Persistent differences in simulated and observed tropical tropospheric warming

Confronting Earth System Model Trends with Observations

The Good, the Bad, and the Ugly

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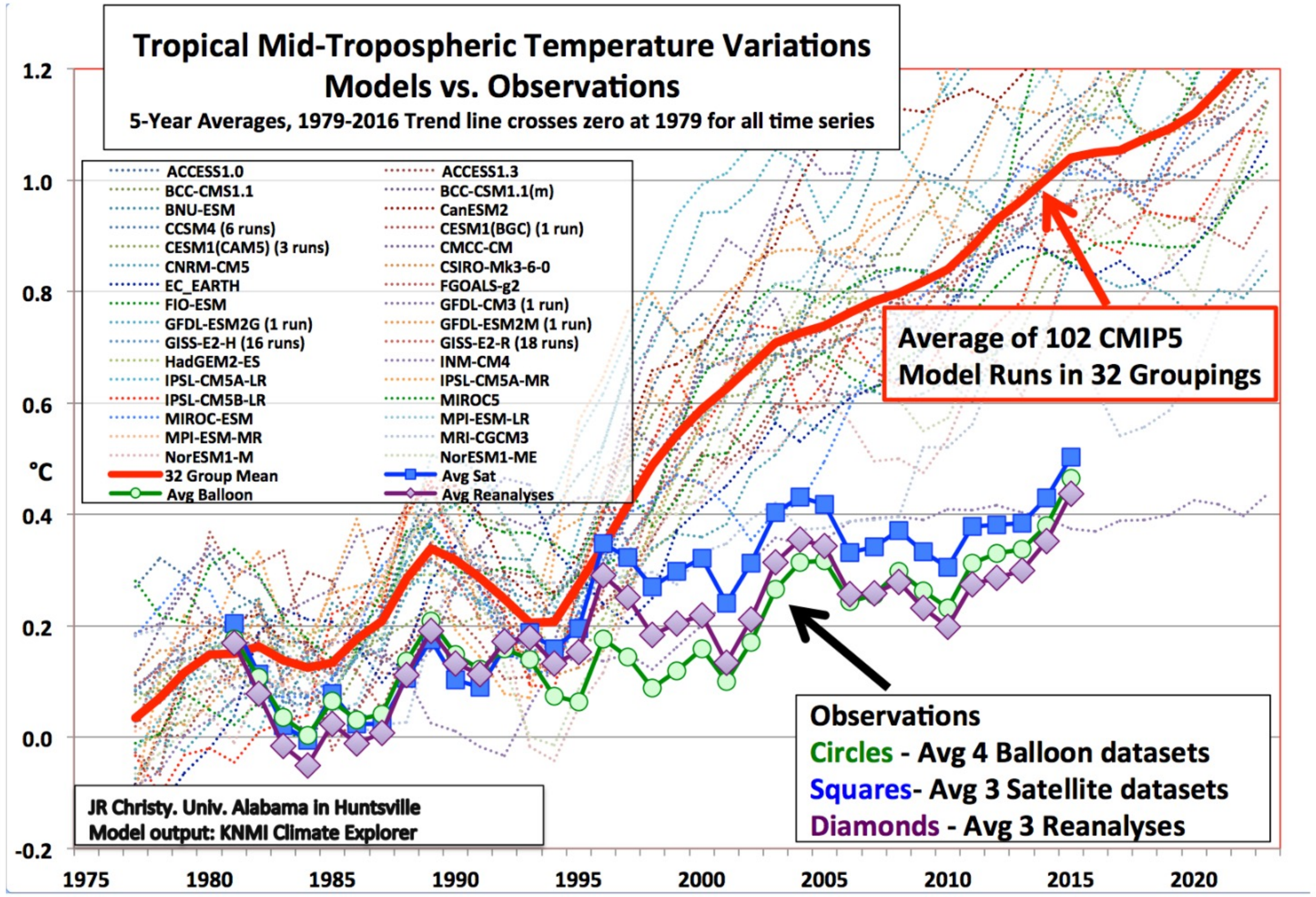
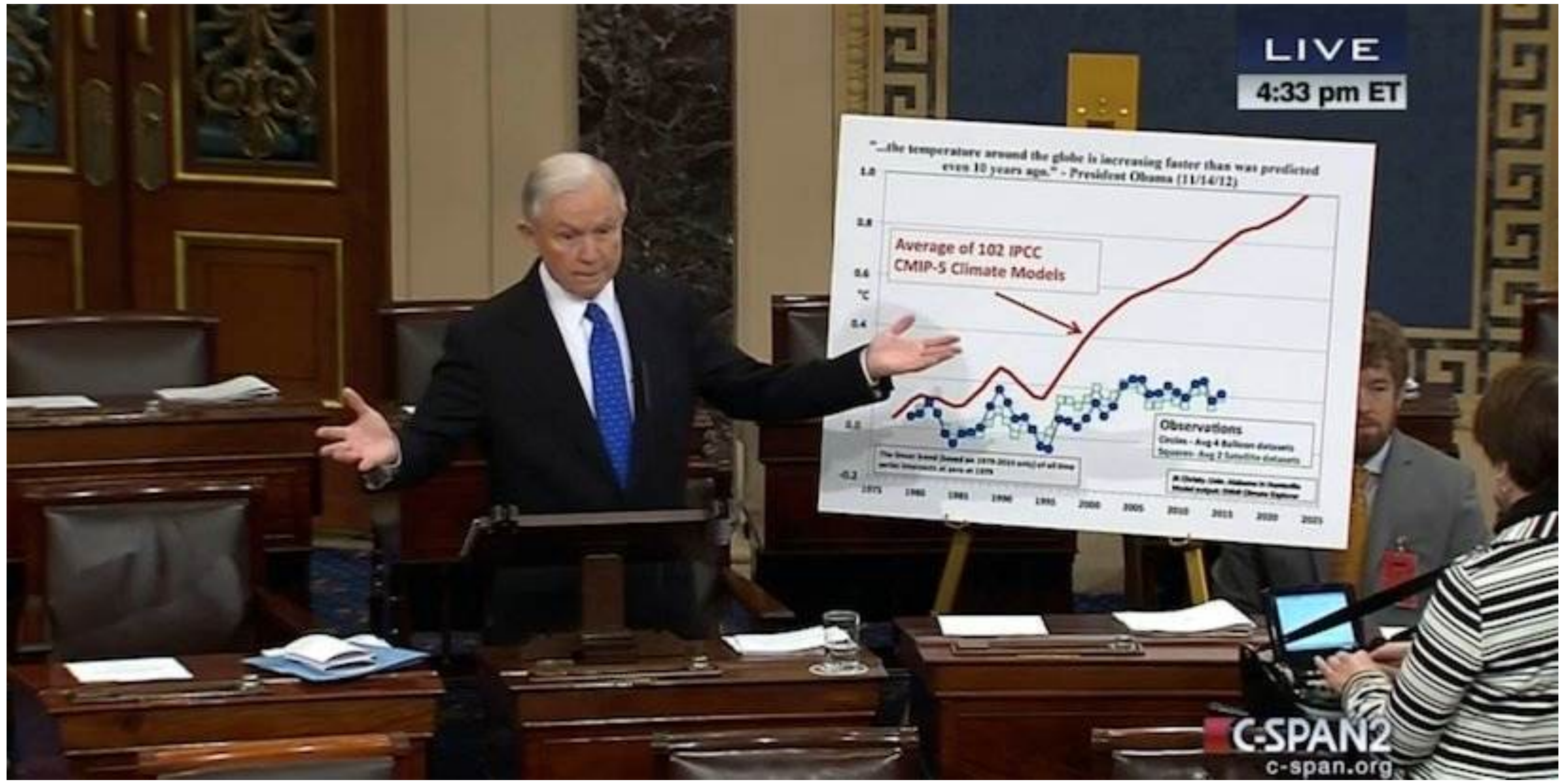
The problem: Climate models exhibit greater tropical tropospheric warming than satellite observations

