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**Key Points:**
- A new metric is used to quantify robustness of alternative adaptations
- The metric is independent of assumptions regarding future climate
- Results show the additional robustness gained through adaptation

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# A climate change range-based method for estimating robustness for water resources supply

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**Abstract** Many water planning and operation decisions are affected by climate uncertainty. Given concerns about the effects of uncertainty on the outcomes of long-term decisions, many water planners seek adaptation alternatives that are robust given a wide range of possible climate futures. However, there is no standardized paradigm for quantifying robustness in the water sector. This study uses a new framework for assessing the impact of future climate change and uncertainty on water supply systems and defines and demonstrates a new metric for quantifying climate robustness. The metric is based on the range of climate change space over which an alternative provides acceptable performance. The metric is independent of assumptions regarding future climate; however, GCM-based (or other) climate projections can be used to create a "climate-informed" version of the metric. The method is demonstrated for a water supply system in the northeast United States to evaluate the additional robustness that can be attained through optimal operational changes, by comparing optimal reservoir operations with current reservoir operations. Results show the additional robustness gained through adaptation. They also reveal the additional insight regarding robust adaptation gained from the decision-scaling approach that would not be discerned using a GCM projection-based analysis.

## 1. Introduction

The effects of climate change and potential nonstationarity in hydrologic variables undermine many assumptions upon which water resources infrastructure has been historically managed and designed [*Milly et al.*, 2008]. Evidence suggests that anthropogenic activities are altering the hydrologic cycle [*Stocker et al.*, 2013], resulting in changes to the probabilistic behavior of hydrologic variables that were previously assumed stationary in time for the purposes of water resources management and planning. Mathematical simulation and optimization models are often used to predict the behavior of system designs and policies over time, assuming that climate variables follow time-invariant probability density functions. While this decision framework has proven very powerful in the past [*Goodwin and Wright*, 2004], the process hinges on an accurate description of the probabilistic behavior of natural conditions (i.e., climate). Management of water resources under uncertain change is a problem previously assumed away, but now there is a need for new strategies to cope with shifting climate regimes [*Kundzewicz et al.*, 2008].

There have been many attempts to assess the impacts of future climate on water resource systems under climate change. These studies often use "top-down" approaches to evaluate system performance by using downscaled climate projections from global climate models (GCMs) which are driven by greenhouse gas emission scenarios [*Manning et al.*, 2009; *Christensen and Lettenmaier*, 2007; *Brekke et al.*, 2009; *Vicuna et al.*, 2010; *Lopez et al.*, 2009; *Wiley and Palmer*, 2008]. Downscaled [*Wilby et al.*, 2009] and bias corrected [*Murphy*, 1999] climate sequences are propagated through hydrologic models and impact models to estimate system performance in the future.

While GCM-based scenarios are useful for evaluating response to particular climate change scenarios, due to biases and incomplete sampling of uncertainties, they are less useful for exploring and evaluating risks [*Brown and Wilby*, 2012]. The inherent uncertainty in these projections related to climate forcings [*Stainforth et al.*, 2005], initial condition ensembles [*Deser et al.*, 2012], and model inadequacies due to poorly understood climate physics and computational complexity [*New and Hulme*, 2000] make it difficult to incorporate

information from these scenarios into adaptation decisions [*Stainforth et al*., 2007]. Additionally, with no associated likelihoods or reliable probability estimates, assessing the relative risk of potential adaptation strategies is not straightforward.

Adaptation strategies such as investments in infrastructure [*Lloyd*, 2008], changes in management practices [*Pahl-Wostl*, 2007], real-options in engineered projects [*Steinschneider and Brown*, 2012], demand management strategies [*Frederick*, 1997], and insurance schemes to hedge risk [*Linnerooth-Bayer and Mechler*, 2006] may help reduce damages due to problematic climate conditions. However, if a system is not vulnerable to climate changes [*Matonse et al*., 2012], investments in adaptations are wasteful. Deep uncertainty (i.e., unknown or differing opinions about the probability distributions used to describe the uncertainty of parameters in models) in future climate projections precludes a precise description of future hydrologic change, suggesting the need for adaptation strategies that are robust [*Lempert et al*., 2006a]. In qualitative terms, an adaptation strategy has been described as robust if it results in satisfactory performance across a range of potential climate changes [*Lempert and Groves*, 2010; *Wilby and Dessai*, 2010; *Dessai and Hulme*, 2007].

This study proposes the application of decision-centric climate risk assessment [*Brown et al*., 2012] for quantifying water resource system robustness under climate uncertainty. A new climate range-based robustness metric is defined to evaluate the effectiveness of system adaptations over a range of climate change space independently of assumptions about future climate. The metric is designed to be informative independent of probabilistic assumptions but can also be conditioned using probabilistic weighting inferred from a range of GCM-based projections or other sources of climate information. This weighting enables the incorporation of judgments regarding the likelihood of different climate changes. The climate range-based metric provides a straightforward way to identify robust adaptation strategies among various alternatives across a wide range of potential futures and immediately makes clear how different assumptions of future climate affect adaptation alternative performance ranking.

Traditionally, system performance has been evaluated using measures such as reliability, resilience, and vulnerability, describing how likely a system is to fail, how quickly it recovers from failure, and the severity of its failure [*Hashimoto et al*., 1982b]. For example, a water supply manager may define failure as the inability to meet water supply demand and may judge performance based on the frequency of, resilience to, and severity of water shortages [*Hashimoto et al*., 1982b]. However, if probability distributions of key climate variables shift in unforeseeable ways under long-term climate change, these performance metrics may no longer be an appropriate paradigm to guide water resources planning and management. Each of these metrics is a function of the single time series of (for example) the reservoir inflows used to make the calculation. The metric is thus conditional on the time series. This may be appropriate under conditions where the single time series is believed to fully represent the uncertainty of future inflows but is less appropriate for conditions of climate change, where many possible future changes, including realizations of variability and mean climate changes, must be considered. Yet planners increasingly seek performance measures that quantify the ability to provide acceptable performance over a range of uncertain futures, i.e., quantification of robustness.

However, there is no metric that quantifies the quality of robustness in the literature that is consistent with this pursuit. *Hashimoto et al*. [1982a] proposed a robustness measure to guide decision-making under uncertain demand conditions. The metric is designed to assess the probability that the cost for a particular design under some future demand condition is less than or equal to some multiple of the least cost design. This metric is essentially a measure of regret. *Allam and Marks* [1983] noted that the metric proposed by *Hashimoto et al*. [1982a] is dependent on a subjective measure of a relative weighting between the mean and variance of regret costs. Also, the variance includes both positive (lower cost) and negative (higher cost) deviations from the mean, and thus this approach penalizes outcomes with low expected costs (regret) just as it penalizes outcomes with high expected costs. Finally, the calculation is dependent on stationary assumptions of future climate.

A number of studies have attempted to incorporate the concept of robustness in optimization routines for water resources planning and design [*Lempert and Collins*, 2007; *Watkins and McKinney*, 1997; *Wong and Rosenhead*, 2000]. For example, *Watkins and McKinney* [1997] study of robust optimization (RO) for a water supply system defines a robust plan as one that maintains a high (but not maximized) expected value of performance metrics across scenarios while also maintaining a small (but not minimized) variance of performance metrics across those scenarios. A modified robust optimization was introduced in *Ray et al*. [2013]

which used single-sided penalties instead of variance and introduced an uncertainty metric. However, like other methods, RO minimizes change in the optimal solution across generated scenarios, which are themselves highly uncertain and dependent on the assumed parameters that may or may not be reliable in the future. Thus, the robustness metrics and analysis are implicitly dependent on assumed distributions of unknown reliability in the future. In addition, robustness is generally not defined as a metric that can be evaluated quantitatively, but rather is typically a general, qualitative goal for assessing the uncertainty in model parameters.

