

Water Resources Research



REVIEW ARTICLE

10.1029/2019WR025502

Key Points:

- This paper reviews dynamic planning studies for water resources systems under climate change framed as optimal control problems
- Multiple sources of uncertainty, including climate and human system dynamics, prevent the identification of an optimal adaptation policy
- Research opportunities remain to link dynamic planning with climate process insights and to identify indicator variables for monitoring

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Citation:

Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2020). Climate adaptation as a control problem: Review and perspectives on dynamic water resources planning under uncertainty. *Water Resources Research*, 56, e24389. <https://doi.org/10.1029/2019WR025502>

Received 6 MAY 2019

Accepted 30 DEC 2019

Accepted article online 7 JAN 2020

Climate Adaptation as a Control Problem: Review and Perspectives on Dynamic Water Resources Planning Under Uncertainty

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Abstract Climate change introduces substantial uncertainty to water resources planning and raises the key question: when, or under what conditions, should adaptation occur? A number of recent studies aim to identify policies mapping future observations to actions—in other words, framing climate adaptation as an optimal control problem. This paper uses the control paradigm to review and classify recent dynamic planning studies according to their approaches to uncertainty characterization, policy structure, and solution methods. We propose a set of research gaps and opportunities in this area centered on the challenge of characterizing uncertainty, which prevents the unambiguous application of control methods to this problem. These include exogenous uncertainty in forcing, model structure, and parameters propagated through a chain of climate and hydrologic models; endogenous uncertainty in human-environmental system dynamics across multiple scales; and sampling uncertainty due to the finite length of historical observations and future projections. Recognizing these challenges, several opportunities exist to improve the use of control methods for climate adaptation, namely, how problem context and understanding of climate processes might assist with uncertainty quantification and experimental design, out-of-sample validation and robustness of optimized adaptation policies, and monitoring and data assimilation, including trend detection, Bayesian inference, and indicator variable selection. We conclude with a summary of recommendations for dynamic water resources planning under climate change through the lens of optimal control.

1. Introduction

Water resources planners face the challenge of adapting to climate change with a portfolio of potential actions, including infrastructure, operating rules, and demand conservation to reduce vulnerability (Füssel, 2007; Hallegatte, 2009). These decisions are often supported by simulation and optimization methods tailored to long-term projections of hydroclimate. However, these projections are clouded by a “cascade” of uncertainty (Wilby & Dessai, 2010), propagated through the chain of greenhouse gas emissions, climate models and their initial conditions, regional downscaling, hydrologic models, and human-environmental systems models, only a portion of which can be captured in ensemble projections (Stainforth et al., 2007). This is particularly the case for the uncertain trends in flood and drought risk that drive infrastructure planning (Asadih & Krakauer, 2017; Dottori et al., 2018; Trenberth et al., 2014).

Under these conditions, it is difficult to apply traditional decision-making methods such as cost-benefit analysis and expected value utility theory, which require exact probabilities and commensurate values (Borgomeo et al., 2018; Dennig, 2017; Lempert, 2015; Tol, 2003). In response, several new computational frameworks have emerged to support climate adaptation. Broadly, these can be grouped into two categories (Figure 1): robust planning, with a focus on identifying alternatives that perform acceptably under a wide range of future conditions, and dynamic planning, which aims to identify adaptation policies that respond to new observations over time. While these are not mutually exclusive—a dynamic policy can also be robust, though the reverse is not necessarily true (Kwakkel & Haasnoot, 2019; Maier et al., 2016)—they face very different challenges in experimental design and implementation.

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Decision support
under long-term
climate uncertainty:

Robust Planning

- Identify alternatives that can withstand a wide range of future conditions
- Low/moderate dependence on uncertainty characterization

Dynamic Planning

- Identify alternatives that respond to new observations over time (i.e., a control problem)
- High dependence on uncertainty characterization

Figure 1. Broad classification of decision support frameworks for water resources planning under climate change. This paper reviews dynamic planning studies (highlighted) under the framing of an optimal control problem. Dynamic plans may also be robust, though the reverse is not necessarily true.

Robust planning frameworks are designed to circumvent the severe uncertainty in climate projections, as they aim to identify the range of scenarios leading to system vulnerabilities (Weaver et al., 2013). These bottom-up approaches have rapidly gained traction, led by frameworks such as Robust Decision Making (Bryant & Lempert, 2010; Lempert, 2002), Info-Gap (Hipel & Ben-Haim, 1999; Korteling et al., 2013), and Decision Scaling (Brown et al., 2012; Poff et al., 2016), which have been extended to incorporate multiple performance criteria (Kasprzyk et al., 2013; Ray et al., 2018; Shortridge & Guikema, 2016). Because vulnerability assessment alone does not result in a set of recommended actions, bottom-up frameworks also often test the robustness of planning alternatives. However, this shift requires the vulnerability space to be reconciled with the likelihood of future scenarios, usually with either uniformly sampled scenarios or ensemble projections treated probabilistically (Shortridge & Zaitchik, 2018; Taner et al., 2017, 2019). The identification of robust alternatives has been addressed both via simulation (e.g., Herman et al., 2014; McPhail et al., 2018) and robust optimization (Eker & Kwakkel, 2018; Giuliani & Castelletti, 2016; Hamarat et al., 2014; Trindade et al., 2017; Watson & Kasprzyk, 2017). A potential limitation of robust planning frameworks is the tendency to favor static alternatives to be implemented in the near term, which could result in costly overdesign, particularly in the case of infrastructure (Borgomeo et al., 2018). Robust planning frameworks have been the subject of several prior reviews and will not be covered in detail here (Dittrich et al., 2016; Giuliani & Castelletti, 2016; Herman et al., 2015; Maier et al., 2016; McPhail et al., 2018).

Dynamic planning frameworks identify policies to select actions in response to new information over time (e.g., Haasnoot et al., 2013; Pahl-Wostl, 2007), recognizing that decisions decades in the future will be revisited as more information is collected (de Neufville & Scholtes, 2011; DiFrancesco & Tullios, 2014; Walker et al., 2001). This goal fundamentally aligns with that of an optimal control problem, though not all dynamic planning studies have been framed this way. Policy design involves optimizing the sequence, timing, and/or threshold values of observed variables to initiate adaptations, which can be supported by optimal control methods such as stochastic dynamic programming (SDP; Fletcher et al., 2019; Hui et al., 2018) or policy search (Kwakkel et al., 2015; Zeff et al., 2016). Additionally, several hybrid frameworks that combine optimization with adaptive management have been used to support the policymaking process, including Dynamic Adaptive Policy Pathways (Haasnoot et al., 2013; Walker et al., 2013) and Engineering Options Analysis, which determines whether infrastructure investments should be made now or deferred (de Neufville & Smet, 2019). The latter has been applied in dam sizing and sequencing (Jeuland & Whittington, 2014), drought planning (Fletcher et al., 2017), and infrastructure expansion (Erfani et al., 2018; Hino & Hall, 2017; Woodward et al., 2011). Similar to robust planning, dynamic planning effectively assigns optimal actions to different regions of the scenario space (Helgeson, 2018). However, dynamic planning also provides a quantitative basis for assimilating new information and reacting to new observations as they occur, aiming to reduce regret if the future unfolds differently than expected. This enables actions that are differentiated not only by the current state of the system but also by new projections generated throughout the planning period. The process of designing a dynamic plan is generally more dependent on the characterization of uncertainty (Figure 1), because it requires specifying not only the severity of uncertain variables but also the sequences of events through time.

This paper reviews studies of dynamic water resources planning under climate change, organized under the framing of an optimal control problem (section 2). The control framing provides a common structure and terminology for climate adaptation studies that include (1) a dynamical system, (2) multistage or continuous decision making, and (3) the development of a control policy as a function of system states, indicator variables, and/or time. We classify recent studies in this area according to components of the experimental design, including policy structure, uncertainty characterization, and solution methods (section 3). In the

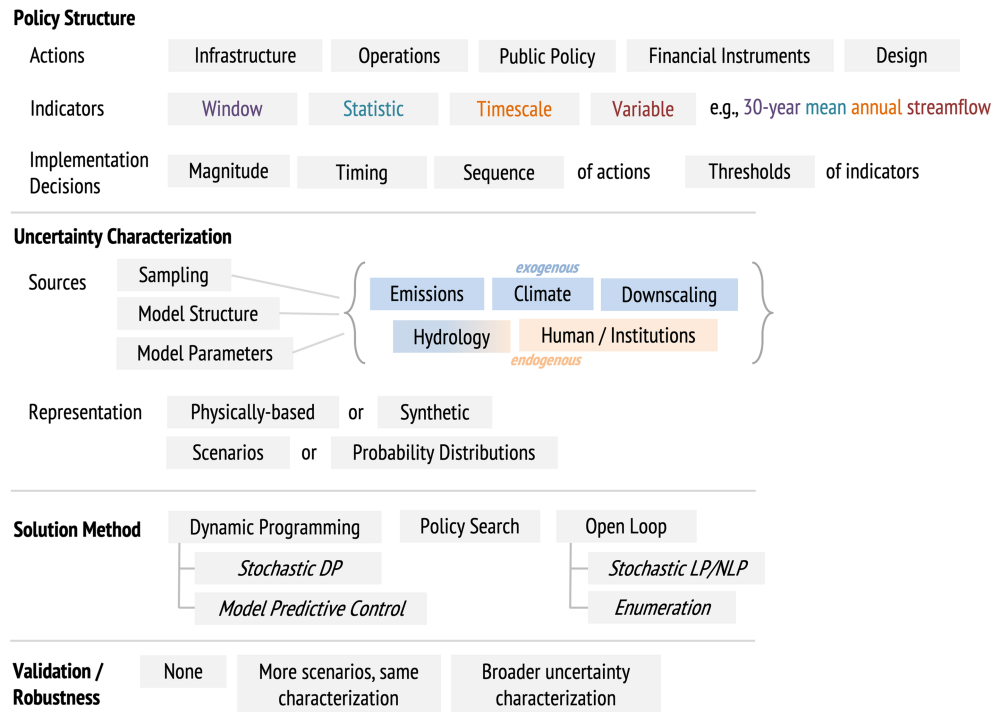


Figure 2. Overview of dynamic water resources planning under climate change, structured as a control problem. Policies are optimized to one or more performance metrics evaluated by the system model according to the state transition equation. The system receives a combination of climate and nonclimate forcing inputs. We assume a watershed-scale planning problem and therefore omit the feedback from the system to global emissions.

process, several key challenges are identified, primarily driven by the unavoidable subjectivity involved in uncertainty characterization. These gaps are then discussed in the context of opportunities to advance control methods to support dynamic planning under climate change (section 4).

2. Problem Formulation and Solution Methods

2.1. Problem Formulation

The problem of dynamic water resources planning under climate change involves designing a policy that maps observed and projected information to actions, that is, a control problem. The formulation presented here involves continuous system states, discrete actions, and nonstationary exogenous forcing (Figure 2). The choice of discrete rather than continuous actions is not required but reflects the common planning situation where a set of alternatives has been preselected based on economic and geographic constraints.

Given system states \mathbf{x}_t , discrete actions \mathbf{a}_t , and stochastic forcing \mathbf{e}_t , the system follows the state transition equation $\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{a}_t, \mathbf{e}_{t+1})$ in a single realization of the stochastic disturbance with a single action. The function $f_t(\cdot)$ is assumed deterministic but time variant to allow for changes in the structure or parameters of the system, for example, to reflect path dependence in the choice of actions. The state variables might include infrastructure storage and conveyance capacity, in addition to the current storage volume. The decision step is typically annual or greater over a planning horizon spanning 30–50 years in the future. Actions could include infrastructure capacity expansions and/or redefining operating rules or conservation policies that act on shorter timescales. Finally, forcing variables are defined by either a scenario ensemble or probability distribution, which could include streamflow, snowpack, and water demand.

The system trajectory τ is the set of state, action, and forcing variables over the time history of the system, up to and including the current time step: $\tau_t = (\mathbf{x}_0, \dots, \mathbf{x}_t, \mathbf{a}_0, \dots, \mathbf{a}_{t-1}, \mathbf{e}_1, \dots, \mathbf{e}_t)$. At each time step t , the decision problem is to select one action from the set of possible actions, $\mathbf{a}_t \in \mathcal{A}$, by applying the policy function π to the current information available: $\mathbf{a}_t = \pi(\mathbf{I}_t)$, where the information \mathbf{I}_t can include a combination of observed or

forecasted states and fluxes in the system. The objectives include one or more cost functions computed from the trajectory at each time step, $J_t(\tau_t)$, which allows for time-variant cost functions (e.g., involving a discount factor or other dynamic changes). These objectives could represent the cost of water supply shortage, flood risk, or environmental damages, in addition to the cost of implementing adaptation actions. The optimization problem is to choose the policy π that minimizes the expected sum of costs over a finite planning horizon H :

$$\begin{aligned} \min_{\pi} \mathbb{E}_{\mathbf{e}_1, \dots, \mathbf{e}_{H+1}} \left[\sum_{t=0}^{H-1} J_t(\mathbf{x}_t, a_t, \mathbf{e}_{t+1}) + J_{H+1}(\mathbf{x}_{H+1}) \right] \\ \text{subject to : } \mathbf{x}_{t+1} = f_t(\mathbf{x}_t, a_t, \mathbf{e}_{t+1}), a_t = \pi(\mathbf{I}_t). \end{aligned} \quad (1)$$

The expectation operator over the stochastic forcing variable could be replaced with a different statistical operation, such as the median or maximum. Similarly, a different statistical operator could be used in place of the inner summation of the cost function over time. The problem can also be extended to multiple objectives, $\mathbf{J} = (J^1, J^2, \dots, J^M)$, resulting in a Pareto-optimal set of policies. These choices in formulating the objective function(s) are crucial to the outcome of the optimization, including their combined effect with the choice of scenarios (e.g., Quinn, Reed, Giuliani, et al., 2017; Quinn, Reed, Giuliani et al., 2019). In many practical applications, these choices are system specific and determined in consultation with stakeholders.

If the forcing variables \mathbf{e}_t are deterministic or follow well-characterized probability distributions, then the optimal policy π can be found subject to several modeling assumptions depending on the solution method. This is generally true even if \mathbf{e}_t represents a nonstationary process. Optimal control problems have long been studied in other areas of water resources, particularly reservoir operations (e.g., Castelletti et al., 2008; Labadie, 2004; Yakowitz, 1982; Yeh, 1985). The shorter timescale of the operations problem (hourly to seasonal decisions) allows quantification of forcing uncertainty through a combination of hydrologic forecasts and climatology and justifies neglecting endogenous uncertainty in the human-environmental system. However, because climate adaptation implies control of an open system decades into the future, it is not possible for a modeled representation of \mathbf{e}_t to fully encompass all sources of uncertainty. This disconnect between a mathematical formulation apparently well suited to a dynamic decision problem and the intractability of satisfying its key assumptions drives much of the discussion in this paper.

2.2. Solution Methods

Numerical methods used to solve dynamic planning problems in the water resources field generally fall into three categories: open loop, dynamic programming, and policy search, all of which will identify the optimal policy subject to several modeling assumptions. The first and simplest of these, open loop control, directly optimizes the sequence of actions over the time horizon, $a_t = \pi(t)$. The actions are based only on time and are not updated as a function of new observations of states or forcing variables. Open loop problems can therefore be solved with any type of optimization method, including linear or nonlinear programming, heuristics, or if the action space is small enough, by enumeration.

Both dynamic programming and policy search methods are closed loop approaches in which decisions are adjusted based on observed conditions. Dynamic programming approaches have been applied extensively in the water resources literature, especially for short-term operation problems and also for long-term planning and capacity expansion; Yakowitz (1982) provides an early review. The most common variant is SDP, in which the value function Q for each state at time t can be found from the recursive Bellman equation (Bellman, 1956):

$$Q_t(\mathbf{x}_t) = \min_{\mathbf{a}_t} \mathbb{E}_{\mathbf{e}_{t+1}} [J(\mathbf{x}_t, a_t, \mathbf{e}_{t+1}) + \gamma Q_{t+1}(\mathbf{x}_{t+1})] \quad (2)$$

where γ is a discount factor. Then the optimal policy can be found by minimizing the Q -function:

$$\pi = \underset{\pi}{\operatorname{argmin}} Q_t(\mathbf{x}_t). \quad (3)$$

The problem is typically discretized to be solved numerically, meaning that the optimal policy is limited by the precision of the state, control, and forcing variables. For example, Figure 2 shows three discretization levels (x_1^1, x_1^2, x_1^3) for the state variable x_1 in the action-value matrix.

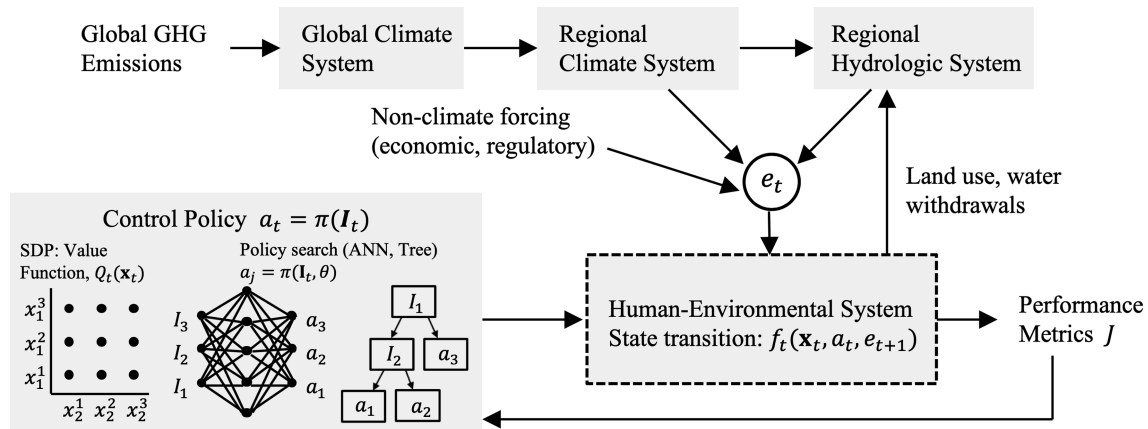


Figure 3. Components of a dynamic planning study, following the control problem framing.

The dynamic programming family of methods includes a number of approximate dynamic programming approaches, one of which is model predictive control (MPC) (Bertsekas, 2005). In an MPC approach, the sequence of actions is optimized on a finite rolling horizon, which is repeated at each time step. This implicitly results in closed loop control, because new information about the system state is included at time $t + 1$ based on the outcome of the optimized decision and the realization of the stochastic forcing \mathbf{e}_t during the time step $[t, t+1)$.

