Equilibrium Climate Sensitivity and the Relative Weightings of Various Climate Forcings on Local Temperature Records

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A Senior Thesis

by

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ABSTRACT

As recently measured amounts of global atmospheric carbon dioxide concentrations have risen 40% from pre-Industrial levels and will likely reach double by mid-century, climate scientists have expressed concern over the future state of the climate system, and have attempted to gauge the consequences of such a large forcing. The principal parameter for climate scientists is equilibrium climate sensitivity, which is the change in temperature following a doubling of atmospheric CO_2 concentrations. Current estimates of climate sensitivity span too expansive of a range to provide a clear understanding of the magnitude of temperature changes one can expect. Therefore, I conduct many individual multivariate analyses as a means of narrowing these ranges of sensitivity and to investigate geographical distributions of sensitivity, at the very least. To do so, I analyze four major climate forcings: greenhouse gas, atmospheric dust, ice volume, and insolation. Using several multiple linear regressions, I calculate the relative weighting of each forcing in driving the temperature signal in 47 local temperature proxy records. The paleoclimate proxy records chosen span glacial cycles over the past 800 kyr. These results provide insight into the geographical distributions of the relative influences of each of the forcings, while working to constrain the range of sensitivity estimates through the weighting of the greenhouse gas forcing. Separating out the individual climate inputs allows me to conclude what percentage of climate change was caused by CO_2 in the past, and by implication how much warming might be expected due to GHG forcing in the future.

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Chapter One: Introduction

1.1 Background

Since the age of industrialization in modern society, the Earth's climate has been changing at an alarming rate. Pre-industrial, global atmospheric concentration amounts of carbon dioxide hovered near 280 parts per million (p.p.m). In 2013, slightly over a century later, scientists recorded the first atmospheric CO_2 concentration of greater than 400 p.p.m in Hawaii (Monastersky, 2013). It is "extremely likely" that these changes in CO_2 concentrations and the subsequent observed rise in global temperatures have been dominated by human influence (IPCC, 2014). The accelerating rise in concentrations has caused concern among scientists, who expect CO_2 concentrations to reach at least double or possibly quadruple pre-industrial levels by 2100. This unease has brought the topic of equilibrium climate sensitivity to the foreground, since any prediction of future warming in response to increased greenhouse gas levels is dependent upon the sensitivity of the Earth's climate to a forcing (Lorius et al., 1990).

Equilibrium climate sensitivity refers to the magnitude of global temperature change following a change in radiative forcing after the system has reached steady state. Given the particular concern over greenhouse gases, climate sensitivity is often cast in terms of the amount of global warming in response to a doubling of atmospheric CO_2 levels starting from pre-industrial concentrations (Knutti and Hegerl, 2008; Rohling et al., 2012). There are, however, many other radiative forcings which affect the climate system, including CH_4 and other greenhouse gases, atmospheric dust and aerosol concentrations, insolation amounts due to orbital changes, and changes in ice sheet cover. Forcings such as these inflict an energy imbalance on the global energy budget, with more energy intake than release for a positive forcing. For the system to rebalance itself, there must be an increased amount of outward long-wave radiation proportional to the increased surface temperatures (Knutti and Hegerl, 2008). This leads to a temporary increased heat flux into the system until the system reaches equilibrium, with the ocean taking up a majority of the excess heat. The climate system reaches steady state when heat uptake by the ocean ceases and the initial forcing becomes balanced by the additional emitted long-wave radiation, mostly through feedback mechanisms (Knutti and Hegerl, 2008). Without the presence of these feedback mechanisms, a doubling of CO_2 concentrations would cause a global temperature increase of about 1.2 ºC (Lorius et al., 1990). However, with any initial radiative forcing, there are many subsequent feedback processes, together amplifying or diminishing the amount of global warming. Adjusted ranges of global temperature increases including feedback mechanisms typically fall between 1.5 and 4.5 ºC, but can extend to even larger values (IPCC, 2014). A range this extensive is particularly concerning since the global temperature difference between the present day and the Ice Age is only around 4 ºC. Therefore, should the actual equilibrium climate sensitivity fall into the higher end of the proposed range, the recently recorded high CO_2 concentrations would be the spell of disaster and create inconceivable changes to the world as we know it (World Bank Group, 2014). The research of Hansen et al. (2007), describes a foreseeable grave situation in which a greenhouse gas forcing overshadows all natural forcings, driving up global temperature significantly. With these increased temperatures, ice melt and devastating sea level rise would be amplified through positive feedback mechanisms out of human control.

Thus, it is important to determine the most accurate estimation of equilibrium climate sensitivity. However, this is challenged by uncertainty in the climate response time and limitations in using local paleoclimate records as measurements of global sensitivity (Lorius et al. 1990; Lea, 2004). Climate sensitivity measures the change in temperature only after the climate system has reached steady state. Response times to a radiative forcing range anywhere from a decade to more than a century, which suggests that temperature records of the past century are insufficient for an accurate estimation of sensitivity. Additionally, recent temperature data allows for error due to potentially unaccounted for climate forcings and variability in temperature unrelated to any forcing (Lorius, et al. 1990). The distributions in sensitivity estimates using recent data are often quite wide and do little to rule out higher estimates since strong ocean warming can hide a strong greenhouse forcing (Knutti and Hegerl, 2008). Alternately, the use of paleoclimate data is preferred for estimating climate sensitivity since changes in radiative forcings over thousands of years were sustained for an adequately long time for the system to reach steady state equilibrium (Lorius et al., 1990).

The second challenge in estimating global equilibrium climate sensitivity is using local temperature proxies to serve as models for global sensitivity. Particularly, it is questionable to use a proxy record that is heavily influenced by ice sheets, such as a record from an Antarctic climate, as a global model since factors unique to the ice sheet may dominate its signals (Lea, 2004). As the ice sheet decreases in size, the albedo of the surface decreases since the amount of reflective ice has also decreased. With a lower albedo, the surface absorbs more sunlight, heating the surface and causing more ice to melt. This process is the ice-albedo feedback mechanism, which is an important feedback in Arctic/Antarctic climates and contributes to polar amplification, but is largely absent elsewhere on the globe (Notz, 2009; Kohler et al. (2010)). One might be compelled to use an Antarctic proxy record because of its prominent correlation with the atmospheric CO_2 signal, suggesting a direct role of the greenhouse gas forcing in the temperature signal (Lea, 2004). However, this is too restrictive and provides a poor understanding of global climate sensitivity by overlooking unique local factors. Alternately, it would prove beneficial to analyze many local temperature proxies, searching for similarities and differences by geographic location.

As stated previously, there are various feedback mechanisms in the climate system, each of which operates on largely varying timescales. In that regard, only a few are important when analyzing climate sensitivity using paleoclimate records. Those mechanisms of importance are critically determined depending on the timescale of interest and the resolution of the data (Rohling et al., 2012). Feedbacks must then be categorized as either 'fast' or 'slow' according to the time needed for the system to reach steady state equilibrium. Using recent temperature data, 'fast' feedbacks would account for changes in water vapor content, lapse rates, cloud cover, and snow and ice albedo (Rohling et al., 2012). Using paleoclimate data, 'fast' feedbacks operate on a centennial scale, where 'slow' feedbacks operate on the order of millennia or longer. The feedbacks with the longest timescales, on the centennial scale, are greenhouse gases (methane and CO_2), dust, ice sheets, and orbital variations. Without any distinction, it is difficult to determine the actual climate response to past natural drivers of climate change, such as changes in insolation due to orbital variations, changes in continental configurations, and geological processes affecting the carbon cycle, among others (Rohling et al. 2012). Changes in temperature during a timescale affect a feedback's impact on the radiative balance, but do not affect radiative forcings. Therefore, a mechanism is a forcing if its impact on the radiation balance is not affected by changes in temperature for a specific timescale (Rohling et al., 2012). Climatic changes within a lifetime are of primary interest today. Since a lifetime spans a number of decades, to analyze sensitivity on a scale of decades changes in greenhouse gas concentrations, orbital variations resulting in insolation changes, changes in sea level, and changes in atmospheric dust concentrations can be considered forcings.

Climate sensitivity is also often estimated using general circulation models (GCMs). GCMs quantify forcings and feedbacks; however, several parameters must be specified to estimate climate sensitivity, including those affecting clouds, precipitation, convection, and radiation, among others (Knutti and Hegerl, 2008). Estimates for sensitivity from model-based calculations range from 2.1 – 4.4 ºC, without ruling out higher values (Knutti and Hegerl, 2008). These estimates closely follow other estimates, but do not provide additional information to narrow the distribution. An alternate method, which has been discussed previously, relies on paleoclimate data to determine climate sensitivity. Research using this approach has yielded estimations between 1 and 6 ºC, a range that is still quite expansive. While this approach leaves room for error from weak signals, oversimplified and erroneous forcing assumptions, among others, the general consensus remains that feedbacks from radiative forcings are strikingly positive, and the issue of greenhouse warming should not be ignored (Knutti and Hegerl, 2008).

Much information can be discovered through the comparison of glacial-interglacial paleoclimate temperature data with simultaneous changes in the Earth's energy balance, mainly those from radiative forcings such as greenhouse gases, orbital variations, atmospheric dust concentrations, and sea level (Lorius et al., 1990). For the most comprehensive results, a multivariate regression analysis should be performed using paleoclimate temperature records and various climate forcings. Such an analysis will provide a relative weighting for each radiative forcing as a fraction of the temperature signal. As research is limited and highly uncertain regarding climate sensitivity, there are only a handful of similar multivariate analyses, the results of which are not entirely conclusive.

1.2 Literature Review of Previous Research

Lean and Rind (2008) explored the distinct geographical distributions and relative weightings of individual forcings on temperatures from 1889 to 2006 through an extensive multivariate regression analysis. As radiative forcings, they chose to use the most recent reconstructions of ENSO, volcanic aerosols, solar irradiance, and anthropogenic influences (greenhouse gases, snow albedo, etc.). They concluded that natural and anthropogenic forcings collectively explained 79% of the variance in the temperature data, suggesting that the majority of the temperature signal can be attributed to the forcings they analyzed. Anthropogenic changes, they concluded, were crucial in explaining the observed historical surface warming, as natural forcings were insufficient. Additionally, they determined that the spatial differences in variance explained by the forcings were most pronounced between 45 ºS and 50 ºN. This is nearly opposite of model estimations, which suggest minimum values in the tropics and a steady increase between 30 to 70 ºN.

Criticizing the inability to narrow climate sensitivity estimations using models and observational temperature data, the research of David Lea (2004) focused primarily on paleoclimate temperature data in estimating sensitivity. Lea performed a multivariate analysis using a 360-kyr sea surface temperature record from the northeastern tropical Pacific, greenhouse gas and dust signals from the Vostok ice core (about 1,000 km from the South Pole), two ice volume records, and insolation curves, both local and seasonal. Instead of relying solely on multivariate analyses, Lea also estimated sensitivity by simple linear regression. After interpolating both the temperature and greenhouse gas records to constant timescale intervals, he calculated the slope and intercept of the regression line between the forcing and response variables, greenhouse gas and temperature, respectively. The result of this method was a strong positive correlation between the two records. While this approach provided a direct estimation of sensitivity, it is naïve in its disregard of other forcings, which most likely influenced the sea surface temperature record to a sizeable degree. Consequently, Lea performed a separate multivariate regression analysis including the other relevant forcings mentioned previously, such as insolation, ice volume, and dust. Stressing the likelihood that many of the forcings were dependent upon each other to some degree, he argued that a multivariate analysis was beneficial to the decomposition of the relative weighting of each factor in the observed temperature record, regardless. On average, he concluded that the greenhouse gas forcing was the most dominant signal in the temperature record, explaining 69% of the variance in the record. However, analyzed on an individual basis, greenhouse gas, dust, and ice volume forcings each explained a significant amount of variance, indicating the difficulty in statistically separating the influence of each forcing. Even considering this issue, however, greenhouse gases remained the most influential forcing. Many discrepancies still remained, however, when creating temperature reconstructions following the model with the dominant greenhouse gas forcings. At 4.4 – 5.6 ºC, sensitivity estimates using Lea's model explaining the most variance in the paleoclimate temperature record fell into the higher end of the range of estimates from other model-based studies.

The research of Lorius et al. (1990) also effectively discusses the benefits of using paleoclimate data in understanding climate sensitivity as opposed to model estimations. They focused their research on an analysis of the Vostok temperature record and five climate forcings, such as greenhouse gases, dust and sulphate concentrations, ice volume, and local insolation. After performing a broad multivariate analysis, they concluded that greenhouse gas was the most dominant forcing, accounting for about 40 - 65% of the variance in the temperature record. Their model using all five radiative forcings explained greater than 90% of the total variance of the temperature record, on average, much greater than the paleoclimate models of Lean and Rind (2008) and Lea (2004). This suggests that these five forcings are the most influential to the temperature signal and any that were not included in analysis are most likely insignificant, or not likely to be a dominant forcing. As the research of Lean and Rind (2008) and Lea (2004) advised, a level of uncertainty remains due to potentially poorly synchronized age models in paleoclimate records and forcings, as well as nonlinearities in the data. Lorius et al. (1990) discussed the advantage of expanding the analysis to various sites and temperature records, as analyzing only one site may be too restrictive to form ideas of global sensitivity.

Combining results from climate model simulations and paleoclimate temperature reconstructions, Schmittner et al. (2011) estimated sensitivity ranges lower than previous studies. Past studies confined sensitivity ranges of 66% probability between 2 to 4.5 ºC, with low probability extreme values exceeding 10 ºC. Despite numerous studies, few had been previously able to firm cap on the upper limit of sensitivity estimates. Using a Bayesian approach, Schmittner et al. (2011) integrated both model and paleoclimate data for the Last Glacial Maximum to determine a more appropriate range of sensitivity estimates. They compared climate models set to 47 unique sensitivity values between 0.3 and 8.3 ºC to see which provided the best fits of the global data. Models set with sensitivity values greater than 6 ºC led to an irreversible runaway ice ball effect, in which the ice-albedo feedback mechanism spirals out of control, resulting in a global ice surface. This model result is implausible because even at the peak of the Last Glacial Maximum (LGM), ice coverage did not extend any lower than about 40 ºN/S. Therefore, an ice planet does not correspond to known paleoclimate evidence, and any sensitivity estimates over 6 ºC are highly unlikely. The model with the best fit to the data had a sensitivity value of 2.4 ºC, near the low end of the range from previous studies. While the model does not account for many discrepancies in the temperature data and over/underestimates some temperature changes, it falls within error. The authors mentioned numerous issues which could have biased their results, such as newer and warmer temperature reconstructions of the LGM and lack of spatial data variance.

Similar to the goals of Schmittner et al. (2011), Kohler et al. (2010) attempted to constrain the range of model-based climate sensitivity estimates using existing temperature and radiative forcing data from the LGM and up to the last 800,000 years. To do so, they focused on determining the relative contributions of each forcing to variations in the global temperature signal. In total, they analyzed greenhouse gas forcing (a combination of CO_2, CH_4, and N_2O records), land cryosphere forcing (combined influence of albedo changes in land ice, sea level, and snow cover), sea ice albedo forcing, land vegetation albedo forcing, and atmospheric dust forcing. After performing their analysis, they concluded that the most likely sensitivity value was 2.4 ºC, within an overall range of 1.4 to 5.2 ºC. Of the total radiative forcing of the LGM, the land cryosphere albedo changes were most influential, followed by greenhouse gases, sea ice cover, dust, and land vegetation.

Genthon et al. (1987) provided some of the earliest insight into the role of greenhouse gases on temperature change. Using the Vostok ice core as temperature data and a CO_2 forcing, they also included both Southern and Northern hemisphere inputs. Relative weightings for each climate input were calculated using a simple, linear multivariate regression analysis, although they stress the likelihood of potential nonlinear interactions between different forcings, which are unable to be determined using their methods. They concluded that CO_2 contributions to the Vostok temperature record were generally between 50 and 84%, with lower values possible.

