Advanced Review

Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks

Christopher P. Weaver,[1*] Robert J. Lempert,[2] Casey Brown,[3] John A. Hall,[4] David Revell[5] and Daniel Sarewitz[6]

In this paper, we review the need for, use of, and demands on climate modeling to support so-called 'robust' decision frameworks, in the context of improving the contribution of climate information to effective decision making. Such frameworks seek to identify policy vulnerabilities under deep uncertainty about the future and propose strategies for minimizing regret in the event of broken assumptions. We argue that currently there is a severe underutilization of climate models as tools for supporting decision making, and that this is slowing progress in developing informed adaptation and mitigation responses to climate change. This underutilization stems from two root causes, about which there is a growing body of literature: one, a widespread, but limiting, conception that the usefulness of climate models in planning begins and ends with regional-scale predictions of multidecadal climate change; two, the general failure so far to incorporate learning from the decision and social sciences into climate-related decision support in key sectors. We further argue that addressing these root causes will require expanding the conception of climate models; not simply as prediction machines within 'predict-then-act' decision frameworks, but as scenario generators, sources of insight into complex system behavior, and aids to critical thinking within robust decision frameworks. Such a shift, however, would have implications for how users perceive and use information from climate models and, ultimately, the types of information they will demand from these models—and thus for the types of simulations and numerical experiments that will have the most value for informing decision making. © 2012 John Wiley & Sons, Ltd.

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*Correspondence to: Weaver.Chris@epamail.epa.gov

[1]National Center for Environmental Assessment, Office of Research and Development, U.S. Environmental Protection Agency, Washington, DC, USA

[2]The RAND Corporation, Santa Monica, CA, USA

[3]Department of Civil and Environmental Engineering, University of Massachusetts, Amherst, MA, USA

[4]Strategic Environmental Research and Development Program/Environmental Security Technology Certification Program, U.S. Department of Defense, Alexandria, VA, USA

[5]Environmental Science Associates—Environmental Hydrology, San Francisco, CA, USA

[6]Consortium for Science, Policy, and Outcomes, Arizona State University, Tempe, AZ, USA

INTRODUCTION

Assessment of environmental and societal risks from climate change, and the design and evaluation of strategies to build readiness and resilience in the face of these risks, is a generational scientific challenge. How should society steer climate research to best meet this challenge? How should we attempt to use insights and information from climate science to inform decision making about responses to climate change? These questions are particularly relevant now, as national governments and international scientific bodies are discussing how best to organize research efforts and to deliver knowledge, data, tools, and advice—climate services—to a potentially huge universe of clients.[1–3]

There has been some self-organization around two strategic framings of the problem. The first (dominant) paradigm assumes the need to improve our ability to predict, using physically based computer models, multidecadal, regional climate change as a prerequisite for effective planning; the second to instead improve our understanding of regional and sectoral climate-related vulnerabilities, and the cognitive, social, and institutional contexts within which these will be managed, in light of the deep uncertainties associated with climate change and its possible impacts. These two conversations have to date largely occurred in parallel.

The purpose of this paper is to discuss potential synergies between climate modeling for decision support as currently practiced, and the more bottom-up approaches to climate change vulnerability and impacts assessment, as a pathway to more effectively informing climate-related decisions. We argue that currently there is a severe underutilization of climate models as tools to support decision making. This underutilization stems from a double challenge noted by a growing number of scholars: a widespread, but limiting, conception that the potential usefulness of climate models in planning begins and ends with ever-finer regional-scale predictions of multidecadal climate change; and the general failure so far to incorporate learning from the decision and social sciences into climate-related decision support in key sectors such as water resources, coastal protection, agriculture, and public health.

In this paper, we argue that alleviating this problem will require expanding the conception of climate models, not simply as prediction machines within 'predict-then-act' decision frameworks, but as aids to exploratory modeling—for scenario generation, insight into complex system behavior, and supports for critical thinking—within so-called 'robust' decision frameworks. Such frameworks, combined with this broader perspective on the value of climate models for supporting decision making, have the potential to simultaneously and effectively address the challenge above.

Such a shift, however, would have implications for the ways in which users perceive and use information from climate models and, ultimately, the types of information they will demand from these models—and thus for the types of simulations and numerical experiments that will have the most value for societal applications. In this context, we review the use of, and demands on, climate modeling to support these frameworks, in the context of improving uptake of climate information into decision making.

LONG-TERM CLIMATE PREDICTION IS DIFFICULT . . .

As noted by various commentators,[4,5] one of the most oft-repeated statements in the climate impacts literature goes something like this: 'Accurate, high-resolution predictions of future climate are a prerequisite for developing effective responses to climate change impacts at regional scales.' A number of recent papers and editorials have called for increased efforts to deliver these improved predictions.[6–12] At the same time, everyone seems to broadly agree that we are a long way from fulfilling this need. For example:

> The climate science community now faces a major new challenge of providing society with reliable regional climate predictions. Adapting to climate change while pursuing sustainable development will require accurate and reliable predictions of changes in regional weather systems, especially extremes . . . Yet, current climate models have serious limitations in simulating regional weather variations and therefore in generating the requisite information about regional changes with a level of confidence required by society.[12]

And so on (see also Refs[8–10,13,14] and many others) (Box 1).

As the number of legal and political mandates for incorporating climate change information into decision making increase, the demands on climate science and modeling to deliver so-called 'actionable' information in direct support of planning will also continue to increase—as will scrutiny of their ability to do so.

It is well understood that current limits on scientific understanding and computing power result in deficiencies in simulating impact-relevant climate system elements—clouds, precipitation, winds, BOX 1

NOTES ON LANGUAGE: PREDICTION, PROJECTION, AND SCENARIO

According to the IPCC[15]: 'A climate prediction or climate forecast is the result of an attempt to produce an estimate of the actual evolution of the climate in the future, for example, at seasonal, interannual, or long-term time scales. Since the future evolution of the climate system may be highly sensitive to initial conditions, such predictions are usually probabilistic in nature.' Here, the term 'prediction' refers to attempts to answer questions posed as 'What will happen (in the future)?' This definition also suggests that various factors will prevent us from achieving 100% accuracy, and that an important part of any climate prediction is our degree of belief that it will come true. The IPCC also distinguishes prediction from two other common terms, 'projection' and 'scenario':

Climate Projection: 'A projection of the response of the climate system to emission or concentration scenarios of greenhouse gases and aerosols, or radiative forcing scenarios, often based on simulations by climate models. Climate projections are distinguished from climate predictions in order to emphasize that climate projections depend on the emission/concentration/radiative forcing scenario used, which are based on assumptions concerning, for example, future socioeconomic and technological developments that may or may not be realized and are therefore subject to substantial uncertainty'.

Climate Scenario: 'A plausible and often simplified representation of the future climate, based on an internally consistent set of climatological relationships that has been constructed for explicit use in investigating the potential consequences of anthropogenic climate change, often serving as input to impact models. Climate projections often serve as the raw material for constructing climate scenarios, but climate scenarios usually require additional information such as about the observed current climate. A climate change scenario is the difference between a climate scenario and the current climate'.

All three terms are entrenched in the climate literature, but with some semantic confusion surrounding their use. A number of authors suggest that many, instead of using them to describe distinct objects, essentially employ them as shorthand for a continuum of decreasingly confident statements about the future, from prediction, through projection, to scenario, using them to manage expectations created by the word prediction.[16–22] In addition, the IPCC definition of projection above still implies that at least the climate portion is deterministic, and it is only the future emissions pathway that is non-deterministic and thus must be captured via a set of scenarios.

Rather than using projection and scenario as if they are simply a kind of less-accurate prediction, it would seem to make more sense to adopt functional definitions that relate to how the different objects are actually used to support decision making. How would one envision using a climate prediction to support an actual planning decision, and how would that use differ from how one would use a climate scenario? Attention to how best to judge the 'success' of a scenario[23] is useful here. One potential casualty of such a functional approach to these definitions is the word 'projection', which seems to be uneasily perched between these two different uses.

the diurnal cycle, and the atmospheric moisture balance[24–27]—as well as major weather patterns such as the Indian Monsoon,[28] the mid-latitude storm tracks,[29] and the El Nino-Southern Oscillation (ENSO).[30]

Spatio-temporal resolution is clearly part of the story. High resolution is crucial for representing key processes with realism, but is also extremely computationally intensive. And the most relevant spatial and temporal scales for resource management or ecosystem processes are those for which the obstacles to prediction are the greatest.[31] Various downscaling techniques, while important for many applications, offer no free way out.[32,33] Other dimensions that compete for computing resources include model complexity (biogeochemistry, aerosols, land-use change, ice sheet dynamics, etc.), integration length, ensemble size, and specification of initial conditions.

Progress in research and technology over time will presumably improve this situation somewhat, but the challenge is great:

> The past 40 years of climate simulation have made it apparent that no shortcut is possible; every process can and ultimately does affect climate and its variability and change. It is not possible to ignore some

component or some aspects without paying the price of a gross loss of realism.[34]

Other issues make long-term climate system prediction an even more difficult problem.[35] Once we start considering timescales beyond a decade or two, the changing human influence on climate cannot be ignored. Societies will likely react in complex ways to climate change, ways that will alter the trajectory of subsequent changes (e.g., in greenhouse gas emissions, land use, and geoengineering), with further feedbacks on human behavior, and these changes will likely be unpredictable.[36–38]

Furthermore, detailed predictive skill beyond a few seasons is not yet a reality.[39–41] Because of the long timescales involved, it is impractical to directly assess the skill of multidecadal climate forecasts (in contrast with short-term weather forecasting) leaving us to rely on indirect methods.[42,43] However, we do not yet have the scientific understanding to convincingly measure climate model skill this way. Because future climate will be a not-yet-experienced state of the Earth system, it may ultimately be impossible to *a priori* calibrate a given climate model in such a way as to ensure that it will produce a meaningful long-term forecast.[43–49] We lack a generally accepted set of metrics for evaluating climate model performance, either in general or in a sector-specific[50] way. The aspects of observed climate that must be simulated correctly to ensure reliable future forecasts are not known; agreement across a collection of models does not provide a rigorous basis for assessing how much we should believe a future prediction either.[14,42,43,51–56] (It is important to note that the obstacles to skillful prediction on shorter timescales—say, a decade—are likely not nearly as great, as discussed extensively elsewhere[37,57] but these efforts are still in their infancy.)

Finally, despite strenuous efforts, it is clear that current models and simulations capture only a subset of our scientific uncertainty about how the climate system works (and how to encapsulate our understanding in a model).[22,37,58–63] So far, the more model variants we create, the more complexity we add, and the more simulations we carry out, the greater the range of scientifically justifiable future climates (and the corresponding range of societal outcomes[64]) that result.

