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A DECISION-ANALYTIC APPROACH TO MANAGING CLIMATE RISKS: APPLICATION TO THE UPPER GREAT LAKES[1]

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ABSTRACT: In this paper, we present a risk analysis and management process designed for use in water resources planning and management under climate change. The process incorporates climate information through a method called decision-scaling, whereby information related to climate projections is tailored for use in a decision-analytic framework. The climate risk management process begins with the identification of vulnerabilities by asking stakeholders and resource experts what water conditions they could cope with and which would require substantial policy or investment shifts. The identified vulnerabilities and thresholds are formalized with a water resources systems model that relates changes in the physical climate conditions to the performance metrics corresponding to vulnerabilities. The irreducible uncertainty of climate change projections is addressed through a dynamic management plan embedded within an adaptive management process. Implementation of the process is described as applied in the ongoing International Upper Great Lakes Study.

(KEY TERMS: climate change; decision analysis; risk management; planning under uncertainty.)

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INTRODUCTION

Water resources planners have traditionally planned for uncertainty by modeling system performance using forecasts of supply and demand and alternative system configurations. This has served us well. However, growing awareness of the weakness in the assumption of hydrologic stationarity has contributed to interest in new methodologies that are less dependent on that assumption. Due to growing dissatisfaction with traditional stochastic hydrologic approaches for water resources planning, the question as to how to conduct a planning exercise amid nonstationarity remains an open one.

This paper presents a practical methodology for water resources planning under climate change. It describes how in practical terms decision analysis can be gainfully employed as a framework for identifying priority climate information. It also describes how a plan can be designed to provide robustness amid a large range of uncertainties related to the future. Decision analysis is an established methodology that uses estimated or known probabilities of future states to indicate the "best" expected outcomes. The application of decision analysis to climate change is hindered

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by a lack of consensus on the appropriateness of estimating probabilities from climate change projections or a methodology for doing so (cf. Grübler and Nakicenovic, 2001; Mastrandrea and Schneider, 2004).

Many analyses instead use a scenario-based approach that takes a small number of internally consistent climate scenarios and uses them to project impacts under those scenarios. The scenarios typically attempt to box the range of possibilities without assigning probability to any. An accepted, systematic methodology for incorporating scenarios into decisions has not emerged.

Decision analysis is best applied where key uncertainties are well characterized. Climate change presents uncertainties that are both potentially significant to water resources planning and poorly characterized (Lempert *et al.*, 2004). However, the analytic framework employed in decision analysis can be usefully employed to identify which uncertainties are important from the viewpoint of the decision maker. In the case of climate change, the framework facilitates the identification of climate information that is critical to the planning decision. As a result, decision analysis provides an analytic framework that can be exploited to link bottom-up climate vulnerability analysis with the generation of climate change projections. The process is entitled "decision-scaling."

The second tenet adopted here is that the appropriate orientation for adaptation planning, or planning for climate change, is one of acceptance of large climate uncertainties and planning for a wide variety of possible climate futures. This runs contrary to the general scientific orientation of focusing on the reduction of uncertainty and then planning for the accepted expert characterization of the future. Instead, the approach emphasizes robustness over a wide range of climate futures. We describe how the concept of robustness is practically employed in the development of a regulation plan for the Upper Great Lakes. The regulation plan utilizes dynamic responses to evolving conditions and adaptive management of uncertainties and surprise.

In this paper, we describe a general process for water resources planning under climate change based on a decision-analytic approach to identifying and tailoring necessary climate information. The framework links insight from bottom-up analysis, including performance metrics defined by stakeholders with the processing of climate change projections to produce decision-critical information. The climate information may be generated from General Circulation Models (GCMs) or alternative approaches, including qualitative assessments of which of future climate conditions are more probable than others. We then describe the process adopted to develop a robust adaptation planning strategy for the regulation of Lake Superior with implications for Lakes Michigan, Huron, and Erie. The process utilizes a dynamic regulation plan that can respond to changing climate conditions. The regulation plan is embedded within an adaptive management process to address future uncertainties, including those beyond climate change and surprises.

APPROACHES TO CLIMATE CHANGE RISK ASSESSMENT

Assessments of climate change impacts on water resources systems typically rely on approaches that begin with a focus on climate modeling and projections from GCMs (see Figure 1). Typically, output from GCMs is scaled to match existing hydrologic models and then water resources systems models are used to estimate the resultant effects on performance (Christensen *et al.*, 2004; Wiley and Palmer, 2008; Brekke *et al.*, 2009a,b; Vano *et al.*, 2010; Vicuna *et al.*, 2010). The results provide a sample of future consequences of climate change as projected by the GCMs. The large uncertainty from the range of climate change projections is problematic from a decision perspective. A small number of widely divergent outcomes are difficult to accommodate when one may indicate major impacts and another indicates minimal impacts. Bottom-up or vulnerability-based approaches to assessing climate change impacts are an alternative to so-called "top-down" approaches driven by GCM projections. There are a wide variety of methodologies described for conducting vulnerability

