MIT Joint Program on the Science and Policy of Global Change

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To inform processes of policy development and implementation, climate change research needs to focus on improving the prediction of those variables that are most relevant to economic, social, and environmental effects. In turn, the greenhouse gas and atmospheric aerosol assumptions underlying climate analysis need to be related to the economic, technological, and political forces that drive emissions, and to the results of international agreements and mitigation. Further, assessments of possible societal and ecosystem impacts, and analysis of mitigation strategies, need to be based on realistic evaluation of the uncertainties of climate science.

This report is one of a series intended to communicate research results and improve public understanding of climate issues, thereby contributing to informed debate about the climate issue, the uncertainties, and the economic and social implications of policy alternatives. Titles in the Report Series to date are listed on the inside back cover.

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Abstract

Future global climate projections are subject to large uncertainties. Major sources of this uncertainty are projections of anthropogenic emissions. We evaluate the uncertainty in future anthropogenic emissions using a computable general equilibrium model of the world economy. Results are simulated through 2100 for carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulfur hexafluoride (SF_6), sulfur dioxide (SO_2), black carbon (BC) and organic carbon (OC), nitrogen oxides (NO_x), carbon monoxide (CO), ammonia (NH_3) and non-methane volatile organic compounds (NMVOCs). We construct mean and upper and lower 95% emissions scenarios (available from the authors at 1^o x 1^o latitude-longitude grid). Using the MIT Integrated Global System Model (IGSM), we find a temperature change range in 2100 of 0.9 to 4.0 ^{o}C, compared with the Intergovernmental Panel on Climate Change emissions scenarios that result in a range of 1.3 to 3.6 ^{o}C when simulated through MIT IGSM.

Contents

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1. INTRODUCTION

Many human activities cause the release of substances that alter the radiative properties of the atmosphere. Projections intended to represent plausible transient climate change due to anthropogenic forcing must, therefore, rely on emissions projections produced by models of economic activity and technological change that determine the level of human activities and emissions rates from those activities. Such projections of changes in economic and technological forces are, however, subject to considerable uncertainty. The evaluation of uncertainty in economic and technological factors and the effects on forecasts of carbon dioxide emissions has a relatively long history (*e.g.*, Nordhaus and Yohe, 1985; Reilly *et al*., 1987) but the emissions forecasts associated with particular uncertainty limits, heretofore, have not been used to force complex climate models.

A major advance over the past decade has been the development of coupled ocean-atmosphere models combined with development of computational capacity to simulate transient climate change (IPCC, 2001), and complex climate models are now at a state of development where they are capable of using emissions scenarios generated by economic models. A second major advance on the atmospheric modeling front has been the coupling of atmospheric chemistry models with climate models so that the complex interactions of greenhouse gases, urban air pollutants, and other substances can be explicitly represented (Wang *et al*., 1998; Mayer *et al*., 2000). Economic modeling has made major advances as well, most recently in the ability to consistently model and project the human activities that lead to emissions of the many substances that affect climate directly or indirectly (Babiker, *et al*., 2001; Reilly *et al*., 1999; IPCC SRES).

These advances in economic and climate modeling make it timely, therefore, to reconsider uncertainty in emissions projections. In this paper, we describe the development of a consistent set of emissions scenarios with known probability characteristics based on projections of human activities over the next 100 years.[2] To produce these scenarios we make use of recent developments in uncertainty techniques (Tatang *et al*., 1997) and apply them to the Emissions Prediction and Policy Analysis (EPPA) model (Babiker *et al*., 2001), a computable general equilibrium model (CGE) of the world economy that projects the major greenhouse gases as well as other climatically or chemically important substances. We compare our results to the scenarios generated for the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES, 1999).

The next section begins with a brief discussion of uncertainty analysis and details of our approach. We then present the resulting distributions of emissions. Finally, we develop specific emissions scenarios with known probability characteristics and simulate resulting climate change using the MIT Integrated Global Systems Model (IGSM), comparing them to the SRES results also simulated through the MIT IGSM (Prinn *et al*., 1999; Reilly *et al*., 1999).

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[2] These scenarios are gridded at 1° x 1° latitude-longitude, and are available to interested researchers by contacting the corresponding author.

1.1 Uncertainty Analysis

There are two broadly different 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). Both approaches are evident in climate assessments, most notably the recent IPCC reports. Authors for the IPCC Third Assessment Report (TAR) were provided guidance encouraging them to move as far toward uncertainty quantification as possible. TAR authors were asked to identify the most important factors and uncertainties likely to affect conclusions, document ranges and distributions in the literature, quantitatively (when possible) or qualitatively characterize the distribution of values that a parameter, variable or outcome may take, and optionally to use formal probabilistic frameworks for assessing expert judgment (Moss and Schneider, 2000). The IPCC Special Report on Emissions Scenarios (SRES, 1999) uses the plausible scenario approach. The approach there was described as a “story line” analysis where all the scenarios developed were considered “equally valid,” the authors strongly resisting an assignment of quantitative or qualitative likelihoods to scenarios.

There can be great benefit to a “story line” approach as it allows one to explore in detail how particular sets of assumptions produce different or similar outcomes. One advantage is that in assessments involving a set of authors with widely diverging views, it is typically easier to present scenarios without attaching likelihoods. When there exist widely divergent “world views,” a term Edmonds and Reilly (1985) used to describe different views about future energy use and carbon intensity, one expert’s likelihood range may not include another expert’s most likely scenario making it as difficult to reach consensus on a likelihood ranges as on a mean or best guess case. A similar issue of consensus distributions also arises in expert elicitation in the contentious issue of whether or how to combine the judgments of different experts (Keith, 1996; Pate-Cornell, 1996). The scenario or “story line” approach allows scenarios from experts with widely varying “world views” to be considered “equally valid”, avoiding deadlock.

The alternative approach, uncertainty analysis, requires identification of the critical uncertain model parameters, quantification of the uncertainty in those 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 falls within some specified range.

In the end, the difference between formal quantitative uncertainty analysis and the story line scenario approach is not whether a judgment about likelihood of outcomes is needed but rather when and by whom the judgment is made. Scientists can use the tools of uncertainty analysis and their judgment to describe the likelihood of outcomes quantitatively or the assessment of likelihood can be left to those who actually must use the information; *i.e.* policy makers and the public who must ultimately decide whether the risks of climate change are great or small. Our views are that (1) it is important for experts to offer their judgment about uncertainty in their projections and (2) formal uncertainty techniques can eliminate some of the well-known cognitive biases that exist when people deal with uncertainty (Tversky and Kahneman, 1974). The evidence is strong that experts and laymen are equally prone to such biases and quantitative approaches can reduce if not eliminate these biases (Morgan and Henrion, 1990).

A unique aspect of the uncertainty approach we use is that we are able to produce emissions projections that are consistent with underlying economic, demographic, and technological assumptions across substances for any year and over time. Choosing the 95% upper confidence limit for CO_2, SO_2, and CH_4 as derived from an uncertainty analysis, for example, will produce a much more unlikely climate scenario than the 95% upper confidence[3] limit on total radiative forcing unless these emissions are perfectly correlated. We know, however, that coal mining and coal burning are, for practical purposes, perfectly correlated at the global level and that coal mining releases CH_4 and coal burning results in emissions of CO_2 and SO_2. Thus, we expect correlation in emissions of these three substances. The correlation is far from perfect, however, because there are other sources of all of these substances. Moreover, SO_2 and CH_4 emissions are subject to control measures that do not effect CO_2 emissions proportionately and both the sulfur content of coal and CH_4 release from coals mines varies greatly across regions, weakening the correlation among these emissions.

There is also likely to be a correlation structure for distributions across time. For example, a time profile of energy consumption that exhausts much of the cheaply available oil and gas in the first half of the century may lead to much greater reliance on higher emitting coal and shale oil in the latter half of the century whereas a time profile of energy consumption that relies on coal in the first half of the century will have more lower emitting natural gas available in the second half of the century.

Our method also allows us to recover the underlying parameter values that can lead to a particular case, where they lie in the input distributions we used, and the probability characteristics of the outcome associated with the case. By using this set of parameters, the scenario so constructed is consistent with the structure of the underlying model that includes the technological and economic relationships that create correlation among emissions and over time. In principle, one can then explore in detail the sensitivity of results to varying assumptions around such a case, allowing others to form different judgments about the likelihood, and conduct policy analysis using these cases as reference cases. While the set of parameter values associated with a particular set of outcomes is not unique, our approach allows a more structured development of families of scenarios that could serve as a basis for “story line” type analysis. This approach offers greater assurance of having explored a range of outcomes that brackets a specific likelihood range such as the 95 percent confidence limits.

Our approach involves: (1) choice of an appropriate model (2) sensitivity analysis to determine those parameters that are most important for particular outcomes (3) development of probability distributions for the parameters chosen for analysis (4) application of the Deterministic Equivalent Modeling Method (DEMM) approach to produce a polynomial reduced form fit of the EPPA model (5) Monte Carlo simulation of the reduced form polynomial fit developed using DEMM.

An Economic Emissions Model

The EPPA model is well suited for this task, as it was designed to simulate the world economy through time with the objective of producing scenarios of greenhouse gases (GHGs)

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[3] Conditional on a specific set of climate model assumptions.

and their precursors, emitted as a result of human activities. The simulation horizon is through the year 2100, producing emissions scenarios for the major greenhouse gases (carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulfur hexafluoride (SF_6))[4] and other pollutants and climatically or chemically important substances including aerosols and their precursors (from sulfur dioxide (SO_2), black carbon (BC) and organic carbon (OC)), nitrogen oxides (NO_x), carbon monoxide (CO), ammonia (NH_3) and non-methane volatile organic compounds (NMVOCs)). The model is a computable general equilibrium model of the economy with sectoral and regional detail as shown in **Table 1** (Babiker *et al*., 2001, 2000).

