Transient Warming is More Sensitive to Uncertainty in the Radiative Forcing than to Uncertainty in the Radiative Feedbacks

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Key Points:

- The transient climate response is most sensitive to uncertainty in the radiative forcing and not to uncertainty in the radiative feedbacks.
- Reducing uncertainty in the radiative forcing is the most efficient way of reducing uncertainty in the transient climate response
- Radiative feedbacks of climate models that are tuned to the historical record are highly sensitive to the assumed historical forcing.

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Abstract

Earth's transient climate response (TCR) is determined by a number of factors, including the radiative forcing of doubling CO_2 concentrations and the net radiative feedback. Uncertainty in the TCR comes from both the uncertainty in each of these factors and from the TCR's sensitivity to uncertainty in each factor. A two-box energy balance model is used to untangle these two components of uncertainty. Theoretical arguments and a Monte-Carlo analysis of CMIP5 data demonstrate that the TCR is most sensitive to uncertainty in the radiative forcing and not, as is often assumed, to uncertainty in the radiative feedback. Thus reducing the uncertainty in the radiative forcing is the most efficient way of reducing the TCR's uncertainty. Two further implications are that the rate of warming is sensitive to uncertainty in carbon-cycle feedbacks, and that climate models tuned using the historical record are highly sensitive to the assumed historical forcing.

1 Introduction

Predicting how much global-mean surface temperatures will change in response to increased CO_2 concentrations is one of the central goals of climate science. A convenient and effective way of quantifying future warming is the transient climate response (TCR): the response of global-mean surface temperature after 70 years of increasing CO_2 concentrations by 1% per year (i.e., after CO_2 concentrations have doubled). The TCR can be scaled for a given emission scenario, and provides an estimate of future warming on a timescale at which human action is possible to limit or mitigate further warming. However, there is currently a large uncertainty in the TCR's value, with the most recent IPCC report giving a "likely" range of 1.0-2.5K [*Stocker*, 2013], limiting our ability to predict future warming.

The TCR is determined by a number of different factors, including the radiative forcing that causes the climate response, the radiative feedbacks which ultimately bring the climate system back to equilibrium and the rate at which heat is transferred from the surface ocean to the deep ocean (*Gregory* [2000]; *Dufresne and Bony* [2008]; *Held et al.* [2010]; *Geoffroy et al.* [2012]). Uncertainty in the TCR can be decomposed into two components: *(1)* the uncertainty in each of these factors, and *(2)* the sensitivity of the TCR to uncertainty in each factor [*Hamby*, 1994]. The second component of uncertainty is arguably more important than the first, because it identifies the most promising paths for narrowing the uncertainty in the TCR. Conversely, a factor may be highly uncertain but contribute little to uncertainty in the TCR, making it a less urgent topic of research.

Separating out the two components of uncertainty is difficult because the TCR is a transient quantity and because it depends non-linearly on a number of different factors. By contrast, the equilibrium climate sensitivity (ECS, the equilibrated response of global-mean surface surface temperature to a doubling of CO_2 concentrations) is determined by the forcing due to doubling CO_2 (F) and the net radiative feedback which brings the system back into equilibrium (λ):

$$ECS = F/\lambda. \tag{1}$$

Hence the relative uncertainties in F and in λ^{-1} contribute equally to the relative uncertainty in the ECS. The larger relative uncertainty in λ compared to F (Figure 1a) justifies the intense focus in the climate science community on better constraining the net radiative feedback, but λ is not necessarily the most important factor for reducing uncertainty in the TCR, and a different aspect of the climate system may be more relevant for improving predictions of warming over the 21st century.

In this study, we analyze a widely used two-box energy balance model (EBM) of Earth's climate system to quantify the sensitivity of the TCR to uncertainty in each of the factors which determine it. Our analysis includes both theoretical considerations (section 2) and a Monte-Carlo analysis with data from a set of models participating in the Fifth Climate Model Intercomparison Project (CMIP5, section 3), both of which demonstrate that the TCR is most sensitive to uncertainty in the radiative forcing and not, as is often assumed, to sensitivity in the radiative feedbacks. This implies that the most effective way of reducing uncertainty in the TCR is to reduce uncertainty in the radiative forcing, rather than focusing on the radiative feedbacks. In other words, reducing the relative uncertainty in F by 1% reduces the uncertainty in the TCR substantially more than reducing the relative uncertainty in λ by 1%.

