Constraining uncertainty in future climate change under mitigating emissions scenarios

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1 Project Description

1.1 Overview

Many things in this world are uncertain. Much of science is devoted to assessing and reducing these uncertainties, and the field of climate prediction is no different. There are many types of uncertainty in climate prediction (Cox and Stephenson, 2007), and these can be thought of in four broad categories:

- *Initial condition uncertainty* arises from a lack of knowledge about the current state of the weather and climate. On shorter timescales, this is the dominant source of uncertainty.
- *Process uncertainty* arises from our inability to represent all of the components of the process that drive climate in our models. This type of uncertainty is the most difficult to quantify.
- *Parameter uncertainty* is due to our lack of knowledge of the true values of the parameters in our models.
- *Scenario uncertainty* arises because we cannot accurately predict anthropogenic emissions of greenhouse gases into the future. On longer timescales of the order of 100 years, this is the dominant source of uncertainty.

Much research is currently being done in the field of climate prediction, and most of it can be described as quantifying or reducing one or more of these types of uncertainty. The research that I am undertaking as part of my DPhil lies at the interface between parameter and scenario uncertainty.

Until recently, scenario uncertainty was the field of social scientists and IPCC Working Group 3 (WG3). This started to change in 2009 with a series of papers introducing the concept and features of cumulative carbon emissions (Allen *et al.* (2009), Meinshausen *et al.* (2009), Matthews *et al.* (2009), Zickfeld *et al.* (2009)). This concept allows an innovative method of simplifying scenario uncertainty, as these papers show that when considering cumulative emissions, warming is path-independent. Additionally, Allen *et al.* (2009) suggest that the uncertainty on warming is also path independent for a given cumulative emissions total. I will be using the concept of cumulative carbon emissions during my DPhil to explore scenario uncertainty from this new angle.

1.2 Experiments

Over the course of my DPhil I have been carrying out experiments exploring uncertainty, and I hope to do several more over the coming two years. I have given each experiment a code, which is listed in Table 1. The timetable that I hope to follow over the coming two years is given in the Gantt chart in Table 2. Here I outline these experiments: past, present and future.

1.2.1 N1: Simple Model Comparison

Much of my initial work on cumulative carbon emissions has used simple climate models. I have employed simple models for their computational cheapness, and also for their ability to offer incites into the processes that govern the behaviour of the climate system. I started my DPhil with a comparison between some simple climate models, which is documented in Section 2.3.2. This allowed me an insight into process uncertainty, as it is likely that it was different representations of the

processes in the climate system that gave rise to the differences that I found between some of the simple climate models. After this comparison, I decided to work with the box-diffusion model outlined in Section 2.2.2, as it is the simplest of the simple climate models that I compared, and yet it is still able to reproduce the trends of more complex climate models.

1.2.2 O1, O2 & O3: Targets and Floors

I carried out experiments comparing the cumulative emissions metric with other emissions metrics in terms of their correlation with peak warming and peak rate of warming. This experiment is discussed in more detail in Sections 2.3.2 and 2.3.5.

The cumulative emissions metric had never been applied to scenarios with residual emissions that are difficult to mitigate. I applied the metric to these 'emissions floors' and recorded my findings in Section 2.3.3. The correlation between peak warming and cumulative emissions to 2200 was stronger than the correlation with cumulative emissions to 2100, suggesting considering climate policy to 2200 is a more relevant timeframe than the 2100 date often used today.

Next I expanded the emissions floor investigation to include a large ensemble of physics perturbations. This allowed me to find whether emissions floors affected the correlation between cumulative emissions and the likelihood profile of peak warming.

1.2.3 M2: Air Capture and Precipitation

My Masters' Project considered how future emissions targets might need to change as we learn more about the climate. It found that if the climate turns out to be warming faster than anticipated, we may need to resort to air capture (artificial removal carbon from the atmosphere) in order to keep warming below 2ºC.

Allen & Ingram (2002) found a simple empirical relationship between warming, CO_2 concentrations and global mean precipitation. When I apply this relationship to cases in my Masters' Project that involve high rates of air capture, I find that global mean precipitation also increases dramatically. I will be investigating this phenomenon further and then hopefully writing up a paper on the findings according to the schedule outlined in Table 2.

1.2.4 P1 & P2: Representative Concentration Pathways

My initial explorations into parameter uncertainty were done using the box-diffusion model outlined in Section 2.2.2. This was appealing because it is such a simple model that it allows a likelihood profile to be plotted easily from its output. For more a more complete treatment of parameter uncertainty in the atmosphere and ocean I have used climateprediction.net (CPDN) to run the general circulation model (GCM) HadCM3L. For exploring parameter uncertainty in the carbon cycle I would like to use the intermediate complexity carbon cycle model IMOGEN. However if this proves unfeasible, I will use the box-diffusion model. There are currently no carbon cycle models that can run on CPDN.

To explore parameter uncertainty, I will be calculating the uncertainty on the warming caused by the set of representative concentration pathways (RCPs) that are discussed in Section 1.2.4. I will also be calculating the uncertainty on the emissions that give rise to the RCPs when injected into the carbon cycle.

To enable comparisons between different climate models, the Intergovernmental

Panel on Climate Change (IPCC) has recently developed a series of different scenarios to be compared. These representative concentration pathways (RCPs) are four concentration pathways that approximately span the range of projected possible behaviours over the coming century. RCP8.5 and RCP3-PD are roughly at the upper and lower ends of anticipated behaviour over the coming century.

Radiative forcings for each of the RCPs are shown in Figure 1. The wavy nature of each of the profiles comes from the solar cycle. Though this plot shows radiative forcing, the profiles are defined as concentration pathways.

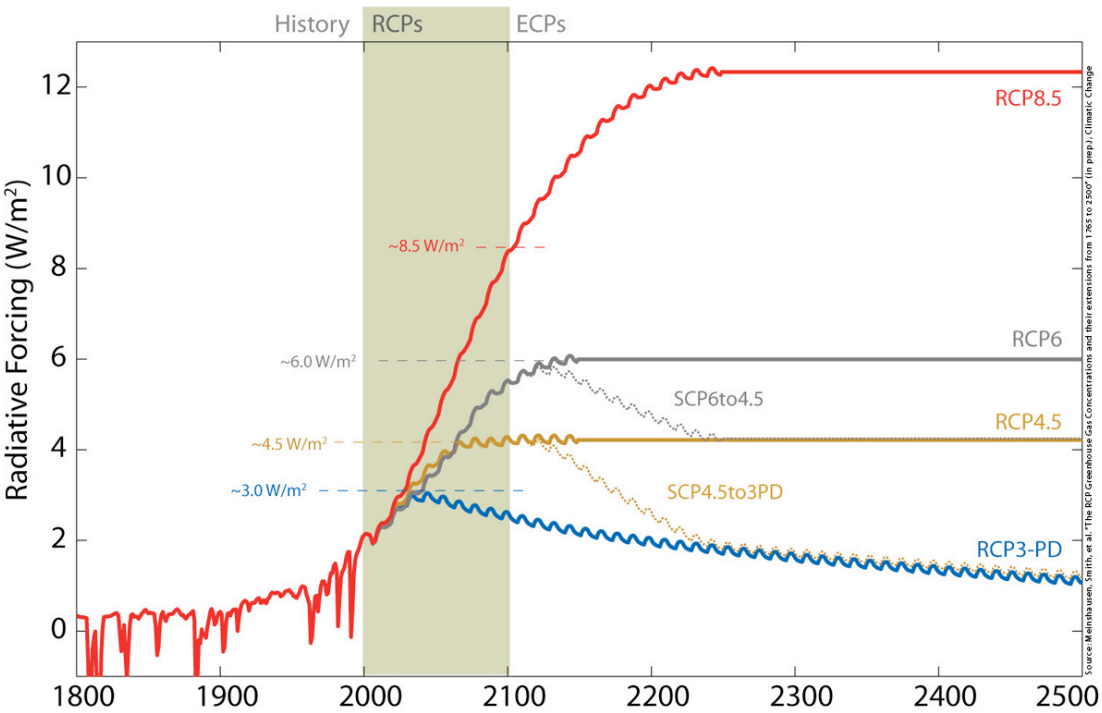


Figure 1: Global anthropogenic radiative forcing for the Representative Concentration Pathways (RCPs). This plot shows only the central estimate of radiative forcing without uncertainty, which is based on the central estimates from the IPCC Fourth Assessment Report (AR4). Two additional supplementary pathways have also been added on this plot, which connect RCP6 and RCP 4.5 (SCP6to4.5) and RCP4.5 to RCP3-PD (SCP4.5to3PD). Source: Potsdam Institute for Climate Impact Research

1.2.4.1 P1: Calculating the uncertainty on warming caused by the RCPs

The IPCC Fourth Assessment Report (AR4) Working Group One (WG1) Summary for Policymakers (2007) contained Figure 2. The grey bars on the right-hand side are the likely range estimates, and are simply 40% below and 60% above the best estimate for each scenario. These numbers were chosen largely through expert elicitation. Experiment P1, named 'Temperature and RCP', attempts to carry out a more systematic calculation of this range for the RCPs in the Fifth Assessment Report (AR5).

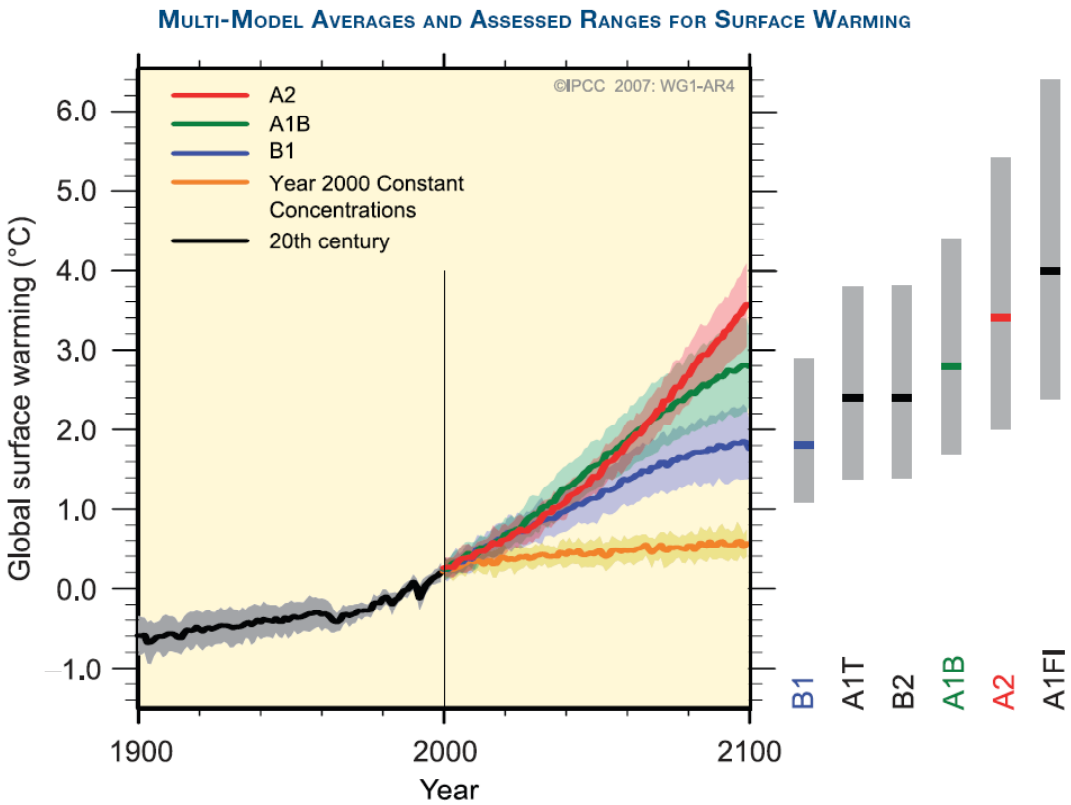


Figure 2: IPCC projections of warming of the 21st Century. Solid lines are multi-model global averages of surface warming (relative to 1980-1999) for scenarios A2, A1B and B1, shown as continuations of the 20th century simulations. Shading denotes the ±1 standard deviation range of individual model annual averages. The orange line is for the experiment where concentrations were held constant at year 2000 values. The grey bars at right indicate the best estimate (solid line within each bar) and the likely range assessed for the six SRES marker scenarios. The assessment of the best estimate and likely ranges in the grey bars includes the atmosphere-ocean global circulation models (AOGCMs) in the left part of the figure, as well as results from a hierarchy of independent models and observational constraints. Source: IPCC AR4 WG1 Summary for Policymakers

Experiment P1 will use HadCM3L on climateprediction.net to run a large ensemble of simulations that are forced by the RCPs. Each simulation will have several hundred physics parameter combinations. This work will be done in collaboration with Dan Rowlands, who has already sampled several hundred parameter combinations that cover the range of parameter space that give relatively good agreement with historic data. The Mahalanobis distance between the parameters' hindcasts and observations was used to determine the chance of each parameter combination being included in our sample. Using the concentrations provided by the RCPs, we will run simulations from 2000 to 2100 and calculate warming in 2100.