Northern and Southern hemisphere influences were less significant than CO_2 forcing on average. They stressed the importance of further investigation and cautionary extrapolation of their results for future climate change, since they cannot even be sure that changes in CO_2 are not in response to changes in temperature rather than vice versa. Additionally, they proposed more research into the mechanisms regarding CO_2 changes, orbital forcings, and climate, since the presence of a distinct precession frequency in the CO_2 record might be a suggestion of the inseparability of CO_2 and orbital forcings.

In my research, I focus on the relative influence of four major radiative forcings on multiple local paleoclimate temperature records, as many of the previous studies did. Since I am only relying on paleoclimate data, the forcings included in my analysis are greenhouse gases (CO_2 and CH_4), orbital changes through various insolation curves, ice volume through sea level, and atmospheric dust concentrations, both regional and global. I will (1) determine the relative weighting of each of the four radiative forcings in driving the temperature signal contained in the local proxy records and (2) use the calculated relative influences to define a better understanding of climate sensitivity and past climate change.

Chapter Two: Methods

While most of the previous studies on climate sensitivity derived global equilibrium sensitivity estimates from local multivariate analyses of climate forcings, they emphasized the limitations of their methods. Owing to unique local factors influencing paleoclimate temperature proxies, the use of restricted geographical data in extrapolating global sensitivity estimates has been widely debated, as mentioned previously. Therefore, I expanded my research to include paleoclimate temperature records of the past 800,000 years spanning the globe, covering five specific geographical regions: tropical Pacific, tropical Atlantic/tropical Indian, north Atlantic, Southern Ocean, and Antarctica. Together with four climate forcings, I performed 47 individual multivariate analyses in order to define several local estimates of equilibrium climate sensitivity. The goal of conducting numerous local analyses is to develop a more involved understanding of climate sensitivity patterns over many geographical locations and to counteract the effects of unique local features impacting temperature proxies for global sensitivity estimates.

2.1 Collecting Data

For temperature data, I used 47 individual, published records in the multivariate analyses, which had been previously compiled and aligned to the same timescale by Professor Shakun. The majority of the records are a combination of Mg/Ca ratios and alkenones in ocean cores as local paleoclimate temperature proxies. The remaining records are from ice cores, which provided temperature records through oxygen isotope ratios. It is important to note that although I performed these multivariate analyses for the past 800 kyr, the majority of the temperature records do not span the entire 800 kyr. Many cover periods of only about 200 kyr in the full range, and many data points in individual proxies are not at constant intervals. I take this into consideration when analyzing the results, and I chose to carry forward in the analyses of these records because of the benefits of using paleoclimate data as opposed to recent temperature data. The temperature proxies are scattered semi-uniformly across the globe, with the most heavily concentrated records in the tropical Pacific and the combined area of the tropical Atlantic and tropical Indian Oceans. For one part of the multivariate analyses, I sorted the records into the five geographical regions described previously. To do so, I merely separated the records using the boundaries of the each of the oceans, respectively. Within the Atlantic Ocean, I categorized the north as any latitude greater than 30 ºN and the tropical as any farther south than 30 ºN. Only a handful of records fell into the North Atlantic region, and they were distinctly such at >35 ºN.

Each of the four global forcings I used for the analyses are available in online databases and as supplementary information to publications. Instead of limiting myself to analyzing only the effects of CO_2 on past temperature change, I used a combined greenhouse gas forcing of both CO_2 and CH_4 signals (W/m^2) for the first forcing (Lüthi, 2008; Loulergue 2008). This greenhouse gas signal spans the past 800,000 years, with a resolution of ~1,000 years. In general, greenhouse gas concentrations are evenly mixed throughout all latitudes. Therefore, it is sufficient to use a singular forcing record for each of the analyses.

The second global forcing used in my analyses is sea level as a measure of changes in ice volume. The sea level record is also partially influenced by a smaller forcing attributed to the albedo difference between land and the ocean. Similar to the greenhouse gas forcing, it is sufficient to use the one record as a global estimate. I chose to analyze the atmospheric dust concentration forcing differently than the previous two forcings. Since dust concentrations vary significantly by region, I approached the multivariate analyses from two different angles. I first performed the analyses using a singular, global dust record. This record spanned the past

800,000 years, with concentration amounts measured from the EPICA Dome C ice core in East Antarctica (Lambert, 2008). Following the completion of the analysis using this global dust record, I performed a separate, secondary analysis using a unique regional dust record from each of the five focal regions of my temperature records. Using the categorization of the temperature records described previously, I substituted the global dust signal for the appropriate regional dust signal and carried out the remainder of the analysis in the same fashion as the analysis using the global record.

The last forcing used in the analysis is the insolation signal, which provides insight into the climatic effect of orbital variations. Previous research has hinted at a fairly insignificant contribution of the insolation forcing to the overall temperature profile, at least in comparison to the other three forcings already described. Therefore, the method I chose to calculate the relevant insolation curve for each record was one that would provide the most generous possible contribution for each record. Following equation 1 in Huybers (2011), I calculated 143 unique insolation curves. Each curve differs in its phase of precession and the relative contributions from precession and obliquity. The phase of precession, ϕ, ranges from 0º to 360º at increments of 30º. The relative contribution from precession and obliquity, α, ranges from 0 to 1 at increments of 0.1. In total, each 30º increment of precession angle has 11 attributing curves with varying relative contributions from precession and obliquity. For example, the curve with parameters $\phi = 0º$ and $\alpha = 0.5$, describes a situation with a more intense Northern Hemisphere summer due to the influence of greater obliquity and a phase of precession which brings the Earth closer to the Sun during that season (Huybers, 2011). I calculated each curve using orbital data from the past 800 kyr, which included details regarding phase and amplitude of precession, obliquity, and eccentricity. I modeled the equation from Huybers (2011) in Matlab, normalizing the output to zero mean and unit variance. To find the curve that provided the most generous contribution of insolation to the temperature signal, I linearly correlated each of the 47 temperature records to each of the 143 total insolation curves. Whichever insolation curve provided the largest r^2 value with each individual record was the curve that was used in the final multivariate analyses. Each temperature record was analyzed separately, although the largest r^2 for each record often resulted in the same handful of particular insolation curves. Following the completion of the analyses, I plotted the geographical distribution of the ϕ and α values corresponding to each temperature record to determine whether there was any correlation between those values and geographical regions (Figures 27, 28).

2.2 Data Analysis

With the finalization of both the calculation and alignment of the four principal climate forcings used in my analysis, I performed the multivariate analyses in Matlab. As stated previously, I chose to conduct two individual analyses of each record, one using the global dust record and the other using five regional dust records. The general method of calculations behind both of the variations is entirely the same, however, with the exception of the substitution of the dust forcing data. One of the main issues to consider when analyzing these four forcings is the relative amount of correlation between each of the forcings; the larger the correlation between each of the forcings, the more difficult it is to statistically separate the effect of each forcing on the temperature record. To account for these correlations most generously, I performed 24 unique multivariate analyses for each of the 47 temperature records, corresponding to the 24 different permutations of the four climate forcings. Each multivariate analysis relies on the ordering of the input parameters into a function I created in Matlab, with the hope of providing insight into the maximum and minimum percent variance explained by each climate forcing.

To analyze each permutation of climate forcings, I compared each forcing to the entire 800-kyr temperature profile, in sequence. First, I computed the variance of the entire temperature signal, which would serve as the basis of the percent variance explained by each of the four forcings. I then computed a linear model of the input temperature curve and the first forcing in the permutation. The percent variance explained by the first forcing in the permutation is simply the variance of the component of the temperature record linearly related to the first forcing, which is the original first forcing multiplied by the slope of the regression line computed from the linear model with the original temperature signal, divided by the total variance of the temperature signal. After the percent variance for the first forcing is calculated, a residual curve must then be computed for the analysis of the remaining forcings in the permutation. This residual curve results from a curve based on the slope and intercept of the regression line computed from the linear model, which is then subtracted from the input temperature signal. A second linear model is then created between the first residual curve and the second forcing in the permutation. The percent variance explained by the second forcing in the permutation is the variance of a modified second forcing curve, which is the original second forcing multiplied by the slope of the regression line computed from the linear model with the first residual, divided by the total variance of the temperature signal. A second residual is then computed for the second forcing from the slope and intercept of the regression line computed from the linear model. The second residual is subtracted from the first residual to give the final second residual graph. The same procedure used to analyze the second forcing in the permutation is used to analyze the third and fourth forcings in the permutation. As the second forcing relied on the first residual and total variance, the third and fourth forcings rely on the second and third residuals, respectively, in addition to the total variance. The output of the function used to perform the multivariate analysis on each of the 24 permutations is a list of 5 percentages, explaining the percent variance of the total variance explained by the forcing of the temperature signal in order of the permutation. The fifth percentage is the percent unexplained by the model using the particular permutation of forcings. This provides an insightful indication of the accuracy of the results and the possibility of more significant climate forcings, which might have influenced the temperature profile, but were not included in my analyses.

Due to the use of 24 unique permutations of the four climate forcings, each temperature record has 24 values of percent variance explained by each forcing, or 120 total percentages for each temperature record. The correlation between each of the forcings is substantial. The two largest r^2 values were 56% and 50% between greenhouse gas and sea level and greenhouse gas and each dust forcing respectively. Dust and sea level r^2 values were about 45% on average. The r^2 value for each forcing with insolation was quite small, at about 2%. The size of these correlations reiterates the importance of the maximum and minimum percent variance for each forcing at each temperature record in the discussion of the results. Additionally, the average value of percent variance for each forcing is also a useful measure to view the geographic distribution of results per region. As stated previously, following the completion of the comprehensive multivariate analyses for each temperature record using the global dust record, a second, separate multivariate analysis was performed using the regional dust records corresponding to the geographic location of each temperature record. Electing to analyze each temperature record as a whole, instead of in sliding windows focusing only on portions of the ice age cycle, simplifies the overall analysis. However, it does not allow for the analysis of certain time windows in the record where the forcings are not as correlated to each other. Being able to do so would have further helped to account for the most accurate fraction of variance explained by each forcing. Analyzing the record as a whole is much simpler, but the level of uncertainty when discussing the results is slightly higher, consequently. Each comprehensive analysis is discussed separately, with the results depicted below.

Chapter Three: Results

Accounting for the 24 different permutations of the four forcings, the results of both methods indicate that the separability of each forcing is quite difficult, since each of the forcings is largely correlated with the others. Therefore, the ranges of the maximum and minimum values of percent variance for each of the four forcings often spanned nearly 40-50%. For the vast majority of each forcing, the minimum percent variance explained is roughly 0.50 – 2.0%. The minimum percent variance resulted from the permutations where the forcing in question was the fourth in the ordering, and thus, the last to be modeled against the temperature residual curves. However, the maximum percent variance explained was often much higher, usually ranging from 10.0 - 70.0%, dependent upon the forcing in question. The maximum percent variance resulted from the permutations where the forcing in question was the first in the ordering and was only compared to the input temperature signal. Interestingly, the best model for each temperature record was only able to account for 30.0 - 70.0% of the variance of the temperature record, on average. Each temperature record's best model was analyzed individually. Since, on average, at least 30% of the temperature signal was unable to be reconstructed from the four forcings used in the analyses, the results should be discussed with a level of uncertainty. As evidenced through previous studies analyzing climate sensitivity and the relative contributions of climate forcings to the temperature profile, the four forcings I examined were the most dominant forcings in the majority of the studies. Therefore, it is highly unlikely that my analyses deliberately discounted a forcing that could have accounted for the remaining unexplained variance in the temperature signal. Possible explanations for this disconnect are offered in a following section.

One of the main objectives in examining the relative contribution of each forcing to the temperature profiles was to calculate an estimate of climate sensitivity. To confine a range of estimates for equilibrium climate sensitivity, I examine both the case where the greenhouse gas forcing is the first position in the permutation (the ordering of the other three forcings is irrelevant) and the case where the greenhouse gas forcing is the fourth position in the permutation. The first case provides insight into the higher end of the range of sensitivity estimates and the second case accounts for the low end of the range. The lower end is more complex to determine since the ordering of the first three forcings influences the resulting estimates, and there are four permutations where the greenhouse gas forcing is in the fourth position. For simplification, I set the lower estimate to be the individual estimate from the best fitting of the four models, instead of taking the average of the four estimates. To calculate the sensitivity estimate for each temperature record, I recorded the slope of the regression line between the greenhouse gas forcing and the original temperature signal or the residual curve, respective to the maximum and minimum sensitivity estimates. After calculating the estimates for each record, I plotted the slopes of both curves for each record against the latitude of each record. The resulting two slopes from the maximum and minimum curve provide the estimates for global equilibrium climate sensitivity (ºC/ W/m^2) (Figures 29, 30). The following figures summarize the results in a series of maps plotting each value at the location of the record. Significant trends are discussed following the figures for each method.

2.3 Method 1

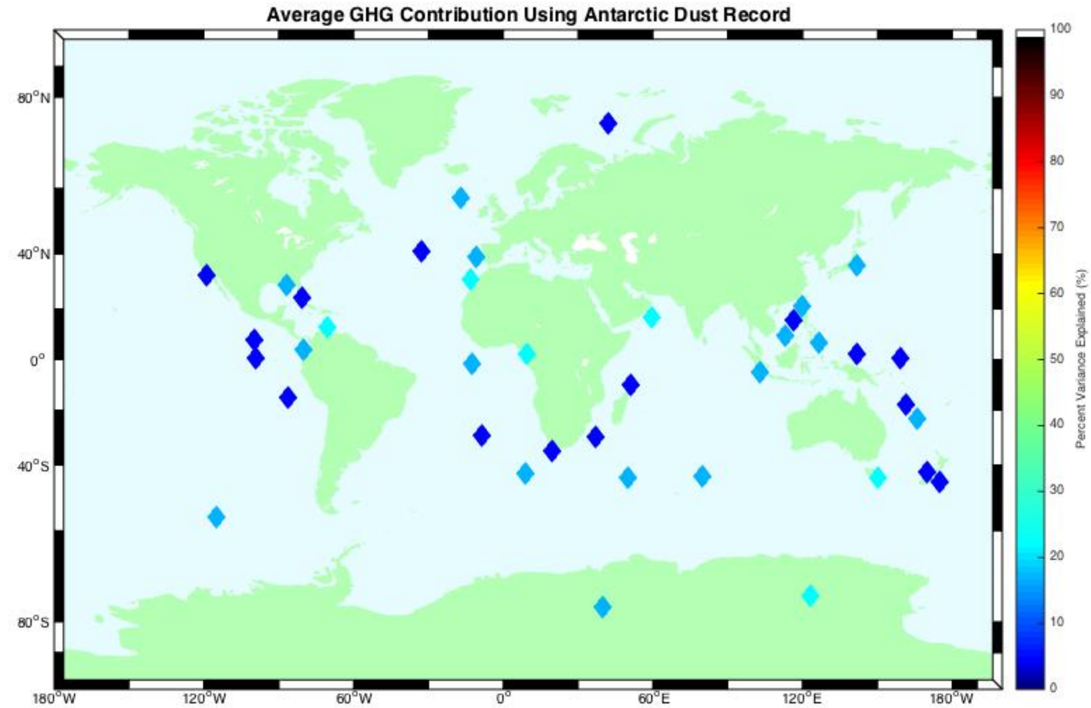

Figure 1. Average percent variance explained by the greenhouse gas forcing (CO_2 and CH_4) using method 1 with the Antarctic dust record.

