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Investigating Performance of Different Neural Network Models and Empirical Equations in Estimating Evaporation Rate from Reservoir Free Surface

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Abstract

Evaporation is a major component of the water cycle in nature and plays an essential role in agricultural studies, hydrology, meteorology, reservoir operation, irrigation and drainage system design, irrigation scheduling, and water resources management. This study investigated various methods, including empirical equations and neural network (ANN), for four meteorological stations around Shahid Rajaei Dam in Sari during a 10-year period. The results obtained from model statistical indicators, distribution diagram, estimated daily evaporation rate and observations showed the neural network method could estimate daily evaporation at the four studied stations with good accuracy. However, the best structure of neural network models was selected for the four stations of Soleiman Tangeh, Sari office, Farim Sahra and Telamadre with seven input variables, one hidden layer and 12, 8, 10 and 12 neurons, respectively, based on MSE and R^2. Correlation coefficients of daily data at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations were obtained as 0.88, 0.91, 0.92 and 0.89, respectively. Moreover, results of monthly evaporation simulation revealed ANN could estimate monthly evaporation at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations with good accuracy by obtaining correlation coefficients of 0.98, 0.98, 0.99 and 0.99 at the confidence level of 95%, respectively. Results of evaluating the empirical equations for evaporation calculation showed Meyer's method was the best for estimating daily evaporation at the studied stations, followed by the Ivanov equation. MSE, R^2 and EF values of monthly evaporation estimation were obtained as 436.9 (mm day^{-1}), 0.97 and 0.3 at Soleiman Tangeh station, respectively, which was the closest station to Shahid Rajaei Dam using Meyer's method. Among the empirical methods used in this study, USBR was determined as the poorest equation for estimating monthly evaporation at Soleiman Tangeh station. Finally, results of daily, monthly and annual evaporation simulation indicated ANN could accurately estimate evaporation at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations with a high correlation coefficient compared to empirical equations.

1. Introduction

Estimating the evaporation rate from free water surfaces in watersheds plays an important role in quantitative and qualitative management of water resources (Chen et al., 2018). In studies of the mass balance of lakes and dam

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reservoirs, the volume of water lost to evaporation is one of the key variables in the balance equation (Wu et al., 2020). A recent study by (Ebrahimi et al., 2025) comparatively evaluated several machine learning algorithms for evaporation estimation in the Shahrood region and demonstrated that data-driven models generally outperform conventional empirical equations under different climatic conditions. Their findings further confirm the growing applicability of machine learning techniques for hydrological modeling and provide an important benchmark for the present study. Evaporation estimation is important in watershed hydrology studies, such as modeling groundwater and surface water systems (Abtew & Melesse, 2012). Also, in research on agriculture, natural resources, and water and soil conservation, knowledge of the evaporation-transpiration rate is particularly important. Neural networks and empirical equations can solve a wide range of problems and thus provide appropriate solutions to complex problems (Abed et al., 2022).

ANNs can handle both continuous and discrete variables in inputs and outputs. ANNs are mathematical and flexible models inspired by the biological nervous system and could be used for modeling complex natural phenomena (Pham et al., 2022). The ability of ANNs to identify and approximate hidden patterns among the observed data of a natural phenomenon makes it possible to use this tool in problems such as pattern identification, pattern separation, nonlinear mapping, and approximation of various functions. In the last two decades, ANNs have been widely used in various studies and sciences (M. M. Abed et al., 2010; Sudheer et al., 2002). Shirsath et al. (2008) compared daily pan evaporation estimates using ANN, linear regression, and climate-based models in New Delhi (India). Results showed the neural networks were more successful at modeling evaporation. Tabari et al. (2010) estimated daily pan evaporation using ANN and nonlinear multivariate regression in Hamadan Province. The results showed that the ANN5 model provided the best evaporation estimate. Benzaghta et al. (2012) predicted evaporation from Batu Dam reservoir in Malaysia using ANN and climate-based models (Penman and Priestley-Taylor). The results showed the ANN4 model provided the best estimate among other models, with an RMSE of 1.22 mm/day, an MBE of 1.13 mm/day, and an R^2 of 96. 0. Abou El-Magd and Ali (2012) estimated evaporative losses in Lake Nasser in Egypt using optical simulation by satellite. Compared with the Penman-Monteith method, a high correlation was obtained (R2 = 0.78), indicating the remote sensing method's high accuracy in estimating evaporative losses. Qasem et al. (2019) modeled monthly pan evaporation using wavelet support vector regression (WSVR) and wavelet artificial neural network (WANN) in arid and humid climates (Tabriz and Antalya). The results showed ANN3, with RMSE=0.701, MAE=0.525, R=0.990 and NSE=0.977, had better efficiency compared to WANN, SVR and WSVR at Tabriz station. Alsumaiei (2020) modeled pan evaporation in hyper-arid climates using ANNs in Kuwait. The results revealed the proposed ANN model was satisfactorily efficient in modeling evaporation in hyper-arid climates. Seyedi et al. (2022) investigated various combinations of eight meteorological variables as inputs to an ANN model for four meteorological stations around Shahid Rajaei Dam in Sari during a 10-year period. The results showed the neural network method could estimate daily evaporation at the four studied stations with good accuracy. Correlation coefficients of daily data at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations were obtained as 0.88, 0.91, 0.92 and 0.89, respectively. Moreover, results of monthly evaporation simulation revealed ANN could estimate monthly evaporation at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations with good accuracy by obtaining correlation coefficients of 0.98, 0.98, 0.99 and 0.99 at the confidence level of 95%, respectively.

Emamdoust et al. (2019) estimated evaporation from the free water surface in Mazandaran plain (Dazmirkandeh Abbandan) and compared it with seven empirical methods, i.e., Meyer, USBR, Shahthin, Hefner, Penman, Marciano and Ivanov. The results showed Ivanov and Shahthin methods were highly precise for determining evaporation from the free surface in this region, respectively. Wang et al. (2008) estimated water surface evaporation using a remote sensing method (MODIS satellite) in Mexico. The results indicated that the remote sensing method could properly estimate the water surface evaporation in summer and calculate transpiration and evaporation in the study area. Salami et al. (2021) investigated and analyzed the sensitivity of empirical methods in estimating evaporation from the free water surface of Choghakhor lake. The results showed that the mean Ivanov and USBR were identified as the best method for calculating monthly evaporation, and the mean Meyer and Shahthin were introduced as the best method for calculating daily evaporation. Mirmohammad Sadeghi et al. (2019) estimated evaporation from the free water surface of Zayanderud Dam using SEBAL and compared it with empirical methods, including Meyer, Marciano, Shahthin, Hefner, Ivanov, Tikhomirov and USBR. The results showed that using remote sensing techniques to calculate evaporation from the free surface is significantly more efficient than using empirical methods. Seyedi et al. (2022) estimated evaporation using data collected over 10 years at the Shahid Rajaei reservoir dam station and empirical methods of Meyer, Marciano, Shahthin, Hefner, Ivanov, and USBR. The results from the empirical evaporation equations showed that Meyer's method was the best for estimating daily evaporation at all four studied stations, followed by Ivanov. RMSE, R and EF statistics of monthly evaporation were obtained as 436.9, 0.97 and 0.3 using Meyer's method at Soleiman Tangeh station, respectively.

Therefore, given that no research has ever been conducted on estimating the evaporative loss from Shahid Rajaei Dam and considering that the evaporation rate from the large lake behind the dam is significant, the present research aims to estimate evaporation using neural network models and compare it with the evaporation rate using an empirical method at four evaporimeter stations around Shahid Rajaei Dam.

2. Material and methods

2.1. Study area

Shahid Rajaei Dam, known as Soleiman Tangeh, which is constructed on Dodangeh headwater originated from the Tajan River in Mazandaran Province, is situated on the northern slopes of the Alborz Mountains in the limestone gorge of Soleiman Tangeh between Afrachal (upstream) and Lowlet (upstream) villages and is 70 km away from Tajan crater on the shore of the Caspian Sea. Dodangeh headwater derived from the Tajan River in Mazandaran Province originates from the elevations of the Siahkoh and Trova mountains and joins to sub-branches of Sefidroud and Langaroud while flowing from the southeast to the northwest and, finally, flows into the Caspian Sea at Kordkheyl after passing through Soleiman Tangeh and joining to other sub-branches, i.e., Lajim and Chahardangeh. This dam is built 40 km south of Sari on the Tajan River to supply drinking water and meet the health, industrial, environmental, and agricultural needs of the surrounding region, and is being operated. The drainage basin area of this dam is 1,244 km^2. The dam reservoir volume is 162.3 million m^3, and its natural inflow is 231 million m3, with planned inflow of up to 212 million m^3 per year. This double-arch concrete dam has the height of 128 m from the bottom of the foundation and includes a crest with the height and width of 425 m and 5 m, respectively. The dam foundation is 16 m and its maximum water elevation is 473 m. Fig. (1) shows the location of the study area. Table 1 presents characteristics of meteorological stations in the study area. The adequacy of the data is examined using the Macus test. The results showed that the minimum number of statistical years is 9 years. Thus, the 10-year statistical period considered in this research is sufficient for analysis. Also, the normal distribution of the data, including relative humidity, minimum temperature, maximum temperature, rainfall, sunshine hours, and wind velocity, is examined using XLSTAT 2017. Results of various tests such as Shapiro-Wilk, Anderson-Darling, Lilliefors, and Jarque-Bera showed that all the data of the four studied stations are normally distributed. Therefore, parametric tests such as one-way analysis of variance (ANOVA) could be used to compare different methods.

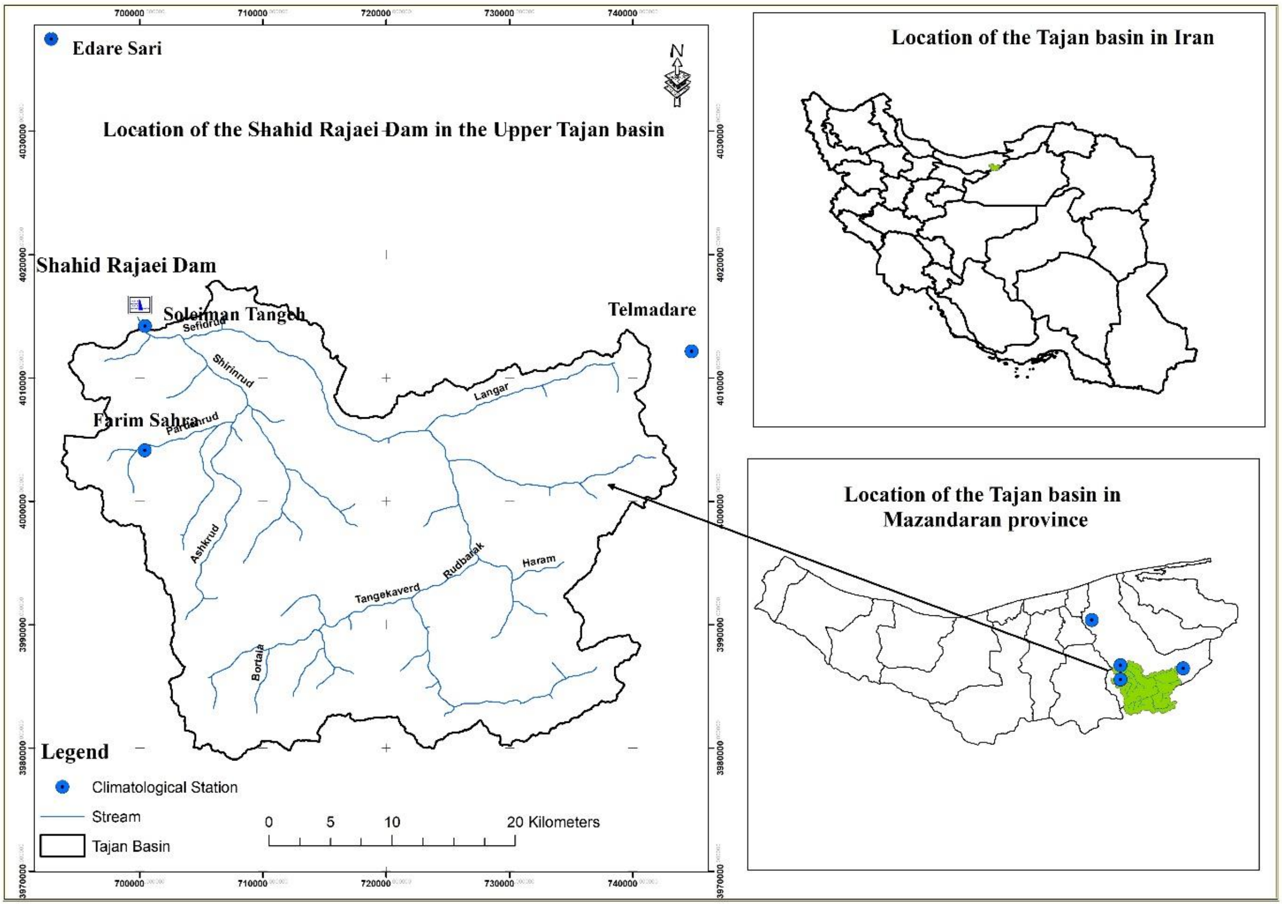

Figure 1. The study area location in the country and province.

