Advancing Regional Water Supply Management and Infrastructure Investment Pathways that are Equitable, Robust, Adaptive, and Cooperatively Stable

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Abstract

Regionalization approaches wherein 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 deeply uncertain risks. Successful regional cooperative investment and management pathways, however, 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 PathwaysERAS), an exploratory modeling framework for developing regional water supply management and infrastructure investment pathways. Our framework explores equity and power relationships within cooperative pathways using multiple rival framings of robustness, each representing a competing hypothesis about how performance objectives should be prioritized. To capture the time-evolving dynamics of infrastructure pathways, DU PathwaysERAS 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 equity. Results further illustrate that regional and individual vulnerabilities are highly interdependent, emphasizing the need to craft agreements that limit counterparty risks from the actions of cooperating partners. Beyond the Research Triangle, these results are broadly applicable to cooperative water supply infrastructure investment and management globally.

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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

Abstract

Regionalization approaches – wherein 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 deeply uncertain risks. Successful regional cooperative investment and management pathways, however, 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. Our framework explores equity and power relationships within cooperative pathways using multiple rival framings of robustness, each representing a competing hypothesis about how performance objectives should be prioritized. To capture the time-evolving dynamics of infrastructure pathways, DU 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 equity. Results further illustrate that regional and individual vulnerabilities are highly interdependent, emphasizing the need to craft agreements that limit counterparty risks from the actions of cooperating partners. Beyond the Research Triangle, these results are broadly applicable to cooperative water supply infrastructure investment and management globally.

1 Introduction

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 (IPCC, 2022; AWWA, 2018). 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 (WUCA, 2016; USGCRP, 2018; Bonzanigo et al., 2018). 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; (Qureshi & Shah, 2014; Haasnoot et al., 2020)). 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; Tran et al., 2019; Riggs & Hughes, 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 (Gleick, 2003; Brandes et al., 2009; Zeff & Characklis, 2013; Kenney, 2014; Gorelick et al., 2018). When expansion is unavoidable, utilities can leverage economies of scale by co-investing in regional supply sources (Riggs & Hughes, 2019; Silvestre et al., 2018; EPA, 2017). 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 (Padula et al., 2013; Cai et al., 2015; Mortazavi-Naeini et al., 2014; Zeff et al., 2016; Baum et al., 2018). 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 (Stakhiv, 2011; Groves et al., 2019). 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 (Madani & Hipel, 2011; Read et al., 2014; Hamilton et al., 2022; Savelli et al., 2022; Gold et al., 2022). These challenges motivate the contribution of the DU Pathways$_{ERAS}$ framework proposed in this study.

DU Pathways$_{ERAS}$ builds on the DU Pathways framework (Trindade et al., 2019) to facilitate the development of cooperative water supply policies that bridge long-term investments with short-term portfolio management. 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 (W. E. Walker et al., 2013; Bonzanigo et al., 2018; Kwakkel et al., 2016; Lempert et al., 2006; Maier et al., 2016). These conditions, collectively known as “deep uncertainty”, challenge traditional decision-making frameworks such as cost-benefit analysis (Lempert, 2002; Kwakkel et al., 2016; Dittrich et al., 2016; Marchau et al., 2019) and have motivated a rapidly growing body of literature focused on bottom-up decision support frameworks (Lempert et al., 2006; Brown et al., 2012; Haasnoot et al., 2013; Kasprzyk et al., 2013). These frameworks typically center on exploratory modeling approaches (Bankes, 1993; Moallemi, Kwakkel, et al., 2020) that use computational experiments to discover policies that are robust to large ensembles of deep uncertainties and 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). To facilitate the discovery of robust policies, DU Pathways and DU PathwaysERAS employ the constructive decision-aiding approach of Many-Objective Robust Decision Making (MORDM; (Kasprzyk et al., 2013), which treats the search for candidate policies as an iterative learning process where stakeholders explore trade-offs across multiple performance metrics (Tsoukiàs, 2008; Kwakkel et al., 2016).

A key concern in bottom-up robustness-focused decision support frameworks is whether they employ static or state-aware contextually appropriate adaptive actions to develop robust policies. Static strategies 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 strategies tend to be costly and may increase vulnerability to unanticipated future scenarios (Anderies et al., 2013). In contrast, adaptive state-aware strategies permit contextually tailored and appropriate changes to actions over time, triggering actions based on state information (W. E. Walker et al., 2013; Haasnoot et al., 2013; S. M. Fletcher et al., 2017; Erfani et al., 2018; Trindade et al., 2020; Giuliani et al., 2021; Pachos et al., 2022). For example, Dynamic Adaptive Policy Pathways (DAPP; (Haasnoot et al., 2013) generates a suite of adaptive actions and identify signposts to monitor system performance and trigger adaptive actions. DU Pathways (Trindade et al., 2019) builds on this approach by using state-aware rule systems to trigger short-term soft path actions (e.g., water restrictions or transfers) and long-term infrastructure investment decisions. The DU Pathways policies can be viewed as state-aware rule systems approximate a closed-loop control policy (Bertsekas, 2012; Herman et al., 2020) that triggers actions tailored to observed future conditions (i.e., termed model-free policy approximation control techniques in recent proposed reinforcement learning taxonomies — see (Bertsekas, 2012; Powell, 2019)). The DU Pathways$_{ERAS}$ framework proposed in this study adopts the state-aware rule system utilized by DU Pathways.

Beyond identifying candidate state-aware robust adaptive policies, it also critical to understand which deep uncertain factors are most consequential for shaping their success and vulnerabilities. A key facet of recent advances in decision making under deep uncertainty is 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). Scenario Discovery (Groves & Lempert, 2007; Bryant & Lempert, 2010; 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). Yet these studies still rely on time-aggregated evaluations of system performance, and do not separate near-term and long-term vulnerabilities. DU Pathways$_{ERAS}$ contributes a pathways-centered time-evolving scenario discovery methodology based on gradient-boosted trees to better capture changing vulnerabilities as well as the mathematical challenges posed by nonlinearly dependent multi-actor failure modes as well as the complex thresholds that adaptive infrastructure investments cause in scenario spaces (e.g., discrete jumps in water supply capacity for an actor).

While adaptive strategies can increase the robustness of infrastructure investment and management policies to deep uncertainty, 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; Hamilton et al., 2022; Gold 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., (Hu, Chen, et al., 2016; Aalami et al., 2020). 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 (Zeff et al., 2014; Jafino et al., 2020). 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 utilities 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'). The DU Pathways$_{ERAS}$

framework facilitates an inclusive participatory many-objective framing of cooperative pathway policies and rigorous exploratory modeling for aiding regional stakeholders to better realize equitable outcomes as they navigate the space of candidate compromises.

A successful regional policy must not only be equitable, but also cooperatively stable, meaning that no partner has incentives to defect from the policy (Dinar & Howitt, 1997; Madani & Hipel, 2011; Madani & Dinar, 2012; Read et al., 2014). Previous work has utilized game theoretic metrics of stability and bargaining frameworks to discover cooperatively stable water supply management strategies (Madani & Hipel, 2011; Parrachino et al., 2006; Ristić & Madani, 2019; Alizadeh et al., 2017). 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 dynamic 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). 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. Gold et al. (2022) introduced Regional Defection Analysis, which evaluates the stability of cooperative infrastructure investment and maps power relationships between regional partners. Building upon this prior work, the DU Pathways$_{ERAS}$ incorporates Regional Defection Analysis as one of the key exploratory modeling evaluation steps to identify how utilities may have power to create or resist change, and power over the performance of their cooperating partners. It also implicitly highlights how utilities may utilize collaborative power (described as *power with* by Avelino and Rotmans (2011)) to improve regional performance.

DU Pathways$_{ERAS}$ represents a holistic exploratory framework for identifying equitable, robust, adaptive, and cooperatively stable urban water infrastructure investment and management regionalization policies. DU Pathways$_{ERAS}$ builds on recent advances in water supply portfolio planning, MORDM, and DAPP to develop adaptive pathway policies that maintain robust performance across deeply uncertain future states of the world and contributes new tools that focus on regional equity and time-evolving vulnerability. The core contributions for DU Pathways$_{ERAS}$ include 1) a formalized process to explore and better realize regionally equitable compromise policies, 2) integration of Regional Defection Analysis (Gold et al., 2022) to evaluate cooperative stability and explore regional power dynamics, 3) a new Infrastructure Disruption Analysis that measures the relative importance of utilities candidate individual and cooperative infrastructure investments, and 4) a time-evolving scenario discovery process that is designed to better inform how to prioritize near term actions and what factors to monitor for maintaining the long-term robustness of adaptive infrastructure pathway policies. Another major facet of this study's contribution is the demonstration of the 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 infrastructure investment and management policies.

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 (the latter managed by the Orange Water and Sewer Authority (OWASA)). The six regional partners seek a regional infrastructure investment and management policy that coordinates short term drought crisis response and long-term infrastructure investment sequencing.

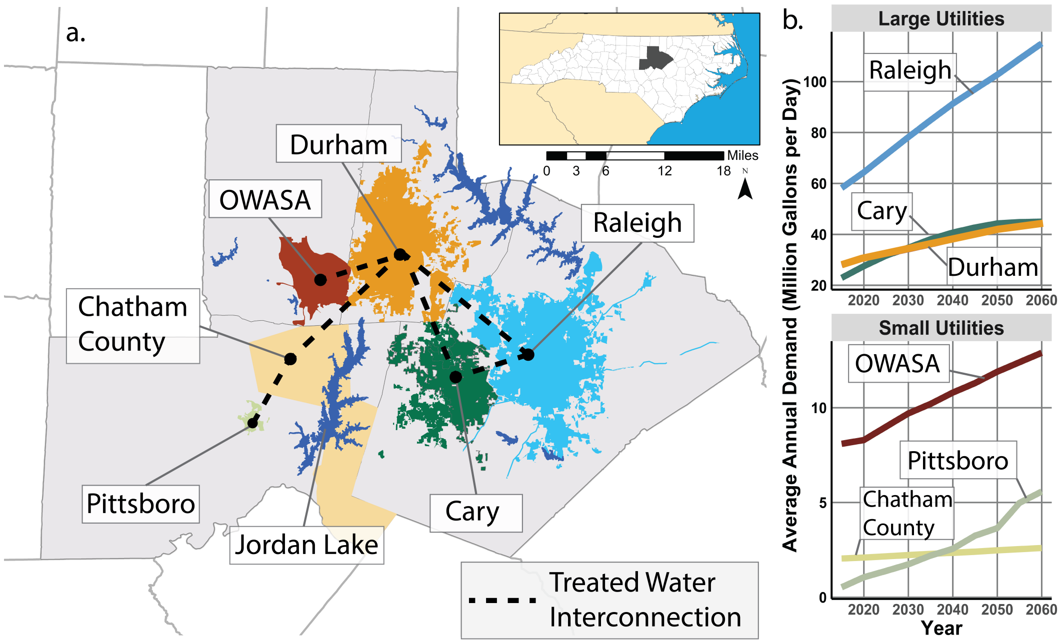

Figure 1. a. The Research Triangle region of North Carolina where six utilities seek cooperative infrastructure investment and management policies b. Demand growth projections for the six utilities

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 (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 1), the utilities plan to invest in new supply infrastructure. A variety of infrastructure options have been identified by each utility (Table 2) 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 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 1) the Western Treatment Plant can benefit cooperating partners and 2) 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 cooperative infrastructure investment and management 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.

