Japan Uncertainty Modelling Project

Assessing the reliability of climate model ensembles using the Last Glacial Maximum

Julia Hargreaves
Research Institute for Global Change, JAMSTEC, Japan
James Annan, Andre Paul, Rumi Ohgaito, T. Yokohata, Ayako Abe-Ouchi.

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JAMSTEC Japan Agency for Marine-Earth Science and Technology
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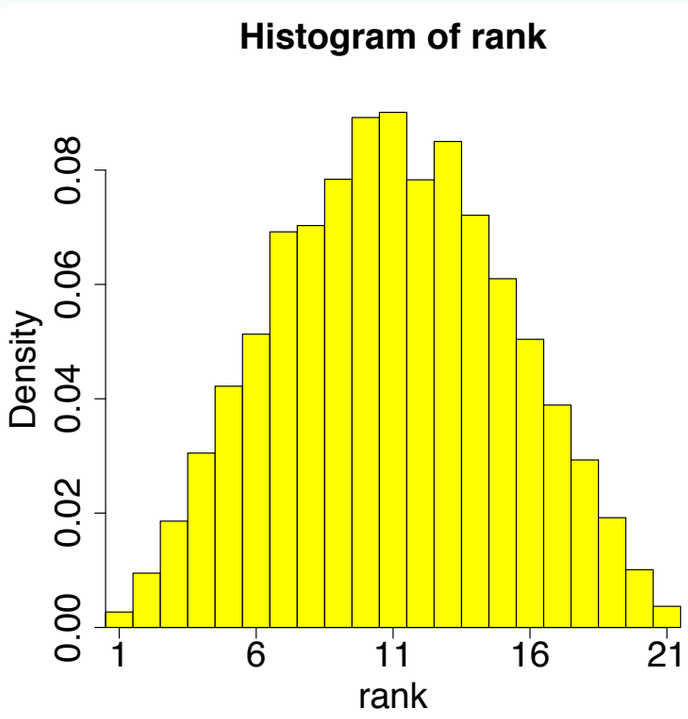

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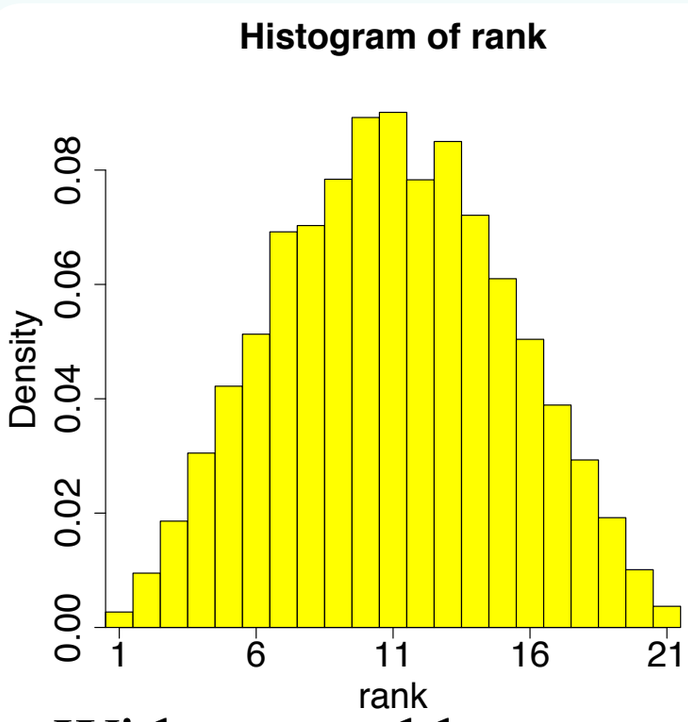

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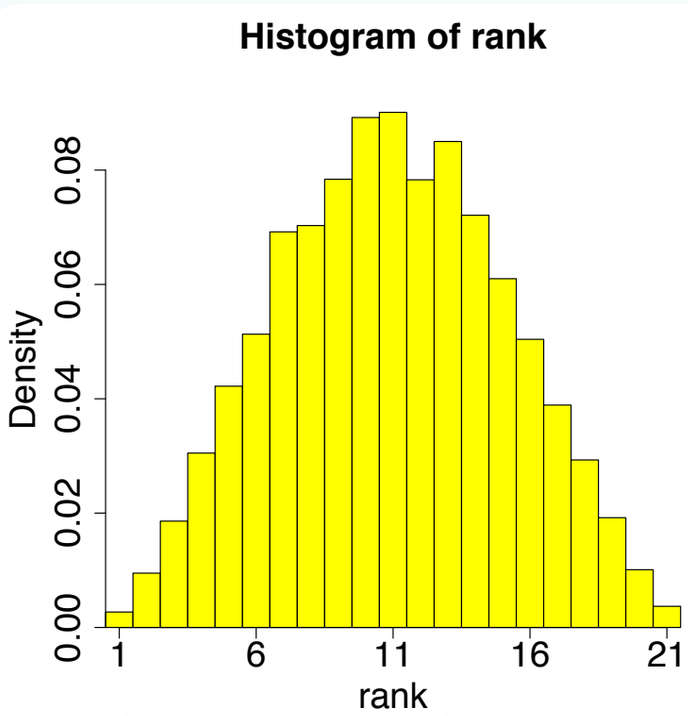

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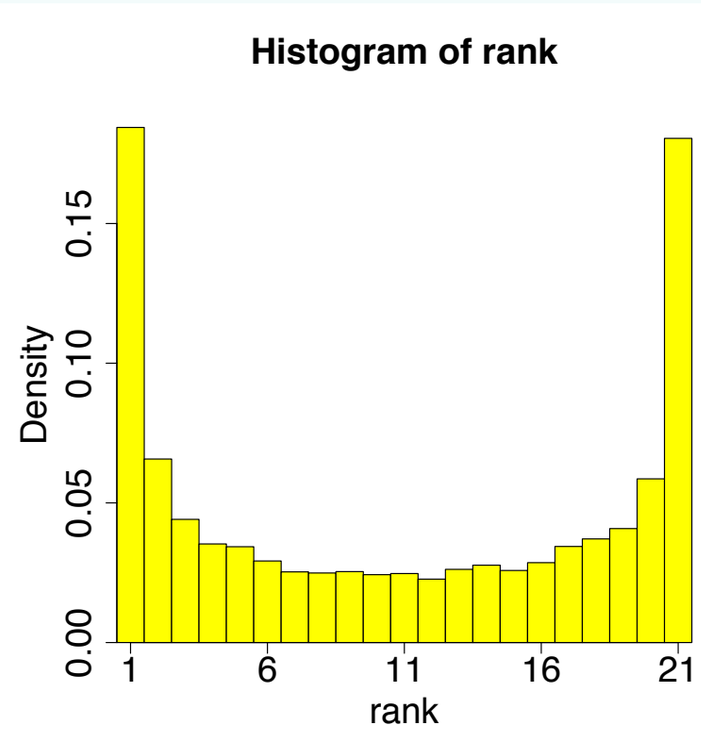

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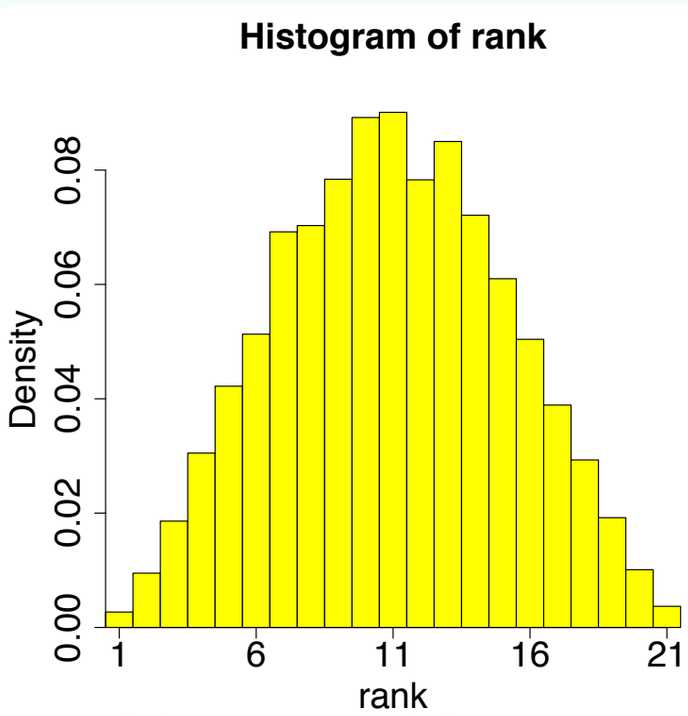

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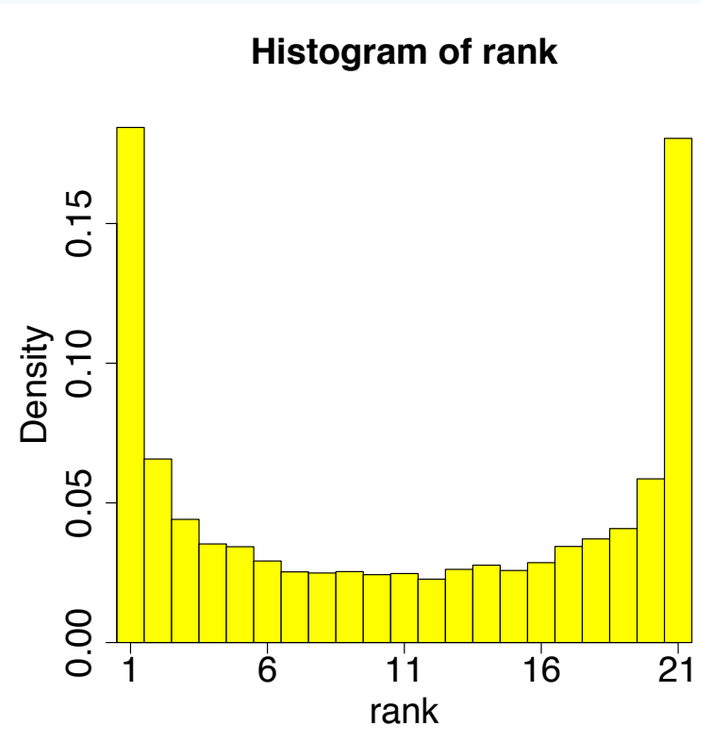

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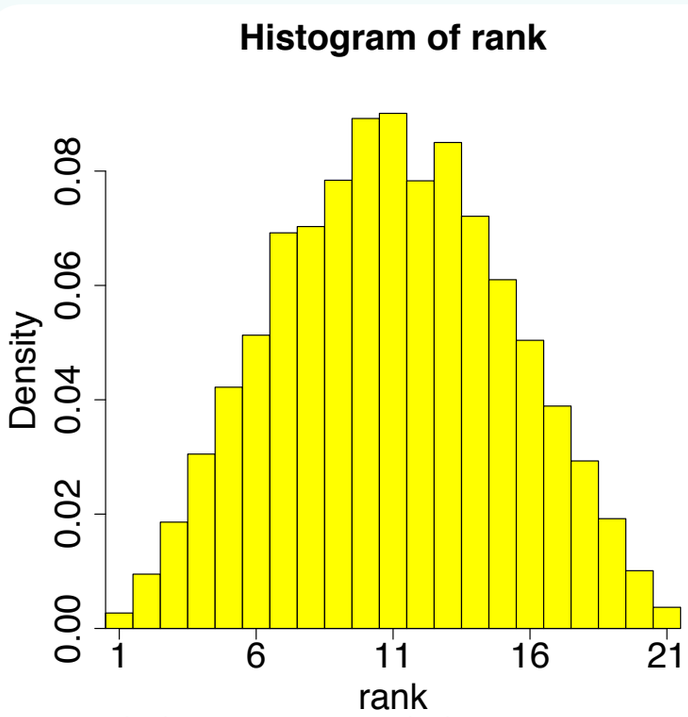

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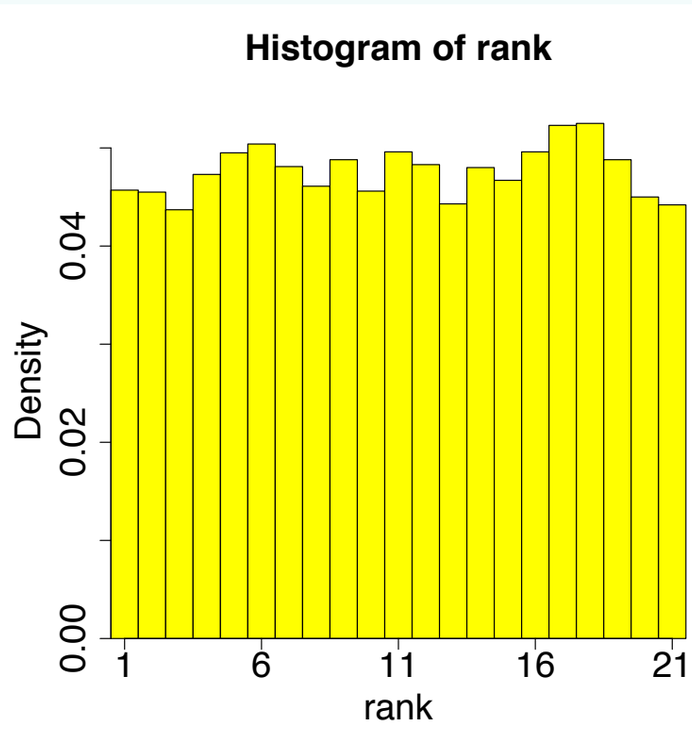

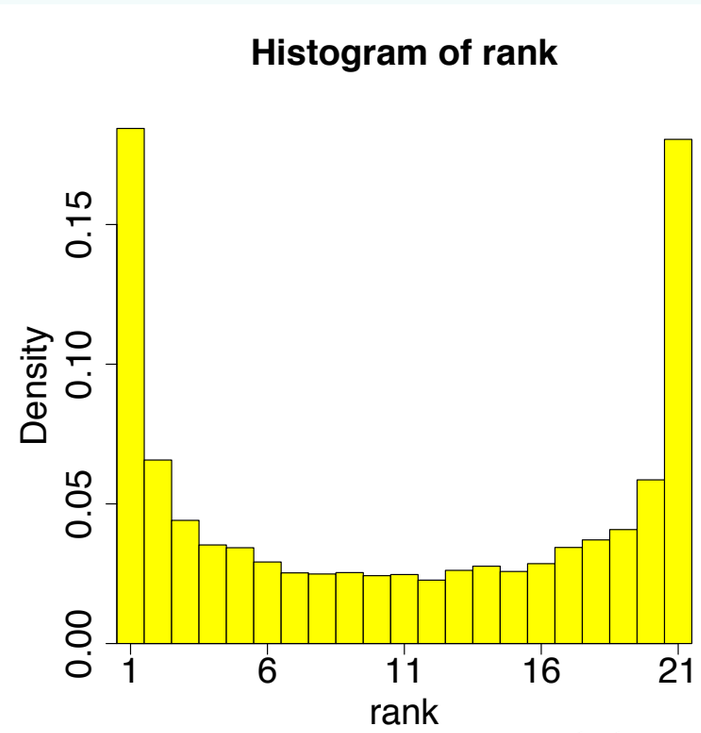

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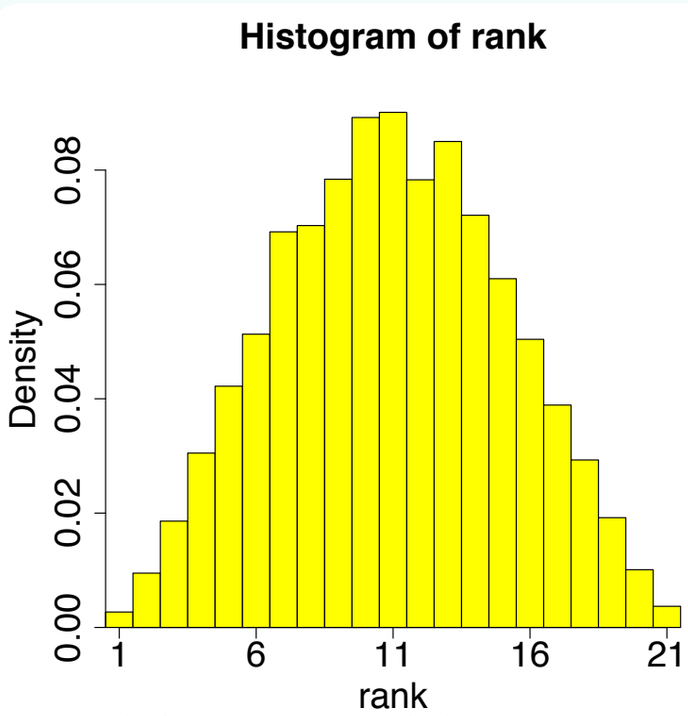