By contrast, a policy search approach assumes a specific structure for the function $\pi(\cdot)$ with parameters θ such that $a_t = \pi(\mathbf{I}_t, \theta)$. The optimization problem then becomes

$$\min_{\theta} \mathbb{E}_{\mathbf{e}_1, \dots, \mathbf{e}_{H+1}} \left[\sum_{t=0}^{H-1} J(\mathbf{x}_t, \pi(\mathbf{I}_t, \theta), \mathbf{e}_{t+1}) + J_{H+1}(\mathbf{x}_{H+1}) \right] \quad (4)$$

subject to : $\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \pi(\mathbf{I}_t, \theta), \mathbf{e}_{t+1})$.

The result is a parameterized function mapping observations to actions, where the parameters of the function are the decision variables to be optimized. In this case, the optimal policy is limited by the type of function chosen and by the numerical convergence of the optimization. Figure 2 shows a policy structured as a neural network to represent an arbitrary function. Many function types have been explored in the water resources literature, largely in the context of short-term operations, ranging from linear decision rules (e.g., Oliveira & Loucks, 1997) to neural networks (Raman & Chandramouli, 1996), radial basis functions (Giuliani et al., 2014; Quinn, Reed, & Keller, 2017), and binary trees (Herman & Giuliani, 2018). The relationship between the policy parameters and the objective function(s) may be multimodal or discontinuous, complicating the use of gradient-based techniques. As a result, heuristic methods such as evolutionary algorithms have been widely used to support policy search (Maier et al., 2014; Nicklow et al., 2010; Reed et al., 2013).

These methods span the fields of optimal control and reinforcement learning, which share the goal of identifying a state-based policy by which an agent, or decision-maker, determines actions through time. Of the methods discussed above, DP methods are drawn from optimal control, while policy search aligns more with reinforcement learning (Busoniu et al., 2010; Recht, 2019), which has had some application in the water resources literature (e.g., Castelletti et al., 2010). Apart from differences in terminology, a key distinction between the two is that DP methods search an approximation of the cost function to find the optimal policy, while reinforcement learning searches the exact cost function (e.g., a simulation model) for an approximation of the optimal policy (Bertsekas, 2019). In this paper, we use the term control to refer broadly to dynamic decision problems, recognizing that policy search methods widely used in the water resources field may also be considered reinforcement learning approaches.

3. Dynamic Planning Under Climate Change: Review and Challenges

Using the control problem framing, we divide dynamic planning approaches into four components as shown in Figure 3: policy structure, uncertainty characterization, solution method, and validation/

robustness testing. The policy structure includes the indicators that are observed over time, the actions to be implemented, and the decision variables that are being optimized to define the policy. The uncertainty characterization includes the sources of uncertainty that are considered and how they are represented in the optimization problem.

Table 1 uses these categories to classify recent climate adaptation studies employing a dynamic planning approach. Papers were selected based on the authors' knowledge of studies applying the three criteria for dynamic planning stated in section 1: (1) a dynamical system, (2) multistage or continuous decision making, and (3) the development of a control policy as a function of system states, indicator variables, and/or time. We classify these studies individually rather than by framework to highlight differences between experimental components that may change even between studies employing the same framework. Several of the studies are focused on planning under deep uncertainty in general, rather than the specific question of climate change; however, the papers selected here include at least some representation of long-term climate uncertainty, even if not drawn directly from climate models. Finally, the references cited in this section are not restricted to the papers in Table 1, as a number of studies in related areas provide relevant discussion despite not performing dynamic planning directly.

3.1. Problem Formulation

3.1.1. Actions

Among the studies in Table 1, adaptation actions are represented either as a set of discrete choices or with the opportunity to optimize the magnitude of implementation as a continuous variable. While the climate adaptation problem is often framed in terms of infrastructure decisions, the success of these plans also depends on the operating rules governing any existing or new infrastructure. Operational changes are generally less costly and more flexible, as they can be reversed unlike most infrastructure investments (Raso et al., 2018). Several studies have explored the range of scenarios over which operations can be adapted before new infrastructure investments would be required (Culley et al., 2016; Giuliani, Anghileri, et al., 2016; Whateley et al., 2014), while others have addressed the more complex question of jointly optimizing infrastructure and operations (Bertoni et al., 2019; Mortazavi-Naeini et al., 2015). Holding infrastructure fixed, the choice of operating rules may impact system performance as much as hydrologic conditions (Tian et al., 2018). Additional noninfrastructure actions to mitigate climate variability include financial instruments and public policy measures such as drought conservation, which have been included alongside infrastructure decisions in several studies (e.g., Trindade et al., 2017; Zeff et al., 2016).

The irreversibility of infrastructure actions presents substantial challenges for the climate adaptation problem. The indicator variables used in the optimized policy must provide reliable information about current and future change or else risk overfitting adaptation triggers to the forcing scenarios or distributions chosen. This problem can be quantified in terms of false positives (investments that ultimately prove unnecessary) and false negatives (failure to adapt), which relates to the choice of indicator variables (Raso et al., 2019; Robinson & Herman, 2019; Rosner et al., 2014). For example, determining an adaptation based on the 50-year moving average of annual streamflow is more likely to result in false negatives, whereas adapting based on the 10-year average will likely result in a higher rate of false positives. Decision-maker preference along this trade-off could be reflected in the objective function or through multiobjective optimization, including the costs of switching between actions (Haasnoot et al., 2019). To reduce the risk of overadaptation, large infrastructure options might instead be treated incrementally, accepting increased marginal cost in exchange for increased flexibility, a key concept in Engineering Options Analysis (de Neufville & Smet, 2019; Jeuland & Whittington, 2014).

3.1.2. Indicator Variables

Indicator variables are the observations used to trigger actions, some of which will be more informative for adaptation than others (Groves et al., 2015; Haasnoot et al., 2015, 2018). Broadly, there are many different climate and environmental indicators that might provide information about the trajectory of climate change and its impacts on a system (Kenney et al., 2018). In general, an indicator represents a combination of a variable (precipitation and temperature) observed over a certain timescale (annual, monthly, daily, and hourly) and aggregated over a moving window (5, 10, and 30 years) using a statistical transformation (mean, variance, and quantile). For example, a 30-year moving average of annual reservoir inflow may be a useful indicator for water supply adaptation; for flood risk, a 50-year estimate of the 99th percentile daily streamflow

Table 1
Classification of Recent Studies Focused on Dynamic Water Resources Planning Under Climate Change, Selected Based on the Authors' Knowledge of Studies Applying (1) a Dynamical System, (2) Multistage or Continuous Decision Making, and (3) the Development of a Control Policy as a Function of System States, Indicator Variables, and/or Time

Reference	Horizon	Actions	Indicator variables	Implementation on decisions	Uncertainty sources (representation)	Solution method	Validation/robustness
Jeuland and Whittington (2014)	100 years	Infrastructure, operations	Time	Sequence, timing, magnitude	Streamflow (5,000 synthetic scenarios)	Enumeration	N/A
Paton et al. (2014)	30 years	Infrastructure, conservation	Reservoir storage (monthly)	Magnitude, thresholds	Withdrawals (three discrete scenarios) Precipitation (10 synthetic scenarios, based on historical + scaled by 1 GCM)	Policy search (MOEA)	Broader uncertainties (252 climate + demand scenarios)
Beh et al. (2014)	40 years	Infrastructure	Time	Sequence, magnitude	Precipitation (1,000 synthetic scenarios), socioeconomic scenarios (6)	Sequencing algorithm	N/A
Woodward et al. (2014)	100 years	Infrastructure	Time, sea level rise	Sequence, timing	Sea level rise (three emissions scenarios, with a normal distribution estimated for each)	Policy search (MOEA)	N/A
Beh et al. (2015, 2017)	50 years	Infrastructure, conservation	Time	Magnitude, timing	Population, temperature, rainfall (14 synthetic scenarios based on GCM properties)	MPC (MOEA)	N/A (robustness included in optimization)
Haasnoot et al. (2015) (Ex. 3)	100 years	Not specified	Streamflow (multiple statistical transformations)	Thresholds	Streamflow, precipitation, potential evaporation, sea levels (60 synthetic scenarios with linear trends based on GCMs)	Enumeration	Thresholds developed relative to reference scenarios without climate change
Kwakkel et al. (2015), Kwakkel, Haasnoot, et al. (2016)	100 years	Infrastructure, public policy	Flood event levels (5-year maximum)	Sequence, thresholds	Streamflow/precipitation (30 synthetic scenarios based on GCMs) Land Use (seven discrete scenarios)	Policy search (MOEA)	N/A (robustness included in optimization)
Mortazavi-Naeini et al. (2015)	50 years	Infrastructure, operations, public policy	Reservoir storage (monthly)	Magnitude, thresholds	Endogenous parameters (synthetic) Streamflow (10,000 synthetic scenarios based on GCM properties)	Policy search (MOEA)	Broader uncertainties (more severe GCM scenarios)

Table 1
(continued)

Reference	Horizon	Actions	Indicator variables	Implementation on decisions	Uncertainty sources (representation)	Solution method	Validation/robustness
Borgomeo et al. (2016)	25 years	Infrastructure, public policy	Time	Magnitude, timing	Streamflow (10,000 synthetic scenarios based on GCM properties)	Open Loop (MOEA)	N/A
Zeff et al. (2016)	50 years	Infrastructure, conservation, financial operations	Risk-of-failure metric (50-year window)	Magnitude, sequence, thresholds	Streamflow (100 synthetic dry scenarios)	Policy search (MOEA)	More scenarios (1,000), same characterization
Culley et al. (2016)	100 years	Operations	Annual precipitation, average temperature	Magnitude, timing	Precipitation, temperature (861 synthetic scenarios and 22 physically based scenarios from combinations of GCM-RCM)	Enumeration	Scenarios in local neighborhood of the one used for optimization
Fletcher et al. (2017)	30 years	Infrastructure	Reservoir storage (annual)	Sequence, timing	Streamflow and population growth (100,000 synthetic scenarios)	Enumeration	Broader uncertainties (100,000 endogenous parameter samples)
Trindade et al. (2017)	50 years	Infrastructure, conservation, financial	Risk-of-failure metric (50-year window)	Magnitude, sequence, thresholds	Streamflow and endogenous parameters (1,000 synthetic scenarios)	Policy search (MOEA)	More scenarios (10,000), same characterization
Borgomeo et al. (2018)	30 years	Infrastructure, public policy	Time	Timing	Streamflow (physically based RCM) and demand scenarios, 600 total	Open loop (MOEA)	N/A (robustness included in optimization)
Erfani et al. (2018)	45 years	Infrastructure, design	Supply-demand gap	Magnitude, timing	Supply and demand (synthetic ensemble used to create scenario tree)	Multistage stochastic NLP	N/A
Hui et al. (2018)	200 years	Infrastructure	Levee height	Magnitude, thresholds, timing	Flood risk distribution (six synthetic PDFs)	SDP with Bayesian updates	N/A
Fletcher et al. (2019)	100 years	Infrastructure, design	Precipitation, temperature (20-year average)	Magnitude, thresholds, timing	Precipitation, temperature (500 synthetic scenarios based on GCM properties)	SDP with Bayesian updates	More scenarios (regret analysis), same characterization

might be more appropriate. Many of the studies in Table 1 use long-term hydroclimatic indicators to trigger infrastructure actions (Fletcher et al., 2019; Hui et al., 2018; Kwakkel et al., 2015; Trindade et al., 2017; Zeff et al., 2016). Others rely on short-term indicators such as reservoir storage to trigger operational actions, which may be adapted over time as a response to climate change (Mortazavi-Naeini et al., 2015; Paton et al., 2014).

3.1.3. Implementation Decisions

Control methods aim to optimize the policy mapping indicators to actions, thus determining the optimal magnitude, timing, and sequence of actions in response to the evolution of the system. Studies in Table 1 using control approaches therefore account for all of these implementation decisions (Fletcher et al., 2019; Hui et al., 2018). Other studies select a subset of these aspects to optimize. When the sequence of actions is optimized, it is typically assumed that candidate actions are reviewed on a fixed time step (e.g., every 5 or 10 years) (Beh et al., 2015; Kwakkel et al., 2015; Mortazavi-Naeini et al., 2014). Other studies directly optimize the timing and magnitude of actions to be implemented (Borgomeo et al., 2016, 2018), while still others optimize observable threshold values to be used as triggers for implementation of particular actions (Mortazavi-Naeini et al., 2015; Zeff et al., 2016).

3.1.4. Limitations

Distilling a control problem formulation from a real-world planning context requires several key simplifying assumptions. The formulation posed here assumes centralized planning, where a single decision-maker controls the full set of candidate actions, which is often unrealistic in a real-world planning process (Giuliani, Castelletti, et al., 2015). The formulation may require iterative input from different sets of stakeholders (Quinn, Reed, Giuliani, et al., 2017; Wu et al., 2016) and could be revised to represent a decentralized process in which multiple agents optimize for their individual benefits (Jenkins et al., 2017). Additionally, where political realities may prevent an optimization approach—for example, due to lack of agreement over which objectives or scenarios to include (Hall & Borgomeo, 2013; Kasprzyk et al., 2015)—other approaches may prove useful, including simulation-driven scenario exploration (Brown et al., 2012; Kingsborough et al., 2016; Lempert, 2002; Thacker et al., 2018), negotiation theory (Islam & Susskind, 2018), and game theory (Madani & Lund, 2011; Sechi et al., 2013). While the optimal control framing implies that climate adaptation problems can be solved definitively, this is not the case in practice (Kasprzyk et al., 2018) as even the most advanced optimization approaches can only identify candidate solutions to be analyzed further.

3.2. Uncertainty Characterization

Dynamic planning methods must identify a set of possible scenarios and models (whether physical or statistical) to quantify uncertainty, either as a probability distribution or an ensemble of realizations. The majority of studies in Table 1 have represented uncertainty with an ensemble of synthetic scenarios describing weather and/or streamflow, using one of two approaches:

1. Using historical observations to parameterize a stationary stochastic process, which is then perturbed according to statistics from GCM projections (e.g., Borgomeo et al., 2016; Culley et al., 2016; Haasnoot et al., 2015).
2. Using GCM projections to directly parameterize a nonstationary stochastic process (e.g., (Borgomeo et al., 2018; Fletcher et al., 2019)).

The structural and parametric uncertainties in either the stationary or nonstationary case usually focus on exogenous hydroclimate and also apply to endogenous uncertainties. Synthetically generated scenarios provide a computationally efficient alternative to the direct use of downscaled GCMs and allow an arbitrarily large number of scenarios that are similar to, but not limited by, variability in the observed record. While this is often done without explicit probabilistic representations, it is worthwhile to question whether it is possible to entirely avoid the concept of probability when comparing planning alternatives. All characterizations of uncertainty require a distribution to be specified, whether implicitly or explicitly, and any comparison of alternative policies based on metrics computed across an ensemble requires scenario weighting. Computational methods targeting the challenge of deep uncertainty face the contradiction of needing to sample variables from distributions that are by definition unquantifiable.

Here we review three primary sources of uncertainty and the extent to which they have been included in the dynamic planning studies in Table 1:

1. Sampling uncertainty, which represents natural variability in forcing that may not be fully captured in the historical or projected record.
2. Uncertainty in exogenous hydroclimate change, which encompasses the chain of physical and statistical models used to create downscaled streamflow projections.
3. Uncertainty in endogenous system dynamics arising from human behavior and environmental processes.

While sampling uncertainty is aleatory (i.e., occurs due to random variations in the variable of interest), the latter two sources of uncertainty contain both aleatory and epistemic components, which arise from lack of knowledge (Beven, 2016).

3.2.1. Sampling Uncertainty

Even assuming a stationary climate, long-term water resources planning has always been challenged by sampling uncertainty (or internal variability). There are few historical observations of the extreme flood and drought events that drive water resources planning and even fewer that could point to a long-term trend to trigger adaptation. In the context of a control problem, sampling uncertainty arises in two key places: (1) inferring parameters of the stochastic process from a finite sample of either historical observations or GCM projections and (2) training and testing an adaptation policy on a finite record (observed or synthetic), where the combination of the number of scenarios and the planning horizon represents the sample size. In the first case, an insufficient sample size will result in a poorly characterized distribution of scenarios, which no amount of sampling can overcome, although parameter uncertainty can be estimated and included in the stochastic generation process (Stedinger & Taylor, 1982). In the second case, an insufficient sample size will result in overfitting policies to the events in the observed or synthetic record and an inability of the policy to generalize to other scenarios.

These issues are especially of concern when performance metrics are driven by extreme events, such as a high or low percentile of the output distribution (e.g., Herman et al., 2014; Quinn et al., 2018) which are difficult to estimate from a small sample. The majority of studies in Table 1 aim to reduce the effects of sampling uncertainty using ensembles of synthetically generated streamflow scenarios in the optimization and/or the validation step. Notably, the sample sizes vary significantly between studies, which is partly a function of different application contexts and also suggests a lack of consensus on experimental design.

3.2.2. Uncertainty in Exogenous Hydroclimate Change

A cascade of structural and parametric uncertainties propagates through the modeling chain used to develop climate change scenario projections for water resources systems (Kundzewicz et al., 2018; Wilby & Dessai, 2010). This includes uncertainty from the GCMs themselves and also the following:

1. Emissions scenarios used to drive the GCMs (Lamontagne et al., 2018).
2. Downscaling approaches used to tailor GCM output for local/regional assessment (Chen et al., 2011; Pielke & Wilby, 2012; Pierce et al., 2014).
3. Hydrologic models used to convert precipitation and temperature projections into streamflow (Broderick et al., 2019; Fowler et al., 2018; Mendoza et al., 2016; Prudhomme et al., 2014; Steinschneider et al., 2012).

We consider these elements exogenous to the basin-scale water resources planning problem, though some feedback to the regional hydrologic system may occur. Given that GCM projections are, at present, the best available source of dynamically evolving future scenarios to support water resources planning, any or all of these uncertain factors may need to be represented in an optimal control problem.

