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Modelling the Impact of Climate Change on the Reservoir Filling Rates of Dams Used for Drinking Water Supply Through Artificial Neural Networks

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Abstract
Climate change has increasingly altered global precipitation patterns and hydrological cycles, posing significant risks to the storage performance and operational reliability of dams. Changes in rainfall regimes, prolonged droughts, and rising evapotranspiration rates directly affect reservoir inflows, making accurate prediction of these variations essential for sustainable water supply management. This study aims to model the effects of climate change on the storage levels of drinking water supply dams located in Ankara, Istanbul, and Izmir using various Artificial Neural Network (ANN) techniques. Among the ANN structures evaluated, dynamic time series, curve fitting, and feedforward distributed time delay networks demonstrated limited performance on the dataset; however, the feedforward backpropagation network demonstrated successful performance. This network type was optimized for the dataset through various modifications to parameters such as training, adaptive learning, performance, and transfer functions, as well as the number of layers and neurons. The findings were supported by regression analyses conducted for dams supplying drinking water. The differences between expected and observed precipitation amounts illustrate the impacts of climate change and water losses in the reservoirs. The models developed in the study exhibited R^2 values ranging between 0.85 and 0.99, with the highest value calculated as 0.994. The results quantitatively demonstrate the divergence between projected and observed precipitation on an individual dam basis, thereby elucidating the susceptibility of drinking water reservoirs to the impacts of climate change. In this context, the study offers robust, data-driven insights that can inform evidence-based revisions of water management and adaptation strategies for major metropolitan regions.

Keywords Climate change · Drinking water · Dam · Regression analysis · Catchment area · Artificial neural network (ANN)

Extended author information available on the last page of the article

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1 Introduction

The concept of climate change, a consequence of global warming, describes the effects resulting from the increase in greenhouse gas concentrations, which is considered one of the major global issues of our time (Mushtaq et al. 2024; Elshafei 2022; Guo et al. 2021). Greenhouse gases are identified in Article 3 of the Kyoto Protocol as CO_2, CH_4, N_2O, HFCs, PFCs, and SF_6. Additionally, chlorofluorocarbons (CFCs), which are not included in the Kyoto Protocol but have significant greenhouse gas effects, are regulated under the Montreal Protocol (Demirbaş 2018). Although climate change is often associated with global warming and rising temperatures, the impacts resulting from changes in precipitation regimes are considered significant causes of drought. Climatic conditions influence the global hydrological system both directly and indirectly. Variables such as evapotranspiration rates, storm intensity, soil moisture, cloud characteristics, and snowfall and melting regimes are affected by temperature changes (Demirbaş 2018).

The reduction of water resources and the expansion of arid and semi-arid areas are among the outcomes of climate change (Sheikh et al. 2025; Torabi Haghighi et al. 2020). A drought period refers to a situation where precipitation, groundwater, or surface water levels are lower than expected under the prevailing climatic conditions of a region (Ustaoğlu et al. 2022). Precipitation and evaporation directly affect drought conditions; during drought periods, precipitation decreases while temperatures increase. The intensifying impacts of drought, coupled with its uncertain onset and conclusion, significantly disrupt both natural and anthropogenic systems. The spatial and temporal variability of precipitation profoundly influences water availability (Çaldağ et al. 2004).

There have been numerous international efforts to thoroughly investigate the causes and consequences of climate change. Notable among these are the Intergovernmental Panels on Climate Change (IPCC), established by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). The panel's assessment reports include the First Assessment Report (FAR) in 1990, the Second Assessment Report (SAR) in 1996, the Third Assessment Report (TAR) in 2001, the Fourth Assessment Report (AR4) in 2007, the Fifth Assessment Report (AR5) in 2014, and the Sixth Assessment Report (AR6) in 2023. These assessment reports provide comprehensive insights into topics such as emission inventories resulting from increased greenhouse gas concentrations contributing to global warming, changes in climate characteristics, adaptation processes to climate change, future projections, and trends (McMullen and Jabbour 2009).

Türkiye, located within the Mediterranean Basin, is considered one of the most vulnerable regions to the challenges posed by climate change. In the Mediterranean Basin, the impacts of climate change, such as difficulties in accessing water resources and a reduction in available water quantities, are experienced more acutely (Gampe et al. 2016). This situation indicates a significant shift toward adverse seasonal precipitation pattern changes and warmer climatic conditions in the region (Giorgi and Lionello 2008). Projections suggest a decline in precipitation, particularly in southern Türkiye, accompanied by an increase in temperatures across the country. These factors negatively affect water resources, resulting in a reduction in water potential in the basins of southern Türkiye. Projections indicate that during this century, water potential could decrease by up to 70% in the Konya Basin, 37% in the Mediterranean Basin, and 10% in the Euphrates and Tigris Basins (Şen 2013).

Dams are defined as reservoirs constructed to store water by utilizing surface or groundwater resources to meet water demands (Hamid et al. 2024; Angelakis et al. 2024). Additionally, dams are critical components of water supply systems. They enable the filling of water to maximum levels during periods of abundant precipitation and provide the required discharge during drought periods (Cüceloğlu 2019). One of the purposes of dam construction is to regulate natural water resources (Wurbs 2021). Other objectives include water retention, controlled distribution according to demand, flood control, hydroelectric power generation, and the supply of drinking and utility water (Pınarlık 2020). In Türkiye, there are over 2,000 dams and ponds (DSI, 2016).

Recent advances in water resources research have increasingly examined the impacts of climate change on reservoir systems and hydrological dynamics. Several studies have developed data-driven and adaptive management approaches to address changing climatic and hydrological conditions. For example, modeling frameworks and optimization techniques have been applied to improve reservoir operations under future climate scenarios (Beça et al. 2023; Tsakiris and Loucks 2023), while deep learning and Artificial Neural Networks (ANNs) have been used to predict inflow and evaporation losses (Latif and Ahmed 2023; Ahi et al. 2023). Other works have explored basin-scale sustainability, system resilience, and the interaction between groundwater and surface water under climate stress (Zhuang et al. 2023; Stojković et al. 2024; Lyra et al. 2025; Getahun et al. 2025). These studies provide a strong scientific basis for modeling the effects of climate change on reservoir storage and performance.

