Uncertainty and Climate Change

Opening remarks to the
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Climate Scenarios and Projections
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This morning I will talk about:

- Sources of uncertainty and the characterization of uncertainty.
- Two basic types of uncertainty.
  - Uncertainty about coefficient values.
  - Uncertainty about model functional form.
- Some strengths and limitations of a scenario approach.
- Recent work on dealing with extreme uncertainty.
- The fact that there are some things we are not likely to know on the time-scale of climate decisions we face.

Probability

Probability is the basic language of uncertainty.

I will adopt a personalistic view of probability (sometimes also called a subjectivist or Bayesian view).

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

$P(X|i)$ 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 2008" does not pass this test. A clairvoyant would need to know things such as:

- Where will the gas 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
- be consistent with available empirical data.

Lots of people ask, why deal with 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.
- 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.

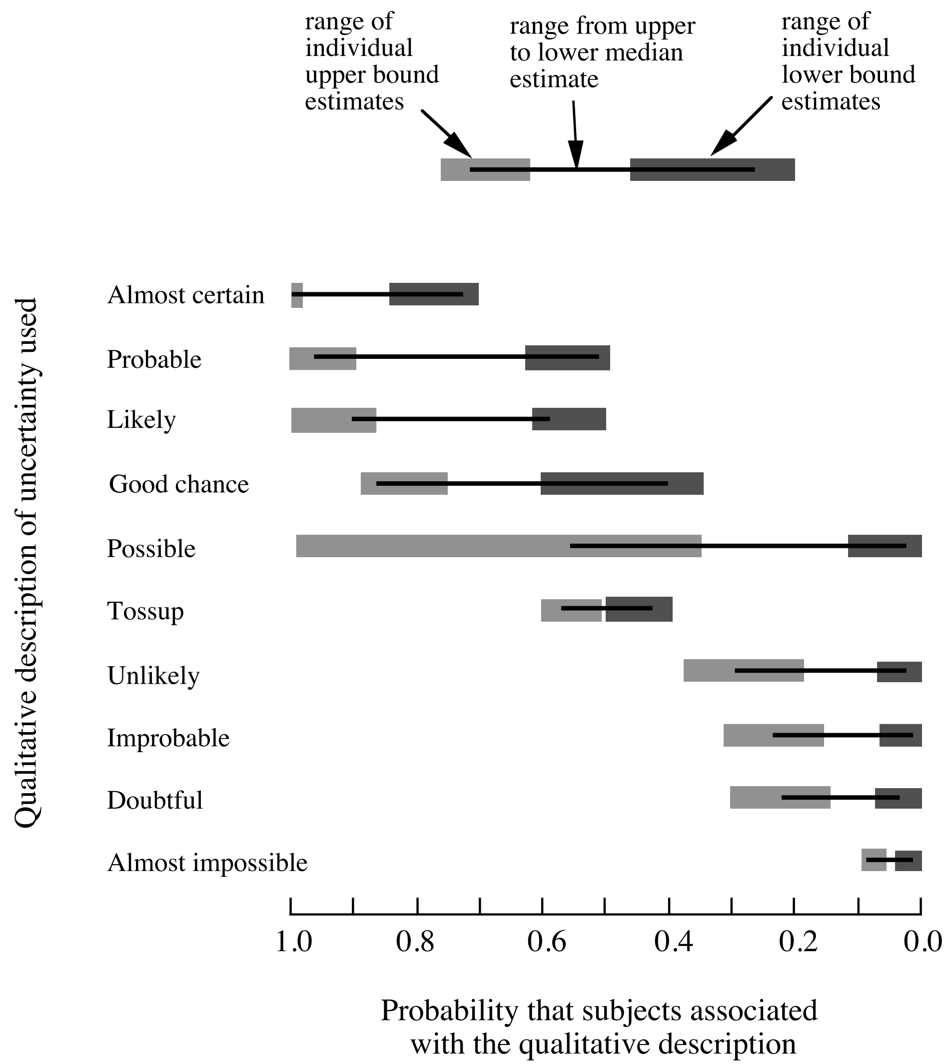


Figure adapted from Wallsten et al., 1986.

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.

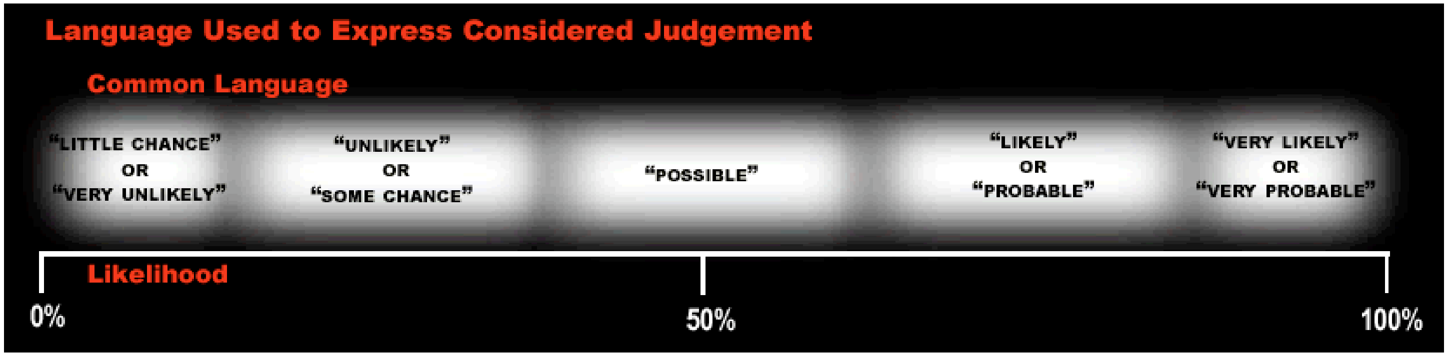
The bottom line

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

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



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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 no not know the values of key coefficients (e.g., 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.

Uncertainty about quantities

Type of quantity	Examples	Treatment of uncertainty
Empirical parameter or chance variable	Thermal efficiency, oxidation rate, fuel price	Probabilistic, parametric, or switchover
Defined constant	Atomic weight, π, joules per kilowatt-hr	Certain by definition
Decision variable	Plant size (utility), emissions cap (EPA)	Parametric or switchover
Value parameter	Discount rate, "value of life," risk tolerance	Parametric or switchover
Index variable	Longitude and latitude, height, time period	Certain by definition
Model domain parameter	Geographic region, time horizon, time increment	Parametric or switchover
Outcome criterion	Net present value, utility	Determined by treatment of its inputs

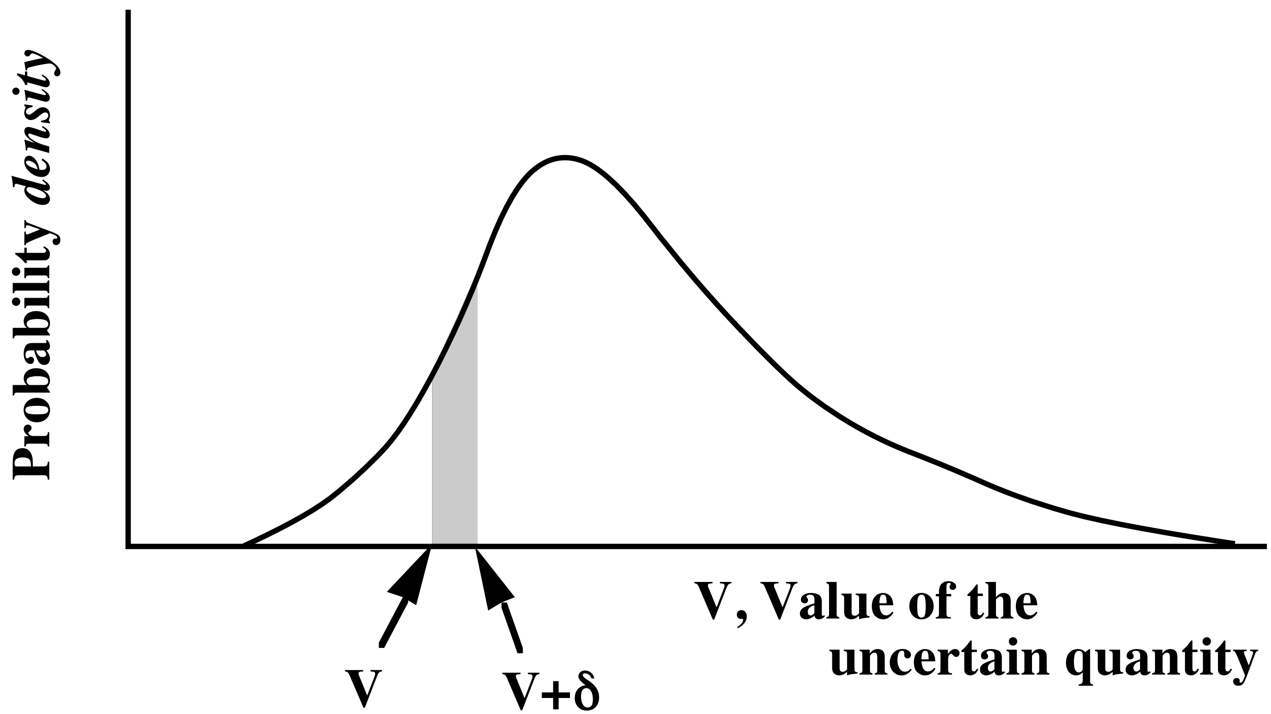
From Morgan and Henrion, *Uncertainty*, Cambridge, 1990/99.