Among these factors, climate models and downscaling approaches consistently contribute the largest uncertainty in hydrologic projections due to the high variance in projected precipitation (Steinschneider, Wi, et al., 2015; Vetter et al., 2017; Wilby & Harris, 2006). One major source of climate model uncertainty arises because the processes that govern precipitation (e.g., local convection, cloud formation) occur at spatial scales that are substantially smaller than a GCM grid cell (Randall et al., 2003). Very high resolution models (<5 km) can improve some aspects of modeled precipitation (Prein et al., 2015) but with increased computational cost, which limits ensemble simulations needed for water resources studies. Model errors also have a large impact on projections of future large-scale atmospheric dynamics (Sigmond et al., 2010; Simpson et al., 2016), which interact with parameterized subgrid processes and orographic effects (Davini et al., 2017; Stevens & Bony, 2013). This dynamical error structure severely complicates efforts to bias correct and downscale GCM output based on simulations under a baseline period, as is commonly done for water resources impact studies (Ehret et al., 2012). Further, the suite of GCMs available across global institutions is not

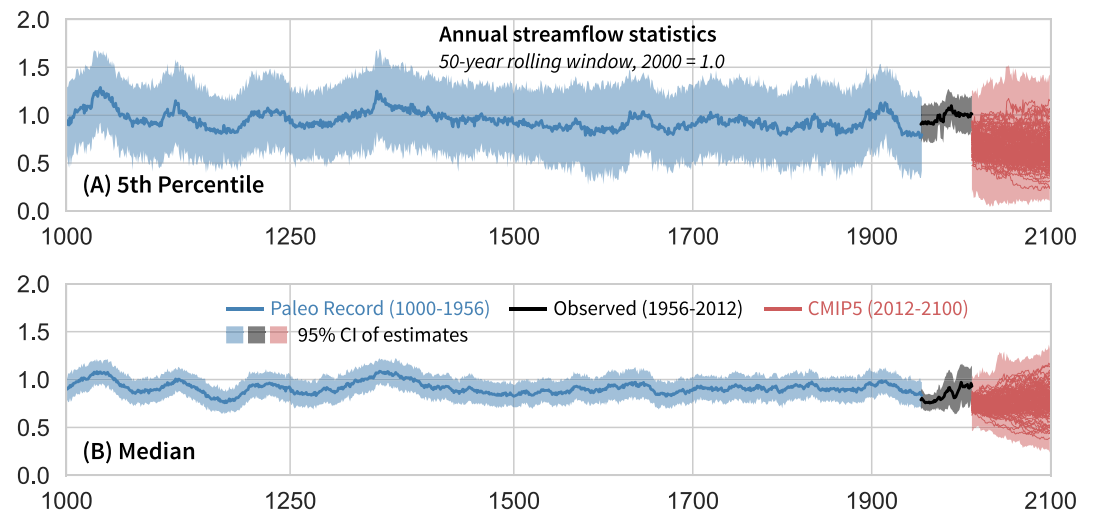


Figure 4. Estimated statistics of annual streamflow for the Sacramento River at Bend Bridge using a 50-year rolling window: (a) 5th percentile and (b) median, normalized to the observed values in year 2000. Paleo and observed data are taken from TreeFlow (Meko & Woodhouse, 2005), along with CMIP5 projections from the U.S. Bureau of Reclamation (Reclamation, 2014). The 95% confidence intervals in all subplots are found from 100 bootstrap resamples of each 50-year window to estimate the standard error. Confidence intervals for paleo data include the standard deviation of residuals.

independent, as submodules are often shared across models (Knutti et al., 2013), resulting in clustered projections of regional climate change that do not reflect added confidence (Shorridge & Zaitchik, 2018; Steinschneider, McCrary, et al., 2015).

To illustrate the exogenous uncertainty in hydroclimate projections, Figure 4 shows ensemble and sampling uncertainty for statistics of annual streamflow (5th and 50th percentiles) using example data for the Sacramento River, California. The choice of an annual timescale and lower percentile reflects a focus on water supply risk rather than floods. These plots compare the paleo record (Meko & Woodhouse, 2005), observed data, and downscaled CMIP5 projections containing multiple emissions scenarios (Reclamation, 2014). Comparison of Figures 4a and 4b suggests a few points. First, these statistics have always shown some variability, subject to the choice of a 50-year rolling window. The confidence intervals tend to be relatively large for the lower percentiles (5th) than for the median, reflecting uncertainty in estimates of extremes. Finally, sampling uncertainty makes up a nontrivial portion of the exogenous uncertainty in future projections, reflected by the light red shaded area. These data include multiple GCMs and emissions scenarios but only one hydrologic model and downscaling procedure, both of which may introduce additional biases in certain aspects of the flow regime.

3.2.3. Uncertainty in Endogenous Human-Environmental Dynamics

Another significant source of uncertainty is the endogenous dynamics of the human-environmental system under consideration, particularly given the long planning horizons involved in climate adaptation problems (Haddeland et al., 2014). In the context of the control problem shown in Figure 2, this uncertainty primarily appears in the state transition equation. It therefore adds another layer of model structural and parametric uncertainty beyond those contributed by climate and hydrologic models and introduces the need to test multiple plausible assumptions for the system simulation model. Uncertainty in human behavior has been identified as one of the major knowledge gaps in the field (Brown et al., 2015; Vogel et al., 2015) and has been found to exceed the impact of climate uncertainty in a majority of studies that have compared their relative influence (Alcamo et al., 2007; Anghileri et al., 2018; Droogers et al., 2012; Fant et al., 2016; Vogel et al., 2011). Uncertainty in human-environmental systems is not limited to the climate adaptation problem; even under a stationary climate, the dynamics and long-term outcomes of social and economic behavior are indeterminate (Ben-Haim, 2012).

Several of the studies in Table 1 include some consideration of uncertainty in the human system, such as water demand (Erfani et al., 2018; Jeuland & Whittington, 2014), population (Beh et al., 2015; Fletcher et al., 2017; Trindade et al., 2017), or land use (Kwakkel et al., 2015; Kwakkel, Haasnoot, & Walker, 2016).

Unlike the streamflow scenarios described above, these are generally implemented as scalar parameters to be sampled rather than time series; none of the studies reviewed here considered structural uncertainty in the state transition equation (or simulation model). Several endogenous feedbacks could be relevant for a water resources planning problem, including, but not limited to, the following:

Indirect impacts of climate change. Elements of the system may respond to nonstationary precipitation and temperature in ways not directly linked to the choice of adaptation policy but which create second-order effects on the objectives. For example, agricultural yields and water demands will respond to rising temperatures, which may trigger land use changes (Jafino et al., 2019; Wada et al., 2013); energy supply and demand are also likely to change, which further influences water demand (Carleton & Hsiang, 2016). Additionally, changes in hydroclimatic forcing may alter the risk attitudes of decision-makers, such as actions taken to mitigate extreme events (Aghakouchak et al., 2014; Viglione et al., 2014).

Institutional uncertainties. A planning organization may not be able to achieve its intended implementation even once a decision has been made, for example, through delays or cost overruns (Grimsey & Lewis, 2002). Adaptation actions may therefore only be effective when the planning agency has the necessary institutional capacity (Rist et al., 2013; Tompkins & Adger, 2004). The model may also need to include adaptations to climate change occurring at other institutional scales that are outside the scope of the control problem under consideration (Adger et al., 2005; Gonzales & Ajami, 2017).

System response to policy actions. The model may need to consider unintended consequences of the adaptation policy (Anderies et al., 2019). For example, reservoir capacity expansion may lead to an increase in water demand and overreliance on the new infrastructure, increasing vulnerability to droughts if the new demands are not flexible (Di Baldassarre et al., 2018).

Response to nonclimate drivers. The system may respond to other social drivers which may or may not be linked to climate change, such as migration, urbanization (Zhao, 2018), population growth, land use, and technology changes.

Feedbacks to the hydrologic system. Any of the above changes might also influence the regional hydrologic system through land use, water withdrawals, and infrastructure impacts on the streamflow regime (Shin et al., 2019), particularly on evapotranspiration and peak flow events.

Environmental dynamics. Long-term environmental changes in water quality, geomorphology, and ecological regimes have not received much consideration in dynamic planning studies, despite their susceptibility to change on decadal timescales as a result of either cumulative “slow” processes or tipping points (Scheffer et al., 2009; Walker et al., 2004). For example, a warmer climate will directly affect water quality and species habitat (Moyle et al., 2013), as will many of the infrastructure and operational adaptations undertaken by human institutions at different scales. On longer timescales, hydroclimatic change and human adaptations alter geomorphic processes (Kondolf & Podolak, 2014), further influencing habitat. All of this could lead to ecological regime shifts, with the caveat that severe environmental degradation may change human attitudes toward water management (Elshafei et al., 2014).

3.3. Solution Methods

A range of solution methods have been used to identify dynamic adaptation plans under climate change. SDP has been used for infrastructure planning in several studies, including levee height optimization with Bayesian updates of the flood risk distribution (Hui et al., 2018), as well as planning reservoir capacity expansion and investment in desalination plants (Fletcher et al., 2019). Several studies optimize the timing of actions directly, either using an open loop approach (Borgomeo et al., 2016, 2018) or MPC in which the short-term plan is updated periodically (Beh et al., 2015, 2017). Finally, a common policy search formulation involves optimizing thresholds of observed or projected variables to trigger actions within a predefined rule structure (Kwakkel et al., 2015; Zeff et al., 2016).

While the choice among solution methods is problem specific, there are a few general advantages and disadvantages of each approach. If a well-characterized model of the stochastic forcing variable(s) can be specified, SDP identifies the exact solution, subject to the discretization scheme, and often the assumption of forcing variables being uncorrelated in time. Given the difficulty of identifying probability distributions for forcing variables in the climate adaptation problem, this advantage may be limited—the ability to find

exact (or even approximate) optimal solutions is less relevant when the problem formulation itself is uncertain (Jeuland & Whittington, 2014). Furthermore, the practical implementation of SDP faces limitations from the curse of dimensionality and the requirement of a mathematical model rather than numerical simulation (Bertsekas, 2019).

Open loop methods are computationally efficient but present a high risk of overfitting to the scenarios or distributions of forcing used in the optimization if not coupled with a validation scheme. These shortcomings could be abated by repeating the open loop optimization as new information becomes available, as in MPC. However, this approach does not identify adaptation rules in response to evolving conditions as in policy search and SDP. Policy search has the additional advantage of flexibly incorporating multiple objectives and multiple indicator variables, which can be included as state variables in SDP but at the cost of significant added computational complexity (Giuliani et al., 2018). However, policy search methods also introduce additional assumptions and challenges in the subjective choice of function type and number of parameters—a poor choice risks either insufficient flexibility in approximating the optimal policy if the function is too simple or overfitting to the training data if the function is too complex. Importantly, none of these approaches avoid the challenge of characterizing uncertainty in forcing variables and system dynamics.

3.4. Validation/Robustness

Finally, many of the studies in Table 1 conclude with some form of robustness assessment by simulating the performance of the optimized policy in a new set of scenarios. This idea borrows from robust planning methods in which alternatives generated through optimization are subjected to a wider range of uncertainty (Kasprzyk et al., 2013). Here we distinguish between testing the robustness of an adaptive policy to (1) more realizations from the same uncertainty characterization used in the optimization, versus (2) scenarios in which new uncertain variables are sampled, or the same variables are sampled from different distributions. The former only tests against sampling uncertainty and can be used to determine whether a policy is overfit to a particular set of scenario realizations. The latter approach could test robustness to other forms of uncertainty, provided that the sampling is informed by some knowledge of the ensemble or endogenous uncertainties. In either case, the ideal outcome is either minimal degradation relative to optimized performance or maintaining acceptable performance in a wide range of scenarios, as discussed in prior studies (Lempert & Collins, 2007).

4. Perspectives: Research Gaps and Opportunities

Based on the concepts reviewed in the previous section, we propose several research gaps and opportunities to improve the use of control methods for dynamic planning under climate change. These research gaps align with the subsections that follow:

1. *Process-based insight for synthetic generation*: Many studies characterize uncertainty in future scenarios based on coarse-timescale GCM statistics, such as annual precipitation. There are opportunities to leverage insight into climate processes and model errors to inform finer-scale uncertainty characterization in synthetic scenarios.
2. *Uncertainty classification*: Depending on the nature, level, and potential for learning of the uncertainties included, they may be treated differently in the experimental design.
3. *Endogenous uncertainty*: Relatively few planning studies have considered endogenous uncertainty; those that do typically only consider parametric rather than structural uncertainty. These uncertainties should be considered when relevant, especially feedbacks in response to adaptation actions.
4. *Policy validation*: There is currently not a unified approach to policy validation and robustness testing, such as whether this step should include more realizations or a different uncertainty characterization altogether and what sample size is adequate.
5. *Computational complexity*: More rigorous comparisons of solution methods could consider their efficiency and effectiveness, scalability as a function of the number of state or indicator variables, and tendency to overfit to training scenarios.
6. *Indicator variables*: Finally, there are significant opportunities to include more observed and projected information as indicator variables for the adaptation policy; only a few of the studies in Table 1 consider more than one indicator variable. This choice can be informed by several monitoring and data assimilation methods.

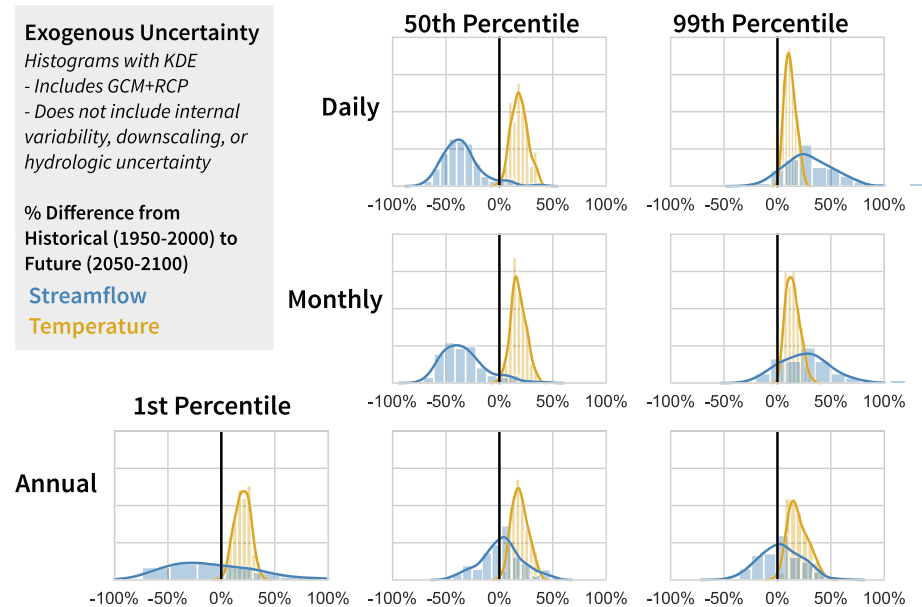


Figure 5. Percent changes in streamflow and temperature from the historical period to end-of-century for the Sacramento River at Bend Bridge (CMIP5 projections from the U.S. Bureau of Reclamation, 2014), to highlight the differences in projections of thermodynamic versus dynamic change. Streamflow across the ensemble typically shows a wider spread of projected changes relative to temperature. Distributions are shown for different timescales and quantiles, indicating that streamflow projections tend to be most variable for droughts (annual, 1%) and floods (daily, 99%), which presents the most difficulty for adaptation planning.

4.1. Process-Based Insight to Improve Uncertainty Characterization

The characterization of uncertainty in the dynamic planning problem can be informed by the physical causes of uncertainties in ensemble projections, for example, whether the projected changes are thermodynamic or dynamic in nature (Emori & Brown, 2005; Seager et al., 2010). Thermodynamic changes relate directly to the increased surface warming of the Earth under anthropogenic forcing and cause more frequent and intense temperature extremes, glacial retreat, reduced snowpack and earlier snowmelt, sea level rise, and the increased moisture holding capacity of the atmosphere (i.e., Clausius-Clapeyron scaling). These trends are consistent with theory and robust in both observations and model projections (Fischer & Knutti, 2016; Collins et al., 2015), leading to high confidence in their future direction, albeit with residual uncertainty in their magnitude. By contrast, dynamic climate change relates to changes in atmospheric circulation (e.g., jet stream dynamics, storm tracks, and seasonal monsoon progression), which play a large role in determining regional precipitation. Dynamic changes are significantly more uncertain than thermodynamic change (Pfahl et al., 2017; Shepherd, 2014; Woollings, 2010) and are difficult to distinguish from internal atmospheric variability especially on timescales (10–30 years) relevant to water resource investment decisions (Knutti & Sedláček, 2013). To illustrate the relative uncertainty in dynamic processes, Figure 5 shows example projections of differences in temperature (thermodynamic) and streamflow (both thermodynamic and dynamic change).

Leveraging such process-based insights, there is an opportunity for new synthetic scenario generation methods to create plausible dynamic projections of climate change for water resources planning studies. The key questions in generating nonstationary scenarios are as follows: what variables should be perturbed, according to what distributions, and along what transient trajectories? In principle, any parameter of a stochastic generator can be perturbed based on climate information, for example, streamflow seasonality (Nazemi et al., 2013; Prudhomme et al., 2010), interannual variance and persistence (Borgomeo et al., 2013; Quinn et al., 2018), or the frequency and severity of drought events (Herman et al., 2016). By contrast, stochastic weather generators are commonly used to alter daily weather characteristics, including the likelihood and persistence of wet and dry days, the intensity and seasonality of precipitation, its interannual persistence, and the magnitude and range of minimum and maximum temperature (Guo et al., 2018; Steinschneider

Table 2
Combination of Uncertainties Involved in Designing Control Policies for Climate Adaptation

Planning horizon	Type of climate change	Timescale of impact	Statistic of interest
Short (10–20 years) +Sampling uncertainty (internal variability)	Thermodynamic (temperature, snowpack, sea level rise) +Emissions uncertainty	Coarse (seasonal-annual, e.g., droughts and snowpack decline)	Central tendency
Long (30+ years) +Endogenous uncertainty	Dynamic (precipitation, streamflow, storm tracks) +Climate model uncertainty	Fine (daily-weekly, e.g., floods and heat waves) +Sampling uncertainty +Hydrologic model uncertainty	Extreme events +Sampling uncertainty

Note. Several of these classifications are subjective choices; in general, all of these uncertainties apply to any climate adaptation planning problem. Here we highlight those that likely dominate the total uncertainty in different planning contexts. The addition symbol indicates only that the uncertainty should be considered; it does not imply that the uncertainties or their effects are additive. The bold items were meant to show the type of uncertainty added in each case. (Some cases do not have any uncertainty added).

& Brown, 2013). These approaches must maintain realistic persistence and covariance structures across space and time and potentially between multiple variables (e.g., precipitation, temperature, and wind speed) (Allard & Bourotte, 2015; Kwon et al., 2009; Steinschneider & Brown, 2013; Verdin et al., 2018), which can be supported by GCM output.

The distribution of perturbations to apply is as important as the choice of variables to perturb. The range of stochastic scenarios can be informed by a process-level understanding of different types of climate change. For instance, hypothesized thermodynamic change can be tested by adjusting the tails of the distribution of local precipitation via a temperature-dependent Clausius-Clapeyron scaling. There are well-documented constraints on the thermodynamically driven increase in extreme precipitation, which is expected to mirror the increase in atmospheric moisture holding capacity ($\sim 7\% \text{ C}^{-1}$) (Fischer & Knutti, 2016; Trenberth, 2011) but at hourly timescales could increase faster due to latent heat release during intense precipitation that further enhances convection and precipitation rates (Bao et al., 2017; Guerreiro et al., 2018). Dynamic changes can be imposed by altering the frequency of different types of storm events (Knighton et al., 2017; Steinschneider et al., 2019), although these perturbations could be conditioned on climate model experiments designed to explore the consistency of such (inherently uncertain) signals against the backdrop of model and parameter uncertainty (e.g., multimodel and perturbed physics ensembles; see Glenis et al., 2015). This type of approach provides a promising avenue to better link stochastic scenario development with process-level insights inferred from GCM ensembles, which is especially important in the case of extreme events (e.g., Serinaldi & Kilsby, 2015).

