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Climate of the Past Discussions

Technical note: Pleistocene climate sensitivity to CO_2 forcing is path dependent in reconstructions

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Abstract. Improved high-resolution paleo records of atmospheric carbon dioxide (CO_2) concentrations and reconstructions of Earth's surface temperature are available. We analyse one authoritative Pleistocene dataset to explore how the climate sensitivity parameter S varies under different system states, using linear regression of mean annual surface temperature changes against CO_2 forcing changes. Data are partitioned by *path* (deglaciation or glaciation). On the whole data set, $S = 2.04K/Wm^{-2}$ and CO_2 forcing explains 64% of the variance in temperature. During deglaciation periods, $S = 2.34K/Wm^{-2}$, explaining 75% of the temperature variance.; during glaciations, $S = 1.59K/Wm^{-2}$ and explains 48% of the temperature variance. Possible process-related explanations for these *path*-related differences are conjectured.

1 Introduction

The climate sensitivity parameter S is somewhat loosely defined in the literature (Myhre et al 2013) as the change with respect to present in mean annual global surface temperature (ΔT) per unit change in forcing with respect to present (ΔF). S is sometimes estimated from data by linear regression: $\Delta T = S \times \Delta F + B + e$ with intercept B and error e. ΔF is $[Wm^{-2}]$ so that S is $[K/(Wm^{-2})]$. The variance of e is estimated as $(SS - SSR)/(N - df - 1)$ where N is the number of observations, df is the number of parameters in the model (here always =1), SS is the sum square deviations from the population mean and SSR is the sum square deviations of the regression estimates from the population mean. SSR/SS is the fraction of variance of ΔT explained by the regression model, termed R^2. The lower is R^2 the more of the variation in ΔT must be attributed to factors other than ΔFCO_2.

It is widely believed that "… the change in surface temperature is directly proportional to the radiative forcing. Hence, this becomes the simplest way of quantifying the effect in a perturbation in greenhouse gas inventory" (Byrne and Goldblatt 2014). Note that ΔT can be proportional to ΔF only if the intercept B is zero. Assuming $B = 0$ forces the trend line to pass through the origin ($\Delta F = 0$, $\Delta T = 0$). This can inflate and skew the errors and can cause the regression model to be a worse predictor of the data than simply predicting the mean of ΔT for each value of ΔF (as happens here, see Figure 1 and associated discussion). Others argue that the regression line "needs to pass through the origin to avoid any biases" (Köhler et al 2017). Different statistical packages have different interpretations of R^2 when $B = 0$ is stipulated, but none has the interpretation as fraction of explained variance (see SI), thereby disabling this important diagnostic. In what follows, we refrain from stating R^2 values if B is set to zero. Of course, the placement of the origin effects the value of S if $B = 0$ is stipulated. For example, Snyder (2019) considers ΔT relative to the average temperature over the last five thousand years, whereas Martinez-Boti et al (2015) define temperature change relative to pre-industrial temperature. If the intercept is estimated this choice is immaterial. In any event, the consequences of stipulating $B = 0$ are large and should be carefully weighed.

Here, we utilize the dataset (Martinez-Boti et al 2015) for the Pleistocene (*1096* records from *0.14* to *798.51 kaBP* (thousand years before present). A second Pleistocene dataset (Snyder, 2019) yields very similar results and is discussed briefly. In recent years, several researchers have studied paleoclimate data for evidence of "state dependence" in the climate sensitivity parameter (e.g. Meraner et al 2013) It has been observed that the linear approximation breaks down in the long tail of high climate sensitivity commonly seen in observational studies (Bloch-Johnson et al 2015). Transient behavior of climate sensitivity has been explored using an energy balance model combined with observational and modeling CMIP5 constraints (Goodwin, 2018). Background state dependence and tipping points in Earth system sensitivity with millennial timescales (von der Heydt et al 2016) motivate the introduction of the more general "climate sensitivity parameter". Others find that climate sensitivity strongly depends on the climate background state, with significantly larger values attained during warm phases (Meraner et al 2013. Friedrich et al 2016). Some authors voice concerns over the simple concepts underlying climate sensitivity and radiative forcing (Knutti et al 2010). Non-linear dependence of land ice albedo forcing is found (Köhler et al 2010), while non-linearity of CO_2 forcing is said to depend on the CO_2 data set. Global mean temperature and CO_2 diverge during intervals of pronounced land ice growth (Köhler et al 2018). The need to distinguish actuo- and paleoclimate sensitivity over different time scales is emphasized (Rohling et al 2018). Averaged glacial and interglacial climate sensitivities are estimated (Shao et al 2019) using Earth system model simulations of the Last Glacial Cycle.