Greenhouse gas emissions (**Table 2**) and emissions of other climatically or chemically important substances (**Table 3**) come from many sources including fossil fuel combustion and production, agricultural production, biomass and waste burning, sewage from industry and households, and other industrial processes. Emissions are associated with specific EPPA sectors (Table 2) with emissions coefficients varying across sectors and regions to reflect differences among countries (Babiker *et al*., 2001). Base year inventories were developed based on existing inventories and literature on emissions coefficients (Babiker *et al*., 2001; Mayer and Hyman,

Table 1. *Dimensions of the EPPA-GTAP Model*

Production Sectors	Name	Countries and Regions	Name
Non-Energy		***Annex B***	
1. Agriculture	AGRI	United States	USA
2. Energy-Intensive Industries	ENERINT	Japan	JPN
3. Other Industries and Services	OTHERIND	Europe[a]	EEC
Energy		Other OECD[b]	OOE
5. Crude Oil including Tar Sands	OIL	Former Soviet Union	FSU
6. Natural Gas	GAS	Central European Associates	EET
7. Refined Oil	REFOIL		
8. Coal	COAL	***Non-Annex B***	
9. Electricity	ELEC	China	CHN
Future Energy Supply		India	IND
10. Shale Oil - producing OIL equivalent		Energy Exporters[c]	EEX
11. Coal Gas - producing GAS equivalent		Brazil	BRA
12. Renewable - Carbon-free electric		Dynamic Asian Economies[d]	DAE
Primary Factors		Rest of World	ROW
Labor			
Capital			
Fixed factor resources for coal, oil, gas, shale oil, and agriculture			

[a] The 15 nations of the European Union as of 1995
[b] Australia, New Zealand, Canada, Turkey, and the European Free Trade Area (Norway, Iceland, Switzerland)
[c] Middle East, Mexico, Venezuela, Indonesia and, because of the aggregation in GTAP, most of Africa except Morocco and South Africa are included in ROW
[d] South Korea, Phillipines, Thailand & Singapore
[e] All countries not included elsewhere, including South Africa, Morocco, much of Latin America and the Asia

[4] CFCs and HCFCs, stratospheric ozone depleting substances, are also greenhouse gases but are not included in EPPA. In simulations of the MIT IGSM future emissions are prescribed to be consistent with their phase-out under the Montreal Protocol (Wang *et al*., 1998).

Table 2. *Gas sources and EPPA Activities for Gases Listed in the Kyoto Protocol*

GAS and SOURCE	EPPA ACTIVITY
CO_2	
Coal, oil, and natural gas combustion	Coal, refined oil, & natural gas consumption in all sectors, and coal gasification
Cement production	Energy intensive industry production
Deforestation, biomass burning	Agriculture production
CH_4	
Coal seams	Coal production
Petroleum production	Oil production
Transmissions and distribution losses	Gas consumption
Landfill, wastewater gas	Household consumption
Industrial sewage, paper and chemicals	Energy intensive industry production
Industrial sewage, food processing	Other industry production
Rice, enteric fermentation, manure management, agr. waste, savannah, & deforestation burning	Agriculture production
N_2O	
Adipic and nitric acid production	Energy intensive industry
Refined oil products combustion	Refined oil consumption in all sectors
Coal combustion	Coal consumption in all sectors
Agricultural soils, manure management, agricultural waste, savannah, and deforestation burning	Agriculture production
HFCs	
Air conditioning, foam blowing, other	Other industry production
PFCs	
Semi-conductor production, solvent use, other	Other industry production
Aluminum smelting	Energy intensive industry production
SF_6	
Electrical switchgear	Electricity production
Magnesium production	Energy intensive industry production

2001). Because of the relatively aggregated structure of EPPA, emissions coefficients are subject to change over time to reflect structural change in economies beyond that represented in the aggregate sectoral structure of EPPA. For regional and local air pollutants (SO_2, carbonaceous aerosols, NO_x, CO, NH_3, and NMVOCs), emissions coefficients also depend on per capita income to reflect the fact that with rising incomes countries control pollution. The relationship between per capita income and emissions was statistically estimated based on the cross-section variation in emissions coefficients and per capita income among regions in the EPPA 1995 data base.

Sensitivity Analysis

The first step in performing an uncertainty analysis is to examine the sensitivity of the outcome of interest to model parameters, where each parameter is varied while holding other parameters to their reference values. The goal of this sensitivity analysis is to identify a limited number of parameters for formal uncertainty analysis. Arbitrarily small deviations can be misleading where uncertainties and equation formulations vary widely. We thus tested sensitivity to approximately two standard deviation changes for each parameter to take into account that the

Table 3. *Gas Sources and EPPA Activities for Other IGSM Gases Not Listed in the Kyoto Protocol*

GAS and SOURCE	EPPA ACTIVITY
SO_2	
Coal, oil, and natural gas combustion	Coal, refined oil, & natural gas consumption in all sectors
Non-ferrous metals, iron & steel, chemicals, & cement	Energy intensive industry production
Refinery processes	Refined oil production
Agricultural waste, savannah, deforestation, biofuels, and uncontrolled waste burning	Agricultural production
Biofuel use in households	Household consumption
NMVOCs	
Coal, petroleum products in transportation, and natural gas combustion	Coal, refined oil, and natural gas consumption in all sectors
Refinery processes	Refined oil production
Natural gas production processes	Natural gas production
Oil production processes	Oil production
Solvents, other industrial processes	Other industry production
Iron & steel, chemicals	Energy intensive industry production
Biofuel use in households	Household consumption
Agricultural waste, savannah, deforestation, biofuels, and uncontrolled waste burning	Agricultural production
NO_x	
Coal, oil, and natural gas combustion	Coal, refined oil, & natural gas consumption in all sectors
Cement, chemical, iron & steel manufacture	Energy intensive industry production
Refinery processes	Refined oil production
Biofuel use in households	Household consumption
Agricultural waste, savannah, deforestation, biofuels, and uncontrolled waste burning	Agricultural production
CO	
Coal, oil, and natural gas combustion	Coal, refined oil, and natural gas consumption
Chemical, iron & steel manufacture	Energy intensive industry production
Refinery processes	Refined oil production
Other industrial processes	Other industry production
Biofuel use in households	Household consumption
Agricultural waste, savannah, deforestation, biofuels, and uncontrolled waste burning	Agricultural production
Black Carbon and Organic Carbon	
Coal, oil, and natural gas combustion	Coal, refined oil, and natural gas consumption
Biomass and waste burning in agriculture	Agricultural production
Biomass burning in households	Household consumption
NH_3	
Manure management and fertilizer use	Agricultural production
Sewage	Household consumption

uncertainty range is much wider for some parameters than for others. Our interests are in emissions of the multiple greenhouse gases and other air pollutants including aerosols. Sensitivity results for CO_2, CH_4, N_2O, HFCs, SO_2, and NO_x for year 2100 emissions over the period 2000–2100, are shown as the range (difference between high and low emissions) as a percentage of reference emissions (**Table 4**). HFCs are representative of how EPPA projects the other high GWP gases, SF_6 and PFCs. SO_2 and NO_x are representative of how EPPA projects other air pollutants.

Table 4. *Sensitivity of Cumulative Emissions 2000-2100 to uncertain EPPA Parameters, Range of Emissions (High – Low) as % of Reference Emissions*

Uncertain Parameter	CO_2	CH_4	N_2O	HFC	SO_2	NO_x
Labor Productivity Growth: Annual Rate	57.7	65.4	47.9	50.2	38.5	54.8
Energy Efficiency Improvement: Annual Rate	51.5	14.3	6.0	6.9	24.5	16.6
Elasticity of Substitution: Energy and Labor-Capital	22.7	8.2	0.1	0.5	12.0	9.3
Elasticity of Substitution: Oil, Coal, and Gas	20.2	7.4	1.7	0.2	10.2	5.3
Elasticity of Substitution: Labor and Capital	17.2	15.5	9.8	9.4	11.4	14.3
Non-Carbon Electricity: Cost	7.1	2.1	0.2	0.0	4.5	3.7
Fossil Resources: Quantity available	5.6	1.0	2.1	0.8	10.1	9.8
Armington Elasticity: Internationally Traded Goods	3.1	2.6	0.5	1.7	0.5	4.4
Capital Stock: Percent Vintaged	2.9	4.9	5.8	6.7	17.7	23.7
Synthetic Gas: Cost	2.5	1.5	0.0	0.0	0.3	0.4
Shale Oil: Cost	1.9	1.5	0.7	0.1	2.9	2.8
Oil Price 2000-2020: Change from 1995	1.3	0.3	1.0	0.6	2.4	2.0
Land in Agriculture: Productivity	0.9	1.3	3.3	1.3	0.3	1.3
Nuclear Generation: Cost	0.2	0.1	0.0	0.0	0.1	0.1
Emissions Coefficients						
CH_4, Industrial Sources	0.0	51.6	0.0	0.0	0.0	0.0
CH_4, Agricultural Sources	0.0	37.9	0.0	0.0	0.0	0.0
Non-GHGs, Fossil Fuel Burning	0.0	0.0	0.0	0.0	143.3	127.0
Non-GHGs, Industrial Sources	0.0	0.0	0.0	0.0	12.3	16.3
Non-GHGs, Agricultural Sources	0.0	0.0	0.0	0.0	7.5	18.9
N_2O, Agricultural Sources	0.0	0.0	126.2	0.0	0.0	0.0
N_2O, Industrial Sources	0.0	0.0	35.3	0.0	0.0	0.0
HFC Emissions	0.0	0.0	0.0	602.7	0.0	0.0
PFC Emissions	0.0	0.0	0.0	0.0	0.0	0.0
SF_6 Emissions	0.0	0.0	0.0	0.0	0.0	0.0

Probability Distributions of Uncertain Parameters

The computational demands of the DEMM approach require limiting the number of independently sampled uncertain parameters where possible. Based on the sensitivity analysis above, we identified 12 parameters shown in **Figures 1** and **2** for the formal uncertainty analysis, normalized so that the median is 1.0. This is reduced to eight independent sets of probability distributions to sample from, and assumes perfect correlation within each set:

1) Labor productivity growth—all regions correlated,
2) AEEI—all regions correlated,
3) Agricultural sources of CH_4 and N_2O,
4) Industrial sources of CH_4 and N_2O,
5) Industrial sources of HFCs, PFCs, and SF_6,
6) Fossil fuel combustion sources of SO_2, NO_x, CO, NMVOC, BC, OC, and NH_3,
7) Agricultural sources of SO_2, NO_x, CO, NMVOC, BC, OC, and NH_3, and
8) Industrial sources of SO_2, NO_x, CO, NMVOC, BC, OC, and NH_3.