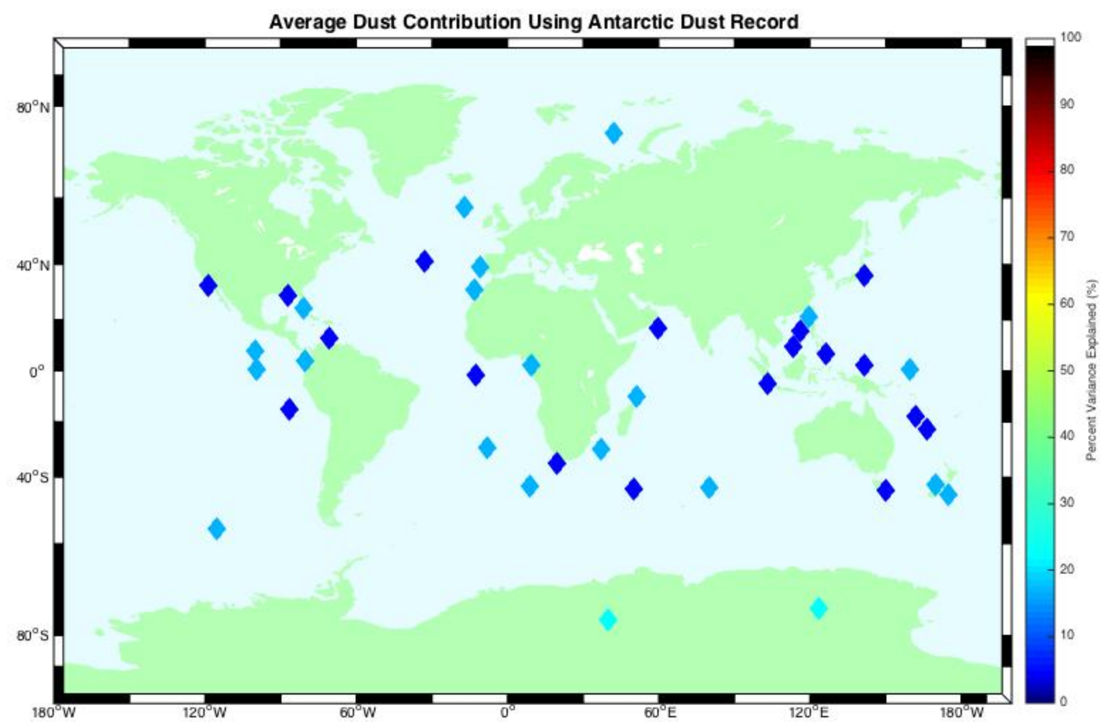

Figure 2. Average percent variance explained by the atmospheric dust forcing using method 1 with the Antarctic dust record.

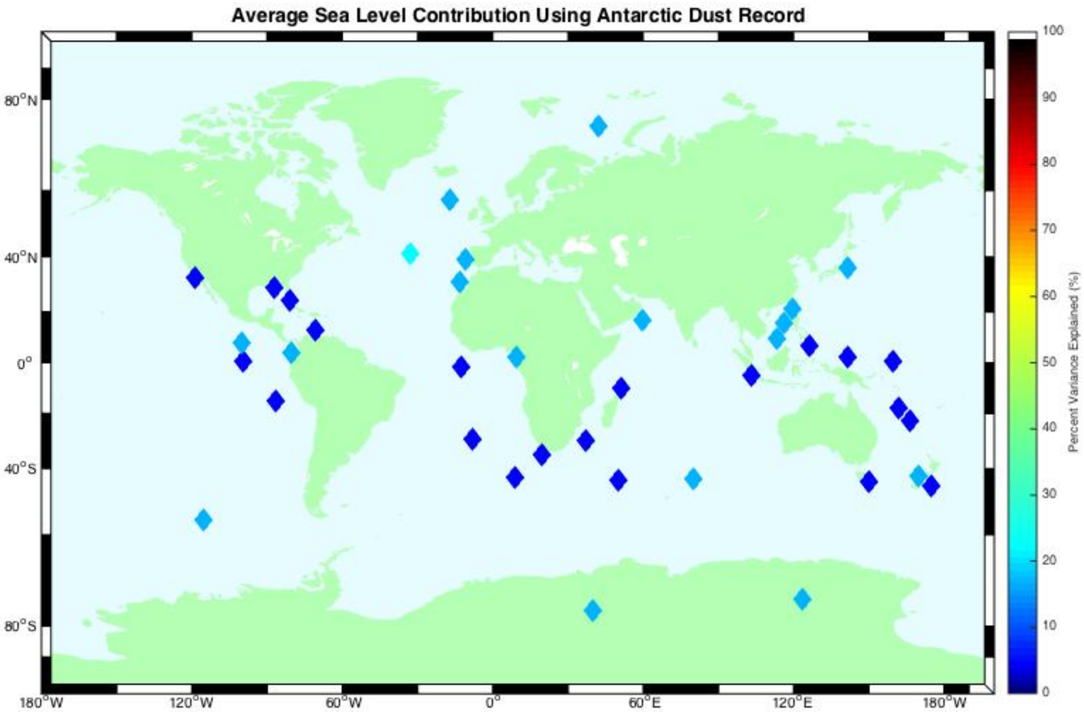

Figure 3. Average percent variance explained by the sea level forcing using method 1 with the Antarctic dust record.

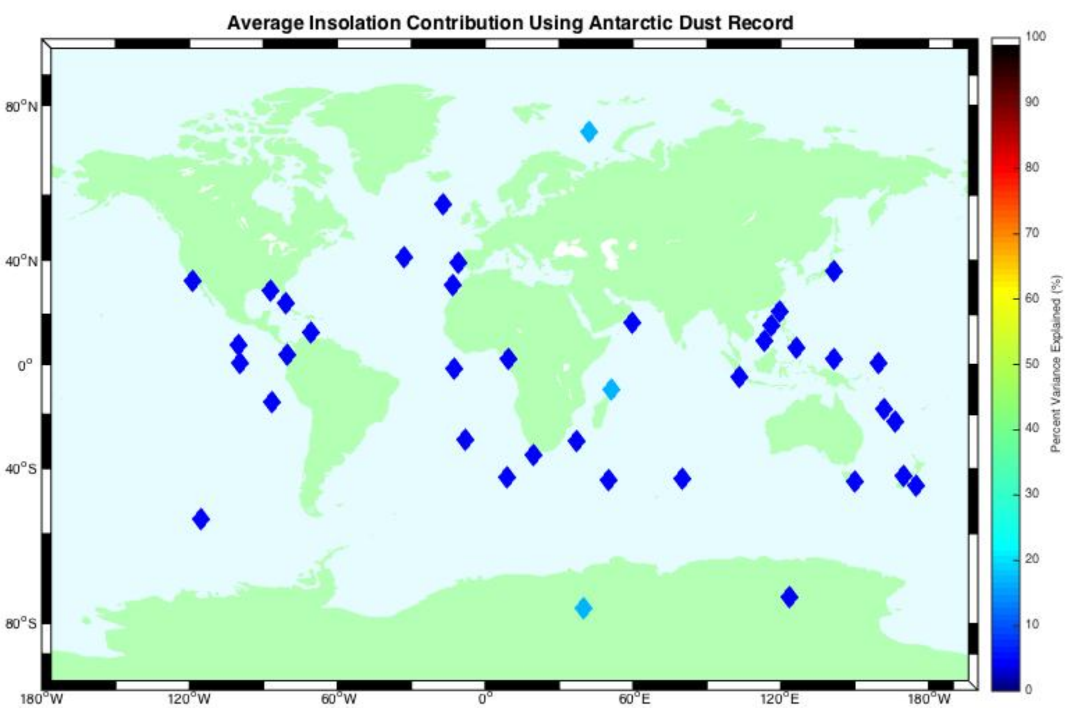

Figure 4. Average percent variance explained by the insolation forcing using method 1 with the Antarctic dust record.

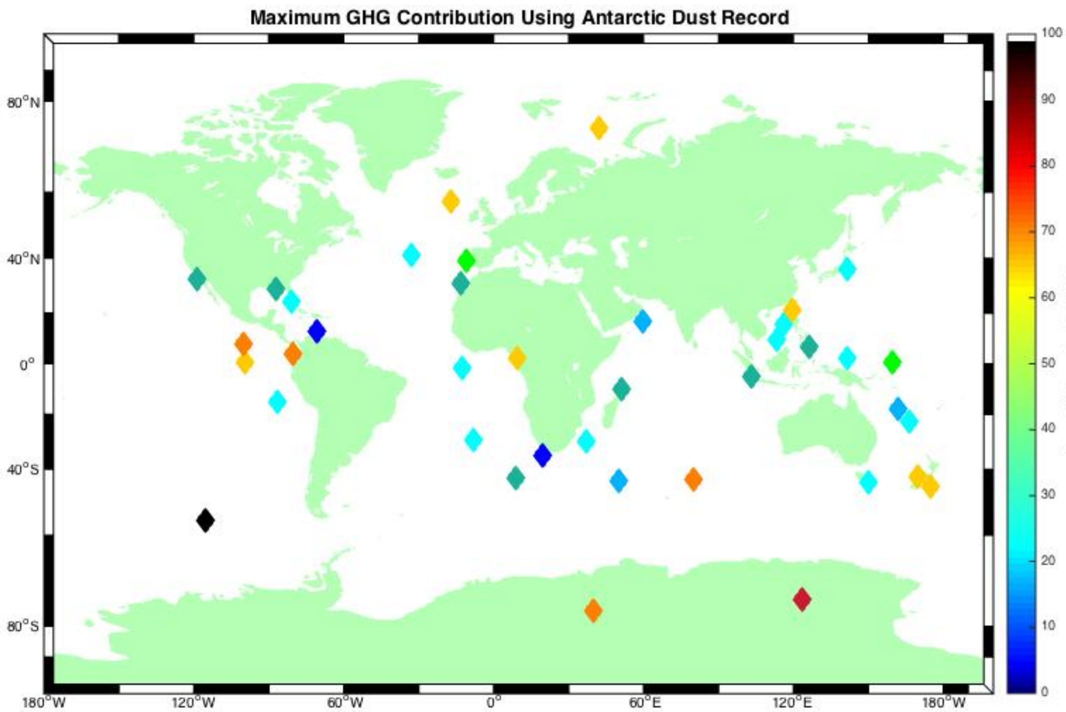

Figure 5. Maximum percent variance explained by the greenhouse gas forcing (CO_2 and CH_4) using method 1 with the Antarctic dust record.

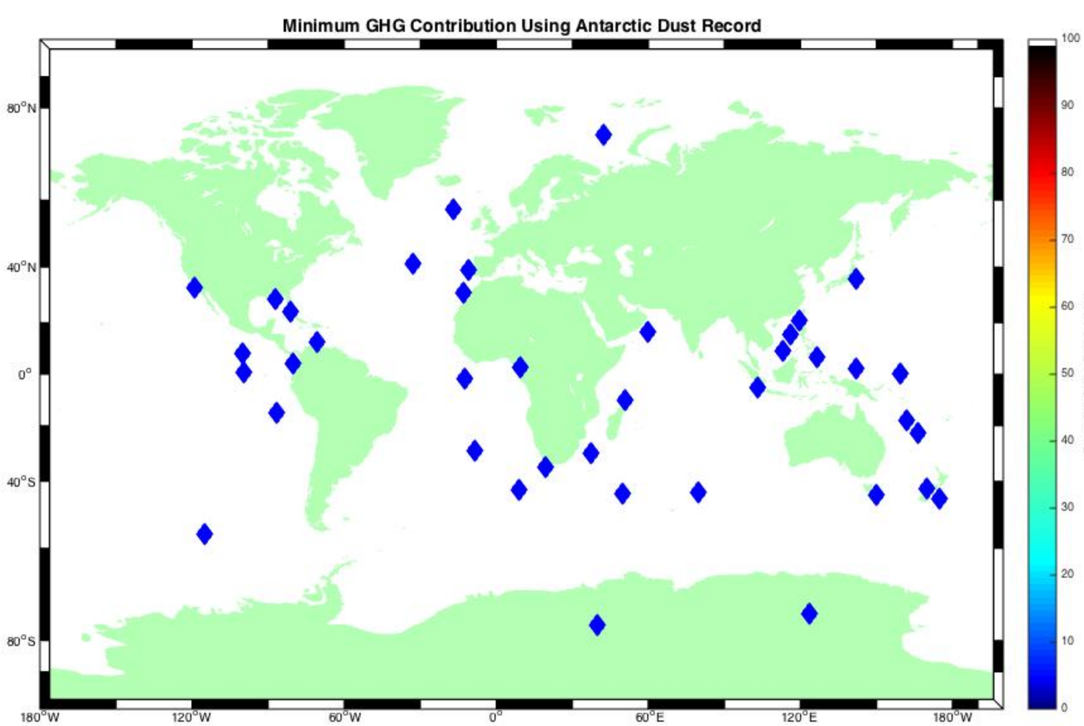

Figure 6. Minimum percent variance explained by the greenhouse gas forcing (CO_2 and CH_4) using method 1 with the Antarctic dust record.

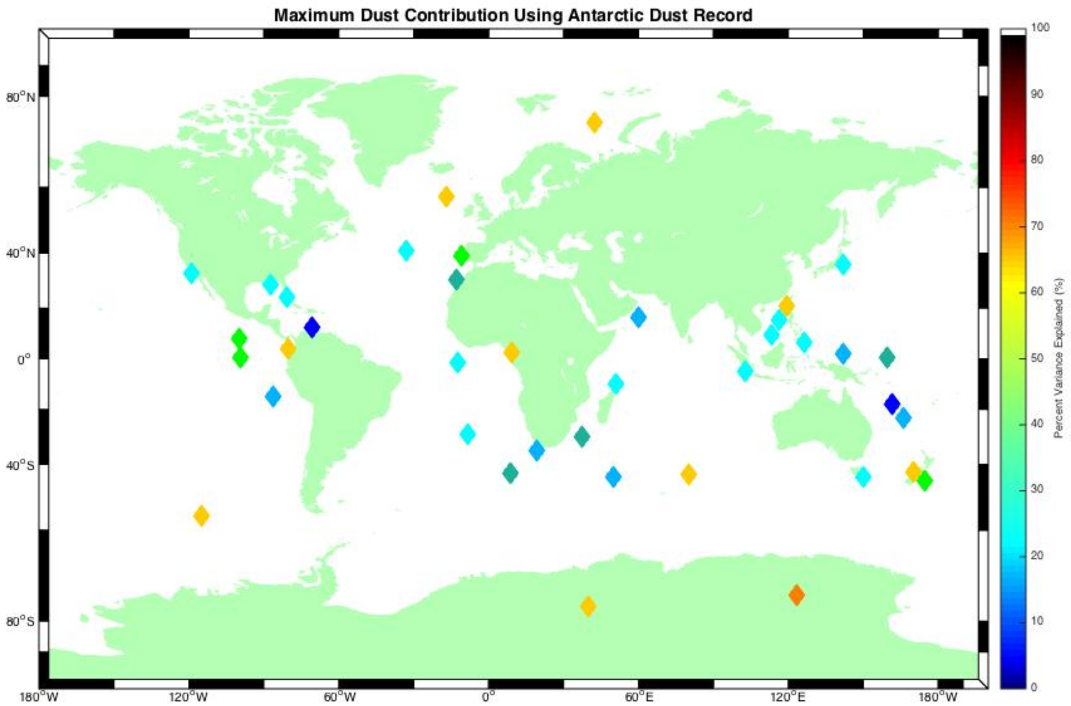

Figure 7. Maximum percent variance explained by the atmospheric dust forcing using method 1 with the Antarctic dust record.

