Detection and attribution approach to analyzing forcing components of late Quaternary climate variability

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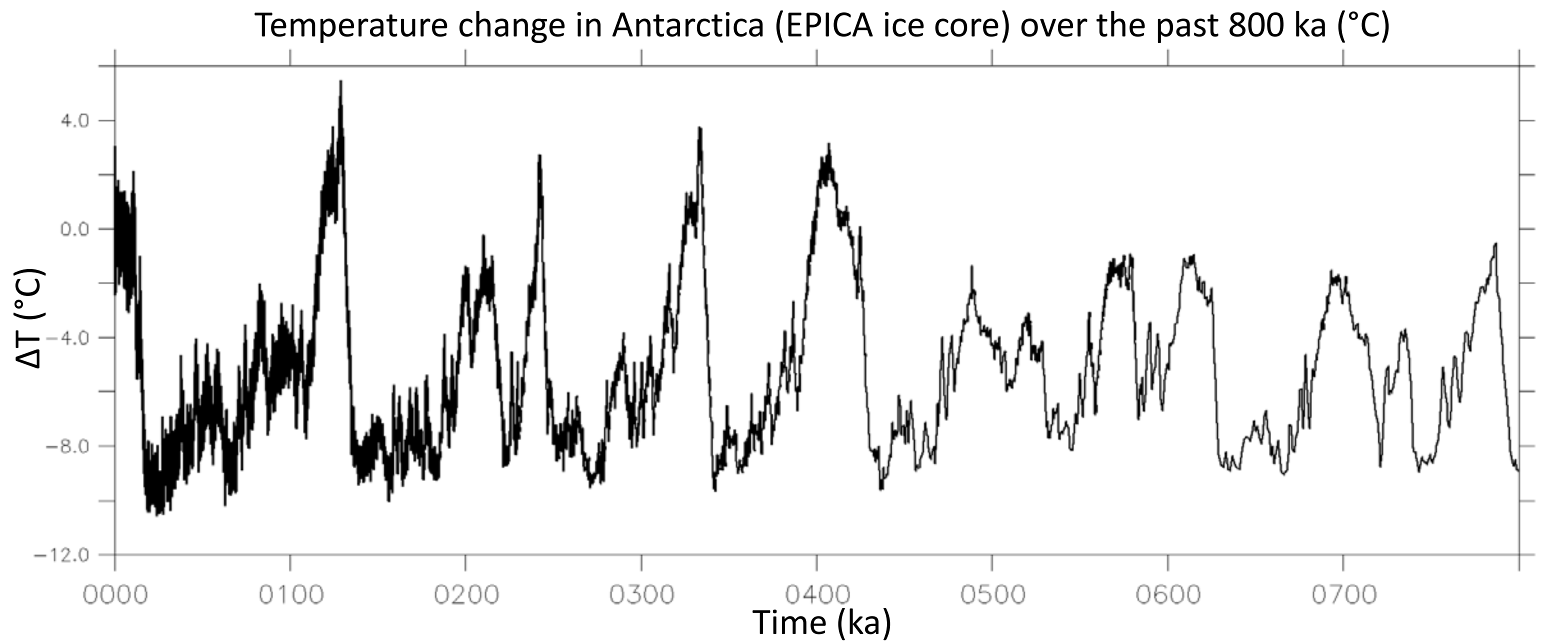
2016 Winter CESM WG Meetings, Boulder, CO, February 9, 2016

Quaternary climate variability

Quaternary climate variability is the net result of concurrent changes in **orbit**, **greenhouse gases**, **ice sheets**, and more.



Through comparison of idealized single-forcing simulations and long proxy records, we estimate the contribution of each factor. Two areas of focus:

- The temperature response to obliquity.
- The effect of ice sheets vs. CO_2 (climate sensitivity).

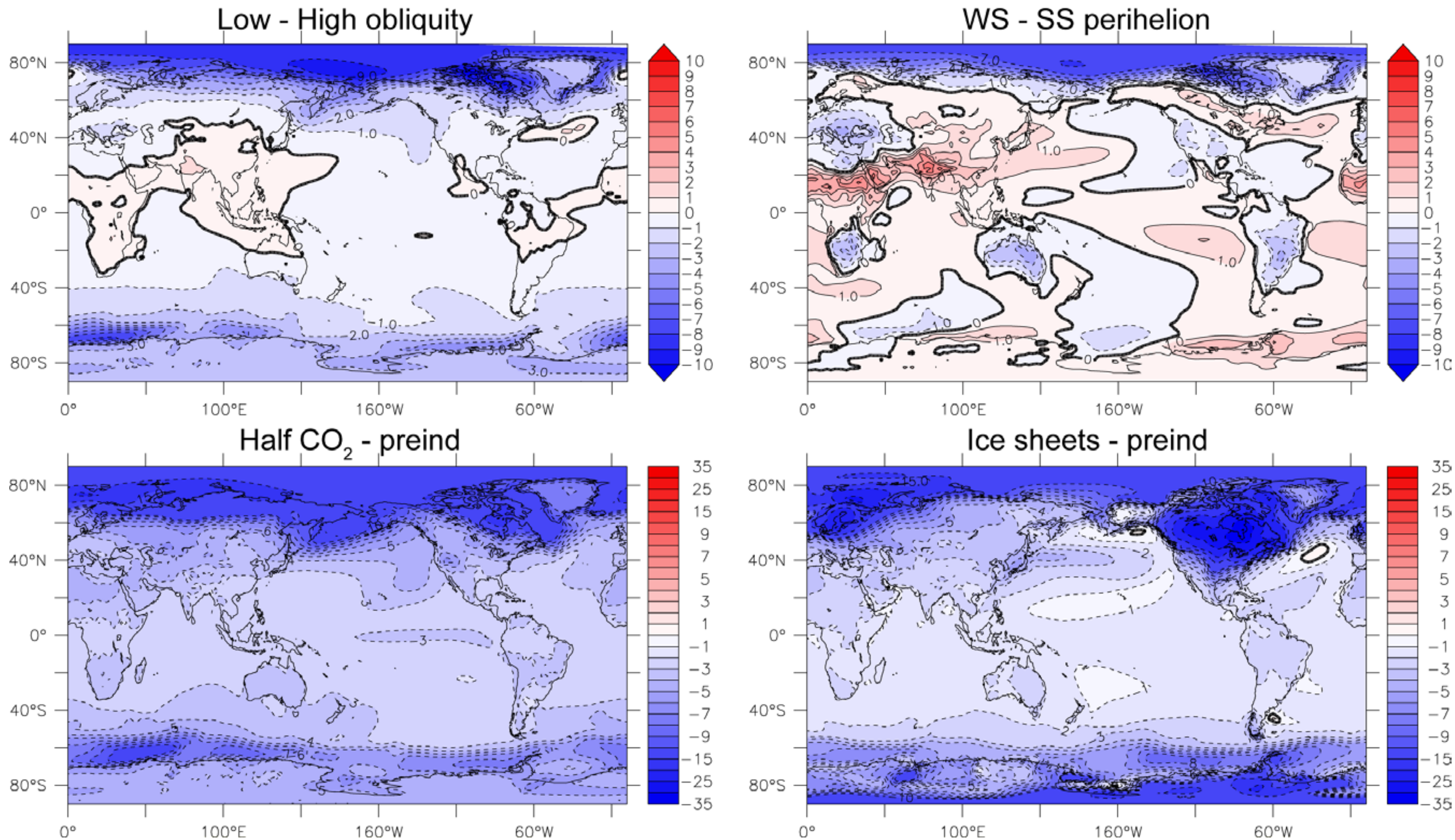
“Fingerprint” simulations

Simulations are conducted with CESM and GFDL CM2.1 to isolate the effects of individual forcings. One forcing is changed while all others remain at preindustrial levels.

