Evaluating Implementation Uncertainties and Defining Safe Operating Spaces for Deeply Uncertain Cooperative Multi-City Water Supply Investment Pathways

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Key Points:

- Entering regional cooperative partnerships may expose water utilities to new risks from the uncertain actions of their partners.
- Implementation uncertainty analysis reveals that modest deviations in utilities' actions can drive significant vulnerabilities in pathways.
- Delineation of safe operating spaces is important to sustain robust and stable cooperative infrastructure investment planning.

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Abstract

Urban water utilities are increasingly exploring cooperative regional water supply investment and management strategies due to climate change and growing demands. Theoretically, regional cooperative agreements promise improved resource efficiency by realizing economies of scale, adding flexibility for achieving improved supply reliability, and, ideally, limiting individual and collective financial risks. However, there has been little research exploring how implementation uncertainties in the partners' cooperative actions shape infrastructure investment and management pathways' robustness and drive counterparty risks. Counterparty risks potentially exacerbate collaborating partners' vulnerability to the supply and financial challenges they initially sought to mitigate through cooperation. To address these concerns, we introduce the Safe Operating Spaces for Deeply Uncertain Water Supply Pathways (DU$_{\mathrm{SOS}}$Pathways) framework. The framework, demonstrated on the multi-city Sedento Valley benchmarking test case, facilitates the formal characterization of the effects of implementation uncertainty within cooperative regional water supply investment and management policy pathways. Results demonstrate the path-dependent effects of implementation uncertainties in short-term operational drought mitigation instruments and long-term infrastructure investments. Our analysis further reveals the potential for increased regional conflict due to asymmetries between partners' vulnerabilities to the actions of cooperating partners that can be exacerbated by other deeply uncertain factors that reduce their robustness (e.g., demand growth rates). The study finally delineates safe operating spaces, beyond which utilities experience robustness degradation and increased vulnerabilities to future uncertainties to guide implementation of cooperative policy pathways. Overall, this framework is broadly applicable to regional systems seeking to navigate complex cooperative regional water supply investment and management policy pathways.

Plain Language Summary

Regional water utilities are increasingly seeking to cooperate in developing more efficient and flexible strategies for using scarce water resources. However, cooperative management and investment actions are susceptible to imperfect implementation. A key question is whether implementation uncertainties result in consequential changes in financial risks and the reliability of the cooperating utilities' systems. This study contributes a framework to help utilities to navigate implementation uncertainties and identify their tolerances to imperfect actions (i.e., 'safe operating spaces'). Our framework is demonstrated on the Sedento Valley, a regional urban water supply test case where three utilities are cooperatively managing their drought management and planning future water supply infrastructure investments. Our results reveal that moderate changes in utilities' actions significantly change cooperative infrastructure plans, increasing their individual and collective vulnerability to changes in future climate and socioeconomic conditions. We use these results to identify ranges in the decision variables that shape investment and management actions where utilities can avoid these adverse effects and maintain effective regional cooperation.

1 Introduction

Urban water utilities worldwide face supply reliability and financial stability challenges stemming from climate change and growing water demands (Farmani & Sweetapple, 2022; Pörtner et al., 2022), which are aggravated by the additional challenge of aging infrastructure. In the United States (U.S.), an estimated $434 billion of investment in maintaining and development water supply infrastructure is required by 2029 (ASCE, 2021). The 2022 Infrastructure Investment and Jobs Act allocates over $55 billion of federal funding for drinking water infrastructure (DeFazio, 2021), but the remaining investment burden will be borne by local governments (Smull et al., 2022). The provision of drinking water in the U.S. is thus dominantly a local issue – balancing the reliable provision of water at affordable rates within the limits of local resources. Public opposition to raised water rates further constrains local utilities' ability to invest in new supply infrastructure and exacerbates their financial risks (Hansen & Mullin, 2022). Furthermore, hard-path approaches that rely almost entirely on centralized infrastructure to store, treat and deliver water supplies (Gleick, 2002) are limited by competing land uses and stricter environmental regulations while often neglecting the opportunities presented by improved demand management, changes in allocation schemes, or regional cooperative agreements (Perry & Praskievicz, 2017). Infrastructure investment requires local water utilities to carefully balance supply reliability with financial risks, as under-investment risks supply failure, while over-investment may result in costly stranded assets (Haasnoot et al., 2019; Qureshi & Shah, 2014). Therefore, water managers are increasingly exploring regionalization strategies, where utilities within close geographic proximity cooperate to use existing infrastructure more efficiently and leverage economies of scale to reduce the financial burden of new infrastructure investments (Bell et al., 2022; Gorelick et al., 2022; Hamilton et al., 2022; Reedy & Mumm, 2012).

The coordinated use of soft-path water management approaches (e.g., financial risk insurance, drought surcharges, demand management, regional water transfers) with traditional supply augmentation in a regional cooperative policy pathways enables the discovery of water supply design alternatives that are adaptive and flexible relative to approaches that consider only hard-path supply expansion options (Gorelick et al., 2022; Mortazavi-Naeini et al., 2014; Trindade et al., 2019). Regionalization presents benefits such as more cost-efficient use of shared resources and lower operational costs (Silvestre et al., 2018), as well as achieving common reliability goals and reducing the risk of stranded assets (de Boer & Bressers, 2013). These benefits have been realized through financial instruments such as third-party and self-insurance (Brown & Carriquiry, 2007; Zeff & Characklis, 2013), regional water transfers agreements (Chang & Griffin, 1992; Characklis et al., 2006; Lund & Israel, 1995; Palmer & Characklis, 2009; Womble & Hanemann, 2020), and more recently, risk-based water policy pathways infrastructure investment strategies (Beh et al., 2015a; Borgomeo et al., 2018; Pachos et al., 2022; Trindade et al., 2019; Zeff et al., 2016). Despite these benefits, regionalization can expose utilities to financial risks driven by the intermittent use of short-term water transfer purchases (Zeff & Characklis, 2013). Furthermore, cooperating utilities within a regional water system have different levels of perceived risk (Bell et al., 2022), which may lead to potential failure to cooperate (Gorelick et al., 2022; Hansen et al., 2020).

The implementation of regional water policy pathways planning and management has been aided by the use of multiobjective evolutionary algorithms (MOEAs) under uncertainty to discover high-performing design alternatives that represent optimal tradeoffs between the conflicting objectives of supply reliability and financial stability (Beh et al., 2015b; Borgomeo et al., 2016; Geressu & Harou, 2015; Gold et al., 2022b; Huskova et al., 2016; Pachos et al., 2022; Trindade et al., 2019). Recent studies couple MOEAs with visual analytics that can aid in communicating the tradeoffs across alternative regional cooperative strategies in major water resources systems (Giuliani et al., 2022; Gonzalez et al., 2021; Maier et al., 2014; Matrosov et al., 2015; Seyedashraf et al., 2022; Smith et al., 2016; Watson & Kasprzyk, 2017). The ability to formulate, solve, and navigate challenging water supply policy pathways problems with MOEAs and visual analytics has enabled the inclusion of adaptive, state-aware strategies that improve water-use efficiency and financial risk management by accounting for the dynamics of long-term infrastructure sequencing and their interactions with short-term drought mitigation actions (Asefa et al., 2014; Erfani et al., 2018; Gold et al., 2022b; Gorelick et al., 2023; Hall et al., 2019; Pachos et al., 2022; Ricalde et al., 2022; Zeff et al., 2016).

These adaptive strategies permit contextually appropriate changes to policy pathways of short-term drought crisis management actions and long-term infrastructure planning actions over time (Cai et al., 2015; Erfani et al., 2018; Mortazavi-Naeini et al., 2014; Padula et al., 2013), continuously monitoring the environment to trigger adaptive actions where necessary (Erfani & Harou, 2021; Malekpour et al., 2015; Walker, 2015). For example, the Dynamic Adaptive Policy Pathways (DAPP) framework (Haasnoot et al., 2013) permits context-specific information to determine appropriate changes to major water planning actions. The outcomes of these actions can inform infrastructure investment and sequence mitigative actions in planning for future extreme climate events (Haasnoot et al., 2019; Kwakkel et al., 2015). More recently, the DAPP framework has been extended to water supply policy pathways management and investment pathways where dynamic risk-of-failure (ROF) focused policies are identified that use state-aware action triggers for short-term drought mitigation (Gold et al., 2019; Palmer & Characklis, 2009; Zeff et al., 2016) and long-term infrastructure investments (Gold et al., 2022a; Gorelick et al., 2022; Hyun et al., 2021; Murgatroyd & Hall, 2021; Trindade et al., 2019).

Nonetheless, coordinating short-term operational management and long-term infrastructure investment actions itself can introduce risks that interact across time horizons. Long-term planning decisions are dependent on the operational assumptions and the dynamic effects of shorter-term management actions (Hall et al., 2019; Walker, 2010). Changes in financial stability, access to capital, and debt rates affect the ability or willingness of a utility to invest in new infrastructure, which is necessary for addressing the long-term persistent vulnerabilities to demand growth rates and extreme climate conditions (Cai et al., 2015; Gorelick et al., 2023; Smull et al., 2022). Therefore, adaptive water supply policy pathways planning frameworks that do not sufficiently account for the interactions between different drivers of supply and financial risk across timescales can result in poor overall performance (Jafino et al., 2020) and conceal consequential future scenarios from planners (Birnbaum et al., 2022). The challenges associated with bridging short-term water management actions and long-term investment pathways are exacerbated by the deeply uncertain nature of plausible future climate and socioeconomic conditions. Formally, deep uncertainty is characterized by stakeholders' disagreements on or the lack of knowledge of the system and its boundaries, probability distributions to describe uncertainty for different system inputs, and the rank-importance of system output design alternatives (Kwakkel, Walker, & Haasnoot, 2016; Lempert et al., 2006; Marchau et al., 2019). Deep uncertainties can limit our understanding of the effectiveness of cooperative regional water utility agreements resulting in inequitable reliability outcomes or financial failures (Gorelick et al., 2020), and if ignored, yield maladaptive infrastructure investments that are more likely to fail under extreme climate scenarios (Huskova et al., 2016).

Regional cooperation in the implementation of such adaptive water supply policy pathways is an additional, but often-neglected, source of deep uncertainty. The performance of a collaborative policy pathway's coordinated drought mitigating actions and investments is driven by participating utilities' behavior, which in turn is affected by their perceptions of risk, individual supply capacities, and financial health (Bell et al., 2022). For this study, implementation uncertainty refers to deviations in how utilities operationalize their collective and individual action policy pathways' rule systems (i.e., adaptive policies are not perfectly implemented (Gold et al., 2019)). Implementation uncertainty raises the question of how much variation in decision variables can be tolerated for policy actions to retain acceptable performance (Beyer & Sendhoff, 2007). Implementation uncertainty can be a contributing factor to counterparty risk (Gorelick et al., 2022), which is the risk that a cooperating utility faces due to uncertainty in the actions of cooperating partners with whom they share investment and operational ties (Feiock, 2013; Gold et al., 2022b; Hansen et al., 2020). To date, most studies do not account for implementation uncertainty in water policy pathways, tacitly assuming the perfect deployment of all adaptive action rule systems. This can cause utilities to overestimate the robustness of their actions and plans (Gold et al., 2019).

The importance of evaluating imperfect implementation of proposed 'optimal' cooperative policies or plans for regional water resource systems has long been recognized (Haimes, 1977). Even so, there have only been a limited number of studies that consider the implications of implementation uncertainty in designing policy pathways (Kwakkel et al., 2015; Kwakkel, Haasnoot, & Walker, 2016). Gold et al. (2019) explore the effects of implementation uncertainty for four regional utilities in the Research Triangle region of North Carolina coordinating their short-term drought mitigation strategies (i.e., week-to-week demand restrictions and/or treated water transfers). They do not consider long-term cooperative or individual water supply infrastructure investments. However, Gold et al. (2019) do demonstrate the importance of identifying the utilities' safe operating spaces (SOS) to help them navigate implementation uncertainty by identifying explicitly tolerable windows of decision deviations where they can individually and collectively maintain acceptable levels of performance in their supply reliabilities and financial stability (i.e., acceptably robust regions in their decision spaces). Additional example applications of the SOS concept include defining limits to global freshwater use (Kwakkel & Timmermans, 2012) and to describe the current state of global green water (Wang et al., 2022).

