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Key Points:

- We present new tools to develop equitable & robust regional water supply investment pathways & clarify their time-evolving vulnerabilities
- We demonstrate how commonly used framings of water supply robustness can have unintended adverse impacts on regional equity
- Cooperative investments can help water utilities maintain regional supply reliability but can also expose utilities to new financial risks

Supporting Information:

Supporting Information may be found in the online version of this article.

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Advancing Regional Water Supply Management and Infrastructure Investment Pathways That Are Equitable, Robust, Adaptive, and Cooperatively Stable

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Abstract Regionalization approaches—where utilities in close geographic proximity cooperate to manage drought risks and co-invest in new infrastructure—are increasingly necessary strategies for leveraging economies of scale to meet growing demands and navigate financial risks. However, regionalization also brings new challenges to water supply planning. Successful regionalization policies must equitably balance the interests of multiple partners while navigating power relationships between regional actors. In long-term infrastructure planning contexts, this challenge is heightened by the evolving system-state dynamics, which may be fundamentally reshaped by infrastructure investment. This work introduces Equitable, Robust, Adaptive, and Stable Deeply Uncertain Pathways (DU Pathways$_{ERAS}$), an exploratory modeling framework for developing regional water supply management and infrastructure investment pathways. DU Pathways$_{ERAS}$ provides an integrated framework for stakeholders to evaluate the equity of policy outcomes across cooperating partners and explore regional power relationships within cooperative infrastructure policies. To capture the time-evolving dynamics of infrastructure pathways, DU Pathways$_{ERAS}$ features new tools to measure the adaptive capacity of pathway policies and evaluate time-evolving vulnerability. We demonstrate our framework on a six-utility water supply partnership seeking to develop cooperative infrastructure investment pathways in the Research Triangle, North Carolina. Our results indicate that commonly employed framings of robustness can have large and unintended adverse consequences for regional partnerships. Results further illustrate that regional and individual vulnerabilities are highly interdependent and emphasize the need to limit counterparty risks through carefully designed cooperative agreements. Beyond the Research Triangle, these results are broadly applicable to cooperative water supply infrastructure investment and management globally.

1. Introduction

1.1. Motivation

Urban water utilities worldwide face growing risks to supply reliability from climate change, increasing water demands, as well as their consequent pressures on financial solvency (AWWA, 2018; IPCC, 2022). Uncertainties within the future projections of demand growth, local climate impacts, and financial conditions increase the difficulty of developing infrastructure investment and management policies that balance supply reliability with financial stability (Bonzanigo et al., 2018; USGCRP, 2018; WUCA, 2016). If water utilities under-invest in supply infrastructure or invest too late, they risk widespread supply shortfalls under challenging future scenarios. However, if challenging conditions do not manifest, particularly in demand growth, the debt burden resulting from large near-term investments raises the risk of financial instability (i.e., stranded assets and high water rates for customers (Haasnoot et al., 2020; Qureshi & Shah, 2014)). Moreover, in many developed regions, regulatory constraints and a dwindling number of suitable locations for new reservoir construction have increased the cost of supply development (Lund, 2013; Perry & Praskievicz, 2017). These challenges are acutely felt by water utilities in the United States (US), where aging drinking water infrastructure requires over $470 billion of investment over the next 20 years (Congressional Research Service, 2022). While the 2021 Infrastructure Investment and Jobs Act allocated over $55 billion in federal funding to improve drinking water infrastructure (DeFazio, 2021), most expenses will fall on local utilities (AWWA, 2012; Smull et al., 2022). In response to this growing financial risk, water utilities in the US are increasingly exploring "regionalization" approaches—regionally cooperative strategies involving coordinated drought management or infrastructure co-investment to improve the economic efficiency of water supply management (Reedy & Mumm, 2012; Riggs & Hughes, 2019; Tran et al., 2019).

For utilities in close geographic proximity, cooperative "soft path" approaches such as water transfers and coordinated water use restrictions can improve the efficiency of existing supply sources, delaying or reducing the need for additional supply expansion (Brandes et al., 2009; Gleick, 2003; Gorelick et al., 2018; Kenney, 2014; Zeff & Characklis, 2013). When expansion is unavoidable, utilities can leverage economies of scale by co-investing in regional supply sources (EPA, 2017; Riggs & Hughes, 2019; Silvestre et al., 2018). Approaches that coordinate soft-path water supply portfolios with long-term infrastructure sequencing and financial instruments have been shown to reduce utility costs further and improve supply reliability (Baum et al., 2018; Cai et al., 2015; Mortazavi-Naeini et al., 2014; Padula et al., 2013; Zeff et al., 2016). However, developing and implementing regionally cooperative policies challenges traditional decision-aiding frameworks in two intersecting ways. First, the decadal planning horizons necessary for infrastructure planning introduce significant uncertainties that are difficult to characterize with known probability distributions (Groves et al., 2019; Stakhiv, 2011). Second, rather than optimizing performance for a single actor, cooperative policies must navigate power dynamics between actors to equitably balance the potentially diverse individual interests (Gold et al., 2022; Hamilton et al., 2022; Madani & Hipel, 2011; Read et al., 2014; Savelli et al., 2022). These challenges motivate the contribution of the deep uncertainty (DU) Pathways$_{ERAS}$ framework proposed in this study.

1.2. Infrastructure Planning Under Deep Uncertainty

Over the decadal planning horizons of infrastructure investment decisions, decision-makers often do not know, or cannot agree on, how to characterize the system and its boundaries, the probability distributions of relevant uncertainties (e.g., changing drought extremes) and/or the outcomes of interest and their relative importance (Bonzanigo et al., 2018; Kwakkel et al., 2016; Lempert et al., 2006; Maier et al., 2016; W. E. Walker et al., 2013). These conditions, collectively known as "deep uncertainty," challenge traditional decision-making frameworks such as cost-benefit analysis (Dittrich et al., 2016; Kwakkel et al., 2016; Lempert, 2002; Marchau et al., 2019). Deep uncertainty within infrastructure planning problems has motivated a rapidly growing body of literature on "exploratory modeling" approaches (Bankes, 1993; Moallemi, Kwakkel, et al., 2020). Exploratory modeling approaches use computational experiments to (a) discover policies that maintain acceptable performance across large ensembles of deep uncertainties (hereon referred to as "robust" policies) and (b) identify which uncertainties have consequential impacts on the system (for recent reviews, see Dittrich et al., 2016; Kwakkel & Haasnoot, 2019; Moallemi, Zare, et al., 2020).

A key concern in robustness-focused decision support frameworks is whether they employ static or adaptive approaches to develop robust policies. Static policies commit to a set of predefined actions that seek to reduce vulnerability in the largest possible range of conditions (W. E. Walker et al., 2013). Unfortunately, static policies tend to be costly and may increase vulnerability to unanticipated future scenarios (Anderies et al., 2013). In contrast, adaptive approaches permit contextually tailored and appropriate changes to actions over time, triggering actions based on state information (i.e., they tailor actions to observed system conditions) (Erfani et al., 2018; S. M. Fletcher et al., 2017; Giuliani et al., 2021; Haasnoot et al., 2013; Pachos et al., 2022; Trindade et al., 2020; W. E. Walker et al., 2013). For example, Dynamic Adaptive Policy Pathways (DAPP; Haasnoot et al., 2013) generates a suite of potential adaptive actions and identifies signposts to monitor system performance and trigger each adaptive action. DU Pathways (Trindade et al., 2019) builds on this approach by using state-aware rule systems to trigger adaptive infrastructure investment and management decisions.

Beyond identifying candidate robust and adaptive policies, it is also critical to understand how deep uncertain factors shape policy vulnerabilities. Recent work has leveraged the growing sophistication and use of machine learning regression and classification techniques to identify consequential drivers of success and failures for achieving defined robustness goals (Reed et al., 2022). One prominent technique, scenario Discovery (Bryant & Lempert, 2010; Groves & Lempert, 2007; Kwakkel & Jaxa-Rozen, 2016) complements adaptive rule systems by revealing how deep uncertainties generate vulnerabilities for infrastructure investment and management policies. Scenario Discovery is commonly performed by applying stakeholder-defined performance thresholds and using machine learning or data mining algorithms to delineate regions of the uncertainty space where policies fail to achieve these thresholds (Jafino et al., 2020).

In water supply systems, supply vulnerability is a function of a utility's capacity-to-demand ratio (Loucks & Van Beek, 2017), and financial vulnerability is heavily dependent on a utility's overall debt burden (AWWA, 2011).

Infrastructure sequencing fundamentally alters both of these system characteristics and may also change relationships and dependencies between supply sources and regional actors within the water resources system. In these contexts, time-aggregated measures of performance may mischaracterize system vulnerability. To capture the time-evolving dynamics of complex systems, Steinmann et al. (2020) introduced behavior-based Scenario discovery, which applies time-series clustering to identify patterns in how a system evolves over time and map how uncertainties generate these behavioral clusters. Studies in support of DAPP and adaptation tipping points have also considered time-dependent dynamics of system vulnerability (Haasnoot et al., 2015; van Ginkel et al., 2021). Robinson et al. (2020) introduced a framework to evaluate long-term water supply vulnerability over a range of lead times to inform the development of adaptive triggers for a reservoir system. Yet these studies still do not separate near-term and long-term vulnerabilities or distinguish how changes in system state (such as large infrastructure investments) may alter system vulnerability. This shortfall may lead to a misrepresentation of water supply vulnerability.

1.3. The Human Dimensions of Regionalization—Equity, Cooperative Stability, and Power

While adaptive strategies can increase the robustness of infrastructure investment and management policies to DU, regionally cooperative policies raise an additional question—robustness for whom? For example, regionally aggregated measures of performance may appear robust for a group while failing to capture adverse impacts on individual actors (De Souza et al., 2011; Gold et al., 2022; Hamilton et al., 2022). Some studies have attempted to directly include regional equity using measures of relative variability such as the Gini index or the coefficient of variation (e.g., Aalami et al., 2020; Hu, Chen, et al., 2016). However, these measures may have unintended consequences—options selected to minimize the variability in system-wide performance can inadvertently penalize the most vulnerable partners (Ciullo et al., 2020). Operationalizing equity by applying Rawls' difference principle—which focuses on improving performance by maximizing the performance of the least well-off actor—has been shown to balance performance across diverse coalitions of stakeholders in water resources problems (Jafino et al., 2020; Zeff et al., 2014). But defining the “least well-off actor” depends on the choice of performance measures (S. Fletcher et al., 2022)—individual actors may have different vulnerabilities. The use of Rawls' difference principle (Rawls, 1999) in equity-focused specifications of objectives or measures is in reality an aspirational “means” to better address the distributional justice of outcomes. However, complex cooperative urban water supply regionalization contexts (e.g., asymmetries in utility size, power, finances, baseline infrastructure, etc.) make it extremely difficult to know if these aspirational means are likely to yield equitable outcomes (“the intended end benefits”).

A successful regional policy must be not only equitable but also cooperatively stable, meaning that no partner has incentives to defect from the policy (Dinar & Howitt, 1997; Madani & Dinar, 2012; Madani & Hipel, 2011; Read et al., 2014). Previous work has utilized game theoretic metrics of stability and bargaining frameworks to discover cooperatively stable water supply management strategies (Alizadeh et al., 2017; Madani & Hipel, 2011; Parrachino et al., 2006; Ristić & Madani, 2019). These methods rely on strong axiomatic assumptions and single objective representations of stakeholder preferences, limiting their applicability to complex water supply planning problems. Alternatively, analyzing regional power dynamics can provide insights into the drivers of cooperative instability and reveal conflict mitigation strategies (Gold et al., 2022). Power in a regional system has been broadly defined as “the (in)capacity of actors to mobilize means to achieve ends” (Avelino, 2021). Gold et al. (2022) introduced Regional Defection Analysis, which evaluates the stability of cooperative infrastructure investment and maps power relationships between regional partners.

1.4. DU Pathways$_{ERAS}$

This paper introduces DU Pathways$_{ERAS}$, a holistic decision support framework for identifying equitable, robust, adaptive, and cooperatively stable urban water infrastructure investment and management regionalization policies. DU Pathways$_{ERAS}$ builds on the recently published DU Pathways framework (Trindade et al., 2019) to develop state-aware adaptive infrastructure investment and management policies (hereon referred to as “pathway policies”). DU Pathways$_{ERAS}$ also incorporates the regional defection analysis introduced by Gold et al. (2022) to examine cooperative stability and map power relationships between cooperating water utilities in regional partnerships. Building on and synthesizing these innovations, the DU Pathways$_{ERAS}$ framework introduces three new methodological innovations to advance the development of cooperative infrastructure investment policies.

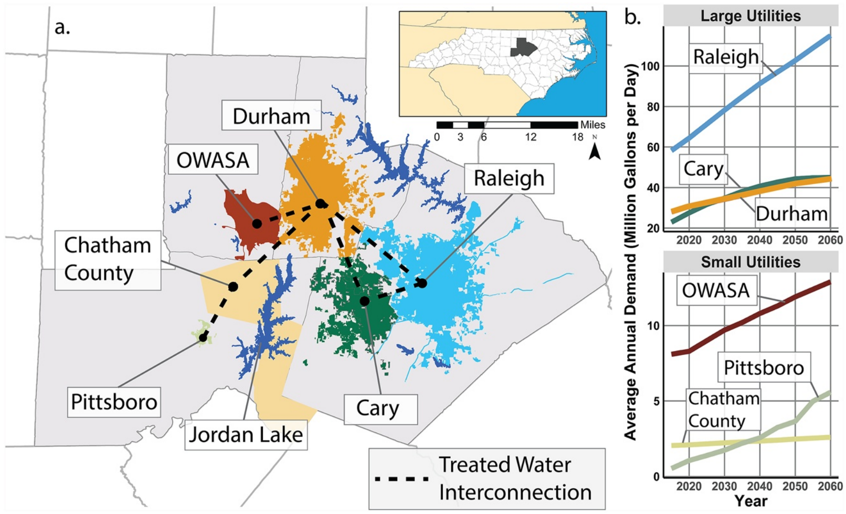

Figure 1. (a) The Research Triangle region of North Carolina where six utilities seek cooperative infrastructure investment and management policies. (b) Demand growth projections for the six utilities.

These innovations include (a) a formalized process to facilitate stakeholders in specifying and exploring competing definitions of robustness to enhance their ability to realize regionally equitable compromise policies; (b) a new Infrastructure Disruption Analysis (IDA) that measures the relative importance of utilities' candidate individual and cooperative infrastructure investments; and (c) a time-evolving scenario discovery process that is designed to better inform how decision-makers prioritize near-term actions and reveal which uncertainties must be monitored to maintain the long-term robustness of adaptive infrastructure pathway policies. This study's broader overall defining contribution is synthesizing all of these innovations into a single integrated framework that explicitly allows decision-makers to better engage with equity, cooperative stability, and power dynamics in cooperative regional water supply planning problems. Moreover, a second major contribution of this study is the demonstration of the integrated DU Pathways$_{ERAS}$ framework in a highly complex multi-actor water supply regionalization context for the Research Triangle region of North Carolina, where six neighboring water utilities seek to develop cooperative pathway policies. This six-utility system represents a highly challenging regionalization problem due to strong asymmetries in size, demand growth, and storage capacity across the partner utilities.

