Challenges in comparing observed and model-simulated trends on regional scales

Clara Deser, NCAR

US CLIVAR Workshop “Confronting Earth System Model Trends with Observations” March 13-15, 2024.

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Assessment of model realism needed for credible predictions and projections, and for informing understanding of observed trends.

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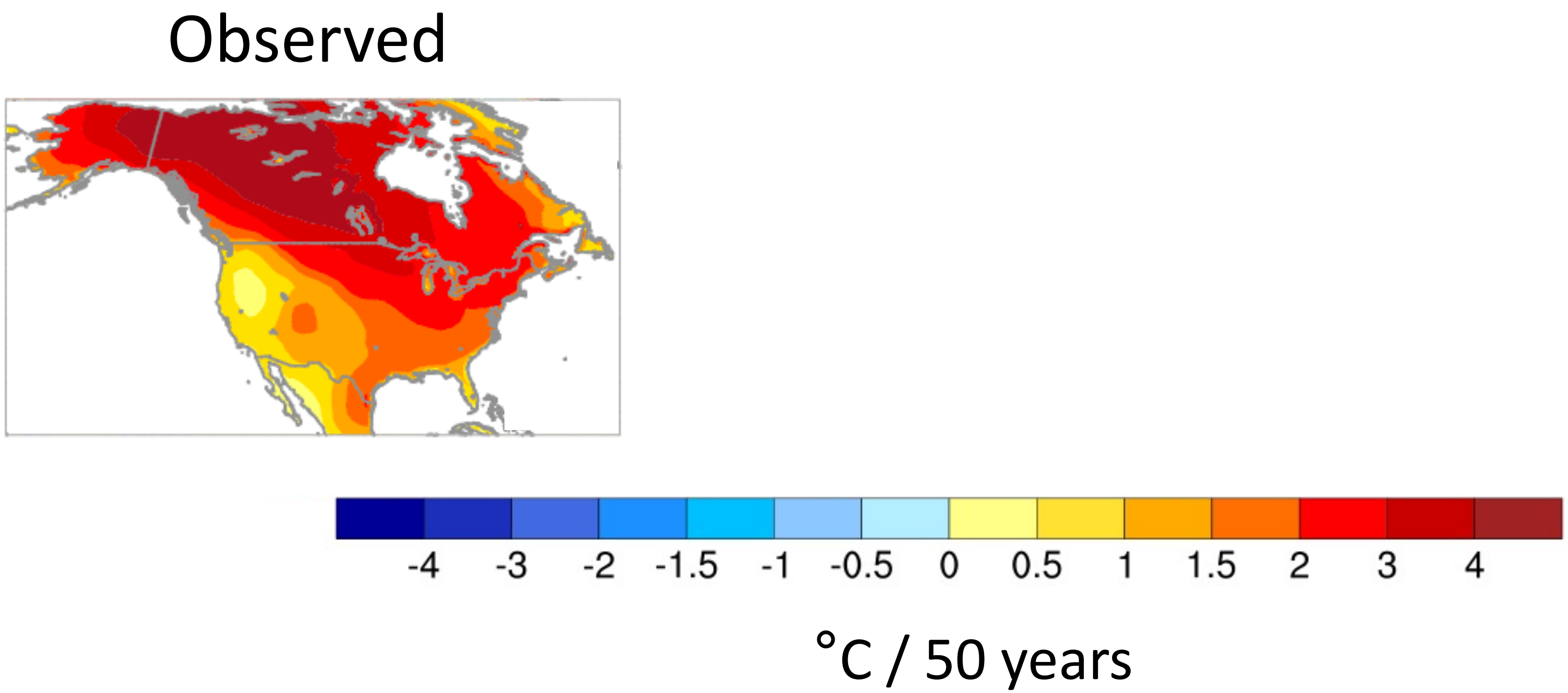
In the old days ...

Winter Air Temperature Trends (1963-2012)

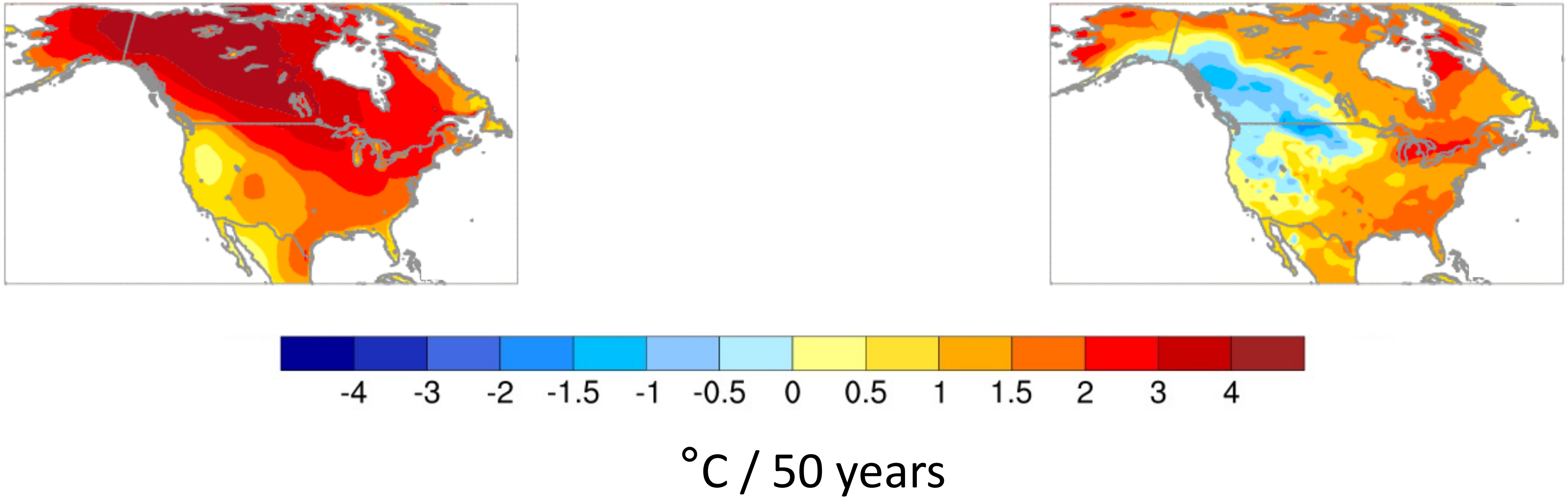


Deser et al., J. Climate 2016

Winter Air Temperature Trends (1963-2012)

Observed

Model simulation



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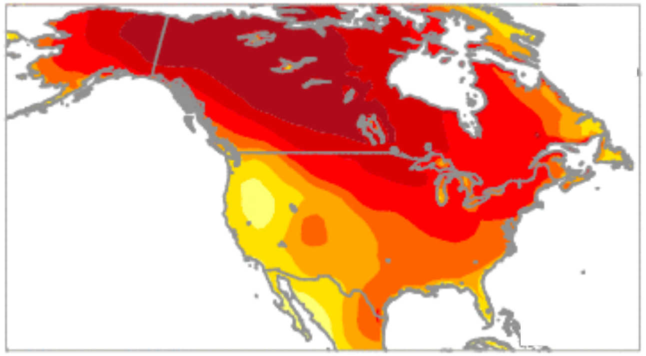
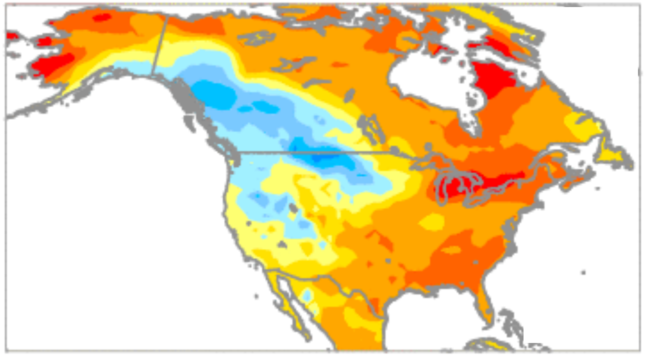
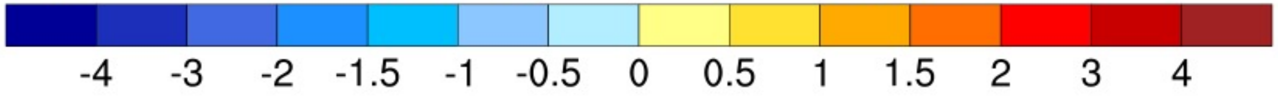


- **Model and/or forcing is erroneous.**

Model simulation





°C / 50 years

Deser et al., J. Climate 2016

Nowadays ...

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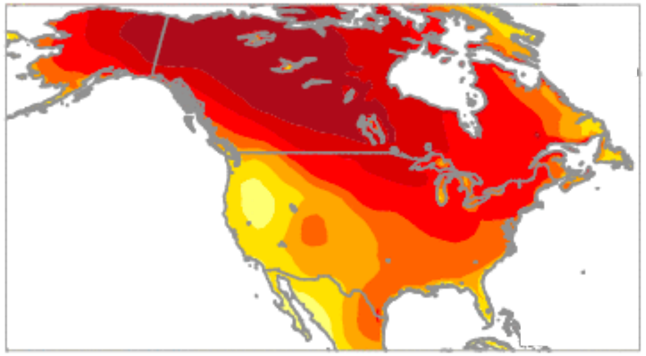
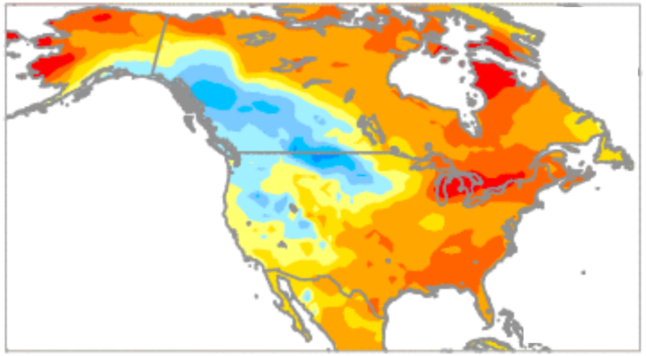
Observed



Model simulation



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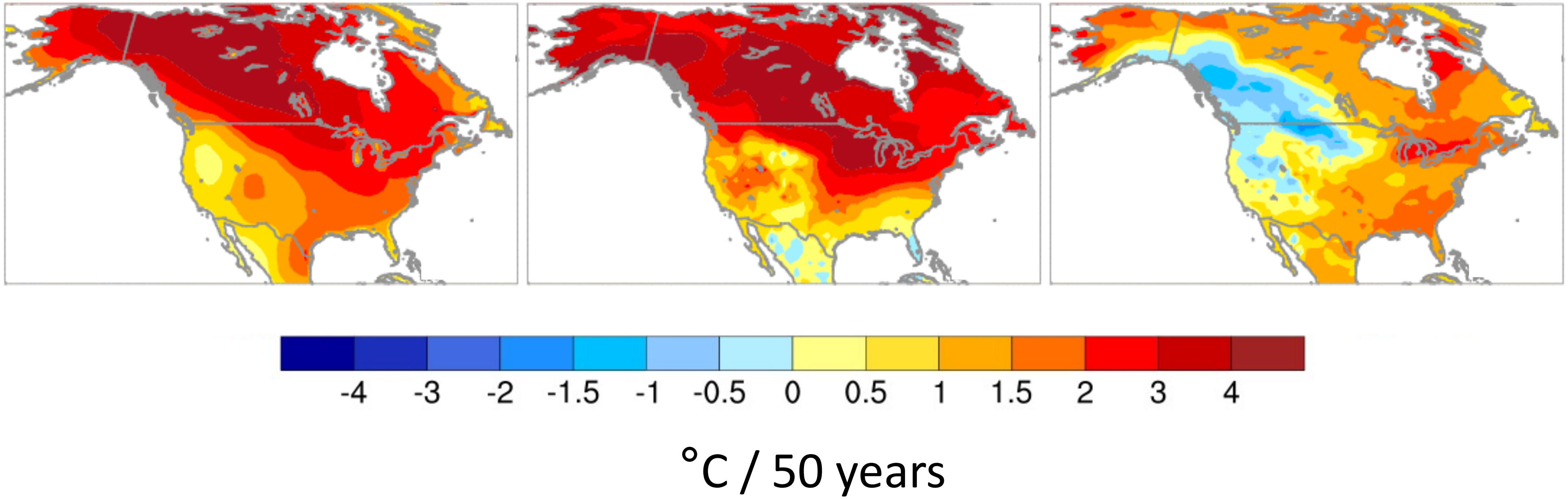
Winter Air Temperature Trends (1963-2012)

Observed | Another simulation of the same model | Model simulation



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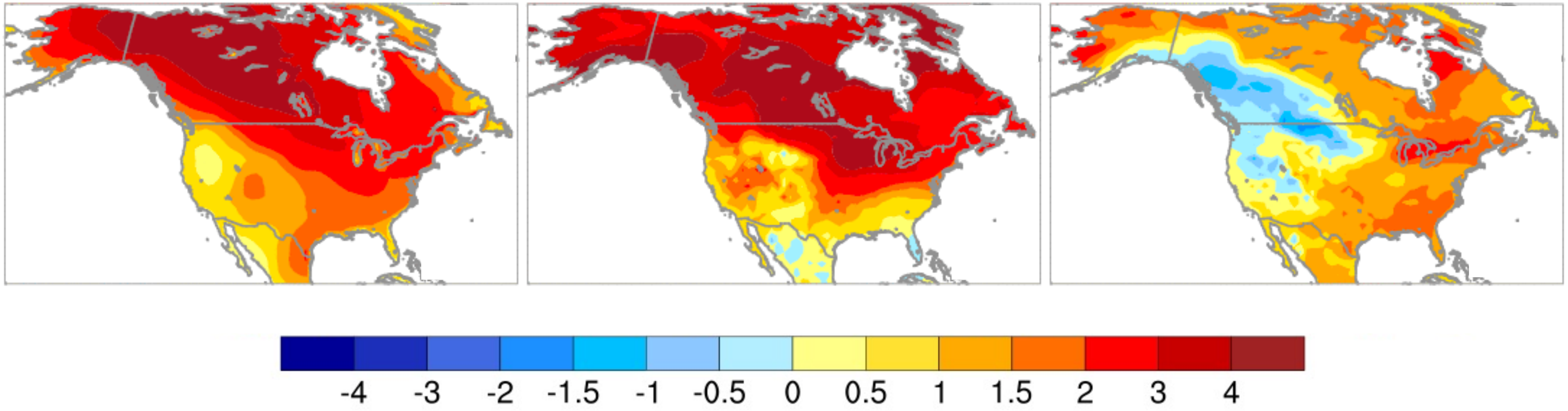

°C / 50 years

Internal

+

Forced

Deser et al., J. Climate 2016

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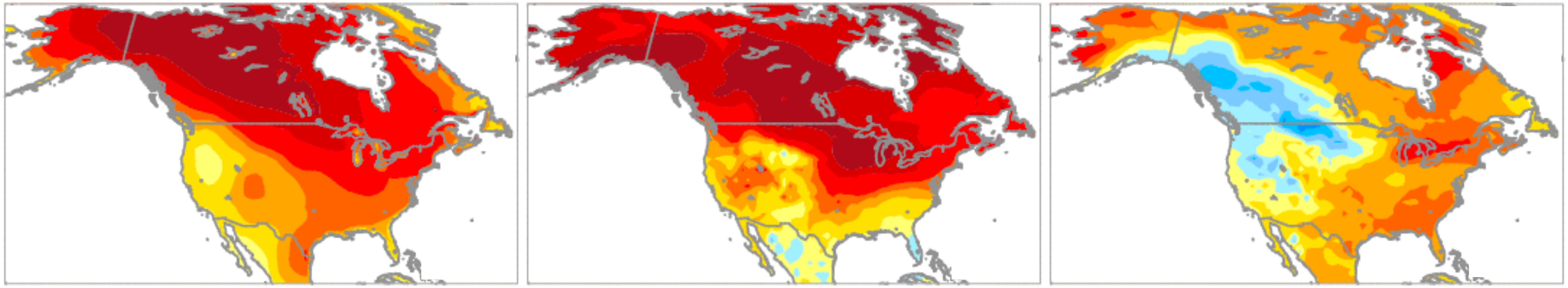

- **Is the model range plausible?**
- **How should we evaluate models given a single observed outcome?**
- **Could another reality have been possible?**

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Deser et al., J. Climate 2016

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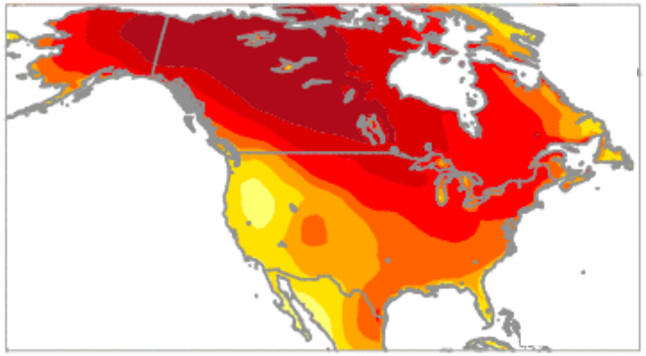

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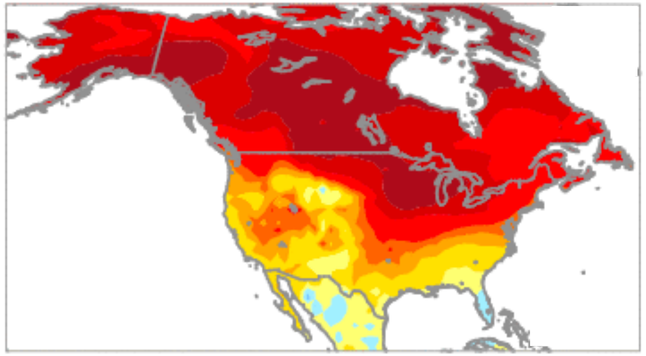

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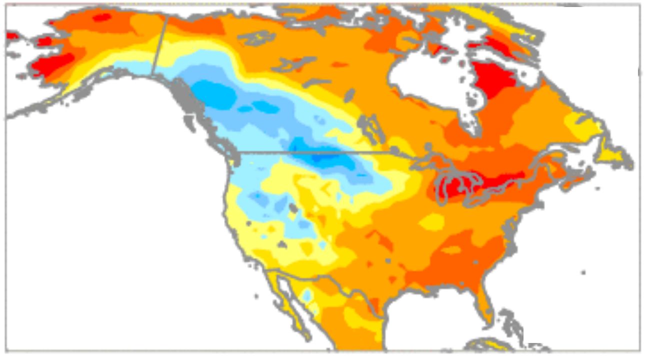

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➢ **New approaches and continued challenges.**

Internal

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  ForceSMIP workshop & hackathon *(Aug 2023, NCAR and ETH)*.
  Extensive comparison of existing methods and development of new ones, using SMILEs as a testbed; double-blind test of the methods, with application to observations.
  (See Robb Wills' poster on Friday.)

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- **Observed forced response:** statistical & dynamical methods. ***ForceSMIP workshop & hackathon*** (Aug 2023, NCAR and ETH).
- **Observed internal variability:** residual from forced response. *Limited to one realization: we don't know where the observed trend lies in the distribution of possible realities.*

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- Determine whether the observed trend lies within the spread of a given SMILE. However, this could be for the "wrong reason": e.g., spread due to internal variability might be too large. Relatedly, the forced response and associated signal-to-noise ratio might be too low.

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- How do we evaluate ensemble spread in a SMILE? Need to construct plausible alternative outcomes for observed trends.

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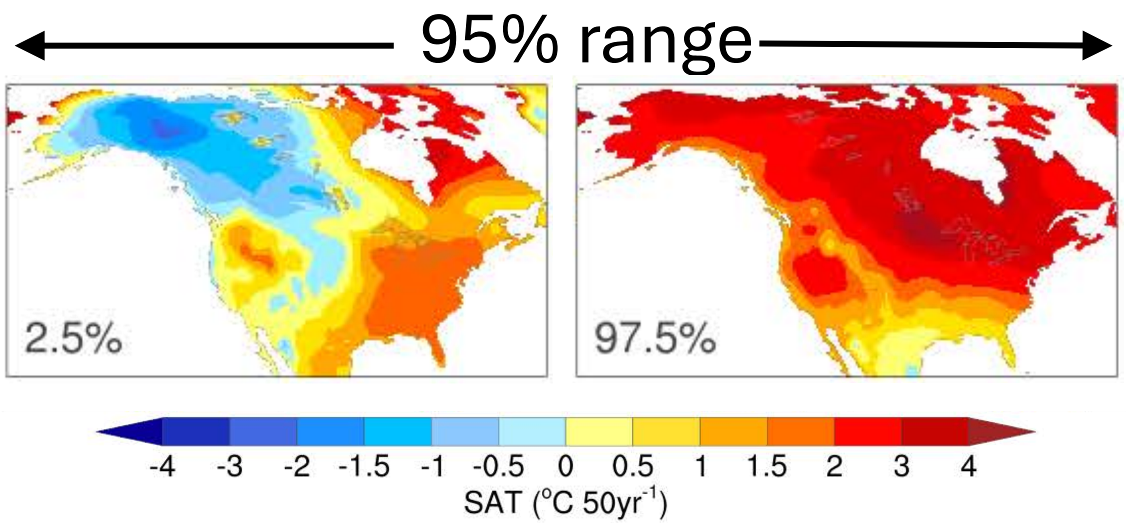
Alternate Realities: Statistical Approach (O-LENS)

Winter Air Temperature Trends (1963-2012)

Internal component from the 1000-member “Obs Large Ensemble” added to forced component from CESM1 SMILE.



