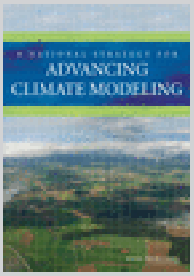


# A National Strategy for Advancing Climate Modeling

ISBN
978-0-309-25977-4

300 pages
7 x 10
PAPERBACK (2012)

Committee on a National Strategy for Advancing Climate Modeling; Board on Atmospheric Studies and Climate; Division on Earth and Life Studies

CHAPTER SIX

# Characterizing, Quantifying, and Communicating Uncertainty

This chapter discusses uncertainty (Box 6.1) both in the context of climate modeling of long-term climate change (decades to centuries) and of seasonal forecasting (intraseasonal to interannual time scales). Many of the uncertainties are similar in the two different contexts, except for uncertainties regarding longer-term future forcing that are relevant mainly to the long-term climate change problem. This chapter discusses different types of uncertainty related to climate modeling, reviews how uncertainty has been quantified, discusses the complex issue of communicating uncertainty, and, finally, provides findings and recommendations.

## TYPES OF UNCERTAINTIES IN THE CLIMATE SYSTEM

From the point of view of developing projections of long-term climate change from results of climate model simulations, there are three major uncertainties: (1) future emissions and concentrations of greenhouse gas and aerosols (forcing); (2) the re-

### BOX 6.1 UNCERTAINTY

Uncertainty is fundamental to all scientific investigations, and many scientific experiments are designed solely to quantify the uncertainty (e.g., in order to place bounds on observational requirements). Many enterprises have embraced the fact that uncertainty exists and have developed methods for operating and decision making under uncertainty. Uncertainty, in its most general definition, refers to lack of knowledge, or imperfect knowledge about specific quantities (e.g., speed of light), or the behavior of a system (e.g., the climate system). Because there is often a random component to uncertainty, it is usually broken down into two basic types: aleatory (randomness) and epistemic (lack of knowledge about something that is in principle knowable). With respect to climate modeling, both types of uncertainty are highly relevant. Uncertainty in climate modeling has been discussed in many contexts (e.g., Hawkins and Sutton, 2009; IPCC, 2007c; Palmer et al., 2005). The main uncertainties discussed are value uncertainty (e.g., uncertainty in data such as observations needed for model development and evaluation), structural uncertainty (e.g., incomplete understanding of processes or how to model them), and unpredictability (chaotic components of the complex system).

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sponse of the climate system to the forcing; and (3) the internal (stochastic) variability of the climate system. In the seasonal-to-decadal prediction context , uncertainties of types 2 and 3 are relevant, but, in addition, there are also uncertainties in the initial conditions of the climate system. The latter arise due to observational errors and errors in the assimilation systems used to generate the initial conditions.

### Uncertainty in Future Climate Forcing

The energy balance of Earth provides the engine that powers the planet's climate. That energy balance in turn is shaped by, among other things, the composition of Earth's atmosphere, which is being altered by emissions of greenhouse gases, aerosols, and short-lived species. Future climate forcing will be shaped by

- emissions of greenhouse gases, aerosols, and short-lived species into the atmosphere;
- processes that control the composition of the atmosphere, such as atmospheric chemistry, terrestrial and marine components of the carbon cycle, and nitrogen cycles; and
- climate processes, including interactions among the atmosphere, ocean, land, and cryospheric systems.

The future of each of these processes is subject to important uncertainties. Human emissions of greenhouse gases, aerosols, and short-lived species are sufficiently large (and growing) that they are significantly changing the composition of the atmosphere. Historical emissions of carbon dioxide ($CO_2$) and other greenhouse gases (GHGs) from fossil fuel use and industrial processes are reasonably well known. Emissions of $CO_2$ and other compounds resulting from land-use and land-cover change are smaller and less well measured. Future projections of all these sources of anthropogenic emissions will be subject to important uncertainties.

The annual global emissions of $CO_2$ can vary by more than an order of magnitude in nonclimate policy intervention scenarios (see, for example, Reilly et al., 1987, 2001; Scott et al., 1999). However, the cumulative nature of the carbon cycle means that variation in the concentration of $CO_2$ in the atmosphere is more constrained. Factors that influence the scale of future anthropogenic emissions include the scale of economic activity, the technologies with which human societies generate and use energy, and the public policy environment in which human activities are conducted. Hence, predicting emissions of GHGs and aerosols requires being able to predict how the entire human world will develop in the future, a truly daunting task fraught with multiple profound uncertainties.