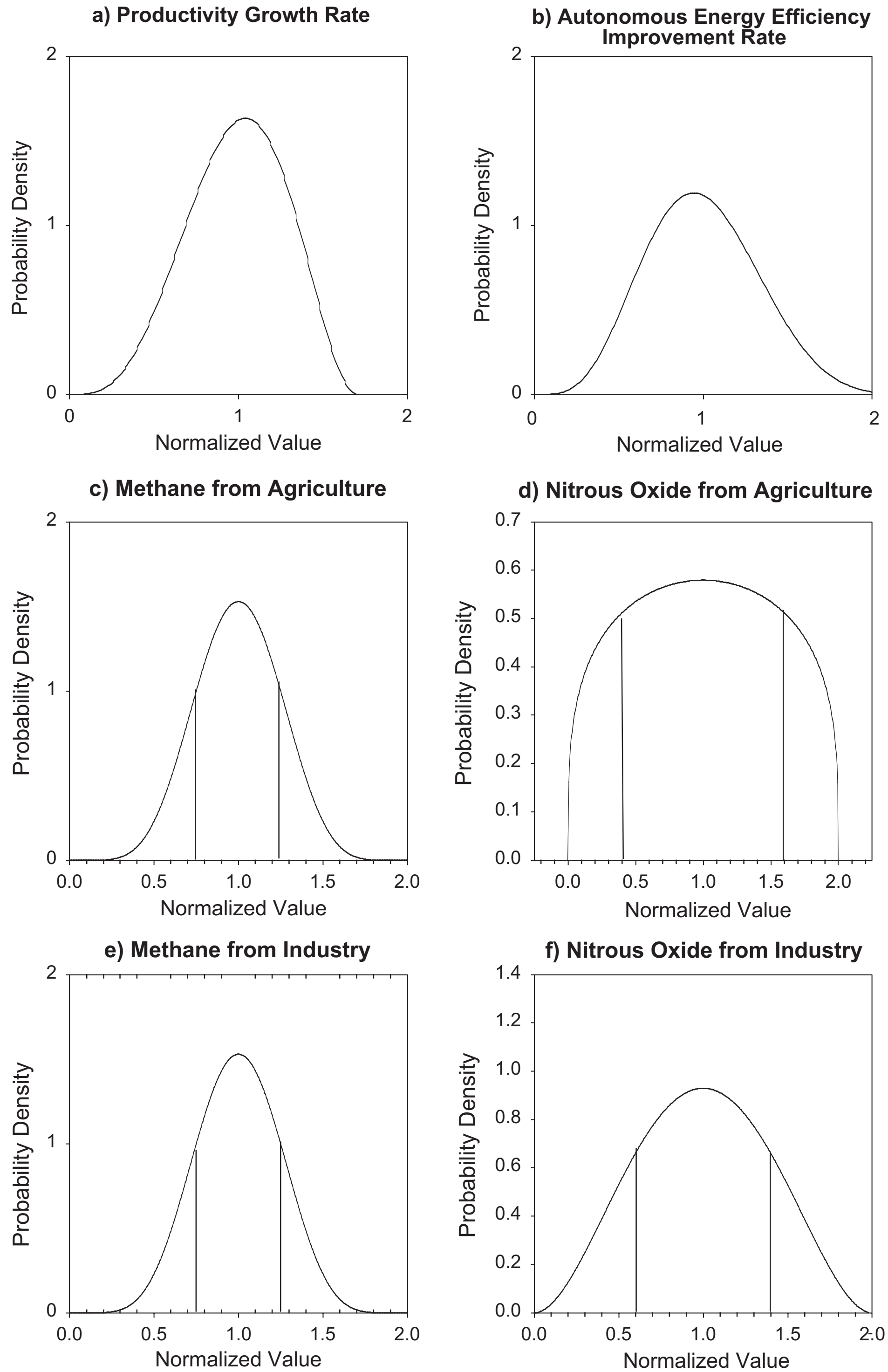

Figure 1. Normalized probability distributions (median = 1.0) for model inputs. Panels (a) labor productivity growth, (b) autonomous energy efficiency improvement rate, (c) CH_4 emissions coefficient from agricultural activities, (d) N_2O emissions coefficient from agricultural activities, (e) CH_4 emissions coefficient from industrial activities, and (f) N_2O emissions coefficient from industrial activities. Vertical lines show the standard deviations used to construct the distributions.

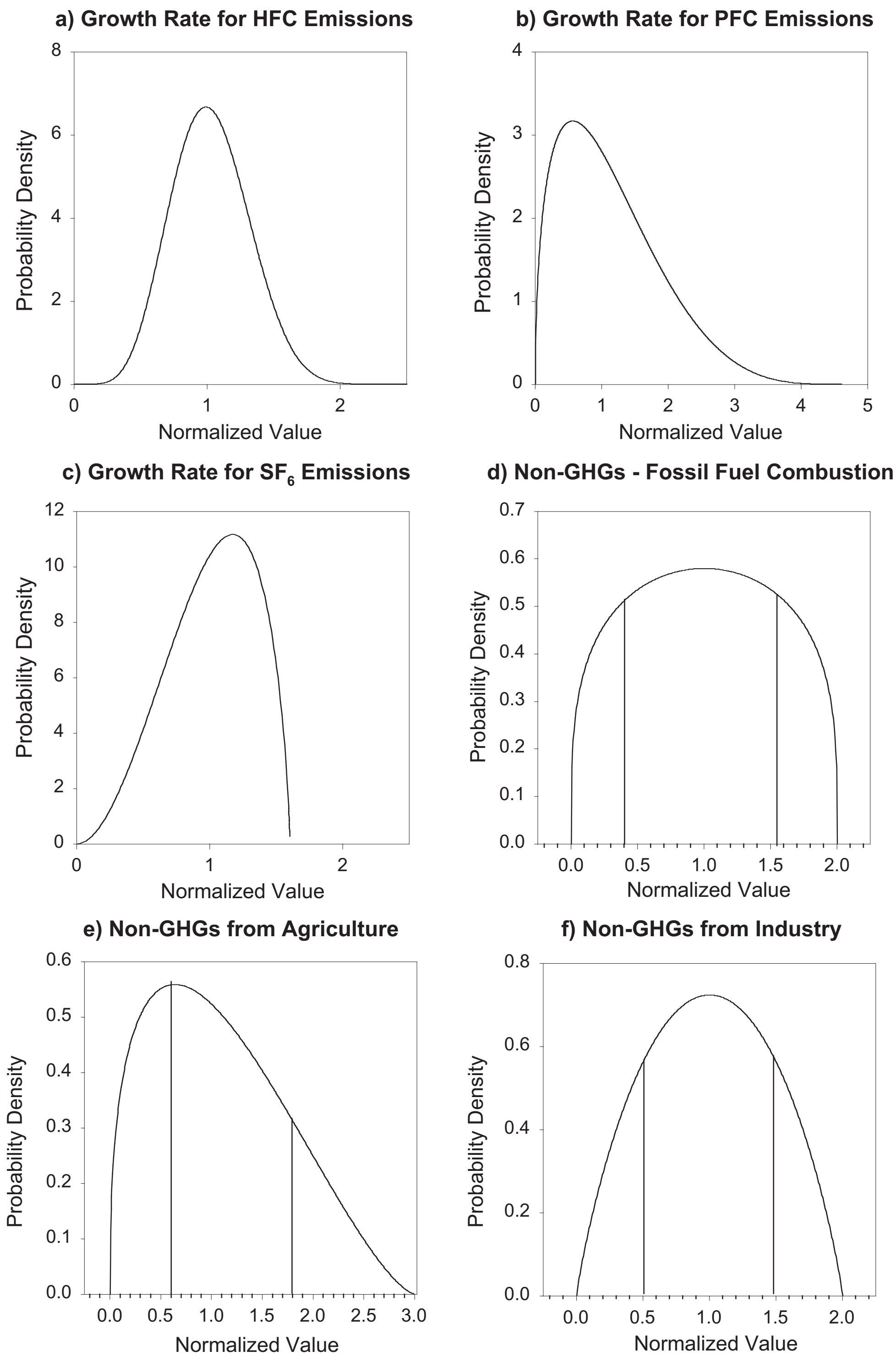

Figure 2. Normalized probability distributions (median = 1.0) for model inputs. Panels (a) HFC emissions growth rate, (b) PFC emissions growth rate, (c) SF_6 emissions growth rate, (d) coefficient of GNP/capita relationship for non-GHGs from combustion, (e) non-GHGs from agricultural activities emissions factor, and (f) non-GHGs from industrial activities emissions factor. Vertical lines show the standard deviations used to construct the distributions.

