Projecting climate responses using an AI Implementation of the Fluctuation-Dissipation Theorem trained on CESM2 Large Ensemble data

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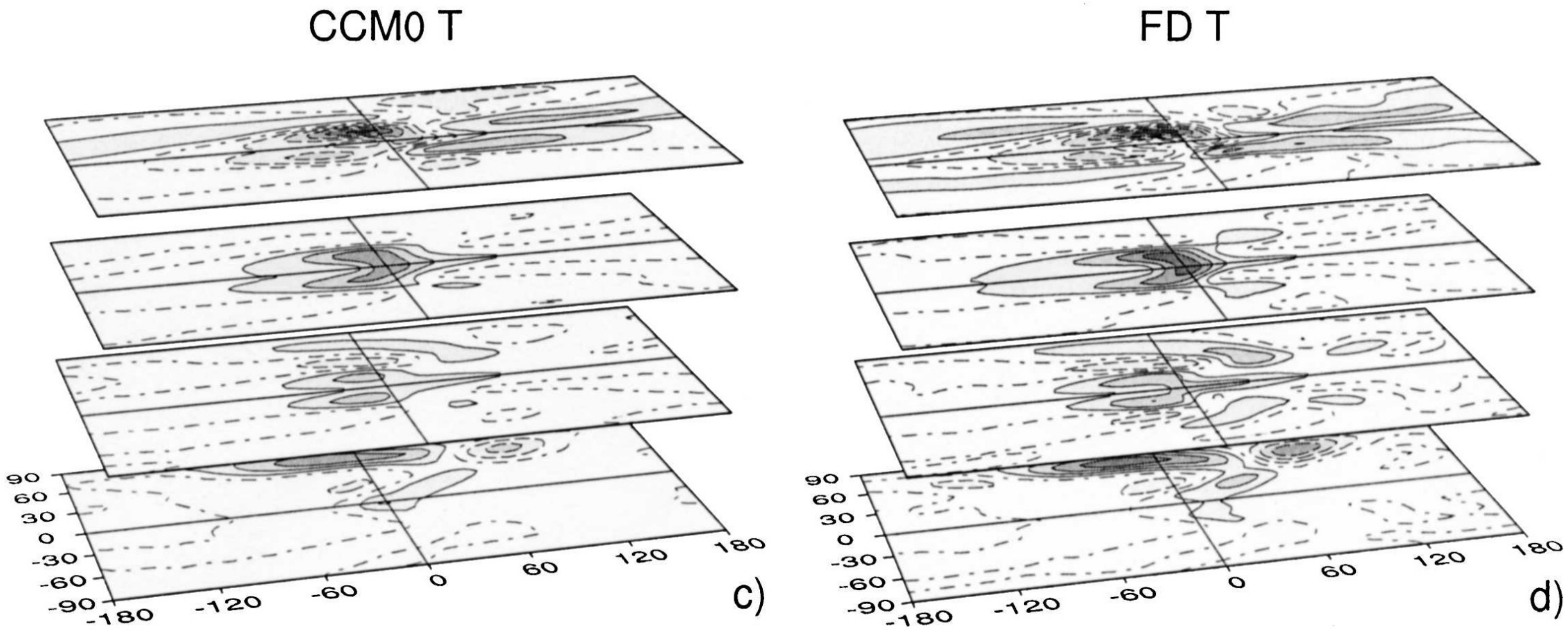
Fluctuation Dissipation Theorem (FDT)

- The FDT states that the response of a dynamical system to a forcing can be estimated from the statistics of internal fluctuations.
- The climate is one such system where the FDT can be applied:



Gritsun and Branstator, 2007

Fluctuation Dissipation Theorem (FDT)

- One common formulation of FDT for climate is in terms of a Linear Response Function $\boldsymbol{L}$ (e.g., Cionni et al., 2004, Gritsun and Branstator, 2007, Liu et al., 2018):

Projected response

Forcing

$$\delta\overline{\boldsymbol{y}}(t) = \boldsymbol{L}\delta\boldsymbol{f}(t)$$

Linear Response Function

$$\boldsymbol{L} = \int_{\boldsymbol{0}}^{\infty} \boldsymbol{C}(\tau)\boldsymbol{C}(0)^{-\boldsymbol{1}} d\tau$$

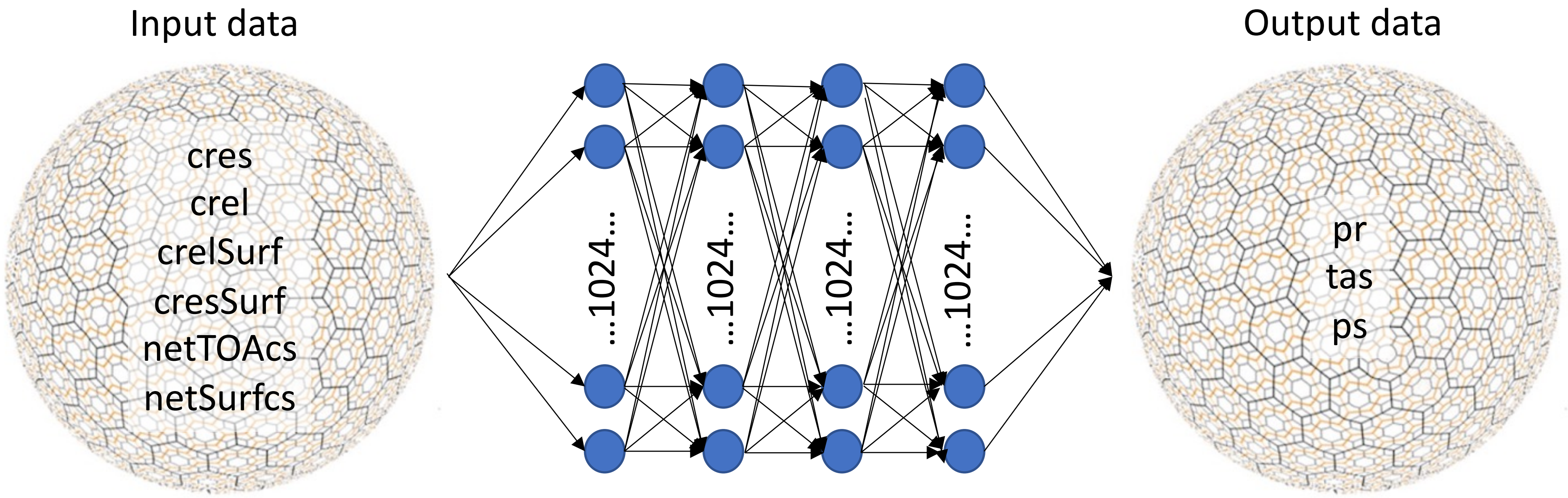
For covariance matrix $\boldsymbol{C}(\tau)$ at time lag τ
and autocovariance matrix $\boldsymbol{C}(0)$