In water resource management, the calculation of evaporation in reservoirs must be considered during the design and operation phases of dams to account for the impact of evaporation on dam efficiency parameters (Lowe et al. 2009). The influence of evaporation on reservoir storage levels is reported to be more significant in arid and semi-arid regions (Mady et al. 2020; Zhang et al. 2024). Therefore, to prevent water shortages, evaporation parameters must be calculated during the dam planning phase. For dams that have entered the operational phase, reducing evaporation through physical and chemical methods is of critical importance (Pınarlık 2020).

In Türkiye, evaporation-related water losses in surface reservoirs are measured between April and September, while evaporation is assumed to be negligible during the remaining months. To mitigate the negative impacts of climate change, such as increased solar radiation, wind, and relative humidity (RH), particularly in regions where meteorological data are not sufficiently monitored, the Hargreaves method is widely used for evaporation calculations during the planning phase (Schuol et al. 2008). The average utilization period of water resources is reported to be approximately 22 years (Dixon et al. 1989). Among the primary solutions for short-lived water resources is the construction of new ones. However, due to the decreasing availability of suitable areas for water resource construction, high construction costs, and environmental impacts, it is crucial to protect the storage capacities of existing dams and reservoirs (Shen and Lai 1996).

Various hydrological modeling approaches, including physically based models such as SWAT and WEAP as well as regression-based techniques, have been widely applied to simulate evaporation, inflow dynamics, and water demand under changing climatic conditions. While these models provide valuable insights at basin and system scales, they often depend on linear assumptions and require extensive calibration and detailed input data, which may limit their performance under complex, nonlinear, and data-scarce hydroclimatic conditions (Wurbs and Ayala 2014). In contrast, ANNs offer a flexible, data-

driven modeling framework capable of capturing nonlinear relationships among climatic variables without explicit physical parameterization. This characteristic makes ANN-based approaches particularly suitable for assessing climate-related impacts on reservoir filling behavior and drinking water supply dams in Türkiye.

ANNs are algorithms capable of processing distributed data and performing parallel computations, designed to mimic biological neural networks. They address existing problems by relying on the principles of learning, memorization, and establishing connections based on data rather than traditional methods (Richards et al. 2019; Hassabis et al. 2017). ANNs can deliver high-performance results even when data are incomplete or uncertain. They have demonstrated successful performance in optimization, classification, and prediction tasks. The most significant advantage of ANNs is their ability to learn and perform calculations within a very short time. However, their most notable disadvantage is the inability to fully analyze the system's functioning. As a result, there is a possibility of failure in the learning process (Yılmaz 2020). Table 1 summarizes studies in the literature similar to this research.

In this study, the changes in precipitation-derived water inflows to dams used for drinking water purposes were modeled using meteorological data and ANN. For this purpose, the reservoir areas of the dams designated for drinking water use were first identified, and the catchment areas of these reservoirs were delineated, along with the meteorological stations located within them. ANN models were developed using data from the meteorological stations, including average actual pressure (hPa), average RH (%), daily maximum wind speed (m/s), daily average temperature (°C), daily average wind speed (m/s), and daily total precipitation (mm = kg/m²). The outputs of the models were statistically evaluated.

This study fills a significant gap in the literature by accurately predicting climate change–induced variations in precipitation for drinking water supply dams in Ankara, Istanbul, and Izmir using ANN models. The use of an extensive meteorological dataset and the comparison of four different ANN architectures further strengthen the study's scientific contribution. Unlike previous studies that mainly focused on runoff or inflow estimation, this research uniquely integrates climate projections with ANN-based reservoir filling rate modeling for urban drinking water systems, providing a methodological framework applicable to other metropolitan areas. The analysis focuses on short- to medium-term hydroclimatic variability (2011–2020) based on the availability of continuous, high-resolution meteorological data. Accordingly, the findings represent recent climatic fluctuations consistent with regional change patterns rather than long-term climatic trends.

2 Materials and methods

2.1 Artificial Neural Network (ANN) Modeling

An ANN is a mathematical structure designed to mimic the biological neural system in terms of the information processing functions of neurons (Ciner et al. 2024; Ongen et al. 2013). ANN models represent a simplified version of human brain networks and are nonlinear, adaptive, and flexible structures capable of solving complex environmental problems. They typically demonstrate high predictive accuracy and computational efficiency when processing large datasets (Guo et al. 2021). The ability of ANNs to represent nonlinear and random data improves as the amount of state data available increases (Alfarra et al. 2024;

Table 1 Similar studies in the literature

Authors	Study Topic
Guo et al. (2021)	Evaporation, temperature, and precipitation simulations were developed using climate modeling, and the inflow to the dam reservoir was predicted using the Soil and Water Assessment Tool (SWAT) model, with an R^2 value of 0.583.
Pınarlık (2020)	The aim was to evaluate the impact of overlooking evaporation and sedimentation during reservoir planning on subsequent operational performance in the Yeşilırmak Basin (Türkiye).
Damla et al. (2020)	The aim was to model the water level in the reservoir of the Gökçe Dam using ANNs based on the flow rate of the stream feeding the dam, dam water discharges, water level measurements, seepage water quantities, and evaporation and precipitation values of the basin. In the developed model, the Levenberg-Marquardt algorithm was used, and the R^2 value was measured as 0.94.
Zhao et al. (2016)	It was proposed to calculate evaporation in 721 dams using a method that combines modeling and remote sensing approaches.
Salam and Keskin (2018)	The water level of the Dibis Dam was predicted using an ANN model.
Sönmez et al. (2017)	The impact of climate change on the water level of the Gökçe Dam was examined.
Terzi et al. (2017)	An operational study was conducted at the Altınapa Dam, constructed on the Meram Stream, using data mining methods.
Pamukcu et al. (2014)	The effects of land use, climate, and forest cover changes on water resources in the Marmara Basin were investigated.
Wurbs and Ayala (2014)	A model was used to investigate the role of surface evaporation in dams for water management and to manage water resources under past and present conditions.
Yarar and Onüçyıldız (2009)	Water level changes in Lake Beyşehir were modeled using ANN.
Çalım (2008)	Reservoir level changes in the Yarseli Dam were modeled using ANNs based on approximately five years of data.
Altunkaynak (2007)	The submergence of coastal areas due to rising water levels in Lake Van over time was modeled.
Gökbulak and Özhan (2006)	The aim was to calculate evaporation in dams and lakes located in Türkiye.

Ongen et al. 2013). The basic structure of an ANN consists of three layers: an input layer, one or more hidden layers, and an output layer (Fig. 1).

