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Future water demand modeling: A multi-sector review using a streamlined methodological approach

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Overview Review

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Abstract

Future water demand modeling is of crucial importance for stakeholders, particularly in the era of rapidly changing climate and socioeconomic conditions. The modeling results can be applied to develop effective adaptation strategies that ensure equitable and sustainable allocation of water to various economic sectors, including institutional, commercial, industrial (ICI), residential and agricultural. However, a comprehensive review of existing future water demand modeling methods that consider both climatic and socioeconomic factors as well as the major economic sectors is currently lacking. This review article contributes to fill this knowledge gap while introducing a more streamlined and comprehensive methodological approach for conducting literature reviews in the environmental sciences domain. At the core of this method is a new framework designed to support research questions formulation and literature search strategies named STAR (Systems, Trouble/Treatment, Alternative, Response). In addition, it presents a data-requirement-based metric as well as a new nomenclature for classification of surveyed methods and approaches to guide the selection process of future water demand modeling methods. Furthermore, it proposes a hybrid modeling approach made up of three components (computational intelligence, dynamic systems and probabilistic scenarios) in the form of a theoretical workflow for future water demand modeling. The proposed workflow ensures broad applicability, making it adaptable not only to water demand management but also to a wide range of challenges across the environmental sciences.

Impact statement

Anticipating future demand is of paramount importance for equitable and sustainable management of water resources, particularly in the context of accelerating climate change and socioeconomic transformations. This article presents a comprehensive and methodologically rigorous review of water demand modeling approaches, with a particular focus on their applicability across socioeconomic sectors (municipal, agricultural, industrial, commercial, and institutional) and spatial scales (municipality, watershed, and region). At the heart of the study is the introduction of the STAR framework (System, Trouble/Treatment, Alternative, Response), which provides a clear and innovative roadmap for conducting literature reviews in environmental sciences and beyond. In addition to this framework, the article presents: (a) a new indicator of parsimony relevant for methods selection based on available data, (b) a new classification framework for existing methods and (c) a hybrid modeling workflow aiming to enhance water management and governance decisions supported by an open-source geospatial web software architecture. Due to its flexible design, the proposed workflow and underlying software architecture have potential applications that extend well beyond the field of water management and the nexus approaches, making it a valuable tool for addressing various environmental issues.

Introduction

Freshwater is an essential but limited natural resource that plays a fundamental role in socioeconomic development. Its demand is set to grow considerably in the upcoming decades, making it a highly coveted resource (Hertel and Liu, 2016). Thus, its availability and management are becoming increasingly critical challenges, especially in the context of prevailing factors such as climate change and socioeconomic growth. These water-demand drivers (Kulshreshtha, 1993; Huber et al., 2021; Jiang et al., 2023) have already led to numerous usage conflicts among economic sectors worldwide (Roson et al., 2015; Khan et al., 2020; Rondeau-Genesse et al., 2024).

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The undesirable situations mentioned above arise, for example, from changes in precipitation patterns and rising temperatures that affect the spatiotemporal availability of water, particularly for agricultural irrigation and industrial uses (Yang et al., 2019; Wang et al., 2018; Tian et al., 2023). While future climate projection scenarios anticipate an increase in water stress (Rowshon et al., 2019; Egerer et al., 2023; Guemouria et al., 2023), the extent and timing of water scarcity will vary regionally, primarily due to different socioeconomic assumptions (Shen et al., 2008). In such a context, future water demand models are often used as planning tools to implement effective adaptation and mitigation strategies. By anticipating future water demands of every economic sector, it is possible to promote equitable and sustainable access to water resources, at different spatial scales. Thus, we argue that a multisector and multiscale approach to water demand modeling would help shape public policies and ensure well-balanced allocations of resources in response to future climatic and socioeconomic conditions.

Recent water conflicts in the province of Quebec (Canada) have raised important concerns regarding future water demand (Bernier and Forcier-Martin, 2025; Gerbet and Dépelteau, 2025), given anticipated climate disruptions due to the accumulation of greenhouse gases in the atmosphere, on the one hand, and the productivity of the province's various economic sectors in response to demographic and economic growth, on the other hand. In this context, the Ministry of Environment, the Fight Against Climate Change, Wildlife and Parks and Ouranos commissioned a participatory research project named *ProjectEau* to strengthen its ability to anticipate future water demand across five key economic sectors, that is, municipal, agricultural, industrial, commercial and institutional. The goal is to propose a methodological water demand projection framework that: (a) reflects the specificities of Quebec's economic activities, (b) integrates both environmental and socioeconomic drivers of the demand and (c) is applicable at several spatial scales, from municipalities to watersheds, with the flexibility of being extended across the entire province. The first phase of the project involved a literature review on existing water demand projection methods to propose a suitable framework for Quebec's socioeconomic sectors given readily accessible data.

Water demand is often analyzed at multiple spatial scales ranging from an urban point of view (city or municipality) to a watershed and regional or national one (Bijl et al., 2018). Each scale brings together several economic sectors, that is, municipal/residential, institutional, commercial and even industrial, which are interconnected. For instance, at the watershed, regional and national scales, these water use sectors often co-exist with additional water uses, such as for agricultural production and energy production (Baccour et al., 2025). Although these sectors can be identified separately, they are interdependent, particularly from a practical point of view. For example, the water is often withdrawn from the same source, a river, lake or aquifer, which, de facto, creates interactions, but also tensions, and sometimes real conflicts over access to the resource (Gharib et al., 2024; Hall et al., 2024). Such a co-existence of multiple sectors within one spatial scale of interest often requires a balanced, optimal distribution and consumption of available water resources. The methodological approaches culminate in what is called the nexus approaches (Endo et al., 2020; Molajou et al., 2023), relevant to the understanding and management of the complex interdependencies between, for example, water, food, energy, land and ecosystems (Kebede et al., 2021; Alamanos et al., 2022). These studies have all indicated that by anticipating future water demands of every economic sector within an integrated framework, it is possible to promote equitable and sustainable access to water resources at different spatial scales. Thus, we argue that the modeling of a multisector, multiscale approach to water demand would contribute to shape fair public policies and ensure well-balanced allocations of resources in response to future climatic and socioeconomic conditions.

An examination of current literature reviews on future water demand modeling methods, including univariate, econometric regression, end-use, system dynamics, agent-based and computational intelligence models, reveals several important limitations. In general, the focus is on a single economic sector (e.g., municipal or industrial) or climatic factors alone, thus failing to account for the combined and even compound influence of climatic and socioeconomic conditions on water demand (Potopová et al., 2022; Cominola et al., 2023; Mazzoni et al., 2023). Accordingly, several reviews have overlooked the full range of interactions within and between sectors (Xu et al., 2019; Wang et al., 2017; Fiorillo et al., 2021). This parochial view of existing literature review efforts does not expose the complex dynamics of drivers such as population growth, urbanization, economic development, technological advancements, agricultural practices, cultural practices and policy changes that often compromise the effectiveness of water management strategies. Again, we argue that a more systemic view of water demand modeling methods is therefore essential to overcome these limitations and support the development of more robust water demand management strategies.

This article addresses the limitations of current literature reviews on future water demand modeling methods discussed above by contributing to: (a) a more comprehensive analysis of current modeling approaches and (b) an integrated workflow that captures intra and inter-sectoral interactions. In addition, it introduces a comprehensive streamlined approach for conducting literature reviews in environmental sciences. At the core of this approach is the STAR (Systems, Trouble/Treatment, Alternative, Response) framework (Celicourt et al., 2025), a methodology guiding our formulation of research questions and literature search strategy. In addition, we used the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses; Page et al., 2022; Moher et al., 2009), a framework providing a structured process for identifying, selecting, appraising and synthesizing studies from the literature. Furthermore, it presents a data-requirement-based metric, as well as a new nomenclature for classifying the methods and approaches surveyed, and ultimately to guide the selection of modeling methods. Finally, it proposes a hybrid methodological workflow made up of three core modeling components: computational intelligence, dynamic systems and probabilistic scenarios. The proposed workflow ensures broad applicability, making it adaptable not only to water demand management but also to a wide range of challenges in environmental sciences.

The article is organized as follows: the following section outlines the methodology adopted for this review; the third and fourth sections present the results and discussions, respectively. The later examines the strengths, limitations, and similarities between the identified methods. The final section concludes with a summary of the different methods for modeling future water requirements and our recommendations for future research.

Methods

To carry out the literature review, we adopted a structured methodological approach to (a) reduce potential biases related to the publications selection and (b) facilitate the reproducibility of the reported results. To this end, we first selected the PRISMA

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framework (Moher et al., 2009; Page et al., 2022) recognized for enabling high-quality systematic reviews in the biomedical field. It consists of a checklist of 27 essential elements to integrate in review or meta-analysis reports, as well as a four-phase workflow (identification, selection, eligibility and inclusion) for the selection of relevant studies.

Although the PRISMA framework aims for a true representation of the available knowledge addressed by a research question, it does not elaborate procedures for: (a) crafting research questions and (b) searching the references in the bibliographic databases. These tasks require the application of, respectively, the CIMO (context, intervention, mechanism, outcome; Denyer et al., 2008) and the PICO (population/patient/problem, intervention, comparison/control, outcome; Methley et al., 2014; Palaskar, 2017). However, PICO and CIMO are designed for applications in biomedical and institutional management research settings, respectively. Thereby, they are limited in effectiveness and scope particularly because elements of some review questions cannot be explicitly mapped to the PICO structure (James et al., 2016). Thus, they are unable to accommodate the complexity of socio-environmental systems. The STAR framework (Celicourt et al., 2025), by design, embodies a broader perspective on literature search and research questions formulation problems specific to the environmental sciences domain. Hence, we have selected it as the most appropriate approach for our review. The elements of the framework and keywords sample used to define our literature search strategy are presented in Table 1.

From the STAR criteria, two research questions were formulated to support the objective of our proposed review:

a. How are *environmental and socioeconomic factors* modeled in current methods and approaches for *sectoral water demand* projection?
b. How parsimonious are the current methods and approaches for future *sectoral water demand* modeling when considering the influence of both *environmental and socioeconomic factors*?

Because of the complexity of our literature review subject, we further defined a more exhaustive list of keywords along with the queries formulated using Boolean operators introduced in Table 2. A targeted search with the keywords or boolean equations was performed in scientific databases like Web of Science, Engineering Village, Scopus, Google Scholar and Proquest Dissertation, to identify the relevant literature. This first step yielded a total of 1,924 references. A snowball sampling approach (Parker et al., 2019), complemented by Google search engine and bibliographic management software such as Mendeley, was also employed. It involves the identification of relevant sources from an initial set of key references, then exploring the references cited therein to find further relevant documents. This process is repeated as new sources are found, gradually broadening the search. This non-systematic search yielded 256 additional references for a total of 2,180 articles, book chapters, conference reports, and theses.

Table 1. Initial STAR-structured keywords used as criteria for our literature search strategy and research questions formulation

STAR elements	Keywords
S (System)	Agricultural sector, municipal sector, industrial sector, commercial sector, institutional sector
T (Trouble)	Climate change, socio-economic factors
A (Alternative)	Water demand scenarios (e.g., Status Quo), socio-economic pathways
R (Response)	Water demand

In Table 3, we define eligibility criteria for selecting the references of relevance to answer our research questions. This assessment of the collected references was conducted in a two-step process, according to the prescriptions of the PRISMA method, that is, based on (a) their titles and abstracts and (b) the full text.

Our article search and selection processes, summarized in Figure 1, resulted in the inclusion of 157 articles, book chapters, theses, and technical reports.