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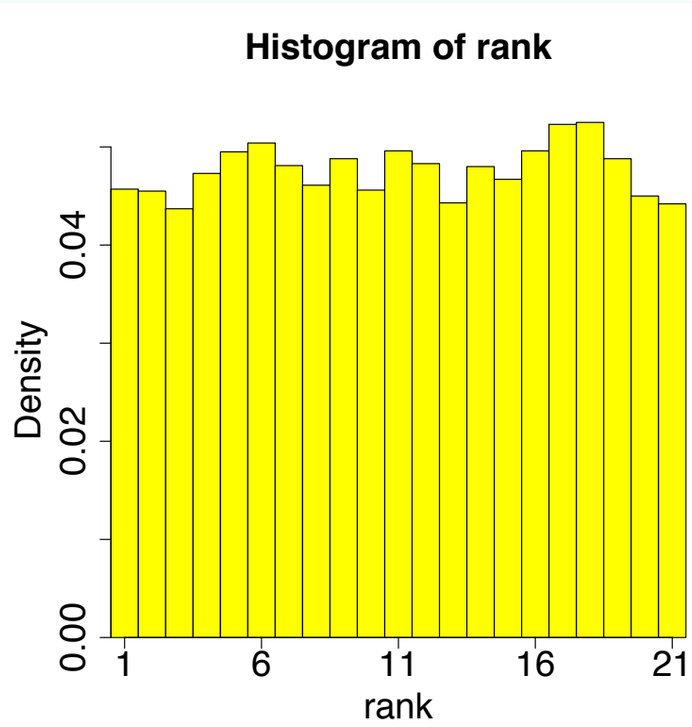
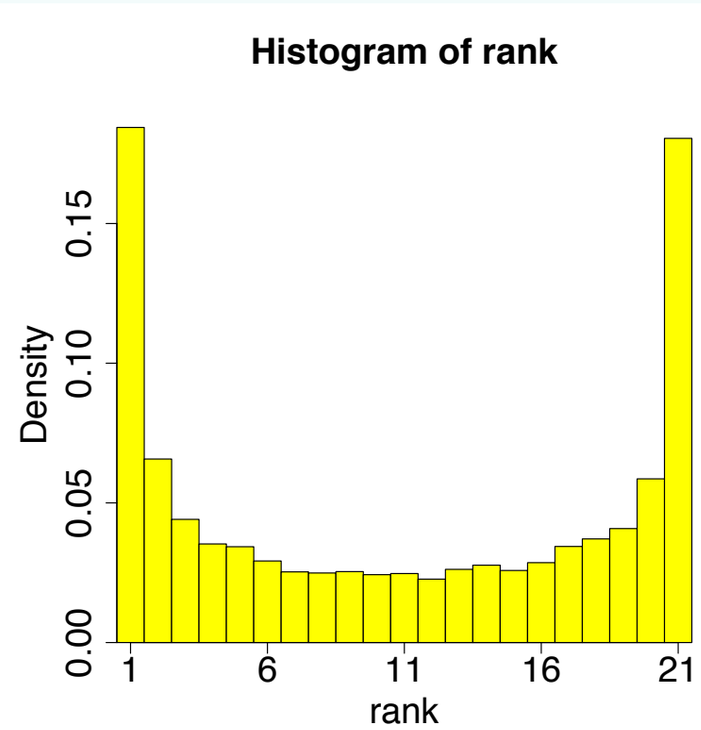


Reliable: ensemble represents our uncertainty.



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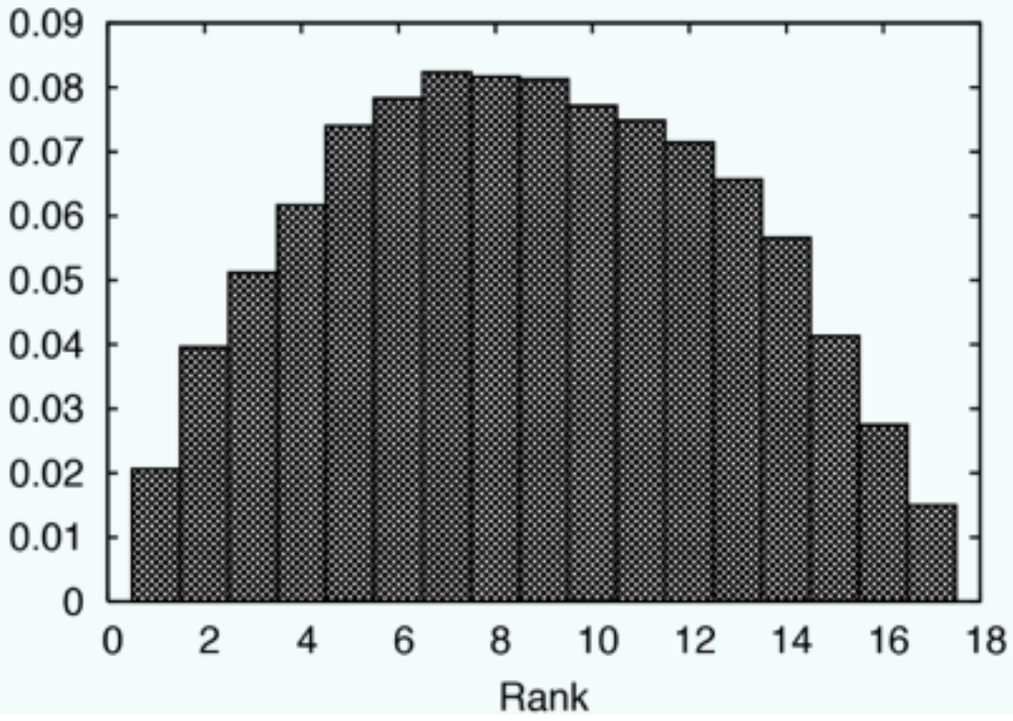

Yokohata et al, Climate Dynamics, 2011
Poster W247B - today!

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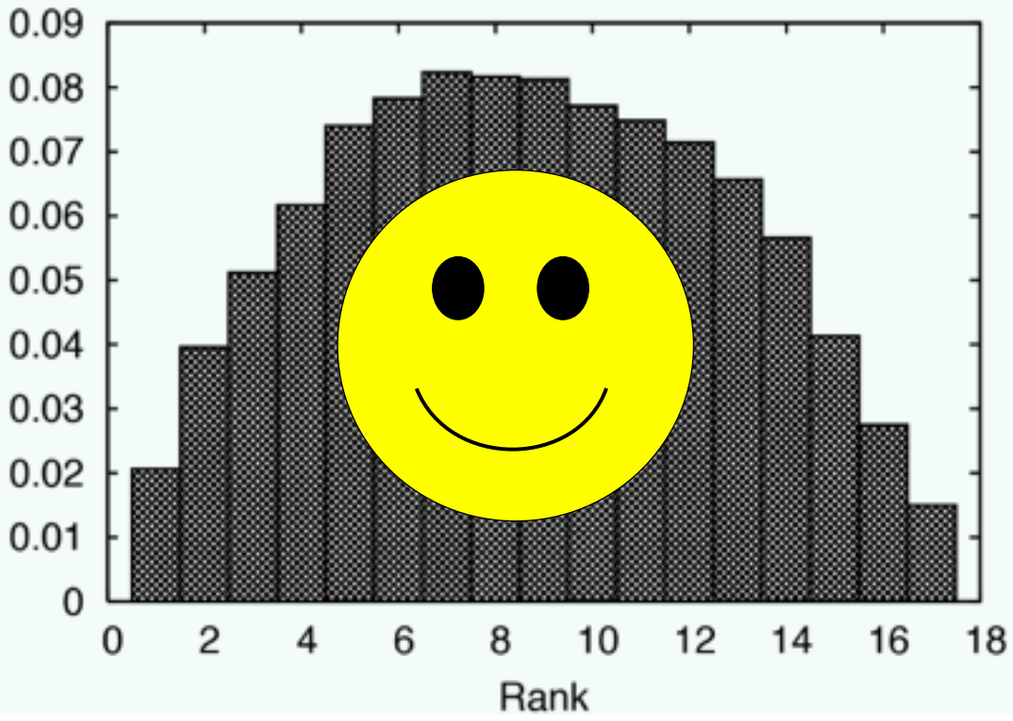

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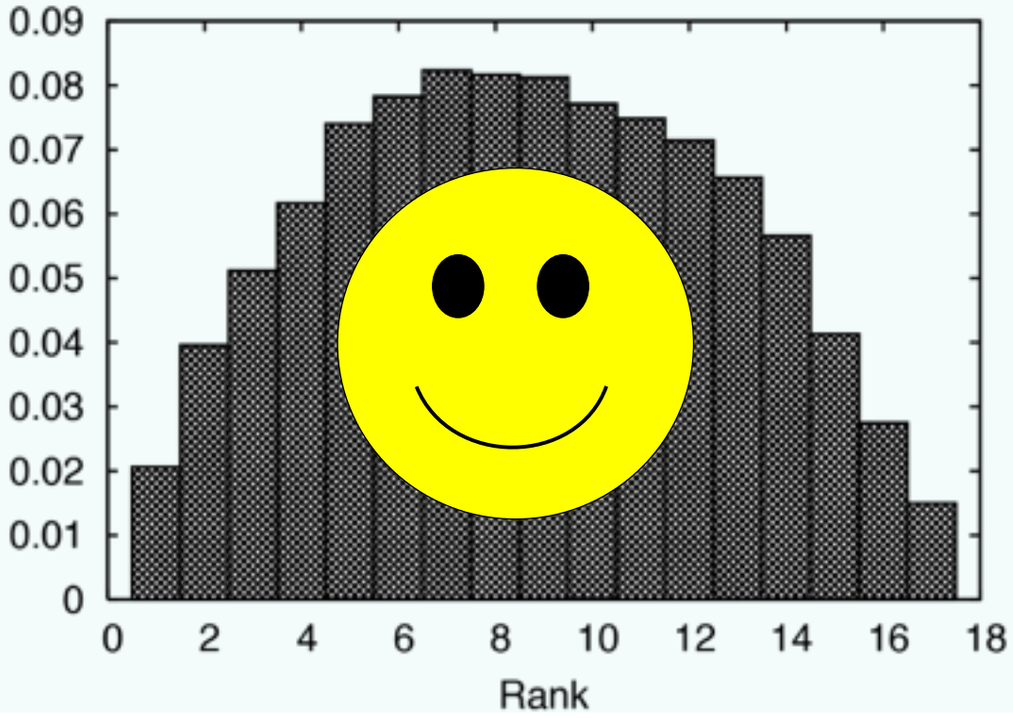

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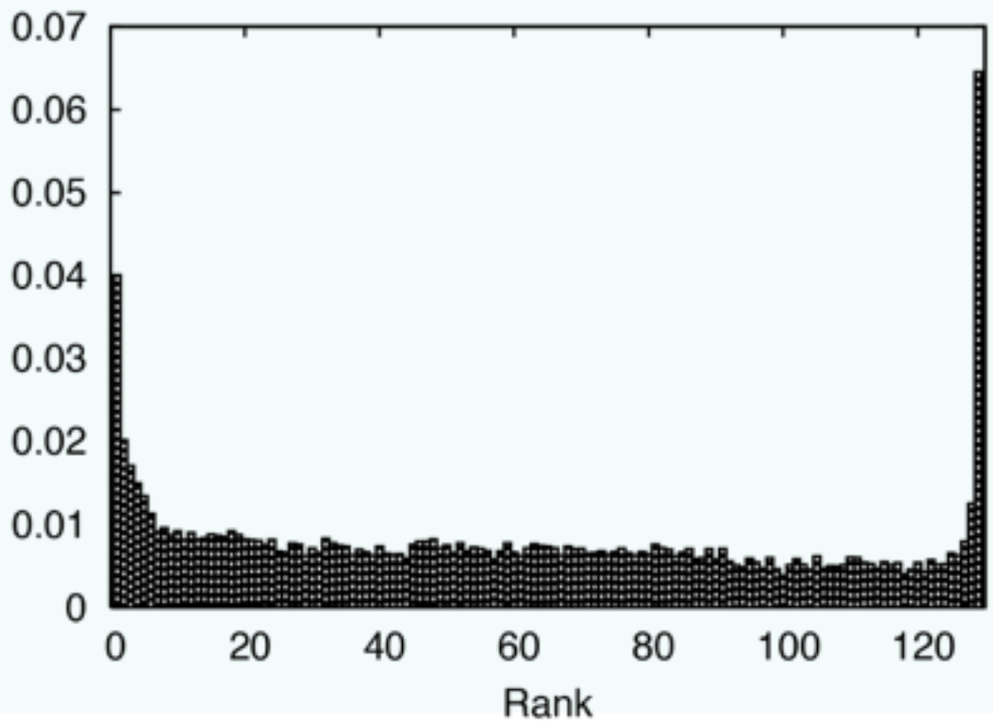

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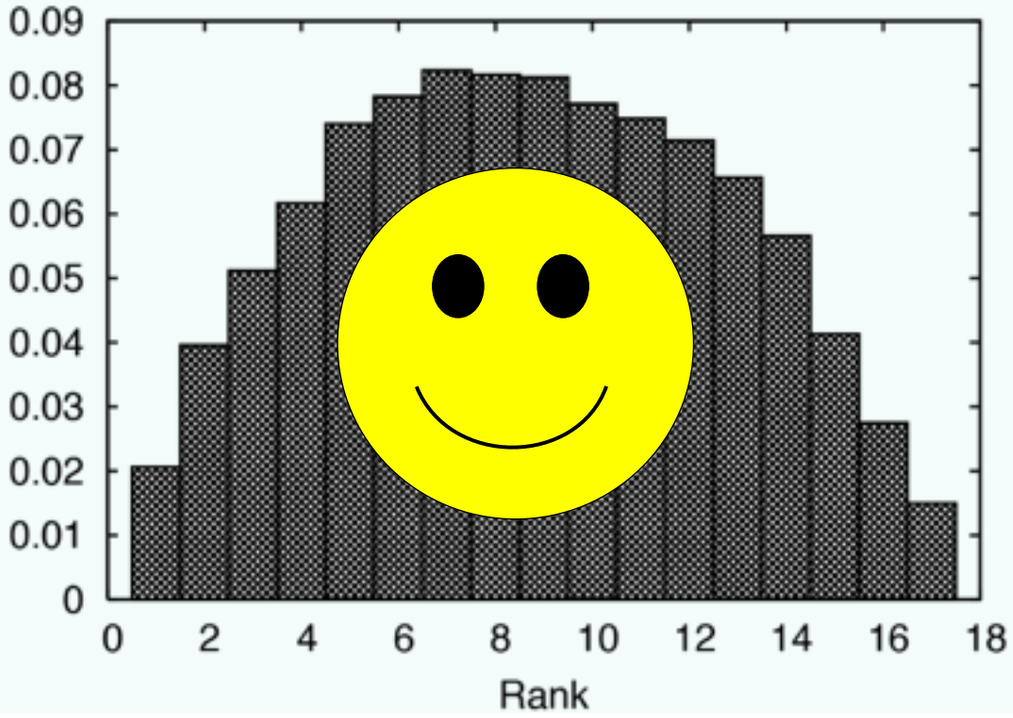

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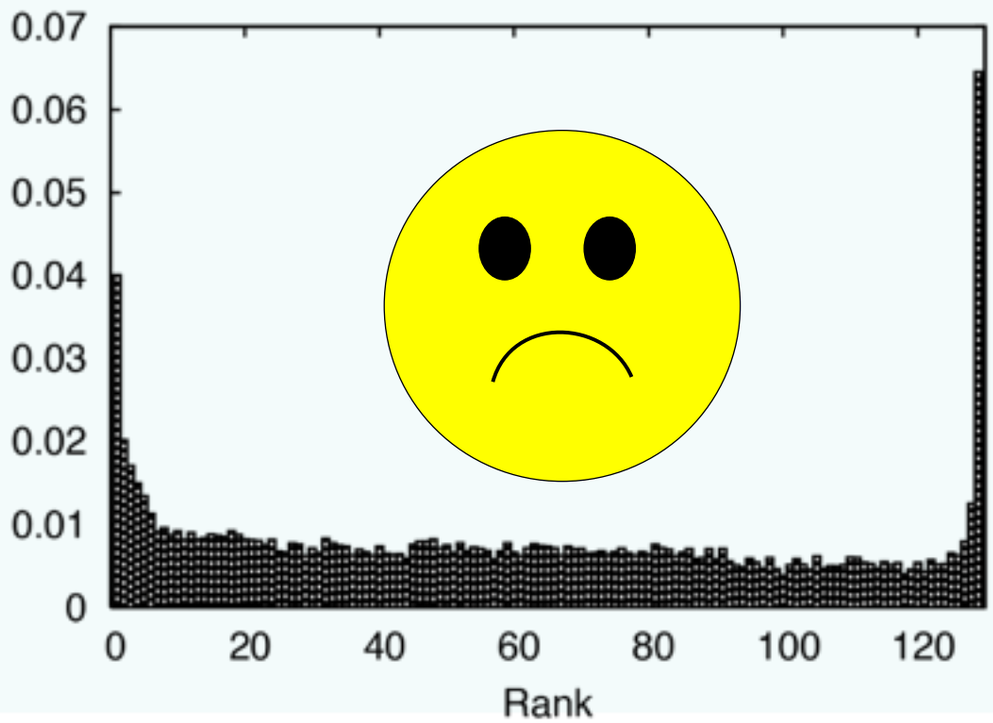

WCRP OSC

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- Assessment of reliability for present day climate does not mean that projections of climate change are reliable.
- Analysis of paleoclimate helps us to assess our confidence.