The present study applies standard regression analysis to study variations in the climate sensitivity parameter, using Pleistocene data from Martínez-Botí et al (2015). Rather than estimating non-linear regression functions, we partition the data into periods of increasing versus periods of decreasing paths of CO_2 concentration corresponding to deglaciation versus glaciation respectively. The SI also looks at partitions into epochs before and after 424 *kaBP* and periods of low, intermediate and high CO_2 concentration. The path dependence is the most important followed by epochal dependence. Dependence on background CO_2 concentration has low explanatory power but does interact with the other two (see SI).

To compute the fraction of explained variance it is necessary to estimate the intercept term. Comparison with regressions in which the intercept B is set to zero shows that the latter have higher values of the climate sensitivity parameter with much

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Climate of the Past
Discussions

less variation over the partition elements. While this data may be subject to errors, random errors would depress the R^2 values. The wide variation of R^2 values across the partition elements argues against a strong random or systematic error across the entire data set.

Given the wide variations in *S*, projections of regression equations to estimate CO_2 concentrations out of sample cannot be considered predictions unless the conditions going forward are very similar to the conditions on which such regressions are based.

2. Analysis of Pleistocene data

A deterministic functional relation between changes in CO_2 concentrations and changes in the induced forcing (ΔFCO_2) is inferred from radiative transfer codes, where *278 ppmv* is taken as the pre-industrial concentration of CO_2:

$$\Delta FCO_2\,(CO_2) = 5.3515 \times \ln(CO_2/278)\ [Wm^{-2}]. \tag{1}$$

Note that the forcing change depends only on the ratio of two CO_2 concentrations and not on their actual values. This assumption is pervasive in the literature. Doubling CO_2 with respect to pre-industrial:

$$\Delta FCO_2\,(556) = 3.71\ [Wm^{-2}]. \tag{2}$$

Regressing mean annual surface temperature (ΔMAT in Martinez-Boti et al 2015) on ΔFCO_2 gives the following equation which explains 64% of the variance in ΔT:

$$\Delta T(\Delta FCO_2) = 2.037 \times \Delta FCO_2 - 0.709 + e \tag{3}$$

The climate sensitivity parameter $S = 2.037[K/Wm^{-2}]$. The values of *S* and *B* in eqn. *(3)* are chosen to minimize the squared distance between the values of ΔT and the linear trend.

To project the effect on temperature of doubling CO_2 above pre-industrial, based on the whole Pleistocene data, substitute $\Delta FCO_2 = 3.71$ in (3) and find $\Delta T(556) = +6.85^\circ K$. Neglecting the intercept term would result in: $2.037[K/Wm^{-2}] \times 3.71\ [W]$

$= +7.56\,^{\circ}K$. This, of course, is incorrect: if we wish to constrain the intercept to be zero, we must find the line passing through the origin minimizing squared distance to ΔT. In that case, $S = 2.531 K/Wm^{-2}$, $\Delta T(556) = +9.391\,^{\circ}K$ (Figure 1).

Eqn. (1) is just a positive affine transformation of $ln(CO_2)$. If we regress ΔT on $ln(CO_2)$, we would also explain 64% of the variance and also find $\Delta T(556) = +6.85\,^{\circ}K$. The only difference would be that the units of the linear coefficient would be $[K/ln(ppmv)]$, instead of $[K/Wm^{-2}]$. The latter dimension suggests physical agency; indeed, a *GHG* induced radiative imbalance at the top of the atmosphere causes warming according to the Stefan Boltzmann law. At the same time, a rise in temperature can raise atmospheric CO_2 concentrations through temperature mediated feedbacks as, for example, when higher ocean temperatures reduce CO_2 uptake in the oceans. We retain the familiar dimension of K/Wm^{-2} for the climate sensitivity parameter while recognizing that it reflects a choice of units rather than physical agency.

