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Emerging investigators series: a critical review of decision support systems for water treatment: making the case for incorporating climate change and climate extremes

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Water treatment plants (WTPs) are tasked with providing safe potable water to consumers. However, WTPs face numerous potential obstacles, including changes in source water quality and quantity, financial burdens related to operations and upgrades, and stringent water quality regulations. Moreover, these challenges may be exacerbated by climate change in the form of long-term climatic perturbations and the increasing frequency and intensity of extreme weather events. To help WTPs overcome these issues, decision support systems (DSSs), which are used to aid and enhance the quality and consistency of decision-making, have been developed. This paper reviews the scientific literature on the development and application of DSSs for water treatment, including physically-based models, statistical models, and artificial intelligence techniques, and suggests future directions in the field. We first set the context of how water quality is impacted by climate change and extreme weather events. We then provide a comprehensive review of DSSs and conclude by offering a series of recommendations for future DSS efforts for WTPs, suggesting that these tools should (1) more accurately reflect the practical needs of WTPs, (2) represent the tradeoffs between the multiple competing objectives inherent to water treatment, (3) explicitly handle uncertainty to better inform decision makers, (4) incorporate nonstationarity, especially with regard to extreme weather events and climate change for long-term planning, and (5) use standardized terminology to accelerate the dissemination of knowledge in the field.

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Water impact

Water treatment plants (WTPs) must reliably provide clean drinking water to their consumers. To do so, water planners must make decisions about WTP infrastructure and operations despite uncertainties about the future. In this paper, we review tools which can aid in this decision-making process and explore potential impacts of future climate on WTPs.

1. Introduction

The production of potable water is ranked among the most important developments in public health,^{1,2} and water treatment plants (WTPs) are responsible for providing this resource to consumers, by treating source water to turn it into potable drinking water (Fig. 1). WTP failures can have devastating impacts on human health and can erode consumer confidence in the safety and reliability of the water supply. To minimize the risk of such failures and promote public health, the United States Environmental Protection Agency

(US EPA)³ and similar entities around the world enact strict laws which regulate potable water quality.⁴ As the impact of contaminants on human health has become more fully understood, additional regulations have been enacted over time. While these laws benefit public health, WTPs must shoulder the fiscal burden to improve their system, if necessary, to remain in compliance.

In addition to meeting the regulations in the near future, WTP planners must also consider whether the plant will remain in compliance for years to come. Nonstationarity, with regard to a changing climate and the shifting nature of extreme weather events,^{5–12} makes forecasting future compliance increasingly difficult because these climatic factors (e.g. drought, extreme precipitation, temperature increase) have

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been linked to source water quality degradation.^{13–20} Furthermore, the physical, chemical, and biological impacts on source waters may have important design, operating, and cost implications for future drinking water treatment processes (Fig. 1).^{16–18} In the US, specifically, changes in source water quality could impact compliance with regulations such as Surface Water Treatment Rules and Disinfectants and Disinfection Byproducts Rules (stage 1 and 2). Concerns about climate change amplify the already complex decision-making problem for WTPs, which face regulatory and budgetary constraints, tradeoffs between performance and cost objectives, and high levels of uncertainty.

To deal with system complexity and improve decision-making, WTPs can employ a decision support system (DSS), which is a computer-based aid for decision-making that codifies stakeholder decision variables (possible actions), objectives (measures that quantify performance), and constraints (relationships that maintain desired performance). DSSs have been used in water treatment and throughout related fields to improve the quality, efficiency, and consistency of decision-making.^{21–24} To date, DSSs in water treatment have aided in operational and infrastructural decision-making on both short- and long-term time horizons.

2. Scope of review

The purpose of this paper is to review existing literature of DSSs regarding WTPs and highlight opportunities for advancement in this field. This review complements other water and wastewater treatment DSS reviews such as Hamouda *et al.*²¹ and Zhang *et al.*²⁴ but differs in that it exclusively focuses on water treatment and addresses climatic impacts on water quality. The paper begins by discussing the effect of climate change and extreme weather on both source and drinking water quality and identifying the types of decisions water managers can choose among to prepare for such events and remain in compliance with regulations. Subsequently, we discuss how DSSs can aid in water treatment decision-making more generally and critically review WTP DSS efforts in the literature. Based on this review, we provide recommendations for the development of future DSSs in the field.

Although this paper covers a wide range of topics, there are many important research areas that were beyond the scope of this work. First of all, this review focuses on WTP



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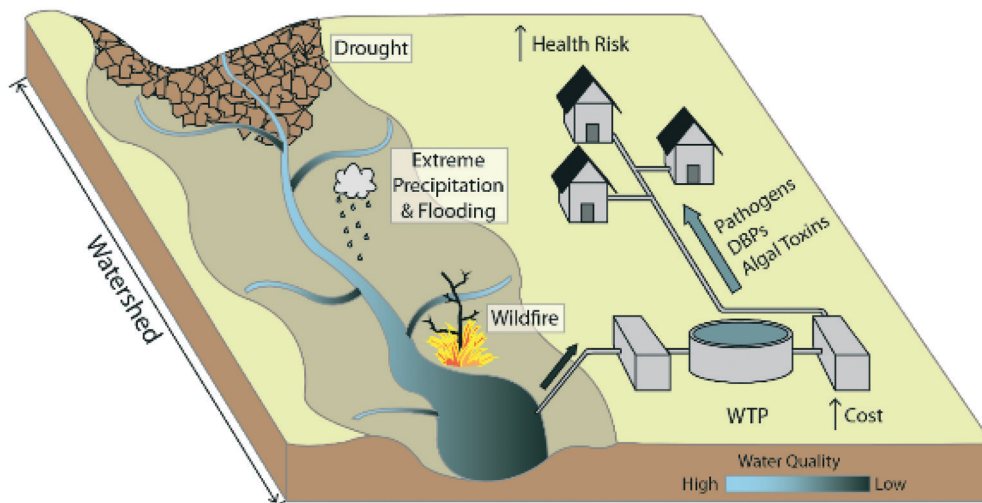


Fig. 1 The impact of climate change and extreme weather events on drinking water quality. Degraded source water quality can lead to higher costs for WTPs and elevated health risk for consumers.

DSSs rather than the entire “catchment to consumer” potable water system which includes source water management, water treatment, and distribution. For more information regarding source water and drinking water distribution decision-making, we direct the interested reader to the following references on the motivation for source water protection and catchment management (Emelko *et al.*¹⁶ and Honti *et al.*²⁵), source water DSS (Arabi *et al.*,²⁶ Borsuk *et al.*,²⁷ Ferguson *et al.*,²⁸ Heberling *et al.*,²⁹ and Rossi *et al.*³⁰) and water distribution DSS (Kleiner *et al.*³¹ and van Zyl *et al.*³²). For a detailed treatment of the impact of climate change and extreme weather events on water quality, the reader should consult Khan *et al.*,¹⁷ Stanford *et al.*,¹⁸ and Delpla *et al.*,¹⁵ since we only cover this topic briefly in this paper.

