Lecture 37
Simulation of Glacial to Interglacial

In the previous lecture, we examined the major factors that contributed to the Earth's warming from the last glacial maximum, around 20,000 years ago, to the present day. The transition involved several key components working together.

The first major factor was ice sheet melting, which reduced the Earth's albedo—the reflectivity of the surface. As ice melted, darker surfaces were exposed, absorbing more sunlight and contributing to warming. Alongside this, there was a significant increase in greenhouse gases, including carbon dioxide (CO_2), methane (CH_4), and water vapor. These gases amplified the warming through the greenhouse effect.

When all these contributions are plotted over time, the warming trend becomes apparent. The temperature change is shown as the combined effect of greenhouse gas increase and ice melt. Spatially, this warming was global, affecting most regions of the Earth.
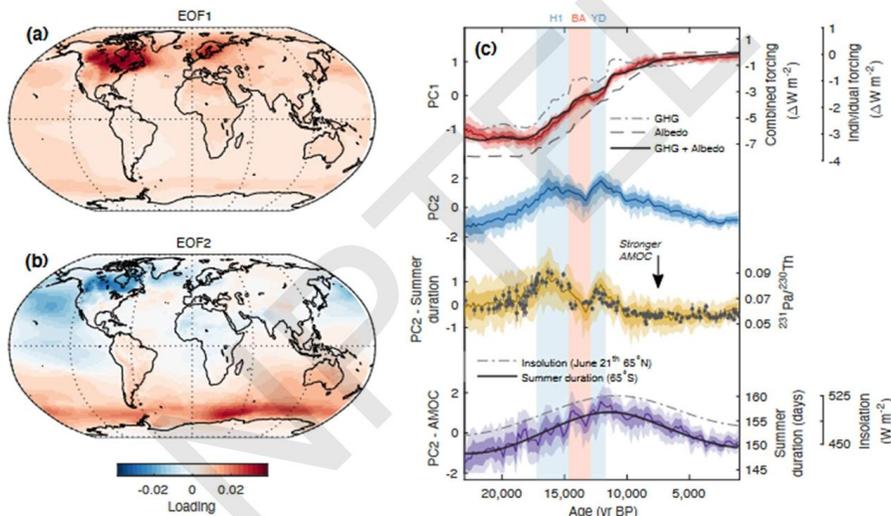
However, another important factor was the role of changes in ocean circulation, particularly the Atlantic Meridional Overturning Circulation (AMOC). The AMOC experienced significant shifts during key events like the Bolling–Allerod warming and the Younger Dryas cooling. These rapid changes are reflected in shaded regions of the timeseries in the figure above, showing how circulation dynamics influenced climate.

Additionally, there were changes in incoming solar radiation, especially over the polar regions. The radiative flux increased from about 450 W/m^2 to roughly 525 W/m^2, and the length of summer expanded from around 145 days to 160 days. Both the intensity and duration of solar input altered the seasonal energy budget, influencing both warming and cooling trends in different periods.

Altogether, the climate transition from the Ice Age to today was driven by a combination of greenhouse gas forcing, ice-albedo feedback, ocean circulation changes, and insolation variations. Understanding this complex interplay requires integrating data from proxy records (which are direct but spatially and temporally sparse) and climate model simulations (which offer full spatial and temporal coverage but include uncertainties and assumptions).

The fusion of these two data sources is done through reanalysis, a process where the continuous output from climate models is constrained and corrected using available proxy observations. This approach takes advantage of the strengths of both methods: the fidelity of proxy data as true observations, and the coverage and continuity of model simulations.

Now we shift our focus on a comprehensive climate model simulation known as TraCE-21K, conducted by the National Center for Atmospheric Research (NCAR). TraCE-21K is a transient simulation that spans the last 21,000 years, from the Last Glacial Maximum to the present. It uses a fully coupled ocean-atmosphere model to capture the key processes of climate evolution.

The atmosphere model in this setup has a horizontal resolution of approximately 3.75° in both latitude and longitude, while the ocean component, based on the Parallel Ocean Program (POP), operates at a finer resolution of about 1°. This resolution balance allows for adequate representation of large-scale dynamics while keeping the simulation computationally feasible over such long timescales.

