[*Steps For Civil, Constructions and Environmental Engineering (SCCEE)*](#)
ISSN: 3005-8198 (online) / 3005-818X (print)
Volume 1, Issue 2 (October – December 2023), pp: 40-50

Research Article

Smart Management of Fresh Water Uses in Syria Using a Neural Network Model

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Received: 12 September 2023 | Revised: 20 November 2023 | Accepted: 27 November 2023 | Published: 20 December 2023

Abstract

This study examines freshwater utilization trends in Syria from 2000 to 2022, focusing on agricultural, industrial, and domestic consumption while analyzing changes in per capita water availability and identifying the optimal usage ratio to bridge the water gap using artificial intelligence (AI) models. A descriptive analytical approach was employed to estimate time trend equations and annual growth rates based on World Bank data, while a multi-layer feed-forward neural network was used to predict the water gap. Findings indicate an overall increase in freshwater consumption for agriculture and domestic purposes, each growing at an annual rate of 0.006% (0.38%), whereas industrial water use declined by 0.07% annually. The per capita freshwater share exhibited a steady decline at -1.26% per year, with a simultaneous increase in the gap between water availability and the poverty threshold by 0.85% annually. AI-based analysis revealed that domestic water consumption has the greatest impact on widening the water gap, and an optimal reduction of 8.19% in total water use was identified as necessary to mitigate this issue. These findings highlight the need for strategic water management policies to ensure sustainable freshwater distribution across sectors.

Keywords: *Sustainable Management, Fresh Water, Artificial Intelligence, Syria.*

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Cite This Article: Naamah, M. F. (2023). Smart Management of Fresh Water Uses in Syria Using a Neural Network Model. *Steps For Civil, Constructions and Environmental Engineering*, *1*(2), 40–50.
https://doi.org/10.61706/sccee12011165

Introduction

It is increasingly evident that the global community is recognizing the urgent need for a comprehensive reassessment of the distribution, management, and utilization of freshwater resources. Despite significant technological advancements and the proliferation of information in the modern era, millions of individuals continue to succumb annually to preventable waterborne diseases, while hundreds of millions more endure severe health conditions. Notwithstanding substantial investments and efforts, by the close of the twentieth century, approximately 2.4 billion people—surpassing the global population of 1940—remained without access to sanitation services comparable to those available to the majority of citizens in ancient Rome. As noted by Panjabi (2014), more than one billion individuals still lack access to safe and sufficient drinking water.

Human activities have had a profound impact on the Earth as our collective habitat. In particular, land use change and management affect hydrology, which in turn determines flood risk, water resources (for human and environmental needs), and pollutant transport and dilution. It is becoming increasingly evident that land and water management are inextricably linked (Wheater & Evans, 2009).

The combined impact of rising temperatures and prolonged drought conditions over the past decade in California, along with court-imposed restrictions on water allocations in the Sacramento River Delta, has significantly reduced the availability of water resources in Southern California. In response to these challenges, water agencies have implemented a range of conservation measures and irrigation regulations, with a primary emphasis on restricting outdoor water use (Lund, 2016).

The City of Los Angeles, the most populous in the United States and the largest among the 88 municipalities in Los Angeles County, has enacted a series of initiatives aimed at reducing residential water consumption. Between 2008 and 2010, three successive phases of water restrictions were introduced to curb usage and promote conservation. The first phase, which was voluntary, commenced in FY 2008. The second phase, which was mandatory, commenced in FY 2009. The third and final phase, which was mandatory and combined with increased prices and decreased total household allotments, commenced in FY 2010 (Mini et al., 2015).

The integration of artificial intelligence (AI) has the potential to enhance the identification of complex patterns within extensive datasets related to dynamic water distribution. This is accomplished through the continuous incorporation of fundamental scientific processes at a micro level. The synergy between these advanced technologies can illustrate how public trust may be strengthened through the implementation of automated and conditional "smart contracts" for water usage, based on secure and immutable data. Furthermore, it plays a vital role in enhancing the accuracy and validation of local water usage data, a key element in global ecosystem changes studies and data-driven decision-making. By leveraging a decentralized intelligent framework for global water governance, blockchain-based security protocols can be integrated with AI algorithms trained on real-time water sensing data. In the realm of remote water distribution, this technological synergy offers substantial benefits in optimizing water availability, improving efficiency, and identifying scarcity trends. Such advancements facilitate the equitable management of multi-source water resources, particularly in the face of climate change (Lin et al., 2018).

The objective of sustainable water resources management is to maintain the ecological, economic and hydrological integrity of the current society and to ensure the viability of future prospects. The application of artificial intelligence methods in urban water resource planning is largely due to their exceptional capacity for reasoning, adaptability, modelling and forecasting of water demand (Xiang et al., 2021).