Table 1. Projected water demands for Research Triangle partners (MGD)

Triangle Utility	2020	2040	2060
Cary	27.5	40.7	45
Chatham County	2.1	2.4	2.6
Durham	30.7	38.1	44.4
OWASA	8.3	10.8	12.9
Pittsboro	1.1	2.6	5.6
Raleigh	64.4	91.3	115
Total (avg MGD)	134.1	185.9	225.5

Table 2. Available infrastructure for Triangle partners. * cost not included in modeling, project underway at time of publication, ^{c} cooperative project

Project (Type)	Utility	Stages	Capacity (MG or MGD)	Capital Cost ($MILLION)	Earliest Availability
Cary WTP Upgrades* (treatment)	Cary	Small/Large	8.0 / 16.0	121.5* / 243*	2015
Cape Fear River Intake in Harnet County (supply)	Cary	Single	12.2	221.4	2032
Sanford Intake^c - Cary (treatment)	Cary	Single	10	56	2015
Sanford Intake^c - Chatham County, Pittsboro (treatment)	Chatham County, Pittsboro	Small/Large	Chatham: 1.0/2.0 Pittsboro: 3.0/9.0	Chatham: 7.9/11.2 Pittsboro: 49.6/69.3	2022/2028
Western Treatment Plant^c (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	1315	22.6	2022
Lake Michie Expansion (supply)	Durham	Small/Large	2500 / 7700	158.3/203.3	2032
Cane Creek Reservoir Expansion (supply)	OWASA	Single	3000	127	2032
Stone Quarry Expansion (supply)	OWASA	Small/Large	1500 / 2200	1.4/64.6	2037
University Lake Expansion (supply)	OWASA	Single	2550	107	2032
Haw River Intake (supply/treatment)	Pittsboro	Single	2 4	18.6/27.9	2017/2020
Falls Lake Reallocation (supply)	Raleigh	Single	5637	142	2022
Little River Reservoir (supply)	Raleigh	Single	3700	263	2032
Neuse River Intake (supply)	Raleigh	Single	16	225.5	2032
Richland Creek Quarry (supply)	Raleigh	Single	4000	400	2055

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 infrastructure investment and management policies. DU Pathways is an exploratory decision support framework that combines the constructive decision aiding approach of MORDM (Kasprzyk et al., 2013) and the adaptive policy formulation of DAPP (Haasnoot et al., 2013) to develop infrastructure investment and management policies that are robust to deeply uncertain futures. DU PathwaysERAS builds on this framework by including new tools to evaluate regional equity, cooperative stability, adaptation, and time-evolving vulnerability. Our core contributions include 1) a formalized process for exploring regional equity using rival framings for selecting cooperative regional compromises, 2) integration of Regional Defection Analysis (Gold et al., 2022) to evaluate cooperative stability and the power relationships between regional actors, 3) a new Infrastructure Disruption Analysis that measures the sensitivity and dependency of a policy to candidate infrastructure investments, and 4) a pathway-focused time-evolving implementation of scenario discovery (Groves & Lempert, 2007; Bryant & Lempert, 2010; Jafino et al., 2020; Jafino & Kwakkel, 2021) that captures how deep uncertainties interact to drive vulnerability over near-term to long-term planning horizons.

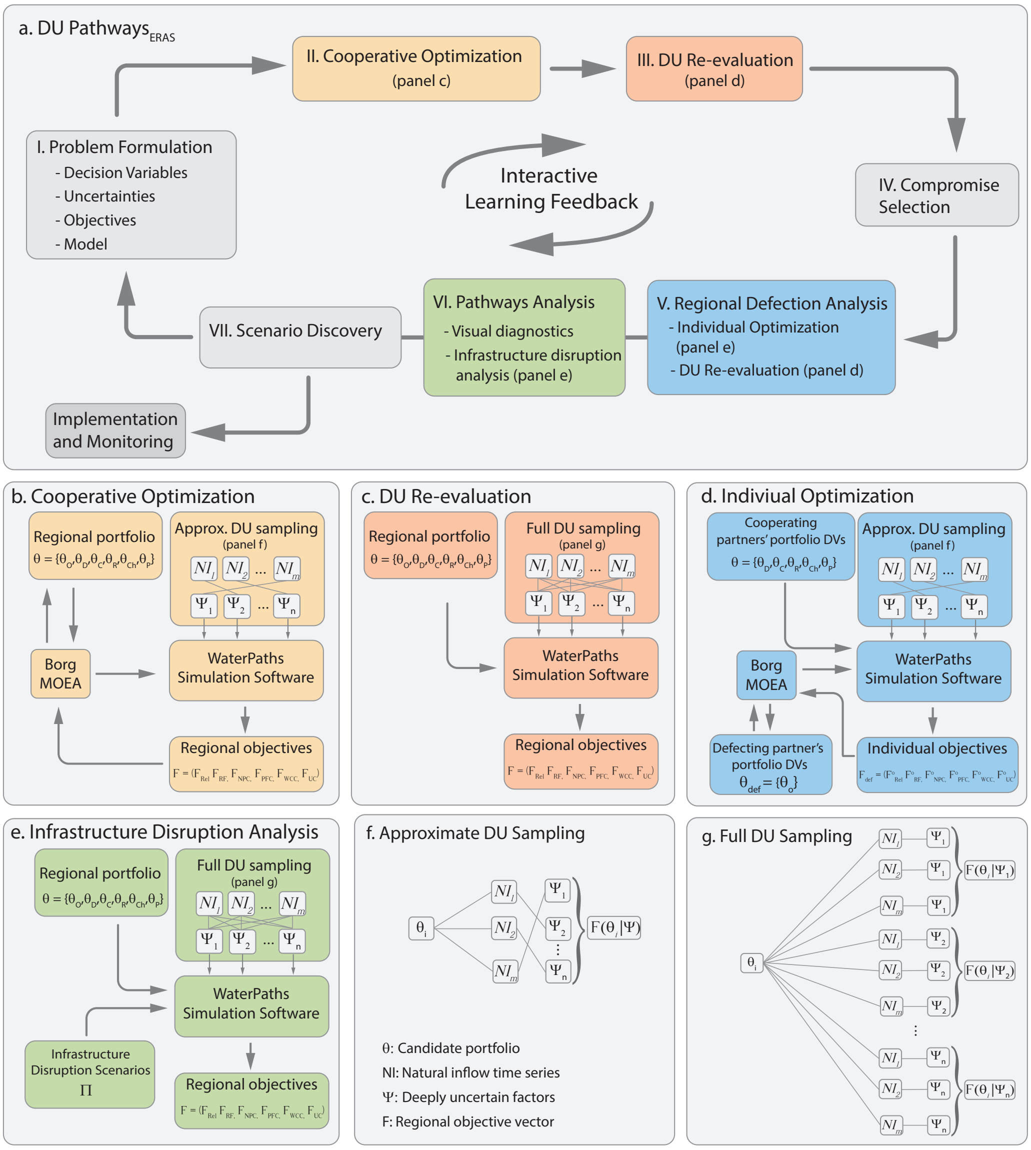

Figure 2. Methodological overview a) DU PathwaysERAS flowchart b) Cooperative optimization c) DU re-evaluation d) Individual Optimization (part of the Regional Defection Analysis) e) Infrastructure Disruption Analysis f) details on approximate DU sampling used for DU optimization g) Full DU sampling used during DU re-evaluation.

Figure 2a shows a flowchart of the DU PathwaysERAS 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 infrastructure investment and management pathway policies (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 searches for robust pathway policies by evaluating candidate policies across an approximate sampling of deeply uncertain states-of-the-world (SOWs) illustrated in Figure 2f. 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.

We use the results of DU optimization and DU re-evaluation to identify a regional policy that maintains equitable and robust performance for all regional actors. This process seeks to ensure the salience and legitimacy (Cash et al., 2003) of DU Pathways$_E RAS$ through a co-production process (Figure 2a, box IV) where decision makers evaluate explore multiple candidate framings of regional performance and seek to aid the selection of a candidate equitable regional compromises after an a posteriori evaluation of candidate alternatives (Bojórquez-Tapia et al., 2022). After identifying one or more candidate compromise policy pathways, we evaluate their 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 PathwaysERAS contributes new diagnostic pathway analysis tools. During Pathways Analysis (Figure 2a, box VI) we use visual analytics to examine pathway policies' infrastructure sequences. We then perform Infrastructure disruption analysis, which measures how each infrastructure option contributes to the robustness of the regional pathway policy by evaluating an ensemble of infrastructure disruption scenarios (Figure 2a, box VI).

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 scenario discovery across three planning horizons: near-term (through 2030), mid-term (through 2045) and long-term (through 2060). 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$_{ERAS}$ builds on the constructive decision aiding approach of MORDM, treating the process of problem formulation as an evolving exploration of hypotheses for specifying decision variables, performance objectives, uncertainties, and modeled relationships (Tsoukiàs, 2008; Kasprzyk et al., 2013). This constructive approach centers on an iterative and exploratory learning process where stakeholders evaluate competing hypotheses (or "rival framings") about how the system should be represented analytically (Majone & Quade, 1980; Quinn et al., 2017). We begin with a formal representation of the Triangle water supply planning problem informed by prior work in the Triangle system (Zeff et al., 2016; Trindade et al., 2019; Gorelick et al., 2022). Formally, the many-objective problem seeks to discover the regional water supply pathway policy, $\boldsymbol{\theta}^*$ whose dynamic and adaptive decisions minimizes the vector or regional objectives, $\boldsymbol{F}$:

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

s.t.

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

Where:

$$\mathbf{F}(\theta, \mathbf{X}, \boldsymbol{\Psi}_{\mathbf{s}}) = \begin{bmatrix} \max_U(1 - f_{\text{REL}}) \\ \max_U(f_{\text{RF}}) \\ \max_U(f_{\text{NPC}}) \\ \max_U(f_{\text{FC}}) \\ \max_U(f_{\text{WFPC}}) \end{bmatrix} \tag{3}$$

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

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

Where $\boldsymbol{F}$ is the vector of regional objectives, $\boldsymbol{\theta}$ is the policy vector of all regional decision variables, $\boldsymbol{X}$ is the vector of ROF system states and $\boldsymbol{\Psi}_s$ is the ensemble of sampled states of the world. $\boldsymbol{U}$ represents the vector of Triangle partners, $\boldsymbol{TT}$ is the vector of transfer triggers, $\boldsymbol{RT}$ is the vector of restriction ROF triggers, $\boldsymbol{IT}$ is the vector of infrastructure triggers, $\boldsymbol{IP}$ is the matrix of infrastructure ranks, $\boldsymbol{RC}$ 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. ME is a generic subset of mutually exclusive infrastructure options within the set of built or potential infrastructure options, BI.

3.1.2 Uncertainty

We partition uncertainty facing the Triangle water supply system into well characterized uncertainty (WCU) and deep uncertainty (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 (Lempert et al., 2006; Kwakkel et al., 2016; W. E. Walker et al., 2003). In the Triangle, we consider the 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 section S1 of this paper's supporting information.

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 states-of-the-world (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

Table 3. DU factors and their sampling ranges. These multipliers are applied to best estimates of each factor by Triangle Utilities

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

natural inflows accurately captures variance in water 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 3f, 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).

3.1.3 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, restriction frequency, infrastructure net present cost, peak financial cost, and unit cost of infrastructure investment. Details on the formulation of each objective are shown in Table 4. The reliability, restriction frequency and worst-case cost objectives, measure utility's ability to manage short-term drought crises. The reliability and restriction frequency 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 restriction frequency while incurring minimal debt burden. Debt burden is not the only financial consideration for water utilities however, also of concern is the Peak Financial Cost 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 that are usually written into bond contracts (AWWA, 2011). 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).

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).

[]

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 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
Infrastrcutrue 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 $CF_{r,U,y}$: the contingency fund value for for utility U in year y of realization r
Wost-Case Cost (min)	The 99% drought mitigation cost across all realizations, defined as the maximum revenue disruption form restrictions and cost of treated transfers	$F_{WCC} = P_{99} \left(\max_{y \in [2015,2060]} \left(\frac{RC_{r,U,y}+TC_{r,U,y}-CF_{r,U,y}}{AVR_{r,U,y}} \right) \right)$	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

Table 4. The six objectives used in many-objective search.

3.1.4 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 deep uncertainty 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 MOEA (MM Borg, (Hadka & Reed, 2012, 2015)) to discover Pareto-approximate infrastructure investment and management 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 (Reed et al., 2013; Gupta et al., 2020). 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 (Trindade et al., 2017) (Figure 2b). DU optimization evaluates each candidate pathway policy across the sampling of WCU and DU SOWs described in Section 5.2.1 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 (Moallemi, Kwakkel, et al., 2020; Kwakkel, 2019). 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 5.2.2. 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 Selection of candidate compromise pathway policies

The Triangle partners seek an equitable and robust pathway policy that balances performance across the six cooperating regional utilities . DU Pathways$_{ERAS}$ facilitates regional partners in the identification of candidate compromise pathway policies through the interactive exploration of multiple and potentially competing hypotheses for framing the individual and/or collective requirements needed for solutions to be acceptable to all parties involved (Tsoukiàs, 2008; Bojórquez-Tapia et al., 2021). The negotiated pathway policy selection processes benefit from exploring alternative framings for compromises because they enhance direct discussions of the performance trade-offs across the utilities' conflicting performance objectives as well as their robustness. It is important to help cooperating urban water utilities recognize and avoid myopic planning that can emerge as an unintended consequence of narrow definitions of "optimality" or "robustness" (Brill et al., 1990; Kasprzyk et al., 2013; Herman et al., 2015; McPhail et al., 2018). Exploring trade-offs (performance or robustness), vulnerabilities, and inter-regional dependencies can help to escape preconceived notions of what is possible and how to achieve it (Gettys & Fisher, 1979; Kasprzyk et al., 2013; Kwakkel et al., 2016).

