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Artificial Intelligence for Water Consumption Assessment: State of the Art Review

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Abstract
In recent decades, demand for freshwater resources has increased the risk of severe water stress. With the growing prevalence of artificial intelligence (AI), many researchers have turned to it as an alternative to linear methods to assess water consumption (WC). Using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, this study utilized 229 screened publications identified through database searches and snowball sampling. This study introduces novel aspects of AI's role in water consumption assessment by focusing on innovation, application sectors, sustainability, and machine learning applications. It also categorizes existing models, such as standalone and hybrid, based on input, output variables, and time horizons. Additionally, it classifies learnable parameters and performance indexes while discussing AI models' advantages, disadvantages, and challenges. The study translates this information into a guide for selecting AI models for WC assessment. As no one-size-fits-all AI model exists, this study suggests utilizing hybrid AI models as alternatives. These models offer flexibility regarding efficiency, accuracy, interpretability, adaptability, and data requirements. They can address the limitations of individual models, leverage the strengths of different approaches, and provide a better understanding of the relationships between variables. Several knowledge gaps were identified, resulting in suggestions for future research.

Keywords PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework · Machine learning applications · Advantages, disadvantages, and challenges of artificial intelligence for water consumption · Artificial intelligence · Hybrid models · Performance indexes · Learnable parameters · Smart water management

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1 Introduction

Water is used for various purposes, including drinking, fire control, garden irrigation, cleaning, and industrial and agricultural processes (Morain and Anandhi 2022). A significant water resource management challenge is ensuring sufficient water to meet human needs (de Souza Groppo et al. 2019). Over the past few years, water resources have become increasingly vulnerable due to several factors, including climate change, population growth, city size, commercial and social conditions of people, supply costs, development of global industries, overexploitation of sea resources, land use/land cover change, and water distribution characteristics (Anele et al. 2017; Anandhi and Kannan 2018; Yang et al. 2023). Monitoring and forecasting water consumption (WC) are among the most critical aspects of making informed decisions to ensure water sustainability (Arsene et al. 2022). Over the last few decades, considerable research has been conducted on using AI models as alternatives to statistical models for estimating and forecasting WC (Alhendi et al. 2022). Several studies, such as Liu et al. (2022), Pacchin et al. (2019), and Rahmati et al. (2014), have tested and compared different AI forecasting models by consideration of their accuracy, performance, and application convenience. In their respective papers, Liu et al. (2019a, b), Vijayalaksmi and Babu (2015), and Wang and Liu (2016) applied single AI models to forecast WC, while Altunkaynak and Nigussie (2018) and González Perea et al. (2018) used multiple models. Similarly, other studies have used AI models to estimate WC (Wei et al. 2022), monitor consumption, extract and cluster consumption events, and predict WC sources (Arsene et al. 2022).

Numerous review articles have addressed different aspects of AI applications in water consumption. Rahim et al. (2020) reviewed the contributions and limitations of AI models in digital water metering. Surendra and Deka (2022) and Niknam et al. (2022) discussed the use of artificial neural network (ANN), fuzzy logic (FL), adaptive neuro fuzzy inference systems (ANFIS), and wavelet transforms (WA) in residential WC. Drogkoula et al. (2023) investigated machine learning (ML) methodologies in water management. The potential of evolutionary computation as a subfield of AI has been reviewed concerning water demand management policies (Oyebode and Ighravwe 2019). An analysis of Strengths, Weaknesses, Opportunities, and Threats (SWOT) was conducted on AI-driven technologies as facilitators or barriers to sustainable development goals, reviewing smart water management and AI applications in agriculture and sanitation services (Palomares et al. 2021). Additionally, some reviews have focused on the application of ANN in the drinking water sector (O'Reilly et al. 2018), Internet of Things in agriculture (Madushanki et al. 2019), FL in hydrology and water resources (Kambalimath and Deka 2020) and agriculture (Jha et al. 2019), and Bayesian approach to water systems in buildings (Wong and Mui 2018).

Despite the coverage of AI applications in water consumption assessment in previous review articles, several unaddressed aspects necessitate further investigation. Therefore, the novelty of this study lies in the following:

- Presenting four focus points of AI's role in water consumption assessment: innovation, application sector, sustainability, and machine learning applications.
- Synthesizing and classifying existing models (e.g., standalone, combined/hybrid) along with their input and output variables and time horizons.
- Classifying learnable parameters (e.g., weights and biases) and performance indexes.
- Synthesizing the advantages, disadvantages, and challenges associated with AI models.

- Translating synthesis to guide AI model selection based on efficiency, accuracy, interpretability, adaptability, and data requirements.
- Identifying knowledge gaps and providing recommendations for future work.

The findings will benefit many stakeholders, including environmental agencies, researchers, practitioners, citizens and communities, municipal governments, utility companies and water managers, and policymakers.

2 Methodology

2.1 Article Selection Process

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol was used to consolidate the scientific knowledge presented in this study. Three major multidisciplinary research databases, Google Scholar (http://scholar.google.com/), EBSCO (https://www.ebsco.com/), and Springer (https://link.springer.com/) were used to identify relevant studies related to this topic. An initial search using the keywords "artificial intelligence" and "water consumption" retrieved 363,000 documents on July 29, 2022. A more streamlined second search was conducted on August 12, 2022, using additional key terms, such as forecasting, prediction, estimation, assessment, machine learning, deep learning, and artificial neural networks. This reduced the number to 262 peer-reviewed articles and were downloaded for full-text review. A third search was conducted on January 10th, 2024, using the same terms to include a few studies (10) from 2023 to enhance the quality of the paper. Snowball sampling was conducted to gather additional studies (29) to identify methods for assigning weights and biases to AI models.

