Power and Pathways: Exploring robustness, cooperative stability and power relationships in regional infrastructure investment and water supply management portfolio pathways

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Abstract

Regional cooperation among urban water utilities is a powerful mechanism for improving supply reliability and financial stability in urban water supply systems. Through coordinated drought mitigation and joint infrastructure investment, urban water utilities can efficiently exploit existing water supplies and reduce or delay the need for new supply infrastructure. However, cooperative water management brings new challenges for planning and implementation. Rather than accounting for the interests of a single actor, cooperative policies must balance potentially competing interests between cooperating partners. Structural imbalances within a regional system can lead to conflict between cooperating partners that destabilize otherwise robust planning alternatives. This work contributes a new exploratory modeling centered framework for assessing cooperative stability and mapping power relationships in cooperative infrastructure investment and water supply management policies. Our framework uses multi-objective optimization as an exploratory tool to discover how cooperating partners may be incentivized to defect from robust regional water supply partnership opportunities and identifies how the actions of each regional partner shape the vulnerability of its cooperating partners. Our methodology is demonstrated on the Sedento Valley, a highly challenging regional urban water supply benchmarking problem. Our results reveal complex regional power relationships between the region's cooperating partners and suggest ways to improve cooperative stability.

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Key Points:

- A novel method for mapping power relationships and examining the potential for conflict in cooperative water supply planning problems is presented
- Advance robustness analysis methods for cooperative systems by accounting for defections by cooperating partners
- Illustrate how power relationships may shape vulnerability in cooperative water supply planning problems

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Abstract

Regional cooperation among urban water utilities is a powerful mechanism for improving supply reliability and financial stability in urban water supply systems. Through coordinated drought mitigation and joint infrastructure investment, urban water utilities can efficiently exploit existing water supplies and reduce or delay the need for new supply infrastructure. However, cooperative water management brings new challenges for planning and implementation. Rather than accounting for the interests of a single actor, cooperative policies must balance potentially competing interests between cooperating partners. Structural imbalances within a regional system can lead to conflict between cooperating partners that destabilize otherwise robust planning alternatives. This work contributes a new exploratory modeling centered framework for assessing cooperative stability and mapping power relationships in cooperative infrastructure investment and water supply management policies. Our framework uses multi-objective optimization as an exploratory tool to discover how cooperating partners may be incentivized to defect from robust regional water supply partnership opportunities and identifies how the actions of each regional partner shape the vulnerability of its cooperating partners. Our methodology is demonstrated on the Sedento Valley, a highly challenging regional urban water supply benchmarking problem. Our results reveal complex regional power relationships between the region's cooperating partners and suggest ways to improve cooperative stability.

1 Introduction

Globally, urban water managers are increasingly challenged by growing water demands and a changing climate (AghaKouchak et al., 2021; Wasley et al., 2020). In the United States (US), drinking water systems require over $400 billion of capital investment by 2029 to maintain aging infrastructure and manage growing demands (ASCE, 2021). Financial pressures stemming from debt burden and access to capital required for this investment are increasing, as major credit rating agencies now require water utilities to comprehensively characterize their vulnerability to long-term risks from climate change and increasing hydrologic uncertainty (Okuji et al., 2017; Williams et al., n.d.; Insoll & Griffiths, 2017). These risks are dominantly driven by droughts that force urban water utilities to confront severe trade-offs between supply reliability and financial stability (Chapman & Breeding, 2016; Borgomeo et al., 2016). Historically, water utilities have managed drought risk by independently investing in new supply infrastructure to maintain high supply capacity-to-demand ratios (Gleick, 2002). However in the US and many heavily urbanized centers globally, most suitable locations for new supply projects have been developed, and regulatory and environmental uncertainties have made this approach no longer acceptable in many regions (Gleick, 2003). These constraints have motivated urban water utilities to explore regionally cooperative investment and water portfolio management approaches that seek to utilize existing sources more efficiently and jointly develop new supply sources (Frone et al., 2008; Riggs & Hughes, 2019; Reedy & Mumm, 2012; EPA, 2017).

With this transition in focus, it is now important to better understand how the development of regionally coordinated water management policies creates new challenges by increasing institutional complexity and exposing cooperating actors to new risks (Frone et al., 2008; Kurki et al., 2016; Sjöstrand, 2017). Rather than evaluating performance trade-offs for a single actor, the design of cooperative strategies must account for the potentially competing interests of all cooperating partners (Madani & Dinar, 2012). Adding to this challenge, regional power dynamics and historical inequities not easily measured by traditional performance objectives shape how water supply risks are manifested across regional actors (Savelli et al., 2021). These dynamics increase the potential for "hidden" sources of conflict that are not readily apparent (Gold et al., 2019). Figure 1 organizes these challenges into four primary topical areas that can serve to to guide cooperative water resources planning: (I) performance trade-offs, (II) robustness, (III) cooperative stability of compromises, and (IV) power and agency. While performance trade-offs, robustness and cooperative stability have been widely discussed in water resources literature (e.g. Borgomeo et al. (2016); Groves et al. (2019); Read et al. (2014)), state-of-the-art infrastructure investment and water portfolio management frameworks to date have largely neglected to account for regional power dynamics and the agency of regional actors, potentially missing important considerations for successful implementation of cooperative infrastructure investment and water portfolio management pathways. This paper contributes a holistic framework for crafting and evaluating cooperative infrastructure investment and water supply management policies that explicitly accounts for all four challenges highlighted in Figure 1.

As noted in Figure 1, the initial focus in cooperative infrastructure investment and water portfolio planning has been to better understand performance trade-offs between

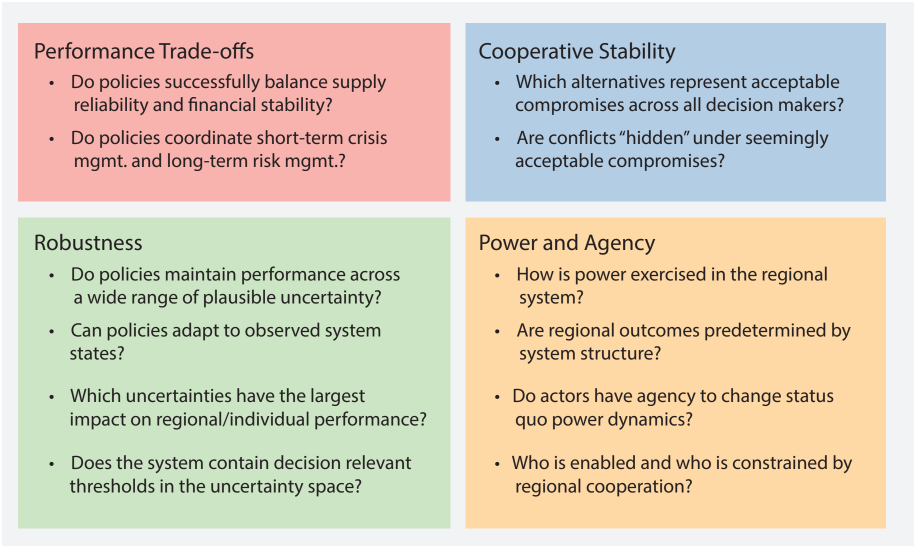

Figure 1. Multi-actor challenges in the design of cooperative water supply planning policies

utilities' ability to meet their communities' supply demands while balancing their own financial stability (Borgomeo et al., 2016; Harou et al., 2009; Matrosov et al., 2012; Ray et al., 2012; Beh et al., 2015). In recent years, regional portfolio approaches have emerged as a key tool for managing these trade-offs (Jenkins & Lund, 2000; Lund et al., 2006; Characklis et al., 2006; Kasprzyk et al., 2009; Mortazavi-Naeini et al., 2014). Regional water supply portfolios combine short-term drought mitigation instruments (e.g., water transfers and demand management), and financial instruments (e.g., index insurance) to minimize supply failures while covering revenue shortfalls and unexpected costs (Zeff & Characklis, 2013). Exploring synergies between short-term water supply portfolio planning and long-term infrastructure investment pathways has the potential to further improve regional reliability and enhance financial stability (Mortazavi-Naeini et al., 2014; Cai et al., 2015; Zeff et al., 2016). This coordination may be aided by the use of many-objective optimization to discover high-performance design alternatives that represent optimal trade-offs between conflicting objectives (Zeff et al., 2014; Beh et al., 2015). Through the *a posteriori* evaluation of performance trade-offs, many-objective optimization allows stakeholders to choose policy alternatives that most align with their preferences for balancing supply reliability and financial stability (Woodruff et al., 2013).

There is a growing recognition that the balance of supply reliability and financial stability is challenged by conditions of deep uncertainty stemming from growing demands, changing drought extremes, and financial risks (Herman et al., 2014; Dittrich et al., 2016; Maier et al., 2016; Groves et al., 2019). Deep uncertainty refers to conditions where parties to a decision do not know or cannot agree upon the probability distributions for uncertain inputs to the system, how to value alternative outcomes and/or the appropriate model to define the system and its boundaries (Lempert et al., 2006; Kwakkel et al., 2016; Marchau et al., 2019). Deep uncertainty requires planners to shift focus from finding strategies that are optimal in expectation across a set of probabilistic scenarios to discovering robust solutions that maintain satisfactory economic, social and environmental performance across a range of challenging and uncertain scenarios (Lempert et al., 2006). This challenge motivates the second consideration highlighted in Figure 1: Robustness.

In recent years, exploratory modeling centered frameworks (Bankes, 1993; Moallemi et al., 2020) and adaptive planning approaches (Walker et al., 2013) have emerged as key innovations that aid the discovery of robust water supply policies. Exploratory modeling frameworks utilize computational experiments to systematically explore plausible future scenarios without a strict focus on seeking to assign their likelihoods in advance (Bankes, 1993). These frameworks allow decision makers to discover how uncertainties may cause undesirable performance outcomes and identify decision relevant thresholds in the uncertainty space (Moallemi et al., 2020). Frameworks such as Robust Decision Making (Lempert et al., 2006), Many-objective Robust Decision Making (MORDM) (Kasprzyk et al., 2013), Info-gap (Ben-Haim, 2006) and Decision Scaling (Brown et al., 2012) have been widely used to examine robustness in water supply planning contexts (for examples see Groves et al. (2019); Herman et al. (2014); Housh and Aharon (2021); Marcos-Garcia et al. (2020)). Adaptive planning approaches provide robustness by using near-term information to inform infrastructure planning and water management decisions (Walker et al., 2013; Erfani et al., 2018). For example, Dynamic Adaptive Policy Pathways (DAPP) (Haasnoot et al., 2013), generates robust and adaptive decision-making pathways by exploring alternative sequences of decisions across multiple futures.

For cooperative systems, robustness conflicts complicate planning under deep uncertainty (Herman et al., 2015; Trindade et al., 2019; Gold et al., 2019). A successful strategy must not only be robust, but also cooperatively stable, meaning it represents an acceptable compromise across all cooperating actors (Parrachino et al., 2006; Madani & Dinar, 2012). These conflicts motivate the third challenge in Figure 1: cooperative stability. Here, we define cooperatively stable alternatives as portfolio pathways that represent acceptable compromises for all regional actors (Read et al., 2014). Cooperative stability can be examined through game theoretic metrics (Gately, 1974; Shapley & Shubik, 1954; Teasley & McKinney, 2011) or bargaining methods (Brams & Kilgour, 2001; Madani et al., 2011; Khatiri et al., 2020). However, both stability measures and bargaining techniques rely on highly simplified and narrow theoretical abstractions of preference for each actor, which limits our understanding of the underlying multi-actor dynamics in the regional systems that must balance complex commitments to supply reliability and financial performance.

To understand multi-actor dynamics within a cooperative system, it is critical to examine the power relationships between actors (Avelino & Rotmans, 2009). Examining power and agency within cooperative systems is the final challenge highlighted in Figure 1. While power has been broadly defined as "the (in)capacity of actors to mobilise means to achieve ends" (Avelino, 2021), the way that power may be exercised within a regional system can provide insights into the nature and drivers of regional robustness conflicts. Power in multi-actor systems may be partitioned into three types of relationships: *power over*, *power to* and *power with* (Avelino & Rotmans, 2011). *Power over* refers to conditions when actor A may exercise power over actor B. *Power to* refers to each actor's ability to act to create or resist change. *Power with* refers to actors' ability to collaborate within the system context to create or resist change. Mapping these power relationships within a regional system reveals which actors have agency to initiate or prevent change, and how regional conflict may be shaped by structural elements of the water resources system (e.g. hydrologic constraints or political power).

This study seeks to formally advance our ability to understand power and agency in cooperative water resources planning problems by expanding the DU Pathways framework, a cooperative infrastructure investment and water supply management pathways framework introduced by Trindade et al. (2019). DU Pathways draws from advances in water supply portfolio planning, DAPP, and MORDM to discover integrated short- and long-term decision making rules that generate cooperative infrastructure investment and water supply portfolio policy pathways.

Our extension of DU Pathways provides a holistic approach for confronting the cooperative planning challenges outlined in Figure 1, guided by the research questions posed therein. We begin our analysis by employing many-objective search to discover cooperative rule systems that equitably maximizes performance across all system actors. Next, we examine portfolio robustness by reevaluating each cooperative infrastructure investment and water management policy across a large ensemble of deep uncertainties. We then contribute game theoretic inspired measures of cooperative stability to evaluate tacit conflicts and incentives for defection within compromises for regional partnerships. Conflicts are evaluated by carefully mapping the participants' power and agency to influence regional compromises via a novel Regional Defection Analysis, which utilizes an additional many-objective search to explore how regional partners may seek to defect from the regional agreement. This analysis maps sources of regional robustness conflicts and examines power structures within the regional partnership. We demonstrate our methodology on the Sedento Valley (Trindade et al., 2020), which has been formulated as a highly challenging multi-actor water supply planning benchmarking test case where three urban water utilities seek to develop cooperative infrastructure investment and water supply portfolio pathways.

2 Regional Test Case

The Sedento Valley (Trindade et al., 2020) is a highly challenging multi-actor water supply planning test case developed for benchmarking new frameworks for water supply planning under deep uncertainty (illustrated in Figure 2a). As a water supply test case, the Sedento Valley contains many important challenges faced by urban water utilities. First, the rapidly growing regional population is stressing the limits of current water supplies, challenging the region's water utilities to develop new strategies for water management. Second, the region contains multiple independent urban water utilities in close proximity that have asymmetric vulnerability to drought due to differences in their water supply capacities, watershed characteristics and local demand profiles. This asymmetry represents an opportunity for cooperative drought mitigation through water transfers, while also shaping regional resource competition. The duality of water transfers being both a mechanism for enhancement of regional water supplies as well as a driver for resource competition strongly complicates cooperative regional water portfolio planning and infrastructure investment pathways. Third, the region has a limited number of suitable locations for new supply development and regional utilities are investigating cooperative investment in new supply infrastructure. Finally, the region's three utilities face financial vulnerability to future droughts, necessitating the careful coordination of financial instruments with drought mitigation and infrastructure investment strategies. The water management actions and infrastructure investment decisions of each utility have the potential to impact the financial risk of neighboring utilities, providing further incentive for the three utilities to coordinate their water management and infrastructure investment strategies.

