Decision-scaling for Robust Planning and Policy under Climate Uncertainty

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CASEY BROWN, University of Massachusetts; International Research Institute for Climate and Society of Columbia University

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INTRODUCTION

According to conventional wisdom, planning for the future is becoming more difficult due to anthropogenic climate change. As the story goes, it is possible that a plan may be made anticipating one climate future and then disaster results when another future climate unfolds. In practice, it is often possible to assess risks and develop robust strategies that arise due to climate uncertainties through a systematic approach to analysis of the decision at hand. However, there is currently a lack of methodology for gleaning decision-relevant information from the spectrum of available projections of the future. In this paper a methodology is described for planning under climate uncertainty and for the development of robust adaptation strategies. In the case of climate change, where the future is deeply uncertain and there is a vast array of data relating visions of the future, the usual approach to science-based decision making may not be effective. In the usual science-based approach, attempts are made to reduce the uncertainty of the future and planning is based on some best guess of the most likely scenario. The approach described here relies on a fundamental reversal of the usual focus of science-based decision making, that is, the quest to reduce uncertainty and select an optimal plan for the likely future. The underlying philosophy is one of accepting irreducible uncertainty and identifying strategies that will perform well over a wide range of climate futures.

When considering the possible effects of climate change on planning and policy making, one particular truth often emerges: plans and policies of the present face considerable risks due to *present* climate variability. This is particularly true in developing nations and especially those located in the tropics where climate variability is strongest (Brown and Lall, 2006). Climate variability has been shown to be a significant impediment to economic growth globally (Brown et al., 2010a) and particularly in sub-Saharan Africa (Brown et al., 2010b). Thus planning specifically for climate change should begin with addressing the current climate risks that a society faces. There remains much that can be done to reduce societal exposure to climate risks such as floods, droughts and other extreme weather events. Investments that reduce the current impacts of climate variability are very likely to be the best adaptation decisions a planner can make.

There remains, however, the challenge of incorporating the possible future climate changes into long-term planning processes. The approach to planning under climate change uncertainty we apply consists of a stakeholder and decision-centered approach that incorporates climate projections. It is a decision analysis method for using climate change projections in planning and risk assessment efforts. The process is called decision-scaling. The approach provides the missing link between the insights into vulnerabilities from bottom-up methods and the information available from state of the science climate projections from Earth system models. As a result, the climate change projections can be tailored to provide decision-relevant information on the critical climate-related uncertainties.

In this paper, we first provide a brief background on common approaches to climate change impact assessment. Next, the process of decision-scaling is described in detail and the differences from other common approaches explained. Following that discussion, a case study of a climate risk assessment using decision-scaling for the Niger River Basin investment program is presented. Finally, recommendations for the appropriate application of this methodology are discussed.

Climate Impact Assessment: Top-Down Or Bottom-Up?

Current approaches to climate change impact analysis may be characterized generally as "top-down" or climate analysis-based and "bottom-up" or vulnerability analysis-based. Top-down analysis refers to the use of climate change projections from General Circulation Models (GCM) as a starting point. These projections that are produced at coarse resolutions (grid sizes of several hundred square kilometers) and are then "down-scaled" for use in impact assessment. Downscaling is conducted either using statistical methods or through the use of regional climate models with higher resolution. Typically, a relatively small number of projections from a few GCMs is used to provide glimpses of what these models estimate future climate will be. A small number is used because of the computational intensity of the downscaling process, often involving statistical corrections to the GCM projections and then additional simulations in "process" models representing the physical environment (e.g., hydrology) and socioeconomic systems (e.g., agricultural production or water supply reliability).

A central issue in top down approaches to planning under climate change uncertainty is the use of GCM projections. They provide forecasts of the future that are potentially informative but also have significant uncertainties and unknown reliability. The reliability of the projections is difficult to assess since we will not know the true outcome for many decades. Technically, this means they are not forecasts at all; instead they are "projections" of our current understanding of the climate response to increasing greenhouse gas emissions. However, they do provide information about the future that may be useful. A prominent question is how should they be used? Certain things are clear: projections cannot be used directly and believed as a reliable indicator of the future without substantial processing (for example, raw GCM output requires various corrections to make it comparable with current climate data).

