Temperature reconstructions for the Last Glacial Maximum as constraints for climate sensitivity

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Abstract. This seminar report reviews studies that constrain climate sensitivity using the Last Glacial Maximum (LGM). I outline the methods that are used in order to combine insights both from climate models and proxy data. Results from selected studies are presented and classified with respect to their limitations and further development in the field. I conclude that studies using the LGM as a benchmark period can definitely be used in order to estimate climate sensitivity and effectively constrain its upper limit.

1 Introduction

Climate sensitivity is considered a key number in climate change science. It is defined as the global mean temperature rise when the amount of the greenhouse gas CO_2 in the atmosphere is doubled with respect to the preindustrial level (from 280 to 560 ppm). As the concept is easy to grasp and the importance of anthropogenic climate change is now widely acknowledged, climate sensitivity has gained popularity in the last decades. It was Swedish chemist and Nobel laureate Svante Arrhenius who in 1896 calculated the effect of increased CO_2 levels on temperature for the first time (Arrhenius, 1896), but the concept only got popular with the so called Charney Report (Charney, 1979). In this study on behalf of the National Academy of Sciences of the United States, which was one of the earliest assessments of global warming, the best estimate 3 ± 1.5°C. Since then it has been subject to many studies and in consequence is included in every IPCC report. In the last assessment report 6 (IPCC, 2021) it is estimated between 2.5°C and 4°C. A comprehensive introduction into the topic is given by Knutti and Hegerl (2008) and a subsequent review paper (Knutti et al., 2017). There are many approaches to estimate climate sensitivity, data from the instrumental period, the last millennium, volcanic eruptions and paleoclimatic periods are used. Figure 1 visualizes probability distribution functions (pdfs) from various studies included in AR4 by the IPCC. The upper limit of these pdfs is often not well constrained, the possibility of really high climate sensitivities poses a problem for risk assessments of climate change impacts. Thus the leading question of my seminar report is not only how these curves are obtained, but if the upper limit can be constrained better.

For this report I focus on the Last Glacial Maximum (LGM), one of the best studied climatic periods of earth's history. Climatologists locate the peak of the glacial extent of this period around 21'000 years ago. During this period large parts of the landmasses on the northern hemisphere were covered by a thick ice shield, current estimates for mean global cooling range from 3°C to 5°C. Estimates from sea level reconstructions with corals lead to the conclusion that the sea level was up to 120 m lower than today according to AR4 (Solomon et al., 2007). The atmospheric composition was substantially different, for instance CO_2 is assumed to have been at 180 ppm instead of the present 400 ppm. This is one of several reasons that makes the LGM a period of high value for assessing climate sensitivity. The cold condition persisted for millennia, which equals near equilibrium conditions and a strong climate signal. Furthermore many kinds of proxy data are available and the different radiative forcings and responses are quite well known. Last there are many LGM simulations that have already been developed and compared to LGM proxy data (von Deimling et al., 2006).

This report is structured as follows: The first section is dedicated to the definition of climate sensitivity in terms of physical quantities, timescales and feedback mechanisms. An introduction into statistical methods is given, which is critical for model data comparison. Then two methods of estimating climate sensitivity with LGM data are presented, I call them the model ensemble and the temperature reconstruction approach. Results from studies using these methods are presented and discussed with regard to caveats and uncertainties.