The simulation incorporates four major time-varying forcings:
1. Orbital parameters (eccentricity, obliquity, and precession), which affect the distribution of solar radiation across the Earth's surface.
2. Greenhouse gas concentrations, primarily CO_2 and CH_4, based on paleo-atmospheric reconstructions from ice cores.
3. Ice sheet extent and topography, which change the surface albedo and influence atmospheric circulation.
4. Meltwater fluxes, derived from sea level rise data, representing the influx of freshwater into the oceans during deglaciation.

One of the key advantages of using a climate model is that isolated sensitivity experiments can be run alongside the full simulation. In TraCE-21K, this was done by

varying each of the four forcings independently, while keeping the others constant. This approach allows researchers to assess the individual contribution of each forcing to the overall climate change:

- One simulation changes only orbital parameters
- Another varies only greenhouse gas concentrations
- A third adjusts only the ice sheet configuration
- The fourth alters only the meltwater input

By comparing these single-forcing simulations to the full simulation (where all forcings vary together), scientists can quantify the relative importance of each driver in shaping the Earth's climate over the past 21,000 years.

The TraCE-21K simulation has successfully reproduced many key features of the deglaciation process, making it a valuable tool for understanding past climate transitions and the mechanisms behind them.
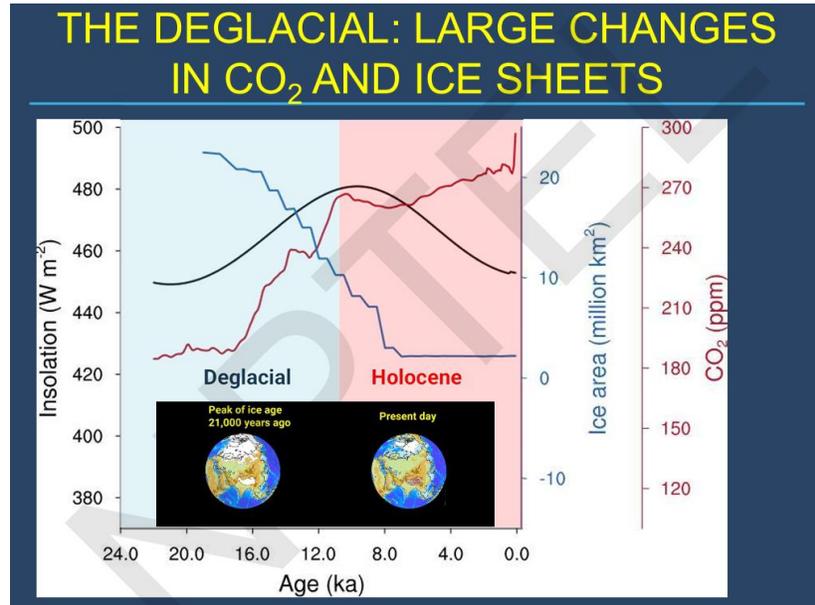
To summarize the major climate changes over the last 21,000 years, several key variables underwent significant transformations that collectively drove global warming.

First, incoming solar radiation at high latitudes increased from about 450 W/m² to a peak of 480 W/m² around 11,000 years ago. Since then, solar insolation has been gradually declining, meaning we are currently in a phase of reduced solar input compared to the early Holocene.

Simultaneously, carbon dioxide concentrations experienced a sharp rise. Around 21,000 years ago, CO_2 levels were approximately 180 ppm. As the planet warmed and deglaciation progressed, CO_2 rose rapidly, first to 240 ppm, and eventually to 280 ppm by the start of the Holocene. In the last 100 years, this natural trend has been overtaken

by human activity, pushing CO_2 levels above 400 ppm, an unprecedented increase on geological timescales.

Another major change was in ice sheet extent. During the Last Glacial Maximum, ice sheets covered over 20 million square kilometers of Earth's surface. These massive ice sheets gradually retreated, and today only about 1 million square kilometers remain, primarily in Greenland and Antarctica. The reduction in ice area significantly altered Earth's albedo and was a strong driver of warming.

