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# Scenario and modelling uncertainty in global mean temperature change derived from emission driven Global Climate Models

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## Abstract

We compare future changes in global mean temperature in response to different future scenarios which, for the first time, arise from emission driven rather than concentration driven perturbed parameter ensemble of a Global Climate Model (GCM). These new GCM simulations sample uncertainties in atmospheric feedbacks, land carbon cycle, ocean physics and aerosol sulphur cycle processes. We find broader ranges of projected temperature responses arising when considering emission rather than concentration driven simulations (with 10–90 percentile ranges of 1.7 K for the aggressive mitigation scenario up to 3.9 K for the high end business as usual scenario). A small minority of simulations resulting from combinations of strong atmospheric feedbacks and carbon cycle responses show temperature increases in excess of 9 degrees (RCP8.5) and even under aggressive mitigation (RCP2.6) temperatures in excess of 4 K. While the simulations point to much larger temperature ranges for emission driven experiments, they do not change existing expectations (based on previous concentration driven experiments) on the timescale that different sources of uncertainty are important. The new simulations sample a range of future atmospheric concentrations for each emission scenario. Both in case of SRES A1B and the Representative Concentration Pathways (RCPs), the concentration pathways used to drive GCM ensembles lies towards the lower end of our simulated distribution. This design decision (a legecy of previous assessments) is likely to lead concentration driven experiments to under-sample strong feedback responses in concentration driven projections. Our ensemble of emission driven simulations span the global temperature response of other multi-model frameworks except at the low end, where combinations of low climate sensitivity and low carbon cycle feedbacks lead to responses outside our ensemble range. The ensemble simulates a number of high end responses which lie above the CMIP5 carbon cycle range. These high end simulations can be linked to sampling a number of stronger carbon cycle feedbacks and to sampling climate sensitivities above 4.5 K. This latter aspect highlights the priority in identifying real world climate sensitivity





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constraints which, if achieved, would lead to reductions on the uppper bound of projected global mean temperature change. The ensembles of simulations presented here provides a framework to explore relationships between present day observables and future changes while the large spread of future projected changes, highlights the ongoing need for such work.

## 1 Introduction

There are important unknowns both in how we understand the current climate system and future socio-economic change, which lead to a broad spread in future projected global mean temperature changes (Cox and Stephenson, 2007; Hawkins and Sutton, 2009). The unknowns external to the climate processes relate to different future pathways of population change, economic growth, technology developmnet and energy use (Nakicenovic et al., 2000), while uncertainties in climate feedbacks (Knutti and Hegerl, 2008; Collins et al., 2011) and carbon cycle processes (Friedlingstein et al., 2006; Booth et al., 2012a) alongside processes which drive natural variability (Lee et al., 2006) lead to differences in how the climate responds to these socio-economic changes. On short lead times (10–15 yr) internal variability represents a large fraction of the total uncertainty, with the uncertainties in model response becoming more dominant as the anthropogenic signal increases through the 21st century. By the end of the century, differences in socio-economic pathways which diverge from present day, dominate the global mean temperature spread. Yet much of our existing information on how these uncertainties play out, is based on General Circulation Models (GCMs), driven by future changes in atmospheric greenhouse gas concentrations (Hawkins and Sutton, 2009), a framework which explicitly ignores uncertainties in carbon cycle processesses (Friedlingstein et al., 2006) which relate emissions to global concentrations. As a result emission driven projections have largely relied on simpler modelling frameworks and to date, no study has explored future global mean temperature uncertainty from the emission driven paradigm, using ensembles of full GCMs.



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GCMs and Earth System Models (ESMs) form the top of the hierarchy of climate modeling tools. Their value is based on representing the climate processes within the climate system. The response of these models to differences in future socio-economic pathways is an emergent, rather than a prescribed property, which results from the interaction of climate processes with the future concentration (GCM) or emission (ESM) changes. Computationally these models are very expensive to run (with some state of the art configurations capable of taking more than a year to simulate 240 climate model years) and so there are limited realisations of these models available. Increasingly we see ESMs incorporating processes controlling the exchange of carbon around the climate system, which are capable of being driven directly by emissions, rather than relying on future concentration pathways. These remain a minority of available simulations.

Due to these computational limits on numbers of simulations with GCMs, much current climate projection information is provided using simpler model frameworks which rely on global energy balance assumptions to constrain the range of future changes. At the simplest level these relate changes in climate forcing to global mean temperature change based on assumptions about the nature of the ocean heat uptake and sensitivity of climate feedbacks, but more commonly are capable of translating global emission changes into concentrations and therefore global temperatures. These relationships form the basis of Simple Climate Models (SCMs) and even some Earth system Models of Intermediate Complexity (EMICs), which in turn are often used as the climate component of Integrated Assessment Models (IAMs). These model frameworks enable much more exhaustive sampling of possible future projections based on different emission scenarios, and are capable of rapidly sampling uncertainties in the responses. For example, the future projection advice in the last IPCC assessment report used a SCM to synthesise the information on future projections (Fig. 10.26, WG1 SPM, IPCC, 2007). Similarly, Murphy et al. (2009) make use of a SCM to capture the response of a number of GCM experiments designed to sample different climate uncertainties, and provide projection information based on how these processes combine within the SCM. Credibility of projections using these tools arises from their ability to capture the range of different future responses of a particular GCM, using a single SCM configuration. While many of these tools provide only information on global mean temperature, models on the more complex end of this spectrum (such as EMICs) often extend these approaches to include spatial scales and other variables.

Here, in a complementary approach to the multi-model GCM assessments of climate uncertainties, we make use of a new ensemble of simulations which samples uncertainty within a single coupled climate model GCM (HadCM3C) using a perturbed physics or perturbed parameter approach. Murphy et al. (2004) demonstrated that uncertainties in the physical model's atmospheric and surface parameters could account for a very large fraction of the uncertainty in Climate Sensitivity (the amount the climate would be expected to warm in response to a doubling of $CO_2$). Since then similar perturbations to Atmosphere-Ocean configuration of this model have been used to explore uncertainties in transient climate change (Collins et al., 2006, 2011). This approach has been extended to look at ocean physics uncertianty (Collins et al., 2007; Brierley et al., 2010) and the land carbon cycle (Booth et al., 2012a). In this latter study Booth et al. (2012a) noted that the uncertainty in future climate projections arising from land carbon cycle processes contributed comparably to future projection uncertainty as Atmospheric feedbacks. The impact of these uncertainties and their interactions, together with perturbations to the sulphur cycle, were explored within a single 57 member ensemble (Lambert et al., 2012) for a central business as usual SRES scenario, A1B.

Here we present a further two experiments which extend the future projections from this ensemble of HadCM3C simulations to encompass a high end business as usual scenario and, at the other end, a scenario for future emissions under aggressive mitigation. These simulations enable us to explore some of the implications for projections, arising from uncertainties in the modelling components. Here we reassess what these uncertainties imply for future changes in atmospheric $CO_2$ and global mean temperature, when considered from the perspective of emissions driven scenarios (as





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opposed to atmospheric concentration) where the full effect of carbon cycle feedbacks are expressed. At the high end these simulations complement the new CMIP5 RCP8.5 emission driven simulations. For the central SRES A1B and the aggrissive mitigation scenario (RCP2.6), these simulations represent a unique sampling of emission driven uncertainty in ESMs.