Results

The modeling processes of future water demand rely on a variety of methodological approaches, adapted to the time scales and sectors of economic activities concerned. Here, we report our findings along four main lines: (1) the fundamental methods for which we propose a degree of parsimony metric that reflects the methods complexity and their data requirements, (2) more sophisticated or hybrid approaches resulting from the extension and compounding of the core methods, (3) the uncertainty assessment approaches and (4) the water demand drivers.

A common denominator of the identified methods is the time scale which often influences the reliability as well as the robustness of informed decisions. From a temporal scale standpoint, methods fall into three broad categories, that is, short, medium, and long term (Billings, 2008; Donkor et al., 2014; Rinaudo, 2015). Short-term methods (less than a year) are generally used by municipalities and water supply agencies for operational planning, that is, pump scheduling, system load balancing, and guaranteeing continuous water supply, in order to manage seasonality and peak water needs, among other things. Medium-term methods (from 1 to 10 years) are used for tactical planning to drive medium-term investment decisions, such as building new wells, increasing storage, or upgrading treatment facilities. Long-term methods (beyond 10 years) are developed for strategic planning, which supports the anticipation of structural, technological and political impacts on water demand to, for example, identify future sources, prepare for population growth and adapt to climate change. These categories of methods are represented with orange color in Figure 2.

Classes of foundational methods using a degree of parsimony indicator

From an analytical standpoint, we identified the five main categories of water demand modeling methods summarized in Table 4 (Billings, 2008; Donkor et al., 2014; Rinaudo, 2015). A notable difference among these methods is what could be called the 'dimensional heterogeneity', which refers to the variability in the number of dimensions or variables required to execute them. We therefore capitalize on this type of heterogeneity to spin off an indicator, a degree of parsimony, to rank these methods and at the same time, answer our second research question. The proposed indicator is defined in terms of the number of variables necessary, the operations (calculations) required to create these variables, and the perceived or anticipated effort in terms of human and computing resources deployment required to support the data acquisition. Accordingly, for a same number of variables, two methods may have different degrees of parsimony if, for example, more resources (calculations, time, mathematical operations) are required to obtain or create the data for one or the other method. In Table 4, we associate the indicator to each of the categories and justify as to why

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Table 2. Summary of the research strategy adopted

STAR Elements	Keywords	Corresponding terms	Search strategies
S	Agricultural water	Irrigation water, livestock water, drinking water	Agricultural water OR Municipal water OR Industrial water OR Commercial water OR Institutional water OR Irrigation water OR Livestock water OR Domestic water OR Residential water OR Urban water OR Hydroelectric water OR Mining water OR Manufacturing water OR Beverage water OR Cooling water OR Steam generation water OR Water for oil and gas extraction OR Bottled water
	Municipal water	Domestic water, household water, residential water, urban water	
	Industrial water	Mining water, manufacturing water, beverage water, cooling water, steam generation water, water for oil and gas extraction	
	Commercial water	Bottled water	
	Institutional water	Beverage water	
T	Climate change	Climate variability, temperature, precipitation, rainfall	Climate change OR Socio-economic factor OR Climate variability OR Temperature OR Precipitation OR Rainfall OR Population growth OR Land use planning OR User behavioral patterns OR Technological advances
	Socio-economic factor	Population growth, land use planning, user behavioral patterns	
A	Scenarios	Status quo, adaptation, mitigation	(Scenario AND Climate change) OR (Pathway AND socio-economic)
R	Water demand	Water consumption, water use, water usage, water withdrawal, water need, water requirement, water supply	(Demand OR Consumption OR Utilization OR Usage OR Use OR Withdrawal OR Need OR Requirement OR Supply) AND Water AND (Future OR Actual OR Projection OR Forecast OR Long term OR Prospection OR Estimation OR Scenario OR Pathway OR Model OR trend)

Note: The keywords of the second and third columns are selected and grouped according to, depending on the STAR element in question, the sector (municipal, agricultural, etc.) or the driver (climatic or socioeconomic). For each element of the STAR framework, we provide a single Boolean equation that is tested against the bibliographic databases to obtain articles relevant to answer the two research questions of the review.

Table 3. Summary table of inclusion and exclusion criteria used for references screening

Categories	List of *criteria*
Inclusion	• Objective of the study: modeling the water demand of at least one of the targeted sectors of activity; • Modeling the impact of at least one climatic (precipitation, temperature) or socioeconomic (population growth, land use planning) factor on water demand; • Use of water for energy production; • Year of publication between 1990 and 2023 as before 1990, the population was considered as the sole main driver of water demand (Amarasinghe and Smakhtin, 2014).
Exclusion	• Use of specialized software (e.g., *CropWat*, *WEAP*) in a black-box way, that is, without the presentation of the underlying equations and assumptions of the software; • Analysis of water availability or quality or allocation or optimization of water use; • Modeling the water requirements of a single crop; • Projection of hydroclimatic data (e.g., temperature, precipitation, discharge); • Analysis of the water footprint of a process or a sector of activity; • Inaccessibility of full text and/or language (e.g., Chinese, German); • Analysis of the impact of climate change on hydrological variables.

the corresponding degree is attributed. These methods are also represented with the blue color in Figure 2.

Advanced water demand modeling methods

Multiple hybridizations of foundational methods are often performed along with more advanced analytical techniques to capture certain complexities in water demand modeling. For instance, we distinguished:

a. Soft methods or computational intelligence methods (CIMs), which could be considered as a subset of the multivariate method, are subdivided into three temporal-scale classes, that is, short, medium and long terms. However, despite their predictive accuracy and their independence from statistical assumptions, they are mainly applied to short-term modeling situations (Adamowski et al., 2012; Mouatadid and Adamowski, 2017; Muhammad et al., 2019). This category is in orange color in Figure 2.

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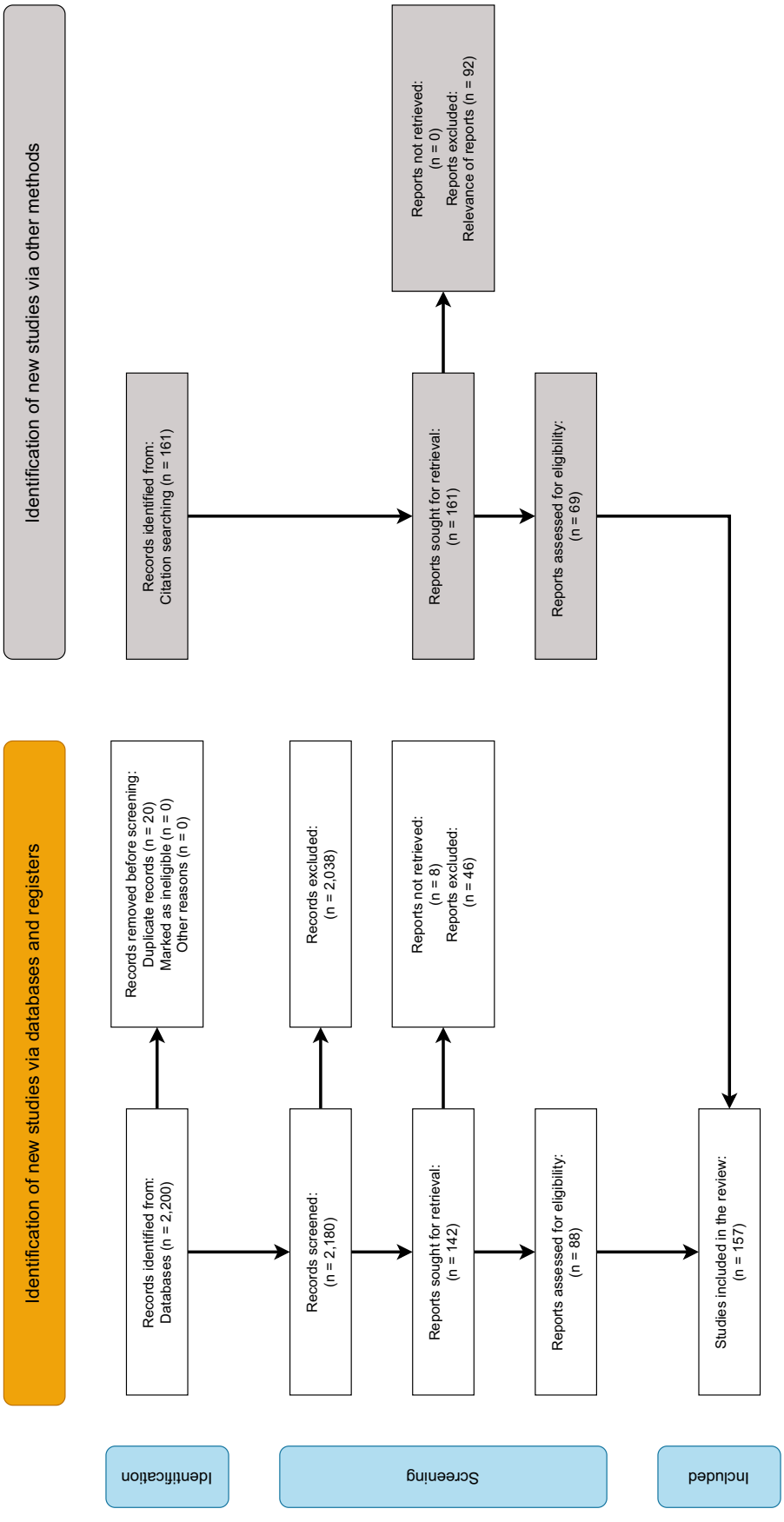


Figure 1. The PRISMA diagram summarizing our references selection process.

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Table 4. Summary of the foundational methods for future water demand modeling and their classification according to the proposed degree of parsimony indicator

Methods	Description	Parsimony level	Parsimony-level justification
Univariate method	The method is based on historical consumption trends and assumes a conservation of the status quo. As the simplest method, it has limited predictive capacity as it does not account for prevailing factors of socioeconomic and environmental nature	First degree	This method needs only one variable, that is, a time series of past water consumption. Thus, relatively minimal effort is required to collect the data necessary to develop this method
Unit consumption ratio	The method is based on a unitary consumption coefficient principle. Its reliability is questionable due to the reliance on expert judgment or rules of thumb to determine the ratio (Donkor et al., 2014)	Second degree	This method needs two variables, that is, a unitary consumption (e.g., per capita demand, per household consumption) and a time series of the corresponding entities (e.g., population, households)
Spatial methods	Typically implemented with GIS software, the method is based on a per geographic-unit consumption coefficient and geographical analysis units. Like the univariate method, socioeconomic and environmental factors are not considered	Third degree	This method uses mainly three variables, that is, spatial units, unitary consumption and a long-term land use management plan
Multivariate method	Also called causal or structural models (Billings, 2008), this category supports the consideration of all available data that may influence the demand, including socioeconomic and climatic factors	Fourth degree	It involves a variety of variables that could include economic, climatic and socio-demographic factors. However, not all variables affect the demand consistently (House-Peters and Chang, 2011). Therefore, an optimal number of variables can be retained using data dimensionality reduction techniques (Viana et al., 2021)
End-Use method	This method requires a detailed knowledge of water use patterns by type of water-consuming appliances or installations. It is more suitable for in-depth and granular investigation of water consumption	Fifth degree	This is the most resource-intensive method as it is subject to extensive data collection campaign on every single appliance or installation in a property of interest. It often requires the deployment of sensors to monitor usage patterns for all water-consuming appliances and installations

b. Single-sector and multisector modeling methods that integrate tailored variables and spatial resolution to model water demand of specific economic sectors. These methods are often integrated in dedicated software tools (Morales et al., 2009; Hejazi et al., 2014; Grouillet et al., 2015). Under this category, we group the econometric methods specific to, for example, the industrial sector represented in yellow in Figure 2.
c. The analytical-performance-based methods classification by House-Peters and Chang (2011), depicted in gray color in Figure 2, distinguishes six classes of methods based on criteria such as: (a) spatial resolution considered, (b) temporal resolution of the data, (c) linear and nonlinear relationships modeling in the data, (d) dynamic modeling (e.g., system dynamics models, agent-based models) of the processes and (e) quantification of uncertainty sources and magnitudes in the data and the analyses. In the next subsection, we present a detailed description of the latest subcategory of methods.