PDFs and CDFs

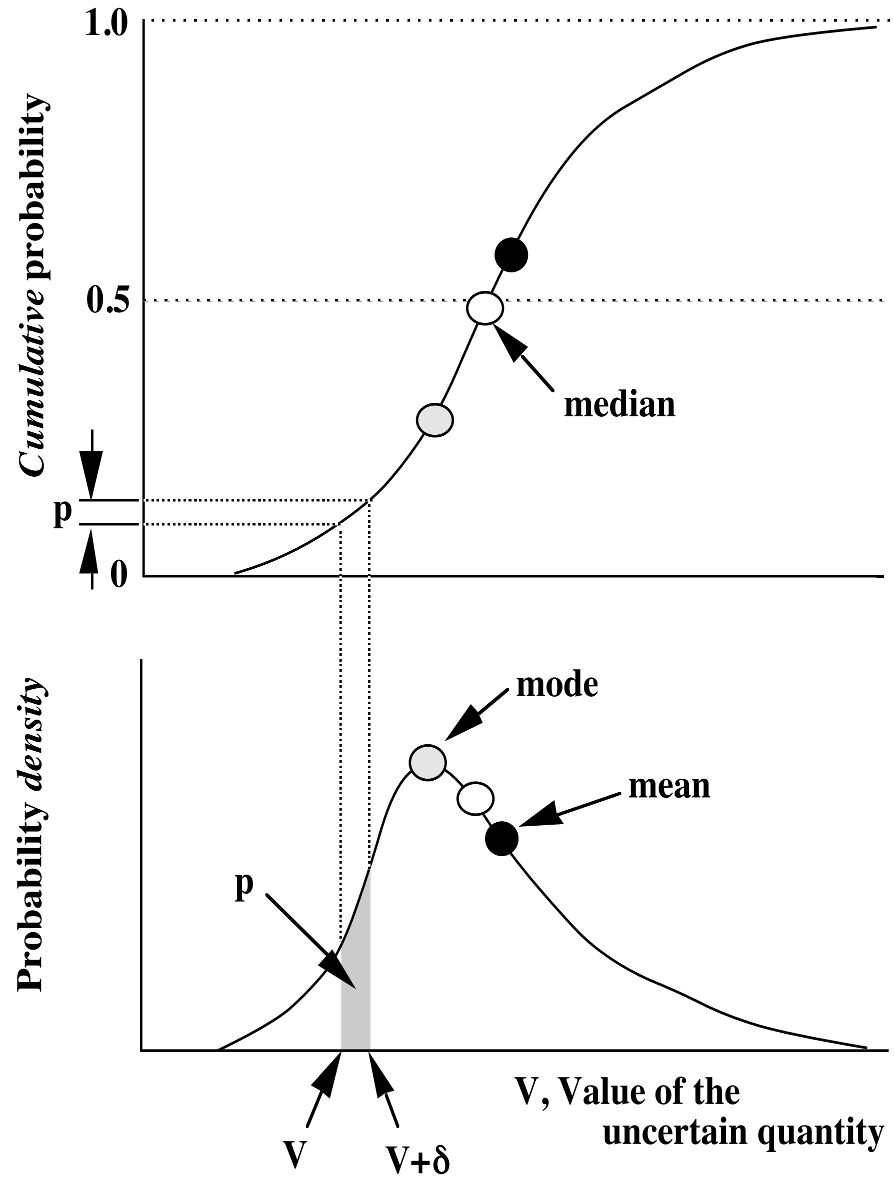
A number of examples I am about to show are in the form of probability density functions (PDFs) or cumulative distribution functions (CDFs).

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

Probability density function or PDF



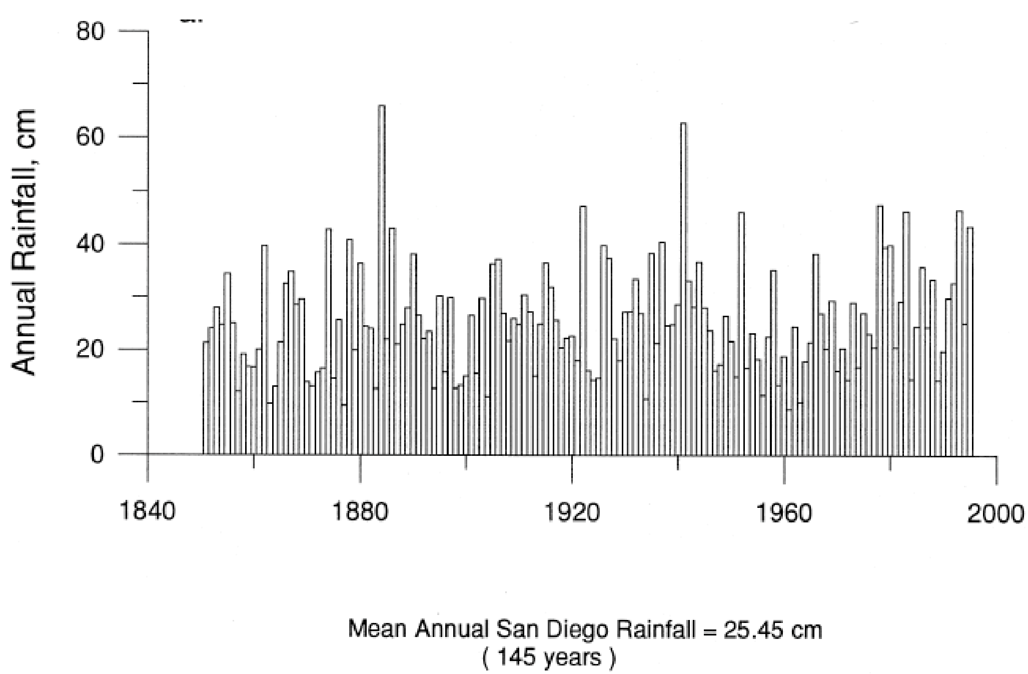
Cumulative distribution function or CDF



NOTE: In asymmetric distributions with long 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, 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)…

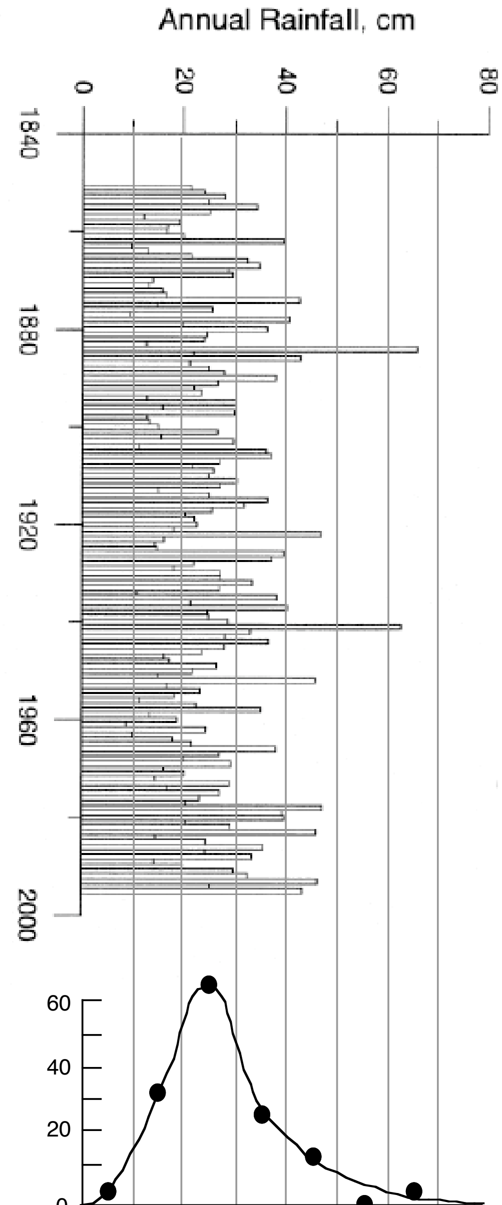


Source: Inman et al., Scripps, 1998.

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.

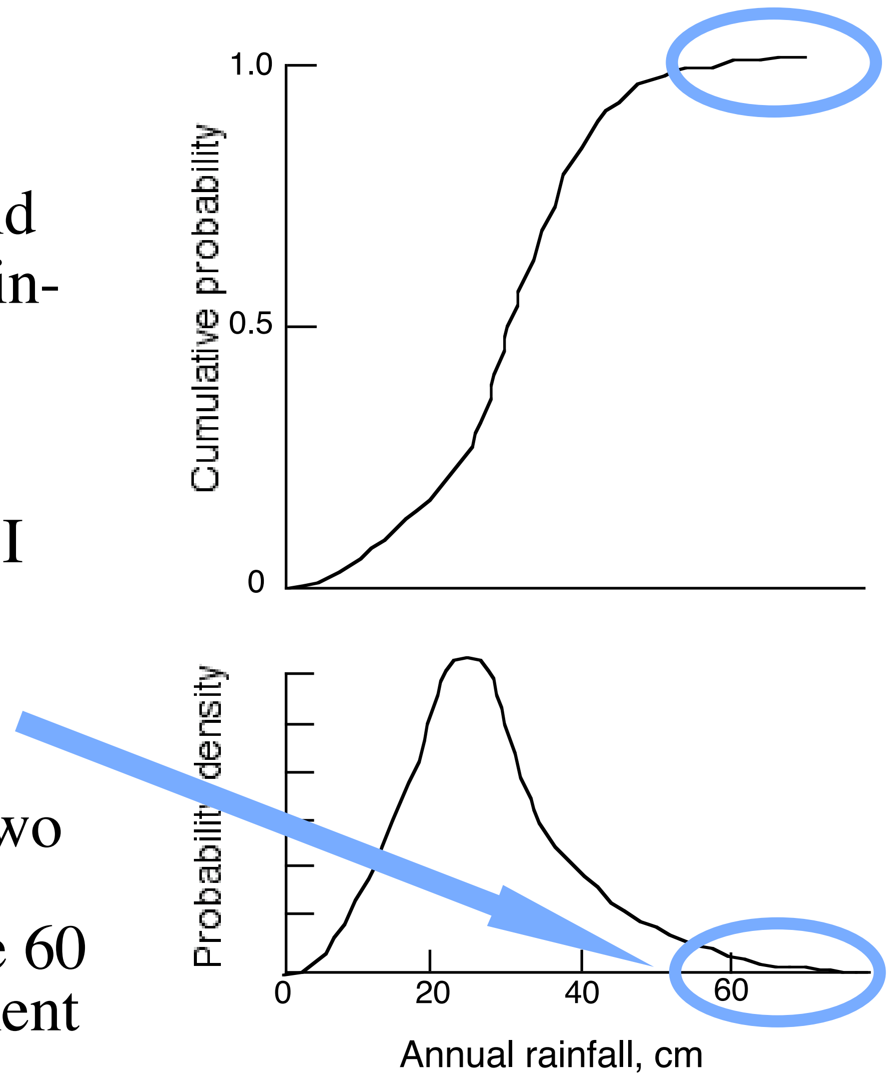


In that way…

…I could construct a PDF and CDF for future San Diego rainfall 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.