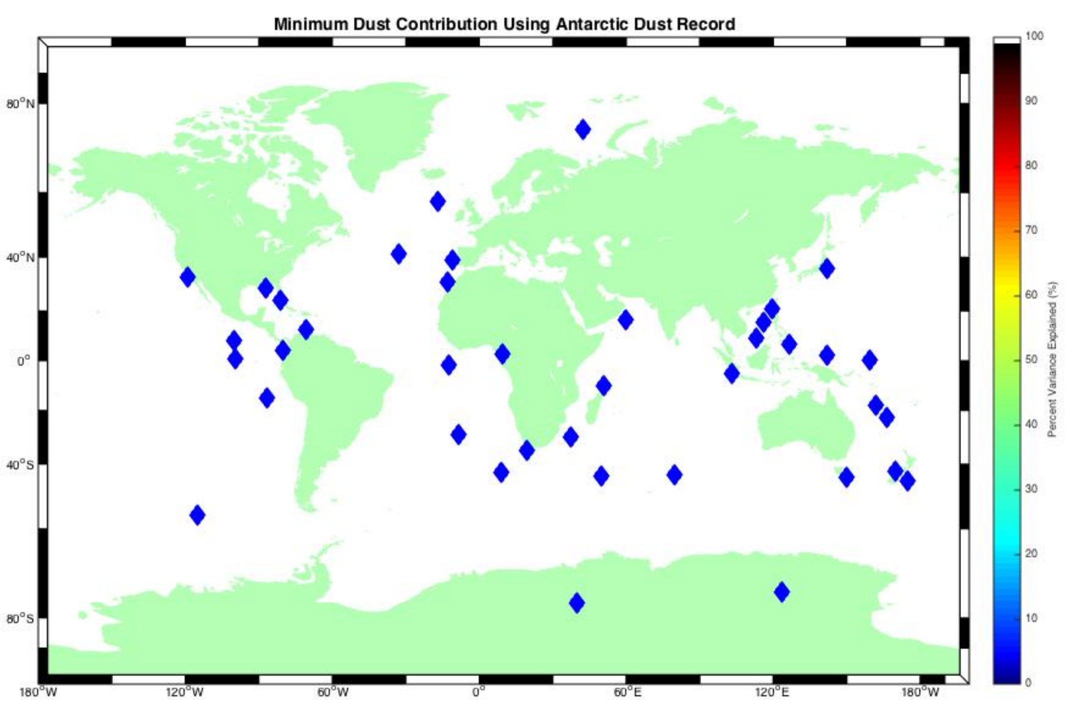

Figure 8. Minimum percent variance explained by the atmospheric dust forcing using method 1 with the Antarctic dust record.

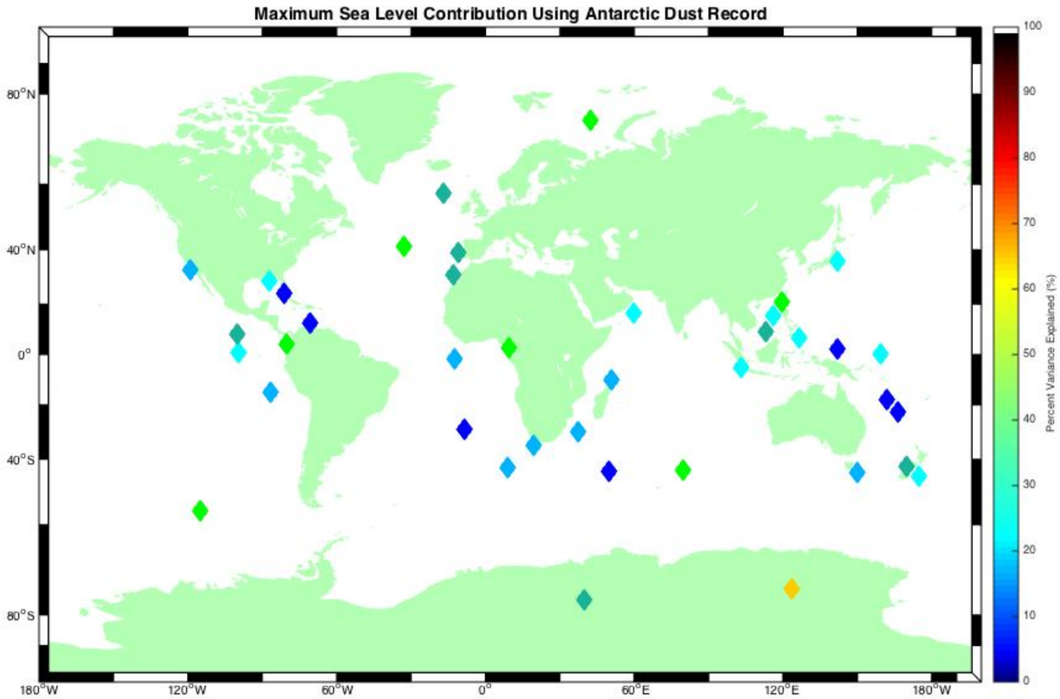

Figure 9. Maximum percent variance explained by the sea level forcing using method 1 with the Antarctic dust record.

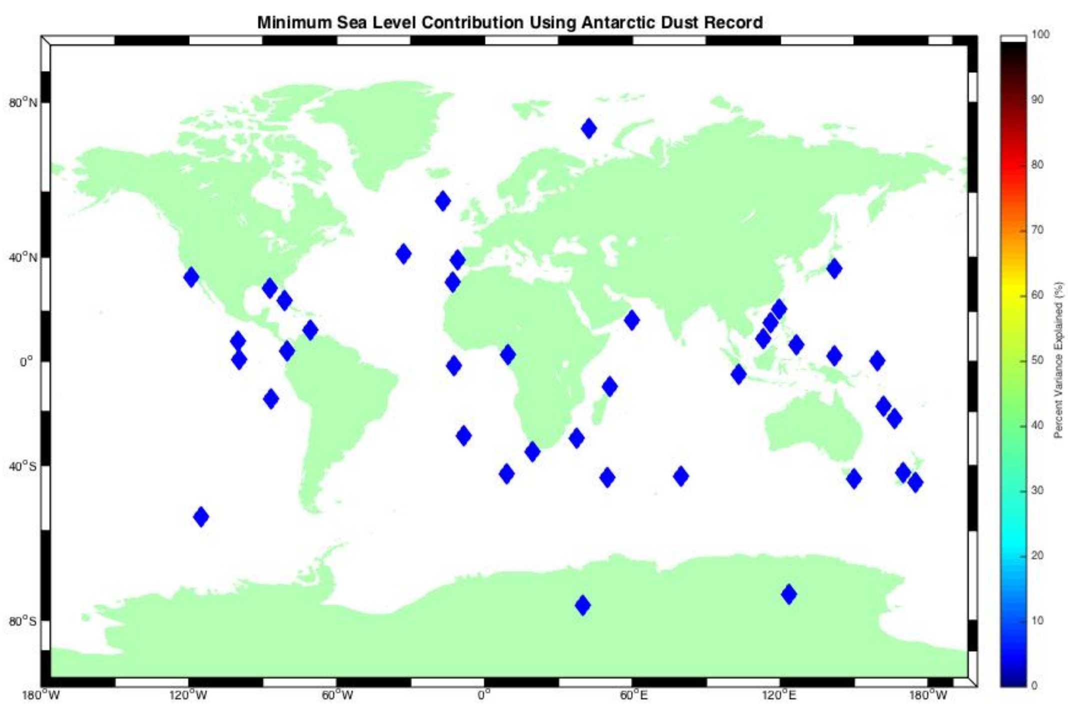

Figure 10. Minimum percent variance explained by the sea level forcing using method 1 with the Antarctic dust record.

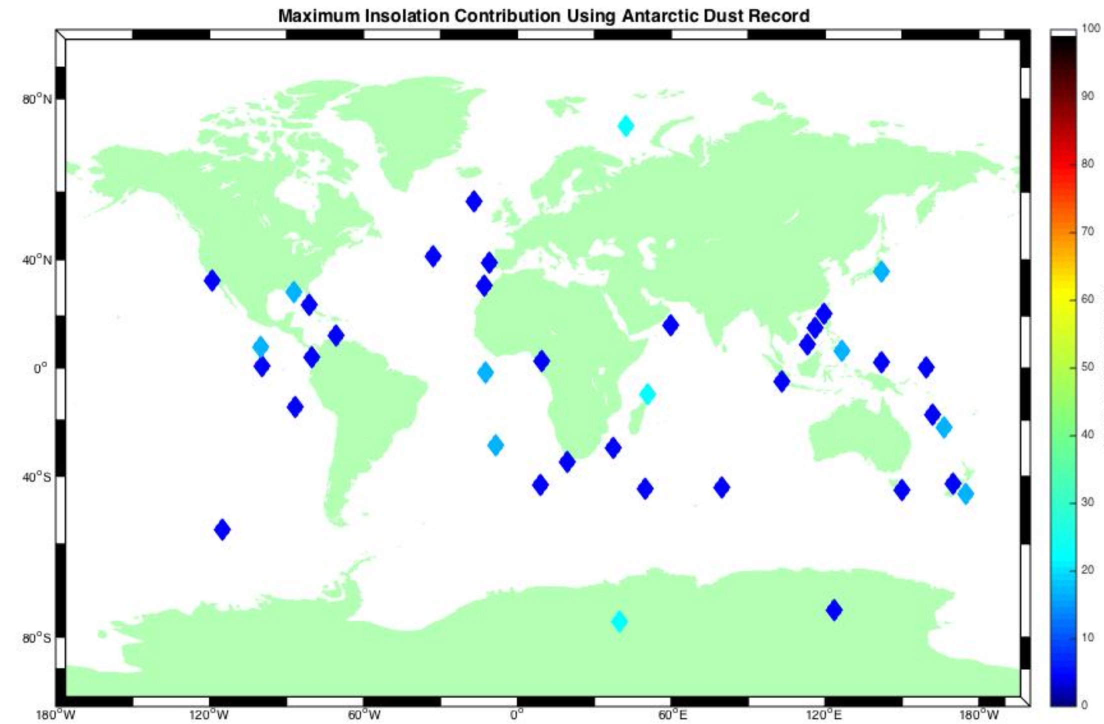

Figure 11. Maximum percent variance explained by the insolation forcing using

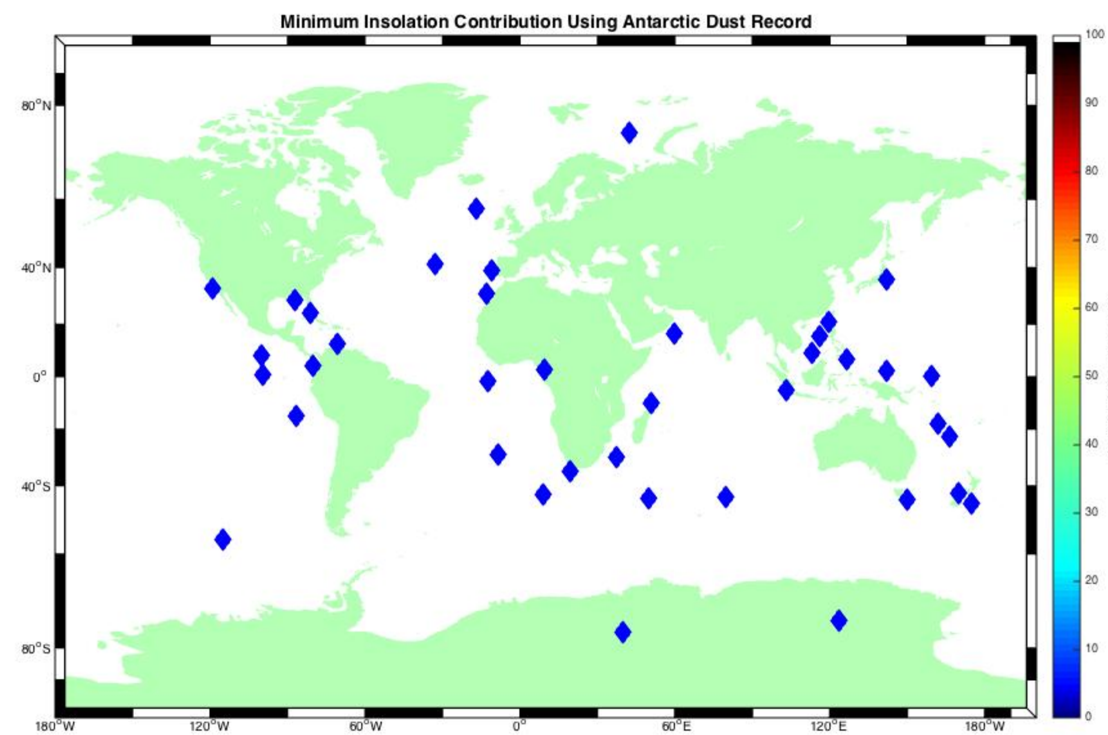

Figure 12. Minimum percent variance explained by the insolation forcing using method 1 with the Antarctic dust record.

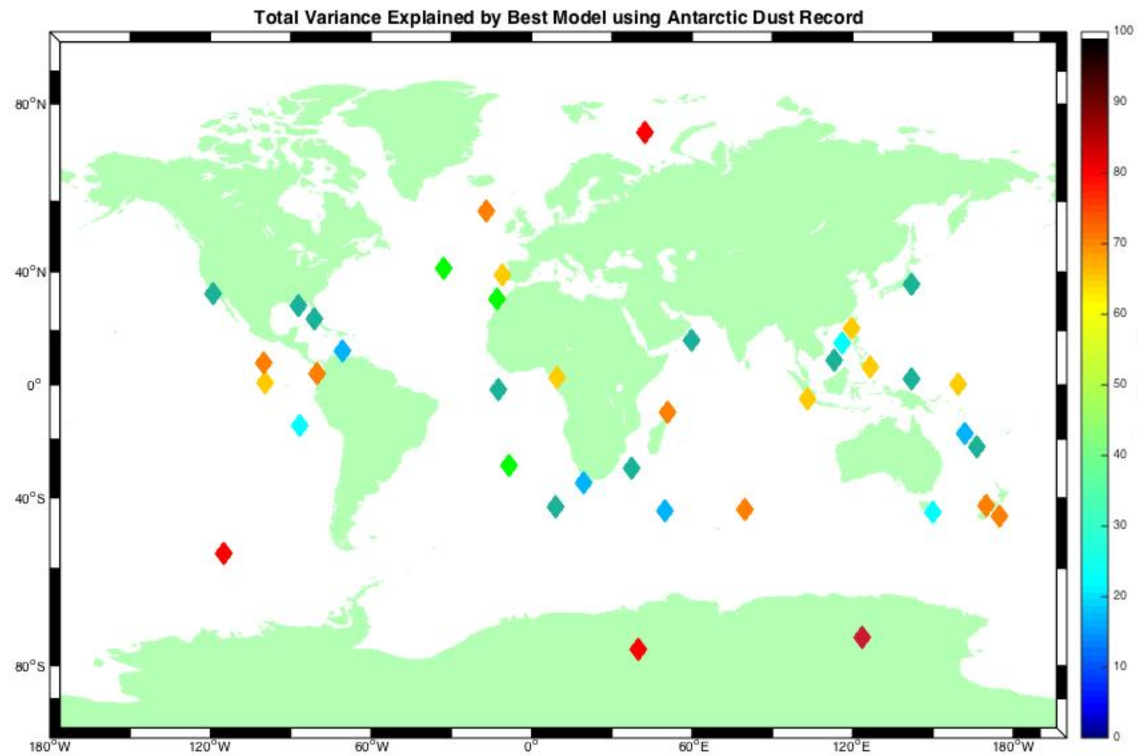

Figure 13. Total variance of each temperature record explained by the best fitting model out of the 24 different permutations for method 1 using the Antarctic dust record.

