Including the efficacy of land ice changes in deriving climate sensitivity from paleodata

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Abstract. The equilibrium climate sensitivity (ECS) of climate models is calculated as the equilibrium global mean surface warming resulting from a simulated doubling of the atmospheric CO_2 concentration. In these simulations, long-term processes in the climate system, such as land ice changes, are not incorporated. Hence, they have to be compensated for when comparing climate sensitivity derived from paleodata to the ECS of climate models. Several recent studies found that the impact these long-term processes have on global temperature cannot be quantified directly through the global radiative forcing they induce. This renders the approach of deconvoluting paleotemperatures through a partitioning based on radiative forcings inaccurate. Here, we therefore implement an efficacy factor $\varepsilon_{[LI]}$, that relates the impact of land ice changes on global temperature to that of CO_2 changes, in our calculation of climate sensitivity from paleodata. We apply our new approach to a proxy-inferred paleoclimate dataset, and base the range in $\varepsilon_{[LI]}$ we use on a multi-model assemblage of simulated relative influences of land ice changes on the Last Glacial Maximum temperature anomaly. We find that $\varepsilon_{[LI]}$ is smaller than unity, meaning that per unit of radiative forcing the impact on global temperature is less strong for land ice changes than for CO_2 changes. Consequently, our obtained ECS estimate of $5.8 \pm 1.3\,\mathrm{K}$, where the uncertainty reflects the implemented range in $\varepsilon_{[LI]}$, is ~50% higher than the result of the old approach that does not consider efficacy.

1 Introduction

Equilibrium climate sensitivity (ECS) expresses the simulated equilibrated surface air temperature response to an instantaneous doubling of the atmospheric CO_2 concentration. The simulated effect of the applied CO_2 radiative forcing anomaly includes the Planck response, as well as the fast feedbacks e.g. through snow, sea ice, lapse rate, clouds and water vapour changes. ECS varies significantly between different state-of-the-art climate models, as for instance the CMIP5 ensemble shows a range of 1.9 to 4.4 K (Vial et al., 2013). Several ways have been put forward to constrain ECS, for example through the usage of paleoclimate data (e.g. Covey et al., 1996; Edwards et al., 2007), which is also the focus of this study. However, unlike results of models, which can be run ceteris paribus, temperature reconstructions based on paleoclimate proxy data always contain a mixed signal of all processes active in the climate system. Among these are long-term processes (or slow feedbacks) such as changes in vegetation, dust, and, arguably most importantly, land ice changes, which are not taken into account in the quantification of ECS. Therefore, it is necessary to correct paleotemperature records for the influence of these processes, in order to make a meaningful comparison to ECS calculated by climate models.

In a co-ordinated community effort, the PALAEOSENS project proposed to relate the temperature response caused by these long-term processes to the global averaged radiative forcing they induce (PALAEOSENS Project Members, 2012). Consequently, the paleotemperature record can be disentangled on the basis of the separate radiative forcings of these long-term processes (e.g. von der Heydt et al., 2014; Martínez-Botí et al., 2015; Köhler et al., 2015, 2017b, 2018; Friedrich et al., 2016). If all processes are accounted for in this manner, the sole effect of CO_2 changes, as is asserted by the ECS, can be quantified. However, several studies have shown that, depending on the type of radiative forcing, the same global average radiative forcing can lead to different global temperature changes (e.g. Stuber et al., 2005; Hansen et al., 2005; Yoshimori et al., 2011). For instance, in a previous article (Stap et al., 2018) we simulated the separate and combined effects of CO_2 changes and land ice changes on global surface air temperature using the intermediate complexity climate model CLIMBER-2 and showed that the specific global temperature change per unit radiative forcing change depends on which process is involved. As a possible solution to this problem, Hansen et al. (2005) formulated the concept of 'efficacy' factors, which express the impact of radiative forcing by a certain process in comparison to the effect of radiative forcing by CO_2 changes.

Based on the concept of Hansen et al. (2005), here we introduce an efficacy factor for radiative forcing by albedo changes due to land ice variability, in our method of deriving climate sensitivity from paleodata. We first validate our refined approach by applying it to transient simulations over the past 5 Myr using CLIMBER-2 (Stap et al., 2018). We compare the results of our approach of obtaining the sole effect of CO_2 changes on global temperature from a simulation forced by land ice and CO_2 changes, to a simulation where CO_2 changes are the only operating long-term process. Hence, we can assess the error resulting from using a constant efficacy factor. Thereafter, we refine a previous estimate of climate sensitivity based on a paleoclimate dataset of the past 800 kyr (Köhler et al., 2015, 2018). In this dataset, the sole effect of CO_2 is not a-priori known. We therefore investigate the influence of the introduced efficacy factor on the calculated climate sensitivity. To do so, we appraise the influence of land ice changes and the associated efficacy using a range that is given by different modelling efforts of the Last

Glacial Maximum (LGM; ~21 kyr ago) (Shakun, 2017). The climate sensitivity resulting from applying this range provides a quantification of the consequence of the uncertain efficacy of land ice changes.

2 Material and methods

In this section, we recapitulate the approach to obtain climate sensitivity from paleodata, used in numerous earlier studies (e.g.
5 PALAEOSENS Project Members, 2012; von der Heydt et al., 2014; Martínez-Botí et al., 2015; Köhler et al., 2015, 2017b, 2018; Friedrich et al., 2016). We also discuss the main refinement we make in this study, which is the inclusion of the efficacy of land ice changes, and a further small refinement that unifies the dependent variable in cross-plots of radiative forcing and global temperature anomalies.

2.1 Approach to obtain climate sensitivity from paleodata

10 Equilibrium climate sensitivity (ECS) is the long-term global average surface air temperature change resulting from a CO_2 doubling, and is usually obtained from climate model simulations. In these simulations, fast feedbacks, i.e. processes in the climate system with timescales of less than ~100 yrs, are accounted for. However, slower processes, such as ice sheet, vegetation and dust changes, are commonly kept constant. The resulting response is also sometimes called 'Charney' sensitivity (Charney et al., 1979). Following the notation of PALAEOSENS Project Members (2012), taking the ratio of the temperature
15 change ($\Delta T_{[CO_2]}$) over the radiative forcing due to the CO_2 change ($\Delta R_{[CO_2]}$), leads to S^a (in $K\,W^{-1}\,m^2$, and where a stands for *actuo*):

$$S^a = \frac{\Delta T_{[CO_2]}}{\Delta R_{[CO_2]}}. \tag{1}$$

The subscript denotes that CO_2 is the only long-term process involved. Analogously, paleoclimate sensitivity (S^p) can be deduced from paleo-temperature reconstructions and paleo-CO_2 records as

$$S^p = \frac{\Delta T_g}{\Delta R_{[CO_2]}}. \tag{2}$$

In this case, the average global paleotemperature anomaly with respect to the pre-industrial (PI) (ΔT_g) is, however, also affected
20 by the long-term processes that are typically neglected in climate simulations. Therefore, a correction to the paleotemperature perturbation is needed to obtain $\Delta T_{[CO_2]}$ from ΔT_g:

$$\Delta T_{[CO_2]} = \Delta T_g (1 - f), \tag{3}$$

or equivalently S^a from S^p:

$$S^a = S^p(1 - f) = \frac{\Delta T_g}{\Delta R_{[CO_2]}}(1 - f). \tag{4}$$

Here, f represents the effect of the slow feedbacks on paleotemperature (e.g. van de Wal et al., 2011). To obtain f, PALAEOSENS Project Members (2012) proposed an approach, which has subsequently been used in numerous studies aiming to constrain

climate sensitivity from paleodata (e.g. von der Heydt et al., 2014; Martínez-Botí et al., 2015; Köhler et al., 2015, 2017b, 2018; Friedrich et al., 2016). Their idea was that the influence of long-term processes (X) on global temperature, is directly proportional to the radiative forcing perturbation they induce ($\Delta R_{[X]}$), hence:

$$f = \frac{\Delta R_{[X]}}{\Delta R_{[CO_2]} + \Delta R_{[X]}} = 1 - \frac{\Delta R_{[CO_2]}}{\Delta R_{[CO_2]} + \Delta R_{[X]}} \tag{5}$$

Combining Eqs. 4 and 5 and following the PALAEOSENS nomenclature, we can then derive the 'specific' paleoclimate sensitivity $S_{[CO_2,X]}$, where X represents the processes that are accounted for in the calculation of f:

$$S_{[CO_2,X]} = \frac{\Delta T_g}{\Delta R_{[CO_2]}}(1 - \frac{\Delta R_{[X]}}{\Delta R_{[CO_2]} + \Delta R_{[X]}}) = \frac{\Delta T_g}{\Delta R_{[CO_2]} + \Delta R_{[X]}} = \frac{\Delta T_g}{\Delta R_{[CO_2,X]}}. \tag{6}$$

If, for instance, only the most important slow feedback in the climate system, namely radiative forcing anomalies induced by albedo changes due to land ice (LI) variability are taken into account, then one can correct S^p to derive the following specific climate sensitivity:

$$S_{[CO_2,LI]} = \frac{\Delta T_g}{\Delta R_{[CO_2]} + \Delta R_{[LI]}} = \frac{\Delta T_g}{\Delta R_{[CO_2,LI]}}. \tag{7}$$

Using this approach, several studies performed a least-squares regression through scattered data from paleotemperature and radiative forcing records (Martínez-Botí et al., 2015; Friedrich et al., 2016; Köhler et al., 2015, 2017b, 2018) relating ΔT_g to $\Delta R_{[CO_2,LI]}$ in a time-independent manner, from which $S_{[CO_2,LI]}$ could be determined. In this way, a state dependency of $S_{[CO_2,LI]}$ as function of background climate has been deduced for those data which are best approximated by a non-linear function. Furthermore, the quantification of $S_{[CO_2,LI]}$ for those state-dependent cases has been formalized in Köhler et al. (2017b). A synthesis of estimates of $S_{[CO_2,LI]}$ from both colder- and warmer-than-present climates has been compiled by von der Heydt et al. (2016).

To obtain S^a, one needs to multiply $S_{[CO_2,LI]}$ by a factor of 0.64 that accounts for the influence of other long-term processes, namely vegetation, aerosol and non-CO_2 greenhouse gas changes (PALAEOSENS Project Members, 2012). Finally, we obtain the equivalent ECS by multiplying S^a by 3.7 W m^{-2}, the radiative forcing perturbation representing a CO_2 doubling (Myhre et al., 1998).

2.2 Refinement 1: Taking the efficacy of land ice changes into account

The validity of the PALAEOSENS approach to calculate f is contingent on the notion that identical global-average radiative forcing changes leads to identical global temperature responses, regardless of the processes involved. However, it has been demonstrated that the horizontal and vertical distribution of the radiative forcing affects the resulting temperature response (e.g. Stuber et al., 2005; Hansen et al., 2005; Yoshimori et al., 2011; Stap et al., 2018) because, e.g. different fast feedbacks are triggered depending on the location of the forcing. To address this issue, Hansen et al. (2005) introduced the concept of 'efficacy' factors, which we will explore further in this study. These factors ($\varepsilon_{[X]}$) relate the strength of the temperature response to radiative forcing caused by a certain process X ($\Delta T_{[X]}/\Delta R_{[X]}$), to a similar ratio caused by CO_2 radiative forcing

$(\Delta T_{[CO_2]}/\Delta R_{[CO_2]})$. This introduction of efficacy requires a reformulation of f as f_ε:

$$f_\varepsilon = \frac{\varepsilon_{[X]}\Delta R_{[X]}}{\Delta R_{[CO_2]} + \varepsilon_{[X]}\Delta R_{[X]}} = 1 - \frac{\Delta R_{[CO_2]}}{\Delta R_{[CO_2]} + \varepsilon_{[X]}\Delta R_{[X]}}, \tag{8}$$

and hence also of $S_{[CO_2,X]}$ as $S_{[CO_2,X]}^\varepsilon$:

$$S_{[CO_2,X]}^\varepsilon = \frac{\Delta T_g}{\Delta R_{[CO_2]} + \varepsilon_{[X]}\Delta R_{[X]}}. \tag{9}$$

In these reformulations, where in principal $\varepsilon_{[X]}$ can take any value, we introduce the superscript ε. This serves to clearly distinguish these newly-derived sensitivities from those of the PALAEOSENS project in which efficacy was not taken into account, implying that identical radiative forcing of different processes leads to identical temperature changes.

To calculate $S_{[CO_2,LI]}^\varepsilon$, we constrain the efficacy factor for radiative forcing by land ice changes ($\varepsilon_{[LI]}$), using the following formulation, which is based on, but slightly modified from Hansen et al. (2005):

$$\frac{\Delta T_{[LI]}}{\Delta R_{[LI]}} = \varepsilon_{[LI]}\frac{\Delta T_g - \Delta T_{[LI]}}{\Delta R_{[CO_2]}}. \tag{10}$$

This leads to:

$$\varepsilon_{[LI]} = \frac{\omega}{1-\omega}\frac{\Delta R_{[CO_2]}}{\Delta R_{[LI]}}, \tag{11}$$

where ω represents the fractional relative influence of land ice changes on the global temperature change ($\omega = \Delta T_{[LI]}/\Delta T_g$). If $\varepsilon_{[LI]}$ is assumed to be constant in time (see Sect. 3.2 and 5), it can be calculated using Eq. 11 from data of any specific moment in time, and consequently applied to the whole record of $\Delta R_{[CO_2]}$ and $\Delta R_{[LI]}$ (Fig. 1a,c). As before, with this $\varepsilon_{[LI]}$ a quantification of $S_{[CO_2,LI]}^\varepsilon$ can be obtained by performing a least-squares regression through scattered data from paleotemperature and radiative forcing records, now relating ΔT_g to $(\Delta R_{[CO_2]} + \varepsilon_{[LI]}\Delta R_{[LI]})$ in a time-independent manner.