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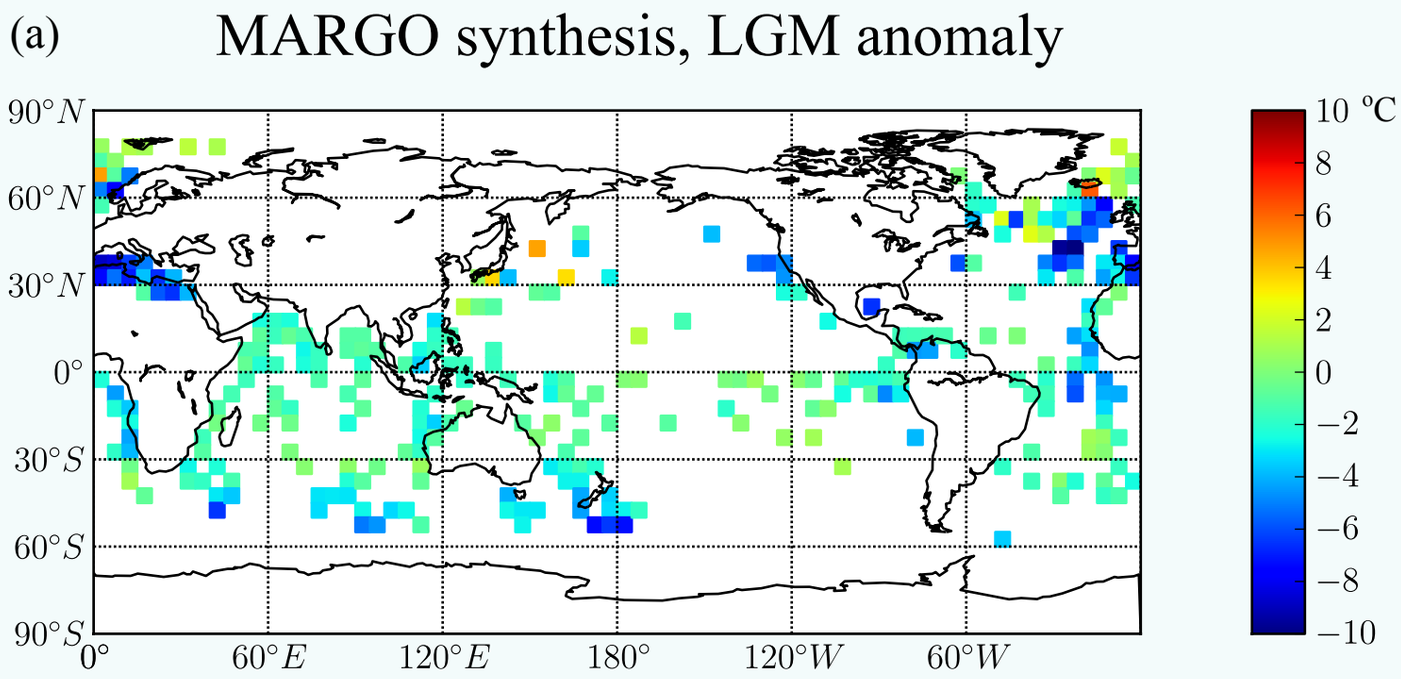
- More dust in atmosphere (not included in models)

Data

MARGO Project Members, Nature Geoscience, 2009

Data


(a) MARGO synthesis, LGM anomaly
90°N
60°N
30°N
0°
30°S
60°S
90°S
0°
60°E
120°E
180°
120°W
60°W
10 ºC
8
6
4
2
0
−2
−4
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−8
−10

Data

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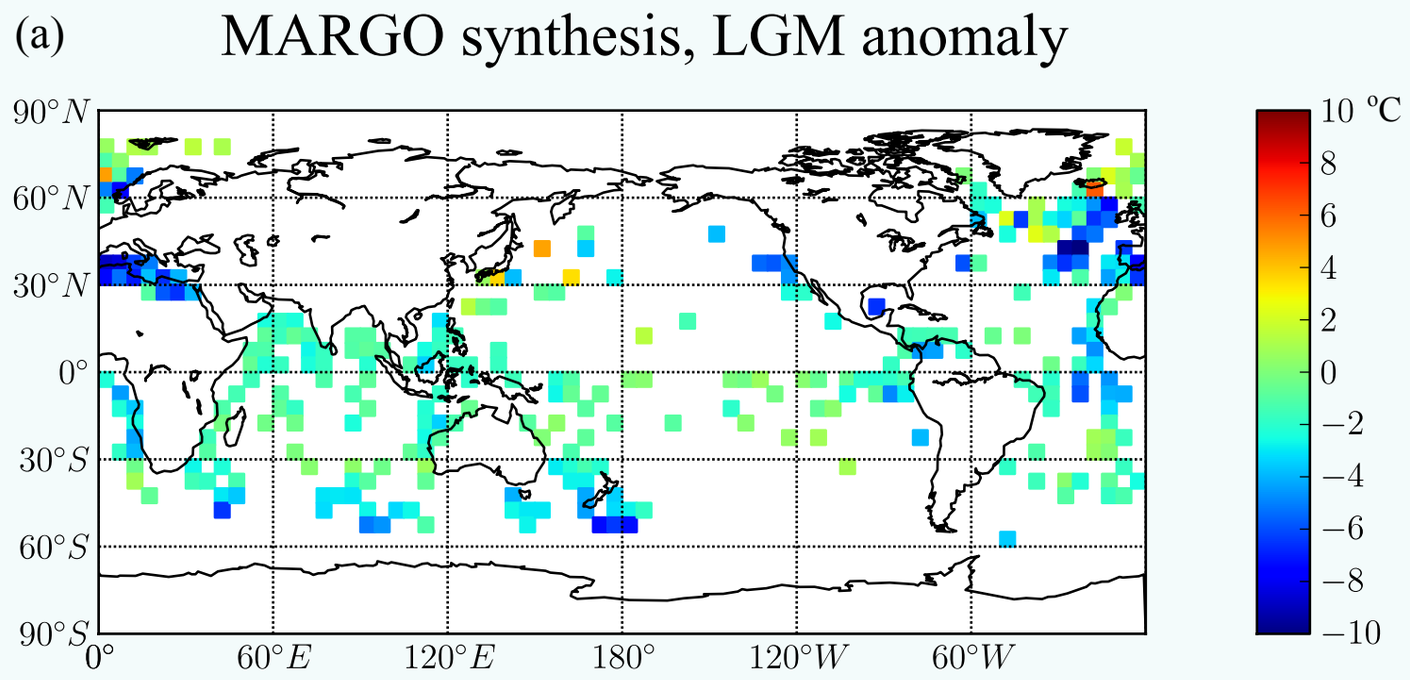

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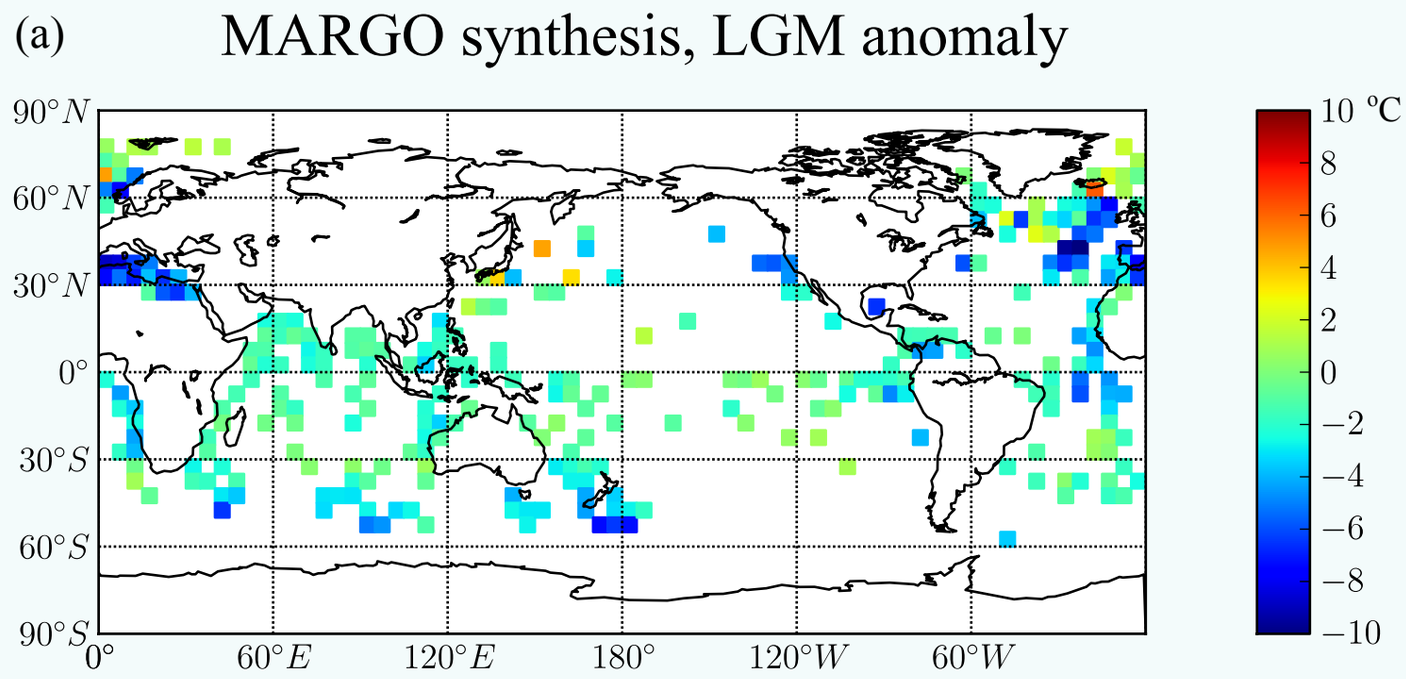

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- Includes an error estimate!

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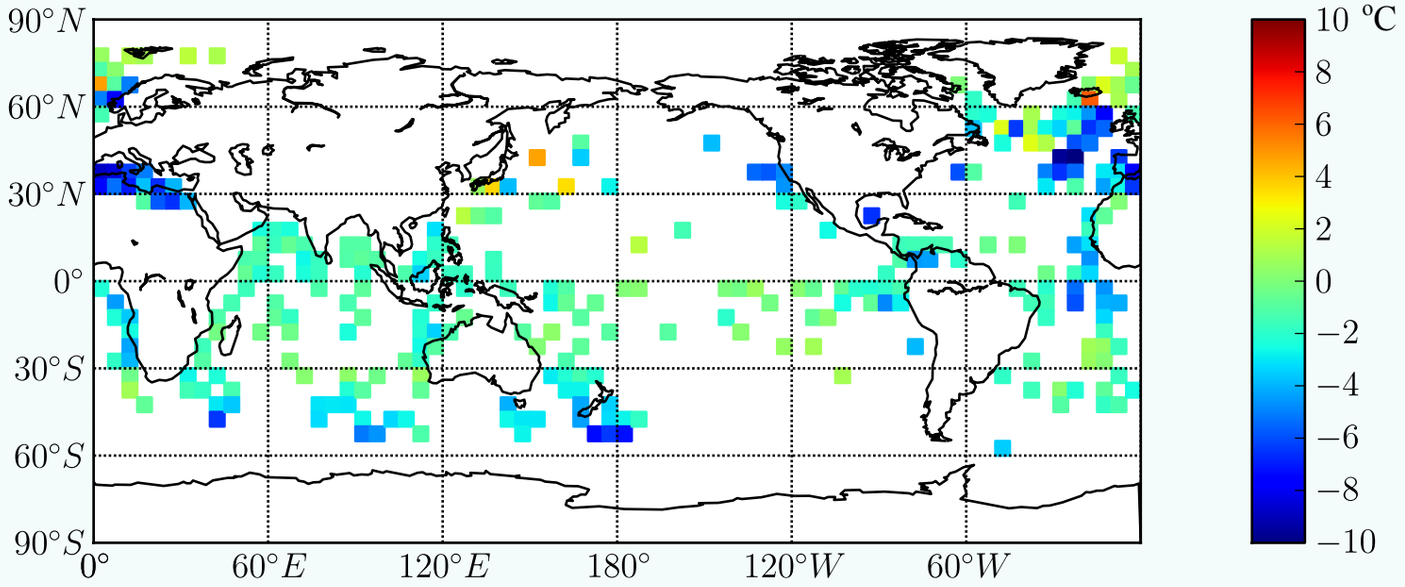
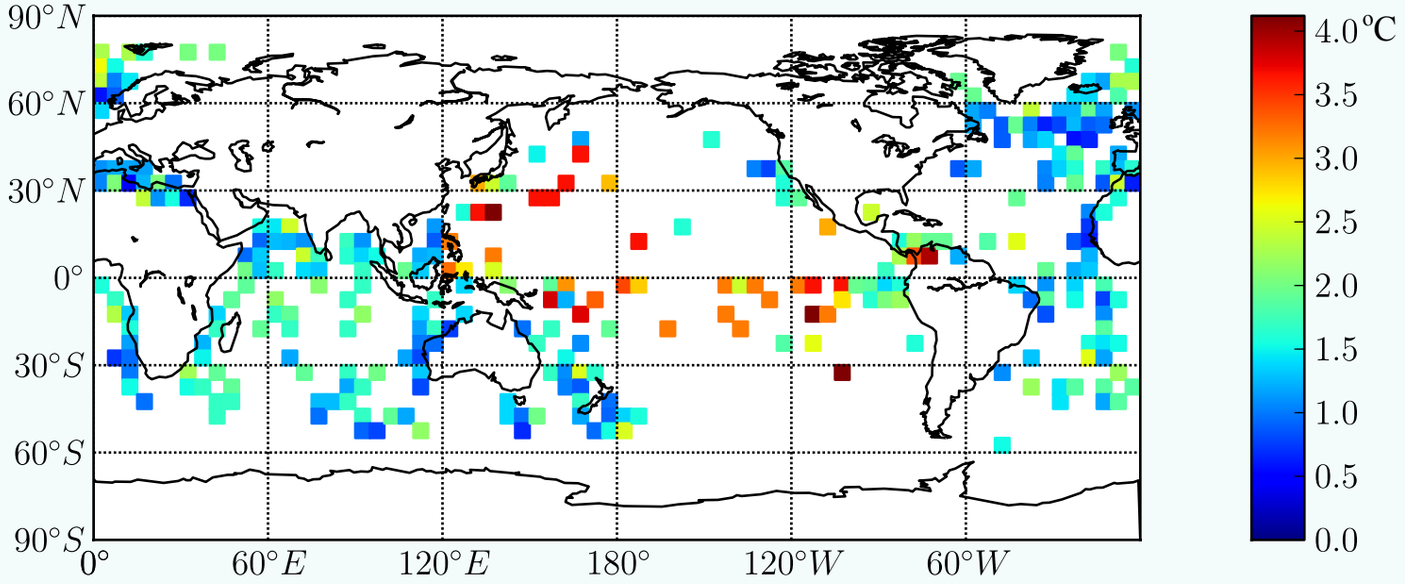


(b) MARGO synthesis, uncertainty in LGM anomaly



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  - ✳ 40 member ensemble with 13 parameters varied tuned to modern climate using EnKF.