In the studies described above, robustness metrics do not address the fundamental challenge of deep uncertainty [*Lempert et al*., 2006b], where there is limited basis for assigning probabilities to future conditions, and consequently disagreement on the scenario generation scheme. Moreover, it is important to recognize the differences in how robustness is defined throughout the literature in other fields; for example, on the subject of resource allocation in parallel and distributed systems a robust system design may be measured by the extent to which a performance feature can deviate from assumed conditions [*Ali et al*., 2003]. In the field of applied soft computing and operations research, robustness is defined as the degree to which a system functions correctly under different inputs [*Jensen*, 2001] and its ability to operate correctly across a wide range of operational conditions [*Gribble*, 2001]. In the study of complex systems, physicists defined robustness as the maintenance of certain desired system characteristics given fluctuations in environmental conditions [*Carlson and Doyle*, 2002]. In the field of disaster risk reduction, the concept of robustness is used to characterize the ability of systems to withstand a given level of stress (e.g., earthquake-generated forces) without experiencing significant losses [*Bruneau et al*., 2003]. When placed in the context of climate change and development, robustness defines a strategy or plan that performs well, but not optimally, across many plausible future scenarios [*Field et al*., 2012]. These are just a few examples of how robustness is defined and used throughout the literature; there are other definitions that can be found in the literature.

Several studies in water resources have adopted robustness as generally meaning acceptable performance over a wide range of future scenarios without formally quantifying the term [*Groves and Lempert*, 2007; *Lempert and Groves*, 2010; *Lempert and Collins*, 2007; *Lempert et al*., 2006a]. For example, *Lempert and Groves* [2010] describe a robust decision-making (RDM) approach that characterizes climate uncertainty by assessing the performance of agency plans over multiple climate futures. These analyses typically generate their scenarios of climate futures using stochastic simulation with model parameters estimated from the observed historical record or downscaled climate model projections. The results are dependent on the generating sources which may be a subject of disagreement, for example, where the historic simulation is not considered indicative of likely future climate and the climate projections are not deemed credible or do not fully sample possible climate futures.

While previous studies seek robust solutions, they do not quantify robustness in a way that can be generalized as an approach for assessing robustness under climate change uncertainty. In particular, the evaluations are conditional on specific predictions of future climate, which themselves are deeply uncertain. That is, the results of the analysis are conditional on the assumptions regarding the probabilities of the climate scenario generating mechanism, typically climate change projections. However, these studies provide the basis for defining a robustness metric that can address the issue of deep uncertainty. The definition of robustness as acceptable performance over a range of future uncertainty provides the path forward for quantifying robustness under climate uncertainty.

A recent group of studies have focused on understanding the response of water resources systems to plausible changes in climate as a starting point for climate risk assessment [*Brown et al*., 2012; *Prudhomme et al*., 2010; *Brown et al*., 2011]. One consequence of this direction of analysis is the potential ability to quantify the range of climate space over which a water resources system can provide acceptable performance. In *Moody and Brown* [2013], the performance of alternative regulation plans for the Great Lakes of North America was modeled over plausible climate change space. Statistics of that space were then evaluated as metrics for system performance in response to climate change. Here we propose a generalization of that approach for application to water supply systems.

In this study, we extend the work of *Moody and Brown* [2013] to develop a generalized metric for quantifying robustness under climate change uncertainty that can be used to compare alternative adaptation strategies for any water supply system. The method presented here synthesizes the ideas of robustness from

the literature to create a quantitative robustness index with broad application. A particularly attractive aspect of the index is that it is not strongly dependent on assumptions of future climate. Instead, it is defined in a decision-centric and scenario neutral manner, with the capability to incorporate updated climate information from GCM projections into the CRI to support water resources decision-making.

The paper proceeds as follows. The methodology, presented next, uses an exhaustive exploration of system performance over plausible changes in climate. The robustness index, demonstrated with an application to a water supply system in the northeast United States, is presented in section 3. The index is used to quantify the current robustness of the system and to evaluate and define the limits of a realistic adaptation to climate change, the optimization of reservoir operations. Results are presented in section 4. The paper concludes with a discussion of results including the implications of assuming a range of plausible climate changes.

## 2. Methodology

The robustness index developed here builds from the methodological framework of decision-scaling [*Brown et al*., 2012], which inverts GCM-based approaches to climate risk assessment by evaluating system performance over a range of climate futures and uses GCM projections to evaluate risks. Here the general methodology is used to quantify robustness of a water supply system. First thresholds for acceptable performance are defined. Next, an exhaustive exploration of system performance is conducted by coupling a climate/weather generator that simulates possible sequences of climate change with a water resources systems model. Finally, a measure of acceptable performance is calculated over the plausible range of climate change space to quantify the robustness index.

### 2.1. Definition of Performance Metrics and Thresholds

Performance thresholds are useful for the quantification of robustness because they differentiate regions of acceptable and unacceptable system performance. Performance thresholds may define, for example, a lower limit of acceptable system functioning that does not significantly diminish the integrity of the system over time. Alternatively, thresholds may be introduced and subsequently increased to define the highest threshold that achieves robustness over an acceptable range. This concept is applied in Info-Gap Decision Theory (IGDT), which seeks to maximize the robustness of a decision based on minimum performance requirements [*Matrosov et al*., 2013], where thresholds set the minimum level of system performance that must be achieved. In water planning applications, thresholds may be related to economics, safety, productivity, or ecological impacts. Note that thresholds may be varied from their initial specification and an analysis may be made conditional on the threshold level, as implied in IGDT analysis [*Ben-Haim*, 2001].

In general, we define a performance indicator, $Y_j$, to be some statistic of performance, where $Y_j$ is a function of a given vector of climate variables, $\mathbf{x_j}$. This vector of climate changes can include statistics like percent change of mean precipitation, degree change of mean temperature, etc. The analysis explores $J$ different vectors of climate changes, $\mathbf{X}=\{\mathbf{x_1},\mathbf{x_2},\ldots,\mathbf{x_J}\}$ (where $J$ is the number of climate realizations). Threshold values, $Y_T$, can be placed on these performance indicators to define acceptable system performance over climate change space. For example, for a water supply utility a target threshold (e.g., 98%) on reliability (as defined by *Hashimoto et al*. [1982b]) is often used for planning purposes. A model or series of models is used to estimate the performance of the system for a specific change in climate, and then the performance is compared to the performance threshold to specify acceptable or unacceptable performance.

### 2.2. Climate Stress Test: Modeling Performance Under Climate Changes

The system performance metrics and thresholds defined in the previous step are then used to explore the response of the system to a wide range of plausible climate changes and to ultimately parse climate change space into regions of acceptable and unacceptable performances. System performance is estimated through an exhaustive sampling of changes in climate variables, such as mean precipitation and temperature, and higher-order statistics can also be considered. The components of the climate stress test are [*Brown et al*., 2012]: (1) the generation of weather/climate sequences that represent plausible climate changes, (2) simulation of system sensitivities to changes in relevant climate statistics, and (3) the characterization of vulnerabilities and sensitivities.

A weather/climate generator is used to provide sequences that when propagated through hydrologic and impact models produce a set of performance indicators ($Y$) for a given water system. These impact models estimate performance $Y_j$ for a given climate sequence representative of a set of consistent climate statistics, $\mathbf{x_j}$ that together define a future climate state. The process is repeated over a wide range of plausible climate changes ($\mathbf{x_0}$ to $\mathbf{x_J}$) to generate a set of performance indicators for each climate state across climate change space. The thresholds ($Y_T$) are used to parse $Y$ into two sets, $Y+$, which are acceptable and $Y-$, meaning less than acceptable performance. The corresponding $\mathbf{x_j}$ are similarly parsed so that $\mathbf{x}-$ defines a set of climate conditions that cause unacceptable performance, while the $\mathbf{x}+$ define the climate conditions over which the system is robust.

The key innovation in this application is that the climate changes $\mathbf{x_j}$ are chosen to sample a range of plausible climate changes without assumptions regarding their relative likelihood, other than the assumption that the entire range considered is plausible. The scenarios $\mathbf{x}+$ and $\mathbf{x}-$ define a climate space and thus the performance of the system is not conditioned on climate projections or historical scenarios of unknown and unknowable future probability.

The analysis requires the generation of realistic climate sequences that represent $J$ possible climate futures to sample the effects of future climate over the plausible range of change. To achieve this, a series of weather sequences are generated for each specified mean climate future ($\mathbf{x_j}$). In this analysis, the climate future is defined in terms of mean degree changes in temperature and mean percent changes in precipitation, and other statistics related to variability are held constant at historical values. Other changes to climate could also be explored including changes in variability, seasonality, and changes to other weather variables. The approach is described as a "climate stress test" [*Steinschneider and Brown*, 2013]. An additional advantage of this approach is that the weather sequences are not dependent on statistics of GCM projections, which in some cases may have significant biases that are not obvious or known to the analyst, and yet may have large effects on the analysis [e.g., *Brown et al.*, 2012].

