Observational Large Ensembles as tools to assess climate variability

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US CLIVAR Large Ensembles workshop

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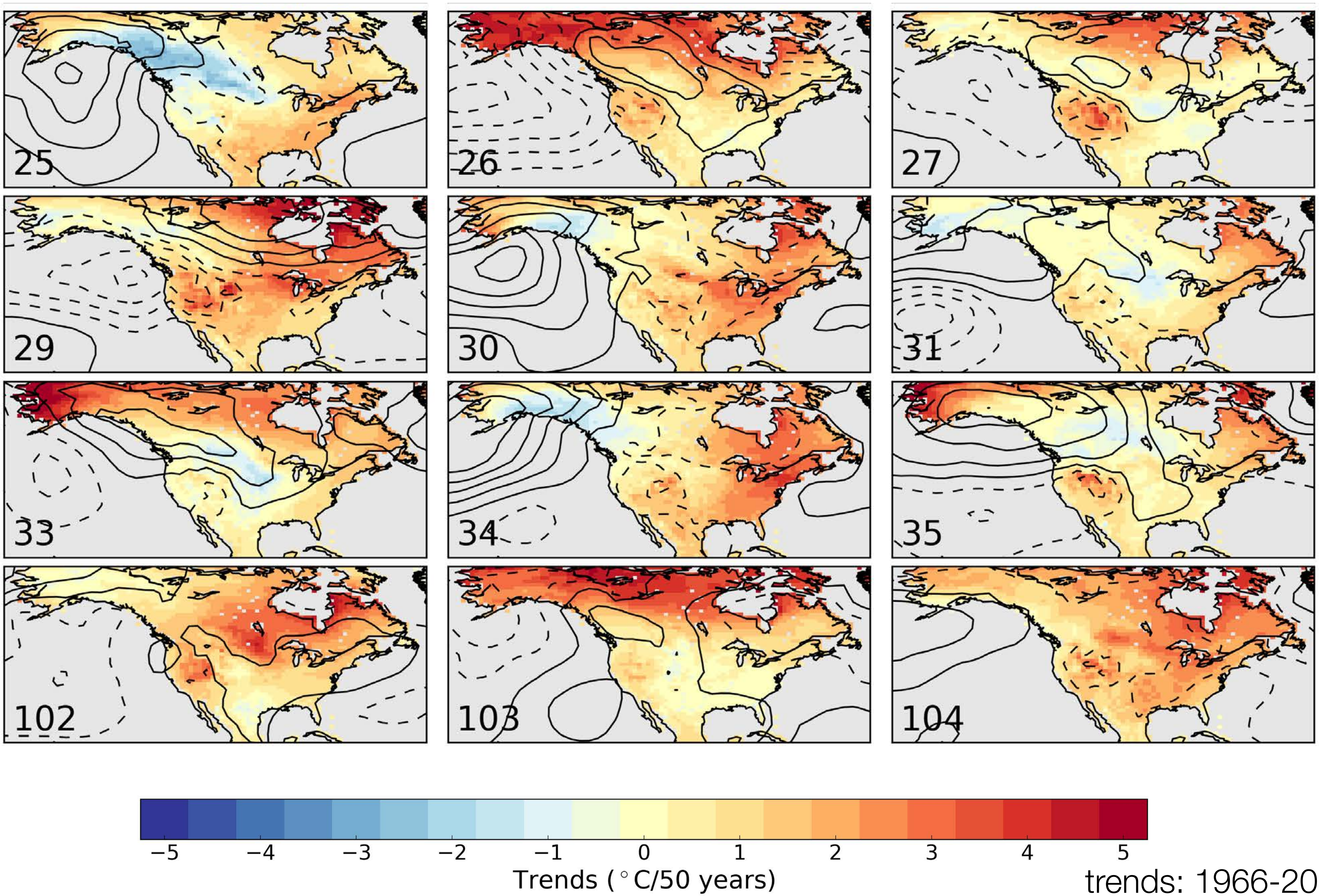
UCLA

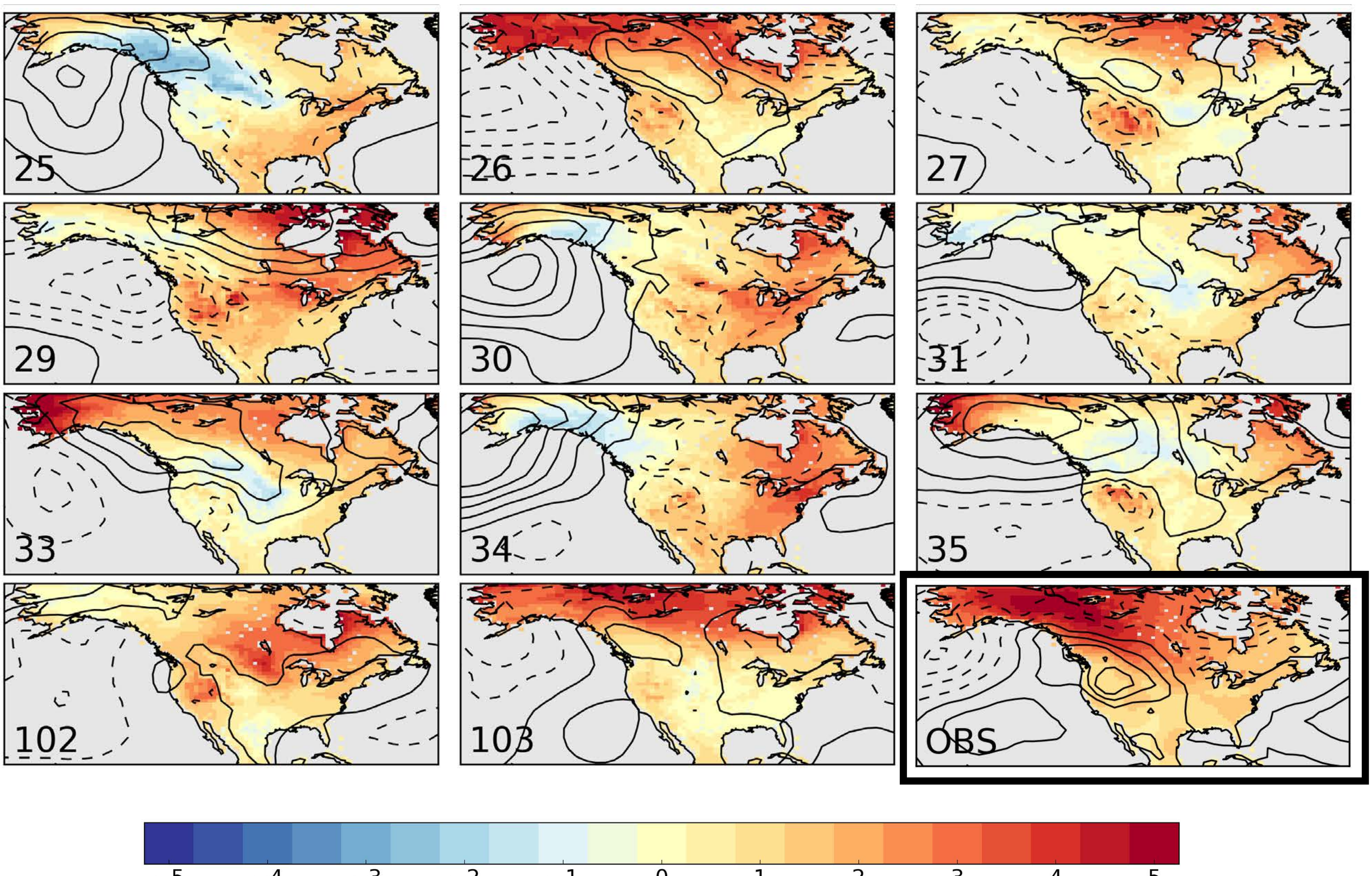
NCAR
NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