We constructed the distributions for uncertain parameters through expert elicitation and from data obtained from the literature. The probability distributions for labor productivity growth and AEEI were obtained by expert elicitation. Five economists[5] participated in a protocol, each providing fractiles for the distribution for these variables. The five probability distributions for each quantity were then combined by equally weighting each expert's assessment. The experts' beliefs about the distribution of GDP growth rather than labor productivity were assessed as the experts indicated greater familiarity with estimates of GDP growth. As modeled in EPPA, there is a very close relationship between GDP growth (an output of EPPA) and the labor productivity growth required to produce that GDP growth, assuming all other parameters at reference values. Separate distributions for labor productivity growth were assessed for each of the EPPA regions, but in this uncertainty study we treat growth in all regions as perfectly correlated. Similarly, distributions for AEEI were elicited from the experts for OECD regions and separately for non-OECD regions, but treated as perfectly correlated during the random sampling.

The remaining parameters reflect uncertainties in emissions per unit of economic activity, which we refer to as emissions coefficients. Uncertainties in current emissions of CH_4 and N_2O from anthropogenic sources are large (**Table 5**) and for N_2O the range of uncertainty differs from agricultural and industrial sources. The range in the estimates of methane emissions is from the EDGAR v2.0 study (Olivier *et al*., 1995). Ranges for N_2O emissions are from Mosier and Kroeze (1998). These ranges are interpreted as one standard deviation from the mean.

Alternative scenarios for emissions of HFCs, PFCs, and SF_6 are given in Harnisch *et al*. (2000). The major uncertainty surrounding these gases is how emissions per unit of economic activity will change in the future as current anthropogenic emissions are relatively well-constrained by measurements of global concentrations. Thus, for these gases, we treated as uncertain the change in their emissions coefficients over time. The time trend that best fits the emissions coefficient data is exponential (HFCs and SF_6) and linear (PFCs). Three sets of time trend parameters were estimated, one each for the reference, the high, and the low cases in Harnisch (2000). For HFCs and SF_6 the estimated equations were of the form:

$$ef(t)_i = a_i e^{c_i t}$$

Table 5. *Annual Global Total Emission Estimates*

	Natural		Anthropogenic			Total	
CH_4 [Tg CH_4]	160	(110 – 210)	375		(300 – 450)	535	(410 – 600)
N_2O [Tg N]	9	(4.3 – 14.7)	7.2		(2.1 – 19.7)	16.2	(6.4 – 34.4)
NO_x [Tg N]	19.3	(6 – 35)	31.1		(16 – 46)	50.4	(22 – 81)
SO_2 [Tg S]	32	(25 – 40)	70		(69 – 76)	102	(95 – 116)
CO [Tg CO]	370	(280 – 960)	925		(600 – 1250)	1295	(880 – 2210)
BC [Tg C]		—	6.5	*fossil fuel*	(1.8 – 13)	13.7	(3.8 – 26)
			7.2	*biomass*	(2 – 13)		
OC [Tg mass]	7.8	(??)	7.5	*fossil fuel*	(0.75 – 15)	59.3	(5.2 – 95)
			44	*biomass*	(4.4 – 80)		

Source : Summarized from Olivier *et al* . (1995), Seinfeld and Pandis (1998), and Mosier and Kroeze (1998).

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[5] The participating experts were: Henry Jacoby, Richard Eckaus, A. Denny Ellerman, John Reilly, and Mustafa Babiker.

where *i* is an index for the case (reference, high, or low), *ef* (*t*) is the emissions coefficient factor in time *t*, a is a constant, and *c* is the estimated trend parameter. For PFCs:

$$ef(t)_i = a_i + c_i t$$

Then, in all cases, the actual emissions are calculated as:

$$emi(t,i) = activitylevel(t) * emicoef(t) * ef(t,i)$$

where *emi* is the emissions (of HFCs, PFCs, or SF_6) at time *t* for sample *i* from the distribution, *activitylevel* is the level of economic activity in the industrial sectors ($), *emicoef* is the reference emissions coefficient (kt/$), and *ef* is the uncertainty factor calculated as above.

Distributions are the best-fit Beta distribution for the *a* parameter where *i* = *reference* is the median and *i* = *high*, *low* are interpreted as the 95 percentile values. The estimates were normalized, with $a_{ref} = 1.0$, so this factor could be used directly as a multiplier to the reference emissions coefficients in EPPA.

Current emissions of the other pollutants, including SO_2, NO_x, CO, NMVOCs, and particulates are subject to a substantial uncertainty (Table 5). As above, emissions from each source activity are treated as independent, while the emissions of each non-GHG from a given activity is perfectly correlated during sampling (*e.g.*, SO_2 and NO_x from agriculture are correlated). Estimates of the uncertainty in emissions from agricultural and industrial activities (not including fuel combustion) are based on Edgar v2.0 data (Olivier *et al*., 1995) and Seinfeld and Pandis (1998). We approximate one standard deviation limits in emissions from industrial sources as ±50% of the mean. Uncertainty in emissions from agricultural sources is somewhat wider and skewed towards higher emissions with an upper standard deviation of +80% of the mean and a lower standard deviation of –40%.

The dominant source of these other pollutants is the combustion of fossil fuels. As described above, the emissions coefficients over time for each species is fit as a power series function of GNP per capita,

$$ef = a * (GNP / capita)^c$$

except for SO_2 emissions, which are fit as an exponential function,

$$ef = a * \exp^{(-c*(GNP / capita))} .$$

The values of the parameters *a* and *c* are estimated based on cross-sectional data, along with an estimate of the standard error. The uncertainty in the emissions from fuel combustion is then represented as the average standard error for the parameter *a* in these functions, which is ±60% of the mean. Uncertainty in the evolution of GNP per capita is driven by the uncertainty in labor productivity growth. Together these two uncertainties encompass a wide range of possible future aerosol and pollutant emissions as a function of the growth of the economy and how emissions are reduced as wealth increases.

In **Table 6** we provide the fractiles for labor productivity for each region and for the AEEI for OECD and Non-OECD. In **Table 7** we show fractiles of 1995 emissions for CH_4, N_2O and the urban air pollutants. We provide emissions rather than the coefficients because they can be more readily compared with other data on emissions. The units associated with the coefficients themselves are MT/dollars of sector activity and are unique to the specific EPPA economic data set and sector aggregation. Table 7 also provides fractiles for the coefficient trend parameters for HFCs, PFCs, and SF_6.

The DEMM Approach

The Deterministic Equivalent Modeling Method (DEMM)[6] is used to obtain approximations for the model responses (Webster and Sokolov, 2000; Tatang *et al*., 1997), and perform Monte Carlo on the approximations. DEMM is similar to response surface replacement methods (Downing *et al*., 1985) in which typically a linear model of the uncertain output as a function of the uncertain parameters is calculated from a fractional factorial design, and Monte Carlo is applied to the response surface. DEMM improves upon these methods with respect to the choice of the basis functions, the choice of points to evaluate, and most importantly the ability to capture low-order non-linearities. DEMM treats uncertain model responses as random variables, which are represented as expansions of orthogonal polynomials. These orthogonal polynomials are derived from the input parameter PDFs. The coefficients of the expansion are calculated from simulations of the model. The method of choosing parameter values at which to run the model is analogous to Gaussian Quadrature (Press *et al*., 1992): the values used are the roots of the orthogonal polynomials one order higher than that of the approximation. These samples will be distributed over parameters' joint probability space. Additional runs must be used to check whether the approximation has a reasonably small error. The roots of the orthogonal polynomials two orders higher than the approximation are used to generate the parameter values for checking, both because they will interleave the points used to solve the approximation and because if a higher order is needed

Table 6. *Fractiles of Initial GDP and AEEI Distributions*

Initial GDP Growth Rate *(% per yr)*			
Region	**2.5%**	**50%**	**97.5%**
USA	1.65	3.34	4.54
JPN	1.22	2.64	3.65
EEC	1.38	2.75	3.72
OOE	1.39	2.79	3.79
EEX	0.70	3.03	5.04
CHN	1.67	5.24	8.51
FSU	1.69	3.32	4.81
IND	1.94	4.84	7.33
EET	1.88	3.84	5.63
DAE	1.34	4.41	7.06
BRA	–0.39	3.20	6.29
ROW	0.37	3.76	6.68
AEEI *(% per yr)*			
OECD	0.25	0.96	1.54
Non-OECD	0.23	1.13	1.79

Note: GDP rates are for the initial period, after which they approach an asymptotic limit of 1% for OECD regions 2% for non-OECD regions.

Table 7. *Fractiles of 1995 Global Emissions Distributions and Trends*

Parameter	2.5%	50%	97.5%	Units
CH_4 Agricultural	41.7	163.5	341.0	MegaTons (MT) CH_4 from Agricultural Sources
CH_4 Industrial	37.0	145.2	302.7	MT CH_4 from Industrial Sources
N_2O Agricultural	0.8	8.4	16.1	MT N_2O from Agricultural Sources
N_2O Industrial	0.3	1.1	1.9	MT N_2O from Industrial Sources
SO_2 from Fossil Fuels	10.4	115.2	220.1	MT SO_2 from Fossil Fuels
SO_2 Agricultural	0.7	7.6	14.5	MT SO_2 from Agricultural Sources
SO_2 Industrial	5.5	31.7	58.0	MT SO_2 from Industrial Sources
HFCs Trend	–9.8%	0%	14.8%	Annual exponential rate of change relative to reference
SF_6 Trend	–6.8%	0%	4.6%	Annual exponential rate of change relative to reference
PFCs Trend	–0.148	0	0.35	Annual rate of departure from reference (MT/yr)

[6] Tatang *et al*. (1997) use the name Probabilistic Collocation Method (PCM), but the method is identical. DEMM has replaced the name PCM because it better describes the method.

these runs are immediately available. DEMM typically converges on estimates of the mean, variance, and extreme fractiles of multiple responses by second or third order expansions (for 2 parameters, 3rd order requires 10 simulations to solve the approximation, plus several more to assess the accuracy) whereas other methods such as Latin Hypercube sampling (LHS) (McKay *et al.*, 1979) requires more runs to accurately represent higher order moments.

