Environmental Modelling & Software 89 (2017) 159–171

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Incorporating deeply uncertain factors into the many objective search process

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ARTICLE INFO

Article history:
Received 18 May 2016
Received in revised form
1 December 2016
Accepted 2 December 2016
Available online 4 January 2017

Keywords:
Multi-objective optimization
Robust decision making
Scenario analysis
Robust optimization
Water resources planning and management
Water markets

ABSTRACT

This paper proposes an approach for including deeply uncertain factors directly into a multi-objective search procedure, to aid in incorporating divergent quantitative scenarios within the model-based decision support process. Specifically, we extend Many Objective Robust Decision Making (MORDM), a framework for finding and evaluating planning solutions under multiple objectives, to include techniques from robust optimization. Traditional MORDM first optimized a problem under a baseline scenario, then evaluated candidate solutions under an ensemble of uncertain conditions, and finally discovered scenarios under which solutions are vulnerable. In this analysis, we perform multiple multi-objective search trials that directly incorporate these discovered scenarios within the search. Through the analysis, we have created multiple problem formulations to show how methodological choices of severe scenarios affect the resulting candidate planning solutions. We demonstrate the approach through a water planning portfolio example in the Lower Rio Grande Valley of Texas.

1. Introduction

Climate change, land use change, and other anthropogenic effects increase the variability of streamflow (Jain et al., 2005; Seager and Vecchi, 2010) and threaten water security (Gober, 2013; Vorosmarty et al., 2000). Population growth and urbanization can exacerbate potential water shortages (Feldman, 2009). Especially in river basins that straddle political boundaries, water shortages can strain political relationships between political actors (Wildman and Forde, 2012).

The hydrological and socioeconomic variables that define these phenomena can be considered deeply uncertain (Knight, 1921; Walker et al., 2013). Under deep uncertainty decision makers and stakeholders cannot agree on the full set of risks and consequences and the probability of their occurrence (Langlois and Cosgel, 1993). Scenario analysis (Arnell et al., 2004; Farber et al., 2008; Mahmoud et al., 2009) is one method for coping with this situation, where a group of experts define plausible storylines of the values of key uncertainties in a problem before the decision making process begins. However, specifying scenarios before performing modeling exercises lacks the ability to determine which scenarios are the most important ones for causing system vulnerabilities. To this end, a set of bottom-up decision making frameworks (as reviewed in Dittrich et al., 2016; Giuliani and Castelletti, 2016; Herman et al., 2015; Kwakkel et al., 2016) have focused on using simulation model runs to identify potentially severe scenarios based on the modeled performance metrics. The goal is to create and evaluate solutions that exhibit robustness. A robust solution is one in which the solutions' performance is insensitive to variations in the estimation of parameters that control the calculation of that performance (Herman et al., 2015; Matalas and Fiering, 1977). In other words, bottom-up frameworks test multiple assumptions about uncertain problem properties and subject planning alternatives to interesting combinations of various factors.

Herman et al. (2015) characterize bottom-up frameworks with four methodological choices: (i) how are alternatives identified or generated; (ii) how are different states of the world sampled; (iii) how are robustness measures calculated; and (iv) how are key uncertainties identified using sensitivity analysis or factor mapping (e.g., the Patient Rule Induction Method, PRIM (Friedman and Fisher, 1999)). This paper is focused on the first methodological choice of Herman et al.'s bottom-up taxonomy: how planning alternatives are generated. Mathematical conditions such as the nonseparability of decision alternatives and noise in the objective function can pose challenges to such generation techniques.

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http://dx.doi.org/10.1016/j.envsoft.2016.12.001
1364-8152/

Multiobjective Evolutionary Algorithms (MOEAs) are a search technique which has been increasingly employed to overcome these challenges (Maier et al., 2014; Reed et al., 2013). MOEA decision support uses a detailed simulation model of a system to characterize performance of solution alternatives, facilitating a realistic depiction of the solutions' performance. Beyond simply suggesting preferred alternatives, MOEAs can aid in analysts and stakeholders' understanding of a decision problem (Piscopo et al., 2015) by generating tradeoff sets that show compromises among the objectives. These tradeoff sets are defined by Pareto optimality. Solutions are Pareto optimal if their performance is not exceeded in any objective by another feasible solution (i.e., for a cost-reliability optimization problem, the optimal tradeoff is the set of least possible costs at every level of reliability). Although MOEAs are effective at generating alternatives, the proper usage of scenario information and uncertainty within MOEA search is still an open question.

A set of approaches broadly classified as robust optimization (RO) has sought to incorporate uncertainty information into optimization (Beyer and Sendhoff, 2007; Deb and Gupta, 2006; Hamarat et al., 2014; McInerney et al., 2012; Mortazavi-Naeini et al., 2015; Mulvey et al., 1995; Ray et al., 2014; Watkins Jr. and McKinney, 1997). Notably, Hamarat et al. (2014) uses an MOEA and incorporates uncertainty into the MOEA search process. In that study, a specific robustness objective function was created in order to optimize trigger points, which define when to enact changes to a base policy under changing future conditions. One potential limitation of such approaches is that it is difficult to combine robustness with respect to multiple objectives into a single objective function. Therefore, this paper will explore how to explore robustness across multiple objectives simultaneously, building on an existing framework termed Many Objective Robust Decision Making (MORDM, Kasprzyk et al., 2013).

MORDM is a bottom-up decision making framework that combines MOEAs with techniques from robust decision making (Lempert et al., 2006). The non-dominated set from MOEA search is subjected to ensembles of randomly generated values of uncertain factors (e.g., different scaling factors on hydrologic inflows or water demands). A set of calculations shows how the solutions' performance changes under this ensemble of uncertain conditions. Solutions that have low deviations in objective function performance in the ensemble are considered robust, and visualizations of robustness metrics are used to guide the choice of one or more candidate solutions. The final step uses statistical data mining techniques to discover the most important uncertain factors that cause the candidate solutions to perform poorly within the uncertainty ensemble.

In the previous applications of MORDM, authors performed the optimization using a single realization of input data termed the baseline scenario: default values of the input parameters and the input data exhibiting historical distributions. One potential limitation of this approach is that the set of decision variables comprising each solution are only “trained” to the historical data and may not be adaptable if the data fundamentally changes (Ignizio, 1998; Zeleny, 2005). Therefore, this paper incorporates multiple combinations of uncertain factors into the MOEA search process itself, with an approach inspired by RO literature.

Specifically, our approach chooses multiple discovered scenarios from the MORDM sensitivity analysis and then performs the optimization under each scenario. The goal is to develop more diverse sets of decision variables that have better objective function performance under extreme conditions. Our methodology seeks to generate a policy that will hold up to many uncertainties without future adjustments by re-evaluating the resulting solution sets under multiple scenarios, using visual analytic techniques (Woodruff et al., 2013) to explore the model results. Importantly, our approach replicates the runs with different assumptions about the properties of the included scenarios, which allows an analyst to interrogate the effect of these chosen scenarios on the optimized results. The ultimate goal is to develop policies that perform well under a wide range of plausible futures by exposing some of those futures directly within the optimization process. A case study of water planning within the Lower Rio Grande Valley (LRGV) of Texas is used to demonstrate the approach in order to best capitalize on previous MORDM work that has utilized this example.