2.2 Quality Assessment and Study Selection Process

The downloaded articles were evaluated for the systematic review. After applying inclusion and exclusion criteria (assessing, judging, and identifying potential bias risks, and appraising internal or external validity; Supplementary Figure A), 72 papers were excluded from the final analysis. Ultimately, 190 papers were selected from the two first searches (July 29 and August 12, 2024), 10 from the third search (January 10th, 2024), and 29 from the snowball sampling, resulting in 229 studies considered for this paper (Fig. 1).

2.3 Data Extraction and Analysis Methods

General characteristics, such as year of publication, keywords, authors and co-authors, and country of origin of the authors and co-authors of the study were extracted from 190 studies. AI model characteristics such as inputs and outputs, learnable parameter determination methods, performance indices, challenges, and advantages and disadvantages of some AI models were also collected. The information generated in this systematic review was analyzed and presented using multiple visualization methods. Line graphs (yearly distribution of publications), network maps (keywords, authors, and co-author collaboration), geographical maps (country of origin of authors and co-authors), pie charts (purpose of the studies), tables (AI models, input, output, sector of application), collapsible trees (learnable parameter

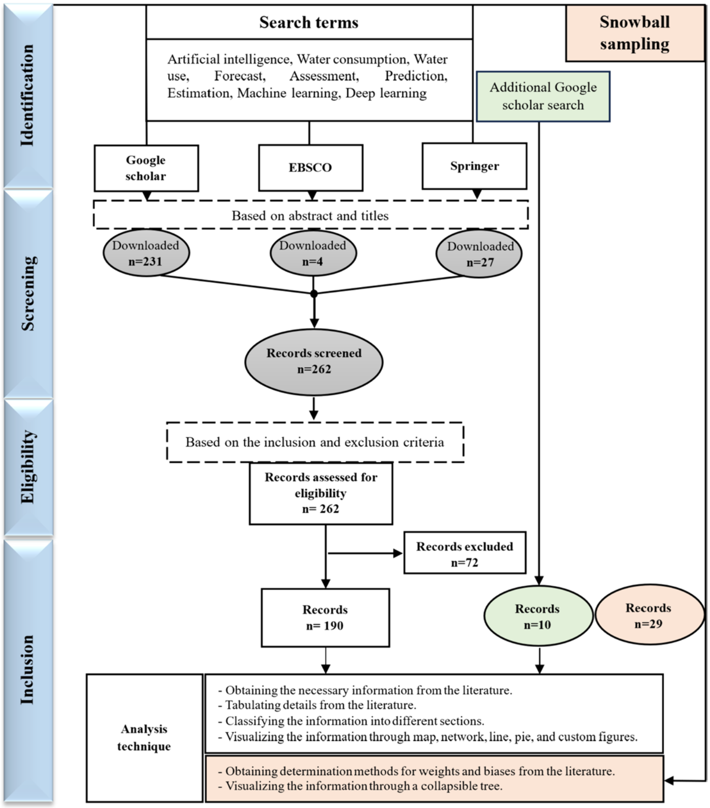

Fig. 1 PRISMA flowchart for article inclusion/exclusion in this systematic review

determination methods), tree maps (performance indexes), and other figures (AI implications and system model in WC assessment) were created. A network collaboration map was created using VOSviewer (more details in the supplementary material). A geographical map was created using MapChart (https://www.mapchart.net/world.html). Tables were created using Microsoft Word, and custom figures were created using PowerPoint. Microsoft Excel was used to design the treemap, CollapsibleTree was created using R (Version 4.2.3.), and MATLAB (Version R2023b) was used to generate the line graph and pie charts. The trend in the number of publications is considered one of the prominent measures to assess the significance and emergence of certain technologies within the subject domain.

3 Results

3.1 Descriptive Aspects of the Studies

Between 2016 and 2021, there was a significant increase in publications on AI-based WC research. More than half of the total studies (64%) were published in the last six years (an average of 18 publications per year), in contrast to 61 publications that were published during the first 17 years of the period (an average of 3.5/year). Interest in AI applications related to WC has increased over the past decade, as indicated below (dotted line in Fig. 2a).

A total of 720 authors produced the articles used in this study**.** The authors and co-authors are geographically affiliated with 22 Asian countries, seven American countries, one country in Oceania, and six African countries. China (16.8%), Spain (8.9%), India (8.4%), Iran (7.8%), the United Kingdom, and Brazil (5.7%) were the top six countries with the highest numbers of authors (Fig. 2b). The publication rates were highest in Asian countries. Moreover, a co-authorship analysis showed that the author Hussein Al-Bugharbe had the highest number of documents and total link strength (documents:4; total link strength:17), followed by Manuel Herrera (Number of documents:4; total link strength:12). These two authors were productive researchers who actively collaborated on research publications.

Furthermore, a cluster analysis revealed four significant collaborations between the authors. Hussein Al-Bugharbee's cluster researched AI applications for predicting urban WC, while Manuel Herrera's cluster focused on using hybrid AI models to forecast short-term urban water demand. Other clusters, such as Plinio Centoamore's, aimed to explore the benefits of implementing AI in industrial WC, while Michael Blumenstein's cluster examined residential WC (Supplementary Figure B). These findings suggest that only a few scholars have established a pattern of close collaboration and contact with