In the DU Pathways$_{ERAS}$ framework, the identification of candidate regional compromise pathway policies begin with the results of cooperative DU optimization, which provides the Triangle partners with a set of Pareto-approximate regional policy alternatives, each representing a non-dominated set of regional performance objectives (Coello et al., 2007; Reed et al., 2013). In practice, the utilities are not interested in the full range of Pareto-approximate alternatives - some may yield unacceptable performance objectives, while others may inequitably distribute costs and benefits across regional partners. Utilities can explore candidate compromises by filtering (or "brushing") the Pareto-approximate set according to a set of criteria that reflect performance priorities, such as maintaining supply reliability or minimizing infrastructure investment costs (Kollat & Reed, 2006; Woodruff et al., 2013).

Here, we demonstrate the facilitated process of selecting an equitable and robust regional compromise by comparing four framings (expressed preferences and specified requirements) 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) and the specific sampling strategy that was used to compute

Table 5. Candidate framings of regional compromise

Name	Performance measures	Aggregation across deep uncertainty
Minimum expected investment (MEI)	Reliability $>$ 98% Restriction Frequency $<$ 20% Worst-case Drought management Cost $<$ 10% AVR Min. Infrastructure net present cost	Expectation across approximate DU sampling used for DU optimization (Figure 2f)
Expected drought performance and financial stability (EDF)	Reliability $>$ 98% Restriction Frequency $<$ 20% Worst-case Drought management Cost $<$ 10% AVR Peak financial cost $<$ 80% AVR Unit Cost of Expansion $<$5/kgal	Expectation across approximate DU sampling used for DU optimization (Figure 2f)
Drought crisis robustness (DCR)	Reliability $>$ 98% Restriction Frequency $<$ 20% Worst-case Drought management Cost $<$ 10% AVR	Satisficing across full DU sampling used for DU re-evaluation (Figure ref{fig:paper3-methods}g)
Drought crisis and long-term financial stability robustness (DFSR)	Reliability $>$ 98% Restriction Frequency $<$ 20% Worst-case Drought management Cost $<$ 10% AVR Peak financial cost $<$ 80% AVR Unit Cost of Expansion $<$5/kgal$	Satisficing across full DU sampling used for DU re-evaluation (Figure 2g)

the performance requirements across the deep uncertainties. 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 (Rawls, 1999; Hammond, 1976). This definition of equity is intended to ensure the provision of consistent minimum performance across all regional partners (Osman & Faust, 2021; S. Fletcher et al., 2022).

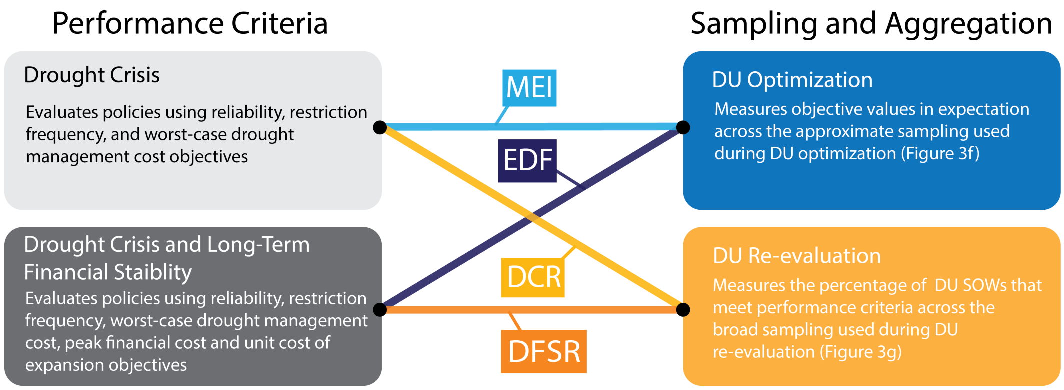

Figure 3. Selected framings of regional compromise. Each framing (represented by the the four lines) combines a prioritized set of performance criteria (shown in panels on the left) with a sampling and aggregation strategy (shown on the right). Selecting a compromise using Minimum Expected Investment (MEI) combines drought crisis performance with performance measures calculated in expectation using the approximate sampling of DU 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

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%, Restriction Frequency < 20% and Worst-Case Drought Management Cost < 10% 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; S. M. Fletcher et al., 2017; Erfani et al., 2014; Pachos et al., 2022). Using the minimum expected investment 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 (Mortazavi-Naeini et al., 2014; Watson & Kasprzyk, 2017; Eker & Kwakkel, 2018; Pachos et al., 2022; Hall et al., 2020). The minimum expected investment compromise emphasizes the equity across regional partners by applying a regional minimax to all performance objectives, defining the regional value for each performance objective as the objective value for the worst-performing regional partner, ensuring that all other utilities perform as well or better (Hammond, 1976).

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. Including the peak financial cost criterion emphasizes budgetary stability. Values of peak financial cost 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 (Raftelis, 2005; Hughes & Leurig, 2013). 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 (Kalin et al., 2019; Haasnoot et al., 2020). 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). Like the minimum expected investment framing described above, the expected drought performance and financial stability compromise measures objectives in expectation across DU optimization sampling (Figure 2f) and emphasizes regional equity using a regional minimax formulation.

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 (Herman et al., 2014; Trindade et al., 2017, 2019; Gold et al., 2019). Using this framing, the utilities evaluate drought crisis performance criteria across the broader DU re-evaluation sampling of deep uncertainties (Figure 3g). Here, we aggregate performance across deeply uncertain states of the world using a satisficing metric, which measures the fraction of DU re-evaluation states of the world where utilities meet the drought performance criteria (Reliability > 98%, Restriction Frequency < 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,

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

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

Here, we prioritize regional equity by evaluating the regional robustness as the robustness of the worst-performing utility.

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 (Figure 3g) used in the drought-focused robustness framing. Like the drought-focused robustness compromise, the regional robustness is defined as the robustness of the worst-performing regional actor.

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 improve their own 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 and revealing the consequences of defection on each utility's cooperating partners. The regional defection analysis also 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 (Gold et al., 2022; Avelino & Rotmans, 2011).

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 original cooperative pathway policy. 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:

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

$$\eta_i^j = \begin{cases} S(\theta_{def})_i^j - S(\theta_{comp})_i^{comp} & if \forall : S(\theta_{def})_{all}^{comp} \\ 0 & otherwise \end{cases} \tag{9}$$

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}.

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 infrastructure disruption analysis 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 infrastructure disruption analysis allows decision makers to assess path-dependency and avoid decision "lock-ins"- which occur when taking adaptive action is expensive or degrades system performance (W. E. Walker et al., 2013; Haasnoot et al., 2020). The infrastructure disruption analysis 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 infrastructure disruption analysis, we develop a set of infrastructure disruption scenarios, $\mathbf{\Pi}$, where infrastructure options become unavailable to Triangle utilities.

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

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.

$$R_{i,BI\ _k}^{IDA} = S(\theta_{comp})_i - S(\theta_B I\ _k)_i \tag{12}$$

Where i is the performance criteria, 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 (Groves & Lempert, 2007; Bryant & Lempert, 2010; 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 (Groves & Lempert, 2007; Bryant & Lempert, 2010). 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-years 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 3g. 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 infrastructure disruption analysis was performed on Stampede2, where 22 infrastructure disruption scenarios were evaluated across the full DU sampling shown in Figure 3g. 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 cooperative infrastructure investment and management 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 5.5.1, 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 5.5.2, we evaluate the cooperative stability of a high-performing and broadly robust pathway policy identified in Section 5.5.1 using regional defection analysis. In Section 5.5.3, 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 5.5.4, 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 infrastructure investment and management 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 (grey 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 minimum expected investment (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 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 drought crisis robustness compromise and the orange line represents the drought and expanded financial robustness compromise.

In Figure 4a, we observe that all four of the candidate compromises maintain high levels of performance for reliability, restriction frequency, and worst-case cost objectives (i.e., drought crisis performance measures). The minimum expected investment 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 minimum expected investment (MEI) compromise policy's low infrastructure net present cost does not translate to long-term financial stability. The MEI solution generates a higher peak financial cost than either of candidate compromise policies that prioritize financial stability criteria (EDF, dark blue and DFSR, dark orange). The minimum expected investment (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 under-utilized. These stranded assets increase budgetary instability and can drive up water rates (Raftelis, 2005; Hughes & Leurig, 2013). This finding 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 $> 98\%$, Restriction Frequency $< 20\%$, 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.

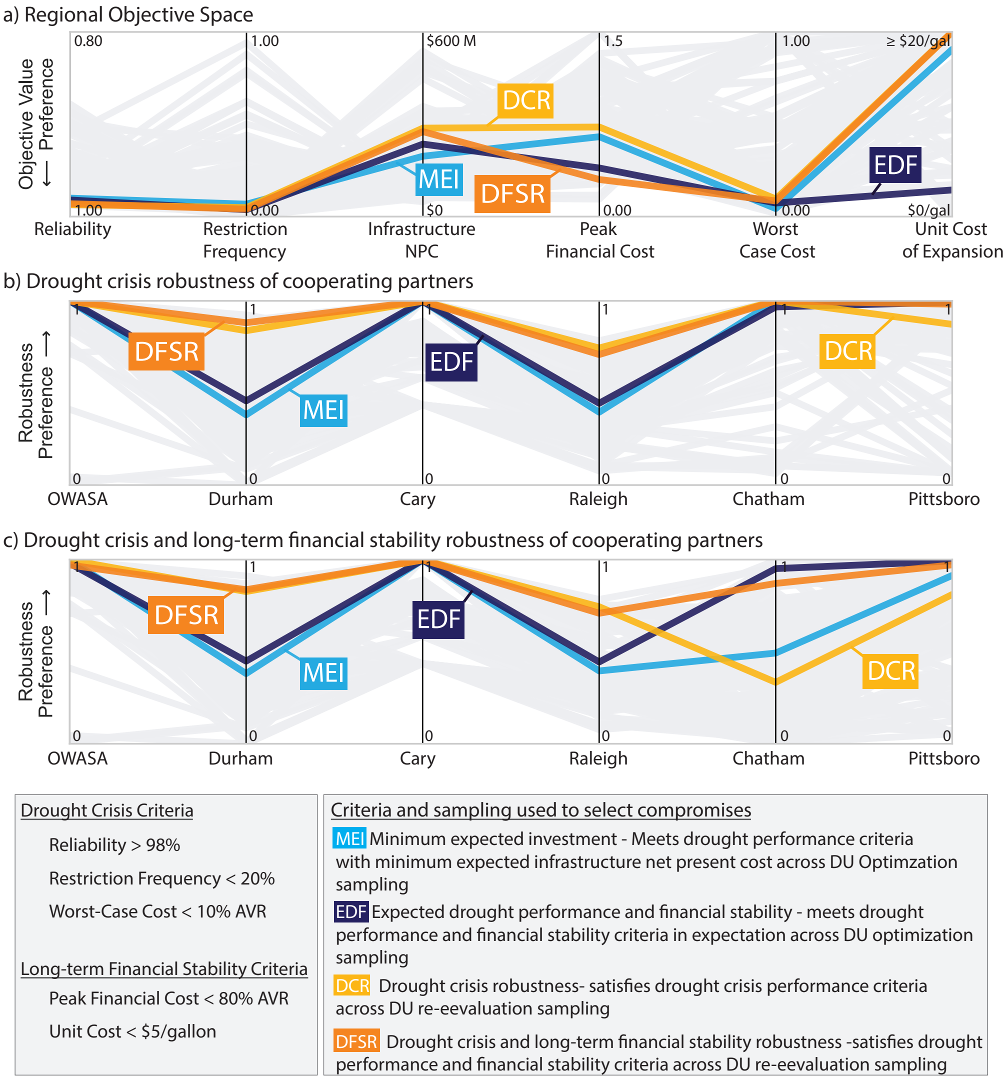

Figure 4. a) the regional objective space, with four compromises highlighted. All four compromises perform well in drought criteria (Rel, RF and WCC). The minimum expected investment compromise (MEI) yields lower infrastructure net present cost, but does not perform well in other financial objectives. B) Drought crisis robustness, defined as the percentage of DU SOWs where drought performance criteria are met for each regional actor.

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 $> 98\%$, Restriction Frequency $< 20\%$, Worst-Case Drought Management Cost $< 10\%$ AVR, Peak Financial Cost $< 80\%$ 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 minimum expected investment (MEI) and drought crisis robustness (DCR) compromise pathway policies. The drought crisis robustness (DCR) compromise policy, which appears to equitably balance performance across the participating regional utilities when evaluated solely using the drought crisis robustness 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-c 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 infrastructure investment and management policies (Herman et al., 2015; Sjöstrand, 2017; Hamilton et al., 2022). 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 grey 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 drought crisis robustness 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 (for example 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 drought crisis robustness 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 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.