In summary…

…one should use available data, and well-established physical and statistical theory, to describe uncertainty 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, I may have to rely on expert judgment. This brings us to the problem of how to "elicit" expert judgment.

Expert elicitation takes time and care

Eliciting subjective probabilistic judgments requires careful preparation and execution.

Developing and testing an appropriate interview protocol typically takes several months. Each interview is likely to require several hours.

When addressing complex, scientifically subtle questions of the sorts involved with most problems in climate change, there are no satisfactory short cuts. Attempts to simplify and speed up the process almost always lead to shoddy results.

Over Confidence

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

Source: Morgan and Henrion, 1990/99.

Over Confidence

	Number of assessed distributions N	Interquartile index (ideal = 50) before	Interquartile index (ideal = 50) after	Surprise index (ideal = 2) before	Surprise index (ideal = 2) after
Alpert & Raiffa (1969)					
Groups 2 & 3	1,670	33	44	39	23
Group 4	600	36	43	21	9
Schaefer & Borcherding (1973)					
Fractiles	396	23	38	39	12
HFS	396	16	48	50	6
Pickardt & Wallace (1974)					
Group 1 (5 sessions)	?	39	49	32	20
Group 2 (6 sessions)	?	30	45	46	24
Schaefer (1976)					
(5 sessions)	660	27	34	25	14
Lichtenstein & Fischhoff (1980)					
(Training on discrete tasks)	924	33	37	41	40

Source: Morgan and Henrion, 1990/99.

Cognitive Heuristics

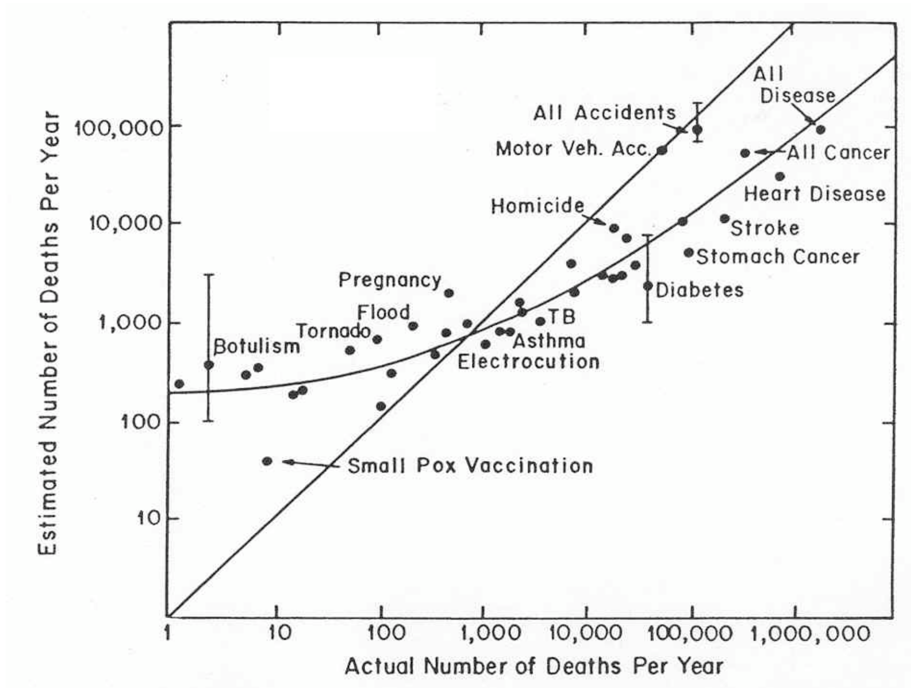
When ordinary people or experts make judgments about uncertain events, such as numbers of deaths from chance events, they use simple mental rules of thumb called "cognitive heuristics."

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.

This can be a problem for experts too.

The three slides that follow illustrate three key heuristics: "availability," "anchoring and adjustment," and "representativeness."

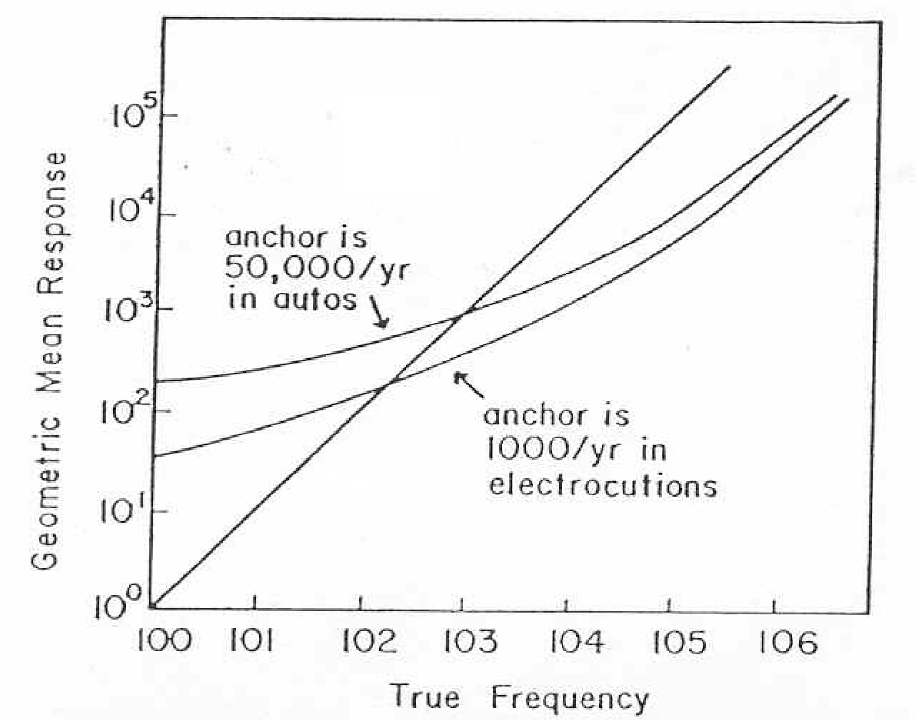
Cognitive bias



from Lichtenstein et al., 1978.

Availability: probability judgment is driven by ease with which people can think of previous occurrences of the event or can imagine such occurrences.

Cognitive bias…(Cont.)



from Lichtenstein et al., 1978.

Anchoring and adjustment: probability judgment is frequently driven by the starting point which becomes an "anchor."

Cognitive bias…(Cont.)

I flip a fair coin 8 times. Which of the following two outcomes is more likely?

Outcome 1: T, T, T, T, H, H, H, H

Outcome 2: T, H, T, H, H, T, H, T

Of course, the two specific sequences are equally likely...but the second seems more likely because it looks more representative of the underlying random process.

Representativeness: people judge the likelihood that an object belongs to a particular class in terms of how much it resembles that class.

Expert elicitation…(Cont.)

In all our elicitation studies, we've focused on creating a process that allows the experts to provide their carefully considered judgment, supported by all the resources they may care to use. Thus, we have:

- Prepared a background review of the relevant literatures.
- Carefully iterated the questions with selected experts and run pilot studies with younger (Post-doc) experts to distil and refine the questions.
- Conducted interviews in experts' offices with full resources at hand.
- Provide ample opportunity for subsequent review and revision of the judgments provided.

All of these efforts have involved the development of new question formats that fit the issues at hand.

Expert elicitation …(Cont.)

Over the past two decades, my colleagues and I have developed and performed a number of substantively detailed expert elicitations. These have been designed to obtain experts' *considered* judgments. Examples include work on:

Health effects of air pollution from coal-fired power plants.

- M. Granger Morgan, Samuel C. Morris, Alan K. Meier and Debra L. Shenk, "A Probabilistic Methodology for Estimating Air Pollution Health Effects from Coal-Fired Power Plants," *Energy Systems and Policy, 2*, 287-310, 1978.
- M. Granger Morgan, Samuel C. Morris, William R. Rish and Alan K. Meier, "Sulfur Control in Coal-Fired Power Plants: A Probabilistic Approach to Policy Analysis," *Journal of the Air Pollution Control Association, 28*, 993-997, 1978.
- M. Granger Morgan, Samuel C. Morris, Max Henrion, Deborah A.L. Amaral and William R. Rish, "Technical Uncertainty in Quantitative Policy Analysis: A Sulfur Air Pollution Example," *Risk Analysis, 4,* 201-216, 1984 September.
- M. Granger Morgan, Samuel C. Morris, Max Henrion and Deborah A. L. Amaral, "Uncertainty in Environmental Risk Assessment: A case study involving sulfur transport and health effects," *Environmental Science and Technology, 19*, 662-667, 1985 August.

Expert elicitation…(Cont.)