2. Regional Test Case

The Research Triangle (Triangle) region of North Carolina (Figure 1a) is a growing urban area home to roughly 2 million people. The region's rapidly growing water demand and history of drought have motivated regional water managers to explore cooperative water supply management strategies. Cooperating partners include water utilities serving three large urban areas—Raleigh, Durham, and Cary and three smaller population centers—Pittsboro, Chatham County, and Chapel Hill (Chapel Hill's water supply is managed by the Orange Water and Sewer Authority [OWASA]). The six regional partners seek a regional pathway policy that coordinates short-term drought crisis response and long-term infrastructure investment sequencing.

To manage drought crises, the utilities currently rely on a mix of voluntary conservation measures, mandatory water use restrictions, drought rate surcharges and regional inter-utility transfers of treated water (Orange Water & Sewer Authority, 2010; Westbrook et al., 2016). Cary operates a water treatment facility on the Jordan Lake, a large regional resource owned and operated by the US Army Corps of Engineers (USACE) and can sell water to other regional partners through regional interconnections. Four other regional partners—Durham, OWASA, Pittsboro and Chatham County—have supply allocations to the Jordan Lake but currently lack the treatment and conveyance capacity to access it.

To manage growing demands (Figure 1b and listed in Table S1 in Supporting Information S1), the utilities plan to invest in new supply infrastructure. A variety of infrastructure options have been identified by each utility (Table 1) that range from small independent investments to large cooperative investments. Four regional utilities—Durham, OWASA, Pittsboro and Chatham County—are investigating the joint construction of the

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Table 1
Available Infrastructure for Triangle Partners

Project (type)	Utility	Stages (small/large or single)	Capacity (MG or MGD)	Capital cost ($MILLION)	Earliest availability
Cary WTP Upgrades[a] (treatment)	Cary	Small/Large	8.0/16.0	121.5[a]/243[a]	2015
Cape Fear River Intake in Harnett County (supply)	Cary	Single	12.2	221.4	2032
Sanford Intake[b]—Cary (treatment)	Cary	Single	10	56	2015
Sanford Intake[b]—Chatham County, Pittsboro (treatment)	Chatham County, Pittsboro	Small/Large	Chatham: 1.0/2.0	Chatham: 7.9/11.2	2022/2028
			Pittsboro: 3.0/9.0	Pittsboro: 49.6/69.3	
Western Treatment Plant[b] (treatment)	OWASA, Durham, Chatham County, Pittsboro	Small/Large	33.0/54.0	243.3/316.8	2020/2022
Reclaimed Water (supply)	Durham	Small/Large	2.2/11.3	27.5/104.4	2022
Teer Quarry (supply)	Durham	Single	1,315	22.6	2022
Lake Michie Expansion (supply)	Durham	Small/Large	2,500/7,700	158.3/203.3	2032
Cane Creek Reservoir Expansion (supply)	OWASA	Single	3,000	127	2032
Stone Quarry Expansion (supply)	OWASA	Small/Large	1,500/2,200	1.4/64.6	2037
University Lake Expansion (supply)	OWASA	Single	2,550	107	2032
Haw River Intake (supply/treatment)	Pittsboro	Single	24	18.6/27.9	2017/2020
Falls Lake Reallocation (supply)	Raleigh	Single	5,637	142	2022
Little River Reservoir (supply)	Raleigh	Single	3,700	263	2032
Neuse River Intake (supply)	Raleigh	Single	16	225.5	2032
Richland Creek Quarry (supply)	Raleigh	Single	4,000	400	2055

Note. The stages column indicates whether infrastructure projects can be constructed in modular stages or as a single project.
[a]Cost not included in modeling, project underway at time of publication. [b]Cooperative project.

Western Treatment Plant, a large water treatment plant on Jordan Lake. Gorelick et al. (2022), examined three regional agreement structure utilities can use to finance the plant, finding that (a) the Western Treatment Plant can benefit cooperating partners and (b) a fixed agreement structure where utilities receive water in direct proportion to their initial cost sharing minimizes counterparty risk of cooperating investors. The six cooperating utilities seek a regional pathway policy to sequence new infrastructure investments and coordinate short-term drought crisis response. A core aim of Triangle partners is to find a compromise policy that maintains robust performance across deeply uncertain future conditions while equitably balancing performance across the six regional partners.

3. Methodology

3.1. Overview

This study introduces DU Pathways$_{ERAS}$, an extension of the DU Pathways framework (Trindade et al., 2019) for identifying equitable, robust, adaptive, and cooperatively stable pathway policies. Pathways is an exploratory decision support framework that combines the iterative and interactive decision-aiding approach of Many Objective Robust Decision Making (Kasprzyk et al., 2013) and the adaptive policy formulation of DAPP (Haasnoot et al., 2013) to develop pathway policies that are robust to deeply uncertain futures. DU Pathways$_{ERAS}$ builds on this framework by including new tools to evaluate regional equity, cooperative stability, adaptation, and time-evolving vulnerability. Our core contributions include (a) a formalized process for exploring regional equity using rival framings for selecting cooperative regional compromises, (b) integration of Regional Defection Analysis (Gold et al., 2022) to evaluate cooperative stability and the power relationships between regional actors, (c) a new IDA that measures the sensitivity and dependency of a policy to candidate infrastructure investments, and (d) a pathway-focused time-evolving implementation of scenario discovery (Bryant & Lempert, 2010; Groves & Lempert, 2007; Jafino et al., 2020; Jafino & Kwakkel, 2021) that captures how deep uncertainties interact to drive vulnerability over near-term to long-term planning horizons.

Figure 2a shows a flowchart of the DU Pathways$_{ERAS}$ framework. Our process begins with problem formulation (Figure 2a, box I), where we develop a hypothesis about how to formulate performance objectives, select decision variables, sample uncertainties, and model the system. We then search for robust regional pathway policies using many-objective optimization under deep uncertainty (DU optimization; Trindade et al., 2017; Figure 2a, box II—detailed in Figure 2b). DU optimization explicitly includes deep uncertainties in the many-objective search process by evaluating candidate policies across an approximate sampling of deeply uncertain states-of-the-world (SOWs) illustrated in Figure 2f. Including DU in the search phase using this strategy has been shown to improve the robustness of candidate pathway policies to deep uncertainties (Trindade et al., 2017, 2019). Next, we stress-test the regional pathway policies discovered through optimization by performing DU re-evaluation (Figure 2a box III and detailed in Figure 2c), which subjects each pathway policy to a broader and more computationally intensive set of deeply SOWs created with the sampling strategy illustrated in Figure 2g. More details on DU optimization and DU re-evaluation are provided in Sections 3.2 and 3.3.

We use the results of DU optimization and DU re-evaluation to explore trade-offs between regional and individual performance objectives and robustness. While cooperative optimization (Figure 2a, box II) uses the framing of the regional planning problem developed during the problem formulation stage (Figure 2a, box I), the Interactive Policy Exploration step (Figure 2a, box IV) provides decision-makers the opportunity to explore multiple framings of system performance and robustness, and examine the implications of a priori assumptions expressed preferences, performance requirements, and risk tolerance. This process is intended to facilitate a co-production process that directly engages regional stakeholders in the design of pathway policies (Bojórquez-Tapia et al., 2022). Through this process, the water utilities either identify one or more candidate compromise policy pathways or return to the problem formulation phase to implement a new problem formulation informed by insights from the interactive policy exploration.

After decision-makers identify one or more candidate regional compromises, we evaluate cooperative stability (practicality) using regional defection analysis (Figure 2a, box V). To perform the regional defection analysis, we run a set of individual DU defection optimizations (Figure 2d) that explore each cooperating partner's incentives to defect from the regional pathway policy across multiple performance objectives. We then re-evaluate each defection alternative using DU re-evaluation (Figure 2d) to measure how defection actions impact the trade-offs and robustness performance of each regional partner.

In addition to exploring the cooperative dynamics of candidate pathway policies, DU Pathways$_{ERAS}$ employs visual analytics and new diagnostic tools to evaluate infrastructure pathways. During Pathways Analysis (Figure 2a, box

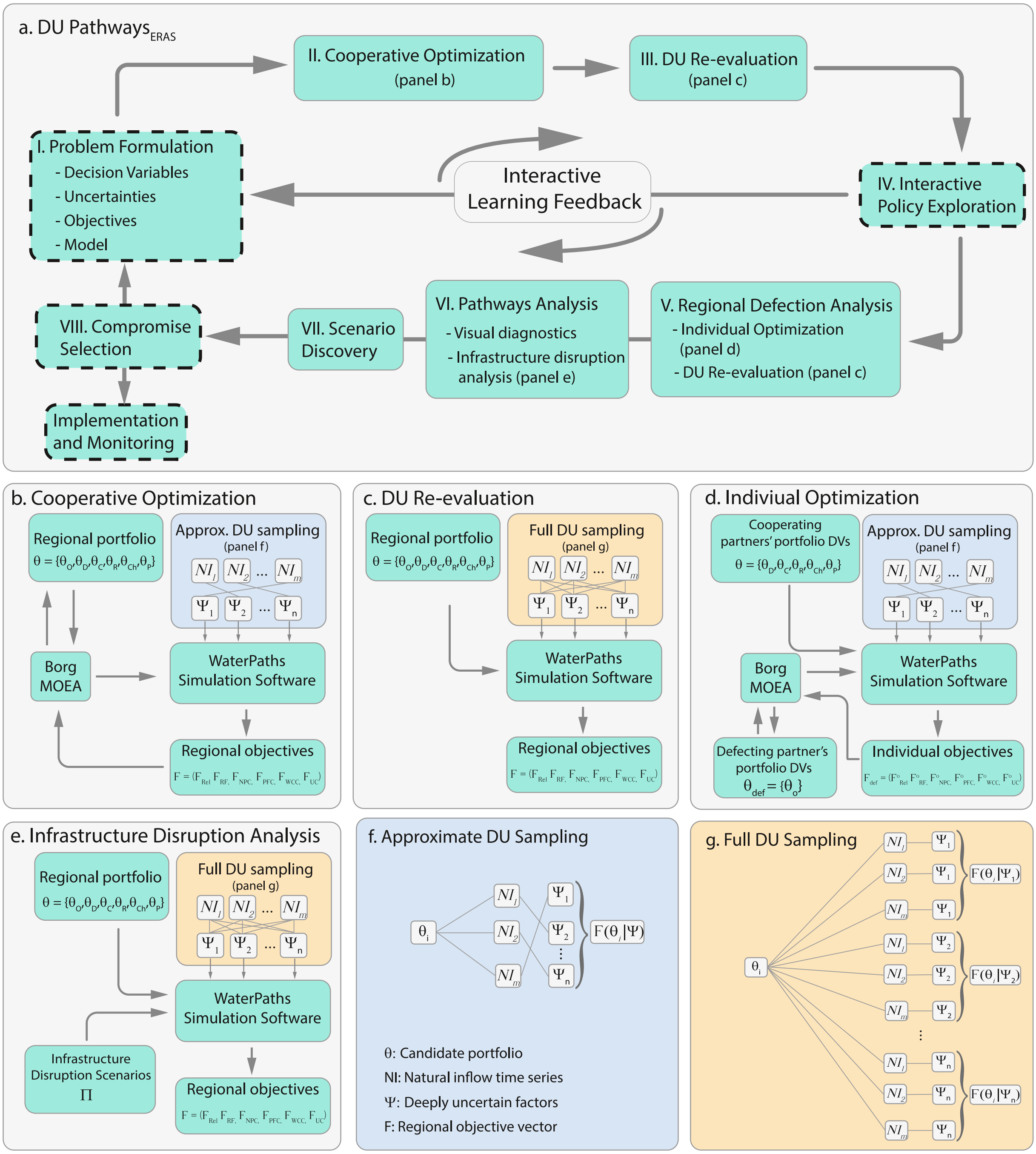

Figure 2. Methodological overview (a) deep uncertainty (DU) Pathways$_{ERAS}$ flowchart—panels outlined with a bold dashed line indicate steps where stakeholders are directly engaged in the planning process. (b) Cooperative optimization. (c) DU re-evaluation. (d) Individual Optimization (part of the Regional Defection Analysis). (e) Infrastructure Disruption Analysis (IDA). (f) Details on approximate DU sampling used for DU optimization. (g) Full DU sampling used during DU re-evaluation and IDA.

VI) we visualize pathway policies' infrastructure sequences across a broad set of future SOWs. We then perform IDA, a new method introduced in this framework to measure how each infrastructure option contributes to the robustness of the regional pathway policy by evaluating an ensemble of infrastructure disruption scenarios (Figure 2e).

Finally, we perform time-evolving scenario discovery (Figure 2a, box VII) to explore how deep uncertainties generate vulnerability for pathway policies. In water supply planning contexts, infrastructure investments fundamentally alter utilities' capacity-to-demand ratios and financial conditions (i.e., debt service schedules). To capture how these evolving state dynamics change utilities' vulnerability to deep uncertainties, we perform

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scenario discovery across three planning horizons: near-term (through 2030), mid-term (through 2045) and long-term (through 2060) (TJCOG, 2014). We use results of time-evolving scenario discovery to develop narrative scenarios that inform a dynamic adaptive implementation and monitoring strategy (W. E. Walker et al., 2013), which allows utilities to monitor potential key vulnerabilities and prepare contingency actions.

