U.S. Climate Change Science Program

Synthesis and Assessment Product 5.2

Best Practice Approaches for Characterizing, Communicating and Incorporating Scientific Uncertainty in Climate Decision Making

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Preface

This report is one of 21 Synthesis and Assessment Products (SAPs) commissioned by the U.S. Climate Change Science Program (CCSP) as part of an interagency effort to integrate federal research on climate change and to facilitate a national understanding of the critical elements of climate change. Most of these reports are focused on specific substantive issues in climate science, impacts and related topics. In contrast, the focus of this report is methodological.

Uncertainty is ubiquitous. Of course, the presence of uncertainty does not mean that people can not act. As this report notes, in our private lives, we decide where to go to college, what job to take, whom to marry, what home to buy, when and whether to have children, and countless other important choices, all in the face of large, and often, irreducible uncertainty. The same is true of decisions made by companies and by governments.

Recent years have seen considerable progress in the development of improved methods to describe and deal with uncertainty. Progress in applying these methods has been uneven, although the field of climate science and impact assessment has done somewhat better than many others.

The primary objective of this report is to provide a tutorial to the climate analysis and decision-making communities on current best practice in describing and analyzing uncertainty in climate-related problems. While the language is largely semi-technical, much of it should also be accessible to non-expert readers who are comfortable with treatment of technical topics at the level of journals such as *Scientific American*. We have also prepared a "Non-Technical

Summary." Readers who lack the time or background to read the detailed report, may prefer to start there, and then sample from the main report as they find topics they would like to learn about in greater depth.

Executive Summary

This report begins with a discussion of a number of formulations of uncertainty and the various ways in which uncertainty can arise. It introduce several alternative perspectives on uncertainty including both the classical frequentist view of probability and the subjectivist view in which probability is an indication of degree of belief, informed by all available evidence. A distinction is drawn between uncertainty about the value of specific quantities and uncertainty about the underlying functional relationships among key variables. The question of when it is and is not appropriate to represent uncertainty with a probability distribution is explored. Part 1 of the report closes with a discussion of "ignorance," and the fact that while research often reduces uncertainty, it need not always do so, and indeed in some cases may actually lead to greater uncertainty as new unanticipated complexities are discovered.

Part 2 argues that it is insufficient to describe uncertainty in terms of qualitative language, using words such as "likely" or "unlikely." Empirical evidence is presented that demonstrates that such words can mean very different things to different people, or indeed, different things to the same person in different contexts. Several simple strategies that have been employed to map words into probabilities in the climate literature are described.

In order to make judgments about, and in the presence of uncertainty, the human mind employs a variety of "cognitive heuristics." In many circumstances these serve well. However, in some settings they can lead to significant biases in the judgments that people make. Part 3 summarizes key findings from the experimental literature in behavioral decision making, and discusses a number of the cognitive biases that can arise, including overconfidence, when reasoning and making decisions in the face of uncertainty.

Once uncertainty has been described in a quantitative form, a variety of analytical tools and models are available to perform analysis and support decision making. Part 4 provides a brief discussion of a number of statistical models used in atmospheric and climate science. This section also discusses methods for hypothesis and model testing as well as a variety of emerging methods and applications. While the treatment is general, the focus throughout is on climate-related applications. A boxed section provides an illustration of frequentist and Bayesian approaches applied to the prediction of rainfall.

Part 5 explores two broad methods for estimating uncertainty: model-based approaches and the use of expert judgment obtained through careful systematic "expert elicitation." In both cases illustrations are provided from the climate literature. Issues such as whether and when it is appropriate to combine uncertainty judgments from different experts, and strategies that have been used to help groups of experts develop probabilistic judgments about quantities and model forms, are discussed.

Part 6 explore the issues of how best to propagate uncertainty through models or other decision making aids, and more generally the issues of performing analysis of and with uncertainty. Again illustrative examples are drawn from the climate literature. Part 7 then explore a range of issues that arise in making decisions in the face of uncertainty, focusing both on classical decision analysis that seeks "optimal strategies," as well as "resilient strategies" that work reasonably well across a range of possible outcomes, and "adaptive" strategies that can be modified to achieve better performance as the future unfolds. This section closes with a discussion of deep uncertainty, surprise, and some additional issues related to the discussion of behavioral decision theory building on ideas introduced in Part 3.

Part 8 addresses a number of issues that arise in communicating about uncertainty, again drawing on the empirical literature in psychology and decision science. Mental model methods for developing communications are outlined. One key finding is that there is no such thing as an expert in communication – in the sense of someone who can tell you ahead of time how a message should be framed, or what it should say. Empirical study is absolutely essential to the development of effective communication. The section closes with an exploration of the views of a number of leading scientists and journalists who have worked on the difficult problems that arise in the communicating about scientific uncertainty.

Finally Part 9 offers some summary advice. It argues that doing a good job of characterizing and dealing with uncertainty can never be reduced to a simple cookbook. One must always think critically and continually ask questions such as:

- Does what we are doing make sense?
- Are there other important factors which are, as or more important, than the factors we are considering?
- Are there key correlation structures in the problem that are being ignored?
- Are there normative assumptions and judgments about which we are not being explicit?

Then, based both on the finding in the empirical literature, as well as the diverse experience and collective judgment of the writing team, it goes on to provide some more specific advice on reporting uncertainty and on characterizing and analyzing uncertainty. That advice can be found on pages 142 through 148.

Non-Technical Summary

Vaclav Smil (2007), one of the most wide ranging intellects of our day, observes that "the necessity to live with profound uncertainties is a quintessential condition of our species." Two centuries ago, Benjamin Franklin (1789), an equally wide ranging intellect of his day, made the identical observation in more colorful and colloquial language when he wrote that "in this world nothing is certain but death and taxes" and of course, even in that case, the date of ones death, and the amount of next year's taxes are both uncertain.

Those views about uncertainty certainly apply to many aspects of climate change and its possible impacts, including:

- How the many complex interactions within and among the atmosphere, the oceans, ice in the Arctic and Antarctic, and the living "biosphere," shape local, regional and global climate;
- How, and in what ways, climate has changed over recent centuries and is likely to change over coming decades;
- How future human activities and choices may result in emissions of gases and fine particles and may change land use and vegetation that together can influence future climate;
- How those changes will affect the climate;
- What impacts a changed climate will have on the natural and human world; and
- How the resulting changes in the natural and human world will feed back on and influence climate in the future.

Clearly the climate system, and its interaction with the human and natural world, is a prime example of what scientists call a "complex dynamic interactive system."

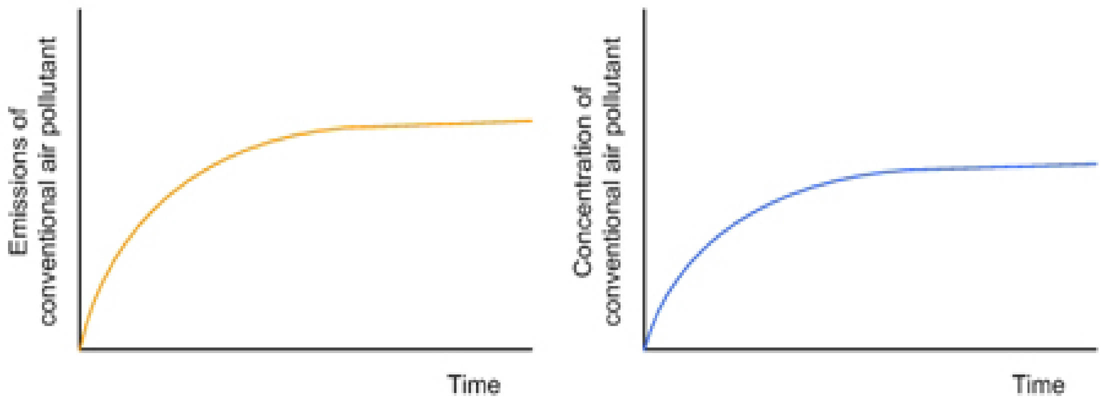
This report is not about the details of what we know, do not know, could know with more research, or may not be able to know until years after climate has changed, but about these complex processes. These issues are discussed in detail in a number of other reports of the U.S. Climate Science Research Program (CCSP), as well as reports of the Intergovernmental Panel on Climate Change (IPCC), the United States National Research Council, and special studies such as the United States National Assessment, and the Arctic Climate Impact Assessment[8].

However, for non-technical readers who may not be familiar with the basics of the problem of climate change, we offer a very simple introduction in Box NT-1

BOX NT-1 Summary of Climate Change Basics

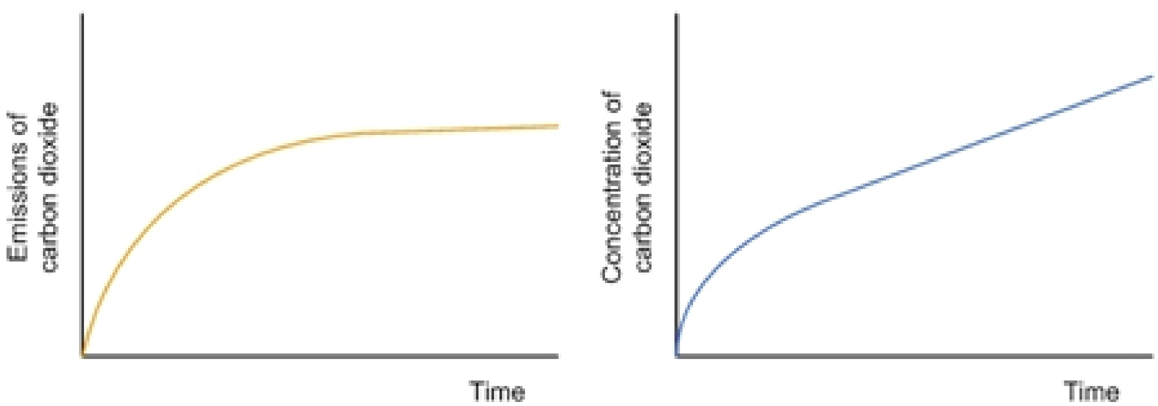
Carbon dioxide is released to the atmosphere when coal, oil or natural gas is burned. Carbon dioxide is not like conventional air pollutants such as sulfur dioxide, oxides of nitrogen or fine particles. When the emissions of such conventional pollutants are stabilized, their atmospheric concentration is also quickly stabilized since these pollutants remain in the atmosphere for only a matter of hours or days. The relationship between emissions and concentrations for these conventional pollutants is illustrated in this simple diagram:

[8] For access to the various reports mentioned in this sentence see respectively: <www.climatescience.gov/>; <www.ipcc.ch>; <www.nationalacademies.org/publications/>; <www.usgcrp.gov/usgcrp/nacc/default.htm>; and <www.acia.uaf.edu/>.

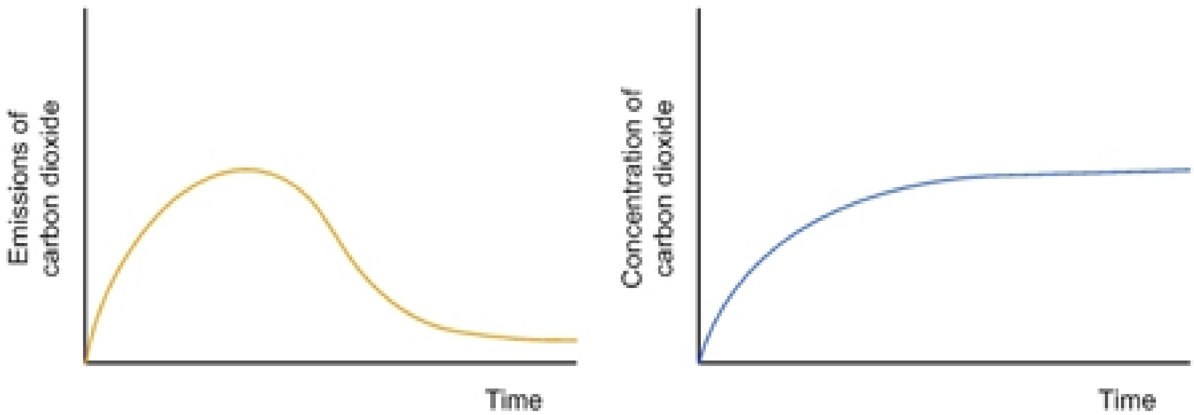


This is not true of carbon dioxide or most other greenhouse gases.

Much of the carbon dioxide that is emitted stays in the atmosphere for over 100 years. Thus, if emissions are stabilized, concentrations will continue to build up, in much the same way that the water level will rise in a bathtub being filled from a faucet that can add water to the tub much faster than a small drain can let its drain out. Again the situation is summarized in this simple diagram:



In order to stabilize atmospheric concentrations of carbon dioxide, worldwide emissions must be dramatically reduced (most experts would say by something like 70 to 90% depending on the assumptions made about the processes involved and the concentration level that is being sought). Again, here is a simple diagram:



Summarizing, there are three key facts that it is important to understand to be an informed participant in policy discussions about climate change:

- When coal, oil and natural gas (*i.e.* fossil fuels) are burned, carbon dioxide (CO_2) is created and released into the atmosphere. There is *no* uncertainty about this.
- Because CO_2 (and other greenhouse gases) trap heat, if more is added to the atmosphere, warming will result that can lead to climate change. Many of the details about how much warming, how fast, and similar issues *are* uncertain.
- CO_2 (and other greenhouse gases) are not like conventional air pollution such as SO_2 , NO_x or fine particles. Much of the CO_2 that enters the atmosphere remains there for more than 100 years. In order to reduce concentration (which is what causes climate change), emissions must be dramatically reduced. There is no uncertainty about this basic fact, although there is uncertainty about how fast and by how much emissions must be reduced to achieve a specific stable concentration. Most experts would suggest that a reduction of between 70 and 90% is needed. This implies the need for dramatic changes in energy and other industrial systems all around the globe.

END BOX NT-1

This report provides a summary of tools and strategies that are available to characterize, analyze and otherwise deal with uncertainty in characterizing, and doing analysis of climate change and its impacts. The report is written to serve the needs of climate scientists, experts assessing the likely impacts and consequences of climate change, as well as technical staff supporting private and public decision makers. As such, it is rather technical in nature, although in most cases we have avoided mathematical detail and the more esoteric aspect of the methods and tools discussed – leaving those to references cited throughout the text.

The report explores eight aspects of this topic. Then, in Section 9, the report concludes with some guidance for researchers and policy analysts that is based both on relevant scientific literature and on the diverse experience and collective judgment of the writing team.

Part 1: Sources and types of uncertainty

Uncertainty arises in a number of ways and for a variety of reasons. First, and perhaps simplest, is uncertainty in measuring specific quantities, such as temperature, with an instrument, such as a thermometer. In this case, there can be two sources of uncertainty.

The first is random errors in measurement. For example, if you and a friend both look at typical back-yard thermometer, and record the temperature, you may write down slightly different numbers because the two of you may read the location of red line just a bit differently. Similar issues arise with more advanced scientific instruments.

The second source of uncertainty that may occur involves a "systematic" error in the measurement. Again, in the case of the typical back-yard thermometer, perhaps the company that printed the scale next to the glass, didn't get it on in just the right place, or perhaps the glass slid a bit with respect to the scale. That could result in all the measurements that you and your friend write down being just a bit high or low, and, unless you checked your thermometer against a very accurate one (*i.e.*, "calibrated" it), you'd never know this problem existed. Again, similar issues can arise with more advanced scientific instruments.

Beyond random and systematic measurement errors lies a much more complicated kind of potential uncertainties. Suppose, for example, you want to know how much rain your garden will receive next summer. You may have many years of data on how much rain has fallen in your area during the growing season, but, of course, there will be some variation from year-to-year. You can compute the average, but if you want to have an estimate for *next* summer, the average does not tell you the whole story. In that case, you will want to look at the distribution of the amounts that fell over the years, and figure out the odds that you will get varying amounts by examining how often that amount occurred in the past.

Continuing with this example, if sum rainfall in your region is gradually changing over the years (either because of natural long-term variability or because of systematic climate change) using the distribution of past rainfall will not be a perfect predictor of future rainfall. In this case, you will also need to look at (or try to predict) the trend over time.

Finally, suppose that you want to know the odds that there will be more rain than the 45 inches, and suppose that over the past century, there has been only one growing season in which there has been more than that much rain. In this case, since you don't have enough data for reliable statistics, you will have talk to experts (and perhaps have them use a combination of models, trend data, and expert judgment) to get you an estimate of odds.

Finally, suppose (like most Americans, the authors included) you know nothing about sumo wrestling, but you need to know the odds that a particular sumo wrestler will win the next international championship. In that case, your best option is probably to carefully interview a number of the world's leading sumo coaches and sports commentators and "elicit" odds from each of them. Analysts often do very similar things when they need to obtain odds on the future value of specific climate quantities. This process is known as "expert elicitation." Doing it well takes careful preparation and execution. Results are typically in the form of distributions of odds called "probability distributions."

All of these examples involve uncertainty about the value of some quantity such as temperature or rainfall. There can also be uncertainty about how a physical process works. For example, before Isaac Newton figured out the law of gravity, that says the attraction between two masses (like the sun and the earth; or an apple and the earth) is inversely proportional to the product of the two masses and inversely proportion to the square of the distance between them, people were uncertain about how gravity worked. However, they certainly knew from experience that something like gravity existed. We call this kind of uncertainty "model uncertainty." In the context of the climate system, and the possible impacts of climate change, there are many cases were we do not understand all the physical, chemical and biological processes that are involved – that is there are many cases in which we are uncertain about the underlying "causal model." This type of uncertainty is often more difficult to describe and deal with than uncertainty about the value of specific quantities, but progress is being made on developing methods to address it.

Finally there is ignorance. For example, when Galileo Galilei first began to look at the heavens through his telescope, he may have had an inkling that the earth revolved around the sun, but he had no idea that the sun was part of an enormous galaxy, and that our galaxy was just one of billions in an expanding universe. Similarly, when astronomers built the giant 200-inch telescope on Mount Palomar they had no idea that at the center of our galaxy lay a massive "black hole." These are examples of scientific ignorance. Only as we accumulate more and more evidence that the world does not seem to work exactly like we think it does, do scientists begin to get a sense that perhaps there is something fundamental going on that they have not previously recognized or appreciated. Modern scientists are trained to keep looking for indications of such situations (indeed that's what wins Nobel prizes) but even when a scientist is looking for such evidence, it may be very hard to see, since all of us, scientists and non-scientists alike, view the world through existing knowledge and "mental models" of how things around us work. There may well still be a few things about the climate system, or climate impacts, about which we are still completely ignorant – and don't even know to ask the right questions.

While Donald Rumsfeld (2002) was widely lampooned in the popular press, he was absolutely correct when he noted that "…there are known unknowns. That is to say, we know there are some things we do not know. But there are also unknown unknowns, the ones we don't know we don't know." But perhaps the ever folksy but profound Mark Twain put it best when he noted "It ain't what you don't know that gets you in trouble. It's what you know for sure that just ain't so."

Part 2: The importance of quantifying uncertainty

In our day-to-day discussion, we use words to describe uncertainty. We say:

"I think it is very likely she will be late for dinner."

"I think it is unlikely that the Pittsburgh Pirates will win next year's World Series."

"I'll give you even odds that he will or will not pass his drivers test."

"They say nuclear war between India and Pakistan is unlikely next year."

"The doctor says that it is likely that the chemical TZX causes cancer in people."

People often ask, “Why not just use similar words to describe uncertainty about climate change and its impacts?”

Experimental studies have found that such words can mean very different things to different people. They can also mean very different things to the same person in different situations.

Think about betting odds. Suppose that to one person "unlikely" means that they think there is only 1 chance in 10 that something will happen, while to another person the same word means they think there is only one chance in a thousand that that same thing will happen. In some cases, that difference could be very important. For example, in the second case, you might be willing to make a big investment in a company if your financial advisor tells you they are "unlikely" to go bankrupt – that is the odds are only 1 in 1000 that will happen. One the other hand, if by unlikely the advisor actually means a chance of 1 in 10, you might not want to put your money at risk.

The same problem can arise in scientific communication. For example, some years ago members of the EPA Science Advisory Board were asked to attach odds to the statement that a chemical was "likely" to cause cancer in humans or "not likely" to cause cancer in humans. Fourteen experts answered these questions. The odds for the word likely ranged from less than 1 in 10 down to about 1 in 1000! The range was even wider for the odds given on the word "not likely." There was even an overlap…where a few experts used the word "likely" to describe the same odds that other experts described as "not likely."

Because of results like this it is important to insist that when scientists and analysts talk about uncertainty in climate science and its impacts, they tell us in quantitative terms what they mean by the uncertainty words they use. Otherwise nobody can be sure of what they are saying.

The climate community has been better than a number of other communities (such as environmental health) in doing this. However, there is still room for improvement. In the final section of the report, the authors offer advice on how they think this should best be done.

Part 3: Cognitive challenges in estimating uncertainty

Humans are very good at thinking about and doing lots of things. However, experimental psychologists have found that the way our brains make some judgments, such as those involved in estimating and making decisions about uncertainty, involves unconsciously using some simple rules. These simple rules (psychologists call them "cognitive heuristics') work pretty well most of the time. However, in some circumstances they can lead us astray.

For example, suppose I want to estimate the odds that when I drive to the airport tomorrow morning, I'll see a state police patrol car. I have made that trip at that time of day many times in the past. So, unless there is something unusual going on tomorrow morning, the ease with which

I can imagine encountering a state police car on previous trips, will probably give me a pretty good estimate of the odds that I'll see one tomorrow.

However, suppose that instead I had to drive to the airport tomorrow at 3:30 a.m. I've never done that before (and hope I'll never have to do it). However, if I try to estimate the odds of encountering a state police car on that trip, experience from previous trips, or my imagination about how many state police may be driving around at that time of night, may not give me a very accurate estimate.

This strategy, that our minds use subconsciously to estimate probabilities in terms of how easily we can recall past events or circumstances, or imagine them in the future, is a "cognitive heuristic" called "availability". We make judgments in terms of how available experience or imagination is when our minds consider an issue of uncertainty.

Section 3 of the report describes several such cognitive heuristics. The description is largely non-technical so readers who find these issues interesting should find they could read this part of the report without much difficulty.

The other issue discussed in Section 3 of the report is overconfidence. There is an overwhelming amount of evidence from dozens of experimental studies done by psychologists and by decision analysts, that when people judge how well they know an uncertain quantity, they set the range of their uncertainty much to narrowly.

For example, suppose you ask a whole bunch of your adult friends how high Mt. McKinley in Alaska is, or how far it is between Philadelphia and Pittsburgh. But, you don't ask them just for their best guess. You ask them for a range. That is, you say, "give me a high estimate and a low estimate of the distance in miles between Philadelphia and Pittsburgh such that there are only 2 chances in 100 that the real distance falls outside of that range." Sounds simple, but when thousands of people have been asked thousands of questions like this, and their uncertainty range is compared with the actual values of the answers, the real answers fall outside of the range they estimated much more than 2% of the time (indeed, sometimes as much as almost half the time!).

What does this mean? It means that we all tend to be overconfident about how well we know things that we know are uncertain. And, it is not just ordinary people making judgments about ordinary things such as the weight of bowling balls or the distance from Philadelphia to Pittsburgh. Experts have the same problem.

What does all this have to do with climate change? It tells us that when scientists make estimates of the value of uncertain quantities, or when they, or decision makers, make judgments about uncertain science involving climate change and its impacts, these same processes will be operating. We can't completely get rid of the biases created by cognitive heuristics, nor can we completely eliminate over confidence. But, if we are aware of these tendencies, and the problems they can lead to, we may all be able to do a better job of trying to minimize their impacts.

Part 4: Statistical methods and models

Statistical methods and models play a key role in the interpretation and synthesis of observed climate data and the predictions of numerical climate models. The section provides a summary of some of the statistical methods being used for climate assessment, including procedures for detecting longer-term trends in noisy records of past climate that include year-to-year variations as well as various more periodic fluctuations. Such methods are especially important in addressing the question, "what long-term changes in climate are occurring?"