This result has two other major implications. First, that the TCR, and transient warming in general, is highly sensitive to uncertainties in the carbon cycle feedbacks which determine the fraction of emitted CO_2 that is removed from the atmosphere. Second, that the radiative feedbacks in models that are "tuned" by fitting to the historical record are strongly controlled by the assumed historical forcing. These are discussed further in section 4, before we end with conclusions in section 5.

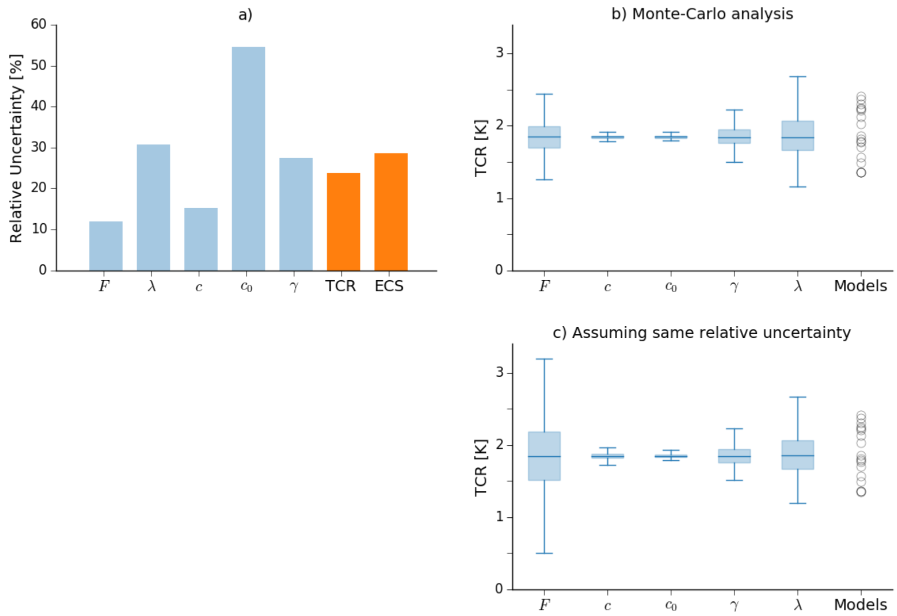

Figure 1. a) The relative uncertainties in each of the five parameters of the EBM (blue bars), based on fitting the EBM to the 18 CMIP5 models, as well as the uncertainties in the ECS and the TCR (orange bars). b) Box-and-whisker plots showing the distributions of TCR from the initial Monte-Carlo analysis. The boxes show ±one standard deviation, the horizontal lines show the mean and the whiskers bracket the 5-95% confidence intervals. The round markers show the models' TCRs. c) Same as panel b) but the Monte Carlo analysis is performed assuming the same relative uncertainty in each parameter.

2 Theoretical Analysis of the Two-Box EBM

The EBM accurately reproduces the evolution of climate models' global-mean surface temperature in simulations in which CO_2 is either instantaneously doubled or in which CO_2 is increased by 1% per year (*Gregory* [2000]; *Held et al.* [2010]; *Geoffroy et al.* [2013a]; Supplemental Figure 1) and consists of a box representing the land surface and the ocean mixed-layer and a box representing the deep ocean. Mathematically, it can be written as:

$$c\frac{dT_1(t)}{dt} = \Delta F(t) - \lambda T_1(t) - \gamma(T_1(t) - T_2(t)), \tag{2}$$

$$c_0\frac{dT_2(t)}{dt} = \gamma(T_1(t) - T_2(t)), \tag{3}$$

with c the heat capacity of the surface box, T_1 the surface temperature anomaly, λ the net radiative feedback, γ the rate of heat exchange between the surface and deep ocean, T_2 the temperature anomaly of the deep ocean and c_0 the heat capacity of the deep ocean.

