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An Alternate Approach to Assessing Climate Risks

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U.S. federal agencies are now required to review the potential impacts of climate change on their assets and missions. Similar arrangements are also in place in the United Kingdom under reporting powers for key infrastructure providers (http://www.defra.gov.uk/environment/climate/sectors/reporting-authorities/reporting-authorities-reports/). These requirements reflect growing concern about climate resilience and the management of long-lived assets.

At one level, analyzing climate risks is a matter of due diligence, given mounting scientific evidence. However, there is no consensus about the means for doing so nor about whether climate models are even fit for the purpose; in addition, several important issues are often overlooked when incorporating climate information into adaptation decisions. An alternative to the scenario-led strategy, such as an approach based on a vulnerability analysis ("stress test"), may identify practical options for resource managers.

General Circulation Model–Based Predictions and Their Limitations

Many climate change predictions are based on ocean-atmosphere general circulation models (GCMs). For instance, *Mote et al.* [2011] describe means of extracting climate change projections from these models and outline a number of concerns, including meeting the needs of end users. As with previous discussions of climate projections, the emphasis is more on the supply than on the demand for information. However, stakeholders often ask, "What climate information do we really need, and how should it be prepared?"

The scientific community has much to say about the latter, but some researchers are beginning to recognize that more effort should be spent identifying what information is needed, given the particulars of the impact system in question. This would then inform how best to prepare climate risk information. For example, from a planning perspective, it is helpful to know what climate risks might reduce benefits or raise costs of a project such as new water infrastructure. For decision making, what are the climate risks that would affect the choice between alternative options? For risk assessment, what individual, sequential, or concurrent climate extremes pose the greatest threat? GCM-based climate projections are not needed to answer these types of questions.

The recognized limitations of GCMs, including the lack of credibility on extremes, imply that GCM-based projections may have difficulty providing the information decision makers typically look for or even adding value to a risk analysis [*Kundzewicz and Stakhiv*, 2010; *Mote et al.*, 2011; *Pielke and Wilby*, 2012]. One problem is the tendency for some stakeholders to perceive and treat projections as forecasts. Indeed, it is difficult to communicate exactly what climate projections mean from a decision standpoint—they simulate what might happen under some conditions but do not preclude other outcomes. In fact, climate analysts are often reluctant to say that one future is more or less likely than others.

In other disciplines such as decision analysis, scenarios are constructed to help decision makers explore the range of uncertainty in the key variables that affect their system or decision. However, climate change projections from GCMs are ill formed for doing so because of incomplete process representation, parameterization, and small effective sample sizes of models. As a result, the possible range of climate changes might not be fully explored if an analysis relies exclusively on climate projections. Instead, climate model projections scope a "minimum range of irreducible uncertainty" [*Stainforth et al.*, 2007]. In other words, the range of projections represents some of the uncertainty in the possible range of future climate but not the full range of possible climate changes. Changes beyond what current models project are possible. The model range represents a partial sampling, not an