The approximation of model responses by DEMM has additional advantages. Information on the sensitivity to individual parameters is accurately represented in the expansion, allowing the evaluation of relative contribution to uncertainty without additional simulations. Finally, alternative PDFs for parameters can be propagated through the approximation without any additional runs of the true model, as long as the new PDFs do not extend beyond the range for which the approximation has been validated. LHS and other methods would require new sets of simulations at additional computational cost.

1.2 Emissions Uncertainty Results

Using DEMM, we propagate the uncertainty in 8 independent sets of input parameters by estimating 4th order polynomial expansions, requiring 1300 runs of EPPA for estimation and verification. The errors in the reduced form model were all less than 0.1% of the mean values, and most are less than 0.01% of the mean. Monte Carlo simulation is then performed on the reduced form model using 10,000 random samples from the parameter distributions. The resulting samples of emissions of each species at each time period are then used to construct probability distributions.

The resulting uncertainty in greenhouse gas emissions is shown in **Figure 3**, which indicate the median, +/- one standard deviation (67%), and +/- two standard deviations (95%) for the emissions of each gas. Also shown in Figure 3 are the emissions from the six representative scenarios from the IPCC SRES. Although the SRES scenarios do not have an associated probability, it is useful to compare them to our probabilistic bounds. CO_2 emissions from the SRES scenarios spread over much of our 95% range (Figure 3a). This is not surprising, since socioeconomic models of many types have been used to project CO_2 emissions for nearly two decades, and modeling studies tend to be fairly consistent (Weyant and Hill, 1999). But while the range itself is similar, the distributions are not. The SRES has a lower bias among its scenarios, with four of the six SRES scenarios well below our median emissions in 2100. Furthermore, two of those project lower CO_2 emissions by 2100 than our 95% lower bound. The time path of emissions is even less consistent between the two methods; the SRES scenarios are biased higher than our distributions before 2040, after which time some of the SRES change the trend.

Emissions projections of other greenhouse gases are less consistent between our ranges and the IPCC's. One significant difference is that the IPCC assumes that global emissions of all gases are known for 1990–2000. In fact, as discussed in the previous section, there is considerable uncertainty in current global emissions, particularly emissions resulting from agricultural activities and emissions from developing countries. Perhaps as a result of our treatment of current uncertainty as well as future trends, we find a larger range of uncertainty in non-CO_2 greenhouse gas emissions than the IPCC does. SRES projections of CH_4 and N_2O span our 67% probability bounds. Four of the six N_2O scenarios are near the lower 67% bound while the other two are near the upper 67% bound, and none are close to our mean.

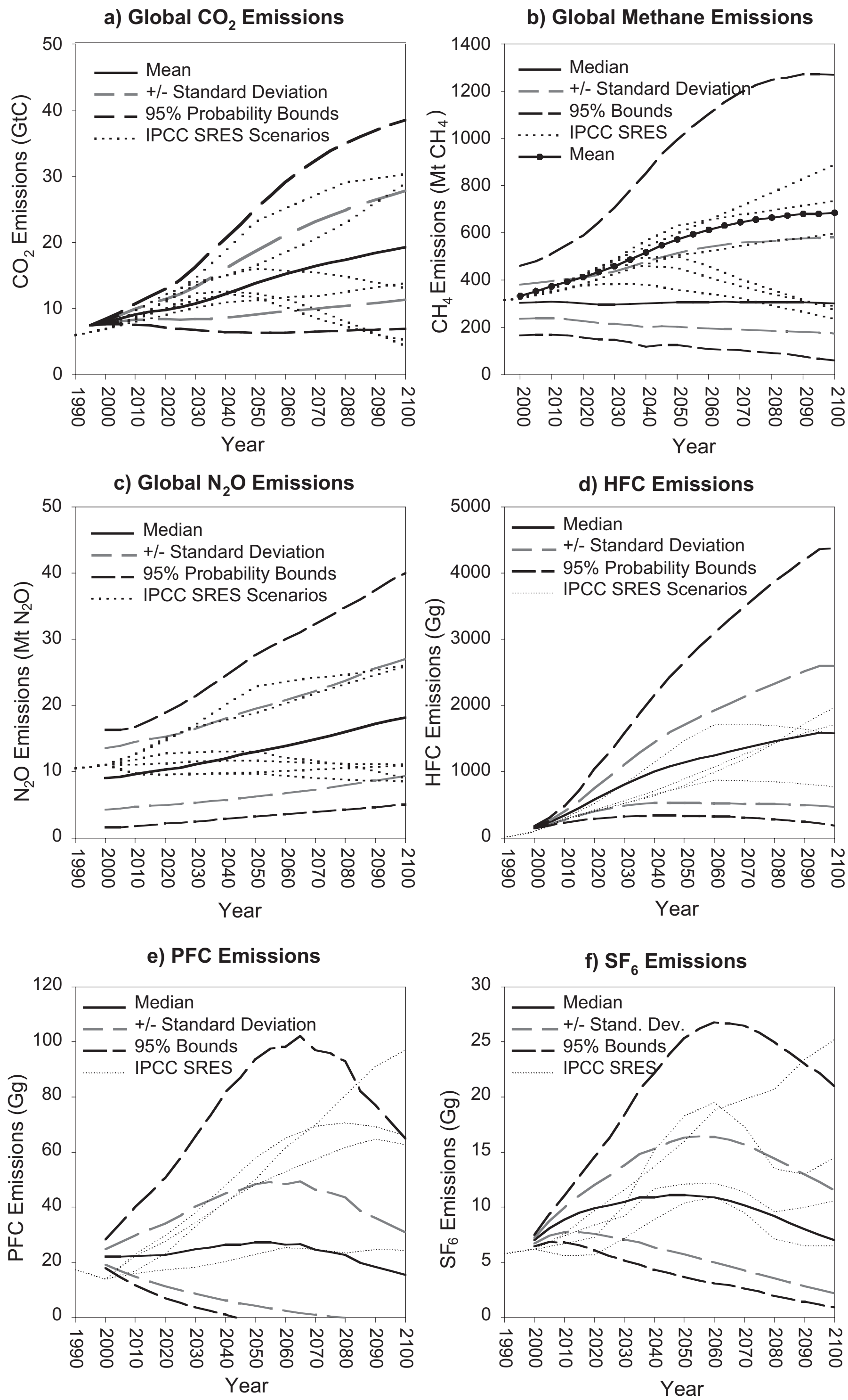

Figure 3. Emissions of primary anthropogenic greenhouse gases. Panels (a) carbon dioxide, (b) methane, (c) nitrous oxide, (d) HFCs, (e) PFCs, and (f) SF_6. The solid lines show the mean emissions based on 10,000 runs, long/gray dashed lines show +/- 68%, shorter/black dashed lines show +/- 95% probability bounds, and dotted lines show the emissions from the six representative SRES scenarios.

For the F-gases (hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride) the IPCC has developed four representative scenarios (Fenhann, 2000; SRES, 2000). Their projections of HFCs emissions span considerably less than our 67% probability range. The higher HFCs emission trajectories in EPPA permit strong increases of emission levels as a consequence of increases of GDP. In contrast, the SRES emissions remain capped because of a prescribed de-coupling of HFCs from increases of GDP due to market saturation. The low HFCs emission levels, which are also possible within EPPA, are also not seen in SRES, as its authors seem fairly pessimistic about the potential for emission control through containment and substitution by alternative fluids. For PFCs the authors of SRES seem skeptical about the availability of technological options to reduce PFCs emissions from aluminum production eventually leading to PFCs free production. The picture is similar for SF_6: SRES again does not allow for a permanent de-coupling of emissions from economic development, which in EPPA becomes possible through technological change. All in all, SRES—with respect to emissions of fluorinated gases—assumes a fairly deterministic emission-GDP relation that does not allow for major technological changes to lead to truly significant reductions of emissions.

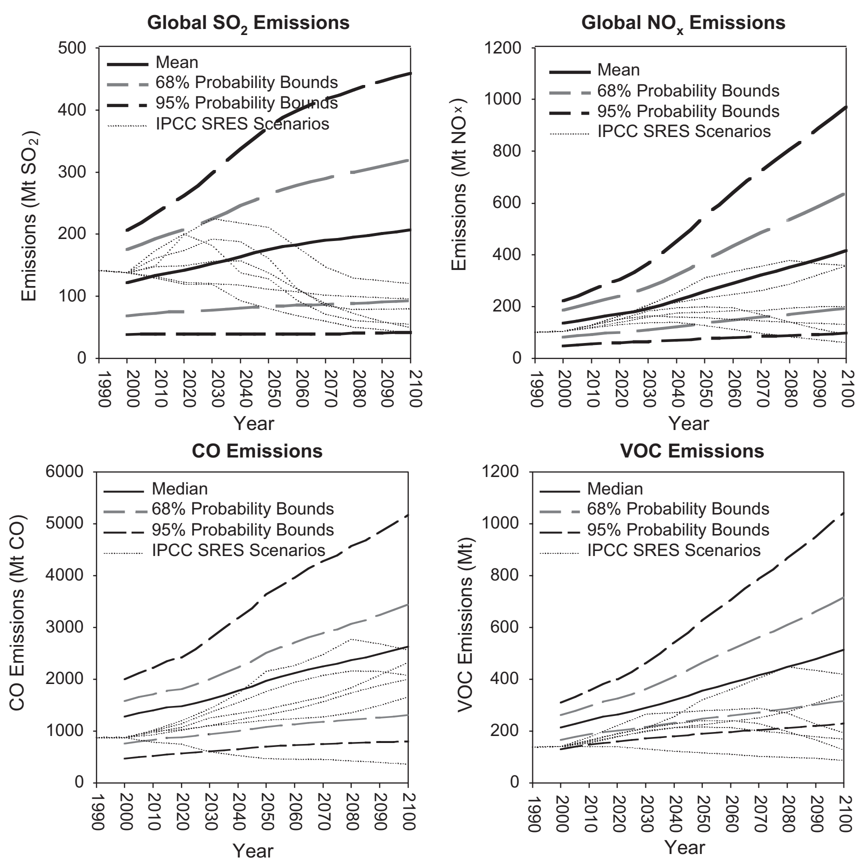

Figure 4. Emissions of air pollutants. Panels (a) SO_2, (b) NO_x, (c) CO, (d) non-methane hydrocarbons. The solid lines show the mean emissions based on 10,000 runs, long/gray dashed lines show +/- 68%, shorter/black dashed lines show +/- 95% probability bounds, and dotted lines show the emissions from the six representative SRES scenarios.

