Title: Revised estimate of paleoclimate sensitivity over the past 800,000 years

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Supplementary Materials

1. Reconstructions of change in global radiative forcing (ΔR)

1.1 $\Delta R_{[GHG]}$ from changes in greenhouse gases

I use estimates of atmospheric GHG concentrations from Antarctic ice cores to reconstruct changes in ΔR from changes in carbon dioxide (Bereiter et al., 2015), methane (Loulergue et al., 2008; Parrenin et al., 2013), and nitrous oxide (Schilt et al., 2010). I calculate the radiative forcing changes for carbon dioxide, methane, and nitrous oxide using the equations from Köhler *et al.* (2010) and Hansen *et al.* (2013), with units of ΔR in W/m^2, CO_2 in ppm, CH_4 in ppb, and N_2O in ppb:

$$\Delta R_{[CO2]} = 5.35 \ln(CO_2/278)$$

$$\Delta R_{[CH4]} = \beta * 0.036 * (\sqrt{CH_4} - \sqrt{742})$$

$$\Delta R_{[N2O]} = 0.12 * (\sqrt{N_2O} - \sqrt{270}) - 0.47 * \log[1 + 2.01*10^{-5} * (N_2O * 715)^{0.75} + 5.31*10^{-15} * 715 * (N_2O * 715)^{1.52}] + 0.47 * \log[1 + 2.01*10^{-5} * (270 * 715)^{0.75} + 5.31*10^{-15} * 715 * (270 * 715)^{1.52}]$$, where N_2O reconstructions are available

$$\Delta R_{[N2O]} = \alpha * (\Delta R_{[CO2]} + \Delta R_{[CH4]})$$, where N_2O reconstructions are not available

I apply 95% intervals for the parameters in the proposed approximations from Köhler *et al.* (2010) and Hansen *et al.* (2013). β is the efficacy of methane and is estimated as being 1.4 (1.0 to 1.8, 95% interval[1]). α is the approximation for $\Delta R_{[N2O]}$ relative to the sum of $\Delta R_{[CO2]}$ and $\Delta R_{[CH4]}$ and is estimated as being 0.12 (0 to 0.24, 95% interval). I assume a 20% (95% interval) uncertainty in each of the equations above. To estimate $\Delta R_{[GHG]}$, I sum randomly selected time series of $\Delta R_{[CO2]}$, $\Delta R_{[CH4]}$, and $\Delta R_{[N2O]}$ to produce an ensemble of 10,000 time series of $\Delta R_{[GHG]}$ (Fig.1a).

1.2 $\Delta R_{[LI]}$ from changes in ice sheets and sea level

As the Earth moves between interglacial and glacial periods, there are dramatic changes to the reflectivity of the earth surface (surface albedo). As the planet cools, continental ice sheets expand to cover more of the Earth surface, and sea levels drop to expose continental shelf (which has a higher albedo than ocean water). Global climate model simulations of the LGM estimated that changes in surface albedo from ice sheet growth directly caused a change in ΔR ranging from -2.3 W/m^2 to -3.2 W/m^2 and that sea level changes caused changes in ΔR about 20% the size of that from continental ice sheets of -0.5 W/m^2 to -0.6 W/m^2 (Hansen et al., 1993; Hansen et al., 2008; Hansen et al., 2013; Hewitt and Mitchell, 1997; IPCC, 2013; Köhler et al., 2010). I assign a distribution of -2.7 W/m^2 (-1.7 to -3.7 W/m^2, 95% interval) for ΔR due to continental ice

[1] All intervals specified for assumed parameters/values are for normal distributions unless otherwise specified.

sheets, and -0.5 W/m^2 (-0.3 to -0.7 W/m^2, 95% interval) for ΔR due to sea level change for a combined $\Delta R_{[LI]}$ at the LGM of -3.2 W/m^2 (-2.2 to -4.2 W/m^2, 95% interval).

I reconstruct the combined changes in $\Delta R_{[LI]}$ using the following three equations:

- $\Delta R_{[LI]} \sim \Delta$*sea level*: linear relationship with sea level (Hansen et al., 2008; Hansen et al., 2013; Martinez-Boti et al., 2015; Rohling et al., 2012)
- $\Delta R_{[LI]} \sim (\Delta$*sea level*$)^{0.8}$: sea level to an exponent of 0.8 (Hansen et al., 2008)
- $\Delta R_{[LI]} \sim (\Delta$*sea level*$)^3$: a more recent proposal of sea level to a third-order polynomial (Köhler et al., 2015)[2]

The impact on estimates of climate sensitivity and correlation from changing functional forms is much smaller than the uncertainty introduced by different sea level reconstructions (Fig.6a-b,e-f). I place equal weighting on the three functional forms in the final overall estimate (Fig.1b).

I employ thirteen different proxy-based reconstructions of changes in sea level. Grant *et al.* (2014) and Rohling *et al.* (2014) estimate sea level using surface planktonic oxygen isotopes from Red Sea and Mediterranean Sea sediments, respectively. Elderfield *et al.* (2012) estimate sea level by calculating deep-water temperature using Mg/Ca ratios from bottom-dwelling foraminifera, and then estimating the residual ice volume signal from the oxygen isotope record. Bates *et al.* (2014) estimate sea level from oxygen isotope records from benthic foraminifera shells using regression analysis for ten different deep-ocean records, using a much simpler model for the relationship between benthic oxygen isotopes and deep-water temperature as well as older age models than the other three reconstructions. The sea level records are scaled to $\Delta R_{[LI]}$ in iterations using randomly selected values from the distributions of $\Delta R_{[LI]}$ at the LGM, and the final ensemble equally weights the median of the ten cores from Bates *et al.* (2014) with the other three proxy reconstructions to produce an ensemble of 12,000 time series of $\Delta R_{[LI]}$ (Fig.1b).

1.3 $\Delta R_{[AE]}$ from changes in atmospheric dust

Atmospheric mineral dust increases during glacial periods by five main mechanisms: 1) increased wind speeds bring more dust into the atmosphere; 2) reduced hydrological cycle causes less dust removal by rain; 3) changes in vegetation causes more bare ground, increasing dust sources; 4) reduced precipitation causes more dry soils, increasing dust sources; and 5) ice sheet activity is a direct source of glaciogenic dust (Harrison et al., 2001; Mahowald et al., 2006).

Estimates of change in $\Delta R_{[AE]}$ from dust at the LGM relative to preindustrial conditions are highly uncertain: IPCC (2013) produced a best estimate of -1 W/m^2 with a range of +0.1 W/m^2 to -3 W/m^2; Köhler *et al.* (2010) estimate -1.88 ± 0.94 (1σ) W/m^2; Mahowald *et al.* (2006) estimate -0.6 W/m^2; Schneider von Deimling *et al*. (2006) and Annan and Hargreaves (2006) both estimate -1.2 W/m^2; Hansen *et al.* (1993) estimate -0.9 W/m^2; and Hoffert & Covey (1992) estimate -0.9 ± 0.7 W/m^2. There also have been two high $\Delta R_{[AE]}$ estimates from Harvey (1988) of -1.9 W/m^2 to -3.3 W/m^2, and from Chylek and Lohman (2008) of -3.3 ± 0.8 (1σ) W/m^2. Both high estimates have been subsequently critiqued as 2-10 fold overestimates (Anderson and

[2] A third-order polynomial was estimated by regressing Köhler *et al.* (2015)'s estimate of $\Delta R_{[LI]}$ as a function of change in sea level (ΔSL): $\Delta R_{[LI]} \sim 1$ (±0.01) *ΔSL + 0.65 (±0.04) *ΔSL^2 + 0.2 (±0.03) *ΔSL^3 with an $R^2 = 0.95$. The uncertainty ranges were doubled for the coefficients.

Charlson, 1990; Ganopolski and Schneider von Deimling, 2008). I assign a gamma distribution[3] to match the asymmetrical distribution of IPCC (2013) for $\Delta R_{[AE]}$ at the LGM due to changes in dust: with a median estimate of -1.2 W/m^2 and a 95% interval of +0.1 W/m^2 to -3 W/m^2.