These insights can be used in a variety of ways to generate plausible scenarios of future change and to distinguish these from implausible ones. Broadly, we propose the following recommendations:

1. A large variance in projected climate (particularly precipitation) should not immediately mark the ensemble as uninformative, as it likely represents the combination of internal variability and different thermodynamic and dynamical signals.
2. Conversely, in the case of climate model agreement—which does add some confidence of the direction of change—it may indicate a shared bias rather than an accurate prediction. That is, outlier projections cannot be disregarded either, as they may represent plausible future outcomes.
3. Closer coordination is needed with the climate science community, which dedicates significant effort to assessing the regionally specific suitability of different climate models to support local adaptation based on the fidelity of large-scale dynamics. If conducted carefully, expert elicitation of future likelihoods can help with these challenges (Dessai et al., 2018; Morgan, 2014; Refsgaard et al., 2006).
4. Relevant uncertainties can be qualitatively identified from the context of the planning problem. Table 2 shows an example, based on a handful of key studies that have examined the relative impacts of one or more of the uncertainties described above (Deser et al., 2012; Greve et al., 2018; Haddeland et al., 2014; Hawkins & Sutton, 2011). By contrast, only a few water resources planning studies have attempted to decompose the sources of uncertainty influencing decisions (e.g., Paton et al., 2013; Schlef et al., 2018).

Table 3
An Example Classification of Uncertainties According to Their Nature, Level, and Potential for Learning, Following Kwakkel et al. (2010), Döll and Romero-Lankao (2017), and Fletcher et al. (2017)

Type	Level	Nature	Potential for learning
Sampling	Shallow	Aleatory	Low
Climate model	Deep	Both	Medium
Emissions	Medium	Epistemic	High
Hydrologic (exogenous)	Medium	Both	Medium
Human-env. system	Deep/ignorance	Epistemic	Medium

Note. This classification is only an example and would vary substantially between case studies.

4.2. Uncertainty Classification to Inform Experimental Design

If the problem context yields physically based insights to help identify relevant uncertainties, it may also inform how they are treated in a dynamic planning study. This may point to appropriate optimization methods, indicator variables, and monitoring efforts to support planning, as well as sources of uncertainty that do not need to be considered. The dominant sources of uncertainty vary widely between studies, regions, and scales and are thus highly specific to the context of the planning problem. An important first step is therefore to identify the sources of uncertainty that most strongly influence the choice and timing of actions, possibly using some form of sensitivity analysis (Saltelli et al., 2004) and to devise methods to reduce these uncertainties, select actions that are robust to a wide range of outcomes, and/or prioritize responses to impacts of climate change that are currently better understood.

Uncertainties may be treated differently in the experimental design depending on their nature, level, and potential for learning (Döll & Romero-Lankao, 2017; Fletcher et al., 2017; Kwakkel et al., 2010). The nature of each uncertainty is either aleatory—irreducible uncertainty due to random variations in the variable of interest—or epistemic, arising from a lack of knowledge about the nature of the process of interest and how it should be modeled (Beven, 2016). The level of uncertainty refers to whether a variable can be well characterized by probability distributions or not (Döll & Romero-Lankao, 2017). Many uncertainties in projections of regional climate change can be considered deep, where an exact quantification is not possible (Spence & Brown, 2018). Table 3 shows an example classification, recognizing that this type of classification in practice is specific to individual case studies. Relative contributions to total uncertainty in climate change assessments vary widely across space and time (Greve et al., 2018; Vetter et al., 2017), and the columns in Table 3 add another layer of subjectivity that prevents a generalizable classification. However, if this exercise can be performed as part of a planning study, it can provide a foundation for the experimental design.

Different signals of climate change might then be treated differently in the control framework. For instance, certain impacts of thermodynamic climate change have already been observed and are projected with high confidence to continue (e.g., reduced snowpack, rising sea level, and more intense storms), though with some uncertainty in their magnitude. Because emissions uncertainty has a high potential for learning over time, infrastructure expansion can be staged in response via endogenous learning, potentially using emissions observations as an indicator variable. Adaptation of water supply and flood control systems to dynamic climate change (and associated shifts in regional precipitation) is more difficult, since the direction and plausible magnitudes of change are often poorly understood. In addition, the large degree of internal, multidecadal climate variability poses a significant barrier to endogenous learning of emergent trends (Doss-Gollin et al., 2019). This emphasizes the need for a solution that is either robust or reversible, acknowledging the significant potential to have an incorrect uncertainty characterization in the optimization problem and/or in the postoptimization test set. Recognizing that some probabilistic assumptions are inevitable, they should be made explicit and justified in the problem formulation (Beven, Almeida, et al., 2018; Beven, Aspinall, et al., 2018). It may be more informative to determine the sensitivity of the optimized policies to the choice of uncertainty characterization, rather than only validating against more realizations of the same uncertainty characterization. This partially depends on the decision framework being used (Brekke et al., 2009; Refsgaard et al., 2013) but in general may reveal weaknesses or sensitivities of the decision-making framework to new or surprising information that would not be apparent otherwise.

4.3. Uncertainty in Endogenous Human-Environmental Model Structure

Unlike some forms of parametric or exogenous uncertainty, the uncertainty in endogenous model structure is not easily sampled or characterized. However, the sensitivity of optimized policies to alternative structural assumptions about how humans respond to climate change can be assessed, similar to their sensitivity to alternative distributions of climate forcing. For example, different structures and feedbacks can be tested as discrete hypotheses to determine if they are influential relative to the many other uncertainties discussed previously, in terms of one or more system performance metrics.

Capturing all of these multiscale dynamics in a simulation model remains difficult, but sensitivity testing can help prioritize their inclusion. Global-scale earth system models have made significant advances in this direction (Pokhrel et al., 2016; Wada et al., 2017), as have local-to-regional scale models in recent years (Konar et al., 2019). In practice, however, regional socioeconomic scenarios are often considered exogenous factors in planning studies, which may inadequately capture dynamic relationships between these and climate forcing (Verburg et al., 2016). Accounting for these feedbacks and dynamic preferences is key to any retrospective assessment of human behaviors or descriptive modeling of future system evolution (Di Baldassarre et al., 2017; Mason et al., 2018).

Reducing this uncertainty requires better scientific understanding of human-environment interactions, including the representative feedbacks described in section 3.2.3. While the consideration of human and ecological water needs has always been a part of the systems analysis field, focus has only recently shifted to the question of how to model endogenous system dynamics that are driven by the coevolution of hydroclimatic forcing and human behavior (Sivapalan & Blöschl, 2015; Thompson et al., 2013). This coupled modeling has been addressed in several ways:

1. Hydroeconomic models: water demand is a function of availability, assuming rationality (Draper et al., 2003; Kahil et al., 2018)
2. Descriptive models: infer behavioral rules from observational data or theory, originating in cognitive psychology and the social sciences (Camerer et al., 2004; Sanderson et al., 2017) or directly from observational data (Giuliani & Herman, 2018; Turner et al., 2019)
3. Dynamical systems models: a set of differential equations, including socioecological systems (Anderies et al., 2004) and sociohydrology (Di Baldassarre et al., 2016; Sivapalan et al., 2014).
4. Agent-based models: rule-based individual actions, for example, in response to short- and long-term water scarcity conditions (Giuliani, Li, et al., 2016; Schlüter & Pahl-Wostl, 2007).

Opportunities exist to incorporate findings from recent studies that empirically measure human responses to climate change into simulation models using similar methods (e.g., Carleton & Hsiang, 2016). Moreover, the increasing availability of large observational data sets describing human activities (Sanderson et al., 2002) creates new possibilities for advancing data-driven behavioral modeling (Cominola et al., 2018, 2019). The extent to which dynamic simulation models can provide a reliable and unbiased representation of human behavior remains an important research question (Melsen et al., 2018).

4.4. Policy Validation and Robustness

One strategy to address the impacts of deep uncertainty in the control problem is testing optimized policies on scenarios or probability distributions other than those used in the optimization. The key question is not whether an adaptive policy can be optimized to a nonstationary climate scenario (it can) but whether the sequence, timing, and magnitude of actions in this optimized policy can generalize to other plausible realizations of climate and other uncertainties. The concept of testing optimized decisions has been explored extensively in the robust decision-making literature (e.g., Kasprzyk et al., 2013), as well as several of the dynamic planning studies in Table 1.

Here we distinguish two related goals of such testing (Figure 6a): (1) robustness to sampling uncertainty, represented by more realizations using the same uncertainty characterization—which we refer to as validation, in the machine learning sense—and (2) robustness to other uncertain variables or probability distributions not considered in the optimization. The first goal investigates whether the adaptation policy is overfit to the particular scenarios used in the optimization, especially given the strong dependence of control methods to the sampling of uncertainties over time. The second goal tests whether the adaptation policy is sensitive to key assumptions in the uncertainty characterization. The choice of which uncertainties to include in the optimization versus testing is highly subjective, but it is generally difficult to optimize to all possible sources of deep uncertainty, which would risk overdesign unless the uncertainties are included as indicator variables in the policy optimization.

As shown in Figure 6b, a few benchmarks in the validation step can help provide context for the optimization results and suggest improvements in the experimental design. Specifically, each validation scenario or set of scenarios can be evaluated with a few measures of system performance: (1) the optimized policy re-evaluated in this scenario (validation); (2) a policy specifically optimized to this scenario, to establish an ideal

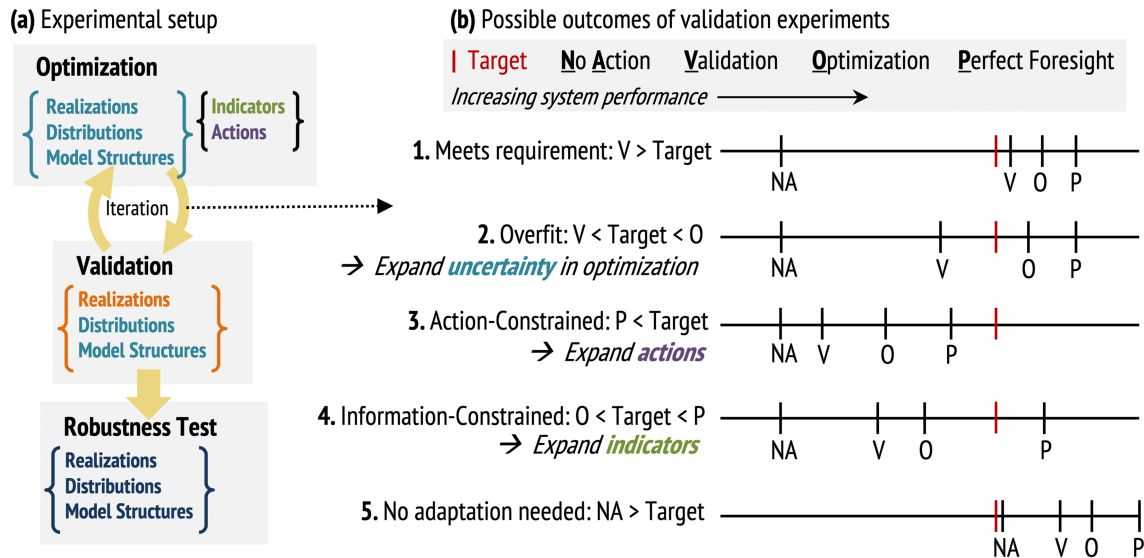


Figure 6. (a) Experimental setup for dynamic planning using control methods. The validation step tests the performance of an optimized policy against more realizations of the same uncertainty characterization, while the robustness step tests the performance over samples generated under other key assumptions, such as model structures and distributions not included in the optimization. (b) Outcomes of validation experiments and how the experimental setup might be modified in each case.

outcome (perfect foresight); and (3) a “no-action” scenario, to establish baseline system performance if no adaptations are implemented. All of these are compared to a target level of performance or possibly multiobjective targets, determined in consultation with stakeholders and decision-makers. The possible outcomes are then:

1. *Meets requirement*: the performance in validation exceeds the target performance.
2. *Overfit*: performance in optimization exceeds the target but validation does not. The optimization should include a larger sample size of scenarios, with attention paid to extreme events.
3. *Action-constrained*: even with perfect foresight, the target cannot be met. This suggests that the set of actions is too limited to adapt to future change.
4. *Information-constrained*: optimized performance does not meet the target, but perfect foresight does, suggesting that better indicator variables could improve the policy.
5. *No adaptation needed*: The target is met even if no action is taken, which might be the case if the current system is already robust to the range of projected future changes.

The outcomes shown in Figure 6b assume that the policy performs better in optimization and validation than no action, which is not guaranteed in practice. Additionally, comparing the actions taken by the optimized policies to those obtained from the perfect foresight optimization would show whether the actions chosen (sequence, timing, and magnitude) remain roughly the same, which could serve as a diagnostic step for policies performing poorly in validation. These experiments can be repeated on several types of scenarios (e.g., wet vs. dry) to investigate whether a similar series of optimal actions, or conditions to trigger them, might be reasonable even without exact knowledge of the future climate. Performing these comparisons in the decision space and objective space could also provide a basis to distinguish policies which show similar performance yet very different actions, that is, the case of equifinality in the optimization results.

Finally, in the robustness step a number of additional uncertainties can be considered, including model structure, variables, and distributions that were not modified in the validation step. The focus is not necessarily choosing the most robust policy, which likely comes at high cost. Instead, as with robust planning methods, the goal is to understand the sensitivity of the optimized policy to the key assumptions regarding deeply uncertain variables. In the dynamic planning problem this challenge is exacerbated by the need to represent deeply uncertain variables as time series, which contain nearly infinite possible sequences of events over a decades-long planning horizon and are therefore unlikely to be fully represented by an

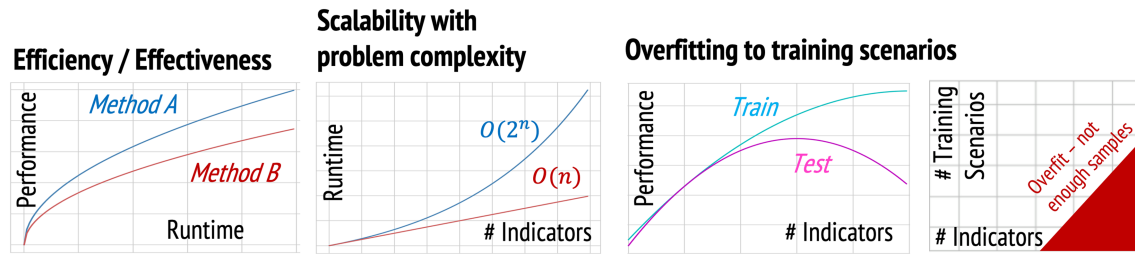


Figure 7. Open research questions in comparing the computational complexity of solution methods for control methods applied to climate adaptation problems. The illustrative performance metric assumes maximization.

ensemble of any size. Still, this process can identify key assumptions for refinement, iteratively informing the optimization step if policies are found to be overly sensitive.

4.5. Computational Complexity

The choice of solution method is arguably not the most pressing issue in dynamic planning studies under climate change, because all methods face a number of other challenges discussed previously. However, several important research questions remain related to the computational complexity of using these methods to design and test optimal adaptation policies. The concepts presented in Figure 7 draw some inspiration from prior diagnostic studies of optimization algorithms (e.g., Reed et al., 2013; Zatarain Salazar et al., 2016), here with a specific focus on the dynamic planning problem:

1. *Efficiency/effectiveness*: For a given level of performance (possibly multiobjective), which method has the best runtime and vice versa? These experiments assume a fixed problem formulation and possibly a benchmark level of performance determined with perfect foresight. Heuristic methods will require multiple random trials.
2. *Scalability with problem complexity*: How does the runtime needed to converge (e.g., to a predefined acceptable level of performance) increase with the number of indicator variables? This type of analysis would reflect the curse of dimensionality in the dynamic programming family of methods and would confirm whether policy search methods can flexibly include more indicator variables at the cost of an approximate policy. Here the number of indicator variables is assumed to be a proxy for the complexity of the problem, since it will increase the size of the search space roughly exponentially depending on the policy structure. There may be opportunities to reduce the computational effort through aggregate proxy indicators that combine multiple sources of information while maintaining key dynamic signals (Zaniolo et al., 2018).
3. *Overfitting to training scenarios*: As the problem complexity increases, the resulting policy should improve in validation, to a point. After that, the more complex policy will not generalize well to other scenarios. This is not so much a comparison between methods as an important threshold to identify within each method. The point at which overfitting occurs also depends on the number (or length) of scenarios used in training, because more complex policies will require more training data to avoid overfitting. If policy interpretability is a concern, it is possible that the level of desired complexity will occur well before overfitting.

These experiments could be performed on a single case study but would be stronger if devised within a generalizable testing framework where the properties of the problem can be modified along with the properties of the solution methods. The results would then indicate which solution methods are most applicable to certain problem contexts and/or the extent to which the problem formulation would need to be modified in order to use each method.

4.6. Monitoring and Data Assimilation

Finally, the studies in Table 1 suggest significant potential to expand the set of indicator variables used to trigger adaptation, particularly using policy search approaches. Indicators must be chosen to ensure they are indicative of emerging trends and not merely noise (Haasnoot et al., 2018). We discuss three statistical approaches that might improve the use of information in dynamic adaptation to climate change: trend

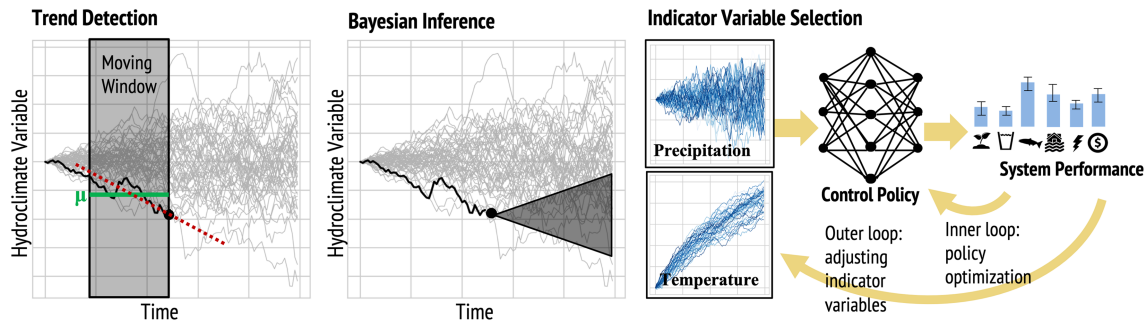


Figure 8. Statistical approaches to improve the use of information in dynamic adaptation to climate change.

detection, Bayesian data assimilation, and formal approaches to indicator variable selection (Figure 8). While these approaches apply equally to hydroclimatic variables and endogenous variables, such as water demand and land use, most of the water resources literature focuses on the former.

