Quantifying the sources of spread in climate change experiments

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Energy-balance models (EBM) constitute a useful framework for summarizing the first-order physical properties driving the magnitude of the global mean surface air temperature response to an externally imposed radiative perturbation. Here the contributions of these properties to the spread of the temperature responses of an ensemble of coupled Atmosphere-Ocean General Circulation Models (AOGCM) of the fifth phase of the Coupled Model Intercomparison Project (CMIP5) are evaluated within the framework of a state-of-the-art EBM. These partial contributions are quantified (in equilibrium and transient conditions) using the analysis of variance method. The radiative properties, particularly the strength of the radiative feedback to the global equilibrium surface warming, appear to constitute the most primary source of the spread.

1. Introduction

The equilibrium climate sensitivity ECS (the equilibrium mean surface air temperature response to a doubling of carbon dioxide concentration) and the transient climate response TCR (the temperature response at the time of 2xCO_2 in a 1% y^{-1} CO_2 increase experiment) are two metrics commonly used in climate model analysis and climate change study. The spread in their AOGCM estimates remains large from one phase of the CMIP project to another [Meehl and Coauthors, 2007]. The identification of the key mechanisms responsible for this spread and the quantification of their contributions constitute a necessary step in the improvement of climate change understanding and modeling.

For a given externally imposed radiative perturbation, the first-order transient surface temperature response is driven by two main properties of the climate system: the strength of the radiative response and the ocean thermal inertia [Dickinson, 1981; Hansen et al., 1984; Wigley and Schlesinger, 1985; Knutti and Hegerl, 2008]. Previous studies, based on individual model or multimodel analysis, attempted to estimate the role of these properties in the spread of AOGCMs responses. Multimodel studies have shown that the strength of the radiative feedback due to the cloud component constitutes the primary source of differences in the equilibrium temperature response [Soden and Held, 2006; Dufresne and Bony, 2008]. By decomposing the transient temperature response into the sum of contributions due to the Planck response, the forcing magnitude, the radiative feedbacks and the ocean heat uptake, Dufresne and Bony [2008] concluded that the main contributor to the spread in the TCR is the cloud feedback. Such conclusion is supported by individual model studies suggesting that the atmosphere component is the major source of differences of transient responses (e.g. Williams et al. [2001]; Meehl et al. [2004]; Collins et al. [2007]).

However, by analyzing the inter-model correlation between the transient surface temperature response, the ECS and the mixing layer depth at high latitudes, Boé et al. [2009] suggested that the role of the deep-ocean heat uptake has been underestimated. The source of the spread of the transient responses is thus a topic of debate. Moreover, these studies are limited in two ways. First, they do not provide a quantitative estimate of the magnitude of the different contributions to the spread. Secondly, some key processes that can contribute significantly to the spread are not taken into account, mainly the tropospheric adjustment of the radiative forcing [Gregory and Webb, 2008; Colman and McAvaney, 2011] and the possible change in the global feedback strength during the transition due to the impact of the deep-ocean heat uptake on the spatial structure of the surface temperature pattern [Winton et al., 2010; Geoffroy et al., 2012b, thereafter G12b].

To overcome these two main limitations, the use of a state-of-the-art energy-balance framework and a suitable statistical method are combined in order to investigate the different contributions of each climate system parameter/property to the spread in the responses of a given set of AOGCMs. After a presentation of the EBM framework (Section 2), the statistical method is described (Section 3). This method is applied to 14 CMIP5 AOGCMs and results are presented and discussed in Section 4.

2. Two-box EBM framework

The two-box energy-balance model with an efficacy factor of deep-ocean heat uptake (hereafter EBM-ε) predicts the time-evolution of the mean surface air temperature response T and the deep-ocean temperature response T_0 to an external radiative perturbation according to the following system of equations [Held et al., 2010, G12b]:

$$C\frac{dT}{dt} = \mathcal{F} - \lambda T - \varepsilon\gamma(T - T_0), \quad (1)$$

$$C_0\frac{dT_0}{dt} = \gamma(T - T_0). \quad (2)$$

In this framework, the climate system is described by 3 radiative parameters, the forcing reference amplitude (such as $\mathcal{F}_{2xCO_2}$), the equilibrium feedback parameter λ and the efficacy factor of deep-ocean heat uptake ε, and 3 thermal-inertia parameters, the first-layer (atmosphere/land/upper-ocean) surfacic heat capacity C, the second-layer (deep-ocean) surfacic heat capacity C_0 and the heat exchange coefficient between the two layers γ.

