UNCERTAINTY ANALYSIS OF CLIMATE CHANGE AND POLICY RESPONSE

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Abstract. To aid climate policy decisions, accurate quantitative descriptions of the uncertainty in climate outcomes under various possible policies are needed. Here, we apply an earth systems model to describe the uncertainty in climate projections under two different policy scenarios. This study illustrates an internally consistent uncertainty analysis of one climate assessment modeling framework, propagating uncertainties in both economic and climate components, and constraining climate parameter uncertainties based on observation. We find that in the absence of greenhouse gas emissions restrictions, there is a one in forty chance that global mean surface temperature change will exceed 4.9 °C by the year 2100. A policy case with aggressive emissions reductions over time lowers the temperature change to a one in forty chance of exceeding 3.2 °C, thus reducing but not eliminating the chance of substantial warming.

1. Introduction

Policy formulation for climate change poses a great challenge because it presents a problem of decision-making under uncertainty (Manne and Richels, 1995; Morgan and Keith, 1995; Nordhaus, 1994; Webster, 2002; Hammit et al., 1992). While continued basic research on the climate system to reduce uncertainties is essential, policy-makers also need a way to assess the possible consequences of different decisions, including taking no action, within the context of known uncertainties. Here, we use an earth systems model to describe the uncertainty in climate projections under two different policy scenarios related to greenhouse gas emissions. This analysis propagates uncertainties in emissions projections and uses observations to constrain uncertain climate parameters. We find that with a policy of no restrictions on greenhouse gas (GHG) emissions, there is one chance in two that the increase in global mean temperature change over the next century will exceed 2.4 °C and one

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chance in twenty that it will be outside the range 1.0–4.9 °C. A second hypothetical policy case with aggressive emissions reductions over time lowers the temperature change to one chance in two of exceeding 1.6 °C and one chance in twenty of being outside the range 0.8–3.2 °C; thus this policy reduces the chance of high levels of global warming but does not eliminate the chance of substantial warming.

Decision-making under uncertainty is an appropriate framework for the climate problem because of two basic premises: (i) the cumulative nature of atmospheric greenhouse gases, and the inertia of the oceans, means that if one waits to resolve the amount of climate change in 2050 or 2100 by perfectly observing (or forecasting) it, it will take decades or centuries to alter the observed trends – effective mitigation action must be started decades before the climate changes of concern are actually observed; (ii) a significant part of our uncertainty about future climate change may be unavoidable – details of climate and weather over longer periods are likely to remain unpredictable to some degree, and uncertainty in projecting future levels of human activities and technological change is inevitable. Thus, informed climate policy decisions require current estimates of the uncertainty in consequences for a range of possible actions. Furthermore, the use of consistent and well-documented methods to develop these uncertainty estimates will allow us to track the changes in our understanding through time.

Recognition of the importance of providing uncertainty estimates has been increasing in recent years. Authors for the Third Assessment Report (TAR) of the Intergovernmental Panel on Climate Change (IPCC) were encouraged to quantify uncertainty as much as possible (Moss and Schneider, 2000) and indeed, uncertainty was quantified for some aspects of climate change in the TAR. Uncertainty in key results, however, such as the increase in global mean surface temperature through 2100, was given only as a range without probabilities (Houghton et al., 2001). Since the IPCC TAR was published, several studies have recognized this shortcoming and contributed estimates of the uncertainty in future climate change (Schneider, 2001; Allen et al., 2000; Wigley and Raper, 2001; Knutti et al., 2002; Stott and Kettleborough, 2002).

These previous attempts to describe uncertainty have, however, been limited in significant ways. First, recent climate observations were not used to constrain the uncertainty in climate model parameters in some studies (Wigley and Raper, 2001). Second, by using only one Atmosphere-Ocean General Circulation Model (AOGCM), uncertainties in climate model response are reduced to uncertainty in a single scaling factor for optimizing the model's agreement with observations (Stott and Kettleborough, 2002). Third, the IPCC's emissions scenarios were not intended to be treated as equally likely, yet some authors have assumed that they were (Wigley and Raper, 2001). Indeed, Schneider (2001, 2002) has demonstrated the ambiguity and potential dangers that result from the absence of probabilities assigned to emissions scenarios. Fourth, other authors estimated uncertainty in future climate change only applied to specific IPCC emissions scenarios rather than providing equal treatment of the uncertainty in the emissions projections

(Allen et al., 2000; Knutti et al., 2002; Stott and Kettleborough, 2002). As such, these studies analyzed the uncertainty only in the climate system response without characterizing the economic uncertainty except through individual IPCC emissions scenarios. Finally, none of these previous studies have examined the uncertainty in future climate change under a policy scenario leading to stabilization of GHG concentrations.

Our study builds on previous estimates of uncertainty in future climate changes but with three significant improvements: (1) we use explicit probabilities for different emissions projections, based on judgments about the uncertainty in future economic growth and technological change (Webster et al., 2002) and on documented uncertainty in current levels of emissions (Olivier et al., 1995); (2) we use observations to constrain the joint distributions of uncertain climate parameters so that simulated climate change for the 21st century is consistent with observations of surface, upper-air, and deep ocean temperatures over the 20th century (Forest et al., 2000, 2001, 2002); and (3), we estimate uncertainty under a policy constraint as well as a no policy case, to show how much uncertainty remains even after a relatively certain cap on emissions is put in place. Using this approach, we provide a more comprehensive picture of the relative likelihood of different future climates than previously available.

The no policy and policy constraint cases are modeled as once-and-for-all decisions, with no learning or change in policy along the way. In reality, climate policy will be revised as we continue to learn and respond to new information and events. Policy decisions are therefore better modeled as sequential decisions under uncertainty (Webster, 2002; Hammitt et al., 1992; Manne and Richels, 1995). In order to perform such analyses, however, the uncertainty in projections must first be quantified. Thus the work presented here is a necessary precursor to a more sophisticated treatment of climate policy. Also, we present here an analysis of uncertainty in one modeling framework, which does not treat all of the structural uncertainties.

The quantification of probabilities for emissions forecasts has been the topic of some debate. There are two distinct ways to approach the problem of forecasting when there is substantial uncertainty: uncertainty analysis (associating probabilities with outcomes), and scenario analysis (developing ‘plausible’ scenarios that span an interesting range of possible outcomes). The IPCC Special Report on Emissions Scenarios (SRES) (Nakicenovic, 2000) used the plausible scenario approach, where all the scenarios developed were considered ‘equally valid’ without an assignment of quantitative or qualitative likelihoods.

One benefit of a scenario approach is that it allows detailed exploration of what outcomes are produced by particular sets of assumptions. In assessments involving a set of authors with widely diverging views, it is typically easier to avoid an impasse by presenting equally valid scenarios without attaching likelihoods.

Uncertainty analysis requires identification of the critical uncertain model structures and parameters (or inputs), quantification of the uncertainty in those structures and parameters in the form of probability distributions, and then sampling from those distributions and performing model simulations repeatedly to construct probability distributions of the outcomes. With this approach, one can quantify the likelihood that an outcome of a model (or range of models) falls within some specified range. Hence, unlike the scenario approach, uncertainty analyses indicate better the likelihood of the potential consequences, or risks, of a particular policy decision.

It has been argued that when it comes to socio-economic processes that drive emissions, there should be no attempt to assign probabilities. However, if emissions projections are presented without relative likelihoods, non-experts will substitute their own judgment (Schneider, 2001). One analysis has assumed that all of the IPCC SRES scenarios were equally likely (Wigley and Raper, 2001). Other studies have used one or two representative scenarios to calculate future uncertainty (Allen et al., 2000; Knutti et al., 2002; Stott and Kettleborough, 2002), which then require judgments about the likelihood of the emissions scenarios that were used if they are to be relevant to policy. By using formal techniques to elicit judgments from those who are expert in the underlying processes that contribute to uncertainty in future emissions, one can provide this additional information for policymaking.