4.6.1. Trend Detection

In the context of climate change, trend detection typically refers to the challenge of distinguishing nonstationarity from natural variability in an observation of interest (Hegerl & Zwiers, 2011). While a statistically significant trend is not a requirement for adaptation to occur, it is one of many possible indicator variables that could be used to trigger adaptation, including future values predicted by extrapolating a trend. Detecting trends in the impacts of thermodynamic climate change, such as snowpack decline and sea level rise (Ceres et al., 2017; Thorarinsdottir et al., 2017), is often more feasible than for dynamic climate changes and extreme events such as floods. In this case, a key question is how much information will need to be observed before a significant trend can be detected, which for precipitation may exceed relevant planning timescales of 50 years or more (Pielke et al., 2012). The length of observations needed to detect a trend could inform the choice of moving window over which an indicator variable is aggregated. Several related studies have focused on the development of nonstationary hazard functions to characterize the frequency and severity of extreme events, particularly floods (Luke et al., 2017; Read & Vogel, 2015) estimates of which are updated through time based on observed precipitation trends. These methods are primarily concerned with failure to detect change (Type II error) (Rosner et al., 2014; Yu et al., 2015), which relates to false negatives for infrastructure adaptation.

Trend detection could support the development of indicator variables for dynamic planning in several ways. First, a trend could serve as a binary indicator variable for the policy, to trigger an action when statistical significance is detected. This would implicitly try to minimize false positives for infrastructure planning or to trigger action based on the expected costs of a false negative (Rosner et al., 2014). These methods could also be used to detect when the current or projected future scenario is trending outside the range of the scenario(s) against which the current policy was trained. Additionally, stochastic scenario generation enables controlled experiments to test adaptive policies based on trend detection methods. For instance, transient scenarios can be generated to combine physically based trends using parameterized representations of thermodynamic and dynamic climate change alongside spurious trends using high autocorrelation to test if a policy overadapts or underadapts to multidecadal internal climate variability and secular climate change. Such efforts provide a promising avenue to further advance adaptive control policies with an enhanced process-level understanding of regional climate variability and change.

4.6.2. Bayesian Inference

Observations of hydroclimatic and other variables that occur during the planning horizon can condition the characterization of stochastic forcing used in the control problem. For example, new observations might eliminate some emissions trajectories, refine estimates of climate sensitivity, or assimilate new GCM ensembles. An adaptive policy can be designed to incorporate these updates; for studies using formal probabilistic approaches, this could be done with Bayesian methods. As discussed previously, many of the uncertainties in long-term planning are not readily described by probability distributions. Bayesian methods still require probabilistic formulations just as scenario-based methods require scenario selection. However, the choice of prior distribution can be tailored to the information available, ranging from precise, data-driven priors to uninformative priors chosen to allow data collected over time to be the primary driver of the resulting

posterior. Further, the extent to which priors are truly uninformative can be tested via sensitivity on the priors (Gelman et al., 2013). In either case, prior estimates can be updated dynamically with observations, reducing uncertainty as more information becomes available and informing adaptive planning.

In the climate science field, Bayesian methods have been employed to reconcile simulation model output with observed data (e.g., Smith et al., 2009; Tebaldi & Knutti, 2007), building on a foundation of applications in water resources and environmental sciences (Bates et al., 2003; Hobbs, 1997; Hong et al., 2005). For optimal control problems, the formal probabilistic treatment of Bayesian methods lends itself to SDP approaches (Fletcher et al., 2019; Hui et al., 2018) and can also be accommodated within policy search methods by probabilistically weighting performance under different scenarios or by conditioning probabilistic indicator variables. In addition to forcing variables, such approaches can also be used to infer system parameter values and tipping points (Singh et al., 2018) to reduce endogenous uncertainty.

The idea of characterizing stochastic forcing based on dynamic future observations suggests that one could instead describe the nonstationary scenarios by means of stochastic models with state-dependent parameters (Priestley, 1988), as long as the parameters are changing slowly relative to the dynamics of the system under study (Young et al., 2001). Following this approach, the parameters of the stochastic forcing models would be defined as a function of other observable variables in the system that can be sampled over time (Young, 2000). The parameters can then be recursively estimated using the Kalman filter or associated algorithms (Kalman, 1960). Thus, as changes in the state are observed, changes in the parameters in the stochastic process change in response. The state space representation of the parameters of the stochastic forcing models makes this approach particularly suitable for the design of closed loop control policies (Taylor et al., 2000).

4.6.3. Indicator Variable Selection

Indicator variables should be a parsimonious subset of forcing and state variables that can effectively inform policy actions. To some extent, this choice can be initialized by analyst judgment. However, since the set of candidate indicator variables and their statistical transformations is technically infinite, comprising many redundant variables and their transformations, the process may benefit from formal techniques for Input Variable Selection (IVS) (Galelli et al., 2014; Guyon & Elisseeff, 2003). These methods provide flexibility to capture nonlinear interactions between input variables and the computational efficiency to handle potentially many candidate variables over long time series. Generally, IVS problems arise every time a variable of interest is modeled as a function of a subset of potential explanatory variables, or predictors, but there is uncertainty about which subset to use (George & Foster, 2000).

To the authors' knowledge, IVS methods to support the optimization of climate adaptation policies are still unexplored, but they can draw inspiration from studies of short-term reservoir operations that have dealt with the topic in more detail. For example, extending the framework proposed by Giuliani, Pianosi, et al. (2015), an IVS procedure for climate adaptation might involve the following steps:

1. Assume a single future scenario as truth and solve a deterministic optimization problem with perfect foresight, yielding an ideal reference solution.
2. Find the minimum subset of indicator variables that, when used to optimize a policy, best approximates the sequence of optimal adaptive decisions from the perfect foresight solution.
3. Once the best subset of indicator variables is identified, they can be used in the optimization of the adaptive policy.
4. Iterate multiple times using different reference scenarios to avoid overfitting, ideally identifying a common set of indicator variables selected across a wide range of scenarios.

The effectiveness of such an approach for a long-term climate adaptation problem remains an open question, along with several more general questions. For example, it is not clear whether there is an advantage to choosing a climate indicator or a second-order variable that is strongly correlated but may be easier to measure, such as reservoir storage. Indicator variables may need to be adjusted dynamically after an infrastructure adaptation is triggered by the policy, and therefore, the system behavior is changed. Also, nonstationary indicator variables may undergo different types of change, such as a step change rather than a gradual transient signal. The choice of indicators is strongly linked to the objective function; in multiobjective problems, a complex combination of information may be needed, a challenge that applies to both operations and planning (Quinn et al., 2019).

5. Conclusions

While optimal control methods cannot directly solve the climate adaptation problem any more than other public policy problems (Kwakkel, Walker, et al., 2016; Rittel & Webber, 1973), they are still a valuable component in decision support. It remains the primary approach to frame a dynamic planning problem in which actions are taken in response to observed and projected states and fluxes and provides a useful way to define and classify recent studies in this area. The past decade of research suggests that dynamic planning has become a candidate successor to the stationary paradigm of water management (Milly et al., 2008) because of its ability to identify and adapt to nonstationary trends and also to navigate the numerous and interacting sources of uncertainty in long-term climate projections.

Going forward, we propose the following summary points to support the evolving science and practice of dynamic water resources planning under climate change:

Water Resources Systems Sciences:

1. The purpose of optimal control for long-term planning is not necessarily to implement the policy directly (unlike short-term operations) but rather to provide decision support by identifying near-term plans that can best prepare the system for the long-term future. Policies will eventually be updated as new observations and projections become available.
2. Uncertainty in endogenous system dynamics may equal or exceed that contributed by climate change on long planning horizons. Dynamic planning would therefore benefit from an improved understanding of the nonlinear dynamics linking climate and hydrology with human behavior, including land use and water demand across multiple scales. As noted by Brown et al. (2015), the traditional prescriptive focus of the field cannot be separated from these descriptive questions of how water resources systems will evolve in the presence or absence of policy interventions.
3. No uncertainty characterization can be proven correct but can be justified according to the timescale, variable, and time horizon of the problem. An optimized adaptation policy implicitly reflects the probabilities of events that it was trained against, and how the objective function is aggregated, whether or not explicit probability distributions are defined.
4. Given that any future projection will not occur exactly, optimal control methods should employ sensitivity analyses to identify: (1) the sensitivity of the system to structural and parametric uncertainties throughout the modeling chain and (2) the sensitivity of an optimized policy to the approach used for uncertainty characterization.

Climate and Hydrologic Sciences:

1. The control problem requires dynamic sequences of hydroclimatic inputs which are physically plausible across timescales. GCM projections can inform these dynamic sequences, despite their known limitations in resolving precipitation processes. Stochastic weather and streamflow generators are rapidly improving and may be able to leverage physically based insights from the climate modeling field.
2. Ideally, ensemble projections made available to planners could include a broader set of uncertainties beyond GCM and emissions scenarios, such as perturbation of initial conditions, uncertainty in downscaling methods, and hydrologic models, in order to better validate the robustness of solutions from dynamic planning models.
3. A particularly valuable opportunity for collaboration is the identification of planning signposts from internal climate states and processes, rather than inferring these from streamflow alone. This can support the selection of indicator variables for policy search approaches, which remains underexplored.

Water Resources Agencies and Practitioners:

1. Dynamic planning methods are an important tool to design climate adaptation policies that adapt as uncertainties in both the climate and human system unfold over time.
2. Long-term planning studies cannot be expected to encompass all sources of uncertainty in climate forcing, human behavior, and natural variability. This underscores the need for careful problem formulation, framing, and interpretation of results.
3. Different impacts of climate change can be more accurately represented in scenarios or probability distributions than others. Some impacts are sufficiently well understood, as the direct consequence of rising temperatures, to begin planning adaptations in the near term.

4. When the uncertainty in climate impacts is difficult to quantify (e.g., extreme events), dynamic planning can still add value by asking: what future observations of precipitation and streamflow would necessitate action—either because the system is vulnerable or expected to become vulnerable—and what actions should be taken under those conditions?
5. Deep uncertainty regarding human responses to climate change can be studied according to how optimal planning decisions differ under alternative model assumptions defining these feedbacks.

In many ways, climate change only exacerbates uncertainties that have always been present in water resources planning, owing to the difficulty of enumerating all possible futures on decadal timescales. However, the increased uncertainty driven by climate change has pushed traditional planning methods beyond their limits—and also illuminated their limitations even in the absence of climate change. The challenge of dynamically mapping new observations and uncertain projections to actions will remain at the core of climate adaptation studies for the foreseeable future.

Data Availability Statement

No original data were created in this study. The downscaled streamflow projections shown in Figures 4 and 5 were produced and made available by the World Climate Research Program’s Working Group on Coupled Modeling and the climate modeling groups listed in the appendix.

Appendix A

This appendix describes the source of the hydrologic projections under climate change used in example Figure 4 and Figure 5.

Modeling center (or group)	Institute ID	Model name
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1.0
	BCC	BCC-CSM1.1
Canadian Centre for Climate Modelling and Analysis National Center for Atmospheric Research Community Earth System Model Contributors	BCC	BCC-CSM1.1(m)
	CCCMA	CanESM2
	NCAR	CCSM4
	NSF-DOE-NCAR	CESM1(BGC)
Euro-Mediterranean Center on Climate Change	CMCC	CMCC-CM
	CSIRO-Queensland Climate Change Centre of Excellence	CSIRO-Mk3.6.0
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	LASG-CESS	FGOALS-g2
	FIO	FIO-ESM
The First Institute of Oceanography, SOA, China	NASA	GEOS-5
	GMAO	
NOAA Geophysical Fluid Dynamics Laboratory	NOAA	GFDL-CM3
	GFDL	GFDL-ESM 2G
		GFDL-ESM 2M
NASA Goddard Institute for Space Studies	NASA	GISS-E2-H-CC
	GISS	GISS-E2-R
National Institute of Meteorological Research/Korea Meteorological Administration		GISS-E2-R-CC
	NIMR/KMA	HadGEM2-AO
Met Office Hadley Centre	MOHC	HadGEM2-CC

Table A1
(continued)

Modeling center (or group)	Institute ID	Model name
Institute for Numerical Mathematics Institute Pierre-Simon Laplace	INM	HadGEM2-ES INM-CM4
	IPSL	IPSL-CM5A-MR
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC	IPSL-CM5B-LR MIROC-ESM
		MIROC-ESM- CHEM MIROC5
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC	MIROC5
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-MR
Meteorological Research Institute Norwegian Climate Centre	MRI	MPI-ESM-LR MRI-CGCM3
	NCC	NorESM1-M

Acknowledgments

We thank Dr. Holger Maier and three anonymous reviewers for their thoughtful input on the structure and content of this review. This work was partially supported by the U.S. National Science Foundation grants CNH-1716130, CBET-1803563, and CBET-1803589. Any opinions, findings, and conclusions are those of the authors and do not necessarily reflect the views or policies of these funding agencies.

References

- Adger, W. N., Arnell, N. W., Tompkins, E. L., Neil Adger, W., Arnell, N. W., & Tompkins, E. L. (2005). Successful adaptation to climate change across scales. *Global Environmental Change, 15*(2), 77–86. <https://doi.org/10.1016/j.gloenvcha.2004.12.005>
- Aghakouchak, A., Feldman, D., Stewardson, M. J., Saphores, J.-D., Grant, S., & Sanders, B. (2014). Australia's drought: Lessons for California. *Science, 343*(6178), 1430–1431. <https://doi.org/10.1126/science.343.6178.1430>
- Alcamo, J., Florke, M., & Marker, M. (2007). Future long-term changes in global water resources driven by socio-economic and climatic changes. *Hydrological Sciences Journal, 52*(2), 247–275. <https://doi.org/10.1623/hysj.52.2.247>
- Allard, D., & Bourotte, M. (2015). Disaggregating daily precipitations into hourly values with a transformed censored latent Gaussian process. *Stochastic Environmental Research and Risk Assessment, 29*(2), 453–462. <https://doi.org/10.1007/s00477-014-0913-4>
- Anderies, J. M., Janssen, M. A., & Ostrom, E. (2004). A framework to analyze the robustness of social-ecological systems from an institutional perspective. *Ecology and Society, 9*(1), 1–18.
- Anderies, J. M., Mathias, J.-D., & Janssen, M. A. (2019). Knowledge infrastructure and safe operating spaces in social-ecological systems. *Proceedings of the National Academy of Sciences of the United States of America, 116*(12), 5277–5284. <https://doi.org/10.1073/pnas.1802885115>
- Anghileri, D., Botter, M., Castelletti, A., Weigt, H., & Burlando, P. (2018). A comparative assessment of the impact of climate change and energy policies on Alpine hydropower. *Water Resources Research, 54*(11), 9144–9161. <https://doi.org/10.1029/2017WR022289>
- Asadieh, B., & Krakauer, N. Y. (2017). Global change in flood and drought intensities under climate change in the 21st century. *Hydrology and Earth System Sciences Discussions, 1–22*. <https://doi.org/10.5194/hess-2017-253>
- Bao, J., Sherwood, S. C., Alexander, L. V., & Evans, J. P. (2017). Future increases in extreme precipitation exceed observed scaling rates. *Nature Climate Change, 7*(2), 128–132. <https://doi.org/10.1038/nclimate3201>
- Bates, S. C., Cullen, A., & Raftery, A. E. (2003). Bayesian uncertainty assessment in multicompartment deterministic simulation models for environmental risk assessment. *Environmetrics, 14*(4), 355–371. <https://doi.org/10.1002/env.590>
- Beh, E. H. Y., Dandy, G. C., Maier, H. R., & Paton, F. L. (2014). Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives. *Environmental Modelling and Software, 53*, 137–153. <https://doi.org/10.1016/j.envsoft.2013.11.004>
- Beh, E. H. Y., Maier, H. R., & Dandy, G. C. (2015). Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty. *Water Resources Research, 51*, 1529–1551. <https://doi.org/10.1002/2014WR016254>
- 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. *Environmental Modelling and Software, 93*, 92–105. <https://doi.org/10.1016/j.envsoft.2017.03.013>
- Bellman, R. (1956). Dynamic programming and lagrange multipliers. *Proceedings of the National Academy of Sciences, 42*(10), 767–769. <https://doi.org/10.1073/pnas.42.10.767>
- Ben-Haim, Y. (2012). Why risk analysis is difficult, and some thoughts on how to proceed. *Risk Analysis, 32*(10), 1638–1646. <https://doi.org/10.1111/j.1539-6924.2012.01859.x>
- Bertoni, F., A. Castelletti, M. Giuliani, and P. M. Reed (2019). Discovering dependencies, trade-offs, and robustness in joint dam design and operation: An ex-post assessment of the Kariba Dam, *Earth's Future, 7*. <https://doi.org/10.1029/2019EF001235>
- Bertsekas, D. (2019). *Reinforcement learning and optimal control*. Belmont, MA: Athena Scientific.
- Bertsekas, D. P. (2005). Dynamic programming and suboptimal control: A survey from ADP to MPC, in *European Journal of Control, 11*(4–5), 310–334, Lavoisier. <https://doi.org/10.3166/ejc.11.310-334>
- Beven, K. (2016). Facets of uncertainty: Epistemic uncertainty, non-stationarity, likelihood, hypothesis testing, and communication. *Hydrological Sciences Journal, 61*(9), 1652–1665. <https://doi.org/10.1080/02626667.2015.1031761>