An advanced artificial neural network (ANN) framework, integrating a constriction coefficient-based particle swarm optimization and gravitational chaotic search algorithm (CPSOCGSA), was employed to predict monthly salinity levels. The model was developed and validated using historical monthly data on total dissolved solids (TDS) and electrical conductivity (EC) of the Euphrates River at Musayyib and Babylon, alongside relevant climatic variables from 2010 to 2019. To evaluate its performance, the CPSOCGSA-ANN approach was compared with alternative optimization techniques, including the slime mold algorithm (SMA-ANN), particle swarm optimization (PSO-ANN), and the multi-verse optimizer (MVO-ANN). Results demonstrated that data preprocessing significantly enhanced data quality and facilitated the identification of the optimal forecasting scenario. Moreover, the CPSOCGSA-ANN model outperformed the comparative methods across multiple statistical performance metrics. The proposed approach demonstrated high predictive accuracy in modeling TDS and EC time series, yielding R^2 values of 0.99 and 0.97, respectively, and scatter index (SI) values of 0.003 for both parameters (Khudhair et al., 2022).

An advanced intelligent management system has been developed to address water scarcity in Palestine, focusing on four key aspects: water scarcity assessment, protection of traditional water resources, implementation of rainwater harvesting (RWH), and the application of dynamic intelligent water management strategies. The smart RWH system has demonstrated the capability to fulfill approximately 41% of household water demands. Moreover, the smart dual water system has exhibited greater reliability in meeting water needs compared to the standalone smart RWH system. Through the integration of dynamic management strategies and an innovative supply framework, the smart dual system has proven its effectiveness in mitigating water scarcity comprehensively across all elevation levels within the study area. Additionally, the use of a smaller storage tank has been identified as a critical factor in optimizing system performance, with potential implications for the social and economic development of the region (Judeh, 2022).

In the United States, increasing urban populations, rising living standards, limited expansion of new water sources, and the depletion of existing supplies have created a growing imbalance where the demand for treated municipal water surpasses available resources. The amount of water used for irrigating residential urban landscapes is influenced by various factors, including landscape type, management practices, and regional geographic conditions. In general, however, landscape irrigation can account for a significant proportion of household water use, with figures ranging from 40% to 70%. It is therefore recommended that the primary focus of water conservation efforts be the efficient use of irrigation water in urban landscapes. Furthermore, plants in typical residential landscapes are frequently irrigated with greater quantities of water than is necessary to sustain essential ecosystem functions, including carbon regulation, climate control, and the maintenance of aesthetic appeal (Hilaire et al., 2008).

Effective water demand management is essential for water utilities, as they play a critical role in delivering safe drinking water from sources to end users through distribution networks. To ensure both current and future system performance, utilities must make informed decisions regarding water distribution. In this context, data-driven approaches, including artificial intelligence models, can be utilized to predict water demand, enabling the development of advanced tools to enhance overall water management (Zanfei et al., 2023).

Jafar et al. (2023) studied the surface water quality of Lake Seine in the Latakia Governorate using multiple linear regression (MLR) and machine learning (ML) models to predict the Water Quality Index (WQI). Their research analyzed water samples collected from a key drinking water source in Latakia, Syria, during 2021–2022, assessing water quality through statistical performance metrics such as the coefficient of determination (R^2) and root mean square error (RMSE). The findings demonstrated that the MLR model, along with three ML techniques—linear regression (LR), least angle regression (LAR), and Bayesian ridge (BR)—exhibited strong predictive accuracy in estimating WQI. The MLR model achieved an R^2 of 0.999 with an RMSE of 0.149, while the ML models demonstrated near-perfect prediction accuracy, attaining an R^2 of 1.0 and an RMSE close to zero. These results highlight the effectiveness of both statistical and ML-based approaches in water quality prediction, offering a reliable framework for enhancing water management strategies and ensuring sustainable water resource planning.

Chamizo-Checa et al. (2020) conducted a comprehensive study on the Mezquital Valley in Mexico, utilizing the Water Evaluation and Planning System (WEAP) to model water balance scenarios from 2005 to 2050. Their research assessed the impacts of climate change on water availability, considering both steady-state and transient scenarios influenced by projected climate perturbations. The study highlighted the region's reliance on untreated wastewater from Mexico City for agricultural irrigation and examined the implications of implementing wastewater treatment and advanced irrigation techniques. Findings indicated that while measures like drip irrigation could reduce agricultural water demand by 42%, they might not suffice to meet downstream hydroelectric requirements, especially with anticipated reductions in imported wastewater. This underscores the necessity for integrated water resource management strategies to address future water scarcity challenges in the region.

