Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-objective optimization under deep uncertainty

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ABSTRACT

Emerging water scarcity concerns in many urban regions are associated with several deeply uncertain factors, including rapid population growth, limited coordination across adjacent municipalities and the increasing risks for sustained regional droughts. Managing these uncertainties will require that regional water utilities identify coordinated, scarcity-mitigating strategies that trigger the appropriate actions needed to avoid water shortages and financial instabilities. This research focuses on the Research Triangle area of North Carolina, seeking to engage the water utilities within Raleigh, Durham, Cary and Chapel Hill in cooperative and robust regional water portfolio planning. Prior analysis of this region through the year 2025 has identified significant regional vulnerabilities to volumetric shortfalls and financial losses. Moreover, efforts to maximize the individual robustness of any of the mentioned utilities also have the potential to strongly degrade the robustness of the others. This research advances a multi-stakeholder Many-Objective Robust Decision Making (MORDM) framework to better account for deeply uncertain factors when identifying cooperative drought management strategies. Our results show that appropriately designing adaptive risk-of-failure action triggers required stressing them with a comprehensive sample of deeply uncertain factors in the computational search phase of MORDM. Search under the new ensemble of states-of-the-world is shown to fundamentally change perceived performance tradeoffs and substantially improve the robustness of individual utilities as well as the overall region to water scarcity. Search under deep uncertainty enhanced the discovery

of how cooperative water transfers, financial risk mitigation tools, and coordinated regional demand management must be employed jointly to improve regional robustness and decrease robustness conflicts between the utilities. Insights from this work have general merit for regions where adjacent municipalities can benefit from cooperative regional water portfolio planning.

1 INTRODUCTION

Understanding and exploring the combined states-of-the-world (SOWs) that shape water supply risks is a fundamental challenge in any drought mitigation application, defining perceptions and preferences related to key performance objectives, vulnerabilities, and/or the robustness of a system. Fundamental to this challenge is the choice of what uncertain factors should be sampled or included in generating alternative scenarios. Broadly, there are two dominant methodologies that are at present used in water supply planning contexts: (1) pre-specified deterministic scenarios/narratives and (2) globally sampled stochastic scenario analysis. As an example of deterministic scenario-based planning, Liu et al. (2008) analyzed four semi-arid river basins in the south-western United States seeking to find water management strategies based on integrated modeling that would minimize lasting or irreversible environmental impacts (mostly on local vegetation) while allocating enough water for competing uses. The authors analyzed a pre-specified set of scenarios based on their *a priori* specified problem definition and input from stakeholders as well as water management experts. As an alternative example of stochastic scenarios, Brown et al. (2012) and Moody and Brown (2013) use ensembles of reservoir inflows estimated using regression techniques to estimate climate vulnerability. Climate vulnerability analysis focuses on reducing risks, or losses, calculated as the product of a loss function times subjective probabilities for the climate scenarios. The probabilities are elicited by contrasting a mixture of global climate model projections, paleodata (if available), and synthetically generated weather. These approaches are termed Decision Scaling, and have been recently expanded by Ghile et al. (2014) and Lownsbery (2014) to include hydroeconomic sensitivities.

The Decision Scaling example relates to a broader body of literature focused on planning under deep uncertainty. Deep uncertainties cannot, as described by Knight (1921, p. xiv), be treated as “a gamble on a known mathematical chance”. In other words, they lack consensus on their underlying probability distributions as well as on individual or collective outcomes. Such uncertainties have also been termed Knightian, or scenario uncertainties, by multiple authors, including Walker et al. (2013); Lempert et al. (2006) and Kwakkel et al. (2016b). Exploratory modeling (Bankes et al., 2001) — which involves running planning models across broad global samples of hypothesis — has emerged as a primary strategy for discovering which combinations of deeply uncertain factors are of high consequence in decision problems, as opposed to considering one most likely future projection (Walker et al., 2003; Lempert et al., 2006; Walker et al., 2013; Zeff et al., 2014; Herman et al., 2014). As noted by Dessai et al. (2009), the intent of exploratory modeling is to shift focus from predicting future conditions to understanding which conditions lead to decision relevant consequences. Given a better understanding of the consequences related to these discovered conditions, decision makers can then evaluate their relative importance or plausibility.

As reviewed by Herman et al. (2015), the selection of decision alternatives to analyze in exploratory modeling frameworks can either be done *a priori* or with computational search. In the case of decision alternatives that are specified *a priori*, the decision analysis then takes the form of a classical discrete choice among those alternatives based on their interpreted robustness. This approach has been commonly employed across the full range of decision support frameworks in this area (Brown et al., 2012; Moody and Brown, 2013; Hipel and Ben-Haim, 1999; Lempert et al., 2006; Bryant and Lempert, 2010). Conversely, a growing number of studies are using search strategies to discover high performing design alternatives in their initial stage of analysis and then evaluating their robustness to inform design selection (Korteling et al., 2013; Kasprzyk et al., 2013; Hamarat et al., 2014; Kwakkel and Haasnoot, 2015; Giuliani and Castelletti, 2016; Singh et al., 2015; Hadka et al., 2015).

This study advances the Many-Objective Robust Decision Making (MORDM) framework

initially introduced by Kasprzyk et al. (2013) by demonstrating the value of progressively transitioning from sampling well-characterized uncertainties only to also sampling deeply uncertain factors during the MORDM search phase. The inclusion of deeply uncertain factors in the search phase of the MORDM framework seeks to design portfolios of drought mitigation actions that perform well under a wide range of SOWs — where a SOW is defined here as a fully specified world, comprised of one fully specified sampled vector of deeply uncertain factors (Ψ) and one streamflow time series for each reservoir. With this change, deep uncertainty sampling is performed for both generating candidate management alternatives and evaluating their robustness. This study builds on the hypothetical western water market test case explored by Watson and Kasprzyk (2016), which shows the value for increasing robustness by including deeply uncertain factors in the computational search and alternative generation phases of MORDM. Their study demonstrates that there were potential robustness benefits for a hypothetical water supply portfolio analysis for a single city in the Lower Rio Grande. In contrast, this study focuses on the Eastern U.S. using the Research Triangle region of North Carolina, engaging the water utilities serving Raleigh, Durham, Cary, Chapel Hill and Carborro in cooperative and robust regional water portfolio planning under deep uncertainty.

The Research Triangle region poses a multi-jurisdictional decision making context, where each municipality faces its own performance supply reliability and financial tradeoffs. Moreover, each of the utilities' water portfolio planning actions can have strong negative impacts on the neighboring systems. Efforts to maximize the individual robustness of any of the mentioned utilities have been shown to potentially significantly degrade the robustness of the others. Therefore, this study focuses on three core contributions: (1) demonstrate that adequately combining dynamic risk-triggered conservation and transfers with financial hedging requires the inclusion of deeply uncertain factors in the search phase of MORDM; (2) demonstrate that searching adaptive risk-based action triggers under a comprehensive sample of deeply uncertain factors may promote the discovery of a larger and more diverse suite

of candidate solutions that meet stakeholder requirements in a broader variety of hypothetical future SOWs; and (3) illustrate how the number and diversity of robust water portfolios can aid in reducing planning conflicts among utilities (i.e., robustness tradeoffs across the municipalities).