While top-down approaches provide a vision of possible future climates, the large degree of uncertainty that stems from climate change projections makes the results of such an analysis difficult for use in decision making. There are many sources of uncertainty that affect the projections, including uncertainty in the response of the Earth's climate system to greenhouse gas emissions, errors in the ways the models represent the Earth's climate system, and the unknown greenhouse gas emissions of the future. In some cases, the differences between projections from different models are so wide that planning for one climate projection would contradict planning for another. In addition, and critically important from a risk assessment standpoint, the projections from GCMs do not represent the full range of future

possible climates; the full range is unknown. Therefore, the range of GCM projections may not uncover all the climate impacts that are possible.
In recognition of the need for climate change information that is useful for decision makers and the limitations of current climate change projections, bottom-up or vulnerability-based approaches are increasingly employed. Bottom-up approaches begin with assessments of the socio-economic system of interest and then attempt to identify the vulnerabilities or risks related to climate. There is a wide variety of methodologies described for conducting risk assessments of climate change impacts (e.g., Johnson and Weaver, 2009; Hayhoe et al., 2008; Jones, 2001). However, there are some common themes. In general, these approaches begin with an assessment of the socioeconomic system and its vulnerabilities to climate impacts, as opposed to the top down approach of beginning with climate change projections. Instead, historical climate extremes or variations in the historical climate are used to identify and undersant climate impacts. . Natural climate variability is often also addressed in climate risk management approaches. Given a characterization of the system, a climate sensitivity analysis is applied to quantify the response of the system to climate variation. Finally, the vulnerabilities of the system to climate change are identified and prospects for managing those vulnerabilities are considered. Often the process involves the input of stakeholders at various stages, especially in the setting of thresholds for undesirable climate impacts. (Pittock and Jones, 2000).

Bottom-up approaches are appealing because they begin with an analysis of the system or decision that is of interest to the planner. However, a methodology for using GCM projections within a bottom up analysis has not emerged. Some methods use the GCMs as scenario generators (Johnson and Weaver, 2009; Lempert et al., 2006). As discussed above, this does not necessarily capture the full range of possible climate futures and says nothing about which outcomes may be more likely. Other methods disregard the GCM projections entirely and focus solely on what the vulnerability analysis has revealed (Desai et al., 2009; Sarewitz et al., 2000). In disregarding GCM projections, possibly useful information is being left out of the analysis. In some cases, this is due to the belief that the available climate information is too uncertain to be beneficial. It may also be due to a lack of methodology for incorporating the information into bottom up approaches.

The limited or lack of use of GCM projections in bottom-up analysis reveals a methodological gap. The process we call decision-scaling represents an innovative attempt to fill the gap by using the insights that are revealed in a bottom-up analysis to tailor or scale the GCM projections. Through decision-scaling the processing of GCM projections can be focused on the critical climate conditions that are revealed to be critical through the bottom up analysis. The approach uses a decision analytic framework and sensitivity analysis to categorize the key climate conditions that influence planning, and uses GCM projections to characterize the relative likelihood of those conditions. By using GCM projections in the final step of the analysis, the initial findings are not diluted by the uncertainties that accompany them. The result is the use of climate change projections that have been tailored to address the key concerns of the planner or decision maker. In cases where climate projections are not available or not trusted, steps 2 and 3 of this process reveal the sensitivities of a planning decision to climate, including plausible climate changes, and can form the basis for adaptation planning.

Decision-scaling: Linking bottom up and top down

The key innovation of decision-scaling is the way it links the insights provided by bottom-up analyses with the information from climate models and informs decisions and risk assessment. In simple terms, the process can be described as identifying what kind of climate changes would cause problems and then turning to the climate models to estimate whether those climate changes are likely. The process can also be applied to decisions. A decision model is used to identify the climate conditions that favor one decision over another. Then, the probability of those climate conditions is assessed using climate model projections, possibly in combination with other sources of climate information or expert judgment. The process inverts the typical direction of analysis in climate change impact assessments (Figure 1). By reserving the use of uncertain climate projections until late in the analysis, it reduces the propagation of those uncertainties through all steps of the analysis. As a result, the decision-scaling process enhances the ease of interpretation of the results. Also, it allows a focused use of climate change projections, which ensures that the result of a climate modeling effort matches the information needed for assessing risks and making decisions. Finally, it is transparent in the way climate information influences the resulting recommendations, allowing subjective view points on relative credibility of climate information to be brought to the discussion. The decision-scaling process consists of the three steps described below.

Step 1. Bottom-Up Analysis: Identification of key concerns and decision thresholds.

A key principle of decision-scaling is tailoring the analysis to address the key concerns of the decision makers. In many other methods (both top-down and bottom-up), analysis begins with the assumption that downscaled climate projections are needed and proceeds to design the downscaling process. However, without knowing the kind of climate conditions that influence one decision over another or that cause key risks, will the downscaling process produce results that inform the decision? That approach can lead to considerable effort producing downscaled climate conditions that do little to inform a decision process. Decision-scaling is designed to address this issue by beginning with a