Limitations of classic FDT

- Applying FDT typically assumes:
    1. Dimension reduction
    2. Near-Gaussian statistics
    3. Linear responses
    4. Large reference internal variability datasets
- Can we loosen some of these requirements using AI?

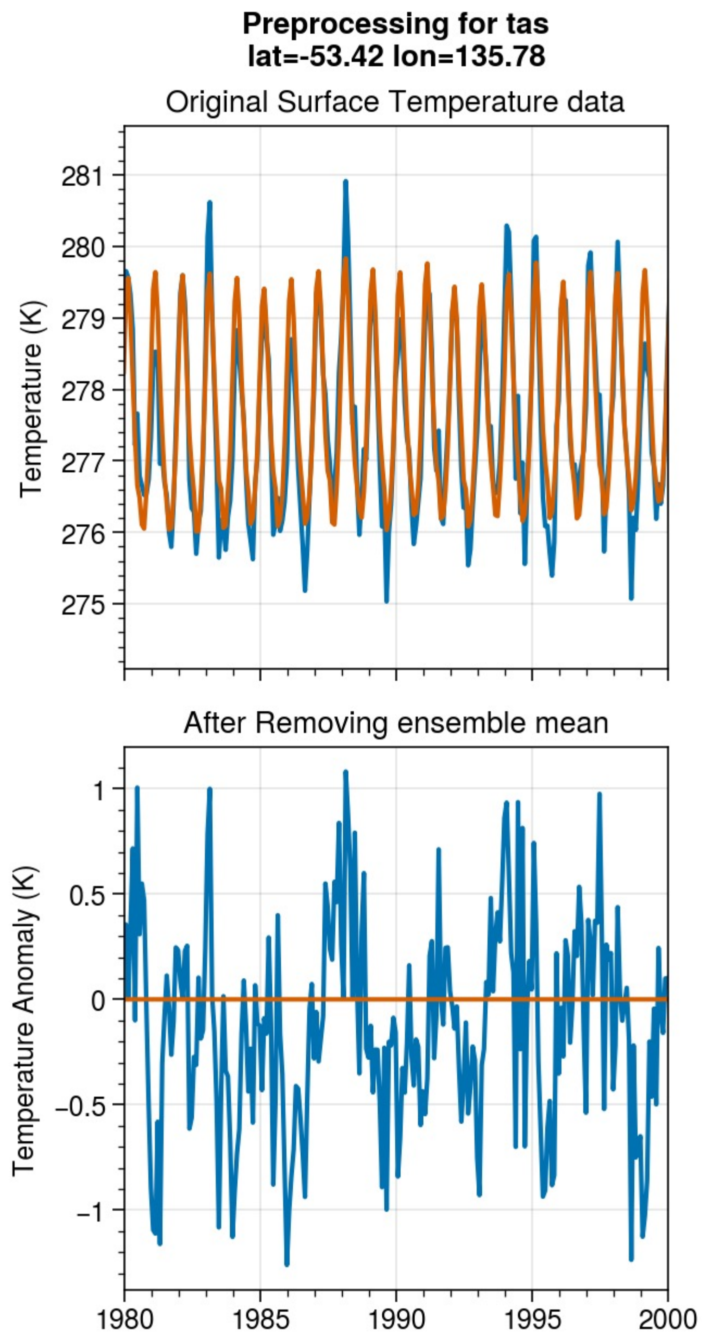
AI Model Design

- We developed a spherical Multilayer Perceptron (MLP) model
- Maps monthly mean radiation anomalies to select climate variables at different time lags
- Data is regridded to spherical icosahedral grid to avoid dealing with grid area variations



CESM2 LE Training data

- Large amount of internal variability information is required to train this AI model
- We use data from the CESM2 smoothed biomass burning historical simulations
- Data is preprocessed by removing the ensemble mean for each grid point and month in the time series



Applying FDT with AI models

- We train the AI model on at a range of time lags τ
- The AI models (A_τ) are regression models that map from an input field $\vec{x_i}$ to the average of possible trajectories of $\vec{y_i}$ for a given lag:

$$A_\tau(\vec{x_i}) \colon \vec{x_i}(t) \; \rightarrow \overline{\vec{y_i}(t+\tau)}$$

