Probabilistic Assessment of the Rate of Future Climate Change

Andrew J. Ross

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ABSTRACT

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The chapters in this thesis examine the overall rate of future climate change as it relates to the concept of rapid climate change under a probabilistic framework for quantifying climate model uncertainty. The first study uses a simple climate model to estimate the likely range of rates of temperature change associated with the implementation and removal of climate engineering. We found that following the removal of climate engineering, high rates of temperature change were sustained for two decades; rates of change of 0.5 (0.3, 0.1) °C per decade were exceeded over a 20-year period with 15% (75%, 100%) likelihood. Our results suggest that climate engineering in the absence of deep emissions cuts could arguably constitute an increased risk of dangerous anthropogenic interference in the climate system. The second study uses an intermediate complexity climate model to assess the likelihood of varying climate system properties through the use of probability density functions of climate sensitivity and ocean diffusivity. We found that the most probable maximum rate of temperature change occurred between 0.3 and 0.5 °C per decade with a most likely value of 0.36°C per decade. Our results also suggest that changes in ocean diffusivity in the model have a significant effect on the rate of transient climate change in the upper end climate sensitivity simulations, but show little influence in the lower end. Many of the high rates of warming obtained in both studies could potentially cause widespread physical and biological damage, exceeding the adaptive capacity of healthy functional ecosystems.

Contributions of Authors

The research presented throughout this thesis was co-authored by the following authors: A.J. Ross, H.D. Matthews, and A. Schmittner. As the first author, I was responsible for developing the experimental and research design, data acquisition, analyzing results, and presenting findings in the form of this thesis. H.D. Matthews provided advice with the experimental design; support and training associated with running the model, and provided some writing guidance throughout the manuscript. A. Schmittner contributed to the methodology of calculating ocean diffusivity probability density functions.

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List of Acronyms

BAU – business as usual

C.S. – climate sensitivity

FAR – fourth assessment report

IPCC – Intergovernmental Panel on Climate Change

MAGICC – Model for the Assessment of Greenhouse Gas Induced Climate Change

OS – overshoot

PDF – probability density function

RC – rapid change

SC – slow change

SRES – Special Report on Emission Scenarios

TAR – third assessment report

THC – thermohaline circulation

UNFCCC – United Nations Framework Convention on Climate Change

UVic ESCM – University of Victoria Earth System Climate Model

Introduction

The climate system is very dynamic and undergoes constant change through a series of physical and biogeochemical interactions with other environmental processes. Unfortunately, anthropogenic interference on the climate system has altered these natural cycles of change and disrupted a crucial state of natural flux, which no longer persists in the global environment. Consequently, the scientific community has made efforts to understand, quantify, and explain these changes through the use of empirical observations and environmental modeling. However, because the climate system is complex and temporally extensive, analyzing these potential climate changes with simple experimental designs that rely on empirical observations is extremely difficult. As a result, the latter of the two methods (environmental modeling) has taken a leading role in the quest to understand anthropogenic climate change and to investigate the possible ways to avert future dangerous impacts.

Climate modeling studies and experiments rely heavily on past observations and paleo-climate data for validation measures. Therefore, their accuracy is linearly dependent on and constrained to our ability to gather observational data and process information. That being the case, it is nearly impossible and highly improbable to perfectly simulate such a dynamic structure as the global climate system. Despite their acclaimed robustness and precision, all climate models are tainted with some form of uncertainty, which ultimately causes inter-model variability. Quantifying this uncertainty is crucial to understanding the possible ranges of future climate change impacts and communicating the risks involved to key decision makers in the context of climate change mitigation.

For the most part, climate model uncertainty can be attributed to varying representations of certain physical properties in the climate systems, which are often controlled by key physical parameters within the models. Different variations of these parameters have the potential to yield very different results, thus providing different depictions of certain climate system properties (Forest et al, 2001). For example, cloud feedbacks possess great uncertainty in terms of their net effect on the global average temperature, therefore creating a large uncertainty in determining the overall climate sensitivity (the equilibrium change in global mean surface temperature following a doubling of the atmospheric (equivalent) CO_2 concentration)(Meehl, 2007). Another example is the rate of deep ocean heat uptake, which is controlled by ocean vertical diffusivity. Ocean diffusivity is also very uncertain and often estimated differently in different climate models (Schmittner et al, 2009). Climate model uncertainty is dependent on a number of key physical model parameters that possess very uncertain physical properties, which have the potential to yield a wide range of results.

Quantifying uncertainty within climate models requires an approach that utilizes a probabilistic framework to assess the likelihood of different variations of certain climate system properties. The most commonly used measure is a probability density function (PDF), which calculates the probability of a certain distribution of a particular variable such as climate sensitivity or ocean vertical diffusivity (both are key uncertain parameters). According to Forest (2002), by systematically varying these climate parameters, in an attempt to reproduce the historical climate record and performing a statistical comparison, a PDF of each can be calculated.

Different combinations with varying intensities of these two uncertain parameters have the potential to yield a wide range of climate responses, each with their own probability of occurring. Typically, however, these climate changes are measured with the overall surface air temperature change, with respect to a chosen reference point. An equally important measure, despite being overlooked or not even accounted for in most of the literature, is the rate at which the temperature changes in the atmosphere. This under-researched phenomenon has profound implications on the global climate system and poses as a valuable indicator for the degree of stability throughout our planet's ecosystems. Many environmental systems and the adaptive capacity of species are dependent on the rate of climate change. Our ability to adapt to future climate changes, too, depends heavily on the possibility of avoiding dangerous tipping points or surpassing certain thresholds that could potentially initiate abrupt or rapid climate change.

The threat of rapid or abrupt climate change is entirely relevant to climate change research because it entails so much uncertainty and potentially the most negative environmental impacts. In particular, ecosystem collapse, species extinction and the weakening of the meridional overturning circulation are all potential outcomes of different degrees of rapid climate change. It is naturally difficult to define such a loose term as "rapid" because there are different levels of climate change that occur. What constitutes "rapid climate change" may vary depending on the time and spatial scale. In any case, the concept of rapid climate change is directly related to adaptability. The size and extent of impacts following rapid or abrupt climate change is dependent on both the rate of climate change and the overall capacity of nature to adapt (Niemeyer et al. 2005). Consequently the possible existence of unforeseen thresholds, as proposed by the Intergovernmental Panel on Climate Change (IPCC), will most definitely affect the proposed trajectory of adaptability.

This newly emerging threat has prompted climate scientists to consider more radical solutions, such as geoengineering, with the potential to stop or at least slow down the effects of climate change. Geoengineering can be defined as the intentional large-scale manipulation of the natural environment to counteract anthropogenic climate change (Keith, 2000). In general, geoengineering schemes aim to avert a climate catastrophe and reduce the overall risk of unwanted environmental impacts. However, geoengineering carries its own suite of risks that could potentially overwhelm the desired or intended effects. It is conceivable that a future dependency on some form of large-scale geoengineering technology could accelerate our climate into a state of rapid warming in the wake of a sudden failure or stoppage. Much uncertainty surrounds this issue and the possible impacts of such a scenario are not well understood. Therefore, quantifying that uncertainty and examining its possible climatic effects is crucial for climate change mitigation.

Literature Review

Quantifying uncertainty in climate models

Although climate models represent the best available tool to assess climate change impacts and formulate projections into the future, there is still uncertainty surrounding several of the climate system properties. Since the scientific community is so dependent on these models, it becomes crucial that this inherited uncertainty be quantified or at least measured, in order to properly evaluate the variability and probability in model simulations. In general, there exists two types of uncertainties: 1) the representation of physical processes in models used for climate projections and 2) the forcing scenarios which are used to create these projections (Forest et al. 2001). For the purpose of this review, the former will be emphasized.

The two most uncertain properties in the climate system that control the decadal response in transient climate change are climate sensitivity and the rate of deep ocean heat uptake (Forest et al. 2002). Previous simulations and estimates reveal that these two properties have considerable variability between different climate models and are measured differently (Forest et al. 2002). Fortunately, a method known as fingerprint detection, developed by Forest et al. (2001), can be used to quantify and estimate the uncertainty of both of these parameters (climate sensitivity and ocean diffusivity). This method compares a model's response to known forcings versus climate observations for that same period. By appropriately varying climate sensitivity and ocean diffusivity, followed by a linear regression analysis, these parameters are constrained probabilistically (Forest et al. 2001). In addition, the probability density functions of both properties are estimated. Forest et al. (2002) uses this method to estimate a 5 to 95% confidence interval of climate sensitivity, which yielded a range of 1.4 to 7.7 Kelvin. This estimated interval represents one of the first attempts to constrain climate sensitivity and limit its uncertainty.

In a related study, Hegerl et al. (2006) demonstrated that this range could be tightened further by using reconstructions of Northern Hemisphere temperature over the past several centuries. By accounting for the uncertainty involved in these reconstructions, a tightened range of 1.5-6.2 Kelvin climate sensitivity can be measured. As a result, the larger amount of uncertainty associated with the higher end values of climate sensitivity are reduced, which further reduces the probability of very high climate sensitivity.

The Intergovernmental panel on climate change (IPCC) fourth assessment report (FAR) (Meehl et al. 2007) provides its own estimate of climate sensitivity by using an entire suite of climate sensitivity probability density functions (PDF). From these previously published estimates a better quantification of a most likely value, instead of just a subjective range of uncertainty, can be calculated. The IPCC estimates a most likely value of 3 Kelvin and states that the climate sensitivity is "likely" to lie in the range of 2 to 4.5 Kelvin. Figure 1 shows multiple PDFs of climate sensitivity estimated by various studies (left column) and their 5 to 95% ranges that include the medians (circles) and maximum probabilities (triangles) (right column). They are also grouped according to their different constraints. Box a) represents the PDFs which are constrained by past transient temperature evolution; whereas box c) shows the PDFs which are constrained by present-day climatology. Last, box e) shows the unweighted distributions of climate sensitivity.

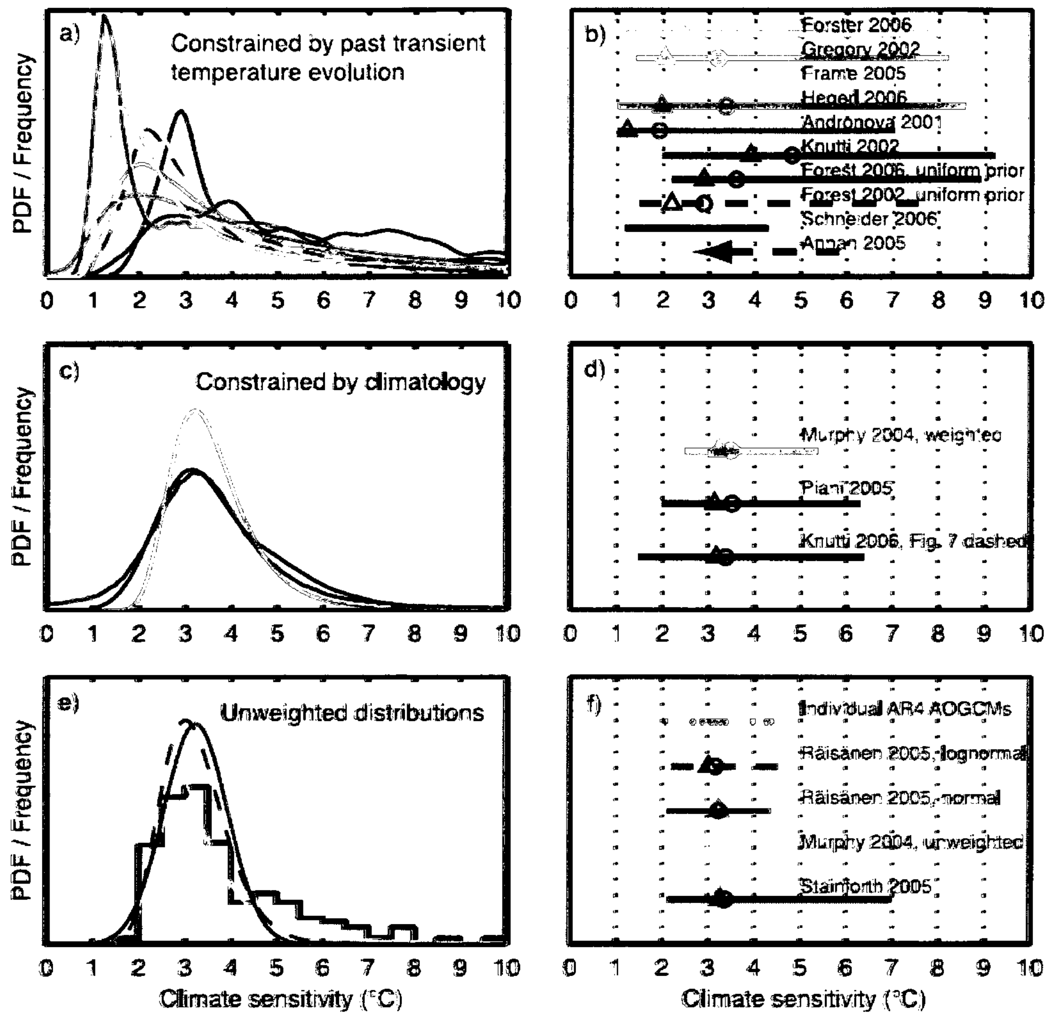


Figure 1: (a) PDFs or frequency distributions constrained by the transient evolution of the atmospheric temperature, radiative forcing and ocean heat uptake, (b) as in (a) but 5 to 95% ranges, medians (circles) and maximum probabilities (triangles), (c) and (d) as in (a) but using constraints from present-day climatology, and (e) and (f) unweighted or fitted distributions from different models or from perturbing parameters in a single model. (Meehl et al. 2007)

Besides climate sensitivity, ocean heat uptake also plays a critical role in this observed uncertainty within climate models because it helps to regulate the overall transient climate response. The oceans diffuse surface heat downwards in the low latitudes and then transport it to the higher latitudes where this heat is released back into the atmosphere (Raper et al. 2002). According to Raper et al. 2002, there is an apparent relationship between climate sensitivity and the efficiency of ocean heat uptake. Their study explains that higher climate sensitivity yields greater surface warming and thus results in a warming through a deep layer of the high-latitude oceans. In turn, this affects ocean diffusivity and the overall transient climate response.

However, Forest et al. 2006 explains that most atmosphere-ocean general circulation models have a tendency to mix heat into the deep ocean too efficiently. This conclusion is supported by the fact that their revised estimate of the rate of deep-ocean heat uptake includes the effect on 20th century temperature changes of natural and anthropogenic forcings. They calculated a rate of ocean diffusivity ranging from 0.05 to 4.1 cm^2/s.

Climate sensitivity and the rate of ocean heat uptake represent the two most uncertain climate properties in climate models and as a result, efforts to reduce this uncertainty are essential for more accurate predictions of future climate change. A major component of this quantification process involves an approach that emphasizes probabilistic measures.