We do not use initial condition ensembles as we have found initial conditions to make little difference in HadCM3L to warming results on the timescales that we are considering.

We aim to have Experiment P1 written up as a paper and submitted in time for the IPCC AR5 deadline of summer 2011.

1.2.4.2 P2: Inverse calculation of the emissions that produce the RCPs

Having determined the global warming caused by the RCPs over the 21st Century, we can now use this information, in conjunction with the original RCPs, to make an estimate of the range of emissions that would result in each given concentration and temperature pathway. We can do this using an inverse calculation of the emissions each year. This is the aim of Experiment P2, 'RCPs and Emissions'.

To do this work, I hope to use the intermediate complexity carbon cycle model IMOGEN (Huntingford *et al.* 2010). However if this does not look feasible during the time available, then I will use the carbon-cycle component of the box-diffusion model outlined in Section 2.2.2. Regardless of which model I use, this work will be done in collaboration with Dr. Chris Huntingford at the Centre for Ecology and Hydrology.

Currently the inverse function in the code for the box-diffusion model is not complete, so if we do not use IMOGEN then I intend to spend some of Hilary Term 2011 to finish coding this feature (see Table 2 for the project Gantt chart).

By perturbing carbon cycle parameters, we can calculate a range of emissions that could produce a given emissions concentration for a given temperature pathway. This will allow us to put a range on the emissions that result in the RCPs.

1.2.5 Q1 & Q2: Cumulative Emissions with a GCM

Experiments P1 & P2 are the first step towards the more ambitious Q1 & Q2 experiments, which will be undertaken during my DPhil if time allows. In Q1 & Q2 I hope to explore the concept of cumulative carbon emissions with a GCM on CPDN. This would allow me to extend my exploration of the interface between parameter uncertainty and scenario uncertainty with state-of-the-art apparatus.

The plot in Figure 3 was created by Allen, *et al.* (2009) using the box-diffusion model outlined in Section 2.2.2. The aim of Experiments Q1 & Q2 is to reproduce this figure using a GCM.

These experiments could use the same methodology as Experiments P1 & P2, but with many more concentration pathways and fewer physics perturbations.

To obtain the concentration pathways, we would simply use a subset of the emissions pathways introduced in Section 2.2.1. These would be run through the box diffusion model with best guess parameters (see Section 2.2) to obtain a series of concentration pathways. These would then be used as the input to an experiment to calculate temperatures with a GCM and then to calculate emissions through an inverse calculation, as in P1 & P2.

As with P1 & P2, for each temperature we would have a series of emissions pathways, and so the grey shaded bands in Figure 3 would go horizontally on the plot instead of vertically. For each concentration pathway there would be a series of temperature pathways, and for each temperature pathway there would be a series of emission pathways.

Each of the emissions pathways would have a likelihood associated with them, derived via the process outlined in Section 2.2.3 and in Allen et al. (2009a, Supplementary Information). This could be combined with an estimate of the likelihood of each GCM parameter combination obtained by Dan Rowlands.

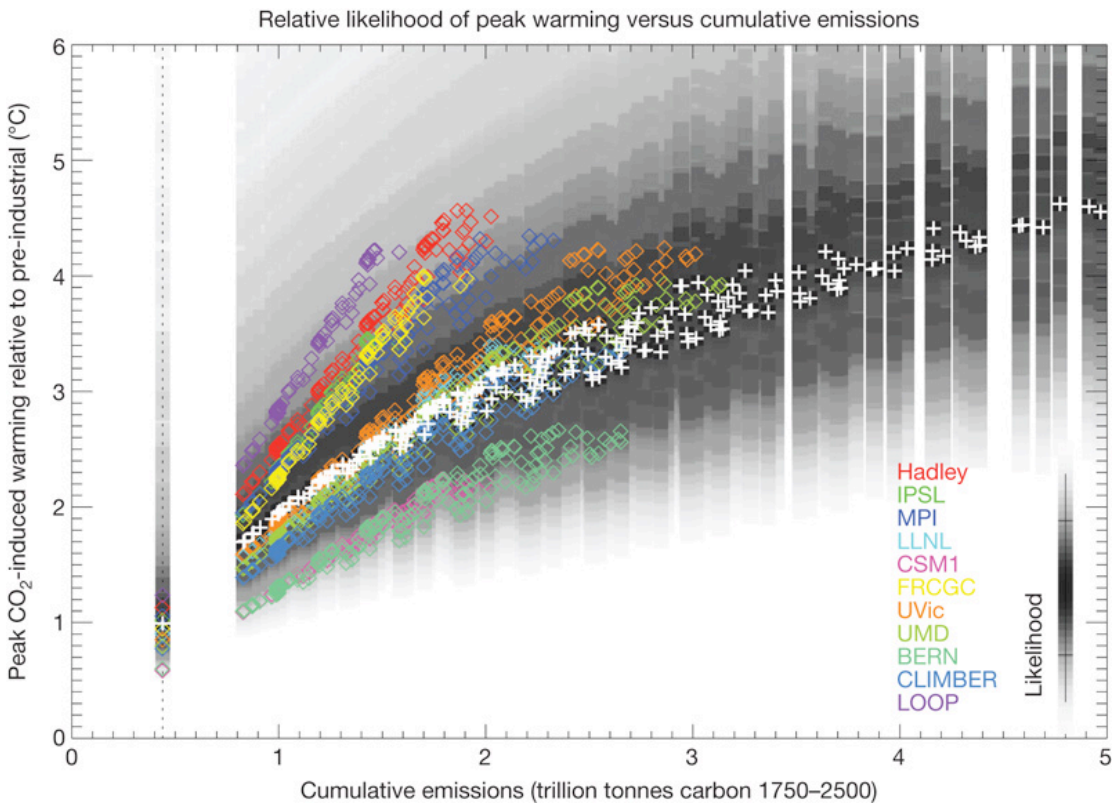


Figure 3: Peak CO_2-induced warming as a function of total cumulative emissions 1750–2500 for 250 idealized emission scenarios. White crosses correspond to best-fit values of simple climate model parameters, with each cross corresponding to a single scenario. Grey shading shows relative likelihood of other parameter combinations, plotted in order of increasing likelihood, showing the uncertainty in peak warming arising from parameter uncertainty in the simple model. Coloured diamonds show responses of the HadSCCCM1 model with parameters fitted to Earth System Models (ESMs) in the C^4MIP experiment, with colours indicating the corresponding ESM. Diamonds are plotted only where temperatures remain within 0.5ºC of the range of the tuning data set (the SRES A2 scenario) to ensure a valid emulation. Bar and symbols at 0.44 TtC show peak warming assuming zero emissions after 2000. Source: Allen *et al.* (2009)

Experiment Code	Experiment name	Model	Input	Output	Ensemble breakdown	Aims to learn	Completed by	Written up by	Current status
M1	Adaptive Learning	Box-diffusion	Emissions pathways that change as the simulation progresses	Temperature	Each emissions pathway has a unique associated physics parameter combination	How to change emissions targets as we learn more about the climate	Easter 2009	Easter 2009	Completed as Masters' project
N1	Simple Model Comparison	Box-diffusion, MAGICC 4.3, MAGICC 6 & HadSCCCM1	E1 emissions	Concentrations and temperature	Range of physics perturbations for each pathway	How the output from a number of simple climate models differs	Easter 2010	Summer 2010	Completed as AVOID project report
O1	Target Comparison	Box-diffusion	Emissions pathways	Temperature pathways	Best-guess physics only	How different emissions metrics and better suited for different targets	Christmas 2010	Christmas 2010	Submitted to a journal
O2	Cumulative with Floors	Box-diffusion	Emissions pathways including emissions floors	Temperature	Best-guess physics only	Whether the cumulative emissions metric still holds for pathways with floors	Easter 2010	Christmas 2010	Submitted to a journal
O3	Likelihood with Floors	Box-diffusion	Emissions pathways including emissions floors	Temperature	5000 physics parameter combinations for each pathway	Whether the findings in 'cumulative with floors' hold for less likely physics parameterisations	Easter 2010	Christmas 2010	Submitted to a journal

Table 1 continued on next page…

Experiment Code	Experiment name	Model	Input	Output	Ensemble breakdown	Aims to learn	Completed by	Written up by	Current status
M2	Air Capture and Precipitation	Box-diffusion with simple precipitation	Emissions scenarios calculated in 'Adaptive Learning'	Global mean precipitation	Best guess physics only (though may be extended in future)	How using large amounts of air capture can alter global mean precipitation	Easter 2010 (or Christmas 2010 if physics is extended)	Summer 2011	Best guess physics experiment completed
P1	RCPs and Temperature	HadCM3L on CPDN	Concentrations from RCP8.5, RCP4.5 and RCP3PD	Temperature	Range of physics perturbations for each pathway	About the uncertainty in temperature response to RCP profiles	Summer 2011	Summer 2012	Setting up experiment
P2	RCPs and Emissions	IMOGEN or Box-diffusion	Input and output from 'RCPs and Temperature'	Emissions	Range of physics perturbations for each pathway	About the uncertainty in emissions pathways that lead to RCP profiles	Christmas 2012	Easter 2012	Finalising experimental design
The following experiments will only be completed if time allows									
Q1	Mitigation with a GCM	HadCM3L on CPDN	A wide range of concentration pathways	Temperature	Range of physics perturbations for each pathway	About the uncertainty in temperature response to a range of mitigation scenarios	Christmas 2011	Christmas 2012	Finalising experimental design
Q2	Cumulative Emissions with a GCM	IMOGEN or Box-diffusion	Input and output from 'Mitigation with a GCM'	Emissions	Range of physics perturbations for each pathway	What is the uncertainty in cumulative warming commitment according to a GCM	Easter 2012	Christmas 2012	Finalising experimental design

Table 1: An outline of all of the experiments that I hope to complete as part of my DPhil project. The greyed out 'Adaptive Learning' experiment was completed as part of my Masters project, but is included because the 'Air Capture and Precipitation' experiment builds on its findings. Deadlines for experimental completion and writing up are included, as is the current status of each experiment. Each experiment is discussed in more detail in Section 1.2. Experiments below the dotted line will only be carried out if time is

available to do so.

1.3 Timeline

Gantt Chart		1st Year			2nd Year			3rd Year			4th Year
Experiment Code	Experiment or Task	Michaelmas 2009	Hilary 2010	Trinity 2010	Michaelmas 2010	Hilary 2011	Trinity 2011	Michaelmas 2011	Hilary 2012	Trinity 2012	Michaelmas 2012
N1	Simple Model Comparison										
O1	Target Comparison										
O2	Cumulative with Floors										
O3	Likelihood with Floors										
	Targets and floors paper										
M2	Air Capture and Precipitation				(if required)						
	Air capture paper										
P1	RCPs and Temperature										
P2	RCPs and Emissions										
	RCP paper										
	DPhil Report First Draft										
	DPhil Report Final Draft										
	DPhil Viva										
The following tasks will only be completed if time allows											
Q1	Mitigation with a GCM										
Q2	Cumulative Emissions with a GCM										
	Cumulative Emissions Paper										

Table 2: A Gantt chart illustrating the project schedule. Darker solid colours represent periods when experiments (or vivas) are to be carried out. Lighter colours depict periods when writing up will be carried out. The time allocated for paper writing extends to when the final manuscript is handed to the editors once the peer-review process is complete. The dark green period labelled 'if required' represents time that will be used if the physics in the air capture and precipitation experiment is expanded. The tasks below the dotted lines will only be completed if time allows.

2 Project Progress

Having outlined what I hope to achieve during my DPhil, I will now endeavour to document what I have achieved thus far. I will begin by introducing some basic concepts such as cumulative carbon emissions, before moving on to my own research. Much of this research has already been submitted as part of briefings to the Department for Energy and Climate Change, AVOID Project briefings, or as a submission to a Special Report on 4 Degrees of Climate Change to be published by the Philosophical Transaction of the Royal Society. I have carried out all of the research, and I am the lead author and drafted all of the text, however the text has also been edited by my supervisors and Dr. Chris Huntingford of the Centre for Ecology and Hydrology in Wallingford. These individuals have also given me suggestions for improvements on all of the figures contained within.