## 2 Methods

### 2.1 Model framework

#### 2.1.1 Perturbed parameter ensembles of HadCM3C

The model which underpins these ensembles (HadCM3) has been in use for over 10 yr. The resolution is coarser than a number of more recent models but still performs credibly, relative to multi-model GCMs, when compared to observed climate (Reichler and Kim, 2008). The relatively lower resolution means that the computational cost of running a number of versions of the model (an ensemble) to explore uncertainty can be contemplated. This is what is done here using HadCM3C, a coupled carbon cycle configuration of the model (whose setup is described in Booth et al., 2012a).

The framework presented here is the culmination of experiments done to explore the uncertainty in future climate projects using ensembles of GCM simulations which each sample a different part of plausible model parameter space (Murphy et al., 2007). The simulations presented here combine configurations previously used to explore uncertainties in atmospheric physics (Collins et al., 2011), land carbon cycle (Booth et al., 2012a), ocean physics (Collins et al., 2007) and aerosol sulphur cycle (discussed in Murphy et al., 2007; Lambert et al., 2012). We refer to these 4 previous experiments as the constituent ensembles. In the new simulations presented here (and in Lambert et al., 2012) we combine each configuration from the constituent ensembles with different combinations from the other three. So for example, the highest climate sensitivity





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configuration is paired up with different combinations from the land carbon cycle, ocean physics and sulphur cycle configurations. The result is a 68 member coupled carbon cycle climate model ensemble which samples each configuration from the constituent ensembles 4 times. 11 members of this ensemble were subsequently rejected on the basis of errors in reproducing past vegetation distribution and global temperature. The design and subsequent rejection criteria are all discussed in detail in Lambert et al. (2012). We will refer to this resulting 57 ensemble as the Earth System Ensemble (or ESE).

### 2.1.2 CMIP5 emission driven simulations

Before analysing the Earth System Ensemble it is useful to provide a context of the climate response with other available models. Until recently the obvious comparison would have been with the Coupled Climate Carbon Cycle Model Inter-comparison Project ($C^4$MIP). Differences between the SRES A2 scenario used for $C^4$MIP and the scenario implementation ($CO_2$ emissions only) mean that this comparison is not straight forward to do. Booth et al. (2012a) addressed this by utilising a simple climate model, fitted to both HadCM3C and $C^4$MIP to explore the differences in responses. With the advent of emission driven historical and future scenarios in CMIP5 database, the response of the ESE can be directly compared to multi-model ensemble, without the need for simpler model tools.

Data for atmospheric $CO_2$ and global temperature change is available for 10 CMIP5 emission driven simulations at the time of writing. These models are: BNU-ESM, CanESM2, GFDL-ESM2, HadGEM2ES, INM's INMCM4, IPSL-CM5A-LR, MIROC-ESM, MPI-ESM-LR, MRI-ESM1 and NCAR's CESM1-BGC. GFDL-ESM2M also exists on the archive (differing from GFDL-ESM2G presented here, only in the ocean physics representation). Given the strong similarity in response between these two configurations, we've considered them here, for global mean $CO_2$ and temperature responses, to be one model. The historical and future scenario used to drive these CMIP5 models is discussed in the next section.





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## 2.2 Scenarios

Here we consider 3 future emission pathways, one (SRES A1B) chosen to provide continuity with previous ensembles, and two (RCP8.5 and RCP2.6) chosen to sample the full spread of scenarios used by CMIP5 simulations.

The first of these pathways, the SRES A1B scenario (referred here after as A1B) represents future emissions from greenhouse gases and aerosols under a business as usual socio-economic scenario. The implementation of the boundary data to drive the Earth System Ensemble is fully described in Collins et al. (2006). The exception is $CO_2$ which, inline with the experimental design, is prescribed as an emission rather than an atmospheric concentration (as described in Booth et al., 2012a).

The Representative Concentration Pathways (RCPs) are a series of future scenarios of greenhouse and aerosols emissions consistent with a range plausible future socio-economic scenarios and form the basis of the modelling work that will contribute to the fifth assessment report of the IPCC (Taylor et al., 2012). The two most extreme pathways are examined here. RCP8.5 lies at the upper end of these pathways and is likely to represent a fossil fuel intensive future. The "8.5" denotes the radiative forcing in 2100 (as estimated by the IAMs used to develop the RCP). These concentration pathways are typically used for AOGCM simulations, and while individual AOGCMs may differ somewhat in the magnitude of modelled radiative forcing, the RCP value is a good indicator the the typical radiative forcing at the end of the century. In addition to enabling concentration driven simulations, equivalent emission pathways for the RCPs are also available, based on SCM relationship emissions and concentation (Meinshausen et al., 2011b). Prescribing emissions, rather than concentrations, enables the carbon cycle processes within a GCM to calculate the resulting $CO_2$ concentration changes explicitly. This has been done for a number of CMIP5 coupled climate cycle models for RCP8.5 (detailed in the previous section) and the ESE. The subsequent $CO_2$ concentrations may result in higher or lower concentrations than the representative pathway – and





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consequently the radaitive forcing in 2100 within these scenarios may also be higher or lower.

The other RCP examined here is RCP2.6. This was developed to represent a radiative forcing in 2100 of 2.6 W m$^{-2}$. Unlike the other pathways considered here (or more broadly within other sets drawn from the SRES or RCPs), this pathways is based on assumptions of extensive and coherent mitigation of greenhouse gas emissions. With these assumptions in place the radiative forcing peaks at 3 W m$^{-2}$ in the next 40 yr and then declines to 2.6 W m$^{-2}$ by the end of the century. RCP2.6 marks the first agressive mitigation scenario used extensively by the full Climate Model Intercomparison Project (CMIP). Within the fifth phase of this, CMIP5, this is done using concentration pathways (Taylor et al., 2012). There is no official emission driven equivalent (as there is with RCP8.5) to provide multi-model simulations with which to compare the ESE simulations presented here.

For the two RCP emission driven experiments simulated by the ESE, the implementation of the boundary conditions is as described for HadGEM2ES in Jones et al. (2011). There are a number of model processes (typically aerosol species beyond sulphates) that are included in the HadGEM2 models but which are not represented with the HadCM3C framework used in the ESE (for example Black carbon, biogenic and dust aerosols). The setup differed from Jones et al. (2011) for $CO_2$, were emission timeseries were provided rather than concentrations. This approach is the same as that taken in the CMIP5, esmRCP85 scenario (Taylor et al., 2012).

The RCP and SRES historical boundary conditions also differ. These differences are small for most of the historic periods but become slightly more significant after the 1990s where (aerosols in particular) start to diverge. The differences in implementation are due to current uncertainties in the nature of historical changes. To account for these scenario differences, historical simulations from 1860 onwards were performed for every configuration (Lambert et al., 2012) and parallel RCP historical simulations were forked from these runs in 1945 when discrepancies between the two historical





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estimates are small. This ensures that future projections (for SRES A1B, RCP8.5 and RCP2.6) are run on from historical states that were consistent.