Weather sequences consistent with a specified climate future can be developed over any range of potential climate change. The selection of this range (e.g., mean temperature changes from $T_1$ to $T_i$ degrees Celsius, where $T$ can take on any value) is an open research question. The range may be selected in a number of ways, but in general the approach is to specify a large enough range that will expand the climate space beyond that explored by GCM projections (in view that the projections do not delimit the plausible range of change) and ensure that the endpoints of the range do not arise in a meaningful way in the analysis. The key is to ensure the range is wide enough to reveal the vulnerabilities of the system or else be so wide that any vulnerabilities beyond that range would not be of concern. If the marginal cost of generating an additional sequence is low as is often the case, there is little concern in setting a range that is implausibly large. If these "implausible" sequences reveal risks or weaknesses, their plausibility can be discussed in the final step of the analysis, and if deemed implausible, the risks dismissed. Given the general tendency of human judgment to be overconfident and underestimate probability of surprise, revealing risks under even implausible conditions is likely beneficial. However, practically there may be a need to be more selective in the range considered if models of the system being investigated require significant resources to run.

Simulations of system performance are used to characterize system vulnerabilities and sensitivities to change over the plausible range of climate change space. Then, the thresholds are used to parse the climate space into regions of "acceptable" and "unacceptable" performances. Characterizing the climate change space in this way makes it apparent which future climate states will present the most challenges to operations. Using the thresholds of acceptable performance for a system, the vulnerability of the system can be characterized with a binary performance function:

$$\begin{aligned} \Lambda(\mathbf{x_j}) &= 1 \quad \text{if} \quad Y_j \geq Y_T \\ &= 0 \quad \text{if} \quad Y_j < Y_T \end{aligned} \tag{1}$$

The binary performance function, $\Lambda(\mathbf{x_j})$, returns a value of 1 (acceptable performance) or 0 (unacceptable performance) for each climate state, $\mathbf{x_j}$, by comparing the performance variable $Y_j$ with the predefined threshold, $Y_T$ elicited in step 1. Characterizing vulnerabilities using the binary performance function can provide stakeholders with a sense of the climate conditions that pose a threat to system performance or favor a particular adaptation strategy.

### 2.3. Calculation of Robustness Index

The objective of the robustness index is to develop a metric that quantifies the ability to provide acceptable performance over a wide range of future climate. A particular need of the robustness index is that it be robust to the uncertainty of future climate, and thus not dependent on assumed probabilities about that future climate. The parsing of climate change space into regions of acceptable and unacceptable behavior makes that possible. The robustness index (RI) is calculated by integrating the binary performance function (equation (1)) over the range of climate conditions and then dividing by the area (or hyperspace) of the entire climate change space (equation (2)). The result is a fraction between 0 and 1 that gives an indication of the degree of acceptable system performance for plausible future climate explored.

$$RI = \frac{\int_{\mathbf{x_0}}^{\mathbf{x_J}} \Lambda(\mathbf{x_j})dx}{\int_{\mathbf{x_0}}^{\mathbf{x_J}} dx} \tag{2}$$

Equation (2) illustrates the RI calculation for a single climate variable (i.e., $x$ is a scalar); however, any number of climate variables can be explored by using multiple integrals over a vector of climate changes. The RI based on equation (2) is implicitly conditional on a uniform probability distribution over the plausible climate states because that is the scenario generating distribution. This is consistent with the definition of robustness, describing the ability of a system to provide acceptable performance over a wide range of future climate. The wider the range, the more robust the system. Thus, equation (2) defines robustness in a way that is largely independent of assumed scenarios except for the endpoints in the range, which are unlikely to affect the results except in rare cases. Such a case occurs when a vulnerability is revealed only at the end of the range. If the range considered is wide enough, it might be straightforward to disregard that vulnerability and elect not to address it. This is the preferred approach. However, vulnerabilities that are beyond the range of projections but not near the edges of the range warrant further consideration. *Moody and Brown* [2013] discuss the concept of plausibility as a weaker form of probability. They propose a framework where climate changes that are consistent with historical trends and climate change projections represent greater plausibility than changes that are consistent with only one or none of these information sources. Our sense is that while the use of these methods to reveal vulnerabilities can be illustrated in a straightforward manner, the decisions related to address the vulnerabilities will be made by decision makers on a case by case basis, as they should be.

The metric is independent of assumptions regarding the probability of the future climate space, other than a low stakes judgment regarding the endpoints of plausibility. This form of the index can support adaptation decisions in at least two ways. First, the index provides advice for water planners attempting to determine if adaptation is necessary. If the robustness index is near one and the emerging problematic climate conditions are deemed not very plausible (see above), then planners may conclude adaptation to the climate changes considered is not a priority. Second, if planners are considering a specific adaptation, $A_1$, the robustness index for the adaptation, $RI(A_1)$, may be compared to the status quo robustness index, $RI(A_0)$. The gain in robustness index may be considered in terms of the additional robustness added for a given cost of adapting.

In addition, a graphical analysis of RI can be used to determine if an adaptation is "robustness dominant" over alternate adaptations or the status quo. That is, if an adaptation provides adequate performance ($Y+$) over a range of climate change space that encompasses and surpasses the range of climate space that is robust under the status quo, then that adaptation may be considered robustness dominant (i.e., $\Lambda(\mathbf{x_j}|A_1) \geq \Lambda(\mathbf{x_j}|A_0) \forall j \in J$).

In many cases, the range of climate change space of acceptable performance may include space that does not overlap (i.e., adaptations perform acceptably ($Y+$) over distinct regions of the climate space) for $I$ alternative adaptations ($A_1,\ldots,A_i,\ldots,A_I$). In these cases, it may be beneficial to assign probabilities to the climate space to weight the alternatives. A robustness score can be weighted by the probability of the climate space over which acceptable performance is achieved. The assignment of probabilities may be based on climate projections, historical data, expert judgment, or some combination thereof. The probability weighted version of the robustness index is defined as the "climate-informed" robustness index (CRI) as according to equation (3).

$$CRI = \int_{\mathbf{x_0}}^{\mathbf{x_J}} \Lambda(\mathbf{x_j}) f(\mathbf{x_j}) dx \tag{3}$$

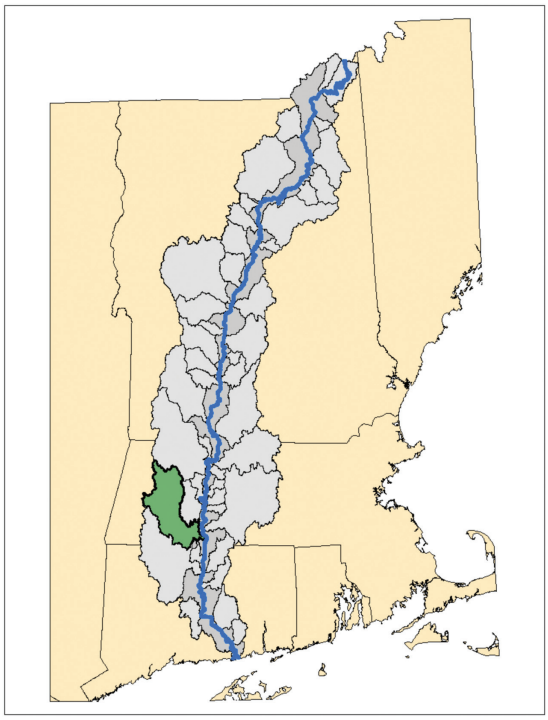

**Figure 1.** Map of the Connecticut River Basin with the Westfield Basin (focus of this study) shaded green.

where $f()$ is a probability density function describing the probability distribution of climate changes, X.

The CRI allows the use of various projections of climate futures to weight the robustness according to the assumed probability of a given climate change. As described above, there may be cases where decision makers are interested in assigning differential probabilities to different climate states. For example, there may be interest in using GCM projections to subjectively define probabilities of climate changes in order to rank adaptation alternatives. In this case, $f(\mathbf{x_j})$ in equation (3) can be defined using a distribution and parameter values selected to appropriately represent the sample of projections. The effect of alternative assumptions regarding an appropriate distribution for representing future climate probabilities is an interesting research question not yet explored.

The framework presented here also provides a direct means to incorporate recent innovations in climate science modeling that attempt to quantify uncertainties in future climate projections. Recently, there have been significant efforts to develop formal probability distributions of global and regional climate variables. These approaches, which are often Bayesian by design, utilize initial condition ensembles [*Stainforth et al*., 2005], perturbed physics ensembles [*Murphy et al*., 2004; *Rougier et al*., 2009], multimodel ensembles [*Tebaldi et al*., 2005], or combinations thereof [*Sexton et al*., 2012; *Sexton and Murphy*, 2012] to develop pdfs of response variables. These pdfs can be directly applied in the CRI.