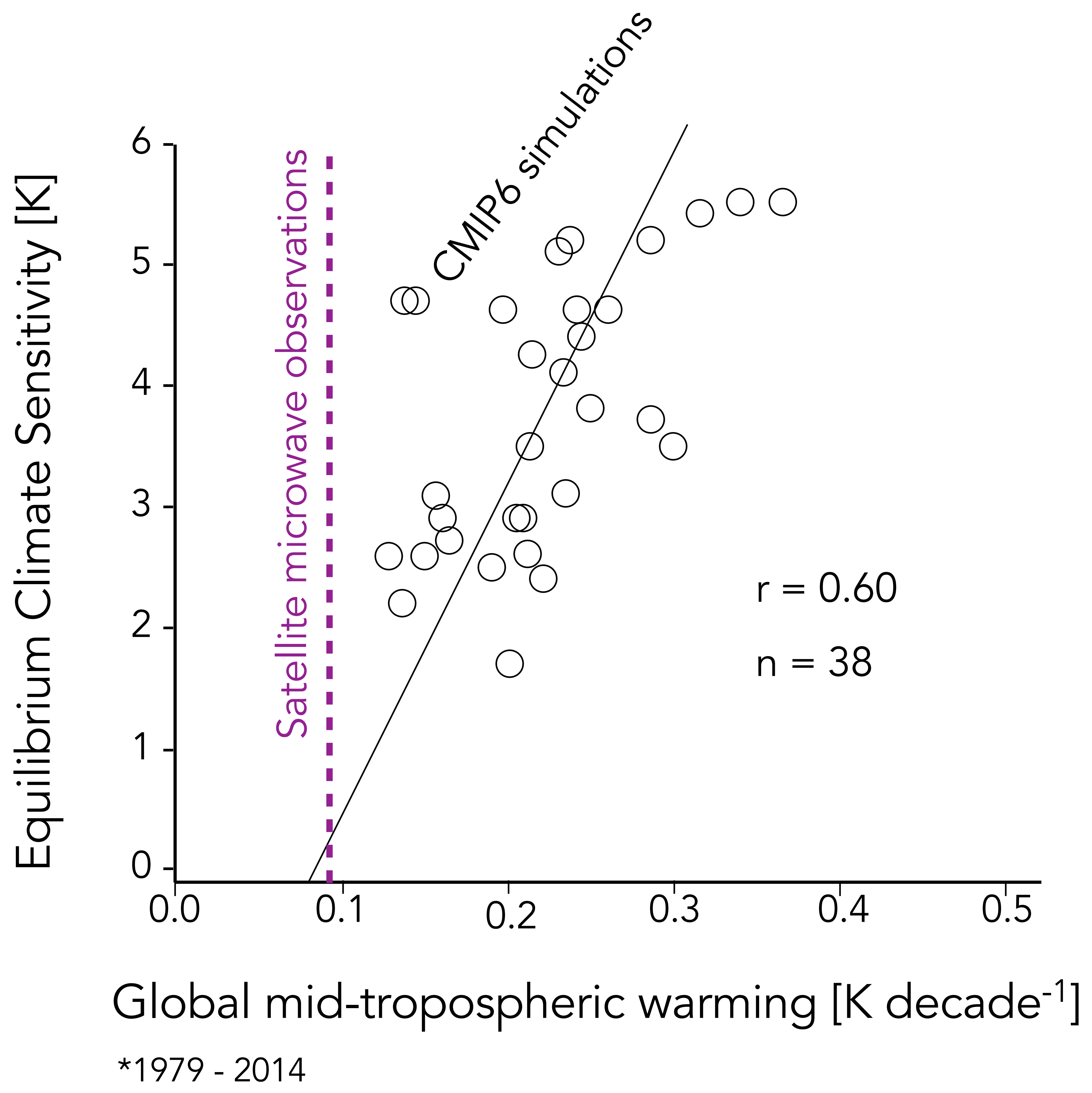
- **CMIP3**: Multimodel average trend 2 - 6 times greater than observations
- **CMIP5**: Multimodel average trend 2 - 3 times greater than observations

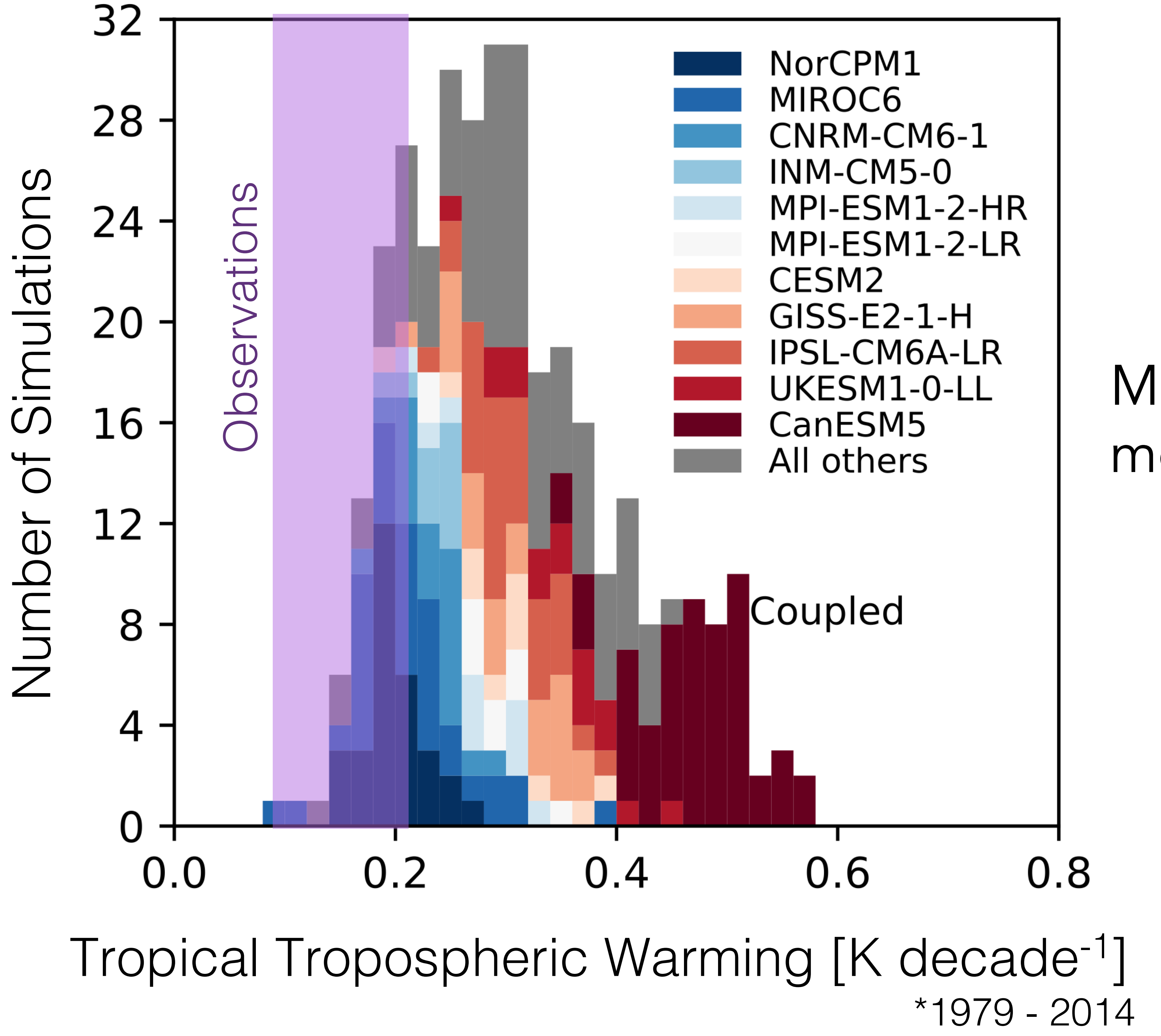




Wallace et al. (2000); Karl et al. (2006); McKitrick et al. (2010); Christy et al. (2010); Santer et al. (2017a,b)

Are climate models too sensitive?



