Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector

Casey Brown,[1] Yonas Ghile,[1] Mikaela Laverty,[1] and Ke Li[1]

Received 29 July 2011; revised 28 June 2012; accepted 2 August 2012; published 21 September 2012.

[1] There are few methodologies for the use of climate change projections in decision making or risk assessment processes. In this paper we present an approach for climate risk assessment that links bottom-up vulnerability assessment with multiple sources of climate information. The three step process begins with modeling of the decision and identification of thresholds. Through stochastic analysis and the creation of a climate response function, climate states associated with risk are specified. Climate information such as available from multi-GCM, multirun ensembles, is tailored to estimate probabilities associated with these climate states. The process is designed to maximize the utility of climate information in the decision process and to allow the use of many climate projections to produce best estimates of future climate risks. It couples the benefits of stochastic assessment of risks with the potential insight from climate projections. The method is an attempt to make the best use of uncertain but potentially useful climate information. An example application to an urban water supply system is presented to illustrate the process.

Citation: Brown, C., Y. Ghile, M. Laverty, and K. Li (2012), Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector, *Water Resour. Res.*, *48*, W09537, doi:10.1029/2011WR011212.

1. Introduction

[2] The implications of climate change are a growing concern for water managers. Even simple extrapolation of current trends in temperature makes clear that a warming climate can significantly affect hydrologic conditions with negative impacts on many facets of society and ecosystems. The impacts on water resources derived from the projections of general circulation models (GCM) present a range of concerns, including increased drought, increased floods, reduced mean water availability and harmful effects on aquatic ecosystems [*Kundzewicz et al.*, 2007]. The sum of these troubling effects, although highly uncertain, motivates efforts to assess and manage potential climate change impacts.

[3] The primary approach to assessing climate change impacts has been through the use of GCM projections of future precipitation and temperature. The raw climate variables from GCMs have significant biases which must be corrected prior to their use and are produced at coarse spatial scales. Downscaled and bias corrected climate variables [e.g., *Wood et al.*, 2004; *Tebaldi et al.*, 2005; *Hidalgo et al.*, 2008] then serve as input to hydrologic models, the output of which is used to drive water systems models, which are used to estimate the impacts on variables of societal interest.

[4] This approach to climate change impact assessment provides information about the potential impacts associated with anthropogenic climate change according to the available projections. However, from a decision making perspective, it is often difficult to utilize the results due to a number of incongruities between the typical results and the needs of decision makers [*Wilby and Desai*, 2010; *Hallegatte*, 2009; *Stainforth et al.*, 2007; *Rohmsdahl and Pyke*, 2009]. An alternative is to use stochastic methods for hazard identification and to use climate projections to estimate relative probabilities of these hazards, yielding risk estimates. Such an approach is described here.

[5] Here we describe a new approach to using climate information within a decision making framework that links bottom-up, stochastic vulnerability analysis with top down use of GCM projections. To describe this methodology we introduce the term "decision-scaling," which refers to the use of a decision analytic framework to reveal the scaling of climate information that is needed to best inform the decision at hand. In decision scaling, the premise is that discussion of appropriate downscaling methods should follow and be informed by the formal modeling of the decision of interest. It facilitates the use of a large number of climate sources, including GCM runs, for decision making under climate change. It differs from current methodologies by utilizing the climate information in the latter stages of the process within a decision space to guide preferences among choices. The methodology first identifies the climate conditions that are *relevant* to the decision and then uses that information to link to what is *credible* in available climate information. The underlying premise is that since a given ensemble of GCM-based climate projections represent the

[1]Department of Civil and Environmental Engineering, University of Massachusetts Amherst, Amherst, Massachusetts, USA.

Corresponding author: C. Brown, Department of Civil and Environmental Engineering, University of Massachusetts Amherst, 12B Marston Hall, 130 Natural Resources Rd., Amherst, MA 01003-9293, USA. (cbrown@ecs.umass.edu)

0043-1397/12/2011WR011212

irreducible *lower* bound on the range of climate uncertainty [see *Stainforth et al.*, 2007], they should not be used to identify risks, but rather as a potential prioritization weighting on risks.

[6] A novel aspect of the approach is that it uses decision analysis as a framework for characterizing the climate future, and consequently, climate projections, in terms of their position relative to decision thresholds. In doing so, it uses stochastic analysis for risk identification and uses GCM projections for risk estimation, assigning probabilities to hazards, thus linking the two methods. As a result, climate information may be tailored to address key concerns and transparent assessment of the effect of a particular source of climate information (e.g., a particular GCM or downscaling approach) in terms of influence on the decision. Probabilities may be derived as a quantification of the range of climate change information available and are best understood as model based or subjective. They represent a "weighting" of the risks identified via stochastic analysis [*Raiffa and Schlaifer*, 1961]. The results do not attempt to provide "optimal" solutions in the traditional decision analytic sense. Instead, the approach identifies the best decision conditional on the weight of the climate projection-based evidence. Given the uncertainty of future climate (and other) changes, consideration for enhancing the robustness of such a decision is warranted.

[7] This paper introduces the methodology and illustrates it with a conceptual example of water supply reliability. The next section reviews current approaches to assessing impacts and risks of climate change to the water sector, followed by the presentation of our proposed process. An illustrative example is presented and the paper ends with some discussion of limitations and concluding remarks.

2. Background on Climate Change Impact Assessment

[8] The dominant approach to climate change impact analysis uses GCM projections as the driver of the assessment [*Wilby and Dessai*, 2010]. These studies use a "top down" methodology that begins with climate change projections, downscales them to match the spatial and temporal scales of hydrologic models, and uses the hydrologic projections of climate change to drive water resource systems models. *Vano et al.* [2010] provides a state of the science example of climate change impact assessment on an urban water supply system using this approach. Twenty GCM projections are used to project hydrologic changes and subsequently changes in reservoir storage and reliability using water resources systems models of water systems in the Puget Sound region. Similar approaches have been applied in *Wiley and Palmer* [2008], *Christensen and Lettenmaier* [2007], *Brekke et al.* [2009] and *Manning et al.* [2009]. *Rajagopalan et al.* [2009] used stochastic simulation of climate changes to streamflow including assumed trends consistent with most GCM projections to assess impacts on the Colorado River. *Vicuna et al.* [2010] use sampling stochastic dynamic programming to model reservoir operations and adaptation with a large number of GCM runs. *Lopez et al.* [2009] demonstrate the utility of a large ensemble of GCM projections from Phase 3 of the Coupled Model Intercomparison Project (CMIP3) and from a perturbed physics ensemble based on a single GCM, to assess implications for a water resources system, finding the results differed in important ways by choice of ensemble.

[9] In these approaches the uncertainties are described by using projections from multiple GCMs. In some cases extreme members of a GCM ensemble are chosen to attempt to capture the range of uncertainty, although the true range of climate uncertainty remains unknown [*Stainforth et al.*, 2007]. If the range of climate scenarios is very wide, it presents the planner with difficult choices. For example, the ranges might include one scenario where no action is necessary and another where very costly investments are necessary [*Brekke et al.*, 2008, 2009]. There are considerable potential regrets to planning for either. Given the costs typically associated with addressing some of the worst case impacts, a water manager is unlikely to be comfortable committing resources on the basis of a single or small number of projections.

[10] Due to the sizeable uncertainties associated with climate change, *Lempert et al.* [2004] advocate the "assess risk of policy" approach as more appropriate for decision making under climate change uncertainty. Risk-based "bottom up" methodologies have been proposed for the assessment of climate change risks. *Jones* [2001] described a risk-based approach that focuses on identifying risks using GCM projections and managing them. *Johnson and Weaver* [2009] describe a similar methodology for identifying and addressing risks. Risk-based approaches are more directly applicable to decision making processes but do not circumvent the difficulty in using GCM projections. The methodologies generally still use a top down approach to GCM projection use, incorporating them as starting points for risk analysis. *Lempert et al.* [2006] describes this use of GCM projections as "scenario generators."