In many cases, generally referred to as deep or true uncertainty [*Davidson*, 1991], it is difficult or perhaps impossible to prescribe reliable probabilities to future climate conditions in which decision makers have confidence. Equation (3) allows a decision maker to evaluate the effect of alternative assumptions of the future on the robustness of the system by altering the density function $f(x)$. A particular strength of the robustness index presented here is that it makes the choice and effect of probabilities of future climate explicit, and consequently easy to evaluate as a sensitivity parameter. In top-down approaches, the assumptions of future climate likelihoods are implicit in the creation of the scenarios; their impact on system performance is thus hidden from the decision-making process.

The CRI can be used to evaluate adaptation measures without assumptions of future climate and to evaluate the effect of different assumptions. Consequently, different sources of probabilities, introduced in the final step of the analysis, can be interpreted by stakeholders in a context relevant to decision-making that clearly reveals the implications of assuming a particular probability distribution. In the example presented next, a low-regrets adaptation (i.e., changing reservoir operations) is evaluated using the CRI. The use of the CRI in decision-making is illustrated in an application of a stylized water supply system.

## 3. Application: A Case Study of an Urban Water Supply System

The framework presented above was developed for evaluating robustness for water supply systems in an uncertain future. A case study of a municipal water supply system in the northeast United States is used to demonstrate the applicability of the methodology. The example application evaluates the robustness of the

system under climate uncertainty and then uses the robustness index to compare the status quo system with a possible adaptation, namely, alternative reservoir release operations.

### 3.1. The Little River Water Supply System

The water system evaluated in this study is based on the Little River Water Supply System managed by the Springfield Water and Sewer Commission (SWSC). The Little River system, located in the Westfield River Basin (Figure 1), consists of three major reservoirs: Cobble Mountain Reservoir (22,829 million gallons (MG)), Borden Brook Reservoir (2500 MG), and Littleville Reservoir (10,560 MG). The Cobble Mountain Reservoir is the second largest water supply in Massachusetts. For the purposes of this analysis, Cobble Mountain is modeled as a major storage reservoir and Borden Brook as a run-of-river facility.

Reliability and cost of water supply are the performance metrics used in this analysis. An inability to meet at least 80% of average daily water supply demands ($D_t$) (assumed here to be 30 mgd) is considered a shortage ($Sh$):

$$Sh(t)=\begin{cases} 0 & \text{if } 0.8\,D_t - S_t \leq 0 \\ 1 & \text{if } 0.8\,D_t - S_t > 0. \end{cases} \tag{4}$$

where $S_t$ is the water supplied to the city on a given day.

A quantitative metric for water supply reliability ($R$) [*Hashimoto et al*., 1982b] is calculated as the difference between unity and the ratio of the total number of shortage days that occur and the total number of days in the record ($T$):

$$R=1-\frac{\sum_{t=1}^{T} Sh(t)}{T} \tag{5}$$

For the purposes of the present analysis, a performance threshold of 95% is placed on the reliability performance indicator.

Normalized shortage costs ($C_N$) were developed for this analysis to represent economic losses that Springfield staff indicated occurred during shortage. Cost penalties ($C_s(t)$) for not meeting water supply demand on a given day were adapted from SWSC's drought management plan [*Westphal et al*., 2005], with increasing costs applied to shortages of 10 and 20 percent of average daily demands. For each climate change scenario, cumulative shortage costs were divided by the base case shortage cost, $C_B(t)$ (calculated under current climate conditions) to compute a normalized shortage cost metric:

$$C_N=\frac{\sum_{t=1}^{T} C_S(t)}{\sum_{t=1}^{T} C_B(t)} \tag{6}$$

In this case, the performance threshold was defined as no change in cost from the base case (i.e., a ratio of 1).

### 3.2. System Models

Time series of daily weather data, namely precipitation and temperature, were used to drive a hydrologic model, which generated hydrologic time series. Hydrologic sequences were used as input to reservoir operations models, which incorporate physical characteristics of the reservoirs, system operating rules, and water demands to produce measures of system performance (i.e., reliability and shortage costs). Two reservoir models, including both a simulation and optimization models, were used in combination to evaluate the ability of status quo operations to meet water management objectives and the possible operational improvements that could be made to meet objectives given optimal policies. All systems models were either written in the R programming language or LINGO, an optimization modeling software, which was coupled with R for rapid assessment over a large number of scenarios. System models (i.e., hydrologic model, simulation model, and optimization model) used in this analysis are described next.

#### 3.2.1. Hydrologic Model

The "abcd" conceptual, lumped parameter hydrologic model was adapted from *Thomas* [1981] and used in this analysis to estimate daily streamflow in the Westfield River Basin. An additional snow component (i.e., the addition of a snow storage zone) was included in this analysis because of the influence of snow accumulation/melt on hydrologic processes in the northeast United States [*Steinschneider et al*., 2012; *Martinez and Gupta*, 2010]. This conceptual lumped-parameter model was used in the present study because of its parsimonious nature (i.e., few and physically meaningful parameters) and geographic and hydrologic compatibility with the case study location.

The model was manually calibrated to fit daily historic flows at the West Branch Westfield River station at Huntington, MA (USGS 01181000). Calibration of the model yielded a Nash-Sutcliffe efficiency of 0.5802, which was deemed adequate for a water supply system with no flood risk concerns. Hydrologic model error is not expected to be significant in this case per conclusions in an earlier study [*Steinschneider et al*., 2012].

#### 3.2.2. Water Supply Reservoir Simulation Model

A simulation model was designed to estimate the behavior of the urban water supply system under future climate changes. Functions in the model are based on current reservoir operating policies reproduced from the SWSC's drought management plan. In this study, two storage thresholds (i.e., "normal" and "moderate" drought severity levels) are specified and water restrictions are imposed on the system when these storage targets are not met. For the purposes of this analysis, the plan was used to guide status quo system operations based on reservoir storage levels (see details in Appendix A). With status quo operations, the model simulated past reservoir releases and storages adequately.

A simple adaptation of adjusting reservoir operations was explored in this analysis. The adaptation is modeled using an optimization model, which provides an upper limit on system performance.

#### 3.2.3. Water Supply Reservoir Optimization Model

In order to estimate the limits of adapting reservoir release operations to changing climate conditions, an optimization model of the system was developed. It represents the best operations that could be achieved without physical changes to the reservoir. Because the optimization routine uses the full record of inflows to choose the reservoir release schedule, it also implicitly assumes perfect inflow forecasts. As such it represents an upper limit on possible operations-based adaptations. The optimization model was built using the linear modeling software LINGO 12.0 to explore an operational alternative to the current system. The model computes reservoir releases that optimize an objective function, in this case, minimizing the cost of water supply shortfalls (equation (7)). The cost of a shortfall was estimated with a piecewise linear cost function.

$$\text{minimize} C_1 S_{M1} + C_2 S_{M2} + C_3 S_{M3} \tag{7}$$

where a shortfall of a certain magnitude ($S_{Mi}$) is defined by the difference between water supply demand and releases at time $t$. In this case, an inability to meet at least 80% of water supply demands occurs when $i = 3$ (i.e., shortfalls are of magnitude $S_{M3}$). Cost penalties are implemented based on the magnitude of water supply deficiencies as described in the simulation model; however, in this case, shortfalls are not determined by SWSC's reservoir operating policies, but instead by optimal operations (Appendix A).

Decision variables and constraints for this model include continuity equations that ensure all mass balance requirements are met, capacity constraints, shortfalls, and water supply releases over the 62 years evaluated. Overall, this model determines optimal operations for minimizing the cost of shortfalls given perfect foresight. As such, the results are not meant to represent what may actually be achieved but rather are used to demonstrate how the framework developed here can be used to evaluate different adaptations. The risk discovery step described next is designed to identify system vulnerabilities to plausible changes in climate conditions that could be problematic and require alternative adaptations.

### 3.3. Risk Discovery Modeling Framework

The risk discovery step is completed using a climate/weather generator to create sequences that exhaustively sample a range of plausible climate changes [*Steinschneider and Brown*, 2013]. Each sequence is then used to drive the physically based hydrologic model, and then the system performance is assessed using the simulation and optimization models of reservoir operations described above.