Krishnan et al. (2022) highlight the growing urgency of effective water management amid the escalating global water crisis, emphasizing the need for advanced harvesting, recycling, and distribution strategies. As population density increases, intelligent water management systems become essential for optimizing resource utilization, conserving water, and maintaining quality standards. Their study explores key advancements in wastewater recycling, rainwater harvesting, and irrigation management through the application of Artificial Intelligence (AI) and Deep Learning (DL) within an Internet of Things (IoT) framework. Given the complexity of water management data, adaptable AI-driven models are necessary to provide integrated solutions across various sectors. Through case studies and statistical analyses, the research presents a structured framework for enhancing decision-making in water resource management, demonstrating the transformative potential of AI and IoT in addressing global water challenges.

Fu et al. (2022) explored the transformative impact of deep learning techniques on urban water system planning and management, emphasizing their potential to revolutionize economies, environments, and societies worldwide. While deep learning has been applied across various aspects of water management, a comprehensive review of its current applications and future potential remains limited. To address this gap, the study examines key areas where deep learning is being utilized, including water demand forecasting, leakage detection, contamination assessment, sewer defect evaluation, wastewater system state prediction, asset monitoring, and urban flood modeling. Despite its promise, deep learning applications in urban water management are still in their early stages, with most studies relying on benchmark networks, synthetic datasets, or pilot systems, and only limited real-world implementation. Among these applications, leakage detection has shown the most progress in practical deployment. The study further identifies five critical research challenges that must be addressed to advance deep learning in this field: data privacy, algorithm development, explainability and trustworthiness, multi-agent systems, and digital twins. Overcoming these challenges is expected to drive greater intelligence and autonomy in urban water systems, accelerating innovation and digital transformation within the global water sector. By highlighting these key areas, the study encourages further research and development, leveraging deep learning to enhance sustainable water management and optimize resource efficiency.

Vallejo-Gómez et al. (2023) conducted a systematic review focusing on smart irrigation systems that integrate artificial intelligence (AI) and Internet of Things (IoT) technologies in both urban and rural agricultural settings. The study analyzed 170 articles, identifying key technologies such as fuzzy logic, neural networks, and machine learning as pivotal in enhancing irrigation efficiency. These technologies enable real-time monitoring and precise control of irrigation processes, optimizing water usage and improving crop yields. The review highlights the potential of AI and IoT in transforming traditional irrigation practices, emphasizing their role in promoting sustainable agriculture through efficient resource management.

Jung et al. (2021) developed an artificial neural network (ANN)-based model to predict surface water quality in the Nam River watershed, South Korea. By integrating meteorological data and water quality parameters, the study aimed to enhance the accuracy of water quality forecasts. The ANN model demonstrated high predictive performance, with coefficients of determination (R^2) ranging from 0.810 to 0.929 for dissolved oxygen (DO) and 0.671 to 0.863 for biochemical oxygen demand (BOD_5). The results underscore the efficacy of ANN models in capturing the nonlinear relationships between meteorological factors and water quality indicators, offering a reliable approach for water quality management and decision-making processes.

Methods

The study was conducted at the national level in the Syrian Arab Republic, situated on the eastern coast of the Mediterranean Sea, within the geographical coordinates of 35° to 42° east longitude and 32° to 37° north latitude. Covering the period from 2000 to 2022, the research utilized statistical data from the Central Bureau of Statistics on annual freshwater withdrawals for agricultural, industrial, and domestic purposes, as well as per capita freshwater availability. The study analyzed key variables, with agricultural, industrial, and domestic water usage serving as independent variables, while the water gap was identified as the dependent variable. A descriptive analytical approach was employed to examine the trends in freshwater utilization over time, applying mathematical equations to assess the disparity between per capita freshwater availability and the water poverty threshold. Additionally, artificial intelligence (AI) models were integrated to predict the future water gap for the period 2024–2030, utilizing a neural network, specifically a perceptron model, to enhance forecasting accuracy and support sustainable water resource planning.

Results and Discussions

The Evolution of Water Use for Agricultural Purposes

The evolution of freshwater utilization in agriculture has been extensively studied, revealing notable fluctuations over time. In 2000, the mean annual volume of water withdrawn for agricultural purposes peaked at approximately 761,541.07 cubic meters, before declining to 749,889.64 cubic meters in 2007. Following this decline, agricultural water consumption exhibited a gradual increase until 2022. Despite the fact that certain agricultural lands in Syria remained unutilized between 2012 and 2016 due to emergency conditions, the overall rate of water use for agricultural purposes remained stable. This stability may be attributed to the more efficient utilization of cultivated land and a strategic emphasis on crops with higher water demands in regions with secure water resources. The general trend line equation for the development of agricultural water use indicates a consistent upward trajectory between 2000 and 2022, with an average annual increase of 0.06%. The estimated trend equation is presented in **Table 1**, while **Figure 1** provides a visual representation of these trends.