2 METHODOLOGICAL FRAMEWORK

2.1 Overview

As discussed in the introduction, this study advances the MORDM (Many-Objective Robust Decision Making) framework initially introduced by Kasprzyk et al. (2013) by demonstrating the value of progressively transitioning from sampling well-characterized uncertainties only to also sampling deeply uncertain factors during search. The inclusion of deeply uncertain factors in the search phase of the MORDM framework seeks to identify alternatives that perform well under a wide range of SOWs. With this change, deep uncertainty sampling is performed for both generating and evaluating the robustness of candidate management alternatives. Following the taxonomy presented in Herman et al. (2015), the proposed MORDM methodology has the following four core component steps:

1. Sampling States of the World: Selection and definition of well-characterized and deeply uncertain factors that will be used to generate ensembles of SOWs.
2. Generation of alternatives: For one or more candidate problem formulations (i.e., objectives, decisions, constraints, and SOWs), exploiting many-objective evolutionary search under uncertainty to discover the Pareto approximate solutions.
3. Choosing Measures of Robustness: Evaluation of tradeoff alternatives' robustness across a broader ensemble of Ψ vectors using stakeholder elicited measures of acceptability (e.g., regret or satisficing-based robustness measures, as in Lempert et al. 2006 and Herman et al. 2014, respectively). Multiple candidate robustness measures may be elicited over iterations with stakeholders as part of a constructive learning feedback process (Tsoukias, 2008).

- 132 4. Discovering the Factors that Control Robustness: Use global sensitivity analysis and/or
133 factor mapping to discover which uncertain factors control the robustness of Pareto
134 approximate alternatives and warrant further potential monitoring or actions [e.g.,
135 scenario-discovery presented by Bryant and Lempert (2010)]. Sensitivity analysis
136 methods can be used to rank order the most important factors (i.e., factor prioritiza-
137 tion, as in Saltelli et al. 2008, 2006), or for factor mapping to find specific factors' value
138 ranges that cause conditions of concern (i.e., categorical classification as introduced
139 by Friedman and Fisher 1999; Breiman et al. 1984, respectively).

140 More detailed descriptions for each of these four component steps for the MORDM framework
141 are provided in Sections 2.2 to 2.5, below.

142 **2.2 States of the World**

143 Related to the present study, Zeff et al. (2014) accounted for a single source of well-
144 characterized uncertainty (WCU) in their analysis of the Research Triangle's water supply
145 tradeoffs through 2025, namely streamflows. Uncertain streamflows were included in the
146 model using synthetically generated stochastic streamflow time series following the method-
147 ology presented by Kirsch et al. (2013). In Zeff et al. (2014), multiobjective search was used
148 to identify candidate water portfolio designs. During the search phase of their study, all
149 other factors such as regional demand trajectories, consumer response to water restrictions,
150 prices for water transfers, etc., however, were treated deterministically. Transitioning the
151 Research Triangle from planning solely based on deterministic historical streamflow records
152 to synthetically generated streamflows showed that the region's planners were underestimat-
153 ing the severity and impacts of droughts. The initial use of the streamflow WCU served
154 two benefits: (1) it highlighted that the region needs to more carefully consider transfers,
155 financial risk mitigation, and conservation actions and (2) it illustrated consequential results
156 that motivated the consideration of a broader range of uncertainties (e.g., demand growths,
157 transfer pricing, imperfect responses to restrictions, demand hardening, etc.).

Building on the WCU optimization by Zeff et al. (2014), Herman et al. (2014) evaluated the robustness of the candidate water portfolios using a Latin Hypercube Sampling (LHS) of the 13 deeply uncertain parameters shown in Table 1, as a means of ensuring a good representation of possible futures. Figure 1 illustrates what we term the deep uncertainty re-evaluation (DU re-evaluation) used in the robustness calculations. For the Research Triangle test case, the DU re-evaluations pair the original synthetically generated stream flows, as used in Equation 16, with each LHS sampled set of deeply uncertain factors. For this study, the 1,000 original synthetic inflows used in Zeff et al. (2014) and Herman et al. (2014) are used in conjunction with 10,000 LHS sampled sets of deeply uncertain factors (Ψ) to create 10 million SOWs. The 13 deeply uncertain factors in Table 1 can be grouped into four categories representing different aspects of the problem. The categories account for future hydrologic uncertainties, uncertainties in demand projections regarding timing and magnitude, legal and physical factors related to future storage capacities, and fluctuations in the water transfers' pricing. Ranges for deeply uncertain factors from which samples were developed collaboratively with the Research Triangle utilities. As noted by Bryant and Lempert (2010), global sampling of deeply uncertain factors, with subsequent participatory assessments that facilitate the discovery of consequential combinations, allows for an improved *a posteriori* assessment by stakeholders of where to focus their attention and actions.

2.3 Alternatives Generation

In the context of the Research Triangle, Zeff et al. (2014) employed multiobjective evolutionary algorithms to identify water supply portfolios combining water transfers, financial risk instruments, and demand management. Each portfolio evaluation was based on multiple realizations of synthetically generated streamflows coupled with a set of deterministic base values for each of the 13 deeply uncertain factors presented in Table 1, representing what we term in this study the WCU optimization was used initially to identify design alternatives (see Figure 2a). Transitioning the Research Triangle from planning solely based on the deterministic historical streamflow record to synthetic streamflows (Kirsch et al., 2013) as

FIG. 1. Schematics of the deep uncertainty re-evaluation of candidate water portfolio solutions (termed DU re-evaluation). A set of objectives is calculated for each 1,000 SOW's that share the same Ψ . These objectives are in turn used to calculate overall robustness and overall objectives for alternative θ .

TABLE 1. Uncertainty Factors and Sampling Ranges for Many-Objective Robust Decision Making (vector Ψ in Equations 5 and 9).

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

a well established uncertainty characterization tool showed that the region's planners were underestimating the severity and impacts of droughts.

FIG. 2. WCU (a) and DU (b) optimization factor sampling schemes. The former creates states of the world by coupling synthetically generated set of streamflows with a base projection for 13 deeply uncertain factors, while the latter couples each set of synthetically generated streamflows with a different projection for the 13 deeply uncertain factors, shuffling the coupling at every function evaluation.

The study transitions from the WCU optimization used in the prior published analysis of the Research Triangle to include deep uncertainties in the search and identification of candidate water portfolios. This transition poses a challenging multi-objective search problem that motivated our use of the Borg algorithm, a multi-objective evolutionary algorithm (MOEA) introduced by Hadka and Reed (2013). The Borg MOEA is an adaptive algorithm that encompasses multiple operators chosen by probabilistic rules updated every iteration based on operators' performances. The Borg MOEA has demonstrated superior performance when applied to different challenging multiobjective problems, such as benchmarking test problems, water supply portfolio planning, pollution control given ecological thresholds, groundwater monitoring design, and reservoir control (Hadka and Reed, 2012; Reed et al., 2013; Zatarain Salazar et al., 2016; Ward et al., 2015). The coupling of sampling of deeply uncertain factors with the computational search provided by the Borg MOEA provides direct feedbacks between the alternative generation and selection of SOWs steps of the MORDM framework. More specifically, it results in an alternative generation scheme that evaluates each candidate solutions against different SOWs, each with its own streamflow

time series and vectors samples of 13 DU factors, for each function evaluation performed during the computational search. This alternative generation scheme, illustrated in Figure 2b, is termed here Deep Uncertainty (DU) optimization. In Figure 2b, the green boxes represent one alternative water portfolio, each red box represent a different set of synthetic reservoir inflows that are randomly paired with one of 1,000 samples of 13 DU factors. The new alternative generation scheme seeks to yield more robust alternatives, as Borg MOEA will search for alternatives whose performance should be acceptable under a broad range of SOWs. The DU optimization’s sampling scheme shown in Figure 2b approximates the much broader and computationally demanding sampling used in the DU re-evaluation illustrated in Figure 1. It is intractable to include all 10 million DU re-evaluation SOWs to evaluate each candidate water portfolio.

2.4 Robustness Measures

As reviewed by Herman et al. (2015), the three most common types of robustness measures are: expected value, regret and satisficing; all three can be employed in either univariate or multivariate contexts. The three measures are described in detail in Lempert and Collins (2007), the latter two being further developed and tested in the context of water supply portfolio analysis in Herman et al. (2015). Herman et al. (2014) have used the domain criterion robustness measure (i.e., percent of states of the world in which given performance criteria are met) on the Research Triangle problem, which was used in this work again because it best aligned with utilities preferences (Herman et al., 2015). As was discussed above in Section 2.2, the implementation of the domain criterion robustness measure for the Research Triangle problem is illustrated in the DU re-evaluation approach in Figure 1. This choice of robustness calculation was the motivation behind the computational search sampling scheme presented in this work (DU optimization, Figure 2b), which was intended to approximate the computationally intensive DU re-evaluation scheme (Figure 1) during the Borg MOEA search phase described in Section 2.3 for the sake of computational tractability.

