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Key Points:
- Fallback bargaining methods can be used to find compromises to regional robustness conflicts
- Implementation uncertainty can exacerbate robustness conflicts within cooperative regional water portfolio planning
- Delineating operational safe operating spaces can assist stakeholders in finding actionable compromise water supply portfolios

Supporting Information:
- Supporting Information S1

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Identifying Actionable Compromises: Navigating Multi-City Robustness Conflicts to Discover Cooperative Safe Operating Spaces for Regional Water Supply Portfolios

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Abstract Regional cooperation among water utilities can improve the robustness of urban water supply systems to challenging and deeply uncertain futures. Through coordination mechanisms such as water transfers and regional demand management, water utilities can improve the efficiency of resource allocation and delay the need for new infrastructure investments. Though cooperation provides utilities with the potential for reduced cost strategies for improving the reliability of their services, two important challenges are worthy of careful consideration. First, regional utilities often have to navigate robustness conflicts stemming from potential asymmetries in their risk exposure, demand dynamics, and the availability of supply resources. Second, successful implementation of candidate compromise water portfolios requires that cooperating utilities understand their operational tolerances to deviations from the recommended regional actions ("imperfect implementation"). This study contributes a framework for identifying compromises across regional robustness conflicts and quantifying tolerances to implementation uncertainties. The framework is demonstrated on a system of four interdependent but institutionally independent water utilities in the Research Triangle region of North Carolina that are confronting robustness conflicts given asymmetries in their vulnerabilities to growing demands and hydroclimatic uncertainties. Our findings highlight that seemingly balanced compromise management strategies can yield significant and potentially surprising unintended consequences that could degrade regional cooperation. Moreover, asymmetries in regional robustness can be amplified with modest deviations from their agreed upon actions. Results of this analysis are broadly applicable to water supply regionalization as a global challenge and provide insights for discovering robust compromises and safe operating spaces for multi-actor water supply systems.

Plain Language Summary Cooperation among neighboring urban water utilities can help water managers face challenges stemming from climate change and population growth. Water utilities can cooperate by coordinating water transfers and water restrictions in times of water scarcity (drought) so that water is provided to areas that need it most. In order to successfully implement these policies, however, cooperative partners must find a compromise that is acceptable to all regional actors, a task complicated by asymmetries in resources and risks often present in regional systems. The possibility of deviations from agreed upon actions is another complicating factor that has not been addressed in water resources literature. Our study focuses on four urban water utilities in the Research Triangle region of North Carolina who are investigating cooperative drought mitigation strategies. We contribute a framework that includes the use of simulation models, optimization algorithms, and statistical tools to aid cooperating partners in finding acceptable compromises that are tolerant modest deviations in planned actions. Our results can be used by regional utilities to avoid or alleviate potential planning conflicts and are broadly applicable to urban regional water supply planning across the globe.

1. Introduction

Rapid urbanization, climate change, and increasingly vulnerable ecosystems necessitate a transition from traditional water supply planning to sustainable freshwater management (Gleick, 2018). For urban water utilities in the United States, this transition requires a shift to "soft path" approaches that manage water scarcity through increasing the efficiency of existing infrastructure rather than relying on continual supply expansion (Gleick, 2002, 2003). Regional cooperation through water transfer agreements is a promising soft path approach that can delay or alleviate the need for water supply expansion (Palmer & Characklis, 2009; Zeff et al., 2016). In regions with existing interconnected infrastructure, water transfers allow a group of water utilities to exploit their collective capacity-to-demand ratio, utilizing existing supply sources more efficiently than relying on independent sources (Green & Hamilton, 2000; Israel & Lund, 1995; Olmstead, 2010; Vaux & Howitt, 1984). In the eastern United States, water transfers may occur in the form of cooperative agreements, where a group of urban utilities in close geographical proximity agree to cooperatively manage drought scarcity risks (Gorelick et al., 2018; Palmer & Characklis, 2009; Zeff et al., 2014). The design of drought management strategies that require regional cooperative agreements represents a challenging multi-objective water supply management problem that requires water managers to navigate trade-offs between system reliability and their financial risks.

Recent research has highlighted portfolio based water management approaches that couple cooperative drought mitigation instruments with financial hedging to develop flexible strategies that balance supply reliability and financial risks (Caldwell & Characklis, 2014; Characklis et al., 2006; Palmer & Characklis, 2009). The design of cooperative water supply portfolios is aided by the use of multi-objective evolutionary optimization, a heuristic approach that seeks to discover a set of design alternatives that represent optimal trade-offs between conflicting objectives (Reed et al., 2013; Zeff et al., 2014). Multi-objective optimization allows stakeholders to assess trade-offs a posteriori, choosing design alternatives that most align with their preferences with a direct knowledge of their implied performance compromises (Coello et al., 2007; Woodruff et al., 2013). This a posteriori approach is useful for multi-actor systems, where a suite of regional alternatives can be discovered and aid in framing feasible compromises.

The selection of compromise alternatives that meet regional requirements is complicated by the presence of deep uncertainty (Bonzanigo et al., 2018). Deep uncertainty in a decision problem may refer to conditions where decision makers do not know or cannot agree on how to characterize uncertainties by known probability distributions, the outcomes of interest and their relative importance, and/or the system and its boundaries (Kwakkel, Walker, et al., 2016; Lempert, 2002; Walker et al., 2013). It may also refer to problems where the intertemporal dynamics of individual decisions prevent decision makers from considering them independently (Haasnoot et al., 2013; Hallegatte et al., 2012; Kwakkel, Walker, et al., 2016). Planning under deep uncertainty shifts the requirements on decision makers away from expected value optimal management decisions that require clear likelihoods and consensus on predicted future conditions, to the discovery of robust and adaptive alternatives that perform well across a wide range of plausible futures (Dessai et al., 2009).

Recent research has focused on approaches that use exploratory modeling (Bankes, 1993; Kwakkel, 2017) to evaluate the performance of planning alternatives under deep uncertainty (see recent reviews by Dittrich et al., 2016; Herman et al., 2015; Kwakkel & Haasnoot, 2019; Maier et al., 2014; Popper, 2019; Thissen et al., 2017). In their traditional early forms, methods such as decision scaling (Brown et al., 2012), robust decision making (Lempert, 2002), and info-gap (Ben-Haim, 2006) sought to identify decision relevant thresholds in the uncertainty space that cause pre-specified planning alternatives to fail to meet stakeholder performance criteria. Many-objective robust decision making (MORDM; Kasprzyk et al., 2013) extends the exploratory modeling concepts by including multi-objective evolutionary optimization to discover candidate actions and characterize how their vulnerabilities and trade-offs vary across deeply uncertain futures. More recently, several studies (Eker & Kwakkel, 2018; Trindade et al., 2017; Watson & Kasprzyk, 2017) have demonstrated that the inclusion of deep uncertainties in the search phase of the MORDM framework can improve solutions' robustness and discovered performance trade-offs between conflicting objectives.

Beyond the discovery of robust planning alternatives, exploratory modeling approaches also enable decision makers to discover consequential future scenarios that cause vulnerabilities in candidate alternatives (Lempert et al., 2006). Typically, the process of scenario discovery utilizes data mining, machine learning, and/or multi-objective optimization to delineate critical thresholds in the uncertainty space that cause proposed alternatives to fail to meet performance criteria defined by stakeholders (Bryant & Lempert, 2010; Groves & Lempert, 2007; Kwakkel, 2019). In the MORDM framework, scenario discovery is a core component of an iterative problem formulation process, which allows stakeholders to learn from exploratory modeling results to improve their understanding of their preferences and potential actions (Kasprzyk et al., 2013; Kwakkel, Walker, et al., 2016). Scenario discovery also provides a basis for incorporating planned adaptation into management strategies to preserve performance across deeply uncertain future conditions (Kwakkel & Haasnoot, 2019). Scenario discovery plays a significant role in Dynamic Adaptive Policy Pathways (Haasnoot et al., 2013) by informing the design of signposts (i.e., system states) that trigger pre-specified adaptive actions. The use of signposts has similarities and connections to recent MORDM studies focusing on the design of adaptive rule systems that approximate closed loop control where observations of system states trigger adaptive actions (e.g., see Trindade et al., 2017; Quinn, Reed, & Keller, 2017; Quinn, Reed, Giuliani, et al., 2017).

Although the exploratory modeling techniques discussed above assist stakeholders in discovering robust design alternatives and identifying consequential uncertainties, they have not strongly focused on the challenges and implications for navigating multi-stakeholder robustness conflicts. In cooperative water resources systems, the robustness of planning alternatives may vary across regional actors resulting in robustness conflicts within cooperative partnerships (Herman et al., 2014). Robustness conflicts imply that actions taken to hedge against uncertainty for one regional actor may heighten the vulnerability of its partners which increases the difficulty of discovering acceptable regional compromises. Navigating robustness conflicts within regional partnerships is a central challenge in the design of cooperative soft path strategies for water resources systems planning (Bonzanigo et al., 2018). One promising approach to the resolution of conflicts in water resources systems is fallback bargaining (Brams & Kilgour, 2001). Fallback bargaining has been shown to suitably predict the outcome of environmental management problems where competing interests are present (Madani et al., 2011). As opposed to "social planner methods" which seek an alternative that optimizes the well-being of the collective group (Madani et al., 2014; Read et al., 2014), fallback bargaining seeks to minimize the maximum dissatisfaction among a group of bargainers. Fallback bargaining can lead to the discovery of alternatives that serve as stable (feasible) compromises across regional actors (Madani et al., 2011). In water resources systems, fallback bargaining has been applied for conflict resolution in the Caspian Sea negotiations (Sheikhmohammady & Madani, 2008; Sheikhmohammady et al., 2010), waste load allocation (Mahjouri & Bizhani-Manzar, 2013), inter-basin water transfers (Jafarzadegan et al., 2014) and water allocation (He et al., 2018; Madani et al., 2011). In cooperative water supply planning problems, fallback bargaining has the potential to assist utilities in navigating robustness conflicts to discover compromise portfolios for regional systems.

Thus far, we have reviewed key methodological advances for water supply portfolio planning that aid systems in balancing conflicting objectives, discovering consequential deep uncertainties, and navigating regional robustness conflicts through fallback bargaining. In the design of cooperative water supply portfolios one question still remains, can the portfolio be successfully implemented? Uncertainty in implementation has long been an element of robust industrial design through the consideration of tolerances to deviations and actuator precision (Caro et al., 2005; Chen et al., 1996; Zhu & Ting, 2001). In their review of robust optimization techniques, Beyer and Sendhoff (2007), rank uncertainty in our ability to implement prescribed actions as one four key types of uncertainty encountered in engineering design problems. In water resources literature, Haimes and Hall (1977) termed uncertainty in decisions as "sensitivity" and recommend its inclusion in evaluations of candidate management strategies for water resources systems. However, with the exception of two studies on flood protection planning in the Waas test case (Kwakkel et al., 2015; Kwakkel, Haasnoot, et al., 2016), literature in water resources planning and management under deep uncertainty has ignored issues regarding tolerances to uncertain implementation.

In this paper, we define and explore implementation uncertainty in the context of individual and regional tolerances to deviations in recommended water portfolio action rule sets in terms of their impacts on robustness and key performance objectives. In the design of water supply portfolios, human behavioral deviations during implementation are common and typically not considered in the planning process. The potential for implementation deviations in the decision space has important implications for the regional and individual robustness of multi-city water supply portfolios. The complex and highly nonlinear mapping between water supply portfolio composition and objective performance makes quantifying the implications of deviations from prescribed decision variables impossible a priori. For cooperative water supply planning problems, implementation uncertainty has the additional potential to destabilize regional partnerships by changing experienced performance trade-offs and exacerbating regional robustness conflicts.

One useful concept for evaluating a portfolio's tolerance to implementation deviations is the "safe operating space" (SOS) drawn from the socio-ecological systems literature (Carpenter et al., 2015; Rockstrom et al., 2009, 2015). A SOS in a socio-ecological system delineates thresholds that bound favorable system conditions (Carpenter et al., 2015). Kwakkel and Timmermans (2012) first applied the concept of SOS to water resources systems, using exploratory modeling techniques to discover limits to global fresh water use. Here, we build on exploratory modeling methodology of Kwakkel and Timmermans (2012) to discover operational SOSs within the decision space for water supply portfolios. Delineating operational SOSs provides stakeholders with information on the allowable operational tolerances of a water supply portfolio which can help clarify the feasibility of successful implementation of candidate portfolios. This information can be helpful in conjunction with the regional bargaining processes to assist the discovery of compromise alternatives.