50 year DJF temperature and SLP trends in the CESM1 Large Ensemble



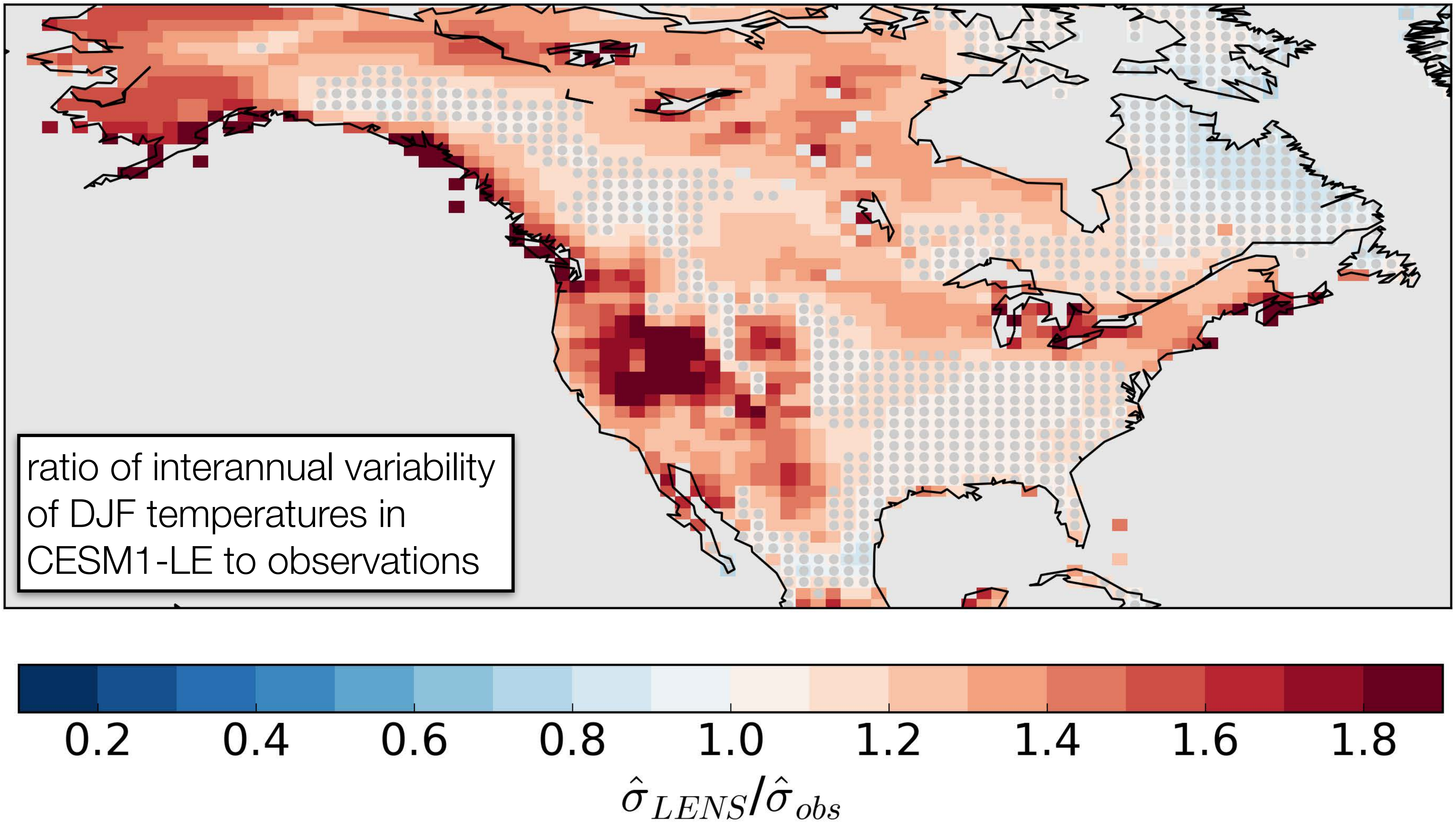
trends: 1966-2015

Are the observations interchangeable with members of the CESM1-LE?



trends: 1966-2015

It depends! But for regional temperature and precip, large biases in variability



stippling: observations and model are *not* significantly different using a False Discovery Rate of 0.1