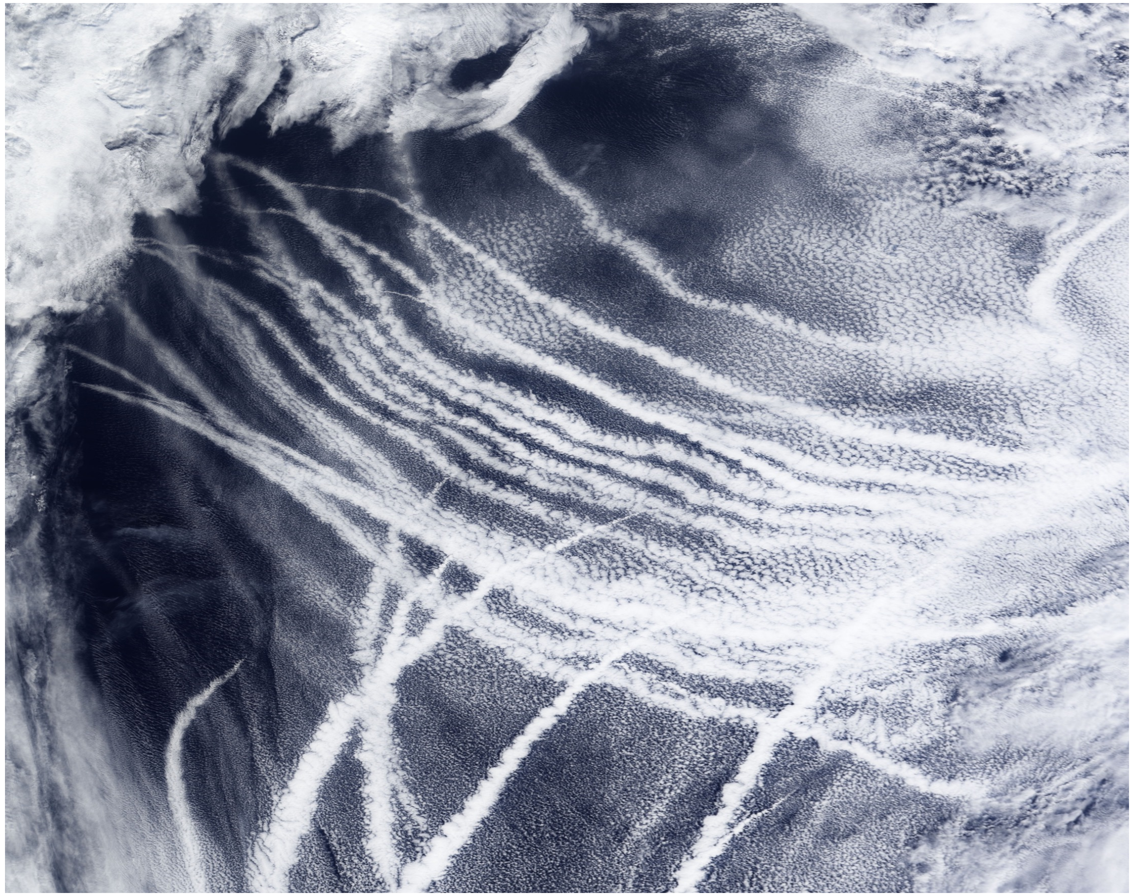
- To project a climate response $\langle \vec{y}(t) \rangle$, we integrate over the AI projections, which are the average of emulated responses to N different input fields $\vec{x_i}$:

$$\langle \vec{y}(t) \rangle = \sum_{\tau=0}^{T_{MAX}} \frac{1}{N} \sum_{i=0}^{N} \left(A_\tau(\vec{x_i} + \delta \vec{f}(t-\tau)) - A_\tau(\vec{x_i}) \right)$$

- Where $\tau_{MAX} = 60$ months

Test case: Marine Cloud Brightening

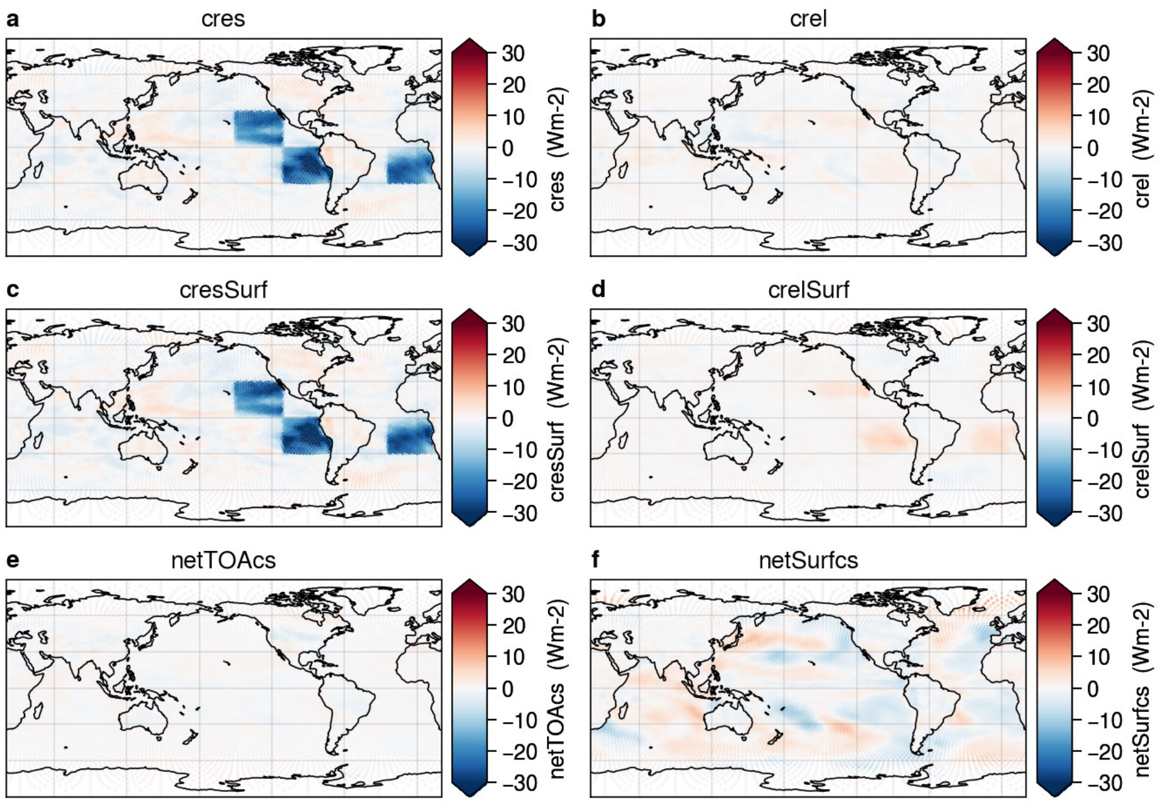
- Marine Cloud Brightening (MCB) is a proposed solar radiation geoengineering technology
- Sea salt aerosol is injected into marine boundary layer clouds to increase their albedo
- Wide range of possible MCB forcing patterns, which are not practical to assess with ESMs