Probabilistic projections of future climate change

As described in Article 2 of the United Nations Framework Convention on Climate Change (UNFCCC):

> "The ultimate objective of this Convention ... is to achieve ... stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. Such a level should be achieved *within a time frame sufficient to allow ecosystems to adapt naturally to climate change...* " [emphasis added] (UNFCCC, 1992)

Dangerous anthropogenic interference in the climate system can be defined as impacts that: 1) do not allow ecosystems to adapt naturally to climate change; 2) threaten food production; 3) do not enable economic development to proceed in a sustainable manner (UNFCCC, 1992). Dangerous climate change can also be measured in terms of the consequences or vulnerabilities to certain climate changes. For example, the IPCC identified some key vulnerabilities that could be used as a metric for assessing dangerous climate change: magnitude, timing, persistence and reversibility, likelihood and confidence, potential for adaptation, and importance of the vulnerable system. In general, dangerous levels of climate change can be regarded as circumstances that could lead to global and unprecedented consequences, extinction of keystone species, loss of entire ecosystems and human cultures, and substantial increases in mortality levels (Schellnhuber et al. 2006). Therefore, the probability of dangerous climate change should be quantified, thus a probabilistic approach to forecasting future climate change is necessary.

This process entails conceptualizing and quantifying the uncertainty surrounding future climate impacts (Mastrandrea & Schneider, 2004). It is paramount that climate change assessments include probability frameworks to ensure that environmental consequences are reflected consistently and as originally intended by the authors; otherwise, policy-makers will probably make their own assumptions (Mastrandrea & Schneider, 2004). Mastrandrea and Schneider (2004) state that probabilistic methods are valuable for communicating an accurate depiction of the current state of scientific knowledge to the stakeholders involved in decision-making. In their study, they present a method for assessing dangerous anthropogenic interference that involves a cumulative density function of the threshold of dangerous climate change. In other words, they mapped various climate impacts onto probability distributions of future climate change. Mastrandrea and Schneider (2004) advocate that a probabilistic framework that includes probability distributions and risk diagrams represents the most effective method to represent the results from scientific assessments since the majority of policy-makers have extensive knowledge and training dealing with uncertainty and risk management (Mastrandrea & Schneider, 2004).

Predicting future climate change has its own caveats, namely the validation and robustness of climate models, but the uncertainty in certain climate system parameters makes it increasingly more difficult to accurately assess potential climate impacts. Carbon cycle feedbacks represent one of these uncertain components, where their strength and onset remains undetermined. Probabilistic assessments of future climate change attempt to incorporate this level of uncertainty in order to estimate the likelihood of future warming (Matthews & Keith, 2007). Matthews and Keith (2007) introduce a similar approach to that of Mastrandrea and Schneider (2004) by incorporating carbon-cycle feedbacks with a similar probabilistic assessment approach of future warming. Their novel approach revealed that the inclusion of carbon-cycle feedbacks in their coupled climate-carbon model lead to large increases in extreme warming probabilities. In some cases, their simulations yielded greater warming potentials by as much as 22%. Their study highlights the importance of incorporating probability measures in climate prediction, and it helps to emphasize the relevancy of limiting the uncertainty within different magnitudes of warming, while considering temperature stabilization targets. However, a more comprehensive assessment of future climate change should include uncertainties in ocean heat uptake (Matthews & Keith, 2007). Matthews and Keith (2007) used constant ocean mixing parameters in their simulations and neglected the possible effect of a varying rate of ocean heat uptake. As a result, a small positive bias is introduced, since higher climate sensitivities used in their simulations are more consistent with higher rates of ocean heat uptake (Forest et al., 2006). Therefore, a more accurate representation of future climate change under a probabilistic framework should include both climate sensitivity and ocean heat uptake uncertainty.

To further reduce this uncertainty, a multi-thousand member ensemble of stabilization scenarios and probability density functions of climate sensitivity was used to generate probabilistic predictions of temperature and sea level rise (Knutti et al., 2005). Knutti et al. (2005) considered both uncertainties in climate sensitivity and ocean heat uptake to produce a large suite of probabilistic projections of future climate change that was intended for the Fourth Assessment Report (FAR) of the IPCC. With a focus on stabilization targets similar to Matthews and Keith (2007), Knutti et al. (2005) suggests that presenting them in a probabilistic assessment helps to illustrate that the ultimate choice of a future emissions path does not depend only on agreed warming limits, but also on the potential risk of exceeding these limits (Knutti et al., 2005). Their contributions to IPCC FAR are summarized in chapter 10.5.4 of that document (see "Sampling Uncertainty and Estimating Probabilities") and also in additional reports on probabilistic assessments. The IPCC FAR emphasizes that most of the progress from the third assessment report (TAR) has been made through probabilistic projections of future climate change. By using multi-model ensemble approaches the IPCC FAR provides uncertainty ranges and probabilities for global and regional climate change. However, different methods exist for deriving different probability distributions, which ultimately depend to varying degrees on the nature and use of observational constraints (Meehl et al., 2007). Much uncertainty stems from model error in Bayesian methods, which deals with the uncertainty that affects the calculation of the likelihood of different model versions, but knowledge and awareness of this issue is mounting.

The overall rate of temperature change is largely dependent on the forcing scenario used to predict future climate change in conjunction with the strength of the physical feedbacks that govern the efficiency of the deep ocean to remove heat from the atmosphere (Collins et al. 2007). Therefore, quantifying the uncertainty related to such a physical component is key to understanding the overall transient climate response that can be expected under prescribed forcing scenarios. Collins et al. (2007) perturbed three key ocean physical processes (the diffusivity of tracers along isopycnal surfaces, the calculation of the depth profile of wind-mixing energy in the ocean mixed layer, and the vertical diffusivity of tracers) in their climate model to measure the transient climate response. They found that the perturbations had little effect on the rate of ocean heat uptake, and therefore had very little impact on the overall rate to transient climate change. Unfortunately, no concrete explanation for this outcome is provided; instead the authors allude to the notion that further research is needed to explain this consequence. In other words, a better understanding of how perturbations in climate sensitivity and ocean heat uptake in climate models affect the overall rate of temperature change or transient climate response is required.

Rates of Warming and Rapid Climate Change

Over the course of Earth's history there have been numerous episodes of rapid climate change that are caused by internal and external non-linear forcings (Rial, 2004). Until now climate change has been regarded as a gradual change that occurs at a historically high rate but still within the range projected by the IPCC (Arnell, 2005). However, the threat of rapid climate change is beginning to surface, and there is more concern that we are in fact much closer to dangerous levels of change than previously anticipated. Clearly the magnitude of this change is an important factor to consider but so is the rate at which this change occurs. The adaptability and survival of the planet's ecosystems depend heavily on the latter. Unfortunately there is no clear definition of "rapid climate change", but according to the IPCC's FAR, the magnitude and timing of impacts that will ultimately be realized by such a change depends heavily on the amount as well as the rate of climate change (IPCC, 2007). So although there is no specific range for dangerous levels of rates of change, the report still acknowledges the fact that the rate at which the climate changes is a large factor in deciding how much and to what extent the impacts will be felt.

To properly assess the impacts of rapid climate change and possibly predict future rapid climate change scenarios, it is necessary to quantify specific rates of temperature change and their associated environmental effects. Only a select few studies have examined rates of climate warming. The first study was by O'Neil and Oppenheimer in 2004, where they assess how the potential for dangerous climate change impacts may change depending on various pathways to greenhouse gas stabilizations. The authors define three different pathways, which are labeled as slow change (SC), rapid change (RC), and overshoot (OS). The SC pathway leads to medium rates of warming that slowly decline over time from an initial rate of 0.16°C per decade. Their low stabilization run yielded medium rates of change that fell under 0.1°C per decade. A high stabilization level simulation gave 0.15°C per decade or above. The other two pathways, RC and OS, produce rates of temperature change that are significantly higher compared to the SC case. For example, a low stabilization level run had a rate of change of approximately 0.2°C per decade. Their overshoot case led to substantial additional warming that ranged from 0.1 to 0.6°C per decade. According to O'Neil and Oppenheimer (2004), rates such as these could entail widespread physical and biological damage. For example, coral reefs and other niche ecosystems may be sensitive to temperature increases greater than 1°C from recent levels. In addition, 0.3°C per decade warming creates a shutdown in the Thermohaline Circulation (THC); a model-dependent result (Stocker and Schmittner, 1997). O'Neil and Oppenheimer mention that differences in transient rates of warming could significantly impact global ecosystems, and sustained rates of warming that are greater than 0.1°C per decade could potentially exceed the adaptive capacity of some sensitive ecosystems.

A more complete synthesis of the present knowledge surrounding rapid climate change is presented in Chapters 11 and 12 of "Avoiding Dangerous Climate Change" by Schellnhuber et al. (2006), where the authors refer to different levels of climate change in the form of overall rates of temperature change. Within these two chapters there is a focus on the widespread ecological impacts of climate change on various biomes. For example, it clearly states that a warming rate over 0.1°C per decade, would threaten most ecosystems and prohibit them from adapting naturally. In fact, a rate of temperature increase of 0.05°C per decade is the proposed threshold to protect ecosystems; above this amount, there will be ecosystem damage. With increasing rates of change there is progressively more ecosystem loss, increased vulnerability, reduced biodiversity and aggressive opportunistic species dominance across the globe. At a rate of 0.4°C/decade almost all ecosystems experience rapid deterioration. The chapter concludes that tighter political climate protection targets are needed to cope with the greater vulnerability of species and ecosystems across the planet.

The general concern with certain levels of climate change, particularly the higher rates of temperature change, is the notion of potential tipping points in the climate system - the point at which a certain level of climate change will trigger an abrupt collapse in the climate system. Therefore, it is entirely relevant to consider some of the possible consequences of rapid climate change.

According to Arnell et al. 2005, there are two types of rapid climate change. The first can be considered as *abrupt* changes and can be denoted as a sudden transition into a new climate state caused by a global or regional threshold crossover. Changes of this sort include the collapse of the Thermohaline Circulation (THC) or the rapid melting of the planet's ice sheets. The second type falls under the notion of *accelerated* change, which is simply how fast temperature or climate change. This often comes in the form of large positive feedbacks, such as the release of methane into the atmosphere following rapid warming of permafrost or seabed zones. Abrupt changes are generally on a much larger scale that affects large geographic areas, whereas accelerated change may or may not result in an abrupt change in the climate.

The collapse of the THC is perhaps the most researched phenomenon in relation to rapid or abrupt climate change because it stands out as having the greatest potential impact on our global climate. Since one of the major functions of the THC is to transport warm water to the North Atlantic and provide relatively mild climates to Western Europe, a collapse in the system would substantially alter the climate in this region. In fact, there is evidence that the THC is currently weakening and approaching a critical threshold that could possibly trigger a collapse. Peltier (2007) explains that the most compelling argument that explains rapid climate shifts in the Northern Hemisphere in the past is the variability in the strength of the THC. Vellinga and Wood (2002) suggest that disruptions in the THC can produce abrupt climate changes and can also lead to a global reduction in net primary production by the terrestrial vegetation by about 5%. This does not necessarily mean that the THC is the only mechanism that can trigger abrupt change. It is, however, the only mechanism that operates on a large enough spatial and temporal scale where impacts are clearly visible in the paleo-record. Pitman and Stouffer (2006) note that a common feature to all climate model projections shows an increase of northern hemisphere high latitude temperature and precipitation. This makes the high latitude surface waters lighter and therefore the stability on the water column is enhanced.

This increased stability hinders the formation of North Atlantic Deep Water and weakens the THC, potentially to the point of collapse, which leads to abrupt climate change.

Rapid climate change inherits the possibility of ecosystem collapse and selective species evolution. Generally, if climate changes abruptly there is an overall reduction in biodiversity through the selection for mobile or opportunistic species. In many cases ecosystems are expected to lag behind equilibrium, which creates vulnerability to pests and diseases. Yasuhara et al. (2008) looked at the deep-sea fossil record of benthic species during periods of rapid climate change over the past 20,000 years and determined that many of the recorded ecosystem collapses coincided with rapid climate changes, which affected deep-ocean circulation.

Coral reefs are also expected to suffer greatly from rapid climate change. Hoegh-Guldberg et al. (2007) predicted that the existence of coral reefs will be dependent on the rate at which climate changes. The acidification process of the oceans that comes with increasing CO_2 will undoubtedly facilitate high levels of carbonate dissolution and compromise the carbonate reef structures. Heogh-Guldberg et al. (2007) state that "Coral reefs are among the most biologically diverse and economically important ecosystem on the planet" (p.1737).

According to Jump and Penuelas (2005), the current rate of climate change has the potential to render many species incapable of adapting. They explained that the migration rates among different species will diverge greatly between different plant species and consequently the formation of new plant communities will begin to surface. The divergence of different plant populations in relation to climate demonstrates the strong selective pressures on natural populations from global climate change. Despite the natural occurrence of inter-annual variability, short-term variability is tolerated through a mechanism known as phenotypic plasticity (the ability of an organism to change its phenotype in response to changes in the environment). Therefore when rates of climate change exceed the threshold of phenotypic plasticity, distributional and evolutionary change become inevitable. According to Jump and Penuelas (2005), this change dramatically alters the genetic composition of many plant species. Although this climate-related genetic variation may be occurring presently in many natural populations across the planet, it does not necessarily imply that adaptation to these new climatic conditions will in fact occur. In other words, the rate of adaptation may not match the forecasted rate of climate change. Figure 2 (taken from Jump and Penuelas (2005)) diagrams this relationship between rapid climate change and habit fragmentation.

Table 1 summarizes some of predicted impacts for different rates of climate change from some of the most pertinent literature.