A simple linear regression model to generate an initial condition-like ensemble

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Temperature, precipitation, (sea level pressure)

=

Forced component

+

Dependence on large-scale SST modes (ENSO, PDO, AMO)

+

Residual variability

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Temperature, precipitation, (sea level pressure)

=

$\beta_i F_t$

+

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Residual variability

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$\beta_i F_t$

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$\sum_m \beta_{i,m} M_{t,m}$

+

Residual variability

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Temperature, precipitation, (sea level pressure)

$$=$$

$$\beta_i F_t$$

$$+$$

$$\sum_m \beta_{i,m} M_{t,m}$$

$$+$$

$$\varepsilon_{i,t}$$

A simple linear regression model to generate an initial condition-like ensemble

Temperature, precipitation, (sea level pressure)

=

Forced component ($\beta_i F_t$)

+

Dependence on large-scale SST modes ($\sum_m \beta_{i,m} M_{t,m}$)

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Residual variability ($\varepsilon_{i,t}$)

Step 1: fit model parameters to observations (1920-2015)

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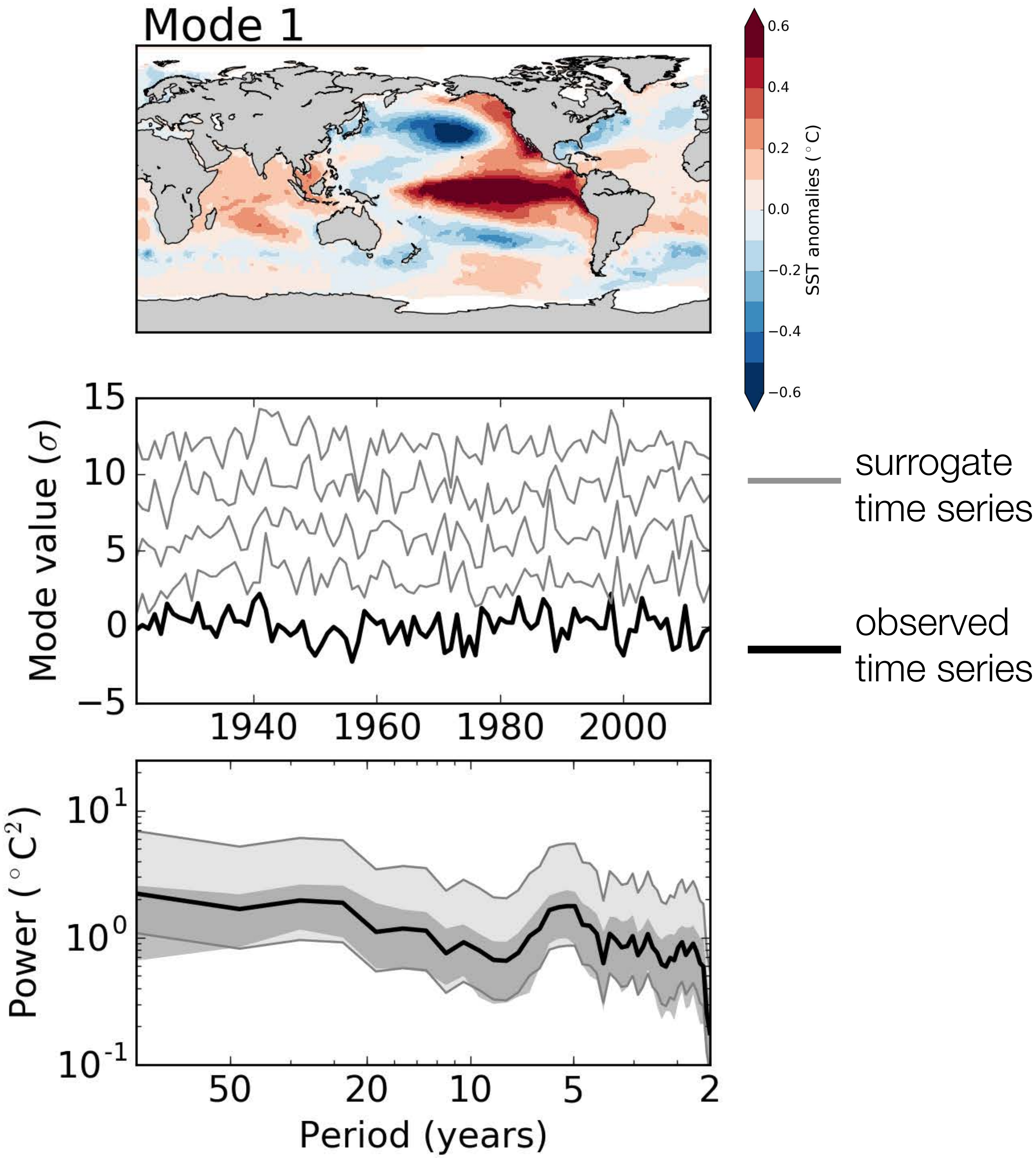
Residual variability ($\varepsilon_{i,t}$)