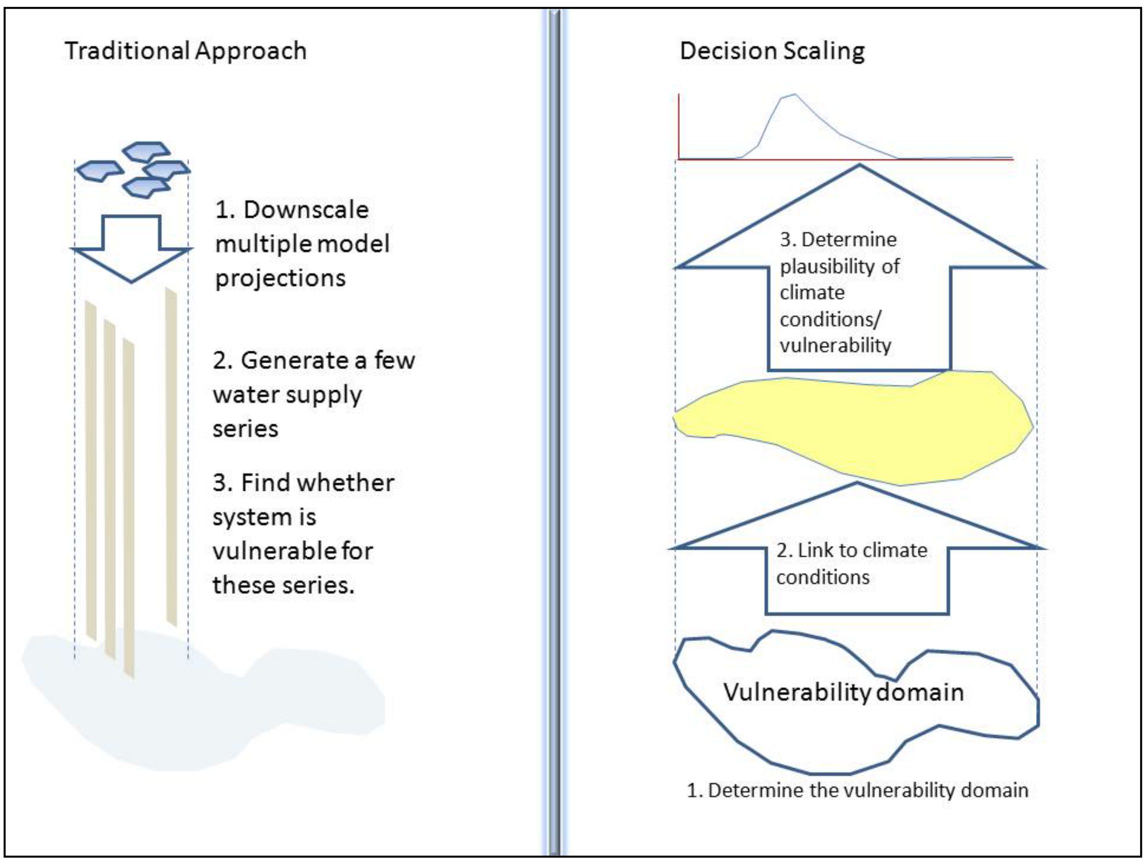

Figure 1. Decision-scaling begins with a bottom up analysis (where climate vulnerabilities are explored, defining what is termed here the "vulnerability domain") to identify the climate states that impact a decision and then uses sources of climate information such as GCMs that is tailored based on the bottom up analysis to provide insight to the decision.

systematic appraisal of the true climate sensitivity of a system or decision. This facilitates the identification of the climate information needs for a given analysis. The first step of decision-scaling is a bottom-up analysis of key climate concerns and thresholds, where appropriate. This step is conducted with decision makers to identify and characterize objectives, performance indicators and thresholds. For example, in a decision process, the stakeholder groups are facilitated in developing a list of objectives for a decision and the performance indicators used to evaluate alternatives through semi-structured discussion. In a risk assessment process, climate impacts of concern are identified, often drawing from the examples of historical climate events, and thresholds of impact that would be deemed unacceptable and warrant preventative action are described. In some complex systems, building the understanding of how a system is impacted by climate may be difficult, and may also be one of the most useful outcomes of the analysis. In an ongoing study of the Great Lakes of North America, an iterative dialogue between analysts and stakeholders was necessary to build this understanding and establish meaningful impact thresholds and performance indicators for each of the affected groups (Brown et al., 2011). This step builds on the documented practices of vulnerability-based approaches to climate change assessment from the literature.

Step 2. Modeling the response to changing climate conditions.

With key aspects of the assessment or decision process characterized, the next step is to formalize this understanding using the framework of decision modeling. In most cases a formal model of the natural, engineered or socio-economic system is created that relates climate conditions to the impacts or performance indicators that are identified in step 1. The models are mathematical representations of physical, social or economic processes that allow the analysts to systematically explore the potential effects of changes in climate on the system. The models might be quite complex or can be quite simple, depending on the available resources for the analysis. For example, simple statistical models, such as ordinary least squares regression, that relate temperature and precipitation variation to impacts can be developed using historical data. In some cases, the existing and trusted models of the stakeholders are used. In other cases new models are constructed using the available data that describes system responses to climate. In this case, the services of an experienced modeler are required. Models are validated with available data to ensure they appropriately represent the system of interest in the terms the stakeholders utilize for decision making.

