PART 5. METHODS FOR ESTIMATING UNCERTAINTY

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

Model-Generated Uncertainty Estimates

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

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

Expert Elicitation

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A technical facilitator/integrator (TFI):

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

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

Protocols for Individual Expert Elicitation

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

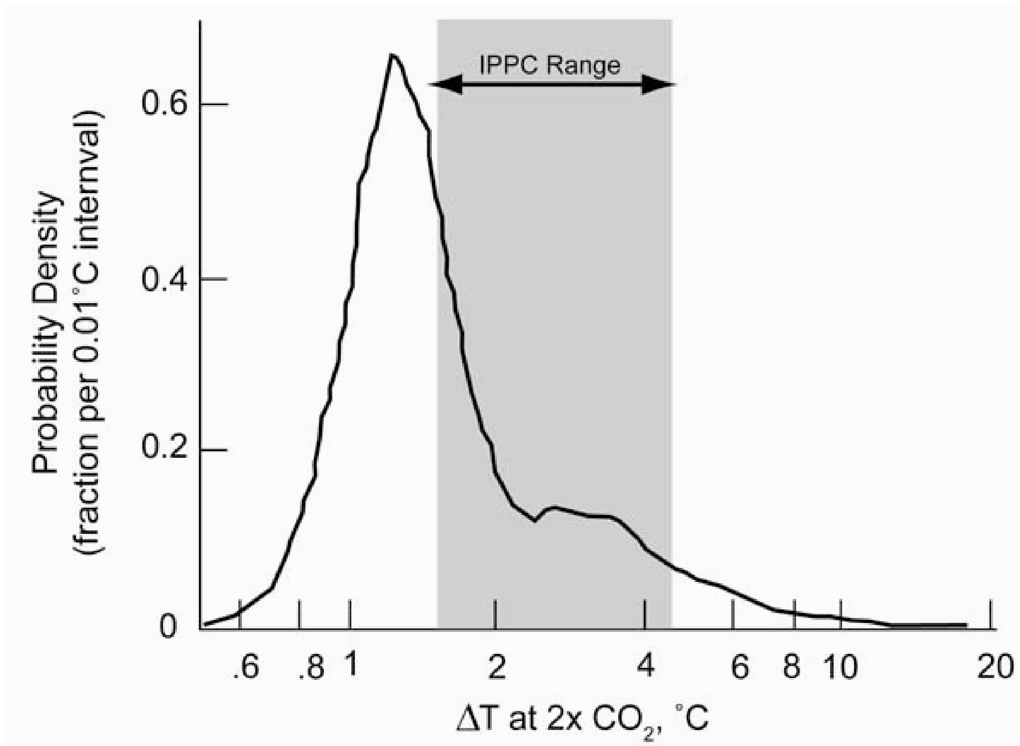

Figure 5.1 The probability density function for climate sensitivity (ΔT at 2x) estimated by Andronova and Schlesinger (2001). Using coupled atmosphere-ocean models, the observed near-surface temperature record and a bootstrap re-sampling technique, the authors examined the effect of natural variability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

Climate sensitivity: Pole-to-equator temperature gradient:

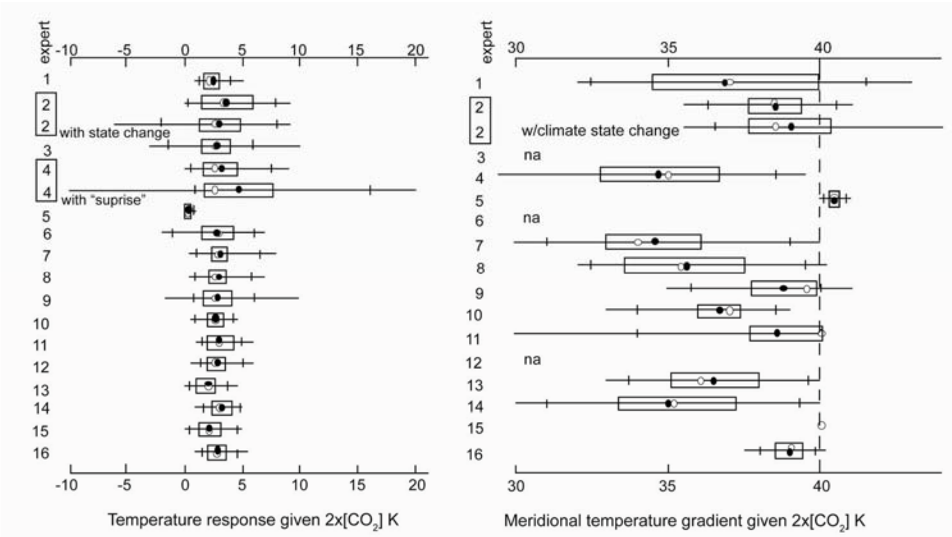

Figure 5.2 Examples of results from expert elicitations conducted by Morgan and Keith (1995) reported as box plots. Climate sensitivity is shown on the left and pole-to-equator temperature gradient on the right. Lines show the full range of the distribution; vertical tick marks show the 0.95 confidence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

