The Effect of Emissions Uncertainty on Projected Climate Change

Kelly Lee Huennekens

This thesis has been submitted in partial fulfillment of a Bachelor of Science degree in Environmental Science with honors at Brown University

May 2002

The author thanks Brian O'Neill for his advice and generous support of this thesis, and Timothy Herbert and Michael Oppenheimer for their helpful comments and suggestions. Many thanks also to the faculty and students of the Center for Environmental Studies at Brown University, the wonderful individuals who inhabit MacMillan Hall room 104, and friends and family for their encouragement.

This thesis is dedicated to Chris McCallum.

Abstract

The Intergovernmental Panel on Climate Change (IPCC) recently issued its Third Assessment Report (TAR, 2001), which gives a range of 1.4° to 5.8°C possible global mean temperature increase from 1990 to 2100 in the absence of policy to limit climate change. Providing temperature projections in terms of simply a range of values with no indication of likelihood gives only a partial basis for determining risk and designing climate policy. Wigley and Raper (2001) attempt to provide more guidance by giving climate projections in probabilistic terms. In their probabilistic model, the key uncertainties are represented as distributions approximated using commonly accepted values, except for emissions uncertainty. They use the 35 emissions scenarios from IPCC's Special Report on Emissions Scenarios (SRES), which are explicitly given no probability estimates. In the absence of guidance from the SRES authors on the likelihood of the scenarios, Wigley and Raper assume equal probability for each scenario. In this study, I test the sensitivity of the global mean temperature distribution to varying the likelihood assumption for emissions in a probabilistic model. I show that the warming distribution is affected to a small degree by changing the emissions likelihood assumption to various plausible distributions. The effect of varying the emissions likelihood assumption is tempered because other uncertainties in the climate modeling process contribute along with emissions to the uncertainty in the outcome, which can be reduced a limited amount by changing only one uncertain input.

Introduction

The Third Assessment Report (TAR) (*1*) of the Intergovernmental Panel on Climate Change (IPCC) gives 1.4° to 5.8°C as a range of possible global mean temperature rise between 1990 and 2100, in the absence of policy specifically aimed at mitigating climate change. This is significantly higher than the previous estimate of 0.8 – 3.5 °C given in the Second Assessment Report (*2*), and reflects the work of hundreds of scientists and climate change experts from many nations, as well as current data and more robust models and techniques. Interpretation of this range is problematic because it includes no indication of likelihood. We are left to guess at the probability of global temperature increase over the next century falling within the range (i.e., what confidence interval or other measure of likelihood does the range represent?) and how likely values close to the center of the range might be compared to those at the ends. As Schneider argued in a recent editorial essay (*3*), this information is needed for risk assessment, which requires some understanding of both consequences and probability. If policy makers are expected to make informed decisions about risks associated with climate change, scientists must provide them with some form of guidance regarding the likelihood of climate change projections.

Many climate change experts (*3*, *4*, *5*, *6*) have called for the uncertainty in climate change projections to be provided in probabilistic terms whenever projections are given. Current projections cover a wide range of possible temperature change, resulting in a wide range of possible impacts. Schneider, perhaps the most vocal participant in this discussion, reasoned in his editorial essay (*3*) that any clarification beyond merely a range of values makes the information more useful.

Past studies (*7, 8*) have identified the major uncertainties that complicate projections of climate change as: uncertainties within the carbon cycle, the climate sensitivity, the ocean mixing rate, and radiative forcing due to aerosols. In addition to unknowns in the climate system as a whole, future emissions of climatically important substances are uncertain. Some of these uncertainties are due to insufficient information required to calculate a parameter. For instance, past land use emissions are not well known because incomplete information about the use of land in the past and incomplete understanding of long-term carbon storage in soil makes it difficult to quantify the amount of carbon lost and sequestered by all of the world's ecosystems and agricultural lands. In other cases, uncertainties are the result of unknowable information, such as future emissions of greenhouse gases, which will depend on many social, political, and economic factors that are very difficult to predict. In either case, a range of possible values is known, usually well enough such that a "best guess" or most likely value, along with high and low extremes can be used to construct a distribution of probable values.

Although the basic workings and many aspects of the global climate system are well understood, uncertainty concerning some components and interactions remains, and this uncertainty must be accounted for in climate models. One typical method of accounting for uncertainties is the scenarios approach, which involves running the model several times, each with a different future emissions scenario and different assumed model parameter values, resulting in several corresponding climate change projections. These multiple results depend on the values chosen for the uncertain parameters in the model, and must be qualified as such.

An alternative to such an approach is probabilistic modeling. This method entails using probability density functions (p.d.f.s) that describe the likelihood of the model's uncertain parameters falling within a certain range, rather than attempting to choose one "best" value for each. The results may then be shown as a p.d.f. that indicates not only a range of possible future climate change, but the probability of the "true answer" falling within different portions of that range. This provides more complete information concerning what is indicated by the range of possible results.

In order to obtain probabilistic results, the uncertain model inputs must be given in probabilistic terms as well. This is problematic for those employing the IPCC Special Report on Emissions Scenarios (SRES) scenarios (*9*), because the 35 emissions scenarios created for use in climate modeling are not accompanied by likelihood estimates. The authors of the scenarios were unable to come to consensus on probability estimates, so there is no single central or "best guess" scenario, and probabilities are not assigned to individual scenarios. Although the scenarios are not assigned likelihood, they are meant to cover the range of future emissions the authors considered plausible. The authors recommend that the smallest set of scenarios used should include the four scenarios designated as markers and the two additional illustrative scenarios.

Wigley and Raper (*10*) recently published the results of a probabilistic climate change projection. The study presents climate results in probabilistic terms, which provides more complete and useful information than simply giving a range of possible temperature change results. They create realistic p.d.f.s for each of the uncertain parameters in their model, *except* for future emissions, which are represented by the 35

IPCC SRES scenarios. For lack of guidance from the IPCC on how likely the emissions scenarios provided in SRES are, they assume each emissions scenario to be equally likely across the set of 35. While the authors of the SRES scenarios report no preference for one scenario over another, there is also no basis to assume equal likelihood across them, calling the Wigley and Raper assumption into question.

Schneider suggests that those with the most expertise, the authors of the scenarios, are most qualified to assign them likelihood estimates, and should do so. If users are not given guidance, they will make their own judgments on likelihood, which, in almost all cases, will be less well informed than the estimates that would be given by those creating the projections. Others (*11*) have argued that likelihood estimates for future emissions of greenhouse gases and aerosols are so difficult to create that any attempt to do so would result in likelihood estimates that are misleading. Whether emissions scenarios can and should be assigned probabilities is a current debate, and a central question to it is how much would probabilistic estimates of future emissions affect the results of climate projections.

The probabilities used to represent emissions may have a considerable effect on the outcome, but so far this effect has not been investigated. It is important to address this issue, because emissions scenarios vary widely and it has been suggested that they have a large effect on the outcome—possibly as much as half of the uncertainty associated with projected change in global average temperature is due to emissions uncertainty (*1*). Webster *et al.* (*12*) investigated the uncertainty involved with future emissions using expert opinion and a model of the world economy to obtain probability density functions for greenhouse gas emissions. That study found a 95% confidence interval for temperature change of 0.9° to 5.3°C in 2100, with a 1% probability of exceeding 5.8°C, compared to IPCC's range of 1.4° to 5.8°C. Different assumptions about the likelihood of emissions are feasible, and an investigation of the influence of the assumption used on the model results would be constructive. In this study, I examine how future emissions scenarios' representation in a probabilistic climate model affect projections of future climate change.