Forcing parameters for CESM simulations

		Obliquity (°)	Longitude of perihelion (°)	Eccentricity	CO_2 (ppm)	Ice sheets
	Preindustrial	23.441	102.72	0.0167	284.7	0 ka BP
Obliquity	Low obliquity	22.079	---	---	---	---
	High obliquity	24.480	---	---	---	---
Precession	AE perihelion	---	0	0.0493	---	---
	WS perihelion	---	90	0.0493	---	---
	VE perihelion	---	180	0.0493	---	---
	SS perihelion	---	270	0.0493	---	---
	Zero eccentricity	---	---	0	---	---
	Half CO_2	---	---	---	142.35	---
	Ice Sheets	---	---	---	---	21 ka BP

“Fingerprint” simulations

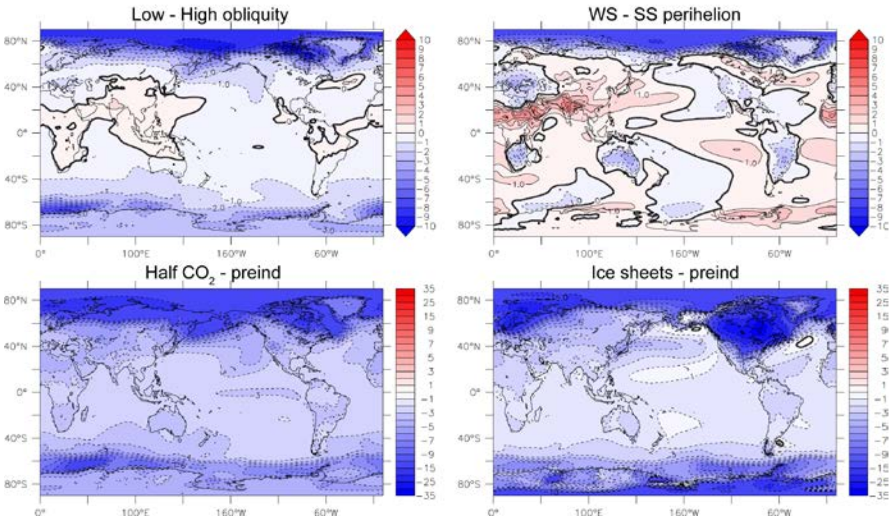


Annual-mean temperature anomalies due to changes in obliquity, precession, CO_2, and ice sheets in CESM.

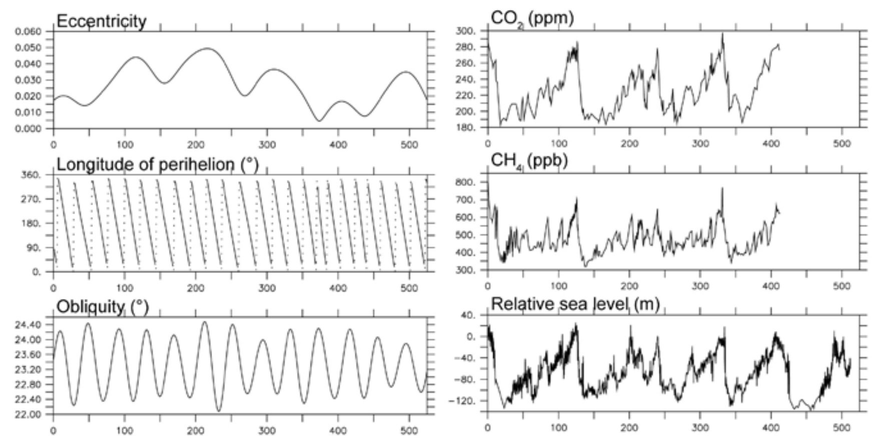
Linear climate reconstructions

To compare these single-forcing "fingerprint" simulations to data, linear climate reconstructions are computed. These are made by scaling the modeled climate responses by time-varying forcings.

Annual-mean ΔT (°C)

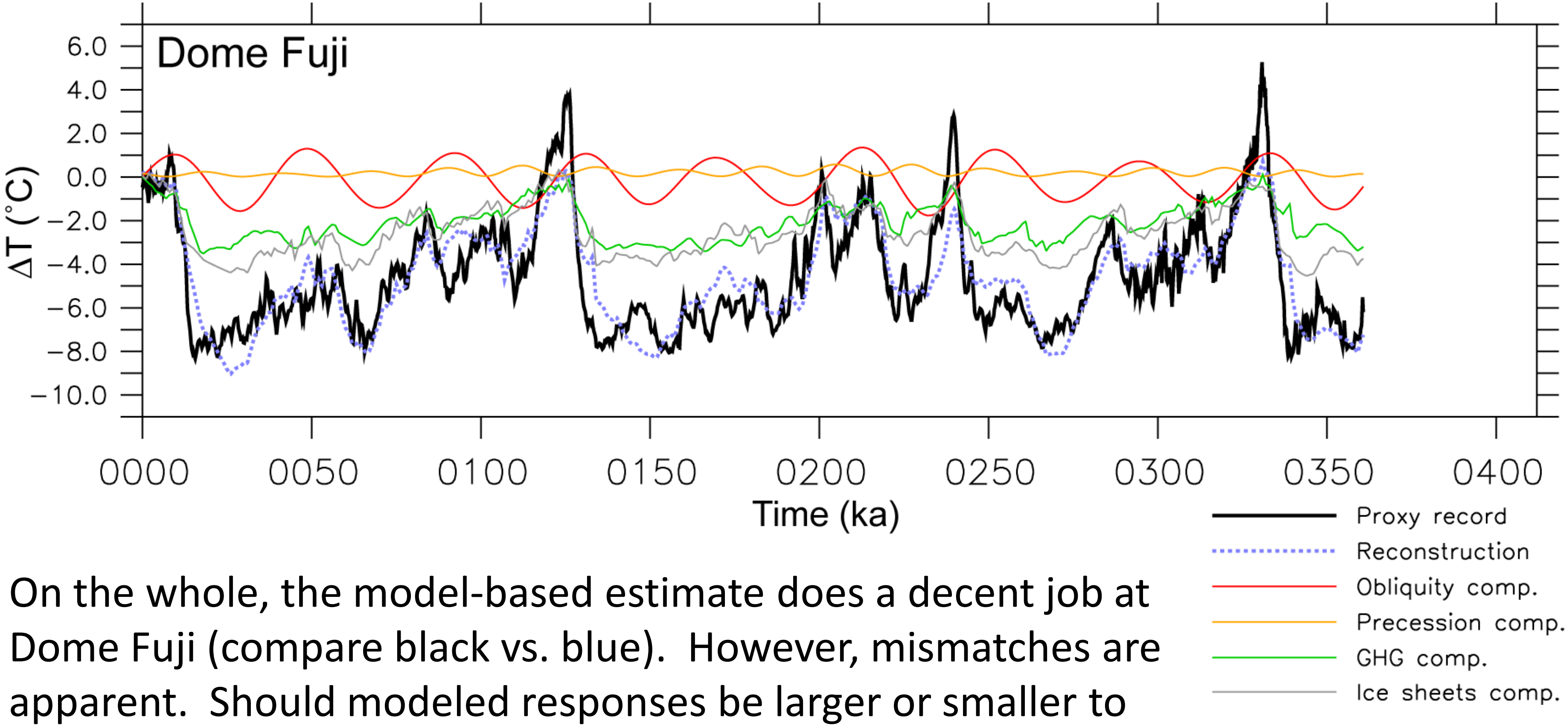


Time-varying forcings



Example of a linear reconstruction

The Dome Fuji temperature record can be compared to the model-based linear reconstruction at that location.