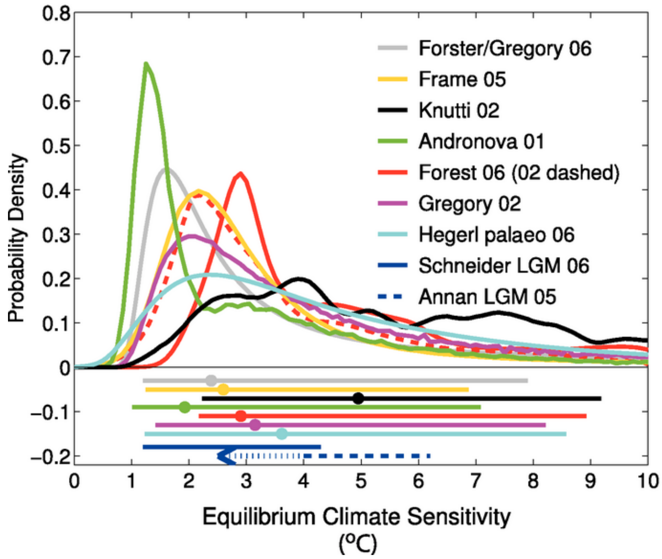

Figure 1. Figure taken from AR4 (9.6.2.1) (Solomon et al., 2007). It shows pdfs for Equilibrium Climate Sensitivity. Below the 5 to 95% confidence intervals are shown. The studies used very different kind of data in order to assess Equilibrium Climate Sensitivity and are not limited to the LGM. The graphs are representative for many climate sensitivity studies due to the characteristic of constraining the lower limit well in comparison to the upper limit which is not well constrained. The possibility of really high climate sensitivity causes uncertainties in predicting anthropocentric climate change.

2 Definitions of Climate Sensitivity

When talking about climate sensitivity we need to differentiate between three concepts, *Transient Climate Response (TCR)*, *Equilibrium Climate Sensitivity (ECS)* and *Earth System Sensitivity (ESS)* (Knutti and Hegerl, 2008). TCR is defined as the warming in response to increasing the atmospheric concentration of CO_2 at a rate of 1% per year, hence the warming after 70 years. The timescales looked at here are a few decades, thus TCR depends strongly on the ocean heat uptake. As it characterizes the speed of imminent climate change TCR is favored to describe anthropogenic impact on climate and therefore the value primarily communicated to policy makers. It is a value closely linked to the emission pathways outlined in the IPCC reports and the *Transient Climate Response To Cumulative Carbon Emission* (TCRE), which is the temperature increase per ton of emitted carbon.

Equilibrium climate sensitivity is the change in global mean temperature until a new equilibrium state is reached. In practice the earth system never is in perfect equilibrium, such that near equilibrium states are considered. The timescale goes up to millennia, therefore climate feedbacks like increased water vapor, changes in lapse rate, albedo and clouds that by themselves additionally influence temperature are considered (Figure 2). For paleoclimatologists ECS is the value of central interest and also the climate sensitivity I looked at during my literature research.

On long time scales it is often debated if earth-system responses beyond the point of reaching near equilibrium, like slowly changing vegetation patterns, ice shields or the deep ocean currents should be included. These adaptations of the earth system will also alter earth's temperature on the long run. In climate models these components are often fixed and can not change, such that this is often neglected. In recent years a third definition for climate sensitivity has been introduced, *Earth System Sensitivity (ESS)* which includes also feedbacks that have effects after a (near) equilibrium state is reached, but is the most difficult to properly simulate and not subject to my literature review.

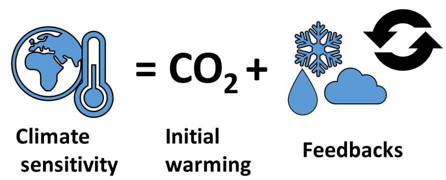

Figure 2. Visualization of the meaning of Equilibrium Climate Sensitivity. The warming caused by CO_2 triggers feedback mechanisms like changes in water vapor content, lapse rate and clouds in the atmosphere that by themselves can reduce or increase further warming. Taken from Femkemilene via Wikimedia Commons.

2.1 Climate sensitivity from an energy balance perspective

Having introduced these definitions we can now look at climate sensitivity from a more physical perspective with respect to the underlying forcings.

A climate forcing is the change of energy flux (energy per time per area) in response to natural or anthropogenic influences on the climate system. Considering the earth's radiative (im)balance is thus the starting point of our considerations

$$\Delta Q = \Delta F - \frac{1}{\lambda}\Delta T \tag{1}$$

ΔQ is the heat flux in W/m^2 in response to a radiative forcing ΔF and the corresponding temperature increase of the system, ΔT. It is scaled by a factor $\lambda = \frac{\Delta T}{\Delta F - \Delta Q}$, the climate sensitivity parameter, which is the temperature change per difference of radiative forcing and resulting heat flux. Considering a situation of equilibrium for ECS the heat flux is set to zero. The other fundamental characteristic of ECS is that the forcing due to doubled CO_2, so we explicitly denote it as ΔF_{2xCO_2}. This imbalance caused by doubled CO_2 is estimated to be around $3.7 W/m^2$ in the TAR (Forster et al., 2007). Hence we get for equation 1

$$\frac{1}{\lambda}\Delta T = \Delta F_{2xCO_2} \tag{2}$$

The difficulty lies in estimating λ. Assuming that it is an inherent fixed value of our earth system we can calculate it from the cooling ΔT_{LGM} and the forcings ΔF_{LGM} during the LGM. As the LGM is also assumed to be in near equilibrium the heat flux ΔQ_{LGM} is set to zero. Hence we get a simple formula to calculate ECS with prior knowledge about the LGM.