It is worth highlighting that the assessment of the methods uncertainty, especially for long-term projections of water demand, has given rise to even more complex methods enabled by the continuous improvement in computational power and data collection (Herrera et al., 2022). As uncertainties can lead to systems being oversized – resulting in increased costs – or undersized and cause constraints on use in times of shortage as well as opportunity costs (Rinaudo, 2015) and ultimately to system failure (Mijic et al., 2024), the quantification of uncertainties in water demand models become even more necessary for tactical and strategic planning.

Approaches to uncertainty assessment and treatment in water demand modeling methods

Two main approaches have been proposed to deal with uncertainties in future-water-demand modeling methods: (a) the contrasting scenarios approach (Cosgrove, 2013; Dong et al., 2013; Sivagurunathan et al., 2022) and (b) the stochastic or probabilistic approach (Qi and Chang, 2011; Alhendi et al., 2022).

The contrasting scenarios approach

Scenarios are narratives developed according to a logical framework that explain how events might unfold (Schwartz, 1997). According to the case study presented by Cosgrove (2013), the Shell company initially developed the scenario-based approach to forecast long-term availability of fossil resources around 50 years ago. However, its use as a water resource management tool, to guide policymaking and decision-making, only emerged in the late 1990s. The uncertainty associated with the evolution of climatic and socioeconomic conditions is one of the main reasons for applying the contrasting scenario approach to water (Dong et al., 2013). From a methodological point of view, we distinguish and define two generations of scenario-based approaches.

a. The *first generation* comprises scenarios developed without a reference framework. This category covers the spectrum from an idiosyncratic method to an approach using at most one reference scenarios framework, that is, with consideration of environmental factors alone or socioeconomic factors alone or policy assumptions alone. Here, we refer to those scenarios proposed by the Intergovernmental Panel on Climate Change and the climate change research community which include: the long-term GHG emission scenarios (SA90, IS92, and the Special Report on Emissions Scenarios (SRES); Nakicenovic et al., 2000; Moss et al., 2010); the representative concentration pathways (RCPs; Van Vuuren et al., 2011); the shared socioeconomic pathways (SSPs; O'Neill et al., 2014; O'Neill et al., 2017; Kriegler et al., 2012) and the shared climate policy assumptions (SPAs; Kriegler et al., 2014). Studies by Neale et al. (2007) and Liu (2020) in Canada, Boland (1997) and

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Figure 2. Diagram summarizing the different methods and approaches used to classify future water demand estimation methods. Concentric circles represent increasing levels of specificity: core methodological categories (inner ring), subcategories (middle ring) and detailed components or applications (outer rings).

Sanchez et al. (2020) in the United States, Grouillet et al. (2015) in France and Spain and Wang et al. (2023) and Dang et al. (2024) in China fall under this category.

b. The *second generation* encompasses those realized according to a set of the aforementioned reference scenarios framework integrated into a comprehensive multi-dimensional framework with consideration for quantitative and/or qualitative analyses. The need for this category of scenarios has been raised since the beginning of the 21st century by Vorosmarty et al. (2000), Alcamo et al. (2009), and Moss et al. (2010), who advocated for a more holistic perspective to the scenarios built at finer geographical scales (local, watershed and regional) to account for external factors capable of inducing changes at these scales. We noticed a scant application of this category of scenarios to assess the impacts of global change on water resources, and more specifically on water demand. Hanasaki et al. (2013) were certainly the first to develop qualitative and quantitative scenarios compatible with climate forcing rates (RCP) and future socioeconomic conditions (SSP) for projecting the water consumption of several sectors of economic activity (agricultural, industrial and municipal) at a global scale. At the same scale, Arnell and Lloyd-Hughes (2014) estimated the impacts of climate change on water scarcity and river flood frequencies in 2050 and 2080, under different combinations of SSPs and RCPs. Fujimori et al. (2017) estimated the future water abstraction of the industrial sector, again on a global scale, using SSPs with or without SPAs. Yao et al. (2017) carried out water consumption projections for the industrial, agricultural and domestic sectors of the Pearl River Delta economic zone (regional scale) in China using SSPs and RCPs. Giuliani et al. (2022) assessed the long-term impacts of climate change mitigation policies linked to land-use change emissions on local water demands in several watersheds in southern and western Africa. Alizadeh et al. (2022) used SSPs in conjunction with RCPs to create local-scale narrative frames as part of an iterative participatory process to quantify, among other things, the water demand of the agricultural sector in Pakistan.

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The stochastic or probabilistic approach

The scenario-based approach suffers from three major limitations: (a) the limited number of quantitative scenarios considered, (b) the implicit and incomplete characterization of uncertainties and (c) the lack of transparency in the implementation of expert judgment procedures (Dong et al., 2013; Sivagurunathan et al., 2022). The probabilistic approach addresses the first two limitations by extending the range of possible scenarios based on a repeated execution of forecasting models either with a random variation of input parameters(sensitivity analysis) or according to predefined statistical distribution functions. Examples of studies that apply this approach include the following. In the United States, Hazen and Sawyer (2004) developed the Long-Term Demand Forecasting System tool used by the Tampa Bay Water operator in Southwest Florida to forecast regional water demand, and Lee et al. (2010) produced long-term water consumption maps using Bayes' Maximum Entropy geostatistical model for the city of Phoenix in Arizona. Haque et al. (2014) implemented a Monte Carlo simulation to quantify long-term water demand using three future climate scenarios (A1B, A2 and B1 from the SRES framework) and four distinct levels of water restrictions (an implicit SPA) in the Blue Mountains region, in Australia. Yang et al. (2016) proposed a framework for probabilistic prediction of urban water consumption and uncertainty estimation in a context of incomplete information in China. Bobojonov et al. (2016) developed a stochastic optimization model to study the impact of climate change (SRES) on farm income and efficiency of water use in western Uzbekistan. Rasifaghihi et al. (2020) undertook a stochastic approach to forecasting water consumption under the combined influence of driving variables and climate change (RCP framework) for the city of Montreal, Canada. Sharafati et al. (2021) quantified the relationship between the uncertainty of climate variable projections (RCP) made using a framework incorporating a stochastic model and the variability of water demand for the city of Neyshabur, Iran.

Complementarity of the scenario-based and stochastic approaches

This literature review revealed a remarkable absence of probabilistic models in scenario-based water demand estimation, especially when considering the second-generation scenarios mentioned above. However, the probabilistic approach makes it possible to attach a probability to each of the variables or factors (climatic and socio-economic) of a scenario, or on the other end, a sensitivity analysis can be considered in the event of difficulty in specifying probability distributions. Thus, for each scenario, a range of values within which future water demand is likely to evolve is computed. We found two examples of publications that underscore the inclusiveness and complementarity of the scenario-based and stochastic water demand modeling approaches to form a *probabilistic-scenarios approach*: Qi and Chang (2011) who used a system dynamics and regression model to test, through sensitivity analysis, the impact of a variation in layoff rates on water demand in Manatee County, Florida, USA, and Donkor et al. (2014) who proposed a probabilistic framework based on the Bayesian method to support the implementation of more robust water resource planning and management scenarios. We hypothesize that a *probabilistic-scenarios approach* would deliver a more credible and reliable future water demand to operators or stakeholders in the water sector.

Water demand drivers

Drivers of water demand can be classified into five major categories according to the elements of the STEEP (social, technology, economic, environmental and political factors) framework (Hammoud and Nash, 2014): (a) *social* factors (e.g., population), (b) *technological* factors (e.g., water use efficiency), (c) *environmental* factors (e.g., natural: precipitation, temperature; physical: household size, household density, crop type, cultivated area), (d) *economics* (e.g., household income, water prices) and (e) *political* factors (e.g., operating or withdrawal permits) (Grafton et al., 2011; Cominola et al., 2023; Mazzoni et al., 2023; Costa et al., 2024). Although these drivers or factors do not influence the different economic sectors in the same way (as illustrated in Supplementary Appendix 1–4), the per capita *water demand* parameter (social factor) is often used in practice as a universal variable for domestic/residential/municipal, ICI sectors, and losses in water distribution networks (Renzetti, 2002; Vaughan et al., 2012).

Urban/municipal/residential water demand drivers and modeling methods

We need to highlight that the residential/municipal/urban sector is the most studied among the five economic sectors of interest in this article. For instance, a number of researchers such as Arbués et al. (2003), Inman and Jeffrey (2006), Corbella and Saurí i Pujol (2009), House-Peters and Chang (2011), Bich-Ngoc and Teller (2018), Abu-Bakar et al. (2021), and Cominola et al. (2023) have carried out literature reviews on the different methods for estimating residential/urban/municipal water demand as well as the influencing factors. Among the others, the use of the univariate method was not observed, which would be due to the growth of more sophisticated methods to accommodate the complexity of climatic and socio-economic factors affecting demand since the 1990s. It was at this time that washing machines, dishwashers and swimming pool installations began to become ubiquitous in homes (Frost et al., 2016). However, end-use methods (Boland, 1997; Makki et al., 2015; Sharvelle et al., 2017; Mostafavi et al., 2018; Liu, 2020), unit consumption ratio (Wang et al., 2017; 2023), multivariate statistics (e.g., Neale et al., 2007; Ashoori et al., 2017; Parkinson et al., 2016; Wang et al., 2023) and spatial methods (Boland, 1997; Neale et al., 2007; Sharvelle et al., 2017) are those that are commonly found in the literature. A variety of emerging approaches have addressed the growing urgency of understanding and predicting the impacts of climate change and changing socio-economic conditions on municipal water demand and management, as well as informing the adoption of advanced scientific approaches by water service providers, public authorities, and decision-makers. These include the computational intelligence approach (e.g., Liu, 2020; Mumbi et al., 2021; Fu et al., 2023; Loucks, 2023; Zolghadr-Asli et al., 2024), system dynamics (e.g., Wu et al., 2013; Chang et al., 2015; Cai et al., 2019; Liu, 2020), the scenario approach (e.g., Boland, 1997; Neale et al., 2007; Grouillet et al., 2015; Chen et al., 2022) and the probabilistic approach (e.g., Monte Carlo simulation; Haque et al., 2014).

As per the determinant of water demand, social, environmental and economic factors remain the most relevant ones. Of the social factors, population plays a predominant role and is calculated using a variety of mathematical models (see Supplementary Appendix 1). A wide range of quantitative and qualitative variables that influence residential water demand are found in the literature. For instance, important social variables include population, education level, age, gender, tenure, immigration rate (House-Peters and Chang, 2011; Bich-Ngoc and Teller, 2018; Abu-Bakar et al., 2021; Cominola et al., 2023); environmental (natural) variables include precipitation, temperature, evapotranspiration (lawn watering) and wind speed (House-Peters and Chang, 2011; Abu-Bakar et al., 2021); economic

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variables include water price, household income, property value, Gross Domestic Product and water metering (Arbués et al., 2003; House-Peters and Chang, 2011; Dong et al., 2013; Bich-Ngoc and Teller, 2018; Cominola et al., 2023; Wang et al., 2023); environmental (physical) variables include household size, household density, number of bedrooms, garden or lawn area, presence of swimming pools (Makki et al., 2015; Bich-Ngoc and Teller, 2018; Cominola et al., 2023); variables concerning technological advances include the rate of equipment with hydro-economical appliances, the water-use efficiency of appliances, landscaping (Neale et al., 2007; Cominola et al., 2023); and political variables include water conservation policies, tariff structure (billing frequency), regulations (Corbella and Saurí i Pujol, 2009; House-Peters and Chang, 2011; Dong et al., 2013; Abu-Bakar et al., 2021).

