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(C) [redacted]

EPA-3346

| | |
|---|---|
| **William Perkins/DC/USEPA/US** | To: Jason Samenow |
| 12/07/2009 05:54 PM | cc: |
| | bcc: |
| | Subject: Re: volume 9 looks ok |

thanks Jason. Once I get green light from the folks still touching volumes we'll drop this.

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Jason Samenow didn't see anything that jumped out at... 12/07/2009 05:53:32 PM

From: Jason Samenow/DC/USEPA/US
To: William Perkins/DC/USEPA/US@EPA
Date: 12/07/2009 05:53 PM
Subject: volume 9 looks ok

didn't see anything that jumped out at me.

EPA-3347

**Lesley Jantarasami**

04/01/2010 03:56 PM

To

cc

bcc

Subject UPLOAD F:\Endangerment\RTCs 1st Round Review\RTC Volume 11 LJ.doc

(b)(5) Deliberative [redacted] - RTC Volume 11 LJ.doc

EPA-3348

**William Perkins/DC/USEPA/US**
12/07/2009 06:06 PM

To "Stambaugh, Sandi", ktuberson, CDeLoose
cc Carole Cook, Mausami Desai
bcc
Subject Need to replace 7 of the RTC volumes on staging with these revised ones

Sandi,

Once you have those 7 RTC files replaced with these on staging, let me know and we will do a very quick sanity check and then plan on giving you the green light to go live. Thank you.

Cheers,

Bill

(b)(5) Deliberative [redacted] RTC Volume 11.doc
(b)(5) Deliberative [redacted] RTC Volume 3.doc
(b)(5) Deliberative [redacted] RTC Volume 4.doc
(b)(5) Deliberative [redacted] RTC Volume 6.doc
(b)(5) Deliberative [redacted] RTC Volume 7.doc
(b)(5) Deliberative [redacted] RTC Volume 8.doc
(b)(5) Delibera ive [redacted] RTC Volume 10.doc

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EPA-3349

"Stambaugh, Sandi" <SStambaugh@icfi.com>

12/07/2009 06:11 PM

To William Perkins, "Tuberson, Kyle", "DeLoose, Christopher"

cc Carole Cook, Mausami Desai

bcc

Subject RE: Need to replace 7 of the RTC volumes on staging with these revised ones

Bill, all 7 pdfs have been replaced on staging.

---

**From:** Perkins.William@epamail.epa.gov [mailto:Perkins.William@epamail.epa.gov]
**Sent:** Mon 12/7/2009 6:06 PM
**To:** Stambaugh, Sandi; Tuberson, Kyle; DeLoose, Christopher
**Cc:** Cook.Carole@epamail.epa.gov; Desai.Mausami@epamail.epa.gov
**Subject:** Need to replace 7 of the RTC volumes on staging with these revised ones

Sandi,

Once you have those 7 RTC files replaced with these on staging, let me know and we will do a very quick sanity check and then plan on giving you the green light to go live. Thank you.

Cheers,

Bill

(See attached file: RTC Volume 11.doc)(See attached file: RTC Volume 3.doc)(See attached file: RTC Volume 4.doc)(See attached file: RTC Volume 6.doc)(See attached file: RTC Volume 7.doc)(See attached file: RTC Volume 8.doc)(See attached file: RTC Volume 10.doc)

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EPA-3350

**Lesley Jantarasami**
04/01/2010 03:56 PM

To
cc
bcc
Subject UPLOAD F:\Endangerment\RTCs 1st Round Review\RTC Volume 7 LJ.doc

(b)(5) Deliberative
[redacted] - RTC Volume 7 LJ.doc

EPA-3351

**Lesley Jantarasami**

04/01/2010 03:56 PM

To

cc

bcc

Subject UPLOAD F:\Endangerment\RTCs 1st Round Review\RTC Volume 6 LJ.doc

(b)(5) Deliberative [redacted] - RTC Volume 6 LJ.doc

EPA-3352

**William Perkins/DC/USEPA/US**
12/07/2009 06:27 PM

To "Stambaugh, Sandi", ktuberson, CDeLoose
cc Carole Cook, Mausami Desai
bcc
Subject Please replace the current Volume 2 with this one

Errors were introduced into the title of the document when it was converted to PDF. Thank you.