I use four different dust flux reconstructions:

- Two linear, $\Delta R_{[AE]} \sim \Delta dust$: Eastern tropical Pacific ocean dust flux (Winckler et al., 2008) and Central tropical Pacific ocean dust flux (Winckler et al., 2008)
- Two logarithmic, $\Delta R_{[AE]} \sim \log(\Delta dust)$: the logarithm of iron mass accumulation rates from the Southern Atlantic ocean (Martínez-Garcia et al., 2011) and the logarithm of Antarctic dust flux from Dome Concordia (Lambert, 2008)

Previous studies had used only the Antarctic dust data (Hansen et al., 2008; Köhler et al., 2010; Rohling et al., 2012). Before being scaled, the records are first normalized as a change from present (Mahowald et al., 2006). The four dust records are equally weighted and linearly scaled to $\Delta R_{[AE]}$ in iterations using randomly selected values from the distribution of $\Delta R_{[AE]}$ at the LGM due to changes in dust to produce an ensemble of 20,000 time series of $\Delta R_{[AE]}$ (Fig.1c).

1.4 $\Delta R_{[VG]}$ from changes in vegetation

Vegetation changes between interglacial and glacial periods, because of the changes in temperature, precipitation, and carbon dioxide concentrations. During glacial periods, vegetation models estimate large expansions of grasses, especially across Eurasia (Crucifix and Hewitt, 2005). Grasses cause increased reflectivity of the land surface, especially in areas with snow cover, and thus decrease ΔR. Models also predict that vegetation changes at the LGM will change latent heat fluxes and circulation patterns that result in cloud changes that net increase ΔR (Crucifix and Hewitt, 2005).

The model experiments of Crucifix *et al.* (2005) estimate that the net $\Delta R_{[VG]}$ change from LGM vegetation change was a positive feedback: increase in surface albedo of -1.4 W/m^2 but a change in clouds that increased ΔR +0.4 W/m^2, leaving a net $\Delta R_{[VG]}$ change of -1 W/m^2. Others have estimated similar net $\Delta R_{[VG]}$ effects of LGM vegetation of -0.7 W/m^2 to -1.2 W/m^2 (Annan and Hargreaves, 2006; Broccoli and Manabe, 1987; Hansen et al., 1993; Schneider von Deimling et al., 2006) and -1.1 ± 0.6 (1σ) W/m^2 (Köhler et al., 2010). I assign a distribution of -1.1 W/m^2 (-0.3 to -1.9 W/m^2, 95% interval) for the net $\Delta R_{[VG]}$ at the LGM from changes in vegetation.

Model experiments find that temperature change, especially in the Northern Hemisphere, drove much of the vegetation change that altered $\Delta R_{[VG]}$ (Crucifix and Hewitt, 2005). Therefore, I use change in ΔT (Snyder, 2016) as a proxy for northern temperature change (Köhler et al., 2010). Other research has used changes in sea level as a proxy for changes in vegetation (Hansen et al., 2008; Hansen et al., 2013). Therefore, I also use the four sea level reconstructions described above with weights as above. The temperature and sea level records are linearly scaled to $\Delta R_{[VG]}$ ($\Delta R_{[VG]} \sim \Delta sea\ level$ or $\Delta R_{[VG]} \sim \Delta T$) in iterations using randomly selected values from the distribution of $\Delta R_{[VG]}$ at the LGM, and the final ensemble equally weights the two approaches of ΔT and sea level reconstructions to produce an ensemble of 10,000 time series of $\Delta R_{[VG]}$ (Fig.1d).

[3] I use the gamma function in R: rgamma(1, shape =17.2, scale = 0.189) - 2) * -1.

2 Supplementary Results

Table S1. Empirically-estimated frequency distributions for regression analyses of ΔT in ºC and $\Delta R_{[GHG,LI,AE,VG]}$ in W/m^2 from the past 800kyr. Parentheses show 95% credible intervals and "Quad-ANOVA" shows the median p-value from an ANOVA test comparing the improvement of the quadratic model over the linear model. "WLS" stands for weighted least squares and "W-SIMEX" stands for weighted simulation extrapolation regression methods.

$\Delta T \sim \beta_0 + \beta_1 * \Delta R_{[GHG,LI,AE,VG]} + \beta_2 * \Delta R_{[GHG,LI,AE,VG]}^2$						
Equation	**Data subset**	**Regression method**	β_0 (ºC)	β_1 (ºC/W/m^2)	β_2 (ºC/W^2/m^4)	**Quad-ANOVA**
Linear without intercept	Full	WLS		0.79 (0.45 to 1.23)		
		W-SIMEX		0.88 (0.48 to 1.49)		
	Within 3.5ºC of present	WLS		0.63 (0.17 to 1.23)		
		W-SIMEX		0.84 (0.2 to 1.92)		
Linear with intercept	Full	WLS	-0.09 (-2.35 to 1.49)	0.77 (0.36 to 1.21)		
		W-SIMEX	1.08 (-2.08 to 3.58)	1.07 (0.42 to 1.91)		
	Within 3.5ºC of present	WLS	-0.06 (-1.66 to 1.27)	0.65 (0.13 to 1.22)		
		W-SIMEX	1.01 (-1.55 to 3.38)	1.14 (0.17 to 2.46)		
	Colder than 3.5ºC from present	WLS	-3.38 (-5.41 to -1.13)	0.28 (0.05 to 0.7)		
		W-SIMEX	-1.88 (-5.04 to 3.41)	0.53 (0.08 to 1.52)		
Quadratic without intercept	Full	WLS		0.85 (0.18 to 1.68)	0.01 (-0.09 to 0.11)	0.00069
	Within 3.5ºC of present	WLS		0.69 (-0.04 to 1.74)	0.02 (-0.16 to 0.21)	0.064
Quadratic with intercept	Full	WLS	0.21 (-2.21 to 1.75)	0.99 (0.23 to 1.81)	0.03 (-0.06 to 0.11)	0.0014
	Within 3.5ºC of present	WLS	0.09 (-1.61 to 1.53)	0.85 (0.09 to 2.04)	0.05 (-0.07 to 0.25)	0.077

$\Delta R_{[GHG,LI,AE,VG]} \sim \beta_0 + \beta_1 * \Delta T$						
Equation	**Data subset**	**Regression method**	β_0 (W/m^2)	β_1 (W/m^2/ºC)		
Linear without intercept	Full	WLS		1.1 (0.65 to 1.74)		
		W-SIMEX		1.17 (0.68 to 1.9)		
	Within 3.5ºC of present	WLS		0.95 (0.34 to 1.71)		
		W-SIMEX		1.13 (0.4 to 2.18)		
Linear with intercept	Full	WLS	-1.09 (-3.12 to 0.85)	0.88 (0.58 to 1.34)		
		W-SIMEX	-0.45 (-2.54 to 1.71)	1.06 (0.68 to 1.72)		
	Within 3.5ºC of present	WLS	-1.19 (-3.09 to 0.55)	0.58 (0.31 to 1)		
		W-SIMEX	-0.88 (-2.82 to 0.92)	0.79 (0.39 to 1.42)		

Table S2. Empirically-estimated frequency distributions for the paleoclimate sensitivity parameter, $S_{[GHG,LI,AE,VG]}$, for subsets of ΔT from the past 800kyr above specified ΔT breakpoints, using weighted simulation extrapolation regression methods. Parentheses show 95% credible intervals and "Quad-ANOVA" shows the median p-value from an ANOVA test comparing the improvement of the quadratic model over the linear model.

ΔT Breakpoint	$S_{[GHG,LI,AE,VG]}$ in ºC/W/m^2	Quad-ANOVA p-value
-2 ºC	0.66 (0.02 to 2.2)	0.21
-2.1 ºC	0.70 (0.05 to 2.2)	0.20
-2.2 ºC	0.70 (0.06 to 2.2)	0.19
-2.3 ºC	0.73 (0.07 to 2.2)	0.17
-2.4 ºC	0.77 (0.10 to 2.1)	0.14
-2.5 ºC	0.78 (0.12 to 2.1)	0.13
-2.6 ºC	0.79 (0.12 to 2.1)	0.13
-2.7 ºC	0.80 (0.14 to 2.1)	0.11
-2.8 ºC	0.80 (0.15 to 2.0)	0.11
-2.9 ºC	0.82 (0.16 to 2.0)	0.096
-3 ºC	0.82 (0.16 to 1.9)	0.086
-3.1 ºC	0.82 (0.16 to 1.9)	0.083
-3.2 ºC	0.83 (0.18 to 1.9)	0.074
-3.3 ºC	0.83 (0.19 to 1.9)	0.071
-3.4 ºC	0.84 (0.19 to 1.9)	0.065
-3.5 ºC	0.84 (0.20 to 1.9)	0.064
-3.6 ºC	0.84 (0.21 to 1.9)	0.060
-3.7 ºC	0.85 (0.21 to 1.9)	0.056
-3.8 ºC	0.85 (0.21 to 1.9)	0.055
-3.9 ºC	0.86 (0.21 to 1.9)	0.056
-4 ºC	0.87 (0.23 to 1.9)	0.053
-4.1 ºC	0.87 (0.23 to 1.9)	0.051
-4.2 ºC	0.87 (0.25 to 1.9)	0.047
-4.3 ºC	0.87 (0.25 to 1.9)	0.045
-4.4 ºC	0.88 (0.25 to 1.9)	0.044
-4.5 ºC	0.88 (0.26 to 1.9)	0.041
-4.6 ºC	0.88 (0.29 to 1.8)	0.035
-4.7 ºC	0.88 (0.30 to 1.8)	0.030
-4.8 ºC	0.88 (0.32 to 1.8)	0.024
-4.9 ºC	0.88 (0.34 to 1.7)	0.018
-5 ºC	0.88 (0.36 to 1.7)	0.014

Table S3. Same as in Table S1 except for only the past 450kyr instead of the past 800kyr.