Table 1. Characteristics of meteorological stations in the study area.

Station name	Station type	Geographical coordinates		Elevation (m)	Year of establishment	Station code
		Longitude	Latitude			
Telamadre	Evaporimeter	53° 43′ 24''	36° 13′ 24''	174	2000	351-13
Soleiman Tangeh	Evaporimeter	53° 13′ 52''	36° 15′ 8''	400	1957	019-13
Farim Sahra	Evaporimeter	53° 13′ 42''	36° 9′ 41''	860	2002	032-13
Sari office	Evaporimeter	53° 0′ 52''	36° 32′ 40''	17	1982	044-13

Table 2. Mean monthly and annual pan evaporation rate measured at Soleiman Tanghe station in a 10-year period (mm).

Annually	Sep	Aug	July	Jun	May	Apr	Mar	Feb	Jan	Dec	Nov	Oct
564.5	70.3	91.7	73.2	75.2	55.8	45.8	34.1	23.4	14.4	15.8	21.5	43.2

2.2. Research method

In this research, daily, monthly and annual evaporation rates from the surface of Shahid Rajaei reservoir are estimated during 10 water years (from water years 2005-2006 to 2014-2015) using ANN and empirical methods at four meteorological stations listed in Table 1 and compared with the values obtained from the evaporation pan. The dataset was divided chronologically rather than randomly to preserve the temporal dependency of the data. Specifically, the first 70% of the observations were used for model training, the subsequent 15% for validation (evaluation), and the final 15% for independent testing. This approach ensures that the model is trained on past observations and evaluated on future unseen data, thereby preventing information leakage and reducing potential bias in model performance assessment. More than 30 different input scenarios, consisting of combinations of 2 to 8 effective parameters, were evaluated. Some of the best ANN scenarios are shown in table 3. The results indicated that the scenario with seven input parameters (ANN2) at the four studied stations provided the best performance. Therefore, this configuration was selected as the optimal input structure and used as the basis for comparison with empirical methods.

Table 3. The input variables included in each ANN scenario.

ANN Scenario	Input Variables
ANN1	RH + Tmin + Tmax + Sunshine Duration + Wind Speed + e_s + e_a + Rainfall
ANN2	RH + Tmin + Tmax + Sunshine Duration + Wind Speed + e_s + e_a
ANN3	RH + Tmin + Tmax + Sunshine Duration + Wind Speed
ANN4	RH + Tmin + Tmax + Sunshine Duration
ANN5	RH + Tmin + Tmax
ANN6	Tmin + Tmax + Sunshine Duration + Wind Speed
ANN7	RH + Tmin + Tmax + Wind Speed
ANN8	RH + Mean Temperature + Sunshine Duration + Wind Speed

2.2.1. Neural network

In this study, a feed-forward multilayer perceptron (MLP) neural network was employed to estimate evaporation using meteorological variables including wind speed, rainfall, minimum, mean and maximum air temperature, relative humidity, actual vapor pressure, saturated vapor pressure, and sunshine duration as input variables. Measured evaporation was considered as the output variable. The MLP architecture consisted of three layers: an input layer, one hidden layer, and an output layer. The neurons in adjacent layers were fully connected through weighted links. During the training process, the network adjusted the connection weights and biases to minimize the prediction error between the observed and estimated evaporation values. A sigmoid transfer function (tansig) was used in the hidden layer, while a linear transfer function (purelin) was employed in the output layer. The network was trained using the Levenberg–Marquardt (LM) backpropagation algorithm implemented in MATLAB. To identify the optimal network architecture, the number of neurons in the hidden layer was varied from 2 to 20 and more than 30 different combinations of meteorological input variables were evaluated. The optimal number of hidden neurons was selected through a trial-and-error procedure based on the performance of the network on the validation and testing datasets.

A maximum of 1000 training epochs was specified, while the remaining training parameters were kept at MATLAB default settings. Initial weights and biases were randomly assigned by the software. The available dataset was chronologically divided into three subsets: the first 70% of the data were used for model training, the subsequent 15% for validation (evaluation), and the final 15% for independent testing. The training subset was used to update the network parameters, the validation subset was used to monitor the generalization capability of the model and prevent overfitting, and the testing subset was used for the final evaluation of model performance. The training termination was not based solely on the epoch limit. MATLAB's validation-based early stopping mechanism was employed, whereby training was automatically halted when the validation error failed to improve for several consecutive iterations, thereby reducing the risk of overfitting. The performance of models was assessed using statistical criteria including the coefficient of determination (R^2), mean squared error (MSE), and Model efficiency (EF). The final model was selected as the architecture that achieved the best overall predictive performance on the validation dataset.

2.2.1.1. Network training

MLP networks are mostly learned by the error backpropagation method, which is presented in several algorithms and forms. Levenberg-Marquardt (LM) is among the most efficient methods in the MATLAB package. This method greatly increases rate of convergence and speeds up conclusion. Tunable network parameters affecting LM network training termination include the number of iterations, performance error, training duration and maximum Mu value (used optimization algorithm indices). Accordingly, whichever happens earlier, network training will stop. However, the network error never reaches zero due to the complexity of the relationship between flow rate and sediment rate. Considering the importance of this issue, the network is not limited to time. Therefore, the number of iterations is the most important criterion for termination, which should be carefully chosen to avoid network overfitting. If Mu value reaches its maximum value during the training, the network will stop automatically.

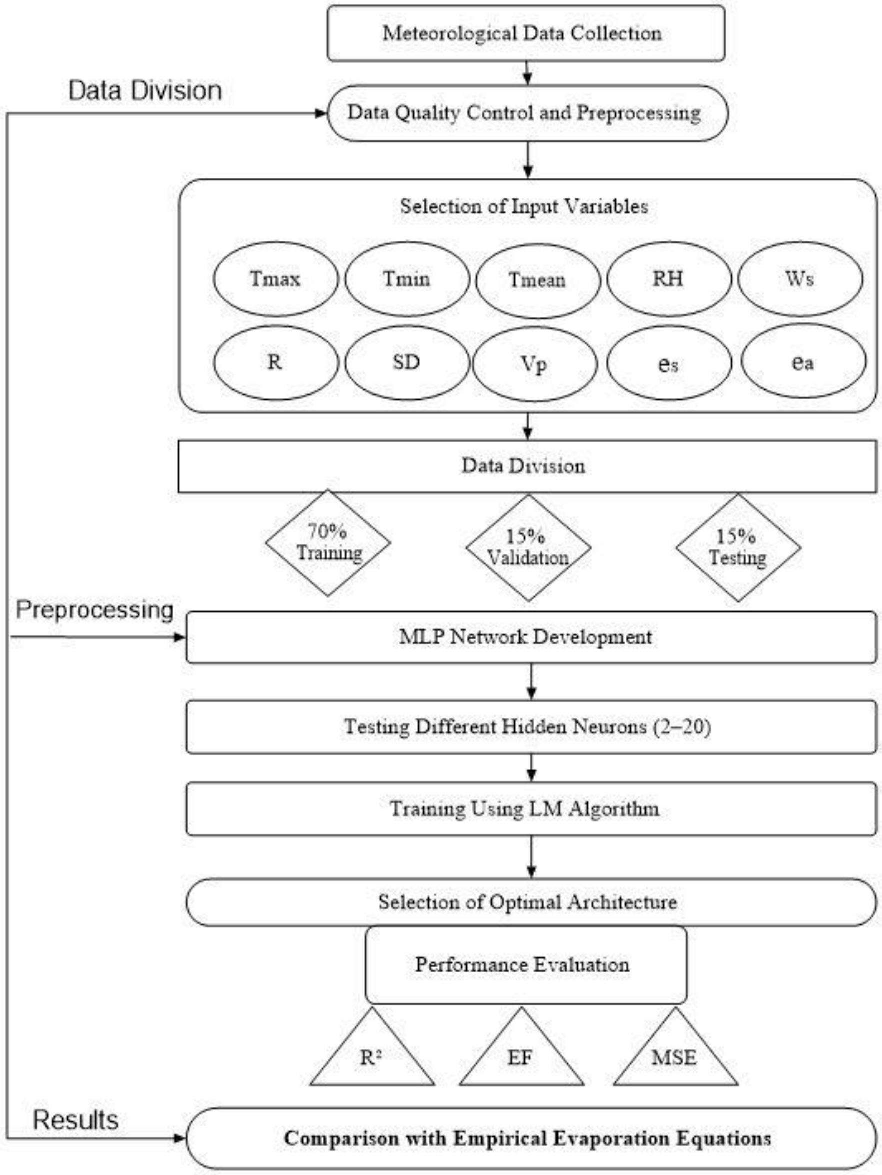

Figure 2. Flowchart summarizing the overall methodology, from data preparation to modeling and evaluation.

2.2.2.2. Network testing

Network testing is the most important step in working with the intelligent neural network, in which the simulated data are compared with the real statistics. In this way, the network adequacy is confirmed or violated. For this purpose, new data are applied to the network as the test data that are not included in network training. It could be stated that the network is properly trained if the network output corresponds to the real data. Otherwise, the network training stage is repeated by changing the network variables. In the testing phase, the trained neural network is evaluated using an independent dataset that was not involved in the training or validation processes. This step is essential for assessing the true generalization ability of the model and ensuring that the obtained results are not affected by overfitting. The performance of the ANN during testing is typically quantified using statistical indicators such as MSE, R^2, and EF, which provide complementary information about prediction error and goodness of fit. A low MSE together with a high R^2 and EF values indicates that the model can reliably reproduce the nonlinear relationship between meteorological inputs and evaporation under unseen conditions. In addition, graphical evaluation of observed versus simulated values is commonly used to visually confirm the consistency and stability of the model predictions. Overall, the testing results demonstrate the robustness and practical applicability of the proposed ANN framework for evaporation estimation in the studied region.

2.2.2. Empirical equations

Using empirical methods to estimate the evaporation rate from the free water surface of drainage basin plays an important role in the quantitative and qualitative management of water resources due to their simplicity, if the parameters are optimized. Most of the empirical methods presented to estimate evaporation are based on Dalton equation and conservation of mass principle. Thus, the evaporation rate from fresh water unit could be calculated using the mass transfer method based on Dalton's law:

$$E_{fw} = [f(u_w)]\{e_{sat}(T_{fw}) - [RH][e_{sat}(T_a)]\} \quad (1)$$

where $f(u_w)$ is the wind function and is usually empirical, RH is the relative humidity, esat(Tfw) and esat(Ta) are water vapor pressure at fresh water temperature (T_{fw}) and air temperature (T_a), respectively. In this equation, $\{e_{sat}(T_{fw}) - [RH][e_{sat}(T_a)]\}$ represents lack of saturated steam. The wind function is usually expressed as a linear function:

$$f(u_w) = C_1 + C_2 u_w \quad (2)$$

where C1 and C2 are empirical coefficients (knapp, 1985). According to the above explanations, most of the empirical equations are developed based on the described equation and conservation of mass principle.