The section also discusses a number of other issues such as methods to assess how well alternative mathematical models fit existing. Methods for hypothesis testing and model selection are presented, and emerging issues in the development of statistical methods are discussed.

Rather than give a detailed technical tutorial, the focus of this section is more on identifying key strategies and analytical tools, and then referring expert readers to relevant review articles and more detailed technical papers.

Many non-technical readers will likely find much of the discussion in this section too detailed to be of great interest. However, many may find it useful to take a look at the boxed section "Predicting Rainfall: An illustration of frequentist and Bayesian approaches" that appears at the end of the section in which the problems of developing probabilistic descriptions (or odds) on the amount of future rainfall in some location of interest are discussed, first in the presence of various random and periodic changes (wet spells and dry spells) and then in the more complicated situation in which climate change (a long-term trend) is added.

Part 5: Methods for estimating uncertainty

Many of the facts and relationships that are important to understanding the climate system and how climate may change over the coming decades and centuries will likely remain uncertain for years to come. Some will probably not be resolved until substantial changes have actually occurred.

While a variety of evidence can be brought to bear to gain insight about these uncertainties, in most cases no single piece of evidence or experimental result can provide definitive answers. Yet research planners, groups attempting to do impact assessment, policy makers addressing emissions reductions, public and private parties making long-lived capital investment decisions, and many others, all need some informed judgment about the nature and extent of the associated uncertainties.

Two rather different strategies have been used to explore the nature of key uncertainties about climate science, such as the amount of warming that would result if the concentration of carbon dioxide in the atmosphere is doubled and then held constant (this particular quantity is called the "climate sensitivity").

The first section of Section 5 discusses a number of different ways in which climate models have been used in order to gain insight about, and place limits on the amount of uncertainty about key aspects of the climate system. Some of these methods combine the use of models with the use of expert judgments.

The second section of Section 5 discusses issues related to obtaining and using expert judgments in the form of probability distributions (or betting odds) from experts on what a key value might be based on their careful consideration and synthesis of all the data, model results and theoretical arguments in the literature. Several figures in the latter part of this discussion show illustrations of the types of results that can be obtained in such studies. One of the interesting findings is that when these methods are used with individual experts, the resulting impression of the overall level of uncertainty appears to be somewhat greater (that is the spread of the distributions is somewhat wider) than the results that emerge from consensus panels such as those of the IPCC.

Part 6: Propagation and analysis of uncertainty

Probabilistic descriptions of what is known about key quantities, such as how much warmer it will get as the atmospheric concentration of carbon dioxide rises or how much the sea level will increase as the average temperature of the earth increases, can have value in their own right as an input to research planning and in a variety of assessment activities. Often, however, annalists want to incorporate such probabilistic descriptions in subsequent modeling and other analysis. Today, this is usually done by running the analysis over and over again on a fast computer, using different input values, from which it is possible to compile the results into probability distributions. This approach is termed "stochastic simulation." Today a number of standard software tools are available to support such analysis.

Some climate analysis uses a single model to estimate what decision or policy is "optimal" in the sense that it has the highest "expected value" (*i.e.*, offers the best bet). However, others argue that because the models used in such analysis are themselves uncertain, it is not wise to search for a single "optimal" answer but rather one should search for answers or polices that are likely to be pretty good across a wide range of models and future outcomes. Section 6 presents several examples of results from such analysis.

Part 7: Making decisions in the face of uncertainty

There are a number of things about climate change, and its likely consequences, that are unique. However, uncertainty, even irreducible uncertainty, is not one of them. In our private lives, we decide where to go to college, what job to take, whom to marry, what home to buy, when and whether to have children, and countless other important choices, all in the face of large, and often, irreducible uncertainty. The same is true of decisions made by companies and by governments.

A set of ideas and analytical methods called "decision analysis" have been developed to assist in making decisions in the face of uncertainty. If one can identify the alternatives that are available, identify and estimate the probability of key uncertain events, and specify preferences (utilities) among the range of possible outcomes, these tools can provide help in framing and analyzing complex decisions in a consistent and rational way. Decision analysis has seen wide adoption by private sector decision makers – such as major corporations facing difficult and important decisions. While more controversial, they have also seen more limited application to public sector decision making, especially in dealing with more technocratic issues.

Of course, even if they want to, most people do not make decisions in precise accordance with the norms of decision analysis. A large literature, based on extensive empirical study, now exists on "behavioral decision theory." This literature describes how and why people make decisions in the way that they do, as well as some of the pitfalls and contradictions that can result. Section 8 provides a few brief pointers into that literature, but does not attempt a comprehensive review. That would require a paper at least as long as this one.

For both theoretical and practical reasons there are limits to the applicability and usefulness of classic decision analysis to climate-related problems. Two strategies may be especially appealing in the face of high uncertainty:

- Resilient Strategies**:** In this case, the idea is to try to identify the range of future circumstances that one might face, and then seek to identify approaches that will work reasonable well across that range.

- Adaptive Strategies**:** In this case, the idea is to choose strategies that can be modified to achieve better performance as one learns more about the issues at hand and how the future is unfolding.

Both of these approaches stand in sharp contrast to the idea of developing optimal strategies that has characterized some of the work in the climate change integrated assessment community, in which it is assumed that a single model reflects the nature of the world with sufficient accuracy to be the basis for decision making and that the optimal strategy for the world will be chosen by a single decision maker.

The "precautionary principle" is another decision strategy often proposed for use in the face of high uncertainty. There are many different notions of what this approach does and does not entail. In some forms, it incorporates ideas of resilient or adaptive policy. In some forms, it can also be shown to be entirely constant with a decision analytic problem framing. Precaution is often in the eye of the beholder. Thus, for example, some have argued that while the European Union has been more precautionary with respect to CO_2 emissions in promoting the wide adoption of fuel efficient diesel automobiles, the United States has been more precautionary with respect to health effects of fine particulate air pollution, stalling the adoption of diesel automobiles until it was possible to substantially reduce their particulate emissions.

Part 8: Communicating uncertainty

Many weather forecasters and other technical professionals have argued that one should not try to communicate about uncertainty to non-technical audiences. They suggest laypeople won't understand and that decision makers want definitive answers – that is, advice from what are often referred to as "one armed scientists"[9].

We do not agree. Non-technical people deal with uncertainty, and statements of probability, all the time. They don't always reason correctly about probability, but they can generally get the gist (Dawes, 1988). While they may make errors about the details, for the most part people manage to deal with probabilistic precipitation forecasts from the weather bureau, point spreads at the track, and similar probabilistic information. The real issue is to frame things in familiar and understandable terms.

[9]The reference, of course, being to experts who always answered his questions "on the one hand…but on the other hand…," the phrase is usually first attributed to Senator Edmund Muskie.

When should probability be communicated in terms of odds (the chance that the Pittsburgh Pirates will win the World Series this year is about 1 in 100) or in terms of probabilities (the probability that the Pittsburgh Pirates will win the World Series this year is 0.01)? Psychologist Baruch Fischhoff and colleagues (2002) suggest that:

- Either will work, if they're used consistently across many presentations.
- If you want people to understand one fact, in isolation, present the result both in terms of odds and probabilities.
- In many cases, there's probably more confusion about what is meant by the specific events being discussed than about the numbers attached to them.

Section 7 briefly discuses some empirical methods that can be used to develop and evaluate understandable and useful communications about uncertain technical issues for non-technical and semi-technical audiences. This approach uses "mental model" methods to learn in some detail what people know and need to know about the topic. Then having developed a pilot communication, working with members of the target audience, the message is extensively tested and refined until it is appropriately understood. One key finding in this literature is that there is no such thing as an expert in communication – in the sense of someone who can tell you ahead of time how a message should be framed, or what it should say. Empirical study is absolutely essential to the development of effective communication.

The presence of high levels of uncertainty offers people who have an agenda with an opportunity to "spin the facts." Combine this with the fact that many reporters are not in a position to make their own independent assessment of the likely accuracy of scientific statements, the tendency of the press to seek conflict and to find and report the views of those holding widely divergent views, and do so in just a few words and with very short deadlines, and it is small wonder that the issue of climate change and its associated uncertainties has presented particularly challenging issues for members of the press who are trying to cover the issue in a balanced and responsible way.

In an environment in which there is high probability that many statements a scientist makes about uncertainties will immediately be seized upon by advocates in an ongoing public debate, it is small wonder that many scientists choose to just keep their heads down, do their research, and limit their communication to publication in scientific journals and presentations at professional scientific meetings.

While we do not reproduce it here, the latter portion of Section 8 contains some thoughtful reflection on these issues from several leading scientists and members of the press.

Part 9: Some simple guidance for researchers

The final section of the report provides some advice and guidance to practicing researchers and policy analysts who must address and deal with uncertainty in their work on climate change, impacts, and policy.

However, before turning to specific recommendations, the section begins by reminding readers that doing a good job of characterizing and dealing with uncertainty can never be reduced to a simple cookbook. Researchers and policy analysts must always think critically and continually ask themselves questions such as:

- Does what we are doing make sense?
- Are there other important factors which are, as or more important, than the factors we are considering?
- Are there key correlation structures in the problems that are being ignored?
- Are there normative assumptions and judgments about which we are not being explicit?

The balance of the final section provides specific guidance to help researchers and analysts to do a better job of reporting, characterizing and analyzing uncertainty. Some of this guidance is based on available literature. However, because doing these things well is often as much an art as it is a science, the recommendations also draw on the very considerable[10] and diverse experience and collective judgment of the writing team.

Rather than reproduce those recommendations here, readers are referred to the discussion at the end of Section 9.

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PART 1. SOURCES AND TYPES OF UNCERTAINTY[11]

There are a number of things about climate change, and its likely consequences, that are unique. However, uncertainty, even irreducible uncertainty, is not one of them. Uncertainty is ubiquitous in virtually all fields of science and human endeavor. As Benjamin Franklin wrote in 1789 in a letter to Jean-Baptiste Leroy, "In this world nothing is certain but death and taxes." And, even in those cases, the timing and nature of the events are often uncertain.

Sometimes uncertainty can be reduced through research, but there are many settings in which one simply cannot resolve all-important uncertainties before decisions must be made. In our private lives, we choose where to go to college, what career to pursue, what job to take, whom to marry, whether and when to have children, all in the face of irreducible uncertainty. Similarly, corporations and governments regularly choose what policies to adopt, and where to invest resources, in the face of large and irreducible uncertainty.

By far the most widely used formal language of uncertainty is probability[12]. Many of the ideas and much of the vocabulary of probability were first developed in a "frequentist" framework to describe the properties of random processes, such as games of chance, which can be repeated many times. In this case, assuming that the process of interest is stable over time, or "stationary," probability is the value to which the event frequency converges in the long run as the number of

[11] Portions of the discussion in this section draw heavily on ideas and language from Morgan and Henrion (1990).
[12] There are a few alternative "languages" that have been advanced to describe and deal with uncertainty. These are briefly discussed in Section 2.

trials increases. Thus, in this frequentist or classical framework, probability is a property of a theoretically infinite series of trials, rather than of a single event.

While today some people stick to a strict classical interpretation of probability, many statisticians, as well as many of the experimental scientists we know, often adopt a "personalist", "subjectivist" or "Bayesian" view. In many settings, this has the consequence that probability can be used as a statement of a person's degree of belief given all available evidence. In this formulation, probability is not only a function of an event, but also of the state of information i that is available to the person making the assessment. That is, the probability, P, of event X is represented as $P(X|i)$ where the notation "$|i$", reads "conditional on i". Thus, $P(X|i)$ means the probability given that all the information is available to the person making the judgment at the same time when the value of the probability P is made. In this framework, obviously a person's value of P may change as more or different information, i, becomes available.

In a personalist or Bayesian framework, it is perfectly appropriate to say, based on a subjective interpretation of polling data, results from focus group discussions, and ones own reading of the political climate, "I think there is an 80% chance that Jones will win the next congressional election in this district." However, because it involves the outcome of a single unique future event, such a statement has no meaning in a frequentist framework.

In the face of large amounts of data on a repeating event, and a belief that the process being considered is stationary, the subjectivist probability should reduce to the same value as the classical probability. Thus, for example, if you need to estimate the probability that the mid-morning high speed Shinkansen train from Kyoto will arrive on time in Tokyo on a Tuesday morning next month, and you have access to a data set of all previous arrival times of that train, you would probably want to simply adopt the histogram of those times as your probability distribution on arrival time.

Suppose, however, that you want to estimate how long it takes to complete the weekly shopping for a family of four in your community. If you happen to be the person doing the shopping for a family of four on a regular basis in that community, then, as in the case with the Shinkansen, you will have hundreds of observations to rely on in estimating a probability distribution. The large amount of data available to you helps you understand that the answer has features that depend on the time of day, day of the week, special occasions, and so on. If you do not shop that often, your ability to estimate time for shopping will be less informed and more likely to be in error.

Does a subjectivist view mean that one's probability can be completely arbitrary? "No," Morgan and Henrion (1990) answer "…because if they are legitimate probabilities, they must be consistent with the axioms of probability." For example, if you assign probability *p* that an event *X* will occur, you should assign 1-*p* to its complement, that *X* doesn't occur. The probability that one of a set of mutually exclusive events occurs should be the sum or their probabilities. In fact, subjective probabilities should obey the same axioms as objective or frequentist probabilities, otherwise they are not probabilities…"

Subjective probabilities are intended to characterize the full spectrum of degrees of belief one might hold about uncertain propositions. However, there exists a long-standing debate as to whether this representation is sufficient. Some judgments may be characterized by a degree of ambiguity or imprecision distinct from estimates of their probability. Writing about financial matters, Knight (1921) contrasted risk with uncertainty, using the first term to refer to random processes whose statistics were well known and the latter term to describe unknown factors poorly described by quantifiable probabilities. Ellsberg (1961) emphasized the importance of this difference in his famous paradox, where subjects are asked to play a game of chance in which they do not know the probabilities underlying the outcomes of the game[13]. Ellsberg found that many subjects make choices that are inconsistent with any single estimate of probabilities, which nonetheless reflect judgments about which outcomes can be known with the most confidence.

Guidance developed by Moss and Schneider (2000) for the IPCC on dealing with uncertainty describes two key attributes that they argue are important in any judgment about climate change: the amount of evidence available to support the judgment being made and the degree of consensus within the scientific community about that judgment. Thus, they argue, judgments can be sorted into four broad types as shown in Figure 1.1. Many decisions involving climate change entail judgments in all four quadrants of this diagram.

Subjective probabilities seem clearly appropriate for addressing the established cases across the top of this matrix. There is more debate about the most appropriate methods for dealing with the others. A variety of approaches exist, such as belief functions, certainty factors, second order

[13]Specifically consider two urns each with 100 balls. In urn 1, the color ratio of red and blue balls is not specified. Urn 2 has 50 red and 50 blue balls. If asked to bet on the color of a ball drawn from one of these urns most people do not care if the ball is drawn from urn 1 or 2 and give a probability to either color of 0.5. However, when asked to choose an urn when betting on a specified color most people prefer urn 2. The first outcome implies $p(r_1)=p(r_2)=p(b_1)=p(b_2)$, while the second, it is argued, implies $p(r_1)<p(r_2)$ and $p(b_1)<p(b_2)$. Ellsberg and others discuss this outcome as an illustration of an aversion to ambiguity.

probabilities, and fuzzy sets and fuzzy logic, that attempt to quantify the degree of belief in a set of subjective probability judgments[14]. Each of these approaches provides an alternative calculus that relaxes the axioms of probability. In particular, they try to capture the idea that one can gain or lose confidence in one of a mutually exclusive set of events without necessarily gaining or losing confidence in the other events. For instance, a jury in a court of law might hear evidence that makes them doubt the defendant's alibi without necessarily causing them to have more confidence in the prosecution's case.

A number of researchers have applied these alternative formulations to the challenge of characterizing climate change uncertainty and there is no final consensus on the best approach. However, so long as one carefully specifies the question to be addressed, our judgment is that all four boxes in Figure 1.1 can be appropriately handled through the use of subjective probability, allowing a wide range or a multiple set of plausible distributions to represent the high levels of uncertainty, and retaining the axioms of probability. As Smithson (1988) explains:

> "One of the most frequently invoked motivations for formalisms such as possibility and Shaferian belief theory is that one number is insufficient to represent subjective belief, particularly in the face of what some writers call "ignorance"…Probabilist reply that we need not invent a new theory to handle uncertainty about probabilities. Instead we may use meta-probabilities [such as second order probability]. Even such apparently non-probabilistic concepts as possibility can be so represented…One merely induces a second-order probability distribution over the first-order subjective probabilities."

When the subjective probabilistic judgments are to be used in decision making, we believe, as outlined in Section 7, that the key issue is to employ decision criteria, such as robustness, that are appropriate to the high levels of uncertainty.

[14] For reviews of these alternative formulations see Smithson (1988) and Henrion (1999).

Much of the literature divides uncertainty into two broad categories, termed opaquely (for those of us who are not Latin scholars), aleatory uncertainty and epistemic uncertainty. As Paté-Cornell (1996) explains, aleatory uncertainty stems "…from variability in known (or observable) populations and, therefore, represents randomness" while epistemic uncertainty "…comes from basic lack of knowledge about fundamental phenomena (…also known in the literature as ambiguity)"[15].

While this distinction is common in much of the more theoretical literature, we believe that it is of limited utility in the context of climate and many other applied problems in assessment and decision making where most key uncertainties involve a combination of the two.
A far more useful categorization for our purposes is the split between "uncertainty about the value of empirical quantities" and "uncertainty about model functional form." The first of these may be either aleatory (the top wind speed that occurred in any Atlantic hurricane in the year 1995) or epistemic (the average global radiative forcing produced by anthropogenic aerosols at the top of the atmosphere during 1995). There is some disagreement within the community of experts on whether it is even appropriate to use the terms epistemic or aleatory when referring to a model.

Empirical quantities represent properties of the real world, which, at least in principle, can be measured. They include"…quantities in the domains of natural science and engineering, such as the oxidation rate of atmospheric pollutants, the thermal efficiency of a power plant, the failure rate of a valve, or the carcinogenic potency of a chemical, and quantities in the domain of the

[15]The Random House Dictionary defines *aleatory* as "of or pertaining to accidental causes; of luck or chance; unpredictable" and defines *epistemic* as "of or pertaining to knowledge or the conditions for acquiring it."

social sciences, such as demand elasticity's or prices in economics, or judgmental biases in psychology. To be empirical variables must be measurable, at least in principle, either now or at some time in the future.

These should be sufficiently well specified so that they can pass the clarity test. Thus it is permissible to express uncertainty about an empirical quantity in the form of a probability distribution. Indeed, we suggest that the only types of quantity whose uncertainty may appropriately be represented in probabilistic terms are empirical quantities[16]. This is because they are the only type of quantity that is both uncertain and can be said to have a true, as opposed to an appropriate or good value"[17].

Uncertainty about the value of an empirical quantity can arise from a variety of sources: these include lack of data; inadequate or incomplete measurement; statistical variation arising from measurement instruments and methods; systematic error and the subjective judgments needed to estimate its nature and magnitude; and inherent randomness. Uncertainty about the value of empirical quantities can also arise from sources such as the imprecise use of language in describing the quantity of interest and disagreement among different experts about how to interpret available evidence.

Not all quantities are empirical. Moreover, quantities with the same name may be empirical in some contexts and not in others. For example, quantities which represent a decision maker's own

[16]This advice is not shared by all authors. For example, Cyert and DeGroot (1987) have treated uncertainty about a decision maker's own value parameters as uncertain. But, see our discussion about in the next paragraph.

[17]Text in quotation marks in this and the preceding paragraph come directly from the writings of two of the authors, Morgan and Henrion (1990).

value choice or preference, such as a discount rate, coefficient of risk aversion, or the investment rate to prevent mortality ("value of life") represent choices about what he or she considers to be appropriate or good. If decision makers are uncertain about what value to adopt, they should perform parametric or "switchover" analysis to explore the implications of alternative choices[18]. However, if an analyst is modeling the behavior of *other* decision makers, and needs to know how they will make such choices, then these same quantities become empirical and can appropriately be represented by a probability distribution[19].

Some authors refer to some forms of aleatory uncertainty as "variability." There are cases in which the distinction between uncertainty about the value of an empirical quantity and variability in that value (across space, time or other relevant dimensions) is important. However, in many practical analyses, maintaining a distinction between uncertainty and variability is not especially important (Morgan and Henrion, 1990) and maintaining it can give rise to overly complicated and confusing analysis. Some people who accept only a frequentist notion of probability, insist on maintaining the distinction because variability can often be described in terms of histograms or probability distributions based only on a frequentist interpretation.

A model is a simplified approximation of some underlying causal structure. Debates, such as whether a dose-response function is really linear, and whether or not it has a threshold below

[18]In this example, a parametric analysis might ask, "what are the implications of taking the value of life to be 0.5, or 1 or 5, or 10 or 50-million dollars per death averted?" A "switchover" analysis would turn things around and ask "at what value of life" does the conclusion I read switch from Policy A to Policy B?" If the policy choice does not depend upon the choice of value across the range of interest, it may not be necessary to further refine the value.

[19]For a more detailed discussion of this and similar distinctions see the discussion in Section 4.3 of Morgan and Henrion (1990).

which no health effect occurs, are not really about what model is "true". None of these models is a complete, accurate representation of reality. The question is what is a more "useful" representation given available scientific knowledge and data and the intended use that is to be made of, or decisions to be based on, the analysis. In this sense, uncertainty about model functional form is neither aleatory nor epistemic. The choice of model is part pragmatic. Good (1962) described such a choice of model as "type II rationality" - how can we choose a model that is a reasonable compromise between the credibility of results and the effort to create and analyze the model (collect data, estimate model parameters, apply expert judgment, compute the results, *etc.*).

Uncertainty about model functional form can arise from many of the same sources as uncertainty about the value of empirical quantities: inadequate or incomplete measurements and data which prevent the elimination of plausible alternatives; systematic errors which mislead folks in their interpretation of underlying mechanisms; inadequate imagination and inventiveness in suggesting or inferring the models which could produce the available data; and disagreement among different experts about how to interpret available evidence.

In most of the discussion that follows, by "model functional form" we will mean a description of how the world works. However, when one includes policy-analytic activities, models may also refer to considerations such as decision makers’ "objectives" and the "decision rules" that they apply. These are, of course, normative choices which a decision maker or analyst must make. A fundamental problem, and potential source of uncertainty on the part of users of such analysis, is that the people who perform such analysis are often not explicit about the objectives and decision rules they are using. Indeed, sometimes they skip (unknowingly and inconsistently) from one to another decision rule in the course of doing an analysis.

All of the preceding discussion has focused on factors and processes that we know or believe exist, but, about which our knowledge is in some way incomplete. In any field as climate change and its impacts, there are also things about which we are completely ignorant. While Donald Rumsfeld (2002) was widely lampooned in the popular press, he was absolutely correct when he noted that "…there are known unknowns. That is to say, we know there are some things we do not know. But there are also unknown unknowns, the ones we don't know we don't know."

Things we know we do not know can often be addressed and sometimes understood through research. Things about which we do not even recognize we don't know, are only revealed by adopting an always-questioning attitude toward evidence. This is often easier said than done. Recognizing the inconsistencies in available evidence can be difficult, since as Thomas Kuhn (1962) has noted we interpret the world through mental models or "paradigms" that may make it difficult to recognize and pursue important inconstancies. Weick and Sutcliffe (2001) observe that "A recurring source of misperception lies in the temptation to normalize an unexpected event in order to preserve the original expectation. The tendency to normalize is part of a larger tendency to seek confirmation for our expectations and avoid disconfirmations. This pattern ignores vast amounts of data, many of which suggest that trouble is incubating and escalating." Weick and Sutcliffe (2001)

Freelance environmental journalist Dianne Dumanoski (1999) captured this issue well when she noted:

> Scientific ignorance sometimes brings many surprises. Many of the big issues we have reported on involve scientist quibbling about small degrees of uncertainty. For example, at the beginning of the debate on ozone depletion, there were arguments about whether the level or erosion of the ozone layer would be 7% or 13% within 100 years. Yet in 1985, a report came out from the British Antarctic survey, saying there was something upwards to a 50% loss of ozone over Antarctica. This went far beyond any scientist's worst-case scenario. Such a large loss had never been a consideration on anyone's radar screen and it certainly changed the level of the debate once it was discovered. Uncertainty cuts both ways. In some cases, something that was considered a serious problem can turn out to be less of a threat. In other cases, something is considered less serious than it should be and we get surprised…

Perhaps the ever folksy but profound Mark Twain[20] put it best when he noted "It ain't what you don't know that gets you in trouble. It's what you know for sure that just ain't so."