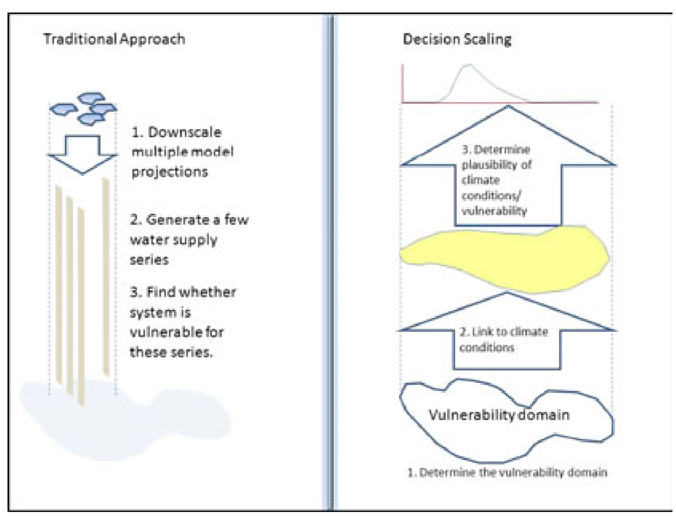

FIGURE 1. Decision-Scaling Begins With a Bottom-Up Analysis to Identify the Climate States That Impact a Decision and Then Uses Climate Information to Provide Insight to the Decision.

assessments of climate change impacts (e.g., Jones, 2001; Brekke *et al.*, 2009a,b; Johnson and Weaver, 2009). However, there are some common themes. In general, these approaches begin with assessment of the socioeconomic or natural system and its vulnerabilities to climate impacts, which are not limited to climate change. Natural climate variability is often a prominent consideration. Given an understanding of the vulnerable system, a vulnerability analysis is conducted to identify key impacts of concern. Prospects for managing those vulnerabilities are considered. Often the process involves the input of stakeholders at various stages (Pittock and Jones, 2000).

Although these approaches are appropriately described as "bottom-up," the methods cited above utilize climate change projections in the early stages of the analysis with downscaling and other processing conducted prior to the identification of vulnerabilities. The scaling of the climate information is not typically tailored to the vulnerabilities identified. Rather, the climate projections are used to identify vulnerabilities. This may limit the effectiveness of these bottom-up approaches. Given the uncertainties associated with climate change projections, it is not clear that the use of projections will uncover the risks and vulnerabilities associated with a changing climate. While projections span a range of future climate conditions, they do not define the actual range of possibility. Also, given the wide range of choices available for downscaling, it may be possible to improve the use of climate projections by tailoring them based on insights from the vulnerability analysis. This is not currently carried out.

Here, we describe a process that attempts to improve the bottom-up analysis of climate change impacts by employing the insights from the vulnerability analysis to inform the processing of the GCM information. This allows tailoring of the climate information to attempt to maximize its credibility and utility in the assessment. The process that uses a decision-analytic framework provides a missing link between bottom-up approaches and the use of climate change projections.

Decision analysis has long been applied to decision making under uncertainty in water resources and advocated for addressing climate change (Rogers and Fiering, 1989). Hobbs *et al.* (1997) applied decision analysis to questions related to the regulation of Lake Erie under climate change. In Hobbs *et al.*'s (1997) analysis climate change is treated relatively simplistically as a discrete event, either it happens or it does not and its probability is treated as a sensitivity parameter, that is, it is varied to assess how the decision changes for changes of this value. At present, the question is not whether climate change is occurring, but what specific changes will occur. The paper concludes that the decision analysis is useful for investments that are influenced by climate change, and notes that climate change is not dissimilar from other uncertainties that affect long-term decisions. Given the wide range of possibilities, generation of the probabilities needed for Bayesian decision analysis appears problematic. The approach described here builds from this conclusion by describing how the decision-analytic framework can be applied with the current state of knowledge regarding future climate.

A primary source of information for assessing the current state of climate change knowledge is GCMs. As stated in the IPCC and elsewhere, the use of projections from a large number of climate models (~20) and multiple runs of each model is recognized as the best approach for addressing the limitations of individual models and the chaotic nature of the earth's climate system (Gleckler *et al.*, 2008). Multimodel ensembles are important for a decision-analytic approach because they can be used to generate needed probabilities. For example, ensembles can be used to calculate the frequency of occurrence for climate conditions that cross thresholds identified in the vulnerability analysis. Although these frequencies do not strictly represent probabilities of future outcomes, they can be used as our best estimate of the probabilities of some climate conditions relative to others based on the models and estimated emissions scenarios. Also, probability distributions from ensembles of GCM projections have been produced for a range of climate variables and for regional projections of precipitation and temperature (Tebaldi *et al.*, 2005). Increasingly, it is recognized that there is a need to generate probabilities to quantify the relative likelihood of different climate outcomes (Dessai and Hulme, 2003). Probabilistic approaches offer a quantification of the uncertainty associated with climate change projections. Still, there has been little methodological link between risk-based climate impact assessments and the use of probabilistic information from GCMs.

DECISION-ANALYTIC FRAMEWORK FOR CLIMATE RISK ASSESSMENT

The challenges associated with GCM projections make clear the need for substantial processing prior to use in risk assessment and adaptation planning. In common practice, this processing, often via downscaling, is accomplished as an initial step in impact assessment or adaptation planning. The premise of decision-scaling is that the results of this processing may be improved if it is informed by the results of a bottom-up decision-analytic approach. The assessment of climate risks may be framed as a typical decision made under uncertainty. Bayesian decision analysis is a statistical approach to decision making under uncertainty. As traditionally developed, it is dependent on the ability to estimate probabilities associated with uncertain future states of the world. For our purposes, these states correspond to future climate conditions.

