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Simulation of Pan Evaporation Rate by ANN Artificial Intelligence Model in Damghan Region

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ABSTRACT

Regarding different aspects of management of drainage basins and droughts, prediction of evaporation is very important. Evaporation is an essential part of the water cycle and plays an important role in the evaluation of climatic characteristics of any region. The purpose of this research is to predict daily pan evaporation rate of Damghan city using an artificial neural network model. The data applied in this research are daily minimum and maximum temperatures, average relative humidity, wind speed, sunshine hours, and evaporation during the statistical time period of 16 years (2002-2018). Also, the artificial neural network was used as a non-linear method to simulate evaporation. Since the units of the inputs and outputs of the prediction model were different, all the data were normalized. In the ANN model, seven different scenarios were considered. About 70 and 30 percentage of the data were used for training and testing, respectively. The model was analyzed by appropriate statistics such as coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Results showed that the seventh scenario including minimum and maximum temperatures, average relative humidity, wind speed, sunshine hours, and pressure proved to be the superior scenario among others. The values of R^2, RMSE, and MAE for the superior scenario were 0.8030, 2.75 mm/day, and 1.88 mm/day, respectively.

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1. Introduction

Management of water resources for supplying the water required for farming is a method to handle the scarcity of the water required for agriculture that is caused by low water use efficiency and overuse of the existing water resources [1]. Iran is an arid and semi-arid region [2], and according to international definitions, it is in a critical circumstance and experiences water scarcity [3]. Iran is faced with a severe water crisis [4]. In many places of Iran, water consumption has become far greater than 43% of the renewable water resources, to the extent that in most of the basins, the exploitation of water is practically more than their total annual renewable water [3,5].

Evaporation is one of the main components of the water balance of a region, and it is an essential item for an irrigation plan. In most hot and dry climates, a great volume of water held by dams, agricultural irrigation pools, and water storages are wasted by evaporation [6]. Evaporation plays an important role in a region's water resources, climatic changes, and agriculture [7]. Regarding the climate change issue, researchers have worked extensively on evaporation and its role in the hydrologic cycle [8,9].

Evaporation could be predicted by soft computing technique [10–12]. The multilayer perceptron (MLP) model of neural network is a model for estimation of evaporation pan with the input layer of variables (such as temperature and sunshine hours) and the output layer of evaporation rate. In what follows, the studies of the application of soft computing for the estimation of pan evaporation will be outlined.

Eslamian et al. [13] compared artificial neural network (ANN) and support vector machine (SVM) algorithms to estimate the greenhouse evaporation. The obtained correlation coefficients of the ANN and SVM were 0.92 and 0.96, respectively. These values indicate the ability of SVM and ANN models to estimate greenhouse evaporation.

Piri et al. (2009) [14] were among the first to use ANNs to model pan evaporation rates in arid and semi-arid climates. They reported satisfactory performance for ANNs used in a research site located in the southeast of Iran. Their study reported R^2 = 0.93 for an ANN model with an optimal combination of 4 meteorological inputs.

Kişi (2009) [10] compared the multi-layer perceptrons (MLP), radial basis neural networks (RBNN), and generalized regression neural networks (GRNN) models for estimation of daily pan evaporation. Meteorological data of air temperature, solar radiation, wind speed, pressure, and humidity were considered as the factors affecting the evaporation. The results indicated the superiority of the MLP and RBNN models.

Tezel and Buyukyildiz (2016) [15] used SVM and ANN models to analyze the monthly evaporation in weather station of Beyşehir city. This research was conducted in the statistical time period of 1972 to 2005. Temperature, relative humidity, wind speed, and precipitation were the applied data. Results showed that the MLP functions properly.

Qasem et al. [16] used the three models of support vector regression (SVR), ANN, and their combination with the wavelet transforms of wavelet support vector regression (WSVR) and

Wavelet artificial neural networks (WANN) to predict the evaporation rate in Tabriz, Iran, and the Turkish city of Antalya. In both stations, the ANN model showed better results than other models.

