Water Resources Management (2023) 37:2607–2624
https://doi.org/10.1007/s11269-022-03365-0

Reservoir Evaporation Forecasting Based on Climate Change Scenarios Using Artificial Neural Network Model

Yeşim Ahi[1] · Çiğdem Coşkun Dilcan[1] · Daniyal Durmuş Köksal[2] · Hüseyin Tevfik Gültaş[3]

Received: 5 May 2022 / Accepted: 17 October 2022 / Published online: 4 November 2022

Abstract
Climate plays a dominant role in influencing the process of evaporation and is projected to have adverse effects on water resources especially in the wake of a changing climate. In order to understand the impact of climate change on water resources, artificial intelligence models that possesses rapid decision-making ability, are used. This study was carried out to estimate evaporation in the Karaidemir Reservoir in Turkey with artificial neural networks (ANNs). The daily meteorological data covering the irrigation season were provided for a 30-year reference period and used to develop artificial neural network models. Predicted meteorological data based on climate change projections of HadGEM2-ES and MPI-ESM-MR under the Representative Concentration Pathway (RCP) 4.5 and 8.5 future emissions scenarios between 2000–2098 were utilized for future evaporation projections. The study also focuses on optimal crop patterns and water requirement planning in the future. ANNs model was run for each of the scenarios created based on ReliefF algorithm results using different testing-training-validation rates and learning algorithms of Bayesian Regularization (BR), Levenberg–Marquardt (L-M) and Scaled Conjugate Gradient (SCG). The performance of each alternative model was compared with coefficient of determination (R^2) and mean square error (MSE) measures. The obtained results revealed that the ANNs model has high performance in estimation with a few input parameters, statistically. Projected surface water evaporation for the long term (2080–2098) showed an increase of 1.0 and 3.1% for the RCP4.5 scenarios of the MPI and HadGEM model, and a 14% decrease and 7.3% increase for the RCP8.5 scenarios, respectively.

Keywords Climate change · Machine learning algorithms · Modelling · Water resources · Agricultural water use

Highlights

- The study proved that the artificial neural network model is superior in predicting surface evaporation.
- The study reveals the change in current water resource potential based on climate scenarios.
- It is important to make accurate future projections in terms of water resources management.
- The study focused on the irrigated area estimation based on water allocated from reservoir.
- The model could also guide decision-makers and stakeholders in the context of sectoral water needs.

Extended author information available on the last page of the article

1 Introduction

Fresh water which is a scarce natural resource globally, is required for utilization in domestic, agricultural, industrial, ecological and recreational use among other purposes. As a result of rapid industrialization, spurred global population growth, excessive surface and groundwater use in agriculture and climate change effects, water resources have decreased in quality and quantity. (UNESCO 2020) Therefore, effective water resources management requires the implementation of the basin-based management and an interdisciplinary concept that entails the protection, development, control, regulation, and beneficial use of water to achieve sustainability whilst reaping the benefits of water exploitation (Islam 2011). Therefore, solutions for the future management of water should be in an interdisciplinary perspective and the integration of latest technologies such as decision support systems. Forecasting of potential change in water quality or quantity could be one of the main areas of implementation to improve the water resources management for all sectors and stakeholders.

According to the Intergovernmental Panel on Climate Change (IPCC 2001, 2007) reports, the Mediterranean region is declared to be the most sensitive region in the world to climate change and its impacts. In addition to extreme weather events such as increased floods and/or droughts, global climate change causes lower and more unstable rainfall combined with increased temperature, thus resulting in higher evaporation and water demand. An increase in temperatures could lead to a net deficit in atmospheric water content, thus excessive evaporation from soil, water and plant surfaces. Land ecosystems would consequently require more water to match increased water demand to prevent drought. Since the agricultural sector consumes about two thirds of all fresh water resources globally, there is a growing concern over the impacts of future climate change on the water resources and agricultural production. Thus, it is important to provide information on future regional changes in climate and possible scenarios and policy implications for the future.

Estimation of evaporation loss, which is a major component of the hydrologic cycle, is important for water resources planning especially agricultural water scheduling as well as agricultural modeling in regards to climatic conditions. The evaporation process consists lots of meteorological factors such as solar radiation, air temperature, wind speed, relative humidity and atmospheric pressure etc. (Fan et al. 2018). These factors are complicated, not easy to measure in nature and are highly non-linear to be able to calculate. The available empirical methods like class A pan, Penman–Monteith, Priestley-Taylor and etc. are inadequate due to the non-linearity and complexity of the evaporation process. Therefore, the usage of new approaches such as machine learning algorithms could be much more useful to estimate and forecast the evaporation losses. Artificial intelligence applications, such as neural networks and fuzzy systems are successfully used in many areas to model non-linear and complex systems.

Beside the empirical estimation methods of evaporation loss (Penman 1948; Priestley and Taylor 1972; Jensen et al. 1990); researchers suggested machine learning algorithms methods such as Adaptive neuro fuzzy inference system (ANFIS), generalized regression neural networks (GRNN), support vector machines (SVM), ANN, CANFIS and MLR to be able to offer simple solutions for nonlinear multi-variable functions (Sanikhani et al. 2012; Feng et al. 2017; Kim et al. 2012). These models have been gaining popularity also in modelling the hydrological water cycle and assessing the impact of climate change using different climate change scenarios (El-Mahdy et al. 2021).

The current study utilized a feature selection-based method i.e. 'ReliefF' algorithm to identify the appropriate input variables combination for the estimating and also forecasting the reservoir evaporation based on climate scenarios using artificial neural network model. The ReliefF algorithm which is one of the feature selection methods aims to remove irrelevant or redundant variables, in order to overcome the problems encountered in storing and analyzing big data sets (Budak 2018). Statistical methods i.e. correlation coefficients or machine learning algorithms were also used to select the input parameters for the estimation of the evaporation losses. Nourani et al. (2019) preferred to use the single-input single-output NN based-input sensitivity analysis for the selection of input parameters for the simulation of evaporation via several AI models. The recently published articles have been mentioned in detail above and summarized in Table 1.