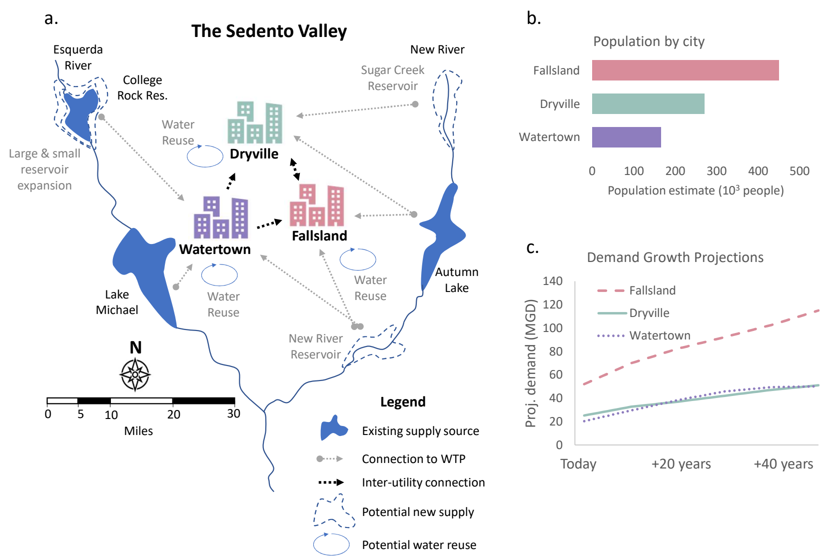

Figure 2. a) A map of the Sedento Valley region, where three urban water utilities in the seek cooperative long term water management strategies. b) Population by city c) Demand growth projections by city

The Sedento Valley regional water supply system is composed of two medium sized cities, Fallsland and Dryville, and a smaller city, Watertown. The populations of each city are shown in Figure 2b. Each city receives water from their own independent water utility. Dryville and Fallsland share access to Autumn Lake, a large reservoir that they each access via independent water treatment facilities. Watertown owns and operates a water treatment plant on Lake Michael, a large regional resource controlled by the federal government. Watertown also draws water from College Rock Reservoir, where it owns and operates an additional water treatment facility. The managers of the three utilities face pressure from growing demands (Figure 2c) as well as uncertainties stemming from how quickly demand will grow and how a changing climate will impact the region's reservoir inflows and and evapotransporation.

The cities within the Sedento Valley have significant disparities in their access to regional water supplies. Fallsland, the city with the largest urban population, does not have a proportionally larger access to supply. Conversely, Watertown, the smallest of the three cities, has direct access to a large and currently unallocated portion of Lake Michael. All three utilities may request Lake Michael supply allocations from the federal government. However, the reservoir is limited to a single suitable location for a water treatment plant, thus requiring Fallsland and Dryville to purchase treated transfers from Watertown to access their allocations. In recent decades, the three utilities have invested in large interconnections, allowing Dryville and Fallsland to access potential allocations without significant capacity constraints.

Historically, the three utilities have managed water supply challenges by imposing short-term water use restrictions during acute periods of drought and independently investing in supply expansions to mange long-term risk. However, when used too frequently, water use restrictions are unpopular with local residents and threaten financial stability due to revenue disruptions (Hughes & Leurig, 2013). The majority of the region's suitable supply expansion locations have been developed, significantly increasing the cost of new infrastructure development. The utilities are seeking to increase the use of treated transfers from Lake Michael as part of their drought mitigation strategies. These transfers allow Dryville and Fallsland to access Lake Michael, potentially reducing the frequency of water use restrictions and /or delaying the need for new infrastructure investments. The addition of water transfers comes at the cost of increased volatility in utility revenues. This volatility creates challenges for utility budgets, which have been traditionally focused on meeting the fixed costs associaed with their debt burden.

To jointly improve the region's supply reliability and collectively reduce financial risks, the three utilities are exploring the development cooperative infrastructure investment pathways that center on coordinated drought mitigation and co-investment in shared infrastructure. To facilitate the development of these cooperative infrastructure pathways, the utilities are employing a portfolio based approach that links short-term drought mitigation with long-term risk reduction. In times of drought, each utility may impose water use restrictions to temporarily curtail water demand. Dryville and Fallsland may also purchase treated transfers at cost from Watertown. A regional portfolio coordinates the use of these drought mitigation instruments to maximize the efficiency of regional sources. To mitigate financial volatility from restrictions and transfers, portfolios also include financial instruments in the form of self insurance and third-party insurance. As part of the regional agreement the utilities will also determine how to share the unused portion of Lake Michael.

The regional cooperative infrastructure investment pathways seek to sequence new infrastructure investment in coordination with short-term drought mitigation policies. Each utility has identified a set of potential supply expansion projects that include both the development of new supply sources and the implementation of water reuse strategies. Watertown and Fallsland are also exploring the construction of the New River Reservoir, a large new supply source that would be shared between the two cities. A list of potential infrastructure projects for each utility can be found in Table 1.

The Sedento Valley test case's cooperative infrastructure investment and water supply portfolio management pathways represents a highly challenging multi-actor decision context. A key driver of the test case's challenging decision context is the multi-actor dynamics within the regional system. In the next section, we outline an approach for exploring these dynamics to discover cooperative strategies that represent robust and cooperatively stable regional compromises for the Sedento Valley water utilities.

3 Methodology

This study extends the DU Pathways framework (Trindade et al., 2019) by adding Regional Defection Analysis (RDA), a new exploratory modeling centered methodology that enables decision makers to examine cooperative stability, power relationships, and actors' agency when developing cooperative infrastructure investment and water portfolio management pathways. The DU Pathways framework serves as a bridge between from the constructive decision aiding approach of MORDM (Kasprzyk et al., 2013) and the adaptive policy formulation central to DAPP (Haasnoot et al., 2013). RDA formalizes the analysis of how multi-actor dynamics impact negotiated trade-off analyses, robustness assessments, and scenario discovery, filling a significant technical gap in the tra-

Table 1. Potential new infrastructure options in the Sedento Valley.

Infrastructure	Utility (allocation %)	Capital Cost ($\$10^6$)	Storage or Production	Permiting 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 MG	17
Dryville Reuse	Dryville	30	35 MGD	5
New River Reservoir	Fallsland (50%) Watertown (50%)	263	3700 MG	17
Fallsland Reuse	Fallsland	50	35 MGD	5

ditional forms of DAPP and MORDM. Our approach is outlined in Figure 3a, which overviews DU Pathway methodology and highlights our RDA contribution. The problem formulation stage (Figure 3a, Box i), includes specification of the system model(s), relevant decisions, uncertainties and regional objectives. Next, we search for the high performance cooperative infrastructure investment and water supply management portfolio pathways using Deep Uncertain optimization (DU optimization) (Trindade et al., 2017) and examine trade-offs between system objectives (Figure 3a, Box ii and detailed in Figure 3b). This set of solutions is then stress-tested by re-evaluating each portfolio under a broader set of States Of the World (SOWs) generated by utilizing a larger independent sampling of the relevant deep uncertainties identified in the problem formulation (Figure 3a, Box iii and detailed in Figure 3c). The results of this Deep Uncertainty re-evaluation (DU re-evaluation) serve as the basis for computing the robustness of each alternative regional water portfolio management and infrastructure investment policy for each of the cooperating system actors. This information is then used to inform a negotiated design selection process (Figure 3a, Box iv), where we select one or more robust compromise alternatives for further analysis.

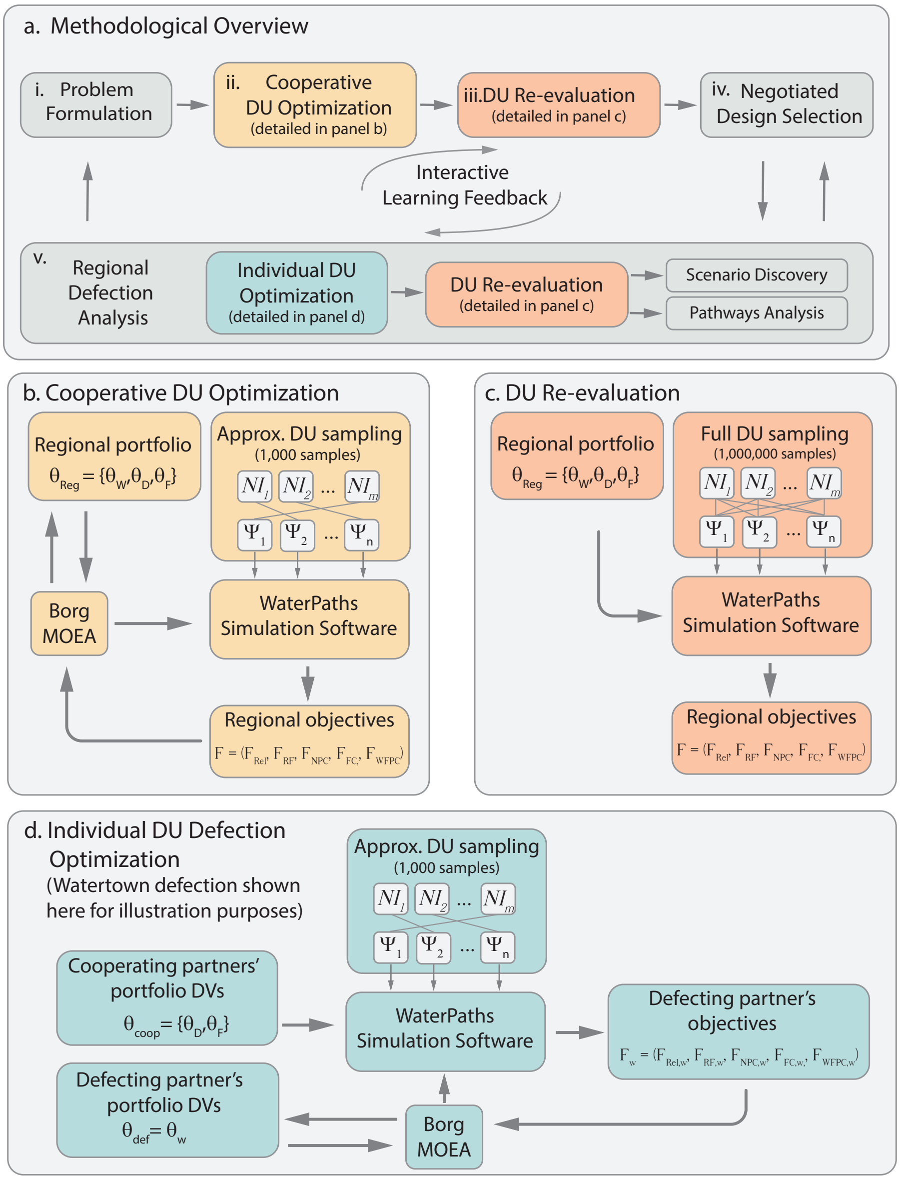

Figure 3. a) An overview of the expanded MORDM framework for cooperative decision making under deep uncertainty, adapted from Kasprzyk et al. (2013). b) flow chart of cooperative DU optimization used to discover an initial set of regional water supply portfolios, c) flow chart of DU re-evaluation d) Individual DU defection optimization in the regional defection analysis

In this study, we contribute a formal exploratory modeling methodology to carefully evaluate cooperative stability and regional power dynamics through RDA (Figure 3a, Box v). RDA first uses many-objective optimization as an exploratory tool to examine how each cooperating utility partner may defect from the regional partnership, then examines how these defections shape their own self-interests, broader regional cooperative stability, actors' vulnerabilities to deep uncertainties as well as their resulting infrastructure pathways. RDA is comprised of four main steps (Figure 3a, Box v). First, we perform a set of individual DU defection optimizations (detailed in Figure 3d) that explore the benefits and trade-offs for each cooperating partner to defect from the regional infrastructure investment and water portfolio management compromise policy. This analysis asks the question: can a regional partner unilaterally increase their reliability or financial stability by defecting from the regional partnership? This step yields a set of defection alternatives (i.e., new investment and management decisions) tailored to each actor that reveal how they may gain from defection and what actions they may be incentivized to take. As shown in Figure 3d, in the DU defection optimization one defecting utility is allowed to deviate in its decisions while all other partners are held to the actions in a given regional compromise solution being considered. We use the solutions discovered through individual defection optimization to examine how regional defection alters drought mitigation actions and the resulting infrastructure pathways. Next, we re-evaluate defection alternatives across a broad set of DU SOWs to explore how defection may impact the robustness for each cooperating partner. Finally, we perform scenario discovery to determine how each actor's defection from compromise policies changes which SOWs are the most consequential in their impacts on other actors vulnerabilities. The RDA methodology contributed here provides a comprehensive assessment of the cooperative stability of negotiated compromises, regional power structures, and the potential drivers of regional conflict. These insights have value for designing monitoring efforts as part of the implementation of a cooperative agreements as well as informing the development new agreement structures if needed.

3.1 Problem Formulation

A candidate infrastructure investment and water portfolio problem formulation is a formalized hypothesis about how the cooperative planning problem should be represented analytically (Zeleny, 1981; Kasprzyk et al., 2013). Drawing from MORDM, the

DU pathways framework treats problem formulation as a constructive learning process where stakeholders and analysts collaborate to develop a shared understanding of system challenges and search for promising design alternatives (Tsoukiàs, 2008; Kwakkel et al., 2016). This constructive decision aiding process allows stakeholders to explore competing hypotheses for how the system should be represented (also termed rival framings), potentially exposing hidden biases that may underlie single formulations (Majone & Quade, 1980; Quinn et al., 2017). For a candidate problem formulation, we determine performance objectives, specify a system model, translate actions into decision variables, identify relevant uncertainties and define how those uncertainties are sampled (Lempert et al., 2006).

Formally, we seek to find the vector of cooperative decision variables, $\boldsymbol{\theta^*_{coop}}$, that minimizes regional objective vector F:

$$\boldsymbol{\theta_{coop}}^* = \text{argmin}_\theta \ \mathbf{F} \tag{1}$$

s.t.

$$|\text{ME}| \leq 1 \ \forall \ \text{ME} \subseteq \ \text{BI} \tag{2}$$

Where:

$$\mathbf{F} = \begin{bmatrix} f_{\text{REL}} \\ f_{\text{RF}} \\ f_{\text{NPC}} \\ f_{\text{FC}} \\ f_{\text{WFPC}} \end{bmatrix} \tag{3}$$

$$f_{\text{REL}} = \min_u \big(- f_{\text{REL,u}} \left(\mathbf{x_s}, \ \theta_{\mathbf{coop}}, \ \mathbf{\Psi_s} \right) \big) \ \forall \ u \in U \tag{4}$$

$$f_{\text{RF}} = \min_u \big(f_{\text{RF,u}} \left(\mathbf{x_s}, \ \mathbf{x_{srof}}, \ \theta_{\mathbf{coop}}, \ \mathbf{\Psi_s} \right) \big) \ \forall \ u \in U \tag{5}$$

$$f_{\text{NPC}} = \min_u \big(f_{\text{NPC,u}} \left(\mathbf{x_s}, \ \mathbf{x_{lrof}}, \ \theta_{\mathbf{coop}}, \ \mathbf{\Psi_s} \right) \big) \ \forall \ u \in U \tag{6}$$

$$f_{\text{FC}} = \min_u \big(f_{\text{FC,u}} \left(\mathbf{x_s}, \ \mathbf{x_{srof}}, \ \mathbf{x_{lrof}}, \ \theta_{\mathbf{coop}}, \ \mathbf{\Psi_s} \right) \big) \ \forall \ u \in U \tag{7}$$

$$f_{\text{WFPC}} = \min_{u} \left(f_{\text{WFPC,u}} \left(\mathbf{x_s},\ \mathbf{x_{srof}},\ \mathbf{x_{lrof}},\ \theta_{\mathbf{coop}},\ \mathbf{\Psi_s} \right) \right)\ \forall\ u \in U \tag{8}$$

$$\theta_{\mathbf{coop}} = [\theta_{\mathbf{W}}, \theta_{\mathbf{D}}, \theta_{\mathbf{F}}] \tag{9}$$

$$\theta_{\mathbf{W}} = [\theta_{\text{rt,W}},\ \theta_{\text{arfc,W}},\ \theta_{\text{irt,W}},\ \theta_{\text{it,W}},\ ICO_W,\ \theta_{\text{lma,W}}] \tag{10}$$

$$\theta_{\mathbf{D}} = [\theta_{\text{rt,D}},\ \theta_{\text{tt,D}},\ \theta_{\text{arfc,D}},\ \theta_{\text{irt,D}},\ \theta_{\text{it,D}},\ ICO_D,\ \theta_{\text{lma,D}}] \tag{11}$$

$$\theta_{\mathbf{F}} = [\theta_{\text{rt,F}},\ \theta_{\text{tt,F}},\ \theta_{\text{arfc,F}},\ \theta_{\text{irt,F}},\ \theta_{\text{it,F}},\ ICO_F,\ \theta_{\text{lma,F}}] \tag{12}$$

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_{\text{srof}} \\ \mathbf{x}_{\text{lrof}} \\ \mathbf{x_s} \end{bmatrix} \tag{13}$$

Where $\mathbf{F}$ is a vector based objective function containing regional objectives f_{Rel}, reliability, f_{RF}, restriction frequency, f_{NPC}, net present value of infrastructure investment, f_{FC}, financial cost of drought mitigation and debt payment, and f_{WFPC}, the worst-first-percentile cost of the f_{FC} and U is the set of all cooperating utilities.