Note that apart from the formulation based on Hansen et al. (2005) followed here, other formulations of the efficacy factor are possible. For instance, one can define an alternative efficacy factor ($\varepsilon_{[LI],alt}$) such that it relates the effect of land ice changes on global temperature directly to the radiative forcing anomaly caused by CO_2 changes, leading to:

$$S_{[CO_2,X],alt}^\varepsilon = \frac{\Delta T_g}{\Delta R_{[CO_2]} + \varepsilon_{[LI],alt}\Delta R_{[CO_2]}}. \tag{12}$$

In this alternative case, the efficacy factor $\varepsilon_{[LI],alt}$ relates to our original $\varepsilon_{[LI]}$ as:

$$\varepsilon_{[LI],alt} = \varepsilon_{[LI]}\frac{\Delta R_{[LI]}}{\Delta R_{[CO_2]}}. \tag{13}$$

This implies that if $\varepsilon_{[LI]}$ is indeed constant, any non-linearity in the relation between $\Delta R_{[CO_2]}$ and $\Delta R_{[LI]}$ would demand a more complex formulation of the alternative efficacy factor $\varepsilon_{[LI],alt}$ (e.g. via a higher-order polynomial). Since we find such a non-linearity in our data (Fig. 2), using an F test to determine that a second order polynomial is a significantly (p value < 0.0001) better fit to the data than a linear function, we refrain from following this alternative formulation further.

2.3 Refinement 2: Unifying the dependent variable

In the cross-plots of radiative forcing and global temperature anomalies used to calculate $S^\varepsilon_{[CO_2,LI]}$, the radiative forcing on the x-axis is caused by a combination of CO_2 and land-ice changes. To more readily compare $S^\varepsilon_{[CO_2,LI]}$ to other specific paleoclimate sensitivities $S^\varepsilon_{[CO_2,X]}$, where more and/or different long-term processes are considered, the dependent variable

5 has to be unified. Here, we therefore reformulate our equation to get $\Delta R_{[CO_2]}$ in the nominator, enabling the use of cross-plots that now have $\Delta R_{[CO_2]}$ on the x-axis.

$$S^\varepsilon_{[CO_2,X]} = \frac{\Delta T_g}{\Delta R_{[CO_2]} + \varepsilon_{[X]}\Delta R_{[X]}} = \frac{\Delta T_g}{\Delta R_{[CO_2]}}\frac{\Delta R_{[CO_2]}}{\Delta R_{[CO_2]} + \varepsilon_{[X]}\Delta R_{[X]}} = \frac{\Delta T^\varepsilon_{[-X]}}{\Delta R_{[CO_2]}}. \tag{14}$$

Here, $\Delta T^\varepsilon_{[-X]}$ is the global temperature change (with respect to PI) stripped of the inferred influence of processes X, defined as:

$$\Delta T^\varepsilon_{[-X]} := \Delta T_g \frac{\Delta R_{[CO_2]}}{\Delta R_{[CO_2]} + \varepsilon_{[X]}\Delta R_{[X]}}. \tag{15}$$

Hence, for the calculation of $S^\varepsilon_{[CO_2,LI]}$ we use:

$$\Delta T^\varepsilon_{[-LI]} := \Delta T_g \frac{\Delta R_{[CO_2]}}{\Delta R_{[CO_2]} + \varepsilon_{[LI]}\Delta R_{[LI]}}. \tag{16}$$

10 Now, we quantify $S^\varepsilon_{[CO_2,LI]}$ by performing a least-squares regression (regfunc) through scattered data from $\Delta T^\varepsilon_{[-LI]}$ and $\Delta R_{[CO_2]}$. We use the precondition that no change in CO_2 is related to no change in $\Delta T^\varepsilon_{[-LI]}$, meaning the regression intersects the y-axis at the origin ($(x,y) = (0,0)$). Following Köhler et al. (2017b), for any non-zero $\Delta R_{[CO_2]}$, we calculate $S^\varepsilon_{[CO_2,LI]}$ as:

$$S^\varepsilon_{[CO_2,LI]}\bigg|_{\Delta R_{[CO_2]}} = \frac{\text{regfunc}}{\Delta R_{[CO_2]}}\bigg|_{\Delta R_{[CO_2]}}. \tag{17}$$

If $\Delta R_{[CO_2]} = 0\,\text{W}\,\text{m}^{-2}$, as is among others the case for pre-industrial conditions, $S^\varepsilon_{[CO_2,LI]}$ is quantified as:

$$S^\varepsilon_{[CO_2,LI]}\bigg|_{\Delta R_{[CO_2]}=0} = \frac{\delta(\text{regfunc})}{\delta(\Delta R_{[CO_2]})}\bigg|_{\Delta R_{[CO_2]}=0}. \tag{18}$$

15 Equations 17 and 18 yield a quantification of $S^\varepsilon_{[CO_2,LI]}$, which can be compared to the value obtained for $S_{[CO_2,LI]}$ using the approach without considering efficacy (equivalent to using $\varepsilon_{[LI]} = 1$) (Köhler et al., 2018).

In this study, we continue to use a multiplication factor of 0.64 to obtain S^a from $S^\varepsilon_{[CO_2,LI]}$. Note that this scaling still assumes unit efficacy for processes other than land ice changes. Therefore, it is a source of uncertainty to be investigated in future research. The equivalent ECS (in K per CO_2 doubling) can again be calculated by multiplying S^a by $3.7\,\text{W}\,\text{m}^{-2}$.

20 3 Validation of the approach using model simulations

In this section, we validate our refined approach by applying it to transient simulations over the past 5 Myr using CLIMBER-2 (Stap et al., 2018). We compare the results of our approach of obtaining the sole effect of CO_2 changes on global temperature

from a simulation forced by land ice and CO_2 changes, to a simulation where CO_2 changes are the only operating long-term process. By doing so, we assess the error resulting from using a constant efficacy factor.

3.1 CLIMBER-2 model simulations

Using the intermediate complexity climate model CLIMBER-2 (Petoukhov et al., 2000; Ganopolski et al., 2001), climate
5   simulations over the past 5 Myr were performed and analysed in Stap et al. (2018). CLIMBER-2 combines a 2.5-dimensional statistical-dynamical atmosphere model, with a 3-basin zonally averaged ocean model (Stocker et al., 1992), and a model that calculates dynamic vegetation cover based on the temperature and precipitation (Brovkin et al., 1997). In brief, the simulations are forced by solar insolation which changes due to orbital (O) variations (Laskar et al., 2004), and further by land ice (I) changes on both hemispheres (based on de Boer et al., 2013), and CO_2 (C) changes (based on van de Wal et al., 2011). In the
10   reference experiment (OIC) all input data are varied, while in other model integrations the land ice (experiment OC) or the CO_2 concentration (experiment OI) is kept fixed at PI level. The synergy of land ice and CO_2 changes is negligibly small, meaning their induced temperature changes add approximately linearly when both forcings are applied. Furthermore, the influence of orbital variations is also very small, so that experiment OC approximately yields the sole effect of CO_2 changes on global temperature ($\Delta T_{[OC]}$). As in Stap et al. (2018), we use the simple energy balance model of Köhler et al. (2010) to analyse the
15   applied radiative forcing of land ice albedo and CO_2 changes and simulated global temperature changes, after averaging to 1,000 year temporal resolution (Fig. 1a,b).