Risk can be defined in quantitative terms as the product of the probability associated with a hazardous event and the consequences of that event (Plate, 2004):

$$R(x) = \int_0^\infty C(x) f(x) \mathrm{d}x, \tag{1}$$

where $f(x)$ is the probability density function (pdf) of the event (e.g., the occurrence of a future climate state) and $C(x)$ is the consequences associated with the event on the system of interest. For the hydrologic risks such as on the Great Lakes, $f(x)$ can be defined as the pdf of future lake level, x, or of climate variables that influence lake levels, such as temperature and precipitation. The consequence function yields the consequences (e.g., values of the performance metrics) resulting from a particular value of x, say mean annual lake level. The term consequence function is used because changes in lake levels may yield benefits as well as damages (de Neufville, 2004). In top-down approaches to climate change impact assessments, the emphasis is often on attempting to estimate the future $f(x)$, that is, the future distribution of climate or hydrologic variables. In our approach, the initial emphasis is on $C(x)$, the response of the system to all the possible values of x, possible future climates, without regard to the probability associated with those values.

From a planning perspective, the interest is in identifying how different plans affect the response of the system to a wide range of possible future climate conditions. This can be specified as $C(x|D)$, the consequence function conditional on a specific plan choice or decision, D (Plate, 2004). By varying the climate conditions, the function $C(x|D)$ can be evaluated to identify the optimal plan D^* for each future climate state. In some cases, it may be found that a plan D^* is superior to others over all climate conditions. In this case, the decision can move forward without specifying probabilities of future climate states or use of GCM output. In other cases, there may be a subset of plans that perform worse in terms of the decision criteria than other plans for all future climate conditions, meaning that for the full range of possible climate conditions considered, there is some other plan that does better. These inferior plans may be eliminated from further consideration.

In many cases, the dominance analysis described above will yield an incomplete ordering; some plans will perform better than others for different ranges of x or different future climate conditions. In these cases, our interest is in identifying the plans with the best expected performance, given our expectations of future climate conditions. Then the climate risk associated with a specific plan choice, D, is:

$$\bar{R}(x) = \int_0^\infty C(x|D) f(x) \mathrm{d}x, \tag{2}$$

where $\bar{R}$ is the expected climate risk for a given decision, D. Note that for clarity we include the costs of a particular decision in the consequence function so the risk here is the expected *net* loss. The challenge for the planner now is to choose a plan that minimizes the risk of future climate impacts. One can evaluate the expected risks for the set of possible decisions, from the nondominated set D^*_i, $i = 1, \ldots, N$, for N possible decisions and select the risk-minimizing decision:

$$\min_D Z = \int_0^\infty C(x|D) f(x) \mathrm{d}x. \tag{3}$$

The risk associated with a given decision and, as a result, the choice of optimal plan are now contingent on the value of $f(x)$ in addition to $C(x|D)$. In the case of climate change, this is problematic due to the difficulty of specifying $f(x)$ with confidence. That is, there is limited evidence that we can reliably estimate the probability distributions of future climate conditions. For this reason, the application of traditional decision analysis appears problematic.

Nonetheless, the decision analysis process identifies the climate conditions that cause a particular decision to be favored over another. That information can then inform the processing of climate products to be most relevant to the decision. That is, the insight into the climate conditions that cause a decision to be favored over another can be used to tailor climate information to provide credible estimates of the relative probability of those climate conditions.

DECISION-SCALING FOR ADAPTATION PLANNING

Using an example based on the Great Lakes, the decision-scaling approach can be described in terms of a discrete decision between competing regulation plans. A decision tree may be used to illustrate the choice between two regulation plans for Lake Superior, say Plan A and Plan B, where a regulation plan

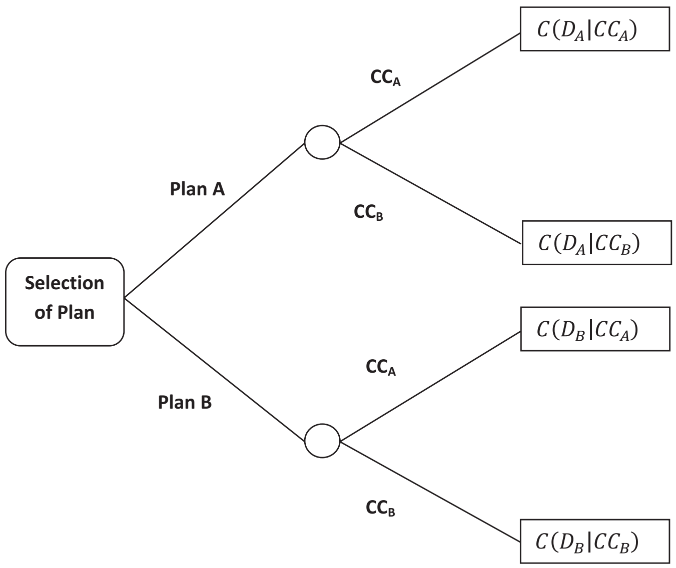

FIGURE 2. Decision Tree Depicting the Selection of an Optimal Plan Based on the Probability of Climate States CC_A and CC_B and the Consequences of Each Plan Under Those Climate States $C(D_i | CC_j)$, for $i = A, B$ and $j = A, B$.