3.1.1. Problem Formulation

DU Pathways$_{ERAS}$ centers on a constructive decision-aiding approach which treats the process of problem formulation as an evolving exploration of hypotheses for specifying decision variables, performance objectives, uncertainties, and modeled relationships (Kasprzyk et al., 2013; Tsoukiàs, 2008). This constructive approach represents an iterative and exploratory learning process where stakeholders evaluate competing hypotheses (or "rival framings") about how the system should be represented analytically (Lempert & Turner, 2021; Majone & Quade, 1980; Quinn et al., 2017; Wheeler et al., 2018). We begin with a formal representation of the Triangle water supply planning problem informed by prior work in the Triangle system (Gorelick et al., 2022; Trindade et al., 2019; Zeff et al., 2016). Formally, the many-objective problem seeks to discover the regional water supply pathway policy, $\boldsymbol{\theta}$* whose dynamic and adaptive decisions minimize the vector of regional objectives, $\boldsymbol{F}$:

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

$$\mathbf{F}(\theta, \mathbf{X}, \boldsymbol{\Psi}_\mathbf{s}) = \begin{bmatrix} \max_U(1 - f_{\text{REL}}) \\ \max_U(f_{\text{RF}}) \\ \max_U(f_{\text{NPC}}) \\ \max_U(f_{\text{PFC}}) \\ \max_U(f_{\text{WCC}}) \\ \max_U(f_{\text{UC}}) \end{bmatrix} \tag{2}$$

s.t.

$$|\text{ME}| \le 1\ \forall\ \text{ME} \subseteq\ \text{BI} \tag{3}$$

where $\boldsymbol{F}$ is the vector of regional objectives, $\boldsymbol{\theta}$ is the policy vector of all regional decision variables (described in Equation 4 and discussed in detail in Section 3.1.2), $\boldsymbol{X}$ represents a vector of system states captured by the utility's evolving short-term and long-term risk-of-failure (shown in Equation 5 and described in detail in Section 3.1.2), and $\boldsymbol{\Psi}_s$ is the ensemble of sampled SOWs (described in detail in Section 3.1.3). In Equation 2, $\boldsymbol{U}$ is a vector representing the six water utilities, f_{REL} is the reliability objective, f_{RF} is the Restriction Frequency (RF) objective, f_{NPC} is the infrastructure net present cost objective, f_{PFC} is the Peak Financial Cost (PFC) objective, f_{WCC} is the worst case cost objective and f_{UC} is the unit cost of infrastructure investment objective. Details on each objective are presented in Section 3.1.4. In Equation 3, *ME* is a generic subset of mutually exclusive infrastructure options within the set of potential infrastructure options, *BI*.

$$\boldsymbol{\theta} = [\boldsymbol{TT}, \boldsymbol{RT}, \boldsymbol{IT}, \boldsymbol{IP}_{rank}(\boldsymbol{BI}), \boldsymbol{RC}, \boldsymbol{JLA}, \boldsymbol{TCA}] \tag{4}$$

$$\boldsymbol{X} = [\boldsymbol{x}_{LTROF}, \boldsymbol{x}_{STROF}] \tag{5}$$

In Equation 4, $\boldsymbol{TT}$ is the vector of transfer triggers, $\boldsymbol{RT}$ is the vector of restriction risk-of-failure (ROF) triggers, $\boldsymbol{IT}$ is the vector of infrastructure triggers, $\boldsymbol{IP}_{\boldsymbol{rank}}$ is the matrix of infrastructure ranks, $\boldsymbol{BI}$ is the set of potential infrastructure options, $\boldsymbol{RC}$ is the vector of reserve fund contributions, $\boldsymbol{JLA}$ is the vector of Jordan Lake Allocations and $\boldsymbol{TCA}$ is the vector of treatment capacity fractions for each utility. In Equation 5, $\boldsymbol{x}_{LTROF}$ is a vector of the long-term risk-of-failure system states for each utility and $\boldsymbol{x}_{STROF}$ is a vector of short-term risk-of-failure system states for each utility. Details on risk-of-failure are provided in Section 3.1.2.

3.1.2. Decision Variables

A distinguishing feature of the DU Pathways framework is the use of water supply portfolios that incorporate state-aware adaptive infrastructure sequencing and multiple coordinated drought crisis management actions. Pathway policies center on ROF-based triggers for adaptive drought mitigation and infrastructure investment decisions.

Table 2
Decision Variables

Decision variable	Description	Bounds
Restriction trigger (RT)	The short-term risk-of-failure (ROF) threshold that triggers the water use restrictions	[0,1]
Transfer trigger (TT)[a]	The short-term ROF threshold that triggers the purchase of treated transfers	[0,1]
Reserve fund contribution (RC)	The annual reserve fund contribution as a fraction of a utility's annual volumetric revenue	[0,1]
Infrastructure trigger (IT)	The Long-term ROF threshold that triggers construction of new infrastructure	[0,1]
Infrastructure ranks (IP)	A vector ranking the priority of all available infrastructure project	[0,1]
Jordan lake allocation (JLA)	Jordan Lake Supply allocation	Varies by utility
Western Treatment Plant allocations (TCA)[b]	Treatment allocation to the Western Jordan Lake Treatment facility	Varies by utility

[a]Not used by Cary, the supplier of transfers. [b]Only used by the four Western Treatment Facility partners.

ROF-based policies can be viewed as state-aware rule systems that approximate a closed-loop control policy (Bertsekas, 2012; Herman et al., 2020). Simply put, these rule systems are designed to trigger actions tailored to observed future conditions (i.e., termed model-free policy approximation control techniques in recently proposed reinforcement learning taxonomies—see Bertsekas, 2012; Powell, 2019). We utilize ROF-based rule systems as the basis for pathway policies for two reasons—first, they provide a dynamic representation of the evolving dynamics of each utility's storage-to-demand ratio (Caldwell & Characklis, 2014; Palmer & Characklis, 2009), and second, they are currently in use by the Triangle region's water utilities to trigger short term drought mitigation actions (Orange Water & Sewer Authority, 2010).

To confront drought conditions, the utilities employ short-term ROF (STROF) that trigger water use restrictions and the purchase of treated transfers. STROF is a dynamic measure of each utility's current storage-to-demand ratio, calculated each week as the probability that a utility's total reservoir storage will drop below 20% of total capacity at any point during the next 52 weeks. Each utility assigns two short-term triggers, one to trigger water use restrictions and a second to trigger treated transfers. To mitigate financial disruptions from water use restrictions (revenue losses) and treated transfers (unplanned costs), each utility may also contribute annually to a reserve fund.

To manage long-term supply risk, the utilities employ long-term ROF (LTROF), which measures each utility's ratio of total capacity to demand. Long-term ROF is calculated on an annual basis as the probability that a utility's total storage will drop below 20% of capacity over the following 78 weeks, assuming all reservoirs start the year at full capacity. Each utility also rank orders its possible infrastructure options. When a utility's LTROF crosses the trigger, it will start construction on the top-ranked infrastructure option available. The four partners in the Western Treatment Plant also determine the treatment fraction (and proportional cost) that is assigned to each cooperating partner. Finally, all utilities in the regional system determine how much allocation to the Jordan Lake to request from USACE, which dictates the available water from treated transfers and treatment from the Western Treatment Plant. A summary of all decision variables can be found in Table 2.

3.1.3. Uncertainty

We partition uncertainty facing the Triangle water supply system into well characterized uncertainty (WCU) and DU. WCU represents system parameters that are stochastic but have reliable historical data or known probability density functions (Trindade et al., 2017). DUs represent system parameters that are known to be uncertain but do not have known or agreed upon probability density functions (Kwakkel et al., 2016; Lempert et al., 2006; W. E. Walker et al., 2003). In the Triangle, we consider the historical natural variability of reservoir inflows to be WCU, as there is over 80 years of historical data on all catchments. Because the 80-year historical record is only a single draw of a stochastic process, we utilize a synthetic streamflow generator introduced by Kirsch et al. (2013) to expand the envelope of reservoir inflow inputs. Details on the synthetic generation can be found in Text S2 in Supporting Information S1.

DUs facing the system include changes to inflow distributions due to climate change, demand growth, financial variables and parameters governing infrastructure permitting and construction. The full set of DU parameters used in this study can be found in Table 3. To construct an ensemble of future SOWs for many-objective search, we first generate an ensemble of 1,000 natural inflow samples (NI) using the synthetic streamflow generator. Trindade et al. (2020) found that an ensemble size of 1,000 natural inflows accurately captures variance in water

Table 3
Deep Uncertainty Factors and Their Sampling Ranges

Factor	Description	Range (multiplier factor)
Near-term demand growth	Demand growth multiplier for the first 15 years of the planning horizon	0.25–2.25
Mid-term demand growth	Demand growth multiplier for the second 15 years of the planning horizon	0.25–2.25
Long-term demand growth	Demand growth multiplier for the final 15 years of the planning horizon	0.25–2.25
Bond term	A multiplier for number of years over which infrastructure capital costs are repaid as debt service	0.8–1.2
Bond interest rate	A multiplier that adjusts fixed interest rate on bonds for infrastructure	0.6–1.2
Discount rate	A multiplier for the discount rate, affecting how future infrastructure investment is discounted to 2015	0.6–1.4
Restriction efficacy	A multiplier that determines how effective use restrictions are at reducing water demand	0.8–1.2
Lake evaporation	A multiplier applied to the rate water is evaporated from regional reservoirs	0.9–1.1
Western Treatment Plant permitting period	A multiplier that brings forward or delays the year after which the Western Treatment Plant can be constructed	0.75–1.5
Western Treatment Plant construction time	A multiplier that lengthens the construction time that would be needed to build the Western Treatment Plant	1.0–1.2
Streamflow sinusoid amplitude	A component of a sinusoidal multiplier applied to the historical log-mean streamflow to simulate climate-change impacts in the region	0.8–1.2
Streamflow sinusoid frequency	A component of a sinusoidal multiplier applied to the historical log-mean streamflow to simulate climate-change impacts in the region	0.2–0.5
Streamflow sinusoid phase	A component of a sinusoidal multiplier applied to the historical log-mean streamflow to simulate climate-change impacts in the region	$-\pi/2$–$\pi/2$

Note. These multipliers are applied to best estimates of each factor by Triangle Utilities. Ranges for deeply uncertain parameters were chosen to reflect plausible ranges for future variables. Demand growth ranges are informed by estimates of regional population growth and per capita water demand (TJCOG, 2014). Details on the use of sinusoid multipliers used to simulate climate change impacts on streamflow can be found in Text S2 in Supporting Information S1. The ranges of each streamflow multiplier were calibrated by Trindade et al. (2020) to increase or decrease reservoir inflows by no more than 20%, in line with current predictions on climate change impacts in the region. All other ranges were selected as plausible estimates to inform an exploration of system vulnerability.

supply performance measures. We then pair each natural inflow with a different sample of DU factors (Ψ) generated using Latin Hypercube Sampling (LHS). This DU optimization sampling strategy, detailed in Figure 2f, has been shown to discover solutions that outperform other sampling strategies when evaluated over much broader ensembles of DU SOWs (Trindade et al., 2017, 2019).

3.1.4. Performance Objectives

Based on elicitations of the Triangle utilities, they defined drought crisis management and long-term financial stability as primary performance considerations for evaluating water supply portfolio management and infrastructure investment pathways. Here, we translate these considerations into six formal objectives for many-objective search: reliability, RF, infrastructure net present cost, PFC, worst-case cost, and unit cost of infrastructure investment. Details on the formulation of each objective are shown in Table 4. The reliability, RF and worst-case cost objectives, measure utility's ability to manage short-term drought crises. The reliability and RF objectives measure a utility's ability to maintain reliable water supply without subjecting customers to exceedingly high levels of restrictions. Worst-case cost measures the magnitude of financial shocks that result from intermittent and unpredictable drought management costs. These shocks may take the form of revenue disruptions from water use restrictions of payments for treated transfers. The infrastructure net-present cost objective measures the present-value cost of all infrastructure investment for each utility. Including this objective prioritizes the discovery of portfolio pathways that manage reliability and RF while incurring minimal debt burden. Debt burden is not the only financial consideration for water utilities. Also of concern is the PFC in any given year, the ratio of all spending (drought mitigation costs plus debt service payments) to the annual revenue. This measure is analogous to debt covenants—legally binding requirements commonly written into water utilities' financial governance documents and specify minimum ratios of annual utility revenue to debt service payments (AWWA, 2011; Gorelick et al., 2022). Finally, the unit cost of the infrastructure investment objective measures the efficiency of infrastructure investments and incentivizes the discovery of solutions that minimize stranded assets (i.e., long periods of time where excess water supply capacity goes unused).

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Table 4
The Six Objectives Used in Many-Objective Search

Objective name (max/min)	Description	Formulation	Variable key
Reliability (max)	The frequency of annual supply failures	$F_{Rel} = \frac{\max_y(\sum_r F_{r,U,y})}{N_r}$ $F_{r,U,y} = \begin{cases} 1 & if\,\frac{S_{U,y}}{U} \leq 20\% \forall y \in Y \\ 0 & otherwise \end{cases}$	$S_{U,y}$: the vector of total utility storage for utility U, during year y N_r: the number of states-of-the-world (SOWs) used in evaluation C_U: total storage capacity of utility U Y: the total number of years used in the full simulation
Restriction frequency (min)	The fraction of simulation years when water use restrictions are imposed at least once	$F_{RF} = \frac{\sum_r \sum_y R_{r,U,y}}{N_r N_y}$ $R_{r,U,y} = \begin{cases} 1 & if\,NRU_y \geq 1 \\ 0 & otherwise \end{cases}$	NRU_y: the number of instances water use restrictions were imposed in year y
Infrastructure net present cost (min)	The net present cost of infrastructure investment summed across all realizations	$F_{NPC} = \frac{\sum_r \sum_y \frac{DS_{r,U,y}}{(1+d)^{y-1}}}{N_r}$	$DS_{r,U,Y}$: the debt service of utility U in year y, realization r N_r: the number of SOWs used in evaluation d: discount rate
Peak financial cost (min)	The maximum ratio of utility expenses to annual volumetric revenue across all simulation years, averaged across all realizations	$F_{PFC} = \frac{\sum_r \max_{y\in[2015,2060]}\left(\frac{DS_{r,U,y}+CFC_{r,U,y}+RC_{r,U,y}+TC_{r,U,y}}{AVR_{r,U,y}}\right)}{N_r}$	$DS_{r,U,Y}$: the debt service of utility U in year y, realization r CFC: the contingency fund contribution RC: revenue loss from restriction use TC: transfer costs AVR: annual volumetric revenue N_r: the number of SOWs used in evaluation
Worst-case cost (min)	The 99% drought mitigation cost across all realizations, defined as the maximum revenue disruption form restrictions and cost of treated transfers	$F_{WCC} = P_{99}\left(\max_{y\in[2015,2060]}\left(\frac{RC_{r,U,y}+TC_{r,U,y}-CF_{r,U,y}}{AVR_{r,U,y}}\right)\right)$	$CF_{r,U,y}$: the contingency fund value for utility U in year y of realization r RC: revenue loss from restriction use TC: transfer costs AVR: annual volumetric revenue
Unit cost of infrastructure investment (min)	The infrastructure investment cost per gallon of demand growth—a measure of the efficiency of infrastructure investment and stranded assets	$F_{UC} = \frac{\sum_r \sum_y \frac{\frac{DS_{r,U,y}}{(1+d)^{y-1}}}{D_{r,U,y}-D_{U,2015}}}{N_r}$	$DS_{r,U,Y}$: the debt service of utility U in year y, realization r N_r: the number of SOWs used in evaluation d: discount rate D: water demand

To discover regionally equitable portfolio pathways, we employ a regional minimax formulation to aggregate objectives across the six partner utilities (Zeff et al., 2014). Here, the regional value for each objective is defined as the objective value of the worst-performing utility. This minimax formulation is an application of Rawl's difference principle, guaranteeing that all utilities will perform at least as well or better as the regional objective (Hammond, 1976; Rawls, 1999).

3.1.5. System Model

We use WaterPaths simulation software (Trindade et al., 2020) to model the regional water supply system. WaterPaths is an open-source C++ model designed for stochastic simulation of water supply systems. WaterPaths is selected for this work because of its ability to facilitate many-objective search for multi-actor water supply systems and efficiently accommodate large ensembles of DU on parallel high-performance computing systems. WaterPaths' customizable code base also provides a flexible platform to evaluate both short-term drought crisis actions and long-term infrastructure investment sequences. WaterPaths contains functionality to efficiently calculate both short- and long-term ROFs, facilitating state-aware rule systems that support adaptive policy pathways. In addition, WaterPaths can export detailed time-series output of various system states and performance measures, allowing users to perform detailed diagnostics of pathway policies.