In addition to the greenhouse gas emissions, we use the 10,000 simulations to quantify uncertainty in other climatically relevant emissions. In **Figure 4**, we show the uncertainty in emissions of SO_2, NO_x, CO, and non-methane hydrocarbons. As with the greenhouse gases, our probability bounds account for uncertainty in current global emissions of these species as well as economic growth, while the IPCC assumes that current emissions are known. SO_2 emissions, a precursor to sulfate aerosols, are especially important in climate projections because of the strong negative radiative forcing effect of those aerosols. The difference between the SRES projections of SO_2 emissions to our projections is striking. In all six of the representative scenarios, the IPCC projects that after about 2040, SO_2 emissions will begin to steadily decline. The IPCC assumes that policies will be implemented to reduce sulfur emissions, even in developing countries, in all imaginable cases. By contrast, our study imagines 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 includes the possibility of continuing increases in SO_2 emissions over the next century, as well as declining emissions consistent with SRES. Similarly, though not as striking, SRES projections of NO_x, CO, and NMVOC emissions all fall within the lower half of our probability distributions of emissions.

Finally, we project emissions of other climatically relevant substances not treated in the IPCC SRES: black carbon aerosols, organic carbon aerosols, and ammonia. Recently there has been an increased interest in the radiative forcing properties of black carbon or elemental carbon aerosols, primarily produced from incomplete combustion (Hansen *et al*., 2000). Black carbon aerosols are light absorbing, and therefore have a different effect on radiative forcing than sulfate aerosols. Aerosols in both polluted and remote areas contain a wide range of organic compounds, resulting from direct emissions or secondary chemical production in atmosphere. Organic aerosols, like sulfate aerosols, have negative radiative forcing. Finally, ammonia emissions are important because the primary form of sulfate and nitrate aerosols are as ammonium salts. While the influence of changing emissions of ammonia and carbonaceous aerosols has not been explicitly formulated in the current version of the MIT climate-chemistry model, we project these emissions for the new version of the IGSM currently being developed. Probabilistic bounds on emissions of these substances are given in **Figure 5**.[7]

2. SCENARIOS FOR CLIMATE SIMULATIONS

Quantifying uncertainty in emissions with probability distributions, as illustrated above, is an important step towards treating uncertainty in climate projections and, ideally, the uncertainty in emissions scenarios would be jointly considered with uncertainty in climate models. For many climate models it is not computationally feasible to run hundreds of scenarios, and instead modelers must simulate a selected set of scenarios, such as those developed in the IPCC SRES. Our approach allows us to select scenarios where we can describe the associated likelihoods.

There remain some limits to this approach that separates uncertainty analysis in emissions from uncertainty in climate modeling because there are multiple climatically or chemically important substances of interest. If there were only one substance that mattered for climate projections, CO_2 for example, scenarios could simply be defined as the various fractiles of the distributions; *i.e*., the mean and the upper and lower 67% or 95% emissions shown above.

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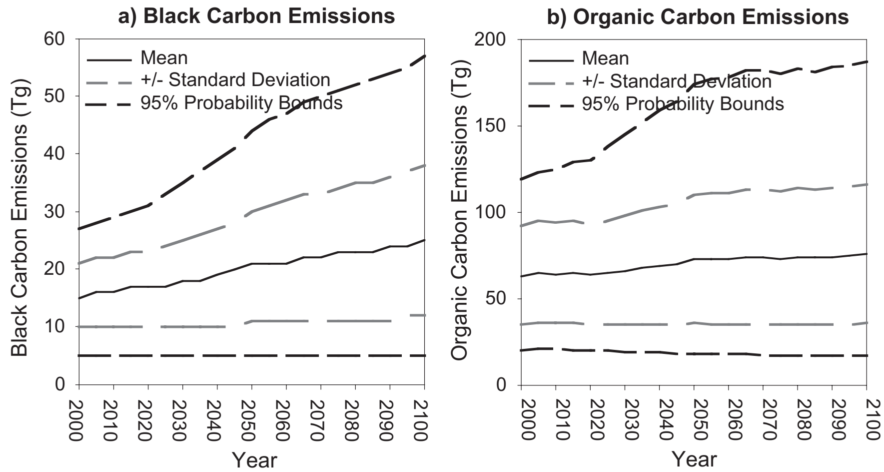
[7] The IPCC does not project emissions of these substances, so there are no comparisons in the figure.



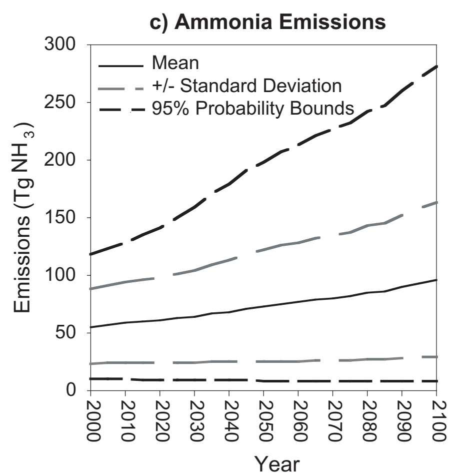


Figure 5. Emissions of other aerosols and aerosol precursors. Panel (a) black carbon (soot) particulates, (b) organic carbon particulates, and (c) ammonia. The solid lines show the mean emissions based on 10,000 runs, long/gray dashed lines show +/- 68%, shorter/black dashed lines show +/- 95% probability bounds.

In fact, there are many emissions that influence the climate, including several greenhouse gases, aerosols, and precursors of climatically relevant substances. The uncertainty in the emissions of each of these substances is neither completely independent nor completely dependent (perfectly correlated) with each other. For example, emissions of CO_2 and CH_4 have a correlation coefficient of 0.81. It is important to accurately capture this probabilistic relationship in designing scenarios. If three different probabilities are used for each of the four groups of independently varying emissions in this study, mean, upper 95%, and lower 95%, then there are 3^4 or 81 scenarios that describe every possible combination, an impractically large number for simulations for coupled AOGCMs. Further, this method will result in some scenarios that have extremely low probabilities. For example, choosing the upper 95% value on all four groups has a likelihood of being exceeded of $(0.025)^4 = 3.9 \times 10^{-7}$ or an approximately 1 out of 2,560,000 chance.

We "pare" the decision tree to a few of the most interesting scenarios. The single largest driver of climate outcomes is CO_2 emissions, so we begin by choosing three emissions scenarios for CO_2 that result in the median, upper 95% and lower 95% emissions levels. In order to keep the overall probability of the scenarios at 2.5% and 97.5%, we fix the other greenhouse gas and non-GHG emissions at their median levels where the median is conditional on CO_2 at median, the upper 95% and the lower 95% emissions. With positive correlation between CO_2 and CH_4 emissions, for example, median emissions of CH_4 conditional on CO_2 at its upper 95% level will be higher than median emissions of CH_4 conditional on CO_2 at its median. This process is illustrated in **Figure 6**.

It is possible to construct other scenarios. For example, we illustrate in Figure 6 with dashed lines a set of scenarios focused on uncertainty in other GHGs or other pollutants conditioned on median outcomes for CO_2 or all GHGs. Such a set of scenarios would be useful in exploring the possible range of atmospheric chemistry and climate responses to extreme variations in the relative increase of different substances. Since there are complex and non-linear interactions among GHGs and other pollutants, different emissions of gases would result in potentially widely different atmospheric lifetimes of substances or in different levels of urban air pollution. Yet, because emissions of many substances are tied to the same human activities, one would like to construct scenarios where one knew whether the widely diverging emissions scenarios for different gases were consistent with the underlying structure and trends in human activity as well as the specific likelihood of such diverging emissions scenarios.
A particular application might explore the uncertainty in sulfate aerosols given a median estimate of GHG emissions, as reductions in sulfate aerosol loadings projected in the IPCC SRES scenarios figured prominently in shifting the 2100 warming estimates for the IPCC TAR as compared with the Second Assessment Report (IPCC, 2001). Other scenarios may also be of interest and can be easily constructed in the future. In the end, the most useful emissions scenarios will be those that provide probabilistic bounds in terms of their aggregate contribution to radiative forcing or to global mean temperature change. An uncertainty study of a climate model equivalent to this study of an emissions model would be required to build such scenarios.[8]

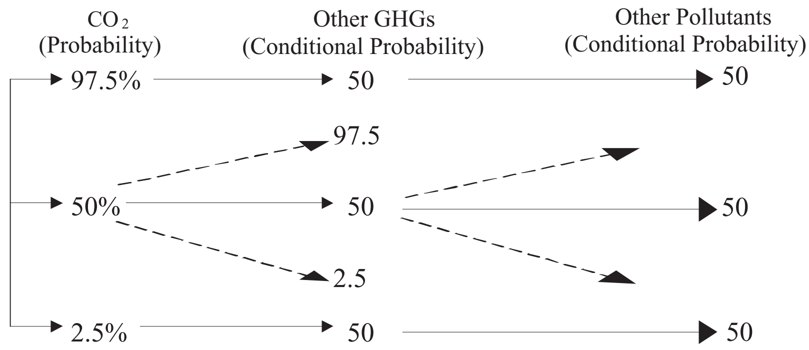


Figure 6. Probabilities for jointly varying emissions.