Patle et al. [17] compared MLR and ANN models to estimate monthly pan evaporation in two regions in northern India. Results of this research indicated that ANN model works better than the MLR model.

Alsumaiei [18] used ANN to model daily evaporation rate in Kuwait. The studied station was the Kuwait international airport (KIA). The meteorological input data of the network included mean temperature, wind speed, and relative humidity that were presented in four scenarios. Results of this research indicated that the combined scenario of average temperature and wind speed as inputs for the estimation of daily evaporation showed a better function than other scenarios.

Neural network-based group method of data handling was used by Karami et al. [19] to estimate and simulate pan evaporation rate in the synoptic station of Garmsar city, located in Semnan province, Iran. For this purpose, daily meteorological data of evaporation, minimum and maximum temperatures, wind speed, relative humidity, air pressure, and sunshine hours during the nine years of 2009-2018 were used. This study showed that R^2, RMSE, and MAE values in the test stage were 0.84, 2.65, and 1.91, respectively, in the most optimal state. From the third layer onwards, the amount of RMSE of the validation data have converged to 0.062, and it is not affordable to use more layers for modeling of the evaporation pan in this station. Table 1 shows some recent studies of evaporation using the ANN model. Based on this table and the results of the present study, the ANN model can have good performance in estimating evaporation.

Table 1
Literature review on estimating pan evaporation using MLP neural network.

Research	Case study	Methods	Meteorological parameters	Summary of results
Ashrafzadeh et al. (2019) [20]	Anzali and Astara, Iran	MLP, krill herd optimization – the MLP-KH model	rainfall; air temperature (maximum, minimum and mean); relative humidity (maximum, minimum and mean); actual sunshine hours; and wind speed	Results presented here collectively suggest that MLP-KH is a good choice to be used as an estimation model in the study area.
Qasem et al. (2019) [16]	Tabriz, Iran	SVR ANN WSVR WANN	Air temperatures, Solar radiation, relative humidity, wind speed, evaporation	The ANN model had better results than the other presented models.
Alsumaiei (2020) [18]	Kuwait International Airport	ANN	mean temperature, wind speed and mean relative humidity	The proposed ANN was satisfactorily efficient in modeling pan evaporation in these hyper-arid climatic conditions.
Patle et al. 2020 [17]	Gangtok and Imphal, India	MLR ANN	Minimum and maximum air temperatures, maximum and minimum relative humidity, wind speed, sunshine hours	The ANN model performs better than MLR model.

The purpose of this study is to use ANN (MLP) to model pan evaporation rate at Damghan weather station, Semnan province, Iran. In the process of modelling for calculation of daily evaporation, different scenarios are presented. The scenarios are composed of effective meteorological parameters of minimum and maximum temperatures, relative humidity, wind speed, sunshine hours, and pressure. The best scenario is the one that comes up with the more precise prediction of pan evaporation rate. Figure. 1 shows the flowchart of the steps in this study.

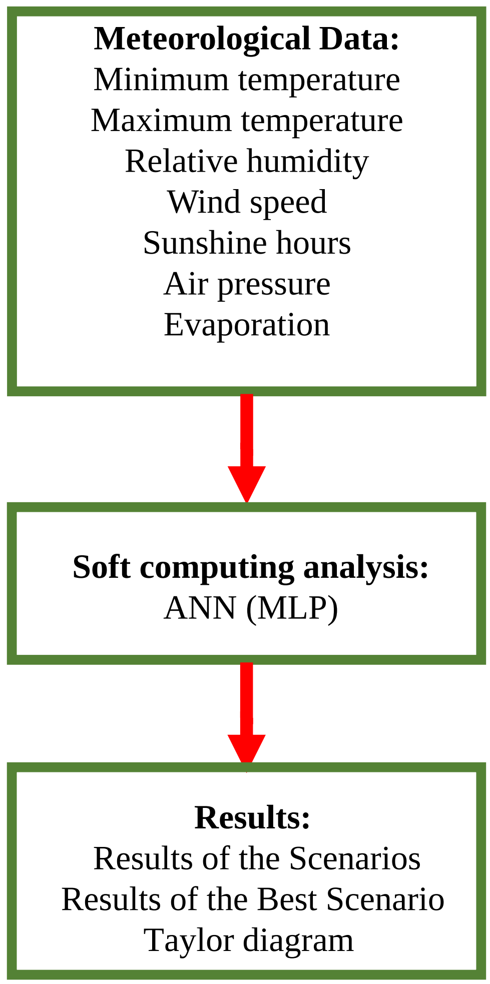


Fig. 1. Flowchart of the proposed methodology.