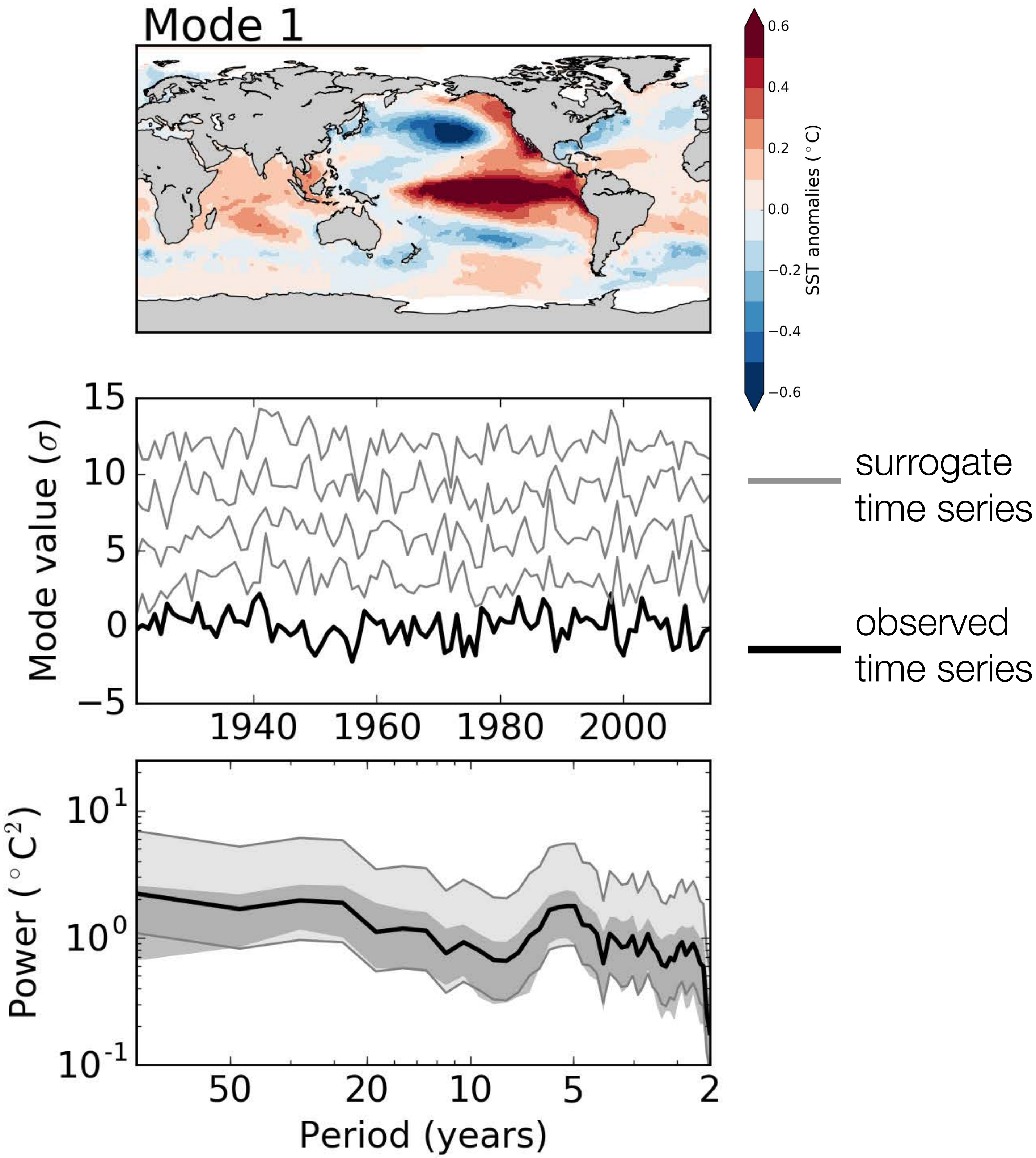
Step 1: fit model parameters to observations (1920-2015)

Step 2: use model to create surrogate climate realizations

Creating surrogate climate data with phase randomization and bootstrapping



Creating surrogate climate data with phase randomization and bootstrapping



Residual variability is block bootstrapped with a block length of 2 years such that full spatial structure is maintained.

A simple linear regression model to generate an initial condition-like ensemble

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Forced component ($\beta_i F_t$)

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Dependence on large-scale SST modes ($\sum_m \beta_{i,m} M_{t,m}$)

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Residual variability ($\varepsilon_{i,t}$)

Step 1: fit model parameters to observations (1920-2015)

Step 2: use model to create surrogate climate realizations

Step 3: center the ensemble on an estimate of the forced component

result: the Observational Large Ensemble (Obs-LE)

Model assumptions and evaluation for the Observational Large Ensemble

Assumptions

a) Stationarity in both the mode time series and the residual variability!

