Constraining the Ratio of Global Warming to Cumulative CO₂ Emissions Using CMIP5 Simulations*

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ABSTRACT

The ratio of warming to cumulative emissions of carbon dioxide has been shown to be approximately independent of time and emissions scenarios and directly relates emissions to temperature. It is therefore a potentially important tool for climate mitigation policy. The transient climate response to cumulative carbon emissions (TCRE), defined as the ratio of global-mean warming to cumulative emissions at CO₂ doubling in a 1% yr⁻¹ CO₂ increase experiment, ranges from 0.8 to 2.4 K EgC⁻¹ in 15 models from phase 5 of the Coupled Model Intercomparison Project (CMIP5)—a somewhat broader range than that found in a previous generation of carbon–climate models. Using newly available simulations and a new observational temperature dataset to 2010, TCRE is estimated from observations by dividing an observationally constrained estimate of CO₂-attributable warming by an estimate of cumulative carbon emissions to date, yielding an observationally constrained 5%–95% range of 0.7–2.0 K EgC⁻¹.

1. Introduction

Global warming has been shown to be almost independent of emissions pathway and approximately proportional to cumulative carbon dioxide emissions in simulations of the response to a range of emissions scenarios with previous generation carbon climate models (Allen et al. 2009; Matthews et al. 2009; Zickfeld et al. 2009). This suggests that a model's climate response to

carbon dioxide emissions can be well characterized by the ratio of the temperature increase to the cumulative carbon emissions. This ratio is a combined measure of both a model's carbon cycle response to emissions and its physical climate response to an increase in atmospheric CO₂, making it a useful benchmark for model intercomparison. Because it directly relates warming to emissions, it also has the potential to be of use in climate change mitigation policy; for example, this ratio can be used to calculate the cumulative emissions consistent with a 2°C warming target (Allen et al. 2009; Matthews et al. 2009). We note, however, that the transient climate response to cumulative carbon emissions (TCRE) is not directly applicable to emissions of non-CO₂ greenhouse gases and other forcing agents. Matthews et al. (2009) propose that the TCRE of a model is defined as the ratio of warming to cumulative CO₂ emissions in a simulation with a prescribed 1% yr⁻¹ increase in CO₂ at the time when CO₂ reaches double its preindustrial

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concentration, paralleling the definition of the transient climate response (TCR), which is defined as the warming at this time. Defined in this way, Matthews et al. (2009) find a TCRE range of 1.0–2.1 K EgC⁻¹ in 11 carbon–climate models that took part in the Coupled Carbon Cycle Climate Model Intercomparison Project (C⁴MIP) project. Note that TCRE is the same as the carbon–climate response defined by Matthews et al. (2009), but we use the name TCRE to more clearly distinguish this metric from a similar measure based on peak warming (Allen et al. 2009).

As well as a metric for the comparison of carbon–climate models, TCRE may also be assessed from observations. Because it is approximately independent of cumulative emissions, Matthews et al. (2009) estimate TCRE by dividing an observationally constrained estimate of CO₂-attributable warming over the twentieth century by an estimate of cumulative CO₂ emissions over the same period and obtain a 5%–95% confidence range of 1.0–2.1 K EgC⁻¹. Allen et al. (2009) report a ratio of warming to cumulative emissions in 2000 of 1.4–2.5 K EgC⁻¹. They note that the ratio of peak warming to cumulative emissions could be higher than this if climate sensitivity is relatively high.

Many of the models included in phase 5 of the Coupled Model Intercomparison Project (CMIP5) are earth system models (ESMs), which include coupled carbon cycles, allowing TCRE to be directly assessed for these models (Arora et al. 2013). This study therefore consists of two parts: the first part describes the calculation of the TCRE of 15 CMIP5 models and examines the extent to which warming is proportional to cumulative emissions in each model. The second part derives a new observationally constrained estimate of TCRE, first by using CMIP5-simulated temperature and temperature observations to estimate CO₂-attributable warming to 2010 and then by dividing this by an estimate of cumulative CO₂ emissions up to this time. Our analysis takes advantage of the most recent surface temperature observations, new estimates of historical CO₂ emissions, and the newly available CMIP5 output.

2. Models and data

We use output from prescribed CO₂ simulations from 24 CMIP5 models in this study. Of these, 15 are ESMs providing the output necessary to directly diagnose CO₂ emissions and hence calculate TCRE (see Table 1 for further details). Monthly-mean atmosphere–ocean and atmosphere–land biosphere carbon fluxes were globally integrated with appropriate area weighting and summed over time to derive cumulative atmosphere–ocean and atmosphere–land fluxes. The atmospheric

CO₂ concentration in the 1% yr⁻¹ CO₂ increase (1PCT) simulations starts at its preindustrial value of close to 285 ppm (the actual specified preindustrial CO₂ concentration differs by at most 1.3 ppm from this value in the simulations used) and increases by 1% yr⁻¹. Summing the increase in atmospheric CO₂ in petagrams of carbon and the cumulative globally integrated atmosphere–land and atmosphere–ocean CO₂ fluxes gives the derived cumulative emissions: anthropogenic emissions that when specified in a free CO₂ simulation would have given the same evolution of atmospheric CO₂. We focus mainly on the 1PCT simulations here because TCRE is a metric of the response to CO₂ only and it is conventionally defined using such simulations (Matthews et al. 2009). We also examine the response in simulations in which the CO₂ concentration is instantaneously quadrupled and then held constant (4×CO₂) for 10 CMIP5 models for which the necessary output is available (Table 1). Note that we diagnose CO₂ emissions purely from the carbon flux data available on the CMIP5 archive and the specified CO₂ concentration and disregard any contribution from any other prescribed changes in CO₂, such as a restoring term specified in the GFDL-ESM models, which is small relative to other terms (Dunne et al. 2013).