2. Methods

2.1. Multi-objective evolutionary algorithms

MOEAs are heuristic search algorithms that mimic evolutionary processes to approximate the optimal tradeoff set of solutions to multi-objective optimization problems (Coello et al., 2007). Recall that a MOEA's tradeoff set is defined using the concept of Pareto optimality; a solution is Pareto-optimal if no other feasible solution exhibits improvement in an objective without sacrificing performance in another objective. For non-trivial problems, MOEAs can only approximate the true Pareto-optimal set, so the sets are often termed the non-dominated set or the Pareto-approximate set. By linking to a simulation model, the algorithms use realistic depictions of the modeled processes and can optimize based on meaningful objective functions. MOEAs are gaining prominence in the water resources community, both within real water planning activities within water utilities (Asefa, 2015; Basdekas, 2014) and in research applications, as reviewed in Nicklow et al. (2010) and Maier et al. (2014).

This study employs the Borg MOEA (Hadka and Reed, 2013) to generate alternatives. The Borg MOEA is a search framework that adapts its use of seven different variation operators (simulated binary crossover, differential evolution, parent-centric recombination, unimodal normal distribution crossover, simplex crossover, polynomial mutation, and uniform mutation) based on problem properties. The algorithm also features epsilon-dominance, which uses a user-defined epsilon grid to control the precision of each objective as well as maintains an epsilon-dominance archive of the best solutions in the search (Laumanns, 2002). Additionally, adaptive population sizing adapts the search population size to provide more diverse solutions to explore as the search continues. The Borg MOEA was chosen due to its favorable performance on the LRGV problem in diagnostic analyses (Kasprzyk et al., 2016; Reed et al., 2013), and the algorithm was also successfully applied to the LRGV problem using thousands of parallel processors (Reed and Hadka, 2014). Note that the methods presented in this study are not specific to the particular Borg MOEA, and researchers can use other modern MOEAs to explore similar concepts.

2.2. Many objective robust decision making

The many objective robust decision making framework (MORDM) is a planning framework for complex environmental systems that integrates MOEA optimization with the RDM framework to optimize and select planning strategies under conditions of deep uncertainty. MORDM has been applied to a multi-reservoir system with several different actors coordinating among each other (Herman et al., 2014), for water quality management (Singh et al., 2015), and to the LRGV (Kasprzyk et al., 2013), the example which will be used in the current study. In the remainder of the paper, XLRM terminology (Lempert et al., 2006) will be used to define the MORDM components. Uncertainties (X) are exogenous factors beyond the decision maker's control; they are typically represented by assumed values or factors that control probability distributions. Decision levers (L) are actions the decision maker can take to interact with the system and potentially change its performance. The relationship (R) maps actions to outcomes; typically, the relationship is equivalent to the run of a quantitative simulation model. Performance metrics (M) are quantitative values used to measure the success of different planning strategies (objectives and constraints within optimization).

MORDM comprises the following steps[1]: (1) problem formulation, (2) generating alternatives, (3) uncertainty analysis, and (4) scenario discovery to illuminate vulnerabilities. These steps are briefly described below.

1 The problem formulation step is carried out in conjunction with the decision maker and stakeholders to determine what system elements and decisions are important (i.e., XLRM components).
2 The MOEA uses this problem formulation to generate a set of alternative solutions. Each solution is defined by values for its decision levers, a set of performance metric values, and additional information that can be obtained by running the problem's simulation model. The result of this MOEA optimization is a Pareto-approximate set, which represents a suite of different solutions from which a decision maker could choose.
3 Uncertainty analysis is performed to expose the solution set to a range of plausible values for variables that represent deep uncertainties (e.g., scaling of inflows, population growth rates). Latin Hypercube Sampling (LHS, McKay et al., 1979) is used to sample the variables within specified ranges to generate an ensemble of plausible States of the World (SOWs). Each solution is run under the entire ensemble of SOWs. One or more candidate solutions are chosen, based on a user-defined calculation of the deviation in performance between the baseline SOW and other SOW in the ensemble.
4 Scenario Discovery (SD, Bryant and Lempert, 2010) is used to determine combinations of uncertainties that cause the candidate solutions to perform poorly. To do this, the analyst first sets thresholds on the performance metrics; SOWs that exceed the thresholds are considered acceptable and SOWs that violate the thresholds are considered vulnerable. SD employs a statistical clustering analysis called the Patient Rule Induction Method (PRIM, Friedman and Fisher, 1999) to define multi-dimensional scenario boxes, or ranges of uncertainty that cause vulnerabilities.

In prior MORDM work, the MOEA optimizations always done using a baseline SOW (default values for each of input parameter and distribution). Previous MORDM authors acknowledged that decision makers may need to adapt to the discovered scenarios after step 4, but this type of adaptation has not yet been directly demonstrated. This is the aim of the current paper. In this study, we re-run MOEA optimization under multiple SOWs from SD, and evaluate the Pareto approximate sets under multiple scenarios to determine the robustness of solutions from each MOEA run. The full explanation of our new methodology is provided in Section 4 below.

[1] Although the steps are often discussed sequentially, there are feedbacks between each step, such that the steps can occur out of order. For example, the current study can be seen as the results of step (4) of the process feeding back in to steps (1) and (2).

3. Case study

3.1. Decision context for Lower Rio Grande Valley water resources

The case study for our MORDM modifications is a water resources problem in the LRGV basin in south Texas, USA. The lower portion of Rio Grande River, shared by the United States and Mexico, is the primary water source for the LRGV. Diversions are stored in the Amistad and Falcon reservoirs, with a combined storage volume of 7,154 million cubic meters (Mm^3), excluding a flood storage volume of 2,590 Mm^3 (Characklis et al., 2006). Diversions and consequent storage from the Rio Grande River provide 99% of water for all uses (Schoolmaster, 1991). Licensed water rights in Texas are akin to property rights, in which they may be sold, transferred, or leased under a specific set of rules (Kaiser, 1987; Schoolmaster, 1991). There are two surface water State licensing systems, one applying to the Lower and Middle Rio Grande below the Amistad Dam, which includes the LRGV (Fernandez et al., 2003; Wurbs, 2014) and another applying to the rest of the state.

The LRGV is an agricultural community, producing cotton and citrus fruits (Levine, 2007), and as of 1999, irrigation accounted for 85% of regional water use (Characklis et al., 1999). However, the recent growth in the urban sector has led to population growth and changes in water use (Leidner et al., 2011), including transfers in a water market among and between willing sellers in agricultural sectors and willing buyers in municipal sectors (Schoolmaster, 1991).

The specific decision context for the LRGV case study is a single hypothetical city in the LRGV that must decide how much water to allocate from multiple market-based supply instruments: rights, options, and leases. The case study is adapted from prior work (Characklis et al., 2006; Kirsch et al., 2009) and has been coupled with MOEA-based multi-objective search in a suite of subsequent papers (Kasprzyk et al., 2013, 2012, 2009; Reed and Hadka, 2014). The model serves as a screening level analysis (Walker and Veen, 1987) since the form of the supply instruments does not strictly correspond to the current market in the LRGV. Instead, the work has developed from a desire to determine if a flexible, adaptable market-based approach could work for LRGV and arid region water supply management (Characklis et al., 1999).

3.2. Simulation model and decision levers

The LRGV case study uses a Monte Carlo-based mass balance simulation model that tracks the city's water in its multiple supply accounts. The reader is encouraged to consult Kirsch et al. (2009) for the full description of the model. As shown in Table 1, the city's supply portfolio is described by eight real-valued decision lever variables: N_r, $N_{o,low}$,$N_{o,high}$ ξ, $\alpha_{Jan\text{-}Apr}$, $\beta_{Jan\text{-}Apr}$, $\alpha_{May\text{-}Dec}$, $\beta_{May\text{-}Dec}$. All water for the city and other regional users (such as irrigators) is assumed to come from a single reservoir water source. The city creates a portfolio of three different supply instruments – rights, options, and leases.