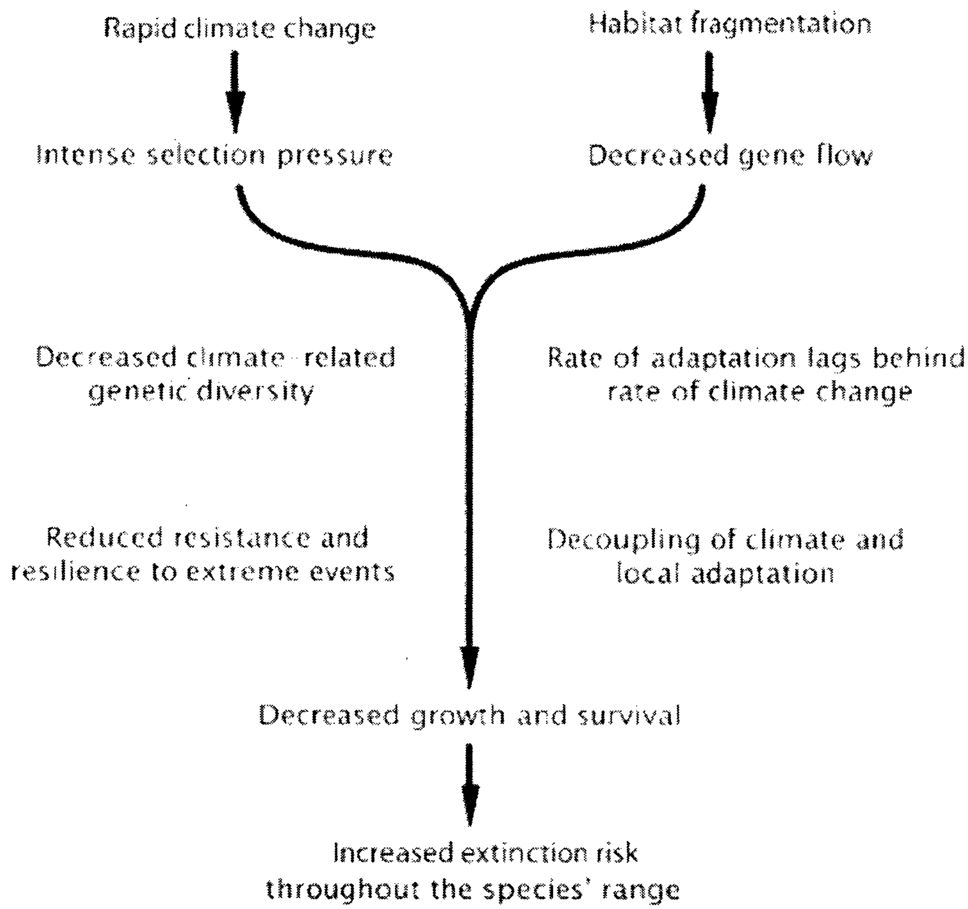


Figure 2: The interaction of rapid climate change and habitat fragmentation. (Jump & Penuelas, 2005, p. 1011)

Rate of Temperature Change	Impact	Source
0.05°C/decade	Proposed threshold to protect ecosystems	Vliet & Leemans (2006)
0.1°C/decade	50% of ecosystems can adapt	Leemans & Eickhout (2003)
0.3°C/decade	Collapse of Thermohaline Circulation	Stocker & Schmittner (1997)
0.3°C/decade	30% of ecosystems can adapt	Leemans & Eickhout (2003)
0.4°C/decade	All ecosystems rapidly deteriorate	Schellnhuber et al. (2006)

Table 1: Predicted impacts on ecosystems and physical processes for different rates of temperature change.

Geoengineering and Climate Intervention

As many of the above climate-related impacts from increasing rates of temperature change become more apparent and the sense of environmental urgency continues to mount, debate on whether geoengineering or climate intervention strategies could possibly eliminate or at least delay this threat have increased.

The term geoengineering was first used by Cesare Marchetti in 1976, who proposed the injection of carbon dioxide into the ocean as a strategy to reduce the environmental effects of fossil fuel combustion (Keith, 2000). It was not until 1992 that the term geoengineering (related to climate change) actually became accepted in the scientific literature, with the publication of the 1992 National Academy of Sciences assessment publication (Panel on Policy Implications of Greenhouse Warming, 1992). Soon thereafter, the 1995 Intergovernmental Policy on Climate Change (IPCC) report mentioned geoengineering very briefly in a section labeled "Concepts for

Counterbalancing Climate Change" where there is a very general description of some of the methods involved in such a strategy, including enhancing oceanic carbon sinks and albedo alterations. Over the next several years, numerous studies and articles have been written, addressing geoengineering and some of the ethical implications involved in deliberately manipulating the climate. For example, Jamieson (1996) looked at the ethics on intentional climate change, and emphasized that a set of ethical conditions, such as: (1) the project is technically feasible; (2) its consequences can be predicted reliably; (3) it would produce states that are socio-economically preferable to the alternatives; (4) implementing the project would not seriously and systematically violate any important, well-founded ethical principles or considerations; must be met before embarking on continued research into geoengineering. Both Bodansky (1996) and Schelling (1996) raise the issue of geoengineering being politically and diplomatically problematic. Moreover, they raise very pertinent questions regarding financial responsibilities towards geoengineering technologies; as well as the risks of accidentally creating negative climatic effects for certain nations.

Govindasamy and Caldeira (2000) performed the first climate model experiment to assess the possible impacts of geoengineering on the climate system. They analyzed the effects of solar radiation reduction in a doubled CO_2 concentration world. The study showed that geoengineering schemes (scattering or reflecting sunlight technologies) could markedly diminish regional and seasonal climate change. In other words, geoengineering may be a promising strategy for counteracting climate change. They furthermore demonstrated that contrary to previous expectations, it is not necessary to replicate the same radiative forcing patterns (in their models) exhibited by greenhouse gases in order to offset their climate warming effects.

Keith (2000) defined geoengineering and included a detailed taxonomy of geoengineering proposals. He also provided an interesting discussion on the policy implications involved with geoengineering technologies. The following year, Keith wrote a short entry in Nature summarizing the notion of geoengineering and some of the main proposals along with their suggested technologies (Keith, 2001). This review was accompanied by an interesting editorial by Stephen H. Schneider. His commentary, "Earth Systems: Engineering and Management", took a different approach to the geoengineering debate by examining some of the geopolitical consequences of a geoengineered climate and the relationship between global economic development and global warming as a consequence. At the same time, Schneider (2001) reviewed some of the different beliefs shared by the leading actors in the climate science field on the topic of geoengineering. He outlined some of the uncertainties with certain proposals that were mentioned in Keith (2001) and pointed out numerous times that the cost of adopting a geoengineering technology without the full understanding of the potential environmental consequences may lead to complications in maintaining a favorable climate for the human race.

Paul Crutzen re-ignited the debate in 2006 with an editorial paper published in *Climatic Change.* In his paper, Crutzen (2006) discussed the implications of injecting sulfate aerosols into the stratosphere as a strategy to offset climate warming while at the same time reducing the concentration of anthropogenic sulfate aerosols in the lower troposphere. He acknowledged that such actions might have negative impacts on stratospheric ozone concentrations, but he argued that the loss of ozone might be tolerable given that the Mount Pinatubo volcanic eruption in 1991 did not have any serious negative effects on the environment. This relatively new and optimistic look at geoengineering sparked debate in climate science circles around the world and fueled an onslaught of responses. One study in particular (Wigley (2006)), combined an economic analysis of geoengineering with climate mitigation and emphasized that using both simultaneously would create an optimal strategy for solving the problem of climate change.

Research Question

The following two chapters in this thesis are based on the over-arching theme of a probabilistic assessment of rates of temperature change. The first examines the risk of climate engineering and the possible effects on the global rate of temperature change with the use of a simple one-dimensional energy balanced model. The second examines more closely the relationship between certain climate system properties in an intermediate complexity climate model and the overall rate of temperature change. Both chapters take into account the multi-dimensional effects of increasing rates of warming as it relates to the impacts on global ecosystems and other environmental processes.

Chapter 1:

Climate engineering and the risk of rapid climate change

Ross, A., & Matthews, H. D. (2009). Climate engineering and the risk of rapid climate change. Environmental Research Letters, 4(4), 045103.

Introduction:

It has become evident in recent years that efforts to reduce greenhouse gas emissions through international policies, like the Kyoto Protocol, have fallen far short of reaching their goals (Raupach et.al, 2007). Many of the outlined emissions targets that have been set in place for some time now, in several international frameworks, are very far from being attained. These continued sluggish efforts to mitigate climate change in conjunction with the increasing evidence that suggests our planet may be closer to unsafe levels of anthropogenic climate change than previously anticipated (Hansen, 2005), have prompted numerous climate scientists to look towards an alternate solution to the impending problem. As a result, there has been recent renewed interest in direct climate intervention or geoengineering as a possible means to offset greenhouse gas-induced climate change (Crutzen, 2006).

Geoengineering is defined as the, "…intentional large-scale manipulation of the environment…" to counteract anthropogenic climate change (Keith, 2000). Some proposed geoengineering schemes include: atmospheric scatters (sulfate injections into the stratosphere), space-based scatters, land surface albedo modifications, ocean fertilization, carbon capture and sequestration (Keith, 2000). Climate engineering refers more specifically to those schemes, which are aimed at decreasing incoming solar radiation. Previous modeling studies showed that geoengineering schemes could effectively stabilize global temperatures, albeit with some regional variability in effectiveness (Govindasamy & Caldeira, 2000). It has also been suggested that a combined approach of emissions reduction and geoengineering could create an optimal economic strategy for solving the problem of climate change (Wigley, 2006). Typically, geoengineering schemes aim to avert catastrophic climatic impacts and thus reduce the risks of dangerous climate change. However, geoengineering carries its own risks. For example, Trenberth and Dai (2007) and Bala et al. (2008) identified possible impacts of albedo geoengineering on the hydrological cycle, and Tilmes et al. (2008) showed that stratospheric ozone could be affected by stratospheric sulphate aerosol injection. Matthews and Caldeira (2007) showed that in the case of an abrupt termination of geoengineering, there would be the potential for very rapid warming as climate re-adjusts to high greenhouse gas levels in the atmosphere without the countervailing influence of geoengineering.

In this study, we focus on the potential for rapid climate change associated with removal of geoengineering. The importance of the rate of temperature change (in addition to the amount of change) was recognized in the Article 2 of the United Nations Framework Convention on Climate Change (UNFCCC). According to this Article:

> "The ultimate objective of this Convention ... is to achieve ... stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. Such a level should be achieved *within a time frame sufficient to allow ecosystems to adapt naturally to climate change...*" [emphasis added] (UNFCCC, 1992)

While this statement does not explicitly define what constitutes "dangerous" climate change, it can be inferred that both the absolute magnitude of climate change (as determined by the greenhouse gas stabilization level) and the rate of climate change (as determined by the time frame over which stabilization is achieved) can contribute to the possibility of dangerous anthropogenic interference in the climate system.

In this study, we highlight the relationship between geoengineering and rapid climate change by quantifying the risk of abrupt temperature change in a scenario where climate engineering is used to stabilize temperatures in the context of business as usual (BAU) greenhouse gas emissions. In particular, we estimate the likelihood of rapid temperature change following the removal (or failure) of climate engineering technologies. We compare our estimated rates of temperature change with available estimates of ecosystem resiliency to the rate of climate change, and argue, based on this analysis, that geoengineering could in fact contribute to increased risk of dangerous anthropogenic interference in the climate system, as defined by the UN Framework Convention on Climate Change.

Methods:

In this study we use the MAGICC (Model for the Assessment of Greenhouse-gas Induced Climate Change) (Wigley et al. 2000) climate model to quantify the effects of the implementation and subsequent removal of climate engineering on the climate system. MAGICC is a set of coupled gas-cycle, climate and ice-melt models, which allows the user to determine the global mean temperature and sea-level responses to user-specified greenhouse gas and sulfur dioxide emissions. The MAGICC model is described in detail in Wigley et al. (2000) and is one of the primary models used in the IPCC reports to project future global-mean temperature and sea level rise.

We applied geoengineering in the MAGICC model as follows: net radiative forcing values from greenhouse gases and aerosols were obtained by running the model under a mid-range business as usual emissions scenario (AIB). We felt that a mid-range emissions scenario was most representative. In a second simulation, geoengineering was implemented as a specified forcing of equal magnitude (but opposite sign) to the forcing from anthropogenic greenhouse gases and aerosols. This geoengineering forcing was applied in the year 2020 and removed in 2060. These paired business as usual and geoengineering simulations were repeated approximately 40 times each, varying the climate sensitivity of MAGICC from 0.5 to 10°C.

We used the estimated climate sensitivity probability density function from Hegerl et al. (2006) to assign likelihood values to each set of model simulations. Climate sensitivity is defined as the equilibrium response of global-mean surface air temperature to a doubling of the carbon dioxide concentration (Meehl et al, 2007). According to the IPCC FAR (Fourth Assessment Report), equilibrium climate sensitivity is likely to lie in the range 2°C to 4.5°C, with a most likely value of 3°C. Hegerl et al (2006) estimated a likely range of climate sensitivity of between 1.5°C and 6.2°C, with a most likely value of 2.5°C; we take this estimate to be broadly representative of the range of climate sensitivity probability distributions presented in Meehl et al (2007), though note that the specific values we report here are dependent on this choice of climate sensitivity probability distribution.

The emissions scenario used in all of the model simulations was taken from the IPCC SRES (special report on emissions scenarios) library and is called A1B-AIM (Nakicenovic et al., 2000). According to the report, the A1B scenario group assumes a "balanced" approach in the future, in which there are no technologies that gain an overwhelming advantage. This scenario group includes the A1B marker scenario developed using the AIM model. In the A1B-AIM marker scenario, the global average per capita energy demand grows from 54 GJ in 1990 to 247 GJ in 2100 (IPCC, 2000). Throughout this time carbon intensity declines relatively slowly until 2050, which results in a rapid increase in carbon dioxide emissions in the first decades of the century. However, after 2050, when the balanced structural changes in the energy sector begin to take effect, carbon intensity drops quickly. The overall result is that growing energy demands from an increasing prosperous population is offset and carbon emissions decline between the years 2050 and 2100 (IPCC, 2000). It should also be noted that this midcentury drop in carbon intensity can be seen as a decrease in the rate of temperarture between 2040 and 2050 (see Figure 4A on page 30).

Results:

Figure 3 shows the temperature change with respect to the year 1990 for the business as usual scenario (BAU) and the case where climate engineering was applied from 2020-2059. With no climate engineering, temperature increased consistently throughout the 21st century; temperature increases from 1990 to 2100 ranged from 0.6 to 5.1 °C for climate sensitivities from 0.5 to 10 °C. CO_2 concentrations at the year 2100 varied from 690 to 739 ppmv, where higher climate sensitivities led to slightly higher CO_2 concentrations due to the effect of positive climate-carbon cycle feedbacks. In the climate engineering simulations, temperatures returned close to year-1990 temperatures between 2020 and 2059. When the engineered forcing was removed temperatures increased abruptly towards a level consistent with atmospheric greenhouse gas concentrations. Furthermore, the temperature change following the removal of climate engineering increased with higher values of climate sensitivity yielding a temperature change between 0.15°C - 4.5°C between 2060 and 2100. The final CO_2 concentrations in the geoengineering runs were comparable to those in the BAU simulations (between 689 and 722 ppmv).