3.2 Analysis

First, we analyse experiment OC, which will serve as a target for our refined approach as deployed later in this section. We use a least-squares regression through scattered data of $\Delta R_{[CO_2]}$ and $\Delta T_{[OC]}$ to fit a second order polynomial (Fig. 3a). Using a
20   higher order polynomial rather than a linear function allows us to capture state dependency of paleoclimate sensitivity. Fitting even higher order polynomials leads to negligible coefficients for the higher powers, and is not pursued further. From the fit, we calculate a specific paleoclimate sensitivity $S^{\varepsilon}_{[CO_2, LI]}$ of 0.74 $K\,W^{-1}\,m^2$ for PI conditions ($\Delta R_{[CO_2]} = 0\ W\,m^{-2}$) using Eq. 18. Note that, in this case, $S^{\varepsilon}_{[CO_2, LI]}$ is equal to $S^{\varepsilon}_{[CO_2]}$, $S_{[CO_2, LI]}$ and $S_{[CO_2]}$ as there are no land ice changes and therefore also no efficacy differences. The fit further shows decreasing $S^{\varepsilon}_{[CO_2, LI]}$ for rising $\Delta R_{[CO_2]}$.
25   Now, we apply our approach to the results of experiment OIC, in which both CO_2 and land ice cover vary over time, with the aim of deducing the sole effect of CO_2 changes on global temperature. We calculate the efficacy of land ice changes for the Last Glacial Maximum (21 kyr ago; LGM) from experiment OI, in which the CO_2 concentration is kept constant. We obtain $\omega = \Delta T_{[LI]}/\Delta T_g = \Delta T_{[OI]}/\Delta T_{[OIC]} = 0.54$. Consequently, we find $\varepsilon_{[LI]} = 0.58$ from Eq. 11, and apply this value to the whole record of $\Delta R_{[CO_2]}$ and $\Delta R_{[LI]}$. In this manner, we calculate $\Delta T^{\varepsilon}_{[-LI]}$ using Eq. 16. We then fit a second order polynomial to the
30   scattered data of the thusly obtained $\Delta T^{\varepsilon}_{[-LI]}$ from the results of experiment OIC, and $\Delta R_{[CO_2]}$ (Fig. 3b). Between $\Delta R_{[CO_2]} = -0.5\,W\,m^{-2}$ and $\Delta R_{[CO_2]} = 0.5\,W\,m^{-2}$, outliers resulted from division by small numbers (not shown in Fig. 3b). To remove these outliers, we first calculate the root mean square error (RMSE) between the fit and the data in the remainder of the domain. We then exclude all 144 values from the range $\Delta R_{[CO_2]} = -0.5\,W\,m^{-2}$ to $\Delta R_{[CO_2]} = 0.5\,W\,m^{-2}$ where the fit differs from

the data by more than $3 \times$ RMSE, and perform the regression again. This yields an $S^{\varepsilon}_{[\mathrm{CO_2, LI}]}$ of $0.72\,\mathrm{K\,W^{-1}\,m^2}$ for PI (Fig. 3b), which supports our approach since it is only slightly lower than the $S^{\varepsilon}_{[\mathrm{CO_2, LI}]}$ of $0.74\,\mathrm{K\,W^{-1}\,m^2}$ obtained from experiment OC, which it should approximate. The relationship between $\Delta T^{\varepsilon}_{[-\mathrm{LI}]}$ and $\Delta R_{[\mathrm{CO_2}]}$ (Fig. 3b) is more linear than that between $\Delta T_{[\mathrm{OC}]}$ and $\Delta R_{[\mathrm{CO_2}]}$ (Fig. 3a), hence the state dependency of $S^{\varepsilon}_{[\mathrm{CO_2, LI}]}$ is reduced. However, the difference between the

5    $S^{\varepsilon}_{[\mathrm{CO_2, LI}]}$ obtained from both experiments remains smaller than $0.07\,\mathrm{K\,W^{-1}\,m^2}$ through the entire 5-Myr interval, indicating that a constant efficacy is an acceptable assumption which only introduces a negligible additional uncertainty. However, the possible time-dependency of efficacy could be investigated more rigorously in future research using more sophisticated climate models.

In principal, $\varepsilon_{[\mathrm{LI}]}$ can be obtained using data from any moment in time, preferably when the radiative forcing anomalies

10   are large to prevent outliers resulting from divisions by small numbers. For example, using the results from all glacial marine isotope stages of the past 810 kyr (MIS 2, 6, 8, 10, 12, 14, 16, 18, and 20), instead of just the LGM, leads to a mean ($\pm 1\sigma$) $\varepsilon_{[\mathrm{LI}]}$ of 0.56 ± 0.09. The resulting PI $S^{\varepsilon}_{[\mathrm{CO_2, LI}]}$ is $0.73^{+0.06}_{-0.05}\,\mathrm{K\,W^{-1}\,m^2}$ (Fig. 3c).

The old approach, which is equal to using $\varepsilon_{[\mathrm{LI}]} = 1$ in the refined approach, yields a PI $S_{[\mathrm{CO_2, LI}]}$ of $0.54\,\mathrm{K\,W^{-1}\,m^2}$ (Fig. 3d). This is clearly much more off-target than the results of our refined approach, signifying the importance of considering efficacy.

15   ## 4   Application to proxy-inferred paleoclimate data

In this section, we compare our refined approach to calculate $S^{\varepsilon}_{[\mathrm{CO_2, LI}]}$ incorporating efficacy, to our previous quantification of $S_{[\mathrm{CO_2, LI}]}$ (Köhler et al., 2018), by reanalysing the same paleoclimate dataset (introduced in Köhler et al., 2015). Other than for climate model simulations, the influence of land ice changes on global temperature perturbations cannot be directly obtained from proxy-based datasets, and is hence a-priori unknown. We therefore base the value of $\varepsilon_{[\mathrm{LI}]}$ we implement here on a multi-

20   model assemblage of simulated relative influences of land ice changes on the Last Glacial Maximum (LGM) temperature anomaly (Shakun, 2017).

