

Variability in Sea-Surface Temperature and Sea Ice Patterns from Coupled Data Assimilation, 1850–present

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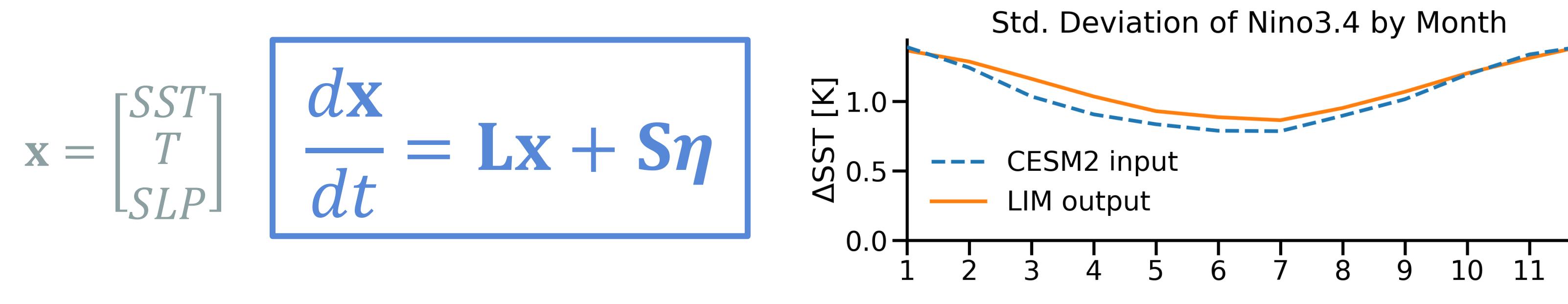
Motivation

- First, see HadISST vs. NOAA ERSST trends in SST (bottom-right figure)
- Climate feedbacks depend on spatial patterns of SST and sea ice
- Substantial disagreements across existing SST datasets come from different infilling methods applied to unobserved regions
- We don't know how satellite-era trends compare to pre-1980 variability because of the disagreements across datasets
- We need to quantify uncertainty in SST and sea-ice patterns
 - And identify where additional data could help constrain past variability
- There is an opportunity to combine obs of ship-based SST, land-based air temperature, and sea-level pressure using coupled data assimilation

Methods

Linear Inverse Model (LIM)

- Coupled online data assimilation (DA) with climate models is not feasible, so we build linear inverse models (LIMs) to represent climate models
- LIMs contain linear dynamics (L) and stochastic noise (S), which together can reproduce the original statistics of the input climate model



- We build "cyclostationary" (monthly) LIMs separately for:
 - CESM1, CESM2, MRI-ESM2-0, HadCM3, GISS-E2R

$$L_j = \tau^{-1} \ln[C_j(\tau)C_j(0)^{-1}], \quad j = 1, \dots, 12 \text{ (months); } \tau = 1$$

(Shin et al. 2021; Penland & Sardeshmukh 1995)

Data Assimilation (DA)

- LIM produces monthly "prior" forecasts, and the Kalman filter produces the "posterior" analysis (accounting for model and observation uncertainty)
- Forecasts are launched from previous analysis (i.e., this DA framework has "memory" of past observations)

