PART 6. PROPAGATION AND ANALYSIS OF UNCERTAINTY

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

> We find model versions as realistic as other state-of-the-art climate models but with climate sensitivities ranging from less than 2K to more than 11K. Models with such extreme sensitivities are critical for the study of the full range of possible responses of the climate system to rising greenhouse gas levels, and for assessing the risks associated with a specific target for stabilizing these levels…
>
> The range of sensitivity across different versions of the same model is more than twice that found in the GCMs used in the IPCC Third Assessment Report…The possibility of such high sensitivities has been reported by studies using observations to constrain this quantity, but this is the first time that GCMs have generated such behavior. (Stainforth *et al.*, 2005)

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

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

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

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

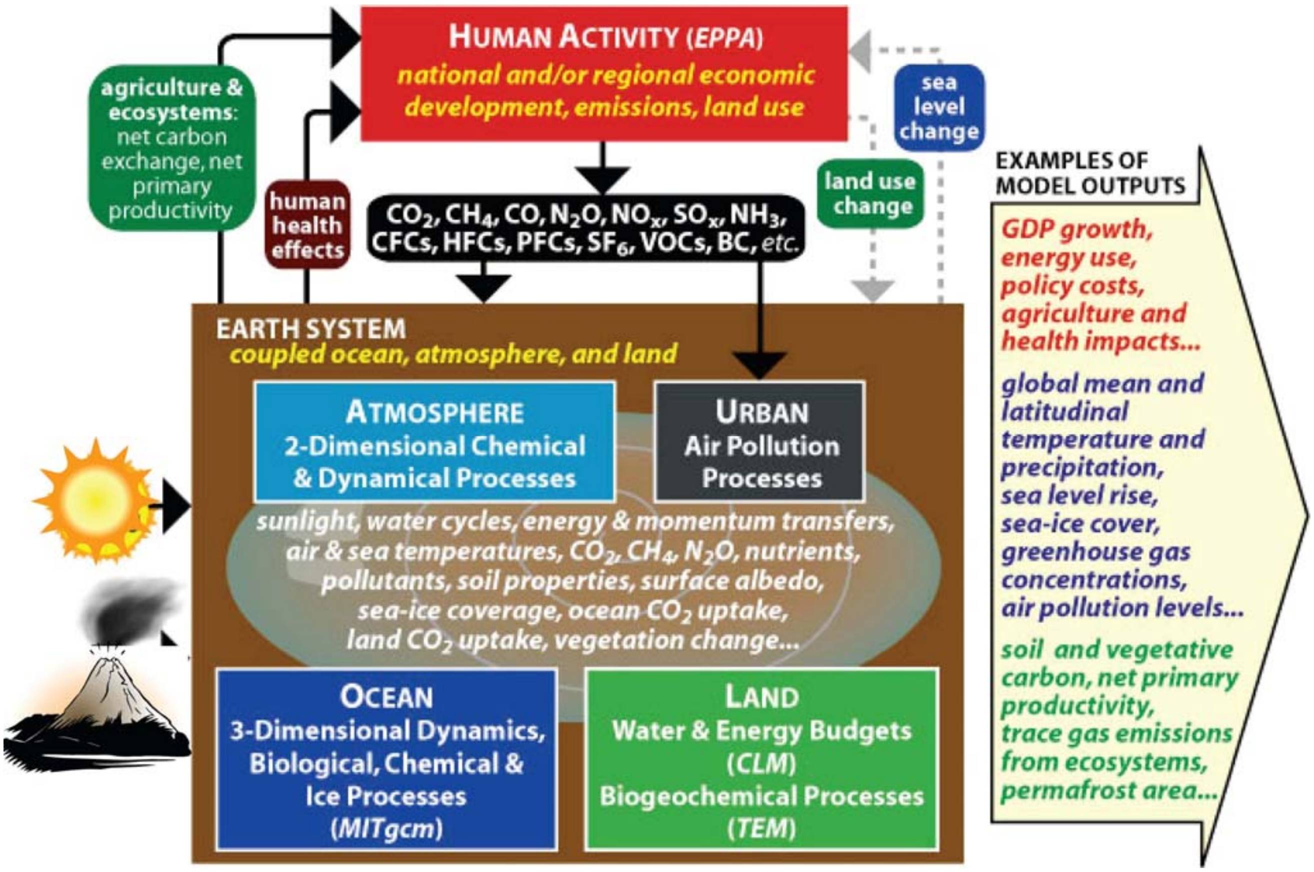

Figure 6.1 Simplified block diagram of the MIT Integrated Global System Model (IGSM) Version 2. Source: MIT Global Change Joint Program. Reprinted with permission.

