Variability in Transient Climate Response in a large-ensemble global climate model simulation

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Abstract
The transient climate response (TCR), defined to be the warming in near-surface air temperature after 70 years of a 1% per year increase in CO₂, can be estimated from observed warming over the 19th and 20th centuries. Such analyses yield lower values than TCR estimated from global climate models (GCMs). This disagreement has been used to suggest that GCMs’ climate may be too sensitive to increases in CO₂. Here we critically evaluate the methodology of the comparison using a large ensemble of a fully coupled GCM simulating the historical period, 1850–2005. We find that TCR estimated from model simulations of the historical period can be much lower than the model’s true TCR, replicating the disagreement seen between observations and GCM estimates of TCR. This suggests that the disagreement could be explained entirely by the details of the comparison and undercuts the suggestions that GCMs overestimate TCR.

Introduction
The transient climate response (TCR) is frequently used to quantify the sensitivity of our climate system to increases in greenhouse gases. It is defined to be the warming in near-surface air temperature after 70 years of a 1% per year increase in atmospheric CO₂. As described below, it can be estimated from observed warming over the 19th and 20th centuries, yielding most-likely TCR values of 1.3-1.6 K [Bengtsson and Schwartz, 2013; Otto et al., 2013; Richardson et al., 2016; Lewis and Curry, 2018]. These values lie below the CMIP5 ensemble average TCR of 1.8 K [Forster et al., 2013]. This disagreement has been used to cast doubt on the fidelity of model simulations of future climate change.

We will test the methodology of this comparison using a large model ensemble, an increasingly popular tool to study the impact of internal variability on the climate system. The most appropriate ensemble for this type of problem contains many runs of a single model with
identical physics and external forcing but different initial conditions. As each ensemble member evolves in time, internal variability of the different members is out of phase, leading to differences in the climate states among the ensemble members. In fact, one can think of our observational record as one member of a theoretical ensemble of Earth’s climate trajectories. A model ensemble therefore gives us insight into what alternative climate histories may have looked like.

**Data**

We analyze output from an ensemble of 100 runs of the fully-coupled Max Planck Institute Earth System Model version 1.1 (MPI-ESM1.1) covering the period 1850-2005. The ensemble was used by Dessler et al. [2018] to characterize the impact of internal variability on estimates of the equilibrium climate sensitivity (ECS); they found that internal variability can lead to significant errors in ECS inferred from historical observations. Hedemann et al. [2017] analyzed this ensemble to determine potential causes of the so-called warming hiatus that occurred in the 2000s.

This model consists of the ECHAM6.3 atmosphere and land model coupled to the MPI-OM ocean model. The atmospheric resolution is T63 spectral truncation, corresponding to about 200 km, with 47 vertical levels, whereas the ocean has a nominal resolution of about 1.5 degrees and 40 vertical levels. MPI-ESM1.1 is a bug-fixed and improved version of the MPI-ESM used for CMIP5 [Giorgetta et al., 2013] and nearly identical to the MPI-ESM1.2 model being used to provide output to CMIP6, except that the historical forcing is from the MPI-ESM. Each of the 100 members simulates the years 1850-2005 and use the same evolution of historical natural and anthropogenic forcings. The members differ only in their initial conditions — each starts from a different state sampled from a 2000-year pre-industrial control simulation.

We calculate effective radiative forcing $F$ for the ensemble by subtracting top-of-atmosphere flux $R$ in a run with climatological sea surface temperatures (SSTs) and a constant pre-industrial atmosphere from average $R$ in an ensemble of three runs using the same SSTs but the time-varying atmospheric composition used in the historical runs [Hansen et al., 2005; Forster et al., 2016]. The three-member ensemble begins with perturbed atmospheric states.
We estimate $F_{2xCO_2}$ using the same approach in a set of fixed SST runs, one with a pre-industrial atmosphere and one in which CO$_2$ increases at 1% per year. We estimate $F_{2xCO_2}$ as the average difference in top-of-atmosphere flux over years 62-78, which produces a value of 3.7 W/m$^2$. This is lower than the value used in Dessler et al. [2018], 3.9 W/m$^2$, which was estimated as one-half of the average over years 130-150. We feel the value of 3.7 W/m$^2$ is a more appropriate estimate of 2xCO$_2$ forcing in this model.