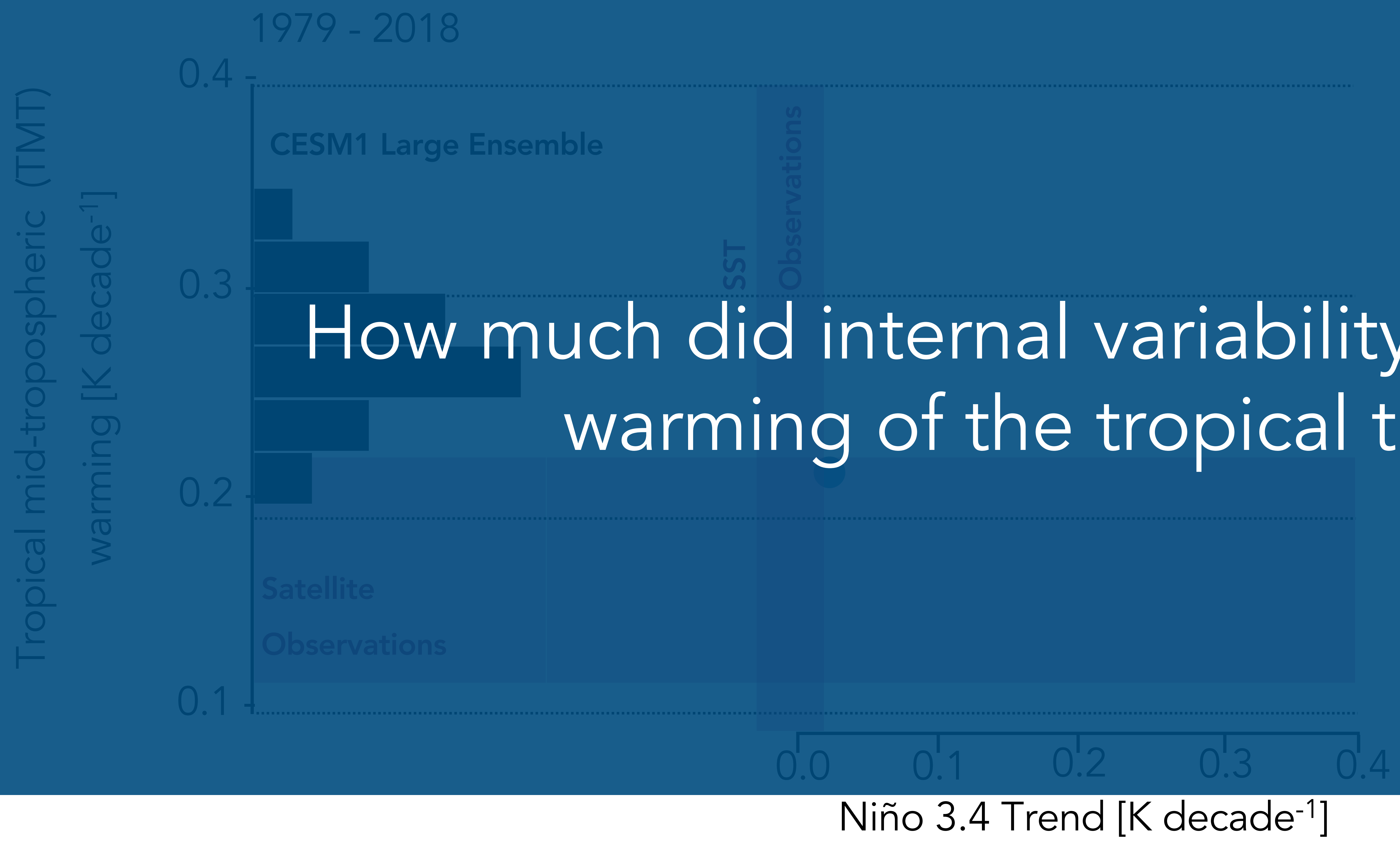


Models still exhibit ~2x too much model warming (on average)

Figure reproduced from McKitrick and Christy (2020); see also Tokarska et al. (2020)

Po-Chedley et al. (2021)

The imprint of multidecadal variability



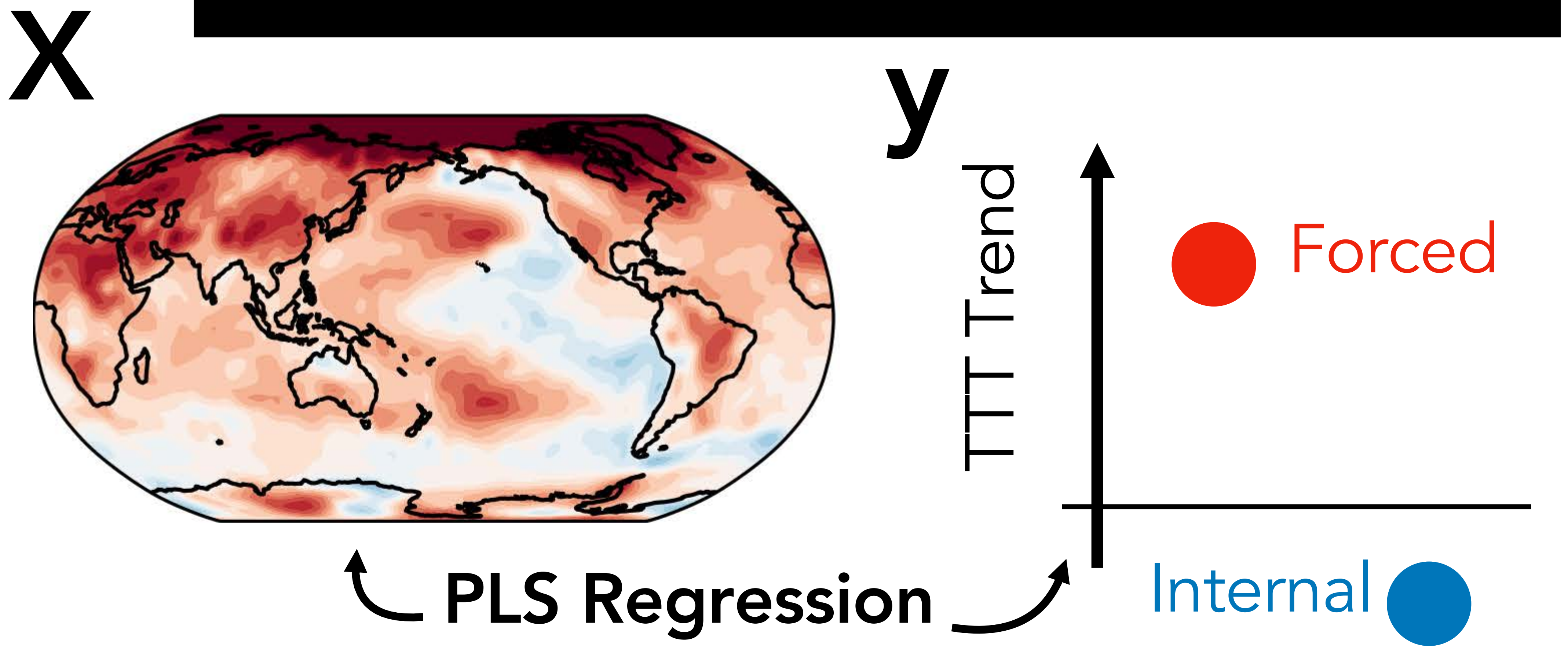
How much did internal variability reduce satellite-era warming of the tropical troposphere?

Casas et al. (2022); Mitchell et al. (2020); Suárez-Gutierrez et al (2017); Kamae et al (2015); Kosaka and Xie (2013)