2.1 Introduction

A substantial fraction of the carbon dioxide (CO_2) released into the atmosphere by human activity remains there, in effect, for centuries to millennia. Changes in ocean chemistry, which can be described through the Revelle buffer factor (Archer 2005) limit oceanic removal of CO_2 (Solomon, *et al.* 2009) while the potential for terrestrial vegetation to take up CO_2 is also predicted to fall as the climate warms (Cox, *et al.* 2000), although the size of this feedback is uncertain (Friedlingstein, *et al.* 2006). Complete removal requires geological timescales, (Le Quere, *et al.* 2009) or assistance from large-scale air capture technologies (Lackner and Brennan 2009; Nikulshina, *et al.* 2009; Pielke 2009).

This feature of the climate implies that bringing future emissions to zero would not reduce temperatures except in the very long term, but would rather hold temperatures almost steady (Matthews and Caldeira 2008; Lowe, *et al.* 2009; Matthews and Weaver 2010). Several recent studies have sought to exploit this observation in order to provide a simple link between levels of cumulative emissions and future warming (Allen, *et al.* 2009a; Matthews, *et al.* 2009; Meinshausen, *et al.* 2009; Zickfeld, *et al.* 2009).

Allen *et al.* (2009a), considered the cumulative carbon emissions summed between pre-industrial times and 2500, linking them to peak warming. Meinshausen *et al.*, (2009) examined multi gas pathways and used a cumulative emissions metric between years 2000 and 2050 to relate to the probability of exceeding a 2°C target, rather than the amount of warming. The German Advisory Council on Global Change (WBGU 2009), argued for a cumulative limit between 2010 and 2050, while Matthews *et al.* (2009) argues that warming by a given date is proportional to cumulative emissions to that date.

These papers show how cumulative emissions provide an attractive and concise metric for use by policy makers interested in avoiding some level of peak global warming. The recent Copenhagen Accord (UNFCCC 2009) contains an aim of limiting warming to no more than 2°C above pre-industrial levels and draws on earlier targets from the EU and G8 (den Elzen and Meinshausen 2006; G8 2008). Using the results in Allen *et al.* (2009a) a 2°C limit on the most likely peak CO_2-induced warming could be achieved by limiting cumulative emissions to one trillion tonnes of carbon (1TtC).

Cumulative emissions targets represent the sum of emissions over time, and therefore these cumulative emissions could be distributed over time in a number of ways. For example, an early peak in emissions could be followed by a relatively slow rate of post-peak decline, or a later peak followed by a much more rapid decline. One real-world difference between the pathways is that it may not be technically feasible or economically desirable to decrease emissions at rates much in excess of 3 or 4% per year so that peaking later may not be viable (den Elzen, *et al.* 2007).

This paper addresses the problem of CO_2-induced warming. This is a central but not exhaustive component of dangerous anthropogenic interference with the climate system. Most multigas pathways of future radiative forcing that currently exist in the literature result in a total anthropogenic warming that either approximately equals or exceeds CO_2-induced warming (Nakicenovic, *et al.* 2000). This is due to the warming effect of non-CO_2 greenhouse gases usually equalling or exceeding the cooling effect of aerosols. Hence, avoiding dangerous levels of CO_2-induced warming is a necessary, albeit not always sufficient, condition for avoiding potentially dangerous anthropogenic interference in the climate system.

In this paper, we begin by comparing the carbon cycle and temperature responses of three simple climate models. We then use one of the models to explore in more detail how cumulative emissions targets relate to more widely known policy targets, such as limiting emissions rates in 2020 or 2050. First, we analyze the relative skill of different emissions measures in predicting resultant future peak warming, comparing cumulative emissions over a range of periods and actual emissions rates at years 2020 and 2050.

Second we investigate whether the cumulative emissions metric still holds for a class of emissions pathways that do not assume all emissions can be mitigated over the coming centuries. It may not be technically or economically feasible to eliminate emissions of all greenhouse gases while, for example, preserving global food security. This limit has been referred to as an 'emissions floor' (UK Committee on Climate Change 2008; Chakravarty, *et al.* 2009). It is difficult to estimate where this emissions floor might lie, or the extent to which it can reduce over time as new technologies become available. If the emissions floor is constant, then we refer to it as a 'hard floor'. If society is able to continue to reduce residual CO_2 emissions, eventually to the point where net emissions are zero, then we call this a 'decaying floor'.

Third, we recognise that mitigation alone will not avoid all potential impacts of climate change, even if global warming does remain below two degrees (Adger 2007; Parry, *et al.* 2009). Since some adaptation will be required in the future, policy makers also need information on the rates of future climate change. This will determine how quickly a response is needed. Neither the cumulative total metric, nor 2°C warming targets, provides information on short-term rates of change in global warming (Kallbekken 2009). Here we analyse correlations between rates of CO_2-induced warming and short-term emissions rates, noting that warming rates are also strongly influenced by non-CO_2 climate forcing agents.

2.2 Methods

Our method consists of deriving a range of idealised CO_2 emissions pathways and using a simple coupled climate carbon-cycle model to estimate the resulting climate change. As many parameters in the model are uncertain, a likelihood method is used to identify the values that give the best agreement with observations of the recent past or model studies with more complex carbon cycle-climate models (Allen, *et al.* 2009a).

Unless we are calculating likelihood profiles, as in Section 2.3.4, we run one simulation for each selected emissions pathway, using the parameters that were previously found to give the best agreement with observations and more complex models. The model is run between the years 1751 and 2500. By running large ensembles containing hundreds of different emissions pathways, we can begin to analyse trends across emissions pathways. This method allows us to ask questions such as "what is it about an emissions pathway that controls the resulting peak rate of global mean temperature increase?"

2.2.1 Emissions pathways

The emissions pathways that are used in the model follow the algorithm outlined by Allen *et al.* (2009a Supplementary Information). This gives the rate of change of future emissions according to by the equations below

$$E_a = \begin{cases} H(t) & \text{for} \quad t < t_0 \\ a\,\mathrm{e}^{bt} & \text{for}\, t_0 \le t < t_1 \\ c\,\mathrm{e}^{dt^2+et} & \text{for}\, t_1 \le t < t_2 \\ f\,\mathrm{e}^{gt} & \text{for} \quad t \ge t_2 \end{cases},$$

where E_a is the carbon emissions[1] in year t, $H(t)$ is historical emissions data, and a, b, c, d, f, g, and h are constants. t_0 is the year at which historical data is replaced by emissions pathways. The parameters b, and g, representing the initial rate of exponential growth and final rate of exponential decline, depend on the specification of the emissions pathway and are allowed to vary between emissions pathways. t_1, and t_2 are the times of transitions, and also vary between emissions pathways. The remaining constants are determined by the requirement that emissions are continuous everywhere, and that rates of change of emissions are continuous everywhere except at t_0.

A number of discrete options were selected for parameters b, g, t_1, and t_2. Each combination of these parameters represents a different possible emissions pathway. Parameter options were selected such that there are 12,750 possible emissions pathways of the type outlined here. The ranges of the parameters were chosen to give a range of emissions pathways with cumulative emissions to 2200 between 0.7GtC and 3GtC. The parameters were also chosen so that most emission pathways had a maximum rate of emissions decline of less than 4% per annum, but with some pathways decreasing by up to 10% per annum.

A new set of pathways, extending those described above have been developed with

[1] Note that E_a is measured in tonnes of carbon, as opposed to tonnes of CO_2. To convert to tonnes of CO_2 one would simply multiply our emissions and cumulative emissions values by a factor of $\frac{44}{12}$.

"emissions floors" to represent the emissions that are potentially technologically, economically, or politically unfeasible to mitigate. We use two type of emissions floor: a hard floor F_H, and a decaying floor, F_D. These two floors take the forms

$$F_H \geq A$$

$$F_D \geq B\exp\left(-\frac{t - t_{2050}}{\tau}\right),$$

where A and B are constants with units of gigatonnes of carbon per year (GtC/yr) as given in the legend in Figure 7, and represent the emissions that we cannot mitigate in the year 2050 and τ is a time constant set to 200 years. Emissions floors are caps below which emissions are not able to fall, so for all t where $t = t_0$ we take whichever is the larger of $E_a(t)$ and $F(t)$ to be our emissions pathway. If we take into account five alternative emissions floors, (1) no floor, (2) low hard floor, (3) high hard floor, (4) low decaying floor, (5) high decaying floors, which could apply to each of the 12,750 possible pathways described above, we have 63,750 possible emissions pathways. We do not use all of these possible pathways, but rather pick a random subset of them to investigate with the simple coupled climate carbon-cycle model. 15 of these pathways are plotted in Figure 4, alongside their resulting warming trajectories as simulated by the simple model outlined below.

2.2.2 Models

Following Allen *et al.*, (2009a, Supplementary Information) our analysis is based on a simple combined climate-carbon cycle model with a time step of one year. The model uses a three-component atmosphere-ocean carbon cycle, in which we assume that the atmospheric CO_2, measured by a concentration C, can be split into three components, C_1, C_2, and C_3. Physically, C_1 can be thought of as representing the concentration of CO_2 in long-term stores such as the deep ocean; $C_1 + C_2$ as representing the CO_2 concentration medium term stores such as the thermocline and the long-term soil-carbon storage; and $C = C_1 + C_2 + C_3$ as the concentration of CO_2 in sinks that are in equilibrium with the atmosphere on time-scales of a year or less, including the mixed layer, the atmosphere itself and rapid-response biospheric stores. Each of these components, C_1, C_2 and C_3, is then associated with some fraction of the emissions into the atmosphere, E, and a particular removal mechanism.

$$\frac{\mathrm{d}C_3}{\mathrm{d}t} = b_3 E$$

$$\frac{\mathrm{d}C_2}{\mathrm{d}t} = b_1 E - b_0 C_2$$

$$\frac{\mathrm{d}C_1}{\mathrm{d}t} = b_4 E - b_2 \int_0^t \frac{\mathrm{d}C_1(t')}{\mathrm{d}t'} \frac{\mathrm{d}t'}{\sqrt{t - t'}}$$

where b_3 (= 0.1) is a fixed constant representing the Revelle Buffer Factor, b_1 is a fixed constant such that $b_1 + b_3 = 0.35$ (Allen, *et al.* 2009a Supplementary Information). b_1 represents the fraction of atmospheric CO_2 that would remain in the atmosphere following an injection of carbon in the absence of the equilibrium response and ocean advection. b_0 represents an adjustable time-constant, the inverse of which is of order 200 years. The third equation in our simple carbon cycle model, which relates to C_1, accounts for advection of CO_2 into the thermocline and land-biosphere. b_2 represents an adjustable diffusivity, while $b_1 + b_3 + b_4 = 0.85$ is

the fraction of CO_2 that would remain in the atmosphere within a year of a pulse injection (Allen, *et al.* 2009a Supplementary Information).

The surface temperature response, *T*, to a given change in atmospheric CO_2 is calculated from an energy balance equation for the surface, with heat removed by either a radiative damping term or by diffusion into the deep ocean. It is described by

$$a_1 \frac{\mathrm{d}T}{\mathrm{d}t} = a_3 \ln\left(\frac{C}{C_0}\right) - a_0 T - a_2 \int_0^t \frac{\mathrm{d}T(t')}{\mathrm{d}t'} \frac{\mathrm{d}t'}{\sqrt{t-t'}}$$

Here, a_1 is a fixed heat capacity, which we approximate as the effective heat capacity per unit area of a 75m ocean mixed layer. a_3 corresponds to a doubling of atmospheric CO_2 levels causing a forcing of 3.74 Wm^{-2} (Ramaswamy 2001). a_0 and a_2 are both able to vary, and control the climate sensitivity, and rate of advection of heat through the thermocline, respectively. This is a simple energy balance equation, where the term on the left hand side represents the thermal inertia of the system; the first term on the right hand side (r.h.s.) is the atmospheric CO_2 forcing; the second term on the r.h.s. is a linearised temperature feedback, and the third term on the r.h.s. is a diffusive term representing the flux of heat into the deep ocean.