$\Delta T \sim \beta_0 + \beta_1 * \Delta R_{[GHG,LI,AE,VG]} + \beta_2 * \Delta R_{[GHG,LI,AE,VG]}^2$						
Equation	**Data subset**	**Regression method**	β_0 (ºC)	β_1 (ºC/W/m^2)	β_2 (ºC/W^2/m^4)	**Quad-ANOVA**
Linear without intercept	Full	WLS		0.79 (0.45 to 1.24)		
		W-SIMEX		0.88 (0.48 to 1.49)		
	Within 3.5ºC of present	WLS		0.63 (0.17 to 1.22)		
		W-SIMEX		0.84 (0.2 to 1.93)		
Linear with intercept	Full	WLS	-0.06 (-2.3 to 1.48)	0.78 (0.36 to 1.22)		
		W-SIMEX	1.11 (-2.04 to 3.56)	1.08 (0.42 to 1.92)		
	Within 3.5ºC of present	WLS	-0.03 (-1.62 to 1.27)	0.66 (0.13 to 1.22)		
		W-SIMEX	1.04 (-1.53 to 3.35)	1.16 (0.17 to 2.46)		
	Colder than 3.5ºC from present	WLS	-3.32 (-5.4 to -1.13)	0.29 (0.05 to 0.7)		
		W-SIMEX	-1.75 (-5.02 to 3.47)	0.55 (0.08 to 1.52)		
Quadratic without intercept	Full	WLS		0.84 (0.18 to 1.68)	0.01 (-0.09 to 0.1)	0.0011
	Within 3.5ºC of present	WLS		0.67 (-0.05 to 1.72)	0.01 (-0.16 to 0.2)	0.08
Quadratic with intercept	Full	WLS	0.23 (-2.15 to 1.73)	0.99 (0.24 to 1.83)	0.03 (-0.06 to 0.11)	0.002
	Within 3.5ºC of present	WLS	0.1 (-1.58 to 1.51)	0.84 (0.08 to 2.02)	0.04 (-0.08 to 0.25)	0.095

Equation	Data subset	Regression method	$\Delta R_{[GHG,LI,AE,VG]} \sim \beta_0 + \beta_1 * \Delta T$ β_0 (W/m^2)	β_1 (W/m^2/ºC)		
Linear without intercept	Full	WLS		1.11 (0.66 to 1.76)		
		W-SIMEX		1.18 (0.69 to 1.92)		
	Within 3.5ºC of present	WLS		0.95 (0.36 to 1.74)		
		W-SIMEX		1.12 (0.41 to 2.2)		
Linear with intercept	Full	WLS	-1.04 (-3.05 to 0.89)	0.89 (0.6 to 1.36)		
		W-SIMEX	-0.42 (-2.5 to 1.71)	1.07 (0.69 to 1.74)		
	Within 3.5ºC of present	WLS	-1.16 (-3.14 to 0.6)	0.59 (0.32 to 1.01)		
		W-SIMEX	-0.86 (-2.88 to 0.97)	0.79 (0.4 to 1.44)		

Table S4. Linear regression results of $S_{[GHG,LI,AE,VG]}$ in ºC/W/m^2 for climate states within 3.5ºC from present as a function of the assumed values of ΔR at the LGM in W/m^2. Parentheses show 95% intervals.

	$S_{[GHG,LI,AE,VG]} \sim \beta_0 + \beta_1 * \Delta R$		
ΔR	β_0 (ºC/W/m^2)	β_1 (ºC/W^2/m^4)	**Adjusted R^2**
$\Delta R_{[LI,AE,VG]}$ **at the LGM**	1.86 (1.84 to 1.88)	0.12 (0.12 to 0.12)	0.14
$\Delta R_{[LI]}$ **from ice sheets at the LGM**	1.6 (1.58 to 1.63)	0.22 (0.21 to 0.23)	0.068
$\Delta R_{[AE]}$ **from dust at the LGM**	1.09 (1.08 to 1.1)	0.15 (0.15 to 0.15)	0.074
$\Delta R_{[VG]}$ **from vegetation at the LGM**	1.06 (1.05 to 1.07)	0.14 (0.13 to 0.15)	0.018

Table S5. Same as Table S1 except with periods of increasing and declining obliquity analyzed separately over the past 800kyr.

$\Delta T \sim \beta_1 * \Delta R_{[GHG,LI,AE,VG]}$				
Equation	**Data subset**	**Regression method**	**Obliquity**	β_1 (ºC/W/m^2)
Linear without intercept	Full	WLS	All	0.79 (0.45 to 1.23)
			Increasing	0.78 (0.47 to 1.25)
			Decreasing	0.79 (0.42 to 1.25)
		W-SIMEX	All	0.88 (0.48 to 1.49)
			Increasing	0.86 (0.49 to 1.46)
			Decreasing	0.91 (0.46 to 1.57)
	Within 3.5ºC of present	WLS	All	0.63 (0.17 to 1.23)
			Increasing	0.64 (0.24 to 1.26)
			Decreasing	0.64 (0.11 to 1.23)
		W-SIMEX	All	0.84 (0.20 to 1.92)
			Increasing	0.80 (0.27 to 1.86)
			Decreasing	0.89 (0.13 to 2.02)

3. R code

2.1. R code for creation of Global Average Radiative Forcing (ΔR) reconstructions

As described in the Methods, this research estimates ΔR from various reconstructions, and the following R code can be used to implement the method.

```
## Input data already interpolated to 1kyr intervals (see Methods)

## Change in Radiative Forcing from CO2
## CO2.data is a data file with (time, CO2 estimate, and CO2 uncertainty)
n.sim <- 10000
tt <- dim(CO2.data)[1]
YY <- matrix (NA, ncol = n.sim, nrow = tt)

## Simulating measurement uncertainty in CO2
CO2.rn <- data.frame (YY)
for (j in 1:n.sim) { CO2.rn[,j] <- CO2.data[,2] + rnorm(tt, mean = 0, sd = CO2.data[,3]) }

## Calculating radiative forcing for CO2
c.0 <- 278
CO2.rad.force <- 5.35 * log(CO2.rn/c.0)

## Adding 20% uncertainty (2sd) in radiative forcing equation
CO2.rad.force.rn <- data.frame (YY)
for (j in 1:n.sim) { CO2.rad.force.rn[,j] <- CO2.rad.force[,j] * rnorm(1, mean = 1, sd = 0.1) }

## Creating deviation from 5kyr for final simulation
CO2.rad.force.rn.5ka.dev <- data.frame (YY)
for (j in 1:n.sim) { CO2.rad.force.rn.5ka.dev[,j] <- CO2.rad.force.rn[,j] -
        mean(CO2.rad.force.rn[1:5,j], na.rm=T) }
CO2.RF <- CO2.rad.force.rn.5ka.dev


## Change in Radiative Forcing from CH4
## CH4.data is a data file with (time, CH4 estimate, and CH4 uncertainty)
n.sim <- 10000
YY <- matrix (NA, ncol = n.sim, nrow = 800)

## Simulating measurement uncertainty in CH4
CH4.rn <- data.frame (YY)
for (j in 1:n.sim){ CH4.rn[,j] <- CH4.data[,2] + rnorm(800, mean = 0, sd = CH4.data[,3]) }

## Calculating radiative forcing for CH4
m.0 <- 742
CH4.rad.force <- 0.036 * ( sqrt(CH4.rn) - sqrt(m.0) )
```

```
## Adding 20% uncertainty (2sd) in radiative forcing equation
CH4.rad.force.rn <- data.frame (YY)
for (j in 1:n.sim){ CH4.rad.force.rn[,j] <- CH4.rad.force[,j] * rnorm(1, mean = 1, sd = 0.1) }

## Adding indirect factor of 1.4 (1,1.8)
CH4.rad.force.rn.indirect <- data.frame (YY)
for (j in 1:n.sim){ CH4.rad.force.rn.indirect[,j] <- CH4.rad.force.rn[,j] * rnorm(1, mean = 1.4, sd
        = 0.2) }

## Creating deviation from 5kyr for final simulation
CH4.rad.force.rn.indirect.5ka.dev <- data.frame (YY)
for (j in 1:n.sim){ CH4.rad.force.rn.indirect.5ka.dev[,j] <- CH4.rad.force.rn.indirect[,j] -
        mean(CH4.rad.force.rn.indirect[1:5,j], na.rm=T) }
CH4.RF <- CH4.rad.force.rn.5ka.dev
```

