Estimating radiative forcing with a nonconstant feedback parameter and linear response

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Key Points:

- We present a new method for estimating effective radiative forcing and apply it to abrupt4xCO_2, historical, and future scenario experiments
- Including a time-scale dependent feedback parameter results in stronger forcing estimates for the 21st century
- The temperature responses to the new forcing are well described by a linear response

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Abstract

A new algorithm is proposed for estimating time-evolving global forcing in climate models. The method is a further development of the work of Forster et al. (2013), taking into account the non-constancy of the global feedbacks. We assume the non-constancy of this global feedback can be explained as a time-scale dependence, associated with linear temperature responses to the forcing on different time scales. With this method we obtain stronger forcing estimates than previously assumed for the representative concentration pathway experiments in the Coupled Model Intercomparison Project Phase 5 (CMIP5). The reason for the higher future forcing is that the global feedback parameter is more negative at shorter time scales than at longer time scales, consistent with the equilibrium climate sensitivity increasing with equilibration time. Our definition of forcing provides a clean separation of forcing and response, and we find that linear temperature response functions estimated from experiments with abrupt quadrupling of CO_2 can be used to predict responses also for future scenarios. In particular, we demonstrate that applying this response to our new forcing estimate predicts the modelled response up to year 2100 quite well for most models.

1 Introduction

Diagnosing the magnitude of a climate forcing is necessary for determining the climate responses to this forcing. However, defining a clear separation between forcing and response is challenging, and no clear distinction exists (Sherwood et al., 2015). In this paper we attempt to apply a separation within a linear temperature response framework, also incorporating the possibility of globally nonconstant atmospheric feedbacks. We test this method on models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5).

In the most common forcing-feedback framework, the radiative imbalance at the top of the atmosphere (N) is described as

$$N = \lambda T + F \tag{1}$$

where T is the temperature response, λ is the feedback parameter, and F is the radiative forcing, all evaluated as the global mean. According to this equation, forcing is the initial radiative imbalance, before the global mean surface temperature starts to respond. However, as discussed by Hansen et al. (2005), there are many ways of defining the forcing, including various fast feedbacks before diagnosing the radiative imbalance. Forcing estimates are therefore method and model dependent. Some studies even consider multi-annual adjustments to the application of the forcing, reaching into the ocean (Williams et al., 2008; Rugenstein, Gregory, et al., 2016; Menzel & Merlis, 2019). A main motivation for this study is therefore to find an estimation method aiming for a clean separation between forcing and response.

The uncertainties associated with forcing estimates are large, not just because of the different fast feedbacks between models, but also largely due to differences in the parameterizations of the radiative transfer (Soden et al., 2018). The instantaneous forcing spread contributes to about half of the total intermodel spread in forcing (Chung & Soden, 2015), and the remaining spread is largely due to fast cloud adjustments (Zelinka et al., 2013). These uncertainties have led to a large effort aiming to better characterize the forcing used for the new CMIP6 model versions (Forster et al., 2016; Pincus et al., 2016).

In experiments with a time-varying forcing, forcing estimates may be even more uncertain than in idealized experiments with constant forcing. Forster et al. (2013), hereafter F13, computes forcing time series $F(t)$ by rearranging Eq. (1). Their method consists of first determining λ following the regression method of Gregory et al. (2004) using idealized step-forcing simulations, and then using time series of $N(t)$ and $T(t)$ from any experiment to compute what they call adjusted forcing:

$$F(t) = N(t) - \lambda T(t) \tag{2}$$

We note that adjusted forcing in F13 does not mean the same as adjusted forcing in Hansen et al. (2005), where the latter allows only fast stratospheric adjustments to take place before the forcing is estimated from the top of the atmosphere imbalance in an idealized step-forcing experiment. Forcing estimates based on regressions in a Gregory plot, such as in Andrews et al. (2012) and F13 are what Forster et al. (2016) refers to as regression-based methods, assuming a constant feedback parameter.

But several recent studies have pointed out that λ is not a constant (Armour et al., 2013; Geoffroy, Saint-Martin, Bellon, et al., 2013; Andrews et al., 2015; Gregory & Andrews, 2016; Proistosescu & Huybers, 2017; Rugenstein et al., 2020). Armour et al. (2013) demonstrate that locally constant feedbacks can result in a globally time-dependent feedback parameter because the pace of sea surface temperatures (SST) equilibration depends on the location, weighting the local feedbacks. Other studies demonstrated that also locally, feedbacks change their magnitude with equilibration time (e.g. Andrews et al., 2015; Andrews & Webb, 2018; Rugenstein, Caldeira, & Knutti, 2016; Proistosescu & Huybers, 2017; Rugenstein et al., 2020) and also throughout the historical time period (Paynter & Frölicher, 2015; Gregory & Andrews, 2016; Armour, 2017; Marvel et al., 2018; Dessler, 2020). The entire Tropics, the tropical Pacific specifically, the east-west gradient in the tropical Pacific, the relative warming of midlatitude or global oceans to the West Pacific warm pool, the North Atlantic, and the mid- and high latitudes have all been suggested to influence global feedbacks strongly (e.g. Winton et al., 2010; Trossman et al., 2016; Andrews & Webb, 2018; Dong et al., 2020; Zelinka et al., 2020). The mechanism most often invoked is the dependence of lower tropospheric stability on the ratio of local and far-field SSTs. Regions warming faster than the West Pacific warm pool — which sets the temperature of the free troposphere through deep convective clouds — show a reduced lower tropospheric stability, a decrease in low-cloud coverage, and thus, a strong cloud and net radiative effect at the top of the atmosphere (e.g. Zhou et al., 2016; Ceppi & Gregory, 2017). In the CMIP6 models, the shortwave cloud feedbacks in the extratropics appear to be more important for the nonconstancy of λ than clouds in the tropics (Zelinka et al., 2020; Bacmeister et al., 2020), but the relatively short record of global cloud observations makes it difficult to assess cloud modeling against the observations (Loeb et al., 2020). Some studies explain also the changing feedback strength as a temperature-dependence (Meraner et al., 2013; Rohrschneider et al., 2019; Bloch-Johnson, Rugenstein, Stolpe, et al., 2020).