Geoffroy et al. [2012a] (thereafter G12a) and G12b propose a calibration method to derive these 6 thermal parameters from an AOGCM step-forcing experiment. They show that this simple model represents fairly the transient response of a given AOGCM to a gradual increase of CO_2. The use of the EBM-ε framework has several advantages. First, all parameters are adjusted consistently within a single framework. Then, the inclusion of the efficacy factor of deep-ocean heat uptake ε allows a refined representation of the radiative imbalance evolution likely resulting in a better estimation of the parameters driving the transient climate change. Thus one can assume that the set of thermal parameters derived by this method can be used to quantify the contribution to the spread of the transient temperature responses simulated by a set of AOGCMs.

In the following of this section, a "process-oriented" decomposition of the transient surface temperature response is proposed. This decomposition allows to quantify the contributions of each process to the magnitude of the response and provides an insight of the different mechanisms responsible for the spread of $T(t)$. As shown in G12b, the surface temperature response can be decomposed as the sum of three contributions: $T(t) = T_{eq}(t) + T_D(t) + T_U(t)$. The first term is the instantaneous equilibrium temperature $T_{eq}(t) = \mathcal{F}(t)/\lambda$. The remaining contribution $T_U + T_D$ is the temperature perturbation associated with the climate system heat uptake T_H [Winton et al., 2010, G12a, b] where T_U and T_D are the temperature perturbations associated respectively with the upper- and the deep-ocean heat uptake [G12b]. More precisely, T_D can be decomposed as the sum of two contributions, $T_D^\lambda(t) = T_D(t)/\varepsilon$ representing the flux to deep ocean and $T_D^d(t) = T_D(t)(1 - 1/\varepsilon)$ representing the impact of the deep-ocean heat uptake on the radiative imbalance due to the modification of the temperature pattern. The four terms involved in this decomposition allows to distinguish the thermal fluxes at play in the energy balance when associated with the scale factor λ. The sum $T_H^\lambda = T_U + T_D^\lambda$ represents the instantaneous rate of heat storage of the climate system, $-\lambda T_H^\lambda$ being the top-of-the-atmosphere radiation imbalance. The contribution T_D^d is a deviation from T_{eq} due to the effect of the deep-ocean heat uptake on the strength of the radiative feedbacks during the transition. The sum $T_{eq} + T_D^d$ can be viewed as an apparent instantaneous equilibrium surface temperature during the transition.

For the 14 CMIP5 AOGCMs listed in Table S1 in the auxiliary material, the multi-model mean of the calibrated analytical surface temperature response in the 1% y^{-1} CO_2 increase experiment and its decomposition in T_{eq}, T_U, T_D^λ, and T_D^d are plotted in Fig. 1. For comparison, the multimodel mean of the AOGCMs temperature responses is also represented. The difference with the analytical solution is small (which is also the case for individual model) supporting that the EBM framework is suitable for the present study. Note that this bias decreases during the second half of the simulations (period 70-140 yr from $2xCO_2$ to $4xCO_2$). The TCR and the ECS are respectively of the order of 2 K and 3.5 K. The inter-model standard deviation of the ECS (about 1 K) is larger than the standard deviation of the TCR (about 0.4 K) because the ocean heat uptake reduces the spread [Raper et al., 2002]. This results from the dependancy between T_{eq} and the negative contribution T_H. In particular, both are scaled by a factor $1/\lambda$. The term T_H is dominated by the deep-ocean heat uptake temperature representing the flux to deep ocean T_D^λ, with an ensemble mean amplitude of -1 K. The mean amplitude of T_D^d is as large as the mean amplitude of T_U with a value of about -0.3 K but is associated with a larger spread, suggesting a non negligible role of the efficacy factor of deep-ocean heat uptake to the spread.