4.1   Proxy-inferred paleoclimate dataset

The investigated dataset contains reconstructions of ΔT_{g}, $\Delta R_{[\mathrm{CO_2}]}$, and $\Delta R_{[\mathrm{LI}]}$. Although it covers the past 5 Myr, here we focus on the past 800 kyr (Fig. 1c,d) because over this period $\Delta R_{[\mathrm{CO_2}]}$ is constrained by high-fidelity ice core CO_2 data,

25   whereas Pliocene and Early Pleistocene CO_2 levels are still heavily debated (e.g. Badger et al., 2013; Martínez-Botí et al., 2015; Willeit et al., 2015; Stap et al., 2016, 2017; Chalk et al., 2017; Dyez et al., 2018). Radiative forcing by CO_2 is obtained from Antarctic ice core data compiled by Bereiter et al. (2015), using $\Delta R_{[\mathrm{CO_2}]} = 5.35\,\mathrm{W\,m^{-2}} \cdot \ln(CO_2/(278\,\mathrm{ppm}))$ (Myhre et al., 1998). Revised formulations of $\Delta R_{[\mathrm{CO_2}]}$ following Etminan et al. (2016) lead to very similar results with less than 0.01 $\mathrm{W\,m^{-2}}$ differences between the approaches for typical late Pleistocene CO_2 values (Köhler et al., 2017a). Radiative forcing

30   caused by land ice albedo changes, as well as the global surface air temperature record (ΔT_{g}), are based on results of the 3D ice-sheet model ANICE (de Boer et al., 2014). ANICE was forced by northern hemispheric temperature anomalies with respect to a reference PI climate, obtained from a benthic δ^{18}O stack (Lisiecki and Raymo, 2005) using an inverse technique.

This provided geographically specific land ice distributions, and hence radiative forcing due to albedo changes with respect to PI on both hemispheres. In Köhler et al. (2015), the northern hemispheric (NH) temperature anomalies (ΔT_{NH}) are translated into global temperature perturbations (ΔT_{g1} in Köhler et al. (2015)) using polar amplification factors ($f_{\mathrm{PA}} = \Delta T_{\mathrm{NH}}/\Delta T_{g}$) as follows: at the LGM, $f_{\mathrm{PA}} = 2.7$ is taken from the average of PMIP3 model data (Braconnot et al., 2012), while at the mid-

5 Pliocene Warm Period (mPWP, about 3.2 Myr ago), $f_{\mathrm{PA}} = 1.6$ is calculated from the average of PlioMIP results (Haywood et al., 2013). At all other times, f_{PA} is linearly varied as a function of NH temperature. In Appendix A, we investigate the influence of the chosen polar amplification factor (Köhler et al., 2015) on our results. The temperature dynamics follow from a benthic δ^{18}O stack and are unconstrained by climatic boundary conditions such as insolation and greenhouse gases, since ANICE only simulates land ice dynamics. Therefore, these results are here considered to be more similar to those of proxy-

10 based reconstructions than of climate-model-based simulations. The temporal resolution of the dataset is 2,000 years.

Analysing this dataset, Köhler et al. (2018) found a temperature-CO_2 divergence appearing mainly during, or in connection with, periods of decreasing obliquity related to land ice growth or sea level fall. For these periods, a significantly different $S_{[\mathrm{CO2,LI}]}$ was obtained than for the remainder of the time frame. However, in the future we expect sea level to rise, hence these intervals of strong temperature-CO_2 divergence should not be considered for the interpretation of paleodata in the context of

15 future warming, e.g. by using paleodata to constrain ECS. In the following analysis, we therefore exclude these times with strong temperature-CO_2 divergence, leaving 217 data points as indicated in Fig. 1c,d.

4.2 Analysis

Shakun (2017) compiled the simulated relative impact of land ice changes on the LGM temperature anomaly (ω in Eq. 11) using a 12-member climate model ensemble, and found a range of 0.46 ± 0.14 (mean $\pm 1\sigma$, full range $0.20 - 0.68$). Applying these

20 values, in combination with the LGM values (taken here as the mean of the data at 20 and 22 kyr ago) $\Delta R_{[\mathrm{CO_2}]} = -2.04\,\mathrm{W\,m^{-2}}$ and $\Delta R_{[\mathrm{LI}]} = -3.88\,\mathrm{W\,m^{-2}}$, yields $\varepsilon_{[\mathrm{LI}]} = 0.45^{+0.34}_{-0.20}$. Implementing this range for $\varepsilon_{[\mathrm{LI}]}$ in Eq. 16, we calculate $\Delta T^{\varepsilon}_{[-\mathrm{LI}]}$ over the whole 800-kyr period. Fitting second order polynomials by least-squares regression to the scattered data of $\Delta T^{\varepsilon}_{[-\mathrm{LI}]}$ and $\Delta R_{[\mathrm{CO_2}]}$, we infer a PI $S^{\varepsilon}_{[\mathrm{CO_2,LI}]}$ of $2.45^{+0.53}_{-0.56}\,\mathrm{K\,W^{-1}\,m^2}$ (Fig. 4a). The substantial uncertainty given here only reflects the 1σ uncertainty in $\varepsilon_{[\mathrm{LI}]}$. Similar to Köhler et al. (2018), we also detect a state dependency with decreasing $S^{\varepsilon}_{[\mathrm{CO_2,LI}]}$ towards

25 colder climates for this dataset, more strongly so in case of lower $\varepsilon_{[\mathrm{LI}]}$. This state dependency is opposite to the one found in the CLIMBER-2 results. The difference may be related to the fact that fast climate feedbacks are too linear, or that some slow feedbacks are underestimated in intermediate complexity climate models like CLIMBER-2 (see Köhler et al., 2018, for a detailed discussion). At $\Delta R_{[\mathrm{CO_2}]} = -2.04\,\mathrm{W\,m^{-2}}$, the LGM value, $S^{\varepsilon}_{[\mathrm{CO_2,LI}]}$ is only $1.45^{+0.33}_{-0.37}\,\mathrm{K\,W^{-1}\,m^2}$. The old approach, which does not consider efficacy and is therefore equivalent to the new approach using $\varepsilon_{[\mathrm{LI}]} = 1$, yields $S_{[\mathrm{CO_2,LI}]} =$

30 $1.66\,\mathrm{K\,W^{-1}\,m^2}$ for PI, and $S_{[\mathrm{CO_2,LI}]} = 0.93\,\mathrm{K\,W^{-1}\,m^2}$ for the LGM (Fig. 4b). The specific paleoclimate sensitivities we find using the refined approach are hence generally larger than those obtained by using the old approach. This is because, for the range of the impact of land ice changes on the LGM temperature anomaly implemented ($\omega = 0.46 \pm 0.14$), the efficacy factor $\varepsilon_{[\mathrm{LI}]}$ is smaller than unity. In other words, these land ice changes contribute comparatively less per unit radiative forcing to the global temperature anomalies than the CO_2 changes.