This study extends the MORDM framework to assist utilities in the selection and evaluation of cooperative water supply portfolios that better balance robustness conflicts across regional actors and clarify tolerances in their deviations from accepted management policies or rules. Our methodology 1) identifies potential compromise portfolios through fallback bargaining, 2) quantifies the vulnerability of selected compromise portfolios to operational deviations from chosen compromise portfolios, 3) identifies the nature of operational deviations that cause such vulnerabilities, 4) delineates a safe operating space which specifies operational tolerances to ensure the performance of the compromise portfolios across regional actors, and 5) identifies consequential scenarios that lead to portfolio vulnerability due to both exogenous deep uncertainties and implementation uncertainties. The framework is demonstrated on system of four water utilities in the Research Triangle of North Carolina who seek to design a regional water supply portfolio of water transfers and financial instruments to balance reliability and cost objectives. This paper represents the culmination of several recent studies aimed on regional water management in the Research Triangle. Table 1 provides a summary of recent publications involving this test case and highlights the novel contributions and key findings from each.

This paper is organized as follows. Section 2 presents background, the Research Triangle test case. Section 3 describes our methodology including the problem formulation, many-objective search, scenario discovery, and analysis of implementation tolerances. Section 4 presents the results of this analysis and provides a discussion of the implications of planning under deep uncertainty for multi-actor systems. Section 5 concludes with a summary of key findings and potential for future work.

2. Regional Test Case

2.1. The Research Triangle Water Supply Planning Problem

The Research Triangle region of North Carolina (Triangle, shown in Figure 1), located in the southeastern US, is home to over two million residents whose water supply is primarily provided by four public utilities: Raleigh, Durham, Cary and OWASA (the Orange Water and Sewer Authority, serving the municipalities of Chapel Hill and Carrboro). In recent decades, rapidly growing urban demand coupled with the increased difficulty posed by new infrastructure development has increased the Triangle region's sensitivity to water scarcity. The region's utilities currently receive water from nine existing reservoirs within the Cape Fear and Neuse River basins illustrated in Figure 1a and listed in Table 2. Municipal supply allocations from two flood control reservoirs operated by the U.S. Army Corps of Engineers serve as the primary water sources for Raleigh and Cary. Raleigh receives 100% of the municipal supply allocation of Falls Lake, and Cary receives 35.5% of supply allocation to Jordan Lake (NCDENR, 2002). Durham and OWASA also have access to the Jordan Lake, with 10% and 5%, respectively, as secondary allocations for use during times of scarcity (NCDENR, 2002). A large portion of the Jordan Lake is designated by U.S. Army Corps of Engineers for municipal water supply. However, Cary is the only utility that operates a water treatment plant on the Jordan Lake, so to access the Jordan Lake municipal supply pool the three other utilities must currently purchase treated transfers from Cary through shared infrastructure.

Growing urban demands are a significant factor that has made the region's existing supply increasingly vulnerable to drought. Regional urban water demand is projected to grow by 33% through 2025, the minimum time horizon over which the region's utilities are expected to remain without investing in new water supply infrastructure (Figure 1b; NCDENR, 2002). The region's water utilities currently manage water shortages by imposing water use restrictions on customers, which reduces revenue and is disliked by customers (Buchan & Black, 2011; Goodwin, 2015; Water & Authority, 2010; Westbrook et al., 2016). Recent work has

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Table 1
Literature Summary of the Research Triangle Test Case

Paper	Research Question	Type of Uncertainties Considered	Novel Contribution	Key Findings
Zeff et al. (2014)	Do regionally coordinated treated transfers and financial instruments improve water supply portfolios?	(a) Well-characterized stochastic hydrology	Many-objective optimization of cooperative water supply portfolios	Interutility transfers and financial instruments can improve the performance of water supply portfolios.
Herman et al. (2014)	Are water supply portfolios discovered through optimization under well characterized uncertainty robust to deep uncertainties? Which uncertainties control	(a) Well-characterized stochastic hydrology and (b) exogenous deep uncertainties including regional demand growth, climate change factors, and financial risk.	Application of MORDM to cooperative water supply portfolios	Although robustness conflicts exist between the cooperating utilities, coordinated regional demand management can reduce regional tensions.
Herman et al. (2015)	How should robustness be defined for systems planning under change?	(a) Well-characterized stochastic hydrology and (b) exogenous deep uncertainties including regional demand growth, climate change factors, and financial risk.	A taxonomy of robustness frameworks	Rankings of portfolio preferability change significantly depending on the robustness metric employed.
Trindade et al. (2017)	Does including deep uncertainties in many -objective search improve the robustness of regional water supply portfolios?	(a) Well-characterized stochastic hydrology and (b) exogenous deep uncertainties including regional demand growth, climate change factors, and financial risk.	Improving the robustness of portfolios discovered with MOEAs by including deep uncertainties in search	Including deep uncertainties in the search phase increases the robustness of discovered solutions and better captures robustness conflicts.
Gold et al., This manuscript	Are regional water supply portfolios discovered through many-objective optimization practical to implement given robustness conflicts and the potential for implementation uncertainty?	(a) Well-characterized stochastic hydrology, (b) exogenous deep uncertainties including regional demand growth, climate change factors, and financial risk, and (c) uncertainty in water supply portfolio implementation.	A new framework for navigating robustness conflicts in cooperative systems, analyzing the impacts of implementation uncertainty, and delineating cooperative safe operating spaces.	Fallback bargaining represents a promising means of navigating robustness conflicts, implementation uncertainty can exacerbate robustness conflicts in cooperative regional water portfolio planning, delineating operational safe operating spaces, and including implementation uncertainty in scenario discovery can assist stakeholders in finding actionable compromise water supply portfolios.

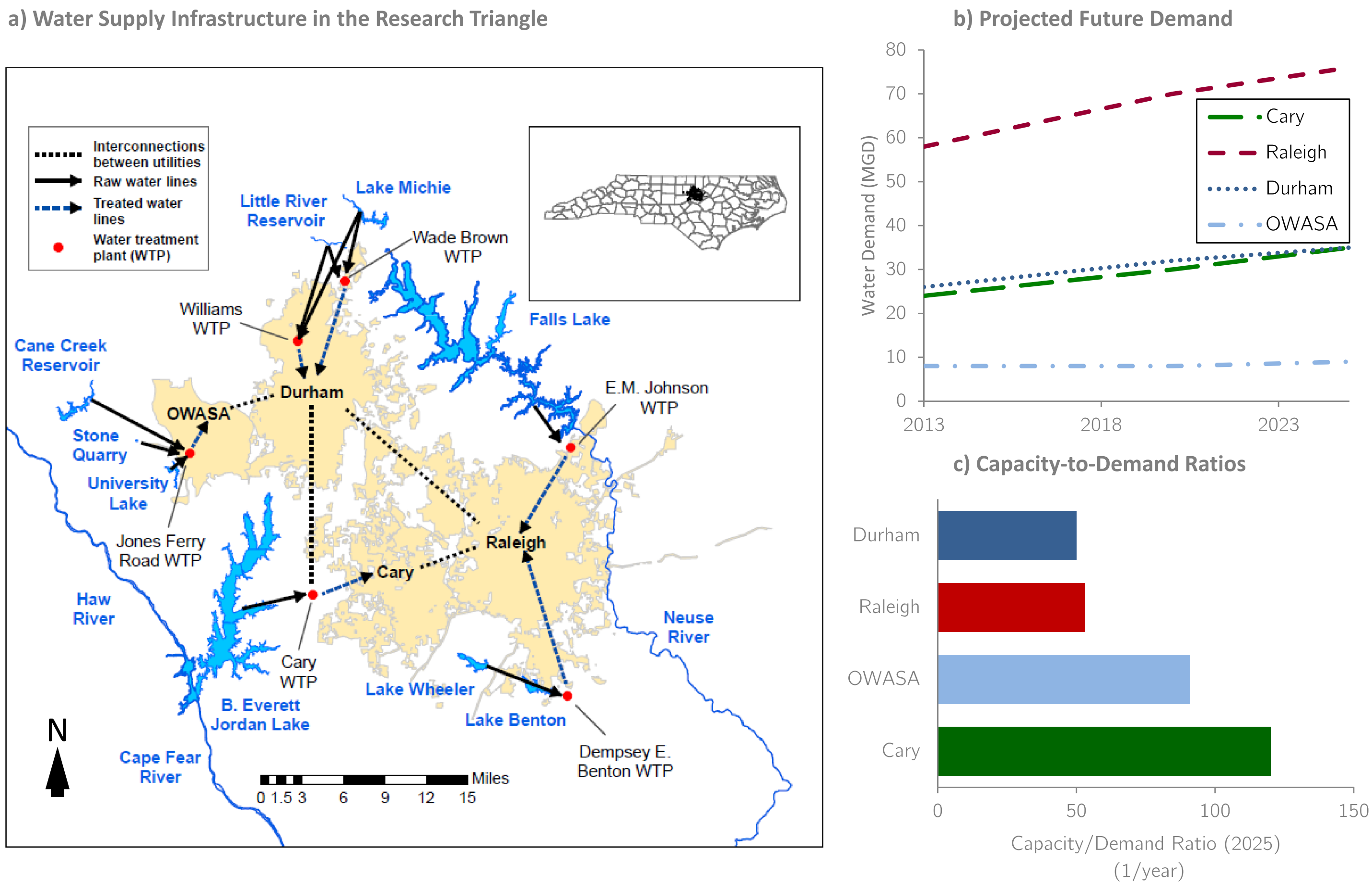

Figure 1. Overview of water supply in the Research Triangle. (a) Water supply infrastructure and service areas of the four water utilities (Raleigh, Cary, Durham, and OWASA); (b) projected demand, 2013-2025 (MGD) for each of the region's water utilities; (c) capacity-to-demand ratios, the ratio of total utility storage to annual consumptive demand, of the four regional water utilities. Higher capacity-to-demand ratios indicate improved ability to meet demand during drought conditions. The differing ratios across the four utilities leads to asymmetric drought vulnerabilities in the region. (Adapted from Zeff et al. (2014) and Herman et al. (2014)).

found that incorporating regional treated transfers from the Jordan Lake through Cary's treatment plant into drought mitigation planning can improve supply reliability and reduce the frequency of water use restrictions throughout the Triangle region (Caldwell & Characklis, 2014; Palmer & Characklis, 2009; Zeff et al., 2014). Treated transfer agreements exploit the region's variable capacity-to-demand ratios across the four utilities, as illustrated in Figure 1c. While the region as a whole has similar demand growth projections and relatively homogeneous hydroclimatic conditions, the differing capacity-to-demand ratios of the four water utilities cause drought vulnerability to vary considerably. Regionally coordinated transfers agreements exploit this variability to improve the efficiency of current infrastructure and reduce the impact of drought conditions (Caldwell & Characklis, 2014; Palmer & Characklis, 2009; Zeff et al., 2014).

Although treated transfer agreements can improve the region's efficiency and reliability in meeting water supply demands, they also create a new source of financial risk for water utilities. The water rates set by

Table 2
Reservoirs and Total Storage Capacities for the Four Research Triangle Water Utilities (Adapted from Herman et al., 2014)

Utility	Reservoirs	Total Capacity (BG)	Allocation
Durham	Little River, Lake Michie	6.4	100%
OWASA	Cane Creek, Stone Quarry, University Lake	3.0	100%
Raleigh	Falls Lake, Lake Wheeler, Lake Benton	14.7	42.4% (100% of municipal supply)
Cary	Jordan Lake	14.9	12.7% (35.5% of municipal supply)

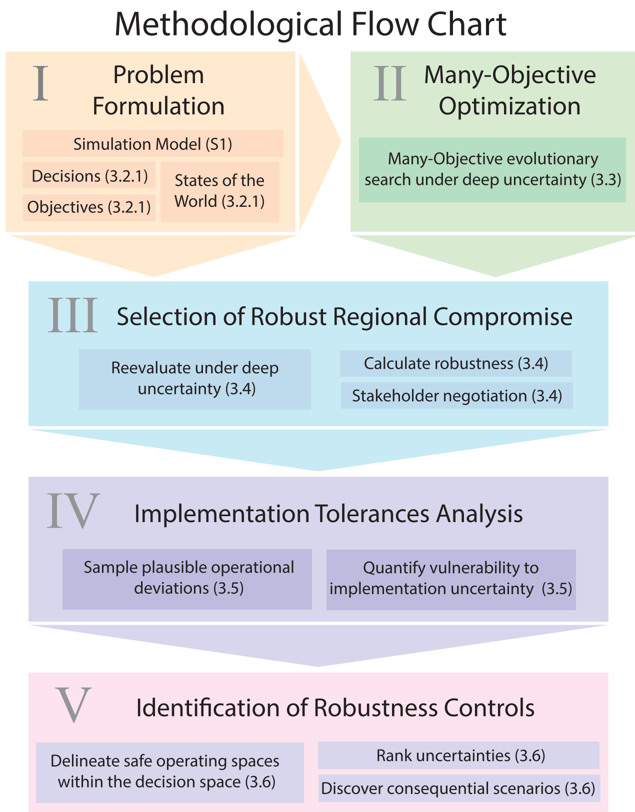

Figure 2. Methodological flow chart for selection and evaluation of regional compromise water supply portfolios given robustness conflicts across cooperating regional water utilities.

public utilities are typically designed to cover costs composed mostly of fixed annual debt service payments. Adding unplanned expenses, such as transfer purchases, may cause utilities to miss debt payments and increase future borrowing costs (Hughes & Leurig, 2013). The region's four utilities have taken a portfolio approach that includes financial risk management instruments to improve their supply reliability while minimizing financial risk (Characklis et al., 2006). Regional water supply portfolios combine drought mitigation instruments (water use restrictions and treated transfers) with financial hedging to mitigate unplanned financial losses. Building off prior work (Herman et al., 2014; Trindade et al., 2017; Zeff et al., 2014), this study extends the MORDM framework (Kasprzyk et al., 2013) to better account for implementation uncertainty, described in section 3.1, while aiding the discovery of robust regional water supply management compromises for the four utility cooperative partnership. A detailed description of the system model used in this study can be found in the supporting information Text S1 of this paper.

