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OVERVIEW REVIEW

Future Water Demand Modeling: A Multi-Sector Review Using a Streamlined Methodological Approach

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Abstract

Future water demand modeling is of crucial importance for stakeholders, particularly in the era of rapidly changing climate and socio-economic 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 socio-economic factors as well as the major economic sectors is currently lacking. This review paper 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.

Keywords: climate change adaptation, literature review, PRISMA guidelines, STAR framework, sectoral water modeling workflow

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 socio-economic transformations. This article presents a comprehensive and methodologically rigorous review of water demand modeling approaches, with a particular focus on their applicability across socio-economic sectors (municipal, agricultural, industrial, commercial, and institutional) and spatial scales (municipality, watershed, 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

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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.

1. Introduction

Freshwater is an essential but limited natural resource that plays a fundamental role in socio-economic development. Its demand is set to grow considerably in the upcoming decades, making it a highly coveted resource (Hertel et al. 2016). Thus, its availability and management are becoming increasingly critical challenges, especially in the context of prevailing factors such as climate change and socio-economic 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).

The undesirable situations mentioned above arise, for example, from changes in precipitation patterns and rising temperatures that affect the spatio-temporal availability of water, particularly for agricultural irrigation and industrial uses (J. Yang et al. 2019; X.-J. 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 socio-economic 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 multi-sector and multi-scale approach to water demand modeling would help shape public policies and ensure well-balanced allocations of resources in response to future climatic and socio-economic conditions.

Recent water conflicts in the province of Quebec (Canada) have raised important concerns regarding future water demand (Gerbet et al. 2025; Bernier et al. 2025), given anticipated climate disruptions due to the accumulation of greenhouse gases in the atmosphere, on 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 (MELCCFP) and Ouranos commissioned a participatory research project named *ProjectEau* to strengthen its ability to anticipate future water demand across five key economic sectors, i.e., 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 socio-economic 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, i.e., municipal/residential, institutional, commercial and even industrial, that 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,

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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 (Alamanos et al. 2022; Kebede et al. 2021). 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 multi-sector, multi-scale approach to water demand would contribute to shape fair public policies and ensure well-balanced allocations of resources in response to future climatic and socio-economic 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 socio-economic 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; W. 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 paper 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 paper is organized as follows: Section 2 outlines the methodology adopted for this review; Sections 3 and 4 present the results and discussions, respectively. The later examines the strengths, limitations, and similarities between the identified methods. Finally, Section 5 concludes with a summary of the different methods for modeling future water requirements and our recommendations for future research.

2. 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 framework (Page et al. 2022; Moher et al. 2009) 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, 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.

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

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 1924 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 2180 articles, book chapters, conference reports, and theses.

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Table 2. Summary of the research strategy adopted. 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 socio-economic). For each element of the STAR framework, we provide a single Boolean equation that is tested against the bibliographic databases to obtain papers relevant to answer the two research questions of the review.

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)

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, i.e., based on: (a) their titles and abstracts and (b) the full text.

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 socio-economic (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 et al. 2014);
Exclusion	• Use of specialized software (e.g., *CropWat*, *WEAP*) in a black-box way, i.e., 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 hydro-climatic 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.