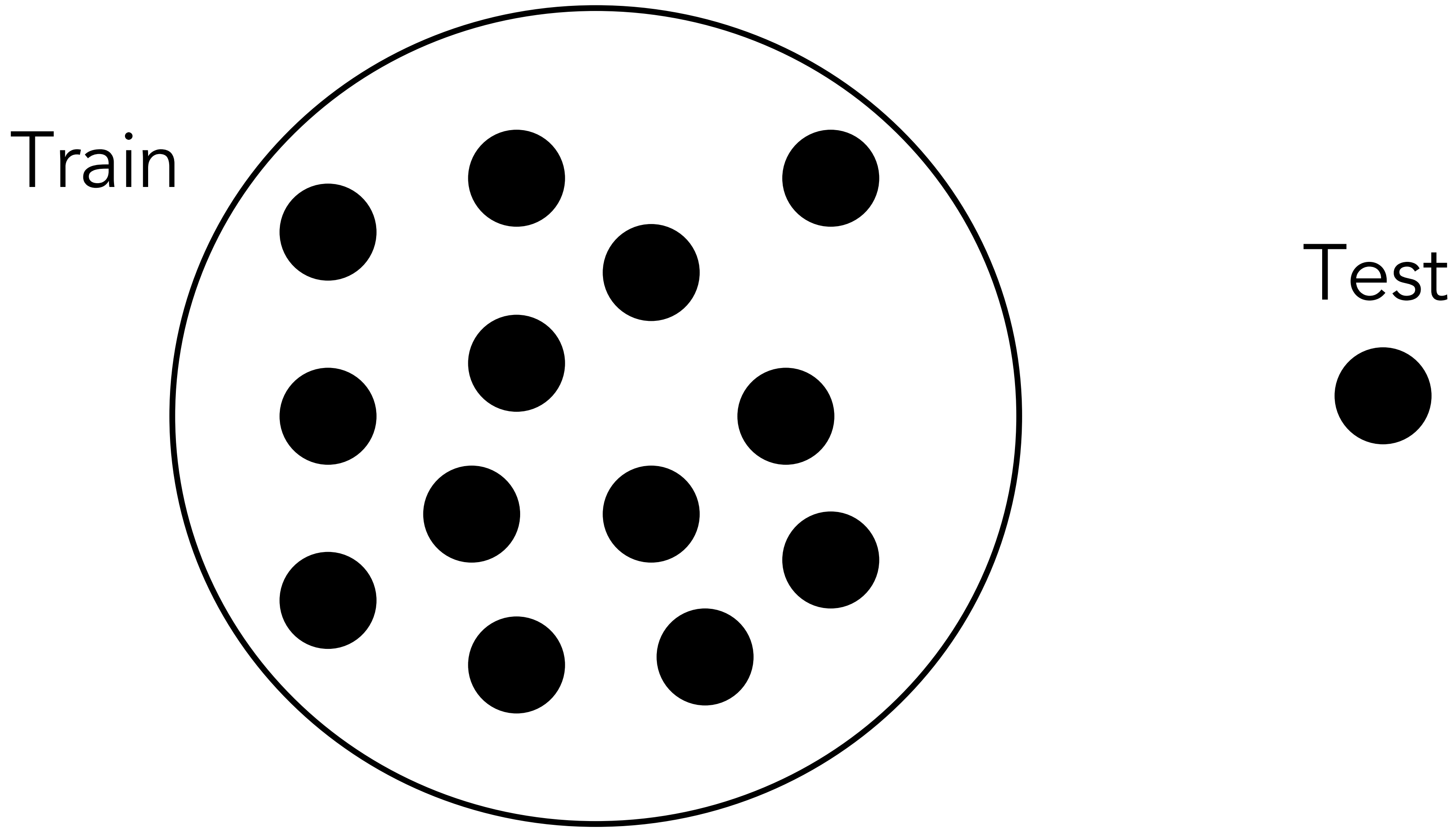
Po-Chedley et al. (2021)

Quantifying satellite era internal variability

Train machine/statistical learning to predict the a) forced and b) unforced component of tropospheric warming based on the surface warming pattern



Use a leave-one-out approach

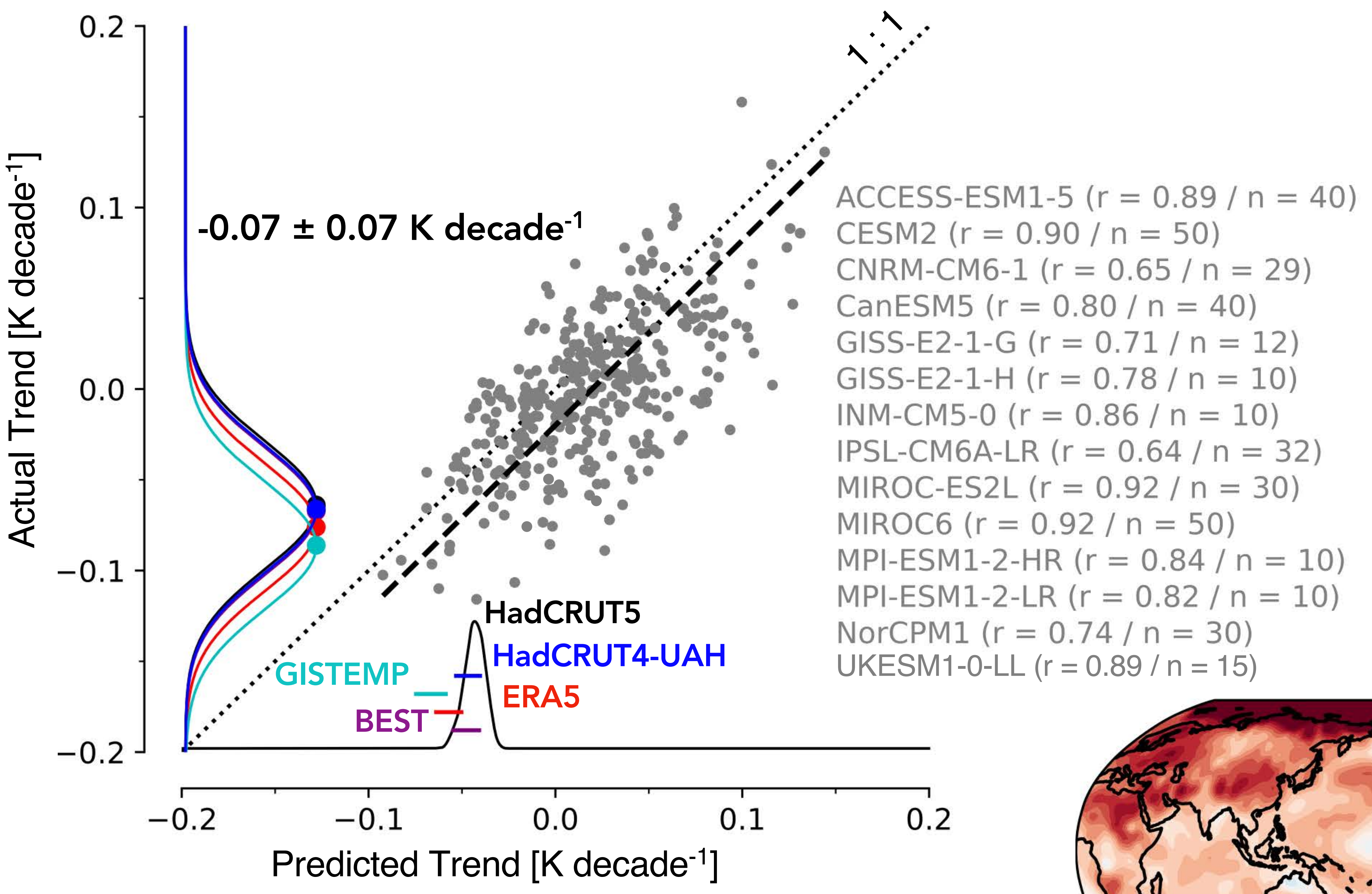


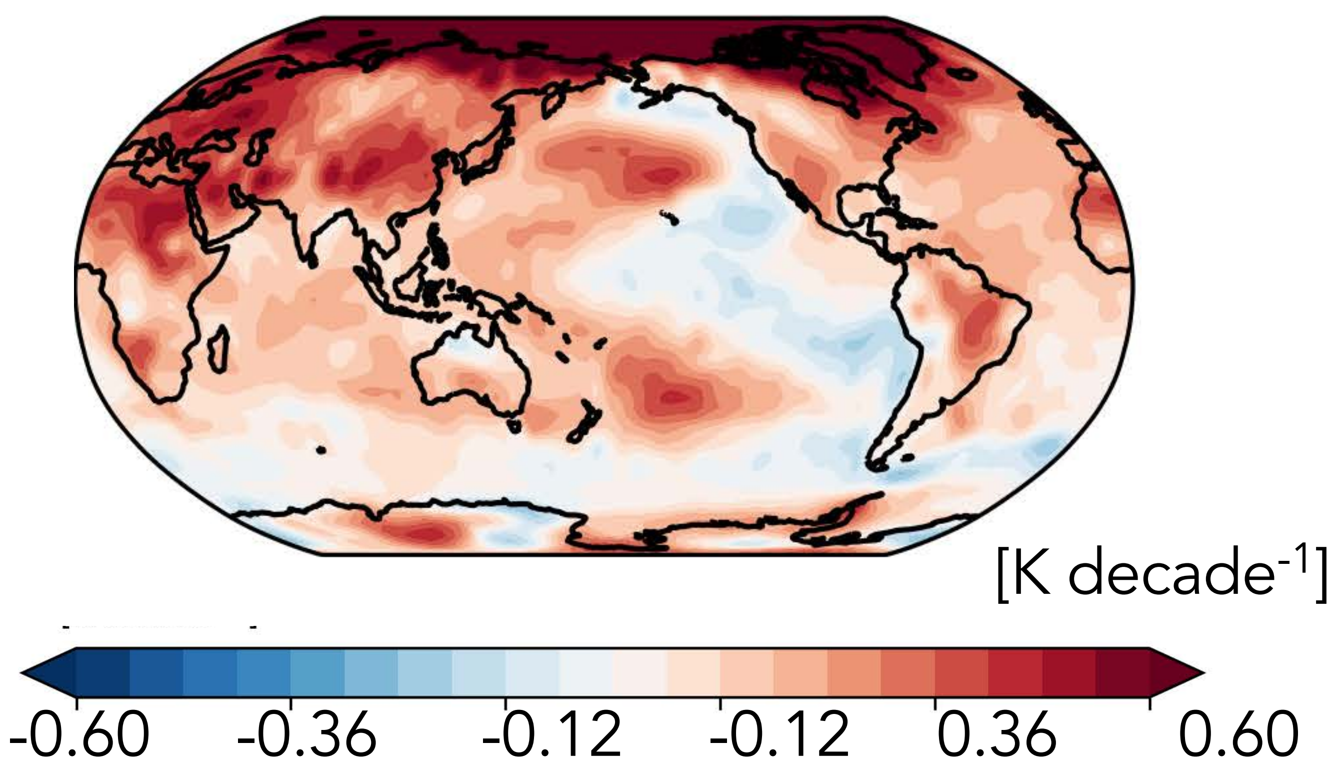
Sample lots of 36-year time periods (across 150+ year historical period, different models, and ensemble members)