[11] A problem with this approach is that GCM projections are relatively poor scenario generators. They describe a "lower bound on the maximum range of uncertainty" [*Stainforth et al.*, 2007]. Even a large multimodel ensemble provides relatively few samples in a typical analysis relative to the size possible through stochastically generated risk analysis. Larger ensembles are becoming available, such as via the climate prediction.net experiment [*Stainforth et al.*, 2004] but still face issues of biases that may preclude the discovery of plausible climate risks. Stochastic analysis enables sampling a wider range of possible climate changes but typically is unable to incorporate the physical response of the Earth's climate to increasing greenhouse gas emissions in the way that a GCM can. One approach would be to develop new stochastic methods combined with robust signals from GCM [*Groves et al.*, 2008; *Rajagopalan et al.*, 2009].

[12] There is growing interest in methods for assessing climate risk or adaptation planning that are not based on GCM projections [*Desai et al.*, 2009; *Wilby and Desai*, 2010]. One alternative is the use of stochastic methods to sample a much wider range of possible scenarios to assess risk [*U.S. Bureau of Reclamation*, 2009; *Rajagopalan et al.*, 2009]. Stochastic hydrology is largely dedicated to estimating risk in water resources systems (hydrologic prediction is another major research area). While stationary statistics may be able to capture the variability of nonstationary timeseries, the link with GCM projections or other climate change information remains nascent.

[13] *Prudhomme et al.* [2010] describe an approach that is similar to the process described here, first creating a response function to simulate future flood risk as a function of climate changes. The function is then used to visualize the implications of an ensemble of climate change projections. *Wilby and Dessai* [2010] describe a process for adaptation planning that emphasizes addressing observed climate variability and change while also assessing the effectiveness of the adaptations for future risks. The process incorporates future climate narratives to inform the assessment. Each of these papers demonstrates a framework that uses climate information in innovative ways and improves its utility for informing decisions.

[14] The approach described here is similar in premise to these studies but uses decision analysis as a framework to link information needed for decisions identified through bottom-up stochastic assessment with projections of future climate from sources such as GCMs. The application of decision analysis to water resources under climate change uncertainty is surprisingly rare in the literature. *Hobbs et al.* [1997] provides an example, applying decision analysis to an irreversible decision on the construction of new infrastructure in the Great Lakes to manage climate change impacts. The future is summarized with two future states of the world, one with climate change and one without, reflecting the lingering uncertainty at the time as to whether climate change was real. *Groves and Lempert* [2007] use a decision analytic approach to define "policy relevant" socioeconomic scenarios for water resources planning in California. The methodology described in this paper uses a similar application of decision analysis to define climate states that correspond to decisions.

3. Methodology

[15] The execution of this methodology inverts the process commonly used in climate change analysis which begins with GCM projections and propagates the projections through simulation and/or optimization models to produce an estimation of the impacts of those projections (see references above). Our method begins with decision analysis, using it as a tool to identify climate states that favor a particular decision over others. In the risk assessment application, the decision is one of taking action or not taking action. Through sampling of the effects of possible changes in climate on the system, the climate conditions that cross decision thresholds are identified. A decision threshold is a point where the optimal decision changes as a function of the climate conditions. In decision theory terminology, the climate conditions are the state variables. Through this process a climate state is identified as the range of climate variables that favors a particular decision option.

[16] Once the decision-influencing climate states are identified, climate information is tailored to estimate probabilities associated with those states. By estimating probabilities for broad categories of climate conditions, two benefits are realized. First, the specificity of information needed from the GCMs is reduced and the results may be more reliable [*Mastandrea et al.*, 2010]. Second, since the climate states are tied directly to the decision, the climate information that is generated will be directly tied to the conditions that influence the decision, thus establishing relevance. We change the question we are attempting to answer from "what will the future climate be?" which is very difficult with an infinite number of possibilities, to "is the climate that favors action A more or less likely than the climate that favors action B?" Appropriately tailored climate information, including GCM projections and stochastically generated conditions from historical and paleodata, and the application of expert judgment, may provide informative answers to this question when approached in the manner described here. With relevance established, the climate science effort can focus on assessing and possibly improving the credibility of the specific climate information sought.

[17] The methodology consists of three steps which are explained below. Figure 1 presents a schematic of the process.

3.1. Identification of Climate Concerns, Hazards, and Thresholds

[18] The first stage of the analysis identifies the climate conditions that cause risks and/or favor a particular decision to be preferred over another. The initial part of the process is conducted through discussion with stakeholders to

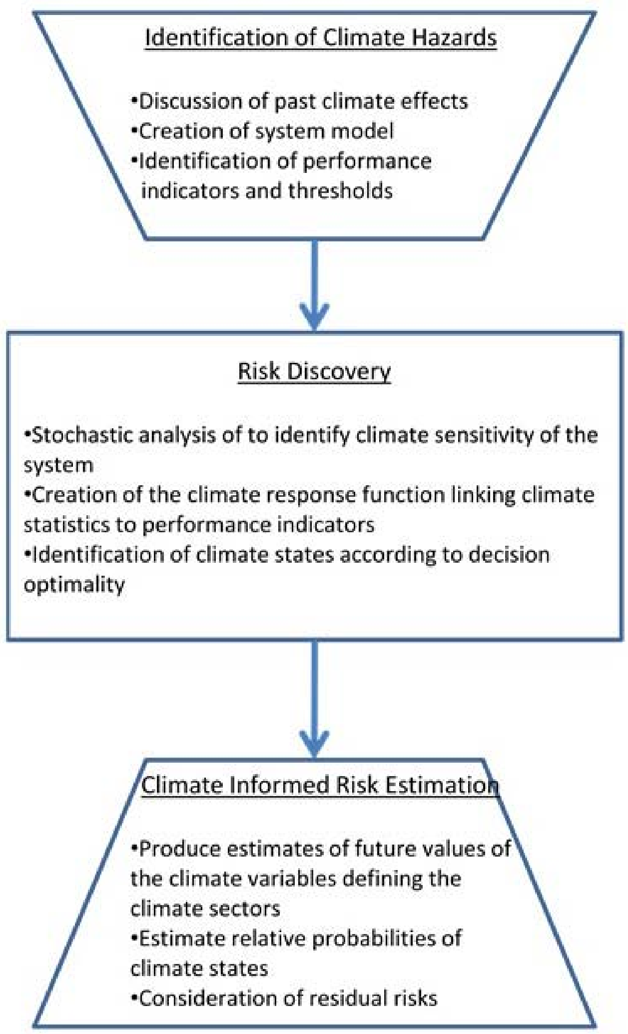


Figure 1. Diagram of the bottom up climate risk assessment and management process.

identify the climate conditions that have caused problems historically or that are otherwise of concern. The historical record is a useful starting point for identifying how climate has impacted the system in the past and the particular climate episodes that are challenging [*Wilby and Dessai*, 2010]. General summaries of climate change projections from the literature or such as those available from the Intergovernmental Panel on Climate Change (IPCC) reports on regional impacts are useful guides for this discussion.

[19] An additional aim of the discussions is to identify thresholds of performance indicators and system performance that when exceeded signify the need for adaptive actions. For example, a level of system performance that is the minimal acceptable might be such a threshold; anything worse and changes to the system would be necessary. In some cases, expected benefit-cost analysis (BCA) can be used to specify decision thresholds. For example, a benefit cost ratio of one or greater might be a threshold for a proposed project. Values of less than one would signify an unacceptable project. In other cases, such as in cases related to environmental functioning where benefits and costs are very difficult to estimate, decision thresholds can be specified based on stakeholder-defined performance indicators as described by analysts and stakeholders. In the conceptual example presented below, reliability of water supply delivery is used as the performance indicator and a decision threshold is specified as a reliability level of 95% as a general planning standard. In an ongoing study of the Great Lakes, thresholds on acceptable lake levels were defined for a variety of stakeholder groups, some based on estimated economic impacts and others not [*Brown et al.*, 2011].

[20] The understanding of the decision and context is then formalized through the creation of a decision system model that simulates system performance as a function of climate inputs. The model is typically composed of supporting models, such as hydrologic models, reservoir operations models or a planning model for large, multiobjective water resource systems. The climate related inputs depend on the models, but generally include precipitation and temperature. In this approach, the models are used to characterize the response of the system to changes in climate. The resulting characterization is used for the discovery of climate risks and the development of a climate response function.

3.2. Risk Discovery: Identifying Climate Conditions That Cause Risks

[21] The next step uses the decision system model to identify and characterize climate states related to decision outcomes. The risk discovery step consists of three aspects. A classic sensitivity analysis to identify problematic climate conditions, the parsing of the climate space according to optimal or best decisions, and the development of a "climate response function." These steps are described below.