The nonconstancy of λ implies that the forcing definition in Eq. (2) is ambiguous. This is particularly apparent for strong temperature responses, when λT more strongly affects the determination of the value of F. Here the magnitude and time-dependence of λ are particularly important. Larson and Portmann (2016) demonstrated for instance that λ obtained from regressions in the first 20 yr time period of abrupt4xCO_2 gives higher forcing estimates compared to regressions in 150 yr time period. This is one of several reasons why Forster et al. (2016) recommends fixed-SST methods instead of regression methods to determine the forcing.

We explore how an alternative definition of effective forcing with a time-scale dependent λ differs from estimates by F13. To compute these alternative estimates, we decompose the temperature response assuming it responds linearly to the forcing, and we demonstrate that the linear temperature response to the new forcing is close to the modelled temperature response in future scenarios for most CMIP5 models. By a linear response, we mean the temperature response determined from a linear non-homogeneous system of differential equations, whose solution can be expressed as a convolution between a Green's function and the forcing. Our results suggest that this forcing estimate appears more appropriate for estimating temperature responses using linear response models.

Our method is an iterative routine, starting with the F13 estimate of forcing, then computing the linear response to this forcing, which is further used to compute a new forcing estimate, etc., until convergence to a final forcing estimate is obtained. Theory and methods are described in Section 2, and the results are shown in Section 3. In Section 4, we discuss the assumptions made in our method, and how it compares to other forcing estimates, before we conclude in Section 5.

2 Theory and methods

The time-scale dependence of λ is analysed by making use of the same decomposition as in Proistosescu and Huybers (2017), hereafter PH17. While PH17 use the method to better understand estimates of climate sensitivity, we are interested in the intersect of the fit with the vertical axis, the initial radiative imbalance. We also estimate parameters using a different approach, mainly because our method simplifies the comparison to methods based on single regression estimates in Gregory plots. The equations that will be presented in this section provide interpretations of the different λ's that may appear in a Gregory plot, as well as interpretations of "forcing estimates" based on regressions on the long time scales. The method is based on the assumption that the temperature response can be decomposed into a sum of K components $T = \sum_{n=1}^{K} T_n$, where each component is the exponential temperature response to the forcing on the time scale τ_n,

$$T_n(t) = c_n \exp(-t/\tau_n) * F(t). \tag{3}$$

The $*$ denotes a convolution, and the factors c_n are the amplitudes of the temperature responses per unit forcing. As further explained in the next subsection, this temperature decomposition can be interpreted as a combination of having different responses in different regions, and that regions responds to forcing on different time scales. c_n therefore depends on both the feedbacks and thermal inertia associated with different regions, and the fraction of the global area involved in the response at time scale τ_n.

Furthermore, the method assumes that constant feedback parameters λ_n exist, with $n = 1, ..., K$ associated with each time scale, such that the terms in Eq. (1) can be decomposed into the following sums:

$$N(t) = \sum_{n=1}^{K} N_n(t) = F(t) + \sum_{n=1}^{K} \lambda_n T_n(t) = F(t) + \lambda(t)T(t) \tag{4}$$

By rewriting Eq. (4), PH17 noted that the time-variation of $\lambda(t)$ can be explained as a weighted average of the feedbacks associated with different components $T_n(t)$ of the global temperature:

$$\lambda(t) = \frac{\sum_{n=1}^{K} \lambda_n T_n(t)}{\sum_{n=1}^{K} T_n(t)} \tag{5}$$

We note that in a $4xCO_2$ experiment, we define the forcing to be a constant, and the slope $\lambda(t)$ must be interpreted as the slope of a line drawn between the fixed forcing F and a point $(T(t), N(t))$. This slope may differ from a linearization around a point $(T(t), N(t))$, e.g. slopes found by linear regression of a range of points (Andrews et al., 2015; Rugenstein, Caldeira, & Knutti, 2016; Ceppi & Gregory, 2019).

Armour et al. (2013) suggested a similar decomposition, but interpreted the components as locally constant feedbacks multiplied by local temperatures with different time evolution. However, recent studies suggest that non-local feedbacks are also important (Andrews et al., 2015; Zhou et al., 2016; Dong et al., 2019; Bloch-Johnson, Rugenstein,

& Abbot, 2020), meaning that temperature changes in one region, and in particular the West Pacific, can influence feedbacks globally.

2.1 Linear model and response

A simple model of temperature changes in the climate system can be constructed by considering different boxes or components that store and exchange energy. If assuming that all anomalous heat fluxes are linearly related to temperature anomalies in the system, the heat uptake in all boxes can be written into a linear non-homogeneous system

$$\mathbf{C}\frac{d\mathbf{T}(t)}{dt} = \mathbf{K}\mathbf{T}(t) + \mathbf{F}(t) \tag{6}$$

By choosing the vector of temperature change components $\mathbf{T}$ to be K-dimensional, the system describes K components that will respond on K different time scales, and the vector $\mathbf{F}$ the atmospheric forcing acting directly on each component. The heat capacities associated with each component are along the diagonal of the diagonal $K \times K$ matrix $\mathbf{C}$, and coefficients for heat exchange between components and heat loss to the atmosphere constitute the matrix $\mathbf{K}$. The left-hand side of this equation describes the heat uptake of each component, and the sum of all heat uptakes must equal the net radiative imbalance N. In this sum of all components, all fluxes between components cancel out, and the sum reduces to Eq. (4).

Linear systems like this have been widely studied, often using one, two or three boxes (e.g. Geoffroy, Saint-Martin, Olivié, et al., 2013; Fredriksen & Rypdal, 2017). Symmetric matrices $\mathbf{K}$ will describe diffusive heat fluxes depending on the temperature difference between two boxes, and feedback parameters will appear on its diagonal. Non-symmetric parts may be due to the dependence of temperature anomalies in one box only. For instance change in sinking processes due to temperature anomalies in the North Atlantic regarded as one box, may by continuity induce horizontal mass and hence energy fluxes from adjacent ocean basins regarded as other boxes, independent of the temperature change in these boxes. $\mathbf{K}$ may also incorporate heat fluxes to the deep ocean if assuming they can be modelled as linear functions of temperature components (e.g. Held et al., 2010; Geoffroy, Saint-Martin, Olivié, et al., 2013).