3. Influence of climate change and extreme weather events on drinking water quality

For WTPs, the physical, chemical, and biological impacts on source waters due to climate change and extreme weather events may have important design, operating, and cost implications for future drinking water treatment processes.^{16–18} This is evidenced by the results of a recent survey by the Water Research Foundation that covered major water utilities in the United States and Australia. In this survey, utilities expressed concern about the impacts of climatic events on drinking water quality.¹⁸ US participants stated that the lead-



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ing water quality issues from extreme events were related to the formation of disinfection byproducts (DBPs) and changes in source water quality. Other areas of concern for water quality included cyanobacteria and related algae blooms and distribution system water quality degradation. The same survey of Australian utilities produced slightly different results, likely due to differences in DBP regulations between the two countries. In both countries, only a minority of utilities expressed concern for long-term climate trends, such as warming temperatures, rising sea level, and a longer hot season. In general, utilities expressed the greatest interest in extreme events, such as rainfall, flooding, and drought.

For utilities looking to mitigate the impact of extreme events, the literature has suggested that planners consider redesigning treatment processes, diversifying water sourcing options, increasing redundancy of plant design, altering long-term operations and maintenance plans, developing effective extreme event response plans, and enhancing water quality monitoring.^{15,17,18} To aid in this decision-making process, we provide information about the water quality implications of climate change and extreme weather events in the following sections.

Because the magnitude of water quality impacts are highly variable and depend on local conditions,¹⁸ we will focus our discussion on general water quality trends. For the sake of illustration, we will discuss the overall water quality implications of climate change and note a few common extremes (*i.e.* drought, wildfire, extreme precipitation, and floods to inform water planners) that will likely be impacted by climate change in the following sections (Fig. 1). Although it is beyond the scope of this paper, planners should also consider other impacts, such as changing land use, which also contributes to nonstationary source water quality.^{33–35}

3.1 Climate change

As noted by the Intergovernmental Panel on Climate Change (IPCC),¹⁰ climate change effects on hydrology show both increasing and decreasing trends in streamflow magnitudes depending on the local geography, precipitation regime and whether the system is snowmelt dominated. However, far fewer studies have assessed the climatic influences on water quality, mostly conducted in isolated studies. Studies from a variety of time periods indicate that in areas with greater precipitation and runoff, pollutant loads tend to increase as more pollutants are continuously transferred from the near surface soil to the channel (*e.g.* Curriero *et al.*;¹⁴ Tetzlaff *et al.*³⁶). Temperature also plays a dominant role in water quality, as greater temperatures promote pathogens³⁷ and algal blooms³⁸ to flourish, thereby producing more dissolved organic matter (*e.g.* Benítez-Gilabert *et al.*³⁹), and less dissolved oxygen.⁴⁰ Though trends are mostly statistically significant from local studies, direct relationships between climate and water quality remain largely unknown on a global scale due to the scarcity of climate change water quality stud-

ies and the spatial heterogeneity of anthropogenic impacts and land use pollutant sources.

3.2 Drought

Reduced rainfall associated with drought decreases runoff within a watershed, altering the transport of materials, such as nutrients and metals, to source waters.^{41,42} Decreased water volumes also increase the impact of point-sources (*e.g.* wastewater treatment effluent) on source water quality. Moreover, droughts may encourage algal blooms by increasing nutrient concentrations, water temperatures, and residence times.^{43,44} Collectively, drought impacts can fundamentally alter nutrient cycling and biota within watersheds and reservoirs for months or even years.⁴²

Although droughts tend to degrade water quality among source waters, the impacts on riverine systems and lakes and reservoirs may differ.⁴¹ Additionally, the timing of droughts determines the severity of water quality impacts; if droughts are in sequence with other extreme events, their adverse impacts on water quality may compound. For instance, storm events following periods of prolonged drought have been found to markedly increase organic matter concentrations.⁴⁵

3.3 Wildfires

Water quality impacts due to wildfires are particularly significant because forest catchments are high quality, high quantity source waters. For instance, forest catchments provide one-third of the 105 largest cities in the world with a significant amount of their drinking water and provide two-thirds of all water supplies in western North America, including drinking water for approximately 180 million U.S. citizens.^{16,46}

Among several impacts on ecosystems, wildfires are known to affect water quality. Wildfires can increase soil erosion rates by several orders of magnitude due to 1) reduced soil stability and 2) increased exposure to precipitation caused by loss of vegetation, and 3) induced soil water-resistance which increases runoff.^{47,48} This erosion often leads to increased levels of suspended sediment and sediment-related contaminants (particularly nutrients, organic carbon, and heavy elements) in source water,^{46,47,49} although better characterization of the mobilization of organic carbon is still being investigated.⁵⁰ While wildfires can cause erosion, the magnitude is dependent on an area's susceptibility to erosion,⁵¹ precipitation patterns, and the severity, spatial extent, and frequency of wildfires.^{52,53}

3.4 Extreme precipitation and floods

Compared to other storm events, floods are responsible for the highest rates of soil erosion in streams.⁵⁴ Increases in extreme precipitation and flooding due to climate change heighten the likelihood of high erosion and subsequent turbidity events due to increased overland flow^{30,55,56} and may intensify bacterial and contaminant metal fluxes.^{57,58} Furthermore, extreme precipitation events are often associated with

waterborne disease outbreaks: heavy rainfall can overwhelm WTPs, cross-contaminate sewage and drinking-water pipes (especially for old systems), and lead to sewage overflow into source waters.^{13,20} In the United States, 51% of waterborne disease outbreaks were preceded by precipitation events above the 90th percentile and 68% by events above the 80th percentile.¹⁴

3.5 Source water quality linked to drinking water quality

In the previous sections, we discussed the potential impacts climate change and extreme events can have on source water quality. In this section, we explore how such source water quality changes can impact drinking water quality. Specifically, we focus on how source water affects three drinking water contaminants of concern: DBPs, pathogens, and algal toxins.

DBPs are unintended byproducts formed as a result of adding disinfectants (e.g. chlorine and chloramine) to treat drinking water. They are formed *via* the reaction between chemical disinfectants and naturally occurring organic matter. Since increased organic matter is often associated with extreme events, this series of events portends a greater potential for DBP formation. DBPs have been associated with cancer risks as well as other acute and chronic effects to human health.⁵⁹ The concentration and type of DBP in drinking water are dictated by source water quality characteristics, such as pH, temperature, presence of organic matter, and levels of bromide and iodide.⁶⁰ By law, US WTPs must adhere to the US EPA's maximum contaminant levels for DBPs—including total trihalomethanes, haloacetic acids, bromate, and chlorite—as well as regulations for the DBP precursor, total organic carbon under stages 1 and 2 of the Disinfectants and Disinfection Byproducts Rules.⁶¹

As described above, flooding and extreme precipitation can increase the occurrence of pathogens in source waters. In the context of drinking water treatment, if pathogen concentrations exceed the removal capacity of the WTP, disease outbreaks and other human health impacts can occur. Bacterial parameters (e.g. *E. coli*, coliform, fecal streptococcal, and *Clostridium perfringens* counts) have been found to increase considerably during extreme runoff events.⁵⁷ Furthermore, increased turbidity levels, such as those caused by wildfires and floods, can cause a decrease in filtration effectiveness and are often associated with elevated levels of viruses, parasites, and bacteria.⁶²

Most closely linked with droughts, projected temperature increases, changes in water quality, and enhanced stratification promote the growth of harmful algal and cyanobacterial blooms.^{43,44} These blooms can produce potent neurotoxins of concern in drinking water, including microcystin.^{60,63} In addition to health risks, algal and cyanobacterial blooms can produce geosmin and 2-methylisoborneol—non-toxic compounds associated with taste and odor issues in water which can lead to distrust among consumers.⁶⁴ Lastly, algae can release DBP precursors within a drinking water system.⁶⁵

In summary, the future occurrence of algal toxins, DBPs, and pathogens in drinking water is projected to increase because of changing extreme events due to climate change. Elevated levels of these contaminants pose a risk to consumer health and may increase the treatment costs associated with drinking water. The extent of these impacts, however, is both uncertain and variable from site to site. So what tools can water planners use to make decisions under such uncertain future conditions? Furthermore, do these tools meet the actual needs of water planners? In the following section, we attempt to answer these questions by looking to DSS literature in water treatment.