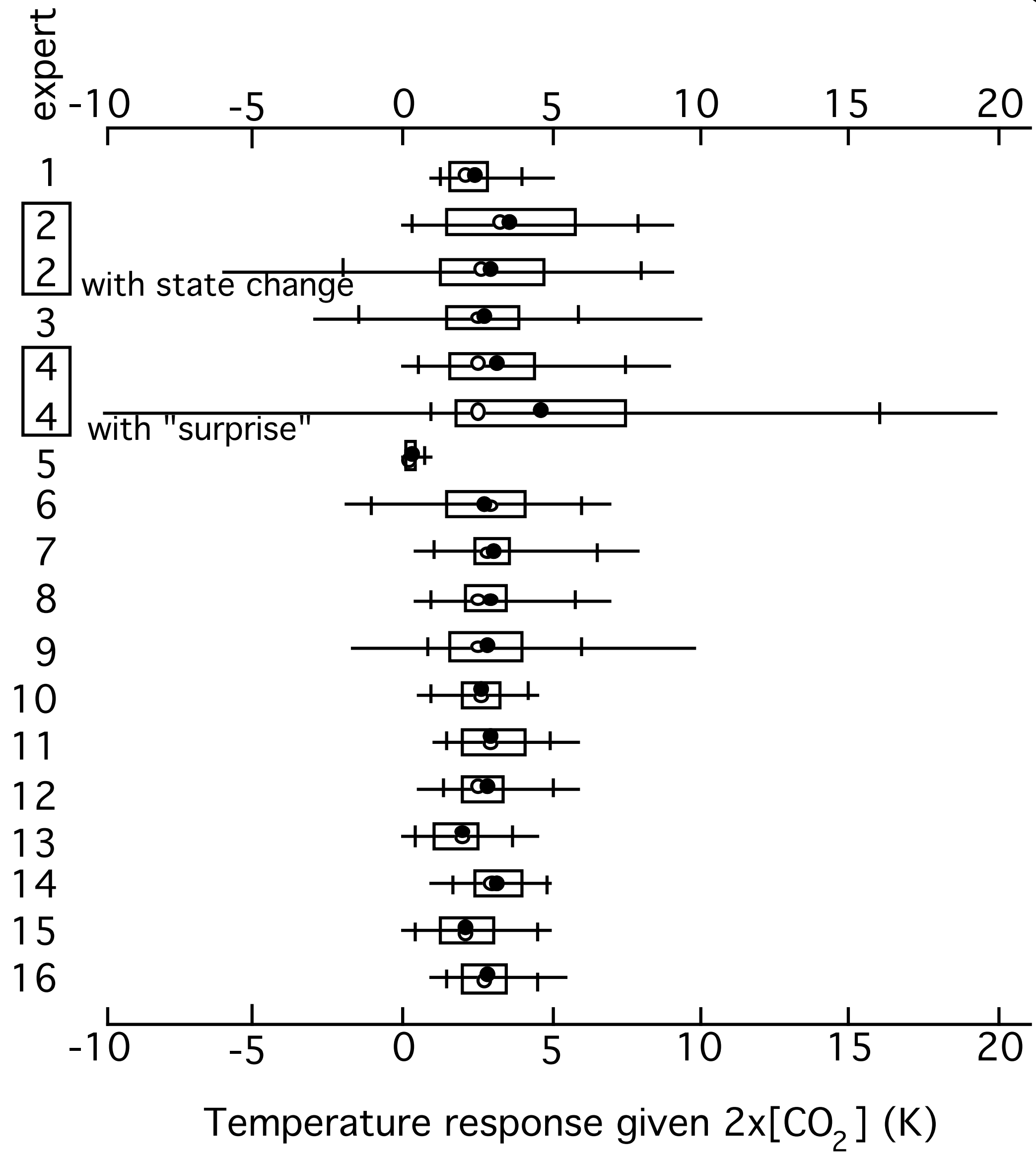
Climate science, climate impacts and mitigation technology:

- M. Granger Morgan and David Keith, "Subjective Judgments by Climate Experts," *Environmental Science & Technology*, *29*(10), 468-476, October 1995.
- Elizabeth A. Casman, M. Granger Morgan and Hadi Dowlatabadi, "Mixed Levels of Uncertainty in Complex Policy Models," *Risk Analysis*, *19*(1), 33-42, 1999.
- M. Granger Morgan, Louis F. Pitelka and Elena Shevliakova, "Elicitation of Expert Judgments of Climate Change Impacts on Forest Ecosystems," *Climatic Change*, *49*, 279-307, 2001.
- Anand B. Rao, Edward S. Rubin and M. Granger Morgan, "Evaluation of Potential Cost Reductions from Improved CO_2 Capture Systems,"*Proceedings of the 2nd National Conference on Carbon Sequestration,* Alexandria, VA, May 5-8, 2003.

Bounding uncertain health risks:

- M. Granger Morgan, "The Neglected Art of Bounding Analysis," *Environmental Science & Technology*, *35*, pp. 162A-164A, April 1, 2001.
- Minh Ha-Duong, Elizabeth A. Casman, and M. Granger Morgan, "Bounding Poorly Characterized Risks: A lung cancer example," *Risk Analysis*, in press.

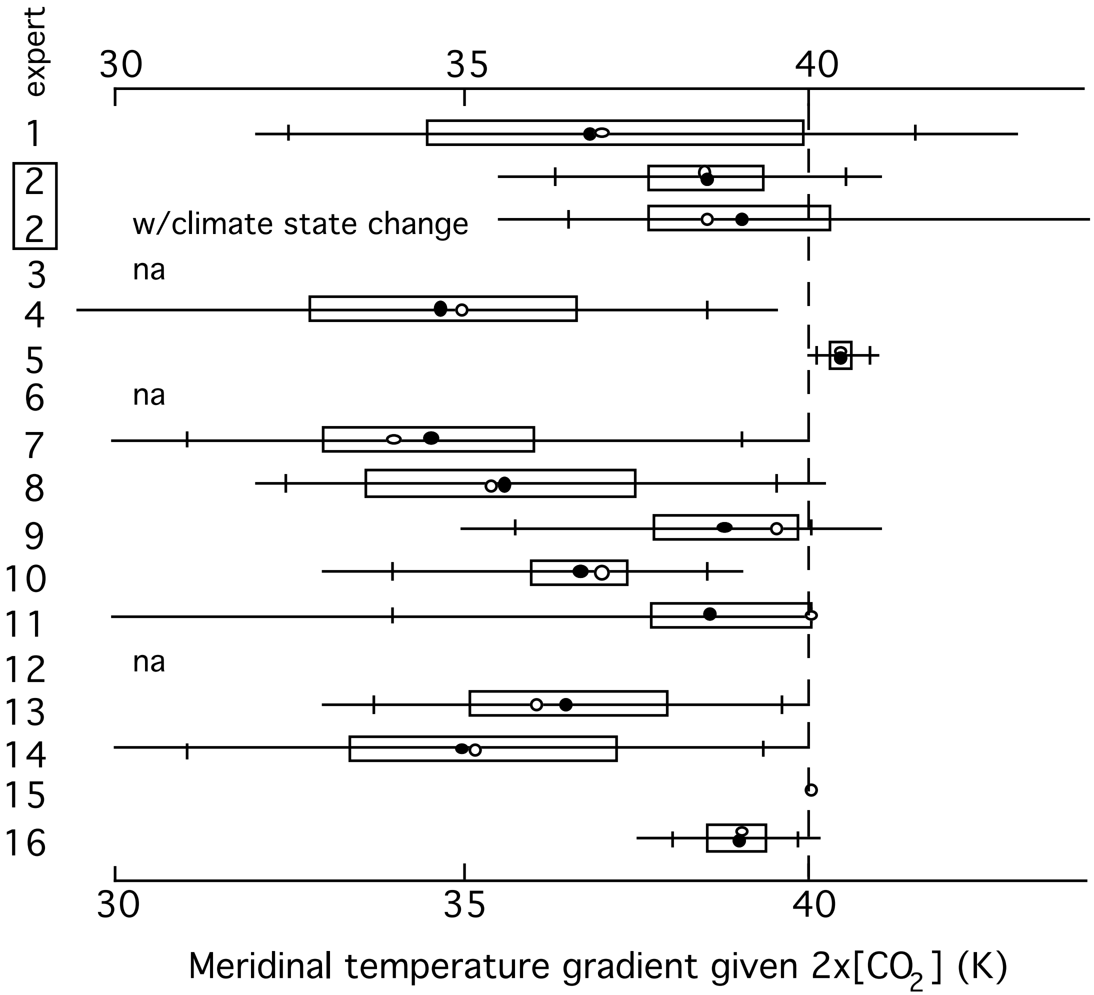
Warming for $2x[CO_2]$



Source:
Morgan and Keith, *ES&T*, 1995.

…and, lest you conclude that most of these experts are in basic agreement…

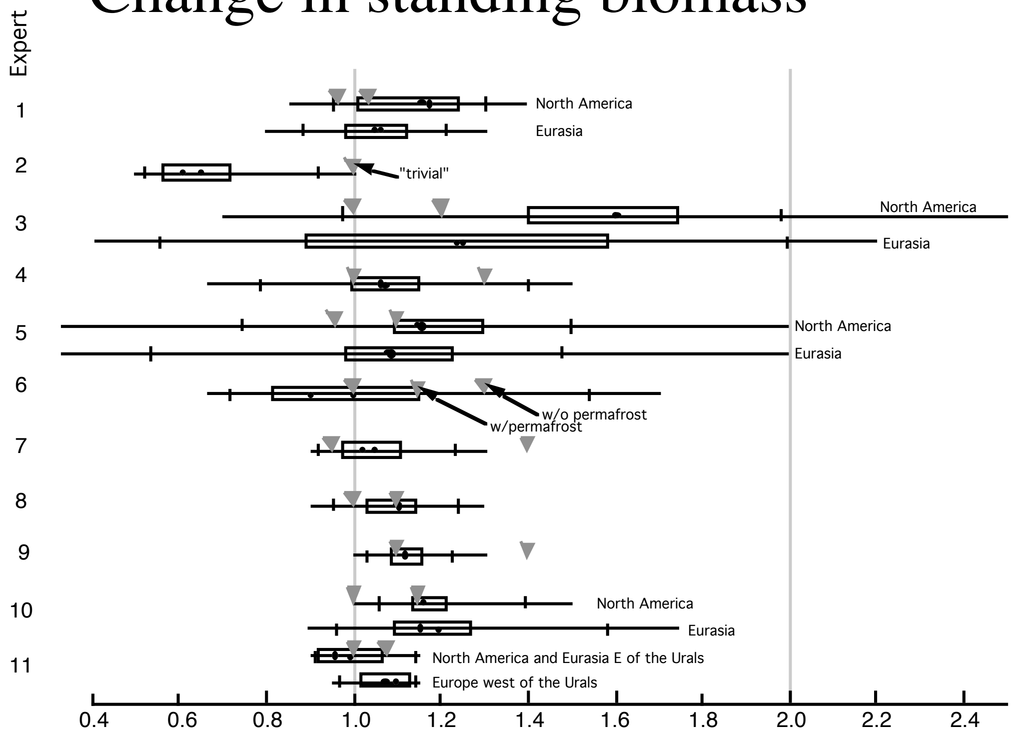
Pole to equator temperature gradient for $2x[CO_2]$



Source: Morgan and Keith, *ES&T*, 1995.