By applying the method variation of parameters, it can be shown that the solution to Eq. (6) is:

$$\mathbf{T}(t) = \int_{-\infty}^{t} e^{(t-s)\mathbf{C}^{-1}\mathbf{K}}\mathbf{C}^{-1}\mathbf{F}(s)\, ds, \tag{7}$$

showing that the temperature at time t is a response to the forcing experienced at all previous times s. If the matrix $\mathbf{C}^{-1}\mathbf{K}$ has only negative eigenvalues, $-1/\tau_n$, the solution for each temperature component $T_k(t)$ will be a weighted sum of K exponential responses to the global average forcing F with time scales τ_n (where the weights β_n are determined by eigenvalues, eigenvectors, and heat capacities),

$$T_k(t) = \int_{-\infty}^{t} \sum_{n=1}^{K} \beta_n e^{(s-t)/\tau_n} F(s)\, ds \tag{8}$$

Furthermore, the global surface temperature is a weighted average of the components $T_k(t)$:

$$\overline{T(t)} = \sum_{n=1}^{K} c_n \int_{-\infty}^{t} e^{(s-t)/\tau_n} F(s)\, ds \tag{9}$$

where we define the new weights c_n to be an area-weighted average of the weights β_n. The vector $\mathbf{F}$ could in principle contain different forcings in different regions. If so, Eq. (9) is still valid if the regional forcings are scaled versions of the global average forcing.

We recognize Eq. (9) as a convolution between a Green's function $G(t)$ and a forcing $F(t)$, consistent with Eq. (3): $T(t) = G(t)*F(t) = \int_{-\infty}^{t} G(t-s)F(s)ds$, with $G(t) = \sum_{n=1}^{K} G_n(t) = \sum_{n=1}^{K} c_n \exp(-t/\tau_n)$, assuming negative eigenvalues.

2.2 Estimating linear response in abrupt 4xCO_2 experiments

To simplify the estimation of parameters of these responses (time scales τ_n and amplitudes c_n), we start by fixing the time scales, such that T and N depend linearly on the remaining parameters c_n. We find that the exact choice of time scales is not important, as long as we choose them well separated, and within the range of expected time scales. Annual time scales are important over land and shallow ocean areas, while decadal and centennial time scales are particularly important in ocean regions with deeper mixing, and hence higher thermal inertia. Following PH17, we use three different time scales. They find three time scales to be the smallest number that well describes the temperature responses. As explained later, we will in addition assume the existence of a fourth time scale explaining slower temperature responses than can be observed in the records studied in this paper.

We analyse data from 21 CMIP5 models, available at `https://esgf-node.llnl.gov/projects/cmip5/`. The variables used are global annual averages of surface air temperatures (tas), and net top-of-atmosphere radiation, computed as the difference between incoming shortwave radiation and outgoing longwave and shortwave radiation (rsdt - rlut - rsut). To minimize the effect of possible drifts, the temperature $T(t)$ and the variables used to compute the net top of atmosphere radiation $N(t)$ time series are defined as deviations from linear trends in the corresponding time period of the control run (trend values for the abrupt4xCO_2 period are given in Table S1, and are very small). With this definition we also avoid non-zero means of $N(t)$ in equilibrium, which is the case for many models (Forster et al., 2013).

The shortest time scale τ_1 is chosen to be a random number between 1 and 6 years, the second time scale τ_2 is a random factor between 5 and 10 multiplied by τ_1, and the third is a randomly chosen time scale between 80 and 1000 years. The random choice is done 1000 times for each model, and finally, for each model, we keep the set of τ_n with the best fit to the modelled temperature evolution for 150 years after an abrupt quadrupling of CO_2. The resulting parameters are dependent on the length of the time series used. If using longer time series the longest time-scale responses may change the most, but these are also the least important for our 21st century analyses.

The temperature response for these step-forcing experiments can be found by computing the integrals in Eq. (9) with a constant forcing $F_{4\mathrm{xCO_2}}$ for $t > 0$. This integral results in

$$T_{4\mathrm{xCO_2}}(t) = \sum_{n=1}^{K} a_n (1 - e^{-t/\tau_n}) \tag{10}$$

where $a_n = c_n \tau_n F_{4\mathrm{xCO_2}}$ is the equilibrium temperature of each component, and the equilibrium climate sensitivity (ECS) is defined as $\frac{1}{2}\sum_{n=1}^{K} a_n$ (equilibrium response to a doubling of CO_2).

The expression for N is derived as:

$$
\begin{aligned}
N_{4\text{xCO}_2}(t) &= F_{4\text{xCO}_2} + \sum_{n=1}^{K} (\lambda_n T_n(t)) \\
&= F_{4\text{xCO}_2} + \sum_{n=1}^{K} \left(\lambda_n a_n (1 - e^{-t/\tau_n})\right) \\
&= F_{4\text{xCO}_2} + \sum_{n=1}^{K} \lambda_n a_n - \sum_{n=1}^{K} \lambda_n a_n e^{-t/\tau_n} \\
&= -\sum_{n=1}^{K} \lambda_n a_n e^{-t/\tau_n}
\end{aligned}
$$

where we in the last step set that $F_{4\text{xCO}_2}+\sum_{n=1}^{K} \lambda_n a_n = 0$, due to the constraint that $N \to 0$ when $t \to \infty$. Introducing the notation that $b_n = -a_n\lambda_n$ gives us $N_{4\text{xCO}_2}(t) = \sum_{n=1}^{K} N_n(t) = \sum_{n=1}^{K} b_n e^{-t/\tau_n}$, and $F_{4\text{xCO}_2} = -\sum_{n=1}^{K} \lambda_n a_n = \sum_{n=1}^{K} b_n$.