4. Decision support systems

DSSs are frameworks designed to aid in decision-making. The nature of DSSs can vary greatly in terms of data requirements, time horizon, and purpose. For instance, many quantitative models (e.g. physically-based models or Bayesian networks) can be used to optimize objective functions such as minimizing cost or maximizing the utility (as defined by the stakeholders) of a set of long-term infrastructural decisions. Contrastingly, a rule-based DSS could be used to inform a water treatment operator how to troubleshoot uncommon water quality issues. In general, DSSs comprise a model and a database and are flexible to accommodate changes in the problem formulation and the decision-making approach of stakeholders.⁶⁶ These types of systems have been successfully used in a range of environmental applications for decision-making, including the development of regional energy strategies,^{67,68} wastewater treatment,^{21,24} and remediation of contaminated soils.^{69,70} In decision-making, there are also tools similar to DSS known as *risk assessment tools* which quantify or diagnose areas of risk and suggest corrective action to mitigate potential failure (see Schijven *et al.*,⁷¹ Smid *et al.*,⁷² Lindhe *et al.*,^{73,74} Arvai *et al.*,⁶⁷ and Ferguson *et al.*²⁸) and are popularly used and developed by organizations such as the World Health Organization, the US EPA, and International Organization for Standardization. The term *risk assessment tool* is often used in public health, microbiology, and risk analysis and management literature but less frequently found in engineering and business management, which use *decision support system* terminology. Based on its similarities with models commonly used in DSSs (e.g. physically-based and data-driven models), we will include risk assessment tools in this review and frame them with DSS terminology.

In the field of water and wastewater treatment DSSs, Zhang *et al.*²⁴ and Hamouda *et al.*²¹ provide comprehensive reviews but dedicate their work predominantly on wastewater rather than water treatment. This emphasis on wastewater DSSs is reflective of the greater body of literature compared to water treatment DSSs. Nonetheless, numerous DSSs for water treatment have been developed in recent decades but they have yet to be compiled into a comprehensive review

until this work. In this paper, we will review DSSs for drinking water treatment, specifically.

In the following sections, we provide a brief overview for DSS development in environmental management. An exact framework for the development of DSSs is not widely agreed upon (McIntosh *et al.*⁷⁵ and Poch *et al.*⁷⁶) but there are common steps found in environmental decision-making literature (see Poch *et al.*,⁷⁶ Cortés *et al.*,⁷⁷ Hamouda *et al.*²¹ for examples). These steps are generally to (1) identify stakeholders, decision makers, and modelers; (2) formulate the problem; (3) collect/analyze data; (4) choose the appropriate DSS; (5) implement and evaluate/verify the DSS. Due to the wide variety of DSSs, we will not attempt to define a general framework for this paper. Instead, we will focus our discussion on steps 1, 2, and 4 listed above, which we feel are widely shared among DSSs and are important to understand for readers interested in DSS development.

4.1 The role of stakeholders, decision makers, and modelers

While DSSs have the potential to improve a project, the amount of information and insight provided from stakeholders and decision makers will ultimately determine the quality and usefulness of the DSS.^{78–80} All parties that have an interest in the WTP need to be identified, such as operators, water managers, and government officials, so the DSS is representative of the objectives of the entire group, the system is realistically constructed, and practical decisions are considered. In gathering information, modelers should be impartial and attempt to represent the stated preferences of the stakeholders as accurately as possible. This is especially important for a class of applications termed “wicked problems”, in which there are a variety of stakeholders and decision makers with conflicting values and diverging ideas for

solutions⁸¹—in which public health and welfare is at stake.^{82–84} To create the DSS, stakeholders must agree on the scope of the DSS in what is known as the *problem formulation*.

4.2 Problem formulation

The problem formulation is made up of decision variables, objectives, and constraints. Decision variables (*D*), also known as decision levers, are parameters a decision maker can realistically change; objectives (*O*) are metrics that seek to quantify the system's performance (*e.g.*, cost, measurements of water quality, and environmental impact); and constraints (*C*) are required aspects of the system that must not be violated, such as stakeholders' desired performance. Fig. 2 illustrates these concepts and how they can be applied to water treatment. Depending on the decision context of the problem, various aspects of the problem formulation may be more or less important. For example, a DSS could be constructed to quantitatively evaluate the performance of a *given* management plan, in which case the decisions could be fixed, but the objective outputs are of paramount importance.²² There could also be a situation in which managers are trying to meet a given regulation, so the set of considered objectives is fixed, but the decisions that could be considered are quite dynamic and need to be found intelligently.

Additionally, the stakeholders must determine the time horizon—the frequency at which a decision problem is evaluated—for their formulation. This is because a DSS can be used regularly, perhaps on a daily basis, or it may only be used once to determine a large, infrastructural decision. Determining the correct time horizon for long-term planning, for example, is important so decision-making plans strike the balance between adaptability and efficiency of decision-making. This and other aspects of long-term decision-making

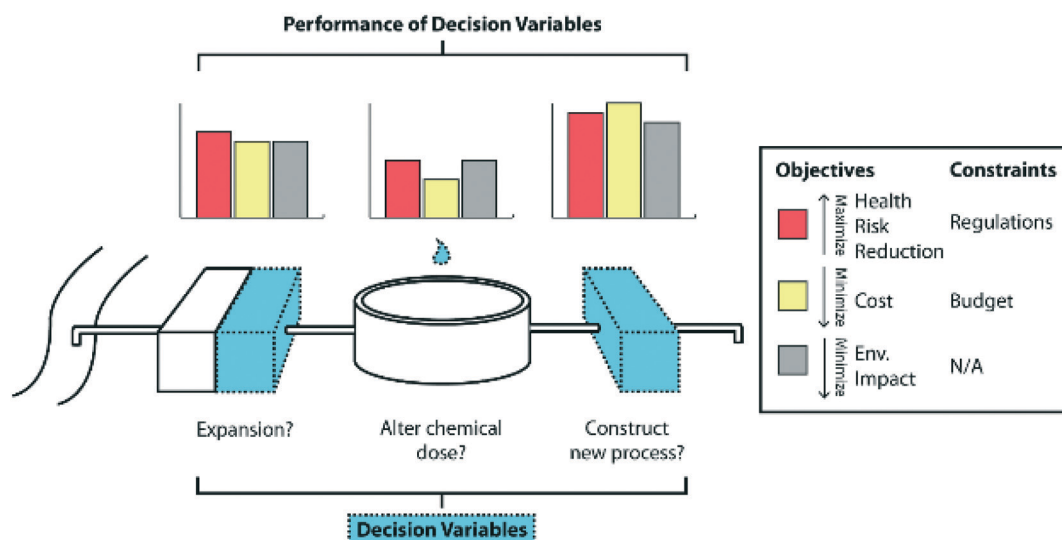


Fig. 2 Illustration of the decision context of water treatment. Water managers have a range of operational and infrastructural decision variables to consider for WTPs. The performance of decision variables can be measured as objectives and, to be acceptable to the decision maker, they cannot violate constraints.

are discussed in more detail in section 5. Once stakeholders agree upon the details of the problem formulation, including the time horizon, the appropriate DSS must be selected for the task.