This study was conducted with the following objectives: (i) to select appropriate input variables combination for ANNs models using 'ReliefF' algorithm; (ii) to calibrate and validate the ANNs models with selected input variables; (iii) to forecast the evaporation losses by using climate change scenarios, (iv) and to evaluate the forecasted evaporation results in regards to agricultural water management.

2 Materials and Methods

2.1 Case Study Area and Data Supply

The study deals with the Karaidemir Dam, which was constructed for irrigation and flood control purposes in the Meriç-Ergene Basin, located on the European side of Turkey (Fig. 1). The reservoir has a capacity of 120.30 hm^3, and the lake area at a normal water level is 15.50 km^2. Its basin area is about 403 km^2 and is located between 27°E longitudes and 40.5°N latitudes. Major irrigated cropping pattern in the basin is rice, alfalfa, maize, sugar beet, sunflower and watermelon, with cultivation rates of 58, 4, 29, 4, 3 and 2%, respectively (GDWM 2021). The case study basin is characterized by semi-continental climatic conditions, with warm, dry summer and cool, wet winter. The long-term averages of annual temperature, relative humidity, wind speed, sunshine duration and total precipitation are 13.2 °C, 70%, 2.3 m s^{-1}, 5.4 h and 584 mm, respectively (TSMS 2020).

Climate change projections for 25 river basins in Turkey have been prepared by the Republic of Turkey, Ministry of Agriculture and Forestry, General Directorate of Water Management within the scope of the "Impact of Climate Change on Water Resources" project. Two climate models have been selected from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive, which forms the basis of the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC). The Hadley Centre Global Environment Model version 2, HadGEM2-ES (HadGEM) and The Max Planck Institute for Meteorology-Earth-System Model, MPI-ESM-MR (MPI) global climate models selected from the CMIP5 archive were carried out under the Representative Concentration Pathway (RCP) 4.5 and 8.5 future emissions scenarios on fine spatial resolution up to 10 km by 10 km, and the projections were evaluated for every 20 years between 2000–2098 by Turkish State of Meteorological Service. The reference data set in this project was calibrated depending on the meteorological data between 1970 and 2000 for future projections.

The reference data set for the region consist of 16 subset covering up to 20 km by 20 km. The daily meteorological data covering the irrigation seasons from March to November

Table 1 Summary of some input selection methods for the evaporation estimation via machine learning based models

References	Input Parameters*	Input selection Methods	Models employed for Ep Estimation**
Moghaddamnia et al. (2009)	T, W, E_d, RH, E	Gamma test	ANN, ANFIS
Kisi (2013)	T_{avg}, SR, u_2, H	Statistical parameters (correlation values)	ENN 1–2, ANN 1–2, ANFIS 1–2, FG 1–2, SS with 9 scenarios
Goyal et al. (2014)	R, T_{max}, T_{min}, H_{max}, H_{min}, S_{hours}	Gamma Test	ANN, LSSVR, Fuzzy Logic, ANFIS with 4 scenarios
Malik et al. (2017)	T_{max}, T_{min}, RH_1, RH_2, S_w, H_{ss}, EP_m	Gamma test, gradient, standard error (SE) and Vratio	MLPNN, CANFIS, RBNN and SOMNN
Feng et al. (2018)	R, T_{avg}, S_{hours}, u_2, RH	–	PSO-ANN, GA-ANN with 9 scenarios
Lu et al. (2018)	T_{max}, T_{avg}, T_{min}, RH, S_w, R_s, R_a	–	M5Tree, RFs, GBDT with 10 scenarios
Ghaemi et al. (2019)	T_{avg}, SR, RH, u_2	The partial autocorrelation function (PACF) and cross-correlation function (CCF)	MARS and M5Tree
Nourani et al. (2019)	RH, S_p, P_r, T_D, T_{max}, T_{min}, T_{mean}, u_{min}, u_{max}, u_{mean}, R_s, E_p	Single-input single-output NN based-input sensitivity analysis	FFNN, ANFIS, SVR, MLR, with 14 scenarios
Bou-Fakhreddine et al. (2019)	T_{avg}, RH, R_s, R_a	–	Multi-variate Nonlinear Regression
Wu et al. (2020)	T_{max}, T_{min}, RH, u, R_a, n/N	Selection depending on literature	FPAELM, WOAELM with 2 scenarios
Seifi and Soroush (2020)	E_p, T_{max}, T_{min}, T_{mean}, u_2, RH_{mean}, n, P	Statistical processing and correlation coefficient	GA, GWO, WOA, ANNs with 9 scenarios
El-Mahdy et al. (2021)	T_{avg}, u_2, RH, R_a, P	–	ANN
Majhi and Naidu (2021)	T_{max},T_{min}, RH, W, S, E_p	By literature (via using the World Meteorological Organization guidelines)	FLANN, MLANN, Linacre and Christiansen with 4 scenarios
Abed et al. (2022)	T_{max}, T_{min}, T_a, S_w, RH, R_s, E_p	The pearson correlation method (PCC)	Random Forest (RF), CNN and DNN
Novotná et al. (2022)	T_{max}, T_{min}, T_a, S_w, RH, u_2, R_s, E, P, elevation, coordinates	–	NN, AN, DT, DR, DM-NN, GB, LARS, EM

* Rainfall (R, P_r), temperature (T), relative humidity (RH, H), wind speed (u, S_w), global solar radiation (R_s, SR), extraterrestrial solar radiation (R_a), sunshine hours (n, H_{ss}), relative sunshine duration (n/N), monthly pan evaporation (EP_m), pressure (P), daily saturation vapour pressure deficit (E_d), daily evaporation (E, E_p), surface pressure (S_p), dew-point temperature (T_D); ** Feed Forward Neural Network (FFNN), Convolutional Neural Network (CNN), Deep Neural Network (DNN), Adaptive Neuro Fuzzy Inference System (ANFIS), Support Vector Regression (SVR), Multilinear Regression (MLR), FLANN (Functional link ANN), MLANN (Multilayer ANN), Linacre and Christiansen (Empirical models), Whale Optimization Algorithm (WOA), Grey Wolf Optimization (GWO), autoneural network (AN), decision tree (DT), Dmine regression (DR), DM neural network (DM NN), gradient boosting (GB), least angle regression (LARS), ensemble model (EM)

