CRAG Symposium:

Uncertainty - From Insight to Action

UNCERTAINTY:
An Introduction

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QUESTION: Why has the center for risk analysis and governance…

…chosen to focus this meeting on uncertainty?

ANSWER: Because risk is the exposure to ***a chance*** of injury or loss.

When an injury or loss is a sure thing we do not use the word risk.

And, of course, the word ***chance*** implies uncertainty.

Before I turn to uncertainty…

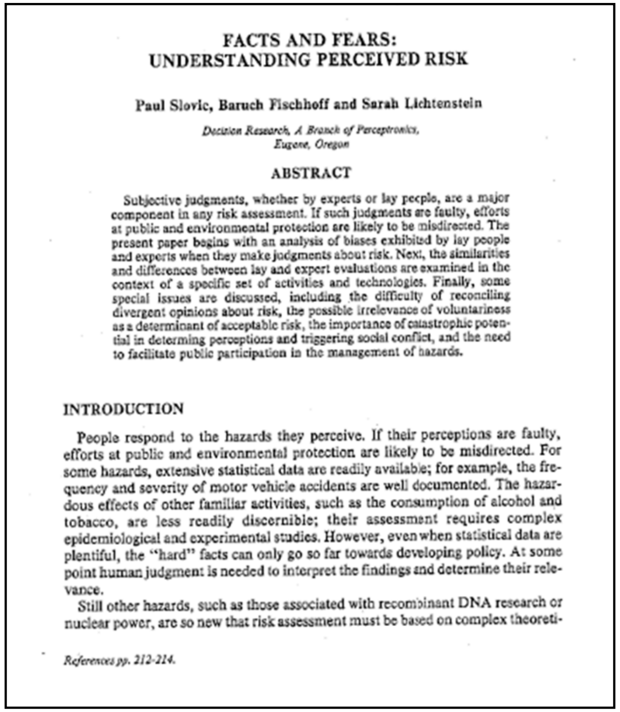
…I should note that the simple assumption often made by many technical people, that risk is the expected value of some loss

$$\mathrm{E}[p*\mathrm{L}]$$

is ***not*** consistent with the way in which we all think about risk in our daily lives.

There is…

…a large literature in behavioral social science that finds that people view risk as a multi-attribute concept.



FACTS AND FEARS:
UNDERSTANDING PERCEIVED RISK

Paul Slovic, Baruch Fischhoff and Sarah Lichtenstein

Decision Research, A Branch of Perceptronics, Eugene, Oregon

ABSTRACT

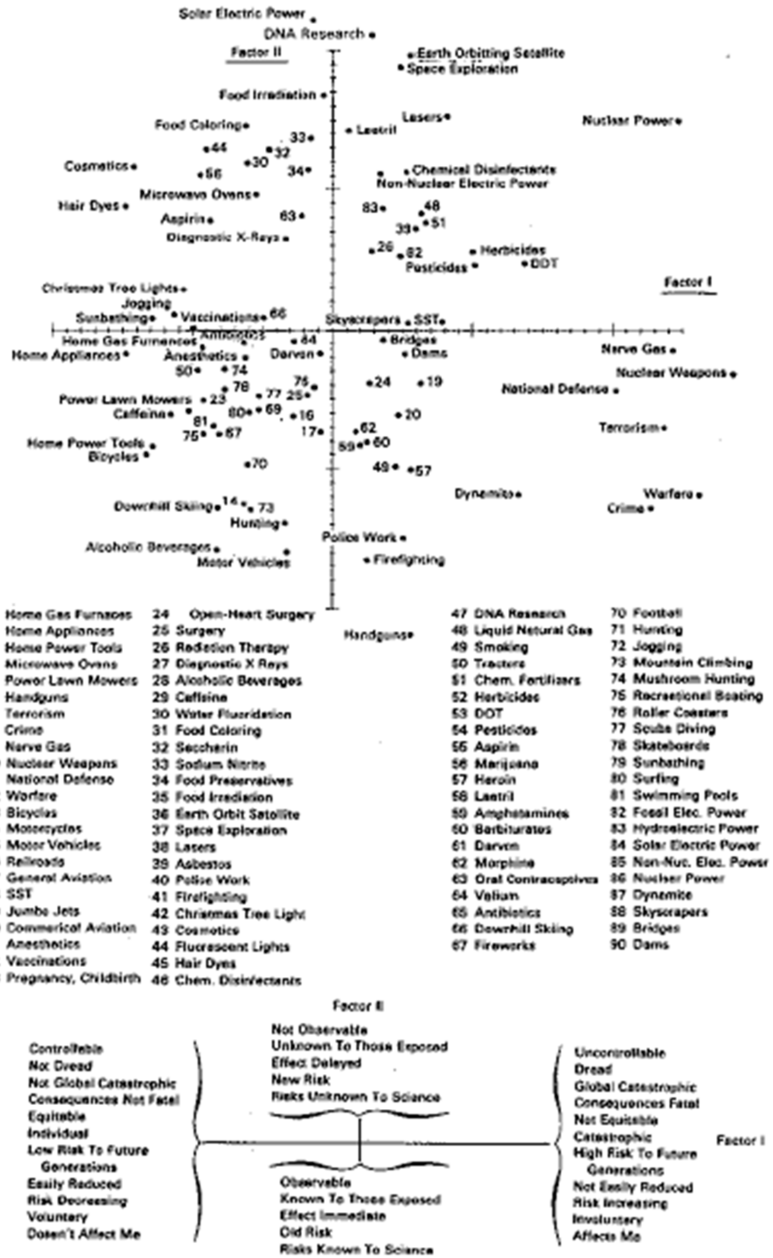
Subjective judgments, whether by experts or lay people, are a major component in any risk assessment. If such judgments are faulty, efforts at public and environmental protection are likely to be misdirected. The present paper begins with an analysis of biases exhibited by lay people and experts when they make judgments about risk. Next, the similarities and differences between lay and expert evaluations are examined in the context of a specific set of activities and technologies. Finally, some special issues are discussed, including the difficulty of reconciling divergent opinions about risk, the possible irrelevance of voluntariness as a determinant of acceptable risk, the importance of catastrophic potential in determing perceptions and triggering social conflict, and the need to facilitate public participation in the management of hazards.

INTRODUCTION

People respond to the hazards they perceive. If their perceptions are faulty, efforts at public and environmental protection are likely to be misdirected. For some hazards, extensive statistical data are readily available; for example, the frequency and severity of motor vehicle accidents are well documented. The hazardous effects of other familiar activities, such as the consumption of alcohol and tobacco, are less readily discernible; their assessment requires complex epidemiological and experimental studies. However, even when statistical data are plentiful, the "hard" facts can only go so far towards developing policy. At some point human judgment is needed to interpret the findings and determine their relevance.

Still other hazards, such as those associated with recombinant DNA research or nuclear power, are so new that risk assessment must be based on complex theoreti-

References pp. 212-214.



FOR DETAILS SEE: Sarah Lichtenstein, Paul Slovic, Baruch Fischhoff, Mark Layman and Barbara Combs, "Judged frequency of lethal events," *Journal of Experimental Psychology, Human learning and memory, 4*, pp. 551-578, 1978 Nov. AND Paul Slovic, Baruch Fischhoff and Sarah Lichtenstein, "Facts and Fears: Understanding perceived risk," pp. 181-216, in *Societal Risk Assessment*, Schwing and Albers (eds.), Plenum, 1980.

When does uncertainty matter in risk and policy analysis?

Decision analysis says it should matter when:

- decision makers' attitudes toward risk are important (e.g., risk aversion);
- uncertain information from different sources must be combined;
- when decisions must be made about acquiring additional information; and
- when the loss function has a significant third order dependency on the uncertain quantity (i.e., is highly asymmetric).

Beyond these formal reasons...

...dealing explicitly with uncertainty:

- helps identify and overcome biases from cognitive heuristics;
- helps in defining and revising models;
- helps decision makers better evaluate the advice they are receiving (e.g., can help them understand the extent to which different experts agree or disagree);
- helps in explicitly separating issues of value from issues of fact; and
- helps analysts more clearly state the implications and limitations of their work.

This afternoon I will talk about:

- Sources of uncertainty and the characterization of uncertainty.
- Uncertainty *versus* variability.
- Two basic types of uncertainty.
  - Uncertainty about coefficient values.
  - Uncertainty about model functional form.
- Analyzing uncertainty.
- The use and abuse of "expert elicitation."
- Some summary guidance on reporting, characterizing and analyzing uncertainty.

Probability

Probability is the basic language of uncertainty.

Risk analysis typically adopts a personalistic view of probability (sometimes also called a subjectivist or Bayesian view).

In this view, probability is a statement about the degree of belief that a person has that a specified event will occur *given* all the relevant information currently known by that person. That is:

$p(X|i)$ where:

X is the uncertain event

i is the person's state of information.

The clairvoyant test

Even if we take a personalist view of probability, the event or quantity of interest must be well specified for a probability, or a probability distribution, to be meaningful.

"The retail price of gasoline in 2015" does not pass this test. In order to give a precise answer, a clairvoyant would need to know things such as:

- Where will the gasoline be purchased?
- At what time of year?
- What octane?

Does a subjectivist view mean your probability can be arbitrary?

NO, because if they are legitimate probabilities, they must:

- conform with the axioms of probability; and
- be consistent with available empirical data.

Many people ask, why deal with formal probability? Why not just use subjective words such as "likely" and "unlikely" to describe uncertainties?

There are very good reasons *not* to do this.

The risks of using qualitative uncertainty language

Qualitative uncertainty language is inadequate because:

- the same words can mean very different things to different people;
- the same words can mean very different things to the same person in different contexts; and
- important differences in experts' judgments about mechanisms (functional relationships), and about how well key coefficients are known, can be easily masked in qualitative discussions.

Mapping words to probabilities

This figure shows the range of probabilities that people are asked to assign probabilities to words, absent any specific context.

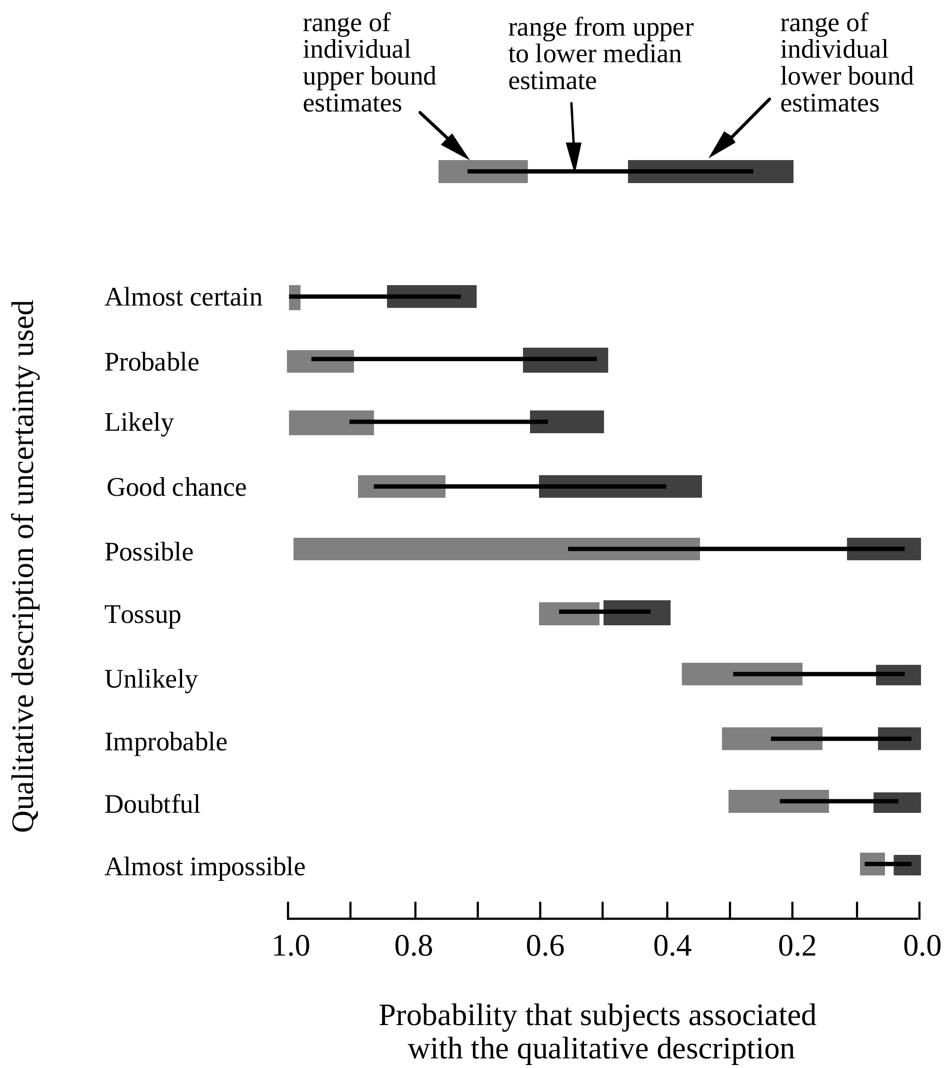


Figure adapted from Wallsten et al., 1986.

Ex Com of EPA SAB

The minimum probability associated with the word "likely" spanned four orders of magnitude.

The maximum probability associated with the word "not likely" spanned more than five orders of magnitude.

There was an overlap of the probability associated with the word "likely" and that associated with the word "unlikely"!