Regional Marine Cloud Brightening

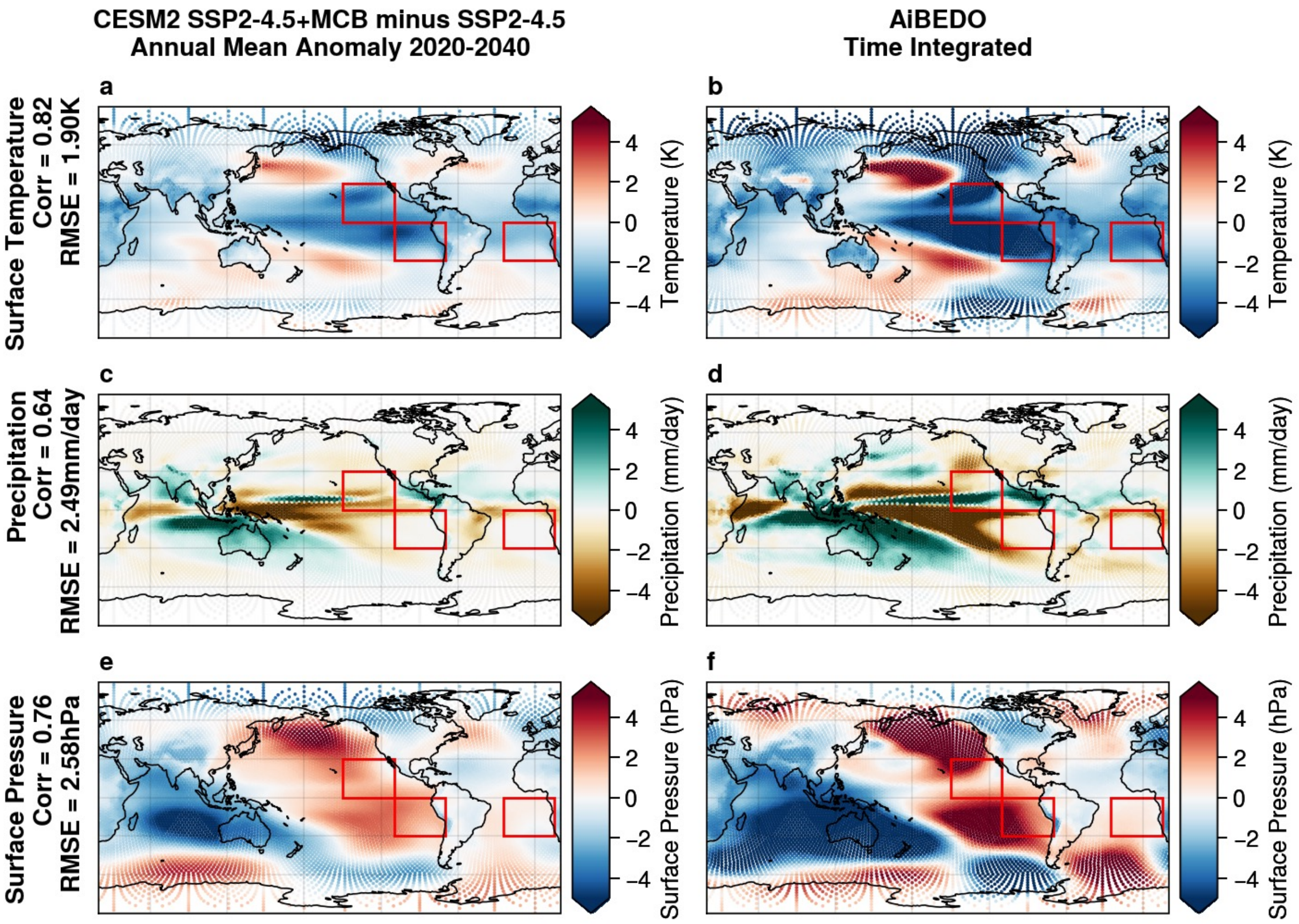
- We impose MCB in CESM2 by setting cloud droplet number concentrations to 600cm^{-3} in three regions
- A constant $\delta\vec{f}$ for the AI model is calculated with radiative flux anomalies (ERF) from fixed-SST simulations