McKinnon and Deser (2018)

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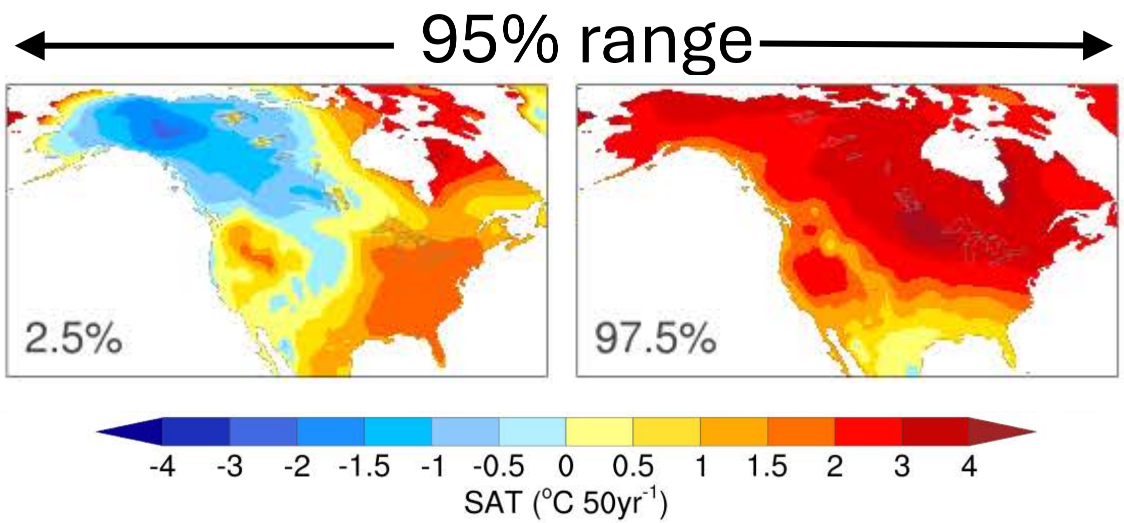

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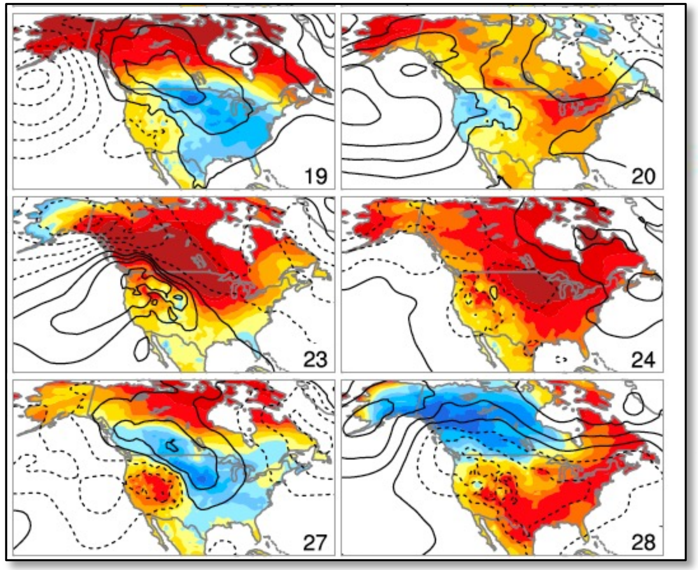
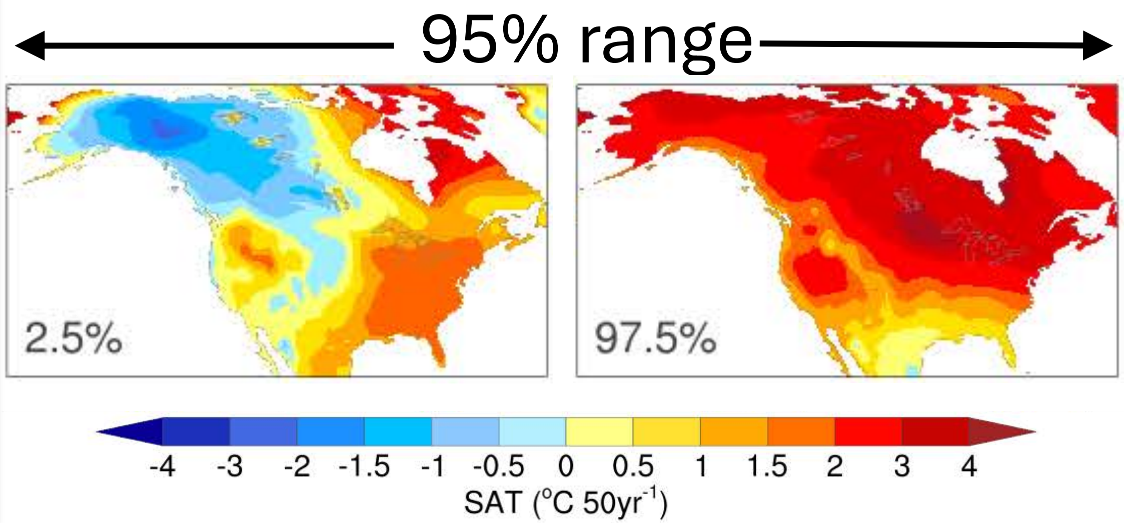


CESM1 SMILE



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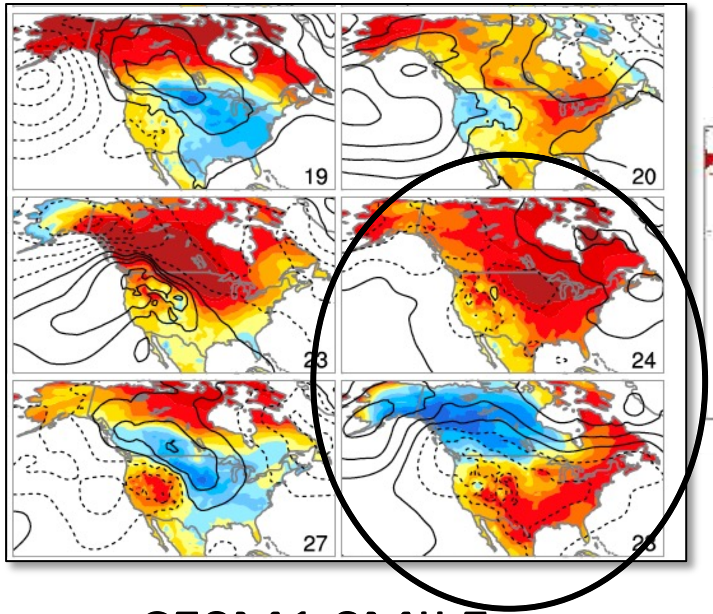
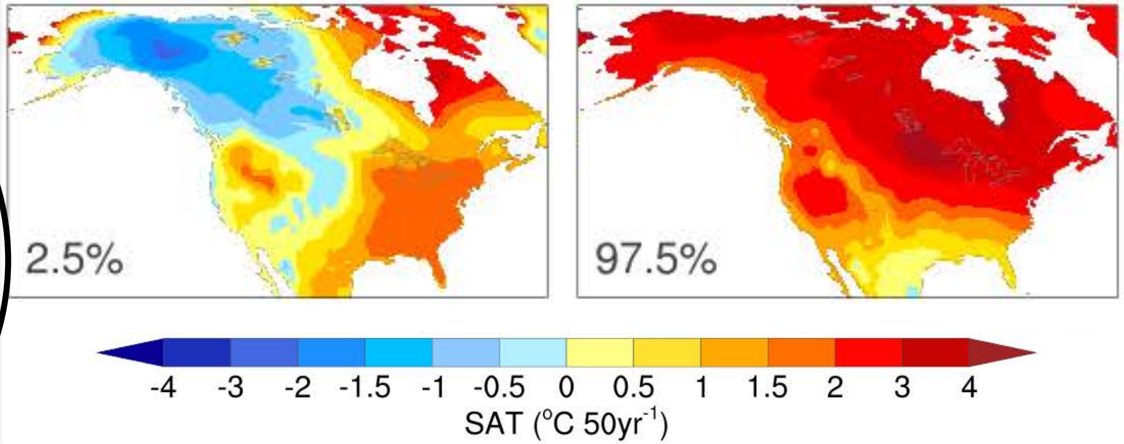


CESM1 SMILE

95% range



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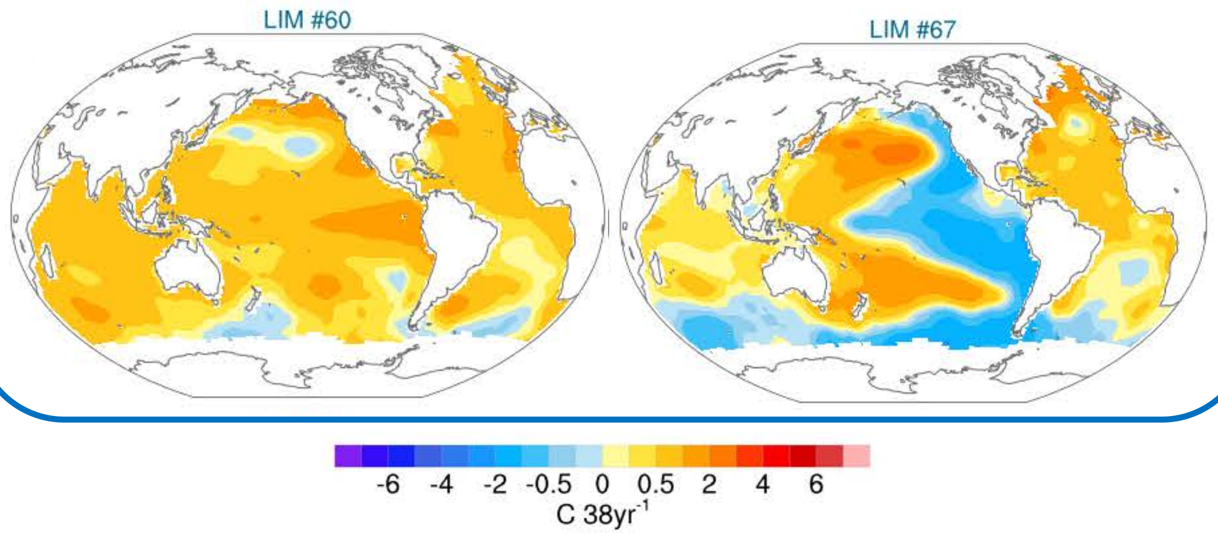
- Dynamical Linear Inverse Modeling (LIM) of global SSTs (Newman et al.). Yields estimated forced response (gravest modes) and internal variability.

Alternate Realities: Dynamical Approach (LIM)

Observed SST (ERSSTv5) Trends (1980-2017)

Two LIM realizations



Courtesy of Matt Newman

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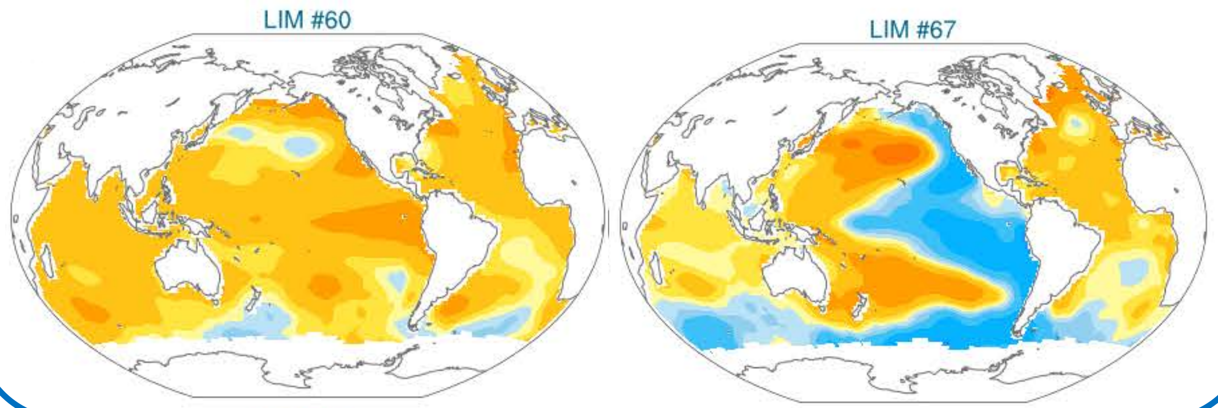

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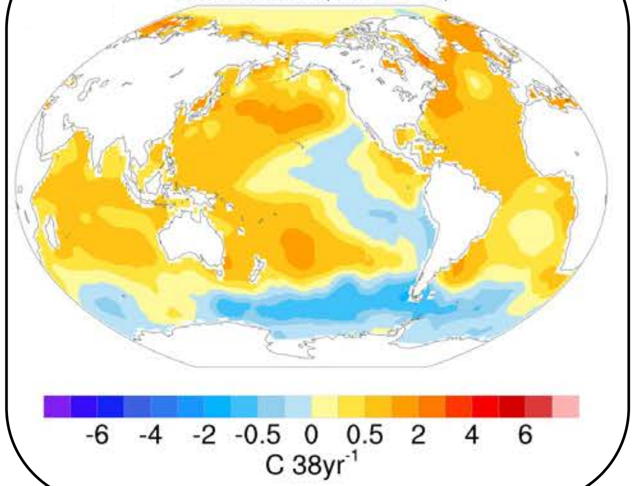
Actual



Alternate Realities: The role of the atmospheric circulation

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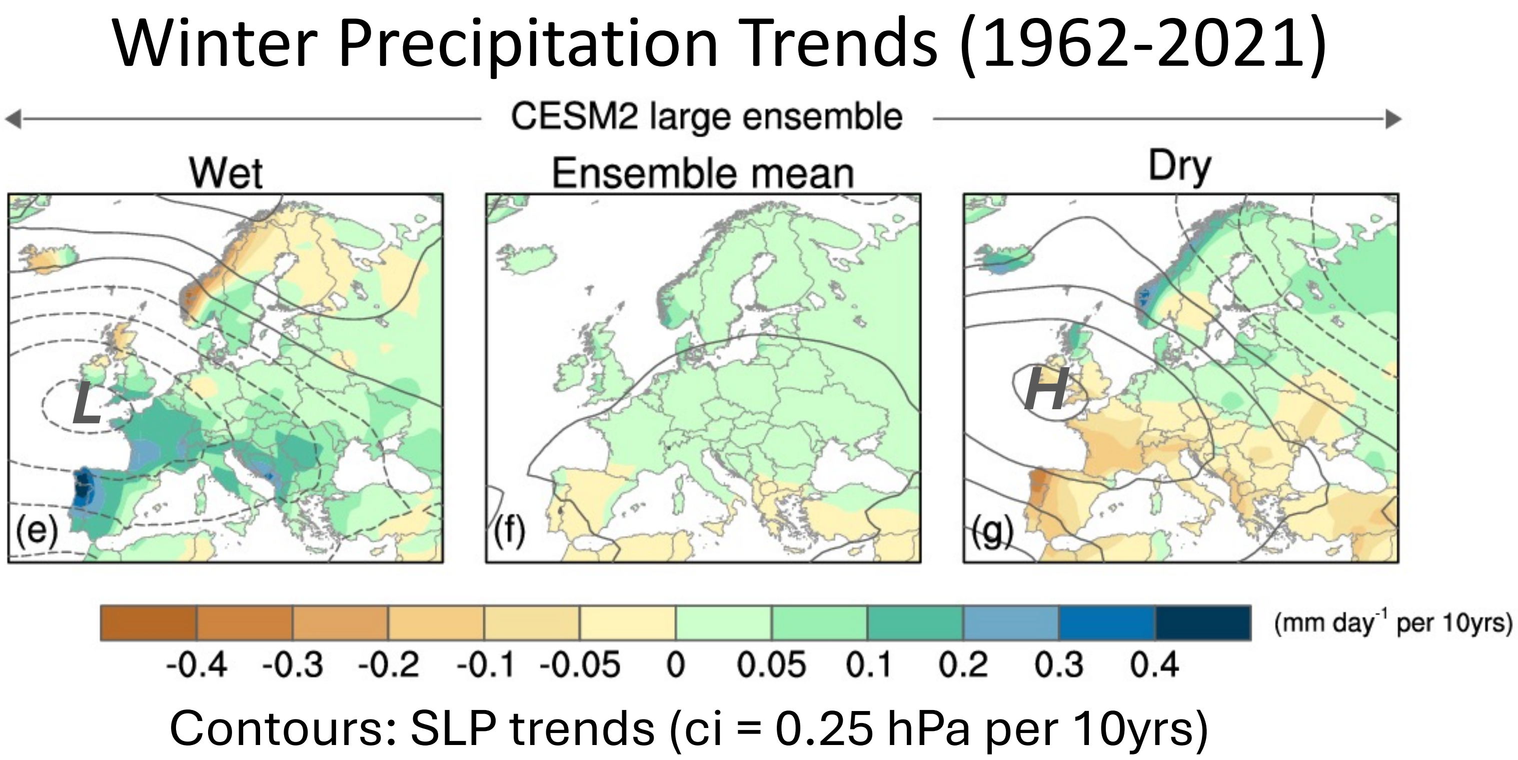
Internal SLP trends are driving most of the spread in precipitation trends.



Deser and Phillips (2023)

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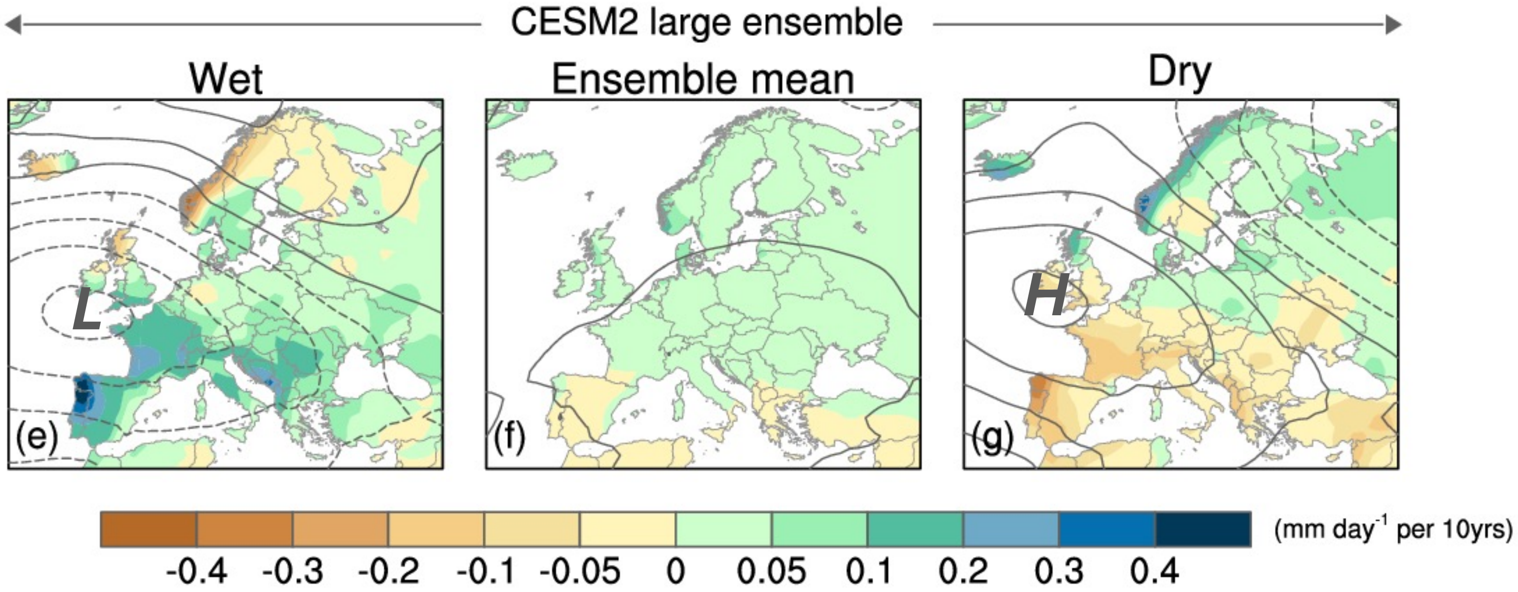
Can we use this fact to estimate the forced component of observed precipitation trends?