In this study, the ANN model was developed and trained using the MATLAB program. A three-layer neural network architecture, consisting of an input layer, a hidden layer, and an output layer, was employed. Meteorological data including average actual pressure (hPa), average RH (%), daily maximum wind speed (m/s), daily average temperature (°C), daily average wind speed (m/s), and daily total precipitation (mm = kg/m²) were obtained from meteorological stations to meet the requirements for training and testing the network.

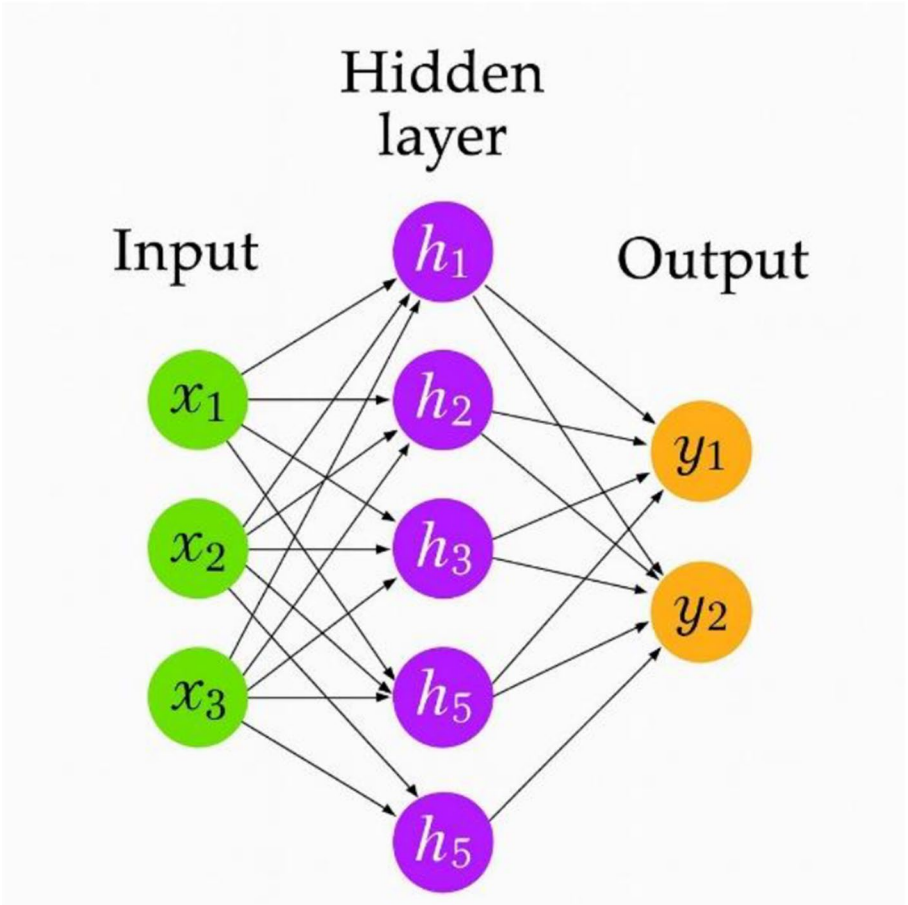


Fig. 1 Structure of an ANN

For each dam, data from stations situated inside the delineated catchment boundary were used; where multiple stations were available, their daily mean values represented basin-level conditions. All data were checked for quality and completeness before being imported into MATLAB for ANN modeling.

Meteorological data were obtained from official observation stations located within or near each reservoir catchment. When no station was situated inside a catchment, data from the nearest surrounding stations were used. For catchments represented by multiple stations, daily averages were calculated to describe basin-level meteorological conditions. All data were quality-checked for completeness and consistency before being imported into MATLAB for ANN modeling.

These parameters, recorded daily between 2011 and 2020, were collected from reservoirs located in Ankara, Istanbul, and Izmir. Data were sourced from a total of 149 meteorological stations: 45 in Ankara, 50 in Istanbul, and 54 in Izmir. Across all parameters, a total of 544,148 data points were recorded from these stations, and approximately three million data points were used in the model for six parameters.

The input variables used in the model include average actual pressure, average RH, daily maximum wind speed, daily average temperature, and daily average wind speed, while the output variable is daily total precipitation. After classifying the data into input and output sets, all variables were transferred into the MATLAB environment, where the precipitation data were used as the target output to be predicted by the ANN.

The data were split into training and testing sets with the aid of MATLAB, which performs this process automatically. In the MATLAB workspace, input data were initially formatted as a 31×12 matrix representing 12 groups of 31 data points each; however, since 10 years of data were required, the correct format was adjusted to a 3653×1 matrix. Based on the characteristics of the dataset, four network types were tested: Dynamic Time Series, Curve Fitting, Feedforward Distributed Time Delay, and Feedforward Backpropagation Networks. The Feedforward Backpropagation Network demonstrated superior performance and was therefore selected for the analysis.

During model development, two alternative feedforward backpropagation network architectures one with 13 neurons and another with 18 neurons in the hidden layer were tested to determine the optimal configuration. The 18-neuron structure provided superior predictive accuracy and stability across training, validation, and testing datasets. Therefore, this configuration was selected as the final ANN model. The Levenberg–Marquardt (trainlm) algorithm was employed for training due to its high convergence efficiency in nonlinear modeling. Network performance was evaluated using the mean squared error (MSE) function. The dataset was divided into 70% training, 15% validation, and 15% testing subsets using MATLAB's dividerand function to ensure unbiased generalization. The network was trained for a maximum of 1000 epochs, with early stopping controlled by a maximum fail value of 1000. The commonly used tansig and purelin transfer functions were applied to the hidden and output layers, respectively.

The ANN application was conducted for drinking water supply dams located in Ankara, Istanbul, and Izmir (Table 2). Table 3 presents the corresponding date ranges, number of days, and the number of input/output data for each dam. Data from the Akyar, Çamlıdere, Çubuk 2, Eğrekkaya, and Kurtboğazı Dams in Ankara; the Alibey, Büyükçekmece, Ömerli, Sazlıdere, and Terkos Dams in Istanbul; and the Balçova and Tahtalı Dams in Izmir were utilized. Evaporation and sediment parameters were not included in the modeling.

