Deviations from linearity in quantifying global climate response, feedbacks and forcings

David J. Long · Matthew Collins

Received: date / Accepted: date

Abstract Experiments with abrupt CO$_2$ forcing allow the diagnosis of the response of global mean temperature and precipitation in terms of fast temperature independent adjustments and slow, linear temperature-dependent feedbacks. Here we compare responses, feedbacks and forcings in experiments performed as part of version 5 of the Coupled Model Inter-comparison project (CMIP5). The experiments facilitate, for the first time, a comparison of fully coupled atmosphere-ocean general circulation models (GCM’s) under both linearly increasing and abrupt radiative forcing. In the case of a 1% per year compounded increase in CO$_2$ concentration, we find that the non-linear evolution of surface air temperature in time, when combined with the linear evolution of the radiative balance at the top of the atmosphere, results in a feedback parameter and effective climate sensitivity having an offset compared to values computed from abrupt 4xCO$_2$ forcing experiments. The linear evolution of the radiative balance at the top of the atmosphere also contributes to an offset between the global mean precipitation response predicted in the 1% experiment using linear theory and that diagnosed from the experiments themselves, and a potential error between the adjusted radiative forcing and that produced using a standard linear formula. The non-linear evolution of temperature and precipitation responses are also evident in the RCP8.5 scenario and have implications for understanding, quantifying and emulating the global response of the CMIP5 climate GCMs.

Keywords CMIP5 · Feedbacks · Forcing · Response

D.J. Long
Exeter Climate Systems, College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, UK, EX4 4QF.
E-mail: D.J.Long@ex.ac.uk

M. Collins
Exeter Climate Systems, College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, UK, EX4 4QF.
E-mail: M.Collins@ex.ac.uk
1 Introduction

The existence of global climate model (GCM) experiments with instantaneous or abrupt CO$_2$ forcing has led to the development a linear framework to understand the global climate system in terms of fast-responses to radiative forcing and slow temperature-dependent feedbacks (Gregory et al, 2004; Gregory and Webb, 2008; Andrews et al, 2009; Lambert and Allen, 2009; Good et al, 2011). In the case of global mean temperature, the fast-response arises because of the rapid adjustment of stratospheric temperatures but also because of changes in cloud cover which can affect the top-of-the-atmosphere (TOA) net radiative balance (Andrews and Forster, 2008; Andrews et al, 2012; Colman and McAvaney, 2011). The slow temperature-dependent feedbacks are associated with the surface black-body response, the water-vapour feedback, snow and sea-ice albedo feedbacks and cloud feedbacks which remain the largest uncertainty in determining the magnitude of the response (Colman, 2003; Soden and Held, 2006; Webb et al, 2006). In the case of global mean precipitation change, the stabilisation of the atmospheric temperature profile leads to a near instantaneous reduction in global mean precipitation when CO$_2$ is abruptly increased, followed by an increase in precipitation which is tied to the tropospheric energy balance and is found to be approximately linear in temperature (Lambert and Webb, 2008; Andrews et al, 2009).

Previous studies have exploited abrupt forcing experiments to diagnose temperature and precipitation feedbacks but have mainly analysed the response of atmospheric GCMs coupled to simple slab/mixed layer oceans (Andrews et al, 2009; Gregory and Webb, 2008; Lambert and Webb, 2008). Such analyses has recently been extended to an ensemble of fully coupled atmosphere-ocean CMIP5 GCMs using abrupt CO$_2$ forcing experiments (Andrews et al, 2012). In the case where abrupt or equilibrium forcing experiments have been compared to more gradual forcing experiments with fully coupled GCMs, the comparison is complicated by the mixing of slab-ocean and fully coupled models (Stouffer and Manabe, 1999; Kiehl et al, 2006; Yokohata et al, 2008). Previous work by Yokohata et al (2008) has pointed to sea-ice and clouds as causes of differences between slab and coupled-GCM responses, which is unsurprising as both projections of sea-ice and the distribution of SSTs, which have a leading-order impact on the distribution of clouds in tropical regions, differ significantly between those types of GCMs. In cases where abrupt and gradual forcing experiments have been performed using the same GCM, the analysis has been limited to one GCM version (Good et al, 2011). A systematic comparison of the abrupt response of GCMs with dynamical ocean components with the response of the same GCMs to more gradual radiative forcing has not been possible to date. The existence of a set of experiments defined as part of the CMIP5 protocol (Taylor et al, 2007) analysed here, facilitate such a systematic comparison. For example, Good et al (2012) have used the abrupt experiments to extend their Good et al (2011) step-function approach to emulate the response of a number of CMIP5 scenario experiments.
Here we compute the feedback coefficients for temperature and precipitation from the abrupt experiments with those estimated from experiments with 1% compounded CO$_2$ increase, as were performed for previous incarnations of CMIP, and investigate the assumptions of the linear framework when used to describe global climate change. We note here that we do not consider long-term variations in feedbacks which occur at high CO$_2$ concentrations or after many centuries of global warming, and may depend themselves on the magnitude of the global temperature response (Senior and Mitchell, 2000; Williams et al., 2008) but focus on feedback variations appropriate for characterisation of climate change in the coming decades.