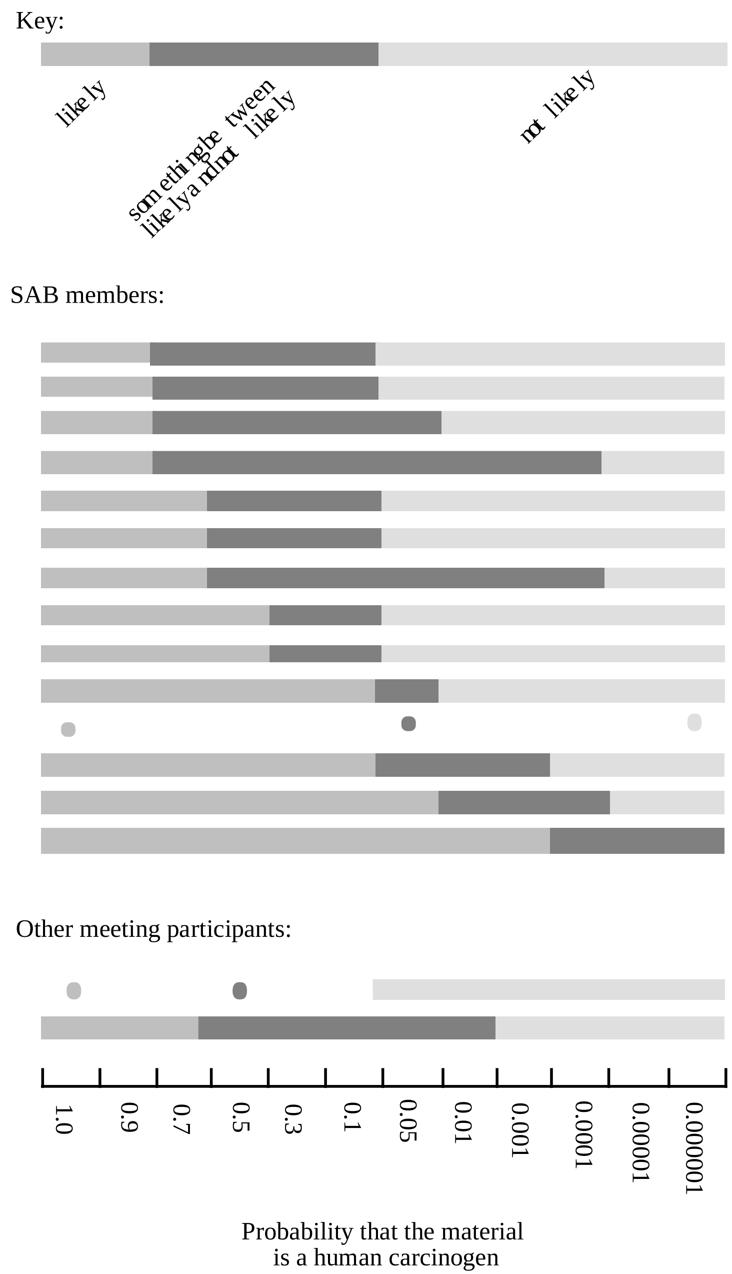


Figure from Morgan, *HERA*, 1998.

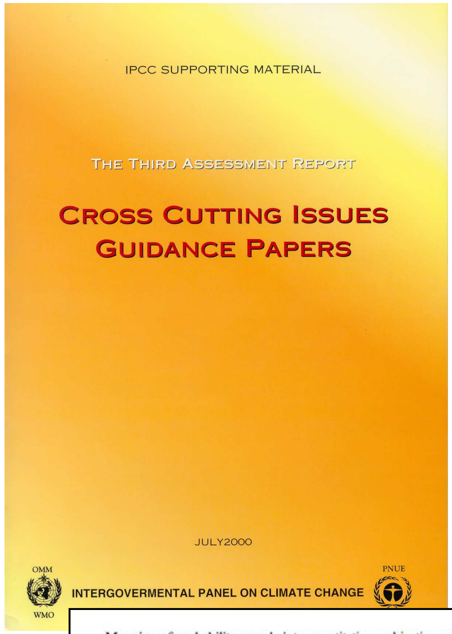
The bottom line:

Without at least some quantification, qualitative descriptions of uncertainty convey little, if any, useful information.

The climate assessment community is gradually learning this lesson.

Steve Schneider and Richard Moss worked hard to promote a better treatment of uncertainty in the work of the IPCC.

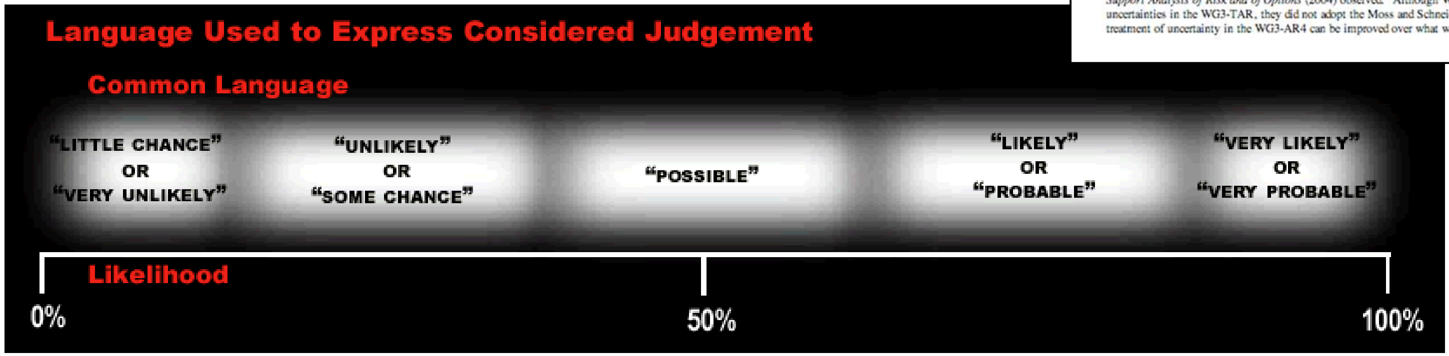
At my insistence, the U.S. national assessment synthesis team gave quantitative definitions to five probability words:



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

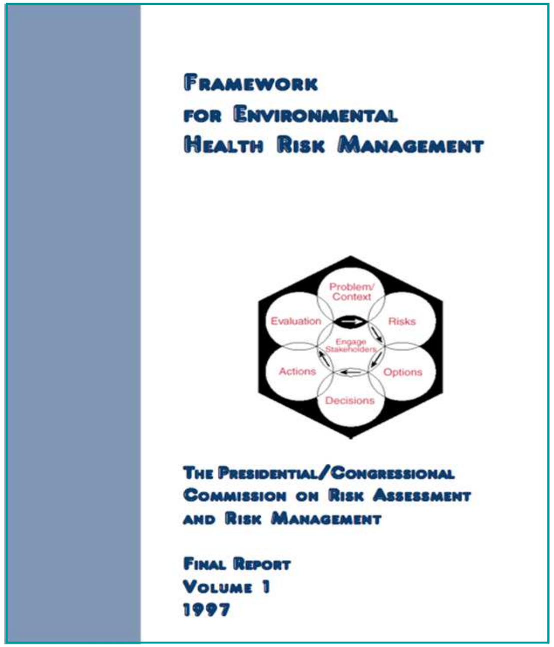
word	probability range
Virtually certain	> 0.99
Very likely	0.9-0.99
Likely	0.66-0.9
Medium likelihood	0.33-0.66
Unlikely	0.1-0.33
Very unlikely	0.01-0.1
Exceptionally unlikely	< 0.01

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."



BUT, in other fields…

…such as biomedical and health effects, progress has been *much* slower.



A concrete example of this is provided by the recommendations of the U.S. Presidential/ Congressional Commission on Risk Assessment and Risk Management (1997) which recommended…"against routine use of formal quantitative analysis of uncertainty in risk estimation, particularly that related to evaluating toxicology."

While analysts were encouraged to provide "*qualitative* descriptions of risk-related uncertainty," the Commission concluded that "quantitative uncertainty analyses of risk estimates are seldom necessary and are not useful on a routine basis to support decision-making."

Such views are changing, but progress continues to be slow.

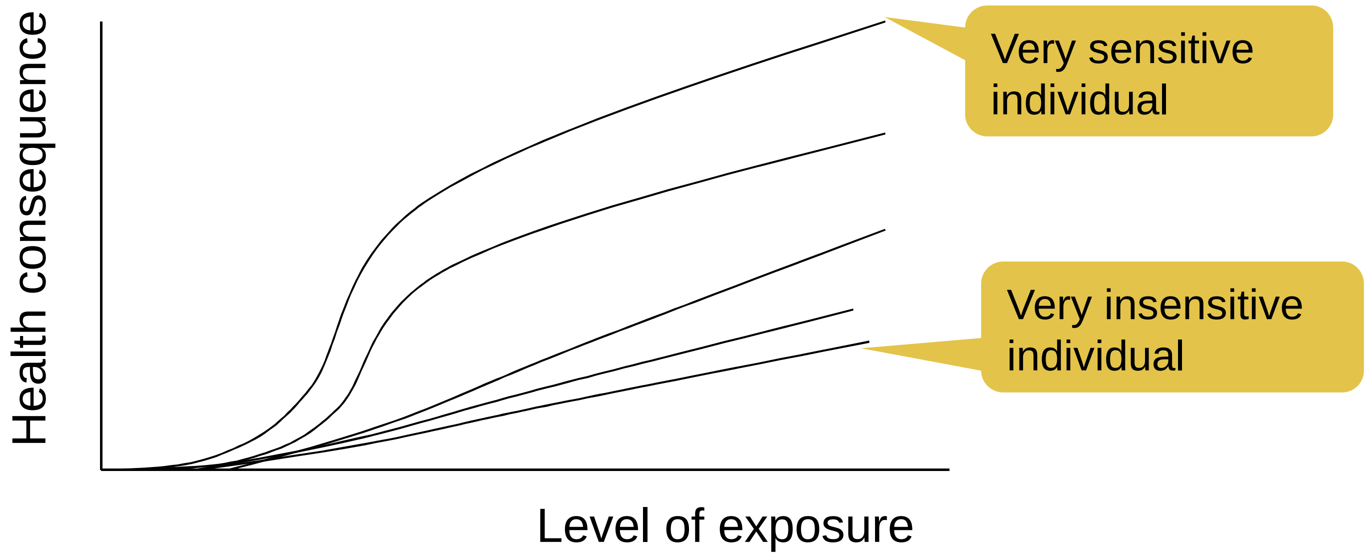
This afternoon I will talk about:

- Sources of uncertainty and the characterization of uncertainty.
- Uncertainty *versus* variability.
- Two basic types of uncertainty.
  - Uncertainty about coefficient values.
  - Uncertainty about model functional form.
- Analyzing uncertainty.
- The use and abuse of "expert elicitation."
- Some summary guidance on reporting, characterizing and analyzing uncertainty.

Uncertainty *versus* variability

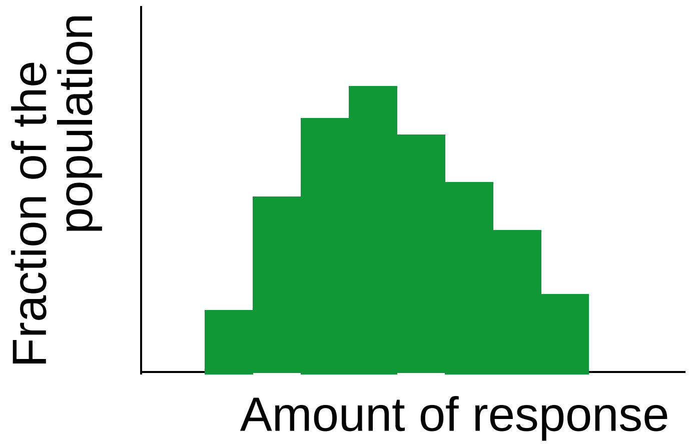
Many processes, such as the rate of flow in a river, or the sensitivity of individuals to a pollutant, show variability over time or across individuals.

For example, consider the case of how different individuals might respond to a pollutant:



Variability can be represented…

…by a histogram, which is a non-subjective statement about a set of data. For example:

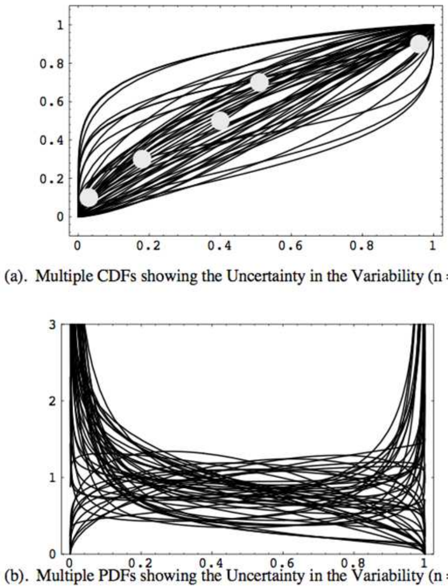


Because histograms showing variability are based on observed data and are not subjective, some who are uncomfortable about using a Bayesian perspective have drawn an overly sharp distinction between variability and uncertainty.

Sometimes it is important…

…to make a distinction between variability and uncertainty, but more typically in risk and policy analysis, variability is just another contributor to the uncertainty that must be characterized and addressed.

Treating the two separately can result in intellectually interesting, complex displays. However, in my view these are rarely helpful in practical risk analysis and risk decision making.



(a). Multiple CDFs showing the Uncertainty in the Variability (n = 50)

(b). Multiple PDFs showing the Uncertainty in the Variability (n = 50)

Source: Frey and Burmaster, *Risk Analysis*, 1997

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We must consider two quite different kinds of uncertainty

1. Situations in which we know the relevant variables and the functional relationships among them, but we do not know the values of key coefficients (e.g., an oxidation rate, the slope of a damage function, or the "climate sensitivity").

2. Situations in which we are not sure what all the relevant variables are, or the functional relationships among them (e.g., will rising energy prices induce more technical innovation?).