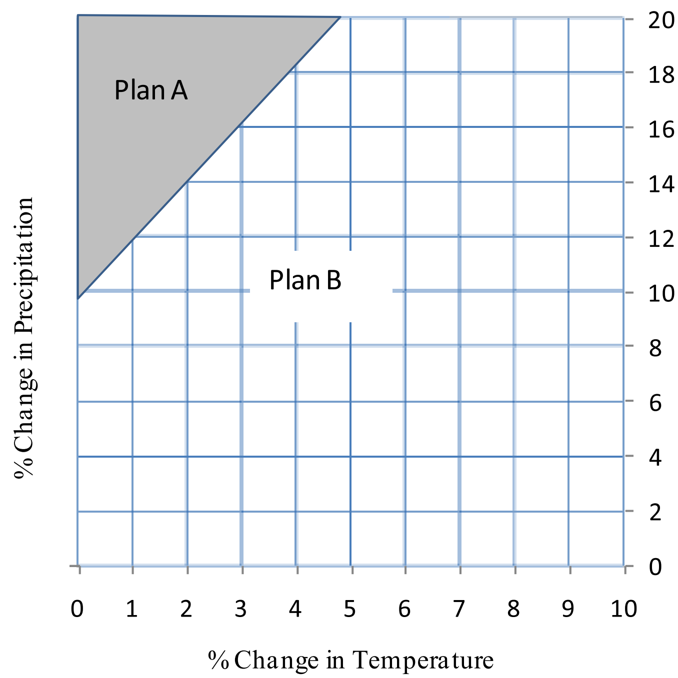

FIGURE 3. Representation of Climate States That Relate to the Climate Change Conditions Where Plan A is Optimal (CC_A) and the Climate Conditions Where Plan B is Optimal (CC_B).

consists of rules for water releases (Figure 2). The performance of a plan can be estimated with a model of plan performance for a set of climate conditions, $C(D_A | x)$, where the performance as measured by performance indicators is a function of the chosen plan, for example, D_A for Plan A conditioned on the state of the climate, x. The function $C(D | x)$ is the climate response function.

Using the climate response function, the state of the climate can be varied to determine under which climate conditions Plan A is preferred and where Plan B is preferred. These results can then be used to specify two (or more) climate states associated with the optimal plan choice, as shown in Figure 3. For example, climate state CC_A would correspond to the climate conditions under which Plan A is optimal and CC_B the same for Plan B. The processing of climate change projections is now tailored to answer a specific question: Are the climate states associated with plan A dominance more or less likely than those associated with Plan B dominance?

Based on this decision analysis, the future expected performance of each plan can be summarized as

$$R_D = \sum_i C(D|CC_i) \Pr(CC_i), \tag{4}$$

where R_D represents the expected performance or risk associated with a particular decision D, $C()$ represents the consequences of the decision and the occurrence of a climate change state (CC_i), and Pr is the probability of that climate change state.

The climate response functions serves as the quantitative link between the bottom-up analytic framework and the tailoring of climate information. Given the identification of climate conditions that are critical to a decision or risk assessment (i.e., CC_i), the processing of GCM projections can be focused on those key aspects. In other methods, the production of climate change information often focuses on an increase in spatial and temporal resolution (i.e., downscaling). Here, the choice of scale is only made after the climate information needed for the decision is identified. Then that choice can be made strategically to improve the credibility of the climate information. This may allow the choice of scale that improves the quality of the climate change projection information.

A key aspect of decision-scaling is that the specification of the climate states, that is the specific climate information that causes a particular decision to be favored over another (or an impact to be large enough to warrant preventative actions, i.e., the identification of thresholds), may allow the credibility of climate information derived from GCM projections (or other sources) to be improved. That is, with the information from the bottom-up, decision-analytic framework in hand, the generation of climate information may be tailored to best provide credible information through the selection of process models, temporal and spatial scales, and scaling techniques given the time and resource constraints that real climate change analyses always face. Depending on the spatial and temporal scales needed, the tailoring may involve statistical or dynamical downscaling, based on the judgment of the analyst of what will best produce the specific information required. Recent studies have just begun to explore the effect of some modeling decisions, such as spatial resolution of hydrologic models, on the concept of credibility (Brekke *et al.*, 2008).

In the decision-scaling process, such insights can inform the analysis in specific regard to what is needed for the decision. The tailoring can be conceptualized as an optimization:

$$\max_{S_t,S_s,M_i} \text{Credibility}\{\Pr(\text{CC}_i)\}. \tag{5}$$

That is, the various process models, M_i (e.g., hydrologic, system, etc.), and the temporal (S_t), and spatial (S_S) scales of analysis, are chosen to maximize the skill of the estimated probabilities, subject to any constraints on expense, computational effort, and available data. In this conceptual model, credibility represents a relative ordering of the level of confidence that one would have in the probabilities generated by particular combination of models and scales. It is evaluated through expert knowledge and accommodates qualitative assessment of model skill. The term skill as often used in forecasting is analogous. However, as we are limited in our means of evaluating skill of GCM climate change projections, we present credibility as a more appropriate conceptualization.