For the analysis of observationally constrained TCRE, we use a detection and attribution analysis first to obtain a multimodel-mean scaling factor on the greenhouse gas response, based on a fit to temperature observations. For such an analysis, we require near-surface air temperature from the historical simulations including all major anthropogenic and natural forcings (ALL), simulations with only greenhouse gas changes (GHG), simulations with only natural forcing changes (NAT), preindustrial control simulations (CTL), and because we estimate TCR from these same models, 1PCT simulations. To be able to use observations up to 2010 in our analysis, we used only those models with simulations extended to at least 2010 for the detection and attribution analysis: such output was available from nine models (Table 1). These nine models have larger GHG ensemble sizes on average than those whose single forcing simulations end in 2005 (Table 1), providing further motivation for our decision to restrict attention to these models in the detection and attribution analysis. Historical simulations were extended from 2005 to 2012 by merging with historical extension simulations where available (CNRM-CM5, GISS-E2-H, GISS-E2-R, and NorESM1-M) or otherwise with representative concentration pathway (RCP 4.5) simulations (CanESM2, CSIRO Mk3.6.0, HadGEM2-ES, and IPSL-CM5A-LR) or, in the case of BCC_CSM1.1, using the full historical simulation, which extended to 2012.

TABLE 1. CMIP5 output used in this study. The second column indicates those models for which TCRE was directly calculated: these are all ESMs including coupled carbon cycles. Models for which the necessary output was available to diagnose cumulative emissions in the abrupt $4\times\text{CO}_2$ simulation are indicated with an “A.” The third column indicates those models for which a detection and attribution analysis was performed: these models had ALL, GHG, and NAT simulations to 2010, and their respective ensemble sizes and the length of control simulation are indicated. The fourth column indicates those models for which the ratio of TCR to 1861–2005 GHG-induced warming was calculated: these models all had GHG simulations to 2005 and the ensemble size is indicated.

Name	TCRE	Detect	TCR vs GHG	Ensemble sizes			Control (yr)
				ALL	GHG	NAT	
Beijing Climate Center, Climate System Model, version 1.1 (BCC_CSM1.1)	Y	Y	Y	3	1	1	500
Beijing Normal University Earth System Model (BNU-ESM)	Y, A	—	Y	—	1	—	—
Second Generation Canadian Earth System Model (CanESM2)	Y, A	Y	Y	5	5	5	996
Community Climate System Model, version 4 (CCSM4)	—	—	Y	—	3	—	—
Community Earth System Model, version 1 biogeochemical (CESM1-BGC)	Y	—	—	—	—	—	—
Centre National de Recherches Météorologiques Coupled Global Climate Model, version 5 (CNRM-CM5)	—	Y	Y	9	5	5	850
Commonwealth Scientific and Industrial Research Organisation Mark 3.6.0 (CSIRO Mk3.6.0)	—	Y	Y	10	3	5	500
Flexible Global Ocean–Atmosphere–Land System Model gridpoint version 2 (FGOALS-g2)	—	—	Y	—	1	—	—
Geophysical Fluid Dynamics Laboratory Climate Model, version 3 (GFDL CM3)	—	—	Y	—	3	—	—
Geophysical Fluid Dynamics Laboratory Earth System Model using the Generalized Ocean Layer Dynamics code base (GFDL-ESM2G)	Y, A	—	—	—	—	—	—
Geophysical Fluid Dynamics Laboratory Earth System Model with MOM4 ocean component (GFDL-ESM2M)	Y	—	Y	—	1	—	—
Goddard Institute for Space Studies Model E, coupled with the HYCOM ocean model (GISS-E2-H)	—	Y	Y	5	5	5	1841
Goddard Institute for Space Studies Model E, coupled with the Russell ocean model (GISS-E2-R)	—	Y	Y	5	5	5	1200
Hadley Centre Global Environmental Model, version 2 (Earth System) (HadGEM2-ES)	Y	Y	Y	4	4	4	545
Institute of Numerical Mathematics Coupled Model, version 4.0 (INM-CM4.0)	Y, A	—	—	—	—	—	—
Institut Pierre-Simon Laplace Coupled Model, version 5A, coupled with Nucleus for European Modelling of the Ocean (NEMO), low resolution (IPSL-CM5A-LR)	Y, A	Y	Y	4	1	3	1000
Institut Pierre-Simon Laplace Coupled Model, version 5A, coupled with NEMO, medium resolution (IPSL-CM5A-MR)	Y, A	—	—	—	—	—	—
Institut Pierre-Simon Laplace Coupled Model, version 5B, coupled with NEMO, low resolution (IPSL-CM5B-LR)	Y, A	—	—	—	—	—	—
Model for Interdisciplinary Research on Climate, Earth System Model (MIROC-ESM)	Y, A	—	Y	—	1	—	—
Max Planck Institute Earth System Model, low resolution (MPI-ESM-LR)	Y, A	—	—	—	—	—	—
Max Planck Institute Earth System Model, medium resolution (MPI-ESM-MR)	Y, A	—	—	—	—	—	—
Meteorological Research Institute Coupled General Circulation Model, version 3 (MRI-CGCM3)	—	—	Y	—	1	—	—
Norwegian Earth System Model, version 1 (intermediate resolution) (NorESM1-M)	—	Y	Y	3	1	1	501
Norwegian Earth System Model, version 1 (intermediate resolution with carbon cycle) (NorESM1-ME)	Y	—	—	—	—	—	—

To examine the ratio of TCR to the historical GHG-induced warming trend (Table 1), 16 models having 1PCT simulations and GHG simulations to at least 2005 were used.