So far, more than 50 empirical equations have been presented by different researchers to estimate evaporation and transpiration. Among these practical and simple equations (Table 4) presented to estimate evaporation from the free water surface, empirical equations of Meyer, Shahthin, Marciano and Hefner are used for daily estimation of evaporation from the free water surface, and empirical equations of Ivanov and USBR are used to calculate monthly evaporation from the free water surface. Wind velocity, relative humidity and temperature are the most important meteorological parameters involved in evaporation. The presented empirical equations reduce the evaporation estimation error considering these parameters. Each equation has been confirmed based on climatic conditions of each region, e.g., Ivanov equation has been proposed for regions with arid and semi-arid climates.

Table 4. Empirical equations for estimating evaporation rate from the free surface.

Station	Neural network input vector parameters	Network structure	MSE			R^2		
			Training	Evaluation	Testing	Training	Evaluation	Testing
Soleiman Tangeh	Relative humidity + minimum temperature + maximum temperature + sunshine hours + wind velocity + saturated vapor pressure + actual vapor pressure + rainfall	7-12-1	0.325	0.297	0.261	0.872	0.889	0.887
Sari Office		7-8-1	0.337	0.303	0.289	0.902	0.909	0.913
Farim		7-10-1	0.294	0.909	0.251	0.913	0.909	0.932
Telamadre		7-12-1	0.969	0.722	0.673	0.851	0.892	0.893

In the above-mentioned equations, E denotes the evaporation from the free water surface (mm/day), U_2 is the wind velocity at the height of 2 m above the ground (km/h), e_S and e_a represent the saturated vapor pressure and actual water vapor pressure in the air (mmHg), respectively, and C is a coefficient that is considered 0.36 and 0.5 for deep and shallow lakes, respectively. In Ivanov and USBR equations, E represents evaporation from the free water surface (mm/month), T denotes the mean air temperature (°C) and RH is the mean relative humidity (%).

2.2.3. Measuring estimation error and comparing models

In this research, to analyze the potential errors of the proposed methods and models, the following statistical measures are used in each test:

a) Mean squared error (MSE)

MSE is among the best measures for comparing and choosing the most appropriate method, to calculate which the following equation is used. A model with lower MSE is more accurate than other models (Kim and Jay, 2009).

$$MSE = \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{N} \tag{3}$$

where MSE is the mean squared error, P_i represents the values predicted by the model, O_i denotes the observed (real) values and N is the number of data in each part of the model.

b) Coefficient of determination (R^2)

This parameter is widely used in statistical comparisons and is obtained as follows:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O})\right]^2}{\sum_{i=1}^{n}(P_i - \bar{P})^2 . \sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{4}$$

where R^2 is the coefficient of determination, $\bar{P}$ is the mean values predicted by the model and $\bar{O}$ is the mean observed values. R^2 ranges from 0 to 1. Values closer to 1 indicate a better match between the model and observations (Qahraman and Sameti, 2014).

c) Model efficiency

Model efficiency indicates the accuracy of data fitting and ranges from -∞ in the worst case to 1 at the time of complete data fitting and is calculated as follows:

$$EF = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{5}$$

where EF is the model efficiency index.

3. Results and discussion

3.1. Daily evaporation

3.1.1. Results of artificial neural network (ANN) approach

Different scenarios with variables affecting evaporation were implemented to simulate evaporation at the station in question, among which ANN2 was chosen as the best scenario both in terms of MSE and correlation coefficient, so that MSE was obtained as 0.325 $(mm\ day^{-1})^2$, 0.297 $(mm\ day^{-1})^2$ and 0.261 $(mm\ day^{-1})^2$ in training, evaluation and testing stages, respectively. The lower the MSE value, the better the model could simulate the evaporation rate. In this study, MSE had the lowest value in the testing stage (0.261 $(mm\ day^{-1})^2$). R^2 value was obtained as 0.872, 0.889 and 0.887 in the training, evaluation and testing stages, respectively. The greater the R^2 value, the better the model could simulate the evaporation rate. In this study, R^2 had the largest value in the testing stage (0.887). It should be noted that input vector parameters for calculating evaporation in ANN2 network include relative humidity, minimum temperature, maximum temperature, sunshine hour, wind velocity, saturated vapor pressure and actual vapor pressure. Finally, according to MSE and R^2 of the objective function, ANN2 station was selected as the most appropriate scenario with 7-12-1 network structure.

Neural network was modeled by 12 proposed scenarios for the other three studied stations. Table 5 presents the simulation results of different neural network scenarios for the four desired stations. As presented in Table 5, the best scenario or neural model at all the four stations is the one with an input vector, consisting of seven variables of relative humidity, minimum temperature, maximum temperature, sunshine hours, wind velocity, saturated vapor pressure and actual vapor pressure. Also, the best neural model has the structure of 7-12-1, 7-8-1, 7-10-1 and 7-12-1 at Soleiman Tengeh, Sari office, Farim Sahra and Telamadre stations, respectively. The training, evaluation and testing results showed MSE was close to 0 at all four stations, indicating high estimation accuracy. Also, R^2 value at all four stations was close to 1, indicating good model simulation.

Table 5. The best input models of MLP neural network at four studied stations.

Station	Neural network input vector parameters	Network structure	MSE $(mm\ day^{-1})^2$			R^2		
			Training	Evaluation	Testing	Training	Evaluation	Testing
Soleiman Tangeh	Relative humidity + minimum temperature + maximum temperature + sunshine hours + wind velocity + saturated vapor pressure + actual vapor pressure	7-12-1	0.325	0.297	0.261	0.872	0.889	0.887
Sari Office		7-8-1	0.337	0.303	0.289	0.902	0.909	0.913
Farim		7-10-1	0.294	0.909	0.251	0.913	0.909	0.932
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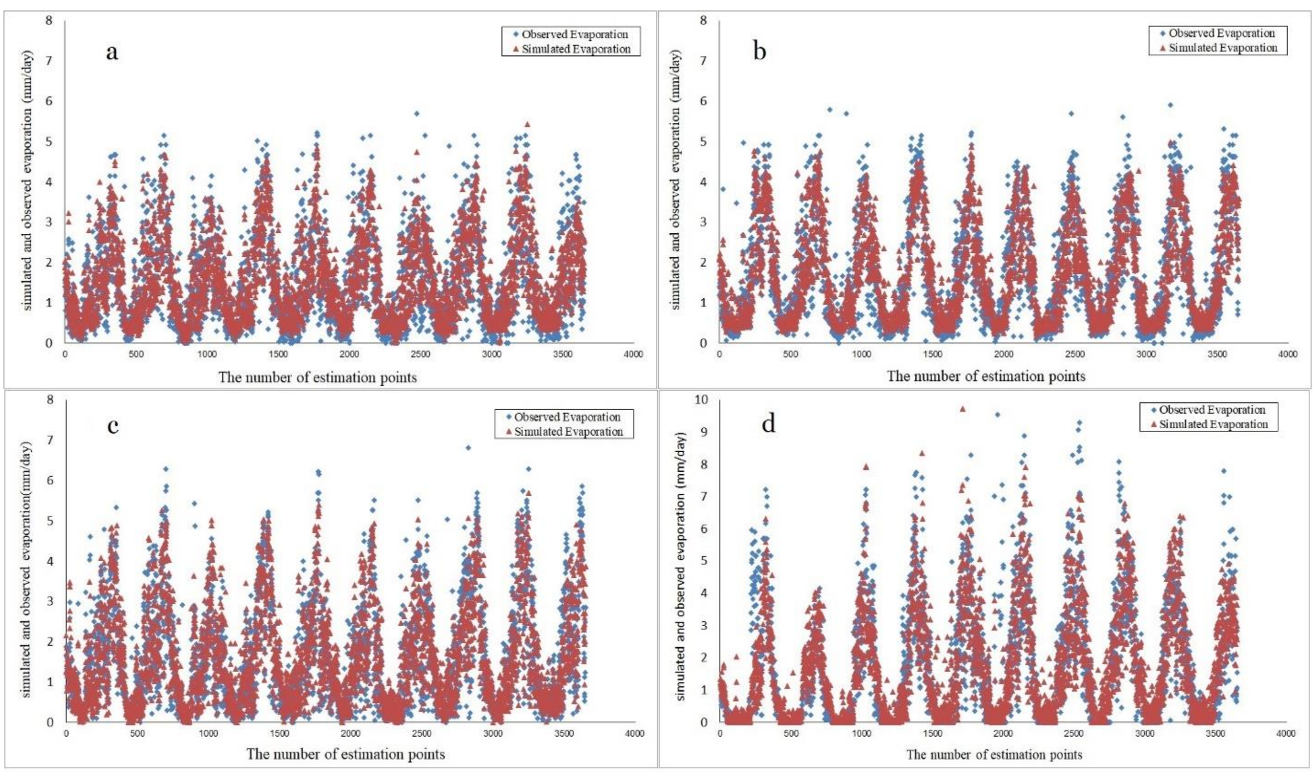

Figure 3. Illustrates distribution of observed and simulated daily evaporation data at the four studied stations.

As indicated in Fig. (3), the estimated evaporation points are very close to the observed points in most parts, indicating the selected neural model is efficient in estimating daily evaporation at all four stations.

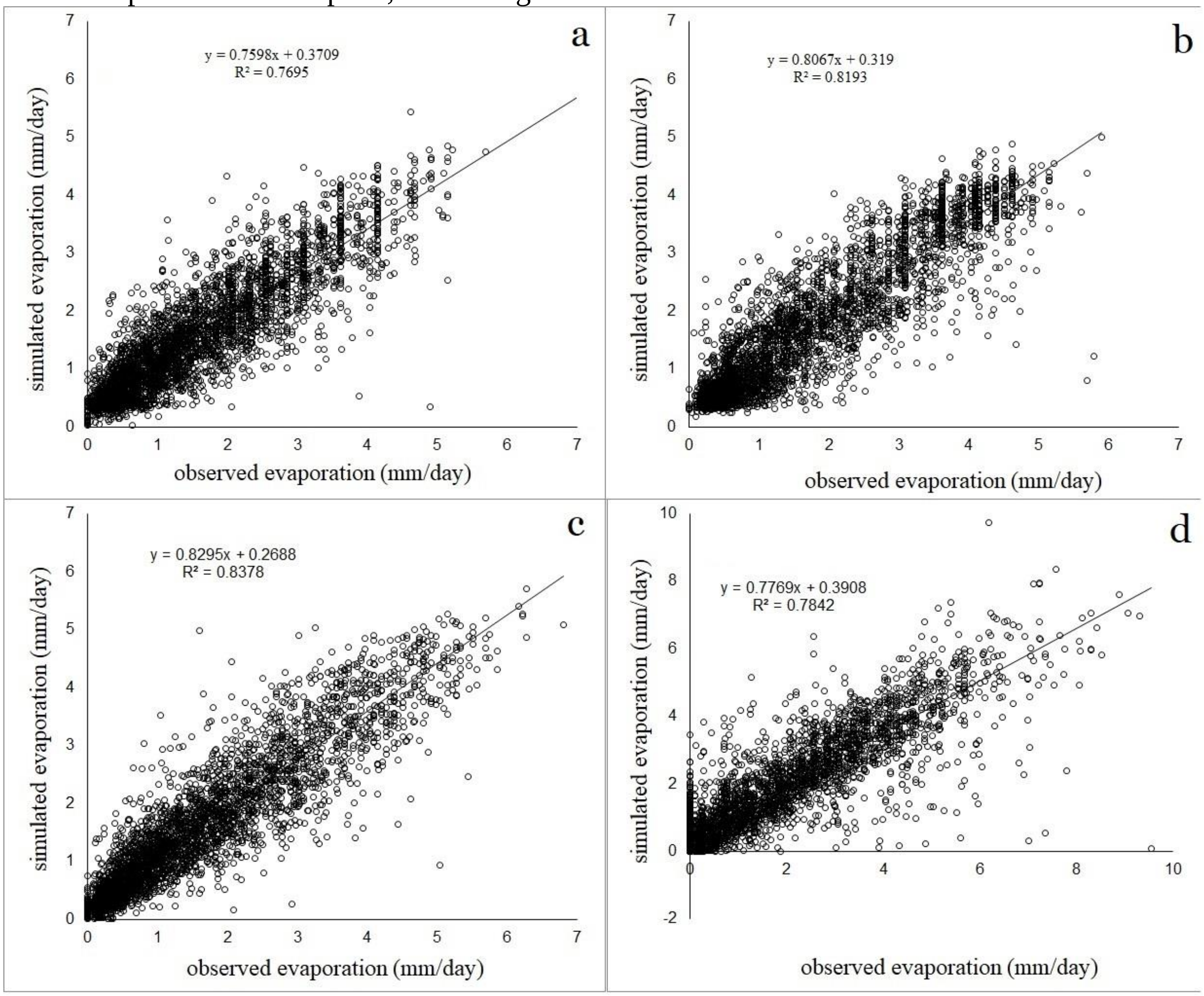

Figure 4. Illustrates correlation between observed and estimated daily evaporation rates at four studied stations.