2. Materials and methods

2.1. Study region

The studied region is city of Damghan, located in the Semnan province, at geographical coordinates of 54° 32' longitude and 36° 14' latitude, and elevation of 1155 m above mean sea level. Record length of the data used in this research is 16 years (2002-2018). These data included minimum and maximum temperature, air pressure, relative humidity, sunshine hours, wind speed, and daily pan evaporation rates.

2.2 Parameters and statistical properties of data

In this research, efficiency of the ANN model for prediction of pan evaporation rate was evaluated by using daily parameters of minimum and maximum temperature, relative humidity, wind speed, sunshine hours, and air pressure. Table 2 shows the studied parameters, symbols, and statistical properties. Figure 2 shows the histogram of the input and frequency data. The input data are normalized by Eq.1 and Table 3 to function better. Therefore, all the data are set between 0.1 and 0.9, and then are used to extend the equation. This is based on the method used by Naderpour and Mirrashid [21] and Ghazvinian et al. [22].

$$Parameter_{Scaled} = \left[(0.8)\left(\frac{Parameter - Parameter_{\min}}{Parameter_{\max} - Parameter_{\min}} \right) \right] + 0.1 \tag{1}$$

Table 2
Statistical properties of data.

Parameter	Unit	Symbol	Mean	Standard deviation	Minimum	Maximum
Minimum temperature	c̊	T_{min}	11.05	9.17	-12	30
Maximum temperature	c̊	T_{max}	23.39	10.94	-4.4	42.6
Relative humidity	%	RH_{mean}	40.39	14.41	10.2	96.00
Wind speed	m/s	WS	8.84	6	0	36.0
Sunshine hours	hr	N	8.6	3.22	0	13.4
Air pressure	hPa	PA	814.18	3.68	0	899.83
Evaporation rate	mm	E	7.42	6.15	0	30

2.3. Artificial neural network

Artificial neural network (ANN) is composed of an arbitrary number of cells, nodes, units, or neurons which connect the set of inputs to outputs. It is used for predicting and solving complicated processes in various fields such as civil and hydraulic engineering [23]. The ANN is a mathematical structure that is formed based on the biological model of the human brain. A neuron is a small set of data processing components in each neural network. Neurons are related to each other by their specific weights. The weights show the information required for the network to find the solution to a problem. A biological neuron consists of three main parts of axon, soma, and dendrite. The signals received from other neurons are corrected by a huge number of dendrites. Soma, namely the body of processing unit, collects the input signals. If the sum of inputs exceeds a certain limit, the processor is activated and some signals will be transmitted through the axon to the next cell. Neural cells work in series and parallel. After processing, the set of parallel neural cells produce a set of outputs. The resulted outputs can be used as the inputs to other sets of neural cells which are connected in series to the primary cells. Consequently, the output of each neuron is multiplied by the weighting coefficients and is given to the non-linear activation function as inputs. The set of parallel neural cells are composed of one layer. Each neural network can have one or a few layers so that it can produce its own output. Usually, these layers are called hidden layers. The last layer produces the output of the network [24,25]. Figure 3 demonstrates the flowchart of the structure of an artificial neuron and the structure of artificial networks.