Beyond the classification of the determinants according to the STEEP framework (Hammoud and Nash, 2014), Abu-Bakar et al. (2021) introduced a triadic classification of the determinants as: (a) *endogenous factors*, that is, those directly influencing water demand (e.g., affluence, education, occupation, tenure), (b) *exogenous factors*, defined as those beyond the water consumer's control (e.g., migration, tourism, rainfall, water availability) and (c) *psychosocial factors* (e.g., users' intentions towards water use). Cominola et al. (2023) proposed a closely similar classification based on the similarities of variables into: (a) *observable determinants*, that is, observable endogenous determinants (e.g., sociodemographic, property characteristics), (b) *latent or psychosocial determinants* (e.g., perception, habits) and (c) *external or exogenous determinants* (water price, temperature and precipitation).

Agricultural water demand drivers and modeling methods

In contrast to the several literature reviews on the residential water sector available in the literature, we have only found a few that partially cover, the agricultural water demand realm. These focus on: (a) the modeling of evapotranspiration used to calculate crop water demand (Wanniarachchi and Sarukkalige, 2022), (b) the cascading effect of climate change impacts on water availability and crop yield (Anwar et al., 2013), (c) precision irrigation scheduling (Gu et al., 2020; Abioye et al., 2022; Bwambale et al., 2022), (d) the impact of drinking water quality on livestock production (Tulu et al., 2023; Tulu et al., 2024) and (e) the economics of agricultural water management (Dudu and Chumi, 2008).

Agricultural water demand is generally a function of (a) environmental factors (e.g., physical: irrigated area, crop types, livestock types; natural: temperature, precipitation, solar radiation), (b) economic factors (e.g., water price, producer profit), (c) technological factors (e.g., irrigation system efficiency) and (d) social factors (e.g., demographic evolution, consumption habits, lifestyle) (see Supplementary Appendix 3). It comes down to estimating the demand of its two key components, that is, irrigation and livestock (Hanasaki et al., 2013; Hejazi et al., 2014; Grouillet et al., 2015; Yao et al., 2017; Agrawal et al., 2022; Alizadeh et al., 2022; Dang et al., 2024; Younis and Davies, 2024). In some cases, water for product washing (Lehto et al., 2014; Vergine et al., 2017) and facility cleaning (Drastig et al., 2016; Krauß et al., 2016; Younis and Davies, 2024) are also accounted for. It is worth highlighting that some researchers argue that farmers' water use decisions are generally insensitive to variations in water prices (Scheierling et al., 2006; Fraiture and Perry, 2007 and that the price elasticity of water demand can vary depending on the type of crop (Pathak et al., 2022). Some studies have considered demography as one of the key variables influencing agricultural water demand, as population and agricultural production are positively related (Wu et al., 2013).

For instance, irrigation water demand for field crops is estimated from a minimum of five key variables (Döll and Siebert, 2002; Hanasaki et al., 2013; Jiang et al., 2023). These include (a) irrigated area, (b) crop evapotranspiration calculated as a function of potential evaporation and a cultural coefficient, (c) effective rainfall, (d) the plant's irrigation water use efficiency coefficient or the irrigation system efficiency and (e) irrigation intensity or crop density. For greenhouse crops, the amount of water allocated is generally estimated from global radiation, implying that water demand is generally equivalent to crop evapotranspiration (Incrocci et al., 2020). It should be emphasized that evapotranspiration represents a critical variable in estimating agricultural water demand whether in greenhouses or in fields, for which at least a dozen nonspatial and spatial models have been developed (Prenger et al., 2002; Fazlil-Ilahil, 2009; Katsoulas and Stanghellini, 2019; Ghiat et al., 2021; Yan et al., 2021; Mokhtari et al., 2023). In some studies, especially on a large or medium scale, vegetation indices, such as leaf area index, and normalized difference vegetation index are also used as proxies or substitutes to estimate evapotranspiration (Paul et al., 2021; Mokhtari et al., 2023). In the context of climate projections, irrigation water demand is typically estimated as a function of temperature variation and rainfall variation (distribution and frequency), with averages spanning long time series. For example, Dang et al. (2024) estimated irrigation water demand as a function of precipitation and actual water use. These projection methods have evolved over the last three decades from simple statistical models (regression of socioeconomic variables; Yao et al., 2017) to hydrological and plant growth models such as CropWat and WaterGAP (Döll and Siebert, 2002; Hanasaki et al., 2013; Grouillet et al., 2015; Dang et al., 2024) to the second-generation scenarios mentioned above (Hejazi et al., 2014; Yao et al., 2017; Jiang et al., 2023).

For livestock water demand, studies consider the biological characteristics (large livestock, small livestock, growth stage) and physiological requirements (basic water requirements) of the animals, as well as ancillary demands (hygiene, for example). More specifically, studies define water use quotas (unit consumption ration method) for large and small livestock (Hejazi et al., 2014; Qin et al., 2018; Cai et al., 2019). For aquaculture, evaporation, infiltration and precipitation are considered (Mauri et al., 2022).

Institutional, commercial and industrial water demand drivers and modeling methods

The literature specific to future-water-demand estimation of the ICI sectors is remarkably limited. These three sectors represent a heterogeneous group of water consumers whose demand has historically been calculated using the unit consumption ratio method with water use coefficients derived from the number of employees and/or the number of occupants in the organization (Morales et al., 2011; Brière, 2012; Grouillet et al., 2015). However, due to the fragmentation and heterogeneity of these sectors, as well as the uniqueness of the facilities and processes implemented by customers, the unit consumption ratio method proves to be very deficient (Frost et al., 2016), particularly in accessing information to differentiate the types of use. To circumvent this problem, Morales et al. (2011) proposed a new approach based on a water use coefficient constructed from publicly accessible heated/air-conditioned area and building water consumption data for the state of Florida, USA. Sharvelle et al. (2017) introduced the Integrated Urban Water Management GIS software for projecting municipal water demand, which categorizes ICI sectors into a single category and determines the demand for each ICI user in a spatial unit by averaging all ICI

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uses and the number of dwellings in that unit. This strategy transforms the method into a kind of unit consumption ratio.

To estimate industrial water demand, we have noted that a range of specific models or approaches have been developed, which we present in Supplementary Appendix 4. Of these, some are based on the organization's output or production and a ratio of consumption per unit of production or added value (Grouillet et al., 2015; Cai et al., 2019). Methods often consider the water demand according to industry type, that is, manufacturing, power generation, oil production and mining (Brière, 2012; Flörke et al., 2013; Younis and Davies, 2024). Flörke et al. (2013) proposed two statistical models for calculating water demand for manufacturing and cooling thermoelectric power plants. For hydroelectricity generation in Quebec, Canada, from water storage dams, Agrawal et al. (2022) proposed a unit consumption ratio of 14 m^3/MWh of electricity generated based on net evaporation. This ratio is, of course, dependent on climatic conditions, and for this purpose, Strachan et al. (2016) reported coefficients for different countries such as Austria, the United States and Norway. It should be highlighted that the work mentioned earlier is limited to estimating water demand without a consideration of the impact of climatic and socioeconomic changes. In this context, for thermoelectric production, Hanasaki et al. (2013) proposed a linear regression model for the industrial sector with the following parameters: (a) the amount of energy produced, (b) the intensity of water use and (c) an efficiency coefficient.

Second-generation scenarios (SSP/RCP; high, medium and low efficiency) have been developed around the *efficiency coefficient* used by Hanasaki et al. (2013). For instance, Wang et al. (2019) developed the Bow River Integrated Model based on a system dynamics model for the projection of water demand for several sectors (industrial, agricultural, municipal, environmental, and recreational) and several of its subcategories under the influence of climate conditions (RCP) and water management policies (SPA) in Alberta (Canada). Yao et al. (2017) used a model developed by Flörke et al. (2013) based on enterprise's value added and a coefficient of technological change or efficiency to project water consumption in the manufacturing sub-sector using second-generation scenarios (SSP and RCP). Fujimori et al. (2017) proposed a regression model to estimate water withdrawal for several subsectors of the industrial sector including pulp and paper, textiles, mining, food processing, using second-generation scenarios consisting in SSP and SPA.

Discussion

This literature review aims to gather knowledge about existing water demand estimation methods to guide the selection of an appropriate one that considers future climatic and socioeconomic conditions. Based on our literature search strategy, we review methods developed since the 1990s using a streamlined methodological approach supported by a juxtaposition of the PRISMA and STAR frameworks. This is an important contribution of the article beyond the reported results as prior to STAR, literature search in environmental sciences were mostly conducted without an enabling systematic framework. Instead, a collection of keywords and 'regular expressions' structured as Boolean equations is generally used, an ad hoc approach that is prone to produce incomplete and inconsistent literature search results.

As another important contribution, we had developed an indicator of the level of parsimony of the foundational methods in relation to the number of variables required and the anticipated effort for data acquisition. This enabled the consideration of multivariate statistical methods as the most appropriate class of methods to accommodate the current level of complex interactions between climatic, economic, sociodemographic, technological, political and geospatial factors likely to influence water demand of a country's economic sectors. The results indicate that the adoption of this family of methods has become very common due to the increasing availability of both temporal and spatial data. However, we noticed a strong emphasis on some sort of unit consumption coefficient (fixed or time-varying) for water demand entities (e.g., population, crop, domestic installations) considered in all economic sectors studied. That coefficient forms the basis of the overall method or approach (e.g., end-use, multivariate statistics, scenarios) applied. Such a strategy simplifies the data collection and processing processes and the implementation of the estimation method or the development of demand projection scenarios.

Data availability has also enabled progress to be made in modeling the relationships between variables of a particular sector (intrasector) or between variables from different sectors (intersector). For example, we have noted that population is a cross-cutting variable in the sense that methods for estimating water demand in all economic sectors use or depend on it (Wu et al., 2013; Sharvelle et al., 2017). It should be highlighted that despite the recognition of the influence of population or estimating water demand in all economic sectors, this relationship has not been explicitly translated into a model for the agricultural sector. Nevertheless, we found that population (sociodemographic factor) alone cannot influence the expansion of irrigated areas, but economic factors must also be considered (Sauer et al., 2010; Puy, 2018; Puy et al., 2020). Often such socio-demographic and economic factors may exist beyond the local agricultural production context, especially when considering concept like virtual water, which accounts for the embedded water used in the production of goods across geographical regions (Chen and Chen, 2013).

The relationships of sectoral or cross-sectoral variables are increasingly modeled using historical data and computational intelligence methods. This notable traction of the so-called *data-driven models* in water and environmental engineering has also been observed by Zolghadr-Asli et al. (2024). This family of methods has proven their ability to reveal non-linear relationships between dependent (output) and independent (input) variables, without the need for traditional statistical assumptions. Such relationships are validated by statistical techniques used to estimate prediction errors before they are implemented in long-term simulation models (Liu, 2020).