As indicated in Fig. (4), the correlation coefficient between these two variables ranged from 0.76 to 0.84 at four stations. Farim and Soleiman Tangeh stations, with 0.84 and 0.76, respectively, had the largest and lowest correlation coefficients, respectively. Therefore, the obtained large correlation coefficients at four stations indicated ANN was efficient in estimating daily evaporation.

3.1.2. Results of empirical equations

Table 6 presents results of the measures calculated to determine daily evaporation using different empirical methods at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre. To determine the estimation accuracy and analyze potential errors of empirical methods, statistical indicators, including mean squared error, coefficient of determination and model efficiency were used. As presented in Table 6, Meyer and Ivanov methods estimated daily evaporation from the free water surface better than other empirical methods, so that Ivanov method (with input parameters of wind velocity and saturated vapor pressure deficit) had the best performance in estimating daily evaporation rate at Soleiman Tangeh station (MSE=1.00 (mm day^{-1})^2, R^2=0.78 and EF=0.26). Ivanov method (with input parameters of wind velocity and saturated vapor pressure deficit) had the best performance in estimating daily evaporation rate at Sari office station (MSE=1.36 (mm day^{-1})^2 and R^2=0.83). As presented in Table 6, Ivanov method (with input parameters of wind velocity and saturated vapor pressure deficit) had the best performance in estimating daily evaporation rate at Farim Sahra station (EF=0.1 and R^2=0.8). Ivanov method (with input parameters of wind velocity and saturated vapor pressure deficit) had the best performance in estimating daily evaporation rate at Telamadre station (MSE=2.90(mm day^{-1}), and R^2=0.81, EF=0.12).

Table 6. Statistical indices obtained from empirical methods at the studied stations are compared.

Station	Empirical methhod	MSE (mm day^{-1})^2	R^2	EF
Soleiman Tangeh	Meyer	1.00	0.78	0.26
	Marciano	2.32	0.62	-0.72
	Shahthin	2.27	0.73	-0.68
	Hefner	2.40	0.62	-0.77
	Ivanov	2.57	0.79	-0.91
	USBR	2.94	0.17	-1.18
Sari office	Meyer	1.36	0.83	0.24
	Marciano	3.02	0.68	-0.68
	Shahthin	2.97	0.79	-0.65
	Hefner	3.12	0.68	-0.73
	Ivanov	1.67	0.81	0.07
	USBR	3.82	-0.41	-1.13
Farim	Meyer	1.60	0.80	0.10
	Marciano	2.99	0.64	-0.69
	Shahthin	2.96	0.76	-0.67
	Hefner	3.07	0.64	-0.73
	Ivanov	0.76	0.76	0.57
	USBR	2.96	-0.28	-0.67
Telamadre	Meyer	2.90	0.81	0.12
	Marciano	4.50	0.69	-0.36
	Shahthin	4.46	0.78	-0.35
	Hefner	4.58	0.69	-0.38
	Ivanov	2.90	0.69	0.12
	USBR	4.06	-0.01	-0.23

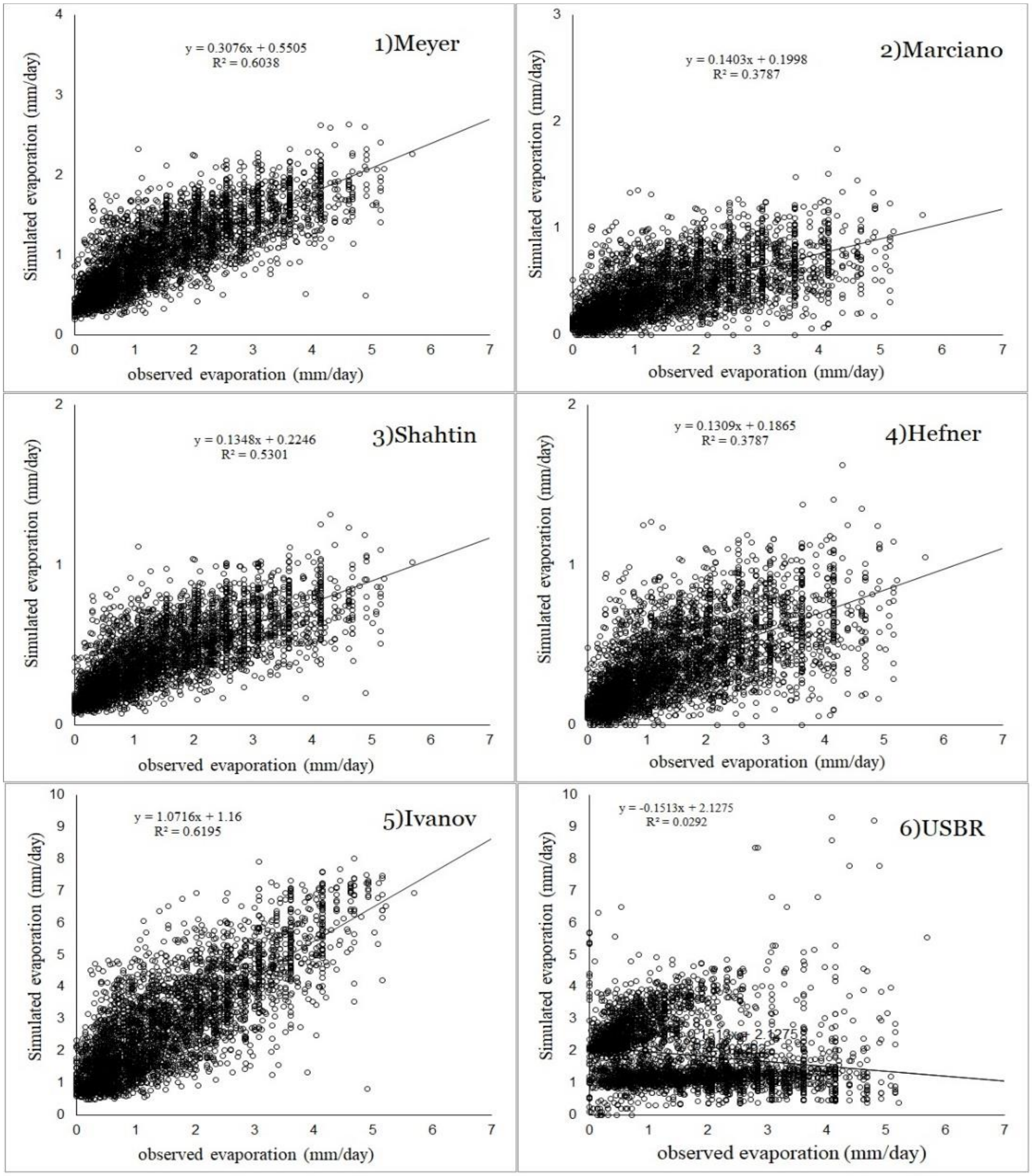

Figure 5. Distribution of observed and estimated daily evaporation data around the line by the studied empirical methods at Soleiman Tangeh station.

A logarithmic diagram was used to better observe data distribution. As indicated in Fig. (5), data distribution around the line in Meyer’s method is less than other empirical methods. It seems that this model estimated daily evaporation better than other methods.

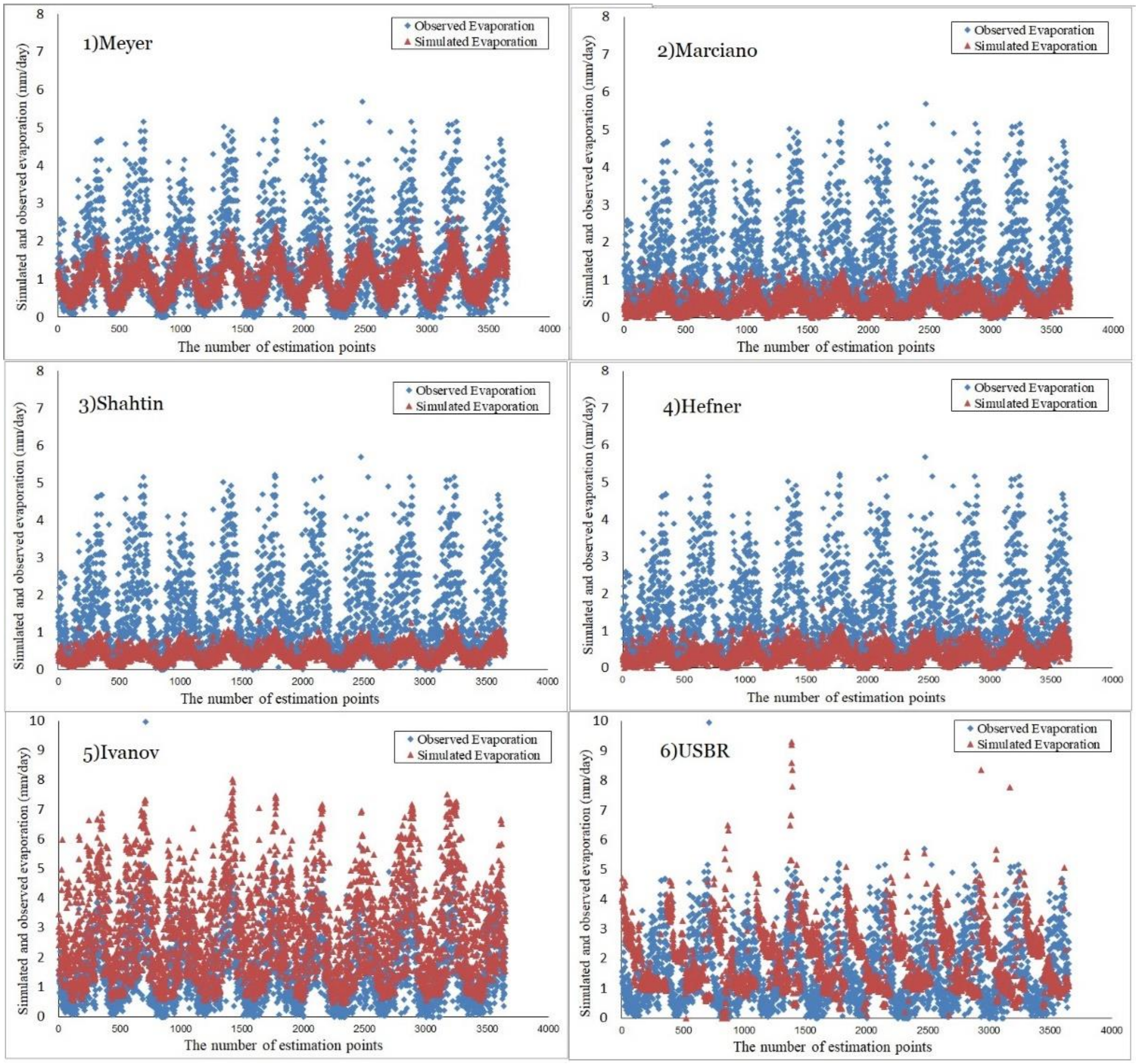

Figure 6. Distribution of simulated and observed daily evaporation points using empirical methods at Soleiman Tangeh station.