. . . AND SO IS CLIMATE-RELATED DECISION SUPPORT

Meeting the scientific and technical challenges of climate prediction would of course not be the only prerequisite for achieving better climate-related decision making. It may not even be the most difficult. A large literature about how decisions are actually made explains the factors that determine whether and how scientific information becomes part of that process. This literature makes clear that scientific knowledge, including products such as predictions, is only one part of a much broader system of decision-making practice.[4,19,65]

This starts with the acknowledgement that information may be scientifically relevant without being decision-relevant. Scientific information can be effective in influencing decision making, but only if this information is perceived as ‘credible, salient, and legitimate’: i.e., scientifically and technically accurate in its evidence and arguments, but also relevant to the needs of the decision makers and having been produced in a way that is unbiased and respectful of their divergent perspectives and values.[66,67] These characteristics tend to result only from a sustained process of close interaction among knowledge producers and users, often facilitated by so-called ‘boundary organizations’.[68] Because different actors perceive the usefulness of scientific information differently,[19] decision support characterized by one-way communication and a focus on ‘products’ (e.g., reports, predictions) as opposed to ‘process’ (of communication, mediation, translation, feedback, and trust building) has been demonstrated to be ineffective.[66,67,69]

This highlights long-understood truths of the decision sciences that no simple relationship exists between more information and better decisions, information does not necessarily precede decision making, important basic questions are often raised in the course of making decisions, and ‘reducing uncertainty’ will likely have different meanings in the context of scientific understanding versus that of decision outcomes.[70–73] Scientific assessments to support decision making should be viewed, fundamentally, as social processes embedded within particular institutional structures.[69] With climate predictions in particular, a suite of technical, cognitive, institutional, and structural factors determine the capacity of decision makers to make use of them. Lemos and Rood[19] write of the ‘uncertainty fallacy,’ in their words ‘a belief that the systematic reduction of uncertainty in climate projections is required in order for the projections to be used by decision makers’. Experience in attempting to use forecasts of seasonal-to-interannual climate variability (e.g., as driven by ENSO cycles) for planning in sectors such as water resources and agriculture clearly illustrates these issues. There is widespread agreement that such forecast information, while having the potential to support improved decision making, is almost universally underutilized in these sectors.[19,74–82]

The use of scientific information for building readiness to much longer-term climate change will certainly require at least a similar level of effort, and at minimum face similar obstacles, as discussed in a number of recent publications.[65,83–87] That climate-related decisions are made at all organizational levels, from individuals to international bodies, precluding the development of 'generic' decision support, compounds the challenge. Combine this with the previously mentioned difficulties in modeling the climate system over these timescales (and thus the poor prospects for forecasts that will likely not have even the credibility of the seasonal forecasts currently available) and we are faced with a significant challenge. Is there a path forward?

HARNESSING CLIMATE MODELING TO THE MACHINERY OF EFFECTIVE DECISION SUPPORT

What are the implications of the above twofold challenge for supporting decision making about adapting to long-term climate change? Social sciences research clearly shows that simply overcoming the extremely difficult scientific and technical obstacles to climate prediction will not suffice. Climate-related decision support is hard, not only because long-term climate prediction is hard, but also because creating decision-relevant processes for the production and uptake of climate information is hard. We suggest that a kind of cognitive dissonance infuses discussions of the social value of climate modeling. On one hand, we recognize that the climate system is almost unimaginably complex and the challenges of modeling it are enormous. On the other hand, we tell ourselves that we urgently need the predictions that only models can supply. We wrestle with the question: 'If climate science is not delivering actionable predictions, then what good is it?'

Sarewitz and Pielke[73] have introduced the idea of 'supply of and demand for science'—the importance of simultaneously reconciling the capabilities and aspirations of both knowledge producers and knowledge users. In the terminology of their 'Missed Opportunity Matrix' (Figure 1) this reconciliation results in 'Empowered users taking advantage of well-deployed research capabilities'.

One major factor in the match of supply and demand is the decision framework within which the scientific information must operate, and by which its relevance is judged. For the case of climate modeling to support decision making, we argue that supply and demand are out of balance because of the predominance of a prediction-based paradigm

		Demand: Can user benefit from research?	
		YES	NO
Study: Is relevant information produced?	NO	Research agendas may be inappropriate	Research agendas and user needs poorly matched; users may be disenfranchized.
	YES	Empowered users taking advantage of well-deployed research capabilities.	Unsophisticated or marginalized users, institutional constraints, or other obstacles prevent information use.

FIGURE 1 | The missed opportunity matrix. (Reprinted with permission from Ref. 73 Copyright 2007 Elsevier Ltd.)

for understanding the value of climate information in decision contexts. Furthermore, in light of the challenges discussed in the previous two sections, we suggest that reconciliation of supply and demand could usefully occur around a class of decision frameworks that rely on bottom-up approaches to assessing risks and seek to develop robust actions that hedge effectively against these risks over the many significant uncertainties in the climate change problem.

Decision-Making Paradigms

The decision sciences recognize multiple paradigms for choosing which actions to take. Here we contrast what is sometimes termed a 'predict-then-act' approach—i.e., where the best available prediction of system behavior drives decision making at a given moment in time—with approaches rooted in different underlying principles.

In the context of the challenges we have been discussing—of climate prediction and of climate-related decision support—we argue that prediction-based frameworks place unrealistic demands on climate science and modeling and artificially limit their use for supporting real decisions. Such thinking reinforces a 'decision support as information product'

TABLE 1 | Two Paradigms

Paradigm 1: 'Predict-then-Act'
Figure out your best-guess future and design the best policy you can for that future
Conceptual framework: Maximize expected utility
Question: 'What is most likely to happen?'
Paradigm 2: 'Seek Robust Solutions'
Identify greatest vulnerabilities across full range of futures and identify the suite of policies that perform reasonably well across this range
Conceptual framework: Minimize regret
Question: 'How does my system work and when might my policies fail?'

frame, contrary to the 'decision support as process' perspective that more accurately describes real-world decision making. In addition, if we are committed to prediction-based frameworks, not only are we stuck having to deliver climate predictions with well-characterized probability distributions, but ultimately also a set of much more difficult ecological and socioeconomic predictions,[8,85–89] including the deeply uncertain behavior of future decision makers,[90] to provide meaningful predictions of impacts.

The predict-than-act paradigm (Table 1) is closely linked with the classical decision-theoretic concept of maximizing expected utility:

> Most traditional decision-analytic methods for risk and decision analysis[91] are designed to identify optimal strategies contingent on a characterization of uncertainty that obeys the axioms of probability theory. These approaches begin with a single best-estimate description of the relevant system, consisting of a system model that generates outcomes of interest given a choice of strategy and a single set of probability distributions over the model's input parameters to characterize the uncertainties.[92]

Although decision approaches that maximize expected utility clearly work best under many conditions, they tend to be difficult to apply when the strategy they suggest is highly sensitive to assumptions about which future is most likely.[22,93] Because they require a quantitative characterization of the problem's uncertainty as a prior input to the decision, these approaches lose value as they become increasingly sensitive to this characterization; in offering no systematic way to choose among several 'best' strategies (each dependent on different, but all plausible, choices of priors and assumptions). These issues create incentives for analysts to focus on the parts of the problem for which the uncertainties are well characterized and ignore deep uncertainties and possible surprises that may be highly relevant to the policy question under consideration,[90] thereby resulting in decisions that may be insufficiently protective.[10,94] They also exacerbate the difficulty of getting diverse stakeholders to agree in advance on the predictions (and probabilities) that are the prerequisites for the decision, while incentivizing particular stakeholders to focus on those predictions and uncertainties most consistent with their interests and world views.

However, there exist other decision paradigms (Table 1) that may be better able to embrace the uncertainties of climate change (and better align with the messy realities of decision support). One particular class of such approaches, with variants such as 'Robust Decision Making (RDM),' 'Decision Scaling (DS),' 'Assess Risk of Policy,' 'Info-gap,' and 'Context-First,' provides an opportunity to overcome the deficiencies of prediction-based frameworks in deciding how to respond to long-term climate change.[90,92,95–107] These share a number of core ideas, beginning with defining a proposed policy or policies, identifying vulnerabilities of these policies under multiple views of the future, seeking in particular those futures under which the policies fail to meet their goals, identifying potential responses to these vulnerabilities, and organizing scenarios to help decision makers determine the circumstances under which they would adopt these responses. Interest in applying these kinds of approaches has increased recently, due to growing recognition of factors such as the importance of extreme and unanticipated events and the need to develop decision support processes that can engage multiple stakeholders with diverse perspectives.[108]

Before discussing robust decision frameworks and the demands they place on (and opportunities they create for) climate science and modeling, we briefly review a number of key concepts from the domain of 'exploratory modeling', to provide a broader context for the integration of climate modeling and decision analysis.

Exploratory Modeling

Argument over the appropriate uses of models has a long history. Many authors have emphasized that models' usefulness rests in their ability to help us think about a system—as heuristic tools to help us understand what we can actually observe or estimate,[109] or as a way to challenge existing formulations and intuitions.[70,110] Models allow one to keep track of more variables than is possible in one's head, as well as processes like feedbacks, stocks and flows, time delays, and nonlinearities that are non-intuitive for most people.[111–113] In the history of science, the twin ideas of explaining the known and predicting the unknown have evolved and interacted, alternating dominance.[114] To be useful, a simulation does not have to be a prediction, or testable as such, but simply to provide a useful description of the world.

Bankes,[115] with criticisms and insights that remain highly relevant for our discussion, articulated such arguments as being rooted in the tension between 'consolidative' and 'exploratory' modeling. Traditionally, models (computer simulations or statistical estimations) have been seen as consolidative, meaning that they bring all known facts together into a single package which, once validated, can be used as a surrogate for the real world (e.g., prediction). This is the situation in which much of climate modeling finds itself today.

However, in many cases models cannot be readily validated, due to missing data, inadequate theory, or a future with elements that are unavoidably unpredictable. In contrast to consolidative modeling, exploratory modeling aspires to construct valid arguments by carrying out experiments with ensembles of models that capture sets of assumptions about the world, and to explore the implications of these varying assumptions (Box 2).

Bankes emphasizes that, in exploratory modeling, models are used not to generate predictions or explicit answers to policy makers' initial questions but instead to generate new information helpful in formulating informed decisions. And he reminds us that even simple models produce surprises:

> By throwing light on treacherous assumptions or revealing unrealized implications of existing information, computer modeling can perform an important service. When used for exploratory modeling, the computer functions as a prosthesis for the intellect, supporting the discovery of implications of a priori knowledge, novel explanations of known facts, or unrealized properties of conjectures.[115]

The three main categories in the above taxonomy suggest different roles for exploratory modeling at different stages of decision analysis, often requiring different models or systems of linked models at each stage. For example, we might (1) use exploratory modeling to identify the possibility of important special cases in system behavior, such as extremes, thresholds, and surprises. We might then (2) use this information to search for policy options capable of satisfactory performance in the face of such special cases, thereby expanding the space of choices for the policy-maker. And, finally, we might (3) evaluate these (and other proposed) options over as wide a range of futures as possible, generated using models (perhaps combined with other sources of information).