This study used a semiparametric weather generator to produce time series of weather consistent with prescribed climate changes [*Steinschneider and Brown*, 2013]. The model is designed to allow for the rapid performance of a "climate stress test." The weather generator parametrically simulates the occurrence of precipitation using a three-state Markov Chain stochastic model that moves between states (i.e., no precipitation, moderate precipitation, heavy precipitation) and determines rainfall amounts using a nonparametric K-Nearest Neighbor (KNN) resampling technique. Climate alterations are imposed on the weather sequences by adding increments to temperature values and adjusting precipitation values using a quantile mapping technique. Climate changes can be imposed seasonally, and other nuanced changes are possible, such as alternative daily rainfall persistence (i.e., altered transition probabilities). The model allows plausible climate change space to be effectively and exhaustively explored.

The weather generator is used to produce 121 daily weather sequences representing various types of climate changes in the Westfield River Basin for a 62 year period of record. Climate changes include percent changes in mean precipitation (±25% in 5% increments) and absolute changes in mean temperature (0–5°C in 0.5°C increments) from baseline values. The climate changes explored in this analysis were designed to extend well beyond the range of future temperature and precipitation changes that are exhibited in GCM projections.

### 3.4. Robustness Index and Climate Information

The robustness index is developed to be calculated independent of assumptions regarding the probability of future climate space by design. In addition, the assignment of probabilities based on climate projections can be used to provide a glimpse of what they imply for future vulnerabilities. This section describes the calculation of the robustness index and the sources of information used to prescribe probabilities for incorporation into the climate-informed robustness index.

#### 3.4.1. Climate Information

Probabilities of future climate conditions were generated from a multimodel ensemble of GCM projections. Probability density functions of precipitation and temperature changes were fit using an ensemble of 39 GCM projections (SRES emission scenario A1B) from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 3 (CMIP3) multimodel data set. We obtained monthly gridded simulated data directly from the GCM models [*Maurer et al*., 2002] at a 2° spatial resolution over the Westfield River Basin. Mean monthly temperature and precipitation were extracted from the data set for the time period between 1950 and 2099 and averaged for future (50 years centered around 2050) and historic (1950–1999) climate conditions. The average over each 50 year period was used to calculate a percent and absolute difference between future and historic precipitation and temperature, respectively, and both a uniform and normal distribution were fit to these projected climate changes. The probabilities derived may be considered conditional on the A1B scenario or otherwise as subjectively defined probabilities [*Lempert et al*., 2001].

#### 3.4.2. Quantitative Robustness Metric

The robustness index couples the binary performance results of the risk discovery stage with a probability distribution to quantify system robustness. In this analysis, three probability estimates of future climate conditions were explored. First, the RI is evaluated using a uniform distribution applied to the defined plausible climate space. Next, the CRI is evaluated for a uniform distribution applied to the GCM space (i.e., the outermost range over which the GCM projections span). Third, a climate-informed version of the robustness metric is evaluated by applying a multivariate normal distribution to an ensemble of GCM projections using a simplistic yet generally applied assumption that each projection is equally likely [*Brekke et al*., 2008; *Räisänen and Palmer*, 2001]. The effect of alternative probability weighting on the index offers decision-makers insight into the effect of alternative means of weighting the future on robust adaptation strategies under extreme climate uncertainty. The use of these density functions in the RI and CRI calculations are described in more detail below.

The RI is calculated for the two reservoir operating policies according to equation (8).

$$\mathrm{RI}_u^{stn} = \int_{t_1}^{t_2} \int_{p_1}^{p_2} \Lambda_{rel}^{stn}(p,t) \frac{1}{(t_1 - t_2)(p_2 - p_1)} dp dt \tag{8}$$

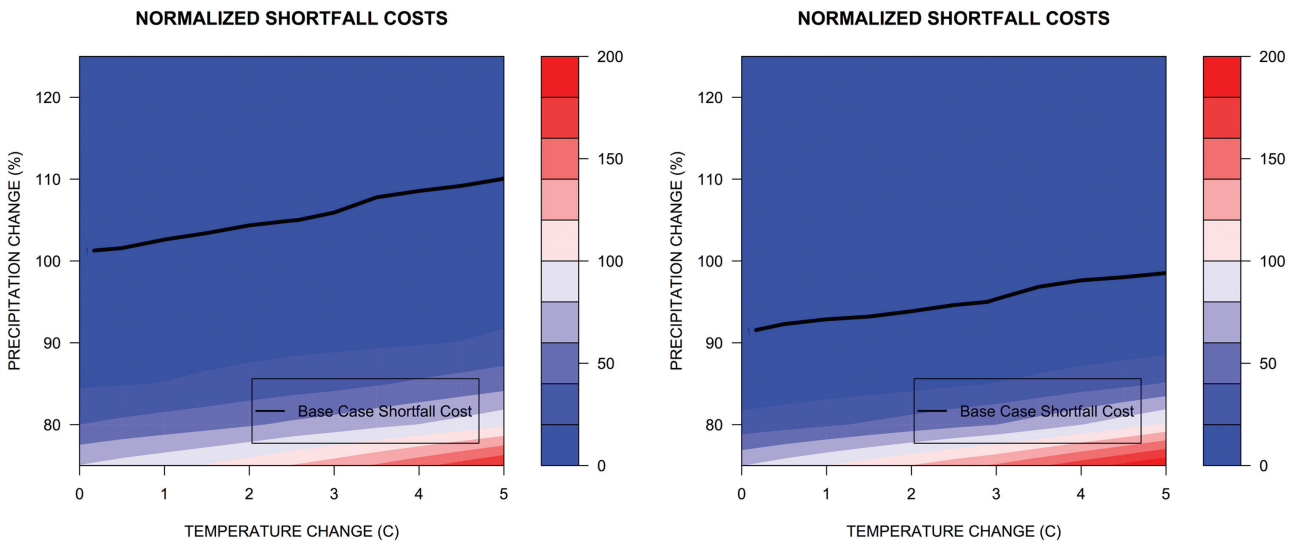


**Figure 2.** Climate response surfaces over climate change space (changes in precipitation and temperature) for normalized shortage costs (a) under standard and (b) optimal operating policies.

where a subscript "$u$" represents a uniform distribution, a superscript "stn" represents the standard operations, and subscript "rel" represents the water supply reliability metric used in this analysis. The uniform distribution in equation (8) applies equal weight to the plausible climate space (with precipitation and temperature limits of $p_1, p_2, t_1$, and $t_2$). In this analysis, the uniform distribution was also applied to the GCM space, where $p_1, p_2, t_1$, and $t_2$ in equation (8) define the maximum and minimum temperature and precipitation changes projected by GCMs.

In equation (9), the climate-informed robustness index is calculated by applying a normal probability distribution to future climate projections. A multivariate normal distribution is used to model the likelihood of future changes in mean precipitation and temperature. The distribution is fit using the mean, standard deviation, and correlation of the ensemble of 39 GCM projections of temperature and precipitation described above. The result is a "climate-informed" CRI based on central tendency and spread of the ensemble of projections:

$$\mathrm{CRI}_{mn}^{stn} = \int_{t_1}^{t_2}\int_{p_1}^{p_2} \Lambda_{rel}^{stn}(p,t)\left(\frac{1}{(2\pi)^{\frac{k}{2}}|\Sigma|^{\frac{1}{2}}} exp(-\frac{1}{2}(X-\mu)^T)\Sigma^{-1}(X-\mu)\right) dpdt \tag{9}$$

where $X$ and $\mu$ are $k$-length vectors of climate variables (i.e., precipitation and temperature) and their means, and $\Sigma$ is a matrix of the covariances. A subscript "mn" represents a multivariate normal distribution.

The alternative probability distributions (uniform, uniform gcm, and multivariate normal) are used to develop alternative measures of robustness for the standard and optimized system operations and reveal the effect of different assumptions about future climate on adaptation decision outcomes. Six robustness indices were calculated for each combination of distribution and systems model: $\mathrm{RI}_u^{stn}$, $\mathrm{RI}_u^{opt}$, $\mathrm{CRI}_{u,GCM}^{stn}$, $\mathrm{CRI}_{u,GCM}^{opt}$, $\mathrm{CRI}_{mn}^{stn}$, $\mathrm{CRI}_{mn}^{opt}$. The subscript "u" or "mn" represents uniform or multivariate normal distribution, respectively, while superscripts "stn" and "opt" represent standard and optimal operations. $\mathrm{CRI}_{u,GCM}$ indicates a uniform distribution applied to GCM-defined space. The RI quantifies robustness across all climate space, while the CRI takes into account the probabilities based on climate projections.