Finally, the climate-carbon cycle feedback is represented by adding an extra, temperature dependent, component to the total anthropogenic emissions emitted each year (E_a) , is given by

$$E = E_a + b_5 T'$$

where T' is the temperature anomaly above the previous 100 years' running average, and b_5 is the adjustable carbon cycle feedback parameter. Since the industrial revolution, models have shown this feedback has been largely linear, however this linearization is unlikely to hold for temperatures greater than 3-4K above pre-industrial temperatures. Further, the equation is unreliable for decreases in temperature, but these are not considered here.

Together these six equations make up the simple coupled climate-carbon cycle model that is used throughout this paper. Figure 4 shows the temperature trajectories simulated by this model for 15 sample emissions pathways.

2.2.3 Likelihoods

Five parameters in this coupled climate-carbon cycle model have been varied in order to sample the their uncertainties, while the rest are kept constant. The five parameters that are varied are a_0, a_2, b_0, b_2, and b_5. The other parameters in the model are not varied because their fractional uncertainties are much smaller than the five parameters listed above.

These five parameters are constrained by five "observations" (either direct, or based on more complex model simulations). These are (1) observed attributable CO_2-induced twentieth-century warming, (2) global heat capacity, inferred from the combination of ocean warming and ocean heat uptake, (3) historical record of atmospheric CO_2 concentrations, (4) the rate of advection of CO_2 in the deep ocean, based on the C4MIP family of climate-carbon cycle GCMs and models of intermediate complexity, and (5) the climate-carbon cycle feedback parameter, again estimated from the C4MIP family of models (Allen, et al. 2009a Supplementary Information). We require C4MIP to help with some of these quantities in the absence of true observations of the carbon cycle. Each of the constraints is assigned a

lognormal distribution from estimates in the literature, as detailed by Allen *et al.* (2009a Supplementary Information).

For each combination of the five model parameters, the simple climate-carbon cycle model is operated, and likelihoods for each of the constraints are calculated, then multiplied together to give a single likelihood. The parameter combinations that better reproduce the constraints are then more likely, and the parameter combination that best reproduces the constraints is considered to be our best guess, or the most likely (Pawitan 2001). Only this best guess parameter combination is used in the coupled climate-carbon cycle model throughout most of this paper, with the exception of Section 2.3.4 where we use several thousand parameter combinations to create 'likelihood profiles'. Fifteen warming trajectories calculated using best guess parameters are shown in Figure 4.

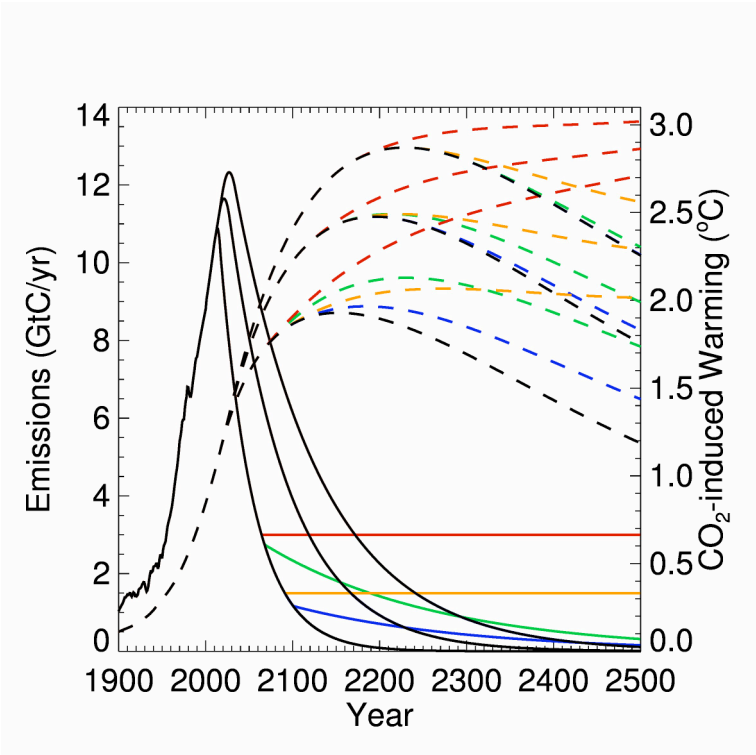


Figure 4: Fifteen emissions pathways and their resulting temperature trajectories. The emissions pathways are in solid lines, and can be read off of the left axis, while the temperature trajectories are in dashed lines, and can be read off of the right axis. The 15 emissions trajectories are created by combining three possible pathways, shown here in black, with five possible emissions floors, shown here in coloured solid lines, as outlined in Section 2.2.1. The upper, middle, and lower plumes of overlapping coloured dashed temperature trajectories correspond to the black emissions profiles that peak the highest, the second highest, and the lowest, respectively. The three emissions pathways with the red highest constant emissions floor have red dashed resultant temperature trajectories. The same correspondence applies between the other colours of emissions floors and their resultant temperature trajectories. The upper, middle and lower black curves have cumulative totals to 2500 of 2TtC, 1.5TtC, and 1TtC respectively.

2.3 Results

2.3.1 N1: Model Comparison

The methodology for the box-diffusion model outlined above is different in certain ways from other simple climate models, such as the Model for Assessment of Greenhouse-Induced Climate Change (MAGICC). We present here a comparison between the box-diffusion model and two distinct setups of MAGICC, while also drawing on results from the Hadley Centre Simple Climate-Carbon Cycle Model (HadSCCCM1).

Simple models have the advantage of being able to emulate multiple more complex models and they can be run in large ensembles without significant computational costs. By the choice of different parameter values, a single simple model can cover a rather large climate response space. Hence, we compare here not the climate models per se, but three simple models in specific setups. A higher temperature response in the one model does hence not necessarily mean that the model per se is warmer; the stronger climate response could simply be due to a higher climate sensitivity setting.
We compare the following setups:

1. The box-diffusion model used by Allen et al. (2009) with historical constraints as described in Section 2.2.2
2. A variant of MAGICC 4.3 (version used in IPCC AR4) with a Monte Carlo sampling of key parameters according to literature-based probability distributions as described by Lowe et al. (2009).
3. MAGICC 6 (Meinshausen et al. 2008) using historical constraints of hemispheric temperatures and heat uptake as described by Meinshausen et al. (2009) in combination with emulations of C4MIP carbon cycle models.
4. HadSCCCM1

The principle results are shown in. All models were driven by the same CO2-only emissions pathway from the 'E1' emissions scenario, which was developed as part of the EU ENSEMBLES project and is plotted in Figure 5a.

Figure 5b shows the resulting CO2 concentrations simulated by each model. . Note that for MAGICC the thin lines correspond to the 10th and 90th percentiles of a Bayesian posterior distribution, while for the box-diffusion model they correspond to the 10-90% confidence interval. These should only correspond exactly in the limit of a fully observationally-constrained Gaussian distribution, although they are often used interchangeably by non-specialists. When they are different, it indicates that results from the Bayesian approach may be heavily influenced by prior sampling decisions, not by the observations. The thick blue, green and red lines represent statistically different quantities. The thick light blue and light green curves are the two MAGICC ensemble means. All of the green and blue curves are based on a probabilistic Bayesian framework, while all of the red curves are based on a frequentist likelihood-based framework. The thick red curve is the best guess, or most likely, box-diffusion model response. Note that the one standard deviation error on the HadSCCCM1 result (orange in Figure 5) is incorrectly expressed symmetrically around the mean; however, a more elaborate treatment would place it will actually be asymmetrically, as in the MAGICC and box-diffusion cases.

For atmospheric CO2 concentration, the box-diffusion model appears to behave similarly to HadSCCCM1 up to 2100. The significant difference between the MAGICC 4.3 ensemble and the box-diffusion model is between their concentration projections, as visible in b. In MAGICC 4.3, concentrations fall within decades following emission reductions, whereas in the box-diffusion model and in HadSCCCM1 they remain high throughout the century, with parameter combinations that give higher responses and indeed actually continuing to increase. We suggest that this difference is probably due to the differences between the models' carbon cycles' treatment of oceanic carbon uptake. The version of MAGICC used here makes use of an impulse response model. The box-diffusion model, on the other hand, includes a diffusive step in the calculation, as shown in the differential equation for C1 in the Section 2.2.2. The diffusive step is driven by concentration gradients between the ocean, the atmosphere and the land-biosphere; consequently ocean and biosphere carbon uptake slows rapidly once emissions stop and CO2 concentrations stop rising. This representation was based on discussions with Hadley Centre carbon cycle experts on the optimal way of representing the behaviour of more complex carbon cycle models. Clearly, the question of whether the real-world response conforms to a generically diffusive process, as in the box-diffusion model or HadSCCCM1, or a more advective process as modelled by MAGICC 4.3, is a matter meriting further research. In layman's terms, the question is whether current uptake of carbon by the oceans and biosphere is driven by the fact that CO2 levels are rising, and hence would slow down if the rise stops, or whether it is driven by the fact that CO2 levels are elevated above their pre-industrial equilibrium, in which case uptake would continue even after CO2 levels stop rising, causing them to fall.

When we consider the full of range of models available to us, Figure 5b shows HadSCCCM1 behaving more like the box-diffusion model and MAGICC 6 than like MAGICC 4.3. Thus between MAGICC 4.3, MAGICC 6 and the box-diffusion model, shows that we have three (at present equally defensible) structural setups of the carbon cycle giving rise to a single emissions pathway resulting in three different CO2 concentration trends in the second half of the 21st century. For the E1 scenario these are continued rise, level or declining concentration. The choice of whether appropriate observational constraints that could be used to distinguish between these three possibilities is a question we suggest merits further research.

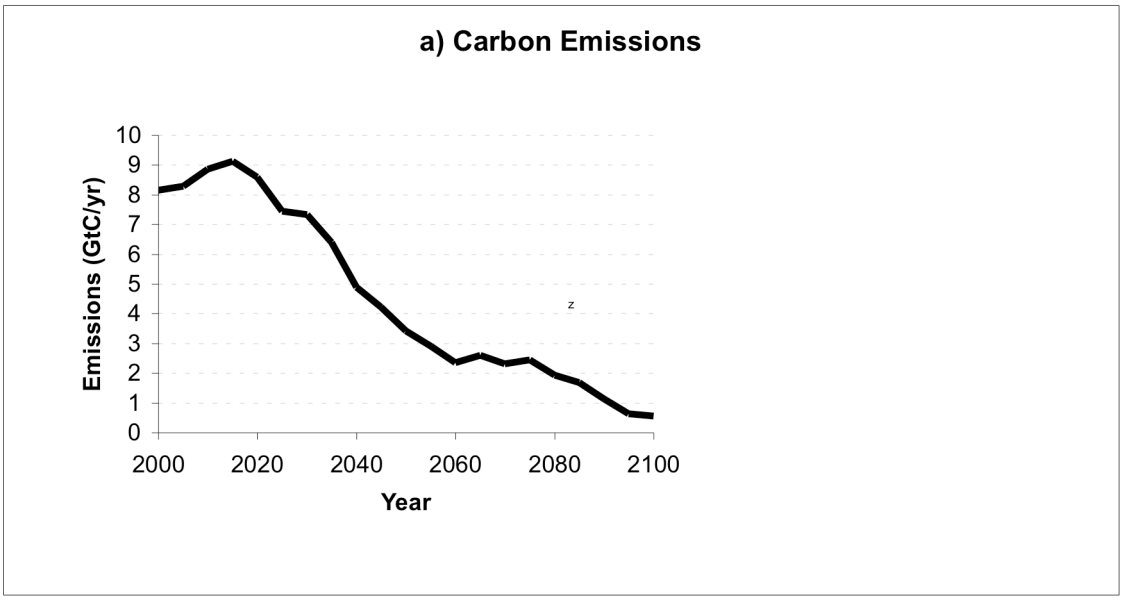
The temperature responses to the CO2 concentrations are shown in Figure 5c. As in b, HadSCCCM1 and the box-diffusion model again have good agreement, while both MAGICC models warm less. We show in Figure 5d that when the concentrations are the same, the box-diffusion temperature response and the MAGICC 4.3 temperature response are more similar. By comparing Figure 5b with Figure 5c, we can see that the temperature response in MAGICC 6 is greater than that of MAGICC 4.3 or the box-diffusion model.