Cheers,

Bill

(b)(5) Deliberative [redacted]
RTC Volume 2.doc

Bill Perkins
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(F) 202.343.2202
(C) (b)(6) [redacted]

EPA-3353

**Lesley Jantarasami**

04/01/2010 03:56 PM

To

cc

bcc

Subject UPLOAD F:\Endangerment\RTCs 1st Round Review\RTC Volume 10 LJ.doc

(b)(5) Deliberative [redacted] - RTC Volume 10 LJ.doc

EPA-3354

"Tuberson, Kyle" <KTuberson@icfi.com>

12/07/2009 06:58 PM

To William Perkins

cc David Chalmers

bcc

Subject RE: Please replace the current Volume 2 with this one

Ok. I'll make the push now.

ICF International
Kyle Tuberson
(o) 703-934-3691

-----Original Message-----
From: Perkins.William@epamail.epa.gov
[mailto:Perkins.William@epamail.epa.gov]
Sent: Monday, December 07, 2009 6:52 PM
To: Tuberson, Kyle
Cc: Chalmers.David@epamail.epa.gov
Subject: RE: Please replace the current Volume 2 with this one

Kyle,

Please go live with the RTCs. Also, please be standing by your phone in case there is an issue and we need to pull them. Thanks,

Bill

Bill Perkins
Climate Change Adaptation Analyst
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Climate Change Division
U.S. Environmental Protection Agency
perkins.william@epa.gov
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(F) 202.343.2202
(C) [redacted] (b)(6)

From: "Tuberson, Kyle" <KTuberson@icfi.com>

To: William Perkins/DC/USEPA/US@EPA, "Stambaugh, Sandi" <SStambaugh@icfi.com>, "DeLoose, Christopher" <CDeLoose@icfi.com>

Cc: Carole Cook/DC/USEPA/US@EPA, Mausami Desai/DC/USEPA/US@EPA

Date: 12/07/2009 06:48 PM

Subject: RE: Please replace the current Volume 2 with this one

Ok. I replaced Volume 2 on staging.

Thanks,
Kyle

ICF International
Kyle Tuberson
(o) 703-934-3691

-----Original Message-----
From: Perkins.William@epamail.epa.gov
[mailto:Perkins.William@epamail.epa.gov]
Sent: Monday, December 07, 2009 6:27 PM
To: Stambaugh, Sandi; Tuberson, Kyle; DeLoose, Christopher
Cc: Cook.Carole@epamail.epa.gov; Desai.Mausami@epamail.epa.gov
Subject: Please replace the current Volume 2 with this one

Errors were introduced into the title of the document when it was converted to PDF. Thank you.

Cheers,

Bill

(See attached file: RTC Volume 2.doc)

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EPA-3356

**William Perkins/DC/USEPA/US**
12/07/2009 07:29 PM

To "Jason Renzaglia"
cc "Jason Renzaglia", "Mae Thomas"
bcc
Subject Re: Refs Missing.doc

Jason,

Got a few of them...

Cheers,

Bill

(b)(5) Deliberative [redacted]
Refs Missing.doc

sap5-2-final-report-all.pdf ar4-wg1-chapter1.pdf Goklany.2007.pdf

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"Jason Renzaglia" Hi Bill, Can you help us by finding th... 12/07/2009 07:02:06 PM

From: "Jason Renzaglia" <Jason.Renzaglia@erg.com>
To: William Perkins/DC/USEPA/US@EPA
Cc: "Jason Renzaglia" <Jason.Renzaglia@erg.com>, "Mae Thomas" <Mae.Thomas@erg.com>
Date: 12/07/2009 07:02 PM
Subject: Refs Missing.doc

---

Hi Bill,

Can you help us by finding the references in the attached Document?