[22] Risk discovery begins with a sensitivity analysis of the water resources system. This may be accomplished using a large stochastic input series (e.g., tens of thousands of years) that samples a wide variety of possible climate conditions. Other methods are possible, including parametrically varying the climate state of the inputs (as demonstrated in the example later in the paper).

[23] Whether created stochastically or deterministically, the key aspect is that the future climate space is sufficiently sampled to evaluate the decision outcome in all remotely plausible climate conditions. Note that at this point in the analysis, the climate range is not limited by concerns over the probability of those climate conditions actually occurring. Those concerns, which are real, are addressed in section 3.3.

[24] The result is a set of atmospheric or hydrologic variables, (X_t) and performance indicators (Y_T) representing a statistic of performance over a period T. As the focus of this analysis is climate related impacts, T is a long-term (30 years or greater) period, and the statistics of X_t are paired with statistics of performance metrics, Y_T, over a concurrent period. From this set, a relationship between climate and performance can be derived. The degree to which the performance metrics can be explained by climate is assessed to determine a subset of climate statistics, v_T, where $v_T = f(X_t)$, that most influence the performance indicators, Y_T. For example, *Vogel and Bolognese* [1995] show that the reliability of many reservoirs can be estimated with the mean, standard deviation and serial correlation of reservoir inflows, contingent on water demand. The result is a reduced set of influential climate conditions that can be explored to identify climate conditions of concern in terms of the relevant performance indicators. Note that the spatial resolution of ν_T may differ from X_t. For example, a possible informative statistic on climate time scales may be the spatial average of a distributed climate variable.

3.2.1. Climate Response Function

[25] In many applications it may be possible and useful to construct a "climate response function," $g(v_T)$ where $Y_T = g(v_T)$. The climate response function acts as a surrogate model, representing the results of a series of models in a computationally efficient form that links climate variables directly to performance indicators. *Shao and Krishnamurty* [2008] review development of surrogate models. The climate response function allows performance indicators to be estimated from a large number of GCM runs. This allows the impediment of computational burden to be overcome in climate impact analysis, for which large ensembles are consistently recommended [see *Brekke et al.*, 2008; *Raisenen and Palmer*, 2001]. In water resources systems analysis, the climate response function may simulate a hydrologic model and a water system model used sequentially. However, note that the climate response function is derived in terms of spatial domains and temporal resolution that characterize the system response to climate. Just as climate is characterized by the statistics of weather, the response may be characterized based on the statistics of the response of process models (i.e., hydrology and systems models) on weather time scales.

[26] An informative aspect of the climate response function is that it illuminates the degree to which the performance indicator values can be explained in terms of climate variables. For a system in which the climate response function provides a good fit, the indication is that climate has a large influence on performance, such as exhibited by large elasticities to climate change. The degree to which decision relevant performance indicators can be explained in terms of climate statistics is often not clear a priori. In several

cases, various measures of water supply performance have been shown to be well modeled with statistics of inflows [*Vogel et al.*, 1999]. Our work has similarly found strong relationships for the occurrence of extreme levels on the Great Lakes of North America and for various performance indicators for the Niger River Basin [*Brown et al.*, 2011; *Brown*, 2011].

[27] On the contrary, where the fit of the climate response function is poor, this indicates climate may not have a large influence on the performance indicators or that the influence is difficult to succinctly characterize. As a result, it would be difficult to gain much utility for decision making from a major climate research effort. Short-term flooding in small basins that are dominated by local weather is one example where such an approach may provide limited insight.

[28] Note that the temporal and spatial scale of the v_t can be varied to determine a set that best explains performance over that period. For example, one could compare the explanatory power of a 30 year mean climate vis a vis a 50 year mean climate. These scales can also be chosen to maximize the credibility of the source of climate change projections, e.g., experimenting with large spatial scales of the v_T because GCM projections are typically more reliable at greater spatial scales.

3.2.2. Definition of Climate States With Decision Model

[29] With this set of climate conditions and responses, the decision analytic framework is used to parse the climate space into states that correspond to the optimal decision over those climate conditions. Often in decision analysis, the future states of the world are defined a priori and the optimal decision for each state is selected in preposterior analysis [*Raiffa and Schlaifer*, 1961]. An alternative is to define states according to the decision that dominates for that range of climate conditions. This method has been applied in weather forecast value analysis and seasonal forecast value use [*Brown*, 2004] but not previously to climate change adaptation.

[30] A formulation of a decision made under climate change uncertainty can be described as

$$\min_d r = \Sigma_i L(d, \theta_i^C)\Pr(\theta_i^C), \quad (1)$$

where the objective is to select the decision d from the set of decisions D = $\{d1, d2, \ldots, d_n\}$ that minimizes the risk or expected loss, $r(d)$ given the loss function $L(d, \theta_i^C)$ and the future states of the world, θ_i^C, and the probabilities associated with the future states of the world, $\Pr(\theta_i^C)$. In our application, the optimal decision for parametrically varied future climate conditions is calculated and θ_i^C is defined as the climate state for which a decision is optimal (Figure 2). The climate states are defined in the same terms as the climate response function, namely the v_T. The formulation of the decision map shows this discrete representation of the states of the future climate θ_i^C, in this case three climate states ($i = 1, 2, 3$) that each correspond to optimal decisions 1, 2, and 3. The estimation of the probabilities is addressed in step 3.

[31] The parsing of the climate space into states has several advantages. It makes clear to stakeholders and analysts the specific climate conditions that pose risk or favor a particular decision. When those climate conditions are presented as changes in climate from the present, stakeholders gain an intuitive sense of what potential climate changes represent to them. In addition, the climate change analysis can be tailored to focus on estimating the relative probability of these climate states. If a particular state is especially threatening, research can be focused accordingly. While thresholds related to decisions are used in the example described below, one could also parse the climate space according to the scales of impact.

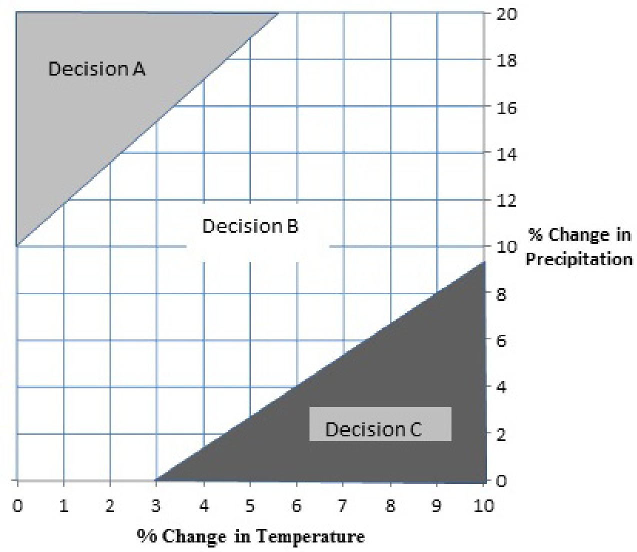


Figure 2. Example of optimal decisions given differing climate conditions. The decision rule creates climate sectors for which subjective probabilities can be estimated from GCM projections or other sources of climate information.

[32] The use of thresholds on acceptable performance of the system requires a special form of the loss function. In place of a continuous loss function, the threshold-based function is binary, corresponding to whether performance is acceptable or unacceptable:

$$\begin{aligned}\Lambda(d, \theta_i^C) &= 1 \quad \text{if } Y_t < \overline{Y}_t \\ &= 0 \quad \text{if } Y_t \geq \overline{Y}_t,\end{aligned} \quad (2)$$

where $\Lambda(–)$ is the binary form of the loss function and $\overline{Y}_t$ is the threshold value of the performance metric. In (1) the product $L(d, \theta_i^C)\Pr(\theta_i^C)$ represents the expected loss, i.e., risk. Using $\Lambda(–)$, the product reduces to the probability of occurrence of unacceptable or acceptable system performance which is equivalent to the probability of the climate states themselves. Thus the estimation of the probability of the climate states directly addresses the probability that a given decision, for example, action or no action, is optimal. Alternately, a continuous loss function could also be used and thresholds based on the expected level of loss.