A Geographic Information System (GIS) was employed to delineate basin boundaries. The Digital Elevation Model (DEM) served as the base layer for spatial modeling. Among the globally available DEM datasets, Shuttle Radar Topography Mission (SRTM)-based and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)-based DEMs are the most widely used (Boulton and Stokes 2018; Uuemaa et al. 2020). SRTM data, which employ radar technology, can partially penetrate vegetation and are therefore more suitable for generating bare-earth surfaces compared to ASTER data, which use photogrammetric techniques (Abrams and Crippen 2019; Eros 2018; González-Moradas and Viveen 2020;

Table 2 The dams where the ANN application was conducted in this study

ANKARA	ISTANBUL	IZMIR
Akyar Dam	Alibey Dam	Tahtalı Dam
Çamlıdere Dam	Büyükçekmece Dam	Balçova Dam
Çubuk 2 Dam	Ömerli Dam	
Kurtboğazı Dam	Sazlıdere Dam	
Eğrekkaya Dam	Terkos Dam	

Table 3 Date Ranges, number of Days, and number of Input/Output data for the dams included in the study

Province	Dams	Date Range and Number of Days for the Data	Number of Input/Output Data	Inputs	Output
Ankara	Akyar Dam	1 January 2016–31 December 2020/1721 day	5 − 1	P, RH, WSmax, Tavg, WSavg	Ppt
	Çamlıdere Dam	1 January 2016–31 December 2020/1721 day	5 − 1		
	Çubuk 2 Dam	1 January 2016–31 December 2020/1721 day	5 − 1		
	Eğrekkaya Dam	1 January 2011–31 December 2020/3575 day	5 − 1		
	Kurtboğazı Dam	1 January 2016–31 December 2020/1778 day	5 − 1		
Province	Dams	Date Range and Number of Days for the Data	Number of Input/Output Data		
Istanbul	Alibey Dam	1 January 2016–31 December 2020/1805 day	5 − 1	P, RH, WSmax, Tavg, WSavg	Ppt
	Büyükçekmece Dam	1 January 2016–31 December 2020/1776 day	5 − 1		
	Ömerli Dam	1 January 2016–31 December 2020/1689 day	4 − 1	RH, WSmax, Tavg, WSavg	
	Sazlıdere Dam	1 January 2016–31 December 2020/1757 day	4 − 1		
	Terkos Dam	1 January 2011- 31 December 2020/ 3357 day	4 − 1		
Province	Dams	Date Range and Number of Days for the Data	Number of Input/Output Data		
Izmir	Tahtalı Dam	3 January 2011- 31 December 2020/ 2842 day	5 − 1	P, RH, WSmax, Tavg, WSavg	Ppt
	Balçova Dam	24 July 2017- 31 December 2020/ 1174 day	4 − 1	RH, WSmax, Tavg, WSavg	

P Average actual pressure (hPa), *RH* Average relative humidity (%), *WSmax* Daily maximum wind speed (m/s), *Tavg* Daily average temperature (°C), *WSavg* Daily average wind speed (m/s), *Ppt* Daily total precipitation (mm, model output)

Gesch et al. 2014). Accordingly, SRTM-based DEMs with a 1 arc-second (~30 m) resolution were employed in this study to delineate catchment boundaries. Basin delineation was performed using the Hydrology Toolset in ArcGIS Desktop 10.8.1 (ESRI, 2024). Dam locations were defined as pour points, and analyses were carried out using SRTM-based DEMs. As a result, basin boundaries were generated in vector format for each reservoir area.

3 Calculation of Expected Precipitation and Water Loss

The term expected precipitation refers to the daily precipitation values predicted by the optimized feedforward backpropagation ANN model using input meteorological parameters (average pressure, relative humidity, temperature, and wind speed). These model-based estimates represent precipitation levels expected under baseline climatic conditions derived from the training dataset.

To assess climate variability effects, predicted (expected) precipitation values were compared with observations from meteorological stations. The difference between expected and observed precipitation ($\Delta P = P_{excepted} - P_{observed}$) was used to identify precipitation anomalies, including drought conditions and shifts in rainfall intensity.

Water loss was defined as the reduction in reservoir filling potential corresponding to negative precipitation deviations. It was estimated using:

$$W_{loss} = \triangle P \times A_{basin} \times C_{runoff} \quad (1)$$

Where A_{basin} is the delineated catchment area (m^2) obtained from SRTM-based DEM analysis, and C_{runoff} is the mean runoff coefficient derived from regional hydrological data. Positive deviations indicate excess inflow potential, while negative values denote potential storage losses due to reduced rainfall and increased evapotranspiration.

This approach quantitatively links precipitation anomalies to changes in reservoir filling rates, providing a data-driven basis for evaluating the vulnerability of urban water supply systems to climate change.

4 Results

Figure 2 shows the precipitation catchment areas of the dams examined in the study conducted in Ankara, Istanbul, and Izmir.

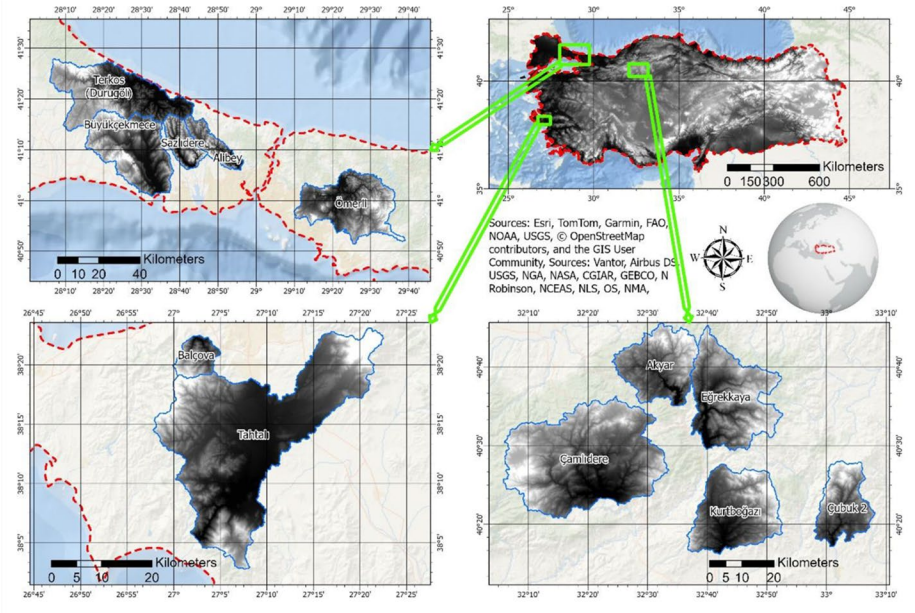


Fig. 2 The Precipitation Catchment Areas of the Dams Examined in the Study Conducted in Ankara, Istanbul, and Izmir

Table 4 The volumes and calculated catchment area sizes of the dams used for drinking water purposes

Province	Dams	Volume (hm^3)	Catchment Area (km^2)	Province	Dams	Volume (hm^3)	Catchment Area (km^2)	Province	Dams	Volume (hm^3)	Catchment Area (km^2)
Ankara	Akyar Dam	56	441.59	Istanbul	Alibey Dam	34	277.98	Izmir	Tahtalı Dam	291.15	863.44
	Çamlıdere Dam	1220	1304.87		Büyükçek-mece Dam	144.688	1121.49		Balçova Dam	7.76	53.28
	Çubuk 2 Dam	22.4	312.32		Ömerli Dam	244.54	1072.87				
	Eğrekkaya Dam	112.3	670.51		Sazlıdere Dam	89.65	298.26				
	Kurtboğazı Dam	92	570.80		Terkos Dam	144.688	1304.88				

The volume and calculated catchment area information for the dams used for drinking water purposes are provided in Table 4.