Thank you!

Jason Renzaglia
Eastern Research Group, Inc. (ERG)
Morrisville, NC
(919)468-7893

[attachment "Refs Missing.doc" deleted by William Perkins/DC/USEPA/US]

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



**U.S. Climate Change Science Program**

Synthesis and Assessment Product 5.2

January 2009

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This Synthesis and Assessment Product, described in the U.S. Climate Change Science Program (CCSP) Strategic Plan, was prepared in accordance with Section 515 of the Treasury and General Government Appropriations Act for Fiscal Year 2001 (Public Law 106-554) and the information quality act guidelines issued by the Department of Commerce and NOAA pursuant to Section 515 <http://www.noaanews noaa.gov/stories/iq.htm>. The CCSP Interagency Committee relies on Department of Commerce and NOAA certifications regarding compliance with Section 515 and Department guidelines as the basis for determining that this product conforms with Section 515. For purposes of compliance with Section 515, this CCSP Synthesis and Assessment Product is an "interpreted product" as that term is used in NOAA guidelines and is classified as "highly influential". This document does not express any regulatory policies of the United States or any of its agencies, or provide recommendations for regulatory action.

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



Synthesis and Assessment Product 5.2
Report by the U.S. Climate Change Science Program
and the Subcommittee on Global Change Research

EDITED BY:
M. Granger Morgan, Hadi Dowlatabadi, Max Henrion, David Keith,
Robert Lempert, Sandra McBride, Mitchell Small, and Thomas Wilbanks

January 2009,

Members of Congress:

On behalf of the National Science and Technology Council, the U.S. Climate Change Science Program (CCSP) is pleased to transmit to the President and the Congress this Synthesis and Assessment Product (SAP) *Best Practice Approaches for Characterizing, Communicating, and Incorporating Scientific Uncertainty in Decisionmaking*. This is part of a series of 21 SAPs produced by the CCSP aimed at providing current assessments of climate change science to inform public debate, policy, and operational decisions. These reports are also intended to help the CCSP develop future program research priorities.

The CCSP's guiding vision is to provide the Nation and the global community with the science-based knowledge needed to manage the risks and capture the opportunities associated with climate and related environmental changes. The SAPs are important steps toward achieving that vision and help to translate the CCSP's extensive observational and research database into informational tools that directly address key questions being asked of the research community.

The purpose of this SAP is to synthesize and communicate the current state of understanding about the characteristics and implications of uncertainty related to climate change and variability to an audience of policymakers, decision makers, and members of the media and general public with an interest in developing a fundamental understanding of the issue. It was developed with broad scientific input and in accordance with the Guidelines for Producing CCSP SAPs, the Information Quality Act (Section 515 of the Treasury and General Government Appropriations Act for Fiscal Year 2001 (Public Law 106-554)), and the guidelines issued by the Department of Commerce and the National Oceanic and Atmospheric Administration pursuant to Section 515.

We commend the report's authors for both the thorough nature of their work and their adherence to an inclusive review process.

Sincerely,

| | | |
|---|---|---|
| Carlos M. Gutierrez<br>Secretary of Commerce<br>Chair, Committee on Climate Change Science and Technology Integration | Samuel W. Bodman<br>Secretary of Energy<br>Vice Chair, Committee on Climate Change Science and Technology Integration | John H. Marburger III<br>Director, Office of Science and Technology Policy<br>Executive Director, Committee on Climate Change Science and Technology Integration |

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## ACKNOWLEDGEMENTS

Funding for this work was provided by NSF cooperative agreement SES-034578 with the Climate Decision Making Center at Carnegie Mellon Universtiy.

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PREFACE

# Report Motivation and Guidance for Using this Synthesis/Assessment Report

**Convening Lead Author:** M. Granger Morgan, Department of Engineering and Public Policy, Carnegie Mellon Univ.

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This Product 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 products are focused on specific substantive issues in climate science, impacts, and related topics. In contrast, the focus of this Product is methodological.