- Beven, K. J., Almeida, S., Aspinall, W. P., Bates, P. D., Blazkova, S., Borgomeo, E., et al. (2018). Epistemic uncertainties and natural hazard risk assessment—Part 1: A review of different natural hazard areas. *Natural Hazards and Earth System Sciences*, 18(10), 2741–2768. <https://doi.org/10.5194/nhess-18-2741-2018>
- Beven, K. J., Aspinall, W. P., Bates, P. D., Borgomeo, E., Goda, K., Hall, J. W., et al. (2018). Epistemic uncertainties and natural hazard risk assessment—Part 2: What should constitute good practice? *Natural Hazards and Earth System Sciences*, 18(10), 2769–2783. <https://doi.org/10.5194/nhess-18-2769-2018>
- Borgomeo, E., Pflug, G., Hall, J. W. & Hochrainer-Stigler, S. (2015). Assessing water resource system vulnerability to unprecedented hydrological drought using copulas to characterize drought duration and deficit. *Water Resources Research*, 51(11), 8927–8948.
- 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>
- Borgomeo, E., Mortazavi-Naeini, M., Hall, J. W., O'Sullivan, M. J., & Watson, T. (2016). Trading-off tolerable risk with climate change adaptation costs in water supply systems. *Water Resources Research*, January, n/a-n/a, 52, 622–643. <https://doi.org/10.1002/2015WR018164>
- 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 Resources Research*, 45, W04411. <https://doi.org/10.1029/2008WR006941>
- Broderick, C., Murphy, C., Wilby, R. L., Matthews, T., Prudhomme, C., & Adamson, M. (2019). Using a scenario-neutral framework to avoid potential maladaptation to future flood risk. *Water Resources Research*, 55, 1079–1104. <https://doi.org/10.1029/2018WR023623>
- Brown, C. M., Ghile, Y., Lavery, M., & Li, K. (2012). Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. *Water Resources Research*, 48, W09537. <https://doi.org/10.1029/2011WR011212>
- Brown, C. M., Lund, J. R., Cai, X., Reed, P. M., Zagona, E. A., Ostfeld, A., et al. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable water management. *Water Resources Research*, 51, 6110–6124. <https://doi.org/10.1002/2015WR017114>
- Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, 77(1), 34–49. <https://doi.org/10.1016/j.techfore.2009.08.002>
- Busoni, L., R. Babuska, B. De Schutter, and D. Ernst (2010), *Reinforcement learning and dynamic programming using function approximators* (Vo. 39). Boca Raton, FL: CRC Press.
- Camerer, C., Loewenstein, G., & Rabin, M. (2004). *Advances in behavioral economics*. New York, NY: Russell Sage Foundation.
- Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304), aad9837. <https://doi.org/10.1126/science.aad9837>
- Castelletti, A., Galelli, S., Restelli, M., & Soncini-Sessa, R. (2010). Tree-based reinforcement learning for optimal water reservoir operation. *Water Resources Research*, 46, W09507. <https://doi.org/10.1029/2009WR008898>
- 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>
- Ceres, R. L., Forest, C. E., & Keller, K. (2017). Understanding the detectability of potential changes to the 100-year peak storm surge. *Climatic Change*, 145(1–2), 221–235. <https://doi.org/10.1007/s10584-017-2075-0>
- Chen, J., Brissette, F. P., & Leconte, R. (2011). Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. *Journal of Hydrology*, 401(3–4), 190–202. <https://doi.org/10.1016/j.jhydrol.2011.02.020>
- Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., et al. (2013) Long-term Climate Change: Projections, Commitments and Irreversibility. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Eds.). Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- Cominola, A., Nguyen, K., Giuliani, M., Stewart, R. A., Maier, H. R., & Castelletti, A. (2019). Data mining to uncover heterogeneous water use behaviors from smart meter data. *Water Resources Research*, 55, 9315–9333. <https://doi.org/10.1029/2019WR024897>
- Cominola, A., Spang, E. S., Giuliani, M., Castelletti, A., Lund, J. R., & Loge, F. J. (2018). Segmentation analysis of residential water-electricity demand for customized demand-side management programs. *Journal of Cleaner Production*, 172, 1607–1619. <https://doi.org/10.1016/j.jclepro.2017.10.203>
- Culley, S., Noble, S., Yates, A., Timbs, M., Westra, S., Maier, H. R., et al. (2016). A bottom-up approach to identifying the maximum operational adaptive capacity of water resource systems to a changing climate. *Water Resources Research*, 52, 6751–6768. <https://doi.org/10.1002/2015WR018253>
- Davini, P., von Hardenberg, J., Corti, S., Christensen, H. M., Juricke, S., Subramanian, A., et al. (2017). Climate SPHINX: Evaluating the impact of resolution and stochastic physics parameterisations in the EC-Earth global climate model. *Geoscientific Model Development*, 10(3), 1383–1402. <https://doi.org/10.5194/gmd-10-1383-2017>
- de Neufville, R., & Scholtes, S. (2011). *Flexibility in Engineering Design*. Cambridge: MIT Press.
- de Neufville, R., & Smet, K. (2019). Engineering Options Analysis (EOA), in *Decision Making under Deep Uncertainty*, pp. 117–132, Cham, Switzerland; Springer International Publishing.
- Dennig, F. (2017). Climate change and the re-evaluation of cost-benefit analysis. *Climatic Change*, 151(1), 43–54. <https://doi.org/10.1007/s10584-017-2047-4>
- Deser, C., Phillips, A., Bourdette, V., & Teng, H. (2012). Uncertainty in climate change projections: The role of internal variability. *Climate Dynamics*, 38(3–4), 527–546. <https://doi.org/10.1007/s00382-010-0977-x>
- Dessai, S., Bhave, A., Birch, C., Conway, D., Garcia-Carreras, L., Gosling, J. P., et al. (2018). Building narratives to characterise uncertainty in regional climate change through expert elicitation. *Environmental Research Letters*, 13, 074005. <https://doi.org/10.1088/1748-9326/aabadd>
- Di Baldassarre, G., Brandimarte, L., & Beven, K. (2016). The seventh facet of uncertainty: Wrong assumptions, unknowns and surprises in the dynamics of human–water systems. *Hydrological Sciences Journal*, 61(9), 1748–1758. <https://doi.org/10.1080/02626667.2015.1091460>
- Di Baldassarre, G., Martinez, F., Kalantari, Z., & Viglione, A. (2017). Drought and flood in the Anthropocene: Feedback mechanisms in reservoir operation. *Earth System Dynamics*, 8(1), 225–233. <https://doi.org/10.5194/esd-8-225-2017>
- Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangelcroft, S., Veldkamp, T. I. E., et al. (2018). Water shortages worsened by reservoir effects. *Nature Sustainability*, 1(11), 617–622. <https://doi.org/10.1038/s41893-018-0159-0>
- DiFrancesco, K. N., & Tullios, D. D. (2014). Flexibility in water resources management: Review of concepts and development of assessment measures for flood management systems. *Journal of the American Water Resources Association*, 50(6), 1527–1539. <https://doi.org/10.1111/jawr.12214>

- Dittrich, R., Wreford, A., & Moran, D. (2016). A survey of decision-making approaches for climate change adaptation: Are robust methods the way forward? *Ecological Economics*, *122*, 79–89. <https://doi.org/10.1016/j.ecolecon.2015.12.006>
- Döll, P., & Romero-Lankao, P. (2017). How to embrace uncertainty in participatory climate change risk management—A roadmap. *Earth's Future*, *5*(1), 18–36. <https://doi.org/10.1002/2016EF000411>
- Doss-Gollin, J., Farnham, D. J., Steinschneider, S., & Lall, U. (2019). Robust adaptation to multiscale climate variability. *Earth's Future*, *7*, 2019EF001154. <https://doi.org/10.1029/2019EF001154>
- Dottori, F., Szewczyk, W., Ciscar, J. C., Zhao, F., Alfieri, L., Hirabayashi, Y., et al. (2018). Increased human and economic losses from river flooding with anthropogenic warming. *Nature Climate Change*, *8*(9), 781–786. <https://doi.org/10.1038/s41558-018-0257-z>
- Draper, A. J., Jenkins, M. W., Kirby, K. W., Lund, J. R., & Howitt, R. E. (2003). Economic-engineering optimization for California water management. *Journal of Water Resources Planning and Management*, *129*(3), 155–164. [https://doi.org/10.1061/\(asce\)0733-9496\(2003\)129:3\(155\)](https://doi.org/10.1061/(asce)0733-9496(2003)129:3(155))
- Droogers, P., Immerzeel, W. W., Terink, W., Hoogeveen, J., Bierkens, M. F. P., Van Beek, L. P. H., & Debele, B. (2012). Water resources trends in Middle East and North Africa towards 2050. *Hydrology and Earth System Sciences*, *16*(9), 3101–3114. <https://doi.org/10.5194/hess-16-3101-2012>
- Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., & Liebert, J. (2012). Should we apply bias correction to global and regional climate model data? *Hydrology and Earth System Sciences*, *16*(9), 3391–3404. <https://doi.org/10.5194/hess-16-3391-2012>
- Eker, S., & Kwakkel, J. H. (2018). Including robustness considerations in the search phase of many-objective robust decision making. *Environmental Modelling and Software*, *105*, 201–216. <https://doi.org/10.1016/j.envsoft.2018.03.029>
- Elshafei, Y., Sivapalan, M., Tonts, M., & Hipsey, M. R. (2014). A prototype framework for models of socio-hydrology: Identification of key feedback loops and parameterisation approach. *Hydrology and Earth System Sciences*, *18*(6), 2141–2166. <https://doi.org/10.5194/hess-18-2141-2014>
- Emori, S., & Brown, S. J. (2005). Dynamic and thermodynamic changes in mean and extreme precipitation under changed climate. *Geophysical Research Letters*, *32*, L17706. <https://doi.org/10.1029/2005GL023272>
- Erfani, T., Pachos, K., & Harou, J. J. (2018). Real-options water supply planning: Multistage scenario trees for adaptive and flexible capacity expansion under probabilistic climate change uncertainty. *Water Resources Research*, *54*, 5069–5087. <https://doi.org/10.1029/2017WR021803>
- Fant, C., Schlosser, C. A., Gao, X., Strzepek, K., & Reilly, J. (2016). Projections of water stress based on an ensemble of socioeconomic growth and climate change scenarios: A case study in Asia, edited by K. L. Ebi. *PLoS ONE*, *11*, e0150633. <https://doi.org/10.1371/journal.pone.0150633>
- Fischer, E. M., & Knutti, R. (2016). Observed heavy precipitation increase confirms theory and early models. *Nature Climate Change*, *6*(11), 986–991. <https://doi.org/10.1038/nclimate3110>
- Fletcher, S. M., Lickley, M., & Strzepek, K. (2019). Learning about climate change uncertainty enables flexible water infrastructure planning. *Nature Communications*, *10*, 1782. <https://doi.org/10.31223/OSF.IO/2TM7X>
- Fletcher, S. M., Miotti, M., Swaminathan, J., Klemun, M. M., Strzepek, K., & Siddiqi, A. (2017). Water supply infrastructure planning: Decision-making framework to classify multiple uncertainties and evaluate flexible design. *Journal of Water Resources Planning and Management*, *143*(10), 04017061. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000823](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000823)
- Fowler, K., Coxon, G., Freer, J., Peel, M., Wagener, T., Western, A., et al. (2018). Simulating runoff under changing climatic conditions: A framework for model improvement. *Water Resources Research*, *54*, 9812–9832. <https://doi.org/10.1029/2018WR023989>
- Füssel, H.-M. (2007). Adaptation planning for climate change: Concepts, assessment approaches, and key lessons. *Sustainability Science*, *2*(2), 265–275. <https://doi.org/10.1007/s11625-007-0032-y>
- Galelli, S., Humphrey, G. B., Maier, H. R., Castelletti, A., Dandy, G. C., & Gibbs, M. S. (2014). An evaluation framework for input variable selection algorithms for environmental data-driven models. *Environmental Modelling and Software*, *62*, 33–51. <https://doi.org/10.1016/j.envsoft.2014.08.015>
- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). *Bayesian data analysis*, (third ed.). Boca Raton: CRC Press.
- George, E., & Foster, D. P. (2000). Calibration and empirical Bayes variable selection. *Biometrika*, *87*(4), 731–747. <https://doi.org/10.1093/biomet/87.4.731>
- Giuliani, M., Anghileri, D., Castelletti, A., Vu, P. N., & Soncini-Sessa, R. (2016). Large storage operations under climate change: Expanding uncertainties and evolving tradeoffs. *Environmental Research Letters*, *11*, 035009. <https://doi.org/10.1088/1748-9326/11/3/035009>
- Giuliani, M., & Castelletti, A. (2016). Is robustness really robust? How different definitions of robustness impact decision-making under climate change. *Climatic Change*, *135*(3–4), 409–424. <https://doi.org/10.1007/s10584-015-1586-9>
- Giuliani, M., Castelletti, A., Amigoni, F., & Cai, X. (2015). Multiagent systems and distributed constraint reasoning for regulatory mechanism design in water management. *Journal of Water Resources Planning and Management*, *141*, 04014068. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000463](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000463)
- Giuliani, M., & Herman, J. D. (2018). Modeling the behavior of water reservoir operators via eigenbehavior analysis. *Advances in Water Resources*, *122*, 228–237. <https://doi.org/10.1016/j.advwatres.2018.10.021>
- Giuliani, M., Herman, J. D., Castelletti, A., & Reed, P. M. (2014). Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. *Water Resources Research*, *50*, 3355–3377. <https://doi.org/10.1002/2013WR014700>
- Giuliani, M., Li, Y., Castelletti, A., & Gandolfi, C. (2016). A coupled human-natural systems analysis of irrigated agriculture under changing climate. *Water Resources Research*, *52*, 6928–6947. <https://doi.org/10.1002/2016WR019363>
- Giuliani, M., Pianosi, F., & Castelletti, A. (2015). Making the most of data: An information selection and assessment framework to improve water systems operations. *Water Resources Research*, *51*, 9073–9093. <https://doi.org/10.1002/2015WR017044>
- 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 Transactions on Control Systems Technology*, *26*(4), 1492–1499. <https://doi.org/10.1109/TCST.2017.2705162>
- Glenis, V., Pinamonti, V., Hall, J. W., & Kilsby, C. G. (2015). A transient stochastic weather generator incorporating climate model uncertainty. *Advances in Water Resources*, *85*, 14–26. <https://doi.org/10.1016/j.advwatres.2015.08.002>
- Gonzales, P., & Ajami, N. (2017). Social and structural patterns of drought-related water conservation and rebound. *Water Resources Research*, *53*, 10.619–10.634. <https://doi.org/10.1002/2017WR021852>
- Greve, P., Kahil, T., Mochizuki, J., Schinko, T., Satoh, Y., Burek, P., et al. (2018). Global assessment of water challenges under uncertainty in water scarcity projections. *Nature Sustainability*, *1*(9), 486–494. <https://doi.org/10.1038/s41893-018-0134-9>

- Grimsey, D., & Lewis, M. K. (2002). Evaluating the risks of public private partnerships for infrastructure projects. *International Journal of Project Management*, 20(2), 107–118. [https://doi.org/10.1016/S0263-7863\(00\)00040-5](https://doi.org/10.1016/S0263-7863(00)00040-5)
- Groves, D. G., Bloom, E., Lempert, R., Fischbach, J., Nevills, J., & Goshi, B. (2015). Developing key indicators for adaptive water planning. *Journal of Water Resources Planning and Management*, 141, 05014008. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000471](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000471)
- Guerreiro, S. B., Fowler, H. J., Barbero, R., Westra, S., Lenderink, G., Blenkinsop, S., et al. (2018). Detection of continental-scale intensification of hourly rainfall extremes. *Nature Climate Change*, 8(9), 803–807. <https://doi.org/10.1038/s41558-018-0245-3>
- Guo, D., Westra, S., & Maier, H. R. (2018). An inverse approach to perturb historical rainfall data for scenario-neutral climate impact studies. *Journal of Hydrology*, 556, 877–890. <https://doi.org/10.1016/J.JHYDROL.2016.03.025>
- Guyon, I., & Elisseeff, A. (2003). An introduction to variable and feature selection. *Journal of Machine Learning Research*, 3, 1157–1182. <https://doi.org/10.1162/153244303322753616>
- 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 Environmental 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. *Environmental Research Letters*, 10, 105008. <https://doi.org/10.1088/1748-9326/10/10/105008>
- Haasnoot, M., van Aalst, M., Rozenberg, J., Dominique, K., Matthews, J., Bouwer, L. M., et al. (2019). Investments under non-stationarity: Economic evaluation of adaptation pathways. *Climatic Change*. <https://doi.org/10.1007/s10584-019-02409-6>
- Haasnoot, M., van't Klooster, S., & van Alphen, J. (2018). Designing a monitoring system to detect signals to adapt to uncertain climate change. *Global Environmental Change*, 52, 273–285. <https://doi.org/10.1016/J.GLOENVCHA.2018.08.003>
- Haddeland, I., Heinke, J., Biemans, H., Eisner, S., Flörke, M., Hanasaki, N., et al. (2014). Global water resources affected by human interventions and climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 111(9), 3251–3256. <https://doi.org/10.1073/pnas.1222475110>
- Hall, J. W., & Borgomeo, E. (2013). Risk-based principles for defining and managing water security. *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences*, 371, 20120407. <https://doi.org/10.1098/rsta.2012.0407>
- Hallegatte, S. (2009). Strategies to adapt to an uncertain climate change. *Global Environmental Change*, 19(2), 240–247. <https://doi.org/10.1016/j.gloenvcha.2008.12.003>
- Hamarat, C., Kwakkel, J. H., Pruyt, E., & Loonen, E. T. (2014). An exploratory approach for adaptive policymaking by using multi-objective robust optimization. *Simulation Modelling Practice and Theory*, 46, 25–39. <https://doi.org/10.1016/j.simpat.2014.02.008>
- Hawkins, E., & Sutton, R. (2011). The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics*, 37(1–2), 407–418. <https://doi.org/10.1007/s00382-010-0810-6>
- Hegerl, G., & Zwiers, F. (2011). Use of models in detection and attribution of climate change. *Wiley Interdisciplinary Reviews: Climate Change*, 2(4), 570–591. <https://doi.org/10.1002/wcc.121>
- Helgeson, C. (2018). Structuring decisions under deep uncertainty. *Topoi*, 1–13. <https://doi.org/10.1007/s11245-018-9584-y>
- Herman, J. D., & Giuliani, M. (2018). Policy tree optimization for threshold-based water resources management over multiple timescales. *Environmental Modelling and Software*, 99, 39–51. <https://doi.org/10.1016/j.envsoft.2017.09.016>
- Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water systems planning under change? *Journal of Water Resources Planning and Management*, 141, 4015012. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000509](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. *Journal of Water Resources Planning and Management*, 142, 04016050. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000701](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000701)
- 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 Resources Research*, 50, 7692–7713. <https://doi.org/10.1002/2014WR015338>
- Hino, M., & Hall, J. W. (2017). Real options analysis of adaptation to changing flood risk: Structural and nonstructural measures. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 3, 04017005. <https://doi.org/10.1061/AJRU6.0000905>
- Hipel, K. W., & Ben-Haim, Y. (1999). Decision making in an uncertain world: Information-gap modeling in water resources management. *IEEE Transactions on Systems, Man, and Cybernetics Part C: Applications and Reviews*, 29(4), 506–517. <https://doi.org/10.1109/5326.798765>
- Hobbs, B. F. (1997). Bayesian methods for analysing climate change and water resource uncertainties. *Journal of Environmental Management*, 49(1), 53–72. <https://doi.org/10.1006/JEMA.1996.0116>
- Hong, B., Strawderman, R. L., Swaney, D. P., & Weinstein, D. A. (2005). Bayesian estimation of input parameters of a nitrogen cycle model applied to a forested reference watershed, Hubbard Brook Watershed Six. *Water Resources Research*, 41, W03007. <https://doi.org/10.1029/2004WR003551>
- Hui, R., Herman, J. D., Lund, J. R., & Madani, K. (2018). Adaptive water infrastructure planning for nonstationary hydrology. *Advances in Water Resources*, 118, 83–94. <https://doi.org/10.1016/j.advwatres.2018.05.009>
- Islam, S., & Susskind, L. (2018). Using complexity science and negotiation theory to resolve boundary-crossing water issues. *Journal of Hydrology*, 562, 589–598. <https://doi.org/10.1016/j.jhydrol.2018.04.020>
- Jafino, B. A., Haasnoot, M., & Kwakkel, J. H. (2019). What are the merits of endogenising land-use change dynamics into model-based climate adaptation planning? *Socio-Environmental Systems Modelling*, 1, 16126. <https://doi.org/10.18174/sesmo.2019a16126>
- Jenkins, K., Surminski, S., Hall, J., & Crick, F. (2017). Assessing surface water flood risk and management strategies under future climate change: Insights from an Agent-Based Model. *Science of the Total Environment*, 595, 159–168. <https://doi.org/10.1016/J.SCTOTENV.2017.03.242>
- Jeuland, M., & Whittington, D. (2014). Water resources planning under climate change: Assessing the robustness of real options for the Blue Nile. *Water Resources Research*, 50, 2086–2107. <https://doi.org/10.1002/2013WR013705>
- Kahil, T., Parkinson, S., Satoh, Y., Greve, P., Burek, P., Veldkamp, T. I. E., et al. (2018). A continental-scale hydroeconomic model for integrating water-energy-land nexus solutions. *Water Resources Research*, 54, 7511–7533. <https://doi.org/10.1029/2017WR022478>
- Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Transactions of the American Society of Mechanical Engineers, Journal of Basic Engineering*, 82(1), 35–45. <https://doi.org/10.1115/1.3662552>
- Kasprzyk, J., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. *Environmental Modelling and Software*, 42, 55–71. <https://doi.org/10.1016/j.envsoft.2012.12.007>
- Kasprzyk, J., Reed, P. M., & Hadka, D. M. (2015). Battling arrow's paradox to discover robust water management alternatives. *Journal of Water Resources Planning and Management*, 142, 04015053. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000572](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000572)