$$ECS = \Delta T_{2xC0_2} = \Delta F_{2xCO_2} \cdot \lambda \tag{3}$$
$$= \Delta F_{2xCO_2} \cdot \frac{\Delta T_{LGM}}{\Delta F_{LGM}} \tag{4}$$

Note that the literature is not consistent with regard to naming λ or its inverse $1/\lambda$ the climate sensitivity parameter.

As seen in Figure 1 probability distribution functions for ECS tend to be rather broad with large tails. The uncertainties in ECS are due to two main reasons. The first one is due to uncertainties in the total forcing, especially with aerosol forcing or ocean heat uptake that are not constrained tightly. This allows for λ to take a range of values. The second reason is the nonlinear relation of ECS to the feedback parameter f that is introduced in the following subsection.

2.2 Climate sensitivity from a climate feedback perspective

Climate feedbacks are processes that amplify or diminish the effects of climate forcings. For instance a warming due to increased CO_2 leads to more evaporation, hence more water vapor, which is also a greenhouse gas into the atmosphere, such that additional warming is caused. On the other hand emission of an aerosol can lead to a more reflective atmosphere hence less radiation enters the atmosphere.

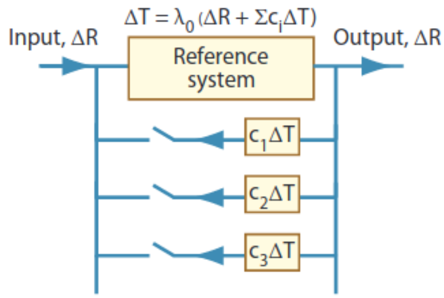

Figure 3. Representation of a feedbacks taken from Roe (2009) The input energy ΔR is processed by the reference system, leading to a temperature increase ΔT. A part of the output energy is fed back into the system via various feedbacks. λ_0 is the climate sensitivity parameter without any feedback.

Following the review article on climate feedbacks by Roe (2009) I introduce a simplified linear feedback models which helps in understanding the large tails of climate sensitivity pdfs.

As depicted in Figure 3 a climate feedback can be understood as a part of the output energy that is fed back into the system. We look at this situation from an energy balance perspective again. The temperature increase ΔT_0 without any feedbacks is just

$$\Delta T_0 = \lambda_0(\Delta F - \Delta Q) = \lambda_0 \Delta R \tag{5}$$

as before. ΔR is the input energy. In a simple linear model, the energy that goes back to the input side is proportional to the output temperature and a scaling factor c for each feedback. Assuming no interaction between the feedbacks all scaling factors can be summed into one feedback factor f:

$$\Delta T = \lambda_0(\Delta R + \sum c_i \Delta T) \tag{6}$$
$$= \lambda_0 \Delta R + f \Delta T \tag{7}$$

Solving this equation for ΔT gives

$$\Delta T = \Delta T_0 \cdot \frac{1}{1-f} \tag{8}$$

Hence the nonlinear relationship between climate feedbacks and temperature response. With regard to the uncertainties in temperature response the error propagation formula states as follows

$$\delta(\Delta T) = \Delta T_0 \cdot \frac{1}{(1-f)^2} \cdot \delta f \tag{9}$$

Thus the uncertainty does not depend on the uncertainty of the feedback parameter alone, but also on the feedback parameter itself. The closer f gets to unity the larger $\delta(\Delta T)$. This explains both asymmetry and large tail of pdfs for ECS.