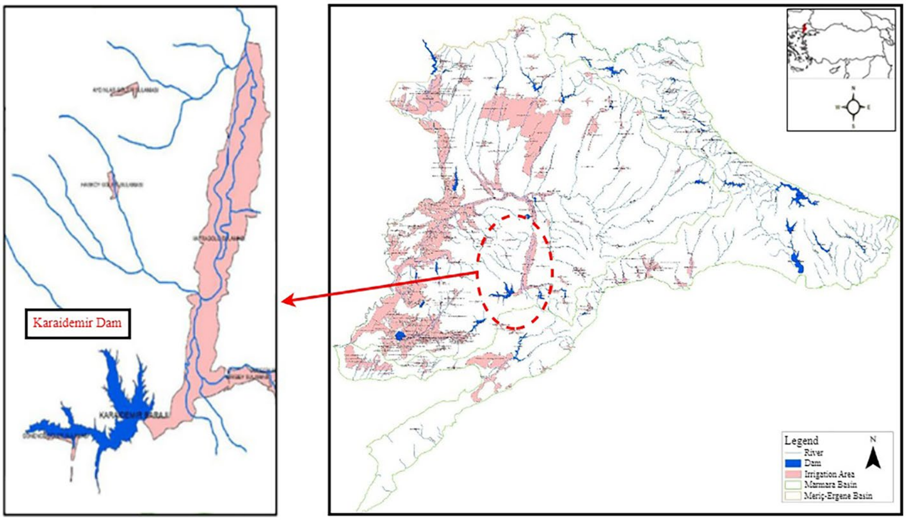

Fig. 1 Location map of Karaidemir dam and irrigation area (GDSHW 2018)

were selected from the reference data set including annual average of 30 years to develop artificial neural network models.

The projected meteorological data utilized in this study for the future evaporation forecasting, were obtained from the climate change projections for the case area. The parameters used for input are mean temperature (T_{mean}), maximum temperature (T_{max}), minimum temperature (T_{min}), sunshine duration (n), solar intensity (SI), precipitation (P), wind speed (u), relative humidity (RH) and evaporation (E) as output in the model.

2.2 Data Set Organization

Descriptive statistics through certain numbers like mean, median and standard deviation are used to describe the basic features of the data in this study and given in Table 2. A total of 3424 MPI/3360 HadGEM data sets were used considering 8 parameters for input data and 1 parameter for output.

In addition, Relief algorithms of statistical-based feature selection methods was used in order to improve the performance of the model and select the input variables that have the strongest relationship with the target variable. The ReliefF algorithm which is a statistical-based feature selection method was used for data classification (Robnik-Šikonja and Kononenko 2003). WEKA software, which includes data pre-processing, classification, regression, clustering and visualization tools such as the ReliefF algorithm, was used to select the appropriate input variables and remove irrelevant ones.

The weight of each independent variable varying from -1 to + 1 was obtained by the relief algorithm independent variables were ranked according to this weight. There are attributes between variables that indicate a better-predicted result as they rise from -1 to + 1. By eliminating the most irrelevant parameters, the number of inputs was reduced and 8 scenarios were created for both HadGEM and MPI.

Table 2 The range of data set for HadGEM and MPI, respectively

	Parameters	Statistical data							
		Min	Max	Mean	SD	Sample Variance	Kurtosis	Skewness	Units
Input	Max. Air Temperature	12.4	35.6	25.3	5.994	35.9	–1.2	–0.1	˚C
		11.8	34.5	25.0	5.360	28.8	–1.1	–0.25	
	Min. Air Temperature	4.7	22.6	14.3	4.247	18.1	–0.9	–0.3	˚C
		5.1	22.6	14.3	3.926	15.5	–0.8	–0.4	
	Mean Air Temperature	9.7	27.6	19.4	5.012	25.2	–1.2	–0.1	˚C
		9.0	26.9	19.5	4.522	20.5	–1.1	–0.4	
	Sunshine Hours	6.9	13.0	11.2	1.503	2.3	0.1	–0.9	hours
		6.9	13.0	10.9	1.439	2.1	–0.1	–0.9	
	Wind Speed	2.5	7.8	4.2	0.788	0.6	0.7	0.8	m/s
		3.0	7.3	4.1	0.593	0.4	3.6	1.5	
	Relative Humidity	32.3	90.2	59.5	14.817	219.9	–0.9	–0.1	%
		34.5	87.5	58.4	12.338	152.6	–1.1	0.2	
	Global Solar Radiation	75.3	367.0	264.3	73.753	5450.1	–0.3	–0.8	kWh/m^2
		70.8	354.4	228.6	65.171	4256.7	–0.7	–0.4	
	Precipitation	0.0	18.7	1.8	1.680	2.9	9.9	2.0	mm
		0.0	11.5	0.8	1.090	1.2	23.4	3.9	
Output	Evaporation	4.19	50.5	15.745	7.625	58.5	1.8	1.3	mm
		2.7	54.1	10.5	8.759	77.3	8.3	2.9	

2.3 Artificial Neural Network Model

The ANNs model is a knowledge extraction model that includes inferences such as the derivation of causal relationships between inputs and outputs, and the identification of hidden neurons, and the analysis of hidden neuron behavior in ANNs classification (Boger and Guterman 1997). The ANNs model is a powerful tool that can learn in the presence of trainer and has an ability on future prediction of a time series.

In the study, ANNs model was built for each of the scenarios created based on ReliefF algorithm. The ANNs script was written using MATLAB R2016a computing environment. Each scenario was tested in the ANN model with Bayesian Regularization (BR), Levenberg–Marquardt (L-M) and Scaled Conjugate Gradient (SCG) learning algorithms and different testing-training rates ranging from 60–80% for training, 0–10% for validation, and 20–40% for testing. The most appropriate scenario that validates the model was selected by considering the coefficient of determination (R^2) and mean square error (MSE). Verification was carried out with the selected scenario.