3.3. Tailoring Climate Information to Assist Decision Making

[33] The final step is the process of tailoring climate information to aid in decision making related to climate risks and opportunities. The process leverages the insights

gleaned in earlier steps to focus tailoring of the climate change analysis to provide the information that is most useful for decision making. That is, with the relevant climate information already identified as the climate states relating to decisions, the climate science effort can focus on producing credible projections that are relevant. In a simple two alternative decision, such as "Take Action" or "Do Not Take Action," the climate space is divided into two sectors corresponding to the climate state for each decision alternative.

[34] Decision scaling consists of using climate information to estimate "climate informed" probabilities associated with each state, with a goal of estimating which state is more probable than the other. The term "climate informed" is used to indicate probabilities based on climate projections which may be derived from GCMs or paleodata or stochastically generated and consequently, may differ from probabilities indicated solely by the historic record.

[35] Given the irreducible uncertainties associated with climate change, estimating the true probabilities is not possible. Rather, the assumption is that the skill of the climate models may be informative for estimating the *relative* probabilities, whether one climate state is more likely than another in the future. In some cases, the probability of each may be close enough that it would not justify specifying one as more likely than another. In many other cases, the climate information may provide some confidence that one climate state and thus one decision is favored over another. It is important to note that the utility of the process depends on the decision as well as the climate information. Model agreement toward a particular climate outcome (e.g., wetter or drier in the future) is not a prerequisite for informative results.

[36] The primary challenge to applying decision analysis to decision making under climate change uncertainty is the uncertain skill associated with GCM projections. The challenge is we do not know $\Pr(\theta_i^C)$, the probabilities associated with the future climate states. Instead, we have GCM projections of uncertain skill. This can be described by a Bayesian decision model of decision making with imperfect information, where GCM projections are the source of information. In this case the decision can be described as

$$\min{}_d\, r = \Sigma_i \Lambda(d, \theta_i^C) \Pr(\theta_i^C | \theta_j^{F,C}) \tag{3}$$

where $\Pr(\theta_i^C | \theta_j^{F,C})$ is the probability of future climate state i given forecast $\theta_j^{F,C}$. The second term relates the expectation of future climate given, or posterior to, the projections. This posterior probability of a future climate state given a forecast can be estimated based on the skill of the forecast according to Bayes theorem:

$$\Pr(\theta_i^C | \theta_j^{F,C}) = \Pr(\theta_j^{F,C} | \theta_i^C) \Pr(\theta_i^C) \tag{4}$$

where $\Pr(\theta_j^{F,C} | \theta_i^C)$ is the conditional probability of the forecast, $\theta_j^{F,C}$, given the climate state, θ_i^C and $\Pr(\theta_i^C)$ is the prior probability of the climate state, θ_i^C, and the normalizing constant is suppressed for clarity. Thus, the posterior probability of a future climate state based on the forecast can be represented as the product of the prior probability of the climate state i and the probability of the forecast of i being correct.

[37] The challenge with climate change is we do not have the repeated experiments and realizations to estimate the forecast skill, $\Pr(\theta_j^{F,C} | \theta_i^C)$. Projections of the future cannot be verified in the present, and verification of historical GCM simulations is limited by the short period of time over which we might expect to see changes to mean climate as a result of anthropogenic greenhouse gas forcings [*Raisenan and Palmer*, 2001]. Consequently, they are not forecasts but projections. Thus we are unable to calculate a posterior probability of the future climate states conditional on the GCM projections and their skill as we would prefer for Bayesian decision analysis.

[38] There is little evaluation of the skill of GCMs and appropriate processing, such as downscaling, in terms of their ability to provide insight for decisions [*Mearns*, 2010]. The decision-scaling approach provides a framework for doing so. At present, in lieu of credible projection skill estimates, there is diagnostic analysis of 20th century GCM runs to summarize some insights that tend to improve the trust one might have in the projections and increase their credibility, essentially the value of $\Pr(\theta_i^C | \theta_j^{F,C})$. They also describe limitations to the projections, including spatial and temporal scales at which they have little skill. Based on the evidence of various studies [*Brekke et al.*, 2009; *Gleckler et al.*, 2008], we use multimodel super ensembles to estimate $\Pr(\theta_i^C)$ and limit the use of projections to variables and scales for which skill is indicated in historical runs. Since using equation (4) is not possible, we describe $\Pr(\theta_i^C)$ as a subjective probability, which is easily accommodated with Bayesian decision analysis [*Hobbs et al.*, 1997].

[39] The resulting process accommodates a variety of approaches for estimating $\Pr(\theta_i^C)$ and thus for the use of climate projections. As presented here and previous analyses, each GCM run is considered an equi-probable possible future climate [*Brekke et al.*, 2009; *Vano et al.*, 2010; *Christensen and Lettenmaier*, 2007]. Model agreement on a climate state is considered an indication that that climate state is more likely than others. Probability is assigned according to the number of runs which fall into each climate state sector [*Raisanen and Palmer*, 2001]. The underlying assumption is that each run is equi-probable. However, there are a number of alternative approaches and their implications for decisions are not clear. The evaluation of alternative processing approaches to GCM projections in terms of decisions is a subject of current work.

[40] At its best, the process described here provides a framework for climate scientists and stakeholders to discuss the generation and use of climate information posterior to understanding how the climate information influences decisions. The use of the binary loss function (2) serves to preserve the probabilities, as they are not masked as a factor in an expected loss value. The probabilities are seen primarily as a prioritization weighting based on climate projections, not as their actual probability of occurrence, and so the use of expected values is avoided. The generation of probabilities also occurs in the final step of the analysis, allowing the implications of different sources of probabilities to be clear to stakeholders, possibly as a "tie breaker" in some cases. It is expected that this will result in the production of

more relevant climate information and better use of that information for decision making.

3.4. Residual Risk and Surprise Management

[41] In recognition of the limitations of any attempts to project the future, we couple risk assessment with management of residual risk and surprise. These are events that may be deemed not cost effective (or by some other criterion) to address directly, largely because they are considered unlikely. However, given climate uncertainty there are two reasons that warrant additional attention to these kinds of events. First, the estimation of hydrologic variables that affect design is compromised by our limited ability to anticipate the effects of climate variability and change. Second, the estimated cost and benefits of decisions represent expected values based on uncertain probabilities. Both effects, each of which is rooted in the challenge of nonstationarity, result in inaccurate risk calculations. As a result, residual risk and surprises may be more significant than any analysis portrays. Additional discussion of these concerns is described in *Brown and Baroang* [2011].

4. Case Study of Municipal Water Supply Reliability

[42] To illustrate the methodology described above, we present a conceptual example of a stylized municipal surface water supply system. This example is based on design parameters of the Quabbin-Wachusett reservoir system which supplies water to the metropolitan Boston area. The Quabbin-Wachusett reservoir system is located in central Massachusetts and includes the Quabbin and Wachusett Reservoirs with a total drainage area of 390 mi^2 (1010 km^2). The system has a storage capacity of 477 billion gallons (1.8 km^3) and an active storage of 255 billion gallons (0.96 km^3) where the active storage is the difference between the spillway storage and the minimum pool volume. The active storage is used for all calculations. The Quabbin-Wachusett reservoir system must release approximately 102 mgd (386,000 $m^3\ d^{-1}$) to meet required minimum streamflows downstream. All of the streamflow calculations are adjusted to account for the required releases.

4.1. Identification of Climate Hazard and Thresholds

[43] The first step in the process is the characterization of the system and identification of relevant decision thresholds. The reservoir system has an estimated "firm" yield of 300 mgd. Although demand has exceeded that value in the past water conservation efforts have resulted in the demand decreasing to a level well below the 300 mgd safe yield. The safe yield is used in all of the demand calculations. It is important to note that the current demand for water is significantly less and so the results of this analysis should not be misconstrued as an estimation of actual future reliability of this system under climate change.