WaterPaths is highly generalizable, and can be instantiated for a wide range of water supply planning contexts. The six utility instance of WaterPaths for the Triangle system used in this work was first developed by Gorelick et al. (2022). During each 45-year simulation, the WaterPaths instance performs a weekly mass balance for all system reservoirs and tracks weekly utility finances. This simulation can be efficiently parallelized to perform both cooperative DU optimization, and DU re-evaluation described in the following sections.

3.2. Cooperative DU Optimization

We use the Multi-master Borg multiobjective evolutionary algorithm (MOEA) (MM Borg, Hadka & Reed, 2012, 2015) to discover Pareto-approximate pathway policies. Overall, MOEAs have been widely applied to water resources problems as they have been shown to solve nonconvex, nonlinear, multimodal, and discrete many-objective problems that challenge traditional search techniques (Maier et al., 2014; Nicklow et al., 2010; Reed et al., 2013). The MM Borg MOEA is a global population-based evolutionary algorithm that features adaptive search operators, epsilon dominance archiving (Laumanns et al., 2002), stagnation detection, and randomized restarts to solve challenging many-objective problems. In its serial implementation, Borg has been shown to perform as well or better than other state-of-the-art MOEAs when applied to challenging water resources applications (Gupta et al., 2020; Reed et al., 2013). The multi-master implementation of the Borg MOEA exploits high-performance computing resources by employing a hybrid parallelization scheme that uses both multiple population and master-worker parallelization strategies to increase the scalability and difficulty of many-objective search problems (Cantu-Paz & Goldberg, 2000; Hadka & Reed, 2015).

To discover regional pathway policies that maintain robust performance across deeply uncertain futures, we use DU optimization (Figure 2b), a computationally efficient strategy for incorporating DU into many-objective search process (Trindade et al., 2017). DU optimization evaluates each candidate pathway policy across the sampling of WCU and DU SOWs described in Section 3.1.3 and shown in Figure 2f. This approximate sampling scheme approximates the much broader and computationally intensive sampling scheme shown in Figure 2g. The DU optimization process begins with randomly generated population of decision variable vectors which are evaluated using WaterPaths over the approximate DU sampling. WaterPaths returns the six objective values, which are passed to the MM Borg MOEA. The MOEA then assesses Pareto dominance and uses recombination operators to generate new decision variable vectors. This process is repeated until the algorithm has reached a specified number of function evaluations.

3.3. DU Re-Evaluation

During DU re-evaluation, we stress test the Pareto-approximate pathway policies discovered through DU optimization across a broader ensemble of SOWs generated using the DU re-evaluation sampling strategy shown in Figure 2g. This stress testing is central to the exploratory modeling process employed by DU Pathways$_{ERAS}$ because it provides a platform for the six utilities to evaluate the robustness of candidate strategies and characterize their vulnerability to over a wide range of plausible future conditions (Kwakkel, 2019; Moallemi, Kwakkel, et al., 2020). The DU re-evaluation sampling scheme represents a significantly more challenging and computationally demanding set of SOWs than the approximate sampling scheme used during DU optimization.

To perform DU re-evaluation, candidate policy pathways are evaluated across an ensemble of 2 million scenarios, each representing a unique paring of WCU inflows (NI_S) and DU SOWs (Ψ), illustrated in Figure 2g. We sample DU SOWs by generating an ensemble of 2,000 parameter combinations using LHS across pre-specified ranges of plausible DU parameter values (shown in Table 3). Each LHS is paired with an ensemble of 1,000 synthetically generated WCU inflows, created using synthetic streamflow generation as detailed in Section 3.1.3. Each DU SOW produces one vector of objectives values, which are aggregated across the 1,000 NI_s as shown in Figure 2g.

3.4. Interactive Policy Exploration

The performance objectives specified during the problem formulation stage (Section 3.1; Figure 2a, box I) represent an initial hypothesis about the collective goals and performance priorities of the regional partners. The Interactive Policy Exploration step (Figure 2a, box IV) provides the cooperating urban water utilities with an opportunity to test whether this problem formulation yielded policies that adequately capture their preferences and equitably balance regional performance. This process is intended to help cooperating partners recognize and avoid myopic planning that can emerge as an unintended consequence of narrow definitions of "optimality" or "robustness" (Brill et al., 1990; Herman et al., 2015; Kasprzyk et al., 2013; McPhail et al., 2018). During Interactive Policy Exploration, the utility partners formulate alternative "rival" framings (expressed preferences and specified performance requirements) of regional performance priorities using the results from DU Optimization and DU re-evaluation. These alternative framings are represented by specifying performance filters to apply across the Pareto-approximate policies and examining performance across both the approximate DU sampling used during DU optimization (Figure 2f) and the more challenging (and more conservative) Full DU Sampling scheme used during DU re-evaluation (Figure 2g).

For the Research Triangle system, we demonstrate the Interactive Policy Exploration by comparing four framings that the Triangle partners could use to define their perspectives on what constitutes equitable and robust system performance. Each framing (Table 5 and diagrammed in Figure 3) pairs an alternative specification of the prioritized performance requirements (Simon, 1966) with a specific sampling strategy that was used to compute the performance requirements across the deep uncertainties. These framings are applied to the set of Pareto approximate policies discovered during DU Optimization and stress-tested during DU re-evaluation. While all four framings prioritize supply reliability, they represent differing levels of sophistication with regard to measuring financial performance and the treatment of DU. Two framings examine average performance across the Approximate DU sampling utilized during DU optimization (Figure 2f). These framings likely favor policies that maintain balanced performance across all SOWs, though they may be sensitive to conditions in the extremes of sampled uncertainties. The other two framings measure robustness across the Full DU sampling strategy used during DU re-evaluation (Figure 2g). These framings likely favor policies that maintain satisfactory performance across a wide range of SOWs. All four framings for selecting candidate compromise pathway policies seek to equitably balance performance across regional utilities by applying Rawls' difference principle through a regional minimax formulation (Hammond, 1976; Rawls, 1999). This definition of equity is intended to ensure the provision of consistent minimum performance across all regional partners (S. Fletcher et al., 2022; Osman & Faust, 2021).

3.4.1. The Minimum Expected Investment Compromise

In the first regional compromise framing, termed minimum expected investment (MEI, represented with a light blue line in Figure 3), the Triangle partners seek to select the portfolio pathway that minimizes regional infrastructure net present cost while meeting three regional drought crisis performance criteria—Reliability >98%, RF <20% and Worst-Case Drought Management Cost <10% annual volumetric revenue (AVR). This framing mirrors approaches widely used in water supply planning literature that seek to balance infrastructure investment cost with tolerable drought risk (Borgomeo et al., 2016; Beh et al., 2015; Erfani et al., 2014; S. M. Fletcher et al., 2017; Pachos et al., 2022). Using the MEI framing, the utilities evaluate objectives in expectation across approximate DU optimization sampling (Figure 2f), reflecting a methodological choice to solely focus on the outcomes of a robust optimization that exploits approximate sampling strategies to discover policies that maintain performance across deeply uncertain futures (e.g., see examples in Eker & Kwakkel, 2018; Hall et al., 2020; Mortazavi-Naeini et al., 2014; Pachos et al., 2022; Watson & Kasprzyk, 2017).

3.4.2. The Expected Drought and Long-Term Financial Stability Compromise

For the second framing, termed expected drought performance and long-term financial stability (EDF, represented with a dark blue line in Figure 3), the utilities replace minimum infrastructure net present cost with two financial stability requirements—peak financial cost <80% AVR and unit cost of expansion <$5/kgal.

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Table 5
Candidate Framings of Regional Compromise

Name	Performance measures	Aggregation across deep uncertainty
Minimum expected investment (MEI)	Reliability >98%	Average across approximate DU sampling used for DU optimization (Figure 2f)
	Restriction Frequency <20%	
	Worst-case drought management cost <10% AVR	
	Min. infrastructure net present cost	
Expected drought performance and financial stability (EDF)	Reliability >98%	Average across approximate DU sampling used for DU optimization (Figure 2f)
	Restriction frequency <20%	
	Worst-case drought management cost <10% AVR	
	Peak financial cost <80% AVR	
	Unit cost of expansion <$5/kgal	
Drought crisis robustness (DCR)	Reliability >98%	Percent satisficing across full DU sampling used for DU re-evaluation (Figure 2g)
	Restriction frequency <20%	
	Worst-case drought management cost <10% AVR	
Drought crisis and long-term financial stability robustness (DFSR)	Reliability >98%	Percent satisficing across full DU sampling used for DU re-evaluation (Figure 2g)
	Restriction frequency <20%	
	Worst-case drought management cost <10% AVR	
	Peak financial cost <80% AVR	
	Unit cost of expansion <$5/kgal	

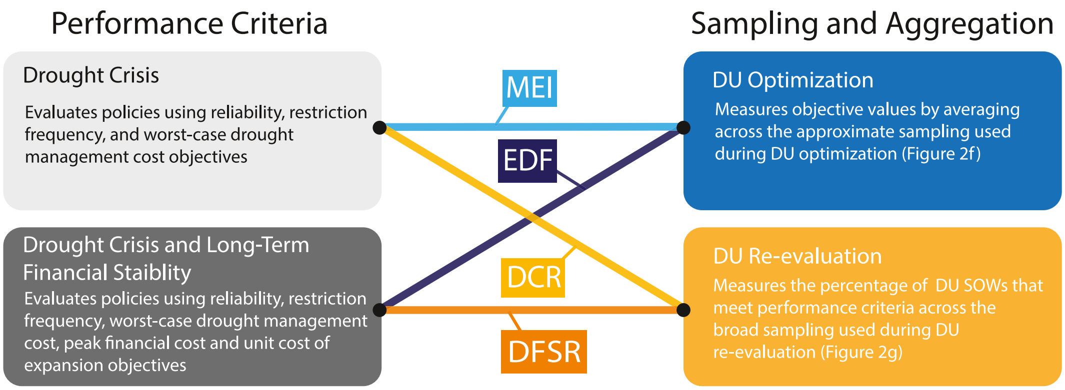

Figure 3. Selected framings of regional compromise. Each framing (represented by the four lines) combines a prioritized set of performance criteria (shown in panels on the left) with a sampling and aggregation strategy (shown on the right). Selecting a compromise using Minimum Expected Investment (MEI) combines drought crisis performance with performance measures calculated in by averaging objective values across the approximate sampling of deep uncertainty (DU) states-of-the-world (SOWs) used for DU optimization. The Expected Drought Performance and Financial Stability framing (EDF), utilizes both drought crisis performance and long-term financial stability measures to evaluate regional performance. The Drought Crisis Robustness framing (DCR) measures regional performance by using a set of drought crisis performance satisficing criteria across DU re-evaluation sampling. Drought Crisis and Long-term Financial Stability Robustness (DFSR) applies satisficing criteria to both drought crisis and long-term financial stability measures across DU re-evaluation sampling.

Including the PFC criterion emphasizes budgetary stability. Values of PFC above 80% risk violating debt covenants, minimum ratios of revenue to expenses stipulated in bond contracts (AWWA, 2011). A debt covenant violation can severely impact utility credit ratings and result in increased water rates (Hughes & Leurig, 2013; Raftelis, 2005). By including unit cost of expansion, Triangle partners prioritize financially efficient infrastructure investments (Gorelick et al., 2019). High values unit cost of expansion suggest that utilities have stranded assets—infrastructure that is still within its design lifetime but does not provide its intended service or has been abandoned (Haasnoot et al., 2020; Kalin et al., 2019). Stranded assets may lead to budgetary instability or increased water rates, as utilities must pay for infrastructure that does not generate as much revenue as expected (AWWA, 2011).

3.4.3. The Drought Crisis Robustness Compromise

The third compromise framing, termed drought crisis robustness (DCR, yellow line in Figure 3), represents the a priori prioritization of performance preferences that the Triangle utilities have used to evaluate pathway policies in previous studies of the Triangle water supply system (Gold et al., 2019; Herman et al., 2014; Trindade et al., 2017, 2019). Using this framing, the utilities evaluate drought crisis performance criteria across the broader DU re-evaluation sampling of deep uncertainties (Figure 2g). Here, we aggregate performance across deeply uncertain SOWs using a satisficing metric, which measures the fraction of DU re-evaluation SOWs where utilities meet the drought performance criteria (Reliability >98%, RF <20% and Worst-Case Drought Management Cost <10% AVR). Satisficing metrics reflect the tendency of decision makers to seek policies that meet one or more performance requirements across many plausible future conditions, even at the expense of optimal performance in a favorable future (Herman et al., 2015; Simon, 1966). We use a domain criterion-based measure of satisficing (Starr, 1963), that measures the fraction of SOWs that a candidate portfolio pathway meets performance criteria:

$$S = \frac{1}{N}\sum_{j=1}^{N}\Lambda_{\theta,j} \tag{6}$$

Where,

$$\Lambda_{\theta,j} = \begin{cases} 1, & \text{if } F(\theta)_j \le \Phi_j \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where Φ is a vector of performance criteria for utility j, θ is the portfolio and N is the total number of sampled SOWs.

3.4.4. The Drought Crisis and Long-Term Financial Stability Robustness Compromise

For the fourth and final compromise framing, termed drought crisis and long-term financial stability robustness (DFSR), orange line in Figure 3, the Triangle partners pair the expanded set of performance measures used in the expected drought and financial objectives framing with satisficing over DU re-evaluation sampling 2g used in the drought-focused robustness framing, by adding the PFC and unit cost of expansion measures to the set of requirements. This framing represents a more conservative version of the DCR framing.

3.5. Regional Defection Analysis

The implementation of a compromise pathway policy relies on the strong assumption that once selected, the regional partners will adhere to the selected compromise. While the cooperative agreement structure implemented in this work was designed by Gorelick et al. (2022) to improve the performance of all Triangles utilities while minimizing conflicts between cooperating partners, utilities may have incentives to improve their performance by defecting from the selected policy. Our regional defection analysis represents a formal test of the cooperative stability of this agreement structure by exploring the incentives that individual utilities may have to defect, revealing the consequences of defection on each utility's cooperating partners, and investigating power relationships between regional actors. To characterize power relationships (Avelino & Rotmans, 2011), suggest a typology that centers on three manifestations of power: power over—referring to conditions when actor A can dictate outcomes for B, power to—conditions when an actor can act to create or resist change and power with—when actors can create or resist change through collaboration. The regional defection analysis investigates power relationships within the regional partnership, revealing which actors have the *power to* unilaterally improve their performance (Avelino & Rotmans, 2011) and whether utilities are seeding their regional partners *power over* their own performance by joining the regional partnership (Avelino & Rotmans, 2011; Gold et al., 2022).

We implement the regional defection analysis in two steps—individual optimization and DU re-evaluation. During the individual optimization step, we utilize the Borg MOEA to search for defection alternatives for each cooperating partner. We perform a total of six individual defection optimizations (one for each regional utility). During each individual defection optimization, the Borg MOEA optimizes the defecting utility's individual objectives using only the decision variables of the defecting utility while keeping the decision variables of all other cooperating partners at the values prescribed by the cooperative pathway policy selected during the Interactive Policy Exploration process. A flow chart of individual defection is shown in Figure 2d. To examine to consequences of defection, we then re-evaluate the defection alternatives for each utility across the sample of DU SOWs described in DU-reevaluation above and detailed in Figure 2g.