3 Statistical methods in climate sensitivity studies

In climate science knowledge of physical fundamentals represents only one side of the coin. As a lot of data with many uncertainties is investigated the other side is statistics. When investigating paleoclimatic periods from a model and a proxy data perspective the challenge lies in reconciling model and observations. This task belongs to the field of *Data assimilation*, which was originally developed for weather forecasting. In the following I briefly go through one basic but crucial theorem, Bayes' theorem and its application in the ensemble Kalman filter. I follow the lecture on data assimilation by Nathan Kutz (Kutz, 2018).

3.1 Bayes theorem

When talking about climate sensitivity we are dealing with probability distribution functions. Bayesian inference tells us how to update probability distributions in light of new information. In the following H stands for hypothesis, E for evidence and the vertical bar stands for conditional probability. The Bayesian formula goes as follows

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)} \tag{10}$$

On the left hand side we find the posterior probability $P(H|E)$, which is the new probability for the hypothesis if evidence is introduced. On the right hand stands how the prior probability $P(H)$, the initial probability for our hypothesis, is updated. It is multiplied with the likelihood $P(E|H)$, which is the probability for the observed evidence given the probability distribution of the hypothesis. The product is divided by the marginal likelihood $P(E)$ which is basically a normalization constant. This simple formula can be applied iteratively. Applying it many times weakens the dependency of the initial hypothesis.

3.2 Data Assimilation - the ensemble Kalman filter

We are now going to apply this theorem. A variable like temperature is predicted by a climate model, this is the hypothesis. Proxy data represents new evidence. The Kalman filter presented here is just the one dimensional formulation, but it is sufficient to show the principle of reconciling model and proxy data. In the following the model is denoted as x and the proxy data as y. Assuming a prior distribution given by the initial model $P(x)$ we would like to estimate how this distribution changes in light of new proxy data y. σ_0 and σ_y represent the errors in model and measurement.

We start with the Bayesian formula

$$P(x|y) = \frac{P(y|x) \cdot P(x)}{P(y)} \tag{11}$$

We assume the prior distribution of the variable x to be normally distributed around a mean value x_0. The likelihood, which is the probability of the measurement with respect to the model distribution, is also assumed to be a Gaussian distribution. c_1, c_2 and c_3 are normalization constants.

$$P(y|x) = c_1 e^{-\frac{1}{2}\left(\frac{y-x}{\sigma_y}\right)^2} \tag{12}$$

$$P(x) = c_2 e^{-\frac{1}{2}\left(\frac{x-x_0}{\sigma_0}\right)^2} \tag{13}$$

Incorporating the marginal distribution $P(y)$ and c_1 and c_2 into the normalization constant c_3 we thus get for the posterior probability

$$P(x|y) = c_3 e^{-\frac{1}{2}\left(\left(\frac{y-x}{\sigma_y}\right)^2+\left(\frac{x-x_0}{\sigma_0}\right)^2\right)} = c_3 e^{-J(x)} \tag{14}$$

Here the cost function $J(x)$ has been introduced. The aim is to maximize the Likelihood, thus find the value $\bar{x}$ where the Likelihood is maximal. Instead of differentiating the whole equation we can just differentiate the cost function in the exponent due to the negative sign

$$\frac{\partial J}{\partial x} = 0 = \left(\frac{y-\bar{x}}{\sigma_y^2}\right) - \left(\frac{\bar{x}-x_0}{\sigma_0^2}\right) \tag{15}$$

$$\Rightarrow \bar{x} = \left(\frac{{\sigma_y}^2}{{\sigma_y}^2+{\sigma_0}^2}\right)x_0 + \left(\frac{{\sigma_0}^2}{{\sigma_y}^2+{\sigma_0}^2}\right)y \tag{16}$$

Introducing the Kalman gain K with $K = \frac{{\sigma_0}^2}{{\sigma_0}^2+{\sigma_y}^2}$ the last equation can be formulated as an update equation.

$$\bar{x} = x_0 + K(y - x_0) \tag{17}$$

This equation tells us how the model mean x_0 goes over into the best value $\bar{x}$ when measuring y. This depends on the ratio of model and measurement errors in the Kalman gain K. The difference between y and x_0 is called the innovation. For instance if the model error σ_0 is small compared to σ_y, K is zero, thus the mean value is not updated. On the other hand if the measurement error σ_y is small the mean value is replaced by the measured value.