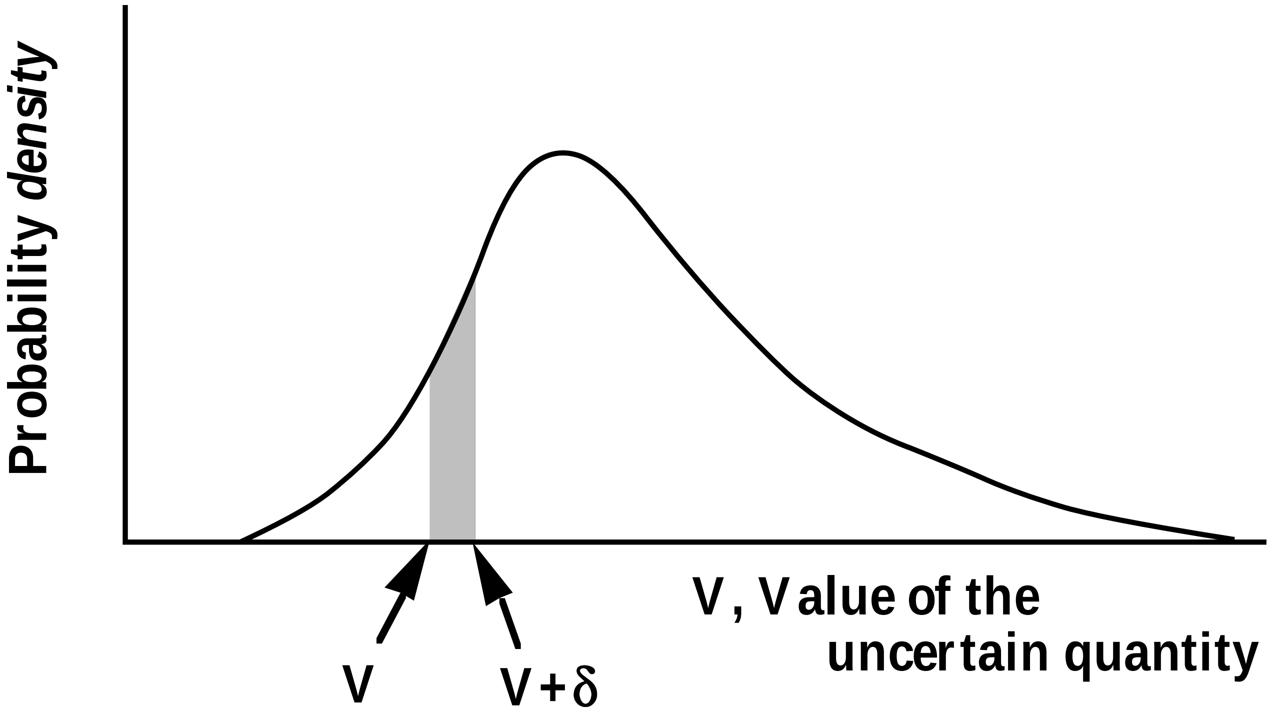
Both are challenging, but the first is much more easily addressed than the second.

PDFs and CDFs

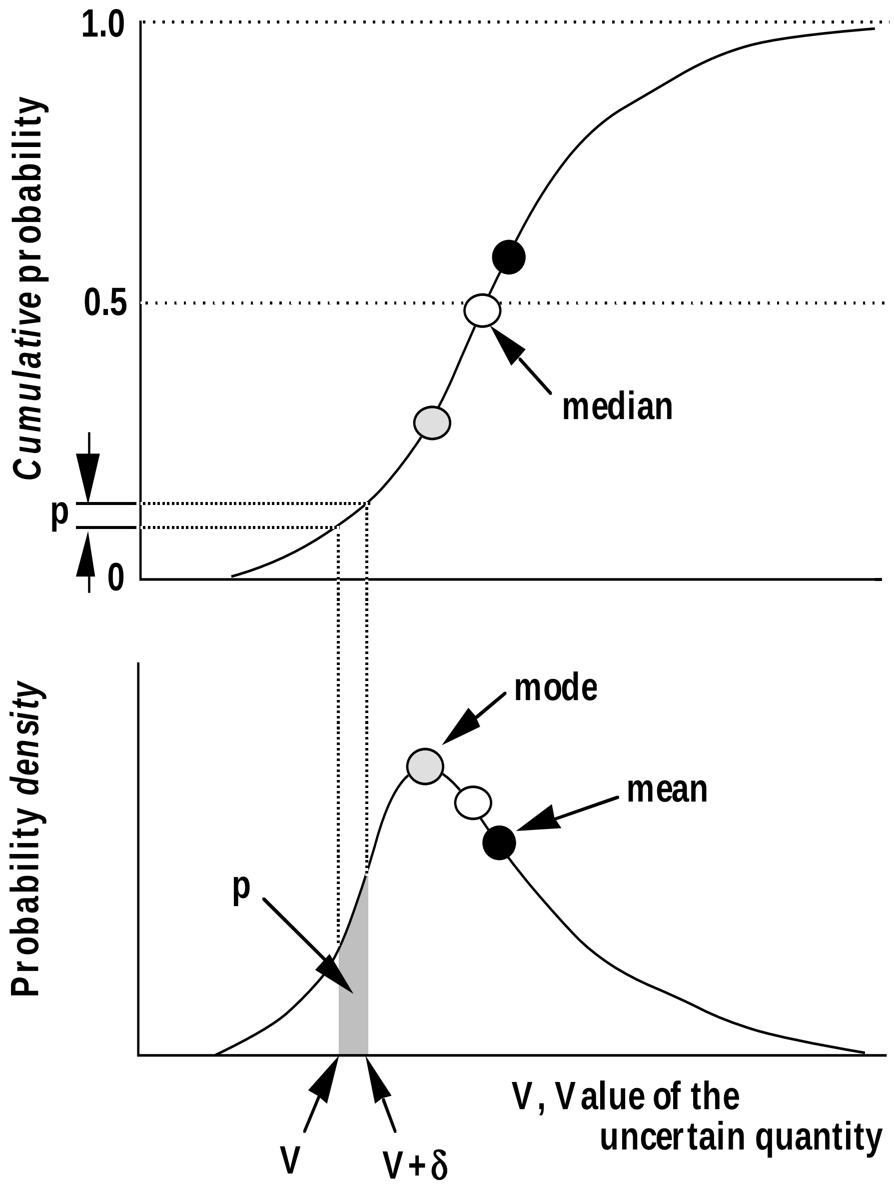
A number of examples I am about to show are in the form of probability density functions (PDFs) or cumulative distribution functions (CDFs).

Since some of you may not make regular use of PDF's and CDF's, let me take just a moment to remind you...

Probability density function or PDF



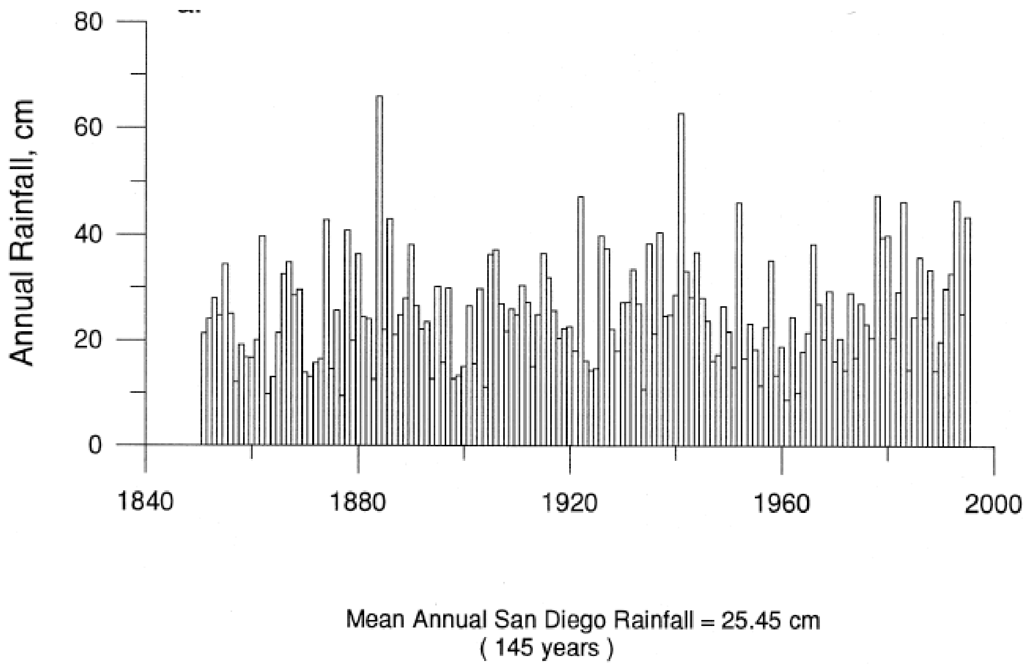
Cumulative distribution function or CDF



NOTE: In asymmetric distributions with long high tails, the mean may be much much larger than the median.

If I have good data...

...in the form of many observations of a random process, then I can construct a probability distribution that describes that process. For example, suppose I have the 145 years of rainfall data for San Diego, California, and I am prepared to assume that over that period San Diego's climate has been "stationary" (that is the basic underlying processes that create the year-to-year variability have not changed)…

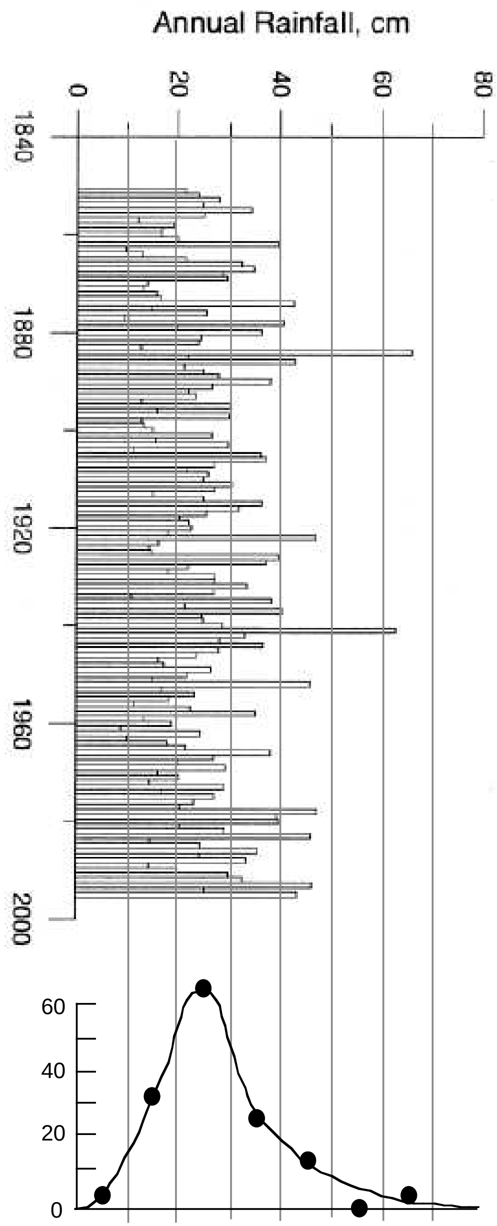


Source: Inman et al., Scripps, 1998.

Then if I want…

…a PDF for future San Diego annual rainfall, the simplest approach would be to construct a histogram from the data, as illustrated to the right.

If I want to make a prediction for some *specific* future year, I might go on to look for time patterns in the data. Even better, I might try to relate those time patterns to known slow patterns of variation in the regional climate, and modify my PDF accordingly.

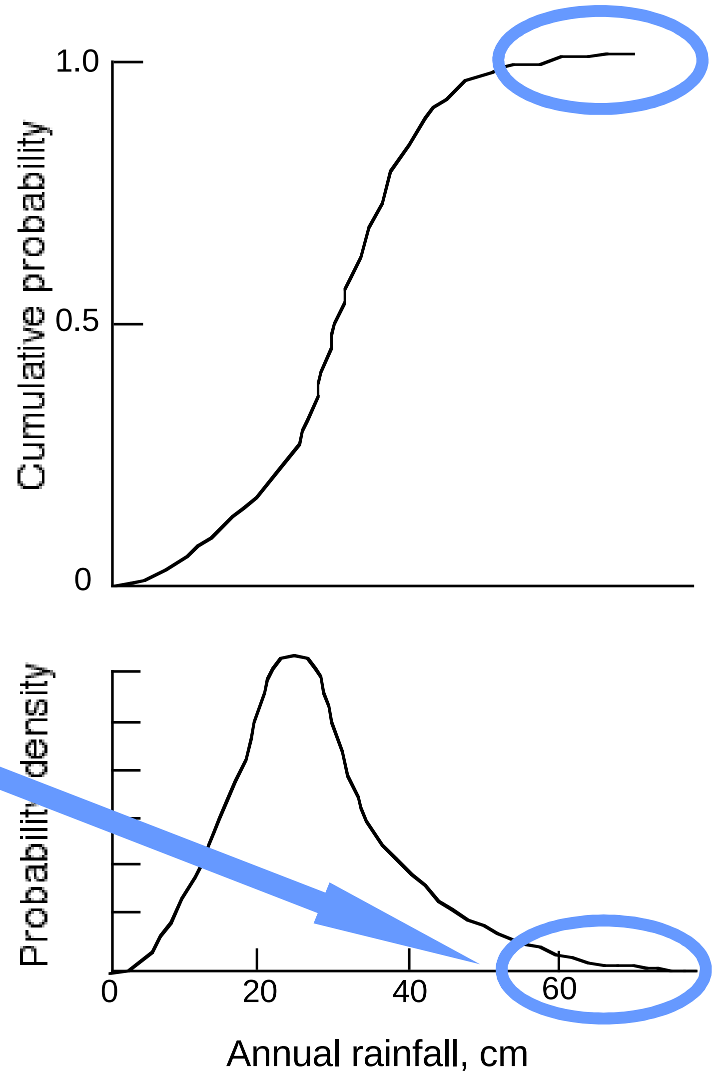


In that way…

…I could construct a PDF and CDF for future San Diego rain-fall that would look roughly like this.

However, suppose that what I really care about is the probability that very large rainfall events will occur.

Since there have only been two years in the past 145 years when rainfall has been above 60 cm/yr over, I'll need to augment my data with some model or physical theory, and perhaps make use of expert judgment.



In summary…

…one should use available data, and well-established physical and statistical theory, to describe uncertainty about the value of key coefficients whenever either or both are available.

However, often the available data and theory are not exactly relevant to the problem at hand, or they are not sufficiently complete to support the full objective construction of a probability distribution.

In such cases, one may have to rely on expert judgment.

I'll say a few more words about that in a moment.