Building on prior work, this study contributes the Safe Operating Spaces for Deeply Uncertain Water Supply Pathways ($\mathrm{DU_{SOS}}$Pathways) framework. The $\mathrm{DU_{SOS}}$Pathways framework is itself an extension of the original DU Pathways framework (Trindade et al., 2019) and provides a holistic approach to confront cooperative challenges by applying many-objective optimization, bottom-up scenario exploration, adaptive infrastructure pathways, and safe operating spaces to identify policy pathway design alternatives that remain robust across a large array of deep uncertainties (e.g., hydro-climatic change, demand growth rates, response rates to restrictions, factors that influence debt rates, etc.), as well as implementation uncertainties across cooperating regional utilities. The key contributions of this work are threefold. First, it characterizes the implications of implementation uncertainty within drought management and infrastructure investment pathway alternatives being considered by cooperating utilities. Second, the $\mathrm{DU_{SOS}}$Pathways framework contextualizes how implementation uncertainties in short- and long-term pathway actions degrade individual utilities as well as a broader region's ability to balance key performance tradeoffs and remain robust to deep uncertainties. Third, it provides a formal delineation of each utility's SOS to provide actionable information that aids the operationalization of coordinated policy pathway rule systems.

2 Regional Test Case

The $\mathrm{DU_{SOS}}$Pathways framework is demonstrated using the highly-challenging Sedento Valley test case (Trindade et al., 2020), which focuses on a three-utility urban water supply regional system developed for benchmarking new design frameworks for cooperative water supply investment and management pathways under deep uncertainty. The Sedento Valley region's rapidly growing population reduces the capacity-to-demand ratios of its three regional water utilities. Consequently, the region's utilities are facing increasing stress on their abilities to meet their demands with currently available supplies. Climate change drives deeply uncertain changes in evapotranspiration rates and inflows, subjecting the region to a wide array of plausible hydro-climatic futures, further challenging their ability to reliably meet the region's growing water demands. The Sedento Valley has a limited number of feasible sites for infrastructure expansion, capturing the constraint that many regions' supply sources have already been developed. This issue is further compounded by the high costs of construction, exacerbating the risks associated with stranded assets and sunken infrastructure investment costs. The three independent utilities within the region have asymmetric vulnerabilities to drought due to heterogeneous watershed characteristics, disproportionate supply allocations, and significant differences across their local demands and respective demand growth rates. The complex regional dynamics of

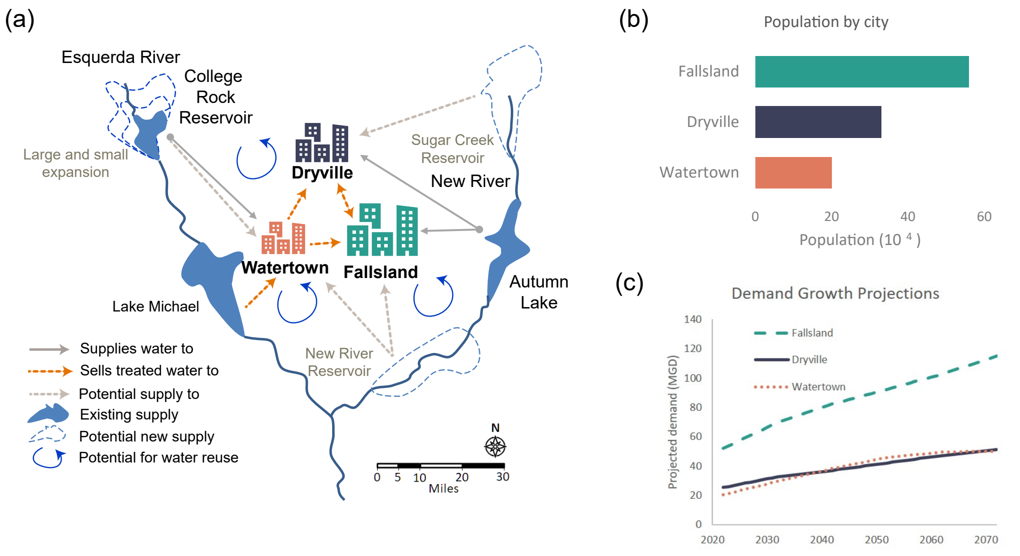

Figure 1: The Sedento Valley test case and its individual utility population and demand projections. (a) The three cooperating utilities in the Sedento Valley region - Watertown (orange), Dryville (navy blue) and Fallsland (green), (b) their populations, and (c) differences in demand.(Adapted from Gold et al., 2022)

the Sedento Valley's interconnected resources and infrastructure network further amplifies these asymmetries, as the actions and plans of one utility have unexpected implications for its counterparts (Gold et al., 2022b). All of these challenges serve to increase the utilities' vulnerability to drought, exacerbate their potential future financial risks, and challenge their ability to meet growing local demands. The three cities that comprise the Sedento Valley are Watertown (a small city), Dryville and Fallsland (two medium-sized cities) as shown in Figure 1a above. The populations of each city are shown in Figure 1b. These utilities serving these cities experience significant disparities due to differences in access to water supply and disproportionate population demand growth rates. Conventionally, the utilities have confronted these disparities and their consequent challenges by relying on independent investments in developing new water supply infrastructure, short-term water-use restrictions, and the purchase of treated water transfers. Further details on the Sedento Valley can be found in Section S1 of the Supporting Information.

However, the geographic proximity and infrastructure interconnectivity that drive regional dynamics present an opportunity for regional cooperation through the use of cooperative infrastructure investment pathways and coordinated drought mitigation policies – an approach the utilities are exploring. Each utility has outlined a set of individual supply expansion or water reuse projects, with the New River Reservoir being a joint investment (see Table 1). The three utilities now seek a strategy to sequence this set of infrastructure options by coordinating long-term infrastructure pathways planning with day-to-day crisis management policies. Furthermore, they are interested in incorporating novel financial tools such as self and third-party insurance to hedge against the variability introduced by drought mitigation actions. This study explores the identification of actionable safe operating spaces for individual utilities with the Sedento valley region to guide cooperative action for the maintenance of individual and collective robustness against deeply uncertain future conditions, as well as utilities' individual and collective implementation uncertainties. The next section presents the DU$_{SOS}$Pathways framework

Table 1: Potential new infrastructure options in the Sedento Valley

Infrastructure	**Utility (allocation%)**	**Capital cost ($\$10^6$)**	**Storage or production**	**Permitting period (years)**
College Rock Reservoir expansion (small)	Watertown	50	500 MG	5
College Rock Reservoir expansion (large)	Watertown	100	1000 MG	5
Watertown Reuse	Watertown	50	35 MGD	5
Sugar Creek Reservoir	Dryville	150	2909 MGD	17
Dryville Reuse	Dryville	30	35 MGD	5
New River Reservoir	Fallsland and Watertown (50/50)	263	3700 MG	17
Fallsland Reuse	Fallsland	50	35 MGD	5

used to explore the Sedento Valley's challenging dynamics and identify safe operating spaces within which the utilities can achieve individual and overall regional robustness goals.

3 Methodology

This paper contributes the DU_{SOS}Pathways framework, an extension of the original DU Pathways framework (Trindade et al., 2019), and evaluates how implementation uncertainty across individual and cooperative regional water supply investment and management pathways influences their robustness to challenging future conditions. The DU_{SOS}Pathways framework also generalizes the implementation uncertainty tolerances analysis introduced by Gold et al. (2019) for coordinated short-term drought crisis actions to also consider how implementation uncertainties influence long-term infrastructure investment pathways, mapping how they influence the vulnerabilities and robustness of regional water supplies. Figure 2 provides an overview of the key steps in our proposed DU_{SOS}Pathways methodology. Stage I develops the candidate problem formulation that defines a regional water supply model, regional and individual performance objectives, candidate decisions, and relevant uncertainties (Figure 2, Stage I). This stage includes search-based identification of policy pathways using many-objective optimization under deep uncertainty (Trindade et al., 2017) and exploration of key performance trade-offs between conflicting objectives using interactive visual analytics (Hadjimichael et al., 2020; Keim, 2002; Kollat & Reed, 2006; Woodruff et al., 2013). Stage II stress tests candidate water policy pathways by reevaluating each policy across an expanded set of DU states-of-the-world (SOWs). This expanded sampling, termed DU Re-Evaluation (Figure 2, Stage II) represents a more challenging and broader computational exploration of DU SOWs compared to the approximate sampling used to initially identify candidate policy pathways in Stage I during DU Optimization. The results of the DU Re-Evaluation are then used to compute the robustness of each policy pathway to inform the selection of robust regional compromise policy pathways for further examination.

After selecting candidate compromises, Stage III of the DU_{SOS}Pathways framework examines the impact of implementation uncertainty by re-evaluating a subset of candidate compromise policy pathways under deep uncertainty (Figure 2, Stage III). Here, plausible operational deviations in policy pathways' decision variables are sampled, and

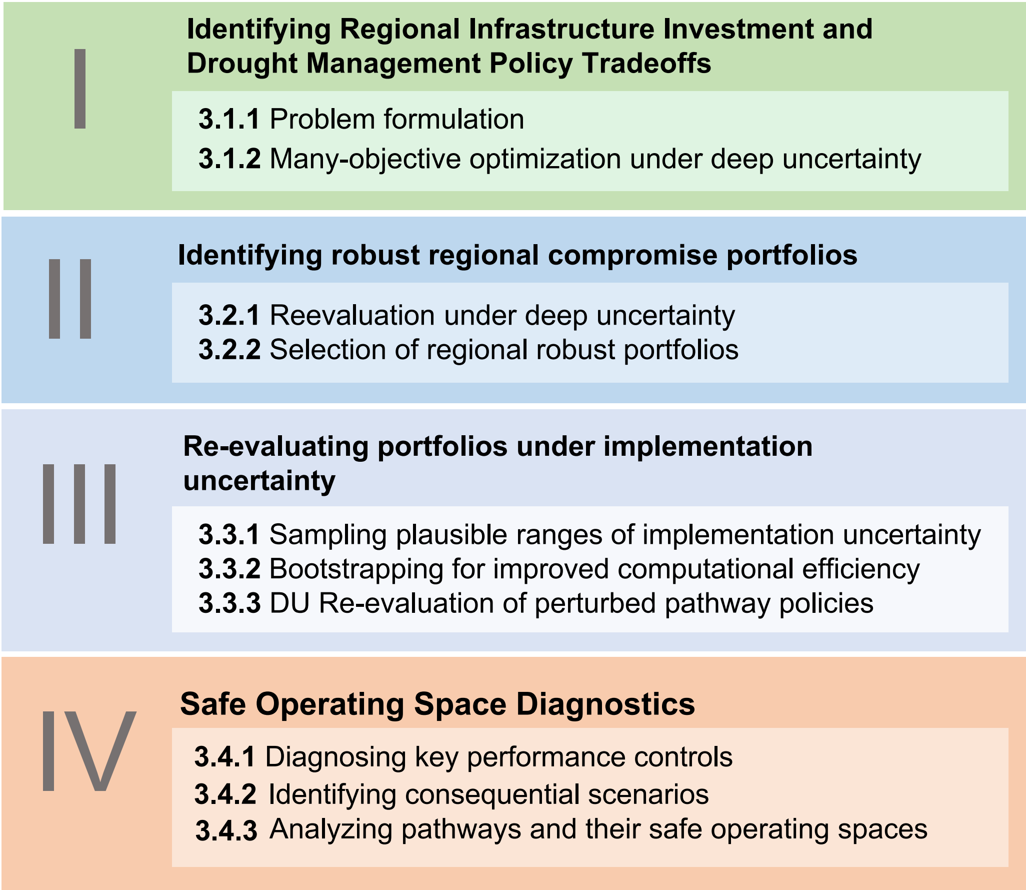

Figure 2: Methodological flow chart for characterizing effects of implementation uncertainty on cooperative regional water supply investment and management pathways.

the effects of imprecise implementation across a broad sampling of DU SOWs are evaluated. Finally, Stage IV (Figure 2 Safe Operating Space Diagnostics) identifies the decision variables whose deviations most strongly influence changes in performance and robustness. At this stage, scenario discovery (Bryant & Lempert, 2010; Groves & Lempert, 2007) is also performed to determine how each utility's deviations from their original set of policy pathways influence individual and regional vulnerability to deep uncertainties. The results of Stage IV are used to explore how implementation uncertainty changes the utilities' infrastructure pathways and identify both short- and long-term actions that drive these changes. Stage IV also focuses on delineating safe operating spaces (SOS) to help utilities identify operational tolerances for safe and effective policy implementation.