The decomposition of the transient surface temperature response presented here is different from the one of Dufresne and Bony [2008]. Their decomposition is expressed with respect to the Planck feedback parameter λ_P rather than λ. Considering that λ_P is roughly model independent, the spread of each term is then associated with one parameter only (within the framework of a one-box EBM) but depends also on T. Because these terms are not a priori independent, their respective variance cannot be simply added, and the resulting decomposition may be misleading. A more accurate quantification of the contribution of each physical parameter to the spread of the temperature responses may be derived based on the statistical method described in the next section.

3. Statistical method

The contribution of each thermal property to the spread of the multimodel global surface warming in the 1% y^{-1} CO_2 experiment is investigated via a multifactor analysis of variance (e.g. Christensen, 1996, p.331). The parameters driving a transient climate change are assumed to be the 6 parameters of the EBM-ε. The transient temperature response T is a time-dependant function of these 6 parameters:

$$T = f(\mathcal{F}_{2\mathrm{xCO}_2}, \lambda, \gamma, C, C_0, \varepsilon). \tag{3}$$

The function f is assumed to be the analytical solution of the EBM-ε described in G12b. For each of the 14 AOGCMs used in this study, the calibrated values of the 6 parameters are summarized in Table S1.

In order to estimate the contribution of each parameter to the spread of T, we need to allow each parameter to vary individually. For this purpose, an ensemble of $N_0 = 14^6$ values of the temperature response $\{T_{i,j,k,l,m,n}\}$ is computed at each time step by considering all possible combinations of the AOGCM parameters:

$$T_{i,j,k,l,m,n} = f(\mathcal{F}_{2\mathrm{xCO}_2,i}, \lambda_j, \gamma_k, C_l, C_{0,m}, \varepsilon_n). \tag{4}$$

where the subscript i denotes that the forcing parameter value is the one of the i^{th} AOGCM and similarly for j, k, l, m, n. The use of the all-parameter combinations ensemble $\{T_{i,j,k,l,m,n}\}$ assumes that the parameters are independent which is roughly the case except potentially for C and γ [G12b], but C does not play an important role, as it will be shown in the following. Also, a dependency between ε and T_{eq} (i.e. $\mathcal{F}/\lambda$) may exist. Following the analysis of variance method, T is decomposed in the sum of one-variable functions:

$$T = f_0 + f_1(\mathcal{F}_{2\text{xCO}_2}) + f_2(\lambda) + f_3(\varepsilon) + f_4(C)$$
$$+ f_5(C_0) + f_6(\gamma) + I(\mathcal{F}_{2\text{xCO}_2}, \lambda, \varepsilon, C, C_0, \gamma), \quad (5)$$

where I is an interaction term (including first-order interactions, second-order, etc). This decomposition is exact but I is potentially significant. The best approximation of T over the set of values considered is then obtained by computing, from the $\{T_{i,j,k,l,m,n}\}$, the mean value $\widehat{f_0} = \overline{T}$, the function $\widehat{f_1}$ such that:

$$\widehat{f_1}(\mathcal{F}_{2\text{xCO}_2,i}) = \frac{1}{N_2 \dots N_6} \sum_{j,k,l,m,n} (T_{i,j,k,l,m,n} - \overline{T}), \quad (6)$$

and similarly, the functions $\widehat{f_2}$ to $\widehat{f_6}$, where $N_1, \dots, N_6$ denotes respectively the number of values taken by the parameters $\mathcal{F}, \dots, \varepsilon$ (in our case, $N_1 = \dots = N_6 = 14$). The interaction term I can then be estimated as a residual from Eq. (5).