We measure the impact of regional defection by analyzing how defection alternatives change robustness for each regional partner. To evaluate the incentives that each utility has for defecting from the regional partnership, we measure the greatest improvement the utility can achieve for each performance criteria without reducing its overall robustness:

$$R_i^{RDA} = \max_j \left[\eta_i^j\right] \ \ \forall\, j \ \in \beta \tag{8}$$

$$\eta_i^j = \begin{cases} S\left(\theta^j\right)i - S(\theta^{comp})_i & if \forall k \neq i \, : \, S\left(\theta^j\right)_k \geq S(\theta^{comp})_k \\ 0 & otherwise \end{cases} \tag{9}$$

where β is the set of all re-optimized alternatives, $S(\theta_{def})_i^j$ is the robustness of the ith performance criteria in the jth re-optimized portfolio, θ_{def}, and $S(\theta_{comp})_i^j$ is the robustness for the ith performance criteria in the selected compromise portfolio, θ_{comp}. The robustness definition used in this step is drawn from the criteria used in the Drought Crisis and Long Term Financial Stability framing described in Section 3.4 as it represents the most strict criteria tested in this study.

For cooperating utilities, we measure the maximum loss in robustness resulting in defection from a cooperating partner:

$$R_i^{RDA} = \max_j \eta_i^j \qquad \forall j \in \beta \tag{10}$$

3.6. Infrastructure Disruption Analysis

DU Pathway$_{ERAS}$ introduces a novel IDA to measure the adaptive capacity of pathway policies and examine how each infrastructure option contributes to the robustness of regional utilities. By measuring the adaptive capacity of pathways, the IDA allows decision makers to assess path-dependency and avoid decision "lock-ins"—which occur when taking adaptive action is expensive or degrades system performance (Haasnoot et al., 2020; W. E. Walker et al., 2013). The IDA supplements the regional defection analysis by revealing how each policy pathways provide robust performance across multiple performance criteria. The contribution of cooperative infrastructure investments to the robustness of individual utilities provides a direct measure of the utilities ability to harness cooperative power (or *power with* as defined by Avelino and Rotmans (2011)).

To conduct IDA, we develop a set of infrastructure disruption scenarios, $\boldsymbol{\Pi}$, where infrastructure options become unavailable to Triangle utilities.

$$\boldsymbol{\Pi} = [\boldsymbol{BI}_k, \boldsymbol{BI}_{k+1}, \ldots, \boldsymbol{BI}_m] \tag{11}$$

where $\boldsymbol{BI}_k$ represents the vector of regional infrastructure options with option k unavailable, and m represents the total number of infrastructure options.

We pair each infrastructure disruption scenario with all 2 million DU re-evaluation scenarios and evaluate each candidate portfolio pathway across the full set of paired samples, as shown in Figure 2f. We examine the impact of pathways disruption by measuring the change in robustness from infrastructure disruption scenarios.

$$R^{IDA}_{i,BI_k} = S(\theta_{comp})_i - S(\theta_{BI_k})_i \tag{12}$$

where i is the performance criteria, θ_{comp} is the compromise policy with no infrastructure disruptions, and BI_k, is the infrastructure disruption scenario for infrastructure option k.

3.7. Time-Evolving Scenario Discovery

In the final step of DU Pathways$_{ERAS}$, we perform scenario discovery (Bryant & Lempert, 2010; Groves & Lempert, 2007; Jafino & Kwakkel, 2021) learn about how uncertainty generates vulnerability for candidate policy pathways, and evaluate how vulnerability changes over time. Using this information, we develop narrative scenarios to inform an implementation and monitoring strategy (Haasnoot et al., 2018). Scenario Discovery uses machine learning and data mining algorithms (e.g., classification, clustering, and regression) to determine which deep uncertainties most strongly influence the performance of a pathway policy and delineating regions of the uncertainty space that are likely to cause performance failures (Bryant & Lempert, 2010; Groves & Lempert, 2007). The infrastructure investments made across the planning horizon change both the physical system and utility financial conditions, likely changing their vulnerabilities as well. To capture evolving system vulnerability, DU Pathway$_{ERAS}$ introduces a time-evolving implementation of scenario discovery. To capture near-term vulnerability, which reflects how the system will perform prior to significant infrastructure investment, we first perform scenario discovery across output from the first 10-year of the simulation period. We then examine how vulnerability evolves by performing scenario discovery using a 22-year planning horizon and a 45-year planning horizon. Under each planning horizon, we search for combinations of deep uncertainties that cause compromise portfolio pathways to fail to meet performance criteria. We classify each DU SOW as either a "success" or "failure" based on the performance criteria. We then use a gradient-boosted trees algorithm (Drucker & Cortes, 1996) to partition the uncertainty space into predicted regions of success and failure. Gradient-boosted trees classification is well suited to scenario discovery in regional water supply planning contexts because it can define boundaries that are nonlinear and non-differentiable, traits that are particularly useful in infrastructure pathways context that contain discrete capacity expansions. Boosted Trees are also easy to interpret, provide a simple means of ranking uncertainties and are resistant to overfitting (Trindade et al., 2019).

4. Computational Experiment

The cooperative DU optimization was performed on Pittsburgh Supercomputing Center's Bridges2 supercomputer, accessed through the NSF XSEDE program (Towns et al., 2014). During the DU optimization, we ran five random seeds of the MM Borg MOEA, using MM Borg's default parameterization (Hadka & Reed, 2012).

Each random seed contained two masters and was run for 150,000 function evaluations. Next, we performed DU re-evaluation by stress-testing each Pareto-approximate policy across the full DU sampling shown in Figure 2g. DU re-evaluation was performed on the Texas Advanced Computing Center's Stampede2 supercomputer, accessed through XSEDE. We used results from DU optimization and DU re-evaluation to select and evaluate candidate compromise policies. We then performed individual optimization for the regional defection analysis on Bridges2. Each individual optimization was run for 50,000 function evaluations across two random seeds of MM Borg, with each seed using two masters. The IDA was performed on Stampede2, where 22 infrastructure disruption scenarios were evaluated across the full DU sampling shown in Figure 2g. Finally, we performed time-evolving scenario discovery using the scikit-learn Python implementation of gradient-boosted trees (Pedregosa et al., 2011). Each classification used an ensemble of 250 trees of depth two and a learning rate of 0.1.

5. Results and Discussion

We use DU Pathways$_{ERAS}$ to explore the consequences of different candidate strategies for selecting comprises across for the six Research Triangle partners. A key goal is to better understand and avoid unintended consequences across the candidate pathway policies. Our results contribute a rigorous evaluation of the effectiveness of the inter-utility agreement structure recommended in Gorelick et al. (2022). We seek a compromise policy that is equitable, robust, adaptive, and cooperatively stable. In Section 5.1, we show how narrowly framing the selection of a regional compromise pathway policy solely on managing short-term drought crises can lead to shallow representations of robustness and unintended regional inequities. In Section 5.2, we evaluate the cooperative stability of a high-performing and broadly robust pathway policy identified in Section 5.1 using regional defection analysis. In Section 5.3, we further examine the adaptive capacity of the high performing compromise policy by quantifying its sensitivity to disruptions in planned infrastructure investment sequences. Lastly, in Section 5.4, we utilize scenario discovery to reveal consequential future scenarios to guide the implementation and monitoring of the suggested compromise pathway policy for the Research Triangle region's utilities.

5.1. Avoiding the Unintended Consequences From Myopic Compromises

We begin by examining how the representation of performance trade-offs shapes our perception of the robustness and regional equity of Pareto-approximate pathway policies. Figure 4 shows three representations of the regional performance of Pareto-approximate policies. Each candidate policy represents a different set of ROF-based management and investment rules that coordinates regional drought mitigation actions, structures the development of the shared regional Western Jordan Lake water treatment plant, and generates its own adaptive set of cooperative infrastructure investment pathways. Figure 4a shows the performance of Pareto-approximate policies across the six-objective regional DU optimization space. Each line (gray and colored) represents a Pareto-approximate regional policy, and each axis represents a regional performance objective calculated across the ensemble of WCU natural inflows, and DU factors developed using the approximate DU optimization sampling scheme (detailed in Figure 2f). The light blue line represents the MEI compromise, which seeks to minimize drought risk with the lowest possible infrastructure net present cost. The dark blue line represents the expected drought performance and financial stability (EDF) compromise, which also seeks to minimize drought risk but prioritizes long-term financial stability in the form of low peak financial and unit costs (Figure 4a). The pathway policy designated by the yellow line in the initial panel of Figure 4 represents the DCR compromise and the orange line represents the drought and expanded financial robustness (DFSR) compromise.

In Figure 4a, we observe that all four of the candidate compromises maintain high levels of performance for reliability, RF, and worst-case cost objectives (i.e., drought crisis performance measures). The MEI compromise (MEI, light blue) achieves this high level of performance with the lowest infrastructure net present cost—spending $30M less than the expected drought performance and financial stability compromise (EDF, dark blue) and $80M less than either compromise selected using satisficing robustness criteria (DCR, yellow and DFSR, dark orange). However, the MEI compromise policy's low infrastructure net present cost does not translate to long-term financial stability. The MEI solution generates a higher PFC than either of candidate compromise policies that prioritize financial stability criteria (EDF, dark blue and DFSR, dark orange). The MEI compromise policy also produces high unit cost for its water supply capacity expansion investments, indicating that despite its low expected net present cost of investment, it may trigger infrastructure development that is underutilized. These stranded assets increase budgetary instability and can drive up water rates (Hughes & Leurig, 2013; Raftelis, 2005). This finding

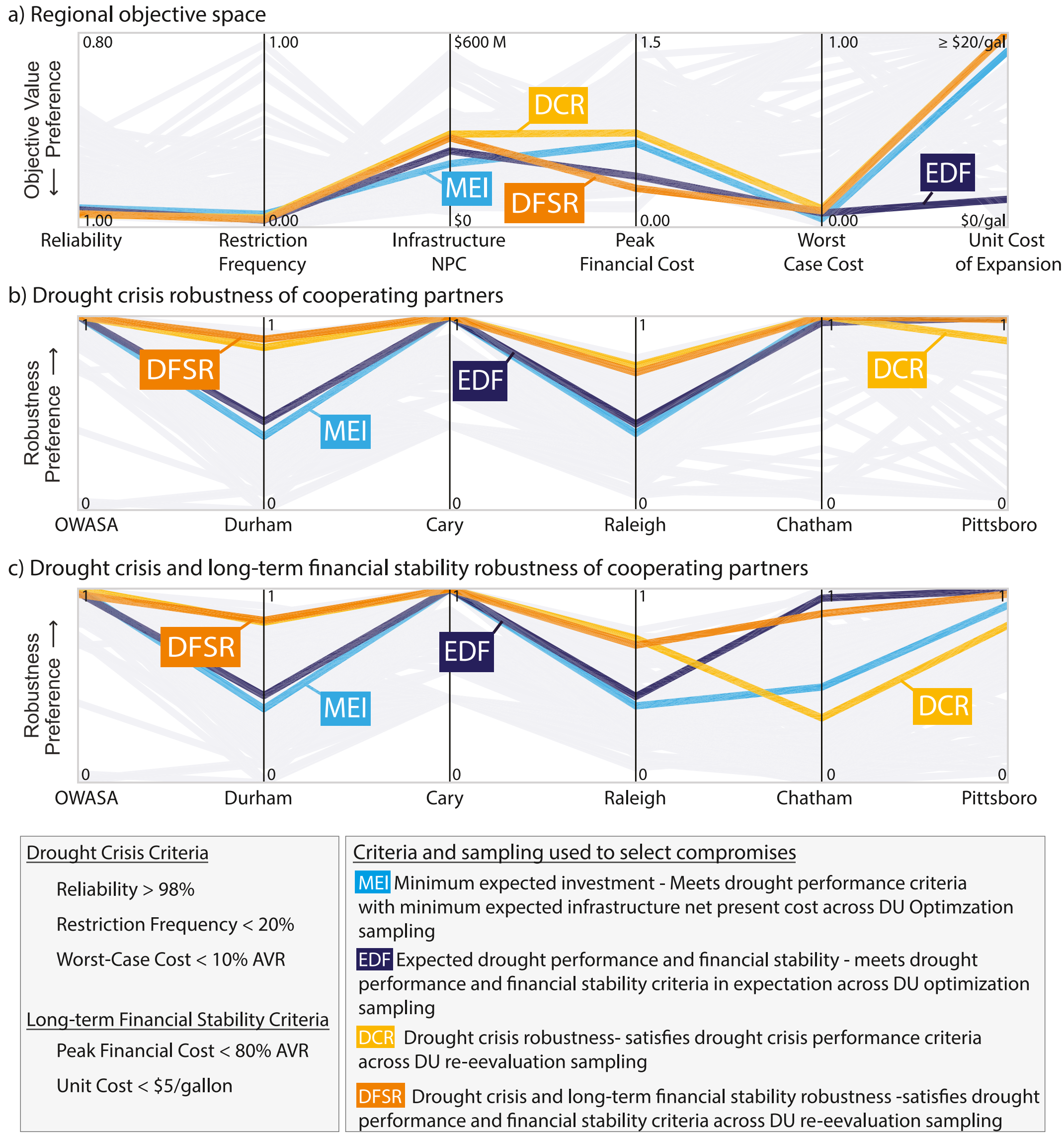

Figure 4. (a) The regional objective space, with four compromises highlighted. Each vertical axis represents a performance objective, and each line represents a pathway policy. (b) Drought crisis robustness (DCR), defined as the percentage of deep uncertainty (DU) states-of-the-world (SOWs) where drought performance criteria are met. Each vertical axis represents the DCR of a regional actor. (c) Drought crisis and long-term financial stability robustness, defined as the percentage of DU SOWs where both drought performance and long-term financial stability criteria are met. Each vertical axis represents the drought crisis and long-term financial stability robustness of a regional actor.

highlights how planning methods that strictly focus on minimizing expected infrastructure investment costs are ill-equipped to evaluate dynamic and adaptive management and investment pathways because they ignore important dimensions of long-term financial stability (Dittrich et al., 2016; Kwakkel, 2020).

Of the four selected compromises shown in Figure 4a, only the expected drought performance and financial stability compromise (dark blue) appears to balance drought crisis and long-term financial stability objectives. However, evaluating performance under the broader ensemble of deep uncertainties used in DU re-evaluation changes this perception. Figure 4b shows the performance of Pareto-approximate policies in terms of the satisficing robustness requirements that focus managing short-term drought crisis performance for each cooperating partner. Each vertical axis represents the robustness of one cooperating partner, measured as the percent of sampled SOWs where the drought crisis focused performance requirements are met (Reliability >98%, RF <20%, and Worst-Case Drought Management Cost <10% AVR) under the broader DU re-evaluation sampling.

Higher values indicate increased robustness. Though all four compromises seek to ensure regional equity, the two compromises that measure performance using regional objective values—including the compromise in dark blue that performed well in Figure 4a—yield highly inequitable robustness, penalizing Durham and Raleigh, the two largest utilities. In contrast, the two policies selected using the two different framings for regional robustness (yellow and orange) are robust for all regional partners.