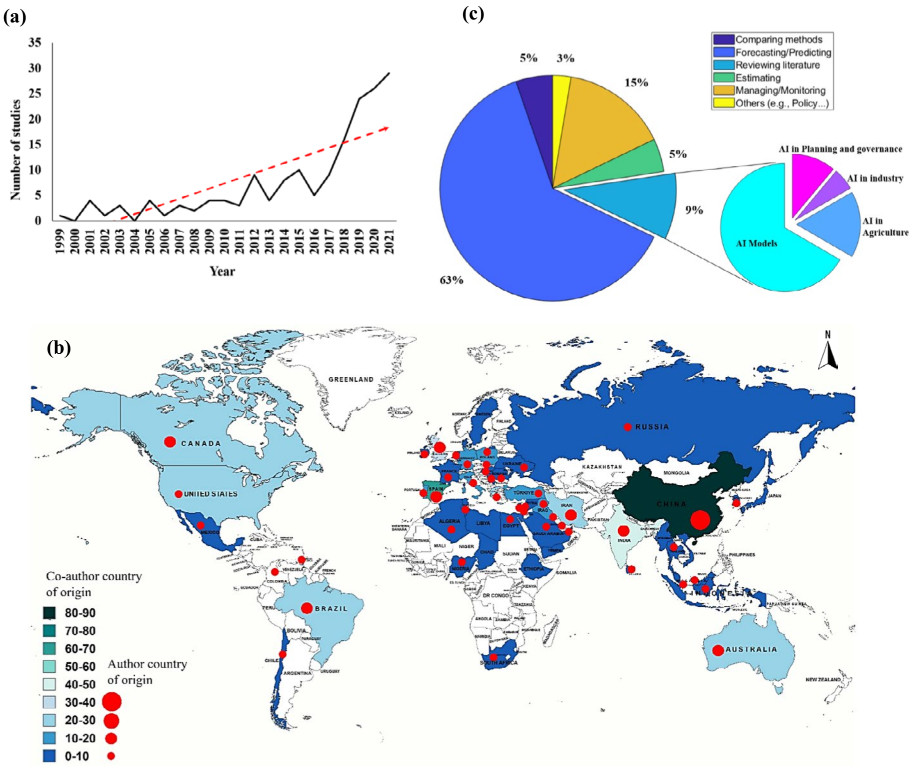

Fig. 2 **a** Spatial distribution according to the country affiliation of authors and co-authors; **b** Annual distribution of the studies; **c** Purpose of the studies

AI applications in WC assessment studies. Therefore, AI experts should cooperate more effectively in studies related to WC assessment. Additionally, most studies on AI applications have focused on evaluating urban WC. Thus, more studies are needed to use AI techniques to assess agricultural and industrial WC in addition to urban WC.

The selected studies for this paper have compared different AI models, predicted WC, reviewed the literature, estimated current WC, and managed and monitored water supply systems (Fig. 2c). Review papers constituted 9% of the 190 publications included in this study. The reviews were on industries, agriculture, water planning, and governance. They highlight various aspects of AI Model applications for predictive analytics, smart metering, leak detection, and AI-driven decision support systems. This paper also conducted a keyword analysis to highlight the core concepts emerging from this study. The analysis has underscored the prevalence of keywords like "water demand," "water consumption," "forecasting," and "prediction," thereby highlighting the significance of distinguishing between the concepts of "water demand" and "water consumption," as well as "forecasting" and "prediction." This distinction is crucial, as these terms are frequently used interchangeably by different authors. The analysis also revealed the use of various AI models, with ANNs emerging as the prevalent model for estimating water consumption. More details are provided in the supplementary material.

3.2 Water Consumption: Artificial Intelligence Implications

Figure 3 illustrates the relevance of AI in WC assessment from four perspectives: innovation, application, sustainability, and machine learning.

3.2.1 Innovation

The recent rise in AI has led to numerous innovations in science and society. Notable examples include implementing smart cities, where technologically modern urban areas use electronic methods and sensors to collect, analyze, and integrate critical information related to water systems (Preciado et al. 2019; Kamyab et al. 2023). Smart water networks, incorporating smart water meters (Candelieri et al. 2015) and sensors, are developed to continuously monitor and diagnose problems, prioritize and manage maintenance issues, and optimize water distribution networks using real-time data (Barroso et al. 2022; Stańczyk et al. 2023). Additionally, AI-driven innovations have extended to smart irrigation systems in agriculture and urban landscape management (Bhoi et al. 2021). This utilizes self-adaptive systems that optimize control decisions by considering natural terrain characteristics (Borodychev and Lytov 2021) and crop water requirements to tailor automatic watering schedules (González Perea et al. 2019). Furthermore, AI has also catalyzed advancements in computer software (e.g., MATLAB, R, and Python) by creating a need for proper programming tools to train, validate, and test AI models (Awad and Zaid-Alkelani 2019; Antzoulatos et al. 2020). These software tools have strong visualization and plotting capabilities and provide access to numerous libraries and packages for classical and modern AI models (Trajer et al. 2021).