Perturbations applied to AI model



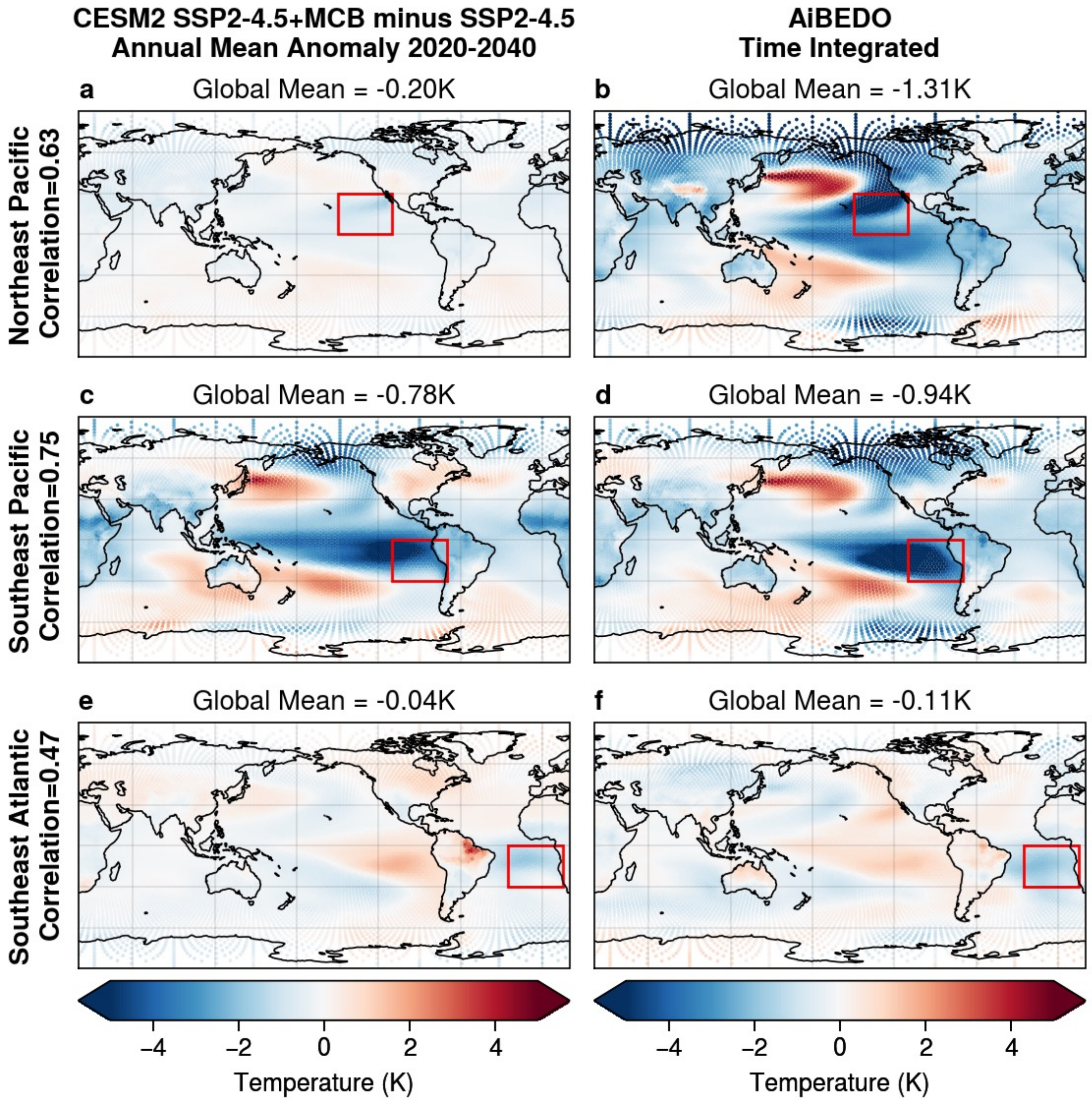
Spatial patterns of AI-FDT projections

- We compare the CESM2 “true” response (left) to the AI model response (right)
- The AI model overestimates the magnitude of the response, but correctly projects the pattern in most regions



Projected response to MCB in different regions

- Larger discrepancies between CESM2 and AI for individual regions
- Most of the total pattern is the result of La Nina-like response to SEP forcing
- AI expects stronger La Nina response to NEP than CESM2
- Non-ENSO signals are also captured (SEA cooling -> Amazon warming)



Conclusions

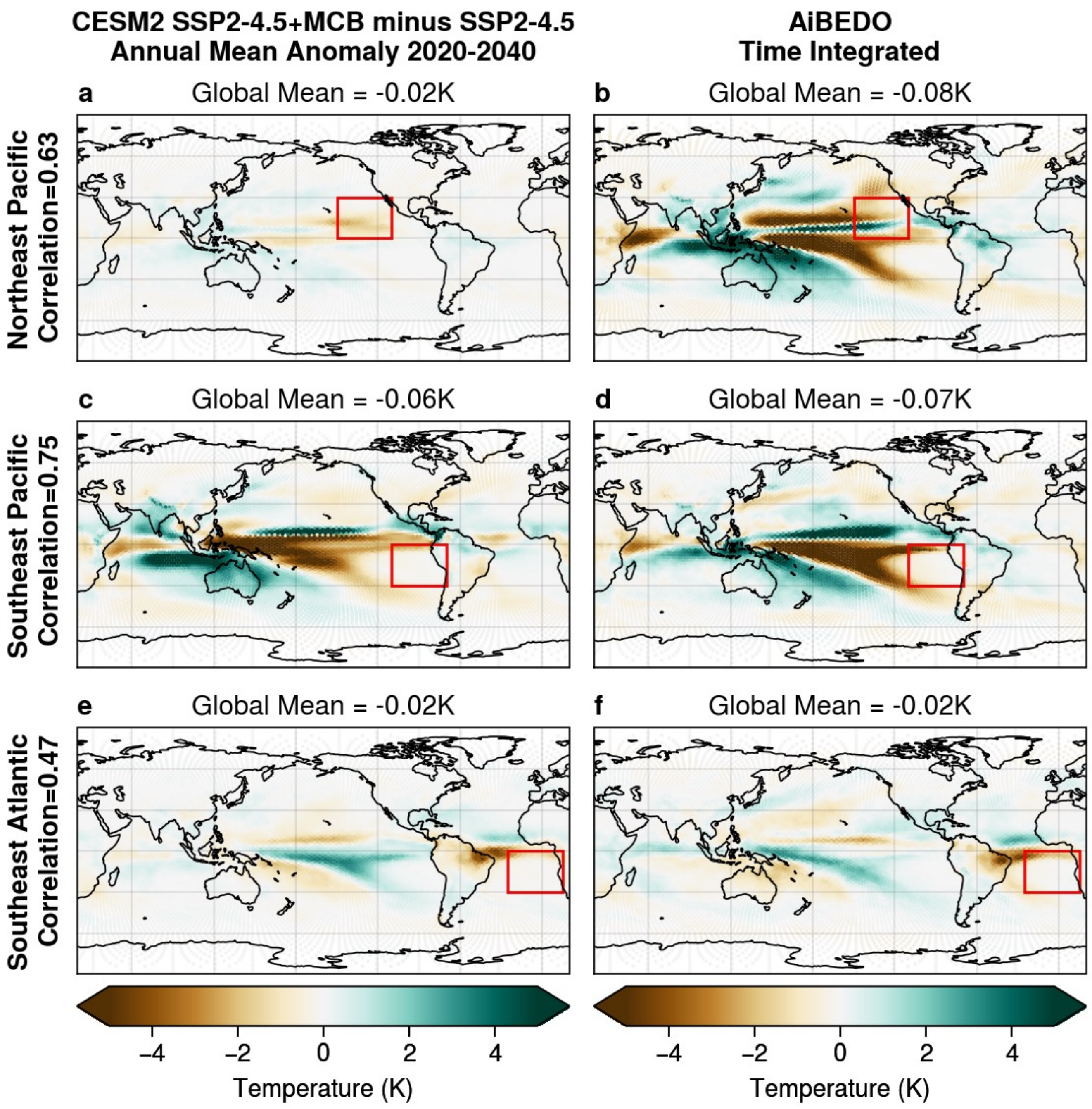
- We have developed an *ad hoc* implementation of FDT using an AI model to generate the response function
- The large data pool provided by the CESM2 LE is crucial for our AI model training
- Our AI-FDT model skilfully projects climate response **pattern** to MCB, but overestimates the magnitude of the response
- AI-FDT could be a useful tool for generating first look estimates of climate responses to forcing
  - E.g., for scenario development