We will also analyze a 68-member ensemble of the MPI-ESM1.1 forced with CO$_2$ increasing at 1%/year (hereafter, “1% runs”). As with the historical ensemble, the 1% ensemble members differ only in their initial conditions — each starts from a different state sampled from a 2000-year pre-industrial control simulation.

**Analysis**

Time series of global-average near-surface air temperature for all 100 members are plotted in Fig. 1 of Dessler et al. [2018]; that plot shows that the model ensemble is in good agreement with observed surface temperatures. TCR can be estimated from the ensemble’s temperature data with this equation [Gregory and Forster, 2008; Otto *et al.*, 2013; Richardson *et al.*, 2016]:

$$TCR_{hist} = \frac{\Delta T}{\Delta F} F_{2xCO_2}$$  \hspace{1cm} (1)

where $\Delta T$ is the change in temperature over the historical period and $\Delta F$ is the change in radiative forcing. In our analysis, $\Delta$ represents the change between the 1859-1882 average, selected because it is not strongly influenced by volcanic eruptions [Mauritsen and Pincus, 2017; Lewis and Curry, 2018], and the average of the last ten years of the runs, 1996-2005. We refer to TCRs estimated this way as TCR$_{hist}$.

We first calculate TCR$_{hist}$ in each ensemble member using global-average near-surface air temperature for $\Delta T$. The calculated values range from 1.32 to 1.94 K (5-95% range 1.48-1.90 K) (Fig. 1a, Table 1). The spread in these TCR estimates is entirely due to internal variability and it is similar to previous estimates [Huber *et al.*, 2014; Hawkins *et al.*, 2016]. The standard deviation of $\Delta T$ from the ensemble is 0.07 K, close to that assumed by Lewis and Curry [2015], implying a similar spread in TCR in their analysis.
TCR is formally defined as the warming of global-average near-surface air temperature in response to CO₂ increasing at 1% per year, at the time of doubling (year 70). This value, which we will call TCR$_{true}$, can be estimated by averaging the warming (relative to pre-industrial) in year 70 of the 68-member ensemble of 1% runs. We find that TCR$_{true}$ for the MPI-ESM1.1 is 1.81 K; this is 0.13 K (7.6%) larger than the average of the ensemble’s TCR$_{hist}$ (1.68 K).

Thus, TCR$_{hist}$ is a low-biased estimate of TCR$_{true}$ in the ensemble. The magnitude, and even the sign, of this bias varies depending on the portion of the historical record being examined (Table 1). Overall, though, we see a clear tendency for the TCR$_{hist}$ to underestimate TCR$_{true}$ (Table 1). Previous papers have suggested that the biases in TCR$_{hist}$ could be due to aerosol forcing efficacy [Kummer and Dessler, 2014; Shindell, 2014; Marvel et al., 2015], although that explanation remains to be validated in this ensemble.

We are now in a position to critically evaluate previous comparisons of TCR from observations and GCMs. TCR estimated from observations, which are TCR$_{hist}$, have most-likely values in the range 1.3-1.6 K [Bengtsson and Schwartz, 2013; Otto et al., 2013; Richardson et al., 2016; Lewis and Curry, 2018], although the uncertainty in the individual estimates is large. The CMIP5 ensemble’s TCR, which are TCR$_{true}$, fall in the range 1.8±0.6 K (average and 5-95% confidence interval) [Forster et al., 2013]. Our analysis of the MPI-ESM1.1 ensemble demonstrates how a model with a TCR$_{true}$ of 1.81 K might nevertheless produce TCR$_{hist}$ in some ensemble members that are much lower (1.3-1.4, Figure 1a) and in agreement with observational estimates. Thus, differences between observational TCRs and GCM TCRs could be mostly or entirely due to these issues.