Mayer's method estimated daily evaporation almost in the same range of the observed daily evaporation and performed better than other methods. As indicated in Fig. (6), Marciano, Shahthin and Hefner methods estimated less than the actual evaporation rates from the free surface. However, Ivanov method estimated more than the actual evaporation rate from the free surface, which could be due to the nature of the parameters used in Ivanov equation, i.e., relative humidity and temperature are used to calculate daily evaporation. Almost no significant correlation was found for USBR at the studied station.

3.1.3. Comparing results of empirical equations and artificial neural network in estimating daily evaporation

To choose the best model for estimating daily evaporation at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations, MSE, R and EF were used, the results of which are provided in Table 7. The statistical indices of empirical methods and neural network were calculated at these four stations and compared with daily pan evaporation. Among different methods used to estimate daily evaporation at Soleiman Tangeh station, ANN was determined as the best simulation model, which obtained the most optimal value with MSE, R and EF of 0.31(mm day^{-1})^2, 0.88 and 0.77, respectively. Among empirical methods, Meyer's method was identified as the best method for calculating daily evaporation based on the studied measures. However, according to the distribution of the simulated and observed data when the evaporation rate is significant, calculations should be done more accurately. As indicated in Table 7, MSE, R and EF values were obtained as 1 (mm day^{-1})^2, 0.78 and 0.26, respectively.

Among different methods used to estimate daily evaporation at Sari office station, ANN was identified as the best simulation model, which obtained the lowest value with MSE, R and EF of 0.33 (mm day^{-1})^2, 0.91 and 0.82, respectively. Among empirical methods, Meyer's method was determined as the best method for calculating daily evaporation based on the studied measures. As presented in Table 7, MSE, R and EF values were obtained as 1.36 (mm day^{-1})^2, 0.83 and 0.24, respectively.

At Farim Sahra station, ANN was identified as the best simulation model for estimating daily evaporation, which obtained the lowest value with MSE, R and EF of 0.29 (mm day^{-1})^2, 0.92 and 0.84, respectively. Among empirical methods, Meyer's method was determined as the best method for calculating daily evaporation based on the studied measures. As presented in Table 7, MSE, R and EF values were obtained as 1.6 (mm day^{-1})^2, 0.80 and 0.1, respectively.

At Telamadre station, ANN was identified as the best simulation model for estimating daily evaporation, which obtained the lowest value with MSE, R and EF of 0.72 (mm day^{-1})^2, 0.89 and 0.78, respectively. Among empirical methods, Meyer's method was determined as the best method for calculating daily evaporation based on the studied measures. As presented in Table 7, MSE, R and EF values were obtained as 2.90 (mm day^{-1})^2, 0.81 and 0.12, respectively.

Therefore, ANN was the best method at all four stations. Among the empirical methods, Meyer and Ivanov estimated daily evaporation from the free water surface better than other empirical methods.

Table 7. Statistical indices obtained from empirical methods at four stations compared to daily pan evaporation.

Station	Empirical method	MSE (mm day^{-1})^2	R^2	EF
Soleiman Tangeh	Meyer	1.00	0.78	0.26
	Neural network	0.31	0.88	0.77
Sari office	Meyer	1.36	0.83	0.24
	Neural network	0.33	0.91	0.82
Farim	Meyer	1.60	0.80	0.10
	Neural network	0.29	0.92	0.84
Telamadre	Meyer	2.90	0.81	0.12
	Neural network	0.72	0.89	0.78

3.2. Monthly evaporation

In this section, the statistical indicators of monthly evaporation from the free water surface obtained by empirical methods and neural network are compared to pan evaporation (actual evaporation) and the corresponding comparative graph is provided considering four stations.

3.2.1. Comparing results of empirical equations and artificial neural network in estimating monthly evaporation at the four studied stations

3.2.1.1. Results of monthly evaporation at Soleiman Tangeh station

The best model for estimating monthly evaporation at Soleiman Tangeh station was determined using MSE, R and EF. The statistical indices obtained from empirical methods and neural network at these four stations were calculated and compared to the monthly pan evaporation. Among different methods used to estimate daily evaporation at all the four stations, ANN was identified as the best simulation model, which obtained the most optimal value with MSE, R and EF of 0.24.2 (mm day^{-1})^2, 0.98 and 0.96, respectively. Among empirical methods, Meyer's method was determined as the best method for calculating monthly evaporation based on the studied measures. As presented in Table 8, MSE, R and EF values were obtained as 436.9 (mm day^{-1})^2, 0.97 and 0.30, respectively. Among the methods used in this study, USBR was identified as the poorest equation for estimating monthly evaporation, the results of which are presented in Table 8.

Table 8. Statistical indices obtained from empirical methods at Soleiman Tangeh station compared to monthly pan evaporation.

Station	Empirical method	MSE(mm day^{-1})^2	R	EF
Soleiman Tangeh	Meyer	436.9	0.97	0.30
	Marciano	1556.7	0.99	-1.50
	Shahthin	1543.8	0.98	-1.46
	Hefner	1639.7	0.99	-1.62
	Ivanov	1539.7	0.97	-1.46
	USBR	1920.2	-0.58	-2.06
	ANN	24.2	0.98	0.96

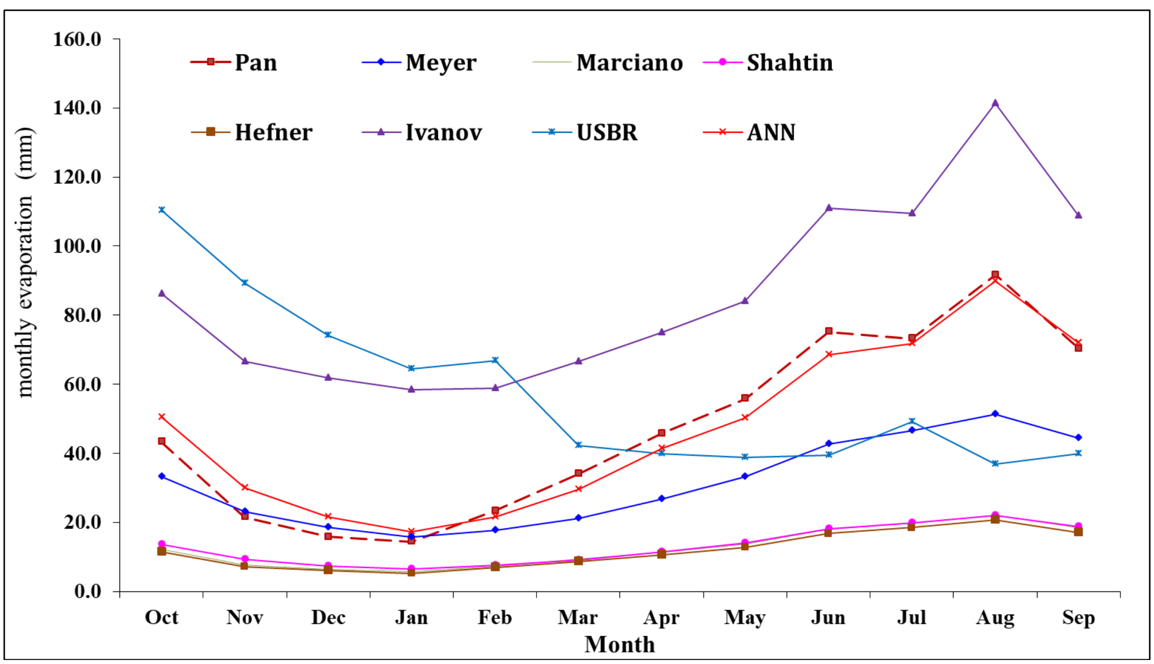

Figure 7. Comparing the observed and estimated monthly evaporation changes at the studied station.

Similar to daily evaporation results, the empirical equations simulated the monthly evaporation rate in summer less than the reality. In Meyer's method, this difference was less than other methods. Comparing the estimated monthly evaporation rate with the simulated evaporation by ANN showed the power and superiority of this method compared to other methods. Results of other studies confirm the accuracy of findings of the present work.

3.2.1.2. Results of monthly evaporation at Sari office station

At Sari office station, ANN was identified as the best simulation model for estimating monthly evaporation, which obtained the most optimal value with MSE, R and EF of 50.5 (mm day^{-1})^2, 0.98 and 0.96, respectively. Among empirical methods, Meyer's method was determined as the best method for calculating monthly evaporation based on the studied measures. As presented in Table 9, MSE, R and EF values were obtained as 844.9.9(mm day^{-1})^2, 0.98 and 0.28, respectively. Among the methods used in this study, USBR was identified as the poorest equation for estimating daily evaporation, the results of which are presented in Table 9.

Table 9. Statistical indices obtained from empirical methods at Sari office station compared to monthly pan evaporation.

Station	Empirical method	MSE (mm day^{-1})^2	R	EF
Sari office	Meyer	844.9	0.98	0.28
	Marciano	2322.4	0.99	-0.97
	Shahthin	2294.7	0.98	-0.95
	Hefner	2413.9	0.99	-1.05
	Ivanov	917.1	0.96	0.22
	USBR	2731.1	-0.572	-1.32
	ANN	50.5	0.98	0.96

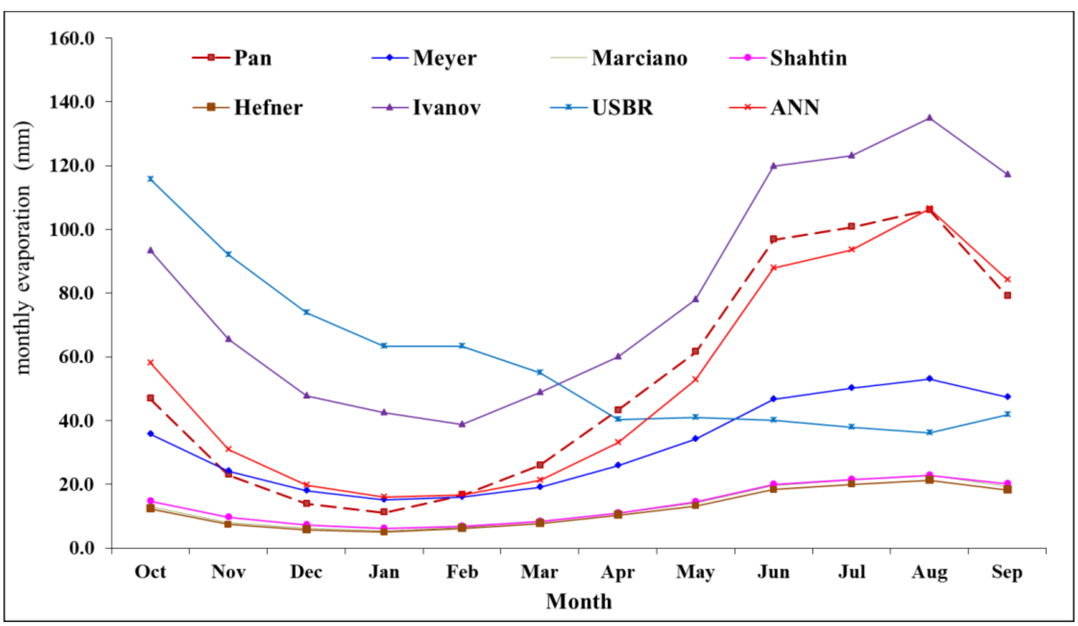

Figure 8. Comparing the observed and estimated monthly evaporation changes at the studied station.

Similar to daily evaporation results, the empirical equations simulated the monthly evaporation rate in summer months less than the reality. In Meyer's method, this difference was less than other methods. Comparing the estimated monthly evaporation rate with the simulated evaporation by ANN showed the power and superiority of this method compared to other methods. Results of other studies confirm the accuracy of our findings.