2.5 Robustness Controls

Scenario discovery is a key step in many RDM frameworks and represents a factor-mapping sensitivity analysis used to determine under which ranges of the deep uncertain factors each alternative may be vulnerable to failures (Bryant and Lempert, 2010; Herman et al., 2014, 2015; Kasprzyk et al., 2013; Lempert et al., 2006; Halim et al., 2015; Kwakkel and Jaxa-Rozen, 2016; Groves and Lempert, 2007). Based on these ranges and on their experience with their system, decision makers can better understand where candidate actions perform acceptably and inform monitoring efforts to detect conditions of concern. PRIM and CART trees are suggested by Lempert et al. (2008), instead of more sophisticated statistical learning algorithms, for assessing scenario discovery due to their high interpretability.

PRIM works by gradually shrinking (peeling) prespecified ranges of factors according to a set confidence interval in order to find multi-dimensional boxes that encompass as high of a proportion of true positives as possible (Friedman and Fisher, 1999). In this application, positives are Ψ vectors for which an alternative fails to meet a given performance criteria. The algorithm returns a series of candidate boxes, each one devised after one peel and described by the following standard box metrics:

1. Density: the ratio of the number cases of interest (fails) inside that box to the total number of cases inside that box. A value of 1 is ideal to this metric.
2. Coverage: the ratio of the number of cases of interest inside that box to the total number of cases of interest in the entire domain. A value of 1 is ideal to this metric.
3. Type II error: the ratio of the number of cases of interest outside the box to the total number of cases outside the box (ratio of false negatives). A value of 0 is ideal to this metric.

The analyst should choose a box according to stakeholders' interests. For example, relative to the water utilities in the Research Triangle, low type II error and high coverage are more important than high density, given the high risk aversion to any failures of the

system. The type II error represents the relative perceived risk water utilities are willing to take of being wrong in their expected system performance. There is not a known universal density versus coverage ratio that can be used to all problems, as they are problem and stakeholder specific (Lempert et al., 2008). The described process of scenario discovery (robustness controls) is described in more detail in Bryant and Lempert (2010).

3 THE RESEARCH TRIANGLE TEST CASE

The Research Triangle region, as illustrated in Figure 3, is comprised of several municipalities, whose water supplies are provided by public utilities in Raleigh, Durham, Cary, and Chapel Hill/Carrboro (i.e., the Orange Water and Sewer Authority, or OWASA). Cary and Raleigh receive water from allocations of Jordan and Falls Lakes, respectively, two large flood control reservoirs operated by the United States Army Corps of Engineers. Volumetric allocations from each lake are designated by the state for municipal water supply. Raleigh has been granted 100% of the municipal water supply allocation to Falls Lake, and Cary holds 39% of the municipal water supply allocation to Jordan Lake. Although Cary is the only utility to operate an intake on Jordan Lake, other utilities also have allocations that can be accessed by purchasing water from Cary’s water treatment plant during conditions of scarcity, subject to Cary’s availability. Rapidly growing demands in the region have accelerated competition for the remaining unallocated portion of Jordan Lake’s water supply pool. A number of municipalities, including Raleigh, the largest in the region, have requested new allocations, and it is likely that the pool will be completely allocated after the most recent round of allocation requests is approved by the state, even without Raleigh’s request (TJCG, 2014).

Table 1 summarizes the region’s reservoir storage dedicated to municipal water supply as well as allocations for all four utilities. The Research Triangle is projected to experience a total demand growth of 33% through the planning horizon year of 2025 considered in this study (average of annual growth of 2.4%) (NCDENR, 2002). Given that the regional municipalities cannot bring new sources online before 2025, Jordan Lake represents the only

FIG. 3. Map of the North Carolina Research Triangle region. Adapted from Zeff et al. (2014).

major supply source that still has unallocated water for municipal use. Consequently, it is a current source of regional resource conflicts.

Although the municipalities are in close geographic proximity and share the same hydro-climatic conditions, their different demand-to-capacity ratios yield highly variable drought impacts across the region's utilities. In severe droughts, transferring water from Jordan Lake via the existing Cary water treatment plant offers a means of more efficiently using the region's existing supply capacity to overcome water scarcity challenges (Caldwell and Characklis, 2014; Zeff et al., 2014). Transfers from existing sources can help to delay or avoid the costs of building new supply infrastructure, but they do create financial risks for utilities. Utilities typically set rates with the aim of returning revenues that cover their costs,

TABLE 2. Summary of reservoir storages, demands, and allocations for the Research Triangle Region

Utility	Reservoir	Reservoir capacity reserved for municipal supply (Billion gallons)	Percentage of reservoir capacity reserved for municipal supply allocated to each utility currently in use	2013 Demand (Million gallons /day)	2025 Demand (Estimated) (Million gallons /day)	Demand/Capacity Ratio (2025) ($10^{-3}year^{-1}$)
OWASA	Cane Creek Stone Quarry University Lake Jordan Lake	3.0	100% 100% 100% 5%	8.0	9.0	8.2
Durham	Little River Lake Michie Jordan Lake	6.4	100% 100% 10%	27.5	34.9	14.9
Raleigh	Falls Lake	14.7	100%	57.4	76.2	14.2
Cary	Jordan Lake	14.9	39%	23.1	34.0	6.2

which are dominantly fixed annual debt payments. The additional costs of water transfers during periods of drought can destabilize this budgetary balance. If they are large enough, these swings could harm the ability of a utility to repay their debt on schedule and increase future borrowing costs (Hughes and Leurig, 2013). The costs and financial risks associated with these transfer agreements for several types of financial instruments were studied in detail in Palmer and Characklis (2009), Zeff and Characklis (2013), Caldwell and Characklis (2014) and Zeff et al. (2014).

3.1 Triangle Region Management Model

Zeff et al. (2014) is the first study to present a fully detailed water supply simulation for the Research Triangle region's water utilities using drought mitigation instruments based on short term conservation, water transfers, and financial hedging. This work represents the culmination of several prior efforts (risk-of-failure triggers in Palmer and Characklis 2009, index insurance in Zeff and Characklis 2013, and water transfers in Caldwell and Characklis 2014). Zeff et al. (2014) used the model to find tradeoffs between reliability focused choices and their inherent financial risks when formulating drought management policies for the utilities in the Research Triangle. The WCU optimization formulation in that study considered

hydrologic variability as the sole source of uncertainty. The policies consisted of different combinations of financial instruments and risk-of-failure (ROF, described in equations 8 below) triggered drought mitigation instruments. Herman et al. (2014) then used the same model to assess the robustness of the solutions found by Zeff et al. (2014) by testing them against a broader ensemble of uncertainties, some of them deep, finding that multiple utilities had significantly low robustness values. This study builds on these prior studies, seeking to discover if including deep uncertainties in the search phase of MORDM will result in improving the individual utilities as well as the whole Triangle region's robustness to drought. Given the growing complexity of the Research Triangle problem formulations as well as the evolving treatments of uncertainty, this section provides a careful mathematical description of the model linking the prior studies to the proposed DU optimization explored here.