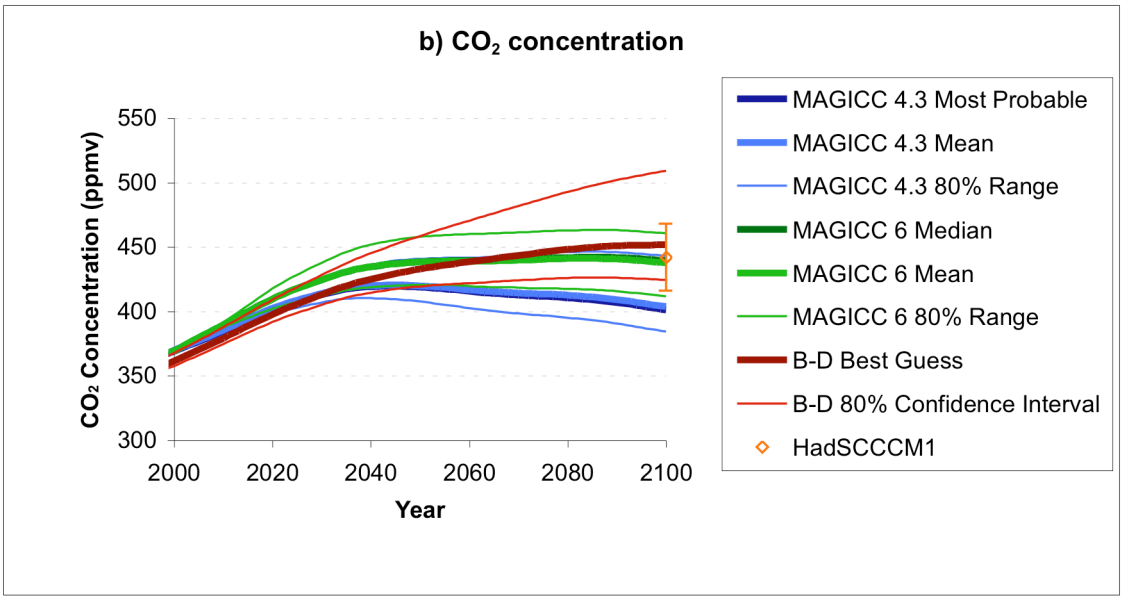
We can explain some of these differences in warming for a given CO2 concentration by considering the transient climate response (TRCR) used in each of the models setups. The TCR used in MAGICC 6 is analysed by Meinshausen et al. (2009), while Allen et al. (2009) consider the TCR in the box-diffusion model. The TCR in Meinshausen et al (2009) is biased low relative to Allen et al. (2009). The TCR in Meinshausen et al. (2009) has been obtained from their climate sensitivity, while Allen's is obtained from observational constraints on past warming rates. The TCR probability function in Meinshausen et al. (2009) peaks roughly 0.5°C cooler the one in Frame et al. (2005), which is constrained by the same observations as used by

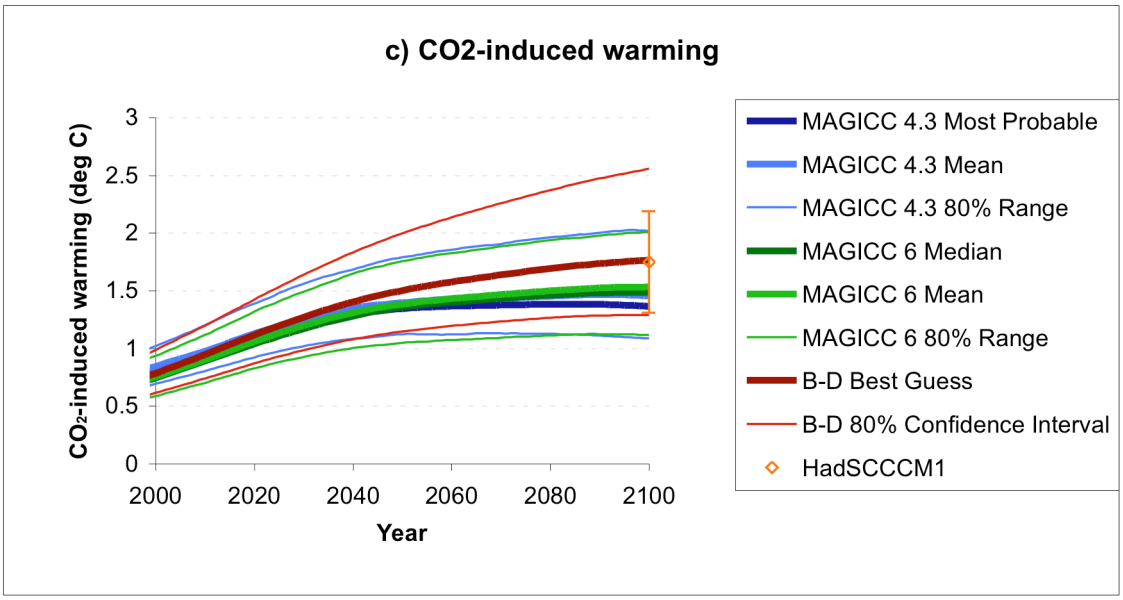
Allen et al. (2009). This can be observed in Figure 1 of Meinshausen et al. (2009), which also shows an apparent bias between the TCRs of GCMs, and the peak of Meinshausen's posterior TCR distribution. This difference with Allen et al. (2009) suggests that MAGICC 6 would run cooler than the box-diffusion model, which we confirm by comparing Figure 5b with Figure 5c. MAGICC 4.3 used the TCR given by Murphy et al. (2004), which is more symmetric and higher than that of MAGIC 6.

In this section we conclude that we cannot yet rule out any of the modelling frameworks we considered here. However, differences in their post 2050 behaviour will be important when considering long-term climate change and improving understanding is important.

Now that we have performed a simple comparison between these three models, we can now use one model, the box-diffusion model, to investigate the different types of emissions targets.







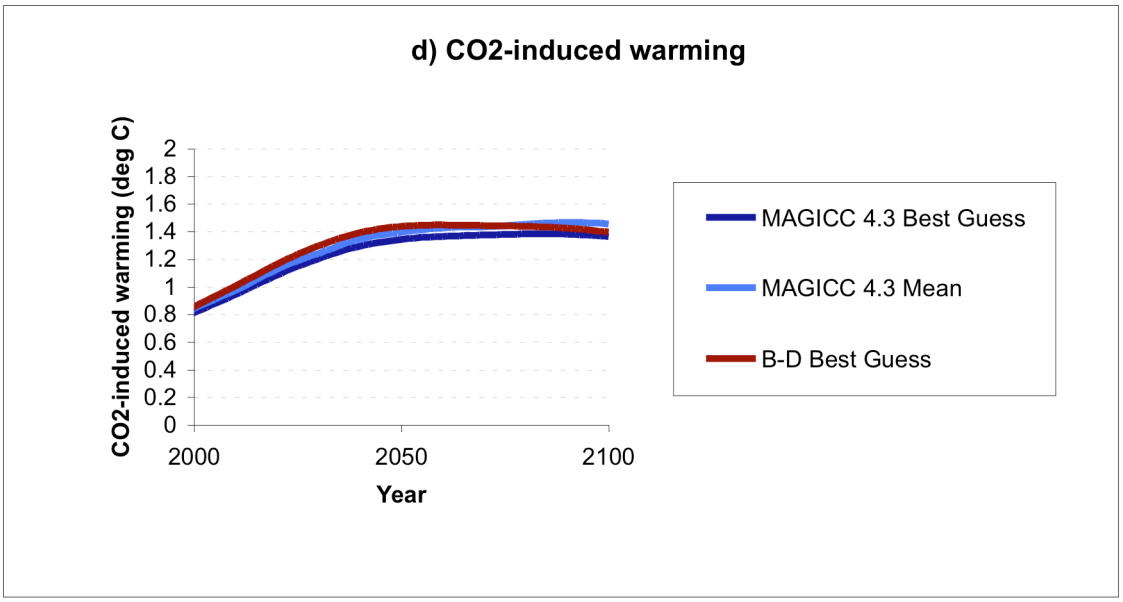


Figure 5: A comparison between the box-diffusion model, MAGICC 4.3, MAGICC 6 and HadSCCCM1. Panel a shows the E1 emissions scenario that was used in each case. Historic emissions data was used before 2000. Panels b, c and d show the CO2 concentration and CO2-induced warming relative to pre-industrial times projected by each of the models. The box-diffusion (B-D) model is represented by red lines, MAGICC 4.3 by blue lines, MAGICC 6 by green lines, and HadSCCCM1 by orange symbols. Thick lines represent central tendencies, i.e. means, medians, best guesses and most probable outcomes. Thin lines represent 80% ranges and confidence intervals. For MAGICC, darker green thick lines represent the median, darker blue thick lines represent most likely outcomes under this particular setup, while lighter thick lines represent the mean. The orange diamond and associated error bars show the mean from HadSCCCM1, while the error bars show the one standard deviation spread in results. Panels b and c show the CO2 concentrations and temperatures projected by each of the four coupled climate-carbon cycle models when driven by the E1 emissions scenario. Panel d shows the response of the uncoupled temperature component of the box-diffusion model to the most

probable MAGICC 4.3 concentration pathway. The MAGICC 4.3 lines from Panel c are included in Panel d for reference.

2.3.2 O1a: A comparisons of different types of emissions targets

We compare the performance of a range of emissions and cumulative emissions targets for estimating peak CO_2-induced warming. This comparison is done by constructing an initial set of 395 different emissions pathways, each with zero emissions floor, which have been randomly selected from the 12750 possible pathways with no emissions floor outlined in Section 2.2.1. Once we have randomly selected our 395 emissions pathways, we use the simple coupled climate-carbon cycle model described in Section 2.2.2, to estimate quantities such as the most likely peak warming for each pathway. These results can be used to analyse the usefulness of each of six emissions metrics of interest. We consider cumulative CO_2 emissions a) from pre-industrial times to the time of peak warming and b) from year 2000 to year 2050. We also consider the actual emissions rates at c) year 2020 and d) year 2050. Additionally we consider e) the peak emissions rate and f) the year in which emissions peak.

The performance of each emissions metric is shown in Figure 6, where the emissions metrics are plotted against the peak warming. The bars in the plot indicate the range for each metric in pathways with resultant values of peak warming at or very near to two and three degrees. Black bars only consider the pathways represented by black crosses with rates of emissions decline less than 4%. The grey bars include both black crosses and grey diamonds, corresponding to emissions pathways with rates of decline as high as 10%. For example, in Figure 6d, pathways with a resultant warming of 2°C have emissions in year 2050 between 4.5GtC/yr and 6.4GtC/yr, giving a range of 1.9GtC.

Based on the metrics presented in Figure 6 we conclude that for cases with no emissions floor, the strongest correlation across all pathways occurs between peak warming and the cumulative emissions from pre-industrial times to the time of that peak warming, as shown in Figure 6a. The correlation is almost as strong if cumulative emissions out to 2500 are considered (shown in black squares in Figure 7a) because the vast majority of the emissions in these zero emissions floor pathways have occurred by the time of peak warming. Note that due to the idealised nature of the climate model used here, it may not be quantitatively reliable above 3-4°C of warming.

An interesting feature of the tight correlation present in Figure 6a is the curvature, which is due to the functional form of CO_2 forcing. Forcing due to CO_2 is proportional to the logarithm of the fractional change in atmospheric CO_2 since the pre-industrial era (Ramaswamy 2001). If the forcing were linear, the model used in this paper suggests that there would be a more linear relationship between cumulative emissions and peak warming.

For Figure 6b to Figure 6f, grey diamonds, representing emissions pathways with a maximum rate of decline between of between 4% and 10%, generally appear to the right and below the black crosses, representing emissions pathways with peak rates of decline between 0% and 4%. For a given peak warming, and so for a given cumulative total, pathways with a faster rate of emissions decline will have relatively more of their cumulative total emitted sooner than for pathways with slower rates for decline. As a result these rapidly declining pathways will have higher cumulative

emissions between 2010 and 2050, higher 2020 emissions, higher peak emissions, and a later year of peak emissions. This effect also holds for 2050 emissions above 5GtC/yr. For emissions pathways with cumulative emissions less than 1TtC, corresponding to a peak warming of 2°C, 2050 emissions occur once the pathway has been declining exponentially for a considerable period, and so rapidly declining pathways will have relatively lower emissions in 2050.