## 3 Results

### 3.1 Implications for future projections

As acknowledged in Hawkins and Sutton (2009), "progress in climate science may sometimes broaden rather than narrow uncertainty". They were referring to processes which lie outside climate modelling systems and the impact that quantification will have for spread of responses when they are included. Of course the underlying uncertainty has not really increased in any real sense, but rather the increased spread accounts for uncertain processes which previously lay outside the quantifiable framework. The primary example at the time Hawkins and Sutton (2009) was written was carbon cycle processes (which were not quantifiable in their analysis due to availability of simulations).

We show the global mean temperature response, arising from the earth system uncertainties explored in the ESE, give rise to broad spread in future responses (Fig. 1a). By 2011, the median ensemble response (RCP scenarios) is already 1.1 K above the 1900 to 2000 baseline climate. Differences in the last 10 yr compared to the observations are evident (Observations warm by 0.5 K relative to same baseline) but these still lie within the ESE envelope. Future temperature projections diverge in the future depending on differences in the emissions scenario, ranging between a 2.3 K median response above baseline for the aggressive mitigation scenario to a median response of 6.1 K for the high end business as usual scenario. The spread of these responses is broader than previous concentration driven GCM simulations, and is discussed further in the following sections.

While the emission driven ESE simulations point towards a greater projection uncertainty for global mean temperature than previous concentration driven simulations,





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they do not imply any fundamental change to the timescale on which different sources of uncertainties play dominant roles. Previous work using concentration driven GCMs (Hawkins and Sutton, 2009) point to the role different sources of climate projection uncertainty play, on timescales. Despite marked increases in future projection spread within the emission driven ensemble, the ESE produces a remarkably similar picture. Over the shorter 30–50 yr term, the impact of different emissions scenarios or adoption (or not) of explicit climate mitigation policies is not a significant factor in determining the global mean temperature range. Here, the key uncertainties remain in climate response (largely physical feedbacks) and internal variability within the climate system (Fig. 1b). Whilst differences in emissions pathways will not significantly affect temperatures during this period, it should be noted that emissions and mitigation actions over the next 30 yr will be the significant determinant of climate as we move towards the end of the century.

In comparison with Hawkins and Sutton (2009) assessment, Figure 1b shows a small scenario component to the total variance in the next 30 yr. This does not, as might be inferred at first glance, imply that the emission scenario uncertainty is playing a larger role on this timescale. Instead it represents differences between the SRES and RCP implementation of present day and historical climate forcings. The RCP implementation made revisions to estimates of a number of emission and concentration changes and while small, highlights that there are current uncertainties in some of the historical drivers of climate change. This uncertainty is likely to have a small, but appreciable, impact on projections over the next 30 yr, an aspect that has not previously been appreciated.

As we look out to the end of the century, uncertainties in future global temperatures rapidly increases and differences between different emission scenarios becomes apparent (Fig. 1a). The inclusion of carbon cycle uncertainties within this GCM assessment leads to a much broader range of temperature responses for a given scenario than previous estimates using concentration driven GCMs (discussed in more detail in the next subsection). Differences in future emission pathways is still the dominant





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uncertainty by 2100 despite the increase in model uncertainty illustrated here (Fig. 1b). In other words, despite large climate change uncertainties, differences between possible future emissions will have the biggest impact on what we can say about what the climate system will look like in 2100. Differences between the ensemble median responses of the two emission pathways which bound the high and low end (RCP8.5 and RCP2.6) are larger than the Hawkins and Sutton (2009) range largely due to the inclusion in this analysis of an emissions pathways which accounts for aggressive mitigation (RCP2.6) and one which lies closer to the upper end of business as usual type scenarios (compared to SRES A2 used in Hawkins and Sutton (2009)).

What is not discussed in Hawkins and Sutton (2009) is that there is a strong dependence of the uncertainty in the model response and the particular scenario. Yip et al. (2011) characterised this as an additional, interaction uncertainty but did not go further and highlight that the dependence is based on the magnitude of future emission changes. The model response uncertainty (using simulated spread between 10–90 percentiles) more than doubles from 1.7 K in RCP2.6 to 3.9 K in RCP8.5 (Table 1), highlighting how mitigating future emissions not only reduces future global mean temperature change but also reduces the spread.

### 3.2 Responses of the Earth System Ensemble

We can break down the plume of future projections (Fig. 1a) into the component atmospheric $CO_2$ and temperature responses for each scenario (Fig. 2). For RCP8.5 the $CO_2$ and temperatures continue to rise during the 20th century, reaching 1106 ppm (ensemble median, 864–1389 ppm 10–90 percentile range, see Table 1 for summary statistics) and 6.1 K (ensemble median, 4.2–8.1 K 10–90 percentile range). This can be compared with the projections using the SCM MAGICC6 (Meinshausen et al., 2011b) for RCP8.5 (Meinshausen et al., 2011a) based on SCM fits to the climate response of 19 CMIP3 concentration driven GCMs and 9 $C^4$MIP coupled carbon cycle climate models (Meinshausen et al., 2011c). The ESE projections span the MAGICC6 RCP8.5 $CO_2$ and global temperature responses over the coming century, from the low to the





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high bounds. In addition a number of stronger ESE $CO_2$ and temperature responses lie above this SCM range (something we return to in the next section).

Under aggressive mitigation (RCP2.6) the mean ESE response is 451 ppm (10–90 range: 390–514 ppm). The mean response is 2.3 K (10–90 range: 1.5–3.2 K). Comparisons with the SCM projections for the same RCP2.6 scenario (Meinshausen et al., 2011c) shows that the median ESE responses tend to be larger magnitude by 2100. Whether this is due to real differences between the ESE and response that CMIP3/$C^4$MIP simulations would have produced under this emission pathway or whether it points to difficulties in establishing carbon cycle responses to emission cuts in $CO_2$ using SCMs is an open question. Lowe et al. (2009) illustrated that once atmospheric $CO_2$ concentrations have reached a certain level, they are remarkably resistent to future reduction driven by subsequent emission cuts. That the SCM RCP8.5 projections lie within the ESE range, but there is a suggestion that the SCM RCP2.6 appears to diverge suggests that this maybe the case. If so, this highlights the importance of aggressive mitigation scenarios for coupled carbon cycle climate models with which to calibrate SCMs responses, currently data which is not commonly available. As Meinshausen et al. (2011b) note, the RCP scenarios represent a rather stringent test as the future pathways fall well outside the SRES scenarios that the SCM was calibrated against.

Another evident feature of the RCP2.6 responses is that the inherient uncertainty in ESE climate system representation, is much reduced (1.7 K 10–90 range compared to 3.9 K in RCP8.5). Even under aggressive mitigation, a small number of models suggest a large global mean temperature response is possible (with one model suggesting $CO_2$ could exceed 500 ppm and with 3 models with temperature responses in excess of 4 K), implying that high levels of climate change cannot be ruled out – something we return to in Sect. 4.