Change in Radiative Forcing from N2O

```
## N2O.data is a data file with (time, N2O estimate, and N2O uncertainty)
time <- c(1:13, 29:57, 66:134, 182:215, 293:336, 358:425, 465:527, 546:626, 667:712, 722:736,
        744:791)*1000  #subset of time with available N2O estimates
n.sim <- 10000
YY <- matrix (NA, ncol = n.sim, nrow = length(time))

## Simulating measurement uncertainty in N2O
N2O.rn <- data.frame (YY)
for (j in 1:n.sim){ N2O.rn[,j] <- N2O.data[,2] + rnorm(length(time), mean = 0, sd =
        N2O.data[,3]) }

## Calculating radiative forcing for N2O
m.0 <- 715
n.0 <- 270
NN <- N2O.rn
N2O.rad.force <- (0.12 * ( sqrt(NN) - sqrt(n.0) )
        - 0.47 * log (1 + 2.01E-5 * (NN * m.0)^0.75 + 5.31E-15 * m.0 * (NN * m.0)^1.52 )
        + 0.47 * log (1 + 2.01E-5 * (m.0 * n.0)^0.75 + 5.31E-15 * m.0 * (m.0 * n.0)^1.52 ) )

## Adding 20% uncertainty (2sd) in radiative forcing equation
N2O.rad.force.rn <- data.frame (YY)
for (j in 1:n.sim){ N2O.rad.force.rn[,j] <- N2O.rad.force[,j] * rnorm(1, mean = 1, sd = 0.1) }

## Creating deviation from 5kyr for final simulation
N2O.rad.force.rn.5ka.dev <- data.frame (YY)
for (j in 1:n.sim){ N2O.rad.force.rn.5ka.dev[,j] <- N2O.rad.force.rn[,j] -
        mean(N2O.rad.force.rn[1:5,j], na.rm=T) }
```

```
## Inputting N2O approximation for time points without N2O estimates, using radiative forcing
        approximation of 0.12 (0, 0.24) * sum of CO2 and CH4 radiative forcing
Time.edges.est <- c(14,  28,58, 65,135, 181,216, 292,337, 357,426, 464,528, 545,627, 666,713,
        721,737, 743,792)
Time.edges.data <- c(13, 29,57, 66,134, 182,215, 293,336, 358,425, 465,527, 546,626, 667,712,
        722,736, 744,791)
n.sim = 10000
YY <- matrix (NA, nrow=800, ncol = n.sim)
N2O.est.sim <- data.frame(YY)
for (j in 1:n.sim){
        scalar.j <- rnorm (1, mean=0.12, sd=0.06)
        for (t in 1:800){
                if (sum(Time.N2O==t*1000)==1) N2O.est.sim[t,j] <-
        N2O.RF.partial[Time.N2O==t*1000,j]
                else N2O.est.sim[t,j] <- scalar.j*(CO2.RF[t,j]+CH4.RF[t,j]) }
        for (k in 1:20){
                        N2O.est.sim[Time.edges.est[k],j] <- (N2O.est.sim[Time.edges.est[k],j] +
        N2O.est.sim[Time.edges.data[k],j]) /2  #slight smoothing of edges
                        }
                }

## Creating deviation from 5kyr for final simulation
N2O.est.sim.5ka.dev <- data.frame (YY)
for (j in 1:n.sim){ N2O.est.sim.5ka.dev[,j] <- N2O.est.sim[,j] - mean(N2O.est.sim[1:5,j],
        na.rm=T) }
N2O.RF <- N2O.est.sim.5ka.dev


## Change in Radiative Forcing from Total GHGs (CO2, CH4, and N2O)
n.sim <- 1000
YY <- matrix (NA, ncol = n.sim, nrow = 800)
Total.approximation.GHG.forcing.Sim <- data.frame (YY)
for (j in 1:n.sim){ Total.approximation.GHG.forcing.Sim[,j] <- CO2.RF[1:800,j] + CH4.RF[,j] +
        N2O.RF[,j] }

## Creating deviation from 5kyr for final simulation
Total.approximation.GHG.forcing.Sim.dev <- data.frame (YY)
for (j in 1:n.sim){ Total.approximation.GHG.forcing.Sim.dev[,j] <-
        Total.approximation.GHG.forcing.Sim[,j] -
        mean(Total.approximation.GHG.forcing.Sim[1:5,j], na.rm=T) }
GHG.RF <- Total.approximation.GHG.forcing.Sim.dev

#Final ensemble size of 10,000 iterations
```

Change in Radiative Forcing from Ice Sheets and Sea Level Rise

```
## Input data files: "RSL.m" as matrix of RSL reconstructions (first column is median across 10
        reconstructions from Bates et al. 2014); "RSL.sd" as matrix of uncertainty in RSL
        reconstructions
n.sim = 1000
AA <- matrix(NA, ncol=n.sim*3*dim(RSL.m)[2], nrow=2000)
BB <- matrix(NA, nrow=n.sim*3*dim(RSL.m)[2], ncol=3)
RESULTS <- data.frame(AA)
RESULTS.info <- data.frame(BB)
v.source <- c("RSL-Bates.median","RSL-Elderfield","RSL-Grant","RSL-Rohling")
v.equation <- c("RSL-linear", "RSL-0.8_exponent","RSL-third_order")

for (i in 1:dim(RSL.m)[2]){ # Loop over RSL reconstructions
        for (j in 1:3){ # Loop over equations
                for (k in 1:n.sim){
                        n.col <- (i-1)*3*n.sim + (j-1)*n.sim + k
                        RESULTS.info[n.col,1] <- v.source[i]
                        RESULTS.info[n.col,2] <- v.equation[j]
                        # Scaling from RSL to ESL
                        ss =1
                        if (i == 3) ss = 1.2 # Grant et al.
                        if (i == 4) ss = 1.23 # Rohling et al.
                        # Simulating uncertainty in RSL
                        RSL.kk <- (RSL.m[,i] + rnorm(2000,0,RSL.sd[,i]))/100*ss
                        # Applying functional form to RSL
                        if (j == 1) RF.unscaled.kk <- RSL.kk
                        if (j == 2) RF.unscaled.kk <- (abs(RSL.kk)^0.8)*abs(RSL.kk)/RSL.kk
                        if (j == 3) RF.unscaled.kk <- RSL.kk + rnorm(1,0.65,0.08)*(RSL.kk^2)+
                                rnorm(1,0.2,0.06)*(RSL.kk^3)
                        # Selecting LGM value randomly from -2.7 W/m2 (-1.7 to -3.7) for ice
                                sheets and -0.5 W/m2 (-0.3 to -0.7) for sea level
                        lgm.kk <- rnorm(1,-2.7,0.5) + rnorm(1,-0.5,0.1)
                        RESULTS.info[n.col,3] <- lgm.kk
                        # Calculating and applying LGM scalar (mean estimate / LGM value)
                        scalar = lgm.kk / (mean(RF.unscaled.kk[19:23])-
                                mean(RF.unscaled.kk[1:5]))
                        RESULTS[,n.col] <- (RF.unscaled.kk -mean(RF.unscaled.kk[1:5]) )*
                                scalar
                }
        }
}
ICE.RF <- RESULTS

#Final ensemble size of 12,000 time series
```