The parameters a_n, b_n could be found using linear regression, but that does sometimes violate the physical assumption that these should have the same sign as the forcing. Therefore we have used the non-negative least squares algorithm to ensure positive parameters. This is used only for finding a_n, and the resulting temperature responses are shown in Figure 1 b). This method could also have been used to find b_n, but this does not seem to provide a sufficiently good fit on the short scales. Instead, λ_n are determined in a Gregory plot, and then used to compute $b_n = -\lambda_n a_n$.

2.3 Algorithm for estimating $\boldsymbol{\lambda_n}$

The λ_n, $n = 1, \ldots, K$ are all determined from linear fits in a Gregory plot, as shown in Figure 1 a). We start with estimating λ_3 corresponding to time scale τ_3, then we estimate λ_2, and finally λ_1. We assume that the sum $\sum_{n=1}^{3} a_n$ underestimates the equilibrium response, since the sum excludes the response on the multi-millennial scale τ_4. We assume τ_4 is so large, that we can make the following approximations for $t \leq$ 150 years:

$$
\begin{aligned}
T_4(t) &= a_4 \left(1 - e^{-t/\tau_4}\right) \approx 0 && (11) \\
N_4(t) &= b_4 e^{-t/\tau_4} \approx b_4 && (12)
\end{aligned}
$$

Hence $T(t) \approx \sum_{n=1}^{3} T_n(t)$ and $N(t) \approx b_4+\sum_{n=1}^{3} N_n(t)$, where b_4 could be interpreted as a constant heat flux going into the deeper oceans, not leading to more surface warming on short scales. We made the somewhat arbitrary choice of setting $\tau_4 = 5000$ years, and assume $\lambda_4 = \lambda_3$. The results are not sensitive to the choice of τ_4 as long as the approximations in Eqs. (11) and (12) are fair. In the 150 year long runs considered in this paper we have no information about λ_4, but longer runs show that the feedback parameter changes little on the longer time scales (Rugenstein et al., 2020).

Determining λ_3**:** We consider only temperatures larger than the equilibrium temperature of the first two components, such that $T_1(t) + T_2(t) \approx a_1 + a_2$, and we have: $N(t) \approx -\lambda_3(a_3-T_3(t))+b_4$. The total temperature is therefore approximated by $T(t) \approx a_1+a_2+T_3(t)$, resulting in $N(t) \approx -\lambda_3(a_1+a_2+a_3-T(t))+b_4$. This shows that N is approximately a linear function of T with slope λ_3 for $T > a_1 + a_2$. Therefore, λ_3 is computed by linear regression of these points, and the equilibrium temperature found by following this line until $N = 0$. This equilibrium estimate should be a higher estimate than $\sum_{n=1}^{3} a_n$, and the difference we recognize as a_4. Whenever the unphysical result $a_4 < 0$ is obtained (at least according to our assumed model), we exclude the chosen time scales from our analysis. b_4 is computed as $b_4 = -\lambda_3 a_4$.

Determining λ_2: First we subtract our estimates of $T_3(t)$, $T_4(t)$ and $N_3(t)$, $N_4(t)$ from the time series $T(t)$ and $N(t)$, respectively. We then obtain estimates of $T_1(t)+T_2(t)$ and $N_1(t)+N_2(t)$, and these points are the gray dots in Figure 1a). For $a_1 < T_1(t)+T_2(t) < a_1+a_2$, $T_1(t)+T_2(t)$ is approximately $a_1+T_2(t)$, and should equal the equilibrium value $a_1 + a_2$ when $N_1(t) + N_2(t) = 0$. In this range, $N_1(t) + N_2(t) \approx -\lambda_2(a_2 - T_2(t))$, approximately linearly related to $T_1(t) + T_2(t)$. Therefore, λ_2 is estimated using a least-squares algorithm forcing the linear fit to go through the point $(a_1+a_2, 0)$.

Determining λ_1: We subtract estimates of $(T_2(t), N_2(t))$ from the gray dots to obtain estimates of $T_1(t)$ and $N_1(t)$ (light gray dots in Figure 1). We have now that $N_1(t) \approx -\lambda_1(a_1-T_1(t))$, and we can as previously use least squares to compute λ_1, forcing the linear fit to pass the point $(a_1, 0)$.

In the least squares fits, we also include an upper time limit to the set of points to be included in the calculation. This limit is set to the first time step after reaching 99% of the equilibrium temperature of the component of interest. In this way, our slope is associated with the response on the particular time scale τ_n, and little influenced by the fluctuations around the equilibrium values. Changing this limit to e.g. 90% or 95% has only minor effects on the results. Feedback parameters associated with fluctuations around the base state, or more precisely, radiative restoring coefficients are studied in several papers (Colman & Power, 2010; Colman & Hanson, 2013; Lutsko & Takahashi, 2018; Bloch-Johnson, Rugenstein, & Abbot, 2020). Depending on the model, they can be similar or different from those associated with the final fluctuation after a quadrupling of CO_2 (Rugenstein et al., 2020), and they may also differ from feedbacks associated with forced responses (e.g. Zhou et al., 2015; Dessler & Forster, 2018).

2.4 New estimates of effective forcing

Using our parameter estimates from the previous subsections, we can for any experiment compute a new estimate of the effective forcing as follows:

1. Compute $F(t)$ using F13's method (a single estimate of λ), and take this as the initial estimate of the effective forcing.
2. Use this forcing estimate and amplitudes $c_n = \frac{a_n}{\tau_n F_{4xCO_2}}$ estimated from $4xCO_2$ experiments to compute the components $T_n(t)$ from Eq. (3) by performing convolution integrals.
3. A new estimate of $F(t)$ can then be computed as:

$$F(t) = N(t) - \sum_n \lambda_n T_n(t) \tag{13}$$

4. Repeat steps 2-3 until convergence of $F(t)$.

We demonstrate how the method can be applied to study the forcing for the historical period and the four representative concentration pathways (RCPs) RCP2.6, RCP4.5, RCP6.0 and RCP8.5.