For the SRES A1B scenario (chosen as a central marker scenario within the SRES range) the changes are not as large (median 794 ppm and 10–90 range 635–972 ppm; median 4.3 K, 10–90 range 2.8 to 6.1 K) but still substantially greater than during the last century. Here we can compare the temperature response from the ESE ensemble with that sumulated by the equivalent concentration driven ensemble (Collins et al., 2011). The 2100 temperature response lies between 2.50 K and 7.30 K in A1B which compares to the much smaller temperature range for the concentration driven A1B scenario between 2.50 K and 4.65 K (black and orange box and whisker bars, figure 2d). The concentration driven simulations are broadly in line estimates from multi-model concentration driven GCMs (Collins et al., 2011).

The previous IPCC report which put the *likely* range to be between 1.7 and 4.4. This upper bound is considerably smaller that suggested by the emission driven ESE. This range was largely informed by a combination of available Atmosphere-Ocean Global Climate Models (AOGCMs) and ranges from SCMs. Knutti and Hegerl (2008) show that a number of sources of information (notably $C^4$MIP simulations and Knutti et al.'s, 2003, emulation) were not available to inform the SRES A1B range in previous assessments. However, their inclusion with the information for the A2 scenario raises the upper bound for this projection (by almost 2 degrees in the case of Knutti et al. (2003)). The temperatures presented here for the ESE in SRES A1B are more in line with the underlying uncertainty explored within this latter study.

Lambert et al. (2012) show that the ESE temperature distribution range is broadly consistent with what would be expected from interactions between climate and carbon cycle feedbacks using a SCM tuned to reproduce the atmospheric (Collins et al., 2011), carbon cycle (Booth et al., 2012a), ocean physics (Collins et al., 2007) and sulphur cycle (Lambert et al., 2012) within the component GCM ensembles that make up the ESE. While Lambert et al. (2012) found evidence of interactions between the components, this does not lead to a significant broadening of the expected range. The reasons for the increase to the upper temperature bound, over many previous estimates, are linked to ranges of climate sensitivies and carbon cycle feedbacks and are discussed in more detail in the following two section sections.

It is worth highlighting the comparison of the range of future atmospheric $CO_2$ concentration projections with the concentration pathways used for multi model ensembles.





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The SRES A1B concentration (dashed red line, Fig. 2c) lies well toward the lower portion of the ESE distribution. This is a concentration pathway based on the standard Bern-CC configuration which provided the SRES concentrations based on SRES emissions. The carbon cycle feedbacks of this model are known to be on the low end of the multi-model response (Friedlingstein et al., 2006; Booth et al., 2012a). Under SRES A1B, only 11 of the 57 ESE GCMs simulated lower $CO_2$ concentrations by the end of the century compared to the representative pathway/Bern-CC. In contrast 46 simulations produce larger concentrations than Bern-CC (704 ppm), reaching as high as 1060.4 ppm in 2100 in one of the models. We see a similar picture in both RCPs examined with ESE. This is because the SCM used to map emissions to concentrations for the RCPs, MAGICC6.0 (Meinshausen et al., 2011b), is tuned to match the carbon cycle response from Bern-CC.

### 3.3 Context within CMIP5 simulations

The Earth System Model ensemble responses illustrated in Figs. 1 and 2 are unique, but it is important to relate them to other available information to provide a context for these climate projections. The advent of emission driven historical and future (RCP8.5) simulations under the CMIP5 protocol of experiments provides common basis for this comparison. It is interesting to note the relative role of physical climate responses and carbon cycle feedbacks within CMIP5 runs. The ordering of future responses for both temperature and $CO_2$, is only partly determined by the magnitude of climate sensitivity (indicated by colours in Fig. 3).

The first aspect of the comparison of global temperature that is immediately evident (Fig. 3a and b) is that while the ESE ensemble explores a broader range of temperature, the ensemble mean is also substantially larger than that of the CMIP5 ensemble mean (6.13 K relative to #). The ESE range explores temperatures substantially larger than CMIP5 and does not capture temperature responses below 4 K for the RCP8.5 scenario. While most CMIP5 models (7 out of 10) fall within the ESE range, 3 models (INM, GFDL-ESM2 and MRI-ESM) explore temperatures below the ESE's lower bound





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(3.1, 3.4 and 3.3 K respectively). The reasons for these differences at both the high and low end, relate to differences in physical climate feedbacks and carbon cycle responses between the two ensembles. These are discussed later.

In contrast, when comparing future atmospheric $CO_2$ concentrations (Fig. 3c and d) the ESE is able to encompass the full range of the CMIP5 projections (ranging from MRI-ESM on the lower bound, up past MIROC-ESM on the upper bound). In addition the ESE ensemble simulates responses that lie above the CMIP5 range and there are reasons to do with the differences in carbon feedbacks why we would expect this. Firstly, recent analysis of CMIP5 carbon cycle responses (Arora et al., 2012) suggests that upper bound of carbon cycle sensitivity is likely to be smaller than in $C^4$MIP. Uncoupled experiments for the ESE which would enable use to make direct comparisons are not currently available. What we can say is that one factor which may contribute to this reduction in upper bound is because the model which marked the $C^4$MIP upper bound, HadCM3L (the lower resolution version of the standard HadCM3C configuration, perturbed in the ESE), was not submitted to CMIP5. So we would expect a larger upper bound in the ESE compared to CMIP5 on this basis alone. In addition, perturbations to HadCM3C span most of the $C^4$MIP range and sample a handful of stronger carbon cycle responses than the standard HadCM3C configuration (Booth et al., 2012a), which will also contribute to the larger upper bound. It is worth noting that the carbon cycle spread is not centred around a high carbon feedback model variant. 51 out of 57 ESE simulations lead to smaller atmospheric $CO_2$ concentrations in 2100 than the standard HadCM3C, despite many of these configurations having larger climate sensitivities.

To understand why the ESE and CMIP5 explore different parts of the future range, it is useful to compare the climate sensitivities of the models which make up these ensembles (Fig. 3e). The most obvious difference between the two, are the 5 atmospheric configurations with climate sensitivities above the most sensitive CMIP5 model (MIROC-ESM). Plotting only those ESE configurations with sensitivities within the CMIP5 climate sensitivity range (grey and blue lines, Fig. 3a) excludes most of the high temperature responses within the ESE ensemble. So differences in the upper





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bound of climate sensitivity appear to explain most but not all of the temperature responses above the CMIP5 range. Even if we were able to exclude those models with larger climate sensitivities, for example though better observation constraints, there would still be a small number of configurations that simulate Atmospheric $CO_2$ concentrations well above the CMIP5 range, which even with the smaller upper climate sensitivity values lead to stronger warming. This is related to the inclusions of models with stronger carbon cycle feedbacks than CMIP5 (see discussion above). Excluding the high sensitivity simulations leads to a slightly lower median ESE $CO_2$ concentration by 2100 (1078 ppm compared to 1106 ppm in the full ensemble) as climate-carbon cycle feedbacks respond to smaller temperature changes across the ensemble. However, inclusion of models with high climate sensitivities appears to have only small impact on the range of atmospheric $CO_2$ for business as usual scenarios (10–90 range actually increases for RCP8.5, see Table 1). This is in contrast with the mitigation scenario where the climate sensitivity does have a larger impact on the range of $CO_2$ responses.