3. Transient response to cumulative emissions in the CMIP5 models

The global-mean temperature anomaly relative to the corresponding control simulation is shown against

diagnosed cumulative carbon emissions for the 1PCT simulations in Fig. 1. As in the C⁴MIP simulations (Matthews et al. 2009), the two quantities are approximately proportional. While most simulations were 140 yr long, extending to the time of a quadrupling of preindustrial CO₂, 1PCT simulations from the two GFDL models had atmospheric CO₂ held constant after year 70 (i.e., at CO₂ doubling) and therefore only the portion of the simulations up to year 70 is shown to maintain comparability. Dashed lines show the relationship for each model based on its TCRE (i.e., a straight line passing through the origin and the 20-yr-mean temperature anomaly and cumulative emissions centered on year 70), corresponding to doubled preindustrial CO₂ concentration and approximately 1 EgC cumulative emissions. In absolute terms, the deviations from these straight lines are largest at the end of the simulation, where diagnosed emissions are around 3 EgC, well above the 2 EgC emissions below which Matthews et al. (2009) reported proportionality. In BNU-ESM, CanESM2, and HadGEM2-ES the warming at the end of the simulation is more than 1 K less than that predicted based on each model's TCRE. In fractional terms, these residuals are about 20% of the warming (Fig. 1c). Fractional deviations are also large for cumulative emissions <1 EgC, where the signal-to-noise ratio is lower and there appears to be a tendency for positive residuals at <1 EgC, which is consistent with an overall tendency for the ratio of warming to cumulative emissions to decrease with cumulative emissions in these models and consistent with the findings for C⁴MIP (Matthews et al. 2009). Linearity is hard to assess for the two GFDL models because atmospheric CO₂ concentration was not increased beyond double its preindustrial value. The remaining 10 models all show a close to linear relationship between warming and cumulative emissions in the 1PCT simulations. None of the models considered here exhibit an increasing ratio of warming to cumulative emissions as emissions increase beyond CO₂ doubling. The proportionality of warming to cumulative emissions depends in part on a cancellation of the saturation of carbon sinks with increasing cumulative emissions (leading to a larger airborne fraction of cumulative emissions for higher emissions) and the logarithmic dependence of radiative forcing on atmospheric CO₂ concentration [leading to a smaller increase in radiative forcing per unit increase in atmospheric CO₂ at higher CO₂ concentrations; Matthews et al. (2009)]. Negative deviations from a constant TCRE in some models imply that the radiative saturation effect is dominating.

Under the more extreme conditions of an instantaneous quadrupling of preindustrial atmospheric CO₂,

deviations of the temperature response from the relationship predicted by each model's TCRE are larger (Fig. 1b). In this case, deviations are of both signs with BNU-ESM and CanESM2 warming substantially less than expected based on their TCRE and GFDL-ESM2G warming up to 50% more than expected based on its TCRE. Although the 4×CO₂ simulations of BNU-ESM and CanESM2 warm less than predicted based on their TCRE, their temperature responses are similar to those in their 1PCT simulations for the same cumulative emissions. The consistency of the behavior of GFDL-ESM2G in the two simulations cannot be assessed because its 1PCT simulation did not extend beyond double preindustrial CO₂. MIROC-ESM shows an inconsistency between the two simulations, with the 4×CO₂ simulation warming considerably more than the 1PCT simulation for the same cumulative emissions (disregarding the first 20 yr of the 4×CO₂ simulation). This appears to be related to a much more rapid saturation of the terrestrial carbon sink in this model relative to that of the other models, with the terrestrial biosphere becoming a net carbon source much sooner than in the other models at around year 10 of the simulation. Matthews et al. (2009) found that the University of Victoria (UVic) Earth System Climate Model (an intermediate complexity model) exhibits a consistent proportionality between warming and cumulative emissions in a 4×CO₂ simulation and a 1PCT simulation: these results demonstrate that such close proportionality in the 4×CO₂ simulations is not seen in every model.

Although TCRE is approximately constant for a given model in the 1PCT simulations, as expected it differs between models (Fig. 1). Such differences in TCRE may be caused by differences in the carbon cycle response or by differences in the physical climate response to changes in atmospheric CO₂ between models. Following Matthews et al. (2009), we can write TCRE as

$$\text{TCRE} = \frac{\Delta T}{E} = \frac{\Delta T}{C} \frac{C}{E}, \quad (1)$$

where ΔT is the global-mean temperature anomaly at CO₂ doubling (i.e., TCR), E is the cumulative emissions at CO₂ doubling in exagrams of carbon, and C is the atmospheric CO₂ burden anomaly at CO₂ doubling in exagrams of carbon. Thus, TCRE is a product of the temperature response per unit change in the CO₂ burden and the cumulative airborne fraction at CO₂ doubling. Because C is the same in all the models, the former quantity is proportional to TCR (disregarding the small differences in preindustrial atmospheric CO₂ concentration between models). Figure 2a therefore represents each model's TCRE as a rectangle, with height equal

FIG. 1. (a) Temperature anomaly plotted as a function of calculated cumulative CO_2 emissions in the 1PCT simulations of 15 CMIP5 models. (b) The corresponding instantaneous $4\times\text{CO}_2$ simulations of 10 models (thick lines). Also included here for reference are $1\% \text{ yr}^{-1} \text{ CO}_2$ experiments of these models (thin lines). Straight dashed lines show the relationship based on each model's calculated TCRE, evaluated at the time at which atmospheric CO_2 reaches twice its preindustrial concentration (approximately at 1 EgC cumulative emissions). (c) Fractional residuals from the straight line fit for the 1PCT simulations.