ΔF is the radiative forcing due to increasing CO_2 concentrations at time t, which can be approximated as $\Delta F(t) = Flog(C(t)/C_0)$ (*Myhre et al.* [1998]; *Etminan et al.* [2016]), where $C(t)$ is the carbon dioxide concentration at time t and C_0 is the pre-industrial atmospheric concentration of CO_2. For a 1% per year increase in atmospheric CO_2 concentrations this leads to

$$\Delta F(t) \approx \frac{Ft}{70years}. \tag{4}$$

The TCR is equal to T_1 after 70 years of increasing CO_2 concentrations by 1% per year. In equilibrium the derivatives of T_1 and T_2 vanish and it can be readily verified that the ECS= F/λ.

Using this approximation for the forcing, the EBM can be solved for T_1 and T_2 (*Geoffroy et al.* [2013a]) to give

$$T_1 = \frac{F}{70\lambda}\left[t - \tau_f a_f(1 - e^{-e/\tau_f}) - \tau_s a_s(1 - e^{-e/\tau_s})\right], \tag{5}$$

$$T_2 = \frac{F}{70\lambda}\left[t - \phi_f \tau_f a_f(1 - e^{-e/\tau_f}) - \phi_s \tau_s a_s(1 - e^{-e/\tau_s})\right], \tag{6}$$

where τ_f and τ_s are the time-scales of a fast mode of response and a slow mode of response, respectively, and a_f and a_s are the contributions of the fast and slow modes to the heat uptake temperature $T_H(t) = ECS - T_1(t)$. Expressions for the τs and as are given in Supplemental Table 1, but clearly the relationship of the TCR to the five free parameters in the EBM (F, λ, γ, c and c_0) is complex in this setting.

More simply, the EBM can be transformed to frequency space and solved for T_1, giving:

$$\hat{T_1} = \frac{\omega F/70}{\lambda + ic\omega + \gamma\left(1 - \gamma/(ic_0\omega + \gamma)\right)}, \tag{7}$$

where the overhat denotes a Fourier transform, ω is frequency and we assume that the five co-efficients are independent of frequency. This equation makes clear that uncertainty in $\hat{T_1}$ is always linearly proportional to uncertainty in F, while its dependence on λ is more complex. At high frequencies (large ω) the term in the brackets in the denominator is approximately equal to 1 and the contribution of uncertainty in λ to uncertainty in $\hat{T_1}$ is minimized. It is only at low frequencies – the time-scales on which the deep ocean warms significantly – that uncertainty in λ plays a comparable role to uncertainty in F.

Physically, the contribution of λ to uncertainty in T_1 is reduced on short time-scales because of ocean heat uptake. Before the deep ocean has warmed up substantially the EBM can be approximated as

$$c\frac{dT_1(t)}{dt} \approx \frac{tF(t)}{70} - (\lambda + \gamma)T_1(t), \tag{8}$$

so even if λ were zero, the "climate resistance" ($\lambda+\gamma$ *Gregory and Forster* [2008]) would not be zero because of heat transfer to the deep ocean, and would still oppose warming, resulting in a finite TCR (but an infinite ECS)[1]. The dependence on uncertainty in F is still linear, and on long timescales, when the deep ocean is approximately in equilibrium with the surface, the sensitivity to λ becomes comparable to the sensitivity to F.

3 Monte Carlo Analysis

To be more quantitative, we have fit equation 1 to simulations with 18 climate models participating in the fifth Climate Model Intercomparison Project (CMIP5, see Supplemental Text 1 and Supplemental Table 2). The relative uncertainty in each parameter, here defined as the standard deviation of the intermodel spread divided by the ensemble-mean, is shown in Figure 1a. The largest relative uncertainty is in c_0, followed by λ and then γ, c and finally F. We note that correlations between the variables are generally weak, except for γ and c, which have an r^2 value of 0.37 (Supplemental Table 3).

The distributions for the parameters from the fits can be used to analyze the sensitivity of the TCR to the uncertainty in each parameter, allowing us to identify the main sources of uncertainty in the TCR and, more importantly, to interrogate the sensitivity of the TCR to uncertainty in each parameter. To do this, a Monte-Carlo analysis was performed using the results of the fitting. First, distributions were created for each of the five parameters (F, λ, γ, c and c_0) using the ensemble-means and standard deviations from the model fittings and assuming that each parameter is normally distributed. The EBM was then integrated 10 000 times for 140 years with CO_2 concentrations increasing at 1% per year for the first 70 years and then held fixed, and with the parameters fixed at their ensemble means, except for one parameter for which a random draw

[1] If λ and γ are perfectly correlated, then T_1 is as sensitive to uncertainty in λ as to uncertainty in F. However in CMIP5 models the correlation between λ and γ is weak (Supplemental Table 3)

was made from the corresponding normal distribution for each integration. With five parameters, this made 50 000 integrations in total.