BOX 2

TAXONOMY OF EXPLORATORY MODELING ARGUMENTS[115]

Hypothesis Generation and Existence Proofs: Show that an ensemble of model simulations has a member exhibiting some property of the world and/or suggest a particular class of models as a possible explanation of that property. A plausible model displaying unexpected behavior is useful in that it can reorient an analysis to confront an expanded range of possibility. This argument encompasses identification of bounding cases, surprises, and unknown worst cases.

Reasoning from Special Cases: Computer search can discover special cases that suggest arguments relevant to a decision. For example, previously unexpected disaster scenarios can suggest precautionary measures; unexpected opportunities can suggest policies to exploit these opportunities; a fortiori arguments can strengthen policy choices; extreme cases where the uncertainties are all one-sided can simplify choice. This argument encompasses the identification of hedging strategies to avoid worst-case outcomes when risk aversion is prudent.

Assessing Properties of the Entire Ensemble: If all cases examined have property X, assert X true for the entire ensemble (for example decision A dominates decision B everywhere in the parameter space of the problem). This argument encompasses the search for cases that distinguish between alternative decision options using satisficing criteria such as robustness over a wide range of views of the future.

Exploratory Modeling for Robust Decision Frameworks

How do robust decision frameworks connect modeling to decision making in a way that addresses the principal challenges we have recognized here: i.e., the current and foreseeable limits on climate prediction and the need to incorporate scientific knowledge about climate change into a highly contextualized and participatory process of decision support?

First, modeling in robust decision frameworks is explicitly exploratory rather than consolidative, fitting neatly into the threefold exploratory modeling taxonomy of describing the range of possible system behavior, identifying policy options capable of relatively better performance under important extreme cases, and evaluating all proposed options across possible futures to clarify the tradeoffs associated with each. Rather than suggest a single, best-guess path to an optimal decision, robust frameworks are asked to assess the implications of various assumptions, uncover unanticipated vulnerabilities, characterize the few deep uncertainties most important to the problem, and generally orient the analysis so as to most efficiently guide the search for the most useful policy alternatives.[100]

Faced with deep uncertainty about the future, robust decision frameworks suggest that it is most effective to work backwards from the decision context to the technical and information requirements of the problem, relying heavily on participatory processes that bring together the analysis team and the various parties to the decision to structure the problem appropriately for meeting stakeholder needs. This premise is shared generally with all 'bottom-up', 'risk-based', or 'vulnerability-based' climate change impacts frameworks.[84,116–119] One example is RDM, which has recently been applied in a number of climate-related decision problems. In RDM, problems are structured according to three major concepts: multiple views of the future, a 'robustness' criterion, and an iterative vulnerability-and-response-option analysis (Figure 2).

The use of robustness as a satisficing criterion provides a major point of departure from predict-then-act approaches. Decision analytic frameworks that attempt to maximize expected utility will tend to rank alternative policy options contingent on the best-estimate probability distributions to suggest a single best option. Robust frameworks instead suggest a set of choices that perform reasonably well compared to the alternatives across a wide range of future scenarios, often sacrificing some performance in order to reduce sensitivity to broken assumptions and thus minimize regret under particular futures.

RDM and related approaches offer not only a quantitative methodology for incorporating large volumes of information from sophisticated models into decision processes, but also a heuristic framework for planning and project design. Without using simulation models, decision makers can think through the combinations of climatic and socioeconomic factors that would cause one or more proposed policies to fail to achieve their goals (see Refs 120,121 for examples related to road design and forest management). In addition, relatively simple models are often at the core of such analyses. For example, in the sea-level rise case study we discuss later, the cost–benefit model used to evaluate the robustness of the different policy alternatives was essentially a simple spreadsheet. This relates to the feasibility, particularly for resource-limited, local projects, of constructing large numbers of futures for assessing the viability of policy options over as comprehensive a set of assumptions as possible. As detailed in the case studies below, often the conversion of an existing, computationally inexpensive management model with which the users are already familiar (e.g., to run overnight in 'batch' mode) suffices for quickly and simply testing assumptions over many inputs.

The idea of using multiple views of the future to explore policy options is not unique to robust decision frameworks, but also informs traditional scenario planning methods. Such methods rest on the presumption that a small collection of stories about different futures can help planners better prepare for surprises.[122] Scenarios can be either normative, exploratory, or have aspects of both. Normative scenarios are prescriptive and explicitly values-based, in that they describe a future that may be realized only through specific policy actions (e.g., a greenhouse gas stabilization scenario). In contrast, exploratory scenarios describe the future according to known processes of change and pose 'what if?' questions.[20] However, traditional scenario methods struggle to address two questions: which futures to highlight, and how to inform real decisions. Robust decision frameworks address these issues, in part by viewing scenarios as cases where a candidate strategy fails to meet decision makers' goals and standards, as evaluated against a large number of future states of the world.[123]

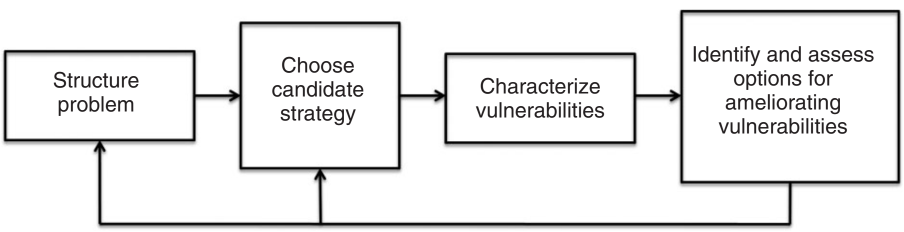

FIGURE 2 | Steps in a robust decision-making analysis. (Reprinted with permission from Ref. 104 Copyright 2010 Elsevier Ltd.)

To explore these concepts further, specifically in the context of using climate modeling in decision support, we turn to a few cases of real-world applications. These examples highlight the following:

(1) Advantages of robust decision frameworks when compared to traditional prediction-based approaches, in particular for the types of information typically available from climate models today.
(2) The importance of considering climate models, not as a standalone element of the analysis, but as part of linked systems of multiple models (and multiple lines of scientific evidence) with different roles at different stages of the analysis.
(3) Areas where useful developments in climate modeling research and practice could occur that would better enhance the value of climate model-derived information in robust decision frameworks.

Illustrative Case Studies

Managing for Uncertainty at a California Water Agency

Water agencies have always considered hydrologic uncertainty in their planning, but typically only in year-to-year conditions about a historically stationary mean and not in long-term trends. Most water agencies develop a single best estimate of how water needs will evolve in the long term under projected future demand and historical hydrologic conditions, along with associated schedules of capital improvements and program implementation to meet performance goals. Under climate change, the assumption that the hydrologic conditions of the past will be a good guide to the future will likely be even less valid, compromising well-established water planning concepts such as 'reliability'.[96,124]

Here we describe an application of RDM for Southern California's Inland Empire Utilities Agency (IEUA), a wholesale water and wastewater provider in Southern California's Riverside County.[104] The IEUA region is in the midst of rapid urban growth and socioeconomic transformation, with a regional population that is anticipated to grow from 800,000 in the mid-2000s to approximately 1.2 million by 2025, placing new demands on the water supply and wastewater treatment system, a challenge typical for southern California and the American Southwest.

Also typical for the region, IEUA's 2005 Urban Water Management Plan[125] was a static 25-year plan that emphasized improved groundwater management and large increases in wastewater recycling to address the water demands of the region's projected growth. As required by the state, IEUA's plans must demonstrate that the agency can successfully accommodate future demand under historical climate conditions, but, like the others developed previously, the 2005 plan does not consider how it would perform under altered future climate. IEUA assembled a team of researchers and analysts to use RDM to assess the vulnerabilities of their 2005 plan in the face of climate change, as well as help identify options for addressing and managing these vulnerabilities.

There were a number of factors that led to IEUA's management agreeing to participate in this RDM demonstration. The first was that the agency regards itself as a thought-leader in the water sector; in fact, based in part on the results of this effort, other agencies (e.g., Metropolitan Water District of Southern California, U.S. Bureau of Reclamation, Denver Water, California Department of Water Resources, and the World Bank) have subsequently begun to explore the use of similar RDM analyses for their planning. IEUA's leaders also recognized the need for improved ways to include their community in discussions of climate uncertainties and long-range planning. They guessed (correctly, as it turned out) that the analysis would support the policy directions they had already been advocating to deal with this challenge.

The first phase of an RDM analysis structures the problem by (1) defining the key performance metrics an organization should use to judge the success of alternative strategies, (2) articulating a set of such strategies that might achieve these objectives, (3) identifying potentially significant uncertainties about the future that would impact the performance of these strategies, and (4) adapting or developing a computer simulation model(s) that can compute strategy performance contingent on these uncertainties. RDM-based processes are, by definition, participatory. Here, the analysis team carried out these steps in collaboration with IEUA planners and presented the results to the agency's stakeholders and decision makers via a series of workshops at IEUA headquarters.

A critical aspect of this participatory process was the solicitation of information about key uncertainties in the management system. Through interviews with IEUA planners and stakeholders, the analysis team identified six uncertain factors potentially important to the ability of IEUA to achieve its objectives, along with a plausible range of uncertainty for each (Table 2). To represent a range of climate futures, the analysis team developed a large ensemble of synthetic monthly temperature and precipitation sequences that reflect both local weather variability and the range

TABLE 2 | Uncertainties Addressed in the IEUA RDM Analysis (Reprinted with permission from Ref. 104 Copyright 2010 Elsevier Ltd.)

Uncertain Key Factors	Representation Within WEAP Model
Future climate key factors	450 Sequences of monthly temperature and precipitation reflecting trends in temperature −0.4°C to +2.75°C and precipitation from −27% to +19% over 30 years
Future water demand	Water intensity of new development ranging from 0% to 30% more efficient than existing housing stock
Impact of climate change on imported supplies	Range of maximum climate change-induced declines in imported supplies between 30% and 50%
Response of groundwater basin to urbanization and changes in precipitation patterns	Change in percentage of precipitation that percolates into the groundwater basin (e.g., runoff) from 0% to 10%
Achievement of management strategies	Delay in recycling program achievement between 0 and 10 years; achievement in groundwater replenishment goals between 80% and 100%
Future costs	Annual cost increase in imported supplies between 2.5% and 8%; annual cost increases in efficiency achievement between 2.5% and 8%

WEAP, Water Evaluation and Planning.

of regional trends simulated by a variety of leading climate models.[126]

The analysis team then developed a simulation model of the IEUA water management system within the Water Evaluation and Planning (WEAP) modeling environment[127] that incorporated representations of these uncertainties. An initial application to the 2005 plan revealed significant future climate-related vulnerabilities, in conjunction with the other uncertain factors. The analysis team then worked with IEUA planners to identify a set of potential modifications to the plan that might address these vulnerabilities. By running WEAP over 450 different parameter combinations drawn from the ranges of the six uncertain factors, the team was able to evaluate the performance of each of these water management strategies throughout this space of future uncertainties, using metrics such as the costs to the agency of incurring water shortages.