Our inferred PI $S^{\varepsilon}_{[CO_2,LI]}$ is equivalent to an S^a of $1.6^{+0.3}_{-0.4}\,\mathrm{K\,W^{-1}\,m^2}$, and an ECS of $5.8\pm1.3\,\mathrm{K}$ per CO_2 doubling. This is on the high end of the results of other approaches to obtain ECS (Knutti et al., 2017), e.g. the 2.0 to 4.3 K 95%-confidence range from a large model ensemble (Goodwin et al., 2018), and the 2.2 to 3.4 K 66% confidence range from an emerging constraint from global temperature variability and CMIP5 (Cox et al., 2018). Hence, the low end of our ECS estimate is in the best agreement with these other estimates. This could mean that the influence the relative influence of land ice changes on the LGM temperature anomaly is on the high side, or possibly higher than, the 0.46 ± 0.14 range we consider here. Alternatively, the factor of 0.64 we use to convert $S_{[CO_2,LI]}$ to S^a is an overestimation, which could be caused by a larger-than-unity efficacy of long-term processes besides CO_2 and land ice changes.

5 Conclusions

We have incorporated the concept of a constant efficacy factor (Hansen et al., 2005), that interrelates the global temperature responses to radiative forcing caused by land ice changes and CO_2 changes, into our framework of calculating specific paleoclimate sensitivity $S^{\varepsilon}_{[CO_2,LI]}$. The aim of this effort has been to overcome the problem that land ice and CO_2 changes can lead to significantly different global temperature responses, even when they induce the same global-average radiative forcing. Firstly, we have shown the importance of considering efficacy differences by applying our new approach to results of 5-Myr CLIMBER-2 simulations (Stap et al., 2018), where the separate effects of land ice changes and CO_2 changes can be isolated. In the results of these simulations, the error from assuming the efficacy factor to be constant in time is negligible. Thereafter, we have used our new approach to reanalyse an 800-kyr proxy-inferred paleoclimate dataset (Köhler et al., 2015). We have inferred a range in the land ice change efficacy factor $\varepsilon_{[LI]}$ from the 0.46 ± 0.14 (mean $\pm1\sigma$) relative impact of land ice changes on the LGM temperature anomaly simulated by a 12-member climate model ensemble (Shakun, 2017). The thusly obtained efficacy factor $\varepsilon_{[LI]}$ is smaller than unity, implying that the impact on global temperature per unit of radiative forcing is less strong for land ice changes than for CO_2 changes. Consequently, our derived PI $S^{\varepsilon}_{[CO_2,LI]}$ of $2.45^{+0.53}_{-0.56}\,\mathrm{K\,W^{-1}\,m^2}$ is $\sim50\%$ larger than the result of the old approach. The uncertainty in this estimate is only caused by the implemented range in $\varepsilon_{[LI]}$. The equivalent S^a and ECS corresponding to this $S^{\varepsilon}_{[CO_2,LI]}$ are $1.6^{+0.3}_{-0.4}\,\mathrm{K\,W^{-1}\,m^2}$ and $5.8\pm1.3\,\mathrm{K}$ per CO_2 doubling respectively.

Data availability. The CLIMBER-2 dataset is available at https://doi.pangaea.de/10.1594/PANGAEA.887427, and the proxy-inferred paleoclimate dataset is available at https://doi.pangaea.de/10.1594/PANGAEA.855449, from the PANGAEA database. For more information or data, please contact the authors.

Appendix A: Influence of the polar amplification factor

In the analysis performed in Sect. 4.2, we have used a global temperature record that was obtained from northern high-latitude temperature anomalies using a polar amplification factor f_{PA} that varies from 2.7 at the coldest to 1.6 at the warmest conditions (Sect. 4.1). However, recent climate model simulations of the Pliocene using updated paleogeographic boundary conditions

show that in warmer times polar amplification could have been nearly the same as in colder times (Kamae et al., 2016; Chandan and Peltier, 2017). We therefore repeat the analysis using the same range in $\varepsilon_{[\text{LI}]}$ and the same dataset, but with an applied constant $f_{\text{PA}} = 2.7$ over the entire past 800 kyr to generate ΔT_g (ΔT_{g2} in Köhler et al. (2015)).

5   The constant polar amplification used here counteracts increasing state dependency towards low temperatures, as the temperature differences are no longer amplified by changing polar amplification. Hence, $S^{\varepsilon}_{[\text{CO}_2,\text{LI}]}$ is smaller at PI, $1.96^{+0.42}_{-0.44}\,\text{K}\,\text{W}^{-1}\,\text{m}^2$ compared to $2.45^{+0.53}_{-0.56}\,\text{K}\,\text{W}^{-1}\,\text{m}^2$ using the variable f_{PA}, but diminishes less strongly towards colder conditions (Fig. A1a cf. Fig. 4a). As before, the old approach (equivalent to the new approach using $\varepsilon_{[\text{LI}]} = 1$), yields a lower PI $S_{[\text{CO}_2,\text{LI}]}$ of $1.34\,\text{K}\,\text{W}^{-1}\,\text{m}^2$ (Fig. A1b). The PI $S^{\varepsilon}_{[\text{CO}_2,\text{LI}]}$ inferred here using the refined approach corresponds to an S^a of $1.3^{+0.2}_{-0.3}\,\text{K}\,\text{W}^{-1}\,\text{m}^2$, and an ECS of $4.6^{+1.0}_{-1.3}\,\text{K}$ per CO_2 doubling.

10   *Author contributions.* L.B.S. designed the research. L.B.S. and P.K. performed the analysis. L.B.S. drafted the paper, with input from all co-authors.

Competing interests. The authors declare that they have no conflict of interest.