Adding long-term financial stability requirements in the evaluation of the candidate regional pathway policies' robustness has the potential to strongly change the utilities' perceptions and preferences when selecting a compromise alternative. Figure 4c shows the robustness of cooperating partners using satisficing across both drought performance and long-term financial stability criteria across the larger SOWs ensemble used in DU re-evaluation (Reliability >98%, RF <20%, Worst-Case Drought Management Cost <10% AVR, PFC <80% and Unit Cost of Expansion <$5/kgal). Using this expanded set of requirements, the robustness of Chatham County and Pittsboro, the two smallest regional partners, are significantly reduced under the MEI and DCR compromise pathway policies. The DCR compromise policy, which appears to equitably balance performance across the participating regional utilities when evaluated solely using the DCR framing (Figure 4b), shows particularly reduced robustness for Chatham County, meeting the expanded set of drought crisis and long-term financial stability criteria in only 33% of sampled DU SOWs.

Together, Figures 4a–4c reveal how myopic strategies for identifying candidate regional compromise pathway policies can lead to solutions with potentially severe unintended consequences for some of cooperating Research Triangle partners. Figure 4b shows how the sole focus on traditional trade-off analyses using only performance in the objective space (MEI, light blue and EDF, dark blue lines) fail to yield robust drought crisis responses for Durham and Raleigh, the region's two largest utilities. In other words, they do not trigger sufficient infrastructure investment to maintain reliable capacity-to-demand ratios under challenging future scenarios. Figure 4c adds further insights, showing how policies that do not prioritize long-term financial stability lead to financial failure for the smallest utilities, drawing them into financially risky cooperative investments. In sum, these results demonstrate how balancing the performance of cooperating partners with diverse interests and asymmetric vulnerabilities is a core challenge when crafting regionally cooperative pathway policies (Hamilton et al., 2022; Herman et al., 2015; Sjöstrand, 2017). Our findings also highlight how methods that advocate conflict resolution using a priori assumptions about performance criteria—even when formulated as multi-objective problems (e.g., Hu, Wei, et al., 2016; Tian et al., 2019)—may lead to overly optimistic evaluations of regional performance. These findings emphasize the need for exploring multiple rival problem framings when seeking equitable solutions to cooperative planning problems (Quinn et al., 2017; S. Fletcher et al., 2022).

To understand more about how and why the four compromise policies lead to differing performance across utilities, we examine how the performance of each policy is distributed across the broader evaluation of DU SOWs. Figure 5 shows the cumulative distributions of utility performance across the broad ensemble of DU SOWs used to conduct DU re-evaluation. Each panel represents the performance of one utility in one objective. As in Figure 4, colored lines represent compromise policies, and gray lines represent brushed policies. Vertical dashed lines in Figure 5 represent the satisficing threshold for each objective. Panels 5a and 5f reveal that for Raleigh and Durham, the reliability objective explains the differences in DCR shown in Figure 4b. The policies selected using objective space performance (MEI, light blue and EDF, dark blue) fail to meet reliability criteria roughly 60% of DU SOWs for both utilities. This result highlights the importance of stress-testing candidate rule systems across broad and challenging ensembles of DU SOWs. Though the approximate DU sampling scheme was able to discover pathway policies that maintain supply reliability for all four utilities (e.g., the DSFR compromise, shown in orange), performance in the reliability objective does not directly translate from the approximate DU sampling used for DU optimization and the much more challenging and computationally intensive sampling used during DU re-evaluation. Selecting compromise policies using only the performance of approximate sampling schemes can cause utilities to over-estimate the robustness and under-estimate disparities between regional partners.

In addition to revealing differences in reliability for the region's largest utilities, Figure 5 reveals the extent of vulnerability for the region's smallest partners. Under the DCR compromise (DCR, yellow), Chatham County incurs unsustainable peak financial costs (Figure 5m), and high values of unit cost of expansion (Figure 5o) under a large percentage of SOWs. This suggests that under many scenarios, the compromise triggers infrastructure investments that cause Chatham County to violate debt covenants and ultimately end up as stranded assets. Pittsboro also shows increased vulnerability under the DCR compromise, though its primary failure mode is in

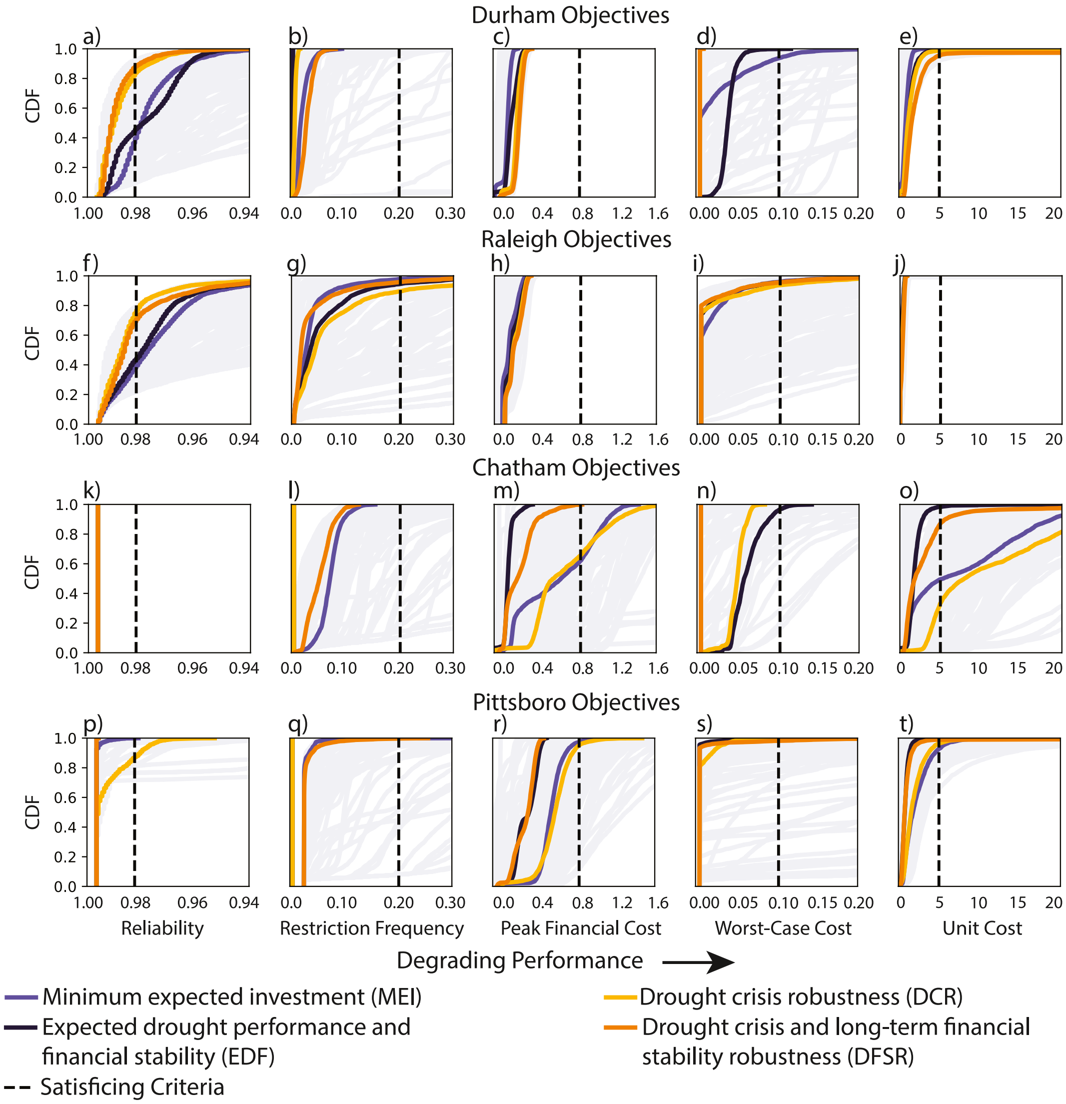

Figure 5. Cumulative distribution of performance across deeply uncertain states-of-the-world (SOWs). Orange Water and Sewer Authority and Cary are omitted from this plot because they maintain high performance across all sampled deep uncertainty SOWs. The four compromise policies are highlighted in color, and the remaining Pareto-approximate policies are shown in gray. The dashed line represents the satisficing criteria for each performance criteria.

reliability. While Pittsboro is able to maintain near 100% under the other compromise framings, its performance under the DCR compromise illustrates how regionally aggregated measures of performance can fail to capture the interests of all cooperating by focusing on regionally aggregated measures of performance, even when those measures are explicitly designed to maintain regional equity.

Our exploration of candidate framings of regional compromise illustrates how a priori assumptions about performance priorities can lead to myopic policy choices that fail to equitably balance the interests of the six regional partners. Of the four highlighted regional compromises, only the drought and expanded financial robustness compromise (orange) equitably achieves high levels of robustness for all cooperating partners. Though the compromise shows a high regional unit cost of expansion when measured in the objective space (shown in Figure 4a), Figure 5 reveals that it maintains low unit cost of expansion for all utilities across the majority of DU SOWs. The high expected value of the regional unit cost of supply expansion objective in the DU optimization results is actually a result of bias in the expected value by a small number of SOWs (for details see Text S4 in Supporting Information S1). This compromise appears to be a strong candidate for implementation, yet important questions about its practicality and performance remain: Do cooperating partners have incentives to adhere to the regional policy once it's been implemented? Does the level of coordination specified by the regional policy expose utilities to new risks from their regional partners? Do regional power dynamics constrain utilities' ability to successfully cooperate? To answer these questions, we analyze this policy using the next step in DU Pathways$_{ERAS}$, regional defection analysis.

5.2. Cooperative Stability and Regional Power Dynamics

Our regional defection analysis formally tests the cooperative stability of the inter-utility agreement structure recommended by Gorelick et al. (2022). The ROF-based rules used to implement this agreement can produce significant differences in performance and robustness, as demonstrated by the differing performance of the four policies evaluated in Section 5.1. The drought crisis and long-term financial stability (DFSR) compromise solution appears to be the overall most equitable of the four compromise pathway policies. However, a key question remains: does it create tensions between the cooperating regional utilities that endanger their willingness to cooperate? Addressing this question warrants a careful examination of the potential for regional robustness conflicts. Figure 6a explores the relative equity of regional robustness—defined as the robustness value of the worst-off cooperating partner—for each Pareto-approximate policy, ranked in descending order. We highlight the equitable compromise (DFSR, orange) along with the policies that maximize robustness for Raleigh (red), Durham (purple), Pittsboro (green), and Chatham County (cyan). While Raleigh's preferred policy only slightly reduces regional robustness, the preferred policies of Pittsboro, Durham, and Chatham County incur large reductions in regional robustness, increasing the potential for conflicts with at least one other utility.

The inter-utility robustness trade-offs shown in Figure 6b illustrates these conflicts. Each axis in the figure represents the robustness of a utility based on the drought crisis and long-term financial stability criteria, and each line represents a Pareto-approximate policy. The equitable compromise (DFSR, orange) achieves strong robustness for all regional partners; however, four utilities—Raleigh, Durham, Chatham County, and Pittsboro—achieve higher robustness through other regional pathway policies. While the individual robustness gains are modest relative to the equitable (DFSR, orange) compromise, each utility's maximally robust pathway policy yields potentially severe consequences for the other regional partners. The results shown in Figure 6b suggest that each utility may have incentives to exploit the investments of their cooperating partners to improve their own performance (i.e., defect from the DFSR compromise (Gold et al., 2022)). This potential for conflict raises three questions about how the underlying power relationships (Avelino, 2021) between the cooperating utilities could impact the practicality of the DFSR compromise policy. First, do utilities have the power to improve their robustness through regional defection from the regional partnership? Second, by entering the regional agreement, do utilities yield power over their performance to their regional partners? Third, if these power dynamics are present, will they destabilize the cooperative regional partnership? To answer these questions, we turn to the results of the regional defection analysis.

Figure 7 shows the results of the regional defection analysis. Each panel represents the change in robustness for one utility under a different defection scenario. Blue bars on the right side of the plots indicate that defection improves robustness, and brown bars on the left side indicate that defection degrades robustness. Cary and OWASA are omitted from this figure because individual optimization for two utilities failed to discover any defection alternatives. Overall, Figure 7 shows that the regional agreement structure developed by Gorelick et al. (2022) limits the incentives for utilities to defect and minimizes the impacts of any defections on cooperating partners. While Figure 6 shows a utility's preferred pathway policy may come at the cost of a cooperating partner's robustness (e.g., Durham in purple), individual utilities do not have the power to unilaterally enact those policies. Instead, Figure 7 shows that these individually optimal policies would require the cooperation of some or all partners to implement—unlikely, given the adverse impacts on those partners—and that of the six Triangle Partners, only Chatham County, and Raleigh have clear incentives to defect from the regional partnership (Figures 7b and 7d). These defections do not adversely impact other regional partners. Moreover, while Figures 7a and 7c indicate that Durham and Pittsboro defection may degrade performance of their partners, these defection actions do not benefit the defecting utilities. Instead of being a cause for concern, the impacts of defections in Figure 7 reveal how utilities can strengthen the cooperative agreement to reduce the potential for conflict between partners.