Winter Precipitation Trends (1962-2021)



Contours: SLP trends (ci = 0.25 hPa per 10yrs)

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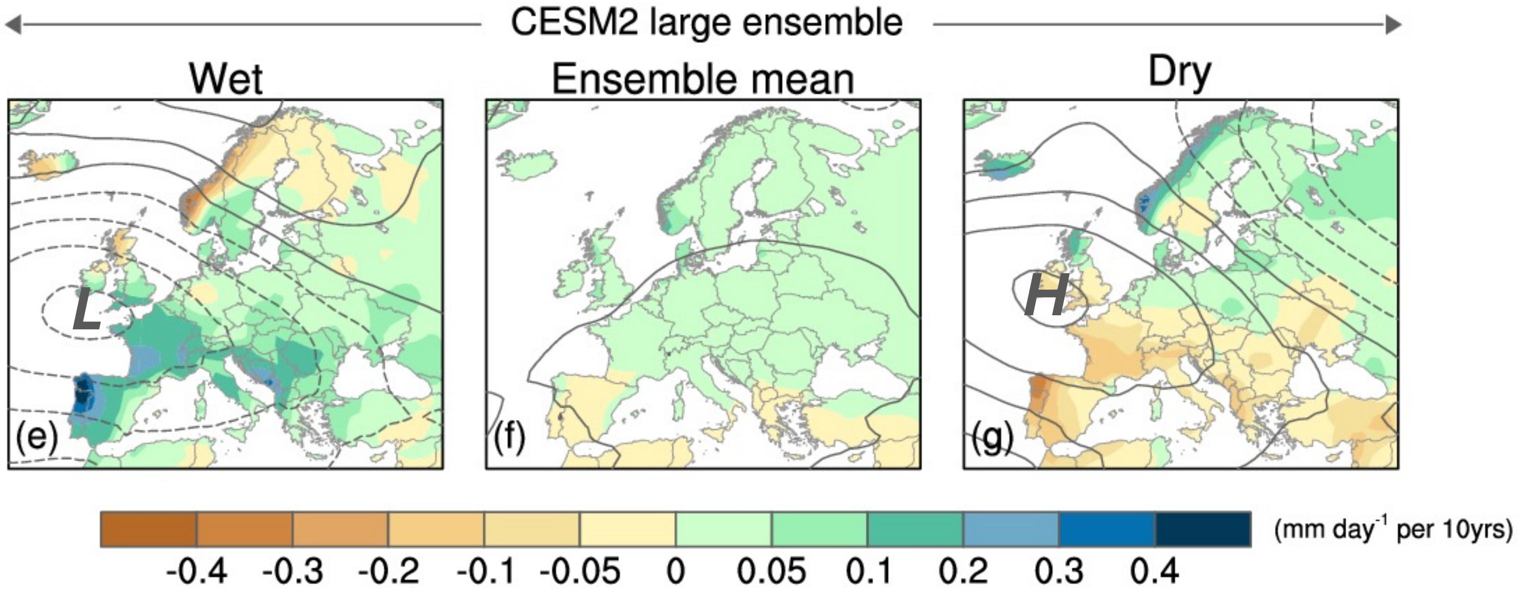

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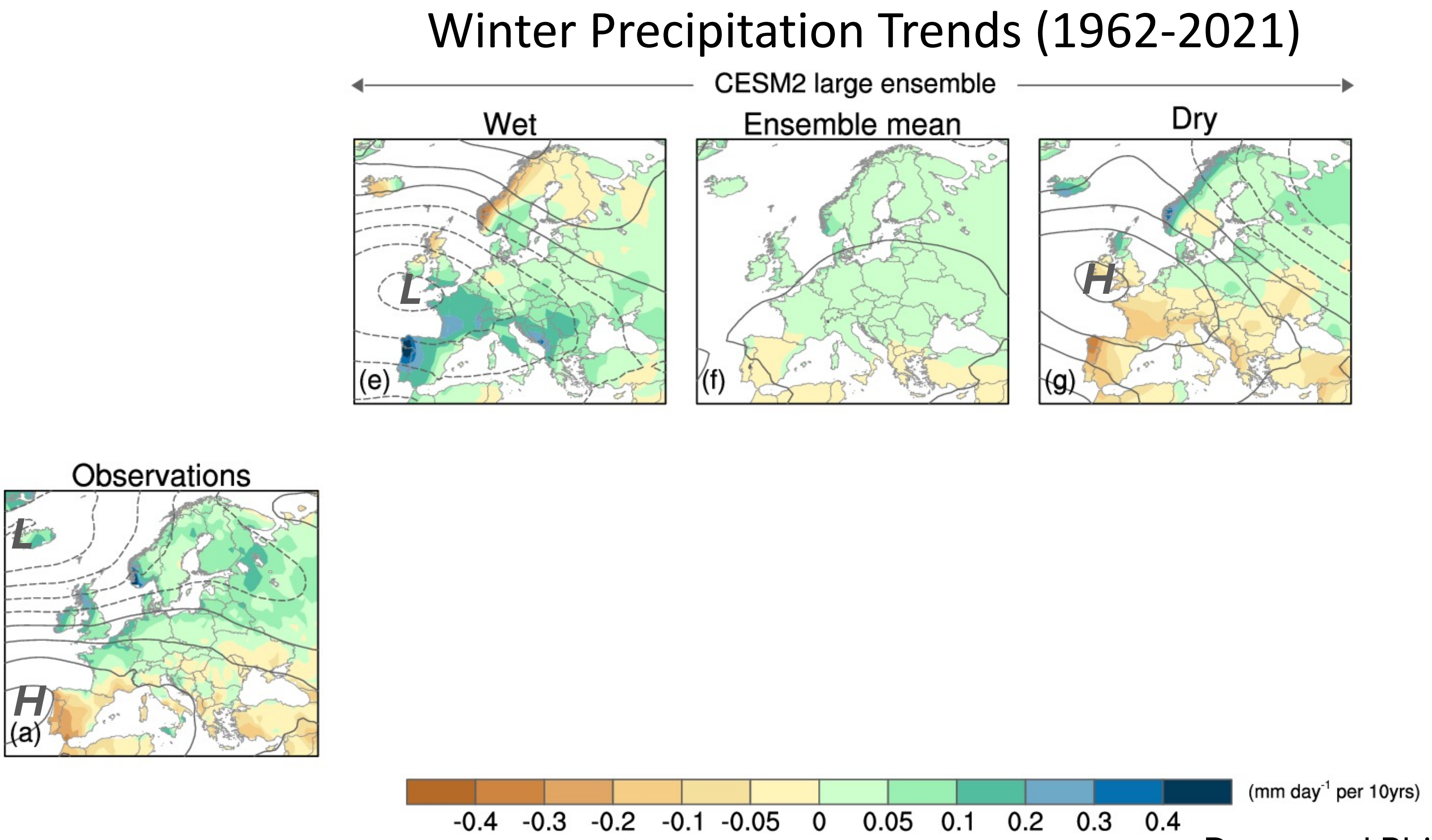
Remove an empirical estimate of the dynamically-induced component to obtain the forced component (thermodynamic) as a residual. "Dynamical Adjustment" procedure based on constructed circulation analogs using observed interannual SLP and precipitation relationships (Deser et al. 2018; Wallace et al. 2012).

Alternate Realities: The role of the atmospheric circulation



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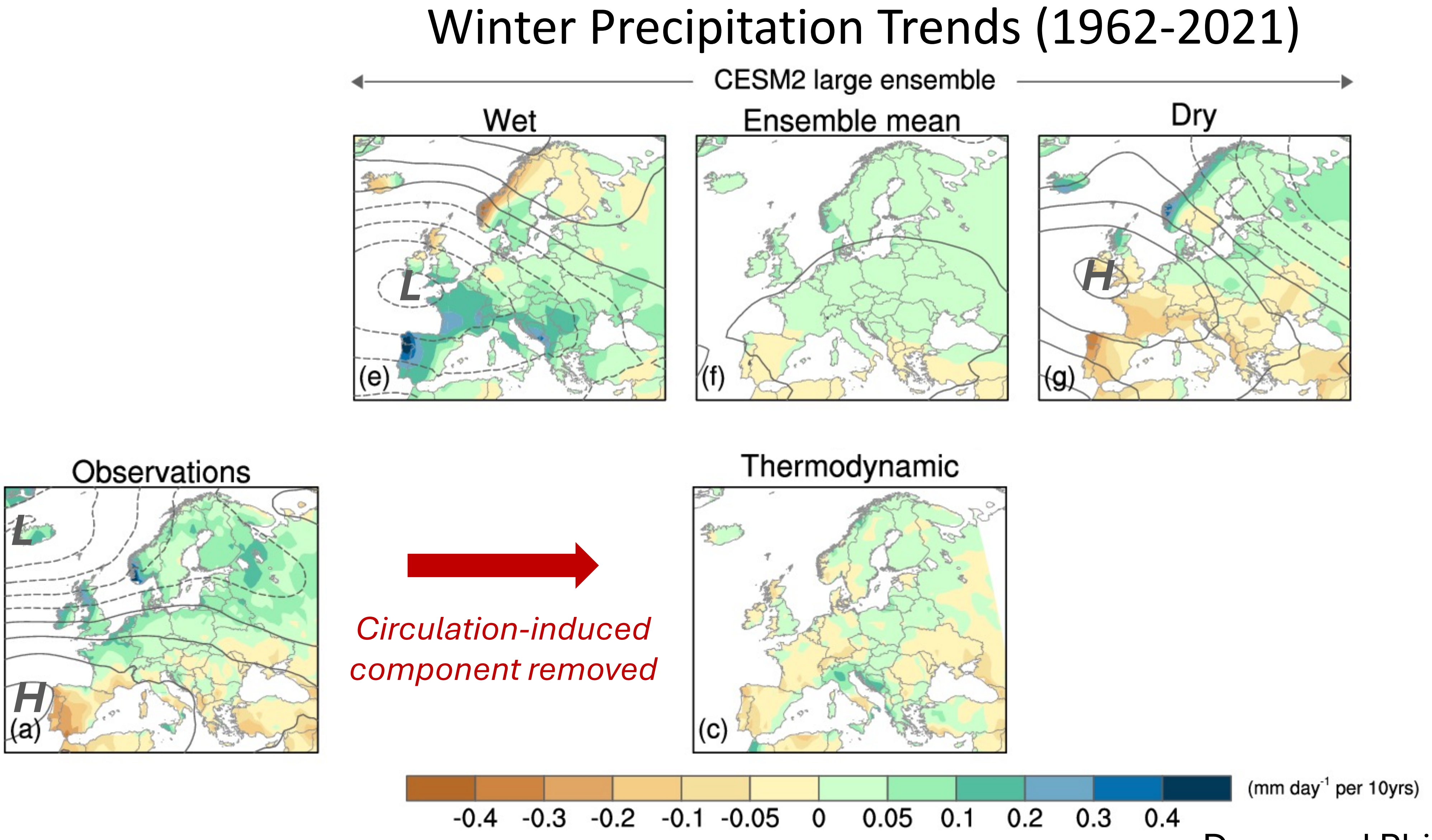

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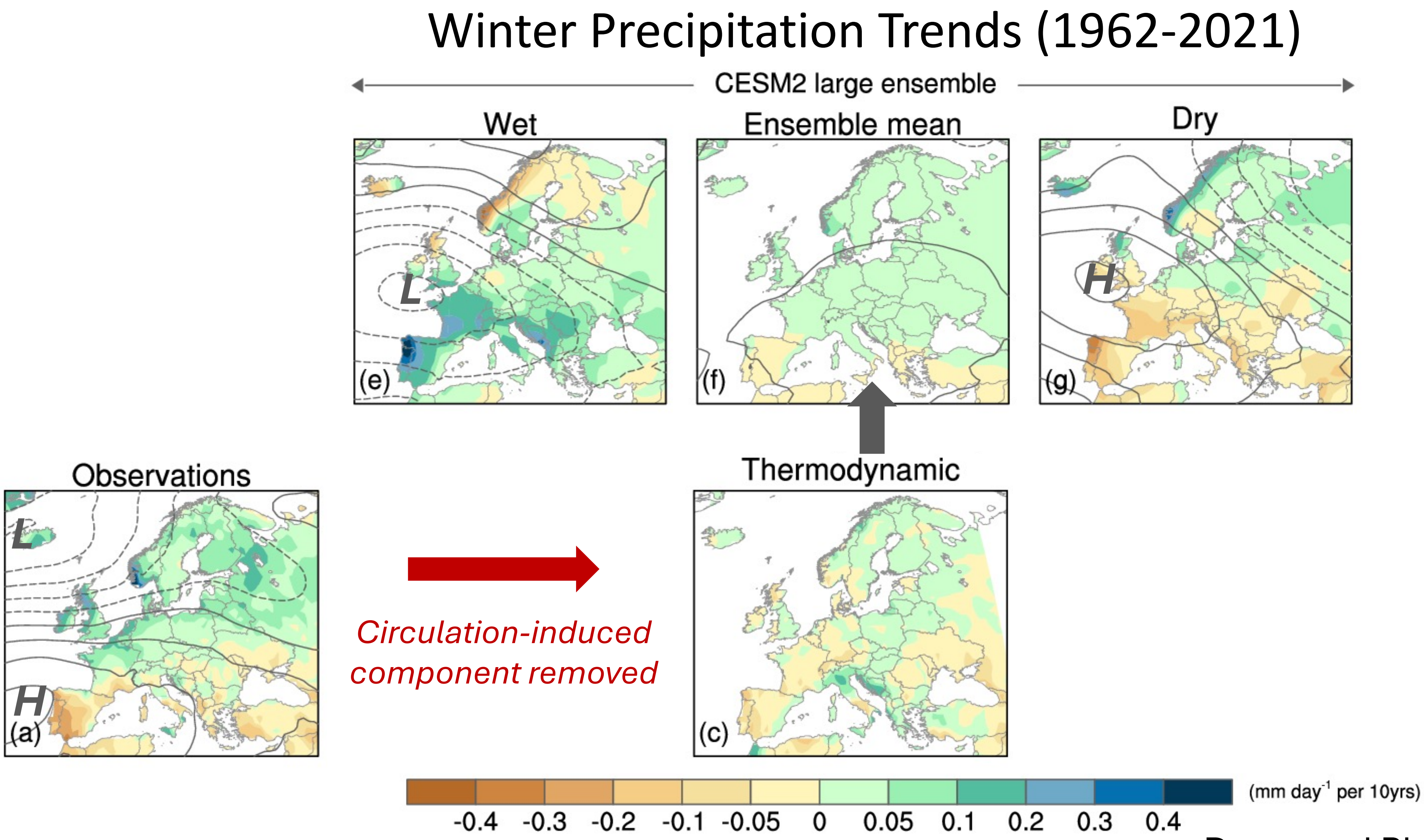

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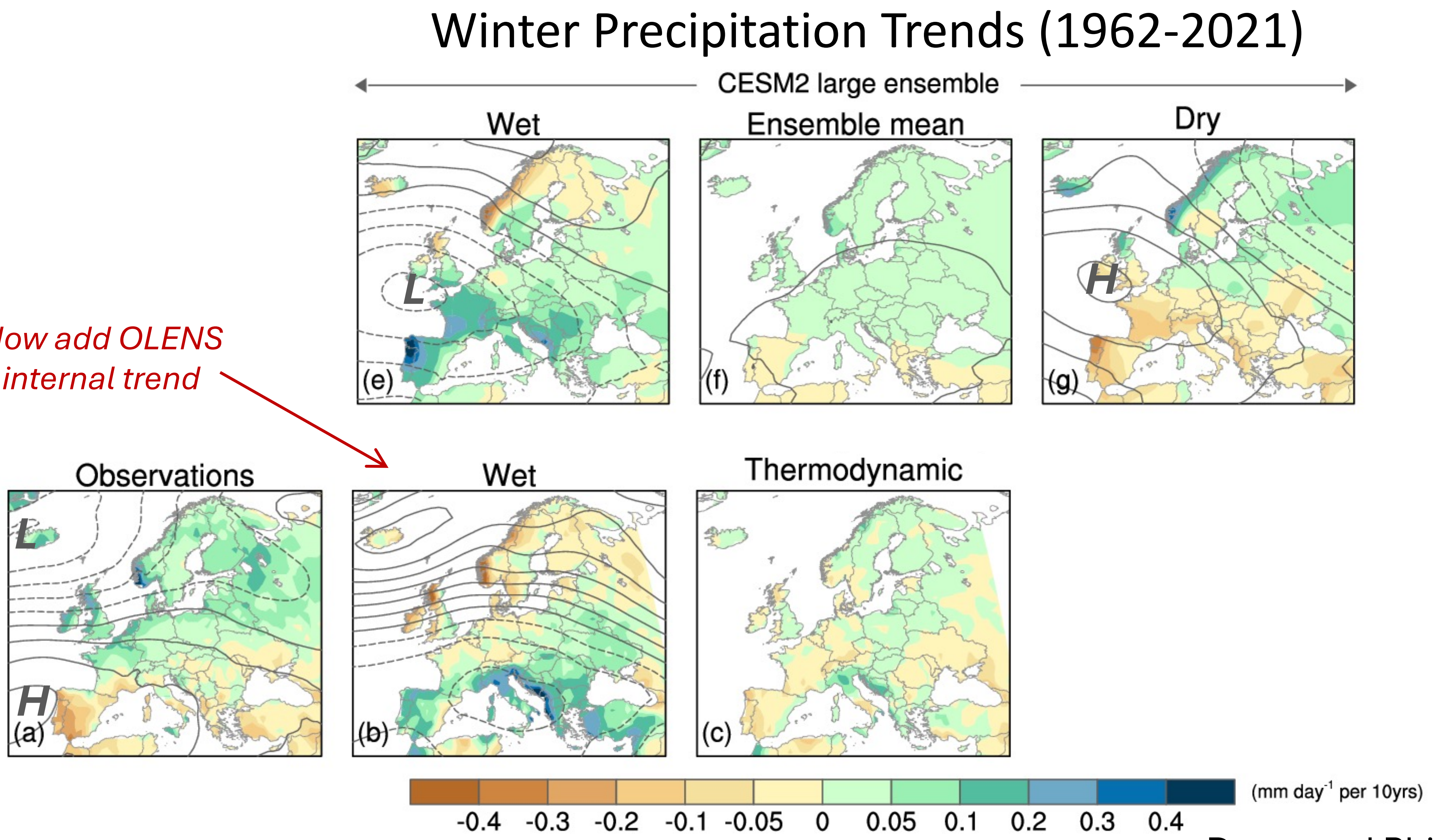
Alternate Realities: The role of the atmospheric circulation

Now add OLENS internal trend



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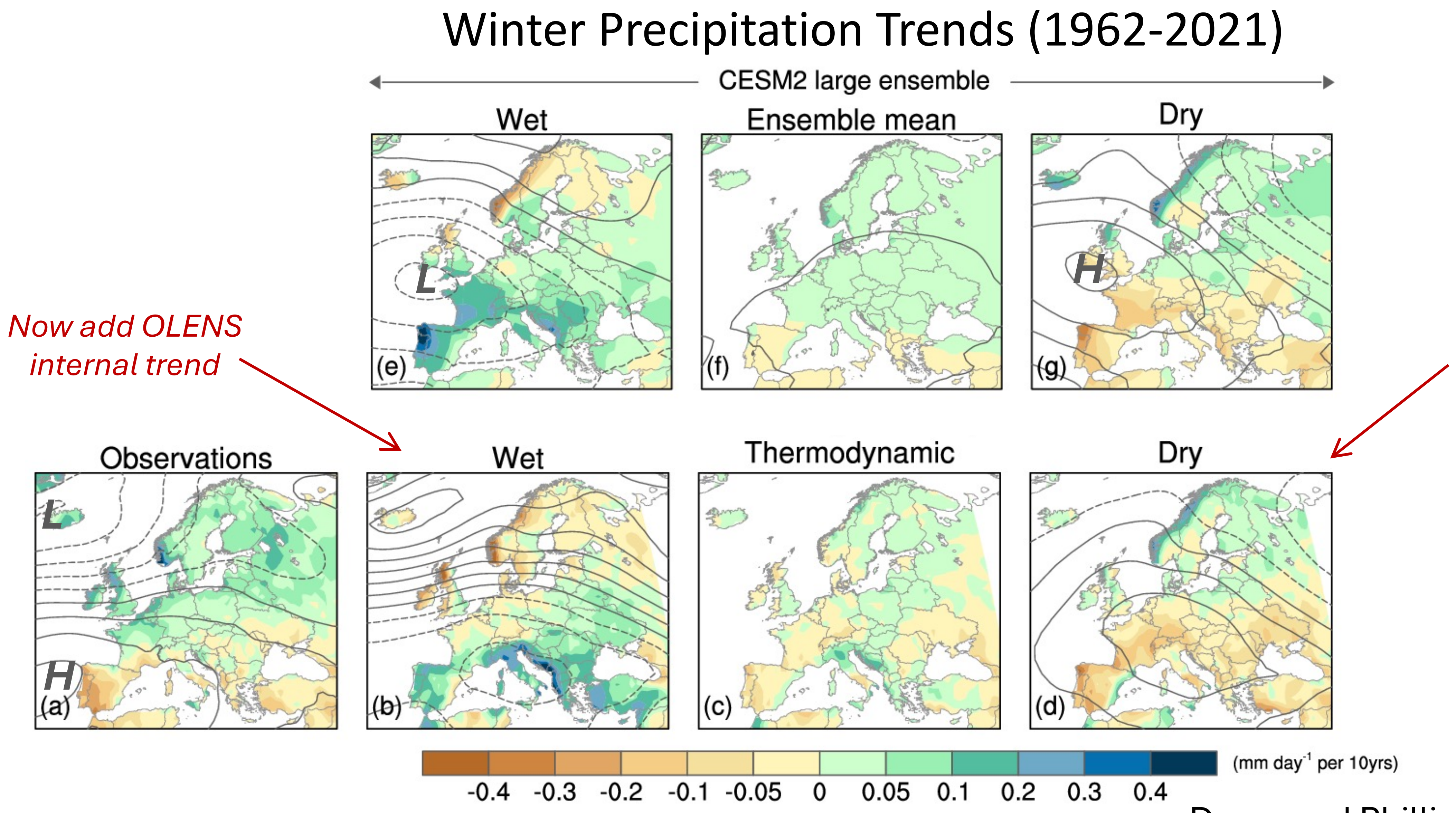

