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Beyond engineering: A review of reservoir management through the lens of wickedness, competing objectives and uncertainty

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ABSTRACT

Traditionally, reservoir management has been synonymous with the operation of engineering infrastructure systems, with the majority of literature on the topic focusing on strategies that optimize their operation and control. This is despite the fact that reservoirs have major impacts on society and the environment, and the mechanics of how to best manage a reservoir are often overshadowed by both environmental changes and higher-order questions associated with societal values, risk appetite and politics, which are highly uncertain and to which there are no "correct" answers. As a result, reservoirs have attracted more controversy than any other type of water infrastructure. In this paper, we address these often-ignored issues by providing a review of reservoir management through the lens of wickedness, competing objectives and uncertainty. We highlight the challenges associated with reservoir management and identify research efforts required to ensure these systems best serve society and the environment into the future.

1. Introduction

Arguably, there is no other type of water infrastructure in the world that has attracted more controversy than reservoirs and dams. On the one hand, these systems have been used by many civilizations for over 5000 years to provide various services, from traditional water supply and irrigation (Panagopoulos & Giannika, 2023) to flood control and mitigation, and more recently to hydro-power generation and environmental water management (McCully, 1996; MDBA, 2021). And there is renewed interest in dam construction due to the ever-increasing demand for water and power (World Bank, 2009). On the other hand, the construction of large dams is heavily criticized, due to not only their high cost but also the increased awareness of the associated social and environmental impacts that cannot be easily assessed in monetary terms (Ho et al., 2017; World Commission on Dams, 2000). The way reservoirs are managed adds to this controversy, as reservoirs often serve competing purposes (e.g., water supply security and flood mitigation) and the way they perform is governed by subjective decisions about potential tradeoffs in the face of imperfect information and uncertainty in both the natural environment and human society. Therefore, reservoir management, which includes operation, maintenance, rehabilitation, redevelopment or repurposing of existing reservoir systems, has been referred to as a wicked problem (Lund, 2012; Mamatova et al., 2016; Reed and Kasprzyk, 2009).)

Given their far-reaching impacts on sustainability, their multiple and competing management objectives that are often associated with diverse societal values, risk appetite and politics (i.e. the wickedness of the problem), and the deeply uncertain future environmental processes (e.g. climate change) that affect their management, it is surprising that the majority of previous reviews on how to manage reservoir systems have been rather narrowly focused on solution techniques and models (Fayaed et al., 2013; Hossain and El-shafie, 2013; Milanović and Vasić, 2021; Simonovic, 1992; Wurbs, 1993; Yakowitz, 1982; Yeh, 1985), often targeting the operation of reservoirs (Ahmad et al., 2014; Dobson et al., 2019; Parvez et al., 2019). There are only limited reviews that have looked at other aspects of reservoir management, such as climate change

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impact (Şen, 2021), problem formulation of reservoir optimization (Giuliani et al., 2021), and river ecological management (Barbour et al., 2016). However, the full set of challenges associated with reservoir management due to its wicked nature has not been reviewed thus far. Consequently, the objectives of this paper are to 1) present an overview of the key challenges in reservoir management through the lens of wickedness, competing objectives and uncertainty; 2) provide a review of how these challenges have been addressed historically and at present; and 3) identify key areas where research efforts need to be directed in order to better manage reservoir systems to serve the needs of society and the environment into the future.

The rest of this paper is organized as follows. The characteristics of wicked problems and the challenges to reservoir management arising from this wickedness are presented in section 2. Section 3 critically reviews the various approaches that have been used to address these challenges. The next section discusses the direction of future research needed. Finally, conclusions are presented in section 5.

2. What are the challenges in reservoir management?

The management of reservoir systems is a very complex issue and is often considered a wicked problem (Mamatova et al., 2016). In order to understand the "wickedness of reservoir management", one needs first to understand what a wicked problem is. The concept of wicked problems was first introduced in social planning by Churchman (1967) as "a class of social system problems that are ill-formulated, where the information is confusing, where there are many clients and decision makers with conflicting values, and where the ramifications in the whole system are thoroughly confusing". Therefore, these problems are difficult to define and, arguably, can never be completely solved, as opposed to "tame" problems that can be solved using methods developed in the fields of engineering or the physical sciences (Rittel and Webber, 1973). Typically, wicked problems in any given area can be defined by several characteristics (Conklin, 2006), which include 1) they do not have a definitive formulation (e.g., definition of system boundary, management objectives and potential actions); 2) they do not have a final unique solution; 3) no solution is completely right or wrong; 4) there is no fixed number of alternative solutions; and 5) every problem is unique, and so is every solution. As a result, the solution to a wicked problem is often subject to significant uncertainty in environmental processes in the future (e.g., due to climate change) and dependent on the formulation of the problem. The latter can be highly variable due to the potentially drastically different views and values of the stakeholders involved (note, stakeholders in this study include analysts, decision makers, experts, and the public and other stakeholders following the definition by Wu et al. (2016), and therefore stakeholders are potentially involved in all aspects of a solution process) (Badham et al., 2019). The formulation of the problem (and therefore its possible solutions) can also change with time due to changes in both the physical system, the physical environment surrounding it and/or its social and political environment, such as stakeholder preferences and government policies. Consequently, a wicked problem is never solved definitively (Mamatova et al., 2016).

To illustrate the "wickedness" and challenges associated with solving reservoir management problems, consider the 2021 Eastern Australia floods as an example. In late March 2021, the heaviest rain since 1961 fell over a five-day period in the Nepean and Hawkesbury catchments in western New South Wales (NSW), Australia. The heavy rainfall caused the worst flooding in 60 years in Sydney, the largest city in Australia (Smith, 2021). Sydney's main dam – the Warragamba Dam - spilled, releasing 450gigaliters (GL) of water a day downstream, which is nearly the capacity of Sydney Harbor (Gralow and Jose, 2021). Across the state of NSW, over 40,000 people were affected by evacuation orders (Nguyen and Stuart, 2021) and nearly $500 million in damages were reported (Dye, 2021). The flood caused heated debate between the NSW Emergency Services Minister and the Water Minister on the operation of Warragamba dam, arguing whether or not the dam should have been drained to just 20–25% of its capacity based on weather forecasts before the floods (Smith, 2021). However, weather forecasts are largely uncertain and if the dam had been drained and the rain did not come, Sydney could have run out of water. The flood also raised questions about what should be done to prepare for similar events in the future, which are becoming increasingly likely due to climate change. There is currently a proposal to increase the height of the dam wall by 14–17 m, which will create another 1000 GL storage on top of the current 2000 GL storage available for flood mitigation (9 NEWS, 2021). However, raising the dam wall will not only have significant environmental and cultural impacts upstream, but may also inflate the perception of flood immunity downstream, thereby encouraging further development in the floodplain and actually increasing flood risk. As an alternative extreme view, people have questioned whether there will be a day when the dam will need to be removed due to the high costs associated with maintaining the aging infrastructure or the need to restore the damaged river on which it is located. This dam removal trend has been observed in the USA (Ryan Bellmore et al., 2017), where more than 1700 dams have been removed since 1912 (Cherney, 2020). Although the Warragamba Dam example is from Australia, there are examples from all around the world that demonstrate similar challenges of reservoir management (Flecker et al., 2022; Hein et al., 2019; Holdren and Turner, 2010; Tran et al., 2019).

As elucidated in the example above, the challenges of reservoir management, which includes the operation, maintenance, rehabilitation, redevelopment, or repurposing of existing reservoir systems, can be grouped into four categories. The first three categories are defined based on the needs of reservoir management to consider 1) multiple uses and competing management objectives (e.g., water supply and flood mitigation in the Warragamba Dam example), 2) stochastic uncertainty (e.g., in weather forecasts in the Warragamba Dam example - also see BOX 1) and 3) deep uncertainty (e.g., climate change and differences in stakeholders' views in the Warragamba Dam example - also see BOX 1). Reservoir management problems can be further complicated by the interactions between these three challenges, which is defined as the fourth category of challenges in this paper. Details of these four categories of challenges in reservoir management and the extent to which they have been considered in past studies are discussed in this section.

2.1. Multiple purposes, management objectives and jurisdictions

The first challenge is that reservoirs often serve multiple purposes, and that the management of reservoirs often requires the need to satisfy multiple, often competing, objectives that may change over the life of the reservoir system. In this context, it is important to clearly distinguish between multiple purposes and multiple objectives. Although, globally, the majority of dams are built for a single purpose, such as water supply (10.4% of large dams in the world), agricultural irrigation (27%) or hydro-electrical power generation (25%), close to a third of reservoirs cater to multiple design purposes, such as water supply and flood control or irrigation and hydropower generation (McMahon and Petheram, 2020). In addition, many reservoirs are also used for recreation in addition to their primary design purpose(s) (Speirs, 2019). In general, management objectives are directly related to reservoir performance. For example, achieving water supply security is a typical management objective of a reservoir built for water supply. These reservoir management objectives are often related to different priorities regarding economic efficiency, equity and environmental sustainability, which are often conflicting (Jakeman et al., 2016; Molle, 2008).

A further complicating factor is that many of the large river basins and reservoir systems in the world are multi-national (Beck et al., 2014). In this case, the objectives of each of the countries involved may be conflicting. The best way to deal with these problems is through international treaties or agreements for sharing water resources (Brochmann, 2012). However, many large international river basins do not have such agreements in place (Song and Whittington, 2004). Consequently, the remainder of this section deals with the management of reservoirs that are operated by a single country.

Multi-purpose management of reservoirs can be evaluated in either a single or a multiple objective framework. For example, water supply, irrigation and power generation can all be included in an economic framework where all decisions are evaluated in terms of the single objective of maximizing net economic benefits (Hu et al., 2015). More commonly, reservoir management solutions are evaluated in terms of multiple and often competing objectives, such as increasing water supply security, reducing flood risk or maximizing hydroelectric power generation. For example, Hakimi-Asiabar et al. (2010) considered the operation of a three-reservoir system in Iran intended for the supply of water for domestic and agricultural purposes, hydropower generation and controlling river water quality. They undertook multi-objective optimization using the following three objectives: minimizing unsatisfied water demand, maximizing power generation, and minimizing the volume of diverted river flows and wastewater to control salinity in the river.

Furthermore, reservoir management objectives can be much broader than those considered in the initial reservoir design. This is first because reservoir management objectives associated with operation, maintenance, rehabilitation, or redevelopment often have to be considered, especially for older reservoir systems. For example, the minimization of dam failure risk needs to be considered through regular maintenance work (Mihnea et al., 2008) or recovery of storage volumes through reservoir rehabilitation processes (De Vincenzo et al., 2017). In addition, unexpected changes external to the reservoir system, such as climate change, may lead to degradation in the level of service (e.g. flood protection level) the reservoir system is intended to provide. Therefore, rehabilitation or redevelopment may be required to restore the service level (Jun et al., 2020). Other management objectives can come to the fore over time due to improved understanding in science or a changed social or political environment, which often manifests itself as changed stakeholders' views. For example, the Hume Dam in Australia was initially constructed in 1936 for water supply and irrigation. However, it is now primarily used for regulating and conserving water for both human consumption and the environment, with secondary uses of hydroelectric power generation and flood mitigation. This change is mainly due to the increased awareness of environmental issues in the Murray Darling Basin (MDBA, 2021). As a result, the management objectives for Hume dam have evolved from simply increasing water supply security to pursuing multiple economic, environmental, and social objectives.

These reservoir management objectives are often conflicting (Salas and Hall, 1983). For example, a limited drawdown level is required to increase water supply security, providing a higher probability of meeting demand in future droughts (e.g., for human consumption, irrigation, or environmental flow). However, this reduces the "free space" available to attenuate the peaks of incoming floods, thus increasing future flood risk (Cheng et al., 2017). Another example relates to the potential conflict of providing water for human needs while maintaining environmental flows in the river system (Derepasko et al., 2021). Prioritizing one objective over the other(s) without understanding the full impact may result in undesirable (or unintended) outcomes (Derepasko et al., 2021; Hwang and Masud, 1979; Perera et al., 2021; Razavi et al., 2020; Wu et al., 2010). Therefore, a multi-objective approach is often required to identify Pareto optimal solutions that characterize the tradeoffs between competing objectives of reservoir management (Barbour et al., 2016; Changchit and Terrell, 1993; Giuliani et al., 2014a; Horne et al., 2016; Tsoukalas and Makropoulos, 2015; Wu et al., 2022).

Many reservoir management objectives, especially those acquired over time after initial construction, can be difficult to quantify and therefore difficult to formulate using traditional engineering methods such as mathematical models. Examples of such objectives include cultural conservation objectives (Davies et al., 2021), ecological management objectives (Barbour et al., 2016; Derepasko et al., 2021), as well as benefits sharing between different countries if reservoirs are located on international rivers (Mamatova et al., 2016). These objectives contribute to the wickedness of reservoir management problems and represent an important emerging challenge in reservoir management.

2.2. Stochastic uncertainty

Some reservoir management decisions, such as operational decisions about when to release water and by how much, are typically made on a sub-daily or daily basis. However, the impacts of these decisions may not eventuate until several days or months after the decisions are made (Cheng et al., 2017; Li et al., 2018; Wu et al., 2022). For example, it may take several days or weeks for water released to travel to downstream locations where the impact is realized. Therefore, these decisions are subject to uncertainty during the time between water release and impact realization. A similar situation arises when deciding to prerelease water from a reservoir in anticipation of a future flooding event as the actual volume and peak of the future flood is uncertain. This uncertainty is mainly due to natural variability in system inputs, such as rainfall, soil moisture, inflow, evaporation, and demand during the travel time of water and is referred to as stochastic uncertainty (see Box 1 for definition). Stochastic uncertainty is generally applied over a shorter time scale in the immediate future (e.g., from several days to several months), rather than the service life of reservoirs (e.g., 50–100 years). This is because most of the studies looking into uncertainty and its impact on system performance in the immediate future, such as reservoir operation studies, are more concerned with stochastic uncertainty. However, in some recent studies, stochastic uncertainty has also been used to characterize natural variability in system inputs under given future conditions due to long-term drivers such as climate change (Kiem et al., 2021).

Reservoir inflow (or input variables affecting inflow, such as rainfall) is undisputedly the most commonly considered source of stochastic uncertainty in reservoir management, and has been considered in all papers reviewed on this topic, including studies by Chaves et al. (2004), Mortazavi et al. (2012), Bekri et al. (2015), Tsoukalas and Makropoulos (2015), Pan et al. (2015), Cote and Leconte (2016), Sahu and McLaughlin (2018), Ramaswamy and Saleh (2020), Hooshyar et al. (2020), Celeste et al. (2021), Muronda et al. (2021) and Wu et al. (2022). Other sources of stochastic uncertainty, such as temperature (Bekri et al., 2015), evaporation (Ortiz-Partida et al., 2019), demand (Soleimani et al., 2016), storage level and release (Huang et al., 2018), as well as model parameterization (Bekri et al., 2015), have also been considered in several studies. In contrast, soil moisture, which has recently been found to have a significant impact on the generation of stream flows and therefore reservoir management (Sharma et al., 2018), has not been considered as a source of stochastic uncertainty for reservoir management.

Stochastic uncertainty can be quantified explicitly and therefore incorporated in mathematical models relatively easily (Cote and Leconte, 2016; Mujumdar and Nirmala, 2007; Wu et al., 2020a), facilitating its inclusion in solving reservoir management problems. However, in some studies the variability of system inputs due to stochastic uncertainty is generated based on short historical records, which cannot provide meaningful evaluation of extreme events, such as extreme floods or droughts. Failure to consider all important sources of stochastic uncertainty or the whole range of variability due to stochastic uncertainty may lead to biased assessment of system performance and thus ill-informed decisions.

2.3. Deep uncertainty

The management of water infrastructure, including reservoirs, is also subject to deep uncertainty (see Box 1 for definition). These systems have traditionally been designed and operated under the assumption of

BOX 1
Stochastic and deep uncertainty

In this paper, stochastic uncertainty refers to uncertainty that results from natural variability in inputs (e.g., rainfall due to climate variability) and uncertainty in model parameters and structures (Duan et al., 2019). This type of uncertainty can be quantified using traditional mathematical methods such as probability distributions (Nair and Sasikumar, 2019), ensemble predictions (Ramaswamy and Saleh, 2020; Wu et al., 2020a) or error models (Bennett et al., 2021). Stochastic uncertainty is associated with an uncertain, but single, plausible future (Maier et al., 2016).