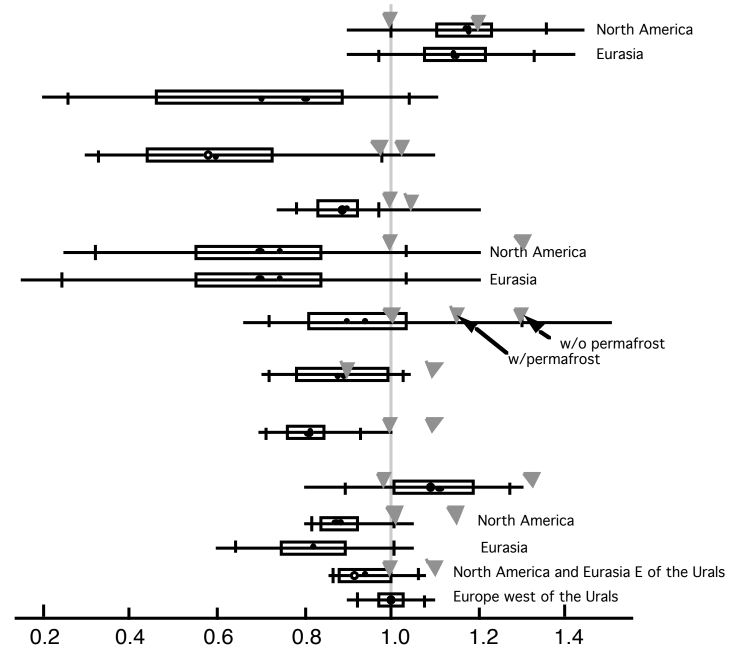
Biomass in Northern Forests w/ $2xCO_2$ climate change

Change in standing biomass



Change in standing biomass in minimally disturbed Northern Forests between 45°N and 65°N under specified 2x[CO2] climate change.

Change in soil carbon

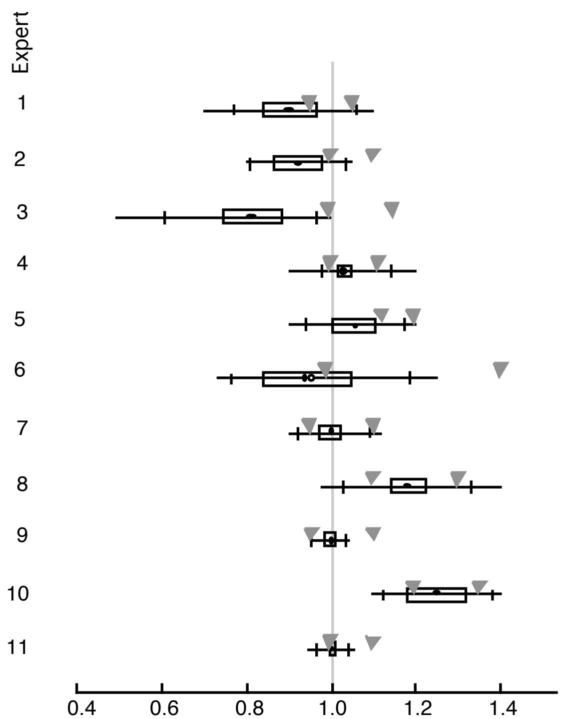


Change in soil carbon in minimally disturbed Northern Forests between 45°N and 65°N under specified 2x[CO2] climate change.

Source: Morgan et al., *Climatic Change*, 2001.

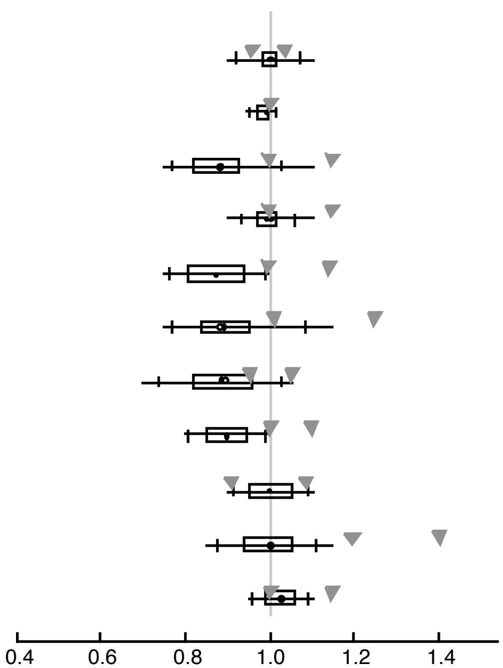
Biomass in Tropical Forests w/ 2xCO_2 climate change

Change in standing biomass



Change in standing biomass in minimally disturbed Tropical Forests between 20°N and 20°S under specified 2xCO_2 climate change.

Change in soil carbon



Change in soil carbon in minimally disturbed Tropical Forests between 20°N and 20°S under specified 2xCO_2 climate change.

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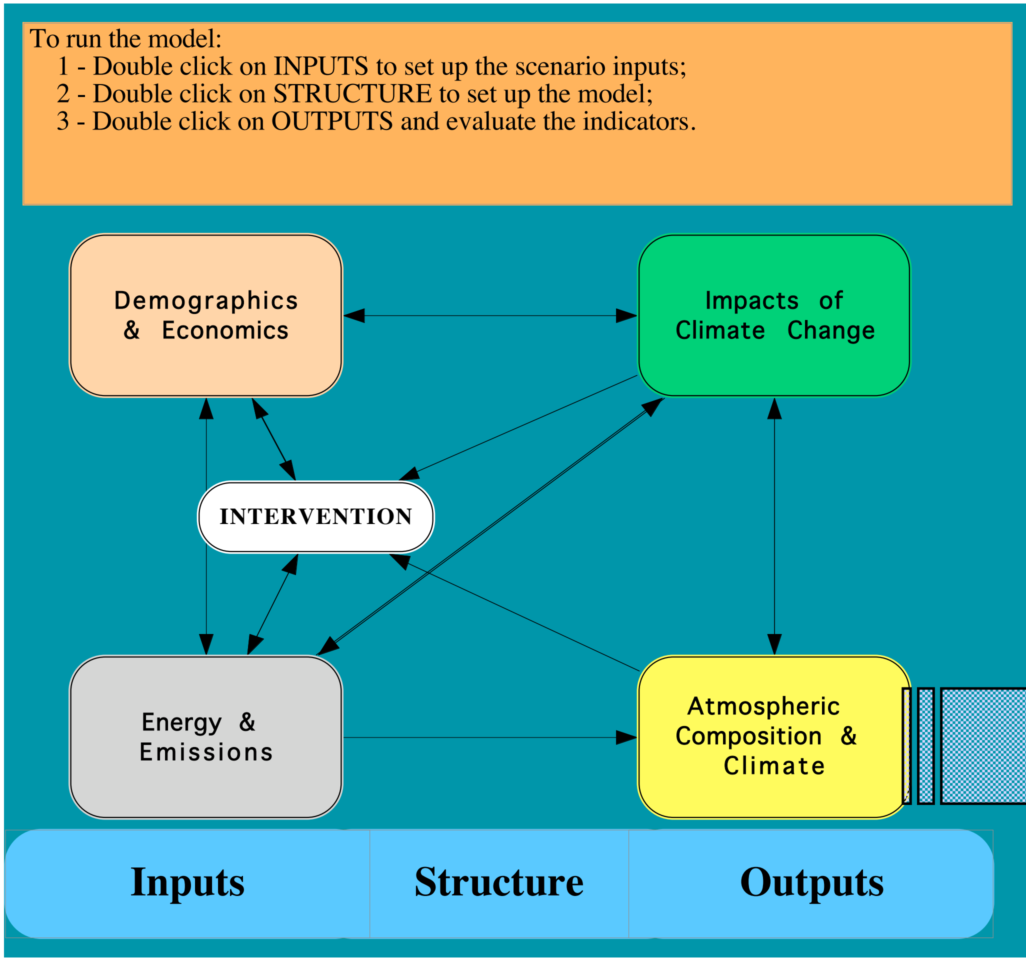
Uncertainty about model form

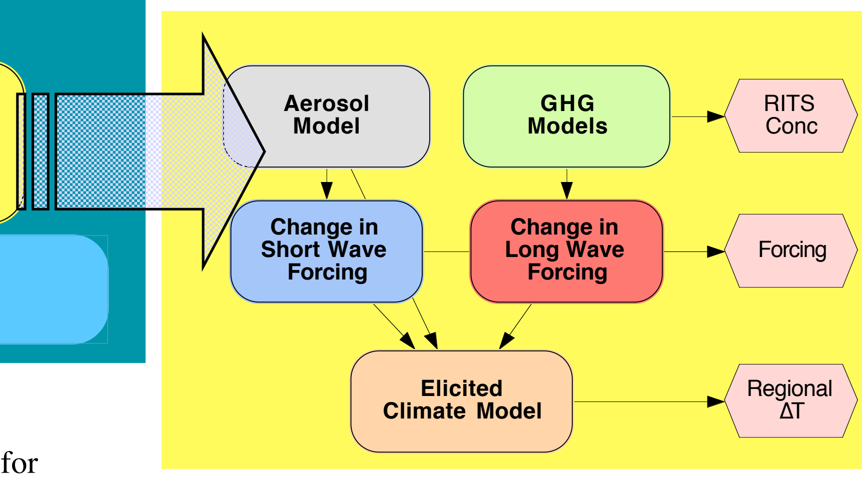
Often uncertainty about model form is as or more important than uncertainty about values of coefficients. Until recently there had been little practical progress in dealing with such uncertainty, but now there are several good examples:

- John Evans and his colleagues at the Harvard School of Public Health (Evans et al., 1994).
- Alan Cornell and others in the seismic risk (Budnitz et al., 1995).
- Hadi Dowlatabadi and colleagues at Carnegie Mellon in Integrated Assessment of Climate Change (ICAM) (Morgan and Dowlatabadi, 1996).