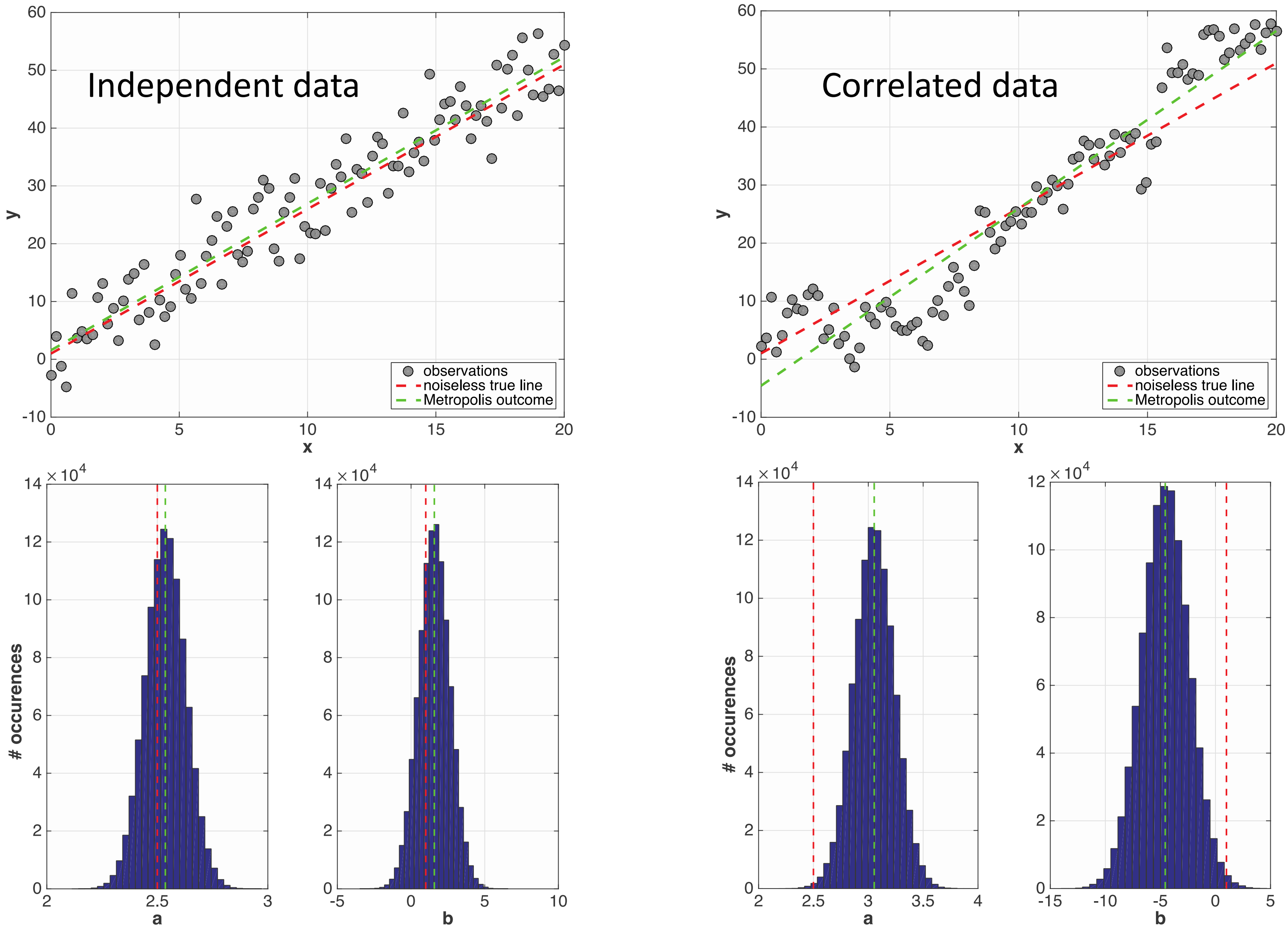


On the whole, the model-based estimate does a decent job at Dome Fuji (compare black vs. blue). However, mismatches are apparent. Should modeled responses be larger or smaller to best match the data?

Detection and Attribution

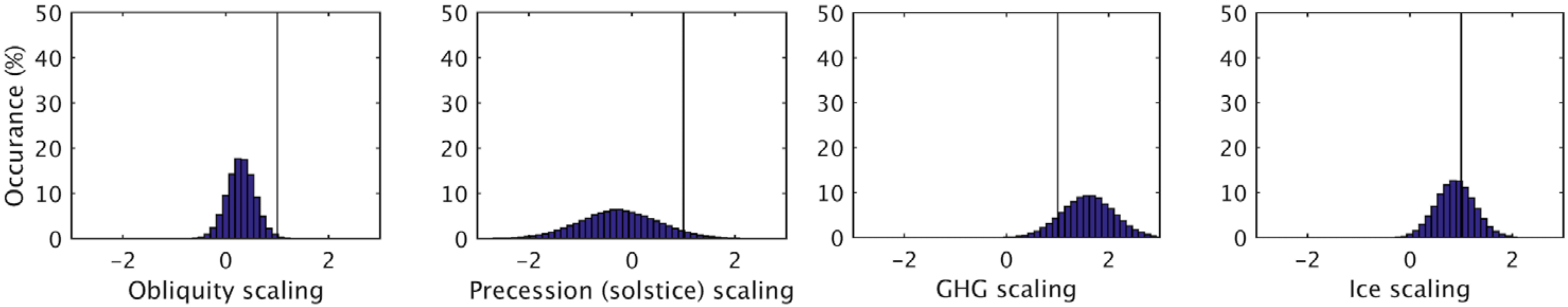
- Each fingerprint is a hypothesis.
- Models estimate fingerprints, data determines amplitudes.
- Scatter around fit line provides information about uncertainty. (Common device in Bayesian inference)
- Method uses time and space from multiple proxies to help determine amplitudes of signal that explain all the data.

Uncertainties are affected by number of independent data points AND Identifyability of different signals.

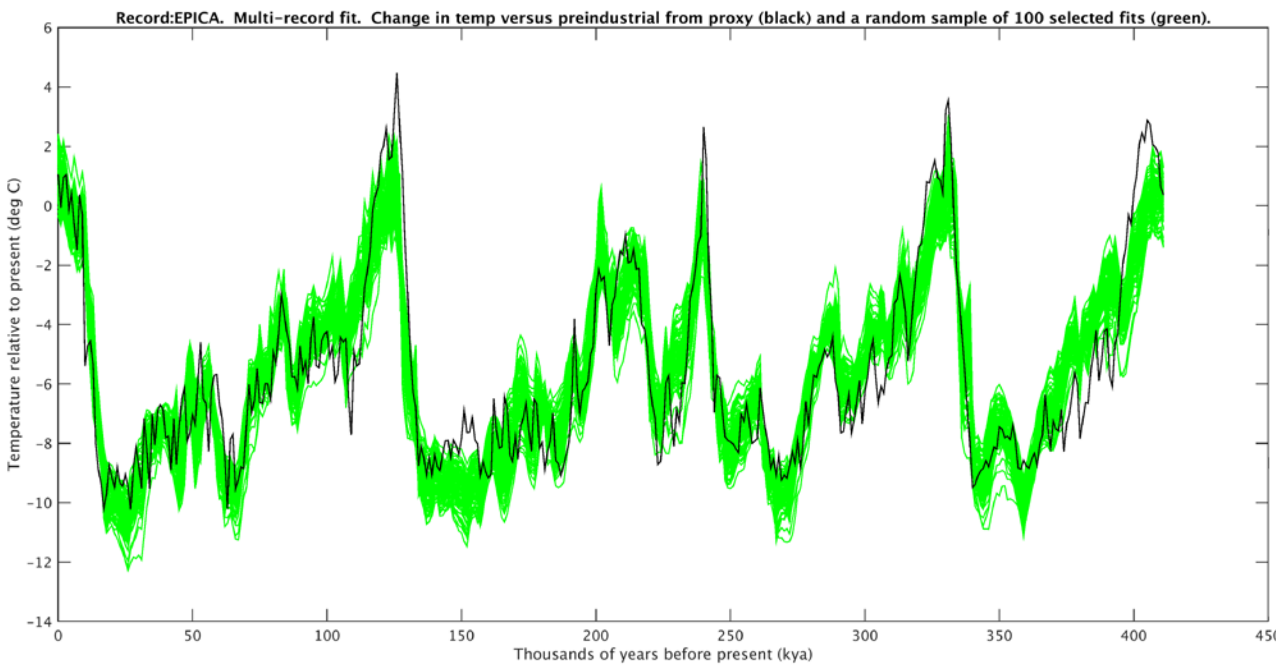


EPICA

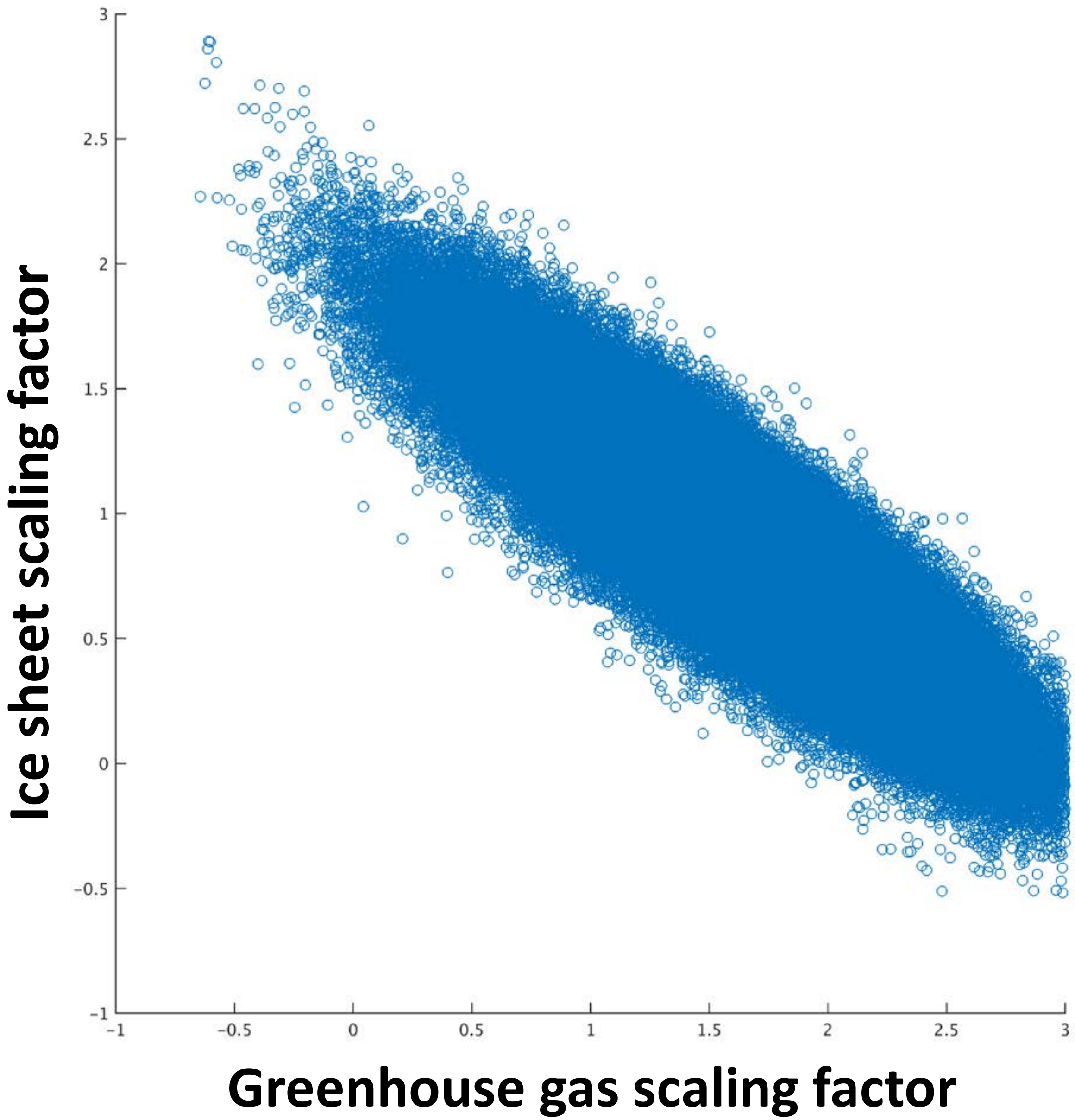
Joint probability distributions for scaling parameters