Because judgments are ultimately required for policy decisions, the difference between formal quantitative uncertainty analysis and the scenario approach is not whether a judgment about likelihood of outcomes is needed but rather when and by whom the judgment is made. The evidence is strong that experts and non-experts are equally prone to well-known cognitive biases when it comes to assigning probabilities, but also that formal quantitative approaches can reduce these biases (Morgan and Henrion, 1990; Tversky and Kahneman, 1974). Thus, unless scientists who develop future climate projections use the tools of uncertainty analysis and their judgment to describe the likelihood of outcomes quantitatively, the assessment of likelihood will be left to other scientists, or policy makers, or the public who will not have all the relevant information behind those projections (Moss and Schneider, 2000). Our views are that: (1) experts should offer their judgment about uncertainty in their projections, and (2) formal uncertainty techniques can eliminate some of the cognitive biases that exist when people deal with uncertainty. Of course, there will remain a need for experts and non-experts to make judgments about uncertainty results: uncertainty analysis is an important contributor to policy making but it may be no easier to achieve expert consensus for a particular distribution of outcomes than it is to achieve consensus about a point estimate.

Further, model-based quantitative uncertainty analysis cannot easily account for uncertainty in processes that are so poorly understood that they are not well represented in the models. For example, there is considerable evidence that there can be abrupt collapses in the ocean's thermohaline circulation (e.g., Higgins et al., 2002.) No coupled GCM has yet shown such an abrupt change on the time scale that we have considered, up to 2100, but the fact that these same models give very diverse projections for changes in the thermohaline circulation (Cubasch et al., 2001) is evidence that our ability to model these processes is poor. Thus, similar to many other assessment models, our modeling framework presented below does not currently reproduce many of the abrupt state changes discussed in Higgins et al. (2002). Such abrupt changes could certainly affect the probability distribution of outcomes if they could be included (see e.g., distributions from experts nos. 2 and 4 in the elicitation by Morgan and Keith, 1995). As the state of the art in models and representation of these mechanisms improves, their effects should be included in uncertainty analyses.

2. Methods

We specifically consider uncertainty in: (1) anthropogenic emissions of greenhouse gases [carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulfur hexafluoride (SF_6)]; (2) anthropogenic emissions of short-lived climate-relevant air pollutants [sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO), ammonia (NH_3), black carbon (BC), organic carbon (OC), and non-methane volatile organic compounds (NMVOCs)]; (3) climate sensitivity (S); (4) oceanic heat uptake as measured by an effective vertical ocean diffusivity (K_v); and (5) specific aerosol forcing (F_{aer}).

We constrain uncertainty in climate model parameters to be consistent with climate observations over much of the past century (Forest et al., 2002), and we use uncertainty estimates in anthropogenic emissions (Webster et al., 2002) for all relevant greenhouse gases (GHGs) and aerosol and GHG precursors as estimated using the MIT Emissions Prediction and Policy Analysis (EPPA) model (Babiker et al., 2000, 2001). These results (Webster et al., 2002; Forest et al., 2002) provide input distributions that we use for the earth systems components of the MIT Integrated Global System Model (IGSM) (Prinn et al., 1999; Reilly et al., 1999), an earth system model of intermediate complexity (Claussen, 2002). The MIT IGSM has been developed specifically to study uncertainty quantitatively. It achieves this by retaining the necessary complexity to adequately represent the feedbacks and interactions among earth systems and the flexibility to represent the varying parameterizations of climate consistent with the historical data. At the same time, it remains computationally efficient so that it is possible to make hundreds of multi-century simulations in the course of a few months with a dedicated parallel processing computer system. Using efficient sampling techniques, Latin Hypercube sampling (Iman and Helton, 1998), a sample size of 250 is sufficient to estimate probability distributions for climate outcomes of interest.

2.1. STRUCTURE OF THE MIT IGSM

The MIT IGSM components include: (a) the EPPA model, designed to project emissions of climate-relevant gases and the economic consequences of policies to limit them (Babiker et al., 2000, 2001), (b) the climate model, a two-dimensional (2D) zonally-averaged land-ocean (LO) resolving atmospheric model, coupled to an atmospheric chemistry model, (c) a 2D ocean model consisting of a surface mixed layer with specified meridional heat transport, diffusion of temperature anomalies into the deep ocean, an ocean carbon component, and a thermodynamic sea-ice model (Sokolov and Stone, 1998; Wang et al., 1998, 1999; Holian et al., 2001), (d) the Terrestrial Ecosystem Model (TEM 4.1) (Melillo et al., 1993; Tian et al., 1999), designed to simulate carbon and nitrogen dynamics of terrestrial ecosystems, and (e) the Natural Emissions Model (NEM) that calculates natural terrestrial fluxes of CH_4 and N_2O from soils and wetlands (Prinn et al., 1999; Liu, 1996).

The version of the MIT IGSM used here contains certain other unique and important features. It incorporates a computationally efficient reduced-form urban air chemistry model derived from an urban-scale air pollution model (Mayer et al., 2000). Also, TEM is now fully coupled with the 2D-LO ocean-atmosphere-chemistry model.* In previous simulations (Prinn et al., 1999; Reilly et al., 1999), an iterative coupling procedure was performed to include the effect of climate change on the carbon uptake by land ecosystems. The new fully integrated version includes direct monthly interaction between the climate and ecosystem components: the 2D-LO climate model provides monthly averaged temperature, precipitation, and cloud cover and TEM returns the carbon uptake or release from land for the month. The coupling of the zonally averaged 2D-LO climate model to a latitude-longitude grid to drive TEM requires scaling the present-day longitudinal distribution of climate data by the projected zonally averaged quantities, which has been shown to work well as compared with input from three-dimensional models (Xiao et al., 1997).

A simple representation of sea level change due to melting of mountain glaciers has been incorporated into the IGSM. Change in the volume of glaciers from year t_0 to year t (expressed as the equivalent (expressed as the equivalent volume of liquid water) is calculated as

$$dV = \int_{t_0}^{t} Sg(t)\left(B_0 + \frac{dB}{dTg}\Delta Tg(t)\right) dt,$$

where B_0 is the rate of increase in global sea level due to melting of glaciers in the year t_0, dB/dTg is the sensitivity of this rate of increase to changes in global

* Anthropogenic emissions of greenhouse gases from human activities are treated parametrically in the EPPA model. A version of the ecosystems model that includes human-induced land-use change, including a mechanistic model of GHG emissions from land use is being developed for future versions of the IGSM.

average annual mean surface temperature, Tg, and Sg is the total glacial area. Sg in a year t is calculated as

$$Sg(t) = Sg(t-1) + dSg(t-1),$$

dSg is assumed to be proportional to dV. Change in sea level is computed using the total ocean surface area Ao as

$$dh = \frac{dV}{Ao}.$$

In all our calculations we use year 1990 as t_0. Values of B_0 and dB/dTg, 0.4 mm/year and 0.61 mm/year/degree respectively, were derived from the published results of transient climate change simulations with a number of coupled atmosphere-ocean GCMs (Church et al., 2001). The differences in these parameters as simulated by the different models were small compared to the uncertainty in projections of changes in Tg associated with other uncertainties, such as climate sensitivity. Thus by taking fixed values of these parameters, we are assuming that the major uncertainty in dV is due to the uncertainty in dTg. This approach is a simplified version of that used by Gregory and Oerlemans (1998).