[44] The decision system model in this case consisted of a simulation model of the reservoir system and a statistical model of reservoir inflows. The simulation model was created in the Stella modeling environment and is previously described in *Fisher and Palmer* [1995]. Annual reservoir inflows were estimated based on regressions developed for the northeastern U.S. Since the reservoir depends on over year storage, the annual time step is appropriate as subannual variability including changes in timing of streamflow, have no impact on reliability. For this paper, log linear regression equations for the mean and standard deviation of annual streamflow for the northeastern United States [*Vogel et al.*, 1999] are used. These equations incorporate drainage area, annual precipitation, and annual average temperature into the calculation. The effectiveness of log linear regression models for estimating streamflow in the humid Northeastern U.S. is well documented [*Vogel et al.*, 1999]. Regression was used for simplicity for the purposes of this example and is not essential. In a detailed analysis of a particular location, a physically based model should be used to address concerns related to extrapolation of hydrologic response to climate change.

[45] With the system described in terms of the model, the next step is to set thresholds on acceptable and unacceptable performance. An acceptable water supply reliability threshold was set at 95%. The threshold represents the boundary between a reliability that would require action to be taken (below 95%) and reliabilities for which no action would be deemed warranted (95% or greater). In this illustrative example, the number is chosen arbitrarily as representative of a typical water supply planning target. In a detailed application, stakeholder discussions would be conducted to elicit a reliability threshold that was meaningful for their planning purposes. The setting of a decision threshold is used to establish the link between the stakeholders decision and the insight provided by the climate information. It allows the partitioning of the climate space and consequently, the climate projections into those that project action is required and those that do not.

4.2. Climate Risk Discovery

[46] A climate sensitivity analysis of the system was conducted using 50,000 years of stochastically generated monthly net basin supplies (NBS) (inflows less evaporation) to the reservoir system. NBS were modeled with a periodic moving average lag 1 autoregressive model. The performance of the reservoir was quantified in terms of reliability, the probability of not failing, i.e., delivering the desired water volume demanded in each time period [*Hashimoto et al.*, 1982]. The results of the simulation analysis were then used to assess the climate sensitivity of the system. The 50,000 year simulation was segmented into 50 year periods, representing periods of mean climate. For each segment the reliability ($N = 50$ years) and statistics of NBS were calculated, including annual mean, monthly mean, higher-order statistics and autocorrelation at several lags. Exploratory data analysis revealed that the annual mean explained the vast majority of the variance ($R^2 = 0.98$) in system reliability for each 50 year segment. This result is consistent with previous studies of reliability for systems with over year storage [*Vogel and Bolognese*, 1995].

[47] The strong relationship between mean NBS and reservoir reliability provided confidence that a climate response function could be successfully derived in terms of climate variables. *Vogel et al.* [2001] derived a model of reservoir reliability in terms of statistics of inflow, specifically, the mean, standard deviation and annual autocorrelation of inflow, which is effectively a climate response function. The reliability is linked directly with climate statistics that can be derived directly from GCMs, namely precipitation and

temperature through a hydrologic model. For the purposes of this analysis, a simple statistical model was used. The result represents a climate response function as the performance indicator is expressed in terms of climate statistics, as demonstrated in *Vogel et al.* [2001]. We utilize this simple model for this example.

[48] Using the gridded sampling approach, values of precipitation and temperature can be sampled over a range encompassing the output of all GCM-based or other plausible climate change projections. Historical values of standard deviation and serial correlation were held constant at the historical values. For simplicity, increases in evaporation from the reservoir surface due to temperature increases were not considered.

[49] Figure 3 shows the resulting climate response function as a function of changes in mean temperature and precipitation. The figure shows that for a large region of the climate space, the reliability function is relatively flat, indicating low sensitivity to these climate changes. In the portion of the space where temperature increases are large and precipitation increases are small (far left corner), the reliability falls rapidly. The analysis reveals that the climate conditions of concern are those associated with increasing temperature (associated with increased evapotranspiration and decreased streamflow) and small increases in precipitation (which do not overcome the increases in evapotranspiration to increase streamflow).

[50] Next the decision analytic framework is used to parse the climate space into two states, θ_1^C corresponding to no action as the optimal decision and θ_2^C corresponding to the action warranted decision. Figure 4 shows the climate space partitioned by the decision threshold of 95% reliability. The larger area indicates climate conditions pertaining to reliability of greater than 95% while the smaller area in the upper left corresponds to the climate conditions that warrant action. This figure corresponds to Figure 2, where the climate space is divided into regions corresponding to the optimal decision.

4.3. Estimation of Climate Informed Risks

[51] With the climate space divided into two states corresponding to the decision outcomes, the final step of decision scaling is to quantify the evidence in terms of the relative probability of those two sectors. The objective of the climate analysis is to estimate the probabilities of these climate states, $\Pr(\theta_i^C)$, where θ_1^C represents a problematic climate and θ_2^C indicates the climate conditions that are not problematic.

[52] In this case, the projections of temperature and precipitation from 39 climate projections (emissions scenario A1B) from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel data set, runs were used to estimate future reliability probabilistically. The projections were obtained from a database of bias corrected and spatially disaggregated climate change projections derived from CMIP3 data and served at: http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/, described by *Maurer et al.* [2007]. Mean annual temperature and precipitation were extracted for four future time periods, 2000–2025, 2025–2050, 2050–2075, and 2075–2100. In each case the average over each 26 year period is used as the estimate of the mean annual values of temperature and precipitation in order to reduce the effects of

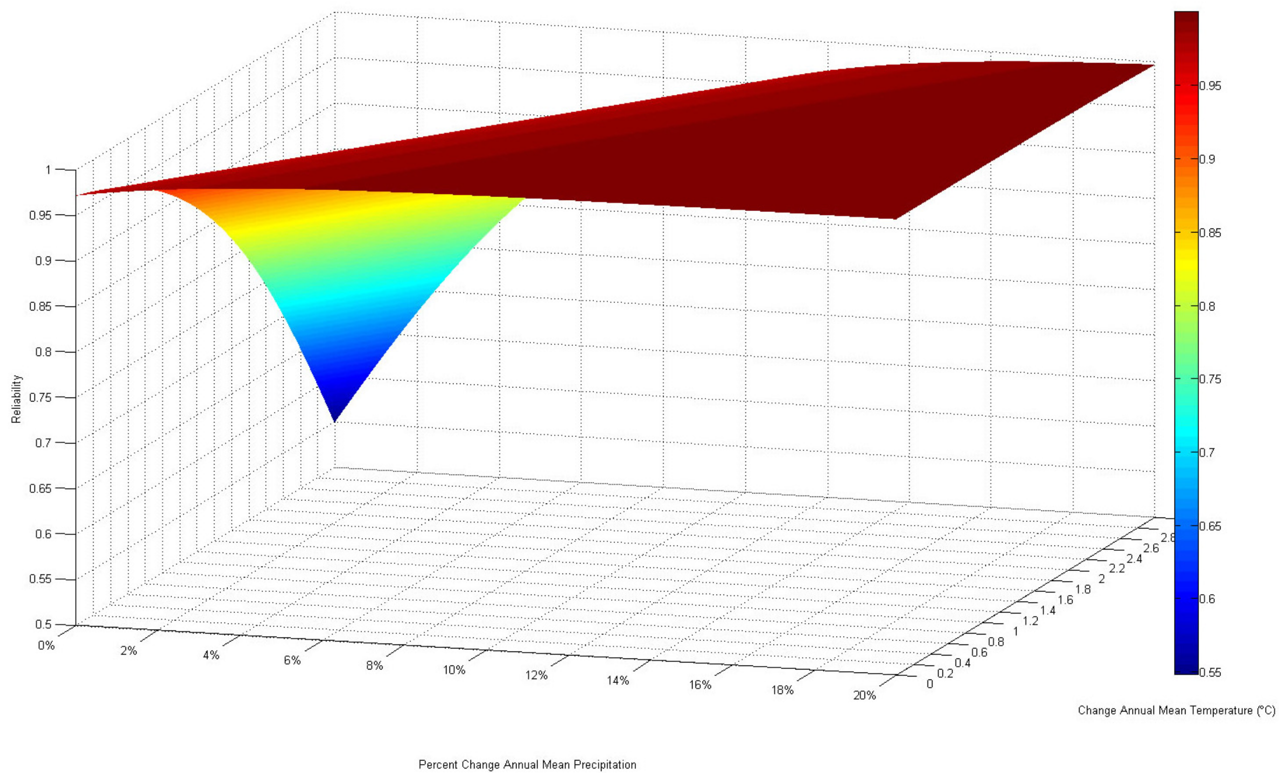


Figure 3. Reservoir reliability as a climate response function of departures from current mean temperature (degrees C) and precipitation (mm yr^{-1}).

internal model variability in any individual run. These values present climate "means" that are then input to the climate response function which is defined in equivalent terms.