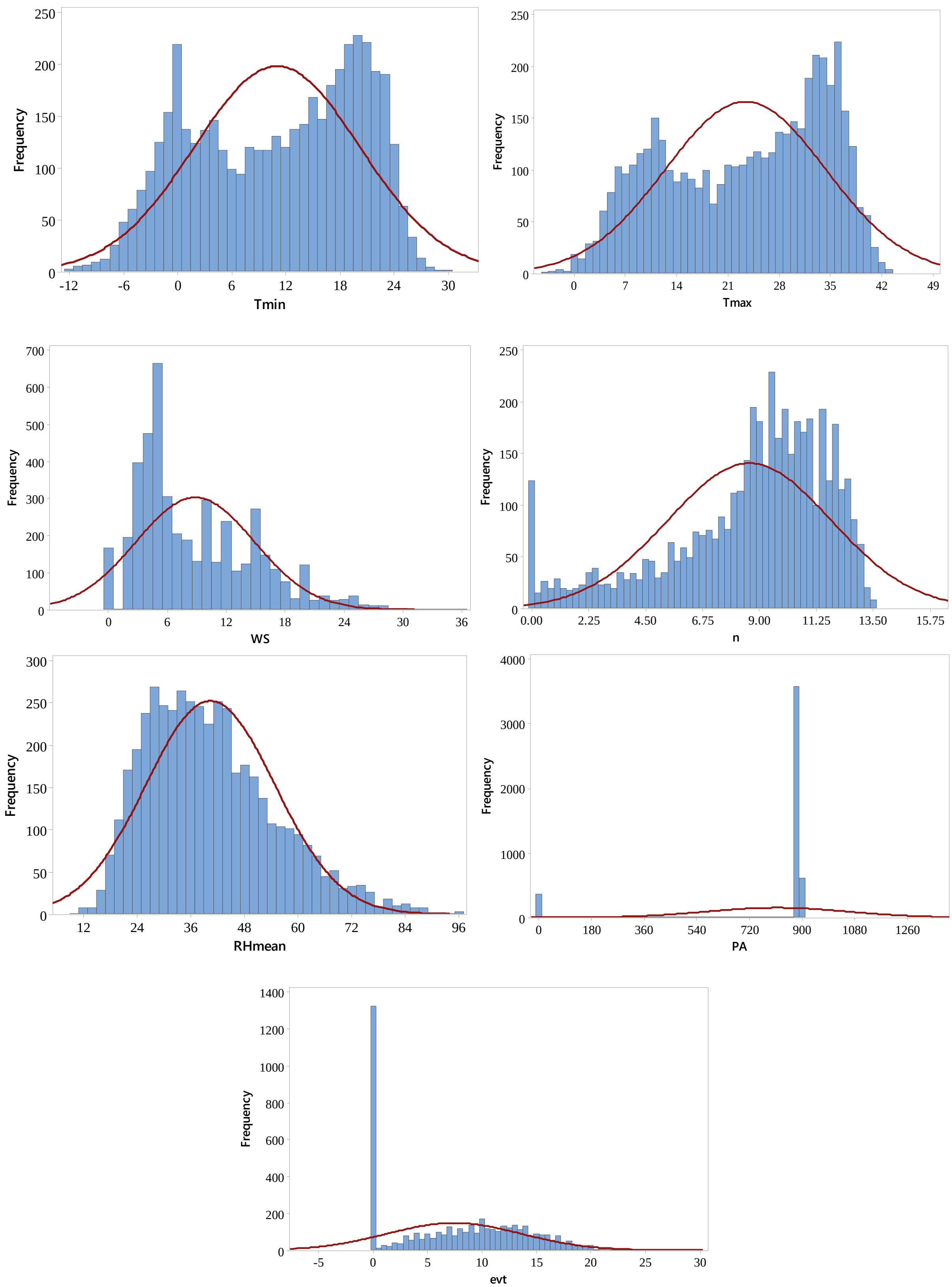


Fig. 2. Histograms of the input data.

Table 3
Normalization of the input data.