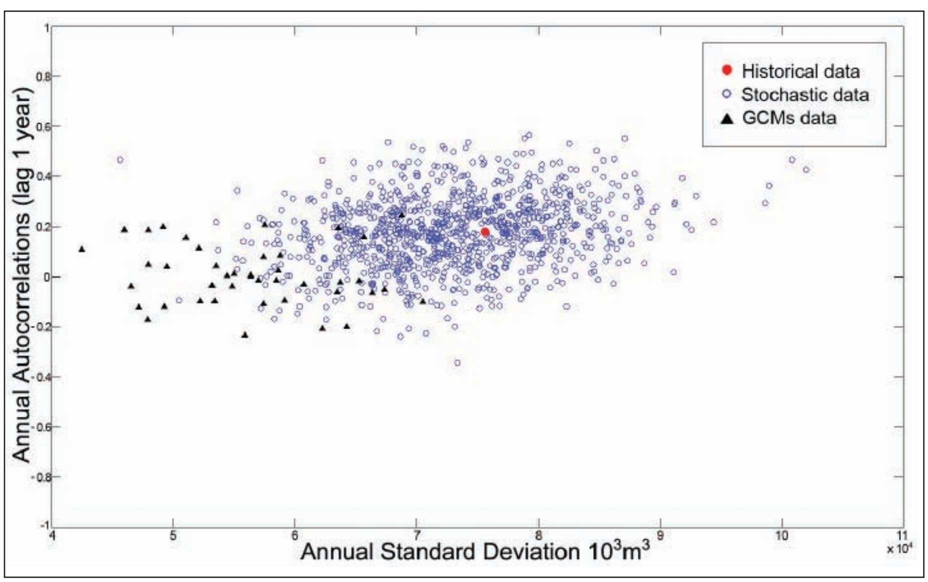

Fig. 1. Variability statistics of bias-corrected, statistically downscaled historical general circulation model (GCM) 30-year simulations (triangles) and resampled historical 30-year streamflow (circles). The actual historical value is indicated by the red dot. The climate model simulations show underestimation of the variability statistics relative to the observed values and resampled historical data. Historical data is from Maurer et al. *[2002]. Climate projection is from* Maurer et al. *[2007], available at the Bias Corrected and Downscaled WCRP CMIP3 Climate Projections archive at http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections.*

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exhaustive exploration of climate change. So if a decision maker wants to conduct a formal scenario analysis, restricting the analysis to this minimum range of uncertainty could result in a lack of consideration of possible climate outcomes.

Multimodel experiments such as the Coupled Model Intercomparison Project phase 3 (CMIP3), ENSEMBLES, Climateprediction.net, and others have helped to characterize aspects of climate uncertainty but not necessarily for those variables of greatest relevance to natural resource managers, such as variability statistics. Other climate modelers assert that the spread of uncertainty may be reduced by adjusting known model biases in simulating present climate [*Boberg and Christensen*, 2012]. Some researchers are beginning to think that it is better to generate climate scenarios in such a way that one can control, by design, the range of climate changes in the specific variables of interest [e.g., *Prudhomme et al.*, 2010; *Brown et al.*, 2011].

As an example of the drawbacks of GCM-based analyses, Figure 1 shows statistics of variability (standard deviation and autocorrelation) of annual streamflow for a region of the northeast United States based on a widely used, bias-corrected and statistically downscaled source of GCM projections [*Maurer et al.*, 2007]. These two variables are critical to the reliability of water supply systems, especially those with overyear storage. The downscaled GCMs underestimate both the standard deviation and autocorrelation when compared with observations. It is reasonable to assume that projections of future climate from these GCMs would be biased in the same way despite an expectation for climate variability to increase [see, e.g., *Kundzewicz et al.*, 2007]. If GCM projections alone were used to assess risks to such a water supply system, the range of outcomes would no doubt be wide but nonetheless underestimated in this case, though the use of techniques that blend historical variability with projections may better evaluate variability [*Salas et al.*, 2012]. In addition, in risk assessments the choice of downscaling technique(s) would be tailored to meet assessment requirements and would be a further source of uncertainty [*Wilby et al.*, 2009].

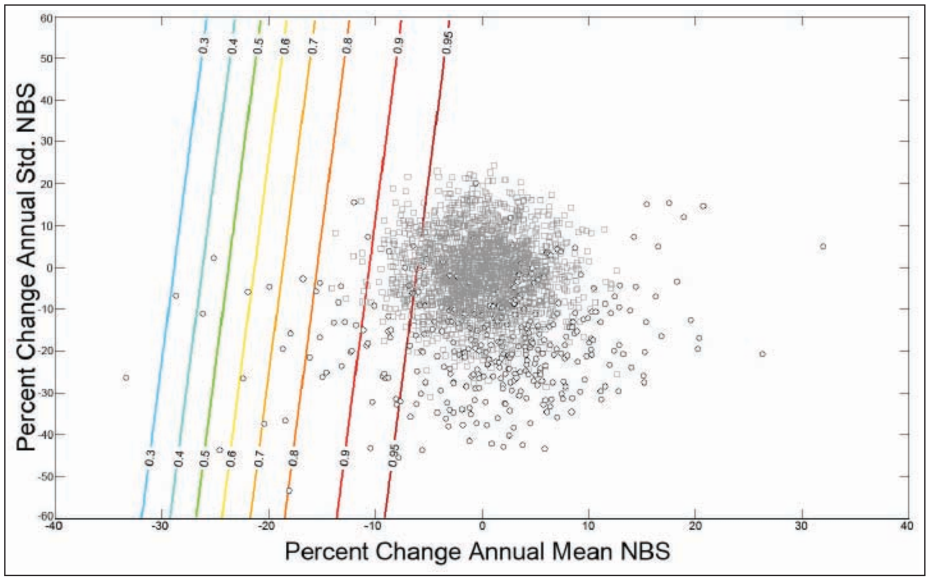

Fig. 2. A climate response function for water supply reliability (contours) as a function of changes in annual mean and annual standard deviation of net basin supply (NBS, inflows net evaporation) based on the water supply system serving a metropolitan area in Massachusetts. Circles represent GCM simulations of the historical period, and boxes indicate the historical range of variability generated by resampling observed data.