To implement long-term water demand projection, some studies coupled computational intelligence methods with a system dynamics (SD) model. This is becoming a modern approach that stands out from other approaches aiming at an integrated modeling of environmental and socioeconomic factors that govern the evolution of economic sectors, with feedback loops. More importantly, the SD model makes it possible to consider political factors that may influence water demands, hence, to produce more accurate projections (Qi and Chang, 2011). As demonstrated by the analysis of Kelly et al. (2013) as well as by results presented in Supplementary Tables 5–8 (in Supplementary Appendix), the SD modeling technique is rapidly gaining ground, especially in the field of integrated water management. A notable example of the implementation of this hybrid approach in long-term projection scenarios is that of Liu (2020).

Although, the hybrid approach of computational intelligence and system dynamics models holds great promise for more robust

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long-term water demand projections, the results of this literature review also revealed that the modeling chain would be incomplete without taking into account uncertainties in the data and/or in the projection results. To this end, the contrasting scenarios approach and the stochastic or probabilistic approach have been proposed, which we discussed in this article. We argue that these approaches are inclusive and complementary. Hence, a probabilistic scenarios approach based on a sensitivity analysis would allow the advantages of both uncertainty-based approaches to be exploited. An extension of the *computational intelligence* and *SD* components with a *probabilistic scenarios* component would lead to an even more *comprehensive workflow for future water demand estimation*. Such a methodological framework is, therefore, positioned to support sustainable water resources management in highly complex social and ecological systems settings.

This discussion of future water demand estimation methods and approaches leads us to recommend a hybrid approach made up of three modeling components: computational intelligence, SD, and second-generation probabilistic scenarios. As House-Peters and Chang (2011) suggest, this proposal appears to represent an approach halfway between the parsimony of traditional methods and the high complexity of emerging methods. Advances in the open-source software movement, including the publication of source codes and libraries created using high-level programming languages such as Python, have improved the accessibility for the implementation of the proposed approach. For instance, the development of the PySD library (Houghton and Siegel, 2015; Martin-Martinez et al., 2022; Toba and Nguyen, 2022) as well the XMILE standard file format for SD models (Eberlein and Chichakly, 2013; Gadewadikar and Marshall, 2024) make it possible to completely program and run an SD model in a Python development environment, without the use of commercial software systems. Here, we present the architecture of a web-based geographic information system implemented with the Python programming language that integrates the components of the proposed approach (Figure 3).

The proposed workflow, powered by a spatial database that implements the observations data model (Horsburgh et al., 2016), also caters to the requirement of extensive qualitative and quantitative knowledge that encompasses stakeholder views and perspectives, time series and spatial socioeconomic and climatic data (Giupponi et al., 2024). However, the proposed method as well the accompanying workflow are theoretical in nature and have not been evaluated to fully weigh their technical expertise requirements. In addition, its consideration of the integration of system dynamics models in a geographic information system environment, that is, spatial system dynamics, makes it an apparently sophisticated method. But, when implemented at the watershed level where, for example, at least two economic sectors co-exist, that is, municipal and agricultural, the method can integrate scenario-based land use/land cover projection models, which is relevant to anticipate spatiotemporal water demand dynamics. The method can also incorporate future water availability (supply) data in the form of climatic or hydrologic data projection such as precipitation, temperature and river flow. Consequently, the proposed method along with the modeling workflow could play an essential role in informing adaptive water management and governance decisions such as water rights allocation, the prioritization of critical sectors (e.g., municipal/residential, agricultural) whenever the available resource (supply) is inferior to the demand.

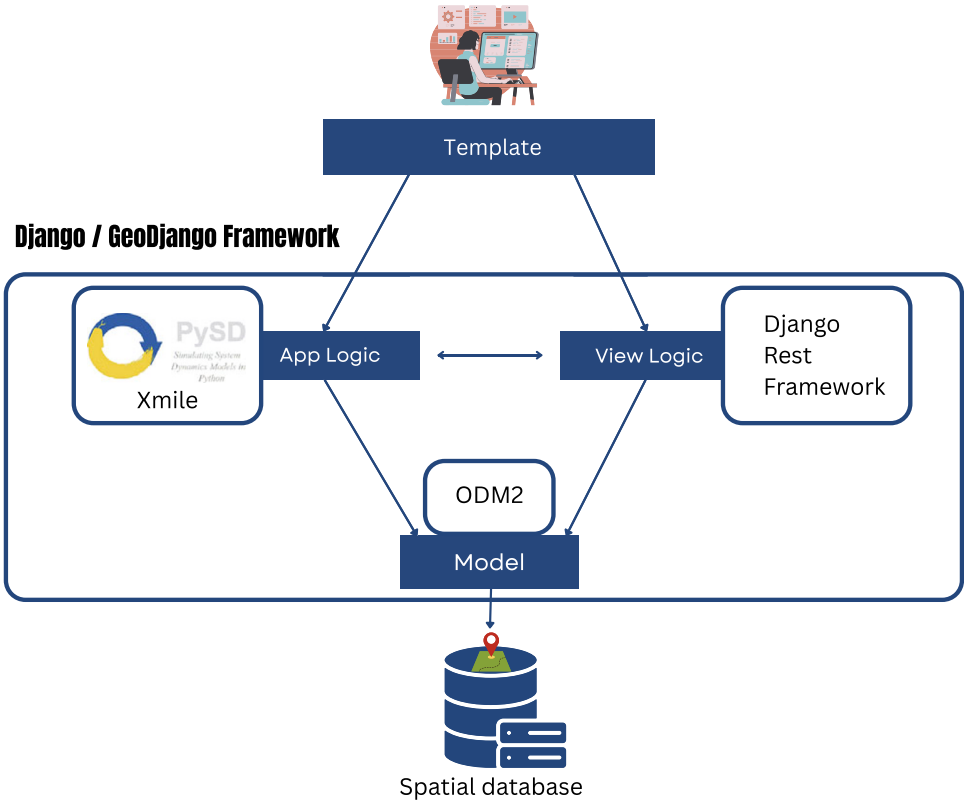


Figure 3. A proposed representative software workflow for the implementation of multisectoral and multifactorial projections of future water demand based on the Django, GeoDjango, Django REST Framework libraries ecosystem as well as the PySD library.

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We want to point out that our literature review was not intended to be an exhaustive assessment of future water estimation methods for each of the targeted economic sectors. Moreover, given the criteria for selecting the references, such as the time frame considered (1990–2024), our review could not be exhaustive. However, we did ensure that we covered the universe of methods for future water demand estimation by two complementary search approaches: a systematic approach and a snowball approach. This exercise enabled us to list a range of methods and approaches, from the simplest (e.g., linear regression) to hybrid approaches featuring second-generation scenarios (RCP, SRES, SSP, SPA) integrating quantitative and qualitative data through narrative frameworks. Despite this nonexhaustive evaluation, the references identified enabled us to respond adequately to our two research questions. Beyond the limitations relating to the exhaustiveness of the study, our review could have presented statistics concerning, for example, the temporal distribution of the references consulted. This was not possible because of what we would call a partial contamination of the temporal information, either at the level of the bibliographic databases (improper indexing) or when formatting the attributes of the searched references (years of publication, authors) for export. The problem could also arise at the level of the references processing tool, Rayyan (Johnson and Phillips, 2018), during the references importation step.

Conclusion

This literature review contributes a fairly comprehensive account of the body of knowledge accumulated on future water demand estimation methods. It represents the cornerstone for the development of a modern method for short to long term water demand estimation that: (a) considers the specific features of the main national economic sectors as well as the influence of environmental and socioeconomic factors and (b) is capable of being applied to several nested geospatial scales from the municipal scale to the national scale.

The paper proposes a streamlined methodological approach that adheres to the standards of state-of-the-art literature reviews. For instance, we applied the emerging framework named STAR in conjunction with the standard PRISMA framework to support, respectively, the implementation of reference search strategies as well as the formulation of research questions and the screening of retrieved references from selected bibliographic databases. Our analysis of the data extracted (e.g., factors, variables, methods/models/approaches, spatiotemporal scale) from the references allowed us to introduce a new parsimony indicator for existing water demand estimation methods, as well as new nomenclature for the classification of quantitative and qualitative scenario-based approaches. The analysis also revealed that a hybrid method featuring three emerging approaches, computational intelligence, SD, and probabilistic scenarios, would be the most appropriate for integrated modeling of linear and nonlinear relationships between variables in the various factors and economic sectors of interest over the long term. To support the implementation of such a method, we propose a comprehensive workflow based on the Python programming language and some key libraries such as the PySD, Django and GeoDjango. The purpose is to support the complete execution of spatial SD models, especially within a nexus modeling approach context, using a Python development environment, thus without the use of commercial software systems.

As future directions go, we plan to assess the complexity of the method through the simulation of future water demand of two critical economic sectors: agricultural and municipal of a pilot watershed, that of the Nicolet River, in Quebec. This case study will adopt the proposed probabilistic scenario-based approach where scenarios are co-created with water stakeholders of the pilot watershed. Additional sectors can be added after this initial evaluation effort. Putting the method into practice in an incremental or agile manner should provide useful feedback on its robustness and relevance for integrated water demand planning. The specific features of the proposed method and associated workflow will be presented in concrete terms through an assessment at the two spatial scales, that is, municipality and watershed.

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Data availability statement. The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

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Author contribution. Conceptualization: A.T.S., H.J.C., and P.C.; methodology: A.T.S., H.J.C., and P.C.; data curation: A.T.S. and H.J.C.; writing – original draft: A.T.S., H.J.C., and P.C.; writing – review and editing: M.J.L, A.N.R, S.J.G., and P.K.; project administration, funding acquisition, methodology, conceptualization, supervision: P.C.; all authors approved the final submitted draft.

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Ethical standard. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

References

Abioye EA, Hensel O, Esau TJ, Elijah O, Abidin MSZ, Ayobami AS, Yerima O and Nasirahmadi A (2022) Precision irrigation management using machine learning and digital farming solutions. *AgriEngineering* **4**(1), 70–103.

Abu-Bakar H, Williams L and Hallett SH (2021) A review of household water demand management and consumption measurement. *Journal of Cleaner Production* **292**, 125872.

Adamowski J, Chan HF, Prasher SO, Ozga-Zielinski B and Sliusarieva A (2012) Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. *Water Resources Research* **48**(1), 1–14.

Agrawal N, Patrick T, Davis M, Ahiduzzaman M and Kumar A (2022) Analysis of Canada's water use: Tracing water flow from source to end use. *Canadian Water Resources Journal/Revue canadienne des ressources hydriques* **47**(1), 19–39.

Alamanos A, Koundouri P, Papadaki L and Pliakou T (2022) A system innovation approach for science-stakeholder interface: Theory and application to water-land-food-energy nexus. *Frontiers in Water* **3**, 744773.

Alcamo, J., & Gallopín, G. C. (2009). *Building a 2nd generation of world water scenarios. United Nations World Water Assessment Programme (WWAP)*, pp. 1–16. Turkey. Available at http://docs.gip-ecofor.org/libre/Alcamo_2009.pdf. Accessed March 22, 2025.

Alhendi AA, Al-Sumaiti AS, Elmay FK, Wescaot J, Kavousi-Fard A, Heydarian-Forushani E and Alhelou HH (2022) Artificial intelligence for

water–energy nexus demand forecasting: A review. *International Journal of Low-Carbon Technologies* **17**, 730–744.

Alizadeh MR, **Adamowski J and Inam A** (2022) Integrated assessment of localized ssp–rcp narratives for climate change adaptation in coupled human-water systems. *Science of the Total Environment* **823**, 153660.