Symbol	Parameter	Normalized value
T_{min}	Minimum temperature	$T_{\min_{normal}} = 0.8\frac{T_{\min} - (-12)}{30 - (-12)} + 0.1$
T_{max}	Maximum temperature	$T_{\max_{normal}} = 0.8\frac{T_{\max} - 4.4}{42.6 - (-4.4)} + 0.1$
RH_{mean}	Relative humidity	$RH_{mean_{normal}} = 0.8\frac{RH_{mean} - 10.2}{96 - 10.2} + 0.1$
WS	Wind speed	$WS_{normal} = 0.8\frac{WS - 0}{36} + 0.1$
n	Sunshine hours	$PA_{normal} = 0.8\frac{PA}{899.82} + 0.1$
PA	Air pressure	$n_{normal} = 0.8\frac{n - 3.73}{8.81} + 0.1$
E	Evaporation rate	$E_{normal} = 0.8\frac{E}{30} + 0.1$

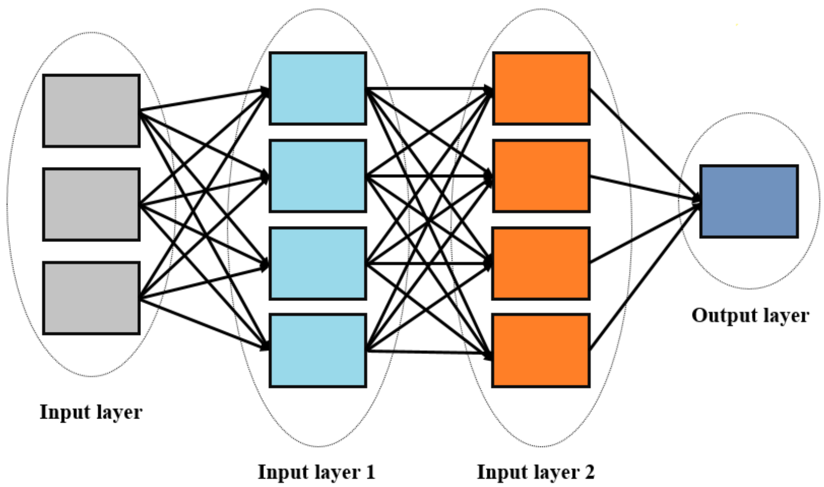


Fig. 3. The structure of artificial neural networks.

In order to predict daily evaporation rate by ANN (MLP) model, 70% of the total series of daily data (years 2002 to 2018) were chosen for training and the remaining 30% of data (years 2002 to 2018) was devoted to testing. Eight and one neurons were used in the input and output layers, respectively. Also, in the hidden layer, different number of layers were used and their optimum number was determined by trial and error in order to minimize the error. In the hidden layer, the hyperbolic tangent transfer function and in the output layer, the nonlinear transfer function was used. For training, the Levenberg-Marquardt algorithm was used with 2000 constant iterations. In order to find out the possibility of using different combinations of meteorological data for a more precise simulation of daily evaporation, seven different scenarios including various meteorological data were defined (Table 4). Then, these scenarios were applied for simulation of evaporation rates.

Table 4
The input scenarios used in ANN.

Scenario No.	Input parameters
1	T_{min} - T_{max}
2	RH_{mean} - WS
3	T_{min} - T_{max} - RH_{mean}
4	T_{min} - T_{max} - WS
5	T_{min} - T_{max} - RH_{mean} - WS
6	T_{min} - T_{max} - RH_{mean} – WS - PA
7	T_{min} - T_{max} - RH_{mean} – WS – PA - n

2.4. Evaluation criteria

In order to evaluate and analyze the proposed models, the error indexes must be calculated with several functions [26]. In this research, the preciseness and ability of the models are evaluated by correlation coefficient (R^2), root mean square error (RMSE), mean square error (MSE) and mean absolute error (MAE) based on Eqs. (2)-(5). The best values for these three criteria are 1, 0, 0, and 0, respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \right]^2 \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{N}} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|(y_i - x_i)\right| \tag{4}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - x_i)^2 \tag{5}$$

here, N is number of data, x_i is daily measured evaporation, y_i is predicted daily evaporation, $\bar{x}$ is average value of measured evaporation, and $\bar{y}$ is average value of predicted evaporation.