The results of these integrations, shown in Figure 1b, demonstrate that the net radiative feedback λ produces the largest range of TCR values, followed by the forcing F. Uncertainty in the rate of ocean heat uptake γ also contributes a substantial amount of spread, while the contributions of the heat capacities are negligible, despite the large relative uncertainty in c_0. However, this analysis combines the two components of uncertainty – the uncertainty in each parameter and the sensitivity of T_1 to each parameter. For example, the relative uncertainty in λ is more than twice as large as the relative uncertainty in F (∼30% compared to ∼12%), yet the contribution of F to the uncertainty in the TCR is almost as large as that of λ. Thus in order to investigate the sensitivity of T_1 to uncertainty in each parameter, the Monte-Carlo analysis was repeated assuming that all the parameters have the same relative uncertainty as λ (24.9%). That is, the standard deviation of each of the other four distributions was set equal to 0.249 times the mean of the distribution. This new analysis reveals that the TCR is almost twice as sensitive to uncertainty in F as it is to uncertainty in λ (Figure 1c), with the other parameters being similar to before.

So although the net radiative feedback λ is the largest source of uncertainty in the TCR, this is only because the relative uncertainty in λ is more than twice as large as the relative uncertainty in F. Agreeing with the analysis in the previous section, the Monte Carlo analysis again demonstrates that the TCR is more sensitive to uncertainty in the forcing than to uncertainty in the feedbacks, so that a small reduction in the uncertainty of F is equivalent to a much larger reduction in the uncertainty of λ. Put another way, if the uncertainty in F were as large as the uncertainty in λ the spread in TCR across models would be ∼0.5-3.5K, instead of 1-2.5K. We also note that the TCR's sensitivity to the rate of ocean heat uptake (γ) is even smaller than to the feedback parameter.

Taking this further, Figure 2 shows the ratio of the sensitivity of T_1 to uncertainty in each of the parameters apart from F divided by the sensitivity of T_1 to uncertainty in F, as a function of time. In other words, the standard deviation of the values of T_1 at the end of each year in the integrations with varying λ, c, etc., divided by the standard deviation of T_1 at the end of each year in the integrations with varying F. Ratios smaller (larger) than one indicate that the sensitivity of T_1 at time t to F is larger (smaller) than to the other considered quantity. The sensitivity to λ increases with time relative to the sensitivity to F (dotted line), but even after 140 years the ratio is approximately 0.9, while the sensitivity to γ decreases after about 20 years, as the deep ocean warms up and the $(T_1(t) - T_2(t))$ term becomes small on longer time-scales. T_1 is highly sensitive to the value of c for the first five years, because the upper layer's heat capacity determines the time-scale of the fast response to the forcing, but after the first ten years the sensitivity of T_1 to uncertainty in c is negligible.