Deep uncertainty refers to uncertainty due to the existence of multiple plausible futures (Lempert et al., 2003; Maier et al., 2016). It is widely recognized that deep uncertainty can result from long-term unknowns such as climate change, social-economic development, technological advances, and political reforms (Maier et al., 2016). Underpinned by the existence of multiple plausible futures, deep uncertainty can also arise from human involvement. This is mainly due to the radically different values and views various stakeholders may hold and the fact that only a limited number of stakeholders can be involved in problem formulation (e.g., the definition of system boundaries, management objectives and potential actions) and solution processes (Wu et al., 2016). Stakeholder values and views can also change with time (Mamatova et al., 2016). These multiple plausible futures often cannot be represented using a single model, and therefore are often evaluated using scenario-based approaches (BOX 2) (Maier et al., 2016). Stochastic and deep uncertainty often affect various stages of the systems approach, as illustrated in Fig. B1.

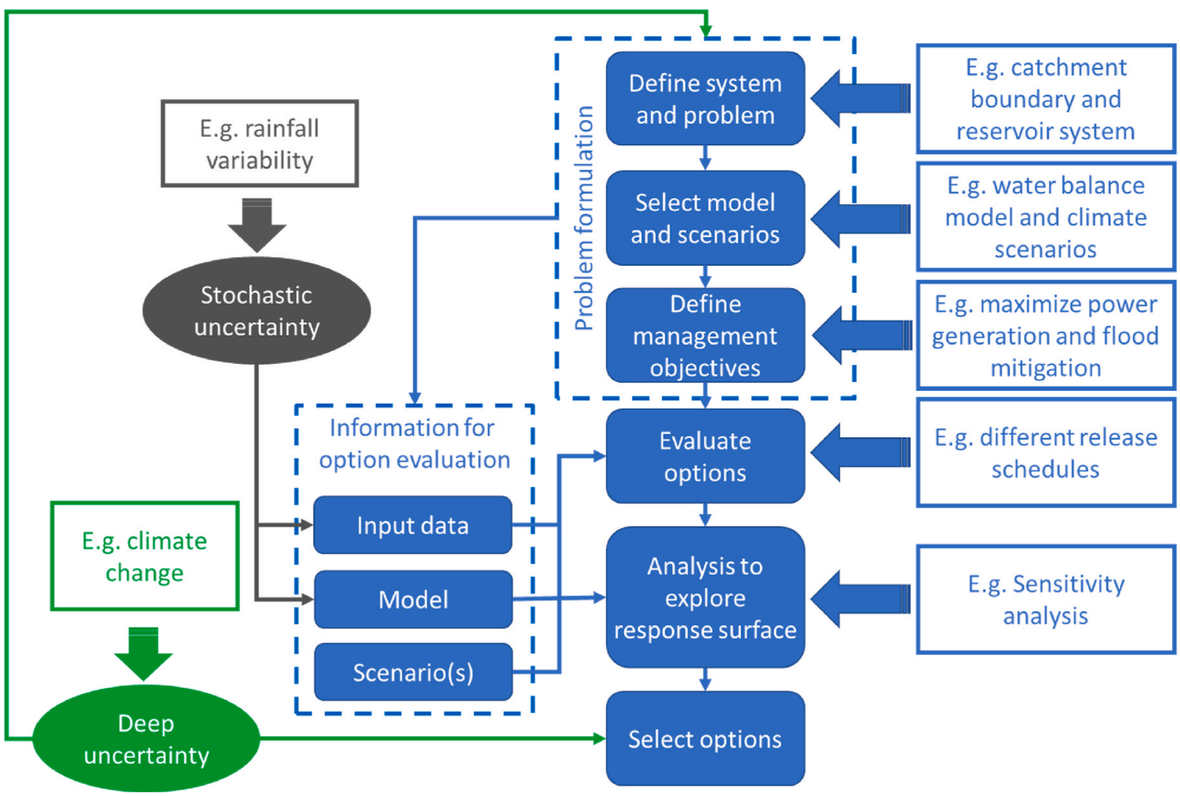

Fig. B1. Potential influence of stochastic and deep uncertainty on the systems approach for solving environmental engineering problems, with reservoir management as an example (Adapted from Biswas (1976)).

stationarity, typically climate stationarity. As a result, system states are often represented by exogeneous variables that fluctuate within a constant envelope of variability (i.e., stochastic uncertainty due to natural variability, as discussed above), and therefore their plausible future states can be represented using past observations (Milly et al., 2008). While reservoir operation models based on historical observations help simulate past conditions, they may fail to simulate system performance in the distant future due to unknown values of these exogeneous variables (Giudici et al., 2021). These long-term unknowns due to long-term changes such as climate change, demographic change, technological development, intersectoral and global policy changes, and the compound effects of their interactions, are the first source of deep uncertainty (Maier et al., 2016; Wu et al., 2020b). Consequently, it is vital to understand which plausible future conditions have the biggest impact on system performance (Culley et al., 2021; Giudici et al., 2020). In addition, the cascading effects of these drivers of change need to be considered, such as the impact of climate change on wildfires (Partington et al., 2022), which have an impact on catchment conditions and runoff, and hence on reservoir inflows and performance.

Apart from the long-term unknowns in the future, deep uncertainty also arises from the inherent wickedness of reservoir management problems themselves. For example, in any analysis involving reservoir systems, the formulation of the problem that needs to be solved (e.g., the definition of system boundaries, management objectives and potential actions), and the outcomes of interest and their relative importance, are dependent on stakeholders' (typically decision makers') preferences. There are potentially radically different values and views of stakeholders (including decision makers, analysts, brokers, experts and the public (Wu et al., 2016)). As there can only be a limited number of stakeholders involved for each problem formulation, the level of agreement reached by stakeholders is deeply uncertain depending on the sample of stakeholders involved at different stages of the solution process (Di Matteo et al., 2019; Lempert et al., 2003). This leads to multiple alternative system boundaries, models, objectives and potential solutions, as well as alternative rankings of the solutions (Kwakkel et al., 2016), and therefore multiple plausible futures. In addition, stakeholders' values and views can also change over time due to improved understanding in science and changed social or political environments, further contributing to deep uncertainty. For example, Mamatova et al. (2016) showed that the operating rules of reservoirs that were constructed during the Soviet Union period needed to be revisited after the independence of the Central Asian countries in order to cater to new socio-political conditions and transboundary water agreements.

Under deep uncertainty, traditional "predict-and-plan" management strategies derived without considering the different plausible futures have become obsolete (Brown et al., 2012; Herman et al., 2016; Razavi et al., 2020; Weaver et al., 2013). In addition, consideration of deep uncertainty generally also requires the use of alternative system performance metrics, primarily based on the concept of robustness (McPhail et al., 2018, 2021). Neglecting deep uncertainty due to long-term unknowns in exogeneous variables may have irreversible consequences for water-dependent sectors, for example leading to flooding of homes and irreversible damage to people's lives, expensive infrastructure upgrades well before these upgrades are required, or even premature system failure (Culley et al., 2016). Such consequences can also extend to the rest of the economy through ripple effects (Eamen et al., 2021; Hall et al., 2014). In addition, solutions developed based on preferences and views of a single sample of stakeholders at a single snapshot in time may fail to cater to other stakeholders' preferences and changing preferences with time, thereby causing possible conflicts.

2.4. Interactions between management objectives, and stochastic and deep uncertainty

The three challenges of reservoir management introduced above cannot be considered in isolation, as they often interact with each other in practice, which further increases the complexity of reservoir management problems. The interactions between the three challenges of reservoir management and examples of how they may impact the solution process are illustrated in Fig. 1.

The interactions between stochastic uncertainty and the other two challenges (e.g., multiple managment objectives and deep uncertainty) are reasonably straightforward to address, given stochastic uncertainty mainly results from natural variability in system inputs and therefore can be quantified using existing mathematical methods such as probabilistic distributions or ensemble forecasts, as mentioned previously. When the management objectives are also quantifiable using mathematical models, the tradeoffs between different objectives are often represented as non-dominated solutions on a Pareto optimal front that can be obtained using the traditional engineering approach of simulation and optimization modeling. The consideration of stochastic uncertainty in addition to multi-objective tradeoffs means that the Pareto optimal front formed by the objective function values of management decisions is no longer deterministic (as shown in the top rectangular box in Fig. 1), but probabilistic (as shown in the top-left oval in Fig. 1). Consequently, a range of performance values (represented by the gray shaded area in Fig. 1), instead of a single value, is to be expected for any solution considering stochastic uncertainty. When the management objectives cannot be quantified using mathematical models (e.g., due to deep uncertainty as discussed above), new methods, for example methods based on qualitative assessments, are required to account for the joint impact of uncertainty and these objectives on potential solutions. Similarly, the consideration of stochastic uncertainty, in addition to deep uncertainty, introduces probabilistic information into the scenarios representing plausible futures, as illustrated in the bottom oval in Fig. 1.

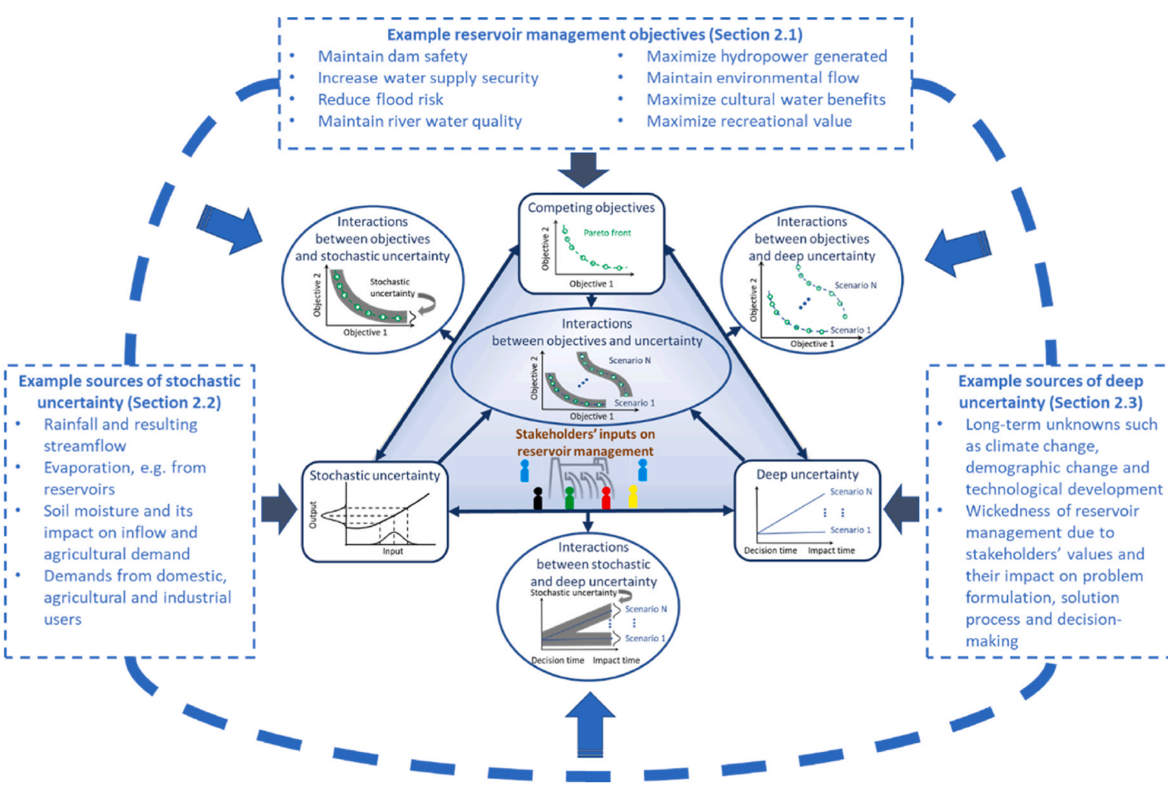

Fig. 1. Examples of interactions between multiple and often competing management objectives and stochastic and deep uncertainty for reservoir management.

The interactions between management objectives and deep uncertainty can lead to some of the most difficult challenges in solving reservoir management problems. When the objectives are quantifiable using mathematical models, these challenges are less acute, as intuitive solution methods can be used, such as considering either the tradeoffs between competing management objectives within each scenario representing different plausible futures (as shown in the top right oval in Fig. 1) or across the scenarios using, for example, a scenario-neutral approach (Culley et al., 2016; Danner et al., 2017). However, this is often not the case for real-world reservoir management applications, the objectives of which can sometimes be difficult to quantify due to the wickedness of the problem arising from stakeholders' involvement and their differing values.

In addition, new management objectives may emerge over time as some of the long-term impacts of dams, such as land and coast erosion, water quality degradation and groundwater depletion (and thus drying out floodplains downstream of the dam), may only become apparent many years after the construction of the dams (McCully, 1996). Also, as science develops over time, new methods will be developed that enable the evaluation of management objectives that could not be quantified previously. Reservoir management problem formulation, especially formulation of objectives, may also evolve over time due to changed stakeholder views and values, typically influenced by changes in social and political environments. Consequently, the interactions between management objectives and deep uncertainty mean that each scenario representing a plausible future can no longer be formulated as a fixed (or static) pathway leading to a single destiny into the future, but as a dynamic pathway leading to a number of plausible futures.

Finally, the interactions between all three challenges will further complicate reservoir management problems, as the tradeoffs between different management objectives need to be evaluated across different scenarios, as well as considering the fluctuation in system states within these scenarios; and the system states within these scenarios may also change with time. Thus, the solution process will become more complex, and the computational cost associated with the identification of suitable solutions is also likely to increase accordingly.

3. How can challenges in reservoir management be addressed?

3.1. Methods to incorporate multiple and competing objectives

3.1.1. Methods to incorporate multiple competing objectives in optimization

As mentioned in Section 2.1, most reservoir management problems are multi-objective. In those cases where a single objective can be clearly defined, and good models of the system are available, single objective optimization techniques can be applied to find the best solution. An example of this is when the reservoir is operated for a single purpose such as water supply for a local community and the objective is to minimize the probability of having to impose severe restrictions. Another example is when all objectives can be expressed in dollar terms (e.g., hydropower production and releases for agriculture) and the objective is to maximize the net economic benefits of system operation. However, reservoirs are typically managed for multiple purposes with competing objectives and the issue arises as to how to identify the best set of solutions. A number of potential classes of techniques for dealing with multi-objective problems are discussed below.

One of the simplest techniques used is to reduce a multi-objective problem to a single objective problem, for example by using a weighted sum method (Ehteram et al., 2018; Zhu et al., 2018). This technique is easy to explain and easy for stakeholders to understand. Solving a single objective optimization problem is significantly easier than solving a multi-objective problem, although this depends on the degree of convexity of the constraints. The disadvantages of this approach, however, include the fact that weights need to be selected before the relative achievement of each objective is known, and the impact of the weights on the final solution obtained is often not considered. It is possible to carry out sensitivity analysis on these weights (Hyde and Maier, 2006), but this becomes more difficult when there are three or more objectives because of the large number of combinations involved.

Another relatively simple technique for dealing with multiple objectives is to change all of the objectives except one into constraints and set minimum or maximum desired levels for each (Porse et al., 2015). Like the previous approach, this is easy to explain and easy for stakeholders to understand. It reduces a multi-objective optimization problem to a single objective problem and so is relatively easy to solve. However, it suffers from similar disadvantages to the previous technique in that the target levels for all but one of the objectives need to be specified *a priori* and it is difficult to carry out sensitivity analysis on these targets for problems with three or more objectives.

Goal programming is an alternative technique to reduce the complexity of multi-objective optimization problems. It has some similarities with the constraint technique in that targets (or goals) need to be set for each objective (Xevi and Khan, 2005). A single objective optimization model is then set up to minimize weighted deviations from these goals. Relative weights can be set for each goal and the penalties for each goal can be set for overachievement and/or underachievement. This technique is more difficult for stakeholders to understand than the previous two techniques and has the disadvantage that targets and weights both need to be set for all objectives, and it is, therefore, more difficult to implement in practice. It is also difficult to carry out sensitivity analysis for all of the targets and weights for problems with three or more objectives.

Another class of techniques that can be used to solve multi-objective reservoir management problems is based on choosing a solution that is the minimum distance from an ideal solution in objective space. Examples of these techniques include Compromise Programming (Wu et al., 2017) and TOPSIS (Shiau and Wu, 2013). The ideal solution is one that simultaneously achieves the best possible value of all objectives. As this can rarely be achieved in practice, compromises between the various objectives need to be made. In Compromise Programming, weights are put on the distance that each objective is from the ideal solution. The distance can be measured in various ways (e.g., Euclidean distance or city block distance). The multi-objective problem is therefore transformed into a series of single objective optimization problems. TOPSIS is similar to Compromise Programming, except that a solution is chosen based on the scaled distance between the ideal solution and the worst possible solution. Both methods can be difficult for stakeholders to understand, and both require the selection of weights for each objective.