Methods

The carbon cycle model I use is from Jain *et al*. (*13*). It is a one-dimensional upwelling-diffusion ocean model with a well-mixed surface layer, well-mixed atmosphere, and 6-box terrestrial biosphere (see Figure 1). The other gas models, except for methane, are constant lifetime models based on the lifetimes given in the IPCC TAR(*1*). The methane model is from Osborn and Wigley (*14*). The climate model is from Hoffert *et al*. (*15*), and is a one-dimensional upwelling-diffusion ocean model. See Hoffert *et al*. for details.

I follow the methodology of Wigley and Raper (*10*), using probability density functions to represent the uncertain parameters of a series of models which translate emissions of greenhouse gases into atmospheric concentrations, radiative forcing, and global average temperature change. The input parameters that are represented as p.d.f.s in the models are: emissions of direct and indirect greenhouse gases, climate sensitivity,

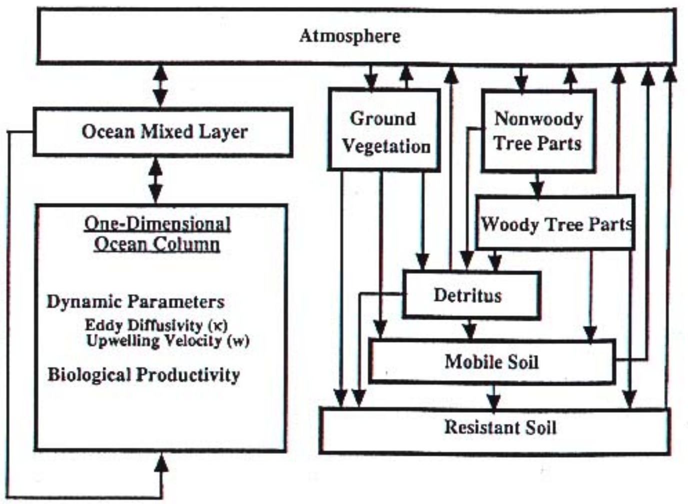

Figure 1. Schematic of the global carbon cycle model used. From Jain *et al*. (*12*).

and a fertilization factor governing terrestrial carbon uptake. Wigley and Raper (*10*) also include p.d.f.s for aerosol forcing and ocean mixing (diffusivity) rate, noting that these two uncertainties have little effect on the temperature outcome, and for this reason we do not include them here. Another difference to note in the treatment of carbon cycle uncertainty is that in the Wigley and Raper study (*10*), both carbon dioxide and temperature feedbacks are included, whereas we only consider the carbon dioxide fertilization feedback.

Carbon cycle uncertainty

The two major sources of uncertainty within the carbon cycle are the CO_2 fertilization feedback and the temperature feedback. Increases in atmospheric carbon dioxide concentrations and increase in global mean temperature both tend to enhance the terrestrial biosphere's capacity for carbon uptake. The extent to which these feedbacks operate is not known. Past land use emissions are uncertain due both to difficulties in measuring carbon emissions from changes in land use patterns globally and to uncertainty about past land use itself. The uncertainty of land use emissions creates uncertainty about the degree to which increases in atmospheric carbon dioxide increases primary productivity in forests and other land carbon sinks, known as the carbon dioxide fertilization factor. Carbon emissions due to land use are estimated to be 0.6 and 2.5 Gt/year average over the 1980's, distributed over a 90% confidence interval with a best guess of 1.7 Gt/year, which is a rather large range. The range of values given for the CO_2 fertilization factor is constrained by the uncertainty regarding both this past land use and by historical atmospheric CO_2 data. The strength of the fertilization factor is calculated by balancing estimates of fossil fuel emissions, changes in atmospheric CO_2 concentration, modeled net ocean carbon uptake, and estimates for land use change emissions. As mentioned earlier, the model I used does not include a temperature feedback, so this uncertainty is not accounted for in this study.

I used the carbon cycle model described above to calculate values for the fertilization factor. Since the fertilization factor affects the emissions of carbon dioxide from land use over time, it is necessary to re-run the model from 1765, when industrialization began and carbon began to accumulate in the atmosphere, to 1990, for each new fertilization factor used. Thus, I create a state of the carbon cycle in 1990 for each fertilization factor chosen. Values for the fertilization factor are calculated inversely based on the assumption that the low, high, and best guess values given by the IPCC for land use emissions averaged over the 1980's are equivalent to a 90% confidence interval and median value for land use change. I fit an exponential-normal distribution to the fertilization factor values for the median and bounds of the 90% confidence interval. The median value is 0.715 and the bounds of a 90% confidence interval are 0.305 and 1.037. See Figure 2.

This is a simplified method of accounting for the carbon cycle uncertainties. In addition to carbon dioxide fertilization, a temperature feedback adds to model uncertainty. However, for simplification, uncertainty regarding carbon dioxide fertilization is treated as the uncertainty in the entire carbon cycle, including the temperature feedback in the terrestrial biosphere, and ocean sink uncertainty. This simplification is acceptable because the sinks and feedbacks within the carbon cycle are balanced by each other. The mechanism for calculating the uncertainty in carbon cycle sinks is unimportant as long as the total amount of carbon sink uncertainty is accounted for.

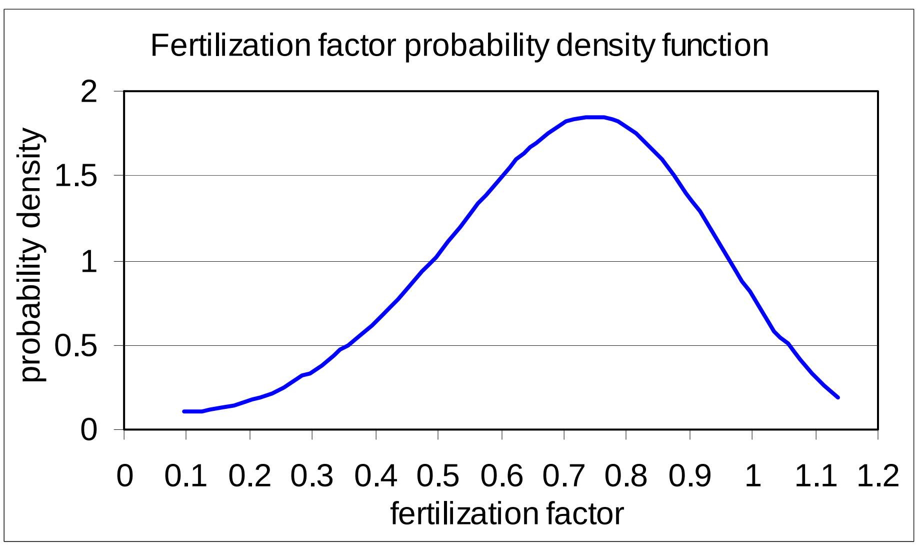

Figure 2. Probability density function for carbon dioxide fertilization factor.

Climate model uncertainty

The climate sensitivity p.d.f. is identical to that used by Wigley and Raper (*10*): the 90% confidence interval is assumed to be 1.5° to 4.5°C ,with 2.6°C as the median value. The confidence interval is based on past work of the IPCC (*2*). The IPCC climate results are based on a simple climate model that uses a range of climate sensitivity values that covers mean values of the seven TAR AOGCMs (*1*). A log-normal distribution was then fit to these estimates, assuming the best guess to be the distribution's median. See Figure 3. Wigley and Raper (*10*) test the effect of using a uniform distribution for climate sensitivity, and found that the results were affected little by this change.