[53] Figure 5 shows mean annual precipitation and temperature for each of the runs in each time period. In Figure 4, mean climate change values averaged over 2000–2100 are superimposed on the climate decision states. A plot of mean climate variables such as Figure 4 without the decision space underlain is often used in climate change analyses to choose "fence post" or the extreme points to "box" or encompass the uncertainty. A plot like Figure 4 shows that the extremes in terms of climate space may not be extreme in terms of the decision space and so may not actually encompass the range of possible impacts from a decision standpoint. Runs with low-precipitation changes and moderately high increases in temperature produce reliability values close to or below the decision threshold but runs with the highest temperature increases do not.

[54] The climate response function is then used to calculate the reservoir reliability as a function of the precipitation and temperature estimate for each GCM run and each time period. The calculations require a small fraction of the computation typically required in other approaches. Figure 6 shows a box plot of the reliability values for each of the 39 GCM runs and each time period. In each time period, the highest values and the median reliability are well above the threshold of 95%. However, there are a small number of runs that are below the threshold and one run which is well below. Although they may be considered to have low probability, awareness that such conditions are possible can be valuable to a decision maker when considering risks and surprises.

[55] The reliability values for each GCM run were then used to estimate probability distributions of reliability as a function of the climate change projections. The distributions were estimated using a nonparametric empirical probability distribution. The cumulative probability distribution of reliability over each time period is shown in Figure 7. In all four time periods the probability of θ_2^C corresponding to a reliability below the threshold of 95%, is low. For calculations of relative probability, the nonparametric cumulative distribution functions were used.

[56] The relative probability of the two climate states are estimated next. Figure 8 shows the probability of climate conditions that favor no action θ_1^C (reliability equal to or greater than 95%) and the probability of θ_2^C, climate conditions favoring action (reliability less than 95%). In each time period the probabilities estimated from this analysis favor no action by a wide margin. According to the analysis, the probability based on 39 GCM projections of climate conditions causing an unacceptable decrease in reliability is less than 15%.

5. Discussion

[57] While GCM projections are marked by considerable uncertainty, the analysis framework shows that in this example there is general consensus among them that the climate conditions that warrant action are relatively less probable than the conditions that favor no action. In this

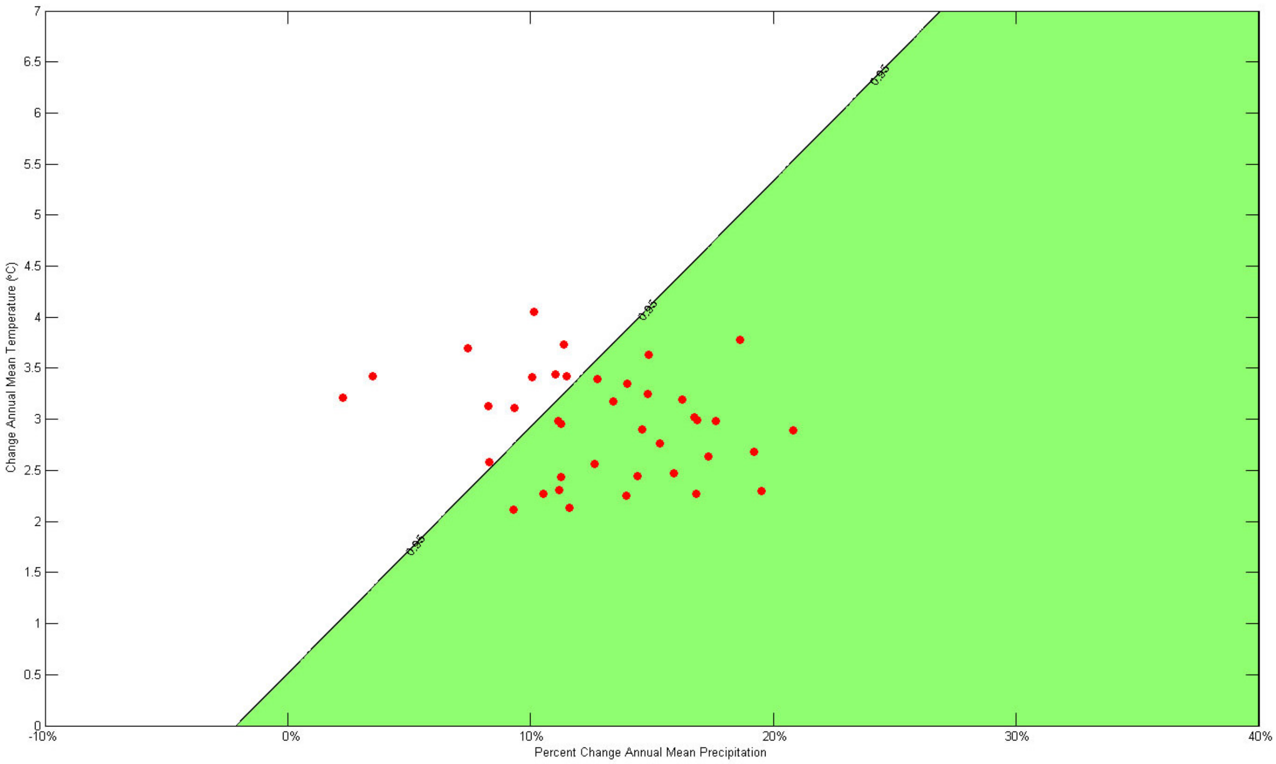


Figure 4. Scatterplot of departures from present mean precipitation and temperature from GCM runs superimposed on the decision states. Decisions states are identified corresponding to reliability greater than 0.95 (No Action; Shaded) and less than 0.95 (Action). Note that changes are calculated as a function of current mean temperature (degrees C) and precipitation (mm yr^{-1}).

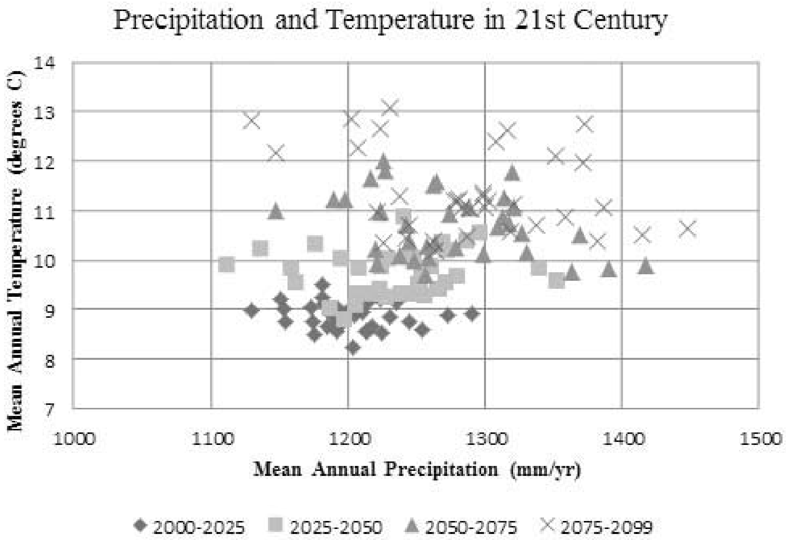


Figure 5. Scatterplot of mean precipitation and temperature for 39 climate projections averaged over four time periods used in this study.

case the evidence of the climate projections suggests that no immediate action is warranted for addressing climate change risk to the reliability of the reservoir system. While this is the decision led to by the use of climate information, the uncertainty associated with that information must remain in mind. Assuming the stakeholders accept this decision, the next step is consideration of the residual risk associated with that decision. That is, if the decision is to take no action, the risk that action should be taken remains. For example, there is residual risk associated with the assumed continuation of historical interannual variability (serial correlation and standard deviation) under future climate conditions.