In sum, the DSFR compromise policy identified in Section 5.1 represents a cooperatively stable (practical) regional pathway policy. Despite the potential for robustness conflicts (Figure 6b), these results indicate that the primary power dynamic in the Triangle region emerges from regional cooperation (described as *power with* by

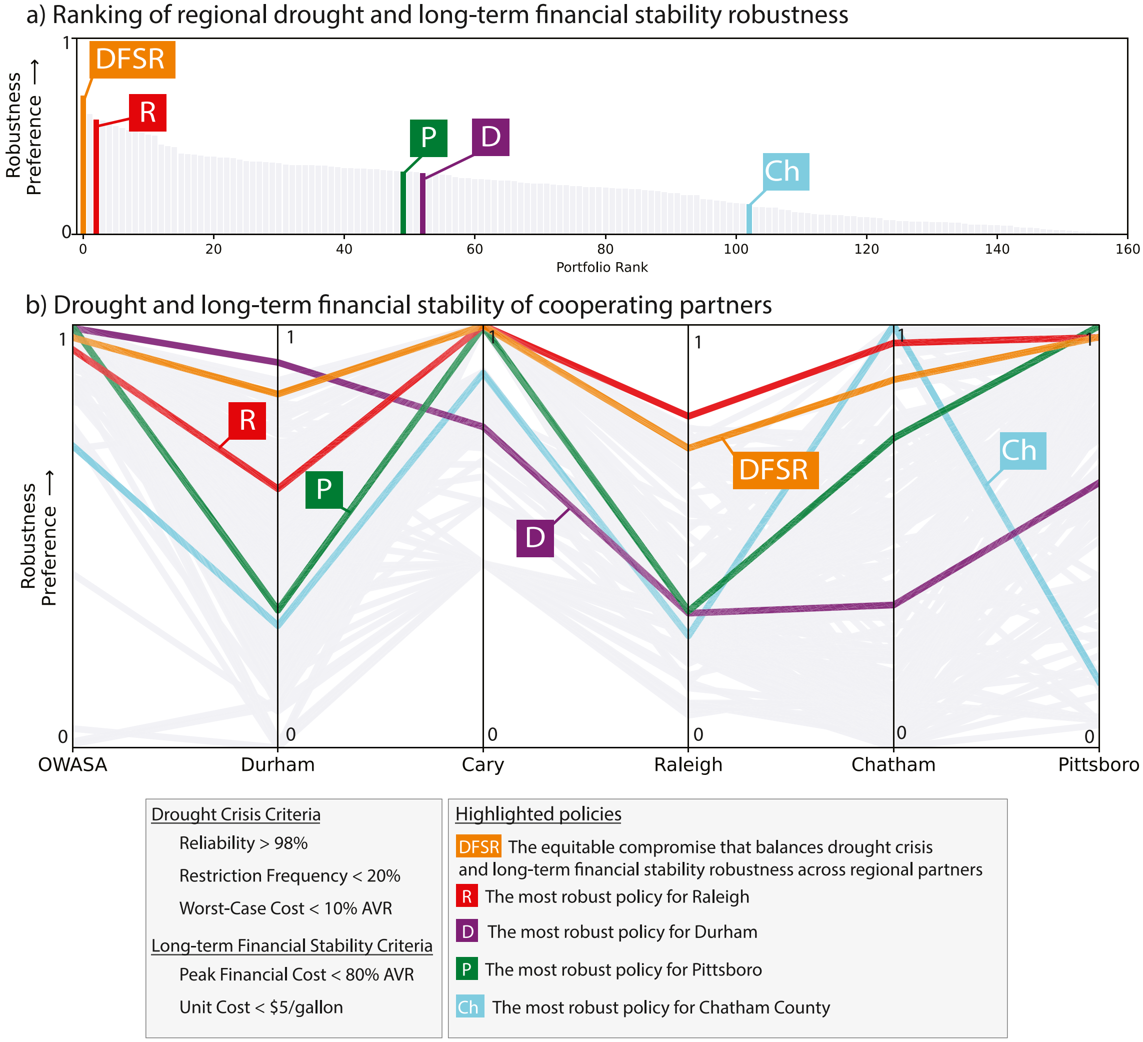

Figure 6. (a) Regional ranking of Pareto-approximate policies by robustness. Each bar represents a cooperative policy, colored bars represent highlighted policies, and gray bars represent brushed policies. (b) Robustness conflicts between regional partners. Each axis represents the robustness of one utility, and each line represents a Pareto-approximate policy. Colored lines represent highlighted policies, and gray lines represent brushed policies.

Avelino and Rotmans (2011)). Through coordinated drought management and cooperative infrastructure investment, Triangle utilities can improve their robustness to deeply uncertain future scenarios.

5.3. Pathways Analysis

5.3.1. Adaptive Infrastructure Pathways

DU Pathways$_{ERAS}$ balances regional drought crisis and long-term financial stability robustness through planned adaptation (W. E. Walker et al., 2013) guided by the regional pathway policy's ROF-based rule system. This rule system generates a state-aware dynamic and adaptive infrastructure pathway tailored to the unique challenges of each sampled SOW. In this section, we visualize how these infrastructure pathways adapt to varying conditions represented in the DU SOWs. Figures 8a–8f show the infrastructure pathways generated by the drought performance and long-term financial stability compromise policy across 1,000 SOWs, each representing one LHS of DU factors paired with one realization of synthetic inflows. Some SOWs require higher infrastructure investment than others, and the compromise regional pathway policy adapts by triggering investments at different times and intensities for each of the utilities. To facilitate a visual exploration of the ensemble of pathways generated across DU SOWs, we used a k-means algorithm to cluster and classify representative pathway results that capture high, medium, or low infrastructure intensities depending on how early and often investments are triggered. The

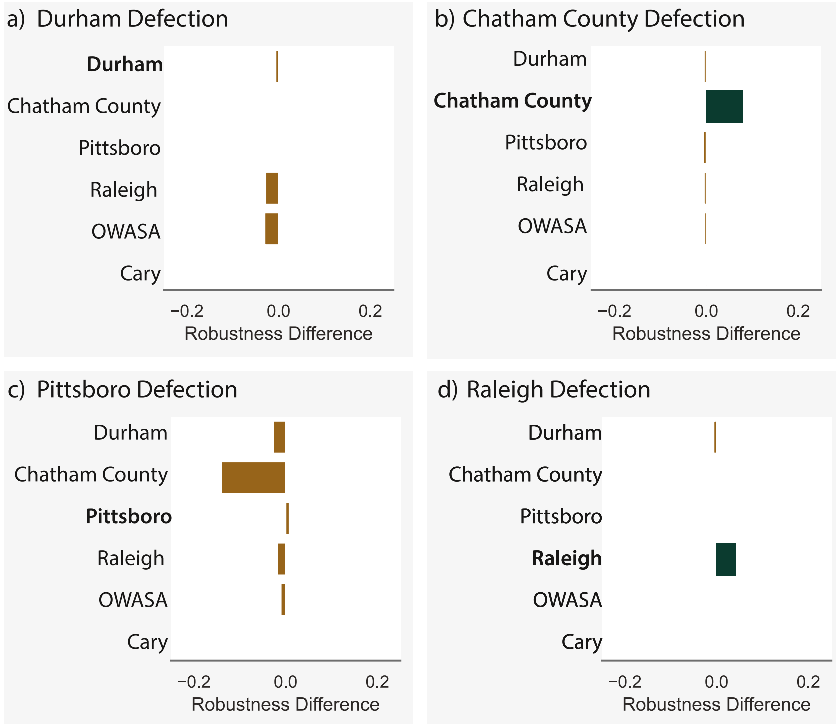

Figure 7. Results of the regional defection analysis. Each panel represents the impacts of regional defection from a different regional partner. Blue bars to the right indicate that a utility can improve its robustness through defection and brown bars to the left indicate that a utility's robustness is degraded from defection.

median week that each infrastructure option is triggered for each intensity is traced in green, and the frequency that each instruction option is triggered across all SOWs during each simulation year is shown by the shading behind the green lines.

Figures 8a–8d establish cooperative infrastructure investment as central to the regional pathway policy. The Western Treatment Plant—jointly developed by Durham, OWASA, Chatham County, and Pittsboro—is constructed under all futures, though sequenced differently across SOWs. Under mild and moderate SOWs (represented by the light and medium green lines), the partners construct the large version of the treatment plant, usually in the third decade of the planning period. Under challenging SOWs that require heavy infrastructure investment (represented as the dark green lines), the utilities construct the small plant early in the planning period and subsequently expand it in the fourth decade. To manage moderate and challenging SOWs, Chatham County and Pittsboro (Figures 8i and 8k) take further adaptive action by constructing the cooperative Sanford Intake.

Cary and Raleigh (Figures 8e and 8f) both utilize infrastructure investments to confront challenging SOWs. Both utilities construct minimal infrastructure in mild SOWs and increase the scope and scale of investments under moderate and challenging SOWs. The difference between infrastructure pathways of all six utilities under mild, moderate, and challenging SOWs highlights the benefits of state-aware rule systems that generate adaptive infrastructure sequences (Trindade et al., 2019; Zeff et al., 2016). Though challenging SOWs require intensive infrastructure investment, the ROF-based management and investment rules—trained through exposure to an ensemble of DU SOWs—avoid triggering extensive infrastructure development under mild future conditions.

5.3.2. Measuring the Benefits of Infrastructure Investment

The DU Pathways$_{ERAS}$ framework builds on prior published work by contributing an IDA that provides a deeper look into the sensitivity and dependency of the compromise pathway policy's ROF-based rule system to each candidate infrastructure investment. The IDA complements existing methods for analyzing adaptive infrastructure pathways (e.g., Gold et al., 2022; Haasnoot et al., 2013; Trindade et al., 2019), to explicitly map how each infrastructure option contributes to regional and individual robustness. Figures 9g–9i show the results of the IDA for each utility. In each panel, columns represent performance criteria, and each row represents an infrastructure

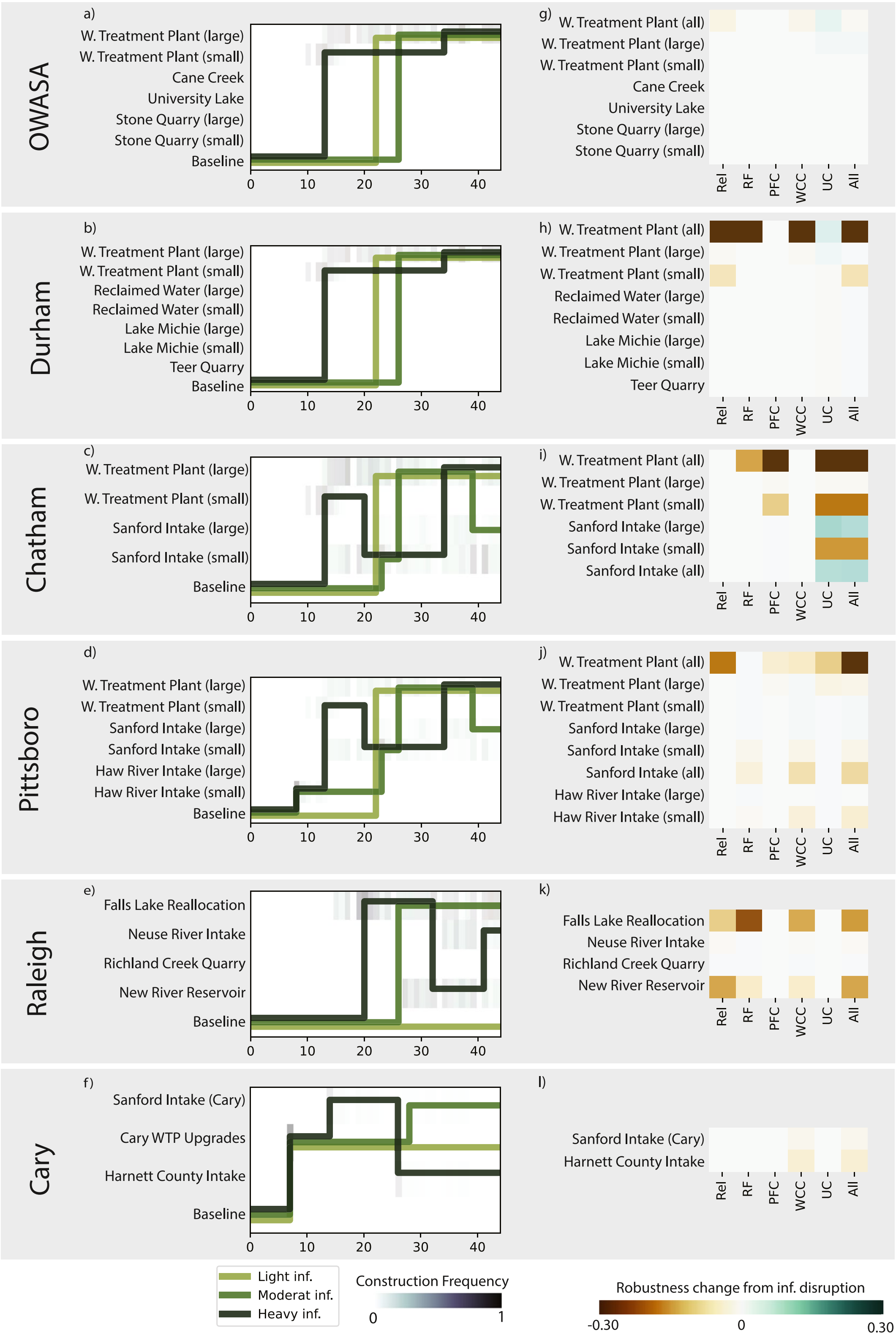
OWASA
a)
W. Treatment Plant (large)
W. Treatment Plant (small)
Cane Creek
University Lake
Stone Quarry (large)
Stone Quarry (small)
Baseline
0 10 20 30 40
g)
W. Treatment Plant (all)
W. Treatment Plant (large)
W. Treatment Plant (small)
Cane Creek
University Lake
Stone Quarry (large)
Stone Quarry (small)
Rel RF PFC WCC UC All
Durham
b)
W. Treatment Plant (large)
W. Treatment Plant (small)
Reclaimed Water (large)
Reclaimed Water (small)
Lake Michie (large)
Lake Michie (small)
Teer Quarry
Baseline
h)
W. Treatment Plant (all)
Chatham
c)
Sanford Intake (large)
Sanford Intake (small)
i)
Sanford Intake (all)
Pittsboro
d)
Haw River Intake (large)
Haw River Intake (small)
j)
Raleigh
e)
Falls Lake Reallocation
Neuse River Intake
Richland Creek Quarry
New River Reservoir
k)
Cary
f)
Sanford Intake (Cary)
Cary WTP Upgrades
Harnett County Intake
l)
Light inf.
Moderat inf.
Heavy inf.
Construction Frequency
0 1
Robustness change from inf. disruption
-0.30 0 0.30

Figure 8.

disruption scenario—a future where one infrastructure option is unavailable. For infrastructure options that can be implemented sequentially (such as the Western Water Treatment Plant), we run one scenario to remove each sequential option and an additional scenario where all options are removed. Brown shading in Figures 8g–8l indicates infrastructure disruption results in decreased robustness, and teal shading indicates increased robustness.

Figures 8g–8k show that the cooperative Western Treatment Plant provides strong and diverse benefits for its four investors. The treatment plant plays a crucial role in maintaining drought crisis performance (reliability, RF, and worst-case cost) for all four partner utilities, providing particularly large drought crisis benefits for Durham (Figure 8h) and Pittsboro (Figure 8j). The treatment plant also plays a key role in Chatham County's long-term financial stability (Figure 8i). Removing the treatment plant reduces Chatham County's robustness in PFC and unit cost of supply expansion, suggesting that the joint treatment plant represents the most economically efficient investment of the available infrastructure options. These results clarify how the cooperative investment benefits regional partners (i.e., what partners gain from power with) and support recent findings that regional water supply planning can exploit economies of scale to maintain supply reliability in a financially efficient manner (Reedy & Mumm, 2012; Tran et al., 2019).

However, Figure 8 also illustrates how cooperative investment can lead to conflict between regional partners. Figures 8i and 8j show that the Sanford Intake, a joint infrastructure project available to Chatham County and Pittsboro, is a potential source of tension between the two utilities. Removing the intake from the available supply sources reduces Pittsboro's robustness in RF and worst-case cost criteria (Figure 8j). However, removing the project improves Chatham County's robustness in the unit cost of expansion criteria without hurting performance in any other performance measure (Figure 8i). Here, the regional pathway policy dictates that Chatham County should make an investment solely to benefit its cooperating partner, an unlikely action for a utility facing financial risk.

Figure 8 also contains a possible resolution to this problem. The Sanford Intake is a flexible infrastructure option that utilities can implement sequentially. Figure 8i reveals that the large intake option is the source of financial risk for Chatham County, while the smaller version represents an economically efficient investment. Pittsboro benefits from both intake projects, but removing the large project does not degrade its performance as long as the small option remains available. Therefore, if two utilities modify the pathway policy by removing the large version of the Sanford Intake, Pittsboro can maintain the robustness benefits of the small intake without risking costly stranded assets for Chatham County.