3. Methodology

3.1. Many-Objective Robust Decision Making for Regional Water Supply Planning

This study contributes a new methodology for navigating robustness trade-offs in cooperative regional water portfolio planning systems and a formalized framework to assess the impacts of imprecise implementation on selected water supply portfolios. Our methodology builds off the MORDM framework (Kasprzyk et al., 2013) to discover robust regional water supply portfolios, find acceptable compromises across regional actors, evaluate the impacts of implementation uncertainty, and identify potential vulnerabilities to a broader suite of deep uncertainties than has been considered in past studies. This is the first study to incorporate fallback bargaining methods for navigation of robustness conflicts and to explicitly include implementation uncertainty in the MORDM process. Figure 2, adapted from the taxonomy of robustness frameworks presented in Herman et al. (2015), illustrates our proposed extension of the MORDM framework.

To begin our analysis, we develop candidate problem formulations by defining performance objectives, examining the composition of water supply portfolios, identifying a simulation model, and developing a relevant set of potential future states of the world (SOWs; Figure 2, Box I). Next, we perform a many-objective evolutionary search using the Borg Multiobjective Evolutionary Algorithm (MOEA) to discover a set of Pareto approximate water supply portfolios for the regional system (Figure 2, Box II). The portfolios discovered through search represent Pareto approximate trade-offs across multiple regional performance criteria. We then reevaluate this set of trade-off portfolios across a broader sampling of deep uncertainties to quantify their robustness. Portfolio robustness is computed in this study using a multivariate satisficing metric (Starr, 1963) representing the percent of sampled worlds that meet minimum performance criteria for all regional actors. Portfolio robustness is used to perform fallback bargaining to select regional compromises portfolios that are candidates for implementation (Figure 2, Box III).

Compromise portfolios considered for implementation are evaluated for their stability to implementation uncertainties across regional actors. The vulnerability of the selected compromise portfolios to implementation uncertainty is evaluated by sampling plausible operational deviations from the selected portfolios and reevaluating them across a broad sampling of deeply uncertain SOWs (Figure 2, Box IV). We quantify the vulnerability of each regional compromise by measuring the change in robustness across all regional actors due to deviations from original decision variables. The final step in our analysis is the identification of robustness controls, the uncertainties within the system that are most responsible for failure to satisfy stakeholder requirements (Figure 2, Box V; Herman et al., 2015). We use logistic regression models to examine how implementation uncertainty influences a portfolio's ability to meet stakeholder performance requirements. We further examine the vulnerability of each compromise portfolio by globally ranking all uncertainties within the system using the delta moment-independent sensitivity index (Borgonovo, 2007). We then determine operational tolerances for each decision variable by using the Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999) to delineate SOS for portfolio implementation. Finally, we identify consequential scenarios that can inform monitoring to confirm that an implemented portfolio's performance is staying within its SOS. To aid the comprehension of our methodology we have provided a glossary of key terms in Appendix A.

3.2. Problem Formulation

Our exploration of how to navigate robustness trade-offs within a region's water suppliers builds on several prior studies (Herman et al., 2014; Trindade et al., 2017; Zeff et al., 2014). Following the mathematical notation of Trindade et al. (2017), the problem formulation explored in this study abstracts the preferences of Triangle utilities using a regional minimax formulation where each regional objective value is taken as the value of the objective for the worst-performing utility, which guarantees that all other utilities will perform at least as well or better than the regional value (an application of Rawls' Difference Principle; Hammond, 1976). While this aggregation has the advantage of reducing the dimensionality of the many-objective optimization framing, it simultaneously yields the potential for complex winner-loser dynamics in stakeholder compromises.

We specify the search for robust regional water supply portfolios, θ^*, as a minimization problem of regional objective function vector **F**.

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

where

$$\boldsymbol{F} = \begin{bmatrix} -f_{REL}(\boldsymbol{x_s}, \boldsymbol{\theta_{rt}}, \boldsymbol{\theta_{tt}}, \boldsymbol{\theta_{jla}}) \\ f_{RF}(\boldsymbol{x_{rof}}, \boldsymbol{\theta_{rt}}, \boldsymbol{\theta_{tt}}, \boldsymbol{\theta_{jla}}) \\ f_{JLA}(\boldsymbol{\theta_{jla}}) \\ f_{AC}(\boldsymbol{x_{rof}}, \boldsymbol{\theta_{rt}}, \boldsymbol{\theta_{tt}}, \boldsymbol{\theta_{jla}}, \boldsymbol{\theta_{arfc}}, \boldsymbol{\theta_{irt}}) \\ f_{WCC}(\boldsymbol{x_{rof}}, \boldsymbol{\theta_{rt}}, \boldsymbol{\theta_{tt}}, \boldsymbol{\theta_{jla}}, \boldsymbol{\theta_{arfc}}, \boldsymbol{\theta_{irt}}) \end{bmatrix}, \tag{2}$$

$$\boldsymbol{\theta} = [\boldsymbol{\theta_{jla}}, \boldsymbol{\theta_{arfc}}, \boldsymbol{\theta_{irt}}, \boldsymbol{\theta_{rt}}, \boldsymbol{\theta_{tt}}]^T. \tag{3}$$

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x_{rof}} \\ \boldsymbol{x_s} \end{bmatrix}, \tag{4}$$

where F is the vector-based regional objective function, f_{REL} is the reliability objective, f_{RF} is the restriction frequency objective, f_{JLA} is the Jordan lake allocation objective, f_{AC} is the average drought management cost objective, and f_{WCC} is the worst-case cost objective. The formulation of each objective is presented in detail in Text S3. Vector θ represents regional water supply portfolios containing $\boldsymbol{\theta_{jla}}$, a vector of Jordan Lake allocations for each Triangle utility, vectors of financial instruments, $\boldsymbol{\theta_{arfc}}$ and $\boldsymbol{\theta_{irt}}$, and vectors of drought mitigation triggers, $\boldsymbol{\theta_{rt}}$ and $\boldsymbol{\theta_{tt}}$. Each portfolio decision variable is described in detail in section 3.2.1.

The system state across utilities and time is represented by state vector **X**; $\boldsymbol{x_{rof}}$ is a vector of risk-of-failures that is described in detail in section 3.2.1, and $\boldsymbol{x_s}$ is a vector of combined utility storage states for simulation week w, defined as

$$\boldsymbol{x_s} = f(\boldsymbol{x_s^{w-1}}, \boldsymbol{C}, \boldsymbol{D^w}, \boldsymbol{TF^w}, \boldsymbol{NI^w}, \boldsymbol{E^w}, \boldsymbol{SP^w}, \boldsymbol{R^w}|\boldsymbol{\Psi}), \tag{5}$$

$$\boldsymbol{D^w} = f(x^w_{rof}, \theta_{rt}), \tag{6}$$

$$\boldsymbol{TF^w} = f(\boldsymbol{x^w_{rof}}, \boldsymbol{\theta_{tt}}). \tag{7}$$

In equation (5), C is a vector of reservoir capacities, D is a vector the demands for each utility, TF is a vector of the transfer volumes for each utility, NI is a vector of the natural inflows in each reservoir, E is a vector of the evapotranspiration volumes in each reservoir, SP is a vector of the spillage of each reservoir, R is a vector of the minimum environmental releases of each reservoir, and $\boldsymbol{\Psi}$ is a vector of the deeply uncertain factors for the associated SOW.

3.2.1. Decision Variables

The decision variables that compose each candidate regional water supply portfolio, θ shown in equation(3), define a risk-of-failure focused rule that specifies how the region's utilities will respond to drought conditions and manage financial assets. Vector $\theta_{\boldsymbol{jla}}$ represents the total Jordan Lake allocations afforded to each utility, $\theta_{\boldsymbol{arfc}}$ represents the annual reserve fund contribution by each utility (percent of total annual revenue) and $\theta_{\boldsymbol{irt}}$ represents the index insurance trigger, specified by restriction stage, for each utility.

Decision variables $\theta_{\boldsymbol{rt}}$ and $\theta_{\boldsymbol{tt}}$ represent the vectors of risk-of-failure triggers (ROF; Palmer & Characklis, 2009) that are used to trigger water use restrictions and treated transfers, respectively. The drought mitigation instruments are implemented when a utility's ROF state, $x_{\boldsymbol{rof}}$, reaches the trigger values defined in the regional portfolio. A utility's ROF state at week w represents the number of years in the historical record whose natural inflows would cause the utility's reservoir storage to drop below a critical threshold at least once in the 52 weeks following week w, given the utility's storage volume at week w. This is calculated by running N_h year-long simulations using historical natural inflows starting from week w, where N_h is the number of years in the historical record. The ROF state for utility j at week w, $x^w_{rof,j}$ and defined as

$$x^w_{rof,j} = \frac{1}{N_h} \sum_{y \in HNI} f^w_{y,i}, \tag{8}$$

where HNI is the set of years in the historical record and,

$$f^w_y = \begin{cases} 0, \ \forall w' \in \{(y,w), \ldots, (y, w+51)\} : \frac{x^{y,w'}}{C_j} \leq S_c \\ 1, \ \text{otherwise} \end{cases}. \tag{9}$$

$$x^{y,w'}_{s',j} = f(C_j, UD^w_j, \boldsymbol{NI^{w'}_j}, \boldsymbol{E^{w'}_j}, \boldsymbol{SP^{w'}_j}, \boldsymbol{R^{w'}_j} | \Psi), \tag{10}$$

where w' denotes a week in one year of N_h year-long simulations, C_j represents the combined reservoir storage for utility j, and S_c represents a critical storage level. $x^{y,w'}_{s',j}$ is the storage state calculated in the year-long simulation that assumes the occurrence of year y of HNI following week w. UD^j is a the unrestricted demand utility j, NI_j are the natural inflows drawn from HNI in each of utility $j's$ reservoirs, E_j are the evapotranspiration volumes drawn from HNI in each reservoir, SP_j are the spillage of each reservoir, R_j are the environmental releases of each reservoir, and $\boldsymbol{\Psi}$ is a vector of the deeply uncertain factors for the associated SOW. If w' is greater than 52, weeks of the following historical year are used. For details on the risk-of-failure metric, see Palmer and Characklis (2009).

Unlike other system state variables, such as days of supply remaining or minimum storage levels, ROFs represent a dynamic and constantly updated measure of a utility's evolving capacity to meet demand. By updating on a weekly timescale, ROFs capture intra-annual variations in risk that stem from seasonal patterns of inflows and demands. The use of ROFs to trigger drought mitigation action means that decisions are made in direct response to observed system states rather than taking the same prescribed action across all future SOWs. A water supply portfolio will thus produce a different set of actions in every future scenario it encounters (i.e., a rule-based closed loop feedback).

3.2.2. Sampling States of the World

Uncertainty facing the regional system can be partitioned into well-characterized uncertainty (WCU) and deep uncertainty (DU). WCU represents system parameters that are inherently stochastic and have significant data support for statistical modeling. In short-term water supply planning problems, natural reservoir inflows (*NI*) can be considered well-characterized if the system has a significant record of historical observation and a relatively short planning horizon. The Research Triangle system has 80 years of historical record (1933–2013) and drought mitigation planning has a 12-year horizon, so natural reservoir inflows are considered as WCU. We sample WCU natural inflows by creating an ensemble of 1,000 weekly 12-year synthetic streamflow records that expand upon the observed historical record. Synthetic records are generated using the method proposed by Kirsch et al. (2013). The sample size of 1,000 synthetic was chosen based on empirical assessments conducted by Trindade et al. (2017). Details on the synthetic streamflow generation procedure can be found in Text S2.