The first instrument is permanent rights (determined by the decision lever N_r), assumed to be allocated *pro rata* based on reservoir inflows, which is a departure from the typical management in the LRGV. The goal is to show that even if permanent rights are allocated in this fashion, the city can still maintain sufficient supply to meet its demands.

The other instruments are market-based: an adaptive options contract (defined by contract volumes $N_{o,low}$,$N_{o,high}$ and a supply/demand threshold used to select between the two volumes, ξ) and spot leases. These market-based instruments represent transfers of water from agricultural use and are assumed to always be available. Allocations of water to the options contract and spot leasing are controlled by two anticipatory thresholds, both compared to the ratio of the city's current supply to its expected demand. The first threshold decision lever, α, decides "when" the city purchases water. In other words, if the ratio of the city's current supply to its expected demand is lower than α, the city must purchase water using the market (either from the options contract or a spot lease). The amount of water that the city purchases is then dependent on a second threshold decision lever, β. In this study, separate values of alpha and beta are used depending on the time of the year; one set is used from May–December and another is used from January–April.

During the simulations, the model keeps track of the reservoir mass balance, which affects lease pricing and the availability of water for the city's supply. The simulation also keeps track of the city's supply account; for example, if a transfer has been allocated to the city but is not actually used within 12 months, it expires. Each simulation is carried out for two situations, both with a monthly time step: a ten-year planning horizon and a severe single year drought. The ten-year simulation is replicated for 5,000 random trials of sampled inflow, reservoir variation, and lease pricing. The drought is a deterministic 12 month simulation that combines the highest demands with the lowest inflows from the dataset (Kasprzyk et al., 2009). Output metrics are calculated using expected values and other statistical measures from this distribution of Monte Carlo trials. Section 3.4 below discusses how the uncertain factors in the MORDM framework modify these statistical samples within the LRGV model.

3.3. Performance measures

A solution's performance within the Monte Carlo simulation model can be measured by a series of performance measures, M, in the XLRM terminology (see Table 2). When the LRGV simulation is connected to MOEA search, these measures are used as indicators for judging a solution's performance. The MOEA optimization seeks to modify values of decision levers in order to improve the values of some performance measures treated as objectives, and other performance measures that are treated as constraints in the optimization. In Table 2, the Description column for the 10-year simulation describes how the calculation is performed for one Monte Carlo ensemble member. After those calculations are done, the final metric value for 10-year metrics is always taken as an expected value of all 5,000 metric values. The one exception to this is the cost variability metric, which uses a calculation based on the high tail of the distribution. For example, cost is taken as an expected value of the sum of costs in the 10-year simulation, whereas the cost variability measure uses a calculation of the high tail of the cost distribution. For the drought simulation, the metric calculations are deterministic and are calculated as described in the Table. For the full set of equations see Kasprzyk et al. (2013).

The problem formulation for MOEA optimization involves objectives (equation (1)) and constraints that must be preserved for solutions to be feasible (equations (2)–(5)). All objectives are minimized, with the exception of $f_{10\ yr\ crit\ rel}$, which is maximized. The vector **x** describes the solution (a value for each of the 8 decision levers, subject to a given upper and lower bound).

$$\mathrm{F}(\mathrm{x}) = \Big(f_{10\ yr\ cost}, f_{10\ yr\ surplus}, f_{10\ yr\ crit\ rel}, f_{10\ yr\ dropped}, f_{10\ yr\ num\ leases}, f_{dr\ trans\ cost}\Big) \quad \text{(Eq. 1)}$$

Subject to:

$$f_{10\ yr\ rel} \geq 0.98 \quad \text{(Eq. 2)}$$

$$f_{10\ yr\ crit\ rel} \geq 0.99 \quad \text{(Eq. 3)}$$

$$f_{10\ yr\ cost\ var} \leq 0.98 \quad \text{(Eq. 4)}$$

$$f_{dr\ vuln} = 0 \quad \text{(Eq. 5)}$$

The inclusion of constraints in the problem formulation reduces the number of solutions and restricts solutions to meet realistic needs of a decision maker. Reliability (eq. (2)) and critical reliability (eq. (3)) constraints, however, ensure surviving solutions sufficiently meet demands for most timesteps in the analysis, similar to the drought vulnerability constraint (eq. (5)) which ensures adequate water in the drought simulation. In addition to these performance constraints, the cost variability ($c_{costvar}$) constraint guarantees that high costs at the tail of the cost distribution are not significantly greater than the average cost in a planning year of the 10 year simulation. Because of the presence of constraints, any solution within the tradeoff set can be considered to be a highly performing solution (Piscopo et al., 2015).

3.4. Factors to explore deep uncertainty

The final component of the problem formulation is a set of values that are termed deeply uncertain factors, represented by X in the XLRM terminology. There are two types of deep uncertain factors considered in the LRGV case study: (i) parameters that control probability distributions shown in Table 3(a) and (ii) scalar values shown in Table 3(b). These factors were sampled within the prior MORDM paper (Kasprzyk et al., 2013) and will be used in the optimization scenarios in this paper (see Section 4).

For factor type (i), parameters of probability distributions, a simple normalizing factor is used to emphasize extremes in the distribution. To increase the likelihood of either the lowest or highest 25% of the distribution, an integer scaling factor between 1 and 10 was sampled to reweight the tails, thus forcing the extremes to be between 1 and 10 times more likely. For future MORDM applications, different re-weighting strategies can be used such as the method of Stedinger and Kim (2010). The resulting distributions represent low inflow, high loss, high demand, high lease price, and loss in reservoir storage cases. The losses in reservoir storage refers

Table 1
Descriptions of decision lever variables within the LRGV simulation model.

Decision lever		Units	Description
Permanent Rights Volume	N_R	[m^3]	Non-market instrument allocating an annual percentage of inflows to the city.
Adaptive Options Contracts Volume	N_{Olow} N_{Ohigh}	[m^3]	Market instrument used to purchase lease rights to either a low or high volume of water at the beginning of the year at a fixed price as determined by an anticipatory threshold.
Adaptive Options Contract Threshold	ξ	[-]	
Transfer Thresholds	α	[-]	Market variable issuing "when" water should be acquired through adaptive options contracts and spot leases.
	β	[-]	Market variable issuing "how much" water should be acquired through adaptive options contracts and spot leases.

Table 2
Descriptions of performance measures (objectives and constraints) for the LRGV simulation model optimization. The subscripts on the performance metrics identify whether the performance metric is computed for the 10 year long term planning simulation or the single year severe drought simulation.

Performance Measure			Units	Description
Efficiency	10-yr cost	$f_{10\ yr\ cost}$	[10^6 USD]	Annual cost combines costs from permanent rights, initial purchasing cost of the adaptive options contract, subsequent exercise cost of options, and purchased leases. Sum over 10 years.
	10-yr surplus water	$f_{10\ yr\ surplus}$	[10^6 m^3]	Determine the volume of water held at the end of each planning year. Take an average across the 10 years.
	10-yr dropped leases	$f_{10\ yr\ dropped}$	[10^6 m^3]	Since water from options and leases is considered to expire after one year of non-use, track the whole and fractional volumes of water that went unused. Sum over the 10 years.
	10-yr cost variability	$f_{10\ yr\ cost\ var}$	[-]	For every year, take the annual cost. Then, sort the annual costs from all Monte Carlo simulations from highest to lowest, and find the mean of the costs above the 95th percentile, this is called CVAR. Divide CVAR by the annual cost, and this is the metric. Take the highest value across the 10 years.
	Drought transfers cost	$f_{dr\ trans\ cost}$	[10^6 USD]	Within the drought, the sum of the cost of exercising of leases and options.
Risk Indicator	10-yr reliability	$f_{10\ yr\ rel}$	[-]	Reliability for a given year is the number of months that the city can meet demands. Take the minimum value across the 10 years.
	10-yr critical reliability	$f_{10\ yr\ crit\ rel}$	[-]	Similar to the calculation of 10-yr reliability; instead of a failure being that demand is greater than supply, define failure as supply unable to meet 60% of the demand.
	Drought vulnerability	$f_{dr\ vuln}$	[-]	If there is a failure within the drought, the maximum difference between supply and demand within the drought scenario; else 0
Market Use	10-yr number of leases	$f_{10\ yr\ num\ leases}$	[-]	Number of leases to be purchased by the city in all months of the simulation; average across Monte Carlo simulations. Since this measure sums number of leases rather than lease volume, this performance measure serves as a proxy for transactions costs.