3 Results

The results of the linear response fit for $T(t)$ and $N(t)$ following an abrupt quadrupling of CO_2 are given for the model NorESM1-M in Figure 1, and the estimated parameters are listed in Table 1. We note from Figure 1a) that both the forcing and equilibrium temperature estimates are higher than when obtained from a straight line fit. The narrow spread of the light blue lines also indicate that the choice of time scales is of little importance, and hence not affecting the overall conclusions. Similar plots are shown for the other models listed in Table 1 in the Supporting information. The uncertainty in both the forcing estimate and ECS estimate vary substantially from model to

Table 1. Estimated parameters, where we define F_{2x} and T_{2x} to be half the forcing and equilibrium temperature estimated for a quadrupling of CO_2. The parameters in parentheses $(-\lambda)$, (F_{2x}) and (T_{2x}) are estimated from a single linear regression over years 1-150 in a Gregory plot. The results differ slightly from the numbers reported from the Gregory method by Andrews et al. (2012), possibly because of minor differences in the way global annual average values are constructed. For one model (GFDL-ESM2G) the best fit consists of two exponential responses, where we estimate $a_2 = 0$ and report $\lambda_2 = b_2/a_2$ as 'NaN'.

	τ_1	τ_2	τ_3	$-\lambda_1$	$-\lambda_2$	$-\lambda_3$	$(-\lambda)$	F_{2x}	(F_{2x})	T_{2x}	(T_{2x})
ACCESS1-0	2.43	12.79	231.10	1.30	1.12	0.56	0.78	3.72	2.97	4.33	3.83
ACCESS1-3	1.13	5.80	150.10	1.46	1.30	0.56	0.82	3.60	2.89	4.12	3.53
CanESM2	2.86	26.39	279.11	1.30	1.01	0.91	1.04	4.24	3.83	3.83	3.69
CCSM4	1.04	5.52	197.28	1.32	1.77	0.90	1.18	4.02	3.47	3.19	2.94
CNRM-CM5	1.45	10.71	392.15	1.38	1.09	1.22	1.14	3.87	3.71	3.20	3.25
CSIRO-Mk3-6-0	1.62	11.29	308.98	1.86	1.12	0.41	0.63	3.94	2.58	4.94	4.08
GFDL-CM3	3.28	32.58	98.81	1.21	0.80	0.63	0.75	3.61	2.99	4.24	3.97
GFDL-ESM2G	2.98	17.50	291.97	1.76	NaN	0.90	1.29	3.65	3.09	2.67	2.39
GFDL-ESM2M	1.03	5.77	240.02	1.52	1.58	1.22	1.38	3.58	3.36	2.52	2.44
GISS-E2-H	1.56	10.43	186.27	2.02	1.83	1.40	1.65	4.21	3.81	2.39	2.31
GISS-E2-R	1.51	10.61	232.40	2.98	1.02	1.42	1.79	5.09	3.78	2.25	2.11
HadGEM2-ES	1.01	8.39	367.62	1.96	0.89	0.35	0.63	4.02	2.90	5.91	4.61
inmcm4	1.02	5.65	597.43	1.90	1.48	1.28	1.43	3.18	2.98	2.14	2.08
IPSL-CM5A-LR	1.72	16.54	163.83	1.03	0.84	0.58	0.75	3.43	3.10	4.55	4.13
IPSL-CM5B-LR	1.21	8.01	80.30	2.39	1.11	0.91	1.02	3.64	2.64	2.68	2.60
MIROC-ESM	1.78	11.32	266.35	1.96	0.92	0.68	0.91	5.37	4.26	5.21	4.67
MIROC5	2.77	15.17	89.28	1.72	1.43	1.36	1.52	4.38	4.13	2.80	2.72
MPI-ESM-LR	1.81	9.20	202.56	1.30	1.50	0.86	1.13	4.53	4.09	3.91	3.63
MPI-ESM-MR	1.02	6.23	158.54	2.27	1.45	0.94	1.18	5.15	4.07	3.67	3.46
MRI-CGCM3	1.42	11.61	233.73	2.22	1.34	0.96	1.25	4.05	3.24	2.76	2.60
NorESM1-M	1.75	9.34	273.12	1.87	1.52	0.78	1.11	3.88	3.10	3.17	2.80

model. Models with a rapid initial warming, like GISS-E2-R, have fewer points constraining the regression estimate for the shortest time scale, implying larger uncertainty of the forcing.

An overview of all our estimates of the 4xCO_2 forcing are also presented in Figure 2. In addition, we compare our forcing estimates to regression estimates done for years 1-20 and years 1-150. In all except one model, the 1-20 year regression gives a higher estimate than the 1-150 year regression. And in all but two models, our best forcing estimate is even higher than estimates obtained from regression of years 1-20.

Using global annual means of $N(t)$ and $T(t)$ from the coupled models for the historical and RCP experiments, we apply the algorithm described in Section 2.4 to compute forcing estimates for the time period 1850 - 2100. Our new forcing estimate for the historical and RCP8.5 experiment for NorESM1-M diverges from the forcing estimate using a single feedback parameter when approaching the end of the 21st century (Figure 3a). The difference is about 2 W/m^2 in 2100, and only smaller differences are seen during the historical period. As a result, the sum of the linear responses we compute by convolving with the two forcing estimates according to Eq. (3) also diverge (dashed curves in Figure 3b), reaching a difference of almost 1 degree in year 2100. We note that the linear response to our new forcing (dashed blue curve) is remarkably close to the climate