In addition to WCU natural inflows, we identify 13 deeply uncertain factors within the Research Triangle regional test case. Relevant deep uncertainties include climatic variables, demand projections, supply capacity and financial variables. The identified factors and plausible ranges can be found in Table 3. We construct

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Table 3
Deeply Uncertain Factors and Sampling Ranges Used to Generate Vector Ψ in the MORDM analysis

Category	Name	Estimated Value	Lower Bound	Upper Bound
Climate	Inflow multiplier	1.0	0.8	1.2
	Evaporation multiplier	1.0	0.8	1.2
	Consumer reductions multiplier	1.0	00.5	1.2
	Consumer reductions lag (weeks)	0	0.5	4
Demand	Mean peaking factor	1.0	0.5	2.0
	Demand growth multiplier	1.0	0.8	2.0
	Standard deviation of demand variation	1.0		2.0
	Falls Lake municipal supply allocation	1.0	0.8	1.2
Capacity	Jordan Lake municipal supply allocation	1.0	0.8	1.2
	Cary treatment plant capacity	1.0	1.0	2.0
	Transfer connection capacity multiplier	1.0	1.0	2.0
Costs	Transfer cost	3000	2500	5000
	Insurance premium multiplier	1.2	1.1	1.5

10,000 future SOWs by using Latin hypercube sampling (LHS) of the 13 DU factors across their plausible ranges to ensure a good representation of possible future scenarios. Each SOW, **Ψ**, constitutes a unique LHS sample of the 13 DU factors. The DU factors and their ranges are drawn from discussions with the Triangle utilities from prior published work (Herman et al., 2014, 2015; Trindade et al., 2017). Details on each DU factor identified can be found in Herman et al. (2014). The sufficiency of the DU sample size was evaluated through visual factor mapping of model output to ensure that relevant subspaces in the deep uncertainty space contained sufficient density of samples. Additionally, sampling effects were evaluated by examining the consistency of results across the alternative global sensitivity analysis techniques described in section 3.6 (Lamontagne et al., 2019; Quinn et al., 2018).

Figure 3a shows the sampling scheme employed in the DU optimization which directly incorporates deep uncertainties into the search process (Trindade et al., 2017). The DU optimization evaluates each candidate water supply portfolio across the full ensemble 1,000 WCU inflows and each inflow is paired with one of the 10,000 SOWs representing a sample of DU factors. The DU optimization sampling scheme shown in Figure 3a approximates the much broader and computationally demanding DU reevaluation, shown in

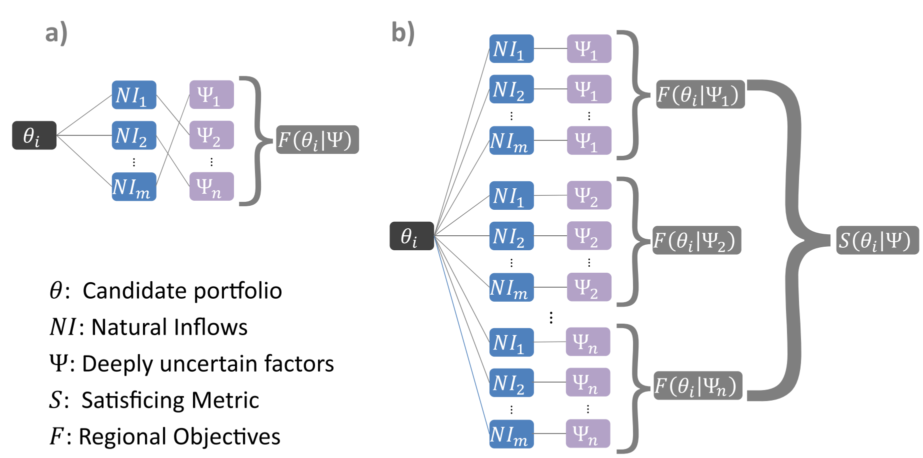

Figure 3. (a) Schematic of DU optimization sampling scheme. Each function evaluation pairs a sampled natural inflow with a different sample of deeply uncertain factors **Ψ**, regional objectives are calculated across all samples. (b) Schematic of DU reevaluation sampling scheme, to quantify the robustness of Pareto approximate portfolios, each portfolio is reevaluated across a broader set of uncertainties representing combinations of natural inflows and deeply uncertain factors. Each natural inflow sample is paired with each sample of deeply uncertain factors for a total of 10 million function evaluations.

Figure 3b, where each natural inflow is paired with each of the 10,000 DU samples (more detail on DU reevaluation is provided in section 3.4). This approximation allows for a computationally tractable evaluation of water supply portfolios across a wide array of DU futures (Trindade et al., 2017). We use DU optimization in this study to discover a set of Pareto approximate water supply portfolios, allowing stakeholders make an a posteriori assessment of trade-offs between conflicting objectives.

3.3. Many-Objective Optimization

We couple the simulation model described in Text S1 with the Borg MOEA (Hadka & Reed, 2012) to discover a set of Pareto approximate water supply portfolios that represent non-dominated trade-offs between regional objectives. MOEAs are global population-based search algorithms that emulate the natural processes of mating, mutation, and selection to evolve sets of Pareto approximate solutions for multi-objective problems (Coello et al., 2007). MOEAs can solve nonlinear, nonconvex, multimodal, and discrete problems which cause traditional search techniques to perform poorly or fail and have been demonstrated to effectively solve complex water resources problems (Maier et al., 2014; Nicklow et al., 2010). The Borg MOEA was chosen for this analysis because it has been shown to meet or exceed the performance of other state-of-the-art MOEAs across a wide array of challenging water resources problems (Reed et al., 2013). The Borg MOEA employs an adaptive search that uses multiple operators probabilistically selected every iteration based on their ability to generate quality solutions (Hadka & Reed, 2012). The Borg MOEA also utilizes epsilon dominance archiving (Laumanns et al., 2002) with search stagnation detection and randomized restarts to avoid local optima. This work used standard values of parameters of the Borg MOEA v1.4 Master-Worker (see Hadka & Reed, 2012 for specific values) and the DU optimization sampling scheme presented in Figure 3b to search for regional water supply portfolios. The pairing of the Borg MOEA with the DU optimization sampling scheme guides the algorithm to discover robust water supply portfolios whose performance is acceptable across a diverse set of future SOWs (Trindade et al., 2017).

3.4. Selection of a Robust Regional Compromise

We quantify regional robustness and explore portfolio vulnerabilities for each Pareto approximate portfolio discovered through DU optimization using the DU reevaluation sampling scheme, as show in Figure 3b. During reevaluation, the ensemble of 1,000 WCU streamflow time series is paired with each of the 10,000 SOWs sampled from DU factors creating a total of 10 million simulation runs for each Pareto approximate portfolio (Trindade et al., 2017). We use the performance of Pareto approximate portfolios during DU reevaluation to evaluate portfolio robustness. The choice of metric to quantify robustness may vary according to decision context and stakeholder risk tolerance or preference (McPhail et al., 2018). Herman et al. (2015), and McPhail et al. (2018) present comprehensive reviews of commonly used robustness metrics and discuss the strengths and weaknesses of each metric. Common metrics include measures of regret, satisficing, expected value, performance maximization, and minimization of variance or a higher-level moment (Herman et al., 2015; McPhail et al., 2018). For the Research Triangle water supply portfolio problem, a satisficing metric (Starr, 1963) has been chosen as it aligns well with the decision context, risk tolerance, and preferences of the regional stakeholders. The satisficing metric, S, defined in this study represents the fraction of SOW that a portfolio is able to meet predefined performance criteria set forth by regional stakeholders.

$$S = \frac{1}{N}\sum_{j=1}^{N}\Lambda_{\theta,j}, \tag{11}$$

where

$$\Lambda_{\theta,j} = \begin{cases} 1, & \text{if} \quad F(\theta)_j \le \Phi_j \\ 0, & \text{otherwise} \end{cases}, \tag{12}$$

where $\boldsymbol{\Phi}$ is a vector of performance criteria for utility j, θ is the portfolio, and N is the total number of sampled SOWs.

Differences in preference across actors with respect to the choice of regional portfolio may render portfolios that are most robust for the regional system, unstable for the cooperative partnership (Madani, 2010; Madani & Hipel, 2011; Read et al., 2014). To discover acceptable regional compromises, we simulate a regional fallback bargaining process using utility robustness to represent preferences for each regional actor. Several variants of fallback bargaining exist, including unanimity fallback bargaining, q-approval fallback bargaining, fallback bargaining with impasse, and stochastic fallback bargaining (Madani et al., 2011). In this study,

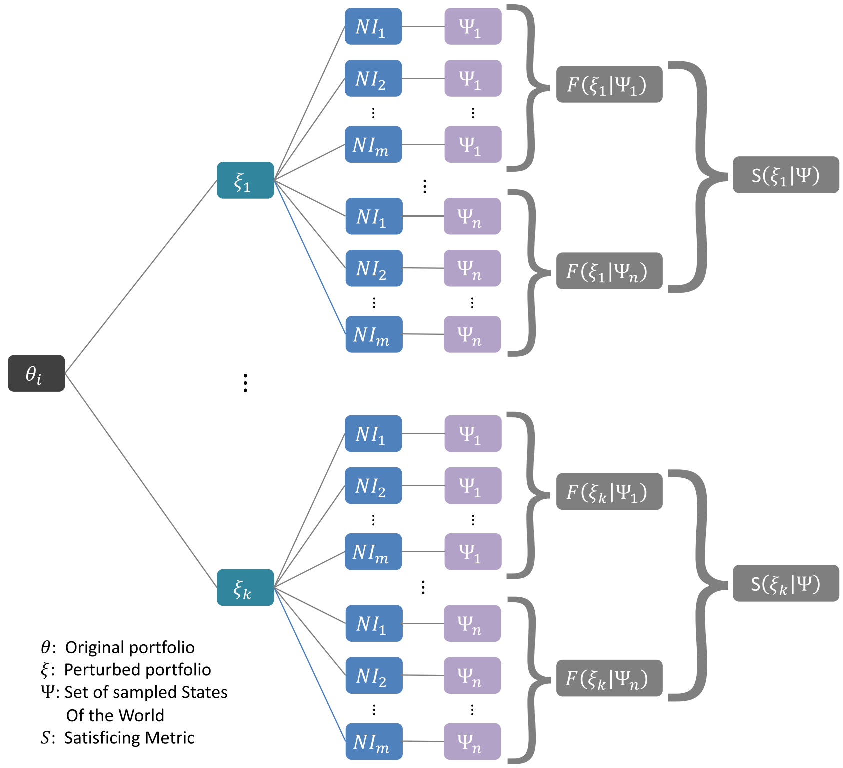

Figure 4. Implementation tolerances analysis sampling scheme. Each perturbed variant (ξ) of compromise portfolio (θ) is reevaluated through the system model across 1,000 synthetically generated reservoir inflows (*NI*) and 1,000 SOWs representing LHS samples of DU factors ($\mathbf{\Psi}$).

we employ unanimity fallback bargaining because it maximizes the minimum satisfaction across all bargainers and ensures any selected compromise is Pareto optimal (Madani et al., 2011). Under unanimity fallback bargaining, bargainers rank order their preferences across potential alternatives, if a single alternative is the most preferable to all regional actors, it is selected, if the most preferable alternative differs among actors, they each fall back, in lockstep, to less desirable alternatives until an alternative is found that satisfies all bargainers (Brams & Kilgour, 2001).

3.5. Implementation Tolerances Analysis

While prior investigations of the Triangle water supply planning problem have examined portfolio robustness to hydroclimatic and socioeconomic factors (Herman et al., 2014; Trindade et al., 2017), no prior study has examined the possibility of uncertainty in implementation of a selected water supply portfolio. In this study, we assess the vulnerability of compromise portfolios to implementation uncertainty by sampling plausible operational deviations around the selected compromise portfolios' decision variables using the sampling scheme shown in Figure 4. We first identify the range of plausible deviations for each decision variable, δ, and generate a set of 1,000 perturbed variants of each compromise portfolio, ξ, by taking 1,000 LHS of δ and adding each to the existing vector of decision variables, θ.

$$\xi_i = \theta + \delta_i. \tag{13}$$

The ranges of plausible deviations for each decision variable can be found in Table 4. As no data involving historical precision of portfolio implementation is available and no study has evaluated implementation uncertainty for the Triangle system, our sampling represents a bottom up vulnerability analysis (Brown et al., 2012; Nazemi & Wheater, 2014; Weaver et al., 2013) that seeks to discover vulnerable implementation scenarios rather than predict how portfolios may be implemented. The set of perturbed portfolios generated through equation(13) is reevaluated over a new set of sampled uncertainties created by pairing ensemble of 1,000 WCU streamflow time with 1,000 unique SOWs, $\mathbf{\Psi}$, for a total of 1 million model simulations for each sampled perturbation, as shown in Figure 4. We quantify the robustness of each perturbed variant of

Table 4
Sampling Ranges of Decision Variable Deviation

Decision Variable	Minimum Value	Maximum Value	Sampling Range
Water Use Restriction Trigger	0.0	1.0	± 0.04
Transfer Trigger	0.0	1.0	± 0.04
Reserve Fund Contribution	0.0	0.1	± 0.04
Index Insurance Trigger	1	5	± 2
Jordan Lake Allocation	0.0	0.69	± 0.04

the compromise portfolios using the satisficing metric described in section 3.4 and examine the effects of implementation uncertainty across performance criteria for each regional stakeholder using visual analytics.

3.6. Identification of Robustness Controls

After quantifying the vulnerability of selected portfolios to implementation uncertainty, we construct logistic regression models to identify how operational deviations and exogenous uncertainties impact portfolio performance. These models predict the probability that a portfolio will meet stakeholder performance criteria across the sampled range of each decision variable and deeply uncertain factors. Results from these models are used evaluate how portfolio robustness may change due to operational deviations within the sampling range δ. A detailed description of the logistic regression models can be found in Text S4.