Amarasinghe UA and Smakhtin V (2014) *Global Water Demand Projections: Past, Present and Future*, Vol. **156**. Colombo, Sri Lanka: IWMI

Anwar MR, **Liu DL**, **Macadam I and Kelly G** (2013) Adapting agriculture to climate change: A review. *Theoretical and Applied Climatology* **113**, 225–245.

Arbués F, **Garcıa-Valiñas MÁ and Martınez-Espiñeira R** (2003) Estimation of residential water demand: A state-of-the-art review. *The Journal of Socio-Economics* **32**(1), 81–102.

Arnell NW and Lloyd-Hughes B (2014) The global-scale impacts of climate change on water resources and flooding under new climate and socio-economic scenarios. *Climatic Change* **122**, 127–140.

Ashoori N, **Dzombak DA and Small MJ** (2017) Identifying water price and population criteria for meeting future urban water demand targets. *Journal of Hydrology* **555**, 547–556.

Baccour S, **Tilmant A**, **Albiac J**, **Espanmanesh V and Kahil T** (2025) Probabilistic trade-offs analysis for sustainable and equitable management of climate-induced water risks. *Water Resources Research* **61**(2), e2024WR038514.

Bernier S and Forcier-Martin C (2025) *Les égouts et l'eau potable empêchent les villes de se développer* [in fr]. Available at https://ici.radio-canada.ca/nouvelle/2164656/egouts-eau-potable-fiscalite-municipale. Accessed 1 October 2025.

Bich-Ngoc N and Teller J (2018) A review of residential water consumption determinants. In Gervasi O, Murgante B, Misra S, Stankova E, Torre CM, Rocha AMAC, Taniar D, Apduhan BO, Tarantino E, Ryu Y (eds), *A Computational Science and its Applications–ICCSA 2018: 18th International Conference, Melbourne, Vic, Australia, July 2–5, 2018, Proceedings, Part V 18*, 685–696. Melbourne, Australia: Springer.

Bijl DL, **Biemans H**, **Bogaart PW**, **Dekker SC**, **Doelman JC**, **Stehfest E and van Vuuren DP** (2018) A global analysis of future water deficit based on different allocation mechanisms. *Water Resources Research* **54**(8), 5803–5824.

Billings B (2008) *Forecasting urban water demand*. Denver, CO: American Water Works Association, *Chapter* Vol **9**, pp 147–178.

Bobojonov I, **Berg E**, **Franz-Vasdeki J**, **Martius C and Lamers JPA** (2016) Income and irrigation water use efficiency under climate change: An application of spatial stochastic crop and water allocation model to western Uzbekistan. *Climate Risk Management* **13**, 19–30.

Boland JJ (1997) Assessing urban water use and the role of water conservation measures under climate uncertainty. *Climatic Change* **37**(1), 157–176.

Brière FG (2012) *Distribution et Collecte Des Eaux*. Presses inter Polytechnique.

Bwambale E, **Abagale FK and Anornu GK** (2022) Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review. *Agricultural Water Management* **260**, 107324.

Cai Y, **Cai J**, **Xu L**, **Tan Q and Xu Q** (2019) Integrated risk analysis of water-energy nexus systems based on systems dynamics, orthogonal design and copula analysis. *Renewable and Sustainable Energy Reviews* **99**, 125–137.

Celicourt P, **Drapeau J**, **Lovince HB**, **Azima S**, **Thiaw CMM**, **Louis REA**, **Célicourt L**, **Mertilus F**, **Louis MJ**, **Said AT**, **Chery HJ**, **Petit-Homme Y**, **Pierre GJ**, **Rousseau AN**, **Kabore P and Gumiere SJ** (2025) Star: A transposition of the pico framework to environmental sciences, engineering and beyond. https://doi.org/10.21203/rs.3.rs-6475550/v1.

Chang Y-T, **Liu H-L**, **Bao A-M**, **Chen X and Wang L** (2015) Evaluation of urban water resource security under urban expansion using a system dynamics model. *Water Science and Technology: Water Supply* **15**(6), 1259–1274.

Chen L, **Gan X**, **Yi B**, **Qin Y and Lu L** (2022) Domestic water demand prediction based on system dynamics combined with social-hydrology methods. *Hydrology Research* **53**(8), 1107–1128.

Chen Z-M and Chen GQ (2013) Virtual water accounting for the globalized world economy: National water footprint and international virtual water trade. *Ecological Indicators* **28**, 142–149.

Cominola A, **Preiss L**, **Thyer M**, **Maier HR**, **Prevos P**, **Stewart RA and Castelletti A** (2023) The determinants of household water consumption: A review and assessment framework for research and practice. *npj Clean Water* **6**(1), 11.

Corbella HM and Saurí i Pujol D (2009) What lies behind domestic water use?: A review essay on the drivers of domestic water consumption. *BAGE. Boletín de la Asociación Española de Geografía* **50**, 297–314.

Cosgrove W (2013) Water futures: The evolution of water scenarios. *Current Opinion in Environmental Sustainability* **5**(6), 559–565.

Costa S, **Meireles I and Sousa V** (2024) Understanding residential water demand: Insights from a survey in a Mediterranean city. *Urban Water Journal* **21**(4), 521–537.

Dang C, **Zhang H**, **Yao C**, **Mu D**, **Lyu F**, **Zhang Y and Zhang S** (2024) Iwram: A hybrid model for irrigation water demand forecasting to quantify the impacts of climate change. *Agricultural Water Management* **291**, 108643.

Denyer D, **Tranfield D and Van Aken JE** (2008) Developing design propositions through research synthesis. *Organization Studies* **29**(3), 393–413.

Döll P and Siebert S (2002) Global modeling of irrigation water requirements. *Water Resources Research* **38**(4), 1–8.

Dong C, **Schoups G and Van de Giesen N** (2013) Scenario development for water resource planning and management: A review. *Technological Forecasting and Social Change* **80**(4), 749–761.

Donkor EA, **Mazzuchi TA**, **Soyer R and Roberson JA** (2014) Urban water demand forecasting: Review of methods and models. *Journal of Water Resources Planning and Management* **140**(2), 146–159.

Drastig K, **Palhares JCP**, **Karbach K and Prochnow A** (2016) Farm water productivity in broiler production: Case studies in Brazil. *Journal of Cleaner Production* **135**, 9–19.

Dudu H and Chumi S (2008) *Economics of irrigation water management: A literature survey with focus on partial and general equilibrium models [Technical report]*. World Bank, Washington, D.C. Available at https://download.ssrn.com/worldbank/4556.pdf (accessed December 14, 2024).

Eberlein R and Chichakly K (2013) Xmile: A new standard for system dynamics. *System Dynamics Review* **29**(July). https://doi.org/10.1002/sdr.1504.

Egerer S, **Puente AF**, **Peichl M**, **Rakovec O**, **Samaniego L and Schneider UA** (2023) Limited potential of irrigation to prevent potato yield losses in Germany under climate change. *Agricultural Systems* **207**, 103633.

Endo A, **Yamada M**, **Miyashita Y**, **Sugimoto R**, **Ishii A**, **Nishijima J**, **Fujii M**, **Kato T**, **Hamamoto H**, **Kimura M**, **Kumazawa T and Qi J** (2020) Dynamics of water–energy–food nexus methodology, methods, and tools. *Current Opinion in Environmental Science & Health* **13**, 46–60.

Fazlil-Ilahil WF (2009) *Evapotranspiration Models in Greenhouse*. Wageningen, the Netherlands: Wageningen agricultural University.

Fiorillo D, **Kapelan Z**, **Xenochristou M**, **De Paola F and Giugni M** (2021) Assessing the impact of climate change on future water demand using weather data. *Water Resources Management* **35**(5), 1449–1462.

Flörke M, **Kynast E**, **Bärlund I**, **Eisner S**, **Wimmer F and Alcamo J** (2013) Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: A global simulation study. *Global Environmental Change* **23**(1), 144–156.

Fraiture Cde and Perry CJ (2007) Why is agricultural water demand unresponsive at low price ranges? In Molle F and Berkoff J (eds), *Irrigation Water Pricing: The Gap between Theory and Practice*. Wallingford, UK: CABI. pp 94–107.

Frost D, **Sversvold D**, **Wilcut E and Keen DJ** (2016) Seven lessons learned studying phoenix commercial, industrial, and institutional water use. *Journal-American Water Works Association* **108**(3), 54–64.

Fu G, **Sun S**, **Hoang L**, **Yuan Z and Butler D** (2023) Artificial intelligence underpins urban water infrastructure of the future: A holistic perspective. *Cambridge Prisms: Water* **1**, e14.

Fujimori S, **Hanasaki N and Masui T** (2017) Projections of industrial water withdrawal under shared socioeconomic pathways and climate mitigation scenarios. *Sustainability Science* **12**, 275–292.

Gadewadikar J and Marshall J (2024) A methodology for parameter estimation in system dynamics models using artificial intelligence. *Systems Engineering* **27**(2), 253–266.

Gerbet T and Dépelteau M (2025) *Les pénuries d'eau frappent de plus en plus aux quatre coins du québec* [in fr]. https://ici.radio-canada.ca/nouvelle/2190865/manque-eau-municipalites-quebec. Accessed 1 October 2025.

Gharib AA, **Arabi M**, **Goemans C**, **Manning DT and Maas A** (2024) Integrated water management under different water rights institutions and population

patterns: Methodology and application. *Water Resources Research* **60**(11), e2024WR037196.

Ghiat I, **Mackey HR and Al-Ansari T** (2021) A review of evapotranspiration measurement models, techniques and methods for open and closed agricultural field applications. *Water* **13**(18), 2523.

Giuliani M, **Lamontagne JR**, **Hejazi MI**, **Reed PM and Castelletti A** (2022) Unintended consequences of climate change mitigation for African river basins. *Nature Climate Change* **12**(2), 187–192.

Giupponi C, **Balabanis P**, **Cojocaru G**, **Vázquez JF and Mysiak J** (2024) Decision support tools for sustainable water management: Lessons learned from two decades of using Mulino-dss. *Cambridge Prisms: Water* **2**, e4.

Grafton RQ, **Ward MB**, **To H and Kompas T** (2011) Determinants of residential water consumption: Evidence and analysis from a 10-country household survey. *Water Resources Research* **47**(8), 1–14.

Grouillet B, **Fabre J**, **Ruelland D and Dezetter A** (2015) Historical reconstruction and 2050 projections of water demand under anthropogenic and climate changes in two contrasted mediterranean catchments. *Journal of Hydrology* **522**, 684–696.

Gu Z, **Qi Z**, **Burghate R**, **Yuan S**, **Jiao X and Xu J** (2020) Irrigation scheduling approaches and applications: A review. *Journal of Irrigation and Drainage Engineering* **146**(6), 04020007.

Guemouria A, **Chehbouni A**, **Belaqziz S**, **Epule Epule T**, **Brahim YA**, **El Khalki EM**, **Dhiba D and Bouchaou L** (2023) System dynamics approach for water resources management: A case study from the Souss-Massa basin. *Water* **15**(8), 1506.

Hall SA, **Whittemore A**, **Padowski J**, **Yourek M**, **Yorgey GG**, **Rajagopalan K**, **McLarty S**, **Scarpare FV**, **Liu M**, **Asante-Sasu C**, **Kondal A**, **Brady M**, **Gustine R**, **Downes M**, **Callahan M and Adam JC** (2024) Concurrently assessing water supply and demand is critical for evaluating vulnerabilities to climate change. *JAWRA Journal of the American Water Resources Association* **60**(2), 543–571.