The cooperative water supply policy is represented by $\theta_{\mathbf{coop}}$, a vector containing all of the decision variables for the three utilities ($\theta_W,\ \theta_D,\ \theta_F$). Decision variables controlling short term drought mitigation actions are θ_{rt}, representing restriction triggers, and θ_{tt}, representing transfer triggers. Decision variable regulating financial instruments are θ_{arfc}, representing annual reserve fund contributions, and θ_{irt}, representing insurance restriction triggers. Long-term infrastructure sequencing is controlled by θ_{it}, representing lROF infrastructure construction triggers and ICO, a matrix containing infrastructure construction ordering for each utility. Details on the decision variables can be found in section 3.1.2.

Matrix $\mathbf{X}$ has values of decision-relevant state variables for all utilities and includes $\mathbf{x_{srof}}$, a vector of sROF states used to trigger drought mitigation, $\mathbf{x_{lrof}}$, a vector of lROF states used to trigger infrastructure investment and $\mathbf{x_s}$,a vector of system states.

The regional objectives are also subject to the SOW, $\mathbf{\Psi_s}$, which contains vector samples of deeply uncertain time series and parameters, found in Table 2. Deeply uncertain factors considered include changes in future streamflow trends (for details see Trindade et al. (2020)), economic uncertainties including demand growth rate, bond rates/terms and discount rate, effectiveness of water use restrictions and uncertainties involving infrastructure construction and permitting.

In Equation 2, ME represents a generic subset of mutually exclusive infrastructure options within the set of built or prospective infrastructure BI.

3.1.1 Performance Objectives

The three utilities of the Sedento Valley seek to discover water supply portfolios that balance the conflicting objectives of maximizing supply reliability, minimizing the frequency of water use restrictions as well as minimizing drought mitigation and infrastructure investment cost. We formulate this water supply planning problem as a many-objective design problem with five objectives: maximize system reliability, minimize restriction frequency, minimize the net present value of infrastructure spending, minimize the peak financial costs, and minimize the worst first percentile financial cost. Details on the formulation of each objective can be found in Section 1 of the supporting information to this paper. To maximize the equity of regional solutions discovered through optimization, we employ a regional minimax formulation where each regional objective value is taken as the value of the objective for the worst-performing utility. This application of Rawls' difference principle guarantees that all other utilities will perform at least as well or better than the regional value (Rawls, 1999; Hammond, 1976; Helgeson, 2020).

3.1.2 System Model

We develop a system model using WaterPaths simulation software, a generalizeable, open-source exploratory modeling system explicitly designed to inform decision support for water supply planning under conditions of deep uncertainty (Trindade et al., 2020). WaterPaths' customizeable code base provides a flexible platform for examining both short- and long-term water supply portfolio instruments. WaterPaths also provides advanced computational support for many-objective optimization algorithms and scales efficiently across high performance computing resources. This scaling capability allows candidate water supply portfolios to be evaluated across large ensembles of potential future SOWs.

3.1.3 Uncertainty

A core challenge to water supply planning in the Sedento Valley is the uncertainty concerning future SOWs. We partition this uncertainty into two categories, well characterized uncertainty (WCU) and deep uncertainty (DU). WCU includes model parameters that are stochastic and have known probability distributions or enough data to estimate their probability density functions (Trindade et al., 2017). In the Sedento valley, the natural variability of reservoir inflows and evaporation rates are modeled as WCUs as there is over 80 years of historical data. To provide a thorough representation of these stochastic parameters, we employ a synthetic streamflow generator which samples from the historical record to generate future natural inflow time series that preserve the temporal and spatial patterns of the historical record (Kirsch et al., 2013). Details on the synthetic streamflow generation process can be found in Trindade et al. (2020). We define DUs facing the system as model parameters that do not have known probability density functions (Lempert, 2002; Kwakkel et al., 2016). In the Sedento Valley, these factors include possible climate change impacts to the system and human factors such as demand growth rate. A full list of DUs in our modeling can be found in Table 2. DU samples are generated through Latin Hypercube Sampling (LHS), which ensures all quantiles of each parameter are evenly represented.

We define a SOW as a pairing of one WCU natural inflow time series (NI) and one LHS of DU factors (Ψ). To evaluate the performance of water supply policies, we utilize two sampling strategies. "Full DU sampling" generates 1,000,000 SOWs by pairing 1,000 NI time series with each of 1,000 samples of DU factors. "Approximate DU sampling" creates an independent sample of 1,000 SOWs by pairing each of the 1,000 NI time series with one LHS of DU factors. The sample sizes used in this work were chosen based off bootstrap analysis conducted by (Trindade et al., 2020).

3.1.4 Decision Variables

As described in Section 2, the Sedento Valley utilities employ portfolio approach to manage water supply decisions under deep uncertainty. A cornerstone of this port-

Table 2. Deep uncertainties considered for the Sedento Valley test problem. Unless specified otherwise the same minimum and maximum values for each uncertainty were applied for all utilities and infrastructure.

Category	Factor name	Min	Max
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

folio approach is the use of state-aware action triggers that adaptively respond to changing system conditions. Drought mitigation actions are coordinated using short-term risk-of-failure (sROF; (Caldwell & Characklis, 2014)), a dynamic measure of each utility's evolving storage-to-demand ratio, updated on a weekly basis. At any given week, a utility's sROF represents the probability that its reservoir storage will drop below 20% of total capacity at any point during the subsequent 52 weeks. Each drought mitigation instrument is assigned an associated sROF trigger, and drought mitigation actions are implemented if the sROF exceeds the trigger on any given week.

New infrastructure investment is triggered by long-term ROF (lROF; (Zeff et al., 2016)), a measure of each utility's capacity to demand ratio, calculated on an annual basis. lROF is calculated once per year, and measures the probability that a utility's total storage will drop below 20% of total capacity over the subsequent 78 weeks, if all reservoirs begin full. Each utility has a single lROF trigger for infrastructure, and an associated ranking of infrastructure options. When an utilities' lROF crosses the lROF trigger, it will begin construction on the top ranked infrastructure option. To mitigate revenue volatility resulting from drought mitigation, the water supply portfolio also contains several financial instruments. These instruments include self insurance, through annual reserve fund contributions, and third party index insurance purchased from an outside party. Details on all decision variables and their ranges can be found in Table 3.

3.2 Many-objective Search Under Deep Uncertainty

We employ the Borg Multi-objective Evolutionary Algorithm (MOEA) (Hadka & Reed, 2012) to discover high performing portfolio management policies. Many-objective search with the Borg MOEA yields a Pareto approximate set composed of pathway policy solutions whose performance in one objective can only be improved by degrading performance in one or more of the remaining objectives (Coello et al., 2007). The Borg MOEA has been shown to outperform many state-of-the art MOEAs on challenging real world problems that are non-linear, non-convex and mulitmodal (Reed et al., 2013; Gupta et al., 2020). The Borg MOEA is a steady-state algorithm (Deb, 2014) that utilizes adaptive population sizing (Kollat & Reed, 2006), epsilon dominance archiving (Laumanns et al., 2002), and auto-adaptive operator selection to tailor its search strategies as it discovers what is most effective for a given problem (Hadka & Reed, 2012).

Decision Variable	Utility	Lower Bound	Upper Bound
Restriction sROF trigger	All	0%	100%
Transfer sROF trigger	Dryville, Fallsland	0%	100%
Lake Michael Allocation - Watertown	Watertown	33.4%	90%
Lake Michael Allocation - Dryville	Dryville	5%	33.4%
Lake Michael Allocation - Fallsland	Fallsland	5%	33.4%
Insurance sROF trigger	All	0%	100%
Infrastructure construction lROF trigger	All	0%	100%
Annual reserve fund contribution (% annual revenue)	All	0%	10%
Infrastructure rankings	All	1^{st}	# inf options

Table 3. Decision variables and their bounds

The DU optimization formulation is formally a stochastic many-objective search problem that specifically focuses on enhancing the robustness of identified infrastructure investment and water portfolio management solutions (Trindade et al., 2019). DU Optimization is part of a growing number of robust multiobjective optimization applications that directly integrate stochastic sampling of deep uncertainties have emerged focusing on improving the robustness of solutions discovered through search (Eker & Kwakkel, 2018; Watson & Kasprzyk, 2017; Bartholomew & Kwakkel, 2020). DU optimization has been shown to yield improved robustness for water supply planning problems when compared with traditional optimization conducted under deterministic or well-characterized conditions (Trindade et al., 2017, 2019). In this work, DU optimization is performed over the approximate sampling of DU SOWs described in Section 3.1.3 and illustrated in Figure 3b. DU optimization was specifically developed for design of adaptive rule systems such as the ROF centered portfolios used in this work. By exposing these rule systems to a diverse set of future SOWs, DU optimization yields a higher degree of adaptivity and exploitation of information feedback when compared to optimization under WCU conditions (Trindade et al., 2017).

3.3 Deep Uncertainty Re-evaluation

During DU re-evaluation, we stress-test each Pareto approximate infrastructure pathway policies over the set DU SOWs generated through Full DU sampling (described in Section 3.1.3 and illustrated in Figure 3). The robustness of each Pareto-approximate solution is calculated using a satisficing metric (Lempert et al., 2006; Herman et al., 2015), an approximation of Starr's domain criteria (Starr, 1963). Our satisficing metric, S, measures the fraction of SOWs that each solution meets a set of performance criteria defined by the stakeholders, as show in equation 14:

$$S = \frac{1}{N}\sum_{j=1}^{N}\Lambda_{\theta,j} \tag{14}$$

Where,

$$\Lambda_{\theta,j} = \begin{cases} 1, & \text{if } F(\theta)_j \leq \Phi_j \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

Where Φ is a vector of performance criteria for utility j, θ is the portfolio and N is the total number of sampled SOWs. The sample size of 1,000,000 was chosen based off a formal analysis by Trindade et al. (2020), which found that robustness values in the Sedento Valley remained stable at or beyond this level sampling.

The satisficing metric was chosen because it reflects the risk tolerance and preferences of the cooperating utilities. In the Sedento Valley test case, each utility has specified that they would like solutions to meet the following criteria: Reliability $>$ 98%, Restriction Frequency $<$ 10% and Worst First Percentile Cost $<$ 10% annual volumetric revenue following the requirements that have been provided in actual regional water pathway analyses (Herman et al., 2014; Trindade et al., 2019).

3.4 Negotiated Design Selection

Information on solution robustness and trade-offs between performance objectives within the Pareto approximate set provide the basis for negotiated design selection between cooperating partners. Here we illustrate two potential outcomes of the negotiated design selection process by implementing two contrasting framings of a cooperative compromise: a "social planner's" framing, that seeks to maximize the well-being of the region as a whole, and a "pragmatist's" framing, that seeks to discover a practical solution that is likely acceptable to all actors (Read et al., 2014). To select a compromise for the social planner's framing, we use a Least Squares metric (Read et al., 2014), which selects the solution that minimizes the sum of dissatisfaction across negotiating parties:

$$LS = min_j \sum_{i=1}^{m} (w_i(S_i^* - S_{i,j}))^2 \tag{16}$$

Where S_i^* is the maximum robustness achieved for utility i in the Pareto-approximate set, $S_{i,j}$ is the robustness for utility i resulting from solution j, m is the total number of negotiating actors and w_i is a weighting applied to utility i, here set to 1 for all utilities so all actors are weighted equally.

To select a compromise for the pragmatist's framing, we employ the power index, a metric that derives from game theory and economic literature and has been used to identify cooperatively stable solutions for multi-actor negotiation problems (Read et al., 2014; Teasley & McKinney, 2011). The power index measures of the relative gains of one actor against the relative gains of the group. Actors that achieve greater power index values for a given solution are receiving a higher proportion of the gains when compared with other negotiators. Dinar and Howitt (1997) suggest that a feasible solution that distributes power across actors most equally will be an acceptable alternative to all parties. Thus, a solution that minimizes the coefficient of variation of the power index across all actors can be defined as the most cooperatively stable alternative.

$$PW = min_j(CV) \tag{17}$$

$$CV_j = \frac{\sigma_j}{\bar{\alpha}_j} \tag{18}$$

$$\alpha_{i,j} = \frac{w_i(S_i^* - S_{i,j})}{\sum_{i=0}^{m}(S_i^* - S_{i,j})} \tag{19}$$

Such that:

$$\sum_{i=0}^{m} \alpha_i = 1 \tag{20}$$

Where $\bar{\alpha}_j$ and σ_j are mean and standard deviations of power index values $\alpha_{i,j}$ across all negotiators, i for solution j, S_i^* is the best achievable robustness for actor i, $S_{i,j}$ is the robustness achieved under solution j for actor i and m is the total number of negotiators.

3.5 Regional Defection Analysis

The selection of compromise solutions within cooperative infrastructure pathway trade-off analyses relies on the strong assumption that once selected, all regional partners will adhere to the compromise. To examine the consequences of this assumption, we illustrate the RDA methodology using the social planner and pragmatist compromise solutions. The addition of RDA to the DU Pathways framework provides a formal mechanism to reveal which cooperating partners have incentives to defect from the negotiated regional partnership (i.e. which utilities may improve reliability and/or financial stability through defection), discover tacit trade-offs that are not apparent in the initial negotiated pathway policy selection, examines how each actor's defection influences the vulnerabilities of other actors and better maps underlying sources of regional conflict. Results of the regional defection analysis are intended to inform conflict mitigation strategies for regions seeking to cooperatively enhance the robustness of their infrastructure investment and water portfolio management pathways.

3.5.1 Individual Defection Optimization Under Deep Uncertainty

We explore the incentives each utility may have for defecting from the regional compromises using many-objective search with the Borg MOEA as an exploratory modeling tool within broader infrastructure pathway policy spaces of the individual regional water utilities. For this optimization, the Borg MOEA optimizes the defecting utility's individual objectives using only its decision variables while all of the remaining utilities' decision variables are held to be same as what was specified in the given compromise regional pathway policy of focus. as shown in Figure 3d. A formal description of the individual optimization is shown in equations 21-24:

$$\boldsymbol{\theta_{def}}^* = \text{argmin}_{\theta}\ \mathbf{F_{def}} \tag{21}$$

s.t.

$$|\text{ME}| \leq 1\ \forall\ \text{ME} \subseteq\ \text{BI} \tag{22}$$

Where:

$$\mathbf{F_{def}} = \begin{bmatrix} f_{\text{REL,def}}\left(\mathbf{x_s},\ \theta_{\mathbf{def}},\ \theta_{\mathbf{coop}},\ \mathbf{\Psi_s}\right) \\ f_{\text{RF,def}}\left(\mathbf{x_s},\ \mathbf{x_{srof}},\ \theta_{\mathbf{def}},\ \theta_{\mathbf{coop}},\ \mathbf{\Psi_s}\right) \\ f_{\text{NPC,def}}\left(\mathbf{x_s},\ \mathbf{x_{lrof}},\ \theta_{\mathbf{def}},\ \theta_{\mathbf{coop}},\ \mathbf{\Psi_s}\right) \\ f_{\text{FC,def}}\left(\mathbf{x_s},\ \mathbf{x_{srof}},\ \mathbf{x_{lrof}},\ \theta_{\mathbf{def}},\ \theta_{\mathbf{coop}},\ \mathbf{\Psi_s}\right) \\ f_{\text{WFPC,def}}\left(\mathbf{x_s},\ \mathbf{x_{srof}},\ \mathbf{x_{lrof}},\ \theta_{\mathbf{def}},\ \theta_{\mathbf{coop}},\ \mathbf{\Psi_s}\right) \end{bmatrix} \tag{23}$$

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_{\text{srof}} \\ \mathbf{x}_{\text{lrof}} \\ \mathbf{x_s} \end{bmatrix} \tag{24}$$

Where $f_{REL,def}$, $f_{RF,def}$, $f_{NPC,def}$, $f_{FC,def}$ and $f_{WFPC,def}$ are the five objectives for the defecting utility, θ_{def} is the vector of decision variables for the defecting utility and θ_{coop} is the vector of decision variables for the non-defecting utilities, which remain constant. The objectives and decision variables for the individual defection optimization parallel the regional optimization described in Section 3.1 (equations 1-13), but represent the decisions and objectives of the defecting utility, rather than the region as a whole.

