# Technical Appendix: Updated projections of global emissions and temperatures

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This technical appendix details scientific updates to the global climate modelling used since 2008 to guide advice from the Committee on Climate Change on the UK's 2050 target and first three carbon budgets. Modifications are made to account for key developments regarding uncertainty in climate projections, including the recently released working group one of the IPCC Fifth Assessment Report (AR5).

To account for developments since 2008 in observed and forecast global emissions, five new emissions pathways are chosen which have emissions in the year 2050 from 20 to 24 GtCO2eq/yr in line with the previous advice of the Committee. These have been developed to assess the likelihood of crossing global temperature thresholds by 2100.

Temperature projections are made using a new method based on Transient Climate Response (TCR), which is potentially more robust than the original method based on Equilibrium Climate Sensitivity (ECS). It is found that the choice between the ECS and TCR methods makes less of a difference to the projections than the specific probability distribution chosen for ECS or TCR from those available in AR5.

IPCC AR5 also includes quantification of some additional climate feedbacks for the first time, such as carbon release from melting permafrost. These are incorporated into the model framework to provide a tentative estimate of their impact on temperature projections.

The emissions and temperature data outlined in this report are available in the accompanying data files.

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# 1. Introduction

In 2008 the Committee on Climate Change (CCC) and Met Office Hadley Centre (MOHC) carried out a modelling study to guide advice on the UK's 2050 target and first three carbon budgets (Smith et al 2008, CCC08 from here on). This used a climate modelling framework which sampled major uncertainties in climate projections, such as the sensitivity of global temperatures to atmospheric $CO_2$ concentrations and climate-carbon cycle feedback, to derive constraints on future emissions needed to meet the CCC's climate objective.

Since CCC08 there have been a number of scientific developments, including the release of working group one (WG1) of the IPCC Fifth Assessment Report (AR5). To ensure that the projections used by the CCC take account of the most recent research, various aspects of the modelling system are readdressed in this study and where appropriate updated to assess the potential impact of various emerging areas of climate science.

The first two scientific areas addressed by this study are the new distributions of Equilibrium Climate Sensitivity[*] (ECS) documented by AR5 and the potential use of Transient Climate Response[†] (TCR) as a constraint on climate projections. The latter is being considered because it is a measure of climate response for a period of increasing radiative forcing, which is more comparable to the current real world situation. There is also some evidence that TCR may offer a tighter constraint on projections of future response.

Another emerging science area examined is that of Earth system feedbacks. While carbon cycle processes and feedbacks have been studied for some time and the inclusion of sophisticated carbon cycle components in climate models is now becoming more common, there is an increasing body of research acknowledging the role of other potentially significant Earth system processes and feedbacks. While complete understanding is still some way off there is now enough information in the literature to take an initial look at how these may alter the climate outcome for a given emission pathway. Processes involved in the real climate system include thawing of permafrost, atmospheric dust, fire, and methane emissions from wetlands. Our preliminary and tentative assessment of the potential impact of these additional Earth system feedbacks is made based on research included in the AR5.

Since CCC08 several years have passed in which global emissions have continued to rise. Therefore, additional emissions scenarios are also developed which peak in 2020, which is later than the original peak of 2016, but which still meet the targets for 2050 global emissions to be between 20 and 24 $GtCO_2e/yr$.

Projected temperature changes in 2100 for the new scenarios and alternative modelling approaches outlined in this report are available in the accompanying data file.

[*] ECS is the long-term temperature response to a doubling of atmospheric $CO_2$ concentrations.
[†] TCR is formally derived from pathways where atmospheric $CO_2$ concentrations increase by 1% per year and is defined as the increase in global average temperature over a twenty-year period centred on the year that $CO_2$ levels doubled (70 years).

# 2. Emissions scenarios

New emissions scenarios are required for this study. In developing new emissions scenarios there are two primary options, using either idealised scenarios or those derived from Integrated Assessment Models (IAM) which usually combine fairly simple representations of the global climate, energy systems and the economy. IAM scenarios have been used as the basis for the Representative Concentration Pathways (RCPs) examined by AR5.

The difficulty in using IAM scenarios directly is that the range of differing assumptions encapsulated in IAMs leads to a wide range of emergent behaviour in terms of how quickly global emissions peak and how quickly they can decline. These assumptions, physical, economic, technological and social, are by their very nature under revision as understanding develops.

Rather than use IAM scenarios directly, which risk becoming harder to justify over time, or place over reliance on the output of a single IAM, we draw on a wide range of outputs from the IAM community to guide some characteristics of future emissions but retain the use of the idealised scenario approach of CCC08. While this benefits from providing a simple and entirely transparent methodology to defining emissions scenarios, technical and economic feasibility is less readily assessed and is not discussed further here.

## 2.1 Overview of scenario development

Our method for generating future emissions scenarios follows CCC08. Specifically, a baseline with no explicit climate mitigation policy in its story-line is chosen. This is used to define global emissions until mitigation starts, which is 2027 at the latest in this work. Consistent with CCC08 and more recent emissions trends we use SRES A1B as our baseline. For reference, the radiative forcing in 2100 in A1B is just over 6 $Wm^{-2}$, which is comparable to RCP 6.0 used in AR5.

Mitigation scenarios are developed from A1B by specifying a number of parameters describing how $CO_2$ emissions change with time once they have deviated from the baseline. Non-$CO_2$ greenhouse gases are predominantly determined from their ratio to $CO_2$ emissions in a widely used low emissions scenario from IPCC, SRES B1.

The parameters which determine $CO_2$ emissions are the year in which emissions deviate from the baseline; the post-peak emissions reduction rate; and the long term minimum emissions rate that is possible (referred to as the emissions floor). Following CCC08, and informed by consideration of the literature, in most of the scenarios we consider, emissions of $CO_2$ are assumed to peak seven years after deviation from the baseline starts.

The peaking phase is modelled here by fixing the second differential of emissions rate with respect to time at the year that emissions deviate from the baseline, such that emissions peak seven years after deviating from the baseline. This is then held constant until the post peak $CO_2$ emissions reductions rate is met. As a result the time taken to peak after action starts has an effect on how quickly the desired reduction rate is achieved after emissions peak.

Once the desired emissions reductions rate is met, it is held constant until the emissions floor is reached. The long term emissions floor for $CO_2$ is zero for most trajectories, with around 5 $GtCO_2e$/yr from other greenhouse gases. This is referred to from herein as "low" for consistency with CCC08.

Emissions of other non-$CO_2$ gases, specifically halogen-containing compounds included in the Kyoto Protocol, $CH_4$, $N_2O$ and other indirect GHGs (CO, NOx, VOCs and $SO_2$) are modelled as per CCC08.

In a development to the methodology of CCC08 we include, as a sensitivity experiment, a scenario in which technology leading to large scale negative $CO_2$ emissions becomes available for the latter half of the century. This reflects the fact that many mitigation scenarios in the literature assume that carbon capture and storage (CCS) will play a significant role in reducing $CO_2$ emissions and that, if this technology were to be used in conjunction with bio-fuels, it could theoretically lead to negative $CO_2$ emissions. The scenario included here which includes negative $CO_2$ emissions is based on as yet uncertain assumptions regarding the full life-cycle emissions of Bio-Energy CCS (BECCS), availability of land for fuels and the scalability and efficiency of CCS. A key pathway used in the latest IPCC report, RCP2.6, assumes significant use of BECCS.

We estimate the potential scale of negative emissions by using the Extended Land Conversion (ELC) bio-fuel scenario from the CCC Bioenergy Review (2012) combined with a number of optimistic further assumptions The examination of ELC does not indicate endorsement of such a scenario by the authors and is chosen as a basis for an illustrative example.

The ELC scenario, which assumes 80% of abandoned agricultural land is used for bio fuels, has 400 Mha available for fuel crops. We assume that no other bio fuel use is necessary to meet the target reduction rate of $CO_2$ emissions before BECCS is included. It is further assumed that BECCS is 100% efficient; that 50% of dry biomass is carbon (upper estimate from Schlesinger, 1991); and the productivity of this land is 5 t/ha/yr of dry biomass (CCC Bioenergy Review 2012). The combination of these assumptions leads to an estimate of maximum negative emissions of -3.67 $GtCO_2$/yr. For comparison, by the end of the century, RCP2.6 has very small emissions into the atmosphere from anthropogenic fossil fuel and industry sources and the use of BECCS provides a net negative $CO_2$ emissions (excluding land use) in RCP2.6 of -3.44 $GtCO_2$/yr.

In our studies, where there are negative $CO_2$ emissions, these are added to the emissions scenario assuming linear growth from zero in 2030 to their full scale in 2050, remaining at this level for the rest of the century. As this is added to the existing $CO_2$ emissions the *net* $CO_2$ emissions may not necessarily become negative. No further analysis of the feasibility of such a scale of negative emissions use is provided here, but it is worth noting that a contribution of -3.67 $GtCO_2$/yr is smaller than some estimates of the net negative emissions from IAM cost-optimising mitigation scenarios that limit global warming to under 2 °C (UNEP Emissions gap report 2013).

### 2.2 New scenarios used in this study.

In addition to the SRES **A1B baseline** and the "**2016 4% low**"[‡] scenario examined in CCC08, five new emissions scenarios are developed in this study which have 2050 emissions from 20 to 24 $GtCO_2eq$/yr (Figure 1). Emissions data for all scenarios examined

‡ "2016 4% low" peaks global emissions in 2016 and reduces $CO_2$ emissions by 4% per year after the peak until the low emission is reached. See CCC08 for details.

in this study are available in the accompanying spreadsheet "*Future global emissions pathways*".