3. CLIMATE IMPACTS OF REPRESENTATIVE SCENARIOS

We use the MIT 2D climate-chemistry model to compute the climate impacts resulting from the three representative scenarios presented above. We compare these scenario results to the climate impacts of the six representative SRES scenarios, also as simulated by the MIT climate model. We do not consider, here, the further uncertainties in climate that stem from uncertainties in climate models themselves (Webster and Sokolov, 2000).

The MIT Integrated Global System Model is a set of coupled sub-models that includes the EPPA model as well as submodels that comprehensively cover atmosphere, ocean, and terrestrial earth systems. Emissions scenarios from EPPA are used as inputs into a coupled chemistry/climate model along with scenarios of natural emissions of GHGs from a Natural Emissions Model (for wetland CH_4 and natural N_2O emissions) and other natural emissions preprocessor (Prinn *et al*., 1999; Wang *et al*., 1998). The chemistry and climate model is a two-dimensional

[8] Such a study is in progress at the MIT Joint Program on the Science and Program of Climate Change.

(2D) land-ocean (LO) resolving climate model, which is coupled to a 2D model of atmospheric chemistry and a 2D or three-dimensional (3D) model of ocean circulations (Sokolov and Stone, 1998; Wang *et al*., 1998; Wang and Prinn, 1999). In addition to the 2D global chemistry, the IGSM includes a 3D urban air chemistry model for treating emissions in urban areas (Mayer *et al*., 2000). The TEM model of the Marine Biological Laboratory (Melillo *et al*., 1993; Tian *et al*., 1999; Xiao *et al*., 1997, 1998) simulates carbon and nitrogen dynamics of terrestrial ecosystems. These features allow the IGSM to project concentrations of the relevant trace gases, accounting for photochemical processes and the feedback of climate on natural emission sources; radiative forcing from these trace gases; temperature and precipitation at different latitudes (longitudinally averaged) and global mean; and sea level rise due to thermal expansion of the oceans.

We find that the CO_2 concentration by 2100 reaches 465 ppm, 662 ppm, and 1090 ppm in the low, median, and high scenarios, respectively (**Figure 7a**). The SRES span a similar range, from 518 ppm to 965 ppm because of the comparable ranges in CO_2 emissions. Radiative forcing due to CO_2 alone in our scenarios ranges from 3.0 to 8.4 W/m^2 by 2100, and the SRES scenarios result in a similar range. In contrast, the ranges of radiative forcing resulting from other radiatively active substances exhibit greater differences between our scenarios and the SRES. For methane forcing, our scenarios range from 0.4 to 2.3 W/m^2 by 2100, while the SRES covers a smaller range and is biased towards lower forcings, from 1.1 to only 1.3 W/m^2. Recall that although parameters that drive both CO_2 and CH_4 are at extreme values in the high and low cases, other uncertainties specific to CH_4 are at median values; our range is not as large as a full 95% confidence interval for CH_4 forcing would be. Radiative forcing from N_2O in the SRES covers a more similar range to that of our scenarios, but the SRES are biased towards higher forcings in this case. The combined radiative forcing effects of HFCs, PFCs, SF_6, and CFCs are also biased higher in the SRES. Our three scenarios have radiative forcings of 0.2, 0.5, and 0.9 W/m^2, while the SRES scenarios range from 0.4 to 0.9 W/m^2.

Perhaps the most important differences are the sulfate aerosol contributions to radiative forcing in our analysis compared with the SRES scenarios. The sulfate forcing in our scenarios is –0.4, –1.0, and –1.6 W/m^2 by 2100 in the low, median, and high scenarios, respectively. By contrast, the range of forcings from the SRES scenarios is –0.3 to –0.7 W/m^2. Our wider range stems from two factors: (1) we represent uncertainty in existing sulfate loading, recognizing that SO_2 emissions come from many sources (*e.g*., energy and biomass burning and industrial processes) that are not all monitored and measured with great accuracy; and (2) we relate reductions in emissions of SO_2 per unit of fuel combustion and other sources to growth in per capita income to reflect the growing demand for environmental clean-up with rising incomes that has been observed. As a result of (1), once the wide uncertainty range for emissions in 2000 is represented in the climate chemistry IGSM there is an immediate response, representing uncertainty in current levels of radiative forcing. As a result of (2) and other assumptions about the trend in emissions coefficients, we find the possibility of either increasing or decreasing sulfate aerosol forcing. The SRES scenarios include no uncertainty in current emissions of SO_2 and all scenarios show radiative forcing in 2100 to be below current levels of forcing. There are other ways to represent uncertainty in future SO_2 emissions that could change our results but, apart from any modeling, an adequate representation of uncertainty would seem to involve some measurable chance that SO_2 emissions might increase rather than decrease. Figure 7(f) shows the resulting global mean temperature change from 1990 as a result of our three scenarios and the six representative SRES scenarios.

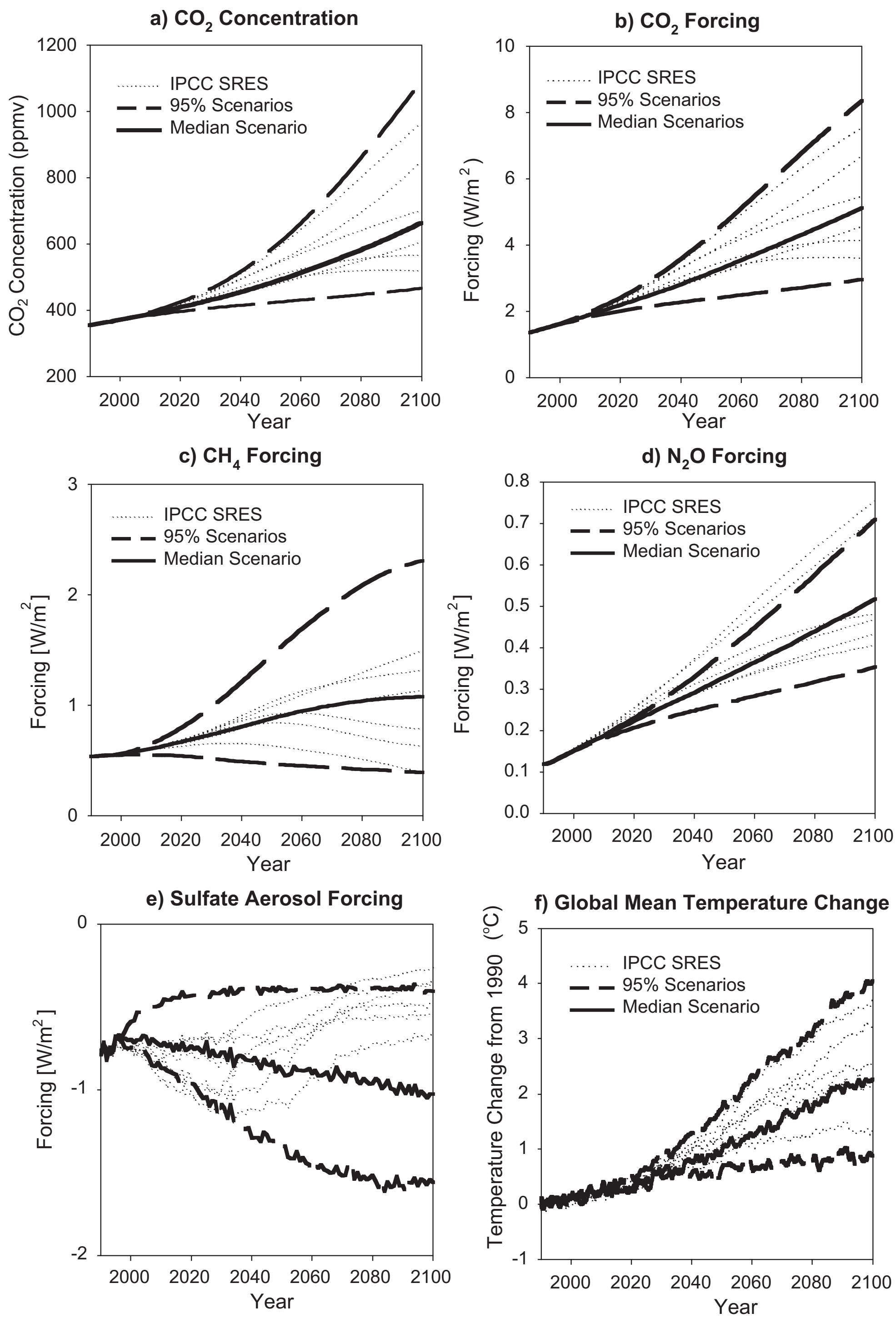


Figure 7. Concentrations and radiative forcing. Panel (a) CO_2 concentrations, (b) Radiative forcing due to CO_2, (c) Radiative forcing due to CH_4, (d) Radiative forcing due to N_2O, (e) Radiative forcing due to sulfate aerosols, (f) Global mean temperature change from 1990. Solid lines show median scenario, dashed lines show 95% high and low scenarios as in Fig. 6, and dotted lines show the IPCC SRES scenarios.

Because CO_2 is the largest single driver, the ranges of temperature changes are not extremely different: our scenarios range from 0.9 to 4.0 ^oC, and the SRES range from 1.3 to 3.6 ^oC. However, it is interesting to note that the temperature change in five of the six SRES scenarios is greater than or equal to the temperature change in our median scenario of 2.2 ^oC. The main reason for the difference in the median or central tendency of the two sets of scenarios is the difference in sulfate aerosol forcing. It is important to be clear that the range of global mean temperature change between our low and high scenarios is not a 95% confidence bound on temperature change from the MIT model. To give this range will require applying the methods described here to a full uncertainty analysis of the climate model.