For the Pleistocene data of Martinez-Boti et al (2015), the mean $\Delta T = -2.816\,^{\circ}K$. Letting i index the *1096* data points, summing the squared deviations from the mean of the black regression line ($B = 0$) in Figure 1 left gives $SSR = \Sigma_i\,(2.531\times \Delta FCO_2(i) + 2.816)^2 = 2969 > 2942 = \Sigma_i\,(\Delta T(i) + 2.816)^2 = SS$. Using the black line as a predictor of ΔT is a bit worse than predicting the population mean of ΔT for each value of $\Delta FCO_2(i)$. For the red regression line (B estimated), $SSR = \Sigma_i\,(2.037\times \Delta FCO_2(i) - 0.709 + 2.816)^2 = 1896$, which explains $1896/2942 = 0.644$ *(64%)* of the variance of ΔT.

Neglecting to clarify whether the intercept is inferred or stipulated invites confusion. In this data, setting $B = 0$ inflates the S values and suppresses the differences over different partition elements. Table 1 compares results with and without the intercept assumption.

2. Partitioning the data

Figure 2 shows CO_2 as a function of age in *kaBP*, with local minima and maxima identified with blue *resp* red arrows. This enables us to distinguish episodes of increasing (deglaciation) and decreasing (glaciation) CO_2 concentrations. Note that increasing CO_2 episodes generally transpire more quickly than decreasing CO_2 episodes. Dividing the data into two subsets consisting of increasing or decreasing episodes allows us to determine whether the climate sensitivity parameter is CO_2-path dependent. Figure 2 also suggests that the Earth's climate system changed around the inception of Marine Isotope Stage 11 in 424 *kaBP,* midway between a glacial maximum and a glacial minimum. The SI examines epochal dependence by comparing sensitivity in the periods before and after 424 *kaBP* and the results are in Table 1.

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Preprint. Discussion started: 28 April 2020

The results show evidence of path dependence. Note that if the intercept is estimated the differences in the climate sensitivity parameter between glaciation and deglaciation *(1.5885, 2.3352)* are larger than if the intercept is stipulated to be zero *(2.5051, 2.552)*. The same is true for the projected temperature at *522ppmv* CO_2: with the intercept estimated these are *(4.72, 8.32)* but with intercept stipulated these are *(9.16, 9.47)*. The right panel of Figure 2 showing glaciation also illustrates how stipulating the intercept can lead to inferior predictions. Summing over the 583 data points in the right panel, the square differences between ΔT and the prediction with intercept = 0 (red line) is *674.1*, whereas when the intercept is estimated this sum is (blue line) *478.7*. Note also the difference in explanatory power in the two panels. During deglaciation the blue regression line explains three fourths of the variance in ΔT whereas during glaciation less than half of the variance is explained. The interpretation is that during glaciation factors other than CO_2 account for the variation in ΔT.

A more recent study (Snyder 2019) presents a Pleistocene data set that contains 799 records, evenly spaced in steps of 1000yr. Modeling, subjective probabilities and Monte Carlo analysis are applied in Snyder (2019) to quantify uncertainties in data and variable relationships. Changes in temperature with respect to the average over the last 5000 years are regressed on the total change in forcing (ΔR) from Green House Gases, Land Ice, dust and vegetation. A good comparison with Martinez-Boti et al (2015) is obtained by considering just the medians of the various terms. With respect to Snyder (2019) data, regressing the median of ΔT (termed Global Annual Surface Temperature GAST) on the median of $\Delta FGHG$, with intercept, yields:

$$\Delta T(\Delta FGHG) = 1.962 \times \Delta GHG - 0.788 + e; \; \Delta T(556) = +6.49K$$

which compares well with eqn. (3), above, especially if we consider that Snyder (2019) estimates change in temperature with respect to the average surface temperature over the last 5000 years which, according to Martinez-Boti et al (2015), is 0.45K higher than the pre-industrial reference value in their analysis. Hence we should compare 6.49 + 0.45 = +6.94K to +6.85K from eqn. (3). The medians of the separate forcing terms $\Delta R_{[GHG]}$, $\Delta R_{[LI]}$, $\Delta R_{[AE]}$, $\Delta R_{[VG]}$ are all highly correlated with each other and with ΔT. Separating these forcing contributions means assuring that, on 1000yr timescales, land ice, dust and vegetation forcings are not already bleeding into the GHG forcing. This issue is avoided by focusing just on GHG forcing. The penalty is that conclusions are wedded to the 1000yr timescale.