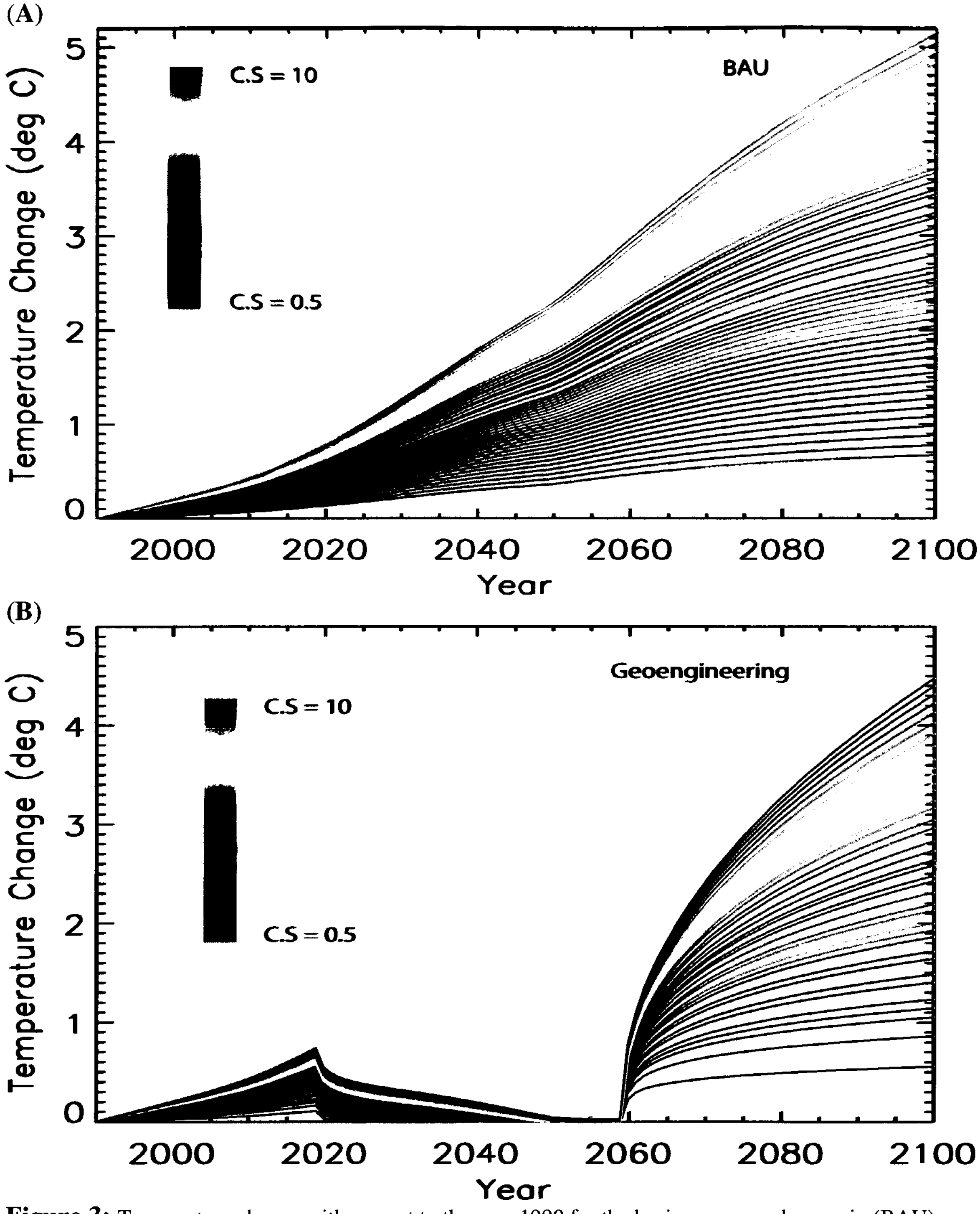


Figure 3: Temperature change with respect to the year 1990 for the business as usual scenario (BAU) (A), and the case where geoengineering is applied from 2020-2059 (B). Each line represents different climate sensitivity as indicated in the color bar.

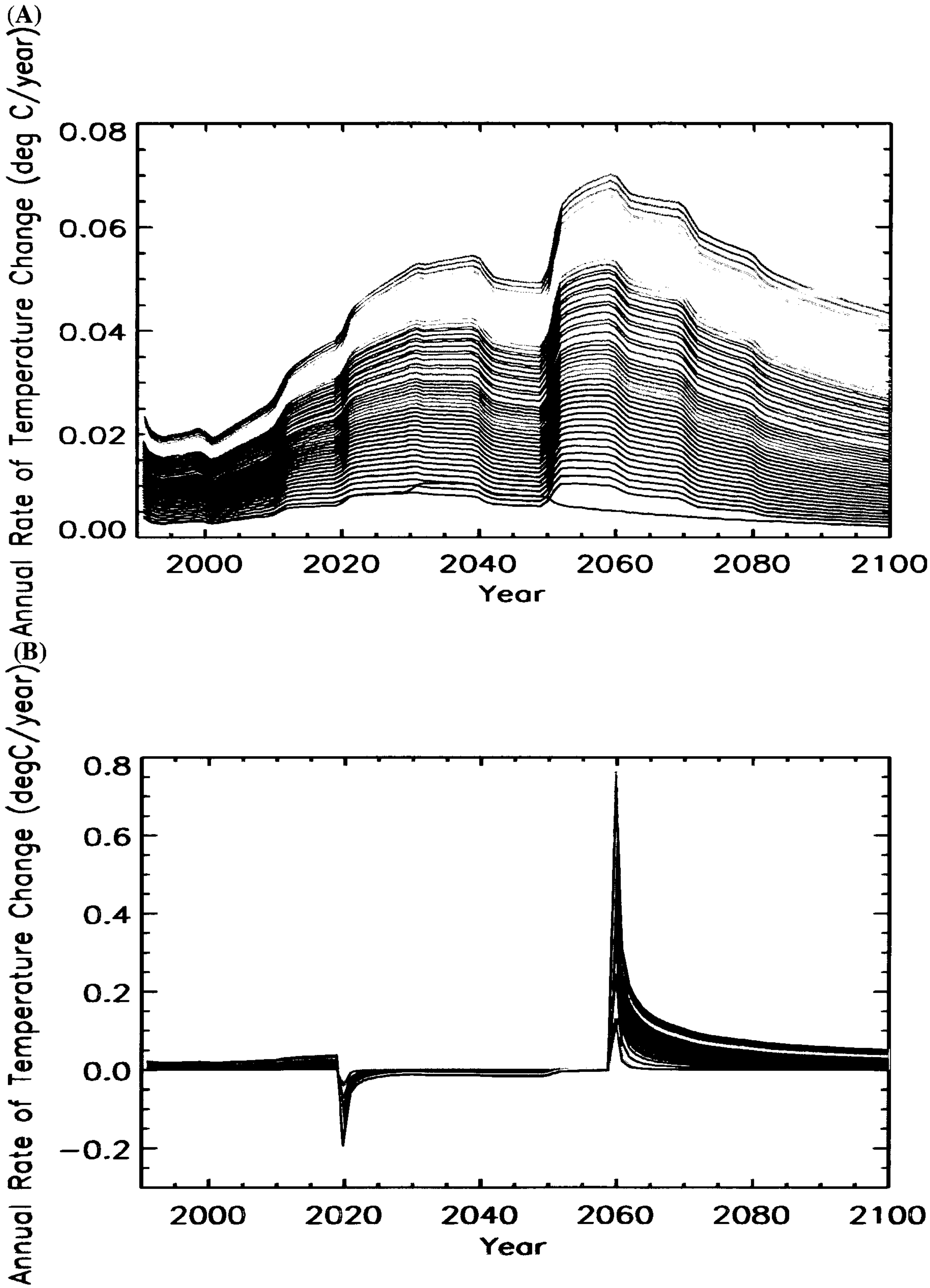


Figure 4: Annual rate of temperature change for the business as usual scenario (BAU) (A), and the case where geoengineering is applied from 2020-2059 (B). Each line represents different climate sensitivity as indicated in the color bar.

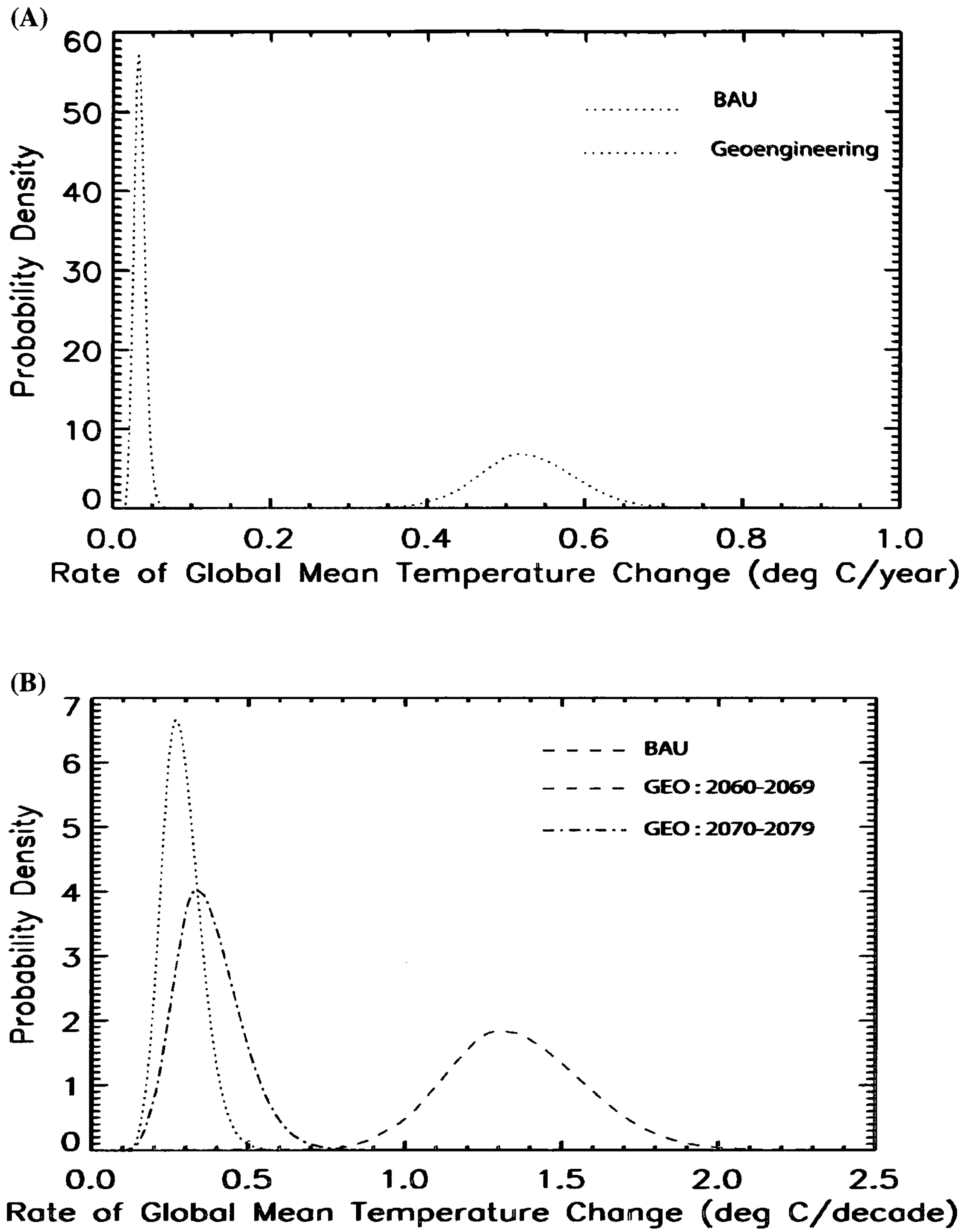
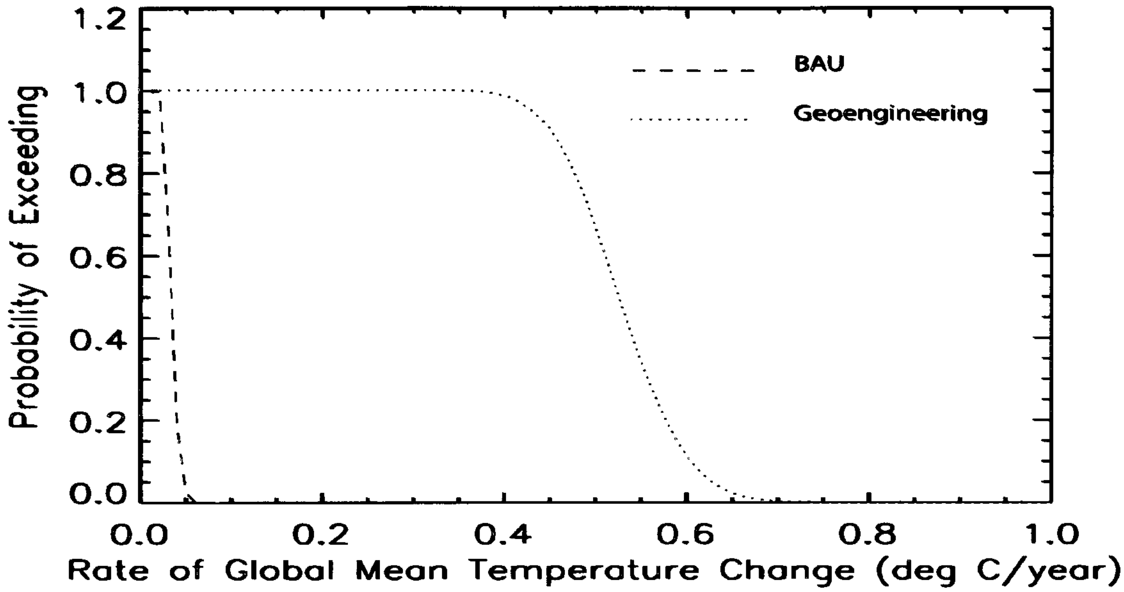


Figure 5: Probability density functions for the maximum annual rate of global mean temperature change (A) and for decadal rates of global mean temperature change (B) between 1990 and 2100. Decadal temperature changes represent the maximum decadal rate in the BAU simulations (red line), and temperature changes during the first (green line) and second (blue line) decades following the removal of geoengineering.

(A)



(B)

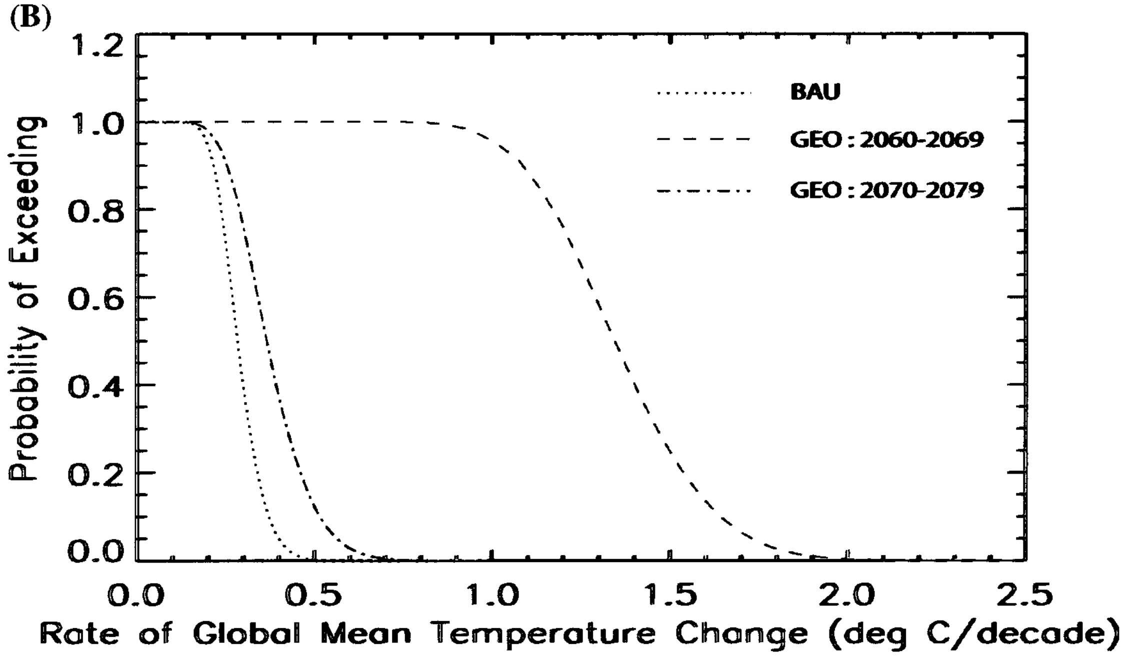


Figure 6: Probability of exceeding the maximum annual rate of temperature change (A) and decadal rates of temperature change (B) between 1990-2100. Decadal temperature changes represent the maximum decadal rate in the BAU simulations (red line), and temperature changes during the first (green line) and second (blue line) decades following the removal of geoengineering.