- Kasprzyk, J., Smith, R. M., Stillwell, A. S., Madani, K., Ford, D., McKinney, D., & Sorooshian, S. (2018). Defining the role of water resources systems analysis in a changing future. *Journal of Water Resources Planning and Management*, *144*, 01818003. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0001010](https://doi.org/10.1061/(ASCE)WR.1943-5452.0001010)
- Kenney, M. A., A. C. Janetos, and M. D. Gerst (2018), A framework for national climate indicators, *Climatic Change*, 1–14, <https://doi.org/10.1007/s10584-018-2307-y>
- Kingsborough, A., Borgomeo, E., & Hall, J. W. (2016). Adaptation pathways in practice: Mapping options and trade-offs for London's water resources. *Sustainable Cities and Society*, *27*, 386–397. <https://doi.org/10.1016/j.scs.2016.08.013>
- Knighton, J., Steinschneider, S., & Walter, M. T. (2017). A vulnerability-based, bottom-up assessment of future riverine flood risk using a modified peaks-over-threshold approach and a physically based hydrologic model. *Water Resources Research*, *53*, 10,043–10,064. <https://doi.org/10.1002/2017WR021036>
- Knutti, R., Masson, D., & Gettelman, A. (2013). Climate model genealogy: Generation CMIP5 and how we got there. *Geophysical Research Letters*, *40*, 1194–1199. <https://doi.org/10.1002/grl.50256>
- Knutti, R., & Sedláček, J. (2013). Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change*, *3*(4), 369–373. <https://doi.org/10.1038/nclimate1716>
- Konar, M., Garcia, M., Sanderson, M. R., Yu, D. J., & Sivapalan, M. (2019). Expanding the scope and foundation of sociohydrology as the science of coupled human-water systems. *Water Resources Research*, *55*, 874–887. <https://doi.org/10.1029/2018WR024088>
- Kondolf, G. M., & Podolák, K. (2014). Space and time scales in human-landscape systems. *Environmental Management*, *53*(1), 76–87. <https://doi.org/10.1007/s00267-013-0078-9>
- Korteling, B., Dessai, S., & Kapelan, Z. (2013). Using information-gap decision theory for water resources planning under severe uncertainty. *Water Resources Management*, *27*, 1149–1172. <https://doi.org/10.1007/s11269-012-0164-4>
- Kundzewicz, Z. W., Krysanova, V., Benestad, R. E., Hov, Ø., Piniewski, M., & Otto, I. M. (2018). Uncertainty in climate change impacts on water resources. *Environmental Science & Policy*, *79*, 1–8. <https://doi.org/10.1016/j.envsci.2017.10.008>
- Kwakkel, J. H., and M. Haasnoot (2019), Supporting DMDU: A taxonomy of approaches and tools, in *Decision Making under Deep Uncertainty*, pp. 355–374, Cham, Switzerland: Springer International Publishing.
- 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., Haasnoot, M., & Walker, W. E. (2016). Comparing robust decision-making and dynamic adaptive policy pathways for model-based decision support under deep uncertainty. *Environmental Modelling and Software*, *86*, 168–183. <https://doi.org/10.1016/j.envsoft.2016.09.017>
- Kwakkel, J. H., Walker, W. E., & Haasnoot, M. (2016). Coping with the wickedness of public policy problems: Approaches for decision making under deep uncertainty. *Journal of Water Resources Planning and Management*, *142*, 1816001. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000626](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000626)
- Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010). Classifying and communicating uncertainties in model-based policy analysis. *International Journal of Technology, Policy and Management*, *10*(4), 299–316. <https://doi.org/10.1504/IJTPM.2010.036918>
- Kwon, H.-H., Lall, U., & Obeysekera, J. (2009). Simulation of daily rainfall scenarios with interannual and multidecadal climate cycles for South Florida. *Stochastic Environmental Research and Risk Assessment*, *23*(7), 879–896. <https://doi.org/10.1007/s00477-008-0270-2>
- Labadie, J. W. (2004). Optimal operation of multireservoir systems: State-of-the-art review. *Journal of Water Resources Planning and Management*, *130*(2), 93–111. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2004\)130:2\(93\)](https://doi.org/10.1061/(ASCE)0733-9496(2004)130:2(93))
- Lamontagne, J. R., Reed, P. M., Link, R., Calvin, K. V., Clarke, L. E., & Edmonds, J. A. (2018). Large ensemble analytic framework for consequence-driven discovery of climate change scenarios. *Earth's Future*, *6*(3), 488–504. <https://doi.org/10.1002/2017EF000701>
- Lempert, R. J. (2002). A new decision sciences for complex systems. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7309–7313. <https://doi.org/10.1073/pnas.082081699>
- Lempert, R. J. (2015). Embedding (some) benefit-cost concepts into decision support processes with deep uncertainty. *Journal of Benefit-Cost Analysis*, *5*(3), 487–514. <https://doi.org/10.1515/jbca-2014-9006>
- Lempert, R. J., & Collins, M. T. (2007). Managing the risk of an uncertain threshold responses: Comparison of robust, optimum, and precautionary approaches. *Risk Analysis*, *27*(4), 1009–1026. <https://doi.org/10.1111/j.1539-6924.2007.00940.x>
- Luke, A., Vrugt, J. A., AghaKouchak, A., Matthew, R., & Sanders, B. F. (2017). Predicting nonstationary flood frequencies: Evidence supports an updated stationarity thesis in the United States. *Water Resources Research*, *53*, 5469–5494. <https://doi.org/10.1002/2016WR019676>
- Madani, K., & Lund, J. R. (2011). A Monte-Carlo game theoretic approach for multi-criteria decision making under uncertainty. *Advances in Water Resources*, *34*(5), 607–616. <https://doi.org/10.1016/j.advwatres.2011.02.009>
- 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? *Environmental Modelling and Software*, *81*, 154–164. <https://doi.org/10.1016/j.envsoft.2016.03.014>
- Maier, H. R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L. S., Cunha, M. C., et al. (2014). Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. *Environmental Modelling and Software*, *62*, 271–299. <https://doi.org/10.1016/j.envsoft.2014.09.013>
- Mason, E., Giuliani, M., Castelletti, A., & Amigoni, F. (2018). Identifying and modeling dynamic preference evolution in multipurpose water resources systems. *Water Resources Research*, *54*, 3162–3175. <https://doi.org/10.1002/2017WR021431>
- 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>
- Meko, D. M., & Woodhouse, C. A. (2005). Tree-ring footprint of joint hydrologic drought in Sacramento and Upper Colorado river basins, western USA. *Journal of Hydrology*, *308*(1–4), 196–213. <https://doi.org/10.1016/j.jhydrol.2004.11.003>
- Melsen, L. A., Vos, J., & Boelens, R. (2018). What is the role of the model in socio-hydrology? Discussion of “prediction in a socio-hydrological world”. *Hydrological Sciences Journal*, *63*(9), 1435–1443. <https://doi.org/10.1080/02626667.2018.1499025>
- Mendoza, P. A., Clark, M. P., Mizukami, N., Gutmann, E. D., Arnold, J. R., Brekke, L. D., & Rajagopalan, B. (2016). How do hydrologic modeling decisions affect the portrayal of climate change impacts? *Hydrological Processes*, *30*(7), 1071–1095. <https://doi.org/10.1002/hyp.10684>
- Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R., 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>

- Morgan, M. G. (2014). Use (and abuse) of expert elicitation in support of decision making for public policy. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(20), 7176–7184. <https://doi.org/10.1073/pnas.1319946111>
- Mortazavi-Naeini, M., Kuczera, G., & Cui, L. (2014). Application of multiobjective optimization to scheduling capacity expansion of urban water resource systems. *Water Resources Research*, *50*, 4624–4642. <https://doi.org/10.1002/2013WR014569>
- 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. *Environmental Modelling and Software*, *69*, 437–451. <https://doi.org/10.1016/j.envsoft.2015.02.021>
- Moyle, P. B., Kiernan, J. D., Crain, P. K., & Quiñones, R. M. (2013). Climate change vulnerability of native and alien freshwater fishes of California: A systematic assessment approach, edited by M. G. Chapman. *PLoS ONE*, *8*, e63883. <https://doi.org/10.1371/journal.pone.0063883>
- Nazemi, A., Wheeler, H. S., Chun, K. P., & Elshorbagy, A. (2013). A stochastic reconstruction framework for analysis of water resource system vulnerability to climate-induced changes in river flow regime. *Water Resources Research*, *49*, 291–305. <https://doi.org/10.1029/2012WR012755>
- Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., et al., & ASCE Task Committee on Evolutionary Computation in Environmental and Water Resources Engineering (2010). State of the art for genetic algorithms and beyond in water resources planning and management. *Journal of Water Resources Planning and Management*, *136*(4), 412–432. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000053](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000053)
- Oliveira, R., & Loucks, D. P. (1997). Operating rules for multireservoir systems. *Water Resources Research*, *33*(4), 839–852. <https://doi.org/10.1029/96WR03745>
- Pahl-Wostl, C. (2007). Transitions towards adaptive management of water facing climate and global change, in. *Water Resources Management*, *21*, 49–62. Springer Netherlands
- Paton, F. L., Maier, H. R., & Dandy, G. C. (2013). Relative magnitudes of sources of uncertainty in assessing climate change impacts on water supply security for the southern Adelaide water supply system. *Water Resources Research*, *49*, 1643–1667. <https://doi.org/10.1002/wrcr.20153>
- Paton, F. L., Maier, H. R., & Dandy, G. C. (2014). Including adaptation and mitigation responses to climate change in a multiobjective evolutionary algorithm framework for urban water supply systems incorporating GHG emissions. *Water Resources Research*, *50*, 6285–6304. <https://doi.org/10.1002/2013wr015195>
- Pfahl, S., O’Gorman, P. A., & Fischer, E. M. (2017). Understanding the regional pattern of projected future changes in extreme precipitation. *Nature Climate Change*, *7*(6), 423–427. <https://doi.org/10.1038/nclimate3287>
- Pielke, R. A., & Wilby, R. L. (2012). Regional climate downscaling: What’s the point?. *Eos, Transactions of the American Geophysical Union*, *93*(5), 52–53. <https://doi.org/10.1029/2012EO050008>
- Pielke, R. A., Wilby, R. L., Niyogi, D., Hossain, F., Dairuku, K., Adegoke, J., et al. (2012). In A. S. Sharma, A. Bunde, V. P. Dimri, & D. N. Baker (Eds.), *Dealing with complexity and extreme events using a bottom-up, resource-based vulnerability perspective*, (pp. 345–359). Washington, DC: American Geophysical Union.
- Pierce, D. W., Cayan, D. R., Thrasher, B. L., Pierce, D. W., Cayan, D. R., & Thrasher, B. L. (2014). Statistical downscaling using localized constructed analogs (LOCA). *Journal of Hydrometeorology*, *15*(6), 2558–2585. <https://doi.org/10.1175/JHM-D-14-0082.1>
- Poff, N. L., Brown, C. M., Grantham, T. E., Matthews, J. H., Palmer, M. A., Spence, C. M., et al. (2016). Sustainable water management under future uncertainty with eco-engineering decision scaling. *Nature Climate Change*, *6*(1), 25–34. <https://doi.org/10.1038/nclimate2765>
- Pokhrel, Y. N., Hanasaki, N., Wada, Y., & Kim, H. (2016). Recent progresses in incorporating human land–water management into global land surface models toward their integration into Earth system models. *Wiley Interdisciplinary Reviews Water*, *3*(4), 548–574. <https://doi.org/10.1002/WAT2.1150>
- Prein, A. F., Langhans, W., Fosser, G., Ferrone, A., Ban, N., Goergen, K., et al. (2015). A review on regional convection-permitting climate modeling: Demonstrations, prospects, and challenges. *Reviews of Geophysics*, *53*, 323–361. <https://doi.org/10.1002/2014RG000475>
- Priestley, M. (1988). *Non-linear and non-stationary time series analysis*. London: Academic Press.
- Prudhomme, C., Giuntoli, I., Robinson, E. L., Clark, D. B., Arnell, N. W., Dankers, R., et al. (2014). Hydrological droughts in the 21st century, hotspots and uncertainties from a global multimodel ensemble experiment. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3262–3267. <https://doi.org/10.1073/pnas.1222473110>
- 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. *Journal of Hydrology*, *390*(3–4), 198–209. <https://doi.org/10.1016/j.jhydrol.2010.06.043>
- Quinn, J. D., Reed, P. M., Giuliani, M., & Castelletti, A. (2017). Rival framings: A framework for discovering how problem formulation uncertainties shape risk management trade-offs in water resources systems. *Water Resources Research*, *53*, 7208–7233. <https://doi.org/10.1002/2017WR020524>
- Quinn, J. D., Reed, P. M., Giuliani, M., & Castelletti, A. (2019). What is controlling our control rules? Opening the black box of multireservoir operating policies using time-varying sensitivity analysis. *Water Resources Research*, *55*, 5962–5984. <https://doi.org/10.1029/2018wr024177>
- 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 Resources Research*, *54*, 4638–4662. <https://doi.org/10.1029/2018WR022743>
- Quinn, J. D., Reed, P. M., & Keller, K. (2017). Direct policy search for robust multi-objective management of deeply uncertain socio-ecological tipping points. *Environmental Modelling and Software*, *92*, 125–141. <https://doi.org/10.1016/j.envsoft.2017.02.017>
- Raman, H., & Chandramouli, V. (1996). Deriving a general operating policy for reservoirs using neural network. *Journal of Water Resources Planning and Management*, *122*(5), 342–347. [https://doi.org/10.1061/\(ASCE\)0733-9496\(1996\)122:5\(342\)](https://doi.org/10.1061/(ASCE)0733-9496(1996)122:5(342))
- Randall, D., Khairoutdinov, M., Arakawa, A., Grabowski, W., Randall, D., Khairoutdinov, M., et al. (2003). Breaking the cloud parameterization deadlock. *Bulletin of the American Meteorological Society*, *84*(11), 1547–1564. <https://doi.org/10.1175/BAMS-84-11-1547>
- Raso, L., Barbier, B., & Bader, J.-C. (2018). Modeling dynamics and adaptation at operational and structural scales for the ex-ante economic evaluation of large dams in an African context. *Water Resources and Economics*, *26*, 100125. <https://doi.org/10.1016/J.WRE.2018.08.001>
- Raso, L., Kwakkel, J., Timmermans, J., & Panthou, G. (2019). How to evaluate a monitoring system for adaptive policies: Criteria for signposts selection and their model-based evaluation. *Climatic Change*, *153*(1–2), 267–283. <https://doi.org/10.1007/s10584-018-2355-3>
- Ray, P. A., Bonzanigo, L., Wi, S., Yang, Y.-C. E., Karki, P., Garcia, L. E., et al. (2018). Multidimensional stress test for hydropower investments facing climate, geophysical and financial uncertainty. *Global Environmental Change*, *48*, 168–181. <https://doi.org/10.1016/J.GLOENVCHA.2017.11.013>