The Evolution of Water Use for Industrial Purposes

The study analyzed the evolution of freshwater utilization for industrial purposes in Syria from 2000 to 2022, as depicted in **Figure 2**. Industrial water withdrawal peaked in 2002 at approximately 33,583.54 m^3 before declining to its lowest level in 2006 at around 31,013.37 m^3, followed by a continued gradual decrease until 2022. Despite the economic and infrastructural challenges faced between 2012 and 2016, industrial water use remained relatively stable due to a shift in focus toward water-intensive industries such as chemical and textile manufacturing, which offset production declines in other sectors. The general trend line equation for industrial water use, as presented in **Table 2**, indicates an overall downward trajectory, with an average annual decrease of 0.07%. This decline is largely attributed to the impact of war conditions that have prevailed throughout the study period.

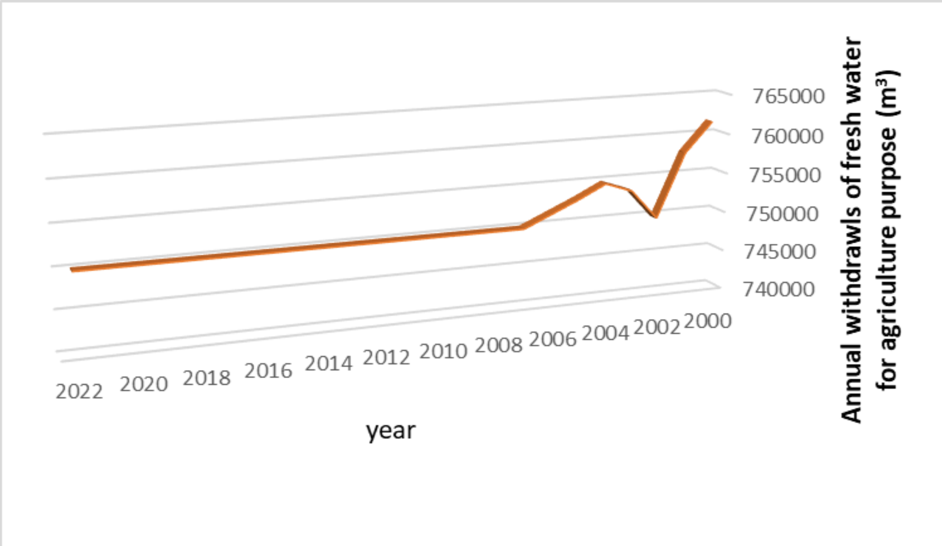

Figure 1. Annual Freshwater Withdrawals for Agricultural Purposes (m^3) in Syria (2000–2022)

Table 1. General Trend Equation for the Development of Agricultural Water Use in Syria (2000–2022)

General Trend Equation	R^2	F	Growth Rate%
Ln Y = 13.52 + 0.01/t (0.00)** (0.00)**	0.83	102.30**	0.06

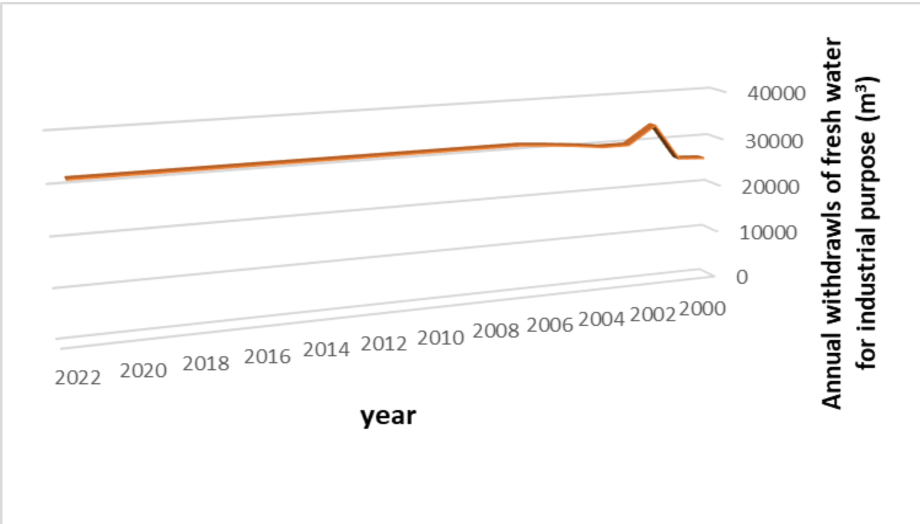

Figure 2. Annual Freshwater Withdrawals for Industrial Purposes (m^3) in Syria (2000–2022)