Figure 4 shows the annual rate of temperature change between 1990-2100 for each set of simulations. In the BAU ensemble (Figure 4A) the annual rate of temperature change increased steadily until the year 2060, after which greenhouse gas emissions decline in the A1B emissions scenario (Nakicenovic et al. 2000) leading to a decreased rate of temperature change. In the climate engineering runs (Figure 4B), the rate of temperature change was small up to the year 2020, whereupon temperatures decreased following the abrupt implementation of geoengineering. The rate of temperature change was negligible up until 2060, at which point temperatures increased very abruptly in response to the removal of climate engineering. The maximum rate of warming varied from 0.13°C to 0.76°C per year, though these very high rates of warming were not sustained for more than a few years; within a decade, rates of temperature change had decreased to less than 0.1°C per year. The maximum rate of sea-level rise in the geoengineering simulations was also higher than in the BAU simulations (not shown), though the difference was less extreme on account of the slower response time of ocean temperatures to external forcing.

Figure 5A shows the probability density functions for the maximum annual temperature change between 1990 and 2100. For the business as usual (BAU) simulation the most likely maximum annual temperature change was only 0.031°C per year. In the geoengineering simulation the most likely maximum rate of temperature change was just under 0.5°C per year, occurring in the year 2060. Figure 5B shows the probability density functions for the maximum decadal rate of global mean temperature change. The highest decadal temperature changes occurred immediately following the termination of climate engineering (2060-2069), with rates ranging from 1.0 to 1.7 °C per decade (5-95%

confidence interval), and a most likely rate of 1.3 °C per decade. By the second decade (2070-2079), the most likely warming rate had decreased to 0.33 °C per decade (5-95% confidence interval: 0.28 to 0.55 °C/decade), slightly higher than the most likely decadal warming in the BAU simulations (0.29 °C/decade; 5-95% confidence interval 0.2 to 0.41°C/decade).

Figure 6A shows the probability of exceeding a given rate of annual temperature change. In the climate engineering simulations (green line) there was a 65% probability of exceeding a rate of 0.5°C per year; for the same rate of warming in the business as usual simulation (red line) the probability of exceeding was 0%. Figure 6B shows the probability of exceeding a given decadal rate of global mean temperature change. In the first decade following the removal of climate engineering (2060-2069: green line) there was a 96% change of exceeding 1 °C warming, and a 25% chance of exceeding 1.5 °C. In the second decade (2070-2079: blue line) the probability of exceeding 0.5 (0.3, 0.1) °C warming per decade, was 15% (75%, 100%). In the BAU simulations, these same thresholds (1.0, 0.3, 0.5, 0.1 °C per decade) were exceeded with 0, 1.5, 42.5 and 100% likelihood, respectively.

Discussion:

In this paper, we showed that the use of planetary-scale geoengineering carries a risk of rapid climate change in the case of its abrupt removal or sudden failure. The sustained high rates of warming in these simulations could have serious environmental impacts on many biomes and natural systems, and could compromise the ability of ecosystems to "adapt naturally to climate change" as required by the UNFCCC.

No consensus exists in the literature as to what rate of climate change could result in dangerous ecosystem impacts. The Summary for Policymakers of the IPCC's *Fourth Assessment Report* stated clearly that the magnitude and timing of impacts that will ultimately be realized depends both on the amount and the rate of climate change (IPCC, 2007). Vliet & Leemans (2006) assessed the ecological impacts of climate change on various biomes in response to different ranges of rates of temperature change. For example, Vliet & Leemans (2006) stated that a warming rate greater than 0.1°C per decade would threaten most ecosystems and decrease their ability to adapt naturally. The proposed rate of temperature increase of 0.05°C per decade is a threshold to protect ecosystems; above this amount, ecosystem damage is increasingly likely to occur (Vliet & Leemans, 2006). The authors argued that with increasing rates of change there would be progressively more ecosystem loss, increased ecosystem vulnerability, decreased biodiversity and aggressive opportunistic species dominance across the globe.

In a similar study, Leemans and Eickhout (2004) looked at rates of climate change based on global mean temperature in 2100 and used ecosystem shifts as the major impact indicator. They found that at a rate of warming of 0.1°C per decade, 50% of all impacted ecosystems are able to adapt within a century but only 36% of all impacted forests adapt within the same timeframe. As the rate of change increased the adaptive capacity of ecosystems rapidly decreased. For example, at a rate of 0.3°C per decade, only 30% of all impacted ecosystems and only 17% of all impacted forests would be able to adapt (Leemans & Eickhout, 2004). Higher rates lead to degraded ecosystems and consequently, impact carbon storage reservoirs and economic sectors that depend heavily on healthy functional ecosystems (Leemans & Eickhout, 2004). These thresholds were exceeded with high probability in both the BAU and climate engineering simulations. However, the climate engineering scenarios resulted in much higher rates of warming, with rates of temperature change returning only to levels comparable to the maximum rates in the BAU simulations two decades after the forcing was removed.

High rates of warming associated with climate engineering could also affect marine ecosystem functions. Abrupt climate change has been linked to overall reductions in marine ecosystem biodiversity through selection for mobile or opportunistic species. Yasuhara et al. (2008) investigated the deep-sea fossil record of benthic ostracodes during periods of rapid climate change to determine its impact on deep-sea ecosystems. Their results demonstrated that ecosystem community collapses coincided with abrupt changes in the deep-ocean circulation and climate changes and that abrupt climate changes had a direct effect on the surface primary production of food source for benthic species. Similarly, Aoyama et al. (2008) showed that biodiversity and plankton community dynamics were significantly altered due to abnormally high rates of surface air temperature change in their study area. The apparent shift in phytoplankton community structure coincided with the largest warming rate (0.6°C-1.0°C per decade) observed in the historical data for this particular geographic region in Japan, called the Kuroshio Current. These rates of warming were comparable to the temperature changes we simulated in the first decade following the removal of climate engineering (1.0°C - 1.7°C per decade).

There are indications right now that suggest that the movement of plant species to higher elevations and latitudes is occurring and large-scale adaptation is already underway for many species across the globe (Jump & Penuelas, 2005). However, when compared with reported rates of past migrations of plant species, the current rapid rate of climate change has the potential to exceed the adaptive capacity of many species. High rates of warming associated with the removal of climate engineering would likely exacerbate this problem. Furthermore, Jump and Penuelas (2005) showed migration rates among different species diverge greatly between different plant species, leading to the formation of novel plant communities. Current differentiations of populations in relation to climate demonstrate the strong selective pressures that climate asserts on natural populations (Jump and Penuelas, 2005). Although inter-annual variability is a common phenomenon and is a normal occurrence, such short-term variability is tolerated through phenotypic plasticity. When rates of climate change exceed the threshold of phenotypic plasticity, distributional and evolutionary changes become increasingly likely. An important question is whether the rates of warming following the removal of climate engineering would be short-term enough to be tolerated. It seems likely that two decades of very high rates of warming would be sufficient to severely stress the adaptive capacity of many species and ecosystems, especially if preceded by some period of engineered climate stability.

In this study, we have considered a hypothetical on/off geoengineermg scenario in which climate engineering was both implemented and removed abruptly. This is clearly an extreme case and the risks we have reported here of rapid climate warming could be substantially mitigated by a more gradual implementation and decommissioning of climate engineering technology. However, one can imagine scenarios in which abrupt removal of geoengineered climate forcing may be unavoidable, either due to technological failure, or due to the emergence of unforeseen negative impacts of climate engineering. Even in an extreme case of abrupt termination of geoengineering, the risk of rapid climate change could also be decreased by successfully mitigating greenhouse gas emissions during the period of climate engineering. In this case, it becomes critically important to know to what extent greenhouse gas emissions are decreased in the coming decades, and also to what extent the successful application of climate engineering may affect other mitigation efforts. Clearly, a case where the perceived success of geoengineering leads to decreased incentive to decrease greenhouse gas emissions would represent a potentially dangerous situation of increasing geoengineering dependence to avoid the risk of rapid climate warming that we have reported here.

We note also that the specific warming rates and probabilities we reported here are dependent on both our choice of emission scenario (A1B) and our choice of probability density function for climate sensitivity (Hegerl et al, 2006). In addition, we considered only climate sensitivity uncertainty and not additional uncertainty associated with ocean heat uptake, natural and anthropogenic forcings or carbon cycle feedbacks. These additional uncertainties would affect the transient climate response of the model, and may therefore affect the decadal-scale rates of temperature change we have reported. In addition, the MAGICC model is a simple one-dimensional climate model that does not fully represent the timescales of ocean circulation and heat uptake changes; as a result, the temperature response to the abrupt removal of climate engineering that we have reported may be both somewhat faster and also less sustained than what would be simulated by a more sophisticated ocean model. These additional uncertainties are non-negligible (Forest et al, 2006, Matthews and Keith, 2007, Meehl et al., 2007) and would invariably change the specific numbers provided here. However, our intent here was not to conduct a full probabilistic assessment of all relevant uncertainties, but rather to highlight the order-of-magnitude risks associated with geoengineering and rapid climate change. The general conclusions we presented here are robust, and would hold in a more comprehensive probabilistic analysis.

Conclusion:

In this study we used a hypothetical scenario of business-as-usual greenhouse gas emissions, in which geoengineering is implemented at the year 2020, and removed abruptly after 40 years. By varying the climate sensitivity of the MAGICC model, and using previously published estimates of climate sensitivity likelihoods, we derived a probability distribution for the rate of temperature change following the removal of geoengineering. Our analysis showed that abrupt termination of climate engineering would carry substantial risk of very high rates of warming, which would likely exceed the maximum rate of warming under a business-as-usual emissions scenario for up to 2 decades after termination.

Studies of ecosystem sensitivity to temperature change suggest that species extinctions and ecosystem collapses are possible consequences of very rapid climate changes. The adaptive capacity of these ecological systems are sensitive to the rate at which temperature changes, and could be affected readily by the risk of high rates of temperature changes associated with climate engineering. In addition to the potential impacts on ecological systems we outlined here, there would clearly be significant impacts on human systems with associated large economic damages from such rates of climate changes (Goes et al., 2009). These findings suggest that the use of planetary-scale geoengineering carries its own risk of dangerous anthropogenic interference in the climate system, as defined by the U.N. Framework Convention on Climate Change, which must be weighted against the risks of unmitigated climate change.

Chapter 2:

Probabilistic assessment of climate system properties and their effect on the rate of climate change

This article will be submitted to the Journal of Climate in 2010.

Introduction:

Anthropogenic interference in the climate system has altered natural cycles in the system and pushed our climate into a state of disequilibrium. Efforts to reduce and understand these effects on the climate are heavily dependent on global climate modeling. However, our understanding of the natural environment and its associated properties is still limited and constrained by our ability to gather data and process information. As a result, all climate models come with uncertainty in both projections and simulations of historical climate change. Therefore, it is crucial that this uncertainty within climate models be quantified so as to better constrain future warming projections.

All climate models contain a variety of uncertain representations of physical properties in the climate system, resulting in different manifestations of key climate system properties (Forest et al, 2001). Two important uncertain climate system properties are: climate sensitivity (the equilibrium change in global mean surface temperature following a doubling of the atmospheric CO_2 concentration (Meehl, 2007) and the rate of deep ocean heat uptake (controlled to first order by vertical diffusivity parameters in ocean models) (Forest et al. 2002). Variations of either climate sensitivity and ocean diffusivity will yield very different climate responses to anthropogenic forcings. Previous simulations and estimates reveal that these two parameters vary considerably among the current generation of global climate models (Forest et al. 2002).

A probabilistic approach can be used to assess this parameterized uncertainty. This approach is useful as a way of conceptualizing and quantifying the uncertainty surrounding future climate impacts (Mastrandrea & Schneider, 2004). For example, by varying values of climate sensitivity (C.S.) and ocean heat uptake, and taking probabilities from a probability density function, a range of climate responses can be obtained, each with their own likelihood of occurring. This approach has also been applied to carbon cycle feedback uncertainty; Matthews and Keith (2007), for example, found that the inclusion of carbon-cycle feedbacks in their coupled climate-carbon model lead to large increases in extreme warming probabilities. Probabilistic methods, like these, can be a valuable tool for communicating a policy-relevant depiction of the current state of scientific knowledge to the actors involved in decision-making (Mastrandrea & Schneider, 2004).

Typically, climate responses are measured with measurements of overall temperature change with respect to some baseline level. Until recently, climate change has been regarded as a gradual change that occurs at a historically high rate but still within the range projected by the IPCC (Arnell, 2005). However, the threat of rapid climate change is beginning to surface and there is increasing concern that we are in fact much closer to dangerous levels of change than previously anticipated (Hansen et al, 2008). Clearly, the magnitude of this change is an important factor to consider but so is the rate at which this change occurs. The adaptive capacity of the planet's ecosystems is likely more dependent on rates of change rather than on absolute magnitudes. There is no clear definition in the literature of rapid climate change; however, the IPCC's FAR clearly states that the magnitude and timing of impacts that will ultimately be realized depend heavily on the amount as well as the rate of climate change (IPCC, 2007). However, the overall rate of temperature change is largely dependent on the forcing scenario used to predict future climate change in conjunction with the strength of the physical feedbacks that govern the efficiency of the deep ocean to remove heat from the atmosphere (Collins et al. 2007). Therefore, quantifying the uncertainty related to such a physical component is key to understanding the overall climate response that can be expected under prescribed forcing scenarios. For example, Collins et al. (2007) perturbed three key ocean physical processes (the diffusivity of tracers along isopycnal surfaces, the calculation of the depth profile of wind-mixing energy in the ocean mixed layer, and the vertical diffusivity of tracers) in their climate model to measure the transient climate response to imposed forcings. They found that the perturbations had little effect on the rate of ocean heat uptake, and therefore concluded that the overall rate of transient climate change was relatively insensitive to perturbations to ocean model parameters.