4.3 DSS selection and review

To begin a discussion about the selection of appropriate DSSs, it is important to note that, given the broad definition of DSSs, the terminology used to categorize DSS models is not widely agreed upon within environmental and water management. We invite the interested reader to compare between Cortés *et al.*,⁷⁷ Poch *et al.*,⁷⁶ Hamouda *et al.*,²¹ Kelly (Letcher) *et al.*,²² Denzer,⁸⁵ Rizzoli and Young,⁸⁶ and Zhang *et al.*²⁴ to explore various classifications. In this paper, we will discuss three categories of DSSs: those based on physically-based models (PBMs), statistical models (SMs), and artificial intelligence (AI). This aligns most closely with the classification found in Cortés *et al.*,⁷⁷ Poch *et al.*,^{75,76} and Hamouda *et al.*²¹ In this section, we discuss both the theory behind DSS selection and review how these have been applied to water treatment literature (Table 1). In Table 1, we review DSSs (or major DSS components) found in WTP literature, provide a brief description of these tools, their objectives, the water quality parameters considered, their treatment of uncertainty, and their intended time horizon for decision-making (*e.g.* short- or long-term).

We begin with a discussion of PBMs and SMs because there is overlap between the techniques used in these DSSs. PBMs simulate systems based on equations which represent their fundamental physics and chemistry. SMs, on the other hand, represent systems based on data and are commonly presented as probability distributions. Next, we discuss AI DSS which are used to mimic human reasoning. Within this diverse class of DSS, there are knowledge-based systems (KBSSs), Bayesian networks (BNs), and artificial neural networks (ANNs). KBSSs, also known as expert systems, consist of a knowledge base and rules or a procedure to make a decision.⁸⁷ BNs and ANNs are both data-driven models but are distinct in their approach to decision support. BNs represent decision-making using conditional probabilities, while ANNs comprise interconnected neurons capable of predictive modeling of non-linear relationships.

4.3.1 Physically-based and statistical models. Because PBMs are derived from theory, they are particularly useful for prediction problems for which it is impractical or impossible to collect the data required for a SM. For example, if engineers are designing infrastructure for extreme weather, data on such events is inherently rare. In this case, PBMs may offer a superior level of accuracy of how the system might perform than a SM based on limited data would. However, these two models are by no means mutually exclusive. At times, models may include a hybrid approach, using both physically-based and empirical equations, for example. Moreover, within these two types of models, they can be further divided into deterministic and stochastic (or probabilistic).

For deterministic models, each set of inputs produces only one set of outputs each time the model is run. This deterministic approach, which is more common for PBMs than SMs (see Table 1), does not accurately reflect the uncertainty of real-world water planning problems. In the case of planning and managing WTPs, for example, the removal efficiency of the plant may be slightly variable over time and deviate from the theoretical conditions in the model. Stochastic models, on the other hand, can incorporate this randomness. While these uncertainties exist in the system, they are not always incorporated into modeling efforts.

To better reflect uncertainties in model parameters, two techniques are typically applied to models: sensitivity analyses, which seek to test the sensitivity of system performance to perturbations of uncertain model parameters,⁸⁸ and Monte Carlo simulations, which sample from probability distributions of uncertain parameters in order to develop distributions of model outputs.^{89,90} In addition to the previously mentioned uncertainties, decision makers should be aware of how model structure impacts predictions as it is a primary source of uncertainty. However, for practical reasons, this so-called structural uncertainty is rarely considered in environmental modeling due to its difficulty.⁹¹ The interested reader can refer to Boccelli *et al.*⁹² for an example on dealing with model structure uncertainty in water treatment simulation, Refsgaard *et al.*⁹¹ regarding a framework for dealing with uncertainty due to model structure, and Refsgaard *et al.*⁹³ on a general framework for dealing with uncertainty in environmental modeling.

Lastly, techniques coupled with PBMs and SMs, such as scenario analysis and optimization, are necessary to generate and choose between various alternatives. In scenario analysis, a user can explore the system performance for a range of decisions and conditions. For instance, in WTP planning, a stakeholder may want to determine what plant design will perform best, on average, for two different seasons. To approach this problem using scenario analysis, the modeler may specify two influent water quality conditions representative of the different seasons and three design alternatives for a total of six scenarios. Based on the cost and effluent water quality for each model run, the user could then decide which of the three alternatives performs the best, on average. Alternatively, optimization techniques can be coupled with models to explore preferred decisions in a more automated fashion (Fig. 3).

When performing optimization using a model, one should refer to the objective (or objectives) defined in the problem formulation. The most common optimization approach in this review is known as *least-cost optimization*. In this method, cost is minimized and regulations constrain the effluent water quality. Because there is a single objective to optimize, this process yields a single solution. In multi-objective formulations, a concept referred to as Pareto optimality defines a set of multiple solutions for the problem. In a Pareto set, each solution represents one compromise between the multiple objectives; a solution is Pareto optimal if

Table 1 Decision support systems and decision support system components in water treatment

Source	DSS or DSS component	Description	Objective(s)	Water quality parameters	Treatment of uncertainty	Decision time horizon
Pike ¹²⁰	BN	Determine likelihood of major violations related to operator decisions and system characteristics	Minimize water quality violations	Total coliform, turbidity, treatment chemicals, inorganic compounds, and synthetic and volatile organic compounds	Inherent to BNs	Short-term
Zhu and McBean ¹¹⁹	BN	Select maximum utility design and operations using stakeholder-defined utility functions	Minimize cost, cancer risk, bacterial contamination risk	TOC, pH, alkalinity, DBPs, and treatment chemicals	Inherent to BNs	Short-term
Lindhe <i>et al.</i> ⁷³	Fault tree analysis	Perform an integrated, probabilistic risk analysis of drinking water systems from source to tap to identify potential failures in water quality and quantity	Minimize risk	Any water quality regulations	Monte Carlo sampling and Bayesian modeling	Long-term
Schijven <i>et al.</i> ¹⁰¹	Statistical analysis	Perform risk assessment for the treatment of surface water to drinking water that aids decision makers in formulating mitigation strategies and preventative measures for water safety	Maximize efficiency and consistency of microbial risk assessment	Concentration of pathogenic organisms	Monte Carlo sampling	Long-term
Schijven <i>et al.</i> ⁷¹	PBM, statistical analysis, and risk assessment	Predict risk of waterborne and foodborne infectious disease based on climate change scenarios ⁶	Minimize risk and guide climate change adaptation strategies on infectious disease	Temperature, annual precipitation, <i>Campylobacter</i> , <i>Cryptosporidium</i> , and noncholera <i>Vibrio</i> species	Sensitivity analysis, Monte Carlo sampling,	Long-term
Collins and Ellis ¹⁰²	ANN, regression, and expert system	Determine chemical doses from predictive models coupled with expert systems	Maximize efficacy of chemical dose	pH, turbidity, and treatment chemicals	N/A	Short-term
Zhu and Simpson ¹⁰⁶	Decision and fault trees	Advise operations and diagnose problems using expert systems	Minimize cost	Turbidity and treatment chemicals	N/A	Short-term
Chowdhury <i>et al.</i> ^{107,108}	Fuzzy set theory	Evaluate plant design and operations using fuzzy set theory and analytical hierarchy process	Minimize health risk, cost; maximize technical feasibility and disinfectant performance	DBPs, taste/odor, color, and disinfection achieved	Inherent to fuzzy set theory	Long-term
Lamrini <i>et al.</i> ¹⁰⁹	ANN, expert systems, and fuzzy set theory	Select optimal coagulant dose using artificial neural networks, expert opinion, and fuzzy set theory	Maximize efficiency of coagulant dose	Turbidity, TSS, temperature, pH, conductivity, and DO	Inherent to fuzzy set theory	Short-term
Mirsepasi <i>et al.</i> ¹²³	ANN	Predict treated water quality and optimal alum and polymer doses using a supervised learning algorithm	Minimize error in alum and polymer dose prediction	pH, turbidity, apparent color, true color, temperature, polymer dose, and alum dose	N/A	Short-term
Baxter <i>et al.</i> ¹²²	ANN	Presents four ANNs for source water quality prediction, water demand forecasting, and process models	Minimize error in water parameter prediction	Flow rate, color, precipitation, air and water temperature, water demand, pH, turbidity, hardness, alkalinity, chemical dose, and overflow rate	N/A	Short-term
Maier <i>et al.</i> , Van Leeuwen <i>et al.</i> , and Zhang and Stanley ^{103,125,126}	ANN, multi-variate regression, and linear regression ¹⁰³	Predict treated water quality and optimal alum dose to be used in automation	Minimize error in alum dose prediction	Turbidity, pH, color, UV ₂₅₄ , alkalinity, alum dose, and alum residual	N/A	Short-term