Minimization Problem

Here, we define the optimization problem as finding the optimal policy θ^* that minimizes the objective function vector $\mathbf{F}$, i.e.

$$\theta^* = \underset{\theta}{argmin} \mathbf{F} \quad (1)$$

where,

$$\mathbf{F} = \begin{bmatrix} -f_{REL}(\mathbf{x}_s, \theta_{rt}, \theta_{tt}, \theta_{jla}) \\ f_{RF}(\mathbf{x}_{rof}, \theta_{rt}, \theta_{tt}, \theta_{jla}) \\ f_{JLA}(\theta_{jla}) \\ f_{AC}(\mathbf{x}_{rof}, \theta_{rt}, \theta_{tt}, \theta_{jla}, \theta_{acfc}, \theta_{irt}) \\ f_{WCC}(\mathbf{x}_{rof}, \theta_{rt}, \theta_{tt}, \theta_{jla}, \theta_{acfc}, \theta_{irt}) \end{bmatrix} \quad (2)$$

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_{rof} \\ \mathbf{x}_s \end{bmatrix} \quad (3)$$

$$\theta = [\theta_{rt}, \theta_{tt}, \theta_{jla}, \theta_{acfc}, \theta_{irt}] \quad (4)$$

where $\mathbf{F}$ is the vector-based objective function, f_{REL} is the reliability objective, f_{RF} is the restriction frequency objective, f_{JLA} is the Jordan Lake allocation objective, f_{AC} is the average cost objective, f_{WCC} is the worse case cost objective, $\mathbf{X}$ is the state vector across the utilities and time, $\mathbf{x}_{rof}$ is a vector of approximately calculated risk of failures (Equation 8), $\mathbf{x}_s$ is a vector of combined utility storage, θ_{rt} is a vector of restriction triggers, θ_{tt} is a vector of transfer triggers, θ_{jla} is a vector of Jordan Lake Allocations, θ_{acfc} is a vector of annual contingency fund contributions, and θ_{irt} is a vector of insurance restriction triggers. The storage state $\mathbf{x}_s$ can be defined as:

$$\mathbf{x}_s^w = f(\mathbf{x}_s^{w-1}, \mathbf{C}, \mathbf{D}^w, \mathbf{TF}^w, \mathbf{NI}^w, \mathbf{E}^w, \mathbf{W}^w | \Psi) \quad (5)$$

$$\mathbf{D}^w = f(\mathbf{x}_{rof}^w, \theta_{rt}) \quad (6)$$

$$\mathbf{TF}^w = f(\mathbf{x}_{rof}^w, \theta_{tt}) \quad (7)$$

where $\mathbf{C}$ is a vector of reservoir capacities (7 reservoirs, some utilities have more than 1), $\mathbf{D}$ are the demands for each utility, $\mathbf{TF}$ are the transfer volumes for each utility, $\mathbf{NI}$ are the natural inflows in each reservoir, $\mathbf{E}$ the evapotranspiration in each reservoir, $\mathbf{W}$ the spillage of each reservoir, and Ψ is a vector of deeply uncertain factors such as population growth, future allocations yet to be negotiated, etc.

The approximate risk-of-failure (ROF) state x_{rof} is used in conjunction with decision variables θ_{rt} and θ_{tt} to trigger drought mitigation instruments. The primary drought mitigation instrument currently used by utilities is water use restrictions, which is triggered independently by each utility according to rules based on either days of supply remaining, minimum storage levels, or simplified risk calculations (Department of Water Management, 2009; The City of Raleigh Public Utilities Department, 2011; Goodwin, 2009; Orange Water and Sewer Authority, 2010). Despite being important system state variables, days of supply

remaining and storage levels do not comprehensively represent the water supply systems' dynamics. Therefore, action triggers should be based on metrics that incorporate more representative dynamics in available capacity and evolving demands (Palmer and Characklis, 2009). The proposed approach based on ROF calculations allows instead for the inclusion of information from a wider range of state variables while making stakeholder decisions focus on risk-based action triggers. The scenarios for the ROF calculations are described by past recorded inflows and by assumptions about the deeply uncertain factors in Ψ presented in Table 1. The inflows are assumed to be statistically stationary, given this is a short-term planning study through 2025.

The drought mitigation measures are triggered in a given week if the calculated value of the ROF state x_{rof} reaches the trigger values θ_{rt} and θ_{tt} . The values of x_{rof} in week w are calculated by running N_h year-long simulations starting from week w , where N_h is the number of years in the historical record. Each simulation uses a year of recorded inflows starting from week w . The calculations of x_{rof} for utility j in week w can be summarized as follows:

$$x_{rof,j}^w = \frac{1}{N_h} \sum_{y \in HNI} f_{y,j}^w \quad (8)$$

where,

$$f_{y,j}^w = \begin{cases} 0 & \forall w' \in \{(y, w), \dots, (y, w + 51)\} : \frac{x_{s',j}^{y,w'}}{C_j} \geq s_c \\ 1 & \text{otherwise} \end{cases}$$

and,

$$x_{s',j}^w = f(C_j, UD_j^w, \mathbf{NI}_j^w, \mathbf{E}_j^w, \mathbf{W}_j^w | \Psi) \quad (9)$$

where UD^w is the unrestricted demand (no restrictions or transfers) in week w , f is a binary variable that equals 0 for failure (combined storage C for utility j falling below critical storage S_c) and 1 for success, w' denotes a week in one of the N_h year-long simulation following w used to calculate the risk of failure utility j , C_j is the combined storage capacity utility j ,

and $x_{s',j}^{y,w'}$ is the storage state calculated in the year-long simulation that assumes occurrence of year y of N_h following week w . In the calculations of $x_{s',j}^{y,w'}$, it is assumed that if w' is greater than 52, weeks of the following historical year will be used. More details about the risk-of-failure metric can be found in Palmer and Characklis (2009).

Financial Model

Financial losses are accumulated when a utility purchases transfers or enacts conservation, and are equal to the total transfer costs plus the revenue losses resulting from reduced water sales. Utilities can attempt to offset these losses through payouts from third party contracts, and/or annual contributions made to contingency funds (self-insurance). Both were jointly explored in this study.

By purchasing third-party financial insurances, a utility pays an upfront fee — a premium — in exchange for a payout in the event of a drought. For contractual purposes, the drought conditions that trigger insurance payouts are defined as inflow values that would trigger a pre-determined demand restrictions schedule. To define these inflows, system simulations are run with projected demand values for the following year. The insurance triggers are set as the maximum cumulative values, through each week from the beginning of the simulation, where storage drops sufficiently (and, consequently, for the ROF to increase enough) for water use restrictions corresponding to θ_{irt} to be triggered in the simulations. Inflows rather than the enactment of restrictions are used as insurance criterion in order to avoid moral hazards, given that utilities would be able to artificially enact restrictions on times of financial need in order to get a payout. More details about the insurance model can be found in Zeff and Characklis (2013). The insurance payout (*IPO*) is set for each utility in the beginning of the simulation as the expected value of revenue losses if restriction stage θ_{irt} is enacted given the historical inflows:

$$\mathbf{IPO} = E[\mathbf{RL}^w] = E[\mathbf{UD}^w \cdot \mathbf{UWP} - \mathbf{D}^w \cdot \mathbf{WP}^w] \quad (10)$$

$$\mathbf{WP}_w = f(\mathbf{x}_{\mathbf{rof}}^w, \theta_{\mathbf{rt}}) \quad (11)$$

where RL is the vector of revenue losses, UWP is the vector of unrestricted water prices (independent of time), and WP is the vector of water prices subject to restrictions.

The insurance premium (IP) is calculated based on the expected total payouts made during each historical year ($YIPO$) plus a loading (IPR) based on the variance of such total payouts to account for volatility.

$$\mathbf{IP} = E[\mathbf{YIPO}] + \mathbf{IPR} \quad (12)$$

$$\mathbf{IPR} = f(\sigma_{\mathbf{YIPO}}^2) \quad (13)$$

The total payouts $YIPO$ that inform the insurance price can be expressed as:

$$\mathbf{YIPO}^y = f(\theta_{\mathbf{irt}}, \mathbf{IPO}, \mathbf{NI}^y) \quad (14)$$

where y denotes a year.