Table 2. General Trend Equation for the Development of Industrial Water Use in Syria (2000–2022)

General Trend Equation	R^2	F	Growth Rate%
Ln Y = 10.37 + 0.22/t (0.00)** (0.00)**	0.70	42.48**	-0.07

The Evolution of Water Use for Domestic Purposes

The study examined the evolution of freshwater utilization for domestic purposes in Syria from 2000 to 2022, as depicted in **Figure 3**. The mean annual volume of water withdrawn for domestic use peaked in 2007 at approximately 75,391.62 m³ and has since shown a gradual upward trend through 2022. The general trend line equation for domestic water consumption, presented in **Table 3**, indicates a consistent increase over the study period, with an average annual growth rate of 0.38%. This steady rise reflects the growing demand for freshwater in residential sectors, driven by population growth and urban expansion.

The Evolution of Syria's Per Capita Share of Fresh Water

The study analyzed the evolution of per capita freshwater availability in Syria from 2000 to 2022, as illustrated in **Figure 4**. In 2000, the per capita share of freshwater peaked at approximately 460.11 cubic meters before steadily declining to its lowest recorded value of 313.76 cubic meters in 2013 (Central Bureau of Statistics). To assess water scarcity, the discrepancy between per capita freshwater availability and the United Nations-defined water poverty threshold of 1,000 cubic meters per person per year was calculated. The water gap was found to be at its maximum in 2013, reaching approximately 686.24 cubic meters, while the smallest gap was recorded in 2000 at around 539.89 cubic meters, as shown in **Figure 5**. The estimated general trend line equation, presented in **Table 4**, illustrates the long-term trajectory of per capita freshwater availability and its deviation from the water poverty threshold. The analysis indicates a persistent decline in Syria's per capita freshwater share, with an annual reduction rate of -1.26%, while the water gap has shown a steady increase at a rate of 0.85% per year over the study period. These trends underscore the growing freshwater scarcity in Syria, emphasizing the urgent need for strategic water management interventions.

Building a Predictive Model for the Water Gap Using a Neural Network (Perceptron Network)

The study utilized a neural network model to analyze the relationship between water consumption for agricultural, industrial, and domestic purposes (independent variables) and changes in the water gap (dependent variable). Time series data spanning 23 years were used to train and test the network, as detailed in **Table 5**. The training phase was conducted using 19 years of data, achieving an accuracy rate of 82.6%, while the testing phase, based on 4 years of data, yielded an accuracy rate of 17.4%. The selected neural network architecture consisted of three layers: an input layer, a processing layer, and an output layer. The input layer comprised three cells, corresponding to the three independent variables, while the output layer contained a single cell representing the dependent variable. As shown in **Table 6**, the processing layer included three computational units, facilitating the network's capacity to model complex relationships between water usage and the evolving water gap.

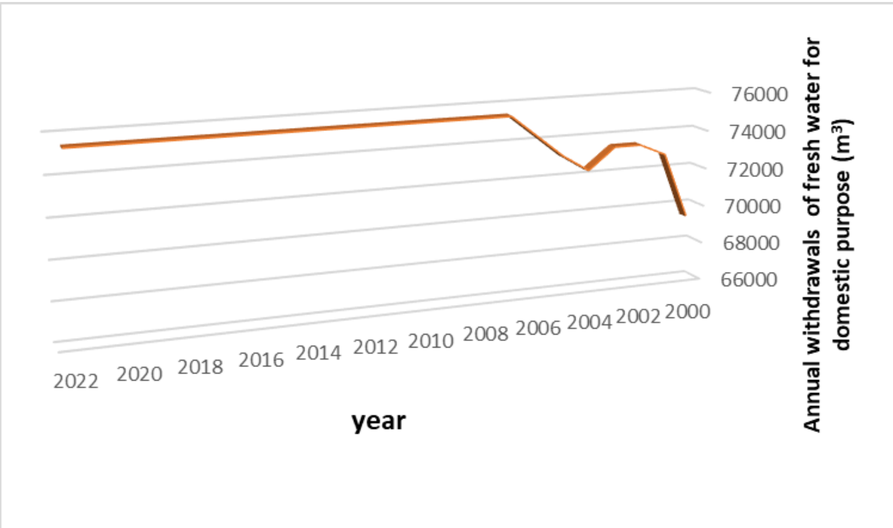

Figure 3. Trends in Freshwater Use for Domestic Purposes in Syria (2000–2022)