2 Linear Theory

Let $T$ be the global mean temperature change computed from a GCM climate change experiment, expressed as an anomaly with respect to a long, stable control simulation. $N$ is the net TOA radiative imbalance diagnosed from the experiment (positive downward) and $F$ is the radiative forcing. We write the standard formula (Gregory et al., 2004)

$$N = F + \alpha T,$$

where $\alpha$ is the climate feedback parameter. We adopt a sign convention such that a negative $\alpha$ indicates a negative feedback (the planet radiates more energy to space as it warms). If $F_{2X}$ is the radiative forcing for a doubling of atmospheric CO$_2$, then $\text{CS}= -F_{2X}/\alpha$ is the effective climate sensitivity (Murphy et al., 2004).

The linear theory encapsulated in equation 1 has proved useful in diagnosing global-scale feedbacks in GCMs in many different applications. It provides a simple leading-order way of partitioning forcing, feedback and response. However, in cases where equation 1 breaks down, it may be hard to diagnose if this is due to non-linearities in the evolution of the forcing, the feedback or the response, without further diagnostics. The term ‘non-linear’ is often taken to imply a dependence of the feedback parameter, $\alpha$, on climate state. However, we adopt a more general definition of non-linearity as meaning a breakdown in the validity of equation 1. As detailed below, this general definition of non-linearity occurs when variables in equation 1 have different time-dependent characteristics, i.e. all variables display linear evolution in time while one displays non-linear evolution in time. We refer therefore to ‘non-linear-in-time’ to clarify the use of this definition.

For GCM experiments involving a step increase in radiative forcing applied instantaneously and subsequently held fixed, both $\alpha$ and $F$ may be computed via regressing $T$ against $N$. The slope of the linear fit gives $\alpha$ and the intercept may be interpreted as the radiative forcing $F$ (Gregory et al., 2004; Andrews et al., 2012). Under such an approach, which we refer to as the “regression method”, estimates of $F$ (sometimes referred to as the “adjusted radiative forcing”) include the influence of any processes happening on shorter time
scales than those used to average GCM responses (Williams et al., 2008). If annual-mean responses are used for regression then \( F \) includes the effects of stratospheric adjustment, rapid changes to tropospheric cloud cover and land-surface adjustment (Gregory and Webb, 2008; Andrews et al., 2012). Using the regression method, if the step increase in radiative forcing is a doubling of CO\(_2\) concentration, then the value of CS is simply given by the \( T \) intercept (Gregory et al., 2004).

For transient climate change experiments, if time varying values of \( N, F \) and \( T \) are known, it is possible to diagnose a value of \( \alpha \) at any point during the integration using equation 1 (Gregory and Mitchell, 1997; Murphy, 1995; Raper et al., 2002; Senior and Mitchell, 2000), i.e.

\[
\alpha = \frac{\bar{N} - \bar{F}}{\bar{T}}, \tag{2}
\]

where the overbar indicates some time averaging to smooth out the noise of natural internal variability. For this study we use the common approach of 20 year averages. Subsequent values of CS can then also be diagnosed at any point during the transient experiment, and has been interpreted as the response to 2xCO\(_2\) forcing that would occur if the GCM was run to equilibrium with \( \alpha \) held fixed at values diagnosed for each specific time, as long as an estimate for \( F_{2x} \) is provided. We shall refer to this method of diagnosing CS as the “averaging method”. While previous studies have diagnosed \( F_{2x} \) for transient climate change experiments using off-line radiation calls, e.g Forster and Taylor (2006), here we make use of the CMIP5 experimental design and calculate the adjusted forcing \( F_{2x} \) directly for each GCM using the above regression method and the abrupt CO\(_2\) forcing experiment (described below). Since we are investigating transient climate change experiments with a 1\% compound increase in CO\(_2\) (again, see below), as in Good et al (2012), we use values of \( F_{2x} \) from each independent GCM to determine the time series of \( F \) for such experiments. Here we assume that radiative forcing increases linearly in time under a 1\% compound increase in CO\(_2\), since forcing is accurately known to depend logarithmically on CO\(_2\) concentration (Myhre et al., 1998), and is thus given by,