Apply climate-model based learning to observations to estimate real-world forced and unforced tropical tropospheric temperature trend

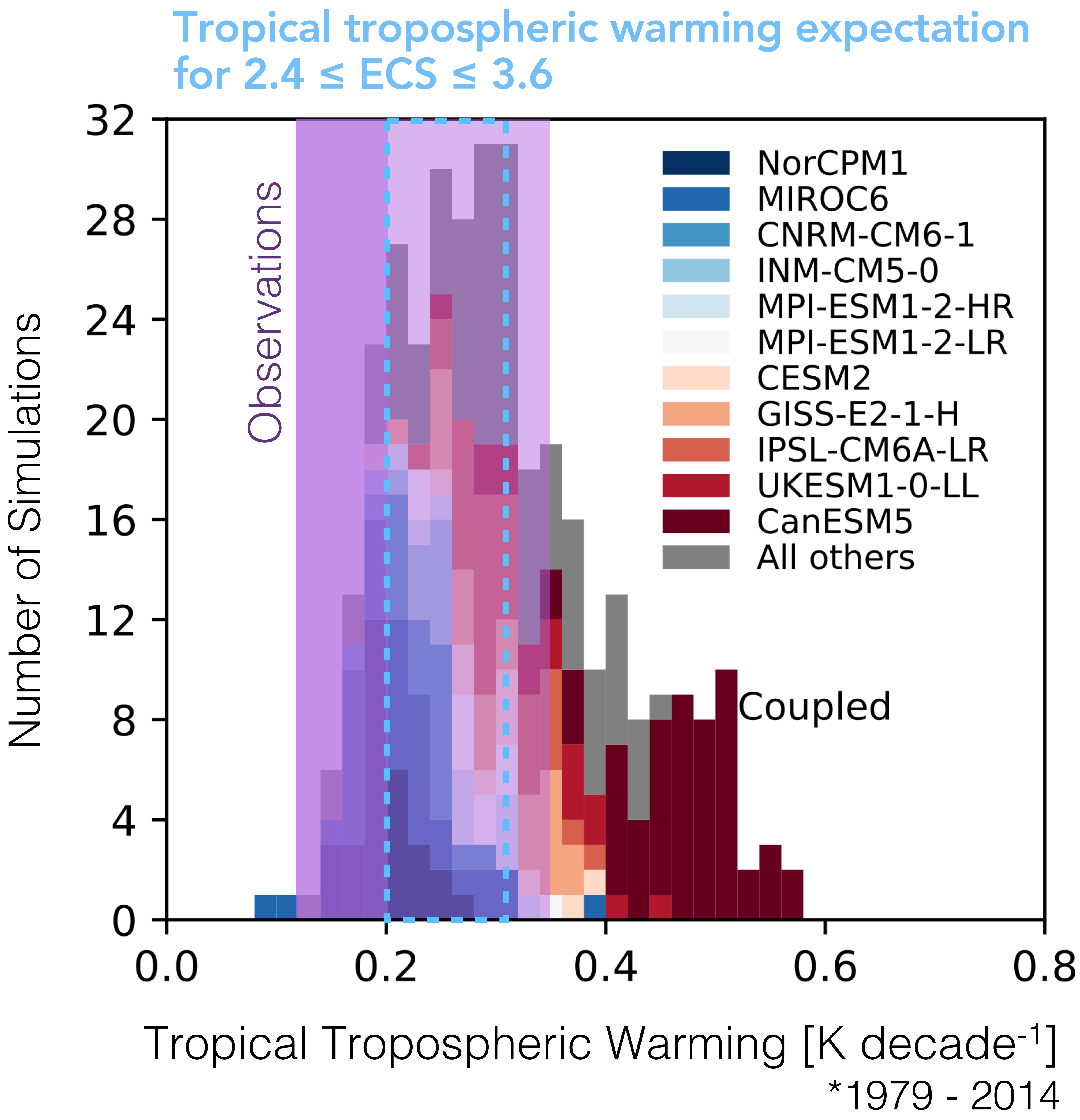
Quantifying satellite era internal variability

Internal variability component of tropical tropospheric warming [1979 – 2014]