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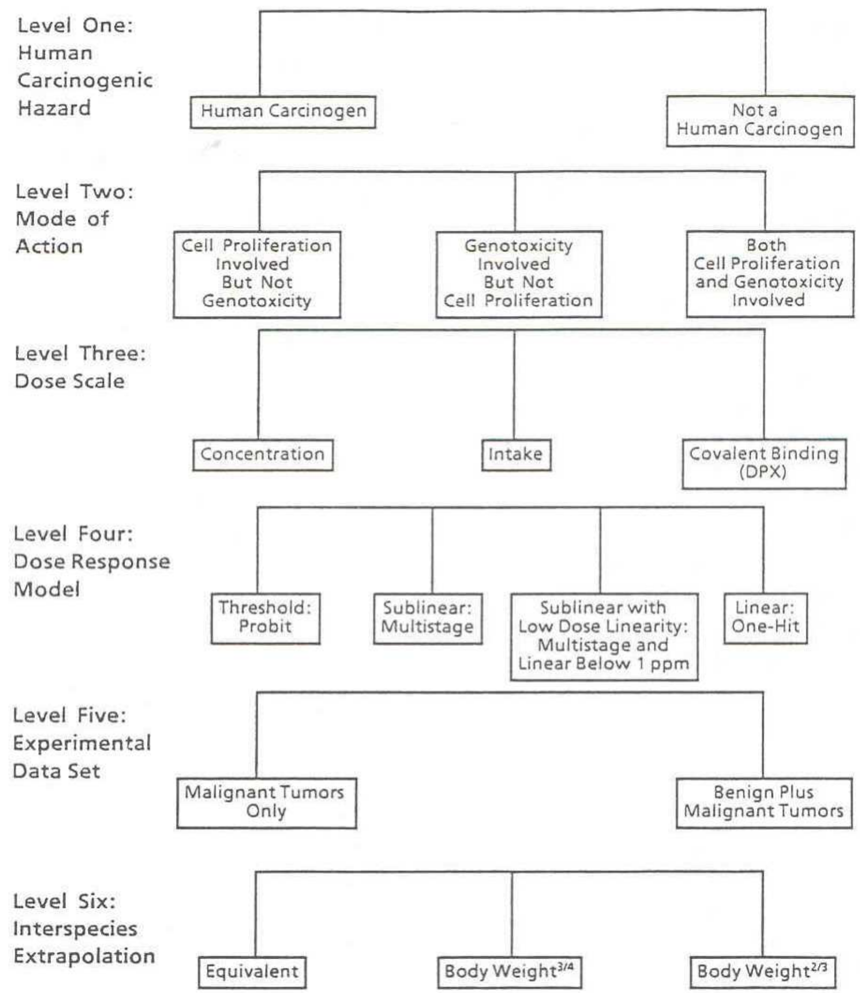
Uncertainty about model form

Often uncertainty about model form is as or more important than uncertainty about values of coefficients. Until recently there had been little practical progress in dealing with such uncertainty, but now there are several good examples:

- John Evans and his colleagues at the Harvard School of Public Health (e.g., Evans et al., 1994).
- Alan Cornell and others in the seismic risk (e.g., Budnitz et al., 1995).
- Hadi Dowlatabadi and colleagues at Carnegie Mellon in Integrated Assessment of Climate Change - ICAM (e.g., Morgan and Dowlatabadi, 1996).
- Also on climate, Lempert and colleagues at RAND (e.g., Lempert, Popper, Bankes, 2003).

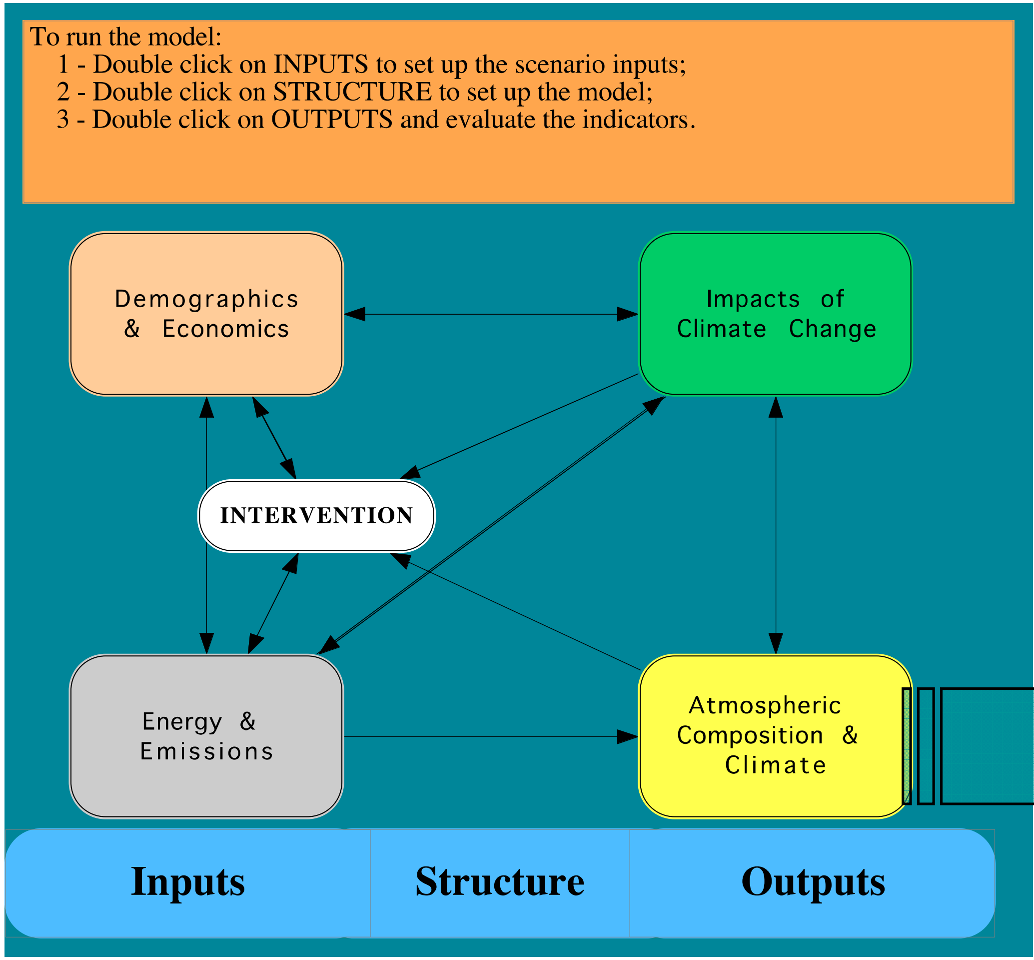
John Evans and colleagues…

…have developed a method which lays out a "probability tree" to describe all the plausible ways in which a chemical agent might cause harm. Then experts are asked to assess probabilities on each branch.

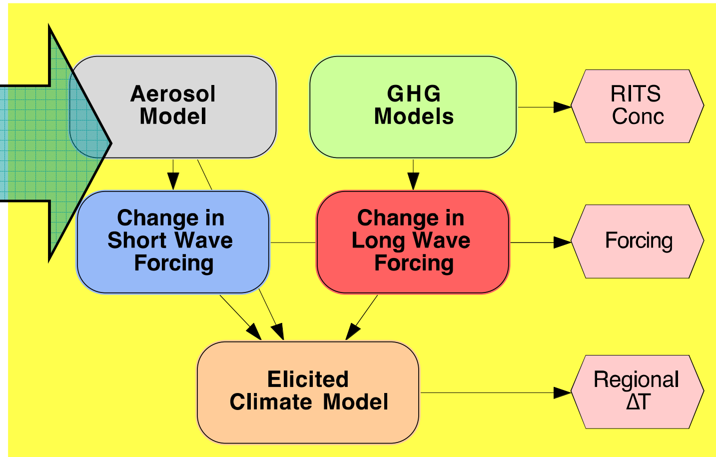


For details see: John S. Evans et al., "A distributional approach to characterizing low-dose cancer risk," *Risk Analysis, 14*, 25-34, 1994; and John S. Evans et al., "Use of probabilistic expert judgment in uncertainty analysis of carcinogenic potency," *Regulatory Toxicology and Pharmacology*, *20*, 15-36, 1994.

ICAM
Integrated Climate Assessment Model



A very large hierarchically organized stochastic simulation model built in Analytica®.



For details see:
Hadi Dowlatabadi and M. Granger Morgan, "A Model Framework for Integrated Studies of the Climate Problem," *Energy Policy*, *21*(3), 209-221, March 1993.
AND
M. Granger Morgan and Hadi Dowlatabadi, "Learning from Integrated Assessment of Climate Change," *Climatic Change*, *34*, 337-368, 1996.

ICAM dealt with...

…both of the types of uncertainty I've talked about:

1. It dealt with uncertain coefficients by assigning PDFs to them and then performing stochastic simulation to propagate the uncertainty through the model.
2. It dealt with uncertainty about model functional form (e.g., will rising energy prices induce more technical innovation?) by introducing multiple alternative models which can be chosen by throwing "switches."

ICAM

I won't take the time to present details from our work with the ICAM integrated assessment model. Here are just four conclusions:

1. Different sets of plausible model assumptions give *dramatically* different results.
2. No policy we looked at is dominant over the wide range of plausible futures we examined.
3. The regional differences in outcomes are so vast that few, if any, policies pass muster globally for similar decision rules.
4. Different metrics of aggregate outcomes (e.g., $s *versus* hours of labor) skew the results to reflect the OECD or developing regional issues respectively.

More generally we…

…concluded, that prediction and policy optimization are pretty silly analytical objectives for much assessment and analysis related to the climate problem.

It makes much more sense to:

- Acknowledge that describing and bounding a range of futures may often be the best we can do.
- Recognize that climate is not the only thing that is changing, and address the problem in that context.
- Focus on developing adaptive strategies and evaluating their likely robustness in the face of a range of possible climate, social, economic and ecological futures.

Work by Robert Lempert and colleagues takes a very similar approach (e.g., Lempert, Popper, Bankes, 2003).

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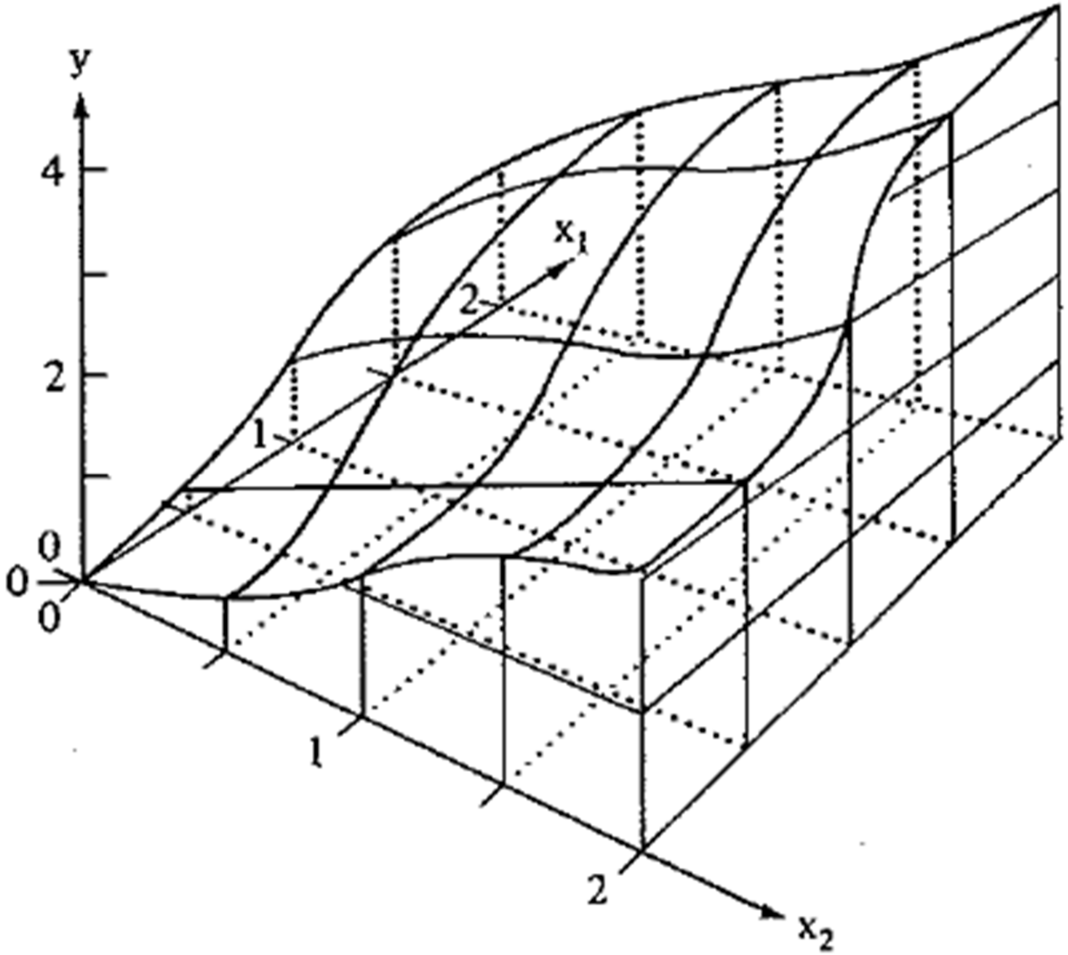
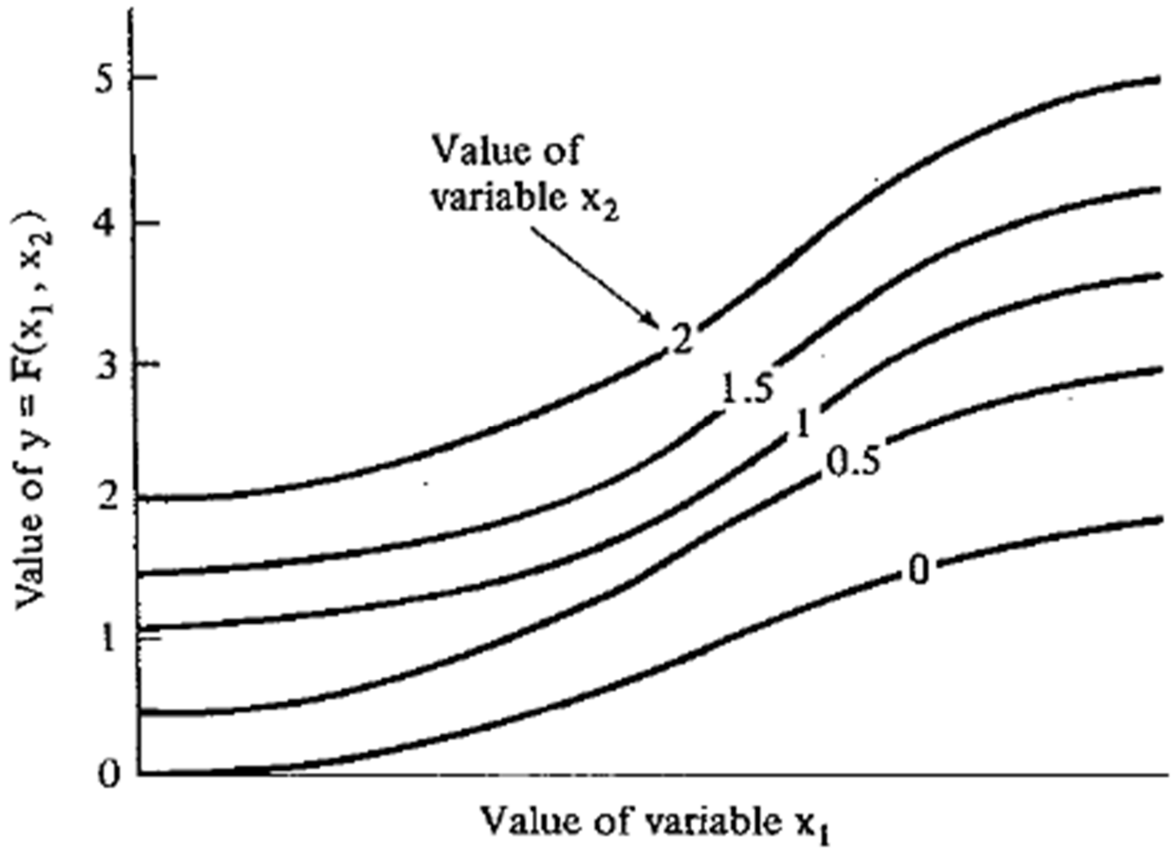
Consider a simple model…

… $y=f(x_1,x_2)$ where the values of both x_1 and x_2 may be uncertain.