The final class of techniques is genuine multi-/many-objective optimization, which involves identifying the full Pareto optimal surface between all objectives (Chakraei et al., 2021; Hakimi-Asiabar et al., 2010). Many-objective optimization is a term applied to cases with four or more objectives. A set of techniques that is commonly used to identify Pareto optimal surface involves multi-objective evolutionary optimization. This approach was used by Wu et al. (2017) for a water resources planning problem that included reservoir operations with four objectives and Zatarain Salazar et al. (2016) for a reservoir operations problem with six objectives. This approach generally requires considerable computing power, especially for cases with more than three objectives. In addition, the increased dimensionality of the resulting Pareto fronts presents new challenges in communicating the results to decision makers and other stakeholders. Therefore, results interpretation methods, such as the OpenMORDM developed by Hadka et al. (2015) and the many-objective visualization methods developed by Kasprzyk et al. (2013), have been adopted to assist with this task.

3.1.2. Methods to account for environmental and social objectives

A key motivation for using multiple objectives in reservoir management arises when environmental and social objectives compete with economic objectives. Valuing environmental and social outcomes in monetary terms is fraught with difficulty, as it can be highly subjective and biased (Conklin, 2006). While working directly with environmental and social objectives avoids monetization, there remain fundamentally difficult challenges.

3.1.2.1. Accounting for environmental objectives. The construction and operation of large reservoirs can have a significant impact on the local environment, which need to be considered (Best, 2019; Flecker et al., 2022). Potential environmental objectives of reservoir management include a wide range of considerations, such as flow regimes and water quality, that have an impact on ecological outcomes of the river system. In their review of optimization in managing river ecosystems, Barbour et al. (2016) identified four challenges, two of which are of particular relevance here: specification of ecosystem objectives, and inclusion of ecosystem behavior in simulation models. Ecosystems represent a complex interacting web of organisms producing a diverse range of outcomes. However, the reviews of Barbour et al. (2016) and Horne et al. (2016) make it clear that there is no broad consensus on how to value a collection of diverse ecological outcomes. The response to this problem therefore involves implementation of a (possibly implicit) strategy that reduces the dimensionality of the valuation until it is deemed to be meaningful and manageable. This is a subjective process guided by the scientific knowledge and beliefs of experts and values of stakeholders.

In the context of reservoir management, the focus of existing studies is often on flow-dependent ecosystems. Two broad approaches (Barbour et al., 2016) have been developed to make valuation meaningful and manageable for decision makers. The first uses an indirect (or proxy) approach, which relies on targeting system states that can be modeled and managed and that are associated with ecological outcomes. The flow-based approach (Poff et al., 2015) uses flow regime as the proxy. The target (or baseline) ecological outcome is associated with a natural (unimpaired) flow regime with ecological decline represented by deviations from the baseline. The primary advantage of this approach is that it does not require specific knowledge of the ecosystems in the reaches impacted by river regulation. However, for deviations from the baseline to be meaningful, there has to be an *a priori* corpus of scientific knowledge that documents the association between flow regime deviations and some measure of ecological decline in ecosystems similar to that under consideration. Characterizing a flow regime potentially involves many metrics that have ecological significance such as duration, magnitude, flashiness, seasonality and so on. As a result, the problem of high dimensionality in valuation arises. There is a significant amount of literature on selection of metrics and their aggregation (e.g., IHA, RVA by Richter et al. (1997), and ELOAH by Poff et al. (2010)).

The second approach to valuation directly targets a set of ecological outcomes. Once again, the dimensionality problem has to be managed, requiring for example, the number of locations and species, to be manageable. In principle, directly targeting ecological outcomes of importance to stakeholders appears superior to the proxy approach. However, this greater specificity comes at a cost. The direct approach requires inclusion of an ecological response model within the simulation of the river system. This model takes endogenous inputs from the river system model (which are controlled to some degree by operators) and exogenous inputs to simulate ecological outcomes of interest (e.g., the Murray flow assessment tool in Young et al. (2003) and the eco-hydrology model in Nichols et al. (2017)). An implicit assumption is made that the proxy or direct approach has sufficient skill to predict ecological outcomes meaningfully (Rigosi and Rueda, 2012). This is particularly important if optimization is used (Szemis et al., 2013, 2014). If the optimization does not "see" the true uncertainty in the ecological response to control, it will be over-confident and lead to poor solutions (Ascough et al., 2008). Barbour et al. (2016) and Horne et al. (2016) commented on the lack of adoption of optimization methods in practice. As a result, there has been no opportunity to compare modeled and field outcomes to assess the credibility of the process.

In addition to flow-depended ecological objectives, water quality is another environmental objective that is important for reservoir management and it is often considered in reservoir operation related studies (Chaves and Kojiri, 2007; Kerachian and Karamouz, 2006; Rieker and Labadie, 2012; Saadatpour et al., 2020). There is a large body of literature on reservoir operation optimization considering water quality objectives, where a number of water quality variables are considered. They include oxygen level related variables such as dissolved oxygen and biochemical oxygen demand (Chaves and Kojiri, 2007; Chaves et al., 2004; Saadatpour et al., 2020), concentration of organic matter or nutrient loads using variables such as total nitrogen and total phosphorus (Chaves and Kojiri, 2007; Chaves et al., 2004), waste load discharge (Hakimi-Asiabar et al., 2010; Maeda et al., 2010), salinity (Galelli et al., 2015; Hakimi-Asiabar et al., 2010; Kerachian and Karamouz, 2006), sediment transport (Flecker et al., 2022), and temperature (Galelli et al., 2015; He et al., 2022; Rieker and Labadie, 2012). These are all important indicators of ecological health of the water body. In the vast majority of these studies, a simulation-optimization-based framework is used to optimize reservoir operation, where either a process-based or surrogate water quality model is used to simulate the system and estimate the values of the water quality variables.

3.1.2.2. Accounting for social objectives. Social objectives in water management can include a wide range of measures such as fairness and equity, political and legal feasibility and human health (Hajkowicz and Collins, 2007). The first challenge in incorporating social objectives in reservoir management is that they are difficult to quantify. Several studies have used surrogate measures as social objectives or constraints in optimization models. For example, Yu et al. (2021) used the deficit and excessive socio-economic water demand in the region as a social objective in a model for the optimal operation of the Three Gorges dam in China. Castelletti et al. (2008) included constraints to ensure that various water users each received an adequate share of the allocated water in a general model for the operation of a multiple reservoir system.

The second challenge arises when fairness and equity need to be considered. For example, an important social objective is the equitable distribution of the benefits and costs resulting from reservoir operation. It is common to maximize the net economic benefits of reservoir operation regardless of who benefits and who incurs the costs (Emami et al., 2021). When net economic benefits are maximized, it is assumed that these benefits and costs can be distributed among members of society via costless transfers. In fact, such transfers are not costless, and in practice, rarely, if ever take place (Dandy et al., 2018). For this reason, the equitable distribution of the benefits and costs of reservoir operation among members of society should be considered as an objective. This is demonstrated by Tiwari et al. (1999), where the distribution of the net present value of a reservoir system to the government, farmers and society are considered as three separate objectives in an optimization model.

3.1.3. *Methods to deal with multi-national reservoir systems*

As mentioned in Section 2.1, where a river basin and/or reservoir system is multi-national, the objectives of the individual countries need to be taken into account. The best way to deal with sharing the benefits of an international water resources system is for the participating countries to develop a treaty or agreement that specifies how the water resources will be shared (Brochmann, 2012; Grey and Sadoff, 2003). Such agreements are aimed at ensuring that each country can meet their objectives while ensuring that the other countries can meet theirs. Obviously, this will usually involve some compromises on the part of each of the signatories to the agreement. It is outside of the scope of this paper to discuss how treaties and agreements are developed and conflicts are resolved in this process.

Although qualitative approaches are often required to resolve issues related to multi-national reservoir systems, a number of papers describe how optimization techniques can be applied to reservoir operation so as to optimize the objectives of several countries that share the water resources. The techniques presented include stochastic dynamic programming (Luchner et al., 2019; Serrat-Capdevila and Valdés, 2007), stochastic dual dynamic programming (Guan et al., 2018), genetic algorithms (Digna et al., 2018), the epsilon dominance nondominated sorting genetic algorithm-II (Chen et al., 2020) and the analytic hierarchy process (Srdjevic and Srdjevic, 2014). Approaches that combine formal optimization and negotiation could also be used (see Di Matteo et al. (2017)).

3.2. Methods to incorporate stochastic uncertainty

The simplest approach to investigate the impact of stochastic uncertainty on reservoir management is to use simulation-based sensitivity or uncertainty analysis such as Monte Calo simulation (Labadie, 2004; Saltelli et al., 2021), where a simulation model of the reservoir system is used to assess the changes in objective function values and system constraints of existing management strategies across the range of values of input(s). This approach does not involve any optimization and is therefore easy to apply and the results obtained are easy to present to and understood by decision makers. Therefore, this approach has been used widely in reservoir management studies to understand the uncertainty of current management strategies (Huang et al., 2018) or propose strategies for both single- and multi-objective reservoir management problems (Liu and Luo, 2019; Muronda et al., 2021; Zhao and Zhao, 2014b). However, this approach does not account for stochastic uncertainty in the development of management strategies and therefore the derived solutions may not be robust considering the variability in system inputs.

Stochastic uncertainty has been incorporated into reservoir operation optimization using traditional optimization techniques, such as linear programming (Cai et al., 2001; Hu et al., 2015; Ortiz-Partida et al., 2019), nonlinear programming (Wang et al., 2018), and dynamic programming (Ramaswamy and Saleh, 2020; Zhao and Zhao, 2014a). These methods are often applied to a long period of input time series that captures the statistical attributes of the input(s) in historical observations (Haro-Monteagudo et al., 2017; Macian-Sorribes and Pulido-Velazquez, 2020). This approach is easy to implement; however, the solution obtained is only applicable to the unique input data used (Labadie, 2004). To address this limitation, stochastic optimization methods such as Stochastic Dynamic Programming (SDP) have been developed (Sahu and McLaughlin, 2018). In traditional SDP algorithms, uncertainty in system inputs, typically inflow, is often taken into account using probability distributions, which enables them to robustly estimate the probability of realization of the uncertain disturbances (Chaves et al., 2004; Loucks et al., 1981; Mujumdar and Nirmala, 2007; Soleimani et al., 2016; Tsoukalas and Makropoulos, 2015). Variations of SDP algorithms have also been developed to account for stochastic uncertainty using scenarios or ensembles of input variables and have been found to outperform traditional SDP algorithms (Cote and Leconte, 2016). However, SDP-based approaches suffer from several major limitations when dealing with large systems (Bellman, 1957; Dobson et al., 2019; Hooshyar et al., 2020; Sahu & McLaughlin, 2018), simulation models (Mortazavi et al., 2012; Tsitsiklis and van Roy, 1996) and multiple objectives (Powell, 2007). These limitations have been referred to as the three curses of dimensionality, modeling, and multiple objectives (Giuliani et al., 2021).

Several improvements have been made to address some of the limitations of SDP-based methods. Examples of such methods include the Stochastic Quasi-Gradient Method (Sechi et al., 2019), the multi-stage stochastic optimization method (Ortiz-Partida et al., 2019; Schwanenberg et al., 2015), the Iterative Linear Decision Rule (ILDR) method (Pan et al., 2015), the scenario tree-based stochastic optimization method (Sun et al., 2018) and the Aggregation-Decomposition Reinforcement Learning (ADRL) method (Hooshyar et al., 2020). However, similar to SDP-based methods, most of these stochastic optimization methods impose severe restrictions on either the form of the simulation models used and/or the formulation of the optimization problem (Mortazavi et al., 2012), which makes it difficult to cater to the variations in problem formulation or multiple competing objective functions (with the exception of Reinforced Learning (Castelletti et al., 2013), which approximates Pareto fronts).

The advancement in evolutionary algorithms (EAs) has encouraged the development of new methods to account for stochastic uncertainty in reservoir management. Due to the independence of EAs from the simulation models used and the flexibility they allow for problem formulation, stochastic uncertainty can be incorporated into the optimization process in various ways when EAs are used. For example, stochastic uncertainty can be accounted for as probability constraints (Ghimire and Reddy, 2014; Saadatpour et al., 2020; Tsoukalas and Makropoulos, 2015), or considering the worst-case scenario (Chen et al., 2018; Zatarain-Salazar et al., 2017). Alternatively, the reliability of solutions across the range of input values can be directly incorporated into objective functions, for example as an added penalty on low reliability solutions (Han et al., 2012; Mortazavi et al., 2012), or as an additional reliability objective to supplement management objectives (Mahootchi et al., 2010). Regardless of how stochastic uncertainty is incorporated in reservoir management when an EA is used, the most significant advantage of this approach is that multiple competing objective functions can be incorporated via a genuine multi-objective optimization framework, where the tradeoffs between competing management objectives (or between management objectives and uncertainty measures) can be investigated.

Finally, stochastic uncertainty in the immediate future is most relevant when it comes to real-time operation of reservoir systems. In such cases, stochastic model predictive control (MPC) has been a popular approach and is often combined with optimization algorithms mentioned earlier (Castelletti et al., 2023). MPC determines a sequence of operation decisions based on predicted system state over a future horizon, when stochastic uncertainty in system state is considered (Bertsekas, 2005; Scattolini, 2009). MPC mitigates the curse of dimensionality of traditional SDP-based algorithms when deterministic optimization is used for each forecast sequence in an ensemble. The use of real-time ensemble forecasts of system inputs such as inflow allows MPC to adapt to continuously evolving conditions of system state due to the knowledge of future system state provided by the feedback. Various variations of stochastic MPC have been developed to account for stochastic uncertainty. They include the traditional Open-loop feedback control introduced by Bertsekas (1976), chance-constrained MPC (Mesbah, 2016), scenario-based MPC (Tian et al., 2019; Velarde et al., 2019) and tree-based MPC (Raso et al., 2014). However, MPC currently can only deal with a single objective function; and when multiple objective functions need to be considered, they are often combined into a single objective function using the weighted sum method (Castelletti et al., 2023).

3.3. Methods to incorporate deep uncertainty

In the current literature, deep uncertainty is mainly incorporated into the management of water resources systems, including reservoir systems, using scenario-based modeling or analysis approaches (Box 2). Depending on how the scenarios are developed and used, these approaches can be divided into two conceptually different categories (see Fig. 2), namely (1) a static approach and (2) a dynamic approach (Maier et al., 2016). These approaches are mainly defined by the management outcomes obtained, for example to develop adaptive reservoir operation rules, reduce maximum allowed drawdown level or raise dam wall, as illustrated in Fig. 2.

A static approach (see plot a in Fig. 2) identifies a *single, fixed* strategy that performs well under a number of plausible future scenarios (Maier

BOX 2
Scenarios

The most common approach for evaluating the impact of deep uncertainty (see BOX 1) associated with multiple plausible futures is to use scenarios (Bankes, 1993; Bankes et al., 2001, 2013; Maier et al., 2016; McPhail et al., 2020; Refsgaard et al., 2007). Scenarios have been referred to as the "possible" or "a concise summary of" future "states of worlds" (Herman et al., 2015; IPCC, 2012; Lempert, 2013; Mahmoud et al., 2009) or "alternative hypothetical (or diverse) futures" (Groves and Lempert, 2007; van Notten et al., 2005). They are often derived from "alternative plausible conditions under different assumptions" (Mahmoud et al., 2009) or "different perspectives in past, present and future developments" (van Notten et al., 2005) including "decision makers' view" (or sometimes stakeholders' view) (Groves and Lempert, 2007). There are different types of scenarios, including predictive, explorative and normative, each aiming to answer different types of questions (Börjeson et al., 2006). In most deep uncertainty related studies, probabilities of occurrence are not assigned to scenarios (Maier et al., 2016; Porter, 1985). Therefore, in the context of model-based decision frameworks, scenarios can be defined based on either assumed values of exogenous variables that are external to the system under consideration and we have no control over, or different problem formulations (e.g., the definition of system boundaries, management objectives and potential actions) that are influenced by stakeholders' (often decision makers') views, as illustrated in Fig. B2. Natural variability in an exogenous variable contributes to stochastic uncertainty; and the non-stationarity of an exogenous variable contributes to long-term unknowns, which is a source of deep uncertainty.