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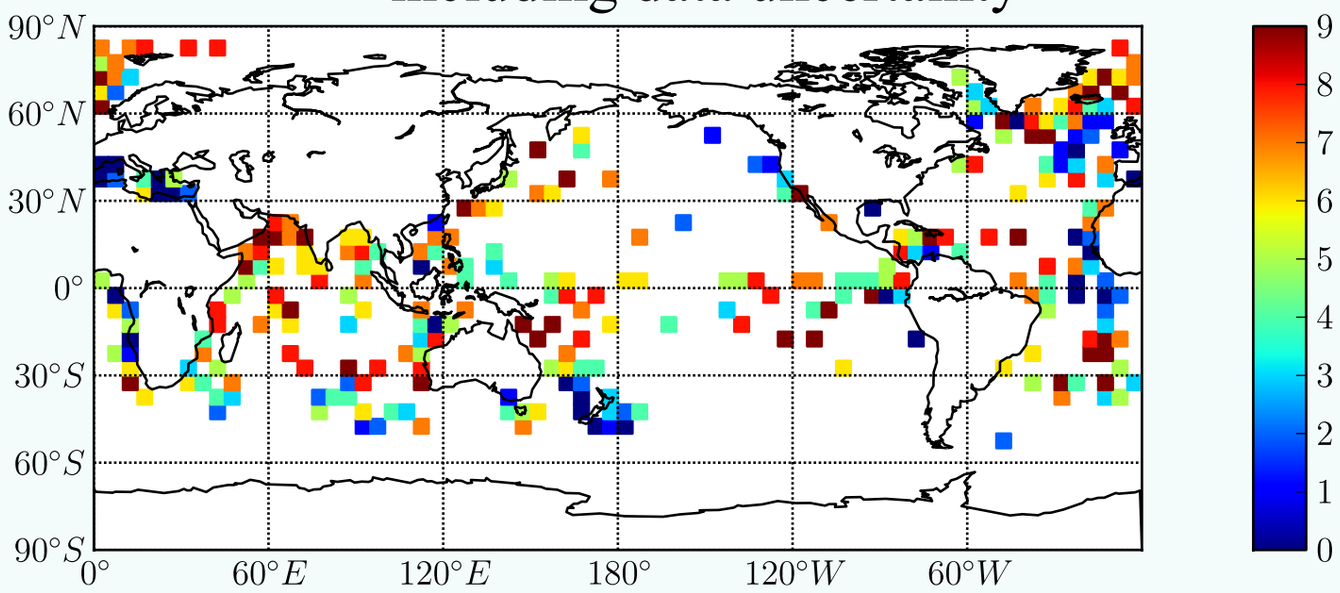
- Apply a random error of this size to each model point, and recalculate the rank histogram

Reliability with data error included

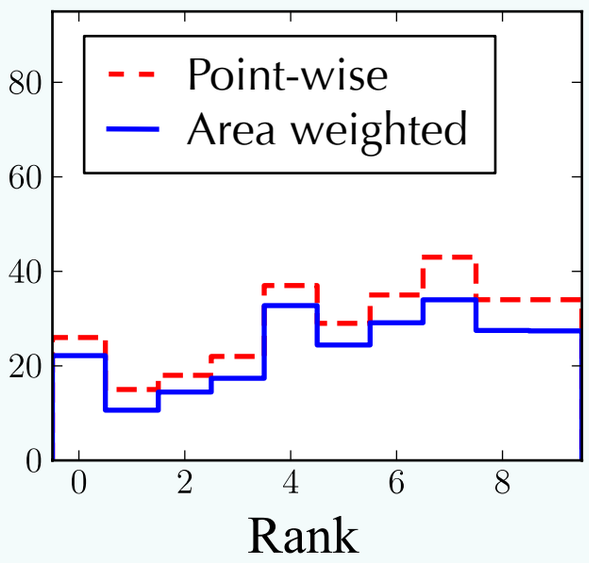
Hargreaves et al, Climate of the Past, 2011

Reliability with data error included

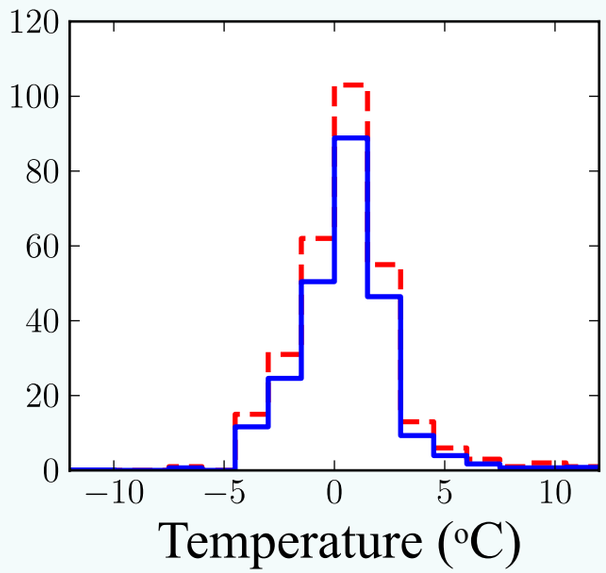
Rank of MARGO data in PMIP2 ensemble, including data uncertainty



(b) Rank histogram



(c) Ensemble mean bias



Hargreaves et al, Climate of the Past, 2011

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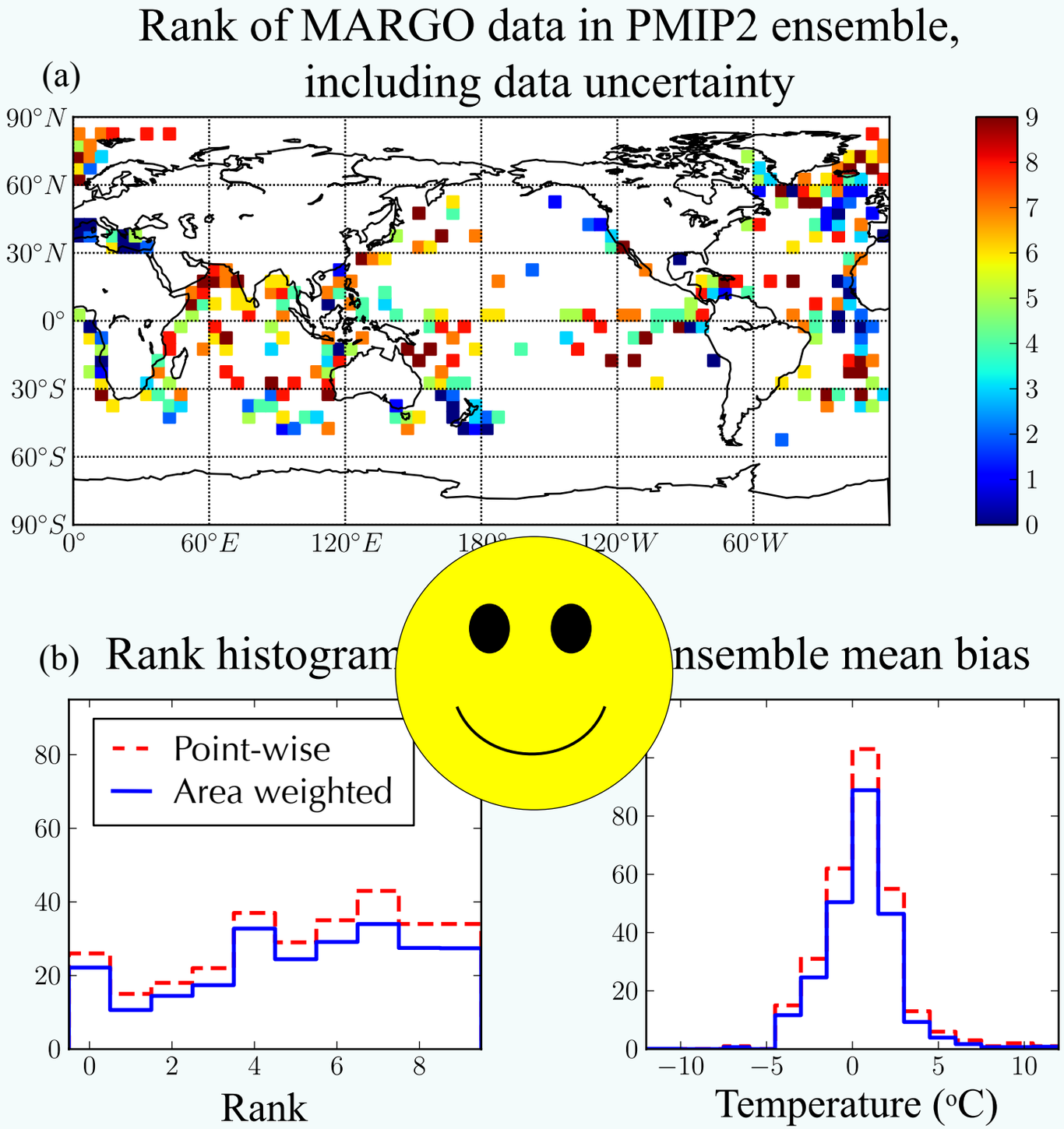

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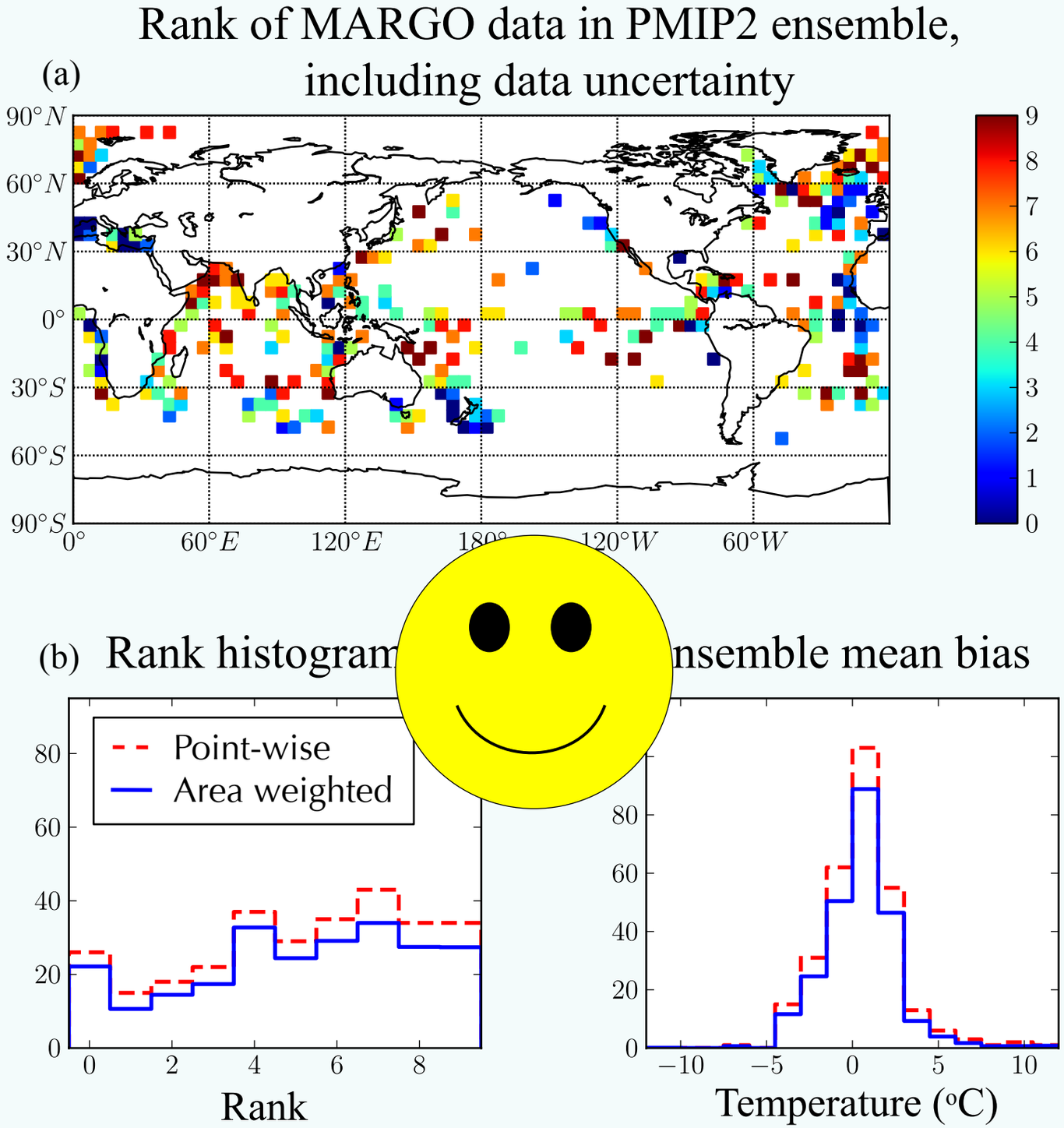