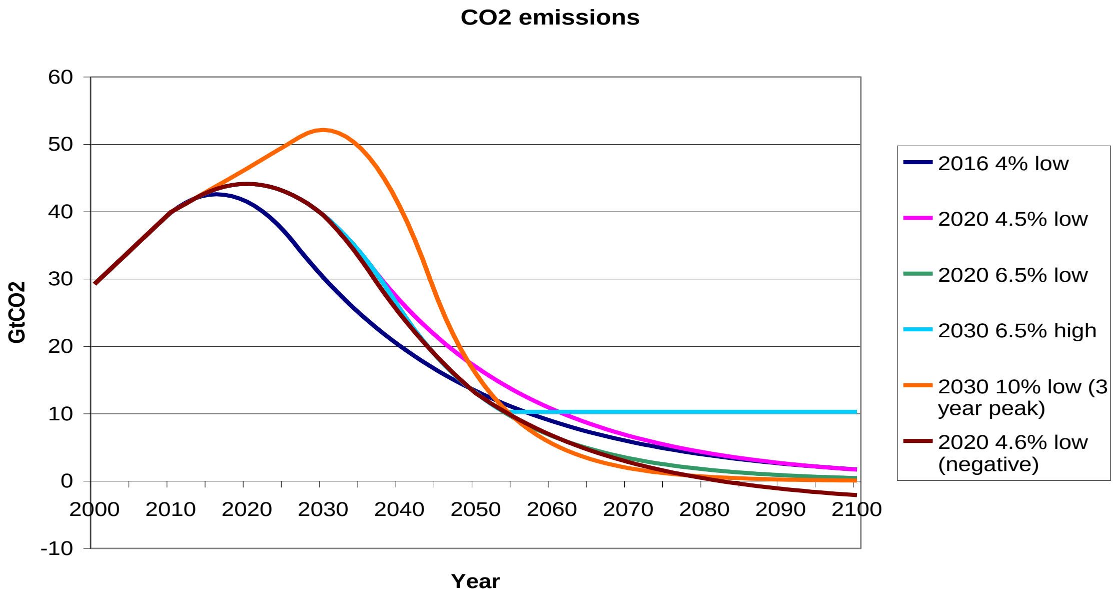
"**2020 4.5% low**": This scenario peaks global emissions in 2020 with a post peak $CO_2$ emissions reduction rate of 4.5% per year to the "low" emissions floor. Emissions in 2050 are 24 $GtCO_2$.

"**2020 6.5% low**": This scenario also peaks global emissions in 2020 with a post peak $CO_2$ emissions reduction rate of 6.5% per year to reach 2050 emissions of 20 $GtCO_2$. This has the "low" emissions floor.

"**2020 6.5% high**": This scenario is the same as "2020 6.5% low" except that it has a higher long term $CO_2$ emissions floor of around 10 $GtCO_2$/yr.

"**2030 10% low**": In this scenario the peak in global emissions is delayed until 2030. In order to reach 2050 emissions within the 20 to 24 $GtCO_2$e/yr range (23 $GtCO_2$e/yr) the condition that emissions took seven years to peak after action starts had to be relaxed to three years along with a post-peak $CO_2$ emissions reduction rate of 10% per year. While there is little evidence at present that such a large emissions reduction rate is feasible, this scenario is included to illustrate the increase in required action should emission reductions be delayed. This scenario also uses the "low" emissions.

"**2020 4.6% (negative)**": This scenario peaks global emissions in 2020 with a post peak $CO_2$ emissions reduction rate of 4.6% per year. The scenario uses the "low" emissions floor but also includes a substantial negative emissions component which linearly increases over 20 years to -3.67 $GtCO_2$/yr in 2050. This leads to 2050 emissions of 20 $GtCO_2$e/yr and net $CO_2$ emissions that become negative in 2083 and reach -2.1 $GtCO_2$/yr in 2100. For comparison RCP2.6 (based on the IMAGE IAM) also has net negative $CO_2$ emissions from 2083 onwards and slightly smaller 2100 net (including land use) $CO_2$ emissions of -1.54 $GtCO_2$/yr.



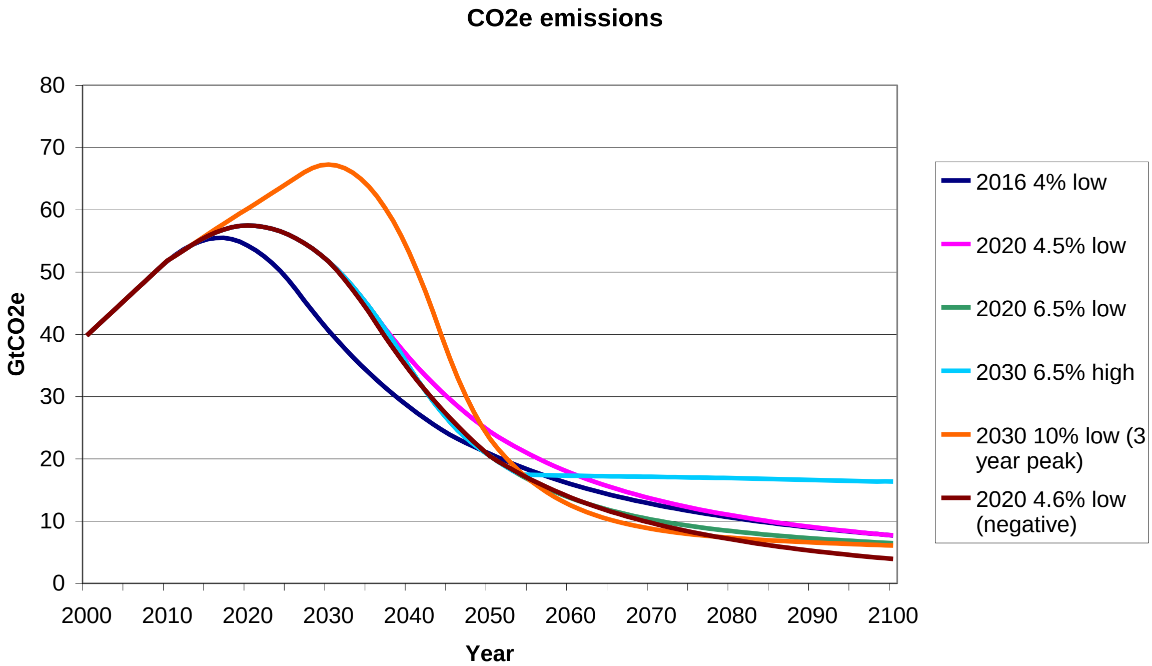



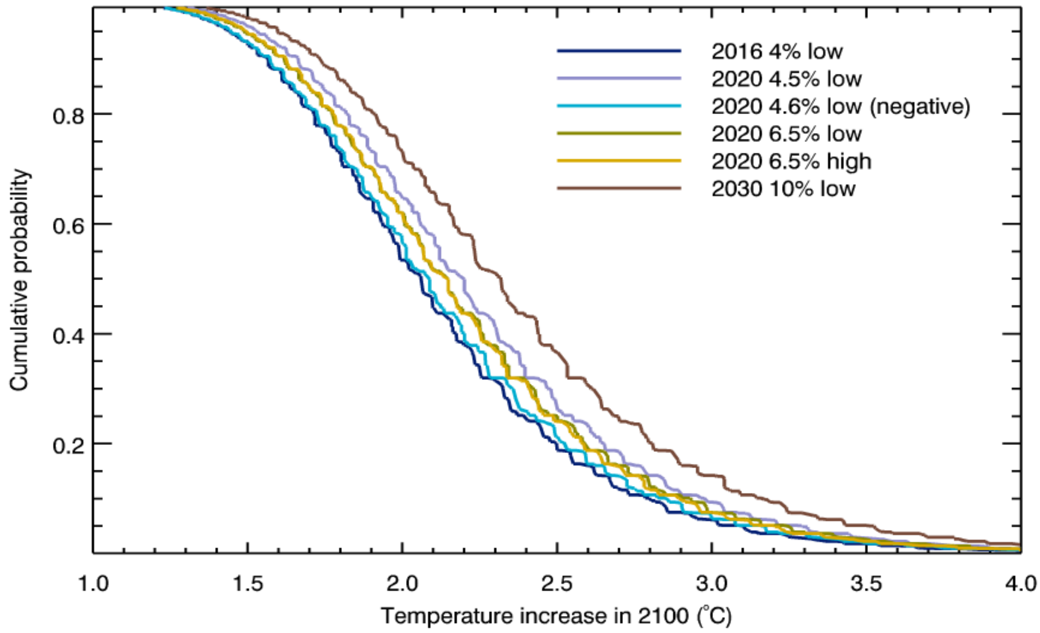

**Figure 1: Emission of $CO_2$ (top) and total greenhouse gases (bottom) for scenarios developed in this study and the "2016 4% low" scenario from CCC08.**

### 2.3 Comparing results for the new emissions scenarios

To compare projections for the new emission pathways developed for this study we use the CCC08 configuration, with the same ranges of ECS, ocean diffusivity and uncertainty in the climate-carbon cycle interaction. Projections of 2100 temperature are available for each scenario in two accompanying spreadsheets, which also include results from the two different approaches detailed in sections 3 and 4[§] and the inclusion of additional Earth system feedbacks detailed in section 5[**].