Natural systems involving dynamical and biogeochemical processes that proceed at both large and fine scales are subject to different, though overlapping, uncertainties. There is some confidence associated with descriptions of the very long term (1,000+-year) processes that determine the average abundance of carbon in the atmosphere, but the forces shaping decadal to century atmospheric composition are less well understood (Kheshgi et al., 1999). Uncertainty in the carbon cycle is such that the maximum annual emissions that would limit long-term $CO_2$ concentrations to 550 ppm are uncertain by ±20 percent (Smith and Edmonds, 2006).

Finally, there are also uncertainties in the natural forcing of the climate system, namely fluctuations in solar irradiance and aerosol emissions due to volcanic activity. Although there is some periodicity to solar irradiance that can be estimated (Lean and Rind, 2009), it is not precise, and future forcing from volcanoes is currently completely unpredictable. The latter can substantially reduce receipt of solar radiation for short periods (e.g.,1-2 years).

### Uncertainty in the Climate System Response to Radiative Forcing

Climate system uncertainty is explored through the application of global and regional climate models. While most of these models are carefully constructed to incorporate many climate-related processes and are carefully evaluated, they do not necessarily respond in the same way to a given future forcing scenario. These differences are due to scientific uncertainties about how the climate system works, differences in the way various subsystems are modeled (e.g., land-surface processes), and differences in how unresolved processes are parameterized (e.g., convection). These uncertainties are explored and characterized by analyzing the results of different types of ensembles of climate model simulations. The most common is the multimodel ensemble (MME) based on simulations with different climate models that are subjected to the same future radiative forcing. These MMEs play a central role in the analyses that contribute to the Intergovernmental Panel on Climate Change (IPCC) assessments (e.g., IPCC, 2007c). There are also ensembles developed from a single climate model whose parameters are varied in systematic ways, which are referred to variously as parameter permutation experiments or perturbed physics ensembles (PPEs) (e.g., Murphy et al., 2007).

A primary integrated metric of uncertainty related to the climate system response to radiative forcing is the value of the climate sensitivity of the climate system. Equilibrium climate sensitivity is defined as the average annual change in global mean temperature that results from forcing a climate model with the radiative equivalent of doubled concentration of $CO_2$. For many years, this sensitivity was described as a range between 1.5°C and 4.5°C, but it has now been quantified using probabilistic approaches (Meehl et al., 2007).

Uncertainty also arises because certain processes or features are not included in most climate models or are modeled poorly or incompletely. These include ice sheets, interactions of sea ice and ocean circulation, aerosols and aerosol-cloud interactions, complexities in the carbon cycle (e.g., role of methane clathrates), interactions between the stratosphere and troposphere, and tropical convection; see Chapter 4 for more details. Note that because ensembles composed of current climate models do not represent many of these processes, these ensembles do not take into account these structural uncertainties and thus do not represent all the known uncertainties. It is very likely that progress in including these aspects of climate in models will be made over the next 10-20 years, thereby reducing structural uncertainty in models.

Finally, there is uncertainty due to the spatial scale of simulations (see Chapter 3) due not only to the fairly coarse resolution of global climate models, but also to that introduced in downscaling the results of the atmosphere-ocean general circulation models (AOGCMs) to even higher resolutions. These downscaling methods include dynamical downscaling with regional climate modeling or variable resolution techniques as well as statistical downscaling techniques. Regional climate models (RCMs), like general circulation models, are subject to uncertainty related to grid resolution and physics parameterizations but also introduce additional uncertainty associated with the lateral boundaries (including their placement) and large-scale boundary conditions and methods to assimilate them (Kerr, 2011). Statistical downscaling makes use of statistical relationships between local climate and the large-scale climate to infer changes at the local level from climate change projections from AOGCMs (Wilby et al., 1998). It adds uncertainty to the regional climate projections by assuming that these statistical relationships do not change over time (Schmith, 2008).