## 4. Results

The decision framework was used to parse the climate space into regions of acceptable ($Y_+$) and unacceptable ($Y_-$) performances based on stakeholder-driven thresholds ($Y_T$). The value of the performance metrics

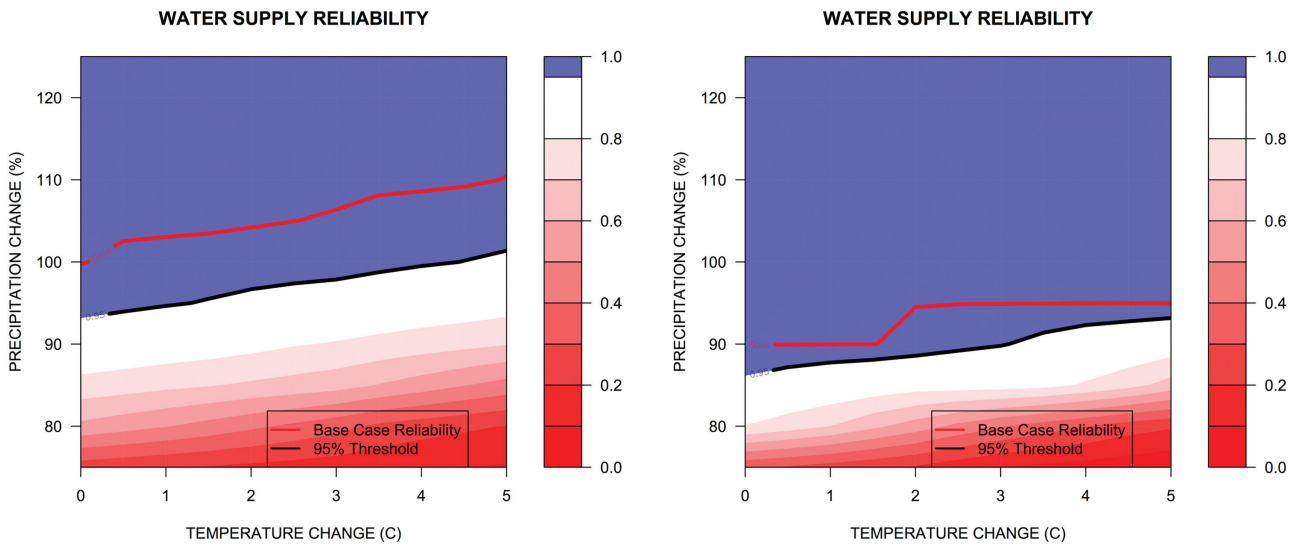


**Figure 3.** Climate response surfaces over climate change space (changes in precipitation and temperature) for water supply reliability (a) under standard and (b) optimal operating policies.

was calculated for each climate state (121 points) within climate change space. Figure 2 shows the results in the form of a contour plot with the system performance representing the *z*-dimension. In Figure 2a, system performance is measured by normalized shortage costs under status quo conditions. The black line indicates the contour with a shortage cost equal to the shortage cost in the base case. This value is used to represent the threshold of acceptable performance (defined in section 3.1) in terms of cost. Figure 2b illustrates system performance under optimal operating policies for the range of climate change conditions considered. As expected, optimization of the operations results in better performance, which can be seen in the figure as a change in location of the black line. The threshold of acceptable performance has moved down resulting in the region of acceptable performance covering a greater area of the climate change space. For example, at a 5% reduction of precipitation (95% of historic precipitation), the normalized

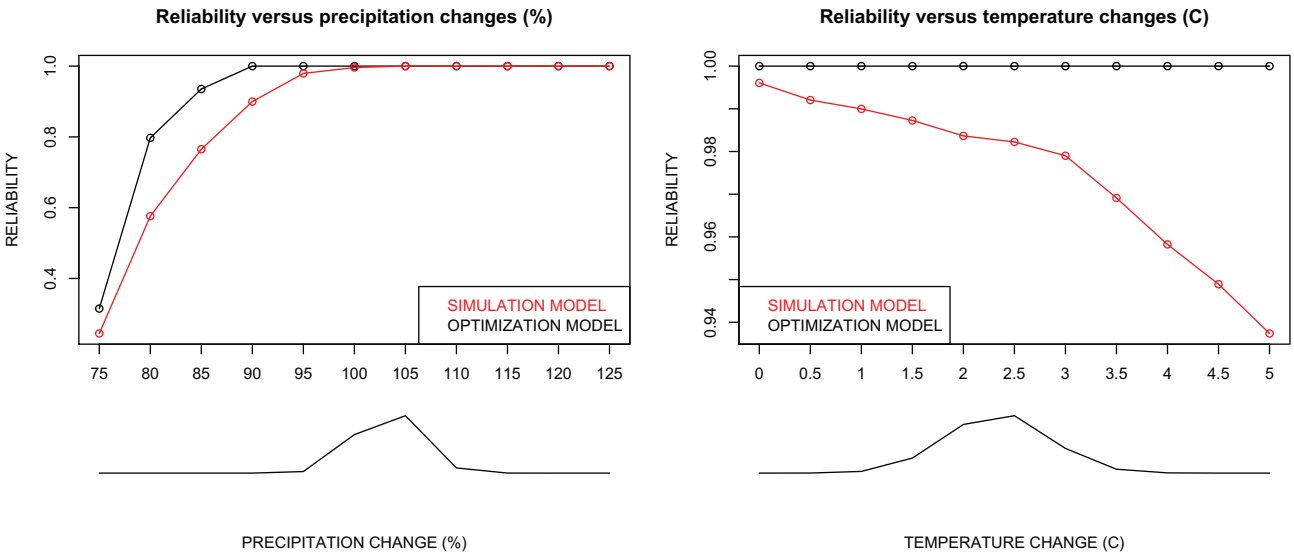


**Figure 4.** Two-dimensional plots of water supply reliability given (a) changes in precipitation and (b) temperature. Comparisons are made for standard operations (red line) and optimal operations (black). A pdf of precipitation and temperature changes based on an ensemble of 39 GCM projections (SRES emission scenario A1B) from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 3 (CMIP3) multimodel data set is illustrated on the *x* axis of each figure.

shortage costs are equal to costs of current operations for the historical mean precipitation. This suggests that optimal operating policies are able to produce the same costs as status quo operations with less available water.

Figure 3 illustrates the climate response surfaces for water supply reliability (equation (5)) under status quo (a) and optimal (b) operations. The red contour line illustrates the base case reliability (i.e., reliability under no change in climate), and the black line represents the threshold of acceptable performance, which was set at a reliability threshold of 95%. The results indicate that under status quo operations the system becomes vulnerable beginning at a 6% reduction in mean precipitation and a mean temperature increase of 4.5°C (Figure 3a). In comparison, optimal operating policies improve overall system performance, and reliability does not drop below the 95% threshold line until precipitation has decreased by 15% (Figure 3b). One can see in Figures 3a and 3b that the climate space over which performance is acceptable is larger for optimal operations (4b) compared to status quo operations. This is an indication of an increase in robustness with optimal operations, as expected.

Figure 4 shows the reliability for mean changes in precipitation and temperature individually while the other is held constant. With parallel axes, the probability density functions for precipitation and temperature changes are also shown, based on the multimodel ensemble of GCM projections (see section 3.4.1). The reliability is plotted for both the current operations and optimal operations.

Figure 4a shows that the alternative system operations do not improve water supply reliability until there is a decrease in historic precipitation of 6% or greater. At this point, optimal operations result in improved performance over status quo operations as mean precipitation decreases. However, there is a limited additional range of precipitation reduction that optimal operations can mitigate as seen in the figure. When mean precipitation is reduced below 90% of the historic value the reliability decreases under optimal operations as well, showing the limits that could be achieved by adapting operation policies. Beyond this change in precipitation, other adaptations would be necessary. Note, however, that the pdf shows the probability of such precipitation changes are low according to the ensemble of GCM projections explored in this study. However, probability distributions conditional on other methodological assumptions, such as different greenhouse gas emissions trajectories, could be used to assess a broader range of plausibility.