2.2. UNCERTAINTY IN IGSM CLIMATE PARAMETERS

The century-scale response of the climate system to changes in the radiative forcing is primarily controlled by two uncertain global properties of the climate system: the climate sensitivity and the rate of oceanic heat uptake (Sokolov and Stone, 1998; Sokolov et al., 2003). In coupled Atmosphere-Ocean General Circulation Models (AOGCMs) these two essentially structural properties are determined by a large number of equations and parameters and cannot easily be changed. The sensitivity, S, of the MIT climate model, however, can be easily varied by changing the strength of the cloud feedback (i.e., we can mimic structural differences in the AOGCMs). Mixing of heat into the deep ocean is parameterized in the MIT model by an effective diffusion applied to a temperature difference from values in a present-day climate simulation. Therefore, the rate of the oceanic heat uptake is defined by the value of the globally averaged diffusion coefficient, K_v. By varying these two parameters the MIT climate model can reproduce the global-scale zonal-mean responses of different AOGCMs (Sokolov and Stone, 1998). Because of this flexibility our results for these responses are not as model dependent as they would be if we had used a single AOGCM for all of our analysis. There is also significant uncertainty in the historical forcing mainly associated with uncertainty in the radiative forcing in response to a given aerosol loading, F_{aer}. Thus, in the MIT IGSM, these three parameters (S, K_v, and F_{aer}) are used to characterize both the response of the climate system and the uncertainty in the historical climate forcing.

A particularly crucial aspect of our uncertainty work was estimating the joint pdfs for the climate model parameters controlling S, K_v, and F_{aer}. Previous work

Table I

Fractiles of posterior marginal distributions for climate sensitivity, rate of heat uptake by the deep ocean, and radiative forcing uncertainty from aerosols

Parameter	Fractile						
	0.025	0.05	0.25	0.5	0.75	0.95	0.975
S (°C)	1.3	1.4	1.95	2.38	2.96	4.2	4.7
K_v (cm^2/s)	0.65	1.32	4.6	9.4	16.8	33.6	37.8
F_{aer} (W/m^2)	–0.94	–0.88	–0.74	–0.65	–0.45	–0.25	–0.18

has used pdfs based on expert judgment or results from a set of climate models (Hammit et al., 1992; Wigley and Raper, 2001; Titus and Narayan, 1995; Webster and Sokolov, 2000). Our method uses observations of upper air, surface, and deep-ocean temperatures for the 20th century to jointly constrain these climate parameters, while including natural climate variability as a source of uncertainty (Forest et al., 2002). The method for estimating pdfs relies on estimating goodness-of-fit statistics, r^2 (Forest et al., 2000, 2001, 2002), obtained from an optimal fingerprint detection algorithm (Allen and Tett, 1999). Differences in r^2 provide a statistic that can be used in hypothesis testing, and thereby provide probability estimates for parameter combinations (Forest et al., 2000, 2001). We compute r^2 by taking the difference in the modeled and observed patterns of climate change and weighting the difference by the inverse of the natural variability for the pattern. This method requires an estimate of the natural variability (i.e., unforced) for the climate system over very long periods. Ideally, observed climate variability would be used but reconstructed data are not of sufficient accuracy. Our estimate was obtained from long control runs of particular AOGCMs (Forest et al., 2002). Estimates of the variability from other AOGCMs could change the results.

Starting with a prior pdf over the model parameter space, an estimate of the posterior pdf is obtained by applying Bayes Theorem (Bayes, 1763), using each diagnostic to estimate a likelihood function, and then each posterior becomes the prior for the procedure using the next diagnostic. In the work presented here, expert priors for both S and K_v were used (Webster and Sokolov, 2000), but sensitivity to alternative assumptions will be presented.* Fractiles for the final posterior distributions used here for the climate model parameters are shown in Table I. The three diagnostics are treated as independent observations and, therefore, weighted equally in the Bayesian updating procedure.

* There is debate over whether and how to combine subjective probability distributions from multiple experts for use in an uncertainty analysis; see, e.g., Titus and Narayanan (1996), Paté-Cornell (1996), Keith (1996), and Genest and Zidek (1986).

The result is a joint pdf for these three parameters with correlation among the marginal pdfs (e.g., a high climate sensitivity is only consistent with observed temperature under some combination of rapid heat uptake by the ocean and a strong aerosol cooling effect). The pairwise correlation coefficients are 0.243 for S-F_{aer}, 0.093 for K_v-F_{aer}, and 0.004 for S-K_v,

2.3. SPIN-UP OF CLIMATE MODEL IN MONTE CARLO EXPERIMENTS

A further issue in the Monte Carlo analysis is the so-called 'spin-up' of the IGSM components required with different sampled values of changes in S, K_v, and F_{aer}. There is inertia in the ocean and carbon cycle models, as well as TEM, so that one cannot start 'cold' from the year 2000 with different values for climate parameters. The computational requirements for running the full model starting from pre-industrial times through 2100 for each of the 250 runs necessitated a two-stage spin-up procedure. For the first stage, a simulation of the IGSM in spin-up mode was carried out with reference values for S, K_v, and F_{aer} for the period Jan. 1, 1860 to Jan. 1, 1927. In this mode, the climate model uses estimated historical forcings while the ocean carbon-cycle model (OCM) and TEM are forced by observed changes in CO_2 concentrations and the climate variables as simulated by the climate model. Carbon uptake by the OCM and TEM are not fed back to the climate model in this stage. The model states in 1927 for the climate model and TEM from this run were saved and then used as initial conditions for the second spin-up stage with the different sets of model parameters sampled in the Monte Carlo analysis. During this second stage the IGSM was run in the same mode as the first stage from Jan. 1, 1927 to Jan. 1, 1977, but using the different sampled values for the climate parameters. Given the inertia in the OCM, that model component was run from 1860 in all simulations and the required climate data up to 1927 were taken from the climate simulation for reference parameter values. Test runs of the full IGSM spun-up from 1860 using extreme values of the uncertain parameters were compared with results from this shortened spin-up procedure and showed no noticeable difference in the simulation results by 1977, confirming that this shortened spin-up period would not affect projections of future climate.

The full version of the IGSM was then run beginning from Jan. 1, 1977 using historical anthropogenic emissions of GHGs and other pollutants through 1997 and predicted emissions for 1998 through 2100. During this stage of the simulations all IGSM components are fully interactive: carbon uptake by the OCM and TEM are used in the atmospheric chemistry model and soil carbon changes simulated by TEM are used in NEM. Concentrations of all gases and aerosols as well as associated radiative forcings are calculated endogenously. The atmospheric chemistry model and NEM components use the same initial conditions for 1977 in all simulations. Short-lived species do not require a long spin-up period because they have relatively little inertia, while the long-lived species, including CO_2, N_2O, CH_4, and

CFCs, have been prescribed during spin-up and are restricted to observations over 1977–1997.

The 1977 to 1997 period provides additional information on the consistency of the ocean and terrestrial carbon uptake. Given data on anthropogenic emissions and actual atmospheric concentrations, total carbon uptake by the ocean and terrestrial systems can be estimated to have averaged 4.3 TgC/year during the 1980s. Carbon uptake by the ocean strongly depends on the values of climate parameters, especially K_v. Across the 250 runs, the implied distribution for oceanic carbon uptake averaged over the 1980s has a mean of 2.1 TgC/year with 95% bounds of 0.9 and 3.2 TgC/year. This distribution is quite similar to results from a more complete treatment of uncertainty in the OCM (Holian et al., 2001). Because we do not treat uncertainty in TEM for this study, carbon uptake by the terrestrial ecosystem shows too little variance. Thus for every sample parameter set, we calculate an additional sink/source needed to balance the carbon cycle for the decade 1980–1989, and retain this sink/source as a constant addition for each individual through the year 2100.

During the spin-up phase, as described in Forest et al. (2001), aerosol forcing is parameterized by a change in surface albedo and depends on historical SO_2 emissions and a scattering coefficient that sets the forcing level in response to the prescribed aerosol loading. In each simulation, this coefficient is used to set the sampled value of F_{aer}. In the period beyond 1977 using the full version of the IGSM, the sampled value of F_{aer} is now a function of the aerosol optical depth multiplier and the initial SO_2 emission. Based on the results of preliminary simulations, the following formula was obtained for the aerosol optical depth multiplier Cf (see Table 6 in Forest et al., 2001):

$$Cf = A * F_{aer}^{(1+x)}/E^{(1+y)},$$

where E is the global SO_2 emissions, $x = 0.035$ and $y = 0.0391$ and the value of A was defined from a reference simulation. The dependence on the initial SO_2 emissions reflects uncertainty in the present day aerosol loading. We use the aerosol optical depth multiplier to provide the sampled value of F_{aer}. Thus, the choice of parameters in each period of the simulation ensures a smooth transition in the net forcing between different stages of the run as well as consistency with the historical climate record.