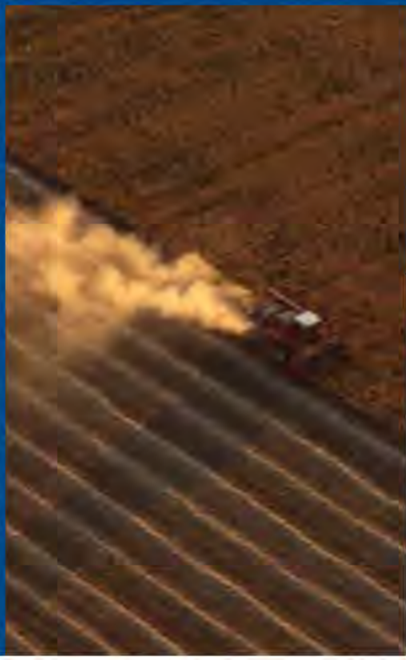
Uncertainty is ubiquitous. Of course, the presence of uncertainty does not mean that people cannot act. As this Product notes, in our private lives, we decide where to go to college, what job to take, whom to marry, what home to buy, when and whether to have children, and countless other important choices, 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 Product 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 the treatment of technical topics at the level of journals such as Scientific American.

Because the issue of how uncertainty is characterized and dealt with is of broad importance for public policy, we have also prepared a "Non-Technical Summary". Readers who lack the time or background to read the detailed Product may prefer to start there, and then sample from the main Product as they find topics they would like to learn about in greater depth.

# EXECUTIVE SUMMARY



***Lead Author:*** M. Granger Morgan, Carnegie Mellon Univ.

***Contributing Authors:*** Hadi Dowlatabadi, Univ. of British Columbia; Max Henrion, Lumina Decision Systems; David Keith, Univ. of Calgary; Robert Lempert, The RAND Corporation; Sandra McBride, Duke Univ.; Mitchell Small, Carnegie Mellon Univ.; Thomas Wilbanks, Oak Ridge National Laboratory

This Product begins with a discussion of a number of formulations of uncertainty and the various ways in which uncertainty can arise. It introduces several alternative perspectives on uncertainty including both the classical or frequentist view of probability, which defines probability as the property of a large number of repeated trials of some process such as the toss of a coin, 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 Product closes with a discussion of "ignorance" and the fact that while research often reduces uncertainty, it need not always do so; indeed, in some cases, it 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 subconsciously employs a variety of simplified strategies or "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 Part 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. Box 4.1 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 explores 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 explores 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 on "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 Part 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 empirical study is absolutely essential to the development of effective communication. With this in mind, there is no such thing as an expert in communication—in the sense of someone who can tell you ahead of time (*i.e.*, without empirical study) how a message should be framed, or what it should say. Part 8 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 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 that are equally 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?
- Is information about the uncertainties related to research results and potential policies being communicated clearly and consistently?

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. This advice can be found on pages 71 through 74.


**Lead Author:** M. Granger Morgan, Carnegie Mellon Univ.

**Contributing Authors:** Hadi Dowlatabadi, Univ. of British Columbia; Max Henrion, Lumina Decision Systems; David Keith, Univ. of Calgary; Robert Lempert, The RAND Corporation; Sandra McBride, Duke Univ.; Mitchell Small, Carnegie Mellon Univ.; Thomas Wilbanks, Oak Ridge National Laboratory

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 one's death and the amount of next year's taxes are both uncertain.

These 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 human activities and choices may result in emissions of gases and particles and in changes in land use and vegetation, which 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 Product 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[1].