Hammoud MS and Nash DP (2014) What corporations do with foresight. *European Journal of Futures Research* **2**, 1–20.

Hanasaki N, **Fujimori S**, **Yamamoto T**, **Yoshikawa S**, **Masaki Y**, **Hijioka Y**, **Kainuma M**, **Kanamori Y**, **Masui T**, **Takahashi K and Kanae S** (2013) A global water scarcity assessment under shared socio-economic pathways–part 1: Water use. *Hydrology and Earth System Sciences* **17**(7), 2375–2391.

Haque MM, **Rahman A**, **Hagare D and Kibria G** (2014) Probabilistic water demand forecasting using projected climatic data for blue mountains water supply system in Australia. *Water Resources Management* **28**, 1959–1971.

Hazen and Sawyer (2004) *The Tampa Bay water long-term demand forecasting model: Tampa Bay water*. Clearwater, FL, USA: Tampa Bay Water

Hejazi M, **Edmonds J**, **Clarke L**, **Kyle P**, **Davies E**, **Chaturvedi V**, **Marshall-Wise PP**, **Eom J**, **Calvin K**, **Moss R and Kim S** (2014) Long-term global water projections using six socioeconomic scenarios in an integrated assessment modeling framework. *Technological Forecasting and Social Change* **81**, 205–226.

Herrera PA, **Marazuela MA and Hofmann T** (2022) Parameter estimation and uncertainty analysis in hydrological modeling. *Wiley Interdisciplinary Reviews: Water* **9**(1), e1569.

Hertel T and Liu J (2016) Implications of water scarcity for economic growth (OECD Environment Working Papers No. 109). Paris: OECD Publishing. Available at https://doi.org/10.1787/5jlssl611r32-en (accessed December 14, 2024).

Horsburgh JS, **Aufdenkampe AK**, **Mayorga E**, **Lehnert KA**, **Hsu L**, **Song L**, **Jones AS**, **Damiano SG**, **Tarboton DG**, **Valentine D**, **Zaslavsky I and Whitenack T** (2016) Observations data model 2: A community information model for spatially discrete earth observations. *Environmental Modelling & Software* **79**, 55–74.

Houghton J and Siegel M (2015) Advanced data analytics for system dynamics models using pysd. *Revolution* **3**(4), 1–27.

House-Peters LA and Chang H (2011) Urban water demand modeling: Review of concepts, methods, and organizing principles. *Water Resources Research* **47**(5).

Huber L, **Rüdisser J**, **Meisch C**, **Stotten R**, **Leitinger G and Tappeiner U** (2021) Agent-based modelling of water balance in a social-ecological system: A multidisciplinary approach for mountain catchments. *Science of the Total Environment* **755**, 142962.

Incrocci L, **Thompson RB**, **Fernandez-Fernandez MD**, **De Pascale S**, **Pardossi A**, **Stanghellini C**, **Rouphael Y and Gallardo M** (2020) Irrigation management of European greenhouse vegetable crops. *Agricultural Water Management* **242**, 106393.

Inman D and Jeffrey P (2006) A review of residential water conservation tool performance and influences on implementation effectiveness. *Urban Water Journal* **3**(3), 127–143.

James KL, **Randall NP and Haddaway NR** (2016) A methodology for systematic mapping in environmental sciences. *Environmental Evidence* **5**(1), 7.

Jiang Q, **Ouyang X**, **Wang Z**, **Wu Y and Guo W** (2023) System dynamics simulation and scenario optimization of China's water footprint under different SSP-RCP scenarios. *Journal of Hydrology* **622**, 129671.

Johnson N and Phillips M (2018) Rayyan for systematic reviews. *Journal of Electronic Resources Librarianship* **30**(1), 46–48.

Katsoulas N and Stanghellini C (2019) Modelling crop transpiration in greenhouses: Different models for different applications. *Agronomy* **9**(7). ISSN: 2073–4395. https://doi.org/10.3390/agronomy9070392.

Kebede AS, **Nicholls RJ**, **Clarke D**, **Savin C and Harrison PA** (2021) Integrated assessment of the food-water-land-ecosystems nexus in Europe: Implications for sustainability. *Science of the Total Environment* **768**, 144461.

Kelly RA, **Jakeman AJ**, **Barreteau O**, **Borsuk ME**, **ElSawah S**, **Hamilton SH**, **Henriksen HJ**, **Kuikka S**, **Maier HR**, **Rizzoli AE**, **van Delden H and Voinov AA** (2013) Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling & Software* **47**, 159–181.

Khan S, **Mu J**, **Jamnani MAR**, **Hafeez M and Gao Z** (2020) Modelling water futures using food security and environmental sustainability approaches. In *International Congress on Modelling and Simulation (modsim05): Advances and Applications for Management and Decision Making,* 1963–1969. Melbourne, Australia: Modelling, Simulation Society of Australia, and New Zealand Inc. (MSSANZ).

Krauß M, **Drastig K**, **Prochnow A**, **Rose-Meierhöfer S and Kraatz S** (2016) Drinking and cleaning water use in a dairy cow barn. *Water* **8**(7), 302.

Kriegler E, **Edmonds J**, **Hallegatte S**, **Ebi KL**, **Kram T**, **Riahi K**, **Winkler H and Van Vuuren DP** (2014) A new scenario framework for climate change research: The concept of shared climate policy assumptions. *Climatic Change* **122**, 401–414.

Kriegler E, **O'Neill BC**, **Hallegatte S**, **Kram T**, **Lempert RJ**, **Moss RH and Wilbanks T** (2012) The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways. *Global Environmental Change* **22**(4), 807–822.

Kulshreshtha SN (1993) World water resources and regional vulnerability: Impact of future changes. https://es.ircwash.org/sites/default/files/Kulshreshtha-1993-World.pdf. Accessed January 10, 2025.

Lee S-J, **AWentz E and Gober P** (2010) Space–time forecasting using soft geostatistics: A case study in forecasting municipal water demand for Phoenix, Arizona. *Stochastic Environmental Research and Risk Assessment* **24**, 283–295.

Lehto M, **Sipilä I**, **Alakukku L and Kymäläinen H-R** (2014) Water consumption and wastewaters in fresh-cut vegetable production. *Agricultural and Food Science* **23**(4), 246–256.

Liu H. 2020. *Municipal water demand forecasting in the short and long term with ANN and SD models*. Edmonton, Alberta, Canada

Loucks DP (2023) Hydroinformatics: A review and future outlook. *Cambridge Prisms: Water* **1**, e10.

Makki AA, **Stewart RA**, **Beal CD and Panuwatwanich K** (2015) Novel bottom-up urban water demand forecasting model: Revealing the determinants, drivers and predictors of residential indoor end-use consumption. *Resources, Conservation and Recycling* **95**, 15–37.

Martin-Martinez E, **Samsó R**, **Houghton J and Ollé JS** (2022) Pysd: System dynamics modeling in python. *The Journal of Open Source Software* **7**, (78), 4329.

Mauri M, **Pandey K**, **Giuliani M and Castelletti A** (2022) Integrating local and global projections for the generation of water demand scenarios in the red river basin, Vietnam. *IFAC-PapersOnLine* **55**(5), 43–48.

Mazzoni F, **Alvisi S**, **Blokker M**, **Buchberger SG**, **Castelletti A**, **Cominola A**, **Gross M-P**, **Jacobs HE**, **Mayer P**, **Steffelbauer DB**, **Stewart RA**, **Stillwell AS**, **Tzatchkov V**, **Yamanaka V-HA and Franchini M** (2023) Investigating the

characteristics of residential end uses of water: A worldwide review. *Water Research* **230**, 119500.

Methley AM, **Campbell S**, **Chew-Graham C**, **McNally R and Cheraghi-Sohi S** (2014) Pico, Picos and spider: A comparison study of specificity and sensitivity in three search tools for qualitative systematic reviews. *BMC Health Services Research* **14**(1), 1–10.

Mijic A, **Dobson B and Liu L** (2024) Towards adaptive resilience for the future of integrated water systems planning. *Cambridge Prisms: Water* **2**, e11.

Moher D, **Liberati A**, **Tetzlaff J**, **Altman DG** and **for the PRISMA Group** (2009) Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *BMJ* **339**.

Mokhtari A, **Sadeghi M**, **Afrasiabian Y and Yu K** (2023) Optram-et: A novel approach to remote sensing of actual evapotranspiration applied to sentinel-2 and landsat-8 observations. *Remote Sensing of Environment* **286**, 113443.

Molajou A, **Afshar A**, **Khosravi M**, **Soleimanian E**, **Vahabzadeh M and Variani HA** (2023) A new paradigm of water, food, and energy nexus. *Environmental Science and Pollution Research* **30**(49), 107487–107497.

Morales MA, **Heaney JP**, **Friedman KR and Martin JM** (2011) Estimating commercial, industrial, and institutional water use on the basis of heated building area. *Journal-American Water Works Association* **103**(6), 84–96.

Morales MA, **Martin JM and Heaney JP** (2009) *Methods for estimating commercial, industrial, and institutional water use*. FSAWWA Water Conference.

Moss RH, **Edmonds JA**, **Hibbard KA**, **Manning MR**, **Rose SK**, **Van Vuuren DP**, **Carter TR**, **Emori S**, **Kainuma M**, **Kram T**, **Meehl GA**, **Mitchell JFB**, **Nakicenovic N**, **Riahi K**, **Smith SJ**, **Stouffer RJ**, **Thomson AM**, **Weyant JP and Wilbanks TJ** (2010) The next generation of scenarios for climate change research and assessment. *Nature* **463**(7282), 747–756.

Mostafavi N, **Shojaei HR**, **Beheshtian A and Hoque S** (2018) Residential water consumption modeling in the integrated urban metabolism analysis tool (IUMAT). *Resources, Conservation and Recycling* **131**, 64–74.

Mouatadid S and Adamowski J (2017) Using extreme learning machines for short-term urban water demand forecasting. *Urban Water Journal* **14**(6), 630–638.

Muhammad AU, **Li X and Feng J** (2019) Artificial intelligence approaches for urban water demand forecasting: A review. In Zhai X, Chen B, Zhu K (eds) *Machine Learning and Intelligent Communications. MLICOM 2019. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*, vol **294**. Cham: Springer.

Mumbi AW, **Li F**, **Bavumiragira JP and Fangninou FF** (2021) Forecasting water consumption on transboundary water resources for water resource management using the feed-forward neural network: A case study of the Nile river in Egypt and Kenya. *Marine and Freshwater Research* **73**(3), 292–306.

Nakicenovic N, **Alcamo J**, **Gerald Davis BdeV**, **Fenhann J**, **Gaffin S**, **Gregory K**, **Grubler A**, **Jung TY**, **Kram T**, **Rovere EL La**, **Michaelis L**, **Mori S**, **Morita T**, **Pepper W**, **Pitcher H**, **Price L**, **Riahi K**, **Roehrl A**, **Rogner H-H**, **Sankovski A**, **Schlesinger M**, **Shukla P**, **Smith S**, **Swart R**, **Rooijen S van**, **Victor N and Zhou D** (2000) Special report on emissions scenarios. Lawrence Berkeley National Laboratory. LBNL Report #: LBNL-59940. Available at https://escholarship.org/uc/item/9sz5p22f (accessed January 15, 2025).

Neale T, **Carmichael J and Cohen S** (2007) Urban water futures: A multivariate analysis of population growth and climate change impacts on urban water demand in the Okanagan Basin, BC. *Canadian Water Resources Journal* **32**(4), 315–330.