Table 1 (continued)

Source	DSS or DSS component	Description	Objective(s)	Water quality parameters	Treatment of uncertainty	Decision time horizon
Serodes <i>et al.</i> ¹²⁸	ANN	Develop methodology to predict optimal chlorine dose or residual concentration at critical locations in the water treatment and distribution system	Minimize error in chlorine dose and residual prediction	Turbidity, color, temperature, flow, chlorine dose, and residual chlorine	N/A	Short-term
Kulkarni and Chellam ²⁹	ANN	Predict DBP formation after chlorine disinfection of drinking water	Minimize error in DBP prediction	DOC, UV ₂₅₄ , Br ⁻ , chlorine dose, pH, contact time, and temperature	N/A	Short-term
Wiesner <i>et al.</i> ⁹⁵	PBM	Determine least-cost design and configuration of unit processes for particle removal using nonlinear optimization program	Minimize cost	Particle size distribution and concentration of suspended solids	N/A	Long-term
Wu and Chu ⁹⁷	PBM	Determine least-cost basin sizes and chemical feed rates for the design and operation of new or existing plant using nonlinear optimization program	Minimize cost	Corrosivity, alum feed rate, turbidity, total coliform, alkalinity, and chlorine disinfection	N/A	Long-term
Mhaisalkar and Bassin ⁸⁸	PBM	Determine least-cost design using dynamic programming considering uncertainty in design	Minimize cost	SS concentration	Sensitivity analysis of optimal design	Long-term
Dharmappa <i>et al.</i> ⁹⁶	PBM	Determine least-cost design and operations which meet regulations using nonlinear programming	Minimize cost	SS parameters and effluent water quality	N/A	Long-term
Boccelli <i>et al.</i> ^{89,133}	PBM	Determine least-cost design using dynamic programming while incorporating model parameter uncertainty and influent variability	Minimize cost	Particle size distribution and concentration of suspended solids, and temperature	Sensitivity analysis and Monte Carlo simulations	Long-term
Gupta and Shrivastava ⁹⁰	PBM	Determine least-cost, reliability constrained design using genetic algorithm	Minimize cost	Suspended solids concentration and temperature	Monte Carlo simulations	Long-term
Rietveld <i>et al.</i> ⁹⁹	PBM	Simulate and control of WTP to reduce costs and improve water quality, stability of performance, and understanding of the process for plant operators	Minimize cost and environmental impact	pH, temperature, DOC, calcium, alkalinity, UV ₂₅₄ , organic micro-pollutants, AOC, bromide, and treatment chemical doses	Quantify uncertainty in calibration	Short- and long-term
Worm <i>et al.</i> ⁹⁸	PBM	Simulate and control of WTP using a SCADA-like interface and integrated hydraulic, water quality, and process control models	Minimize costs and emissions	Extensive water quality parameters contained in Stimela sub-model	N/A	Short- and long-term
Ribera <i>et al.</i> ¹⁰⁰	PBM and risk analysis	Perform life cycle and human health risk assessment that serves as a multi-criteria tool for determining percent of water to be treated by nanofiltration	Minimize environmental impact and human health risk	DBPs	N/A	Long-term
Delpla <i>et al.</i> ¹¹⁰	PBM, decision tree, and risk analysis	Recommend risk reduction strategies for environmental change, including river basin management, water treatment process design, maintenance, performance, and monitoring considering catchment and treatment characteristics for small to medium plants ^a	Minimize health risk	DOC, pH, temperature, micropollutants, and DBPs	Sensitivity analysis	Long-term

^a Denotes DSS which addresses climate change. Definitions. Short-term: time horizon generally less than one year. Long-term: time horizon generally greater than one year. Abbreviations. AOC: assimilable organic carbon. Br⁻: bromide ion concentration. DO: dissolved oxygen. DOC: dissolved organic carbon. SS: suspended solids. TOC: total organic carbon. TSS: total suspended solids. UV₂₅₄: ultraviolet absorbance at 254 nm and one cm path length.

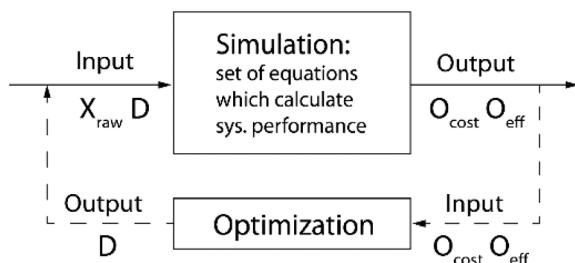


Fig. 3 Example of optimization of a PBM. In this model, the raw water quality (X_{raw}) and a set of decisions (D) are the inputs. They are then simulated and processed into outputs of the objectives: cost (O_{cost}) and effluent water quality (O_{eff}). Additionally, this simulation model could be coupled with an optimization model to generate one or more optimal solutions.

it is not exceeded in any of its objectives by another feasible solution.⁹⁴

In water treatment DSS literature, PBMs are commonly used for design applications (Table 1). Most PBMs have been developed for individual WTPs and were based off of a least-cost plant design optimization approach outlined in Wiesner *et al.*⁹⁵ For least-cost optimization, the performance of the treatment plant is constrained by water quality regulations and the cost is minimized. New optimization techniques, sensitivity analyses, improved model physics, and new treatment technologies advanced this approach,^{88,96,97} but until Boccelli *et al.*⁸⁹ the uncertainty in these models was not comprehensively considered. To choose designs that are robust across a range of uncertainties, Boccelli *et al.*⁸⁹ stressed the importance of considering the inherent variability and uncertainty in a decision-making framework. In a shift from least-cost optimization PBMs, recent literature has explored scenario-based modeling for multiple objectives. Both Worm *et al.*⁹⁸ and Rietveld *et al.*⁹⁹ use scenario-based numerical models to inform operational decision-making. Furthermore, Ribera *et al.*¹⁰⁰ uses a scenario-based approach to perform a life cycle and human health risk assessment on nanofiltration alternatives.