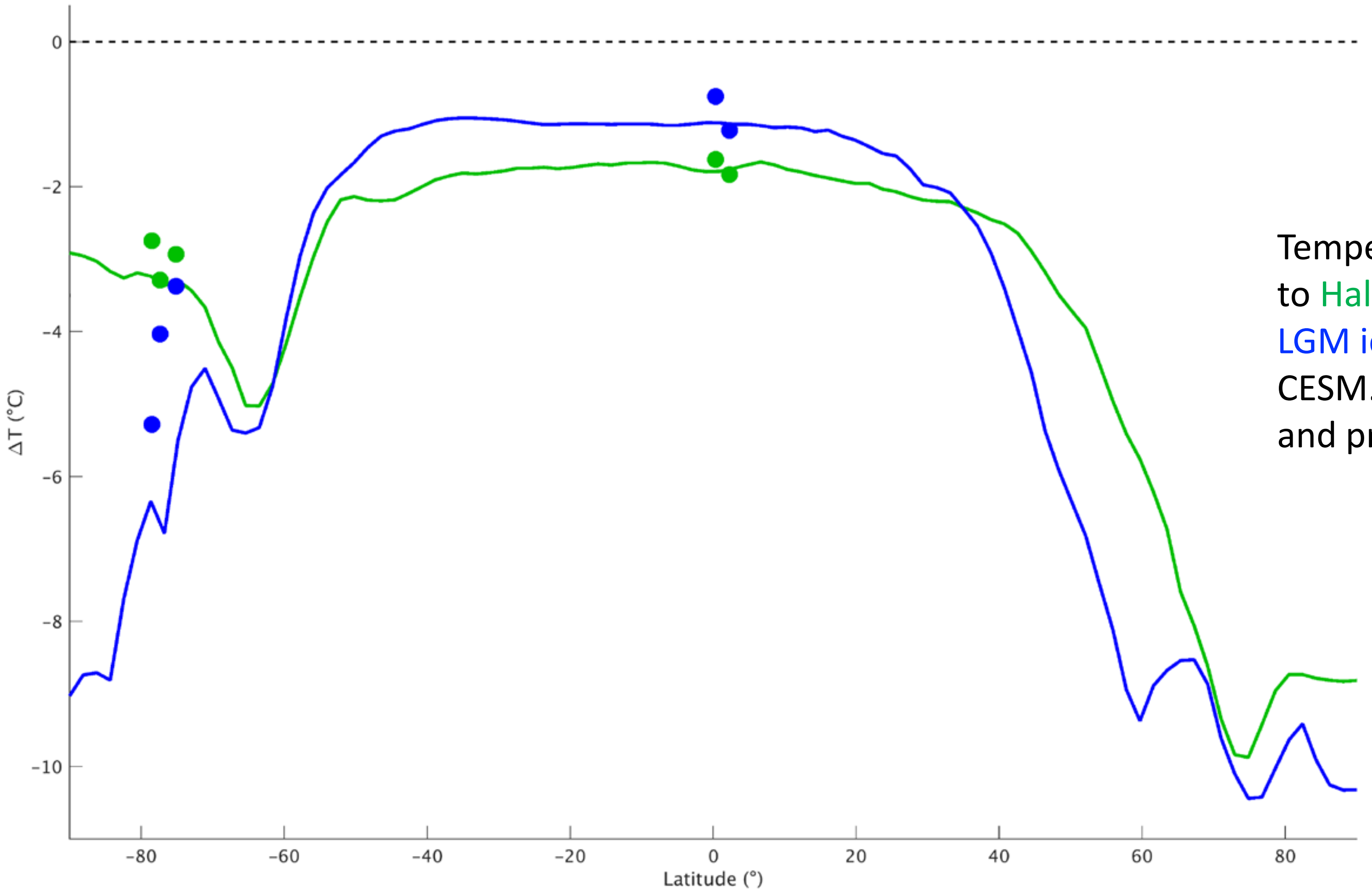
Samples representing uncertainty in the fit to EPICA



It is difficult to uniquely identify greenhouse gas signal in EPICA data.



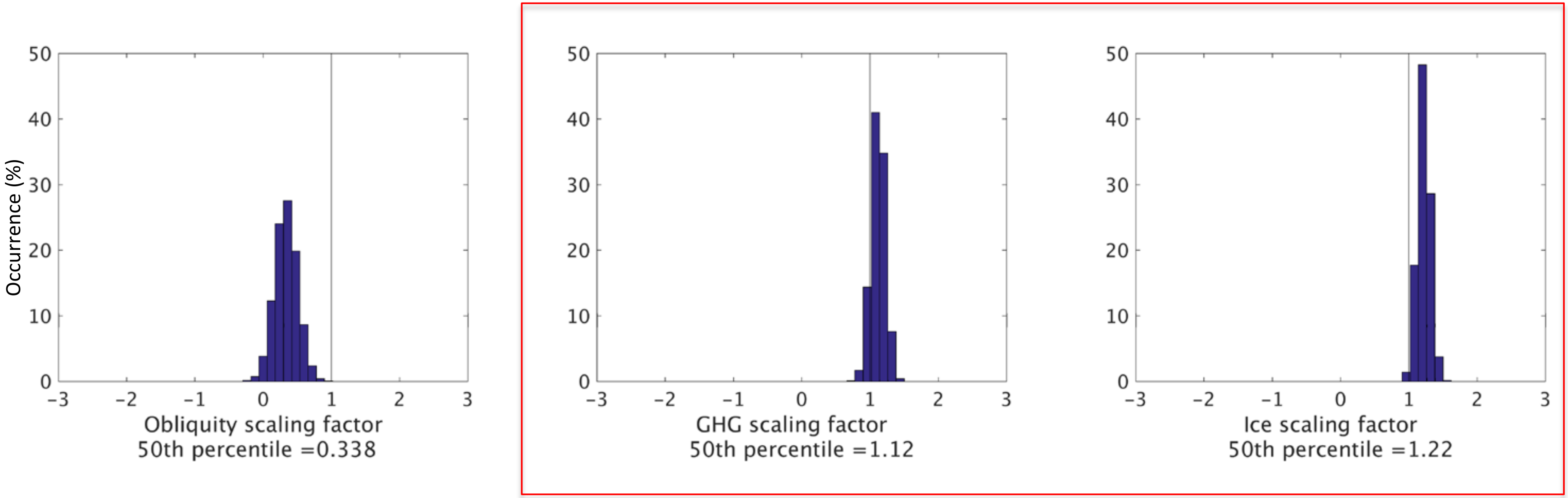
Latitudinal differences in temperature response to GHG vs. ice sheets



Temperature changes due to Half CO2 (green) and LGM ice sheets (blue) in CESM. Zonal-means (lines) and proxy locations (dots).

Ice sheets affect tropical temperatures, but have a larger polar amplification than CO_2. These latitudinal differences should help distinguish the effect of CO_2 vs. ice sheets in the proxy record.