Examples of relative credibility may illustrate the concept. Climate change probabilities generated from a multimodel ensemble are typically considered more credible than from a single model. Based on our knowledge of model performance, estimates of mean climate are more credible than estimates of climate variability. Also, estimates of climate variables are generally more credible over larger spatial areas than over smaller spatial areas, and over longer temporal averaging periods than shorter increments (e.g., annual *vs.* daily). Relative credibility will be dependent on the particular region and system of concern. That does not prevent the concept and its maximization from being a useful tool in any particular impact or adaptation study.

The next step in the process is to use climate information to assign probabilities to the climate states, CC_i. The climate change states are those identified through sensitivity analysis to be those that cause an action to be taken or a decision to be favored over another, as described above. By clustering the range of possible climate futures into states corresponding to preferred decisions, the objective is to increase the credibility of the GCM information as used in the decision, by reducing the required specificity of the information. The GCM projections need only inform the analyst as to which of a small number of climate states is more probable than another.

The estimation of credible probabilities from GCM projections remains an open research question, given the limited ability to assess the skill of GCM output. In traditional Bayesian analysis, the probability of an uncertain event would be derived from the skill of the forecast based on historical forecast skill:

$$\Pr(CCtype_i) = \sum_i \Pr\left(CC_i|\widehat{CC_l}\right)\Pr(\widehat{CC_l}), \tag{6}$$

where the forecast skill is the probability of CC_i occurring given $\widehat{CC_l}$, a forecast of CC_i and the probability of that forecast being made, $\Pr\left(\widehat{CC_l}\right)$. In the case of climate change, estimating the probability of a particular climate change type based on the skill of the projections is not easily done. As 20th Century runs from GCM can be compared with observed climate variables only in terms of summary statistics, the sample size for assessing skill is relatively small. However, it is generally accepted that when there is consensus among multiple GCM and multiple ensemble members that there is evidence of a more probable climate change signal and the corresponding climate conditions are more likely. Also, by specifying information relative to the climate states identified through the sensitivity analysis, the needed resolution of the GCM output in terms of output (i.e., degree of change) is reduced in many cases. The information needed relates to the probability of a climate state representing a range of values of the climate variables instead of specific values.

The application of decision-scaling benefits from the estimation of probabilities associated with the identified climate states, CC_i. The process need not specify how those probabilities must be derived since the procedure can utilize probabilities independent of method. In the application to the Great Lakes, a multimodel, multirun ensemble of GCM projections is used in combination with stochastically generated time series, including those informed by paleodata to describe probabilities. Given the uncertainties associated with the estimation of probabilities, the term "plausibility" has been adopted in its place. The concept of plausibility is best described as a stakeholder developed, subjective ranking of the probability of specific climate states. The concept borrows from the practice of shared vision modeling, in that the estimation of probabilities is not a black box process, but rather a tool for discussion and ranking relative uncertainties during the planning process.

The plausibility of a climate state is generally based on the frequency of occurrence of that state in the climate simulations and the source of the simulation. For example, climate state that occurs in many runs from multiple GCMs and also occurs in the paleodata-based stochastic simulation is more plausible than a climate state that occurs rarely in a small number of sources. Where the relative plausibility is less clear cut, a discussion of the different sources of the occurrence of the climate states (e.g., specific GCMs) and relative merits of those sources is discussed among the decision makers facilitated by the analysts. The goal is to use a wide range of climate information in a transparent manner to facilitate comfort for the decision makers in the use of that information for decisions.

The risks associated with climate conditions that are deemed "unlikely" must still be considered and planned for once a particular decision is in place. Decision-scaling cannot eliminate the irreducible uncertainty associated with climate as well as other factors that will affect the performance of a particular plan. For this reason, the planning process is not complete until the residual risks associated with a particular plan are addressed. We define the residual risk of a decision D_i as:

$$RR_i = \int_0^\infty C(x|D_i)f(x)\mathrm{d}x. \tag{7}$$

Typically, a plan may leave particular unlikely hydrologic events largely unmitigated. For example, a levee may be designed to withstand the estimated 500-year return period flood but not larger floods due to the extra costs and small expected benefits of doing so. In terms of the Great Lakes, a selected plan may have plausible but seemingly unlikely risks of extreme high or low lake levels. Given our limited ability to accurately estimate $f(x)$ and thus the magnitude of an event such as the 500-year flood reliably for the future, it is vitally important to consider and address the impacts of floods of greater than the design value. How will a given plan perform when the design events it is based on are exceeded? What are the consequences when the very unlikely actually occurs? And importantly for the planner, how can a plan's performance during such an exceedance event be improved?

These questions should be addressed during the planning because the uncertainty associated with climate change implies that the design values may be off in the future. In addition, given the deep uncertainties and very large reach of the Great Lakes, the risk of low probability but high consequence events, or surprises, must be seriously considered. In some cases, this will entail emergency response planning and evaluation of early warning systems. In all cases, there should be monitoring of potential changes or trends in climate variables and consideration of triggers or thresholds that instigate a review of and possible changes to plans. In the case of the Upper Great Lakes, this is accomplished through an adaptive management process.