In water treatment DSS literature, SMs have been generally used for risk assessment and as predictive models. For instance, in risk assessment, Schijven *et al.*¹⁰¹ collected quantitative microbial, source water quality, and water treatment data to analyze microbial risk from drinking water produced from surface water. These data were then fitted to probability distributions and sampled using Monte Carlo techniques to determine exposure and infection risk and inform decision-making. Additionally, both Collins and Ellis¹⁰² and Van Leeuwen *et al.*¹⁰³ use statistical regression techniques for predictive modeling to inform operational decision-making for WTPs. These regression models are quite similar to ANNs (discussed in section 4.3.2.3) in that they are data-driven, predictive models. While these models could have been discussed alongside one another as “predictive models”, due to their differing roots—ANNs were created by artificial intelligence engineers and computer scientists while statisticians developed statistical models—we have followed convention of considering ANNs AI rather than a statistical technique.¹⁰⁴ A

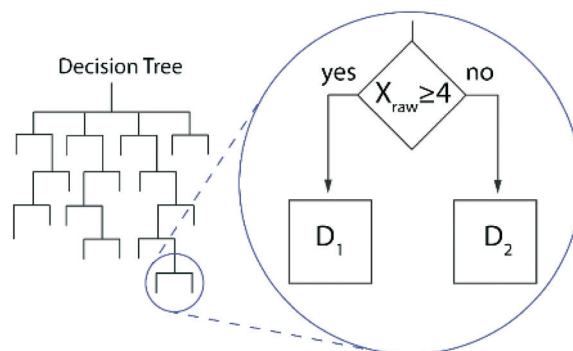
similar argument could be made for considering BNs (see section 4.3.2.2) as SMs since they are heavily based on statistical methods.

4.3.2 Artificial intelligence. Artificial intelligence (AI) has been widely used in water treatment literature to mimic human decision-making. These include knowledge-based systems (KBSs), Bayesian networks (BNs), and artificial neural networks (ANNs), which span from simple to complex in their DSS architecture. Broadly speaking, AIs have focused on operational decision support in water treatment literature, and in recent times, data-driven AI methods, such as BNs and ANNs, have grown in popularity with the rise of ‘big data’.

4.3.2.1 Knowledge-based systems. Knowledge-based systems, also known as expert systems, consist of a knowledge base and rules or a procedure to make a decision.⁸⁷ KBSs include rule-based models, in which “if-then” rules guide the decision maker through possible alternatives; case-based models, in which past events are used to inform decisions regarding similar events; and logic-based models, in which a decision is made based on a series of logical statements. Like many AI tools, these decision-making structures, often conceptualized as decision trees, are relatively intuitive to users because they mimic human reasoning.

While there are many more complex variations, a simplistic decision tree is represented by Fig. 4. The left side of this figure represents the entirety of the tree, with several levels of branches that lead to an ultimate decision. The call out section on the right illustrates one possible pathway. Within the call out, the KBS tests if some numerical data (X_{raw}), which represents a raw water quality parameter, is greater than 4 units. If it is greater, decision D_1 is chosen. If it is less than 4, the alternative is chosen. The other branches in this graphic could be used to classify other aspects of the plant, such as plant size, geographic location, type of disinfectant, whether it has advanced treatment or not, *etc.* to inform decision-making.

KBSs are advantageous in that, like BNs, they can systematically incorporate expert opinions into decision-making¹⁰⁵ and they can also handle both quantitative and qualitative



information. Furthermore, the scope of these models can range in detail from the detailed analysis of a small number of specific processes, to the holistic modeling of an entire system. Unlike BNs, which explicitly express uncertainty, KBSs do not commonly incorporate uncertainty into rules or their knowledge base.²²

In water treatment DSS literature, the majority of KBSs have been developed to advise operational decision-making in WTPs by incorporating expert opinion. These systems were designed to codify the accumulated knowledge of plant operators about chemical dosages and problem diagnoses.^{102,106} Over time, more advanced techniques, such as fuzzy set theory and multi-criteria analysis, have been used in decision-making.^{107–109} Even with improved techniques, KBSs alone cannot be used to represent all types of problems. By coupling KBSs with other types of DSSs, however, authors have been able to look at more complex problems. For instance, Delpla *et al.*,¹¹⁰ which couples a PBM and a KBS, created a practical decision support tool for small and medium treatment plants planning for climate change. In this two-part DSS, the KBS is used to make catchment management and treatment recommendations based on semi-quantitative data associated with catchment type, climatic conditions, and treatment operations, and the PBM is used to assess the health risk of the plant considering both current and projected water quality levels.

Additionally, a logic-based KBS, known as fault tree analysis, has been used for risk analysis from catchment to consumer in Lindhe *et al.*^{73,74} In general, “a fault tree analysis is a risk estimation tool with the ability to model interaction between events... [and] identifies potential causes of system failure.”⁷³ Using primarily expert judgment and some historical data, Lindhe *et al.* defines hundreds of probability distributions for model variables to describe the system's potential risk due to events that could lead to water quality or quantity failure. Based on this method, users can estimate the probability of failure, mean failure rate, and overall mean downtime of the system and individual sub-systems.

4.3.2.2 Bayesian networks. A BN is a stochastic model which defines causal influences between system variables—such as decisions and objectives—and quantifies the strength of these relationships through conditional probabilities.^{111–113} BNs are represented by a directed acyclic graph which links nodes (random variables) to represent the relationships between variables; specifically, a node is classified as either a *parent* or *child* node.¹¹⁴ A child node is one that is dependent on one or many parent nodes, which is graphically represented by arrows linking related nodes. A node with no parent is an input variable, whereas a node with no child is an output variable.

With the exception of input variables, each variable has an associated conditional probability distribution based on observed data or expert judgment.¹¹⁵ For example, if there is a node which represents the cost of a given decision, the probability distribution could be based on an operational cost dataset collected by the WTP. If there are no data available, a

WTP expert could estimate this distribution given their accumulated knowledge in the field. These probability distributions are considered conditional because they vary depending on the value of the parent node. Using this information, decision makers can determine the most likely value of their objectives for a given set of decisions and also understand the level of uncertainty involved in their decision. This probabilistic approach to decision-making is what sets BNs apart from most other DSSs. We illustrate this approach for a water treatment application in Fig. 5.

The inputs of the illustrative BN in Fig. 5 are influent raw water quality parameters (X_{raw}) and a set of operational or infrastructural decision variables (D). X_{raw} and D are distinct types of input variables. D is deterministic, meaning that users will define a set of their choosing. Contrastingly, X_{raw} is a random variable which represents uncertain raw water quality characteristics as a probability distribution. Based on these input variables, conditional probability distributions for three objectives—cost (O_{cost}), effluent water quality (O_{eff}), and environmental impact (O_{env})—are generated. Furthermore, a conditional probability distribution for a fourth objective, human health risk (O_{health}), is created based on its parent node O_{eff} . In this example, decision makers can determine the likely performance of various decisions and raw water qualities for the four objectives.