This representation of the system and its response to changing climate conditions is termed a "climate response function." It is used to define the climate conditions that result in differential performance of alternatives leading to preferences for decision making. Inputs to the climate response function are the climate conditions, the change in which is the issue in a climate change analysis. To develop the climate response function, the climate conditions are systematically varied to diagnose how such climate changes affect the system. For example, the mean climate (e.g., temperature and precipitation averages) is repeatedly varied over a plausible range of possible climate changes, say between +20 and -20% (IPCC regional reports are a good source for choosing the possible range) and for each "scenario" the climate response function is used to calculate the values of the performance metrics. If a threshold for acceptable performance has been established, the climate conditions under which such a threshold is not met are noted. If a decision between several alternatives (e.g., infrastructure investment strategies) is being analyzed, the climate conditions under which certain alternatives are favored is tracked. Using these results, the climate space, or realm of future possible climate conditions, can be parceled into a small number of sectors that represent conditions associated with either risk (in the case of performance metrics not being met) or with the preference of one decision over another.

The development and use of the climate response function is a critical step in decision-scaling. The delineation of climate conditions associated with risks or preferences of specific decision alternatives is a very powerful result. In some cases it might be found that the system is relatively insensitive to changes in climate and further analysis is unnecessary. Or it may be found that one decision alternative is preferred in all future climate conditions. In both cases, further investigation of what the future climate conditions may be unnecessary.

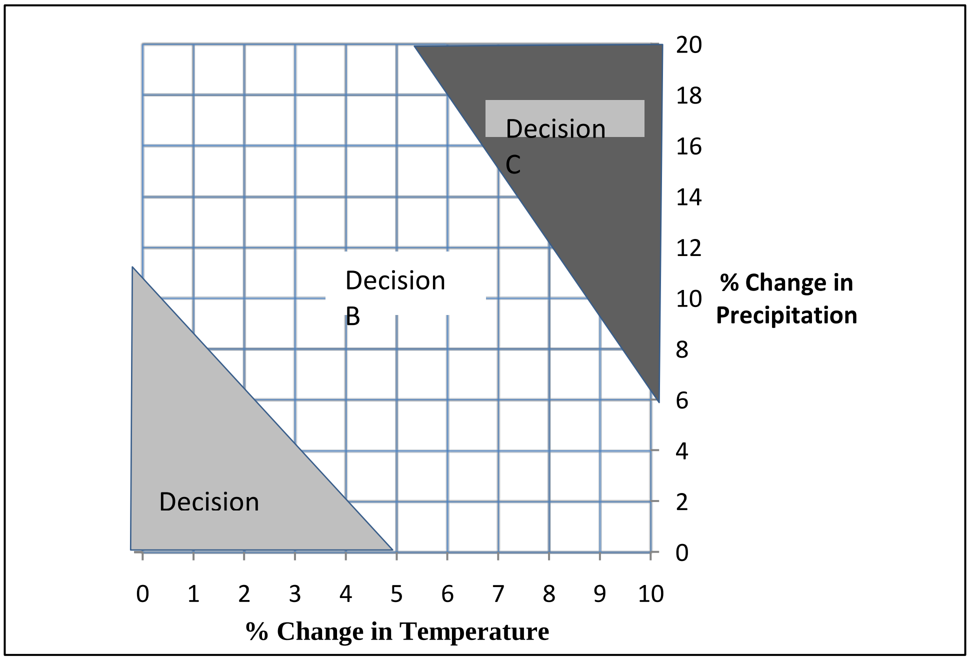

Figure 2. Graphical example of the division of climate space by the optimal decision according to the climate response function. Each sector corresponds to the climate conditions for which a particular decision is preferred.

More likely, the climate response function may uncover key climate risks to an engineered system. Or critical failings of a design or strategy may emerge. The climate response function is used to test the system in the widest possible range of conditions to ensure that weakness or risks are discovered. Thus, the risks are exhaustively explored and identified by testing a very wide variety of possible climate futures, not just the small number that might be available in a typical GCM analysis. For example, for the analysis of the Great Lakes of North America, over 16,000 climate futures were analyzed (Brown et al., 2011). Given the irreducible uncertainty associated with future climate, this is crucial to decision making that produces robust plans for the future. In top-down approaches, the system is often evaluated or tested with only a small number for future scenarios. Even if these scenarios are taken from the extreme members of climate change simulations, they do not necessarily represent the true possible range of climate conditions. Therefore, such an analysis may not truly test a decision for the conditions that will occur, resulting decisions that may not be robust as the climate conditions evolves into the future.