[§] Accompanying spreadsheet "*Projections of global temperature in 2100 (no new feedbacks)*"
[**] Accompanying spreadsheet "*Projections of global temperature in 2100 (including new feedbacks)*"

Figure 2 shows the cumulative probability of limiting temperature in 2100 to a range of levels for the scenarios examined in this study. The projections for “2020 6.5% low” and “2020 6.5% high” are remarkably similar despite the difference in long term $CO_2$ emissions floor. The reason for this is that once the $CO_2$ emissions floor is reached in “2020 6.5% high” then not only are $CO_2$ emissions higher than the correspondingly “low” scenario, but it also has higher aerosol emissions as these are directly linked to $CO_2$ emissions in this scenario. As the forcing from the aerosols is strong but short-lived, this means than in the ~20 years after the $CO_2$ floor is reached, “2020 6.5% high” is actually cooler than its counterpart owing to the aerosol forcing. Once the impact of the higher $CO_2$ emissions starts to be more completely realised, temperatures increase. By 2100 temperatures in “2020 6.5% high” are increasing more rapidly than the “low” scenario, but it is by chance that the distribution in 2100 happen to be so similar. This is shown in the time series of median warming in the two scenarios in Figure 3



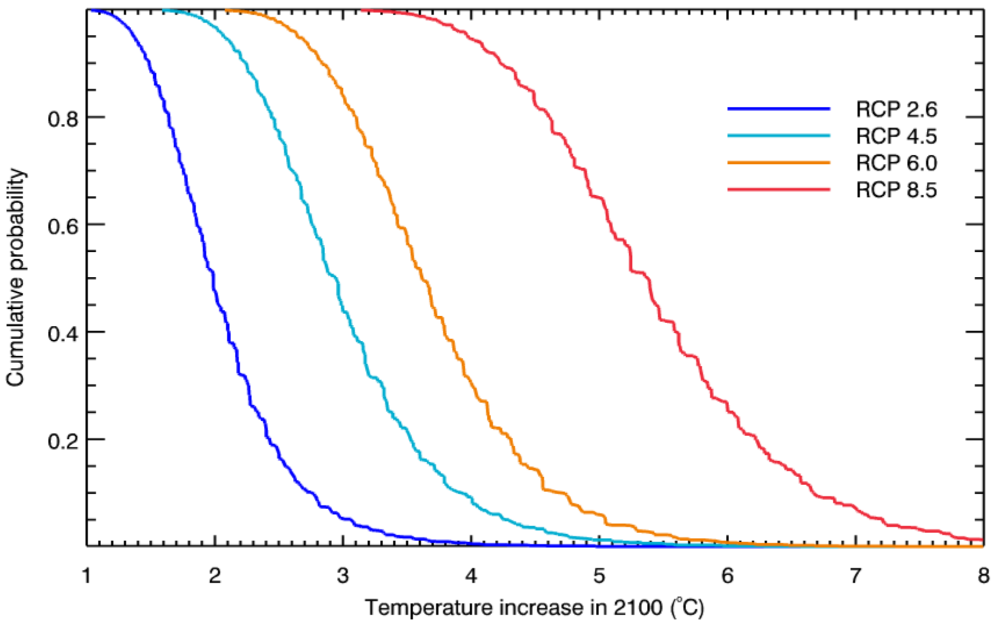




**Figure 2: Projected chance of exceeding temperatures in 2100 for scenarios in this report (top) and the RCPs (bottom) using the CCC08 model framework. Note the change of scale in the lower panel.**

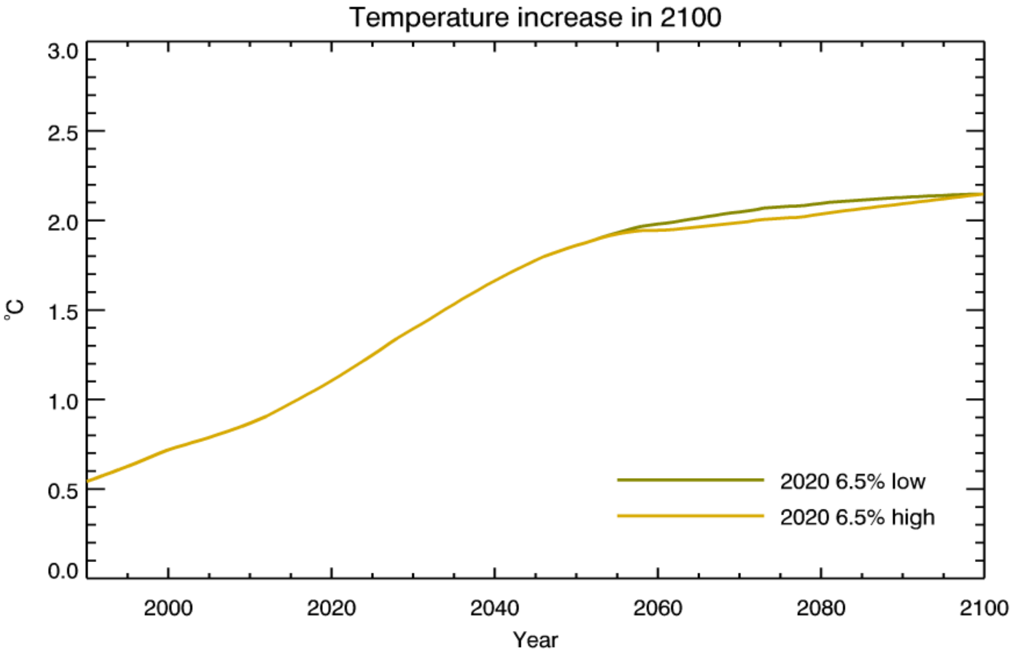



**Figure 3: Median warming under “2020 6.5% low” and “2020 6.5% high” using the CCC08 model framework.**

# 3. Climate modelling approach and use of alternative ECS distributions

The modelling approach used in this study is a modified version of that in CCC08. A brief overview is provided here with detailed descriptions provided only for the updates to the modelling system. The reader is referred to CCC08 and Lowe et al (2009) for full details.

### 3.1 Modelling framework

The basis of the modelling framework is the simple climate model (SCM) MAGICC 4.1 (Wigley, 1993; Wigley and Raper, 2001; Wigley, 2008). MAGICC has demonstrated skill in emulating global average surface temperature response when set up and tuned to represent the large-scale emergent behaviour of a wide range of more complex models, as shown in CCC08, and variants of this modelling approach have been used extensively during several IPCC assessments. In CCC08 uncertainty in future global temperature was sampled by perturbing the values of ECS (defined as the equilibrium global mean temperature increase for a doubling of atmospheric carbon $CO_2$), the ocean mixing rate (which determines how quickly the warming at the surface is diffused throughout the ocean) and a measure of the climate-carbon cycle feedback strength (regulating how much carbon is emitted and absorbed naturally in response to climate change).

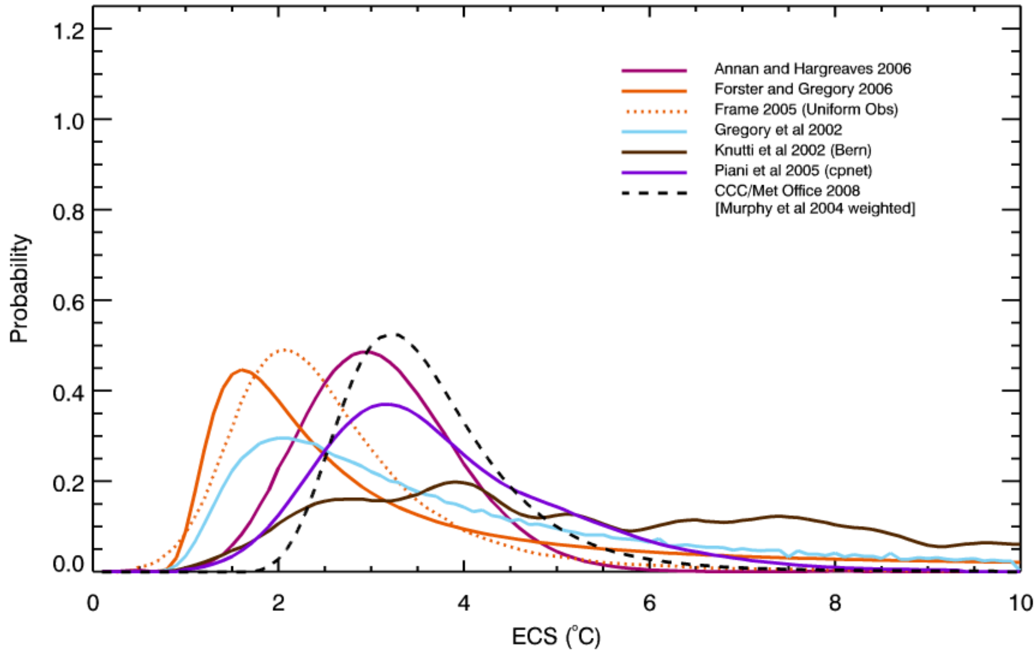
In this current work the approach to the carbon cycle uncertainty (based on C4MIP - Friedlingstein et al., 2006) and the uncertainty in the ocean diffusivity (based on earlier IPCC assessment) used in CCC08 is retained in this study. The focus is then on using updated scientific understanding to assess the effect of alternative climate sensitivity distributions (both equilibrium sensitivity and transient climate responses are considered from the literature) and to take a first look at the effect of adding additional Earth system feedbacks.

### 3.2 Equilibrium Climate Sensitivity Distributions

It is currently not possible to narrow the ECS to a single value, but estimates of the uncertainty distribution of ECS have been derived. CCC08 used a single ECS distribution from Murphy et al (2004), which weighted climate model outputs by their fit to observations, sampled with 9 bins. Many other estimates of the uncertainty distribution of ECS have been derived from a number of different approaches, such as climate model output, use of the instrumental record combined with simple models, paeleoclimate data or a combination of approaches. There is no consensus over which type of approach or particular study is most robust. This update uses a large number of ECS distributions from AR5 to more fully incorporate uncertainty in possible climate outcomes relating to ECS.

Alternative ECS probability distributions are sampled with equal width bins with a maximum value of 10 °C. This range was chosen to be consistent with the range over which AR5 normalised ECS distributions. However it should be noted that some distributions included in AR5 (and previous IPCC assessments) have small but non-zero probabilities beyond 10 °C.

The number of bins used to sample ECS distributions has been increased to 100 from 9 in this study to ensure that each of the various distributions are well sampled. A study by the AVOID programme demonstrated that increases in the number of bins used to sample the distribution should not materially alter projected climate changes (Gohar et al., 2011). The distributions examined are shown in Figure 4 for those from AR4 (upper) and AR5 (lower).