The annual contingency fund contribution decision variable is used to set aside a percentage of the annual revenue into a contingency fund, which rolls over to future years indefinitely. The amount of money in a contingency fund is updated yearly according to the following expression:

$$\mathbf{CF}^{y+1} = \mathbf{CF}^y \cdot (1 + r) + \theta_{\mathbf{acfc}}^y \cdot \mathbf{ATR}^y \quad (15)$$

where CF is the total amount of money in the contingency fund, ATR is the annual total revenue, and r is the fund's interest rate. Contingency funds work as a utility's savings account for protection against financial instabilities that can arise from multiple causes.

Utilities are expected to contribute annually to their own contingency funds with a percentage of the annual revenue. Although a contingency fund can be set large enough to attempt to provide financial protection against any drought or sequence of droughts, large funds would require high annual contributions resulting in opportunity costs relative to more efficient financial management strategies. Moreover, large contingency funds could be appropriated by municipal governments for other purposes. The annual contingency fund contribution is the percentage of annual revenue a utility should deposit in its contingency fund.

Objectives

1. *Reliability*: The reliability objective is an approximation of the system reliability calculated as the fraction of considered states of the world which may cause the storage level of any reservoir used by a given utility to drop below 20% of its maximum capacity in any given week (failure condition):

$$\text{maximize } f_{REL} = \min_j \left[\min_y \left(\frac{1}{N_r} \sum_{i=1}^{N_r} g_{i,j}^y \right) \right] \quad (16)$$

where,

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

where $g_{i,j,y} = 0$ if there was a week in a given year of a particular realization where reservoir storage falls below S_c of capacity (20% in this study), and 1 otherwise, N_r is the number of realizations in one function evaluation, y is the simulation year, N_{ys} is the number of years in the project horizon, i is the simulation realization index, and j is the utility index. Although the term reliability generally denotes a probability, this is not the case for f_{REL} , as the inclusion of the deep uncertainty factors in the calculation makes the SOWs not equally likely and not guaranteed to exhaust all possible future scenarios. However, f_{REL} can be used as a proxy for reliability

for decision making purposes as a way of assessing how a utility can rely on each alternative relative to each other, given the uncertainty space defined by the utilities. Therefore, f_{REL} will be further referred to in this work as reliability for the sake of readability.

2. *Restriction Frequency*: Restriction frequency represents the fraction of years over the course of the planning horizon for which at least one week of restricted water use is expected:

$$\text{minimize } f_{RF} = \max_j \left[\frac{1}{N_{ys} \cdot N_r} \sum_{i=1}^{N_r} \sum_{y=1}^{N_{ys}} h_{i,j}^y \right] \quad (17)$$

where,

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

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

3. *Drought Management Cost*: The average cost objective represents the expected yearly cost of all noninfrastructure water portfolio assets used to manage droughts over the planning horizon. These costs are revenue losses from restrictions, transfer costs, contingency fund contributions, and third party insurance contract costs:

$$\text{minimize } f_{AC} = \max_j \left[\frac{1}{N_{ys} \cdot N_r} \sum_{i=1}^{N_r} \sum_{y=1}^{N_{ys}} SYC_{i,j}^y \right] \quad (18)$$

where,

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

where CFC is the one time contribution to a contingency fund in a given year y , IP is the insurance contract cost, RL is the revenue losses from water use restrictions,

TC is the transfer costs, $YIPO$ is the total insurance payout over year y , CF is the available contingency funds, and ATR is the total annual volumetric revenue. All these variables are dollar values.

4. *Exposure to Financial Risk (worse case cost)*: The worse case cost objective represents the 1% highest single-year drought management costs observed across all analyzed SOWs over the planning horizon:

$$\text{minimize } f_{WCC} = \max_j \left\{ \text{quantile}(SYC_{i,j}, 0.99) \right\}_{i \in N_r} \quad (19)$$

5. *Jordan Lake allocation*: The Jordan Lake allocation objective represents the allocation of the Jordan Lake water municipal supply pool to be granted to a utility, such that:

$$\text{minimize } f_{JLA} = \sum_{j=1}^{N_u} JLA_j \quad (20)$$

where JLA is the percent of the pool allocated to utility j , and N_u is the total number of utilities in the system.

The regional water supply portfolio problem formulated in equations 1 - 20 represents a challenging multi-jurisdictional planning problem, given its number of stakeholders and objectives, and its stochastic and non-linear nature. The transition to searching for appropriate decision triggers that effectively use a balanced portfolio of conservation, transfers, and financial risk measures has broad value beyond the Research Triangle region. Section 2.1 describes our extensions of the multi-stakeholder MORDM framework in more detail.

4 COMPUTATIONAL EXPERIMENT

4.1 Multiobjective Optimization Algorithm

As benchmarked in Reed et al. (2013), the Borg MOEA (Hadka et al., 2013) has been shown to provide competitive or superior performance relative to other top performing MOEAs in multiple test and more realistic problems. The Borg MOEA combines ϵ -dominance

based archiving (Laumanns et al., 2002) with an adaptive operator selection (Vrugt and Robinson, 2007) based on probabilities calculated from solutions in its archive (Hadka et al., 2013), making it suitable across a wide range of problems. The standard values of parameters of the Borg MOEA v1.4 Master-Slave were used in this work (see Hadka et al. 2013 for the specific values).

4.2 Hydrologic Scenarios and DU Optimization Runs

The number of Monte Carlo realizations used to estimate the objective functions' evaluations was 1,000 — empirical assessments with ensemble sizes varying from 100 to 5,000 showed that 1,000 evaluations per run is sufficient for approximating the mean and variances of the Monte Carlo distributions used for computing candidate solutions' objectives. This approach for determining sampling rates originates from early studies of metaheuristic search dynamics given a single noisy objective function (e.g., Miller and Goldberg 1996; Smalley et al. 2000), where it was shown that relatively small Monte Carlo samples per function evaluation can provide good approximations when verified with much larger verification samples post search. These early results were translated to multi-objective evolutionary algorithms in subsequent studies (see Goh and Tan 2007; Singh and Minsker 2008; Kasprzyk et al. 2012; and Reed et al. 2013), which empirically test a step-wise increase in Monte Carlo sampling rates per function evaluation with subsequent verification tests with much larger samples. The deeply uncertain factors were sampled using the Latin Hypercube Sampling technique, based on the ranges presented in Table 1.

The synthetic reservoir inflows were created using the method described in detail in Kirsch et al. (2013) and Herman et al. (2016), which approximates auto and multisite correlation by means of Cholesky decomposition and bootstrap resampling, respectively. The synthetic streamflows generation process begins by creating a matrix of standard normal weekly inflows $\mathbf{Z}_{\mathbf{k}} \in \mathbb{R}^{80 \times 52}$ from the log-normal historical weekly recorded inflows matrix $\mathbf{Q}_{\mathbf{k}} \in \mathbb{R}^{80 \times 52}$ at each gauge k , which contains the 52 weeks long inflows time series recorded for each of the 80 years in record (1933-2013). Then 52 vectors $\mathbf{T}^{\mathbf{w}} \in \mathbb{I}^{1,000 \times 1}$ containing 1,000 bootstrap

samples of the 80 years for which streamflow data is available $(1, 2, \dots, 80)$ are created. In order to approximately preserve the spatial correlation, vectors $\mathbf{T}^w$ are used to create a matrix $\mathbf{C}_k \in \mathbb{R}^{1,000 \times 52}$ for each site, in which column w corresponds to the inflows record for week w in years $\mathbf{T}^w$. Cholesky decomposition is then used to find an upper triangular matrix $\mathbf{U}_k \in \mathbb{R}^{52 \times 52}$ such that $\text{corr}(\mathbf{Z}_k) = \mathbf{U}_k^T \mathbf{U}_k$. Finally, in order to preserve autocorrelation, the matrix of synthetic streamflows for gauge k is calculated by performing the operation $\mathbf{S}_k = \mathbf{C}_k \cdot \mathbf{U}_k$ and transforming $\mathbf{S}_k$ back into real-space. In order to improve interyear correlations for the resulting synthetic streamflows of arbitrary length, Kirsch et al. (2013) repeat this process for matrix $\mathbf{Q}'_k$, a shifted version of $\mathbf{Q}_k$ beginning in week 27 of the year and ending at week 26 of the following year, to create $\mathbf{U}'_k$, while $\mathbf{C}'_k$ is created by separately shifting $\mathbf{C}_k$ to ensure continuity between $\mathbf{S}'_k$ and $\mathbf{S}_k$. The final set of streamflows is comprised of columns 27-52 of $\mathbf{S}_k$ and weeks 1-26 of $\mathbf{S}'_k$.