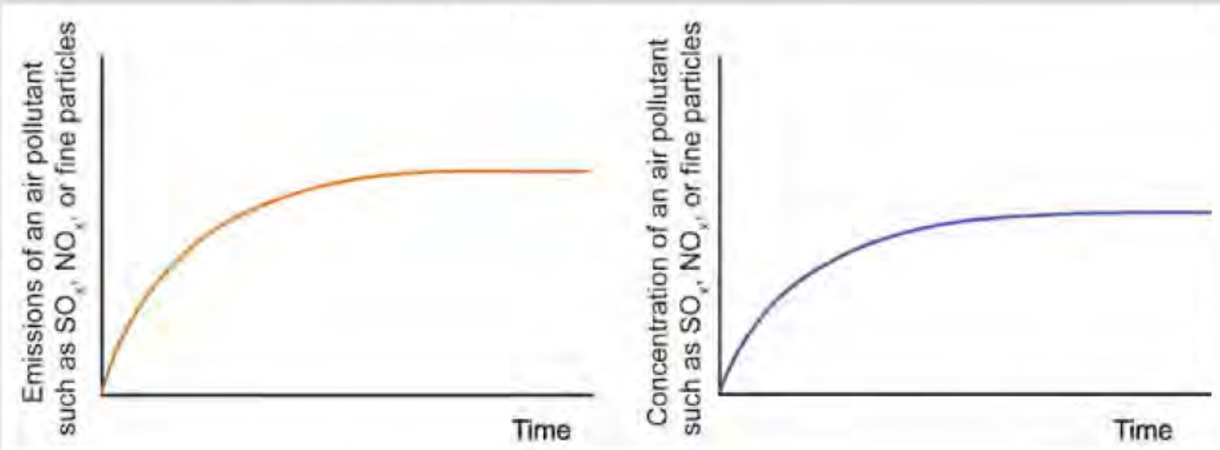
[1] For access to the various reports mentioned in this sentence, see respectively: <http://www.climatescience.gov/>;
<http://www.ipcc.ch>; <http://www.nationalacademies.org/publications/>;
<http://www.usgcrp.gov/usgcrp/nacc/default.htm>; and <http://www.acia.uaf.edu/>.

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.

This Product 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 Product 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 aspects of the methods and tools discussed—leaving those to references cited throughout the text.

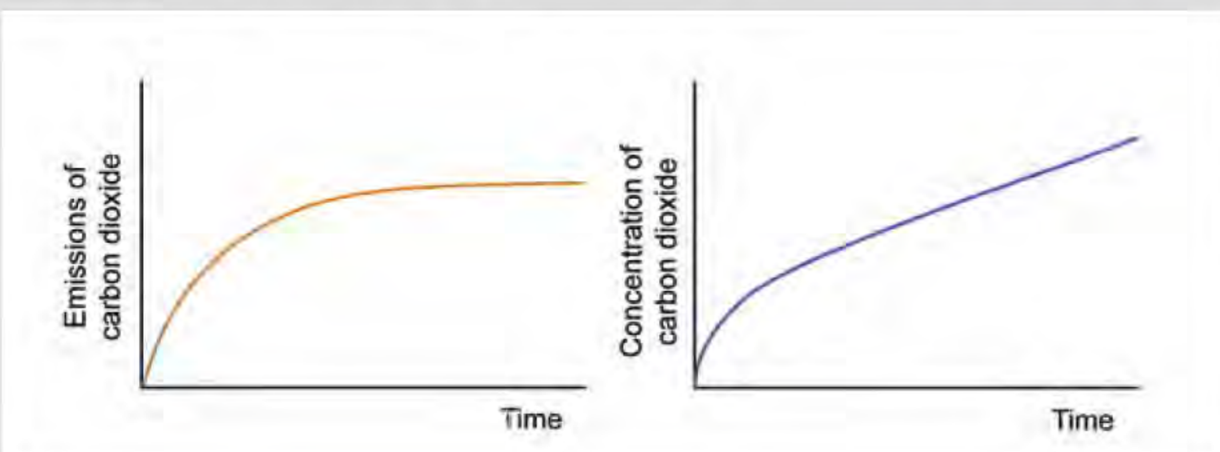
**BOX NT.1: Summary of Climate Change Basics**