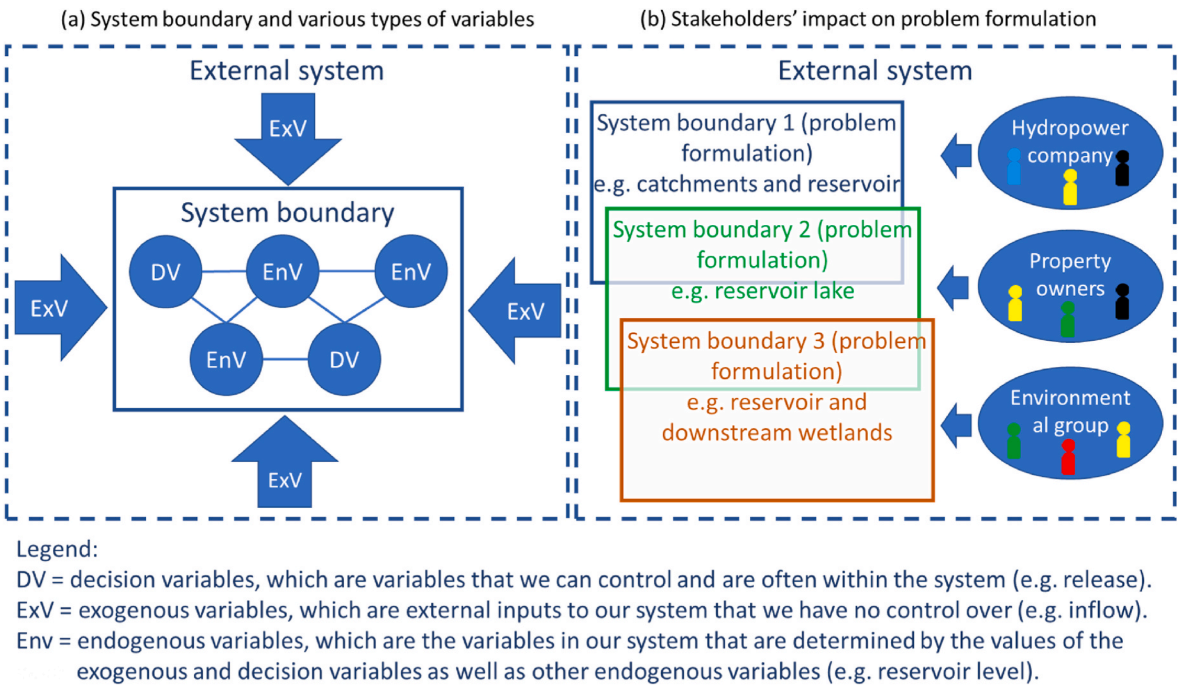

Fig. B2. Illustration of several factors affecting scenarios, with reservoir management as an example.

et al., 2016). Although in most studies a static approach is used in combination with endpoint scenarios that describe a snapshot in time in the future (Maier et al., 2016), this approach can also be used together with static or fixed time series scenarios that describe static changes from the present to different plausible futures (Beh et al., 2015b, 2017). Regardless of whether endpoint or fixed time series scenarios are used, the resulting management policies with this approach remain fixed during the planning horizon. The main difference between the two variations of the static approach is that due to the consideration of time series scenarios, the latter variation allows contingency actions to be taken along the pathways to stay on course (Walker et al., 2001) or occasionally provides opportunities to switch between strategies (Kang and Lansey, 2014). Most of the existing methods developed to account for deep uncertainty in reservoir management, such as robust optimization (Ben-Tal and Nemirovski, 1999; Cuvelier et al., 2018; Gauvin et al., 2017; Housh et al., 2011; Kim et al., 2021; Mulvey et al., 1995; Pan et al., 2015) or scenario-neutral approaches (Borgomeo et al., 2018; Brekke et al., 2009; Giuliani et al., 2014b; Gong et al., 2021; Huang et al., 2022; Prudhomme et al., 2010; Quinn et al., 2018; Ren et al., 2019) belong to the static category.

While the static approach is easy to implement and communicate to stakeholders, it has a tendency to favor more conservative strategies due to the fixed endpoint or time series scenarios used, typically resulting in costly overdesigns (Fletcher et al., 2019; Maier et al., 2016). For example, it may lead to a major infrastructure intervention option well before it is needed, as demonstrated in Fig. 2c. In highly uncertain systems, such as water resources systems including reservoirs, although being conservative, the fixed strategies developed using a static approach might still fail if the future unfolds differently from the assumed states of the world considered in the scenarios (Maier et al., 2016). To address this issue, a dynamic approach can be used.

A dynamic approach (see plot b in Fig. 2) leads to a collection of flexible strategies that are tailored to different future conditions and can also change over time as new information about the future state of the system becomes available (Maier et al., 2016). This approach requires the use of transient scenarios that describe dynamic changes of trends, events and interactions between system states and society with time during the planning horizon (Haasnoot et al., 2011, 2015). For this approach, it is crucial to identify alternative strategies and their adaptation tipping points (Kwadijk et al., 2010). An adaptation tipping point is a point in time when policy changes are required because a given strategy is no longer considered satisfactory and cannot meet the

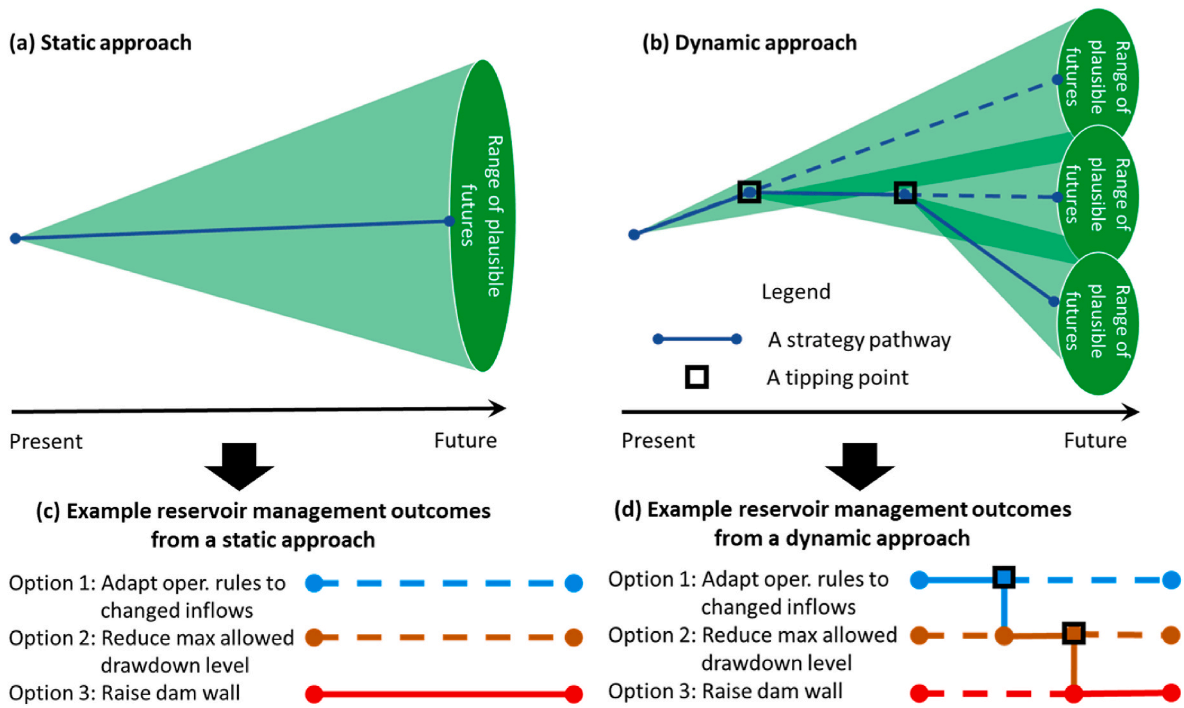

Fig. 2. Static (plot a) versus dynamic (plot b) approaches to account for deep uncertainty, and example outcomes (plots c and d) for reservoir management.

management objectives (Haasnoot et al., 2019; Kwakkel et al., 2015). The timing of adaptation for a given strategy is scenario dependent. Analyzing the distribution of adaptation time for various strategies across a wide range of transient scenarios provides insight into the point in time where a new strategy needs to be activated because its predecessor can no longer meet its objective (Beh et al., 2015a; Haasnoot et al., 2013). The timing of adaptation is also determined by the time it takes to implement a strategy (Haasnoot et al., 2013). If the implementation time is longer than the rate of the change of the system - as in water supply infrastructure augmentation - sufficient implementation time could be allowed by considering adaptation at fixed time intervals over the planning horizon (Beh et al., 2015a; Maier et al., 2016). Although this dynamic approach has been discussed in policy planning studies (Haasnoot et al., 2013; Kwakkel et al., 2015) and demonstrated for water resources management under climate change (Beh et al., 2015a; Haasnoot et al., 2012, 2015; Lawrence and Haasnoot, 2017), there has been limited application of this approach in reservoir management.

Regardless of whether a static or dynamic approach is used, these scenario-based approaches have been developed to account for deep uncertainty associated with long-term unknowns, especially climate change, which has been the biggest driver for researchers to develop adaptation plans as decision support tools (Kwakkel et al., 2016; Marchau et al., 2019). For example, different Representative Concentration Pathways (RCP) of emissions defined by the Intergovernmental Panel on Climate Change are often used to account for the impact of climate change (Changchit and Terrell, 1993). Alternatively, hypothetical scenarios from different historical or future time periods (e.g., 1980–2010 and 2020–2050) have been adopted to provide insights into the potential impact of climate change (Li et al., 2018). In the majority of these studies, problem formulation (e.g., the definition of system boundaries, management objectives and potential actions) are considered known and deep uncertainty due to stakeholder involvement is not considered. However, underpinned by the existence of multiple plausible futures, deep uncertainty due to human impact can also be accounted for using these approaches described above, as long as representative scenarios can be developed.

3.4. Methods to account for interactions between competing objectives and stochastic and deep uncertainty

The development of EAs enables the integration of stochastic uncertainty and multi-objective tradeoffs using a genuine multi-objective optimization framework that identifies a set of Pareto solutions (Saadatpour et al., 2020; Tsoukalas and Makropoulos, 2015). Therefore, they have become popular for reservoir management considering multiple competing objective functions (Chen et al., 2018; Mortazavi et al., 2012; Saadatpour et al., 2020; Zatarain-Salazar et al., 2017; Tsoukalas and Makropoulos, 2015). Due to the flexibility provided by EAs, stochastic uncertainty has been incorporated using various methods in a multi-objective reservoir operation optimization framework, including through objective function evaluation (Chen et al., 2018; Zatarain-Salazar et al., 2017), as constraints (Saadatpour et al., 2020; Tsoukalas and Makropoulos, 2015) or as an additional robustness optimization objective (Mortazavi-Naeini et al., 2015). However, the relative performance of these different methods is unknown.

To deal with multiple competing objectives under deep uncertainty, different approaches have been adopted depending on data availability and the purpose and scale of the study. The simplest approach is to convert a multi-objective optimization problem into a single-objective one (see section 3.1.1) so it can be included in an existing framework accounting for deep uncertainty (e.g., Ren et al. (2019) and Kim et al. (2021)). Alternatively, a more comprehensive approach can be used where a multi-objective optimization model is developed as a part of a framework that accounts for deep uncertainty (e.g., Giuliani et al. (2014b) and Herman et al. (2014); Giuliani et al. (2018); Quinn et al. (2018); Geressu and Harou (2019)). The latter approach has become more popular due to developments in multi-objective EAs.

The studies that account for both stochastic and deep uncertainty can be divided into two classes. The first class adopts a two-step approach: in the first step Pareto optimal solutions are identified in an optimization process for each plausible future scenario representing deep uncertainty where only stochastic uncertainty is considered; then in the second step the performance of these solutions is evaluated under a wide range of plausible future scenarios developed considering deep uncertainty. This approach is sometimes referred to as post-optimization robustness analysis and has been used in studies by Herman et al. (2014), Trindade et al. (2017), Quinn et al. (2018), Ren et al. (2019), Kim et al. (2021) and Huang et al. (2022). The second class consists of studies that apply stochastic methods to generate input variables, such as inflows, within future scenarios, to incorporate stochastic uncertainty and deep uncertainty. This class of methods mainly includes, but is not limited to, robust optimization techniques, and has been used in a number of studies (e.g., Beh et al. (2015a); Mortazavi-Naeini et al. (2015); Pan et al. (2015); Gauvin et al. (2017); Giuliani et al. (2018); Geressu and Harou (2019); Kiem et al. (2021)).

A number of existing methods can be used to account for interactions between competing management objectives and stochastic and deep uncertainty. The most prevalent approach is to use multi-objective EAs to obtain Pareto optimal tradeoffs between competing objectives for a number of scenarios representing different combinations of plausible future conditions, with stochastic uncertainty embedded in each scenario using statistical methods such as probability distributions (e.g., Herman et al. (2014); Mortazavi-Naeini et al. (2015); Trindade et al. (2017); Quinn et al. (2018); Geressu and Harou (2019); Ren et al. (2019); Huang et al. (2022)). There are two major limitations of this approach. First, robustness is not considered as an explicit objective as part of the multi-objective optimization process but is assessed post-optimization. Beh et al. (2017) addressed this issue by including robustness as one of the objectives in a multi-objective optimization process explicitly, which was made possible by emulating the performance of the computationally expensive simulation model of the water resources system under investigation with the aid of a computationally efficient artificial neural network metamodel. Second, deep uncertainty is catered to by developing a single, static solution for each of the scenarios considered. Beh et al. (2015a; b, 2017) overcame this limitation by developing solutions that change over time based on changes in future conditions. However, in Beh et al. (2015b; 2017), these adaptive solutions are static, as they correspond to assumed changes in future conditions for each of the scenarios considered. Only Beh et al. (2015a) presented an approach that enables adaptive solutions to be developed dynamically based on changes in actual future conditions.

4. Future research needs

As part of this review, a number of research needs have been identified. These have been summarized in Fig. 3. A detailed discussion of these research needs is included in the two sub-sections below.

4.1. Research on deep uncertainty due to the wickedness of reservoir management

Reservoir management has historically been viewed as an 'engineering problem,' where every element of the problem can supposedly be quantified and accounted for in a quantitative manner. Perhaps, the view was born (and maintained) after the construction of the first reservoirs in the modern era with primary objectives that could be directly monetized, such as hydropower generation or irrigation. However, there has been growing awareness in the past decades that there is a variety of interests or costs associated with reservoir management that can relate to various human dimensions of water resources and the environment, or the wickedness of reservoir management. Unlike engineering problems, which have foundational and universal rules, human related interests or costs can change both spatially and temporally depending on local geography, demography, and social and cultural values, and therefore are (1) difficult, if not impossible, to quantify, and/or (2) often hidden or ignored at the time of decision-making. Future research needs related to these challenges are discussed below.

First, novel approaches need to be developed to address two major challenges related to environmental objectives. Although environmental objectives have been the most widely researched and discussed indirect factors in reservoir management (Barbour et al., 2016), they have been considered primarily through the lens of an engineering problem by developing thresholds as problem constraints, typically based on limited empirical evidence, to maintain ecosystem function (Wang et al., 2013; Zolfagharpour et al., 2021). This traditional, and still mainstream, approach is now facing two major challenges. Challenge 1: it is now known that reservoirs, and in general human intervention with flow regimes, can have long-term and cascading impacts on both aquatic (e.g., fish habitat and algal blooms) and terrestrial (e.g., land cover change, wildlife, and land subsidence) ecosystems that are often difficult to

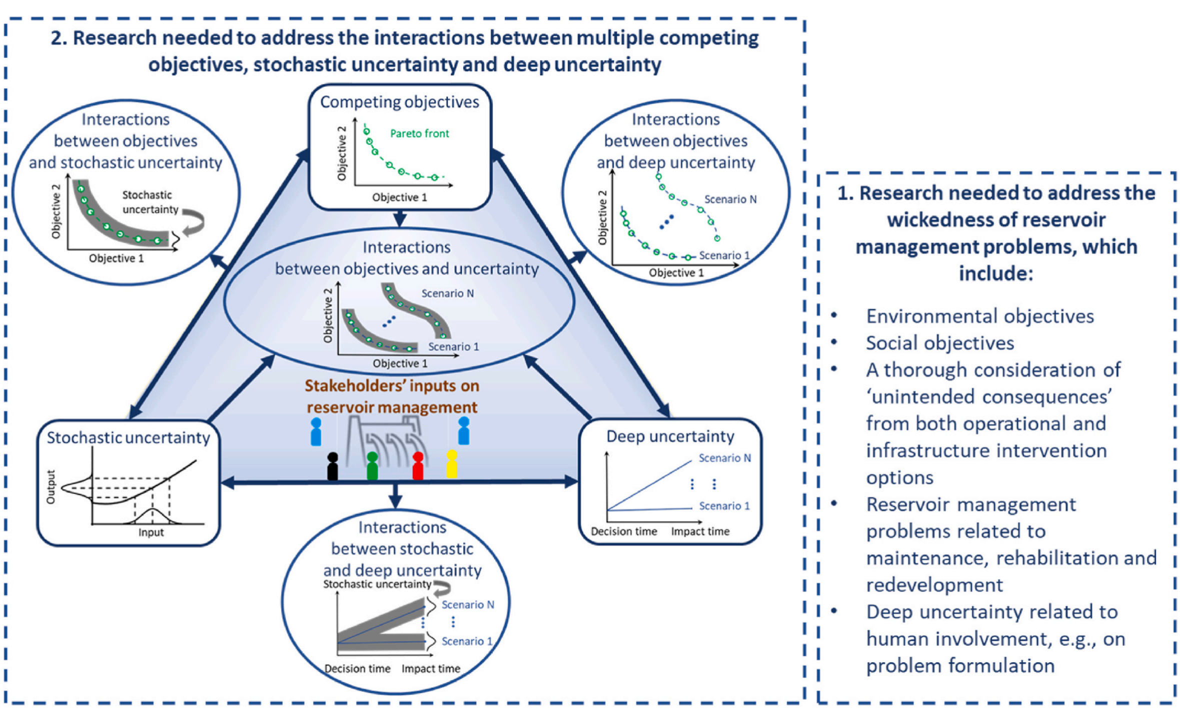

Fig. 3. Summary of future research needs in reservoir management.

predict due the complexity of such systems and a lack of relevant empirical data. Challenge 2: economic valuation of environmental impacts, even if they are known *a priori*, is very difficult as it depends on perceptions of associated risks and benefits in affected communities and their social and cultural values.