The regional climate modeling approach has been applied particularly frequently in recent years, and a number of programs have been developed to compare the responses of different RCMs to boundary forcing from different AOGCMs (e.g., ENSEMBLES over Europe [Christensen et al., 2009], NARCCAP over North America [Mearns et al., 2009], RMIP over China [Fu et al., 2005], and CLARIS over South America [Boulanger et al., 2010; Menendez et al., 2010]). A new global framework, the Coordinated Regional Climate Downscaling Experiment (Giorgi et al., 2009), should provide a more rigorous evaluation of downscaling products and the uncertainty associated with them, which is much needed because the high demand for regional climate projections (Kerr, 2011).

## Internal Variability of the Climate System

Climate predictions and projections are subject to uncertainty resulting from the internal variability of the climate system. The relative role of this type of uncertainty, compared to other sources of uncertainty, is a function of the future time horizon being considered and the spatial scale of analysis (Hawkins and Sutton, 2009, 2011). Hawkins and Sutton note that internal variability dominates on decadal or shorter time scales and is more important at smaller (e.g., regional) space scales. Natural variability is usually explored by running ensembles of climate model simulations using different initial conditions for each simulation. Traditionally the number of ensemble members has not been large (e.g., around three in the Coupled Model Intercomparison Project, Phase 3 [CMIP3] data set), nor has it been based on rigorous statistical considerations. In addition, estimation of natural variability using models is limited by inherent uncertainty in the models because of parametric and structural uncertainty.

In this regard, the role of internal variability has been underinvestigated in the exploration of future climate change, although recent research on larger ensembles (e.g., Deser et al., 2010) has developed improved measures of natural variability and underscored how substantial it can be particularly on regional scales (Deser et al., 2012).

### *Uncertainty in Intraseasonal to Interannual (ISI) Climate Predictions*

Intraseasonal to interannual (ISI) climate predictions, which have recently been extended to lead times of a decade or longer (CMIP5; Taylor et al., 2012), rely on two important sources of predictability—processes or variables such as upper ocean heat content and soil moisture that have memory relevant to the ISI time scale, and predictable patterns of variability, such as teleconnection patterns associated with the El Niño/Southern Oscillation, which involve complex dynamics of atmosphere-ocean feedback. Incomplete knowledge of all the relevant long-memory reservoirs, as well as the imperfect ability of models to accurately simulate patterns or modes of variability, and intrinsic loss of predictability due to chaotic behavior of the Earth system, all contribute to uncertainty in ISI predictions. Last, ISI predictions are limited by our inability to accurately initialize the climate system, as a result of instrumental and algorithmic uncertainty in measurements, as well as uncertainty in synthesizing these measurements using data assimilation systems used to derive the initial conditions.

**Finding 6.1: There are important uncertainties in the response of the climate system to future forcings, including uncertainties due to inadequate representation**

**and spatial resolution of some processes and features in current climate models, and uncertainties inherent in both dynamical and statistical downscaling methods for making local climate projections. Climate predictions and projections are subject to uncertainty resulting from the incomplete knowledge of initial conditions of the relevant components and internal variability of the climate system, which depends on the time scale being considered.**

## QUANTIFYING UNCERTAINTIES

Quantitative estimates of uncertainty are often required by users of climate model-based information and are also important in the developing and improving climate model predictions and projections. Among the several types and sources of uncertainty described above, some are more quantifiable than others.

### Weighting of Models

One of the important further developments since the IPCC Fourth Assessment Report is the consideration of the relative value of simulations from different (global) climate models in, for example, MMEs. Most prior work assumed that all climate models have the same value for producing information regarding climate change (Meehl et al., 2007), and thus models should be equally weighted (i.e., taking the simple average of all simulations). However, some work has been produced that allowed for the weighting of models differentially based, for example, on the magnitude of model biases (Christensen et al., 2007; Giorgi and Mearns, 2003), the exclusion of "poor performing" models (e.g., Dominguez et al., 2010; Smith and Chandler, 2010), or other criteria (e.g., Watterson, 2008). Others assert that understanding of the models or the climate system is inadequate to make such distinctions (Gleckler et al., 2008; Knutti, 2008; Pincus et al., 2010), while still others have suggested that the ensembles and/or the record lengths are too small to robustly establish weights that are significantly different from each other (DelSole et al., 2011; Deque and Somot, 2010; Knutti, 2010; Pierce et al., 2009). There is some question about how different models are from one another (Palmer et al., 2005; Pennell and Reichler, 2011).