Change in Radiative Forcing from Dust

```
## Input data files: "IV.data" as matrix of dust reconstructions (already transformed if relevant,
        see Methods); "IV.SD.data" as matrix of uncertainty in dust reconstructions
v.names <- c("EPICA","Martinez-Garcia","Winckler-central","Winckler-eastern")
n.sim = 5000
AA <- matrix(NA, ncol=n.sim*4, nrow=2000)
BB <- matrix(NA, nrow=n.sim*4, ncol=2)
RESULTS <- data.frame(AA)
RESULTS.info <- data.frame(BB)

for (i in 1:4){
                for (k in 1:n.sim){
                        n.col = (i-1)*n.sim +k
                        # Selecting LGM value randomly from -1.2W/m2 (+0.1 W/m2 to -3
                                W/m2, 95% interval), using a gamma distribution due to the
                                asymmetry in the uncertainty
                        lgm.kk <- (rgamma (1, shape =17.2, scale = 0.189) - 2) * -1
                        RESULTS.info[n.col,1] <- v.names[i]
                        RESULTS.info[n.col,2] <- lgm.kk
                        # Simulating measurement uncertainty in Dust
                        DUST.kk <- IV.data[,i] + rnorm(2000,0,IV.SD.data[,i])
                        DUST.kk.dev <- DUST.kk - mean(DUST.kk[1:5], na.rm=T)
                        # Calculating and applying LGM scalar (mean estimate / LGM value)
                        RESULTS[,n.col] <- DUST.kk.dev * lgm.kk/mean(DUST.kk.dev[19:23])
                }
        }
DUST.RF <- RESULTS

#Final ensemble size of 20,000 time series
```

Change in Radiative Forcing from Vegetation

```
## Input files: "RSL.m" and "RSL.sd" as above and "GAST" is the simulation set for GAST
## Simulating measurement uncertainty in RSL
n.sim.R = 2000
RSL.sim <- matrix(NA,2000,n.sim.R*4)
for (i in 1:4){
        for (j in 1:n.sim.R){ RSL.sim[,(i-1)*n.sim.R+j] <- RSL.m[,i] + rnorm(2000,0,RSL.sd[,i])
        }
}
v.RSL.code <- c(rep("RSL-Bates.median",n.sim.R), rep("RSL-Elderfield",n.sim.R), rep("RSL-
        Grant",n.sim.R), rep("RSL-Rohling",n.sim.R))

## Simulating radiative forcing using both RSL and GAST
n.sim =5000
AA <- matrix(NA, ncol=n.sim*2, nrow=2000)
```

```
BB <- matrix(NA, nrow=n.sim*2, ncol=2)
RESULTS <- data.frame(AA)
RESULTS.info <- data.frame(BB)
for (i in 1:n.sim){
        # Selecting LGM value randomly from -1.1 W/m2 (-1.9 to -0.3)
        lgm.ii <- rnorm(1,-1.1,0.4)
        RESULTS.info[i,1] <- "Veg-GAST"
        RESULTS.info[i,2] <- lgm.ii
        ii = sample(dim(GAST)[2],1)
        # Calculating and applying LGM scalar (mean estimate / LGM value)
        RESULTS[,i] <- (GAST[,ii] - mean(GAST[1:5,ii],na.rm=T)) *
                lgm.ii/(mean(GAST[19:23,ii],na.rm=T)- mean(GAST[1:5,ii],na.rm=T))
}
for (i in 1:n.sim){
        # Selecting LGM value randomly from -1.1 W/m2 (-1.9 to -0.3)
        lgm.ii <- rnorm(1,-1.1,0.4)
        ii = sample(n.sim*4,1)
        RESULTS.info[i+n.sim,1] <- v.RSL.code[ii]
        RESULTS.info[i+n.sim,2] <- lgm.ii
        # Calculating and applying LGM scalar (mean estimate / LGM value)
        RESULTS[,i+n.sim] <- (RSL.sim[,ii] -mean(RSL.sim[1:5,ii],na.rm=T))*
        lgm.ii/(mean(RSL.sim[19:23,ii],na.rm=T) -mean(RSL.sim[1:5,ii],na.rm=T))
}
VEG.RF <- RESULTS

#Final ensemble size of 10,000 time series
```

Change in Total Radiative Forcing (from GHGs, Ice Sheets and Sea Level Rise, Dust, and Vegetation)

```
n.sim = 50000
Total.RF <- data.frame(matrix(NA,800,n.sim))
for (k in 1:n.sim){
        gg <- sample (dim(GHG.RF)[2],1)
        dd <- sample (dim(DUST.RF)[2],1)
        vv <- sample (dim(VEG.RF)[2],1)
        ii <- sample (dim(ICE.RF)[2],1)
        Total.RF[,k] <- GHG.RF[1:800,gg] + DUST.RF[1:800,dd] + VEG.RF[1:800,vv] +
        ICE.RF[1:800,ii]
}
NA.vector <- apply(Total.RF[1:5,],2,function(x) sum(is.na(x)))
Total.RF.final <- Total.RF[,NA.vector<5]

#Final ensemble size of 50,000 time series
```

2.2. R code for SIMEX calculations

As described in the Methods, due to the variable (heteroscedastic) uncertainty in the reconstructions, it is necessary to use simulation extrapolation regression methods to remove potential bias in the statistical estimators. To implement such regression analysis, I define the following SIMEX functions to represent the methodology of Cook and Stefanski (1994). These functions produce equivalent results to the "simex" package in R (https://cran.r-project.org/web/packages/simex/index.html), but allow functional variations as specified below.

```
#inputs
#B <- #number of simulations
#X.data <- #X values
#X.Var <- #vector of variances in X
#Y.data <- #Y values
#Y.Var <- #vector of variances in Y

## Ordinary least-squares SIMEX function
my.simex.ols <- function(B,X.data,X.Var,Y.data){

lambda <- seq(0,2,length=9)
alphahatlambda <- rep(0,length(lambda))
betahatlambda <- rep(0,length(lambda))
alphahatTemp <- rep(0,length(lambda))
betahatTemp <- rep(0,length(lambda))
n <- length(X.data)
tauhatsqdlambda <- matrix(0,2,length(lambda))
tauhatsqdlambdaarray <- array(0,dim=c(2,2,length(lambda)))
tauhatsqdTemp <- array(0,dim=c(B,2,length(lambda)))
ParamEst <- array(0,dim=c(B,2,length(lambda)))
ssqdlambda <- array(0,dim=c(2,2,length(lambda)))

for(b in 1:B){
W <- rep(1,length(lambda)) %o% X.data + sqrt(lambda) %o% (rnorm(n,sd=sqrt(X.Var)))
for(l in 1:length(lambda)){
LM <- lm(Y.data~W[l,])
ParamEst[b,,l] <- c(coef(LM)[[1]],coef(LM)[[2]])
alphahatTemp[l] <- coef(LM)[[1]]
betahatTemp[l] <- coef(LM)[[2]]
tauhatsqdTemp[b,,l] <- ((summary(LM)$coef)[,2])^2
}
alphahatlambda <- alphahatlambda + alphahatTemp/B
betahatlambda <- betahatlambda + betahatTemp/B
tauhatsqdlambda <- tauhatsqdlambda + tauhatsqdTemp[b,,]/B
}
for(l in 1:length(lambda)){
tauhatsqdlambdaarray[,,l] <- diag(tauhatsqdlambda[,l])
```

```
ssqdlambda[,,l] <- cov(ParamEst[,,l])
}

alpha0 <- coef(lm(alphahatlambda~lambda + I(lambda^2)))[[1]]
alpha1 <- coef(lm(alphahatlambda~lambda + I(lambda^2)))[[2]]
alpha2 <- coef(lm(alphahatlambda~lambda + I(lambda^2)))[[3]]
beta0 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[1]]
beta1 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[2]]
beta2 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[3]]
ParamEstVar <- tauhatsqdlambdaarray - ssqdlambda
LM1 <- lm((ParamEstVar[1,1,]~lambda + I(lambda^2)))
LM2 <- lm((ParamEstVar[1,2,]~lambda + I(lambda^2)))
LM3 <- lm((ParamEstVar[2,2,]~lambda + I(lambda^2)))
gamma0 <- coef(LM1)[[1]]
gamma1 <- coef(LM1)[[2]]
gamma2 <- coef(LM1)[[3]]
delta0 <- coef(LM2)[[1]]
delta1 <- coef(LM2)[[2]]
delta2 <- coef(LM2)[[3]]
epsilon0 <- coef(LM3)[[1]]
epsilon1 <- coef(LM3)[[2]]
epsilon2 <- coef(LM3)[[3]]
alphahatSIMEX <- alpha0 - alpha1 + alpha2
betahatSIMEX <- beta0 - beta1 + beta2
alphaSIMEXVar <- gamma0 - gamma1 + gamma2
alphabetaSIMEXCov <- delta0 - delta1 + delta2
betaSIMEXVar <- epsilon0 - epsilon1 + epsilon2

#SIMEX results
simex.results <- data.frame(matrix(NA,2,3))
names(simex.results) <- c("Coefficient", "Coeff-se", "Covariance")
simex.results[2,1] <- (betahatSIMEX)
simex.results[2,2] <- (sqrt(betaSIMEXVar))
simex.results[1,1] <- (alphahatSIMEX)
simex.results[1,2] <- (sqrt(alphaSIMEXVar))
simex.results[1:2,3] <- (alphabetaSIMEXCov)
simex.results
}
```