Second, social objectives such as fairness and equity, political and legal feasibility and human health need to be considered, some of which have also been identified for general water resources management problems (Badham et al., 2019). Most studies on reservoir management totally ignore social objectives or else use metrics such as demand shortfall or reliability of supply as surrogate measures for social impacts. In particular, the distributions of benefits and costs among various groups in society should be considered in addition to total net economic benefits. Reservoir operations in the future can be improved by explicitly considering social objectives - studies by Tiwari et al. (1999), Yin et al. (1999), Mimi and Sawalhi (2003), Atwi and Chóliz (2011), and De Marinis and Sali (2020) suggest suitable measures and techniques to assist with this important endeavor.

Third, a thorough consideration of any ‘unintended consequences’ is a grand challenge and generally missing in the current generation of approaches to reservoir management. The ‘unintended consequences’ around reservoir design and management are often initially hidden but realized years after commencement of reservoir operation. For example, building reservoirs in flood prone areas may boost economic activities downstream and human settlement in the floodplain, which, in turn, will quietly change factors controlling flood risk and its human perceptions, even possibly leading to a flood risk paradox (McCully, 1996; Razavi et al., 2020). As a result, a flood disaster may hit a community harder because of the existence of an upstream reservoir. In addition, the cost of public unrest in the wake of natural disasters such as flooding, or costs related to the health and wellbeing (physically and mentally) of the people affected, are typically excluded from the engineering problem of reservoir management. Such costs can be extensive and long-lasting, incurred by society in various ways depending on the existence of public or private health and social assistance systems in a region.

Fourth, the view of reservoir management as an "engineering problem" and the subsequent development of mathematical methods to solve these engineering problems has led to abundant research on operation related reservoir management issues, while reservoir maintenance, rehabilitation and redevelopment related issues have received little attention from the research community. This is evident from the literature review process where the absolute majority of the papers found are on the topic of reservoir operation. This lack of attention to reservoir maintenance, rehabilitation and redevelopment in the current literature may also be attributed to the fact that these aspects of reservoir management are closely linked to the wickedness of reservoir management discussed above. As any infrastructure interventions as such will be more likely to lead to more visible impact and the "unintended consequences" discussed above. Therefore, compared to operational interventions such as changing operational policy, these infrastructure interventions will also draw more attention from stakeholders with various views, especially those on environmental and social issues. Therefore, these management options require solution methods that go beyond the existing and commonly used mathematical or engineering methods.

Attempts to address this challenge are further complicated by the fact that there is often a power imbalance in the representation of different interests and views in the problem formulation (e.g., the definition of system boundaries, management objectives and potential actions), which is rarely considered in reservoir management studies. For example, there are instances where indigenous peoples felt their voice was not considered in reservoir management and valuation of cultural flows (e.g., Pearce (2021) and Gooley (2022)). We need more holistic approaches to water management that go beyond traditional engineering methods and are as inclusive as possible. This will require new ways of thinking on how to enhance our engineering models so they can accommodate a highly qualitative world, while being mindful of the limits to the collective comprehension of all stakeholders involved (Jakeman et al., 2016). This involvement of the human dimension has also been identified as a grand challenge in general environmental modeling (Elsawah et al., 2020) and can partially be addressed by monitoring and evaluating interdisciplinary team research (Zare et al., 2021) and using participatory modeling approaches (Elsawah et al., 2020).

4.2. Research on interactions of multiple competing objectives and stochastic and deep uncertainty

The need for research on the interactions of the three challenges of reservoir management can be best demonstrated by using interactions between multiple competing objectives and stochastic uncertainty. Both tradeoffs from competing management objectives and stochastic uncertainty due to natural variability in system input (e.g., as a result of uncertainty in environmental processes) are important aspects to consider in reservoir management and have been considered in many studies on reservoir operation. However, multi-objective tradeoffs and stochastic uncertainty have been mostly considered in isolation, although their collective impact may affect the effectiveness of reservoir management decisions, especially those related to system operation, as explained in section 2.4. This is traditionally due to the increased complexity in problem representation when interactions are considered, and the lack of suitable methods to provide improved realism to reflect this increased problem complexity. Therefore, assumptions have been made to simplify problem representation, for example using the weighted sum method to convert a multi-objective optimization problem into a single-objective one, so that existing methods to deal with stochastic uncertainty, such as SDP and its variations, can be used to account for the increased number of objective functions.

Advances in EA-based simulation-optimization modeling frameworks in the past decades have provided a partial solution to the challenge of considering the interactions between competing objectives and stochastic uncertainty. The independence of the simulation model and optimization algorithm within the EA-based simulation-optimization modeling framework removes some of the required simplification assumptions, as discussed in section 3.2. Although there is no agreed-upon approach in terms of how to integrate multi-objective tradeoffs and stochastic uncertainty considerations into reservoir optimization simultaneously, simulation-optimization frameworks provide the opportunity for analysts to increase the completeness and accuracy of system representation, as well as the evaluation of other quantitative measures such as objective functions and system constraints.

However, the development of more complicated engineering methods aiming to directly address the technical challenges of reservoir management may not lead to a more effective solution. This is mainly due to the complex and multidisciplinary nature of reservoir management. While increasing complexity in the representation of processes and interactions improves realism, this comes at a cost, ultimately forcing decision makers to give less weight to rationality and to rely more on “intuitive, unconscious or implicit decision-making” (Rizzo and Dold, 2021). Consequently, it is not surprising to see that accounting for interactions between multi-objective tradeoffs and stochastic uncertainty using a genuine multi-objective framework has received limited attention. Most existing studies employ some simplifying assumptions to incorporate stochastic uncertainty, while the assessment of robustness in multi-objective tradeoffs due to stochastic uncertainty is often not thoroughly investigated.

Similarly, the consideration of the interactions between multi-objective tradeoffs and stochastic and deep uncertainty will further increase the complexity of reservoir management problems. The development of more advanced engineering techniques to push for increased realism in the problem formulation and/or solution process will not lead to a more effective solution without simultaneously improving the collective comprehension of stakeholders. Consequently, the key in advancing reservoir management by considering all three categories of challenges lies in the development of tools for not only visualizing and communicating increased complexity in problem representation and results to stakeholders (such as those developed for interpreting many-objective optimization results (Hadka et al., 2015; Kasprzyk et al., 2013)), but also for using the results effectively and efficiently in subsequent decision-making processes (e.g., see Di Matteo et al. (2017) and McPhail et al. (2021)).

5. Conclusions

In this paper, we have provided a review of the ever-growing body of literature in the field of reservoir management, which includes not only operation but also maintenance, rehabilitation, redevelopment, or repurposing of existing reservoir systems in response to changing circumstances. In contrast with previous reviews, which mainly focused on solution techniques, particularly those involving simulation optimization modeling, we considered a broader range of challenges related to reservoir management through the lens of wickedness, competing objectives and uncertainty. We analyzed the management objectives required, as well as the stochastic and deep uncertainty that affect reservoir management and their interactions. We have also reviewed current methods that have been used to address these challenges and discussed their advantages and limitations.

We found that there are often well-developed methods to address the individual challenges related to multiple management objectives, stochastic uncertainty, and deep uncertainty. However, the interactions between the individual challenges are often ignored or tackled with simplifying assumptions. This is likely due to the increase in complexity of the problem when more (categories of) challenges are considered in reservoir management, and thus the diminishing ability of analysts and stakeholders to not only formulate and solve the problems, but also to understand the results and make informed decisions. In addition, major research gaps exist in addressing the wickedness of reservoir management problems, especially those involving human dimension. Although a final definitive solution that is accepted by all stakeholders may never be found for reservoir management due to its wickedness, we have highlighted steps that can be taken to improve the acceptability of solutions that are supported by the best available science. Ultimately, we hope this review will inspire researchers to develop appropriate tools to address some of the issues identified, bridging the gap between scientific research and real-world applications.

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Data availability

No data was used for the research described in the article.

References

9 NEWS, 2021. High Warragamba Dam Wall Would Not Have Stopped Floods, Experts Say. 9NEWS.

Ahmad, A., El-Shafie, A., Razali, S.F.M., Mohamad, Z.S., 2014. Reservoir optimization in water resources: a review. Water Resour. Manag. 28 (11), 3391–3405. https://doi.org/10.1007/s11269-014-0700-5.

Ascough, J.C., Maier, H.R., Ravalico, J.K., Strudley, M.W., 2008. Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. Ecol. Model. 219 (3), 383–399. https://doi.org/10.1016/j.ecolmodel.2008.07.015.

Atwi, M., Chóliz, J.S., 2011. A negotiated solution for the Jordan Basin. J. Oper. Res. Soc. 62 (1), 81–91.

Badham, J., Elsawah, S., Guillaume, J.H.A., Hamilton, S.H., Hunt, R.J., Jakeman, A.J., Pierce, S.A., Snow, V.O., Babbar-Sebens, M., Fu, B., Gober, P., Hill, M.C., Iwanaga, T., Loucks, D.P., Merritt, W.S., Peckham, S.D., Richmond, A.K., Zare, F., Ames, D., Bammer, G., 2019. Effective modeling for Integrated Water Resource Management: a guide to contextual practices by phases and steps and future opportunities. Environ. Model. Software 116, 40–56. https://doi.org/10.1016/j.envsoft.2019.02.013.

Bankes, S., 1993. Exploratory modeling for policy analysis. Oper. Res. 41 (3), 435–449. https://doi.org/10.1287/opre.41.3.435.

Bankes, S.C., Lempert, R.J., Popper, S.W., 2001. Computer-assisted reasoning. Comput. Sci. Eng. 3 (2), 71–77. https://doi.org/10.1109/5992.909006.

Bankes, S., Walker, W.E., Kwakkel, J.H., 2013. In: Gass, S.I., Fu, M.C. (Eds.), Encyclopedia of Operations Research and Management Science. Springer US, Boston, MA, pp. 532–537.

Barbour, E.J., Holz, L., Kuczera, G., Pollino, C.A., Jakeman, A.J., Loucks, D.P., 2016. Optimisation as a process for understanding and managing river ecosystems. Environ. Model. Software 83, 167–178. https://doi.org/10.1016/j.envsoft.2016.04.029.

Beck, L., Bernauer, T., Siegfried, T., Böhmelt, T., 2014. Implications of hydro-political dependency for international water cooperation and conflict: insights from new data. Polit. Geogr. 42, 23–33. https://doi.org/10.1016/j.polgeo.2014.05.004.

Beh, E.H.Y., Maier, H.R., Dandy, G.C., 2015a. Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty. Water Resour. Res. 51 (3), 1529–1551. https://doi.org/10.1002/2014WR016254.

Beh, E.H.Y., Maier, H.R., Dandy, G.C., 2015b. Scenario driven optimal sequencing under deep uncertainty. Environ. Model. Software 68, 181–195. https://doi.org/10.1016/j.envsoft.2015.02.006.

Beh, E.H.Y., Zheng, F., Dandy, G.C., Maier, H.R., Kapelan, Z., 2017. Robust optimization of water infrastructure planning under deep uncertainty using metamodels. Environ. Model. Software 93, 92–105. https://doi.org/10.1016/j.envsoft.2017.03.013.

Bekri, E., Disse, M., Yannopoulos, P., 2015. Optimizing water allocation under uncertain system conditions for water and agriculture future scenarios in alfeios river basin (Greece)-Part B: fuzzy- boundary intervals combined with multi-stage stochastic programming model. Water 7 (11), 6427–6466. https://doi.org/10.3390/w7116427.

Bellman, R., 1957. Dynamic Programming. Princeton University Press., Princeton, USA.

Ben-Tal, A., Nemirovski, A., 1999. Robust solutions of uncertain linear programs. Oper. Res. Lett. 25 (1), 1–13. https://doi.org/10.1016/S0167-6377(99)00016-4.

Bennett, J.C., Robertson, D.E., Wang, Q.J., Li, M., Perraud, J.-M., 2021. Propagating reliable estimates of hydrological forecast uncertainty to many lead times. J. Hydrol. 603, 126798 https://doi.org/10.1016/j.jhydrol.2021.126798.

Bertsekas, D., 1976. Dynamic Programming and Stochastic Control. Academic Press, New York.

Bertsekas, D.P., 2005. Dynamic programming and suboptimal control: a survey from ADP to MPC. Eur. J. Control 11 (4), 310–334. https://doi.org/10.3166/ejc.11.310-334.

Best, J., 2019. Anthropogenic stresses on the world's big rivers. Nat. Geosci. 12 (1), 7–21. https://doi.org/10.1038/s41561-018-0262-x.

Biswas, A.K., 1976. Systems Approach to Water Management. McGraw-Hill, New York.

Borgomeo, E., Mortazavi-Naeini, M., Hall, J.W., Guillod, B.P., 2018. Risk, robustness and water resources planning under uncertainty. Earth's Future 6 (3), 468–487. https://doi.org/10.1002/2017EF000730.

Börjeson, L., Höjer, M., Dreborg, K.-H., Ekvall, T., Finnveden, G., 2006. Scenario types and techniques: towards a user's guide. Futures 38 (7), 723–739. https://doi.org/10.1016/j.futures.2005.12.002.

Brekke, L.D., Maurer, E.P., Anderson, J.D., Dettinger, M.D., Townsley, E.S., Harrison, A., Pruitt, T., 2009. Assessing reservoir operations risk under climate change. Water Resour. Res. 45 https://doi.org/10.1029/2008wr006941.

Brochmann, M., 2012. Signing River treaties—does it improve river cooperation? Int. Interact. 38 (2), 141–163. https://doi.org/10.1080/03050629.2012.657575.

Brown, C., Ghile, Y., Laverty, M., Li, K., 2012. Decision scaling: linking bottom-up vulnerability analysis with climate projections in the water sector. Water Resour. Res. 48 (9) https://doi.org/10.1029/2011WR011212.

Cai, X., McKinney, D.C., Lasdon, L.S., 2001. Solving nonlinear water management models using a combined genetic algorithm and linear programming approach. Adv. Water Resour. 24 (6), 667–676. https://doi.org/10.1016/S0309-1708(00)00069-5.

Castelletti, A., Pianosi, F., Soncini-Sessa, R., 2008. Water reservoir control under economic, social and environmental constraints. Automatica 44 (6), 1595–1607. https://doi.org/10.1016/j.automatica.2008.03.003.

Castelletti, A., Ficchì, A., Cominola, A., Segovia, P., Giuliani, M., Wu, W., Lucia, S., Ocampo-Martinez, C., De Schutter, Maestre, J.M., 2023. Model Predictive Control of water resources systems: A review and research agenda. Ann. Revi. Contr. 55, 442–465. https://doi.org/10.1016/j.arcontrol.2023.03.013.

Castelletti, A., Pianosi, F., Restelli, M., 2013. A multiobjective reinforcement learning approach to water resources systems operation: Pareto frontier approximation in a single run. Water Resour. Res. 49 (6), 3476–3486. https://doi.org/10.1002/wrcr.20295.