[58] In the risk assessment exercise, it is worth considering the scenario where the serial correlation increases significantly which would cause a decrease in reliability as consecutive low-flow years would be more probable. Decision makers could strategize for mitigative responses to multiyear droughts under that scenario. Also, the analysis identified a single run that would result in a very low reliability in comparison to the decision threshold and most other runs. Although a single outlier run may be assumed to have low probability, consideration should be given to the possibility of surprise, that this low-probability climate future became reality. At this point it would probably be adequate to be aware of the possibility, monitor evolving climate conditions and keep abreast of future, presumably improved, climate model projections to see if this scenario remains a possibility or becomes more probable. Planners should not fall into the trap of believing that something that is not likely is actually impossible.

[59] The methodology presented here is designed to assist in the difficult process of incorporating uncertain climate information in decisions that are sensitive to climate

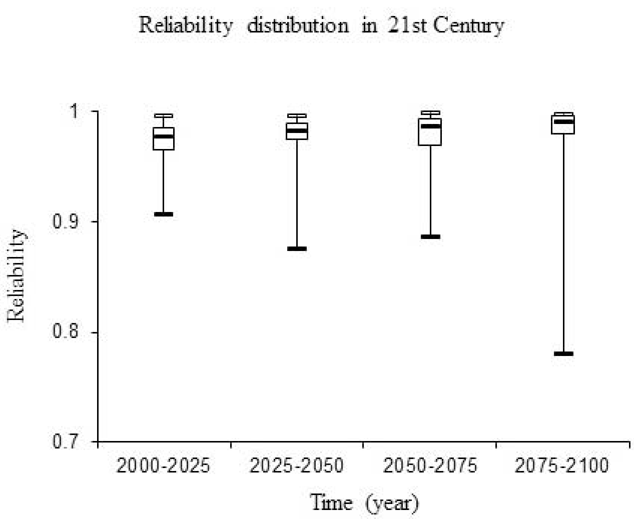


Figure 6. Box plot of reservoir reliability as a function of GCM projections for the given time periods.

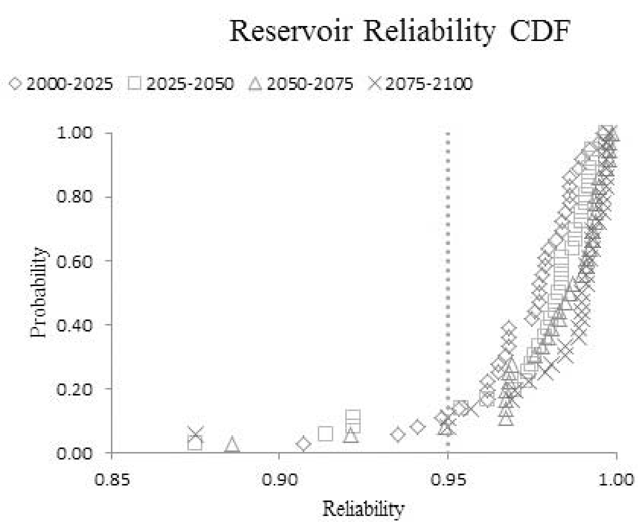
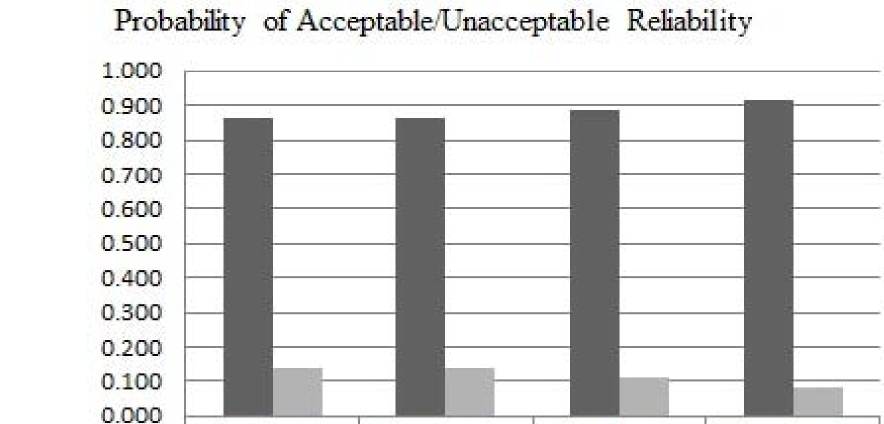


Figure 7. Cumulative distribution function (CDF) of reservoir reliability based on GCM projections using a nonparametric distribution (plotting position formula).



	2000-2025	2025-2050	2050-2075	2075-2100
Prob (R>95%)	0.861	0.861	0.889	0.917
Prob(R<95%)	0.139	0.139	0.111	0.083

Figure 8. Probability of acceptable and unacceptable reliability based on GCM projections for the given time periods.

uncertainty. One aspect of the analysis involves the creation of a climate response function. A climate response function is created to link the decision relevant performance indicators to climate conditions. Through the creation of this surrogate model, some accuracy is inevitably lost. In the example presented here, the uncertainty in the climate response function is not addressed. The loss of accuracy is not likely to be significant for decision purposes relative to the uncertainty associated with climate change. However, in some cases the relationship between performance indicators and statistics of climate may not be robust enough to derive a climate response function. If the relationship between climate changes and performance indicators is not strong, it is an indication that any climate change analysis methodology is unlikely to be effective. In this methodology at least that finding is discovered prior to major efforts to assess future climates from GCMs or other sources.

[60] The ability of the framework to accommodate large and complex systems with multiple performance metrics has not been demonstrated in the example provided. Large systems often involve greater complexity for the decision maker and for the modeling of the system. At present the methodology is being applied to decisions related to very large systems. The results of those studies will provide insight as to the ultimate scope for the decision-scaling approach, but the authors believe it is quite broad.

6. Conclusion

[61] This paper presents a methodology for climate risk assessment of water resource systems that links bottom-up stochastic analysis with the use of climate change projections. The process is innovative in that it inverts the typical process of climate change assessments, here beginning with a decision and proceeding back to the uncertain climate change projections. Decision theory provides the analytic framework that allows the linking of stochastic analysis and GCM projections. The process identifies climate conditions that are relevant to the decision and links those conditions to what is credible from available climate information. The process allows tailoring climate projections to estimate probabilities of the climate states that are significant to the decision. In this paper the process was applied to risk assessment of a reservoir system, where the decision is to take action or not. The process is general and accommodates weighting of GCM projections, use of stochastic simulation and paleodata, and expert opinion, although these are not presented here.

[62] The process is designed specifically to support decision making. Stochastic analysis or deterministic sampling generates a much greater range of possibilities for the identification of risks. GCM projections are then able to described which of these risks may be of more concern. The estimation of probabilities associated with specific decision-relevant climate states are not the true (and unknowable) probabilities of those conditions but rather are best construed as subjective probabilities, a weighting of the risks identified. They provide a pathway for the incorporation of uncertain but possibly useful climate information as one contribution of expert opinion to the typically complex human decision process. The decision-scaling approach also provides a straightforward framework for evaluating the implications in terms of the decision of alternative methods for generating climate information.

[63] The example provided here examines water supply reliability and the risk due to climate change. The simple example allows clear demonstration of the analytic process. The applicability of this methodology depends on the ability of the analyst to summarize decision sensitivities to climate change in a systematic way. We are currently exploring application to larger and more complex water resource systems, including the Great Lakes of North America and the Niger River Basin of West Africa.

[64] **Acknowledgments.** We acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modeling (WGCM) for their roles in making available the WCRP CMIP3 multimodel data set. Support of this data set is provided by the Office of Science, U.S. Department of Energy.

References

Brekke, L. D., M. D. Dettinger, E. P. Maurer and M. Anderson (2008), Significance of model credibility in estimating climate projections distributions for regional hydroclimatological risk assessments, *Clim. Change*, *89*, 371–394.

Brekke, L. D., J. D. Anderson, E. P. Maurer, M. D. Dettinger, E. S. Townsley, A. Harrison, and T. Pruitt (2009), Assessing reservoir operations risk under climate change, *Water Resour. Res.*, *45*, W04411, doi:10.1029/2008WR006941.

Brown, C. (2004), *Adaptive Management of Groundwater with Seasonal Climate Forecasts*, 145 pp., Harvard Univ., Cambridge, Mass.

Brown, C. (2011), Decision-scaling for robust planning and policy under climate uncertainty, World Resour. Rep., World Resour. Inst., Washington D.C. (Available online at http://www.worldresourcesreport.org.)