FIG. 2. (a) The area of each colored box represents each model's TCRE, which is proportional to a product of the airborne fraction of cumulative emissions at CO₂ doubling (x axis) and the temperature anomaly at CO₂ doubling or TCR (y axis), evaluated in a 1PCT experiment. The TCRE for each model (K EgC⁻¹) is shown in the legend. (b) The airborne fraction of cumulative emissions is equal to one minus the sum of the ocean and land fractions of cumulative emissions. The colored bars represent the airborne (solid), land (close hatching), and ocean (wide hatching) fractions of cumulative emissions at CO₂ doubling for each model.

to the model's TCR (i.e., ΔT) and width equal to its airborne fraction of cumulative emissions at CO₂ doubling (C/E). The area of the rectangle is thus proportional to its TCRE. All quantities are calculated based on 20-yr means centered on the year of doubled preindustrial CO₂

concentration in the 1PCT simulations. The range of TCRE for the models assessed here is 0.8–2.4 K EgC⁻¹, which is somewhat broader than the C⁴MIP range of 1.0–2.1 K EgC⁻¹ (Matthews et al. 2009). If we assume that model TCRE values are all drawn from the same

distribution, then the probability P that the TCRE of another model drawn from this distribution will exceed the maximum value among N models is $P \approx \ln 2/N$ (Gillett et al. 2000). Thus, given that $N = 15$ this range of TCRE can be interpreted as a 5%–95% range of model TCRE. Alternatively, we may note that there is no significant correlation between the airborne fraction at doubling and the TCR across the models ($r = 0.17$). Thus, we can calculate an ensemble of synthetic values of TCRE by taking the product of the temperature response per unit change in atmospheric CO₂ burden for the i th model and the airborne fraction from the j th model:

$$\text{TCRE}_{ij} = \frac{\Delta T_i C_j}{C_i E_j}.$$

Doing this for all i and j , we obtain a distribution with a 5%–95% range of 1.0–2.4 K EgC^{−1}. If we make the additional assumption that the real world TCRE is drawn from the same distribution as the models' TCRE, which we will revisit later, then we could interpret this as the confidence range on the real world TCRE.

Variations in TCRE between models are clearly caused both by variations in TCR and variations in airborne fraction, although variations in TCR are the most important (Fig. 2). TCR ranges from 1.0 to 2.6 K in these models with a mean of 1.9 K, which is close to the phase 3 of the Coupled Model Intercomparison Project (CMIP3) model mean of 1.8 K (Meehl et al. 2007). The cumulative airborne fraction is determined by the uptake of carbon by the land biosphere and ocean (Fig. 2b). Variations in land uptake are the dominant factor driving variations in the cumulative airborne fraction in these models (Arora et al. 2013), with the four models with the highest airborne fraction having the CO₂ fertilization effect limited either by an explicit (NorESM1-ME and CESM1-BGC) or implicit (CanESM2 and MIROC-ESM) parameterization of nitrogen availability (Fig. 2b). The strength of the CO₂ fertilization effect in CanESM2 is “down-regulated” based on the response of plants grown in ambient and elevated CO₂ following Arora et al. (2009). The MIROC-ESM uses an empirical approach to model photosynthesis, which implicitly includes the response to nutrient limitation (Ito and Oikawa 2002). MPI-ESM-LR has the lowest airborne fraction because of a strong land uptake (Fig. 2b; see also Arora et al. 2013) and INM-CM4.0 has the second lowest airborne fraction and the highest fraction of emissions taken up by the ocean at CO₂ doubling, which is associated with a much higher atmosphere–ocean CO₂ flux than in other models and may be associated with strong vertical mixing (E. Volodin 2012, personal communication).

4. Constraining the transient response to cumulative emissions with observations

While the TCRE of climate models is a useful summary metric that describes their response to CO₂ emissions, the most relevant quantity for policymakers and other stakeholders is the TCRE of the real climate system. Because TCRE depends both on the carbon cycle and on the physical climate system, constraining it with observations requires both carbon cycle and temperature observations. TCRE may be constrained from observations in various ways (Allen et al. 2009; Matthews et al. 2009), but perhaps the most direct approach is to first use surface temperature observations to derive an estimate of CO₂-attributable warming to the present and then divide this by an estimate of cumulative CO₂ emissions (Matthews et al. 2009). Estimating TCRE in this way relies on the assumption that TCRE is constant as a function of cumulative emissions between present day cumulative emissions (~0.5 EgC) and cumulative emissions at CO₂ doubling (~1 EgC). Figure 1 shows that this is a reasonable assumption, though it suggests that TCRE calculated in this way may be biased high by ~10%. Note that we estimate CO₂-attributable warming using a fit to 150 yr of temperature observations rather than directly from a single annual mean, making our estimate subject to less noise than those shown in Fig. 1 for a 0.5 EgC cumulative emission. This method also relies on the assumption that the actual increase in atmospheric CO₂ is the same as that which would have occurred had CO₂ emissions been the only climate forcing present. Because the historical increases in radiative forcings associated with aerosols and non-CO₂ greenhouse gases have approximately cancelled each other out (Forster et al. 2007) and large trends in volcanic and solar forcings have not occurred over this period, CO₂ concentration changes caused by the temperature response to non-CO₂ forcings are probably small. Although we include an estimate of land use change emissions and its uncertainty range in our analysis, calculating land use change emissions remains a challenge (e.g., Arora and Boer 2010). Anthropogenic land use change not only leads to direct emissions but also reduces the capacity of the terrestrial biosphere to sequester carbon because forests are replaced by croplands, which are frequently harvested, an effect not accounted for here (the 1PCT experiments we use are performed with vegetation from circa 1850). Although our approach relies on several assumptions, it has the virtue of relative simplicity, and it does not depend, for example, on fitting a particular carbon cycle model to observations.