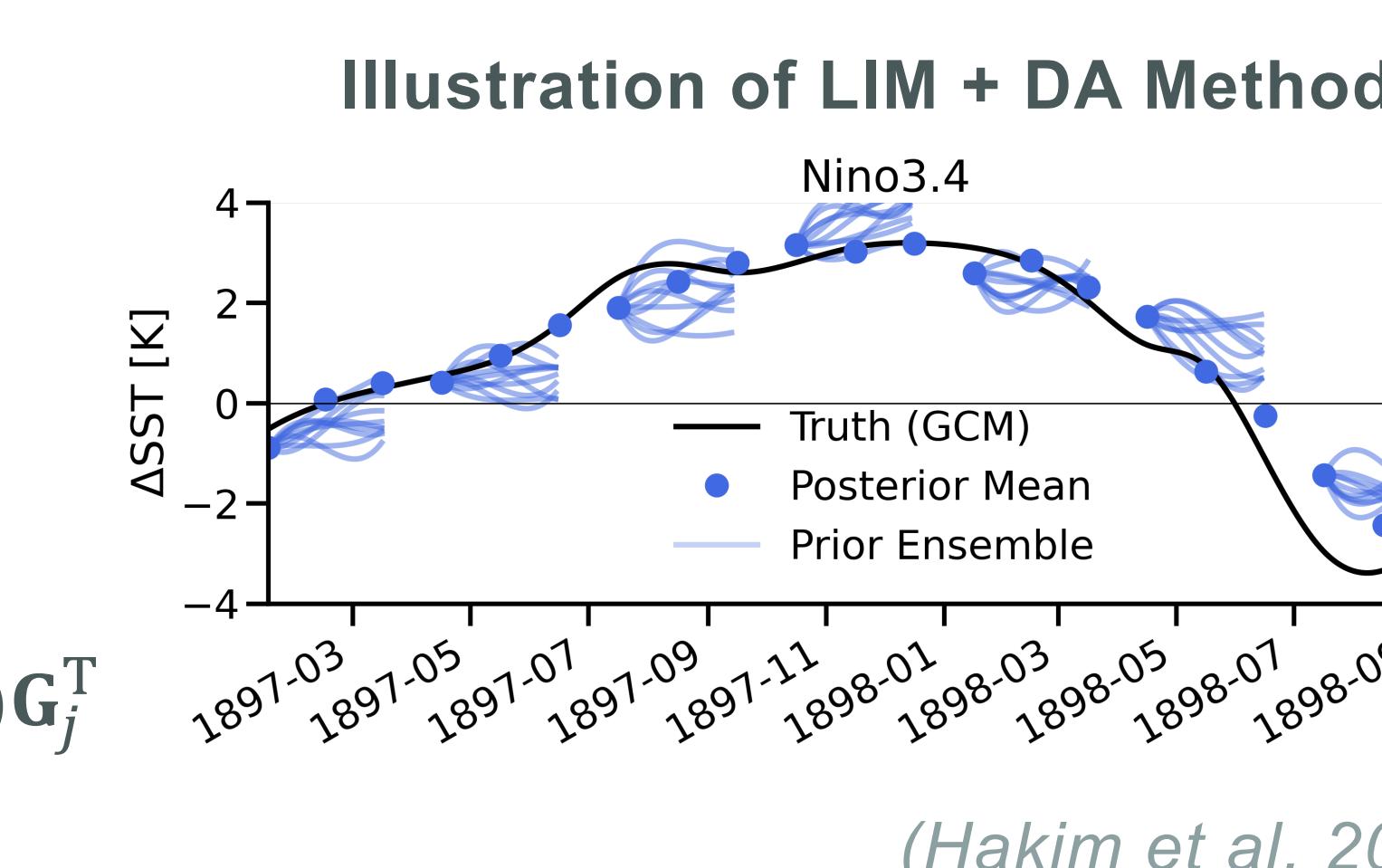
Ensemble Mean (\bar{x})

$$G_j = \exp(L_j \delta t)$$

- 1) Forecast: $\bar{x}_f(t + \delta t) = G_j \bar{x}_a(t) + \eta$
- 2) Assimilation: $\bar{x}_a = \bar{x}_f + K(y - H\bar{x}_f)$
 $K = P_f H^T [H P_f H^T + R]^{-1}$

Covariance (P)

- 1) Forecast: $P_f(t + \delta t) = G_j P_a G_j^T + N_j$
 $N_j = C_j(0) - G_j C_j(0) G_j^T$
- 2) Assimilation: $P_a = (I - KH)P_f$