Regarding the error of the new posterior distribution it can be shown that $\bar{\sigma}$ is both smaller than σ_0 and σ_y. Hence the advantage of combining both model and measured data. We get a new distribution with a smaller error.

4 Reviewed studies of ECS constraints with paleoclimatic LGM data

4.1 Model ensembles

The basic idea of the model ensemble approach to constrain climate sensitivity is to tune a climate model. The tuned climate model should simulate the LGM according to proxy data and the rise of global mean temperature in a scenario with doubled CO_2 concentration.

The direct advantage of this approach is that one does not have to assume a direct relationship between the climate sensitivity parameters for both climate states. The climate sensitivity arises as a consequence of many factors, it is an emergent property of the climate model. However, the main assumption here lies in trusting the climate models to reproduce the change in climate feedbacks correctly.

In detail the procedure can be divided into five steps.

1. In order to tune the climate model the investigators select parameters that are going to be varied along a range of values. This is called perturbation. Doing so is valid because climate models heavily rely on parameterization and many equations are empirically based. Depending of the climate model this procedure is applied to only one parameter or to a whole set of parameters. In the latter case Monte Carlo techniques are used in a way that the parameter space is efficiently sampled. Possible correlations between the parameters of the climate model need to be considered in the resulting pdfs.

2. The climate model is run for preindustrial or present day boundary conditions for each configuration of perturbed parameters. This is a viability check. Configurations leading to climate states not in accordance with the data record are discarded.

3. The climate model is run in a scenario of doubled CO_2 concentration for some millennia until an equilibrium state is reached. Like this each parameter configuration can be associated to the according change in global mean temperature, the Equilibrium Climate Sensitivity.

4. The climate model is run with LGM boundary conditions, the most important ones being ice sheet coverage, atmospheric composition, lower sea lea level and the orbital configuration.

5. Finally the viability of the simulated LGM state is assessed by comparison with proxy data, which is usually done with techniques of Bayesian inference as presented in the previous section.

Steps 2 to 5 are repeated for all sets of parameter configurations, such that a probability distribution for equilibrium climate sensitivity can be obtained. The challenge lies in doing a good model data comparison. The change in global mean surface temperature can be attributed to different types of forcings by testing various configurations, for instance by only changing the atmospheric composition, holding ice shields fixed or by excluding dust and vegetation models.

The climate models chosen are of intermediate complexity. They should not be too intensive computation-wise because they are run for thousands of years for thousands of different parameter configurations. Before I proceed with presenting some results from this type of study I want to briefly answer the question why it is even necessary to do the LGM model runs and why a model data comparison for the preindustrial/present day simulation is not sufficient in the first place.

Wigley et al. already investigated in 1997 if the observed global warming can constrain climate sensitivities (Wigley et al., 1997). The authors came to the conclusion that the uncertainties regarding the forcings make it impossible to narrow the range of climate sensitivity estimates. For instance parts of the greenhouse gas forcing could have been canceled out by aerosols. The climate sensitivity range that is compatible with the recent climate record is larger than what is obtained by the paleoclimatic studies. Since the study by Wigley et al. this has been established as a fact. Thus the necessity for using paleoclimatic data arose.

4.1.1 Studies

To my knowledge Annan et al. (2005) were the first who used the approach of climate model ensemble runs. The authors used the atmospheric component of the MIROC3.2 model where 25 parameters were varied. For the ocean they referred to a slab ocean, thus possible circulation changes in the ocean were not considered. For the proxy data comparison the study relies on tropical ocean temperatures for the LGM. The authors assumed the estimates of global average temperatures available at that time (2005) to be not good enough. Experiments with different levels of LGM constraints were done, leading to a most likely climate sensitivity of around 4.5°C. Nonetheless, the authors came to the conclusion that their model is biased toward too high climate sensitivities. Hence they do not give a final estimate for equilibrium climate sensitivity. The central result of the study is that the probability for climate sensitivity exceeding 6°C is estimated with less than 7%, such that it can be considered unlikely. Another interesting side result is that a statistically significant linear correlation between LGM cooling and ECS is observed. According to this study uncertainties in the response of their model inhibits tight climate sensitivity estimates even in case of better LGM reconstructions.