Carbon dioxide ($CO_2$) is released to the atmosphere when coal, oil, or natural gas is burned. Carbon dioxide is not like air pollutants such as sulfur dioxide ($SO_2$), oxides of nitrogen ($NO_x$), or fine particles. When emissions of these pollutants are stabilized, their atmospheric concentration is also quickly stabilized since they remain in the atmosphere for only a matter of hours or days. The relationship between emissions and concentrations for these pollutants is illustrated in this simple diagram:



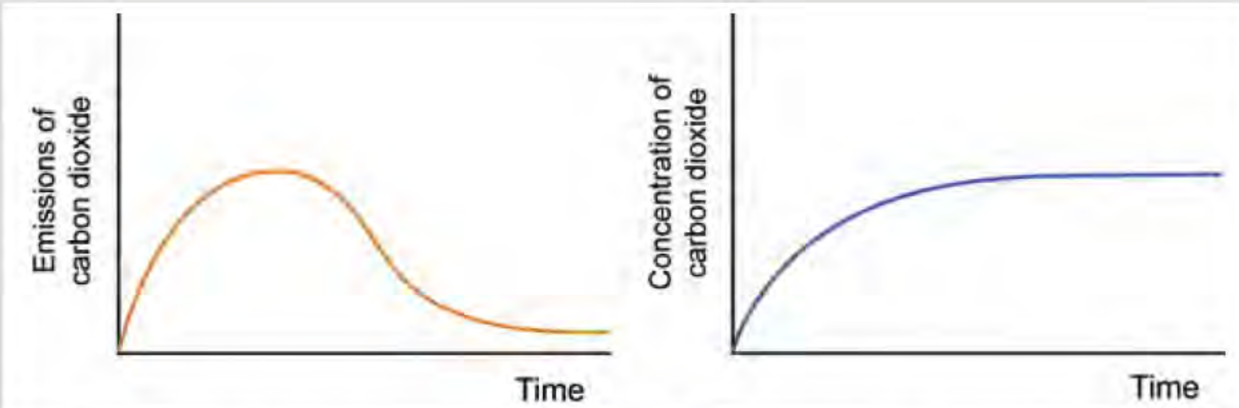

This is not true of carbon dioxide or several other greenhouse gases.

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 it drain out. Again, the situation is summarized in this simple diagram:



**BOX NT.1: Summary of Climate Change Basics** *Cont'd*

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 percent from today's levels 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 are 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 or land is cleared or burned, $CO_2$ 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 $CO_2$ emissions of between 70 and 90 percent from today's levels is needed. This implies the need for dramatic changes in energy and other industrial systems all around the globe.

This Product explores eight aspects of this topic. Then, in Part 9, the Product 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 a typical backyard thermometer and record the temperature, you may write down slightly different numbers because the two of you may read the location of the 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 backyard 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. This 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. Errors can also result in the recording, reporting, and archiving of measurement data.

Beyond random and systematic measurement errors lies a much more complicated kind of potential uncertainty. 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 and from place to place. You can compute the average of past measurements, but if you want to have an estimate for *next* summer at a specific location, the average does not tell you the whole story. In this 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. If the place where the rain gauge is located gets a different amount of rain than the amount your garden gets, you'll also need to factor that in.

In the context of the climate system, and the possible impacts of climate change, there are many cases where we do not understand all the physical, chemical, and biological processes that are involved.

Continuing with this example, if the sum of all 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.

Suppose that you want to know the odds that there will be more rain than 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 the 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 this 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, which says the attraction between two masses (like the Sun and the Earth; or an apple and the Earth) is proportional to the product of the two masses and inversely proportional 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 where 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 as 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"[2].

## 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 driver's 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, this 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 1,000 that it will happen. On 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.

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.

The same problem can arise in scientific communication. For example, some years ago members of the U.S. Environmental Protection Agency (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 1,000! 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 Part of this Product, the authors offer advice on how they think this should best be done.



[2] < http://www.quotedb.com/quotes/1097>.

## 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.

Part 3 of the Product 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 Product without much difficulty.