Returning to the 3 CMIP5 models with low magnitudes of global warming. These lie outside the distribution of modelled ESE responses presented here. It is not the case that the component of these responses due to carbon cycle processes, lie outside the ESE model range (the ESE spans the CMIP5 atmospheric $CO_2$ concentrations, Fig. 3). Nor is it the case that that these models are outside the climate sensitivity range (only INM lies below the ESE range of climate sensitivities, Fig. 3e). The experimental design (a latin hypercube, see Lambert et al., 2012) is set up to span ESE response space but not to explicitly explore the corners. The ESE does not sample this low carbon cycle feedback, low climate sensitivity corner. This is illustrated (Fig. 3, dashed blue lines) by showing the $CO_2$ and temperature responses of 4 ESE configurations using the low climate sensitivity, where carbon cycle combinations lead to mid/high atmospheric $CO_2$ concentrations. If there was only a single CMIP5 model in this particular low carbon cycle, low sensitivity part of model space, we could perhaps assume that this was just chance sampling of possible model processses. The fact that there are 3 CMIP5 models suggests that it is unlikely to be the lower limit of all possible coupled carbon





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climate model responses. Therefore, is it more probable that there are structural differences in HadCM3C which limits its ability to capture the low end of possible emission driven responses (Arora et al., 2012).

## 4 Discussion and conclusions

What we have shown is that sampling uncertainty from the emission, rather than concentration, prespective can lead to a very broad range of future atmospheric concentrations and resulting temperature changes. It is important to note here, that no attempt has been made to formally assess which of these projections are more likely. This is an important step before information from these kind of simulations can be most effectivley used in understanding future climate change. For example a number of the ESE members diverge from observed $CO_2$ values in present day. This is also evident for CMIP5's MRI-ESM which under estimates the observed trend. Uncertainties in the historical carbon emissions, not sampled in the ESE, will first need to be accounted for before we could use these present day values to weight the models. One of the primary motivations for developing the ESE simulations presented here, is that they will provide a framework with which to explore simulated and observed climate changes. Cox et al. (2012) points to metrics via which we can relate observable properties of the climate system to aspect of the future projections. The strength of the ESE is that it simulates broad ranges of responses within which we can explore these and other relationships, and these simulations are expected to help inform this future work.

In the previous section we touched on the relationship between climate sensitivity and the ESE temperature responses. We can use this to illustrate the implication for what we could say if we could narrow the climate sensitivity range. The previous IPCC assessment estimated the likely range of climate sensitivity as being between 1.5 K and 4.5 K. Work done to constrain the range based on observational metrics suggests that it is very unlikely that the value of the real world lies below this range. However, as the last assessment notes: "Values substantially higher than 4.5 K cannot be excluded,



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but agreement with observations is not as good for those values". The relationship between high climate sensitivity and temperature response in this ensemble implies that if we can constrain the climate sensitivity of the real world below this value then we can exclude many of the warm outliers. In particular this would drop the worst case temperature response under RCP2.6, from 4.1 to 3.2 K. For the high end RCP8.5, rejecting high sensitivity models would lead to the 90th percentile dropping from 8.1 to 6.8 K. Knutti and Hegerl (2008) in their review of climate sensitivity, show that it is very difficult to narrow this upper range despite drawing information from a very broad range of sources. There are more recent suggestions (Sexton et al., 2012; Sexton and Murphy, 2012) that systematic comparisons of modelled and observed climate may provide a stronger constraint than previously but this question is still very much an open one. These results highlights why it is so important to narrow down the range of climate sensitivity consistent with the real world.

We find interesting behaviour of the carbon cycle between different scenarios. There is a relationship between high climate sensitivity and high atmospheric $CO_2$ in the RCP2.6 (presumably acting via larger climate-carbon cycle feedbacks). The relationship is much weaker under RCP8.5 where, for example, the largest $CO_2$ response is not linked to these high climate sensitivity configurations. This means that different carbon cycle configurations determine the high end $CO_2$ response, depending on the future emission pathways. This implies that we will need to find constraints for different aspects of carbon cycle to narrow future uncertainties depending on the future scenario. Much more work will need to be done on this, but having an ensemble of this kind will enable us to identify and explore mechanisms behind these questions.

We have shown in this paper that sampling uncertainties arising from atmospheric physics, land carbon cycle, ocean physics and sulphur cycle can lead to a broad range of future atmospheric $CO_2$ and temperature responses for 3 future emissions scenarios. Lambert et al. (2012) demonstrate that for A1B this range is largely consistent with what would be expected from energy balance and simple carbon cycle assumptions alone, based on information from the component Atmospheric Physics (Collins





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et al., 2011), Land carbon Cycle (Booth et al., 2012a), Ocean Physics (Collins et al., 2007) and sulphur cycle (Lambert et al., 2012). Interactions between the components represented a quantifiable but smaller contribution to the overall spread (Lambert et al., 2012). Our ensemble simulates a range of future $CO_2$ concentrations which span CMIP5 RCP8.5 emission driven runs, and extends above CMIP5 to capture larger responses. With temperature the ESE range is both broader and offset to larger values. The differences in the upper bound can be linked both to differences in the upper range climate sensitivities sampled, and to a number of configurations which produce strong $CO_2$ responses. Differences on the lower temperature bound between CMIP5 and ESE suggest that there may be structural differences between the two ensembles which limits the ESE's ability to capture low temperature responses for emission driven simulations.

We've returned to analysis, previously done with concentration driven GCM ensembles (Hawkins and Sutton, 2009) to establish whether previous inferences of the source of different climate uncertainties on different timescales, still holds for emission driven simulations. We find that differences between the emission driven scenarios considered here, remain small over the next 30–50 yr, but become the dominant uncertainty by the end of the century. It remains an open question for the reader whether we consider each of these scenarios to be equally realisable over the next century. It is worth noting that both this and the previous analysis on timescales that different sources of uncertainties play a role on are largely based on greenhouse gas driven scenarios. Emerging understanding of importance of other drivers, such as aerosols (Booth et al., 2012b) or land use changes, may mean that there will be a larger dependence on the scenario earlier in the century (than estimated here or in Hawkins and Sutton, 2009) particular as we move way from global mean responses and consider regional changes.

Overall, assessing the relative importance of climate uncertainties for different timescales confirms much of the same analysis originally done with concentration driven AOGCMs. The range of projections arising from this ensemble of emission



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driven Earth System models is broader than previous concentration driven estimates. The atmospheric $CO_2$ and global temperature responses span the range of RCP8.5 Simple Climate Model projections, calibrated against previous $C^4$MIP/CMIP3 simulations. A number of simulations also suggest larger responses than this SCM estimate, which is linked to larger climate sensitivities sampled more frequently in the atmospheric physics (Collins et al., 2011) than CMIP3 and a small number of stronger carbon cycle responses than $C^4$MIP (Booth et al., 2012a). These simulations provide a framework within which we can look for observable properties to provide indications of which simulations are more plausible.