The correlation between peak warming and cumulative emissions between year 2010 and year 2050, which is the emissions metric used by The German Advisory Council on Global Change (WBGU 2009), is plotted in Figure 6b. We see that the correlation here is not as good as in Figure 6a. Emissions before 2010 are not allowed to vary across emissions pathways, so there can be no contribution to the spread in peak warming from this historical time period. The majority of the spread comes from the variation in post-2050 emissions, which will have a significant impact on peak temperatures, but which by definition are not included in 2010-2050 metrics. We see that in cases where post-2050 emissions are small, the spread is much tighter, as shown by those pathways with cumulative emissions less than 0.3TtC between 2010 and 2050. This is because the majority of future cumulative emissions in these pathways are emitted before 2050. This means that up to roughly 1.8°C, the cumulative emissions between 2010-2050 has some skill, but this is reduced for higher temperatures.

We also consider whether there is skill in using the actual emissions rates at a particular year; here we use year 2020 and year 2050. The former year is chosen because most of the Copenhagen accord emissions reduction pledges are quoted for this year (UNFCCC 2009). The latter is chosen because several reduction targets for 2050 have also been presented (G8 2008; G8 2009). Figure 6c and Figure 6d show 2020 and 2050 emissions against peak warming. As in (Lowe 2010), we find that emissions in the year 2020 are not a good indicator of peak warming, presumably because they are largely a function of current emissions, and are not a key determinant of cumulative emissions.

For Figure 6d, year 2050 emissions do seem to be a good indicator at lower rates of emission, particularly at values that cause roughly two degrees of warming or less. However they are found not to be a good indicator of peak resultant warming at higher rates of emission. This is in part a consequence of the choice of pathways, as we have considered only smooth pathways with a single maximum and exponential tails (see Section 2.2.1 for more detail on how the emissions pathways are chosen). A wider range of functional forms to describe emissions pathways would be expected to reduce the strength of the relationship between 2050 emissions and peak warming.

We also compare the peak emissions rate and the year of peak emissions with the peak CO_2-induced warming. As shown in Figure 6e and Figure 6f, the spread is very large for both of these metrics, and there is little correlation, save the rapidly declining emissions pathways (grey diamonds) appearing to the right of the slowly declining pathways (black crosses), as explained earlier.

Under the assumption that society will work to avoid crossing a key temperature threshold, from Figure 6a the cumulative emissions metric confirms that we have a choice of high emissions soon followed by rapid decarbonisation, or more stringent emissions cuts occurring soon with a lower rate of decarbonisation in the future. As

in (Allen 2009b), this actually forces the many potential emissions pathways considered here, which have the same cumulative total, to cross around the middle of the 21st Century. Lower cumulative totals, and thus pathways that result in lower levels of warming, leave less flexibility, and thus all pathways must intersect in roughly the same place. At higher cumulative totals, there is more flexibility about when carbon is emitted, and thus pathways do not cross in the same place, resulting in the wider spread of pathways at warmer peak temperatures. Thus, pathways with lower rates of emission in 2050 are likely to result in a similar amount of peak warming, while higher rates of emission in 2050 can lead to varying levels of peak warming, as seen in Figure 6d.

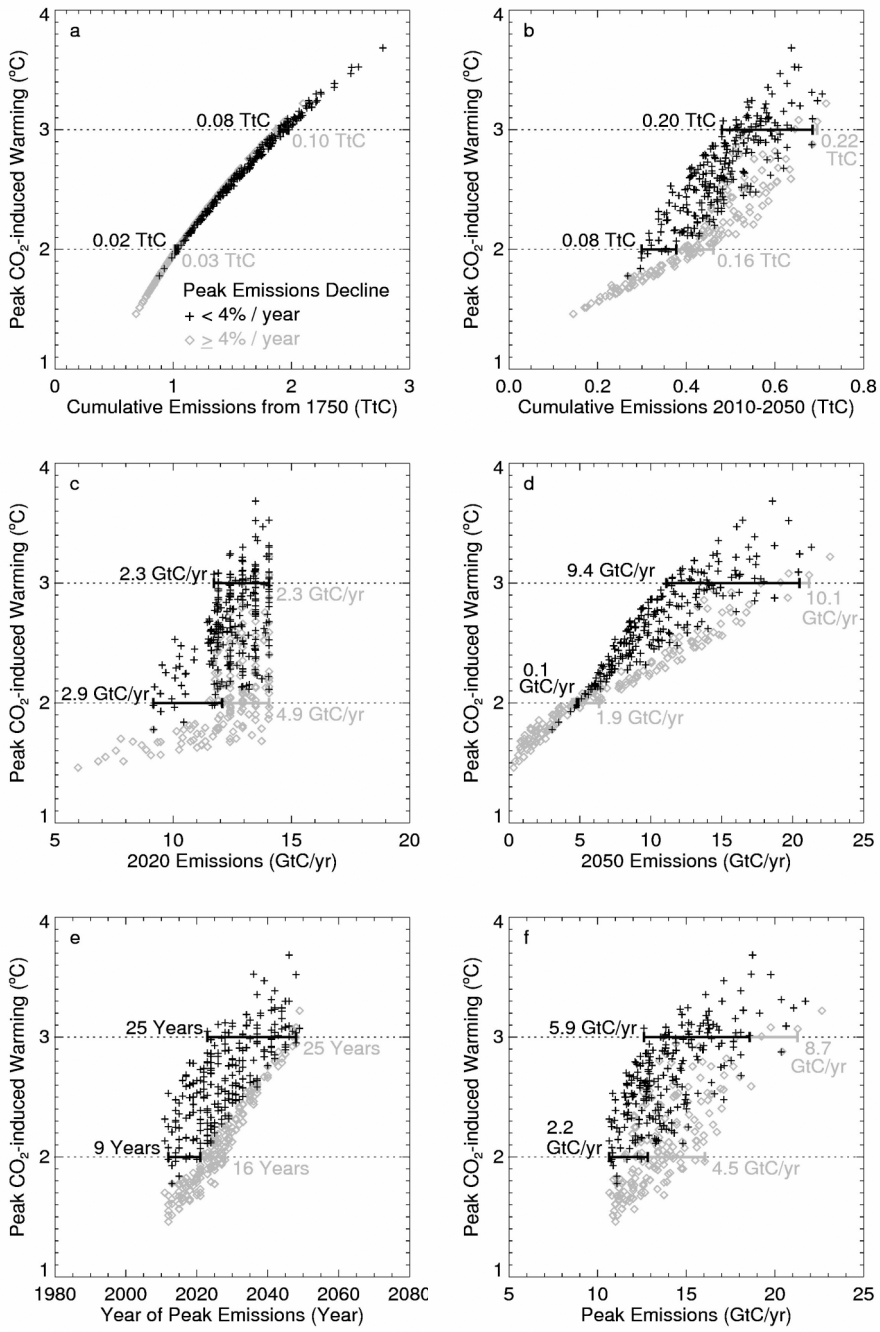


Figure 6: Scatter plots showing the relationship between most likely peak CO_2-induced warming and various global CO_2 emissions metrics for 395 emissions pathways. The x axes show for each panel shows a) emissions time-integrated between 1750 and 2500, b) emissions time-integrated between 2000 and 2050, c) emissions in the year 2020, d) emissions in the year 2050, e) the year in which emissions peak, and f) the peak or maximum in emissions. Black crosses indicate emissions pathways in which the maximum rate of emissions decline is less than 4% per year; grey diamonds indicate the converse. The bars show the spreads of the metrics for pathways with a resultant peak warming of 2°C or 3°C. The black bars show the spread in pathways with peak rates of emissions decline less than 4%, while the grey bar shows the spread in all emissions pathways. We see that the strongest correlation is in Panel a, between peak warming and cumulative emissions between 1750 and 2500.

2.3.3 O2: The effect of Emissions floors

In Figure 4 we calculated the warming trajectories not only for emissions pathways with zero emissions floors, but also for pathways with non-zero floors. We show in Figure 6 that cumulative emissions to the time of peak warming are tightly correlated with peak CO_2-induced warming for the case with no emissions floor, and here we investigate whether emissions floors affect this correlation. Figure 7 shows the impact of emissions floors on different cumulative emissions metrics, and each of the panels has the same form as Figure 6a.

We have plotted most likely peak temperatures as a function of four different cumulative emissions metrics: year 1750 to year 2500 (Figure 7a), year 1750 to the time at which peak warming occurs (Figure 7b), 1750 to year 2100 (Figure 7c), and year 1750 to year 2200 (Figure 7d).

In Figure 7a, we can see that pathways with larger emissions floors are shifted to higher cumulative totals. This occurs because the cumulative totals include contributions for portions of the emissions floor that are emitted after the time of peak warming, which can have no effect on peak warming, as illustrated by the green curves in Figure 4.

We find that if a hard, or non-varying emissions floor becomes too large, then the emissions cannot balance the natural processes that remove carbon from the atmosphere. Although we highlight that at present the precise value of the emissions when the floor becomes too large is uncertain, and may be model specific. This is illustrated by the red curves in Figure 4. Consequently, for large hard emissions floors, atmospheric levels of carbon dioxide continue to rise throughout our 750 year simulation, and are still increasing at the end of the of the experiment, along with associated levels of mean global warming. With enough computing power and a good enough model, we would be able to do extended simulations of the pathways that do not peak by 2500 and establish when and whether they are projected to peak. We would also be able to extend the range of our plots to include pathways with cumulative emissions of more than 3GtC and a resultant warming of more than 3-4°C. We have not plotted cases where temperatures do not peak by 2500 in Figure 7 or Figure 8, since we are unable to project when they would peak. All pathways with no floor, and all pathways with a decaying floor, had peaked by 2500, however some pathways with a hard emissions floor had not.

We believe that there is currently a lack of observational constraints that might inform whether, after a significant injection of carbon dioxide into the atmosphere, certain emissions floors will cause temperatures to stabilise, decline, or keep rising. Additionally, when considering an emissions floor, it could be argued temperatures will be rising or falling so slowly that actively intervening with the carbon cycle, or simply reducing or increasing emissions by an amount substantially smaller than has already been achieved a century earlier, could change a slowly rising temperature into a slowly falling one, or vice versa. The maximum rate of increase of CO_2 concentrations beyond 2200 associated with the emissions pathways in Figure 4 is 28 parts per million by volume (ppmv)/century. The rate of associated warming shown in Figure 4 beyond 2200 is at most 0.27°C/century. In contrast the associated maximum rates in 2100 are a concentration rise of 99 ppmv/century and a warming of 0.88°C/century. It could well be argued that a society capable of achieving the kind of rates of emissions reduction in 2100 that are assumed under these scenarios would almost certainly be able to convert a static emission floor into a decaying one,

and hence the scenario of very rapid reductions followed by a completely stable floor is not necessarily policy relevant.

Figure 4 shows that the size and type of emissions floor determine how temperatures will behave after they peak. Several studies have suggested that near-zero emissions are required to stabilise temperatures (Matthews and Caldeira 2008, Anderson and Bows 2008, Zickfeld et al. 2009). Our simple model's simulations suggest that temperatures will peak then fall slowly under near-zero emissions (Figure 4), contrasting the results of the studies above. At present there appears to be insufficient understanding and possibly a lack of suitable observations of the carbon cycle to constrain behaviour during the regime when temperatures decline. In light of this lack of observational constraints we do not feel confident in relying upon the simple model's simulations long after the time at which temperatures peak, and will therefore discuss this time period no further.

Figure 7b shows peak warming plotted against cumulative emissions integrated between the year 1750 and the time of peak warming. The correlation in this figure is much better than that in Figure 7a. Figure 7b shows that a decaying emissions floor does not significantly alter the shape of the relationship between cumulative emissions and peak temperature, as the peak warming is still a function of the cumulative emissions. Emissions floors do, however, affect the lower ends of the curves with low values of cumulative emissions. Consider two emissions pathways, both with a cumulative total of 1TtC, but one with a decaying emissions floor, and one with no emissions floor: the pathway without an emissions floor will cause a temperature peak earlier than the pathway with the decaying floor, as the emissions floor causes emissions to be emitted over a longer time period. Consequently, in the case with an emissions floor, there will have been more time for carbon to be removed from the atmosphere, presumably resulting in slightly lower atmospheric concentrations at the end of our simulation period than in the no floor case. As forcing is a function of atmospheric concentrations, the case with no emissions floor and higher concentrations will result in a higher peak temperature.

This phenomenon can be observed in Figure 4 by comparing the lowest green and yellow emission pathways and temperature trajectories. The yellow emissions pathway has a higher cumulative total than the green one, when integrated to the time when temperatures peak. Despite this higher cumulative total, the green curve has a higher peak warming than the yellow curve because its emissions are put into the atmosphere over a shorter time period. It is this phenomenon that causes the hard emissions floors to 'peel away' from the soft emissions floors in Figure 7b.