The other issue discussed in Part 3 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 too narrowly.

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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 two percent 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 overconfidence. 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. This Part 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?"

This Part also discusses a number of other issues, such as methods to assess how well alternative mathematical models fit existing evidence. 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, this Part focuses 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 Part too detailed to be of great interest. However, many may find it useful to take a look at Box 4.1 "Predicting Rainfall: An Illustration of Frequentist and Bayesian Approaches" that appears at the end of Part 4. 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 Part 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 Part 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,

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.

analysts want to incorporate such probabilistic descriptions in subsequent modeling and other analyses. 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 analyses use 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 analyses are themselves uncertain, it is not wise to search for a single "optimal" answer; it is better to search for answers or policies that are likely to yield acceptable results across a wide range of models and future outcomes. Part 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.

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.

A set of ideas and analytical methods called "decision analysis" has 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, such analysis has 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. Part 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 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 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 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"[3].

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, people, for the most part, manage to deal with probabilistic weather forecasts about the likelihood of rain or snow, point spreads at the track, and similar probabilistic information. The real issue is to frame things in familiar and understandable terms.

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[4])? 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.

Part 8 briefly discusses 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 is that empirical study is absolutely essential to the development of effective communication. With this in mind, there is no such thing as an expert in communication—in the sense of someone who can tell you ahead of time (*i.e.*, without empirical study) how a message should be framed, or what it should say.

The presence of high levels of uncertainty offers people who have an agenda with an opportunity to "spin the facts". In addition, many reporters are not in a position to make their own independent assessment of the likely accuracy of scientific statements, seek conflict, and report the views of those holding widely divergent views in just a few words and with very short deadlines. Thus, it is not surprising 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.

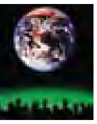
In an environment in which there is high probability that many statements a scientist makes about uncertainties will immediately be seized upon by advocates in an ongoing public debate, it is perhaps understandable that many scientists choose to just keep their heads down, do their research, and limit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

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

Many technical professionals have argued that one should not try to communicate about uncertainty to non-technical audiences. 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.

[3] 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.

[4] Strictly odds are defined as p/(1-p) but when p is small, the difference between odds of 1 in 99 and 1 in 100 is often ignored when presenting results to non-technical audiences.



## PART 9: SOME SIMPLE GUIDANCE FOR RESEARCHERS

The final Part of the Product 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, this Part 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 that are equally 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?
- Is information about the uncertainties related to research results and potential policies being communicated clearly and consistently?"

The balance of the final Part 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 and diverse experience and collective judgment of the writing team.

Rather than reproduce these recommendations here, we refer readers to the discussion at the end of Part 9.


# Sources and Types of Uncertainty[1]

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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 these 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.

By far, the most widely used formal language of uncertainty is probability[2]. 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, that 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 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 $P(X|i)$

[1] Portions of the discussion in this Part draw heavily on ideas and language from Morgan and Henrion (1990).

[2] There are a few alternative "languages" that have been advanced to describe and deal with uncertainty. These are briefly discussed in Part 2.

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 one's own reading of the political climate, "I think there is an 80 percent 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.

Subjective probabilities—a statement of a person's degree of belief given all available evidence—are intended to characterize the full spectrum of degrees of belief one might hold about uncertain propositions.

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 dataset 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 $1\text{-}p$ to its complement that $X$ doesn't occur. The probability that one of a set of mutually exclusive events occurs should be the sum of 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[3]. 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

[3] 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.