2.4. DATA FOR PARAMETER DISTRIBUTIONS

The critical input data for uncertainty analyses are the probability distribution functions (pdfs) for the uncertain parameters. A key error frequently made in assembling such pdfs is to use the distribution of point estimates drawn from the literature rather than from estimates of uncertainty (e.g., standard deviation) itself. Examples of such errors are estimates of future emissions uncertainty based on literature surveys of emissions projections, or estimates of uncertainty in climate sensitivity based on their distribution from existing climate models. There is nothing inherently wrong with using literature estimates, but the point estimates of uncertain parameters should span the population of interest and not simply a distribution of mean estimates from different studies.

There can be a variety of problems with using literature estimates. For example, the distribution of emissions scenarios based on a literature review showed maximum probability at the level of one of the central emissions scenarios produced by the second assessment report of the IPCC (Houghton et al., 1996). However, subsequent evaluation of the same literature (Nakicenovic et al., 1998) indicates that many analysts simply adopted this scenario as a convenient reference to conduct a policy study, rather than to conduct a new and independent forecast of emissions. The frequent reappearance of this estimate in the literature should not be interpreted as indicating a particular judgment that the scenario was much more likely than others. Similarly, the fact that the IPCC scenarios span the range in the literature provides no evidence of whether they describe uncertainty in future emissions, although recent analyses (Wigley and Raper, 2001) have attempted to interpret them as such. Basing the distribution of climate sensitivity on the distribution of estimates from a set of climate models makes a similar mistake. There is no reason to expect that the climate sensitivities in this set of models provide an unbiased estimate of either the mean or the variance, because some models are simply slight variants, or use parameterizations similar to those in other models. But, just because one parent model has given rise to more models does not mean that the sensitivities of this group of models should be weighted more than another model – more versions does not make it more likely to be correct. The goal is to perform internally-consistent uncertainty analysis to understand the likelihood of different outcomes.

2.5. ANTHROPOGENIC EMISSIONS PROBABILITY DENSITY FUNCTIONS

Uncertainties in anthropogenic emissions were determined using a Monte Carlo analysis of the MIT EPPA model, which is a computable general equilibrium model of the world economy with sectoral and regional detail (Babiker et al., 2000, 2001). As emissions projections for all substances are derived from a single economic model, the projections are self-consistent with the economic activity projections. The correlation structure among emissions forecasts reflects the structure of the model. Specifically, because energy production and agriculture are simultaneous sources of many GHGs and air pollutants, there is a strong correlation among emissions of the various gases and aerosols (Webster et al., 2002). An approach that used different models for different sets of emissions might erroneously treat the distributions of emissions as independent. We used an efficient and accurate method for sampling the input parameter space to produce a reduced form (response surface) model (Tatang et al., 1997) of the underlying EPPA model. A full Monte Carlo analysis is then conducted using the response surface model.

Based on sensitivity analysis of the EPPA model, a limited set of EPPA input parameters was identified for uncertainty treatment. These were: labor productivity growth; autonomous energy efficiency improvement (AEEI); factors for emissions per unit of economic activity for agricultural and industrial sources of CH_4 and N_2O; factors for emissions per unit of economic activity in fossil fuel, agricultural and industrial sources of SO_2, NO_x, CO, NMVOC, BC, OC, and NH_3; and emissions growth trends for HFCs, PFCs, and SF_6. The underlying distributions were based on a combination of expert elicitation of the distributions (labor productivity and AEEI), on estimates of uncertainty in emission coefficients from the literature (i.e., not a distribution of point estimates), and statistical analysis of cross-section dependence of emissions per unit of economic activity on per capita income. Thus, we account for the uncertainty in today's global emissions, as well as the uncertainty in how quickly different economies around the globe will reduce pollutants as their wealth increases. Many derivative factors traditionally treated as uncertain parameters, such as energy prices, introduction of new technologies, sectoral growth, and resource exhaustion, are endogenously calculated in EPPA. The projections of these economic processes (and thus emissions from different activities) are uncertain but that uncertainty derives from the more fundamental uncertainty in productivity growth and energy efficiency and from the structure of the model.

2.6. LATIN HYPERCUBE SAMPLING UNCERTAINTY ANALYSIS

Sampling from the probability distributions for the uncertainty analysis is performed using Latin Hypercube Sampling (LHS) (Iman and Helton, 1988). LHS divides each parameter distribution into n segments of equal probability, where n is the number of samples to be generated. Sampling without replacement is performed so that with n samples every segment is used once. Samples for the climate parameters are generated from the marginal pdfs, and the correlation structure among the three climate model parameters is imposed (Iman and Conover, 1982). This ensures that the low probability combinations of parameters are not over-represented, as would be the case if the correlations were neglected.

We conducted two LHS uncertainty analyses for the period 1860–2100, in both cases using $n = 250$. One analysis included uncertainty in climate variables and emissions in the absence of policy. The second analysis restricted the emissions path for greenhouse gases, by assuming a policy constraint. The policy scenario chosen was one used in previous work (Reilly et al., 1999), which comes close to a 550 ppm stabilization case for reference climate model parameter values. It assumes that the Kyoto Protocol caps are implemented in 2010 in all countries that agreed to caps in the original protocol (i.e., including the United States even though the U.S. has indicated it will not ratify the protocol) (United Nations, 1997). The policy scenario also assumes that the Kyoto emissions cap is further lowered by 5% every 15 years so that by 2100 emissions of all greenhouse gases in all countries under the original Kyoto cap are 35% below 1990 levels. With regard to countries not capped by the Kyoto Protocol, the policy scenario assumes that they take on a cap in 2025 with emissions 5% below their (unconstrained) 2010 emissions levels. The cap is then reduced by 5% every 15 years thereafter so that these countries are 30% below their 2010 emissions by 2100. Because we assume no uncertainty in these caps, the emissions uncertainty is greatly reduced. Some emissions uncertainty remains, however, because there is no cap on any nation until 2010 and the cap for the developing countries is started even later and depends on their uncertain 2010 emissions. This cap is only applied to CO_2, and does not explicitly constrain other greenhouse gases or air pollutants, but because of the correlation between sources captured in the structure of the model, there will be some corresponding reduction in these other emissions as well.

3. Results and Discussion

3.1. ANALYSIS OF UNCERTAINTY WITH AND WITHOUT POLICY

In the absence of any climate policy, we find that the 95% bounds on annual CO_2 emissions by 2100 are 7 to 38 GtC/yr^{-1} with a mean of 19 GtC/yr^{-1}. This range is similar to that of the six SRES marker scenarios. However by explicitly providing the probability distribution, we reduce the chances that someone would incorrectly assume that scenarios resulting in 7 and 38 GtC/yr^{-1} are as likely as those that result in 19 GtC/yr^{-1}.