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## References


Andrews, T., Gregory, J. M., Webb, M. J., and Taylor, K. E.: Forcing, feedbacks and climate sensitivity in CMIP5 coupled atmosphere-ocean climate models, Geophys. Res. Lett., 39, L09712, doi:10.1029/2012GL051607, 2012. 1084

Arora, V. K., Boer, G. J., Friedlingstein, P., Eby, M., Jones, C. D., Christian, J. R., Bonan, G., Bopp, L., Brovkin, V., Cadule, P., Hajima, T., Ilyina, T., Lindsay, K., Tjiputra, J. F., and Wu, T.: Carbon-concentration and carbon-climate feedbacks in CMIP5 Earth system models, J. Climate, submitted, 2012. 1070, 1072

Booth, B. B. B., Jones, C. D., Collins, M., Totterdell, I. J., Cox, P. M., Sitch, S., Huntingford, C., Betts, R. A., Harris, G. R., and Lloyd, J.: High sensitivity of future global warming to land carbon cycle processes, Environ. Res. Lett., 7, 024002, doi:10.1088/1748-9326/7/2/024002, 2012a. 1057, 1059, 1060, 1061, 1062, 1068, 1069, 1070, 1074, 1075

Booth, B. B. B., Dunstone, N. J., Halloran, P. R., Andrews, T., and Bellouin, N.: Aerosols implicated as a prime driver of twentieth-century north atlantic climate variability, Nature, 484, 228–232, doi:10.1038/nature10946, 2012b. 1074

Brierley, C. M., Collins, M., and Thorpe, A. J.: The impact of perturbations to ocean-model parameters on climate and climate change in a coupled model, Clim. Dynam., 34, 325–343, doi:10.1007/s00382-008-0486-3, 2010. 1059

Collins, M., Booth, B. B. B., Harris, G. R., Murphy, J. M., Sexton, D. M. H., and Webb, M. J.: Towards quantifying uncertainty in transient climate change, Clim. Dynam., 27, 127–147, 2006. 1059, 1062

Collins, M., Brierley, C. M., MacVean, M., Booth, B. B. B., and Harris, G. R.: The sensitivity of the rate of transient climate change to ocean physics perturbations, J. Climate, 20, 2315–2320, 2007. 1059, 1060, 1068, 1074

Collins, M., Booth, B. B. B., Bhaskaran, B., Harris, G. R., Murphy, J. M., Sexton, D. M. H., and Webb, M. J.: Climate model errors, feedbacks and forcings: a comparison of perturbed physics and multi-model ensembles, Clim. Dynam., 36, 1737–1766, doi:10.1007/s00382-010-0808-0, 2011. 1057, 1059, 1060, 1068, 1073, 1075, 1082, 1084

Cox, P. M. and Stephenson, D. B.: A changing climate for prediction, Science, 317, 207–208, 2007. 1057






ESDD
3, 1055–1084, 2012

Emission driven global change

B. B. B. Booth et al.

Cox, P. M., Pearson, D., Booth, B. B. B., Friedlingstein, P., Huntingford, C., Jones, C. D., and Luke, C. M.: Carbon dioxide variability constrains the sensitivity of tropical carbon to climate change, Nature, submitted, 2012. 1072

Hawkins, E. and Sutton, R.: The potential to narrow uncertainty in regional climate predictions, B. Am. Meteorol. Soc., 90, 1095, doi:10.1175/2009BAMS2607.1, 2009. 1057, 1064, 1065, 1066, 1074

Friedlingstein, P., Cox, P., Betts, R., Bopp, L., von Bloh, W., Brovkin, V., Cadule, P., Doney, S., Eby, M., Fung, I., Bala, G., John, J., Jones, C., Joos, F., Kato, T., Kawamiya, M., Knorr, W., Lindsay, K., Matthews, H. D., Raddatz, T., Rayner, P., Reick, C., Roeckner, E., Schnitzler, K., Schnur, R., Strassman, K., Weaver, A. J., Yoshikawa, C., and Zeng, N.: Climate-carbon cycle feedback analysis: Results from the $C^4$MIP model intercomparison, J. Climate, 19, 3337–3353, 2006. 1057, 1069

IPCC: Climate change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge Univ. Press, 2007. 1058

Jones, C. D., Hughes, J. K., Bellouin, N., Hardiman, S. C., Jones, G. S., Knight, J., Liddicoat, S., O'Connor, F. M., Andres, R. J., Bell, C., Boo, K.-O., Bozzo, A., Butchart, N., Cadule, P., Corbin, K. D., Doutriaux-Boucher, M., Friedlingstein, P., Gornall, J., Gray, L., Halloran, P. R., Hurtt, G., Ingram, W. J., Lamarque, J.-F., Law, R. M., Meinshausen, M., Osprey, S., Palin, E. J., Parsons Chini, L., Raddatz, T., Sanderson, M. G., Sellar, A. A., Schurer, A., Valdes, P., Wood, N., Woodward, S., Yoshioka, M., and Zerroukat, M.: The HadGEM2-ES implementation of CMIP5 centennial simulations, Geosci. Model Dev., 4, 543–570, doi:10.5194/gmd-4-543-2011, 2011. 1063

Knutti, R. and Hegerl, G.: The equilibrium sensitivity of earth's temperature to radiation changes, Nat. Geosci., 1, 735–743, 2008. 1057, 1068, 1073

Knutti, R., Stocker, T. F., Joos, F., and Plattner, G.-K.: Probabilistic climate change projections using neural networks, Clim. Dynam., 21, 257–272, doi:10.1007/s00382-003-0345-1, 2003. 1068

Lambert, F. H., Harris, G. R., Collins, M., Murphy, J. M., Sexton, D. M. H., and Booth, B. B. B.: Interactions between perturbations to different Earth system components simulated by a fully-coupled climate model, Clim. Dynam., submitted, 2012. 1059, 1060, 1061, 1063, 1068, 1071, 1073, 1074, 1084





ESDD
3, 1055–1084, 2012

Emission driven global change

B. B. B. Booth et al.

Lee, T. C. K., Zwiers, F. W., Zhang, X., and Tsao, M.: Evidence of Decadal Climate Prediction Skill Resulting from Changes in Anthropogenic Forcing, J. Climate, 19, 5305–5318, doi:10.1175/JCLI3912.1, 2006. 1057

Lowe, J. A., Huntingford, C., Raper, S. C. B., Jones, C. D., Liddicoat, S. K., and Gohar, L. K.: How difficult is it to recover from dangerous levels of global warming?, Environ. Res. Lett., 4, 014012, doi:10.1088/1748-9326/4/1/014012, 2009. 1067

Meinshausen, M., Raper, S. C. B., and Wigley, T. M. L.: Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration, Atmos. Chem. Phys., 11, 1417–1456, doi:10.5194/acp-11-1417-2011, 2011a. 1066