The variance $Var(T)$ of the ensemble $\{T_{i,j,k,l,m,n}\}$ can be decomposed as the following:

$$Var(T) = \frac{1}{N} \sum_{i,j,k,l,m,n} (T_{i,j,k,l,m,n} - \overline{T})^2,$$
$$Var(T) = \frac{1}{N_1} \sum_i \widehat{f_1}(\mathcal{F}_{2\text{xCO}_2,i})^2 + \dots$$
$$+ \frac{1}{N_6} \sum_n \widehat{f_6}(\varepsilon_n)^2 + Var(I), \quad (7)$$
$$Var(T) = (\widehat{c}_{\mathcal{F}} + \dots + \widehat{c}_\varepsilon + \widehat{c}_I) Var(T), \quad (8)$$

where $\widehat{c}_x$ denotes the estimated contribution of the parameter x to the variance of $\{T_{i,j,k,l,m,n}\}$:

$$\widehat{c}_x = \frac{1}{Var(T)} \frac{1}{N_x} \sum_i \left[\frac{1}{N_y \dots N_z} \sum_{j \dots n} (T_{i,j,k,l,m,n} - \overline{T}) \right]^2 \quad (9)$$

Note that the term $\widehat{c}_I$ is somewhat more complicated and not explicitly written here (see e.g. Christensen, 1996). In the case of two models, the present method is equivalent to the factorial method [Montgomery, 2005] used by Teller and Levin [2008] to evaluate the relative contributions of thermodynamic conditions and microphysical characteristics to variations in precipitation.

4. Contributions of the physical parameters.

The frequency distributions of the TCR and the ECS obtained for all-parameter combinations ensemble (14^6 elements for the TCR and 14^2 elements for the ECS) are shown in Fig. 2. Both distributions are highly skewed with a long tail due to the non linear relationship between the climate sensitivity and the feedback factor [Knutti and Hegerl, 2008]. The time-evolution of the variance of the inter-model and of the all-parameter combinations ensemble for $T(t)$ and $T_{eq}(t)$ is represented in Fig. 3a. The variance of $T_{eq}(t)$ increases as a square function of time and roughly similarly for $T(t)$. In each case, the spread of the all-parameter combinations ensemble is larger than the inter-model spread (see also Fig. 2). Nevertheless, the all-parameter combinations variances $Var(T)$ and $Var(T_{eq})$ (e.g. respectively 1.15 K^2 and 5.87 K^2 at $4xCO_2$) are well within the 5-95% confidence interval of their respective inter-model spread (respectively 0.42 to 1.6 K^2 and 2.54 to 9.60 K^2 at $4xCO_2$). Figure 3b,c show the time-evolution of the contributions associated with the thermal parameters and the interaction term to the spread of $T(t)$. Note that the contributions to $T_{eq}(t)$ do not vary in time. The magnitude of the different contributions to the TCR and the ECS are summarized in Fig. 3d. The interaction term explains about 3 % and 1 % of the spread respectively of the TCR and of the ECS. These low values suggest that the analysis of variance decomposition is accurate to quantify the contributions to the spread in the responses.

The equilibrium temperature response is a function of the adjusted radiative forcing and the equilibrium radiative feedback parameter only. Their respective contributions to the spread of the ECS are respectively of 12 % and 87 %. The inter-model spread of the radiative feedback parameter is by far the main contributor to the spread of the ECS. Many studies suggest that the spread of λ is due to the cloud feedback [Soden and Held, 2006; Dufresne and Bony, 2008]. The methodology presented here could be extended to quantify the contribution of each independent radiative feedback (water vapor plus lapse rate, cloud and surface albedo) by using a decomposition of the global radiative feedback parameter. Similarly, a decomposition of the adjusted radiative forcing could be performed in order to evaluate the contribution of fast adjustments to the spread.

During the transition, the total contribution of $\mathcal{F}_{2xCO_2}$ and λ is reduced due to the role of the other parameters. After few decades, λ remains the main contributor to the spread, but less strongly than in equilibrium, with a value of 54 % at the time of $2xCO_2$. On the contrary, the transient contribution of $\mathcal{F}_{2xCO_2}$ is enhanced in comparison with the equilibrium one. It decreases with time and reach a value of the order of 28 % after 70 years of simulations. This emphasizes the importance of the forcing magnitude during a climate transition and the uncertainty associated with the tropospheric adjustment. The efficacy ε is the third factor that contributes most to the TCR spread with a $2xCO_2$ value of 10 %. This support Winton et al. [2010]'s finding that ε needs to be taken into account in EBM studies. Finally, the spread of the TCR is mostly due to the radiative parameters λ, $\mathcal{F}_{2xCO_2}$ and ε with a total value of about 92 %. Note that they are also the main contributors to the spread of T_U, T_D^λ and T_U^d (not shown). The efficacy ε is the main contributor for T_D^d whereas the spread of T_U and T_D^λ is mainly dominated by λ.