The stochastic nature of these models means that they explicitly handle uncertainties based on assumptions about the system. BNs are also unique in that they can incorporate stakeholder objectives and can be used to optimize the expected utility of these stated objectives. These qualities make BNs successful in fields of water management, such as water resources and environmental management.^{114,116,117} BNs are relatively simple to construct because although they are capable of representing complex systems, they do not explicitly model each process. On the other hand, if stakeholders were concerned with the detail of a specific process,

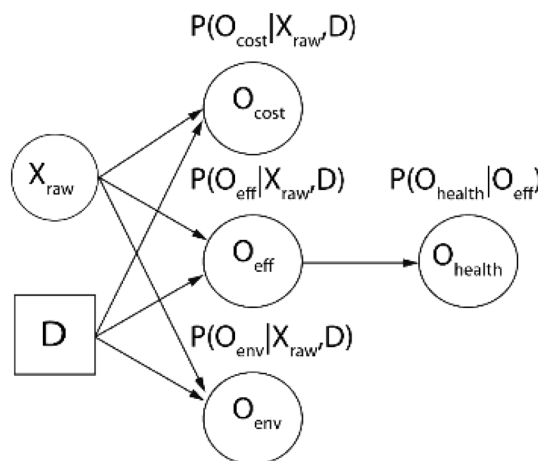


Fig. 5 Example of Bayesian network for water treatment in which probabilistic information about objectives—cost, effluent water quality, environmental impact, and human health risk—are determined based on influent raw water quality parameters (X_{raw}) and decisions (D).

BNs would not be suited for such an application. For a detailed discussion about evaluating the performance and uncertainty of BNs, see Marcot.¹¹⁸

In water treatment literature, BNs have been used to better represent the uncertainties involved in decision-making and to diagnose treatment issues. Zhu and McBean¹¹⁹ used BNs to represent the tradeoff among uncertainties in a decision maker's belief and the expected utility of infrastructural and operational decisions for multiple objectives. To quantify the benefit of various objective values, the authors created what are known as *utility functions*. Utility functions (U) represent the expected utility—between 0 and 1—that a stakeholder gains from an objective. For instance, a simple cost utility function could be represented by eqn (1).

$$U_{\text{cost}} = \begin{cases} 0.0, & O_{\text{cost}} > \$100000 \\ 0.5, & \$10000 < O_{\text{cost}} \leq \$100000 \\ 1.0, & O_{\text{cost}} \leq \$10000 \end{cases} \quad (1)$$

The decision that yields the highest utility, based on the summation of all utility functions, is the preferred solution. With regard to diagnosis, Pike¹²⁰ used BNs, which were informed by expert opinions and quantitative data, to pinpoint the cause of water quality violations at treatment plants—finding most violations could be attributed to human errors. For readers new to BNs used for water quality decision-making, Kragt¹²¹ provides concise explanations on BN theory, multiple examples of real BN applications in the field, and a comparison of applicable software.

4.3.2.3 Artificial neural networks. An artificial neural network (ANN) is an artificial intelligence method inspired by the biological nervous system.^{122,123} Constructed from multiple layers of interconnected neurons, ANNs are able to model non-linear relationships between parameters.¹²³ By training ANNs with large amounts of data, the strength of the connection between neurons adapts to minimize error between the neural network prediction value and the known parameter value. Their ability to deal with non-linear relationships makes them well-suited to predict complex water treatment processes.¹²⁴ To eliminate the need for routine jar testing for coagulation, for example, several papers suggest using ANNs to predict the optimal alum dose for plant operation.^{103,122,123,125,126} Fig. 6 represents a simplistic architecture for an ANN used for such an application.

In Fig. 6, any water quality parameters that are useful indicators of coagulant dose would serve as input nodes (e.g. turbidity, pH, color, UV₂₅₄, alkalinity, etc.). Any hidden layers—in this example there is only one—then connect the input water quality parameters to the output alum dose prediction. The performance of an ANN is dependent on the architectural parameters chosen by the modeler, such as the number of hidden layers, the number of neurons within each layer, the rate at which the model “learns”, and initial weights on the connections between neurons.¹²⁷

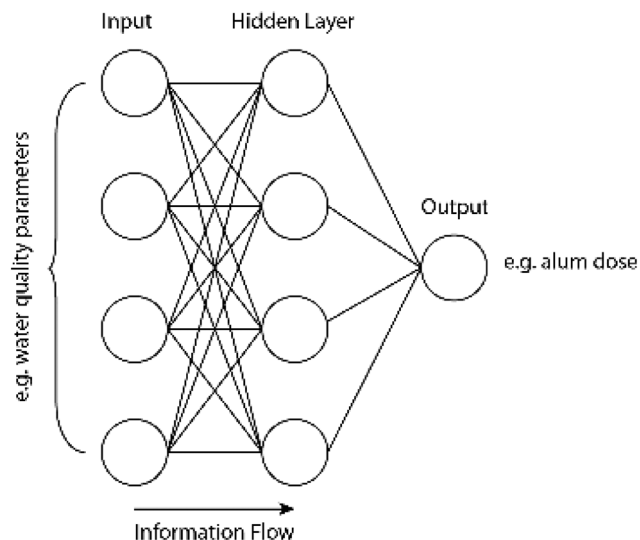


Fig. 6 Simplistic architecture of an ANN for the prediction of the optimal alum dose during coagulation.

In addition to their use in coagulant dose prediction, water treatment ANNs have been used for optimal chlorine disinfection dosage,¹²⁸ the prediction of DBPs,¹²⁹ and modeling nanofiltration^{127,130} and are generally geared toward the optimization of operations. For guidelines on developing ANNs for water treatment, we direct the interested reader to Baxter *et al.*,¹²⁴ Wu *et al.*,¹³¹ and Maier *et al.*¹³²

ANNs have the advantage of being flexible, able to handle non-linear water quality relationships, and can be used in process automation. For instance, neural networks can be trained using common operational data and can adjust predictions over time based on new data.¹²⁸ Moreover, when integrated into supervisory control and data acquisition (SCADA) systems, ANNs can inform plant operators about optimal chemical doses and chemical costs in real-time or can automate these processes directly.¹²² However, ANNs require large quantities of representative historical data to make useful predictions¹²⁸ in contrast with mechanistic models which require little input data. Furthermore, unlike mechanistic models which are grounded in the fundamental physics and chemistry behind a process, ANNs are criticized for their lack of explanatory power due to the ‘black box’ nature of their hidden layers.

5. Analysis of DSSs and recommendations for future work

The reviewed DSSs consider a wide range of decisions and objectives in water treatment for numerous time horizons. Predictive models, such as ANNs and some SMS, can aid operators in day-to-day decision-making, such as selecting optimal coagulant and disinfectant doses. Optimization using PBMs can inform least-cost designs and do not require large amounts of data to make accurate predictions. KBSs, such as case-based reasoning, can help operators troubleshoot

when a treatment plant experiences conditions beyond their level of expertise. BNs explicitly acknowledge the uncertainty involved in real-world decision-making by representing choices probabilistically. This ensemble of DSSs presents a number of options for water managers or researchers interested in computer-assisted decision-making for water treatment. However, future research in this field should be improved in a number of areas. Based on our review of DSSs for water treatment, we recommend that future work should have the following characteristics:

(1) More accurately reflect the practical needs of WTPs.