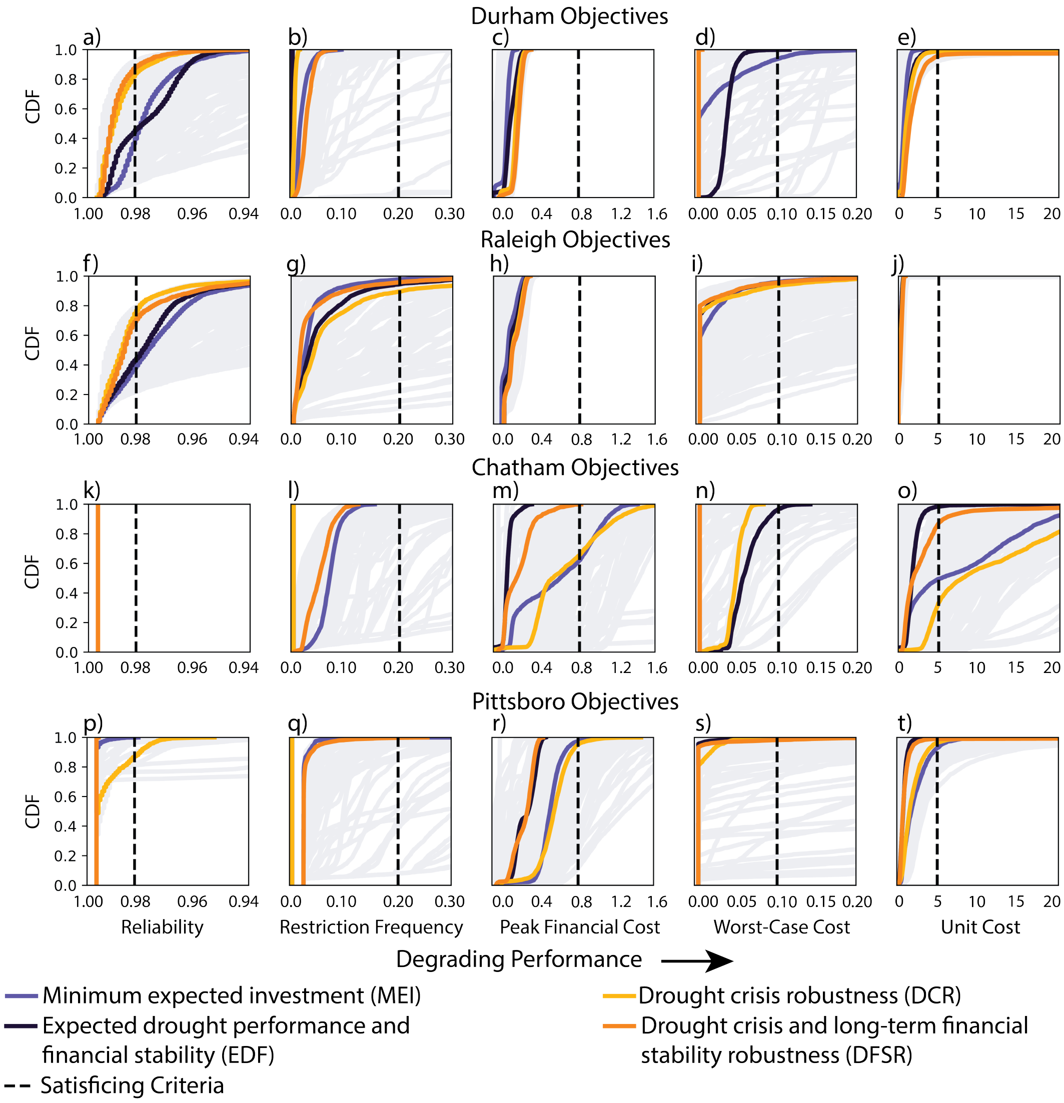

Figure 5. Cumulative distribution of performance across deeply uncertain states of the world. OWASA and Cary are omitted from this plot because they maintain high performance across all sampled DU SOWs. The four compromise policies are highlighted in color, and the remaining Pareto-approximate policies are shown in grey. The dashed line represents the satisficing criteria for each objective.

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 5a), 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 this paper's S3 of this paper's supporting information). 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 specific parameterized ROF-based rules that are used to implement the suggested inter-utility agreement structure however matter greatly as captured by the significant differences in the performance and robustness behaviors of the four compromise pathway policies evaluated in Section 5.6.1. The drought crisis and long-term financial stability (DFSR) compromise solution appears to be the overall most equitable of the 4 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 7a 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 7b 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.

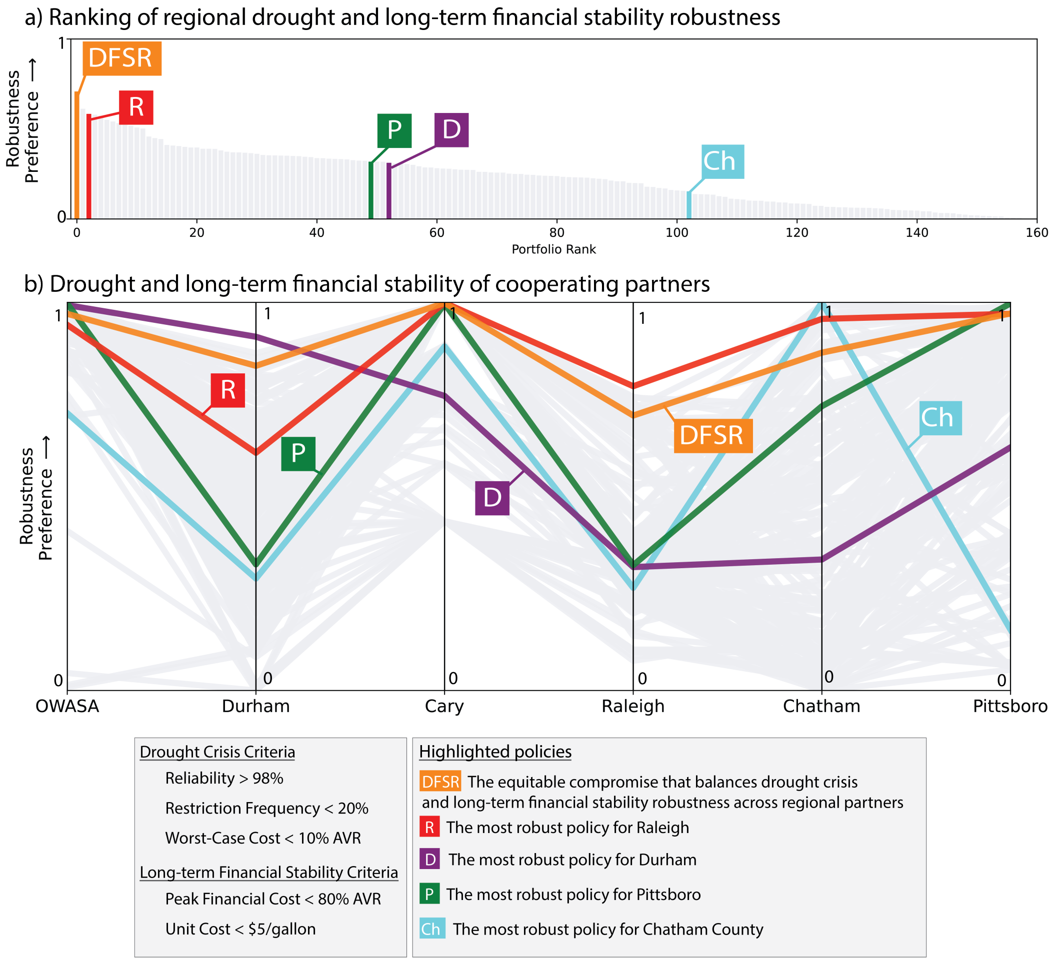

Figure 6. a) Regional ranking of Pareto-approximate policies by robustness. Each bar represents a cooperative policy, colored bars represent highlighted policies, and grey bars represent brushed policies. b) Robustness conflicts between regional partners. Each axis represents the robustness of one utility,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

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 Figure 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.

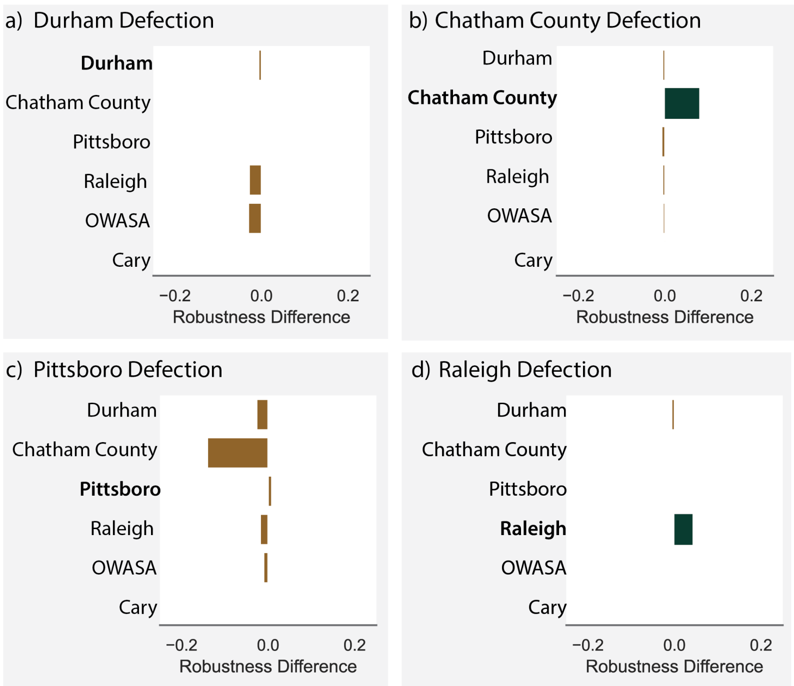

Figure 7. Results of the regional defection analysis. Each panel represents the impacts of regional defection from a different regional partner. Blue bars to the right indicate that a utility can improve its robustness through defection and brown bars to the left indicate that a utility's robustness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

In sum, the DSFR compromise policy identified in Section 5.7.1 represents a cooperatively stable (practical) regional infrastructure investment and management 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 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-f 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 clustered and classified representative pathway results that capture high, medium, or low infrastructure intensities depending on how early and often investments are triggered. The 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-d 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 9i and 9k) take further adaptive action by constructing the cooperative Sanford Intake.

Cary and Raleigh (Figures 8e and 8f), not participants in the joint infrastructure projects, develop a similarly adaptive set of infrastructure pathways. Both utilities construct no 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 (Zeff et al., 2016; Trindade et al., 2019). 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.