5.4. Scenario Discovery: Finding Time-Evolving Drivers of Failure

Where IDA reveals how each infrastructure option contributes to robustness, scenario discovery explores which deep uncertainties generate vulnerabilities for the compromise pathway policy. In the DU Pathways$_{ERAS}$ framework, we contribute a time-evolving scenario discovery, that identifies: (a) which deeply uncertain factors most strongly influence the performance of a pathway policy, (b) how these factors influence drought crisis performance and long-term financial stability, and (c) how these vulnerabilities evolve over time. Figure 9 presents the results of scenario discovery conducted across three different planning horizons for four of the six regional partners. Cary and OWASA are omitted from this figure because both utilities meet performance criteria under nearly all sampled DU SOWs. For each utility and each time horizon, we present scenario discovery results in three ways. The top plot in each panel of Figure 9 shows a factor map containing each planning horizon's two most important deep uncertainties as determined by gradient-boosted trees. Each point on the factor map represents a DU SOW—white points indicate DU SOWs where all performance criteria are met, and red points indicate SOWs where at least one criterion is not met. Blue shaded regions indicate regions of the uncertainty space predicted by gradient-boosted trees classification to meet all performance criteria, while red shaded areas represent regions predicted to cause failure. Below each factor map is a bar plot showing the percentage of failure SOWs that are attributed to each performance criteria (e.g., for Durham under the 10-year planning horizon, reliability failures occur in roughly 90% of failure SOWs). The heatmap below each bar plot shows the importance

Figure 8. (a–f) Infrastructure pathways generated by the compromise pathway policy across 1,000 deep uncertainty states-of-the-world (SOWs). Three clusters summarizing infrastructure pathways are plotted as green lines which represent the median week that options are triggered. The frequency that each option is triggered across all SOWs is plotted as the shading behind the lines. (g–l) Results of the Infrastructure Disruption Analysis. Each row represents an infrastructure disruption scenario, each column represents a performance criterion: Reliability (Rel), Restriction Frequency (RF), Peak Financial Cost (PFC), Worst Case Cost (WCC), Unit Cost of Infrastructure Investment (UC), and all criteria (All).

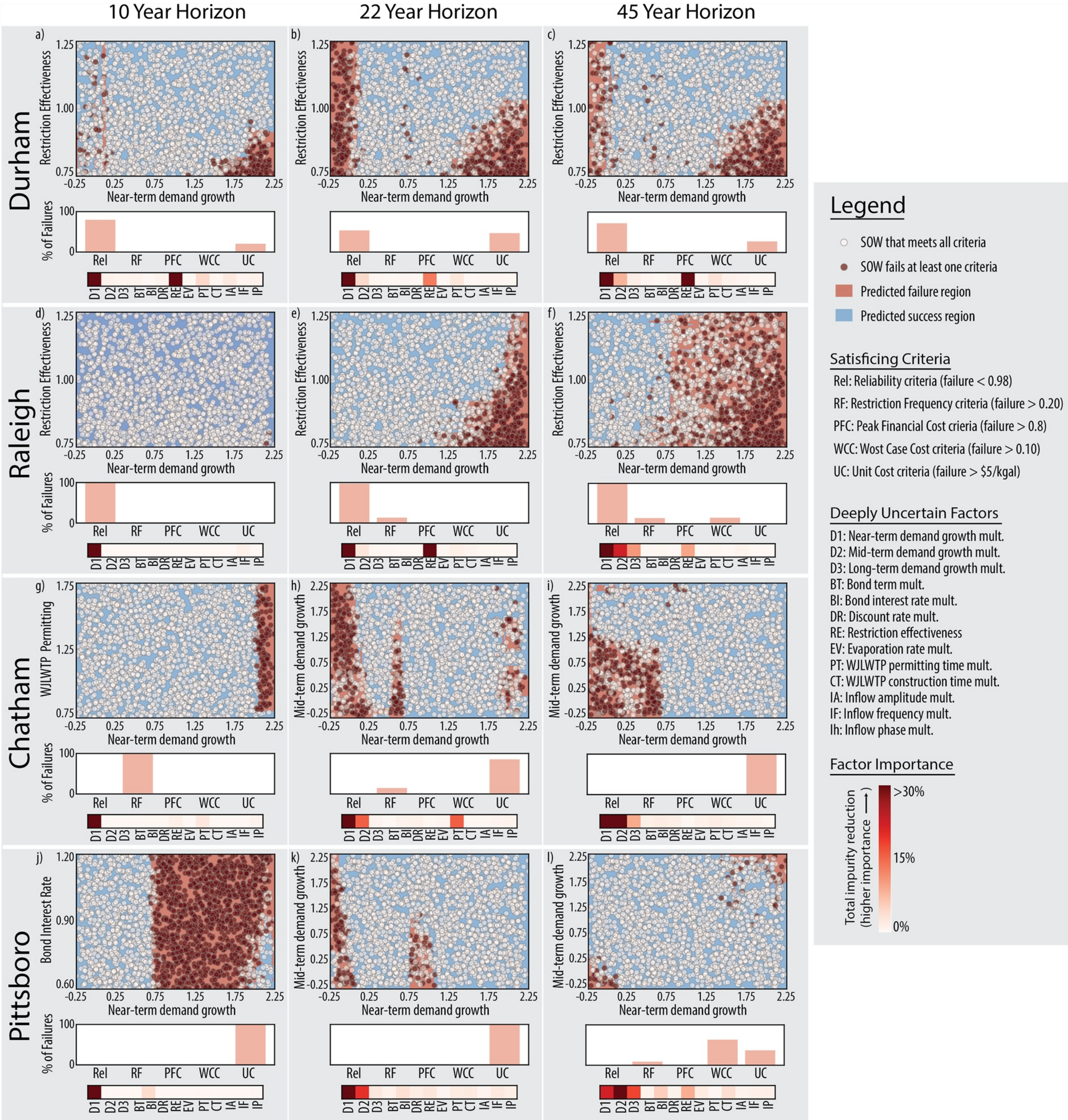

Figure 9. Scenario discovery results. The top plot is a factor map showing vulnerability to the top two deep uncertainties. Each points represent deep uncertainty (DU) states-of-the-world (SOWs), white points represent SOWs where performance criteria are met and red points represent SOWs where that fail at least one performance criterion. Red-shaded areas are regions of the uncertainty space predicted to cause failure by gradient-boosted trees, and blue regions represent regions predicted to succeed. Details on factor map creation can be found in Text S5 in Supporting Information S1. Bar plots below each factor map show the % of failure SOWs that fail each performance criteria. The heatmap at the bottom of each panel shows the importance of DU factors determined by gradient-boosted trees.

of each DU factor as determined by gradient-boosted trees. Dark shading indicates high factor importance, while light shading indicates low factor importance.

Figure 9 shows that utilities' vulnerability evolves over time. For example, under the 10-year planning horizon (Figure 9j), Pittsboro appears highly vulnerable to failures in unit cost of supply expansion, but this vulnerability decreases as the planning horizon increases. This evolution is likely due to significant infrastructure investments made early in the simulation period (Figure 9d), which do not appear to be efficient until Pittsboro's demand has had time to grow sufficiently. Under the 45-year planning horizon (Figure 9l), Pittsboro has two primary vulnerabilities, high demand growth, which causes failures in worst-case cost, and low demand growth, which generates stranded assets.

Chatham County's vulnerability evolves in the opposite direction. Under the 10-year planning horizon, Chatham County (Figure 9g) appears to be only vulnerable to RF failures that result from high near-term demand growth. However, when evaluated under a 45-year planning horizon (Figure 9i), Chatham County appears vulnerable to low-demand growth futures, which cause failure in the unit cost of supply expansion criteria. This evolving vulnerability reveals a potential trap for Chatham County—while the risk of supply failures suggests the need for early infrastructure investment, overreaction to this risk can lead to financial instability. This finding highlights how performing scenario discovery across time reveals vulnerabilities that are not apparent with a single time horizon (Haasnoot et al., 2018; Steinmann et al., 2020).

Figure 9 further illustrates that each partner's vulnerability is governed by interactions between multiple deep uncertainties. For example, under all three planning horizons, Durham is vulnerable to combinations of high near-term demand and low restriction effectiveness, which cause failure in the reliability objective (Figure 9a). Durham's vulnerability to restriction effectiveness reveals that the policy pathway relies on Durham's water use restrictions to manage drought in high-demand growth futures. When the utility maintains restriction effectiveness at or above the nominal estimate (value of 1.0), it can manage demand growth more than twice the current projection. However, if restrictions are less effective than estimated, Durham will be unable to maintain reliable supply in high-demand futures. This finding provides actionable information for improving the pathway policy—if Durham can develop methods to ensure the effectiveness of water use restriction (e.g., Halich & Stephenson, 2009), or control demand growth (e.g., Kenney, 2014), it can mitigate its vulnerability to supply failures.

Yet controlling demand growth is a delicate balance for Durham. Figures 9a–9c reveal that Durham is also vulnerable to a second form of failure—high unit cost of supply expansion. When near-term demand does not grow (demand growth multiplier ≤ 0), the policy may cause Durham to over invest in supply infrastructure. Durham appears most vulnerable over-investment when evaluated under the 22-year planning horizon in SOWs with low near-term demand growth. This vulnerability persists under the 45-year planning horizon, suggesting that low near-term demand is a strong indicator of the long-term risk of stranded assets.

Near-term demand growth represents a key signpost for all four utilities shown in Figure 9. For the Western Treatment Plant partners (Durham, Chatham County and Pittsboro), near-term demand growth can foreshadow both stranded assets and future supply failures. If utilities observe very low near-term demand growth, they should reconsider the development of the Western Treatment Plant, which may become a stranded asset. In these scenarios, utilities can focus on the smaller, less expensive treatment plant option or delay the start of construction. In contrast, if near-term demand growth is higher than expected, Durham should investigate strategies for improving the effectiveness of water use restrictions, while Pittsboro should investigate alternative financial instruments to mitigate worst-case drought management costs (e.g., Zeff & Characklis, 2013). Near-term demand growth can also inform long-term planning for Raleigh, as it represents a predictive indicator for supply failures under the 22 and 45-year planning horizons. Under the highest demand growth scenarios, Raleigh cannot avoid supply failures, suggesting that if the utility observes rapid near-term demand growth, it should consider additional sources of supply expansion beyond the alternatives included in the pathway policy.

We synthesize the results shown in Figure 9 into a set of narrative scenarios (Table 6) to guide implementation and monitoring of the compromise pathway policy (Groves & Lempert, 2007; Haasnoot et al., 2015). These narrative scenarios supplement the autonomous adaptation of the ROF-generated infrastructure pathways by guiding anticipatory monitoring (Groves et al., 2015; Haasnoot et al., 2018), and offering contingency actions to mitigate challenging future conditions (Lempert, 2002; G. Walker, 2013).

6. Conclusion

This study presents DU Pathways$_{ERAS}$, a framework for identifying infrastructure investment and management policies that are robust, equitable, adaptive, and cooperatively stable. In the Triangle system, our exploration of regional compromise reveals that a priori assumptions about performance priorities can unintentionally lead to inequitable regional compromises. Although all four framings of regional compromise place significant value

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on regional equity by applying Rawls' difference principle, we find that the choice of performance measures included in robustness assessment fundamentally shapes the equity of regional comprise policies.

For the Triangle partners, our Regional Defection Analysis reveals that the cooperative agreement structure minimizes the exposure of each actor to the actions of their cooperating partners and demonstrates that the primary power dynamic in the regional system is from collaboration (*power with*). The IDA further illustrates how this cooperative power dynamic manifests through the shared Western Treatment Plant, which improves the robustness of all cooperative partners. The infrastructure defection analysis also reveals a decision lock-in for Chatham County and a simple means of adjusting the policy to avoid stranded assets. Finally, the time-evolving scenario discovery reveals that utility vulnerabilities evolve over time and highlights adaptive contingency actions the utilities can take to maintain performance under challenging future scenarios. Beyond the Triangle system, DU Pathways$_{ERAS}$ can be broadly applied to cooperative infrastructure investment problems facing DU.

Table 6
Narrative Scenarios to Guide Implementation and Monitoring

Scenario	Utility	Consequence	Signpost	Contingency action
Rapid demand growth stresses Durham's water supply	Durham	Supply failure	Near-term demand >1.25× projection	Invest in restrictive effectiveness
Rapid demand growth stresses Raleigh's water supply	Raleigh	Supply failure	Near-term demand >0.75× projection	Develop additional infrastructure
Rapid demand growth causes Chatham County over-restriction	Chatham County	Over-restriction	Near-term demand >2× projection	Prepare customers for potential restrictions
Rapid demand growth drives Pittsboro worst-case cost	Pittsboro	Unmanageable worst-case cost	Near-term demand growth >1.25× projection	Financial instruments
Stagnant demand generates stranded assets for Western Treatment Plant partners	Durham, Chatham County, Pittsboro	Stranded assets	Near-term demand growth <0.25	Delay or shrink Western Treatment Plant

6.1. Challenges and Future Work

The simultaneous pressures of climate change, financial risk, and growing demands for limited resources create strong incentives for water utilities to develop regionally cooperative infrastructure investment and management strategies. This study engages with key challenges to developing successful regional water supply policies, including asymmetry in regional power dynamics, evolving vulnerability to DU, and financial risk. To successfully implement DU Pathways$_{ERAS}$, cooperating water utilities must have a well-calibrated system model and access to high-performance computing resources—assets that are possessed by many urban water utilities in the United States (Water Utility Climate Alliance, 2010), but are less common in smaller communities and the global south. The use of the DU Pathways$_{ERAS}$ framework will also be subject to regulatory constraints and local politics, considerations that need to be accounted for on a case-by-case basis.

This study focuses on the development of regionally cooperative water supply planning and management policies that equitably balance performance across water utilities with strong asymmetries in size, demand growth, and storage capacity. Water supply planning and management problems often contain other important equity considerations that are beyond the scope of this study. These include modeling water affordability within the communities served by regional water utilities, particularly in low-income areas, and the spatial distribution of supply disruptions (Mack & Wrase, 2017; Rachunok & Fletcher, 2023). Future work could expand the DU Pathways$_{ERAS}$ framework to explicitly incorporate these considerations into the design of cooperative water supply management policies.

The regional defection analysis implemented as part of DU Pathways$_{ERAS}$ examines cooperative stability by investigating the potential for individual defection by cooperating partners but does not assess the potential for partners to form competing alliances. Future work could expand this methodology by investigating the potential for partner utilities to form sub-coalitions within the regional system and assess the impact of potential sub-coalitions on regional stability and power dynamics.

This study finds stranded assets to be a key concern for maintaining the long-term financial stability of utility partners. While this work utilizes unit cost of expansion as a proxy for stranded assets, future work should examine alternative measures to capture this vulnerability and study how applying different metrics can change resulting infrastructure pathways. Future work should also consider implementation uncertainty to guide the development of actionable policy pathways.

Data Availability Statement

All data used and generated by this study, including required input files and full results, can be found in Gold et al. (2023b). The code used in this study and instructions for replicating the full computational experiment can be found in Gold et al. (2023a).

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