A detection and attribution analysis can be used to derive an observationally constrained estimate of

GHG-attributable warming (Hegerl et al. 2007; Stott et al. 2003) by fitting observed temperature changes to simulated GHG, other anthropogenic (OTH), and NAT (consisting of volcanic and solar forcing) responses by regression and then multiplying the simulated GHG-induced warming trend by the GHG regression coefficient. Here, we require an estimate of the CO₂-attributable warming. We do not attempt to constrain CO₂-attributable warming directly in a detection and attribution analysis because the temperature response to CO₂ is unlikely to be sufficiently distinct from the temperature response to other anthropogenic greenhouse gases. An alternative approach is therefore to scale simulated 2010 CO₂-induced warming up or down based on a regression coefficient for the overall greenhouse gas response. Unfortunately, simulations with only historical CO₂ variations are available for just one model (CanESM2), although CO₂-only 1PCT simulations are available for all models considered here, allowing an observationally constrained multimodel estimate of TCR to be derived. This may then be scaled by the ratio of 2010 CO₂-induced warming to TCR in CanESM2, a ratio that is likely to be relatively model independent, because both simulations are forced only with monotonically increasing atmospheric CO₂. Using this method we obtain an observationally constrained estimate of TRCE:

$$\text{TRCE} = \frac{\beta_{\text{GHG}}^{\text{Multi}} \text{TCR}^{\text{Multi}} \frac{\Delta T_{\text{CO}_2-2010}^{\text{CanESM2}}}{\text{TCR}^{\text{CanESM2}}}}{E_{2010}}, \quad (2)$$

where $\beta_{\text{GHG}}^{\text{Multi}}$ is a multimodel estimate of the factor by which the GHG response must be scaled to best match observations, $\text{TCR}^{\text{Multi}}$ is the mean TCR for the same set of models, $\Delta T_{\text{CO}_2-2010}^{\text{CanESM2}}$ is the 5-yr-mean warming in 2010 relative to the preindustrial values in an ensemble of CanESM2 simulations with prescribed historical CO₂ changes only, $\text{TCR}^{\text{CanESM2}}$ is the TCR of CanESM2, and E_{2010} is the total anthropogenic cumulative emissions of CO₂ to 2010. Relative to a corresponding simpler expression using simulations of CanESM2 only [$\text{TCRE} = (\beta_{\text{GHG}}^{\text{CanESM2}} \Delta T_{\text{CO}_2-2010}^{\text{CanESM2}}) / E_{2010}$], Eq. (2) allows for a more robust estimate of β_{GHG} based on the output from multiple models.

We start by estimating $\beta_{\text{GHG}}^{\text{Multi}}$ using a detection and attribution analysis. Figure 3 shows global-mean temperature anomalies in the simulations used for this analysis. While the responses to each forcing are broadly similar across models, there are some differences and not only in the magnitude of response. In particular, the OTH response differs considerably between models. We regress observed decadal-mean temperature anomalies

FIG. 3. Decadal global ensemble-mean 1861–2010 temperature anomalies in the ALL, GHG, and NAT simulations of nine CMIP5 models, as well as the OTH response calculated by subtracting GHG and NAT from ALL. Anomalies are shown relative to 1861–80 and after sampling in grid cells with observations. The observed (HadCRUT4) global-mean temperature is plotted in black over the ALL simulations.

taken from the gridded observational temperature dataset Hadley Centre/Climatic Research Unit, version 4 (HadCRUT4; Morice et al. 2012; the median realization of the observations was used), onto the simulated GHG, OTH, and NAT responses using a total least squares regression (Allen and Stott 2003). We used T4 spherical harmonics of decadal-mean temperature from 1861 to 2010 and a 30 EOF truncation for this analysis. Spherical harmonics were used to retain only scales greater than 5000 km: Stott and Tett (1998) demonstrated that the anthropogenic response projects most strongly on spatial scales larger than this. Intraensemble anomalies were generated by taking 150-yr segments of individual ensemble members, subtracting the ensemble mean, and inflating the variance to allow for this subtraction of the ensemble mean (e.g., Gillett et al. 2012). A common set of EOFs derived from all available intraensemble anomalies from all models was used in all cases, along with a common set of control segments for deriving confidence intervals, consisting of nonoverlapping 150-yr segments of all available control simulations from these

nine models (Table 1). A GHG response is detected in analyses using seven of the nine models (its regression coefficient is inconsistent with zero), and OTH is detected using five of the nine models (left section of Fig. 4a). CanESM2 and IPSL-CM5A-LR show relatively low and tightly constrained GHG regression coefficients and TCR, as reported by Gillett et al. (2012). An analysis using GISS-E2-R resulted in even lower estimates of TCR and GHG-attributable warming, though in this case the best estimate of the OTH response is negative, suggesting that the simulated OTH response may be unrealistic. None of the forcings are detectable using GISS-E2-H, possibly because of unrealistic simulated responses to the forcings. The NAT response is detected using seven of the nine models, though in all these cases the best estimate of its regression coefficient is less than one. This could in part relate to a simulated response to Krakatoa, which was not observed and is included in the longer analysis period considered here (Gillett et al. 2012; Joshi and Jones 2009). A combined anthropogenic response was detected using all nine models (see Fig. S1 of the supplemental material).