3.1 Identifying Regional Infrastructure Investment and Drought Management Policy Tradeoffs

3.1.1 Problem Formulation

A regional cooperative water supply investment and management policy pathway's problem formulation is a formalized hypothesis for how utilities should analytically represent their cooperative water supply planning problem (Kasprzyk et al., 2013; Zeleny, 1981). Within the context of $\mathrm{DU_{SOS}}$Pathways, collaborative problem formulation can be viewed as an iterative learning process that seeks to explore multiple rival framings of the cooperative system and stakeholder values. The problem formulation step identifies performance objectives, a suitable simulation model, decision variables to approximate actions, acceptable uncertainty ranges, and an uncertainty sampling strategy. For the Sedento Valley test case, we formulate the development of regionally cooperative water supply investment and management policy pathways as a many-objective regional minimax problem as shown in Equation 1. Utilities seek to maximize supply reliability (f_{REL}), minimize restriction frequency (f_{RF}), minimize the allocation to Lake Michael (f_{LMA}), minimize their peak financial cost (f_{FC}), and minimize their worst-case drought management cost (f_{WCC}). Water supply infrastructure investment and management pathways are composed of a set of robust portfolio of policy actions that combine short-term drought mitigation actions with long-term infrastructure investment decisions, $\boldsymbol{\theta^*}$. Short-term policy levers include water-use restrictions, treated transfers, annual contributions to a reserve fund to cover unplanned expenses from transfer purchases and revenue losses from water-use restrictions, and the purchase of third-party insurance to mitigate financial disruptions. Long-term policy levers include a risk-based trigger for new infrastructure investment and construction orders for candidate infrastructure investments.

The many-objective search problem is formally presented in Equation 1. The vector objective function, $\boldsymbol{F}$, has component values specified by the value attained by the worst-performing utility $\boldsymbol{j}$ as shown in Equations 2-5. Further details on the mathematical formulation for the objectives can be found in Section S2 of the Supporting Information.

$$\boldsymbol{\theta^*} = argmin_{\theta}\boldsymbol{F} \tag{1}$$

where

$$\boldsymbol{F} = \begin{cases} \boldsymbol{-f_{REL}(\theta_{rt}, \theta_{tt}, \theta_{lma}, \theta_{it}, \theta_{inf}, ICO, x_{srof}, \Psi_s)} \\ \boldsymbol{f_{RF}(\theta_{rt}, \theta_{tt}, \theta_{lma}, \theta_{it}, \theta_{inf}, ICO, x_{srof}, \Psi_s)} \\ \boldsymbol{f_{LMA}(\theta_{lma})} \\ \boldsymbol{f_{PFC}(\theta_{rt}, \theta_{tt}, \theta_{lma}, \theta_{arfc}, \theta_{it}, \theta_{ip}, \theta_{inf}, ICO, x_{srof}, x_{lrof}, \Psi_s)} \\ \boldsymbol{f_{WCC}(\theta_{rt}, \theta_{tt}, \theta_{lma}, \theta_{arfc}, \theta_{it}, \theta_{ip}, \theta_{inf}, ICO, x_{srof}, x_{lrof}, \Psi_s)} \\ \boldsymbol{f_{INPC}(\theta_{inf}, ICO, x_{lrof}, \Psi_s)} \end{cases} \tag{2}$$

such that

$$\boldsymbol{\theta = [\theta_{rt}, \theta_{tt}, \theta_{lma}, \theta_{arfc}, \theta_{it}, \theta_{ip}, \theta_{inf}, ICO] \forall j \in J} \tag{3}$$

subject to

$$\boldsymbol{|ME| \leq 1 \; \forall \; ME \subseteq BI} \tag{4}$$

$$\boldsymbol{J = \{Watertown, Dryville, Fallsland\}} \tag{5}$$

Regional objectives are functions of the vector of regional decision variables θ (Equation 3), where $\boldsymbol{\theta_{arfc}}$ is a vector of annual reserve fund contributions formulated as a percentage of annual revenue saved in a utility's reserve fund, $\boldsymbol{\theta_{ip}}$ is a vector of each utility's annual payments to a third-party insurer, and θ_{lma} is a vector of Lake Michael allocations. The remaining variables are formulated as risk of failure (ROF) triggers, where the vector of restriction ROF triggers is represented by $\boldsymbol{\theta_{rt}}$, and $\boldsymbol{\theta_{tt}}$ is a vector of water transfer ROF triggers. Finally, $\boldsymbol{\theta_{it}}$ is a vector of insurance ROF triggers, $\boldsymbol{\theta_{inf}}$ is the vector of long-term infrastructure construction ROF triggers, and $\boldsymbol{ICO}$ is the vector of infrastructure construction orders. The infrastructure triggers $\boldsymbol{\theta_{inf}}$ are subject to available infrastructure options, where in Equation 4, ME represents a generic subset of mutually exclusive infrastructure options within the set of built or prospective infrastructure BI. Further information on the decision variable ranges used in the problem formulation can be found in Table S1 in Section S3 of the Supporting Information.

ROFs represent a state-aware measure of each utility's evolving capacity-to-demand ratio (Caldwell & Characklis, 2014). In the DU_{SOS}Pathways framework, two types of ROF action triggers are used: short-term ROF triggers ($sROF$) that trigger short-term drought mitigation actions (Caldwell & Characklis, 2014), and long-term ROF triggers ($lROF$) that trigger the new candidate infrastructure investments (Zeff et al., 2016) in a utility's infrastructure pathways. These triggers induce action when a specific risk threshold is crossed. The use of these ROFs enable utilities to use real-time information to trigger infrastructure planning decisions and mitigative drought policy actions. Therefore, they can capture variations in risk inherent to an evolving and highly uncertain socio-hydrological system as they unfold across multiple deeply uncertain SOWs. The resulting policy pathway provides a contextually-tailored set of candidate actions for every future scenario encountered, approximating a closed-loop feedback system (Bertsekas, 2019).

A utility's ROF is identified using a matrix of state-action sample pairs consisting of reservoir storage levels and their associated ROF threshold calculated across a 50-year moving window of both historical and synthetically-generation streamflow data. The optimized final ROF policy action vectors will therefore be those that attain high performance (i.e., Pareto approximate) over a specified planning period across the sampled DU SOWs based on the coupled dynamics of reservoir storage levels and water supply demands (Trindade et al., 2019). More detailed information on how these ROF triggers are calculated can be found in Section S4 of the Supporting Information.

Matrix $\boldsymbol{X}$ is a time-varying state matrix where x_{srof} and x_{lrof} are vectors of short and long-term dynamic, state-dependent ROFs as shown in Equation 6 below.

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x_{srof}} \\ \boldsymbol{x_{lrof}} \\ \boldsymbol{x_s} \end{bmatrix} \tag{6}$$

In Equation 6, $\boldsymbol{x_s}$ is the vector of combined utility storage states, where each of its elements is a storage value at week w. The storage state $\boldsymbol{x_s^w}$ is described by Equation 7.

$$\boldsymbol{x_s^w = f(x_s^{w-1}, C, D^w, TF^w,}\text{NI}^{\boldsymbol{w}}\boldsymbol{, E^w, S^w, R^w) \cdot D(\cdot)} \tag{7}$$

$$\boldsymbol{D^w = f(x_{srof}^w, x_{lrof}^w, \theta_{rt})} \tag{8}$$

$$\boldsymbol{TF^w = f(x_{srof}^w, x_{lrof}^w, \theta_{tt})} \tag{9}$$

In Equation 7, $\boldsymbol{C}$ is a vector of reservoir capacities, $\boldsymbol{D^w}$ (described in Equation 8) is a vector of demand at week w, $\boldsymbol{TF^w}$ (described in Equation 9) is a vector of transfer volumes for each utility at week w and $\text{NI}^{\boldsymbol{w}}$ is a vector of the natural inflows in each reservoir at week w. For each reservoir, $\boldsymbol{E^w}$ is a vector of evapotranspiration volumes, $\boldsymbol{S^w}$ is a vector of the spillage, and $\boldsymbol{R^w}$ is a vector of the minimum environmental releases, all at week w. The value of $\boldsymbol{x_s}$ is determined using a combination of these DU hydrologic and demand parameters denoted $\boldsymbol{\Psi_S}$ described in Equation 11.

$$\boldsymbol{\Psi_s} = \begin{cases} -\boldsymbol{\Psi_{s,0}}- \\ -\boldsymbol{\Psi_{s,1}}- \\ \qquad\vdots \\ -\boldsymbol{\Psi_{s,n}}- \end{cases} \tag{10}$$

$\boldsymbol{\Psi_S}$ is generated using Latin Hypercube Sampling (LHS) to generate a sample of thirteen DU factors within the Sedento Valley test case. LHS was selected as it was previously found that it resulted in a sufficiently-dense DU sample space (Lamontagne et al., 2019; Quinn et al., 2018). This step draws 1,000 LHS samples of thirteen DU factors across their plausible ranges, shown in Table 2 below. One set of evaluated DU samples forms one SOW, $\boldsymbol{\Psi_{DU}}$, that constitutes a unique LHS sample of all 13 DU factors.

Table 2: Sedento Valley water supply policy pathways deeply uncertain factors and their ranges.

Category	**Factor Name**	**Lower bound**	**Upper bound**
Future streamflow	Streamflow sinusoid amplitude	0.8	1.2
	Streamflow sinusoid frequency	0.2	0.5
	Streamflow sinusoid phase	$-\pi/2$	$\pi/2$
Economic variables	Demand growth multiplier	0.5	2.0
	Bond interest rate multiplier	1.0	1.2
	Bond term multiplier	0.6	1.0
	Discount rate multiplier	0.6	1.4
Drought mitigation instruments (restriction effectiveness multiplier)	Watertown	0.9	1.1
	Dryville	0.9	1.1
	Fallsland	0.9	1.1
New infrastructure	Permitting time multiplier	0.75	1.5
	Construction time multiplier	1.0	1.2

Each $\boldsymbol{\Psi_{DU}}$ is then paired with one of 1,000 random natural inflow (NI) samples of weekly 45-year synthetic streamflow records that expand upon the historical observed record using the Kirsch Method (Kirsch et al., 2013). For further details on stochastic scenario generation for the Sedento Valley, please refer to Trindade et al. (2020).

3.1.2 Many-Objective Optimization Under Deep Uncertainty

We use many-objective optimization under deep uncertainty, or DU Optimization (Trindade et al., 2019) to discover a set of Pareto-approximate (Coello et al., 2007) water supply investment and management policy pathways using many-objective search under deep uncertainty. These policies represent non-dominated alternatives that compose the optimal tradeoffs between the specified performance objectives. These alternatives are often referred to as "Pareto-approximate" solutions. DU Optimization couples the WaterPaths simulation model (Trindade et al., 2020) with the Borg Multi-Objective Evo-

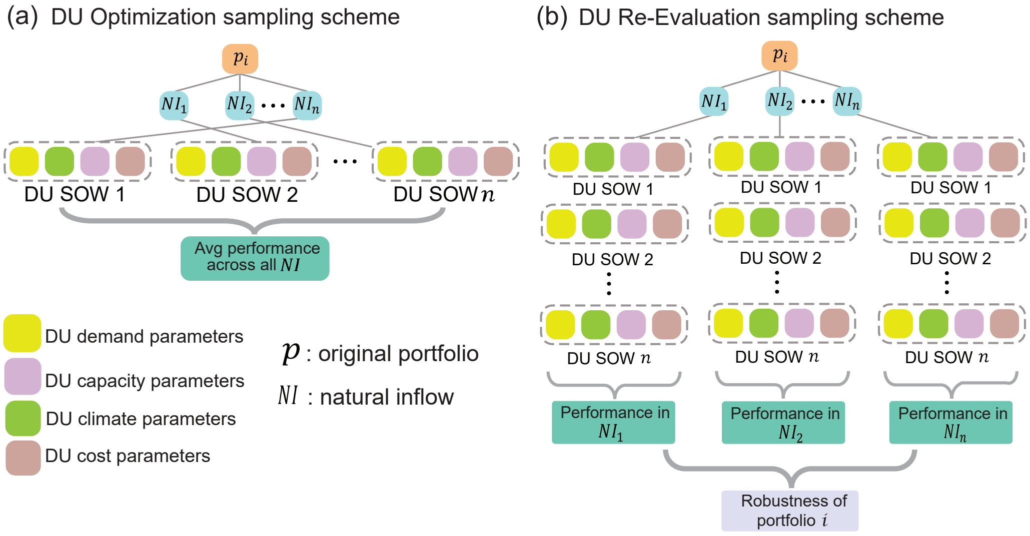

Figure 3: (a) Uncertainty sampling scheme for DU Optimization and (b) DU Re-Evaluation, and their associated evaluation schemes of each policy pathways p across the set of DU SOWs that consist of the DU parameters denoted by the colored boxes. The yellow boxes represent DU demand parameters, the purple boxes represent DU storage capacity parameters, the lime-green boxes represent DU hydro-climate parameters, and the brown boxes represent DU financial (cost) parameters. The dark green boxes denote the performance of the policy pathways across all DU SOWs.

lutionary Algorithm (MOEA), referred to as the Borg MOEA henceforth. The Borg MOEA (Hadka & Reed, 2013) is a probabilistic, population-based evolutionary search algorithm. It uses a suite of search operators that render it uniquely suited for the exploration and optimization of complex, high-dimensional problems with stochastic non-linear and non-convex performance objective spaces. Its search operators include auto-adaptive crossover and mutation that are stochastically selected based on their ability to produce high quality solutions. The Borg MOEA also employs randomized restarts and ϵ-dominance archiving to prevent search stagnation and avoid converging to local optima. The Borg MOEA has an established record of successfully addressing challenging water policy pathways management and investment pathway applications (Bell et al., 2022; Gorelick et al., 2022; Trindade et al., 2020, 2019). More broadly, the algorithm has been carefully diagnosed on its ability to meet or exceed the performance of other state-of-the-art MOEAs across a wide range of mathematically challenging water resources applications (Gupta et al., 2020; Reed et al., 2013).