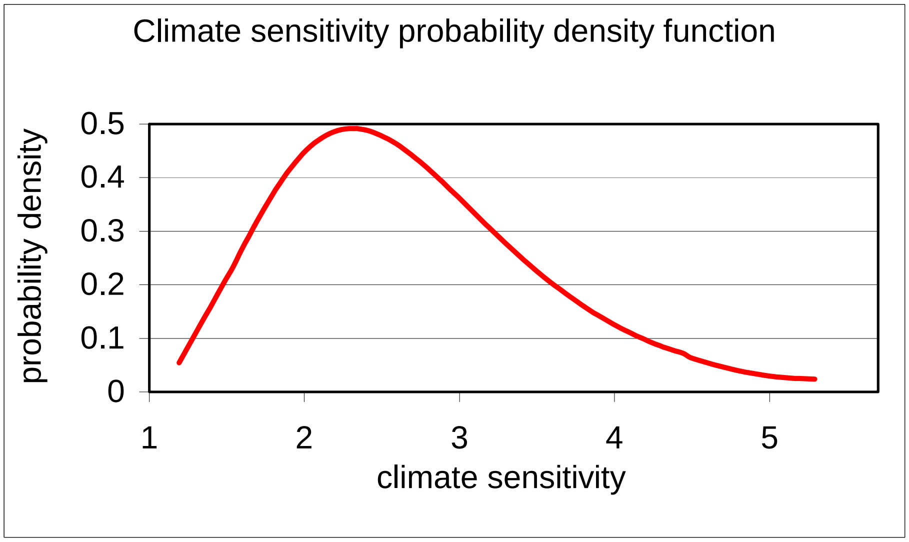

Figure 3. Probability density function for climate sensitivity, in degrees C warming from a doubling of atmospheric CO_2.

In order to run the climate model, and the carbon cycle model beforehand to obtain projections for CO_2 concentration, actual values must be chosen for each uncertain parameter. Choosing several different values for each variable from its distribution as defined above and using combinations of them to run the model many times gives a probability density function for the outcome. Here, the outcome is global average temperature change over the twenty-first century. The two most straightforward methods for choosing a set of values for each uncertain parameter are Monte-Carlo sampling, and determining a series of equiprobable values to use. With Monte-Carlo sampling, values are chosen from the distribution according to their probability. If values are chosen from the distribution randomly or semi-randomly, many values must be chosen in order to accurately represent the distribution. This requires running the model many times, which may be unnecessarily time-consuming. Choosing equiprobable values allows more freedom in choosing how many values to use to represent the variable's distribution.

I employ the method of creating a set of equiprobable values by dividing the distribution into equiprobable fractiles and using the medians of the fractiles. In this way, we chose 15 values for the climate sensitivity parameter, and 5 values for the carbon cycle uncertainty. I originally used only 5 values for the climate sensitivity as well, but found that this was not enough to cover the range of values used by the IPCC (*1*) and Wigley and Raper (*10*). With only 5 values, the lowest and highest values were significantly greater and less, respectively, than the lower and upper bounds of the 90% confidence interval for the climate sensitivity distribution, and caused the output distribution to cover less than the full uncertainty range. Using 15 values covers the range more fully, which is more important for the climate sensitivity parameter than the fertilization factor because the distribution of climate sensitivity is more skewed and climate sensitivity uncertainty contributes more to outcome uncertainty than fertilization factor uncertainty does. Ideally, one would use a greater number of values from the distribution of the fertilization factor, however additional values requires more model runs. It may be useful to determine the lowest number of values for each uncertain parameter that cover enough of its range to give accurate results. Wigley and Raper (*10*) use 5 values for the fertilization factor and 25 for the climate sensitivity. With the addition of the 35 SRES emissions scenarios, we drive the model using every combination of the values, resulting in 2,625 (15*5*35) outcomes. This process is referred to as “exhaustive fractile sampling” by Wigley and Raper (*10*), and their study employs it as well.

This methodology also allows for a simple way to test the effect of changing the uniform probability assumption regarding emissions. The steps for testing the sensitivity of the model results to changes in the emissions scenario p.d.f. are as follows: 1) run the model as many times as needed to exhaust all possible combinations of the uncertain input parameters, keeping track of the input values resulted in each model outcome; 2) create a p.d.f. for the temperature change results; 3) choose a new probability assumption for emissions scenarios; 4) weight the outcomes according to the new probability assumption for emissions; 5) based on the weighted outcomes, create a new p.d.f. for the temperature change results; 6) compare the p.d.f.s for results based on different emissions likelihood assumptions.

Emissions uncertainty

The IPCC Special Report on Emissions Scenarios (SRES) (*9*) provides a set of emissions scenarios from 1990 to 2100 for all climatically important gases. 40 scenarios include emissions of carbon dioxide, and 35 of those scenarios provide emissions for all gases. The scenarios were created using a storyline approach, in which 4 storylines, or plausible paths for regional and global demographic, economic, technological, social, environmental, and policy “futures,” were chosen. Each of the storylines is considered plausible, and none is given more weight than the others. Using each of the storylines as a set of assumptions, 6 integrated assessment models (IAs) were used to create 40 emissions scenarios. The scenarios that come from the same storyline belong to the same family. The families are referred to as A1, A2, B1, and B2. The A1 family contains several subgroups based on technological emphasis on different types of energy production: coal (A1C), oil and gas (A1G), non-fossil energy sources (A1T), and a balance across all sources (A1B). The A1C and A1G subgroups are often combined into one fossil-intensive group (A1FI). Four of the scenarios are designated as “marker” scenarios that represent each family (A1B, A2, B1, B2), plus two more reference scenarios to represent the A1T and A1FI groups. The SRES authors encourage users to include a minimum of the six marker scenarios in order to capture the range of emissions possibilities.

The approach used to create the scenarios attempts to capture uncertainty in future emissions from two sides. The storyline/family approach addresses the uncertainty in the driving forces behind emissions, such as population growth and economic development.

Since future behavior and social trends are almost impossible to predict far into the future, providing a few different plausible futures is one way to deal with that uncertainty. The multi-model approach addresses the uncertainty in the translation of the driving force assumptions to gas and aerosol emissions. Within each family, different IA models result in very different emissions scenarios, because each model quantifies the storyline assumptions differently. Some scenarios from different families and models converge, as well.

I use the 35 (*16*) emissions scenarios defined in the IPCC Special Report on Emissions Scenarios (*9*). Wigley and Raper (*10*) assume all 35 scenarios to be equally likely, as I do here as a reference case for comparison. Various aspects of the assumption that the SRES emissions scenarios are equally likely are problematic. Some of these stem from the process by which the scenarios were created. Others are due to the lack of likelihood estimates given to the scenarios by their authors. As the equal likelihood assumption is questionable, I test the effect on projected temperature change results of choosing various other likelihood assumptions for future emissions. The tests fall under two categories. The first is testing for the effects of assuming a slightly different process for determining a set of emissions scenarios on the results. The second is testing for the effects of using all 35 SRES scenarios as they are, while making various assumptions about the probabilities of the scenarios other than equal likelihood.

Climate Model Results

The outcome of each model run represents the temperature change between 2000 and 2100. Since each of the values of the uncertain parameters is defined as equally likely, each of the 2,625 reference case results is also necessarily equally likely. The results can be separated into bins in order to create a probability density function for temperature change over the 21st century. The reference case results are shown in Figure 4.

Overall, my reference case results are similar, though slightly lower than those found by Wigley and Raper (*10*) and by the IPCC TAR (*1*). The 90% confidence interval for the global average temperature change between 2000 and 2100 in the reference case—assuming all SRES scenarios equally likely—is 1.26° to 4.13°C, with a median of 2.44°C. The Wigley and Raper results under the same assumptions give a 90% confidence interval of 1.68° to 4.87°C with a median of 3.06°C warming between 1990 and 2100. The IPCC gives a range of 1.4° to 5.8°C warming over the same time period, and this range may or may not indicate an approximate 90% confidence interval.