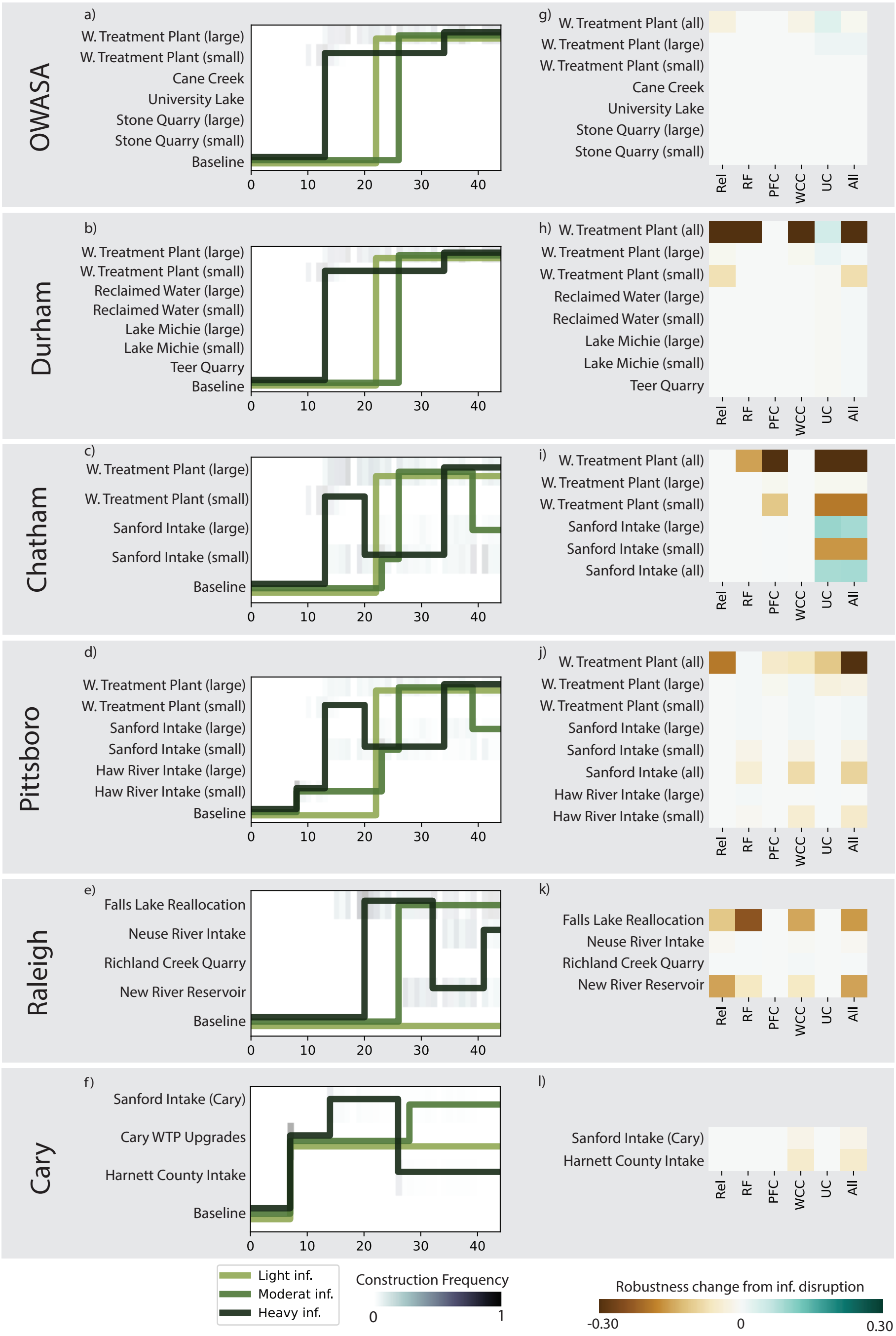

Figure 8. a-f) infrastructure pathways generated by the compromise pathway policy across 1,000 DU SOWs. Three clusters summarizing infrastructure pathways are plotted as green lines which represent the median week that options are triggered. The frequency that each option is triggered across all SOWs 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.

5.3.2 Measuring the benefits of infrastructure investment

The DU Pathways$_{ERAS}$ framework builds on prior published work by contributing an Infrastructure Disruption Analysis 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., (Haasnoot et al., 2013; Trindade et al., 2019; Gold et al., 2022) to explicitly map how each infrastructure option contributes to regional and individual robustness. Figures 9g-I show the results of the Infrastructure Disruption Analysis for each utility. In each panel, columns represent performance criteria, and each row represents an infrastructure 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-l indicates infrastructure disruption results in decreased robustness, and teal shading indicates increased robustness.

Figures 8g-k 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, restriction frequency, 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 peak financial cost 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 restriction frequency 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 9i 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. 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 Infrastructure Disruption Analysis 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: 1) which deeply uncertain factors most strongly influence the performance of a pathway policy, 2) how these factors influence drought crisis performance and long-term financial stability, and 3) how these vulnerabilities evolve over time. Figure 10 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 10 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 (for example, 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 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 l), 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 restriction frequency 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).

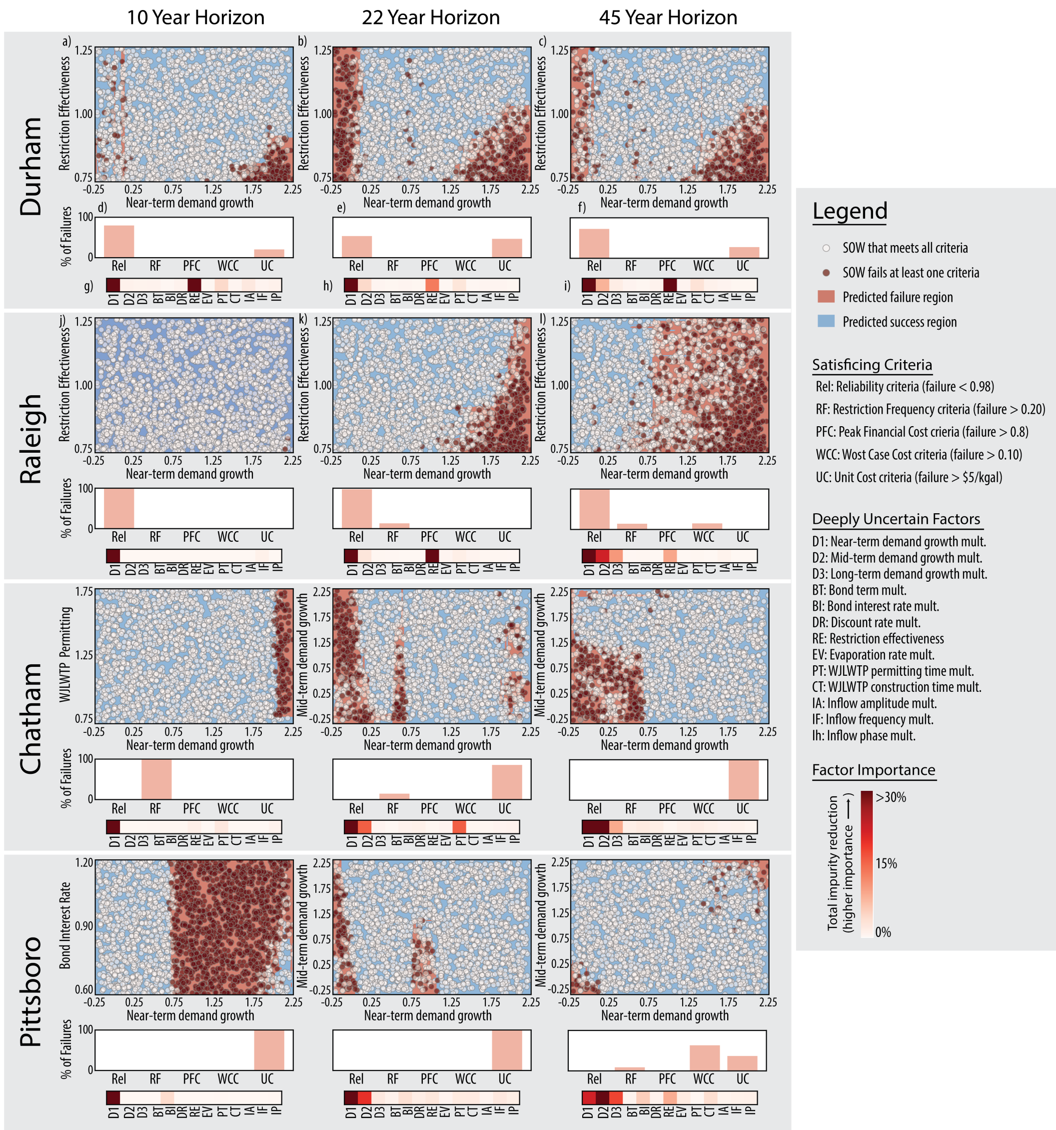

Figure 9. Scenario discovery results. The top plot is a factor map showing vulnerability to the top two deep uncertainties. Each points represent DU SOWs, white points represent SOWs where performance criteria are met and red points represent SOWs where that fail at least one performance criterion. Red shaded areas are regions of the uncertainty space predicted to cause failure by gradient-boosted trees, blue regions represent regions predicted to succeed. 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.

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 and 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-c 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 $\geq$ 0), the pathway policy may to 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 on regional equity by apply Rawls' difference principle, we find that the

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 > 1.25x projection	Invest in restrictive effectiveness
Rapid demand growth stresses Raleigh's water supply	Raleigh	Supply Failure	Near-term demand > 0.75x projection	Develop additional infrastructure
Rapid demand growth causes Chatham County over-restriction	Chatham County	Over-restriction	Near-term demand > 2x 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 x 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

choice of performance measures included in robustness assessment fundamentally shape 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 Infrastructure Disruption Analysis 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 evolves 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 deep uncertainty.

This study finds stranded assets to be a key concern for maintaining long-term financial stability of utility partners. While this work utilizes unit cost of expansion 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.

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Data availability Statement

All data and code for this work, including a) input data, b) final results, c) instructions for replicating the computational experiment and d) figure generation can be found at `https://github.com/davidfgold/DUPathwaysERAS.git`.

References

Aalami, M. T., Nourani, V., & Fazaeli, H. (2020). Developing a surface water resources allocation model under risk conditions with a multi-objective optimization approach. *Water Supply*, *20*(4), 1167–1177.

Alizadeh, M. R., Nikoo, M. R., & Rakhshandehroo, G. R. (2017). Developing a multi-objective conflict-resolution model for optimal groundwater management based on fallback bargaining models and social choice rules: a case study. *Water Resources Management*, *31*(5), 1457–1472.

Anderies, J. M., Folke, C., Walker, B., & Ostrom, E. (2013). Aligning key concepts for global change policy: robustness, resilience, and sustainability. *Ecology and society*, *18*(2).

Authority, O. W. . S. (2010). *Orange water and sewer authority water shortage response plan* (Tech. Rep.).

Avelino, F. (2021). Theories of power and social change. power contestations and their implications for research on social change and innovation. *Journal of Political Power*, 1–24.

Avelino, F., & Rotmans, J. (2011). A dynamic conceptualization of power for sustainability research. *Journal of Cleaner Production*, *19*(8), 796–804.

AWWA. (2011). *Fundamentals of water utility capital financing.* American Water Works Association. Retrieved from `https://books.google.com/books?id=qaEQezFGZD0C`

AWWA. (2012). Buried no longer: Confronting america's water infrastructure challenge.

AWWA. (2018). *State of the water industry report* (Tech. Rep.). Retrieved from `https://www.awwa.org/Portals/0/AWWA/Development/Managers/2018_SOTWI_Report_Final_v3.pdf`

Bankes, S. (1993, June). Exploratory Modeling for Policy Analysis. *Operations Research*, *41*(3), 435–449. Retrieved 2018-09-11, from `https://pubsonline.informs.org/doi/abs/10.1287/opre.41.3.435` doi: 10.1287/opre.41.3.435

Baum, R., Characklis, G. W., & Serre, M. L. (2018). Effects of geographic diversification on risk pooling to mitigate drought-related financial losses for water utilities. *Water Resources Research*, *54*(4), 2561–2579.

Beh, E. H., Maier, H. R., & Dandy, G. C. (2015). Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty. *Water Resources Research*, *51*(3), 1529–1551.

Bertsekas, D. (2012). *Dynamic programming and optimal control: Volume i* (Vol. 1). Athena scientific.

Bojórquez-Tapia, L. A., Eakin, H., Hernández-Aguilar, B., & Shelton, R. (2021). Addressing complex, political and intransient sustainability challenges of transdisciplinarity: The case of the megadapt project in mexico city. *Environmental Development*, *38*, 100604.

Bojórquez-Tapia, L. A., Eakin, H., Reed, P. M., Miquelajauregui, Y., Grave, I., Merino-Benítez, T., & Molina-Pérez, E. (2022). Unveiling uncertainties to enhance sustainability transformations in infrastructure decision-making. *Current Opinion in Environmental Sustainability*, *55*, 101172.

Bonzanigo, L., Rozenberg, J., Felter, G. C., Lempert, R. J., & Reed, P. M. (2018, December). *Building the Resilience of WSS Utilities to Climate Change and*

Other Threats : A Road Map (Tech. Rep. No. 133227). The World Bank. Retrieved 2019-03-17, from `http://documents.worldbank.org/curated/en/425871546231664745/Building-the-Resilience-of-WSS-Utilities-to-Climate-Change-and-Other-Threats-A-Road-Map`

Borgomeo, E., Mortazavi-Naeini, M., Hall, J. W., O'Sullivan, M. J., & Watson, T. (2016). Trading-off tolerable risk with climate change adaptation costs in water supply systems. *Water Resources Research*, *52*(2), 622–643. Retrieved 2019-03-17, from `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2015WR018164` doi: 10.1002/2015WR018164

Brandes, O., Brooks, D. B., & Gurman, S. (2009). *Making the most of the water we have: The soft path approach to water management.* Routledge.

Brill, E. D., Flach, J. M., Hopkins, L. D., & Ranjithan, S. (1990). Mga: A decision support system for complex, incompletely defined problems. *IEEE Transactions on systems, man, and cybernetics*, *20*(4), 745–757.