One of the challenges faced in this and other RDM analyses is in representing the richness of these multiple-criteria evaluations of a variety of management plans over such a large number of futures in ways that communicate clearly and simply the important nuances of the problem. RDM uses a systematic, computer-aided process of ‘scenario discovery’[128] to identify a small number of combinations of uncertain parameter values that best represent those future states where a given management plan performs poorly. This allows the analysis team to provide a concise description of representative cases that best summarize such poorly performing strategies with a small number of scenarios meaningful to decision makers.

For IEUA and its candidate plans, this scenario discovery process suggested that, of the six uncertain parameters considered, a specific combination of three of them—large declines in precipitation, larger-than-expected impacts of climate change on the availability of imported supplies, and reductions in percolation of precipitation into the region’s groundwater basin—would cause the agency to suffer high costs. This finding motivated IEUA to identify a further suite of modifications to the 2005 plan that reduced these vulnerabilities without significantly increasing costs (or other measures of agency effort) and begin implementing a more adaptive strategy consistent with the analysis findings. This new strategy calls for IEUA to accelerate efforts to expand the agency’s dry-year-yield program and to implement its recycling program, making additional investments in efficiency and storm-water capture if monitoring suggests approaching shortages. IEUA has committed itself to this new plan, often citing the RDM analysis in support of their decision.

The above summarizes the main points of this case study. What of the lessons about climate modeling to support this type of analysis? This particular application of RDM did not use a large, sophisticated, and customized set of climate simulation data. Rather, it relied on basic information developed for other purposes and accessible to a variety of users. In this context, this example provides two important lessons about the use of, and demands on, climate models to support planning processes designed to account for future climate change.

First, and most fundamentally, the story of this case is about stakeholder acceptance of climate model outputs as useful inputs to planning. On the basis of various stakeholder interactions carried out as part of the analysis process, including formal evaluations of the impact of the RDM analysis,[104] it was clear that many of the stakeholders would have distrusted the coarse-scale climate model outputs, spanning a wide range of values for key variables, if they were presented as predictions. In other words, the supply of climate predictions would not have met the demand for confidence in those predictions. Under the RDM paradigm, however, the available supply of model-derived climate information was sufficient to meet the demands of an analysis of vulnerability and robust responses. Here, the stakeholders were only asked to consider how much the climate would have to change before the current IEUA plan would begin to generate shortages, and then to believe that such changes were sufficiently plausible to warrant consideration of potential responses. The users were able to perceive the same climate model output with greater salience, credibility, and legitimacy. Even without agreement across parties as to the level and meaning of the uncertainty in the climate futures, trust in the process allowed for trust in the management plan eventually arrived at.

Second, this example highlights how RDM is structured to consider adaptive management approaches explicitly within a quantitative decision support framework. This is a particular advantage, as adaptive strategies are obviously useful for planning under conditions of deep uncertainty but often prove difficult for public agencies to implement, for a variety of reasons. In addition, theoretical trade-offs between adaptability and prediction uncertainty have been noted.[129] The RDM-based decision support provided to IEUA created the opportunity for that agency to identify and evaluate an adaptive management alternative to its current plan, as well as the justification to ultimately adopt this alternative. In this context, RDM specifically allows for the quantification of how adaptive a policy need be and how valuable would be attempts to acquire new scientific knowledge about the observed state of the given system (monitoring and assessment) and its possible range of behaviors and likely future evolution (process modeling and prediction).[103] This quantification can help decision makers weigh investments in, for example, new and improved climate modeling, against the costs of acquiring other types of information about the system or making specific decisions that would obviate the need for that information. We build on both of these lessons in our next case study.

Rapid Sea Level Rise and the Port of Los Angeles

One critical reason for turning to robust frameworks is the growing recognition of the potential for abrupt climate changes with important consequences for natural systems, human communities, and socioeconomic sectors.[130–133] A key challenge for planning is to incorporate the possibility of such abrupt and impactful changes for which uncertainty is both deep and poorly characterized.

The Port of Los Angeles (PoLA) is one of the largest container shipping facilities in the world, and it faces the challenges of planning for the uncertain probability but potentially large impact of extreme sea level rise over the coming century. Such extremes can affect infrastructure investments but are difficult to incorporate into decision processes because of their deep uncertainties. Complicating matters, available information about these factors may span a wide range of uncertainties, from well characterized to deep. Both annual means and short-term extremes of future sea level are expected to differ in the future, due to effects such as thermal expansion, changes in oceanic structure, melting of land-based ice, shifts in oceanic and atmospheric circulation, and changes in the terrestrial water balance.[134] While some of these processes are relatively well understood, others remain deeply uncertain, such as rapid flows of land-based ice and changes in the frequency and intensity of future extreme wave events and storm surges.[135–137]

This application is therefore amenable to a robust decision approach. An interdisciplinary analysis team conducted an RDM analysis for PoLA to help them assess one particular decision—whether PoLA should harden their container ship terminals against future sea level rise during the next major upgrades of those terminals (Figure 3).[105] At some time in the future, the Port will upgrade its terminals, and at that time it can decide to spend an additional sum to protect against higher future sea levels during the terminal lifetime, thereby suffering no further costs through the next upgrade time. If PoLA decides not to harden, the terminal may prove vulnerable during its lifetime to sea level rise and storm surges, with the potential for significant extra cost.

The RDM analysis attempted to answer two questions:

(1) Under what future conditions would PoLA find it advantageous to have hardened its terminal at the next upgrade?
(2) Does current science and other available information suggest these conditions are sufficiently likely to justify a decision to harden at the next upgrade?

The parameters identified as relevant to PoLA's decision fell into two categories: eight describing future sea level and six describing the terminal and its

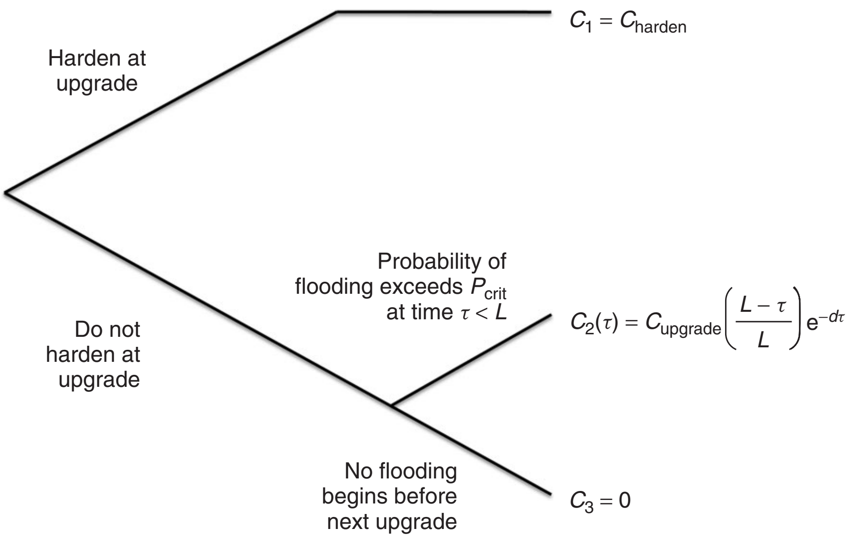

FIGURE 3 | Simplified representation of the Port of Los Angeles' decision regarding whether or not to harden the terminal at its next upgrade and the costs resulting from its choices.

future management (see table 1 in[105]). Some of these parameters have known values, some are relatively well understood and can be represented with well-characterized probability distributions, and some are deeply uncertain. The analysis team constructed an analytical cost–benefit model for terminal hardening that incorporated representations of these different uncertainties.

The team carried out 500 runs of this cost–benefit calculation over this space and performed scenario discovery on the resulting database of outputs to succinctly characterize the conditions where an early hardening would meet a cost–benefit test. This phase of the analysis identified a number of futures, characterized by a near-term, rapid increase in mean sea level, a significant increase in sea level variability (e.g., due to storm surges), and a long terminal lifetime, where PoLA might regret a decision not to harden at the next upgrade. In particular, if the probability of occurrence of these conditions were at least 7%, it would make sense to invest in early hardening.

This led to the second analysis question: how likely do the PoLA decision makers judge these futures to be? Answering this question entails evaluating the available scientific evidence to determine whether this scenario is sufficiently likely to justify a decision to harden. Here is where we confront the limits of today's scientific knowledge. Current climate models do not provide the right kind of information to evaluate either extreme sea level rise or changes in the frequency of storm surges.[135,138,139] The team therefore assembled various lines of observational and theoretical evidence, as well as insights from other types of models (e.g., Earth system models of intermediate complexity), drawing from a number of recent studies.[140–142] This assessment suggested that the requisite combination of extreme sea level rise, storm surge increase, and longer-than-expected terminal lifetime were sufficiently unlikely, given current knowledge, to warrant hardening at only one of the four facilities analyzed.

Building on our first case study, this example highlights a number of important elements of RDM, including how to employ climate information with different levels of uncertainty in the same analysis and combining this uncertain climate information with uncertain information about relevant socioeconomic factors. Combining the different types of information considered in this case, e.g., statistical fits to observed data, probabilistic estimates, and model-based process studies, provides a concrete illustration of how one does not have to 'build the big model' (i.e., do consolidative modeling) to provide decision-relevant information about the behavior of a complex system.

In addition, similarly to the IEUA example, the supply of information about factors such as rapid sea level rise due to ice sheet disintegration or increased storminess would not have been sufficient to meet the demand for high confidence under a prediction paradigm but was, however, sufficient to support the RDM analysis. At the same time, this case suggested ways in which climate science and modeling could progress to improve the bounding analyses for these deeply uncertain factors. It provided a quantification of the value of such new knowledge by specifying the degree of change in the range estimate that would alter the choice of decision.

More generally, the imprecise probability interval for a particular threshold is decision-relevant but not, in general, what the climate modeling community would currently attempt to provide. Even significantly improved scientific knowledge of climate-induced threshold crossing in human and natural systems is unlikely to do much to improve predictions of impacts, being more likely to suggest scientific plausibility and the presence of risk rather than information such as precise timing. RDM, on the other hand, has proven to be a useful framework for incorporating these uncertain thresholds (see also Ref 106). This suggests that an increase in the use of RDM and related decision frameworks would increase demand for improved scientific knowledge about the potential for exceeding key thresholds, even if that information were not sufficient to support decision making under prediction-based frameworks.