Weighted least-squares SIMEX function

```
my.simex.wls <- function(B,X.data,X.Var,Y.data,Y.Var){

lambda <- seq(0,2,length=9)
alphahatlambda <- rep(0,length(lambda))
betahatlambda <- rep(0,length(lambda))
```

```
alphahatTemp <- rep(0,length(lambda))
betahatTemp <- rep(0,length(lambda))
n <- length(X.data)
tauhatsqdlambda <- matrix(0,2,length(lambda))
tauhatsqdlambdaarray <- array(0,dim=c(2,2,length(lambda)))
tauhatsqdTemp <- array(0,dim=c(B,2,length(lambda)))
ParamEst <- array(0,dim=c(B,2,length(lambda)))
ssqdlambda <- array(0,dim=c(2,2,length(lambda)))

for(b in 1:B){
W <- rep(1,length(lambda)) %o% X.data + sqrt(lambda) %o% (rnorm(n,sd=sqrt(X.Var)))
for(l in 1:length(lambda)){
LM <- lm(Y.data~W[l,],weights=1/Y.Var)
ParamEst[b,,l] <- c(coef(LM)[[1]],coef(LM)[[2]])
alphahatTemp[l] <- coef(LM)[[1]]
betahatTemp[l] <- coef(LM)[[2]]
tauhatsqdTemp[b,,l] <- ((summary(LM)$coef)[,2])^2
}
alphahatlambda <- alphahatlambda + alphahatTemp/B
betahatlambda <- betahatlambda + betahatTemp/B
tauhatsqdlambda <- tauhatsqdlambda + tauhatsqdTemp[b,,]/B
}
for(l in 1:length(lambda)){
tauhatsqdlambdaarray[,,l] <- diag(tauhatsqdlambda[,l])
ssqdlambda[,,l] <- cov(ParamEst[,,l])
}

alpha0 <- coef(lm(alphahatlambda~lambda + I(lambda^2)))[[1]]
alpha1 <- coef(lm(alphahatlambda~lambda + I(lambda^2)))[[2]]
alpha2 <- coef(lm(alphahatlambda~lambda + I(lambda^2)))[[3]]
beta0 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[1]]
beta1 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[2]]
beta2 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[3]]
ParamEstVar <- tauhatsqdlambdaarray - ssqdlambda
LM1 <- lm((ParamEstVar[1,1,]~lambda + I(lambda^2)))
LM2 <- lm((ParamEstVar[1,2,]~lambda + I(lambda^2)))
LM3 <- lm((ParamEstVar[2,2,]~lambda + I(lambda^2)))
gamma0 <- coef(LM1)[[1]]
gamma1 <- coef(LM1)[[2]]
gamma2 <- coef(LM1)[[3]]
delta0 <- coef(LM2)[[1]]
delta1 <- coef(LM2)[[2]]
delta2 <- coef(LM2)[[3]]
epsilon0 <- coef(LM3)[[1]]
epsilon1 <- coef(LM3)[[2]]
epsilon2 <- coef(LM3)[[3]]
```

```
alphahatSIMEX <- alpha0 - alpha1 + alpha2
betahatSIMEX <- beta0 - beta1 + beta2
alphaSIMEXVar <- gamma0 - gamma1 + gamma2
alphabetaSIMEXCov <- delta0 - delta1 + delta2
betaSIMEXVar <- epsilon0 - epsilon1 + epsilon2

#SIMEX results
simex.results <- data.frame(matrix(NA,2,3))
names(simex.results) <- c("Coefficient", "Coeff-se", "Covariance")
simex.results[2,1] <- (betahatSIMEX)
simex.results[2,2] <- (sqrt(betaSIMEXVar))
simex.results[1,1] <- (alphahatSIMEX)
simex.results[1,2] <- (sqrt(alphaSIMEXVar))
simex.results[1:2,3] <- (alphabetaSIMEXCov)
simex.results
}
```

Weighted least-squares SIMEX function with fixed intercept at origin

```
my.simex.wls0 <- function(B,X.data,X.Var,Y.data,Y.Var){

lambda <- seq(0,2,length=9)
betahatlambda <- rep(0,length(lambda))
betahatTemp <- rep(0,length(lambda))
n <- length(X.data)
tauhatsqdlambda <- matrix(0,1,length(lambda))
tauhatsqdlambdaarray <- array(0,dim=c(2,1,length(lambda)))
tauhatsqdTemp <- array(0,dim=c(B,1,length(lambda)))
ParamEst <- array(0,dim=c(B,1,length(lambda)))
ssqdlambda <- array(0,dim=c(2,1,length(lambda)))

for(b in 1:B){
W <- rep(1,length(lambda)) %o% X.data + sqrt(lambda) %o% (rnorm(n,sd=sqrt(X.Var)))
for(l in 1:length(lambda)){
LM <- lm(Y.data~0+W[l,],weights=1/Y.Var)
ParamEst[b,,l] <- coef(LM)[[1]]
betahatTemp[l] <- coef(LM)[[1]]
tauhatsqdTemp[b,,l] <- ((summary(LM)$coef)[,2])^2
}
betahatlambda <- betahatlambda + betahatTemp/B
tauhatsqdlambda <- tauhatsqdlambda + tauhatsqdTemp[b,,]/B
}

beta0 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[1]]
beta1 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[2]]
beta2 <- coef(lm(betahatlambda~lambda + I(lambda^2)))[[3]]
betahatSIMEX <- beta0 - beta1 + beta2
```

```
#SIMEX results
simex.results <- data.frame(matrix(NA,1,1))
names(simex.results) <- c("Coefficient")
simex.results[1,1] <- (betahatSIMEX)
simex.results
}
```