Future Work

1. Uncertainty estimation:
   - Inter-ESM variability uncertainty : Train on different ESM Large Ensembles (SMILEs)
   - Inter-ESM forcing uncertainty : Apply ERF fields estimated from different ESMs
2. Assess AI-FDT projections of greenhouse gas and stratospheric aerosol injection (SAI) forcing
3. Optimizing MCB or SAI forcing patterns to produce specific climate responses in target regions (e.g., key regions for tipping points)

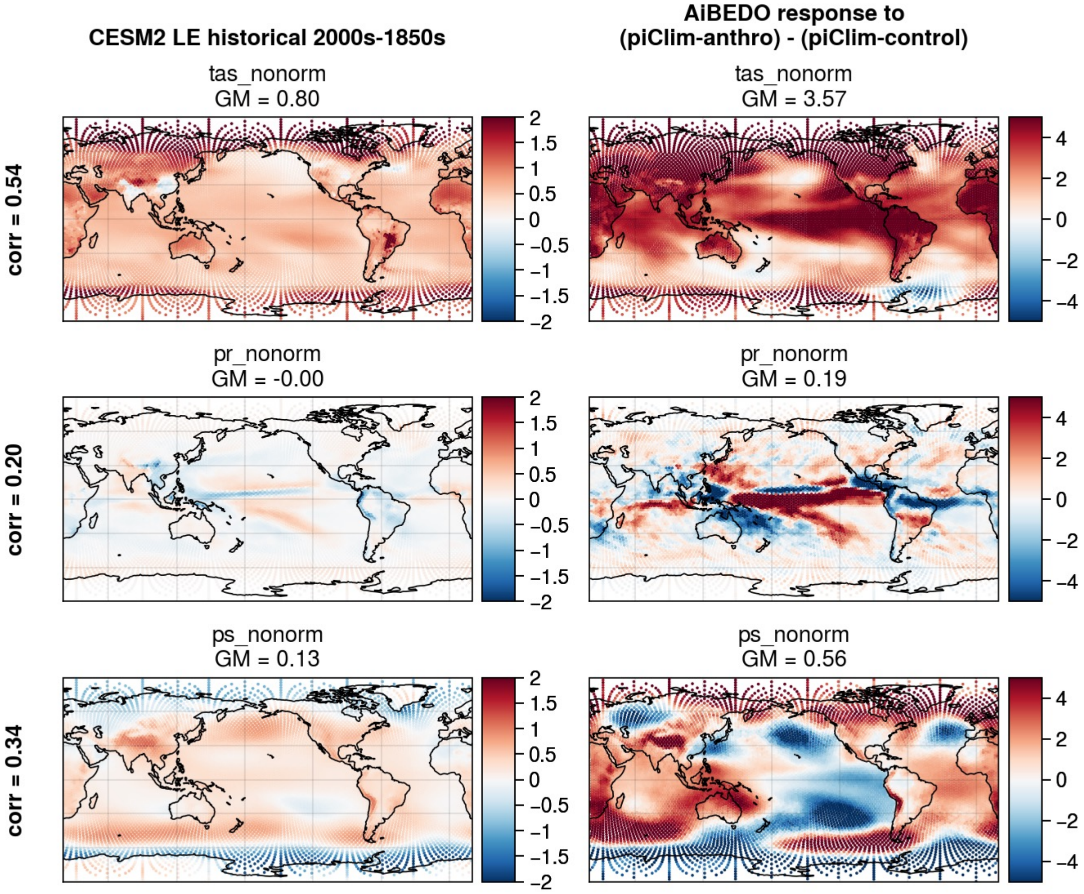
AI FDT projection procedure

- For each time lag τ:
  - Select N sample radiation anomaly fields $\overrightarrow{x_i}$ from a preprocessed dataset
  - Run AI (A_τ) on the N input field to obtain N control projected output fields $\overrightarrow{y_i}$ for each lag τ
  - Perturb each of the input radiation anomaly fields by $\delta\vec{f}$, $\overrightarrow{x_i'} = \overrightarrow{x_i} + \delta\vec{f}$
  - Run AI on the N perturbed input fields to obtain N perturbed output fields $\overrightarrow{y_i}$ for each lag τ
  - Compute average across the N control and perturbed output fields
- Compute Simpson's integration over the time lags τ at each grid point