We also employ global sensitivity analysis using the delta moment-independent sensitivity index (Borgonovo, 2007) to rank all uncertainties; including both implementation uncertainty and deeply uncertain factors. This global sensitivity index provides a measure of each uncertainty's effects on the entire distribution of a performance metric. The delta moment-independent method can accurately estimate global sensitivity indices from given data without out requiring a specific structured sampling strategy (Plischke et al., 2013). We calculate delta indices for each performance criteria of each regional actor using the SALib python library (Herman & Usher, 2017). Results of this global sensitivity analysis reveal important sensitivities for both the regional partnership and individual actors and provide a quantitative comparison of the effects of implementation uncertainty and other deeply uncertain exogenous factors.

Information from the logistic regression models and global sensitivity analysis yield insights into the nature of portfolio vulnerability, but they do not provide operational information to regional actors regarding the necessary level of implementation precision. Building on the work of Kwakkel and Timmermans (2012), we delineate the SOS around a compromise portfolio's decision variables using PRIM (Friedman & Fisher, 1999). PRIM identifies multidimensional "boxes" in the decision space that are likely to cause degradation from the performance of the original portfolio. PRIM seeks to maximize coverage, the total fraction of perturbed portfolios that lie within the box, and density, the fraction of portfolios within the box that fail to meet the performance criteria. The SOS constitutes operational tolerances (tolerable ranges for each decision variable) of a selected water supply portfolio, providing critical insight into portfolio feasibility. Details on PRIM analysis can be found in Text S2.

Scenario discovery (Bryant & Lempert, 2010; Lempert et al., 2006) supports the generation of narrative scenarios by evaluating the performance of planning alternatives over a set of plausible SOWs and determining which regions of the uncertainty space are likely to cause performance failure. In this work, we include implementation uncertainty within the scenario discovery process to discover consequential scenarios that incorporate both exogenous and implementation uncertainty. To identify key scenarios, the logistic regression models described above are used to predict the probability that a portfolio can meet performance criteria under a sample drawn from both exogenous deep uncertainties and operational deviations, should the sample occur (Quinn et al., 2018). Stakeholders can then divide the uncertainty space into success or failure regions based on their risk tolerance. The scenarios generated through the logistic regression modeling complement the SOS to provide information regarding the practicality of portfolio implementation and the nature of portfolio vulnerability.

In sum, the robustness controls described in this section provide four key pieces of information to decision makers that aid regional bargaining and portfolio selection. First, insight on how portfolio performance may vary due to operational deviations is provided by logistic regression. Second, a global ranking of all uncertain factors is provided by global sensitivity analysis. Third, operational tolerances represented by SOSs are

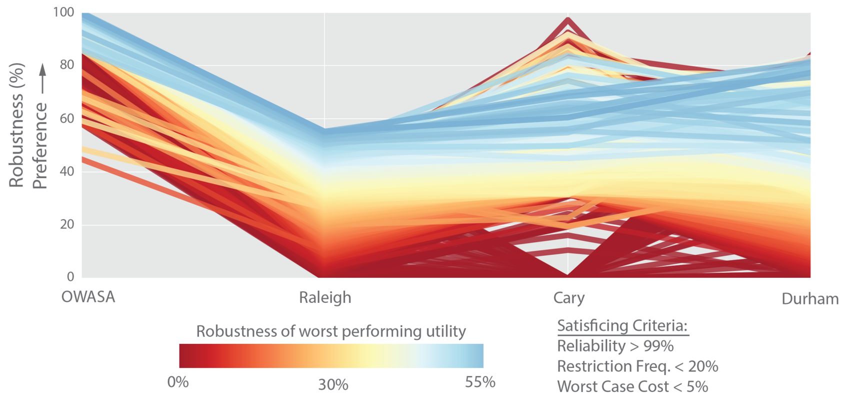

Figure 5. Robustness trade-offs within the Pareto approximate set of water supply portfolios discovered by Trindade et al. (2017). Each axis represents the robustness of a regional utility. Each line maps the satisficing performance for a different Pareto approximate water supply portfolio. The color of the lines represents the robustness of the worst-performing utility for that portfolio.

delineated using PRIM. Finally, consequential scenarios that expose portfolio vulnerability are discovered through further exploration of the logistic regression models.

4. Results

4.1. Many-Objective Optimization Under Deep Uncertainty

Figure 5 presents a parallel axes plot of the relative robustness of the Pareto approximate portfolios discovered by Trindade et al. (2017) for each of four Research Triangle utilities. Each parallel vertical axis reports the robustness of one of the regional actors and each line represents one Pareto approximate regional water supply portfolio. The location that each line crosses each vertical axis corresponds to the portfolio's robustness. Portfolio robustness is defined as the fraction of SOWs that the portfolio represented meets three satisficing performance criteria set by the utilities: reliability greater than 99%, restriction frequency less than one in 5 years (20%), and worst-case cost below 5% annual volumetric revenue (AVR). Ideal performance in Figure 5 is 100% satisficing at the top of each vertical axis. The color of each line represents the robustness of the worst-performing utility under that portfolio, with red indicating poor robustness and blue indicating higher robustness. Figure 5 highlights potentially strong robustness conflicts between the cooperating utilities, as no single portfolio can achieve the best robustness for all four utilities. Strong conflicts are visually evident by the steepness of diagonal lines between utilities. The red colored portfolios at the top of Cary's axis indicate that the most robust portfolios for Cary perform very poorly for one or more of the other utilities. Interestingly, Figure 5 highlights that regionalization of water management can inadvertently increase regional tensions as has been noted in prior analyses of this system (Herman et al., 2014; Trindade et al., 2017). There are several instances where very high robustness for one utility greatly diminishes performance for others. Resolving robustness conflicts is further challenged by recent commitments of 31% of the Jordan Lake water supply pool to utilities outside of the Research Triangle partnership. Figure 5 presents a core technical challenge that has not been well-addressed in the robustness literature to date: "how should we evaluate and navigate robustness conflicts in multi-actor systems to identify a compromise regional portfolio?".

Building from the challenge presented by Figure 5, the negotiated selection of a regional portfolio should seek an acceptable compromise across regional actors (Madani, 2010; Madani & Hipel, 2011; Read et al., 2014). To find a regional compromise, we employ fallback bargaining, as described in section 3.4, utilizing each individual utility's robustness to rank order preferences for candidate portfolios. To gain a better understanding of the potential consequences for alternative compromises across the utilities' robustness trade-offs, we have conducted the fallback bargaining process twice, with the portfolio selected from the first bargaining process removed before the second analysis. Identifying two representative compromise portfolios aids our illustration of the broader concern that the multi-actor implications of even modest changes regional actors' relative robustness can be quite complex.

Figure 6 illustrates the performance of the two compromise portfolios attained from the two rounds of fallback bargaining as well as their associated portfolio decision variables. Using the same style of parallel axes

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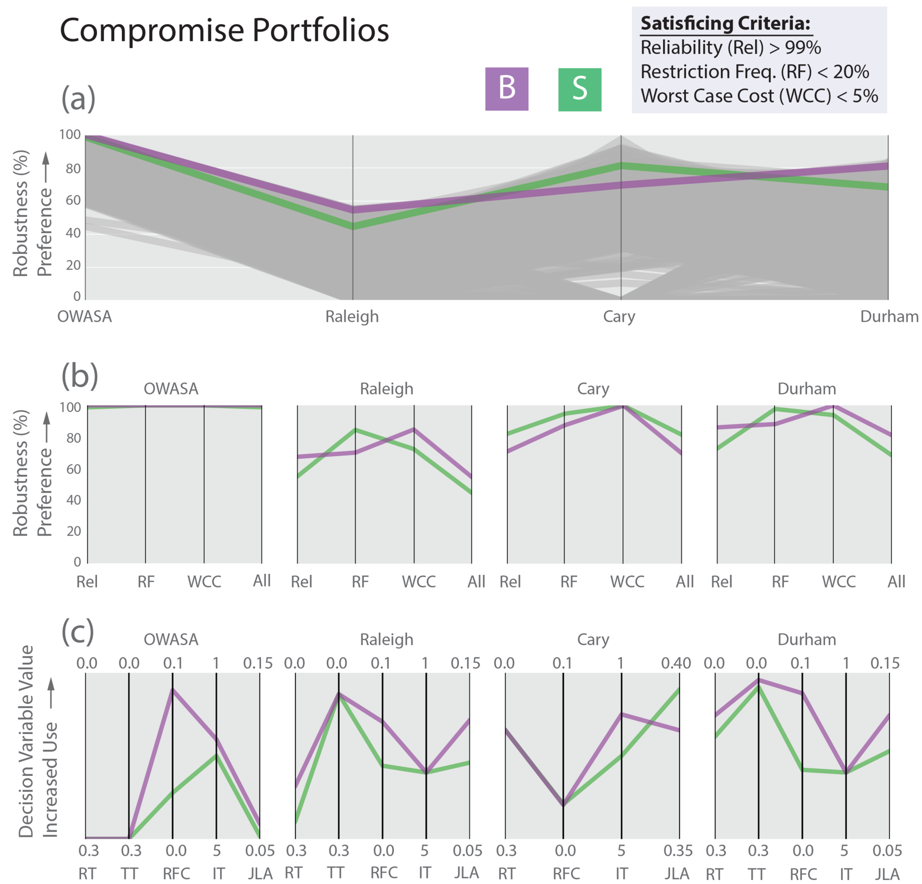

Figure 6. Panel (a) shows the robustness of the two regional compromise portfolios selected through fallback bargaining. Portfolio S, favors Cary, the supplier of treated transfers, while Portfolio B, favors Durham and Raleigh, the buyers of transfers. Panel (b) shows the two compromise portfolios disaggregated across the three satisficing criteria for each utility: Reliability (Rel), Restriction Frequency (RF), and Worst-Case Cost (WCC) and for all criteria simultaneously (All). Panel (c) shows the decision variables that compose the two compromise portfolios.

plotting as Figure 5, Figure 6a shows the robustness of the two compromise portfolios. The remainder of the water supply portfolios not selected through the fallback bargaining process are shaded in gray (i.e., they were brushed out from consideration). Portfolio S, illustrated in green (Figure 6), favors Cary, the supplier of regional treated water transfers. In contrast, portfolio B (colored purple in Figure 6) favors Raleigh and Durham, the buyers of treated transfers. Portfolio S is the more risk averse choice for Cary as it can satisfy performance criteria across a wider range of SOWs, while portfolio B represents the more risk adverse choice for Raleigh and Durham.

A closer examination of the compromise portfolios through Figures 6b reveals more information on the nature of the regional trade-off and the performance across individual satisficing criteria. In Figure 6b, each subplot represents a water utility and each vertical axis represents a satisficing criterion. The two lines represent the performance of the compromise portfolios in each criterion and the location that each line crosses the vertical axes represents the number of states of the world that the portfolio met the given criteria. Upon closer inspection, the improved robustness for Raleigh and Durham under portfolio B is manifest in improved robustness to the reliability criteria. This however, comes at the cost of increased restriction frequency. The choice between the two compromise portfolios for Raleigh and Durham thus also represents a valuation of the utilities' risk aversion and willingness to pay for improved reliability (Borgomeo et al., 2016).