The average values for the percent variance explained by each forcing do not provide much insight into the actual behavior of each forcing in method 1, using the Antarctic dust record (Figure 1 – Figure 4). Since the forcings themselves are quite correlated, the different permutations give a wide range of values for each forcing. Taking the average of these values dampens any trends that were previously there due to the extremely low values from the cases where the forcing is the fourth in the order of the permutation (Figures 6, 8, 10, 12). The distribution of maximum values of percent variance explained offers more insight into trends than the average and minimum values (Figures 5, 7, 9, 11). The greenhouse gas forcing contributes more towards the overall temperature curve near the poles, at > 70%, than other regions of the globe, which generally range between 30 - 50%. Both the atmospheric dust and sea level forcings followed quite similar trends, geographically and numerically. While explaining a slightly smaller fraction of variance than the greenhouse gas forcing, these two illustrated a similar amplification near the poles. The largest values for the dust forcing were < 70%, and those for the sea level forcing were < 60%. While not entirely significant on the global plot, the values of percent variance explained for the sea level forcing in the North Atlantic were consistently near the higher range of percentages, which follows in trend with current knowledge of heightened ice sheet influence in the North Atlantic. In stark contrast to the other three forcings, the global distribution of percent variance explained by the insolation forcing was quite insignificant. The highest values were barely greater than 20%, and there were no significant geographical trends, unlike the slight polar amplification of the other forcings. The map showing the total variance of the temperature record explained by the best fitting model is indicative of the quality of the results (Figure 13). On average, the forcings were able to explain most of the variance in the temperature signal near the poles, > 70%, while some models in the tropical Atlantic and Indian regions were only able to account for < 50%. This variability is a testament to the possible influence of unique local factors, which were not accounted for in my analyses.

The most dominant forcing resulting from method 1 is the greenhouse gas forcing, followed by atmospheric dust concentrations, sea level changes, and the insolation forcing. While significant differences may be present between regions for each forcing, this order of relative weightings is based upon the maximum values of percent variance for each. Since the minimum values of percent variance for each forcing are relatively equal, this must be included in the final results summary. Although the greenhouse gas forcing may appear to be the most dominant among all temperature records, the severe minimum values associated with them introduce a large amount of uncertainty, which must be included when considering the results of the multivariate analyses for every forcing.

3.2 Method 2

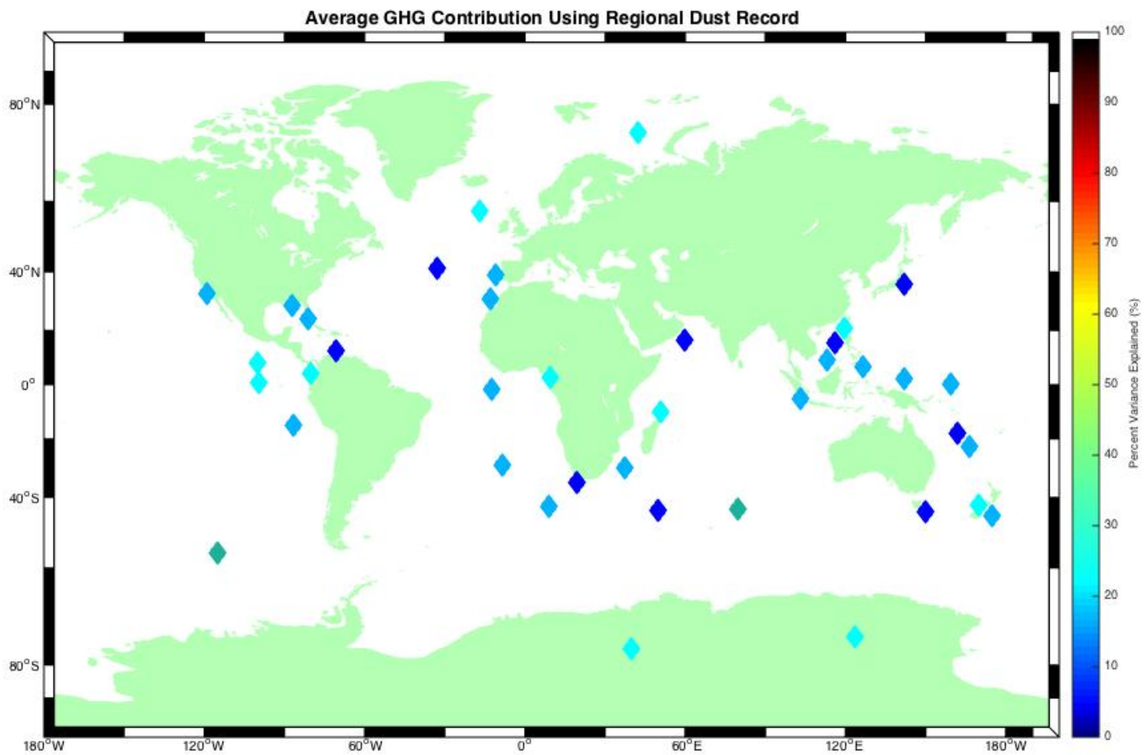

Figure 14. Average percent variance explained by the greenhouse gas forcing (CO_2 and CH_4) using method 2 with the regional dust records.

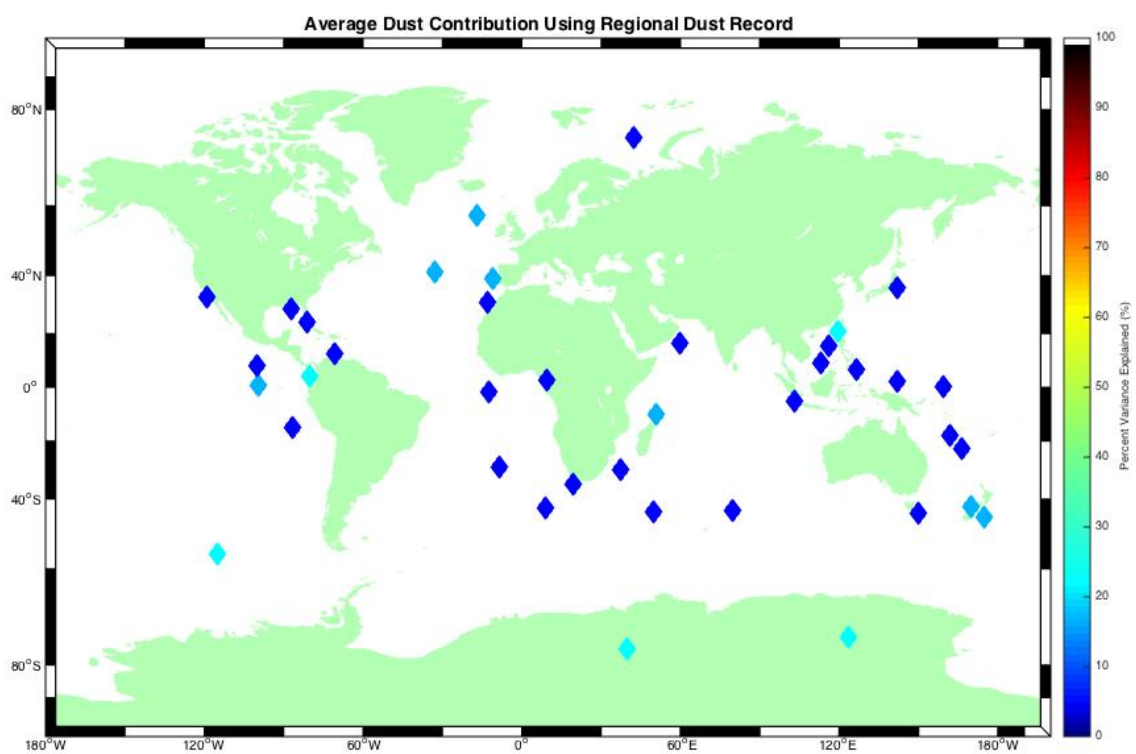

Figure 15. Average percent variance explained by the atmospheric dust forcing using method 2 with the regional dust records.

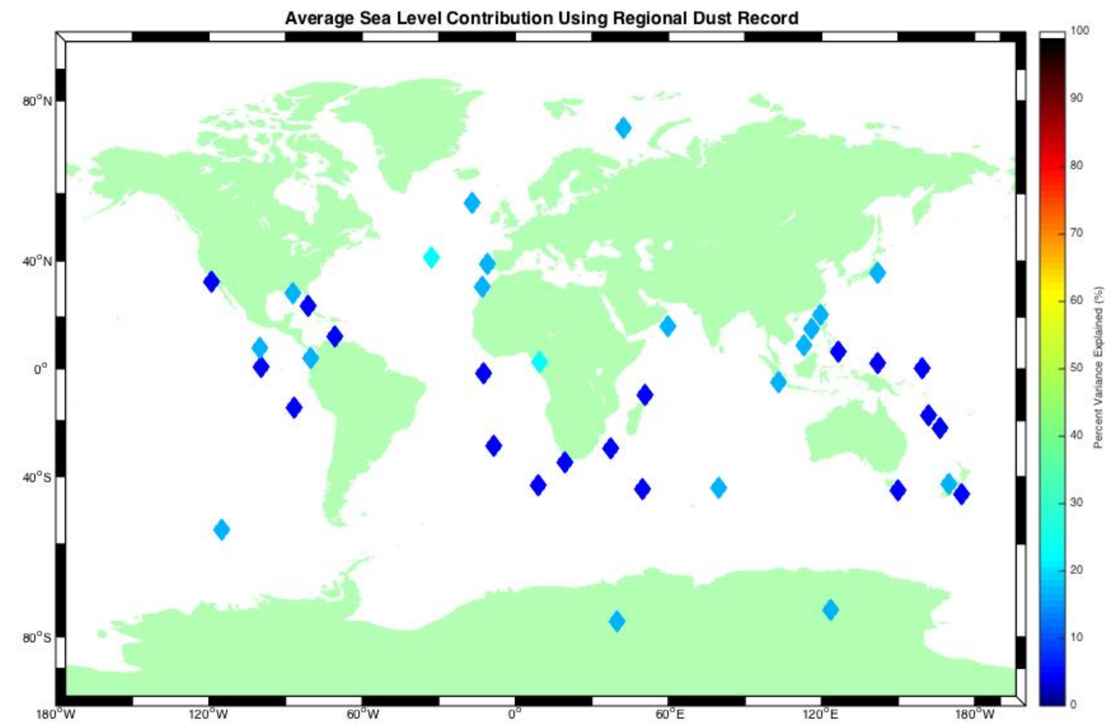

Figure 16. Average percent variance explained by the sea level forcing using method 2 with the regional dust records.

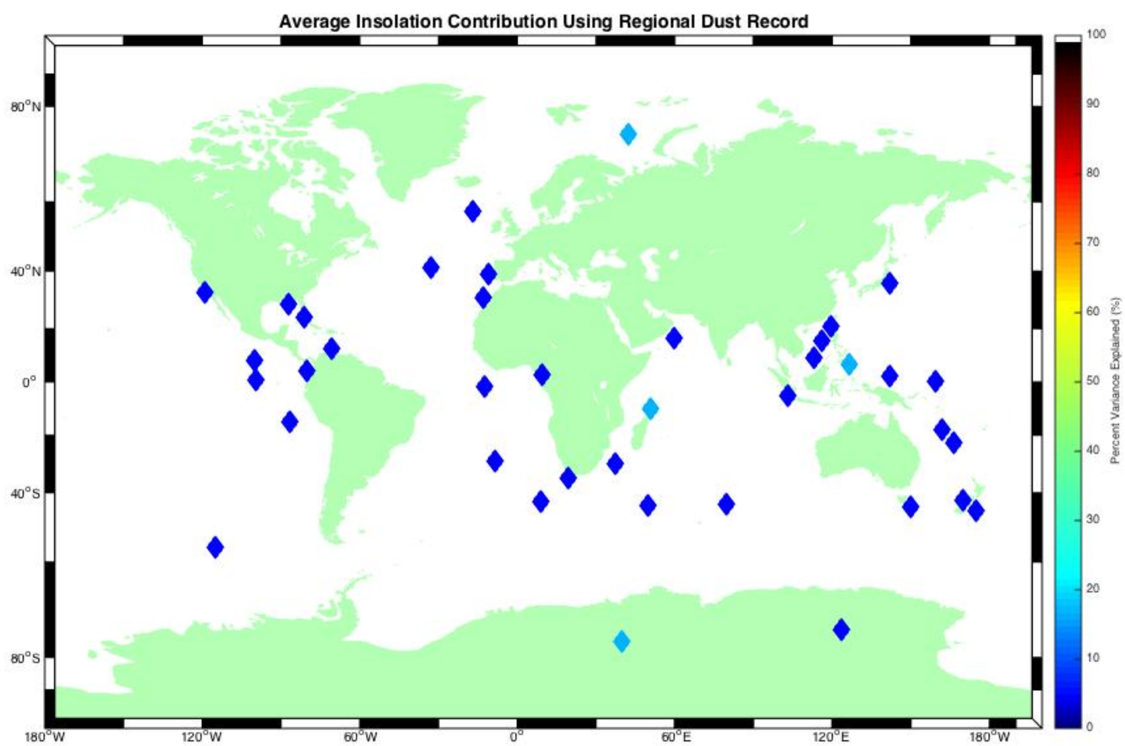

Figure 17. Average percent variance explained by the insolation forcing using method 2 with the regional dust records.

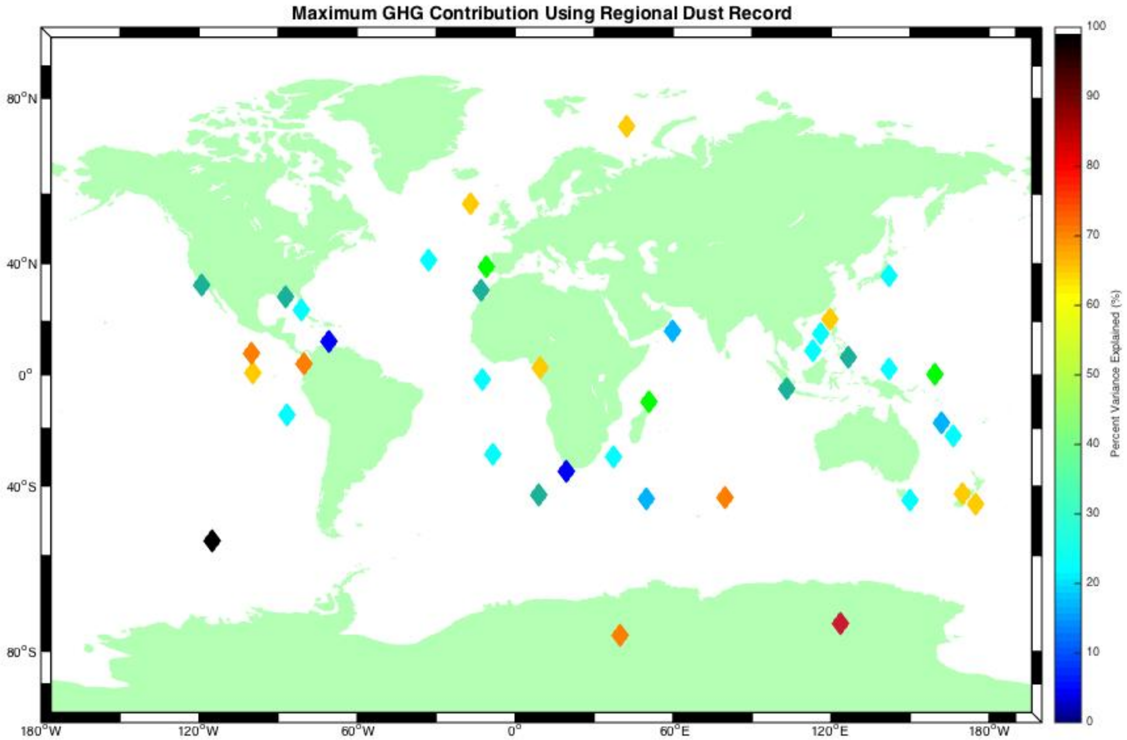

Figure 18. Maximum percent variance explained by the greenhouse gas forcing (CO_2 and CH_4) using method 2 with the regional dust records.