Some uncertainties, such as structural uncertainty due to incomplete or poor representation of processes in climate models, do not readily lend themselves to quantification. This is a very important issue, because without recognition of structural uncertainty, the probability distribution functions derived from ensembles can be seriously misinterpreted. Neither MMEs nor PPEs includes consideration of all the known uncertainties, which could lead to overconfidence about the characterization of uncertainty (Curry and Webster, 2011). There remains an important research topic in how to combine quantifiable uncertainties (e.g., from ensembles) with unquantifiable uncertainties (e.g., incomplete representation of processes).

MMEs are also used in ISI prediction as a simple approach for quantifying forecast uncertainty (Kirtman and Min, 2009; Palmer et al., 2004). Some studies using MME from the DEMETER (Development of a European Multimodel Ensemble System for Seasonal to Interannual Prediction) seasonal prediction archive showed that MME often outperforms any individual model (e.g., Jin et al., 2008). Besides MME, PPE and stochastic physics have also been used to quantify ISI forecast uncertainty, but it is not clear how different methods compare or whether combining different methods or different ways to combine models within MME and PPE may further improve prediction skill.

### Advances in Probabilistic Methods

There has been considerable recent development in quantifying uncertainty using probabilistic methods. Generally these methods are applied either to MMEs (i.e., simulations based on different models but that used the same external forcings) or to PPEs. Some studies have sought to determine unequal weights for different models (Brekke et al., 2008; Buser et al., 2009; Furrer et al., 2007; Greene et al., 2006; Pitman and Perkins, 2009; Smith et al., 2009; Suppiah et al., 2007; Tebaldi et al., 2005; Watterson, 2008). Other studies have eschewed weighting (Giorgi, 2008; Ruosteenoja et al., 2007). With the development of ensembles of regional climate model simulations, methods particularly adapted to that context are emerging (e.g., Deque and Somot, 2010; Sain et al., 2011). These studies are being used in impacts analysis; for example, Tebaldi and Lobell (2008) adopted the methods of Tebaldi et al. (2005) for rendering probabilities of climate change and adapted it to generate probabilities of crop yield magnitudes under future climate.

There has also been considerable progress in generating methods for presenting joint probabilities, typically of temperature and precipitation (e.g., Tebaldi and Lobell, 2008; Tebaldi and Sanso, 2009; Watterson, 2012; Watterson and Whetton, 2011). This approach is particularly useful for application to impacts of climate change, because temperature and precipitation are the two most fundamental variables used for calculating many impacts.

Applying weightings to MME or PPE have also been explored in ISI prediction using, for example, a superensemble technique (Krishnamurti et al., 1999) and Bayesian combination (Rajagopalan et al., 2002; Robertson et al., 2004). An important distinction

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between uncertainty quantification for climate change and ISI prediction is that hindcasts play a more important role in the latter; models that perform better in hindcast are more likely to perform better in forecast on shorter time scales when the effects of nonstationarity are more minor, for example, as in ISI versus decadal to century time scales. In this sense, optimal selection and weighting of models can be an important piece of an overall strategy not only for quantification, but also for reduction, of uncertainty, leading to improvement in ISI prediction skill.

Uncertainty in weather and climate model parameterizations of subgrid-scale physical processes is being addressed through stochastic parameterization methods, which have been reported to improve the probabilistic reliability of seasonal forecasts by some climate models (see Chapter 4).