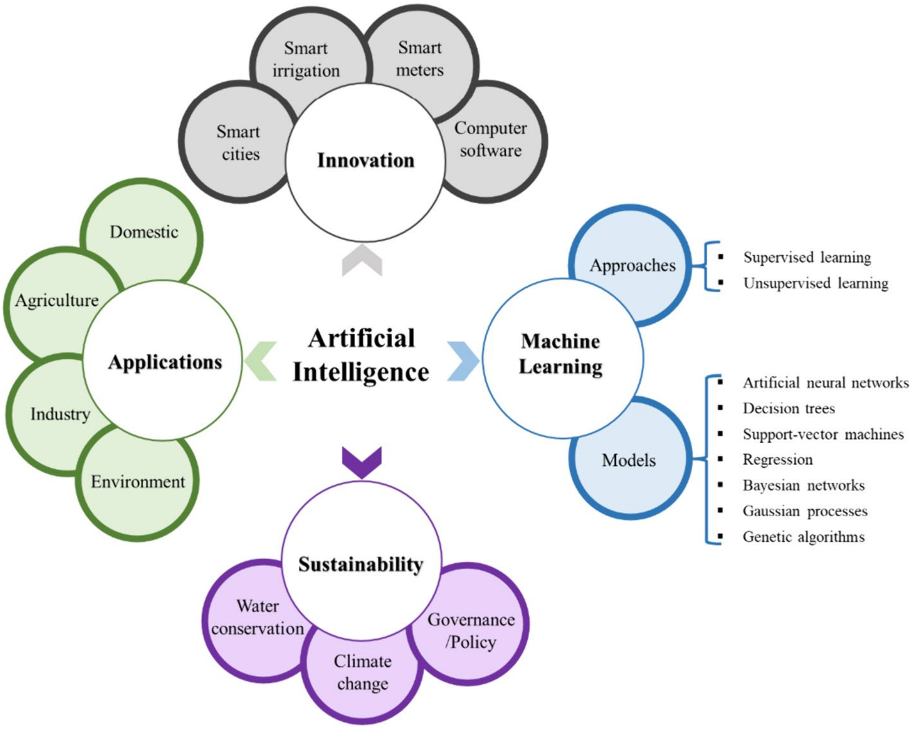

Fig. 3 Implications of AI in water consumption assessment

3.2.2 Applications

AI applications were used for a variety of functions. (1) Monitoring household real-time WC through smart meters, detecting plumbing system anomalies, increasing water accessibility, and identifying consumer needs (Alcocer-Yamanaka et al. 2012). Forecasting urban residential WC, determining key water end-use categories, and monitoring drinking water distribution systems with greater efficiency and accuracy (Bennett et al. 2013; Al-Zahrani and Abo-Monasar 2015). (2) For improving agricultural WC forecasts and irrigation scheduling (Ehret et al. 2011; Borodychev and Lytov 2021). Smart irrigation systems are equipped with wireless monitoring sensors for automated crop irrigation, which can lead to improved water efficiency and increased crop yield (Bhoi et al. 2021). (3) For detecting waste and overuse in industrial water monitoring systems, reducing water costs and improving operational decisions (Murali et al. 2021). AI has also facilitated data collection in wastewater management, improved dam operation safety, and flood risk mitigation in cities (Gomes et al. 2020). Additionally, AI can assist construction cost management by accurately forecasting WC (Peng et al. 2020; Murali et al. 2021). (4) for assessing ecological WC (Guo and Yu 2021). Implementing AI in dam management has offered significant environmental benefits by augmenting water availability and ensuring efficient water distribution to populations (Gomes et al. 2020).

3.2.3 Sustainability

Increased WC can lead to the depletion and scarcity of water resources. Introducing AI into water management systems in areas with limited water resources and regions affected by climate change is a promising approach to ensure the sustainability of water resources (Bülbül and Öztürk 2022). Smart technologies such as smart meters, automatic sprinklers, and rain sensors can support water conservation. AI can detect dam leaks, improve water distribution efficiency, and prevent water wastage (Gomes et al. 2020; Glynis et al. 2023). Developing successful water management plans and policies requires effective water governance through cross-scale and cross-level interactions (Palomares et al. 2021). AI can provide accurate data, solve complex problems, and manage large amounts of data (Uhlenbrook et al. 2022). These accurate estimates and predictions are crucial for sustainable water governance.

3.2.4 Machine Learning

The use of ML has increased in various fields in the era of big data technology (Sun et al. 2021). In addition to enhancing the estimation techniques, it provides insights into how multiple models work together by understanding their functionalities and the impact of modifying their parameters (Ambrosio et al. 2019). ML models can be categorized into supervised learning, which utilizes labeled data to learn the data structure, and unsupervised learning, which operates on unlabeled data to autonomously to learn the data structure (Ghalehkhondabi et al. 2017; González Perea et al. 2019). Supervised approaches are generally more accurate (Gourmelon et al. 2021). However, combining unsupervised ML clustering models with supervised ML forecasting models improved performance significantly (Bata et al. 2020), reduced training data requirements, and lowered certain model implementation barriers (Bethke et al. 2021). The following section discusses these models in detail.

3.3 AI Models Used for WC Forecasting

AI models can forecast WC based on past and present observations (Anele et al. 2017). Additionally, the AI models forecast WC based on the time horizon categorized as short- (one hour to one week), medium- (one week to one year), or long-term (one year and more) (Babel and Shinde 2011; Alhendi et al. 2022). They are classified as standalone and combined models. More details are provided in Supplementary Tables 1 and 2 regarding the models, application sectors, input and output variables, and time horizon.

3.3.1 Standalone AI Models

- Artificial Neural Networks

  ANNs are ML algorithms created to replicate the structure and functionality of the human brain. These models consist of interconnected artificial neurons (nodes) arranged in layers, with each layer element fully connected to the next (Niknam et al. 2022). Each node in the input layer receives a distinct input variable, and the nodes in the hidden layers transform these inputs using a series of nonlinear functions before producing an output in the final layer (Nunes Carvalho et al. 2021). A typical example of an ANN is represented by simplified Eq. 1 (Nunes Carvalho et al. 2021) where Y_k

is the output, f_{outer} is the output layer transfer function, f_{inner} is the input layer transfer function, and W is the weight and bias.

$$Y_k = f_{outer}\left[\sum_{i=j}^{M} W_{kj} f_{inner}\left[\sum_{i=j}^{d} W_{ji}X_i + W_{j0}\right] + W_{k0}\right] \tag{1}$$

They can learn complex patterns and relationships in data, making them highly beneficial for tasks that may be challenging when using non-AI models (Babel and Shinde 2011). Various ANNs, such as GRNN (General Regression Neural Network) (Al-Zahrani and Abo-Monasar 2015), CCNN (Cascade Correlation Neural Network) (Firat et al. 2010), FFNN (Feed Forward Neural Network) (Firat et al. 2009), and BPNN (Back-propagation Neural Network) (Liu et al. 2019b) have been used as standalone models to predict domestic WC. The FFCNN (Feed Forward Computational Neural Networks) provided precise irrigation predictions when input data from the preceding two days were used (Pulido-Calvo et al. 2007). Other ANNs, such as MLP (Multilayer Perceptron), were used to predict urban WC based on meteorological data (Babel and Shinde 2011; Setiyowati et al. 2019). Similarly, LSTM (Long Short-Term Memory) forecasted domestic WC using similar data (Gautam et al. 2020; Kim et al. 2022). The BPNN and MLP are the most commonly used neural networks (NN) (Tian and Xue 2017; Liu et al. 2019b). NNs generally comprise multiple layers of interconnected nodes.