In Figure 7b, at the upper end of the curve, where cumulative totals are large, the existence of an emissions floor seems to make little difference to the peak temperature. This is because the fraction of the cumulative total that is part of the emissions curve is much larger than the fraction that is in the emissions floor. For the decaying emissions floor in particular, the floor will have decayed to near-zero by the time that $E(t) = F_D(t)$, as the pathway will reach the floor at a later time than it would have if it had a smaller cumulative total. In general, if the cumulative emissions over the duration of the emissions floor are small compared to the overall emissions, then the floor is not particularly important. If the cumulative emissions over the duration of the floor are a large fraction of the cumulative total, then the level of the floor is a crucial determinant of peak warming. This phenomenon is illustrated in Figure 4 by considering the upper yellow and black emissions and temperature

curves. The emissions pathway is so large that the yellow emissions floor does not affect it until 2240, and as a result the yellow and black temperature trajectories are indistinguishable until after temperatures have peaked. This illustrates why emissions floors have less impact on peak warming for scenarios with high cumulative totals.

In Figure 7c, we see that the correlation between peak warming and cumulative emissions to 2100 is relatively weak. The points furthest to the right of the plot, however, are all black crosses, representing emissions pathways with zero emissions floor. This is because for pathways with zero emissions floor, more of the total cumulative emissions have been emitted by 2100 than for pathways with non-zero emissions floors. We see in Figure 4 that all of the 15 temperature trajectories are still warming beyond 2100, and all emissions pathways are still emitting beyond 2100. These emissions beyond 2100 are not accounted for in this metric, but will influence the peak warming, which accounts for most of the lack of correlation in Figure 7c.

The best correlation of all of the panels in Figure 7 can be observed in Figure 7d. This suggests that cumulative emissions, when calculated between 1750 and 2200, are a strong indicator of most likely peak CO_2-induced warming regardless of the type of emissions floor chosen. This is presumably because most of the warming trajectories peak within a few decades of 2200. Those trajectories that do not peak near 2200 have all warmed to within a small fraction of their peak warming by this date, and therefore the emissions emitted in these pathways after 2200 only serve to maintain temperatures, not induce more warming. This phenomenon is illustrated by the lowest yellow curve, which peaks in 2273, but has warmed to 99% of its peak warming by 2200. This example illustrates how emissions after 2200 have a very small influence on its peak temperature, provided the emissions floor is not too high.

One way this work can inform current policy targets is for policy makers to view cumulative emissions budgets as spread over, say, four periods: (1) 2010-2020; (2) 2020-2050; (3) 2050-2100 and (4) 2100-2200. Subject to the constraints and caveats outlined above, decision makers have some flexibility in moving emissions from period to period; the important thing for a maximum temperature target is that the overall budget not be exceeded, since this is the primary determinant of peak warming. The inter-period flexibility regarding peak temperature targets ought to be of practical value to policy makers, since it allows them to make informed trade-offs between near-term emissions and emissions in the longer term.

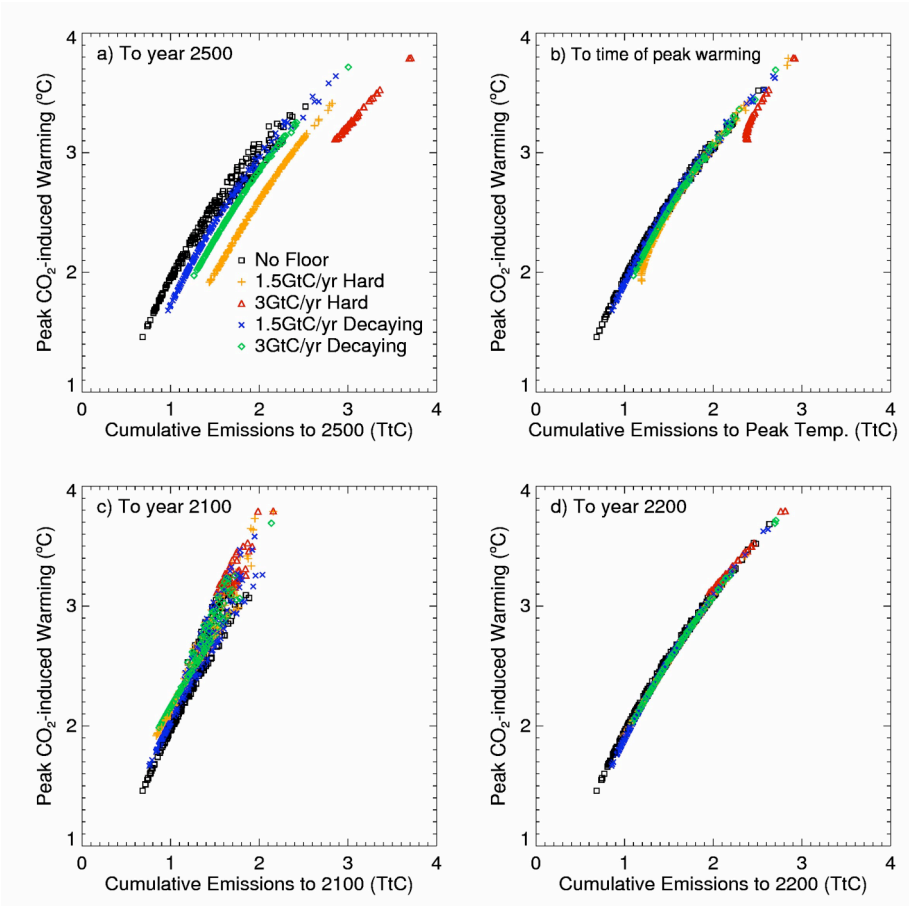


Figure 7: Most likely peak warming as a function of cumulative emissions for different emissions floors. The type of cumulative emissions metric varies between the plots. Panel a uses cumulative emissions to 2500, Panel b uses cumulative emissions to the time of peak warming, Panel c to 2100, and Panel d to 2200. The axes in this figure are as Figure 6a, but with different floors preventing emissions from dropping below certain values at certain times. The black squares represent pathways in which no floor is present so emissions are allowed to fall to zero. The yellow crosses and red diamonds indicate pathways in which a 'hard' floor is set at 1.5GtC or 3GtC per year; in these pathways emissions are unable to fall below the floor and so remain at these values indefinitely. The blue crosses and green diamonds are pathways with an exponentially decreasing emissions floor, which has a decay time of 200 years. The blue crosses pass through 1.5GtC per year in the year 2050 while the green diamonds pass through 3GtC/yr in that year. Emissions floors used here are the same as those in Figure 4, and use the same colour code. We observe the strongest correlation in Panel d, between peak warming and cumulative emissions to 2200.

2.3.4 O3: Likelihood profiles

In Section 2.3.2 we confirmed the very tight correlation between cumulative emissions and peak CO_2-induced warming, refined in Section 2.3.3 to consider the affect of non-zero emissions floors. We find even with non-zero emissions floors cumulative emissions, particularly cumulative emissions to the year 2200, correlate well with resultant peak warming.

However, thus far, and in Figure 6 and Figure 7, our estimates have been of 'best-guess' or 'most likely' warming, as defined in Section 2.2.3. In this section we estimate our level of confidence in these results.

We re-run our model, but with perturbed parameterisations for each ensemble member. For each ensemble member we can determine a relative likelihood through comparison against our knowledge of the historical record. As explained in Section 2.2.3, models that better reproduced our constraints have higher relative likelihoods.

In Figure 8, we do not plot the location of each ensemble member, but instead we plot the outline of the entire ensemble. This allows our likelihood profile to be independent of sampling strategy, provided that we have sufficiently explored parameter space.

For each emissions profile with within 1% of 1.0, 1.5 or 2.0 TtC cumulative emissions between 1750 and 2200 we calculate a likelihood profile, such that each panel in Figure 8 actually contains dozens of likelihood profiles plotted on top of each other. All of these likelihood profiles are quite similar, which shows that not only is the best guess peak warming independent of emissions pathway for a given cumulative total, but the entire likelihood profile shares this property.

We repeat this process for each type of emissions floor so that we can compare likelihood profiles between types. By comparing the likelihood profiles for emissions pathways with the same cumulative total but different emissions floors (e.g. the profiles in Figure 8d, Figure 8e and Figure 8f) we find that the likelihood profile is unaffected by the types of emissions floor.

We note that Figure 8c only contains three likelihood profiles, as we only consider three emission pathways with a hard emissions floor and a cumulative total to 2200 of within 1% of 1TtC. Cumulative emissions to 2000 are approximately 0.5TtC, and a 1.5GtC/yr emissions floor between 2000 and 2200 has a cumulative total of 0.3TtC, which leaves only 0.2TtC remaining if the pathways is to have a cumulative total of 1TtC. This forces the emissions profile to have a high rate of decline, which could make these profiles socio-economically unfeasible.(den Elzen, *et al.* 2007)

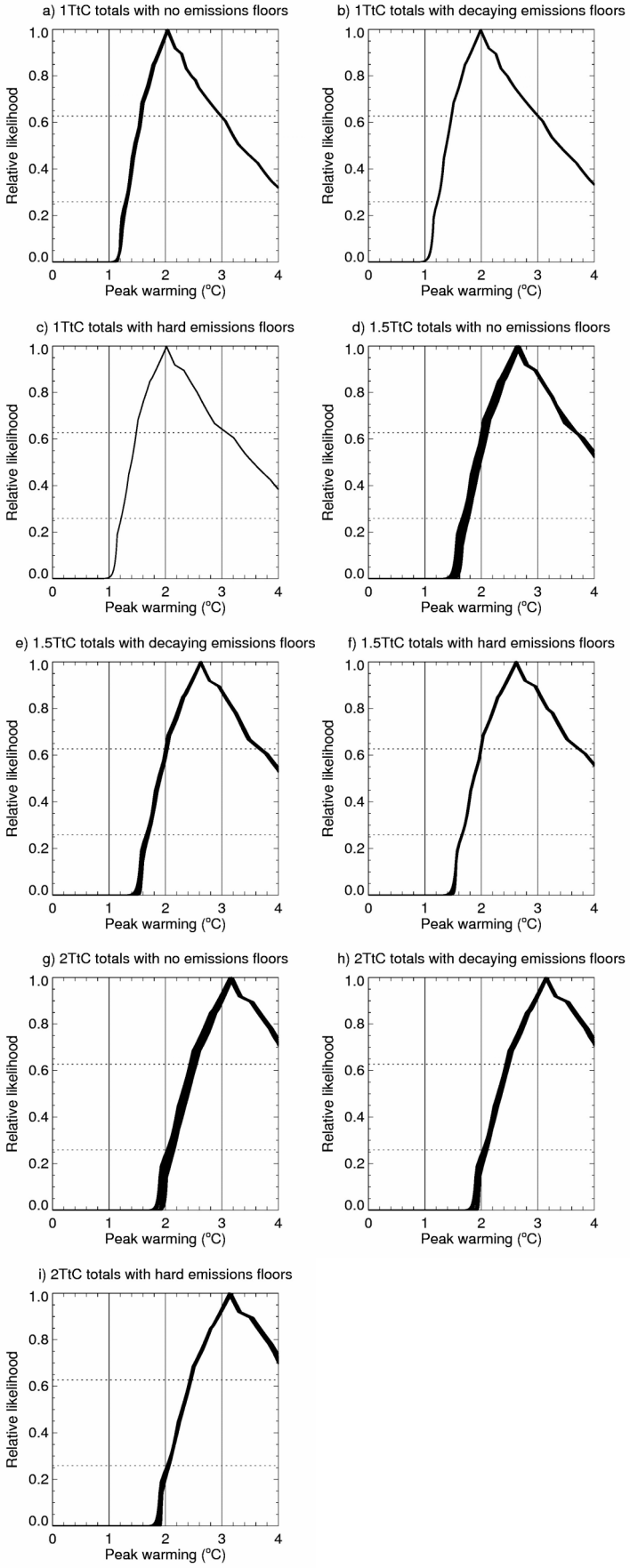

a) 1TtC totals with no emissions floors
b) 1TtC totals with decaying emissions floors
c) 1TtC totals with hard emissions floors
d) 1.5TtC totals with no emissions floors
e) 1.5TtC totals with decaying emissions floors
f) 1.5TtC totals with hard emissions floors
g) 2TtC totals with no emissions floors
h) 2TtC totals with decaying emissions floors
i) 2TtC totals with hard emissions floors
Relative likelihood
Peak warming (°C)
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4

Figure 8: Peak warming for different cumulative totals and different emissions floors. These likelihood profiles are produced as in Allen *et al.* (2009a) fig. 3. Panels a, d and g have no emissions floor so emissions are allowed to fall to zero. Panels b, e and h have a 'decaying' (i.e. exponentially decreasing with a 200-year lifetime, passing through 1.5GtC/yr in 2050) emissions floor. Panels c, f and i have a 1.5GtC/yr hard emissions floor. In each panel, we plot likelihood profiles over each other for every emissions pathway with a cumulative total from 1750 to 2200 within 1% of the stated cumulative total. A sample emissions pathway for each of the plots above is given in Figure 4, alongside its resultant warming trajectory. The profiles with no emissions floors appear to be drawn thicker only because more emissions profiles have been plotted upon one another. We see that the introduction of an emissions floor has little influence on the likelihood profile.