There are nascent efforts to reduce the climatological biases of models through multivariate optimization of uncertain parameters. Stainforth et al. (2005) randomly perturbed a set of uncertain parameters in a version of the UKMO climate model and compared 2,017 resulting models against a suite of climatological error metrics; the best of the perturbed models had a modest 15 percent error reduction over the control model. Jackson et al. (2008) used a more systematic multivariate sampling and optimization approach on the CAM3 atmospheric general circulation model, finding 6 configurations of more than 500 tested that improved an overall measure of climatological error by 7 percent compared to the regular model. These improvements are significant but modest, and the parameter optimization needs to be repeated each time a new model version or a change in grid resolution is introduced. This experience suggest that, as models get more complex, periodic automatic parameter optimization may be valuable, but perhaps more as a device to save human effort involved in trial-and-error optimization (at the cost of more computer time) rather than as a method to make a model of substantially higher fidelity. Furthermore, it suggests that the systematic errors related to uncertain parameters in climate models are heavily compensating, such that improvements in one field are balanced by degradation in another so that the overall result is something of a wash.

Hence, it seems likely that structural errors in parameterizations or inadequacies in grid resolution not correctable by parameter tuning are probably a larger driver of systematic errors and projection uncertainty than suboptimal choices of existing uncertain parameters. In this environment, there is a tradeoff between maintaining fluidity of the model development process and the huge investment of computer time needed to apply the rigorous principles of uncertainty quantification and optimization. Some modeling groups, such as the Geophysical Fluid Dynamics Laboratory, are experimenting with some automatic parameter tuning as a routine part of model development; what is needed is developing pragmatic methodologies that get most of the benefit with a minimum of time waiting for simulations to finish.

While there has been considerable development in quantifying uncertainties regarding climate models, uncertainty quantification (UQ) is a field important to many different disciplines, particularly those that use models (NRC, 2012a). The climate modeling community could benefit from assessing new methods being developed in other disciplines (NRC, 2012a). Certain government agencies, such as the Department of Energy, are supporting multiple research efforts in such topics as advancing UQ in modeling, simulation, and analysis of complex systems.[1]

In general, more careful consideration of uncertainty can serve multiple purposes of model improvement and better utilization of model predictions and projections.

## Reducing Uncertainties in the Climate Change Problem

Although there has been much progress in characterizing and quantifying uncertainty about future climate change, less progress has been made in the arena of reducing uncertainty. This is a complex issue, because it depends on what type of uncertainty is being reduced and how that particular uncertainty is quantified.

There has been steady reduction in uncertainty about the causes of current climate change, as expressed in the series of IPCC reports, such that in the 2007 report (IPCC, 2007d) it is stated that "[m]ost of the observed increase in global temperatures since the mid-20th century is very likely (i.e., 90% confidence) due to the observed increase in greenhouse gas concentrations." This is primarily due to observation of continuing global warming and many of its anticipated corollaries consistent with the range of climate model predictions.

However, uncertainty in projections of future climate change is reducing more slowly. Before 2070, uncertainty about climate sensitivity is most important for projection of global-mean climate change. IPCC assessments suggest this uncertainty has not significantly decreased since 1990. It is unclear by how much this metric of uncertainty will be reduced over the next decade. Large regional projection uncertainties, especially in subtropical and summertime midlatitude precipitation, are added to this uncertainty in climate sensitivity; again, more research may beat these uncertainties down, but this may take time. Past 2070, uncertainty about GHG concentrations due to emissions uncertainty (which is difficult to reduce) is more important to projection of

[1] http://science.energy.gov/ascr/funding-opportunities/faq-for-math/ (accessed October 11, 2012).

global surface air temperature than is climate model uncertainty (IPCC, 2007c, Figure 10.29). Morgan et al. (2009) has noted that "in some cases, all the research in the world may not eliminate key uncertainties on the timescale of decisions we must make."

**Finding 6.2: The climate science community has made considerable progress in quantifying uncertainty in climate simulations, but progress in reducing certain types of uncertainty has been slow, and further reduction may not be possible for certain aspects of long-term projections.**

## COMMUNICATING UNCERTAINTY

Communicating uncertainty is a relevant topic for advancing climate modeling because it relates to decision making (see next section) for adaptation, mitigation, and regarding what aspects of a model may be most important to improve. The appropriate approach to communication depends on the particular audience and on the purpose of the communication. Moreover, the appropriate approach to communication partially depends on the purpose of the communication. Is it for general education, making people aware of important issues, or is it to inspire specific actions regarding managing climate resources, or is it for the sake of shaping the needs for future climate model development? Communications of scientists to scientists about uncertainty are very different from their communication with the lay public.