In the TraCE-21K simulation, these forcings - solar radiation, greenhouse gases, and ice sheet extent - were examined both together and individually. One simulation included all changes simultaneously to reproduce the full climate transition. In parallel, individual sensitivity experiments were conducted, each varying only one forcing while keeping the others constant. This approach helps quantify the relative contribution of each factor to the overall warming. Together, these experiments show that the Earth's deglaciation was driven by the combined effects of insolation changes, greenhouse gas increases, and the retreat of ice sheets.
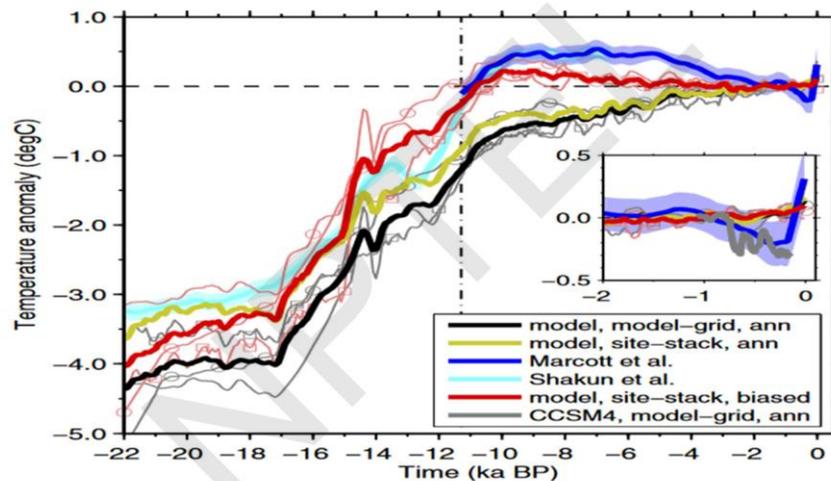
The above figure presents a comparison between model simulations and proxy-based temperature reconstructions. The black line represents the TraCE-21K simulation using all forcings combined. It starts about 4.5°C colder than present and gradually increases, reaching near-present temperatures.

This simulation is compared with two proxy datasets: the light blue and dark blue lines, derived from ice cores and ocean cores. The Shakun et al. proxy data shows global mean temperatures about 0.5°C warmer than the model, while the Marcott et al. data (covering the last 12,000 years) shows values about 1°C higher than the simulation.

This discrepancy arises because the model computes a true global average across all grid points, whereas proxy datasets can only average over locations where measurements

exist, which are not globally uniform. This sampling limitation affects how well the proxies represent the true global mean.

As discussed earlier, proxy data used in reconstructions like Shakun et al. do not cover all parts of the globe. Their spatial distribution is limited to select regions, such as the Arctic, Antarctic, and some coastal zones. In contrast, climate models compute global mean temperature by averaging over all grid points on Earth. This discrepancy in data coverage introduces a key difference between model-based and proxy-based global mean temperatures.

To explore this, modelers compared different averaging methods using the TraCE-21K simulation. The black line represents the ensemble mean of the full model simulation, averaged over all grid points. Then, they recalculated the average only over the locations where proxy data existed. This is shown as the yellow line. This line is slightly warmer than the black line, showing that spatial sampling can bias the result. The difference between the black and yellow lines reflects the error introduced by limited spatial coverage in the proxy data.

Furthermore, they examined another source of bias: seasonality in the proxies. Proxies like foraminifera or species abundance do not always reflect annual mean temperatures. Many species are seasonally sensitive and their abundance may respond more to summer temperatures than the yearly average. So, the modelers repeated the averaging, this time computing only the summer seasonal mean at proxy locations. This seasonal-biased averaging produced temperature estimates that closely match Shakun and Marcott reconstructions. The warming signal became stronger, closing the gap between models and proxies.

This demonstrates two major issues with interpreting proxy-derived global mean temperatures:
1. Spatial bias: Proxies are sparsely and unevenly distributed, leading to sampling errors in estimating global means.
2. Seasonal bias: Many proxies reflect seasonal extremes (often summer), not the full annual mean.

The comparison clearly shows that proxy data, while valuable, must be interpreted cautiously. Their limitations can lead to overestimates or underestimates if not properly accounted for. On the other hand, climate models also have limitations as they may not capture all real-world processes but provide complete spatial and temporal coverage.

Despite these limitations, when both model and proxy data are carefully treated using spatially and seasonally consistent methods, the agreement improves significantly. In fact, the difference between properly averaged model output and proxy data reduces to about 0.25°C, which is considered remarkably close for paleoclimate reconstructions.