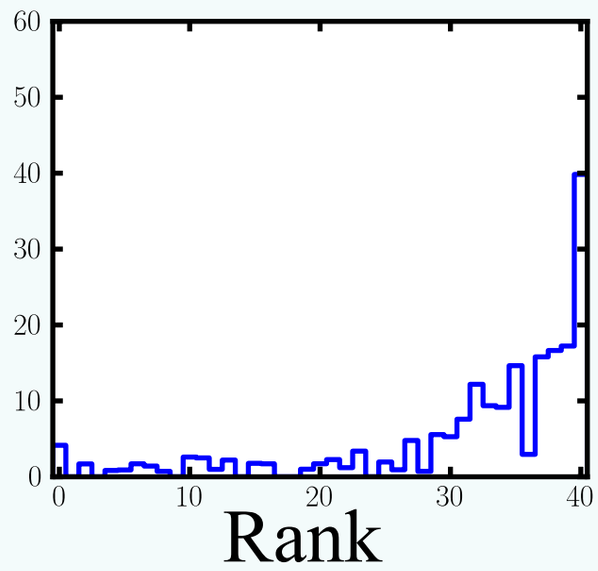

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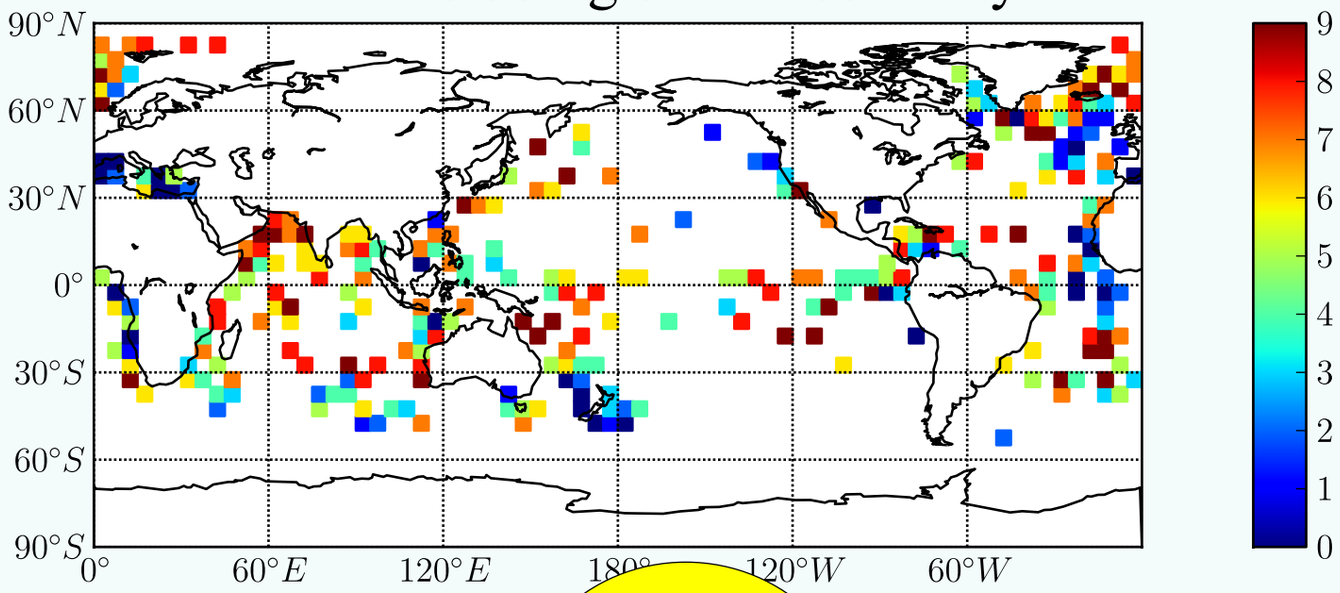
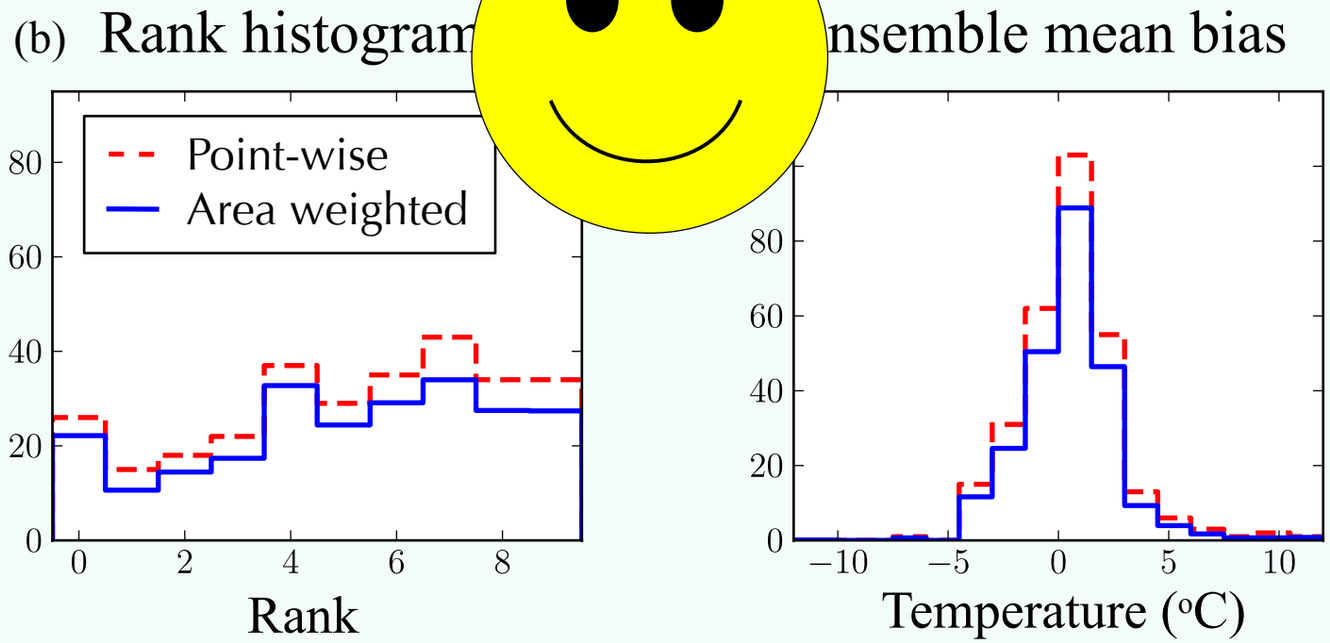
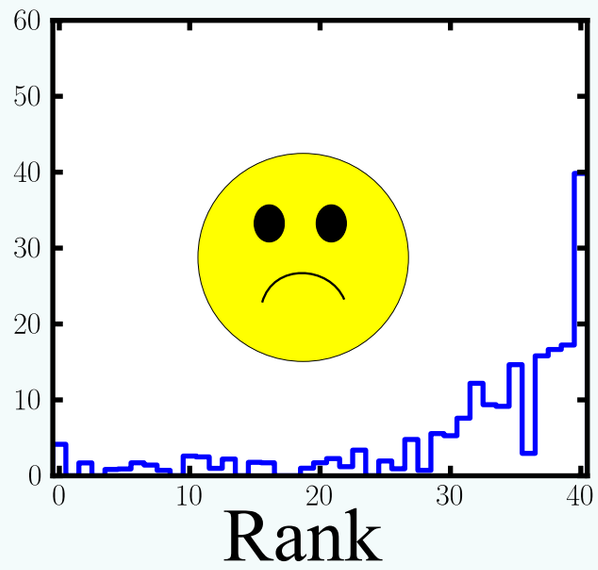




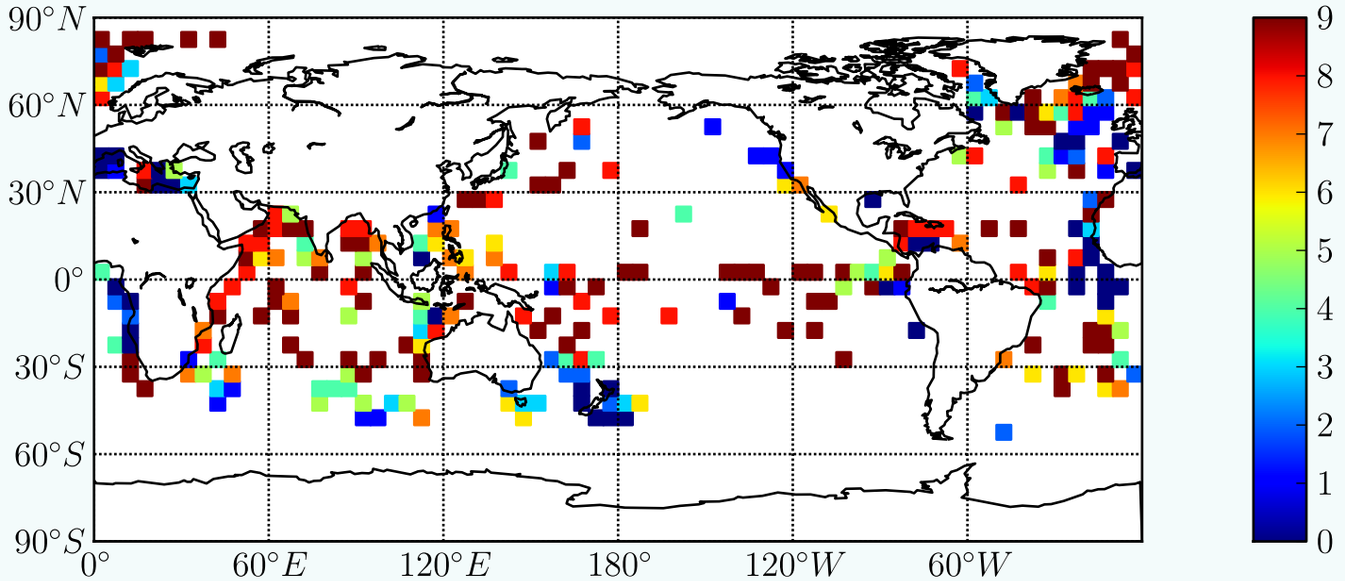
SME - MIROC



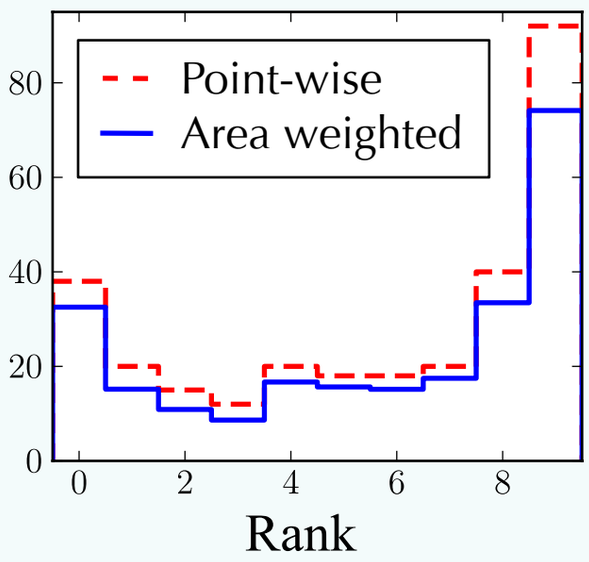
Hargreaves et al, Climate of the Past, 2011

Data error not included, PMIP2

(a) Rank of MARGO data in PMIP2 ensemble



(b) Rank histogram



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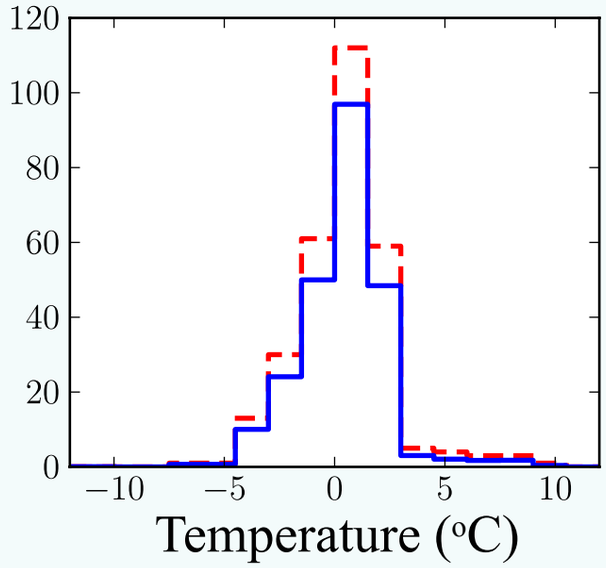

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Statistically unreliable at 5% level - PMIP2 too sensitive.

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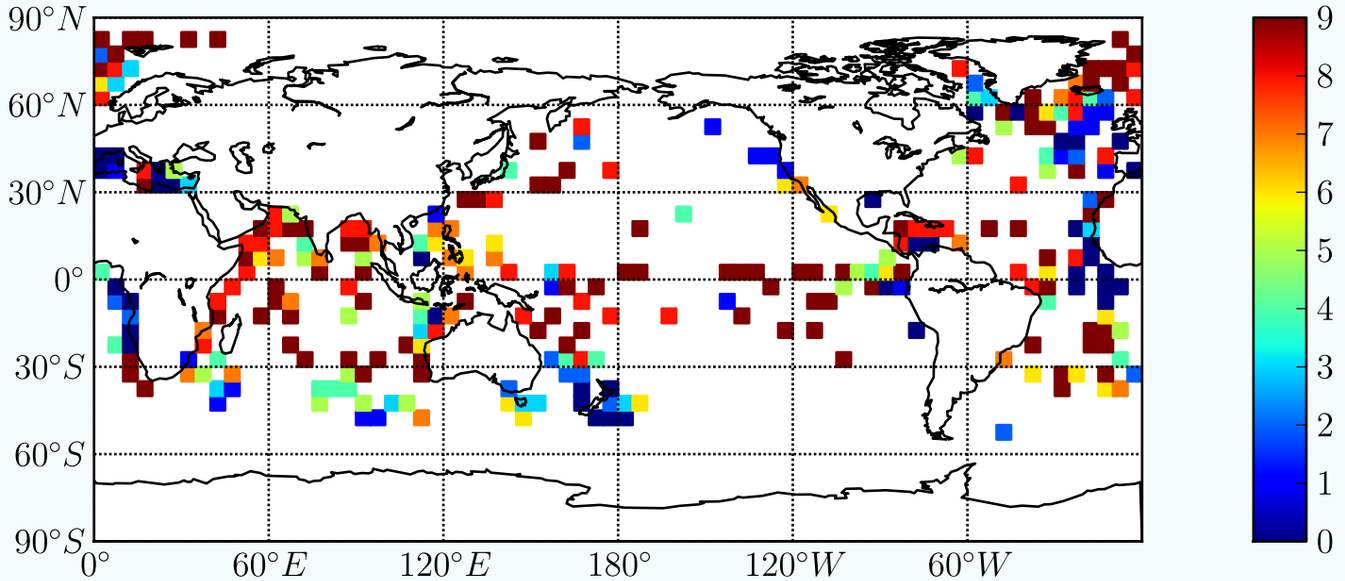

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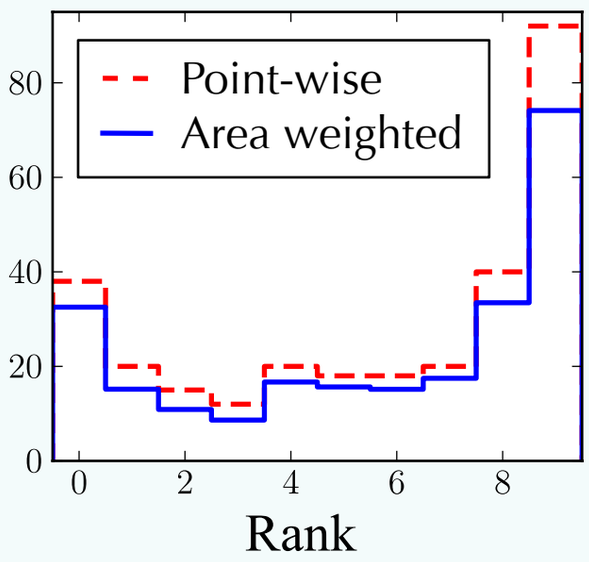
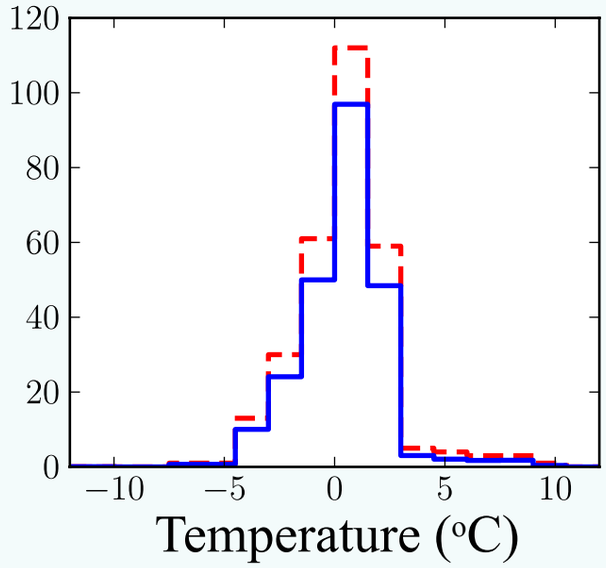


(c) Ensemble mean bias



Hargreaves et al, Climate of the Past, 2011

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Inclusion of data error very important in analyses of paleoclimate models