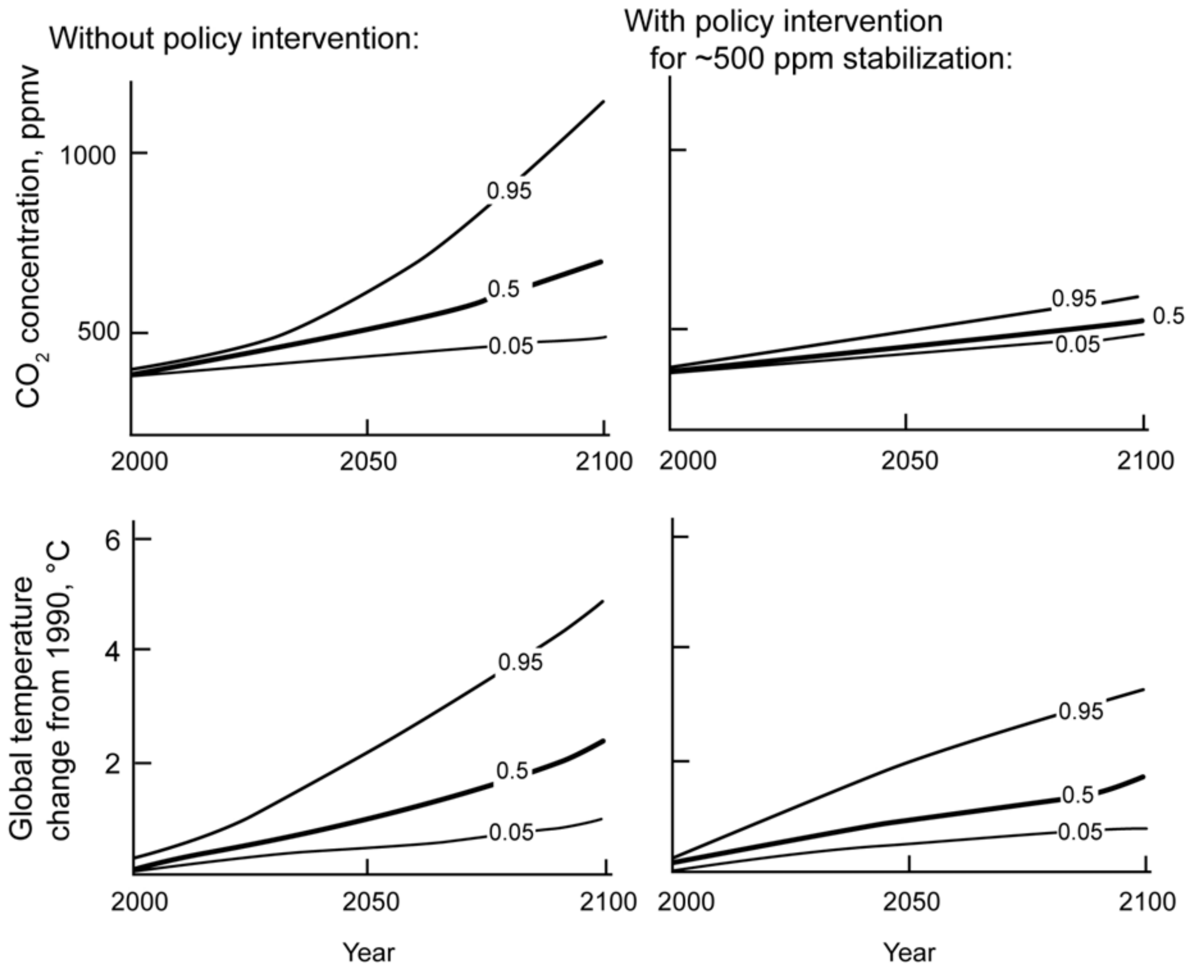

Figure 6.2 Results of simulation conducted by Webster *et al.* (2003) which use an earlier version of the MIT IGSM model with probability distributions on model inputs that are constrained by past performance of the climate system. Results on the left are the authors' projection for no policy intervention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