DU Optimization uses the default parameterization of the Borg MOEA Master-Worker, and set each objective's precision goals (i.e., ϵ-values) as recommended in prior studies (Gold et al., 2019; Trindade et al., 2019). This step couples the Borg MOEA with the WaterPaths simulation software exploiting the DU Optimization sampling scheme to identify a set of Pareto-approximate cooperative water supply investment and management policy pathways that perform well and remain robust under a wide range of challenging SOWs. The DU Optimization-sampled SOWs are then evaluated across 1,000 future scenarios, each representing one NI record paired with one DU SOW. This approximate sampling strategy, illustrated in Figure 3a, represents a computationally-efficient means of approximating the much broader and computationally intensive sampling scheme shown in Figure 3b, which evaluates each policy across 1,000 NI which are each paired with 1,000 DU SOWs. This sampling scheme is called DU Re-Evaluation, which is further explained in the following subsection.

3.2 Identifying Robust Regional Compromise Policy Pathways

3.2.1 Re-Evaluation under Deep Uncertainty

During DU Re-Evaluation, we stress-test each Pareto-approximate policy pathway by evaluating it across the wider and more challenging sampling scheme illustrated in Figure 3b. This process reveals the policy's behavior across a large ensemble of plausible future scenarios that include tail cases and extreme events. Here, each DU SOW sample generated using LHS is paired with every NI sample. The outcomes of this step are used to calculate the robustness of each policy pathway, which is measured using a set of satisficing criteria (Lempert et al., 2006; Starr, 1963), all of which have to be satisfied for the performance of a policy pathway within a specific SOW to be considered a success. This is expressed in Equation 12:

$$\boldsymbol{\Phi_s} = \begin{cases} 1, \text{ if } F(\theta)_j \leq \boldsymbol{\Phi_j} \\ \quad\quad 0 \text{ otherwise} \end{cases} \tag{11}$$

where $\boldsymbol{\Phi}$ is a vector of satisficing criteria for utility j and θ is the set of decision variables or policy actions. This study measures robustness of utility j as the fraction of total sampled scenarios $N = 1,000$ where all the satisficing criteria are met, summarized in Equation 12:

$$S_j = \frac{\sum_{n=1}^{N} \Lambda_{\theta,j}}{N} \tag{12}$$

The water utilities in the Sedento Valley seek to satisfy the following three performance criteria: $REL \geq 98\%$, $RF \leq 10\%$ and $WCC \leq 10\%$ of annual volumetric revenue, where N is the total number of simulations such that N=1000.

3.2.2 Selection of Regional Robust Compromise Policy Pathways

Overall, the DU Optimization and DU Re-Evaluation steps yield a significant amount of information in terms of water policy pathways performance and robustness tradeoffs. There are many ways in which this information can be used to guide decision making and compromises (e.g., see Gorelick et al., 2022; Trindade et al., 2020, 2019). To illustrate the DU_{SOS}Pathways framework, two different robust regional policy pathway compromise strategies are selected from the overall set of robust solutions that compose the Sedento Valley's tradeoffs. The first is the Social Planner policy pathway, selected using a least-squares formulation that minimizes the average loss of potential robustness of each member utility within the Sedento Valley. It relies strongly on regional cooperation, and assumes that utilities are similarly willing to cooperate, even at the cost of individual loss in performance and robustness. In this compromise strategy, all stakeholders are assumed to have the same resources and ability to cope with systemic risk and vulnerability to deep uncertainty. It aims to achieve the highest possible compromise robustness for the Sedento Valley region but may conceal performance disparities between the cooperating utilities.

The second illustrated compromise policy pathway is termed the Pragmatist solution. This compromise framing seeks to discover a practical solution that evenly distributes the potential loss of robustness incurred across the three cooperating Sedento Valley utilities. This formulation assumes that the most acceptable policy pathway is one that distributes power most evenly between stakeholders (Dinar & Howitt, 1997). It is deemed 'cooperatively stable' and assumes that a utility will view the others as having their fair share of gains and losses. However, the Pragmatist also reveals a utility's potential to improve their allocation using a loss-to-gain ratio. The higher this ratio, the more likely they are to not cooperate, unintentionally or otherwise. Although it may be seen as a more practical way of selecting a regional compromise when compared to the Social Planner compromise, the Pragmatist approach can also conceal its region-wide performance and robustness implications, as well as impacts on cooperating members' performance. Both the Social Planner and Pragmatist compromises are selected from the Pareto-approximate set of cooperative regional water supply policy pathways discovered by Trindade et al. (2020) using the Borg MOEA (Hadka & Reed, 2013). Detailed information on the mathematical formulation of both the Social Planner and Pragmatist compromise policy pathways can be found in Section S5 of the Supporting Information.

3.3 Re-Evaluating Compromise Policy Pathways Under Implementation Uncertainty

The Social Planner and Pragmatist compromise policy pathways have state-aware, adaptive actions that emphasize different cooperative decision-making assumptions. However, it is unlikely that these policies will be implemented with perfect precision. To evaluate the effects of relatively modest implementation uncertainties, we adapt the sampling approach introduced in Gold et al. (2019) where 1,000 perturbed instances of both the Social Planner and the Pragmatist policy pathways' decision variables within a ±4% range of their nominal values $\boldsymbol{\theta_s}$ are generated using Latin Hypercube sampling, as demonstrated in Figure 4.

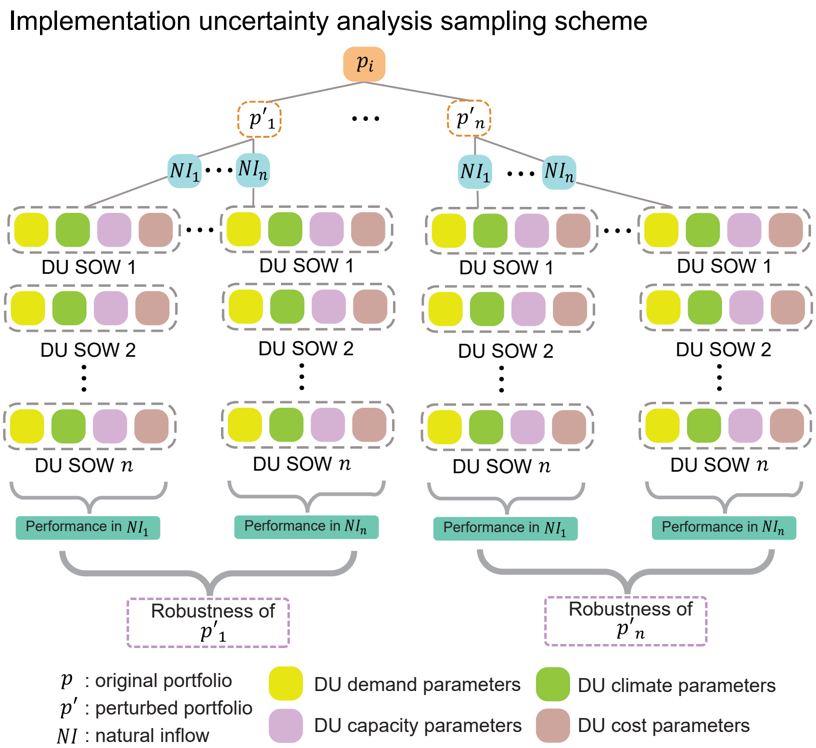

Figure 4: Implementation uncertainty analysis sampling and evaluation scheme.

This sampling scheme is summarized in Equation 13:

$$\boldsymbol{\theta_s} = \begin{cases} \boldsymbol{\theta^*_{p,0}} \\ \boldsymbol{\theta^*_{p,1}} \\ \vdots \\ \boldsymbol{\theta^*_{p,1000}} \end{cases} \tag{13}$$

Where $\boldsymbol{\theta_p}$ is the original compromise policy pathways selected from the initial Pareto-approximate set of solutions, and $\boldsymbol{\theta^*_{p,n}}$ is its n^{th}-perturbed instance. This range of perturbation is termed the envelope of 'implementation uncertainty' and it is based on the concept of mapping decision variable tolerances within the systems engineering literature (Beyer & Sendhoff, 2007). The sampling ensemble size and decision variable range are chosen drawing on prior work conducted by Gold et al. (2019) and the analysis confirming that it is sufficient to capture significant changes in the Sedento Valley utilities' performance and robustness tradeoffs.

Following this, we bootstrapped the 1,000 original NI, D, and E realizations to reduce the number of hydro-climatic realizations needed to re-evaluate the Social Planner and Pragmatist policy pathways and reduce the computational demand associated with maintaining an adequate sampling of hydro-climatic extremes. The 1,000 perturbed instances of the original Social Planner and Pragmatist policy pathways are re-evaluated under the 500 bootstrapped NI, D, and E realizations, which are each matched with the full 1,000 DU SOWs as shown in Figure 4 for a total of 500,000 DU scenarios. For more information on the bootstrapping process, see Section S6 of this paper's Supporting Information. Finally, to measure robustness degradation, we use the satisficing metric, shown in Equation 11. We then compare the robustness of each perturbed sample to the robustness value obtained by the compromise policy with its original decision variables discovered through DU Optimization. This step was was executed on the Hopper Supercomputing Cluster at Cornell University using a total of 200 cores distributed across 10 computer nodes.

3.4 Safe Operating Space Diagnostics

3.4.1 Diagnosing Key Performance Controls

We apply the The Delta Moment-Independent method (Borgonovo, 2007) in our diagnostic sensitivity analysis to better understand the complex interactions between the decision variables, the DU parameters, and the output performance objectives of the Sedento Valley. It has the advantage of not solely relying on lower-order statistical moments such as variance or mean to describe the dependence of the model on its inputs, thus being "moment independent" (Borgonovo, 2007). The Delta Moment Independent method has been demonstrated to be effective in complex, highly nonlinear water resources applications (Chaney et al., 2015; Hadjimichael et al., 2020). This global sensitivity analysis method compares the entire probability distribution of both input and output parameters to estimate the sensitivity of the output to a specific input parameter. This study implements Delta Moment-Independent sensitivity analysis using the SALib Python package (Herman & Usher, 2017; Iwanaga et al., 2022) to identify candidate actions whose perturbations are most likely to change the region and its member utilities' performance and robustness. Another advantage of the Delta Moment-Independent sensitivity analysis method is its ability to exploit our existing implementation tolerance sampling illustrated in Figure 4 and summarized in Section 3.3.

3.4.2 Identifying Consequential Scenarios

Identifying which decision variables dominantly influence policy pathways' pathway performance is a key step in discovering consequential implementation uncertainties. However, it is also necessary to understand how the implementation uncertainties shape the broader vulnerability of the region and the individual utilities in combination with the deeply uncertain factors that shape their future scenarios. To explore this, we employ scenario discovery on the sampling of the perturbed policy pathways (Figure 4) to clarify the most consequential vulnerabilities that an imperfectly implemented policy pathway may face. The scenario discovery analysis uses machine learning and data mining algorithms to explicitly map what combinations of DU SOW values result in a policy being more likely to fail (Bryant & Lempert, 2010). In this study, scenario discovery is implemented using Boosted Trees (Freund & Schapire, 1999), which is a decision tree-based, machine learning method that uses an ensemble of weak learners to generate a higher fidelity statistical model (strong learner) for predicting a policy pathway's probability of success or failure. The weak learner trees are iteratively updated to improve their ability to classify regions of success or failure, ultimately yielding strong learning models.

In this study, we use Boosted Trees to evaluate both the original compromise policies and the policies perturbed with implementation uncertainty. We choose Boosted Trees because the time-varying, state-dependent investment and management actions introduce complex nonlinear, non-convex, and discontinuous failure regions (Trindade et al., 2019). Boosted Trees provides a model-free, unbiased approach that can classify nonlinear success-failure regions while remaining cognitively easy to interpret. This study executes Boosted Trees using the `scikit-learn` Python package (Pedregosa et al., 2011) with an ensemble of 200 trees of maximum depth 3 and learning rate of 0.1. The factor maps of both the original compromise and the perturbed instance with the worst-case robustness for both the Social Planner and Pragmatist policy pathways are generated using Boosted Trees to compare the shifts in regions of success and failure driven by implementation uncertainty.