DS for Lake Superior

Our final case provides an example of DS. Like RDM, DS is a member of the family of robust decision frameworks that we have been discussing, and that, with RDM, shares a number of the key features of such frameworks.[97]

A team of researchers and managers are currently working to develop a long-term management strategy for Lake Superior, the largest managed freshwater body in the world, under the auspices of the International Upper Great Lakes Study (IUGLS), an independent study board comprised of U.S. and Canadian members established in 2007 by the Great Lakes International Joint Commission. The charge to IUGLS is to review the operating rules and management criteria for the governance of the lake system and recommend changes to the lake's regulation plan.[98,143]

IUGLS has already rejected the traditional process of selecting an optimal plan based on a 'most likely' future scenario, because of the uncertainties associated with future climate change, and hence lake levels, on top of large uncertainties associated with ecosystem responses to future change and the various socioeconomic drivers of lake use and conditions. Instead, they have chosen a more bottom-up, vulnerability-based approach that will explicitly account for these uncertainties in identifying a regulation plan design that performs well over a very broad range of possible futures (Figure 4), using DS to integrate local and user-based perspectives on significant vulnerabilities of key lake management goals with information on future climate derived from climate models.

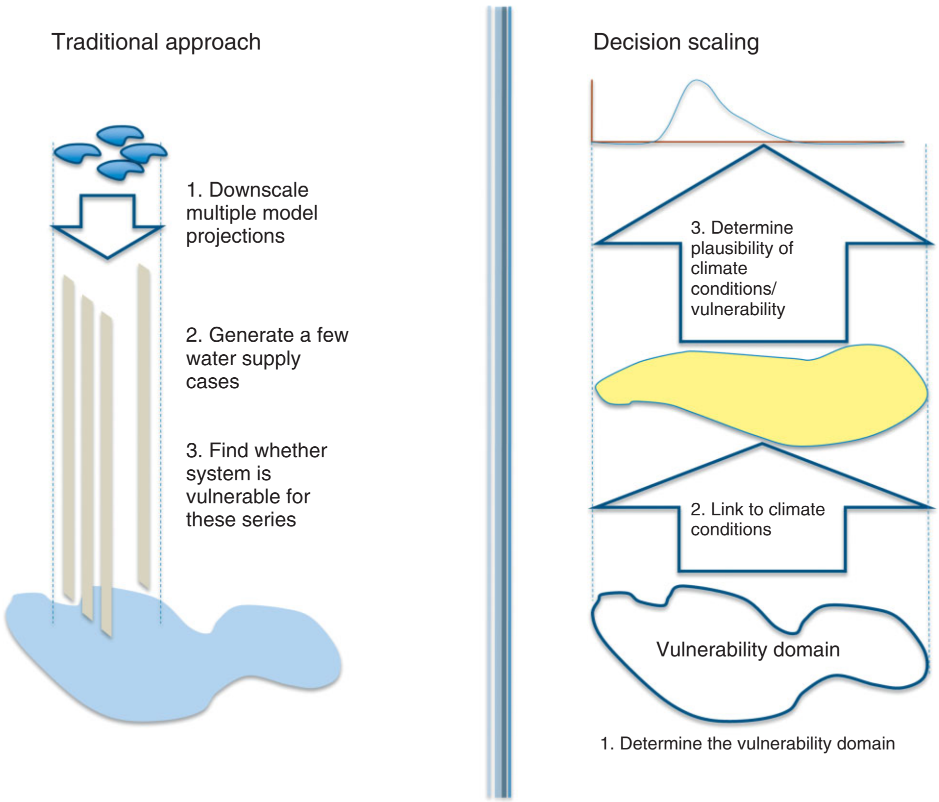

FIGURE 4 | Decision scaling begins with a bottom-up analysis to identify the climate states that impact a decision and then uses climate information to provide insight to the decision. (Reprinted with permission from Ref. 98 Copyright 2007 Wiley Blackwell.)

The strategy rests on using the insights from a vulnerability analysis to inform the selection and processing of the climate model information—to tailor the choice and use of model outputs to maximize their credibility and utility in the assessment. Two key elements of the DS decision-analytic process in this example make possible this linking of the bottom-up and top-down information sources:

(1) Holding a series of technical meetings with stakeholder experts to define three 'coping zones'—i.e., lake levels that were deemed A (acceptable), B (significant negative impacts but survivable), or C (intolerable without policy changes)—for meeting use goals and limiting impacts in areas such as ecosystems, hydropower, shipping, water systems, coastal systems, and recreation and tourism
(2) Developing a set of 'climate response functions' that relate the occurrence of climate-driven changes in Net Basin Supplies (i.e., the sum of precipitation, runoff, releases, inflows and diversions, and evaporation) to the consequences for and of a particular lake management decision

The coping zones provide the bottom-up context for identifying the regional climate states that would tip the lake system into a new regime—i.e., over the thresholds from acceptable to survivable to intolerable. The process of defining these coping zones for each sector systematizes the participation of stakeholders in the analysis. It also subsequently allows the analysis team to ask tailored questions of the climate models and, in the context of this climate information, evaluate plan performance in a comparable way across impact sectors.

The complementary concept of a climate response function serves as the quantitative link between the coping zones and this tailoring of climate information. Given the identification of climate conditions that are critical to a decision, processing of information about future climate change derived from models can be focused on those key aspects, as opposed to beginning with a pre-determined set of scenarios as input to the analysis. For example, the choice of climate models, spatial and temporal scale, and associated process models need only be made after the specific information needed for a particular decision context is identified. This choice can then be made strategically to improve the relevance of the climate information in the decision process.

The climate response function concept in DS is very similar to the concept of 'scenario neutral' analysis, developed for assessing flood risk in the UK,[144] where sensitivity analyses of watershed responses to climate in a river flow model were used to construct a response surface that was then used to answer questions about policy vulnerabilities in the face of uncertain future climate change: e.g., what fraction of members of a given ensemble of climate scenarios would be accommodated by a given design safety margin?

As with the RDM cases already discussed, DS increases the credibility and salience of the climate model information for use in the decision process by changing the requirements for the information. For Lake Superior, the synthesis of stakeholder- and system-specific decision information in coping zones and climate response functions then facilitates precise evaluation of the decision options with respect to any set of climate futures:

> 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.[98]

This study emphasizes the general importance of multi-model ensembles, in an exploratory modeling context, for decision-analytic approaches to climate change, citing their usefulness for estimating the frequency of occurrence of climate conditions that may lead to threshold crossing in the system of interest. Although these frequencies will not, in general, represent true probabilities of future outcomes, they can be viewed as providing a lower bound on the maximum range of uncertainty, and thus a 'non-discountable' envelope of futures.[45] Here, one uses simulation models to make this envelope as wide as possible, ensuring that the decision options incorporate, and are evaluated against, the range of possible system behaviors (including extreme cases).

Though this effort is ongoing, this DS analysis of Lake Superior has so far facilitated a number of significant outcomes. For example, the lake regulation strategy now incorporates what is being termed 'robust adaptation', a hierarchical approach for managing uncertainty and to facilitate adaptation to climate change (among other unanticipated changes). This involves the development of a dynamic regulation plan that selects from a portfolio of plans developed for a wide range of climate conditions, coupled with an adaptive management process for continuously reviewing performance (via monitoring) and recommending improvements as they become necessary.[98]

SYNTHESIS: OPPORTUNITIES AND IMPLICATIONS OF ROBUST DECISION FRAMEWORKS FOR CLIMATE MODELING

Decisions made with support of climate modeling can follow multiple pathways, from a focus on resilience and supporting adaptive management within the full range of what the models have to say, to a more rigid path that places great reliance on producing an accurate forecast of the future. We have argued that a prediction-based paradigm is poorly suited for overcoming the twin physical and social sciences challenges of (1) long-term, regional-scale climate prediction and (2) providing decision-relevant information about potential future climate change within the kinds of stakeholder-focused, participatory processes that lead to better decision making. In contrast, the class of robust decision frameworks offers an opportunity to address these challenges in a way that more fully harnesses knowledge and insights produced by climate science and modeling.

In our case studies, we have seen how the use of robust decision frameworks can confer greater credibility, salience, and legitimacy on the types of information typically provided from climate models today. By beginning with bottom-up articulations of management contexts and system vulnerabilities, such processes guide the search for tailored climate information and provide specific questions that can then be asked of models. This promotes greater stakeholder acceptance of model-derived information. In addition, such frameworks allow flexibility in defining relevant climate futures based on the different risk tolerances that different decision-making entities may have. These examples have also illustrated how the use of such frameworks can suggest avenues for new research to improve the quality of climate information—and specifically to quantify the value of this new knowledge for a particular decision.

What our examples have also indirectly highlighted, however, is that current applications of robust decision frameworks have not been particularly demanding of climate models. Existing archives of basic model outputs such as monthly temperature and precipitation, potentially enhanced with some spatial and temporal downscaling and other kinds of post-processing, have provided sufficient raw material to meet the needs of these initial forays into robust decision frameworks. Extrapolating from these examples, however, suggests new emphases in climate modeling that could increase both the richness of our understanding of climate system behavior and the decision support value of this richer understanding. We suggest that these new emphases fall into the following categories:

(1) Model applications
(2) Model structures and complexity
(3) Technical and technological considerations

The view from the perspective of both exploratory modeling and robust decision frameworks implies at least two distinct roles for climate modeling: to help structure the problem by exploring the limits of possible system behaviors; and in the 'scenario generator' role, to help explore the performance of decision options over as wide a range of futures as possible. The first suggests an increased focus on climate model applications like the development of bounding and extreme cases, identification of potential warning signs, and the assessment of relative likelihoods and probable contingencies for future events, including the potential for rapid or accelerating change and threshold crossing in natural and human systems. The second suggests complementary, redoubled efforts to expand the space of climate model formulations and structures, as well as to sample this space more comprehensively.

In addition, for most applications we are concerned with coupled systems, such as linked climate and hydrologic systems. We will often not be able to explore the full richness of interactions and behaviors in such systems, nor generate appropriately diverse model formulations (and hence scenarios), without paying attention to issues of model structure and model complexity. For example, the development of the climate response functions for our Lake Superior case imply some degree of interoperability between climate models and hydrologic models to properly capture important interactions between the two systems. In general, improving climate and impacts model interoperability and integration will help alleviate the problem of developing transfer functions that may fail to represent key system behaviors. Extending to better integration with management models (such as WEAP) will make it easier to address questions of the full, coupled human-natural system, such as those related to unintended consequences of policies and other possible feedbacks from decisions taken, as well as explore non-climatic pressures.