3. Results

3.1. Results of the scenarios

In this research, daily evaporation rate was prediced by ANN for Damghan region by using different inputs in 7 scenarios. Different scenarios were analyzed to choose the optimum structure of each model. Table 5 presents the values of R^2, RMSE, and MAE of the ANN model in training and testing stages. According to the results, the seventh scenario of the ANN model with R^2 = 0.803, RMSE = 2.75 mm/day, and MAE = 1.88 mm/day was chosen as the best pattern. The third scenario ranked second. In this scenario, daily evaporation rate could be simulated with allowable error only by using minimum and maximum temperature and daily relative humidity inputs.

3.2. Results of the best scenario

Figure 4 shows time series of the measured evaporation values and simulated by ANN in the best scenario (namely the seventh scenario). The more the simulated values correspond to the measured values, the more accurate the model is.

Figure 5 shows the evaporation rates predicted by the ANN based on the seventh scenario at two stages of training and testing. As it is evident, there is an almost strong correlation between the measured and simulated evaporation data at two stages of training and testing with R^2 values of 0.8096 and 0.803, respectively. Moghaddamnia et al. (2009) [27] used the ANFIS method on a research site located in the Southeast. The R^2 value was reported 0.91 for the best performance of the ANFIS model during the validation period. However, a similar prediction orientation was observed for the ANFIS model.

Table 5
Results of error criteria for different scenarios.

Scenario No.	Stage	R^2	RMSE	MAE	MSE
1	Training	0.592	9.991	6.421	99.820
	Testing	0.612	8.312	6.012	69.089
2	Training	0.574	10.012	7.733	100.240
	Testing	0.593	9.732	7.105	94.692
3	Training	0.770	4.442	3.323	19.731
	Testing	0.780	4.321	2.991	18.671
4	Training	0.704	5.768	4.887	33.269
	Testing	0.710	5.021	3.993	25.210
5	Training	0.719	5.070	4.904	25.704
	Testing	0.728	4.786	4.020	22.906
6	Training	0.750	4.819	3.981	23.223
	Testing	0.766	3.025	3.652	9.151
7	Training	0.809	2.679	1.909	7.177
	Testing	0.803	2.750	1.881	7.562