### Review of Communication Approaches

There has been a steady increase in the attention that communicating about climate and climate change has received, and this communication has been carefully considered within the community of scientists. For example, in IPCC (2007c) there were descriptions of scientific understanding and likelihood of specific results. A standard language was developed with narrative terms; for example, "likely" was linked to quantitative statistics, >66 percent probability. An entire Synthesis and Assessment Report (SAP) of the Climate Change Science Program (CCSP, 2009) was dedicated to establishing best practice approaches of characterizing and communicating uncertainty (Morgan et al., 2009). In *Advancing the Science of Climate Change* (NRC, 2010b), considerable effort is devoted to describing the terminology of uncertainty, the nature of uncertainty in the culture of science, and the use of uncertainty in decision making. This section emphasizes and discusses some issues associated with the communication of uncertainty that have evolved or emerged since these earlier works and that are relevant to climate modeling.

The primary focus of the works cited above is how scientists can communicate uncertainty about climate change. From these, it is apparent that there is no simple formulaic way to communicate uncertainty, and in order to develop effective communication strategies, social-science based empirical studies are needed.

Lemos and Morehouse (2005) introduce another element of communication in their study of the effective use of climate information. They document that teams of both scientists and nonscientists working in a problem-solving environment to cogenerate solution strategies are effective. The communication of uncertainty of climate change involves not only scientists providing their descriptions to decision makers, but also learning what is usable information for the decision makers. The question becomes: does what we are doing make sense to and for the decision maker?

As stated in the SAP on transportation (CCSP, 2008):

> Transportation decision makers are well accustomed to planning and designing systems under conditions of uncertainty on a range of factors—such as future travel demand, vehicle emissions, revenue forecasts, and seismic risks. In each case, decision makers exercise best judgment using the best information available at the time. In an ongoing iterative process, plans may be revised or refined as additional information becomes available. Incorporating climate information and projections is an extension of this well developed process.

With this in mind, uncertainty about climate change is often not the most important or largest uncertainty faced by the decision maker. This suggests that descriptive statements about climate change uncertainty that are appropriately placed in the context of these other uncertainties could constitute effective communication that would accelerate the use and effectiveness of climate change knowledge in decision making.

The ways decision makers use information about climate change uncertainty complicate the problem of effectively communicating that information. Common, intuitively communicative language is necessary, but not sufficient. How decision makers view the definition and role of uncertainty must be taken into account. A model developer will identify uncertainties associated with comparisons of models to observations and uncertainties from processes not included in the model. A user of climate information will have uncertainty associated with its perception of the process of model evaluation or validation. As discussed above, other sources of uncertainty referred to by climate modelers include boundary conditions, initial conditions, formulation of physics, parametric, numerical formulation, downscaling, and so on. These different ways of

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describing sources of uncertainty are all useful, perhaps definitive, in their context, but collectively they amplify the challenges of communication.

This complex texture of types of uncertainty suggests the need for multiple strategies of communication. Above, uncertainty communication was implicitly framed as communication to nonscientist decision makers. However, when developing a strategy for improving the U.S. climate modeling enterprise, the communication to and subsequent use of information by scientific program managers is also important. It may seem attractive to pose scientific programs guided by uncertainty reduction, but this may not be realized in a systematic way in complex problem solving. Similarly, it is consistent with scientific culture to work toward quantification of uncertainty, reducing the definition of uncertainty to a small set of numbers that does not express the complexity of the climate. Again, this might be necessary, but it certainly is not sufficient. It does not represent the "expert judgment" form of uncertainty.

**Finding 6.3: There is no simple, formulaic way to communicate uncertainty. To develop effective and consistent communication strategies, social science-based empirical studies are needed.**

### Examples of Current Approaches to Communicating Uncertainty

It is hoped that approaches to communicating uncertainty will become much more sophisticated in the coming decades, that the different needs for quantification in different science and policy communities will be well recognized, that means of presenting uncertainties will have greatly advanced so as to match the needs of the particular community, and that more creative ways of communicating uncertainty to the lay public and policy makers alike will be developed. These advances will entail greater interdisciplinarity—embracing climate modelers and climate analysts, experts in quantifying and communicating uncertainties and in decision making under uncertainty, and the target audiences themselves. More strategic approaches in communication are needed as summarized by Pidgeon and Fischhoff (2011):