Results of the individual optimizations represent defection alternatives for the defecting utility. To quantify the incentives and consequences of defection, we introduce a new measure of cooperative stability that we term "cooperative regret". Cooperative regret was inspired by traditional regret based metrics, which measure the consequences of incorrect assumptions regarding future states of the world (Savage, 1951; Lempert & Collins, 2007; Herman et al., 2015). In cooperative planning contexts, our metric measures the the decision relevant consequences of incorrect assumptions about the cooperative stability of a candidate regional infrastructure investment and water portfolio management policy. Positive values of cooperative regret indicate that a utility benefits from defection, and negative values of indicate that a utility is hurt by defection. For a defecting utility, cooperative regret measures the greatest gain in each objective that can be achieved through defection:

$$R_i^{obj} = max_j[D_i^j] \ \ \forall\ j\ \in \beta \tag{25}$$

$$D_i^j = \begin{cases} \frac{F(x)_i^j - F(x)_i^*}{F(x)_i^{crit}} & if \; \forall \; k \neq i : F(x)_k^* \leq F(x)_k^j \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

Where β is the set of all re-optimized portfolios for the defecting utility, $F(x)_i^*$ is the objective value for the i^{th} objective in the compromise portfolio, $F(x)_i^j$ is the objective value for the i^{th} objective in teh j^{th} re-optimized portfolio and $F(x)_i^{crit}$ is a specified performance criteria for objective i. Importantly, for defecting utilities, the calculated regret in each objective is only positive if improvement in that objective does not come at the cost of degradation in another objective, which would indicate a change of preference between objectives rather than improved performance.

For the non defecting utilities cooperative regret is defined as:

$$R_i^{coop} = min_j[D_i^j] \;\; \forall \; j \;\in \beta \tag{27}$$

$$D_i^j = \frac{F(x)_i^j - F(x)_i^*}{F(x)_i^{crit}} \tag{28}$$

Where β is the set of all re-optimized portfolios for the defecting utility, $F(x)_i^*$ is the objective value for the i^{th} objective in the compromise portfolio, $F(x)_i^j$ is the objective value for the i^{th} objective in the j^{th} re-optimized portfolio and $F(x)_i^{crit}$ is a specified performance criteria for objective i.

We further explore cooperative stability and regional power dynamics through policy and pathway diagnostics. Policy and pathways diagnostics uses visual analytics (Keim, 2002) to illustrate how regional partners choose to defect and examine how defection shapes regional infrastructure pathways. Patterns within the decision space reveal opportunities for utilities to exploit their regional partners. These patterns may also illustrate structural imbalances in power and agency between regional partners. Specifically, they allow us to map each actors *power to* effect change effect in the system (Avelino & Rotmans, 2009). When coupled with visual analytics, this mapping provides a comprehensive picture of the vulnerability of the regional partnership to cooperative defections. This analysis provides guidance on how the problem formulation may be adjusted to reduce the potential for regional defection and increase the cooperative stability of robust regional compromises.

3.5.2 DU Re-evaluation of Defection Alternatives

After examining the consequences of defection in the objective space, we re-evaluate all defection alternatives under deep uncertainty. For DU re-evaluation, we stress-test defection alternatives across the full set of DU SOWs described in section 3.1.3. Results are used to calculate the robustness of each defection alternative. The resulting change in robustness due to defection provides insight into the nature of robustness conflict and the effects of deep uncertainties on cooperative stability. For defecting utilities, we measure the greatest improvement in robustness the utility can achieve through defection for each satisficing criteria without reducing robustness in any other criteria:

$$R_i^{rob} = max_j[\eta_i^j] \;\; \forall \; j \; \in \beta \tag{29}$$

$$\eta_i^j = \begin{cases} S(x)_i^j - S(x)_i^{comp} & if \; \forall \; k \neq i : S(x)_k^{comp} \leq S(x)_k^j \\ 0 & \text{otherwise} \end{cases} \tag{30}$$

Where β is the set of all re-optimized solutions, $S(x)_i^j$ is the robustness of the i^{th} performance criteria in the j^{th} re-optimized portfolio, and $S(x)_i^{comp}$ is the robustness for the i^{th} performance criteria in the selected compromise portfolio.

For cooperating utilities, we measure the maximum loss in robustness resulting from defection by another utility:

$$R_i^{rob} = max_j[\eta_i^j] \;\; \forall \; j \; \in \beta \tag{31}$$

$$\eta_i^j = S(x)_i^j - S(x)_i^{comp} \tag{32}$$

Where β is the set of all re-optimized solutions, $S(x)_i^j$ is the robustness of the i^{th} performance criteria in the j^{th} re-optimized portfolio, and $S(x)_i^{comp}$ is the robustness for the i^{th} performance criteria in the selected compromise portfolio.

Positive changes in robustness indicate that a utility benefits from defection from the cooperative compromise, and negative values of indicate that a utility is hurt by defection. For defecting utilities, positive changes in robustness indicate that they have power to unilaterally improve their robustness to deep uncertainties. For non-defecting utility, negative changes in robustness indicate a loss of agency to control robustness.

Taken together, robustness change and cooperative regret provide a comprehensive picture of the cooperative stability of a compromise portfolio. The metrics reveal the implications of a compromise across multiple objectives for each actor. The two metrics also illustrate opportunities and vulnerabilities that result from selection of a given compromise. Additionally, comparing the two metrics help to reveal how system uncertainty shape conflict within the system.

3.5.3 Scenario Discovery

Beyond direct measures of performance changes, our RDA extension of the DU Pathways framework employs scenario discovery (Groves & Lempert, 2007) to learn how defection changes the utilities' vulnerabilities to deep uncertainties. Scenario discovery provides an alternate framing for evaluating a cooperative policy. Rather than measuring how well a policy performs across deeply uncertain futures, scenario discovery searches for combinations of deep uncertainty cause the policy to fail, and identifies thresholds in system inputs that result in failure (Groves & Lempert, 2007). In the context of our regional defection analysis, scenario discovery strengthens our understanding of regional power dynamics by revealing how actor can shape the vulnerability of their cooperating partners. During the scenario discovery process, each DU SOW that a given solution has been evaluated under is classified as either a "success" or a "failure" based on whether the solution meets the satisficing criteria for the given SOW. Then, a classification algorithm is applied to partition the uncertainty space into regions that likely result in success or failure, and rank the importance of uncertain factors for predicting success (Bryant & Lempert, 2010). Common algorithmic choices include the Patient Rule Induction Method (PRIM; (Friedman & Fisher, 1999)), Classification and Regression Trees (CART; (Loh, 2011)) and logistic regression (Quinn et al., 2018). In this study, we employ a Boosted Trees algorithm (Drucker & Cortes, 1996), which is better suited to scenario discovery in infrastructure investment and water portfolio pathway planning because it can capture non-linear and non-differentiable boundaries in the uncertainty space that are particularly prevalent with discrete capacity expansions, provide a clear means of ranking the importance of uncertain factors, are resistant to overfitting and yield results that are easily interpretable by decision makers (Trindade et al., 2019).

4 Computational Experiment

We start with a Pareto-approximate set of cooperative water supply portfolios discovered by Trindade et al. (2020) using the Borg Multi-objective Evolutionary Algorithm (MOEA) (Hadka & Reed, 2012). The Borg MOEA was parameterized following recommendations in Hadka and Reed (2015). The optimization by Trindade et al. (2020) was performed using nine random seeds, each run for 125,000 function evaluations. Each function evaluation represents 1,000 realizations of synthetic streamflow/evaporation time series, each pared with a different DU SOW. To ensure convergence, runtime diagnostics were performed by evaluating the change in hypervolume indicator (Fonseca et al., 2006) achieved by each seed over the optimization run. ϵ-values used for each decision varaible and details on runtime diagnostics can be found in Trindade et al. (2020). The final Pareto-approximate set was taken as the set of non-dominated solutions across all random seeds. Optimization was conducted on the Stamepede2 Supercomputer from the Texas Advanced Computing Center (TACC) accessed through the NSF XSEDE Program (Towns et al., 2014).

We re-evaluated each of the Pareto-approximate portfolios under deep uncertainty across the full set of one million SOWs. This DU re-evaluation was conducted on the Comet Supercomputer from the San Diego Super Computing Center accessed through the NSF XSEDE program (Towns et al., 2014). Results of this DU re-evaluation are used to select the Least Squares and Power Index compromises.

Next, we performed individual optimizations for each utility under both compromise portfolio. Each individual optimization run was for 50,000 function evaluations across four random seeds. Runtime diagnostics for each defection scenario can be found in Section 2 of the supporting information to this paper. Regional defection optimization runs were performed on TACC's Stampede2 super computer accessed through the NSF's XSEDE program (Towns et al., 2014). Finally, we re-evaluated each each Pareto-approximate set across the full set of DU SOWs. This DU re-evaluation was conducted on he Comet Supercomputer from the San Diego Super Computing Center accessed through the NSF XSEDE program (Towns et al., 2014).

We perform scenario discovery with boosted trees using the scikit-learn Python package (Pedregosa et al., 2011). Each classification used an ensemble of 500 trees of depth four with a learning rate of 0.1.

5 Results

In this section, we illustrate how and why regional conflict may occur in seemingly robust cooperative regional infrastructure investment and water supply portfolio policy pathways. We use these insights to map asymmetries in regional power and explore dimensions of cooperative stability that have been ignored in regional water supply planning studies. Our results are presented as follows: first, we present two regional compromise policies, and examine how they differ in regional performance, robustness and their underlying policy rule systems. Next, we explore the potential incentives for and consequences of regional defection by measuring cooperative regret across the five performance objectives. We then show how regional defections would change policy rule systems and infrastructure pathways to benefit individuals versus the region, and illustrate how this alters the power dynamics between the cooperating actors. Next, we explore the implications of defection on utility robustness and illustrate changes in regional vulnerability using scenario discovery, illustrating the potential for inter-actor choices to change what deeply uncertain factors yield the most consequential vulnerabilities. We conclude by discussing the importance of power and agency to deeply uncertain infrastructure pathways and presenting actionable alternatives to improve the cooperative stability of the regional system.

5.1 Compromise Policies: The Social Planner versus The Pragmatist

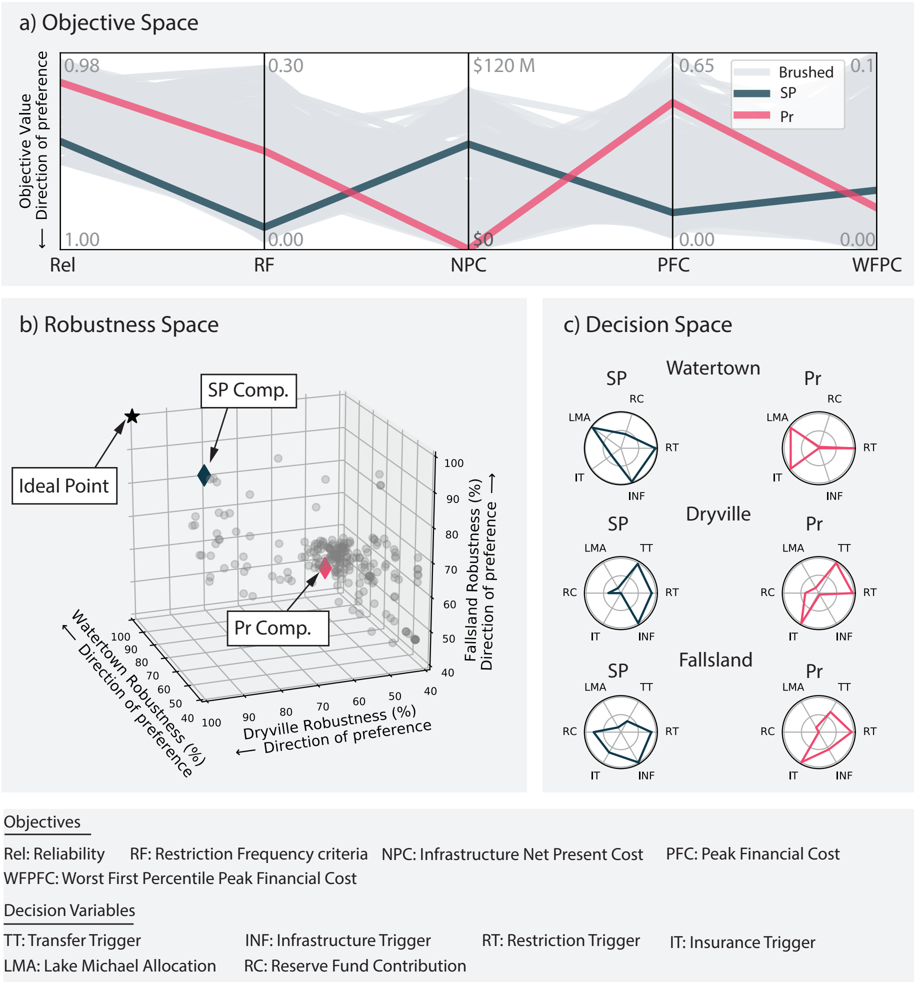

Figure 4. Selected compromise policies. Panel a) shows the regional objective space. Each axis represents a regional performance objective, and each line represents a different policy. The dark blue line represents the social planner's compromise, and the light red line represents the pragmatist's compromise, grey lines represent Pareto approximate policies that were not selected. b) the robustness of candidate policies for each water utility. c) the decision space for the two selected compromise portfolios.

Although visual analytics and trade-off analyses can capture a wide variety of individual and regional preferences, here we demonstrate the negotiated design selection process outlined in section 3.4 to select two regional compromise infrastructure investment and water portfolio management policies using robustness as a measure of utility preference. The social planner's compromise seeks to maximize collective regional robustness, while the pragmatist's compromise seeks to equalize the potential loss of benefits due too compromise across all actors. Figure 4a shows the Pareto approximate set of cooperative policies for the five regional objectives, with the two compromises highlighted. In Figure 4a, each parallel axis represents a regional objective, and each line represents a Pareto approximate regional pathway policy. The location that each line crosses each vertical axis corresponds to the policy's objective value. Though selected through robustness, Figure 4a reveals that the two regional compromises have fundamentally different behaviours in the objective space. The social planner's compromise yields relatively high regional reliability along with relatively low restriction frequency. These benefits come at the cost of a significant dependence on increased regional infrastructure investment, shown in the NPC objective. The social planner's compromise relies on strong regional cooperation to coordinate infrastructure investment. In contrast, the pragmatist's compromise has an infrastructure investment cost of zero, at the expense of lower reliability and increased restriction frequencies. The pragmatist's compromise also has a much higher peak financial cost when compared to the social planner's compromise, though the two compromises have similar worst first percentiles costs. The low infrastructure investment cost and high peak financial cost (which is mostly comprised of drought mitigation cost) suggests that the pragmatist's compromise employs a dominantly "soft-path" strategy (Gleick, 2003) that relies more heavily on short term drought mitigation.