Figure 4b illustrates reliability versus changes in mean temperature. In this case, system operations play an important role in water supply reliability as mean temperatures increase. Optimal operations maintain a high level of reliability for all temperature changes. The status quo operations, however, show a rapid reduction in reliability with mean temperature increases. The difference in system performance may be due to a shift in the hydrograph that accompanies changes in temperature due to changes in the timing and magnitude of snow accumulation and the spring melt. While the optimization model can foresee these changes and alter operations to hedge against failures, the status quo operations cannot and are susceptible to decreases in the spring peak and increases in winter streamflow. This indicates that updating reservoir operations in response to increasing temperatures is likely to be adequate, which is significant because unlike projections of precipitation changes in the future, there is more confidence in projections of increases in temperature.

Figure 4 also includes pdfs based on an ensemble of GCM projections. Projections are centered around an increase in mean precipitation of 3% and range between a 5% decrease to a 10% increase. Over this range of projections, both operational policies achieve similar results. Note that an assessment of operating policies based only on precipitation changes from GCM projections would show little difference between the status quo and optimal operations. The mean of the pdf of GCM projections for temperature changes is 2.33°C, and optimal operations offer significant improvement over status quo operations given this level of change. Overall, altering operations may have an important role as an adaption to climate change in the future if temperature increases are consistent with climate projections.

In Figure 5, density values from the multivariate normal distribution based on the ensemble of climate change projections are superimposed on the climate space along with the 39 GCM projections indicated by black circles. Figure 5 shows the projected changes in climate from GCMs encompass only a small extent of possible impacts compared to the wide range of plausible climate changes explored in this study.

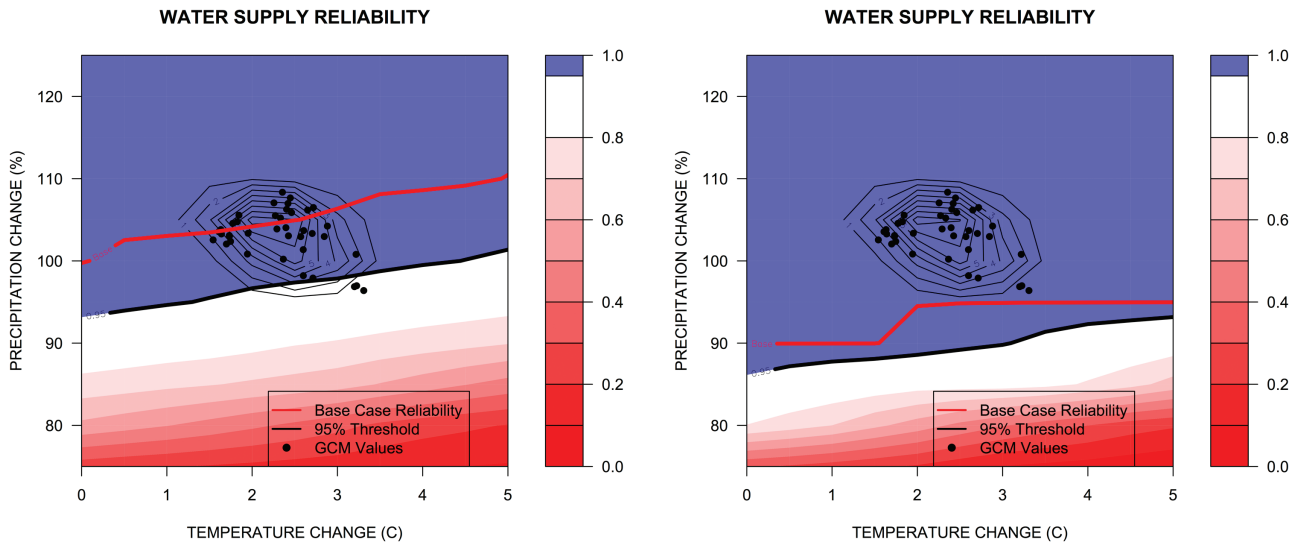


**Figure 5.** Climate response surfaces over climate change space for water supply reliability under (a) standard operations and (b) optimal operations. PDFs from climate change projections are superimposed over climate change space to observe likelihoods of future climate changes.

According to these projections, the likelihood of falling below the reliability threshold (red region) is small under both status quo and optimal policies. Moreover, models indicate that given the mean climate change scenario (i.e., temperature increases of 2.33°C and precipitation increases of 3%) water supply reliability under both policies will remain unchanged.

Figure 6 illustrates the grid space over which the RI, $CRI_{u,GCM}$, and CRI were evaluated. The RI was conditioned on a uniform probability distribution over all grid cells in Figure 6, the $CRI_{u,GCM}$ was conditioned on a uniform distribution applied to the shaded grid cells (GCM space), and the CRI was conditioned on a multivariate normal distribution applied to the black circles (ensemble of GCM projections) (see section 3.4.2). Robustness indices were calculated for each combination of distribution and systems model (see section 3.3) and are shown in Table 1. Table 1 illustrates that optimal operations improve robustness. The RI, $CRI_{u,GCM}$, and CRI for optimal operations increase from the status quo by 0.15, 0.45, and 0.01, respectively.

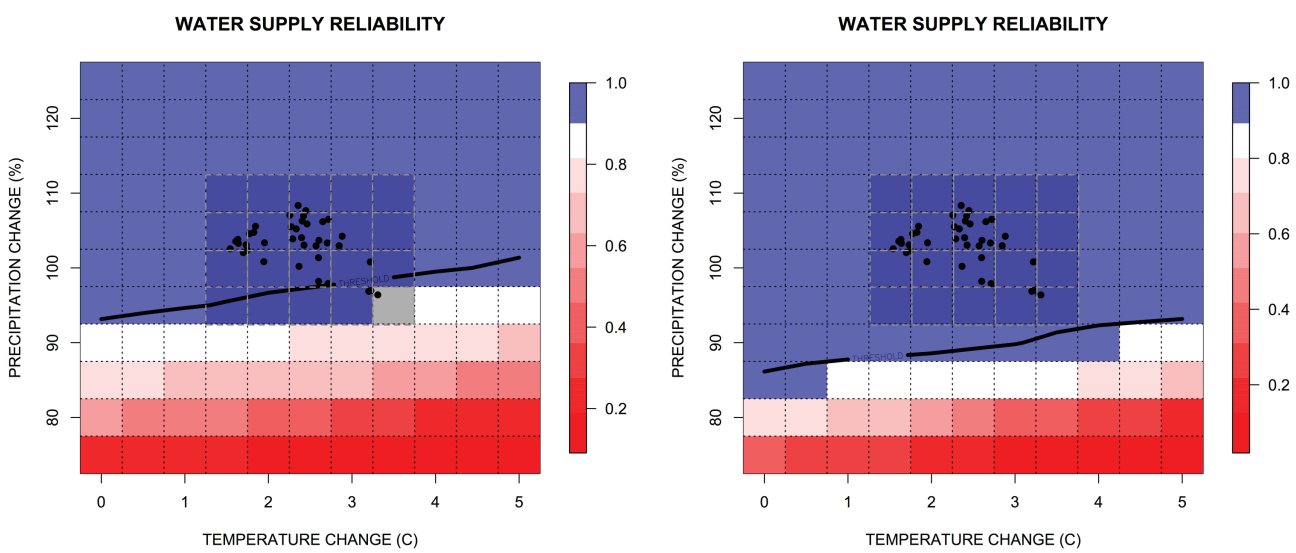


**Figure 6.** Climate response surfaces over climate change space for water supply reliability under (a) standard operations and (b) optimal operations. Climate change projections are superimposed over the climate change space with shaded grid cells encompassing their spread.

**Table 1.** Climate Robustness Indices Under Status Quo and Optimal Operations Given Assumptions of the Multivariate Normal (CRI) and Uniform Distributions Over Both Climate Change Space (RI) and GCM Space ($CRI_{u,GCM}$)

| Operations | RI | ΔRI | $CRI_{u,GCM}$ | $\Delta CRI_{u,GCM}$ | CRI | ΔCRI |
|---|---|---|---|---|---|---|
| Status quo | 0.55 | | 0.50 | | 0.94 | |
| Optimal | 0.70 | 0.15 | 0.95 | 0.45 | 0.95 | 0.01 |

These results are consistent with Figure 5, which also shows that adaptation increases the area of climate space over which acceptable performance is achieved. However, the similarity between the CRI under status quo and optimal operations in Table 1 suggests that calculation of the CRI alone would make it difficult to distinguish between the status quo and proposed alteration. This is because the normal distribution, which is heavily weighted nearest the mean, assigns a great deal of probability to climate space where both operating policies provide acceptable performance.