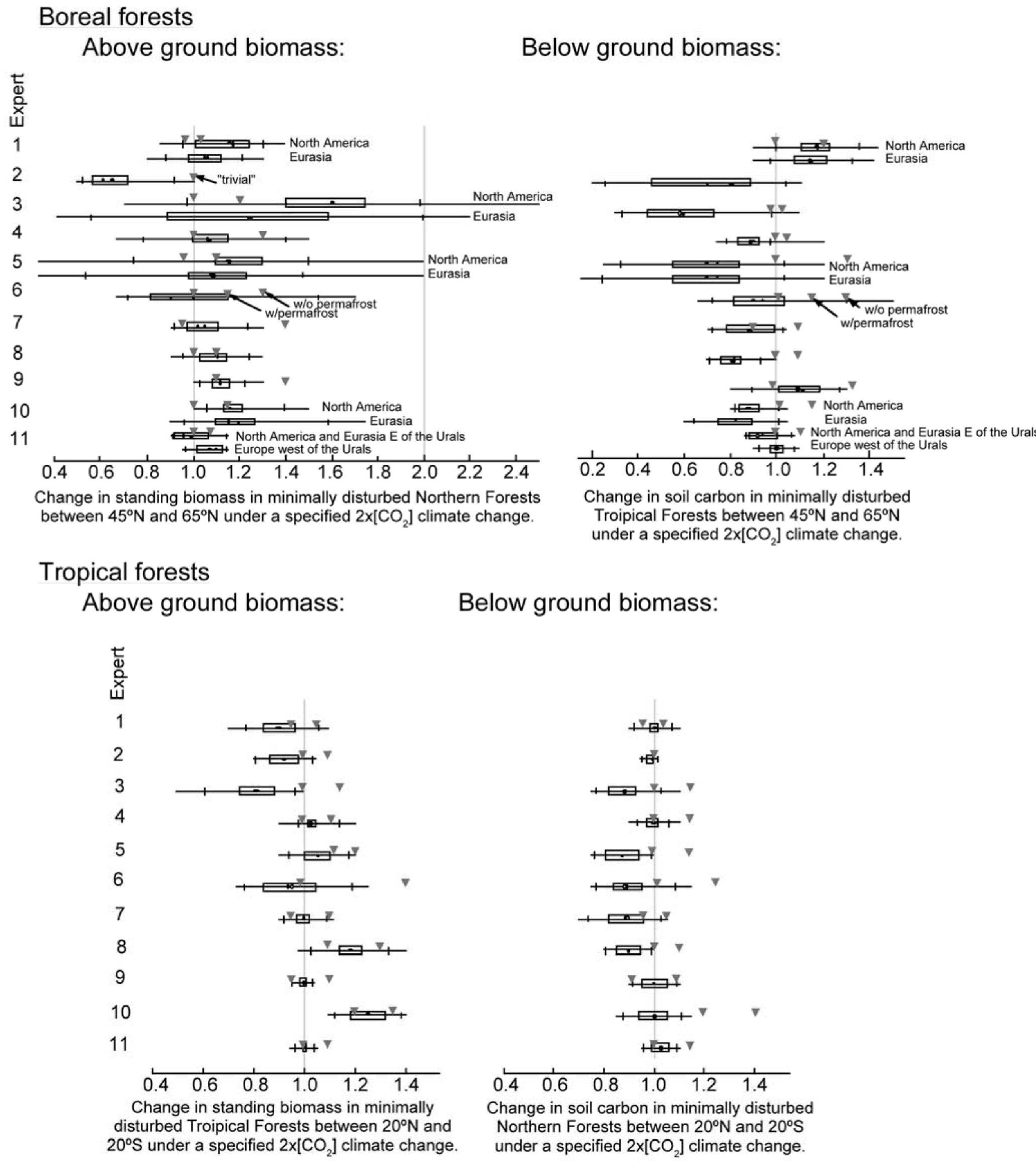

Figure 5.3 Examples of results from expert elicitations of forest ecosystem experts on change in above and below ground biomass for a specified $2xCO_2$ climate change forcing (Morgan *et al.*, 2001). Note that in several cases there is not even agreement about the sign of the impact on carbon stocks.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

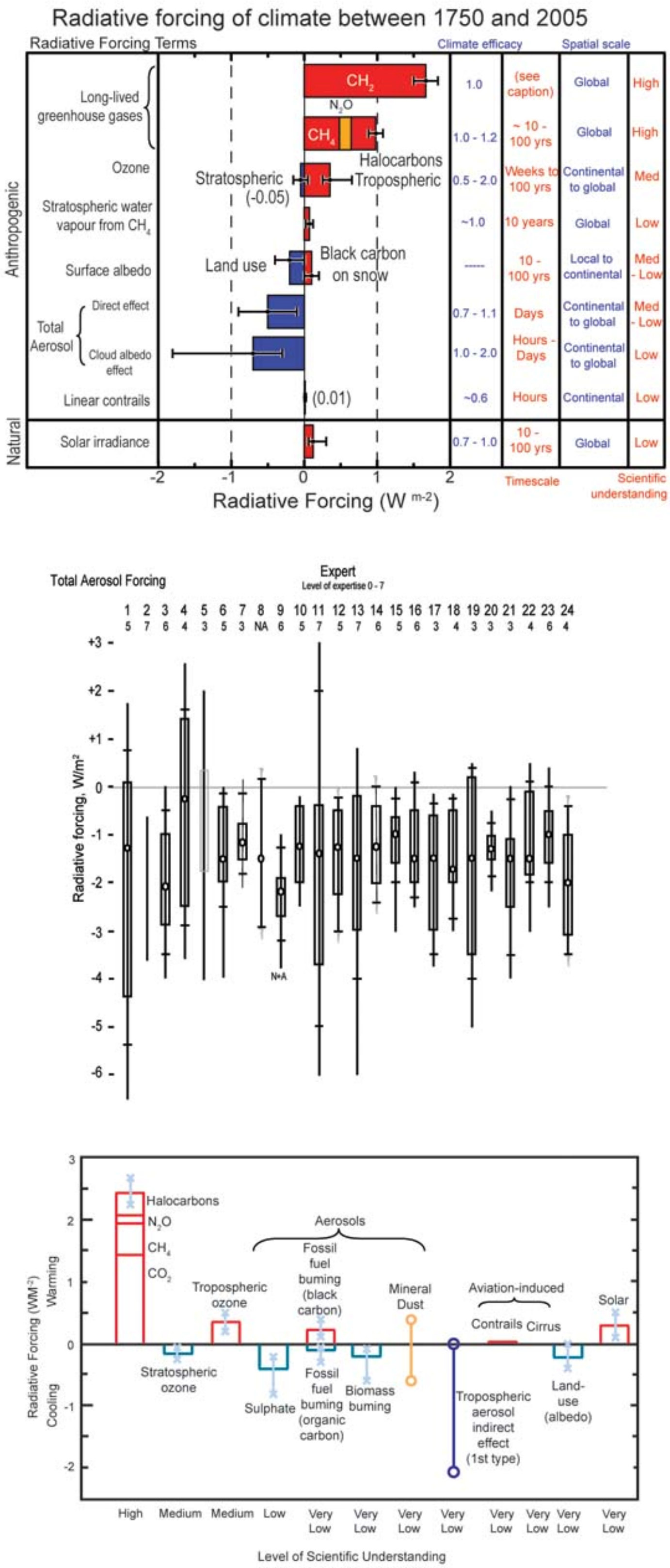

Figure 5.4 Comparison of estimates of aerosol forcing from the IPCC Third Assessment or TAR (bottom), an expert elicitation of 24 leading aerosol experts (center) and the IPCC Fourth Assessment or FAR (top). All radiative

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

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