ROBUST ADAPTATION FOR THE UPPER GREAT LAKES

In 2007, the International Joint Commission (IJC) established an independent study board composed of United States (U.S.) and Canadian members to review the operation of structures controlling Lake Superior outflows and to evaluate improvements to the operating rules and criteria governing the system. The study is known as the International Upper Great Lakes Study (IUGLS). The Board is expected to publish recommendations in March 2012 for near-term changes to the regulation plan of Lake Superior, the largest managed freshwater body in the world (Clites and Quinn, 2003). The regulation of Lake Superior affects lake level, navigation, and hydroelectricity production on Lakes Michigan, Huron, and Erie, comprising an immense water resources system.

As a result of the considerable uncertainty associated with future climate and lake levels, as well as other sources of uncertainty such as ecosystem responses and the state of the navigation industry, a process of selecting the optimal plan based on a most probable future scenario was rejected. Instead, a bottom-up process for identifying vulnerabilities and assessing risk from climate change utilizing decision-scaling was adopted. This paper is being written as those efforts are proceeding; it summarizes the implementation of the approach.

Lake levels in the Upper Great Lakes exhibit a significant degree of natural variability in the historical record (Clites and Quinn, 2003). This variability has caused considerable challenges in the design of regulation plans for Lake Superior in the past with changes being implemented several times in the 20th Century. Given the lack of success in designing regulation plans that were robust to natural variability in the past and the additional uncertainty associated with climate change in the future, a change to the traditional regulation plan design was warranted. Underlying the process is the premise that we are limited in our ability to anticipate the future and therefore any recommended plan must perform well over a very broad range of possible futures. Of additional concern are surprises, low probability events that could have very large impacts. While incorporating unknown surprises into a regulation plan appeared infeasible, a strategy for managing their occurrence was prioritized. Finally, it was recognized that the identification of vulnerabilities must be led by those who understand the specific aspects of the lakes best, the stakeholders.

With these considerations, the Lake Superior regulation strategy incorporates a hierarchical approach for managing uncertainty and to facilitate adaptation to changing climate, and other unanticipated changes. The approach is dubbed "robust adaptation" because it is not an attempt to adapt to a foreseen future climate but rather is a strategy that allows adaptation amid deep uncertainty regarding what the future will bring. The uncertainty is not only due to changing climate but also due to the relatively poorly understood lake dynamics in response to changing conditions and also the possibility of changing objectives for lake management.

The strategy comprised three embedded processes: (1) identification of vulnerabilities by stakeholders and definition of acceptable and unacceptable lake levels for each impact area; (2) dynamic regulation plan that selects regulation rules from a portfolio of plans developed for a wide range of climate conditions; and (3) an adaptive management process for reviewing the performance of the dynamic regulation plan, monitoring program and stakeholder preferences, and recommending improvements as necessary. The strategy is depicted in Figure 4 and described in more detail below.