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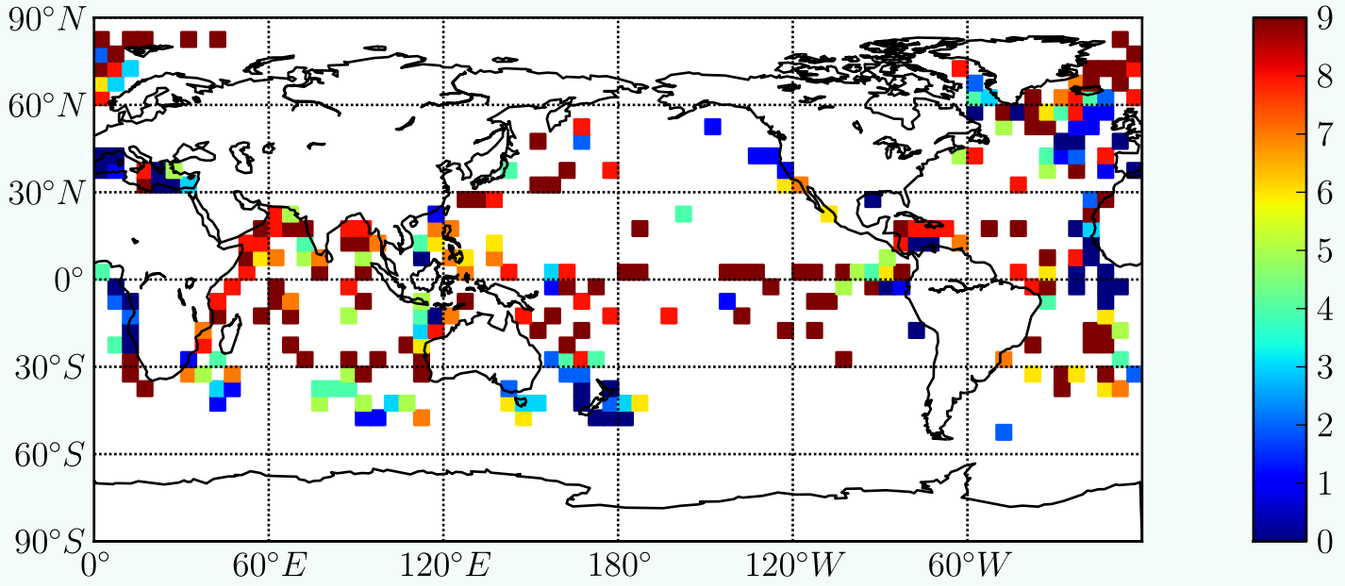

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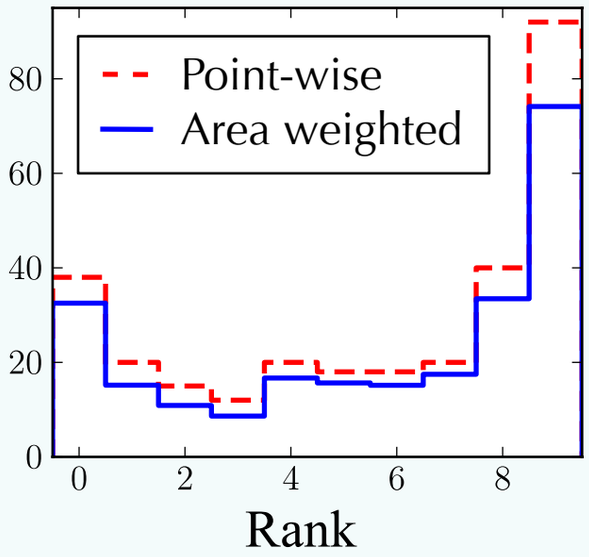

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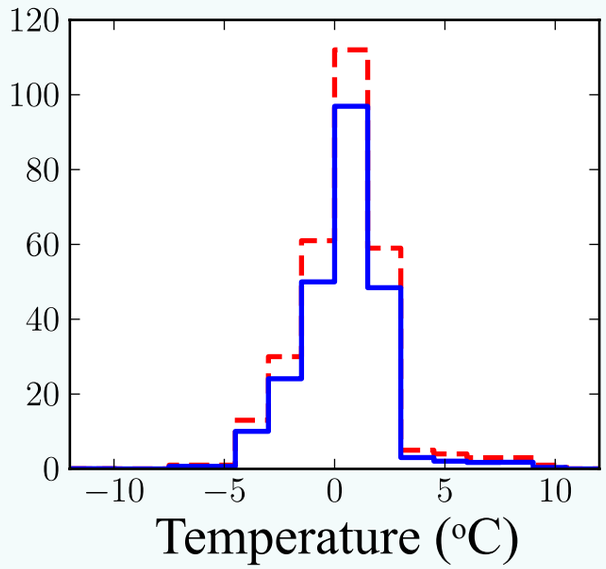

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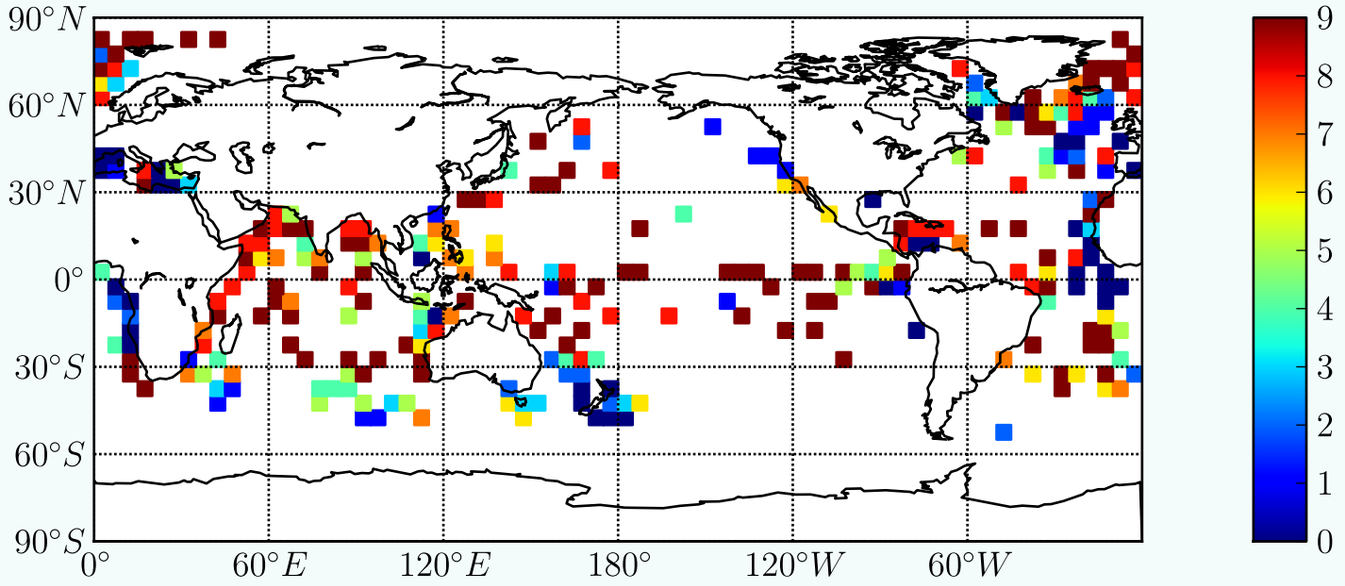

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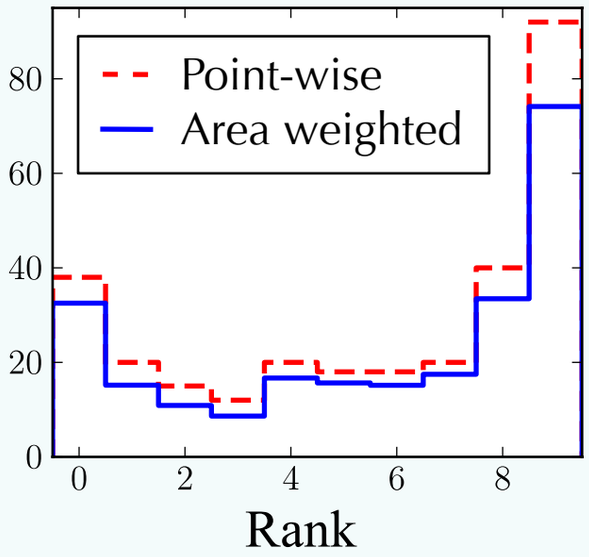

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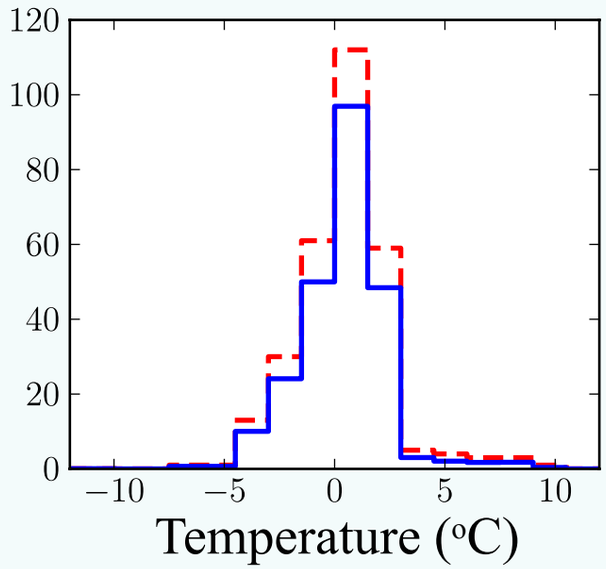

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Do Climate Models have skill?

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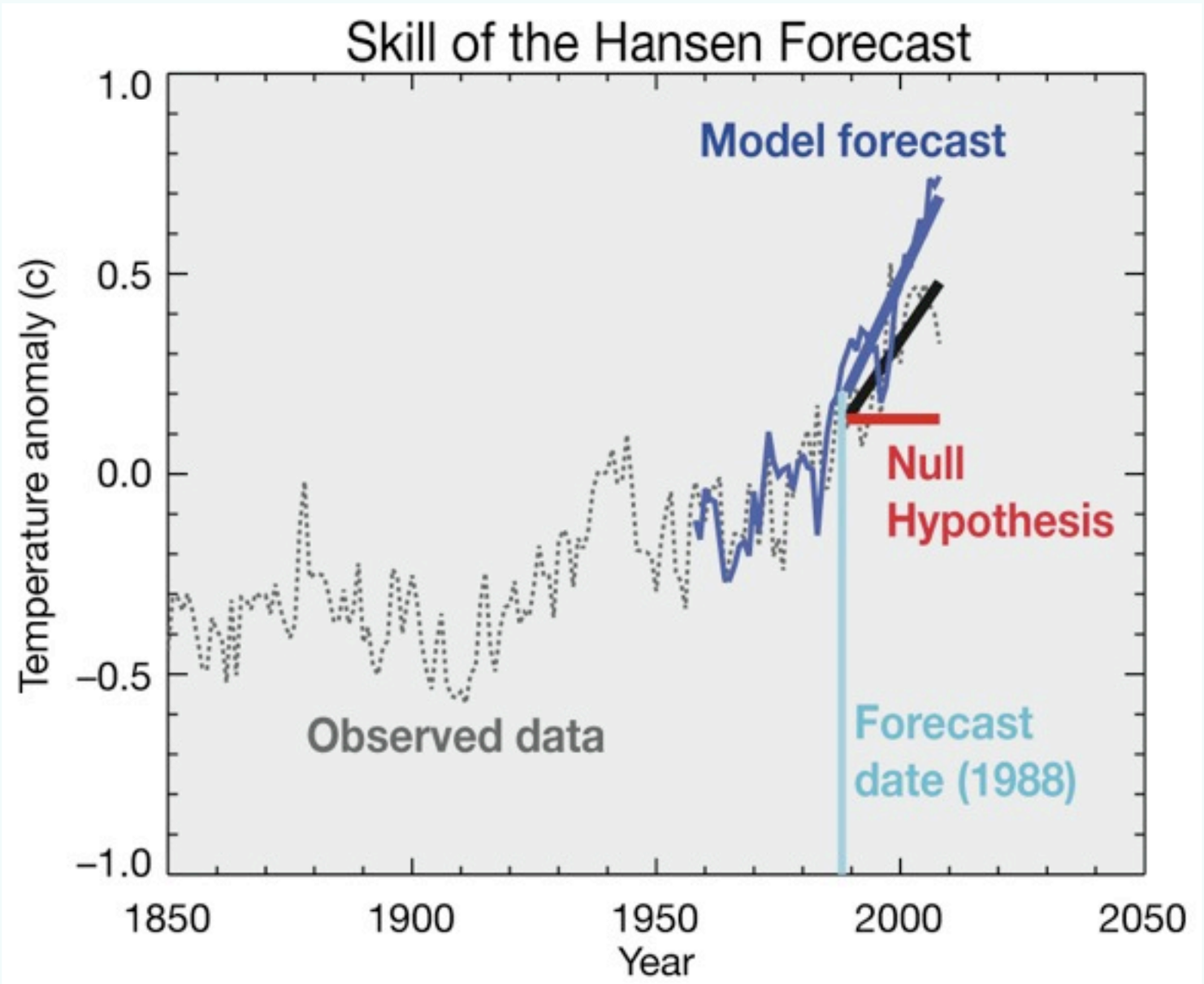
- Climate prediction: Forecasts are not yet realised, so skill calculations generally not possible.

Skill analysis of a climate forecast



This Figure re-created by Hans von Storch's draftsman, Gruss Beate Gardeike

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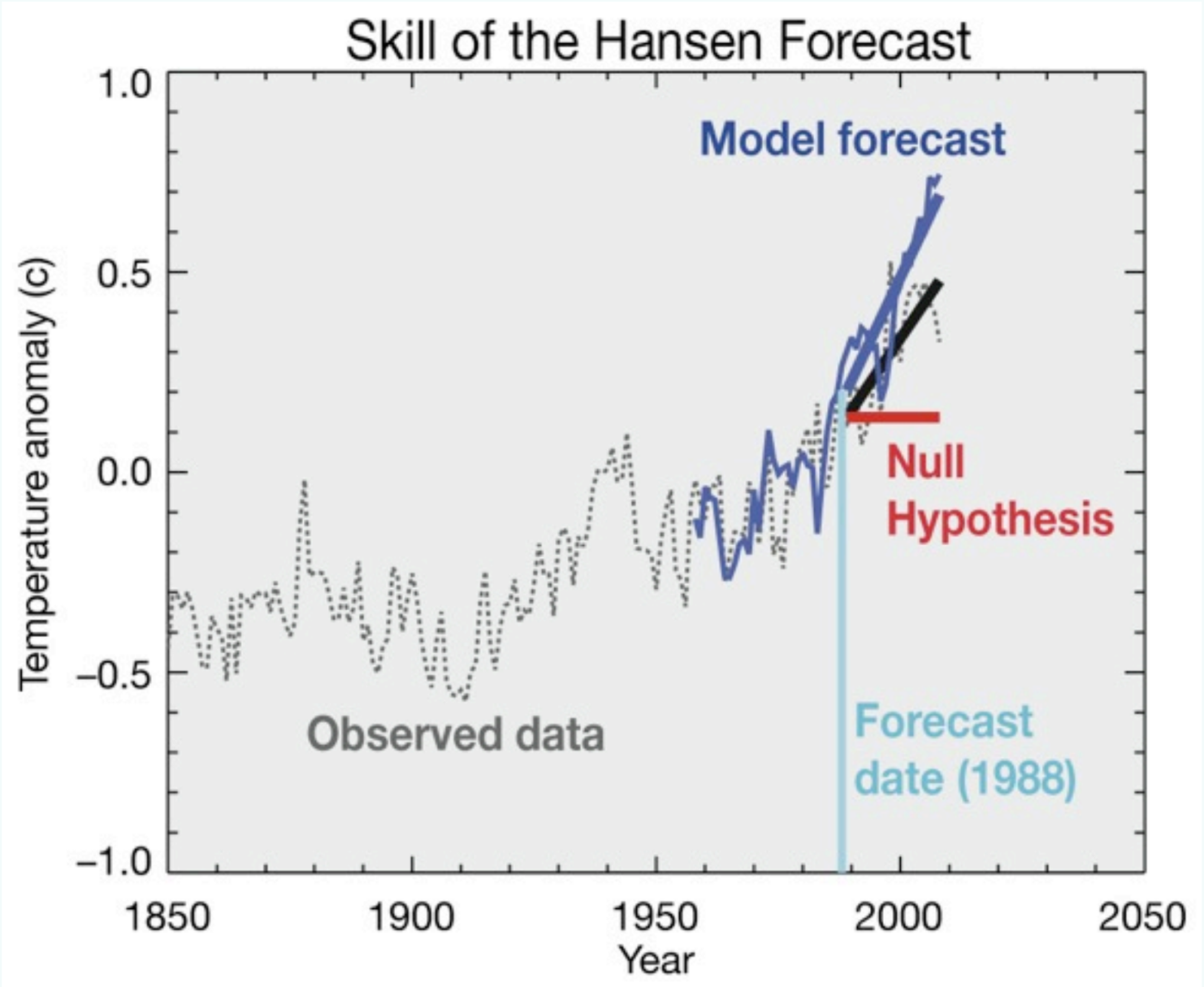