3.2.1.3. Results of monthly evaporation at Farim Sahra station

At Farim Sahra station, ANN was identified as the best simulation model for estimating monthly evaporation. ANN obtained the most optimal value with MSE, R and EF of 23.2 (mm day^{-1})^2, 0.99 and 0.97, respectively, which had the lowest value among the stations. Among empirical methods, Ivanov was determined as the best method for calculating monthly evaporation based on the studied measures. As presented in Table 10, MSE, R and EF values were obtained as 253.0 (mm day^{-1})^2, 0.98 and 0.71, respectively. Among the methods used in this study, USBR was identified as the poorest equation for estimating monthly evaporation, the results of which are presented in Table 10.

Table 10. Statistical indices obtained from empirical methods at Farim Sahra station compared to monthly pan evaporation.

Station	Empirical method	MSE (mm day^{-1})^2	R	EF
Farim Sahra	Meyer	848.7	0.98	0.02
	Marciano	2049.7	0.99	-1.38
	Shahthin	2027.6	0.98	-1.45
	Hefner	2121.3	0.99	-1.46
	Ivanov	253.0	0.98	0.71
	USBR	1828.3	-0.49	-1.12
	ANN	23.2	0.99	0.97

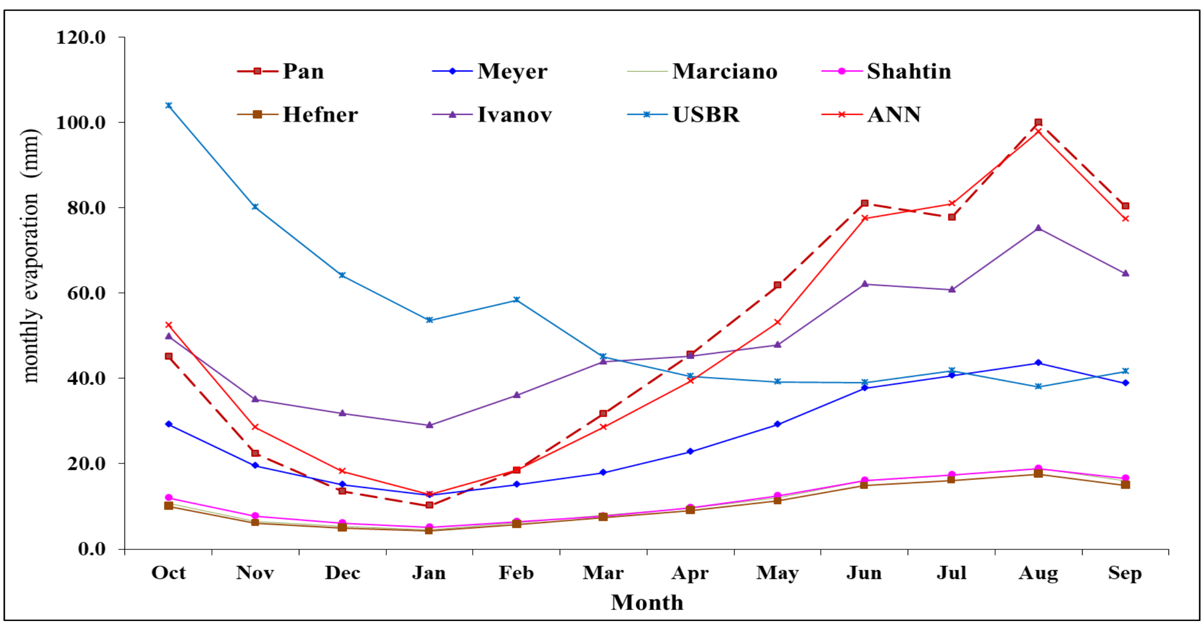

Figure 9. Comparing the observed and estimated monthly evaporation changes at the studied station.

Similar to daily evaporation results, the empirical equations simulated the monthly evaporation rate in summer less than the reality. In Meyer's method, this difference was less than other methods. Comparing the estimated monthly evaporation rate with the simulated evaporation by ANN showed the power and superiority of this method compared to other methods. Results of other studies confirm the accuracy of our findings.

3.2.4.1. Results of monthly evaporation at Telamadre station

At Telamadre station, ANN was identified as the best simulation model for estimating monthly evaporation. ANN obtained the most optimal value with MSE, R and EF of 32.7 (mm day^{-1})^2, 0.99 and 0.98, respectively, which had the lowest value among the stations. Among empirical methods, Ivanov was determined as the best method for calculating monthly evaporation based on the studied measures. As presented in Table 11, MSE, R and EF values were obtained as 930.7 (mm day^{-1})^2, 0.99 and 0.52, respectively. Among the methods used in this study, USBR was identified as the poorest equation for estimating monthly evaporation, the results of which are presented in Table 11.

Table 11. Statistical indices obtained from empirical methods at Telamadre station compared to monthly pan evaporation.

Station	Empirical method	MSE(mm day^{-1})^2	R	EF
	Meyer	1695.4	0.99	0.12
	Marciano	3083.2	0.99	-0.60
	Shahthin	3063.5	0.99	-0.59
Telamadre	Hefner	3162.2	0.99	-0.64
	Ivanov	930.7	0.99	0.52
	USBR	2468.0	-0.13	-0.28
	ANN	32.7	0.99	0.98

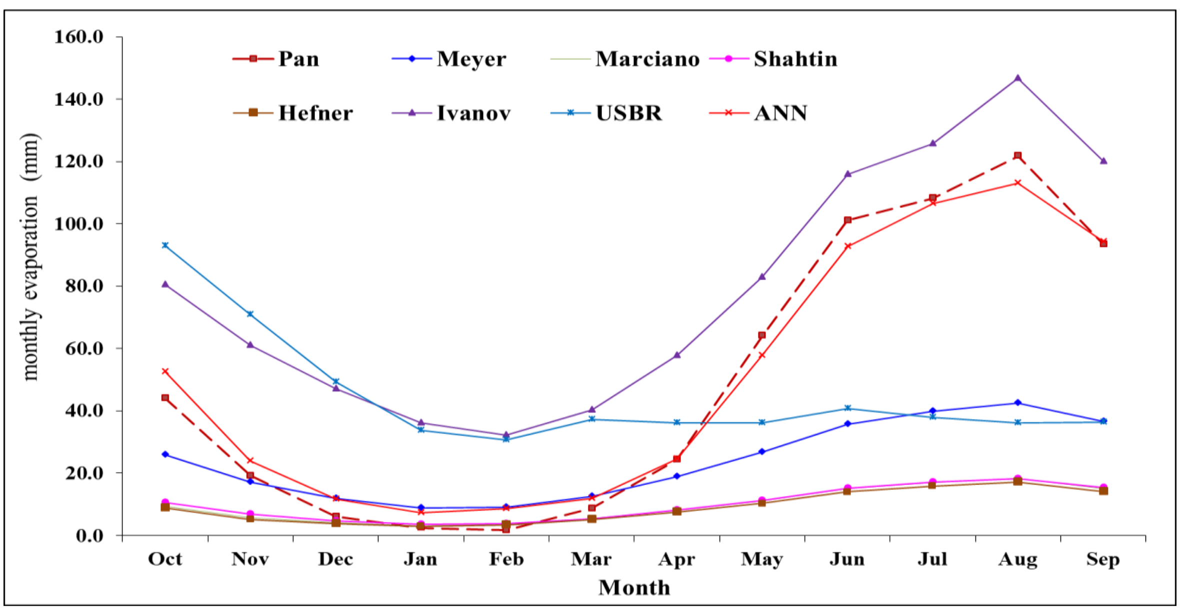

Figure 10. Comparing the observed and estimated monthly evaporation changes at the studied station.

Similar to daily evaporation results, the empirical equations simulated the monthly evaporation rate in summer less than the reality. In Meyer's method, this difference was less than other methods. Comparing the estimated monthly evaporation rate with the simulated evaporation by ANN showed the power and superiority of this method compared to other methods. Results of other studies confirm the accuracy of our findings.

3.3. Comparing results of empirical equations and artificial neural network in estimating annual evaporation at four studied stations

In this section, the comparison of empirical methods and neural network is discussed to estimate the annual evaporation at the four studied stations in a 10-year period.

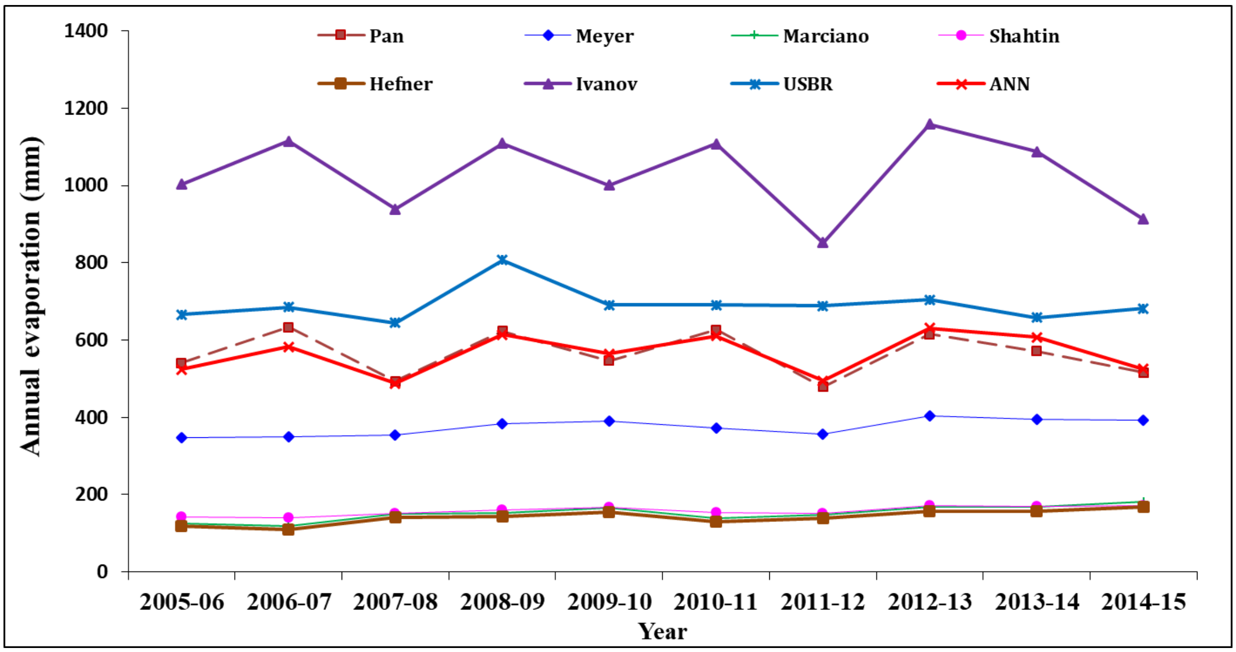

Figure 11. Comparing empirical methods and neural network to estimate the annual evaporation at Soleiman Tangeh station in a 10-year period.

As indicated, ANN and Ivanov method are the best and poorest model for simulating evaporation at Soleiman Tangeh station, respectively.However, "Ivanov" and "Hefner, Shahthin and Marciano" methods estimated evaporation rate significantly more and less than the real value, respectively.