The robustness of the Pareto approximate policies is shown in Figure 4b. Each point in Figure 4b represents a cooperative pathway policy, and each axis represents the robustness of a cooperating water utility. Figure 4b clearly shows the difference between the social planner's and pragmatist's strategies for selecting a compromise. The social planner's compromise, shown in dark blue, is a clear outlier, and represents the closest point to the regional ideal. In contrast, the pragmatist's compromise lies in the middle of the Pareto approximate set, but is similarly distant from the ideal point in all three dimensions. Additionally, Figure 4b illustrates that for the two selected policies, cooperative infrastructure investment - a strong component of the social planner's compromise - increases the robustness for all three utilities, but widens the performance disparities between the utilities.

The differences between the two compromise policies are further revealed by examining their decision spaces, shown in Figure 4c. Each subplot in Figure 4c contains a radial plot of the compromise pathway policies' decision variables, with each axis representing a decision variable, and values further from the center representing increased use of the given decision variable. Figure 4c illustrates several key differences in the two compromises that explain their differences in performance. First, infrastructure investment (INF), is a core part of all three utility's water supply portfolios under the social planner's compromise but has very low use under the pragmatist's compromise. Interestingly, in the social planner's selection, all three utilities also make extensive use of water use restriction triggers, though the regional restriction frequency objective is near its minimum value (as shown Figure 4a). The pragmatist's compromise also employs high use of water use restrictions, which in the absence of infrastructure investment yields a higher regional restriction frequency in Figure 4a. The two compromises are very similar in terms of the allocation of Lake Michael - under both compromises Watertown is close to its maximum allocation while Dryville and Fallsland are near their minimums. This suggests that regardless of the level of infrastructure investment, Lake Michael is an important supply source for Watertown. Lake Michael still plays a role in the water supply policies of Dryville and Fallsland, despite their low allocations. For Dryville, both compromise policies make extensive use of treated transfers, suggesting that Dryville likely uses transfers as a first response to drought in coordination with water use restrictions. Fallsland purchases treated transfers more readily under the pragmatist's compromise, but still favors water use restrictions under both policies, indicating that it will use treated transfers under severe drought conditions, but relies on water use restrictions as a first response.

The two compromises also differ in their use of financial instruments. Under the social planner's compromise, both third party insurance and reserve funds are employed by Watertown and Fallsland, while Dryville employs only a reserve fund. The use of the reserve fund allows the utilities to maintain financial stability under the large debt burden from infrastructure investment. The use of third-party insurance covers financial disruptions from low-probability drought events. Under the pragmatist's compromise, which has low infrastructure investment, all three utilities make very low reserve fund contributions, instead making extensive use of third-party insurance. Without the debt burden from infrastructure investment, the utilities can maintain high performance with only the purchase of third party insurance to offset the cost of drought mitigation. The differences in how the two compromises incorporate financial instruments highlights the importance of jointly assessing supply reliability and the utilities' finances. Both compromise policies demonstrate careful coordination of financial instruments, drought mitigation and infrastructure sequencing, allowing the utilities to balance the conflicting objectives of supply reliability and financial health.

Under the metrics shown in Figure 4, the two compromise portfolios offer different, but plausible cooperative compromises for the regional system. Yet important questions remain. Do the utilities incur new risks by entering into a regional agreement? Do the cooperating partners have incentives to leave the regional agreement once it has been implemented? How do the actions of one partner influence the performance and vulnerability of the others? Our RDA extension of deeply uncertain pathways methodology enables a rigorous examination of these questions and clarifies important power dynamics within the regional system.

5.2 Individual Defection Optimization

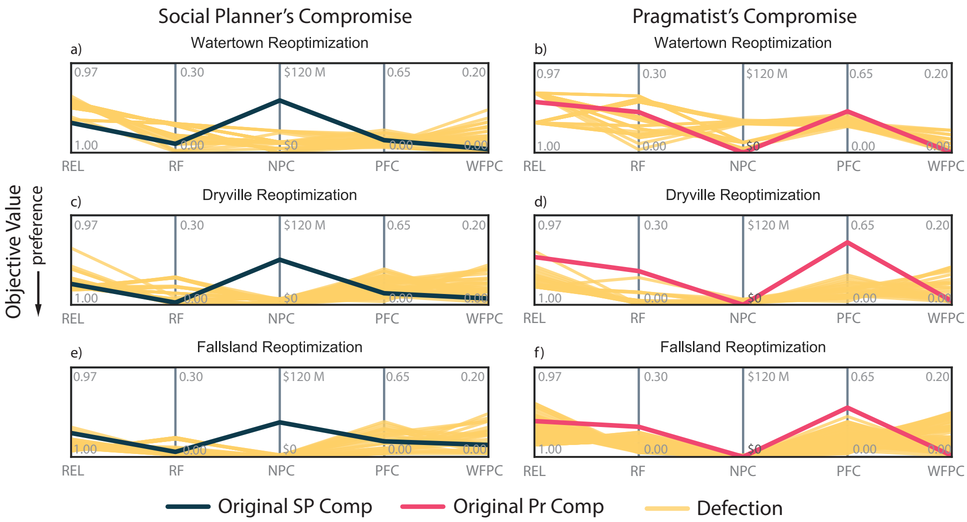

Figure 5. Results of individual defection optimization. The left column (panels a, c and e) represent defection from the Social planner's compromise for Watertown, Dryville and Fallsland respectively. The right column represents defection from the pragmatist's compromise. Each parallel axis represents an objective for the individual utility and each line represents a different policy. The social planner's compromise is shown in dark blue and the pragmatist's compromise is shown in light red. Each yellow line represents a defection policy. Results indicate that all three utilities can benefit from regional defection, though how they benefit varies between the two compromises and across the three utilities.

The results of the individual defection optimization runs described in section 3.5.1 are shown in Figure 5. Each panel contains a parallel axis plot showing the Pareto-approximate set of defection solutions discovered in each individual defection optimization. Each axis represents a performance objective for the individual utility, and each line represents a water supply policy. Dark blue lines represent the social planner's compromise, light red lines represent the pragmatist's compromise and yellow lines represent defection alternatives. Examination of Figure 5 reveals that all three utilities may substantially benefit from defection under both compromises, but how they benefit differs significantly between the two compromise pathway policies. Under the social planner's compromise, Watertown could reduce its overall infrastructure investment while maintaining relatively high performance across the remaining objectives, as shown in Figure 5a. Under the pragmatist's compromise, Watertown has no room for improvement in infrastructure spending, but could improve reliability, restriction frequency and peak financial costs, as shown in Figure 5b. Like Watertown, Dryville and Fallsland may both reduce their infrastructure spending through defection under the social planner's compromise as shown in Figure 5c and 5e. Under the pragmatist's compromise both Dryville and Fallsland can improve their reliability, reduce restriction frequency and peak financial cost without increasing their infrastructure spending.

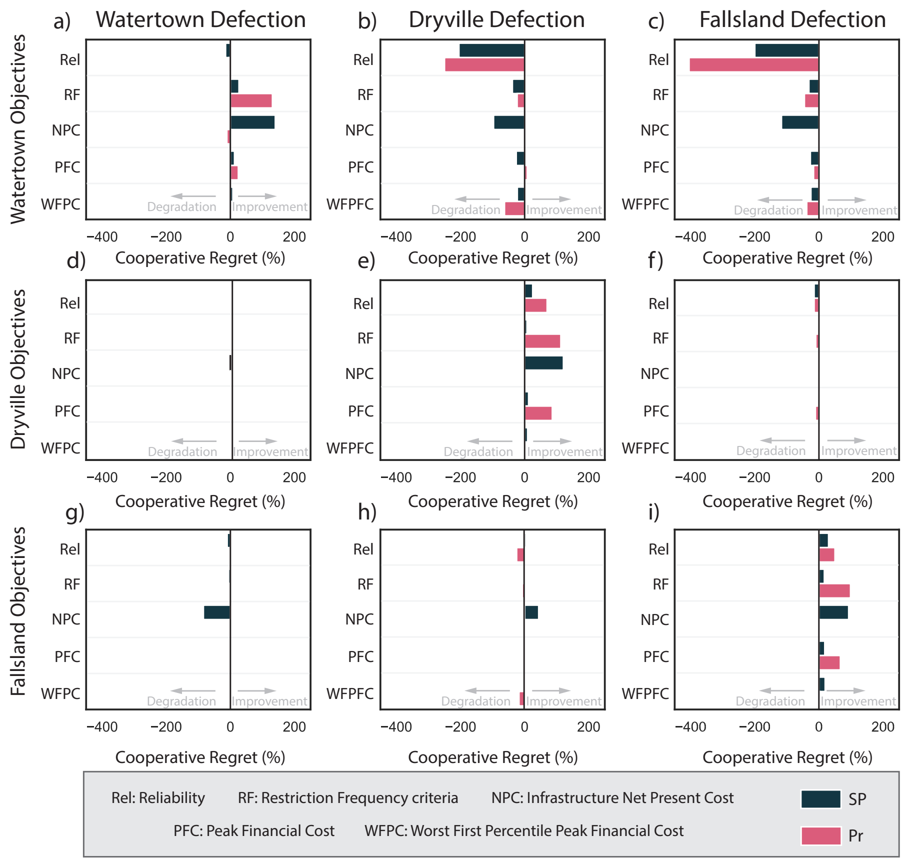

Figure 6. Cooperative regret. Each panel contains the cooperative regret for a single utility under a defection scenario. The five performance objectives are represented on the vertical axis and the cooperative regret is shown on the horizontal axes. The effect of defection on Watertown is shown in the top row of panels, Dryville is in the middle row and Fallsland is on the bottom. Each column represents defection by a different utility, with Watertown defection on the far left, Dryville in the center and Fallsland on the right. Dark blue bars represent regret from the social planner's compromise, while light reg bars represent regret from the pragmatist's compromise.

While the results in Figure 5 suggest that the utilities may have incentives to defect from the regional partnership, are limited in the information they provide on how regional defection may shape the cooperative stability of the selected compromises. To further explore cooperative stability, Figure 6 shows the cooperative regret for each utility under both compromise portfolios. Each panel illustrates regret for a single utility under a different defection scenario. Cooperative regret from the social planner's compromise is shown in dark blue bars, and cooperative regret from the the pragmatist's compromise is shown in light red bars. Bars on the right side of the plots indicate that the utility may benefit from defection, while bars on the left side of the plots indicate that utility objectives are degraded from defection.

Examining cooperative regret reveals several important insights into cooperative stability of both compromise portfolios. First, all three utilities can clearly benefit from defection under both compromise portfolios as demonstrated in Figure 6a, e and i, though the benefits differ across the three utilities and the two portfolios. Figure 6a reveals that under social planner's compromise Watertown can greatly reduce its infrastructure investment cost without sacrificing performance in the other objectives. Under the pragmatist's compromise, Watertown can reduce its restriction frequency, but cannot meaningfully improve in its performance in other objectives. Figure 6e shows that under the social planner's compromise, Dryville can reduce its infrastructure spending and modestly improve its reliability. Under the pragmatist's compromise, Dryville can increase its reliability, reduce its restriction frequency, and reduce its peak financial cost. Figure 6i illustrates that Fallsland benefits from defection in a similar manner to Dryville. Under the social planner's compromise, Fallsland defection reduces infrastructure spending and modestly increase reliability. Under the pragmatist's compromise Fallsland may improve reliability, restriction frequency and peak financial cost objectives.

The consequences of defection from the regional agreement are highly asymmetric across the three utilities. Figure 6d shows that Watertown defection has little impact on Dryville under either compromise. Conversely, Dryville defection greatly reduces Watertown's reliability under both compromises, as shown in Figure 6b. Under the social planner's compromise, Dryville defection causes Watertown's infrastructure cost to increase significantly. Under the pragmatist's compromise Watertown's restriction frequency and worst case peak financial cost are also degraded by Dryville defection. A similar asymmetry is present between Watertown and Fallsland, though to a lesser extent. Figure 6g illustrates how under the social planner's compromise, Watertown defection increases Fallsland's infrastructure cost, suggesting that the coordinated infrastructure investment exposes Fallsland to risk from its cooperating partner. The impact of Fallsland defection on Watertown differs notably between the two compromises. When Fallsland defects from the social planner's compromise, Watertown is forced to increase its infrastructure spending, but also loses reliability, as shown in Figure 6c. When Fallsland defects from the pragmatist's compromise, Watertown sees a precipitous decline in reliability and small performance degradations in restriction frequency and worst case cost. Unlike Watertown, Fallsland faces very little regret from Dryville defection, and the utility even benefits slightly in infrastructure cost under the social planner's compromise as shown in Figure 6h. Likewise, Fallsland defection has very little impact on Dryville performance as shown in Figure 6f.

Figure 6 illustrates two new dimensions of regional stability not captured in the original robustness based metrics used to select the two compromises. First, it reveals that the incentives to defect from the regional partnership - the potential causes of regional conflict - fundamentally differ between the two compromises. Under the social planner's compromise, which relies on careful coordination of infrastructure investment between the three utilities, defection allows all three utilities to drastically reduce their infrastructure spending while maintaining performance across other objectives. This suggests that under the social planner's compromise, each utility can exploit the investments made by their neighbors to increase their own performance. Conversely, under the soft-path centered pragmatist's compromise, the incentives to defect manifest as improvements to reliability, restriction frequency and peak financial cost. Under the pragmatist's compromise, all three utilities may reduce their restriction frequency and Dryville and Fallsland may improve their reliability and peak financial cost objectives. In the absence of binding enforcement of the regional agreement, all three utilities are found to have the power to unilaterally improve their performance with respect to the original comprise. Acknowledging this power, and mapping the incentives to defect can inform the design of contractual agreements that reduce these incentives.

The second new dimension of regional stability revealed by Figure 6 is the differing consequences of defection between the two compromise portfolios. Under both compromises, Watertown's performance across multiple objectives is reduced by defection from either cooperating partner. Fallsland faces increased infrastructure investment cost under the social planner's compromise, and no consequences under the pragmatist's compromise. Dryville faces little to no consequences from defection under either compromise. The disparity between the three utilities suggests that Dryville and Fallsland have the power to fundamentally shape Watertown's performance through defection, while Watertown has limited power to shape the performance of its partner utilities. This power dynamic is not apparent from the original metrics of cooperative stability and may inform the creation of new cooperative agreements. However, to make this information actionable, we must explore the decisions each utility is incentivezed when defecting from the regional partnership.

5.3 Defection Alternatives and Infrastructure Pathways

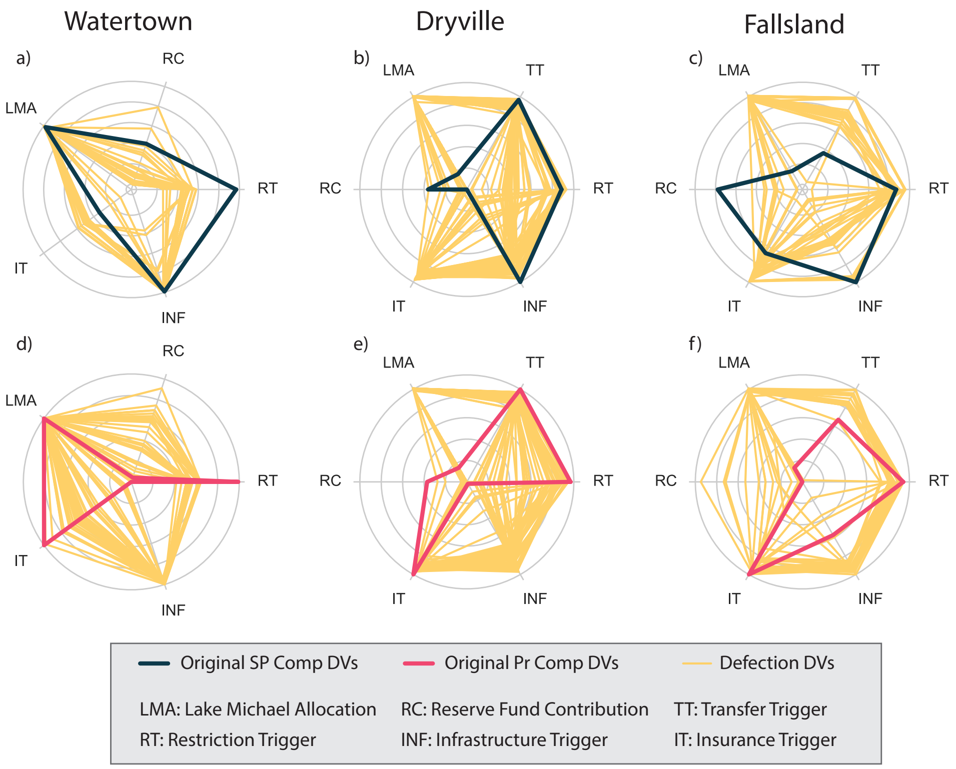

Figure 7. Decision variables of defection alternatives. Each panel shows the set of defection alternatives for one utility under one compromise policy. Each axis on the radial plot represents a decision variable, and each line represents a different policy. The distance from the origin represents increased use of each variable. The top row of panels shows defection from the social planner's compromise, while the bottom shows defection from the pragmatist's compromise. The original compromise portfolios are shown in dark blue and light red. Defection alternatives are shown in yellow lines.