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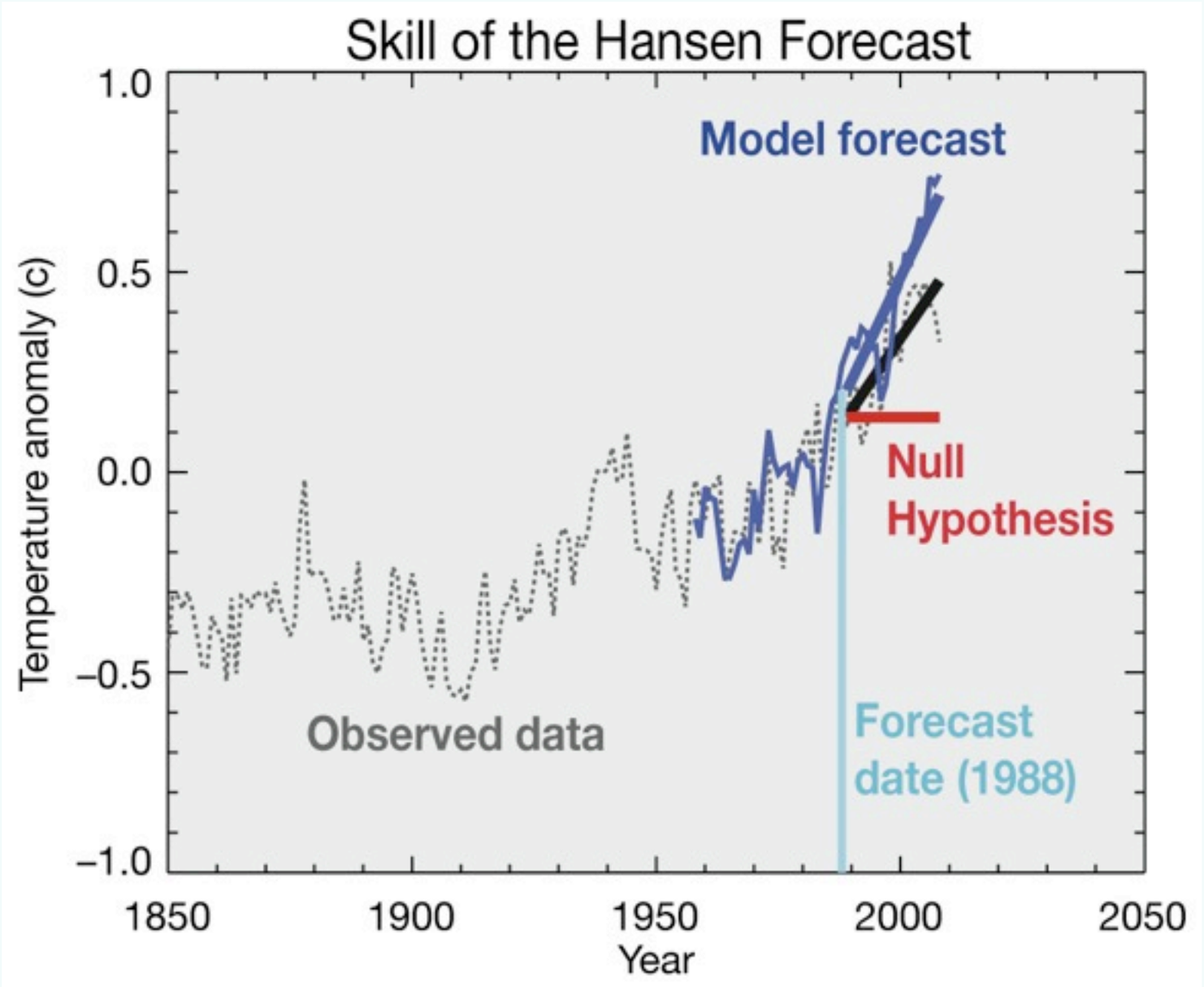

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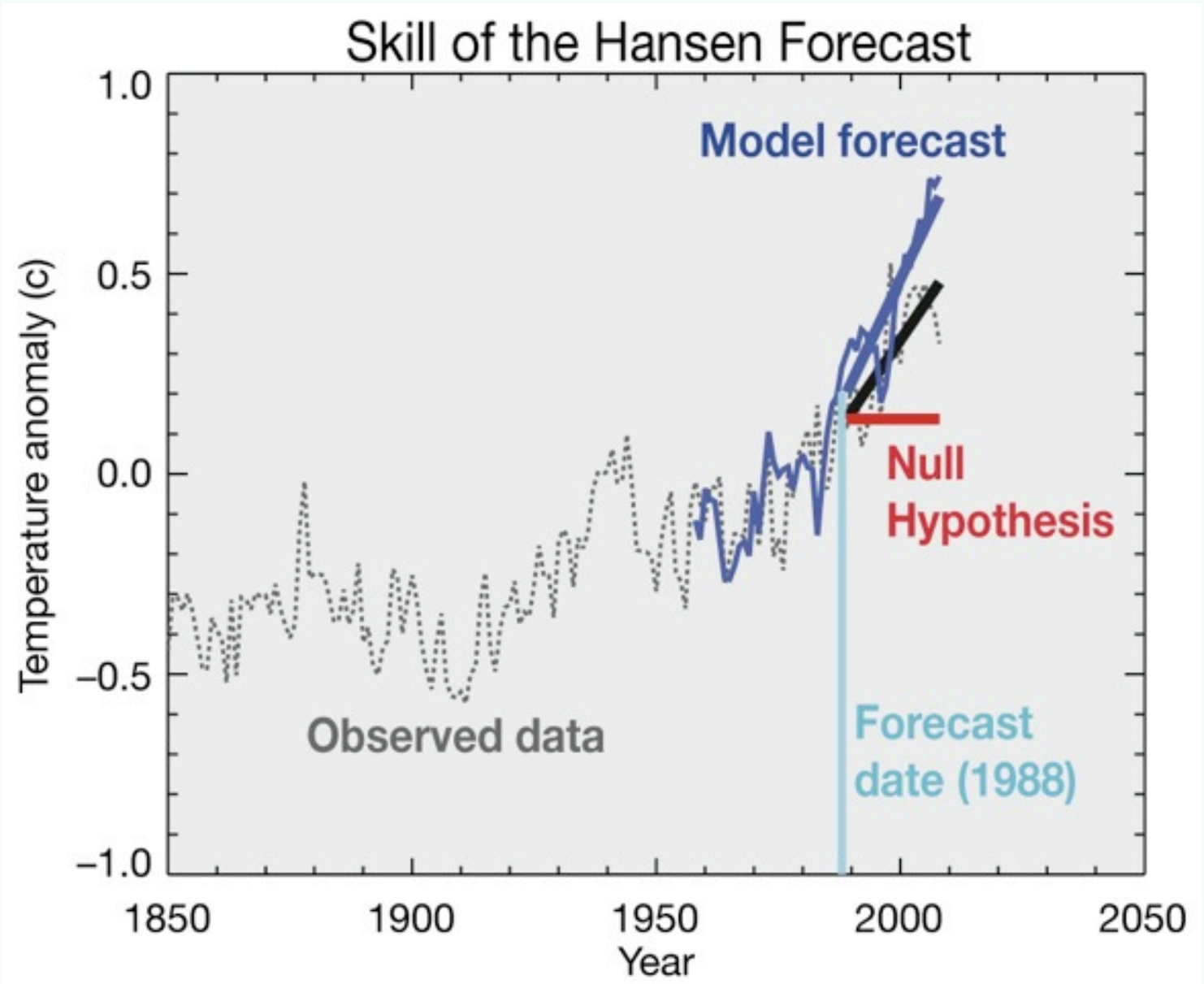

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Hargreaves, WIREs 2010

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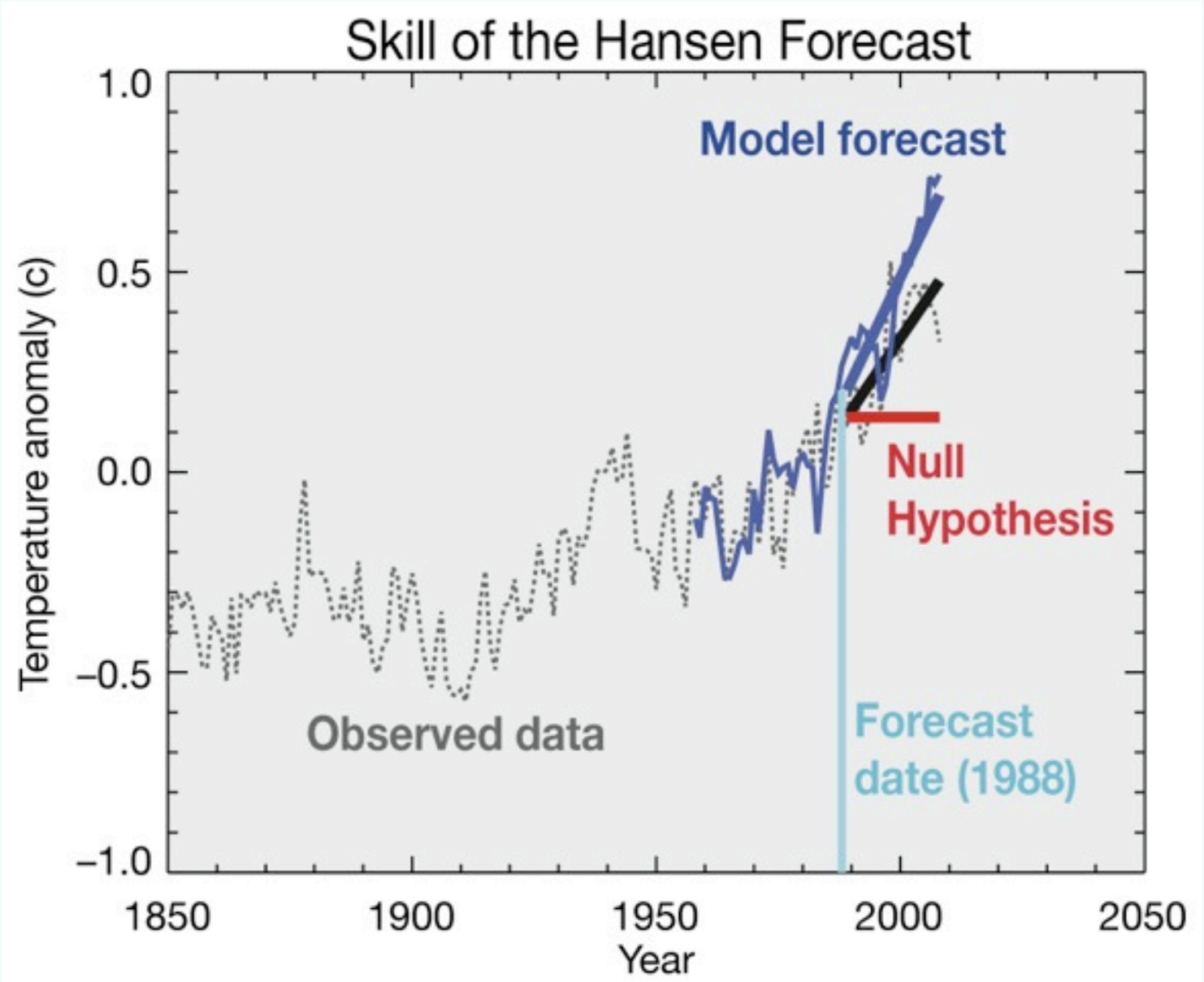

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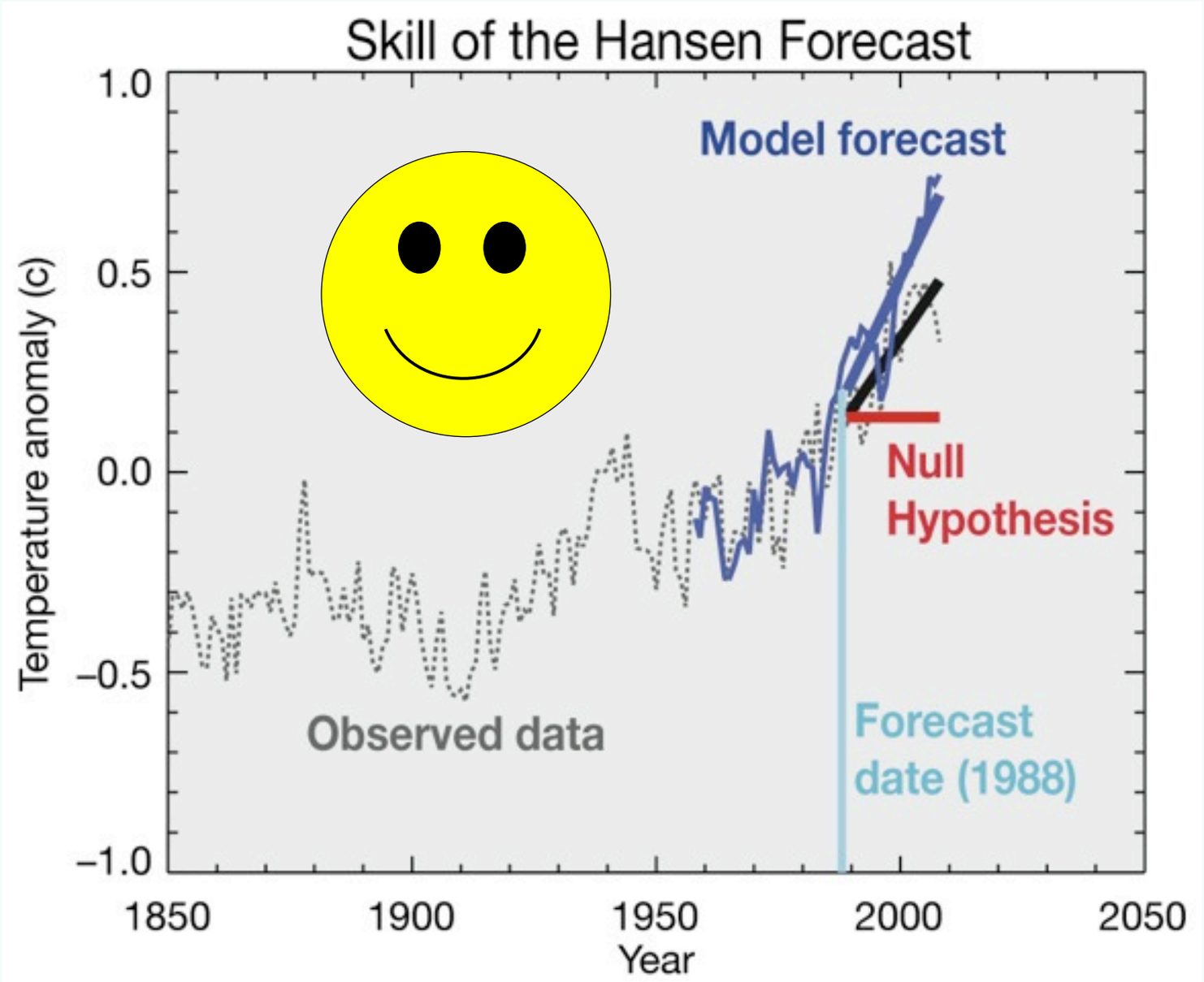