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

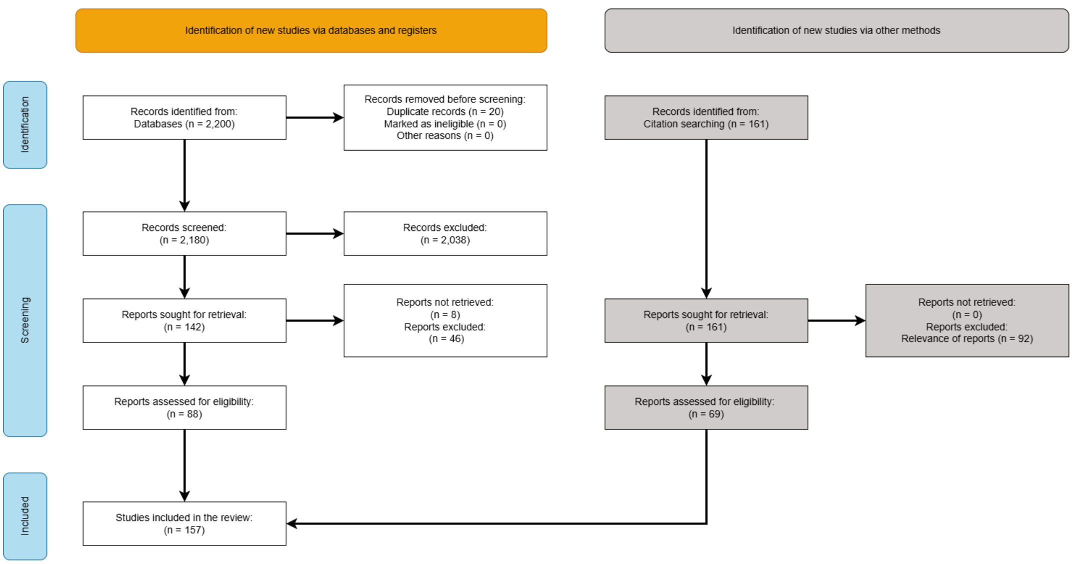

Figure 1. The PRISMA diagram summarizing our references selection process.

3. 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, i.e, short-, medium-, and long-term (Billings 2008; Rinaudo 2015; Donkor et al. 2014). Short-term methods (less than a year) are generally used by municipalities and water supply agencies for operational planning, i.e., 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 one to ten 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 ten 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.

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

3.2 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 (CIM), which could be considered as a subset of the multivariate method, are subdivided into three temporal-scale classes, i.e., 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 et al. 2017; Muhammad et al. 2019). This category is in orange color in Figure 2.
b. Single-sector and multi-sector modeling methods which 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 et al. (2011), depicted in gray color in Figure 2, distinguishes six (6) classes of methods based on criteria such as:

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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 socio-economic and environmental nature.	1st degree	This method needs only one variable, i.e., 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).	2nd degree	This method needs two variables, i.e., 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, socio-economic and environmental factors are not considered.	3rd degree	This method uses mainly three variables, i.e., 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 socio-economic and climatic factors.	4th 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 et al. 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.	5th 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.

(a) spatial resolution considered, (b) temporal resolution of the data, (c) linear and non-linear relationships modeling in the data, and (d) dynamic modeling (ex: 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.

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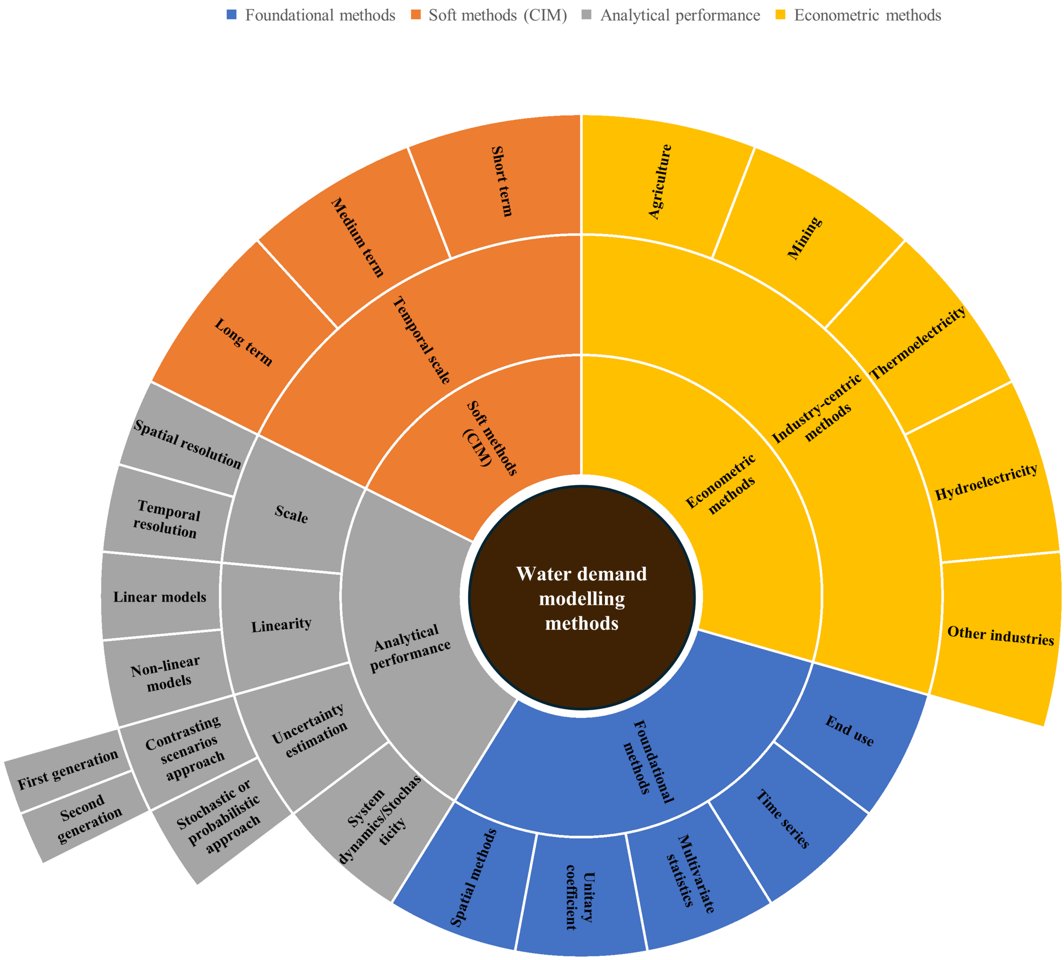