\[
F_y = (y/70)F_{2x}, \tag{3}
\]

where \( y \) is the year of the 1\% compound increase experiment.

A linear framework approach has been developed for the response of the global mean precipitation, \( P \) (Lambert and Allen, 2009),

\[
LP = k_T T + R, \tag{4}
\]

where \( L \) is the latent heat of fusion of water, \( k_T \) is the hydrological sensitivity parameter and \( R \) is a parameter which describes the fast response of the hydrological cycle to an imposed radiative forcing. \( R \) is dependent on the type of forcing and is negative for greenhouse gases and absorbing aerosols (Andrews et al., 2010; Lambert and Allen, 2009). In the case of a GCM experiment in which the radiative forcing from a greenhouse gas is instantaneously
applied and held constant, the coefficients of equation 4 may be calculated using a regression approach akin to that describe above for \( T \). In experiments in which both the radiative forcing and temperature response vary with time, separating the fast response from the temperature-dependent feedbacks is not possible.

In addition to using equation 1 to diagnose the magnitude of feedbacks in climate change experiments, the formula may also be re-arranged to compute the radiative forcing in experiments with SRES or RCP forcing (for example Forster and Taylor (2006)). The assumptions being that feedback parameter, \( \alpha \), remains constant. \( T \) and \( N \) are taken from the GCM experiment and \( F \) is calculated as \( N - \alpha T \).

3 CMIP5 Models and Experiments

This study uses CMIP5 output from those GCMs shown in table 1. All GCMs consist of an atmospheric component coupled to a dynamical ocean with land surface schemes of various complexity. Some GCMs include earth-systems processes associated with carbon cycle feedbacks and chemistry but all the experiments examined here are driven by CO\(_2\) concentrations not emissions. Two idealised experiments are analysed, involving an abrupt quadrupling and 1% per year compound increase in CO\(_2\) concentration, referred to as “Abrupt4xCO2” and “1pctCO2” respectively, initiated from a control run with CO\(_2\) held at pre-industrial levels (Taylor et al, 2007). We take one initial-condition ensemble member per GCM. The response to increased CO\(_2\) is determined from the global annual-mean difference between experimental fields and corresponding control runs for each GCM. Control drift is judged to be small for all the GCMs and variables examined and hence no de-trending is performed. In addition, the responses from the 21st-century under the RCP8.5 experiment are also analysed and compared to those from the 1pctCO2 experiment. Since, at the time of writing, some modelling groups have not yet archived Abrupt4xCO2, 1pctCO2 and RCP8.5 output, there is not a complete match between the GCMs used in the analysis of all experiments.

4 Temperature Response

An example of \( T \), \( P \) and \( N \) response in the abrupt 4xCO\(_2\) and 1% experiments from the MIROC-ESM GCM are shown in figures 1 (a) and (b) respectively. The linear relationship between \( T \) and \( N \) in the abrupt experiment allows the calculation of \( \alpha = -0.88 \pm 0.07 \) W m\(^{-2}\) K\(^{-1}\) and \( F_{2x} = 4.18 \pm 0.21 \) W m\(^{-2}\) using the regression method described above, as shown in figure 1 (c). Here responses for the abrupt experiment have been divided by 2 to achieve an estimate of forcing applicable to 2xCO\(_2\) conditions (Gregory and Webb, 2008). Using the above estimates of \( \alpha \) and \( F_{2x} \), the effective climate sensitivity of MIROC-ESM calculated from linear regression is therefore 4.56 ± 0.48 K (uncertainties quoted...
above and subsequently are the 5-95% uncertainties bounds). The correlation
in figure 1 (c) is $R=0.95$, proving that here a linear relationship between
$N$ and $T$ is a good approximation under such abrupt quadrupling of CO$_2$