Scaling parameters (posterior PDFs)



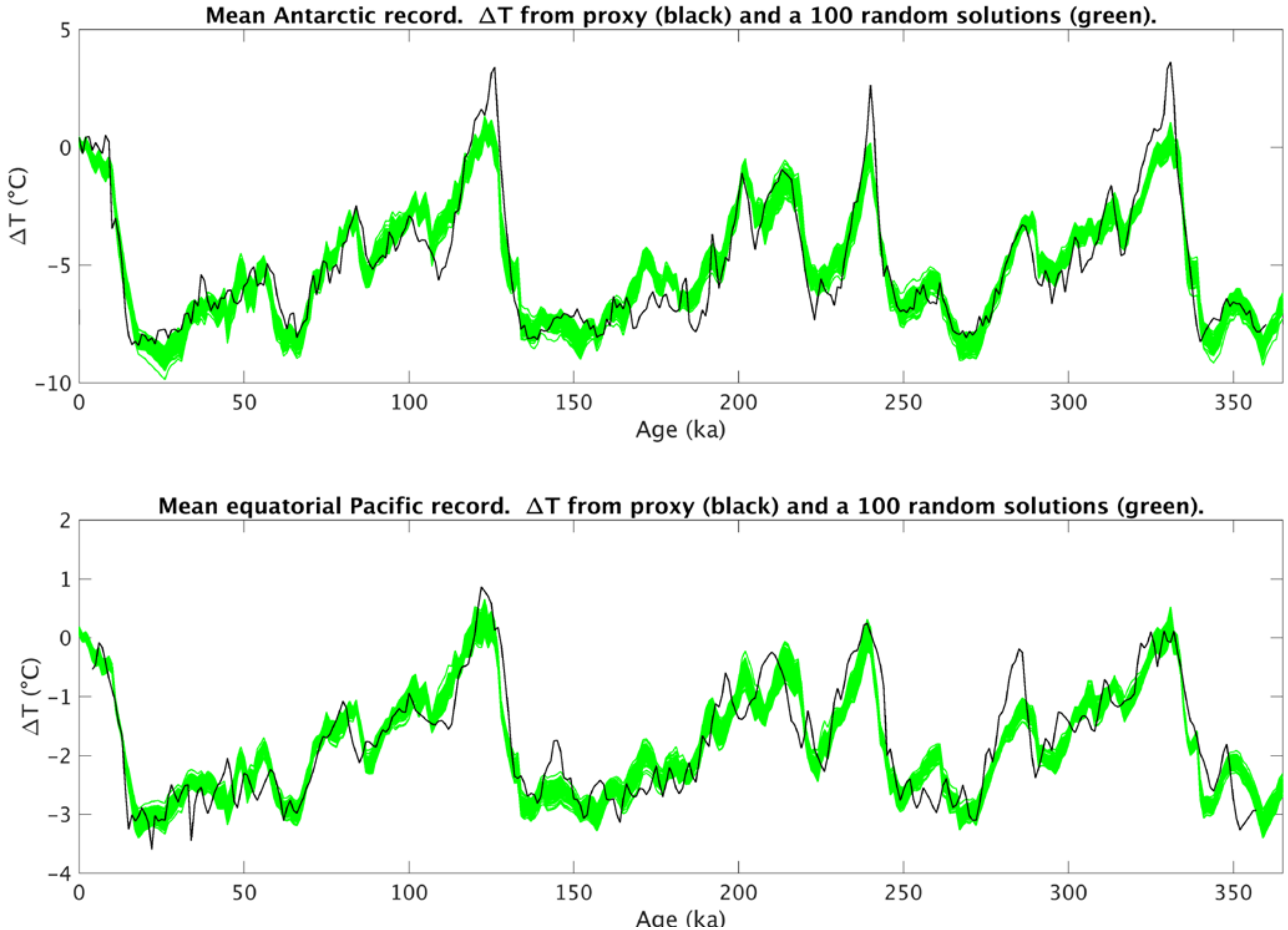
- The proxies support only a small response to obliquity (34% of the modeled response).
- The proxies do not offer a good constraint on precession (not shown).
- The GHG and ice sheet responses should both be slightly stronger to best match the proxies (112% and 122%, respectively).

Reconstructions vs. proxy records

Each component of the reconstruction (obliquity, precession, GHGs, and ice sheets) is allowed to scale up or down in a Bayesian framework to best match the mean proxy records.

100 solutions of the Bayesian matching.

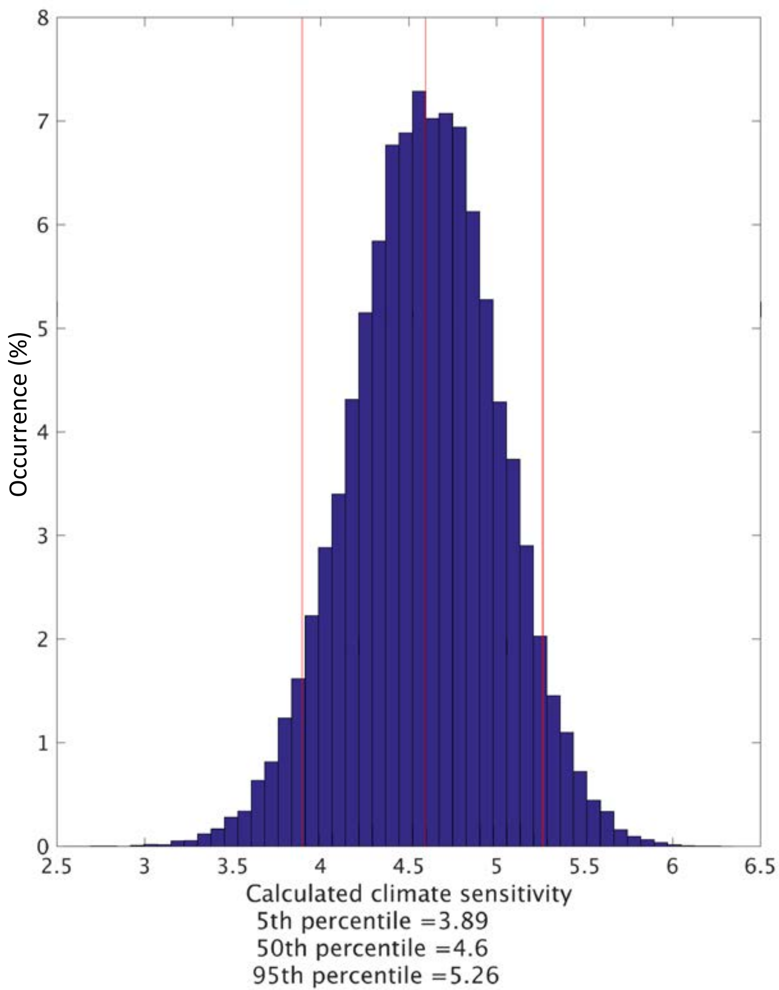
The reconstruction does a good job matching variability in both Antarctica (top) and the equatorial Pacific (bottom).