The discrepancy between my results and those of Wigley and Raper and the IPCC is due mostly to differences between the models used for these studies. The IPCC uses a simple model with climate sensitivity based on those of a collection of seven different ocean-atmosphere coupled general circulation models (AOGCMs) that are calibrated with different climate sensitivities and other uncertain parameters. The range of climate sensitivities used to produce the IPCC results is 1.7° to 4.2°C, whereas my results, like the Wigley and Raper results, are based on a log-normal distribution of climate sensitivity with median 2.6° and a 90% confidence interval of 1.5° to 4.5°C. However, unlike the Wigley and Raper model and the IPCC models, the model used in this study does not include a temperature feedback, which tends to increase global mean warming. Omission of a temperature feedback in my model is likely the major cause of the range and distribution of the results being slightly lower. Also, the Wigley and Raper results are for 1990 to 2100, while mine cover only 2000 to 2100.

The difference between the projected warming results given by my model compared with those of the IPCC and Wigley and Raper does not affect the conclusions drawn from the results of the exercises performed using this model. I do not compare these temperature change results with those of the IPCC or Wigley and Raper, because the purpose of the study is to determine how sensitive the results are to changes in the assumption of equal likelihood for emissions scenarios. In order to do this, we need only compare the results of the same model. Since the results are reasonable, it is irrelevant that they do not exactly match the results of previous work.

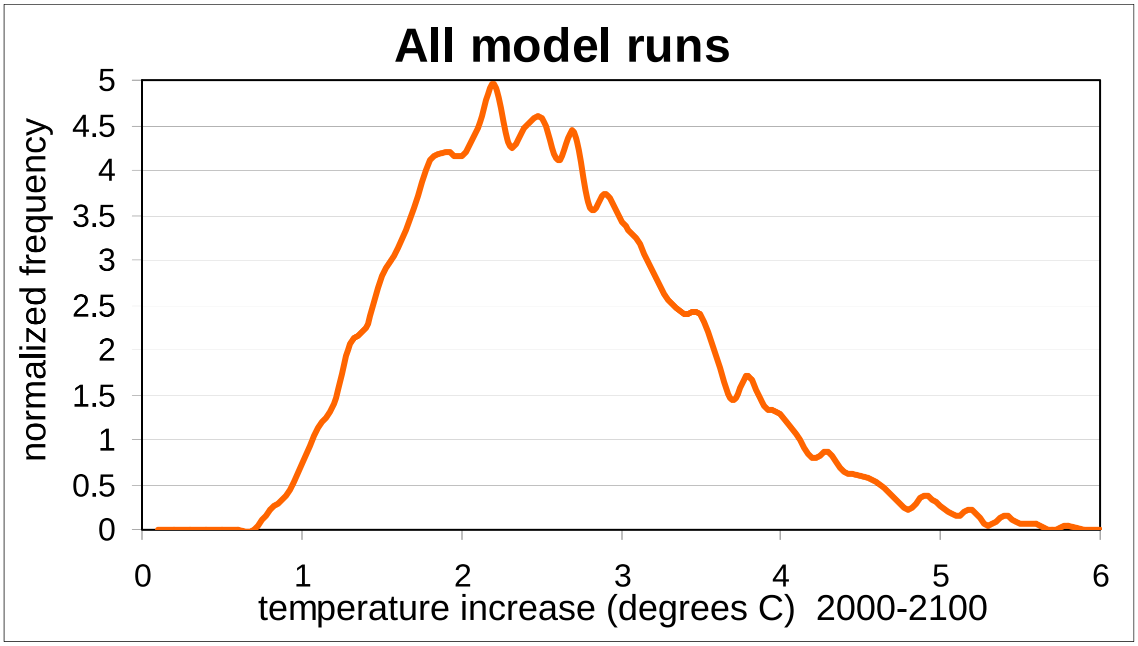

Figure 4. Reference results using all 5 fertilization factor values, 15 climate sensitivity values, and the 35 SRES emissions scenarios. All values are assumed equally probable. Bins are 0.1°C. The median is 2.44°C, and the 90% confidence interval is 1.26° to 4.13°C.

The effect of possible biases within the SRES scenario creation process

The A1 is divided into three to four subgroups in order to perform a technology analysis. Each of the subgroups within the A1 family is based on a different assumption of what type of energy technology will be dominant in the future. Due to this analysis, the A1 family contains many more scenarios than any of the other families. The A1 family contains 15 scenarios, while A2 and B2 contain 6 each, and B1 contains 8 scenarios. This uneven distribution of scenarios among families weights the overall collection of scenarios towards those in the A1 family, and so if all scenarios are assumed equally likely, the A1 storyline is effectively counted as more likely than the other families. This was not the intent of the SRES authors, nor is there any reason to believe that the A1 storyline is indeed any more likely than any other storyline. I test the effect of this unequal distribution of scenarios between the families by comparing the reference case temperature change results with the results when one assumes each family to be equally likely rather than each scenario.

The result of changing the emissions likelihood assumption to equal probability between SRES families rather than between individual scenarios is a 90% confidence interval of 1.25° to 3.96°C with a median value of 2.36°C for the temperature change distribution. The upper bound of the confidence interval is about 0.2°C lower than in the baseline scenario (90% c.i.= (1.26, 4.13), median=2.44). This is a significant difference, indicating the large proportion of scenarios contained by the A1 family skews the distribution towards higher temperature change. A 90% confidence interval indicates the bounds between which the "true" result is 90% likely to fall, with 5% chance of the result exceeding the upper bound and 5% chance of being below the lower bound. The upper bound of the confidence interval implies the highest temperature change that is reasonably likely, so a change in this value is important to note. In studies like that of Wigley and Raper, the threshold value above which there is less than 5% probability of global mean warming between 2000 and 2100 would most likely be about 0.2°C lower than is under the equal likelihood assumption if the families were not unevenly weighted due to the technology analysis in family A1.

Another question regarding the assumption of uniform likelihood over all scenarios is whether the multi-model approach to creating the SRES scenarios resulted in a more balanced set of scenarios. In other words, how well does using several models result in a set of scenarios that cover the range of emissions uncertainty? Five integrated assessment models (AIM, ASF, IMAGE, MESSAGE, and MINICAM) (*9*) were used to create the 35 emissions scenarios used in this study. Each model is calibrated differently and deals with various future social, economic, and demographic factors differently; so models give different emissions estimates given the same input assumptions. The five IA models used by the SRES authors is a subset of all possible IA models that could have been used. How different would the temperature change distribution in 2100 be if a different set of models was used? In order to test how much the use of the five models to create the scenarios affects the resulting temperature change distribution, I compare the reference case results to the results when I use only the scenarios created using four of the models, leaving the fifth model out.

Using only the scenarios from four out of the five IA models at a time changes the distributions and confidence intervals somewhat (see Figure 5 and Table 1). Leaving the MESSAGE model out increases the lower bound of the confidence interval by about 0.12°C, which indicates that the MESSAGE model skews the results toward lower temperatures. This is also apparent in the distribution (Figure 5).