b) We have sufficiently sampled the *relevant* range of variability

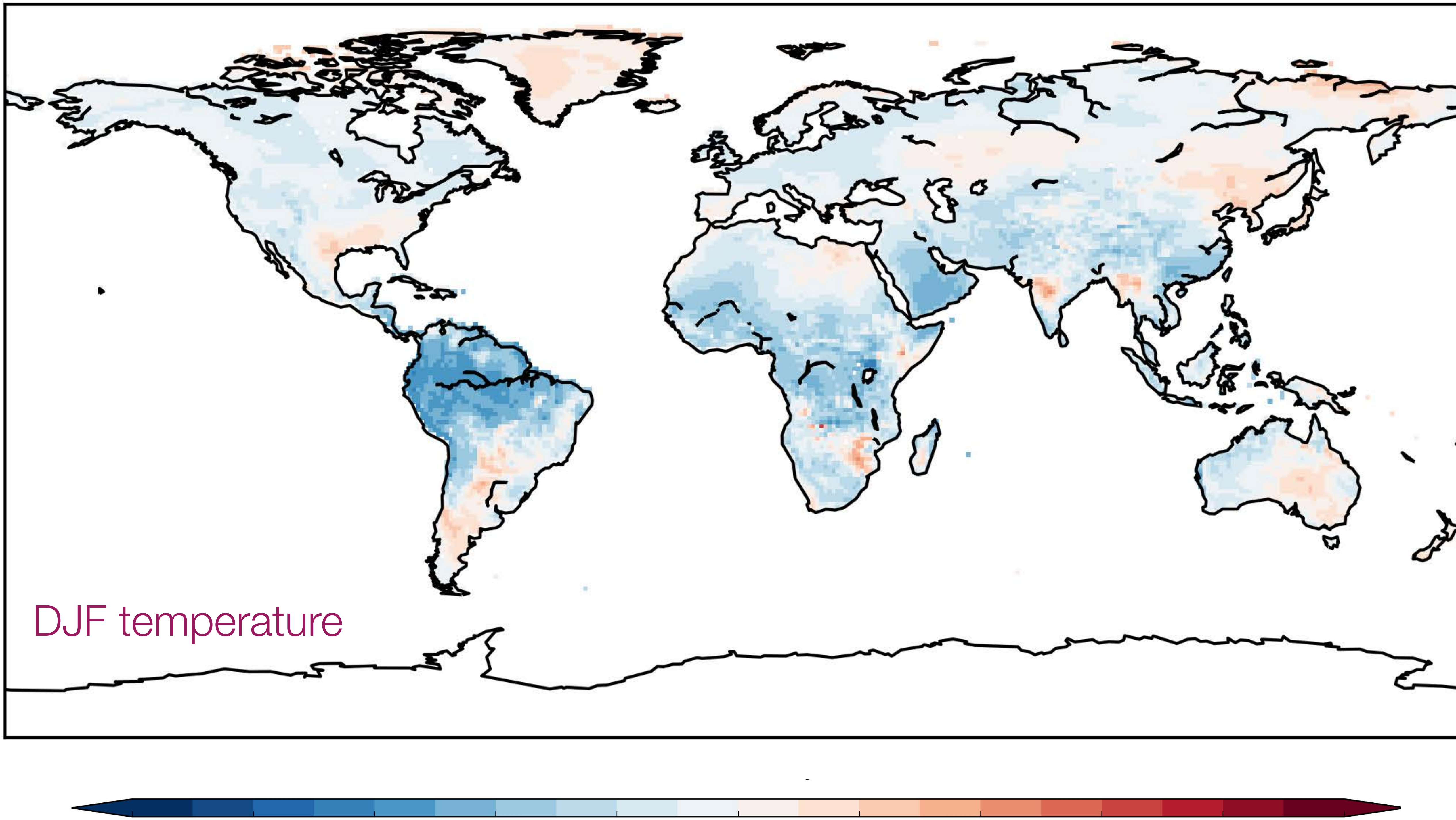
Evaluation

repeat exercise treating each member of the CESM1 Large Ensemble as the observations

Metric

spread in 50-year trends across each ensemble (CESM1-LE and Obs-LE)

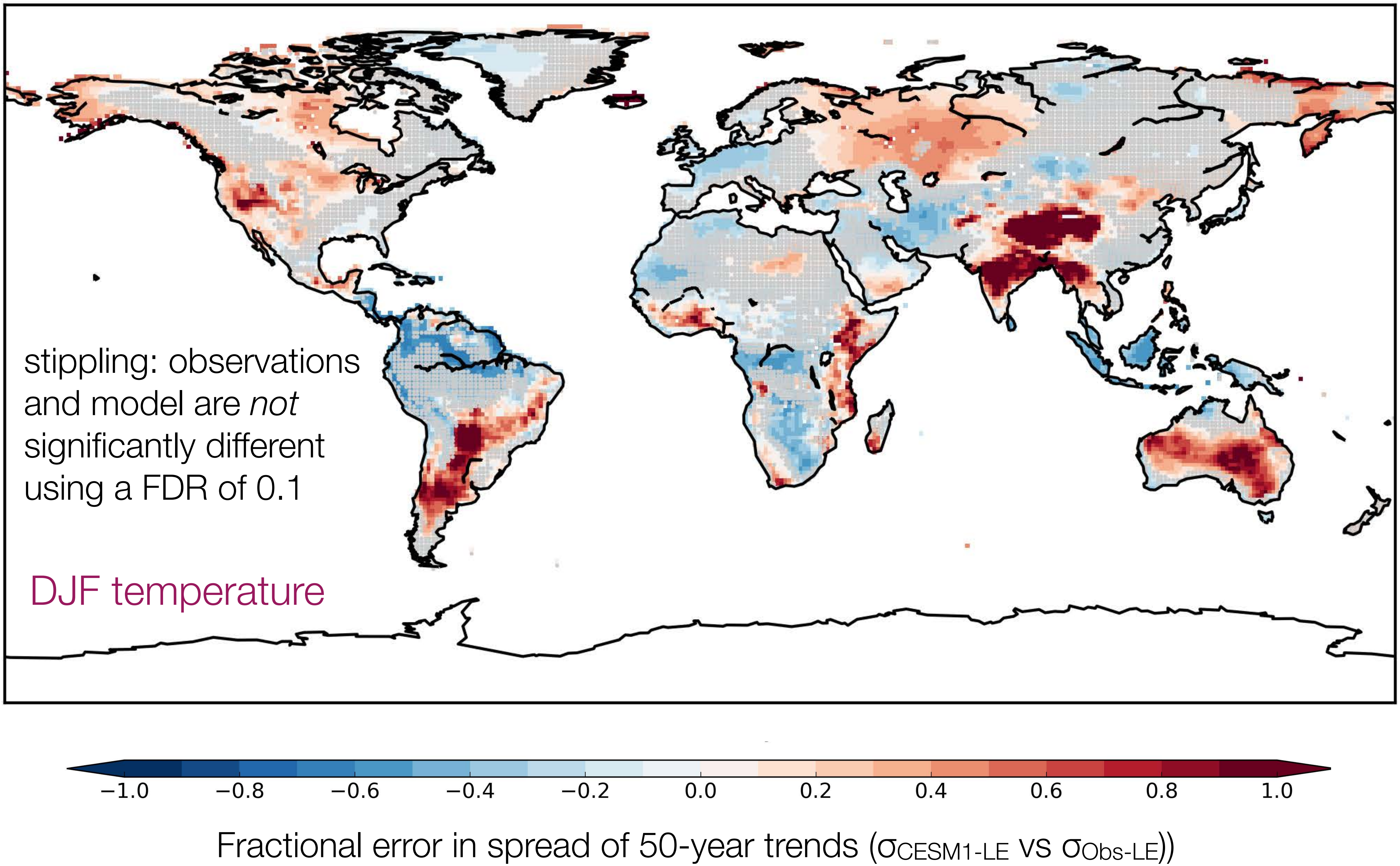
Fractional errors induced by Obs-LE methodology typically 10-20%