A pictograph of example results from a climate response function is shown in Figure 2. In this case the analysis has revealed that conditions that are close to the long-term historical conditions (represented by small percentage changes for precipitation and temperature) favor Decision A, while large changes indicative of wetter and hotter conditions favor Decision C. Notice, that even without the use of GCM projections, much is learned from the analysis for the decision makers. The stakeholders could stop here without using GCMs and based a decision on their subjective feelings about what future climate is more probable. Or they may consult experts to get their subjective estimates. Nonetheless, we believe the methodology is most powerful when linked with the scientific information available from GCM projections and other quantitative sources of climate data. With the climate sectors defined, the use and analysis of climate data can be very focused on estimating the relative likelihood of the conditions defined by these sectors. Thus the scaling of climate projections can be tailored to maximize the credibility of the information relative to what is needed for the decision.

Step 3. Estimating relative probability of changing climate conditions.

The final step in the decision-scaling process is the creation of probabilities that characterize the relative likelihood of the climate sectors defined in step 2. This step consists of the estimation of probabilities for the climate sectors using appropriate climate information. These estimates are best considered subjective probabilities. This information is drawn from the latest and best understanding of the state of climate science for the climate conditions that are needed. Depending on the particular climate variables that are of interest, this may involve the use of projections from GCMs, or stochastic simulations from historical data or paleoclimatological data, or narrative assessments of future climate based on local and regional knowledge.

A logical starting point for the estimation of probabilities is an assessment of the projected future climate from GCM simulations. For reasons of model uncertainty and the internal variability of the Earth's climate system (which is reproduced in model projections), a multi-model, multi-run ensemble is recommended as the best representation of the various projections from GCM. Climate change projections from models used by the IPCC are freely available from a number of online sources (see for example, www.climatewizard.org). A good understanding of appropriate use of the projections is necessary in any analysis, however. For most planning exercises, the time frame of analysis extends no more than 50 years into the future. When that is the case, the SRES emissions scenarios of greenhouse gas emissions has relatively little influence on the climate projections prior to 2050. Thus any SRES emissions scenario should be considered (e.g., A2, B1, A1B). It should be realized that although often thought of as "worst," "best," and intermediate emissions scenarios, in fact, they are not intended to frame the range of possible emissions. Rather they represent different, internally consistent emissions futures, which result in higher or lower emissions.

The projections from GCMs typically require significant processing prior to the generation of probabilities for decision-scaling. Knowledge about the particular strengths and weaknesses of the projections, along with the insights into the climate information needed generated in steps 2 and 3, can be used to tailor the projections appropriately to maximize their credibility for a given estimation. This is a key advantage of the decision-scaling approach. For example, the projections from GCM are best for estimating probabilities associated with mean conditions, especially over longer time periods such as mean annual precipitation or mean seasonal temperatures. They are also more effective over larger spatial scales. The use of single grid cells for estimation of future conditions within that area can be problematic due to spatial biases in the GCMs. The knowledge of the relative credibility of GCM projections at different spatial and temporal scales can improve the reliability of the estimated probabilities.

There are a variety of approaches for generating raw probabilities from GCM projections. The most straightforward approach is to assign each GCM projection an equal probability of occurrence. Because it is very difficult to select a "best" GCM and the theoretical basis for doing so is often tenuous, this simple approach may be optimum. Other approaches are available. For example, Tebaldi et al. (2003) generated regional probabilities of precipitation and temperature with a weighting scheme that applied more weight to projections that agreed with the unweighted mean projection.

In our experience, the generation of probabilities from GCM projections is a starting point for discussion of what the final probabilities should be. In an adaptation study for the Upper Great Lakes of North America, the GCM projections of future climate will be compared with results from a 50,000 year stochastic (stationary climate) simulation of climate conditions, as well as a stochastic simulation generated from paleoclimate data. Initial probabilities of problematic climate conditions will be estimated from this “super ensemble” of historical, simulation and GCM data. In order to maintain transparency and to improve the confidence of the decision makers in the process for providing decision supporting information, the final probabilities will evolve based on a discussion of the strengths and weaknesses of each of the sources of climate information in addition to the raw probabilities they produce.

In a decision-making context, decision-scaling produces a specification of the preferable decisions for a range of climate conditions, an initial estimate of probabilities for those climate conditions, indicating which is relatively more likely based on the aggregated climate information, and finally a listing of the number and source of climate information (e.g., GCM from a specific climate research center, or a stochastically generated dataset) that favor the relative probability of each climate sector (and corresponding decision) over another. In a risk assessment context, the climate conditions associated with risk (e.g., causing performance of a system below an acceptable threshold) are identified in step 2. Step 3 involves estimating probabilities associated with those risks in order to determine what, if any, action should be taken to address risks. As described above, the output from GCM and other sources of climate information are aggregated to estimate initial probabilities associated the climate conditions causing risk.