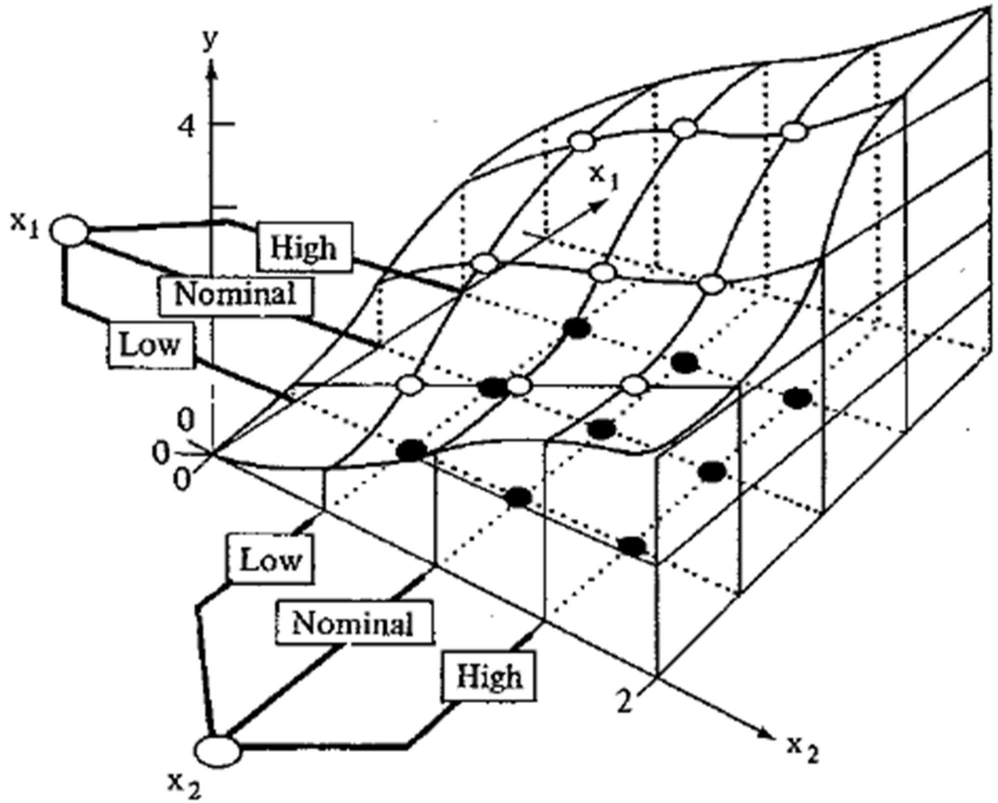
Source: Morgan and Henrion, 1990

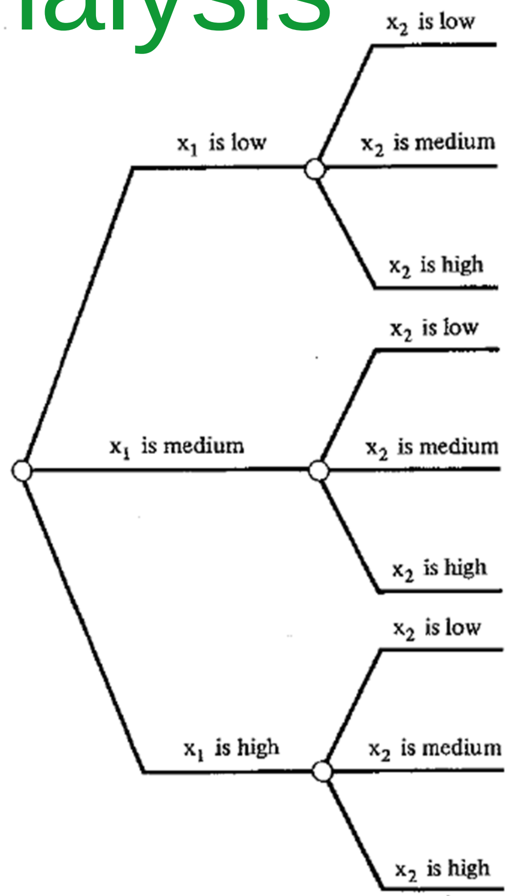
Parametric analysis



Source: Morgan and Henrion, 1990

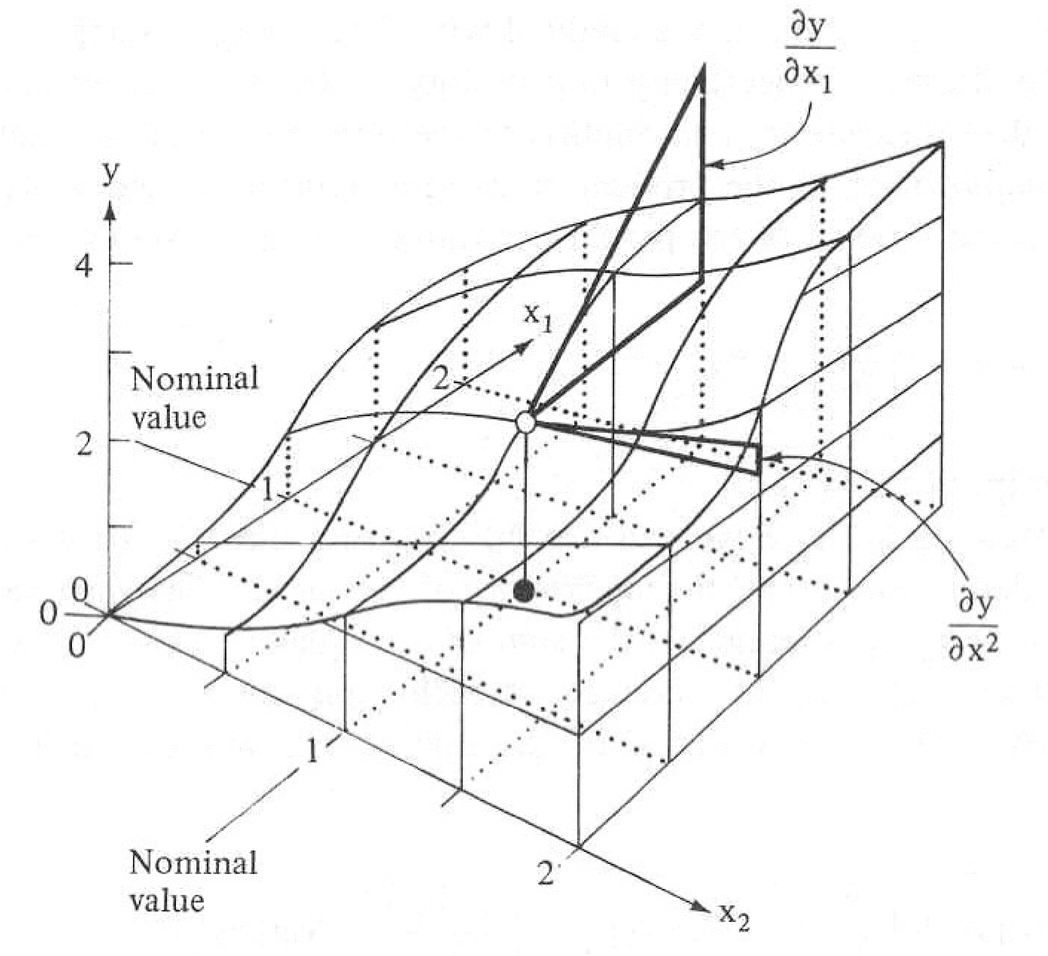
Combinatorial analysis





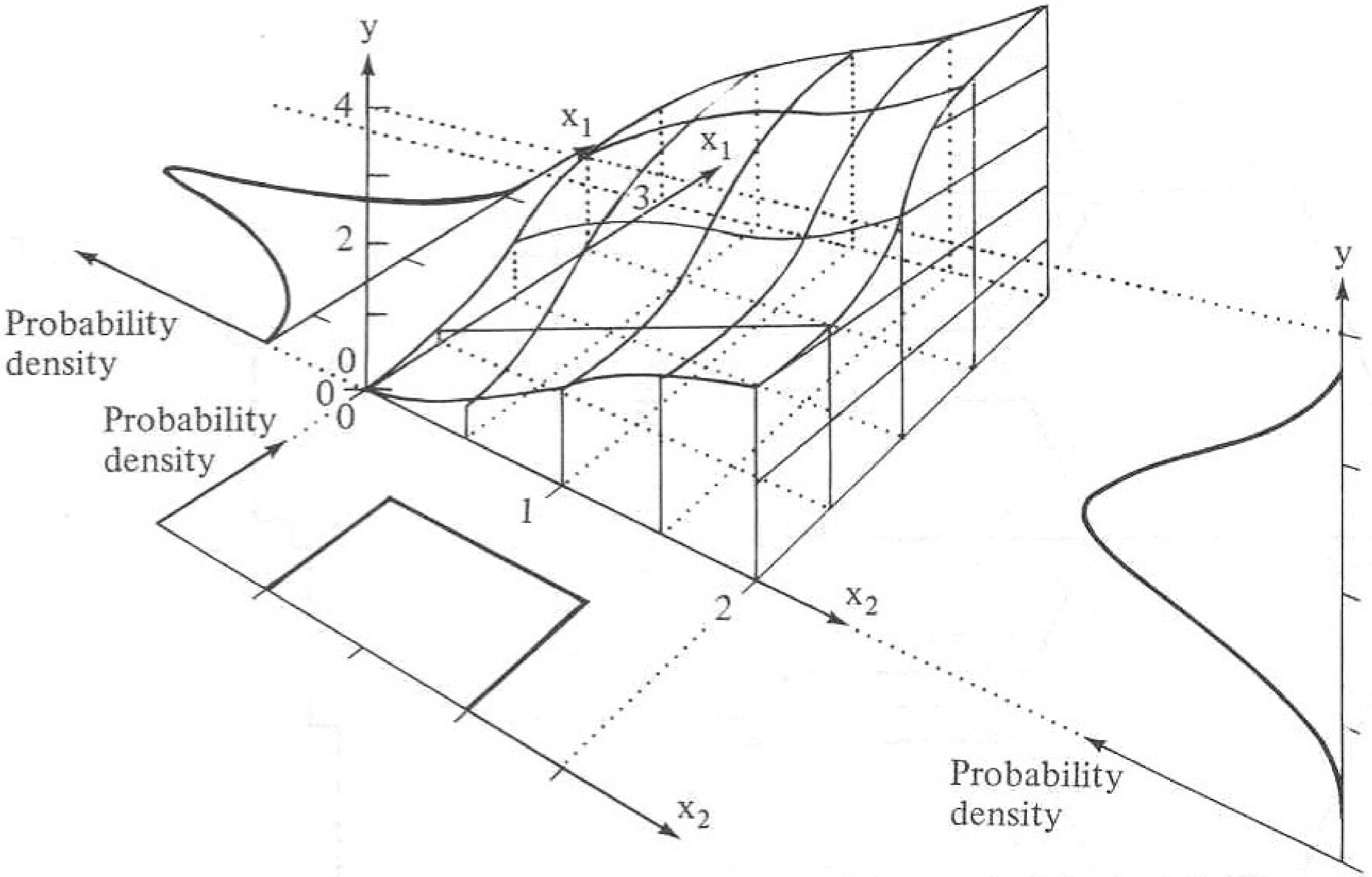
Source: Morgan and Henrion, 1990

Sensitivity Analysis



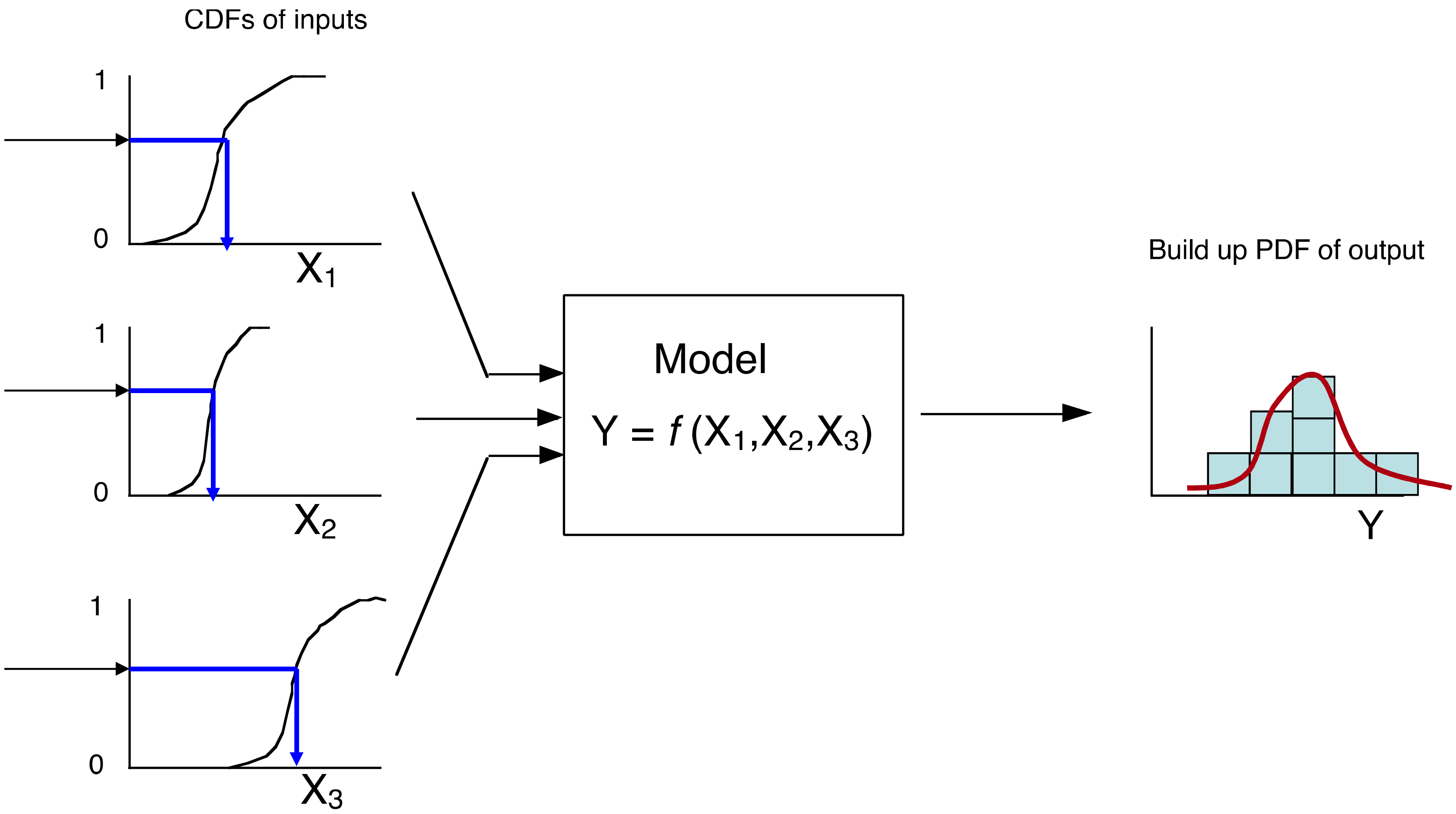
Source: Morgan and Henrion, 1990

Propagation of continuous distributions



Source: Morgan and Henrion, 1990

Monte Carlo Simulation



Tools for analysis

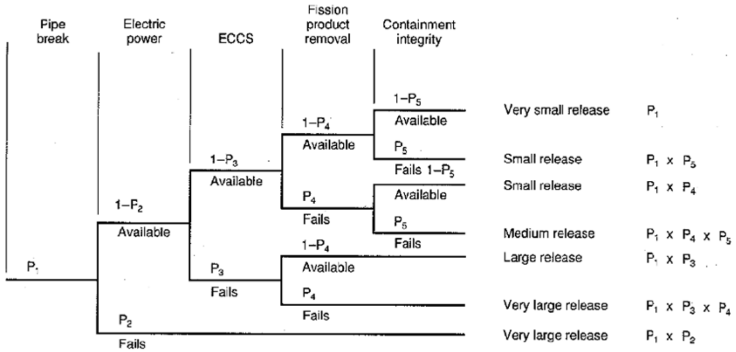
Tools for continuous processes:

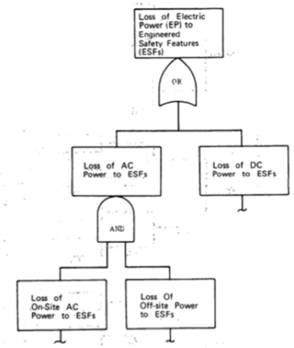
- Exposure models
- Dose response functions
- etc.

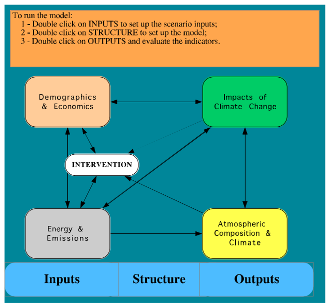
In the past, using some of these tools was very challenging and time consuming. Today, such analysis is facilitated by many software tools (e.g., Analytica®, @risk®, Crystal Ball®, etc.).

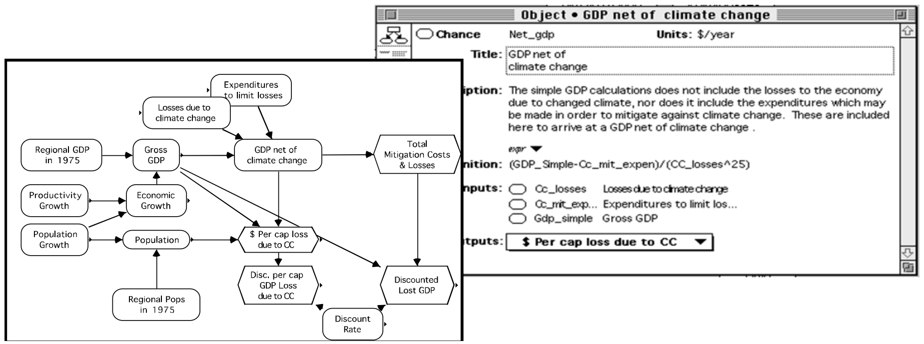
Tools for discrete events:

- Failure modes and effects analysis
- Fault tree models
- etc.









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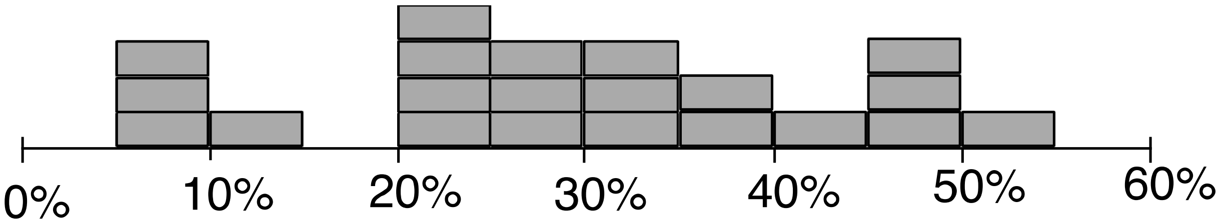
- Two basic types of uncertainty.
  - Uncertainty about coefficient values.
  - Uncertainty about model functional form.
- Analyzing uncertainty.
- The use and abuse of "expert elicitation."
- Some summary guidance on reporting, characterizing and analyzing uncertainty.

Expert elicitation

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 the intuition of experts. Elicitation can be a useful tool in support of research planning, private decision making, and the formulation of public policy.

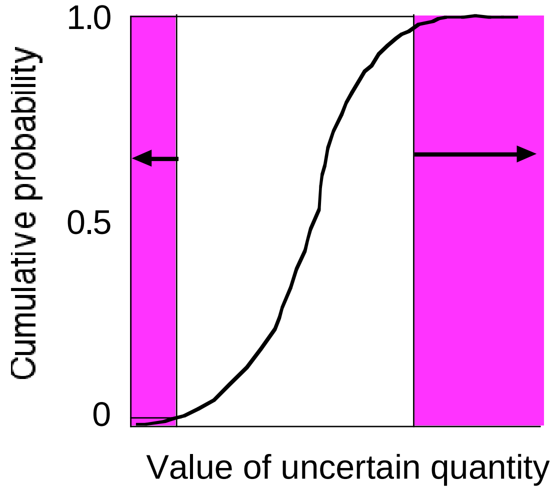
HOWEVER the design and execution of a good expert elicitation takes time and requires a careful integration of knowledge of the relevant substantive domain with knowledge of behavioral decision science.

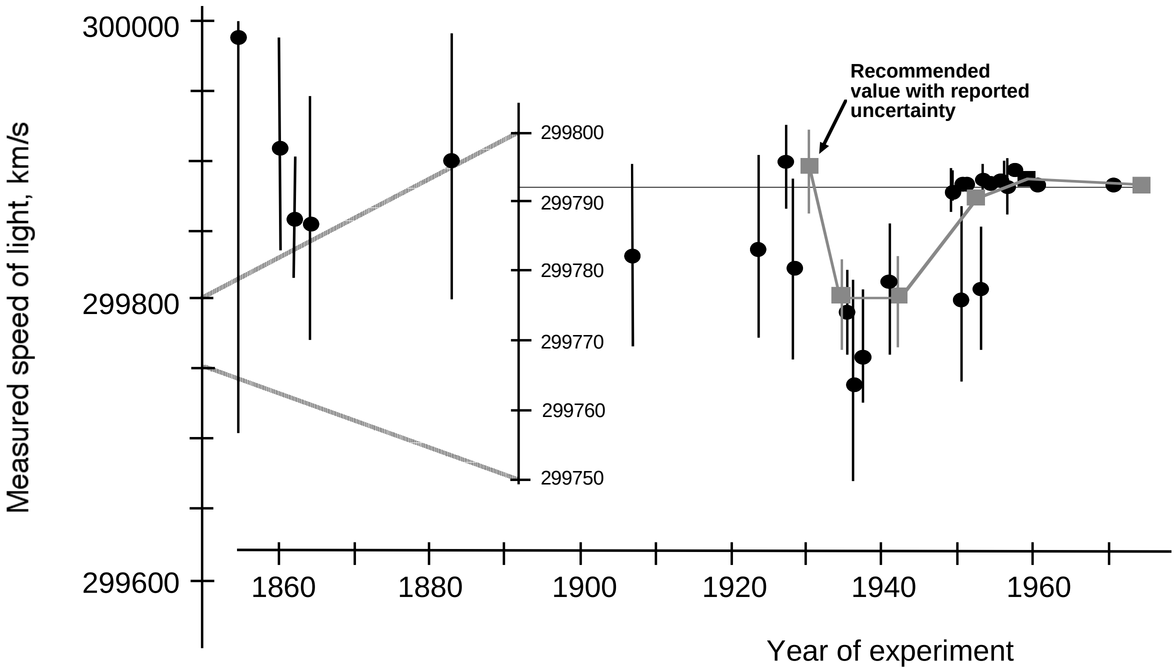
Over Confidence



Percentage of estimates in which the true value lay outside of the respondent's assessed 98% confidence interval.

2% probability that true value lies below the 1% lower bound or above the 99% upper bound.





For details see: Henrion and Fischhoff, "Assessing Uncertatinty in Physical Constants," *American Journal of Physics*, 54, pp791-798, 1986.

Cognitive heuristics

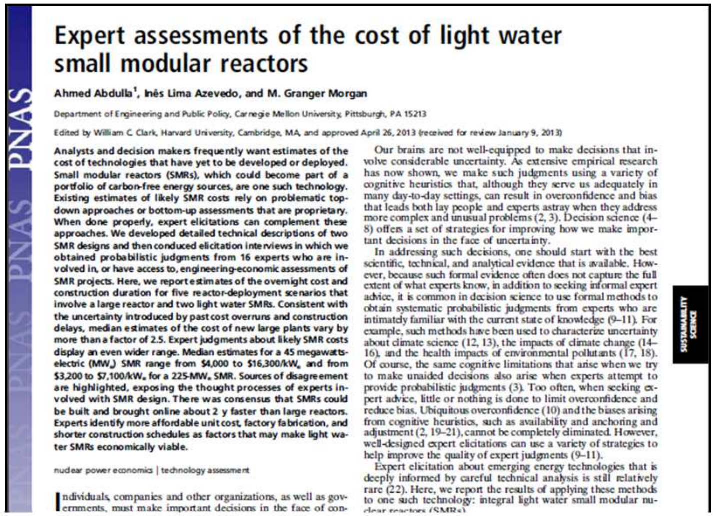