Although a standard residual test indicated regression residuals were consistent with simulated internal variability in all cases (Allen and Tett 1999; Allen and Stott 2003), Ribes and Terray (2013) argued that this test may be too permissive. We therefore also tested the consistency of the residuals using an alternate approach. First, the standard regression was carried out with one ALL ensemble member withheld, and the residual sum of squares was calculated. Second, the observations were substituted with the withheld ALL ensemble member, and the procedure was repeated. The latter step was repeated using each ALL ensemble member in turn. The residual sum of squares from the regression of the observations was then compared with the sample of residual sums of squares for each ALL ensemble member using a Student's *t* test. Such an approach tests whether the fit to observations is significantly worse than the fit to a model's own ALL simulations. Such an exercise indicated that residual observed variability was too large at the 5% level for regressions using CanESM2, CNRM-CM5, GISS-E2-H, and GISS-E2-R but consistent for the other models.

The results of a simple multimodel analysis (Multi; Gillett et al. 2002) are compared with a multimodel analysis in which the effects of model uncertainty are estimated based on intermodel differences in response [error in variables (EIV); Huntingford et al. 2006; Fig. 4a]. The residual test described above indicated consistent residuals for the multimodel analysis. Unlike in most previous implementations of EIV (Hegerl et al. 2007; Huntingford et al. 2006), in this case model uncertainty

considerably inflates the uncertainties in the regression coefficients, perhaps because of large intermodel differences in the OTH response. EIV results were found to be sensitive to the normalization applied to the intermodel covariance matrix (Huntingford et al. 2006): in this case, we weighted this matrix by an estimate of the ratio of the variance attributable to internal variability in the simulated response patterns to that in the observations [μ in Huntingford et al. (2006)], an approach that was found to reduce but not eliminate bias in Monte Carlo tests. We also report the sensitivity of our estimate of TCRC to the use of the standard multimodel regression approach. The use of only global-mean information (GM) gives results consistent with those derived using spherical harmonics, albeit with inflated uncertainties (Stott et al. 2006). Results based on the EIV analysis are found to be consistent for truncations of 10, 20, and 40, though there is some variation in best estimates and confidence ranges. An EOF truncation of 30 was chosen for subsequent analyses, because this number of EOFs lies well below the number of degrees of freedom of the intraensemble variability estimates, and the results are similar to those obtained at higher and lower truncations. Results are not strongly sensitive to the period over which the analysis is applied (Fig. 5b), although the GHG regression is most closely constrained when the analysis is applied over the full 1861–2010 period (Gillett et al. 2012): the confidence range on the GHG regression coefficient is approximately 10% narrower when evaluated over 1861–2010 than when evaluated over either the 1901–2010 or 1861–2000 periods. The best estimate of the GHG regression coefficient is 16% lower for the analysis using data to 2010 compared to the analysis using data to 2000 only.

Observational uncertainty is a further source of uncertainty not usually accounted for in detection and attribution analyses (e.g., Hegerl et al. 2007). However, HadCRUT4 consists of an ensemble of 100 realizations that sample over observational uncertainty. We therefore repeated the EIV analysis using each of these realizations (Fig. 5a). The contribution of observational uncertainty was added in quadrature to the calculated regression coefficient uncertainties to give an overall confidence range (bars labeled ObsU in Fig. 4a). While the contribution of observational uncertainty is not negligible, the GHG response was detected using all 100 realizations of HadCRUT4, and observational uncertainty was found to make a smaller contribution to the regression coefficient uncertainty than internal variability.

As might be expected, estimates of GHG-attributable warming (obtained by scaling the simulated GHG-induced warming trend by the GHG regression coefficient) are

FIG. 4. Regression coefficients of observed 1861–2010 decadal-mean T_4 spherical harmonic temperatures against simulated GHG (red), OTH (green), and NAT (blue) responses with associated 5%–95% confidence ranges, divided into sets of bars by dotted vertical lines. (a) The first set of bars shows results based on nine CMIP5 models individually; the second set shows the results of a multimodel analysis following Gillett et al. (2002) (Multi), a multimodel analysis in which model uncertainty is accounted for following Huntingford et al. (2006) (EIV), and a similar analysis based on global mean (GM); the third set shows the sensitivity of the EIV result to the EOF truncation; and the final set (ObsU) shows results of the EIV analysis with observational uncertainty also accounted for. The EOF basis was derived using intraensemble anomalies from ensemble means, and uncertainties were assessed from multimodel control variability. An EOF truncation of 30 was used in all cases except GM, which used the maximum possible truncation of 14, and the sets of bars showing sensitivity to truncation. Regression coefficients consistent with one (shown by the horizontal solid line) indicate that the simulated and observed responses are of a consistent magnitude. (b) The attributable trends [$K (150 \text{ yr})^{-1}$] associated with each forcing for each of the attribution analyses shown in (a). The horizontal solid line shows the observed trend over this period. In addition, for the individual model results, observationally constrained TCR is shown (black), calculated as the product of each model's GHG regression coefficient and its TCR.