Meinshausen, M., Smith, S. J., Calvin, K. V., Daniel, J. S., Kainuma, M., Lamarque, J. F., Matsumoto, K., Montzka, S. A., Raper, S. C. B., Riahi, K., Thomson, A. M., Velders, G. J. M., and van Vuuren, D.: The RCP greenhouse gas concentrations and their extension from 1765 to 2300, Climatic Change (Special Issue), 109, 213–241, doi:10.1007/s10584-011-0156-z, 2011b. 1062, 1066, 1067, 1069

Meinshausen, M., Wigley, T. M. L., and Raper, S. C. B.: Emulating atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 2: Applications, Atmos. Chem. Phys., 11, 1457–1471, doi:10.5194/acp-11-1457-2011, 2011c. 1066, 1067

Murphy, J. M., Sexton, D. M. H., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M., and Stainforth, D. J.: Quantification of modelling uncertainties in a large ensemble of climate change simulations, Nature, 430, 768–772, 2004. 1059

Murphy, J. M., Booth, B. B. B., Collins, M., Harris, G. R., Sexton, D. M. H., and Webb, M. J.: A methodology for probabilistic predictions of regional climate change from perturbed physics ensembles, Philos. T. R. Soc. A, 365, 1993–2028, 2007. 1060

Murphy, J. M., Sexton, D. M. H., Jenkins, G. J., Boorman, P. M., Booth, B. B. B., Brown, C. C., Clark, R. T., Collins, M., Harris, G. R., Kendon, E. J., Betts, R. A., Brown, S. J., Howard, T. P., Humphrey, K. A., McCarthy, M. P., McDonald, R. E., Stephens, A., Wallace, C., Warren, R., Wilby, R., and Wood, R. A.: UK Climate Projections Science Report: Climate change projections. Met Office Hadley Centre, Exeter, UK, available at: http://ukclimateprojections.defra.gov.uk/22566 (last access: 6 September 2012), 2009. 1058

Nakicenovic, N., Alcamo, J., Davis, G., Vries, B. D., Fenhann, J., Gaffin, S., Gregory, K., Grubler, A., Jung, T. Y., and La Rovere, T. K., Michaelis, L., Moria, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Raihi, K., Roehrl. A., Rogner, H. H., Sankovski, A., Schlesinger, M., Shukla,





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3, 1055–1084, 2012
Emission driven global change
B. B. B. Booth et al.

P., Smith, S., Swart, R., van Rooijen, S., Victor, N., and Dadi, Z.: IPCC Special Report on Emission Scenarios, Cambridge, 2000. 1057
Reichler, T. and Kim, J.: Uncertainties in the climate mean state of global observations, reanalyses, and the GFDL climate model, J. Geophys. Res., 113, D05106, doi:10.1029/2007JD009278, 2008. 1060
Sexton, D. M. H. and Murphy, J. M.: Multivariate prediction using imperfect climate models Part II: robustness of methodological choices and consequences for climate sensitivity, Clim. Dynam., 38, 2543–2558, doi:10.1007/s00382-011-1209-8, 2012. 1073
Sexton, D. M. H., Murphy, J. M., Collins, M., and Webb, M. J.: Multivariate probabilistic projections using imperfect climate models Part I: outline of methodology, Clim. Dynam., 38, 2513–2542, doi:10.1007/s00382-011-1208-9, 2012. 1073
Taylor, K., Stouffer, R., and Meeh, G.: An overview of cmip5 and the experiment design, B. Am. Meteorol. Soc., 93, 485–498, doi:10.1175/BAMS-D-11-00094.1, 2012. 1062, 1063
Yip, S., Ferro, C. A. T., Stephenson, D. B., and Hawkins, E.: A Simple, Coherent Framework for Partitioning Uncertainty in Climate Predictions, J. Climate, 24, 4634–4643, 2011. 1066





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**Table 1.** The distribution of the range of Atmospheric $CO_2$ (ppm) and global temperature (K) responses in ESE, are given below. These give the lower bound, 10th percentile, 25th percentile, mean, 75th and 90th percentiles and the upper bound for each scenario. The same statistics are also provided for the ensemble if the high climate sensitivity simulations are excluded from the distribution. The temperatures are based on 5 yr averages at the end of the century, in kelvin. The $CO_2$ is the 2099 value in ppm. Comparable statistics are provided for concentration driven SRES A1B.

| | | Lower bound | 10th | 25th percentile | Median | 75th percentile | 90th | Upper bound | 10–90 |
|---|---|---|---|---|---|---|---|---|---|
| Full ESE range | | | | | | | | | |
| RCP8.5 | $CO_2$ | 808 | 864 | 998 | 1106 | 1234 | 1389 | 1596 | 525 |
| | Temp. | 4.0 | 4.2 | 5.1 | 6.1 | 7.2 | 8.1 | 9.3 | 3.9 |
| SRES A1B | $CO_2$ | 615 | 635 | 723 | 794 | 876 | 972 | 1099 | 367 |
| | Temp. | 2.5 | 2.8 | 3.6 | 4.3 | 5.2 | 6.1 | 7.3 | 3.3 |
| RCP2.6 | $CO_2$ | 387 | 390 | 422 | 449 | 474 | 514 | 574 | 124 |
| | Temp. | 1.3 | 1.5 | 2.0 | 2.3 | 2.6 | 3.2 | 4.1 | 1.7 |
| ESE range subsampled to exclude climate sensitivities above the CMIP5 range | | | | | | | | | |
| RCP8.5 | $CO_2$ | 808 | 821 | 959 | 1078 | 1193 | 1374 | 1596 | 553 |
| | Temp. | 4.0 | 4.2 | 4.9 | 5.5 | 6.0 | 6.8 | 8.1 | 2.6 |
| SRES A1B | $CO_2$ | 615 | 617 | 689 | 771 | 854 | 932 | 1060 | 315 |
| | Temp. | 2.5 | 2.9 | 3.3 | 3.7 | 4.1 | 4.8 | 5.7 | 1.9 |
| RCP2.6 | $CO_2$ | 387 | 402 | 420 | 441 | 465 | 486 | 496 | 84 |
| | Temp. | 1.3 | 1.4 | 1.7 | 2.0 | 2.3 | 2.6 | 3.2 | 1.2 |
| Concentration driven ensemble sampling the same Atmospheric Physics | | | | | | | | | |
| A1B | $CO_2$ conc. | | | | 708 | | | | |
| | Temp. | 2.5 | 2.6 | 3.0 | 3.6 | 4.1 | 4.5 | 4.7 | 1.9 |