The biggest difference between our emissions distributions and the SRES (Nakicenovic et al., 2000) scenarios are for SO_2 projections. First, unlike the IPCC analysis, we consider the uncertainty in current annual global emissions, which is substantial: 95% bounds of 20 to 105 TgS/yr^{-1} with a mean of 58 TgS/yr^{-1} in 1995 (Olivier et al., 1995; Van Aardenne et al., 2001). Secondly, we consider the uncertainty in future SO_2 emissions controls. In all six of the SRES marker scenarios reported in the IPCC TAR, SO_2 emissions begin to steadily decline after about 2040. Thus, all these SRES scenarios assume that policies will be implemented to reduce sulfur emissions, even in developing countries, for all imaginable futures. In contrast, our study assumes that the ability or willingness to implement sulfur emissions reduction policies is one of the key uncertainties in these projections. Accordingly, our 95% probability range by 2100, 20 to 230 TgS/yr^{-1} with a mean of 100 TgS/yr^{-1}, includes the possibility of continuing increases in SO_2 emissions over the next century, or of declining emissions consistent with SRES. Neither extreme is considered as likely as a level similar to today's emissions. A large part of our uncertainty in SO_2 emissions can be traced to the fact that we are uncertain about current emissions. While there are many inventories of emissions by governments that purport to track emissions of pollutants, the apparent accuracy suggested by them does not reflect the underlying problems in measurement

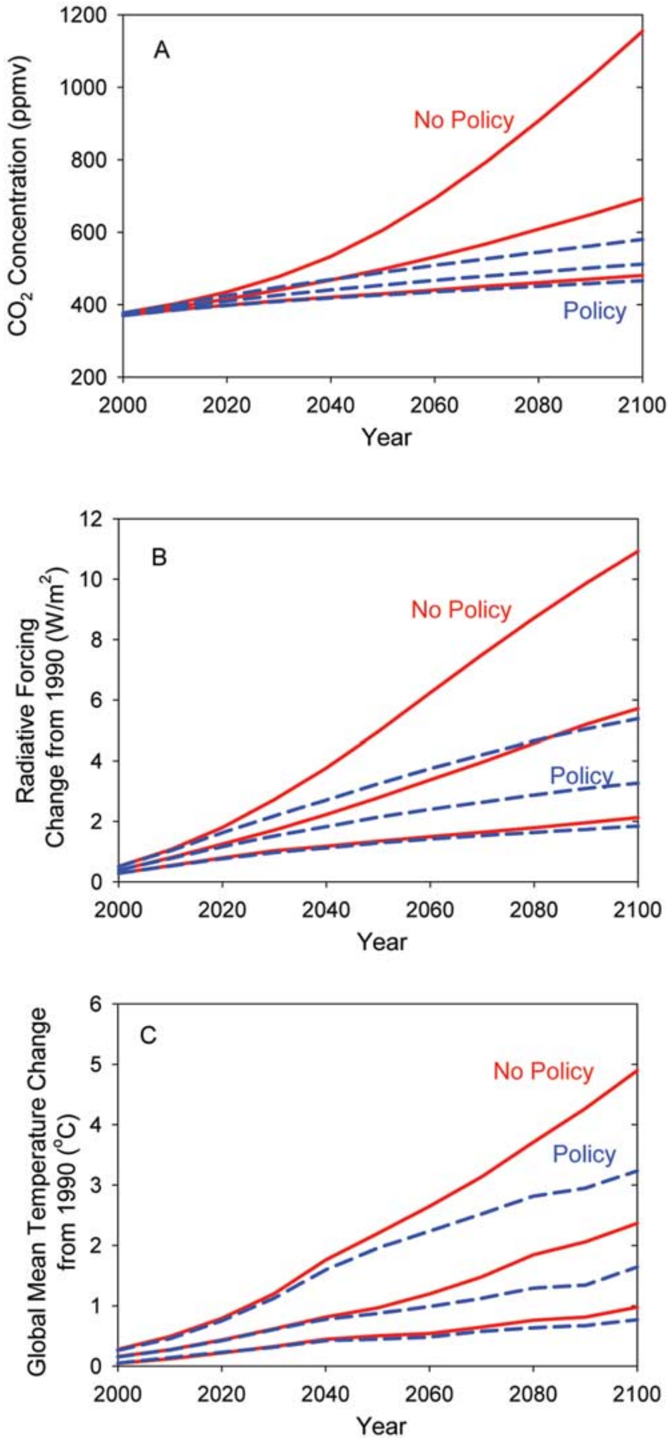

A
No Policy
Policy
CO2 Concentration (ppmv)
1200
1000
800
600
400
200
2000
2020
2040
2060
2080
2100
Year
B
No Policy
Policy
Radiative Forcing Change from 1990 (W/m2)
12
10
8
6
4
2
0
2000
2020
2040
2060
2080
2100
Year
C
No Policy
Policy
Global Mean Temperature Change from 1990 (°C)
6
5
4
3
2
1
0
2000
2020
2040
2060
2080
2100
Year

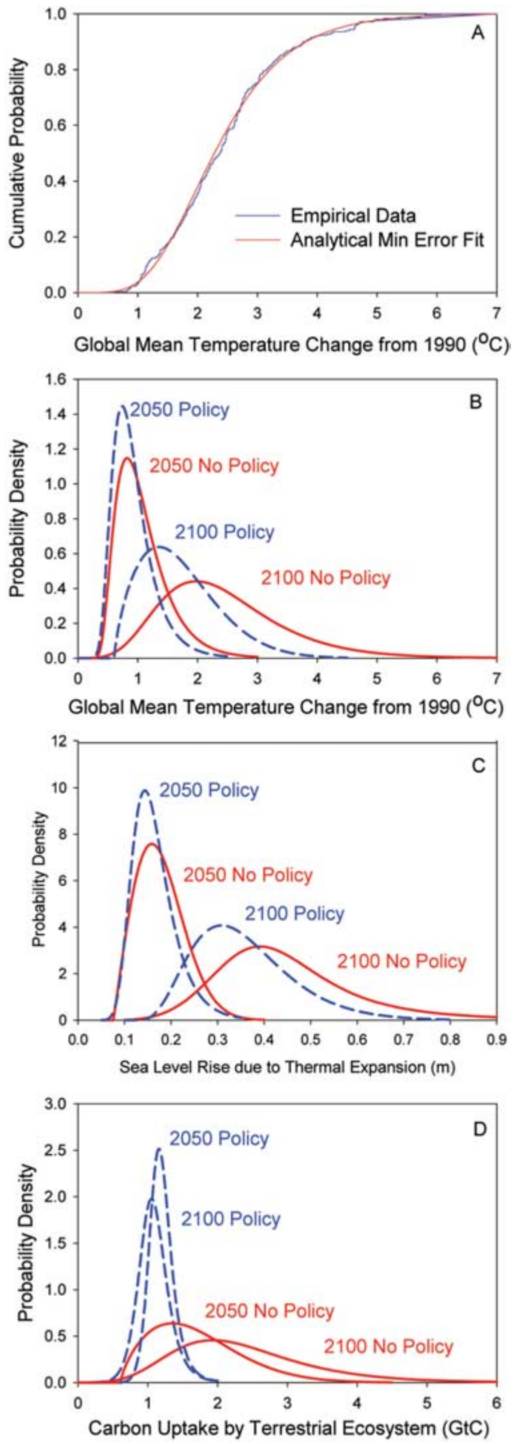
Figure 1.

or lack of comprehensive measurement of all sources. Thus emissions estimates often cannot be easily and accurately reconciled with observed pollutant levels. In considering emissions uncertainty, in contrast to the SRES approach, it is therefore essential to evaluate uncertainty in current emissions where that is important as well as in factors that affect growth in emissions.

The stringent policy causes the median CO_2 concentration in 2100 to be nearly 200 ppm lower (Figure 1A), the median radiative forcing to be about 2.5 Wm^{-2} lower (Figure 1B), and the global mean temperature to be about 1.0 °C lower (Figure 1C) than in the no policy case. The policy reduces the 95% upper bound for the increase in temperature change by 2 °C (from 4.9 to 3.2 °C).