Table 3(a)
Descriptions of uncertain parameters of probability distributions in the LRGV simulation model.

Uncertainty input variable		Description	Scaling factor		Reweighting
			Lower bound	Upper bound	
(i) Probability Distribution	Inflows	Sampled from historical data as an empirical monthly distribution.	1	10	Lowest 25%
	Losses	Sampled from historical data as an empirical monthly distribution	1	10	Highest 25%
	Demands	City water demands sampled from a set of 12 normal distributions with parameters estimated using historic data.[2]	1	10	Highest 25%
	Lease pricing	Derived from the agricultural market to represent pricing between the agricultural sector and municipal sector. Partitioned into two empirical monthly distributions based on reservoir volume.	1	10	Highest 25%
	Reservoir variation	Change in volume of stored water by historical forcings, such as precipitation and evaporation, represented by an empirical monthly distribution.	1	10	Lowest 25% of the reservoir variation distribution

Table 3(b)
Descriptions of uncertain scalar parameters in the LRGV simulation model.

Uncertainty input variable		Description	Parameter value		Sampling
			Lower bound	Upper bound	
(ii) Scalar Parameter	Initial rights	Initial condition representing amount of water available in first month of simulation.	0	0.4	0 to 40% of permanent rights volume
	Demand growth rate [%]	Projected growth of demand in LRGV region.	1.1	2.3	1.1%–2.3% growth rate
	Initial reservoir level [10^6 m^3]	Initial volume of reservoir, which impacts lease pricing.	987	2,714	987×10^6 m^3 to $2,714 \times 10^6$ m^3

to the renormalization of the lowest 25% of the reservoir variation distribution. The focus of this approach is not on assuming that a single distribution is correct, but rather in how interesting combinations of the scaling factors can cause vulnerabilities in the alternatives generated through this approach.

For factor type (ii), we explored exogenous parameters that are input to the LRGV and typically considered constant. Specifically, parameter values represent the baseline conditions for the initial permanent water rights (i.e., initial condition designating the amount of water available to the city in the first month of the simulation), demand growth rate, and the initial reservoir volume. To re-define parameters set as fixed values in the Monte Carlo simulation, a lower and upper bound for sampling each parameter value was determined.

In Kasprzyk et al. (2013), the factors were sampled within an ensemble to fully explore the uncertainty space. The final step was to use SD to determine critical values of the uncertain factors that caused a selected candidate solution to fail. The result of the SD analysis was a set of multi-dimensional boxes that contain the ranges of SOWs that caused vulnerabilities for the selected solution. In the current study, we choose values from those SD boxes (i.e., a single value of each factor) and re-optimize with those SOW. These specific scenarios will be discussed in section 4.

Table 4
Scenarios explored in this paper, defined by the scaled deep uncertainties injected into the MOEA search.

Scenario	Uncertainty	Scaling factor	Description
1: Baseline	No scaling factor adjustment		Baseline probability distributions and model parameter value estimates for uncertainties
2: Moderate	Low Inflows	2	Extremes twice as likely
	High Losses	2	
	Losses in Reservoir Storage	2	
	High Lease Prices	2	
	High Demands	2	
3: Cost	Low Inflows	4	Scaled uncertainty combination that incurred high cost and cost variability for the robust solution
	High Losses	2	
	High Demands	4	
4: Reliability	Low Inflows	7	Scaled uncertainty combination that resulted in low reliability, critical reliability, and drought reliability for the robust solution
	High Losses	2	
	High Demands	6	
5: Market	Low Inflows	8	Scaled uncertainty combination that caused the city to use a high number of leases for the robust solution
	High Losses	4	
	High Demands	7	

4. Computational experiment

The prior study (Kasprzyk et al., 2013) followed the four steps of the MORDM procedure summarized in section 2.2. First, optimization was performed under the baseline scenario, and each resulting tradeoff solution was subjected to a large ensemble of possible values for the deeply uncertain factors. The solutions' deviation from baseline performance was used to choose a single candidate solution to use for the rest of the MORDM experiment; this is termed the robust solution and also solution 0 in the results below. This robust solution was subjected to a scenario discovery procedure that revealed values of the uncertain factors that caused that solution to perform poorly. The point of departure of this study is that in this work we are re-optimizing the problem by using multiple discovered scenarios from MORDM to modify the input data for the search, and thereby generating new tradeoff sets that potentially have different properties than the original set.

There are two phases of the computational experiment. The methods for each phase are described in the following sections. In Phase I we aim to understand how optimizing under different assumptions of statistical Monte Carlo simulations impacts the optimized alternatives and their tradeoffs. This constitutes running MOEA optimization under five scenarios. Consequently, in Phase II we evaluate each scenario's optimized decision levers under the other four scenarios to analyze the loss or gain in performance across all measures (in other words, in one experiment we take solutions optimized under scenario 1 and evaluate them under a selection of other scenarios such as scenario 5). Both phases of the computational experiment were completed on the Janus supercomputer[3] at the University of Colorado Boulder.

4.1. Phase I: how do scenarios impact the tradeoffs?

The first step of this phase is to identify scenarios based on the output of the scenario discovery process (step 4 in section 2.2). Although the scenario discovery process yields a range of values for each factor, our scenarios assume a single value of each uncertain factor to facilitate being used in the function evaluations of search. The scenarios here focus on the probability scaling factors, but other combinations of factors could also have been used.

Table 4 shows the five scenarios investigated in our computational experiment. For each scenario, the variables in Table 4 were used to re-scale the probability distributions of input data such that the Monte Carlo ensembles were modified within solution evaluation during search. Scenario 1, also termed the baseline scenario, does not alter the uncertain inputs into the LRGV model and is equivalent to the input data explored in prior work (Kasprzyk et al., 2013, 2012). Scenario 2 represents a moderate scenario in which all uncertain distributions are scaled by a factor of two. Scenarios 3, 4, and 5 were derived directly from the minimum values of the scaling factor ranges identified in the MORDM study. These three scenarios were selected because they caused violations in a specific set of performance metrics; for example, scenario 3 caused the robust solution in the prior study to exhibit high costs.

The second step of phase I was to perform MOEA search using each scenario separately, and then visualize the results to compare the tradeoff sets with one another (Beh et al., 2015; Kasprzyk et al., 2012). Based on the consistent performance of the Borg MOEA in Reed et al. (2013), the algorithm's default parameterization was used (as shown in Table 7, the MOEA parameters used within Borg). Visualizations of search progress were used to determine an appropriate search duration, which was 100,000 function evaluations for each run. Additionally, the search was replicated for 50 random seed trials to guarantee that the final sets were not a product of artifacts of random seed generation (i.e., the initial random population of solutions and the search operators). The final sets that are discussed in this paper are the result of a non-dominated sorting procedure that is performed across the 50 random seed replicates for each scenario. Table 5 summarizes the epsilon resolutions for search and sorting, and Table 6 presents the upper and lower bounds for each decision variable in the computational experiment.