Around the same time a similar type of study was carried out by von Deimling et al. (2006). They used the CLIMBER-2 model (which also includes an ocean model), where 11 parameters were perturbed. The proxy data used for model data comparison was limited to the tropical Atlantic. Initially the authors also thought of estimating climate sensitivity by Bayesian inference, however they found a linear correlation between LGM cooling and ECS even stronger than in the study by Annan et al. (see Figure 4). Hence they linearly extrapolated an ECS range from the LGM cooling range. The ECS estimate lies in the range of 1.2-4.3°C. The authors emphasize the capacity of being able to constrain the upper limit of ECS. They do not take the robustness of the quasi-linear relationship between LGM cooling and ECS for granted.

The third study I would like to present is the study by Schmittner et al. (2011). It used the University of Victo-

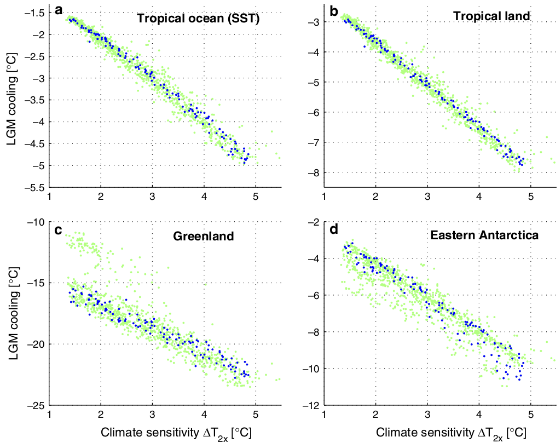

Figure 4. Relationship between LGM cooling and climate sensitivity for various regions found in the study by von Deimling et al.. The blue dots represent simulation runs that fitted to stricter constraints than the simulations represented by green dots. The correlation found here is stronger than the one found in other studies and is rather surprising. It could be due to an inherent property of the earth system, or what is more likely, of the climate model used. Taken from von Deimling et al. (2006).

ria climate model where one parameter was perturbed. The novelty in this study consisted of using global proxy data for the LGM and not only regionally limited data sets. This was made possible by results from the Multiproxy Approach for the Reconstruction of the Glacial Ocean (MARGO)-project in particular. This new data suggests that the LGM was warmer than previously assumed. As a consequence the study by Schmittner came to a lower best estimate of 2.3°C in a range of 1.7-2.6°C for ECS. From sensitivity tests of including proxy data from specific regions only the authors concluded that global data coverage is crucial for estimating ECS.

4.2 Proxy reconstructions

The straight forward approach to estimate ECS is to calculate it from formula 4. To that end the following question has to be answered: How cool was the LGM and how large was the radiative forcing?

The recent study by Tierney et al. (2020b) focuses on the part of reconstructing LGM temperature. The idea was to simulate the Last Glacial Maximum and regularly update the simulation with proxy data using data assimilation as presented in the second section. The simulated climate state thus serves as the prior distribution. The study used the isotope-enabled Community Earth System Model. The isotope component allowed for a posterior verification of the simulated temperatures with data from δ^{18}O records. The time resolution of the updating procedure was fifty ears.

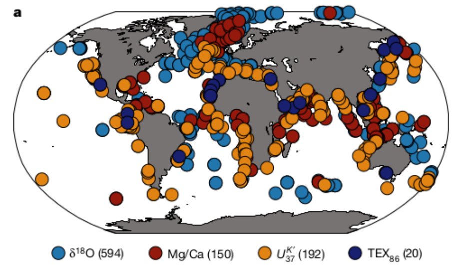

Figure 5. Proxy locations used by Tierney et al. The proxies are purely marine based, but globally distributed. The data obtained from the marine sediments proxies (all except δ^{18}O) was used at a 50 year resolution in order to enhance the LGM simulation via data assimilation. δ^{18}O was used for later validation due to the model being isotope enabled. Taken from Tierney et al. (2020b).