We estimate probability distributions (Figure 2) for global mean temperature change, sea level rise, and carbon uptake by the terrestrial biosphere. For each model output, the cumulative distribution (CDF) of the 250 results is fit to an analytical distribution that minimizes the squared differences between the empirical and analytical CDFs. The comparison between the empirical and analytical distributions is shown only for temperature change in 2100 with no policy (Figure 2A) to illustrate the approximate nature of the fits and the caution needed in evaluating small probability regions (e.g., the tails of the distribution). Without policy, our estimated mean for the global mean surface temperature increase is 1.1 °C in 2050 and 2.4 °C in 2100. The corresponding means for the policy case are 0.93 °C in 2050 and 1.7 °C in 2100. The mean outcomes tend to be somewhat higher than the modes of the distribution, reflecting the skewed distribution – the mean outcome of the Monte Carlo analysis is higher than if one were to run a single scenario with mean estimates from all the parameter distributions. One can also contrast the distribution for the no policy case with the IPCC range for 2100 of 1.4 to 5.8 °C (Houghton et al., 2001). Although the IPCC provided no estimate of the probability of this range, our 95% probability range for 2100 is 1.0 to 4.9 °C. So, while the width of the IPCC range turns out to be very similar to our estimate of a 95% confidence limit, both their lower and upper bounds are somewhat higher. When compared to our no-policy case, our policy case produces a narrower pdf and lower mean value for the 1990–2100 warming (Figure 2B). But, even with the reduced emissions uncertainty in the policy case, the climate outcomes are still quite uncertain. There remains a one in forty chance that temperatures in 2100 could be greater than 3.2 °C and a one in seven chance that temperatures could rise by more than 2.4 °C, which is the mean of our no policy case. Hence, climate policies can reduce the risks of large increases in global temperature, but they cannot eliminate the risk.

Figure 1 (facing page). Projected changes in (A) atmospheric CO_2 concentrations, (B) radiative forcing change from 1990 due to all greenhouse gases, and (C) global mean surface temperature from 1990. The solid red lines are the lower 95%, median, and upper 95% in the absence of greenhouse gas restrictions, and the dashed blue lines are the lower 95%, median, and upper 95% under a policy that approximately stabilizes CO_2 concentrations at 550 ppm.



A
Cumulative Probability
Empirical Data
Analytical Min Error Fit
Global Mean Temperature Change from 1990 (°C)
B
Probability Density
2050 Policy
2050 No Policy
2100 Policy
2100 No Policy
Global Mean Temperature Change from 1990 (°C)
C
Probability Density
2050 Policy
2050 No Policy
2100 Policy
2100 No Policy
Sea Level Rise due to Thermal Expansion (m)
D
Probability Density
2050 Policy
2100 Policy
2050 No Policy
2100 No Policy
Carbon Uptake by Terrestrial Ecosystem (GtC)

Figure 2.

We also report uncertainty in sea level rise due to thermal expansion of the ocean and melting of glacial ice (Figure 2C). These two processes are expected to be the primary sources of sea level rise over the next century,⋆ and the policy reduces the 95% upper bound for sea level rise by 21 cm (from 84 cm to 63 cm).⋆⋆ Finally, the uptake of carbon into the terrestrial biosphere (Figure 2D) is much more uncertain and has higher mean values in the no policy case than in the policy case, due to the larger and continual increases in atmospheric CO_2 concentrations in the no policy case (Figure 1A).

As changes in surface temperature will not be uniform across the surface of the earth, it is useful to examine the dependence of projected temperatures on latitude (Figure 3). As in all current AOGCMs, the warming at high latitudes, as well as the uncertainty associated with this warming, is significantly greater than in the tropics, and the 95% upper bound warming with no policy is quite substantial in the high latitudes: there is a one in forty chance that warming will exceed 8 °C in the southern high latitudes and 12 °C in the north.

3.2. ROBUSTNESS OF RESULTS

To test the robustness of the results, we propagated a second set of probability distributions for the uncertain climate parameters. Instead of beginning with prior pdfs from expert judgment and using the observation-based diagnostics to constrain the pdfs, we begin with uniform priors (i.e., equal likelihood over all parameter values) and then constrain based on observations. This results in a joint pdf with greater variance, and is the pdf described in Forest et al. (2002). The resulting uncertainty in temperature change by 2100 is somewhat greater: the 95% probability bounds are 0.8° to 5.5 °C (Figure 4A). A larger increase in uncertainty is seen in sea level

Figure 2 (facing page). Cumulative probability distribution of 250 simulated global mean surface temperature change compared with fitted analytical probability distribution (A), and probability density functions for global mean surface temperature change (B), sea level rise from thermal expansion and glacial melting (C), and carbon uptake by the terrestrial biosphere (D) for 2050 and 2100. Solid red lines show distributions resulting from no emissions restrictions and dashed blue lines are distributions under the sample policy.

⋆ We exclude contributions from the Greenland and Antarctic ice sheets, but most studies indicate these would have a negligible contribution in the next century (IPCC, 2001; Bugnion, 2000).

⋆⋆ For cases of stabilization such as these, one observes about 70% of equilibrium warming by the time stabilization occurs, and the remaining 30% would be realized gradually over the next 200 to 500 years. Sea level rise takes even longer to equilibrate: at the time of stabilization one sees only about 10% of the ultimate equilibrium rise, with the remaining 90% occurring over the next 500 to 1000 years. Climate 'equilibrium' is, itself, a troublesome concept as there is natural variation in climate that takes place on many different time scales. And, stabilization is at best an approximate concept (Jacoby et al., 1996).

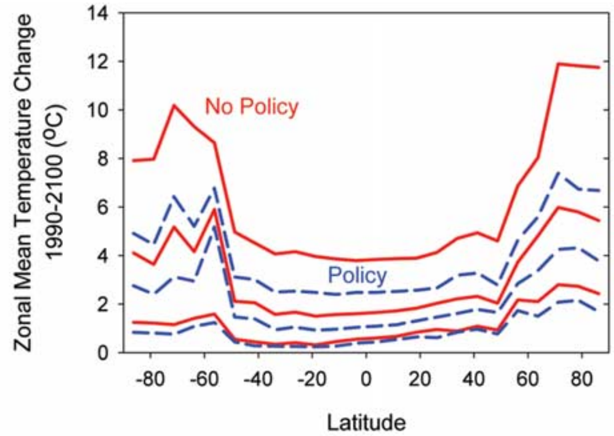


Figure 3

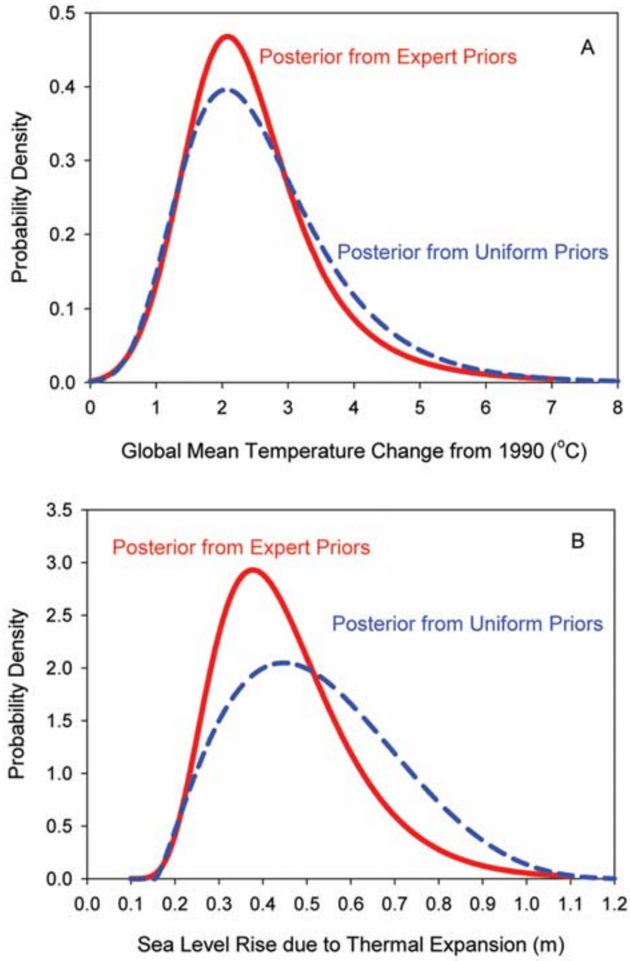


Figure 4

rise due to thermal expansion: the upper 95% bound increases from 83 cm to 87 cm and the probability that sea level rise will exceed 50 cm by 2100 increases from 32% to 49% (Figure 4B). This is largely due to the inability of the climate change diagnostics to constrain the uncertainty in rapid heat uptake by the deep ocean (Forest et al., 2002).