The decision variables that compose the defection alternatives for each utility are shown on the radial plots in Figure 7. Each utility's decision variables are plotted on a radial axis, with increased use of each variable corresponding from values further from the center. Each line corresponds to a different water supply policy. The top row of plots shows the social planner's compromise, with dark blue lines representing the original decision variables and yellow lines representing defections. The bottom row of subplots shows the pragmatist's selection, with the light red line representing decision variables of the original compromise and yellow lines representing defection.

Watertown lowers its reliance on water use restrictions when defecting from both compromise portfolios, suggesting that Watertown either uses restrictions to aid regional partners in the original compromises or needs more conservative restriction policies to maintain robust performance under the broader DU sampling. Under the social planner's compromise, Watertown may also raise the level of risk it tolerates before investing in new infrastructure, explaining its ability to reduce infrastructure spending. Under the pragmatist's compromise, many of Watertown's defection alternatives increase the use of infrastructure, suggesting that Watertown can unilaterally improve its reliability and restriction frequency by investing in infrastructure. To offset the risk of high debt burden from infrastructure investment, Watertown increases its reserve fund contribution in many defection alternatives. Across both compromise portfolios Watertown continues to maximize its allocation of Lake Michael under all defection alternatives.

Like Watertown, Dryville also seeks to maximize its Lake Michael allocation. Under all defection alternatives for both compromise policies, Dryville maximizes its own allocation of Lake Michael. It also maintains its high reliance on treated transfers, indicating that these portfolios heavily rely on water from Lake Michael to augment Dryville's water supply in times of drought. Many of Dryville's defection alternatives from the social planner's compromise maintain a high use of infrastructure investment. Surprisingly, results shown in Figure 5 indicate that this does not translate into increased infrastructure spending. This suggests that the supply augmentation from Lake Michael lowers Dryville's baseline risk level enough to only trigger new infrastructure under extreme scenarios. This phenomenon can also be observed under the pragmatist's compromise, where many of Dryville's defection alternatives also increase use of infrastructure investment though its investment cost objective remains low.

Like Dryville, Fallsland maximizes its Lake Michael allocation in all defection alternatives under both compromise portfolios. It correspondingly increases its use of treated transfers when defecting from both portfolios, suggesting that it also heavily relies on Lake Michael to augment its water supply in times of drought. Under the social planner's compromise, the majority of Fallsland's defection alternatives decrease the use of infrastructure investment, while under the pragmatist's compromise many defection alternatives increase the use of infrastructure investment. However, as illustrated in Figure 5e and f, all defection alternatives under both compromises have low infrastructure cost for Fallsland. This suggests that like Dryville, the increased allocation from Lake Michael is enough to lower Fallsland's baseline risk, reducing the need to invest in new infrastructure.

The changes to water supply policies shown in Figure 7 illustrate the careful coordination between cooperating partners present in the both original compromises. This is most strongly emphasized by how the use of treated transfers from Lake Michael differ between the original compromises and defection alternatives. Under both original compromises Watertown is granted the majority of the Lake Michael allocation, but provides treated transfers readily when its cooperating partners are in need. Watertown's high use of restrictions in both of the original compromises suggests the solutions tacitly assume that in times of drought it will be willing reduce its own withdrawls from Lake Michael, while providing treated transfers to its cooperating partners. Under all defection alternatives however, Dryville and Fallsland maximize their allocation to Lake and take advantage of treated transfers to augment their existing supplies.

Results in Figure 7 further suggest that the allocation of Lake Michael is the most likely driver of regional conflict. Under both original compromises, Watertown is assigned its maximum Lake Michael allocation while Dryvile and Fallsland are assigned allocations near their minimums. In all defection alternatives, each utility seeks to maximize its own allocation at the expense of its partner utilities. This exploitation would not be possible in the absence of the original agreements; under the original compromise portfolios, all three utilities heavily rely on water use restrictions, so when a utility increases its Lake Michael allocation, it is exploiting the other utilities' restrictions to access augment supply during time of shortfall. For both Dryville and Fallsland, increased reliance on treated transfers can alleviate the need for infrastructure investment while maintaining high reliability, low restriction frequency and low financial risk. But access to Lake

Michael is controlled by Watertown, who owns the only water treatment facility on the reservoir. Should Dryville and Fallsland seek to increase their allocations, they risk sparking a conflict with Watertown and loses access to transfers entirely. The dynamics leading to this potential conflict can be further explored by examining how regional defection alters the infrastructure pathways generated by the compromise policies.

Figure 8 shows infrastructure pathways under the social planner's compromise (the pragmatist's compromise is not shown as it has very little infrastructure). Pathways generated from full cooperation are shown in the panels on the left, while pathways resulting from a selected defection alternative for each of the three utilities are shown in the other columns. Watertown pathways are shown in the top row of plots, Dryville in the middle row and Fallsland on the bottom row. Within each panel, a utility's infrastructure options are shown on the vertical axis, and the horizontal axis represents the time each infrastructure option is triggered. The dynamic state-aware rule system used in the Sedento Valley cooperative portfolios create a unique sequence of infrastructure development under each future SOW. To visualize the dynamics of these pathways, Figure 8 summarizes the actions of each utility by clustering high, medium and low infrastructure SOWs and plotting the average time each infrastructure is triggered for each cluster. The frequency that each infrastructure option is triggered across all SOWs is represented as the shading behind the clusters.

Figure 8 reveals how each utility may reduce their reliance on infrastructure investment through defection, and how other cooperating partners are impacted by each utility's defection. Through defection, Watertown may drastically reduce its infrastructure investment, eliminating individual infrastructure investments and only constructing the New River Reservoir, which it shares with Fallsland, near the end of the planning horizon. Similarly, when Fallsland defects, it only constructs the shared New River Reservoir late in the planning horizon. The most dramatic impact of defection however can be observed in Dryville's pathways, where infrastructure investment is almost entirely eliminated. Defection by Dryville and Fallsland have little impact on each other, while Watertown is forced to build to invest early or more heavily in new infrastructure when either cooperative partner defects.

Results of the individual optimizations reveal that all three utilities have incentives to defect from the regional partnership and that this defection may have severe and asymmetry consequences for utility performance and the resulting infrastructure pathways. But these results only examine performance changes in expectation across on the smaller DU sampling strategy employed during search. This raises the question - does our perception of cooperative stability change when inter-utility robustness trade-offs are evaluated under the broader DU re-evaluation exploration of SOWs?

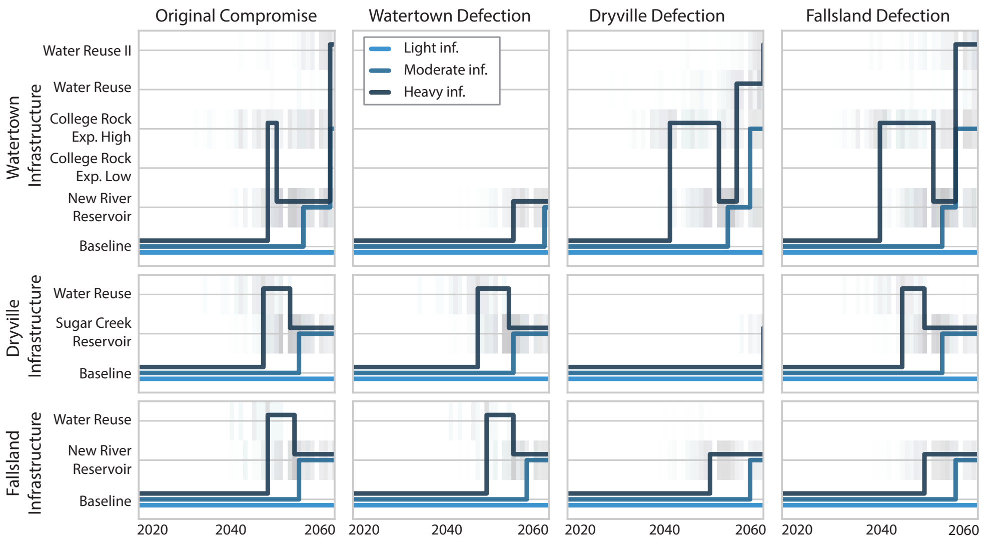

Figure 8. Changes to Infrastructure Pathways by defection from the social planner's compromise. The vertical axis contains possible infrastructure options for each utility, and the horizontal axis represents time. As each SOW generates a unique infrastructure pathway, we visualize a policy by clustering the SOWs by infrastructure intensity. Three clusters were generated using K-nearest neighbor clustering, shown as the three lines on each plot. Shading in each row represents the frequency that each infrastructure option was triggered at a given time across all SOWs. Infrastructure pathways generated by the original compromise are shown in the column to the left, while the most robust defection alternative for each utility are shown in the other three columns.

5.4 Cooperative Stability and Deep Uncertainty

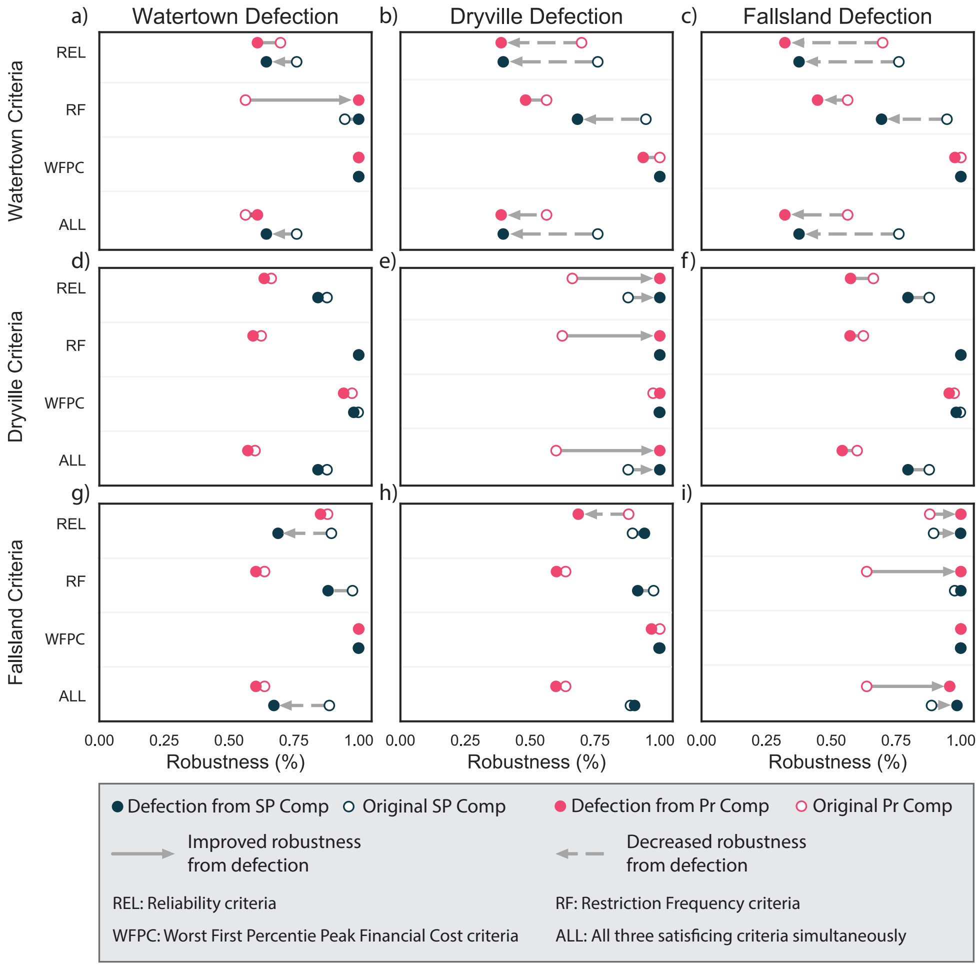

Figure 9. Changes to robustness from defection across the saticificing criteria. Each panel contains the robustness change for a single utility under a defection scenario. The three satisficing criteria are represented on the vertical axis and the robustness change is shown on the horizontal axes. The effect of defection on Watertown is shown in the top row of panels, Dryville is in the middle row and Fallsland is on the bottom. Each column represents defection by a different utility, with Watertown defection on the far left, Dryville in the center and Fallsland on the right. Open circles represent the robustness of the original compromise, while closed circles represent the robustness after defection. Dark blue points/lines represent the robustness of the social planner's compromise, while light reg points/lines represent robustness of the pragmatist's compromise.

Figure 9 shows how defection affects each utility's robustness to deeply uncertain futures. Each subplot shows change in robustness for a single utility under a different defection scenario. The robustness of the original compromise portfolios are shown as open circles, and the robustness after defection are shown as closed circles. Dark blue circles represent the social planner's compromise, and light red circles represent the pragmatist's compromise. Improvement in robustness is indicated by a solid grey arrow moving right, decrease in robustness is shown as a grey dashed line moving left.

Figure 9 highlights important differences between evaluating stability with robustness versus cooperative regret based on changes in the individual utilities' performance objectives. Watertown, which has a clear incentive to defect when measured by cooperative regret, does not have a clear incentive when defection incentives are assessed using robustness. In fact, under the social planner's compromise, defection decreases Watertown's robustness as shown Figure 9a. This indicates that though defection may improve Watertown's performance in expectation across an approximation of the full deep uncertainty space, its defection actions may expose it to new vulnerabilities captured in the larger DU re-evaluation. Watertown's decrease in robustness is primarily due to a small decrease in its ability to meet the reliability criteria. Watertown is subject to a similar decrease in reliability robustness under the pragmatist's compromise, though it also has the potential to greatly improve it's robustness in terms of its restriction frequency criteria.

Unlike Watertown, Dryville and Fallsland have clear and consistent incentives to defect from both compromise portfolios when defection is evaluated from the perspective of robustness. Under both portfolios defection from the cooperative agreement has the potential to make both utilities nearly 100% robust to deep uncertainties, meaning they can meet their performance criteria in nearly all of the one million SOWs used in the DU re-evaluation. This improvement in robustness for Dryville and Fallsland comes at a price for their regional partners. Like cooperative regret, changes in robustness show that Watertown's performance is severely degraded by defections under both compromise selections. Additionally, robustness changes reveals tension between Dryville and Fallsland that is not captured through the cooperative regret results in Figure 6. When Dryville defects from the pragmatist's compromise, Fallsland's robustness in reliability is significantly reduced, as shown in Figure 9h. Under the social planner's compromise however, Fallsland's robustness is not signicantly a effected by Dryville defection. When

Fallsland defects, Dryville's robustness is reduced under both compromise portfolios, primarily driven by reductions in reliability robustness. These changes demonstrate that in the regional system, the perception of regional tension changes depending on the scope of future scenarios evaluated during the planning process.