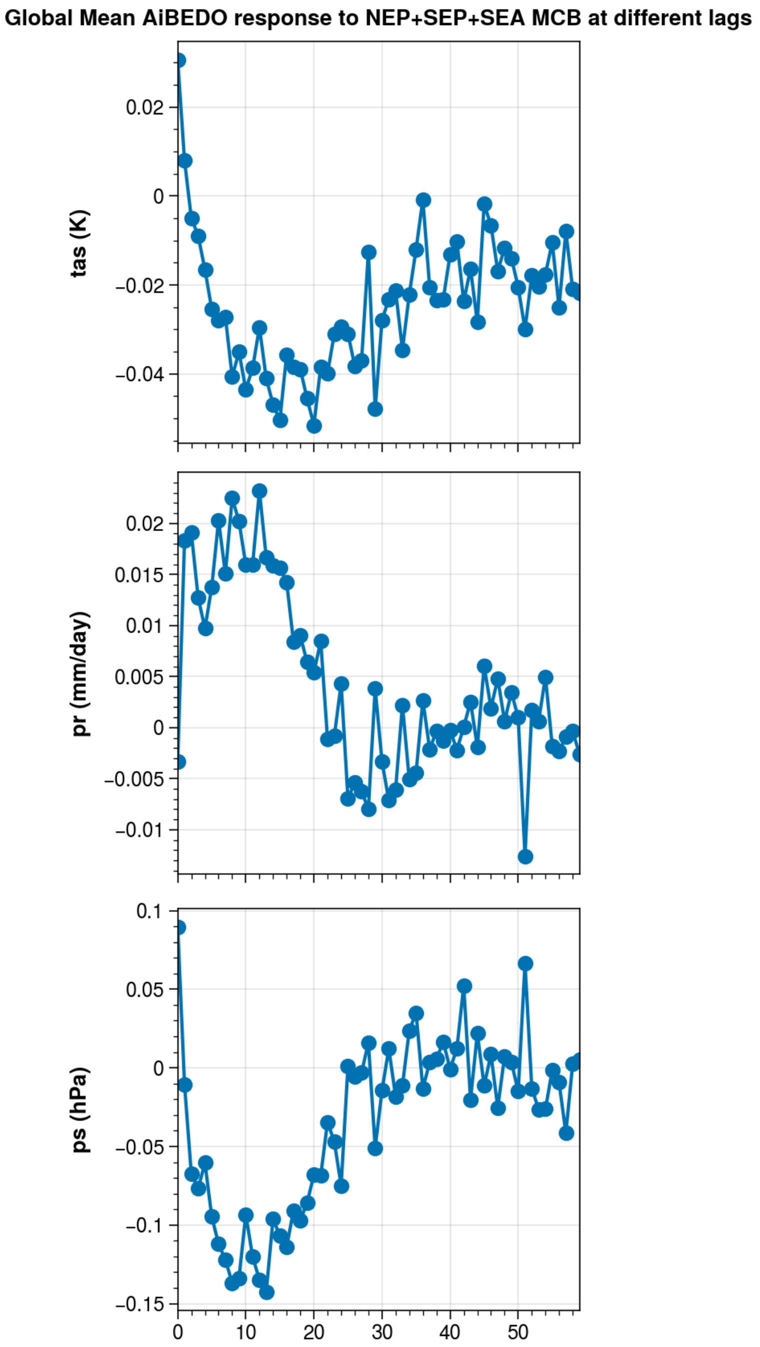
CESM2 SSP2-4.5+MCB minus SSP2-4.5
Annual Mean Anomaly 2020-2040
AiBEDO
Time Integrated
Northeast Pacific
Correlation=0.63
Southeast Pacific
Correlation=0.75
Southeast Atlantic
Correlation=0.47
a
Global Mean = -0.02K
b
Global Mean = -0.08K
c
Global Mean = -0.06K
d
Global Mean = -0.07K
e
Global Mean = -0.02K
f
Global Mean = -0.02K
−4
−2
0
2
4
Temperature (K)
−4
−2
0
2
4
Temperature (K)