This process of reviewing the results of a variety of climate sources in terms of their influence on the decision is effectively a “credibility review” of the results of the probability estimation. Often, the estimation of probabilities from a variety of sources and using a variety of statistical methods can leave decision makers confused or skeptical of the numbers that result. Rarely do decision makers accept the results from “black box” processes that leave them little room for negotiation. In our experience, stakeholders and decision makers have differential levels of acceptance and comfort with different climate information sources. Some are very skeptical of stochastic simulations based on historical data, concerned that statistically-generated values may not be physically plausible. Others are skeptical of GCM output altogether and prefer to trust historical values and trends until GCM simulations improve. Through the transparent presentation of the results from the variety of sources, and their results in terms of decisions, the decision makers have the opportunity to review, understand and draw their own conclusions in regard to relative likelihood of conditions. And since those conditions are associated with a specific decision or a specified risk, the decision maker is able to synthesize in their own way the selection of a decision, the relative probability of that decision being the preferred one in the future based on the aggregation of a variety of climate information, and the source of climate information that favors one decision over another (or implies that a risk is more or less probable).

The decision-scaling process is designed to transform climate information to be relevant and useful for real decision making and risk assessment. It does so through linking a bottom-up vulnerability assessment approach with climate information generation using a decision analytic framework. In view of the uncertainty associated with future climate, the process is designed to accommodate the use of numerous sources of climate information. It also is designed to be transparent in the use of climate information and responsive to the concerns of stakeholders regarding the relative value of different sources. In sum, it's an attempt to make the best use of the considerable and sometimes overwhelming amount of information available and to overcome the paralysis that can result due to conflicting views of the climate future from different sources.

Climate Risk Assessment of Niger Basin Investment Program with Decision-Scaling

The decision-scaling process may be best demonstrated through a description of a recent application involving stakeholders and the use of GCM projections. This case study describes the completed risk assessment of the major infrastructure investment program planned for the Niger River Basin in West Africa conducted for the World Bank.

The decision-scaling process for the Niger Basin investment program began with the elicitation of the priority concerns and key decision thresholds of the stakeholder countries through a workshop conducted with the Niger Basin Authority in Ougadougou, Burkina Faso in May 2010. This represents the first step in decision-scaling, beginning with a stakeholder-based bottom-up analysis. In general, the priority concerns related to the original objectives of the investment program, which included increased water availability for irrigated agriculture, increased hydroelectricity production and improved navigation, as well as concerns related to water availability to sustain the natural river environment. In order to facilitate the discussion, initial results that portrayed the climate sensitivity of these objectives were presented. Using those preliminary results, small group discussions were convened to attempt to define thresholds of acceptable versus unacceptable

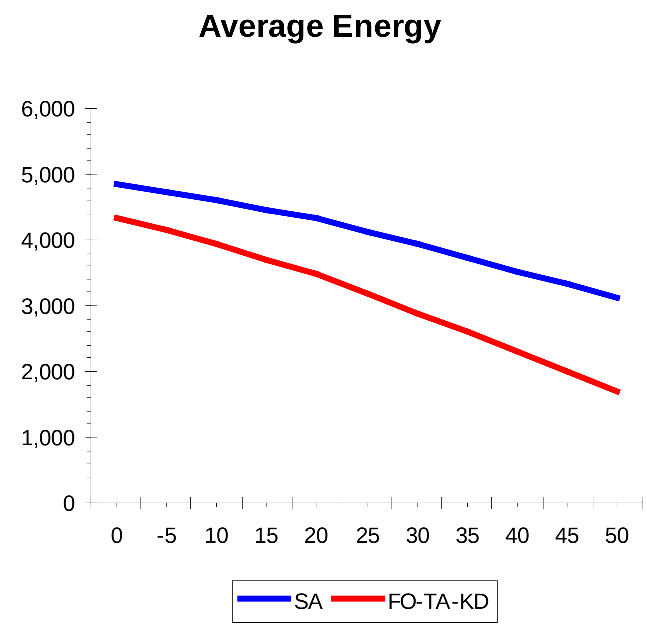

Figure 3. The climate response function for energy production in the Niger Basin. The lines indicate the expected average hydroelectricity production from the basin investments (y – axis) as a function of a percent change in climate conditions (x –axis). The blue line indicates the investment scenario and the red line indicates the current infrastructure.

performance in terms of the identified project objectives. In the course of the meeting, it was found that defining thresholds in terms of specific magnitudes of the objectives (e.g., hectares of potentially irrigable land, KWh of energy production) was not meaningful to the participants. Instead, relational thresholds were defined as percentage decreases from the baseline expectations of performance under current climate conditions. It was ultimately agreed by the workshop participants that decreases in average performance of less than 20% from the baseline conditions was considered an acceptable level of risk, while decreases of 20% or greater were defined as unacceptable.

With the performance metrics and thresholds of acceptable performance elicited, the next step was the definition of climate conditions that would cause unacceptable performance. This was performed by modeling the response of the basin investment plan performance to changes in climate conditions. The existing water resources systems model of the Niger Basin Authority was used for this purpose. This model produces estimates of all the major objectives of the investment program for a given time series of streamflow or runoff. To elucidate the effect of changing climate conditions, the mean streamflow over an approximately 30 year historic record was varied from an increase of 10% to a decrease of 30%. The historical variability of streamflow was retained. The results showed a nearly linear relationship between the values of the performance metrics and changes in streamflow. Figure 3 shows this relationship for hydroelectricity production in the basin.