Brown, C., Ghile, Y., Laverty, M., & Li, K. (2012). Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. *Water Resources Research*, *48*(9). Retrieved 2019-03-17, from `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011WR011212` doi: 10.1029/2011WR011212

Bryant, B. P., & Lempert, R. J. (2010, January). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, *77*(1), 34–49. Retrieved 2019-03-25, from `http://www.sciencedirect.com/science/article/pii/S004016250900105X` doi: 10.1016/j.techfore.2009.08.002

Cai, X., Zeng, R., Kang, W. H., Song, J., & Valocchi, A. J. (2015). Strategic planning for drought mitigation under climate change. *Journal of Water Resources Planning and Management*, *141*(9), 04015004.

Cantu-Paz, E., & Goldberg, D. E. (2000). Efficient parallel genetic algorithms: theory and practice. *Computer methods in applied mechanics and engineering*, *186*(2-4), 221–238.

Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., … Mitchell, R. B. (2003). Knowledge systems for sustainable development. *Proceedings of the national academy of sciences*, *100*(14), 8086–8091.

Ciullo, A., Kwakkel, J. H., De Bruijn, K. M., Doorn, N., & Klijn, F. (2020). Efficient or fair? operationalizing ethical principles in flood risk management: A case study on the dutch-german rhine. *Risk analysis*, *40*(9), 1844–1862.

Coello, C. C., Lamont, G. B., & Veldhuizen, D. A. v. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems* (2nd ed.). Springer US. Retrieved 2019-03-17, from `https://www.springer.com/us/book/9780387332543`

Congressional Research Service. (2022, January). *Infrastructure investment and jobs act (iija): Drinking water and wastewater infrastructure* (Tech. Rep.).

DeFazio, P. A. (2021). Hr 3684-117th congress (2021-2022): Infrastructure investment and jobs act. In */bill/117th-congress/house-bill/3684.*

De Souza, S., Medellín-Azuara, J., Lund, J. R., & Howitt, R. E. (2011). Beneficiary pays analysis of water recycling projects. *Report for the California Water Resources Control Board, University of California, Davis*.

Dinar, A., & Howitt, R. E. (1997). Mechanisms for allocation of environmental control cost: empirical tests of acceptability and stability. *Journal of Environmental Management*, *49*(2), 183–203.

Dittrich, R., Wreford, A., & Moran, D. (2016, February). A survey of decision-making approaches for climate change adaptation: Are robust methods the way forward? *Ecological Economics*, *122*, 79–89. Retrieved 2019-03-17, from `http://www.sciencedirect.com/science/article/pii/S0921800915004887` doi: 10.1016/j.ecolecon.2015.12.006

Drucker, H., & Cortes, C. (1996). Boosting decision trees. *Advances in neural infor-*

mation processing systems, 479–485.
Eker, S., & Kwakkel, J. H. (2018). Including robustness considerations in the search phase of many-objective robust decision making. *Environmental Modelling & Software*, *105*, 201–216.
EPA. (2017). *Water system partnerships: State programs and policies supporting co-operative approaches for drinking water systems* (Tech. Rep.). US EPA.
Erfani, T., Binions, O., & Harou, J. J. (2014). Simulating water markets with transaction costs. *Water Resources Research*, *50*(6), 4726–4745. Retrieved 2019-03-17, from `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2013WR014493` doi: 10.1002/2013WR014493
Erfani, T., Pachos, K., & Harou, J. J. (2018). Real-options water supply planning: Multistage scenario trees for adaptive and flexible capacity expansion under probabilistic climate change uncertainty. *Water Resources Research*, *54*(7), 5069–5087.
Fletcher, S., Hadjimichael, A., Quinn, J., Osman, K., Giuliani, M., Gold, D., ... Gordon, B. (2022). Equity in water resources planning: A path forward for decision support modelers. *Journal of Water Resources Planning and Management*, *148*(7), 02522005.
Fletcher, S. M., Miotti, M., Swaminathan, J., Klemun, M. M., Strzepek, K., & Siddiqi, A. (2017). Water supply infrastructure planning: decision-making framework to classify multiple uncertainties and evaluate flexible design. *Journal of Water Resources Planning and Management*, *143*(10), 04017061.
Gettys, C. F., & Fisher, S. D. (1979). Hypothesis plausibility and hypothesis generation. *Organizational behavior and human performance*, *24*(1), 93–110.
Giuliani, M., Lamontagne, J., Reed, P., & Castelletti, A. (2021). A state-of-the-art review of optimal reservoir control for managing conflicting demands in a changing world. *Water Resources Research*, *57*(12), e2021WR029927.
Gleick, P. H. (2003, November). Global Freshwater Resources: Soft-Path Solutions for the 21st Century. *Science*, *302*(5650), 1524–1528. Retrieved 2019-03-17, from `http://science.sciencemag.org/content/302/5650/1524` doi: 10.1126/science.1089967
Gold, D. F., Reed, P., Trindade, B., & Characklis, G. (2019). Identifying actionable compromises: Navigating multi-city robustness conflicts to discover cooperative safe operating spaces for regional water supply portfolios. *Water Resources Research*, *55*(11), 9024–9050.
Gold, D. F., Reed, P. M., Gorelick, D. E., & Characklis, G. W. (2022). Power and pathways: Exploring robustness, cooperative stability, and power relationships in regional infrastructure investment and water supply management portfolio pathways. *Earth's Future*, *10*(2), e2021EF002472.
Gorelick, D. E., Gold, D. F., Reed, P. M., & Characklis, G. W. (2022). Impact of inter-utility agreements on cooperative regional water infrastructure investment and management pathways. *Water Resources Research*, *58*(3), e2021WR030700.
Gorelick, D. E., Zeff, H. B., Characklis, G. W., & Reed, P. M. (2018, September). Integrating Raw Water Transfers into an Eastern United States Management Context. *Journal of Water Resources Planning and Management*, *144*(9), 05018012. Retrieved 2019-03-17, from `https://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0000966` doi: 10.1061/(ASCE)WR.1943-5452.0000966
Gorelick, D. E., Zeff, H. B., Hughes, J., Eskaf, S., & Characklis, G. W. (2019). Exploring treatment and capacity-sharing agreements between water utilities. *Journal: American Water Works Association*, *111*(9).
Groves, D. G., Bloom, E., Lempert, R. J., Fischbach, J. R., Nevills, J., & Goshi, B. (2015). Developing key indicators for adaptive water planning. *Journal of Water Resources Planning and Management*, *141*(7), 05014008.

Groves, D. G., & Lempert, R. J. (2007). A new analytic method for finding policy-relevant scenarios. *Global Environmental Change*, *17*(1), 73–85.

Groves, D. G., Molina-Perez, E., Bloom, E., & Fischbach, J. R. (2019). Robust decision making (rdm): application to water planning and climate policy. In *Decision making under deep uncertainty* (pp. 135–163). Springer, Cham.

Gupta, R. S., Hamilton, A. L., Reed, P. M., & Characklis, G. W. (2020). Can modern multi-objective evolutionary algorithms discover high-dimensional financial risk portfolio tradeoffs for snow-dominated water-energy systems? *Advances in Water Resources*, *145*, 103718.

Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013, April). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Global Environmental Change*, *23*(2), 485–498. Retrieved 2018-09-11, from `http://www.sciencedirect.com/science/article/pii/S095937801200146X` doi: 10.1016/j.gloenvcha.2012.12.006

Haasnoot, M., Schellekens, J., Beersma, J., Middelkoop, H., & Kwadijk, J. C. J. (2015). Transient scenarios for robust climate change adaptation illustrated for water management in the netherlands. *Environmental Research Letters*, *10*(10), 105008.

Haasnoot, M., van Aalst, M., Rozenberg, J., Dominique, K., Matthews, J., Bouwer, L. M., ... Poff, N. L. (2020). Investments under non-stationarity: economic evaluation of adaptation pathways. *Climatic Change*, *161*(3), 451–463.

Haasnoot, M., van't Klooster, S., & Van Alphen, J. (2018). Designing a monitoring system to detect signals to adapt to uncertain climate change. *Global Environmental Change*, *52*, 273–285.

Hadka, D., & Reed, P. (2012, March). Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework. *Evolutionary Computation*, *21*(2), 231–259. Retrieved 2018-09-11, from `https://doi.org/10.1162/EVCO_a_00075` doi: 10.1162/EVCO_a_00075

Hadka, D., & Reed, P. (2015). Large-scale parallelization of the borg multiobjective evolutionary algorithm to enhance the management of complex environmental systems. *Environmental Modelling & Software*, *69*, 353–369.

Halich, G., & Stephenson, K. (2009). Effectiveness of residential water-use restrictions under varying levels of municipal effort. *Land Economics*, *85*(4), 614–626.

Hall, J. W., Mortazavi-Naeini, M., Borgomeo, E., Baker, B., Gavin, H., Gough, M., ... others (2020). Risk-based water resources planning in practice: a blueprint for the water industry in england. *Water and Environment Journal*, *34*(3), 441–454.

Hamilton, A. L., Zeff, H. B., Characklis, G. W., & Reed, P. M. (2022). Resilient california water portfolios require infrastructure investment partnerships that are viable for all partners. *Earth's Future*, *10*(4), e2021EF002573.

Hammond, P. J. (1976). Equity, arrow's conditions, and rawls' difference principle. *Econometrica*, *44*(4), 793–804. Retrieved from `http://www.jstor.org/stable/1913445`

Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2020). Climate adaptation as a control problem: Review and perspectives on dynamic water resources planning under uncertainty. *Water Resources Research*, *56*(2), e24389.

Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015, October). How Should Robustness Be Defined for Water Systems Planning under Change? *Journal of Water Resources Planning and Management*, *141*(10), 04015012. doi: 10.1061/(ASCE)WR.1943-5452.0000509

Herman, J. D., Zeff, H. B., Reed, P. M., & Characklis, G. W. (2014, October). Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. *Water Resources Research*, *50*(10), 7692–7713. Retrieved 2018-09-11, from https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2014WR015338 doi: 10.1002/2014WR015338

Hu, Z., Chen, Y., Yao, L., Wei, C., & Li, C. (2016). Optimal allocation of regional water resources: From a perspective of equity–efficiency tradeoff. *Resources, Conservation and Recycling*, *109*, 102–113.

Hu, Z., Wei, C., Yao, L., Li, C., & Zeng, Z. (2016). Integrating equality and stability to resolve water allocation issues with a multiobjective bilevel programming model. *Journal of Water Resources Planning and Management*, *142*(7), 04016013.

Hughes, J., & Leurig, S. (2013). Assessing water system revenue risk: Considerations for market analysts. *A Ceres and EFC Whitepaper. August*.

IPCC. (2022). Climate change 2022: Impacts, adaptation, and vulnerability. In H. Portner et al. (Eds.), *Contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change.* Cambridge University Press.

Jafino, B. A., Kwakkel, J., Klijn, F., Nguyen, V. D., van Delden, H., Haasnoot, M., & Sutanudjaja, E. H. (2020). Accounting for multisectoral dynamics in supporting equitable adaptation planning: A case study on the rice agriculture in the vietnam mekong delta. *Earth and Space Science Open Archive ESSOAr*.

Jafino, B. A., & Kwakkel, J. H. (2021). A novel concurrent approach for multiclass scenario discovery using multivariate regression trees: Exploring spatial inequality patterns in the vietnam mekong delta under uncertainty. *Environmental Modelling & Software*, *145*, 105177.

Kalin, R. M., Mwanamveka, J., Coulson, A. B., Robertson, D. J., Clark, H., Rathjen, J., & Rivett, M. O. (2019). Stranded assets as a key concept to guide investment strategies for sustainable development goal 6. *Water*, *11*(4), 702.

Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many Objective Robust Decision Making for Complex Environmental Systems Undergoing Change. *Environmental Modelling and Software*, *42*, 55–71. doi: 10.1016/j.envsoft.2012.12.007

Kenney, D. S. (2014). Understanding utility disincentives to water conservation as a means of adapting to climate change pressures. *American Water Works Association*, *106*(1), 36–46.

Kirsch, B. R., Characklis, G. W., & Zeff, H. B. (2013, July). Evaluating the Impact of Alternative Hydro-Climate Scenarios on Transfer Agreements: Practical Improvement for Generating Synthetic Streamflows. *Journal of Water Resources Planning and Management*, *139*(4), 396–406. Retrieved 2019-03-17, from https://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0000287 doi: 10.1061/(ASCE)WR.1943-5452.0000287

Kollat, J. B., & Reed, P. M. (2006). Comparing state-of-the-art evolutionary multiobjective algorithms for long-term groundwater monitoring design. *Advances in Water Resources*, *29*(6), 792–807.

Kwakkel, J. H. (2019). A generalized many-objective optimization approach for scenario discovery. *Futures & Foresight Science*, e8.

Kwakkel, J. H. (2020). Is real options analysis fit for purpose in supporting climate adaptation planning and decision-making? *Wiley Interdisciplinary Reviews: Climate Change*, *11*(3), e638.