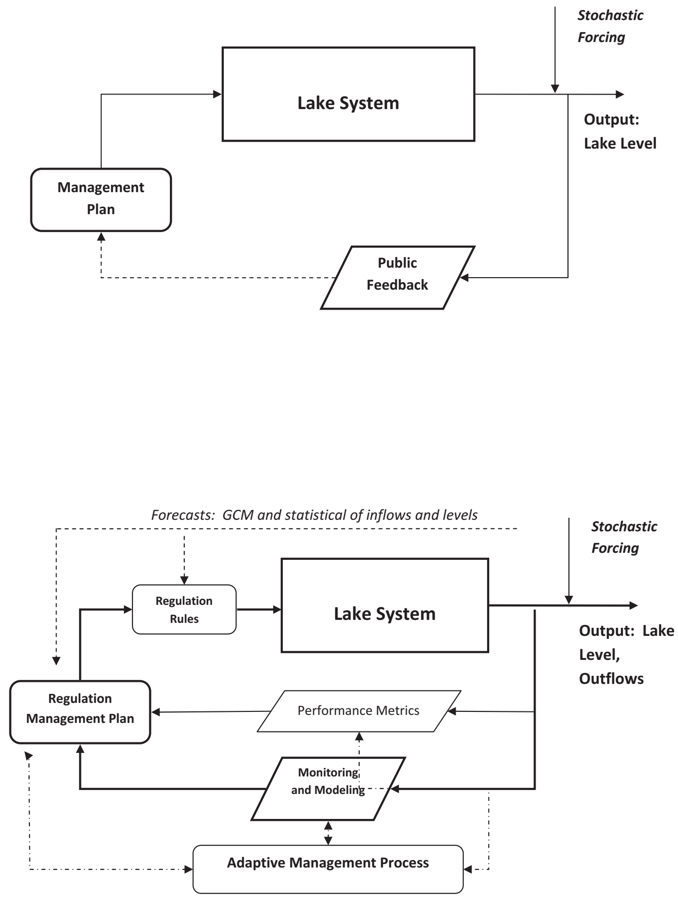

FIGURE 4. Schematic Diagram of the Current and Proposed Lake Vegetation Management Approach. (a) The current approach to management of large water resource systems typically involves selection of a static regulation plan that is optimal for the historical climate period. There is no formal feedback but indirect feedback is observed through public complaint during poor performance of the plan. In the case of Lake Superior, a regulation plan is enacted on the lake system which is subjected to exogenous factors resulting in the observed lake levels. The lake levels result in impacts that are primarily observed by stakeholders. Feedback is provided to the International Joint Commission often as complaints from the public. (b) The proposed hierarchical adaptation strategy for the regulation of Lake Superior will utilize a dynamic regulation plan to select among several regulation approaches depending on the plan performance and the observed climate conditions. Feedback is provided via a monitoring program and ongoing evaluation of performance metrics related to coping zone status. At the highest level of the hierarchy, the performance of the dynamic regulation plan, including the performance metrics themselves and the monitoring program, is evaluated and when necessary, improved through an adaptive management process.

Vulnerability Identification and Definition of Coping Zones

In order to prioritize concerns for the regulation of Lake Superior, stakeholder experts were tasked with identifying the vulnerabilities of the system to climate changes and other changing conditions. Termed technical working groups, stakeholders and technical experts convened in the following impact areas: ecosystems, hydropower, commercial shipping, municipal and industrial water and wastewater systems, coastal systems, and recreational boating and tourism. A primary challenge was the quantification of vulnerabilities in commensurate units. To address this issue, the stakeholder groups were asked to define vulnerabilities in terms of lake levels, including the duration of the lake level. We defined lake levels in three categories we call "coping zones": A (acceptable), B (significant negative impacts, but survivable), and C (intolerable without policy changes). The stakeholder groups defined what combination of lake level and duration led to the kind of impacts consistent with the coping zone descriptions. Figure 5 provides an example of coping zones relative to lake level. The definition of coping zones allows the evaluation of regulation plan performance to be conducted in terms that are comparable across impact sector and defined by the stakeholders. It is a product of the shared vision planning process (Palmer *et al.*, 1993a,b;

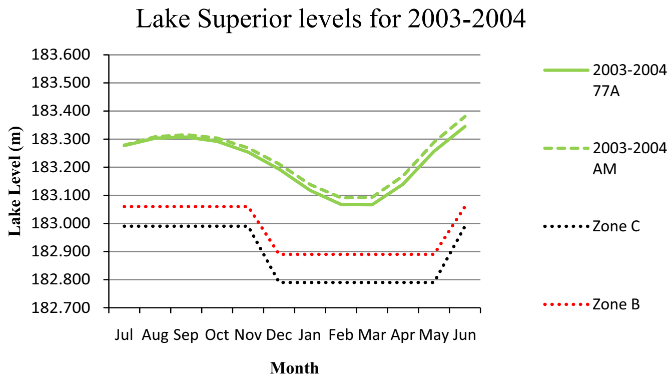

FIGURE 5. The Elevation of Lake Superior Under the Existing Regulation Plan (77A) and an Alternative Plan (AM) During a Simulation of the 2003-2004 Low-Level Season. The figure shows coping Zone B (moderate impacts) and C (irreversible damage) for low lake levels.

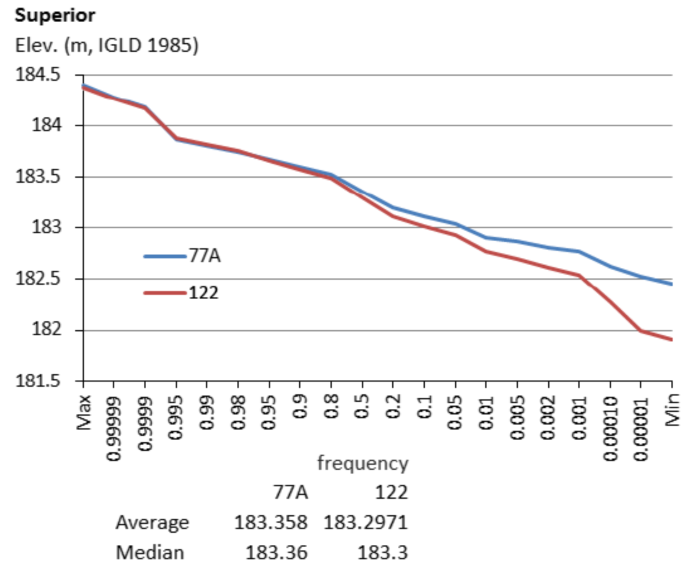

FIGURE 6. The Elevation of Lake Superior Under Two Separate Regulation Plans and a Dry Stochastic Simulation as a Function of Exceedance Probability. Plan 122 draws Lake Superior much lower than Plan 77A under this climate state.

Werick and Palmer, 2004) that involves Great Lakes stakeholders in the development of the plan.

Design of a Dynamic Regulation Plan

Traditional water resources planning often focuses on formulating an optimal design based on performance evaluated with a best estimate of future hydrologic conditions. Frequently, the future hydrologic conditions were simulated using the statistics of the historical hydrologic conditions. This is an apt description for previous approaches to developing regulation plans for Lake Superior (see Clites and Quinn, 2003). Regulation plans for Lake Superior were modified approximately seven times during the regulated period of 1914 to the present. Changes to the regulation plans resulted not only due to hydrologic conditions but also due to evolving societal priorities for regulation, including increasing interest in hydroelectricity production and new emphasis on including impacts on downstream lakes.