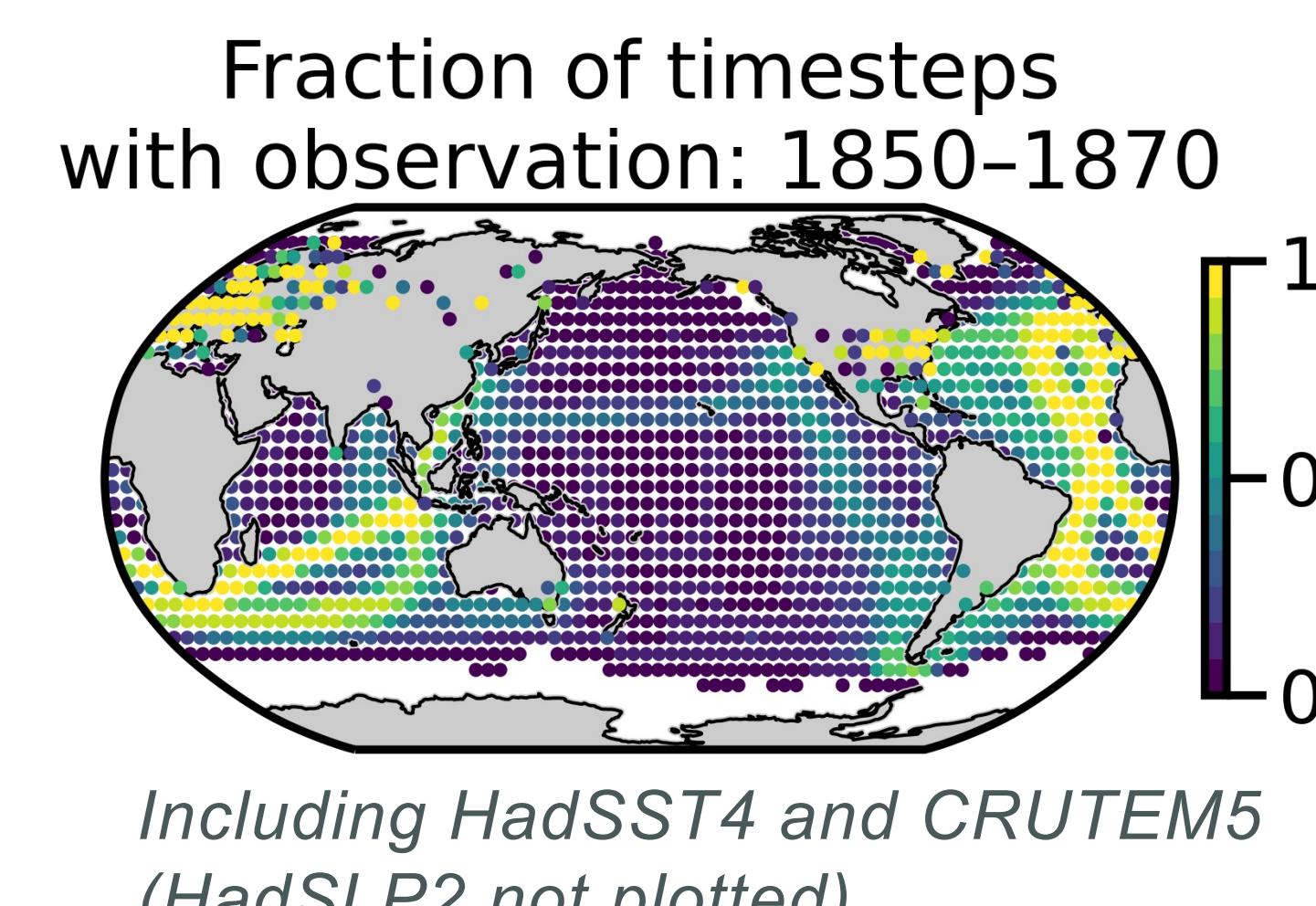
Conclusions & Next Steps

- We combine models and observations to produce spatially complete monthly SST, 2-m air temp., and sea-level pressure back to 1850
- LIM+DA method captures large-scale variability and trends, but perhaps more importantly, quantifies uncertainty and its spatial fingerprints
- Results could be used in atmospheric GCMs to investigate uncertainty in historical feedbacks and its sources in the Tropics, Southern Ocean, etc.
- Method could be extended to investigate past variability in the hydrologic cycle (P-E)