The impacts of regional defection on utility robustness are further illustrated through scenario discovery. Figure 10 contains factor maps, which plot the utilities success and failure in meeting performance requirements (reliability ¿ 98%, restriction frequency ¡ 10% and worst first percentile peak financial cost ¡ 10%), for the most robust defection alternative for each utility (details on the robustness of defection alternatives can be found in Section 3 of the supporting information). Each factor map's vertical and horizontal axes plot the two most influential deep uncertainties for each utility as classified using boosted trees. Grey points represent SOWs where the utility meets all satisficing criteria, while red points represent SOWs where the utility fails to meet all criteria. The percentages next to each uncertainty on the horizontal and vertical axes labels represent the percent decrease in impurity from the tree ensemble by splits on that factor, with higher percentages indicating higher sensitivity to the factor. The color mapped in the background of each factor map represents the predicted success or failure regions for the given utility across the combinations of the two uncertainties. The original compromise portfolios are shown in the left most column, and the columns to the right represent Watertown, Dryville and Fallsland defection scenarios respectively.

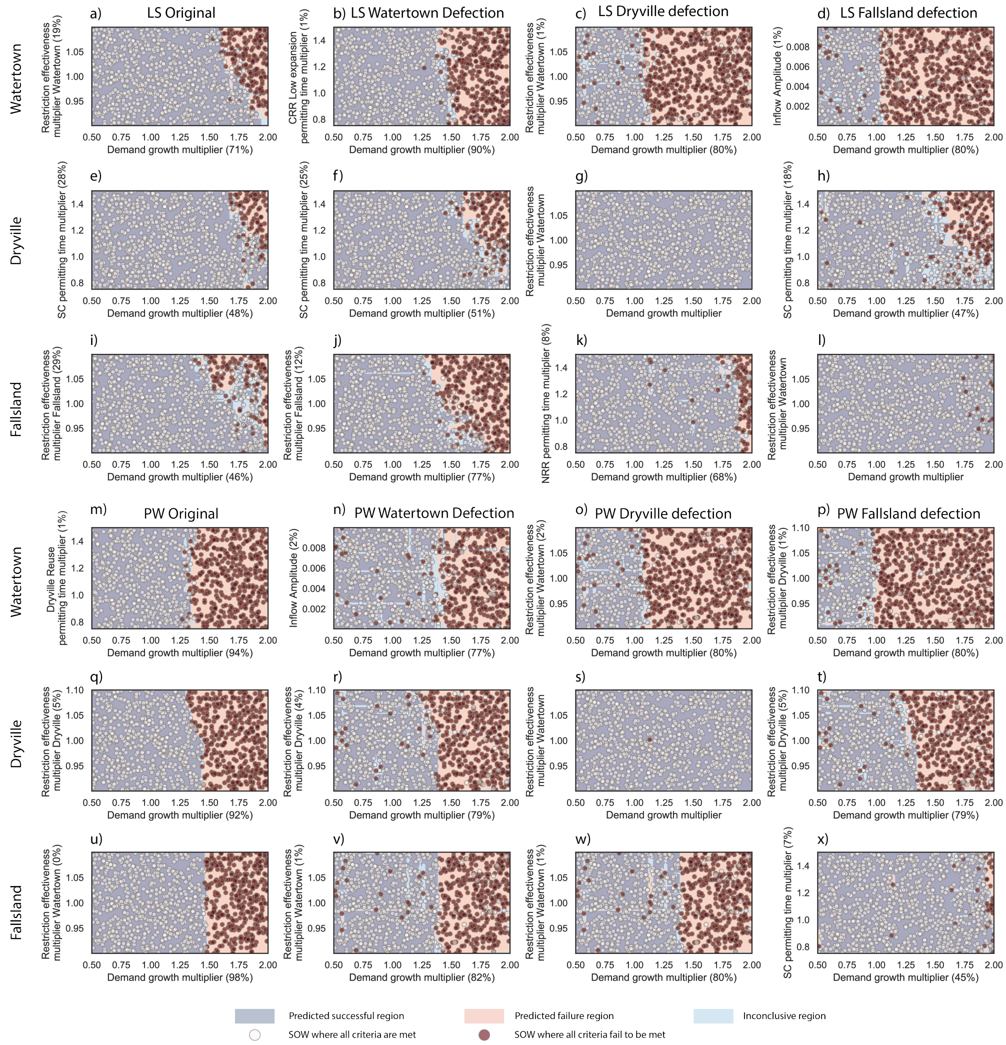

Figure 10. Factor mapping generated using boosted trees for the most robust defection alternative for each utility. Each figure shows the top two factors that control robustness for a utility under a different defection scenario. The original compromises are shown in far left column while each other column represents the most robust defection alternative for one of the partner utilities. Blue shaded regions represent regions of the uncertainty space where utilities are predicted to meet their satisficing criteria (Rel > 98%, RF < 10% and WFPFC < 10% AVR), red shaded regions are areas of the uncertainty space where policies are predicted to fail to meet satisficing criteria.

Figure 10 reveals how defection impact each utility's vulnerability to deep uncertainty. Figure 10a illustrates that under the social planner's compromise, Watertown is vulnerable to SOWs with high demand growth and high restriction frequency effectiveness. High demand growth may stress all three satisficing criteria, lowering reliability, increasing the frequency of water use restrictions and subsequently increasing drought mitigation cost. High restriction effectiveness has the potential to greatly reduce revenue from water sales, exposing the utility to financial failure. Under Watertown's most robust defection alternative this vulnerability changes: Watertown becomes vulnerable at a lower level of demand growth, and the permitting time for the College Rock Reservoir expansion becomes the second most important deep uncertainty, as shown in Figure 10b. This change reflects Watertown's higher risk tolerance with respect to water use restrictions under defection scenarios, exposing it to reliability failures under lower levels of demand growth. When Dryville defects from the social planner's compromise, Watertown becomes vulnerable to much lower levels of demand growth, with failures predicted at values just over the estimated demand growth rate. This shift explains Watertown's large change in robustness under Dryville defection. Watertown sees a similar change in vulnerability under Fallsland defection from the social planner's compromise.

Under the original pragmatist's compromise, Watertown is vulnerable to lower levels of demand growth, with demand growth multiplier values above 1.3 likely leading to failure. However, when Watertown defects from this compromise, it may slightly increase its tolerable level of demand growth, reflecting the small positive change in robustness shown in Figure 9a. Under Dryville and Fallsland defections, Watertown becomes vulnerable to much lower levels of demand growth in a similar manner to defections from the social planner's compromise. Interestingly, under all defection scenarios Watertown has a small number of SOWs that fail under low levels of demand growth, indicating that other factors or combinations of factors may cause vulnerabilities that are difficult to predict.

Transitioning to Dryville, Figure 10e reveals that under the original social planner's compromise, Dryville is vulnerable to a combination of high demand growth and long permitting time for the Sugar Creek reservoir. This highlights Dryville's reliance on infrastructure expansion to manage growing demands underthe social planner's compromise. When either cooperating partner defects from the social planner's compromise, Dryville's failure region increases in both directions, indicating that its cooperating partners may reduce its ability to manage growing demand and increase its reliance on a rapid permitting process for the Sugar Creek reservoir. The importance of the permitting time presents a challenge as this uncertainty is very difficult to predict. Conversely, Figure 10g illustrates that when Dryville defects from the regional agreement it is able to meet its satisficing criteria in all tested SOWs, eliminating its vulnerability to growing demand or infrastructure permitting.

Under the original pragmatist's compromise, demand growth rate is the dominant driver of Dryville's failure, though restriction effectiveness plays a minor role as shown in Figure 10q. When Watertown and Fallsland defect, the main drivers of failure remain the same, though Dryville's vulnerability to demand growth is increased under Fallsland defection. Like Watertown however, Dryville experiences failure in a small number of SOWs with low demand growth, indicating that other combinations of uncertainties may cause failure in ways difficult to predict. As the case under the social planner's solution, when Dryville defects from the pragmatist's compromise, it is able almost completely eliminate vulnerability to deep uncertainty, as shown in Figure 10s.

Examining Fallsland's vulenrability reveals that under the social planner's compromise, Fallsland is vulnerable to a combination of high demand growth rate and high restriction effectiveness, as shown in Figure 10i. When Watertown defects, this vulnerability is increased, though the salient factors remain unchanged. Dryville defection from the social planner's compromise reduces Fallslands vulnerability to all but the most extreme demand growth scenarios. When Fallsland defects, it can eliminate vulnerability in all but a small number of SOWs as shown in Figure 10j.

Under the original pragmatist's compromise demand growth rate is the only driver of failure for Fallsland, as illustrated in Figure 10u. Fallsland is not greatly affected by defection from its partners, though like the other two utilities, defection does cause vulnerability in low demand growth futures that are difficult to predict. Like under the social planner's compromise, Fallsland can almost completely eliminate vulnerability if it should defect from the pragmatist's compromise, as shown in Figure 10x.

5.5 Mapping regional power relationships

Figure 10 highlights how our RDA expansion of the DU Pathways framework broadens our conception vulnerabilities in narrative scenarios by explicitly including the actions of regional partners. Synthesizing our overall results, Figure 11 summarizes the impact of defection actions on the cooperative infrastructure investment and water portfolio management compromise policies. Figure 11a asks the question- how does regional defection impact the performance of the social planner and pragmatist compromise policies? Each row of Figure 11a represents a defection scenario, and each column represents a performance metric for one of the regional partners. The shading of each cell represents significant increases (green) or decreases (purple) to performance (defined as changes in robustness $\geq 5\%$ or changes in infrastructure spending $\geq \$10$ million). This multidimensional representation of defection incentives and consequences represents a straightforward, yet detailed illustration of cooperative stability. While both compromises are vulnerable to regional defection, the incentives and consequences of defection differ between the two compromise portfolios. This information allows regional partners to craft tailored conflict mitigation strategies for each compromise. For example, under the social planner's compromise, Fallsland and Watertown may seek to implement binding defection penalties as a precondition to the exploration of shared infrastructure investment.

a)

Social Planner's Compromise

	Watertown Performance				Dryville Performance				Fallsland Performance			
	Rel	RF	NPC	WFPFC	Rel	RF	NPC	WFPFC	Rel	RF	NPC	WFPFC
Watertown Defection	↓	↑	↑	---	---	---	---	---	↓	↓	↓	---
Dryville Defection	↓	↓	↓	---	↑	---	↑	---	---	↓	---	---
Fallsland Defection	↓	↓	↓	---	↓	---	---	---	↑	---	↑	---

Pragmatist's Compromise

	Watertown Performance				Dryville Performance				Fallsland Performance			
	Rel	RF	NPC	WFPFC	Rel	RF	NPC	WFPFC	Rel	RF	NPC	WFPFC
Watertown Defection	↓	↑	---	---	---	---	---	---	---	---	---	---
Dryville Defection	↓	↓	---	↓	↑	↑	---	---	↓	---	---	---
Fallsland Defection	↓	↓	---	---	↓	↓	---	---	↑	↑	---	---

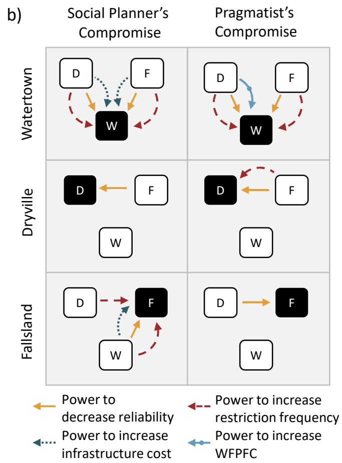

Figure 11. Cooperative stability and regional power dynamics. a) A multi-criteria perspective on cooperative stability from the RDA. Shaded cells represented significant changes in performance from regional defection, defined as changes in robustness $\geq$ 5% or changes in infrastructure spending $\geq$ \$10 million. Green shaded cells with up arrows represent incentives to defect from the regional partnership, while purple shaded cells with down arrows represent consequences of defection. All utilities have incentive to defect from both solutions and defection has consequences for all three utilities. b) A mapping of *power to* relationships within the regional system. For each water utility, we map the power that its cooperating partners have to increase its vulnerability.

To further explore the potential for regional conflict, Figure 11b asks the question-how is each actor vulnerable to the actions of their cooperating partners? In Figure 11b, we map each utility's *power to* degrade the performance of its cooperating partners. Each panel highlights the vulnerability of a water utility under one of the compromise policies. Arrows represent the power that each of the utility's partners have to degrade their performance through defection. Figure 11b illustrates how vulnerability -and conflict- may differ between the two compromise policies. For example, under the social planner's compromise, Fallsland is vulnerable to defection from both Watertown and Dryville, while under the pragmatist's compromise it is only vulnerable to defection by Dryville. With this information Fallsland learns that it must monitor the actions of both Dryville and Watertown should the the social planner's compromise be selected, but only Dryville if the pragmatist's compromise is selected. These insights represent a new dimension to cooperative stability that allow the cooperating partners to monitor how regional conflict may occur prior to selecting a regional compromise.

The *power to* relationships mapped in Figure 11 are results from our exploratory analysis of possible future scenarios, not a prediction of what will happen in the regional system. With their larger populations, Fallsland and Dryville wield more political influence in the region, and may be able to lobby the federal government to increase their allocations to Lake Michael to levels found in defection alternatives. However, Watertown-the most vulnerable utility to cooperative defection- controls the only water treatment plant on Lake Michael and has the *power to* restrict access to treated transfers. The results of the RDA allow the larger utilities to foresee strong reaction from Watertown in the event of regional defection. Importantly, there is also a strong *power with* relationship between the three utilities. Our results demonstrate that if the utilities implement a cooperative compromise without defection, they have the collective ability to achieve robust and high performance cooperative water supply management policies for the regional system. The comprehensive illustration of the benefits and vulnerabilities of cooperative compromise provided in this study allow the three utilities to enter negotiations with a transparent understanding of the regional conflict in the system.

6 Conclusion

This study advances the DU Pathways framework by contributing the exploratory modeling centered RDA to examine the potential for conflict in cooperative water supply planning problems. Our RDA first utilizes many-objective optimization as an exploratory tool to discover how cooperating partners may be incentivized to defect from a cooperative compromise, then uses scenario discovery to examine how regional vulnerability to deep uncertainty is shaped by defection. We examine our results using visual analytics to reveal how cooperating actors may choose to defect, the impact of defection action on infrastructure pathways and the power relationships between regional actors.

We demonstrate our methodology on the Sedento Valley - a regional water supply test case where three urban water utilities seek cooperative infrastructure investment and water supply portfolio pathways. Our findings reveal that seemingly stable cooperative compromises are vulnerable to defection by cooperating partners, and the consequences of defection are asymmetric across partner utilities. We use these results to map regional power relationships, which can be used by stakeholders to anticipate and avoid conflict.

While not the central focus of this study, the contrast between the social planner's compromise and the pragmatist's compromise echo two diverging approaches in the water industry today - public sector control and water utility privatization (Beecher, 2013). The social planner's compromise, with it's strong investment in shared infrastructure, mirrors a public sector approach, while the pragmatist's compromise, which emphasizes drought mitigation and purchases of treated transfers has similarity to a private sector approach. Our results show that both strategies must consider cooperative stability and regional power dynamics in order to meet the stated performance targets. Yet the differing nature of power dynamics and regional vulnerability illustrated in this analysis suggests that public sector and private sector management may be susceptible to differing forms of vulnerability. Future work can use the RDA framework proposed in this work to explicitly evaluate trade-offs between public and private sector management of water resources.

This work focuses on the *a posteriori* examination of conflict in cooperative compromises. Additional future work may investigate how cooperative problem formulations may be improved to incentivize compromise and improve cooperative stability.

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Supporting Information for "Power and Pathways: Exploring robustness, cooperative stability and power relationships in regional infrastructure investment and water supply management portfolio pathways"

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Contents

1 Objective Functions

This section presents the details of the objective formulation for the Sedento valley planning problem. These objectives were first formulated for the Sedento Valley by Trindade et al., (2020).