The relatively frequent rate of adjustment of past regulations plans reinforced the emphasis of this study on robustness, defined as a regulation strategy that could perform acceptably over a wide range of climate conditions. To that end, two modifications to traditional water resources planning were adopted. First, decision-scaling is used to evaluate plan performance under climate change. Following the process described above, the mean climate state can be varied to identify the changes in precipitation and temperature that would cause problematic lake levels for a given regulation plan. For example, Figure 6 shows the differential performance of two alternative regulation plans under a dry climate state.

Climate conditions on the Great Lakes are often summarized in terms of Net Basin Supplies (NBS), where NBS is the sum of precipitation, runoff, releases, inflows and diversions, and evaporation (negative). In the approach described here, NBS is varied and the response in terms of lake levels is quantified to define a climate response function, $C(D \mid CC_i)$, where $C()$ represents the consequences of a decision given the occurrence of a climate change state (CC_i). For the Great Lakes application, the climate response function accepts mean climate conditions (NBS) and, for a given decision (regulation plan), produces estimates of consequences (lake levels and associated performance metrics). By use of stochastic time series of NBS that are representative of changes in mean climate conditions, those that present risks to a regulation plan can be identified. Note that climate model projections have not been used in the analysis to this point. Yet considerable information regarding climate impacts may be revealed.

Once the climate states that cause risks for a regulation plan are identified, the plausibility (relative probability) of those conditions is estimated through tailored climate information. Given the uncertainty associated with the probability estimates even after maximizing credibility, the term "plausibility" is used in place of probability. The decision makers, in this case the Study Board, will be presented with plausibility estimates of climate states associated with each regulation plan and the sources of climate information that assigned probability to that state. The plausibility estimates may be adjusted based on different comfort levels of the Board members with the various climate information sources.

Next, the concept of a dynamic regulation plan is introduced as an alternative to the usual adoption of a static plan. Instead of the selection of a single best plan, a portfolio of plans will be developed that are optimal for a range of conditions (e.g., prevailing high mean lakes levels due to a wetter climate). Then the appropriate plan is implemented based on the prevailing conditions. Triggers for switching between plans will be identified once the portfolio of optimal plans is developed.

Adaptive Management of the Lake Superior Regulation Plan

The use of a dynamic regulation plan is envisioned to produce a robust regulation strategy for a broad range of future climates. However, it is well known that there are other uncertainties, including faulty assumptions and unforeseen surprises, which threaten the success of the regulation plan. For this reason, an adaptive management process is being incorporated into the regulation of Lake Superior. The process consists of long-term monitoring of regulation plan performance and mechanisms for implementing changes when needed. Figure 5 illustrates the historical approach to management of Lake Superior regulation (5a) in comparison with the proposed robust adaptation strategy (5b).

For any adaptive management process, monitoring is critical. The data gathered through carefully designed monitoring allow evaluation of the performance of the regulation plan and the need for changes, including regulation rule changes, changes to plan objectives, or other possibilities that we cannot anticipate. The observations will provide direct feedback on plan performance. In addition, monitoring will be designed to evaluate the degree to which the coping zones are effective in estimating plan performance. Since there is uncertainty in the estimation of the coping zones by the working groups, it is possible that significant negative impacts may be accumulating for a stakeholder group despite lake levels remaining out of Zone C. Adjustment to the zones themselves may be necessary.

In order to sustain monitoring and provide mechanisms for use of the collected data in decision making, an institutional framework for the adaptive management process is required. Previous studies have shown that adaptive management is praised more than used (Walters, 2007). The IUGLS study board is committed to implementing an adaptive management process. An institutional analysis will investigate how the process will be funded, who would be responsible for each element of the plan, and how decisions will be made and implemented. The study board will recommend adaptive management to the IJC, and the common assumption is that a number of U.S. and Canadian agencies would agree to carry out different elements of the plan. This will not guarantee that adaptive management will occur even if these tasks are carried out well. But the adaptive management process has been designed to improve the odds of successful implementation.

CONCLUSION

The prospect of climate change causes concern for planners and managers of water resources systems and for the public officials responsible for those systems. The science and analysis to date has made clear that climate change holds significant and uncertain implications for water resources systems. However, there is a lack of accepted methodologies or tools available for conducting risk assessments and/or managing climate risks during planning exercises. In this paper, we present a process for conducting risk analysis and managing climate risks for water resource systems that utilizes uncertain climate information. The process utilizes a decision-analytic framework as the basis for linking the insights from bottom-up sensitivity analysis with the tailoring of climate change projections. Due to the irreducible uncertainty associated with climate change projections, it focuses on identifying vulnerabilities and managing risks through robust adaptation.

The process is described through its current implementation in a multidisciplinary, multistakeholder study of regulation of the Upper Great Lakes of North America, one of the largest managed water resources systems in the world. We expect the process to benefit from mutual learning among all participants and anticipate the need for flexibility in its execution. The bottom-up framework and processing of climate information and hierarchical approach to managing uncertainties are seen to have broad potential for water resources planning. Current work, and future work, explores the premises presented in this paper through modeling exercises and additional applications to a wide range of water resources systems.

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