3.3. COMPARISON TO OTHER APPROACHES

Using results from model comparisons to describe uncertainty will tend to underestimate the variance in climate outcomes. As an illustration, we compare the transient climate response (TCR), which is defined as the change in global mean temperature at the time of CO_2 concentration doubling with a 1%/yr increase in CO_2 atmospheric concentrations, for the models given in Table 9.1 of the TAR (Cubasch et al., 2001) to the pdf of the TCR from the MIT IGSM (Figure 5). The pdf for the MIT model is calculated by propagating the distributions for climate sensitivity and heat uptake by the deep ocean through a reduced-form approximation of the MIT model response (Webster and Sokolov, 2000). For the IPCC model results, Figure 5 shows an empirical pdf, obtained by dividing the 19 TCR values given in Table 9.1 into 10 equally spaced intervals, and also an analytical distribution fit to the CDF of the empirical values. The central tendency of IPCC estimates is similar to what we have simulated but they exhibit a stronger peak and an overall narrower distribution. This supports the interpretation of the various model results as estimates of the mean or central tendency, and demonstrates that the distribution of the estimates of the mean will tend to underestimate the variance of the distribution.

Further research and observation may be able to resolve uncertainty in the science but much of the uncertainty in future anthropogenic emissions may be irreducible. Thus, another useful exercise is to understand the relative contributions of uncertainty in emissions and in the physical science. To examine the relative contribution of emissions and climate uncertainty, we use a reduced-form version (Sokolov et al., 2003) of our climate model to generate pdfs of temperature change by Monte Carlo analysis (Figure 6) based first on the uncertainty in the climate parameters alone with emissions fixed to reference (median) values, and second based on uncertainty in emissions alone with climate parameters fixed. Although

Facing page

Figure 3. The lower 95%, median, and upper 95% change in surface warming by latitude band between 1990 and 2100. Solid red lines show distributions resulting from no emissions restrictions and dashed blue lines are distributions under the sample policy.

Figure 4. Probability distributions for global mean temperature change (A) and sea level rise from thermal expansion (B) 1990–2100. Solid red lines show results from joint pdf of climate parameters where observations constrain expert judgment priors, and dashed blue lines show results where observations constrain uniform priors.

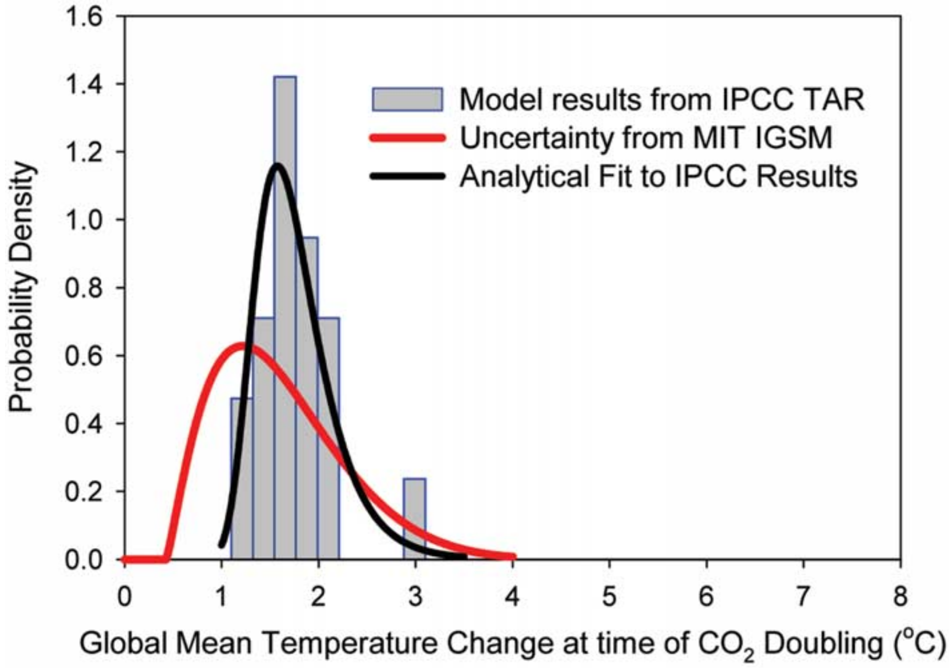


Figure 5

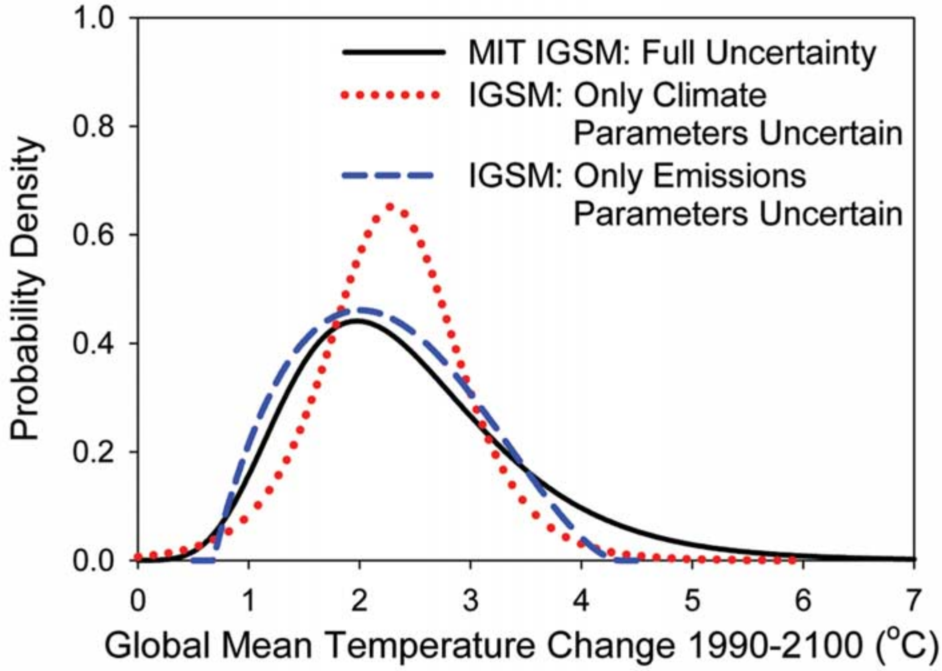


Figure 6

the mean values are similar, the variance in 2100 of either subset of uncertainties is substantially less; the standard deviation is 1.18 °C for all uncertainties, 0.69 °C for climate uncertainties only, and 0.76 °C for emissions uncertainties only. The probability that global mean surface warming would exceed 4 °C is 8.4% for the full study, but only 1.2% for climate uncertainties alone and 0.6% for emissions uncertainties alone. Either of the smaller sets would understate the risk of extreme warming as we understand the science of climate change today. If it were possible to significantly resolve climate science over the next few years, about one-third of the uncertainty, as measured by the standard deviation, could be reduced. Reducing the odds of serious climate change thus requires both improved scientific research and policies that control emissions.