Figure 2 details the time varying CS of the MIROC-ESM model when the
averaging method (eq. 2) is applied by stepping forward year-by-year through
the 1% per year increase and abrupt CO$_2$ quadrupling (scaled to 2xCO$_2$) time
series responses of $T$ and $NS$. As noted above, a 20 year running mean was
applied to all data before values of CS were calculated. Time dependent val-
ues of $F$ for the 1% experiment are calculated from equation 3, while for each
year of the abrupt experiment the value of $F_{2x}$, calculated from the regression
method, is applied. From figure 2 we find that for the MIROC-ESM model the
values of CS calculated in the abrupt experiment are almost time invariant,
i.e. the value of $\alpha$ does not depend on climate state, and are consistent with
the value obtained using the regression method (also plotted). However, it is
clear from figure 2 that CS values calculated from the 1% experiment are con-
sistently smaller than those calculated from the abrupt experiment, although
uncertainties in estimates do overlap. Moreover, as detailed in figure 3(b), this
negative bias is seen in the majority of CMIP5 GCMs when comparing aver-
aging method estimates of CS from both the 1% and abrupt experiments at
the time of CO$_2$ doubling in 1% run (year 70).

Good et al (2011) have formulated a linear step-response simple climate
model to estimate the response to a time-series of annual changes in radiative
forcing. It is assumed that the total response to a series of forcing changes
are equal to the sum of the individual annual responses and that such an-
ual responses scale linearly with the magnitude of forcing change, referred to
as the step-response (SR) linearity assumption. Using the Met Office model,
HadCM3, Good et al (2011) highlight the breakdown of the SR linearity as-
sumption via investigation of the strength of atmospheric feedbacks following
an abrupt doubling and quadrupling of CO$_2$ concentration. They found that
the net feedback is weaker under 4xCO$_2$ forcing compared to 2xCO$_2$, where at
the TOA there is a decrease in the long-wave radiative feedback partly offset
by the short-wave. Such weaker magnitude net feedback (large magnitude CS)
under higher forcing may be consistent with our results presented in Figure 3
(a) and (b) although proof of such agreement would need to be tested with
abrupt 2xCO$_2$ experiment performed with all the CMIP5 models.

Instead we attribute the differences found in figure 3 (a) and (b) to devia-
tions from linearity in equation 2. The response of the TOA fluxes, $N$ in the
1% experiments are judged to be linear-in-time using a simple test of auto-
correlation of residuals from a linear fit (figure 4). Linearity in the evolution
of $T$ response is rejected for all of the CMIP5 GCMs. As can be seen in figure
1 (b), the $T$ response for the MIROC-ESM model has a curved shape with a
shallower slope in the early part of the experiment which steepens with time.
Because the response of $N$ is linear in time for the 1% experiments, but the
response of $T$ is not, the estimate of the feedback parameter and effective
climate sensitivity varies with time.
This non-linear behaviour of global mean surface temperature with time can be replicated by representing the ocean as a simple heat diffusivity term in a 1-d model of the climate system (Huntingford and Cox, 2000). We can construct a simple “one-box” heat balance model which solves the following heat conduction equation,

$$
\frac{\partial T}{\partial t} = c_p \frac{\partial^2 T}{\partial z^2}.
$$

Here $T$ is the change in globally averaged surface temperature, $c_p$ is the volumetric heat capacity of sea water ($JK^{-1}m^{-3}$), $\kappa$ is the effective thermal diffusivity ($Wm^{-2}K^{-1}$) and $z$ is the depth into the ocean. Assuming that all TOA radiative imbalance is absorbed into the ocean, equation 5 may be solved for each CMIP5 GCM over an ocean depth of 5000 m (vertical resolution 100 m) using an implicit numerical scheme with an annual time-step. Transient heat flux boundary conditions at the ocean surface are obtained using equation 1,