- Support Vector Machines (SVM) and Relevance Vector Machines (RVM)

  The SVM is based on the concept that nonlinear trends in the input space can be mapped to linear trends in a higher-dimensional feature space, and it recognizes subtle patterns in complex datasets using a learning algorithm (Ghalehkhondabi et al. 2017). SVM transforms the space where two classes are only separable by a nonlinear line into a new space where it is now possible to separate the classes using a linear line, also known as a hyperplane, for higher-dimensional problems (Antunes et al. 2018). Using meteorological data, Gautam et al. (2020) employed an SVM to forecast domestic WC. Bhoi et al. (2021) used an SVM to suggest irrigation to farmers to reduce water waste based on data such as air temperature, soil temperature, humidity, and soil moisture. Wang and Liu (2016) proposed the application of an RVM) as a sparse probability model based on an SVM. They claimed fewer relevant vectors were used for RVM training than SVM. For regression problems, support vector regression (SVR) can be used (Antunes et al. 2018). SVR employs the same principles as SVM for classification; instead of finding the best hyperplane to separate the data, SVR aims to determine the best data regression hyperplane (Ambrosio et al. 2019). Because the general equation for SVM is not explicitly provided in the selected articles in this study, a general equation for SVR (Setiyowati et al. 2019) is provided in Eq. 2 where Y is the output, $K(xi,xj)$ is the kernel function, x is the testing input data, α^*_i is the Lagrange multiplier, and λ is a scalar variable.

$$Y = \sum_{i=1}^{n} (\alpha^*{}_i) K(x_i, x_j) + \lambda^2 \tag{2}$$

- Other AI-based models

  - Regression

    Regression models were used to estimate the impact of the changes in a group of independent variables on the dependent variable, making them particularly useful for predicting future demand. However, limiting the timeframe for such predictions is essential in maintaining their validity (Niknam et al. 2022). Although regression models are typically associated with statistical models, multiple AI options are available for regression analyses. One particularly successful model is the random forest (RF) approach, which involves growing simple trees that produce numerical response values (Niknam et al. 2022). The predictor set was randomly selected from the same distribution for all the trees (Ambrosio et al. 2019). Multiple RF has been used to forecast urban WC using vegetation indices, evapotranspiration, land cover, and satellite-derived irrigation maps (Hof and Wolf 2014; Wei et al. 2022). Other models, such as regression and decision trees, are supervised algorithms that use a tree structure to build prediction models for classification or regression purposes (Villarin and Rodriguez-Galiano 2019; Jurišević et al. 2021). The general equation for RF is provided in Eq. 3 (Nunes Carvalho et al. 2021), where x_i is the vector of the independent variables, $T_b(x_i)$ is a single regression tree grown using bootstrapped samples and a subset of variables. N is the number of regression trees Chen et al. (2017).

$$Y(x_i)=f_{rf}^{k}\left(x_i\right)=\frac{1}{N}\sum_{b=1}^{N}T_b\left(\mathrm{x}_i\right) \tag{3}$$

– k-means, SOM, DWT, and CWT

In addition to the aforementioned AI models, other models for assessing WC have been identified. These models include k-means, self-organizing maps (SOM), and WA. They are valuable tools in data analysis and preprocessing for AI tasks. k-means and SOM are unsupervised learning algorithms that cluster data points based on similarities. Bethke et al. (2021) used k-means to categorize residential water events based on appliance end-use information. Similarly, Leitão et al. (2019) used the same model to detect urban WC patterns, whereas Ioannou et al. (2021) preferred using SOM based on household needs and behaviors. Another approach for analyzing WC data is to use WA, specifically continuous and discrete wavelet transforms. Zubaidi et al. (2020a) used WA to forecast urban water demand. These transforms help identify patterns in time-series data, making them valuable tools for analyzing WC over time. The typical equations for discrete and continuous wavelet transforms (DWT and CWT) are provided in Eq. 4 (Zubaidi et al. 2020a) and Eq. 5 (Altunkaynak and Nigussie 2017), where Ψ (n) is the mother wavelet, while m and k are the scaling and shifting indices.

$$DWT=\frac{1}{\sqrt{2^m}}\sum_k x[k]\Psi[2^{-m}n-k] \tag{4}$$

$$CWT=\frac{1}{\sqrt{|m|}}\Psi\int_{-\infty}^{+\infty}\left(\frac{n-k}{m}\right)dn \tag{5}$$

3.3.2 Combined AI Models

This study also reviewed hybrid models, which can be combinations of two or more AI models or non-AI and AI models, aiming to address the limitations of individual models and improve their accuracy and efficiency (Altunkaynak and Nigussie 2018; González Perea et al. 2018). Cutore et al. (2008) developed the SCEM-UA ANN (Shuffled Complex Evolution Metropolis Algorithm), Farah et al. (2019) used the FFBP-ANN (Feed-Forward Back-Propagation), and Zubaidi et al. (2020a, b) developed the SMA-ANN (Slime Mould Algorithm), BSA-ANN (Backtracking Search Algorithm), and CSA-ANN (Crow Search Algorithm) models to forecast residential and commercial WC. Altunkaynak and Nigussie (2017, 2018) developed four hybrid models, DWT-MLP, MSA-MLP (Multiplicative Season Algorithm), FOD-MLP (First Order Differencing), and LD-MLP (Linear Detrending), to predict monthly urban WC. In addition, Said et al. (2021) found that combining deep-learning neural networks (DLNN) with MLP, CNN (Convolutional Neural Networks), or LSTM models resulted in more accurate WC predictions than using these models alone. A collaborative model combines the RCG (Residual Correction-based Gray) and LSTM models to generate accurate real-time predictions of WC (Li et al. 2021). Other AI models, such as clustering algorithms, decision trees, when combined with ANNs and SVM, have been shown to improve water demand forecasting accuracy (Adamowski and Karapataki 2010; González Perea et al. 2018). With AI technologies continuing to evolve, hybrid models are likely to become increasingly important in solving complex problems and making accurate predictions (Wang et al. 2023). These models can address the limitations of individual models, take advantage of the strengths of different approaches, and provide a better understanding of the relationships between variables. Refer to Appendix A for further details regarding the abbreviations.