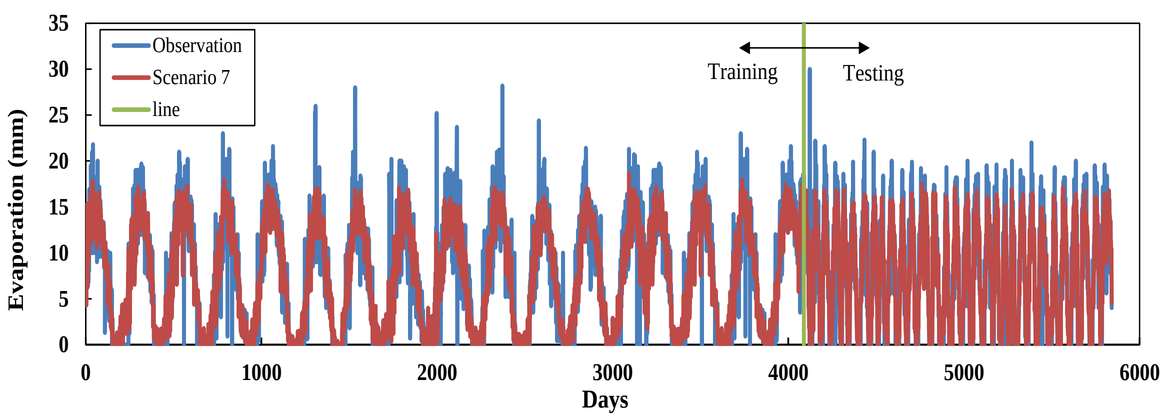
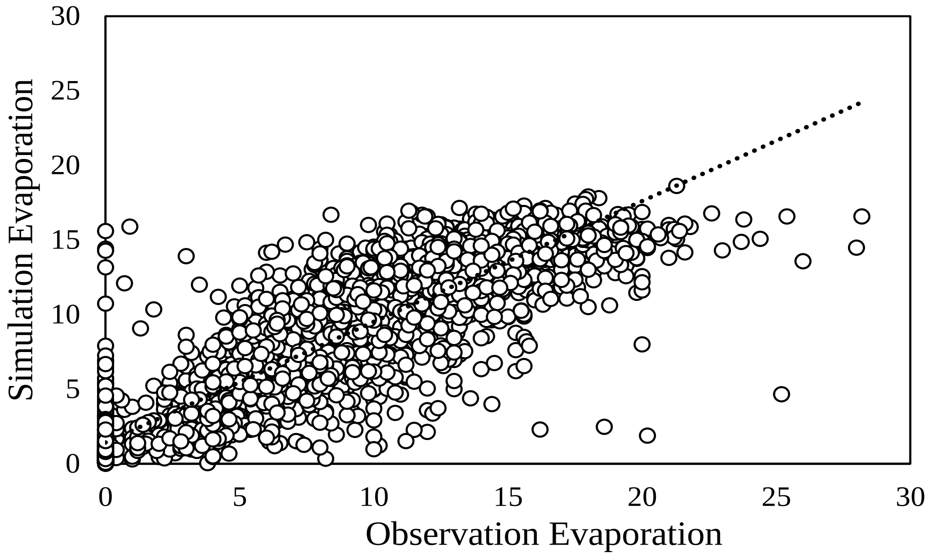
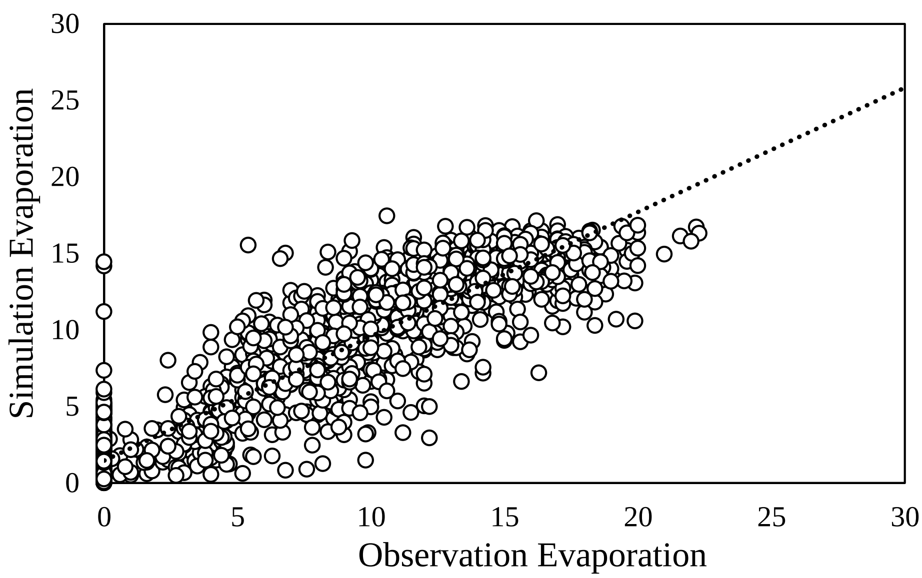


Fig. 4. Time series of the observed values and the values predicted by ANN model at training and testing stages.

Visual display and comparison of the experimental and model results can be illustrated using the Taylor diagram for providing an easy and comprehensive evaluation [28]. Taylor diagrams can reflect the quality of different approaches in comparison with the experimental samples in a diagonal display (Fig. 6). In these diagrams, the Azimuth angle addresses the correlation coefficient between the modeled and the experimentally measured data, while the radial distance from the origin indicates the standard deviation (SD) for the outcomes of each approach. In addition, the concentric circles indicate centered RMSE values, which can be evaluated using the following equation.



(a)



(b)

Fig. 5. Simulated vs. observed daily evaporation rates at different stages: (a) training and (b) testing.