Kwakkel, J. H., & Haasnoot, M. (2019). Supporting dmdu: A taxonomy of approaches and tools. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), *Decision making under deep uncertainty: From theory to practice* (pp. 355–374). Cham: Springer International Publishing. Retrieved from https://doi.org/10.1007/978-3-030-05252-2_15 doi: 10.1007/978-3-030-05252-2_15

Kwakkel, J. H., & Jaxa-Rozen, M. (2016). Improving scenario discovery for handling heterogeneous uncertainties and multinomial classified outcomes. *Environmen-*

tal Modelling & Software, *79*, 311–321.

Kwakkel, J. H., Walker, W. E., & Haasnoot, M. (2016). Coping with the wickedness of public policy problems: Approaches for decision making under deep uncertainty. *Journal of Water Resources Planning and Management*, *142*(3), 01816001. doi: 10.1061/(ASCE)WR.1943-5452.0000626

Laumanns, M., Thiele, L., Deb, K., & Zitzler, E. (2002, September). Combining Convergence and Diversity in Evolutionary Multiobjective Optimization. *Evolutionary Computation*, *10*(3), 263–282. Retrieved 2019-03-17, from https://doi.org/10.1162/106365602760234108 doi: 10.1162/106365602760234108

Lempert, R. J. (2002, May). A new decision sciences for complex systems. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7309–7313. Retrieved 2019-03-20, from https://www.pnas.org/content/99/suppl_3/7309 doi: 10.1073/pnas.082081699

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006, April). A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. *Management Science*, *52*(4), 514–528. Retrieved 2018-09-11, from https://pubsonline.informs.org/doi/abs/10.1287/mnsc.1050.0472 doi: 10.1287/mnsc.1050.0472

Loucks, D. P., & Van Beek, E. (2017). *Water resource systems planning and management: An introduction to methods, models, and applications.* Springer.

Lund, J. (2013). *Some curious things about water management* (Vol. 139) (No. 1). American Society of Civil Engineers.

Madani, K., & Dinar, A. (2012, September). Cooperative institutions for sustainable common pool resource management: Application to groundwater. *Water Resources Research*, *48*(9). Retrieved 2018-09-11, from https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011WR010849 doi: 10.1029/2011WR010849

Madani, K., & Hipel, K. W. (2011, June). Non-Cooperative Stability Definitions for Strategic Analysis of Generic Water Resources Conflicts. *Water Resources Management*, *25*(8), 1949–1977. Retrieved 2018-09-11, from https://doi.org/10.1007/s11269-011-9783-4 doi: 10.1007/s11269-011-9783-4

Maier, H. R., Guillaume, J. H. A., van Delden, H., Riddell, G. A., Haasnoot, M., & Kwakkel, J. H. (2016, July). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? *Environmental Modelling & Software*, *81*, 154–164. Retrieved 2019-03-17, from http://www.sciencedirect.com/science/article/pii/S1364815216300780 doi: 10.1016/j.envsoft.2016.03.014

Maier, H. R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L. S., Cunha, M. C., ... Reed, P. M. (2014). Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. *Environmental Modelling & Software*, *62*, 271 – 299. Retrieved from http://www.sciencedirect.com/science/article/pii/S1364815214002679 doi: https://doi.org/10.1016/j.envsoft.2014.09.013

Majone, G., & Quade, E. S. (1980). *Pitfalls of analysis* (Vol. 8). John Wiley & Sons.

Marchau, V. A., Walker, W. E., Bloemen, P. J., & Popper, S. W. (2019). *Decision making under deep uncertainty: from theory to practice.* Springer Nature.

McPhail, C., Maier, H. R., Kwakkel, J. H., Giuliani, M., Castelletti, A., & Westra, S. (2018, February). Robustness Metrics: How Are They Calculated, When Should They Be Used and Why Do They Give Different Results? *Earth's Future*, *6*(2), 169–191. Retrieved 2019-04-16, from https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017EF000649

Moallemi, E. A., Kwakkel, J., de Haan, F. J., & Bryan, B. A. (2020). Exploratory modeling for analyzing coupled human-natural systems under uncertainty. *Global Environmental Change*, *65*, 102186.

Moallemi, E. A., Zare, F., Reed, P. M., Elsawah, S., Ryan, M. J., & Bryan, B. A. (2020). Structuring and evaluating decision support processes to enhance the robustness of complex human–natural systems. *Environmental Modelling & Software*, *123*, 104551.

Mortazavi-Naeini, M., Kuczera, G., & Cui, L. (2014). Application of multiobjective optimization to scheduling capacity expansion of urban water resource systems. *Water Resources Research*, *50*(6), 4624–4642.

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., ... Zechman, E. (2010, July). State of the Art for Genetic Algorithms and Beyond in Water Resources Planning and Management. *Journal of Water Resources Planning and Management*, *136*(4), 412–432. Retrieved 2019-03-17, from https://ascelibrary.org/doi/10.1061/\%28ASCE\%29WR.1943-5452.0000053 doi: 10.1061/(ASCE)WR.1943-5452.0000053

Osman, K. K., & Faust, K. M. (2021). Toward operationalizing equity in water infrastructure services: Developing a definition of water equity. *ACS ES&T Water*, *1*(8), 1849–1858.

Pachos, K., Huskova, I., Matrosov, E., Erfani, T., & Harou, J. J. (2022). Trade-off informed adaptive and robust real options water resources planning. *Advances in Water Resources*, 104117.

Padula, S., Harou, J. J., Papageorgiou, L. G., Ji, Y., Ahmad, M., & Hepworth, N. (2013). Least economic cost regional water supply planning–optimising infrastructure investments and demand management for south east england's 17.6 million people. *Water resources management*, *27*(15), 5017–5044.

Parrachino, I., Dinar, A., & Patrone, F. (2006). Cooperative game theory and its application to natural, environmental, and water resource issues: 3. application to water resources.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Perry, D. M., & Praskievicz, S. J. (2017). A new era of big infrastructure?(re) developing water storage in the us west in the context of climate change and environmental regulation. *Water Alternatives*, *10*(2).

Powell, W. B. (2019). A unified framework for stochastic optimization. *European Journal of Operational Research*, *275*(3), 795–821.

Quinn, J. D., Reed, P. M., Giuliani, M., & Castelletti, A. (2017). Rival framings: A framework for discovering how problem formulation uncertainties shape risk management trade-offs in water resources systems. *Water Resources Research*, *53*(8), 7208–7233. Retrieved 2019-03-17, from https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017WR020524 doi: 10.1002/2017WR020524

Qureshi, N., & Shah, J. (2014). Aging infrastructure and decreasing demand: A dilemma for water utilities. *Journal-American Water Works Association*, *106*(1), 51–61.

Raftelis, G. A. (2005). *Water and wastewater finance and pricing: a comprehensive guide*. CRC Press.

Rawls, J. (1999). *A theory of justice: Revised edition*. Harvard university press.

Read, L., Madani, K., & Inanloo, B. (2014, January). Optimality versus stability in water resource allocation. *Journal of Environmental Management*, *133*, 343–354. Retrieved 2018-09-11, from http://www.sciencedirect.com/science/article/pii/S030147971300741X doi: 10.1016/j.jenvman.2013.11.045

Reed, P. M., Hadjimichael, A., Malek, K., Karimi, T., Vernon, C. R., Srikrishnan, V., ... Rice, J. S. (2022). *Addressing Uncertainty in Multisector Dynamics Research*. Zenodo. Retrieved from https://immm-sfa.github.io/msd_uncertainty_ebook/ doi: 10.5281/zenodo.6110623

Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J. R., & Kollat, J. B. (2013, January). Evolutionary multiobjective optimization in water resources: The past, present, and future. *Advances in Water Resources*, *51*, 438–456. Retrieved 2018-09-11, from `http://www.sciencedirect.com/science/article/pii/S0309170812000073` doi: 10.1016/j.advwatres.2012.01.005

Reedy, K. A., & Mumm, J. (2012). Managing financial and water supply challenges with regional partnerships. *Journal-American Water Works Association*, *104*(7), 17–20.

Riggs, E., & Hughes, J. (2019). *Crafting interlocal water and wastewater agreements* (Tech. Rep.). Environmental Finance Center.

Ristić, B., & Madani, K. (2019). A game theory warning to blind drivers playing chicken with public goods. *Water Resources Research*, *55*(3), 2000–2013.

Savelli, E., Rusca, M., Cloke, H., & Di Baldassarre, G. (2022). Drought and society: Scientific progress, blind spots, and future prospects. *Wiley Interdisciplinary Reviews: Climate Change*, e761.

Silvestre, H. C., Marques, R. C., & Gomes, R. C. (2018). Joined-up government of utilities: a meta-review on a public–public partnership and inter-municipal co-operation in the water and wastewater industries. *Public Management Review*, *20*(4), 607–631.

Simon, H. A. (1966). Theories of decision-making in economics and behavioural science. In *Surveys of economic theory* (pp. 1–28). Springer.

Sjöstrand, K. (2017). Sustainability and water supply governance: A literature review on regional water governance, multi-criteria decision analysis, cost-benefit analysis and sustainability assessments. *Göteborg, Sweden: Chalmers Univ. of Technology*.

Smull, E., Patterson, L., & Doyle, M. (2022). Rising market risk exposure of municipal water service providers in distressed cities. *Journal of Water Resources Planning and Management*, *148*(2), 05021032.

Stakhiv, E. Z. (2011). Pragmatic approaches for water management under climate change uncertainty 1. *JAWRA Journal of the American Water Resources Association*, *47*(6), 1183–1196.

Starr, M. K. (1963). *Product Design and Decision Theory* (1St Edition edition ed.). Prentice Hall.

Steinmann, P., Auping, W. L., & Kwakkel, J. H. (2020). Behavior-based scenario discovery using time series clustering. *Technological Forecasting and Social Change*, *156*, 120052.

Tian, J., Guo, S., Liu, D., Pan, Z., & Hong, X. (2019). A fair approach for multi-objective water resources allocation. *Water Resources Management*, *33*(10), 3633–3653.

Towns, J., Cockerill, T., Dahan, M., Foster, I., Gaither, K., Grimshaw, A., ... Wilkins-Diehr, N. (2014, Sept.-Oct.). Xsede: Accelerating scientific discovery. *Computing in Science & Engineering*, *16*(5), 62-74. Retrieved from `doi.ieeecomputersociety.org/10.1109/MCSE.2014.80` doi: 10.1109/MCSE.2014.80

Tran, T., Carpenter, A., & Kenel, P. (2019). Doing more with many: Case studies of regional collaboration in management and shared infrastructure. *Journal: American Water Works Association*, *111*(3).

Trindade, B., Gold, D., Reed, P., Zeff, H., & Characklis, G. (2020). Water pathways: An open source stochastic simulation system for integrated water supply portfolio management and infrastructure investment planning. *Environmental Modelling & Software*, *132*, 104772.

Trindade, B., Reed, P., & Characklis, G. (2019). Deeply uncertain pathways: Integrated multi-city regional water supply infrastructure investment and portfolio management. *Advances in Water Resources*, *134*, 103442.