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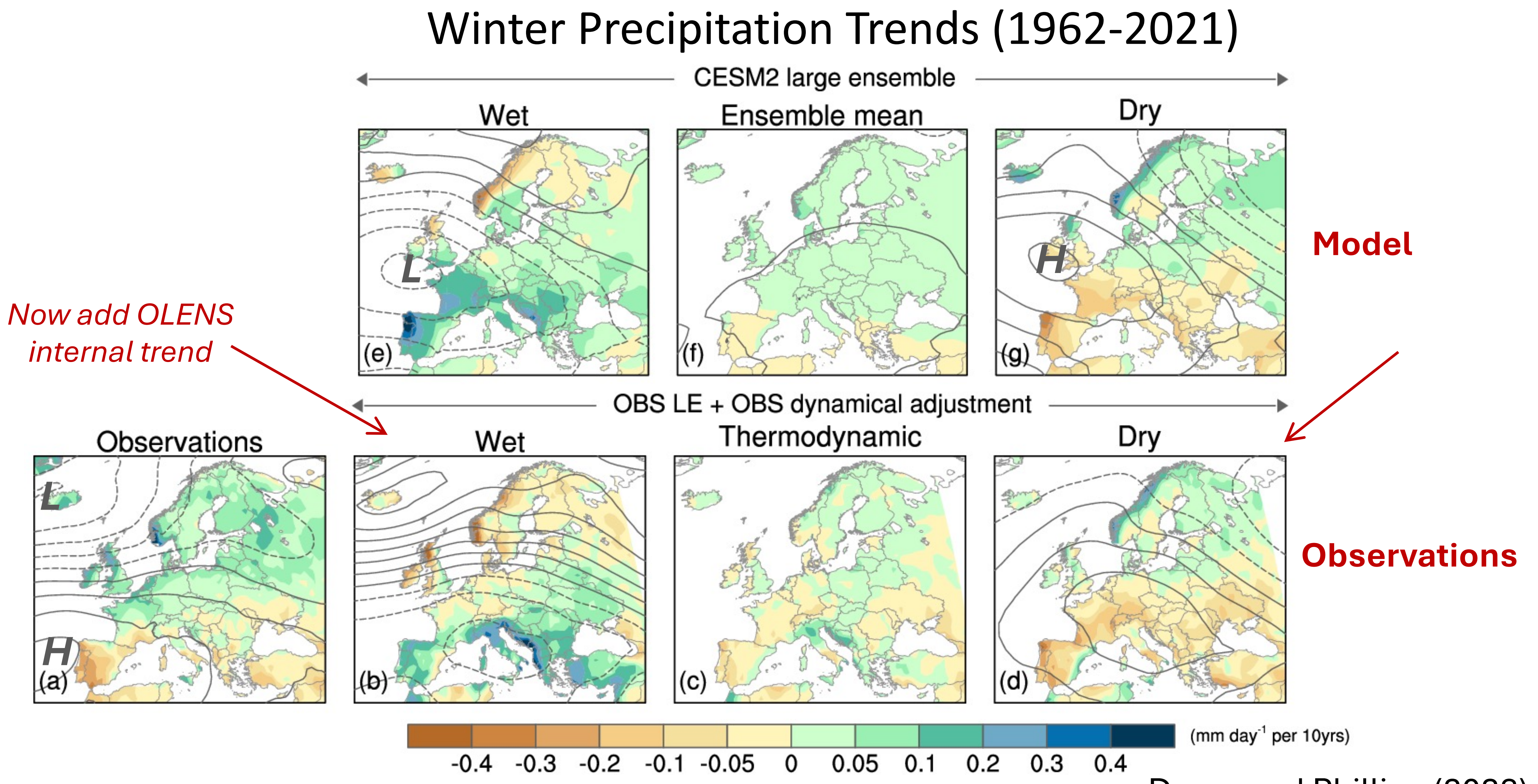

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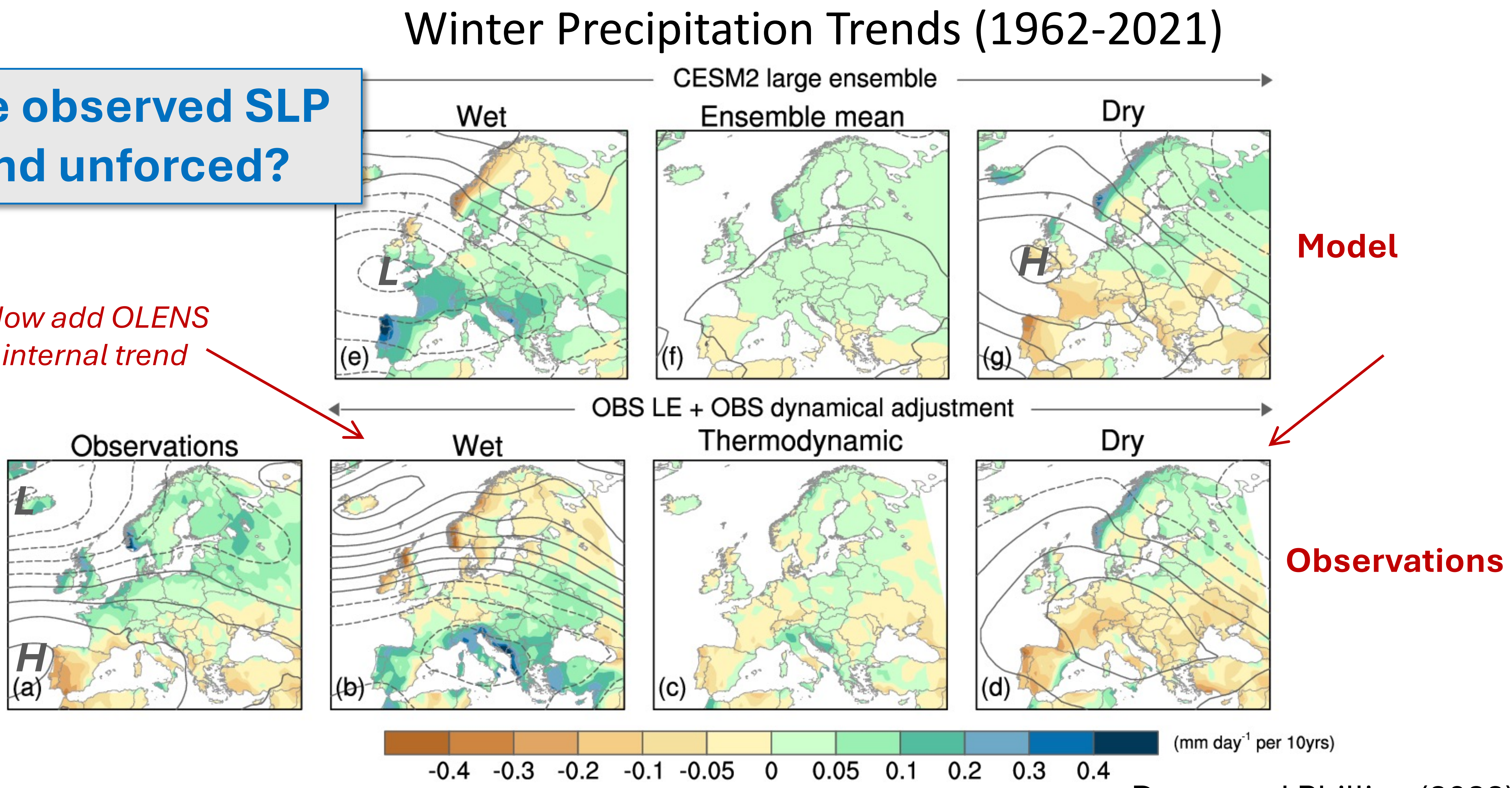
Is the observed SLP trend unforced?

Now add OLENS internal trend



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Additional Challenges and Implications

- The presence of forced trends may corrupt our empirical definitions of modes of internal variability (e.g., AMV, PDV, ENSO …).
- The limited length of the instrumental record restricts our knowledge of the true range of internal variability.
- SST trends may modulate impacts from the 2023/24 El Nino.
- A cautionary note on comparing CMIP5 & CMIP6 models.

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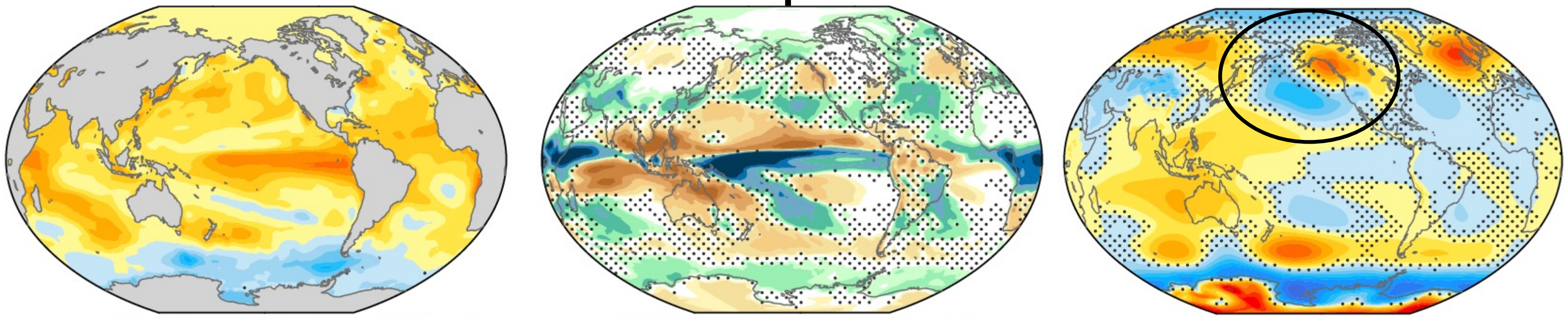
50-member AMIP responses

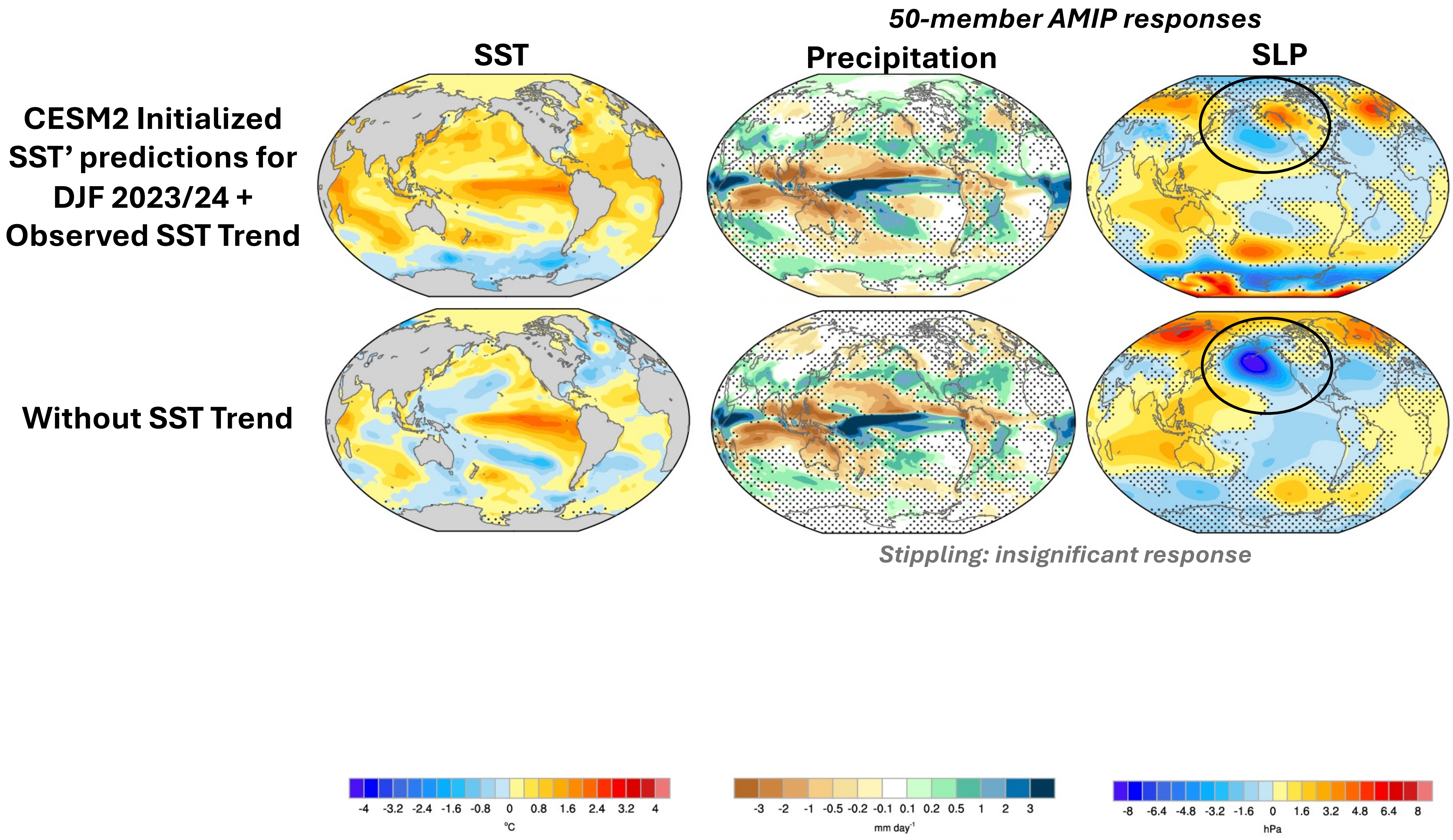
CESM2 Initialized SST' predictions for DJF 2023/24 + Observed SST Trend

SST **Precipitation** **SLP**



Stippling: insignificant response

Deser et al. in preparation



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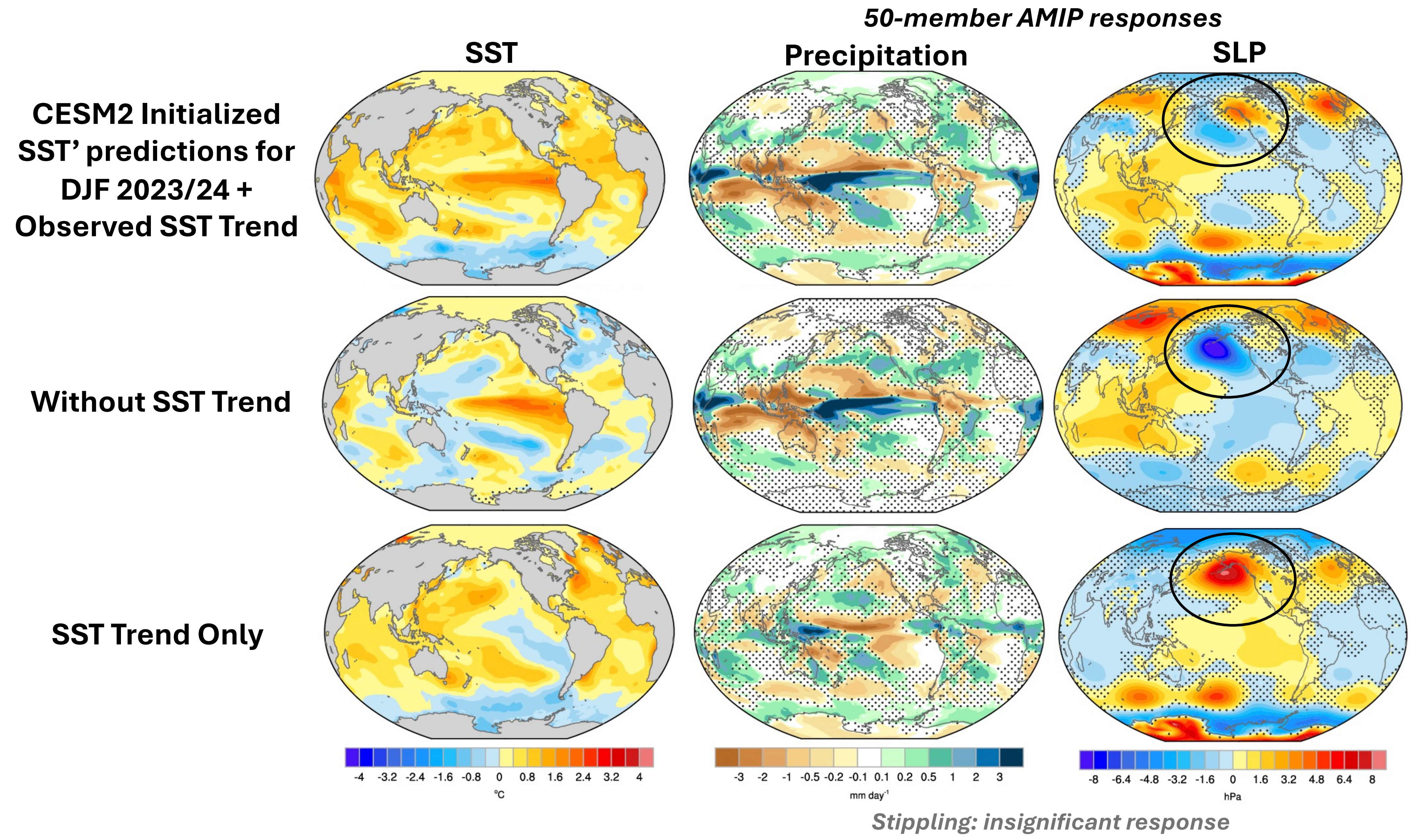

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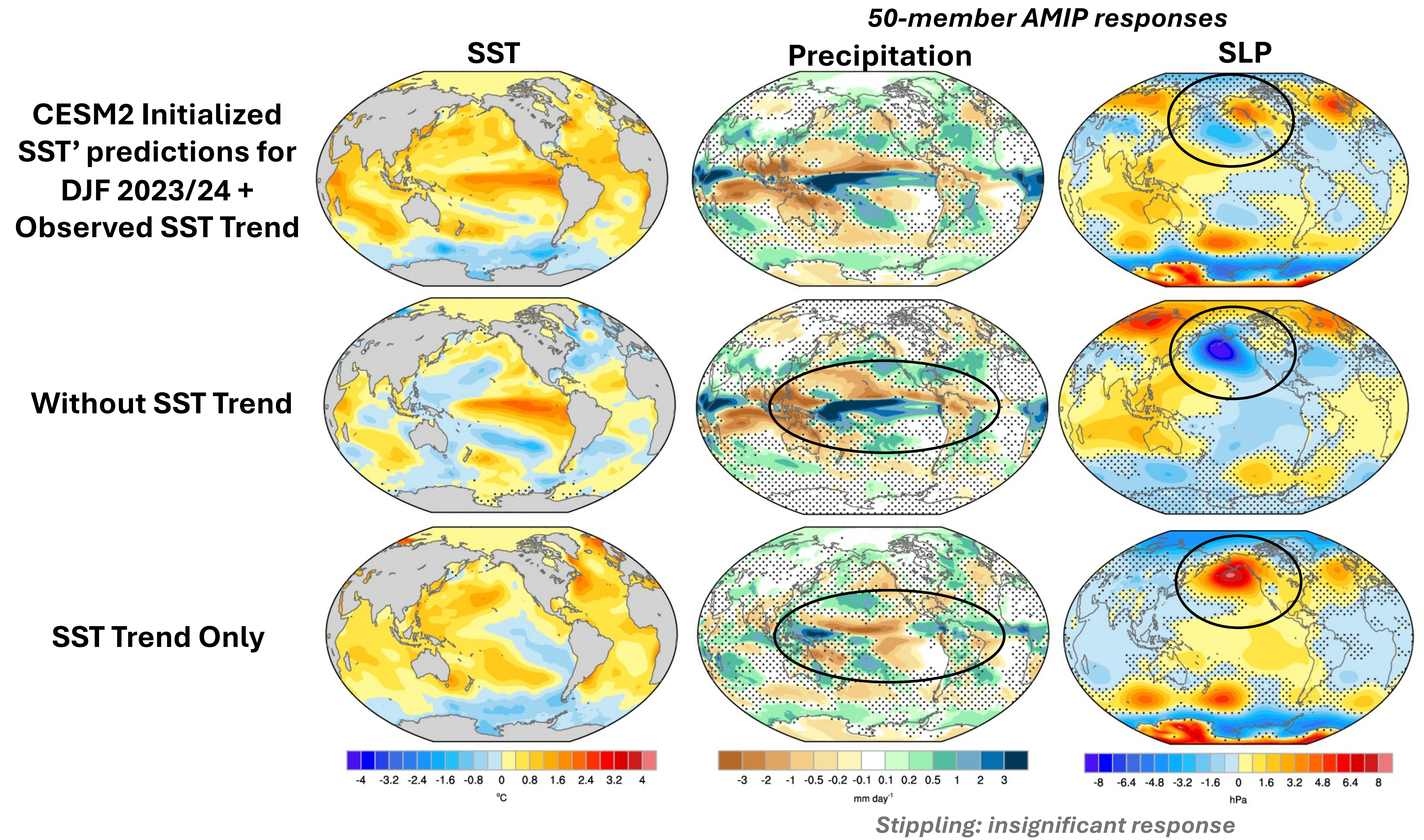