2.4 Statistical Measures

Two statistical measures, MSE and also R-square, were used for performance evaluation of the proposed model. One of the most common methods used to measure the prediction accuracy of a model is MSE. In the following formulas (Wright 1921), X_i is the simulated variable, Y_i is the actual variable and m is the number of variables.

$$\mathrm{MSE} = \frac{1}{m}\sum_{i=1}^{m}\left(X_i - Y_i\right)^2 \tag{1}$$

R-squared ranging from zero to one represents the square of the correlation (r) between two data sets. It can be defined as the convergence rate of the independent variables and the predicted dependent variable.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{m}\left(X_i - Y_i\right)^2}{\sum_{i=1}^{m}\left(\overline{Y} - Y_i\right)^2} \tag{2}$$

2.5 Agricultural Water Use Forecasting

Current study estimates the agricultural water use potential considering meteorological parameters, reservoir characteristics, crop pattern, reference evapotranspiration, crop coefficient, as well as projected evaporation based on ANNs model and climate scenarios. The forecasted water supply in m^3/s and the net irrigation requirement of the irrigated area in $m^3/s/ha$ were estimated and then the command area in ha was calculated. The present study also focused on optimum irrigation regime applied during the whole growing season.

Water loss from the reservoir was calculated according to Yuguda et al. (2020) as follows:

$$\mathrm{WL}_{\mathrm{reservour}} = (10 \times \sum_{t=1}^{lgp} E) \times \mathrm{A_R} \tag{3}$$

where $WL_{reservoir}$ is the volume of evaporated water over each irrigation period (m^3/yr); E is the monthly evaporation (mm/month) and A_R is the area of the reservoir (ha).

Crops grown at Karaidemir irrigation area were used for calculation of crop water requirements according to the crop pattern. The evapotranspiration of irrigated crops was estimated by crop factor approach (Doorenbos and Kassam 1979) where the evapotranspiration is given as;

$$\mathrm{ETc} = \mathrm{kc} \times \mathrm{ET}_o \tag{4}$$

where kc is a crop factor supplied from and ET_0 is the reference evapotranspiration. The daily average of the reference evapotranspiration (ET_0) was estimated by the FAO Penman–Monteith model (Allen et al. 1998) during the crop growth season and it could be described as follows:

$$\mathrm{ET_o} = \frac{0.408\,\Delta\,(\mathrm{R_n} - \mathrm{G}) + \gamma\,\frac{900}{\mathrm{T}+273}\mathrm{u_2}\left(\mathrm{e_s} - \mathrm{e_a}\right)}{\Delta + \gamma\left(1 + 0.34\,\mathrm{u_2}\right)} \tag{5}$$

where ETo is the reference evapotranspiration (mm day^{-1}), Rn is the net solar radiation (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} day^{-1}), T is the mean daily air temperature at 2 m height (°C), Δ is the slope of the saturated vapour pressure curve (kPa °C), y is the psychometric constant (0.066 kPa °C), es and ea are saturated and prevailing actual vapour pressure (kPa), respectively, and U_2 is the mean daily wind speed (m s^{-1}) measured at 2 m height.

The net irrigation water requirement (NIR) of each crop was determined by subtracting effective rainfall (Reff) from crop evapotranspiration (ETc). Moreover, irrigation module (q) was calculated based on irrigation requirement (IR).

$$q\left(\frac{L}{s/ha}\right) = \frac{NIR(mm) * 10\left(\frac{m^3}{ha/mm}\right) * 1000(\frac{l}{m^3})}{31(days) \times 24(hours) \times 60(min) * 60(sec)} \tag{6}$$

$$IR\left(\frac{m^3}{ha} \times year\right) = q \times Duration\left(\frac{day}{year}\right) \times 86.4\,(\frac{sxm^3}{day \times L}) \tag{7}$$

$$\text{Irrigable area (ha)} = \frac{\text{Water allocated of reservoir}\left(\frac{m^3}{day}\right) \times \text{Duration}(\frac{day}{year})}{\text{Irrigation Requirement for one hectar }(\frac{m^3}{ha} \times year)} \tag{8}$$

3 Results and Discussion

3.1 Performance of ANNs Model Based on Climate Projections

According to the results of the ReliefF algorithm given in Tables 3, 4 and 5, the input parameters were arranged in order of importance and consecutive scenarios were created by removing the trivial parameters respectively and then the model's accuracy was re-assessed in each scenario. The relief algorithm results show that the weight of each independent variable ranked from 0.02919 to 0.00763 for HadGEM and from 0.04796 to 0.00880 for MPI. The input parameters for both ANN climate models that arranged by ReliefF algorithm had different ranking, which is an advantage for artificial neural networks in terms of creating the best performance. Considering the sequence estimated by the ReliefF algorithm, 8 scenarios were created by gradually reducing the number of parameters for both of HadGEM and MPI reference data set. Each scenario was trained in the ANN model with different testing-training rates and defined with their mean square error (MSE) and determination coefficient (R^2) of distinctive statistics as seen in Table 4 for the HadGEM and Table 6 for the MPI. The highest correlation (R^2) and minimum mean square error (MSE) of validation performance were taken into account in order to select the best scenario. The fourth scenario with 5 parameters for HadGEM and second scenario with 7 parameters for MPI were selected as the strongest scenarios with the highest R^2 of 0.90 and the lowest MSE of 5.94 and R^2 of 0.98 and MSE of 1.60, respectively. We achieved the best performance at 80% training, 15% testing and 5% validation rates with Levenberg–Marquardt (L-M) learning algorithm. The best performances of selected scenarios were given in Fig. 2. In this figure, the actual evaporation was directly correlated with predicted evaporation values for all data and represented by linear equations with a high coefficient of correlation (R^2) of 0.96 for MPI and 0.90 for HadGEM at a statistical significance level of 1%. Many studies explain that artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS) and other machine learning methods can outperform traditional computational methods to predict evaporation, explain the effects of climate change on water resources and sectoral uses

Table 3 Alternative scenarios based on relief algorithm for HadGEM2-ES reference data set