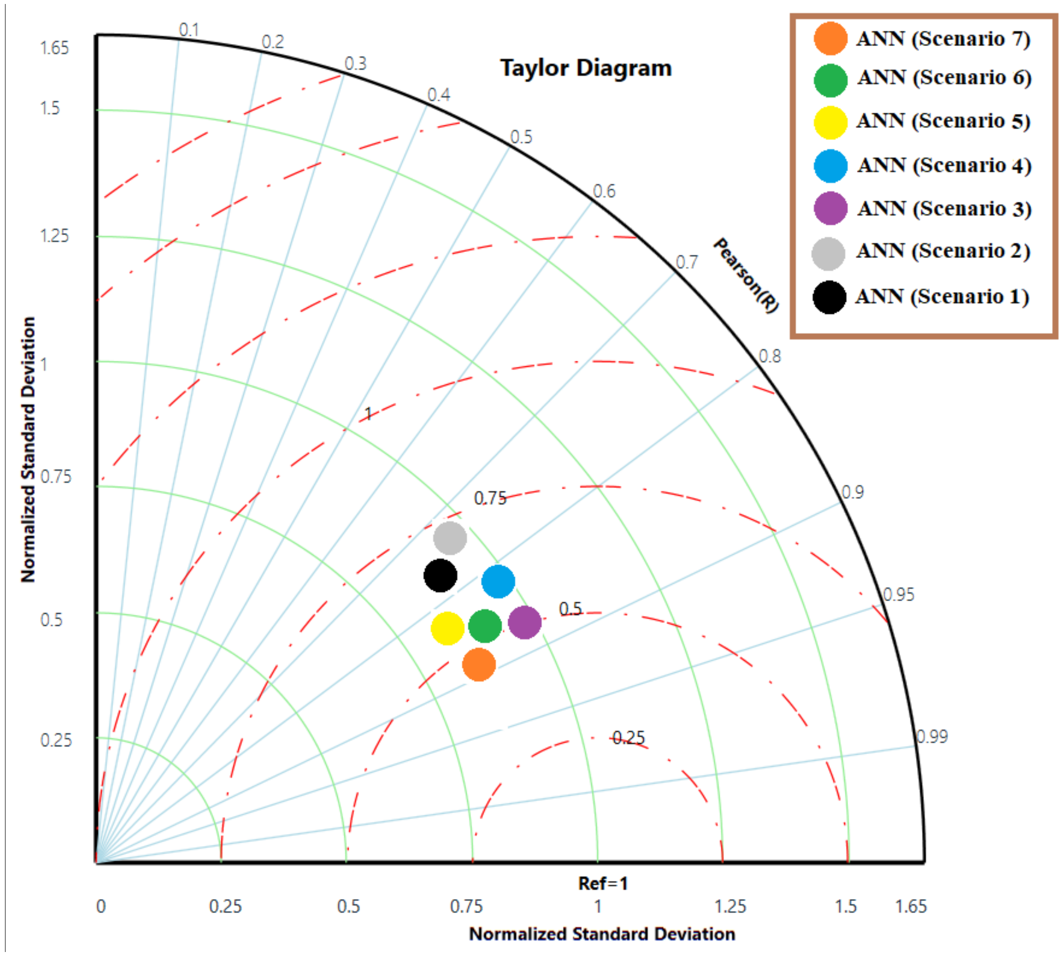


Fig. 6. The Taylor diagram for the estimated evaporation.

4. Conclusions

Evaporation is one of the most important input data of hydrologic systems. Due to the importance of evaporation for arid regions in Iran, this research has been conducted to predict evaporation rates in Damghan region. The process of evaporation is nonlinear, and if the linear regression model is used as a semi-linear method for these kinds of processes. In recent years, various methods have been developed for prediction of climatic variables. Each of these prediction methods has specific weaknesses and strengths. In this research, the ANN model was used for prediction of daily evaporation rates by using 16 years of daily evaporation data of Damghan synoptic station. Seven scenarios presenting different inputs of the model were used to predict evaporation rate. The R^2coefficient for the seven scenarios in the test phase is 0.61, 0.59, 0.78, 0.71, 0.72, 0.76 and 0.80, respectively. Comparison of different scenarios showed that by increasing the number of inputs, the model's function will be improved.

Conflicts of Interest

The authors declare no conflict of interest.

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