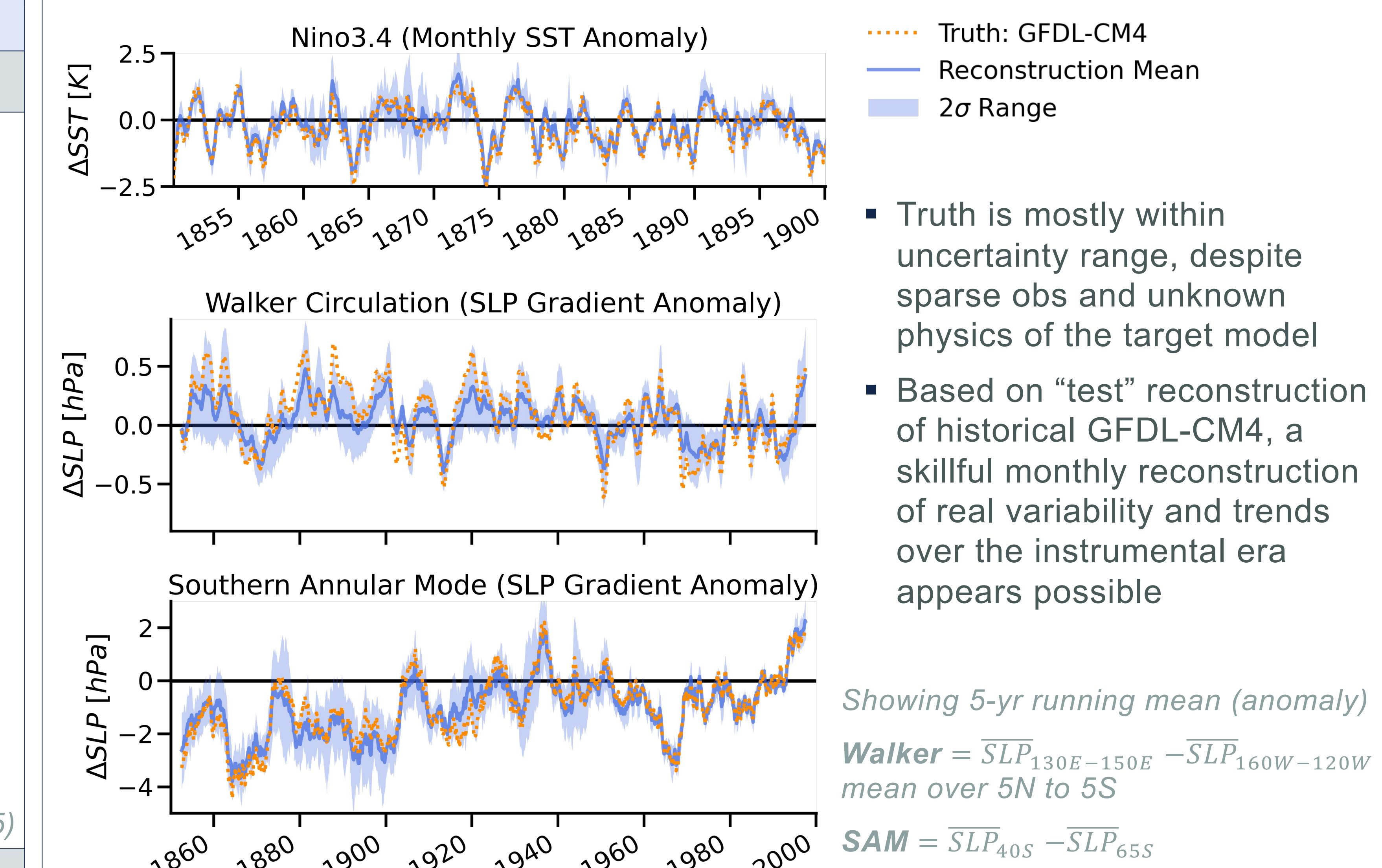
Results: Test Reconstruction of Climate Model

Observation Network

- Monthly mean SST, 2-m air temperature, and sea-level pressure are assimilated from HadSST4, CRUTEM5, and HadSLP2 (1850–2000)
- Imperfect model "test" reconstructions: draw obs from a target climate model (GFDL-CM4 shown below)
 - Locations and errors of the "test" obs (from the target model) are specified to replicate the actual obs