Output Parameters	**Scenarios**			**Input Parameters**					
	ReliefF Range	0.02919	0.02772	0.02182	0.01412	0.00992	0.00894	0.00780	0.00763
Evaporation	1	Minimum Air Temperature	Wind Speed	Relative Humidity	Maximum Air Temperature	Mean Air Temperature	Precipitation	Sunshine Hours	Solar Intensity
	2	Minimum Air Temperature	Wind Speed	Relative Humidity	Maximum Air Temperature	Mean Air Temperature	Precipitation	Sunshine Hours	
	3	Minimum Air Temperature	Wind Speed	Relative Humidity	Maximum Air Temperature	Mean Air Temperature	Precipitation		
	4	Minimum Air Temperature	Wind Speed	Relative Humidity	Maximum Air Temperature	Mean Air Temperature			
	5	Minimum Air Temperature	Wind Speed	Relative Humidity	Maximum Air Temperature				
	6	Minimum Air Temperature	Wind Speed	Relative Humidity					
	7	Minimum Air Temperature	Wind Speed						
	8	Minimum Air Temperature							

Table 4 Performance of each scenario of HadGEM2-ES reference data set based on ANNs

Output Parameters	Scenarios	Training (%)	Validation (%)	Testing (%)	Hidden Neurons Number	Training Function	Epoch	MSE			R^2			MSE	R^2
								Training	Validation	Testing	Training	Validation	Testing		
	1	80	5	15	16	L-M	20	2.44712	2.90706	2.73735	0.96	0.96	0.96	2.51365	0.96
	2	80	5	15	14	L-M	65	2.45683	3.24006	2.77911	0.96	0.96	0.96	2.54433	0.96
	3	80	5	15	14	L-M	47	4.97217	4.77134	5.39082	0.92	0.92	0.90	5.02493	0.92
	4	**80**	**5**	**15**	**12**	**L-M**	**106**	**5.77306**	**5.93152**	**6.80432**	**0.90**	**0.90**	**0.90**	**5.93567**	**0.90**
	5	80	5	15	10	L-M	71	10.73901	10.44716	10.19478	0.81	0.81	0.81	10.6427	0.81
	6	80	5	15	6	L-M	28	16.36254	16.13947	16.41156	0.72	0.77	0.69	16.3587	0.72
	7	80	5	15	6	L-M	31	31.46020	26.99000	36.66739	0.46	0.45	0.35	32.0177	0.45
	8	80	5	15	3	L-M	11	55.63721	57.91833	56.17108	0.04	0.03	0.03	55.8313	0.04

Table 5 Alternative scenarios based on relief algorithm for MPI-ESM-MR reference data set

Output Parameters	**Scenarios**	**Input Parameters**							
	ReliefF Range	0.04796	0.03750	0.03620	0.02160	0.01689	0.01388	0.01279	0.00880
Evaporation	1	Wind Speed	Relative Humidity	Minimum Air Temperature	Precipitation	Maximum Air Temperature	Mean Air Temperature	Sunshine Hours	Solar Intensity
	2	Wind Speed	Relative Humidity	Minimum Air Temperature	Precipitation	Maximum Air Temperature	Mean Air Temperature	Sunshine Hours	
	3	Wind Speed	Relative Humidity	Minimum Air Temperature	Precipitation	Maximum Air Temperature	Mean Air Temperature		
	4	Wind Speed	Relative Humidity	Minimum Air Temperature	Precipitation	Maximum Air Temperature			
	5	Wind Speed	Relative Humidity	Minimum Air Temperature	Precipitation				
	6	Wind Speed	Relative Humidity	Minimum Air Temperature					
	7	Wind Speed	Relative Humidity						
	8	Wind Speed							

Table 6 Performance of each scenario of MPI-ESM-MR reference data set based on ANNs

Output Parameters	Scenarios	Training (%)	Validation (%)	Testing (%)	Hidden Neurons Number	Training Function	Epoch	MSE			R^2			MSE	R^2
								Training	Validation	Testing	Training	Validation	Testing		
	1	80	10	10	16	L-M	12	1.79210	1.71189	1.77313	0.97664	0.97750	0.97614	1.7698	0.98
	2	**80**	**5**	**15**	**22**	**L-M**	**11**	**1.65011**	**1.61801**	**1.59102**	**0.97850**	**0.98110**	**0.97849**	**1.5951**	**0.98**
	3	80	10	10	28	L-M	8	3.57914	3.53127	3.55713	0.95330	0.95464	0.95233	3.7803	0.95
	4	70	10	20	30	L-M	9	4.21761	4.07576	4.11930	0.94646	0.94219	0.94389	4.2771	0.94
	5	80	10	10	30	L-M	9	4.94663	4.90569	4.94120	0.93563	0.93345	0.93541	5.6032	0.93
	6	80	5	15	28	L-M	8	5.33293	5.30830	5.30206	0.92964	0.93783	0.93200	5.6982	0.93
	7	80	10	10	22	L-M	12	23.81988	21.93106	20.79842	0.69064	0.70588	0.72565	23.3983	0.70
	8	70	10	20	14	L-M	6	37.18302	35.89016	35.09030	0.51124	0.53422	0.55020	36.9272	0.52