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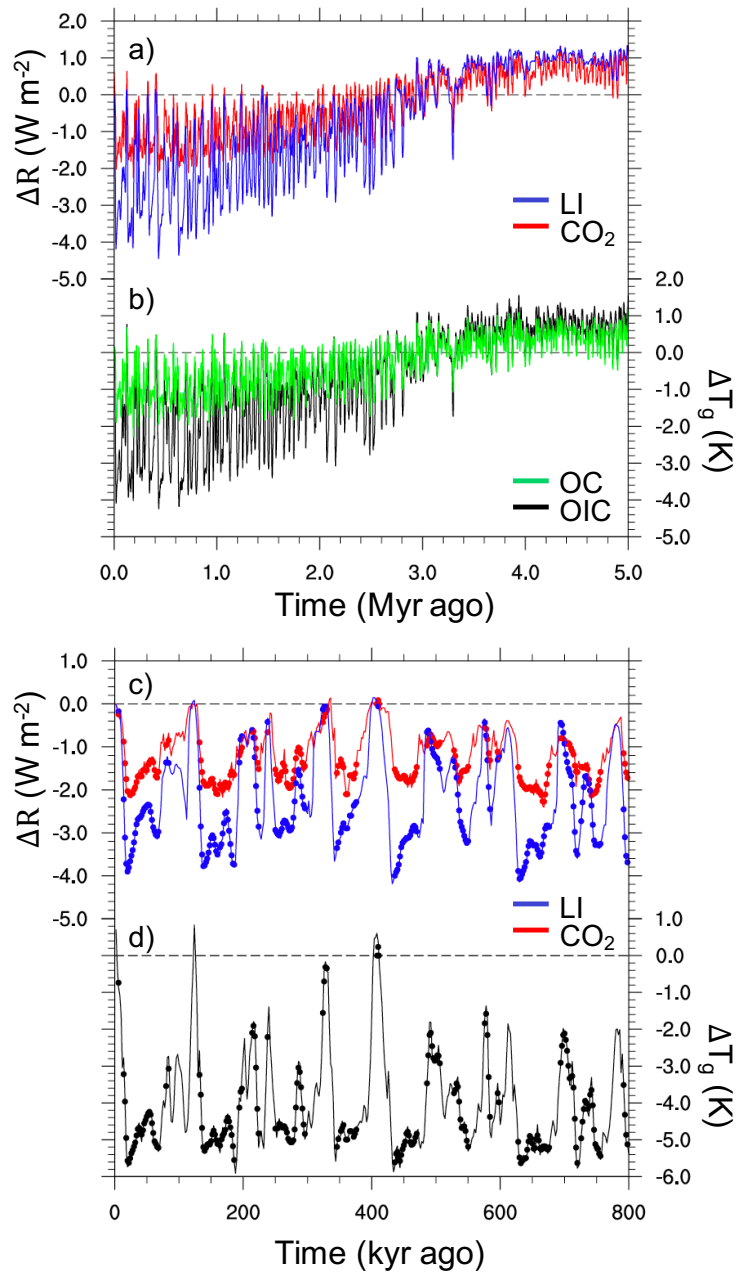
Figure 1. Timeseries of radiative forcing anomalies (ΔR) caused by CO_2 (red) changes and land ice changes (blue), and global temperature anomalies (ΔT_g) with respect to PI, from **a-b)** the CLIMBER-2 model dataset (Stap et al., 2018), with temperature data for experiment OIC in black and for experiment OC in green, and from **c-d)** the proxy-inferred dataset (Köhler et al., 2015), with solid lines for the whole dataset, and dots for the data used in this study which exclude times with strong temperature-CO_2 divergence (see Sect. 4.1). Note the differing axis scales.
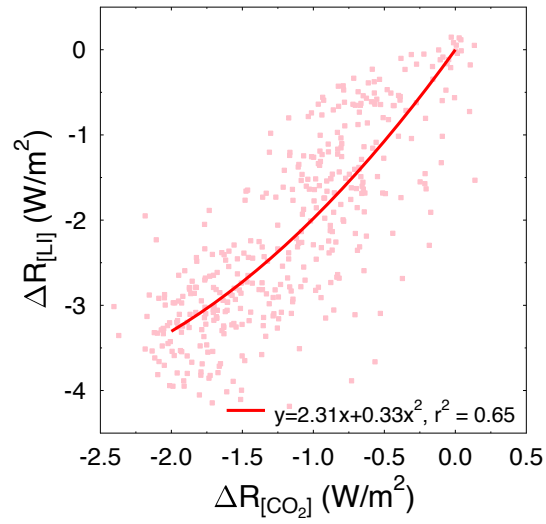
Figure 2. The relation between radiative forcing anomalies caused by CO_2 changes ($\Delta R_{[CO_2]}$) and land ice changes ($\Delta R_{[LI]}$) from the proxy-inferred dataset (Köhler et al., 2015) (pink dots). The red line represents a second order polynomial least-squares regression through the scattered data.
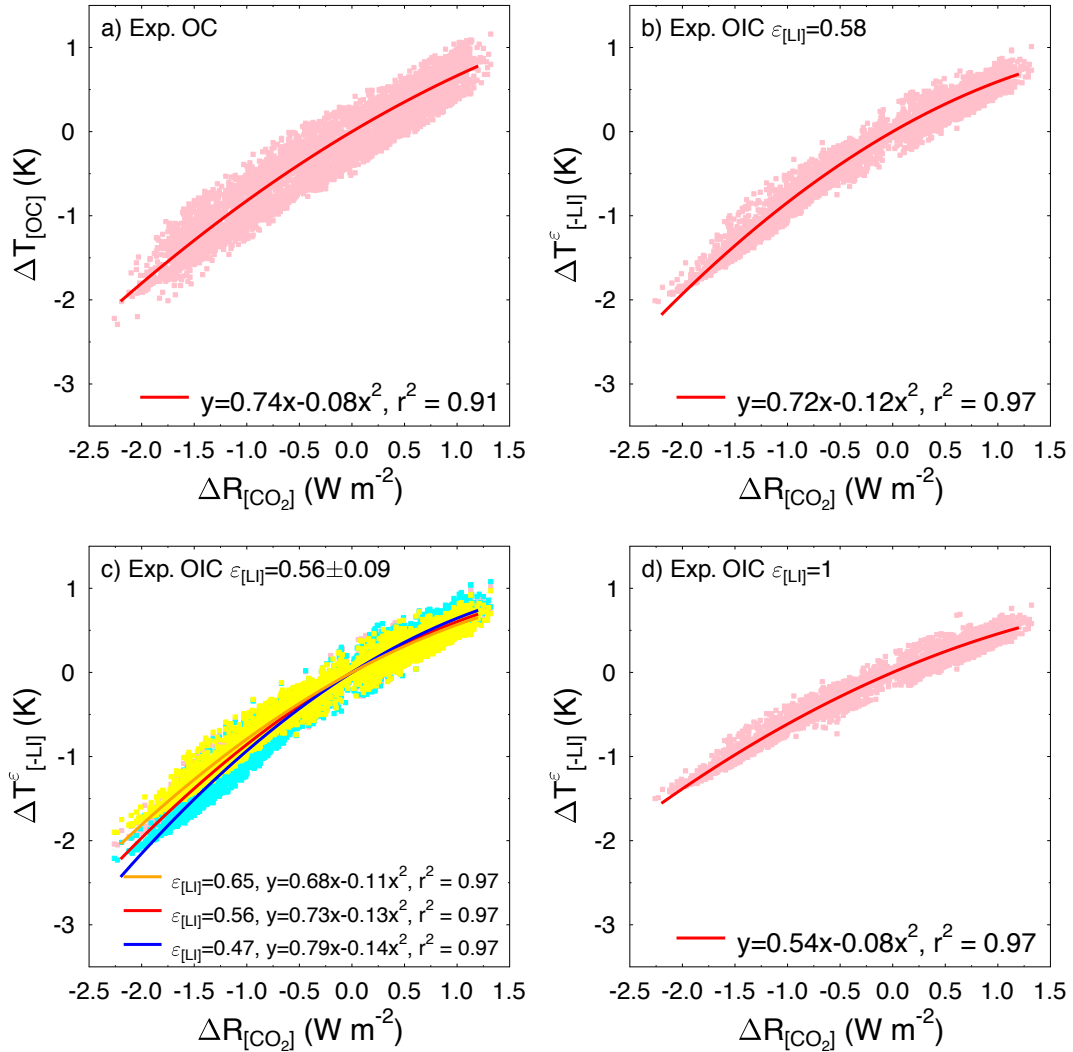
Figure 3. Temperature anomalies with respect to PI over the last 5 Myr from CLIMBER-2 (Stap et al., 2018) against imposed radiative forcing of CO_2. **a)** Simulation with fixed PI land ice distribution (experiment OC) ($\Delta T_{[OC]}$). **b)** Calculated global temperature perturbations from experiment OIC stripped of the inferred influence of land ice ($\Delta T^{\varepsilon}_{[-LI]}$) using Eq. 16 with $\varepsilon_{[LI]} = 0.58$. Here, $\varepsilon_{[LI]}$ is obtained from matching climate sensitivity with the target value at the LGM. **c)** Same as in (b), but using $\varepsilon_{[LI]} = 0.47$ (cyan dots), $\varepsilon_{[LI]} = 0.56$ (pink dots), and $\varepsilon_{[LI]} = 0.65$ (yellow dots), Here, $\varepsilon_{[LI]}$ is obtained from the mean ($\pm 1\sigma$) of matching climate sensitivity with the target value at all glacial marine isotope stages of the past 810 kyr (MIS 2, 6, 8, 10, 12, 14, 16, 18, and 20). **d)** Same as in (b), but using $\varepsilon_{[LI]} = 1$, which is equivalent to the old approach where efficacy differences were not considered. The red lines - and in **(c)** also the orange and blue lines - represent second order polynomial least-squares regressions through the scattered data.