Celeste, A.B., Siqueira, J.Í.P., Cai, X., 2021. Using inflow records to approximate solutions to statistical moment equations of an explicit stochastic reservoir optimization method. J. Water Resour. Plann. Manag. 147 (7), 06021006 https://doi.org/10.1061/(ASCE)WR.1943-5452.0001393.
Chakraei, I., Safavi, H.R., Dandy, G.C., Golmohammadi, M.H., 2021. Integrated simulation-optimization framework for water allocation based on sustainability of surface water and groundwater resources. J. Water Resour. Plann. Manag. 147 (3), 05021001 https://doi.org/10.1061/(ASCE)WR.1943-5452.0001339.
Changchit, C., Terrell, M.P., 1993. A multiobjective reservoir operation model with stochatic inflows. Comput. Ind. Eng. 24 (2), 303–313. https://doi.org/10.1016/0360-8352(93)90016-Q.
Chaves, P., Kojiri, T., 2007. Deriving reservoir operational strategies considering water quantity and quality objectives by stochastic fuzzy neural networks. Adv. Water Resour. 30 (5), 1329–1341. https://doi.org/10.1016/j.advwatres.2006.11.011.
Chaves, P., Tsukatani, T., Kojiri, T., 2004. Operation of storage reservoir for water quality by using optimization and artificial intelligence techniques. Math. Comput. Simulat. 67 (4–5), 419–432. https://doi.org/10.1016/j.matcom.2004.06.005.
Chen, D., Leon, A.S., Chen, Q., Li, R., 2018. A derivative-free hybrid optimization model for short-term operation of a multi-objective reservoir system under uncertainty. Water resour. OR Manag. 32 (11), 3707–3721. https://doi.org/10.1007/s11269-018-2014-5.
Chen, X., Zheng, Y., Xu, B., Wang, L., Han, F., Zhang, C., 2020. Balancing competing interests in the Mekong River Basin via the operation of cascade hydropower reservoirs in China: insights from system modeling. J. Clean. Prod. 254, 119967 https://doi.org/10.1016/j.jclepro.2020.119967.
Cheng, W.-M., Huang, C.-L., Hsu, N.-S., Wei, C.-C., 2017. Risk analysis of reservoir operations considering short-term flood control and long-term water supply: a case study for the da-han creek basin in taiwan. Water 9 (6), 424.
Cherney, M., 2020. Bone-Dry Australia Faces Backlash against Dam Projects. 'Dams Don't Make It Rain'.
Churchman, C.W.M.S., 1967. Wicked problems, 14(4), B141-B142 Manag. Sci. 14 (4), B141–B142. https://www.jstor.org/stable/2628678.
Conklin, J., 2006. Dialogue Mapping: Building Shared Understanding of Wicked Problems. Wiley Publishing, Chichester, England.
Cote, P., Leconte, R., 2016. Comparison of stochastic optimization algorithms for hydropower reservoir operation with ensemble streamflow prediction. J. Water Resour. Plann. Manag. 142 (2) https://doi.org/10.1061/(asce)wr.1943-5452.0000575.
Culley, S., Noble, S., Yates, A., Timbs, M., Westra, S., Maier, H.R., Giuliani, M., Castelletti, A., 2016. A bottom-up approach to identifying the maximum operational adaptive capacity of water resource systems to a changing climate. Water Resour. Res. 52 (9), 6751–6768. https://doi.org/10.1002/2015wr018253.
Culley, S., Maier, H.R., Westra, S., Bennett, B., 2021. Identifying critical climate conditions for use in scenario-neutral climate impact assessments. Environ. Model. Software 136, 104948. https://doi.org/10.1016/j.envsoft.2020.104948.
Cuvelier, T., Archambeau, P., Dewals, B., Louveaux, Q., 2018. Comparison between robust and stochastic optimisation for long-term reservoir management under uncertainty. Water Resour. Manag. 32 (5), 1599–1614. https://doi.org/10.1007/s11269-017-1893-1.
Dandy, G.C., Daniell, T.M., Foley, B., Warner, R.F., 2018. Planning and Design of Engineering Systems. CRC Press. Taylor & Francis Group, Boca Raton, Florida.
Danner, A.G., Safeeq, M., Grant, G.E., Wickham, C., Tullos, D., Santelmann, M.V., 2017. Scenario-based and scenario-neutral assessment of climate change impacts on operational performance of a multipurpose reservoir. JAWRA Journal of the American Water Resources Association 53 (6), 1467–1482. https://doi.org/10.1111/1752-1688.12589.
Davies, S., Wilson, J., Ridges, M., 2021. Redefining 'cultural values' – the economics of cultural flows. Aust. J. Water Resour. 25 (1), 15–26. https://doi.org/10.1080/13241583.2020.1795339.
De Marinis, P., Sali, G., 2020. Participatory analytic hierarchy process for resource allocation in agricultural development projects. Eval. Progr. Plann. 80, 101793 https://doi.org/10.1016/j.evalprogplan.2020.101793.
De Vincenzo, A., Jacopo Molino, A., Molino, B., Scorpio, V., Molino, A.J., 2017. Reservoir rehabilitation: the new methodological approach of Economic Environmental Defence. Int. J. Sediment Res. 32 (2), 288–294.
Derepasko, D., Guillaume, J.H.A., Horne, A., Volk, M., Guillaume, J.H.A., 2021. Considering scale within optimization procedures for water management decisions: balancing environmental flows and human needs. Environ. Model. Software 139, 104991.
Di Matteo, M., Dandy, G.C., Maier, H.R., 2017. A multi-stakeholder portfolio optimization framework applied to stormwater best management practice (BMP) selection. Environ. Model. Software 97, 16–31. https://doi.org/10.1016/j.envsoft.2017.07.012.
Di Matteo, M., Maier, H.R., Dandy, G.C., 2019. Many-objective portfolio optimization approach for stormwater management project selection encouraging decision maker buy-in. Environ. Model. Software 111, 340–355. https://doi.org/10.1016/j.envsoft.2018.09.008.
Digna, R.F., Castro-Gama, M.E., Van der Zaag, P., Mohamed, Y.A., Corzo, G., Uhlenbrook, S., 2018. Optimal operation of the eastern nile system using genetic algorithm, and benefits distribution of water resources development. Water 10 (7), 921.
Dobson, B., Wagener, T., Pianosi, F., 2019. An argument-driven classification and comparison of reservoir operation optimization methods. Adv. Water Resour. 128, 74–86. https://doi.org/10.1016/j.advwatres.2019.04.012.
Duan, Q., Pappenberger, F., Wood, A., Cloke, H.L., Schaake, J.C., 2019. Handbook of Hydrometeorological Ensemble Forecasting. Springer-Verlag GmbH.
Dye, J., 2021. 'The Damage Is Inconceivable': Flood Victims Claim $87 Million in Disaster Payments (Sydney).
Eamen, L., Brouwer, R., Razavi, S., 2021. Integrated modelling to assess the impacts of water stress in a transboundary river basin: bridging local-scale water resource operations to a river basin economy. Sci. Total Environ. 800, 149543 https://doi.org/10.1016/j.scitotenv.2021.149543.
Ehteram, M., Mousavi, S.F., Karami, H., Farzin, S., Singh, V.P., Chau, K.-w., El-Shafie, A., 2018. Reservoir operation based on evolutionary algorithms and multi-criteria decision-making under climate change and uncertainty. J. Hydroinf. 20 (2), 332–355. https://doi.org/10.2166/hydro.2018.094.
Elsawah, S., Filatova, T., Jakeman, A.J., Kettner, A.J., Zellner, M.L., Athanasiadis, I.N., Hamilton, S.H., Axtell, R.L., Brown, D.G., Gilligan, J.M., Janssen, M.A., Robinson, D. T., Rozenberg, J., Ullah, I.I.T., Lade, S.J., 2020. Eight grand challenges in socio-environmental systems modeling. Socio-Environmental Systems Modelling 2, 16226. https://doi.org/10.18174/sesmo.2020a16226.
Emami, M., Nazif, S., Mousavi, S.-F., Karami, H., Daccache, A., 2021. A hybrid constrained coral reefs optimization algorithm with machine learning for optimizing multi-reservoir systems operation. J. Environ. Manag. 286, 112250 https://doi.org/10.1016/j.jenvman.2021.112250.
Fayaed, S.S., El-Shafie, A., Jaafar, O., 2013. Reservoir-system simulation and optimization techniques. Stoch. Environ. Res. Risk Assess. 27 (7), 1751–1772. https://doi.org/10.1007/s00477-013-0711-4.
Flecker, A., Shi, Q., Almeida, R., Angarita, H., Gomes Selman, J., García Villacorta, R., Sethi, S., Thomas, S., Poff, N.L., Forsberg, B., Heilpern, S., Hamilton, S., Abad, J., Anderson, E., Barros, N., Bernal, I., Bernstein, R., Cañas, C., Dangles, O., Encalada, A., Fleischmann, A., Goulding, M., Higgins, J., Jézéquel, C., Larson, E., McIntyre, P., Melack, J., Montoya, M., Oberdorff, T., Paiva, R., Perez, G., Rappazzo, B., Steinschneider, S., Torres, S., Varese, M., Walter, M.T., Wu, X., Xue, Y., Zapata Ríos, X., Gomes, C.P., Garcia Villacorta, R., Canas, C., Jezequel, C., Zapata Rios, X., Gomes, C., 2022. Reducing adverse impacts of Amazon hydropower expansion. Science 375 (6582), 753–760.
Fletcher, S., Lickley, M., Strzepek, K., 2019. Learning about climate change uncertainty enables flexible water infrastructure planning. Nat. Commun. 10, 1782. https://doi.org/10.1038/s41467-019-096. https://rdcu.be/bxaIa.
Galelli, S., Castelletti, A., Goedbloed, A., 2015. High-Performance Integrated Control of water quality and quantity in urban water reservoirs. Water Resour. Res. 51 (11), 9053–9072. https://doi.org/10.1002/2015WR017595.
Gauvin, C., Delage, E., Gendreau, M., 2017. Decision rule approximations for the risk averse reservoir management problem. Eur. J. Oper. Res. 261 (1), 317–336. https://doi.org/10.1016/j.ejor.2017.01.044.
Geressu, R.T., Harou, J.J., 2019. Reservoir system expansion scheduling under conflicting interests. Environ. Model. Software 118, 201–210. https://doi.org/10.1016/j.envsoft.2019.04.002.
Ghimire, B.N.S., Reddy, M.J., 2014. Optimization and uncertainty analysis of operational policies for multipurpose reservoir system. Stoch. Environ. Res. Risk Assess. 28 (7), 1815–1833. https://doi.org/10.1007/s00477-014-0846-y.
Giudici, F., Castelletti, A., Giuliani, M., Maier, H.R., 2020. An active learning approach for identifying the smallest subset of informative scenarios for robust planning under deep uncertainty. Environ. Model. Software 127, 104681. https://doi.org/10.1016/j.envsoft.2020.104681.
Giudici, F., Anghileri, D., Castelletti, A., Burlando, P., 2021. Descriptive or normative: how does reservoir operations modeling influence hydrological simulations under climate change? J. Hydrol. 595, 125996 https://doi.org/10.1016/j.jhydrol.2021.125996.
Giuliani, M., Galelli, S., Soncini-Sessa, R.M., Soncini Sessa, R., 2014a. A dimensionality reduction approach for many-objective Markov Decision Processes: application to a water reservoir operation problem. Environ. Model. Software 57, 101–114.
Giuliani, M., Herman, J.D., Castelletti, A., Reed, P., 2014b. Many- objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. Water Resour. Res. 50 (4), 3355–3377. https://doi.org/10.1002/2013wr014700.
Giuliani, M., Quinn, J.D., Herman, J.D., Castelletti, A., Reed, P.M., 2018. Scalable multiobjective control for large-scale water resources systems under uncertainty. IEEE Trans. Control Syst. Technol. 26 (4), 1492–1499. https://doi.org/10.1109/TCST.2017.2705162.
Giuliani, M., Lamontagne, J.R., Reed, P.M., Castelletti, A., 2021. A State-Of-The-Art Review of Optimal Reservoir Control for Managing Conflicting Demands in a Changing World. Water Resources Research n/a(n/a), e2021WR029927. https://doi.org/10.1029/2021WR029927.
Gong, Y., Liu, P., Liu, Y., Huang, K., 2021. Robust operation interval of a large-scale hydro-photovoltaic power system to cope with emergencies. Appl. Energy 290, 116612. https://doi.org/10.1016/j.apenergy.2021.116612.
Gooley, C., 2022. Warragamba Dam Heritage Assessment 'manifestly Inadequate': Archaeologists (Sydney, Australia).
Gralow, J., Jose, R., 2021. Australia to Rescue Thousands as Sydney Faces Worst Floods in 60 Years (London, UK).
Grey, D., Sadoff, C., 2003. Beyond the river: the benefits of cooperation on international rivers. Water Sci. Technol. 47 (6), 91–96.
Groves, D.G., Lempert, R.J., 2007. A new analytic method for finding policy-relevant scenarios. Global Environ. Change 17 (1), 73–85. https://doi.org/10.1016/j.gloenvcha.2006.11.006.
Guan, Z., Shawwash, Z., Abdalla, A., 2018. Using SDDP to develop water-value functions for a multireservoir system with international treaties. J. Water Resour. Plann. Manag. 144 (2), 05017021 https://doi.org/10.1061/(ASCE)WR.1943-5452.0000858.