Fractional error in reproducing spread in CESM1-LE using the Obs-LE method

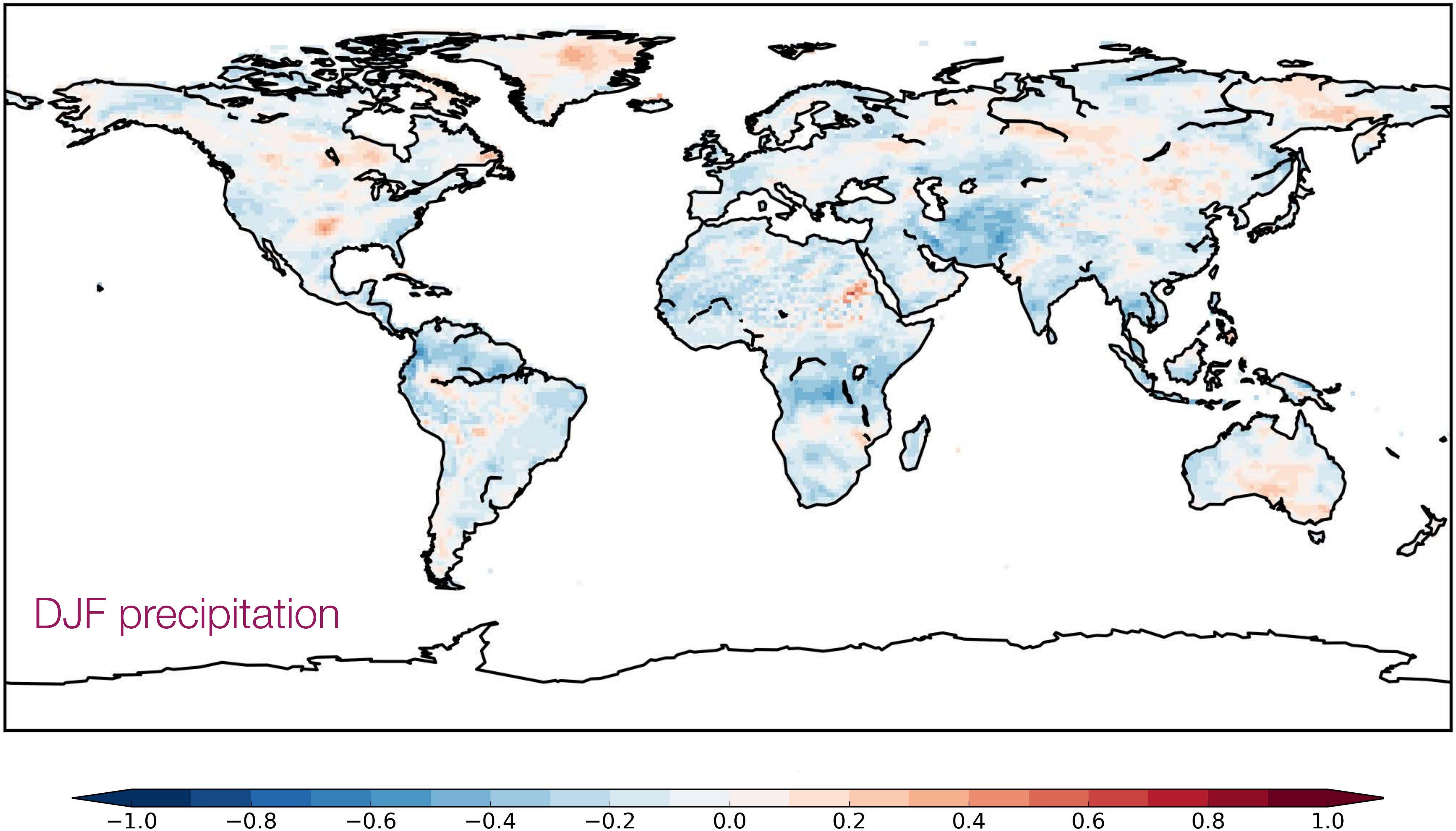
temperature data from BEST

In most regions, larger differences between the CESM1-LE and Obs-LE



temperature data from BEST

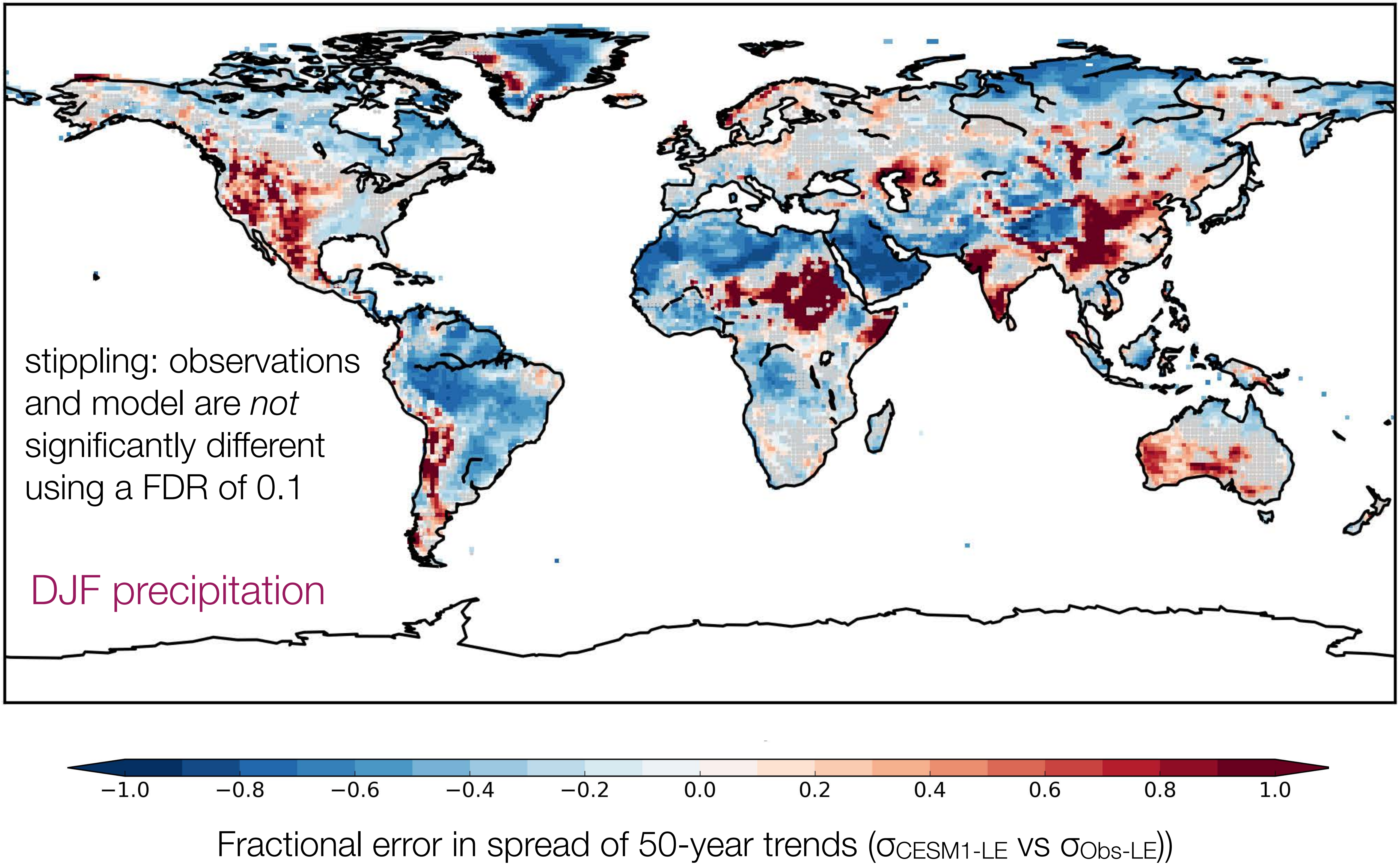
Small errors in Obs-LE for precipitation because less autocorrelated