We can also confirm previous suggestions that two issues with the observed ∆T, masking and blending, are further biasing TCR$_{hist}$ to even lower values [Richardson et al., 2016]. Masking refers to the fact that the observations are geographically incomplete, and that the degree of incompleteness has changed over time, leading to biases in global-average ∆T [Cowtan and Way, 2014]. To test the impact of this on TCR$_{hist}$, we also calculated ∆T in the ensemble using a time-varying mask derived from HadCRUT4 (v4.6.0.0) [Morice et al., 2012]. Using this masked ∆T in Eq. 1, ensemble average TCR$_{hist}$ drops from 1.68 K to 1.59 K (Fig. 1b, Table 2).
The second issue is blending, which refers to the fact that observed $\Delta T$ data sets are usually a blend of near-surface air temperature over land and sea ice but sea surface temperature (SST) over ocean. Because near-surface air temperature is warming faster than SSTs, this blending lowers $\Delta T$ compared to an estimate derived entirely from near-surface air temperature [Cowtan \textit{et al.}, 2015; Santer \textit{et al.}, 2000]. We test this by calculating a blended $\Delta T$ in the ensemble, which we also mask following HadCRUT4. Using this blended and masked $\Delta T$, ensemble average $\text{TCR}_{\text{hist}}$ drops to 1.47 K (Fig. 1d, Table 2). Importantly, none of the individual ensemble members have $\text{TCR}_{\text{hist}}$ as large as the model’s $\text{TCR}_{\text{true}}$.

Finally, we have also calculated blended $\Delta T$ using the temperature of the model’s top ocean layer (representing the top 12 m of the ocean) instead of SST. Using that estimate of $\Delta T$, $\text{TCR}_{\text{hist}}$ drops even further, to an ensemble average of 1.44 K (Fig. 2f, Table 2).

\textbf{Conclusions}

We have investigated why observation-based estimates of TCR tend to be lower than those from GCMs. We have quantified a number of biases: 1) a bias between $\text{TCR}_{\text{hist}}$ and $\text{TCR}_{\text{true}}$, 2) a bias due to incomplete spatial coverage in the observational $\Delta T$ record, and 3) a bias due to the observational $\Delta T$ values being blends of air temperature and SSTs. These three biases are all acting in the same direction, to push $\text{TCR}_{\text{hist}}$ to lower values. The impact of internal variability, which can suppress warming in some members of the ensemble, thereby reducing $\text{TCR}_{\text{hist}}$, is not yet quantifiable. But it has a potentially large magnitude and therefore could also be playing a role in the model-observation difference.

The uncertainty in individual estimates of $\text{TCR}_{\text{hist}}$ from observations are large and the range easily covers most of the $\text{TCR}_{\text{true}}$ values from the CMIP5 ensemble [Lewis and Curry, 2015; Lewis and Curry, 2018; Richardson \textit{et al.}, 2016]. Because of the large uncertainty in other parameters (e.g., aerosol forcing), adding uncertainty due to the issues we discuss in this paper will produce only nominal increases in the total uncertainty of the observational estimates. However, the biases we have investigated are capable of explaining most or all of the disagreement between the central values of the estimates, which has been the focus of much of the discussion.
Our work also informs how future analyses should be done. First, analyses should account for the role of internal variability, most likely by comparing observations to an ensemble of runs. In addition, we should not compare $\text{TCR}_{\text{hist}}$ derived from observations to $\text{TCR}_{\text{true}}$ — unless one can quantify and adjust for the bias between these methods. A better approach would be to compare $\text{TCR}_{\text{hist}}$ from observations to $\text{TCR}_{\text{hist}}$ derived from an ensemble of runs of the GCMs covering the same period as the observations. Finally, one must account for biases in the observations of $\Delta T$ due to masking and blending, most likely by calculating masked and blended $\Delta T$ fields from the model and using those to estimate the model-derived $\text{TCR}_{\text{hist}}$.