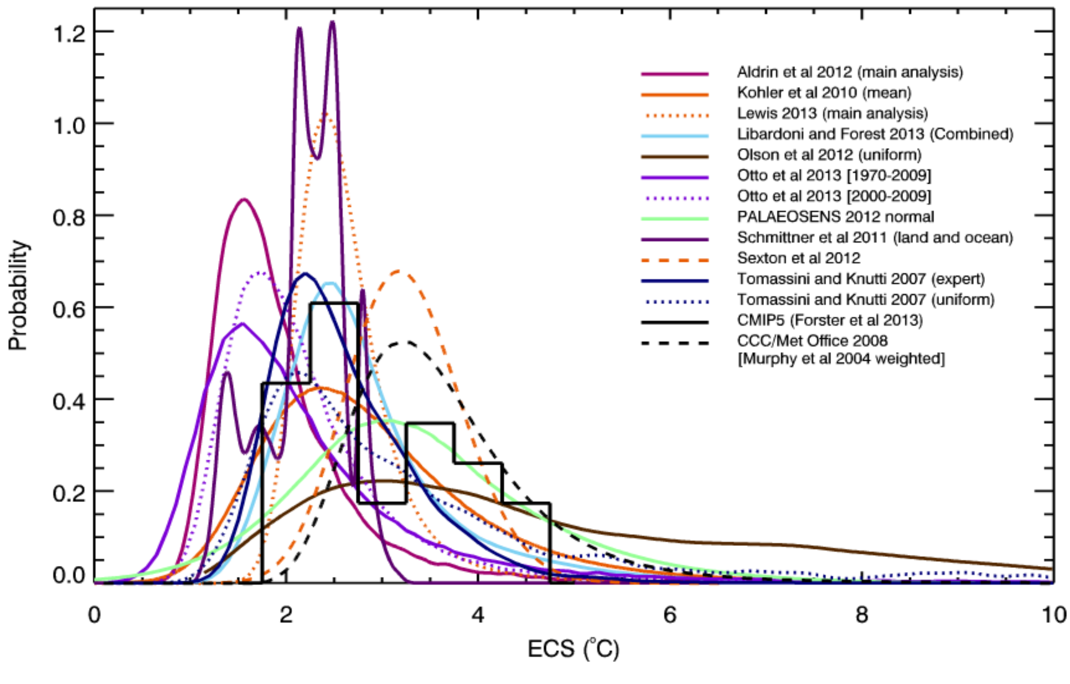




**Figure 4: Equilibrium Climate Sensitivity (ECS) distributions from AR4 (upper) and AR5 (lower). Colours are chosen to match those in AR5. Not all distributions shown in AR5 were available for this study.**

As illustrated below for a mitigation scenario (Figure 5) and our baseline scenario (Figure 6), the use of different distributions of ECS leads to a wide range of projections for temperature rise in 2100. The projections from CCC08 produce median warming that is at the higher end of all of the projections, although it is not the most extreme case. Looking at the likelihood of high end warming (>4 °C) the CCC08 result is nearer to the centre of the range of estimates.

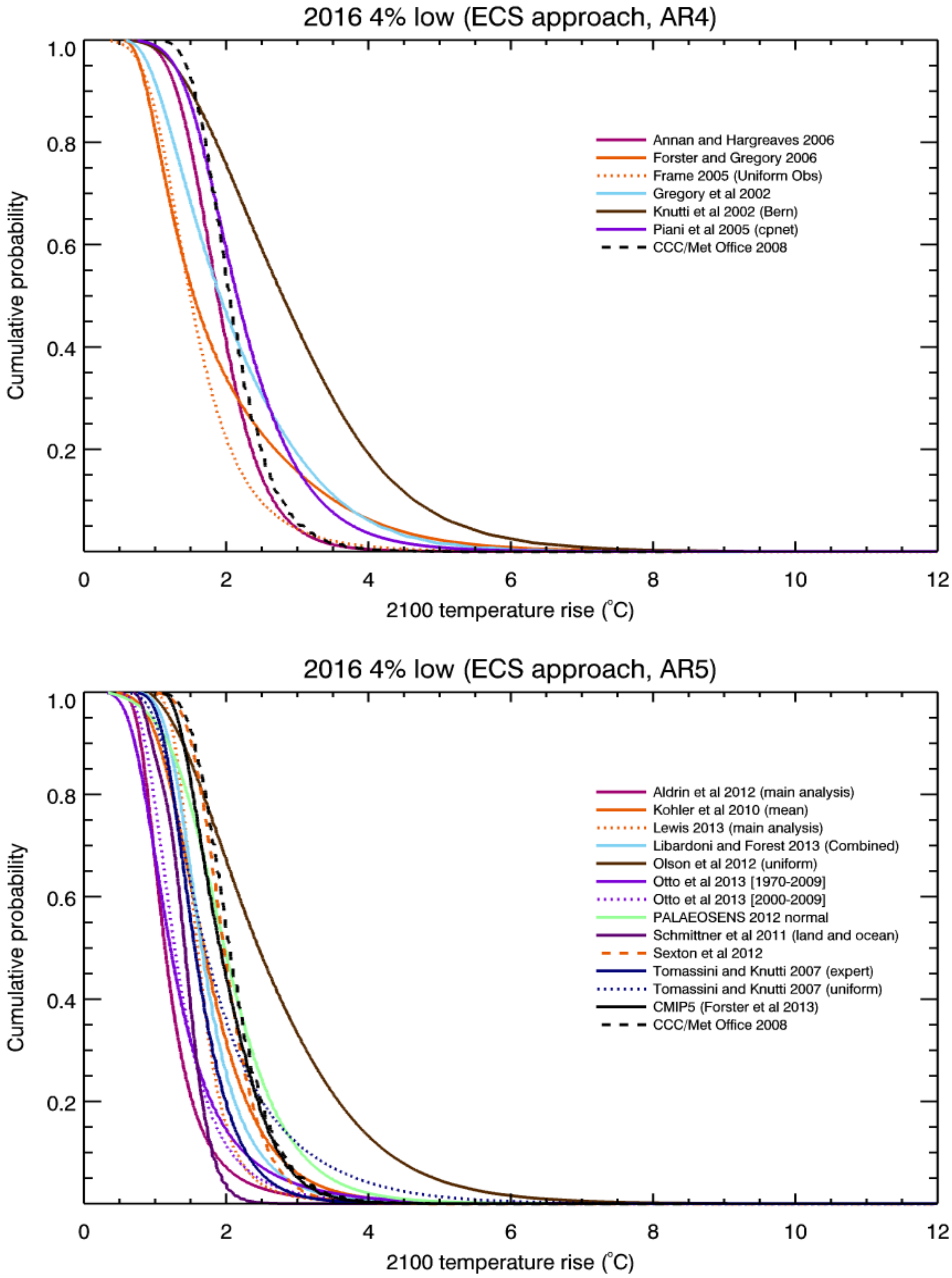



**Figure 5: Projected warming in 2100 for a mitigation scenario ("2016 4% low"). Cumulative probability of exceeding a given temperature is shown for the CCC08 modelling (black dashed) against projections made using ECS distributions from AR4 (top) and AR5 (bottom).**

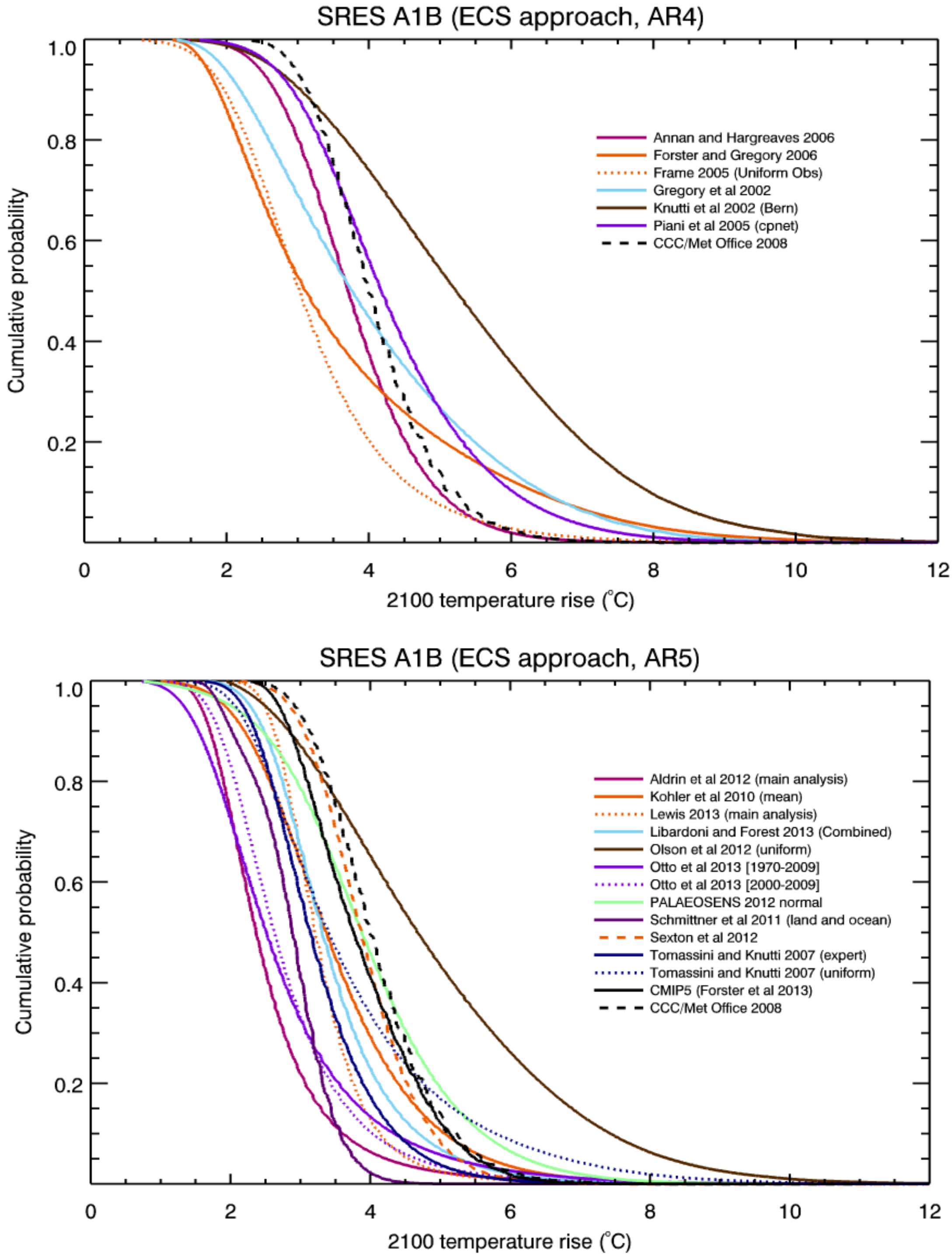



**Figure 6: Projected warming in 2100 for the A1B baseline emissions scenario. Cumulative probability of exceeding a given temperature is shown for the CCC08 modelling (black dashed) against projections made using ECS distributions from AR4 (top) and AR5 (bottom).**