4. CONCLUSIONS

Analysis of possible future climate changes should include quantification of the uncertainty in climate projections. In this paper, we constructed three representative scenarios where the emissions of CO_2 are at median, upper 95%, and lower 95% levels, and all other emissions are at their median levels conditional on the CO_2 emissions. We have compared emissions from the six representative SRES scenarios with our calculated probability distributions of emissions, and also compare the climate impacts of the SRES scenarios with the impacts from our low, median, and high CO_2 scenarios. We find that the SRES CO_2 emissions covers much of our 95% confidence range, but is biased towards lower CO_2 emissions by the end of the century than our distributions. The differences partly reflect the inclusion of policy effects in some of the SRES scenarios, whereas we have tried to develop probability distributions of emissions under no climate policy. Assessments of the effects of policy would require repeating this exercise under the policy assumption, and then comparing the resulting probability distributions and their impacts.

For other greenhouse gases and aerosols, the SRES scenarios tend to encompass much narrower ranges than we find from uncertainty propagation. Further, the SRES emissions are biased higher than our distributions for some species and biased lower for others. One difference is that the IPCC does not include the uncertainty in current emission levels, which is significant in many cases. Finally, the greatest difference between the two methods is found in sulfur emissions. Here, the IPCC has assumed the presence of sulfate reduction policies later in the century seemingly without considering uncertainty in the ability/willingness to implement such policies. In performing the uncertainty analysis, we also include the effect sulfate reductions as economies increase in wealth, but we have also included the uncertainty in how that relationship will hold in other countries in the future.

As a result of the different methods and assumptions in constructing representative scenarios, we find that the IPCC SRES are biased in the direction of higher global mean temperature change by the end of the next century. This bias towards higher temperatures is partly due to the strongly optimistic assumptions about the reductions in sulfur emissions.

A significant motivation for this study was the perceived desire within the climate modeling community for a small set of scenarios that describe a central tendency (mean or median) and high and low cases that bound an explicit probability. We hope these emissions scenarios provide a useful set of scenarios to study climate uncertainties.

Acknowledgments

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REFERENCES

Babiker, M., Reilly, J. and Jacoby, H. (2000). The Kyoto Protocol and Developing Countries. *Energy Policy* **28**: 525-536.

Babiker, M., Reilly, J., Mayer, M., Eckaus, R., Sue Wing, I. and Hyman, R. (2001). *The MIT Emissions Prediction and Policy Analysis Model: Revisions, Sensitivities, and Comparisons of Results*. MIT Joint Program on the Science and Policy of Global Change *Report No. 71*, Cambridge, MA.

Edmonds, J. and Reilly, J. (1985). *Global Energy: Assessing the Future*. Oxford University Press: 317 p.

Downing, D.J., Gardner, R.H. and Hoffman, F.O. (1985). Response Surface Methodologies for Uncertainty Analysis in Assessment Models. *Technometrics* **27**(2): 151-163.

Fenhann, J. (2000). HFC, PFC and SF_6 Emission Scenarios: Recent Development in IPCC Special Report on Emission Scenarios. In: *Non-CO_2 Greenhouse Gases: Scientific understanding, control and implementation: Proceedings of the Second International Symposium on Non-CO_2 Greenhouse Gases*, van Ham, J., Baede, A.P.M., Meyer, L.A. and Ybema, R. (eds.). Kluwer Academic Publishers, Dordrecht, Netherlands.

Harnisch, J., Jacoby, H.D., Prinn, R.G., and Wang, C. (2000). Regional emission scenarios for HFCs, PFCs, and SF_6. In: *Non-CO_2 Greenhouse Gases: Scientific understanding, control and implementation: Proceedings of the Second International Symposium on Non-CO_2 Greenhouse Gases,* van Ham, J., Baede, A.P.M., Meyer, L.A. and Ybema, R. (eds.). Kluwer Academic Publishers, Dordrecht, Netherlands, pp. 231-238.

Hansen, J.E., Sato, M., Ruedy, R., Lacis, A. and Oinas, V. (2000). Global warming in the 21st century: an alternative scenario. *Proceedings of the National Academy of Sciences* **97**(18): 9875-9880.

IPCC (2001). *Climate Change 2001: The Scientific Basis*, J.T. Houghton, *et al*., (eds.). Cambridge University Press, Cambridge, 896 p.

Keith, D. (1996). When is it Appropriate to Combine Expert Judgments? *Climatic Change* **33**: 139-143.

Mayer, M. and Hyman, R., Harnisch, J. and Reilly, J. (2000). *Emissions inventories and time trends for GHGs and other pollutants*. MIT Joint Program on the Science and Policy of Global Change *Technical Note No. 1*.

Mayer, M., Wang, C., Webster, M., Prinn, R.G. (2000). Linking local air pollution to global chemistry and climate. *Journal of Geophysical Research* **105**(D18): 22,869-22,896.

McKay, M.D., Conover, W.J., *et al*. (1979). A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code. *Technometrics* **21**(2): 239-245.

Melillo, J.M., McGuire, A.D., Kicklighter, D.W., Moore III, B., Vorosmarty, C.J. and Schloss, A.L. (1993). Global climate change and terrestrial net primary production. *Nature* **363**: 234-240.

Morgan, M.G. and Henrion, M. (1990). *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis*. Cambridge University Press, Cambridge; New York.

Mosier, A., and Kroeze, C. (1998). A New Approach to Estimate Emissions of Nitrous Oxide From Agriculture and its Implications to the Global N_2O budget. *IGACtivities No. 12*.

Moss, R.H. and Schneider, S.H. (2000). In: *Guidance Papers on the Cross Cutting Issues of the Third Assessment Report*, Pachauri, R., Taniguchi, T. and Tanaka, K. (eds.). World Meteorological Organization, Geneva, pp. 33-57.

Nordhaus, W.D. and Yohe, G. (1983). Future paths of energy and carbon dioxide emissions. In: *Changing Climate*, National Academy Press, Washington D.C., chapter 2.1.

Olivier, J.G.J., Bouwmann, A.F., van der Mass, C.W.M., Berdowski, J.J.M., Veldt, C., Bloos, J.P.J., Visschedijk, A.J.H., Zandveld, P.Y.J. and Haverlag, J.L. (1995). *Description of EDGAR Version 2.0: A set of global emission inventories of greenhouse gases and ozone depleting substances for all anthropogenic and most natural sources on a per country basis and on 1° x 1° grid*, Report no. *771060002. RIVM*, Bilthoven.

Pate-Cornell, E. (1996). Uncertainties in Global Climate Change Estimates. *Climatic Change* **33**: 145-149.

Press, W.H., Teukolsky, S.A., *et al*. (1992). *Numerical recipes in C*. Cambridge University Press, Cambridge, England.

Prinn, R., Jacoby, H., *et al*. (1999). Integrated Global System Model for Climate Policy Assessment: Feedbacks and Sensitivity Studies. *Climatic Change* **41**(3/4): 469-546.

Reilly, J., Edmonds, J., Gardner, R. and Brenkert, A. (1987). Monte Carlo Analysis of the IEA/ORAU Energy/Carbon Emissions Model. *The Energy Journal* **8**(3): 1-29.

Reilly, J., Prinn, R., Harnisch, J., Fitzmaurice, J., Jacoby, H., Kicklighter, D., Melillo, J., Stone, P., Sokolov, A. and Wang, C. (1999). Multi-gas assessment of the Kyoto Protocol. *Nature* **401**: 549-555.

Seinfeld, J.H. and Pandis, S.N. (1998). *Atmospheric Chemistry and Physics*. John Wiley & Sons, Inc., New York.

Sokolov, A., and Stone, P. (1998). A flexible climate model for use in integrated assessments. *Climate Dynamics* **14**: 291-303.

SRES (2000). Nakicenovic, N. and Swart, R. (eds.). *Special Report on Emissions Scenarios*. World Meteorological Organization, Geneva.

Tatang, M.A., Pan, W., *et al*. (1997). An efficient method for parametric uncertainty analysis of numerical geophysical models. *Journal of Geophysical Research* **102**(D18): 21.

Tian, H., Melillo, J.M., Kicklighter, D.W., McGuire, A.D. and Helfrich III, J.V.K. (1999). The sensitivity of terrestrial carbon storage to historical climate variability and atmospheric CO_2 in the United States. *Tellus* **51**B: 414-452.

Tversky, A. and Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science* **185**(September): 1124-1131.

Wang, C., and Prinn, R.G. (1999). Impact of Emissions, Chemistry and Climate on Atmospheric Carbon Monoxide: 100-Year Predictions from a Global Chemistry-Climate Model. *Chemosphere–Global Change Science* **1**(1-3): 73-81.

Wang, C., Prinn, R.G. and Sokolov, A.P. (1998) A Global Interactive Chemistry and Climate Model: Formulation and Testing. *J. of Geophysical Research* **103**(D3): 3399-3417.

Webster, M.D. and Sokolov, A.P. (2000). A methodology for quantifying uncertainty in climate projections. *Climatic Change* **46**(4): 417-446.

Weyant, J.P. and Hill, J. (1999). The Costs of the Kyoto Protocol: A Multi-Model Evaluation; Introduction and Overview. *The Energy Journal* **Special Issue**: vii-xliv.

Xiao, X., Kicklighter, D.W., Melillo, J.M., McGuire, A.D., Stone, P.H., and Sokolov, A.P. (1997). Linking a global terrestrial biogeochemical model and a 2-dimensional climate model: implications for the carbon budget. *Tellus* **49B**: 18-37.

Xiao, X., Melillo, J., Kicklighter, D., McGuire, A., Prinn, R., Wang, C., Stone, P. and Sokolov, A. (1998). Transient climate change and net ecosystem production of the terrestrial biosphere. *Global Biogeochemical Cycles* **12**(2): 345-360.

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