Summary statistics comparing results with and without $B = 0$ are presented in Table 1: the partitions Pre and Post *424 kaBP* are intersected with deglaciation and glaciation periods.

https://doi.org/10.5194/cp-2020-59
Preprint. Discussion started: 28 April 2020

Summary and discussion

Extending previous analyses of Pleistocene climate data of Martinez-Boti et al (2015) and Snyder (2019), one key finding is that imposing a zero intercept tends to mask differences between the climate sensitivity parameter in different subsets of the Pleistocene data. This assumption produces inferior predictions relative to regressions in which estimates of intercept are exploited. Ultimately, this prevents us from appreciating the role of explanatory power in comparing the climate sensitivity parameter in different physical situations.

Explaining why the climate sensitivity parameter is higher during deglaciation than during glaciation is a challenge which deserves attention. One obvious feature is the fact that deglaciation generally transpires faster than glaciation. It may be that certain negative feedbacks with intermediate time scales are allowed to play out during glaciation but are less effective during rapid deglaciation. For example, carbon fertilization would draw down atmospheric CO_2. During glaciation the retreat of plants would tend to retard the cooling and slow the glaciation process. During deglaciation the advance of plants would tend to retard the warming process. However, if the retreat of land and sea ice happened quickly, other changes such as growth of the Hadley cells and desertification might overwhelm the advance of plants and disable this negative feedback. Oceanic CO_2 outgassing during the last deglaciation has been proposed (Shao et al 2019) as a potential disequilibrium process influencing atmospheric CO_2 concentrations. Aerosols, and glacial aerosols specifically, can interact with clouds and influence radiative forcing; paleo-aerosol concentrations are likely to have varied with glaciation pathways. However, the lack of robust reconstructions of glacial aerosol forcing is a key source of uncertainty in paleo-based estimates of climate sensitivity (Friedrich, and Timmermann, 2020). As a further possibility, Xie (2020) posits that non-uniform regional uptake of heat by oceans militates against equilibration with radiative forcing, with spatio-temporal variations in ocean state and currents affecting global climate sensitivity.

These are some conceptual examples of how the interplay of process-related feedbacks with different time scales might alter climate sensitivity in different physical situations. The supplementary material shows that the climate sensitivity parameter is higher after *424KaBP*, than before. Such effects have been attributed to changes in orbital forcing, though a detailed understanding of why heightened forcing raises climate sensitivity has not, to our knowledge, been found.

If the Earth's surface temperature response to CO_2 forcing on millennial time scales does indeed depend on the physical circumstances at the time of the forcing, predictions for the Earth's future response to heightened CO_2 forcing require knowledge of these complex non-linear interactions, understanding how they will evolve and on what timescales. Scrutiny and clarification of assumptions regarding the intercept issue and further analytical investigation with stochastic uncertainty techniques should provide additional insights into the properties of the climate sensitivity parameter and inform discussion of contingent implications.

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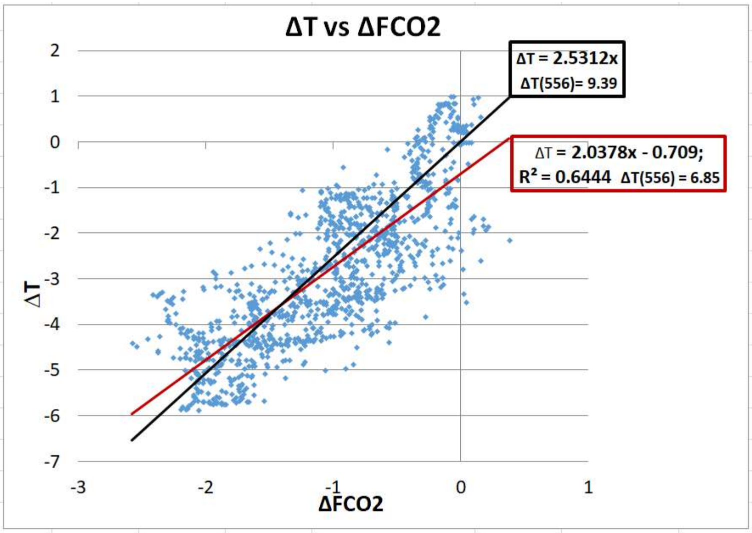
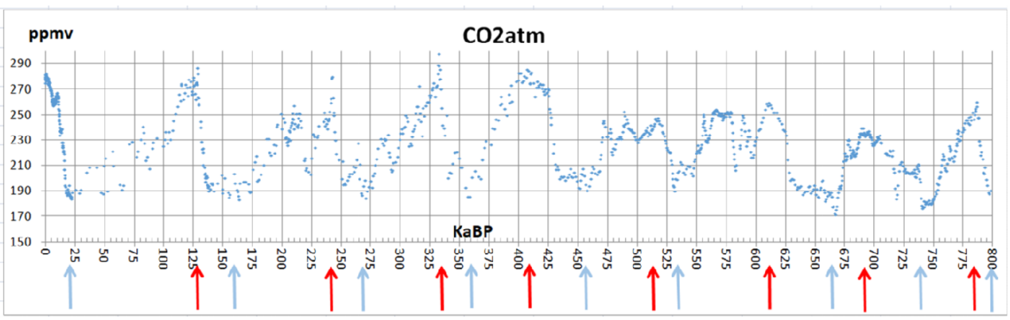