Running 1,000 realizations per function evaluation, however, significantly increases computational burden, which in turn set a requirement for higher computing capacity. The optimization was performed on the Texas Advanced Computing Center's Stampede, where 25 random seed Borg MOEA trial runs each performed a total of 1,000,000 function evaluations while exploiting 2,000 cores (AMD Opteron Quad-Core processors @ 2.3 GHz). The Pareto approximate fronts of all seeds were then combined to form a best known approximation of the global Pareto front (i.e., the reference Pareto set). Table 3 shows the values of ϵ (i.e., significant precisions) used for the optimization and for reference set generation, which are the same as in Zeff et al. (2014).

TABLE 3. Values used for ϵ -dominance.

Objective	Reliability	Restriction Frequency	Jordan Lake Allocation	Average Cost	Worse Case Cost
ϵ	0.005	0.02	0.002	0.05	0.01

5 RESULTS AND DISCUSSION

5.1 Optimization under Deep Uncertainties

A key motivation of this study is to use the search phase of the MORDM framework to identify more robust water portfolios for the Research Triangle region. The DU optimization scheme illustrated in Figure 2b was formulated to approximately sample the more complex DU re-evaluation space shown in Figure 1. As discussed in Section 2.3, it would not be computationally tractable to use the DU re-evaluation scheme within the optimization itself. Figure 4 shows a comparative verification of the tradeoffs attained by the WCU and DU optimization alternatives by showing their average performance across the 10 million SOWs that define the DU re-evaluation space.

In Figure 4, the points where each line (water portfolio alternative) intersects the vertical axes represents the average performance in each objective in the DU re-evaluation space. The plot is oriented such that the ideal alternative would be a horizontal line at the bottom of all of the axes. When comparing alternatives, a downward shift along the axes represents the direction of higher preference and diagonal lines capture pairwise objective tradeoffs. The ranges of the averaged objective values as well as their relative tradeoffs highlight the adaptivity of ROF-based transfers and restrictions in combination with the financial risk instruments in still attaining high levels of average performance despite the increased difficulty of the DU optimization’s formulation. The most striking feature of Figure 4 is the increased use of Jordan Lake allocations, which indicates that the Research Triangle region’s water utilities could face strong contention for this resource.

Figure 4 also illustrates which of the high performing DU optimization alternatives have high levels of performance on average when evaluated against the 10 million SOWs within the DU re-evaluation. In Figure 4, all alternatives whose values failed on average to meet the performance criteria established by the utilities — to attain at least 98.5% average reliability, average restriction frequencies no greater than 20% and average worst case costs no greater than 5% — were filtered out (transparent polylines). The reliability criteria set by the Research Triangle utilities was relaxed by 0.5% from the original 99% because none of

FIG. 4. Average performance objective values for WCU and DU optimization alternatives over the 10 million SOWs from DU re-evaluation. The vertical axes denote average performance in each objective and each polyline represents an alternative. Brown tones represent alternatives from WCU optimization and blue tones represent alternatives from DU optimization. Transparency is applied to alternatives that do not meet a relaxed version of the performance criteria established by the studied utilities: Reliability $> 98.5\%$ (relaxed from 99%), Restriction Frequency $< 20\%$, and Worst-Case Cost $< 5\%$). The color gradient is based on the restriction frequency objective (light for low frequency, dark otherwise, not applicable to highlighted solutions). None of the brown (WCU) alternatives meet the criteria, while 7 out of 2,954 DU solutions do.

the solutions from either the DU or the WCU optimization runs met this criterion without violating the restriction frequency and worse case cost criteria when evaluated against the broader ensemble of 10 million SOWs. Confirming the robustness assessment results in Herman et al. (2014), the alternatives from WCU optimization significantly deteriorated in their worse case costs, reliability and restriction frequencies; therefore all of the re-evaluated brown WCU solutions were filtered in Figure 4 (i.e., shown with a high level of transparency) — the re-evaluated averages for the reliability and worse case cost criteria would have to be relaxed to 95% and 25% respectively for any solutions from WCU optimization to avoid being brushed from Figure 4. The simplified but more comprehensive sampling of uncertainties used in the DU optimization proved to be helpful for generalizing to the DU re-evaluation space.

5.2 Robustness Comparison

Transitioning from the performance tradeoffs to satisficing frequencies, Figure 5 illustrates the significant differences in the robustness of the supply portfolios obtained with the WCU (brown) and DU (blue) optimization runs based on their calculated objectives values for each of the 10,000 samples of Ψ (deeply uncertain factors in Table 1). In this figure, the alternatives from both optimization schemes are rank-ordered (horizontal-axis) based on their robustness (vertical-axis). Figure 5 defined robustness as the percentage of the 10,000 Ψ samples where an alternative was able to meet all of the utilities' requirements as calculated with equations 16-20 for all 1,000 synthetically generated sets of natural inflows. The results show that DU optimization provides far more candidate solutions that are also significantly more robust. Both traits make it more likely that robust satisfactory compromise solutions can be found. However, it cannot be inferred from these results that DU optimization will always lead to more solutions, as the presented results may reflect particular characteristics of this problem's specific decision space.

The use of DU optimization improved the maximum attainable robustness, as calculated by the model, of all utilities but OWASA, who was already able to attain nearly 100% maximum attainable robustness in a majority of the WCU optimization solutions. Figure 5 shows that Cary, who had maximum attainable robustness of 86% for the WCU solutions reached 100% with the DU optimization's results. Likewise, Durham's maximum robustness went from 39% to 85%, and Raleigh's went from 18% to 59%. Although Durham's and Raleigh's robustness may not be as high as desired, their improvement from the DU optimization is substantial. It is important to notice that Figure 4 shows that such improvements in robustness comes at the expense of average expected performance, notably in average costs and Jordan Lake allocation — the transparent blue lines show consistently higher values for these two objectives than the transparent brown lines.

As noted by Herman et al. (2014), beyond their individual levels of attained robustness, it also important to understand and mitigate potential robustness conflicts where one of

FIG. 5. Alternatives (x-axis) were rank-ordered according to robustness (y-axis) delivered to each utility. An alternative's robustness was defined as the percentage of the DU re-evaluation's 10,000 Ψ samples where an alternative meets the original robustness criteria elicited from water utilities. The brown bars represent the robustness of the original 84 WCU optimization's alternatives, while the blue bars represent the robustness of all 2,954 DU optimization's alternatives. Each group of bars is rank ordered by robustness.

the utilities strongly benefits by degrading one or more of the others. Figure 6 shows the robustness tradeoffs among all the utilities for the DU optimization alternatives. The ideal solution would be a horizontal line at 100% robustness for all of the utilities. The gray lines are all the solutions from the DU optimization run, while the blue and brown represent illustrative compromise solutions from the DU and WCU optimization runs, respectively, attained by filtering out solutions of high robustness sacrifice for any of the utilities. The gray diagonal crossing lines and color gradient for the DU optimization results suggest that increases in Raleigh's and Durham's robustness are often at the expense of Cary's, due to the amount of transfers that are being demanded. The brown line representing the candidate

compromise alternative from the WCU optimization solutions shows low attainable system robustness, which confirms the value of DU optimization.