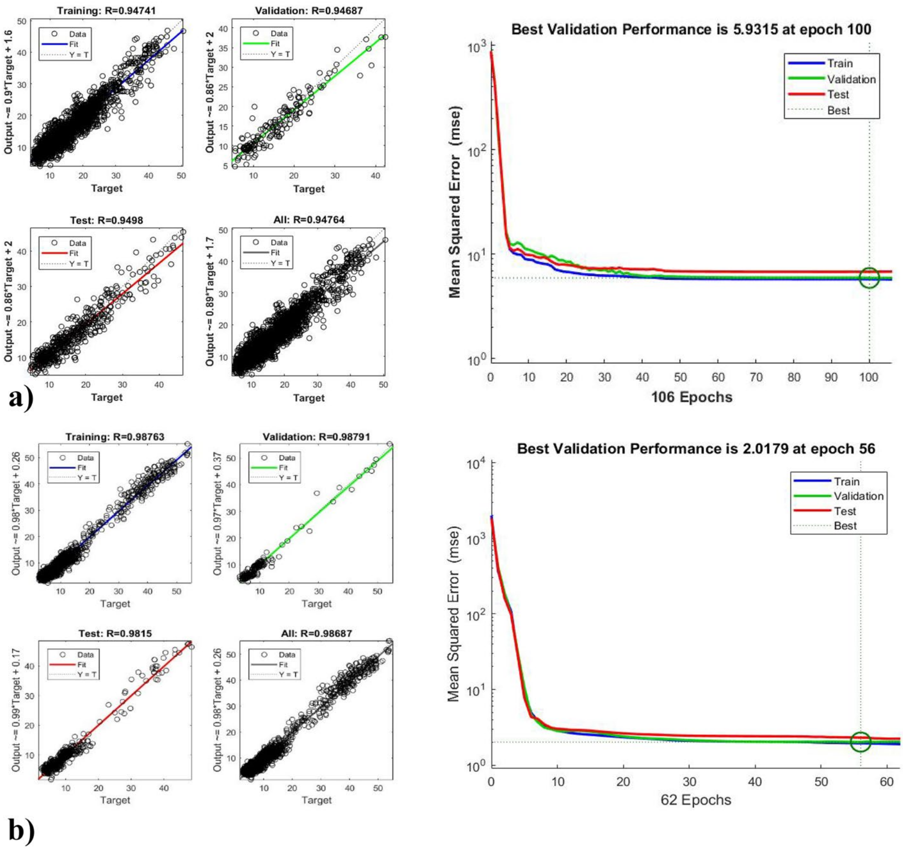

Fig. 2 The model performance results, **a** HadGEM and **b** MPI

(Moghaddamnia et al. 2009; Moazenzadeh et al. 2018; Allawi et al. 2019). Deswal and Pal (2008) used ANN to investigate the impact of various collections of meteorological parameters on reservoir free water surface evaporation. The comparison found a better performance of ANN over the linear regression approach. Keskin and Terzi (2006) predicted daily pan evaporation using the ANN model using 6 meteorological variables in the Eğirdir Lake region.

The results of monthly average evaporation including reference and projected data of MPI and HadGEM with RCP4.5 and RCP8.5 are given in Fig. 3. The projected data covers the years between 2020 and 2098. It is clear that the monthly evaporation of HadGEM are higher than MPI results according to the reference data for all every twenty years. In MPI model, the percent change of projected evaporation was provided for the near-term (2021–2040), mid-term (2041–2060) and long-term (2081–2100) relative to reference period as 1.4, 1.4 and 1.0% for scenario RCP4.5 and -0.5, -7.5, and-14%, for scenario RCP8.5, respectively. In HadGEM model, these changes are -1.1, -0.5 and 3.1% for scenario RCP4.5 and 3.2, 4.0 and 7.3% for scenario RCP8.5, respectively. In accordance these results, the RCP8.5 scenario values contrast to RCP4.5 of HadGEM show an increase, while MPI scenarios show a decrease. The surface water evaporation difference between

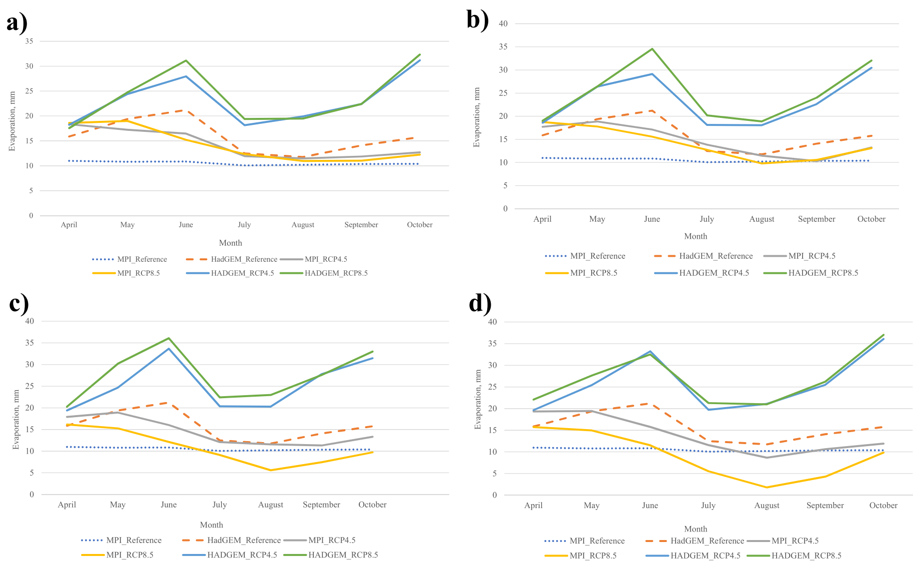

Fig. 3 Monthly average projected evaporation for each 20 years; **a** 2020–2040, **b** 2040–2060, **c** 2060–2080, **d** 2080–2098

RCP4.5 and RCP8.5 changed by nearly 35 mm for MPI, while nearly 38 mm for HadGEM climate model at the end of twenty-first century. According to the yearly average evaporation results, as seen in Fig. 4, HadGEM projected approximately 20 mm higher than MPI model. The difference of two scenarios for HadGEM is lower along near future than distant future results. In parallel, El-Mahdy et al. (2021) informed that the artificial neural network model with 20 neurons with 5 input variables could be used in prediction of surface water evaporation with high accuracy and nearly a 2% increase in lake Nasser evaporation in 2050 depending on CORDEX projections. Also, Senent-Aparicio et al. (2021) proved that

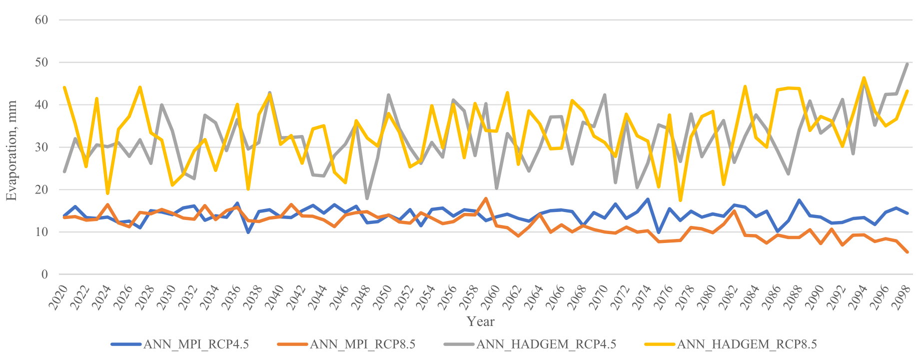

Fig. 4 Time series of yearly average projected evaporation from 2020 to 2098

the climate change impact on the reservoir water volumes under both scenarios (RCP 4.5 and RCP 8.5) by considering future evaporation rates and bathymetric changes.