While three ANN structures (Dynamic Time Series, Curve Fitting, and Feedforward Distributed Time Delay networks) were tested during model development, they exhibited poor performance due to several factors. Specifically, these models demonstrated overfitting and instability in handling non-linear precipitation data and produced inconsistent prediction accuracies across training and testing sets. In contrast, the Feedforward Backpropagation Network provided more stable results with higher R^2 values, making it the most reliable architecture for this dataset. Table 5 summarizes the comparative performance of these alternative ANN methods, highlighting their lower R^2 values and higher RMSE.

To further clarify the methodological differences, the performance metrics of the three ANN models that showed limited performance are summarized in Table 5. These results demonstrate that the Dynamic Time Series, Curve Fitting, and Feedforward Distributed Time Delay networks were unable to provide stable or accurate predictions for precipitation-based inflow estimation under nonlinear and data-limited conditions.

A total of 2871.70 mm of precipitation was recorded over a 5-year period at the Akyar, Çamlıdere, Çubuk 2, and Eğrekkaya Dams. The results of training and testing models conducted using an ANN with 13 neurons are presented in Fig. 3. For an R value of 0.953 and an R^2 value of 0.908, 9835.52 mm of precipitation is expected, as shown in Fig. 3. At the Çamlıdere Dam, a total of 2209.60 mm of precipitation was recorded over a 5-year period. Using ANN with 13 neurons, the calculation presented in Fig. 3 indicates that for an R value of 0.952 and an R^2 value of 0.906, 9695.09 mm of precipitation is expected. At the Çubuk 2 Dam, a total of 2368.90 mm of precipitation was recorded over a 5-year period. Using ANN with 13 neurons, the calculation presented in Fig. 3 shows that for an R value of 0.944 and an R^2 value of 0.891, 8170.87 mm of precipitation is expected.

The average total precipitation over a 10-year period at or near the two stations located in the catchment area of the Eğrekkaya Dam is 5767.05 mm. Using an ANN with 13 neurons, the calculation presented in Fig. 4 shows that for an R value of 0.953 and an R^2 value of

Table 5 Performance comparison of ANN models showing limited performance

ANN Model Type	R^2 (Average)	RMSE (Average)	Observed Issues	Remarks
Dynamic Time Series Network	0.62	0.84	Overfitting during training; poor generalization to test data	Performed inconsistently across datasets
Curve Fitting Network	0.58	0.89	Unable to capture nonlinear precipitation–temperature relations	Limited adaptability for multivariable datasets
Feedforward Distributed Time Delay Networks	0.65	0.81	Unstable output due to noise sensitivity and time lag propagation	Inconsistent predictions for long-term data

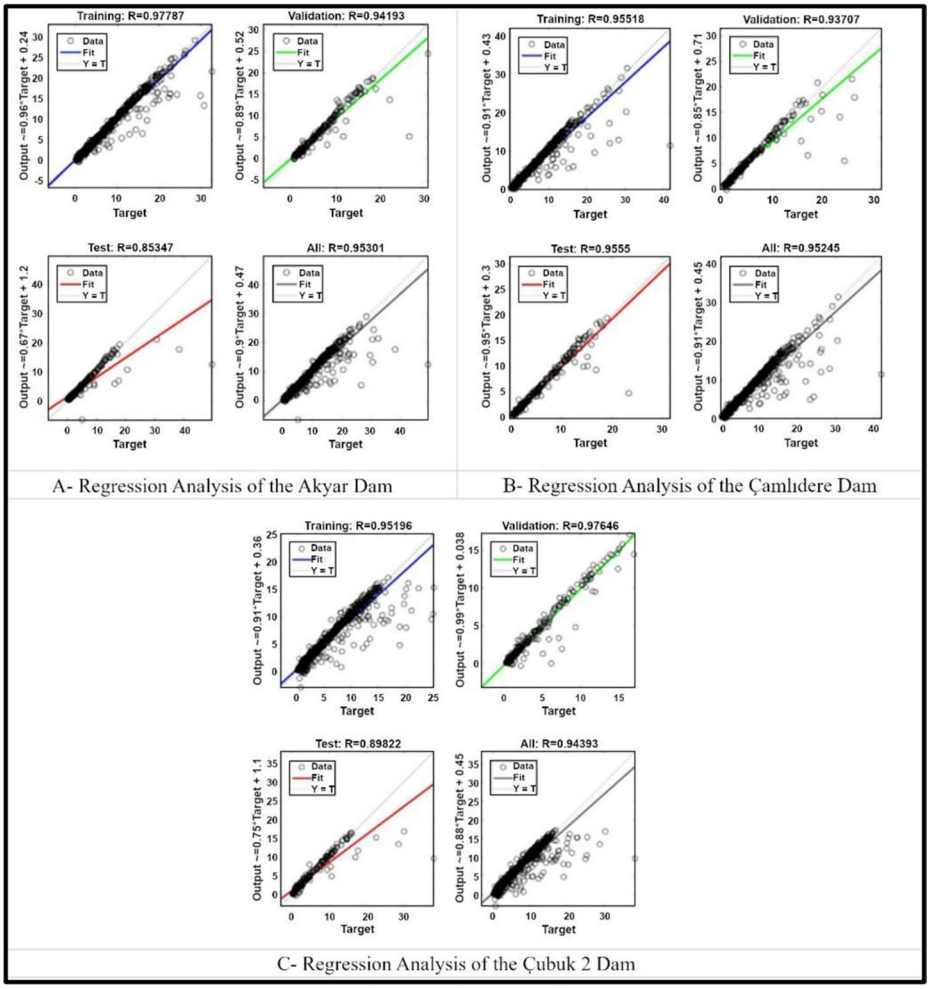


Fig. 3 Regression Analysis Graphs for the Akyar, Çamlıdere, and Çubuk 2 Dams in Ankara Province

0.908, an expected precipitation of 40,384.29 mm is estimated. At the Kurtboğazı Dam, a total of 2368.90 mm of precipitation was recorded over a 5-year period. Using an ANN with 13 neurons, the calculation presented in Fig. 4 indicates that for an R value of 0.942 and an R^2 value of 0.889, an expected precipitation of 7741.18 mm is estimated.