## 5. Discussion

Two key findings emerge from this analysis. First, the operational adaptation evaluated in this study shows improved performance and robustness over climate change space based on the results from the vulnerability analysis. This is also indicated by the robustness index in Table 1. The small difference in the CRI value between strategies suggests that much can be learned from a plausible space approach versus an analysis based only on GCM projections. Figures 3 and 4 and Table 1 (RI and $CRI_{u,GCM}$) show the approach more clearly illustrates the difference between the two strategies. Second, the analysis enabled the definition of the limits of an adaptation strategy by illustrating the mean temperature and precipitation changes that degrade system performance under status quo and optimal reservoir operations (the adaptation) (Figure 4). This would not be uncovered in a conventional GCM-projection-based analysis for this region, which would only sample relatively nonthreatening conditions (see Figure 5, where most climate projections suggest acceptable performance under both status quo and optimal operations). In particular, Figure 4 shows that the optimal operations can mitigate up to a 10% reduction in precipitation, at which point alternative adaptation strategies would be necessary. Likewise, optimal operations would largely mitigate any changes in temperature.

This paper defines a robustness index that is not strongly dependent on assumptions regarding future climate. Under extreme uncertainty, a decision-maker may be better served by exploring the robustness of alternative adaptations without assuming probabilities of given climate changes. Alternatively, they may be interested in the effect of assuming that the range of climate changes is not equally likely across climate space by using probabilities to weight possible changes. The robustness index is designed to accommodate both approaches, incorporating probabilistic information regarding future climate where such judgments are warranted. With the choice and effect of probabilities of future climate explicit, the decision-maker can weigh the benefits of adapting operations according to prior judgments regarding the likelihood of different climate changes and recent advances in climate science.

Table 1 illustrates the strength of the robustness index in comparing alternative operating policies under different assumptions of future climate. In comparing the index across different assumptions of future climate is important to note that the current state of climate projections heavily influences the $CRI_{u,GCM}$ calculation. A shift in the location and spread of climate projections as new information comes available might alter the value of an operational adaptation. The multivariate normal distribution fit to the set of mean precipitation and temperature changes derived from the ensemble of GCM projections is a function of those projections. It represents a relatively extreme weighting of the central tendency of the ensemble relative to the tails, and as such provides a contrast to the RI. It also displays the limited insight that would be gained from an analysis based simply on climate change projections.

This analysis reveals information not otherwise apparent in GCM-projection driven approaches, which may underestimate system vulnerability and risk. The range of climate stress test was chosen to explore a wide range of possible climate changes without regard to their likelihood in order to reveal vulnerabilities. The endpoints of the range do not heavily weigh the results; vulnerabilities due to changes deemed implausible can be disregarded.

## 6. Conclusion

There is widespread interest in making water systems robust to climate change, but little definition or quantification of what that means. In this study, we propose a definition and index that can be generally applied based on the range of climate change space over which acceptable performance can be achieved. In this way, the robustness index can be made independent of strong assumptions regarding future climate based on GCM projections or stationary assumptions. The index is demonstrated for a water supply system and the value of the index is demonstrated showing the additional robustness that optimal operations achieve, which would not have been indicated in a GCM projection driven analysis.

The framework presented in this study is designed to facilitate in confronting the potential challenges of climate impacts through risk assessment and robust adaptation. Ultimately, decision-makers must confront water resources management under an uncertain and changing climate regime. While assumptions can be made about the likelihood of future climate states occurring, it is necessary that system adaptations are robust to a wide range of potential conditions that may be encountered.

The approach presented in this paper is useful for quantifying robustness of alternative adaptations. This approach identifies relevant risks and investigates robustness of adaptations over a wide range of climate futures. GCM-based projections can be used to provide "climate-informed" weightings of future conditions in the later stages. The framework is not limited by the uncertainties and biases of the projections. Rather, GCM projections are used as a lower bound on the range of climate uncertainty, while the system robustness is measured over a wider range representing plausible climate change space. Points of further exploration are the impact of integration endpoints and alternative assumptions of plausibility. In addition, expert judgment can be used to assign probabilities to the space. The incorporation of alternative assumptions of the future using expert judgment and the latest available climate information can be done without needing to rerun the entire analysis sequence.

## Appendix A: Case Study Region

### A1. Systems Models

In this section, we elaborate on some of the details of the systems models developed for this analysis. First introduced in section 3.2.3, the SWSC's current reservoir operating policies that were used to guide status quo system operations in the simulation model (described in section 3.2.3) are illustrated in Figure 7.

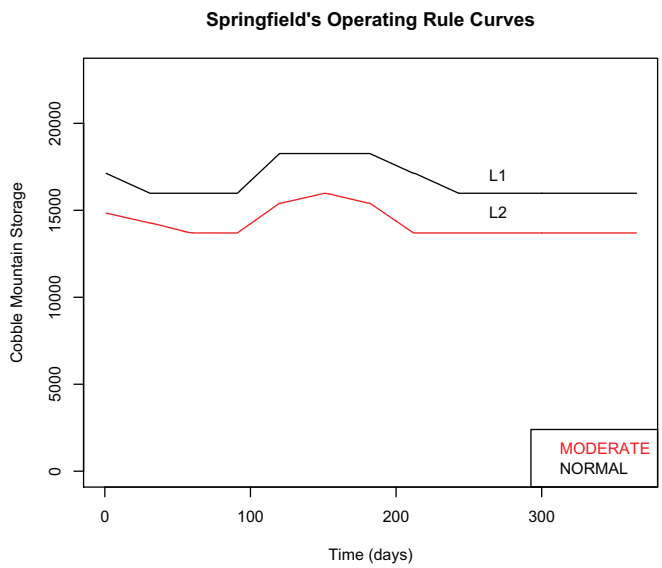


**Figure 7.** Springfield Water and Sewer Commission (SWSC) Drought Severity Levels for the Cobble Mountain Reservoir. Storage levels for "normal" (black) and "moderate" (red) drought conditions are specified for days of the year.

In Figure 7, the black line represents a "normal" drought severity level (L1) and the red line represents a "moderate" drought severity level (L2). A cost function was developed using the drought severity levels in Figure 7 to demonstrate the economic consequences of dropping below storage targets. Storage targets are designed as safeguards to prevent significant shortages during water scarce times of year. The cost function (equation (A1)) applies increasing cost penalties to the model for dropping below normal ($L_1$) and moderate ($L_2$) drought severity levels. Additionally, water restrictions (i.e., percent reductions in demand, $D$) are

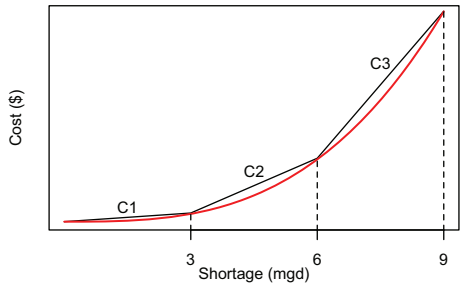


**Figure 8.** Piecewise linear cost function; increasing cost penalties ($) are imposed on the system for increasing magnitudes of shortfalls (mgd) to water supply demand.

imposed on the system when target storage levels are not met. Reservoir storages were accounted for in the model using continuity equations

$$Cost_t = \begin{cases} 0 & \text{if } S_{t-1} > L_{1t-1}, \\ 3C_1 & \text{if } L_{1t-1} > S_{t-1} \geq L_{2t-1}, \\ 3C_1 + 3C_2 & \text{if } L_{2t-1} > S_{t-1} > 0; S_{t-1} + I_t \geq D_t, \\ 3C_1 + 3C_2 + C_3(D_t - R_t) & \text{if } L_{2_t-1} > S_{t-1} > 0; S_{t-1} + I_t < D_t. \end{cases} \quad \text{(A1)}$$

In equation (A1), $S_{t-1}$ represents yesterday's reservoir storage in Cobble Mountain, $I_t$ represents today's inflows into the reservoir, and $R_t$ represents today's releases from the reservoir. Cost coefficients ($C_1$,$C_2$,$C_3$), adapted from SWSCs drought management plan, are $3179, $6358, and $15,895.

As described above, the optimization model was designed to minimize the cost of having water supply shortfalls. Since the optimization model was developed using linear programming software, a piecewise linear cost function was incorporated into the objective function to capture the increasing cost penalties imposed on the system for increasing magnitudes of shortfalls (mgd) to water supply demand (Figure 8).

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