The contribution of γ is small, with a value of 4 % at 70 yr. The time-evolution of its contribution is similar to the one of ε, both being associated with a common process, the deep-ocean heat uptake. The contribution of C_0 increases in time and decreases back after few centuries (not shown). This contribution is very small with a value of about 1 % at 70 yr. As expected, the contribution of C is negligible after few years. Indeed, T_U contributes little to the magnitude of T and is characterized by a very small inter-model spread. During the first years, for which the variance is negligible, the spread is mainly explained by C and $\mathcal{F}_{2\mathrm{xCO}_2}$. This may be due to the fact that initially, the temperature tendency is equal to $\mathcal{F}/C$. Note that the contribution associated with ε, C_0 and C, even if small for long (unrealistic) time-integration, doesn't tend towards 0 whereas the one associated with γ does. Indeed, the asymptotic temperature response deviation associated with the ocean heat uptake $T - T_{eq}$ is equal to $(C + \varepsilon C_0)/\lambda$ and is independent of γ.

5. Conclusion

In this paper, it is shown that the combination of an energy-balance framework and the analysis of variance method allows to quantify the sources of the spread in climate change experiments. Disregarding that radiative processes are not independent of ocean processes, our results strongly support that atmospheric processes constitute the major source of uncertainty in climate model projections. These uncertainties manifest themselves in several ways, primarily in the strength of the radiative feedbacks to the surface warming but also in the tropospheric adjustment and to a lesser extent in the strength of the local radiative feedbacks in the region where the warming is slowed by deep-ocean heat uptake relatively to other regions.

The results presented here are consistent with the conclusion of Dufresne and Bony [2008]. They concur that the spread in the transient temperature response is mainly due to the radiative feedbacks and thus clouds, secondly to the forcing and then to the ocean heat uptake. Note that the method used in both studies are similar in the sense that they are based on an energy-balance framework. However, contrary to Dufresne and Bony [2008], the present study supports an increased importance of the role of the adjusted radiative forcing as a contributor and a very low contribution of the ocean heat uptake. The latter may be explained by the addition of the efficacy factor that damps the previous estimates of the contributions associated with the heat exchange coefficient. Finally, this study is consistent with the statement that the cloud field constitutes the most critical component in climate modeling by introducing uncertainties at various spatial and temporal scales.

Acknowledgments. We gratefully thank Gilles Bellon, Herve Douville, Julien Boe, Laurent Terray for discussions that helped us to improve the manuscript. This work was supported by the European Union FP7 Integrated Project COMBINE.

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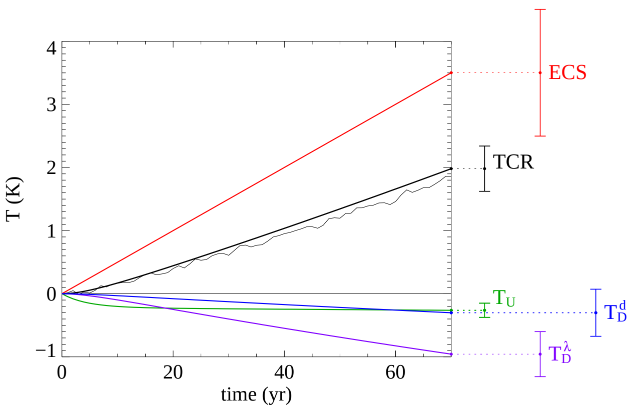

Figure 1. Time-evolution of the multimodel mean of the surface temperature response (thin black) of the 1% y^{-1} CO_2 increase experiment until the time of 2xCO_2 (70 yr), of the calibrated analytical surface temperature response (thick black) and its decomposition in $T_{eq}(t)$ (red), T_U (green), T_D^λ (purple) and T_D^d (blue). The vertical bars at right indicate the ± 1 inter-model standard deviation for each variable at the time of 2xCO_2.