- Read, L. K., & Vogel, R. M. (2015). Reliability, return periods, and risk under nonstationarity. *Water Resources Research*, *51*, 6381–6398. <https://doi.org/10.1002/2015WR017089>
- Recht, B. (2019). A tour of reinforcement learning: The view from continuous control. *Annual Review of Control, Robotics, and Autonomous Systems*, *2*(1), 253–279. <https://doi.org/10.1146/annurev-control-053018-023825>
- Reclamation (2014). *Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Hydrology Projections, Comparison with preceding Information, and Summary of User Needs*. Denver, Colorado: U.S. Department of the Interior, Bureau of Reclamation, Technical Services Center.
- Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J., & Kollat, J. B. (2013). Evolutionary multiobjective optimization in water resources: The past, present, and future. *Advances in Water Resources*, *51*, 438–456. <https://doi.org/10.1016/j.advwatres.2012.01.005>
- Refsgaard, J. C., Arnbjerg-Nielsen, K., Drews, M., Halsnæs, K., Jeppesen, E., Madsen, H., et al. (2013). The role of uncertainty in climate change adaptation strategies—A Danish water management example. *Mitigation and Adaptation Strategies for Global Change*, *18*(3), 337–359. <https://doi.org/10.1007/s11027-012-9366-6>
- Refsgaard, J. C., van der Sluijs, J. P., Brown, J., & van der Keur, P. (2006). A framework for dealing with uncertainty due to model structure error. *Advances in Water Resources*, *29*(11), 1586–1597. <https://doi.org/10.1016/j.advwatres.2005.11.013>
- Rist, L., Felton, A., Samuelsson, L., Sandström, C., & Rosvall, O. (2013). A new paradigm for adaptive management. *Ecology and Society*, *18*, 63. <https://doi.org/10.5751/ES-06183-180463>
- Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences*, *4*(2), 155–169. <https://doi.org/10.1007/BF01405730>
- Robinson, B., & Herman, J. D. (2019). A framework for testing dynamic classification of vulnerable scenarios in ensemble water supply projections. *Climatic Change*, *152*(3–4), 431–448. <https://doi.org/10.1007/s10584-018-2347-3>
- Rosner, A., Vogel, R. M., & Kirshen, P. H. (2014). A risk-based approach to flood management decisions in a nonstationary world. *Water Resources Research*, *50*, 1928–1942. <https://doi.org/10.1002/2013WR014561>
- Saltelli, A., Tarantola, A., Campolongo, F., & Ratto, M. (2004). *Sensitivity analysis in practice—A guide to assessing scientific models*. Chichester: John Wiley and Sons.
- Sanderson, E. W., Jaiteh, M., Levy, M. A., Redford, K. H., Wannebo, A. V., & Woolmer, G. (2002). The Human Footprint and the Last of the WildThe human footprint is a global map of human influence on the land surface, which suggests that human beings are stewards of nature, whether we like it or not. *Bioscience*, *52*(10), 891–904. [https://doi.org/10.1641/0006-3568\(2002\)052\[0891:thfatl\]2.0.co;2](https://doi.org/10.1641/0006-3568(2002)052[0891:thfatl]2.0.co;2)
- Sanderson, M. R., Bergtold, J. S., Heier Stamm, J. L., Caldas, M. M., & Ramsey, S. M. (2017). Bringing the “social” into sociohydrology: Conservation policy support in the Central Great Plains of Kansas, USA. *Water Resources Research*, *53*, 6725–6743. <https://doi.org/10.1002/2017WR020659>
- Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., et al. (2009). Early-warning signals for critical transitions. *Nature*, *461*(7260), 53–59. <https://doi.org/10.1038/nature08227>
- Schlef, K. E., Steinschneider, S., & Brown, C. M. (2018). Spatiotemporal impacts of climate and demand on water supply in the Apalachicola-Chattahoochee-Flint basin. *Journal of Water Resources Planning and Management*, *144*, 05017020. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000865](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000865)
- Schlüter, M., & Pahl-Wostl, C. (2007). Mechanisms of resilience in common-pool resource management systems: An agent-based model of water use in a river basin. *Ecology and Society*, *12*, 4. <https://doi.org/10.5751/ES-02069-120204>
- Seager, R., Naik, N., Vecchi, G. A., Seager, R., Naik, N., & Vecchi, G. A. (2010). Thermodynamic and dynamic mechanisms for large-scale changes in the hydrological cycle in response to global warming*. *Journal of Climate*, *23*(17), 4651–4668. <https://doi.org/10.1175/2010JCLI3655.1>
- Sechi, G. M., Zucca, R., & Zuddas, P. (2013). Water costs allocation in complex systems using a cooperative game theory approach. *Water Resources Management*, *27*, 1781–1796. <https://doi.org/10.1007/s11269-012-0171-5>
- Serinaldi, F., & Kilsby, C. G. (2015). Stationarity is undead: Uncertainty dominates the distribution of extremes. *Advances in Water Resources*, *77*, 17–36. <https://doi.org/10.1016/j.advwatres.2014.12.013>
- Shepherd, T. G. (2014). Atmospheric circulation as a source of uncertainty in climate change projections. *Nature Geoscience*, *7*(10), 703–708. <https://doi.org/10.1038/ngeo2253>
- Shin, S., Pokhrel, Y., & Miguez-Macho, G. (2019). High-resolution modeling of reservoir release and storage dynamics at the continental scale. *Water Resources Research*, *55*, 787–810. <https://doi.org/10.1029/2018WR023025>
- Shorridge, J. E., & Guikema, S. D. (2016). Scenario discovery with multiple criteria: An evaluation of the robust decision-making framework for climate change adaptation. *Risk Analysis*, *36*(12), 2298–2312. <https://doi.org/10.1111/risa.12582>
- Shorridge, J. E., & Zaitchik, B. F. (2018). Characterizing climate change risks by linking robust decision frameworks and uncertain probabilistic projections. *Climatic Change*, *151*(3–4), 525–539. <https://doi.org/10.1007/s10584-018-2324-x>
- Sigmond, M., Scinocca, J. F., Sigmond, M., & Scinocca, J. F. (2010). The influence of the basic state on the Northern Hemisphere circulation response to climate change. *Journal of Climate*, *23*(6), 1434–1446. <https://doi.org/10.1175/2009JCLI3167.1>
- Simpson, I. R., Seager, R., Ting, M., & Shaw, T. A. (2016). Causes of change in Northern Hemisphere winter meridional winds and regional hydroclimate. *Nature Climate Change*, *6*(1), 65–70. <https://doi.org/10.1038/nclimate2783>
- Singh, R., Quinn, J. D., Reed, P. M., & Keller, K. (2018). Skill (or lack thereof) of data-model fusion techniques to provide an early warning signal for an approaching tipping point, edited by H. Doi. *PLoS ONE*, *13*, e0191768. <https://doi.org/10.1371/journal.pone.0191768>
- Sivapalan, M., & Blöschl, G. (2015). Time scale interactions and the coevolution of humans and water. *Water Resources Research*, *51*, 6988–7022. <https://doi.org/10.1002/2015WR017896>
- Sivapalan, M., Konar, M., Srinivasan, V., Chhatre, A., Wutich, A., Scott, C. A., et al. (2014). Socio-hydrology: Use-inspired water sustainability science for the Anthropocene. *Earth's Future*, *2*(4), 225–230. <https://doi.org/10.1002/2013EF000164>
- Smith, R. L., Tebaldi, C., Nychka, D., & Mearns, L. O. (2009). Bayesian modeling of uncertainty in ensembles of climate models. *Journal of the American Statistical Association*, *104*(485), 97–116. <https://doi.org/10.1198/jasa.2009.0007>
- Spence, C. M., & Brown, C. M. (2018). Decision analytic approach to resolving divergent climate assumptions in water resources planning. *Journal of Water Resources Planning and Management*, *144*, 04018054. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000939](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000939)
- Stainforth, D. A., Allen, M. R., Tredger, E. R., & Smith, L. A. (2007). Confidence, uncertainty and decision-support relevance in climate predictions. *Philosophical Transactions of the Royal Society A - Mathematical Physical and Engineering Sciences*, *365*(1857), 2145–2161. <https://doi.org/10.1098/rsta.2007.2074>
- Stedinger, J. R., & Taylor, M. R. (1982). Synthetic streamflow generation 2. Effect of Parameter Uncertainty. *Water Resources Research*, *18*(4), 919–924. <https://doi.org/10.1029/WR018i004p00919>

- Steinschneider, S., & Brown, C. M. (2013). A semiparametric multivariate, multisite weather generator with low-frequency variability for use in climate risk assessments. *Water Resources Research*, *49*, 7205–7220. <https://doi.org/10.1002/wrcr.20528>
- Steinschneider, S., McCrary, R., Mearns, L. O., & Brown, C. M. (2015). The effects of climate model similarity on probabilistic climate projections and the implications for local, risk-based adaptation planning. *Geophysical Research Letters*, *42*, 5014–5044. <https://doi.org/10.1002/2015GL064529>
- Steinschneider, S., Polebitski, A., Brown, C. M., & Letcher, B. H. (2012). Toward a statistical framework to quantify the uncertainties of hydrologic response under climate change. *Water Resources Research*, *48*, W11525. <https://doi.org/10.1029/2011WR011318>
- Steinschneider, S., Ray, P., Rahat, S. H., & Kucharski, J. (2019). A weather-regime based stochastic weather generator for climate vulnerability assessments of water systems in the Western United States. *Water Resources Research*, *55*, 6923–6945. <https://doi.org/10.1029/2018WR024446>
- Steinschneider, S., Wi, S., & Brown, C. M. (2015). The integrated effects of climate and hydrologic uncertainty on future flood risk assessments. *Hydrological Processes*, *29*(12), 2823–2839. <https://doi.org/10.1002/hyp.10409>
- Stevens, B., & Bony, S. (2013). Climate change. What are climate models missing? *Science*, *340*(6136), 1053–1054. <https://doi.org/10.1126/science.1237554>
- Taner, M. Ü., Ray, P., & Brown, C. M. (2017). Robustness-based evaluation of hydropower infrastructure design under climate change. *Climate Risk Management*, *18*, 34–50. <https://doi.org/10.1016/J.CRM.2017.08.002>
- Taner, M. Ü., Ray, P., & Brown, C. M. (2019). Incorporating multidimensional probabilistic information into robustness-based water systems planning. *Water Resources Research*, *55*, 3659–3679. <https://doi.org/10.1029/2018WR022909>
- Taylor, C. J., Chotai, A., & Young, P. C. (2000). State space control system design based on non-minimal state-variable feedback: Further generalization and unification results. *International Journal of Control*, *73*(14), 1329–1345. <https://doi.org/10.1080/002071700421727>
- Tebaldi, C., & Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society A - Mathematical Physical and Engineering Sciences*, *365*(1857), 2053–2075. <https://doi.org/10.1098/rsta.2007.2076>
- Thacker, S., Kelly, S., Pant, R., & Hall, J. W. (2018). Evaluating the benefits of adaptation of critical infrastructures to hydrometeorological risks. *Risk Analysis*, *38*(1), 134–150. <https://doi.org/10.1111/risa.12839>
- Thompson, S. E., Sivapalan, M., Harman, C. J., Srinivasan, V., Hipsey, M. R., Reed, P. M., et al. (2013). Developing predictive insight into changing water systems: Use-inspired hydrologic science for the Anthropocene. *Hydrology and Earth System Sciences*, *17*(12), 5013–5039. <https://doi.org/10.5194/hess-17-5013-2013>
- Thorarindottir, T. L., Guttorp, P., Drews, M., Kaspersen, P. S., & de Bruin, K. (2017). Sea level adaptation decisions under uncertainty. *Water Resources Research*, *53*, 8147–8163. <https://doi.org/10.1002/2016WR020354>
- Tian, X., Galelli, S., & de Neufville, R. (2018). Impact of operating rules on planning capacity expansion of urban water supply systems. *Urban Water Journal*, *15*(7), 654–661. <https://doi.org/10.1080/1573062X.2018.1534128>
- Tol, R. S. J. (2003). Is the uncertainty about climate change too large for expected cost-benefit analysis? *Climatic Change*, *56*(3), 265–289. <https://doi.org/10.1023/A:1021753906949>
- Tompkins, E. L., & Adger, W. N. (2004). Does adaptive management of natural resources enhance resilience to climate change? *Ecology and Society*, *9*, 10. <https://doi.org/10.5751/ES-00667-090210>
- Trenberth, K. E. (2011). Changes in precipitation with climate change. *Climate Research*, *47*(–2), 123–138.
- Trenberth, K. E., Dai, A., van der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., & Sheffield, J. (2014). Global warming and changes in drought. *Nature Climate Change*, *4*(1), 17–22. <https://doi.org/10.1038/nclimate2067>
- 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. *Advances in Water Resources*, *104*, 195–209. <https://doi.org/10.1016/j.advwatres.2017.03.023>
- Turner, S. W., W. Xu, and N. Voisin (2019). Inferred inflow forecast horizons guiding reservoir release decisions across the United States. *Hydrology and Earth System Sciences Discussions*, 1–25. <https://doi.org/10.5194/hess-2019-486>
- Verburg, P. H., Dearing, J. A., Dyke, J. G., van der Leeuw, S., Seitzinger, S., Steffen, W., & Syvitski, J. (2016). Methods and approaches to modelling the Anthropocene. *Global Environmental Change*, *39*, 328–340. <https://doi.org/10.1016/J.GLOENVCHA.2015.08.007>
- Verdin, A., Rajagopalan, B., Kleiber, W., Podestà, G., & Bert, F. (2018). A conditional stochastic weather generator for seasonal to multi-decadal simulations. *Journal of Hydrology*, *556*, 835–846. <https://doi.org/10.1016/J.JHYDROL.2015.12.036>
- Vetter, T., Reinhardt, J., Flörke, M., van Griensven, A., Hattermann, F., Huang, S., et al. (2017). Evaluation of sources of uncertainty in projected hydrological changes under climate change in 12 large-scale river basins. *Climatic Change*, *141*(3), 419–433. <https://doi.org/10.1007/s10584-016-1794-y>
- Viglione, A., Di Baldassarre, G., Brandimarte, L., Kuil, L., Carr, G., Salinas, J. L., et al. (2014). Insights from socio-hydrology modelling on dealing with flood risk—Roles of collective memory, risk-taking attitude and trust. *Journal of Hydrology*, *518*, 71–82. <https://doi.org/10.1016/J.JHYDROL.2014.01.018>
- Vogel, R. M., Lall, U., Cai, X., Rajagopalan, B., Weiskel, P. K., Hooper, R. P., & Matalas, N. C. (2015). Hydrology: The interdisciplinary science of water. *Water Resources Research*, *51*, 4409–4430. <https://doi.org/10.1002/2015WR017049>
- Vogel, R. M., Yaindl, C., & Walter, M. (2011). Nonstationarity: Flood magnification and recurrence reduction factors in the United States. *Journal of the American Water Resources Association*, *47*(3), 464–474. <https://doi.org/10.1111/j.1752-1688.2011.00541.x>
- Wada, Y., Bierkens, M. F. P., de Roo, A., Dirmeyer, P. A., Famiglietti, J. S., Hanasaki, N., et al. (2017). Human-water interface in hydrological modeling: Current status and future directions. *Hydrology and Earth System Sciences Discussions*, *21*, 4169–4193. <https://doi.org/10.5194/hess-2017-248>
- Wada, Y., Wisser, D., Eisner, S., Flörke, M., Gerten, D., Haddeland, I., et al. (2013). Multimodel projections and uncertainties of irrigation water demand under climate change. *Geophysical Research Letters*, *40*, 4626–4632. [https://doi.org/10.1002/GRL.50686@10.1002/\(ISSN\)1944-8007.GRLCMI5](https://doi.org/10.1002/GRL.50686@10.1002/(ISSN)1944-8007.GRLCMI5)
- Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social-ecological systems. *Ecology and Society*, *9*, 5. <https://doi.org/10.1103/PhysRevLett.95.258101>
- Walker, W. E., Haasnoot, M., & Kwakkel, J. H. (2013). Adapt or perish: A review of planning approaches for adaptation under deep uncertainty. *Journal of Sustainability*, *5*(3), 955–979. <https://doi.org/10.3390/su5030955>
- Walker, W. E., Rahman, S. A., & Cave, J. (2001). Adaptive policies, policy analysis, and policy-making. *European Journal of Operational Research*, *128*(2), 282–289. [https://doi.org/10.1016/S0377-2217\(00\)00071-0](https://doi.org/10.1016/S0377-2217(00)00071-0)
- Watson, A. A., & Kasprzyk, J. (2017). Incorporating deeply uncertain factors into the many objective search process. *Environmental Modelling and Software*, *89*, 159–171. <https://doi.org/10.1016/j.envsoft.2016.12.001>

- Weaver, C. P., Lempert, R. J., Brown, C. M., 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: Climate Change*, 4(1), 39–60. <https://doi.org/10.1002/wcc.202>
- Whateley, S., Steinschneider, S., & Brown, C. M. (2014). A climate change range-based method for estimating robustness for water resources supply. *Water Resources Research*, 50, 8944–8961. <https://doi.org/10.1002/2014WR015956>
- Wilby, R. L., & Dessai, S. (2010). Robust adaptation to climate change. *Weather*, 65(7), 180–185. <https://doi.org/10.1002/wea.543>
- Wilby, R. L., & Harris, I. (2006). A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK. *Water Resources Research*, 42, W02419. <https://doi.org/10.1029/2005WR004065>
- Woodward, M., Gouldby, B., Kapelan, Z., Khu, S. T., & Townend, I. (2011). Real options in flood risk management decision making. *Journal of Flood Risk Management*, 4(4), 339–349. <https://doi.org/10.1111/j.1753-318X.2011.01119.x>
- Woodward, M., Kapelan, Z., & Gouldby, B. (2014). Adaptive flood risk management under climate change uncertainty using real options and optimization. *Risk Analysis*, 34(1), 75–92. <https://doi.org/10.1111/risa.12088>
- Woodings, T. (2010). Dynamical influences on European climate: An uncertain future. *Philosophical Transactions of the Royal Society A - Mathematical Physical and Engineering Sciences*, 368(1924), 3733–3756. <https://doi.org/10.1098/rsta.2010.0040>
- 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: Generic framework and case study. *Environmental Modelling and Software*, 79, 197–213. <https://doi.org/10.1016/j.envsoft.2016.02.012>
- Yakowitz, S. (1982). Dynamic programming applications in water resources. *Water Resources Research*, 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 Resources Research*, 21(12), 1797–1818. <https://doi.org/10.1029/WR021i012p01797>
- Young, P. (2000). Stochastic, dynamic modelling and signal processing: Time variable and state dependent parameter estimation. In P. C. Walden (Ed.), *Nonlinear and Nonstationary Signal Processing*, (pp. 74–114). Cambridge: Cambridge University Press.
- Young, P. C., McKenna, P., & Bruun, J. (2001). Identification of non-linear stochastic systems by state dependent parameter estimation. *International Journal of Control*, 74(18), 1837–1857. <https://doi.org/10.1080/00207170110089824>
- Yu, X., Cohn, T. A., & Stedinger, J. R. (2015). Flood frequency analysis in the context of climate change. In *World Environmental and Water Resources Congress 2015* (pp. 2376–2385). Reston, VA: American Society of Civil Engineers.
- Zaniolo, M., Giuliani, M., Castelletti, A. F., & Pulido-Velazquez, M. (2018). Automatic design of basin-specific drought indexes for highly regulated water systems. *Hydrology and Earth System Sciences*, 22(4), 2409–2424. <https://doi.org/10.5194/hess-22-2409-2018>
- 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. *Advances in Water Resources*, 92, 172–185. <https://doi.org/10.1016/j.advwatres.2016.04.006>
- Zeff, H. B., Herman, J. D., Reed, P. M., & Characklis, G. W. (2016). Cooperative drought adaptation: Integrating infrastructure development, conservation, and water transfers into adaptive policy pathways. *Water Resources Research*, 52, 7327–7346. <https://doi.org/10.1002/2016WR018771>
- Zhao, L. (2018). Urban growth and climate adaptation. *Nature Climate Change*, 8(12), 1034–1034. <https://doi.org/10.1038/s41558-018-0348-x>