4.2. Phase II: how do tradeoff solutions perform under alternate scenarios?

Phase I resulted in a set of optimized decisions for each of the five scenarios. During the search, the MOEA used a particular scenario that controlled the statistical input data for the performance calculations within the optimization. Therefore, it is reasonable to assume that solutions would perform well when evaluated under these conditions. For example, if there are lower than average inflow conditions in a particular scenario (thus lowering allocations

[2] The use of monthly distributions is justified based on Ramsey (2004) which studied the correlation properties of the datasets used to develop the model.

[3] Janus is composed of 1,368 compute nodes, each with 12 cores. Each node contains two hex-core 2.8 Ghz Intel Westmere processors. There is 32 TB total system RAM and roughly 800 TB of high performance storage accessible through the Lustre filesystem.

Table 5
Epsilons for each objective used in the MOEA optimization.

Objective	Optimization epsilon	Sorting epsilon	Units
10-yr cost	30,000	300,000	[USD]
10-yr surplus water	1,233,482	1,233,482	[m^3]
10-yr dropped leases	2,466,964	2,466,964	[m^3]
Drought transfers cost	10,000	100,000	[USD]
10-yr critical reliability	0.002	0.002	[-]
10-yr number of leases	0.3	0.3	[-]

to permanent rights), the optimization will favor solutions that utilize the water market to augment their supplies. However, an important consideration when evaluating solutions is: how do the solutions perform under *other* scenarios that were not considered in the individual optimization runs? Informally, we want to know whether it is better to consider the severe conditions within the optimization first (as proposed in this study) or impose the severe conditions to tradeoff solutions after they have been optimized (the original MORDM methodology).

To carry out phase II, we re-evaluated each solution from each of the five original tradeoff sets under each of the other four scenarios. In other words, the group of solutions that were optimized under scenario 1 was evaluated under scenarios 2, 3, 4, and 5. To preserve consistency, we also performed a re-evaluation of solutions under the scenario that was originally used in optimization (for a total of 25 sets of model runs). After the re-evaluations were complete, we imposed the set of constraints in equations (2)–(5) on the re-evaluated objective values in order to show which solutions remain feasible even under a different combination of uncertainty scaling factors. In doing so, we evaluate whether a solution can continue to perform well even in a scenario that was *not* included in the optimization. Note that every time a solution is re-evaluated within this Phase, the objective function calculations use 5,000 Monte Carlo samples, similar to what was used in the original optimization.

5. Results

This section uses three-dimensional glyph plots and parallel plots, both for showing the objectives and decision levers of all solutions and to facilitate comparisons among runs. Glyph plots are three-dimensional plots that use point shape, size, color, and transparency to communicate up to seven dimensions (Blasco et al., 2008; Kollat and Reed, 2007; Lotov, 2007). Parallel coordinate plots illustrate a pairwise comparison between variables with no limit on the number of dimensions shown (Fleming et al., 2005; Inselberg, 1985; Rosenberg, 2015; Wegman, 1990). For phase I, we focus on how the optimized decision levers respond to and perform under the conditions of optimization for each scenario. For phase II, we compare the performance of all five scenario sets under two plausible scenario conditions and highlight the decision levers that remain implementable under the different scenario conditions.

Table 6
Upper and lower bounds on each decision lever variable used to define acceptable value ranges in the MOEA optimization.

Decision lever variable	Lower bound	Upper bound	Units
N_R	37,004,455	74,008,910	[m^3]
N_{Olow}	0	24,669,637	[m^3]
N_{Ohigh}	N_{Olow}	$2N_{Olow}$	[-]
ξ	0.1	0.4	[-]
$\alpha_{\text{May-Dec}}$	0	3	[-]
$\beta_{\text{May-Dec}}$	$\alpha_{\text{May-Dec}}$	3	[-]
$\alpha_{\text{Jan-Apr}}$	0	3	[-]
$\beta_{\text{Jan-Apr}}$	$\alpha_{\text{Jan-Apr}}$	3	[-]

Table 7
Population and operator parameters for the Borg MOEA.

Parameter	Value
Initial population size	100
Tournament selection size	2
SBX rate	1.0
SBX distribution index	15.0
DE crossover rate	1.0
DE step size	0.5
PCX parents	3
PCX offspring	2
PCX eta	0.1
PCX zeta	0.1
SPX parents	3
SPX offspring	2
SPX epsilon	2
UNDX parents	3
UNDX offspring	2
UNDX eta	0.5
UNDX zeta	0.5
UM rate	1/number of DV
PM rate	1/number of DV
PM distribution index	20

5.1. Phase I: how scenarios impact tradeoffs

In phase I, we performed five optimizations under five different scenarios to develop water supply portfolios, where each portfolio is comprised of eight decision levers with performance measured by the objectives in equation (1). Recall that the five scenarios correspond to baseline conditions (scenario 1), moderate conditions (scenario 2), and combinations of scaled uncertainties that induced vulnerabilities in the robust solution found in previous research (scenarios 3, 4, and 5).

Fig. 1(a) shows the multi-objective tradeoff sets for all five scenarios. In this representation, each cone is a solution, which is an individual water supply portfolio. Spatial coordinates, orientation, and size of the cones show performance measures, while color shows the scenario. The baseline and moderate scenario solutions show similar tradeoffs: improvement in 10-year simulation costs and surplus water volume performance cannot be achieved without using a greater number of leases. These solution fronts consist of conservative portfolios that maintain a high volume of surplus water with little use of leases along with market-based solutions that cut costs. The severe group of scenarios, scenarios 3, 4, and 5, consist of solutions that generally exhibit higher 10-year simulation costs using greater number of leases, a first indicator of increased market use when planning under and for extreme conditions. We see that these solution sets no longer allow for more conservative portfolio alternatives relative to the less severe scenario set. Among all of the scenarios, Scenario 3 portfolios perform the poorest with respect to the drought transfers costs and dropped transfers, suggesting inefficient use of the water market instruments under these conditions.

One notable finding is about the relative value of performance measure values across the optimization runs. Often, the baseline solution set has nominally better values for objective functions than solutions optimized under the other scenarios. So, if the decision makers optimize under a severe planning scenario, they should be aware that the severity of the conditions exposed in the search process is revealed in the performance of the solutions. For example, the severe group of scenarios exhibit lower surplus water volumes, which objectively shows improvement; however, this result is a relic of less water in the LRGV system. This type of

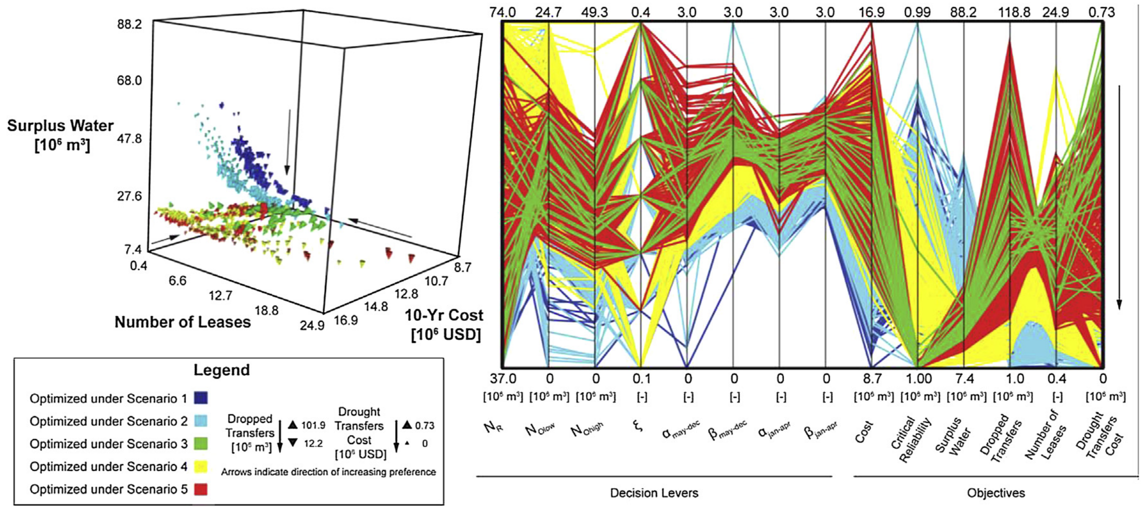

Fig. 1. Phase I results. (a) Three-dimensional glyph plot showing the non-dominated tradeoffs optimized under each of the five scenarios. Each cone represents a water supply portfolio solution and color refers to scenario. Performance is shown in five dimensions: cone spatial position indicates cost, number of leases, and surplus water; cone orientation indicates dropped transfers; and cone size indicates drought transfers costs. (b) Parallel plot showing the non-dominated tradeoffs and decision levers optimized under each of the five scenarios. Each line represents a water supply portfolio solution and color refers to scenario.