Fractional error in reproducing spread in CESM1-LE using the Obs-LE method

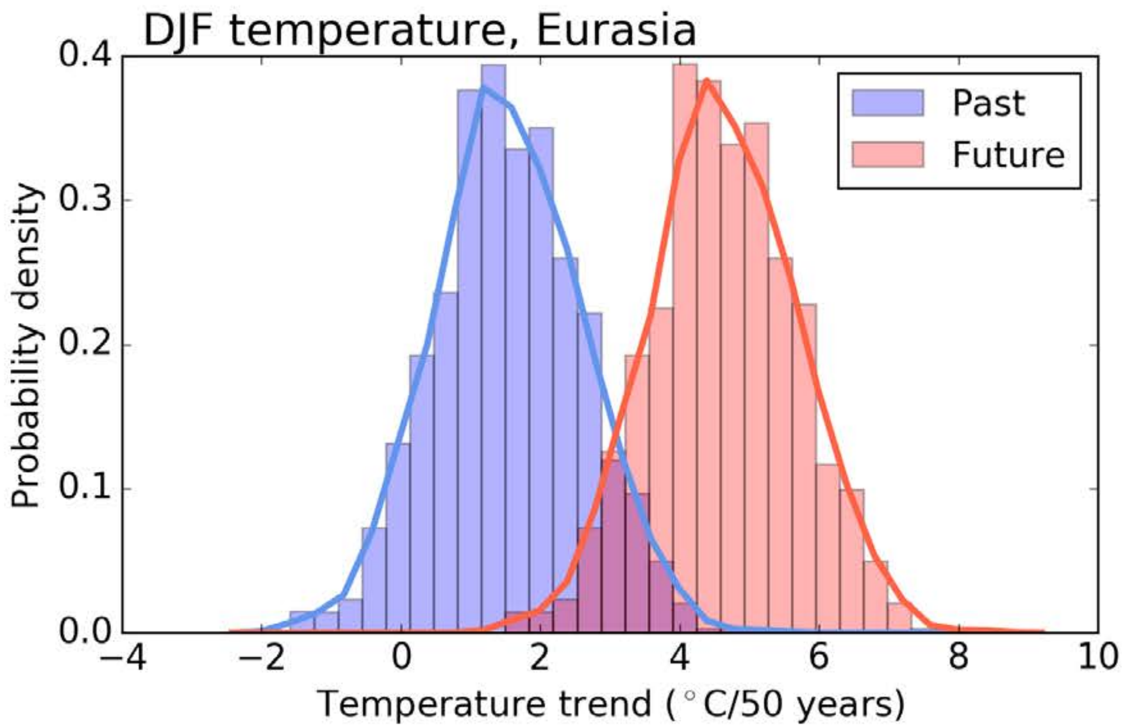
precipitation data from GPCC

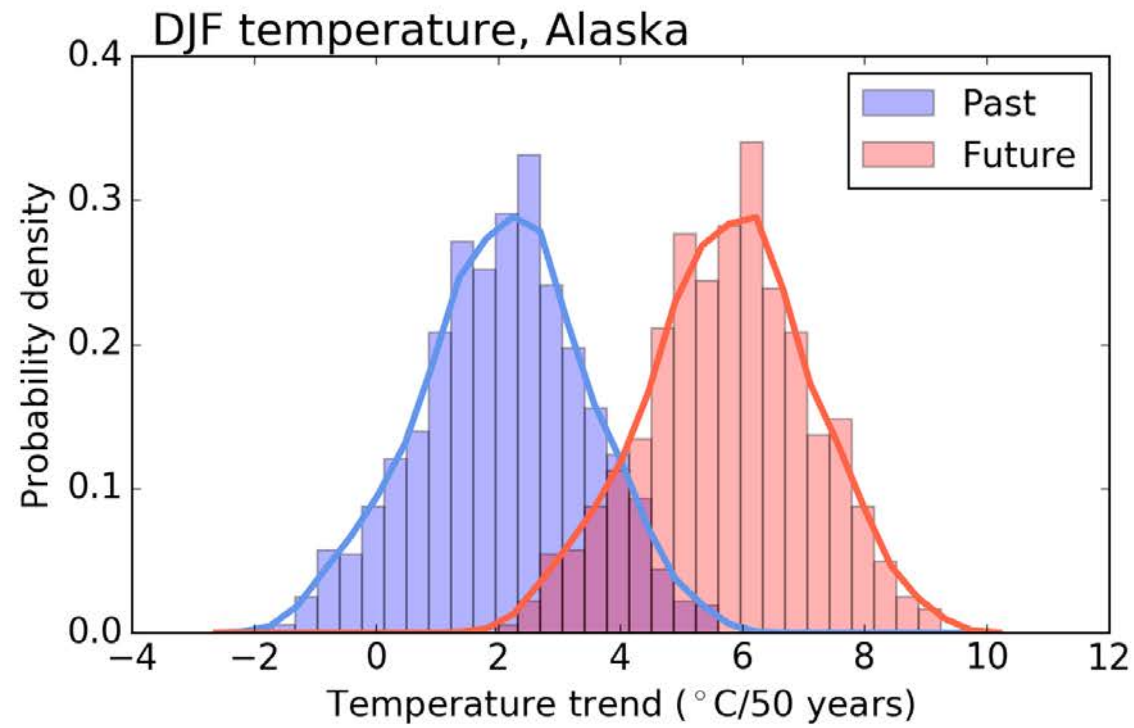
CESM1-LE tends to be underly variable for DJF precipitation trends