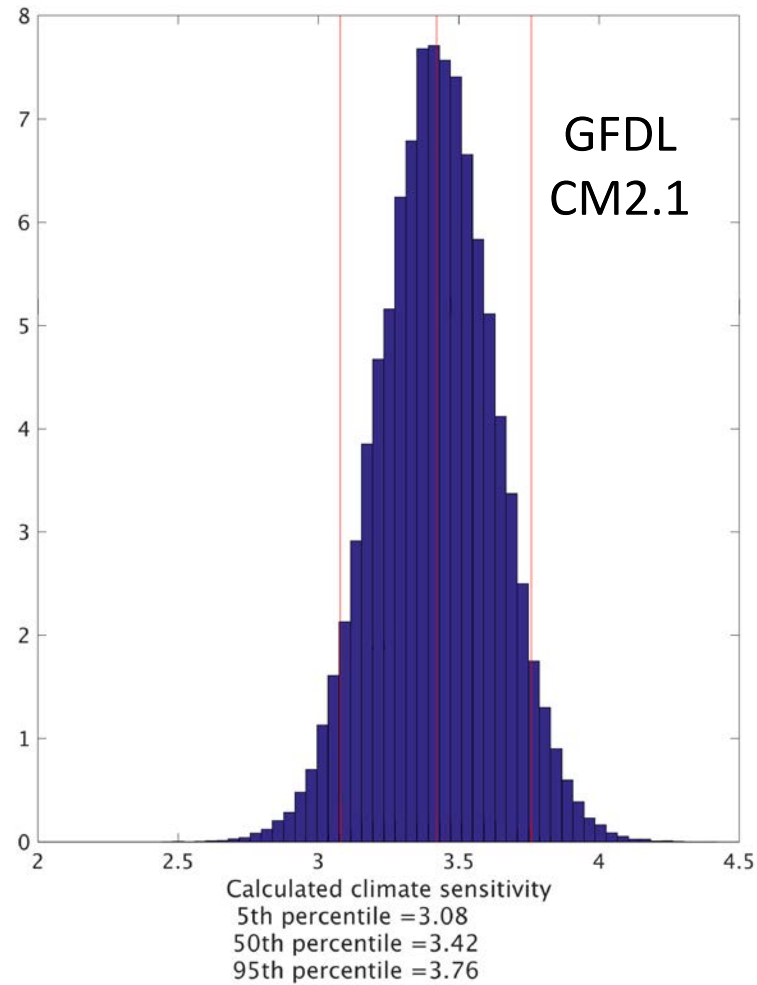


Inferred climate sensitivity

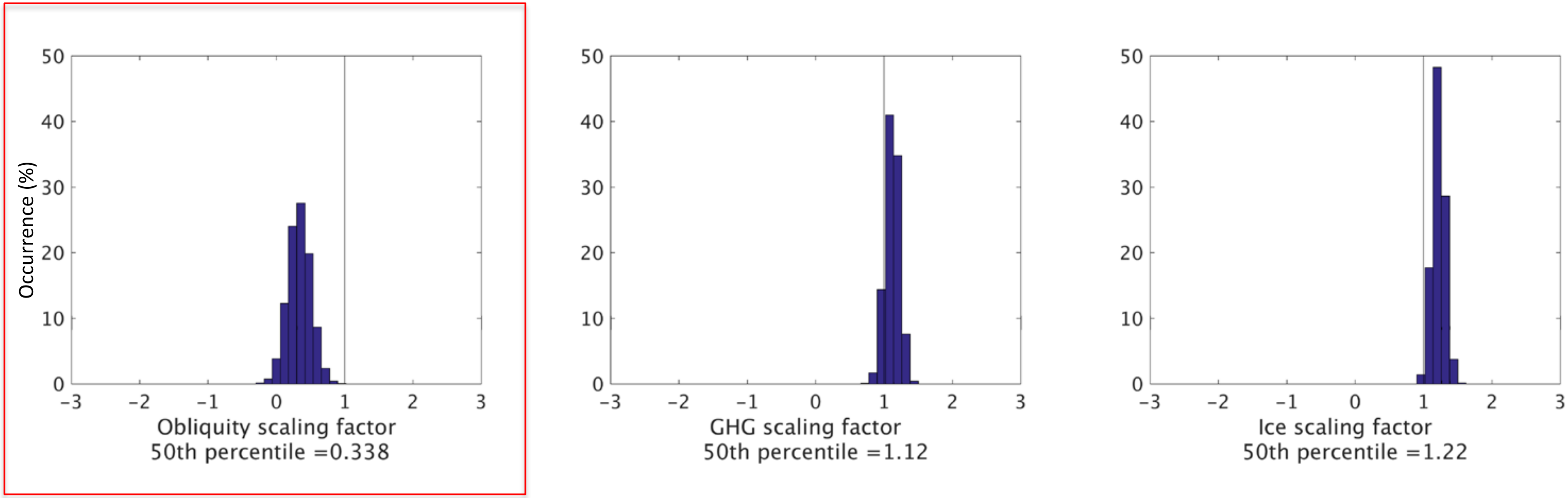
Multiplying the scaling parameter by the climate sensitivity of each model gives an estimate of the proxy-supported (Charney) climate sensitivity.

CESM
(The CO_2 simulation is still equilibrating, so this answer will likely decrease.)





Scaling parameters (posterior PDFs)



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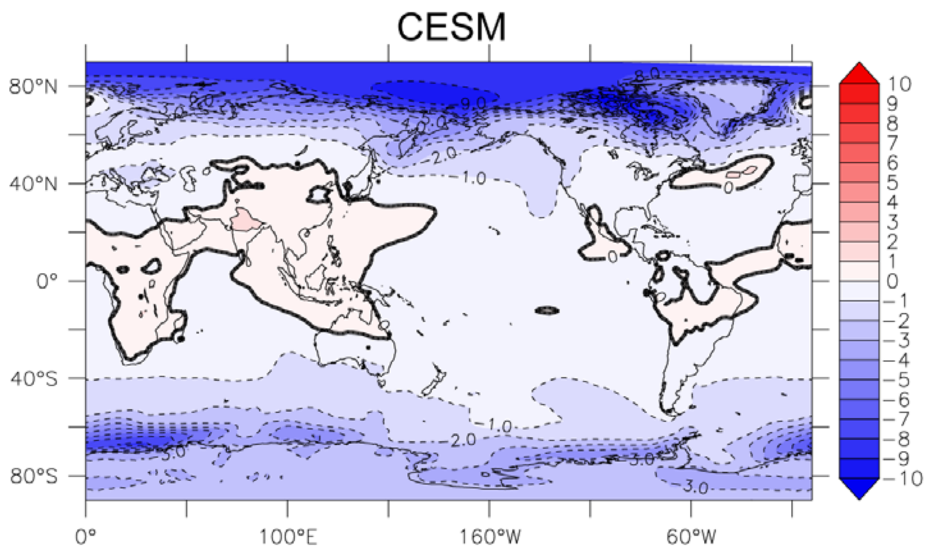
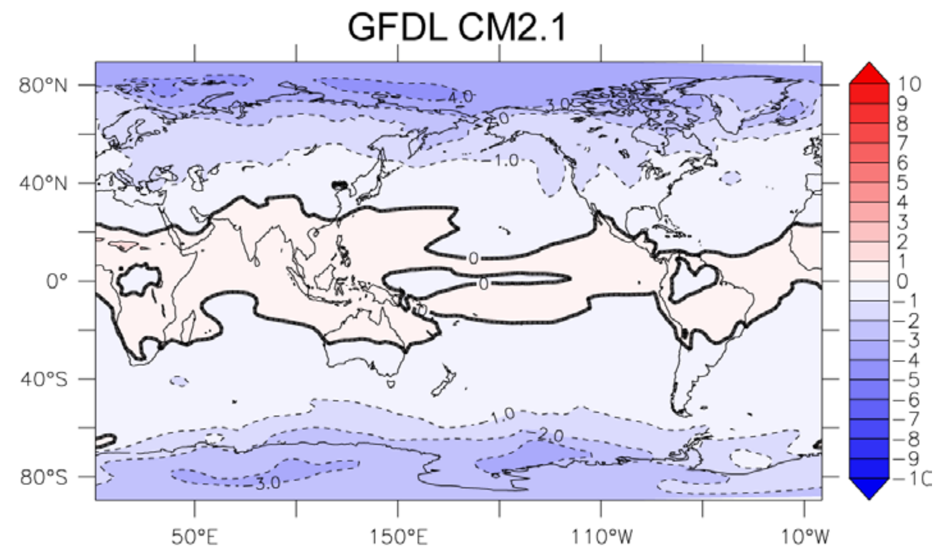
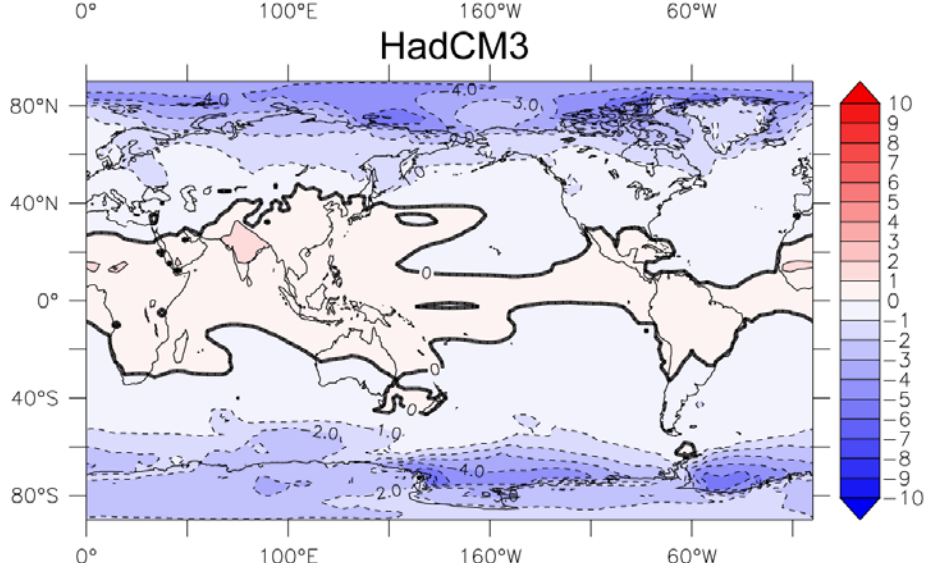
Temperature response to obliquity