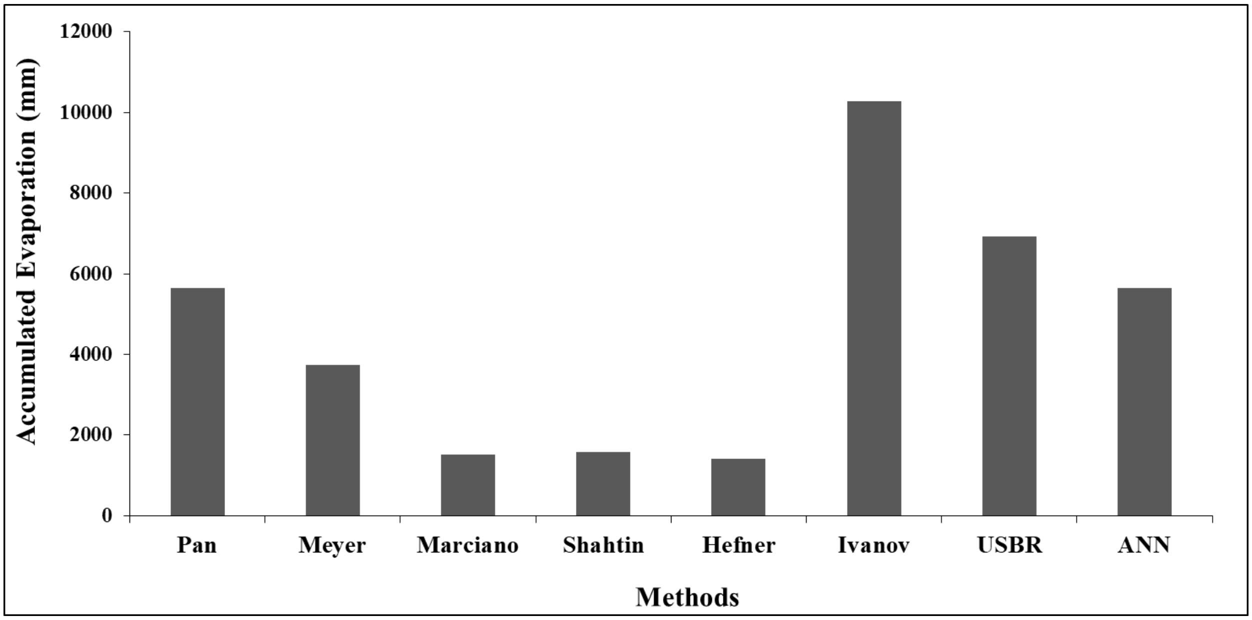

Figure 12. Comparing the mean estimated and observed annual evaporation rates by different methods at Soleiman Tangeh station.

ANN was identified as the best model and Ivanov and Hefner were determined as the poorest models for simulating the annual evaporation at Sari office station.

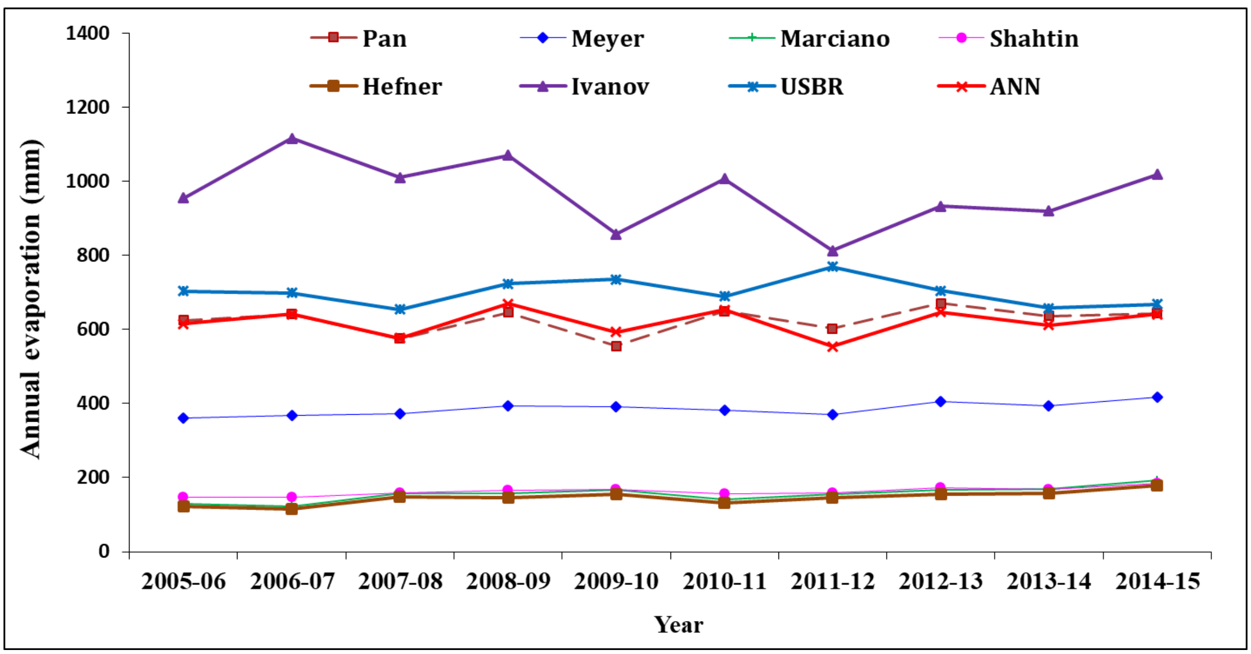

Figure 13. Comparing the estimated and observed evaporation estimation methods at Sari office station in a 10-year period.

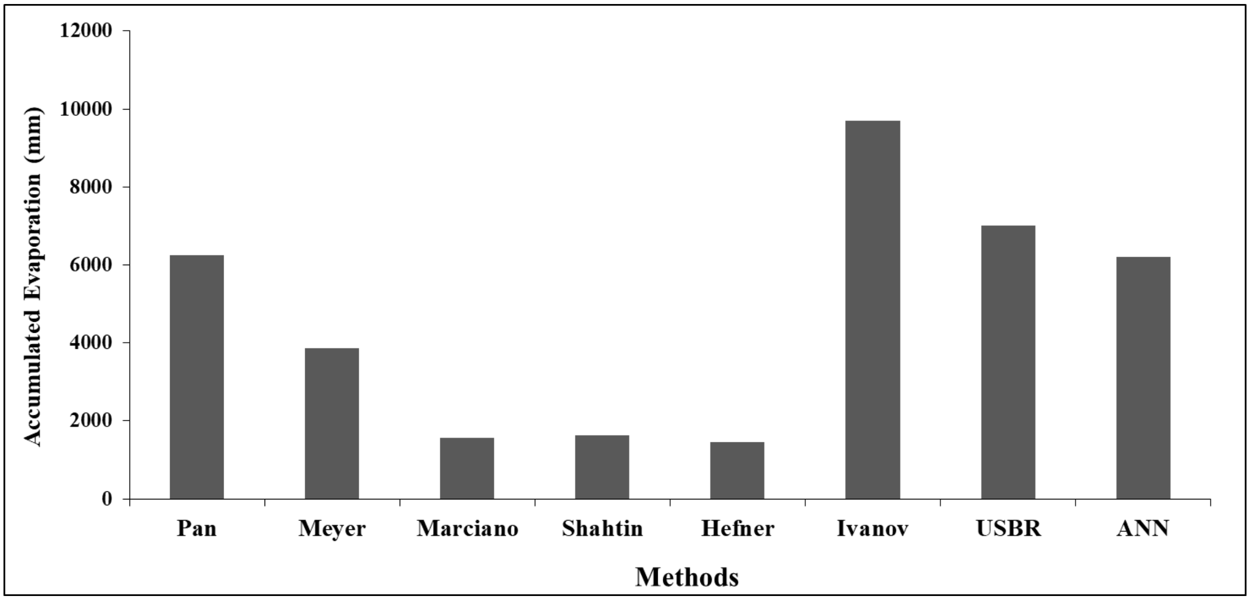

Figure 14. Comparing the mean estimated and observed annual evaporation rates by different methods at Sari office station.

Like the previous station, ANN was identified as the best model and Ivanov and Hefner were determined as the poorest models for simulating the annual evaporation at Farim Sahra station.

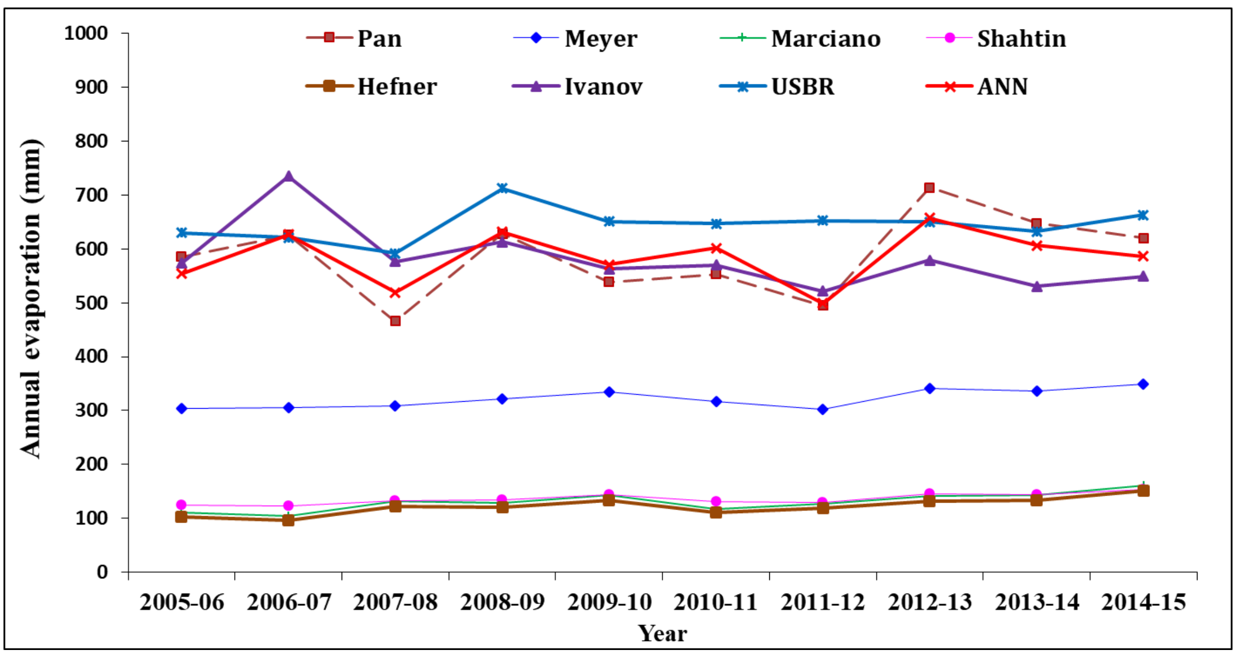

Figure 15. Comparing the estimated and observed evaporation estimation methods at Farim Sahra station in a 10-year period.

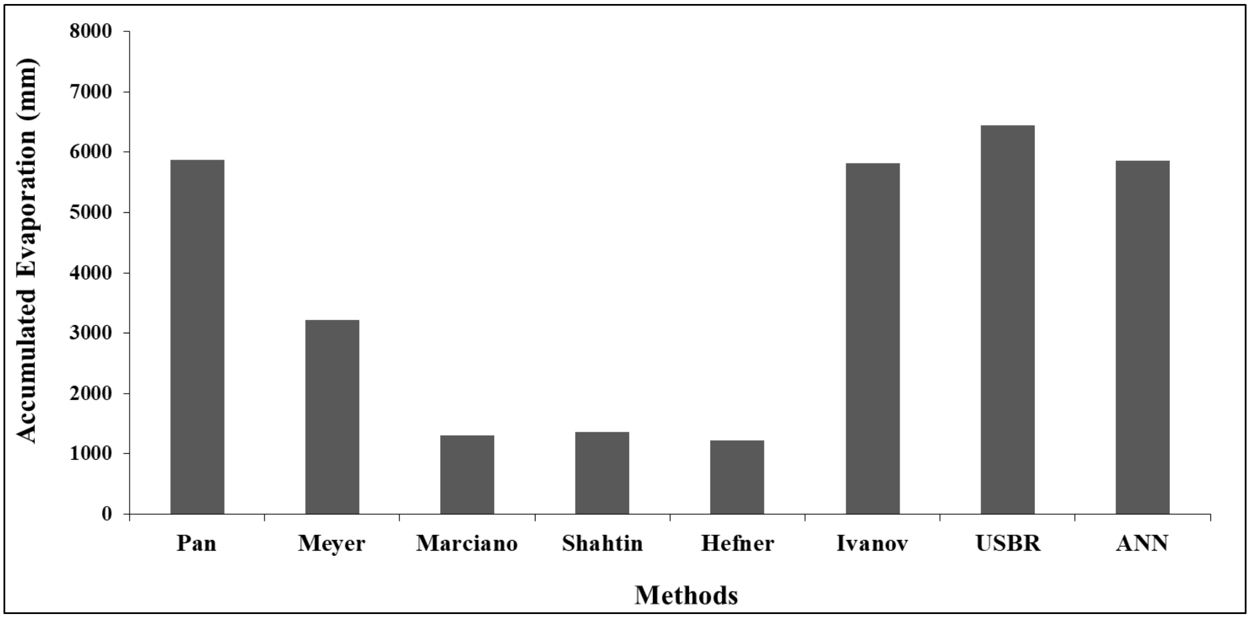

Figure 16. Comparing the mean estimated and observed annual evaporation rates by different methods at Farim Sahra station.