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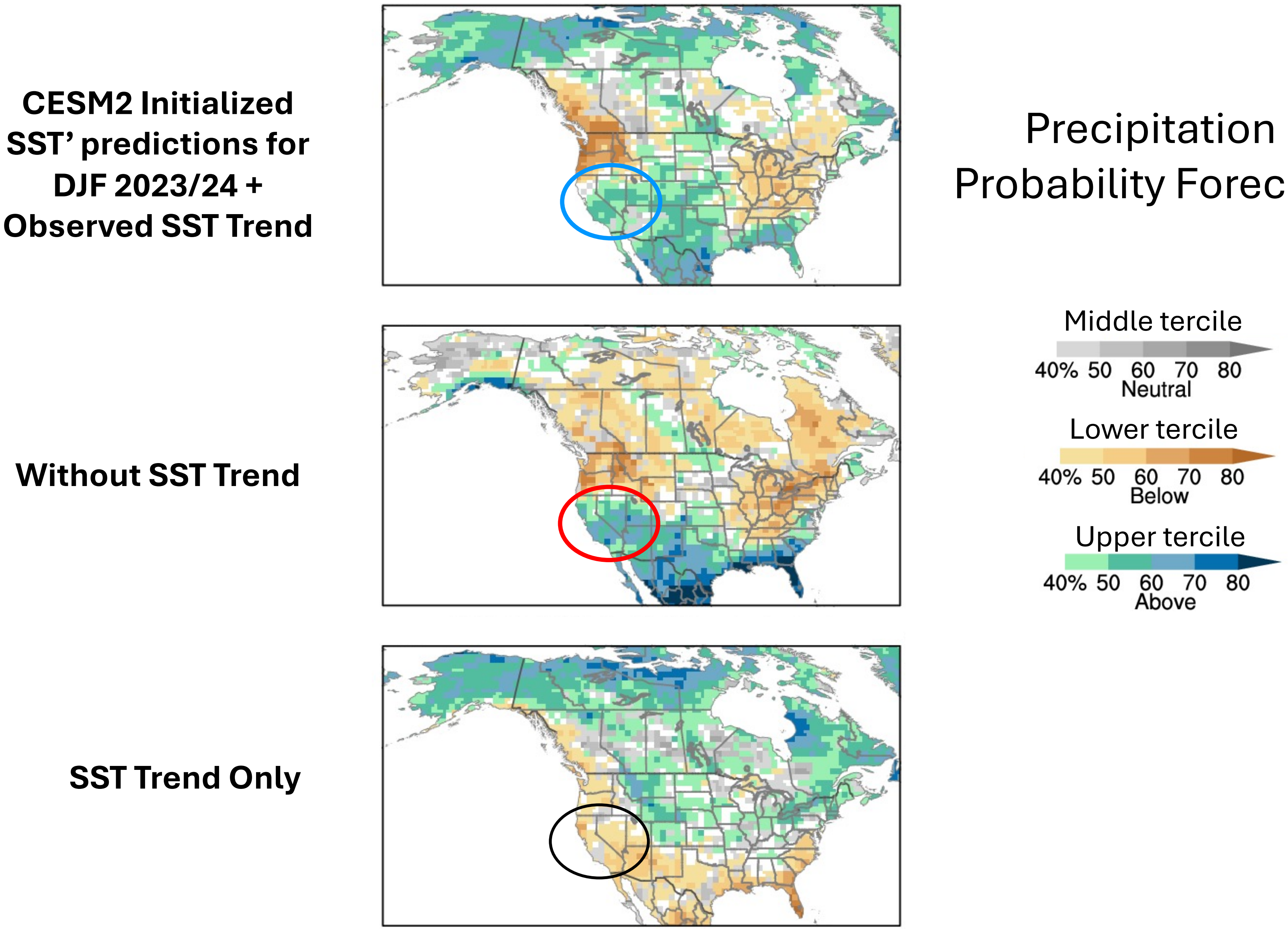
Precipitation Probability Forecast



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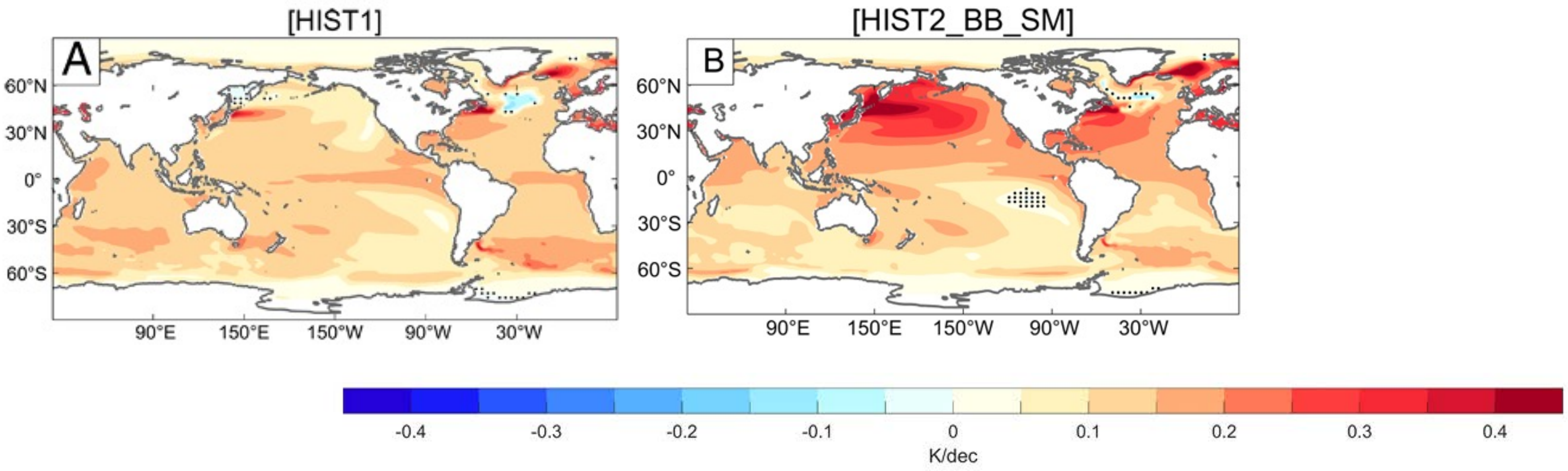
Ensemble Mean SST Trends 1979-2013

CESM1 (40)

CESM2 (50)



Kang et al. 2023

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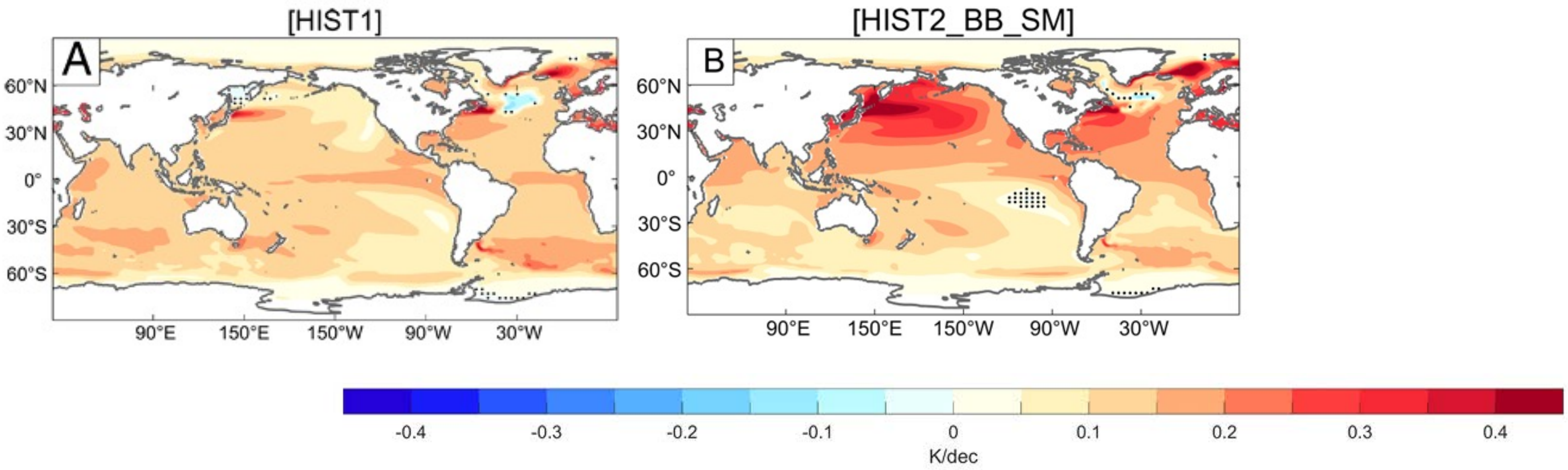

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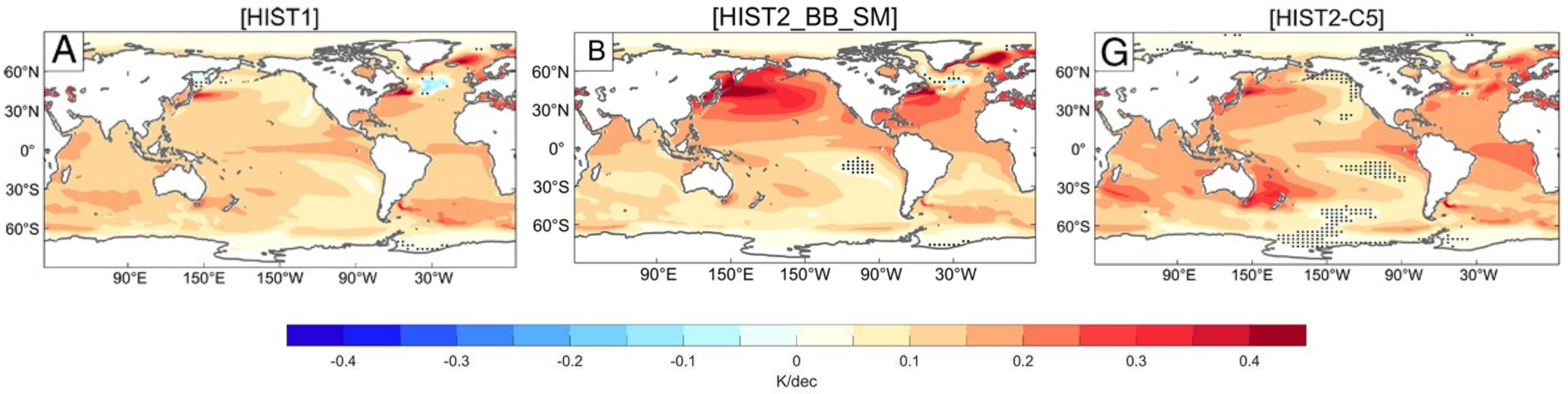
Holland et al. 2024

CESM1 (40) CMIP5 forcing | **CESM2** (50) CMIP6 forcing | **CESM2 CMIP5** forcing (15)



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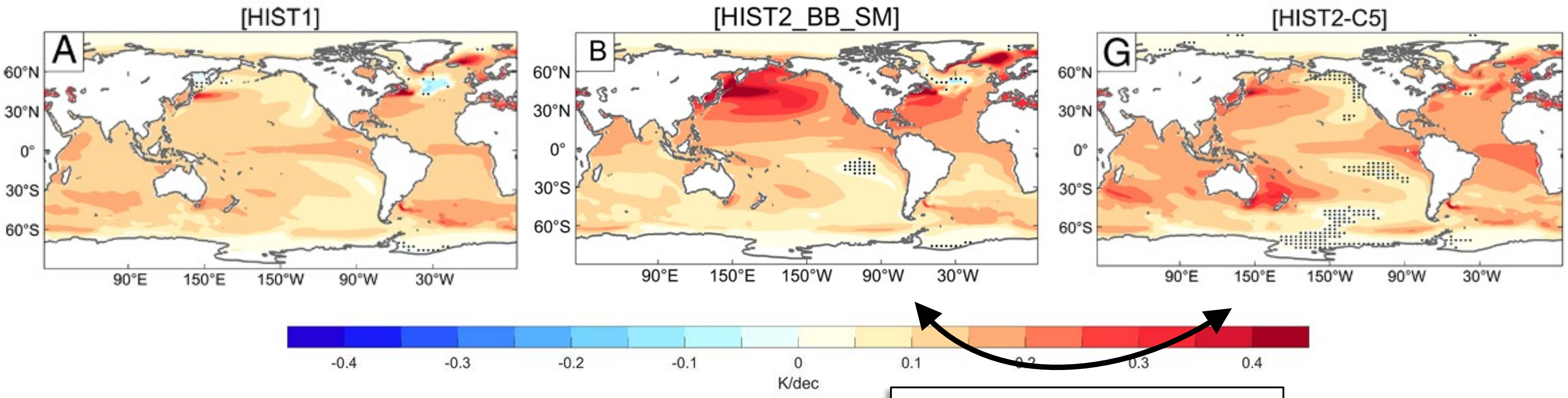

Kang et al. 202

Same model, different forcings.

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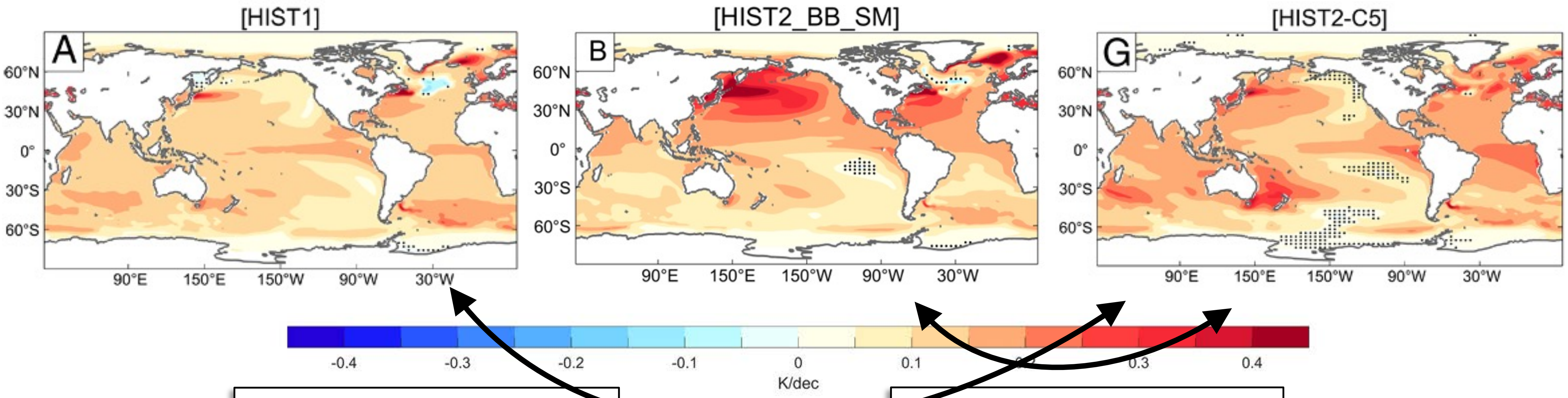

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Kang et al. 2023

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CGD's Climate Analysis Section

Climate Variability Diagnostics Package

for Large Ensembles

https://www.cesm.ucar.edu/projects/cvdp-le

An automated analysis tool and data repository for exploring forced and internal components of climate variability and change.

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- How well does a given model simulate the mean state, long-term trends, and modes of variability such as ENSO, NAO, AMV, PDV?
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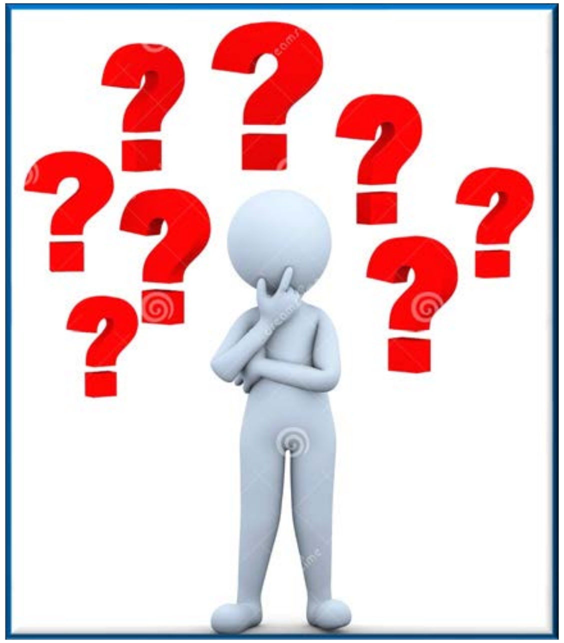

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Null hypothesis for any apparent model bias, inter-model difference, and projected change in variability should be "sampling fluctuations".

Some Tools and Resources

NCAR UCAR
CGD's Climate Analysis Section
Climate Variability Diagnostics Package
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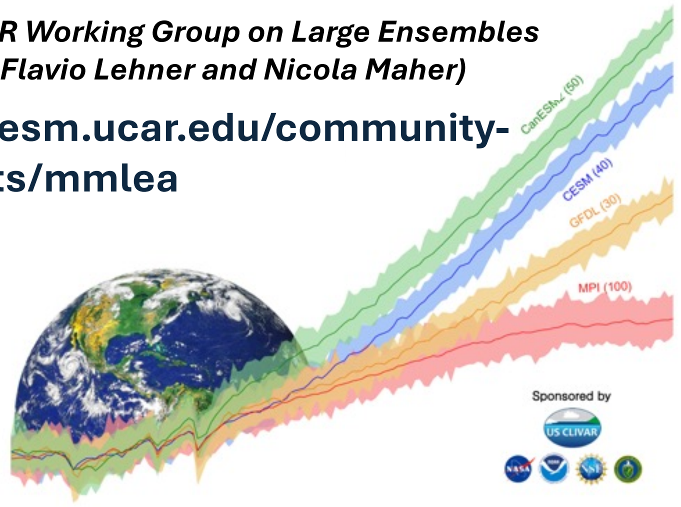
http://www.cesm.ucar.edu/working_groups/CVC/cvdp/

MULTI-MODEL LARGE ENSEMBLE ARCHIVE

US CLIVAR Working Group on Large Ensembles
(credit to Flavio Lehner and Nicola Maher)

www.cesm.ucar.edu/community-projects/mmlea



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National Science Foundation

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Aug. 29-31, 2023

Forced Component Estimation Statistical Method Intercomparison Project (ForceSMIP)

Organizers: Robb Wills, Clara Deser, Karen McKinnon, Adam Phillips, Stephen Po-Chedley, Sebastian Sippel

Aug. 29-31, 2023

Project (ForceSMIP)

Linear Trends (1950-2022)

Precipitation

SST

National Science Foundation

Swiss National Science Foundation

Aug. 29-31, 2023

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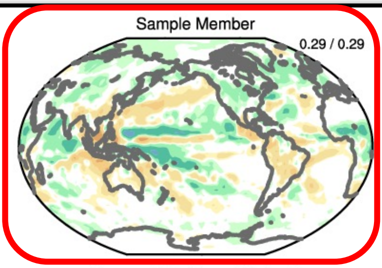

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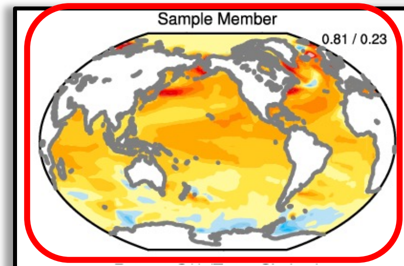

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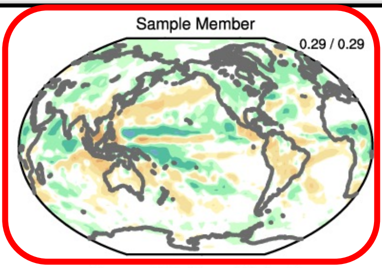

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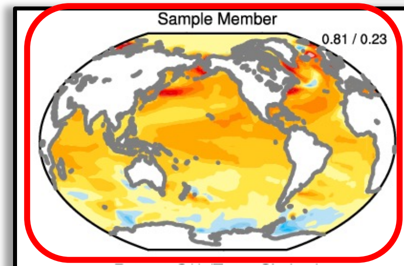

Each participant was asked to determine the forced trend component in the sample member, with no knowledge of the truth.

Methods were developed on a set of "training ensembles" and evaluated using a different set of ensembles. Model identification was removed and all models were put on a common grid.