Interestingly, the results also demonstrated that basin-wide averages of precipitation and temperature provided very good approximations of annual streamflow throughout the basin. This was a fortuitous and not unexpected result because it allowed the creation of the climate response function in terms of basin-wide values of precipitation and temperature. Accordingly, because GCM projections are more credible at large spatial scales (where several grid cells can be averaged instead of relying on single cells) the projections of precipitation and temperature were drawn from GCMs by averaging over the entire basin. Although counter-intuitive, in this case coarse resolution results were acceptable (in fact, preferable) to higher resolution results. Thus the additional uncertainty created by downscaling, as well as considerable additional effort, was avoided. This also improved the credibility of the final results. A linear climate response function was created that related any change in streamflow within the range analyzed to values of the performance metrics. Using a log linear model of runoff as a function of mean temperature and precipitation, the performance metrics were then quantified in terms of climate conditions.

In the final step of the analysis, a multi-model, multi-run ensemble of climate projections with 38 members was used to assess the expectation of future climate conditions according to these models. Because the climate response function was defined in terms of the basin-wide precipitation and temperature changes, the GCM projections were actually scaled up through spatial averaging to produce estimates of changes over the entire basin. As mentioned above, this actually improves the credibility of the projections and also allows significantly eased processing of the projections. Box plots of the range of projected changes in precipitation and temperature for the basin are shown in Figure 4, showing increases in temperature and small increases in precipitation are common responses from the GCMs. Next, the values of precipitation and temperature from each GCM was input to the climate response function for each performance metric, creating a range of GCM estimates in terms of the performance metrics. In this case, a parametric probability distribution was fitted to the estimate, producing probability estimates for the risk categories defined in Step 1. Those results are shown in Figure 5.

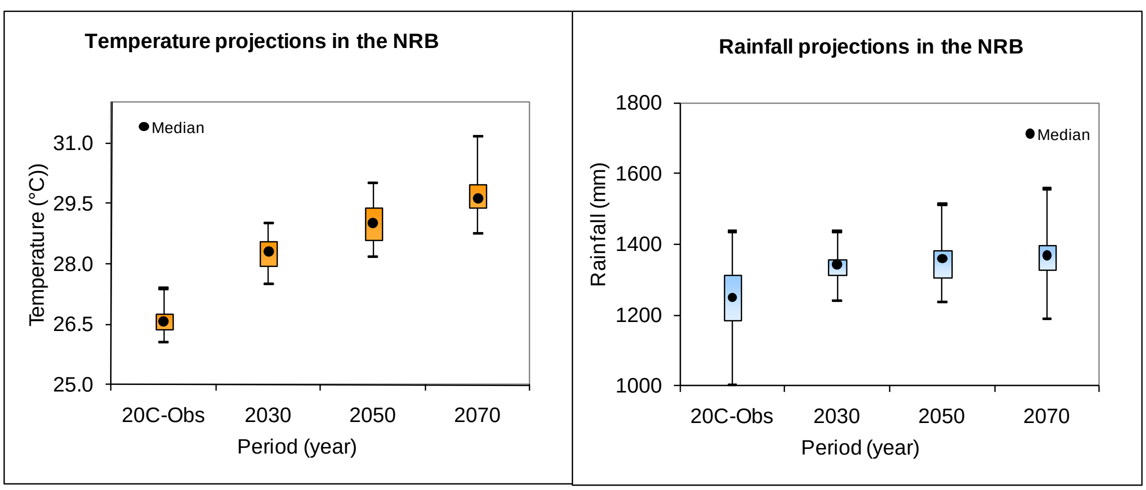

Figure 4. The range of projections of temperature and precipitation for the Niger River Basin based on 38 GCM projections compared to the observed 20th century values.

The results of this process made clear that the sum assessment based on GCM projections for West Africa was that there was relatively small risk due to climate change to the planned investments. Environmental flow indicators were relatively more at risk than other performance indicators. Importantly, risk was specified in the terms defined by the stakeholders. Thus, the final results of the GCM projections were also specified in the stakeholders' terms, presumably the terms that they have identified as most useful for their assessment of problematic risks to the investment program of the Niger River basin.

Conclusions and Recommendations

The process of decision-scaling is designed to generate insightful guidance from the often confusing and conflicting set of climate information available to decision makers. It generates information that is relevant and tailored to the key concerns and objectives at hand. The process bridges the gap in methodology between top down and bottom up approaches to climate change impact assessment. It uses the insights that emerge from a stakeholder-driven bottom-up analysis to improve the processing of GCM projections to produce climate information that improves decisions.