The figure also includes a zoomed-in inset showing the last 2,000 years, where discrepancies become more evident. For example, Marcott et al. suggest a notable cooling trend over the past millennium, which is reproduced by the model when considering seasonal bias. This highlights that the recent 2,000-year trend behaves differently from the broader 20,000-year pattern.

In summary, this exercise reveals the importance of comparing models and proxies carefully, considering both spatial and seasonal aspects. It also demonstrates that with the right approach, model-proxy agreement is strong, lending confidence to both methods when used together.

Note that "sum" and "all" are not the same. Indicates the role of feedbacks
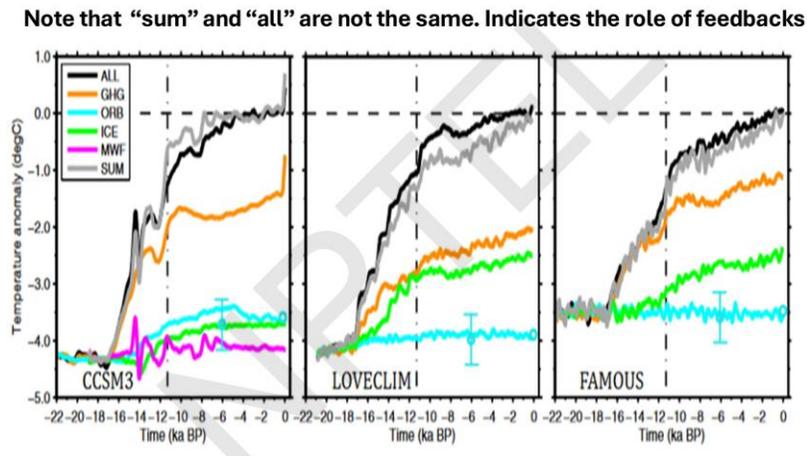
To build confidence in the results, researchers compared the TraCE simulation (using the CCSM3 model) with outputs from two other climate models: LOVECLIM and FAMOUS. Each model represents Earth's climate system slightly differently, so comparing multiple models helps test the robustness of the conclusions.

In all three models' (CCSM3, LOVECLIM, and FAMOUS) temperature anomaly timeseries shown above, the black line represents the simulation that includes all major forcings together: greenhouse gases, orbital changes, ice sheet extent, and meltwater fluxes. This simulation closely reproduces the observed temperature evolution from the last glacial maximum to the present.

The models also ran individual forcing experiments changing only one factor at a time. These include simulations with just greenhouse gases, just orbital variations, just ice sheets, or just meltwater. However, none of these single-factor runs can explain the full warming seen in the Holocene. For instance, greenhouse gases alone produce only modest warming in the TraCE simulation.

A key insight comes from comparing the sum of the individual forcings (the grey line) with the simulation that combines all forcings (the black line). The two are not equal, revealing that the climate system is non-linear and adding individual forcings does not

produce the same outcome as simulating all of them together. This is due to feedbacks between the different components of the climate system.

Among the forcings, greenhouse gases are the most dominant, particularly in the Holocene (last 10,000 years). Orbital forcing and ice sheet retreat were more influential before 10,000 years ago, during the deglacial period. Meltwater fluxes, while crucial during abrupt events like the Younger Dryas, play a limited role in the stable Holocene climate.

Interestingly, the greenhouse gas increase continued even after the large ice sheets had disappeared. One explanation is that this was a natural continuation of carbon cycle processes. But an alternative hypothesis, proposed by William Ruddiman, suggests that early human activity, particularly the spread of agriculture and associated deforestation, increased emissions of methane and carbon dioxide. This idea remains controversial due to uncertainties in past population data and land use changes, and will be explored further in subsequent discussions.
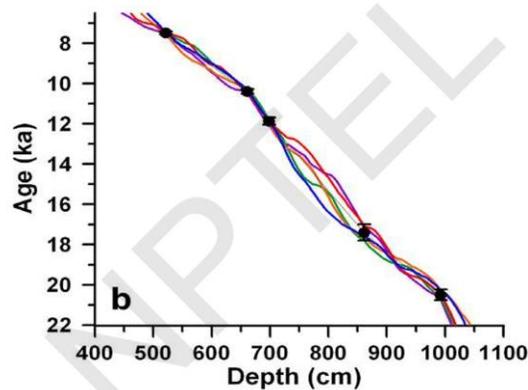

When working with proxy data, it's essential to understand how depth is converted into age. This process involves dating specific layers using methods like the radioactive decay of isotopes such as uranium or carbon. However, such dating is only done at select reference points in the record. For the intervals between these points, interpolation is used, introducing uncertainties in the age assignments.