[20] <www.quotedb.com/quotes/1097>.

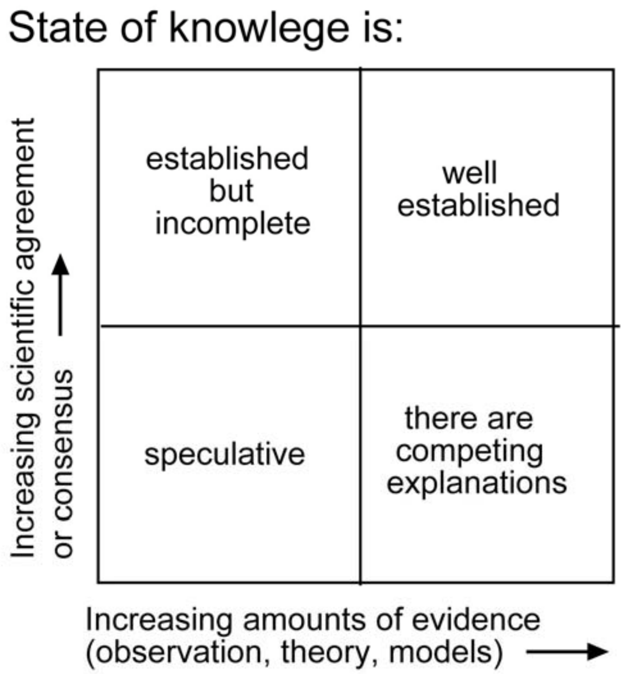

Figure 1.1 Categorization of the various states of knowledge that may apply in different aspects of climate and related problems. Redrawn from Moss and Schneider (2000).

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PART 2. THE IMPORTANCE OF QUANTIFYING UNCERTAINTY

There are a variety of words that are used to describe various degrees of uncertainty: "probable", "possible", "unlikely", "improbable", "almost impossible", *etc*. People often ask, why not simply use such words in describing uncertainty about climate change and its impacts?

Such qualitative uncertainty language is inadequate because: 1) the same words can mean very different things to different people; 2) the same words can mean very different things to the same person in different contexts; and 3) important differences in experts' judgments about mechanisms (functional relationships), and about how well key coefficients are known, can be easily masked in qualitative discussions.

Figure 2.1 illustrates the range of meaning that people attached to a set of probability words, when asked to do so in a study conducted by Wallsten *et al.* (1986), in the absence of any specific context. Mosteller and Youtz (1990) performed a review of 20 different studies of the probabilities that respondents attached to 52 different qualitative expressions. They argue that "in spite of the variety of populations, format of question, instructions, and context, the variation of the averages for most of the expressions was modest…" and they suggest that it might be possible to establish a general codification that maps words into probabilities. When this paper appeared in *Statistical Science* it was accompanied by eight invited comments (Clark, 1990; Cliff, 1990; Kadane, 1990; Kruskal, 1990; Tanur, 1990; Wallsten and Budescu, 1990; Winkler, 1990; Wolf, 1990). While several commenters who have economics or statistical backgrounds commented favorably on the feasibility of a general codification based on shared natural language meaning, those with psychological backgrounds argued strongly that context and other factors make such an effort infeasible.

For example, Mosteller and Youtz argued that on the basis of their analysis of 20 studies "likely" appears to mean 0.69 and unlikely means 0.16. In a study they then did in which they asked science writers to map words to probabilities they obtained a median value for likely of 0.71 (interquartile range of 0.626 to 0.776) and a median value for unlikely of 0.172 (interquartile range of 0.098 to 0.227). In contrast, Figure 2.2 illustrates the range of numerical probabilities that individual members of the Executive Committee of the EPA Science Advisory Board attached to the words "likely" and "not likely" when those words were being used to describe the probability that a chemical agent is a human carcinogen (Morgan, 1998). Note that, even in this relatively small and expert group, the minimum probability associated with the word "likely" spans four orders of magnitude, the maximum probability associated with the word "not likely" spans more than five orders of magnitude, and there is an actual overlap of the probabilities the different experts associated with the two words! Clearly, in this setting the words do not mean roughly the same thing to all experts, and without at least some quantification, such qualitative descriptions of uncertainty convey little, if any, useful information.

While some fields, such as environmental health impact assessment have been relatively slow to learn that it is important to be explicit about how uncertainty words are mapped into probabilities, and have resisted the use of numerical descriptions of uncertainty (Presidential/Congressional Commission on Risk Assessment and Risk Management, 1997; Morgan, 1998) the climate assessment community has made relatively good, if uneven, progress in recognizing and attempting to deal with this issue. Notable recent examples include the guidance document developed by Moss and Schneider (2000) for authors of the IPCC Third Assessment and the mapping of probability words into specific numerical values employed in the 2001 IPCC reports (IPCC WGI and II, 2001) (Table 2.1) and by the National Assessment Synthesis Team of the U.S. National Assessment (2000). The mapping used in the U.S. National Assessment, which the authors attempted to apply consistently throughout their two reports, is shown in Figure 2.3.

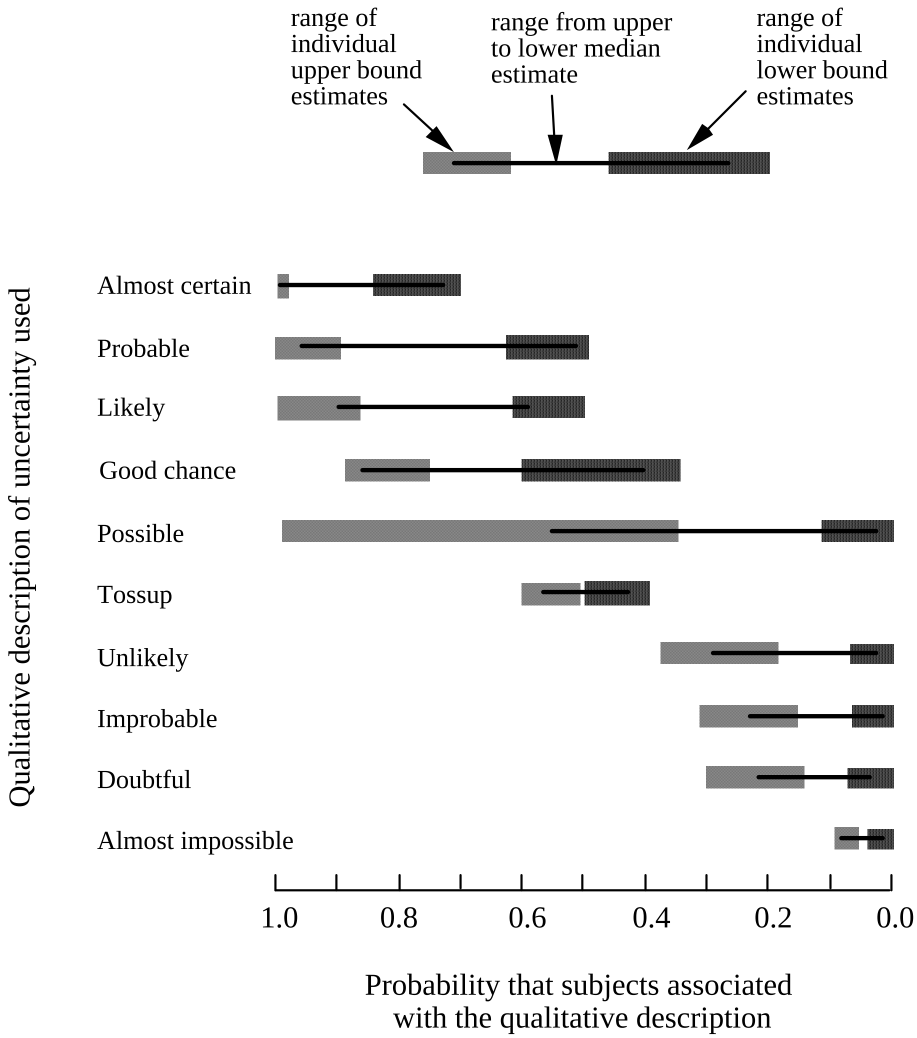

Figure 2.1 Range of numerical probabilities which respondents attached to qualitative probability words in the absence of any specific context. Figure redrawn from Wallsten *et al.* (1986).

Figure 2.2 Results obtained by Morgan (1998) when members of the Executive Committee of the EPA Science Advisory Board were asked to assign numerical probabilities to words that have been proposed for use with the new EPA cancer guidelines (U.S. EPA, 1996). Note that, even in this relatively small and expert group, the minimum probability associated with the word "likely" spans four orders of magnitude, the maximum probability associated with the word "not likely" spans more than five orders of magnitude, and there is an overlap of the probabilities the different experts associated with the two words.

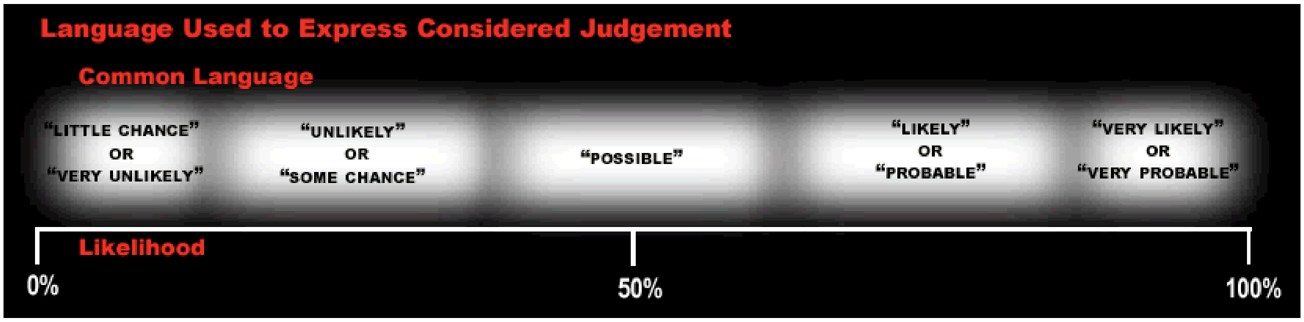

Figure 2.3 Mapping of probability words into quantitative subjective probability judgments, used in their two reports, by the members of the National Assessment Synthesis Team of the United States National Assessment (2000).

Table 2.1 Mapping of probability words into quantitative subjective probability judgments, used by WGI and II of the IPCC Third Assessment (IPCC WGI and II, 2001) based on recommendations developed by Moss and Schneider (2000).

word	probability range
Virtually certain	> 0.99
Very likely	0.9-0.99
Likely	0.66-0.9
Medium likelihood	0.33-0.66
Unlikely	0.1-0.33
Very unlikely	0.01-0.1
Exceptionally unlikely	< 0.01

Note: The report of the *IPCC Workshop on Describing Scientific Uncertainties in Climate Change to Support Analysis of Risk and of Options* (2004) observed: "Although WGIII TAR authors addressed uncertainties in the WG3-TAR, they did not adopt the Moss and Schneider uncertainty guidelines. The treatment of uncertainty in the WG3-AR4 can be improved over what was done in the TAR."

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PART 3. COGNITIVE CHALLENGES IN ESTIMATING UNCERTAINTY

While our brains are very good at doing many tasks, we do not come hard-wired with statistical processors. Over the past several decades, experimental psychologists have begun to identify and understand a number of the "cognitive heuristics" we use when we make judgments that involve uncertainty.

The first thing to note is that people tend to be systematically overconfident in the face of uncertainty – that is, they produce probability distributions that are much too narrow. Actual values, once they are known, often turn out to lie well outside the tails of their previous distribution. This is well illustrated with the data in the summary table reproduced in Figure 3.1. This table reports results from laboratory studies in which, using a variety of elicitation methods, subjects were asked to produce probability distributions to indicate their estimates of the value of a number of well known quantities. If the respondents were "well calibrated," then the true value of the judged quantities should fall within the 0.25 to 0.75 interval of their probability distribution about half the time. We call the frequency with which the true value actually fell within that interval the interquartile index. Similarly, the frequency with which the true value lies below the 0.01 or above the 0.99 probability values in their distribution is termed the "surprise index." Thus, for a well-calibrated respondent, the surprise index should be 2%.

In these experimental studies, interquartile indices typically were between 20 and 40% rather than the 50% they should have been, and surprise indices ranged from a low of 5% (2.5 times larger than it should have been) to 50% (25 times larger than it should have been).

Overconfidence is not unique to non-technical judgments. Henrion and Fischhoff (1986) have examined the evolution of published estimates of a number of basic physical constants, as compared to the best modern values. Figure 3.2 shows results for the speed of light. While one might expect error bars associated with published experimental results not to include all possible sources of uncertainty, the "recommended values" do attempt to include all uncertainties. Note that for a period of approximately 25 years during the early part of the last century, the one standard deviation error bar being reported for the recommended values did not include the current best estimate.

Three cognitive heuristics are especially relevant in the context of decision making under uncertainty: availability; anchoring and adjustment; and representativeness. For a comprehensive review of much of this literature see Kahneman *et al.* (1982).

When people judge the frequency of an uncertain event they often do so by the ease with which they can recall such events from the past, or imagine such events occurring. This "availability heuristic" serves us well in many situations. For example, if I want to judge the likelihood of encountering a traffic police car on the way to the airport mid-afternoon on a work day, the ease with which I can recall such encounters from the past is probably proportional to the likelihood that I will encounter one today, since I have driven that route many times at that time of day. However, if I wanted to make the same judgment for 3:30 a.m. (a time at which I have never driven to the airport), using availability may not yield a reliable judgment.

A classic illustration of the availability heuristic in action is provided in Figure 3.3A which shows results from a set of experimental studies conducted by Lichtenstein *et al.* (1978) in which well educated Americans were told that 50,000 people die each year in the United States from motor vehicle accidents[21], and were then asked to estimate the number of deaths that occurred each year from a number of other causes. While there is scale compression - the likelihood of high probability events is underestimated by about an order of magnitude, and the likelihood of low probability events is overestimated by a couple orders of magnitude - the fine structure of the results turns out to be replicable, and clearly shows the operation of availability. Many people die of stroke, but the average American hears about such deaths only when a famous person or close relative dies, thus the probability of stroke is underestimated. Botulism poisoning is very rare, but whenever anyone dies the event is covered extensively in the news and we all hear about it. Thus, through the operation of availability, the probability of death from botulism poisoning is overestimated. In short, judgments can be dramatically affected by what gets one's attention. Things that come readily to mind are likely to have a large effect on peoples' probabilistic judgments. Things that do not come readily to mind may be ignored. Or to paraphrase the 14th century proverb, all too often out of sight is out of mind.

We can also illustrate "anchoring and adjustment" with results from a similar experiment in which Lichetenstein *et al.* (1978) made no mention of deaths from motor vehicle accidents but instead told a different group of respondents that about 1000 people die each year in the United States from electrocution. Figure 3.3B shows the resulting trend lines for the two experiments.

[21]Today, while Americans drive more, thanks to safer cars and roads, and reduced tolerance for drunk driving, the number has fallen to about 40,000 deaths per year.

Because in this case respondents started with the much lower "anchor" (1000 rather than 50,000) all their estimates are systematically lower.

One of the most striking experimental demonstrations of anchoring and adjustment was reported by Tversky and Kahneman (1974):

> In a demonstration of the anchoring effect, subjects were asked to estimate various quantities stated in percentages (for example, the percentage of African countries in the United Nations). For each quantity a number between 0 and 100 was determined by spinning a wheel of fortune in the subject's presence. The subjects were instructed to indicate first whether that number was higher or lower than the value of the quantity, and then to estimate the value of the quantity by moving upward or downward from the given quantity. Different groups were given different numbers for each quantity, and these arbitrary numbers had a marked effect on the estimates. For example, the median estimates of the percentage of African countries in the United Nations were 25 and 45 for groups that received 10 and 65, respectively, as starting points[22]. Payoffs for accuracy did not reduce the anchoring effect.

Very similar results are reported for similarly posed questions about other quantities such as "what is the percentage of people in the United States today who are age 55 or older."

The heuristic of "representativeness" says that people expect to see in single instantiations, properties that they know that a process displays in the large. Thus, for example, people judge the sequence of coin tosses HHHTTT to be less likely than the sequence HTHHTH because the former looks less random than the latter, and they know that the process of tossing a fair coin is a random process.

Psychologists refer to feeling and emotion as "affect." Slovic *et al.* (2004) suggest that:

> Perhaps the biases in probability and frequency judgment that have been attributed to the availability heuristic…may be due, at least in part, to affect. Availability may work not

[22]Hastie and Dawes (2001) report that at the time the experiment was conducted the actual value was 35%.

> only through ease of recall or imaginability, but because remembered and imagined images come tagged with affect.

Slovic *et al.* (2004) argue that there are two fundamental ways that people make judgments about risk and uncertainty – one, the "analytic system" the other the "experiential system." They note that while the analytic system "…is rather slow, effortful and requires conscious control," the experiential system is "intuitive, fast, mostly automatic, and not very accessible to conscious awareness." They note that both are subject to various biases and argue both are often needed for good decision making:

> Even such prototypical analytic exercises as proving a mathematical theorem or selecting a move in chess benefit from experiential guidance, the mathematician senses whether the proof "looks good" and the chess master gauges whether a contemplated move "feels right", based upon stored knowledge of a large number of winning patterns. (DeGroot, 1970)

Psychologists working in the general area of risk and decision making under uncertainty are somewhat divided about the role played by emotions and feelings (*i.e.*, affect) in making risk and related judgments. Some (*e.g.*, Sjöberg, 2006) argue that such influences are minor, others (*e.g.*, Loewenstein, 1996; Loewenstein *et al.*, 2001) assign them a dominant role. Agreeing with Slovic *et al.'s* conclusion that both are often important, Wardman (2006) suggests that the most effective responses …"may in fact occur when they are driven by both affective and deliberative-analytical considerations, and that it is the absence of one or the other that may cause problems…"

	Number of assessments *N*	Interquartile index (ideal 50%)	Surprise index (ideal 2%)
Alpert & Raiffa (1969)			
Group 1-A	880	33	46
Group 2 & 3	1,670	33	39
Group 4	600	36	21
Hession & McCarthy (1974)			
Fractiles	2,035	25	47
Selvidge (1975)			
Five fractiles	400	56	10
Seven fractiles	520	50	7
Schaefer & Borcherding (1973)			
Fractiles	396	23	39
Hypothetical sample	396	16	50
Pickhardt & Wallace (1974)			
Group 1	?	39	32
Group 2	?	30	46
Seaver, von Winterfeldt, & Edwards (1978)			
Fractiles	160	42	34
Odds-fractiles	160	53	24
Probabilities	180	57	5
Odds	180	47	5
Log-odds	140	31	20
Stael von Holstein (1971)			
Fixed intervals	1,269	27	30
Murphy & Winkler (1974 & 1977)			
Fixed intervals	132	45	27 (ideal 25)
Fractiles	432	54	21 (ideal 25)
Schaefer (1976)			
Fixed interval	660	27	25
Lichtenstein & Fischhoff (1978)			
Fractiles	924	33	41
Seaver (1978)			
Parameters of beta dist.	3,200	29	25

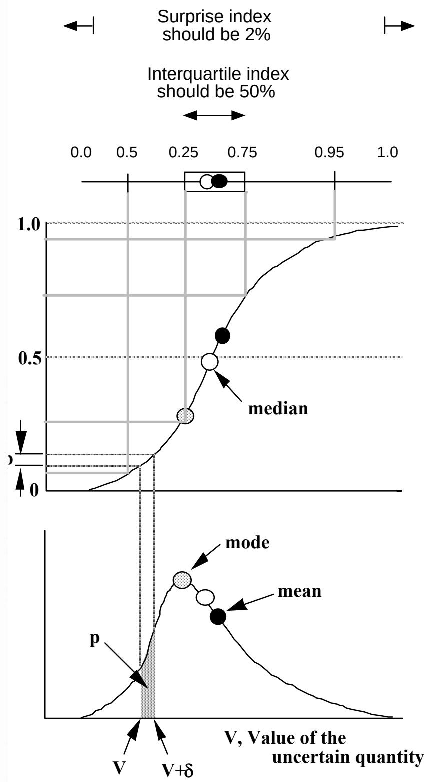

Figure 3.1 Summary of data from different studies in which, using a variety of methods, people were asked to produce probability distributions on the value of well known quantities (such as the distance between two locations), so that their distributions can be subsequently checked against true values. The results clearly demonstrate that people are systematically overconfident (*i.e.*, produce subjective probability distributions that are too narrow) when they make such judgments. The table is reproduced from Morgan and Henrion (1990) who, in compiling it, drew in part on Lichtenstein *et al.* (1982). Definitions of interquartile index and surprise index are shown in the diagram on the right.

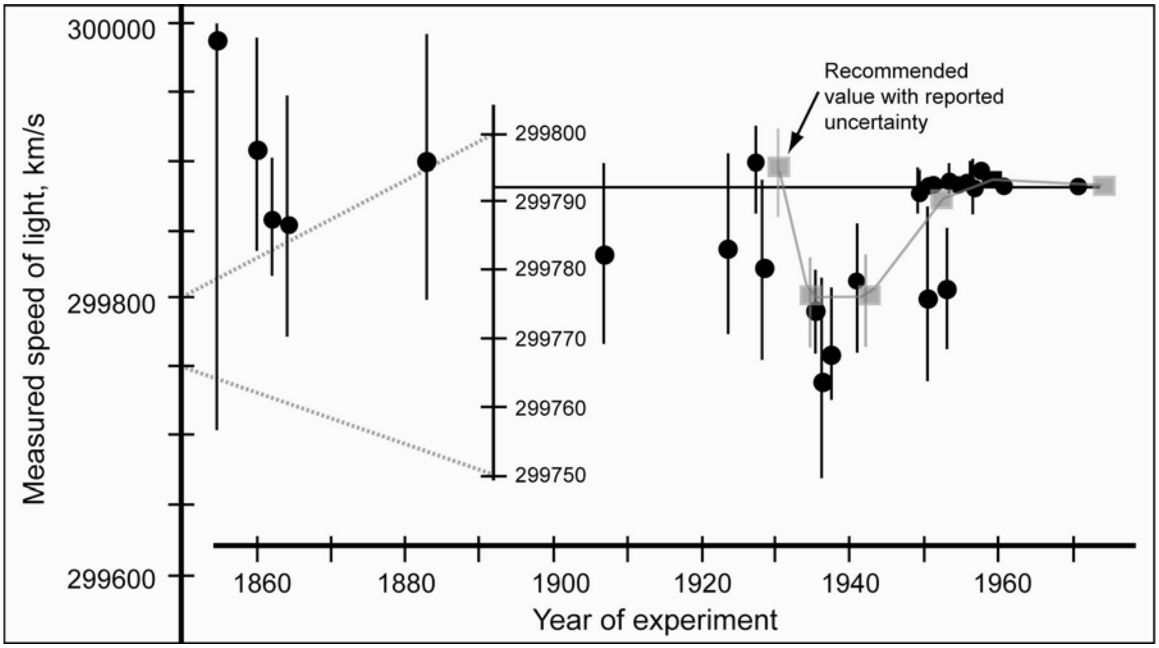

Figure 3.2 Time series of reported experimental values for the speed of light over the period from the mid-1800's to the present (black points). Recommended values are shown in gray. These values should include a subjective consideration of all relevant factors. Note, however, that for a period of approximately 25 years during the early part of the last century, the uncertainty being reported for the recommended values did not include the current best estimate. Similar results obtained for recommended values of other basic physical quantities such as Planck's constant, the charge and mass of the electron and Avogadro's number. For details see Henrion and Fischhoff (1986) from which this figure has been redrawn.