FIG. 6. Robustness tradeoffs among utilities. Each polyline represents an alternative, while the location where a polyline intersects an axes denotes the robustness value of the corresponding alternative for the corresponding utility. The blue lines indicate four illustrative compromise DU alternatives with fairly high robustness for all utilities, the brown line indicates the best compromise WCU alternative from prior work by Herman et al. (2014), while the gray lines represent the remaining DU alternatives.

Figure 6 highlights four compromise alternatives from the DU optimization results that were able to maintain the utilities' robustness levels close to their maximum attained values. The DU optimization effectively exploited the flexibility of the ROF-based transfers and financial instruments under high uncertainty to identify compromise portfolios that strongly reduce regional robustness conflicts. This shows that a more comprehensive approach to uncertainty in the search phase has the potential to not only yield more robust alternatives, but also to decrease regional inter-utility conflicts during negotiations.

Figure 7 shows the decision variables for each utility for the four compromise alternatives. According to the figure, under a compromise scenario, Durham and Raleigh (panels a and c) have low restriction and transfer trigger values, which means they would often make use of these two instruments. In order to compensate for the financial losses due to restrictions and transfers, both utilities would have to rely on substantial contingency funds and possibly on

third party insurances even for mild droughts.

FIG. 7. Decision variables of the 4 compromise solutions for each utility. Different colors represent the different alternatives, and correspond to the ones in Figure 6. The "y" axis represent a scale from low use to high use.

Being a small utility in comparison with the others, OWASA (Figure 7d) is in a more comfortable position, not needing to rely often on restrictions or transfers. As a whole, OWASA seems to be largely insensitive to any of the instruments, as it performs well in most of the tested states of the world. However, due to its small budget and size, a more severe drought poses significant financial risk, which makes it have to rely on relatively low insurances trigger values.

Cary (Figure 7b) would require a significant Jordan Lake allocation to meet its demand because it relies on Jordan Lake as its primary water source. However, being the source of all transfers increases Cary's revenue — Durham and OWASA have allocations from Jordan Lake but have to pay a fee to Cary to use them, given Cary owns the Jordan Lake intake and treatment plant. This would put Cary in a relatively safe position against mild droughts, not strongly needing to set up a large contingency fund — which is mainly an instrument to mitigate financial impacts of mild droughts — or insurances that would be triggered often. However, Cary may not have enough revenue from water transfers in exceptionally dry years, given its water sales can be no greater than the allocations possessed by Durham and OWASA, making it have to rely on contingency funds as a complement to the insurance payouts. Under such scenario, the tradeoffs observed in Figure 6 between Raleigh and

Durham would be more noticeable, given their low transfers trigger values and resulting in possible competition for transfers from Cary, which are limited by conveyance capacities. From these results, it is clear that an increased Falls Lake allocation would be paramount for maintaining Raleigh’s reliability and regional robustness during low frequency extreme events, since Raleigh has the highest demands and Falls Lake is its only direct supply source (see Table 1).

The addition of the deeply uncertain factors in the search phase significantly impacted the underlying decisions that would result from the robust compromise policies. Both Raleigh and Durham are shown to require a substantially greater Jordan Lake allocation relative to the results of the WCU optimization shown in Herman et al. (2014). Additionally, the low values of the transfers ROF trigger for both utilities imply that the allocations are going to be frequently used (i.e., more risk averse ROFs). However, the increased transfers do not prevent both utilities from requiring relatively frequent restrictions when compared to previous results. Increased use of transfers and restrictions also serves to increase the required annual contingency fund contributions for Raleigh and Durham. Another important difference between WCU and DU optimization results is that OWASA transitioned from a very limited to a more significant use of restrictions, transfers, and the contingency funds.

5.3 The Value of Regionally Coordinated Demand Management

Beyond assessing the robustness of the utilities, it is also important to understand the key deeply uncertain factors that control the success or failure of alternative regional water portfolios. Following prior MORDM studies (Kasprzyk et al., 2013; Herman et al., 2014), factor mapping sensitivity analysis, as described in section 2.5, was performed to identify the ranges deeply uncertain factors that were most related to system failures, and the results are shown in Figure 8. This is analogous to the scenario discovery approach as described by Bryant and Lempert (2010). A conservative approach was taken when selecting the PRIM box. Out of the over 80 boxes for each alternative, boxes with high coverage and low type II error were chosen at the expense of the density metric. The implication of this choice is that

the bars on Figure 8 emphasize the ranges of parameters where the compromise alternatives are likely to perform satisfactorily.

FIG. 8. Ranges of deeply uncertain factors which should be avoided in order to improve the robustness of each compromise solution. Demand growth (left box) and Falls Lake municipal supply allocation (right box) are the two most important sources of uncertainty for the four chosen compromise solutions. Utilities are encouraged to incorporate measures in their short-term management plan seeking to mitigate demand and be granted a greater allocation from Falls Lake.

The two deeply uncertain factors that most strongly influence the robustness of the four compromise alternatives performances highlighted in Figure 8 are regional demand growth rates and the Falls Lake municipal supply allocation. The relative importance of Falls Lake municipal supply allocation in comparison to the deeply uncertain factors other than demand growth reemphasizes the importance of new water allocations/sources for the region, which is also expressed in Figure 7 by the high Jordan Lake allocation needed for Cary to be able to provide for frequent transfer requests from Raleigh and Durham. Generally speaking, these results show that utilities should carefully consider regional demand growth rates and possibly monitor the adequacy of the Falls Lake supply as well, depending on the chosen compromise solution. It is important to notice that demand growth multiplier and Falls Lake allocation had a much stronger effect on the system's performance than any climate or inflow factor through the 2025 planning horizon.

5.4 Scenario Discovery

Figure 9 provides a more illustrative view of a representative PRIM box with a low angle well-defined boundary for success versus failure in attaining the utilities performance requirements along the demand growth vertical axis. This clear performance boundary indicates that even though demand growth is not the only influential parameter determining the acceptability of an alternative's performance under a given Ψ , it tends to be the most important one. Any further improvement in robustness for any of the compromise alternatives would then have to be accomplished by first trying to mitigate demand growth.

FIG. 9. Falls Lake Supply allocation vs. Demand growth pass/fail. A solutions performance is more impacted by variations in demand growth than in Falls Lake allocation.

Following this result, a suite of robustness evaluations was performed in order to further understand the effects of changing the demand growth. Figure 10 shows the robustness results of robustness evaluations for new LHSs with the demand growth multiplier factor varying from 0.5 to 0.8, 1.0, 1.2, 1.4, 1.6, and 2.0 (results for 1.8 were similar to 2.0). The 0.8 multiplier represents a 20% reduction of the Research Triangle's demand growth rates relative to their assumed nominal value (i.e., the 1.0 multiplier). From a policy perspective, this would require that the utilities coordinate demand growth reductions from approximately 3%

690 through 2025 to approximately 2.4% (0.8·3%) instead. As seen in Figure 10, demand growth
691 management would be an effective means of mitigating droughts under various tested SOWs.
692 Under scenarios of highly controlled demand growth, Cary, OWASA, and Durham could
693 attain 100% robustness across several water portfolio options. In several of the candidate
694 portfolios Raleigh’s robustness exceeds 80%, which represents a drastic gain compared to
695 allowing the demand to grow twice as much as the projected increase.

696 This work, as well as the prior motivating study (Herman et al., 2014) highlight the
697 value of the water utilities monitoring and innovating their demand management schemes.
698 A key contribution of this study relative to prior work is that the proposed DU optimization
699 facilitated the discovery far more water portfolios with improved robustness. Our results
700 highlight that a high level of adaptivity exists even when the system is confronted with the
701 most challenging SOWs. A more detailed understanding of candidate demand management
702 schemes holds significant value for future research. Cooperative water transfers, financial risk
703 mitigation tools, and coordinated regional demand management must be explored jointly to
704 decrease robustness conflicts between the utilities. The insights from this work have general
705 merit for regions where adjacent municipalities can benefit from cooperative regional water
706 portfolio planning.

