Criddle, Hargreaves-Samani equals 49.38%, 21.32%, 7.58%, respectively. In this study, RRMSE, MAP, SIM, UII, and KGE statistics were used to evaluate the performance of the methods. The average statistics of RRMSE, MAP, UII (reduction mode), and UII, KGE (increasing mode) indicate that the Hargreaves-Samani, Blaney-Criddle methods are high-precision methods. The average reduction of statistics (reduction mode) from Ivanov, Thornthwaite, Blaney-Criddle, Priestley-Taylor, Makkink, Turc to Hargreaves-Samani method is equal to 83.54%, 74.17%, 42.64%, 66.08%, 57.14%, 70.67%, respectively. The highest percentage is related to the Ivanov method and the lowest is related to Blaney-Criddle. The average reduction of statistics (increasing mode) from Ivanov, Thornthwaite, Blaney-Criddle, Priestley-Taylor, Makkink, Turc to Hargreaves-Samani method is equal to 68.68%, 52.56%, 2.5%, 47.68%, 21.87% 46.25%, respectively. In this case, the highest percentage is related to the Ivanov method and the lowest is related to Blaney-Criddle. The Blany- Criddle and Hargreaves-Samani methods have little difference. In multi-criteria decision-making methods, the ranking of AHP and Shannon entropy methods is similar, and the order of better rank in the form of Blaney-Criddle, Hargreaves-Samani, Makkink, Turc, Priestley-Taylor, Thornthwaite, Ivanov. The order of the rankings in the VIKOR method includes Hargreaves-Samani, Blaney-Criddle, Ivanov, Turc, Makkink, Thornthwaite, Priestley-Taylor, respectively. In the merger of the rankings, the methods of Copland and Borda have the same results, but in general, all the methods of integration of the Blaney-Criddle and Hargreaves-Samani and Makkink methods have better ratings. Feng *et al*. (2017) proved that the calibrated Hargreaves-Samani model could estimate ET_0 reasonably compared to the original model. In a study, entropy and TOPSIS approaches were used to rank methods. The results showed that the Priestley-Taylor, Blaney-Criddle models are the most suitable alternatives to the Penman Mantith model (Rajput *et al.,* 2024). According to SIM values higher than 0.8, the Blaney-Criddle method in wet and semi-arid climates and the Hargreaves-Samani method in three climates have acceptable values. Almorox *et al.* (2015) found that the Hargreaves-Samani model performed well in arid, semi-arid, and temperate zones.

Conclusion

ET_0 determining in water resource planning, agricultural policy-making is great of importance. *FAO Penman-Monteith* equation is one of the most standard equations in this field, which requires many input data. In the meantime, choosing a suitable simplified model with optimized parameters is essential because most of these experimental models are based on simplified physical concepts or experimental statistics that define the formula range. Two factors, meteorological data and the type of mathematical equation, play an important role in determining ET_0. Two multi-criteria decision-making approaches and evaluation criteria were used to determine the appropriate method of evapotranspiration and indicate that the Hargreaves-Samani, Blaney-Criddle method is accurate. This result shows the impact of temperature data as an influential factor in evaporation and transpiration calculations. Ranking integration methods take into account all available methods to accurately determine the rank of existing methods. For example, the Shannon entropy method is considered one of the most valid methods for determining weight in multi-criteria decision-making methods, but its performance when uncertainty in input data can affect this method. The disadvantage of the VIKOR method is its initial mental weight, which is challenging to validate. One of the things that affects decision-making methods is the precise determination of weight, which in the case of integration; the weighting error becomes a headache. In the integration section, the Copland and Borda methods have high performance. According to SIM values higher than 0.8, the Blaney-Criddle method in wet and semi-arid climates and the Hargreaves-Samani method in three climates have acceptable values. Therefore, in addition to the data governing the equations, the type of mathematical equation is of great importance. Precise determination of potential evapotranspiration methods has a high impact on irrigation planning and water resources management.

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