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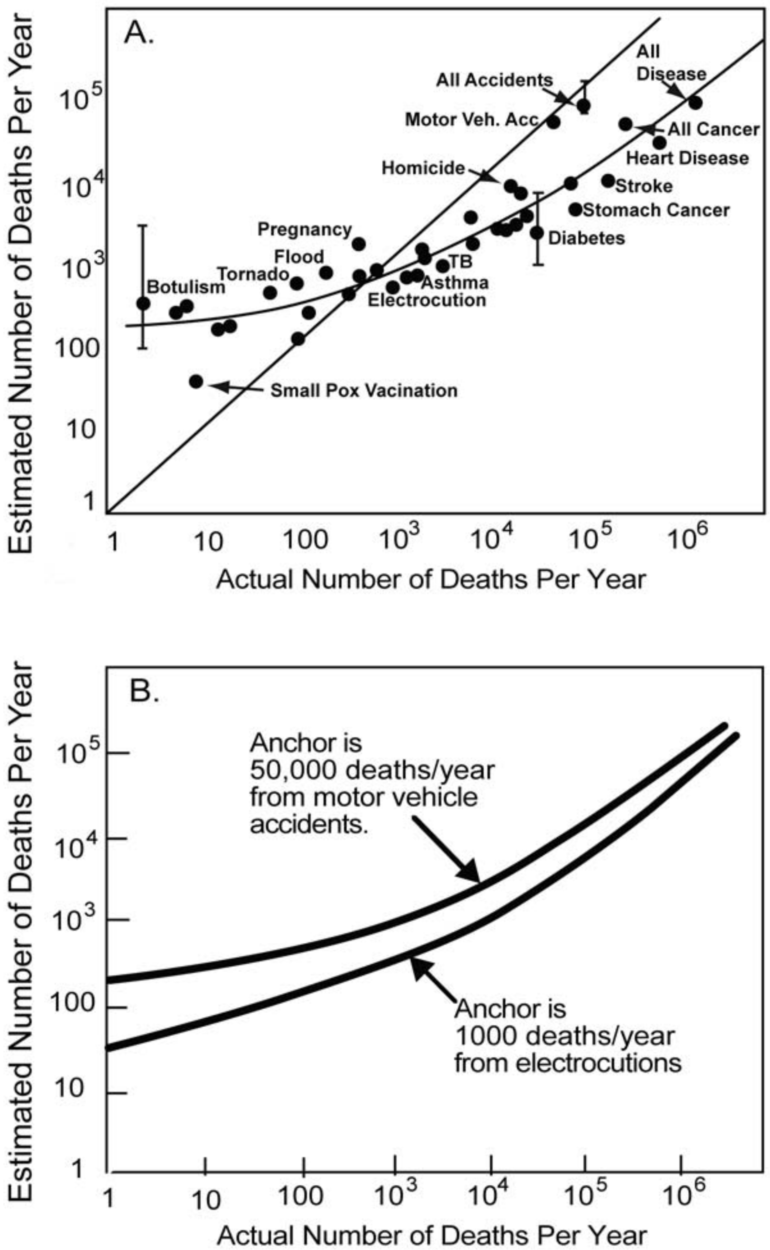

Figure 3.3 Illustration of the heuristic of availability (A) and of anchoring and adjustment (B). In the upper figure, note that stroke lies below the trend line and that botulism lies above the trend line – this is a result of the availability heuristic – we do not learn of most stroke deaths and we do learn of most botulism deaths via news reports. The lower figure replicates the same study with an anchor of 1000 deaths per year. Due to the influence of this lower anchor through the heuristic of anchoring and adjustment, the mean trend line has moved down. Figures are redrawn from Lichtenstein *et al.* (1978).

PART 4. STATISTICAL METHODS AND MODELS

Statistical methods and models play a key role in the interpretation and synthesis of observed climate data and the predictions of numerical climate models. Important advances have been made in the development and application of both frequentist and Bayesian statistical approaches and, as noted previously, the methods yield similar results when either an uninformed prior is used for the Bayesian analysis or a very large dataset is available for estimation. Recent reviews of statistical methods for climate assessment are summarized, including procedures for trend detection, assessing model fit, downscaling, and data-model assimilation. Methods for hypothesis testing and model selection are presented, and emerging issues in statistical methods development are considered.

Levine and Berliner (1999) review statistical methods for detecting and attributing climate change signals in the face of high natural variations in the weather and climate, focusing on "fingerprint" methods designed to maximize the signal-to-noise ratio in an observed climatic dataset (Hasselmann, 1979; 1993). The climate change detection problem is framed in terms of statistical hypothesis testing and the fingerprint method is shown to be analogous to stepwise regression of the observed data (*e.g.*, temperature) against the hypothesized input signals (carbon dioxide concentrations, aerosols, *etc.*). Explanatory variables are added to the model until their coefficients are no longer statistically significant. The formulation and interpretation of the hypothesis test is complicated considerably by the complex spatial and temporal correlation structure of the dependent and explanatory variables, and Levine and Berliner discuss various approaches for addressing these concerns. The selection of the best filter for isolating a climate change signal within the natural climate record is shown to be equivalent to the determination of an optimal (most powerful) statistical test of hypothesis.

Solow (2003) reviews various statistical models used in atmospheric and climate science, including methods for:

- fitting multivariate spatial-time series models, using methods such as principal component analysis (PCA) to consider spatial covariance, and predictive oscillation patterns (PROPS) analysis and maximum covariance analysis (MCA) for addressing both spatial and temporal variations (Kooperberg and O'Sullivan, 1996; Salim *et al.*, 2005);
- identifying trends in the rate of occurrence of extreme events given only a partially observed historical record (Solow and Moore, 2000, 2002);
- downscaling GCM model predictions to estimate climate variables at finer temporal and spatial resolution (Berliner *et al.*, 1999; Berliner, 2003);
- assessing the goodness of fit of GCMs to observed data (McAvaney *et al.*, 2001), where goodness-of-fit is often measured by the ability of the model to reproduce the observed climate variability (Levine and Berliner, 1999; Bell *et al.*, 2000); and
- data assimilation methods that combine model projections with the observed data for improved overall prediction (Daley, 1997), including multi-model assimilation methods (Stephenson *et al.*, 2005) and extended Kalman filter procedures that also provide for model parameter estimation (Evensen and van Leeuwen, 2000; Annan, 2005; Annan *et al.*, 2005).

Zwiers and von Storch (2004) also review the role of statistics in climate research, focusing on statistical methods for identifying the dynamics of the climate system and implications for data collection, forecasting, and climate change detection. The authors argue that empirical models for the spatiotemporal features of the climate record should be associated with plausible physical models and interpretations for the system dynamics. Statistical assessments of data homogeneity are noted as essential when evaluating long-term records where measurement methods, local processes, and other non-climate influences are liable to result in gradual or abrupt changes in the data record (Vincent, 1998; Lund and Reeves, 2002). Statistical procedures are reviewed for assessing the potential predictability and accuracy of future weather and climate forecasts, including those based on the data-model assimilation methods described above. Zwiers and Storch offer that for the critical tasks of determining the inherent (irreducible) uncertainty in climate predictions vs. the potential value of learning from better data and models, Bayesian statistical methods are often better suited than are frequentist approaches.

Methods for Hypothesis and Model Testing

A well-established measure in classical statistics for comparing competing models (or hypotheses) is the likelihood ratio (LR), which follows from the common use of the maximum likelihood estimate for parameter estimation. For two competing models M_1 and M_2, the LR is the ratio of the likelihood or maximum probability of the observed data under M_1 divided by the likelihood of the observed data under M_2, with large values of the likelihood ratio indicating support for M_1. Solow and Moore (2000) applied the LR test to look for evidence of a trend in a partially incomplete hurricane record, using a Poisson distribution for the number of hurricanes in a year with a constant sighting probability over the incomplete record period. The existence of such a trend could indicate warming in the North Atlantic Basin, but based on their analysis, little evidence was apparent. In cases such as that above in which the LR tests models with the same parameterization and simple hypotheses are of interest, the LR is equivalent to the Bayes Factor, which is the ratio of the posterior odds of M1 to the prior odds of M1. That is, the Bayes Factor represents the odds of favoring M1 over M2 based solely on the data, and thus the magnitude of the Bayes Factor is often used as a measure of evidence in favor of M1.

An approximation to the log of the Bayes Factor for large sample sizes, Schwarz's Bayesian Information Criterion or BIC, is often used as a model-fitting criterion when selecting among all possible subset models. The BIC allows models to be evaluated in terms of a lack of fit component (a function of the sample size and mean squared error) and a penalty term for the number of parameters in a model. The BIC differs from the well-known Akaike's Information Criterion (AIC) only in the penalty for the number of included model terms. Another related model selection statistic is Mallow's Cp (Laud and Ibrahim, 1995). Karl *et al.* (1996) utilize the BIC to select among ARMA models for climate change, finding that the Climate Extremes Index (CEI) and the United States Greenhouse Climate Response Index (GCRI) increased abruptly during the 1970s.

Model uncertainty can also be addressed by aggregating the results of competing models into a single analysis. For instance, in the next section we report an estimate of climate sensitivity (Andronova and Schlesinger, 2001) made by simulating the observed hemispheric-mean near-surface temperature changes since 1856 with a simple climate/ocean model forced radiatively by greenhouse gases, sulfate aerosols and solar-irradiance variations. A number of other investigators have used models together with historical climate data and other evidence to develop probability distributions for climate sensitivity or bound estimates of climate sensitivity or other variables. Several additional efforts of this sort are discussed below in Section 5. An increasing number of these studies have begun to employ Bayesian statistical methods (*e.g.*, Epstein, 1985; Berliner *et al.*, 2000; Katz, 2002; Tebaldi *et al.*, 2004, 2005).

As noted in Katz (2002) and Goldstein (2006), Bayesian methods bring a number of conceptual and computational advantages when characterizing uncertainty for complex systems such as those encountered in climate assessment. Bayesian methods are particularly well suited for problems where experts differ in their scientific assessment of critical processes and parameter values in ways that cannot, as yet, be resolved by the observational record. Comparisons across experts not only help to characterize current uncertainty, but help to identify the type and amount of further data collection likely to lead to resolution of these differences. Bayesian methods also adapt well to situations where hierarchical modeling is needed, such as where model parameters for particular regions, locations, or times can be viewed as being sampled from a more-general (*e.g.*, global) distribution of parameter values (Wilke *et al.*, 1998). Bayesian methods are also used for uncertainty analysis of large computational models, where statistical models that emulate the complex, multidimensional model input-output relationship are learned and updated as more numerical experiments are conducted (Kennedy and O'Hagan, 2001; Fuentes *et al.*, 2003; Kennedy *et al.*, 2006; Goldstein and Rougier, 2006). In addition, Bayesian formulations allow the predictions from multiple models to be averaged or weighted in accordance with their consistency with the historical climate data (Wintle *et al.*, 2003; Tebaldi *et al.*, 2004, 2005; Raftery *et al.*, 2005; Katz and Ehrendorfer, 2006; Min and Hense, 2006).

Regardless of whether frequentist or Bayesian statistical methods are used, the presence of uncertainty in model parameters and the models themselves calls for extensive sensitivity analysis of results to model assumptions. In the Bayesian context, Berger (1994) reviews developments in the study of the sensitivity of Bayesian answers to uncertain inputs, known as robust Bayesian analysis. Results from Bayesian modeling with informed priors should be compared to results generated from priors incorporating more uncertainty, such as flat-tailed distributions, non-informative and partially informative priors. Sensitivity analysis on the likelihood function and the prior by consideration of both non-parametric and parametric classes is often called for when experts differ in their interpretation of an experiment or a measured indicator. For example, Berliner *et al.* (2000) employ Bayesian robustness techniques in the context of a Bayesian fingerprinting methodology for assessment of anthropogenic impacts on climate by examining the range of posterior inference as prior inputs are varied. Of note, Berliner *et al.* also compare their results to those from a classical hypothesis testing approach, emphasizing the conservatism of the Bayesian method that results through more attention to the broader role and impact of uncertainty.

Emerging Methods and Applications

While the suite of tools for statistical evaluation of climate data and models has grown considerably in the last two decades, new applications, hypotheses, and datasets continue to expand the need for new approaches. For example, more sophisticated tests of hypothesis can be made by testing probability distributions for uncertain parameters, rather than single nominal values (Kheshgi and White, 2001). While much of the methods development to date has focused on atmospheric-oceanic applications, statistical methods are also being developed to address the special features of downstream datasets, such as streamflow (Allen and Ingram, 2002; Koutsoyiannis, 2003; Kallache *et al.*, 2005) and species abundance (Austin, 2002; Parmesan and Yohe, 2003).

As models become increasingly sophisticated, requiring more spatial and temporal inputs and parameters, new methods will be needed to allow our limited datasets to keep up with the requirements of these models. Two recent examples are of note. Edwards and Marsh (2005) present a "simplified climate model" with a "fully 3-D, frictional geostrophic ocean component, an Energy and Moisture Balance atmosphere, and a dynamic and thermodynamic sea-ice model. . . representing a first attempt at tuning a 3-D climate model by a strictly defined procedure." While estimates of overturning and ocean heat transport are "well reproduced", "*m*odel parameters *we*re only weakly constrained by the data." Jones *et al.* (2006) present an integrated climate-carbon cycle model to assess the implications of carbon cycle feedback considering parameter and model structure uncertainty. While the authors find that the observational record significantly constrains permissible emissions, the observed data (in this case also) "proves to be insufficient to tightly constrain carbon cycle processes or future feedback strength with implication for climate-carbon cycle model evaluation." Improved data collection, modeling capabilities, and statistical methods must clearly all be developed concomitantly to allow uncertainties to be addressed effectively.

Box 4.1: Predicting Rainfall: An Illustration of Frequentist and Bayesian Approaches

Consider how we use probability theory in weather prediction. We have a vast storehouse of observations of temperature, humidity, cloud cover, wind speed and direction, and atmospheric pressure for a given location. These allow the construction of a classic or frequentist table of probabilities showing the observed probability of rainfall, given particular conditions. This underscores the fact that observations of a stable system permit the construction of powerful predictive models, even if underlying physical processes are not known fully.

So long as the same underlying conditions prevail, the predictive model based on historical weather will remain powerful. However, if an underlying factor does change, the predictive power of the model will fall and the missing explanatory variables will have to be discovered. For example, if an underlying condition for cloud stability and formation of rainfall change because of reduced air pollution that cause the concentration of cloud condensation nuclei (CCN) to decline, the historic observations will not provide as powerful a prediction of rainfall as before. Under such conditions it is useful to consider a Bayesian approach in which cloud condensation nuclei are considered a potential additional explanatory variable. We can start with the old model, then modify its probability of rainfall, given different concentrations of cloud condensation nuclei. With each observation, our prior estimates of rainfall will be modified eventually leading to a new more powerful model, this time inclusive of the new explanatory variable.

Ideally, we want the full distribution of rainfall in a location. This has proven difficult to do, using the frequentist method, especially when we focus on high impact events such as extreme droughts and floods. These occur too infrequently for us to use a large body of observations so we must "assume" a probability distribution for such events in order to predict their probability of occurrence. While it may be informed by basic science, there is no objective method defining the appropriate probability distribution function. What we choose to use is subjective. Furthermore, the determinants of rainfall have been more numerous than once believed, often varying dramatically even on a decadal scale. For example, in the mid twentieth century, it was thought possible to characterize the rainfall in any location from thirty years of observations. This approach used the meteorological data for the period: 1931 to 1960 to *define the climate norm* around the earth. By the mid-80s however, it was clear that that thirty-year period did not provide an adequate basis for predicting rainfall in the subsequent years. In short, we learned that there is no "representative" sample of data in the classical sense. What we have is an evolving condition where tele-connections such as El Nino Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO), as well as air pollution and other factors determine cloud formation, stability and rainfall.

As we gain experience with the complex of processes leading to precipitation, we also develop a sense of humility about the incomplete state of our knowledge. This is where the subjectivity in Bayesian statistics comes to the fore. It states explicitly that our predictions are contingent on our current state of knowledge and that knowledge will be evolving with new observations.

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PART 5. METHODS FOR ESTIMATING UNCERTAINTY

Many of the key variables and functional relationships which are important to understanding the climate system and how the climate may change over the coming decades and centuries will likely remain uncertain for years to come. While a variety of evidence can be brought to bear to gain insight about these uncertainties, in most cases no single piece of evidence or experimental result can provide definitive answers. Yet research planners, groups attempting to do impact assessment, policy makers addressing emissions reductions, public and private parties making long-lived capital investment decisions, and many others, all need some informed judgment about the nature and extent of the associated uncertainties.

Model-Generated Uncertainty Estimates

In some cases probability distributions for key climate parameters can be extracted directly from available data and models. Note, however, that the models themselves often contain a myriad of implicit expert judgments. In recent years, several research groups have derived probability distributions for climate sensitivity via statistical comparisons of climate model results to recent climate records. For instance, Figure 5.1 shows an estimate of climate sensitivity (Andronova and Schlesinger, 2001) made by simulating the observed hemispheric-mean near-surface temperature changes since 1856 with a simple climate/ocean model forced radiatively by greenhouse gases, sulfate aerosols and solar-irradiance variations. The authors account for uncertainty in climatic radiative forcing by considering 16 radiative forcing models. To account for natural variability in instrumental measurements of temperature, a bootstrap procedure is used to generate surrogate observed temperature records. Figure 4.1 shows the probability distribution function for estimated climate sensitivity based on 80,000 model runs, aggregated across radiative forcing models and bootstrapped temperature records. The resultant 90% confidence interval for temperature sensitivity is between 1.0° C and 9.2° C. Note that this analysis suggests a much wider spread than the IPCC range, consistent with the observation that experts routinely underestimate uncertainty. A number of other investigators have also used models together with historical climate data and other evidence to develop probability distributions for climate sensitivity or bound estimates of climate sensitivity or other variables. Several additional efforts of this sort are discussed below in Section 6.

Researchers have also used data and models to derive uncertainty estimates for future socio-economic and technological driving forces. For instance, Gritsevskyi and Nakicenovic (2000) and Nakicenovic and Riahi, (2002) have estimated probability distributions for the investment costs and learning rates of new technologies based on the historical distributions of cost and performance for many similar technologies and then used these probability estimates to forecast distributions of future emission paths. Some authors have estimated probability distributions for future emissions by assessing the frequency of results over different emissions models or by propagating subjective probability distributions for key inputs through such emission models (Webster *et al.,* 2003). Such approaches can suggest which uncertainties are most important in determining any significant deviations from a base-case projection and can prove particularly important in helping to make clear when proposed emissions scenarios differ in important ways from past trends. Care must be taken, however, with such estimates because unlike physical parameters of the climate system, socioeconomic and technological factors needs not remain constant over time and may be strongly interrelated and conditional on each other. Since we expect the 21st century will differ in important ways from the 20th, as the 20th differed in important ways from the 19th, *etc.*, we should regard these uncertainty estimates of future socio-economic outcomes with less confidence than those of physical parameters of the climate system when they are thought to be fundamentally constant through time.

Expert Elicitation

Model and data generated uncertainty estimates can be very valuable in many cases. In particular, they are most germane for judgments about well-established knowledge, represented by the upper right-hand corner of Figure 1.1[23]. But in many situations, limitations of data, scientific understanding, and the predictive capacity of models will make such estimates unavailable, with the result that they must be supplemented with other sources of information.

In such circumstances, the best strategy is to ask a number of leading experts to consider and carefully synthesize the full range of current scientific theory and available evidence and then provide their judgments in the form of subjective probability distributions.

Such formal individually-focused elicitation of expert judgment has been widely used in applied Bayesian decision analysis (DeGroot, 1970; Spetzler and Staël von Holstein, 1975; Watson and Buede, 1987; von Winterfeldt and Edwards, 1986; Morgan and Henrion, 1990; Cooke, 1991), often in business applications, and in climate and other areas of environmental policy through the process of "expert elicitation" (Morgan *et al.*, 1978a; Morgan *et al.*, 1978b; National Defense

[23]The drive to produce estimates using model-based methods may also stem from a reluctance to confront the use of expert judgment explicitly.

University, 1978; Morgan *et al.*, 1984; Morgan *et al.*, 1985; Wallsten and Whitfield, 1986; Stewart *et al.*, 1992; Nordhaus, 1994; Evans *et al.*, 1994a; Evans *et al.*, 1994b; Morgan and Keith, 1995; Budnitz *et al.*,1995; Budnitz *et al.*, 1998; Morgan *et al.*, 2001; Garthwaite *et al.*, 2005; Morgan *et al*., 2006). An advantage of such expert elicitation is that it can effectively enumerate the range of expert judgments unhampered by social interactions, which may constrain discussion of extreme views in group-based settings.

Figures 5.2, 5.3 and 5.4 provide examples of results from expert elicitations done respectively on climate science in 1995, on forest ecosystem impacts in 2001, and on aerosol forcing in 2005. These are summary plots. Much greater detail, including judgments of time dynamics, and research needs are available in the relevant papers.

The comparison of individual expert judgments in Figure 5.4 with the summary judgment of the IPCC fourth assessment report (IPCC, 2007) suggests that the IPCC estimate of uncertainty in total aerosol forcing may be overconfident. A private communication from David Keith on the first eight responses of a detailed expert elicitation that he and Shawn Marshall (both of the University of Calgary) are conducting with leading glaciologists, indicates that they are finding even greater signs of overconfidence in the IPCC fourth assessment of sea level rise – suggesting that current strategies for producing IPCC summary statements of uncertainty may need to be reassessed.

Of course, expert judgment is not a substitute for definitive scientific research. Nor is it a substitute for careful deliberative expert reviews of the literature of the sort undertaken by the

IPCC. However, its use within such review processes could enable a better expression of both the diversity of expert judgment and could allow expression of expert judgments, which are not adequately reflected, in the existing literature. It can also provide insights for policy makers and research planners while research to produce more definitive results is ongoing. It is for these reasons that Moss and Schneider have argued that such elicitations should become a standard input to the IPCC assessment process (Moss and Schneider, 2000).

In selecting experts to participate in an expert elicitation, it is important to draw upon representatives from across all the relevant disciplines and schools of thought. At the same time, this process is fundamentally different from that of drawing a random sample to estimate some underlying true value. In the case of expert elicitation, it is entirely possible that one expert, perhaps even one whose views are an outliner, may be correctly reflecting the underlying physical reality, and all the others may be wrong. For this same reason, when different experts hold different views it is often best not to combine the results before using them in analysis, but rather to explore the implications of each expert's views so that decision makers have a clear understanding of whether and how much the differences matter in the context of the overall decision (Morgan and Henrion, 1990; Keith, 1996).

While it has been our experience that when asked to participate in such elicitation exercises, with very few exceptions, experts strive to provide their best judgments about the quantity or issue at hand, without considering how those judgments might be used or the implications they may carry for the conclusions that may be drawn when they are subsequently incorporated in models or other analysis. In addition to the strong sense of professional integrity possessed by most leading experts, the risk of possible "motivational bias" in experts' responses in elicitation processes is further reduced by the fact that even if the results are nominally anonymous, respondents know that they may be called upon to defend their responses to their peers.

As noted in Section 2, unless they are accompanied by some form of quantitative calibration, qualitative summaries of uncertainty can often mask large disagreements, since the same descriptors of qualitative uncertainty can mean very different things to different people. Thus, a quantitative expert elicitation can often provide a better indication of the diversity of opinion within an expert community than is provided in many consensus summaries. For example, the expert elicitation of climate change damage estimates by Nordhaus (1994) revealed a systematic divide between social and natural scientists' considered opinions. Such results can allow others to draw their own conclusions about how important the range of expert opinions is to the overall policy debate. Sometimes apparent deep disagreements make little difference to the policy conclusions; sometimes they are of critical importance (Morgan *et al.*, 1984; Morgan and Henrion, 1990).

We believe that in most cases it is best to avoid discussion of second-order uncertainty. Very often people are interested in using ranges or even second-order probability distributions on probabilities - to express "uncertainty about their uncertainty." In our experience, this usually arises from an implicit confusion that there is a "true" probability out there, in the same way that there is a true value for the rainfall in a specific location last year -- and people want to express uncertainty about that "true" probability. Of course, there is no such thing. The probability itself is a way to express uncertainty. A second-order distribution rarely adds anything useful.