FIG. 10. Robustness improvement due to demand growth control. Demand growth management may lead to a robustness gain of up 30% for the four utilities studied here. Cary, Durham and OWASA have the potential to reach 100% calculated robustness, while Raleigh may reach over 90%.

6 DISCUSSION

While prior studies (e.g., Kwakkel et al. 2015, 2016a; Kasprzyk and Watson 2014) have also advocated for including deep uncertainties into the search for robust management actions, the core of the computational contributions in this work lie in the dynamic and adaptive nature of our ROF-triggered water supply portfolio instruments. Our DU optimization is seeking better risk-based management rules for the Research Triangle’s interdependent regional actors. Each of the utilities is balancing supply reliability focused actions (i.e., transfers and restrictions) with their intrinsic financial risks (i.e., extreme tail costs). The combined use of ROF decision triggers and financial hedging is critical for DU optimization to realize its full value. In contrast, commonly employed average cost water supply formulations that focus on searching a space of non-adaptive decisions (e.g., see recent examples in Beh et al. 2015; Borgomeo et al. 2016; Huskova et al. 2016) are strongly limited in their

ability to respond to challenging combinations of deeply uncertain factors. More specifically, as formulated in equations 8 and 9, ROF is actually a dynamic representation of each utility’s evolving capacity to meet their demand. Each utility’s dynamic ROF state is subject to its ROF decision thresholds, the conditions of the specific SOW sampled, and the choices of the neighboring utilities. A key distinguishing feature of this portfolio formulation is that every sampled SOW yields a different suite of tailored actions taken in each management period subject to the ROF triggers that compose a given candidate solution. Akin to the concept of a closed loop feedback, each observed ROF state has a state-dependent action triggered. Put simply, this represents acting according to the world you are presently observing. In contrast, the more typical abstraction of drought decisions in the water supply literature (see literature in Beh et al. 2015; Borgomeo et al. 2016; Huskova et al. 2016) is for each candidate solution to implement the same fixed set of actions in every sampled SOW and evaluate their expected performance measures (i.e., taking actions based on the average performance measures over possible future worlds). This difference is critical to the success of the DU optimization extension demonstrated in this study. For each candidate DU optimization solution, its ROF triggers yield water portfolio actions that are specific to the conditions observed in each sampled SOW. Consequently, a much higher degree of adaptivity and enhanced exploitation of information feedbacks are employed when the DU optimization confronts challenging SOWs. Moreover, robustness in this study requires the financial risk instruments to successfully mitigate extreme tail costs, making higher levels of restrictions and water transfers financially tenable in the most challenging SOWs encountered in the DU optimization (see Figures 4-6).

Successfully balancing robustness and regret is another potentially more subtle computational contribution in our transition from the WCU optimization to the DU optimization. In both cases, the same risk-based action rules were searched but the resulting action triggers are very different. Challenging SOWs in the DU optimization stressed the ROF-based rules to more fully exploit their potential adaptivity and yielded an strong increase in the num-

ber, diversity, and robustness of candidate solutions (see Figure 5). However, our results also highlight that increasing the robustness of individual Research Triangle utilities frequently increased the potential for regional resource conflicts (see Figure 6). If not properly understood and managed, these increased resource conflicts represent a significant unintended regret that emerges from the DU optimization. As highlighted by Giuliani and Castelletti (2016), robustness focused formulations abstract very high levels of risk aversion by designing for severe SOWs. Consequently, they can be mathematically prone to high levels of regret if solutions are not sufficiently adaptive to take advantage of less severe SOWs. Our results aid in better balancing these types of robustness and regret concerns. Although our most robust solutions are capable to confronting severe SOWs, their underlying ROF-based decision triggers would take actions relative to the world observed. Moreover, our scenario discovery shows that if the Research Triangle’s utilities are willing to coordinate in modestly reducing their demand growth rates by 20%, their collective robustness increases dramatically while reducing large, potentially contentious Jordan Lake allocation requests.

Beyond the Research Triangle, our results have implications for rapidly growing urban regions that are now confronting increasing water scarcity concerns. Planning by nearly all water utilities at present, still relies solely on historical streamflow records, although it is common knowledge that even long streamflow records are poor representations of extreme drought quantiles (e.g., Fiering and Jackson 1971; Lettenmaier and Burges 1978; Potter 1976; Stedinger and Taylor 1982). Shifting from planning based solely on the historical streamflow to synthetic hydrology while also actively accounting for the diversity of factors included in our DU optimization holds significant promise as a means of improving the robustness of regional water supplies. That being said, this recommendation also highlights a rapidly growing gulf between emerging capabilities and the traditional planning frameworks that are currently commonly employed. This study also highlights that high density urban regions with multiple water supply utilities can and likely must carefully combine of highly adaptive reliability-driven actions that are supplemented with careful financial hedging. DU

optimization was critical for discovering a soft path (Gleick, 2002) mixture of conservation, transfers, and financial hedging in this study that could successfully overcome very severe combinations of stressors. This result has broad value for urban systems around the globe confronting climate change, rapid population growth, economic expansion, and limits on new source development.

7 CONCLUSIONS

This study contributes computational advances for a multi-stakeholder variant of the MORDM framework demonstrating how to include deep uncertainties in the generation of candidate policies to improve robustness and reduce regional robustness conflicts. In the water resources context, this work contributes a clear demonstration of the value of integrated regional water supply portfolio planning for mitigating drought risks, particularly for densely populated municipalities that are in close proximity to one another. The Research Triangle test case demonstrates that significant potential drought risks and inter-utility supply conflicts exist between utilities in the planning period of analysis from 2015 to 2025. This region currently encompasses more than 2 million users and trends of very rapid population growth.

This study highlights the need for flexible and scalable modeling frameworks to simulate the broad array of candidate management actions and uncertain stressors in coupled human-natural systems. The contributions of this work extend beyond computational algorithms. The Research Triangle management model that is core to this work requires detailed human system data (reservoir rules, finances, demands, rules for restriction, conditions for transfer, pricing, etc.) as well as natural system data (multiple ensembles of streamflows, evaporation, etc.). Having sufficient abstractions of the human systems strongly constrains the scope of candidate management actions (i.e., transfers, restrictions, and financial instruments) that can be simulated and explored under deep uncertainty. In terms of a broader guidance for future studies, densely populated urban regions with multiple utilities must be carefully abstracted as coupled human-natural systems. A multitude of factors fundamentally shape

the degree to which droughts impact water supplies (e.g., magnitude and duration of rainfall deficits, coordination of crisis management, water treatment and conveyance capacities, population growth, financial stability, infrastructure maintenance, etc.). These interdependent factors yield complex dynamically evolving risks. Moreover, the overall systems behavioral responses to these evolving risks are strongly shaped by asymmetries in regional impacts, highly diverse regional priorities, and conflicting stakeholder preferences. The DU optimization extensions of the MORDM framework contributed in this study act in combination with ROF-based decision triggers to provide a broad ability to explore the coupled humannatural systems dynamics of the Research Triangle. More generally, this work demonstrates that understanding urban water systems management tradeoffs, vulnerabilities, and dependencies requires modeling and analysis frameworks that are capable of capturing dynamic stocks and flows of risk itself.

The inclusion of deep uncertainties in the search phase of the MORDM framework made it possible to both discover a much more diverse range of drought mitigation actions that the municipalities could take while also improving their overall robustness. Robustness in this work is defined in collaboration with regional stakeholders and encompasses requirements for supply reliability, the frequency of demand restrictions, and the stability of financial risks. Across all of these concerns, our results show that regional demand growth rates dominate all other factors in controlling the robustness of alternative portfolios of drought mitigation actions. In combination, this study’s improved search under deep uncertainty and coordinating regional demand management helps to eliminate many key tradeoffs and potential inter-utility conflicts. Future work should consider innovative strategies for coordinating individual and regional demand growth rates. In terms of the broader global water resources field, insights from this work have general merit for regions where adjacent municipalities can introduce cooperative regional water portfolios.

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