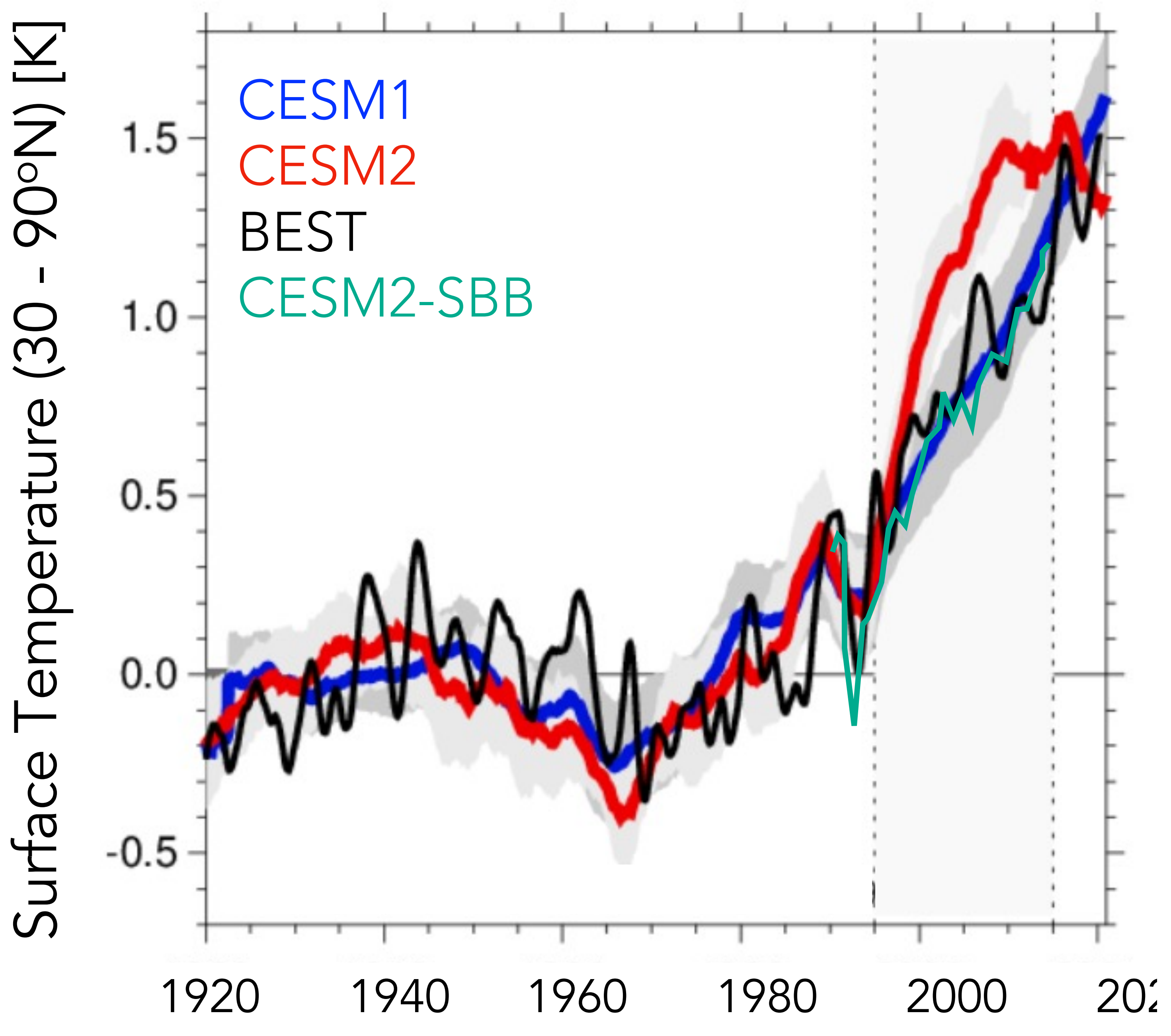


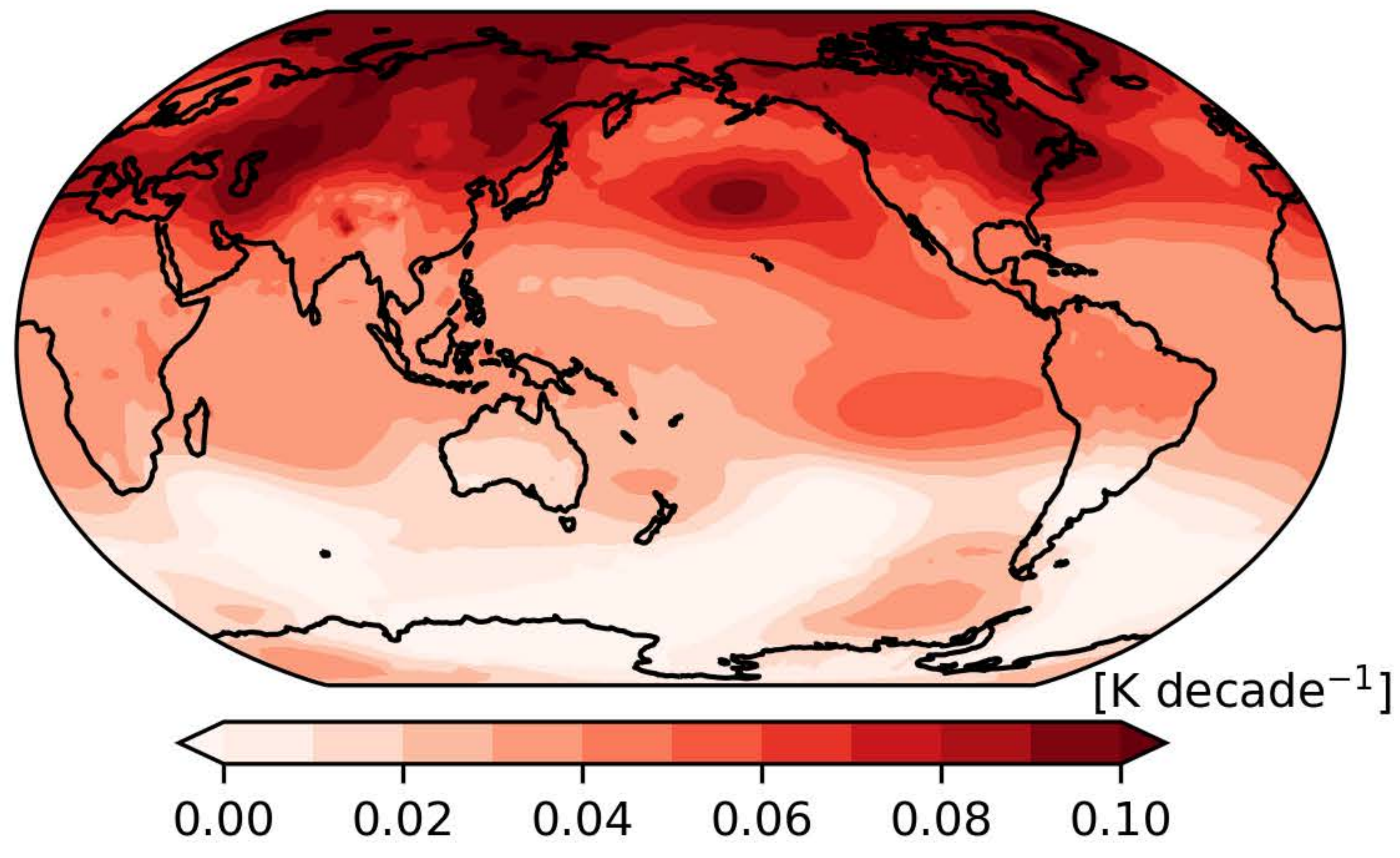


Quantifying satellite era internal variability



The role of forcing biases



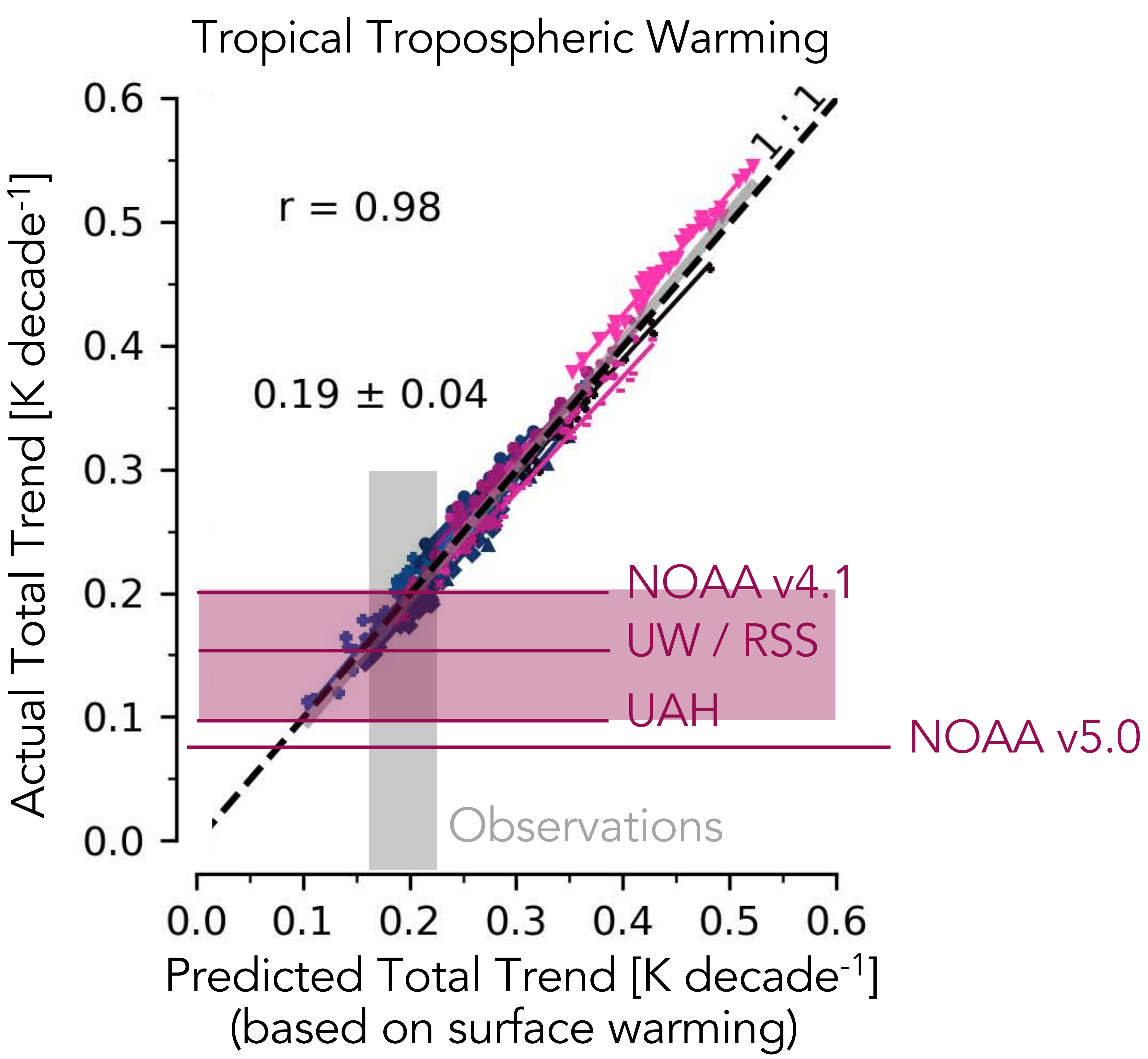


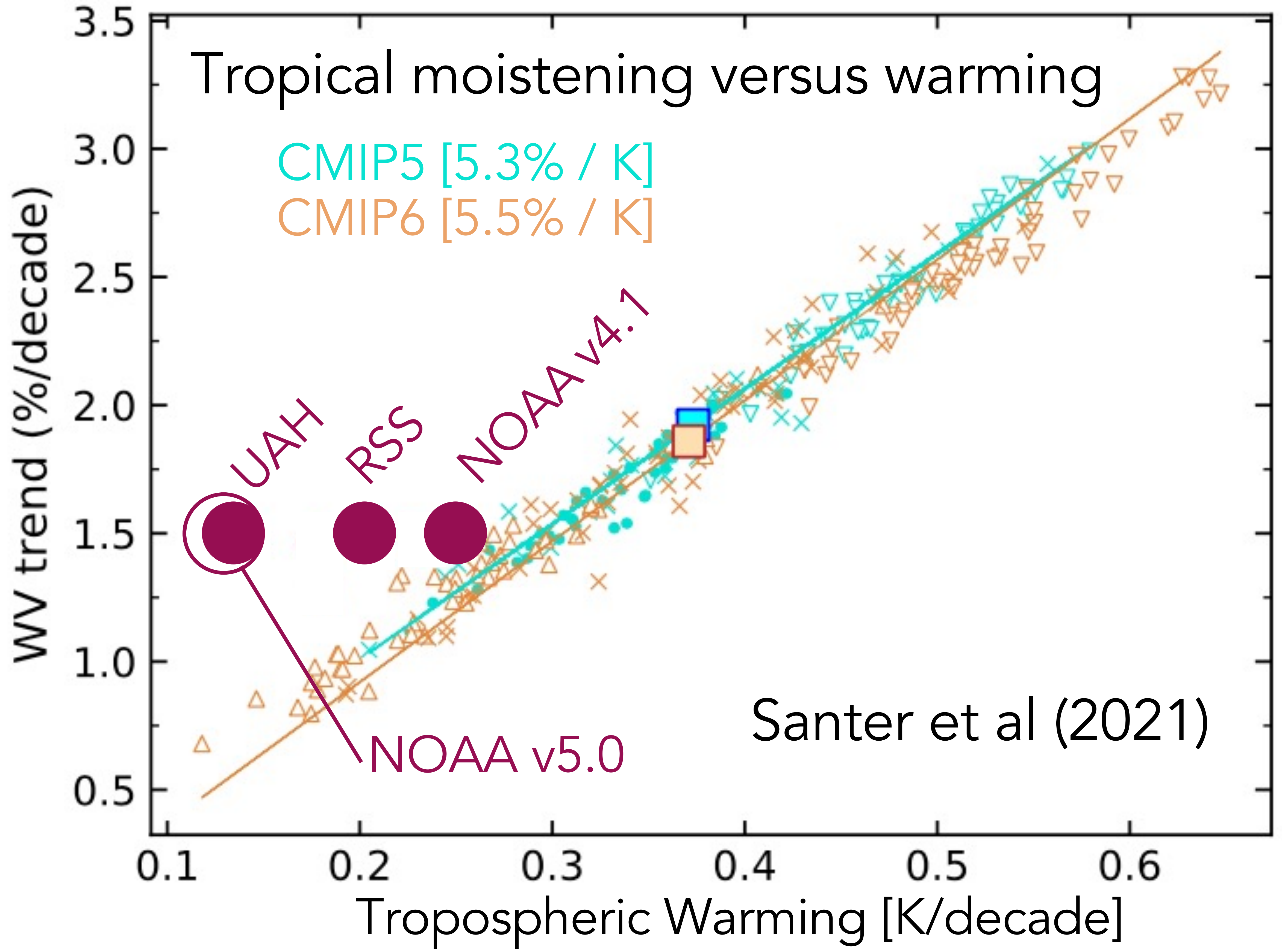
Impact of biomass burning aerosol emissions bias on tropospheric warming (1979 - 2014)