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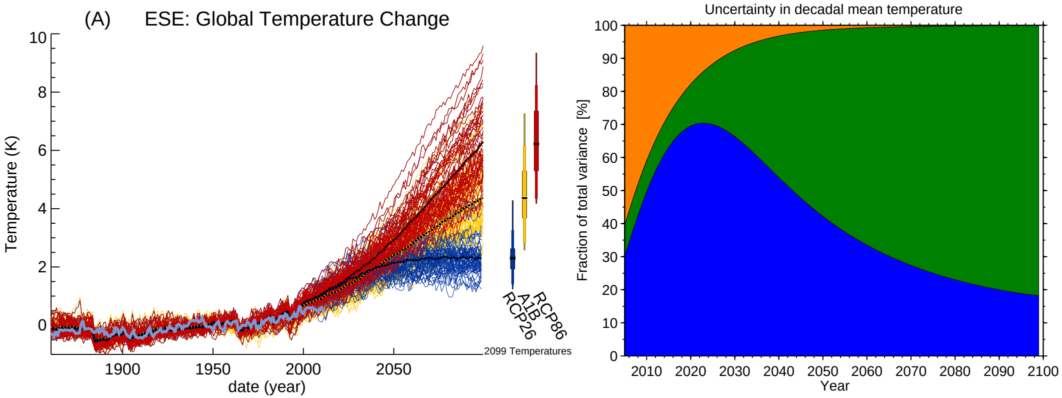


**Fig. 1.** The global mean temperature response to RCP and SRES scenarios. The projected response to RCP8.5 (red), SRES A1B (yellow) and RCP2.6 (blue) are shown for the ESE ensemble (left panel). The mean response of each ensemble is shown (bold line). The fraction of the total variance explained by differences in future scenarios (green), model response (blue) and internal variability (orange) are shown (right panel) for each decade ahead. The observations (HadCRUT3) are overplotted in light grey for the historical period. Differences between the mean ensemble response and the observations are evident in the last 10 yr, though the observations still within the ESE distribution. The second panel shows the fraction of total variance in decadal global mean surface air temperature projections explained by the scenarios uncertainty (green), model response (blue) and internal variability of the climate system (orange), calculated using the methodology described in Hawkins and Sutton (2009).





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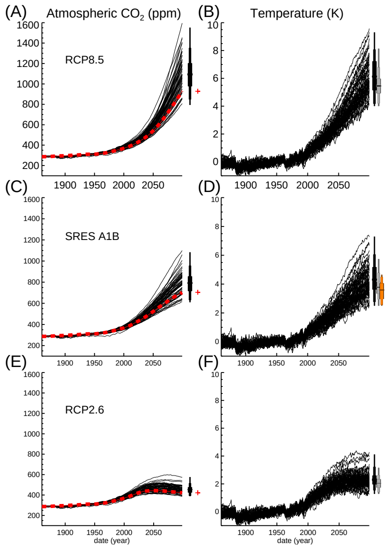


**Fig. 2.** Simulated $CO_2$ (panels **A**, **C** and **E**) and Temperature (panels **B**, **D** and **F**) for RCP8.5 (**A** and **B**), SRES A1B (**C** and **D**) and RCP2.6 (**E** and **F**) are show for the ESE. The concentration profiles (dashed red lines) used to with CMIP5 and CMIP3 concentration simulations also shown. The 2100 values from these concentration pathways, are marked by the red crosses to the right of these panels. The black box and whisker bars (right of panels) indicate the full range (thin line), 10th–90th (medium line) and 25th–75th (thick line) and median (central bar) of the $CO_2$ and global mean temperature at the end of the century. The $CO_2$ value is the annual mean value for 2099 while the global mean is the mean of the last 5 yr (to minimise the impact of internal variability). For temperature panels, box and whisker bars illustrate the distribution of responses if climate sensitivity values larger than CMIP5 models are excluded. Also includedis the distribution of global mean temperature responses, for the equivalent atmospheric physics response, to the concentration driven SRES A1B scenario (orange box and whisker bar, based on Collins et al., 2011).





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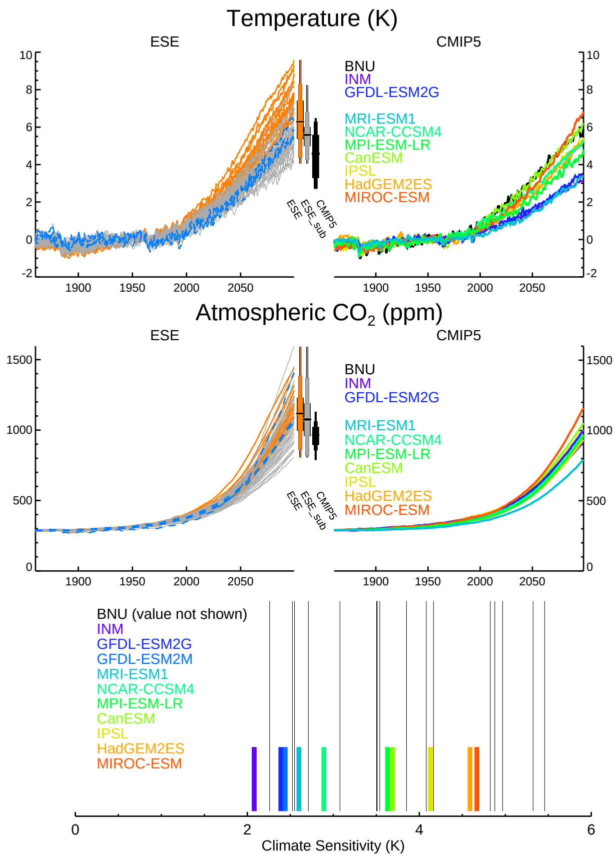


**Fig. 3.** Caption on next page.





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**Fig. 3.** Comparison of ESE and CMIP5 responses. The figure shows projected ESE (left) and CMIP5 emisRCP85 (right) responses for global mean temperature (upper panel) and atmospheric $CO_2$ (central panel). For the ESE projections, colours are used to distinguish between models with climate sensitivities above 4.5 K (orange) and those below (grey). The 4 ESE configurations with the low climate sensitivity configuration are overplotted (dashed blue). The box and whisker bars indicate the full range (thin line), 10th–90th (medium line) and 25th–75th (thick line) and median (central bar). This is presented for the full ESE range (orange), the ESE range when high climate sensitivities are excluded (grey) and the CMIP5 range (black). The colours and the CMIP5 projections (right) indicate the relative magnitude of climate sensitivity of each simulation (based on values in the lower panel). The lower panel shows the ranking for CMIP5 model (short, coloured bars) with estimates for the 17 Atmospheric configurations which make up the ESE ensemble (thin black bars). The original 68 members of the ESE ensemble combines each atmospheric configuration with 4 different combinations of land carbon cycle, ocean physics and aerosol configuration, (Lambert et al., 2012). The resultant 57 members (after 11 combinations were rejected based on 1860 climate, Lambert et al., 2012) therefore contains multiple incidences (up to 4) of each of these climate sensitivities (thin black bars). The climate sensitivities were estimated from 1 percent $CO_2$ ramp experiments for the perturbed HadCM3 configurations (Collins et al., 2011) and CMIP5 estimates are based on Andrews et al. (2012). The exceptions to this are values for NCAR's CCSM4 (T. Andrews, personal communications, based on same methodology, 2012) and BNU for which data was not available at the time of submission. Where the CMIP5 configuration used to estimate the climate sensitivity excluded carbon cycle processes, we make the assumption that the inclusion of these carbon cycle processes in this analysis does not change the climate sensitivity.





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