## 4. TCR approach

Increasing attention in the scientific and related literature has been given to the prospect of using estimates of TCR to inform 21st Century projections of future temperature. It has been argued that this is a more closely aligned metric to the situation that we are experiencing in the real climate, i.e. that of increasing forcing. ECS is more relevant to eventual long-term adjustment in scenarios with stabilised forcing. To highlight some of the differences (following Gregory and Forster 2004) we consider a simple energy-balance representation of the global climate system, where N is the rate of change of total energy storage, F is the radiative forcing, λ is the feedback parameter and T is the surface temperature perturbation driven by the change in forcing.

$$N = F - \lambda T \qquad (1)$$

For a situation of increasing forcing it is possible to approximate the rate of change in energy storage as the product of a heat uptake efficiency, α, and the surface temperature perturbation so that (1) becomes:

$$\alpha T = F - \lambda T \qquad (2)$$

TCR can be derived simply from (2) as the temperature change associated with the forcing ($F_2$) from a doubling of atmospheric $CO_2$ concentration:

$$TCR = \frac{F_2}{\alpha + \lambda} \qquad (3)$$

For a situation long-term readjustment to a doubling of $CO_2$ concentration, total energy storage reaches a fixed value and N=0. Hence from (1):

$$ECS = \frac{F_2}{\lambda} \qquad (4)$$

$$\frac{ECS}{TCR} = 1 + \frac{\alpha}{\lambda} \qquad (5)$$

$$\frac{1}{TCR} = \frac{1}{ECS} + \frac{\alpha}{F_2} \qquad (6)$$

While ECS depends on the forcing $F_2$ and the radiative feedback parameter λ, TCR also depends on α, a measure of the rate at which the ocean is able to delay the eventual surface warming (which is related to the effective ocean diffusivity parameter, K, in the MAGICC model). Both α and $F_2$ are positive, meaning the magnitude of TCR is less than the magnitude of ECS. For forcing pathways that follow a peak and decline trajectory over the next century it is therefore expected that the peak warming will be below the theoretical equilibrium value that could eventually be reached if the forcing were held at the peak.

In deriving TCR and ECS from measurements of the climate over recent decades it is worth noting that TCR requires an estimate of the radiative forcing and the surface warming; both of which involve some degree of uncertainty. For a similar estimation of the ECS the ocean heat uptake is also typically required and the total uncertainty is larger as a consequence.

In addition to TCR being a metric derived from a situation closer to current climate change, there is another key reason for considering a TCR constrained approach; it may offer a tighter constraint on future warming than previous studies using ECS. However, since ECS is not used alone, this will in practice depend on the nature of the assumed ocean diffusivity distribution. Figure 7 shows the simulated relationship between TCR (the contours of the plot), ECS and the ocean diffusivity, K.

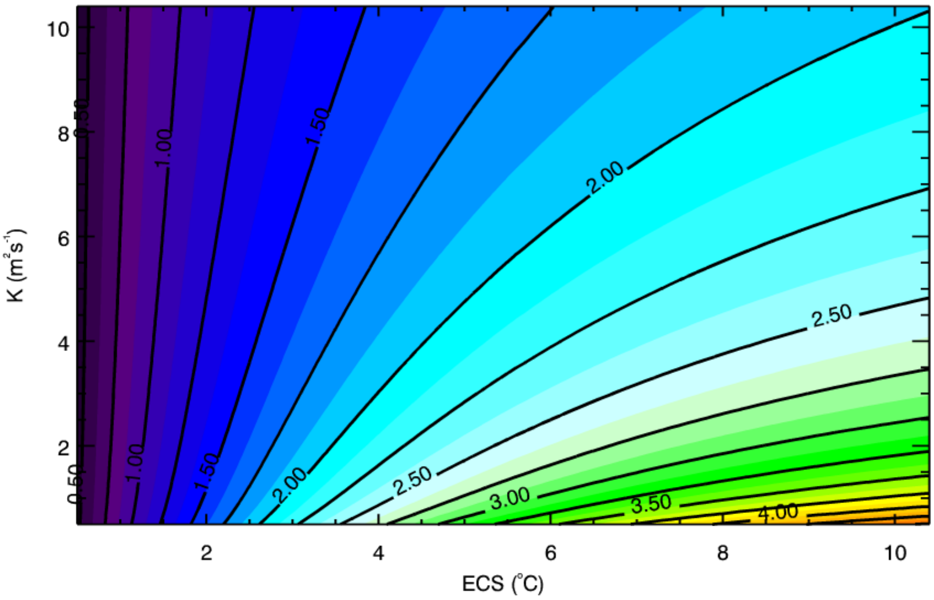



**Figure 7: TCR (numbered contours, in °C) as a function of ECS and K.**

### 4.1 Methodology

To impose a new TCR distribution we initially retained the same model variants used in CCC08 (81 combinations of ECS and K, as carbon cycle feedbacks are initially omitted) and assigned them probabilities based on the TCR that emerges from that particular combination of ECS and K, rather than assuming probabilities for ECS and K individually.

For the range of ECS considered we note that the bins actually utilised in the CCC08 results ranged from 1 to 6 °C, which happens to match the range AR5 considered ECS to be *extremely unlikely* below (<5%) and *very unlikely* to be above (<10%). No upper limit was given at the 5% level in AR5. Reflecting this range, we choose to limit ECS to the upper bin used in CCC08. This provides more traceability to the previous work and, in combination with the range of ocean diffusivity used (0.5 to 10 $cm^2s^{-1}$), samples TCR values up to slightly over 3 °C, which is consistent with the upper range of estimates from the most recent general circulation models used in the AR5.

The lowest values of ECS and K used by CCC08 samples TCR values as low as around 0.75 °C. However, some of the TCR distributions from AR5 show appreciable probabilities at values lower than this and so the lower limit of ECS included is reduced to 0.25 °C to allow for lower TCR values. While a few TCR distributions have appreciable non-zero probabilities below 0.25 °C, TCR values lower than this cannot reliably be modelled with the range of ocean diffusivity used here. Where the TCR distributions used have values lower than this, the cumulative probability of the TCR distribution that is not sampled is readily calculated and this is added as an offset to the cumulative probabilities of projected temperatures. This avoids biasing the results by being unable to sample the very low end of these TCR distributions although in the few cases where this is necessary care should be taken in interpreting the very low temperature end of the resulting future temperature distribution.

Similarly the upper end of a limited number of TCR distributions may not be well sampled. In these cases the cumulative probability of exceeding very high temperatures may fall short of reducing to zero. Where this is case the cumulative probability of the unsampled portion of the distribution is very small (see Figure 8 for TCR values over 3 °C), but some caution should be taken in interpreting the extreme few percent of the highest projected temperatures in these cases.

Finally we also choose to increase the number of ECS bins to ensure that the varying TCR distributions from AR5 are well sampled. The size of the ECS bin size is therefore reduced to 0.1 °C.

Each model variant (which has a particular value of TCR that depends on the combination of ECS and K) is then run for the range of emission scenarios of interest while also sampling uncertainty in carbon cycle feedback strength as in CCC08. The TCR derived weighting, which is taken from published distributions presented in the AR5, is multiplied by the appropriate carbon cycle weighting to give a total weighting for each model variant. Weightings for ECS and K are therefore not applied in the new TCR constrained results.

### 4.2 Illustrative results from TCR approach

To compare the TCR constrained approach with the ECS and K constrained approach used in CCC08 we first diagnose the TCR implied by the choices of ECS and K used in CCC08 using model runs in which $CO_2$ concentration is increased at 1% per year. This is shown in Figure 8 along with TCR distributions from AR5.

The implied distribution is in the upper half of the distributions, but is not an outlier compared to those of AR5. This is in keeping with the relatively high value of the underlying ECS distribution relative to those of AR5.