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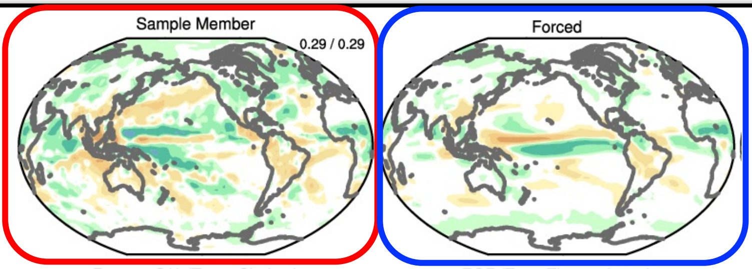
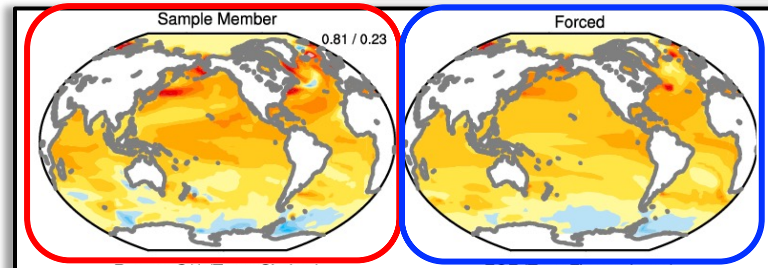


Unknown to participants

SST



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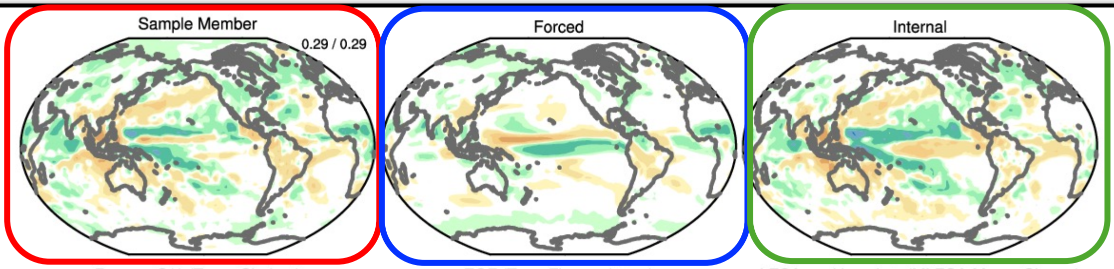

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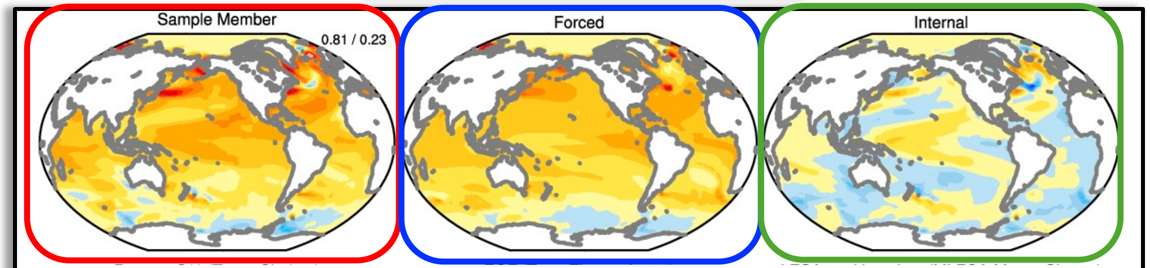

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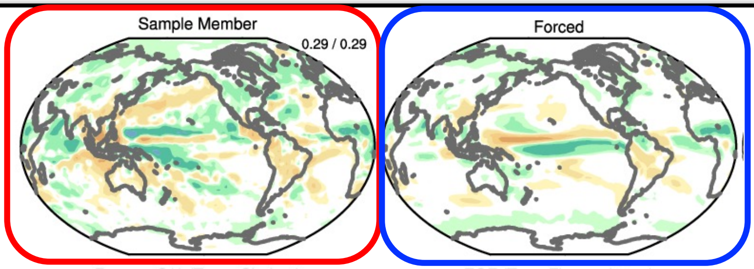

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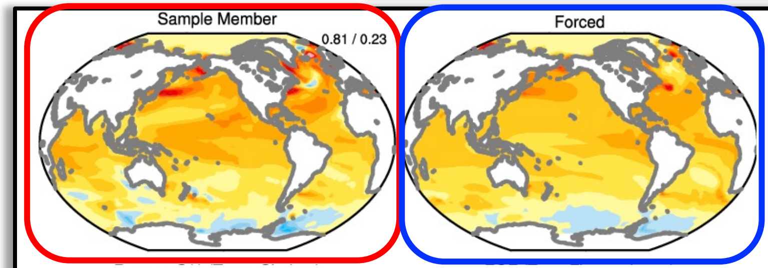

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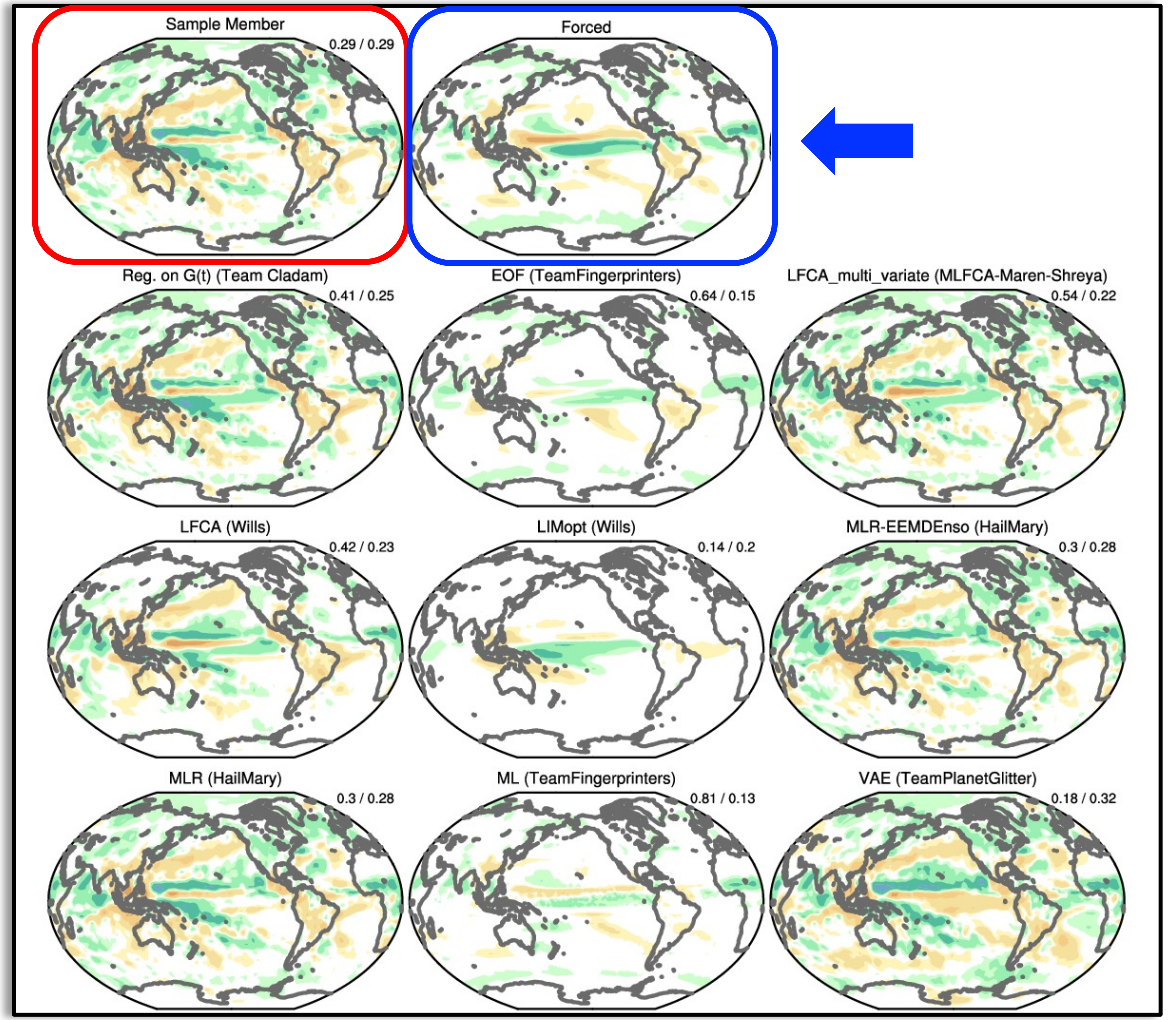

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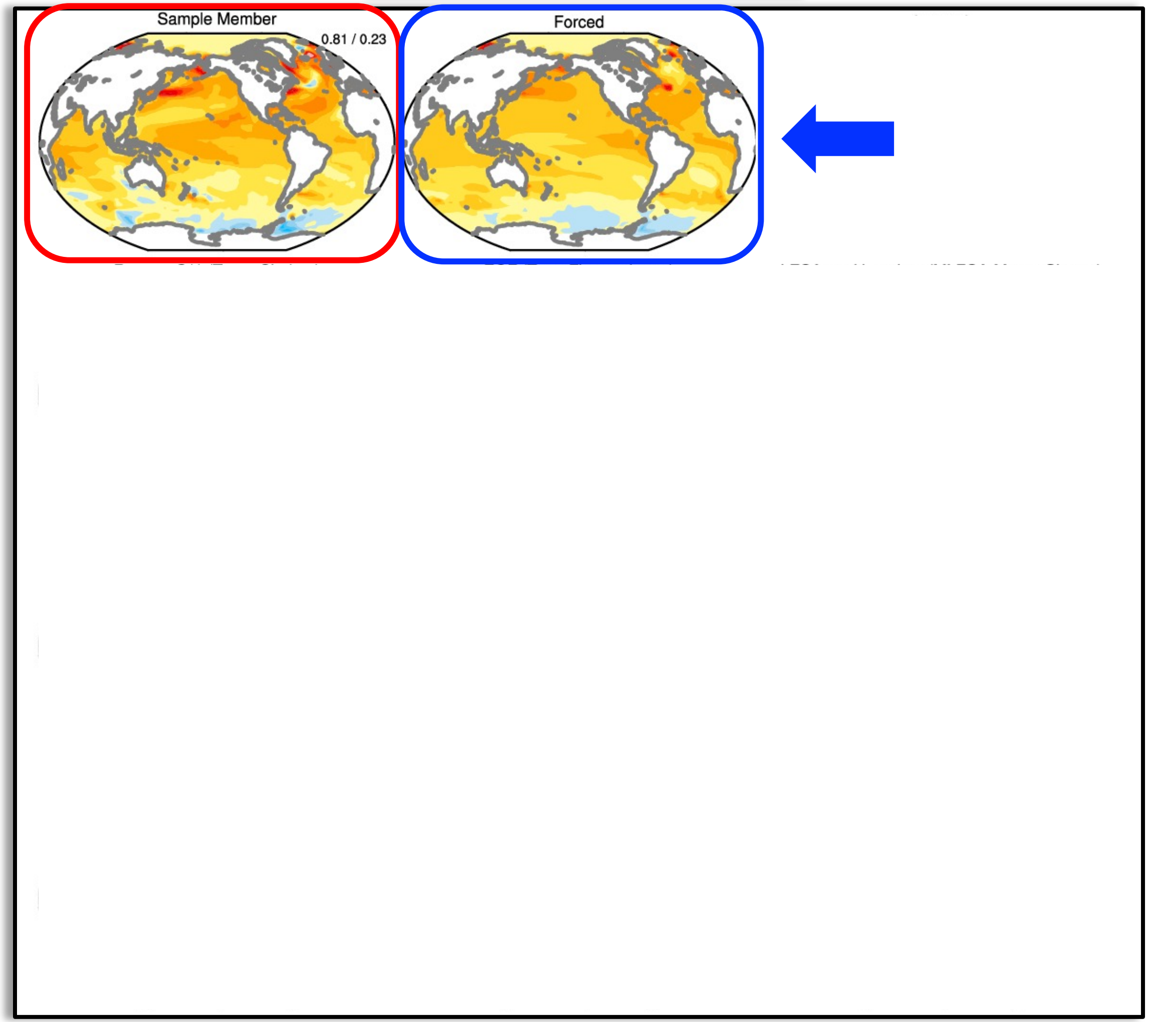

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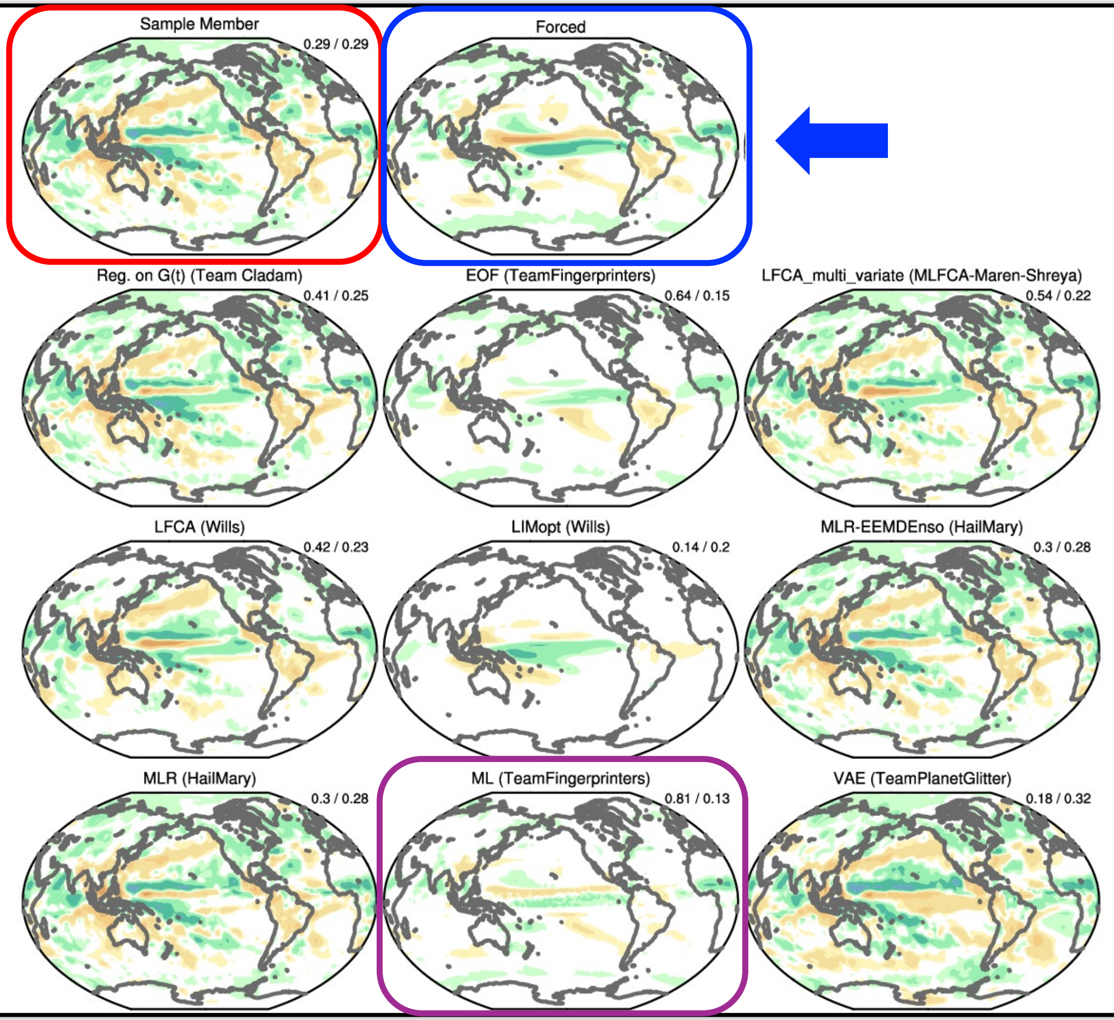

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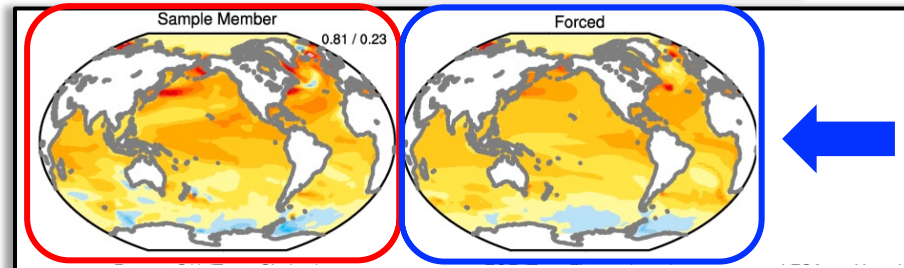

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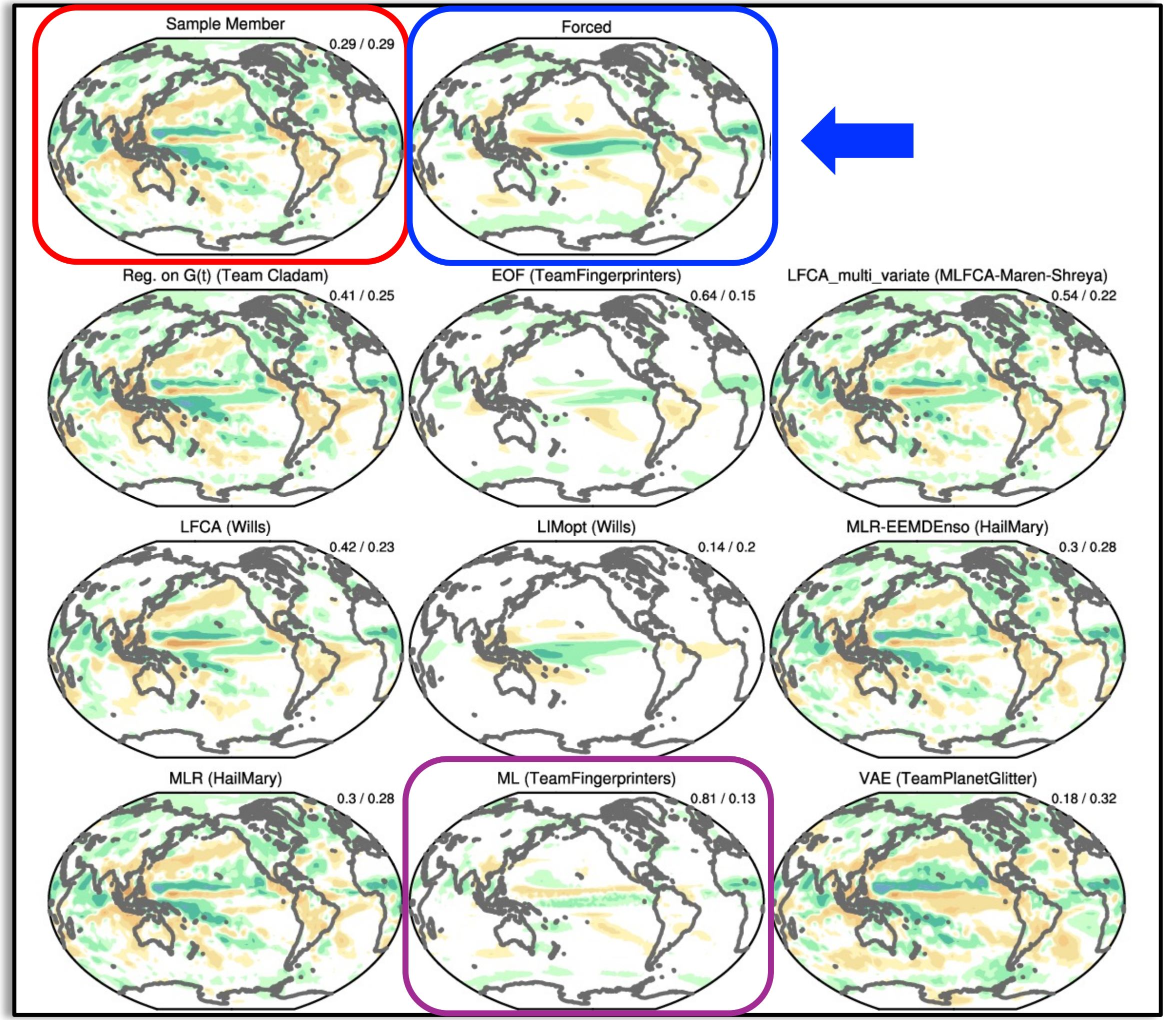