piAnthro effect



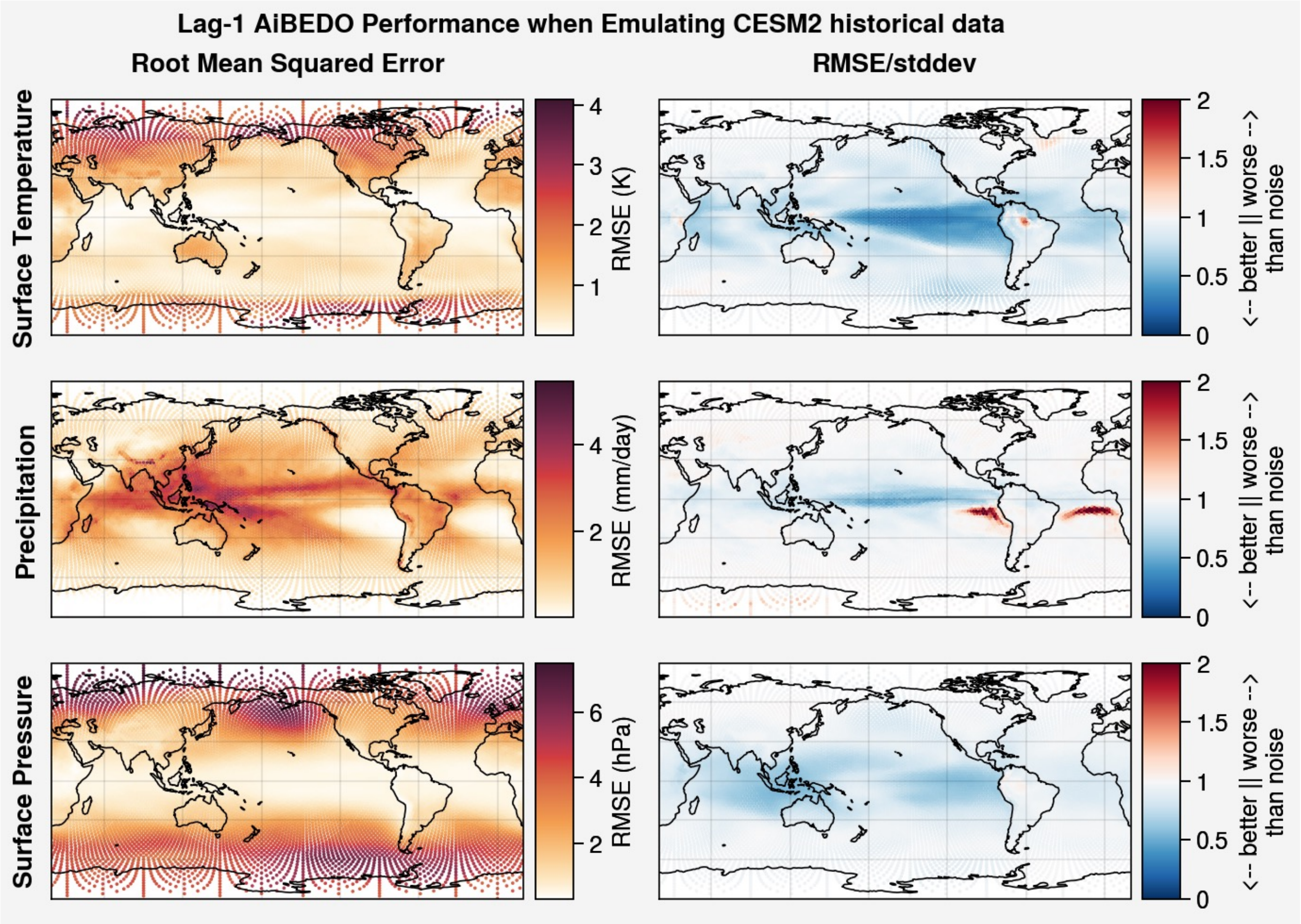
Global Mean AI lagged responses

- AI model suggests a response time scale to the MCB perturbation of 3-years
- Temperature response has not converged to 0 after 60 months, possibly suggesting longer time scales are required.



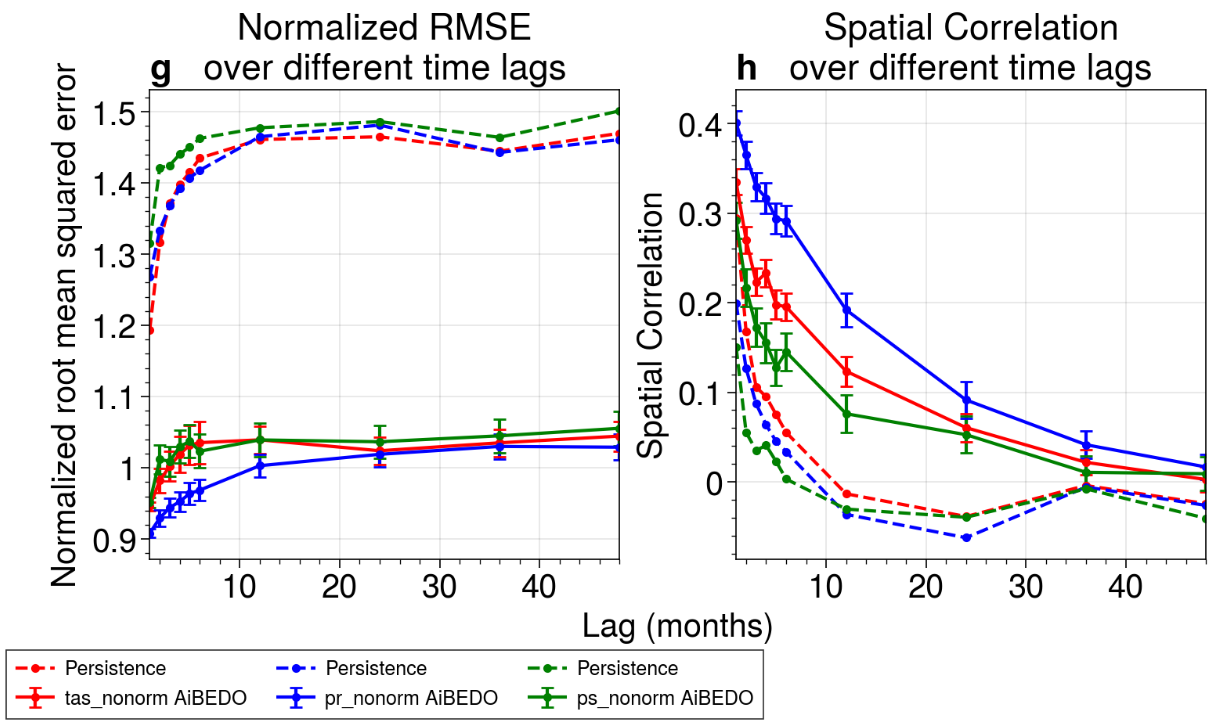
AI Emulation performance

- To test the AI performance, we:
  - Run AI model with CESM2 internal variability as input
  - Compare AI model output (tas, pr, ps) to the original CESM2 variables at the corresponding lag
- The AI model performs well in low latitude oceanic regions, but poorly at high latitudes and over land



AI Emulation performance

- AI model emulation has skill above noise out to ~36 months
- Substantially higher skill in spatial correlation for precipitation than surface temperature/pressure



Comparison between AI models