Fuzzy models with AI models are also popular models to analyze WC and hydrological systems (Ghalehkhondabi et al. 2017). These systems deal with uncertain or imprecise data and are based on fuzzy logic principles that allow the assignment of partial truths or degrees of membership to data points rather than the binary truth values of traditional logic (Yurdusev and Firat 2009). Originally developed to explain human thinking and decision-making processes, fuzzy systems have been adapted to AI to model various engineering systems, including water resources (Yurdusev and Firat 2009). Zubaidi et al. (2020a) used ANFIS to predict urban WC. ANFIS is a combination of NN and fuzzy inference systems (Vijayalaksmi and Babu 2015). Oliveira et al. (2009) used fuzzy logic to model the water demand in building supply systems. Fuzzy cognitive maps were used to create a concrete water usage process from a wastewater management perspective and to predict WC (Markovič 2018; Sánchez-Barroso et al. 2023). Xu and Qin (2015) proposed a novel superiority-inferiority-based sequential fuzzy programming model to support water supply–demand analysis under uncertainty. Altunkaynak et al. (2005) used the Fuzzy Takagi–Sugeno model to forecast WC based on past monthly data, whereas Surendra and Deka (2012) used daily data for the same purpose. Surendra et al. (2022) used the Mamdani fuzzy inference system (MFIS) to estimate WC using rainfall, maximum temperature, minimum temperature, and relative humidity data. The Fuzzy Takagi–Sugeno model is among the most widely used fuzzy models. Further details are provided by Altunkaynak et al. (2005).

3.4 AI Model Performance

3.4.1 Learnable Parameters: Weight and Bias

Weights and biases play a crucial role in the training process of AI models by governing how the model processes the input data, assigns significance to different features, and produces output predictions. The accuracy of the outputs is highly dependent on these (dos Santos and Pereira Filho 2014). In NNs, weights represent the strength of the connections between different nodes, which determine how much influence the output of one neuron has on the input of another (Maltais and Gosselin 2021). Bias allows the model to adjust the output values of the node, regardless of the input (Adamowski and Karapataki 2010). Various methods exist for assigning weights and biases to AI models (Supplementary Figure Da). They can be broadly classified into initialization and optimization methods. Initialization methods help set the initial values of the weights and biases within a model, whereas optimization methods are tasked with adjusting the initial weight and bias values (Balduzzi et al. 2017; Narkhede et al. 2022). Optimization methods are primarily data-driven and rely heavily on available data to update the learnable parameters during training (Maltais and Gosselin 2021). Initialization methods can be classified as random initialization or data-driven initialization (Narkhede et al. 2022). There are also other initialization methods, such as equal, inverse weighting (Abdollahi and Ebrahimi 2020), and zero initialization methods (Narkhede et al. 2022). Random initialization methods, in which numerical values are selected from random distributions, remain the most popular due to simplicity and ease of implementation (Narkhede et al. 2022). Although some of these methods may not be effective for complex problems or deep networks (Balduzzi et al. 2017). Variance-scaling-based (a type of random initialisation method) and data-driven initialization can lead to better performance and faster convergence, particularly for complex problems or deep networks, because it helps prevent vanishing or exploding gradients (Ioffe and Szegedy 2015; Narkhede et al. 2022). Data-driven methods require domain expertise to select the correct initialization and optimization method.

3.4.2 Performance Indexes

Performance indexes are statistical methods used to analyze the residual errors between measured and predicted values and point out their differences (Banihabib and Mousavi-Mirkalaei 2019). They provide a way to measure algorithms' accuracy, efficiency, and effectiveness (Alhendi et al. 2022). The most common indexes used include the root mean square error (RSME, Eq. 6, (Huang et al. 2021)), mean absolute percentage error (MAPE, Eq. 7, (Zubaidi et al. 2020b; Sardinha-Lourenço et al. 2018)), and the coefficient of determination (R^2, Eq. 8, (Adamowski and Karapataki 2010)). The RMSE is used for tasks that minimize the difference between the predicted and actual values (Altunkaynak et al. 2005; Al-Zahrani and Abo-Monasar 2015). The MAPE is also used to measure the accuracy of forecasting models by measuring the difference between the observed and predicted values and providing a percentage error between the actual and forecasted values (Adamowski 2008; Firat et al. 2010). The smaller the error value, the better the model's performance (Jain et al. 2001). In contrast, R^2 measures how well the model fits the data to establish a connection between the input and output variables (Adamowski 2008). The higher the value of R^2, the more accurate the model (Leon et al. 2020). Selecting an appropriate performance index for a model relies on data characteristics and model objectives. n is the number of observations, $\overline{Y}$ is the data set mean, $\hat{Y}_i$ is the forecasted water demand, and Y_i is the actual water demand. Supplementary Figure Db and Table 4 provide more performance indexes and their equations.

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(\hat{Y}_i^2 - Y_i^2)} \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}}\left|\frac{\mathrm{Yi} - \hat{\mathrm{Y}}\mathrm{i}}{\mathrm{Yi}}\right| \tag{7}$$

$$R2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{\mathrm{Y}}\right)2}{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \overline{\mathrm{Y}}\right)2} \tag{8}$$