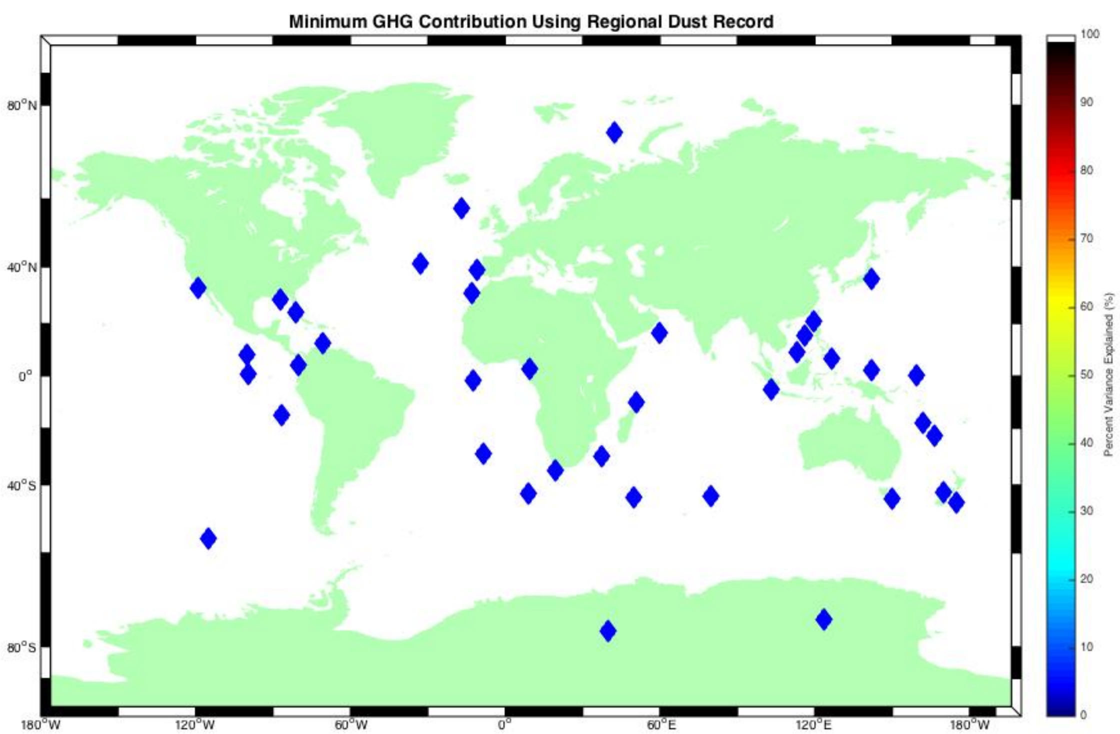

Figure 19. Minimum percent variance explained by the greenhouse gas forcing (CO_2 and CH_4) using method 2 with the regional dust records.

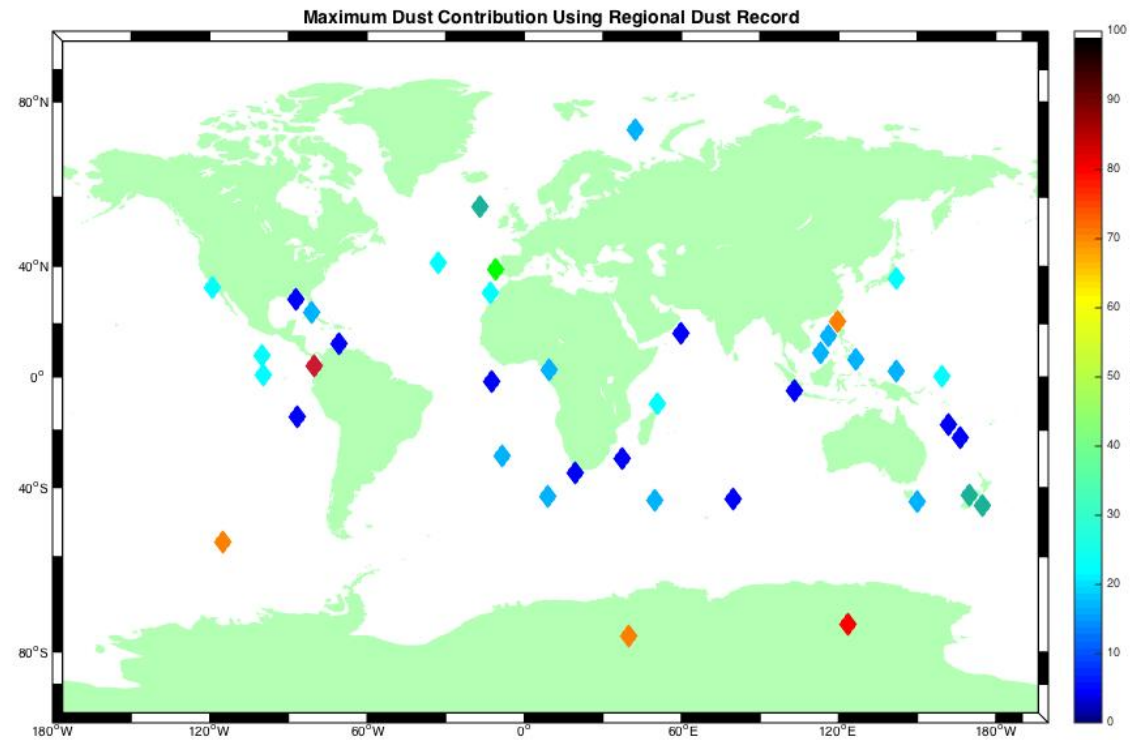

Figure 20. Maximum percent variance explained by the atmospheric dust forcing using method 2 with the regional dust records.

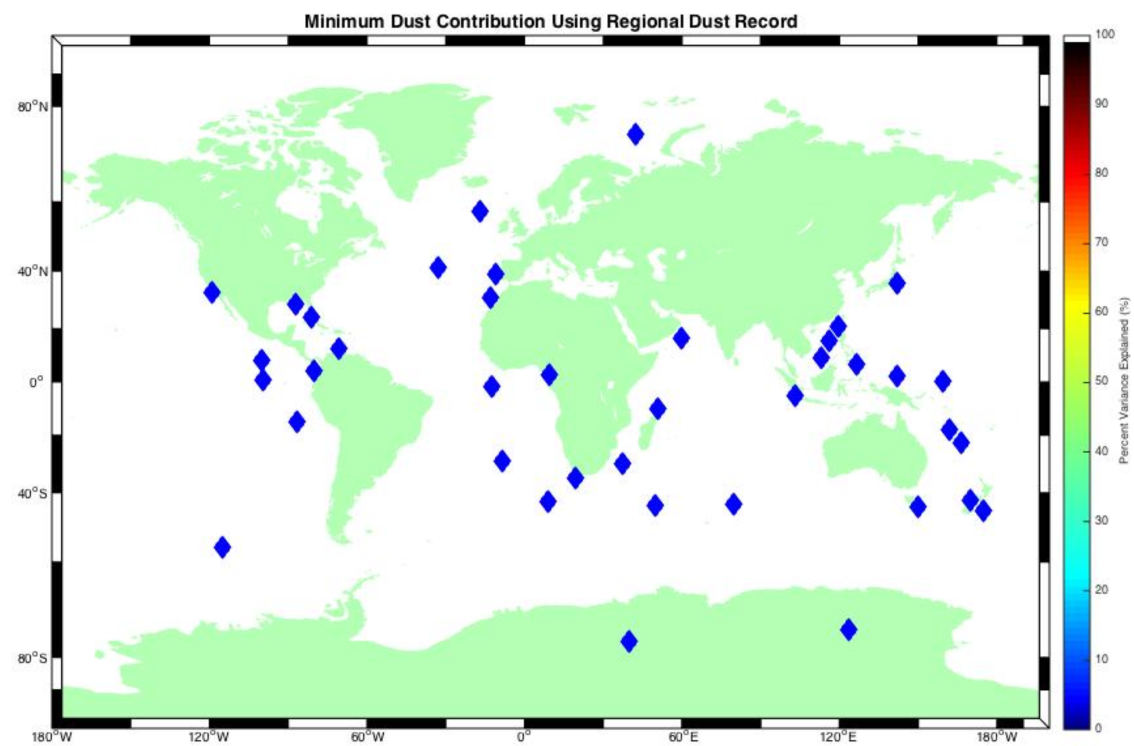

Figure 21. Minimum percent variance explained by the atmospheric dust forcing using method 2 with the regional dust records.

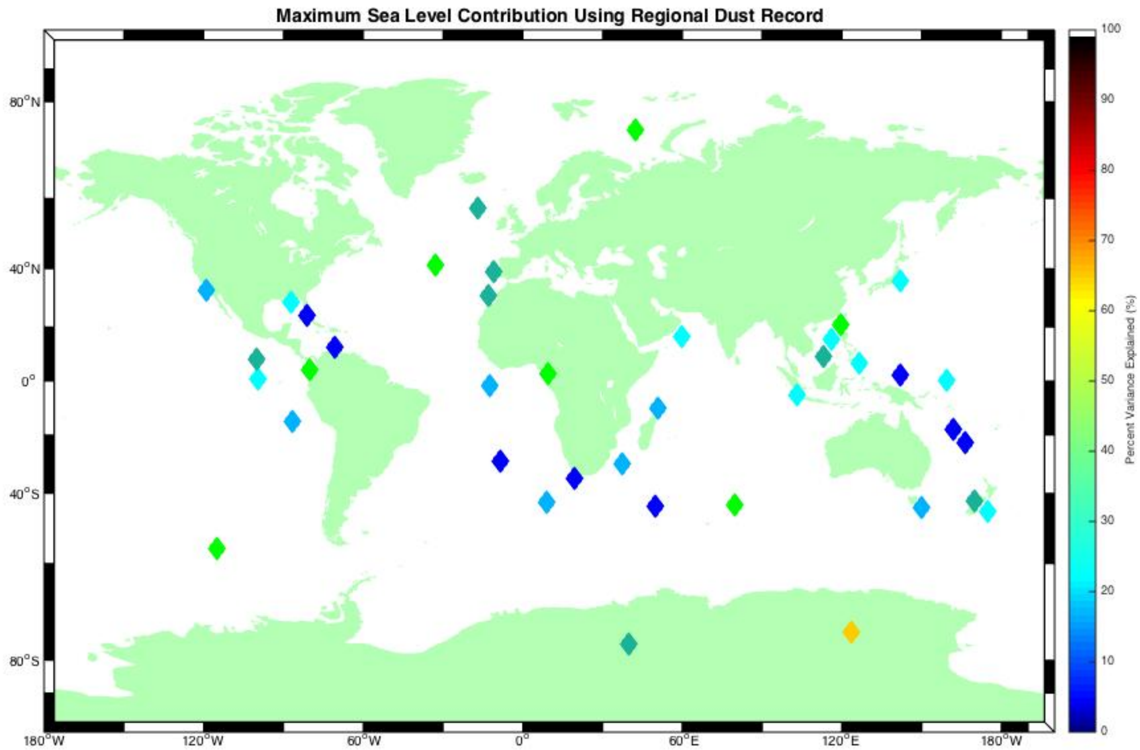

Figure 22. Maximum percent variance explained by the sea level forcing using method 2 with the regional dust records.

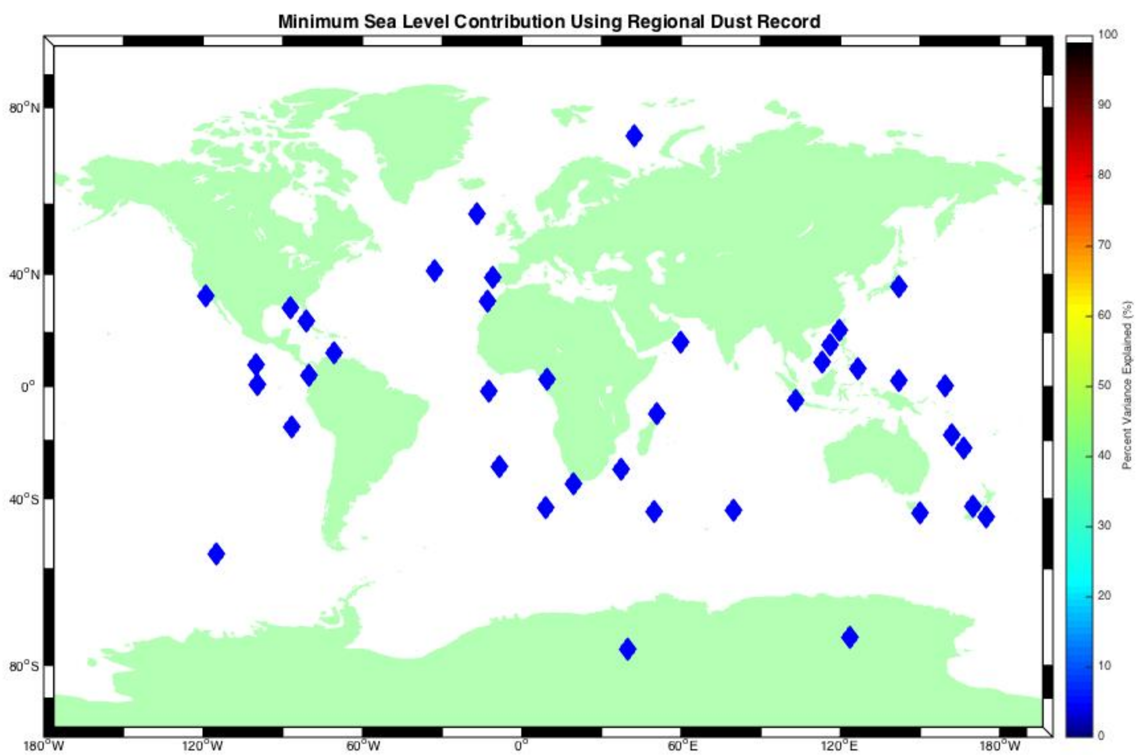

Figure 23. Minimum percent variance explained by the sea level forcing using method 2 with the regional dust records.

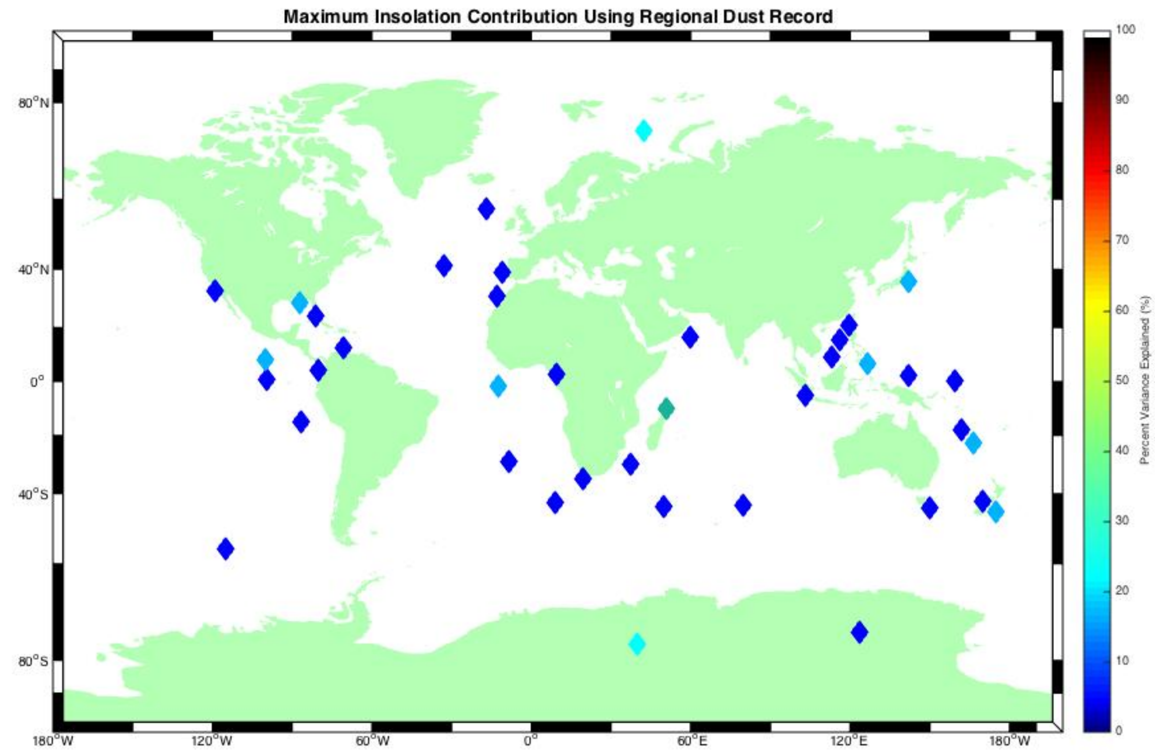

Figure 24. Maximum percent variance explained by the insolation forcing using method 2 with the regional dust records.