As a result, proxy records often carry time uncertainties of at least ±1,000 years. This contrasts with modern instrumental records, where the exact timing of temperature measurements is known to the year or even the day. In proxy data, we infer the timing of events from indirect evidence like sediment or ice deposition rates which makes the dating inherently imprecise.

This uncertainty is critical to remember, especially now that many proxy datasets are publicly accessible online. Researchers from diverse fields, including mathematics and statistics, often apply advanced techniques like machine learning or AI to analyse these

datasets. However, many fail to account for the inherent error bars in the data, sometimes ranging from hundreds to even thousands of years.

Therefore, interpreting results from such analyses without understanding the underlying uncertainties can be misleading. Any use of proxy data, especially for time-sensitive questions or pattern recognition, requires a clear awareness of its limitations and dating imprecision.
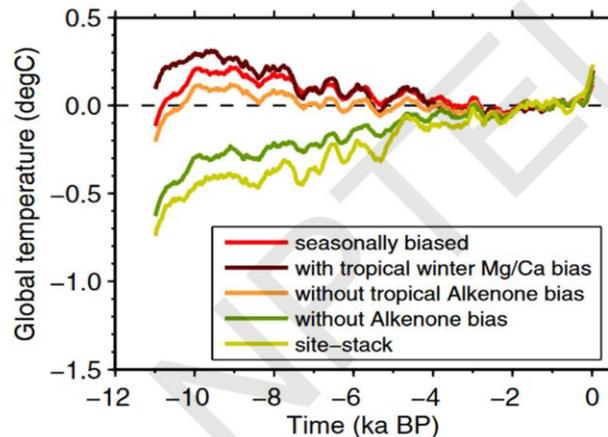
The estimation of global mean temperature from proxy data is affected by biases depending on the proxy used. For example, reconstructions based on the magnesium/calcium ratio in tropical foraminifera or alkenone concentrations in mid-latitudes both introduce systematic biases. These proxies often reflect seasonal temperatures such as summer or winter rather than true annual means. As a result, the global temperature estimates vary across different proxies, and after correction, the differences can be as large as 0.75 K, particularly around 9,000 years ago.

However, in the last 3,000 years, such errors reduce significantly. This improvement is mainly due to the use of tree-ring-based reconstructions, which offer more accurate temperature estimates. Tree ring growth is primarily sensitive to temperature, and hence, these proxies are less biased compared to oceanic proxies that depend on the abundance of specific organisms, which may not reflect the full annual cycle.

Therefore, while using proxy data, especially from marine cores, one must consider that these sources may only represent partial seasonal information, leading to uncertainties in global mean temperature reconstruction.

In the supplementary data of the Shakun et al. (Nature) paper, the authors evaluate the uncertainties in global mean temperature reconstructions by systematically perturbing the proxy records. These proxies inherently contain errors both in the measurement of species abundance (used to infer temperature) and in the dating (age model). When these errors are incorporated into the reconstruction, they show that temperature estimates can

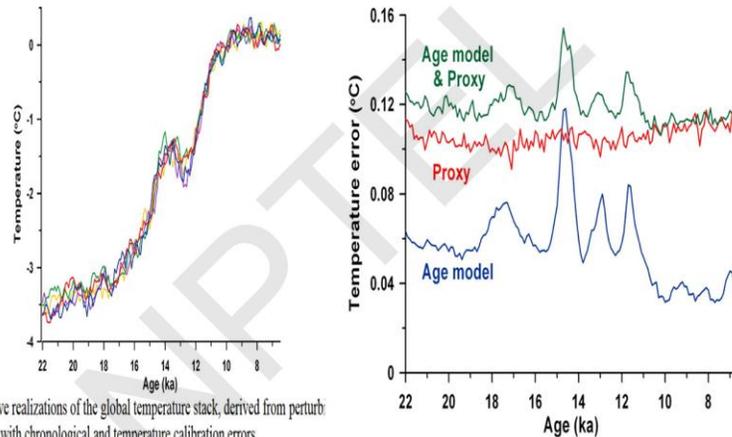vary by as much as 0.5°C, especially during periods of rapid climate change like the Younger Dryas.