When ordinary people or experts make judgments about uncertain events, such as numbers of deaths from chance events, they use simple mental rules of thumb called "cognitive heuristics."

In many day-to-day circumstances, these serve us very well, but in some instances they can lead to bias - such as over confidence - in the judgments we make.

Elicitation protocols should be designed to minimize the impact of three key heuristics: "availability," "anchoring and adjustment," and "representativeness."

However, rather than spend more time talking about "how to" details, I'll show three examples

Example 1:



PNAS

Expert assessments of the cost of light water small modular reactors

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Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213

Edited by William C. Clark, Harvard University, Cambridge, MA, and approved April 26, 2013 (received for review January 9, 2013)

Analysts and decision makers frequently want estimates of the cost of technologies that have yet to be developed or deployed. Small modular reactors (SMRs), which could become part of a portfolio of carbon-free energy sources, are one such technology. Existing estimates of likely SMR costs rely on problematic top-down approaches or bottom-up assessments that are proprietary. When done properly, expert elicitations can complement these approaches. We developed detailed technical descriptions of two SMR designs and then conduced elicitation interviews in which we obtained probabilistic judgments from 16 experts who are involved in, or have access to, engineering-economic assessments of SMR projects. Here, we report estimates of the overnight cost and construction duration for five reactor-deployment scenarios that involve a large reactor and two light water SMRs. Consistent with the uncertainty introduced by past cost overruns and construction delays, median estimates of the cost of new large plants vary by more than a factor of 2.5. Expert judgments about likely SMR costs display an even wider range. Median estimates for a 45 megawatts-electric (MW_e) SMR range from \$4,000 to \$16,300/kW_e and from \$3,200 to \$7,100/kW_e for a 225-MW_e SMR. Sources of disagreement are highlighted, exposing the thought processes of experts involved with SMR design. There was consensus that SMRs could be built and brought online about 2 y faster than large reactors. Experts identify more affordable unit cost, factory fabrication, and shorter construction schedules as factors that may make light water SMRs economically viable.