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References


Table 1. TCR\textsubscript{hist} calculated with different base and end periods

<table>
<thead>
<tr>
<th>base period</th>
<th>end period</th>
<th>average (K)</th>
<th>Full TCR range (K)</th>
<th>5-95% TCR range (K)</th>
<th>width (K)</th>
<th>% diff from true TCR</th>
<th>∆F (W/m\textsuperscript{2})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1859-1882</td>
<td>1940-1949</td>
<td>1.82</td>
<td>0.63-2.88</td>
<td>1.15-2.50</td>
<td>1.35</td>
<td>0.4</td>
<td>0.54</td>
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<tr>
<td>1859-1882</td>
<td>1951-1960</td>
<td>1.96</td>
<td>1.10-3.13</td>
<td>1.32-2.67</td>
<td>1.34</td>
<td>7.6</td>
<td>0.59</td>
</tr>
<tr>
<td>1859-1882</td>
<td>1969-1978</td>
<td>1.71</td>
<td>1.01-2.91</td>
<td>1.24-2.24</td>
<td>0.99</td>
<td>-5.8</td>
<td>0.81</td>
</tr>
<tr>
<td>1859-1882</td>
<td>1996-2005</td>
<td>1.68</td>
<td>1.32-1.94</td>
<td>1.48-1.90</td>
<td>0.42</td>
<td>-7.7</td>
<td>1.85</td>
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<td>1930-1939</td>
<td>1996-2005</td>
<td>1.65</td>
<td>0.97-2.07</td>
<td>1.35-1.99</td>
<td>0.64</td>
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<td>1940-1949</td>
<td>1996-2005</td>
<td>1.62</td>
<td>1.02-2.16</td>
<td>1.28-2.04</td>
<td>0.76</td>
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<tr>
<td>1951-1960</td>
<td>1996-2005</td>
<td>1.55</td>
<td>0.91-2.04</td>
<td>1.20-1.90</td>
<td>0.70</td>
<td>-16.8</td>
<td>1.26</td>
</tr>
<tr>
<td>1970-1979</td>
<td>1996-2005</td>
<td>1.67</td>
<td>0.99-2.42</td>
<td>1.20-2.09</td>
<td>0.90</td>
<td>-8.5</td>
<td>0.99</td>
</tr>
</tbody>
</table>

The bold line is the case primarily discussed in the text. Width is the difference between the 5\textsuperscript{th} and 95\textsuperscript{th} percentile values; % difference is average TCR\textsubscript{hist} minus TCR\textsubscript{true}, 1.81 K, divided by average TCR\textsubscript{hist}, in percent; ∆F is the change in forcing between the base and end periods.

Table 2. TCR\textsubscript{hist} calculated with different versions of ∆T

<table>
<thead>
<tr>
<th>∆Ts</th>
<th>average (K)</th>
<th>5-95% TCR range (K)</th>
<th>% diff from True TCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>TCR</td>
<td>1.68</td>
<td>1.48-1.90</td>
<td>-7.7</td>
</tr>
<tr>
<td>TCR_masked</td>
<td>1.59</td>
<td>1.40-1.80</td>
<td>-13.7</td>
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<td>TCR_blend</td>
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<td>1.37-1.77</td>
<td>-16.2</td>
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<tr>
<td>TCR_blend_masked</td>
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<td>1.28-1.67</td>
<td>-23.5</td>
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<tr>
<td>TCR_blend_oc</td>
<td>1.53</td>
<td>1.34-1.73</td>
<td>-18.6</td>
</tr>
<tr>
<td>TCR_blend_oc_masked</td>
<td>1.44</td>
<td>1.25-1.64</td>
<td>-25.8</td>
</tr>
</tbody>
</table>

The bold line is the base case primarily discussed in the text; % difference is average TCR\textsubscript{hist} minus TCR\textsubscript{true}, 1.81 K, divided by average TCR\textsubscript{hist}, in percent.
Figure 1. Histograms of $\text{TCR}_{\text{hist}}$ (K) from the ensemble. Each panel shows the calculation with a different version of $\Delta T$; see Table 2 for definitions. The solid black line represents the average, the dashed lines are the 5th and 95th percentiles. The dot-dashed line is $\text{TCR}_{\text{true}}$ of the model, 1.81 K.