ICAM
Integrated Climate Assessment Model

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



See for example:
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 deals with...

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

1. It deals with uncertain coefficients by assigning PDFs to them and then performing stochastic simulation to propagate the uncertainty through the model.
2. It deals 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

There is not enough time to present any details from our work with the ICAM integrated assessment model. Here are a few conclusions from that work:

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

These findings lead us...

...to switch from trying to project and examine the future, to using the modeling framework as a test-bed to evaluate the relative robustness, across a wide range of plausible model futures, of alternative strategies that regional actors in the model might adopt.

We populated the model's regions with simple decision agents and asked, which behavioral strategies are robust in the face of uncertain futures, which get us in trouble.

Thus, for example, it turns out that tracking and responding to atmospheric concentration is more likely to lead regional policy makers in the model to stable strategies than tracking and responding to emissions.

Our conclusion

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.

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Scenarios…

…can be a useful device to help think about the future, *but they can also be dangerous*. Remember the discussion of cognitive heuristics.

Here is a scenario from an experiment run by Slovic, Fischhoff, and Lichtenstein:

> Tom is of high intelligence, although lacking in true creativity. He has a need for order and clarity, and for neat and tidy systems in which every detail finds its appropriate place. His writing is rather dull and mechanical, occasionally enlivened by somewhat corny puns and by flashes of imagination of the sci-fi type. He has a strong drive for competence. He seems to have little feel and little sympathy for other people and does not enjoy interacting with others.

In light of these data…

…what is the probability that:

Tom W. will select journalism as his college major?

P = 0.21

Tom W. will select journalism as his college major but become unhappy with his choice?

P = 0.39

Tom W. will select journalism as his college major but become unhappy with his choice and switch to engineering?

P = 0.41

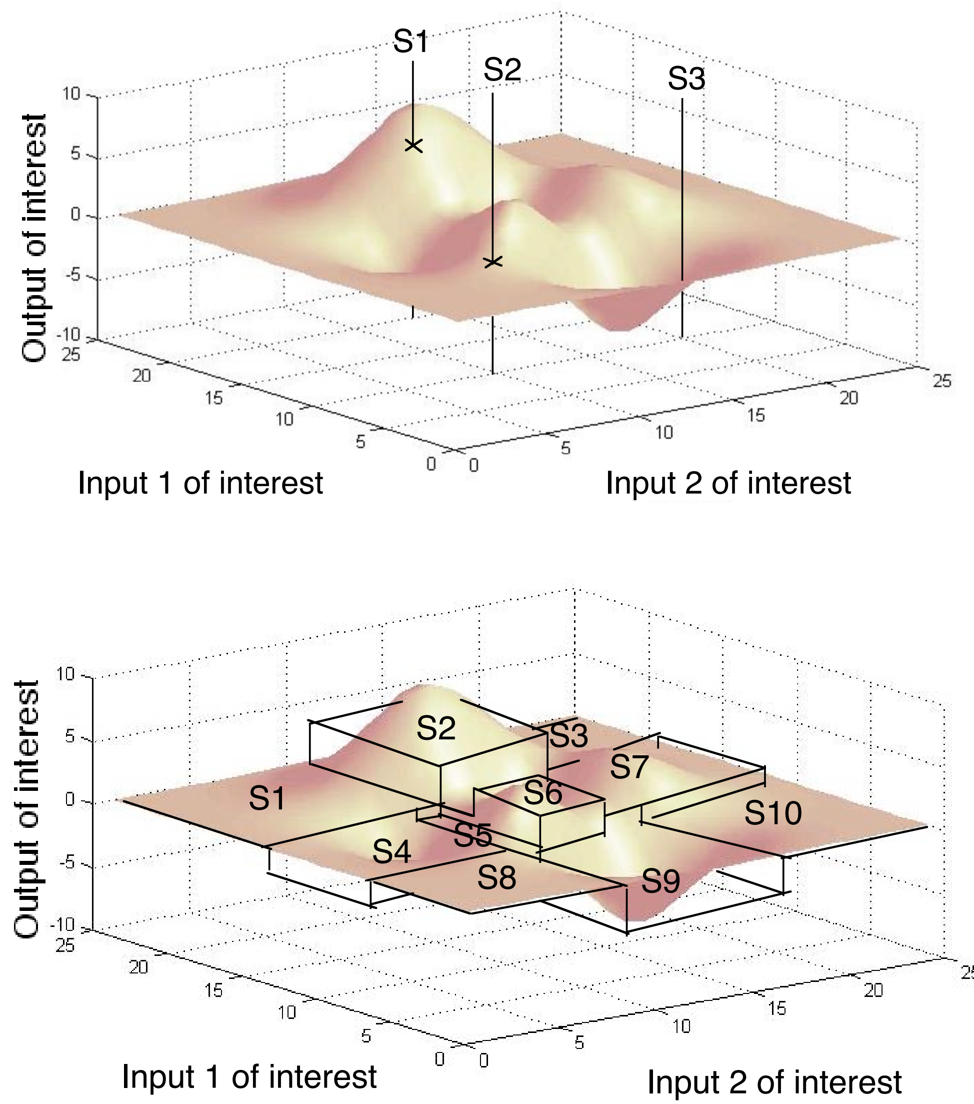
From: P. Slovic, B. Fischhoff, and S. Lichtenstein, "Cognitive Processes and Societal Risk Taking," *Cognition and Social Behavior*, 1976.

Scenarios…

…that describe just some single point in the space of outcomes are of limited use and logically cannot be assigned a probability.

If scenarios are to be used, its better to span the space of interest and then assign a probability to each.

$$\sum_{i=1}^{n} Si = 1$$



Cut the long causal chains

Typically, it is also better not to use detailed scenarios but rather to use simpler parametric methods.

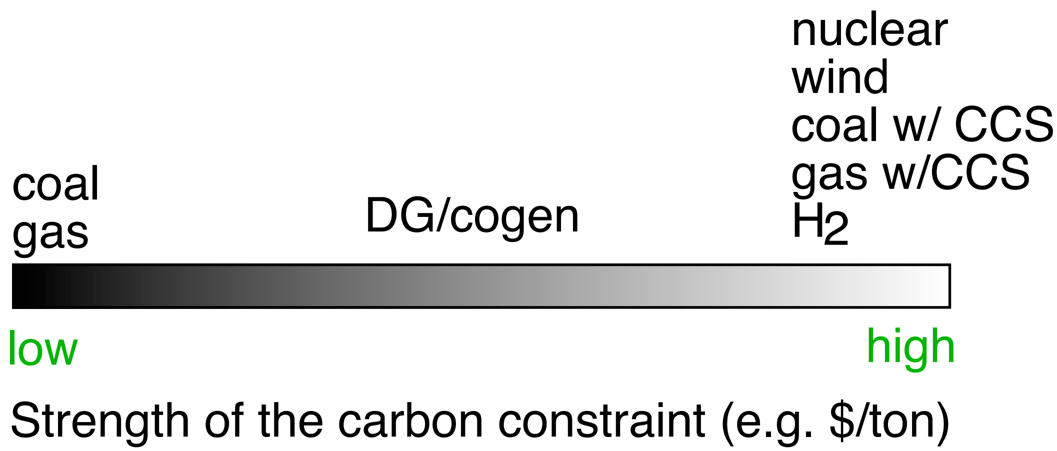
Thus, for example, if future oil prices appear to be critical to a specific class of decisions, rather than develop long detailed stories about how those prices might be shaped by future developments in the U.S. and Canadian Arctic, the Middle East and the Former Soviet Union, it is better to reflect on all the possibilities and then truncate the causal chain by positing a range of possible future oil prices, and work from there.

In multiplicative models, uniform PDFs are often quite adequate to get good first-order estimates.

Having been critical…

…of scenario-based approaches, let me also note an important advantage of scenarios: Thinking about path dependencies.