Biomass Burning Aerosols Emissions Issue enhances tropical tropospheric warming by 0.04 K decade^{-1}.

Fasullo et al. (2022); Rodgers et al. (2021)

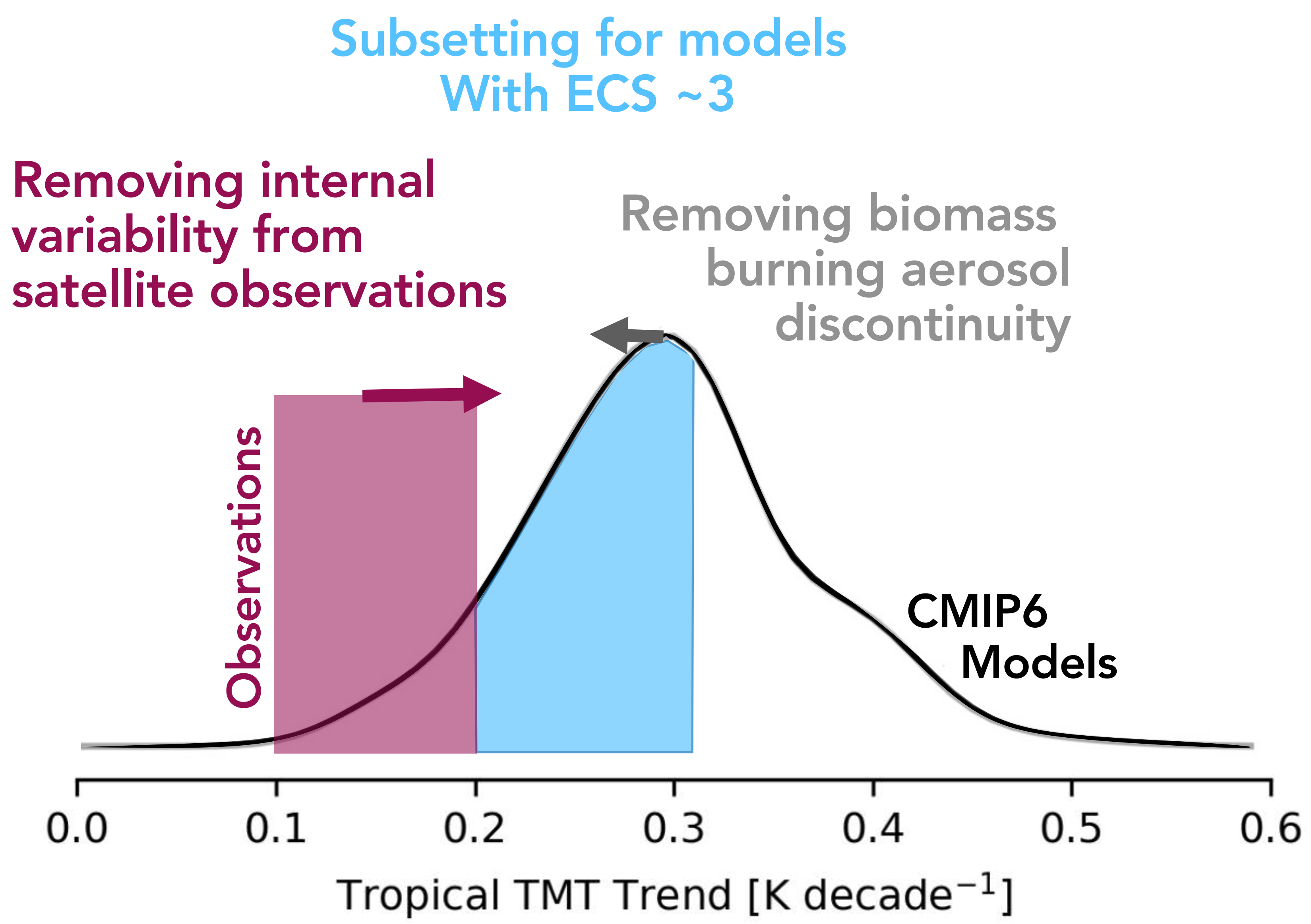
A role for observational biases





SST and water vapor observations are most consistent with the upper-end of MSU dataset trends