Table 3. General Trend Equation Depicting the Development of Domestic Water Use in Syria (2000–2022)

General Trend Equation	R^2	F	Growth Rate%
Ln Y = 11.23 + 0.09/t	0.84	116.84**	0.38
(0.00)** (0.00)**			

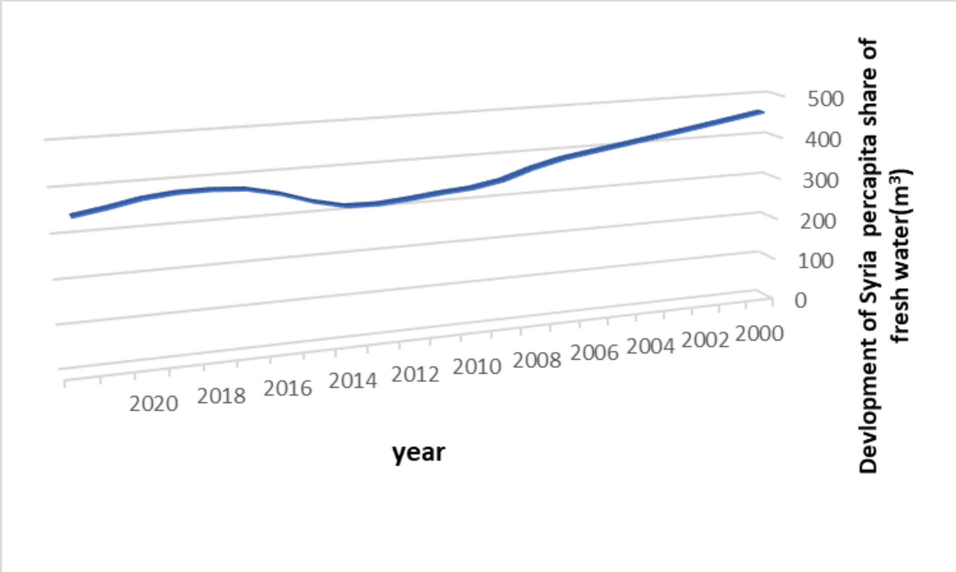

Figure 4. Evolution of Per Capita Freshwater Availability in Syria

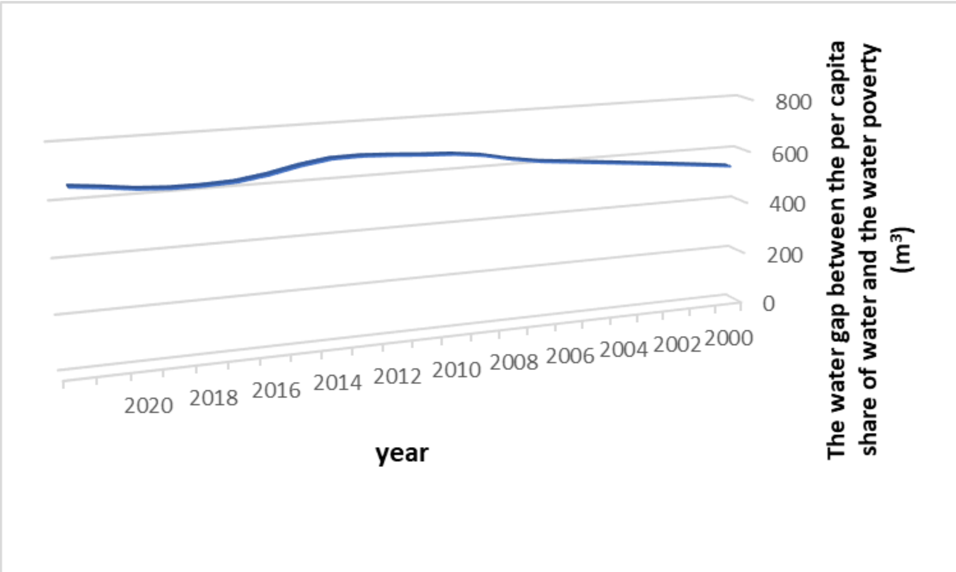

Figure 5. Water Gap Between Per Capita Water Availability and the Water Poverty Threshold in Syria (2000–2022)

Table 4. General Trend Equation for the Development of Per Capita Freshwater Availability and the Gap Relative to the Water Poverty Threshold in Syria (2000–2022)