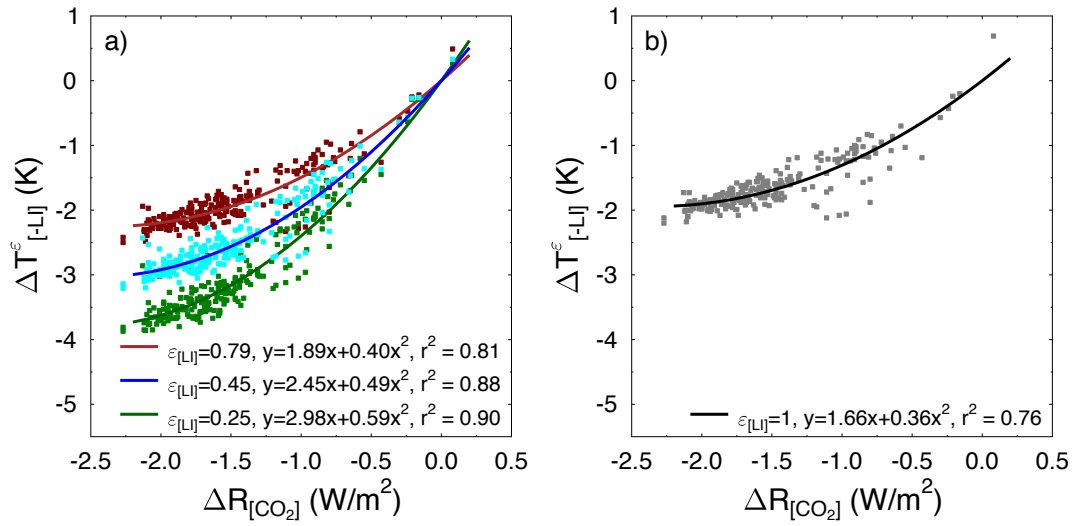
Figure 4. The global temperature perturbations stripped of the inferred influence of land ice ($\Delta T^{\varepsilon}_{[-LI]}$) calculated using Eq. 16 against $\Delta R_{[CO_2]}$ from the proxy-inferred paleoclimate dataset (Köhler et al., 2015), using: **a)** $\varepsilon_{[LI]} = 0.79$ (maroon dots), $\varepsilon_{[LI]} = 0.45$ (cyan dots), and $\varepsilon_{[LI]} = 0.25$ (green dots). Here, $\varepsilon_{[LI]}$ is obtained by converting the multi-model assemblage of simulated relative influences of land ice changes on the LGM temperature anomaly (0.46 ± 0.14) (Shakun, 2017). **b)** Same as in (a), but using $\varepsilon_{[LI]} = 1$ (grey dots), which is equivalent to the old approach. The brown, blue, dark green (**a**), and black lines (**b**) represent second order polynomial least-squares regressions through the data.
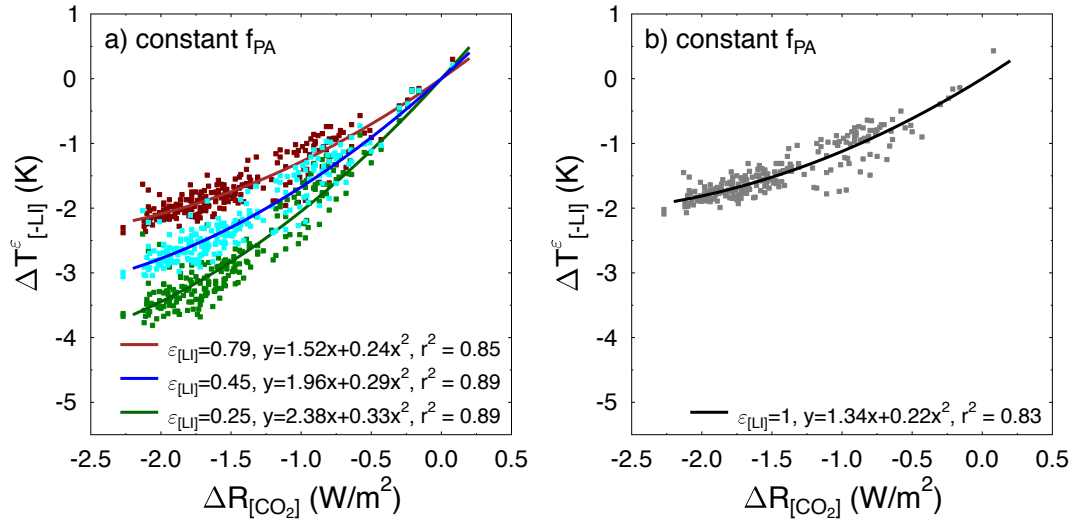
Figure A1. The global temperature perturbations stripped of the inferred influence of land ice ($\Delta T^{\varepsilon}_{[-LI]}$) calculated using Eq. 16 against $\Delta R_{[CO_2]}$ from the proxy-inferred paleoclimate dataset (Köhler et al., 2015), using: **a)** $\varepsilon_{[LI]} = 0.79$ (maroon dots), $\varepsilon_{[LI]} = 0.45$ (cyan dots), and $\varepsilon_{[LI]} = 0.25$ (green dots). Here, $\varepsilon_{[LI]}$ is obtained from converting the multi-model assemblage of simulated relative influences of land ice changes on the LGM temperature anomaly (0.46±0.14) (Shakun, 2017). **b)** Same as in (a), but using $\varepsilon_{[LI]} = 1$ (grey dots), which is equivalent to the old approach. The brown, blue, dark green (**a**), and black lines (**b**) represent second order polynomial least-squares regressions through the data. Here, the global temperature anomalies are derived from the northern high-latitude temperature anomaly reconstruction assuming a constant polar amplification factor (f_{PA}) of 2.7, as opposed to the variable f_{PA} used in Fig. 4.