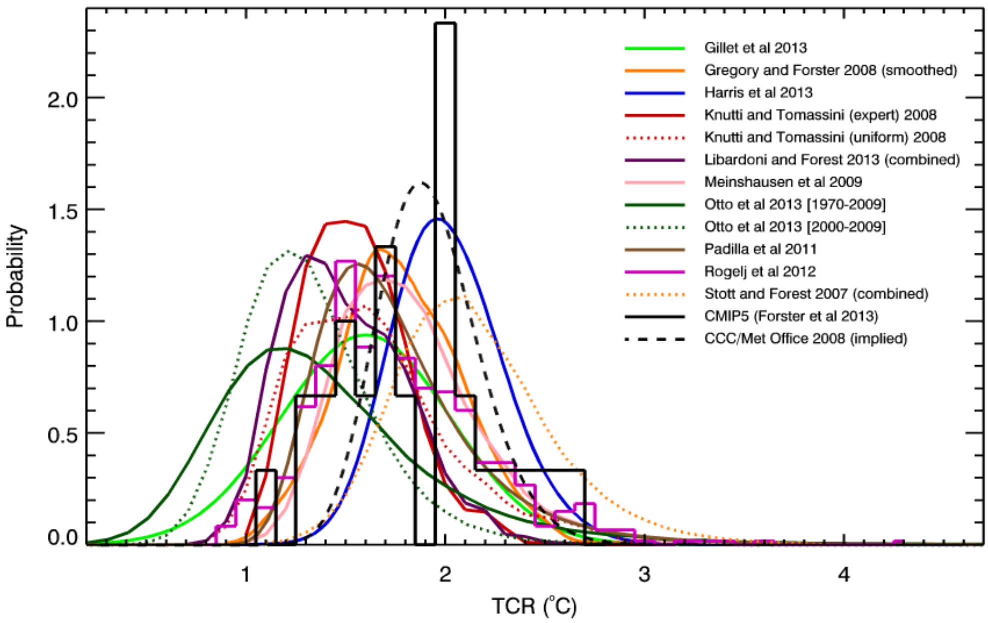
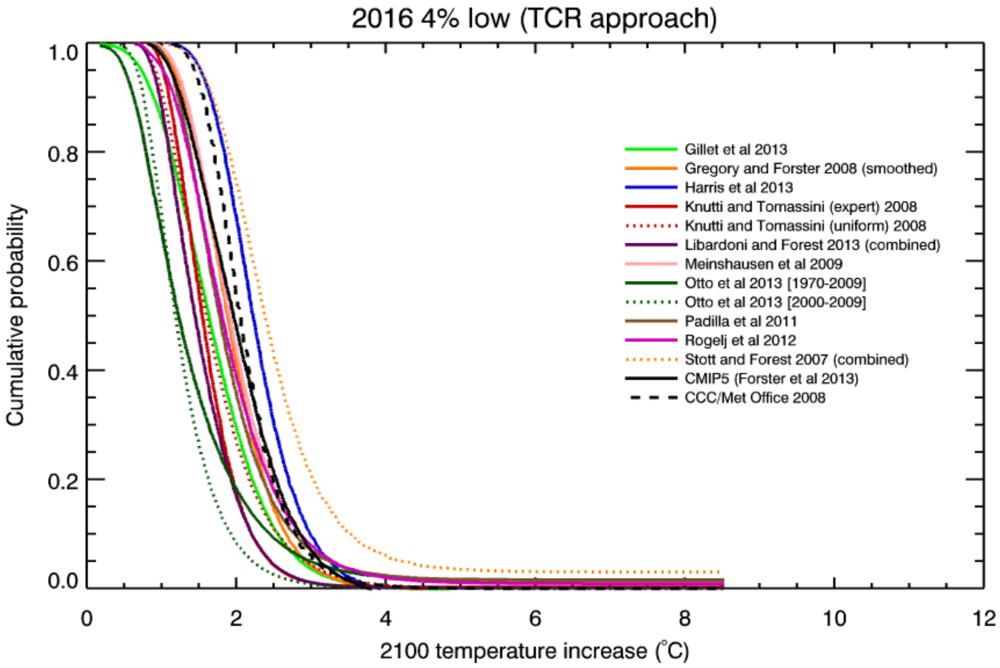



**Figure 8: Distributions of Transient Climate Response (TCR) shown in AR5 along with the implied TCR distribution of the CCC08 study.**

Projected climate outcomes from the TCR-constrained approach were then derived for the emissions pathways of interest. Figure 9 shows the results for a mitigation case and Figure 10 for our baseline scenario. The corresponding plots for the ECS approach are also repeated from Figures 5 and 6 for comparison.

Despite the different approaches to sampling uncertainty, the two methods produce largely similar ranges of projected climate change. In particular, the spread of median warming is fairly similar for both the TCR and ECS approaches when the outlier (Olsen et al., 2012) is excluded from the ECS cases. Differences are more evident in the upper tails of the distributions. For instance, in the mitigation pathway case, the spread of probability covering warming in excess of 3 °C is somewhat greater in the ECS case. The CCC08 case is shown for comparison.



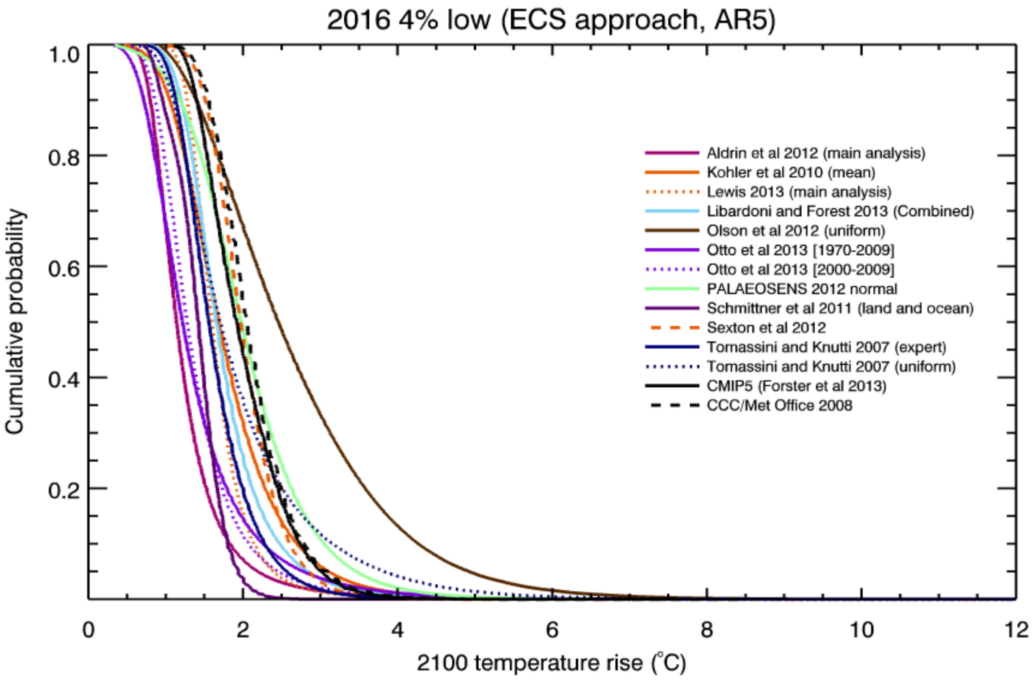




**Figure 9: Projected warming in 2100 using the TCR approach for a mitigation scenario ("2016 4% low" - see CCC08 for details). Cumulative probability of exceeding a given temperature is shown for the CCC08 modelling (black dashed) against projections made using TCR distributions from AR5 (top). For comparison the corresponding projections using the ECS approach with distributions from AR5 are repeated from Figure 5 (bottom).**

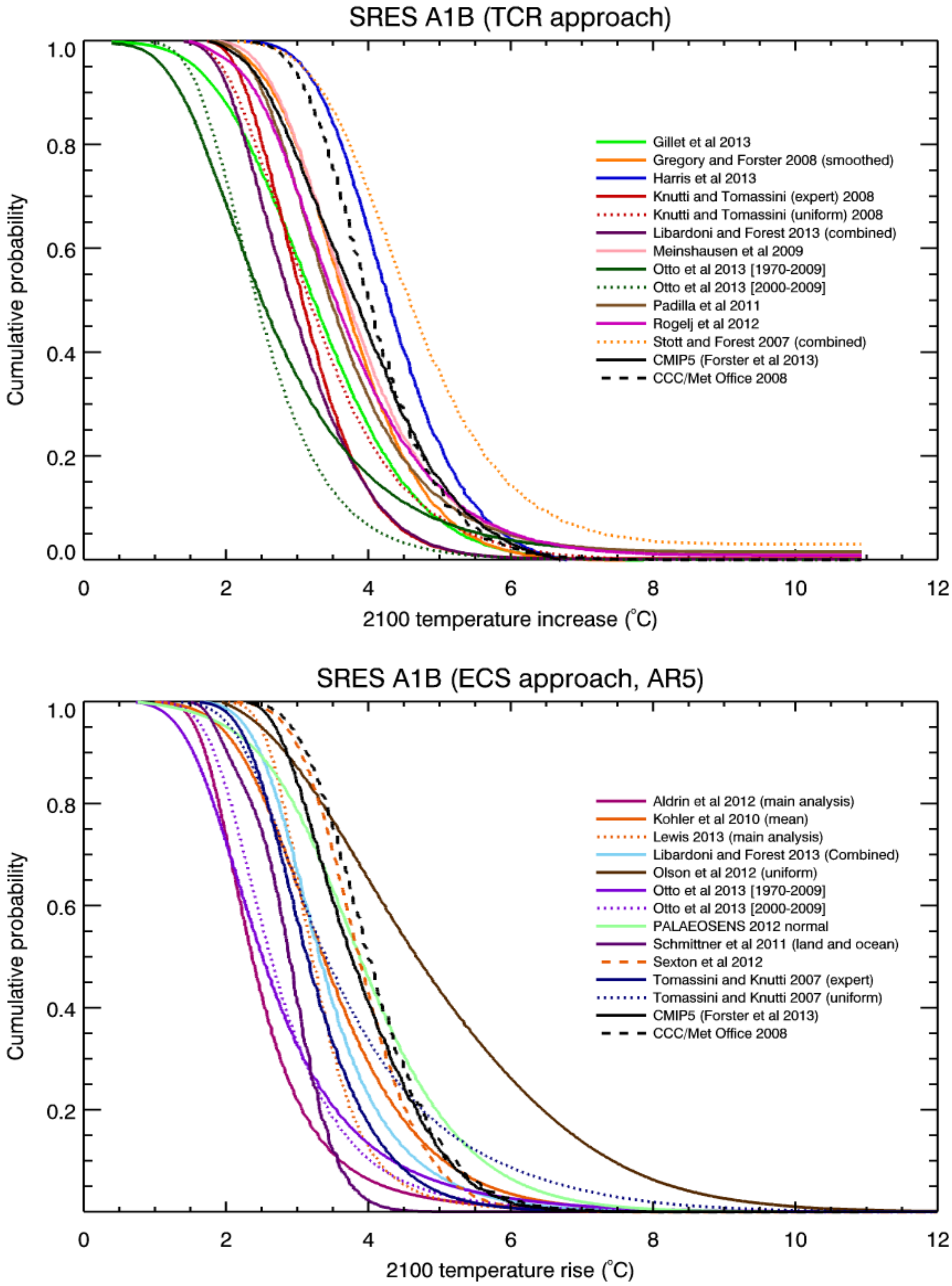



**Figure 10: Projected warming in 2100 using the TCR approach for the A1B baseline emissions scenario. Cumulative probability of exceeding a given temperature is shown for the CCC08 modelling (black dashed) against projections made using TCR distributions from AR5 (top). For comparison the corresponding projections using the ECS approach with distributions from AR5 are repeated from Figure 6 (bottom).**

A more direct comparison of the TCR and ECS constrained approaches is made possible by the fact that some studies reported in AR5 make available consistent probability distributions of both TCR and ECS. Figure 11 shows projections for the baseline emissions scenarios for these cases.