As we make our modeling systems more complex, however, we run the risk of succumbing to the

TABLE 3 | Newly Initiated Efforts in Alternative Frameworks for Climate-Related Decision Support

U.S. Department of Defense Strategic Environmental Research and Development Program (SERDP) Pilot Projects:
Understanding Data Needs for Vulnerability Assessment and Decision Making to Manage Vulnerability of DoD Installations to Climate Change (PI: R. Moss, Batelle, Pacific Northwest Division)
Assessing Climate Change Impacts for DoD Installations in the Southwest United States during the Warm Season (PI: C. Castro, University of Arizona)
Decision Scaling: A Decision Framework for DoD Climate Risk Assessment and Adaptation Planning (PI: C. Brown, University of Massachusetts)
Climate Change Impacts and Adaptation on Southwestern DoD Facilities (PI: R. Sagarin, University of Arizona)
Climate Change Impacts to Department of Defense Installations (PI: V. Kotmarthi, Argonne National Laboratory)
U.S. EPA: Exploring the Use of Robust Decision Making Methods for EPA's National Water Program's Climate Change Responses (PI: R. Lempert, RAND Corporation)
State of California: A Methodology for Predicting Future Coastal Hazards due to Sea-Level Rise on the California Coast (PI: D. Revell, Philip Williams and Associates)

pitfalls of consolidative modeling, with models which are difficult to validate and interpret. There exists a tension between trying to simulate by capturing as much of the dynamics as we can in comprehensive numerical models, and, on the other hand, trying to understand by simplifying and capturing the essence of a phenomenon in an idealized or conceptual model.[145] We gain understanding of a complex system in part by relating its behavior to those of a hierarchy of progressively simpler systems (e.g., much simpler biological systems to improve understanding of more complex organisms like human beings, as per Ref 145). Greater attention to the systematic development and application of the less-complex members of the modeling hierarchy will be essential for extracting the insights we need from exploratory climate and Earth system modeling.

Determining the aspects of model development and application that are important should not occur in a vacuum but rather in the context of the kinds of participatory, bottom-up processes that underlie our case studies. Such processes will likely require new institutional arrangements, including new boundary organizations, knowledge networks, and communities of practice, to accommodate them. One example is the U.S. National Climate Assessment, newly envisioned as a sustained process over time,[3] and explicitly structured around participatory sub-processes (e.g., for scenario development[146]). In addition, one outcome of the symposium that originally inspired this review (see Acknowledgments), at least in part, was a set of new efforts supported (individually) by the U.S. Department of Defense, the U.S. Environmental Protection Agency, and the State of California,[147] designed to explore some of these modeling questions and the value of alternative decision frameworks for supporting climate-related decisions (Table 3).

Finally, all of the above suggests a need for new tools and technologies to be used within these processes and institutional arrangements to systematically generate large ensembles of model runs, select the appropriate ensemble members for the given problem, archive the right outputs from them, and inform the next set of model runs. This will mean, among other things, building from existing efforts to find new ways to construct diverse models and generate bigger ensembles of model runs[148] and discover the families of scenarios of greatest relevance to the problem at hand.[104,105] The computational demands associated with attempting to widen the range of climate impact uncertainty (as opposed to attempting to narrow it) are clearly large and may themselves justify investments in computational capacity to rival those associated with improving climate predictions.

CONCLUSION

As we have argued in this paper, climate-related decision support is hard, not only because, as often stated, multidecadal, regional-scale climate prediction is hard, but also because creating decision-relevant processes for the production and uptake of climate information is hard. This has resulted in climate models significantly falling short of their potential as tools for supporting decision making, thereby limiting the available options for developing informed adaptation and mitigation responses to climate change.

We have proposed addressing the problem, in part, by expanding the conception of climate models: not simply as prediction machines, but as scenario generators, sources of insight into complex system behavior, and aids to critical thinking within robust decision frameworks. Such frameworks are perfectly suited for a large-scale integration with climate modeling (and associated region- or sector-specific impacts models), with the adjustment that climate modeling is viewed from an exploratory rather than a consolidative perspective. Under this paradigm, increasing the quality, complexity, diversity, and amount of climate information generated from climate models has the potential to greatly increase the richness of decision-relevant information.

We have illustrated these arguments with a number of examples. These have shown how use of robust decision frameworks leads to greater stakeholder acceptance of climate model results. They have also suggested new emphases in climate modeling, in the areas of model applications, model development, and technological advances, that could increase both the richness of our understanding of the climate system and the value of information derived from climate models in robust decision frameworks.

The focus of this paper has been climate models, and their use within different decision frameworks, and we certainly believe that models that can represent the climate system with increasing resolution and sophistication will have greater potential value for supporting decision making about responding to climate change. As we highlight in our review, however, likely even more important for successful outcomes than the technical attributes of the models are the decision-analytic and institutional contexts within which they are developed and applied. And finally, the success of robust decision frameworks (and the management approaches they enable) depends on other critical factors not addressed here: e.g., continuous, well-designed, and well-maintained monitoring networks to support adaptive management and learning; good governance and flexible, inclusive institutions; and the technical skills, support, and information products for managers to implement these new approaches into their day-to-day work.[143]

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REFERENCES

1. National Academy of Public Administration (NAPA). *Building Strong for Tomorrow: NOAA Climate Service*. Washington, DC, USA: National Academy of Public Administration; 2010, 116.
2. World Meteorological Organization (WMO). *Climate Knowledge for Action: A Global Framework for Climate Services—Empowering the Most Vulnerable*. Geneva, Switzerland: World Meteorological Organization; 2011, 248.
3. U.S. Global Change Research Program (USGCRP). The National Global Change Research Plan: 2012–2021. A Report by the U.S. Global Change Research Program and the Subcommittee on Global Change Research. Washington, DC, USA: U.S. Global Change Research Program; 2012. Available at http://library.globalchange.gov/u-s-global-change-research-program-strategic-plan-2012-2021.
4. Dessai S, Hulme M, Lempert R, Pielke R Jr. Climate prediction: a limit to adaptation? In: Adger WN, Lorenzoni I, O'Brien KL, eds. *Adapting to Climate Change: Thresholds, Values, Governance*. Cambridge, UK: University Press; 2009.
5. Meyer R. The public values failures of climate science in the US. Minerva 2011, 49:47–70. doi:10.1007/s11024-011-9164-4.
6. Shapiro M, Shukla J, Brunet G, Nobre C, Beland M, Dole R, Trenberth K, Anthes R, Asrar G, Barrie L, et al. An earth-system prediction initiative for the twenty-first century. *Bull Am Meteorol Soc* 2010, 91: 1377–1388.

7. Piao S., Ciais P., Huang Y., Shen Z., Peng S., Li J., Zhou L., Liu H., Ma Y., Ding Y., et al. The impact of climate change on water resources and agriculture in China. *Nature* 2010, 467:43–51.
8. Barron EJ. Beyond climate science. *Science* 2009, 326:643.
9. Collins M. Ensembles and probabilities: a new era in the prediction of climate change. *Phil Trans R Soc A* 2007, 365:1957–1970.
10. Goddard L, Baethgen W, Kirtman B, Meehl G. The urgent need for improved climate models and predictions. *EOS* 2009, 90:39.
11. Doherty SJ, Bojinski S, Henderson-Sellers A, Noone K, Goodrich D, Bindoff NL, Church JA, Hibbard KA, Karl TR, Kajfez-Bogataj L, et al. Lessons learned from IPCC AR4: Scientific developments needed to understand, predict, and respond to climate change. *Bull Am Meteorol Soc* 2009, 90:497–513.
12. Shukla J, Hagedorn R, Hoskins B, Kinter J, Marotzke J, Miller M, Palmer TN, Slingo J. Revolution in climate prediction is both necessary and possible: A declaration at the World Modelling Summit for Climate Prediction. *Bull Am Meteorol Soc* 2009, 90:175–178.
13. Cox P, Stephenson D. A changing climate for prediction. *Science* 2007, 317:207–208.
14. Hurrell J, Meehl GA, Bader D, Delworth TL, Kirtman B, Wielicki B. A unified approach to climate system prediction. *Bull Am Meteorol Soc* 2009, 90:1819–1832.
15. Intergovernmental Panel on Climate Change (IPCC). 2007: Climate change. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL, eds. *Climate Change 2007: The Physical Science Basis: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York: Cambridge University Press; 2007, 996.
16. Parson E, Burkett V, Fisher-Vanden K, Keith D, Mearns L, Pitcher H, Rosenzweig C, Webster M. *Global Change Scenarios: Their Development and Use. Sub-report 2.1B of Synthesis and Assessment Product 2.1 by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research*. Washington, DC, USA: Department of Energy, Office of Biological & Environmental Research; 2007, 106.
17. Morgan MG, Keith DW. Improving the way we think about projecting future energy use and emissions of carbon dioxide. *Clim Change* 2008, 90:189–215.
18. Bray D, von Storch H. "Prediction" or "projection"? The nomenclature of climate science. *Sci Commun* 2009, 30:534–543. doi:10.1177/1075547009333698
19. Lemos MC, Rood RB. Climate projections and their impact on policy and practice. *WIREs Clim Change* 2010, 1:670–682.
20. Rosentrater LD. Representing and using scenarios for responding to climate change. *WIREs Clim Change* 2010, 1:253–259.
21. Rubino A. What will a new generation of world climate research and computing facilities bring to climate long-term predictions? *Theor Appl Climatol* 2011, 106: 473–479. doi:10.1007/s00704-011-0448-2.
22. Smith LA, Stern N. Uncertainty in science and its role in climate policy. *Phil Trans R Soc A* 2011, 369: 4818–4841.
23. Hulme M, Dessai S. Predicting, deciding, learning: can one evaluate the 'success' of national climate scenarios? *Environ Res Lett* 2008, 3:045013.
24. Randall DA, Wood RA, Bony S, Colman R, Fichefet T, Fyfe J, Kattsov V, Pitman A, Shukla J, Srinivasan J, et al. 2007: Cilmate models and their evaluation. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL, eds. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY: Cambridge University Press; 2007.
25. Randall D, Khairoutdinov M, Arakawa A, Grabowski W. Breaking the cloud parameterization deadlock. *Bull Am Meteorol Soc* 2003, 84:1547–1564.
26. Stephens GL, L'Ecuyer T, Forbes R, Gettlemen A, Golaz JC, Bodas-Salcedo A, Suzuki K, Gabriel P, Haynes J. Dreary state of precipitation in global models. *J Geophys Res* 2010, 115:D24211. doi:10.1029/2010JD014532.
27. Liepert BG, Previdi M. Inter-model variability and biases of the global water cycle in CMIP3 coupled climate models. *Environ Res Lett* 2012, 7: doi:10.1088/1748-9326/7/1/014006.
28. Shukla J. Monsoon mysteries. *Science* 2007, 318:204–205.
29. Kidston J, Gerber EP. Intermodel variability of the poleward shift of the austral jet stream in the CMIP3 integrations linked to biases in 20th century climatology. *Geophys Res Lett* 2010, 37:L09708. doi:10.1029/2010GL042873.
30. Neale R, Richter JH, Jochum M. The impact of convection on ENSO: from a delayed oscillator to a series of events. *J Clim* 2008, 21:5904–5924.
31. Hirsch RM. A perspective on nonstationarity and water management. *J Am Water Resour Assoc* 2011, 47:436–446.
32. Castro CL, Pielke RA Sr, Leoncini G. Dynamical downscaling: assessment of value retained and added using the Regional Atmospheric Modeling System (RAMS). *J Geophys Res* 2005, 110:D05108. doi:10.1029/2004/D004721.
33. Pielke RA Sr, Wilby RL. Regional climate downscaling: what's the point? *EOS* 2012, 93:52–53.