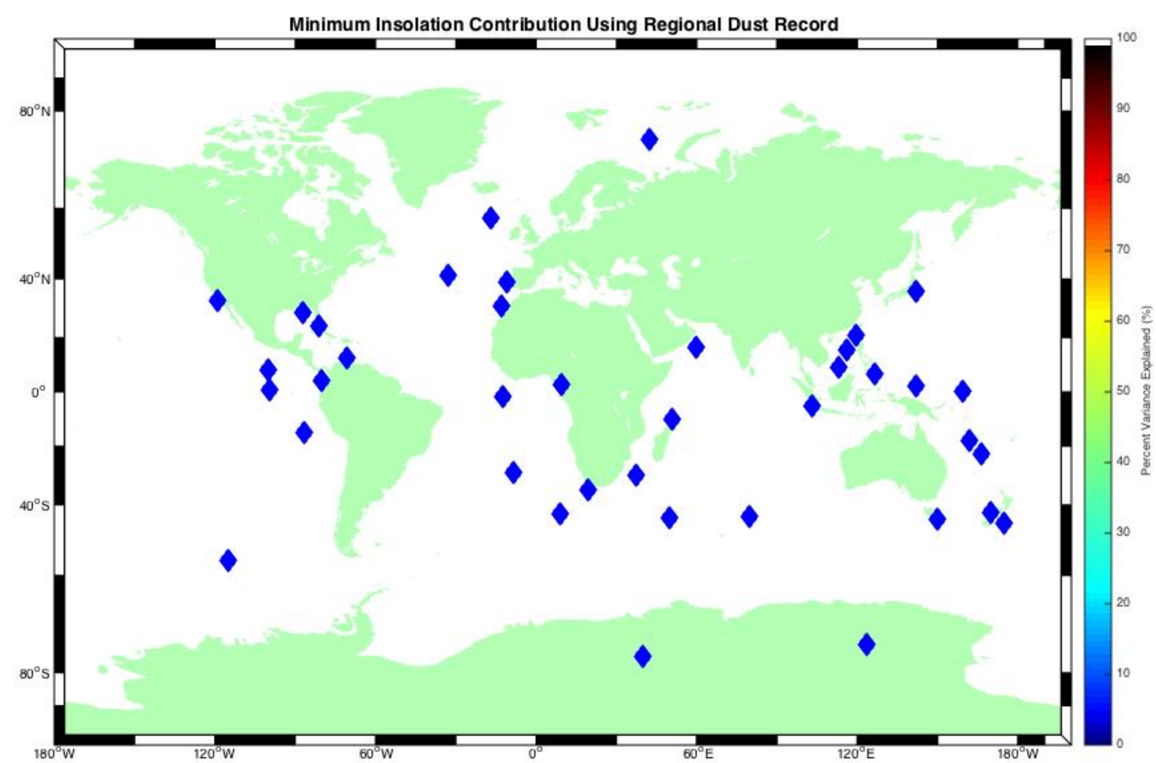

Figure 25. Minimum percent variance explained by the insolation forcing using method 2 with the regional dust records.

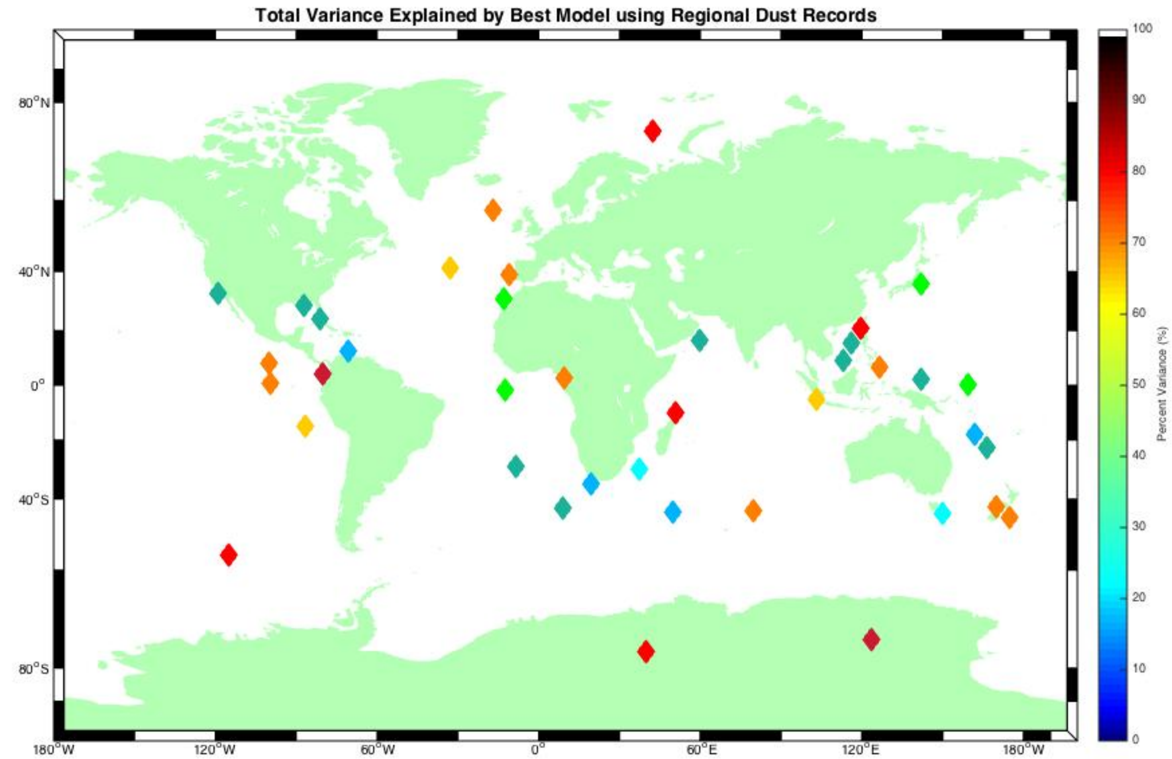

Figure 26. Total variance of each temperature record explained by the best fitting model out of the 24 different permutations for method 2 using the regional dust records.

While not entirely significant for every temperature record, the best fitting models for each record, using the regional dust records, explained a larger percentage of the total variance of the temperature signal than the models from method 1 (Figures 13, 26). This was not a trend globally; however, the differences are notable in the north Atlantic, where regional dust records provide a better model by ~20.0%. Otherwise, the differences vary record-by-record with little trend between and within geographic regions. The average values of percent variance for each forcing using method 2 are insufficient to use for a complete understanding of geographic trends since the differences between the maximum and minimum percent variance explained by each forcing are often ~30 - 50% (Figures 14-17). Therefore, the distributions of the maximum and minimum values are most important, as was the case with method 1. The distributions for the maximum case did not vary much, if any, for the three forcings besides the atmospheric dust forcing from method 1 (Figures 18, 20, 22, 24). Considering the two methods used completely different records for the dust forcing, this provides insight into global atmospheric dust concentration trends. Aside from the Antarctic region and a few records in the surrounding area, the general case was a slight, but visible, decrease in overall percent variance explained by the atmospheric dust forcing using regional dust records. This is significant because it shows that by region, the Antarctic is more sensitive to dust concentrations than other regions. However, this is complicated by the results from method 1, where a significant amount of records were favorably correlated to the Antarctic dust record. Since the only records from method 2 with a significantly larger percentage of the total variance explained by the models were those in the north Atlantic, it is difficult to generalize the global favorability of using a regional versus a global dust forcing record. The minimum values of percent variance explained by each forcing did not vary any between the two methods, even for the dust forcing (Figures 19, 21, 23, 25). This continues to show the inseparability of the forcings, as did the results of method 1.

The results of method 2 suggest the most dominant forcing is the greenhouse gas forcing, followed by sea level changes, atmospheric dust concentrations, and the insolation forcing. The results of method 1 displayed a slightly larger contribution from atmospheric dust than sea level, unlike the results offered by method 2. On a global scale, the distribution of maximum values for both atmospheric dust and sea level are quite similar in method 2. However, while the records with the largest maximum values for atmospheric dust are larger than those for the sea level forcing, there are a greater number of lower-range maximum values associated with the atmospheric dust forcing. In conclusion, the results for both the dust forcing and the sea level forcing for method 2 are nearly equal, and depending on the determining criteria, one or the other might slightly dominate.

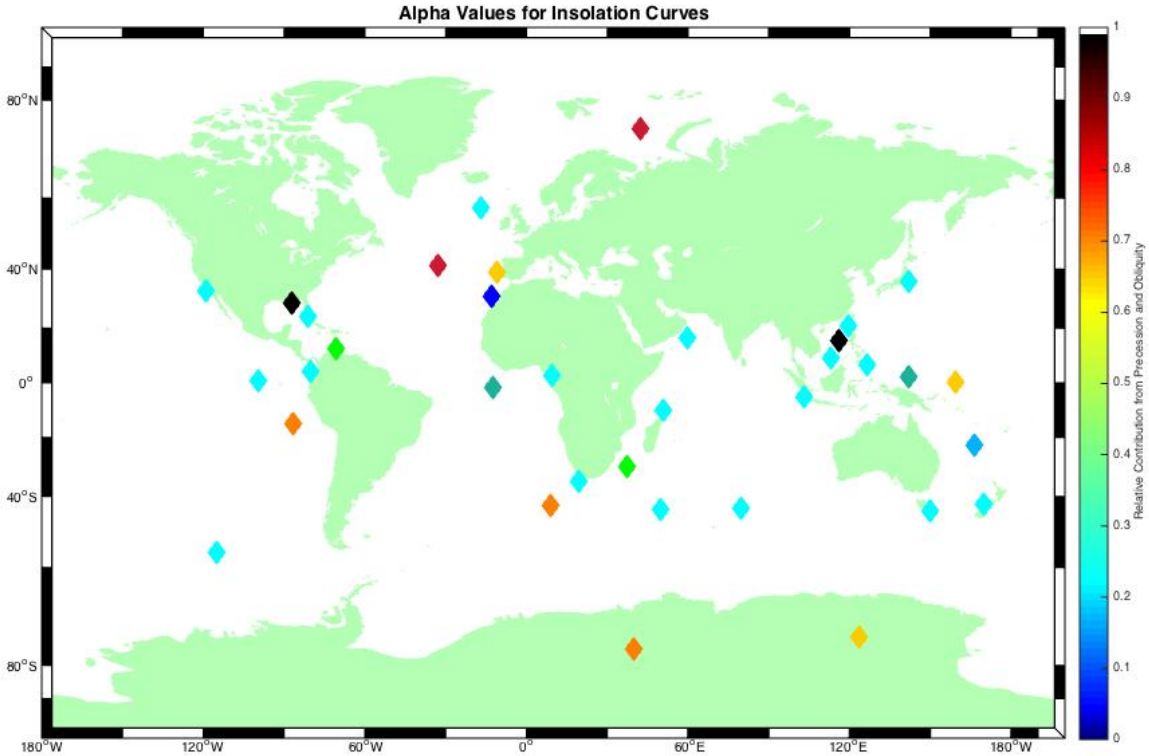

Figure 27. Alpha values, the relative contribution of precession and obliquity, between 0 and 1 used in equation 1 from Huybers (2011) for the best-fitting insolation curve of each temperature record. 0 implies no contribution from precession, 1 implies no contribution from obliquity, and 0.5 implies an even contribution from both.

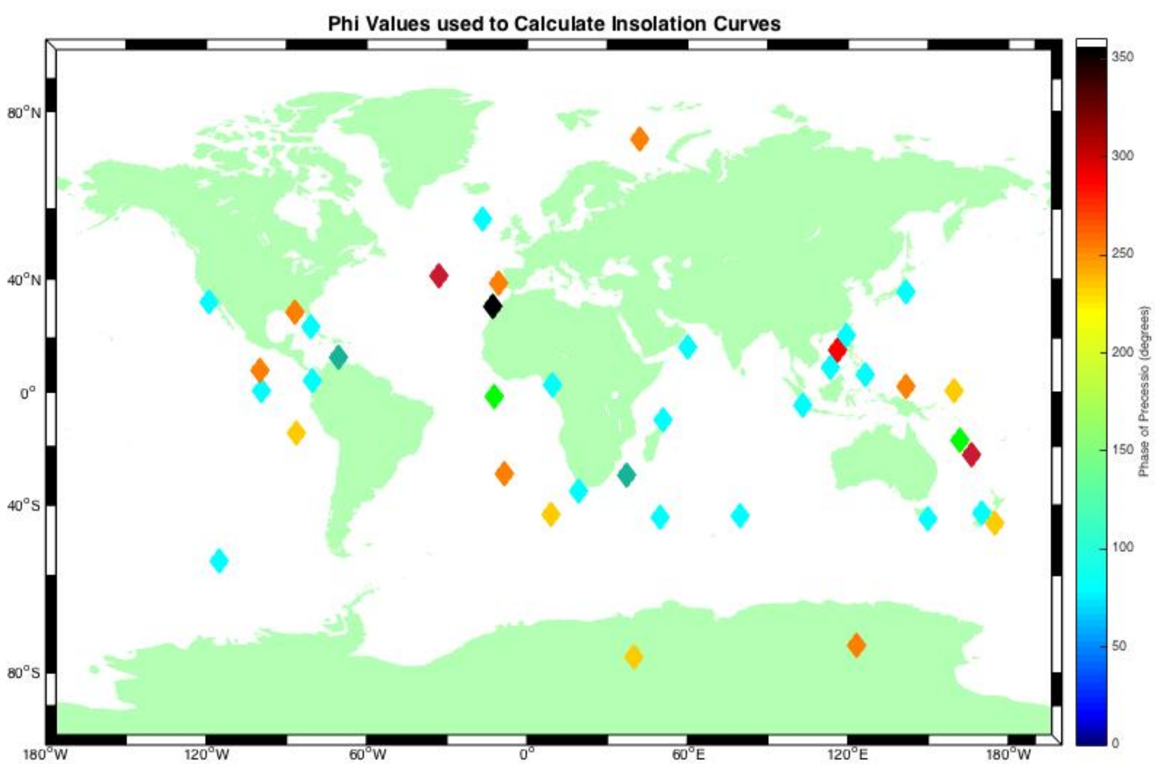

Figure 28. Phi values, the phase of precession, between 0 and 360º used in equation 1 from Huybers (2011) for the best-fitting insolation curve of each temperature record. 0 implies perihelion occurs on March 21, 90 on June 21, 180 on September 21, and 270 on December 21.