3.4.3 Analyzing Pathways and Their Safe Operating Spaces

To understand how adaptive infrastructure investment policies adapt to changing future conditions, this study employs K-Means clustering to identify distinct families of infrastructure pathways that could plausibly emerge for each utility under the DU SOWs that induce high, moderate and low infrastructure intensities. These challenging, moderate, and baseline scenarios are drawn from the DU Re-Evaluation sampling of human and hydro-climatic deep uncertainties. The clustered families of high, moderate, and low infrastructure intensities are then used to clarify the implications of implementation uncertainty on how the different water policy pathways management and investment pathways evolve. Further information on how K-Means clustering is employed in this study can be found in Section S7 of the Supporting Information.

Although the Delta moment-independent sensitivity analysis and Boosted Trees-enabled scenario discovery aid the utilities' in identifying key policy pathways' decision variable controls and vulnerabilities, they do not specify the implementation tolerances for the acceptable level of precision required for their policies to remain robust. Building on prior work (Gold et al., 2019; Kwakkel & Timmermans, 2012), we delineate Safe Operating Spaces (SOS) around a regional water management and investment policy pathway's set of decision variables by discovering their operational tolerance ranges $\left[\boldsymbol{\theta^{SOS}_{min,k}}, \boldsymbol{\theta^{SOS}_{max,k}}\right]$ within which each utility can safely vary its k-decision variables while its robustness remains the same or improves. The SOS represents the set of all decision variable combinations that do not incur robustness degradation when compared with the original compromise policy. Formally, the SOS for each utility j is described in Equations 14 to 16:

$$SOS_j = \left[\boldsymbol{\theta^{SOS}_{min,k}}, \boldsymbol{\theta^{SOS}_{max,k}}\right]_j \; \forall \; k \in [rt, tt, lma, arfc, it, inf] \tag{14}$$

where

$$\boldsymbol{\theta_{min,k}} \leq \boldsymbol{\theta_k^{SOS}} \leq \boldsymbol{\theta_{max,k}} \; \forall k \in [rt, tt, lma, arfc, it, inf] \tag{15}$$

subject to

$$S_j(\boldsymbol{\theta^{SOS}}) \geq S_j(\boldsymbol{\theta_s}) \tag{16}$$

where $\left[\boldsymbol{\theta_{min,k}^{SOS}}, \boldsymbol{\theta_{max,k}^{SOS}}\right]$ is the range of decision variable values that maintain utility j's robustness ($S_j(\boldsymbol{\theta^{SOS}})$) at greater than or equal to the robustness of the solution when perfectly implemented (($S_j(\boldsymbol{\theta_s})$) that itself is a result of the set of solutions with no decision variable perturbations.

4 Results and Discussion

4.1 Implementation Uncertainty Strongly Affects Performance and Robustness Tradeoffs

The tacit assumption under which most regional water supply investment and management pathway design frameworks work is that the recommended set of actions will be implemented exactly. Therefore, their ability to maintain high levels of performance is often dependent upon the assumption of precise implementation. A key concern is whether a deviation from the recommended 'robust' policy pathway's specific decision variable values can result in substantially decreased overall robustness and the loss of the utilities' ability to meet their performance goals. [h!] Figure 5a is the parallel axis plot of

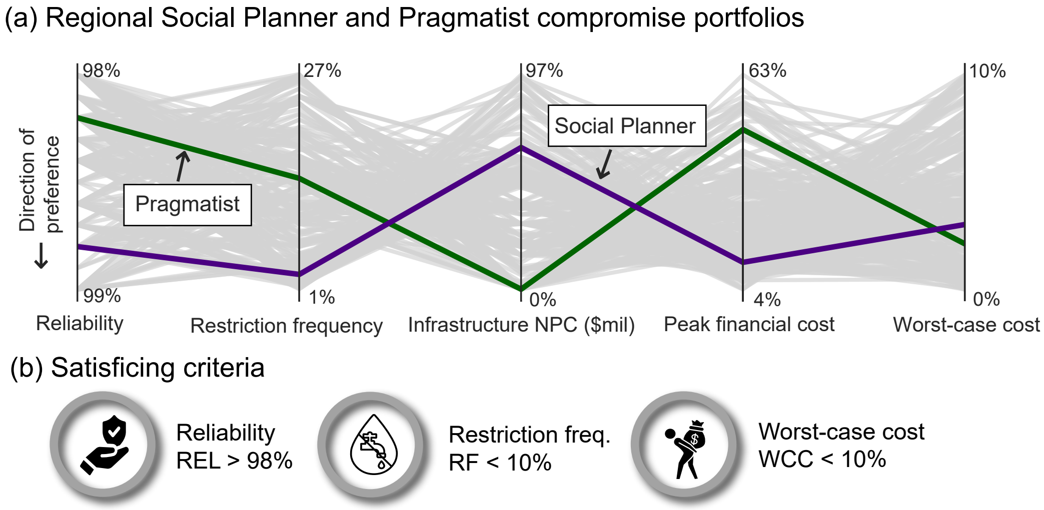

Figure 5: Regional performance objective tradeoffs for all compromise policy pathways. (a) Regional performance tradeoffs discovered via DU Optimization. Each axis represents a regional performance objective, and each line represents a regional policy pathway. The intersection between an axis and a line corresponds to the policy's regional objective value. The purple line indicates the Social Planner compromise, and the green line indicates the Pragmatist compromise. The grey lines represent all other policy pathways. The direction of preference for each axis is downward, where a lower position along the axis is preferable. (b) The three performance goals that utility's compromise policy pathways must meet.

regional performance objectives tradeoffs for the Social Planner compromise (purple) and the Pragmatist compromise (green). Here, each axis represents the five performance objectives: supply reliability, water-use restriction frequency, infrastructure net present cost, peak financial cost of drought mitigation instruments and preexisting debt, and worst-case (first percentile) cost of drought mitigation actions. The Social Planner framing seeks to minimize the average loss of potential robustness by each member utility within the Sedento Valley. It relies strongly on regional cooperation and assumes that all of the stakeholders are similarly willing to cooperate even under conditions of individual loss in their performance objectives and their robustness. The Social Planner framing aims to achieve the highest levels regional robustness overall. In contrast, the Pragmatist compromise seeks to evenly distribute the potential losses in attainable robustness incurred across the cooperating utilities in Sedento Valley. This compromise formulation assumes that the most acceptable regional policy pathway is one that distributes losses most evenly between stakeholders (Dinar & Howitt, 1997) and that the utilities view each other as having their fair share of gains and losses.

Both the Social Planner and Pragmatist compromise policy pathways meet the three performance goals listed in Figure 5b when evaluated with the approximate DU Optimization sampling (see Figure 3a). They are distinctly different in how they each meet the performance goals. Figure 5a shows that the original Social Planner compromise pathway relies predominantly on a 'hard path' approach (Gleick, 2002) that heavily utilizes investments in water supply infrastructure, reflected in the high value of its infrastructure net present cost objective. Increased infrastructure investments are the means by which in the Social Planner pathway attains high regional reliability and low restriction frequency under the assumption of perfect regional cooperation. The Pragmatist compromise policy pathway relies solely on financial instruments and short-term drought mitigation actions with no infrastructure investments made, shown by the zero-value of its regional infrastructure net present cost in Figure 5a. The Pragmatist compromise pathway assumes perfect coordination in employing financial instruments (such as self- or third-party insurance) and drought mitigation actions (such as the purchase of treated water and water-use restrictions), enabling it to delay the construction of new supply infrastructure. The green line designating the Pragmatist compromise pathway in Figure 5a shows that this soft-path strategy results in higher regional peak financial cost and restriction frequency, and lower regional reliability relative to the Social Planner compromise.

Although both of these policy pathways fundamentally differ in their objective space tradeoffs and approach, they are able to meet the performance goals listed in Figure 5b. A key question is, how do these compromise policy pathways behave under moderate deviations in their policies' decision spaces (i.e., implementation uncertainty)? [h!] Figure 6 shows how implementation uncertainty results in the formation of a "performance envelope" representing the effects of modest perturbations to the Social Planner and Pragmatist compromise policy pathways' decision variables. Figures 6a to 6c in purple illustrates the envelope of performance tradeoffs for the perturbed Social Planner compromise policy pathway, and Figures 6d to 6f show the same for the perturbed Pragmatist compromise policy pathway. The color of the lines indicates regional robustness, where a lighter color indicates lower regional robustness, and a darker color indicates higher regional robustness. The solid lines show each of the utility's performance tradeoffs from the original non-perturbed compromise policy. The dashed lines indicate the performance objective tradeoffs resulting from the perturbed solution instances with each of the utility's lowest level of attained robustness.

Under the Social Planner policy pathway, Watertown experiences the widest range of performance degradation in the greatest number of objectives: reliability, restriction frequency and worst-case cost (Figure 6a). However, it could potentially benefit greatly in terms of a lower infrastructure net present cost if it deviates from its original Social Planner policy pathways decisions. Figures 6b and 6c show that Dryville and Fallsland's original set of performance tradeoffs are similar to the perturbed instance that results in their worst robustness. For both of these utilities, the original Social Planner com-

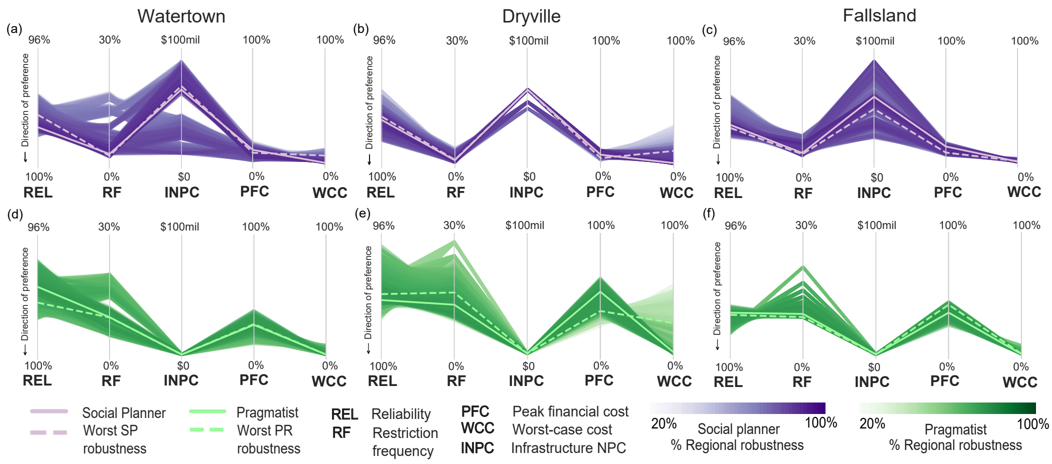

Figure 6: The envelopes of performance tradeoffs for the individual utilities resulting from perturbations in the decision variables that compose the compromise policies. Panels (a) to (c) show the range of changes in performance tradeoffs resulting from 1,000 perturbed instances of the Social Planner compromise. Panels (d) to (e) show the same information for the Pragmatist compromise. The solid line denotes the original compromise policy pathway. The dashed line indicates the performance tradeoff of the perturbed instance with the worst (lowest) utility robustness. The color gradient indicates the change in utility robustness from low robustness (lighter) to high robustness (darker). Each axis represents a performance objective, where a lower position along the axis is preferable. Regional robustness is measured as the percent of sampled DU Re-Evaluation scenarios where all three utilities successfully meet three satisficing criteria when evaluated under a wider, more challenging set of DU SOWs.

promise policy's actions result in reducing their individual levels of attained robustness. This reveals a potential source of counterparty risk as Dryville and Fallsland may have incentives to deviate in their actions to improve their robustness. Dryville's reliability and worst-case cost drive the Social Planner policy's regional robustness, implying that Dryville's actions are most strongly influencing the Sedento Valley region's drive for shared infrastructure investment. Across Figures 6a to 6c, the infrastructure net present cost objective shows the largest variation with the decision variable perturbations, particularly for Watertown and Fallsland. This is due to their shared New River Reservoir infrastructure option. The cooperative construction of the New River Reservoir requires that both Watertown and Fallsland bear the costs of construction. If one utility changes how much they invest in the reservoir, their counterpart will be responsible for the remaining cost of the project which will drastically change their infrastructure net present cost. This highlights the Social Planner compromise's reliance on the careful cooperative development of new supply infrastructure, as well as the hard-path nature of the Social Planner compromise.

Alternatively, the Pragmatist compromise policy pathway shows that Watertown's original set of performance tradeoffs in Figure 6d are similar to that of its perturbed instance resulting in its worst robustness, with only a slight degradation in reliability. Figure 6e shows that its neighbor Dryville will experience the widest range of performance variation in the greatest number of objectives: reliability, restriction frequency, peak financial cost, and worst-case cost. This highlights that Dryville is the most vulnerable to implementation uncertainty. Fallsland's envelope of performance is the narrowest among the three regional partners (Figure 6f) with only a small change in its peak financial cost. All three of the utilities' performance in the infrastructure net present cost objective for the Pragmatist compromise is largely insensitive to moderate degrees of implementation uncertainty, indicating that the utilities are able to avoid major investments in new supply infrastructure.