Validation vs. True Variability in GFDL CM4



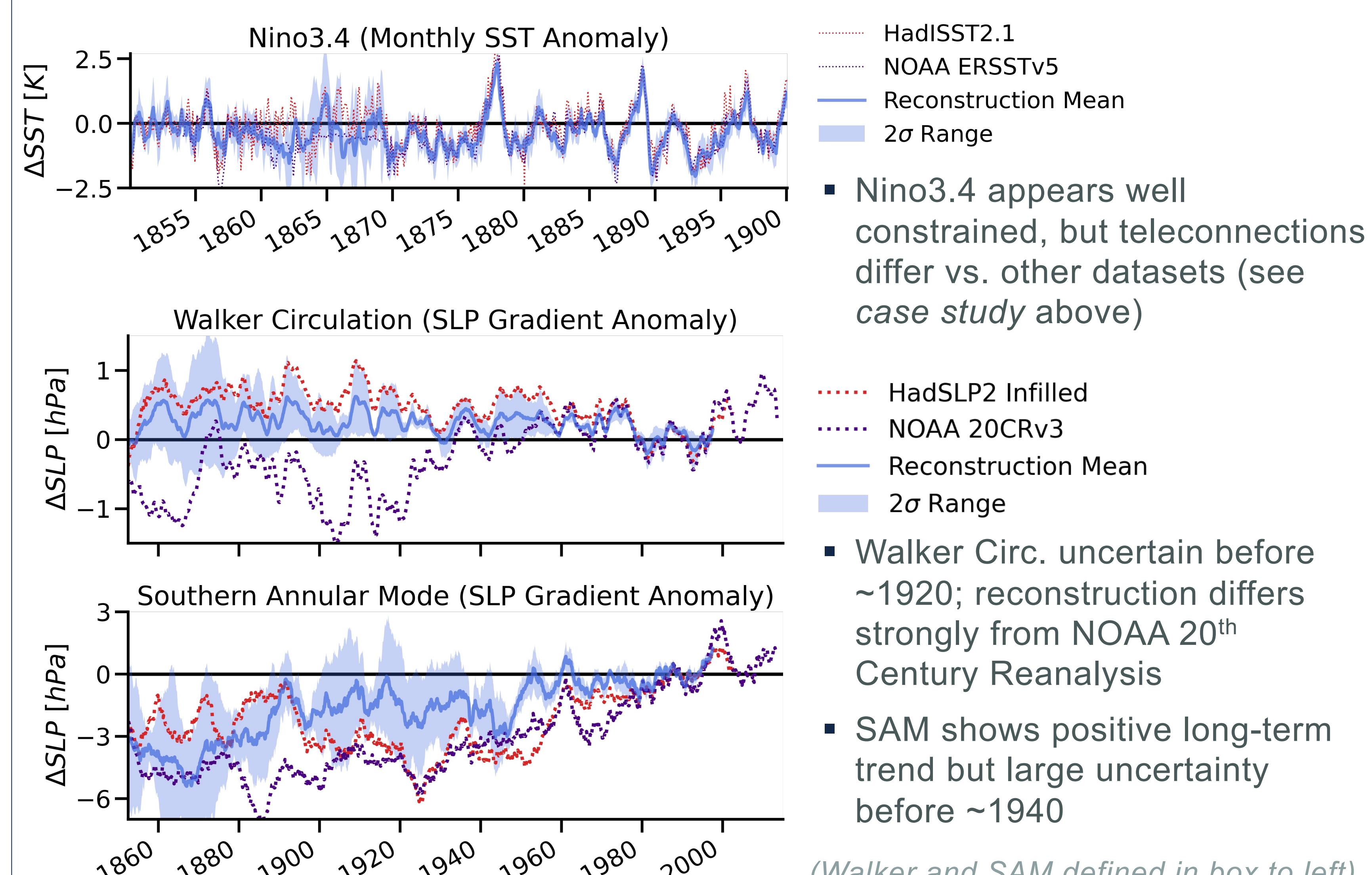
- Truth is mostly within uncertainty range, despite sparse obs and unknown physics of the target model
- Based on "test" reconstruction of historical GFDL-CM4, a skillful monthly reconstruction of real variability and trends over the instrumental era appears possible

Results: Real Reconstruction with Instrumental Obs.