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Skill at the LGM

Two null hypotheses

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1. Persistence: LGM = modern

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2. Testing the pattern: LGM = mean model field at LGM

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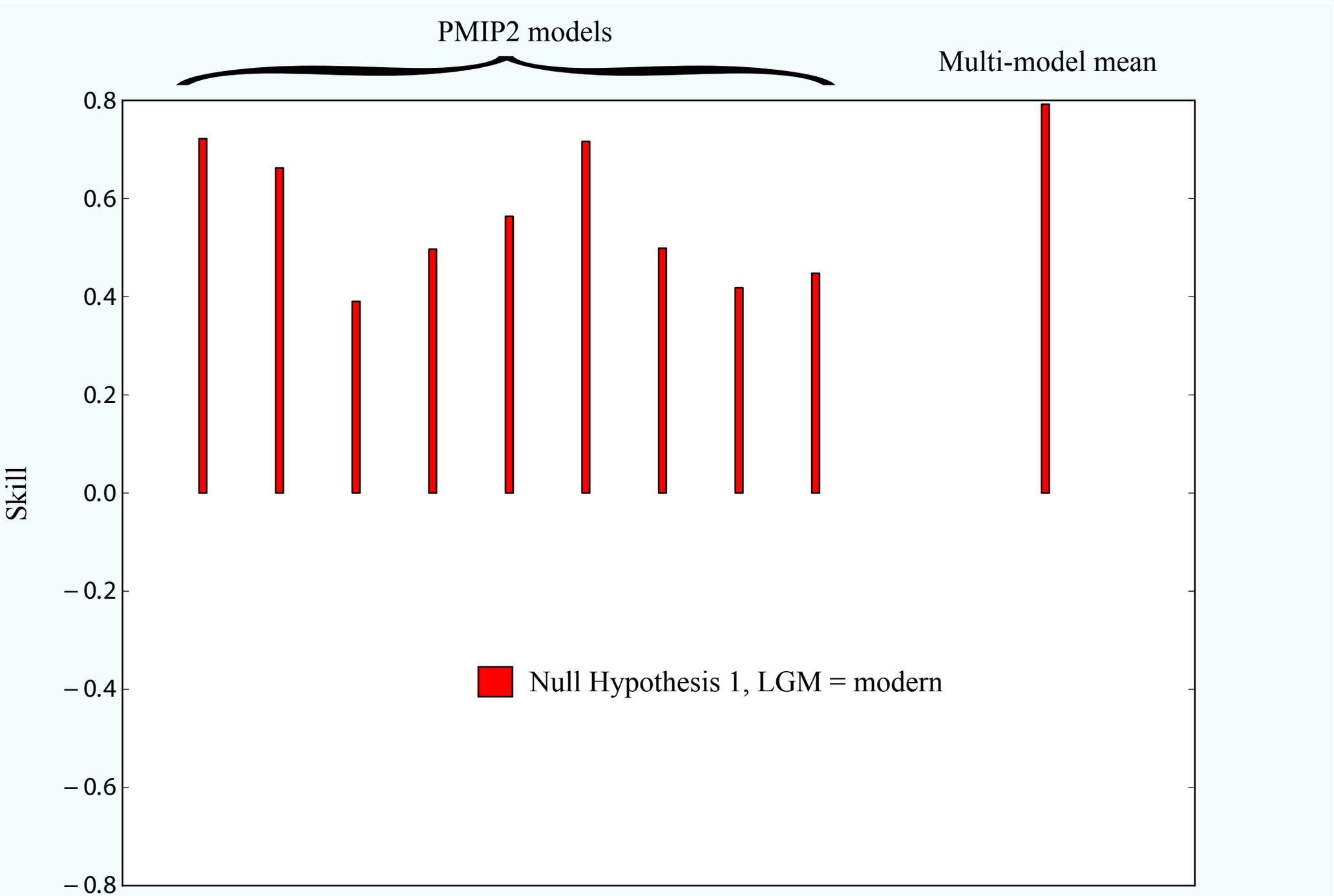

Preliminary results

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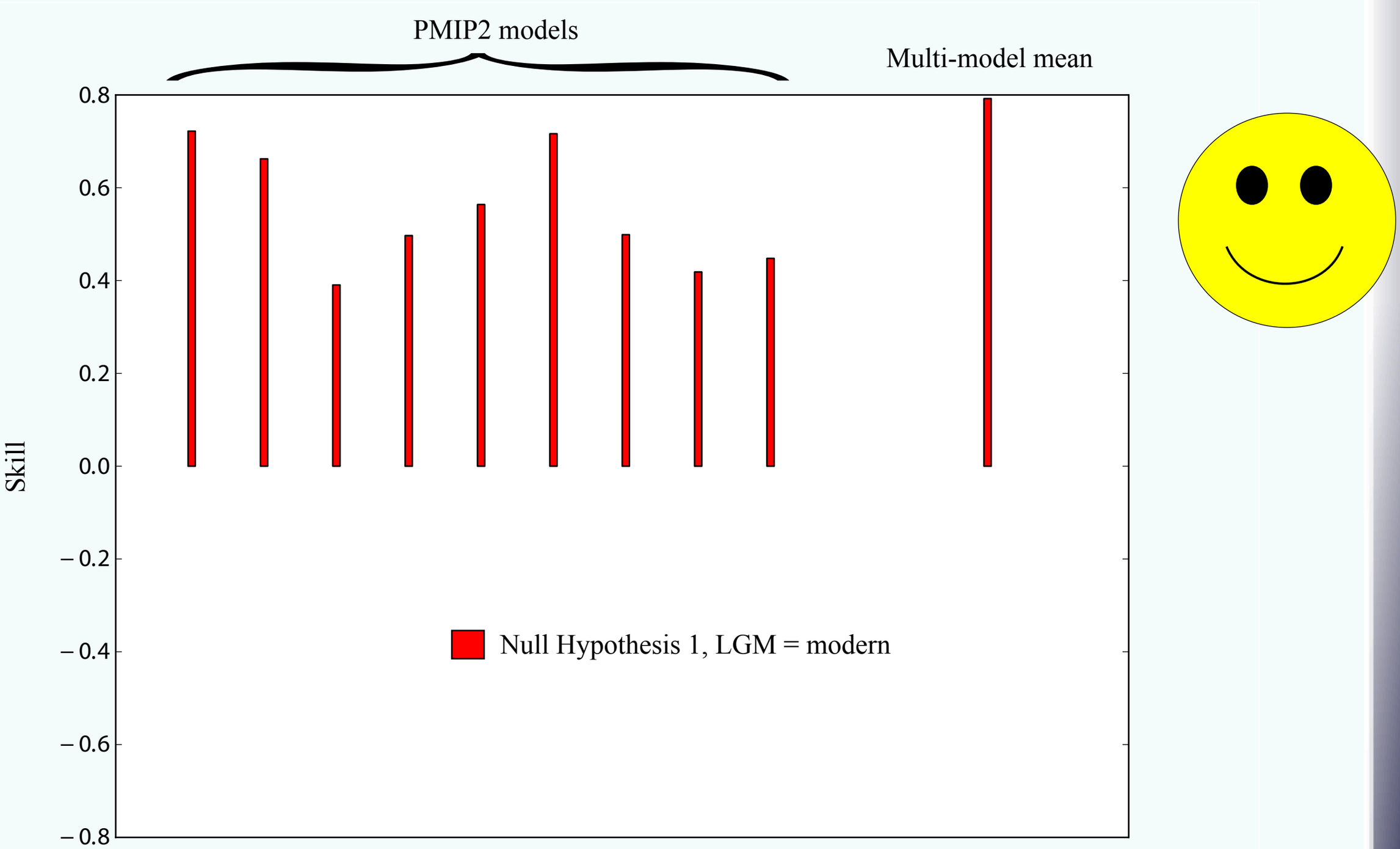
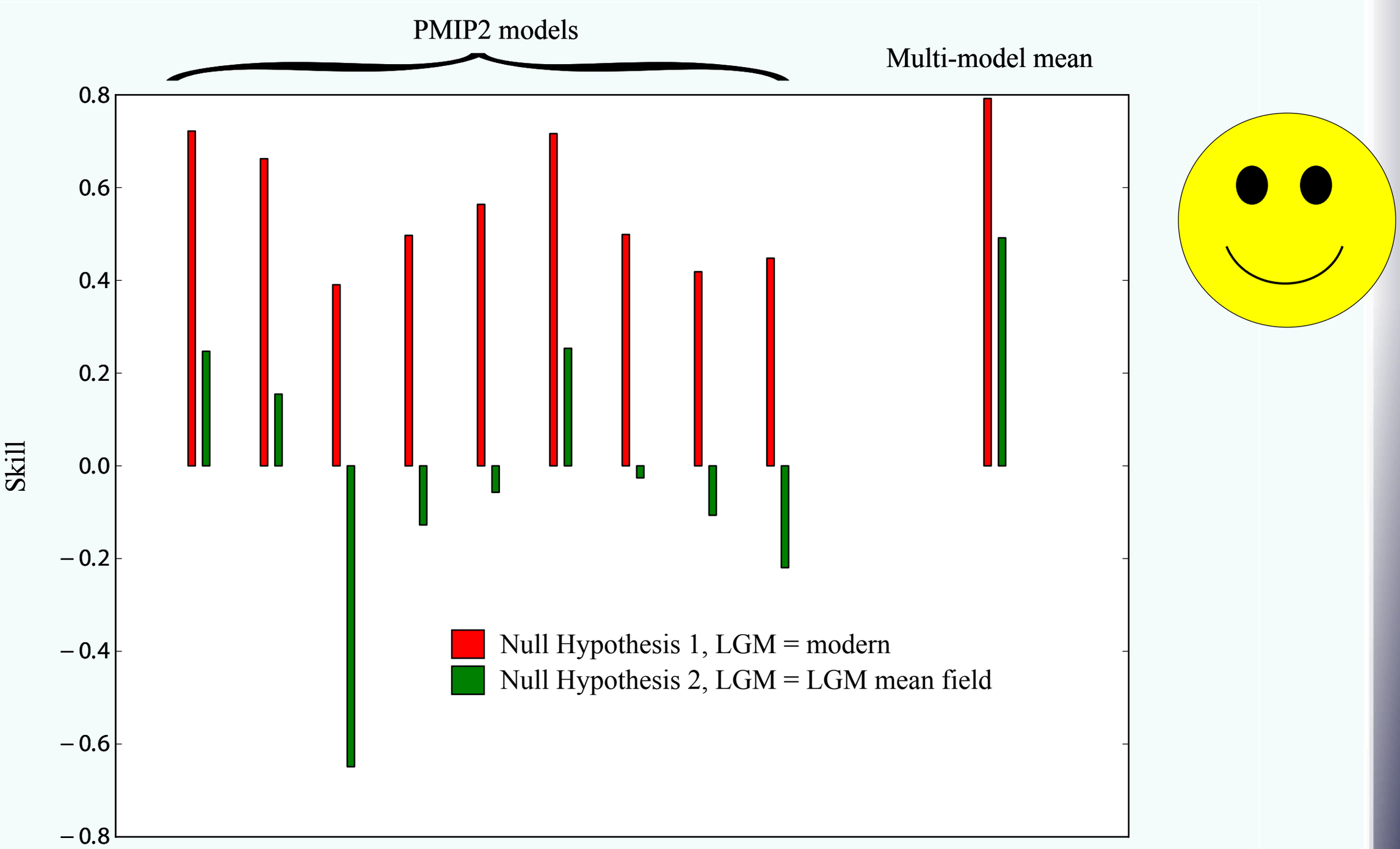


Preliminary results

Japan Uncertainty Modelling Project

Skill at the LGM



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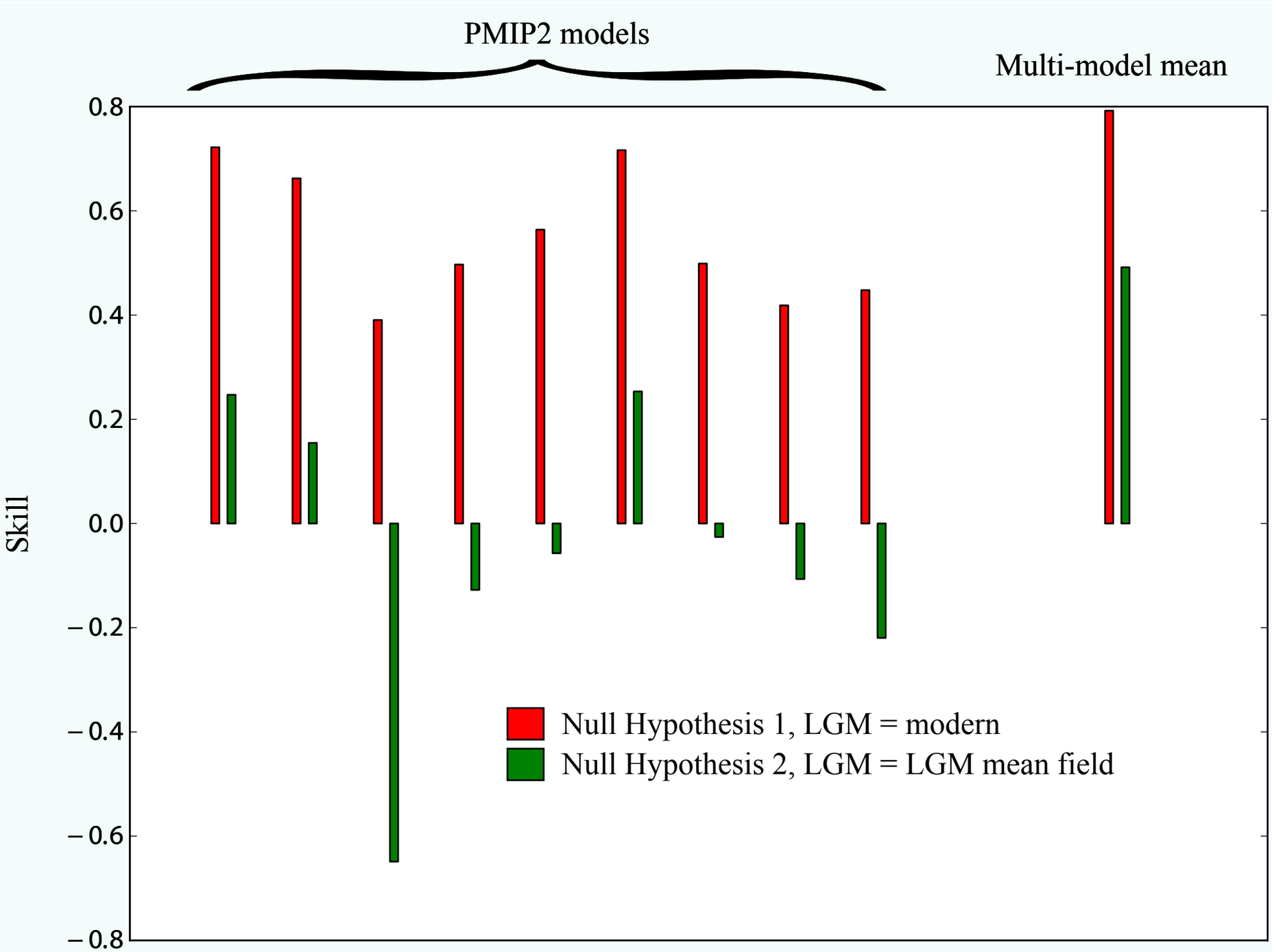

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- Ensembles derived from a single model are usually unreliable.
- Climate models have some skill at the LGM, but not as much as we might like!

Workshop:

Using paleo-climate model-data comparisons to constrain future climate projections

Mar 1-3, 2012

Bishop Museum, Honolulu, Hawaii

(immediately before CMEP workshop)

Contacts: Gavin Schmidt, Valerie Masson-Delmotte

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