Figure S9: Five realizations of the global temperature stack, derived from perturb[ed] proxy records with chronological and temperature calibration errors.

The temperature error due to proxy-temperature conversion is typically around 0.1–0.12°C. A similar magnitude of error arises from uncertainties in the age model, especially further back in time. These errors are smaller in the last 7,000–10,000 years, where both dating and proxy interpretation are more reliable. When combining errors from both sources, some cancellation occurs, leading to a reduced overall uncertainty.

Shakun et al. stand out for their rigorous treatment of these uncertainties, making their work particularly robust. They did not merely compile and average proxy records; they explicitly quantified how errors in species abundance-to-temperature conversion and age dating influence global mean temperature reconstructions. This thorough handling of uncertainties is a key reason why the paper is considered a landmark contribution in paleoclimate reconstruction.
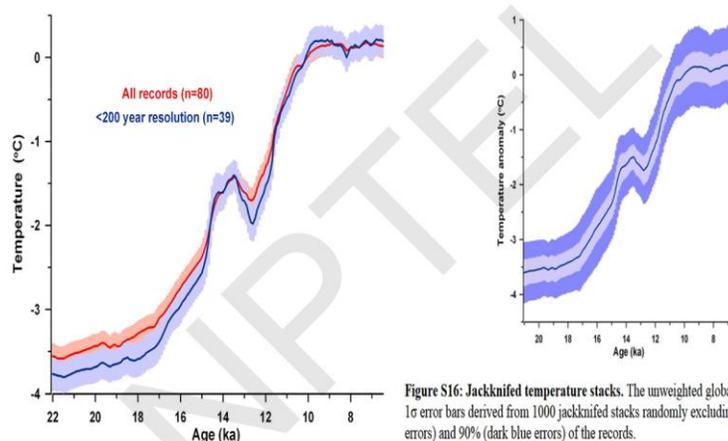

Figure S16: Jackknifed temperature stacks. The unweighted global proxy stack with 1σ error bars derived from 1000 jackknifed stacks randomly excluding 50% (light blue errors) and 90% (dark blue errors) of the records.

Shakun et al. incorporated 80 proxy records in their global mean temperature reconstruction. These proxies vary in their temporal resolution where some provide data every 200 years or less, while others are spaced at 500 to 1,000 years. When all 80 records are used, the result is shown in red, while a subset of 39 high-resolution records

produces the blue curve. The comparison shows that while the two align well in many regions, discrepancies of up to 0.5°C emerge around the Last Glacial Maximum and during the Younger Dryas, illustrating the impact of lower-resolution records on timing and amplitude.

To assess the robustness of their results, the authors employed a jackknifing technique. This involves randomly excluding 50% of the proxy records, repeating the global mean reconstruction multiple times, and then computing the mean and standard deviation. This statistical approach reveals that the uncertainty introduced by proxy selection and data sparsity can again lead to variations of around ±0.5°C.

Overall, these rigorous analyses addressing differences in temporal resolution, proxy reliability, and statistical uncertainty underscore the comprehensiveness and care with which Shakun et al. approached their temperature reconstruction.
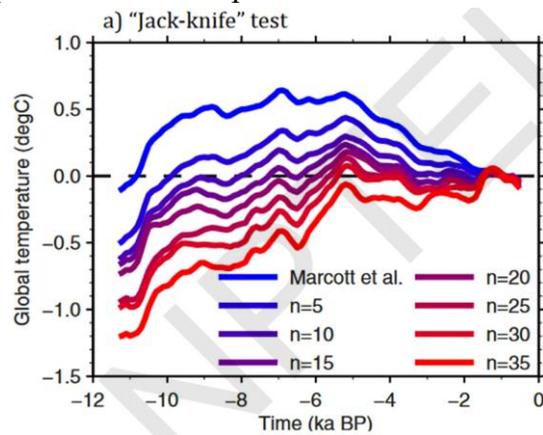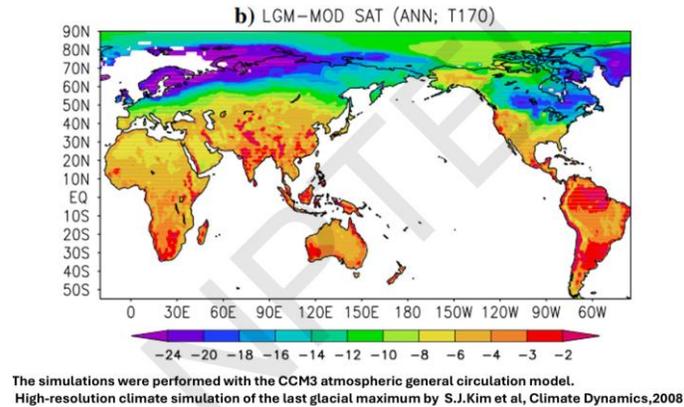