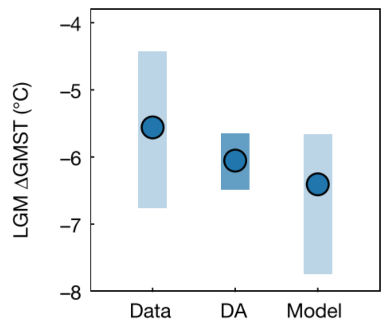

Figure 6. Global mean surface cooling for the LGM as obtained from a purely proxy data based estimate, data assimilation and from the model prior. It shows the strength of reducing the final uncertainty via data assimilation. Just looking at the values it seems that either the proxy data or the model is biased. Taken from Tierney et al. (2020b).

This study represents a real improvement due to its use of a variety of marine proxies on a global scale. The SST proxies used in this study are displayed in the map in Figure 5. Figure 6 visualizes the improvement obtained by using data assimilation in order to reconcile proxy and model data. In comparison to the MARGO estimate the magnitude of LGM cooling was larger, for instance the tropical cooling results being -3.5°C instead of -1.5°C. Using the mentioned formula and literature values for LGM forcing a mean cooling of 6.1°C translates into a best estimate of 3.4°C in a range from 2.4-4.5°C.

Although the LGM reconstruction by Tierney et al. definitely is a very global one due to its wide range of used proxies, proxy data on land has not been considered. One type of proxy data that serves as a reliable paleothermometer on land are noble gases. The theory behind the relationship between temperature at the recharge of groundwater and the solubility of noble gases like Ne, Ar, Kr and Xe is well established. Furthermore noble gases have the advantage of delivering mean-annual data that not sensible to seasonal sensivity and also

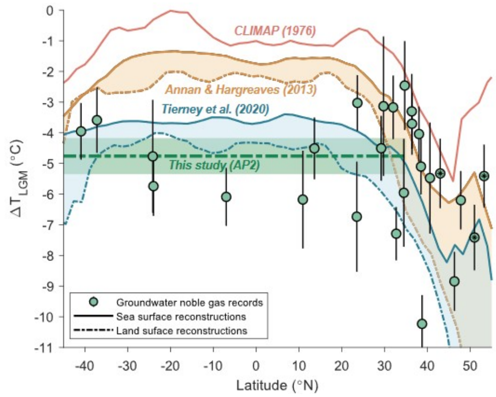

Figure 7. LGM temperature reconstruction obtained by noble gas proxies, shown by the green markers in comparison to previous studies. The samples in the range of the green dash-dotted line give an average cooling of 5.8±0.6°C (fluctuating values on the NH above 35° are excluded). The blue curve represents the already mentioned study by Tierney et al. The red curve represents results from the early CLIMAP used for the Charney estimate, the orange curve is from a global reconstruction by Annan and Hargreaves (2013). The temperatures obtained from the noble gas proxies are lower than these estimates, but considering that the Tierney study was based on marine sediments only it can be considered compatible. Noble gases could be used as a valuable proxy in global LGM reconstructions especially for ground temperatures on land for the low to mid-latitudes in the future. Taken from Seltzer et al. (2021).

serve as a natural low pass filter because slow signals of a thousand years in the aquifer temperature are conserved. The main weakness of noble gases is the difficulty to correctly date the age of the water.

In order to build a bridge between marine proxy records as used by Tierney et al., Seltzer in collaboration with other noble gas experts published an LGM cooling estimate just from noble gases (Seltzer et al., 2021). The publication served as an opportunity to gather noble gas data that had not been published and analyzed on a global scale previously. It uses the many advances in noble gas investigations during the last decades. Models have been developed in order to correctly assess the relationship between surface temperature and the aquifer temperature. The study gives a mean LGM cooling estimate for low-altitude regions on land between 45°S and 35°N of 5.8±0.6°C. Figure 7 shows the noble gas temperature reconstruction in comparison to previous studies. There is no way to directly translate these land-temperature into sea surface temperature, because the land-sea contrast during the LGM is subject to uncertainties, but at least these value can be seen as a support for the lower LGM temperatures as inferred by Tierney et al. and thus also support their best estimate for ECS. The purpose of this publication is not to give a reasonable estimate for ECS but to present noble gas data as a proxy that could be included in future LGM reconstructions.