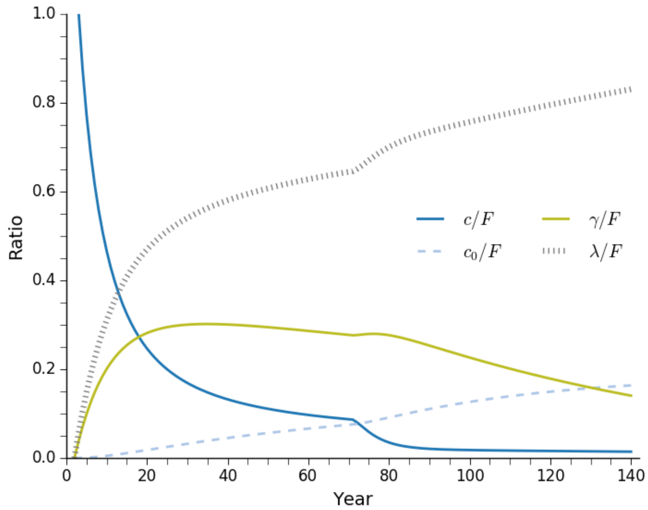

Figure 2. Ratio of sensitivity of T_1 to uncertainty in C to the sensitivity of T_1 to uncertainty in F as a function of time (solid blue line), ratio of sensitivity to C_0 to sensitivity to F (dashed blue line), ratio of sensitivity to γ to sensitivity to F (solid yellow line) and ratio of sensitivity to λ to sensitivity to F (dotted gray line). These sensitivities are calculated using the Monte-Carlo method, and the ratios are calculated using the standard deviation of T_1 as each factor is varied. Note that CO_2 concentrations stop increasing after 70 years.

Finally, we note that an alternative form of the EBM is also commonly used (e.g., *Geoffroy et al.* [2013b]), in which the first equation is modified to

$$c\frac{dT_1}{dt} = \Delta F - \lambda T_1 - \epsilon\gamma(T_1 - T_2), \tag{9}$$

where ϵ is the efficacy of ocean heat uptake [*Winton et al.*, 2010]. Including this term does not affect the central results of the analysis, with the sensitivity to ϵ being comparable to the sensitivity to γ (Supplemental Figure 2), but makes the model more difficult to understand conceptually, and so we have focused on the simpler form of the EBM here.

4 Implications

A first implication of this strong sensitivity of transient warming to F is that the most efficient way of narrowing the uncertainty in the TCR is to develop better constraints on the raw radiative perturbation due to doubling atmospheric CO_2 concentrations (*Collins et al.* [2006]; *Soden et al.* [2018]), as well as on the rapid adjustments of the stratosphere and the troposphere which occur once CO_2 concentrations are increased and that are included in F (*Gregory and Webb* [2008]; *Zelinka et al.* [2013]; *Sherwood et al.* [2015]).

There are at least two additional implications of this sensitivity of the TCR to the radiative forcing. First, it implies an additional strong sensitivity of global-mean surface temperature to the rate at which atmospheric CO_2 concentrations increase, since $\Delta F = Fln(C/C_0)$. The time-evolution of CO_2 concentrations is determined by a combination of the rate at which carbon is emitted to the atmosphere and the carbon-cycle processes which control how efficiently carbon is removed from the atmosphere:

$$C(t) = \alpha(t) \times E(t), \tag{10}$$

where E is the emission of carbon to the atmosphere in a given year and α is the fraction of the emission which stays in the atmosphere. Hence even if the radiative forcing of doubling CO_2 concentrations were perfectly known, uncertainties in the emission scenario and/or in the carbon-cycle feedbacks could overwhelm uncertainties in λ when making predictions of T_1. Moreover, uncertainty in future aerosol forcing and in the forcings due to other greenhouse gases also contribute to uncertainty in the future radiative forcing. We note, however, that recent studies with earth system models suggest that the transient climate response to cumulative carbon emissions (TCRE $= T_1/E$) is more sensitive to uncertainties in physical climate properties (F, λ, etc.) than to uncertainties in carbon cycle processes (i.e., uncertainty in α) (*Gillett et al.* [2013]; *Williams et al.* [2017]).

Second, our results imply that uncertainties in the forcing can strongly affect attempts to tune climate models by fitting to the historical temperature record [*Voosen*, 2016]. By "tuning" we mean both cases in which model parameters are explicitly tweaked to better fit the 20th century temperature record and cases in which a particular model is deemed to be of low quality because it does not fit the record well. We illustrate this through simulations of the 20th century with the two-box model, forcing it with observed CO_2, CH_4 and NO_2 concentrations but varying F (the radiative forcing on doubling) for each of these species from one standard deviation below the ensemble-mean to one standard deviation above the ensemble-mean (see Supplementary Text S2 and Figure 3a). For each forcing assumption, we set c, c_0 and γ to their ensemble-mean values and perform simulations in which λ is varied in increments of $0.01\mathrm{Wm}^{-2}\mathrm{K}^{-1}$, searching for the value that gives the best fit to the 20th century temperature record. Figure 3b shows how the optimal value of λ varies as a function of ΔF at the end of the 20th century in these simulations (circles), with a linear least-squares regression indicating that a 1% change in the estimate of the net forcing resulting in a 1.56% change in the optimal value of λ.