3.3 Insolation and Sensitivity

Figures 27 and 28 illustrate the geographical trends in the alpha and phi values used to calculate the insolation curves of best fit for each temperature record. Collectively, the mid to lower latitudes followed a similar pattern, while the poles showed a different pattern, aside from a few records in each region. The alpha values, indicating the relative contributions of obliquity and precession, in the mid-lower latitudes were typically between 0.3 and 0.5. This suggests contributions for precession and obliquity are equal or slightly favor obliquity. Near the poles, the alpha values range from 0.6 to 0.9, suggesting a higher relative contribution of precession to the insolation curve. Similar trends appear in the global distribution of phi values, which is the phase of precession used in the calculation of the insolation curve. The average phase of precession for the mid-lower latitudes is between 30 - 120º. However, the poles favored precession values greater than 270º, suggesting that they were most correlated to the curves when the Earth was closest to the Sun during the Northern Hemisphere summer. The regional trends for the phi values, however, are less distinct than those of the alpha values, which limits the certainty of any generalizations.

The final calculation of the multivariate analyses is the range of estimates of equilibrium climate sensitivity. I followed the procedure outlined previously to determine the results for both methods. The upper end of the sensitivity estimates follows the slope of the regression line between each temperature record and the greenhouse gas forcing. This value is the same for both methods. For the upper end of the sensitivity estimates, values ranged between about 2 at the lower latitudes to more than 10 (W/m^2) at the upper latitudes (Figure 29). The plot of sensitivity against latitude follows current knowledge of polar amplification. The values for the lower end of the estimate, which were determined using the best fitting model of the four permutations where the greenhouse gas forcing was the fourth in order, are quite insignificant (Figure 30). Average values hover slightly greater than 0.0 W/m^2 across all latitudes, which is much lower than current estimates from recent studies whose lower limit is at least 1.0 W/m^2. Therefore, on average, equilibrium climate sensitivity estimates for my multivariate analyses covering multiple local values range between 0.5 – 10.0 W/m^2, with the poles having a larger values > 10.0 W/m^2.

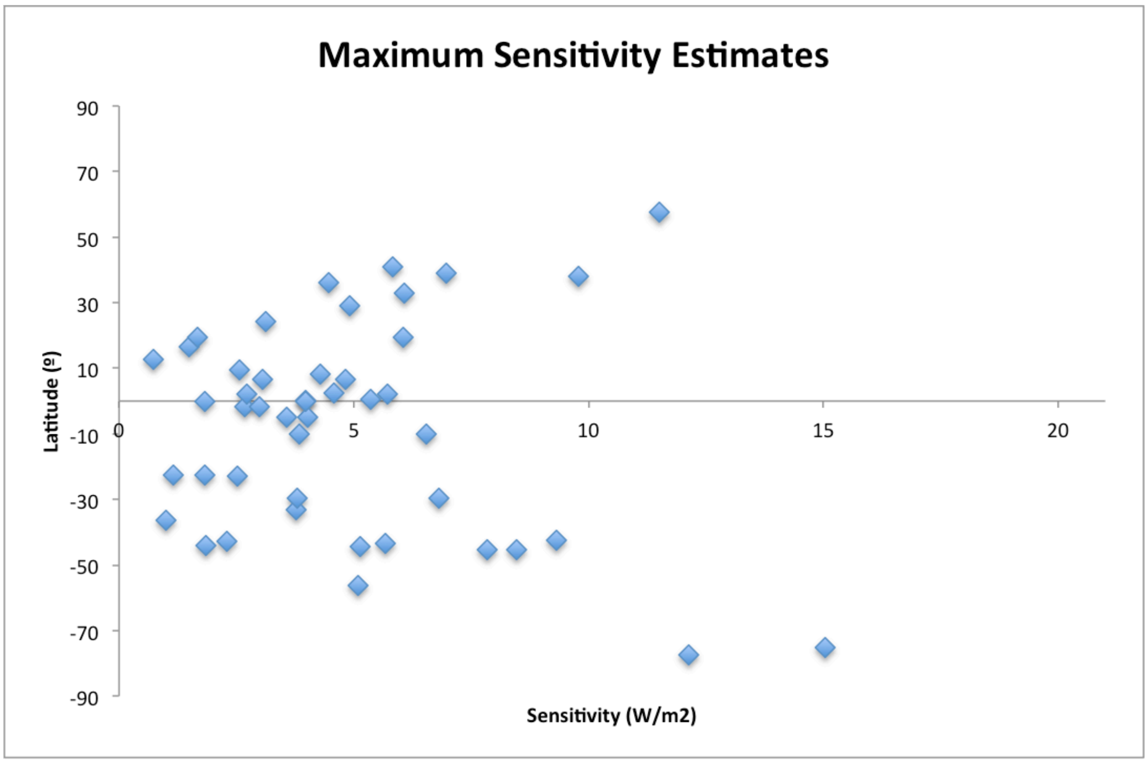

Figure 29. Maximum equilibrium climate sensitivity estimates using the slope of the regression line between the temperature record and the greenhouse gas forcing.

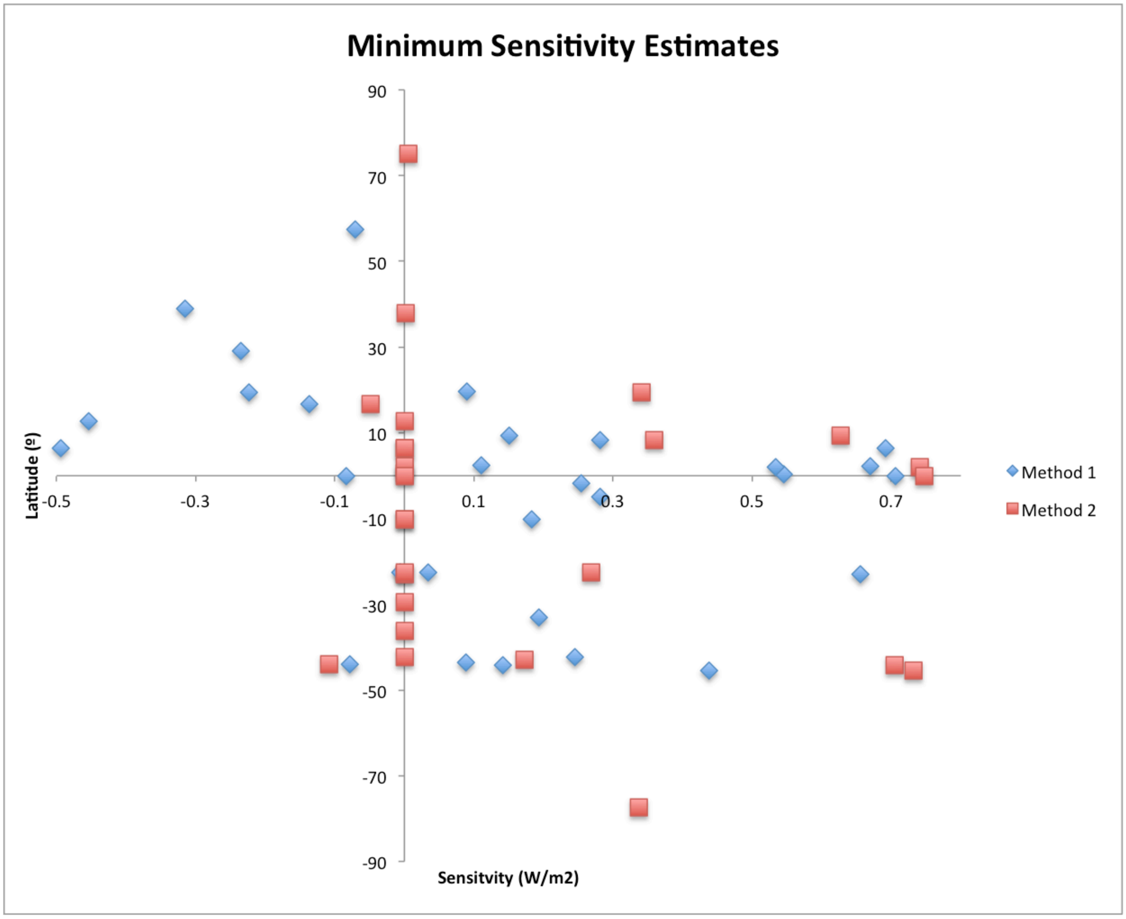

Figure 30. Minimum equilibrium climate sensitivity estimates using the slope of the regression line between the residual temperature curve and the greenhouse gas forcing when it was fourth in the permutation of best fit.

Chapter Four: Discussion

The results of the individual multivariate analyses suggest that the greenhouse gas forcing is the most dominant forcing of the four included. This falls in line with the results of previous studies analyzing individual temperature records. However, the range of values determined by my analyses is noticeably lower than those of previous studies. The research of Lea (2004) on a tropical SST record estimates the relative contribution of the greenhouse gas forcing to be about 69%. While the percent variance explained by the greenhouse forcing for a handful of records in my analyses exceed 70%, the majority fell between 20.0-50.0%. The disparity with these results for the greenhouse gas forcing and the additional concern of the inadequate total percent variance explained by the best model for each temperature record in the multivariate analyses could be a result of a combination of a few factors.

One obvious possible explanation for these lower-end ranges is a general lack of data for each temperature record. While my analysis was quite sufficient in its use of a variety of local temperature records spanning the vast majority of the globe, it could have improved upon the quality and resolution of each temperature record. A handful of the records used presented evenly spaced data points for the entirety of the past 800 kyr. However, the majority of the records only extensively covered data for certain time periods of the past 800 kyr. This limited the quality of the multivariate regressions, since the Matlab code that calculated the regressions was only able to model the values of each forcing against known data points. Additionally, this missing data might have covered a time period where the temperature signal correlated most strongly with a forcing, which could have increased the percent variance explained. Where a few temperature records had fewer than 50 data points out of a possible total of 800, these likely influenced results. The results of these records were most often outliers in their particular geographical region. In future analyses, this limitation can be subdued through the interpolation of the data points of the temperature record to a certain resolution, most likely that of the forcings at 1 kyr, or 800 total data points. This could prove difficult where the number of data points is severely low, in which case it might be more beneficial to discard the record completely than to forge data out of nothing. Another possible improvement is to select only records with an already high enough resolution. This would eliminate the need for interpolation and allow for a more accurate representation of geographic regions. Fewer complete records in each region might not necessarily be as limiting as having many spotty records in each region.

Another possible explanation for the lower values is potential misalignment of the data in time. While each record and forcings were aligned to the same timescale, small errors in alignment of particular records could lead to major discrepancies in the results of the multivariate analyses. For instance, a particular temperature record might be largely correlated to a forcing; however, the correlation might nearly be zero if the data is misaligned. Working with 47 individual temperatures records, it was difficult to ensure that each was aligned correctly. In the future, this is an area that should warrant more dedication and attention to detail. Additionally, a major assumption in regards to the models resulting from my analyses was that temperature should scale linearly with climate forcing. This view might have been too simplistic and may have overlooked many important aspects of climate change. It would be beneficial to explore this area further in future research.

It is difficult to compare the remainder of my results collectively to previous studies, since I analyzed a combination of forcings different from most of the studies. However, even considering the lower trend of relative weightings for each forcing, the distribution of results is quite similar to previous studies. The research of Lorius et al. (1990) suggests that greenhouse gas contributes to over 50% of the variance in temperature, with the other forcings (insolation, dust, and ice volume) accounting for around 5% each. The results of analyses performed by Lea (2004) are quite similar, with his distributions providing insolation with a higher relative contribution (9.0%) and minimal (< 2.0%) relative contributions from both ice volume and dust concentrations respectively. It appears that while the greenhouse gas forcing presents the largest relative contribution to the overall temperature signal, the remaining contributions from the other forcings are less consistent, in both my analyses and previous studies. Since the majority of these studies were limited to the use of a singular temperature record in the extrapolation of the relative weightings of global climate forcings, the results of my analyses seem more substantiated with the use of 47 local temperature proxies and individually correlated insolation curves. However, these results, too, must be considered with an air of uncertainty due the limiting factors mentioned previously with potential misalignment, lower resolution proxies, and possibly incorrect assumptions.

While I was unable to perform this method in my overall analysis, it might be beneficial to conduct a third multivariate analysis breaking down the overall temperature curve into smaller windows. These windows may allow for the analysis of certain time windows where the forcings are not as correlated with each other, and may illustrate the behaviors and variations of the relative contributions of each forcing over time. Additionally, it would be beneficial to follow up on the suggestions mentioned previously to improve the quality of the temperature records themselves to provide more accurate estimates of the relative contributions of each forcing, and consequently, estimates of climate sensitivity.

Chapter Five: Conclusion

As recently measured atmospheric CO_2 concentration amounts breach 400 p.p.m., concerned climate scientists have brought forth the topic of equilibrium climate sensitivity. It is imperative to understand exactly how much warming, across the globe, is to be expected from a doubling of CO_2 concentrations, which is exactly what has been occurring since the pre-Industrial Revolution era where CO_2 amounts were below 280 p.p.m. A highly sensitive climate system, that is, a climate where temperatures increase drastically with small changes in CO_2, would mean disaster for current society. Should extensive warming occur, climate feedback mechanisms would begin to spiral out of human control, with ice sheets melting and sea level rising at unprecedented amounts, among other concerns. Therefore, extensive research into the topic of equilibrium climate sensitivity estimates is rather important, since the current range of estimates spans nearly 4 ºC. Within such a large range, we must expect global temperature increases of both small and extreme levels. The two main objectives of my analyses were to (1) determine the relative influence of various climate forcings driving the temperature signal at local proxy records, and (2) use the calculated relative weightings to determine a range of climate sensitivity estimates. Ideally, my multivariate analyses would have proven most beneficial if they were able to confine the known range of sensitivity estimates, a task many previous studies were also unable to do. However, the results of my analyses do deliver important evidence relating to the magnitude of the relative weightings of various climate forcings.

While the models produced by my analyses do not fully explain the total variance of each temperature record, they provide valuable insight into the behaviors and geographical trends of the relative contributions of four climate forcings to the total temperature signal. My research corroborates previous evidence of the dominance of the greenhouse gas forcing as the most important influence in the resulting temperature signal, followed by smaller contributions from atmospheric dust concentrations, ice volume, and orbital variations. Regionally, maximum values of percent variance explained by the greenhouse gas forcing differ noticeably. However, accounting for > 40% of the total variance in temperature, on average, changes in greenhouse gas concentrations have a significant amount of influence on resulting temperature profiles, which reiterates the importance of and the requirement for a more involved understanding of equilibrium climate sensitivity.

The results of my analyses were unable to narrow the current range of sensitivity estimates. While somewhat influenced by potential shortcomings within the data, as explained previously, these findings, still, are not entirely insignificant. Evidence of polar amplification and heightened sensitivity estimates for the higher latitudes justifies concerns over the rapid increase of the ice-albedo feedback mechanism and reiterates the idea of the poles warming more rapidly and intensely than lower latitudes. Therefore, while the mid-lower latitudes, which are more densely populated than the upper latitudes, may not experience the direct effects of as rapid and intense of warming as the poles, they will undoubtedly face the consequences of the higher sensitivity of the upper latitudes. In any case, these consequences will be even more catastrophic for the mid-lower latitudes, as coastal cities will be swallowed by rising sea levels from melting ice sheets. While the results of my analyses supported the presence of minimum sensitivity estimates of nearly 0.0 ºC as well, it is more beneficial, in my opinion, to understand the implications of a more sensitive planet than those of a less sensitive planet where a doubling of CO_2 has less severe consequences on the climate system and feedback mechanisms.

With the greenhouse gas forcing as the most dominant signal in the overall temperature curve, drastic steps must be taken to restrain current increases in atmospheric CO_2 concentrations. At the upper latitudes and the poles, where the climate system is more sensitive to changes in CO_2, a doubling of pre-Industrial CO_2 concentrations could mean temperature changes of a magnitude of 4 – 5 ºC. A temperature change of even 4 ºC would be enough to push the climate system into another Ice Age – a change for which humanity is wholly unprepared. Knowing the implications of our actions, as a society, in inflating CO_2 emissions and, consequently, atmospheric CO_2 concentrations is not enough to combat the inevitable changes, which are at present rapidly, and almost irreversibly, in place. Action must be taken to control global CO_2 emissions before the climate system begins to control society.

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