It is, of course, possible to use a second-order distribution to express the possible effect of specific new information on a probability. For example, suppose your probability that there will be an increase of more than 1°C in average global temperature by 2020 is 0.5. It makes sense then to ask "what is your current probability distribution over the probability you will assess for that event in five years time, when you will have seen five years more climate data and climate research?" Bayesians sometimes call this a pre-posterior distribution. Note that the pre-posterior distribution is a representation of the informativeness of a defined but currently unknown source of information, in this case the next five years of data. It depends specifically on your beliefs about that information source.

Most people find pre-posterior distributions hard to think about. It is possible to use them in elicitations (Morgan and Keith, 1995). However, in public forums, they are often confused with ambiguity and other kinds of second-order probability and are liable to provoke ideological debates with proponents of alternative formalisms of uncertainty. Hence, our view is that it is usually wisest to avoid them in public forums and reserve them for that sub-set of specialist applications where they are really needed. This is particularly true when one is already eliciting full probability distributions about the value of uncertain quantities.

There is one exception to this general guidance, which perhaps deserves special treatment. Suppose we have two experts A and B who are both asked to judge the probability that a well specified event will occur (*i.e.*, not a full PDF but just a single probability on the binary yes/no outcome). Suppose A knows a great deal about the relevant science and B knows relatively little, but they both judge the probability of the event's occurrence to be 0.3. In this case, A might give a rather tight distribution if asked to state how confident he is about his judgment (or how likely he thinks it is that additional information would modify that judgment) while B might give a rather broad distribution. In this case, the resulting distribution provides a way for the two experts to provide information about the confidence they have in their judgment.

To date, elicitation of individual experts has been the most widely used method of using expert judgment to characterize uncertainty about climate-related issues. After experts have provided their responses, many of these studies later give participants the opportunity to review their own results and those of others, and make revisions should they so desire, but they are not focused on trying to achieve group consensus.

While they have not seen extensive use in climate applications, there are a number of group-based methods, which have been used in other settings. Of these, the best known is the Delphi method (Dalkey, 1969; Linstone and Turoff, 1975). Delphi studies involve multiple rounds in which participants are asked to make and explain judgments about uncertain quantities of interest, and then are iteratively shown the judgments and explanations of others, and asked to make revisions, in the hope that over time a consensus judgment will emerge. Such a procedure typically will not support the depth of technical detail that has been characteristic of some of the protocols that have been used in elicitation of individual climate experts.

Budnitz *et al.* (1995, 1998) have recently developed a much more elaborate group method in the context of probabilistic seismic hazard analysis. Meeting for an extended period, a group of experts work collectively, not as proponents of specific viewpoints but rather as:

> …informed *evaluators* of a range of viewpoints. (These individual viewpoints or models may be defended by proponents experts invited to present their views and 'debate' the panel). Separately the experts on the panel also play the role of *integrators*, providing advice… on the appropriate representation of the composite position of the community as a whole.

A technical facilitator/integrator (TFI):

> …conducts both individual elicitations and group interactions, and with the help of the experts themselves the TFI integrates data, models and interpretations to arrive at the final product: a full probabilistic characterization of the seismic hazard at a site, including the uncertainty. Together with the experts acting as evaluators, the TFI "owns" the study and defends it as appropriate. (Budnitz *et al.,* 1998)

Needless to say the process is very time consuming and expensive, requiring weeks or more of the expert's time.

Protocols for Individual Expert Elicitation

Developing a protocol for an effective expert elicitation in a substantively complex domain, such as climate science or climate impacts, typically requires many months of development, testing and refinement[24]. Typically the designers of such protocols start with many more questions they would like to pose than experts are likely to have patience or the ability to answer. Iteration is required to reduce the list of questions to those most essential and to formulate questions of a form that is unambiguous and compatible with the way in which experts frame and think about the issues at hand. To achieve this latter, sometimes it is necessary to provide a number of

[24]Roger Cooke (1991) and his colleagues have developed a number of elicitation programs in much shorter periods of time, working primarily in problem domains in which the problem is well specified and the specific quantities of interest are well defined.

different response modes. In this case, designers need to think about how they will process results to allow appropriate comparisons of different expert responses. To support this objective, it is often desirable to include some redundancy in the protocol enabling tests of the internal consistency of the experts' judgments.

A number of basic protocol designs have been outlined in the literature (see Chapter 7 in Morgan and Henrion (1990) and associated references). Typically they begin with some explanation of why the study is being conducted and how the results will be used. In most cases, experts are told that their names will be made public but that their identity will not be linked to any specific answer. This is done to minimize the possible impact of peer pressure, especially in connection with requests to estimate extreme values. Next, some explanation is typically provided of the problems posed by cognitive heuristics and overconfidence. Some interviewers in the decision analysis community ask experts to respond to various "encyclopedia questions" or perform other exercises to demonstrate the ubiquitous nature of over confidence in the hopes that this "training" will help to reduce overconfidence in the answers received. Unfortunately, the literature suggests that such efforts have little, if any, effect[25]. However, asking specific "disconfirming" questions, or "stretching" questions such as "Can you explain how the true value could turn out to be much larger (smaller) than your extreme value?" (see below) can be quite effective in reducing overconfidence.

[25]See, for example, the discussion on pp. 120-122 of Morgan and Henrion (1990).

In elicitations they have done on rather well defined topics, Cooke (1991) and his colleagues[26] have placed considerable emphasis on checking expert calibration and performance by presenting them with related questions for which values are well known, and then giving greater weight to experts who perform well on those questions. Others in the decision science community are not persuaded that such weighting strategies are advisable.

While eliciting a cumulative density function (CDF) of a probability distribution to characterize the uncertainty about the value of a coefficient of interest is the canonical question form in expert elicitations. Many of the elicitation protocols used in climate science have involved a wide range of other response modes (Morgan and Keith, 1995; Morgan *et al.*, 2001; Morgan *et al.*, 2006; Zickfeld *et al.*, 2006). In eliciting a CDF, it is essential to first clearly resolve with the expert exactly what quantity is being considered so as to remove ambiguity that might be interpreted differently by different experts. Looking back across a number of past elicitations, it appears that the uncertainty in question formulation and interpretation can sometimes be as large or larger than uncertainty arising from the specific formulation used to elicit CDFs. However, this is an uncertainty that can be largely eliminated with careful pilot testing, refinement and administration of the interview protocol.

Once a clear understanding about the definition of the quantity has been reached, the usual practice is to begin by asking the expert to estimate upper and lower bounds. This is done in an effort to minimize the impact of anchoring and adjustment and associated overconfidence. After receiving a response, the interviewer typically then chooses a slightly more extreme value (or, if

[26] Additional information about some of this work can be found at <http://www.rff.org/rff/Events/Copy-of-Expert-Judgment-Workshop-Documents.cfm#CP_JUMP_21423>. See also Kurowicka and Cooke (2006).

it exists, cites contradictory evidence from the literature) and asks if the expert can provide an explanation of how that more extreme value could occur. If an explanation is forthcoming, the expert is then asked to consider extending the bound. Only after the outer range of the possible values of the quantity of interest has been established does the interviewer go on to pose questions to fill in the balance of the distribution, using standard methods from the literature (Morgan and Henrion, 1990).

Experts often have great difficulty in thinking about extreme values. Sometimes they are more comfortable if given an associated probability (*e.g.*, a 1:100 upper bound rather than an absolute upper bound). Sometimes they give very different (much wider) ranges if explicitly asked to include "surprises," even though the task at hand has been clearly defined as identifying the range of all possible values. Therefore, where appropriate, the investigator should remind experts that "surprises" are to be incorporated in the estimates of uncertainty.

Hammitt and Shlyakhter (1999) have noted that overconfidence can give rise to an underestimate of the value of information in decision analytic applications. They note that because "the expected value of information depends on the prior distribution used to represent current uncertainty, and observe that "if the prior distribution is too narrow, in many risk-analytic cases, the calculated expected value of information will be biased downward." They have suggested a number of procedures to guard against this problem.

Most substantively detailed climate expert elicitations conducted to date have involved extended face-to-face interviews, typically in the expert's own office so that they can access reference material (and in a few cases even ask colleagues to run analyses, *etc*.). This has several clear advantages over mail or web-based methods. The interviewers can:

- Have confidence that the expert is giving his or her full attention and careful consideration to the questions being posed and to performing other tasks;
- More readily identify and resolve confusion over the meaning of questions, or inconsistencies in an expert's responses;
- More easily offer conflicting evidence from the literature to make sure that the expert has considered the full range of possible views;
- Build the greater rapport typically needed to pose more challenging questions and other tasks (such as ranking research priorities).

While developing probabilistic estimates of the value of key variables (*i.e.*, empirical quantities) can be extremely useful, it is often even more important to develop an understanding of how experts view uncertainty about functional relationships among variables. To date, this has received rather less attention in most elicitation studies; however, several have attempted to pose questions that address such uncertainties.

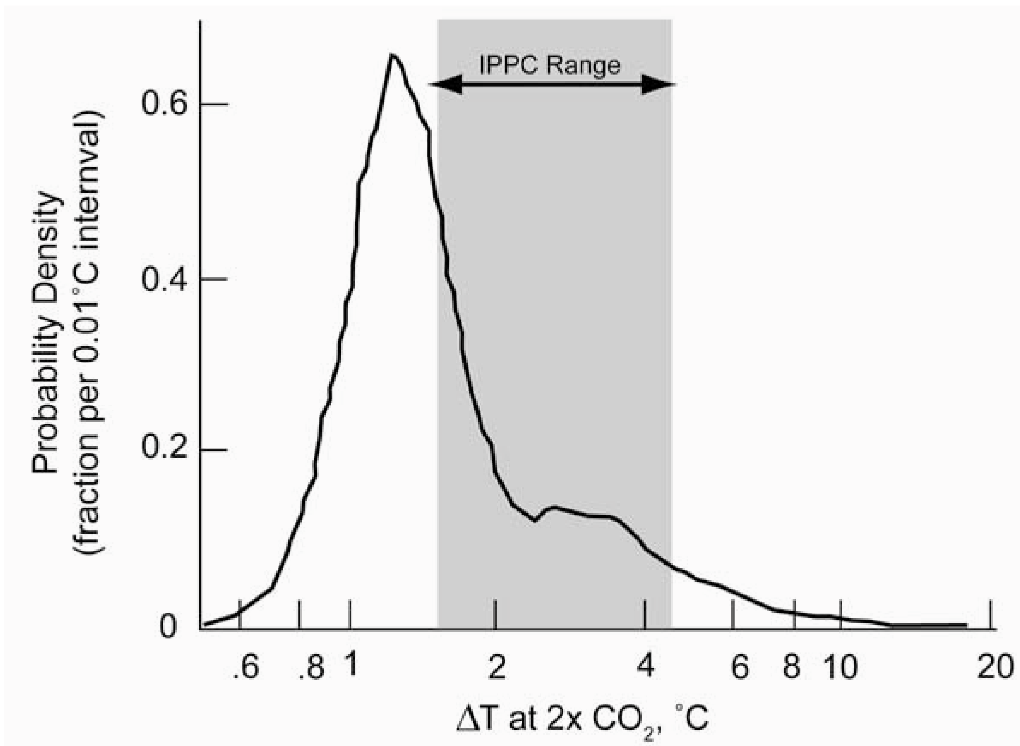

Figure 5.1 The probability density function for climate sensitivity (ΔT at 2x) estimated by Andronova and Schlesinger (2001). Using coupled atmosphere-ocean models, the observed near-surface temperature record and a bootstrap re-sampling technique, the authors examined the effect of natural variability and uncertainty in climatic radiative forcing on estimates of temperature change from the mid-19th century to the present. Their findings show a much wider range of climate sensitivity values to be consistent with our knowledge, than values presented in the IPCC Third Assessment. [Figure redrawn from Andronova and Schlesinger (2001).]

Climate sensitivity: Pole-to-equator temperature gradient:

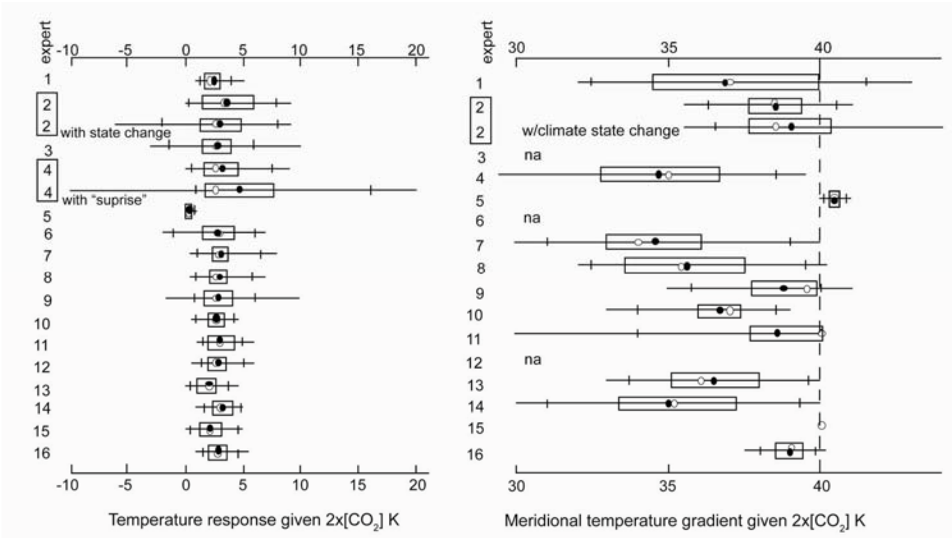

Figure 5.2 Examples of results from expert elicitations conducted by Morgan and Keith (1995) reported as box plots. Climate sensitivity is shown on the left and pole-to-equator temperature gradient on the right. Lines show the full range of the distribution; vertical tick marks show the 0.95 confidence intervals; boxes report the 0.25 to 0.75 central interval; open dots are best estimates and closed dots are means of the distributions. While there is apparently large agreement among all but one of the experts about the climate sensitivity, a quantity that has been widely discussed, judgments about the closely related pole-to-equator temperature gradient show much greater inter-expert variability.

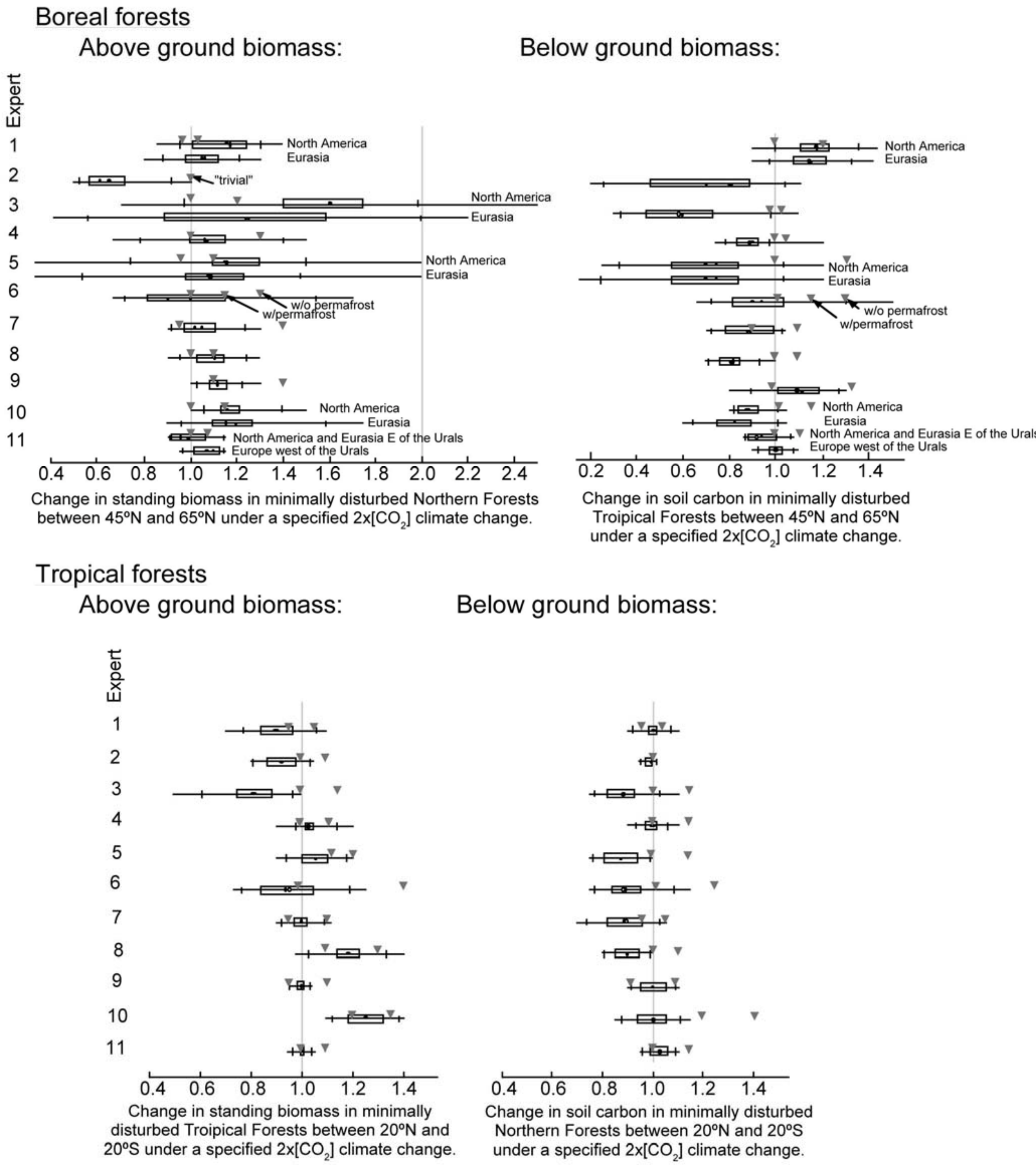

Figure 5.3 Examples of results from expert elicitations of forest ecosystem experts on change in above and below ground biomass for a specified 2xCO_2 climate change forcing (Morgan *et al.*, 2001). Note that in several cases there is not even agreement about the sign of the impact on carbon stocks. Notation is the same as in Figure 4.2. Gray inverted triangles show ranges for changes due to doubling of atmospheric CO_2, excluding a climate effect.

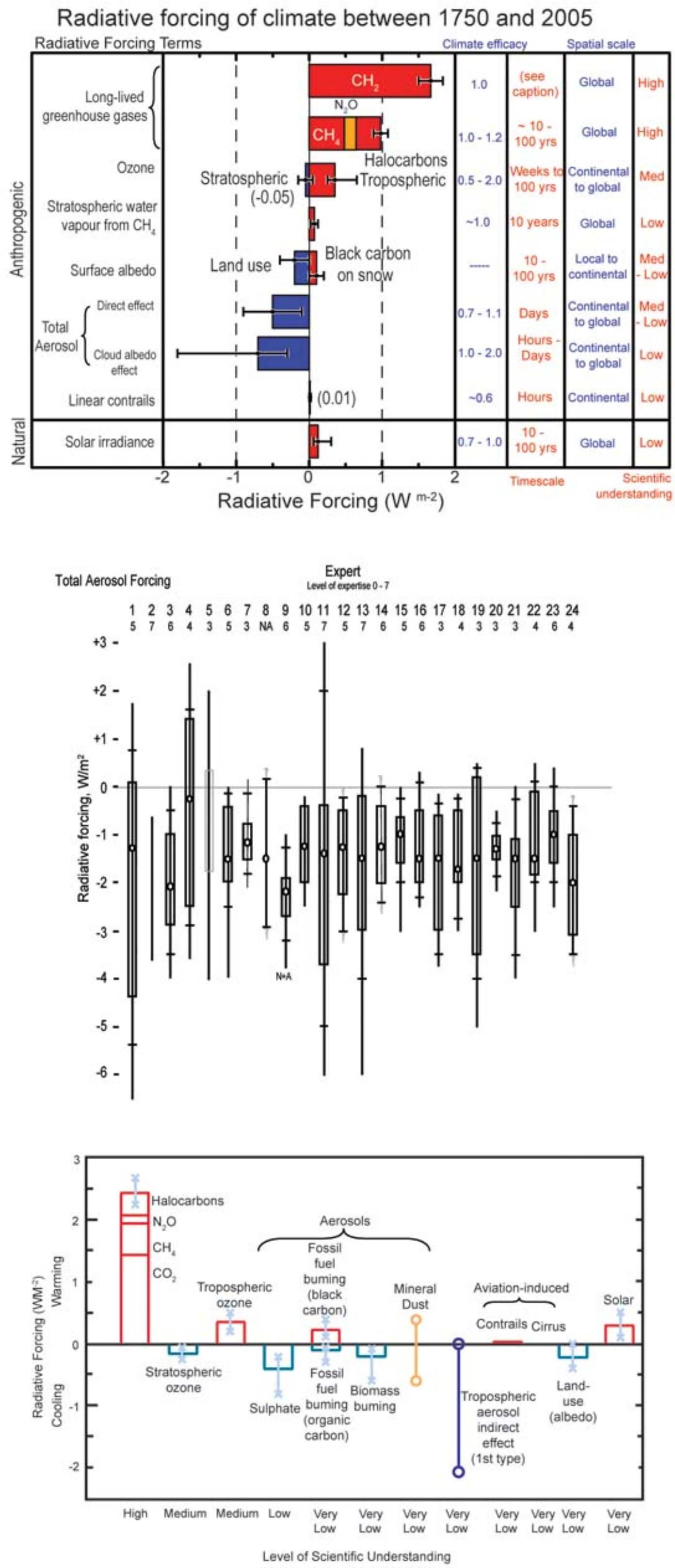

Figure 5.4 Comparison of estimates of aerosol forcing from the IPCC Third Assessment or TAR (bottom), an expert elicitation of 24 leading aerosol experts (center) and the IPCC Fourth Assessment or FAR (top). All radiative

forcing scales (in W per m^2) are identical. In this example, one gains a rather different impression of the state of uncertainty from individual expert elicitations than is reflected in the consensus summary. Uncertainty ranges in the FAR are 90% confidence intervals. The horizontal tick marks on the box plots in center are also 90% confidence intervals. Note that 13 of the 24 experts (54%) interviewed produced lower 5% confidence value that are clearly below that of the FAR, and 7 out of 24 (29%) produced upper 5% confidence values above that of the FAR. This suggests that the consensus statement of uncertainty from FAR may be overconfident.

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PART 6. PROPAGATION AND ANALYSIS OF UNCERTAINTY

Probabilistic descriptions of what is known about some key quantities can have value in their own right as an input to research planning and in a variety of assessment activities. Often, however, analysts want to incorporate such probabilistic descriptions in subsequent modeling and other analysis. A number of closed-form analytical methods exist to perform uncertainty analysis (Morgan and Henrion, 1990). However, as computing power and speed have continued to grow, most the standard methods for the propagation of uncertainty through models, and the analysis of its implications, have come to depend on stochastic simulation.

Such methods are now widely used in environmental, energy and policy research, either employing standard analysis environments such as @risk® <www.atrisk.com>, Crystal Ball® <www.crystalball.com> and Analytica® <www.lumina.com/>, or writing special purpose software to perform such analysis.

While modern computer methods allow investigators to represent all model inputs as uncertain, and propagate them through the model using stochastic simulation, it is often useful to explore how much uncertainty in each input variable contributes to the overall uncertainty in the output of the model. A number of methods are now available to support such an assessment, many of which have recently been reviewed and critiqued by Borgonovo (2006).

Many studies have used Nordhaus' simple DICE and RICE models (Nordhaus and Boyer, 2000) to examine optimal emissions abatement policies under uncertainty. In a more recent work, Keller *et al.* (2005) has used a modified version of the RICE model to examine the implications of uncertainty about potential abrupt collapse of the North Atlantic Meridian Overturning Circulation (Gulf Stream).

Other groups, such as the ICAM effort (Dowlatabadi and Morgan, 1993; Morgan and Dowlatabadi, 1996; Dowlatabadi, 2000) and the MIT Joint Program[27], have propagated uncertainty through more complex integrated assessment models.