The above figure illustrates the jackknife test used to assess the sensitivity of global mean temperature estimates to the number of proxy records included.

In this approach, subsets of the proxy dataset are used, e.g., 20, 25, or 30 records out of the full set of 35 high-resolution proxies, to reconstruct the global mean temperature. The results show that when fewer data points are used, the variation in reconstructed temperatures becomes larger, particularly during the older periods such as the Last Glacial Maximum and deglacial transition. However, in the more recent millennia, especially approaching the Holocene, the discrepancies between different subsets become much smaller.
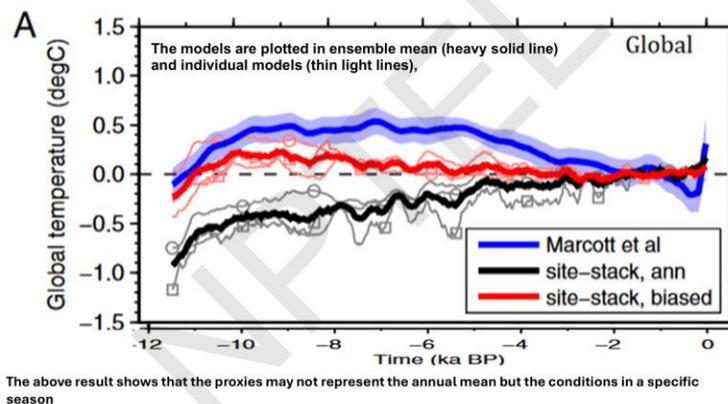
This result confirms that:
- The uncertainty in global mean temperature reconstructions is higher in the distant past, due to both fewer available proxies and greater variability in dating and resolution.
- In contrast, recent periods benefit from denser and higher-quality data, leading to reduced reconstruction errors.

This reinforces the idea that proxy data coverage and quality directly influence the confidence in past climate reconstructions.

b) LGM–MOD SAT (ANN; T170)

The simulations were performed with the CCM3 atmospheric general circulation model.
High-resolution climate simulation of the last glacial maximum by S.J.Kim et al, Climate Dynamics,2008

The above figure compares the climate of the Last Glacial Maximum (LGM) with that of the present, emphasizing the stark spatial contrasts in surface air temperature changes. During the LGM, areas like Siberia and Greenland were colder by as much as 25°C due to the presence of thick ice sheets, while the tropics were only 2–3°C cooler. This large difference highlights the role of ice-albedo feedback, where melting ice in high latitudes led to increased solar absorption and significant regional warming. In contrast, tropical regions, with minimal ice cover, experienced much smaller temperature shifts. This spatial variation is highly relevant today: while global mean temperatures have risen by around 1–1.5°C, the Arctic has warmed by about 4°C, a phenomenon known as Arctic amplification. A global warming of 2°C could correspond to a 10°C rise in Arctic temperatures, which could trigger large-scale permafrost thawing in Siberia and the release of methane, a potent greenhouse gas. Such feedbacks make it critical to understand that warming is not spatially uniform and that polar regions are far more sensitive, with disproportionate impacts on the global climate system.

The above result shows that the proxies may not represent the annual mean but the conditions in a specific season

The discrepancy between climate model simulations and proxy-based reconstructions arises partly due to differences in averaging methods. While models typically provide annual mean temperatures across the globe, proxies often reflect seasonal conditions, especially summer, depending on the biological or geochemical indicators used. This

seasonal bias in proxy records can lead to an overestimation of global mean temperatures when compared to model simulations. When model outputs are recalculated using only the locations and seasonal timing of the proxies, the agreement improves significantly. This highlights the importance of considering both spatial and temporal biases in proxy data when comparing them with model results. The Shakun et al. reconstruction remains central to understanding the deglacial warming and will be further examined in the next lecture.