When the MINICAM model scenarios are left out, the lower bound of the 90% confidence interval is decreased by about 0.1°C compared to the reference case. The shifts in confidence interval bounds from the reference case are not large. Consider the possibility of the SRES authors having chosen four models instead of five. If the four models chosen were the current five minus the MESSAGE model, the lower bound of the

90% c.i. and the median of the resulting temperature change distribution would both be 0.2°C higher than they would be if the four models chosen were the current five minus

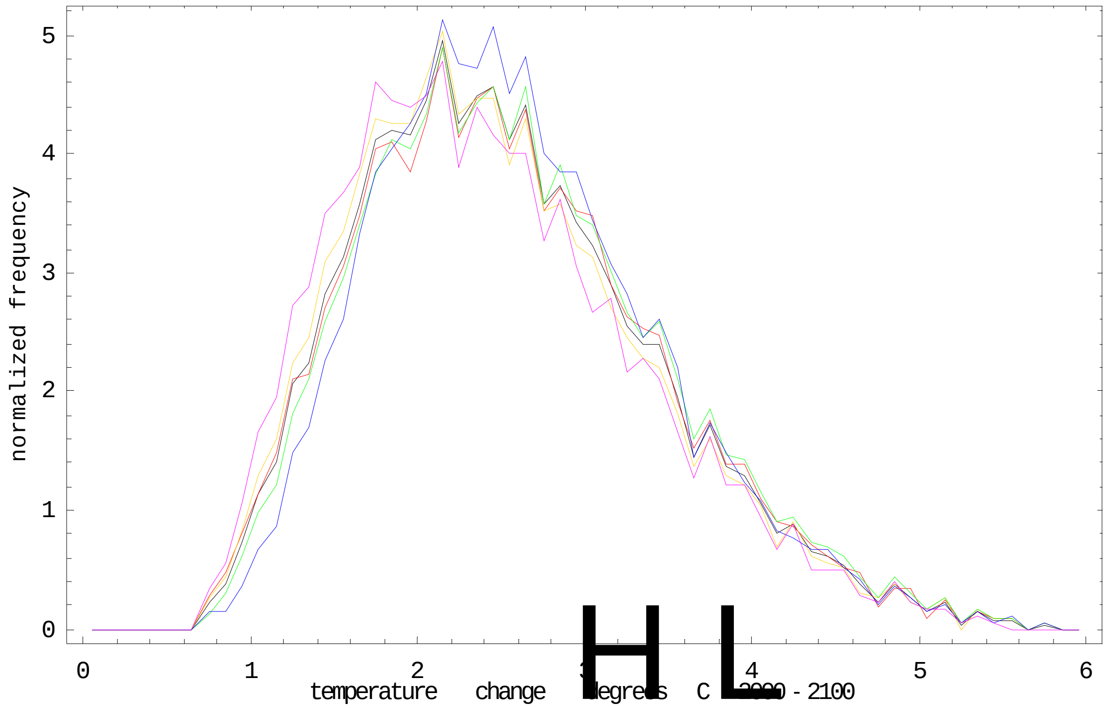

Figure 5. Probability distributions for temperature change in degrees C from 2000 to 2100 using scenarios from four of the five IA models at a time.

model eliminated	**reference**	**AIM**	**ASF**	**IMAGE**	**MESSAGE**	**MINICAM**
90% c.i. lower bound	1.261	1.245	1.235	1.300	1.376	1.182
median	2.442	2.460	2.384	2.487	2.504	2.321
90% c.i. upper bound	4.130	4.188	4.116	4.214	4.127	4.086

a)

	-10%	**-5%**		**+5%**	**+10%**
90% c.i. lower bound	0.974	1.118	1.261	1.404	1.548
median	2.155	2.299	2.442	2.585	2.729
90% c.i. upper bound	3.843	3.986	4.130	4.273	4.417

b)

Table 1. a) Median and 90% confidence interval bounds for temperature change results (in degrees C) from removing all scenarios created using one of the five IA models (listed at top). b) For reference, values 5% and 10% above and below the median and confidence interval bounds of the reference case scenario (all scenarios weighted equally).

the MINICAM model. Again, this is a 0.2°C warming difference in the 95% probability cutoff. Given that there are only five models to begin with, this is not a drastic difference. Since each model produces emissions scenarios that are spread across much of the range of all scenarios, eliminating one does not affect the results greatly.

The effect of changing the likelihood assumption for emissions scenarios

In addition to testing the effects of methodological choices made by the IPCC SRES group in creating the scenarios, I analyze the effect of changing the equal probability assumption. The purpose of this part of the investigation is to determine how sensitive climate model results are to the probability assumption for emissions. Since it is very unlikely that all 35 scenarios are actually equally probable (according to expert elicitation or some other subjective method, as this is the only way to assess likelihood of future emissions), it is useful to understand how a change from this assumption to another reasonable distribution would affect the result.

One possible, reasonable assumption about future emissions is that the values closer to the center of the range are more likely than those close to the extremes. The same reasons that confine an uncertain variable's value to a given range generally also result in a bell-shaped distribution of its likelihood, since the bounds of the range usually signify a cutoff somewhere along a spectrum of declining likelihood, rather than a clear point dividing values that are likely from those that are impossible. While the range of emissions scenarios does not imply the same thing that a range taken from an emissions p.d.f. would, it is reasonable to assume that most people would assume a bell curve to represent the probability function for emissions.

I chose cumulative radiative forcing (*17*) between 2000 and 2100 as the criterion for determining which scenarios are close to the center and which fall toward the outer edges of the range. Other possible criteria for determining this are cumulative CO_2 emissions, cumulative emissions of all greenhouse gases (with or without aerosols), and total temperature change from 2000 to 2100. The reason none of these were chosen is that it is less clear whether it is reasonable to assume that those variables are more likely to fall close to the center of their ranges. For instance, aerosol emissions are highly uncertain and counteract the warming effect of greenhouse gases. There is a correlation between cumulative CO_2 emissions and cumulative radiative forcing between 2000 and 2100 (see Figure 5), indicating that using cumulative emissions would give a similar result. The 35 emissions scenarios are ranked based on cumulative radiative forcing from 2000-2100, then divided into thirds. The scenarios in the middle section are assigned a higher probability than those in the lower and higher sections, and the temperature change distribution resulting from this new probability assumption is compared with the reference case distribution.

The division of the 35 SRES scenarios into thirds and weighting the scenarios in the center third higher, rather than using some other method of applying varying weights to the scenarios, does not necessarily reflect the most realistic assumption for likelihood. However, the actual weightings chosen are inconsequential, as the purpose of the exercise is to determine how sensitive the resulting distribution of global temperature change values are to a change in the likelihood assumption for emissions. The actual weighting of the SRES scenarios could be done any number of ways in order to demonstrate the same idea.