O'Neill BC, **Kriegler E**, **Ebi KL**, **Kemp-Benedict E**, **Riahi K**, **Rothman DS**, **Van Ruijven BJ**, **Van Vuuren DP**, **Birkmann J**, **Kok K**, **Levy M and Solecki W** (2017) The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change* **42**, 169–180.

O'Neill BC, **Kriegler E**, **Riahi K**, **Ebi KL**, **Hallegatte S**, **Carter TR**, **Mathur R and Van Vuuren DP** (2014) A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change* **122**, 387–400.

Page MJ, **Moher D and McKenzie JE** (2022) Introduction to PRISMA 2020 and implications for research synthesis methodologists. *Research Synthesis Methods* **13**(2), 156–163.

Palaskar J (2017) Framing the research question using PICO strategy. *Journal of Dental and Allied Sciences* **6**(2), 55–55.

Parker C, **Scott S and Geddes A** (2019). Snowball Sampling, In Atkinson P, Delamont S, Cernat A, Sakshaug JW and Williams RA (eds), *SAGE Research Methods Foundations*. London: SAGE Publications Ltd. https://doi.org/10.4135/9781526421036831710.

Parkinson SC, **Johnson N**, **Rao ND**, **Jones B**, **van Vliet MTH**, **Fricko O**, **Djilali N**, **Riahi K and Flörke M** (2016) Climate and human development impacts on municipal water demand: A spatially-explicit global modeling framework. *Environmental Modelling & Software* **85**, 266–278.

Pathak S, **Adusumilli NC**, **Wang H and Almas LK** (2022) Irrigation water demand and elasticities: A case study of the high plains aquifer. *Irrigation Science* **40**(6), 941–954.

Paul M, **Rajib A**, **Negahban-Azar M**, **Shirmohammadi A and Srivastava P** (2021) Improved agricultural water management in data-scarce semi-arid watersheds: Value of integrating remotely sensed leaf area index in hydrological modeling. *Science of the Total Environment* **791**, 148177.

Potopová V, **Trnka M**, **Vizina A**, **Semerádová D**, **Balek J**, **Chawdhery MRA**, **Musiolková M**, **Pavlík P**, **Možný M**, **Štěpánek P and Clothier B** (2022) Projection of 21st century irrigation water requirements for sensitive agricultural crop commodities across the Czech Republic. *Agricultural Water Management* **262**, 107337.

Prenger JJ, **Fynn RP and Hansen RC** (2002) A comparison of four evapotranspiration models in a greenhouse environment. *Transactions of the ASAE* **45**(6), 1779.

Puy A (2018) Irrigated areas grow faster than the population. *Ecological Applications* **28**(6), 1413–1419.

Puy A, **Piano SL and Saltelli A** (2020) Current models underestimate future irrigated areas. *Geophysical Research Letters* **47**(8), e2020GL087360.

Qi C and Chang N-B (2011) System dynamics modeling for municipal water demand estimation in an urban region under uncertain economic impacts. *Journal of Environmental Management* **92**(6), 1628–1641.

Qin H, **Cai X and Zheng C** (2018) Water demand predictions for megacities: System dynamics modeling and implications. *Water Policy* **20**(1), 53–76.

Rasifaghihi N, **Li SS and Haghighat F** (2020) Forecast of urban water consumption under the impact of climate change. *Sustainable Cities and Society* **52**, 101848.

Renzetti S (2002) *The Economics of Water demands*. New York, NY: Springer https://doi.org/10.1007/978-1-4615-0865-6.

Rinaudo J-D (2015) Long-term water demand forecasting. In Grafton Q, Daniell K, Nauges C, Rinaudo JD, Chan N (eds) *Understanding and Managing Urban Water in Transition. Global Issues in Water Policy*, vol **15**. Dordrecht: Springer.

Rondeau-Genesse G, **Caron L-P**, **Audet K**, **Da Silva L**, **Tarte D**, **Parent R**, **Comeau É and Matte D** (2024) Storyline analytical framework for understanding future severe low-water episodes and their consequences. *EGUsphere* **2024**, 1–29.

Roson R, and Damania R (2015) Simulating the macroeconomic impact of future water scarcity. In R. Damania and S. Dahan (eds). *The Forgotten Factor in Climate Change–Water*, 73–87. The World Bank Group.

Rowshon MK, **Dlamini NS**, **Mojid MA**, **Adib MNM**, **Amin MSM and Lai SH** (2019) Modeling climate-smart decision support system (CSDSS) for analyzing water demand of a large-scale rice irrigation scheme. *Agricultural Water Management* **216**, 138–152.

Sanchez GM, **Terando A**, **JordanWSmith AMG**, **RWagner C and Meentemeyer RK** (2020) Forecasting water demand across a rapidly urbanizing region. *Science of the Total Environment* **730**, 139050.

Sauer T, **Havlík P**, **Schneider UA**, **Schmid E**, **Kindermann G and Obersteiner M** (2010) Agriculture and resource availability in a changing world: The role of irrigation. *Water Resources Research* **46**(6), 1–12.

Scheierling SM, **Loomis JB and Young RA** (2006) Irrigation water demand: A meta-analysis of price elasticities. *Water Resources Research* **42**(1), 1–19.

Schwartz P (1997) *Art of the Long View: Planning for the Future in an Uncertain World*. West Sussex, England: JohnWiley & Sons

Sharafati A, **Asadollah SBHS and Shahbazi A** (2021) Assessing the impact of climate change on urban water demand and related uncertainties: A case study of neyshabur, Iran. *Theoretical and Applied Climatology* **145**(1), 473–487.

Sharvelle S, **Dozier A**, **Arabi M and Reichel B** (2017) A geospatially-enabled web tool for urban water demand forecasting and assessment of alternative urban water management strategies. *Environmental Modelling & Software* **97**, 213–228.

Shen Y, **Oki T**, **Utsumi N**, **Kanae S and Hanasaki N** (2008) Projection of future world water resources under sres scenarios: Water withdrawal/projection des ressources en eau mondiales futures selon les scénarios du rsse: Prélèvement d'eau. *Hydrological Sciences Journal* **53**(1), 11–33.

Sivagurunathan V, **Elsawah S and Khan SJ** (2022) Scenarios for urban water management futures: A systematic review. *Water Research* **211**, 118079.

Strachan P, **Svehla K**, **Heusler I and Kersken M** (2016) Whole model empirical validation on a full-scale building. *Journal of Building Performance Simulation* **9**(4), 331–350.

Tian X, **Dong J**, **Jin S**, **He H**, **Yin H and Chen X** (2023) Climate change impacts on regional agricultural irrigation water use in semi-arid environments. *Agricultural Water Management* **281**, 108239.

Toba A-L and Nguyen RT (2022). Integrating system dynamics with data science via graphical user interface. In *2022 IEEE International Systems Conference (Syscon)*, 1–8. Montreal, QC, Canada: IEEE.

Tulu D, **Gadissa S and Hundessa F** (2023) Impact of water stress on adaptation and performance of sheep and goat in dryland regions under climate change scenarios: A systematic review. *Journal of Animal Behaviour and Biometeorology* **11**(2), e2023012–e2023012.

Tulu D, **Hundessa F**, **Gadissa S and Temesgen T** (2024) Review on the influence of water quality on livestock production in the era of climate change: Perspectives from dryland regions. *Cogent Food & Agriculture* **10**(1), 2306726.

Van Vuuren DP, **Edmonds J**, **Kainuma M**, **Riahi K**, **Thomson A**, **Hibbard K**, **Hurtt GC**, **Kram T**, **Krey V**, **Lamarque J-F**, **Masui T**, **Meinshausen M**, **Nakicenovic N**, **Smith SJ and Rose SK** (2011) The representative concentration pathways: An overview. *Climatic Change* **109**, 5–31.

Vaughan EG, **Crutcher JM**, **Labatt TW**, **McMahan LH**, **Bradford BR and Cluck M** (2012) *Water for Texas*. Austin, TX, USA: Texas Water Development Board.

Vergine P, **Salerno C**, **Libutti A**, **Beneduce L**, **Gatta G**, **Berardi G and Pollice A** (2017) Closing the water cycle in the agro-industrial sector by reusing treated wastewater for irrigation. *Journal of Cleaner Production* **164**, 587–596.

Viana FAC, **Gogu C and Goel T** (2021) Surrogate modeling: Tricks that endured the test of time and some recent developments. *Structural and Multidisciplinary Optimization* **64**(5), 2881–2908.

Vorosmarty CJ, **Green P**, **Salisbury J and Lammers RB** (2000) Global water resources: Vulnerability from climate change and population growth. *Science* **289**(5477), 284–288.

Wang K, **Davies EGR and Liu J** (2019) Integrated water resources management and modeling: A case study of bow river basin, Canada. *Journal of Cleaner Production* **240**, 118242.

Wang W, **Ding Y**, **Shao Q**, **Xu J**, **Jiao X**, **Luo Y and Yu Z** (2017) Bayesian multimodel projection of irrigation requirement and water use efficiency in three typical rice plantation region of China based on cmip5. *Agricultural and Forest Meteorology* **232**, 89–105.

Wang X-J, **Zhang J-Y**, **Shahid S**, **Xie W**, **Du C-Y**, **Shang X-C and Zhang X** (2018) Modeling domestic water demand in Huaihe river basin of China under climate change and population dynamics. *Environment, Development and Sustainability* **20**, 911–924.

Wang X, **Yu M**, **Sun D and Liu G** (2023) Regional water demand forecasting based on shared socio-economic pathways in the Zhanghe river basin. *Water Policy* **25**(9), 908–926.

Wanniarachchi S and Sarukkalige R (2022) A review on evapotranspiration estimation in agricultural water management: Past, present, and future. *Hydrology* **9**(7), 123.

Wu G, **Li L**, **Ahmad S**, **Chen X and Pan X** (2013) A dynamic model for vulnerability assessment of regional water resources in arid areas: A case study of Bayingolin, China. *Water Resources Management* **27**, 3085–3101.

Xu Q, **Fox G**, **McKenney D and Parkin G** (2019) A theoretical economic model of the demand for irrigation water. *Agricultural Water Management* **225**, 105763.

Yan H, **Acquah SJ**, **Zhang J**, **Wang G**, **Zhang C and Darko RO** (2021) Overview of modelling techniques for greenhouse microclimate environment and evapotranspiration. *International Journal of Agricultural and Biological Engineering* **14**(6), 1–8.

Yang J, **Ren W**, **Ouyang Y**, **Feng G**, **Tao B**, **Granger JJ and Poudel KP** (2019) Projection of 21st century irrigation water requirement across the lower Mississippi alluvial valley. *Agricultural Water Management* **217**, 60–72.

Yang T, **Shi P**, **Yu Z**, **Li Z**, **Wang X and Zhou X** (2016) Probabilistic modeling and uncertainty estimation of urban water consumption under an incompletely informational circumstance. *Stochastic Environmental Research and Risk Assessment* **30**, 725–736.

Yao M, **Tramberend S**, **Kabat P**, **Hutjes RWA and EWerners S** (2017) Building regional water-use scenarios consistent with global shared socioeconomic pathways. *Environmental Processes* **4**, 15–31.

Younis O and Davies EGR (2024) A quantification and analysis of historical sectoral and regional water withdrawals in Canada. *Canadian Water Resources Journal/Revue canadienne des ressources hydriques* **49**(1), 40–63.

Zolghadr-Asli B, **Ferdowsi A and Savić D** (2024) A call for a fundamental shift from model-centric to data-centric approaches in hydroinformatics. *Cambridge Prisms: Water* **2**, e7.

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