Figure 2. Diagram summarizing the different methods and approaches used to classify future water demand estimation methods. Concentric circles represent increasing levels of specificity: core methodological categories (inner ring), subcategories (middle ring), and detailed components or applications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

3.3 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 et al. 2011; Alhendi et al. 2022).

3.3.1 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 policy and decision-making, only emerged in the late 1990s. The uncertainty associated with the

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evolution of climatic and socio-economic 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, i.e., with consideration of environmental factors alone or socio-economic factors alone or policy assumptions alone. Here, we refer to those scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC) 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 Sanchez et al. (2020) in the United States, Grouillet et al. (2015) in France and Spain, and X. 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, 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 socio-economic 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 et al. (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) use 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.

3.3.2 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 et al. (2004) developed the Long-Term Demand Forecasting System

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(LTDFS) 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. T. 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) quantify 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.

3.3.3 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 et al. (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.

3.4 Water demand drivers

Drivers of water demand can be classified into five (5) major categories according to the elements of the STEEP (Social, Technology, Economic, Environmental and Political factors) framework (Hammoud et al. 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 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).

3.4.1 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 et al. (2006), Corbella et al. (2009), House-Peters et al. (2011), Bich-Ngoc et al. (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 (W. Wang et al. 2017; X. Wang et al. 2023), multivariate statistics (e.g.: Neale et al. 2007; Ashoori et al. 2017; Parkinson et al. 2016; X. 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; Zolghadr-Asli et al. 2024; Loucks 2023), 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; L. 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 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 et al. 2011; Bich-Ngoc et al. 2018; Abu-Bakar et al. 2021; Cominola et al. 2023); **Environmental** (natural) variables include precipitation, temperature, evapotranspiration (lawn watering) and wind speed (House-Peters et al. 2011; Abu-Bakar et al. 2021); **Economic** variables include water price, household income, property value, Gross Domestic Product (GDP) and water metering (Arbués et al. 2003; House-Peters et al. 2011; Dong et al. 2013; Bich-Ngoc et al. 2018; Cominola et al. 2023; X. 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 et al. 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 et al. 2009; Dong et al. 2013; House-Peters et al. 2011; Abu-Bakar et al. 2021).

Beyond the classification of the determinants according to the STEEP framework (Hammoud et al. 2014), Abu-Bakar et al. (2021) introduced a triadic classification of the determinants as: (a) **endogenous factors**, i.e. those directly influencing water demand (e.g. affluence, education, occupation, tenure, etc.), (b) **exogenous factors**, defined as those beyond the water consumer's control (e.g. migration, tourism, rainfall, water availability, etc.), 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**, i.e., observable endogenous determinants (e.g., socio-demographic, property characteristics), (b) **latent or psychosocial determinants** (e.g., perception, habits), and (c) **external or exogenous determinants** (water price, temperature, precipitation).