FIG. 5. Sensitivity of the regression coefficients to observational uncertainty and period. (a) Regression coefficients derived as in the EIV bars in Fig. 4, but using each of the 100-member ensembles of possible realizations of the observations from HadCRUT4 (Morice et al. 2012). (b) The first set of bars shows EIV regression coefficients identical to those labeled EIV in Fig. 4, and the other three sets of bars show results of a similar analysis for each of the three other periods indicated.

relatively close in most of the attribution analyses described (Fig. 4b), with the exception of CSIRO Mk3.6.0, for which it is higher, and GISS-E2-H, for which this quantity is not well constrained. An observationally constrained estimate of TCR may also be derived for each model by multiplying its TCR by its GHG regression coefficient (Allen et al. 2000; Hegerl et al. 2007; black bars

in Fig. 4b). The assumption is usually made that a model's TCR is proportional to its GHG-induced warming trend over the historical period (Allen et al. 2000; Hegerl et al. 2007). The fact that observationally constrained estimates of GHG-attributable warming derived using HadGEM2-ES, IPSL-CM5A-LR, and NorESM1-M are very similar while the corresponding estimates of TCR are different

FIG. 6. TCR plotted against the 1861–2005 GHG-induced warming trend in 16 CMIP5 models evaluated from each model's GHG simulation. Bars show 5%–95% confidence ranges based on internal variability, assessed from control simulations of each model and adjusted to account for ensemble size. Tropospheric and stratospheric ozone changes, which would together be expected to cause additional warming, were included in the GHG simulations of CNRM-CM5, GFDL CM3, MIROC-ESM, MRI-CGCM3, and NorESM1-M only (marked with a diagonal cross). The dotted line is an ordinary least squares fit to the data passing through the origin and is included for illustrative purposes only.

(Fig. 4b) suggests that this assumption is violated for these models. Because we wish to derive a multimodel estimate of TCR, it is important to investigate this issue further.

Figure 6 shows the TCR of 16 CMIP5 models plotted against the 1861–2005 warming trend in the GHG-only simulations of these models (we use the period to 2005 in order to include additional models for which simulations finished in 2005). Deviations from a linear relationship are larger than can be explained purely by uncertainties in the GHG-induced trend and TCR associated with internal variability (as shown by the uncertainty bars). Deviations from a linear relationship are not explained by the inclusion of tropospheric ozone changes in some models' GHG-only simulations (indicated by a diagonal cross in Fig. 6), because the models exhibiting a relatively high ratio of GHG-induced warming to TCR are not all those that include ozone forcing. The most likely explanation is that the temperature response to the non-CO₂ GHGs is not proportional to the temperature response to CO₂ in different models, either because of different non-CO₂ GHG radiative forcings in different models or different efficacies of the non-CO₂ GHGs in different models (the efficacy of a greenhouse gas is the ratio of the temperature response per unit change in radiative

forcing due to that gas to the temperature change per unit radiative forcing due to CO₂). This is consistent with Forster et al. (2007) who show considerable uncertainty in the efficacy of the non-CO₂ greenhouse gases. This is thus an important source of uncertainty, which we must consider when we use the multimodel GHG regression coefficient to scale the multimodel TCR. Matthews et al. (2009) attempted to account for this source of uncertainty by using a published uncertainty in the efficacies of non-CO₂ GHGs (Forster et al. 2007). We account for this uncertainty in our analysis by using the spread of the ratio of TCR to GHG-induced warming in the 16 models included in Fig. 6. Specifically, the fractional uncertainty in $\text{TCR}^{\text{Multi}}$ in Eq. (2) is assumed to be equal to the fractional uncertainty in this ratio. By using the ensemble spread of this ratio, rather than the uncertainty in the mean ratio, we are making the assumption that this ratio for the real world is drawn from the same distribution as the ratio for the models (Annan and Hargreaves 2010).

The final elements required for our estimate of TCRE are first the CO₂-induced warming in 2100 in CanESM2, which was derived from the 2008–12 temperature anomalies in an ensemble of five simulations of CanESM2 with historical variations in CO₂ only, relative to its

FIG. 7. (a) TCR and TCRC in individual models (colored crosses) and 5%–95% confidence ranges based on observational constraints (gray bars). (b) The fractional contribution to the variance in the observationally constrained TCR and TCRC caused by uncertainties in (from left to right) the GHG regression coefficient, the ratio of TCR to GHG-attributable warming, temperature observations, cumulative CO₂ emissions, CanESM2 2008–12 CO₂-induced warming, and CanESM2 TCR.

preindustrial control simulation. Second, we require an estimate of anthropogenic CO₂ emissions. Between 1750 and 2010 burning fossil fuels and cement production has resulted in the emission of 357 ± 22 PgC (Boden et al. 2012), while net land use change emissions have resulted in 160 ± 40 PgC (Friedlingstein et al. 2010; Houghton 2008), where a 2σ uncertainty range of $\pm 50\%$ has been assumed. This results in a total estimate of 517 ± 46 PgC (uncertainties here are one standard deviation).

Figure 7a shows an observationally constrained multimodel estimate of TCR derived by multiplying the EIV GHG regression coefficient shown in Fig. 4a by the mean TCR in BCC_CSM1.1, CanESM2, CNRM-CM5, CSIRO Mk3.6.0, GISS-E2-H, GISS-E2-R, HadGEM2-ES, IPSL-CM5A-LR, and NorESM1-M (1.9 K). Contributions to the uncertainty in TCR from the uncertainty in the GHG regression coefficient (Fig. 4a), a component caused by observational uncertainty, and the uncertainty in the relationship between TCR and GHG-induced warming, which is assessed directly from the spread of this ratio across models (Fig. 6), are added in

quadrature. The relative contributions to the uncertainty are shown in Fig. 7b. The calculated 5%–95% confidence range for TCR of 0.9–2.3 K lies mainly within the 1.0–3.5-K range reported by Hegerl et al. (2007) based on the assessment of previous such analyses and is somewhat narrower than the range of TCR in the models used here (Fig. 7a). It is broader than that determined by Gillett et al. (2012) using a single model, likely first due to our taking account of model uncertainty in the derivation of the regression coefficients and second due to our accounting for uncertainty in the radiative forcings and efficacies.