A description of the MIT Integrated Global System Model (IGSM) can be found in Sokolov *et al*. (2005) and on the web at <http://web.mit.edu/globalchange/www/if.html>. As shown in Figure 6.1 anthropogenic and natural emissions models are used to provide forcings for a coupled two-dimensional land- and ocean-resolving model of the atmosphere that is coupled to a three-dimensional ocean general circulation model. Outputs of that model are used as inputs to a terrestrial ecosystems model that predicts land vegetation changes, land CO_2 fluxes, and soil composition. These in turn feed back to the coupled chemistry/climate and natural emissions models.

Webster *et al.* (2003) used an earlier version of the MIT model to perform a stochastic simulation that explores the uncertainty associated with a specific policy intervention that roughly achieves stabilization at 500 ppmv. Results are shown in Figure 6.2.

[27]For a list of publications from the MIT Joint Program see <http://web.mit.edu/globalchange/www/reports.html>.

Using this and similar models, investigators associated with the MIT Joint Center have conducted a variety of uncertainty analyses. For example, Forest *et al.* (2002, 2006) have used an optimal fingerprinting method to bound the range of values of climate sensitivity and the rate of ocean heat uptake that are consistent with their model when matched with the observed climate record of the 20th century. An example of a recent result is shown in Figure 6.3A.

Using a simple global energy balance model and diffusive ocean, Frame *et al.* (2005) have conducted studies to constrain possible values of climate sensitivity given plausible values of effective ocean heat capacity and observed 20th century warming. An example result is shown in Figure 6.3B. The result shown is for uniform weighting across climate sensitivity. Uniform weighting across feedbacks yields somewhat different results. The authors note that their results "fail to obtain a useful upper bound on climate sensitivity unless it is assumed *a priori*."

Frame *et al.* (2005) conclude that:

> …if the focus is on equilibrium warming, then we cannot rule out high sensitivity, high heat uptake cases that are consistent with, but non-linearly related to, 20th century observations. On the other hand, sampling parameters to simulate a uniform distribution of transient climate response… gives an approximately uniform distribution in much more immediately policy-relevant variables … under all SRES emission scenarios. After weighting for observations … this approach implies a 5-95% range of uncertainty in *S* [the climate sensitivity] of 1.2-5.2°C, with a median of 2.3°C, suggesting traditional heuristic ranges of uncertainty in S (IPCC WGI, 2001) may have greater relevance to medium-term policy issues than recent more formal estimates based on explicit uniform prior distributions in either *S* or [feedback strength] λ.

Murphy *et al.* (2004) have completed extensive parametric analysis with the HadAM3 atmospheric model coupled to a mixed layer ocean that they report "allows integration to equilibrium in a few decades." They selected a subset of 29 of the roughly 100 parameters in this model, which they judged to be most important in determining the model's climate sensitivity, and then perturbed them one at a time with respect to their standard values, and created 53 different model versions, each of which was used to simulate present and future 2xCO_2 climate.

Placing uniform probability distributions on all these, they conclude that the implied climate sensitivity has a "median value of 2.9°C with a spread (corresponding to a 5 to 95% probability range) of 1.9 to 5.3°C." By using some analysis and expert judgment to shape the prior distributions, they also produce a "likelihood-weighted" distribution which they report "results in a narrowing of the 5 to 95% probability range to 2.4 to 5.4°C, while the median value increases to 3.5°C" (Murphy *et al.,* 2004). They report:

> Our probability function is constrained by objective estimates of the relative reliability of different model versions, the choice of model parameters that are varied and their uncertainty ranges, specified on the basis of expert advice. Our ensemble produces a range of regional changes much wider than indicated by traditional methods based on scaling the response patterns of an individual simulation.

One of the most exciting recent developments in exploring the role of uncertainty in climate modeling has been the use of a large network of personal computers, which run a version of the HadSM3 model as a background program when machine owners are not making other uses of their machine. This effort has been spearhead by Myles Allen and colleagues at Oxford (Allen, 1999). Details can be found at <http://www.climateprediction.net/index.php>. As of mid-spring 2006, this network involved over 47 thousand participating machines that had completed over 150 thousand runs of a version of the HadSM3 model, for a total of 11.4 million model years of simulations.

Initial results from this work were reported by Stainforth *et al.* (2005) who summarize their findings from a study of 2,578 simulations of the model as follows:

> We find model versions as realistic as other state-of-the-art climate models but with climate sensitivities ranging from less than 2K to more than 11K. Models with such extreme sensitivities are critical for the study of the full range of possible responses of the climate system to rising greenhouse gas levels, and for assessing the risks associated with a specific target for stabilizing these levels…

> The range of sensitivity across different versions of the same model is more than twice that found in the GCMs used in the IPCC Third Assessment Report…The possibility of such high sensitivities has been reported by studies using observations to constrain this quantity, but this is the first time that GCMs have generated such behavior. (Stainforth *et al.*, 2005)

The frequency distribution in climate sensitivity they report across all model versions is shown in Figure 6.4.

While the common practice in many problem domains is to build predictive models, or perform various forms of policy optimization, it is important to ask whether meaningful prediction is possible. At least in the context of predicting the future evolution of the energy system, which is responsible for a large fraction of anthropogenic greenhouse gas emissions, Smil (2003) and Craig *et al.* (2002) have very clearly shown that accurate prediction for more than a few years in the future, is virtually impossible. Figure 6.5 redrawn from Smil, shows the sorry history of past forecasts for United States energy consumption. His summary of forecasts of global energy consumption shows similarly poor performance.

In addition to uncertainties about the long-term evolution of the energy system and hence future emissions, uncertainties about the likely response of the climate system, and about the possible impacts of climate change, are so great that a full characterization of coefficient and model uncertainty in a simulation model can lead to probabilistic results that are so broad that they are effectively useless (Casman *et al.*, 1999). Similarly, if one does parametric analysis across different model formulations, one can obtain an enormous range of answers depending on the model form and other inputs that are chosen. This suggests that there are decided limits to the use of "predictive models", and "optimization" in many climate assessment and policy settings.

The difficulties, or sometimes even impossibility, of performing meaningful predictive analysis under conditions of what has been called "deep" or "irreducible" uncertainty have led some investigators to pursue a different approach based on two key ideas: describing uncertainty about the system relevant to a decision with multiple representations, as opposed to a single best-estimate joint probability distribution, and using a robustness, as opposed to an optimality, as the criteria for evaluating alternative policy options. We turn to a more detailed discussion of these approaches in the latter parts of the next section.

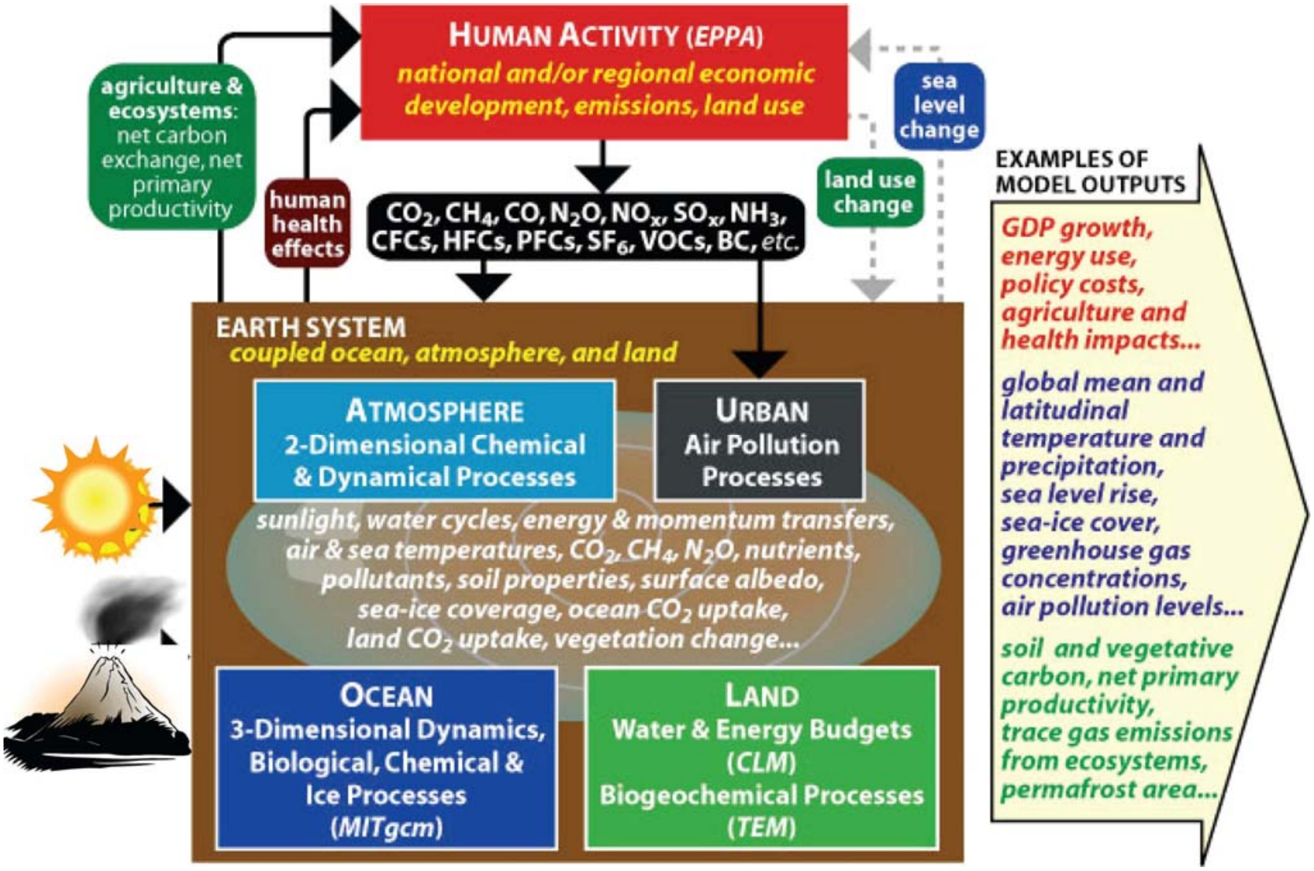

Figure 6.1 Simplified block diagram of the MIT Integrated Global System Model (IGSM) Version 2. Source: MIT Global Change Joint Program. Reprinted with permission.

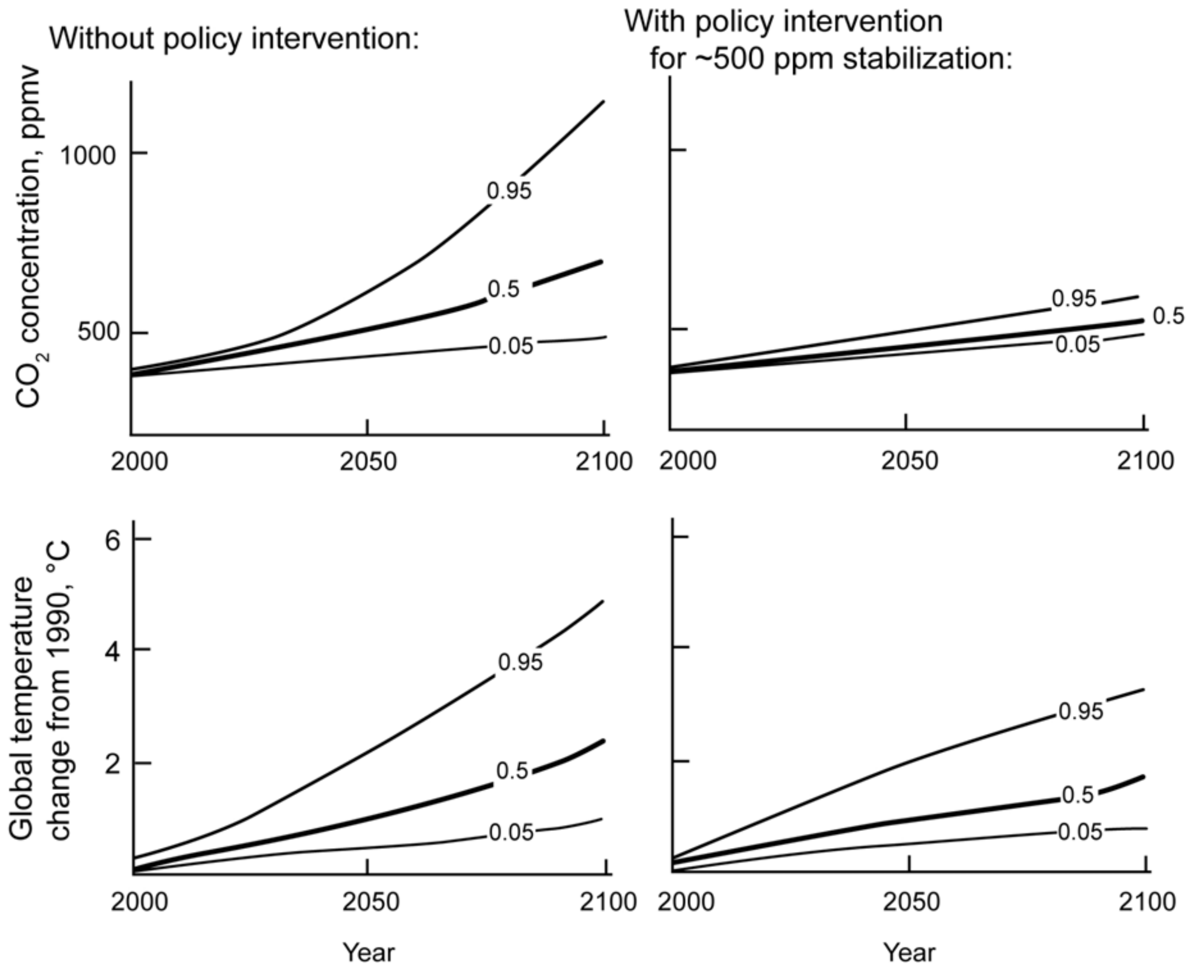

Figure 6.2 Results of simulation conducted by Webster *et al.* (2003) which use an earlier version of the MIT IGSM model with probability distributions on model inputs that are constrained by past performance of the climate system. Results on the left are the authors' projection for no policy intervention and on the right for a specific policy intervention that roughly achieves stabilization at 500 ppmv. Heavy curves show median results from the simulations. Light curves show 0.05 and 0.95 confidence intervals. [Redrawn from Webster *et al.* (2003).]

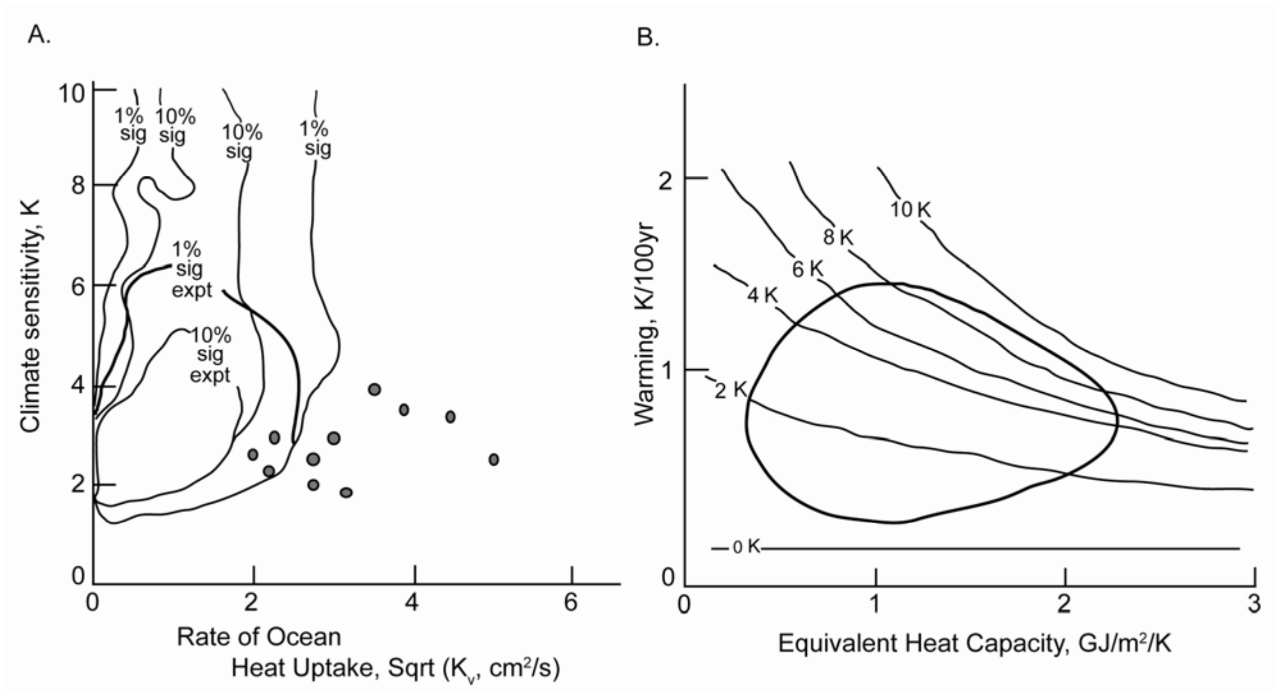

Figure 6.3 Two examples of recent efforts to bound sensitivity and heat uptake or heat capacity by combining expert judgment and model simulations.
A. (redrawn from Forest *et al.*, 2006) shows the marginal posterior probability density function obtained when using uniform probability distributions across all relevant forcings and matching outputs from the ocean and atmospheric portion of the MIT IGSM model. Light contours bound the 10% and 1% significance regions. Similarly, the two dark contours are for an expert PDF on climate sensitivity. Dots show outputs from a range of leading GCMs all of which lie to the right of the high-probability region, suggesting that if Forest *et al.* (2006) are correct, these models may be mixing heat into the deep ocean too efficiently.
B (redrawn from Frame *et al.*, 2005) shows the relationship between climate sensitivity, shown as light contours, effective ocean heat capacity, and 20th century warming for the case of uniform sampling of climate sensitivity (not shown are similar results for uniform sampling across feedback strength). The dark contour shows the region consistent with observations at the 5% level. Note: We have roughly extrapolated the climate sensitivity contours from colored points in the original diagram that report each of many of hundreds of individual model runs. In this diagram, they are only qualitatively correct.
Note that neither of these analyses account for the issue of structural uncertainty.

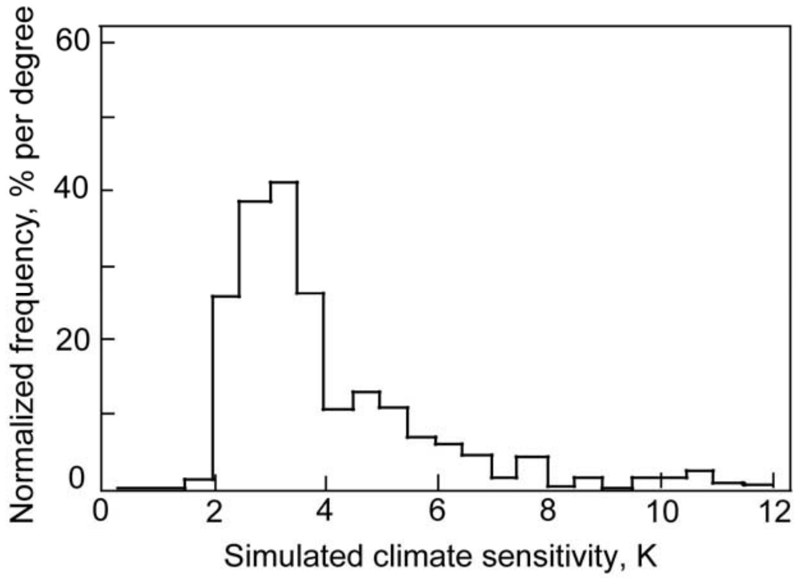

Figure 6.4 Histogram (redrawn) of climate sensitivities found by Stainforth *et al.* (2005) in their simulation of 2,578 versions of the HadSM3 GCM model.

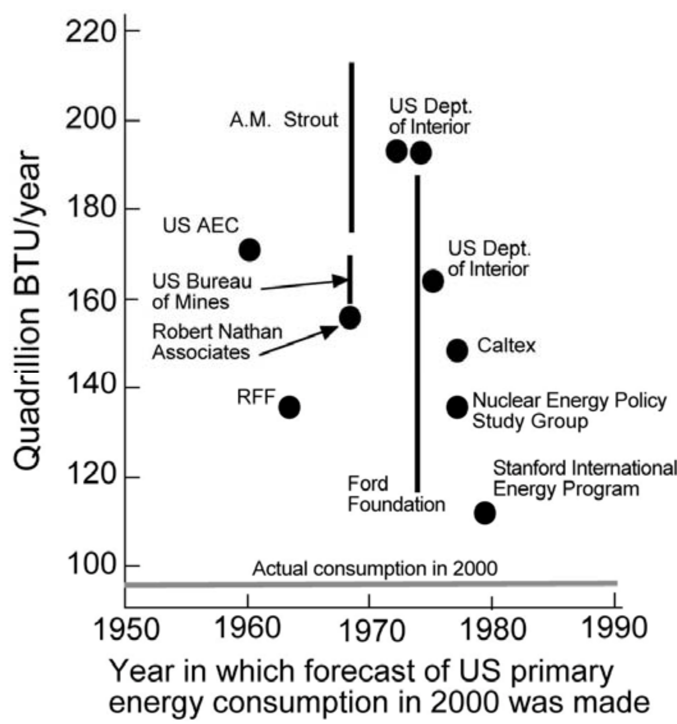

Figure 6.5 Summary of forecasts of United States primary energy consumption compiled by Smil (2003) as a function of the date on which they were made. [Figure redrawn from Smil (2003).]

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PART 7. MAKING DECISIONS IN THE FACE OF UNCERTAINTY

As we noted in the introduction, there are a number of things that are different about the climate problem (Morgan *et al.*, 1999), but high levels of uncertainty is not one of them. In our private lives, we decide where to go to college, what job to take, whom to marry, what home to buy, when and whether to have children, and countless other important choices, all in the face of large, and often irreducible uncertainty. The same is true of decision made by companies and by governments -- sometimes because decisions must be made, sometimes because scientific uncertainties are not the determining factor (*e.g.*, Wilbanks and Lee, 1985), and sometimes because strategies can be identified that incorporate uncertainties and associated risks into the decision process (NRC, 1986).

Classical decision analysis provides an analytical strategy for choosing among options when possible outcomes, their probability of occurrence, and the value each holds for the decision maker, can be specified, decision analysis identifies an "optimal" choice among actions. Decision analysis is rigorously derived from a set of normatively appealing axioms (Raiffa and Schlaifer, 1968; Howard and Matheson, 1977; Keeney, 1982). In applying decision analysis, one develops and refines a model that relates the decision makers' choices to important outcomes. One must also determine the decision maker's utility function(s)[28] in order to determine which outcomes are most desirable. One then propagates the uncertainty in various input parameters through the model (appropriately accounting for possible correlation structures among uncertain variables) to

[28]Many economists and analysts appear to assume that fully articulated utility functions exist in peoples' heads for all key outcomes, and that determining them is a matter of measurement. Many psychologists, and some decision analysts, suggest that this is often not the case and that for many issues people need help in thinking through and constructing their values (von Winterfeldt and Edwards, 1986; Fischhoff, 1991; Keeney, 1992; Fischhoff, 2005).

generate the expected utility of the various choice options. The best option is typically assumed to be the one with the largest expected utility, although other decision rules are sometimes employed.

When the uncertainty is well characterized and the model structure well known, this type of analysis can suggest the statistically optimal strategy to decision makers. Because there are excellent texts that outline these methods in detail (e.*g.*, Hammond *et al.*, 1999), we do not elaborate the ideas further here.

In complex, and highly uncertain contexts, such as those involved in many climate-related decisions, the conditions needed for the application of conventional decision analysis sometime do not arise (Morgan *et al.*, 1999). Where uncertainty is large, efforts can be made to reduce the uncertainties - in effect, reducing the width of probability distributions through research to understand underlying processes better. Alternatively, efforts can be made to improve understanding of the uncertainties themselves so that they can be more confidently incorporated in decision-making strategies.