The process is best applied to situations where the impacts of climate change can be quantified and where models exist or can be created to represent the impacted systems or decisions. Historical data is a necessity. The process can be applied both in conjunction with large climate modeling efforts (as is being conducted in the International Upper Great Lakes Study) and where the analysis depends simply on globally available GCM projections (as was done in the Niger Basin study). It is most effective when conducted with strong engagement and interaction with the decision makers and stakeholders of the planning effort. The transparent nature of the process attempts to make the analysis accessible to nontechnical participants, but having some participants with technical backgrounds is beneficial.

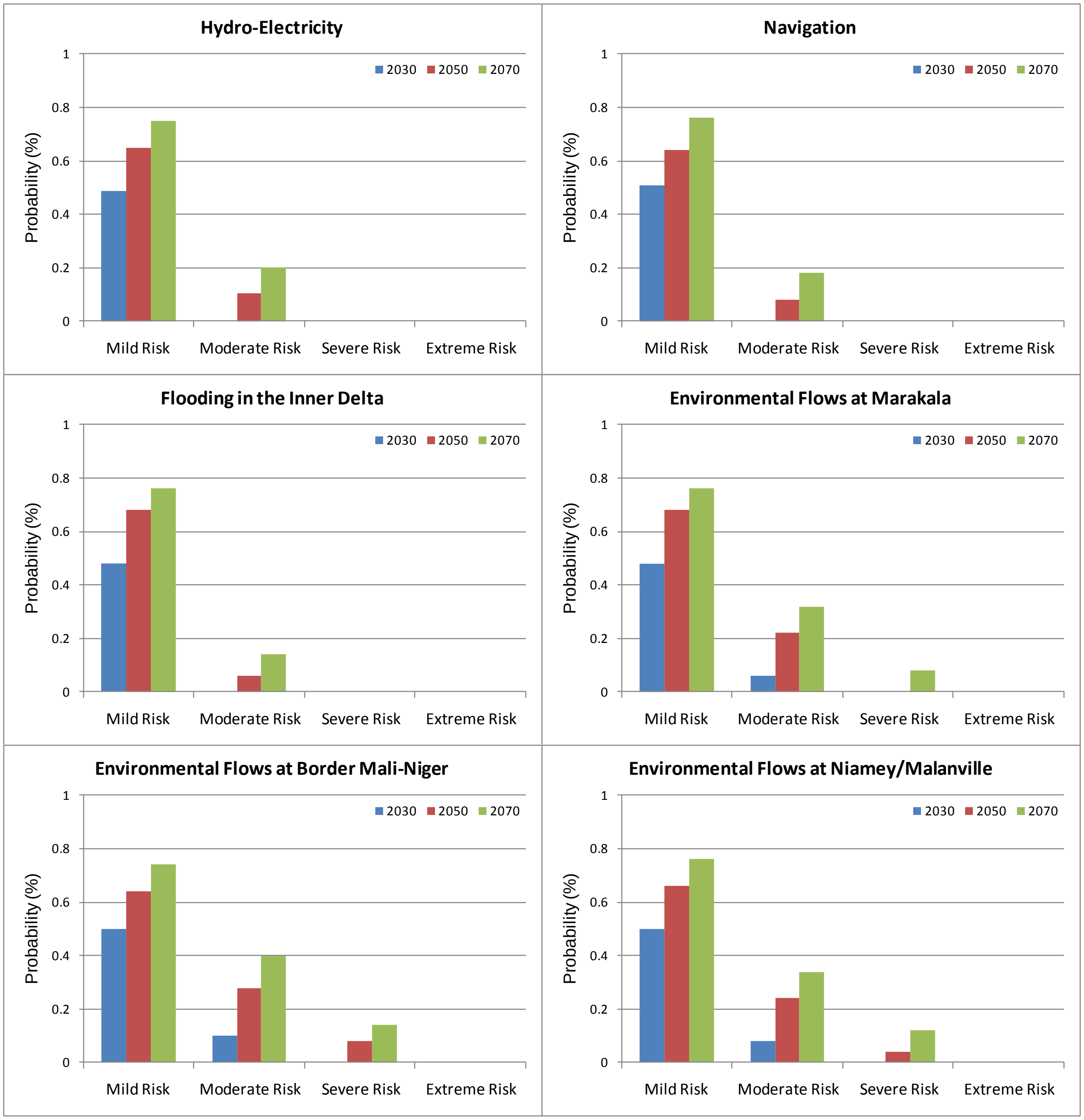

Figure 5. Estimates of probability of specified risk levels based on the climate response function and 38 GCM projections. The risk levels were defined by the stakeholders of the analysis. Mild risk is associated with a reduction of less than 20% of the performance indicator. Moderate risk is a reduction of greater than 20% and less than 40%, and so on. The results indicate mild risk for most of the performance indicators, although risk levels are higher for environmental flows.

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