34. Navarra A, Kinter JL III, Tribbia J. Crucial experiments in climate science. *Bull Am Meteorol Soc* 2010, 91:343–352.
35. Giorgi F. Climate change prediction. *Clim Change* 2005, 73:239–265.
36. Dessai S, Hulme M. Does climate adaptation policy need probabilities? *Clim Policy* 2004, 4:107–128.
37. Hawkins E, Sutton R. The potential to narrow uncertainty in regional climate predictions. *Bull Am Meteorol Soc* 2009, 90:1095–1107.
38. Pielke RA Sr, Pitman A, Niyogi D, Mahmood R, McAlpine C, Hossain F, Klein K, Golewijk U, Nair R, Betts S, et al. Land use/land cover changes and climate: modeling analysis and observational evidence. *WIREs Clim Change* 2011, 2:828–850.
39. Palmer TN, Alessandri A, Andersen U, Cantelaube P, Davey M, Delecluse P, Deque M, Diez E, Doblas-Reyes FJ, Feddersen H, et al. Development of a European multimodel ensemble system for seasonal-to-interannual prediction (DEMETER). *Bull Am Meteorol Soc* 2004, 85:853–872.
40. Boer GJ, Lambert SJ. Multi-model decadal potential predictability of precipitation and temperature. *Geophys Res Lett* 2008, 35:L05706. doi:10.1029/2008GL033234.
41. Hargreaves JC. Skill and uncertainty in climate models. *WIREs Clim Change* 2010, 1:556–564.
42. Raisanen J. How reliable are climate models? *Tellus* 2007, 59A:2–29..
43. Knutti R. The end of model democracy? *Clim Change* 2010. doi:10.1007/s10584-010-9800-2.
44. Stainforth DA, Allen MR, Tredger ER, Smith LA. Confidence, uncertainty, and decision-support relevance in climate predictions. *Phil Trans R Soc A* 2007a, 365: 2145–2161.
45. Stainforth DA, Downing TE, Washington R, Lopez A, New M. Issues in the interpretation of climate model ensembles to inform decisions. *Phil Trans R Soc A* 2007b, 365:2163–2177.
46. Rastetter EB. Validating models of ecosystem response to global change. *BioScience* 1996, 46:190–198.
47. Boer GJ. Changes in interannual variability and decadal potential predictability under global warming. *J Clim* 2009, 22:3098–3109.
48. Reifen C, Toumi R. Climate projections: past performance no guarantee of future skill. *Geophys Res Lett* 2009, 36:L13704. doi:10.1029/2009GL038082.
49. Macadam I, Pitman AJ, Whetton PH, Abramowitz G. Ranking climate models by performance using actual values and anomalies: Implications for climate change impact assessments. *Geophys Res Lett* 2010, 37:L16704. doi:10.1029/2010GL043877.
50. Wilby RL. Evaluating climate model outputs for hydrological applications—opinion. *Hydrol Sci J* 2010, 55:1090–1093.
51. Hagedorn R, Doblas-Reyes FJ, Palmer TN. The rationale behind the success of multi-model ensembles in seasonal forecasting—I. Basic concept. *Tellus* 2005, 57A:219–233.
52. Gleckler PJ, Taylor KE, Doutriaux C. Performance metrics for climate models. *J Geophys Res* 2008, 113:D06104. doi:10.1029/2007JD008972.
53. Weigel AP, Knutti R, Liniger MA, Appenzeller C. Risks of model weighting in multimodel climate projections. *J Clim* 2010, 23:4175–4191.
54. Schaller N, Mahlstein I, Cernak J, Knutti R. Analyzing precipitation projections: a comparison of different approaches to climate model evaluation. *J Geophys Res* 2011, 116:D10118. doi:10.1029/2010JD014963.
55. Pirtle Z, Meyer R, Hamilton A. What does it mean when climate models agree? A case for assessing independence among general circulation models. *Environ Sci Policy* 2010, 13:351–361. doi:10.1016/j.envsci.2010.04.004.
56. Knutti R, Abramowitz G, Collins M, Eyring V, Gleckler PJ, Hewitson B, Mearns L. Good practice guidance paper on assessing and combining multi model climate projections. In: Stocker TF, Qin D, Plattner GK, Tignor M, Midgley PM, eds. *Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Assessing and Combining Multi Model Climate Projections*. Bern, Switzerland: IPCC Working Group I Technical Support Unit, University of Bern; 2010.
57. Keenlyside NS, Ba J. Prospects for decadal climate prediction. *WIREs Clim Change* 2010, 1:627–635.
58. Murphy JM, Sexton DMH, Barnett DN, Jones GS, Webb MJ, Collins M, Stainforth DA. Quantification of modeling uncertainties in a large ensemble of climate change simulations. *Nature* 2004, 430:768–772.
59. Stainforth DA, Aina T, Christensen C, Collins M, Faull N, Frame DJ, Kettleborough JA, Knight S, Martin A, Murphy JM, et al. Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature* 2005, 433:403–406.
60. Stott PA Forest CE. Ensemble climate predictions using climate models and observational constraints. *Phil Trans R Soc Lond* 2007, 365A:2029–2052.
61. Roe GH, Baker MB. Why is climate sensitivity so unpredictable? *Science* 2007, 318:629–632.
62. Lemoine DM. Climate sensitivity distributions dependence on the possibility that models share biases *J Clim* 2010, 23:4395–4415.
63. Pennell C, Reichler T. 2011 On the effective number of climate models *J Clim* 24: 2358–2367.
64. Weitzman ML. On modeling and interpreting the economics of catastrophic climate change *Rev Econ Stat* 2009, 91:1–19.
65. National Research Council (NRC). *Informing Decisions in a Changing Climate. Panel on Strategies and*

Methods for Climate-Related Decision Support, Committee on the Human Dimensions of Global Change. Division of Behavioral and Social Sciences and Education. Washington, DC: The National Academies Press; 2009, 188.

66. Cash DW, Borck JC, Patt AG. Countering the loading-dock approach to linking science and decision making: comparative analysis of El Nino/Southern Oscillation (ENSO) forecasting systems *Sci Tech Hum Val* 2006, 31:465–494.
67. Cash DW, Clark WC, Alcock F, Dickson NM, Eckley N, Guston DH, Jager J, Mitchell RB. Knowledge systems for sustainable development *Proc Natl Acad Sci USA* 2003, 100:8086–8091.
68. Guston DH. Stabilizing the boundary between politics and science: the role of the office of technology transfer as a boundary organization *Social Stud Sci* 1999, 1:87–111.
69. Farrell A, VanDeveer SD, Jager J. Environmental assessments: four under-appreciated elements of design. *Glob Environ Change* 2001, 11:311–333.
70. Fischhoff B. What forecasts (seem to) mean. *Int J Forecast* 1994, 10:387–403.
71. In: Sarewitz D, Pielke RA Jr. Byerly R Jr, eds. *Prediction: Science, Decision Making, and the Future of Nature*. Washington, DC: Island Press; 2000, 405. pp.
72. Pielke RA Jr, Conant RT. Best practices in prediction for decision-making: lessons from the atmospheric and earth sciences. *Ecology* 2003, 84:1351–1358.
73. Sarewitz D, Pielke RA Jr. The neglected heart of science policy: Reconciling supply of and demand for science. *Environ Sci Policy* 2007, 10:5–16.
74. Changnon SA, Kunkel KE. Rapidly expanding uses of climate data and information in agriculture and water resources: causes and characteristics of new applications. *Bull Am Meteorol Soc* 1999, 80:821–830.
75. Jacobs K, Garfin G, Lenart M. More than just talk: connecting science and decision-making. *Environment* 2005, 47:8–21.
76. Rayner S, Lach D, Ingram H. Weather forecasts are for wimps: why water resource managers do not use climate forecasts. *Clim Change* 2005, 69:197–227.
77. Miles EL, Snover AK, Whitely Binder LC, Sarachik ES, Mote PW, Mantua N. An approach to designing a national climate service. *Proc Natl Acad Sci USA* 2006, 103:19616–19623.
78. Vogel C, O'Brien K. Who can eat information? Examining the effectiveness of seasonal climate forecasts and regional climate risk-management strategies. *Clim Res* 2006, 33:111–122.
79. Lemos MC. What influences innovation adoption by water managers? Climate information use in Brazil and the US. *J Am Water Resour Assoc* 2008, 44: 1388–1396.
80. Baethgen WE, Carriquiry M, Ropelewski C. Tilting the odds in maize yields. *Bull Am Meteorol Soc* 2009, 90:179–183.
81. Ziervogel G, Johnston P, Matthew M, Mukheibir P. Using climate information for supporting climate change adaptation in water resource management in South Africa. *Clim Change* 2010, 103:537–554.
82. Buizer J, Jacobs K, Cash D. Making short-term climate forecasts useful: linking science and action. *Proc Natl Acad Sci USA* 2010. doi:10.1073/pnas.0900518107.
83. Moser SC, Luers AL. Managing climate risks in California: the need to engage resource managers for successful adaptation to change. *Clim Change* 2008, 87: S309–S322.
84. Johnson TE, Weaver CP. A framework for assessing climate change impacts on water and watershed systems. *Environ Manag* 2009, 43:118–134.
85. Matthews JH, Wickel AJ. Embracing uncertainty in freshwater climate change adaptation: a natural history approach. *Clim Dev* 2009, 1:269–279.
86. Gober P, Kirkwood CW, Balling RC Jr, Ellis AW, Deitrick S. Water planning under climatic uncertainty in Phoenix: Why we need a new paradigm. *Ann Assoc Am Geogr* 2010, 100:356–372.
87. White. DD, Wutich A, Larson KL, Gober P, Lant T, Senneville C. Credibility, salience, and legitimacy of boundary objects: water managers' assessment of a simulation model in an immersive decision theater. *Sci Pub Policy* 2010, 34:219–232.
88. Reid WV, Chen D, Goldfarb L, Hackmann H, Lee YT, Mokhele K, Ostrom E, Raivio K, Rockstrom J, Schnellnhuber HJ, et al. Earth system science for global sustainability: grand challenges. *Science* 2010, 330:916–917.
89. New M, Cuellar M, Lopez A. Probabilistic regional and local climate projections: False dawn for impacts assessment and adaptation. In: *IPCC TGICA Expert Meeting 'Integrating Analysis of Regional Climate Change and Response Options'*. Meeting Report. Intergovernmental Panel on Climate Change; 2010.
90. Lempert R, Nakicenovic N, Sarewitz D, Schlesinger M. Characterizing climate-change uncertainties for decision-makers. *Clim Change* 2004, 65:1–9.
91. Morgan MG, Henrion M. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge, UK: Cambridge University Press; 1990, 346.
92. Lempert RJ, Groves DG, Popper SW, Bankes SC. A general, analytic method for generating robust strategies and narrative scenarios. *Manage Sci* 2006, 52: 514–528.
93. Polasky S, Carpenter SR, Folke C, Keeler B. Decision-making under great uncertainty: environmental management in an era of global change. *Trends Ecol Evol* 2011, 26:398–404.