In most cases more research reduces uncertainty. Classic decision analysis implicitly assumes that research always reduces uncertainty. While eventually it usually does, in complex problems, such as some of the details of climate science, many years, or even many decades may go by, during which one’s understanding of the problem grows richer, but the amount of uncertainty, as measured by our ability to make specific predictions, remain unchanged, or even grows larger because research reveals processes or complications that had not previously been understood or anticipated. That climate experts understand this is clearly demonstrated in the results from Morgan and Keith (1995) shown in Table 7.1. Unfortunately, many others do not recognize this fact, or choose to ignore it in policy discussions. This is not to argue that research in understanding climate science, climate impacts, and the likely effectiveness of various climate management policies and technologies is not valuable. Clearly it is. But when it does not immediately reduce uncertainty we should remember that there is also great value in learning that we knew less than we thought we did. In some cases, all the research in the world may not eliminate key uncertainties on the timescales of decision we must make.

This raises the question of what considerations should drive research. Not all knowledge is likely to be equally important in the climate-related decisions that individuals, organizations and nations will face over the coming decades. Thus, while it is often hard to do (Morgan *et al.*, 2006), when possible, impact assessors, policy analysts and research planners should consider working backward from the decisions they face to design research programs which are most likely to yield useful insights and understanding.

There are two related decision-making/management strategies that may be especially appealing in the face of high uncertainty. These are:

> *Resilient Strategies:* In this case, the idea is to try to identify the range of future circumstances that one might face, and then seek to identify approaches that will work reasonably well across that range.

*Adaptive Strategies***:** In this case, the idea is to choose strategies that can be modified to achieve better performance as one learns more about the issues at hand and how the future is unfolding.

Both of these approaches stand in rather stark contrast to the idea of developing optimal strategies that has characterized some of the work in the integrated assessment community, in which it is assumed that a single model accurately reflects the nature of the world, and the task is to choose an optimal strategy in that well specified world.

The ideas of resilience and adaptation have been strongly informed by the literature in ecology. Particularly good discussions can be found in Clark (1980) and Lee (1993). A key feature of adaptive strategies is that decision makers learn whatever they can about the problem they face and then make choices based on their best assessment and that of people whose advice they value. They seek strategies that will let them, or those who come after them, modify choices in accordance with insights gained from more experience and research. That is, rather than adopt a decision strategy of the sort shown in Figure 7.1A in which nothing is done until research resolves all key uncertainties, they adopt an iterative and adaptive strategy that looks more like that shown in Figure 7.1B. Adaptive strategies work best in situations in which there are not large non-linearities and in which the decision time scales are well matched to the changes being observed in the world.

A familiar example of a robust strategy is portfolio theory as applied in financial investment, which suggests that greater uncertainty (or a lesser capacity to absorb risks) calls for greater portfolio diversification. Another example arose during the first regional workshop conducted by the National Assessment Synthesis Team in Fort Collins, CO, in preparation for developing the U.S. National Climate Change Assessment (NAST, 2000). Farmers and ranchers participating in the discussion suggested that, if possible climate change introduces new uncertainties into future climate forecasts, it might be prudent for them to reverse a trend toward highly-specialized precision farming and ranching, moving back toward a greater variety of crops and range grasses.

Deep uncertainty

Decision makers face deep uncertainty when those involved in a decision do not know or cannot agree upon the system model that relates actions to consequences or the prior probability distributions on the input parameters to any system model[29]. Under such conditions multiple representations can provide a useful description of the uncertainty.

Most simply, one can represent deep uncertainty about the values of empirical quantities and about model function form by considering multiple cases. This is the approach taken by traditional scenario analyses. Such traditional scenarios present a number of challenges, as documented by Parson *et al.* (2007). Others have adopted multi-scenario simulation approaches (IPCC WGIII, 2001) where a simulation model is run many times to create a large number of fundamentally different futures and used directly to make policy arguments based on comparisons of these alternative cases.

[29] A number of different terms are used for what we call here 'deep uncertainty.' Knight (1921) distinguished risk from uncertainty, using the later to denote factors poorly described by quantified probabilities. Ben-Haim (2001) refers to severe uncertainty and Vercelli (1994) to hard as opposed to the more traditional soft uncertainty. The literature on imprecise probabilities refers to probabilities that can lie within a range.

In the view of the authors of this report, considering a set of different, plausible joint probability distributions over the input parameters to one of more models provides the most useful means to describe deep uncertainty. As described below, this approach is often implemented by comparing the ranking or desirability of alternative policy decisions as a function of alternative probability weightings over different states of the world. This is similar to conventional sensitivity analysis where one might vary parameter values or the distribution over the parameters to examine the effects on the conclusions of an analysis. However, the key difference is one of degree. Under deep uncertainty the set of plausible distributions contains members that in fact would imply very different conclusions for the analysis. In addition to providing a useful description of deep uncertainty, multiple representations can also play an important role in the acceptance of the analysis when stakeholders to a decision have differing interests and hold differing non-falsifiable, perceptions. In such cases, an analysis may prove more acceptable to all sides in a debate if it encompasses all the varying perspectives rather than adopting one view as privileged or superior (Rosenhead and Mingers, 2001).

There exists no single definition of robustness. Some authors have defined robust strategy as one that performs well, compared to the alternatives, over a very wide range of alternative futures (Lempert *et al.* 2003). This definition represents a "satisficing" criterion (Simon, 1959), and is similar to domain criteria (Schneller and Sphicas, 1983) where decision makers seek to reduce the interval over which a strategy performs poorly. Another formulation defines a robust strategy as one that sacrifices a small amount of optimal performance in order to obtain less sensitivity to broken assumptions. This robustness definition underlies Ben-Haim's (2001) "Info-Gap" approach, the concept of robustness across competing models used in monetary policy applications (Levin and Williams, 2003), and to treatments of low probability, high-consequence events (Lempert *et al.*, 2002). This definition draws on the observation that an optimum strategy may often be brittle, that is, its performance may degrade rapidly under misspecification of the assumptions and that decision makers may want to take steps to reduce that brittleness[30], For instance, if one has a best-estimate joint probability distribution describing the future, one might choose a strategy with slightly less than optimal performance in order to improve the performance if the tails of the best-estimate distribution describing certain extreme cases turn out to larger than expected[31]. Other authors have defined robustness as keeping options open. Rosenhead (2001) views planning under deep uncertainty as a series of sequential decisions. Each decision represents a commitment of resources that transform some aspect of the decision-maker's environment. A plan foreshadows a series of decisions that it is anticipated will be taken over time. A robust step is one that maximizes the number of desirable future end states still reachable, and, in some applications, the number of undesirable states not reachable, once the initial decision has been taken.

These definitions often suggest similar strategies as robust, but to our knowledge, there has been no thorough study that describes the conditions where these differing robustness criteria lead to

[30] United States Federal Reserve Chairman Alan Greenspan described an approach to robust strategies when he wrote "…For example policy A might be judged as best advancing the policymakers' objectives, conditional on a particular model of the economy, but might also be seen as having relatively severe adverse consequences if the structure of the economy turns out to be other than the one assumed. On the other hand, policy B might be somewhat less effective under the assumed baseline model … but might be relatively benign in the event that the structure of the economy turns out to differ from the baseline. These considerations have inclined the Federal Reserve policymakers toward policies that limit the risk of deflation even though the baseline forecasts from most conventional models would not project such an event."

[31] Given a specific distribution one can find a strategy that is optimal. But this is not the same as finding a strategy that performs well (satisfices) over a wide range of distributions and unknown system specifications.

similar or different rankings of alternative policy options. Overall, a robustness criterion often yields no single best answer but rather helps decision makers to use available scientific and socio-economic information to distinguish a set of reasonable from unreasonable choices and to understand the tradeoffs implied by choosing among the reasonable options. Robustness can be usefully thought of as suggesting decision options that lie between an optimality and a minimax solution. In contrast to optimal strategies that, by definition, focus on the middle range of uncertainty most heavily weighted by the best estimate probability density function, robustness focuses more on, presumably unlikely but not impossible, extreme events and states of the world, without letting them completely dominate the decision.

One common means of achieving robustness is via an adaptive strategy, that is, one that can evolve over time in response to new information. Two early applications of robust decision making to greenhouse gas mitigation policies focused on making the case for such robust adaptive strategies. These studies also provide an example of a robust strategy as one that performs well over a wide range of futures. Morgan and Dowlatabadi (1996) used variants of their ICAM-2 model in an attempt to determine the probability that specific carbon tax policy would yield net positive benefits. Their sensitivity analysis over different model structures suggested a range that is so wide, 0.15 to 0.95, as to prove virtually useless for policy purposes. Similarly, Table 7.2 illustrates the wide range of effects due to alternative ICAM model structures one finds on the costs of CO_2 stabilization at 500 ppm (Dowlatabadi, 1998). To make sense of such deep uncertainty Casman *et al.* (1999) considered adaptive decision strategies (implemented in the model as decision agents) that would take initial actions based on the current best forecasts, observe the results, revise their forecasts, and adjust their actions accordingly. This study highlights the importance of how we can build in robust strategies by building policies around different state variables. For example, the most common state variable in climate policy is annual emissions of GHGs. This variable suffers from high variability induced by: stochastic economic activity, energy market speculations, and inter-annual variability in climate. All of these factors can drive emissions up or down, outside the influence of the decision-variable itself or how it influences the system (i.e., a shadow price for GHGs). A policy that uses atmospheric concentration of CO_2 and its rate of change, is much less volatile and much better at offering a robust signal for adjusting the decision-variable through time. The study reports that atmospheric forcing, or GHG concentrations are far more robust that alternative state variables such as emission rates or global average temperature over a wide range of model structures and parameter distributions. This finding has important implications for the types of scientific information that may prove most useful to decision makers.

Similarly, Lempert *et al.* (1996) used a simple integrated assessment model to examine the expectations about the future that would favor alternative emissions-reduction strategies. The study examined the expected net present value of alternative strategies as a function of the likelihood of large climate sensitivity, large climate impacts, and significant abatement-cost-reducing new technology. Using a policy region analysis (Watson and Buede, 1987), the study found that both a business as usual and a steep emissions-reduction strategy that do not adjust over time presented risky choices because they could prove far from optimal if the future turned out differently than expected. The study then compared an adaptive strategy that began with moderate initial emissions reductions and sets specific thresholds for large future climate impacts and low future abatement costs. If the observed trends in impacts or costs trigger either threshold, then emissions reductions accelerate. As shown in Figure 7.2, this adaptive strategy performed better than the other two strategies over a very wide range of expectations about the future. It also proved to be close to optimal otherwise. For those expectations where one of the other two strategies performed best, the adaptive strategy performed nearly as well. The study thus concluded the adaptive decision strategy was robust compared to the two non-adaptive alternatives.

These robust decision making approaches have been applied more recently using more sophisticated methods. For instance, Groves (2006) has examined robust strategies for California water policy in the face of climate and other uncertainties and Dessai and Hulme (2007) has applied similar approaches to water resource management in the UK. Similarly, Hall (Hine and Hall, 2007) has used Haim's Info-Gap approach to examine robust designs for the Thames flood control system in the face of future scientific uncertainty about sea level rise.

Surprise

Recent attention to the potential for abrupt climate change has raised the issue of "surprise" as one type of uncertainty that may be of interest to decision-makers. An abrupt or discontinuous change represents a property of a physical or socio-economic system. For instance, similarly to many such definitions in the literature, the United States National Academy of Sciences has defined an abrupt climate change as a change that occurs faster than the underlying driving forces (NRC, 2002). In contrast, surprise represents a property of the observer. An event becomes a surprise when it opens a significant gap between perceived reality and one's expectations (van Notten *et al.*, 2005; Glantz *et al.*, 1998; Hollings, 1986; Schneider *et al.*, 1998).

A number of psychological and organizational factors make it more likely that a discontinuity will cause surprise. For instance, individuals will tend to anchor their expectations of the future based on their memories of past patterns and observations of current trends and thus be surprised if those trends change. Scientists studying future climate change will often find a scarcity of data to support forecasts of systems in states far different than the ones they can observe today. Thus, using the taxonomy of Figure 1.1, the most well established scientific knowledge may not include discontinuities. For example, the sea level rise estimates of the most recent IPCC Fourth Assessment Report (IPCC, 2007) do not include the more speculative estimates of the consequences of a collapse of the Greenland ice sheet because scientists' understanding of such a discontinuous change is less well-developed than for other processes of sea level rise. Planners who rely only on the currently well-established estimates may come to be (or leave their successors) surprised.

The concepts of robustness and reliance provide a useful framework for incorporating and communicating scientific information about potential surprise[32]. First, these concepts provide a potential response to surprise in addition to and potentially more successful than trying to predict them. A robust strategy is designed to perform reasonably well in the face of a wide range of contingencies and thus a well-designed strategy will be less vulnerable to a wide range of

[32] Robustness and resilience are related concepts. The former generally refers to strategies chosen by decision makers while the later is a property of systems. However, the concepts overlap because decision makers can take actions that make a system more resilient.

potential surprises whether predicted or not. Second, the robustness framework aims to provide a context that facilitates constructive consideration of otherwise unexpected events (Lempert *et al.*, 2003). In general, there is no difficulty imagining a vast range of potential outcomes that might be regarded as surprising. It is in fact rare to experience a major surprise that had not been previously imagined by someone (*e.g.*, fall of the Soviet Union, Katrina, Pearl Harbor, 9/11). The difficulty arises in a decision making context if in the absence of reliable predictions there is no systematic way to prioritize, characterize, and incorporate the plethora of potential surprises that might be imagined. A robust decision framework can address this problem by focusing on the identification of those future states of the world in which a proposed robust strategy would fail, and then identify the probability threshold such a future would have to exceed in order to justify a decision maker taking near-term steps to prevent or reduce the impacts of such a future.

For example, Figure 7.3 shows the results of an analysis (Lempert *et al.*, 2000) that attempted to lay out the surprises to which a candidate emissions-reduction strategy might prove vulnerable. The underlying study considered the effects of uncertainty about natural climate variability on the design of robust, near-term emissions mitigation strategies. This uncertainty about the level of natural variability makes it more difficult to determine the extent to which any observed climate trend is due to human-caused effects and thus makes it more difficult to set the signposts that would suggest emissions mitigation policies ought to be adjusted. The study first identified a strategy robust over the commonly discussed range of uncertainty about the potential impacts of climate change and the costs of emissions mitigation. It then examined a wider range of poorly characterized uncertainties in order to find those uncertainties to which the candidate robust strategy remains most vulnerable. The study finds two such uncertainties most important to the strategies' performance: the probability of unexpected large damages due to climate change and the probability of unexpectedly low damages due to changes in climate variability. Figure 5.6 traces the range of probabilities for these two uncertainties that would justify abandoning the proposed robust strategy described in the shaded region in favor of one of the other strategies shown on the figure. Rather than asking scientists or decision makers to quantify the probability of surprisingly large climate impacts, the analysis suggests that such a surprise would need to have a probability larger than roughly 10 to 15 percent in order to significantly influence the type of policy response the analysis would recommend. Initial findings suggest that this may provide a useful framework for facilitating the discovery, characterization, and communication of potential surprises.

Behavioral decision theory

The preceding discussion has focused on decision making by "rational actors." In the case of most important real-world decision problems, there may not be a single decision maker, decisions get worked out and implemented through organizations, in most cases formal analysis plays a subsidiary role to other factors, and in some cases, emotion and feelings (what psychologists term "affect") may play an important role.

These factors are extensively discussed in a set of literatures typically described as "behavioral decision theory" or risk-related decision making. In contrast to decision analysis that outlines how people should make decisions in the face of uncertainty is they subscribe to a number of axioms of rational decision making, these literatures are descriptive, describing how people actually make decisions when not supported by analytical procedures such a decision analysis.

Good summaries can be found in Kahneman *et al.* (1982), Jaeger *et al.* (1998), and Hastie and Dawes (2001). Recently investigators have explored how rational and emotional parts of human psyche interact in decision making (Slovic, *et al.,* 2004; Peters *et al.,* 2006; Loewenstein *et al.,* 2001; Lerner *et al.,* 2003; Lerner and Tiedens, 2006). Far from diminishing the role of affect-based decision making, several of these authors argue that in many decision settings it can play an important role along with more analytical styles of thought.

There are also very large literatures on organizational behavior. One of the more important subsets of that literature for decision making under uncertainty concerns the processes by which organizational structure can play a central role in shaping the success of an organization in coping with uncertainty and strategies they can adopt to make themselves less susceptible to failure (see for example: LaPorte and Consolini, 1991; Vaughan, 1996; La Porte, 1996; Paté-Cornell *et al.,* 1997; Pool, 1997; Weick and Sutcliffe, 2001).

The "precautionary principle" is a decision strategy often proposed for use in the face of high uncertainty. There are many different notions of what this approach does and does not entail. In some forms it incorporates ideas of resilience or adaptation. In some forms, it can also be shown to be entirely consistent with a decision analytic problem framing (DeKay *et al.,* 2002).

However, among some proponents, precaution has often taken the form of completely avoiding new activities or technologies that might hold the potential to cause adverse impacts, regardless of how remote their probability of occurrence. In this form, the precautionary principle has drawn vigorous criticism from a number of commentators. For example Sunstein (2005) argues:

> …a wide variety of adverse effects may come from inaction, regulation and everything in between. [A better approach]…would attempt to consider all of these adverse effects, not simply a subset. Such an approach would pursue distributional goals directly by, for example, requiring wealthy countries – the major contributors to the problem of global warming – to pay poor countries to reduce greenhouse gases or to prepare themselves for the relevant risks. When societies face risks of catastrophe, even risks whose likelihood can not be calculated, it is appropriate to act, not to stand by and merely hope.

Writing in a similar vein before "precaution" became widely discussed; Wildavsky (1979) argued that some risk taking is essential to social progress. Thompson (1980) has made very similar arguments in comparing societies and cultures.

Precaution is often in the eye of the beholder. Thus, for example, some have argued that while the European Union has been more precautionary with respect to climate change and CO_2 emissions in promoting the wide adoption of fuel efficient diesel automobiles, the Unites States has been more precautionary with respect to health effects of fine particulate air pollution, stalling the adoption of diesel automobiles until it was possible to substantially reduce their particulate emissions (Wiener and Rogers, 2002).

Table 7.1 In the expert elicitations of climate scientists conducted by Morgan and Keith (1995), experts were asked to design a 15-year long research program funded at a billion dollars per year that was designed to reduce the uncertainty in our knowledge of climate sensitivity and related issues. Having done this, the experts were asked how much they thought their uncertainty might have changed if they were asked the same question in 15 years. The results below show that like all good scientists the experts understand that research does not always reduce uncertainty. Note: Expert 3 used a different response mode for this question. He gave a 30% increase by a factor of ≥2.5.

Expert Number	Chance that the experts believe that their uncertainty about the value of climate sensitivity would *grow* by >25% after a 15yr. $\$10^9$/yr. research program
1	10
2	18
3	30 (Note 1)
4	22
5	30
6	14
7	20
8	25
9	12
10	20
11	40
12	16
13	12
14	18
15	14
16	8

Table 7.2 - Illustration from Casman *et al.* (1999) of the wide range of results that can be obtained with ICAM depending upon different structural assumptions, in this case, about the structure of the energy module and assumptions about carbon emission control. In this illustration, produced with a 1997 version of ICAM, all nations assume an equal burden of abatement by having a global carbon tax. Discounting is by a method proposed by Schelling (1994). Other versions of ICAM yield qualitatively similar results

		Model Variants								
Model Components		**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**
Are new fossil oil & gas deposits discovered?		no	**yes**	no	no	**yes**	**yes**	no	**yes**	**yes**
Is technical progress that uses energy affected by fuel prices and carbon taxes?		no	no	**yes**	no	**yes**	**yes**	**yes**	**yes**	**yes**
Do the costs of abatement and non-fossil energy technologies fall as users gain experience?		no	no	no	**yes**	no	no	**yes**	**yes**	**yes**
Is there a policy to transfer carbon saving technologies to non Annex 1 countries?		no	no	no	no	no	**yes**	**yes**	no	**yes**
TPE BAU in 2100 (EJ)	Mean	1975	2475	2250	2000	3425	2700	1450	3550	2850
TPE control in 2100 (EJ)	Mean	650	650	500	750	500	500	675	750	725
CO_2 BAU 2100 (10^9TC)	Mean	40	50	50	40	75	55	25	73	55
	Std. Deviation	*28*	*18*	*36*	*29*	*29*	*23*	*22*	*27*	*21*
Mitig. Cost (%Welfare)	Mean	0.23	0.44	0.14	0.12	0.48	0.33	0.05	0.23	0.17
	Std. Deviation	*0.45*	*0.23*	*0.23*	*0.22*	*0.28*	*0.12*	*0.07*	*0.12*	*0.11*
Impact of delay (%Welfare)	Mean	-0.1	0.2	-0.6	0.0	-1	-0.5	-0.1	-0.6	-0.4
	Std. Deviation	*1*	*0.3*	*1*	*0.7*	*1.2*	*0.9*	*0.5*	*0.8*	*0.6*

Notes: TPE = Total Primary Energy.
BAU = Business as Usual (no control and no intervention).
Sample size in ICAM simulation = 400.

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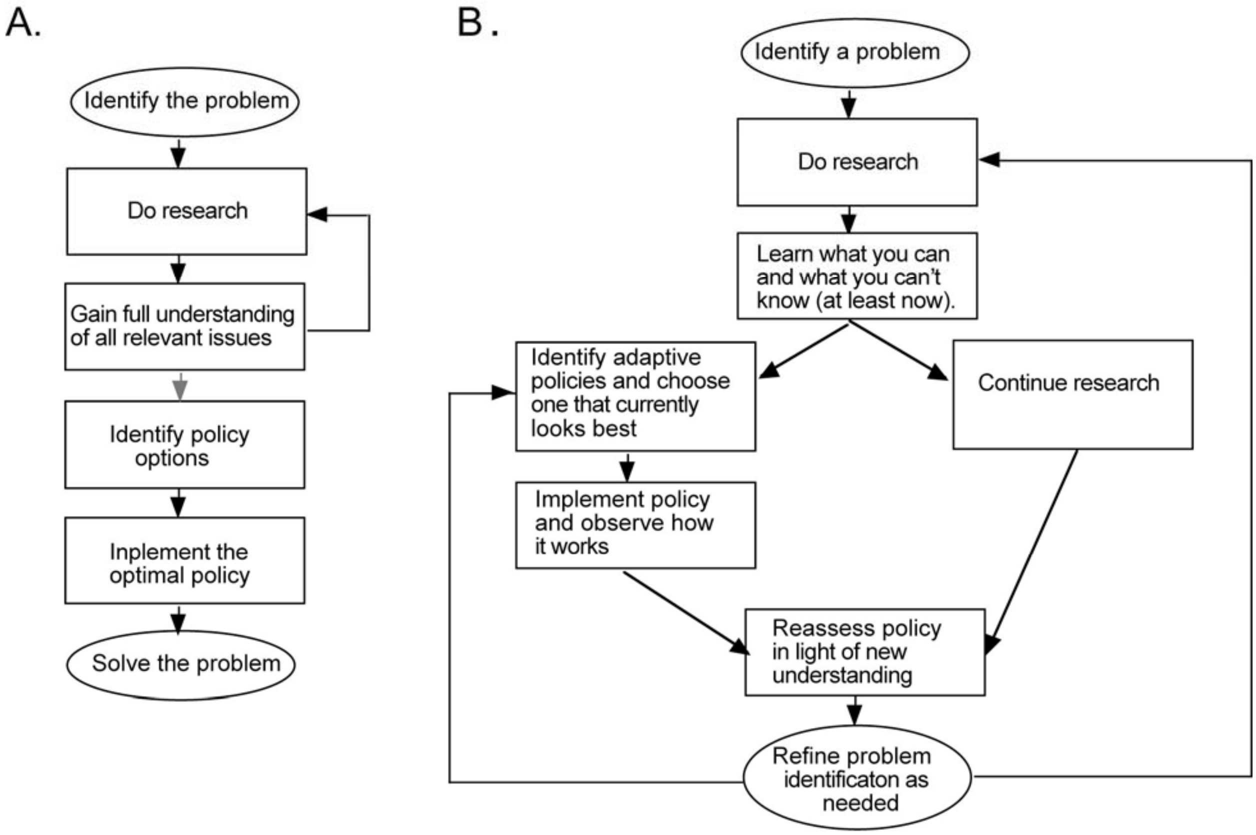

Figure 7.1 In the face of high levels of uncertainty, which may not be readily resolved through research, decision makers are best advised to not adopt a decision strategy in which nothing is done until research resolves all key uncertainties (A), but rather to adopt an iterative and adaptive strategy (B).