Clearly the differences between each approach for a given study (TCR constraint vs. ECS constraint) are systematically smaller than the differences between independent studies. From this figure there is no clear indication that the TCR approach gives projections that are significantly more tightly constrained than the ECS approach (which involves the additional assumption regarding the distribution of K). However, with the limited numbers of studies available providing both ECS and TCR distributions this cannot be robustly assessed here. Further investigation of this issue would be useful.

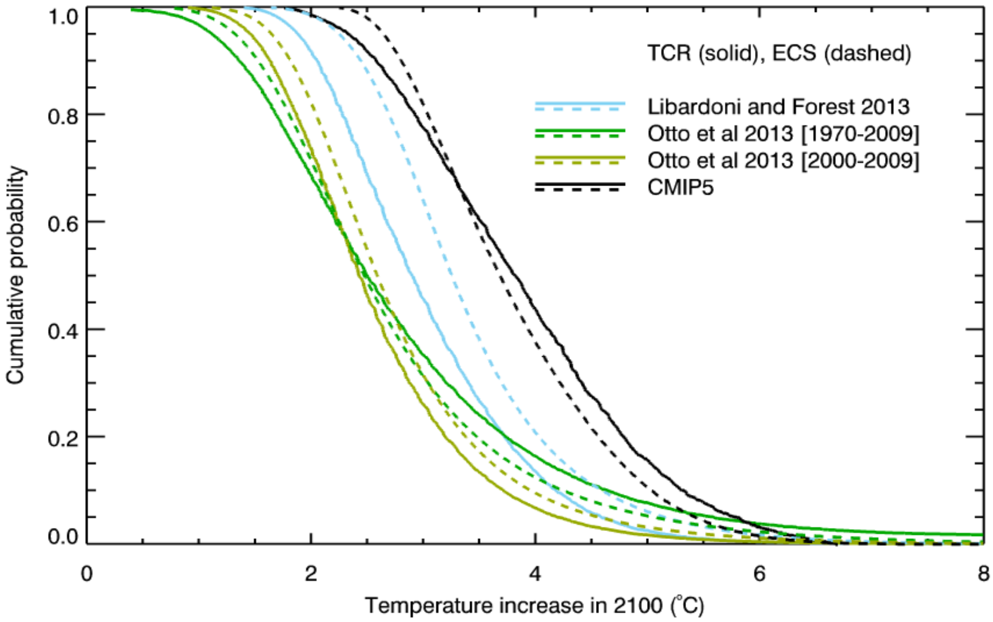



**Figure 11: Projected probability of exceeding given temperatures in 2100 for the A1B baseline emissions scenario using the ECS (solid) and TCR (dashed) approaches for studies where both are estimated.**

## 5. Emerging Earth system feedbacks

A number of known processes in the Earth system are able to alter the concentration of greenhouse gases in the atmosphere as the climate changes. For instance, high-latitude warming is thawing permafrost areas which may lead to enhanced emissions of $CO_2$ and $CH_4$. Consequently, Earth systems processes and feedbacks may have an impact on the allowable emissions for a given climate target. Uncertainty in Earth system feedbacks should be combined with those from other sources, such as those expressed by TCR and ECS that represent the uncertainty in the relationship between radiative forcing and warming.

Recently many more Earth system feedbacks within the climate system have received specific study. While the scientific understanding and modelling ability of many of these areas is still at a relatively early stage, it has progressed to a point where an initial tentative estimate can be made on the temperature response and the uncertainty from Earth system processes compared with that from the choice of TCR or ECS.

IPCC AR5 has extended the methodology of Arneth et al (2010) to characterise many Earth system feedbacks in terms of the additional radiative forcing that occurs per degree of increase in the global average surface temperature. AR5 attributed “low confidence” in quantification of most of these feedbacks.

## 5.1 Application

Here we include the effects of feedbacks shown in the lower portion of Figure 6.20 of WG1 of AR5 (reproduced in Figure 10). Carbon cycle feedbacks are treated as in CCC08. The additional Earth system feedbacks are not explicitly modelled in this study but are applied as an additional forcing per degree of warming; providing a first look at their effect.

Many of the Earth system feedbacks discussed in AR5 contain substantial uncertainties, with some estimates varying by more than an order of magnitude. In at least one case even the sign of the feedback as well as its magnitude is uncertain, and several feedbacks have only a single estimate of their magnitude. To take account of the wide range in strength estimates of the feedbacks and the varying amount of information available on each feedback, the cumulative total magnitudes of these feedbacks are calculated in two different ways.

Firstly the sum of the minimum values of each feedback is calculated along with the sum of the mean, and sum of the maximum values. This estimates the extreme range of all the feedbacks considered. Second, values were also calculated by adding all the minimum values (and mean and maximum) in quadrature but this results in only a small difference. Given the highly uncertain nature of these emerging areas of research we choose to retain the larger range from the simple summation of feedbacks strengths.

Although it is currently considered very unlikely that the actual values of all feedbacks would be at the minimum (or maximum) of the estimates documented in AR5, in lieu of any robust probability information to the contrary we retain the sums of minimum (and maximum) magnitudes as illustrative of a range of possible total feedback strength.

It is also noted that may of the estimates of feedback strength in figure 12 consist of only a limited number of data points. To examine the impact that the less well studied feedbacks may have on projections, feedback strengths (minimum, mean and max values as before) were also calculated including only feedbacks where there are at least 3 data points in figure 12. This consisted of the 3 feedbacks; permafrost; $CH_4$ emissions from wetlands, and ; the climate affect on $CH_4$ lifetimes. Results from applying the combination of these 3x feedbacks were found to be very similar to those from using all feedbacks in Figure 12, so while projections from both sets are provided in the accompanying datasheet, only the results from combining all feedbacks are discussed here.

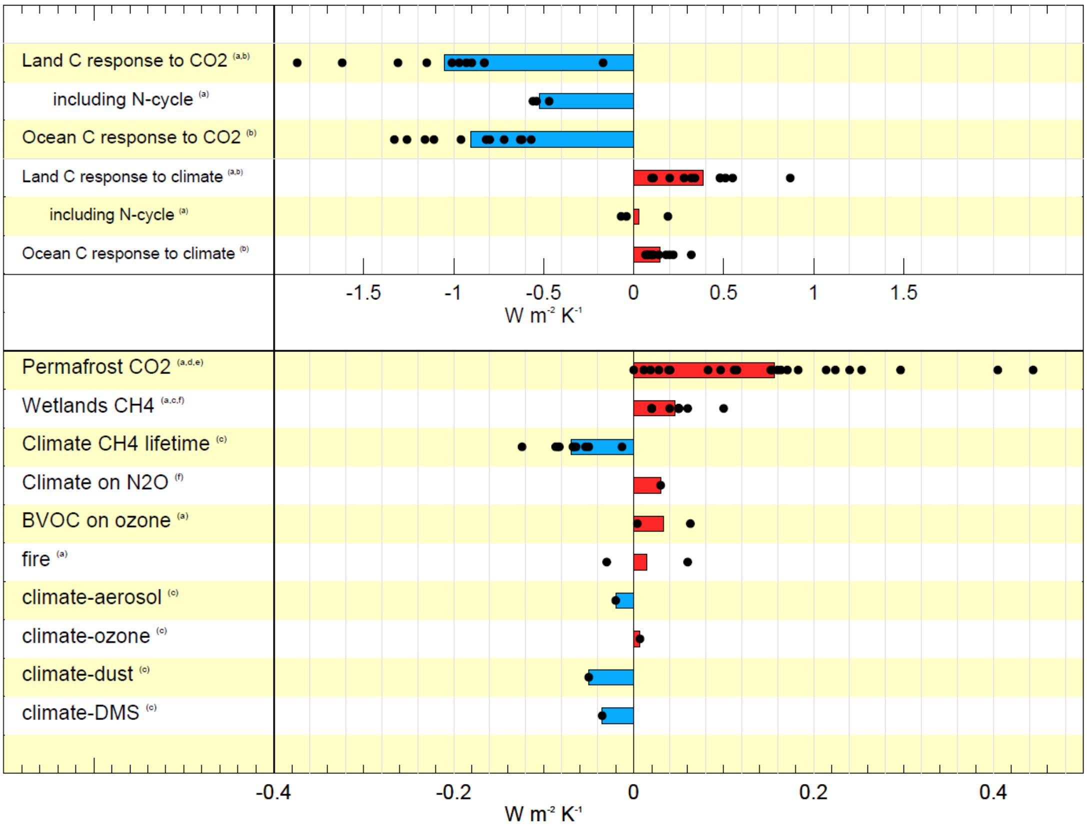



**Figure 12: Estimated feedbacks strengths estimated in AR5. Reproduced from Figure 6.20 of the IPCC Fifth Assessment report, WG1. The feedbacks in the lower portion of the figure are examined here while carbon cycle (C response) feedbacks are already explicitly included in the modelling framework**

## 5.2 Illustrative results

Figure 13 illustrates the impacts of the additional Earth system feedbacks on the temperature increase in 2100 under three scenarios; “2016 4% low”; “2030 10% low” and the A1B baseline scenario. These are calculated using the TCR approach and assuming two different TCR distributions. The first is from Otto et al (2013) based on 2000-2009 data, which as Figure 8 shows, gives a greater likelihood of lower values than many other estimates. The second is the combined distribution from Stott and Forest (2007) which gives a greater likelihood of higher values than many other estimates. The inclusion of the Earth system feedbacks leads to increased chance of exceeding temperature limits in 2100. For example in “2030 10% low” using the Otto et al (2013) distribution there is up to a 45% chance of exceeding 2 °C in 2100, compared to 10% without the feedbacks included. Whilst the spread in median warming is less than that due to choice of ECS or TCR distributions, it is still significant and efforts should be made to reduce it.