The course of the annual evaporation values for the HadGEM and MPI model including two scenarios is shown in Fig. 4. As it would be seen, this figure also enhances the fact that there will be an increase by HadGEM model in both RCP4.5 and RCP8.5, in addition a decrease by MPI.

3.2 Agricultural Water Use Projections

The total irrigation water requirement was obtained as 27,496 m^3/ha. Crop water evapotranspiration calculated with CROPWAT model using climate data with long-term averages, was modified with precipitation and planting rates. The total irrigated area in the basin is 2500 ha and the amount of water allocated from the reservoir to the network is 25% of the total water volume. Considering the water volumes realized in the dam in the last 10 years, the average lake volume is 65.8 MCM as obtained from General Directorate of Water Management records in m^3. The total irrigable area of about 600 ha was calculated by proportioning the volume of water allocated (16.1 MCM) to the network to the need. The total evaporation losses calculated according to climate projections for the end of this century, were found as 31.4 million cubic meter (MCM) and 18.1 MCM, respectively, in the MPI model according to RCP4.5 and RCP 8.5 scenarios, while these values were found as 59.2 MCM and 60.9 MCM for HadGEM, respectively. Considering these amounts, the changes in the reservoir volume were calculated and it was predicted that the irrigated area would decrease by approximately 27–93% depending on the amount of water allocated from reservoir. Many studies (Kolokytha and Malamataris 2020; da Costa et al. 2021; Alejo and Alejandro 2022) offer innovative methodologies to decision makers by combining hydrology, climate change scenarios and decision support systems in the management of the sectoral water budget for climate change adaptation.

4 Conclusion

Within the scope of providing an adaptive and sustainable water management this study used an ANN model, which is one of the artificial intelligence models with a very low margin of error and high reliability, in the estimation of evaporation. It was created by using the input climate parameters of the reference period, which were entered in order of importance according to the RelieF algorithm, and future predictions were made according to the climate scenarios. According to the RCP4.5 and RCP8.5 scenarios of HadGEM and MPI climate models, the estimated total evaporation losses for the near, middle and far periods and agricultural water potential were calculated. However, future estimations based on water level and surface area in the reservoir during the reference period need to be strengthened in future studies. The results also highlight the change in the current water resource potential of the region to meet water needs in irrigated agriculture and provide a tool for optimizing future goals and strategies for water resource planning globally. The model results will also guide decision makers and stakeholders to the sustainable management of water resources.

Authors Contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Yeşim Ahi, Çiğdem Coşkun Dilcan, Daniyal Durmuş Köksal and Hüseyin Tevfik Gültaş. The first draft of the manuscript was written by Yeşim Ahi and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding The authors declare that no funds, grants, or other support were received during the preparation of this manuscript. The authors have no relevant financial or non-financial interests to disclose.

Availability of Data and Materials All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

Declarations

Informed Consent Not applicable.

Consent to Participate All authors agree with the content and that all give explicit consent to submit.

Consent to Publish All authors have read and agreed to the published version of the manuscript.

Research Involving Human Participants and/or Animals Informed Consent Not applicable.

Conflicts of Interest In the study, there is no any potential conflicts of interest. We hereby confirm that this work has not been published elsewhere and that it has not been submitted simultaneously for publication elsewhere. There are no conflicts of interest to disclose.

References

Abed M, Imteaz MA, Ahmed AN, Huang YF (2022) Modelling monthly pan evaporation utilizing Random Forest and deep learning algorithms. Sci Rep 12:13132
Alejo LA, Alejandro AS (2022) Changes in irrigation planning and development parameters due to climate change. Water Resour Manag 36:1711–1726
Allawi MF, Othman FB, Afan AA, Ahmed AN, Hossain S, Fai CM, El-Shafie A (2019) Reservoir evaporation prediction modeling based on artificial intelligence methods. Water 11:1226. https://doi.org/10.3390/w11061226
Allen RG, Pereira LS, Raes D, Smith M (1998) Crop evapotranspiration: Guidelines for computing crop water requirements. FAO Irrig Drain Rome, Italy. p. 56
Boger Z, Guterman H (1997) Knowledge extraction from artificial neural network models. IEEE Int Conf Syst Man Cybern Comput Cybern Simul 4:3030–3035
Bou-Fakhreddine B, Mougharbel I, Faye A, Pollet Y (2019) Estimating daily evaporation from poorly-monitored lakes using limited meteorological data: A case study within Qaraoun dam – Lebanon. J Environ Manag 241:502–513
Budak H (2018) Feature selection methods and a new approach. SDU J Nat Appl Sci 22(SI):21–31
da Costa EMB, Lucio PS, Maia AG (2021) Relevance of reservoir morphometry in the evaporation process: an evaporation model for semi-arid regions. Water Resour Manag 35:4895–4907
Deswal S, Pal M (2008) Artificial neural network based modeling of evaporation losses in reservoirs. Inter J Civil Environ Engin 2(3):18–22
Doorenbos J, Kassam AH (1979) Yield response to water. FAO Irrig Drain Pap No. 33 Rome, Italy, p. 193
El-Mahdy SM, El-Abd WA, Morsi FI (2021) Forecasting lake evaporation under a changing climate with an integrated artificial neural network model: A case study Lake Nasser. Egypt J Afr Earth Sci 179:104191
Fan J, Chen B, Wu L (2018) Evaluation and development of temperature-based empirical models for estimating daily global solar radiation in humid regions. Energy 144:903–914
Feng Y, Peng Y, Cui N (2017) Modeling reference evapotranspiration using extreme learning machine and generalized regression neural network only with temperature data. Comput Electron Agric 136:71–78
Feng Y, Jia Y, Zhang Q (2018) National-scale assessment of pan evaporation models across different climatic zones of China. J Hydrol 564:314–328