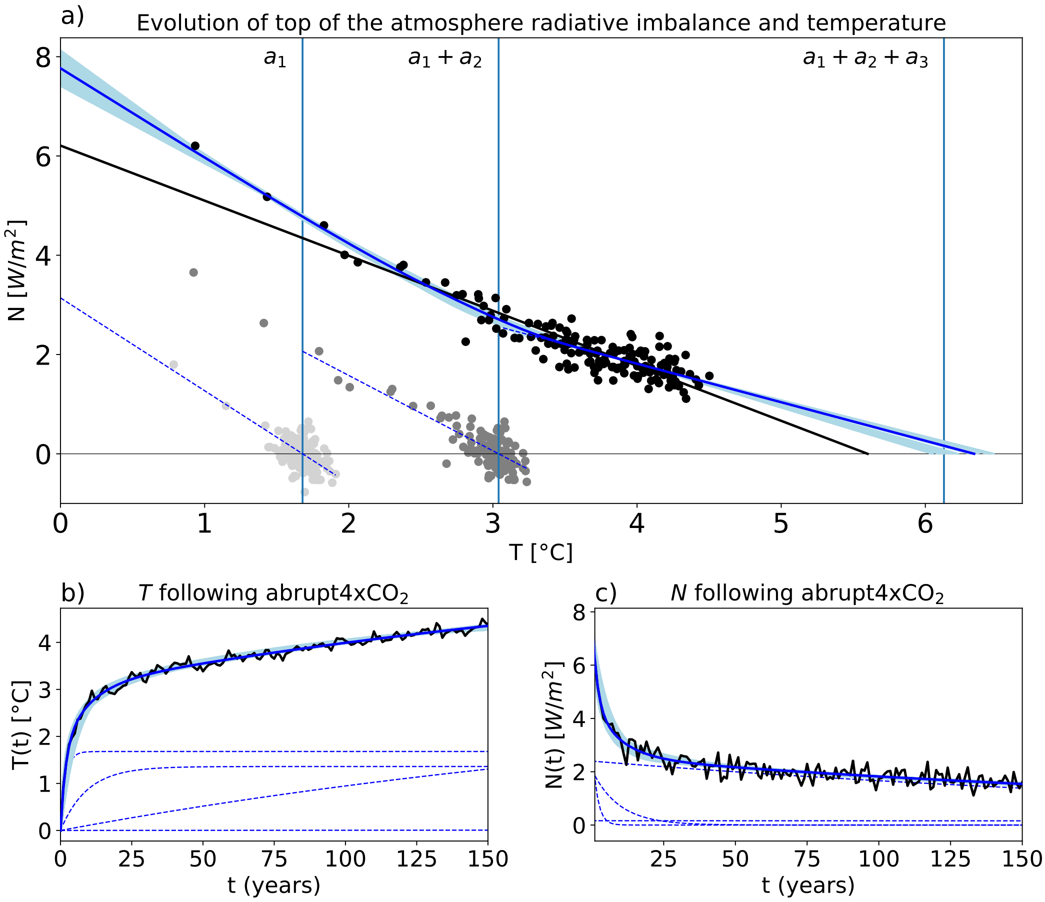

Figure 1. Results for NorESM1-M: a) The black dots and line is a conventional Gregory plot, the light blue lines are our fits to the black points with 1000 different choices of time scales, and the dark blue fit is when using the best fits for the temperature in b). Vertical blue lines are the sums of equilibrium temperatures $\sum_{n=1}^{m} a_n, \quad m = 1, 2, 3$. The gray dots are N vs. T after subtracting components associated with the longer time scales, and the dashed blue lines are fits to these dots. b) The black curve is the climate model temperature output, and the light blue curves are best fits to the modelled temperature using 1000 different choices of time scales. The dark blue curve is the best fit, and the dashed blue curves are the individual components due to the four time scales summed over to obtain this fit. c) As panel b), but for the change in net top of the atmosphere radiation.

model temperature output, indicating that our alternative forcing definition and linear response assumption is a good approximation for this model.

By computing the time-varying feedback parameter $\lambda(t)$ using Eq. (5), we find a generally higher magnitude than the single estimate of λ. During the historical period the global temperature response is often close to 0, causing high fluctuations in the estimated $\lambda(t)$. The estimate becomes more stable for the future scenarios, where we find a slowly decreasing magnitude of $\lambda(t)$, consistent with a higher weighting of the slow responses. For all years in the experiment, the magnitude of $\lambda(t)$ is still considerably higher than the single regression estimate, hence the term $-\lambda(t)T(t)$ gives a higher contribution to the forcing estimate. This effect on the forcing is however only visible when the temperature response is strong.

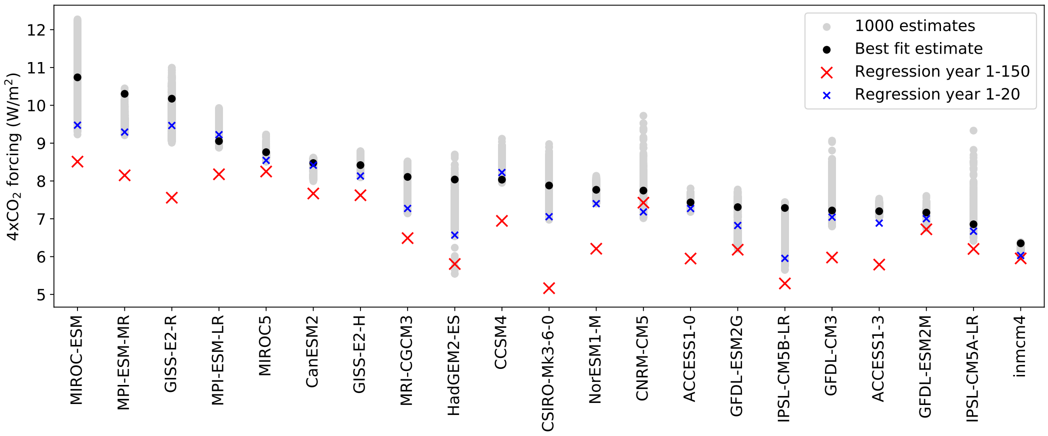

Figure 2. A summary of the $4xCO_2$ forcing estimates made in this paper, to provide an overview of their uncertainties and how they compare to regression estimates.