This section has shown that implementation uncertainty changes the Sedento Valley utilities' performance tradeoffs and their ability to remain robust under challenging DU Re-Evaluation SOWs, often eliminating the intended benefits of regional cooperation to achieve high degrees of regional supply reliability and financial stability. Additional regional-scale results on the implications of implementation uncertainty can be found in Section 9 of the Supporting Information. Following this, the next step is to evaluate how implementation uncertainty drives individual and regional robustness tradeoffs. Specifically, the next section will identify controls that could potentially improve, maintain, or degrade a utility's robustness, and how changes in these controls potentially impact their neighbors.

4.2 Understanding Robustness Controls

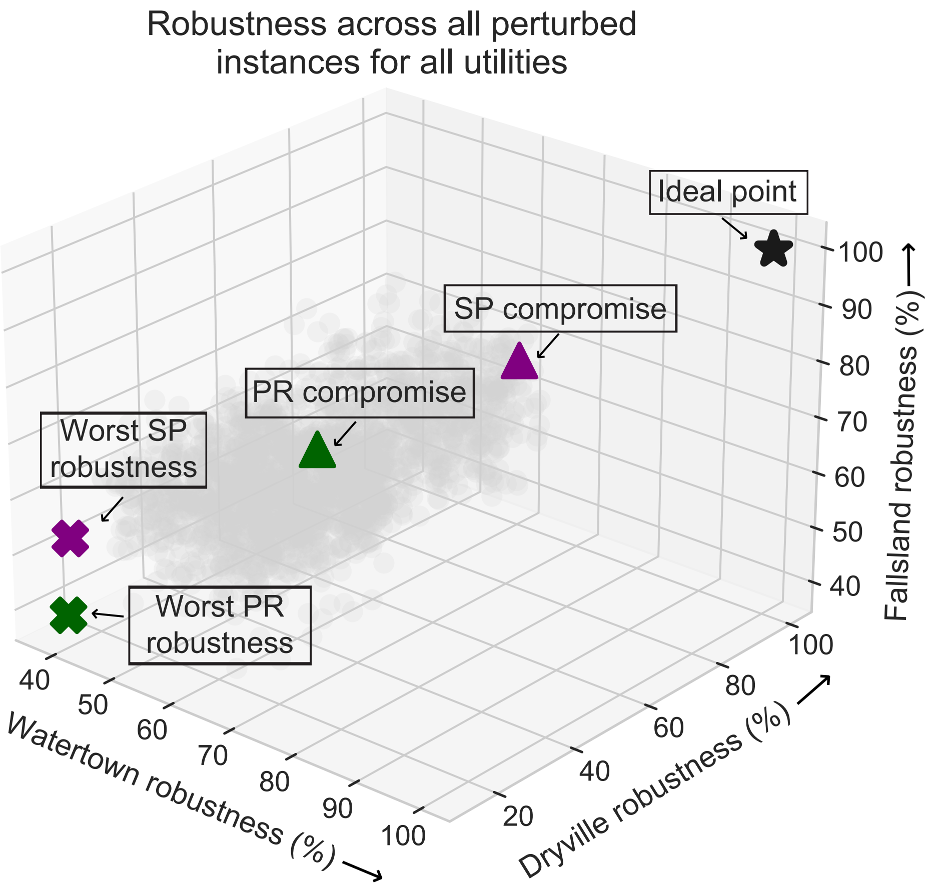

Figure 7: Robustness of the original Social Planner and Pragmatist compromises for Watertown, Dryville and Fallsland indicated by the purple and green triangles respectively. Their least-robust perturbed instances across the three utilities are indicated by the purple and green X's. These points are plotted with respect to the ideal robustness values point, denoted by the star.

Figure 7 demonstrates how implementation uncertainty results in robustness degradation across all three utilities. Assuming precise implementation of the Social Planner and Pragmatist policy pathways, all three utilities are able to achieve relatively high robustness values. Interestingly, all three utilities achieve higher robustness under the Social Planner compromise, with Dryville benefitting the most from the "hard path"-centric regional cooperative structure of this policy pathway. In contrast, the Pragmatist compromise prioritizes achieving a relatively equal power balance across regional stakeholders, which is reflected by approximately equal robustness across all utilities. These are the outcomes when each utility implements its individual financial instruments and drought mitigation actions precisely. However, implementation uncertainty appears to nullify the benefits of cooperative infrastructure development and regional cooperation prioritized by the Social Planner compromise. This is shown by the similar robustness values for the least-robust perturbed instances for all of the utilities, for both the Social Planner and Pragmatist compromises. Across both compromises, Dryville also stands to suffer the largest degree of robustness degradation, emphasizing the observations made in Figure 6 where it was hypothesized that Dryville had the strongest influence over regional robustness.

Figure 7 shows that the Social Planner policy pathway's reliance on joint infrastructure construction and regional cooperation are more robust to deeply uncertain futures, but only if it is implemented precisely. The effects of implementation uncertainty serve to reduce the benefits of cooperation and the added security afforded by the new supply infrastructure. However, implementation uncertainty may leave all of the utilities just as vulnerable to uncertain futures as they had been prior to cooperation. To better understand the degree of impact that implementation uncertainty has on robustness, this study maps the utilities' decision variables that most affect degradation in their robustness. [h!] Figures 8a to 8d further emphasize the "hard path" approach of the Social Planner compromise policy pathway and its reliance on strong regional cooperation. For the Social Planner compromise, the robustness of all of the utilities is strongly dependent on traditional drought mitigation actions such as water-use restrictions, increasing the use of coordinated treated water transfers, and investments in new supply infrastructure. Watertown's robustness, in particular, is the most sensitive to the use of its restriction trigger. Dryville's robustness is the most sensitive to its annual reserve fund contribution and transfer trigger. Fallsland's robustness is the most sensitive to its own and Watertown's infrastructure trigger. These sensitivity analysis results highlight the strong interplay between the Sedento Valley's resource conflicts and the effectiveness of cooperative actions assumed in the Social Planner compromise policy pathway. Specifically, Figures 8a to 8d reveal the dependencies of Dryville and Fallsland on Watertown. Dryville has to purchase water from Watertown; its robustness is, therefore, reliant on it having sufficient reserve funds to trigger treated water transfers under drought scenarios. Fallsland and Watertown cooperatively invest in the New River Reservoir, as shown in Table 1. As Fallsland does not have an independent supply source, it is dependent on Watertown making timely capacity-expanding infrastructure investments as assumed in the original unperturbed Social Planner compromise policy pathway, as well as making its own precisely-timed investments to remain robust across challenging scenarios. The robustness of the Sedento Valley region as a whole is strongly sensitive to implementation uncertainty in Dryville's decision variables (Figure 8i), which is consistent with observations from Figures 6 and 7. This further emphasizes Dryville as being the major driver of vulnerabilities to implementation uncertainties when seeking to maintain regional robustness for the Sedento Valley overall.

In contrast, Figures 8f to 8i illustrate the "soft path" nature of the Pragmatist compromise policy pathway, which results in each of the utilities being sensitive to (1) fewer decision variables and (2) largely implementation uncertainties that they have control over. This compromise is not sensitive to the infrastructure triggers but is in turn highly sensitive to the implementation uncertainties in the decision variables controlling the financial instruments such as the insurance trigger. Watertown and Fallsland are sensitive to modest perturbations to their restriction triggers. Dryville is dominantly sensitive to the implementation of its transfer trigger and insurance trigger. As a region, the robustness of the Pragmatist compromise does not depend on the cooperative expansion

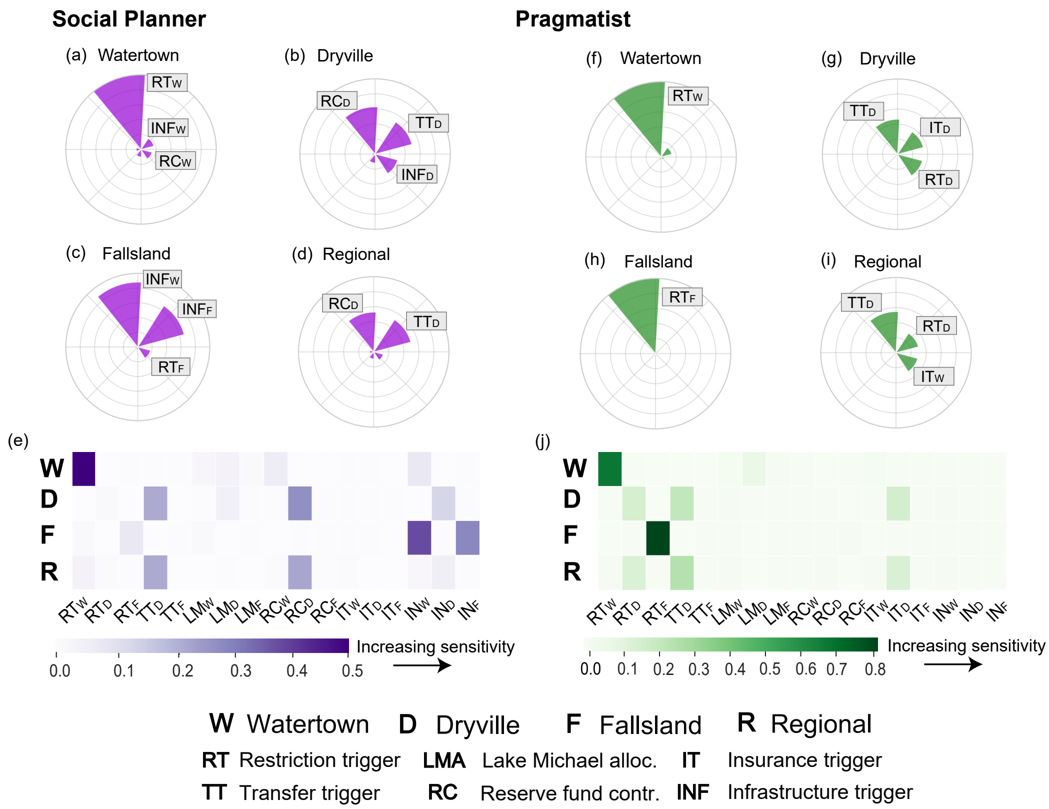

Figure 8: Sensitivity of individual utilities and the region's robustness to the perturbed policy pathways' decision variables. Panels (a) to (d) and (f) to (i) show the decision variables that most strongly control the utilities' robustness performance for the Social Planner and Pragmatist compromise policy pathways, respectively. In these panels, the radii of the colored sectors indicate the relative degree of importance that perturbing decision variables has on robustness. Panels (e) and (j) show Delta Moment-Independent Sensitivity Index heatmaps for the Social Planner and Pragmatist compromise policy pathways, respectively. The subscripts of each of the decision variables indicate the utilities ('W': Watertown, 'D': Dryville, 'F': Fallsland).

or investment in new supply infrastructure, but instead emphasizes the use of third-party and self-insurance financial instruments in combination with conventional drought mitigation actions such as restrictions and treated transfers. Additionally, the degree of robustness degradation that could be experienced by each utility is proportional to the number of decision variables they have to carefully implement, which reflects the Pragmatist compromise path policy's emphasis on distributing each utility's influence over the regional system's robustness. Further details on the robustness of all perturbed instances across the Sedento Valley region can be found in Section S9 of the Supporting Information.

As a whole, the sensitivity analysis summarized in Figure 8 reveals that vulnerabilities to implementation uncertainties vary across the different compromise policy pathways, utilities, and their underlying modes of regional cooperation (e.g., soft versus hard path strategies). Although Figure 7 shows that the Pragmatist compromise policy pathway (which uses fewer cooperative instruments) achieves lower original robustness, Figure 8 shows that a 'more cooperative' policy pathway increases the complexity of its implementation, making it more susceptible to the effects of implementation uncertainty. The inclusion of joint investments, which the Social Planner compromise uses and the

Pragmatist compromise does not, results in an additional dimension of complexity where regional partners have to carefully coordinate their investment decisions to ensure that their robustness goals are achieved. Although this (ideally) should afford the utilities and the region a higher theoretical robustness, any change in willingness for cooperating partners to jointly invest in new infrastructure could eliminate the benefits of cooperation.