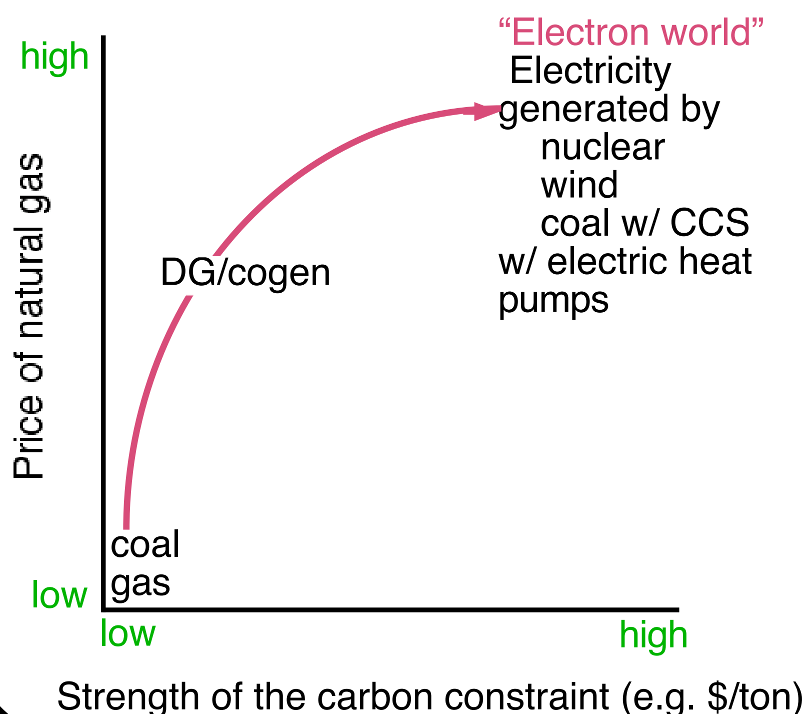
For example, consider the following set of energy technologies:



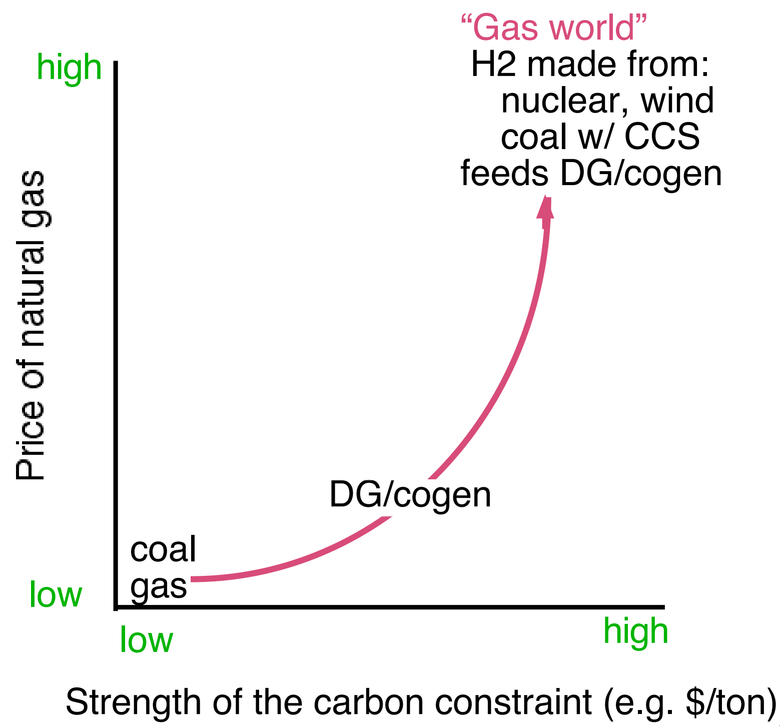
Which ones actually come into play as carbon emissions are constrained will depend on the timing of other factors such as the price of natural gas.

Example of path dependency

Suppose that natural gas first gets expensive and *then* carbon gets constrained.

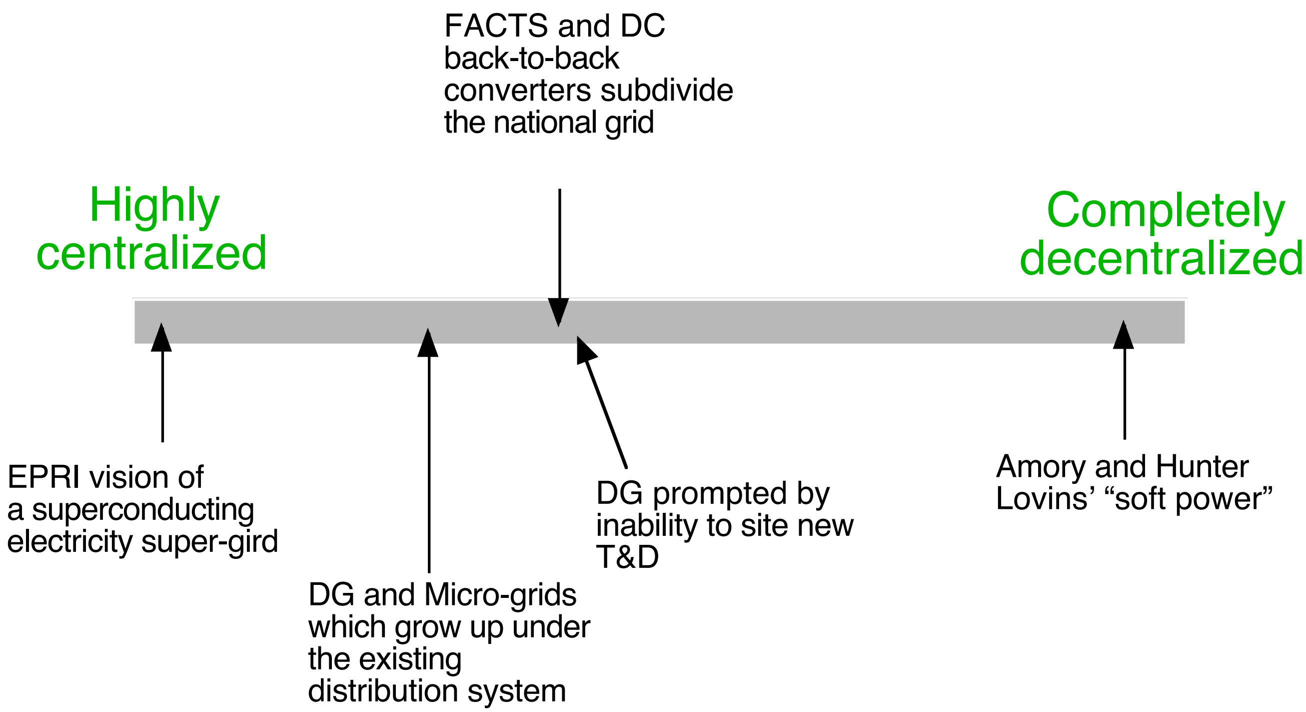


On the other hand, suppose that carbon gets constrained *before* natural gas gets expensive.



Thus…

…thinking about the future structure of socio/economic systems such as the energy system can be facilitated by thinking about the path that could get there, as well as about the end state. Scenarios can be a helpful aid for such thinking *if* the specifics are not taken too seriously.



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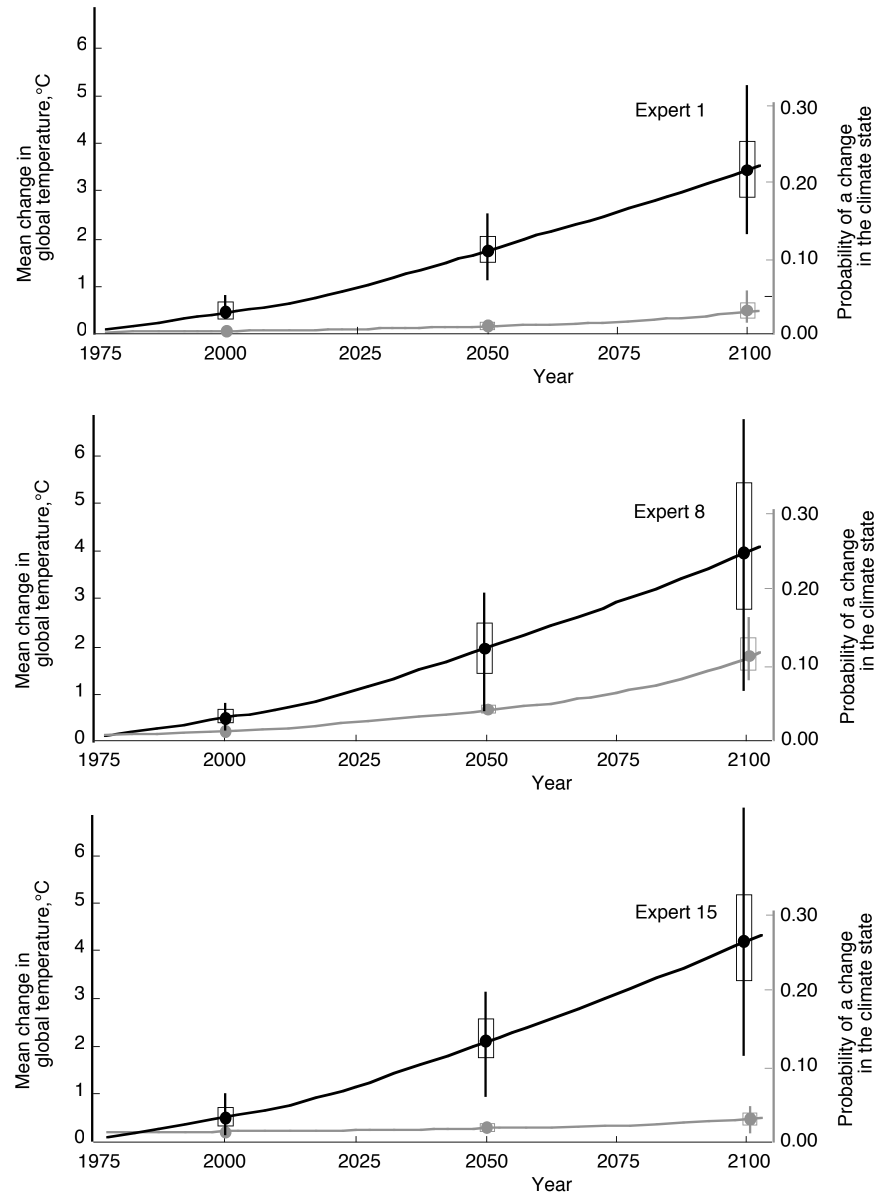
Limited domain of model validity

Examples of warming estimated via the ICAM model (dark curves) and probability that the associated climate forcing will induce a state change in the climate system (light curves) using the probabilistic judgments of three different climate experts.