Haasnoot, M., Middelkoop, H., van Beek, E., van Deursen, W.P.A., 2011. A method to develop sustainable water management strategies for an uncertain future. Sustain. Dev. 19 (6), 369–381. https://doi.org/10.1002/sd.438.
Haasnoot, M., Middelkoop, H., Offermans, A., Beek, E.v., Deursen, W.P.A.v., 2012. Exploring pathways for sustainable water management in river deltas in a changing environment. Climatic Change 115 (3), 795–819. https://doi.org/10.1007/s10584-012-0444-2.
Haasnoot, M., Kwakkel, J.H., Walker, W.E., ter Maat, J., 2013. Dynamic adaptive policy pathways: a method for crafting robust decisions for a deeply uncertain world. Global Environ. Change 23 (2), 485–498. https://doi.org/10.1016/j.gloenvcha.2012.12.006.
Haasnoot, M., Schellekens, J., Beersma, J.J., Middelkoop, H., Kwadijk, J.C.J., 2015. Transient scenarios for robust climate change adaptation illustrated for water management in The Netherlands. Environ. Res. Lett. 10 (10), 105008 https://doi.org/10.1088/1748-9326/10/10/105008.
Haasnoot, M., Warren, A., Kwakkel, J.H., 2019. In: Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), Decision Making under Deep Uncertainty: from Theory to Practice. Springer, Switzerland, pp. 71–92.
Hadka, D., Herman, J., Reed, P., Keller, K., 2015. An open source framework for many-objective robust decision making. Environ. Model. Software 74, 114–129. https://doi.org/10.1016/j.envsoft.2015.07.014.
Hajkowicz, S., Collins, K., 2007. A review of multiple criteria analysis for water resource planning and management. Water Resour. Manag. 21 (9), 1553–1566. https://doi.org/10.1007/s11269-006-9112-5.
Hakimi-Asiabar, M., Ghodsypour, S.H., Kerachian, R., 2010. Deriving operating policies for multi-objective reservoir systems: application of Self-Learning Genetic Algorithm. Appl. Soft Comput. 10 (4), 1151–1163. https://doi.org/10.1016/j.asoc.2009.08.016.
Hall, J.W., Grey, D., Garrick, D., Fung, F., Brown, C., Dadson, S.J., Sadoff, C.W., 2014. Coping with the curse of freshwater variability. Science 346 (6208), 429–430. https://doi.org/10.1126/science.1257890.
Han, J.C., Huang, G.H., Zhang, H., Zhuge, Y.S., He, L., 2012. Fuzzy constrained optimization of eco-friendly reservoir operation using self-adaptive genetic algorithm: a case study of a cascade reservoir system in the Yalong River, China. Ecohydrology 5 (6), 768–778. https://doi.org/10.1002/eco.267.
Haro-Monteagudo, D., Solera, A., Andreu, J., 2017. Drought early warning based on optimal risk forecasts in regulated river systems: application to the Jucar River Basin (Spain). J. Hydrol. 544, 36–45. https://doi.org/10.1016/j.jhydrol.2016.11.022.
He, W., Jiang, A., Zhang, J., Xu, H., Yu, X., Chen, S., Xiao, Y., 2022. Reservoir optimization operation considering regulating temperature stratification for a deep reservoir in early flood season. J. Hydrol. 604, 127253 https://doi.org/10.1016/j.jhydrol.2021.127253.
Hein, T., Funk, A., Pletterbauer, F., Graf, W., Zsuffa, I., Haidvogl, G., Schinegger, R., Weigelhofer, G., 2019. Management challenges related to long-term ecological impacts, complex stressor interactions, and different assessment approaches in the Danube River Basin. River Res. Appl. 35 (5), 500–509. https://doi.org/10.1002/rra.3243.
Herman, J.D., Zeff, H.B., Reed, P.M., Characklis, G.W., 2014. Beyond optimality: multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. Water Resour. Res. 50 (10), 7692–7713. https://doi.org/10.1002/2014WR015338.
Herman, J.D., Reed, P.M., Zeff, H.B., Characklis, G.W., 2015. How should robustness Be defined for water systems planning under change? J. Water Resour. Plann. Manag. 141 (10), 04015012 https://doi.org/10.1061/(ASCE)WR.1943-5452.0000509.
Herman, J.D., Zeff, H.B., Lamontagne, J.R., Reed, P.M., Characklis, G.W., 2016. Synthetic drought scenario generation to support bottom-up water supply vulnerability assessments. J. Water Resour. Plann. Manag. 142 (11), 04016050 https://doi.org/10.1061/(ASCE)WR.1943-5452.0000701.
Ho, M., Lall, U., Allaire, M., Devineni, N., Kwon, H.H., Pal, I., Raff, D., Wegner, D., 2017. The future role of dams in the United States of America. Water Resour. Res. 53 (2), 982–998. https://doi.org/10.1002/2016wr019905.
Holdren, G.C., Turner, K., 2010. Characteristics of lake mead, Arizona–Nevada. Lake Reservoir Manag. 26 (4), 230–239. https://doi.org/10.1080/07438141.2010.540699.
Hooshyar, M., Mousavi, S.J., Mahootchi, M., Ponnambalam, K., 2020. Aggregation-decomposition-based multi-agent reinforcement learning for multi-reservoir operations optimization. Water 12 (10). https://doi.org/10.3390/w12102688.
Horne, A., Szemis, J.M., Kaur, S., Webb, J.A., Stewardson, M.J., Costa, A., Boland, N., 2016. Optimization tools for environmental water decisions: a review of strengths, weaknesses, and opportunities to improve adoption. Environ. Model. Software 84, 326–338. https://doi.org/10.1016/j.envsoft.2016.06.028.
Hossain, M.S., El-shafie, A., 2013. Intelligent systems in optimizing reservoir operation policy: a review. Water Resour. Manag. 27 (9), 3387–3407. https://doi.org/10.1007/s11269-013-0353-9.
Housh, M., Ostfeld, A., Shamir, U., 2011. World Environmental and Water Resources Congress 2011, pp. 3075–3085.
Hu, Z.J., Putz, J., Sutjandra, Y., Chan, A., Mount, E., Baker, K., 2015. The energy authority optimizes water routing and hydroelectric generation on the columbia river. Interfaces 45 (1), 43–57. https://doi.org/10.1287/inte.2014.0768.
Huang, K., Ye, L., Chen, L., Wang, Q., Dai, L., Zhou, J., Singh, V.P., Huang, M., Zhang, J., 2018. Risk analysis of flood control reservoir operation considering multiple uncertainties. J. Hydrol 565, 672–684. https://doi.org/10.1016/j.jhydrol.2018.08.040.
Huang, X., Xu, B., Zhong, P.-a., Yao, H., Yue, H., Zhu, F., Lu, Q., Sun, Y., Mo, R., Li, Z., Liu, W., 2022. Robust multiobjective reservoir operation and risk decision-making model for real-time flood control coping with forecast uncertainty. J. Hydrol. 605, 127334 https://doi.org/10.1016/j.jhydrol.2021.127334.
Hwang, C.-L., Masud, A.S.M., 1979. A Decision Making Approach for Multi-Objective Optimization Considering A Trade-Off Method. Springer-Verlag, New York.
Hyde, K.M., Maier, H.R., 2006. Distance-based and stochastic uncertainty analysis for multi-criteria decision analysis in Excel using Visual Basic for Applications. Environ. Model. Software 21 (12), 1695–1710. https://doi.org/10.1016/j.envsoft.2005.08.004.
IPCC, 2012. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, p. 582 (Cambridge, United Kingdom and New York, NY, USA).
Jakeman, A.J., Barreteau, O., Hunt, R.J., Rinaudo, J.-D., Ross, A. (Eds.), 2016. Integrated Groundwater Management: Concepts, Approaches and Challenges. Springer (open access).
Jun, S.-M., Kang, M.-S., Hwang, S., Park, J., Song, J.-H., Song, J.H., 2020. Flood vulnerability assessment for prioritizing and evaluating rehabilitation of ungauged reservoirs considering climate change. Water 12 (7), 1901.
Kang, D., Lansey, K., 2014. Multiperiod planning of water supply infrastructure based on scenario analysis. J. Water Resour. Plann. Manag. 140 (1), 40–54. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000310.
Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J., 2013. Many objective robust decision making for complex environmental systems undergoing change. Environ. Model. Software 42, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007.
Kerachian, R., Karamouz, M., 2006. Optimal reservoir operation considering the water quality issues: a stochastic conflict resolution approach. Water Resour. Res. 42 (12) https://doi.org/10.1029/2005WR004575.
Kiem, A.S., Kuczera, G., Kozarovski, P., Zhang, L., Willgoose, G., 2021. Stochastic generation of future hydroclimate using temperature as a climate change covariate. Water Resour. Res. 57 (2) https://doi.org/10.1029/2020WR027331, 2020WR027331.
Kim, G.J., Kim, Y.-O., Reed, P.M., 2021. Improving the robustness of reservoir operations with stochastic dynamic programming. J. Water Resour. Plann. Manag. 147 (7), 04021030 https://doi.org/10.1061/(ASCE)WR.1943-5452.0001381.
Kwadijk, J.C.J., Haasnoot, M., Mulder, J.P.M., Hoogvliet, M.M.C., Jeuken, A.B.M., van der Krogt, R.A.A., van Oostrom, N.G.C., Schelfhout, H.A., van Velzen, E.H., van Waveren, H., de Wit, M.J.M., 2010. Using adaptation tipping points to prepare for climate change and sea level rise: a case study in The Netherlands. WIREs Climate Change 1 (5), 729–740. https://doi.org/10.1002/wcc.64.
Kwakkel, J.H., Haasnoot, M., Walker, W.E., 2015. Developing dynamic adaptive policy pathways: a computer-assisted approach for developing adaptive strategies for a deeply uncertain world. Climatic Change 132 (3), 373–386. https://doi.org/10.1007/s10584-014-1210-4.
Kwakkel, J.H., Walker, W.E., Haasnoot, M., 2016. Coping with the wickedness of public policy problems: approaches for decision making under deep uncertainty. J. Water Resour. Plann. Manag. 142 (3), 01816001 https://doi.org/10.1061/(ASCE)WR.1943-5452.0000626.
Labadie, J.W., 2004. Optimal operation of multireservoir systems: state-of-the-art review. J. Water Resour. Plann. Manag. 130 (2), 93–111. https://doi.org/10.1061/(asce)0733-9496(2004)130:2(93).
Lawrence, J., Haasnoot, M., 2017. What it took to catalyse uptake of dynamic adaptive pathways planning to address climate change uncertainty. Environ. Sci. Pol. 68, 47–57. https://doi.org/10.1016/j.envsci.2016.12.003.
Lempert, R., 2013. Scenarios that illuminate vulnerabilities and robust responses. Climatic Change 117 (4), 627–646. https://doi.org/10.1007/s10584-012-0574-6.
Lempert, R.J., Popper, S.W., Bankes, S.C., 2003. Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis. RAND Corporation, Santa Monica, CA.
Li, D., Wan, W., Zhao, J., 2018. Optimizing environmental flow operations based on explicit quantification of IHA parameters. J. Hydrol 563, 510–522. https://doi.org/10.1016/j.jhydrol.2018.06.031.
Liu, X.L., Luo, J.G., 2019. A dynamic multi-objective optimization model with interactivity and uncertainty for real-time reservoir flood control operation. Appl. Math. Model. 74, 606–620. https://doi.org/10.1016/j.apm.2019.05.009.
Loucks, D.P., Stedinger, J.R., Haith, D.P., 1981. Water Resources Systems Planning and Analysis. Prentice-Hall, Englewood Cliffs.
Luchner, J., Riegels, N.D., Bauer-Gottwein, P., 2019. Benefits of cooperation in transnational water-energy systems. J. Water Resour. Plann. Manag. 145 (5), 05019007 https://doi.org/10.1061/(ASCE)WR.1943-5452.0001047.
Lund, J.R., 2012. Provoking more productive discussion of wicked problems. J. Water Resour. Plann. Manag. 138 (3), 193–195. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000190.
Macian-Sorribes, H., Pulido-Velazquez, M., 2020. Inferring efficient operating rules in multireservoir water resource systems: a review. WIREs Water 7 (1), e1400. https://doi.org/10.1002/wat2.1400.
Maeda, S., Kawachi, T., Unami, K., Takeuchi, J., Ichion, E., 2010. Controlling wasteloads from point and nonpoint sources to river system by GIS-aided Epsilon Robust Optimization model. Journal of Hydro-Environment Research 4 (1), 27–36. https://doi.org/10.1016/j.jher.2009.04.002.
Mahmoud, M., Liu, Y., Hartmann, H., Stewart, S., Wagener, T., Semmens, D., Stewart, R., Gupta, H., Dominguez, D., Dominguez, F., Hulse, D., Letcher, R., Rashleigh, B., Smith, C., Street, R., Ticehurst, J., Twery, M., van Delden, H., Waldick, R., White, D., Winter, L., 2009. A formal framework for scenario development in support of

environmental decision-making. Environ. Model. Software 24 (7), 798–808. https://doi.org/10.1016/j.envsoft.2008.11.010.
Mahootchi, M., Ponnambalam, K., Tizhoosh, H.R., 2010. Comparison of risk-based optimization models for reservoir management. Can. J. Civ. Eng. 37 (1), 112–124. https://doi.org/10.1139/l09-165.
Maier, H.R., Guillaume, J.H.A., van Delden, H., Riddell, G.A., Haasnoot, M., Kwakkel, J. H., 2016. An uncertain future, deep uncertainty, scenarios, robustness and adaptation: how do they fit together? Environ. Model. Software 81, 154–164. https://doi.org/10.1016/j.envsoft.2016.03.014.
Mamatova, Z., Ibrokhimov, D., Dewulf, A.R.P.J., 2016. The wicked problem of dam governance in central asia: current trade-offs, future challenges, prospects for cooperation. International Journal of Water Governance 4 (15). https://doi.org/10.7564/15-IJWG110.
Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), 2019. Decision Making under Deep Uncertainty: from Theory to Practice. Springer, Switzerland.
McCully, P., 1996. Silenced Rivers : the Ecology and Politics of Large Dams. Zed Books, Atlantic Highlands, N.J., USA.
McMahon, T.A., Petheram, C., 2020. Australian dams and reservoirs within a global setting. Aust. J. Water Resour. 24 (1), 12–35. https://doi.org/10.1080/13241583.2020.1733743.
McPhail, C., Maier, H.R., Kwakkel, J.H., Giuliani, M., Castelletti, A., Westra, S., 2018. Robustness metrics: how are they calculated, when should they Be used and why do they give different results? Earth's Future 6 (2), 169–191. https://doi.org/10.1002/2017EF000649.
McPhail, C., Maier, H.R., Westra, S., Kwakkel, J.H., van der Linden, L., 2020. Impact of scenario selection on robustness. Water Resour. Res. 56 (9), e2019WR026515 https://doi.org/10.1029/2019WR026515.
McPhail, C., Maier, H.R., Westra, S., van der Linden, L., Kwakkel, J.H., 2021. Guidance framework and software for understanding and achieving system robustness. Environ. Model. Software 142, 105059. https://doi.org/10.1016/j.envsoft.2021.105059.
Mdba, M.D.B.A., 2021. Hume dam, mesbah, A. 2016. Stochastic model predictive control: an overview and perspectives for future research. IEEE Control Syst. Mag. 36 (6), 30–44. https://doi.org/10.1109/MCS.2016.2602087.
Mihnea, I., Mandru, R., Bran, M., 2008. Danube dams - necessity or calamity? CARPATHIAN JOURNAL OF EARTH AND ENVIRONMENTAL SCIENCES 3 (1), 31–37.
Milanović, S., Vasić, L., 2021. Review: methodological approaches and research techniques for addressing construction and remediation problems in karst reservoirs. Hydrogeol. J. 29 (1), 101–122. https://doi.org/10.1007/s10040-020-02280-1.
Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., Stouffer, R.J., 2008. Stationarity is dead: whither water management? Science 319 (5863), 573–574. https://doi.org/10.1126/science.1151915.
Mimi, Z.A., Sawalhi, B.I., 2003. A decision tool for allocating the waters of the Jordan river basin between all riparian parties. Water Resour. Manag. 17 (6), 447–461. https://doi.org/10.1023/B:WARM.0000004959.90022 (ba).
Molle, F., 2008. Nirvana concepts, narratives and policy models: insights from the water sector. Water Altern. (WaA) 1 (1), 131–156.
Mortazavi, M., Kuczera, G., Cui, L., 2012. Multiobjective optimization of urban water resources: moving toward more practical solutions. Water Resour. Res. 48 (3) https://doi.org/10.1029/2011WR010866.
Mortazavi-Naeini, M., Kuczera, G., Kiem, A.S., Cui, L., Henley, B., Berghout, B., Turner, E., 2015. Robust optimization to secure urban bulk water supply against extreme drought and uncertain climate change. Environ. Model. Software 69, 437–451. https://doi.org/10.1016/j.envsoft.2015.02.021.
Mujumdar, P.P., Nirmala, B., 2007. A bayesian stochastic optimization model for a multi-reservoir hydropower system. Water Resour. Manag. 21 (9), 1465–1485. https://doi.org/10.1007/s11269-006-9094-3.
Mulvey, J.M., Vanderbei, R.J., Zenios, S.A., 1995. Robust optimization of large-scale systems. Oper. Res. 43 (2), 264–281.
Muronda, M.T., Marofi, S., Nozari, H., Babamiri, O., 2021. Uncertainty analysis of reservoir operation based on stochastic optimization approach using the generalized likelihood uncertainty estimation method. Water Resour. Manag. 35 (10), 3179–3201. https://doi.org/10.1007/s11269-021-02877-5.
Nair, S.J., Sasikumar, K., 2019. Fuzzy reliability-based optimization of a hydropower reservoir. J. Hydroinf. 21 (2), 308–317. https://doi.org/10.2166/hydro.2019.078.
Nguyen, K., Stuart, R., 2021. NSW Weather: NSW Premier Gladys Berejiklian Warns of 'prolonged 'event — as it Happened.
Nichols, S.J., Powell, S.J., Peat, M., Johnson, W., 2017. An evidence-based approach for integrating ecological, hydrological and consumptive models to optimize flow management: a proof of concept. Pol. Stud. 38 (5), 432–446. https://doi.org/10.1080/01442872.2016.1188905.
Ortiz-Partida, J.P., Kahil, T., Ermolieva, T., Ermoliev, Y., Lane, B., Sandoval-Solis, S., Wada, Y., 2019. A two-stage stochastic optimization for robust operation of multipurpose reservoirs. Water Resour. Manag. 33 (11), 3815–3830. https://doi.org/10.1007/s11269-019-02337-1.
Pan, L.M., Housh, M., Liu, P., Cai, X.M., Chen, X., 2015. Robust stochastic optimization for reservoir operation. Water Resour. Res. 51 (1), 409–429. https://doi.org/10.1002/2014wr015380.
Panagopoulos, A., Giannika, V., 2023. Study on the water resources and the opportunities for sustainable desalination & minimal/zero liquid discharge (MLD/ZLD) practices in Greece (Eastern Mediterranean). Sustainable Water Resour. Manag. 9 (4), 106. https://doi.org/10.1007/s40899-023-00884-5.
Partington, D., Thyer, M., Shanafield, M., McInerney, D., Westra, S., Maier, H., Simmons, C., Croke, B., Jakeman, A.J., Gupta, H., Kavetski, D., 2022. Predicting wildfire induced changes to runoff: a review and synthesis of modeling approaches. WIREs Water 9 (5), e1599. https://doi.org/10.1002/wat2.1599.
Parvez, I., Shen, J., Khan, M., Cheng, C., 2019. Modeling and solution techniques used for hydro generation scheduling. Water 11 (7), 1392.
Pearce, N., 2021. First Nation Declares Sovereignty over Saskatchewan River Delta, Saskatoon. Canada.
Perera, L., Thompson, R.G., Wu, W., 2021. Determining optimum toll charges for freight vehicles considering multi-stakeholder objectives in urban conditions. Transport. J. 60 (2), 171–207. https://doi.org/10.5325/transportationj.60.2.0171.
Poff, N.L., Richter, B.D., Arthington, A.H., Bunn, S.E., Naiman, R.J., Kendy, E., Acreman, M., Apse, C., Bledsoe, B.P., Freeman, M.C., Henriksen, J., Jacobson, R.B., Kennen, J.G., Merritt, D.M., O'Keeffe, J.H., Olden, J.D., Rogers, K., Tharme, R.E., Warner, A., 2010. The ecological limits of hydrologic alteration (ELOHA): a new framework for developing regional environmental flow standards. Freshw. Biol. 55 (1), 147–170. https://doi.org/10.1111/j.1365-2427.2009.02204.x.
Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M.A., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2015. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nat. Clim. Change 6, 25–34. https://doi.org/10.1038/nclimate2765.
Porse, E.C., Sandoval-Solis, S., Lane, B.A., 2015. Integrating environmental flows into multi-objective reservoir management for a transboundary, water-scarce river basin: rio grande/bravo. Water Resour. Manag. 29 (8), 2471–2484. https://doi.org/10.1007/s11269-015-0952-8.
Porter, M.E., 1985. Competitive Advantage. Free Press, New York.
Powell, W.B., 2007. Approximate Dynamic Programming: Solving the Curses of Dimensionality. Wiley, NJ, USA.
Prudhomme, C., Wilby, R.L., Crooks, S., Kay, A.L., Reynard, N.S., 2010. Scenario-neutral approach to climate change impact studies: application to flood risk. J. Hydrol. 390 (3), 198–209. https://doi.org/10.1016/j.jhydrol.2010.06.043.
Quinn, J.D., Reed, P.M., Giuliani, M., Castelletti, A., Oyler, J.W., Nicholas, R.E., 2018. Exploring how changing monsoonal dynamics and human pressures challenge multireservoir management for flood protection, hydropower production, and agricultural water supply. Water Resour. Res. 54 (7), 4638–4662. https://doi.org/10.1029/2018WR022743.
Ramaswamy, V., Saleh, F., 2020. Ensemble based forecasting and optimization framework to optimize releases from water supply reservoirs for flood control. Water Resour. Manag. 34 (3), 989–1004. https://doi.org/10.1007/s11269-019-02481-8.
Raso, L., Schwanenberg, D., van de Giesen, N.C., van Overloop, P.J., 2014. Short-term optimal operation of water systems using ensemble forecasts. Adv. Water Resour. 71, 200–208. https://doi.org/10.1016/j.advwatres.2014.06.009.
Razavi, S., Gober, P., Maier, H.R., Brouwer, R., Wheater, H., 2020. Anthropocene flooding: challenges for science and society. Hydrol. Process. 34, 1996–2000. https://doi.org/10.1002/hyp.13723.
Reed, P.M., Kasprzyk, J., 2009. Water resources management: the myth, the wicked, and the future. J. Water Resour. Plann. Manag. 135 (6), 411–413. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000047.
Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – a framework and guidance. Environ. Model. Software 22 (11), 1543–1556. https://doi.org/10.1016/j.envsoft.2007.02.004.
Ren, K., Huang, S., Huang, Q., Wang, H., Leng, G., Wu, Y., 2019. Defining the robust operating rule for multi-purpose water reservoirs under deep uncertainties. J. Hydrol. 578, 124134 https://doi.org/10.1016/j.jhydrol.2019.124134.
Richter, B., Baumgartner, J., Wiginton, R., Braun, D., 1997. How much water does a river need? Freshw. Biol. 37 (1), 231–249. https://doi.org/10.1046/j.1365-2427.1997.00153.x.
Rieker, J.D., Labadie, J.W., 2012. An intelligent agent for optimal river-reservoir system management. Water Resour. Res. 48 (9) https://doi.org/10.1029/2012WR011958.
Rigosi, A., Rueda, F.J., 2012. Propagation of uncertainty in ecological models of reservoirs: from physical to population dynamic predictions. Ecol. Model. 247, 199–209. https://doi.org/10.1016/j.ecolmodel.2012.08.022.
Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a general theory of planning. Pol. Sci. 4 (2), 155–169. https://doi.org/10.1007/BF01405730.
Rizzo, M.J., Dold, M., 2021. Knightian uncertainty: through a Jamesian window. Camb. J. Econ. 45 (5), 967–988. https://doi.org/10.1093/cje/beab011.
Ryan Bellmore, J., Duda, J.J., Craig, L.S., Greene, S.L., Torgersen, C.E., Collins, M.J., Vittum, K., 2017. Status and trends of dam removal research in the United States. WIREs Water 4 (2), e1164. https://doi.org/10.1002/wat2.1164.
Saadatpour, M., Afshar, A., Solis, S.S., 2020. Surrogate-based multiperiod, multiobjective reservoir operation optimization for quality and quantity management. J. Water Resour. Plann. Manag. 146 (8) https://doi.org/10.1061/(asce)wr.1943-5452.0001252.
Sahu, R.K., McLaughlin, D.B., 2018. An ensemble optimization framework for coupled design of hydropower contracts and real-time reservoir operating rules. Water Resour. Res. 54 (10), 8401–8419. https://doi.org/10.1029/2018wr022753.
Salas, J.D., Hall, W.A., 1983. In: Guggino, E., Rossi, G., Hendricks, D. (Eds.), Operating Rules for Storage Reservoirs. Springer.
Saltelli, A., Jakeman, A., Razavi, S., Wu, Q., 2021. Sensitivity analysis: a discipline coming of age. Environ. Model. Software 146, 105226. https://doi.org/10.1016/j.envsoft.2021.105226.
Scattolini, R., 2009. Architectures for distributed and hierarchical model predictive control – a review. J. Process Control 19 (5), 723–731. https://doi.org/10.1016/j.jprocont.2009.02.003.