assessment corroborates a body of existing work on how to explore so-called unmodeled objectives within optimization (Loughlin et al., 2001; Rosenberg, 2015), since there is not an objective within the system that specifically drives the performance to change less under the new scenarios.

To further understand *why* the five scenario sets perform differently, we explored the decision lever trends that make up each scenario set. Fig. 1(b) is a parallel coordinates plot that connects the tradeoffs presented in Fig. 1(a) to the corresponding decision levers. Each line represents a water portfolio, with color denoting optimized scenario conditions. To refresh, the permanent water rights (N_r) decision is a non-market instrument. The low and high adaptive options exercise volume ($N_{o,low}$ and $N_{o,high}$) decisions are determined according to a decision threshold of ξ. The anticipatory α and β strategy rule decisions are used to establish market use (i.e., exercise options and acquire leases) at the beginning and end of the year. Similarly to Fig. 1(a), the arrow points in the direction of increasing preference for the objectives, which are shown on the last six vertical axes. The ideal water portfolio would result in a line across the bottom axis on the objective portion of the plot, with varying values of decision levers (i.e., there is no preference for having all decision levers have low or high values). Moreover, Fig. 1(b) shows the impact of scenario conditions of optimization on water supply portfolio decisions. In general, the baseline and moderate scenarios' solutions utilize smaller volumes of options and have lower α and β decision values relative to the severe group of scenarios; this result affirms that more probable hydrological and socioeconomic extremes require greater market use to ensure adequate water supply. Furthermore, the solutions within the increasingly more severe scenario sets contain decision values that are not found in the baseline set. This is an important consideration, since it suggests that the original MORDM solution might not have been adaptive enough to thrive under poor conditions because those conditions were never exposed within the scenario used in optimization.

5.2. Phase II: considering alternate scenarios

From phase I, it is evident that optimizing under varying conditions of uncertainty yields different tradeoffs and new decision lever values. In phase II, we explored how the scenario set alternatives perform under different scenarios that were not included in the optimization. In other words, we keep the decision lever values the same, and re-evaluate a new Monte Carlo simulation with different scaling factors for each simulation. In the re-evaluations, the constraints were honored, meaning that solutions that violated the constraint values used in the optimization were removed from the solutions to explore. The main reason for this methodological choice is that our set of constraints represents a delineation between acceptable and unacceptable performance within the search process, so we want to ensure that the solutions meet this set of constraints even if they are being re-evaluated under a new scenario. For simplicity, we focus our discussion in this paper on our re-evaluations of all five tradeoff sets under two scenarios: 1 (baseline) and 5 (most severe). Moreover, we focus on five specific solutions that represent different compromises among planning objectives, as an illustration of what the properties of individual solutions look like.

Fig. 2 presents the performance of all five solution sets under baseline conditions and scenario 5 conditions using the three-dimensional glyph plotting technique explained in Section 5.1. In Fig. 2(a), all solution sets exhibit performance that converges to a single front with individual scenarios clustered along the front. Solutions' performance can be easily characterized by observing the surplus water objective function value of the solutions. Notably, solutions that have the highest surplus water come from the optimizations under scenarios 3, 4, and 5. This demonstrates that because the solutions were exposed to low water conditions within their optimization, when they are evaluated under a less severe scenario they are buying excess water that is wasted in these simulations.

Fig. 2(b) shows the performance of all scenario sets under scenario 5 conditions. The shape of the tradeoffs shifted to low surplus, high lease, and high cost solutions reminiscent of the tradeoffs for the severe scenario sets shown in Fig. 1(a). For this particular exploration, infeasible solutions (due to constraint violations) were no longer considered under the re-evaluations; thus, the plot no longer includes solutions from the scenario 1 and scenario 2 sets due to constraint violations. Primarily, the cost variability constraint was violated in these solutions sets, meaning that high

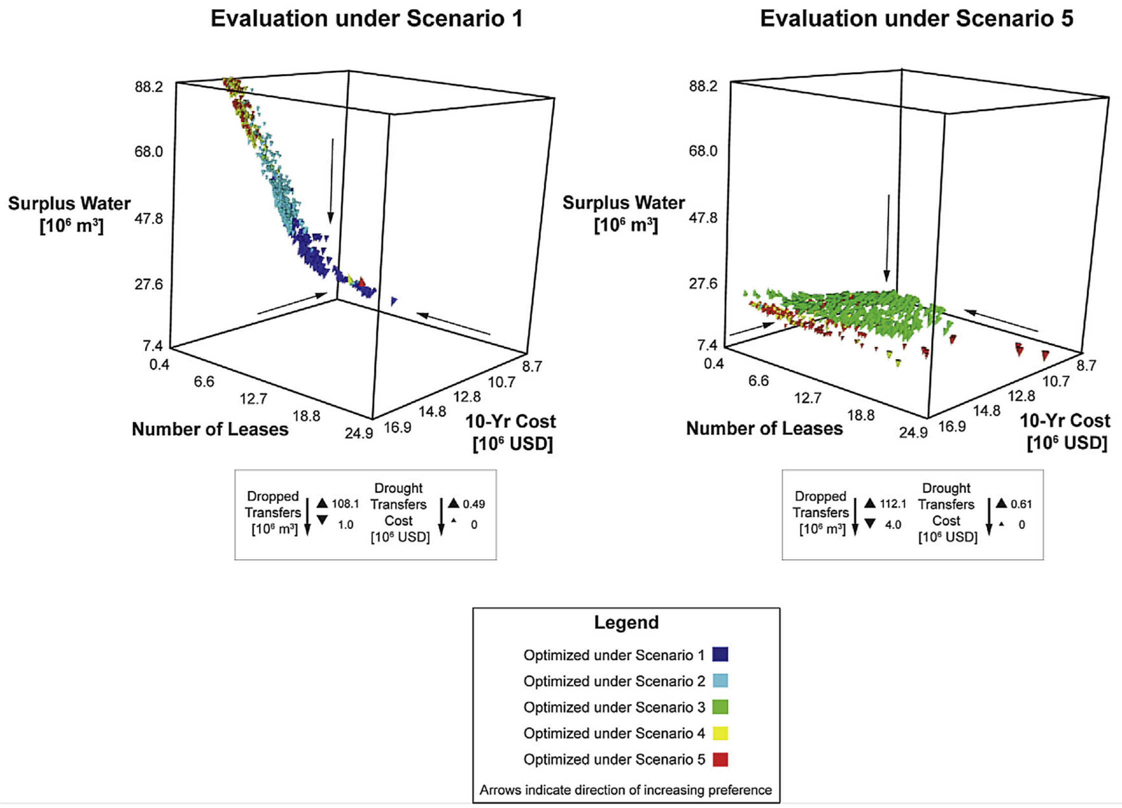

Fig. 2. Phase II results in three-dimensional glyph plot representations that show the non-dominated tradeoffs. (a) Tradeoffs reflect solution set performance under baseline (scenario 1) conditions. (b) Tradeoffs reflect solution set performance under scenario 5 conditions.

costs in the 10-year simulation exceeded the average planning year costs greater than the allowed tolerance. Ultimately, under these harsh conditions that limit water availability and increase the demand in the LRGV system, our suite of feasible alternatives is narrowed to portfolios developed under severe conditions.