The cause of the trade-off between reliability and restriction frequency is revealed by examining the decision variables that compose the two compromise portfolios. Compromise portfolio decision variables are plotted in Figure 6c and listed in Table 5. In Figure 6c, each axis represents a decision variable and each line represents a compromise portfolio. The location that a line crosses the vertical axes represents the decision

Table 5
Compromise Portfolio Decision Variables, Ranges of Sampled Operational Deviations and the Allowable Deviation Before a Portfolio Leaves Its Safe Operating Space

		Compromise Portfolio S			Compromise Portfolio B		
Utility	Decision Variable	Original Value	Sampling Range	Allowable Deviation	Original Value	Sampling Range	Allowable Deviation
Durham	RT (ROF)	12%	8–16%	4%	8%	4–12%	0%
	TT (ROF)	3%	1–7%	0%	1%	1–5%	0%
	RFC (AVR)	4%	2–6%	2%	9%	5–13%	2%
	IT (Stage)	3	1–5	2	3	1–5	2
	JLA (%)	10%	6–14%	4%	12%	8–16%	4%
Raleigh	RT (ROF)	27%	23–31%	4%	21%	17–23%	3%
	TT (ROF)	4%	1–8%	4%	4%	1–8%	2%
	RFC (AVR)	4%	0–8%	4%	7%	3–11%	2%
	IT (Stage)	2	1–4	2	3	1–5	2
	JLA (%)	9.5%	5.5–13.5%	4%	12%	8–16%	4%
OWASA	RT (ROF)	30%	26–34%	4%	30%	26–34%	4%
	TT (ROF)	30%	26–34%	4%	8%	4–12%	4%
	RFC (AVR)	3%	1–7%	4%	9%	5–13%	4%
	IT (Stage)	3	1–5	2	1	1–3	2
	JLA (%)	5%	1–9%	4%	6%	2–10%	4%
Cary	RT (ROF)	10%	6–14%	4%	10%	6–14%	4%
	RFC (AVR)	2%	1–6%	4%	2%	1–6%	4%
	IT (Stage)	1	1–3	2	1	1–3	2
	JLA (%)	39%	35–43%	3%	36.5%	32.5–40.5%	1%

Note. Decision variables include Restriction Trigger (RT), Treated Transfer Risk Trigger (TT), Reserve Fund Contribution (RFC), Insurance Trigger (IT), and Jordan Lake Allocation (JLA).

variable value in the portfolio it represents, with locations higher on the axis representing increased use of the decision variable. A key difference between the two compromise portfolios is the allocation of the Jordan Lake. Portfolio S contains a higher allocation for Cary and a lower allocation for Durham and Raleigh. The increased allocation to Cary partnered with the diminished supply to Raleigh and Durham allows Cary to perform better across all three criteria when faced with challenging future SOWs. In contrast, the increased allocation that Durham and Raleigh receive under portfolio B allows the two utilities to increase purchases of treated transfers to improve reliability under challenging SOWs. The increased use of treated transfers allows Raleigh and Durham to employ a lower risk trigger for water use restrictions, further increasing the reliability of the transfer buying utilities, though decreasing their performance in the restriction frequency criteria. Without the frequent use of treated transfers, a low risk trigger for water use restrictions may lead to severe overuse of such water use restrictions in challenging future SOWs. To cover the cost of increased drought mitigation through treated transfers and water use restrictions, portfolio B employs a higher reserve fund contribution for both Raleigh and Durham. In turn, this leads to an increase in robustness in the worst-case cost criteria. This improvement in worst-case cost comes at the expense of higher average annual cost, an objective not plotted in Figure 6 as it was not included in stakeholder specified satisficing criteria.

It is important to note that both compromise portfolios selected through fallback bargaining contain decision variables outside the range of the utilities' current water shortage mitigation strategies, which rarely contain reserve fund contributions greater than five percent of AVR or ROF restriction triggers greater than three percent (Buchan & Black, 2011; Goodwin, 2015; Water & Authority, 2010; Westbrook et al., 2016). This underscores the value of many-objective search to the success of cooperative drought mitigation planning; the combinations of decision variables that compose the selected compromises would never have been explored if portfolios were informed solely by current operating policies. Despite the trade-off between reliability and restriction frequency, the regionally coordinated mixture of drought mitigation measures and financial instruments allows both compromise portfolios to maintain high performance in conflicting criteria across a wide array of future SOWs. These findings exemplify the benefits of a portfolio planning

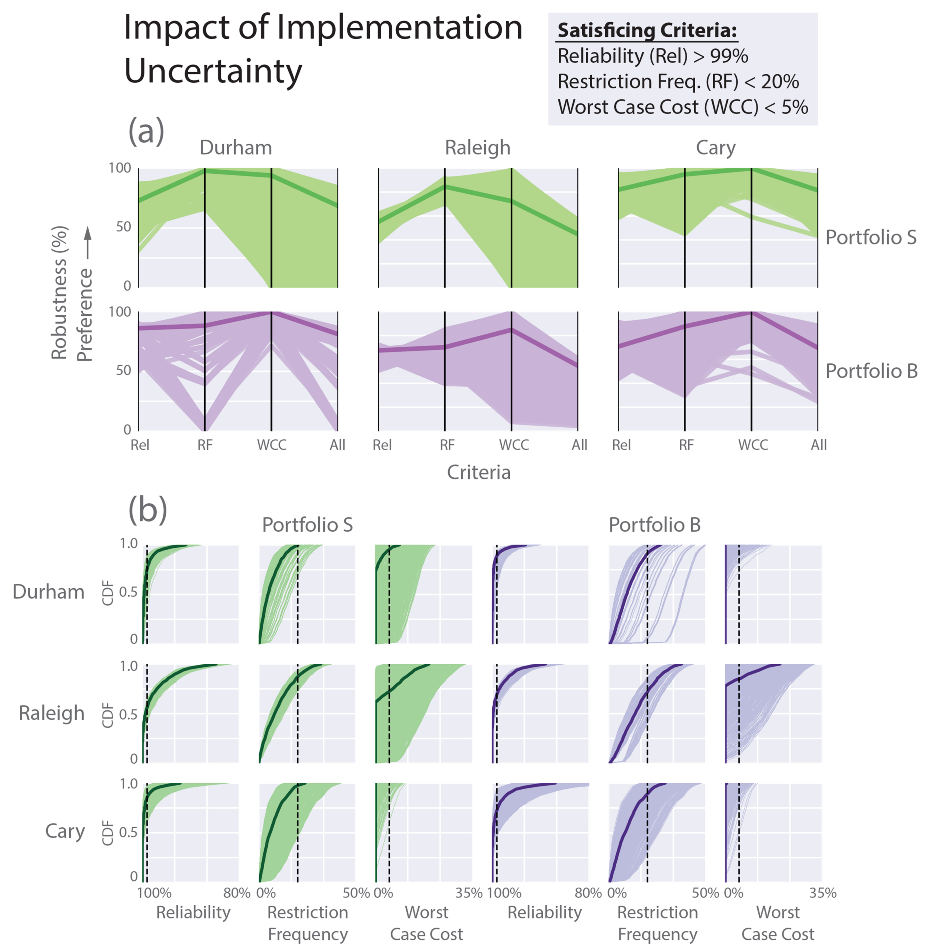

Figure 7. Panel (a) shows the robustness of the original compromise portfolios (dark lines) and sampled operational deviations across the three satisficing criteria. Panel (b) shows cumulative distributions of portfolio performance across the DU SOWs for each satisficing criterion.

approach to water resources management (Characklis et al., 2006; Green & Hamilton, 2000; Lund & Israel, 1995). The importance of a very careful balance of water supply portfolio instruments across Research Triangle actors is clear; this raises the concern of regional vulnerabilities to the assumed or required precision of portfolio implementation. The consequences of imprecise implementation are unknown and represent a potential vulnerability that has largely been ignored in the water systems literature. The implementation tolerances analysis contributed in this study quantifies the vulnerability of the two compromise portfolios to uncertainty in portfolio implementation and delineates operational tolerances for portfolio implementation. Although the results utilize the Research Triangle to illustrate the framework, it is expected that these concerns are present in urban regions globally and pose limits to theoretical applications of soft path water portfolio planning broadly (Gleick, 2002, 2003).

4.2. Vulnerability to Implementation Uncertainty

The implementation tolerances analysis, described in section 3.5, evaluates the effect of implementation uncertainty on the selected compromise water supply portfolios by sampling 1,000 plausible operational deviations from the original portfolios' decision variables. For each compromise portfolio, this sampling yields 1,000 new perturbed variants of its decision rules that are then reevaluated over a set of deeply uncertain SOWs. This exploratory analysis highlights the fragility of the two compromise portfolios: utilities fail more often with modest deviations in their implementation of decisions and they can fail more dramatically. We can see these effects on portfolio performance for Cary, Raleigh, and Durham in Figure 7. OWASA was omitted from further analysis as its performance remained consistent. Figure 7a shows the impact of implementation uncertainty on portfolio robustness, the metric used to select compromise portfolios with fallback bargaining. In Figure 7a, each vertical axis represents an individual satisficing criterion. The dark lines represent the original compromise portfolios and the lightly shaded lines represent the sampled operational deviations. Compromise portfolio S is shown in the top row of plots and compromise portfolio B is shown in the bottom row of plots. These plots illustrate two salient points regarding the vulnerability of portfolios to implementation uncertainty. First, implementation uncertainty can severely degrade both portfolios' ability to meet each of the utility-specified satisficing criteria. Importantly, while the original compromise portfolios only fail to meet the satisficing criteria under a small number of challenging SOWs, certain operational deviations may cause failure in every SOW. Second, the impact of implementation uncertainty manifests differently for each utility and each compromise portfolio. For Durham, imprecise implementation increases failures in worst-case cost under portfolio S while it increases failure in restriction frequency under portfolio B. Implementation uncertainty makes Raleigh vulnerable to failures in worst-case cost under both compromise portfolios, but it also creates a vulnerability to restriction frequency under portfolio B.

In addition to failing more often, Figure 7b shows that imprecise implementation can worsen the extent of failure. The dark lines in Figure 7b represent the cumulative distributions of the original compromise portfolios and the lightly shaded lines represent the sampled operational deviations. The utilities' satisficing criteria are drawn as dashed vertical lines. For Durham, these impacts are seen in worst-case cost under portfolio S and restriction frequency under portfolio B. Raleigh is subject to an extreme increase in worst-case cost under both portfolios, though implementation uncertainty has little effect on tail values of reliability and restriction frequency. Notably, implementation uncertainty can severely degrade Cary's reliability, causing reservoir levels to drop below a critical threshold in one out of five hydrologic realizations in some SOWs.

In sum, the results shown in Figures 7a and 7b suggest that failing to consider the implementation uncertainty in this test case may cause utilities to overestimate the robustness of candidate water supply portfolios and fail to appreciate the potential severity of failures. These findings highlight the careful balance of drought mitigation and financial instruments that compose the two compromise portfolios. To further understand the impacts of operational deviations on the two compromise portfolios, we employ sensitivity analysis to clarify how operational deviations cause degradation in portfolio performance and the defined operational tolerances for each decision variable across the two portfolios. Although the bodies of literature associated with reliability engineering and control systems have a significant history of addressing implementation uncertainty (see review Beyer & Sendhoff, 2007), the multi-actor regional contexts for water supply systems are significantly more complex and institutionally challenging to characterize than the what has been addressed in prior studies.

4.3. Identifying Key Performance Sensitivities

Identifying scenarios where operational deviations contribute to portfolio vulnerability requires a better understanding of the relative impacts of implementation uncertainties and exogenous stressors. We analyze how implementation uncertainty affects compromise portfolios through logistic regression, as discussed in section 3.6. Figure 8 shows the predicted changes to utility robustness from uncertainty within each decision variable. Each decision variable is plotted as a dial on a control panel spanning the sampled range of operational deviations, with the decision variable of the original portfolio marked with the dial's arrow. The color shading on each dial represents the percent change in robustness from the original portfolio predicted by the logistic regression model. Large color gradients on a decision variable dial indicate increased portfolio sensitivity to the decision variable; gray shaded dials indicate decision variables that did not demonstrate predictive value for portfolio robustness (for details on the logistic regression models, see Text S4).

Figure 8 illustrates that the dominant implementation uncertainties that cause vulnerability for Durham fundamentally differ between the two compromise portfolios. Degradation in Durham's robustness under portfolio S is primarily driven by changes in the reserve fund and transfer trigger. A reduced reserve fund causes failures in the worst-case cost criteria while changes to the transfer trigger impact failures in both restriction frequency and reliability. In contrast, under portfolio B, Durham's failures are largely driven by changes in the water use restriction trigger and treated transfer trigger, while its robustness is not affected by deviations in reserve fund contribution. Together, deviations in the water use restriction and treated transfer risk triggers explain the degradation in performance in the restriction frequency and reliability criteria while the initially large reserve fund contribution allows room for deviation without severe penalties in the worst-case cost criteria.

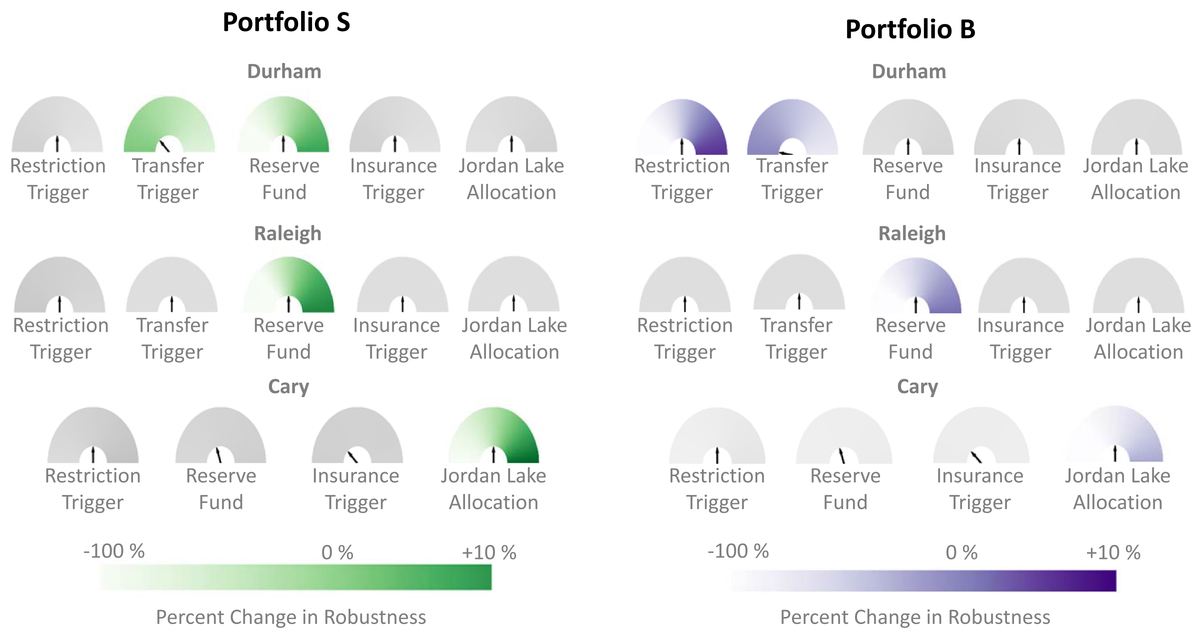

Figure 8. Predicted change in robustness from implementation uncertainty. Each dial represents a decision variable, the shading on the dials represent the predicted percent change in robustness from the original portfolio. The arrows represent the value of the decision variable if implemented as specified. A large color gradient on a dial indicates that its value may strongly impact portfolio robustness. Gray shaded dials indicate decision variables that were not influential in the logistic regression models.