Case Study: Onset of Major ENSO (July 1877)

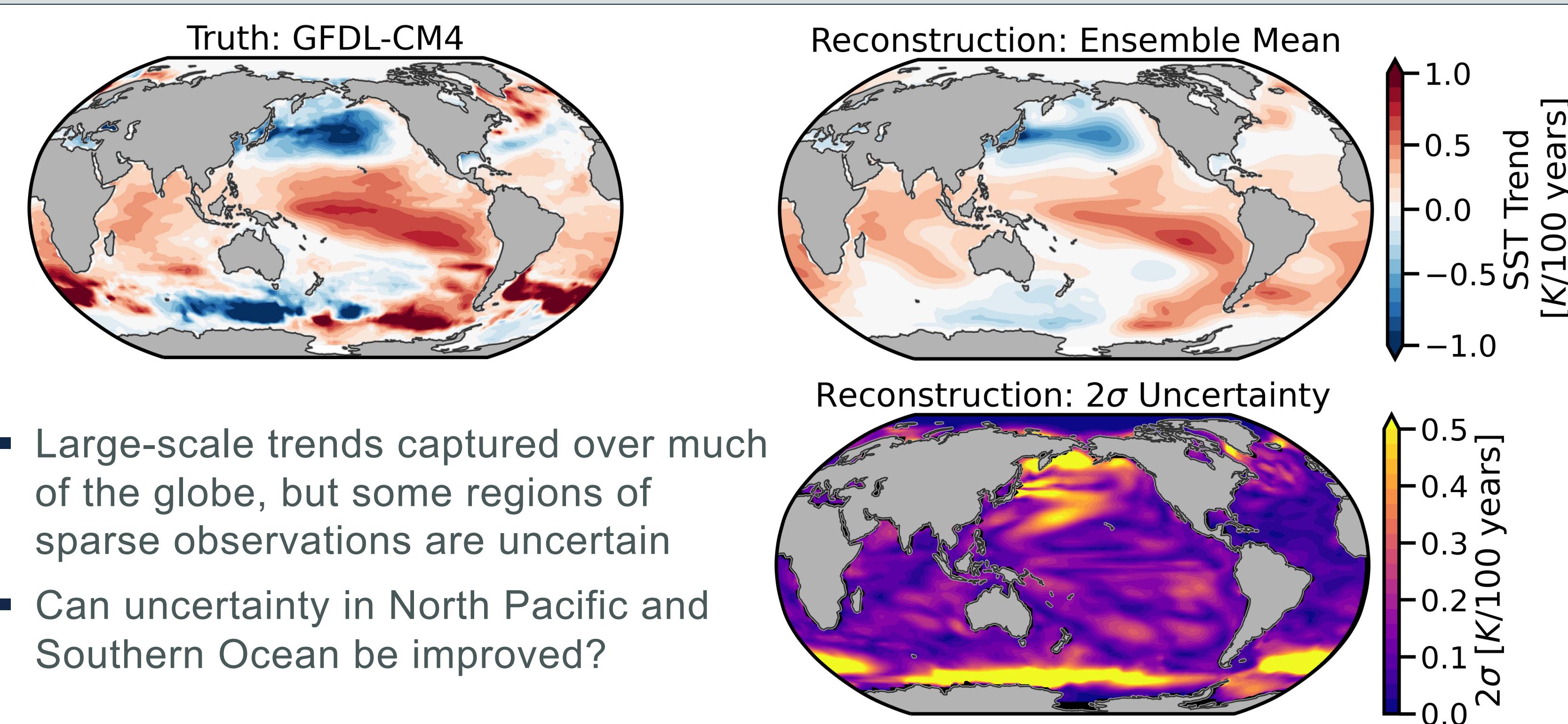
- How does our LIM+DA result compare to existing datasets during the 1877/78 ENSO?
- Despite similar Nino3.4 values, spatial patterns of SST anomalies vary significantly across existing infilled datasets and vs. our reconstruction