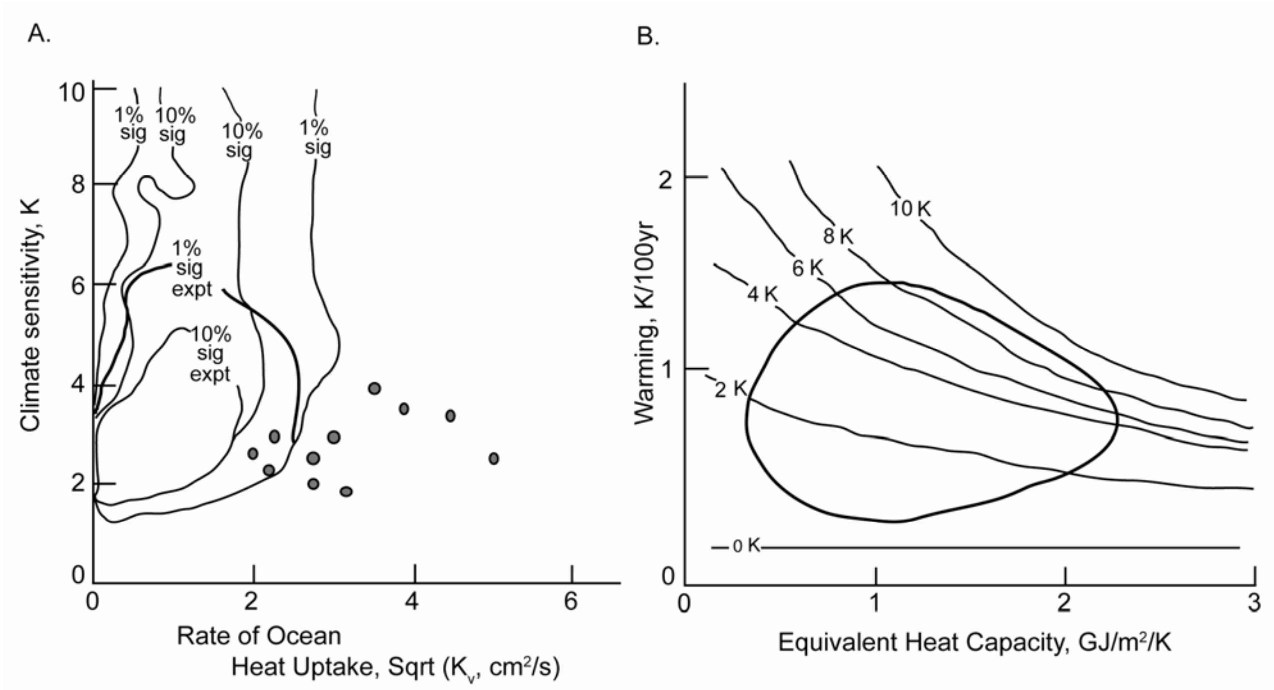

Figure 6.3 Two examples of recent efforts to bound sensitivity and heat uptake or heat capacity by combining expert judgment and model simulations.
A. (redrawn from Forest *et al.*, 2006) shows the marginal posterior probability density function obtained when using uniform probability distributions across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