At the Alibey Dam, the average total precipitation recorded over a 5-year period at two stations is 4037.60 mm. Using an ANN with 18 neurons, the calculation presented in Fig. 5 indicates that for an R value of 0.969 and an R^2 value of 0.939, an expected precipitation of 21,646.78 mm is estimated. At the Büyükçekmece Dam, the average total precipitation recorded over a 5-year period at three stations is 2485.60 mm. Using an ANN with 13 neurons, the calculation presented in Fig. 5 shows that for an R value of 0.956 and an R^2 value of 0.914, an expected precipitation of 13,229.55 mm is estimated.

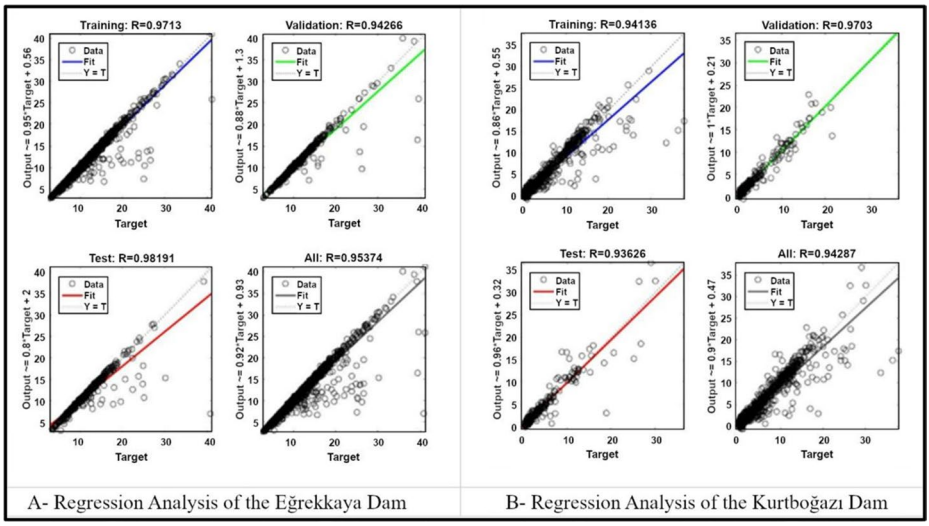


Fig. 4 Regression Analysis Graphs for the Eğrekkaya and Kurtboğazı Dams in Ankara Province

In the catchment area or nearby locations of the Ömerli Dam, the average total precipitation recorded over a 5-year period at two stations is 3040.65 mm. Using an ANN with 13 neurons, the calculation presented in Fig. 5 indicates that for an R value of 0.997 and an R^2 value of 0.994, an expected precipitation of 13,558.26 mm is estimated. At the Sazlıdere Dam, a total of 4416.80 mm of precipitation was recorded over a 5-year period. Using an ANN with 18 neurons, the calculation presented in Fig. 6 shows that for an R value of 0.961 and an R^2 value of 0.924, an expected precipitation of 22,499.35 mm is estimated.

In the catchment area of the Terkos Dam, the average total precipitation recorded over a 10-year period at two stations is 7477.20 mm. Using an ANN with 13 neurons, the calculation presented in Fig. 6 indicates that for an R value of 0.958 and an R^2 value of 0.92, an expected precipitation of 34,895.08 mm is estimated.

At the Balçova Dam, a total of 2213.30 mm of precipitation was recorded over a 3.5-year period. Using an ANN with 13 neurons, the calculation presented in Fig. 7 shows that for an R value of 0.964 and an R^2 value of 0.93, an expected precipitation of 9987.93 mm is estimated. At the Tahtalı Dam, a total of 7708.1 mm of precipitation was recorded over a 10-year period. Using an ANN with 18 neurons, the calculation presented in Fig. 7 indicates that for an R value of 0.96 and an R^2 value of 0.922, an expected precipitation of 24,090.31 mm is estimated.

In the feedforward backpropagation network type, various modifications were tested within the network to achieve solutions for the data. Changes made to training, adaptive learning, performance, transfer functions, as well as the number of layers and neurons, are particularly important for the network's performance. Table 6 presents the results of a feedforward backpropagation network modeled with a training function of trainlm, an adaptive learning function of learngdm, a performance function of mse, and transfer functions of tansig and purelin, with the number of neurons set to 13 and 18.