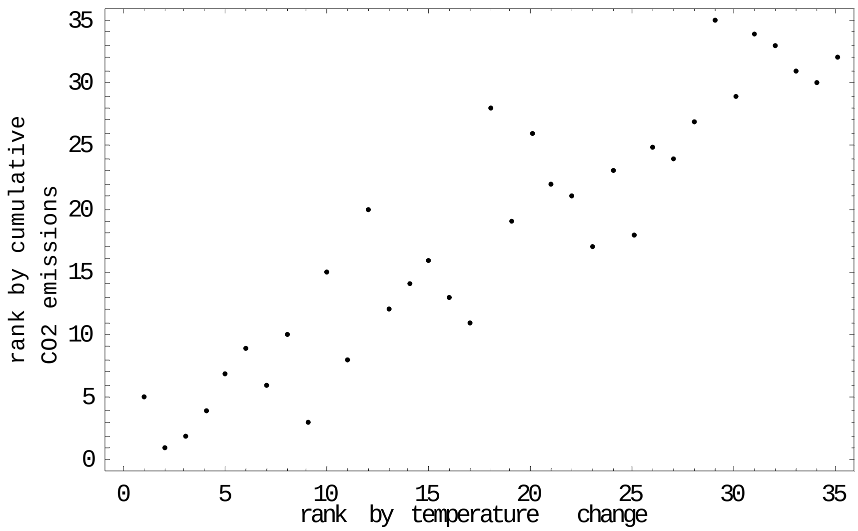

Figure 5. Correlation between scenarios' rank (out of 35 scenarios) based on temperature change/cumulative radiative forcing for the central values for climate sensitivity and fertilization factor (x axis), and rank based on cumulative CO_2 emissions of that scenario (y axis).

weighting on center	reference	2	5	10	infinity
90% c.i. lower bound	1.261	1.331	1.445	1.497	1.568
median	2.442	2.449	2.457	2.459	2.464
90% c.i. upper bound	4.130	4.022	3.865	3.776	3.697

Table 2. Median and 90% confidence interval bounds for temperature change results (in degrees C) from various increases in the probability of the centermost third of the emissions scenarios based on cumulative CO_2 emissions from 2000 to 2100. "Weighting on center section" values refer to how many times more likely the scenarios in the centermost section was made compared to those in the high and low sections.

Assigning the centermost emissions scenarios a higher likelihood than the high and low scenarios does change the temperature distribution and associated confidence interval, although not very much. As shown in Table 2, the difference in the bounds of the 90% confidence interval and median of the distribution changes very little unless the weighting on the center group is very strong. With a weighting of infinity on the center scenarios (meaning the emissions scenarios in the high and low thirds based on cumulative radiative forcing are assumed impossible and left out altogether), the lower bound of the 90% confidence interval increases by about 0.3°C, the upper bound decreases by over 0.4°C, and the median remains almost the same compared to the reference case results. This makes the entire 90% c.i. almost 0.8°C more narrow, which

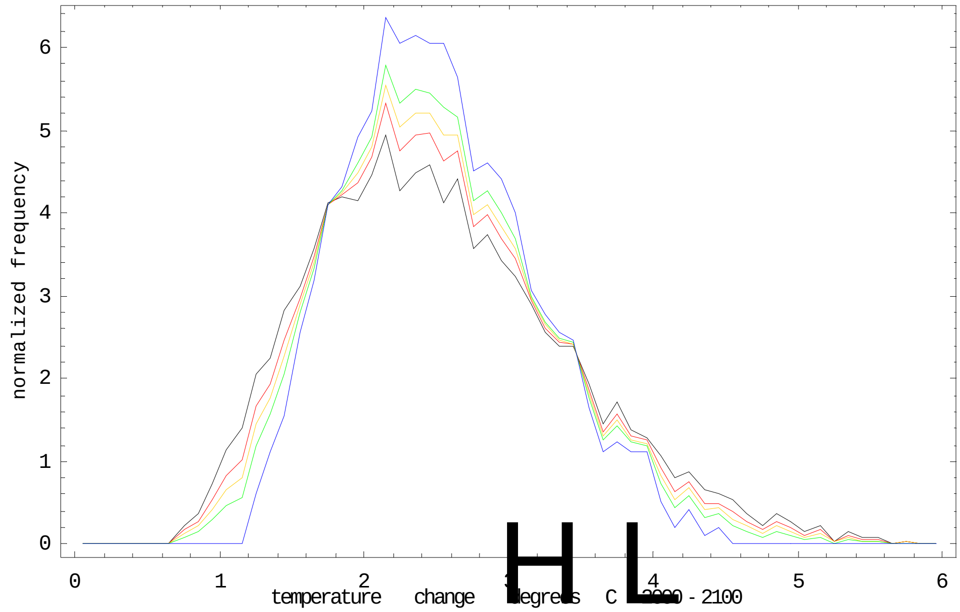

Figure 6. Temperature change distributions for reference case results (unweighted, shown in black) and weighted centermost third of emissions scenarios by a factor of 2 (red), 3 (yellow), 5 (green), and infinity (blue).

is more than a 25% reduction in range. If there was reason to believe that the scenarios towards the center of the radiative forcing distribution are actually much more likely than those towards the extremes, it would significantly narrow the uncertainty range for global mean warming between 2000 and 2100. A result that there is less than 5% probability of exceeding 3.7°C is very different from the same probability of exceeding 4.1°C, and the policy responses might be quite different for these two results. Additionally, if we agree that there is some threshold warming over the 21st century, exceeding which would result in “severe” or “dangerous” impacts, a change in the upper bounds of the confidence intervals would be very important in determining how likely severe impacts are and what the policy response should be. The infinity case demonstrates that there is a limit to the effect that changing the emissions likelihood assumption can have on the distribution of values for global mean temperature. Since each of the three uncertain parameters contribute significantly to the uncertainty in the results of my climate model, changing the assumptions about one of those parameters, namely emissions, can only affect the distribution of results by a limited amount. Therefore, the uncertainty associated with temperature change can only be reduced, and the resulting confidence interval can only change, by a limited amount as well.

In addition to of increasing the probability of the centermost individual scenarios, we also tested the sensitivity of the temperature results to increasing the probability of scenarios in the two most moderate families—B2 and A1B (a subgroup of the A1 family). The reason for doing this is essentially the same as in the previous test, except from a different viewpoint. Instead of assuming higher probabilities based on the cumulative radiative forcing associated with emissions scenarios, this tests the sensitivity of the results to an assumption that the centermost SRES families are more likely than the families that lie towards the extremes. For instance, it might be reasonable to assign higher probabilities to the more central or balanced storylines, simply because they are more moderate than the others. As shown in Table 3, in the most extreme case of weighting, “infinity,” wherein scenarios that do not come from either the A1B subgroup or the B2 family are treated as impossible, the lower bound of the 90% c.i. increases by over 0.3°C, the median increases by about 0.15°C, and the upper bound of the confidence interval increases very little. It is interesting to note that the upper portion of the distribution is almost unaffected by this new probability assumption (see Figure 7). This is because while the A1B and B2 families are those with scenarios closest to the center of the range of all scenarios, but they contain some of the highest scenarios as well.

weighting on A1B, B2	**reference**	**2**	**5**	**10**	**infinity**
90% c.i. lower bound	1.261	1.329	1.428	1.495	1.583
median	2.442	2.482	2.530	2.556	2.585
90% c.i. upper bound	4.130	4.116	4.102	4.097	4.087

Table 3. Median and 90% confidence interval bounds for temperature change results (in degrees C) for various weightings of the scenarios within the A1B and B2 families.

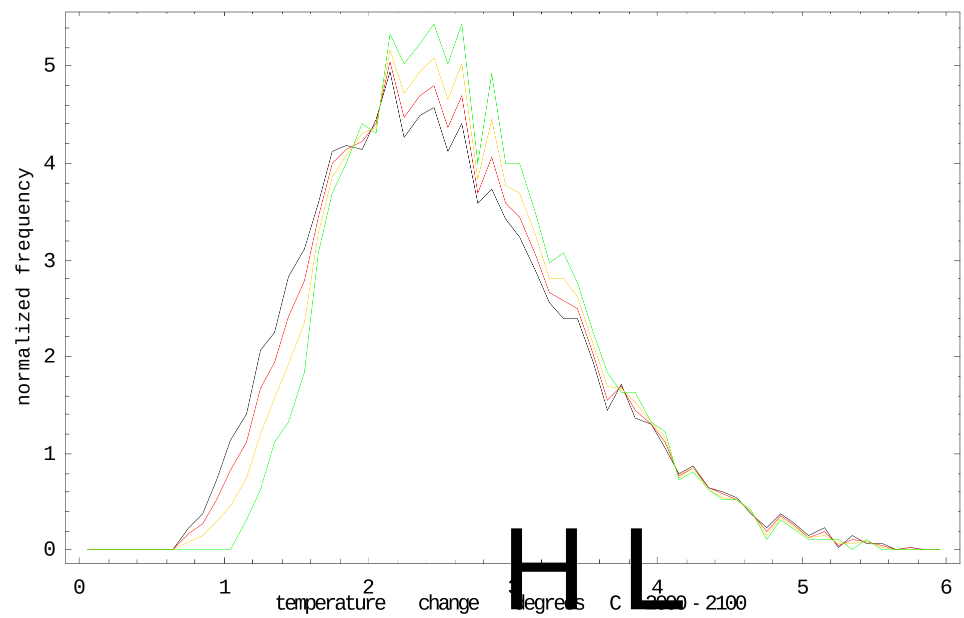

Figure 7. Temperature change distributions for reference case (unweighted, shown in black) and weighted scenarios belonging to the A1B and B2 families by a factor of 2 (red), 5 (yellow), and infinity (green).