3.5 Advantages, Disadvantages, and Challenges Associated with AI Models

AI models have demonstrated effectiveness in estimating and forecasting WC (Jurišević et al. 2021; Kim et al. 2022). They can analyze large datasets to make accurate and reliable predictions. They identify hidden patterns and trends in WC data. AI models can be continuously updated with new data, allowing them to adapt and improve over time. They work with complex systems and incomplete data sets and offer high flexibility and convenience (Vozhehova et al. 2019; Peng et al. 2020). Hybrid models (SCEM-UA and ANN) can help determine model prediction uncertainties (Cutore et al. 2008) and can perform (BSA-ANN) even when missing factors exist (Zubaidi et al. 2020c). A combination of CSA and ANN can accurately forecast WC based on several statistical and graphical tests (Zubaidi et al. 2020a). Fuzzy models require minimal processing time and produce consistent predictions even with slight input-value changes (Altunkaynak et al. 2005). Some models (ANNs, DLNN, UWM-Id) require large amounts of data for training and validation and have a risk of not being able to generalize findings beyond the observed data (Gao et al. 2020; Said et al. 2021). While hybrid models improve predictions, some (BSA-ANN, FFBP-ANN) have relatively slow overall running times (Farah et al. 2019; Zubaidi et al. 2020c). BPNN can accurately predict WC but with poor generalization (Liu et al. 2019a, b). Due to slow convergence, MFIS has a limited performance with many inputs and outputs (Surendra et al. 2022). RF can become slow and ineffective with too many trees (Hof and Wolf 2014) and determining input weights for SOMs is challenging (Ioannou et al. 2021).

Several challenges exist in applying AI for WC assessment. One major challenge is finding a high-performing AI model that is easy to interpret and requires minimal data (Adamowski 2008). Reproducibility is another challenge due to insufficient details researchers provide regarding the variables and model training (Cutore et al. 2008). The type of input variables and poor-quality data can adversely affect AI model performance. These challenges further exacerbate the issue of standardization because of the lack of a normalized performance evaluation and variable selection method (Nunes Carvalho et al. 2021). Data may not be readily available even when the correct input variables are identified. In addition, data uncertainty can be a real challenge, and its unaccountability can sometimes lead to inaccurate estimates and forecasts (Adamowski et al. 2012). Data privacy is also a significant concern, as high-resolution WC data from smart meters may reveal personal information about consumers (Fu et al. 2022; Richards et al. 2023).

3.6 Knowledge Gaps

A detailed analysis of the articles resulted in the identification of the following knowledge gaps.

- Most AI application studies have focused on assessing urban WC. More focus is needed on agricultural and industrial WC and water use to support the environment.

- AI models used to assess WC are typically evaluated using scattered or discontinuous data due to limitations in data availability. Complete and continuous datasets should be used to assess AI models for more accurate performance evaluation (Gourmelon et al. 2021).
- Water leaks significantly affect WC estimates and predictions. A rapid and reliable AI model for detecting water leaks can help develop effective mitigation strategies and adaptation plans (Benítez et al. 2019).
- k-means clustering is the most commonly used clustering method associated with AI-based analysis. However, k-means is more efficient with smaller datasets and requires more time to classify large datasets. Therefore, other clustering models, such as Clustering Large Applications based on RANdom Search (CLARANS), Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH), and Clustering Using Representatives (CURE), should be investigated (Rahim et al. 2020).
- Reproducing AI model applications can often be challenging due to the lack of reported details regarding their testing, training, and variables. Standards must be established to select the appropriate data types, variables, and performance evaluation methods to enhance the reproducibility and transparency of the process (Casali et al. 2022).

4 Discussions

4.1 AI for WC Assessment: Panoramic View and Model Selection

Over the past decade, growing interest in AI has revolutionized WC prediction, modeling, and decision-making methodologies. Numerous studies have been conducted on the application of AI to WC assessments. However, most of these studies have focused on evaluating urban WC, neglecting agricultural and industrial WC, even though agriculture accounts for a significant portion of the total WC (Wei et al. 2022). The lack of collaboration among researchers may limit the potential of experts from diverse backgrounds to collaborate more effectively on various aspects of WC. Improved collaboration could also enhance public understanding of the importance of AI and its role in daily life and the environment, particularly concerning the four perspectives of innovation (smart cities, irrigation, meters, and software), application (agriculture, domestic, industry, and environment), sustainability (water conservation and policy/governance), and ML approaches and models, as illustrated in Fig. 3.

AI can simulate current and future WC through standalone and combined (hybrid) AI models. Ensuring the use of high-performance models is of utmost importance, for accurate and reliable estimates and predictions. The interpretation of reasonable accuracy in the AI models depends on the performance index utilized. For instance, a higher R^2 value indicates superior model performance (Banihabib and Mousavi-Mirkalaei 2019), whereas a lower error (e.g., MAPE, MSE) is preferred for an ideal model (Farah et al. 2019; Gao et al. 2020). It is essential to compare the results of studies using different performance indexes, and other considerations might be necessary. For instance, MSA efficiently forecasts WC for specific urban areas (Altunkaynak and Nigussie 2017). To generalize the results, further studies should be conducted to determine model performance across different geographical and climatic regions, as local factors may affect predictions (Tang et al. 2012). AI models can also forecast WC considering climate change (Ehteram et al. 2021). Other considerations include studying the relationship between WC and the season (Gelažanskas and Gamage 2015; Gautam et al. 2020). The following question remains: What are the critical aspects to be considered when selecting an AI model?

Choosing the appropriate model is critical for effectively accomplishing a task. No one-size-fits-all AI model exists for WC assessment. It is crucial to establish the context of this work, whether it involves estimating or forecasting WC. In addition, defining the scope can help identify the most suitable AI model for each scenario while considering the available technologies to support AI applications. The reliability of any study depends significantly on the data used. Certain AI models may require specific technical input data, such as historical WC (Wu et al. 2020), meteorological (e.g., precipitation, temperature) (Tao et al. 2023), demographic (e.g., population, household size) (Roushangar and Alizadeh 2018), socio-economic (e.g., education, water price) (Azadeh et al. 2012; Bashar et al. 2023), remote sensing (e.g., dam reservoir images, spatial data) (Gonzalez Perea et al. 2021; Sorkhabi et al. 2022), and agricultural (e.g., crop fraction, irrigated area) (Ehret et al. 2011). Therefore, the proper variables must be selected based on the scenario and the scope of the research.