2.3 R code for regression analyses

As described in the Methods, this research estimates climate sensitivity by comparing reconstructions of ΔT and ΔR. The following R code can be used to implement the method.

```
# Data inputs
# Ensuring that all inputs are deviations from mean of the last 5kyr
Data <- Total.RF[1:800,]
Total.RF.dev <- matrix(NA, nrow=dim(Data)[1], ncol=dim(Data)[2])
for (i in 1:(dim(Data)[2])){ Total.RF.dev[,i]<- Data[,i]-mean(Data[1:5,i], na.rm=T)}

Data <- GAST[1:800,]
GAST.dev <- matrix(NA, nrow=dim(Data)[1], ncol=dim(Data)[2])
for (i in 1:(dim(Data)[2])){ GAST.dev[,i]<- Data[,i]-mean(Data[1:5,i], na.rm=T)}

# Ability to subset by time
TIME.i <- 800; time <- 1:TIME.i
Y.Data <- GAST.dev[time,]
X.Data <- Total.RF.dev[time,]

# Ability to subset by radiative forcing threshold
Y.Data.name <- "GAST"; X.Data.name <- "Total.RF"; threshold.1 = -100; threshold.2 = 100

#Estimating quantiles
        v.prob = c(2.5, 50, 97.5)/100
        X.quant <- apply (X.Data, MARGIN = 1, quantile, probs = v.prob, na.rm=T)
        X.sd <- (X.quant[3,]-X.quant[1,])/4
        X.var <- X.sd^2
        Y.quant <- apply (Y.Data, MARGIN = 1, quantile, probs = v.prob, na.rm=T)
        Y.sd <- (Y.quant[3,]-Y.quant[1,])/4
        Y.var <- Y.sd^2

n.sim = 50000  #number of simulations

# Titles for results table
v.NAMES.quad.10 <- c("Independent Variable", "Dependent Variable",
"Start Date", "End Date", "Length of comparison", "WLS- intercept", "WLS- intercept-se",
```

```
"WLS- intercept-p-value", "WLS- coeff", "WLS- coeff-se", "WLS- coeff-p-value", "WLS-
Ajdusted-R2", "WLS- S-residual std error", "WLS0- coeff", "WLS0- coeff-se", "WLS0- coeff-p-
value", "WLS0- Ajdusted-R2", "WLS0- S-residual std error", "WSIMEX- intercept",
"WSIMEX- intercept-se", "WSIMEX- coeff", "WSIMEX- coeff-se", "WSIMEX0- coeff",
"Correlation", "WLS.quad- intercept", "WLS.quad- intercept-se", "WLS.quad- intercept-p-
value", "WLS.quad- coeff", "WLS.quad- coeff-se", "WLS.quad- coeff-p-value", "WLS.quad-
coeff2", "WLS.quad- coeff2-se", "WLS.quad- coeff2-p-value", "WLS.quad- Ajdusted-R2",
"WLS.quad- S-residual std error", "WLS.quad- Predicted-2xCO2", "WLS0.quad- coeff",
"WLS0.quad- coeff-se", "WLS0.quad- coeff-p-value", "WLS0.quad- coeff2", "WLS0.quad-
coeff2-se", "WLS0.quad- coeff2-p-value", "WLS0.quad- Ajdusted-R2", "WLS0.quad- S-residual
std error", "WLS0.quad- Predicted-2xCO2", "WLS-WLS.quad- p-value from anova", "WLS0-
WLS0.quad- p-value from anova")

CC = 5.35 * log(2)

#Regression results output table
        AA <- matrix (NA, nrow = n.sim, ncol = length(v.NAMES.quad.10))
        Results <- data.frame(AA)
        names (Results) <-  v.NAMES.quad.10

for (ii in 1:n.sim){
        #Sampling and cutting data
        ii.XX <- sample(1:dim(X.Data)[2],1)
        X.Data.ii.raw <- X.Data[,ii.XX]
        Y.Data.ii.raw <- Y.Data[,sample(1:dim(Y.Data)[2],1)]
        time.cut.X.ii <- time[is.na(X.Data.ii.raw[time])==0]
        time.cut.Y.ii <- time[is.na(Y.Data.ii.raw[time])==0]
        time.lower <- max(c(min(time.cut.X.ii, na.rm =T),min(time.cut.Y.ii, na.rm =T)))
        time.upper <- min(c(max(time.cut.X.ii, na.rm =T),max(time.cut.Y.ii, na.rm =T)))
        time.cut.ii <- time.lower:time.upper

        time.cut.ii.1 <- time.cut.ii[is.na(Y.Data.ii.raw[time.cut.ii])==0]
        time.cut.ii.2 <- time.cut.ii.1[is.na(X.Data.ii.raw[time.cut.ii.1])==0]
        time.cut.ii.threshold <- time.cut.ii.2[GAST.m[time.cut.ii.2]>threshold.1 &
                GAST.m[time.cut.ii.2]<threshold.2]

        Y.Data.ii <- Y.Data.ii.raw[time.cut.ii.threshold]
        X.Data.ii <- X.Data.ii.raw[time.cut.ii.threshold]
        #cutting weights calculated above
        Y.var.ii <- Y.var[time.cut.ii.threshold]; Y.weights.ii <- 1/Y.var.ii
        X.var.ii <- X.var[time.cut.ii.threshold]; X.weights.ii <- 1/X.var.ii

        #Regressions
        LM.wls <- lm (Y.Data.ii ~ X.Data.ii, weights = Y.weights.ii)
        LM.wls0 <- lm (Y.Data.ii ~ 0 + X.Data.ii, weights = Y.weights.ii)
        LM.wsimex.coef <- my.simex.wls (100, X.Data.ii, X.var.ii, Y.Data.ii, Y.var.ii)
```

```
LM.wsimex0.coef <- my.simex.wls0 (100, X.Data.ii, X.var.ii, Y.Data.ii, Y.var.ii)
LM.wls.quad <- lm (Y.Data.ii ~ X.Data.ii+I((X.Data.ii)^2), weights = Y.weights.ii,
        x=TRUE)
LM.wls0.quad <- lm (Y.Data.ii ~ 0 + X.Data.ii+I((X.Data.ii)^2), weights = Y.weights.ii,
        x=TRUE)
anova.wls.p <-anova(LM.wls, LM.wls.quad)[2,6]
anova.wls0.p <-anova(LM.wls0, LM.wls0.quad)[2,6]

# Outputting Results
nn= 1
#File information
Results[ii,nn] <- as.character(X.Data.name); nn<- nn +1
Results[ii,nn] <- as.character(Y.Data.name); nn<- nn +1
Results[ii,nn] <- min(time.cut.ii.threshold); nn<- nn +1
Results[ii,nn] <- max(time.cut.ii.threshold); nn<- nn +1
Results[ii,nn] <- length(time.cut.ii.threshold); nn<- nn +1
#WLS
Results[ii,nn] <- summary(LM.wls)$coef[1,1]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls)$coef[1,2]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls)$coef[1,4]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls)$coef[2,1]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls)$coef[2,2]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls)$coef[2,4]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls)$adj.r.squared; nn<- nn +1
Results[ii,nn] <- summary(LM.wls)$sigma; nn<- nn +1
#WLS0
Results[ii,nn] <- summary(LM.wls0)$coef[1,1]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls0)$coef[1,2]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls0)$coef[1,4]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls0)$adj.r.squared; nn<- nn +1
Results[ii,nn] <- summary(LM.wls0)$sigma; nn<- nn +1
#W-SIMEX
Results[ii,nn] <- LM.wsimex.coef[1,1]; nn<- nn +1
Results[ii,nn] <- LM.wsimex.coef[1,2]; nn<- nn +1
Results[ii,nn] <- LM.wsimex.coef[2,1]; nn<- nn +1
Results[ii,nn] <- LM.wsimex.coef[2,2]; nn<- nn +1
#W-SIMEX0
Results[ii,nn] <- LM.wsimex0.coef[1]; nn<- nn +1
#Correlation
Results[ii,nn] <- cor(X.Data.ii,Y.Data.ii); nn<- nn +1
#WLS-quad
Results[ii,nn] <- summary(LM.wls.quad)$coef[1,1]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls.quad)$coef[1,2]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls.quad)$coef[1,4]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls.quad)$coef[2,1]; nn<- nn +1
Results[ii,nn] <- summary(LM.wls.quad)$coef[2,2]; nn<- nn +1
```

```
        Results[ii,nn] <- summary(LM.wls.quad)$coef[2,4]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls.quad)$coef[3,1]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls.quad)$coef[3,2]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls.quad)$coef[3,4]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls.quad)$adj.r.squared; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls.quad)$sigma; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls.quad)$coef[2,1] * CC +
                summary(LM.wls.quad)$coef[3,1] * CC^2; nn<- nn +1
        #WLS0-quad
        Results[ii,nn] <- summary(LM.wls0.quad)$coef[1,1]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$coef[1,2]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$coef[1,4]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$coef[2,1]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$coef[2,2]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$coef[2,4]; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$adj.r.squared; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$sigma; nn<- nn +1
        Results[ii,nn] <- summary(LM.wls0.quad)$coef[1,1] * CC +
                summary(LM.wls0.quad)$coef[2,1] * CC^2; nn<- nn +1
        #ANOVA
        Results[ii,nn] <- anova.wls.p; nn<- nn +1
        Results[ii,nn] <- anova.wls0.p; nn<- nn +1
}
```