nuclear power economics | technology assessment

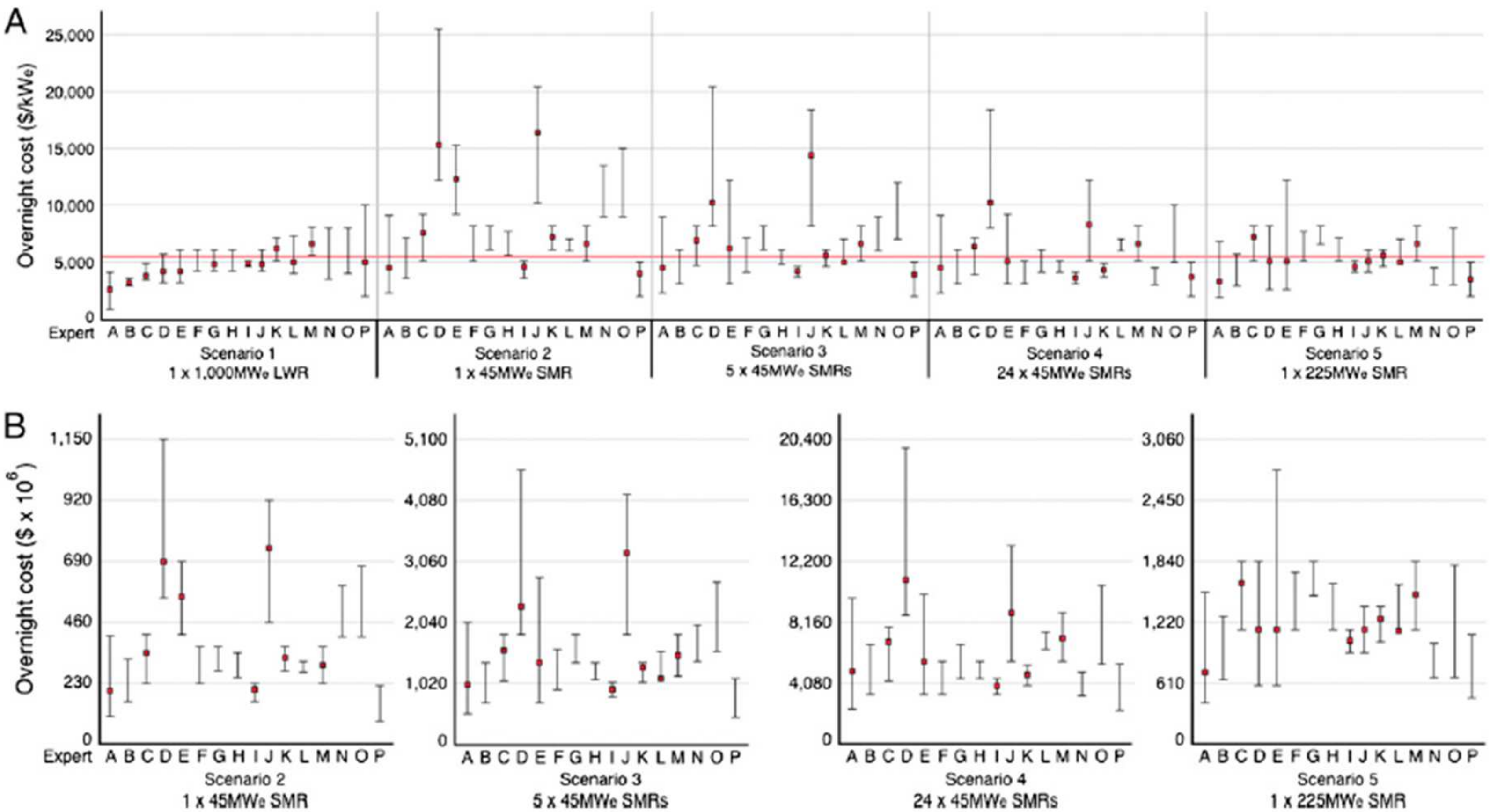
Individuals, companies and other organizations, as well as governments, must make important decisions in the face of con-

Our brains are not well-equipped to make decisions that involve considerable uncertainty. As extensive empirical research has now shown, we make such judgments using a variety of cognitive heuristics that, although they serve us adequately in many day-to-day settings, can result in overconfidence and bias that leads both lay people and experts astray when they address more complex and unusual problems (2, 3). Decision science (4–8) offers a set of strategies for improving how we make important decisions in the face of uncertainty.

In addressing such decisions, one should start with the best scientific, technical, and analytical evidence that is available. However, because such formal evidence often does not capture the full extent of what experts know, in addition to seeking informal expert advice, it is common in decision science to use formal methods to obtain systematic probabilistic judgments from experts who are intimately familiar with the current state of knowledge (9–11). For example, such methods have been used to characterize uncertainty about climate science (12, 13), the impacts of climate change (14–16), and the health impacts of environmental pollutants (17, 18). Of course, the same cognitive limitations that arise when we try to make unaided decisions also arise when experts attempt to provide probabilistic judgments (3). Too often, when seeking expert advice, little or nothing is done to limit overconfidence and reduce bias. Ubiquitous overconfidence (10) and the biases arising from cognitive heuristics, such as availability and anchoring and adjustment (2, 19–21), cannot be completely eliminated. However, well-designed expert elicitations can use a variety of strategies to help improve the quality of expert judgments (9–11).

Expert elicitation about emerging energy technologies that is deeply informed by careful technical analysis is still relatively rare (22). Here, we report the results of applying these methods to one such technology: integral light water small modular nuclear reactors (SMRs).

SUSTAINABILITY SCIENCE



Example 2:

PNAS

Expert judgments about transient climate response to alternative future trajectories of radiative forcing

Kirsten Zickfeld[a,2], M. Granger Morgan[b,1], David J. Frame[c], and David W. Keith[d]

[a]School of Earth and Ocean Sciences, University of Victoria, Victoria, BC V8P 5C2, Canada; [b]Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213; [c]Smith School of Enterprise and the Environment and Department of Physics, University of Oxford, Oxford OX1 2BQ, UK; and [d]Department of Chemical and Petroleum Engineering, University of Calgary, Calgary, AB T2N 1N4, Canada

Edited by Roger E. Kasperson, Clark University, Worcester, MA, and approved June 3, 2010 (received for review August 5, 2009)

There is uncertainty about the response of the climate system to future trajectories of radiative forcing. To quantify this uncertainty we conducted face-to-face interviews with 14 leading climate scientists, using formal methods of expert elicitation. We structured the interviews around three scenarios of radiative forcing stabilizing at different levels. All experts ranked "cloud radiative feedbacks" as contributing most to their uncertainty about future global mean temperature change, irrespective of the specified level of radiative forcing. The experts disagreed about the relative contribution of other physical processes to their uncertainty about future temperature change. For a forcing trajectory that stabilized at 7 Wm^{-2} in 2200, 13 of the 14 experts judged the probability that the climate system would undergo, or be irrevocably committed to, a "basic state change" as ≥0.5. The width and median values of the probability distributions elicited from the different experts for future global mean temperature change under the specified forcing trajectories vary considerably. Even for a moderate increase in forcing by the year 2050, the medians of the elicited distributions of temperature change relative to 2000 range from 0.8–1.8 °C, and some of the interquartile ranges do not overlap. Ten of the 14 experts estimated that the probability that equilibrium climate sensitivity exceeds 4.5 °C is >0.17, our interpretation of the upper limit of the "likely" range given by the Intergovernmental Panel on Climate Change. Finally, most experts anticipated that over the next 20 years research will be able to achieve only modest reductions in their degree of uncertainty.

climate change | climate sensitivity | transient climate response | expert elicitation | uncertainty analysis

Uncertainty about the response of the climate system to future changes in radiative forcing arises from incomplete forcing and climate response data, incomplete understanding of climate system processes, and the limitations of climate models. A number of studies using models of different complexity and different statistical methods have produced probabilistic estimates of equilibrium climate sensitivity (see refs. 1 and 2 for an overview) and projections over the twenty-first century (2, 3). Such modeling studies offer considerable insight about future climate change, its likely impacts, and associated uncertainties.

However, experts working in climate science possess knowledge that is not captured in models. To better explore this knowledge, we have previously employed methods of formal expert elicitation (4–9) to gain additional insight about the likely value of climate sensitivity (10), the likely impact of climate change on tropical and boreal forest ecosystems (11), the likely impacts of climate change on the Atlantic Meridional Overturning Circulation (12) and the likely values of direct and indirect radiative forcing from anthropogenic aerosols (13).

Here we report results from a series of detailed formal face-to-face elicitations conducted with leading climate scientists in North America and Europe (Table 1) on the time-dependent response of the climate system to scenarios of radiative forcing. In a previous expert elicitation conducted with climate scientists (10) we focused on uncertainty in the value of equilibrium climate sensitivity (the equilibrium global mean temperature change resulting from a doubling of the preindustrial atmospheric CO_2 concentration). Whereas that quantity has been widely discussed in the scientific and policy literatures, it is far less relevant to policy making and to the assessment of likely impacts over the coming centuries, than the time-dependent response of the climate system.

To focus attention on the transient climate response, we structured the elicitation around scenarios that reflect a range of plausible future radiative forcing trajectories. Whereas the scenarios we employed were developed prior to the publication of the representative concentration pathways (RCPs) proposed for the climate model simulations in support of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (14), they are similar to the RCPs (Fig. S1).

We constructed three scenarios of net radiative forcing at the top of the atmosphere from anthropogenic sources through the year 2200 (Fig. 1). In a "high" scenario radiative forcing stabilized at 7 Wm^{-2} in 2200, in a "medium" scenario it stabilized at 4 Wm^{-2}, and in a low "overshoot" scenario forcing peaked at about 3 Wm^{-2} in 2070 and then declined to near zero by 2200. We asked experts to assume that forcing from non-CO_2 greenhouse gases and aerosols remained constant at year 2000 levels. Since the year 2000 forcings of these agents nearly compensate each other, the total forcing is very similar to that of CO_2 alone. To improve the match between the experts' knowledge and the question domain, we chose deliberately to specify scenarios of radiative forcing (as opposed to emissions) so as to limit discussion to the uncertainty in the physical rather than biogeochemical processes that determine the response of the climate system to forcing. Most of our respondents have limited expert ecological and other biogeochemical knowledge. Specifying total radiative forcing instead of emissions obviated the need to ask about carbon cycle feedbacks, although two experts did explicitly discuss such effects.

Results and Discussion

Key Factors Influencing Uncertainty in Transient Temperature Response. Before the face-to-face interviews, experts completed an e-mail survey to identify the factors they believed would most contribute uncertainty to their judgments about the change in global mean temperature, $\Delta T(t)$, for each of the three forcing trajectories. From those responses, we compiled the list of factors shown in the left-most column of Table S1.

Author contributions: K.Z., M.G.M., D.J.F., and D.W.K. designed research; K.Z., M.G.M., and D.J.F. performed research; K.Z. and M.G.M. analyzed data; and K.Z. and M.G.M. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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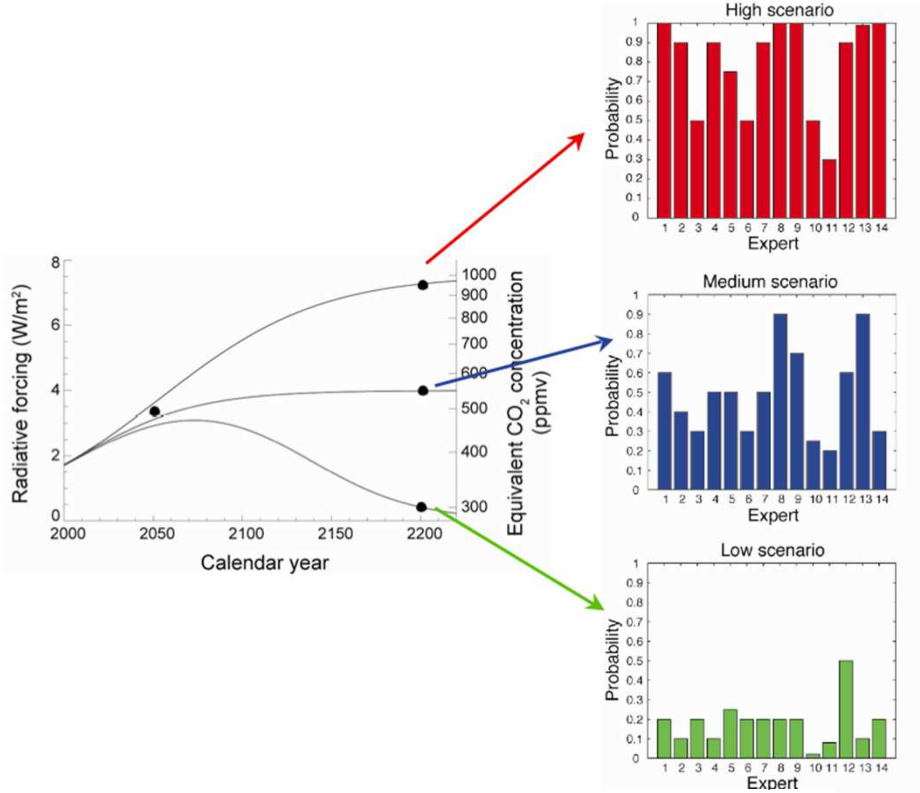
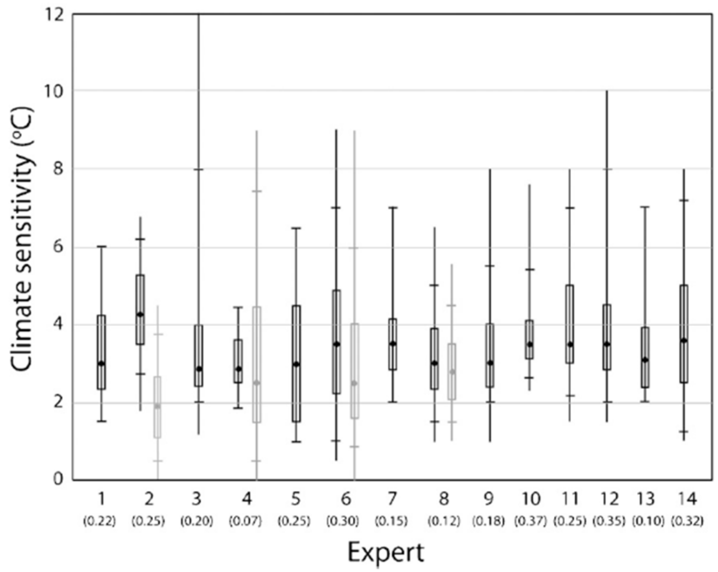
SUSTAINABILITY SCIENCE





Example 3:

Climatic Change (2007) 82:235–265
DOI 10.1007/s10584-007-9246-3

Expert judgements on the response of the Atlantic meridional overturning circulation to climate change

Kirsten Zickfeld · Anders Levermann · M. Granger Morgan · Till Kuhlbrodt · Stefan Rahmstorf · David W. Keith

Received: 9 February 2006 / Accepted: 9 October 2006 / Published online: 22 March 2007

Abstract We present results from detailed interviews with 12 leading climate scientists about the possible effects of global climate change on the Atlantic Meridional Overturning Circulation (AMOC). The elicitation sought to examine the range of opinions within the climatic research community about the physical processes that determine the current strength of the AMOC, its future evolution in a changing climate and the consequences of potential AMOC changes. Experts assign different relative importance to physical processes which determine the present-day strength of the AMOC as well as to forcing factors which determine its future evolution under climate change. Many processes and factors deemed important are assessed as poorly known and insufficiently represented in state-of-the-art climate models. All experts anticipate a weakening of the AMOC under scenarios of increase of greenhouse gas concentrations. Two experts expect a permanent collapse of the AMOC as the most likely response under a 4×CO_2 scenario. Assuming a global mean temperature increase in the year 2100 of 4 K, eight experts assess the probability of triggering an AMOC collapse as significantly different from zero, three of them as larger than 40%. Elicited consequences of AMOC reduction include strong changes in temperature, precipitation distribution and sea level in the North Atlantic area.