Figure 1: Regression of ΔT on ΔFCO_2 for all Pleistocene data; with (red) and without (black) intercept. Out of sample values for doubling pre-industrial CO_2, ΔT(556) are also shown.



https://doi.org/10.5194/cp-2020-59
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Figure 2: CO2 concentrations as function of kaBP. Blue arrows indicate local minima, red arrows indicate local maxima.

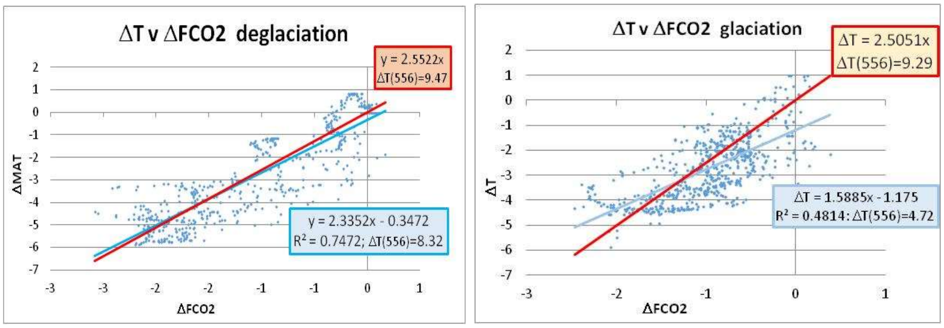

Figure 3: Deglaciation, (left, increasing) and glaciation (right, decreasing) CO2 paths. Regression for B=0 stipulated in Red, with B estimated in Blue.

	Intercept estimated					Intercept stipulated = 0		
	R^2	S	B	SE	ΔT(556)	S	SE	ΔT(556)
All (1096)	0.644	2.038	-0.709	0.978	6.851	2.531	1.047	9.391
ALL Pre 424 (546)	0.419	1.427	-1.535	0.883	3.760	2.489	1.082	9.232
All Post 424 (550)	0.726	2.320	-0.395	0.994	8.212	2.595	1.006	9.626
De-Glaciation (increasing CO_2)								
All (513)	0.747	2.333	-0.348	0.996	8.309	2.552	1.014	9.469
Pre 424 (220)	0.457	1.804	-0.959	1.009	5.733	2.420	1.145	8.977
Post 424 (293)	0.830	2.631	-0.215	0.916	9.545	2.798	0.781	10.381
Glaciation (decreasing CO_2)								
All (583)	0.481	1.588	-1.175	0.908	4.718	2.505	1.076	9.294
Pre 424 (326)	0.352	1.170	-1.833	0.759	2.507	2.593	1.061	9.621
post 424 (257)	0.538	1.744	-0.782	0.980	5.689	2.359	1.080	8.752
Low, Medium, High CO_2								
<210 (305)	0.022	0.485	-3.576	0.779	-1.778	2.367	0.902	8.781
210...250 (493)	0.195	1.913	-0.943	0.953	6.156	2.810	0.978	10.424
>250 (298)	0.201	2.711	-0.396	1.096	9.664	3.670	1.123	13.614

Table 1: Summary of data subset regressions. R^2 is the fraction of variance of ΔT explained by the regression, S is the climate sensitivity parameter, B is the intercept, SE is the standard deviation of the difference between predictions and true values, and ΔT(556) is the projected ΔT corresponding to a doubling of the pre-industrial CO2 concentration (278 ppmv). With the exception

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Climate of the Past Discussions

of "All" and "Pre 424" all S values are outside the 90% confidence bands of the other values within each group. The number of samples is in parentheses.