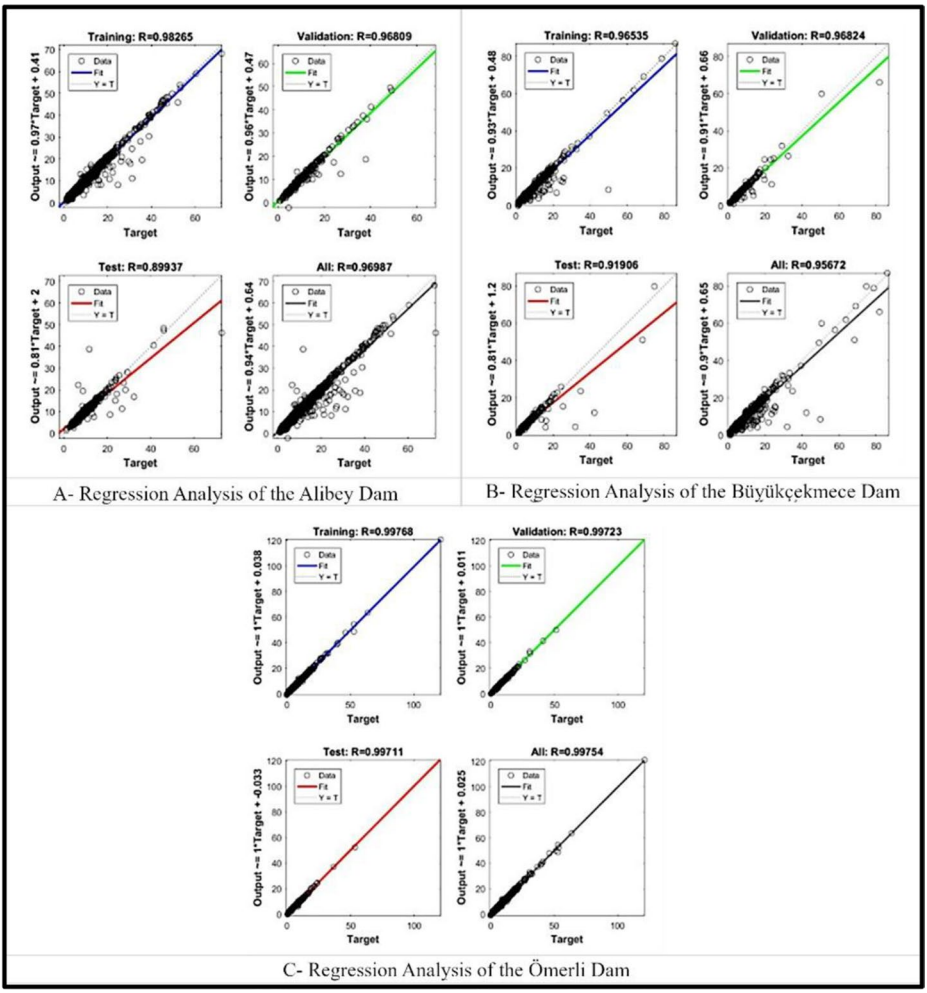


Fig. 5 Regression Analysis Graphs for the Alibey, Büyükçekmece, and Ömerli Dams in Istanbul Province

In general, an R^2 value greater than 0.9 indicates the success of the model. Furthermore, the fact that the R^2 value for training is higher than the R^2 values for validation and testing demonstrates that the model has completed training successfully. In similar studies modeled using comparable methods, as discussed in the literature, the R^2 value has typically been calculated within the range of 0.85 to 0.95.

In the separate model predictions for dams used for drinking water purposes, the differences between the expected precipitation and the actual precipitation have been revealed. The results presented in Table 7 highlight this comparison and demonstrate the damage caused by climate change in the past.

The calculated value for the expected precipitation applies to 1 m^2. When the actual and expected precipitation amounts are multiplied by the surface area of the dam, the loss becomes more apparent. Considering the contribution of precipitation-derived water to the

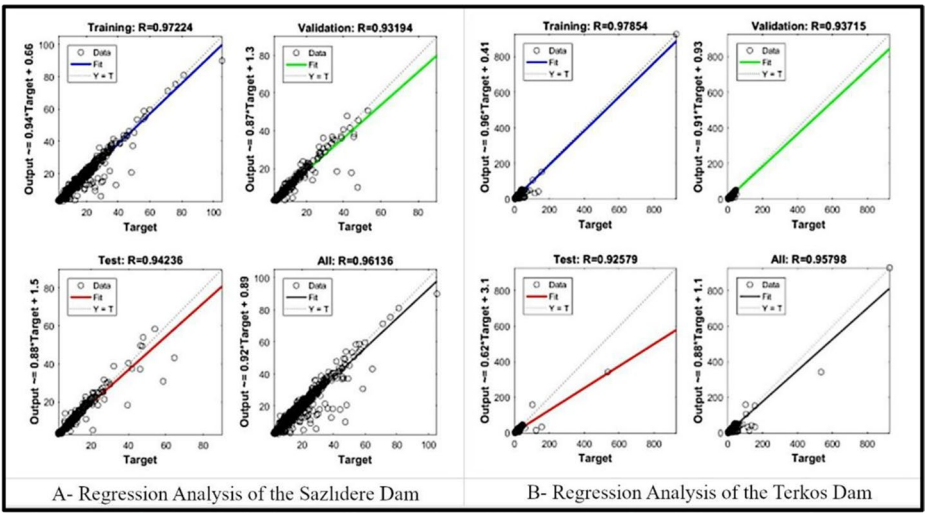


Fig. 6 Regression Analysis Graphs for the Sazlıdere and Terkos Dams in Istanbul Province

storage levels of dams used for drinking water purposes, the significance of the difference between actual and expected precipitation increases. Table 8 presents the water loss in the dam reservoir caused by climate change.

As seen in Table 8, there is a significant difference between the water volumes calculated using the ANN and expected to be collected in the dams, and the actual water volumes collected in the dams.

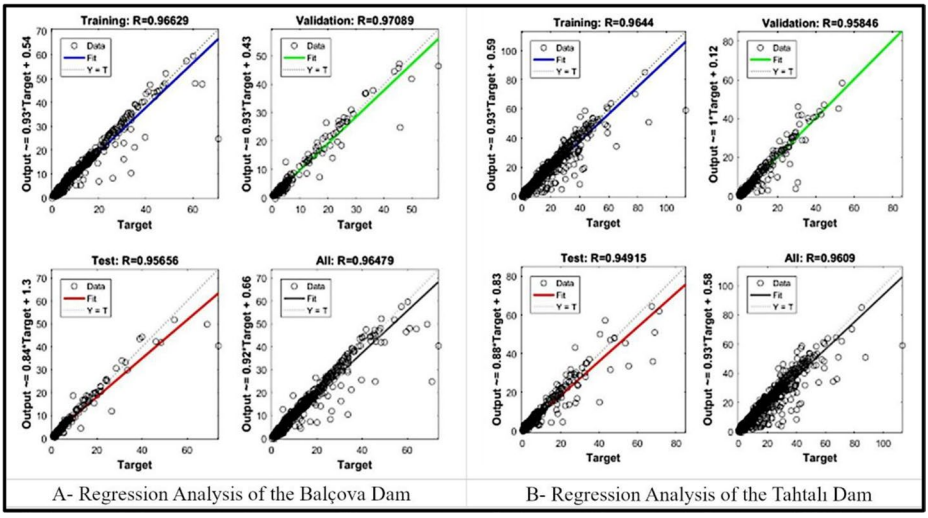


Fig. 7 Regression Analysis Graphs for the Balçova and Tahtalı Dams in Izmir Province