GDSHW (2018) Kızılırmak basin master plan report. General Directorate of State Hydraulic Works, Ministry of Forestry of Water Management, Turkey
GDWM (2021) General directorate of water management database. https://suen.gov.tr/Suen/en/default.aspx. Accessed 26 Mar 2022
Ghaemi A, Rezaie-Balf M, Adamowski J, Kisi O, Quilty J (2019) On the applicability of maximum overlap discrete wavelet transform integrated with MARS and M5 model tree for monthly pan evaporation prediction. Agric for Meteorol 278:107647
Goyal MK, Bharti B, Quilty J (2014) Modeling of daily pan evaporation in sub-tropical climates using ANN, LS-SVR, Fuzzy Logic, and ANFIS. Expert Syst Appl 41(11):5267–5276
IPCC (2001) Climate change 2001: The scientific basis. Contribution of Working Group Ito the 3rd Assessment Report of the Intergovernmental Panel on Climate Change, edited by J. T. Houghton et al., 881 pp., Cambridge Univ. Press, New York
IPCC (2007) Climate change 2007: The scientific basis. Contribution of Working Group Ito the 4th Assessment Report of the Intergovernmental Panel on Climate Change, edited by S. Solomon et al., Cambridge Univ. Press, New York
Islam Z (2011). A review on water resources management modeling. https://doi.org/10.13140/2.1.3496.0168
Jensen ME, Burman RD, Allen RG (1990) Evapotranspiration and irrigation water requirements. ASCE Man Rep Eng Pract No.70, New York, pp. 332
Keskin ME, Terzi O (2006) Artificial neural network models of daily pan evaporation. J Hydrol 11:65–70
Kim S, Shiri J, Kisi O (2012) Pan evaporation modeling using neural computing approach for different climatic zones. Water Res Manag 26(11):3231–3249
Kisi O (2013) Evolutionary neural networks for monthly pan evaporation modeling. J Hydrol 498(12):36–45
Kolokytha E, Malamataris D (2020) Integrated water management approach for adaptation to climate change in highly water stressed basins. Water Resour Manag 34:1173–1197
Lu X, Ju Y, Wu L, Fan J, Zhang F, Li Z (2018) Daily pan evaporation modeling from local and cross-station data using three tree-based machine learning models. J Hydrol 566:668–684. https://doi.org/10.1016/j.jhydrol.2018.09.055
Malik A, Kumar A, Kisi O (2017) Monthly pan-evaporation estimation in Indian central Himalayas using different heuristic approaches and climate based models. Comput Electron Agric 143:302–313
Majhi B, Naidu D (2021) Pan evaporation modeling in different agroclimatic zones using functional link artificial neural network. Inf Process Agric 8:134–147
Moazenzadeh R, Mohammadi B, Shamshirband S, Chau KW (2018) Coupling a firefly algorithm with support vector regression to predict evaporation in northern Iran. Eng Appl Comput Fluid Mech 12:584–597
Moghaddamnia A, Ghafari GM, Piri J, Amin S, Han D (2009) Evaporation estimation using artificial neural networks and adaptive neuro-fuzzy inference system techniques. Adv Water Resour 32:88–97
Nourani V, Elkiran G, Abdullahi J (2019) Multi-station artificial intelligence based ensemble modeling of reference evapotranspiration using pan evaporation measurements. J Hydrol 577:123958. https://doi.org/10.1016/j.jhydrol.2019.123958
Novotná B, Jurík L, Cimo J, Palkovic J, Chvíla B, Kišš V (2022) Machine learning for pan evaporation modeling in different agroclimatic zones of the Slovak Republic (Macro-Regions). Sustain 14:3475
Penman HL (1948) Natural evaporation from open water, bare soil and grass. Proc Royal Society, London 193:120–145
Priestley CHB, Taylor RJ (1972) On the assessment of surface heat flux and evaporation using large-scale parameters. Mon Weather Rev 100(2):81–92
Robnik-Šikonja M, Kononenko I (2003) Theoretical and empirical analysis of ReliefF and RReliefF. Mach Learn 53:23–69
Sanikhani H, Kisi O, Nikpour MR (2012) Estimation of daily pan evaporation using two different adaptive neuro-fuzzy computing techniques. Water Resour Manag 26(15):4347–4365
Seifi A, Soroush F (2020) Pan evaporation estimation and derivation of explicit optimized equations by novel hybrid meta-heuristic ANN based methods in different climates of Iran. Comput Electron Agric 173:105418. https://doi.org/10.1016/j.compag.2020.105418
Senent-Aparicio J, López-Ballesteros A, Cabezas F, Pérez-Sánchez J, Molina-Navarro E (2021) A modelling approach to forecast the effect of climate change on the tagus-segura interbasin water transfer. Water Resour Manag 35:3791–3808
TSMS (2020) Turkish state meteorological agency database. https://www.mgm.gov.tr/eng/forecast-cities.aspx. Accessed 26 Mar 2022
UNESCO, UN-Water (2020) United nations world water development report 2020: water and climate change, Paris

Wright S (1921) Correlation and causation. J Agric Res 20(7):557–585

Wu L, Huang G, Fan J, Ma X, Zhou H, Zeng W (2020) Hybrid extreme learning machine with metaheuristic algorithms for monthly pan evaporation prediction. Comput Electron Agric. https://doi.org/10.1016/j.compag.2019.105115

Yuguda TK, Li Y, Zhang W, Ye Q (2020) Incorporating water loss from water storage and conveyance into blue water footprint of irrigated sugarcane: A case study of Savannah Sugar Irrigation District. Nigeria Sci Total Environ 715:136886

Authors and Affiliations

Yeşim Ahi[1] · Çiğdem Coşkun Dilcan[1] · Daniyal Durmuş Köksal[2] · Hüseyin Tevfik Gültaş[3]

✉ Yeşim Ahi
ysmahi@ankara.edu.tr

Çiğdem Coşkun Dilcan
coskunc@ankara.edu.tr

Daniyal Durmuş Köksal
danyalkoksal@gmail.com

Hüseyin Tevfik Gültaş
huseyin.gultas@bilecik.edu.tr

1 Water Management Institute, Ankara University, Gumusdere Campus, 06135 Ankara, Turkey

2 Agricultural Structure and Irrigation Department, Agriculture Faculty, Ankara University, Gumusdere Campus, 06135 Ankara, Turkey

3 Biosystem Engineering Department, Bilecik Seyh Edebali University, 11230 Bilecik, Turkey