Schwanenberg, D., Fan, F.M., Naumann, S., Kuwajima, J.I., Montero, R.A., dos Reis, A.A., 2015. Short-term reservoir optimization for flood mitigation under meteorological and hydrological forecast uncertainty. Water Resour. Manag. 29 (5), 1635–1651. https://doi.org/10.1007/s11269-014-0899-1.

Sechi, G.M., Gaivoronski, A.A., Napolitano, J., 2019. Optimising pumping activation in multi-reservoir water supply systems under uncertainty with stochastic quasi-gradient methods. Water Resour. Manag. 33 (5), 1881–1895. https://doi.org/10.1007/s11269-019-02219-6.

Şen, Z., 2021. Reservoirs for water supply under climate change impact—a review. Water Resour. Manag. 35 (11), 3827–3843. https://doi.org/10.1007/s11269-021-02925-0.

Serrat-Capdevila, A., Valdés, J.B., 2007. An alternative approach to the operation of multinational reservoir systems: application to the Amistad & Falcon system (Lower Rio Grande/Río Bravo). Water Resour. Manag. 21 (4), 677–698. https://doi.org/10.1007/s11269-006-9035-1.

Sharma, A., Wasko, C., Lettenmaier, D.P., 2018. If precipitation extremes are increasing, why aren't floods? Water Resour. Res. 54 (11), 8545–8551. https://doi.org/10.1029/2018WR023749.

Shiau, J.-T., Wu, F.-C., 2013. Optimizing environmental flows for multiple reaches affected by a multipurpose reservoir system in Taiwan: restoring natural flow regimes at multiple temporal scales. Water Resour. Res. 49 (1), 565–584. https://doi.org/10.1029/2012WR012638.

Simonovic, S.P., 1992. Reservoir systems analysis: closing gap between theory and practice. J. Water Resour. Plann. Manag. 118 (3), 262–280. https://doi.org/10.1061/(ASCE)0733-9496(1992)118:3(262).

Smith, A., 2021. Bitter Dispute between NSW Ministers over Warragamba Dam Spilling (Sydney, Australia).

Soleimani, S., Bozorg-Haddad, O., Loáiciga, H.A., 2016. Reservoir operation rules with uncertainties in reservoir inflow and agricultural demand derived with stochastic dynamic programming. J. Irrigat. Drain. Eng. 142 (11), 04016046 https://doi.org/10.1061/(ASCE)IR.1943-4774.0001065.

Song, J., Whittington, D., 2004. Why have some countries on international rivers been successful negotiating treaties? A global perspective. Water Resour. Res. 40 (5) https://doi.org/10.1029/2003WR002536.

Speirs, D., 2019. Suburban Reservoirs to Be Opened up for Recreation. Government of South Australia, Adelaide, Australia.

Srdjevic, Z., Srdjevic, B., 2014. Modelling multicriteria decision making process for sharing benefits from the reservoir at Serbia-Romania border. Water Resour. Manag. 28 (12), 4001–4018. https://doi.org/10.1007/s11269-014-0723-y.

Sun, Y.M., Zhu, F.L., Chen, J., Li, J.S., 2018. Risk analysis for reservoir real-time optimal operation using the scenario tree-based stochastic optimization method. Water 10 (5). https://doi.org/10.3390/w10050606.

Szemis, J.M., Dandy, G.C., Maier, H.R., 2013. A multiobjective ant colony optimization approach for scheduling environmental flow management alternatives with application to the River Murray, Australia. Water Resour. Res. 49 (10), 6393–6411. https://doi.org/10.1002/wrcr.20518.

Szemis, J.M., Maier, H.R., Dandy, G.C., 2014. An adaptive ant colony optimization framework for scheduling environmental flow management alternatives under varied environmental water availability conditions. Water Resour. Res. 50 (10), 7606–7625. https://doi.org/10.1002/2013WR015187.

Tian, X., Guo, Y., Negenborn, R.R., Wei, L., Lin, N.M., Maestre, J.M., 2019. Multi-scenario model predictive control based on genetic algorithms for level regulation of open water systems under ensemble forecasts. Water Resour. Manag. 33 (9), 3025–3040. https://doi.org/10.1007/s11269-019-02284-x.

Tiwari, D.N., Loof, R., Paudyal, G.N., 1999. Environmental–economic decision-making in lowland irrigated agriculture using multi-criteria analysis techniques. Agric. Syst. 60 (2), 99–112. https://doi.org/10.1016/S0308-521X(99)00021-9.

Tran, D.D., van Halsema, G., Hellegers, P.J.G.J., Hoang, L.P., Ludwig, F., 2019. Long-term sustainability of the Vietnamese Mekong Delta in question: an economic assessment of water management alternatives. Agric. Water Manag. 223, 105703 https://doi.org/10.1016/j.agwat.2019.105703.

Trindade, B.C., Reed, P.M., Herman, J.D., Zeff, H.B., Characklis, G.W., 2017. Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-objective optimization under deep uncertainty. Adv. Water Resour. 104, 195–209. https://doi.org/10.1016/j.advwatres.2017.03.023.

Tsitsiklis, J.N., van Roy, B., 1996. Feature-based methods for large scale dynamic programming. Mach. Learn. 22 (1), 59–94. https://doi.org/10.1007/BF00114724.

Tsoukalas, I., Makropoulos, C., 2015. Multiobjective optimisation on a budget: exploring surrogate modelling for robust multi-reservoir rules generation under hydrological uncertainty. Environ. Model. Software 69, 396–413. https://doi.org/10.1016/j.envsoft.2014.09.023.

van Notten, P.W.F., Sleegers, A.M., van Asselt, M.B.A., 2005. The future shocks: on discontinuity and scenario development. Technol. Forecast. Soc. Change 72 (2), 175–194. https://doi.org/10.1016/j.techfore.2003.12.003.

Velarde, P., Tian, X., Sadowska, A.D., Maestre, J.M., 2019. Scenario-based hierarchical and distributed MPC for water resources management with dynamical uncertainty. Water Resour. Manag. 33 (2), 677–696. https://doi.org/10.1007/s11269-018-2130-2.

Walker, W.E., Rahman, S.A., Cave, J., 2001. Adaptive policies, policy analysis, and policy-making. Eur. J. Oper. Res. 128 (2), 282–289. https://doi.org/10.1016/S0377-2217(00)00071-0.

Wang, J., Dong, Z., Liao, W., Li, C., Feng, S., Luo, H., Peng, Q., 2013. An environmental flow assessment method based on the relationships between flow and ecological response: a case study of the Three Gorges Reservoir and its downstream reach. Sci. China Technol. Sci. 56 (6), 1471–1484. https://doi.org/10.1007/s11431-013-5193-6.

Wang, J., Cheng, C., Shen, J., Cao, R., Yeh, W.W.-G., 2018. Optimization of large-scale daily hydrothermal system operations with multiple objectives. Water Resour. Res. 54 (4), 2834–2850. https://doi.org/10.1002/2017WR021291.

Weaver, C.P., Lempert, R.J., Brown, C., Hall, J.A., Revell, D., Sarewitz, D., 2013. Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks. Wiley Interdisciplinary Reviews: Clim. Change 4 (1), 39–60. https://doi.org/10.1002/wcc.202.

World Bank, 2009. Directions in Hydropower : Scaling up for Development. World Bank, World Bank, Washington, DC.

World Commission on Dams, 2000. Dams and Development A New Framework for Decision-Making: the Report of the World Commission on Dams. World Commission on Dams, Earthscan, London.

Wu, W., Maier, H.R., Simpson, A.R., 2010. Single-objective versus MultiObjective optimization of water distribution systems accounting for greenhouse gas emissions by carbon pricing. J. Water Res. Pl. - ASCE 136 (5), 1–11.

Wu, W., Maier, H.R., Dandy, G.C., Leonard, R., Bellette, K., Cuddy, S., Maheepala, S., 2016. Including stakeholder input in formulating and solving real-world optimisation problems. Environ. Model. Software 79 (May), 197–213. https://doi.org/10.1016/j.envsoft.2016.02.012.

Wu, W., Dandy, G.C., Maier, H.R., Maheepala, S., Marchi, A., Mirza, F., 2017. Identification of optimal water supply portfolios for a major city. J. Water Res. Pl. - ASCE 143 (9). https://doi.org/10.1061/(ASCE)WR.1943-5452.0000811.

Wu, W., Emerton, R., Duan, Q., Wood, A.W., Wetterhall, F., Robertson, D.E., 2020a. Ensemble flood forecasting: current status and future opportunities. WIREs Water 7 (3), e1432. https://doi.org/10.1002/wat2.1432.

Wu, W., Maier, H.R., Dandy, G.C., Arora, M., Castelletti, A., 2020b. The changing nature of the water–energy nexus in urban water supply systems: a critical review of changes and responses. Journal of Water and Climate Change. https://doi.org/10.2166/wcc.2020.276.

Wu, W., Zhou, Y., Leonard, M., 2022. Evolutionary algorithm-based multiobjective reservoir operation policy optimisation under uncertainty. Environmental Research Communications 4 (12), 121001. https://doi.org/10.1088/2515-7620/aca1fc.

Wurbs, R.A., 1993. Reservoir-system simulation and optimization models. J. Water Resour. Plann. Manag. 119 (4), 455–472. https://doi.org/10.1061/(ASCE)0733-9496(1993)119:4(455).

Xevi, E., Khan, S., 2005. A multi-objective optimisation approach to water management. J. Environ. Manag. 77 (4), 269–277. https://doi.org/10.1016/j.jenvman.2005.06.013.

Yakowitz, S., 1982. Dynamic programming applications in water resources. Water Resour. Res. 18 (4), 673–696. https://doi.org/10.1029/WR018i004p00673.

Yeh, W.W.G., 1985. Reservoir management and operations models - a state-of-the-art review. Water Resour. Res. 21 (12), 1797–1818. https://doi.org/10.1029/WR021i012p01797.

Yin, Y.Y., Huang, G.H., Hipel, K.W., 1999. Fuzzy relation analysis for multicriteria water resources management. J. Water Resour. Plann. Manag. 125 (1), 41–47. https://doi.org/10.1061/(ASCE)0733-9496(1999)125:1(41).

Young, W., Scott, A.C., Cuddy, S., Rennie, B.A., 2003. Murray Flow Assessment Tool: A Technical Description. Client Report, CSIRO Land and Water, Canberra.

Yu, Y., Zhao, R., Zhang, J., Yang, D., Zhou, T., 2021. Multi-objective game theory optimization for balancing economic, social and ecological benefits in the Three Gorges Reservoir operation. Environ. Res. Lett. 16 (8), 085007 https://doi.org/10.1088/1748-9326/ac0b69.

Zare, F., Guillaume, J.H.A., ElSawah, S., Croke, B., Fu, B., Iwanaga, T., Merritt, W., Partington, D., Ticehurst, J., Jakeman, A.J., 2021. A formative and self-reflective approach to monitoring and evaluation of interdisciplinary team research: an integrated water resource modelling application in Australia. J. Hydrol. 596, 126070 https://doi.org/10.1016/j.jhydrol.2021.126070.

Zatarain-Salazar, J., Reed, P.M., Herman, J.D., Giuliani, M., Castelletti, A., 2016. A diagnostic assessment of evolutionary algorithms for multi-objective surface water reservoir control. Adv. Water Resour. 92, 172–185. https://doi.org/10.1016/j.advwatres.2016.04.006.

Zatarain-Salazar, J., Reed, P.M., Quinn, J.D., Giuliani, M., Castelletti, A., 2017. Balancing exploration, uncertainty and computational demands in many objective reservoir optimization. Adv. Water Resour. 109, 196–210. https://doi.org/10.1016/j.advwatres.2017.09.014.

Zhao, T., Zhao, J., 2014a. Improved multiple-objective dynamic programming model for reservoir operation optimization. J. Hydroinf. 16 (5), 1142–1157. https://doi.org/10.2166/hydro.2014.004.

Zhao, T.T.G., Zhao, J.S., 2014b. Optimizing operation of water supply reservoir: the role of constraints. Math. Probl Eng. https://doi.org/10.1155/2014/853186, 2014.

Zhu, F., Zhong, P.-a., Sun, Y., 2018. Multi-criteria group decision making under uncertainty: application in reservoir flood control operation. Environ. Model. Software 100, 236–251. https://doi.org/10.1016/j.envsoft.2017.11.032.

Zolfagharpour, F., Saghafian, B., Delavar, M., 2021. Adapting reservoir operation rules to hydrological drought state and environmental flow requirements. J. Hydrol. 600, 126581. https://doi.org/10.1016/j.jhydrol.2021.126581.