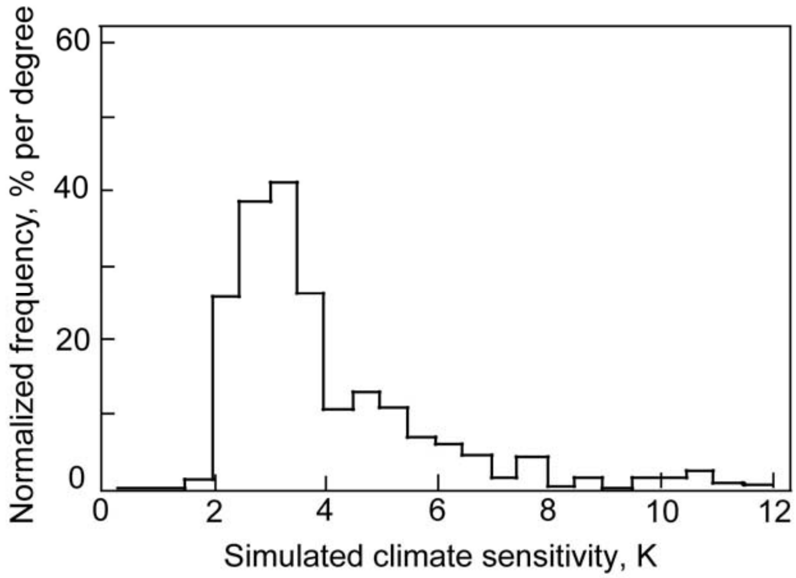

Figure 6.4 Histogram (redrawn) of climate sensitivities found by Stainforth *et al.* (2005) in their simulation of 2,578 versions of the HadSM3 GCM model.

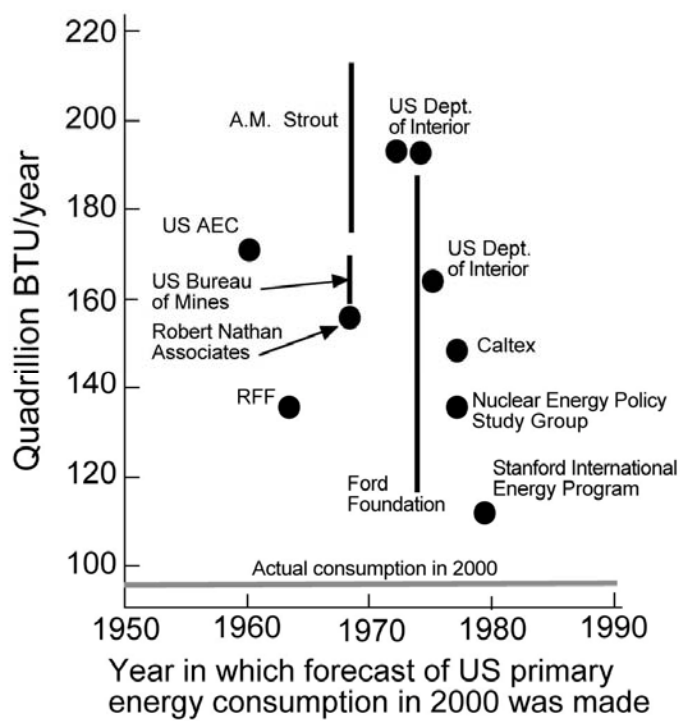

Figure 6.5 Summary of forecasts of United States primary energy consumption compiled by Smil (2003) as a function of the date on which they were made. [Figure redrawn from Smil (2003).]

PART 6 REFERENCES

Allen, M., 1999 October: Do-it-yourself climate prediction. *Nature*, **401**, 642.