Fig. 3 uses parallel coordinate plot visualizations to show the data from Fig. 2, highlighting the trends within all performance measure values as well as the decision levers. We also introduce a set of highlighted solutions that represent interesting compromises among performance measures, shown in bold atop the transparent solutions that compose all sets. Fig. 3(a) represents solutions' performance under their own optimization whereas Fig. 3(b) and (c) correspond to water portfolios experiencing baseline conditions and scenario 5 conditions, respectively. Note that the decision levers are consistent between the three figures, but there are differences in the solutions' performance. To supplement, Table 8 details the performance of the highlighted solutions under all five scenario conditions. In Table 8, solution 0 refers to the robust solution from the prior MORDM study. The coloration of solutions in Fig. 3, and the number in Table 9, corresponds with the scenario that the solution was optimized under. For example, the red solution in Fig. 3 is from scenario 5, so it is listed as solution 5 in the table.

By observing the plot sequence and table, it is evident that constraint violations restricted the number of highlighted solutions in increasingly more severe conditions. Note that solution 0, the robust solution, did not meet the conditions of feasibility in any of the re-evaluations. This result suggests that optimizing only under a baseline assumption of probability (thus generating the solution 0) may not be able to generate solutions that meet performance requirements (i.e., constraints) when experiencing conditions of severe uncertainty. In Table 8, solutions 1 and 2 have the highest number of constraint violations, suggesting that these sets yield solutions that are ineffective under harsher conditions. Additionally, solutions 4 and 5 are infeasible under scenario 3 conditions, which could provide motivation to explore the scenario 3 set more closely in the decision making process. Overall, Fig. 3(b) and (c) illustrate that solutions from scenarios 1 and 2 do not satisfy conditions unlike those of the optimization, and solutions from the more severe scenario optimizations are better suited for harsh conditions and expected (baseline) conditions.

The parallel plots may also be leveraged to understand what values of the decision levers that compose portfolios remain feasible under various uncertain conditions. The decision lever values for the highlighted solutions are provided in Table 9. Ultimately, solutions that favor market mechanisms (i.e., larger high options volume, larger low options volume, and high α and β values) allow the city to meet supply needs under severe conditions. Recall that the LRGV case study is a policy analysis for determining the value of using a market-based approach to the water supply of the region. Therefore, the particular solutions in this table would not actually be implemented in the real system. However, the good performance of the market-based solutions in these results suggests that cities can use water marketing to prepare for plausible uncertainties outside of the historically observed conditions.

6. Conclusions

An important component of bottom-up decision making is to reflect on the evaluation of policies under deep uncertainty and attempting to mitigate vulnerabilities (Hall et al., 2012; Lempert et al., 2006; Lempert and Groves, 2010; Popper et al., 2009). This

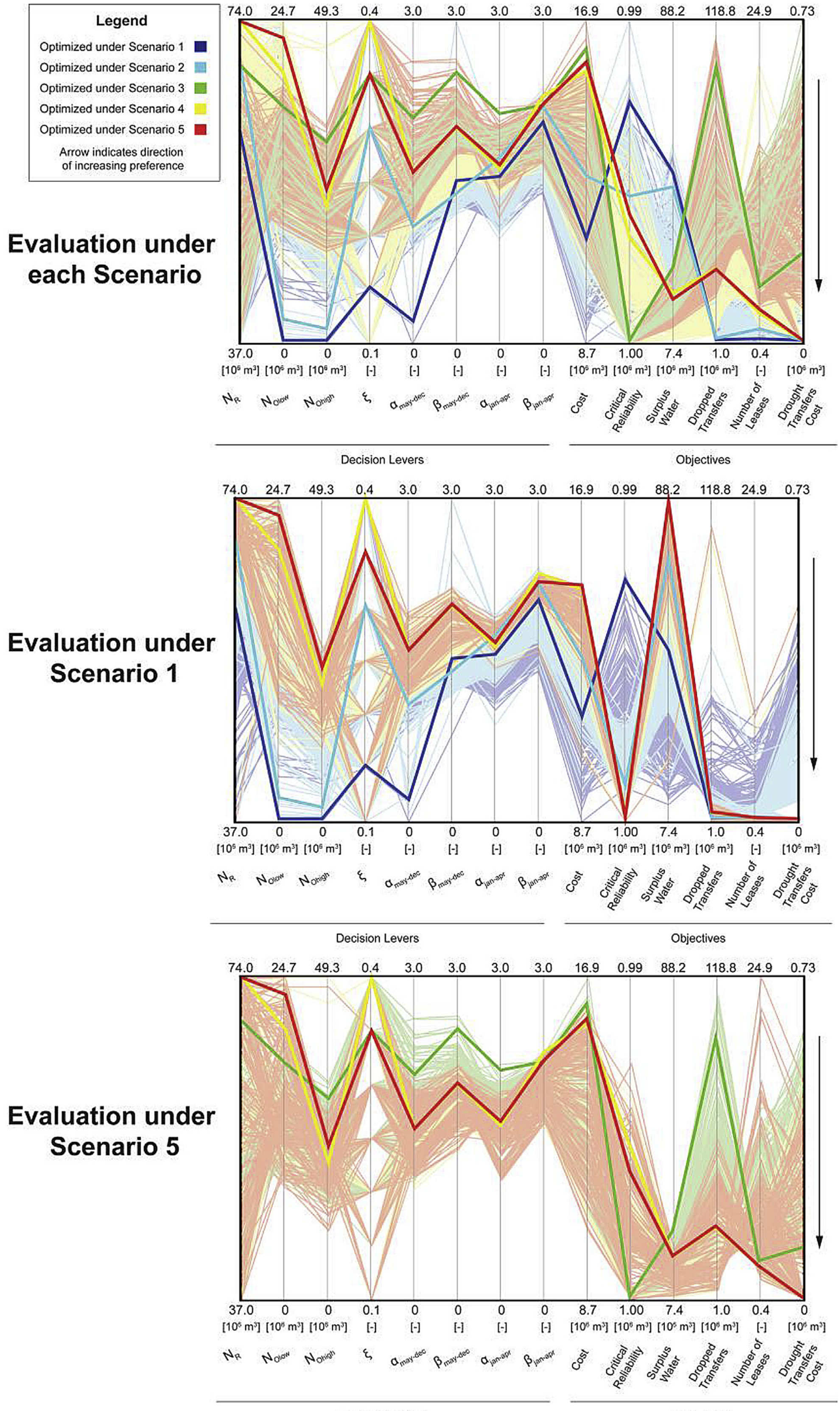

Fig. 3. Phase II results in parallel plot representations that show the non-dominated tradeoffs and decision levers. Highlighted solutions are shown in bold atop transparent solutions, and their colors refer to the scenarios they were optimized under. (a) Tradeoffs reflect solution set performance under the same conditions of optimization. (b) Tradeoffs reflect solution set performance under baseline (scenario 1) conditions. (c) Tradeoffs reflect solution set performance under scenario 5 conditions.