Unlike Collins et al. (2007), here we have used a coupled carbon-climate intermediate complexity climate model and considered the effect of varying climate sensitivity and ocean diffusivity. We used an expert synthesis report on PDFs of C.S. and calculated our own ocean vertical diffusivity PDF using a sophisticated 3D method developed by Schmittner et al. (2009) to generate a probabilistic prediction of maximum rates of temperature warming over the 21st century that occur in response to the SRES A2 emissions scenario.

Methods:

All of our model simulations use the University of Victoria Earth System Climate Model (UVic ESCM) version 2.9, an intermediate complexity climate model, with a spherical grid resolution of 3.6° (zonal) by 1.8° (meridional)(Weaver et al, 2001). The UVic ESCM consists of seven coupled model components: a three-dimensional ocean general circulation model, a thermodynamic/dynamic sea-ice model, an energy-moisture balance atmospheric model with dynamical feedbacks, a dynamic vegetation model, a land surface model, an ocean ecosystem/biogeochemical model, and an inorganic ocean carbon model. Since the UVic ESCM has a three-dimensional ocean general circulation model and the rate of temperature change is largely dependent on ocean processes, we felt the UVic ESCM was a suitable climate model for the simulations we conducted. The UVic ESCM is a coupled climate-carbon model, which allows for a dynamic representation of carbon cycle processes and feedbacks. The model simulates carbon cycle feedbacks interactively, which include strengthened ocean and terrestrial carbon uptake due to elevated atmospheric carbon dioxide levels as well as opposing positive feedbacks whereby carbon sinks are weakened by climate changes (Eby et al, 2009).

Climate sensitivity was varied in the UVic ESCM by adjusting a temperature-longwave radiation feedback as in Zickfeld et al. (2009).

$$L^{*}_{out}(t) = L_{out}(t) - c\,(T(t) - T_0) \qquad [1]$$

where L_{out} is the unmodified outgoing longwave radiation and L^{*}_{out} is the new outgoing longwave radiation. The feedback term is proportional to the difference between global mean surface air temperature and the year 2000 temperature, $T(t) - T_0$. The proportionality constant c, corresponding to specific equilibrium climate sensitivities, were determined from a set of prior model simulations. For those runs (six in total), we specified values of the constant c that we guessed would give rise to climate sensitivities in the chosen range (1.5–7.5 °C). We then forced the model with an instantaneous doubling of the preindustrial CO2 concentration and diagnosed the equilibrium global mean temperature response. The C.S. was phased in over a period of 40 years, beginning in the year 2000 and reaching full effect by 2040. We used this method to create model versions with different climate sensitivities (1.5°C, 2.5°C, 3.5°C, 4.5°C, 5.5°C 6.5°C, 7.5).

The UVic ESCM has state-of-the-art physical parameterizations in the ocean, which allow for diffusive mixing along and across isopycnals, eddy induced tracer advection and a scheme for the computation of tidally induced diapycnal mixing (K_v) over rough topography (Schmittner et al. 2009). Since other sources of mixing are also possible, a globally constant background diffusivity K_{bg} is added to the tidally induced diffusivity K_{tidal} where,

$$K_v = K_{bg} + K_{tidal} \qquad [2]$$

In this study, we have set the value of K_{bg} to 0.05, 0.15, 0.3, and 0.45 cm^2/s to yield 4 different diapycnal mixing rates. For the purpose of brevity the units of K_{bg} (cm^2/s) will be omitted for the remainder of the paper.

The entire ensemble consists of 28 model simulations (7 climate sensitivities x 4 K_{bg} rates of ocean diffusivity). Each version of the model begins with a stable model restart with standard parameter values ($K_{bg} = 0.15$); we then spun up the model for an additional 4000 years with modified K_{bg} at constant pre-industrial forcing until a state of equilibrium was reached. We carried out transient simulations from 1800-2000, forced by historical CO_2 concentration data, and then from 2000-2100 forced by CO_2 emissions from the SRES A2 emissions scenario (Nakicenovic et al, 2000).

We used the estimated C.S. PDF from Claudia Tebaldi (personal communication, March 9, 2010). We also used the synthesis provided in Knutti and Hegerl (2008) on the ranges of C.S. proposed in the literature and further synthesized their expert opinion in a formal PDF for equilibrium C.S. using the method of putting a Gaussian distribution on the feedback parameter (*f*) as in Roe & Baker (2007). This method is contingent on three relevant criteria, which are also consistent with the IPCC C.S. estimates (Meehl et al, 2007): 1) best estimate of 3°C representing the median for the C.S. distribution, 2) at least a 66% probability that the value of C.S. lies within the range of 2 to 4.5°C and 3) there is a 10% or less probability that the value of C.S. is 1.5°C or less. Figure (7A) shows the C.S. PDF taken from Claudia Tebaldi (personal communication, March 9, 2010). We take this estimate of equilibrium C.S. PDF to be representative of the range of PDFs presented in the literature as well as in Meehl et al. (2007), though the values we report here are dependent on this choice and other PDFs would yield slightly different results.

We calculated our own ocean diffusivity PDF using the 3D method (Figure 8A) as used by Schmittner et al. (2009). Schmittner et al. (2009) used nine three-dimensional tracer distributions to calculate probability densities; in the current study, we use ocean temperature as the observational constraint to generate our PDF of ocean diffusivity.

(World Ocean Atlas 2005 data downloaded from ftp.nodc.noaa.gov/pub/data.nodc/woa/WOA05nc). Last, we combined PDFs from C.S. and ocean diffusivity to calculate a joint PDF of both variables (Figure 8B). For simplicity, we assumed independence between both variables; a more complex method using Baye's theorem would yield potentially different results.

A

B

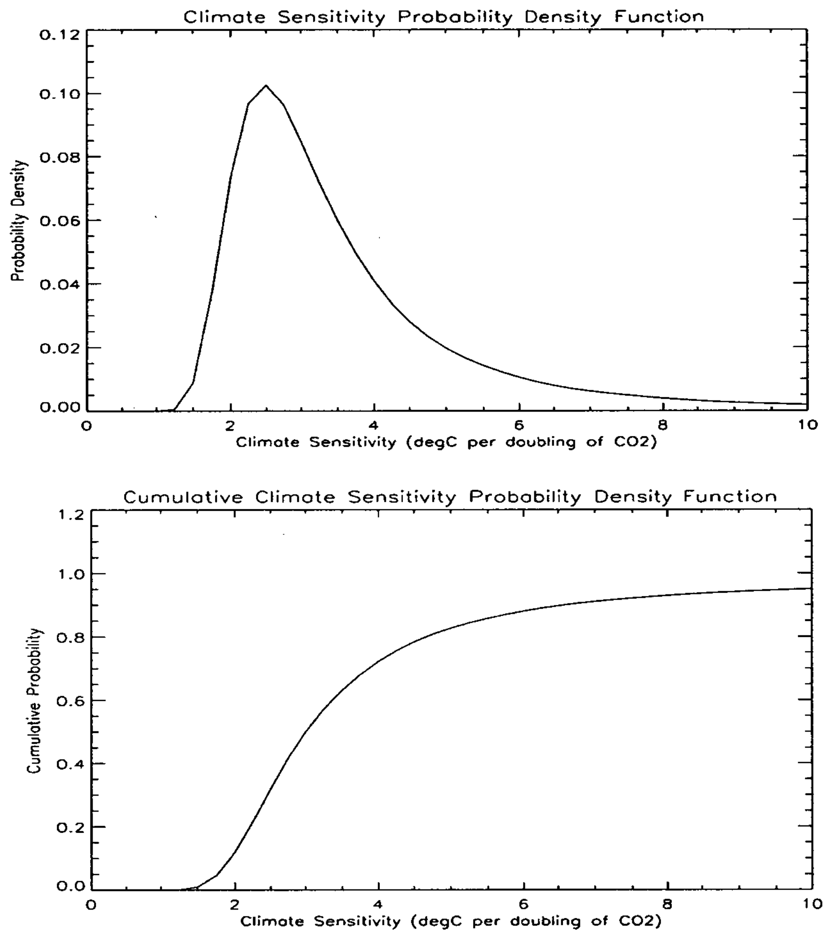


Figure 7: Probability density function (A) and cumulative density function (B) for equilibrium climate sensitivity (per doubling of CO_2).

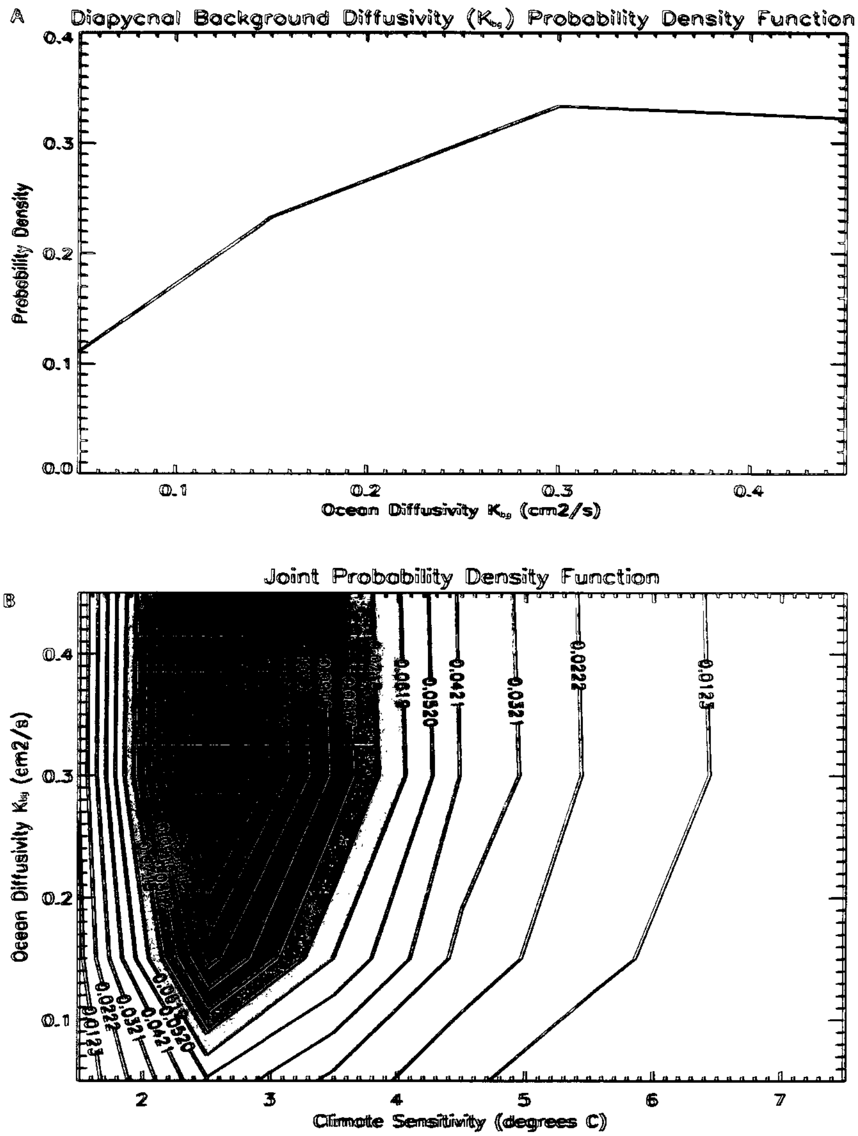


Figure 8: (A) Probability density function, using Schmittner et al. (2009) 3D method for the physical tracer Temperature, as a function of the diapycnal background diffusivity K_{bg}. (B) Joint probability density function of both climate variables (K_{bg} and climate sensitivity).

Results:

Increasing K_{bg} leads to increased heat (figure 9A) and carbon (Figure 9B) uptake due to enhanced mixing of heat and carbon into the deep ocean. Increased ocean heat uptake (Figure 9A) from a higher ocean diffusivity leads to reduced warming of surface waters and delays the subsequent warming of the surface air. Conversely, a lower K_{bg} reduces ocean heat uptake and allows for increased heating of surface waters, which in turn helps to warm surface air temperatures. Increased CO_2 accumulation in the ocean, due to higher rates of ocean diffusivity (K_{bg} 0.3 and K_{bg} 0.45) lead similarly to lower atmospheric CO_2 and thus reduced radiative forcing and atmospheric warming (Figure 9B). In general, both effects of ocean carbon content and heat uptake act in the same direction, higher (lower) K_{bg} leads to increased (decreased) ocean heat and carbon uptake and thus less (more) atmospheric warming.

Figure 10 shows the temperature change for the 21st century for all 4 K_{bg} simulations as well as for each of the 7 different climate sensitivities. Temperature change increases with increasing climate sensitivity, and with decreasing K_{bg} values. In figure 10 (A), where the K_{bg} is smallest, the temperature changes are higher because of lower rates ocean heat and carbon uptake. Temperature changes at a given C.S. decrease progressively with increasing K_{bg} in figures 10B, 10C and 10D. For example, for a C.S. of 3.5°C, figure 10A shows a maximum temperature change in 2100 of approximately 3.54°C, while in 10B, 10C and 10D this temperature change is less; approximately 3.34°C, 3.20°C, and 3.00°C respectively. More interestingly,

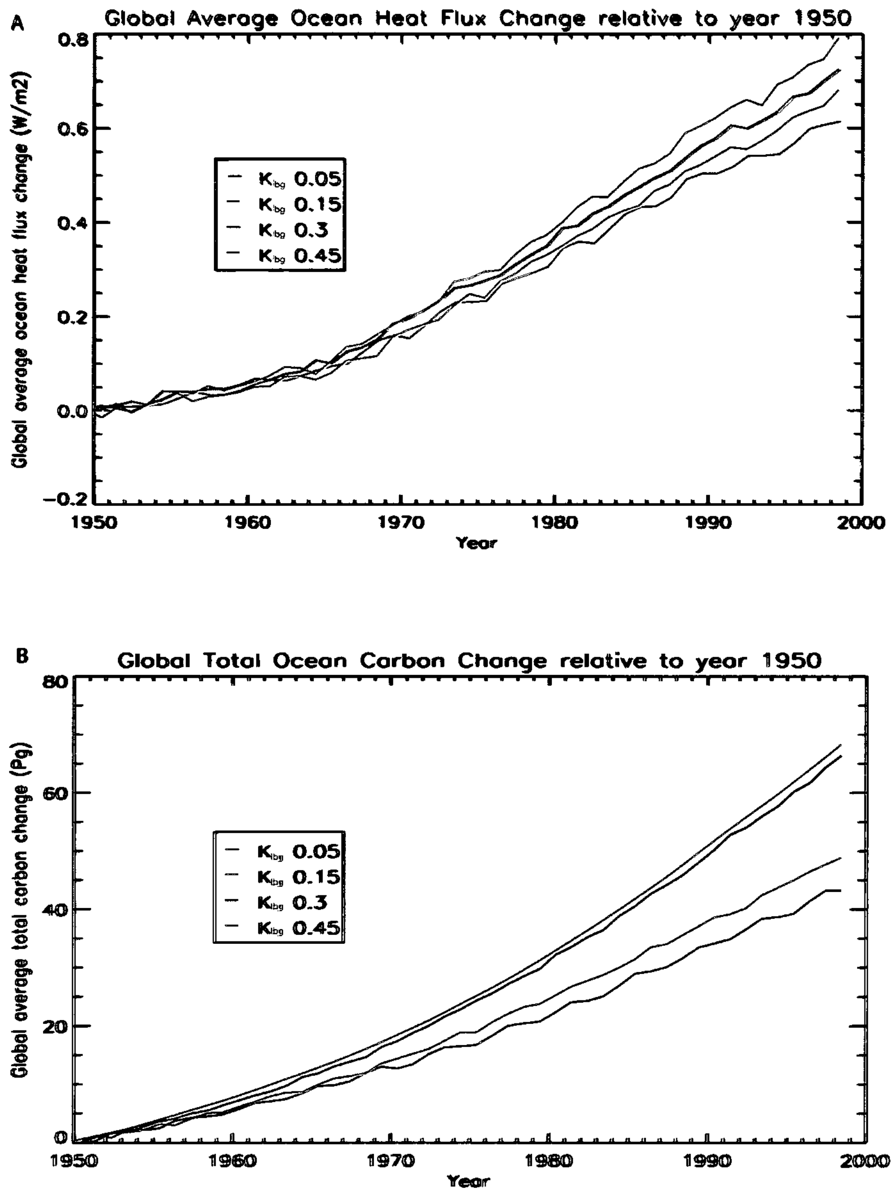


Figure 9: Globally averaged ocean heat flux changes (A) and global total ocean carbon change content (B) between 1950-2000 for different ocean diffusivities with respect to year 1950.