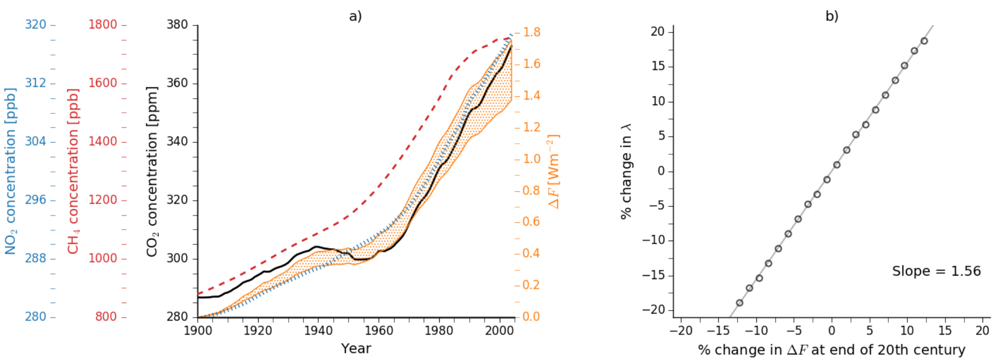

Figure 3. a) Historical CO_2 (black), CH_4 (red) and NO_2 (blue) concentrations for the period 1900 to 2005 (lines) and estimates of the historical radiative forcing by greenhouse gases as F is varied by up to $\pm$ one standard deviation from the ensemble-mean for each species (orange hatching). b) % change in the optimal value of λ as a function of the % change in ΔF (circles). The solid line shows a linear-least squares fit, with the slope indicated in the upper left of the panel. Note that the linearity does not hold for larger fractional changes in ΔF.

These calculations ignore, among other things, the different forcing efficacies of greenhouse gases (*Hansen et al.* [2005]; *Kummer and Dessler* [2014]; *Marvel et al.* [2015]), the question of the historical aerosol forcing [*Stevens*, 2015] and internal variability (*Silvers et al.* [2018]; *Andrews et al.* [2018]), but demonstrate the strong sensitivity of radiative feedbacks in models that are tuned by fitting to the historical temperature record to assumptions made about the forcing over the 20th century. If the same model were tuned twice using historical forcing estimates that differed by 20%, the resulting values of λ would differ by 31%.

5 Conclusion

Using a combination of theory and a Monte-Carlo analysis of data from the CMIP5 archive, we have shown here that the TCR is most sensitive to uncertainty in F, the radiative forcing from doubling CO_2 concentrations, followed by uncertainty in the radiative feedbacks λ. This contrasts with the ECS, which is equally sensitive to uncertainty in F and in λ^{-1}, and arises because of ocean heat uptake. Intuitively, even if λ were zero the TCR would still be finite because of heat transfer to the deep ocean, whereas the ECS would be undefined. This result suggests that more emphasis should be placed on constraining the uncertainty in F, as well as on constraining the historical forcing, as small changes in the assumed historical forcing can have large impacts on the radiative feedbacks in climate models that are tuned using historical data. Furthermore, the sensitivity to F can also be taken to be a sensitivity to the carbon cycle feedbacks which convert CO_2 emissions to atmospheric CO_2 concentrations. Even if the radiative forcing of doubling CO_2 concentrations were perfectly known, uncertainties in the emission scenario and/or in the carbon-cycle feedbacks could overwhelm uncertainties in λ.

As has been recently noted, uncertainty in F could be substantially reduced if the number of radiative transfer parameterizations used in climate models was reduced, so that only parameterizations that have been thoroughly vetted against line-by-line calculations were implemented in climate models [*Soden et al.*, 2018]. Our results emphasize the urgency of this consolidation, as well as the importance of better constraining the rapid adjustments which take place as soon as CO_2 concentrations are increased (particularly in the stratosphere [*Chung and Soden*, 2015]), better constraining the carbon-cycle feedbacks which determine how efficiently carbon is removed from the atmosphere, and better constraining the historical forcing, for which much of the uncertainty comes from uncertainty in the radiative effects of aerosols in the late 19th and early 20th centuries [*Stevens*, 2015].

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