Table 8
Performance of highlighted solutions under all five scenario conditions. The coloration of the solution in Fig. 3, and the bold scenario number in this Table, corresponds with the scenario that it was optimized under. Solution 0 refers to the robust solution from the prior MORDM study.

Solution	Evaluation scenario	Performance measures					
		10-Yr Simulation					Drought simulation
		Cost	Critical reliability	Surplus water	Dropped transfers	Number of leases	Transfers cost
		[10^6 USD]	[-]	[10^6 m^3]	[10^6 m^3]	[-]	[10^6 USD]
0	**1**	Constraint Violation: $f_{cvar} = 1.35$					
	2	Constraint Violation: $f_{cvar} = 1.34$					
	3	Constraint Violation: $f_{rel} = 0.97$, $f_{cvar} = 1.33$					
	4	Constraint Violation: $f_{cvar} = 1.33$					
	5	Constraint Violation: $f_{cvar} = 1.33$					
1	**1**	11.30	0.99	49.86	1.22	0.55	0.00
	2	Constraint Violation: $f_{rel} = 0.95$, $f_{crit\ rel} = 0.97$, $f_{costvar} = 1.26$					
	3	Constraint Violation: $f_{rel} = 0.61$, $f_{crit\ rel} = 0.72$, $f_{costvar} = 1.25$, $f_{dr\ vuln} = 6433.15$					
	4	Constraint Violation: $f_{rel} = 0.69$, $f_{crit\ rel} = 0.79$, $f_{costvar} = 1.22$					
	5	Constraint Violation: $f_{rel} = 0.66$, $f_{crit\ rel} = 0.76$, $f_{costvar} = 1.22$					
2	1	12.81	1.00	73.20	1.38	0.53	0.00
	2	12.90	1.00	46.19	1.74	1.27	0.00
	3	Constraint Violation: $f_{rel} = 0.90$, $f_{crit\ rel} = 0.97$, $f_{costvar} = 1.29$, $f_{dr\ vuln} = 208.13$					
	4	Constraint Violation: $f_{rel} = 0.94$, $f_{crit\ rel} = 0.97$, $f_{costvar} = 1.24$					
	5	Constraint Violation: $f_{rel} = 0.93$, $f_{crit\ rel} = 0.97$, $f_{costvar} = 1.23$					
3	1	Constraint Violation: $f_{cvar} = 1.25$					
	2	Constraint Violation: $f_{cvar} = 1.26$					
	3	16.15	1.00	25.82	101.90	4.38	0.20
	4	16.08	1.00	25.05	97.50	3.11	0.11
	5	16.20	1.00	24.06	96.41	3.09	0.11
4	1	14.54	1.00	87.18	3.26	0.52	0.00
	2	14.62	1.00	58.25	6.50	0.67	0.00
	3	Constraint Violation: $f_{rel} = 0.96$, $f_{crit\ rel} = 0.98$, $f_{costvar} = 1.23$					
	4	15.58	1.00	19.29	27.45	2.44	0.00
	5	15.70	1.00	17.62	26.69	2.69	0.00
5	1	14.65	1.00	87.50	3.47	0.52	0.00
	2	14.73	1.00	58.55	6.74	0.66	0.00
	3	Constraint Violation: $f_{rel} = 0.96$, $f_{crit\ rel} = 0.98$, $f_{costvar} = 1.22$					
	4	15.70	1.00	19.43	28.00	2.45	0.00
	5	15.82	1.00	17.75	27.13	2.71	0.00

Table 9
Decision levers of highlighted solutions. Solution 0 refers to the robust solution from the prior MORDM study.

Solution	Description	Decisions							
		N_R	N_{Olow}	N_{Ohigh}	ξ	$\alpha_{May-Dec}$	$\beta_{May-Dec}$	$\alpha_{Jan-Apr}$	$\beta_{Jan-Apr}$
		[10^6 m^3]	[10^6 m^3]	[10^6 m^3]	[-]	[-]	[-]	[-]	[-]
0	Robust solution from prior study marked by a low volume of permanent rights and market use	38.48	19.84	19.84	–	1.69	1.69	1.69	1.69
1	Dependent primarily on permanent water rights with the lowest market use	61.20	0.00	0.00	0.15	0.18	1.50	1.54	2.05
2	Low use of adaptive options contracts, lower market use (low alpha/beta variations)	69.14	1.62	1.78	0.30	1.07	1.38	1.72	2.20
3	Consistent market use across both planning periods	68.89	18.04	30.66	0.35	2.09	2.52	2.13	2.21
4	Maximum volume of permanent rights, use of low and high adaptive options contracts	74.01	20.69	20.69	0.40	1.58	2.00	1.61	2.30
5	Maximum volume of permanent rights, high volumes of adaptive options contracts	74.01	23.36	23.36	0.35	1.58	2.01	1.65	2.22

paper presented an approach in which MOEA optimization is used in a multi-scenario context, in which multiple plausible scenarios are separately optimized, and their resulting tradeoff sets are compared to determine how solutions' properties change based on scenario assumptions. Without attempting these multiple optimizations, a decision maker may select a solution from an initial optimization without further assessment of how the solution performs in other scenarios. By optimizing separately under multiple scenarios, we found new values of decision variables that work well under multiple conditions. Although these decision variable values might not have been optimal under the baseline scenario, their values might prove to be more adaptable under severe scenarios in which there is limited water availability. One critical methodological choice within the study was the idea that constraint violations were enforced even when solutions were being re-evaluated; future work could include 'soft' constraint treatments that would allow for some flexibility in constraint violation as a modification of the definition of robustness (Watkins Jr. and McKinney, 1997). Another promising area of future work is in adapting the methods suggested here to an adaptive pathways approach (e.g., Haasnoot et al., 2013; Zeff et al., 2016) to show how the choice of scenarios impacts the results if the decisions are modified through time.

Our approach makes extensive use of visual analytics that facilitate comparison of the solution sets. Such comparisons help viewers learn about the problem, properties since the tradeoffs represent relationships among the problems' planning objectives that are modified depending on the scenario considered. Consideration of multiple scenarios within optimization seeks to address an emerging focus on new techniques for bottom-up decision analysis under uncertainty, as highlighted in a recent review (Maier et al., 2016). The results here suggest that optimizing under severe conditions may create solutions that are better suited to handle a wider range of conditions than simply optimizing under a baseline assumption of uncertainty, regardless of how evaluations are performed after solutions are generated. Moreover, this analysis supports the idea that an optimization problem formulation should continually be in flux (Zeleny, 1989), with new assumptions being questioned as the decision support process continues. This adaptation of the problem formulation and scenario analysis is an important dimension of adaptive management that should be a part of the discussion for environmental systems undergoing change.

Software availability

This paper uses a combination of software that is either open source or available for research purposes by request. The Borg MOEA is available by request at http://www.borgmoea.org/. The LRGV model is open source and available on GitHub at https://github.com/jrkasprzyk/LRGV. Some analysis also uses calculations within the MOEAFramework library, an open source project available at http://www.moeaframework.org/. For input files for the LRGV model, as well as submission scripts and processing codes to perform the analysis, please visit https://github.com/jrkasprzyk/watson-ems.

Acknowledgments

This work utilized the Janus supercomputer, which is supported by the NSF (CNS-0821794) and CU Boulder. The Janus supercomputer is a joint effort of CU Boulder, Univ. Colo. Denver, and the National Center for Atmospheric Research. Additionally, Watson was funded in part by the Integrated Teaching and Learning Program under NSF GK-12 grant DGE-0338326. However, these contents do not necessarily represent the policies of the NSF and the endorsement from the US federal government should not be assumed. We acknowledge the constructive comments of peer reviewers in improving the clarity of the manuscript, as well as productive conversations on the approach with Prof. Jon Herman.

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