2.4 R code for breakpoint regression analyses

As described in the Methods, this research explores whether a piecewise or breakpoint regression would estimate two different paleoclimate sensitivity parameters: one for deep glacial conditions and one for interglacial periods and intermediate glacial conditions. I use the *chngpt* package (Fong et al., 2017) to estimate discontinuous single-breakpoint, weighted linear regression models, called segmented models, using a bootstrap estimation approach with multiple iterations. The following R code can be used to implement the method.

```
# Data inputs
# Ensuring that all inputs are deviations from mean of the last 5kyr
Data <- Total.RF[1:800,]
Total.RF.dev <- matrix(NA, nrow=dim(Data)[1], ncol=dim(Data)[2])
for (i in 1:(dim(Data)[2])){ Total.RF.dev[,i]<- Data[,i]-mean(Data[1:5,i], na.rm=T)}

Data <- GAST[1:800,]
GAST.dev <- matrix(NA, nrow=dim(Data)[1], ncol=dim(Data)[2])
for (i in 1:(dim(Data)[2])){ GAST.dev[,i]<- Data[,i]-mean(Data[1:5,i], na.rm=T)}

# Ability to subset by time
TIME.i <- 800; time <- 1:TIME.i
```

```
Y.Data <- GAST.dev[time,]
X.Data <- Total.RF.dev[time,]

# Ability to subset by radiative forcing threshold
Y.Data.name <- "GAST"; X.Data.name <- "Total.RF"; threshold.1 = -100; threshold.2 = 100

#Estimating quantiles
        v.prob = c(2.5, 50, 97.5)/100
        X.quant <- apply (X.Data, MARGIN = 1, quantile, probs = v.prob, na.rm=T)
        X.sd <- (X.quant[3,]-X.quant[1,])/4
        X.var <- X.sd^2
        Y.quant <- apply (Y.Data, MARGIN = 1, quantile, probs = v.prob, na.rm=T)
        Y.sd <- (Y.quant[3,]-Y.quant[1,])/4
        Y.var <- Y.sd^2

n.sim = 20000  #number of simulations

# Titles for results table
v.NAMES.breakpoint <- c("Independent Variable", "Dependent Variable", "Start Date", "End
Date", "Length of comparison", "Correlation", "Breakpoint", "Intercept-1", "Coefficient-1",
"Intercept-2", "Coefficient-2", "Ratio-slopes", “Breakpoint-W", "Intercept-1-W", "Coefficient-1-
W", "Intercept-2-W", "Coefficient-2-W", "Ratio-slopes-W", "Breakpoint-rev", "Intercept-1-rev",
"Coefficient-1-rev", "Intercept-2-rev", "Coefficient-2-rev", "Intercept-1-rev-convert",
"Coefficient-1-rev-convert", "Intercept-2-rev-convert", "Coefficient-2-rev-convert", "Ratio-
slopes-rev-convert", "Breakpoint-rev-W", "Intercept-1-rev-W", "Coefficient-1-rev-W",
"Intercept-2-rev-W", "Coefficient-2-rev-W", "Intercept-1-rev-convert-W", "Coefficient-1-rev-
convert-W", "Intercept-2-rev-convert-W", "Coefficient-2-rev-convert-W", "Ratio-slopes-rev-
convert-W")

#Regression results output table
        AA <- matrix (NA, nrow = n.sim, ncol = length(v.NAMES.breakpoint))
        Results <- data.frame(AA)
        names (Results) <-  v.NAMES.breakpoint

for (ii in 1:n.sim){
#Sampling and cutting data
        ii.XX <- sample(1:dim(X.Data)[2],1)
        X.Data.ii.raw <- X.Data[,ii.XX]
        Y.Data.ii.raw <- Y.Data[,sample(1:dim(Y.Data)[2],1)]
        time.cut.X.ii <- time[is.na(X.Data.ii.raw[time])==0]
        time.cut.Y.ii <- time[is.na(Y.Data.ii.raw[time])==0]
        time.lower <- max(c(min(time.cut.X.ii, na.rm =T),min(time.cut.Y.ii, na.rm =T)))
        time.upper <- min(c(max(time.cut.X.ii, na.rm =T),max(time.cut.Y.ii, na.rm =T)))
        time.cut.ii <- time.lower:time.upper

        time.cut.ii.1 <- time.cut.ii[is.na(Y.Data.ii.raw[time.cut.ii])==0]
```

```
        time.cut.ii.2 <- time.cut.ii.1[is.na(X.Data.ii.raw[time.cut.ii.1])==0]
                time.cut.ii.threshold <- time.cut.ii.2[GAST.m[time.cut.ii.2]>threshold.1 &
                GAST.m[time.cut.ii.2]<threshold.2]

        Y.Data.ii <- Y.Data.ii.raw[time.cut.ii.threshold]
        X.Data.ii <- X.Data.ii.raw[time.cut.ii.threshold]
        #cutting weights calculated above
        Y.var.ii <- Y.var[time.cut.ii.threshold]; Y.weights.ii <- 1/Y.var.ii
        X.var.ii <- X.var[time.cut.ii.threshold]; X.weights.ii <- 1/X.var.ii

#Breakpoint regressions
        fit.ii <- chngptm.xy(X.Data.ii,Y.Data.ii,type="stegmented")
        fit.ii.w <- chngptm.xy(X.Data.ii,Y.Data.ii,type="stegmented", weights = Y.weights.ii)
        fit.rev.ii <- chngptm.xy(Y.Data.ii, X.Data.ii,type="stegmented")
        fit.rev.ii.w <- chngptm.xy(Y.Data.ii, X.Data.ii,type="stegmented", weights =
                X.weights.ii)
        fit.rev.ii.int.1 <- as.numeric(fit.rev.ii$coef[[1]])
        fit.rev.ii.slope.1 <- as.numeric(fit.rev.ii$coef[[2]])
        fit.rev.ii.int.2 <- as.numeric(fit.rev.ii$coef[[1]]+fit.rev.ii$coef[[3]]-
                fit.rev.ii$coef[[4]]*fit.rev.ii$chngpt)
        fit.rev.ii.slope.2 <- as.numeric(fit.rev.ii$coef[[2]]+ fit.rev.ii$coef[[4]])
        fit.rev.ii.w.int.1 <- as.numeric(fit.rev.ii.w$coef[[1]])
        fit.rev.ii.w.slope.1 <- as.numeric(fit.rev.ii.w$coef[[2]])
        fit.rev.ii.w.int.2 <- as.numeric(fit.rev.ii.w$coef[[1]]+fit.rev.ii.w$coef[[3]]-
                fit.rev.ii.w$coef[[4]]*fit.rev.ii.w$chngpt)
        fit.rev.ii.w.slope.2 <- as.numeric(fit.rev.ii.w$coef[[2]]+ fit.rev.ii.w$coef[[4]])

# Outputting Results
        nn= 1
#File information
        Results[ii,nn] <- as.character(X.Data.name); nn<- nn +1
        Results[ii,nn] <- as.character(Y.Data.name); nn<- nn +1
        Results[ii,nn] <- min(time.cut.ii.threshold); nn<- nn +1
        Results[ii,nn] <- max(time.cut.ii.threshold); nn<- nn +1
        Results[ii,nn] <- length(time.cut.ii.threshold); nn<- nn +1
#Correlation
        Results[ii,nn] <- cor(X.Data.ii,Y.Data.ii); nn<- nn +1
#Breakpoint regression results - OLS
        Results[ii,nn] <- as.numeric(fit.ii$chngpt[[1]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii$coef[[1]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii$coef[[2]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii$coef[[1]]+fit.ii$coef[[3]]-fit.ii$coef[[4]]*fit.ii$chngpt);
                nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii$coef[[2]]+ fit.ii$coef[[4]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii$coef[[2]]+ fit.ii$coef[[4]]) / as.numeric(fit.ii$coef[[2]]);
                nn<- nn +1
```

```
# Breakpoint regression results - WLS weighted
        Results[ii,nn] <- as.numeric(fit.ii.w$chngpt[[1]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii.w$coef[[1]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii.w$coef[[2]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii.w$coef[[1]]+fit.ii.w$coef[[3]]-
                fit.ii.w$coef[[4]]*fit.ii.w$chngpt); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii.w$coef[[2]]+ fit.ii.w$coef[[4]]); nn<- nn +1
        Results[ii,nn] <- as.numeric(fit.ii.w$coef[[2]]+ fit.ii.w$coef[[4]]) /
                as.numeric(fit.ii.w$coef[[2]]); nn<- nn +1
#Breakpoint regression results - reversed
        Results[ii,nn] <- as.numeric(fit.rev.ii$chngpt[[1]]); nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.int.1; nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.slope.1; nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.int.2; nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.slope.2; nn<- nn +1
        Results[ii,nn] <- as.numeric(-1*fit.rev.ii.int.1/fit.rev.ii.slope.1); nn<- nn +1
        Results[ii,nn] <- as.numeric(1/fit.rev.ii.slope.1); nn<- nn +1
        Results[ii,nn] <- as.numeric(-1*fit.rev.ii.int.2/fit.rev.ii.slope.2); nn<- nn +1
        Results[ii,nn] <- as.numeric(1/fit.rev.ii.slope.2); nn<- nn +1
        Results[ii,nn] <- as.numeric(as.numeric(fit.rev.ii$coef[[2]]) / fit.rev.ii$coef[[2]]+
                fit.ii$coef[[4]]) ; nn<- nn +1
#Breakpoint regression results - reversed - WLS weighted
        Results[ii,nn] <- as.numeric(fit.rev.ii.w$chngpt[[1]]); nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.w.int.1; nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.w.slope.1; nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.w.int.2; nn<- nn +1
        Results[ii,nn] <- fit.rev.ii.w.slope.2; nn<- nn +1
        Results[ii,nn] <- as.numeric(-1*fit.rev.ii.w.int.1/fit.rev.ii.w.slope.1); nn<- nn +1
        Results[ii,nn] <- as.numeric(1/fit.rev.ii.w.slope.1); nn<- nn +1
        Results[ii,nn] <- as.numeric(-1*fit.rev.ii.w.int.2/fit.rev.ii.w.slope.2); nn<- nn +1
        Results[ii,nn] <- as.numeric(1/fit.rev.ii.w.slope.2); nn<- nn +1
        Results[ii,nn] <- as.numeric(as.numeric(fit.rev.ii.w$coef[[2]]) / fit.rev.ii.w$coef[[2]]+
                fit.ii.w$coef[[4]]) ; nn<- nn +1
}
```

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