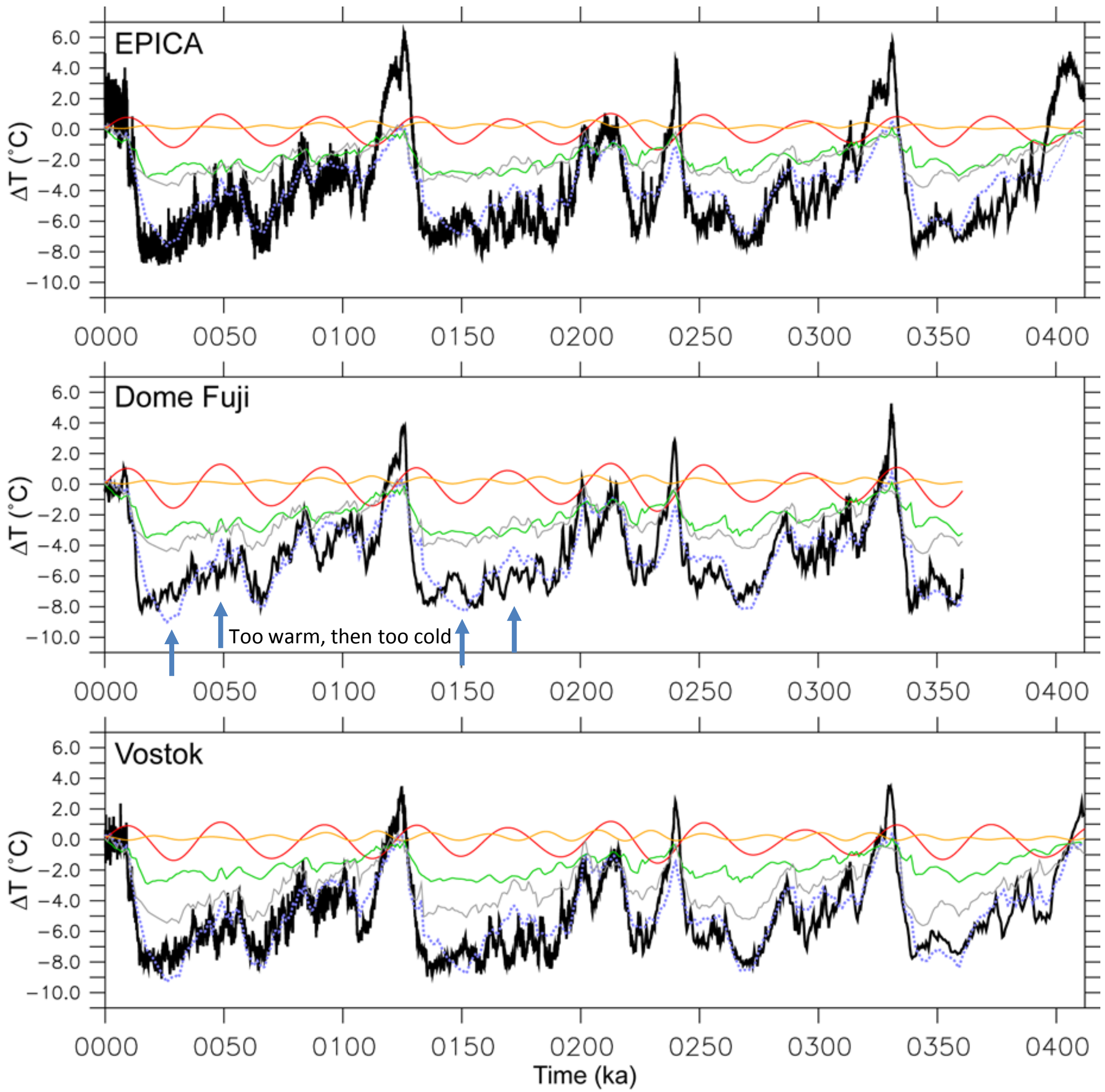


Surface air temperature response to lowered obliquity in three GCMs.

- Small temperature change at low latitudes.
- Large cooling at high latitudes.

HadCM3 result derived from experiments by Paul Valdes.

Linear reconstructions in Antarctica

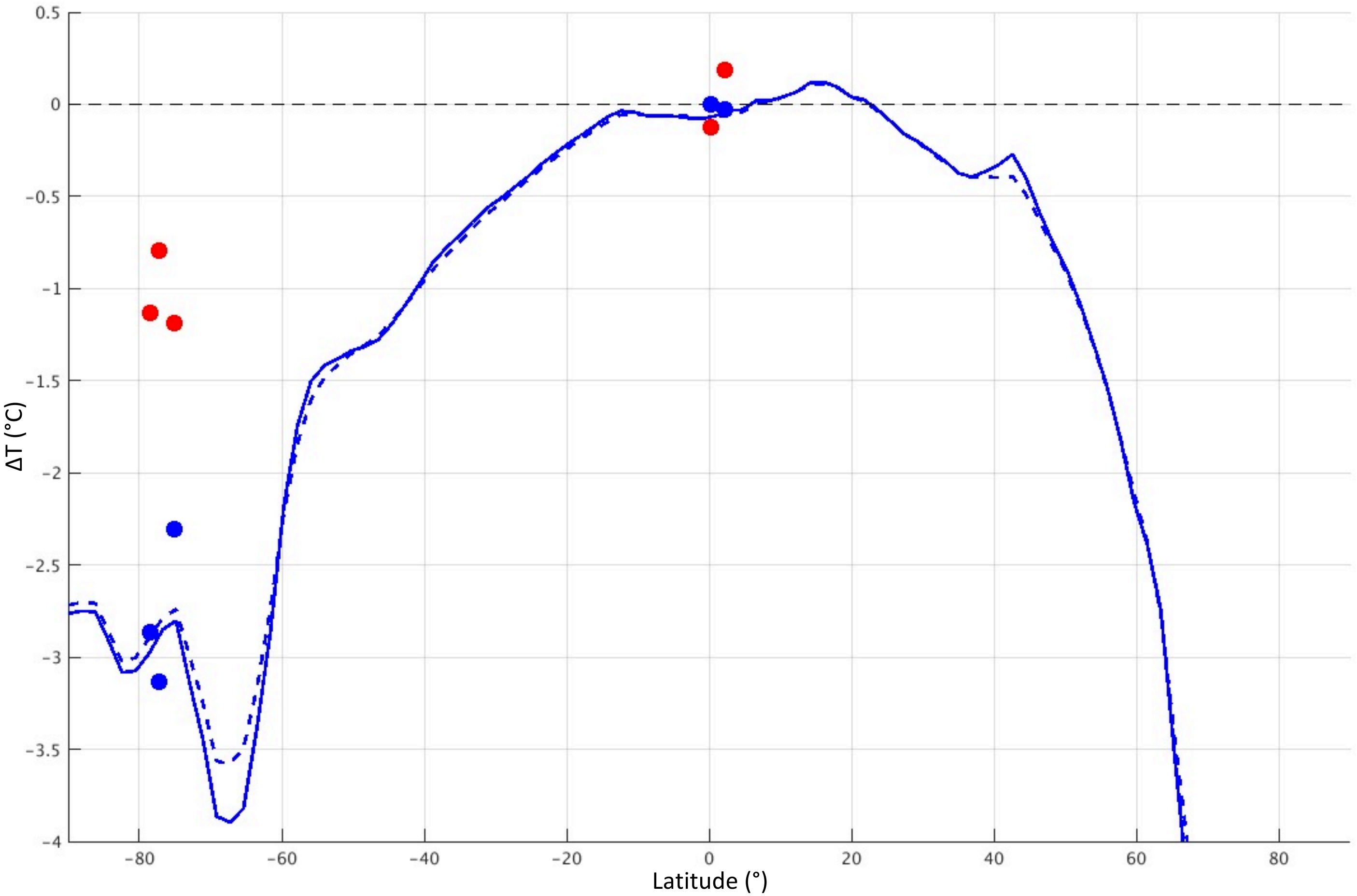


Temperature in **ice cores (black)** vs. **linear reconstructions (dotted blue)** for three Antarctic ice cores.

A mismatch is apparent at the period of obliquity.

By scaling the obliquity response larger or smaller to minimize this mismatch, we can determine the obliquity response best supported by the proxy data.

Small obliquity signal in Antarctic ice cores



Temperature response to lowered obliquity (°C)

Blue: Modeled temperature change for zonal-means (lines; surface and 2m) and proxy locations (dots).

Red: Temperature changes best supported by the proxies.

The linear reconstructions best match Antarctic proxies when the obliquity response is reduced to 15-50% of its modeled value. Low latitude records match well without scaling.

Seasonal bias in ice cores?