Thus far, the prior results have examined how robustness changes with implementation uncertainties in the Sedento Valley's two very different compromise policy pathways. The consequences of these robustness changes on the Sedento Valley and its constituent utilities can change under different scenarios of extreme drought or unexpectedly high rates of population growth. Therefore, it is important to evaluate if an imperfectly implemented regional water supply investment and management pathway can still meet all the satisficing criteria (reliability of more than 98%, restriction frequency of less than 10%, and worst-case cost of less than 10%) under this suite of more challenging scenarios. Towards this end, Gradient Boosted Trees (Boosted Trees) is applied to perform scenario discovery and identify combinations of DU factors that, when coupled with implementation uncertainty in the decision space, cause the utilities to fail to meet their robustness satisficing criteria. As a clarification of language, these performance conditions are termed 'goals' when used to screen objective performance tradeoffs based on the DU Optimization results (see Figure 5) and 'satisficing criteria' when computing robustness relative to the much broader DU Re-Evaluation sampling scheme (3b). Figure 9 illustrates detailed scenario discovery results for the Social Planner and Pragmatist compromise policy pathways. It illustrates the most important drivers of robustness using factor maps that explicitly map which dominant factors and their specific values control the Sedento Valley and its member utilities' success and failure in meeting the satisficing criteria. In comparing the factor maps in Figure 9 across both compromise policy pathways, the most dominant driver of failure is consistently the demand growth rate of each utility.

For the Social Planner compromise policy pathway (Figures 9a and 9b), both Watertown and Dryville experience significant increases in vulnerability to deep uncertainty in their individual demand growth rates under implementation uncertainty. This increase in vulnerability is characterized by the increase in the red area of the factor map, which is most severely felt by Dryville, as well as the Sedento Valley as a whole. This further underscores the role of Dryville as the main driver of regional robustness as previously observed in Figures 6 and 7. Implementation uncertainties for Dryville in the Social Planner compromise policy pathway can cause the Sedento Valley as a region to fail to meet its satisficing criteria even under less-challenging SOWs, as shown by the red region of failure overlapping with triangle in the panel of factor maps in Figure 9b. In contrast, Fallsland's region of failure remains relatively unchanged under implementation uncertainty. These observations show that the robustness implications of imperfectly implemented cooperation are felt disproportionately across utilities, while other partners suffer the full vulnerability consequences when they fail to cooperate as planned.

For the Pragmatist compromise policy pathway (Figures 9c and 9d), only Dryville experiences significant changes in its vulnerability to deep uncertainty in its demand growth rates under implementation uncertainty. Both Watertown's and Fallsland's regions of success and failure remain relatively unchanged. Once again, Dryville appears to drive regional robustness under the Pragmatist compromise. An interesting observation to note is that the regions of failure in the original Pragmatist compromise policy pathway (Figure 9c) are larger than that of the Social Planner compromise policy pathway (Figure 9a). This demonstrates the value of regional cooperation in reducing both individual utilities' and regional vulnerability to deep uncertainty. However, implementation uncertainty resulting in policy perturbations eliminates the robustness benefits of cooperation, leaving utilities as vulnerable to unexpected shifts in demand as they were prior to cooperating. This is reflected in the similarity in the area of the region of failure of both least-

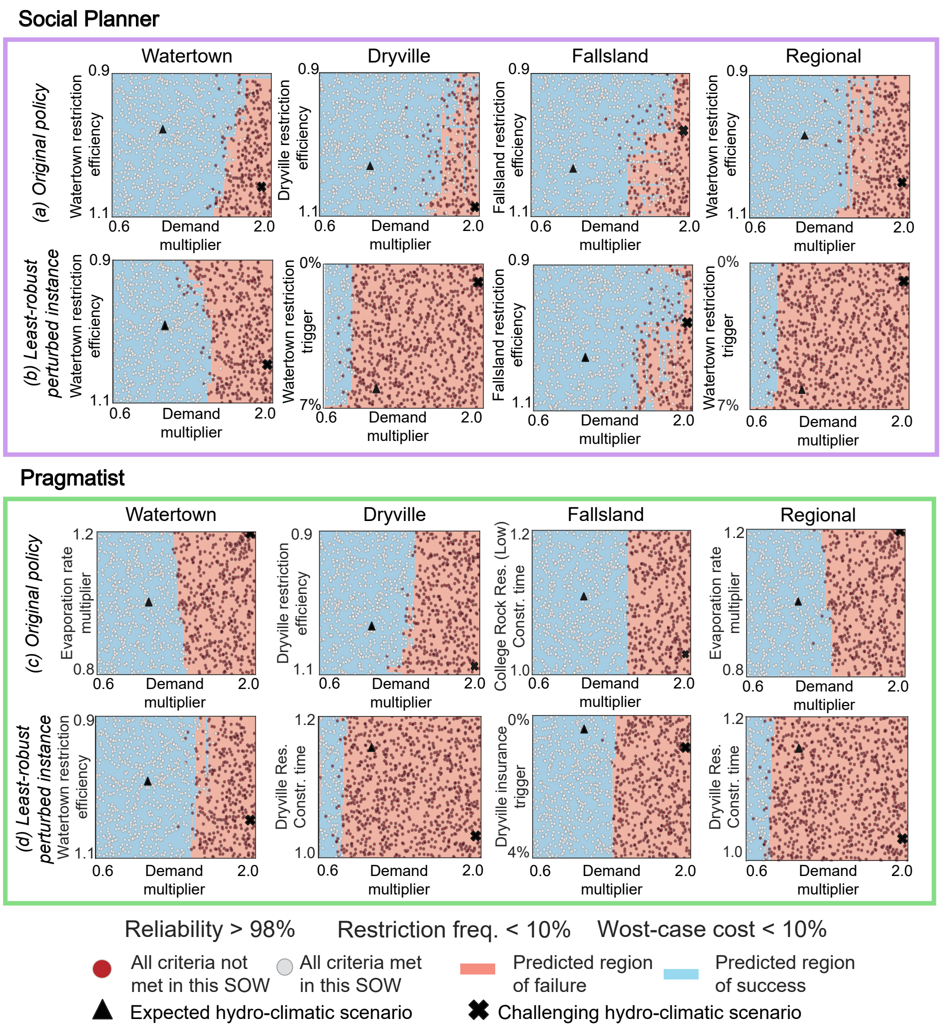

Figure 9: The purple highlighted panels (a) and (b) show the factor maps of the Social Planner compromise for its original instance and the least-robust perturbed instance respectively. The green highlighted panels (c) and (d) show the same information for the Pragmatist compromise policy pathway. Each column represents a utility or the Sedento Valley region. The vertical and horizontal axes of each factor map indicate the two most-influential factors controlling a utility's, or the region's, robustness. The three satisficing criteria that define success or failure are: (1) a reliability $\geq$ 98%, (2) restriction frequency of $\leq$ 10%, and (3) worst-case cost of $\leq$ 10%. The red dots represent SOWs where policy pathways fail to meet all satisficing criteria. The grey dots indicate successful SOWs. The pink region designates the Boosted Trees-classified zones of failure to meet the satisficing criteria, and the blue indicates classified success zones. The triangle denotes the expected hydro-climatic scenario and the cross denotes a challenging (dry) hydro-climatic scenario).

robust perturbed instances (Figures 9b and 9d). Here, implementation uncertainty emerges as the previously-hidden 'second factor', in addition to demand growth rate uncertainty, that drives the robustness of the Sedento Valley and its constituent utilities. Not only does implementation uncertainty result in increased vulnerability to deep uncertainty, but it also leaves utilities having to implement a set of actions complex actions without realizing their promised benefits.

It is clear that implementation uncertainty changes the ability of the region and its individual actors to remain robust when faced with extreme drought and accelerated population growth. This information can be supported by understanding how utilities' long-term infrastructure investment pathways are affected when the need to respond to these DU scenarios becomes more pressing, and how they are compounded when utilities are unable to abide by the recommended set of policy pathways.

4.3 Implementation Uncertainty Effects on Infrastructure Investment Pathways

The interactive effects from the DU Re-Evaluation's sampled SOWs, implementation uncertainty in the decision variables that make up a policy pathway, the selected robustness compromise strategies, and the Sedento Valley utilities' long-term plans can be best understood by formally mapping how their state-aware infrastructure pathways are impacted. Figure 10 shows the infrastructure pathways of the Social Planner compromise across a 45-year planning horizon spanning 2020 to 2065. The Pragmatist compromise is not shown as it has very little to no infrastructure built across all sampled SOWs (i.e., its soft-path focus). The state-aware ROF triggers used to dynamically initiate management and investment actions in the Sedento Valley generate distinctive sequences of short-term drought mitigation actions and long-term infrastructure investments tailored to what is being experienced in each specific sampled SOW. As summarized in Section 3.4.3, K-Means clustering is used to identify three distinct clusters of high, medium, and low infrastructure SOWs and compare how implementation uncertainty affects their response. The grey shading represents the frequency at which each infrastructure option is triggered at a given time across all of the sampled SOWs.

Overall, Figure 10 reveals the potential consequences of implementation uncertainties and challenging DU SOWs on the utilities' long-term infrastructure investment pathways. Compared to Watertown's original set of infrastructure pathways in Figure 10a, Figures 10b to 10d show that Watertown's infrastructure pathways are the most susceptible to perturbations in its own (Figure 10b) and Fallsland's (Figure 10d) set of policy actions. These two figures imply that Watertown attempting to reduce infrastructure investments will result in robustness degradations for both itself and Fallsland. Under a policy perturbation that results in Dryville's worst robustness (Figure 10c), Watertown's infrastructure pathways remain the same, albeit triggering infrastructure investments more frequently and earlier. Figures 10e to 10h show that Dryville reducing its infrastructure investments leads to all of the utilities (including itself) experiencing their worst individual robustness. This agrees with observations from Figures 6 and 7 where Dryville was found to be the main driver of regional robustness. However, Figures 10i and 10j build on the observations drawn from Figures 6 and 8 where Watertown and Fallsland's cooperative investment in the New River Reservoir is a significant driver of Watertown's robustness. Although Fallsland's infrastructure pathway remains the same, it only triggers infrastructure once in the 'high infrastructure' pathway (Figure 10j), which maps to Watertown's worst robustness. Interestingly, a comparison between Figure 10l and Figure 10d show that Fallsland will experience its lowest possible robustness if either itself or Watertown fails to trigger any of their infrastructure options. Both of these options emphasize the Social Planner policy pathways' dependence on perfect cooperation of a "hard-path" policy, as failure to make timely infrastructure investments as agreed upon results in significant robustness degradation for the Sedento Valley region overall.

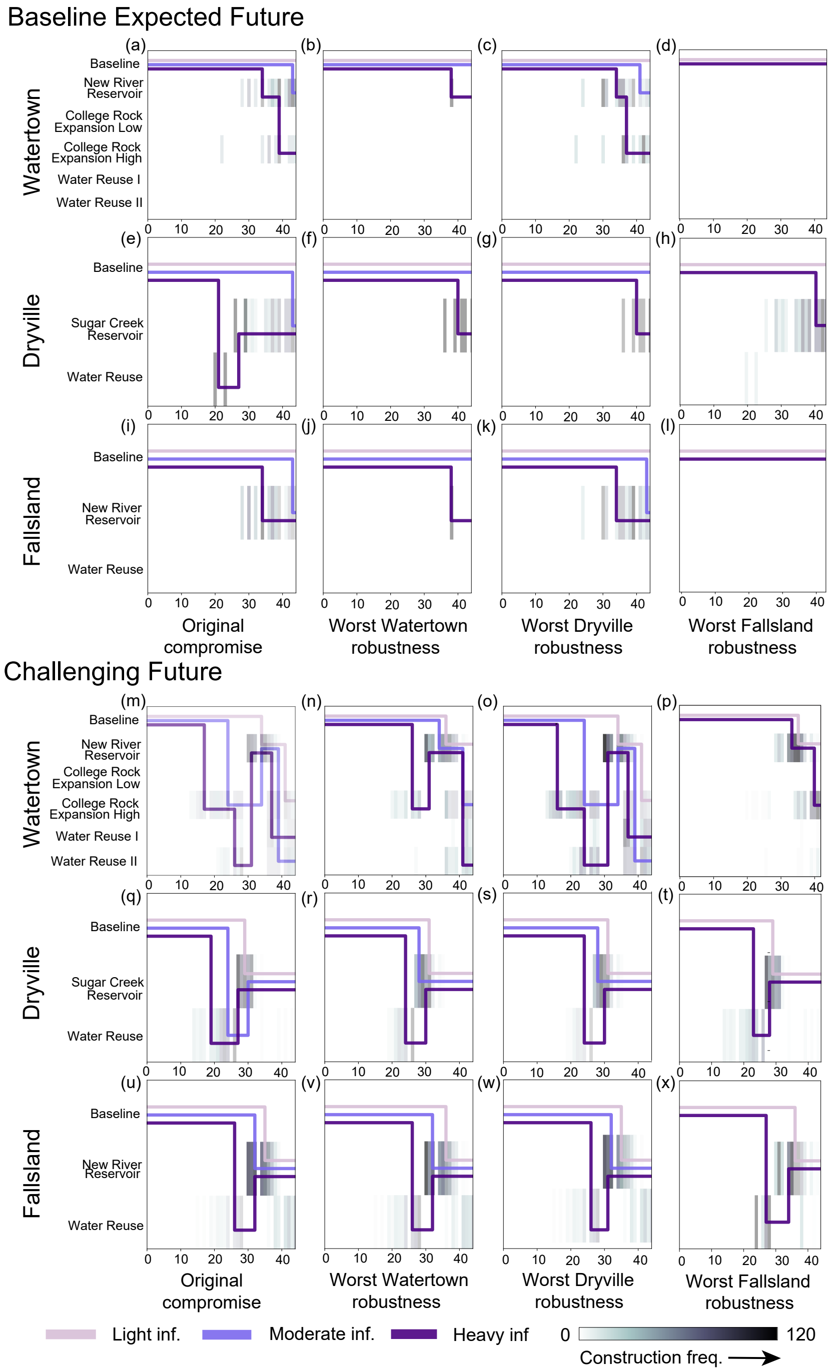

Figure 10: Three distinct clusters of infrastructure pathways that emerge for the Social Planner compromise from 2020 to 2060. Each row illustrates one utility's infrastructure pathways. Each column distinguishes how the infrastructure pathways change between the original unperturbed policies and the least-robust perturbed instances for each utility. Panels (a) to (l) show the original and perturbed pathways that emerge under the baseline expected estimate for hydro-climatic future conditions. Panels (m) to (x) show the original and perturbed pathways under a challenging drought with high demand future. The color of the pathways denotes infrastructure intensity, with dark purple indicating high infrastructure investment, medium purple indicating moderate infrastructure investment, and light purple indicating little to no infrastructure investment. The color gradient of the grey vertical bars represents the frequency at which each infrastructure option is triggered at a given time across all DU SOWs, with a lighter color indicating fewer instances of infrastructure investment being triggered and vice versa.