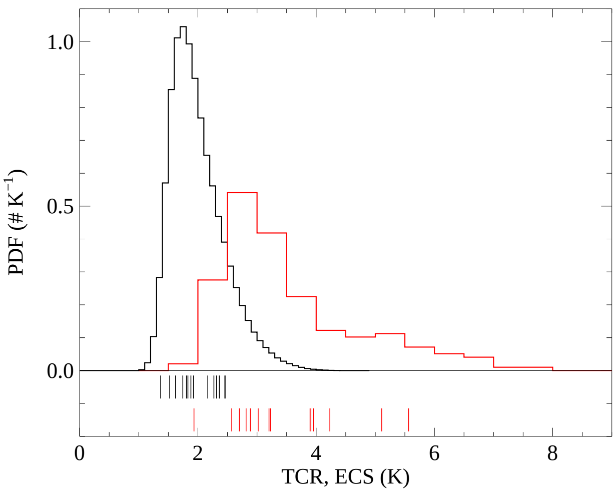

Figure 2. Probability density functions of the TCR (black) and the ECS (red) obtained for all combinations of the parameters of the set of AOGCMs. The vertical lines at bottom indicate the individual model analytical values of the TCR (black) and the ECS (red).

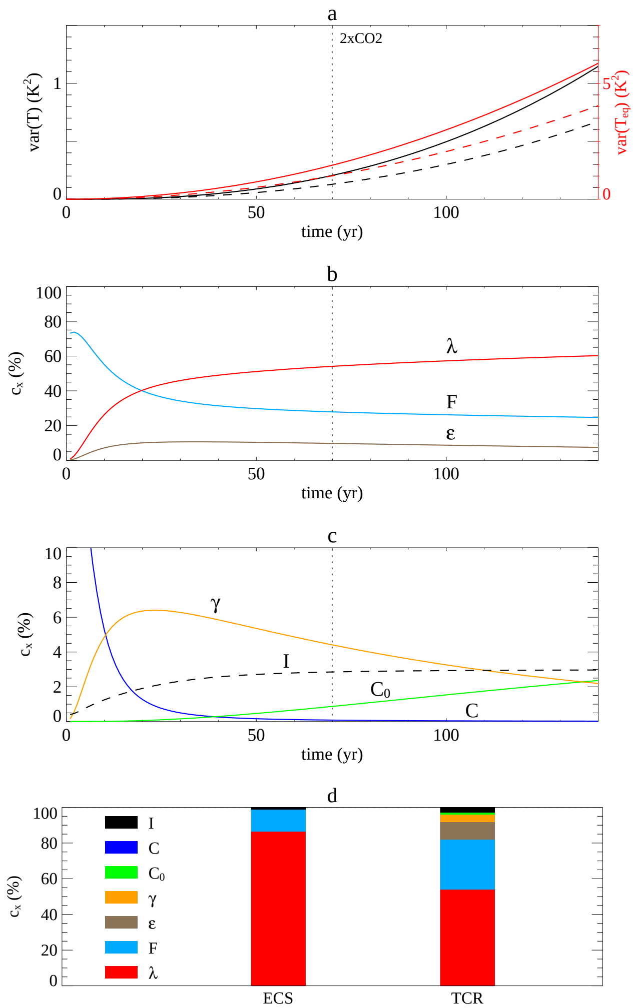

Figure 3. (a) Time-evolution of the variances of the multimodel analytical surface temperature response (black, dashed), and of the all-parameter combinations surface temperature response (black, solid) and equilibrium temperature response (red). Time-evolution (over 140 yr) of the contribution (%) to the spread of the transient surface temperature responses associated with (b) the radiative parameters $\mathcal{F}_{2xCO_2}$, λ, and ε and (c) the thermal inertia parameter C, C_0 and γ. The contribution of the interaction term is also plotted (dashed black line) on (c). (d) Contribution of each parameters and of the interaction term to the ECS and the TCR.