Reconstruction of ENSO, Walker Circulation, and Southern Annular Mode



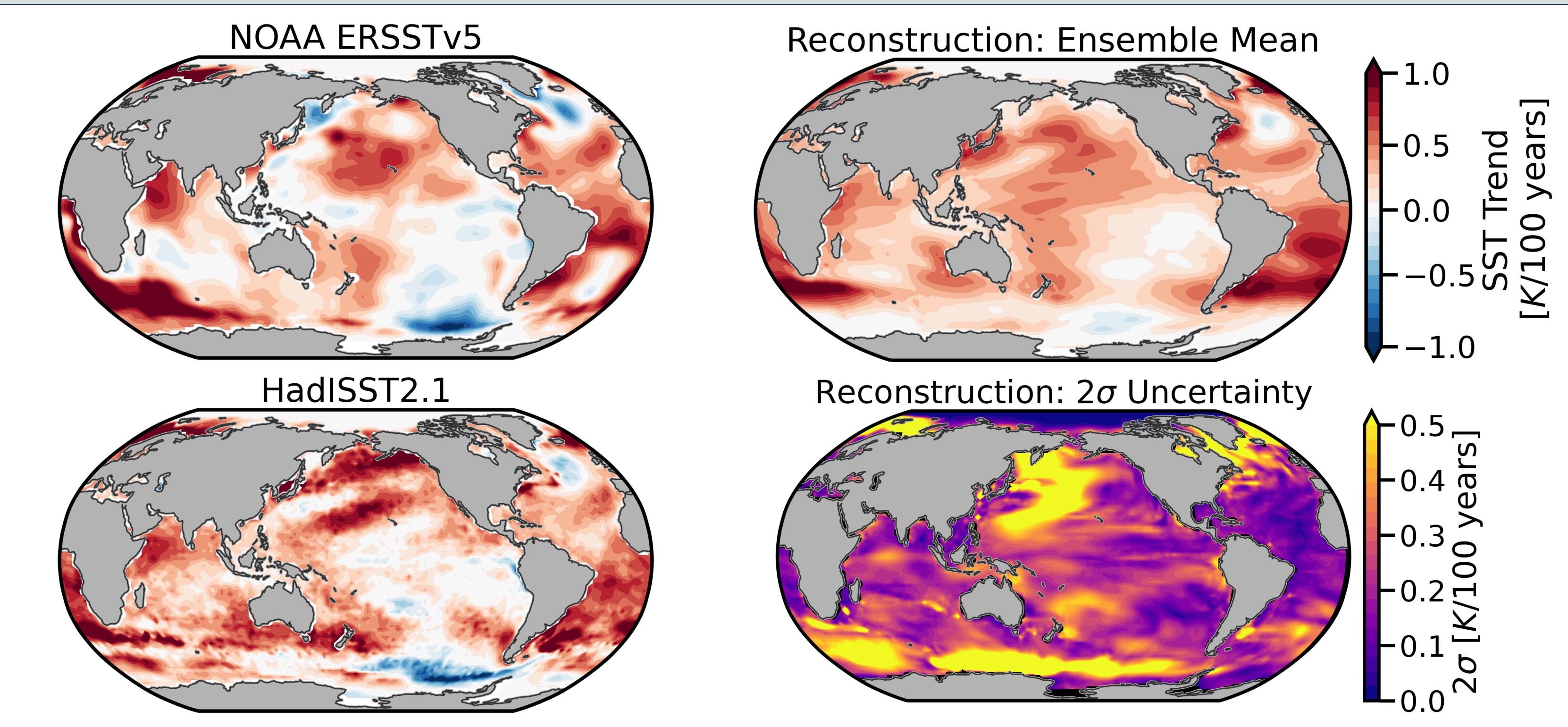
(Walker and SAM defined in box to left)