$$
N = F + \alpha T = -\kappa \frac{\partial T}{\partial z}.
$$

We assume linear forcing in time for the 1% experiment, with both $F_{2x}$ and $\alpha$ diagnosed from the corresponding abrupt forcing experiment for each GCM (figure 3(a)), and subsequent times series of $F$ in equation 6 via equation 3. For each GCM values of $\kappa$ are optimised via reducing the root mean square (rms) error between surface temperatures calculated via equation 5 and those output from the 1% experiment (not shown). Optimised values of $\kappa$ range between 140-610 $Wm^{-2}K^{-1}$ across the ensemble, with an ensemble mean of ~280 $Wm^{-2}K^{-1}$. Figure 3 (e) shows the difference between global mean surface temperatures calculated via equation 5 and those from the 1% experiment, averaged over 20 years centred at the time of 2x$CO_2$ conditions. Here we find that the magnitude of differences ranges between ~0.01-0.17 K across the ensemble with an ensemble rms average of ~0.092 K, indicating that this simple global mean heat-diffusion model is capable of reproducing the non-linear evolution of $T$ under 1% compound increase in $CO_2$ forcing well. However we do find that, for the majority of models, the estimated temperatures when using the 1-d ocean model are slightly greater than corresponding GCM responses. Such overestimation of global surface temperature during this period of the 1% experiment was also found in Good et al (2012) using their step-response linear model (Good et al, 2011).

The non-linear evolution of the 1% $T$ response is reminiscent of the “cold-start” problem highlighted in Keen and Murphy (1997). However, it is not only a feature of the simplified 1% per year $CO_2$ increase experiment. Non-linear evolution $T$ responses are also seen the 21st-century response under RCP8.5 (figure 5) which are all launched from experiments with historical increases in greenhouse gases, plus aerosol and natural forcing. The non-linear response of $T$ with time not only has an impact on our understanding and quantification of climate change in simplified climate change experiments using the linear framework of equation 1, but may also effect our understanding, quantification
and ability to emulate the global response of the climate system under more policy-relevant scenarios.

5 Precipitation Response

As can be seen in figure 1(d) equation 4 provides suitable description of the global mean precipitation response for MIROC-ESM, where linear regression of $LP$ vs $T$ gives a hydrological sensitivity $k_t = 2.1 \pm 0.07 \text{Wm}^{-2} \text{K}^{-1}$ and a fast hydrological response of $R = -1.8 \pm 0.21 \text{Wm}^{-2}$ for the abrupt forcing experiment when scaled to 2xCO$_2$ conditions. (Expressed in terms of relative precipitation, the hydrological sensitivity is $2.54 \pm 0.32 \frac{\%}{\text{K}}$.) Following this approach, values of $k_t$ and $R$ under 2xCO$_2$ conditions are obtained independently for each CMIP5 GCM. Substituting such values into equation 4 and assuming the fast response ($R$) linearly scales with the annual increase in radiative forcing, for each GCM it is possible to obtain predictions of the precipitation response in the 1% run using $T$ responses from the same experiment. When taking 20 year averages centred about year 70 of the 1% experiment (2xCO$_2$ conditions) we find there is a bias between the predicted and actual GCM precipitation responses, with the predictions generally being lower than the GCM simulated values (figure 3(c)).

As with the $T$ response, the $P$ response is non-linear in time in the 1% experiments (figure 4) but, in many GCMs, not as non-linear in time as for $T$. The precipitation response is tied to the tropospheric energy balance which is determined by the sum of the net TOA radiative fluxes and the surface radiative plus sensible heat fluxes (adopting suitable sign conventions). Thus, the linear evolution of the net TOA fluxes, $N$ (i.e. the upper-boundary component of the tropospheric energy balance), causes the deviation of the $P$ response from the simple formula assumed in equ. 4. The surface component of the energy balance primarily displays a linear evolution in time (not shown) for most GCMs but shows some non-linear behaviour with time in other GCMs, warranting further investigation.

Both the results of Good et al (2011) and those from a more recent study (Good, P. et al. ‘A step-response approach for predicting and understanding non-linear precipitation response’, in preparation) have shown that under abrupt forcing experiments the hydrological sensitivity is dependent on the CO$_2$ concentration, where larger step changes in forcing have weaker values of $k_t$. Good et al (2011) suggest that such differences are related to different rates of long-wave cooling per unit K of warming seen under the varying CO$_2$ concentrations, highlighting the strong physical link between long-wave cooling and precipitation. Since we are estimating precipitation at 2xCO$_2$ conditions using the values of $k_t$ from the abrupt forcing experiment (divided by 2), it is possible that such an approach underestimates $k_t$ at 2xCO$_2$ and contributes to the biases between the predicted and actual GCM precipitation responses detailed in Figure 3 (c). However, as in the case of the temperature response,
testing this hypothesis would require a set of CMIP5-model abrupt 2xCO₂ experiments.