Borgonovo, E, 2006: Measuring uncertainty importance: Investigation and comparison of alternative approaches. *Risk Analysis*, **26**, 1349-1361.

Casman, E.A., M.G. Morgan, and H. Dowlatabadi, 1999: Mixed levels of uncertainty in complex policy models. *Risk Analysis*, **19(1)**, 33-42.

Craig, P., A. Gadgil, and J.G. Koomey, 2002: What can history teach US?: A retrospective examination of long-term energy forecasts for the United States. *Annual Review of Energy and the Environment*, **27**, 83-118.

Dowlatabadi, H., 2000: Bumping against a gas ceiling. *Climatic Change*, **46(3)**, 391-407.

Dowlatabadi, H. and M.G. Morgan, 1993: A model framework for integrated studies of the climate problem. *Energy Policy*, **21(3)**, 209-221.

Forest, C.E, P.H. Stone, A.P. Sokolov, M.R. Allen, and M.D. Webster, 2002: Quantifying uncertainties in climate system properties with the use of recent climate observations. *Science*, **295**, 113-116.

Forest, C.E, P.H. Stone, and A.P. Sokolov, 2006: Estimated PDF's of climate system properties including natural and anthropogenic forcings. *Geophysical Research Letters*, **33**, L01705, doi:10.1029/2005GL023977.

Frame, D.J, B.B.B. Booth, J.A Kettleborough, D.A. Stainforth, J.M. Gregory, M. Collins, and M.R. Allen, 2005: Constraining climate forecasts: The role of prior assumptions. *Geophysical Research Letters*, **32**, L09702, doi:10.1029/2004GL022241.

IPCC, 2001: *Climate Change 2001: The Scientific Basis*. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change [Houghton, J.T., Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 881 pp.

Keller, K., M. Hall, S.-R. Kim, D. F. Bradford, and M. Oppenheimer, 2005: Avoiding dangerous anthropogenic interference with the climate system. *Climatic Change*, **73**, 227-238.

Morgan, M.G. and M. Henrion, 1990: *Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, 332 pp.

Morgan, M.G. and H. Dowlatabadi, 1996: Learning from integrated assessment of climate change. *Climatic Change*, **34**, 337-368.

Murphy, J.M., D.M.H. Sexton, D.N. Barnett, G.S. Jones, M.J. Webb, M. Collins, and D.A. Stainforth, 2004: Quantification of modeling uncertainties in a large ensemble of climate change simulations. *Nature*, **430**, 768-772.

Nordhaus, W. D. and J. Boyer, 2000: *Warming the World: Economic models of global warming*. MIT Press, 232 pp.

Smil, V., 2003: *Energy at the Crossroads*. MIT Press, Cambridge, MA, 448 pp.

Sokolov, A.P., C.A. Schlosser, S. Dutkiewicz, S. Paltsev, D.W. Kicklighter, H.D. Jacoby, R.G. Prinn, C.E. Forest, J. Reilly, C. Wang, B. Felzer, M.C. Sarofim, J. Scott, P.H. Stone, J.M. Melillo, and J. Cohen, 2005 July: *The MIT Integrated Global System Model (IGSM) Version 2: Model Description and Baseline Evaluation*. MIT Global Change Joint Program report 124, available at <http://web.mit.edu/globalchange/www/reports.html#rpr03_11>

Stainforth, D.A., T. Aina, C. Christensen, M. Collins, N. Faull, D.J. Frame, J.A. Ketteborough, S. Knight, A. Martin, J.M. Murphy, C. Piani, D. Sexton, L.A. Smith, R.A. Spicer, A.J. Thorpe, and M.R. Allen, 2005: Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature*, **433**, 403-406.

Webster, M., C. Forest, J. Reilly, M. Babiker, D. Kicklighter, M. Mayer, R. Prinn, M. Sarofim, A. Sokolov, P. Stone, and C. Wang, 2003: Uncertainty analysis of climate change and policy response. *Climatic Change*, **61**, 295-350.