Under a more challenging hydro-climatic scenario (Figures 10m to 10x), all of the utilities trigger more infrastructure options at higher frequencies as expected. The shift to a dryer future with higher demand results in Watertown (Figure 10n) experiencing its worst robustness when it fails to trigger the Water Reuse II infrastructure option early enough. Watertown perturbing its infrastructure investment actions to eliminate two infrastructure projects also has adverse effects on Fallsland's robustness (Figure 10p). These conditions also necessitate Dryville to trigger all of its infrastructure options (Figures 10q to 10t). However, the lighter color of the infrastructure construction frequency bars shown in Figures 10r to 10t implies that decreases in individual robustness are primarily due to Dryville's lower frequency of infrastructure construction or investment across all SOWs, versus Dryville entirely failing to invest in infrastructure. This is the same for Fallsland (Figures 10u to 10x). However, all three utilities trigger the construction of the Water Reuse facility under a challenging future, highlighting that this infrastructure option will be necessary under dry, high-demand scenarios. Next, the differences in infrastructure intensity between Figures 10a to 10l and Figures 10m to 10x suggest that, when coupled with extreme hydro-climatic scenarios, modest levels of implementation uncertainty can yield substantial changes in infrastructure pathways yielding much higher infrastructure intensities across more SOWs. Figure 10 clarifies how potential unintended deviations from the original compromise policy pathway yield effects that cascade throughout the region's cooperating utilities. Once again, this analysis demonstrates the complexities of cooperation. If joint investments in infrastructure are made as recommended by the original policy pathways, utilities can afford to expand physical supply infrastructure while remaining robust even under challenging future scenarios. Further detail on the interactions between long-term infrastructure investments and short-term supply reliability to ensure robustness to deeply-uncertain future conditions is demonstrated in Figure S10 in Section S8 in the Supporting Information.

Precise coordination of cooperative investment is therefore vital to ensure individual and regional robustness under a more challenging future. Therefore, utilities should be informed of the level of precision required during implementation for regional cooperative water supply investment and management pathways to perform as expected. Identifying these operational tolerances requires delineating individual safe operating spaces (SOS) which are decision variable operational tolerance ranges which each utility's robustness remains the same or improves from its original robustness value.

4.4 Delineating Safe Operating Spaces

In this study, a utility's SOS is defined to be the range of decision variable values within which a utility can safely operate its policy pathway under the assurance that its robustness will remain the same or improve from its original individual robustness value in the perfectly implemented compromise policy pathway. Figures 11a to 11c shows the delineated SOS for the Social Planner compromise policy pathway where each vertical axis represents a decision variable, and the location along the axis denotes the degree to which a decision is used. The dark regions represent the range of sampled decisions, and the light regions represent the SOS. Similarly, Figures 11d to 11f show the delineated SOS for the Pragmatist compromise policy pathway. Within the light regions, utilities can safely vary their decision variables without adverse implications to their individual or the region's robustness. Defining these SOS regions draws on having a better understanding of the dominant controlling decision variables in Figure 8. In comparing Figures 8 and 11, the decision variables that most affect the utilities' robustness have significant dark regions in each utility's SOS (i.e., decision variable envelopes that yield significant degradation in robustness).

Analysis of the SOS of both compromise policy pathways yields several interesting observations. The comparison between these compromise policies represents the choice between extreme sensitivity to at most two decision variables and easier implementation,

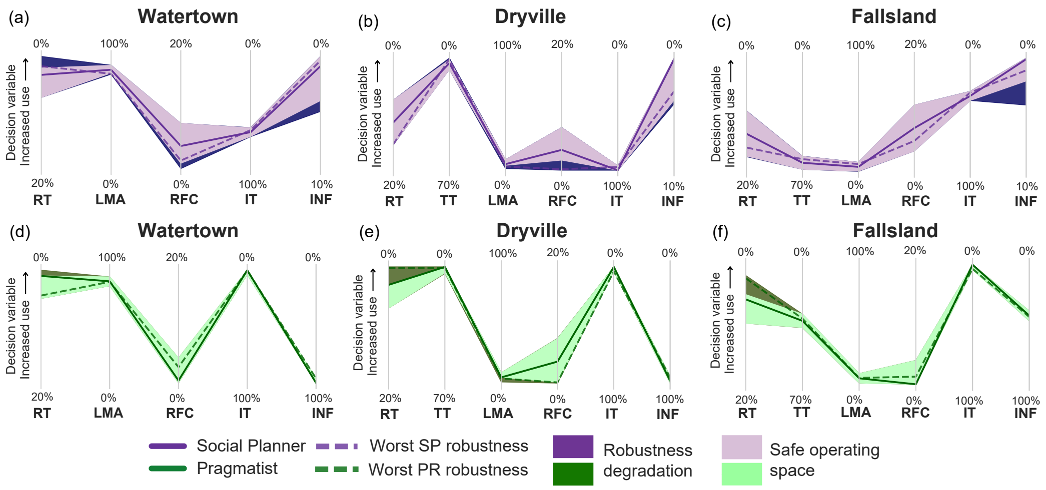

Figure 11: Safe operating spaces of each utility for the Social Planner (purple) and Pragmatist (green) policy pathways. Panels (a) to (c) are parallel axis plots that delineate safe operating spaces for the Social Planner compromise. Panels (d) to (e) show the same information, but for the Pragmatist compromise. Each axis represents one decision variable. More frequent use of an action is indicated by a higher intersection point between a line and an axis. The original set of policy actions is indicated as the thick solid line. The dashed line indicates the perturbed instance that results in the lowest utility robustness. The dark regions indicate decision variable ranges where robustness degradation is certain, while the lighter region denotes the safe operating space.

and moderate sensitivity to a broader suite of decision variables and more complex implementation. Under the Social Planner compromise, Watertown (Figure 11a) has relatively wide SOS ranges but is moderately sensitive to three decision variables. It could potentially experience decreased robustness due to increased use of its water-use restriction trigger, lower-than-recommended contributions to its reserve fund, and less-frequent use of its infrastructure trigger. The dashed line in the figure shows that Watertown's robustness degradation is likely caused by implementing a restriction trigger outside its SOS. Next, Dryville (Figure 11b) is moderately sensitive to its Lake Michael allocation, reserve fund contribution, and infrastructure trigger. Dryville's robustness degradation is dominantly influenced by failing to remain within the SOS of its reserve fund contributions. In contrast, Fallsland is only sensitive to one decision variable, which is its own infrastructure trigger. However, its worst robustness does not exceed the SOS of its infrastructure trigger. This is likely because, as shown in Figure 8c, Fallsland's robustness is most sensitive to Watertown's infrastructure trigger as the driver of its worst-case robustness.

This is not the case for the Pragmatist compromise (Figures 11d to 11f). Here, all of the utilities have a relatively wide SOS for the restriction trigger. For Watertown and Fallsland (Figures 11d and 11f), none of their other decision variables cause robustness degradations within the range of their sampled policy perturbations. Dryville (Figure 11e) is sensitive to both its use of the restriction trigger and its Lake Michael allocation. The utilities' robustness degradation is more likely to be caused by their own implementation of water restrictions that are more frequent than recommended. Excessive use of water-use restrictions and failing to appropriately use its allocated supply causes its robustness to decrease to its lowest-possible value. Broadly speaking, and as suggested by Figures 7 and 8, the Social Planner compromise presents the opportunity for the utilities to attain higher individual and regional robustness at the cost of depending on a more complex policy pathway implementation as compared to the Pragmatist compromise.

5 Conclusion

The DU_{SOS}Pathways framework provides a rigorous quantitative assessment of the impacts of how implementation uncertainty and deeply uncertain future conditions interact to shape the performance and robustness tradeoffs of different candidate cooperative policy pathway structures. It is demonstrated on the highly-challenging Sedento Valley regional water supply planning and management test case where the utilities seek to cooperate but must navigate the complex implications of their interdependent actions related to short-term drought mitigation, long-term investment pathways, financial hedging, as well as their counterparty risks.

The findings of this study are broadly applicable to regions focused on water supply management and infrastructure planning frameworks to identify high-performing and robust regional cooperative policy pathways. They show that implementation uncertainty may cause cooperating utilities to lose the benefits of high performing robust cooperative regional policy pathways even with modest deviations from the assumption of perfect implementation. In addition, implementation uncertainty may nullify the benefits of lower financial risk and higher supply reliability that are assumed to emerge with regional cooperation. This study illustrates strong interactions between implementation uncertainties in short- and long-term decisions on reliability and infrastructure sequencing, where changes in one can yield large changes in the timing or effectiveness of the other. Furthermore, cooperation, while effective in decreasing regional and individual vulnerability to deep uncertainties, increases the complexity of implementing a cooperative policy pathway and increases the potential robustness losses should cooperating actors deviate even modestly in their implementation of recommended actions.

The DU_{SOS}Pathways framework provides actionable information to utilities by delineating safe operating spaces that represent operational tolerances within which utilities can safely vary their decision variables without experiencing decreases in robustness and performance. This is the first known study to include implementation uncertainty in long-term investment pathways for a regional water pathway planning. By revealing how day-to-day decisions in water management and operations affects plans for building new infrastructure (and vice versa), utilities are able to examine the ramifications that their choices have not only on their counterparts, but also on their future supply reliability, financial risk, and infrastructure pathways. With this information, cooperating utilities can select compromise policy pathways that best suit the level of implementation precision that their operational and planning ability allows. Future work should therefore include efforts to incorporate the search for policies that maximize the area of the SOS to further improve the robustness of a discovered policy pathway to exogenous and endogenous uncertainties. It is also important to further the understanding of the dynamic nature of these spaces and identify how they may change over time as more information is obtained and the future unfolds. Additionally, including cooperative regional-scale demand management as an additional decision variable and characterizing the impacts of its uncertain implementation is another avenue for future research to explore.

6 Data Availability Statement

All data and code for this work, including (a) a subset of input data, (b) final results, (c) instructions for replicating the computational experiment, and (d) figure generation can be found at `https://github.com/lbl59/implementation-uncertainty`. DOI: 10.5281/zenodo.7677798

Acknowledgments
The views expressed in this work represent those of the authors and do not necessarily reflect the views or policies of related parties. This work used the Extreme Science and

Engineering Discovery Environment (XSEDE), which is supported by National Science Foundation grant number ACI-1548562. Regional and individual optimizations were carried out on Stampede2 at the Texas Advanced Computing Center (TACC) through XSEDE allocation TG-EA R090013. Deep uncertain re-evaluations was conducted on Comet at the San Diego Super Computing Center (SDSC) through XSEDE allocation TG-EA R090013. Implementation uncertainty re-evaluations were conducted on the Hopper Cluster at the Cornell University Center for Advanced Computing. The authors would also like thank the anonymous reviewers and the editorial team for helping us improve the clarity and contribution of this study. All code and data for this project, including figure generation, can be found at `https://github.com/lbl59/implementation-uncertainty`. All authors declare that they have no conflicts of interest to disclose.

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