6 Adjusted Radiative Forcing

The non-linear behaviour of \( T \) in time, coupled with the linear evolution of \( N \) might also impact on the diagnosis of the adjusted radiative forcing (hereafter AF) using the method of Forster and Taylor (2006) (see section 2 above). Figure 3(d) shows a comparison of the AF at 2xCO₂ conditions in the 1% experiments, assuming a constant feedback parameter calculated from abrupt forcing experiment data using the regression method, with that obtained using the linear formula for \( F \) described by equation 3. The 2xCO₂ AF for many GCMs is smaller than that calculated using the linear formula, with an ensemble mean difference of 0.2 Wm\(^{-2}\) (around 5%). The 1% experiment has a similar magnitude and rate of radiative forcing as that seen in RCP8.5, and hence studies which attempt to estimate the AF using the Forster and Taylor (2006) method might contain similar magnitude errors. Although it may be hard to diagnose such errors unless independent estimates of the radiative forcing in a GCM simulation are available. Hence for many purposes, the AF would be a suitable approximation that may be used to highlight differences in forcing between GCMs and scenarios.

7 Emulation of RCP8.5 Response

To investigate the effect of non-linearity in time on a more policy-relevant scenario we emulate the annual global-mean surface temperature change under historical and RCP8.5 forcing. The forcing is estimated for each independent GCM is obtained using the Forster and Taylor (2006) method above, with values of \( \alpha \) again calculated from corresponding abrupt forcing output. These values of \( \alpha \) are also used in applying the boundary conditions of the simple 1-d model in equation 6. We are then faced with two choices in determining the values of \( \kappa \) in equation 5. We optimise \( \kappa \) values by using the 1-d ocean model to reproduce the surface temperature response of the 1% experiment, either assuming the standard linear formula (equation 3) or by assuming the adjusted radiative forcing for the 1% experiment calculated using the Forster and Taylor (2006) method. In the first case the simple 1-d ocean model can qualitatively reproduce the ensemble mean and inter-model spread (not shown) of the surface temperature response under RCP8.5 but differences in surface temperatures (1-d model estimate minus GCM response) averaged over years 2081-2100 primarily have negative biases (only NorESM1-M has a positive bias, with magnitude of 0.45 K), with an ensemble mean difference of -0.20 K. In the second case the emulation primarily produces negative temperature differences averaged over years 2081-2100, but with reduced magnitudes (an ensemble mean difference of -0.10 K). Such temperature biases are relative
small compared to the GCM RCP8.5 ensemble mean temperature response averaged over years 2081-2100 of (4.45 K) and small compared to ensemble spread. By accepting a non-linear-in-time forcing in the optimisation of \( \kappa \), we obtain a better emulation of the response of the CMIP5 models under RCP8.5 forcing.

8 Conclusions and Implications

The existence of the CMIP5 experiments analysed here has, for the first time, allowed a systematic comparison of the responses and feedbacks in abrupt radiative forcing and more gradual, linear radiative forcing in GCMs with dynamical ocean components. It is not surprising that, in the linear radiative forcing case of the 1% experiment, the global mean temperature response evolves in a non-linear way as this is what would be expected if the ocean acts to diffuse excess heat from the surface of the ocean to depth (equation 5). What is surprising is that the net TOA flux response, and by implication the rate of ocean heat uptake (expressed in Wm\(^{-2}\)), evolves linearly in time. This linear in time ocean heat uptake causes an offset between the feedback parameter and effective climate sensitivity calculated from the two different experiments, a breakdown in the validity of equation 1, and also adds a complication to the calculation of the expected global mean precipitation change and the adjusted radiative forcing.

This may seem like subtle point as, to first order, the spread of effective climate sensitivities in the CMIP5 GCMs is still much greater than the offset seen the in calculations based on the different experiments. Increasingly we use simple energy balance models to replicate the behaviour of more complex GCMs, for example to emulate the response of GCMs under different emissions scenarios for which simulations do not exist, or in probabilistic climate projection (Harris et al, 2006). Inputs to those models are often derived from the simplified-forcing experiments analysed here so this subtle point may need to be taken account of in such studies.

Acknowledgements This work was funded by the UK Natural Environment Research Council under the Changing Water Cycle Programme PAGODA project NE/I006524/1. We thank Theo Economou for advice on statistical matters. We acknowledge the World Climate Research Programme’s Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups (listed in Table 1 of this paper) for producing and making available their model output. For CMIP the U.S. Department of Energy’s Program for Climate Model Diagnosis and Inter-comparison provides coordinating support and led development of software infrastructure in partnership with the Global Organisation for Earth System Science Portals.