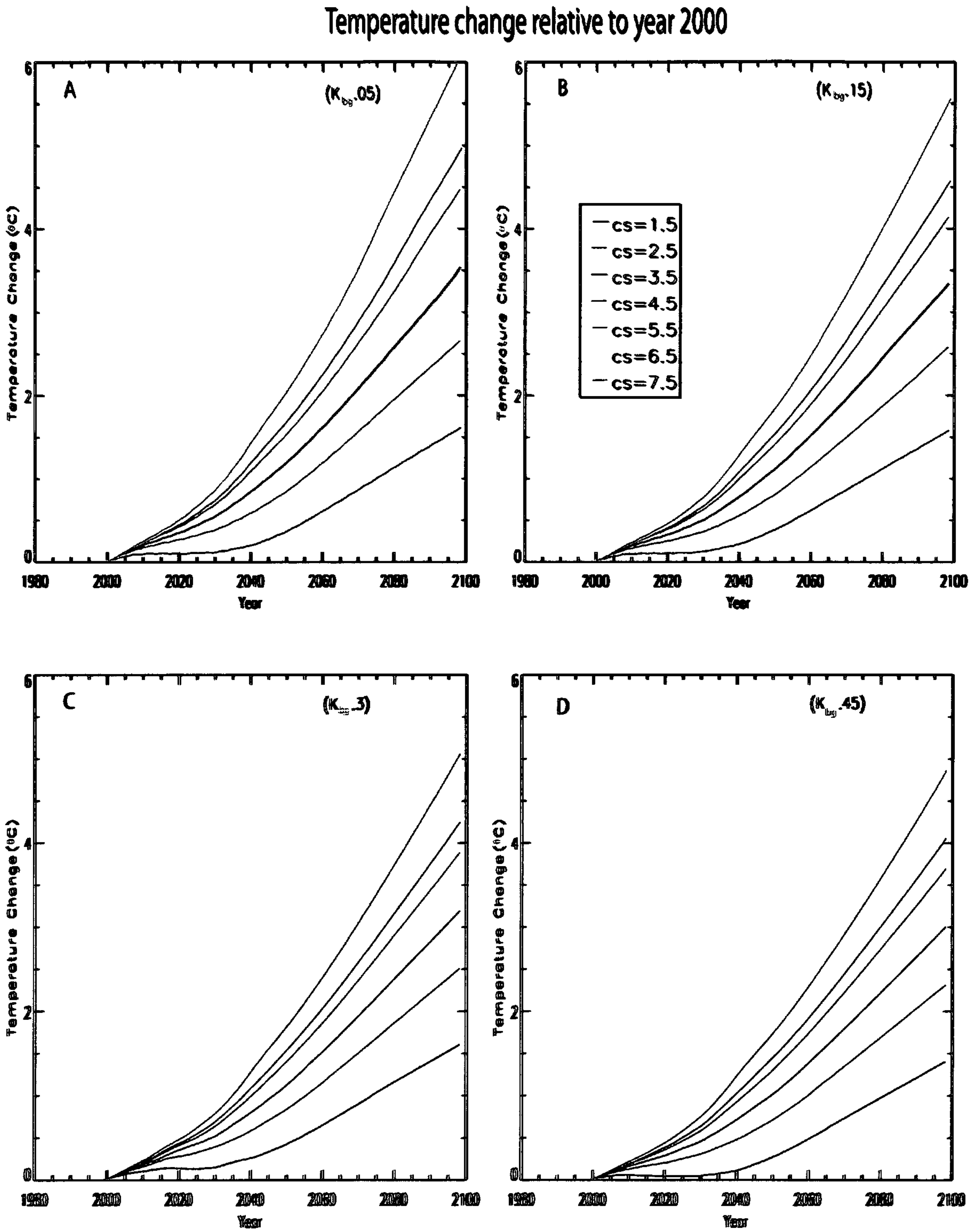


Figure 10: Temperature change (°C) with respect to year 2000 levels for (A) K_{bg}=0.05, (B) K_{bg}=0.15, (C) K_{bg}=0.3 and (D) K_{bg}=0.45; each with 7 different climate sensitivities.

however, the general pattern between C.S. and ocean diffusivity is not linear. At lower climate sensitivities, varying K_{bg} has relatively little effect, whereas at higher C.S. its influence is much stronger. This can be explained by the significantly higher temperature gradient between the ocean and atmosphere in the higher C.S. simulations. This higher gradient accentuates the slower response time of the ocean and increases the sensitivity of the deep ocean heat and carbon uptake to K_{bg} changes. When this gradient is smaller, as in the lower C.S. simulations, the ocean is able to assimilate the increase in temperature more easily, thus resulting in a much smaller difference in temperature change between the varying K_{bg} simulations.

Figure 11 shows the mean decadal rate of temperature change for the 21st century for all 4 K_{bg} simulations along with the 7 different climate sensitivities. The mean was calculated with a ten year moving average. In (A), where K_{bg}=.05, the maximum rate of temperature change varies from 0.27 to 0.92°C/decade for the lowest and highest climate sensitivities, respectively. Figure 11 (B), (C) and (D) show smaller maximum rates of temperature change: approximately 0.26 to 0.84°C/decade, 0.26 to 0.74°C/decade, and 0.25 to 0.73°C/decade respectively, for lowest and highest climate sensitivity runs. Here we can see the nonlinear interaction of climate sensitivity and ocean diffusivity more clearly. All 4 ocean diffusivities show very similar rates of warming at the lower end of C.S. values but diverge more quickly at the higher end.

By assigning probabilities to the maximum rates of temperature change using the C.S. PDF shown in Figure 7A, we can obtain probability density functions for the rate of temperature change in response to A2 CO_2 emissions at a given ocean mixing rate (figure

12). In figure 12A we can see that the most likely maximum rates of temperature change are 0.35, 0.36, 0.39, and 0.41 °C/decade for K_{bg} 0.45, 0.3, 0.05 and 0.15 respectively.

Figure 12 (B) shows the cumulative probability distribution for each of the PDFs in Figure 12 (A), which represents the probability of exceeding a given maximum rate of temperature change (°C/decade). For example, there was a 92.5% probability of exceeding 0.3°C/decade with an ocean diffusivity rate 0.05. For the same rate of temperature change the exceedance probability decreased to 90%, 87.5% and 83% for K_{bg} 0.15, 0.3, and 0.45 respectively. Likely rates of temperature change were within the range of 0.36 to 0.47°C/decade for K_{bg} 0.3 and between 0.35 to 0.46°C/decade for K_{bg} 0.45. As the diffusivity rate decreased (K_{bg} 0.15 and 0.05) the magnitudes of likely range of maximum rate of temperature change increased: between 0.41 to 0.53°C/decade and 0.40 to 0.58°C/decade for ocean diffusivities K_{bg} 0.15 and 0.05 respectively.

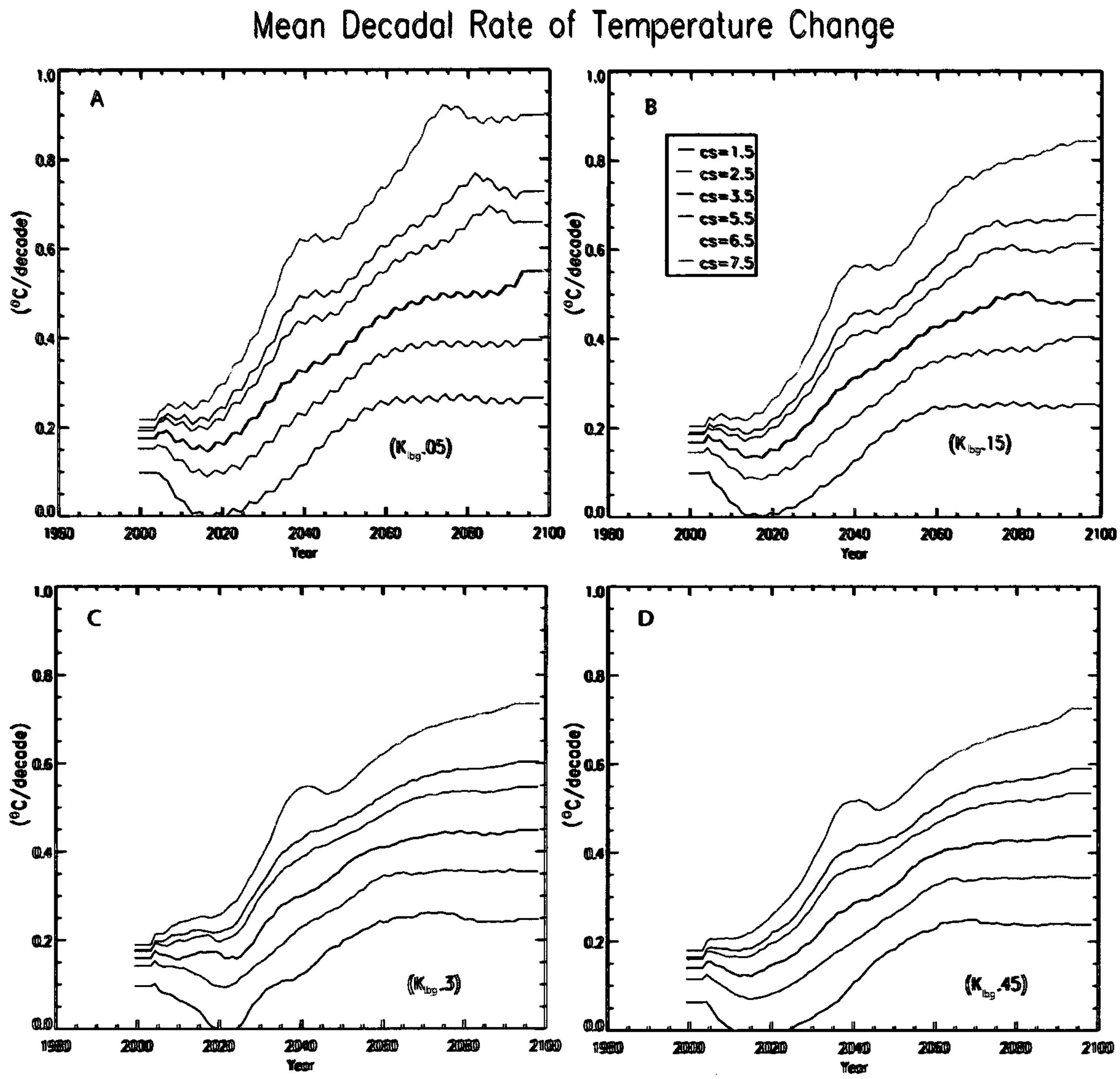


Figure 11: The mean decadal rate of temperature change (°C/decade) for (A) K_{bg}=0.05, (B) K_{bg}=0.15, (C) K_{bg}=0.3 and (D) K_{bg}=0.45; each with 7 different climate sensitivities.

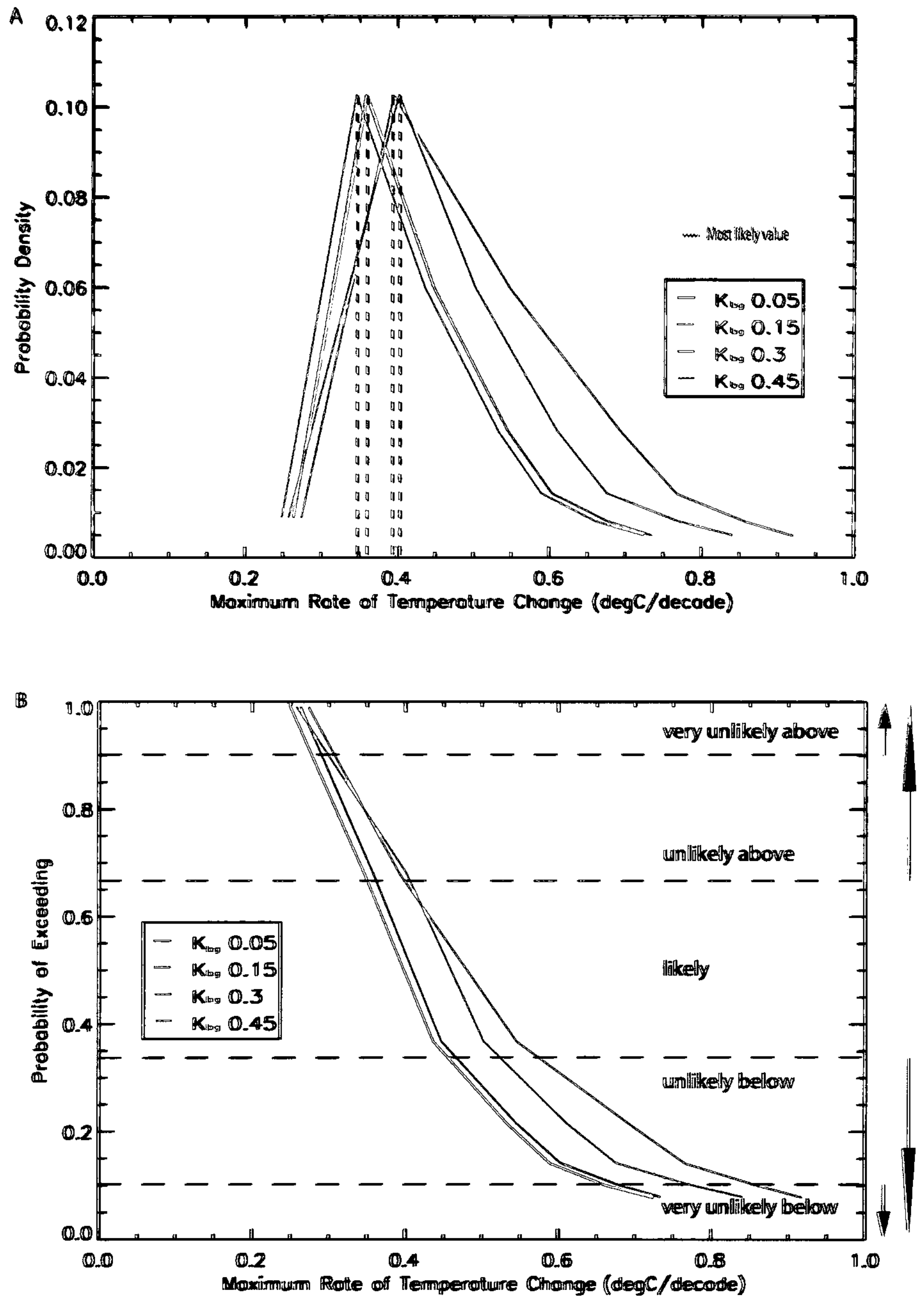


Figure 12: Probability density functions of (A) and probability of exceeding (B) the maximum rate of temperature change with varying ocean diffusivity, K_{bg}. Dashed lines denote likelihood regions (likely = >66%, unlikely = <33%, very unlikely = <10%).