Indicator	General Trend Equation	R^2	F	Growth Rate%
Per Capita Share	$Y= 490.69 - 20.28\ t + 0.66\ t^2$ (0.00)** (0.00)** (0.00)**	0.83	50.1^{**}	-1.26
Water Gap	$Y= 509.30 + 20.28\ t + 0.66\ t^2$ (0.00)** (0.00)** (0.00)**	0.83	50.4^{**}	0.85

Table 5. Overview of the Data Processing Workflow in the Neural Network Model

Case Processing Summary			
		N	**Percent**
Sample	Training	19	82.6%
	Testing	4	17.4%
Valid		23	100.0%
Excluded		0	
Total		23	

Table 6. Specifications of the Neural Network Model Utilized.

Network Information			
Input Layer	Covariates	1	Fresh water for agricultural purposes
		2	Fresh water for industrial purposes
		3	Fresh water for domestic purposes
	Number of Units[a]		3
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Water gap
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

The hyperbolic function, otherwise known as the hyperbolic tangent, was utilized as an activation function within the hidden layer. The term "hyperbolic" is derived from the function's derivation from the hyperbolic function itself. Additionally, the function exhibits properties analogous to those observed in trigonometric functions, as evidenced by the following relationship:

$$\gamma(c) = \tanh(c) = \frac{e^{c} - e^{-c}}{e^{c} + e^{-c}} + Bias$$

Where y: dependent variable, c: independent variables, Bias: bias parameter

The identity function (also known as the neutral or identical function) was employed in the output layer. This is a function whereby each element is associated with itself, or the domain and the corresponding domain are the same set. This is expressed by the following relationship:

$$y(c) = c + Bias$$

Figure 6 illustrates the structural design of a neural network, which is composed of three interconnected layers: the input layer, the hidden layer, and the output layer. The network's architecture allows for one or more hidden layers positioned between the input and output layers, with each neuron in one layer fully connected to every neuron in the subsequent layer. However, neurons within the same layer remain unconnected. Data from the time series are first introduced through the input layer, processed within the hidden layer, and ultimately transformed into predicted continuous values in the output layer.

In this process, input values are multiplied by assigned weights—predefined numerical parameters—and the resulting weighted sums are aggregated to produce a single value. This value is then processed through an activation function, which determines the transformation of input signals. In this study, a hyperbolic function was utilized as the activation function within the hidden layer, while the identity function was applied in the output layer, as illustrated in **Figure 6**. This configuration enhances the network's ability to model complex relationships and optimize predictive accuracy.

The diagram illustrates the configuration of the neural network and the interconnections between its units, which represent the pathways through which the network is fed with information.

Table 7 presents a summary of the neural network model employed, along with the sum of squares of error.

Table 7 presents the results of the training and testing phases, highlighting the performance of the neural network model. The cross-entropy error, which represents the objective function minimized during training, was evaluated for both datasets. The sum of squared errors during the training phase was recorded at 0.21, indicating the model's predictive accuracy. Notably, the entropy error for the test sample (0.11) was lower than that for the training dataset, suggesting that the model achieved a well-fitted state and maintained its generalization capability during testing.

Table 8 provides an analysis of the relative importance of the independent variables in influencing temperature variations, as determined by the neural network model. The findings indicate differing levels of significance among the independent variables, demonstrating the model's ability to capture complex relationships within the dataset.

In the proposed model, the greatest relative impact on the increase in the water gap was attributed to water use for domestic purposes (100%), followed by water use for agricultural purposes (66.7%) and water use for industrial purposes (22.1%).