References


Table 1: Table of CMIP5 models and associated institutions.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Institute ID</th>
<th>Modelling Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCESS1.0</td>
<td>CSIRO-BOM</td>
<td>Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia</td>
</tr>
<tr>
<td>bcc-csm1-1</td>
<td>BCC</td>
<td>Beijing Climate Centre, China Meteorological Administration</td>
</tr>
<tr>
<td>CanESM2</td>
<td>CCCMA</td>
<td>Canadian Centre of Climate Modelling and Analysis</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0</td>
<td>CSIRO-QCCCE</td>
<td>Commonwealth Scientific and Industrial Research Organization / Queensland Climate Change Centre of Excellence, Australia</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>NOAA GFDL</td>
<td>NOAA Geophysics Fluid Dynamics Laboratory, USA</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>MOHC</td>
<td>Met Office Hadley Centre, United Kingdom</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td>INM</td>
<td>Institute for Numerical Mathematics, Russia</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>IPSL</td>
<td>Institute Pierre-Simon Laplace, France</td>
</tr>
<tr>
<td>inmcm4</td>
<td>MIROC</td>
<td>Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>MIROC</td>
<td>Max Planck Institute of Meteorology, Germany</td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>MIROC</td>
<td>Meteorological Research Institute, Japan</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>NCC</td>
<td>Norwegian Climate Centre</td>
</tr>
</tbody>
</table>
Fig. 1 Global mean analysis of output from MIROC-ESM experiments. (a) Time series of $T$, $N$ and $LP$ from the abrupt 4xCO$_2$ experiment. (b) The same fields from the 1% per year CO$_2$ increase experiment. (c) Annual mean $T$ vs $N$ (asterisks) for all 150 years of the abrupt experiment with corresponding linear fit (fitted parameters indicated). (d) Annual mean $T$ vs $LP$ (asterisks) from all 150 years of the abrupt experiment with corresponding linear fit (fitted parameters indicated).

Fig. 2 The effective climate sensitivity of the MIROC-ESM model estimated using the regression method (black dot) and using the averaging method on the abrupt 4xCO$_2$ experiment (black line with grey shading indicating 5-95% uncertainties) and from the 1% experiment (red line and red shading indicating 5-95% uncertainties). For averaging-method approaches, 20-year averages are employed. Error bars are calculated through combining uncertainties associated with both the linear regression parameters and natural variability of the control integrations, assuming Gaussian distributions.
Fig. 3 (a) Feedback parameter computed at the time of CO$_2$ doubling from the 1% per year CO$_2$ experiments (x-axis) vs the feedback parameter computed from the abrupt 4xCO$_2$ experiments using the regression method (y-axis). (b) Effective climate sensitivities derived from the feedback parameter estimates in (a) combined with 2xCO$_2$ forcing estimates from the regression method. (c) The estimated precipitation response multiplied by $L$ (y-axis) vs the actual precipitation response multiplied by $L$ from the 1% experiments (x-axis, see text for method). (d) Linear vs Adjusted (see text) values of forcing in 1% experiment under 2xCO$_2$ conditions. (e) Temperature responses from the 1% experiment vs values computed using equation 5 (see text) computed at the time of CO$_2$ doubling. Different models are denoted by different colours as indicated on the legend. Error bars indicate the 5-95% uncertainties calculated through combining uncertainties associated with both the linear regression parameters and natural variability of the control integrations, assuming Gaussian distributions.
Fig. 4 A diagnostic indicating the degree of departure from a linear fit for the global mean temperature $T$, the net TOA flux, $N$, and the precipitation, $P$, in the 1% per year CO$_2$ increase experiments (see legend). For each time series, the linear fit is found using least squares regression, forcing the slope to go through zero change in the first year of the experiment. The auto-correlation of the residuals between the linear fit and the experiment output are then calculated. The diagnostic shows the percentage of auto-correlations which fall outside the 5-95% uncertainties bounds expected by chance. Hence when the diagnostic is small, the fit is good and the response of the variable is close to linear-in-time. When the diagnostic is large, a linear fit is not a good description of the response of the variable.
Fig. 5 As figure 4 but computed from years 2005-2100 of the CMIP5 RCP8.5 scenario experiments.