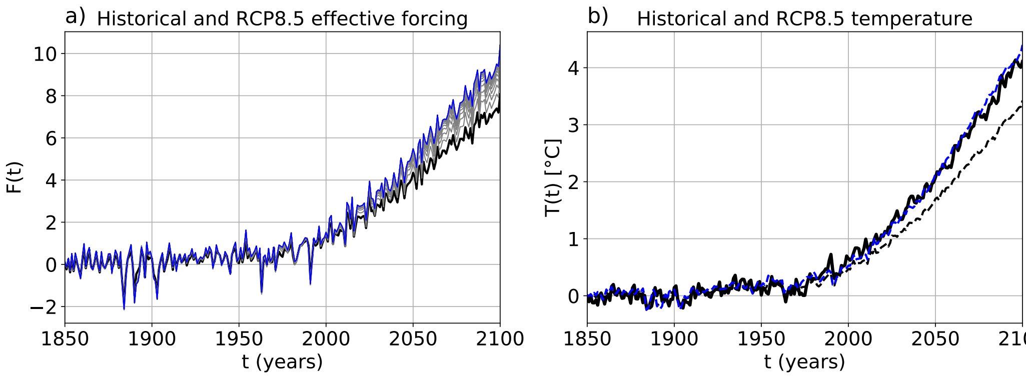

Figure 3. Results for NorESM1-M: a) The black curve is the forcing computed as in F13, using a single and constant value of λ. The gray curves are the iterations of the algorithm described in section 2.4, using three different λ's, and the blue curve the new forcing we have converged to after 20 iterations. b) The thick black curve is the modelled temperature change, and the black and blue dashed curves the linear responses to the black and blue curves in a), applying the same response function as estimated in Figure 1 b).

Repeating the analysis in Figure 3 for all models and scenarios shows that the method presented here works well for many models, but not all (Figures in supporting information). A summary of these results are given in Figure 4, where panel a) compares the mean estimated forcing over years 2091-2100 using the two different methods. The names of the scenarios are constructed to reflect the intended forcing in the end of the 21st century, and these forcing levels are also shown for comparison. We find that model estimates using F13's method are centered at lower values, while our new forcing estimates are centered close to or slightly above the intended levels. However, the intended forcing is difficult to prescribe as it depends on model-specific fast adjustments, so we can only expect these to be approximate values. The GISS-E2-R model might be considered as an outlier, and its response to abrupt4xCO_2 is also visually different from the other models.

Consistent with the increase in forcing level, we observe an increase in the estimated linear temperature responses in panel b). The linear responses to F13 forcing are mostly

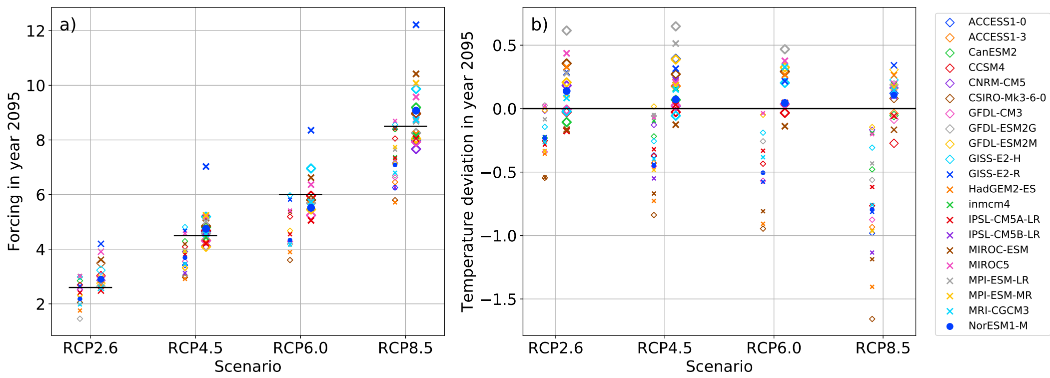

Figure 4. Estimated forcing (a) and temperature difference between the result of the linear response and the climate model output (b). For each scenario, the left points show results using F13's method, and the right points show results using our method. Values in year 2095 are computed by averaging over the ten years 2091-2100. The forcing levels 2.6, 4.5, 6.0 and 8.5 W/m^2 are also shown for reference in a) as horizontal black lines.

lower than the climate model temperature output, and the responses to our new forcing are scattered around, with a center slightly above. Some deviation from the climate model temperature is expected due to internal variability, and to assess this expected uncertainty, we refer to the model spread of the Community Earth System Model Large Ensemble (CESM-LE) (Kay et al., 2015). Here 40 model simulations for the historical + RCP8.5 scenarios from the same model show a model spread of around 0.4 K, which is attributed to internal variability.

Using F13 forcing, the linear response is within these uncertainties for only a few models. For the new forcing, more models are within this uncertainty range than outside. There are also other uncertainties to consider, e.g. associated with our parameter estimation method, probably making the expected uncertainty interval larger than 0.4 K. The uncertainty due to internal variability is also model-dependent (Olonscheck et al., 2020), hence it is difficult to identify models where our linear response hypothesis and forcing estimation method fail.

We note also that the uncertainty of the future scenario forcing estimates is strongly related to the uncertainty of the 4xCO_2 forcing estimates, since both are highly influenced by λ_1. This is particularly apparent for the GISS-E2-R model, where the response of the first few years is so abrupt that forcing estimates, and hence linear responses, are uncertain with both our and F13's estimation method.

In the two models CNRM-CM5 and MIROC5 the two forcing estimates are very similar, because the feedback is close to constant for all years. For these models we find also that the forcing estimate based on a single feedback parameter gives a slightly better estimate of the linear response. So if the global feedback in fact is constant for all years, using all years in the regression should give a more certain estimate of the feedback parameter, and therefore also more certain forcing estimates.

For the three models GFDL-ESM2G, GFDL-ESM2M, and inmcm4 we find that our method is performing less well (see Figures in the Supporting information). The reason is probably linked to the almost constant 4xCO_2 temperature responses over years $\sim 20-70$, $\sim 20-60$ and $\sim 20-120$, respectively. Our linear response with exponentially relaxing temperatures always predicts continuously increasing temperatures, which therefore poorly approximates these 4xCO_2 global temperatures. The flattening of the response could possibly be linked to changes in the ocean circulation, e.g. a slowdown of the Atlantic meridional overturning circulation. In that case, linear systems with complex eigenvalues giving oscillatory responses could be an alternative solution. Hence, we will not disregard linear response in these results, but leave further testing of including oscillations in the responses to future studies.