> Communications worthy of climate change will require sustained contributions from cross-disciplinary teams, working within an institutional framework that provides support for their efforts. Such teams would include, at minimum, climate and other experts, decision scientists, social and communications specialists, and program designers. Once assembled, these teams must be coordinated so that experts stay focused on their aspect of the communication process. For example, subject-matter experts should edit for fact, not style; they should also check that social scientists have not garbled the facts when trying to make them clearer. That coordination must maintain

a rhetorical stance of non-persuasive communication, trusting the evidence to speak for itself, without spin or coloring.

These advances could be facilitated through the creation of resource centers to provide climate modelers with support in designing and empirically evaluating communications, including communication of uncertainty. There are fledgling activities that have begun to emerge that have focused on effective communication of climate science, such as the Yale Project on Climate Change Communication,[2] a nonprofit science and outreach project called Climate Communication,[3] and the commentary site RealClimate.[4] This effort could also be furthered by more actively engaging the media through agencies dedicated to the reporting of science such as the Society of Environmental Journalists,[5] the Yale forum on Climate Change and the Media,[6] and Climate Central.[7]

Although these and other resources (Somerville and Hassol, 2011; Ward, 2008) are starting to become more available, there are very few programs aimed at training climate scientists in lay communication or in targeting groups of scientists or professionals (such as weather forecasters) who play large roles in communicating to the public. One of the most prominent programs is the Climate Change Education Partnership (CCEP) Program from the National Science Foundation. CCEP "seeks to establish a coordinated national network of regionally- or thematically-based partnerships devoted to increasing the adoption of effective, high quality educational programs and resources related to the science of climate change and its impacts."[8] This program, begun in 2010, brings together climate scientists, learning scientists, and education practitioners, to work on issues focused on regional or thematic climate change impacts.

**Finding 6.4: The issue of communication of uncertainty to a wide range of audiences has received more attention over the past few years—at annual scientific meetings, for example—but further progress in developing well-formulated communication strategies is needed.**

**Finding 6.5: Communication of uncertainty is a challenge within the climate modeling community: more sophisticated approaches that include the involvement of experts across disciplines and the consideration of communication from**

[2] http://environment.yale.edu/climate/about/ (accessed October 11, 2012).
[3] http://climatecommunication.org/ (accessed October 11, 2012).
[4] http://www.realclimate.org/ (accessed October 11, 2012).
[5] http://www.sej.org/ (accessed October 11, 2012).
[6] http://www.yaleclimatemediaforum.org/ (accessed October 11, 2012).
[7] http://www.climatecentral.org/ (accessed October 11, 2012).
[8] http://www.nsf.gov/funding/pgm_summ.jsp?pims_id=503465 (accessed October 11, 2012).

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**the beginning of any particular climate model-based research project or program could help address this challenge.**

## UNCERTAINTY AND DECISION MAKING

Although the focus in this report is on advances in climate modeling, it is important to consider what the results of climate models are used for. Many statements are made about the importance of location-specific information to inform decision making regarding coping with climate change. But the decision-making landscape is highly complex and varied. It is difficult to come up with a small collection of robust statements about the needs of decision makers (NRC, 2010d).

There may be major differences regarding how resource managers manage uncertainty about climate now and what will be needed for managing uncertainties about climate and other important elements in the near and long-term future. There is also substantial variability in how uncertainty is managed based on which resource is being managed (e.g., water resources, human health, and transportation infrastructure), the spatial scale of the decision frame (within a municipality, regional, or national), and the time horizon relevant for the decision (annual versus half-century).