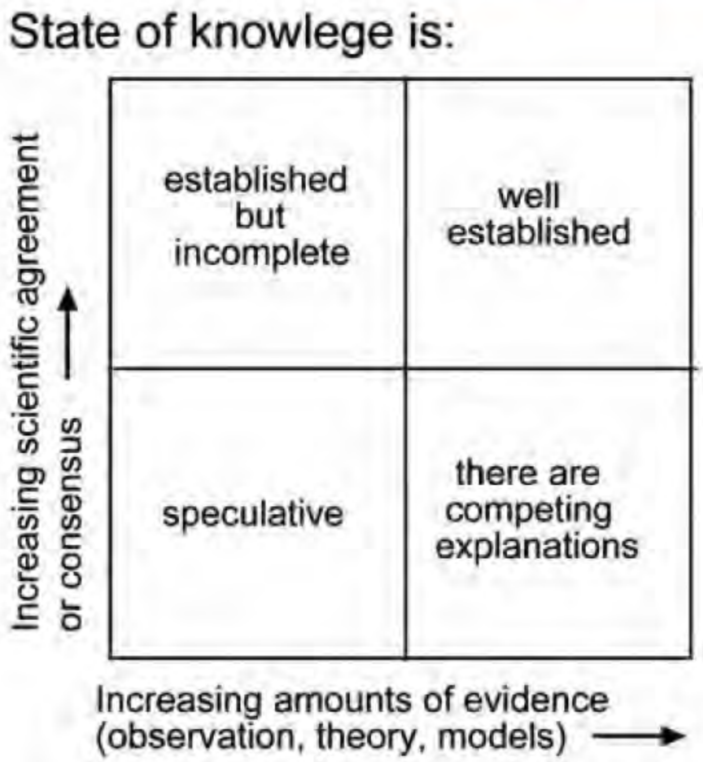


**Figure 1.1** Categorization of the various states of knowledge that may apply in different aspects of climate and related problems. Redrawn from Moss and Schneider (2000). *The Guidance Notes for Lead Authors of the IPCC Fourth Assessment Report on Addressing Uncertainties* (IPCC, 2005) adopted a slightly modified version of this same diagram.

community about that judgment. Thus, they argue, judgments can be sorted into four broad types as shown in Figure 1.1[4]. 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 probabilities, and fuzzy sets and fuzzy logic, that attempt to quantify the degree of belief in a set of subjective probability judgments[5]. 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"… Probabilists reply that we need not in-

[4] The Guidance Notes for Lead Authors of the IPCC Fourth Assessment Report (IPCC, 2005) adopted a slightly modified version of this same diagram.

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

vent 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 Part 7, that the key issue is to employ decision criteria, such as robustness, that are appropriate to the high levels of uncertainty.

To be empirical, variables must be measurable, at least in principle, either now or at some time in the future, we suggest that the only types of quantity whose uncertainty may appropriately be represented in probabilistic terms are empirical quantities.

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)"[6].

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 social sciences, such as demand elasticities 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[7]. 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"[8].

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 that represent a decision maker's own value choice or preference, such as a discount rate, coefficient of risk aversion, or the invest-



[6] 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".

[7] 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.

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

ment 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[9]. 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[10].

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 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 that prevent the elimination of plausible alternatives; systematic errors that mislead folks in their interpretation of underlying mechanisms; inadequate imagination and inventiveness in suggesting or inferring the models that 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 that 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.

It is also important to note that even when the functional form of a model is precisely known, its output may not be well known after it has run for some time. This is because some models, as well as some physical processes such as the weather and climate, are so exquisitely sensitive to initial conditions that they produce results that are chaotic (Devaney, 2003; Lorenz, 1963).

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 such as climate

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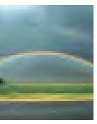
[9] In this example, a parametric analysis might ask, "What are the implications of taking the value of life to be 0.5 or 1 or 5 or 10 or 50 million dollars per death averted?" A "switchover" analysis would turn things around and ask "at what value of life" does the conclusion I read switch from Policy 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.

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

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".

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Freelance environmental journalist Dianne Dumanoski (quoted in Friedman *et al.*, 1999) captured this issue well when she noted:

> Scientific ignorance sometimes brings many surprises. Many of the big issues we have reported on involve scientists 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 percent or 13 percent within 100 years. Yet in 1985, a report came out from the British Antarctic survey, saying there was something upwards to a 50 percent 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[11] 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".



[11] <http://www.quotedb.com/quotes/1097>.