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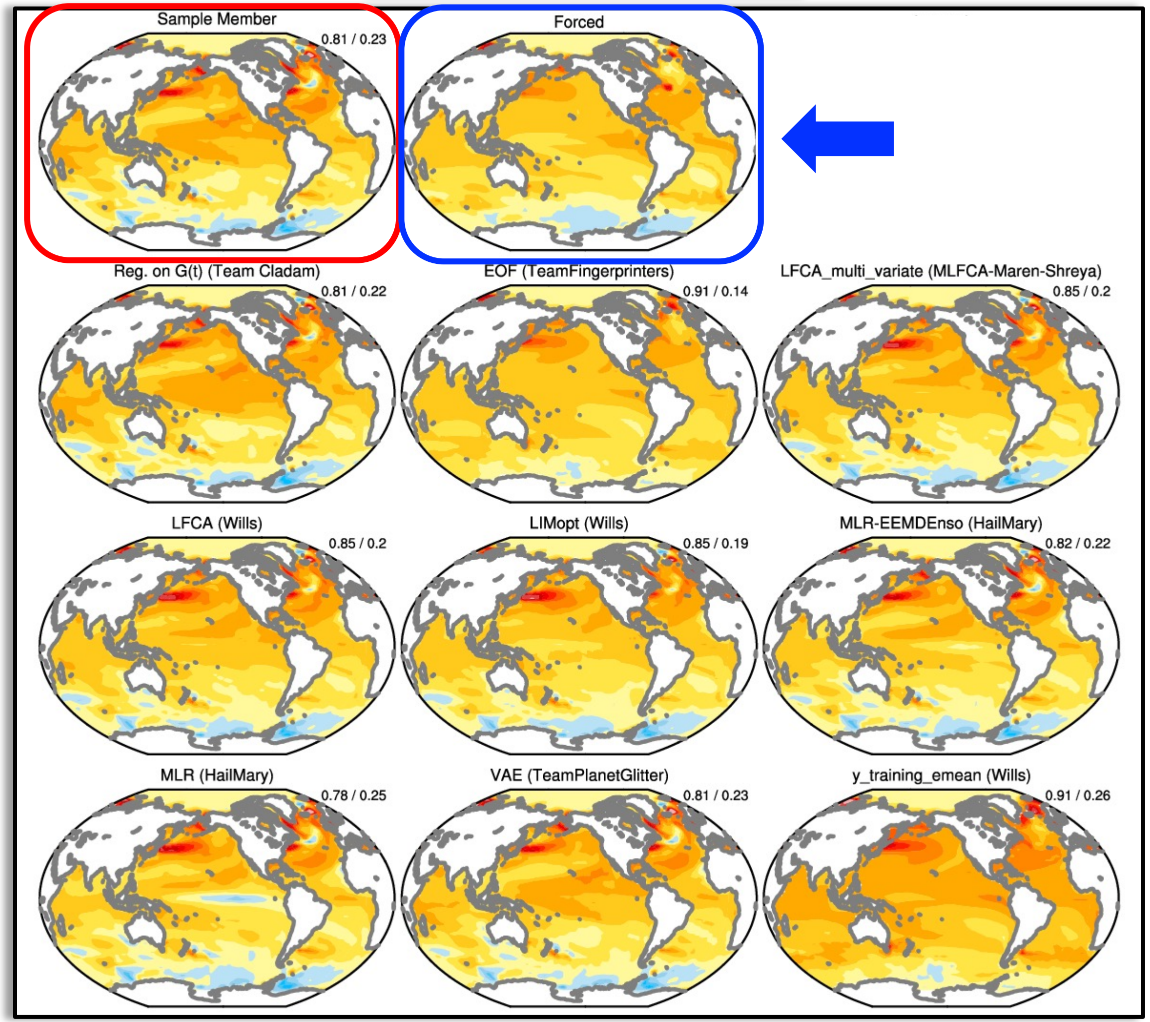

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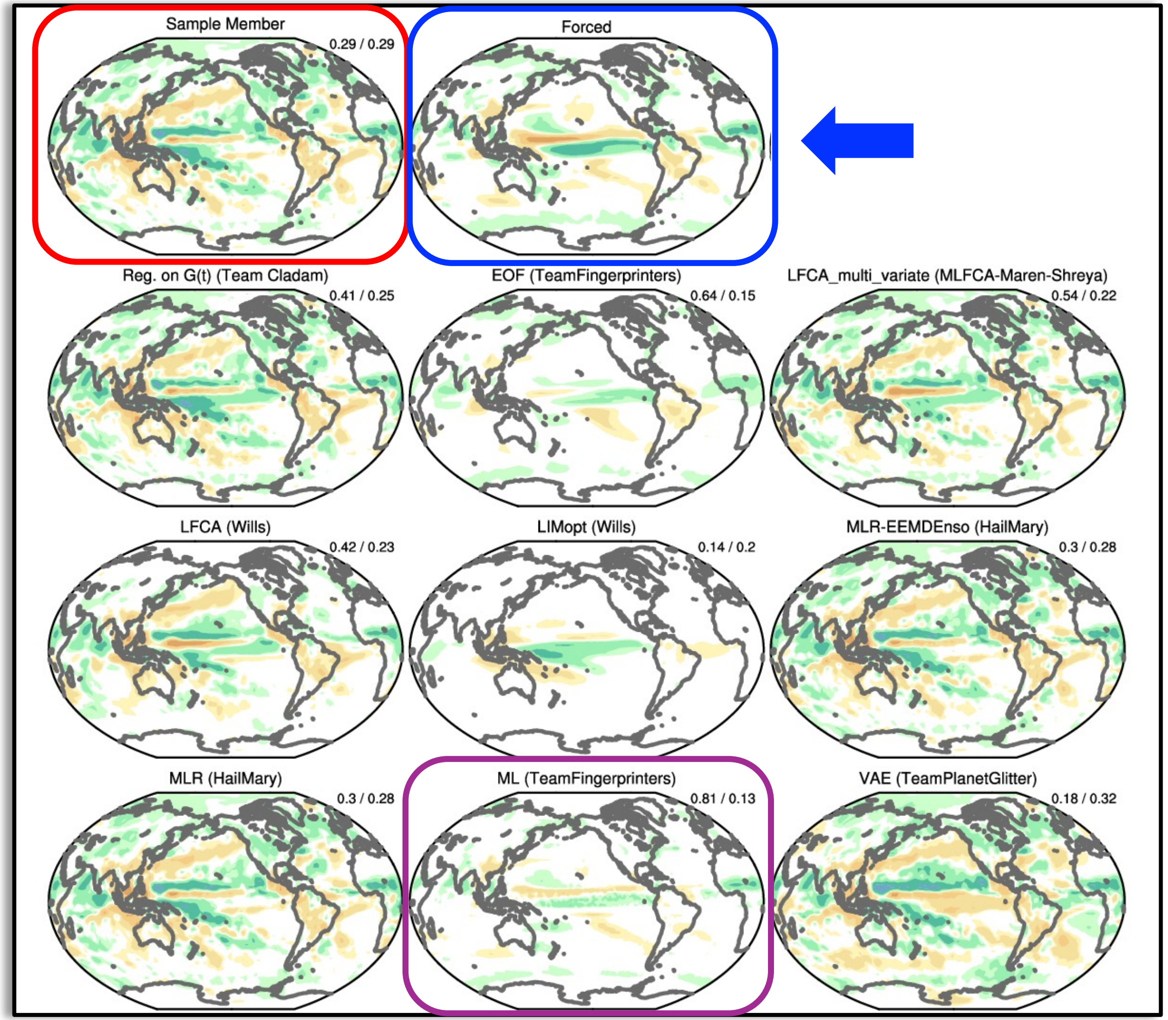

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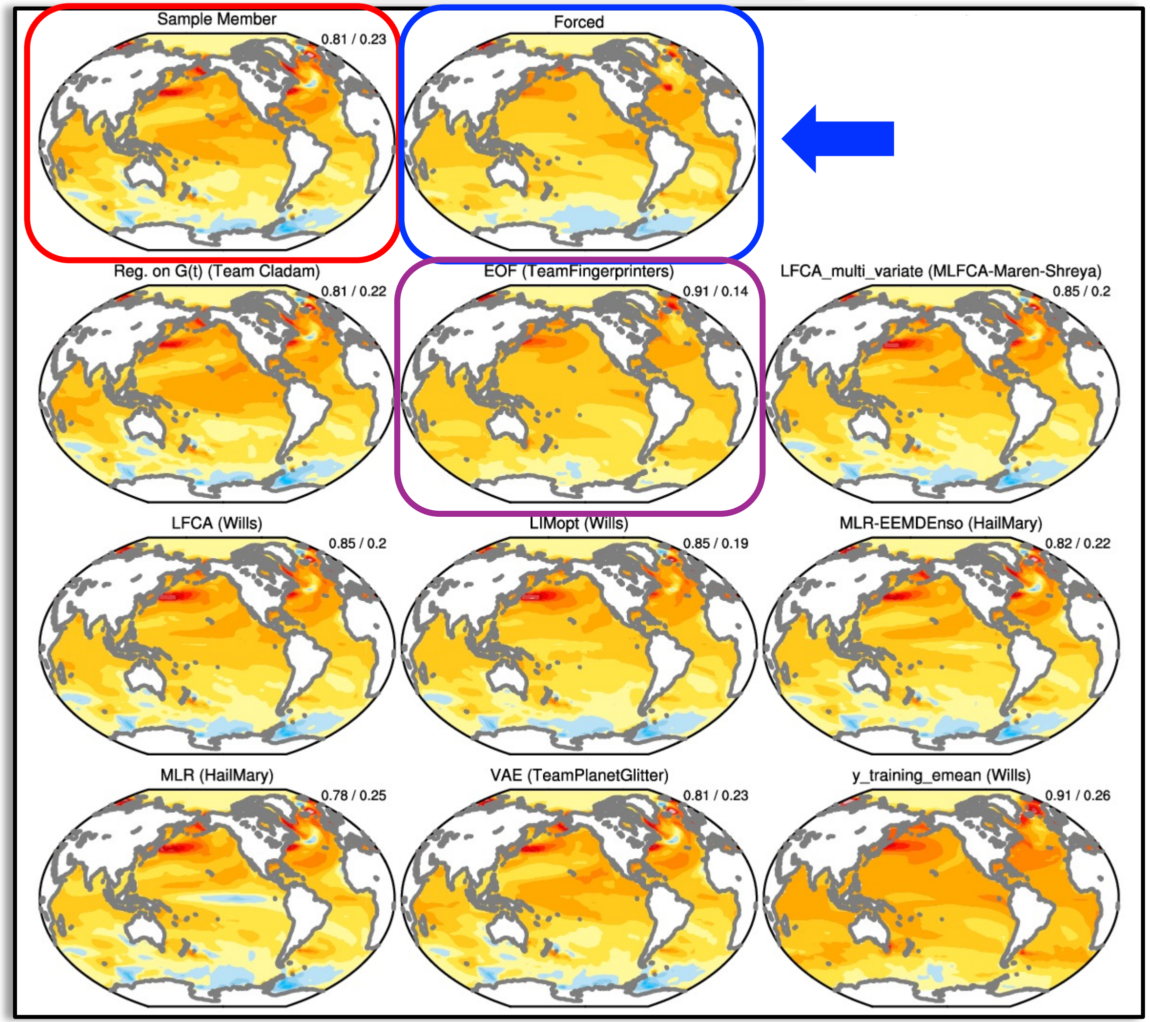
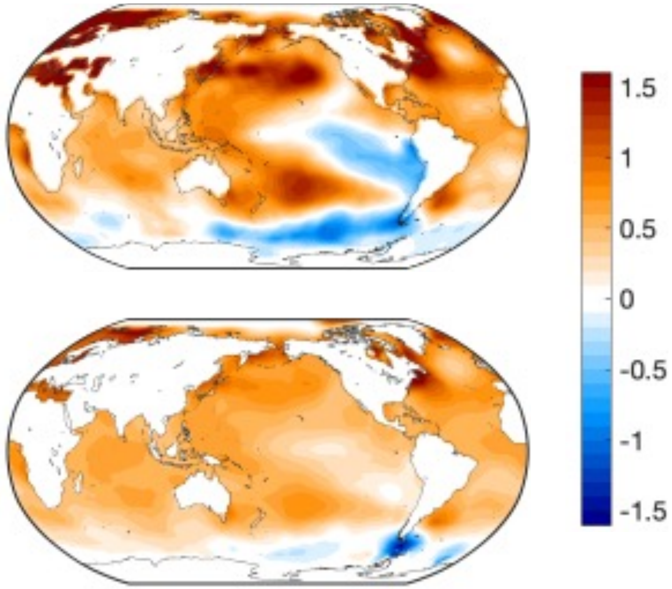


Application to Observed SST Trends (1979-2022)

Raw

Estimated forced response (9 methods)



See Robb Wills' Poster on Friday for further details.

Challenges in comparing observed and model-simulated trends on regional scales

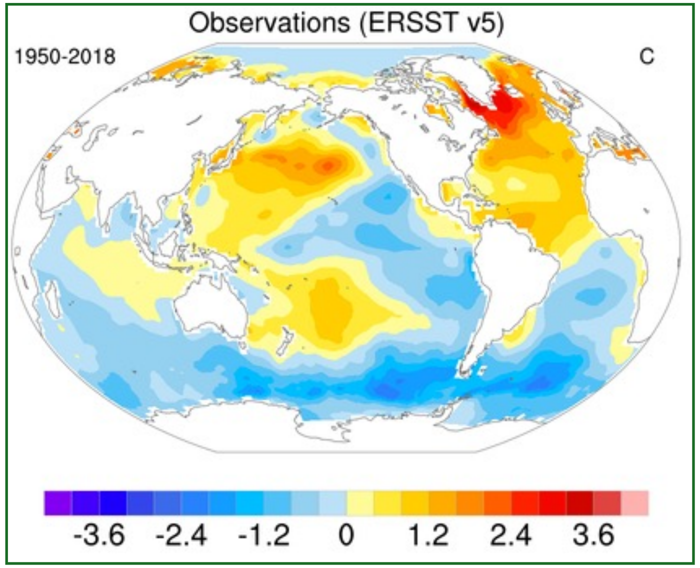
Clara Deser, NCAR

"The lifetime of a trend is the time it takes to be recognized" – *Eugene Rasmussen*

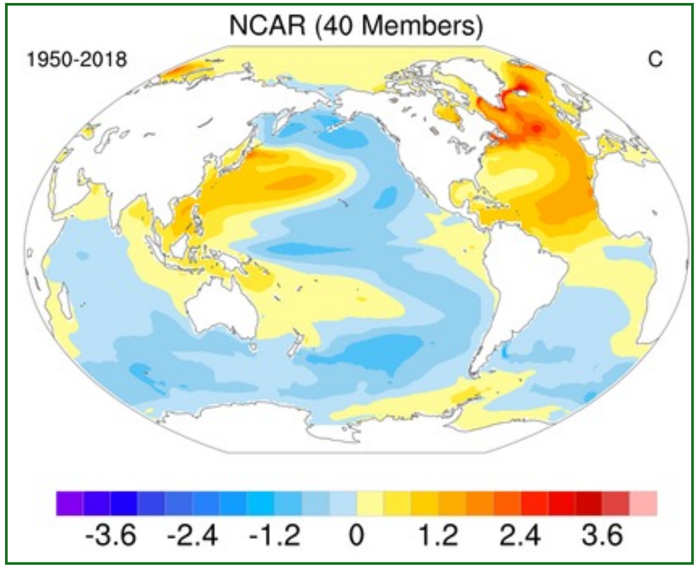
US CLIVAR Workshop "Confronting Earth System Model Trends with Observations" March 13-15, 2024.

Extra Slides

The Atlantic Multidecadal Oscillation (AMO)
Index: 10-year low-pass filtered
North Atlantic SST – Global mean SST (Trenberth and Shea, 2015)



1950-2018



1950-2018

Deser and Phillips (2021)

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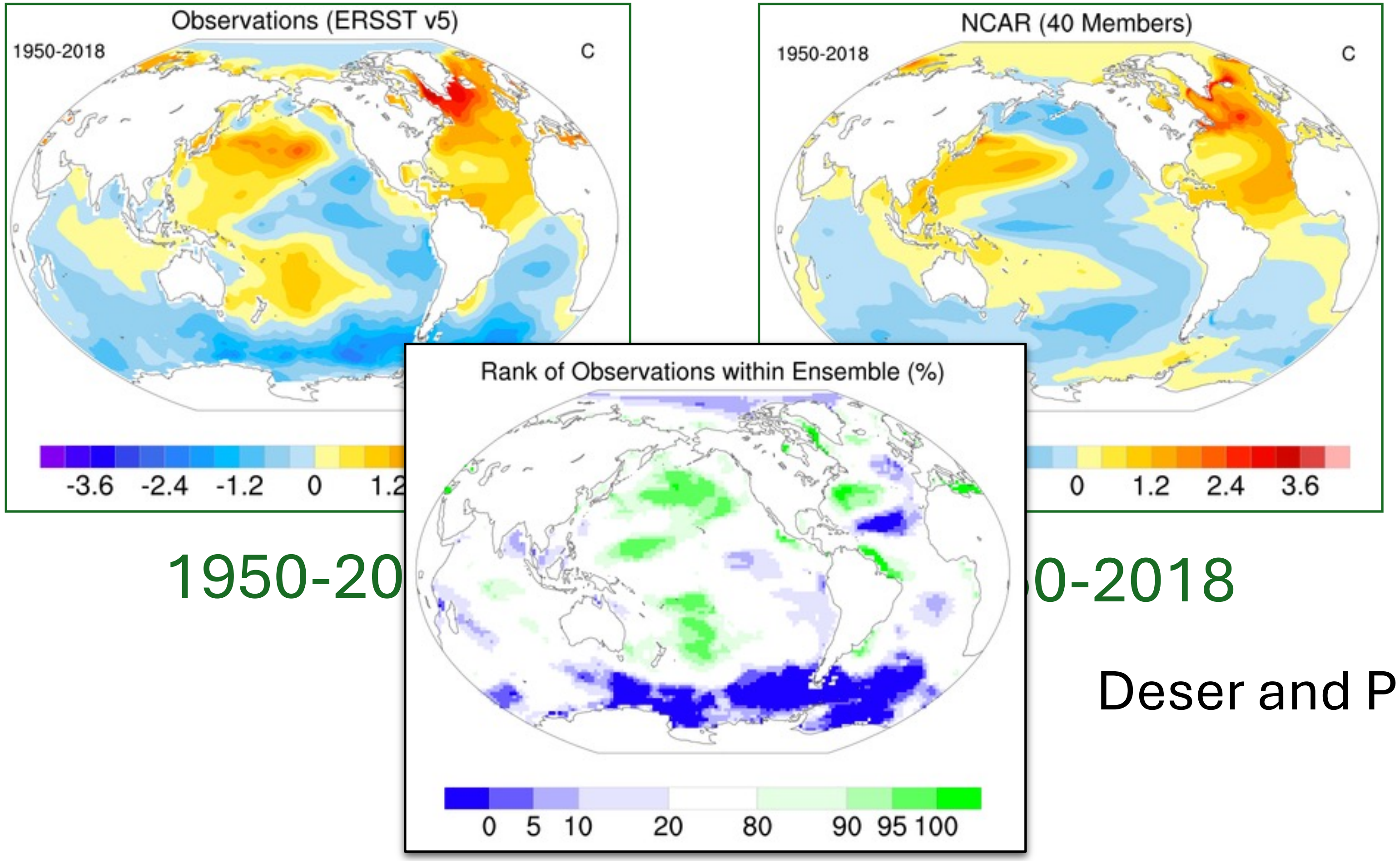

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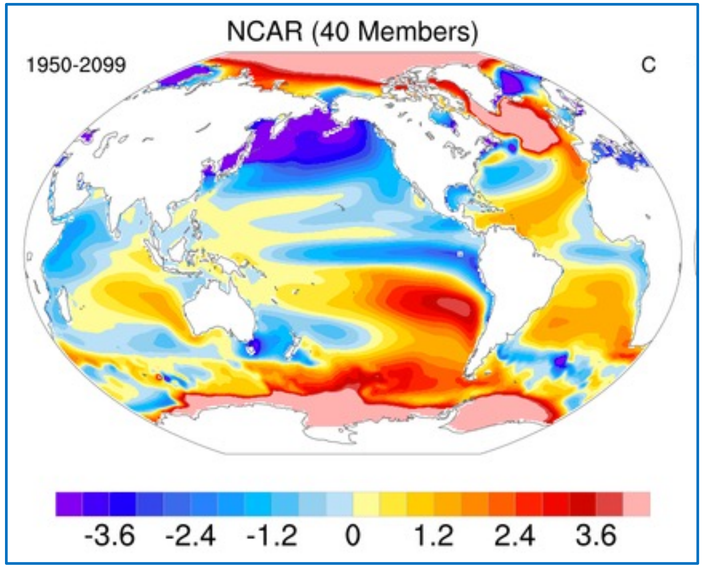
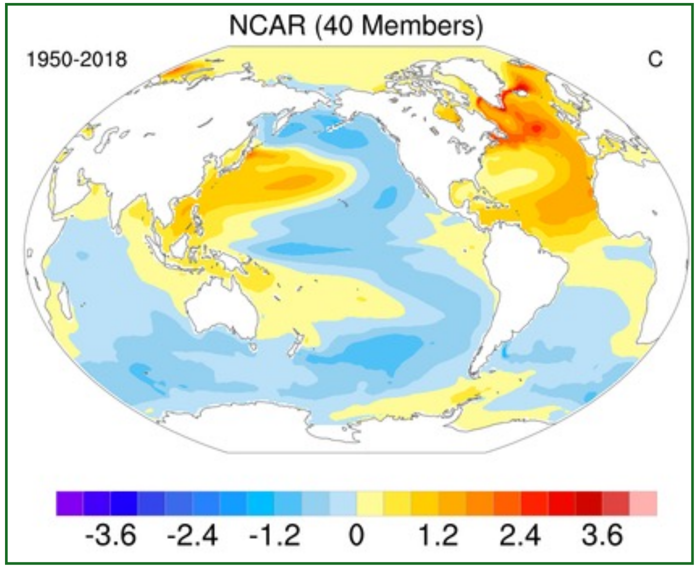