There has been rapid development of new approaches to decision making and application of modes of decision making to new contexts. In these contexts it is well recognized that management decisions involve uncertainty and that in many cases significant uncertainty cannot be eliminated (NRC, 2010d). There has been considerable research about robust decision making (RDM; Lempert et al., 2004). In this approach decisions are made that are robust against the uncertainties to be faced about the future (e.g., climate, population, governance structures, etc.) (Lempert and Groves, 2010). The RDM approach has particularly been applied in the context of water resources, because the infrastructure associated with water resource management is particularly long lived (e.g., dams with lifetimes of 100 years). A related approach is iterative risk management (IRM), wherein it is recognized that we will learn more about the future as the future unfolds, and thus decisions made now may be revisited and perhaps altered as new information about the future becomes available (NRC, 2010d). How important it is to reduce uncertainty of regional climate change depends closely on the approach being used for decision making under uncertainty. The RDM or IRM approaches may be much less in need of a rapid reduction in uncertainty than an approach that needs a high degree of certainty to make any decision at all. The promise of uncertainty reduction, when not realized, stands as a metric of poor management, poor scientific method, or outright scientific failure. A meaningful codification of uncertainty for specific applications (e.g., model development) and alignment of development priorities with addressing those uncertainties stands to improve the communication of climate change to political decision makers and to organize model development priorities. There is new appreciation for involving decision makers directly in both discussions of uncertainty about climate change, and of their decision-making needs for quantification of uncertainties. For example, in work with the integrated Regional Earth System Model (iRESM), regional decision makers and other stakeholders from the pilot region have been engaged in the modeling process to guide, among other things, uncertainty characterization relevant to their decision making (Rice et al., 2012).

The development of the shared socioeconomic pathways that will be related to the representative concentration pathways used for the IPCC Fifth Assessment Report may provide a new opportunity for quantifying uncertainties in possible future socioeconomic conditions. There may also be means of reducing uncertainty regarding future concentrations of greenhouse gases by better characterization of surface processes (including land-use change) contributing to the concentrations of greenhouse gases and aerosols.

**Finding 6.6: Resource managers and decision makers have diverse and evolving methods for handling climate change uncertainty.**

## THE WAY FORWARD

Knowledge about future climate has increased rapidly over the past two decades, and a number of facts about future climate are robust, such as that global temperature will increase, that greater increases in temperature will occur over land than ocean, that sea level will rise, and that substantial changes in the hydrologic cycle will occur. Nonetheless, important uncertainties remain, particularly regarding climate sensitivity, GHG emissions, and regional details about climate change. As new components of the Earth system are included into models, they may in fact (especially over the short term) increase the spread of certain predictions between models, as uncertainty previously not encompassed within the modeling framework is internalized (e.g., removing flux adjustment from coupled models). Some uncertainties are unlikely to be reduced over the next decade or so (for example, uncertainty in future emissions, a very important component of long-term climate change). But uncertainty due to model inadequacy or incompleteness should be reduced in the next 15-20 years. In addition, adding new components to the model helps reduce uncertainty about their response to a perturbed climate. For instance, adding a well-tested sea-ice representation to a climate model is a good strategy for reducing uncertainty about how fast sea ice might be lost during a climate change, even if it does not reduce uncertainty about the accompanying global-mean warming. The committee's strategy for climate modeling in the United States is intended to facilitate these advances and improve the understanding of the uncertainties in climate model projections (Chapter 14).

Although improvements in uncertainty characterization and quantification will proceed, particularly in the context of various kinds of climate model ensembles, it is less clear that convincing means of combining known qualitative (i.e., structural) uncertainties with these quantitative methods will be developed. Moreover, while much attention has been paid recently to developing means of differentially weighting different ensemble methods, we are not yet at a point where a consensus on how to proceed has been reached. Obviously limits to predictability constrain reduction in uncertainty, a possible issue for decadal forecasting. A probabilistic framework, rather than methods used in deterministic prediction, better characterizes uncertainty. Work on better characterizing uncertainty will need to be done on an ongoing basis. The committee suggests that a working group in the proposed annual climate modeling forum would be an appropriate venue to explore these issues (see Chapter 13).

**Recommendation 6.1: Uncertainty is a significant aspect of climate modeling and should be properly addressed by the climate modeling community. To facilitate this, the United States should more vigorously support research on uncertainty, including**

- **understanding and quantifying uncertainty in the projection of future climate change, including how best to use the current observational record across all time scales;**
- **incorporating uncertainty characterization and quantification more fully in the climate modeling process;**
- **communicating uncertainty to both users of climate model output and decision makers; and**
- **developing deeper understanding on the relationship between uncertainty and decision making so that climate modeling efforts and characterization of uncertainty are better brought in line with the true needs for decision making.**