Alternatives to GCM-Based Analyses

Given these concerns, climate risk analysis in a decision-making context should consider analyses other than climate projections. However, continued development of Earth system models is a valuable endeavor that leads to improved process understanding of regional climate variability and change. In some cases, a vulnerability analysis, or stress test, may provide greater insight. Like a sensitivity analysis, a vulnerability analysis provides information on how much a system of interest would respond (how sensitive it is) to changes in climate. Once risks are identified, model projections can be used to assess the plausibility, likelihood, or ranking of climate threats and opportunities based on the latest scientific evidence.

Climate scenarios can be generated parametrically or stochastically to explore uncertainty in climate variables that affect the system of interest [*Prudhomme at al.*, 2010; *Brown et al.*, 2011]. This allows sampling changes in climate that include but are not constrained by the range of GCM projections. The definition of scenarios can be developed as part of a stakeholder-driven, negotiated process, and climate projections can be used in this process [*Hallegatte et al.*, 2012]. Alternatively, a very wide range of climate alterations can be developed independent of their plausibility and used to identify risks. For scenarios in which the climate consequences exceed coping thresholds, it is then fruitful to evaluate the plausibility of the scenarios. Climate projections, paleoclimate reconstructions, and subjective climate knowledge could all inform such discussions.

Hydrologists and engineers are developing methods based on sensitivity analysis that shift attention back on the water system of interest and use GCM projections to inform, rather than drive, the analysis. These include "scenario neutral" approaches and "decision scaling," which uses decision analysis as a framework for incorporating climate information including GCM projections [*Prudhomme et al.*, 2010; *Brown et al.*, 2012]. These approaches might be termed "bottom-up meets top-down," as they focus first on the issues of concern and then on how climate information might add value to the analysis. The basic steps in these methods are to (1) identify the problem, including defining objectives and performance measures; (2) use a stress test to identify the hazard and evaluate the performance of the system under a wide range of nonclimatic and climate variability and change; and (3) evaluate the risk using climate information including model projections.

The example in Figure 2 shows what combinations of change in mean and variability lead to an unacceptable decrease in water supply reliability (where reliability is measured as the frequency with which supplies are sufficient to meet water demanded) based on the water supply system serving a metropolitan area in Massachusetts. For instance, a 10% reduction in the annual mean and more than 10% increase in variability reduce reliability of supplies to 90%. Under historic climate these conditions occur less than 1% of the time. GCM projections can be mapped onto the same surface. Their clustering can be interpreted as the likelihood that these conditions will occur on the basis of the latest understanding and representation of the Earth system. Under climate change scenarios a system reliability of 90% is achieved in 85% of cases.

An additional advantage of sensitivity approaches is that they may preclude the need for an expensive climate impact assessment and associated opportunity costs (i.e., time and money). For example, if a stress test is performed and no risks to operations emerge over a wide range of plausible climates, then a decision maker will have assessed climate risk, found little or none, and satisfied the review requirements without the large effort involved in typical GCM-led end-to-end uncertainty analysis. For instance, for many water systems, climate pressures may not be significant relative to other considerations, especially when economic discount rates in cost benefit analysis diminish the importance of the distant future [*Stakhiv*, 2011].

Furthermore, sensitivity approaches have the benefit that the analysis can be instantly updated as new information becomes available [*Prudhomme et al.*, 2010], such as when CMIP5 projections are released. The climate response surface is unlikely to have changed (unless the physical asset or management regime has also changed), so new projections, whatever the source, can be used to quickly update the "cloud" of estimated impacts.

Sensitivity testing can be performed for multiple variables, but visualizing more than two or three axes at a time can be challenging. In those cases, stakeholders can be consulted about the choice of appropriate metrics and stress axes when presenting study results. While the methods described in this feature cannot reduce the uncertainty associated with climate change, they do attempt to clarify the effect of the uncertainty on the decisions in question.