ANN was identified as the best model for simulating evaporation at Farim Sahra station, as this method estimated evaporation rate very close to the real value during the statistical period. However, “Ivanov” and “Hefner, Shahthin and Marciano” methods estimated evaporation rate significantly more and less than the real value, respectively.

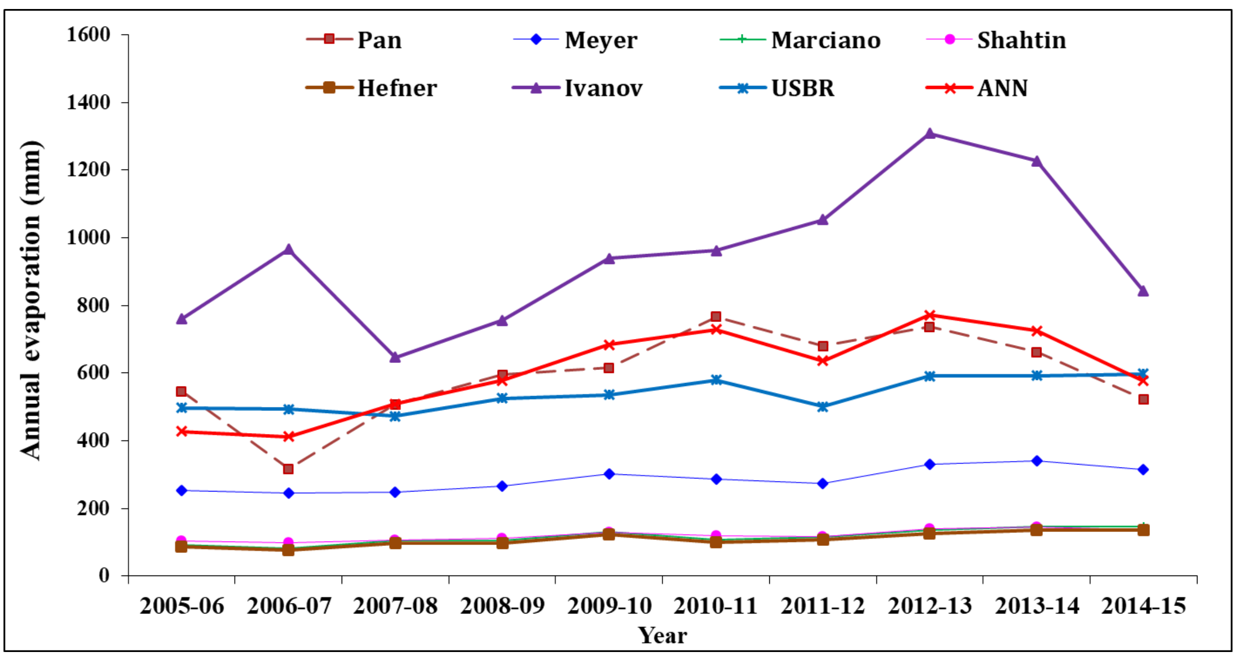

Figure 17. Comparing the estimated and observed evaporation estimation methods at Telamadre station in a 10-year period.

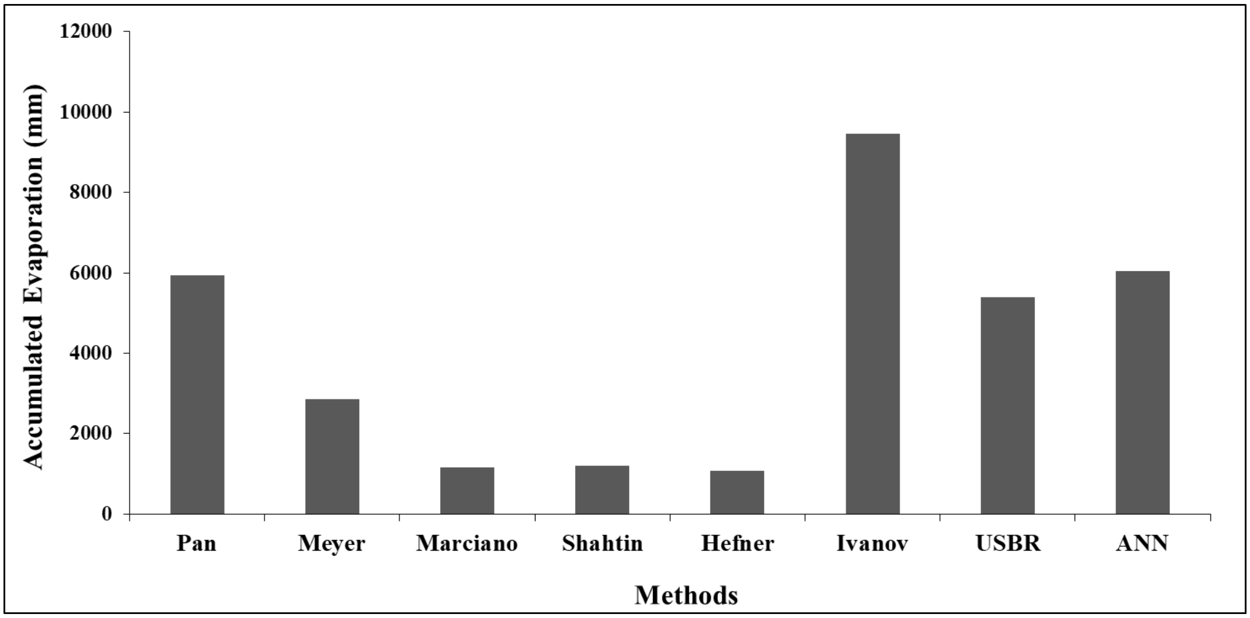

Figure 18. Comparing the mean estimated and observed annual evaporation rates by different methods at Telamadre station.

ANN was identified as the best model for simulating evaporation, as this method estimated evaporation rate very close to the real value during the statistical period. However, "Ivanov" and "Hefner, Shahthin and Marciano" methods estimated evaporation rate significantly more and less than the real value, respectively.

3.3.1. Discussion

The superior performance of ANN is attributed to its ability to capture nonlinear relationships between meteorological variables such as temperature, humidity, wind speed, and radiation. In contrast, empirical equations are based on simplified assumptions and limited climatic variables, which reduces their adaptability to local conditions. The results obtained in this study are consistent with the findings reported by (Ebrahimi et al., 2025), who demonstrated that machine learning algorithms achieve higher prediction accuracy than conventional empirical equations for evaporation estimation. Similar to their conclusions, the present study indicates that ANN provides superior predictive capability across different climatic conditions. However, the current study further extends previous research by evaluating multiple meteorological input combinations and identifying an optimal seven-variable ANN structure applicable to four hydrological stations. The variability in performance of empirical models across stations highlights their sensitivity to climatic heterogeneity. Overall, ANN provides a more flexible and accurate framework for evaporation estimation in complex hydrological systems. The apparent discrepancy between the higher MSE values and relatively high R^2 values at Telmadare station can be explained by the inherent characteristics of these performance metrics.MSE is a scale-dependent error measure and is highly influenced by the magnitude and variability of the observed data. Therefore, stations with higher dispersion or a broader range of evaporation values tend to exhibit larger MSE values, even when the model captures the overall pattern accurately. In contrast, R^2 is a dimensionless metric that reflects the proportion of variance explained by the model and is not affected by the absolute scale of the data. The consistently high R^2

values obtained for Telamadre station indicate that the ANN model successfully captures the underlying relationship between meteorological inputs and evaporation. Additionally, the higher variability of meteorological and evaporation data at this station, as well as the possible presence of extreme values, may have contributed to increased MSE values.

3.4. Limitations

Although the ANN model consistently outperformed the empirical equations, this comparison should be interpreted with some caution. The ANN model was developed using multiple meteorological variables, whereas the empirical equations rely on a considerably smaller number of predictors. Therefore, part of the improved predictive performance of the ANN may be attributed to the availability of richer input information rather than solely to the superiority of the modeling technique itself.

Future studies are recommended to establish a more rigorous comparative framework by developing machine learning models using exactly the same input variables employed by each empirical equation. Such an approach would allow the influence of the modeling methodology to be evaluated independently of the amount of available input information. Furthermore, future research may investigate advanced deep learning algorithms, hybrid machine learning models, and explainable artificial intelligence techniques to further improve evaporation prediction accuracy under different climatic conditions.

4. Conclusion

This study investigated the performance of ANN model and empirical equations in estimating daily, monthly and annual evaporation from Shahid Rajaei Dam reservoir surface using evaporation pan method. The data were analyzed in different combinations considering different input parameters and the final results were obtained for the best combination and scenario. Moreover, the performance of the neural network model was compared with the best empirical regression equations on daily, monthly and annual basis by evaluating the performance of empirical equations of evaporation estimation and extracting new regression equations.

In ANN, different combinations were first examined considering different input variables and the final results were obtained for the best combination and scenario. The results obtained from the statistical indices of distribution diagrams of estimated and observed daily evaporation revealed MLP neural network could properly estimate daily evaporation at the four studied stations. The best scenarios for the four studied stations of Soleiman Tangeh, Sari office, Farim Sahra and Telamadre were those with structures of 7-12-1, 7-8-1, 7-10-1 and 7-12-1 based on MSE and R^2 values. Correlation coefficients were obtained as 0.88, 0.91, 0.92 and 0.89 at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations on a daily basis, respectively. Also, the results obtained from the statistical indices of distribution diagrams of estimated and observed monthly evaporation revealed ANN could properly estimate monthly evaporation at the four studied stations. Correlation coefficients were obtained as 0.98, 0.98, 0.99 and 0.99 at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations, respectively. Results of simulating daily evaporation by empirical equations showed Ivanov with R^2 of 0.79, Meyer's method with R^2 of 0.83, Meyer's method with R^2 of 0.80 and Meyer's method with R^2 of 0.81 were determined as the best equations for estimating daily evaporation at Soleiman Tangeh, Sari office, Farim Sahra and Telamadre stations, respectively. At Soleiman Tangeh station, Meyer's method with R^2 of 0.98 and the minimum MSE value (437.9 (mm day^{-1})^2) was chosen as the best equation for simulating monthly evaporation. Similarly, Meyer's method was chosen as the best equation based on the obtained statistical indicators at the other studied stations.

Moreover, Ivanov estimated monthly evaporation relatively accurately in spring and summer and Meyer's method estimated monthly evaporation relatively accurately in winter and autumn. Among the methods used in this study, USBR was identified as the poorest equation for estimating monthly evaporation. Thus, caution should be taken when this method is used to estimate evaporation from the free water surface in the region.

Therefore, ANNs are powerful tools for hydrometeorological studies that have proven their superiority over other applied methods and have the best performance in determining evaporation from the free surface. Furthermore, comparing R^2, MSE and EF parameters between the neural network and evaporation pan data showed high ability of ANN in determining evaporation from the free surface. Useful and management solutions could be applied to protect the existing water resources and mitigate drought effects by relatively accurate calculation of evaporation from the free water surface by the neural network.

Data Availability

The data used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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