1. *Reliability* (f_{REL}): The reliability objective calculated as the fraction of considered states of the world which may cause the combined storage level of a utility to drop below 20% of its maximum capacity in any given week (failure condition):

$$\text{maximize } f_{REL} = \underset{j}{min}\left[\underset{y}{min}\left(\frac{1}{N_r}\sum_{i=1}^{N_r} g_{i,j}^{y}\right)\right] \tag{1}$$

where,

$$g_{i,j}^{y} = \begin{cases} 0 & \forall w \ : \ \frac{x_{s,i,j}^{w,y}}{C_j} \geq S_c \\ 1 & \text{otherwise} \end{cases}$$

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where $g_{i,j}^{y} = 0$ if there was a week in a given year of a particular realization where the combined storage of utility j falls below S_c of capacity (20% in this study), and 1 otherwise, N_r is the number of realizations in one function evaluation, y is the simulation year, N_{ys} is the number of years in the project horizon, i is the simulation realization index.

2. *Restriction Frequency* (f_{RF}): Restriction frequency represents the fraction of years across all realizations in which water use restrictions were enacted in at least one week:

$$\text{minimize } f_{RF} = \max_{j} \left[\frac{1}{N_{ys} \cdot N_r} \sum_{i=1}^{N_r} \sum_{y=1}^{N_{ys}} h_{i,j}^{y} \right] \tag{2}$$

where,

$$h_{i,j}^{y} = \begin{cases} 0 & \forall w \ : \ x_{srof,i,j}^{y,w} \leq \theta_{rt,j} \\ 1 & \text{otherwise} \end{cases}$$

where $h_{i,j,y} = 0$ if there was a week in a given year of a given realization in which water use restrictions were enacted, and 1 otherwise.

3. *Infrastructure Net Present Cost* (f_{NPC}): The average net present cost of all new infrastructure build across all realizations:

$$\text{minimize } f_{NPC} = \frac{1}{N_r} \sum_{i=1}^{N_r} \sum_{y=1}^{BM} \frac{PMT}{(1+d)^{y}} \tag{3}$$

where BM is the bond term, d is the discount rate (5%), y is the year of the debt service payment PMT since the bond was issued, with PMT being calculated as (assuming a level debt service bond):

$$PMT = \frac{P\left[BR(1+BR)^{BM}\right]}{\left[(1+BR)^{BM} - 1\right]} \tag{4}$$

where P is the principal (construction cost), BR is the interest rate to be paid to the lender BT is the bond term. The stream of payments is then discounted to present values.

4. *Peak Financial Cost* (f_{PFC}): The average cost objective represents the expected yearly cost of debt plus all non-infrastructure water portfolio assets used to manage droughts over the planning horizon. These costs are revenue losses from restrictions, transfer costs, contingency fund contributions, third-party insurance con-

tract costs, and debt repayment:

$$\text{minimize } f_{AC} = \max_j \left[\frac{1}{N_{ys} \cdot N_r} \sum_{i=1}^{N_r} \sum_{y=1}^{N_{ys}} SYC_{i,j}^y \right] \tag{5}$$

where,

$$SYC_{i,j}^y = \frac{\sum_{c \in C_j} PMT_{i,j,c} + \theta_{acfc,j} \cdot ATR_{i,j}^y + IP_{i,j}^y + ATR_{i,j}}{ATR_{i,j}^y}$$

where IP is the insurance contract cost in a given year y, $PMT_{i,j,c}$ is the debt payment for infrastructure option c if it belongs to the set C_j of infrastructure options to be built by utility j and is built in realization i, and ATR is the total annual volumetric revenue. All these variables are dollar values.

5. *Worse First Percentile Cost* (f_{WFPC}): The worse case cost objective represents the 1% highest single-year drought management costs observed across all analyzed SOWs over the planning horizon:

$$SYC_{i,j}^y = \frac{max(RL_{i,j}^y + TC_{i,j}^y - \theta_{acfc,j} \cdot ATR_{i,j}^y - YIPO_{i,j}^y, 0)}{ATR_{i,j}^y} \tag{6}$$

where IP is the insurance contract cost in a given year y, RL is the revenue losses from water use restrictions, TC is the transfer costs, $YIPO$ is the total insurance payout over year y, CF is the available contingency funds, and ATR is the total annual volumetric revenue. All these variables are dollar values. The worse case cost objective is then:

$$\text{minimize } f_{WCC} = \max_j \left\{ \underset{i \in N_r}{quantile}(SYC_{i,j}, 0.99) \right\} \tag{7}$$

S2 Runtime Diagnostics

For reliable search with a MOEA, it is important to run multiple instances of the algorithm to overcome any biases in search generated by the initial population (Salazar et al., 2016). For each defection scenario, four random seeds were run for each utility. The true Pareto set for this problem is not known, so to assess the convergence convergence we measure relative hypervolume (Zitzler et al., 2007), which compares performance of the approximate Pareto sets discovered at set checkpoints within search to the final "reference set", which contains non-dominated solutions across all seeds. If the relative hypervolume is found to plateau, we conclude that the algorithm has converged to a satisfactory approximation of the true Pareto set.

Runtime diagnostics for all defection optimizations are shown in Figure S1. There was very little variance across seeds, and the hypervolume of all defection optimizations plateaued after around 20,000 function evaluations.

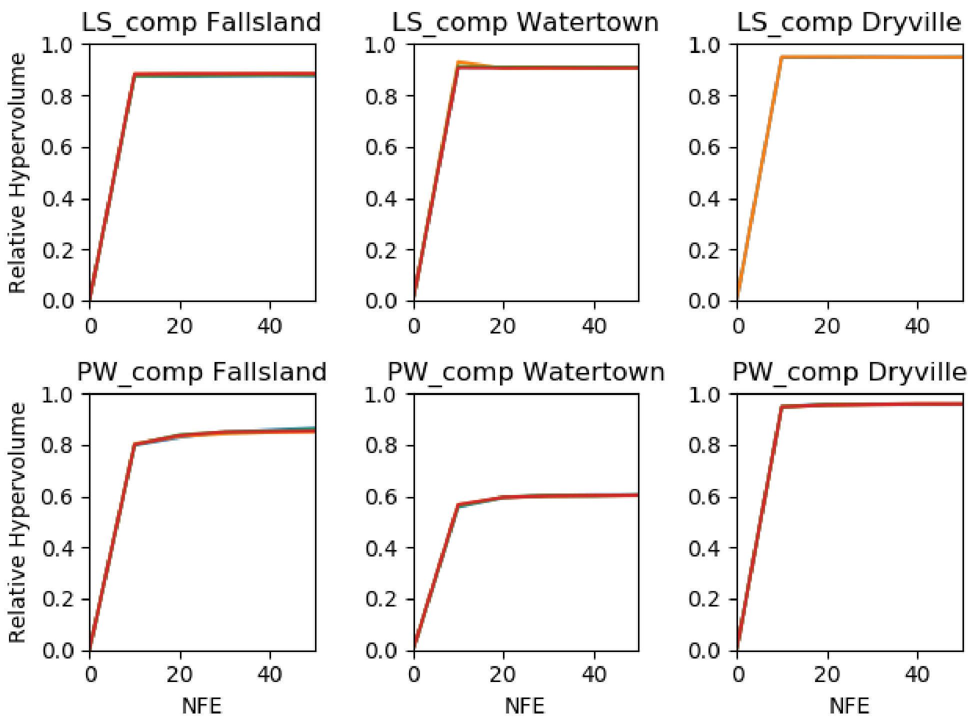

Figure S1. Runtime diagnostics for the individual optimization runs. The plateau of hypervolume across all seeds for all formulations indicates that number of function evaluations (NFE) were enough to achieve maximum attainable convergence.

S3. Robustness of defection alternatives

Figures S2-S4 show the top 30 defection alternatives for each utility under the least squares compromise selection (Social planner's compromise). The robustness of each alternative is plotted on the vertical axes, and the ranking of the solution is plotted on the horizontal axis. The solutions highlighted in black were used to generate the scenario discovery results shown in Figure 10 of the main text.

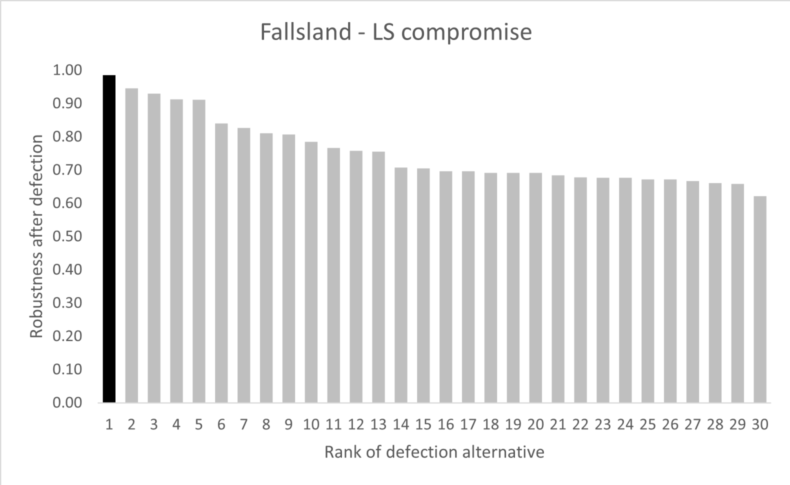

Figure S2. Robustness of defection alternatives for Fallsland under the LS compromise selection.

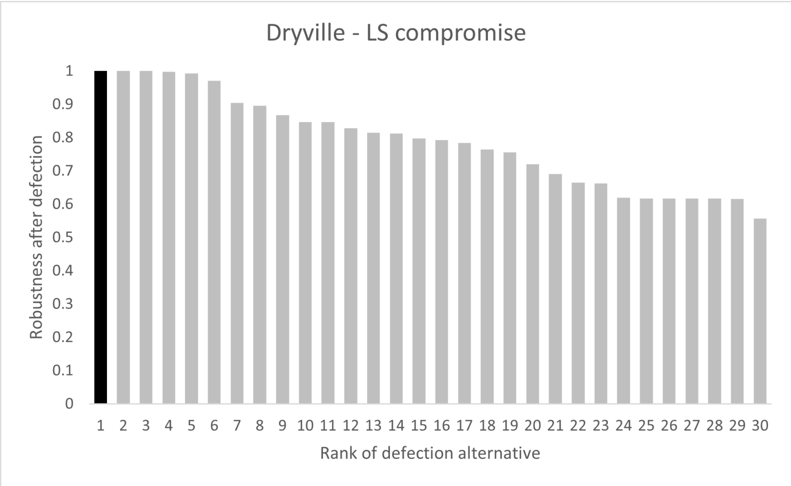

Figure S3. Robustness of defection alternatives for Dryville under the LS compromise selection.

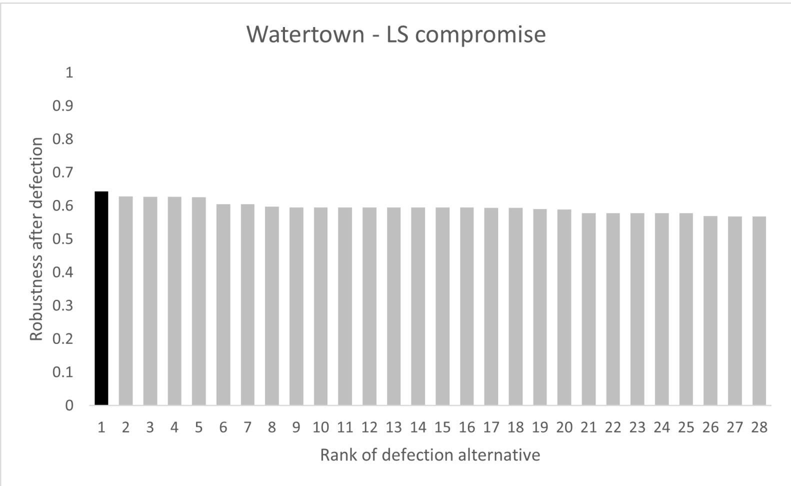

Figure S4. Robustness of defection alternatives for Watertown under the LS compromise selection.

Figures S5-S7 show the top 30 defection alternatives for each utility under the power index compromise selection (pragmatist's compromise). The robustness of each alternative is plotted on the vertical axes, and the ranking of the solution is plotted on the horizontal axis. The solutions highlighted in black were used to generate the scenario discovery results shown in Figure 10 of the main text.

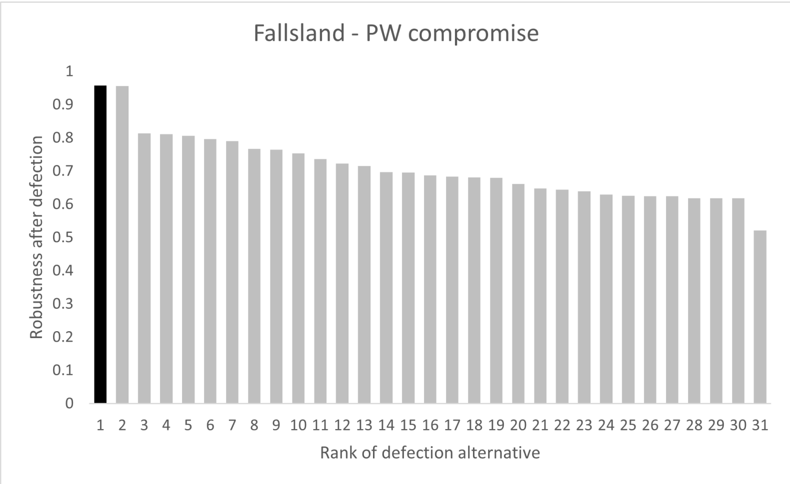

Figure S5. Robustness of defection alternatives for Fallsland under the PW compromise selection.

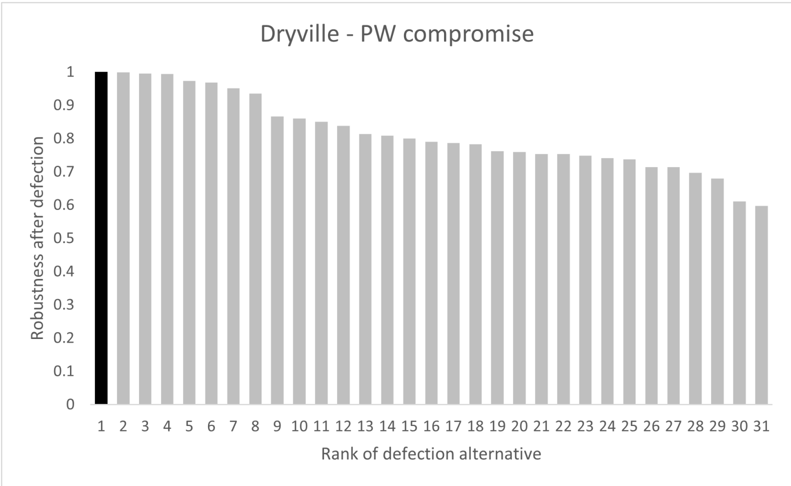

Figure S6. Robustness of defection alternatives for Dryville under the PW compromise selection.

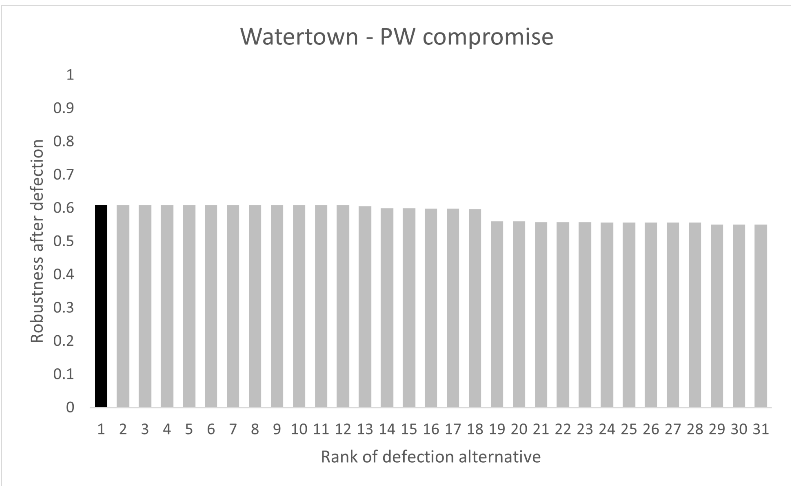

Figure S7. Robustness of defection alternatives for Watertown under the LS compromise selection.

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