precipitation data from GPCC

Obs-LE can inform us about the range of trends possible in the future, and what could have happened in the past





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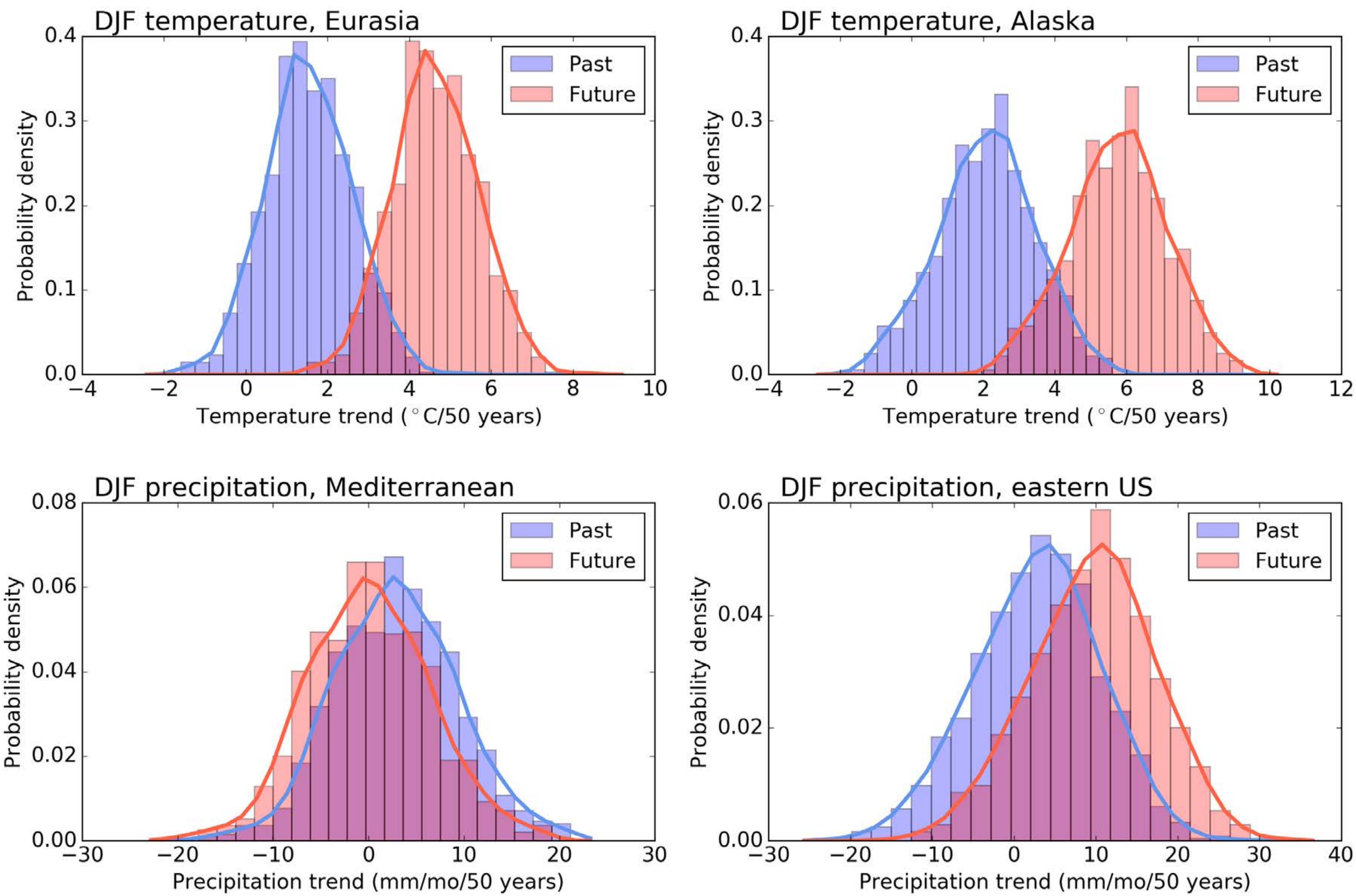

Future work on the Observational Large Ensemble

Improved modeling of SST modes to address variance biases and include seasonal cycle in ENSO variance.

Github repo with documented and modular code.

Testing for different assumptions about the forced trend.

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Testing for different assumptions about the forced trend.

Relaxation of stationarity assumption.

Extension to daily timescales.

A more complete model for teleconnections:

(1) Linking up with surrogate sea surface temperature fields produced from Linear Inverse Models
(2) Incorporation of a spatial model in order to sample uncertainty

New metrics for model validation.

Take home points

Internal variability can be a dominant source of uncertainty for trends at regional scales.

While climate model initial condition ensembles allow us to cleanly separate internal variability from the forced component, they may have large biases in their variability.

Here, we use century-long sets of observations to create a statistical ensemble whose spread results from different sampling of internal variability.

Much work remains, including improved estimates of the forced component from the observational record.

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