DSSs are developed, first and foremost, to inform decision makers. For this reason, DSS studies should inherently be application-oriented and include stakeholder input. However, the practical implications of these models are often overlooked in water treatment literature, as noted by Boccelli *et al.*⁸⁹ and Dharmappa *et al.*⁹⁶ These authors provide context for when DSSs—in their case, least-cost optimization PBMs—are appropriate and discuss their limitations. Moreover, Dharmappa *et al.* creates a practical framework for integrating data from bench- and pilot-scale studies into DSSs throughout the design process. Worm *et al.*⁹⁸ and Rietveld *et al.*⁹⁹ also provide good examples of practical DSS research. Their papers include discussions of the graphical user interface, a case study for DSS implementation, and additional features such as operator training support. Other DSS literature which examine practical case studies include Lindhe *et al.*,^{73,74} Poch *et al.*,⁷⁶ and Kragt.¹²¹ These examples of application-based research serve to narrow the gap between DSS theory and application.

(2) Explicitly handle uncertainty in DSSs to better inform decision makers.

There is uncertainty inherent to any DSS but few of these tools accurately express that uncertainty to the decision maker. BNs and fault tree analyses are notable exceptions; however, there are few examples of these types of DSSs that have been developed for WTPs (Table 1). To more accurately consider the uncertainty of WTP decision-making, DSSs should conduct a sensitivity analysis of the parameters, when applicable, and also consider the systematic (epistemic) and inherit variability in a system. Representing such uncertainties can be improved through techniques such as Monte Carlo simulations,^{89,90} Bayesian methods,^{119,120} and fuzzy set theory,^{107,108} but these are not always used in practice. For example, Bayesian techniques have been proposed to represent model uncertainty in ANNs without adding prohibitive computational cost but these have not been widely adopted.^{134,135}

(3) Incorporate nonstationarity in WTP DSSs, especially with regard to extreme weather events and climate change for long-term planning.

Nearly all models reviewed implicitly assume stationarity in their systems—an assumption which is challenged by climate change, population growth, water demand, and land use change. The stationarity assumption can lead to a misrepresentation of the system for long-term decision-making—sometimes in unanticipated ways. For instance, it is impor-

tant for WTPs to consider changing trends in water use, such as increased uptake water-efficient technologies, because they can cause flows to decrease in the distribution system. Subsequently, low flows increase water age and thus increase the formation of DBPs.^{136,137} Therefore, in this case, treating water demand as stationary over time would underestimate the actual risks posed to consumers.

Until recently, water treatment planners have assumed stationarity in projecting future climate. Due to the effects of anthropogenic climate change, however, stationarity can no longer be assumed.^{5–8} To prepare for possible climate futures in long-term planning, DSSs must consider the implications of nonstationary source water quality parameters and estimate their uncertainty. Nonstationarity amplifies the risk and uncertainty in our natural and manmade water systems, especially with respect to extreme weather events (*i.e.* flooding, drought, heat waves, wildfires, and cyclones).^{9,56,138–140} Thus far, as noted by Khan *et al.*,¹⁷ the impact of extreme weather events on drinking water treatment decision-making remains largely unstudied. Moreover, we also find few examples of DSS which address climate change in this review.^{71,110} There needs to be more effort directed toward the development of DSSs which consider these climatic conditions for long-term planning. By using robust decision-making techniques, creating such a DSS for long-term planning is possible.

Long-term planners often face deep uncertainty, in which decision makers do not know or cannot agree on the extents of the system, their objectives and relative weights of each, or the probability distribution for uncertain inputs to the system.^{141,142} To cope with deep uncertainty, such as when considering a nonstationary climate, decision-making should be robust, *i.e.* largely insensitive to possible future scenarios.^{143,144} Robustness can be either static, in which decision makers implement a fixed policy that will perform reasonably well in practically all conceivable situations,¹⁴² or adaptive, in which decision makers are prepared to change the policy over time, in case conditions change.^{142–144} Such strategies for decision-making under deep uncertainty are increasingly being used in the water resources domain for long-term viability of management plans and strategies,⁸² so it is likely that water treatment DSSs could benefit from these techniques.

(4) Represent the tradeoffs between the multiple competing objectives inherent to water treatment in optimization-based DSSs.

Water treatment is often described as a problem with multiple potentially conflicting goals, including minimizing cost, system failure, health risk, and environmental impact. Nonetheless, for the case of optimization, historically there has been a desire to cast the problem with a singular objective (*e.g.* minimize cost), especially if a regulation calls for a particular set of requirements that must be made. A growing body of evidence suggests, however, that a multi-objective formulation can provide a more holistic view of a problem.^{94,144} In fact, multi-objective optimization techniques have been successfully used to explore tradeoffs in related fields, such as wastewater treatment,^{145,146} water distribution

networks,^{147,148} water resources management,^{149–151} and groundwater remediation.^{152,153}

Consider the problem of designing WTPs facing extreme events. Although it would be ideal to be able to design a plant to meet regulations under all plausible conditions, doing so would make them prohibitively expensive. Therefore, it may be less advantageous to use the traditional least-cost, regulation-constrained optimization, which dictates that the system must not fail even for extreme events. In reality, a WTP that faces extreme conditions may fail in some manner, which leads to consideration of frequency-based performance objectives that have been shown to be popular in the area of water resources planning and other fields. In this case, the decision maker may care about how likely the system is to fail (reliability), how quickly it recovers from failure (resiliency), and how severe the consequences of failure may be (vulnerability).¹⁵⁴ By adding one or more of these failure metrics, the decision maker can better understand the tradeoff between cost and potential failure and make an informed decision accordingly—similar failure metrics were used in fault tree analysis of water systems in Lindhe *et al.*⁷³ While failure could also be represented as a constraint (e.g. 95% reliability) to maintain the single-objective formulation, this would mask the tradeoff between cost and reliability, which could be of interest to the stakeholder. For example, if increasing the reliability from 95% to 97% is cost-effective, the stakeholder may choose a slightly higher cost to the added reduction in risk.

(5) Use standardized terminology to accelerate the dissemination of knowledge in the field.

Lastly, we recommend that standardized terminology be developed in water and environmental management decision support literature. Because drinking water safety is an interdisciplinary field, researchers in public health, environmental and water resources engineering, and risk assessment and management, each have developed decision-making tools which cater to and use the vocabulary of their respective discipline. If a standard terminology cannot be agreed upon, the inconsistencies in wording between these similar decision-making tools, commonly under the names *decision support systems* or *risk assessment tools*, should at least be noted in the literature. Even within reviews of DSSs, there is little consistency in terminology regarding DSS architecture and development frameworks. These inconsistencies in language make it difficult for researchers to find relevant literature and slows progress.¹⁵⁵ We hope that the interdisciplinary nature of this critical review may improve the connectedness of the literature and begins a discussion toward more uniform terminology in water and environmental management decision support.

6. Conclusions

Climate change and shifting climate extremes have been shown to degrade source water quality. Consequently, these changes are expected to adversely impact the performance of WTPs. In response, WTPs are seeking better approaches for

long-term planning and risk management.¹⁸ This paper highlighted how DSSs can be improved to tackle these complex issues. In the process, we critically reviewed DSSs in water treatment more generally in an effort to improve the field as a whole. We found that relative to other branches of water and environmental management, water treatment DSSs receive little attention. Given the complexity nonstationarity adds to decision-making, however, DSSs are more relevant to water treatment than ever. Water planners could benefit from increased uptake of, and improvement upon, water treatment DSSs, especially with regard to long-term planning. Advancements in these DSSs can be informed by the literature referenced in this paper and our recommendations for future work.

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