SST Trends 1880–1980

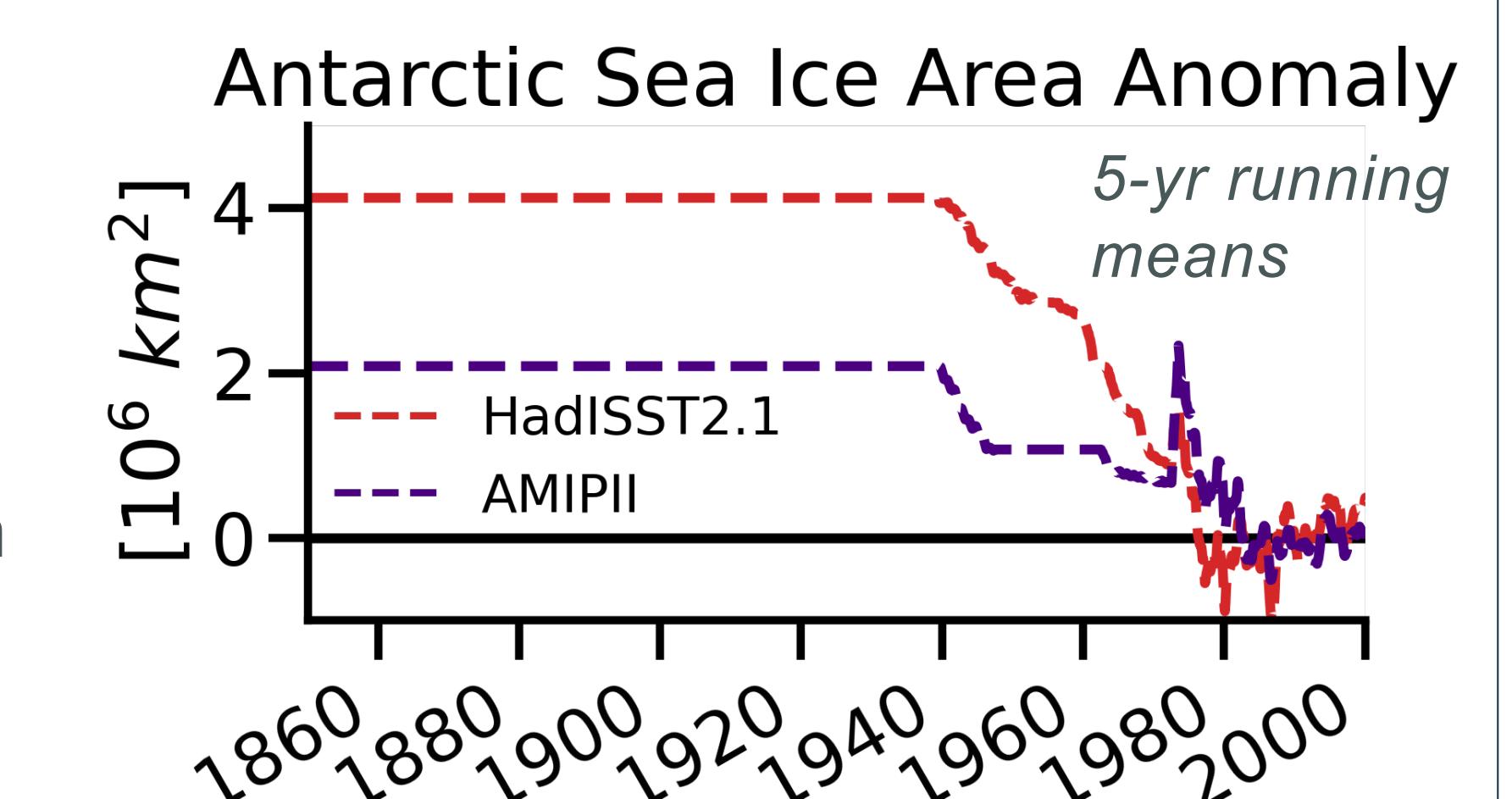


- Large-scale trends captured over much of the globe, but some regions of sparse observations are uncertain
- Can uncertainty in North Pacific and Southern Ocean be improved?

SST Trends 1880–1980



- Existing datasets (left) that are currently used as boundary conditions for AGCMs (e.g., in AMIP-type simulations) differ from our reconstruction
- Reconstruction quantifies spatial distribution of uncertainty: could proxies help?



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