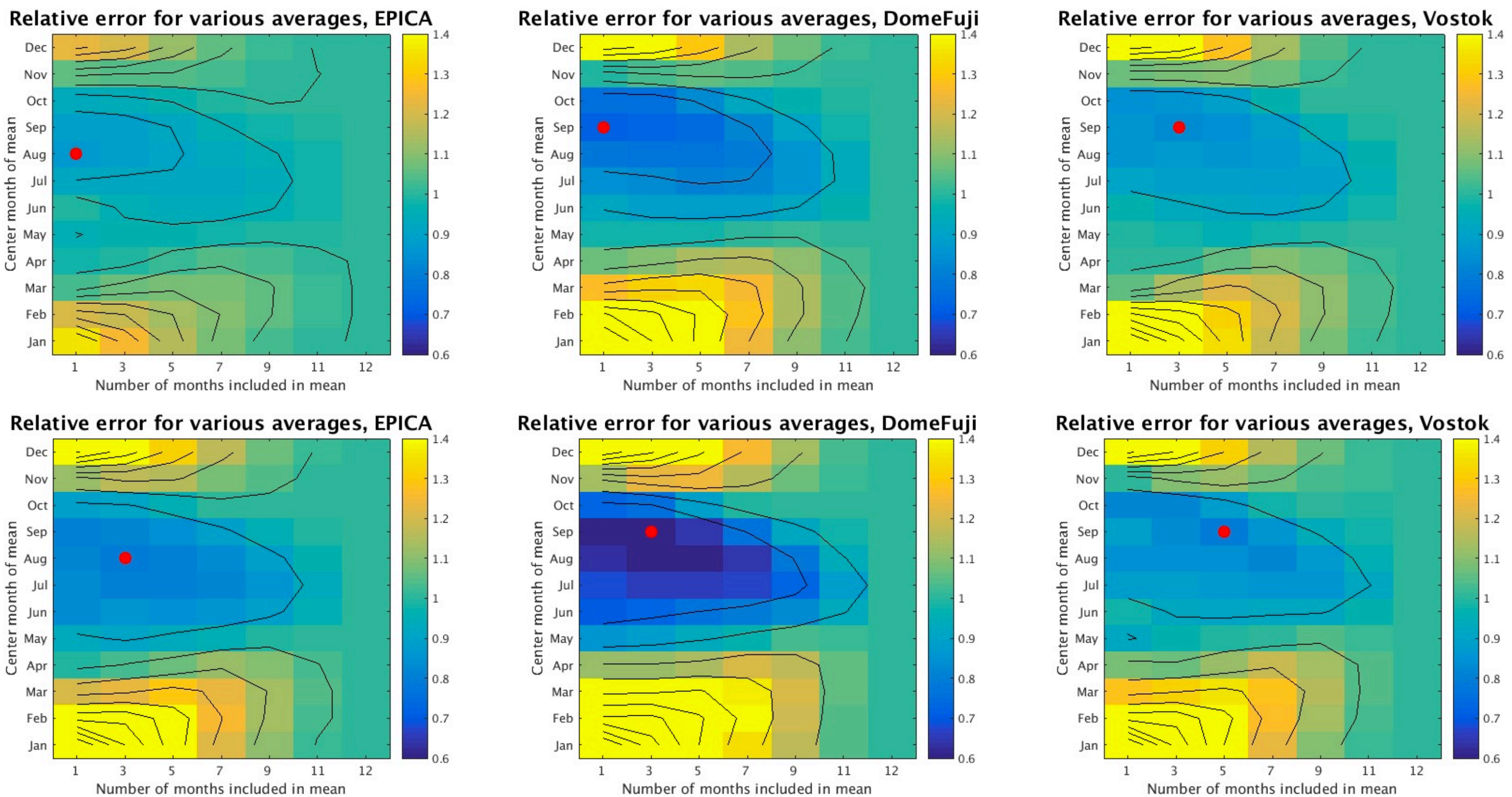
One possible explanation for the obliquity mismatch: a seasonal bias in ice cores.

Instead of scaling the magnitude of the obliquity component, different seasonal averages are computed for the total reconstruction.

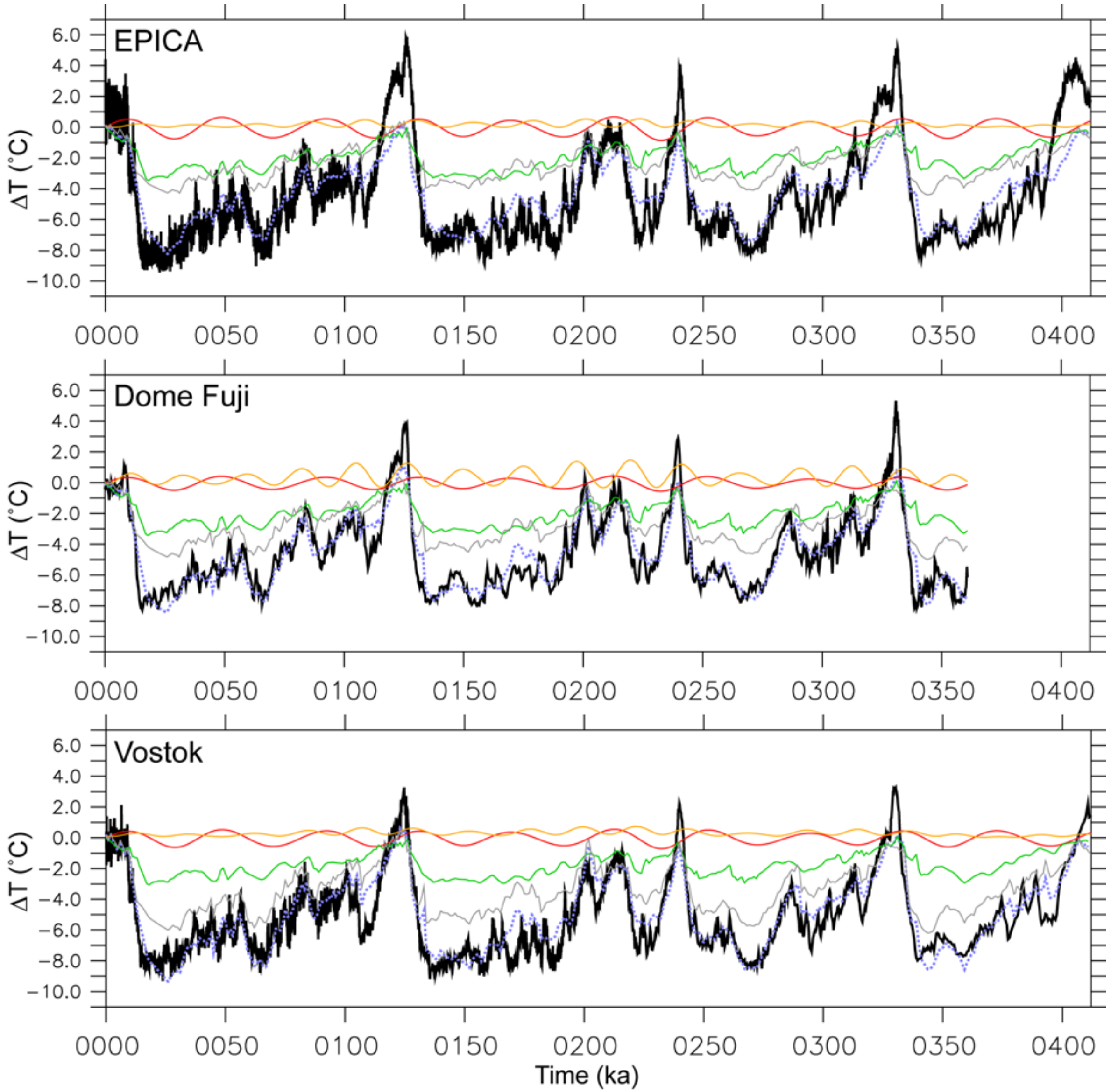
The match to proxy records is improved for means weighted toward ~September.

Relative RMSE for different seasonal averages. (Annual-mean=1; blue is better.)

CESM (top) and GFDL CM2.1 (bottom).



Seasonally-weighted linear reconstructions



Temperature in **ice cores (black)** vs. **linear reconstructions (dotted blue)** for three Antarctic ice cores.

The mismatches have been reduced in the seasonally-weighted reconstructions.

More work must be done to explore a potential seasonal bias in ice cores. Effect of seasonal snowfall and/or sublimation?

Conclusions

- Latitudinal differences in the response to ice sheets and CO_2 helps distinguish the effect of each in the proxy record. Initial analysis suggests a climate sensitivity of ~3-5°C for a doubling of CO_2. (The upper end of this range may reduce as the CESM CO_2 simulation equilibrates.)

- The climate response to obliquity is larger in models than is supported by Antarctic ice cores. This could be explained by a seasonal bias (toward ~September) in Antarctic ice cores.

Data availability

Output from CESM fingerprint simulations is available on Yellowstone.

Please contact Michael Erb (merb@ig.utexas.edu) or Charles Jackson (charles@ig.utexas.edu) for access.

Thank you. Questions?