None of the benefits of this approach can be accomplished without continued scientific effort and development of climate models. Indeed, climate projections can be vital input for designing the stress test and for developing a physical basis for relative ranking of climate risks that are identified. However, decision makers could be helped by a shift of emphasis from the uncertainty-laden scenario-first perspective to a decision-led view, in which the first step is to quantify the sensitivity domain of the managed system under a wide range of climatic and nonclimatic pressures.

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References

Boberg, F., and J. H. Christensen (2012), Overestimation of Mediterranean summer temperature projections due to model deficiencies, *Nat. Clim. Change*, *2*, 433–436, doi:10.1038/nclimate1454.

Brown, C., W. Werick, W. Leger, and D. Fay (2011), A decision-analytic approach to managing climate risks: Application to the upper Great Lakes, *J. Am. Water Resour. Assoc.*, *47*(3), 524–534, doi:10.1111/j.1752-1688.2011.00552.x.

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

Hallegatte, S., A. Shah, R. Lempert, C. Brown, and S. Gill (2012), Investment decision making under deep uncertainty—application to climate change, *Policy Res. Working Pap. WPS 6193*, World Bank, Washington, D. C.

Kundzewicz, Z. W., and E. Z. Stakhiv (2010), Are climate models "ready for prime time" in water resources management applications, or is more research needed?, *Hydrol. Sci. J.*, *55*, 1085–1089, doi:10.1080/02626667.2010.513211.

Kundzewicz, Z. W., L. J. Mata, N. W. Arnell, P. Döll, P. Kabat, B. Jiménez, K. A. Miller, T. Oki, Z. Sen, and I. A. Shiklomanov (2007), Freshwater resources and their management, in *Climate Change 2007: Impacts, Adaptation, and Vulnerability: Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by M. L. Parry et al., pp. 173–210, Cambridge Univ. Press, Cambridge, U. K.

Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier, and B. Nijssen (2002), A long-term hydrologically-based data set of land surface fluxes and states for the conterminous United States, *J. Clim.*, *15*(22), 3237–3251, doi:10.1175/1520-0442(2002)015<3237:ALTHBD>2.0.CO;2.

Maurer, E. P., L. Brekke, T. Pruitt, and P. B. Duffy (2007), Fine-resolution climate projections enhance regional climate change impact studies, *Eos Trans. AGU*, *88*(47), 504, doi:10.1029/2007EO470006.

Mote, P., L. Brekke, P. B. Duffy, and E. Maurer (2011), Guidelines for constructing climate scenarios, *Eos Trans. AGU*, *92*(31), 257, doi:10.1029/2011EO310001.

Pielke, R. A., Sr., and R. L. Wilby (2012), Regional climate downscaling: What's the point?, *Eos Trans. AGU*, *93*(5), 52, doi:10.1029/2012EO050008.

Prudhomme, C., R. L. Wilby, S. Crooks, A. L. Kay, and N. S. Reynard (2010), Scenario-neutral approach to climate change impact studies: application to flood risk, *J. Hydrol.*, *390*, 198–209, doi:10.1016/j.jhydrol.2010.06.043.

Salas, J., B. Rajagopalan, L. Saito, and C. Brown (2012), Special section on climate change and water resources: Climate nonstationarity and water resources management, *J. Water Resour. Plann. Manage.*, *138*(5), 385–388, doi:10.1061/(ASCE)WR.1943-5452.0000279.

Stainforth, D. A., et al. (2007), Issues in the interpretation of climate model ensembles to inform decisions, *Philos. Trans. R. Soc. A*, *365*, 2163–2177, doi:10.1098/rsta.2007.2073.

Stakhiv, E. Z. (2011), Pragmatic approaches for water management under climate change uncertainty, *J. Am. Water Resour. Assoc.*, *47*(6), 1183–1196, doi:10.1111/j.1752-1688.2011.00589.x.

Wilby, R. L., J. Troni, Y. Biot, L. Tedd, B. C. Hewitson, D. G. Smith, and R. T. Sutton (2009), A review of climate risk information for adaptation and development planning, *Int. J. Climatol.*, *29*, 1193–1215, doi:10.1002/joc.1839.

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