Another test of the model results’ sensitivity to changes in the probability assumption for emissions is to weight all scenarios equally, but excluding the lowest and highest 10% emissions scenarios. Again, the lowest and highest scenarios are determined by ranking the scenarios according to cumulative radiative forcing between 2000 and

2100. For 35 scenarios, the highest and lowest 10% is somewhere between 3 and 4 scenarios on each end, and I chose to exclude the highest and lowest 4. There is almost a 0.3°C decrease in the upper bound of the 90% c.i., which is a large effect and is important, as discussed earlier. See Figure 8 and Table 4.

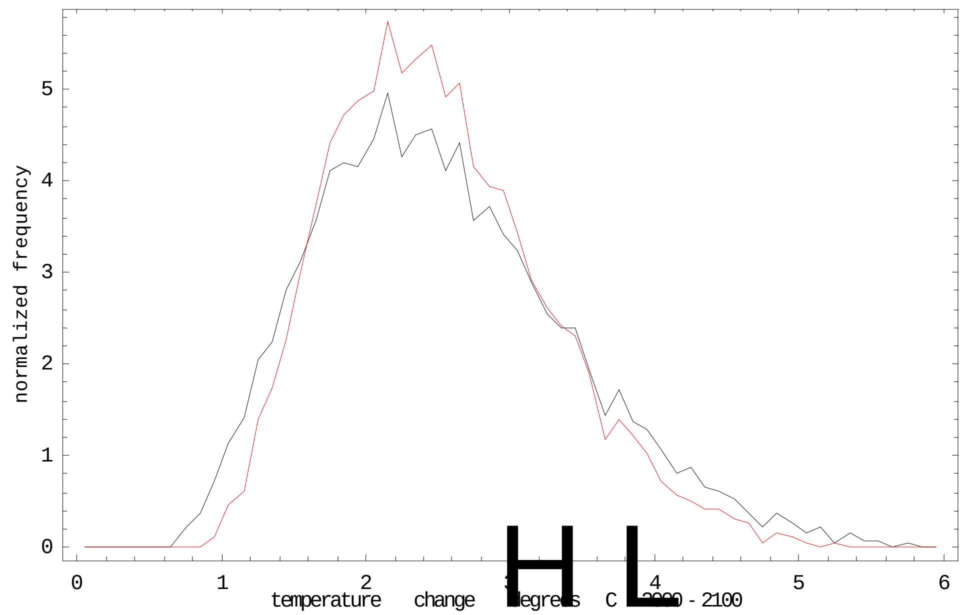

Figure 8. Temperature change distributions for reference case (unweighted, shown in black) and results from using only the centermost 80% of the emissions scenarios.

	reference	**drop extremes**
90% c.i. lower bound	1.261	1.436
median	2.442	2.436
90% c.i. upper bound	4.130	3.865

Table 4. Median and 90% confidence interval bounds for temperature change results (in degrees C) for reference case (unweighted) and centermost 80% (include all scenarios weighted equally, except 10% highest and lowest).

Finally, I test the effect of using only the 6 SRES marker scenarios. Using only the 6 marker scenarios, which is the minimum suggested by the SRES authors, may be problematic. Doing so changes the median value and 90% confidence interval bounds by about 0.2°C each, resulting in a lower median warming value and a 0.4°C wider confidence interval (see Table 5). Using fewer scenarios, in this case, amplifies the uncertainty in the results. There is an obvious difference in the resulting global mean warming projection distribution (see Figure 9), much more so than the differences resulting from other changes in assumptions about emissions likelihood. Possibly counter-intuitively, a smaller, more meaningful range is obtained by using all 35 scenarios. This is because the six marker scenarios are spread across the range of all scenarios and the smaller number of marker scenarios means that each one counts much more in the distribution of results. In the full set of scenarios, there are more scenarios close to the center of the distribution, which offsets the effect of having few scenarios near the outer bounds of the range. These results suggest that SRES users should be encouraged to use the entire set of 35 scenarios, if possible, rather than just the 6 markers.

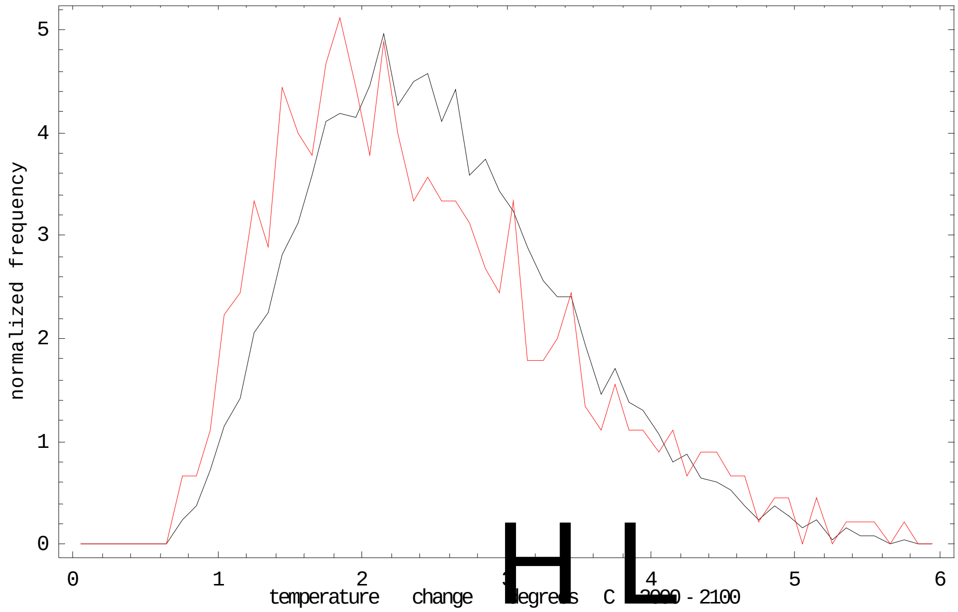

Figure 9. Temperature change distributions for reference case (unweighted, shown in black) and results from using 6 marker emissions scenarios.

	reference	6 markers
90% c.i. lower bound	1.261	1.122
median	2.442	2.248
90% c.i. upper bound	4.130	4.352

Table 5. Median and 90% confidence interval bounds for temperature change results (in degrees C) for reference case (unweighted) and results obtained by using only the 6 marker scenarios.