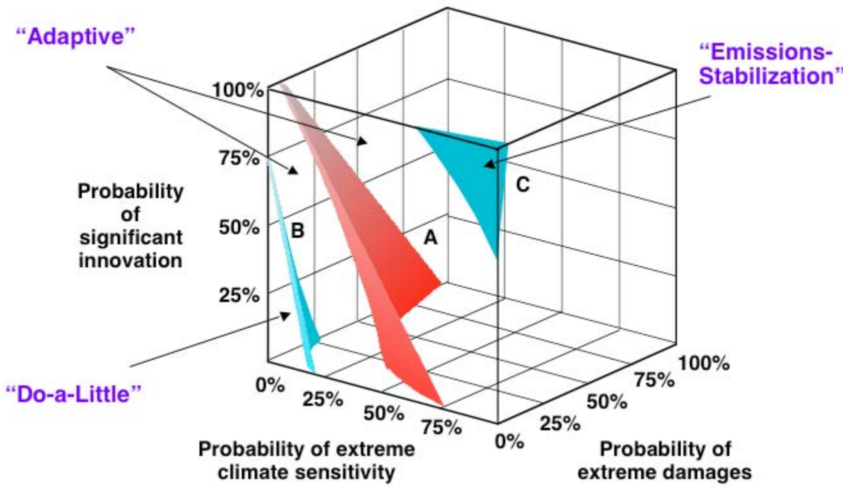

Figure 7.2 Surfaces separating the regions in probability space where the expected value of the "Do-a-Little" policy is preferred over the "Emissions-Stabilization" policy, the adaptive strategy is preferred over the "Do-A-Little" policy, and the adaptive strategy is preferred over the "Emissions-Stabilization" policy, as a function of the probability of extreme damages, significant innovation, and extreme climate sensitivity (Lempert *et al.*, 1996).

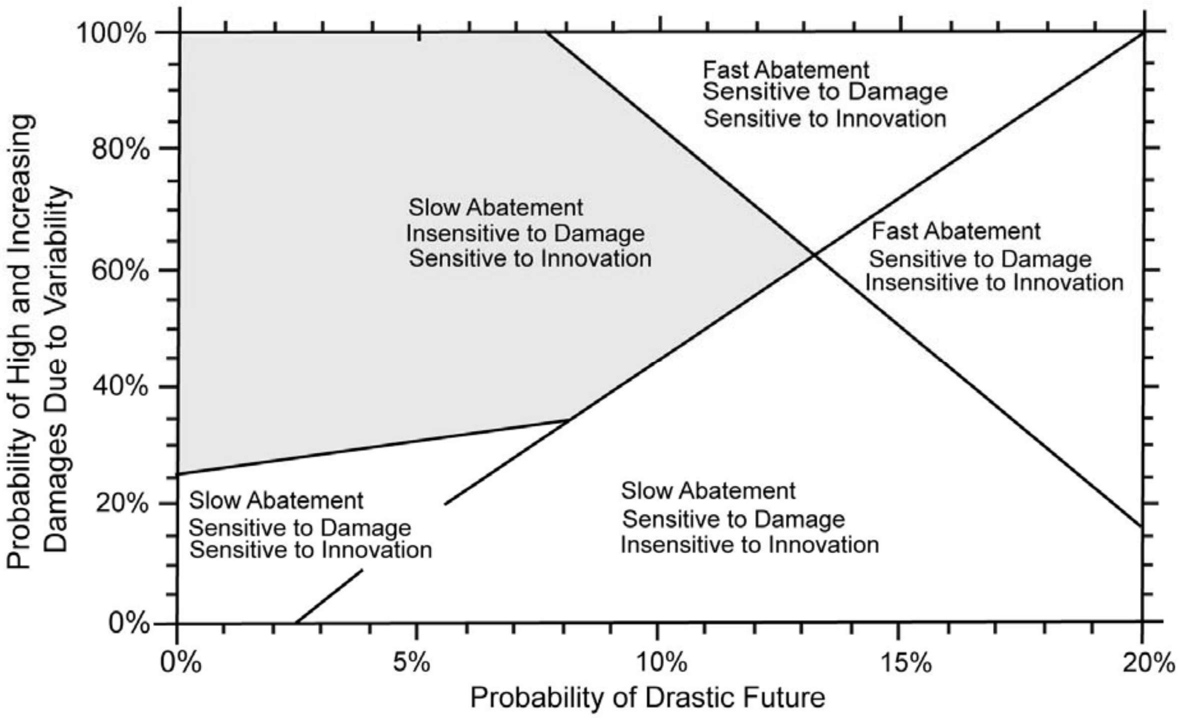

Figure 7.3 Estimates of the most robust emissions abatement strategy as a function of expectations about two key uncertainties -- the probability of large future climate impacts and large future climate variability (Lempert and Schlesinger, 2006). Strategies are described by near-term abatement rate and the near-term indicators used to signal the need for any change in abatement rate. The shaded region characterizes range of uncertainty over which one strategy of interest is robust.

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PART 8. COMMUNICATING UNCERTAINTY

It is often argued that one should not try to communicate about uncertainty to non-technical audiences, because laypeople won't understand and decision makers want definitive answers – what Senator Muskie referred to as the ideal of receiving advice from "one armed scientists"[33].

We do not agree, non-technical people deal with uncertainty, and statements of probability all the time. They don't always reason correctly about probability, but they can generally get the gist (Dawes, 1988). While they may make errors about the details, for the most part they manage to deal with probabilistic precipitation forecasts from the weather bureau, point spreads at the track, and similar probabilistic information. The real issue is to frame things in familiar and understandable terms.

There has been considerable discussion in the literature about whether it is best to present uncertainties to laypeople in terms of odds (*e.g.*, 1 in 1000) or probabilities (*e.g.*, p = 0.001) (Fischhoff *et al.*, 2002). Baruch Fischhoff provides the following summary advice:

- Either will work, if they're used consistently across many presentations.
- If you want people to understand one fact, in isolation, present the result both in terms of odds and probabilities.
- In many cases, there's probably more confusion about what is meant by the specific events being discussed than about the numbers attached to them.

[33] The reference, of course, being to experts who always answered his questions "on the one hand…but on the other hand…," the phrase is usually first attributed to Senator Edmund Muskie.

Ibrekk and Morgan (1987) reached a similar conclusion in their study of alternative simple graphical displays for communicating uncertainty to non-technical people, arguing for the use of more than one display when communicating a single uncertain result. They also report that "rusty or limited statistical knowledge does not significantly improve the performance of semi-technical or laypersons in interpreting displays that communicate uncertainty." (Morgan and Henrion, 1990)

Patt and Schrag (2003) studied how undergraduate respondents interpret both probabilities and uncertainty words that specifically relate to climate and weather. They found that these respondents mediated their probability judgments by the severity of the event reported (*e.g.*, hurricane versus snow flurries). They conclude that "in response to a fixed probability scale, people will have a tendency to over-estimate the likelihood of low-magnitude events, and under-estimate the likelihood of high-magnitude events." This is because, "intuitively people use such language to describe both the probability and the magnitude of risks, and they expect communicators to do the same." They suggest that unless analysts make it clear that they are not adjusting their probability estimates up and down depending on the severity of the event described, policy makers' response to assessments are "…likely to be biased downward, leading to insufficient efforts to mitigate and adapt to climate change." (Patt and Schrag, 2003)

The presence of high levels of uncertainty offers people with an agenda an opportunity to "spin the facts." Dowlatabadi reports that when he first started showing probabilistic outputs from Carnegie Mellon's Integrated Climate Assessment Model (ICAM) to staff on Capitol Hill, many of those who thought that climate change was not happening or was not important, immediately focused in on the low impact ends of the model's probabilistic outputs. In contrast, many of those who thought climate change was a very serious problem immediately focused in on the high impact ends of the model's probabilistic outputs.

This does not mean that one should abandon communicating about uncertainty, there will always be people who wish to distort the truth. However it does mean that communicating uncertainty in key issues requires special care, so that those who really want to understand can do so.

Recipients will process any message they receive through their previous knowledge and perception of the issues at hand. Thus, in designing an effective communication, one must first understand what folks who will receive that message already know and think about the topics at hand. One of the clearest findings in the empirical literature on risk communication is that there is no such thing as an expert who can design effective risk communication messages without some empirical evaluation and refinement of those messages with members of the target audience.

In order to support the design of effective risk communication messages, Morgan *et al.* (2002) and colleagues developed a "mental model" approach to risk communication. Using open-ended interview methods, subjects are asked to talk about the issues at hand, with the interviewer providing as little structure or input to the interview process as possible. After a modest number of interviews have been conducted, typically twenty or so, an asymptote is reached in the concepts mentioned by the interviewees and few additional concepts are encountered. Once a set of key issues and perceptions have been identified, a closed form survey is developed which can be used to examine which of the concepts are most prevalent, and which are simply the idiosyncratic response of a single respondent. The importance of continued and iterative empirical evaluation of the effectiveness of communication is stressed.

One key finding in this literature is that there is no such thing as an expert in communication – in the sense of someone who can tell you ahead of time how a message should be framed, or what it should say. Empirical study is absolutely essential to the development of effective communication.

Using this method, Bostrom *et al.* (1994) and Read *et al.* (1994) examined public understanding and perception of climate change. On the basis of their findings, a communication brochure for the general public was developed, and iteratively refined using read-aloud protocols and focus group discussions (Morgan and Smuts, 1994). Using less formal ethnographic methods, Kempton (1991; Kempton *et al.*, 1995) has conducted studies of public perceptions of climate change and related issues, obtaining results that are very similar to those of the mental model studies. More recently Reiner *et al.* (2006) have conducted a cross-national study of some similar issues.

While the preceding discussion has dealt with communicating uncertainty in situations in which it is possible to do extensive studies of the relative effectiveness of different communication methods and messages, much of the communication about uncertain events that all of us receive comes from reading or listening to the press.

Philip M. Boffey (quoted in Friedman *et al.,* 1999), editorial page editor for *The New York Times*, argues that "uncertainty is a smaller problem for science writers than for many other kinds of journalists." He notes that there is enormous uncertainty about what is going on in China or North Korea and that "economics is another area where there is great uncertainty." In contrast, he notes:

> With science writing, the subjects are better defined. One of the reasons why uncertainty is less of a problem for a science journalist is because the scientific material we cover is mostly issued and argued publicly. This is not North Korea or China. While it is true that a journalist cannot view a scientist's lab notes or sit on a peer review committee, the final product is out there in the public. There can be a vigorous public debate about it and reporters and others can see what is happening.

Boffey goes on to note that "one of the problems in journalism is to try to find out what is really happening." While this may be easier than in some other fields, because of peer-reviewed articles, consensus panel mechanisms such as NRC reports, "there is the second level problem of deciding whether these consensus mechanisms are operating properly…Often the journalist does not have time to investigate…given the constraints of daily journalism." However he notes:

> …these consensus mechanisms do help the journalist decide where the mainstream opinion is and how and whether to deal with outliners. Should they be part of the debate? In some issues, such as climate change, I do not feel they should be ignored because in this subject, the last major consensus report showed that there were a number of unknowns, so the situation is still fluid….

While it is by no means unique, climate change is perhaps the prototypical example of an issue for which there is a combination of considerable scientific uncertainty, and strong short-term economic and other interests at play. Uncertainty offers the opportunity for various interests to confuse and divert the public discourse in what may already be a very difficult scientific process of seeking improved insight and understanding. Combine this with the limited scientific background of many reporters, the tendency of the press to seek conflict and report "on the one hand, on the other hand" and do so in just a few words and with very short deadlines, it is small wonder that there are problems.

Chemist and noble laurite Sherry Roland (quoted in Friedman *et al*., 1999) notes that "…scientists reputations depend on their findings being right most of the time. Sometimes, however, there are people who are wrong almost all the time and they are still quoted in the media 20 years later very consistently."

Despite continued discourse within scientific societies and similar professional circles about the importance of scientists interpreting and communicating their findings to the public and to decision makers, freelance environmental writer Dianne Dumanoski (quoted in Friedman *et al.*, 1999) is correct when she observes that "strong peer pressure exists within the scientific community against becoming a visible scientist who communicates with the media and the public." Combined with an environment in which there is high probability that many statements a scientist makes about uncertainties will immediately be seized upon by advocates in an ongoing public debate, it is small wonder that many scientists choose to just keep their heads down, do their research, and limit their communication to publication in scientific journals and presentations at professional scientific meetings.

The problems are well illustrated in an exchange between biological scientist Rita Colwell (then Director of the National Science Foundation), Peggy Girsham of NBC (now with NPR) and Sherry Roland reported by Friedman *et al.* (1999). Colwell noted that when a scientist talks with a reporter they must be very careful about what they say, especially if they have a theory or findings that run counter to conventional scientific wisdom…"it is very tough to go out there, talk to a reporter, lay your reputation on the line and then be maligned by so called authorities in a very unpleasant way." She noted that this problem is particularly true for women scientists, adding "I have literally taken slander and public ridicule from a few individuals with clout and that has been very unpleasant…" NBC's Girsham (now with NPR) noted that in a way scientist in such a situation cannot win "because if you are not willing to talk to a reporter, then we [in the press] will look for someone who is willing and may be less cautious about expressing a point of view." Building on this point, Rowland noted that in the early day of the work he and Mario Molina did on stratospheric ozone depletion "Molina and I read *Aerosol Age* avidly because we were the 'black hats' in every issue. The magazine even went to far as to run an article calling us agents of the Soviet Union's KGB, who were trying to destroy American industry…what was more disturbing was when scientists on the industry side were quoted by the media, claiming our calculations of how many CFCs were in the stratosphere were off by a factor of 1,000…even after we won the Nobel Prize for this research, our politically conservative local newspaper…[said that while the] theory had been demonstrated in the laboratory…scientists with more expertise in atmospheric science had shown that the evidence in the real atmosphere was quite mixed. This ignored the consensus views of the world's atmospheric scientists that the results had been spectacularly confirmed in the real atmosphere." Clearly, even when a scientist is as careful and balanced as possible, communicating with the public and decisions makers about complex and politically contentious scientific issues is not for the faint hearted!

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PART 9. SOME SIMPLE GUIDANCE FOR RESEARCHERS[34]

Doing a good job of characterizing and dealing with uncertainty can never be reduced to a simple cookbook. One must always think critically and continually ask questions such as:

- Does what we are doing make sense?
- Are there other important factors which are, as or more important, than the factors we are considering?
- Are there key correlation structures in the problem that are being ignored?
- Are there normative assumptions and judgments about which we are not being explicit?

That said; the following are a few words of guidance to help CCSP researchers and analysts to do a better job of reporting, characterizing and analyzing uncertainty. Some of this guidance is based on available literature. However, because doing these things well is often as much an art as it is a science, the recommendations also draw on the very considerable[35] and diverse experience and collective judgment of the writing team.

Reporting uncertainty

- When qualitative uncertainty words such as likely and unlikely are used, it is important to clarify the range of subjective probability values that are to be associated with those

[34] This section is intended to provide guidance for future CCSP assessment efforts.
[35] Collectively the author team has roughly 200 person-years of experience in addressing these issues both theoretically and in practical analysis in the context of climate and other similar areas.

words. Unless there is some compelling reason to do otherwise, we recommend the use of the framework shown below[36]:

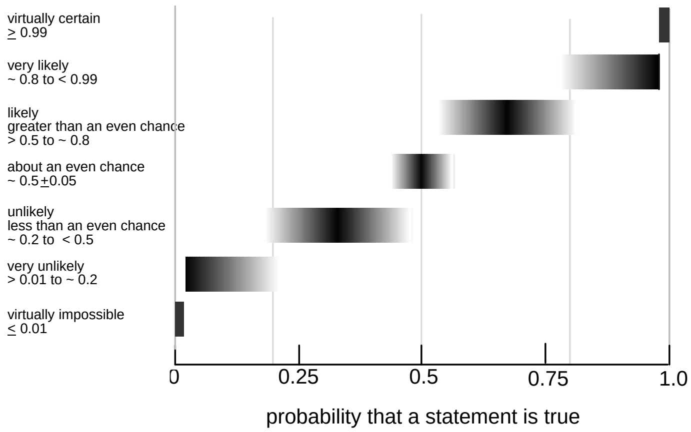

Figure 9.1 Recommended framework for associating common language with subjective probability values

Another strategy is to display the judgment explicitly as shown:

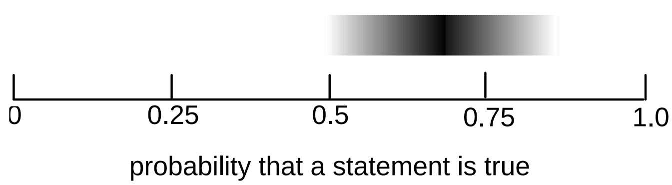

Figure 9.2A method to illustrate the probability that a statement is true

[36] This display divides the interval between 0.99 and 0.01 into 5 ranges, adding somewhat more resolution across this range than the mapping used by the IPCC-WGI (2001). However, it is far more important to map words into probabilities in a consistent way, *and to be explicit about how that is being done*, than it is to use any specific mapping. Words are inherently imprecise. In the draft version of this diagram, we intentionally included significantly greater overlap between the categories. A number of reviewers were uncomfortable with this overlap, calling for a precise 1-to-1 mapping between words and probabilities. On the other hand, when a draft of the United States National Assessment (2000) produced a diagram with such a precise mapping, reviewers complained about the precise boundaries, with the result that in the final version they were made fuzzy (Figure 2.3). For a more extended discussion of these issues see Section 2 of this report.

This approach provides somewhat greater precision and allows some limited indication of secondary uncertainty for those who feel uncomfortable making precise probability judgments.

- In any document that reports uncertainties in conventional scientific format (*e.g.*, 3.5±0.7), it is important to be explicit about what uncertainty is being included and what is not, and to confirm that the range is plus or minus one standard deviation. This reporting format is generally not appropriate for large uncertainties or where distributions have a lower or upper bound and hence are not symmetric. In all cases, care should be taken not to report results using more significant figures than are warranted by the associated uncertainty. Often this means overriding default values on standard software such as Microsoft Excel.
- Care should be taken in plotting and labeling the vertical axes when reporting PDFs. The units are probability density (*i.e.*, probability per unit interval along the horizontal axis), not probability.
- Since many people find it difficult to read and correctly interpret PDFs and CDFs, when space allows it is best practice to plot the CDF together with the PDF on the same x-axis (Morgan and Henrion, 1990).
- When many uncertain results must be reported, box plots (first popularized by Tukey, 1977) are often the best way to do this in a compact manner. There are several conventions. Our recommendation is shown below, but what is most important is to be clear about the notation.

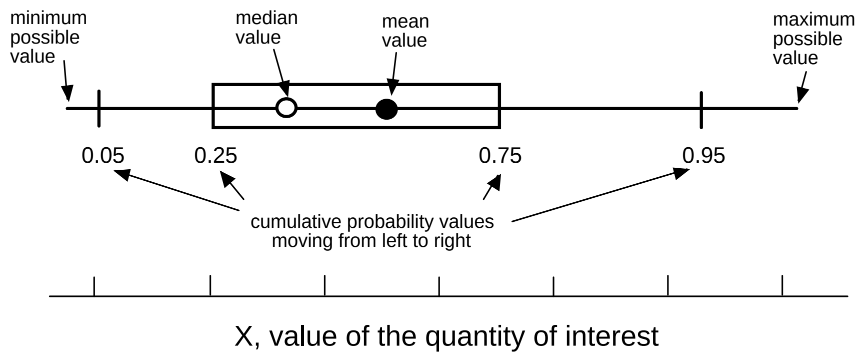

Figure 9.3 Recommended format for box plot. When many uncertain results are to be reported, box plots can be stacked more compactly than probability distributions.

- While there may be a few circumstances in which it is desirable or necessary to address and deal with second-order uncertainty (*e.g.*, how sure an expert is about the shape of an elicited CDF) more often than not the desire to perform such analysis arises from a misunderstanding of the nature of subjective probabilistic statements (see the discussion in Section 1). When second-order uncertainty is being considered, one should be very careful to determine that the added level of such complication will aide in, and will not unnecessarily complicate, subsequent use of the results.

Characterizing and analyzing uncertainty

- Unless there are compelling reasons to do otherwise, conventional probability is the best tool for characterizing and analyzing uncertainty about climate change and its impact.
- The elicitation of expert judgment, often in the form of subjective probability distributions, can be a useful way to combine the formal knowledge in a field as reflected in the literature with the informal knowledge and physical intuition of experts. Elicitation is not a substitute for doing the needed science, but it can be a very useful tool in support of research planning, private decision making, and the formulation of public policy.

However, the design and execution of a good expert elicitation takes time and requires a careful integration of knowledge of the relevant substantive domain with knowledge of behavioral decision science (see discussion above in Section 5).

- When eliciting probability distributions from multiple experts, if they disagree significantly, it is generally better to report the distributions separately. This is especially true if such judgments will subsequently be used as inputs to a model that has a non-linear response.
- There are a variety of software tools available to support probabilistic analysis using Monte Carlo and related techniques. As with any powerful analytical tool, their proper use requires careful thought and care.
- In performing uncertainty analysis, it is important to think carefully about possible sources of correlation. One simple procedure for getting a sense of how important this may be is to run the analysis with key variables uncorrelated and then run it again with key variables perfectly correlated. Often, in answering questions about aggregate parameter values experts assume correlation structures between the various components of the aggregate value being elicited. Sometimes it is important to elicit the component uncertainties separately from the aggregate uncertainty in order to reason out why specific correlation structures are being assumed.
- Methods for describing and dealing with data pedigree (*e.g.*, Funtowicz and Ravetz, 1990) have not been developed to the point that they can be effectively incorporated in probabilistic analysis. However, the quality of the data on which judgments are based is

clearly important and should be addressed, especially when uncertain information of varying quality and reliability is combined in a single analysis. At a minimum, investigators should be careful to provide a "traceable account" of where their results and judgments have come from.

- While full probabilistic analysis can be useful, in many contexts, simple parametric analysis, or back-to-front analysis (that works backwards from an end point of interest) may be as or more effective in identifying key unknowns and critical levels of knowledge needed to make better decisions.
- Scenarios analysis can be useful, but also carries risks. Specific detailed scenarios can become cognitively compelling, with the result that people may overlook many other pathways to the same end-points. It is often best to "cut the long causal chains" and focus on the possible range of a few key variables, which can most affect outcomes of interest.
- Scenarios, which describe a single point (or line) in a multi-dimensional space, cannot be assigned probabilities. If, as is often the case, it will be useful to assign probabilities to scenarios, they should be defined in terms of intervals in the space of interest, not in terms of point values.
- Variability and uncertainty is not the same thing. Sometimes it is important to draw distinction between the two but often it is not. A distinction should be made only when it adds clarity for users.
- Analysis that yields predictions is very helpful when our knowledge is sufficient to make meaningful predictions. However, the past history of success in such efforts suggests great caution (*e.g.,* Chapters 3 and 6 in Smil, 2003). When meaningful prediction is not

possible, alternative strategies, such as searching for responses or policies that will be robust across a wide range of possible futures, deserve careful consideration.

- For some problems there comes a time when uncertainty is so high that conventional modes of probabilistic analysis (including decision analysis) may no longer make sense. While it is not easy to identify this point, investigators should continually ask themselves whether what they are doing makes sense and whether a much simpler approach, such as a bounding or order-of-magnitude analysis, might be superior (*e.g.,* Casman *et al.*, 1999).

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