94. Hall J. Probabilistic climate scenarios may misrepresent uncertainty and lead to bad adaptation decisions. *Hydrol Proc* 2007, 21:1127–1129.
95. Ranger N, Millner A, Dietz S, Fankhauser S, Lopez A, Ruta G. *Adaptation in the UK: A Decision-Making Process*. Policy brief, Centre for Climate Change Economics and Policy, Leeds and London, UK; 2010.
96. Brown C. The end of reliability. *ASCE J Wat Res Plann Manage* 2010, 2:146–148.
97. Brown C, Ghile Y, Laverty M, Li K. Decision scaling: Linking bottom-up vulnerability analysis with climate projections in water sector. *Water Resour Res* 48:1–12 doi:10.1029/ 2011WR011212.
98. Brown C, Werick W, Leger W, Fay D. A decision-analytic approach to managing climate risks: application to the Upper Great Lakes. *J Am Water Resour Assoc* 2011, 47:524–534.
99. Carter TR, Jones RN, Lu SBX, Conde C, Mearns LO, O'Neill BC, Rounsevell MDA, Zurek MB. New assessment methods and the characterisation of future conditions. In: Parry ML, Canziani OF, Palutikof JP, Linden P. J. v. d., Hanson CE, eds. *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press; 2007, 33–171.
100. Dessai S, Hulme M. Assessing the robustness of adaptation decisions to climate change uncertainties: a case study on water resources management in the East of England. *Glob Environ Change* 2007, 17:59–72.
101. Wilby RL, Dessai S. Robust adaptation to climate change. *Weather* 2010, 65:180–185.
102. Groves DG, Lempert RJ. A new analytic method for finding policy-relevant scenarios. *Glob Environ Change* 2007, 17:73–85.
103. Lempert RJ, Collins MT. Managing the risk of uncertain threshold responses: Comparison of robust, optimum, and precautionary approaches. *Risk Anal* 2007, 27:1009–1026.
104. Lempert RJ, Groves DG. Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west. *Technol Forecast Soc Change* 2010, 77:960–974.
105. Lempert RJ, Sriver RL, Keller K. *Characterizing Uncertain Sea Level Rise Projections to Support Investment Decisions*. Prepared for California Energy Commission Public Interest Energy Research Program; 2012.
106. Hall J, Lempert RJ, Keller K, Hackbarth A, Mijere C, McInerney DJ. Robust climate policies under uncertainty: a comparison of robust decision making and Info-gap methods. *Risk Anal* 2012, 32:1657–1672. doi:10.1111/j1539-6924.2012.01802.x.
107. Ben-Haim Y. *Information-Gap Decision Theory: Decisions under Severe Uncertainty*. New York, NY, USA: Academic Press; 2001.
108. US Climate Change Program (CCSP). Best practice approaches for characterizing, communicating, and incorporating scientific uncertainty in decisionmaking. In: Morgan M, Dowlatabadi H, Henrion M, Keith D, Lempert R, McBride S, Small M, Wilbanks T, eds. U.S. Climate Change Science Program and the Subcommittee for Global Change Research, Washington, DC.
109. Ravetz JR. Models as metaphors. In: Kasemir B, Jager J, Jaeger CC, Gardner MT, eds. *Public Participation in Sustainability Science*. Cambridge, UK: Cambridge University Press; 2003, 62–78.
110. Oreskes N, Shrader-Frechette K, Belitz K. Verification, validation, and confirmation of numerical models in the earth sciences. *Science* 1994, 263:641–646.
111. Demeritt D. The construction of global warming and the politics of science. *Ann Assoc Am Geogr* 2001, 91: 307–337.
112. Sterman JD. Risk communication on climate: mental models and mass balance. *Science* 2008, 322: 532–533.
113. Sterman JD. All models are wrong: Reflections on becoming a systems scientist. *Syst Dyn Rev* 2002, 18: 501–531.
114. Oreskes N. Why predict? Historical perspectives on prediction in earth science. In: Sarewitz D, Pielke RA Jr, Byerly R Jr, eds. *Prediction: Science, Decision Making, and the Future of Nature*. Washington, DC: Island Press; 2000, 405.
115. Bankes S. Exploratory modeling for policy analysis. *Oper Res* 1993, 41:435–449.
116. Jones RN. An environmental risk assessment/ management framework for climate change impact assessments. *Nat Hazards* 2001, 23:197–230.
117. Brekke LD, Maurer EP, Anderson JD, Dettinger MD, Townsley ES, Harrison A, Pruitt T. Assessing reservoir operations risk under change. *Water Resour Res* 2009, 45:W04411. doi:10.1029/2008WR006941.
118. Pielke RA Sr. Ben K, Brasseur G, Calvert J, Chahine M, Dickerson RR, Entekhabi D, Foufoula-Georgiou E, Gupta H, Krajewski W, et al. Climate change: the need to consider human forcings besides greenhouse gases. EOS 2009, 90:413.
119. West JM, Julius SH, Kareiva P, Enquist C, Lawler JJ, Petersen B, Johnson AE, Shaw MR. US natural resources and climate change: concepts and approaches for management adaptation. *Environ Manag* 2009, 44:1001–1021.
120. Lempert R, Kalra N. Managing climate risks in developing countries with Robust Decision Making. World Resources Report. Washington, DC, 2012. Available at: http://www.worldresourcesreport.org.
121. McDaniels T, Mills T, Gregory R, Ohlson D. Using expert judgments to explore robust alternatives for forest management under climate change. *Risk Anal* 2012. doi:10.1111/j1539-6924.2012.01822.

122. Schwartz P. *The Art of the Long View—Planning for the Future in an Uncertain World*. New York, NY: Currency-Doubleday; 1996.
123. Lempert RJ. Scenarios that illuminate vulnerabilities and robust responses. *Clim Change* 2012. In press.
124. Milly PCD, Betancourt J, Falkenmark M, Hirsch RM, Kundzewicz ZW, Lettenmaier DP, Stoffer RJ. Stationarity is dead: Whither water management? *Science* 2008, 319:573–574.
125. Inland Empire Utilities Agency (IEUA). *Regional Urban Water Management Plan*. Chino, CA.: Inland Empire Utilities Agency; 2005.
126. Groves DG, Yates D, Tebaldi C. Developing and applying uncertain global climate change projections for regional water management planning. *Water Resour Res* 2008, 44:W12413. doi:10.1029/2008WR006964.
127. Yates D, Purkey D, Sieber J, Huber-Lee A, Galbraith H. WEAP21—a demand-, priority-, and preference-driven water planning model: part 1. *Water Int* 2005, 30:487–500.
128. Bryant BP, Lempert RJ. Thinking inside the box: a participatory, computer-assisted approach to scenario discovery. *Technol Forecast Soc Change* 2010, 77:34–49.
129. Millner A. Climate prediction for adaptation: who needs what?. *Clim Change* 2012, 110:143–167.
130. National Research Council (NRC). *Abrupt Climate Change: Inevitable Surprises*. Washington, DC, USA: National Academies Press; 2002.
131. Schneider SH, Semenov S, Patwardhan A, Burton I, Magadza CHD, Oppenheimer M, Pittock AB, Rahman A, Smith JB, Suarez A, et al. Assessing key vulnerabilities and the risk from climate change. In: Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE, eds. *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press; 2007, 779–810.
132. Keller K, Schlesigner M, Yohe G. Managing the risk of climate thresholds: uncertainties and information needs. *Clim Change* 2008, 91:5–10.
133. Lenton TM, Held H, Kriegler E, Hall JW, Lucht W, Rahmstorf S, Schellnhuber HJ. Tipping elements in the Earth's climate system. *Proc Natl Acad Sci USA* 2008, 105:1786–1793.
134. Milne GA, Gehrels WR, Hughes CW, Tamisiea ME. Identifying the causes of sea-level change. *Nat Geosci* 2009, 2:471–478.
135. Cayan DR, Bromirski PD, Hayhoe K, Tyree M, Dettinger MD, Flick RE. Climate change projections of sea level extremes along the California coast. *Clim Change* 2008, 87:S57–S73.
136. Pollard D. A retrospective look at coupled ice sheet-climate modeling. *Clim Change* 2010, 100:173–194.
137. Rosenzweig C. *Climate Change Adaptation in New York City: Building a Risk Management Response*. New York: 2010.
138. Oppenheimer M, O'Neill BC, Webster M, Agrawala S. The limits of consensus. *Science* 2007, 317: 1505–1506.
139. Rahmstorf S. A new view on sea level rise. *Nat Rep Clim Change* 2010, 4:44–45.
140. Pfeffer WT, Harper JT, O'Neel S. Kinematic constraints on glacier contributions to 21st-century sea-level rise. *Science* 2008, 321:1340–1343.
141. Co-CAT. State of California Sea-Level Rise Interim Report, edited, Coastal and Ocean Working Group of the California Action Team, 2010. Available at: www.opc.ca.gov/webmaster/ftp/project.../SLR_Guidance_Document.pdf.
142. Rahmstorf S. A semi-empirical approach to projecting future sea-level rise. *Science* 2007, 315:368–370.
143. Wilby RL. Wells of wisdom. *Nat Clim Change* 2011, 1:302–303.
144. Prudhomme C, Wilby RL, Crooks S, Kay AL, Reynard NS. Scenario-neutral approach to climate change impact studies: application to flood risk. *J Hydrol* 2011, 390:198–209.
145. Held IM. The gap between simulation and understanding in climate modeling. *Bull Am Meteorol Soc* 2005, 86:1609–1614.
146. U.S. Global Change Research Program (USGCRP). Scenarios for Research and Assessment of Our Climate Future: Issues and Methodological Perspectives for the U.S. National Climate Assessment. National Climate Assessment Report Series: Volume 6. U.S. Global Change Research Program, Washington, DC, USA, 2011. Available at: http://library.globalchange.gov/national-climate-assessment-scenarios-for-research-and-assessment-of-our-climate-future
147. Revell DL, Battalio R, Spear B, Ruggiero P, Vandever J. A methodology for predicting future coastal hazards due to sea-level rise on the California Coast. *Clim Change* 2011, 109:S251–S276. doi:10.1007/s10584-011-0315-2.
148. Murphy JM, Booth BBB, Collins M, Harris GR, Sexton DMH, Webb MJ. A methodology for probabilistic predictions of regional climate change from perturbed physics ensembles. *Phil Trans R Soc A* 2007, 365:1993–2028.