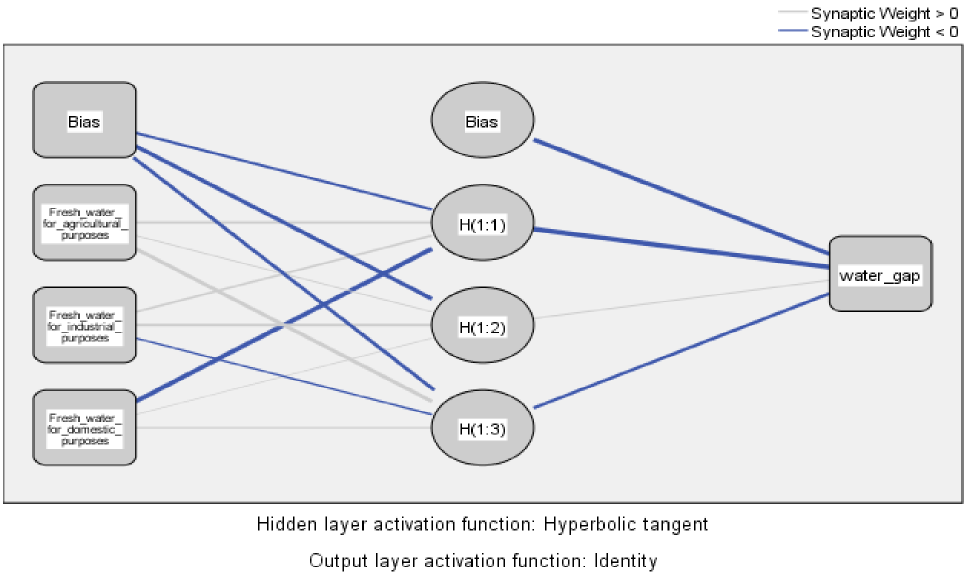

Figure 6. Architecture of the Multi-Layer Perceptron (MLP) Neural Network

Table 7. Summary of the Neural Network Model Used.

Model Summary		
Training	Sum of Squares Error	0.218
	Relative Error	0.026
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	0.110
	Relative Error	0.058
Dependent Variable: Water_Gap		
a. Error computations are based on the testing sample.		

Table 8. Relative Importance of Independent Variables as Determined by the Neural Network Model.

Independent Variable Importance		
	Importance	Normalized Importance
Fresh water for agricultural purposes	0.353	66.7%
Fresh water for industrial purposes	0.117	22.1%
Fresh water for domestic purposes	0.530	100.0%

Determine the Ideal Percentage of Water Use for Domestic Purposes to Minimize the Water Gap

Given the critical role of domestic water consumption in addressing water scarcity, the optimal percentage of water allocated for domestic use to mitigate the water gap was identified, as shown in **Table 9**. To determine this ideal ratio, the governing equation was derived and expressed as:

$$y = 605.96\,x - 4966.49$$

Solving for x, the optimal ratio of domestic water consumption required to reduce the water deficit was calculated as 8.19%. This finding highlights the significance of strategic water allocation in narrowing the water gap and ensuring more sustainable resource management.

Results of Forecasting the Water Gap in Syria During the Period (2023-2030) Using the Neural Network Model

The projected discrepancy between per capita freshwater availability and the water poverty threshold in Syria for the period 2023–2030 was estimated using a neural network model, as detailed in **Table 10**. The forecast indicates a persistent upward trend in the water gap, with an estimated annual growth rate of 0.29%. By 2030, the water gap is expected to reach its highest level, with a projected volume of approximately 666.77 cubic meters. These findings highlight the increasing severity of water scarcity in Syria, underscoring the need for proactive water management strategies to mitigate the growing deficit.

Table 9. Relationship Between the Water Gap and Domestic Water Use.

General Trend Equation	R^2	F
$Y = 20893.04 - 4966.49\ x + 302.98\ x^2$ *(0.00)** (0.00)** (0.00)***	0.86	30.67^{**}

Table 10. Projected Water Gap in Syria for the Period 2023–2030 Based on Neural Network Modeling.

Year	Expected water gap (m3)	Annual growth rate%
2023	651.45	
2024	654.55	
2025	657.32	
2026	659.75	%0.29
2027	661.89	
2028	663.75	
2029	665.37	
2030	666.77	

Conclusions:

The findings of the research indicate a general upward trajectory in the utilization of fresh water for agricultural and domestic purposes. Conversely, there has been a general decline in the utilization of water for industrial purposes over the specified period (2000-2022). The utilization of water for domestic purposes exerted the greatest influence on the widening of the gap. The proposed neural network model indicates that the use of water for agricultural purposes is of greater consequence than the use of water for industrial purposes, with water itself occupying the next highest level of importance.

In light of this, it is imperative that the necessary measures be taken to reduce the consumption of fresh water for domestic purposes. This can be achieved by rationalizing its use, for example through the introduction of modifications to the water networks used and the search for alternative sources, such as the harvesting of rainwater. Furthermore, it is essential to protect water bodies such as rivers and lakes from pollution in all forms. In the context of agricultural production, the implementation of appropriate irrigation techniques is essential. Modern irrigation techniques, such as drip irrigation, take into account the field capacity of each crop, employing artificial intelligence in the field of water management.

Declarations

Author Contribution

M.N: Conceptualization, methodology, Software, validation, formal analysis, investigation and writing – review and editing of the manuscript.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration on the Use of Generative AI and AI-Assisted Technologies

No generative AI or AI-assisted technologies were used in the preparation of this manuscript.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgement

The authors declare that there is no acknowledgement to be made.

Ethics

This study did not involve human participants or animals; hence, no ethical approval was required.

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