Because the climate model parameters can be chosen such that the model reproduces the global scale zonal-mean transient results of a particular AOGCM (Sokolov et al., 2003), we can repeat the above experiment choosing parameter settings corresponding to specific AOGCMs. Three such cases, for GFDL_R15, HadCM3, and NCAR CSM, have been chosen because they represent a wide range of climate change results simulated by AOGCMs (Sokolov et al., 2003). To simulate such results, we first derive the conditional pdf of aerosol forcing from our constrained joint pdf of climate parameters, conditioned on the values of S and K_v that match the IGSM to a particular model (Figure 7A). We then draw 250 Latin Hypercube samples from the conditional aerosol pdf and use the original 250 samples of all emissions parameters. Finally, because of computation time considerations, we perform the Monte Carlo on a reduced-form model fit to the IGSM. The reduced-form model is a 3rd-order response surface fit based on the 500 runs of the IGSM (presented above) and has an R^2 of 0.97.

The simulated pdfs for surface warming 1990–2100 from these models (Figure 7B) indicate that any single AOGCM will have less variance in temperature change than a complete treatment of the uncertainty, not surprisingly, considering that the sensitivity and heat uptake are fixed. The mean estimates of temperature change for the models are ordered as one would expect given the climate parameter values that allow us to reproduce them with the MIT IGSM. In particular,

Facing page

Figure 5. Probability distributions for global mean temperature change at the time of CO_2 doubling with concentrations increasing at 1% per year in the MIT IGSM (no policy case) and for the range of model results summarized in Table 9 of the IPCC TAR.

Figure 6. Pdfs of global mean surface temperature change 1990–2100 from all uncertain parameters (black), only climate model parameters uncertain and emissions fixed (red), and only emissions uncertain with climate model parameters fixed.

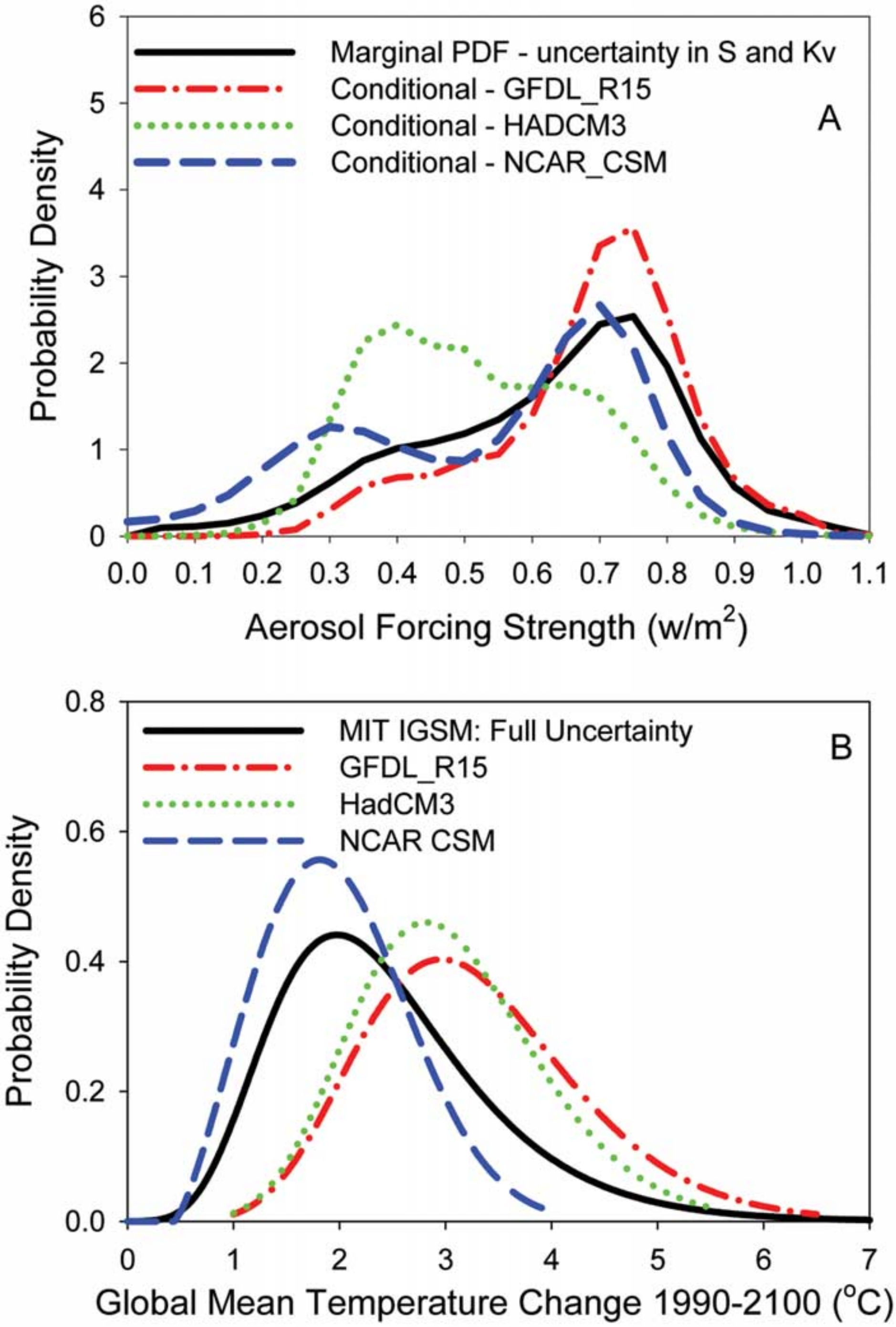


Figure 7. (A) The marginal pdf (black) for aerosol forcing along with three conditional pdfs, each derived from our joint distribution of climate parameters assuming the values for S and K_v that match the MIT IGSM results to GFDL R15 (red), HadCM3 (green), and NCAR CSM (blue). (B) Resulting pdfs of global mean surface temperature change 1990–2100 from the conditional aerosol distributions, the same emissions distributions, and fixed S and K_v.

the HadCM3 and GFDL models have a higher mean for their distribution of temperature change than the NCAR model, with the NCAR mean near the mean of the full distribution but with smaller variance.

4. Conclusions

The Third Assessment Report of the Intergovernmental Panel on Climate Change strove to quantify the uncertainties in the reported findings, but was limited in what could be said for future climate projections given the lack of published estimates. This study is a contribution to help fill that gap in the literature, providing probability distributions of future climate projections based on current uncertainty in underlying scientific and socioeconomic parameters, and for two possible policies over time. In reality, there will be the possibility to adapt climate policy over time as, through research and observation, we learn which outcomes are more likely. But decisions today can only be based on the information we have today. The work presented here is one attempt to bring together current knowledge on science and economics to understand the likelihood of future climate outcomes as we understand the science and economics today. A necessary part of the research on climate change is to repeat this type of analysis as our understanding improves so that we can better understand the policy relevance of these scientific advances.

As with all investigations of complex and only partially understood systems, the results presented here must be treated with appropriate caution. Current knowledge of the stability of the great ice sheets, stability of thermohaline circulation, ecosystem transition dynamics, climate-severe storm connections, future technological innovation, human population dynamics, and political change, among other relevant processes, is limited. Therefore abrupt-changes or ‘surprises’ not currently evident from model studies, including our uncertainty studies summarized here, may occur.

While our approach allows us to simulate climate responses over a range of different structural assumptions in 3D models, other structural features of our modeling system are fixed for this analysis even though alternative assumptions are also possible. We hope that uncertainty studies of other climate models will soon follow, making use of ever-increasing processor speeds, efficient sampling techniques, and reduced-form models to make uncertainty analyses feasible on even larger models that require more computational time.

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We thank Myles Allen for his assistance and support with the detection diagnostics. We also thank Steve Schneider and four anonymous reviewers for helpful comments and suggestions. This research was conducted within the Joint Program on the Science and Policy of Global Change with the support of a government-industry partnership that includes the Integrated Assessment program, Biological and Environmental Research (BER), U.S. Department of Energy (DE-FG02–94ER61937), the Methane Branch of the US EPA (grant X-827703–01–0), NSF grant ATM-9523616, Methods and Models for Integrated Assessment Program of the NSF (DEB-9711626), and a group of corporate sponsors from the United States, the European Community, and Japan.

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