Table 6 Comparison of R^2 values for the modeled network

Feedforward Backpropagation		18 Neurons				13 Neurons			
		Training	Validation	Test	Total	Training	Validation	Test	Total
Ankara	Akyar Dam	0.752	0.803	0.854	0.773	0.955	0.885	0.728	0.908
	Çamlıdere Dam	0.876	0.750	0.797	0.839	0.912	0.878	0.912	0.906
	Çubuk 2 Dam	0.889	0.882	0.918	0.891	0.904	0.953	0.806	0.889
	Eğrekkaya Dam	0.912	0.889	0.841	0.897	0.943	0.887	0.794	0.908
	Kurtboğazı Dam	0.920	0.872	0.889	0.910	0.885	0.941	0.876	0.887
Istanbul	Alibey Dam	0.964	0.937	0.808	0.939	0.9216	0.845	0.916	0.912
	Büyükçek-mece Dam	0.884	0.910	0.887	0.887	0.887	0.897	0.667	0.826
						0.889	0.806	0.785	0.863
						0.931	0.937	0.845	0.914
	Ömerli Dam	0.920	0.887	0.721	0.893	0.996	0.996	0.560	0.834
						0.996	0.994	0.994	0.994
	Sazlıdere Dam	0.945	0.867	0.887	0.924	0.869	0.974	0.752	0.865
						0.937	0.895	0.848	0.914
	Terkos Dam	0.895	0.916	0.878	0.893	0.956	0.878	0.856	0.916
Izmir	Balçova Dam	0.949	0.846	0.757	0.903	0.762	0.642	0.393	0.666
						0.933	0.943	0.914	0.929
	Tahtalı Dam	0.929	0.918	0.901	0.922	0.939	0.837	0.897	0.912

Table 7 Comparison of actual and expected precipitation

Feedforward Backpropagation	Duration (Years)	Highest R^2 Value	Actual Precipitation (mm)	Expected Precipitation (mm)	Percentage of Occurrence (%)
Akyar Dam	2016–2020	0.908	2871.7	9835.52	29
Çamlıdere Dam	2016–2020	0.906	2209.6	9695.09	23
Çubuk 2 Dam	2016–2020	0.891	2368.9	8170.87	29
Eğrekkaya Dam	2011–2020	0.908	5767.05	40384.29	14
Kurtboğazı Dam	2016–2020	0.889	2368.9	7741.18	31
Alibey Dam	2016–2020	0.939	4037.6	21646.78	19
Büyükçekmece Dam	2016–2020	0.914	2845.6	13229.55	22
Ömerli Dam	2016–2020	0.994	3040.65	13558.26	22
Sazlıdere Dam	2016–2020	0.924	4416.8	22499.35	20
Terkos Dam	2011–2020	0.92	7477.2	34895.08	21
Balçova Dam	2017–2020	0.93	2213.3	9987.93	22
Tahtalı Dam	2011–2020	0.922	7708.1	24090.31	32

Table 8 Precipitation-Related water losses in dams caused by climate change

Dams	Duration	Difference (m)	Dam Surface Area (km^2)	Water Loss During the Specified Period (hm^3)
Akyar Dam	2016–2020	6.96	1.92	13.37
Çamlıdere Dam	2016–2020	7.49	32	239.54
Çubuk 2 Dam	2016–2020	5.80	1.2	6.96
Eğrekkaya Dam	2011–2020	34.62	3.47	120.12
Kurtboğazı Dam	2016–2020	5.37	5.5	29.55
Alibey Dam	2016–2020	17.61	4.66	82.06
Büyükçekmece Dam	2016–2020	10.38	43	446.51
Ömerli Dam	2016–2020	10.52	23.2	244.01
Sazlıdere Dam	2016–2020	18.08	11.81	213.55
Terkos Dam	2011–2020	27.42	39	1069.30
Tahtalı Dam	2017–2020	7.77	23.52	182.86
Balçova Dam	2011–2020	16.38	0.35	5.73

5 Conclusions

In this study, the R^2 values obtained from the ANN were found to range between 0.85 and 0.99. A maximum R^2 value of 0.994 was achieved with the model developed for the Ömerli Dam. The ratio between the expected precipitation and the actual precipitation, calculated based on data obtained from the Turkish State Meteorological Service, demonstrates the impact of climate change. The dams with the greatest differences in the amount of actual precipitation compared to expected precipitation were identified as Eğrekkaya, Alibey, Sazlıdere, Terkos, and Tahtalı Dams.

In the modeling conducted in this study, the dams with the highest water loss relative to their storage capacity were identified as Çamlıdere and Eğrekkaya in Ankara, Büyükçekmece, Ömerli, Sazlıdere, and Terkos in Istanbul, and Tahtalı in Izmir. Notably, over a 5-year period, the Büyükçekmece Dam lost the equivalent of three dam capacities, the Sazlıdere Dam lost the equivalent of two dam capacities, and over a 10-year period, the Eğrekkaya and Terkos Dams each lost the equivalent of one dam capacity due to the effects of climate change.

Furthermore, migration could also be considered as an indirect solution. The implementation of measures to promote the decentralization of industry across Anatolia and to facilitate agricultural activities could help redistribute the population currently concentrated in Ankara, Istanbul, and Izmir. As a result of reverse migration, water consumption would decrease, which could have a positive impact on reservoir storage levels in a relatively short time.

One of the major challenges faced by dams used for drinking water purposes is water loss caused by evaporation. With advancing technology, solutions are now being developed for problems that were once considered impossible to address. The idea of placing solar energy panels on the surface of reservoir areas, introduced as a new technology, could become feasible in the coming years. This approach is expected to both harness solar energy for power generation and prevent water loss due to evaporation.

Sedimentation is another challenge faced by dams used for drinking water purposes, as it directly and negatively impacts reservoir storage capacity. To address this issue, structures such as levees, sills, or similar features should be constructed in the area where sediment enters the reservoir. These structures help trap sediment and prevent it from accumulating in the reservoir. Additionally, minimizing water loss and leakage can indirectly contribute positively to the storage levels of dams used for drinking water purposes. By reducing water loss and leakage rates, the amount of water withdrawn from the dam will decrease, subsequently reducing the amount of water used from the reservoir.

Underground dams are proposed as a solution to water-related issues due to their advantages, including the absence of evaporation problems, high resilience to drought, superior water quality, and low expropriation costs.

In summary, the evaluation of alternative ANN models revealed that the Dynamic Time Series, Curve Fitting, and Feedforward Distributed Time Delay networks provided lower accuracy (R^2 between 0.58 and 0.65) and higher RMSE compared to the Feedforward Backpropagation Network. This confirms that the selected architecture offers a more reliable and adaptable framework for representing nonlinear precipitation-inflow relationships under changing climatic conditions.

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Declarations

Ethical Approval Not applicable.

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