3.4.2 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

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on: (a) the modeling of evapotranspiration used to calculate crop water demand (Wanniarachchi et al. 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; Bwambale et al. 2022; Abioye 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 et al. 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 Appendix 3). It comes down to estimating the demand of its two key components, i.e., irrigation and livestock (Hanasaki et al. 2013; Hejazi et al. 2014; Grouillet et al. 2015; Yao et al. 2017; Alizadeh et al. 2022; Agrawal et al. 2022; Younis et al. 2024; Dang et al. 2024).In some cases, water for product washing (Lehto et al. 2014; Vergine et al. 2017) and facility cleaning (Krauß et al. 2016; Drastig et al. 2016; Younis et al. 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 et al. 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 et al. 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 non-spatial and spatial models have been developed (Prenger et al. 2002; Fazlil-Ilahil 2009; Katsoulas et al. 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 (LAI), and normalized difference vegetation index (NDVI) 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 socio-economic variables; Yao et al. 2017) to hydrological and plant growth models such as CropWat and WaterGAP (Döll et al. 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).

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3.4.3 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 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 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, i.e., manufacturing, power generation, oil production, mining (Brière 2012; Flörke et al. 2013; Younis et al. 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) report coefficients for different countries such as Austria, the US, and Norway. It should be highlighted that the work mentioned above is limited to estimating water demand without a consideration of the impact of climatic and socio-economic 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, K. Wang et al. (2019) develop the Bow River Integrated Model (BRIM) 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, etc, using second-generation scenarios consisting in SSP and SPA.

4. 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 socio-economic 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 paper beyond the reported results as prior to STAR, literature search in environmental sciences were mostly conducted without an enabling

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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, socio-demographic, 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 (intra-sector) or between variables from different sectors (inter-sector). 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 (socio-demographic 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 (Z.-M. Chen et al. 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 socio-economic 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 et al. 2011). As demonstrated by the analysis of Kelly et al. (2013) as well as by results presented in Tables 5-8 (in 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 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 paper. 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 **System Dynamics** 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, system dynamics and second-generation probabilistic scenarios. As House-Peters et al. (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 et al. 2015; Toba et al. 2022; Martin-Martinez et al. 2022) as well the XMILE standard file format for SD models (Eberlein et al. 2013; Gadewadikar et al. 2024) make it possible to completely program and run a 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, i.e., 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, i.e., 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 (ex: municipal/residential, agricultural) whenever the available resource (supply) is inferior to the demand.

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 non-exhaustive 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

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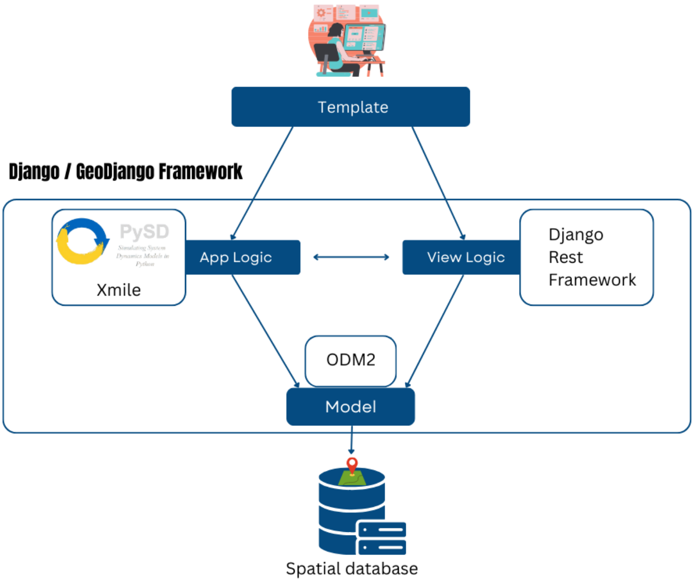

Figure 3. A proposed representative software workflow for the implementation of multisectoral and multifactorial projections of future water demand based on the Django, GeoDjango, Django REST Framework libraries ecosystem as well as the PySD library.

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, etc.) for export. The problem could also arise at the level of the references processing tool, Rayyan (Johnson et al. 2018), during the references importation step.

5. 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 socio-economic 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, spatio-temporal 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, Systems Dynamics (SD), and Probabilistic Scenarios, would be the most appropriate for integrated modeling of linear and non-linear relationships between variables in the various factors and economic sectors of interest over the long term. To support the implementation of such a method,

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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, i.e., municipality and watershed.

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

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Appendices

The appendices are published as supplementary materials available at https://doi.org/10.5281/zenodo.15306774.