Though Raleigh adopts similar strategies to Durham under both portfolios, the causes of its vulnerability to operational deviations differ. While not as sensitive to changes in water use restriction or treated transfer triggers as Durham for either compromise portfolio, Raleigh is sensitive to changes in reserve fund contribution under both portfolios. Raleigh's sensitivity to changes in reserve fund contributions indicates that the worst-case costs failures shown in Figure 7 are driven by lack of financial resources rather than increased cost from drought mitigation.

Unlike Raleigh and Durham, Cary's vulnerability is most affected by changes in the Jordan Lake allocation. As Cary's only water source, reductions in allocations may strongly impact a portfolio's ability to meet Cary's satisficing criteria under unfavorable SOWs. Although it is expected in the Research Triangle that Raleigh and Durham are strongly impacted by changes in allocation of the Jordan Lake, our results in Figure 8 show that these impacts do not manifest as first order effects. Not surprisingly they only emerge as part of interactive effects that Raleigh's and Durham's transfer triggers have on the performance of their portfolios. Like the impact of the Jordan Lake on Raleigh and Durham, regional performance is likely sensitive to higher order interactions between uncertainties in both implementation and exogenous deep uncertainties. To gain a richer understanding of the important uncertainties on compromise portfolios we conduct a global sensitivity analysis using the delta moment-independent sensitivity index.

The heat maps plotted in Figure 9 show the results of globally screening the most influential implementation and exogenous uncertainties using the delta method global sensitivity analysis described in section 3.6. The delta moment-independent sensitivity index of each objective (vertical axis) to each uncertain factor (horizontal axis) is represented by the shading of each cell; white is insensitive and darker sensitive. The global sensitivity analysis summarized in Figure 9 deepens the examination of relevant uncertainties beyond the logistic regression results shown in Figure 8 by providing insights into effects on the entire distribution of performance key objectives rather than an aggregate satisficing robustness. Figure 9 answers the question of how the implementation uncertainties rank when considered jointly with other deep uncertainties that have been considered in prior published work (Herman et al., 2014; Trindade et al., 2017).

Figure 9 reveals that the effects of implementation uncertainty on the two compromise portfolios are comparable to the effects of the most salient deeply uncertain factors, further underscoring the importance of including implementation uncertainty when evaluating performance of water supply portfolios. The demand growth scaling factor is highly influential on performance in both the reliability and restriction

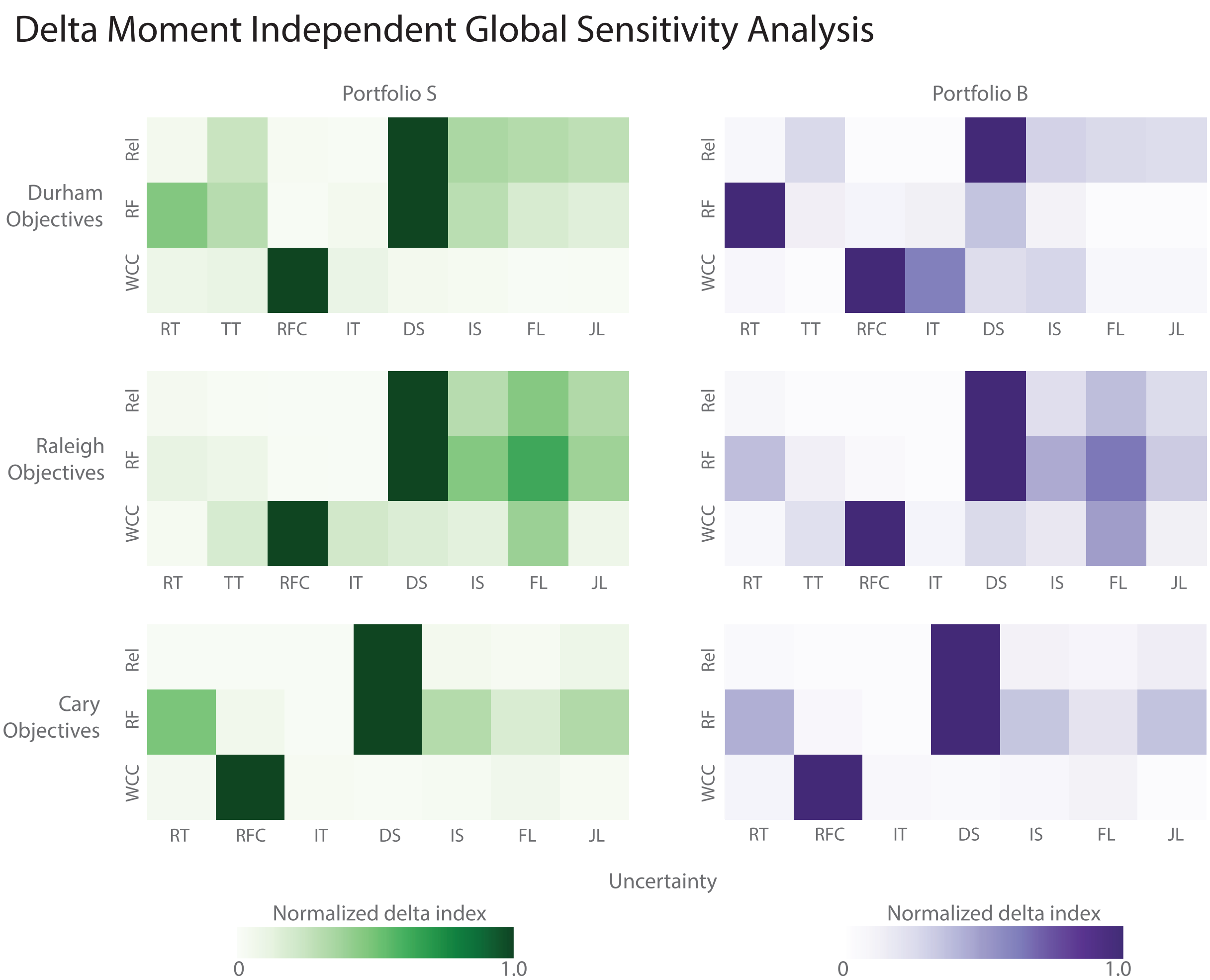

Figure 9. Results of the delta moment-independent global sensitivity analysis. Individual satisficing criteria: Reliability (Rel), Restriction Frequency (RF), and Worst-Case Cost (WCC) are plotted on the horizontal axis. Decision variables and influential deep uncertainties: Restriction Trigger (RT), Transfer Trigger (TT), Reserve Fund Contribution (RFC), Insurance Trigger (IT), Demand Growth Scaling (DS), Inflow Scaling (IS), Falls Lake Allocation (FL), and Jordan Lake Allocation (JL) are represented on the vertical axis. Global sensitivities are represented by the shading in each cell, dark color represents sensitivity and light represents insensitivity.

frequency criteria, supporting previous findings (Herman et al., 2014, 2015; Trindade et al., 2017). The worst-case cost criterion is most sensitive to the reserve fund contribution for all three utilities across both compromise portfolios. For Cary, the reserve fund is the only influential factor for worst-case cost under both portfolios. Figure 7b shows that Cary is able to maintain a worst-case cost of 0% AVR across all states of the world under both compromise portfolios if implemented precisely, indicating that its reserve fund contribution prescribed by both compromise portfolios is enough to cover costs across all sampled SOWs. Reductions in reserve fund contribution cause Cary's worst-case cost to rise in a small percentage of SOWs, though these cost increases do not severely effect portfolio robustness explaining why the reserve fund is not found to have predictive power in the logistic regression model.

In addition to reserve fund contribution, Raleigh's worst-case cost is also influenced by a variety of other factors. The worst-case cost under both portfolios is vulnerable to changes in the Falls Lake allocation, Raleigh's largest supply source, indicating that pressure from reduced supply forces it to resort to costly mitigation measures. Both portfolios are also sensitive to changes in transfer and insurance triggers, which cause increased cost and decreased financial support respectively. Together, these results indicate that the extreme failures in Raleigh's worst-case cost shown in Figure 7b are the result of a combination of factors including decreased supply, increased use of costly drought mitigation measures and decreased financial reserves.

Influential factors on worst-case cost for Durham vary between the two compromise portfolios. Under portfolio S, Durham's reserve fund contribution is the only influential factor, while under portfolio B insurance

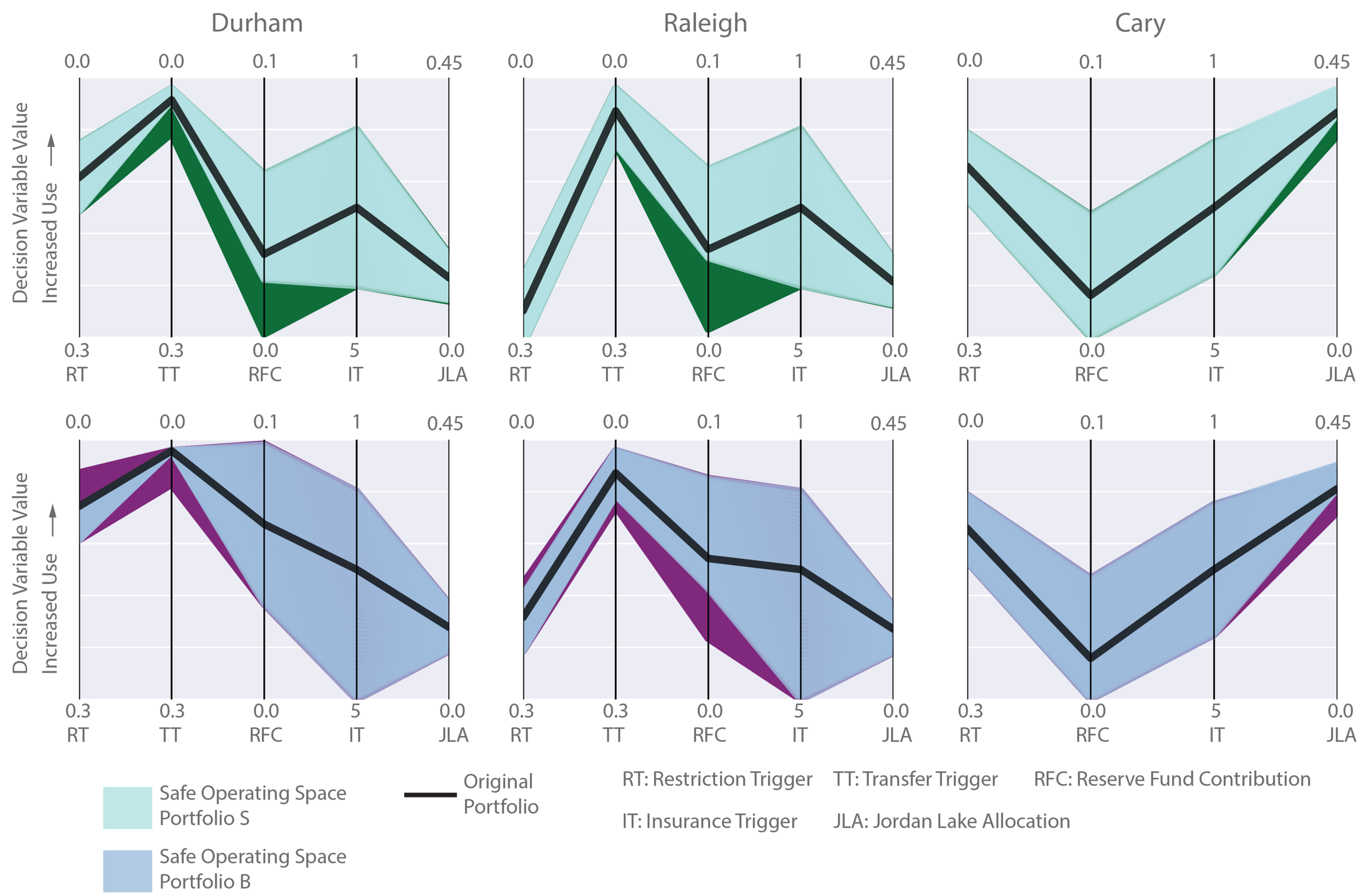

Figure 10. Safe operating spaces for selected compromise water supply portfolios. Each vertical axes represents a decision variable, and the location along the vertical axis indicates the extent to which each decision is used in the portfolio. The black lines represent the decision variables of the compromise water supply portfolios, the dark shaded region represents the sampled ranges of decision variables tested in this experiment and the lightly shaded regions represent the SOS.

trigger, demand growth and inflow scaling are all found to be influential. Portfolio S represents a low mitigation strategy for Durham if implemented precisely; the initial reserve fund contribution is therefore low as revenue shortfalls are not as likely. Paradoxically, this makes portfolio S more vulnerable to reductions in reserve fund contribution. As the primary contributor to worst-case cost sensitivity, reserve fund reductions are responsible for the severe failures shown in Figure 7b.