2.3.5 O1b: Constraining the rates of warming

Thus far we have only considered constraints on peak levels of global warming. A key objection to using peak warming targets in isolation is that the feasibility and cost of adapting to future climate change will also depend strongly on the rate of change and not just the magnitude, of global warming. In order to determine which factors constrain the maximum rate of warming, we use the same model experiments as reported in Figure 6. Thus we use only best-guess or most likely ensemble members, and we only consider emissions profiles with zero emissions floors. We now plot the peak rate of CO_2-induced warming as a function of the emissions metrics, as illustrated in Figure 9.

In Figure 9 we find a very different set of correlations than those presented in Figure 6. The main result, across all the panels in Figure 9, is that the tightest linkage is between peak rate of warming and peak emissions rate. We now explain these results in more detail.

Though cumulative carbon emissions have a tight correlation with peak warming, Figure 9a shows that they share only a very weak correlation with the peak rate of warming. The maximum rate of warming is instead controlled by the peak rate of emission, as indicated in Figure 9f. The gradient of the points in Figure 9f suggests that for each extra GtC/yr on the peak emissions rate, the maximum rate of warming will increase by 0.016°C/decade.

It is known, however, that non-CO_2 greenhouse gases, such as methane and nitrous oxide, which we do not include in this paper, also influence atmospheric radiative forcing (Forster and G. Raga 2007). Although these gases have shorter lifetimes than CO_2 (Forster and G. Raga 2007), they still have the potential to influence rates of warming beyond that induced purely by CO_2.

Figure 9a does show a slight correlation though, which occurs because the peak rate of emission and the cumulative emissions are not completely independent. Consider two emissions pathways with different peak rates of emission and the same rate of emissions decline after the peak: the pathway with the higher peak will lead to a higher cumulative total, as shown in Figure 9. As we cap the maximum rate of emissions decline to 10% per year, higher peak emissions rates will have a bias towards larger cumulative totals, which explains the correlation we observe in Figure 9a.

The grey diamonds in Figure 9 represent emissions pathways that have a maximum rate of emissions decline of between 4% and 10% per year, while the black crosses correspond to rates of decline between 0% and 4%. For a given peak rate of warming, and hence for a given peak emissions rate, pathways with a lower cumulative total or lower emissions in a given year must have a faster rate of decline after the peak. This phenomenon explains why all of the grey diamonds appear to the left of the black crosses in Figure 9a-Figure 9d. The grey diamonds are less visible in Figure 9e and Figure 9f because the black crosses have been plotted over the top of them.

In all of the emissions pathways considered, emissions peaked between 2010 and 2050 by construction, and thus cumulative emissions between 2010 and 2050 are reasonably well correlated to peak emissions rate, particularly when we only consider

pathways with rates of emissions decline between 0% and 4%. This is indicated by Figure 9b, where the black crosses are particularly well correlated.

The initially odd shape in Figure 9c can be understood by considering the emissions pathways of those points with peak rates of warming of 0.2°C per decade. We see that they have 2020 emissions of roughly 12GtC/yr. Figure 9f also shows that a peak emissions rate of 11.5GtC/yr produces a peak rate of warming of 0.2°C per decade, suggesting that the emissions pathways in Figure 9c with 2020 emissions of 11.5GtC are peaking around the year 2020. Thus, the points with rates of warming of more than 0.2°C per decade have peak years of emissions later than 2020, and are less affected by the rate of emissions in 2020. Similarly, points to the left of 11.5GtC/yr generally peak before 2020, and therefore their emissions peaks are largely controlled by the rate of emissions today, and not the emissions in 2020.

Figure 9d shows that the 2050 emissions do not correlate well with the peak rate of warming, as 2050 emissions are not influenced much by the peak emissions rate. There is a slight correlation, however, which can be explained by considering the same mechanism that causes the small correlation in Figure 9a.

Because an emissions peak in the next decade will be heavily constrained by the rate of emission today, Figure 9e appears to have some correlation near the present day, which gets worse as we move into the future. The black crosses and the grey diamonds lie in the same region of Figure 9e, which suggests that the peak rate of warming is not heavily affected by the emissions after the emissions peak.

Figure 9a-Figure 9e appear to correspond with our principle finding that peak emissions rate determines the peak warming rate, which is illustrated in Figure 9f. This means that only two emissions targets, the peak rate and cumulative carbon emissions, are needed to constrain two key indicators of CO_2-induced climate change (peak warming and peak warming rate). We suggest that these targets could provide a simple and natural framework for specifying climate mitigation policy, and comparing the effect of different policies. Inclusion of short-term forcing agents within a rate-of-change target is a natural extension of this approach, and could provide a framework for including both emissions rates, or “flows”, as well as cumulative emissions, or “stocks”, into a set of climate targets that are better informed by current climate science than emissions rates in a given year or long-term concentrations.

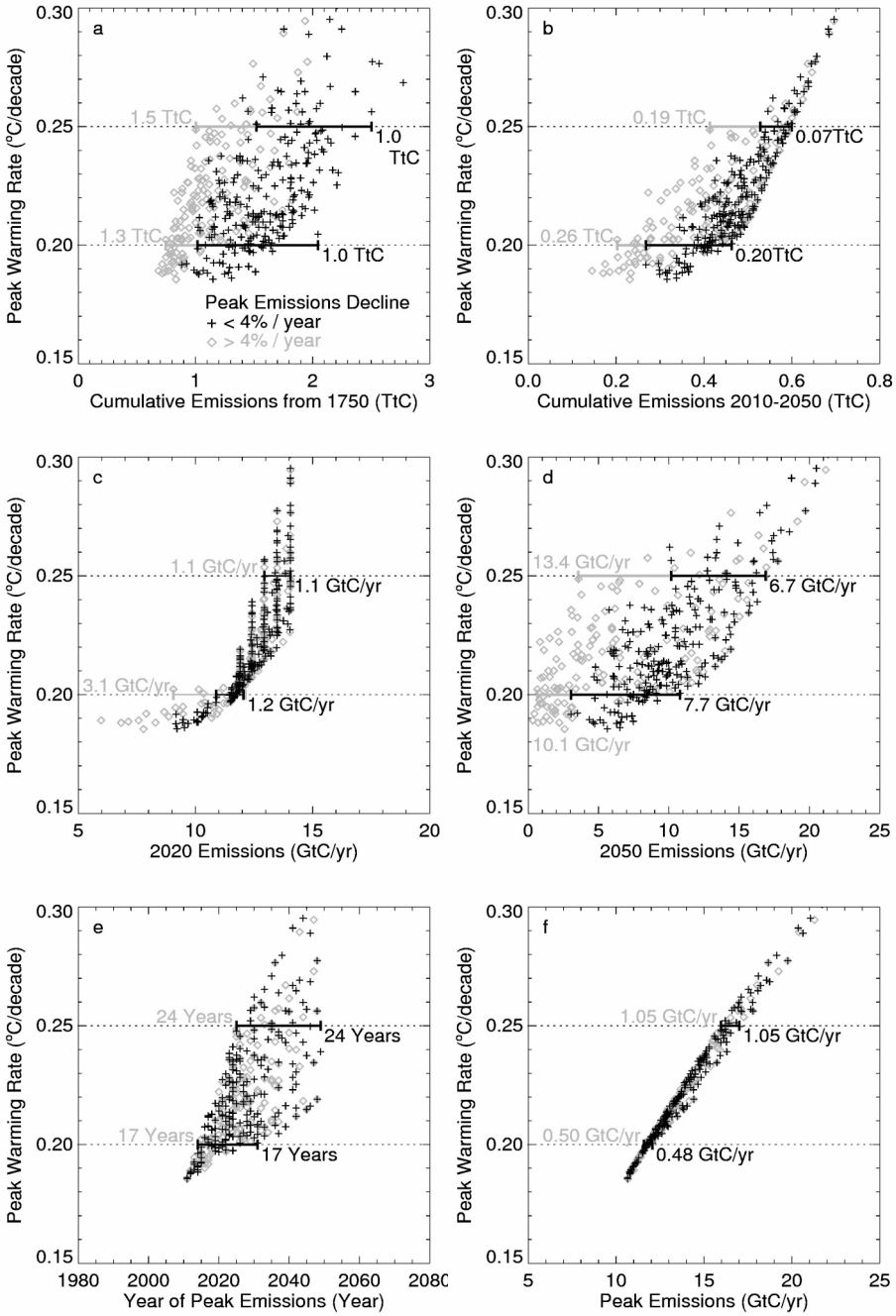


Figure 9: The correlation of emissions metrics with most likely peak warming rate. This figure is as Figure 6, but plotting against peak rate of warming instead of against peak warming. Again, black crosses indicate emissions pathways in which the maximum rate of emissions decline is less than 4% per year; grey diamonds indicate the converse. The bars show the spreads of the metrics for pathways with a resultant peak warming of 2°C or 3°C. The black bars show the spread in pathways with peak rates of emissions decline less than 4%, while the grey bar shows the spread in all emissions pathways. We see that the strongest correlation is in Panel f, between peak rate of warming and peak emissions rate.

3 Conclusion

A number of recent studies have considered the concept of cumulative carbon emissions and their relation to peak warming. Thus far in my DPhil, I have considered how the concept of cumulative emissions interacts with other aspects of global change such as emissions floors and rates of warming.

With my co-authors, I consider other emissions metrics, such as the emissions in year 2020 and year 2050, and find that these cause a much wider range of magnitudes of resultant peak warming than metrics based on cumulative carbon emissions to the time of peak warming. For small cumulative totals, however, 2050 emissions can be a good indicator of peak warming, however as soon as we consider 2050 emissions greater than around 5GtC/yr this relationship breaks down. We also find that for large cumulative totals in particular, cumulative metrics based on integrations over smaller time periods, such as 2010-2050, do not correlate with peak warming as well as cumulative emissions to a given date near the time of peak warming.

We extend the analysis of Allen *et al.* (2009a) of cumulative emissions to consider two types of emissions floors: 'hard' or constant floors, and exponentially decaying 'floors'. In the situation that model temperatures peak before year 2500, we find that cumulative emissions between pre-industrial times and year 2200 are highly correlated with that peak year, regardless of the type of emissions floor used. Floors do, however, provide a lower bound on cumulative totals at low values.

Cumulative emissions, however, say little about rates of global warming, which affect the cost and feasibility of societal and ecosystem adaptation in the short-term. We show that maximum rates of CO_2-induced warming are much more closely correlated with peak emissions rates, and that for each additional GtC/yr on the peak emissions rate, we will observe a best guess increase of 0.016°C in the rate of warming per decade.

We also consider the short-term policy implications of our findings. The relationship between cumulative emissions and peak warming allows us to show how delaying mitigation in the short term creates the need for more rapid emissions reductions later, in order to stay below a given cumulative emissions limit. Our findings relating to rates of warming also show that only two emissions targets (peak emissions rate and cumulative carbon emissions) are needed to constrain two key indicators of CO_2-induced climate change, peak warming and maximum rate of warming. These targets could provide a simple and clear framework for specifying climate change mitigation policy over the next two centuries, and comparing the effect of different policies.

During the second year of my DPhil, I intend to estimate the uncertainty in the warming and emissions associated with the representative concentration pathways using HadCM3L on climateprediction.net (CPDN) and either the box-diffusion model or IMOGEN. I also hope to continue my research into the impact of high rates of air capture, or artificial removal of carbon dioxide from the atmosphere, on global mean precipitation. If there is time remaining once I have completed these tasks I hope to extend my work on CPDN and the box-diffusion model or IMOGEN to look at cumulative carbon emissions again. During the third year of my DPhil I hope to bring all of these ideas together in the writing of my thesis.

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