1950-2099



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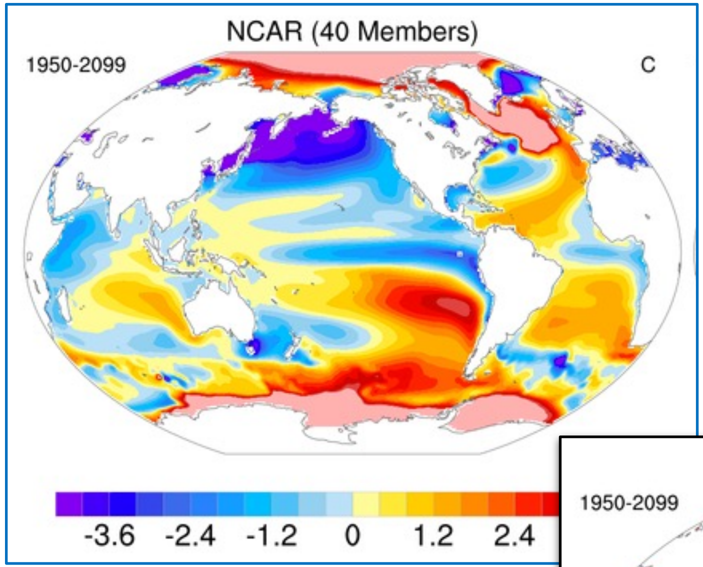

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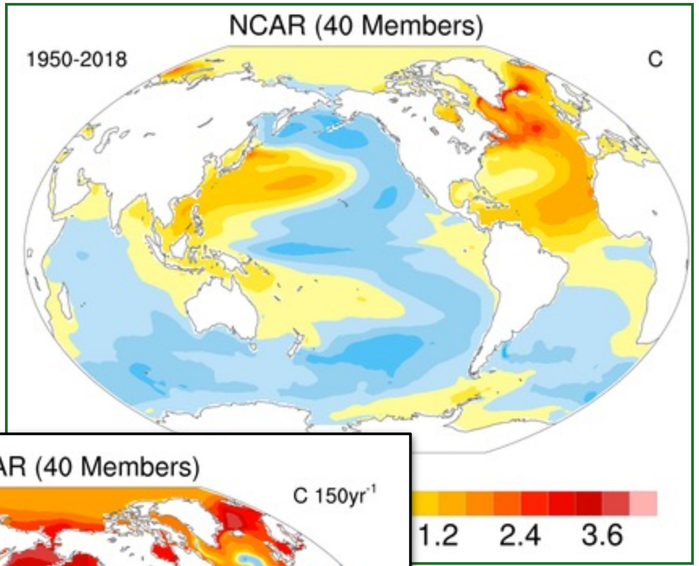

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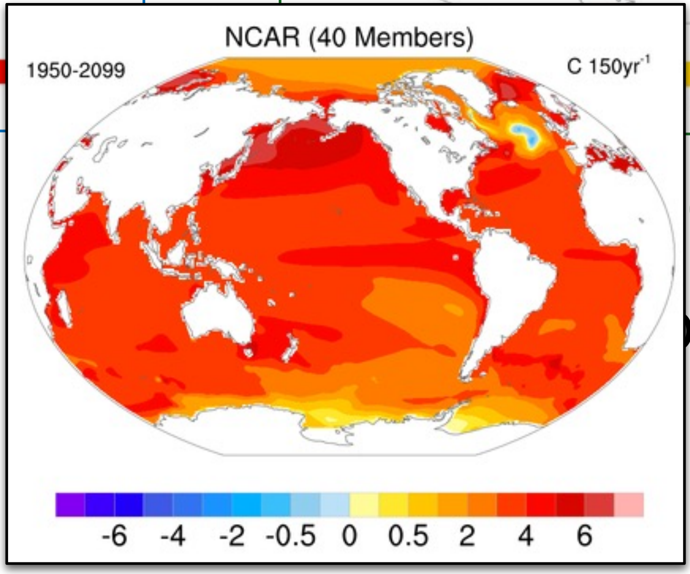
eser and Phillips (2021)



Linear Trend

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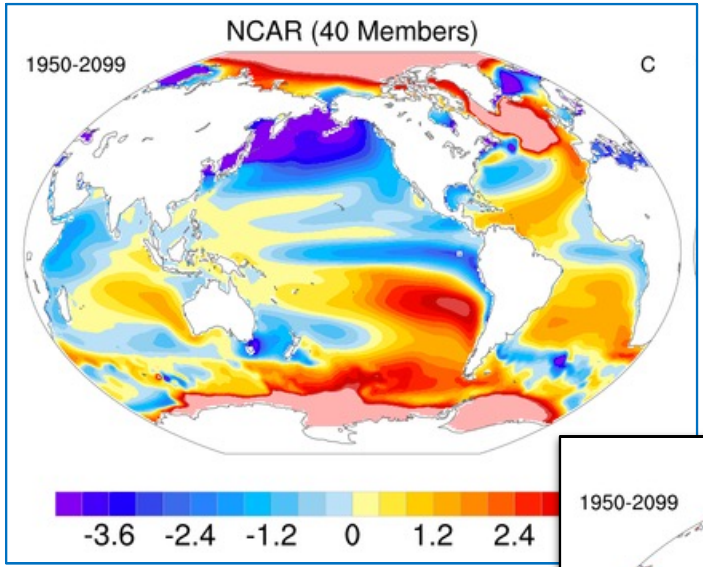
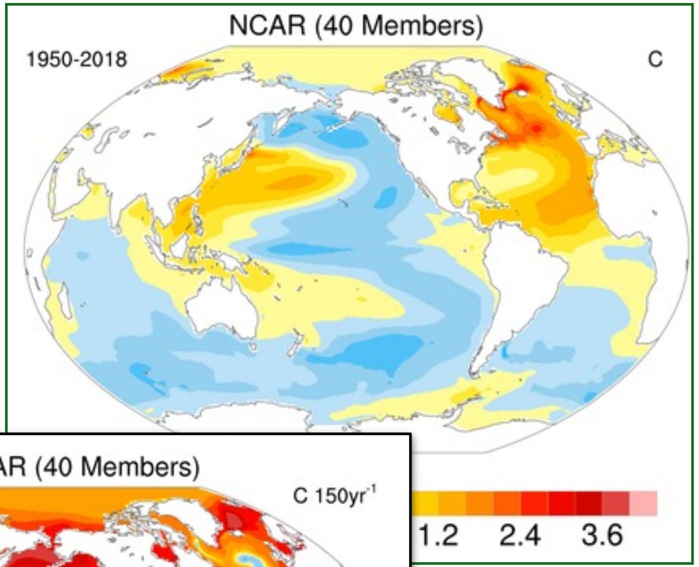


1950-2099



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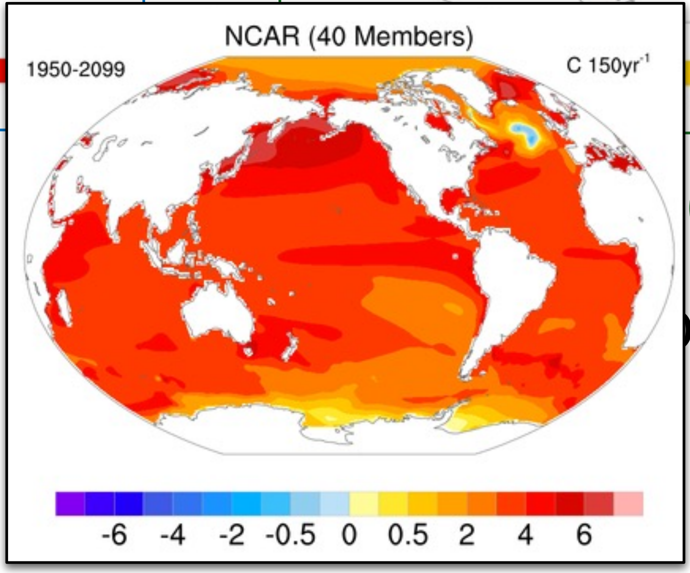
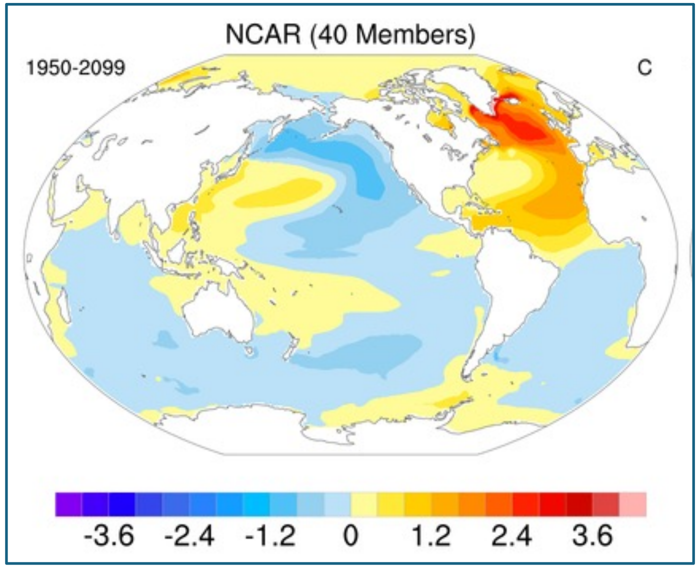
eser and Phillips (2021)

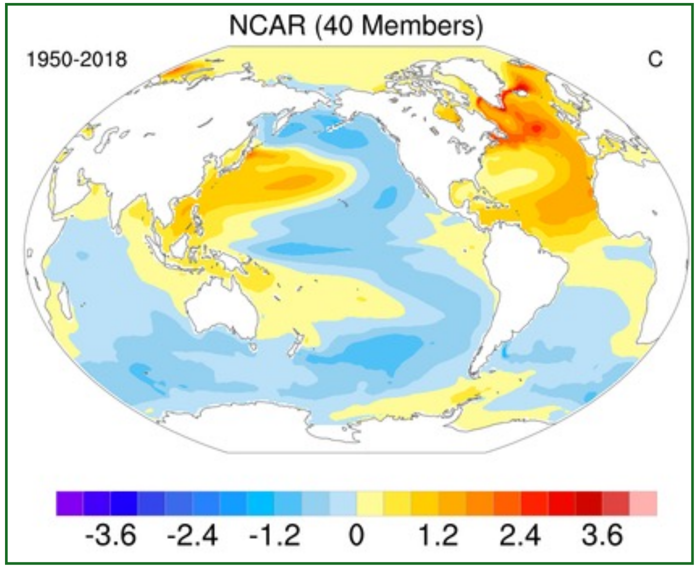
Linear Trend



The **Internal** Atlantic Multidecadal Oscillation (AMO)
Index: 10-year low-pass filtered
North Atlantic SST' (ensemble-mean removed at each location)



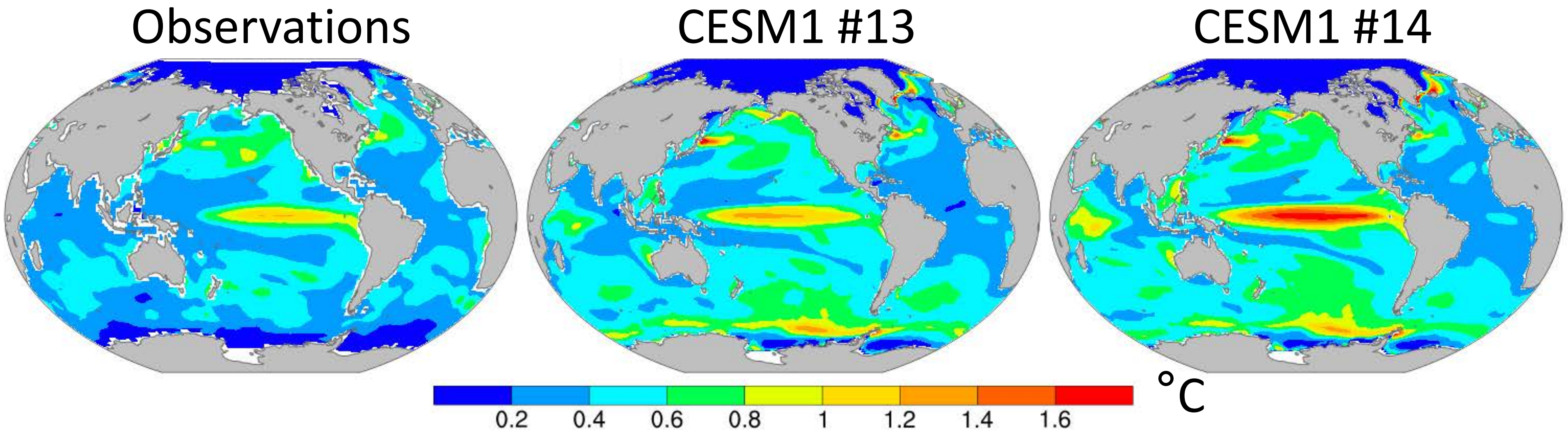
1950-2099



1950-2018

Deser and Phillips (2021)

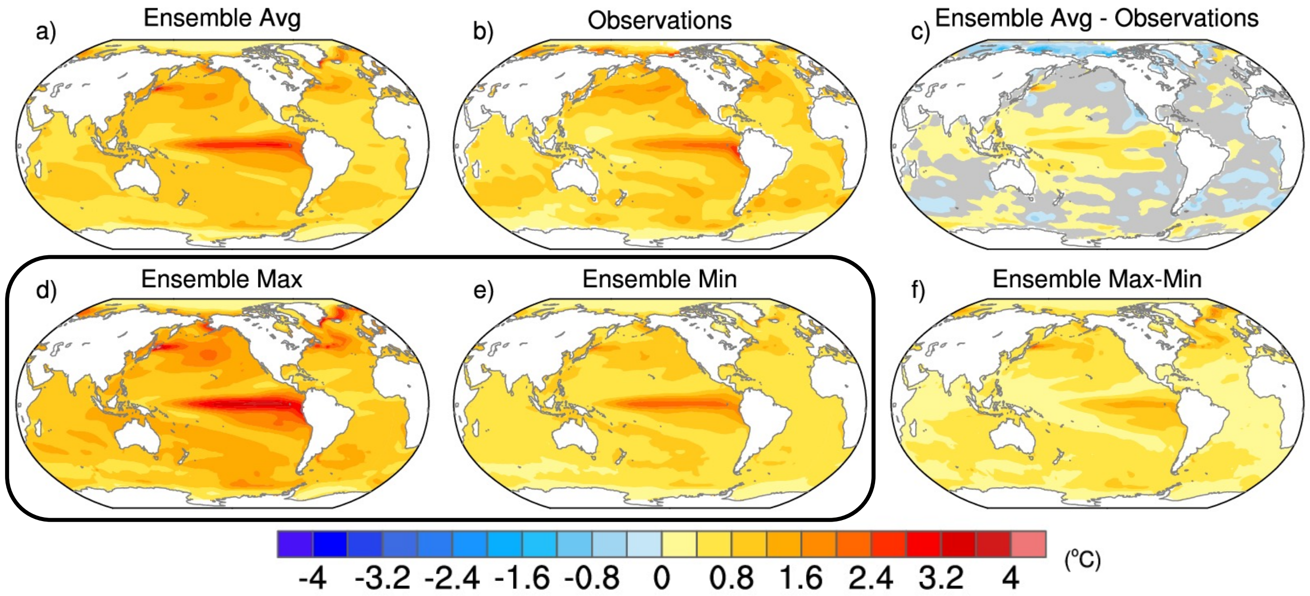
Detrended SST anomaly standard deviation (1920-2015)



Wittenberg et al., 2009; Newman et al., 2011; Deser et al., 2012

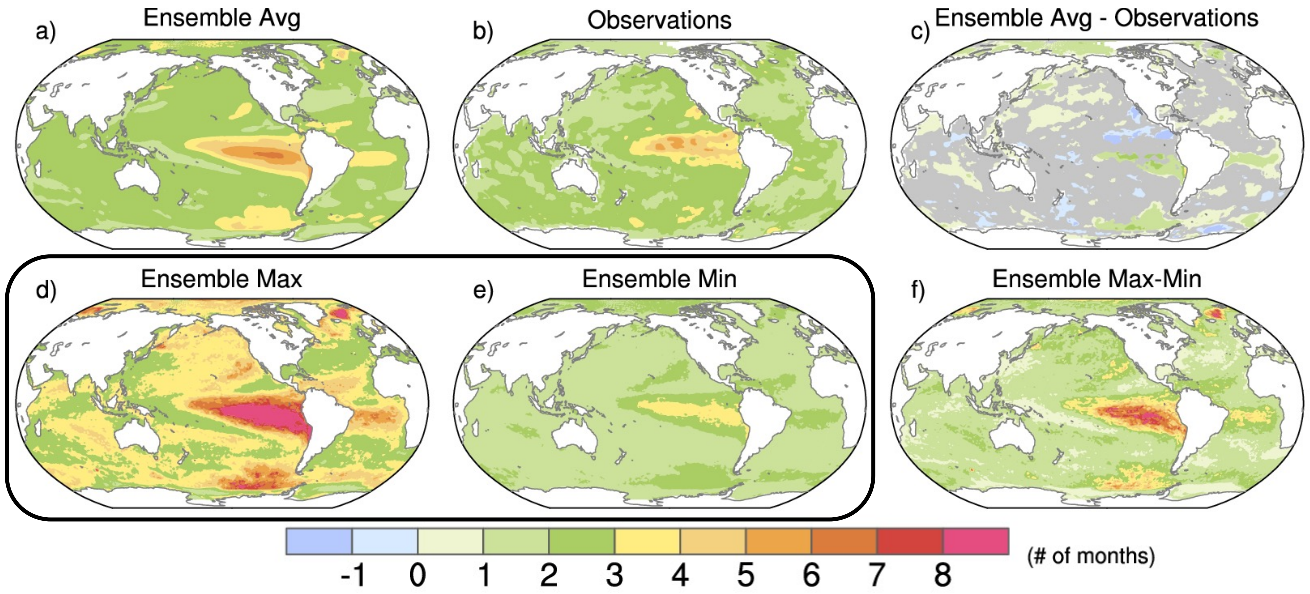
Marine Heatwaves (> 90th percentile SST extremes, 1950-2022)

CESM2
(100-member SMILE)



Composite
Intensity

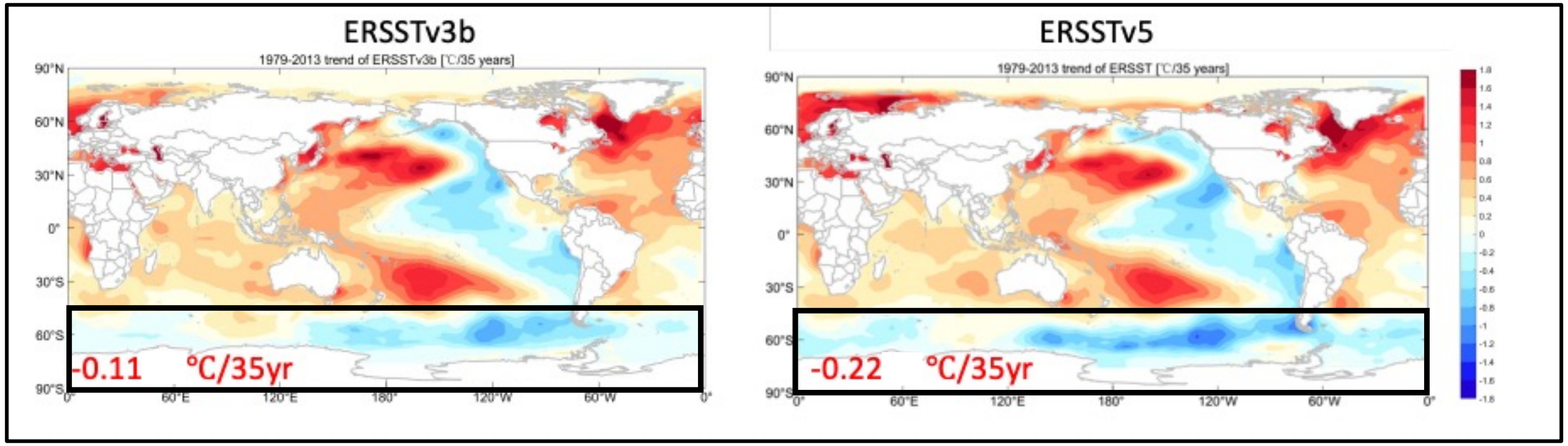
CESM2
(100-member SMILE)



Composite
Duration

Deser et al. (2024)

SST Trends 1979-2013



Kang et al. 2023