Model switching

Schematic illustration of the strategy of switching to progressively simpler models as one moves into less well understood regions of the problem phase space, in this case, over time.

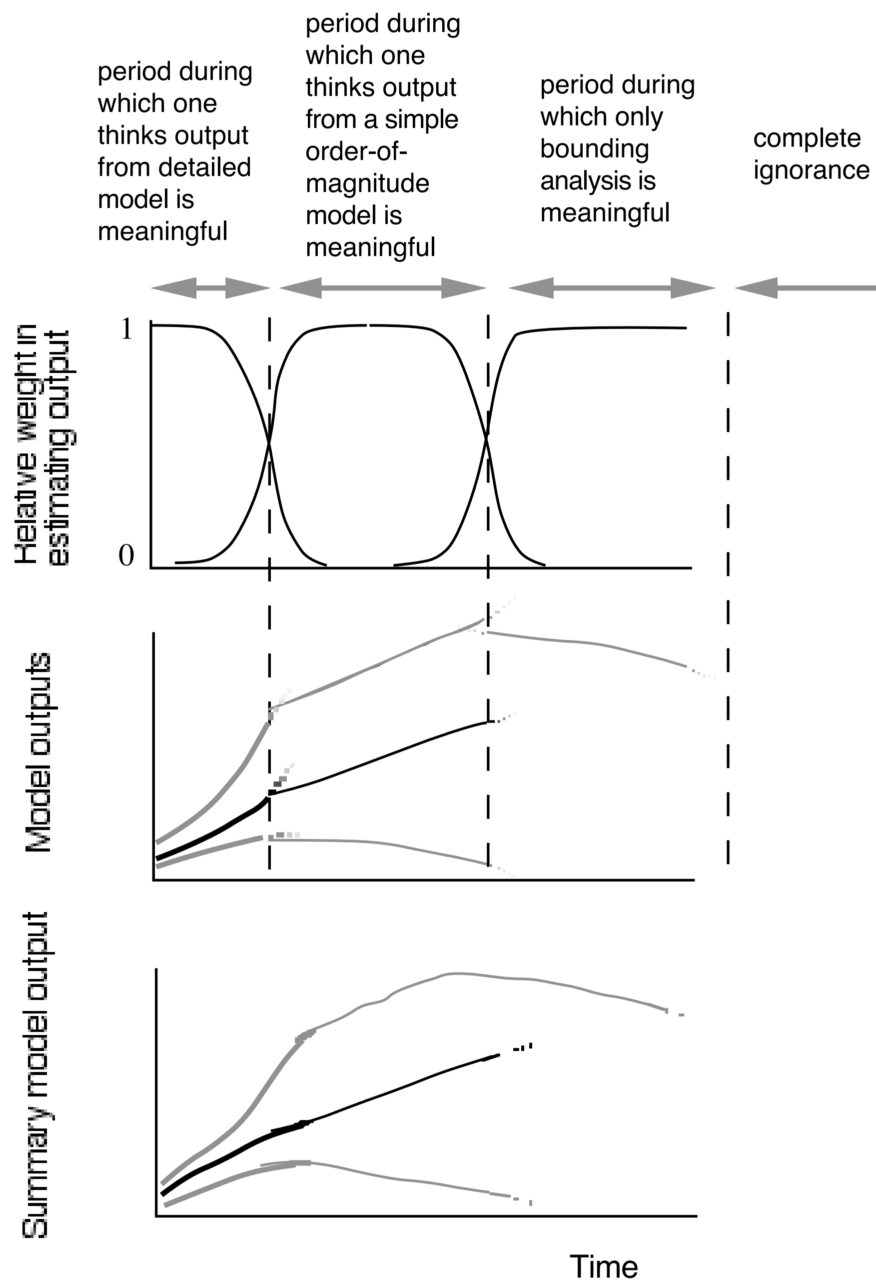
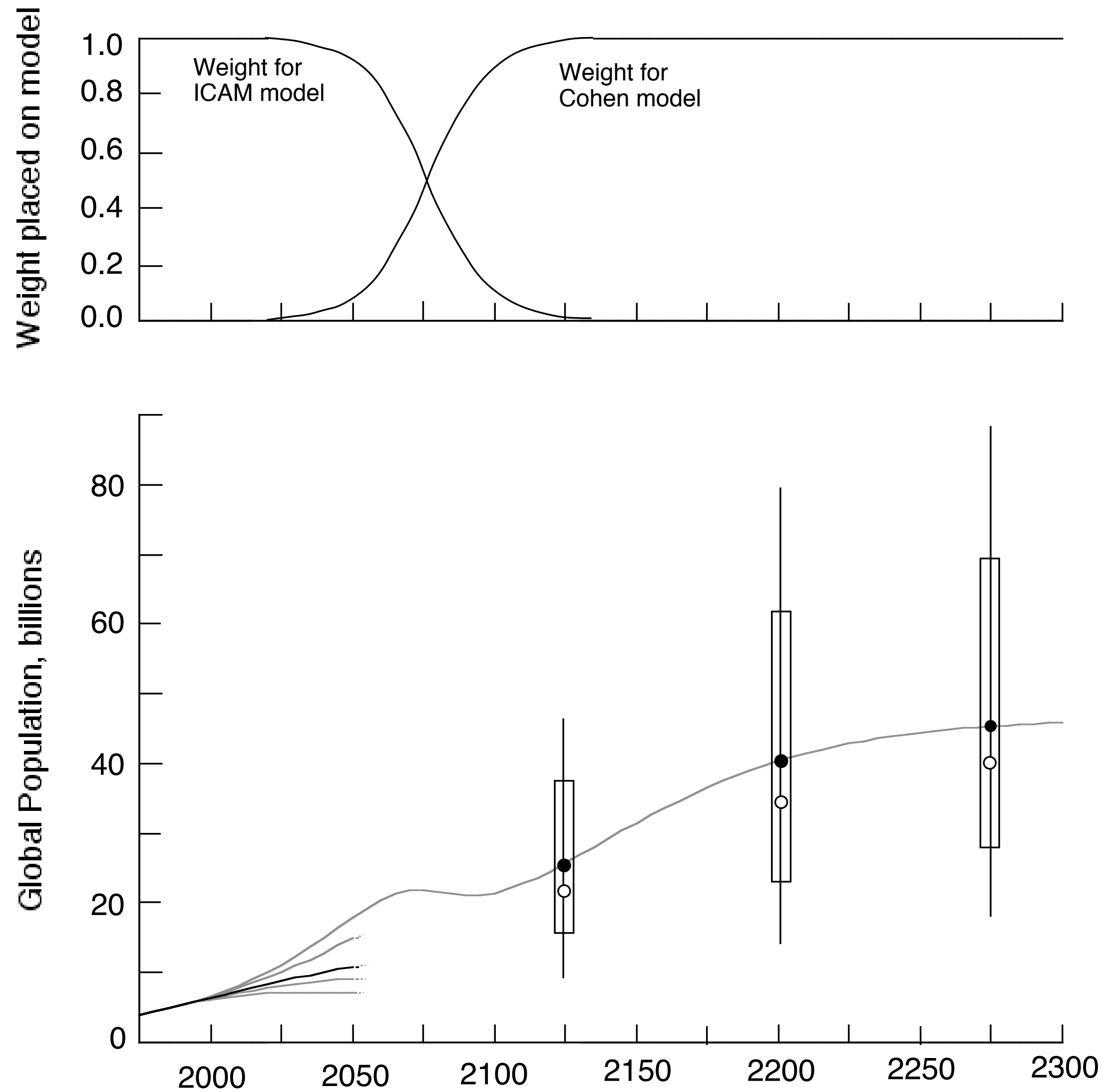


Illustration of model switching

Results of applying the model switch-over strategy to the ICAM demographic model (until about 2050) and an estimate of the estimate of the upper-bound estimate of global population carrying capacity based on J. S. Cohen.



This morning I will talk about:

- Sources of uncertainty and the characterization of uncertainty.
- Two basic types of uncertainty.
  - Uncertainty about coefficient values.
  - Uncertainty about model functional form.
- Some strengths and limitations of a scenario approach.
- Recent work on dealing with extreme uncertainty.
- The fact that there are some things we are not likely to know on the time-scale of climate decisions we face.

this workshop is…

and the unknowable."

those ideas to what I have talked

The only effective way to deal with these cases is with robust and adaptive strategies

- Known precisely
- Known with uncertainty
  - Can be better known on time scale of concern given adequate research
  - Can *not* be better known on time scale of concern given adequate research
- Unknown
  - Can be discovered on time scale of concern given adequate research
    - Known precisely
    - Known with uncertainty
  - Can *not* be discovered on time scale of concern given adequate research

Thanks very much

I've included a couple of additional slides which I will not talk about which may interest some of you.

Multiple Experts

When different experts hold different views it is often best not to combine the results, but rather to explore the implications of each expert's views so that decision makers have a clear understanding of whether and how much the differences matter in the context of the overall decision.

However, sophisticated methods have been developed that allow experts to work together to combine judgments so as to yield a single overall composite judgment.

The community of seismologists have made the greatest progress in this direction through a series of very detailed studies of seismic risks to built structures (Hanks, T.C., 1997; Budnitz, R.J. et al., 1995).

Uncertainty versus variability

Variability involves random change over time or space (e.g., "the mid-day temperature in Beijing in May is variable").

Recently, in the U.S., some people have been drawing a sharp distinction between variability and uncertainty. While the two are different, and sometimes require different treatments, the distinction can be overdrawn. In many contexts, variability is simply one of several sources of uncertainty (Morgan and Henrion, 1990).

One motivation people have for trying to sharpen the distinction is that variability can often be measured objectively, while other forms of uncertainty require subjective judgment.