Study	Year	Proxy data	Main result
Annan	2006	Tropical SST	$P(ECS > 6°C) < 7\%$
von Deimling	2006	Tropical SST	$1.2 - 4.3°C$
Schmittner	2011	Global	$1.7 - 2.3°C$
Tierney	2020	Global (marine sediments)	$2.4 - 4.5°C$
Seltzer	2021	Noble gases	cooling of $5.8 \pm 0.6°C$ on land

Table 1. Main results the studies reviewed in this report. The upper three studies used the model ensemble approach letting a climate model run for both doubled CO_2 and LGM conditions with perturbed parameters. The lower studies rely on assuming that climate sensitivity can be computed from the energy balance formula 4.

5 Discussion and Conclusion

In this report five studies that aim at enhancing ECS estimates with LGM data have been presented. The model ensemble and the temperature reconstruction approach are quite different, as in the first climate sensitivity is an emergent property and in the latter climate sensitivity is calculated from estimates on forcing and the LGM cooling. Basics of statistics that are of great importance in climate sensitivity studies have been introduced. The central results of the reviewed studies are presented in Table 1. Due to the large and fast advances in climate modeling and computation power the publications with respect to the model ensemble approach presented here can be considered already outdated, however I would value their importance as they were the first publications introducing this novel approach.

The noble gas study by Seltzer et al. was presented in order to demonstrate the further potential of including proxy data that has not been used in ECS up to now. It is a rather evident conclusion that more reliable data from the LGM can help to further constrain ECS. The studies presented here already have demonstrated the capacity of limiting especially the higher end of ECS. Nonetheless the uncertainties in climate models are also a crucial point in improving climate sensitivity estimates. An enlightening publication on the problems of constraining ECS with data from the LGM was provided by Crucifix (2006). He performed doubled CO_2 and LGM experiments for four different climate models and obtained climate sensitivities that are rather similar for the LGM but quite divergent for the doubled CO_2 scenarios (see Figure 8). The ECS is hence also strongly dependent on the climate model used. Especially confidence in model components like clouds and their feedback impacts is not very high, they are subject to ongoing investigation. Second the study shows that the inherent climate sensitivity of the earth system does not necessarily have to be constant throughout time. This means one can not simply estimate ECS with a direct one to one calculation from the LGM cooling and forcings, or at least needs to consider additional uncertainties when doing so. The literature I studied for this report mentions these kinds of problems and acknowledge the weakness of using just one climate model. Projects like the Coupled Model Intercom-

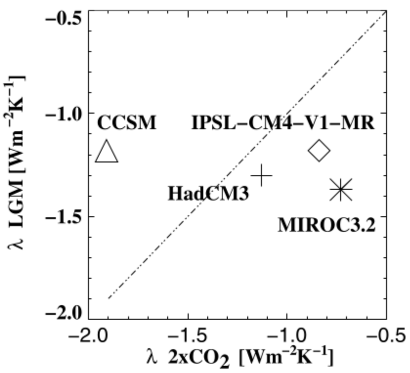

Figure 8. Figure taken from Crucifix (2006) showing how the climate sensitivity parameter varies for different models. The sensitivity parameter for doubled CO_2 is displayed on the vertical axis and the one for LGM on the horizontal axis. According to these results climate sensitivity is model and climate state dependent. Note that in this publication the climate sensitivity parameter was defined inverse to the definition I used in this report.

parison Project (CMIP) will be of great benefit to investigate which climate models better simulate LGM than others.

This report focused on the LGM as a benchmark period for estimating ECS, thus showing only a small part of science related to climate sensitivity. Paleoclimatolgy offers many other possible lines of evidence that can be used and also combined to that end. In a review paper by Tierney et al. (2020a) the authors suggested performing model experiments with an epoch like the Eocene 50 million years ago (CO_2 levels similar to today) or climatic aberrations like the Sturtian snowball earth or the Paleocene-Eocene Thermal Maximum (PETM). Whatever period is investigated the need for bridging the gap between the models and paleoclimate proxy data is manifest. The importance of intense collaboration between experimentalists and models can not be stressed enough.

I would like to close this report by emphasizing that Equilibrium Climate Sensitivity is not to be confused with Transient Climate Response, which is the value of interest for policy making and assessing imminent climate impacts due to anthropogenic climate change. However, the question of survival of human kind should not lower the importance of investigating climate sensitivity and long-term earth system feedbacks as they involve many geophysical insights and also valuable statistical and computational methods.

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