Conclusions and Implications

Probabilistic modeling is the best tool we have to assess the risk of future climate change based on current understanding of the climate system and the relationships that govern it. Uncertainties in the model and data multiply to result in temperature output that is even more uncertain than the individual parameters to the model. The IPCC gives a range of 1.4° to 5.8°C increase in global average temperature over the 21st century. While this range is helpful in assessing the risk of climate change, probabilistic results, or even less specific likelihood estimates would be more helpful. In order to produce probabilistic model results, probabilistic inputs are needed. The SRES emissions scenarios were created for use in modeling, and as helpful as they are in this endeavor, they come without likelihood estimates. There has been some debate recently over whether likelihood estimates should be, and even *can* be, assigned to the SRES (or any set of) emission scenarios.

This study demonstrates the effect of changing the probability assumption for emissions scenarios on the distribution of temperature change. In general, the effects of various changes in emissions likelihood were rather small, near 0.1°C changes in the 90% confidence interval bounds for temperature. The largest change in the 90% confidence interval bounds was about 0.3°C, and was achieved by assuming that only scenarios from the A1B and B2 scenarios are plausible, and weighting all others as 0. If the center one-third (by cumulative radiative forcing rank) scenarios are assumed five or more times as likely as those in the outside thirds, the 90% confidence interval shrinks by about 0.2°C on the low end and about 0.3°C on the high end. Perhaps the most useful finding is that using the six SRES marker scenarios instead of the full set of 35 scenarios increases the range of values covered by 90% of the distribution. This is important to note because many users of the SRES scenarios will use only the six markers, which is the minimum recommended by the IPCC. When choosing how many and which scenarios to use, researchers should be aware of the likely effect that choice will have on the outcome.

One idea to consider is that the uncertainty in climate change projections is rather large, and in the results presented here, that uncertainty stems from three sources: the emissions, the carbon cycle (fertilization factor), and the climate model (climate sensitivity). This series of uncertainties building on one another is referred to as a "cascade of uncertainty" by Schneider (*19*). The effect is that reducing the uncertainty in one of the factors in the cascade, even artificially as I have done here, has a limited effect on the uncertainty in the overall results because there is still great uncertainty contributed by the other uncertain factors. As long as large uncertainties remain in the climate sensitivity and the carbon cycle, reducing the uncertainty in emissions may have little impact on the results. An experiment that would be useful in addressing this question is an evaluation of the relative importance of reduced uncertainty in the probability distributions of each of the uncertain parameters. Specifically, which parameter is responsible for most of the uncertainty? Once that is determined, it might be productive to work toward reducing the uncertainty of that parameter.

Future Research

One of the advantages of explaining climate projection results in probabilistic terms is that it allows us to determine how likelihood of crossing some threshold. For instance, the IPCC (*18*) estimates that any global mean warming above 3.5°C over the 21st century would have "severe" impacts on humans and natural systems. Schneider (*5*) shows that selection of different sets of emissions scenarios from the full SRES set results in large differences in the likelihood of crossing the 3.5°C threshold. It would be useful to examine this in more detail, and determine the probability of crossing that threshold given various assumptions about emissions scenario likelihood.

An interesting result of this study is that, in general, the distribution of global mean warming results do not change dramatically if the probability assumptions regarding emissions scenarios are changed by moderate amounts. If they are changed dramatically, significant changes in the confidence interval bounds, median, and probability of crossing a threshold do occur. However, in order for these results to be useful, it is necessary to investigate how reasonable these dramatic changes in likelihood assumptions about emissions are. The SRES scenarios are meant to cover the range of plausible future emissions, but how likely must a scenario be (subjectively) for it to be considered plausible?

It is important to remember that the SRES scenarios are not the definitive set of emissions scenarios. The MIT Joint Program on the Science and Policy of Global Change (*12*) has created its own probability distributions for emissions based on IA models, and these distributions are very different from those assumed by SRES (*9*). Four of the six SRES marker scenarios fall below the median of the MIT distributions, and two of the markers fall below the 95% confidence interval of the MIT distributions. If these distributions are used in place of the SRES scenarios in probabilistic modeling, the temperature change distribution may change significantly. Future research examining the same issues in this study comparing the SRES scenarios with the MIT distributions for emissions would be helpful in addressing this question. Furthermore, since the SRES and MIT future emissions probability distributions are so different, the question of which is more reliable must be addressed. This will require some level of subjectivity, which is sure to stir up controversy, but it cannot be avoided.

References

1. Intergovernmental Panel on Climate Change. *Climate Change 2001: The Scientific Basis*. Contribution of working group I to the third assessment report of IPCC (eds Houghton, J. T. *et al*.) (Cambridge University Press, 2001).

2. Intergovernmental Panel on Climate Change. *Climate Change 1995*. Contribution of working group I to the second assessment report of IPCC (eds Houghton, J. T. *et al*.) (Cambridge University Press, 1996).

3. Schneider, S. H. Editorial comment: "Can we estimate the likelihood of climatic changes at 2100?", *Climatic Change* 52, 441-451.

4. Pittock, A. B., Jones, R. N. & Mitchell, C. D. "Probabilities will help us plan for climate change", *Nature* 413, 249 (2001).

5. Schneider, S. H. "What is 'dangerous' climate change?", *Nature* 411, 17-19 (2001).

6. Webster *et al*. *MIT Joint Program on the Science and Policy of Global Change: Uncertainty Analysis of Global Climate Change Projections* (Report No. 73, March 2001 [w/ revisions July 2001]).

7. Visser, H. *et al*. "Identifying key sources of uncertainty in climate change projections", *Climatic Change* 45, 421-457 (2000).

8. Titus, J. G. & Narayanan, V. "The risk of sea level rise", *Climatic Change* 33, 151-212 (1996).

9. Intergovernmental Panel on Climate Change. *Special Report on Emissions Scenarios*. (eds Nakicenovic, N. et al.) (Cambridge University Press, 2001).

10. Wigley, T. M. L. & Raper, S. C. B. “Interpretation of High Projections for Global-Mean Warming”, *Science* 293, 451-454 (2001).

11. Grübler, A. & Nakicenovic, N. “Identifying dangers in an uncertain climate: We need to research all the potential outcomes, not try to guess which is likeliest to occur”, *Nature* 412, 15 (2001).

12. Webster *et al. MIT Joint Program on the Science and Policy of Global Change: Uncertainty in Emissions Projections for Climate Models* (Report No. 79, August 2001)

13. Jain, A. K. *et al*. “Distribution of Radiocarbon as a Test of Global Carbon Cycle Models”, *Global Biogeochemical Cycles* 9, 153-166.

14. Osborn, T.J. and Wigley, T.M.L. “A simple model for estimating methane concentration and lifetime variations”, *Climate Dynamics* 9, 181-193 (1994).

15. Hoffert, M. I. *et al.* “The Role of Deep Sea Heat Storage in the Secular Response to Climatic Forcing”, *J. Geophys. Res.* 85, 6667-6679.

16. The 35 scenarios were created by five models only; those scenarios created by the MARIA model do not provide emissions for many greenhouse gases.

17. Total temperature change from 2000 to 2100 for the central fertilization factor and climate sensitivity values is used as proxy for cumulative radiative forcing. It is likely that the correlation is not perfect, but this method should approximately rank the scenarios in terms of cumulative radiative forcing produced.

18. Intergovernmental Panel on Climate Change. *Climate Change 2001: Impacts, Adaptation, and Vulnerability*. Contribution of working group II to the third assessment report of IPCC (eds Houghton, J. T. *et al*.) (Cambridge University Press, 2001).

19. Schneider, S. H. in *Social Science Research and Climate Change: An Interdisciplinary Appraisal* (eds Chen, R. S., Boulding, E. & Schneider, S. H.) 9-15 (Reidel, Boston, 1983).