While these results are illustrative of the potential impacts of emerging science around earth system feedbacks, it is noted that the combination of feedbacks from many sources may lead to projected temperatures, particularly at the upper end of the feedbacks assessed, that may be beyond the range over which each feedback has been assessed in individual studies. The applicability of the linear formulation of feedbacks in AR5 (Figure 12) at such high temperatures is a topic of ongoing research.

Projected temperature changes in 2100 for the new scenarios and alternative modelling approaches outlined in this report are available in the accompanying data file.

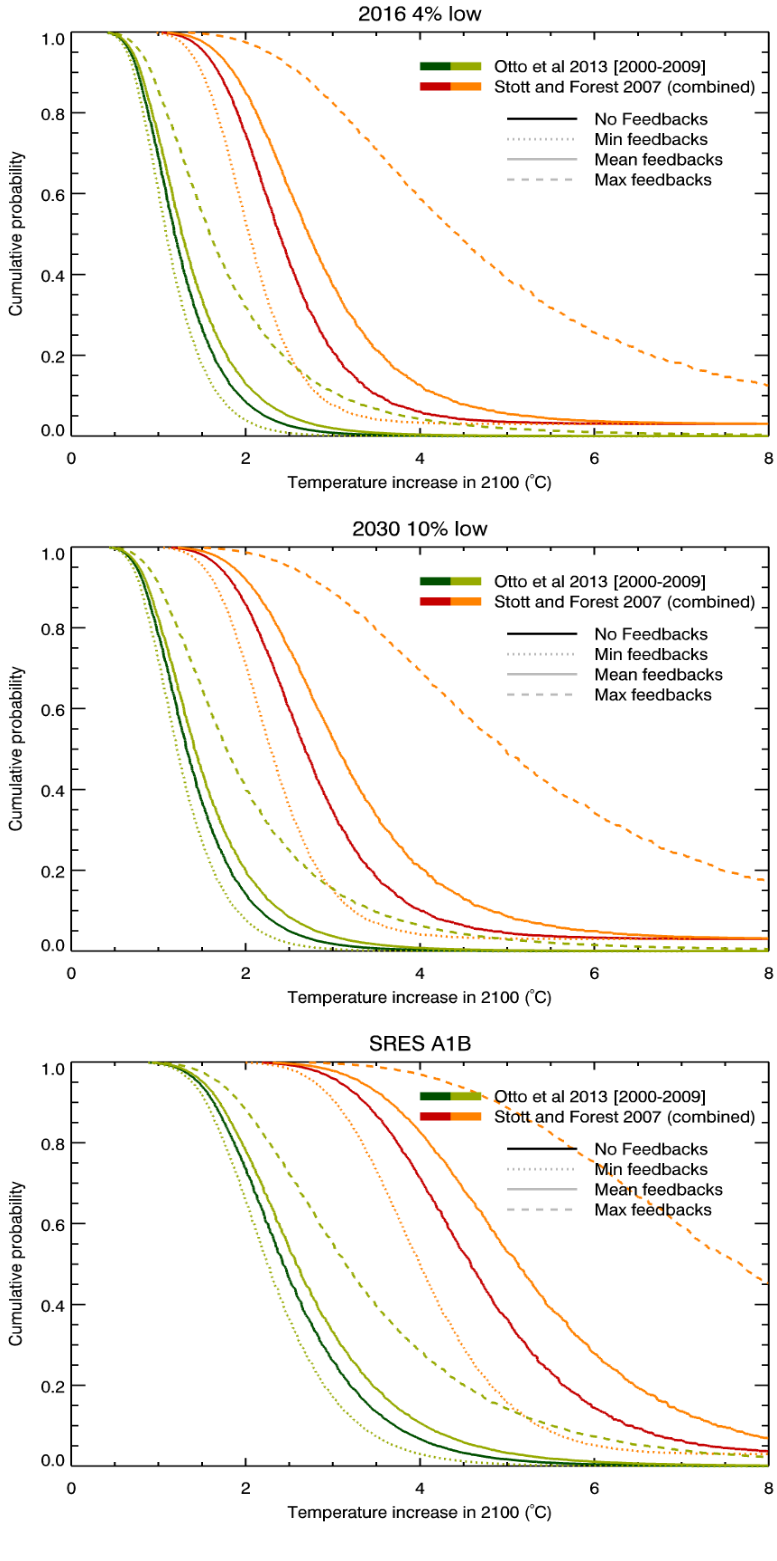



**Figure 13: Projected cumulative probability of exceeding temperatures increase in 2100 using the TCR approach (dark green and red respectively) for the TCR distributions of Otto et al (2013) based on 2000 to 2009 and the Stott and Forest (2007) combined distribution. Impacts of additional feedbacks on projections are also shown (light colours – green and orange). Three scenarios are shown; "2016 4% low" (top); "2030 10% low" (middle); "A1B baseline" (bottom). Where the temperature goes above around 4 to 6°C the results with additional earth system feedbacks should be treated with caution because this is likely to be going beyond the temperatures in the experiments reported in Figure 12 and from which the feedback strengths were estimated.**

## 6. Summary

New research has been carried out to assess the impact of using recently published estimates of the uncertainty in ECS and TCR on future warming under a baseline scenario with no explicit climate mitigation policy, and a range of mitigation pathways. The results illustrate that ECS and TCR still make a major contribution to the uncertainty in climate response for a given set of emissions. The differences between using TCR as a constraint and using ECS plus ocean diffusivity as dual constraints is typically less than the differences between using alternative ECS or TCR distributions. The earlier CCC08 study is found to be at the higher end of median warming, although is not an outlier. In the upper tail of the distribution of projected warming the CCC08 study in nearer to the centre of the range of estimates that can now be made using the same emissions as input.

A first look at the combined effect of additional Earth system processes on 21st century warming shows that these terms have the potential to make an important additional contribution to the total uncertainty in climate response. It should however be noted that IPCC AR5 has only low confidence in these feedback estimates at the present time. The simplicity of the approach means that the higher temperature cases should be used with caution.

Figure 14 summarises the spread in projected warming by 2100 from the different sources of uncertainty considered for the “2016 4% low scenario” from CCC08. It is important to recognise that the ECS or TCR uncertainty, carbon cycle uncertainty and uncertainty in the additional Earth system processes combine to give a total uncertainty range that remains sizeable. One immediate conclusion is that attempting to constrain the likelihood of the higher estimates of earth-system feedback strength is a priority. Furthermore, work to further understand the reliability of the simple approach we have used here and its traceability to more complex models is needed.

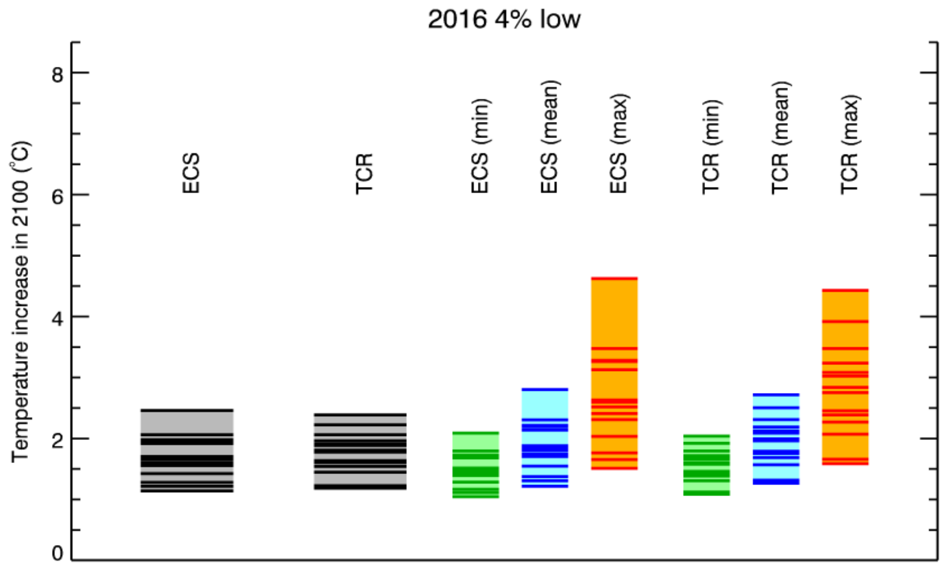



**Figure 14: Median 2100 temperature increases for the “2016 4% low” scenario from CCC08. Grey bars on left show the range of median warming using TCR and ECS distributions from AR5 with the darker lines indicating the individual projections from the different distributions. Similarly shown are projections accounting for new feedbacks in the Earth system when using both the TCR and ECS**

**approaches as the sum on the minimum estimates (min), best estimates (mean) or maximum estimates (max) from studies included in AR5.**

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