4 Discussion

For most abrupt4xCO_2 experiments the Gregory plot follows a convex curve, hence our forcing estimates are mostly higher than those found from simple regression analyses over 150 years (Andrews et al., 2012), or using only the first 20 years (Andrews et al., 2015; Larson & Portmann, 2016). As suggested by PH17, this convexity could be explained by considering different feedback parameters associated with the different time scales of the responses. The time-scale dependence of the feedback parameter could be physically explained simply as feedbacks varying in strength at different time scales, or it could be regionally different feedbacks weighted differently with time in the global average when the pattern of surface warming evolves. Since it is likely a combination of these explanations, an interpretation of our parameters could be summarized into: λ_1: Average of annual-scale feedbacks in regions with strong annual-scale responses, λ_2: Average of decadal-scale feedbacks in regions with strong decadal-scale responses, λ_3: Average of centennial-scale feedbacks in regions with strong centennial-scale responses.

The theory described in this paper does not include an explicit temperature-dependence of the feedback parameter (Rohrschneider et al., 2019; Bloch-Johnson, Rugenstein, Stolpe, et al., 2020), since it is assumed that Eq. (6) is linear and $\mathbf{K}$ is independent of temperature. However, our estimation algorithm does not clearly distinguish between a time-scale dependence and a temperature-dependence of the feedbacks, since these dependencies are intrinsically linked. In particular, the strong temperature responses to 4xCO_2 is invoked on the long time scales, where the responses to the shorter time scales have already been realised, hereby affecting the feedback parameters if they have temperature dependence. If the 4xCO_2 responses have temperature-dependent feedbacks, the model needed to explicitly explain them becomes nonlinear, and our linear approach may perform less well in providing responses to other scenarios with weaker or stronger temperature responses than that of 4xCO_2. We believe this only causes smaller errors in the temperature responses studied here, but it is a potential explanation for our forcing and responses for the future scenarios being slightly overestimated.

The fixed-SST 4xCO_2 forcing estimates reported by Andrews et al. (2012) are also higher than regression-based estimates over 150 years, and our estimated forcing is even higher than the fixed-SST forcing. One reason for this difference is that fixed-SST estimates let atmospheric and land surface temperatures increase before the radiative imbalance is diagnosed. Hence this estimate is more comparable to our radiative imbalance after some months of adjustments of $T(t)$ and $N(t)$. Tang et al. (2019) finds that the fixed-SST forcing is lower than the regression estimate for some models. An important advantage of fixed-SST estimates compared to regression-based estimates is the reduced level of noise (Forster et al., 2016). This noise reduction is important when estimating time-evolving forcing using prescribed-SST methods (Forster et al., 2013). Regression-based estimates are influenced by changes in $T(t)$ arising due to internal variability, e.g. El Niño events, which could drive changes in $N(t)$. In prescribed-SST methods the temperature-driven changes in $N(t)$ is subtracted.

Linear response theory is widely used to describe responses of climate variables. If a forcing record is known, linear response is a computationally cheap tool to estimate e.g. temperature responses compared to running a fully coupled climate model. Many studies assume a Green's function taking a certain form, with unknown parameters that need to be estimated. For box models taking the form of Eq. (6) the Green's function is a sum of exponential functions, but power-laws with fewer parameters have also been used with success (Rypdal & Rypdal, 2014; Fredriksen & Rypdal, 2017). Linear responses to RCP forcing are often studied using a non-parametric approach developed by Good et al. (2011). This method was used in Good et al. (2013) to find the response to RCP scenarios using the forcing computed by F13. They use this to simulate only differences between RCP scenarios, while we attempt to simulate the full temperature evolution since the historical runs started until year 2100. Another difference to our approach is that we obtain a smoother estimate of the expected response to forcing, with fluctuations only coming from the forcing, while the responses of Good et al. (2013) are themselves influenced by internal variability.

5 Conclusions

The method presented here suggests a clean separation between forcing and responses to forcing, where the estimated parameters from abrupt4xCO_2 experiments are used to determine forcing and surface temperature responses for other experiments. The resulting RCP forcing estimates at the end of the 21st century is closer to the target levels than previous estimates by F13. Our high forcing estimates are strongly influenced by the high magnitude of the feedback parameter λ_1 at annual time scales. Unfortunately this value is uncertain, as it depends crucially on the first few years of adjustment. Using more ensemble members of abrupt4xCO_2 experiments may help constrain the estimate of λ_1 (Rugenstein, Gregory, et al., 2016).

Forcing based on fixed-SST methods is often higher than the regression estimate over 150 years (Andrews et al., 2012; Tang et al., 2019), has a smaller uncertainty and is more computationally efficient (Forster et al., 2016). However, these forcing estimates are only available for a few models and scenarios in CMIP5. They will be available for more models and scenarios in CMIP6 (Smith et al., 2020), but far from all. The forcing estimation method presented here could therefore be a valuable supplement in the cases where fixed-SST forcing is unknown, particularly for models where a linear relation between N and T is a poor approximation. Improved forcing estimates could help to quantify the dependency of forcing value on CO_2 concentration in studies comparing e.g. 0.5x, 2x, 4x, 8x CO_2, and temperature dependence of feedbacks (Bloch-Johnson, Rugenstein, Stolpe, et al., 2020).

Putting forcing, linear responses, and nonconstancy of the global feedback parameter into a unified framework provides also an important insight into why the traditional regression-based forcing estimates may be too low. Furthermore, it suggests how these methods can be improved to provide better forcing estimates, resolving the problems caused by assuming a constant feedback parameter in regression-based methods (Forster et al., 2016).

Acknowledgments

The CMIP5 data are available at `https://esgf-node.llnl.gov/projects/cmip5/`. The forcing estimates from this paper will be stored in `https://dataverse.no/`, and can be accessed through `https://doi.org/10.18710/IHUVTB`.

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