Trindade, B., Reed, P., Herman, J., Zeff, H., & Characklis, G. (2017). Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-

objective optimization under deep uncertainty. *Advances in Water Resources*, *104*, 195–209.
Tsoukiàs, A. (2008). From decision theory to decision aiding methodology. *European journal of operational research*, *187*(1), 138–161.
USGCRP. (2018). Impacts, risks, and adaptation in the united states: Fourth national climate assessment. *US Global Change Research Program*, *2*.
van Ginkel, K., Haasnoot, M., & Botzen, W. J. W. (2021). A framework for identifying climate change induced socio-economic tipping points. *Available at SSRN 3935775*.
Walker, G. (2013). A critical examination of models and projections of demand in water utility resource planning in england and wales. *International Journal of Water Resources Development*, *29*(3), 352–372.
Walker, W. E., Haasnoot, M., & Kwakkel, J. H. (2013). Adapt or perish: A review of planning approaches for adaptation under deep uncertainty. *Sustainability*, *5*(3), 955–979.
Walker, W. E., Harremoës, P., Rotmans, J., Van Der Sluijs, J. P., Van Asselt, M. B., Janssen, P., & Krayer von Krauss, M. P. (2003). Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated assessment*, *4*(1), 5–17.
Watson, A. A., & Kasprzyk, J. R. (2017). Incorporating deeply uncertain factors into the many objective search process. *Environmental Modelling & Software*, *89*, 159–171.
Westbrook, V., Miller, S., & Lim, J. (2016). *City of durham water shortage response plan* (Tech. Rep.).
Woodruff, M. J., Reed, P. M., & Simpson, T. W. (2013, July). Many objective visual analytics: rethinking the design of complex engineered systems. *Structural and Multidisciplinary Optimization*, *48*(1), 201–219. Retrieved 2019-03-17, from `https://doi.org/10.1007/s00158-013-0891-z` doi: 10.1007/s00158-013-0891-z
WUCA. (2016). *Water utility climate alliance 2017-2021 strategic plan.*
Zeff, H. B., & Characklis, G. W. (2013). Managing water utility financial risks through third-party index insurance contracts. *Water Resources Research*, *49*(8), 4939-4951. Retrieved from `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/wrcr.20364` doi: 10.1002/wrcr.20364
Zeff, H. B., Herman, J. D., Reed, P. M., & Characklis, G. W. (2016, September). Cooperative drought adaptation: Integrating infrastructure development, conservation, and water transfers into adaptive policy pathways. *Water Resources Research*, *52*(9), 7327–7346. Retrieved 2019-03-26, from `https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2016WR018771` doi: 10.1002/2016WR018771
Zeff, H. B., Kasprzyk, J. R., Herman, J. D., Reed, P. M., & Characklis, G. W. (2014, June). Navigating financial and supply reliability tradeoffs in regional drought management portfolios. *Water Resources Research*, *50*(6), 4906–4923. Retrieved 2018-09-11, from `https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2013WR015126` doi: 10.1002/2013WR015126

Supporting Information for "DU Pathways$_{ERAS}$: Cooperative Water Supply Investments that are Equitable, Robust, Adaptive and Stable"

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Contents

S1 Synthetic streamflow generation

Synthetic streamflow generation by the (Kirsch et al., 2013) generator begins by log transforming and whitening the record of historical weekly inflows, $\boldsymbol{Q_k} \in \boldsymbol{R}^{(80\times 52)}$ to create a matrix $\boldsymbol{Z_k} \in \boldsymbol{R}^{(80\times 52)}$ for each gage k. Next, a matrix of integer indices $\boldsymbol{M} \in \boldsymbol{R}^{(1000\times 52)}$ is generated by sampling with replacement from $(1, 2, \ldots, 80)$. $M_{i,j}$ represents the historical year that will be used to create the streamflow value for synthetic year i in week j. $\boldsymbol{M}$ is used to make a matrix of uncorrelated synthetic flows, $\boldsymbol{C_k}$ with entries $C_{k_{i,j}} = Z_{k_{M_{(i,j)},j}}$. The same matrix $\boldsymbol{M}$ is used to for all sites to preserve spatial correlation for synthetic records. Next, a matrix of historical autocorrelation, $\boldsymbol{p_{H_k}} = corr(\boldsymbol{Z_k})$ is created for each gage and a Cholesky decomposition is used to find an upper triangular matrix $\boldsymbol{U_k} \in \boldsymbol{R}^{(52\times 52)}$ such that $\boldsymbol{p_{H_k}} = \boldsymbol{U_k}\boldsymbol{U_k^T}$. Upper triangular matrix $\boldsymbol{U_k}$ is then used to impose the historical autocorrelation structure on matrix $\boldsymbol{C_k}$ to make a new synthetic record $\boldsymbol{S_k} = \boldsymbol{C_k}{\cdot}\boldsymbol{U_k}$. Finally, $\boldsymbol{S_k}$ is transformed back into real space to gen-

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erate a record of reservoir inflows that preserve the spatial and temporal correlation structures of the historical record.

To improve the inter-annual correlations of synthetic streamflows, this process is repeated using a shifted version of historical inflows, $\boldsymbol{Q_{k'}}$ beginning at week 27 of each year and ending at week 26 of the following year. Matrices $\boldsymbol{Z_{k'}}$, and $\boldsymbol{U_{k'}}$ and created based off this shifted record and $\boldsymbol{C_{k'}}$ is created separately shifting matrix $\boldsymbol{C_k}$. A new matrix of synthetic inflows, $\boldsymbol{S_{k'}}$ is created using the operation $\boldsymbol{S_{k'}} = \boldsymbol{C_{k'}} \cdot \boldsymbol{U_{k'}}$ and transforming the product back to real space. The final set of synthetic streamflows is comprised of columns 27-52 of $\boldsymbol{S_k}$ and columns 1-26 of $\boldsymbol{S_{k'}}$. For more details on the synthetic generation process, refer to Kirsch et al. (2013) and Herman et al. (2016).

The number of streamflow samples used in this paper were chosen based on empirical assessment. (Trindade et al., 2017) empirically assessed the number of the number of realizations needed to estimate the objective functions for the Research Triangle test case by examining sample sizes varying from 100 to 5000 realizations. Results of the empirical assessments showed that 1000 evaluates per modeling run is sufficient to approximate the mean and variances of the Monte Carlo distributions used to determine candidate solutions' objectives. The approach used by (Trindade et al., 2017) is derived from early studies of metaheuristic search dynamics given noisy objective functions (e.g. (Miller & Goldberg, 1996; Smalley et al., 2000)) which show that relatively small Monte Carlo samples per function evaluations can provide good approximations when verified with much larger samples after search has been completed.

S2 Runtime Diagnostics

Multiple instances of MOEA search are run ensure the algorithm has overcome any biases in search generated by the initial population (Salazar et al., 2017). In this experiment, a total of 10 random seeds were run, using the multi-master configuration of the Borg MOEA with two seeds per master. The true Pareto set for this problem is not known, so to assess the convergence convergence we measure relative hypervolume (Zitzler et al., 2003), which compares performance of the approximate Pareto sets discovered at set checkpoints within search to the final "reference set", which contains non-dominated solutions across all seeds. If the relative hypervolume is found to plateau, we conclude that the algorithm has converged to a satisfactory approximation of the true Pareto set.

Runtime diagnostics for all seeds optimizations are shown in Figure S1. There was very little variance across seeds, and the hypervolume of all defection optimizations plateaued after around 50,000 function evaluations.

S3 Distribution of Unit Cost objective for the DSFR compromise

Figure S2 shows the distribution of the unit cost of expansion objective for Durham across the 2,000 SOWs used for DU reevaluation for the DFSR compromise. Of the 2,000 DU SOWs, over 1,900 return unit costs near zero. However, the extreme tail of the unit cost of expansion increases to over $1,000/kgal. This extreme tail explains the high regional value of the unit cost objective shown in Figure 4a - because DU optimization calculates values in expectation across all sampled futures, extreme values in the tails have a large impact on the objective value. Future work may reduce the impact of these extreme SOWs by using other summary statistics such as the median or 90th% unit cost.

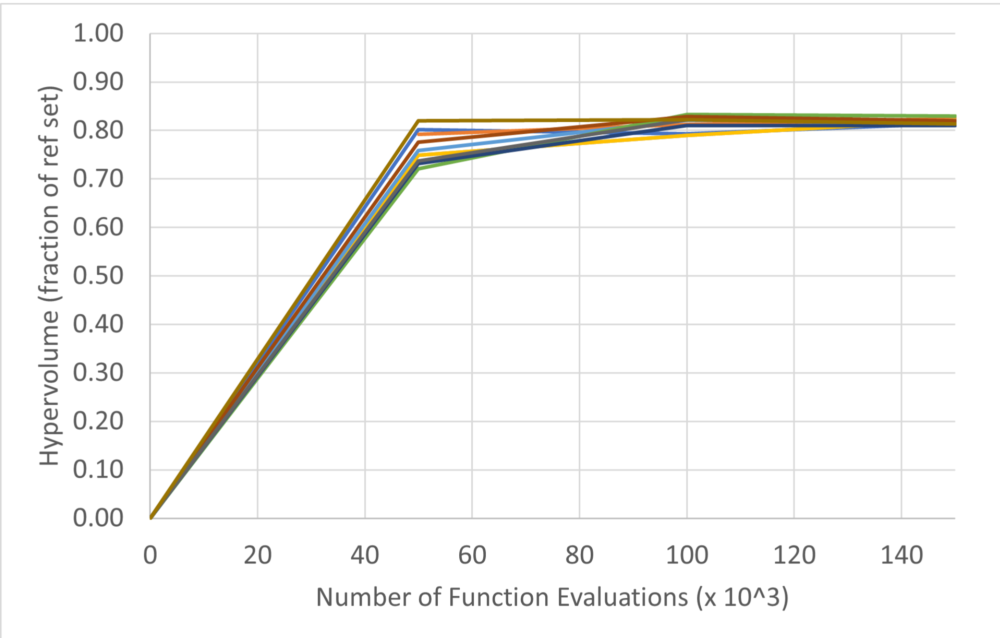

Figure S1. Runtime diagnostics for 10 random seeds. The plateau of hypervolume across all seeds for all formulations indicates that number of function evaluations (NFE) were enough to achieve maximum attainable convergence.

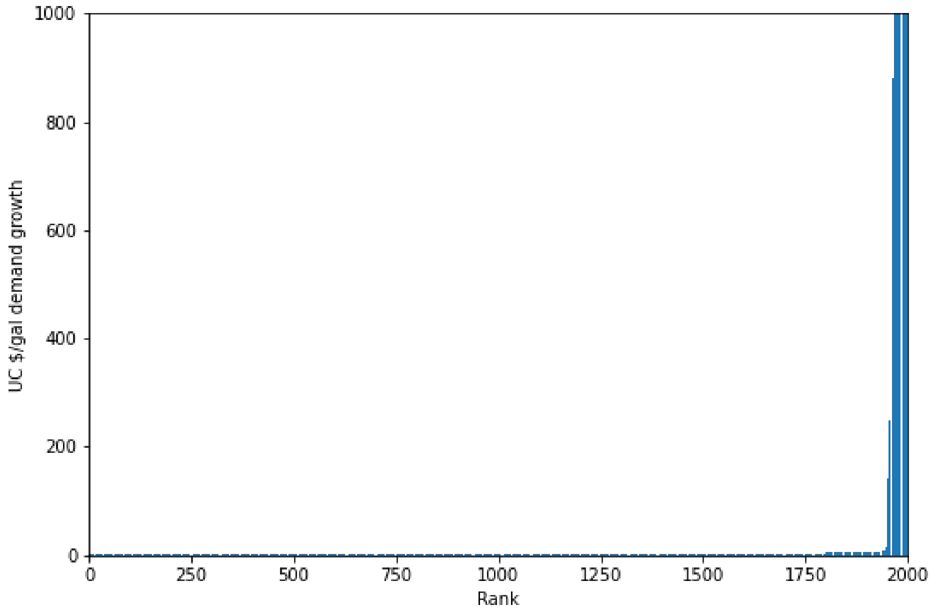

Figure S2. Distribution of Unit Cost for Durham across 2,000 DU SOWs

References

Herman, J. D., Zeff, H. B., Lamontagne, J. R., Reed, P. M., & Characklis, G. W. (2016, November). Synthetic Drought Scenario Generation to Support Bottom-Up Water Supply Vulnerability Assessments. *Journal of Water Resources Planning and Management*, *142*(11), 04016050. Retrieved 2019-03-17, from `https://ascelibrary.org/doi/full/10.1061/(ASCE)WR.1943-5452.0000701` doi: 10.1061/(ASCE)WR.1943-5452.0000701

Kirsch, B. R., Characklis, G. W., & Zeff, H. B. (2013, July). Evaluating the Impact of Alternative Hydro-Climate Scenarios on Transfer Agreements: Practical Improvement for Generating Synthetic Streamflows. *Journal of Water Resources Planning and Management*, *139*(4), 396–406. Retrieved 2019-03-17, from `https://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0000287` doi: 10.1061/(ASCE)WR.1943-5452.0000287

Miller, B. L., & Goldberg, D. E. (1996). Optimal sampling for genetic algorithms. In *Proceedings of the artificial neural networks in engineering (annie'96) conference* (Vol. 6, pp. 291–297).

Salazar, J. Z., Reed, P. M., Quinn, J. D., Giuliani, M., & Castelletti, A. (2017). Balancing exploration, uncertainty and computational demands in many objective reservoir optimization. *Advances in water resources*, *109*, 196–210.

Smalley, J. B., Minsker, B. S., & Goldberg, D. E. (2000). Risk-based in situ bioremediation design using a noisy genetic algorithm. *Water Resources Research*, *36*(10), 3043–3052.

Trindade, B., Reed, P., Herman, J., Zeff, H., & Characklis, G. (2017). Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-objective optimization under deep uncertainty. *Advances in Water Resources*, *104*, 195–209.

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M., & Da Fonseca, V. G. (2003). Performance assessment of multiobjective optimizers: An analysis and review. *IEEE Transactions on evolutionary computation*, *7*(2), 117–132.