Figure 13 shows the likelihoods associated with maximum rates of temperature change between 2000-2100 in °C/decade as a function of both ocean diffusivity (K_{bg}) and C.S. The contour lines remain relatively vertical in the lower end C.S. value, which implies that the influence of varying ocean diffusivity is small. Progressively larger C.S. values show contours that are more slanted, suggesting that ocean diffusivity has a greater influence on the rate of temperature change. The most likely maximum rate of warming value (marked by a star in Figure 13) was 0.36°C/decade. In general, the lower rates of warming (in the range of 0.3°C/decade to 0.5°C/decade) were most probable, whereas rates of temperature change above 0.6°C/decade were increasingly unlikely. It should be noted that due to our limited range of K_{bg} in the upper end the likelihood regions remain somewhat open ended at the top of Figure 13. However, since the contours of rates of change remain relatively vertical in this region, the effect of further increasing ocean diffusivity on rates of warming would be relatively small.

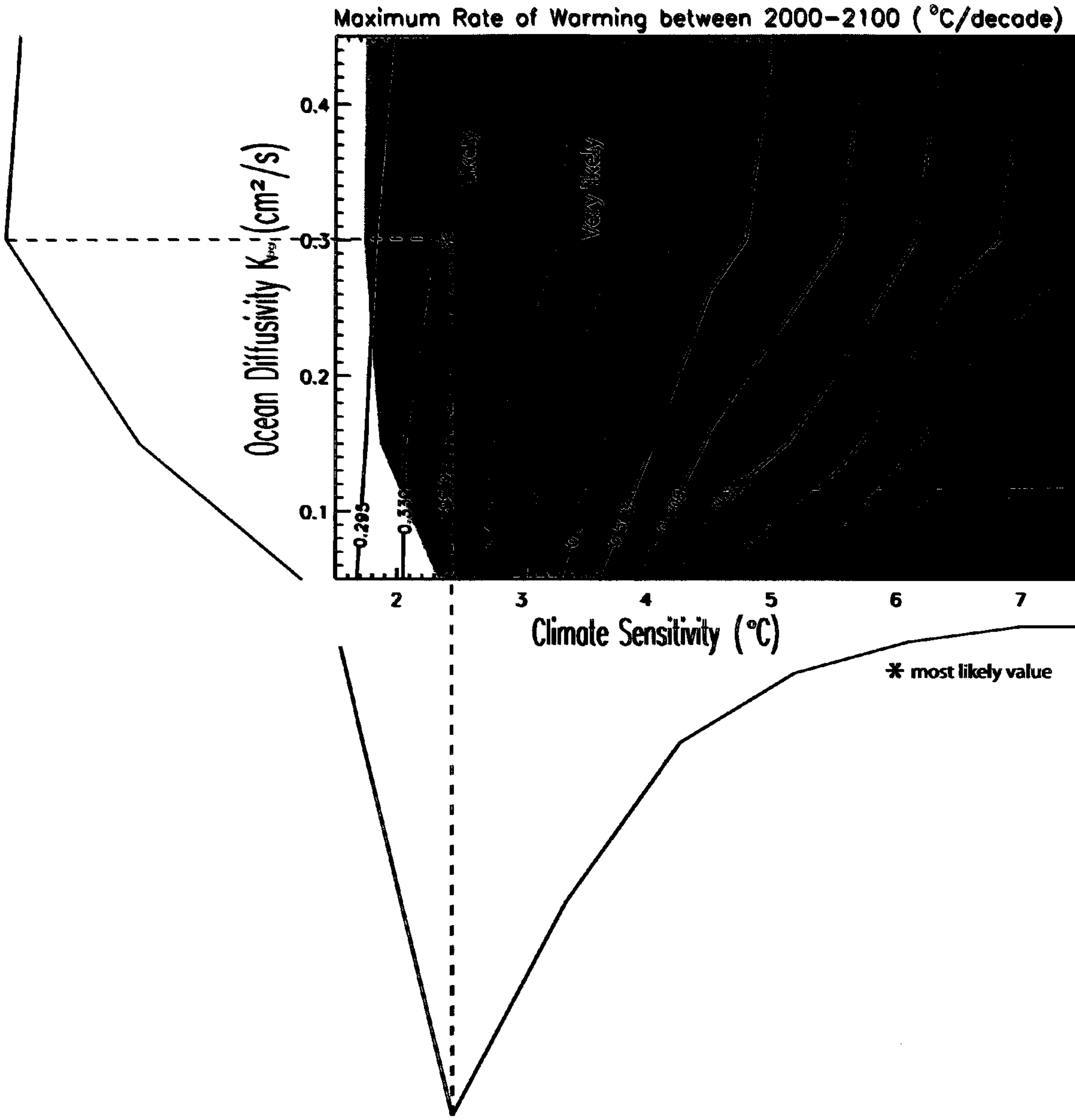


Figure 13: The maximum rate of temperature change in °C/decade between 2000-2100 as a function of ocean diffusivity and climate sensitivity. Likelihood regions are shown in grey (very likely >90%) and in blue (likely >66%).

Discussion:

In this chapter, we have shown that varying C.S. and ocean diffusivity in the UVic ESCM yields a range of different rates of temperature change, all of which carry a different probability. This represents an attempt to quantify the uncertainty surrounding these two climate system properties, and to use a joint PDF to determine the likely range of the maximum rate of temperature change in response to the A2 $C0_2$ emissions scenario. We show that the maximum rate of warming would likely fall between 0.3 and 0.5 °C/decade with a most likely value of 0.36°C/decade during the 21^{st} century. The rates of warming obtained at the higher end of this range represent very rapid climate change and could potentially cause serious environmental impacts on a global scale.

To properly assess the impacts of rapid climate change and possibly predict future rapid climate change scenarios it is necessary to quantify specific rates of temperature change and their associated environmental effects. O'Neil and Oppenheimer (2004) assessed how the potential for dangerous climate impacts may change depending on various pathways to greenhouse gas stabilizations. The authors defined three different pathways, which are labeled as slow change, rapid change, and overshoot. The slow change pathway led to medium rates of warming that slowly declined over time from an initial rate of 0.16°C/decade. However, the rapid change simulation, with stabilization at 600ppm, showed a median rate of change that peaked at 0.29°C/decade. Their overshoot simulation led to substantial additional warming that ranged from 0.1 to 0.6°C per decade. By comparison, our results show similar rates of warming that range from 0.26 to 0.92°C/decade, albeit with a business-as-usual, rather than stabilization emissions scenario. According to O'Neil and Oppenheimer, rates such as these could entail widespread physical and biological damage. For example, coral reefs and other niche ecosystems may be sensitive to temperature increases greater than 1°C from recent levels. In addition, 0.3°C per decade warming could lead to a shutdown in the meridional overturning circulation (Stocker and Schmittner, 1997). O'Neil and Oppenheimer emphasize that differences in transient rates of warming could significantly impact global ecosystems, and sustained rates of warming that are greater than 0.1°C per decade could potentially exceed the adaptive capacity of some sensitive ecosystems.

Many environmental systems and the adaptive capacity of species are dependent on the rate of climate change. Leemans and Eickhout (2004) used rates of temperature change to analyze global ecosystem shifts and impacts. They found that for a rate of warming of 0.1°C/decade, 50% of all impacted ecosystems were able to adapt within a century but only 36% of all impacted forests could adapt. As the rate of change increased, the adaptive capacity of ecosystems rapidly decreased. Rates of temperature change of 0.3°C/decade showed that only 30% of all impacted ecosystems can adapt naturally and furthermore only 17% of all impacted forests could adapt. According to our C.S. PDF (figure 12B) the same rate (0.3°C/decade) of temperature change was exceeded with a probability of over 90%. Furthermore, our combined joint PDF (figure 13) showed that a rate of 0.3°C/decade was well within the range of very likely rates of warming. Leemans and Eickhout (2004) explained that higher rates could lead to degraded ecosystems that consequently impacted carbon storage reservoirs and economic sectors that depend heavily on healthy functional ecosystems.

In comparison to Collins et al. (2007), who found that ocean physics perturbations have little impact on the rate of global warming, our results suggest that changes in ocean diffusivity in the UVic ESCM have a significant effect on the rate of transient climate change in the upper end C.S. simulations, but less influence on the lower end C.S. simulations. In addition, we have shown that the effect of increasing K_{bg} on heat uptake is amplified by increased carbon uptake, leading to an overall increased model sensitivity to K_{bg} changes. At a C.S. of 2.5°C, the maximum decadal rate of temperature change was 0.39°C/decade for a K_{bg} of 0.05, and 0.35°C/decade for a K_{bg} of 0.45, representing a 10.3% decrease in maximum warming rates. However, for the same two values of K_{bg} (0.05 and 0.45) but at a higher C.S. (6.5°C) the maximum decadal rates of temperature change were 0.86°C/decade and 0.66°C/decade representing a change of 23.3%. Consequently, the likelihood of exceeding high rates of warming increased substantially at lower K_{bg} values; for example the probability of exceeding 0.6°C per decade increased from 15% at K_{bg}=0.45 to more than 30% at K_{bg}=0.05. This speaks to the importance of better constraining the rate of ocean mixing in order to improve predictions of future rates of climate warming.

Conclusion:

In this study we used an intermediate complexity climate model (UVic ESCM version 2.9) to quantify the uncertainty in two climate system properties. First, we used an estimated climate sensitivity probability density function taken from an expert synthesis report and assigned likelihood regions to various ranges of rates of warming. Second, we calculated our own probability density function of background ocean diffusivity (K_{bg}) using a sophisticated 3D method, which was developed by Schmittner et al. (2009). Furthermore, we combined both functions to create a joint PDF and calculated a likely range of the maximum rate of warming during the 21^{st} century in response to the A2 emissions scenario. The rates of warming obtained in this study could represent very rapid climate change and pose serious threats to global ecosystems and environmental processes.

Conclusions

The overall rate of climate change is highly dependent on the different variations and combinations of climate system properties; namely the equilibrium climate sensitivity and background ocean diffusivity. At the same time, the future rate of climate change is directly dependent on the mitigation strategy we employ, whether that is a geoengineering approach or not. On this basis, the threat of rapid climate change could potentially exacerbate the unwanted environmental pressures on our planet's global ecosystems and destabilize many of the global environmental processes that help regulate our climate.

In an attempt to quantify the inherent uncertainty within climate models, a probabilistic approach was used to evaluate the likelihood of different rates of global temperature change throughout the 21st Century. As a result, a more comprehensive assessment, which identified the risks associated with probable rates of warming, was used to highlight the potential risks of different degrees of rapid climate change. Probabilistic assessments or reports such as these help communicate better the scientific information to key decision makers among global policy circles.

In the first chapter, we used a simple climate model to estimate the likely range of temperature changes associated with implementation and removal of climate engineering. We found that, in the absence of climate engineering, maximum annual rates of warming were much less compared to a scenario where geoengineering was employed for several decades and then abruptly removed. Sustained high rates of temperature change lead to many negative environmental impacts. These results suggest that climate engineering, in the absence of deep emissions cuts, could arguably constitute increased risk of dangerous anthropogenic interference in the climate system.

In the second chapter, we used an intermediate complexity climate model to estimate the likely rate of temperature changes for different perturbations of climate sensitivity and ocean diffusivity. At the same time, we quantified the uncertainty surrounding these two climate system properties and used a joint probability density function to determine a most likely range of the maximum rate of temperature change during the 21st Century. We found that the most probable maximum rate of temperature change occurred between 0.3 and 0.5 °C/decade with a most likely value of 0.36°C/decade. We concluded that the observed likely rates of warming could entail widespread physical and biological damage and exceed the adaptive capacity of healthy functional ecosystems.

Despite the countless attempts to predict future climate change and evaluate the possible impacts, very few studies have considered the rate of temperature change in their analyses. Such a measure acts as an important indicator for the overall condition of our climate system and should be accounted for. Consequently, the over-arching theme of this thesis, being rates of warming, helps to strengthen the overall significance of this research. In addition, the probabilistic approach used reinforces the significance of the results. Unfortunately, our analyses and discussions of rapid climate change are limited to secondary source comparisons. We did not conduct any model simulations to specifically identify the possible impacts from rapid climate change. Additional research is needed to examine these effects first-hand within the UVic ESCM. For example, a comprehensive analysis on precipitation patterns, land and sea ice volume, ocean and land net primary productivity, and the strength of the meridional overturning stream function would provide a good overall assessment of the potential effects from different rates of warming. Current knowledge for all the above variables is extensive and spans several fields of study, many of which have modeled and measured these variables empirically. Therefore, for comparative reasons and model validation purposes the proposed additional research would compliment this paper nicely.

Although climate sensitivity and ocean heat uptake represent two of the most uncertain climate system properties, aerosol forcing and cloud feedbacks represent the third most uncertain parameter in many climate models. Future research could incorporate this third variable and examine its influence on the other two. Different perturbations and combinations of all three will undoubtedly affect the global rate of temperature change, thereby exploring other probable climate changes while increasing the overall significance of the research.

In conclusion, the presented research in this thesis shows that the overall rate of climate change is an equally important measure, if not more so, compared to the absolute global temperature change. Conveying this message to key decision makers is necessary for climate change mitigation strategies. In addition, the presented research also shows that a probabilistic approach is an effective tool for quantifying uncertainty in climate models and communicating the possible risks of future climate change.

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