Brown, C., and K. M. Baroang (2011), Risk assessment, risk management, and communication: Methods for climate variability and change, in *Treatise on Water Science*, vol. 1, edited by P. Wilderer, pp. 189–199, Elsevier, New York.

Brown, C., W. Werick, W. Leger, and D. Fay (2011), A decision-analytic approach to managing climate risks: Application to the Upper Great Lakes, *J. Am. Water Resour. Assoc.*, *47*(3), 524–534.

Christensen, N. S., and D. P. Lettenmaier (2007), A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River basin, *Hydrol. Earth Syst. Sci.*, *11*, 1417–1434.

Dessai, S., M. Hulme, R. Lempert, and R. Pielke (2009), Climate predictions: A limit to adaptation? in *Adapting to Climate Change: Thresholds, Values, Governance*, edited by N. Adger et al., Cambridge Univ. Press, Cambridge, U.K.

Fisher, S. M., and R. N. Palmer (1995), Managing water supplies during drought, The search for triggers, in *Proceedings of the 22nd Annual National Conference*, pp. 1001–1004, Water Resour. Planning and Manage. Div. of ASCE, Cambridge, Mass.

Gleckler, P. J., K. E. Taylor, and C. Doutriaux (2008), Performance metrics for climate models, *J. Geophys. Res.*, *113*, D06104, doi:10.1029/2007JD008972.

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

Groves, D. G., D. Yates, and C. Tebaldi (2008), Developing and applying uncertain global climate change projections for regional water management planning, *Water Resour. Res.*, *44*, W12413, doi:10.1029/2008WR006964.

Hallegatte, S. (2009), Strategies to adapt to an uncertain climate change, *Global Environ. Change*, *19*, 240–247.

Hashimoto, T., J. R. Stedinger, and D. P. Loucks (1982), Reliability, resiliency and vulnerability criteria for water resource system performance evaluation, *Water Resour. Res.*, *18*, 14–20.

Hidalgo, H. G., M. D. Dettinger, and D. R. Cayan (2008), Downscaling with constructed analogues: Daily precipitation and temperature fields over the United States, *Rep. CEC-500-2007-123*, Calif. Energy Comm., PIER Energy-Related Environ. Res., Sacramento, Calif.

Hobbs, B. F., P. T. Chao, and B. N. Venkatesh (1997), Using decision analysis to include climate change in water resources decision making. *Clim. Change*, *37*, 177–202, doi:10.1023/A:10005376622183.

Johnson, T. E., and C. P. Weaver (2009), A framework for assessing climate change impacts on water and watershed systems, *Environ. Manage.*, *43*, 118–134.

Jones, R. N. (2001), An environmental risk assessment/management framework for climate change impact assessments, *Nat. Hazards*, *23*, 197–230.

Kundzewicz, Z. W., et al. (2007), *Freshwater Resources and Their Management. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by M. L. Parry et al., pp. 173–210, Cambridge Univ. Press, New York.

Lempert, R., N. Nakicenovic, D. Sarewitz, and M. Schlesinger (2004), Characterizing climate-change uncertainties for decision-makers, *Clim. Change*, *65*, 1–9.

Lempert, R., D. Groves, S. Popper, and S. Bankes (2006), A general, analytic method for generating robust strategies and narrative scenarios, *Manage. Sci.*, *52*(4), 514–528.

Lopez, A., F. Fung, M. New, G. Watts, A. Weston, and R. L. Wilby (2009), From climate model ensembles to climate change impacts: A case study of water resource management in the South West of England, *Water Resour. Res.*, *45*, W08419, doi:10.1029/2008WR007499.

Manning, L. J., J. W. Hall, H. J. Fowler, C. G. Kilsby, and C. Tebaldi (2009), Using probabilistic climate change information from a multimodel ensemble for water resources assessment, *Water Resour. Res.*, *45*, W11411, doi:10.1029/2007WR006674.

Mastrandrea, M., N. Heller, T. Root, and S. Schneider (2010), Bridging the gap: Linking climate-impacts research with adaptation planning and management, *Clim. Change*, *100*, 87–101.

Maurer, E. P., L. Brekke, T. Pruitt, and P. B. Duffy (2007), Fine-resolution climate projections enhance regional climate change impact studies, *Eos Trans. AGU*, *88*(47), 504.

Mearns, L. (2010), The drama of uncertainty, *Clim. Change*, *100*, 77–85.

Prudhomme, C., R. L. Wilby, S. Crooks, A. L. Kay, and N. S. Reynard (2010), Scenario-neutral approach to climate change impact studies: Application to flood risk, *J. Hydrol.*, *390*, 198–209.

Raiffa, H., and R. Schlaifer (1961), *Applied statistical decision theory*, pp. 356, Clinton Press, Boston, Mass.

Raisanen, J., and T. N. Palmer (2001), A probability and decision model analysis of a multimodel ensemble of climate change simulations, *J. Clim.*, *14*, 3212–3226.

Rajagopalan, B., K. Nowak, J. Prairie, M. Hoerling, B. Harding, J. Barsugli, A. Ray, and B. Udall (2009), Water supply risk on the Colorado River: Can management mitigate?, *Water Resour. Res.*, *45*, W08201, doi:10.1029/2008WR007652.

Romsdahl, R., and C. Pyke (2009), What does decision support mean to the climate change research community?, *Clim. Change*, *95*, 1–10.

Shao, T., and S. Krishnamurty (2008), A clustering-based surrogate model updating approach to simulation-based engineering design, *ASME J. Mech. Des.*, *130*, 1–13.

Stainforth, D. A., M. R. Allen, D. Frame, J. Kettleborough, C. Christensen, T. Aina, and M. Collins (2004), Climateprediction.net: A global community for research in climate physics, in *Environmental Online Communication*, edited by A. Scharl, pp. 101–112, Springer, London, U.K.

Stainforth D. A., et al. (2007), Issues in the interpretation of climate model ensembles to inform decisions, *Philos. Trans. R. Soc. A*, *365*, 2163–2177.

Tebaldi, C., R. W. Smith, D. Nychka, and L. O. Mearns (2005), Quantifying uncertainty in projections of regional climate change: A Bayesian approach to the analysis of multi-model ensembles, *J. Clim.*, *18*, 1524–1540.

U.S Bureau of Reclamation (2009), Long-term planning hydrology based on various blends of instrumental records, paleoclimate, and projected climate information, technical report, 139 pp, U.S. Dep. of Inter., Washington, D.C.

Vano, J., N. Voisin, M. Scott, C. Stöckle, A. Hamlet, K. Mickelson, M. Elsner, and D. Lettenmaier (2010), Climate change impacts on water management and irrigated agriculture in the Yakima River Basin, Washington, USA, *Clim. Change*, *102*, 287–317.

Vicuna, S., J. A. Dracup, J. R. Lund, L. L. Dale, and E. P. Maurer (2010), Basin-scale water system operations with uncertain future climate conditions: Methodology and case studies, *Water Resour. Res.*, *46*, W04505, doi:10.1029/2009WR007838.

Vogel, R. M., and R. A. Bolognese (1995), Storage-reliability-resilience-yield relations for overyear water supply systems, *Water Resour. Res.*, *31*(3), 645–654.

Vogel, R. M., I. Wilson, and C. Daly (1999), Regional regression models of annual streamflow for the United States, *J. Irrig. Drain. Eng.*, *125*(3), 148–157.

Vogel, R. M., C. J. Bell, R. R. Suresh, and N. M. Fennessey (2001), *Regional assessment of the impact of climate change on the yield of water supply systems, in risk, reliability, uncertainty and robustness of water resources systems, chapter 12*, edited by J. J. Bogardi and Z. W. Kundzewicz, pp. 101–110, Cambridge Univ. Press, New York.

Wilby, R. L., and S. Dessai (2010), Robust adaptation to climate change, *Weather*, *65*(7), 180–185.

Wiley, M. W., and R. N. Palmer (2008), Estimating the impacts and uncertainty of climate change on a municipal water supply system, *J. Water Resour. Planning Manage.*, *134*(3), 239–246.

Wood, A. W., L. R. Leung, V. Sridhar, and D. P. Lettenmaier (2004), Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs, *Clim. Change*, *62*, 189–216.