Selecting an appropriate AI model depends not only on the chosen variables and data availability but also on the model type and performance level. Figure 4 summarizes the main groups of AI models used for this purpose regarding their efficiency, accuracy, interpretability, adaptability, and data requirements (Niknam et al. 2022). Each of these factors can affect the performance of an AI model and should be carefully evaluated to select the most suitable model for a particular task. Efficiency is crucial for real-time applications because it relates to the model's ability to process data quickly. Accuracy determines how closely the model's predictions match the actual data. Interpretability is important because it enables users to understand how a model makes predictions. Adaptability refers to the

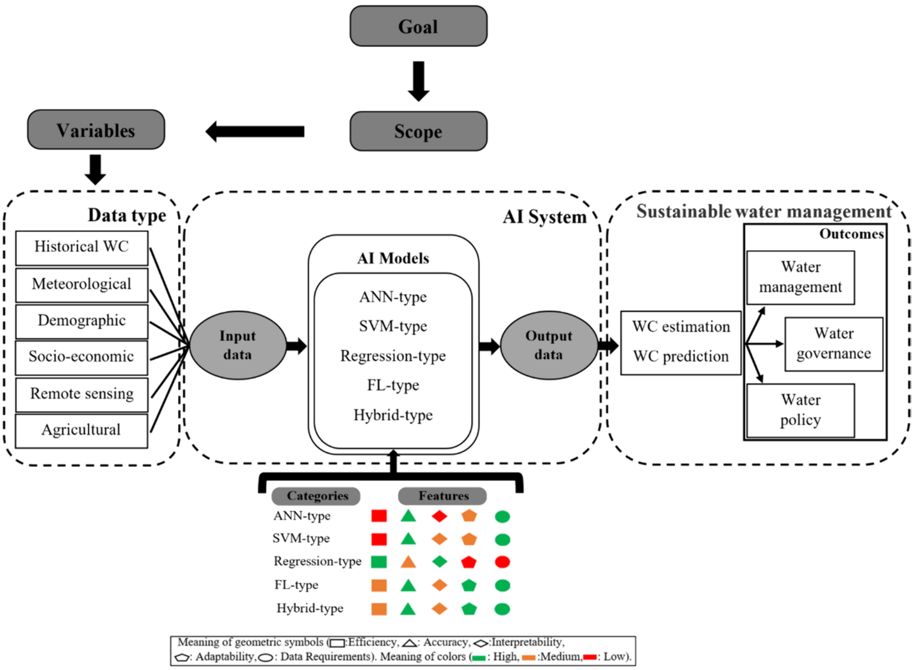

Fig. 4 AI system model in water management

ability of the model to adjust to new data and changing circumstances. Data requirements are related to the amount and type of data required to train the model. Models that require large amounts of data may be challenging to train and not suited for all applications. Similarly, models that require highly specialized data may not be practical in all cases.

Because the models are presented in broad categories, some may not be adequately represented. For instance, RF, classified as a regression model, often provides "high" accurate predictions, while regression, in general, provides "medium" accurate predictions (Niknam et al. 2022). An ideal model is efficient, accurate, interpretable, adaptable, and requires minimal data. Unfortunately, no such model has been developed yet. Therefore, the best approach is to select a model that closely fits the specific situation. Based on the current literature, the authors suggest hybrid models could be a relatively good alternative for estimating and forecasting WC because they exhibit moderate efficiency, high accuracy, medium interpretability, high adaptability, and high data requirements.

4.2 Assumptions, Limitations, and the Next Step

This study was conducted using the PRISMA framework, which was chosen due to its transparent procedures. Peer-reviewed papers were searched on July 29, 2022, August 12, 2022, and January 10th, 2024, using specific search words presented in Section 2.1. Some studies may have been missed, as the search terms were not explicitly mentioned in their titles and abstracts. Different search timelines may have yielded different sets of studies. Therefore, the results do not reflect all available information about AI applications in WC assessments. However, the selected documents contain the information necessary to draw valid and reliable conclusions. Other considerations must be considered in the co-authorship and keyword analyses. For this study, authors who collaborated on two or more documents and keywords with a frequency of five or more in the titles and abstracts of the articles were included. The results would have differed if different selection conditions had been used. Nonetheless, these findings are highly relevant for future scientific research on estimating and forecasting WC. The next step in this research involves assessing the WC in Florida under scenarios of land-use/land cover change using hybrid AI models. The results will be informative for water governance, policy, and decision-making perspectives.

5 Conclusion

This review highlights the valuable role of AI in assessing WC, specifically its involvement from the perspectives of innovation, application, sustainability, and ML applications. Despite the growing interest in AI over the past decade, the findings of this study suggest that only a few authors have established a pattern of close collaboration and contact regarding AI applications in WC assessment studies. It was also found that nonlinear models applied to assess WC, optimization of water resource allocation, and management of water shortages have provided numerous advantages over linear models. Advantages include time-saving, accurate estimates and forecasts, convenience and flexibility, and handling complex systems and vast amounts of data. Despite numerous advantages of AI applications in WC assessments, challenges associated with reproducibility, method standardization, data availability, data uncertainty, and data privacy were highlighted. A significant challenge is selecting the appropriate model with high performance for estimating and forecasting WC. Although various models have been used in the literature, it remains unclear which model performs better, and the selection process must consider several criteria related to performance, data availability, and problem complexity. No one-size-fits-all AI model exists; this study suggests applying hybrid AI models, as they offer flexibility regarding efficiency, accuracy, interpretability, adaptability, and data requirements. Hybrid models can address the limitations of individual models, take advantage of the strengths of different approaches, and provide a better understanding of the relationships between variables. This synthesis has resulted in innovative resources to support the estimation and forecasting of WC and future studies to address challenges, respond to needs, and fill the gaps highlighted in this study.

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Data Availability The data supporting this study's findings are available on request from the corresponding author, A.A.

Declarations

Conflicts of Interest The authors declare no conflicts of interest.

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