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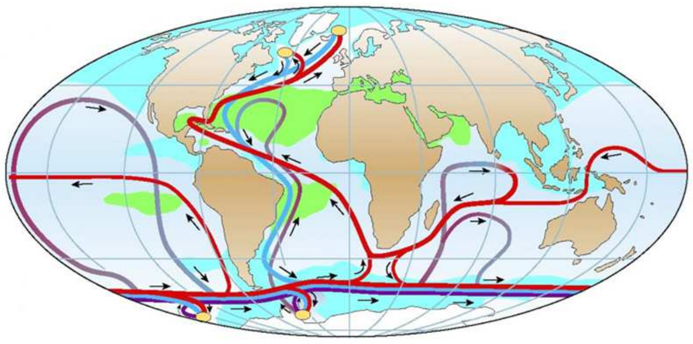
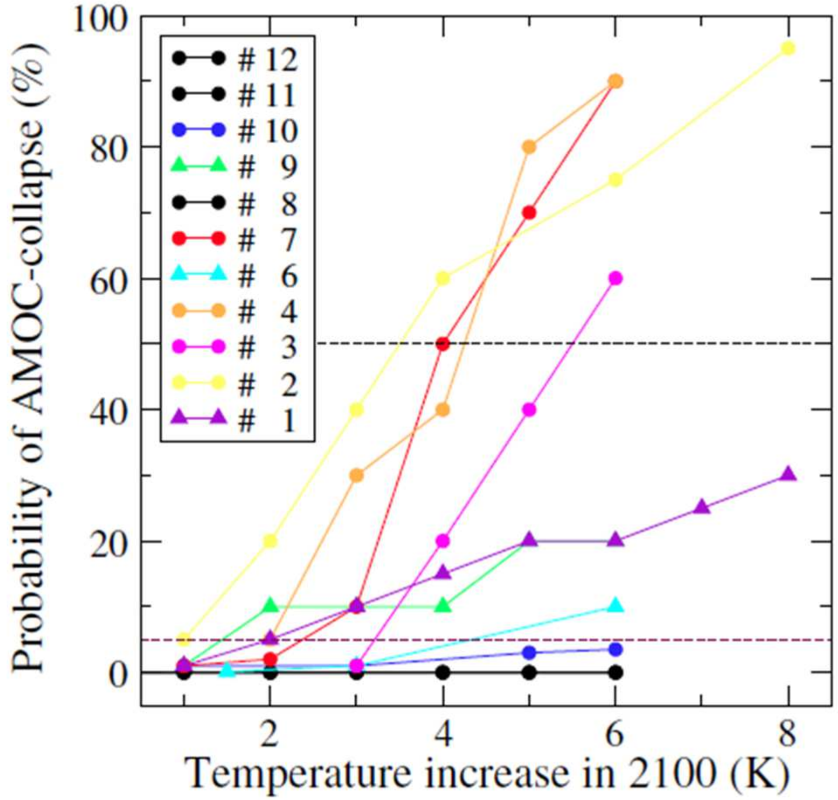


Figure source: Kuhlbrodt et al., 2005.



It may be tempting…

…to view expert elicitation as a low cost, low effort, alternative to doing serious research and analysis.

It is neither.

Expert elicitation should build upon the best available research and analysis and be undertaken only when the state of knowledge will remain insufficient to support timely informed assessment and decision making.

It is also tempting to want to combine the judgments of multiple experts in order to obtain *the* answer. Sometimes this makes sense. However, if different experts base their judgments on very different models of the way in which the world works, or if they produce quite different judgments that will be used as the input to a non-linear model, then combining judgments does not make sense.

This afternoon I will talk about:

- Sources of uncertainty and the characterization of uncertainty.
- Uncertainty versus variability.
- Two basic types of uncertainty.
  - Uncertainty about coefficient values.
  - Uncertainty about model functional form.
- Analyzing uncertainty.
- The use and abuse of "expert elicitation."
- Some summary guidance on reporting, characterizing and analyzing uncertainty.

CCSP Guidance Document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Doing a good job…

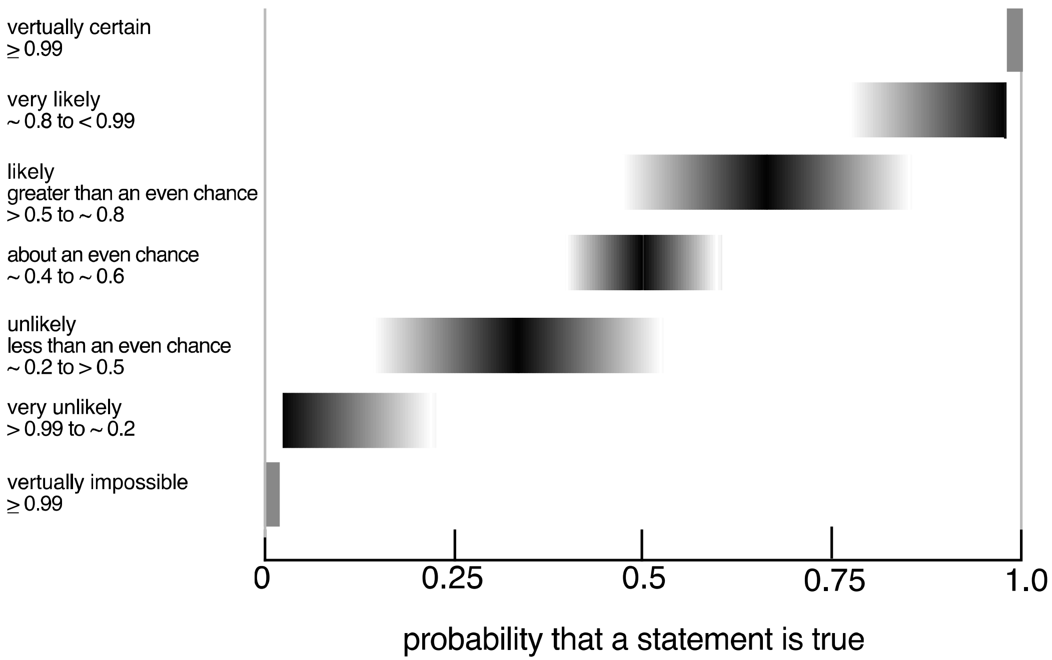
…of characterizing and dealing with uncertainty can never be reduced to a simple cookbook. One must always think critically and continually ask questions such as:

- 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 which 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…

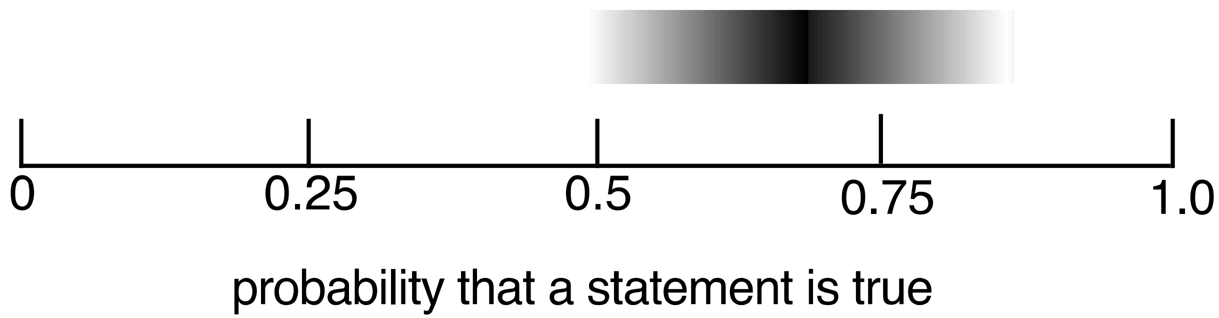
Reporting uncertainty

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 words. Unless there is some compelling reason to do otherwise, I recommend the use of a framework such as the one shown below:



Reporting uncertainty…(Cont.)

Another strategy is to display the judgment explicitly as shown:



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

Reporting uncertainty…(Cont.)

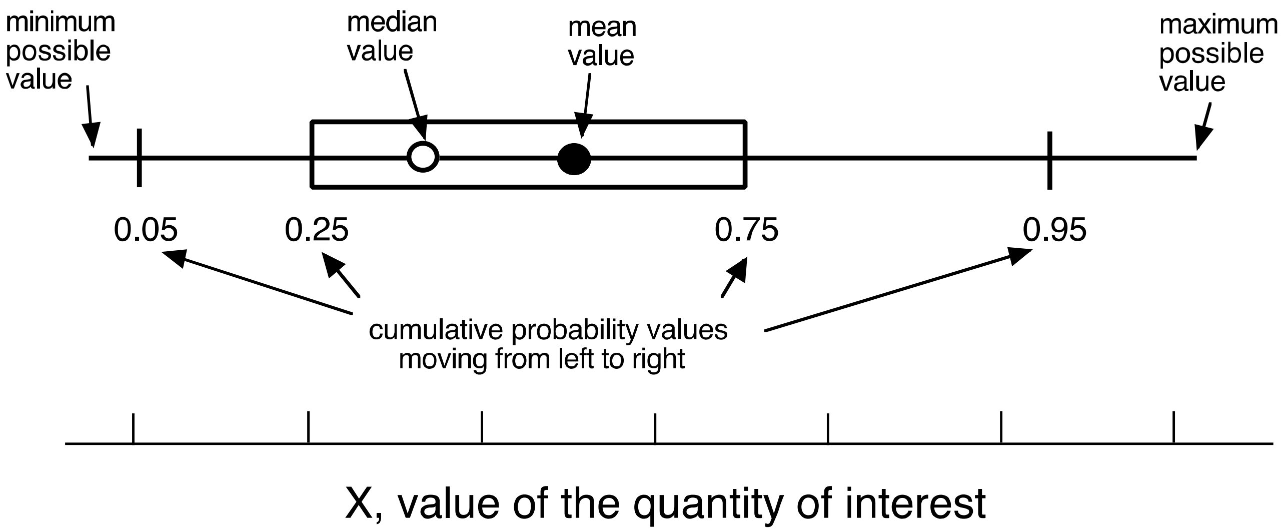
In any document that reports uncertainties in conventional scientific format (e.g., 3.5 ± 0.7), it is important to be explicit about what uncertainty is being included and what is not, and to confirm that the range is plus or minus one standard deviation. This reporting format is generally not appropriate for large uncertainties or where distributions have a lower or upper bound and hence are not symmetric.

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.

Reporting uncertainty…(Cont.)

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.



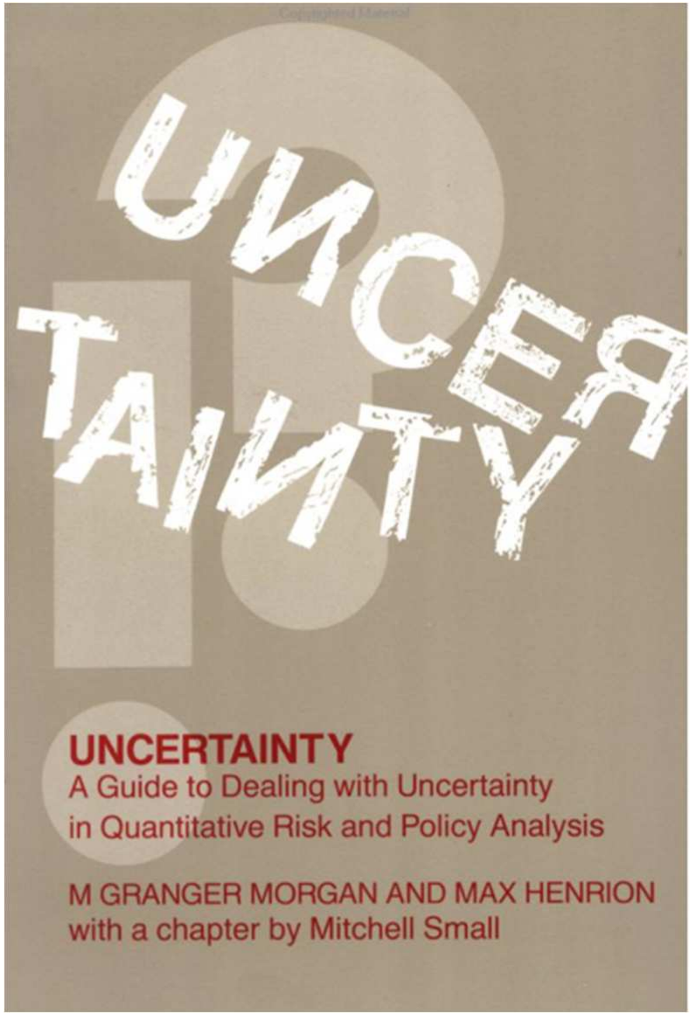
See: Tukey, John W., *Exploratory Data Analysis*, Addison-Wesley, 688pp., 1977.

Reporting uncertainty…(Cont.)

While there may be 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), one should be very careful to determine that the added level of complication will aid in, and will not unnecessarily complicate, subsequent use of the results.

For more details on…

…many of the ideas I've covered in this talk, see:



Cambridge University Press

Thanks very much

In developing the ideas discussed in this talk, I have been fortunate to have generous support from the U.S. National Science Foundation (SES-9209783; BCS-9218045; SES-034578; SES-0345798; SES-0949710; and others), the Department of Energy (DE-FG02-93ER61712; DE FG02-93ER61711; DE-FG02-94ER61916), the Electric Power Research Institute, the Alfred P. Sloan Foundation, the Gordon and Betty Moore Foundation, the Scaife Family Fund, the Doris Duke Charitable Foundation, the MacArthur Foundation, the IRGC, Carnegie Mellon University and a number of others. Thanks also to my many colleagues including Jay Apt, Inês Azevedo, Hadi Dowlatabadi, Baruch Fischhoff, Max Henrion, David Keith, Lester Lave, Sam Morris, Mitchell Small, Patti Steranchak, and a large number of current and former PhD students.