Last, we apply Eq. (2) to calculate an estimate of TCRC, scaling the multimodel estimate of TCR by the ratio of 2010 warming in a CO₂-only simulation of CanESM2 to that model's TCR and dividing by cumulative emissions to 2010. Both the historical CO₂-only and 1PCT simulations from CanESM2 contain only CO₂ forcing so this ratio is not subject to the uncertainty associated with the relative effects of the different GHGs, and we assume its uncertainty is solely due to internal

variability, which is assessed from a control simulation. It is difficult to test this assumption without historical CO₂-only simulations from more models. We may place an upper bound on this contribution to the uncertainty by examining variations in the ratio of warming at year 70 in the abrupt 4×CO₂ simulations compared with each model's TCR. The standard deviation in this ratio is ~0.11 of its mean value and assuming a similar spread in the ratio of CO₂-only historical warming to TCR, our uncertainty estimate of TCRC is inflated by ~8%. This undoubtedly strongly overestimates the true uncertainty in this ratio because the forcing variations in the 1PCT simulation are much closer to those in a historical CO₂-only simulation than they are to the 4×CO₂ simulations; therefore, multimodel variations in this ratio are likely very much smaller, and we disregard them for the present. In this way, we obtain an estimate of CO₂-attributable warming in 2010 relative to preindustrial values of 0.4–1.0 K. Dividing by the estimate of historical cumulative emissions just described gives an estimate of TCRC of 0.7–2.0 K EgC⁻¹ (best estimate of 1.3 K EgC⁻¹; Fig. 7) (If we use the standard multimodel regression coefficients rather than the EIV regression coefficients, we obtain a slightly narrower range of 0.8–1.9 K EgC⁻¹.) The uncertainty range is derived by adding in quadrature uncertainties corresponding to the GHG regression coefficient (Fig. 4a), the ratio of TCR to GHG-induced warming (Fig. 6), temperature observations, the cumulative CO₂ emissions, CanESM2 2008–12 warming, and CanESM2 TCR. Figure 7b shows that the dominant contributions to the overall uncertainty are the uncertainty in the GHG regression coefficient and the uncertainty in the ratio of TCR to GHG-induced warming. This observationally constrained 5%–95% confidence range for TCRC is somewhat narrower than the range spanned by the models themselves, as shown in Fig. 7a, but slightly broader than the observationally constrained range of 1.0–2.1 K EgC⁻¹ derived by Matthews et al. (2009). Matthews et al. (2009) derived their estimate of TCRC based on an estimate of CO₂-attributable warming and cumulative emissions between the first and last decades of the twentieth century. Their estimate of CO₂-attributable warming was in turn based on an estimate of GHG-attributable warming scaled by a ratio of CO₂ to all GHG forcing and also scaled to account for the efficacies of the non-CO₂ GHGs. Our approach uses warming and emissions from preindustrial to present and more fully accounts for uncertainty in forcing and response to non-CO₂ GHGs based on a broader sample of models. Assuming negligible zero emissions commitment, Allen et al. (2009) calculate a value of TCRC of 1.4–2.5 K EgC⁻¹, a somewhat narrower and higher uncertainty range than the range we calculate here. Note

that our wider uncertainty range may be explained by our consideration of the uncertainty in the relationship between the temperature response to CO₂ and the temperature response to all GHGs, a term not considered by Allen et al. (2009).

5. Conclusions

The TCRC of 15 CMIP5 models is found to range from 0.8 to 2.4 K EgC⁻¹ (interpretable as a 5%–95% range), a somewhat broader range than that of the C⁴MIP models, whose TCRCs range from 1.0 to 2.1 K EgC⁻¹ (Matthews et al. 2009), though this difference is not statistically significant. Two CMIP5 models with high TCRC (CanESM2 and MIROC-ESM) have a parameterized limitation on the carbon fertilization effect of the land biosphere, approximating the effect of nitrogen limitation, along with relatively high values of TCR. Both physical climate properties and carbon cycle properties contribute to variations in TCRC across these CMIP5 models, though physical climate properties are the biggest contributor to TCRC variations.

In the second part of the study, the CMIP5 models were used together with updated temperature observations and emissions data to derive an observationally constrained estimate of TCRC. A multimodel attribution analysis applied using a subset of nine CMIP5 models for which the necessary simulations were available indicated a detectable influence of greenhouse gas changes and natural forcings over the 1861–2010 period. Model uncertainty was found to substantially inflate the uncertainty in the regression coefficients. In previous studies deriving observationally constrained estimates of TCR, simulated model-mean TCR has typically been assumed to scale linearly with the response to all GHGs. We find significant deviations from such a linear relationship in a subset of 16 CMIP5 models, likely because the radiative forcings of the various GHGs and the efficacies of the non-CO₂ GHGs differ between models (Forster et al. 2007). Accounting for this source of uncertainty, together with the uncertainty in the GHG regression coefficient and observational uncertainty, we obtain an estimate of TCR of 0.9–2.3 K. Using simulations from CanESM2 of the response to historical CO₂ emissions alone, we scale this estimate to determine an observationally constrained estimate of CO₂-attributable warming to 2010 and divide this by an estimate of CO₂ emissions caused by fossil fuel burning and land use change to derive TCRC. Our derived 5%–95% confidence range of 0.7–2.0 K EgC⁻¹ is broadly consistent with previous estimates of this metric and has an upper bound below the TCRC of four of the models for which we calculate it directly. This suggests

that some of the models (BNU-ESM, CanESM2, MIROC-ESM, and HadGEM2-ES) may have too high a TCRE relative to observations. Overall, we give greater precedence to the observationally constrained range than to the model spread and conclude that TCRE is very likely ($P > 90\%$) between 0.7 and 2.0 K EgC⁻¹. As the observational record lengthens and the relative importance of forcings other than CO₂ declines, it will be possible to more closely constrain TCRE.

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