Durham's vulnerability to deviations in reserve fund under portfolio S is mirrored by its vulnerability to restriction frequency under portfolio B. Sensitivity analysis results indicate that the extreme vulnerability to failures in restriction frequency shown in Figure 7 is largely due to deviations in the portfolio's restriction trigger. Durham's differing sensitivities further exemplify the careful balance each portfolio maintains to meet the utility's conflicting objectives. Portfolio S maintains a reserve fund large enough to mitigate severe worst-case costs in most SOWs but is kept as low as possible to reduce utility average cost. Any further decrease in reserve fund contribution renders the fund too small to mitigate financial losses and results in severe penalties to the worst-case cost criteria. Portfolio B's restriction trigger is kept low to quickly respond to drought conditions and improve reliability, decreasing the risk trigger from the initial value however may result in over restriction in any SOW. These results indicate that previous recommendations to focus on regional demand management (Herman et al., 2014; Trindade et al., 2017) must be paired with careful implementation of the selected compromise portfolio. But how precise does implementation have to be for a portfolio to perform as expected? To specify such operational tolerances, we delineate regional safe operating spaces for each compromise portfolio.

4.4. Delineating Safe Operating Spaces

Transitioning to implementation tolerances for the water portfolios, we draw from the concept of SOS (Carpenter et al., 2015; Rockstrom et al., 2009). We define a SOS for a water supply portfolio as the region of the decision space such that any combination of decision variables sampled within the region is at least as robust as the original water supply portfolio. Figure 10 shows the delineated SOS for both compromise water supply portfolios. Each vertical axes represents a decision variable, and the location along the vertical axis indicates the extent to which each decision is used in the portfolio (a vertical line at the top of each plot would represent a portfolio with the maximum possible use of each decision variable). The black lines in Figure 10 represent the decision variables of the compromise water supply portfolios, the dark shaded region represents the sampled ranges of decision variables tested in this experiment, and the lightly shaded regions represent the SOS. Sampled ranges and allowable deviations for each portfolio are also shown in Table 5.

The SOSs plotted in Figure 10 further highlight the differences between the two compromise portfolios. For Raleigh, the two compromise portfolios represent a choice between extreme sensitivity to one decision variable and increased sensitivity across several decision variables. Under portfolio S Raleigh's reserve fund contribution has a very narrow SOS but no other decision variables cause performance degradation within the sampled range of the decision space. Under portfolio B, the utility has more room for deviation in its reserve fund contribution but may suffer if it fails to implement its restriction trigger or transfer trigger precisely. Raleigh's preference between the two compromise portfolios is thus not only dependent on its preference across objectives and risk tolerance but also on its judgment related to the precision with which it could implement each portfolio decision.

Examination of Durham's SOS under the two portfolios reveals two interesting points. First, Durham's choice of compromise portfolio represents an evaluation of the feasible level of precision between restriction trigger and reserve fund. Second, the small tolerance to deviations in treated transfer triggers under both compromise portfolios exposes the potential fragility of the regional cooperative partnership. Durham's sensitivity to transfer trigger deviations indicates that it is vulnerable to any emerging instabilities within the regional partnership; if Cary cannot or refuses to provide treated transfers for any reason, Durham's ability to meet stakeholder requirements under challenging futures is greatly diminished. Cary's willingness to provide treated transfers is predicated on the availability of excess treatment capacity from the Jordan Lake. Figure 10 reveals that small changes to Cary's Jordan Lake allocation can cause Cary's robustness to degrade and Figure 7 illustrates that such degradation can manifest as severe failures in reliability. Should Cary find itself in a vulnerable position from a reduced allocation, its willingness to assist regional partners through treated transfers may diminish. This scenario is not unlikely; pressure from water utilities outside the Research Triangle makes the future of the Jordan Lake highly uncertain. The presence of this vulnerability within both compromise water supply portfolios indicates a broader instability within the regional cooperative partnership that has the potential to undermine individual and regional performance.

To deepen our understanding of how future scenarios cause vulnerability within the regional partnership, we employ logistic regression to model each portfolio's ability to meet satisficing criteria using both implementation and exogenous uncertainties as model inputs. These logistic regression models capture interactive effects between uncertainties and provide decision makers with consequential scenarios that define “challenging” SOWs that can serve as signposts to trigger new analysis (Haasnoot et al., 2013). Figure 11 shows the predicted probability of meeting the satisficing criteria as a function of the two most important uncertainties for each utility. The base state of the world with portfolios implemented with perfect precision is depicted by the star. The shading on each plot represents the predicted probability that a utility will meet its satisficing criteria in a SOW defined by the parameters plotted on the axes, should that SOW occur (note that this does not represent the probability that the SOW will occur). Previous studies on the Triangle region have identified high demand growth rate as the main driver of regional failure. While demand growth rate was found to be a salient uncertainty for each utility in this study, operational deviations were found to have strong interactions with demand growth rate, indicating that simply controlling demand growth rate without maintaining precise implementation may not lead to acceptable performance. This can be observed in Figure 11 by horizontal movement from the base SOW; even when constrained to the current demand growth projection, Durham may still fail solely due to imprecise implementation. The nature of this horizontal movement once again differs between the two portfolios. The results shown in Figure 11 provide a final distinction between the two compromise portfolios: not only do vulnerabilities

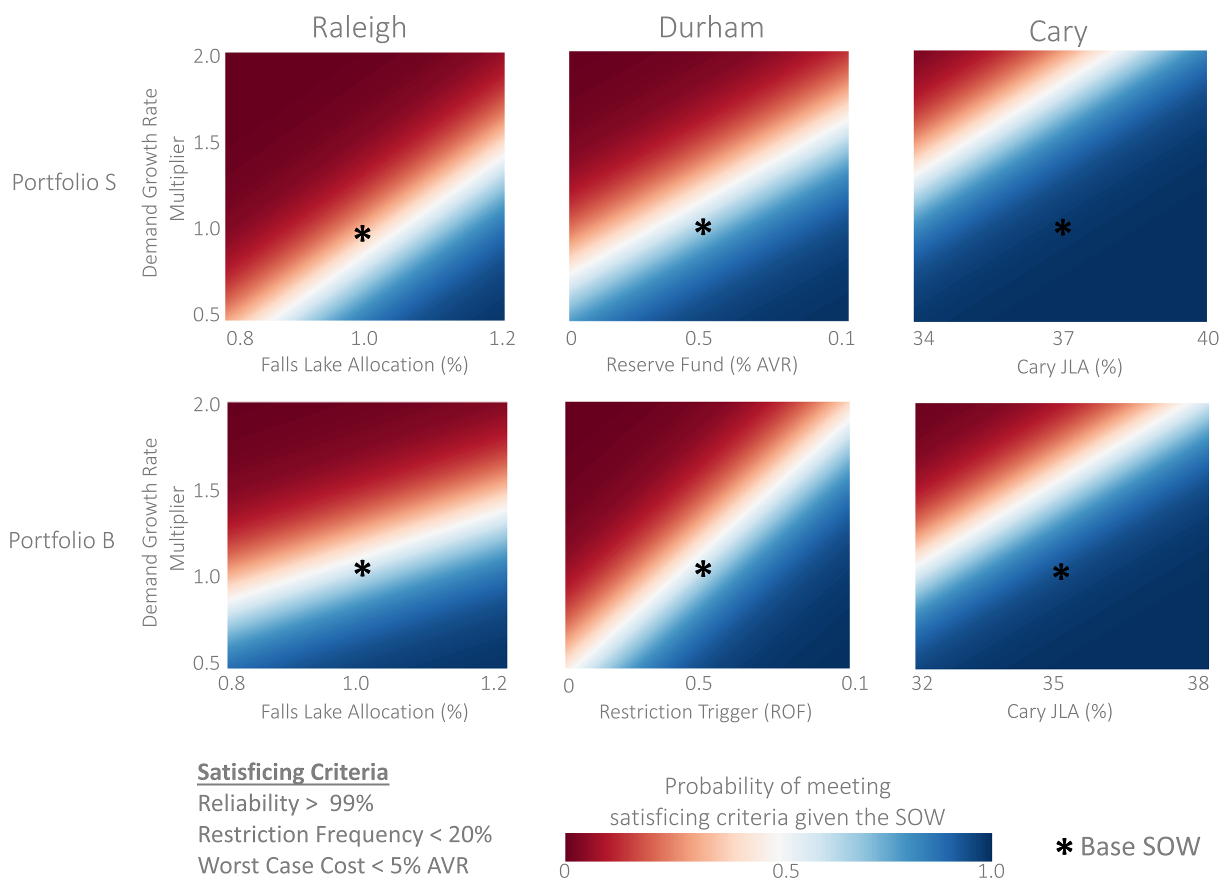

Figure 11. Factor maps for the two compromise portfolios provided by logistic regression. Each subplot represents the two most important sensitivities as determined by global sensitivity analysis, the shading represents the probability of meeting the utility's satisficing criteria if the utility were to be in the state of the world defined by the two parameters. The star represents the base state of the world with original portfolio decision variables.

and sensitivities differ between the portfolios for each utility but the consequential scenarios that define challenging futures also differ.

5. Conclusion

This study advances cooperative water supply portfolio planning by contributing a fallback bargaining centered methodology for navigating robustness conflicts and assessing vulnerabilities of selected compromise water supply portfolios to implementation uncertainty. We demonstrate our methodology on a regional water supply planning problem in the Research Triangle region of North Carolina where the cooperating utilities have conflicts when seeking to maximize their individual robustness to financial and supply reliability vulnerabilities. Our results indicate that even when regional water supply portfolios carefully balance demand management, regional transfers, and financial instruments, they can be vulnerable to assumptions on regional coordination and implementation uncertainties. Through logistic regression and global sensitivity analysis, we discover which uncertainties control portfolio robustness and individual performance objectives. Importantly, vulnerabilities to implementation uncertainty are shown to have the same scale of effects as other more commonly considered stressors (e.g., hydrologic extremes or population pressures).

Our results suggest that failure to include implementation uncertainty in cooperative water supply planning problems causes stakeholders to overestimate the robustness of candidate water supply portfolios and underestimate the potential for regional conflict. Through the delineation of regional SOSs, we provide stakeholders information on the operational tolerances of candidate water supply portfolios. Understanding operational tolerances improves the regional bargaining process by revealing sources of tension that may emerge within the cooperative coalition and quantifying portfolio feasibility. The quantification of portfolio feasibility also represents a critical step between the design and implementation of water supply portfolios that has not been addressed in prior MORDM literature.

This is the first study to include implementation uncertainty in the scenario discovery phase of the MORDM framework. The identification of consequential scenarios that include exogenous and implementation uncertainties allow decision makers to examine how decision choices interact with deeply uncertain factors. The nature and extent of portfolio vulnerability revealed by these global scenarios assists regional decision makers in choosing compromises that minimize the potential for regional conflict. To further minimize the potential for conflict in cooperative water supply planning under deeply uncertain contexts, future work should focus the endogenous incorporation of stability metrics within the search phase of MORDM.

Appendix A: Glossary of Terms

Water supply portfolio A coordinated set of specified drought mitigation actions that include treated transfers, water use restrictions, and financial instruments.

Decision variable A variable that represents a water supply portfolio action whose specific value must be chosen by decision makers.

Objective A measure of water supply portfolio performance.

State of the world (SOW) One realization of the future represented by a fully specified sample of uncertain model parameters.

Deep uncertainty (DU) Conditions where decision makers do not know or cannot agree on how to characterize uncertainties by known probability distributions, the outcomes of interest and their relative importance, and/or the system and its boundaries.

Well-characterized uncertainty (WCU) Conditions where uncertain variables have known probability distributions or a lengthy historical record and decision makers can agree on the system and its boundaries as well as outcomes of interest and their relative importance.

Robustness The fraction of sampled SOWs in which a portfolio satisfies all stakeholder performance requirements (defined in this study as an approximation of Starr's domain criterion).

Implementation uncertainty A lack of knowledge related to how precisely decision variables will be enacted in actual management contexts.

Implementation tolerance The maximum deviation from a prescribed decision variable before a water supply portfolio fails to meet a set of performance criteria.

Safe operating space (SOS) The region of the decision space such that any combination of decision variables sampled within the region is at least as robust as the original water supply portfolio.

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