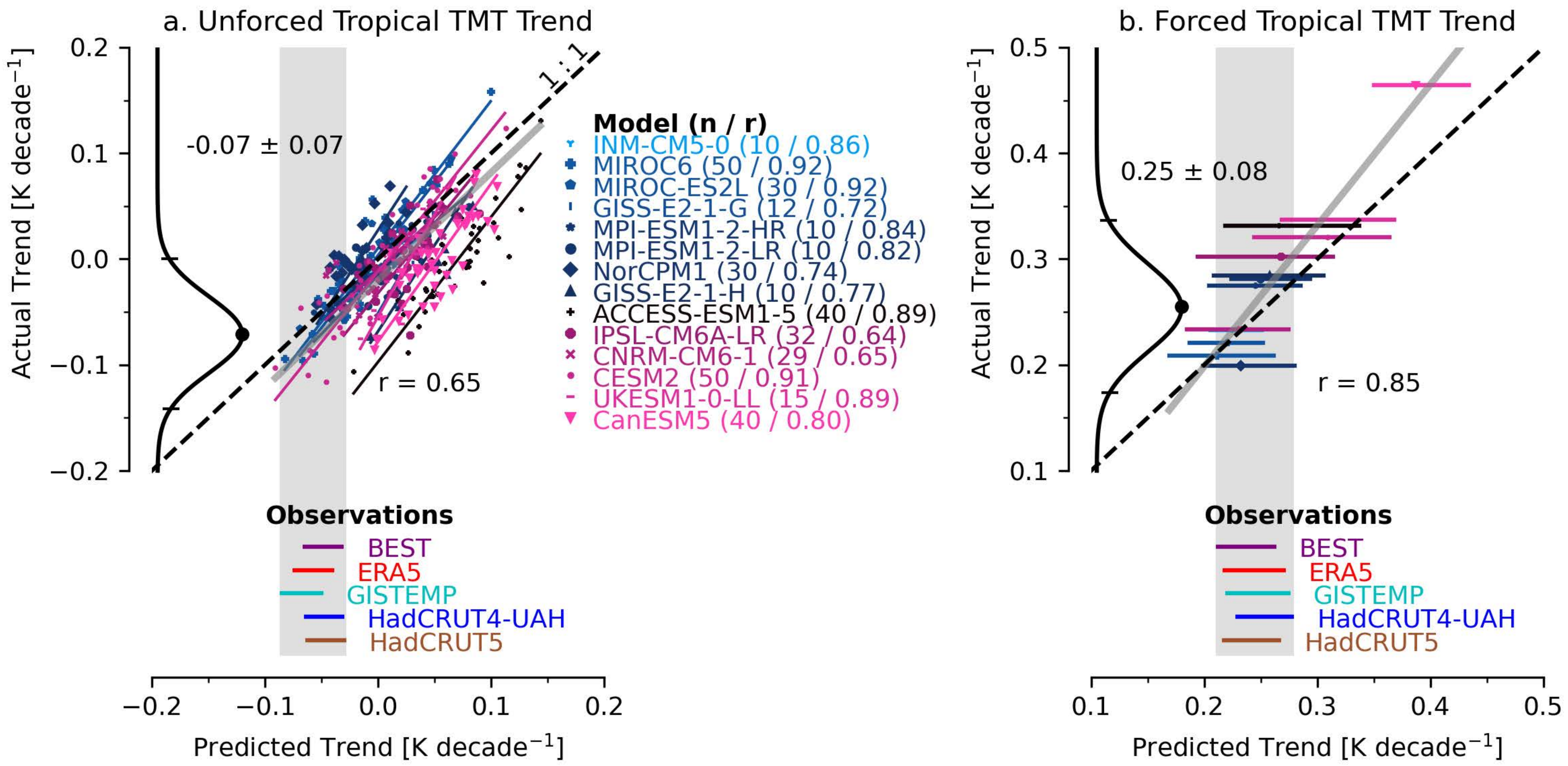
Summary



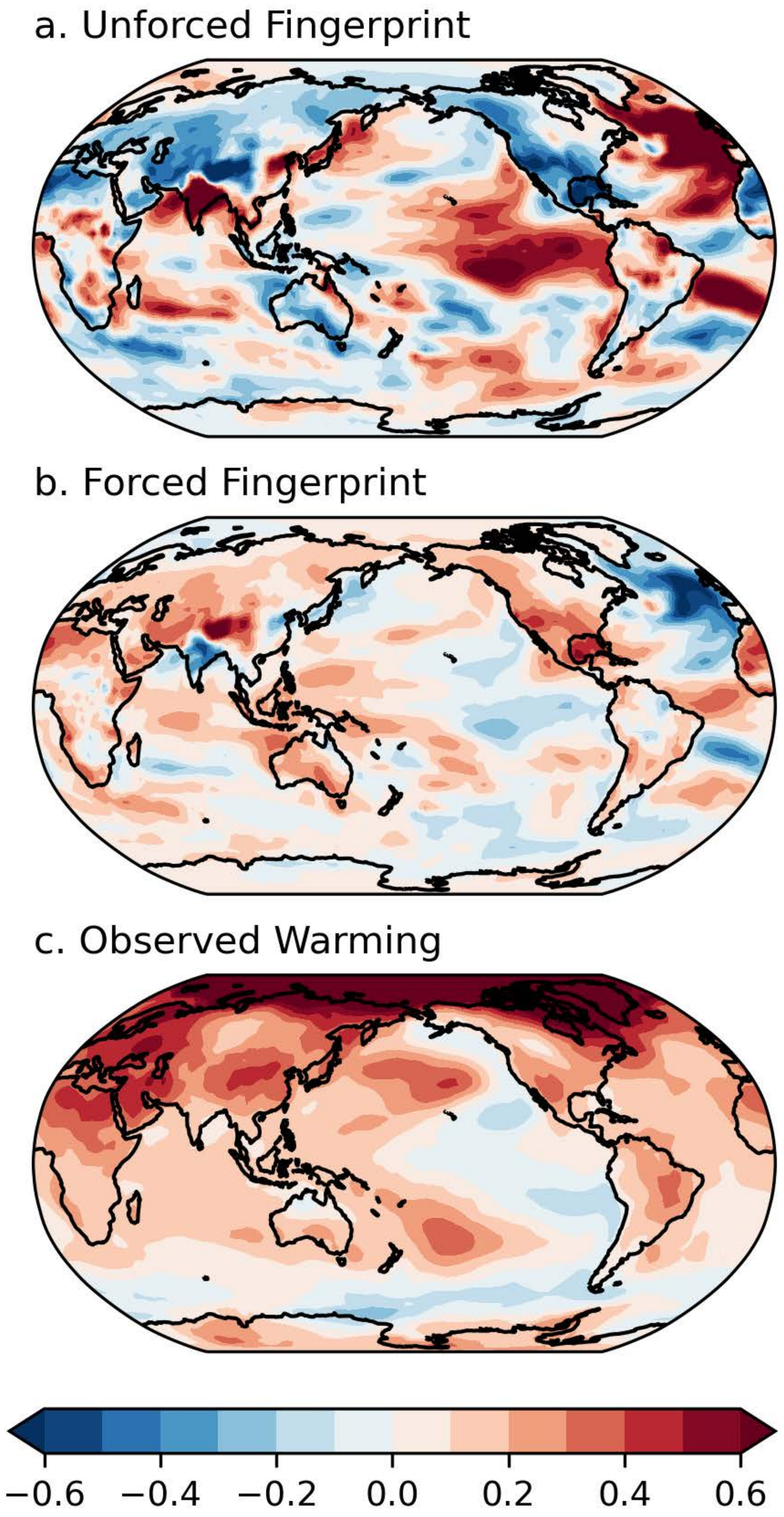
1. Results indicate that internal variability has offset the forced component of warming by about 25%
   - Largely resolves model-observational differences (for ECS ~3K)
   - Results depend on the reliability of climate model simulations
2. A bias in the biomass burning aerosol emissions enhances warming in the CESM2 large ensemble; may effect other CMIP6 models
3. Some satellite datasets have tropical tropospheric temperature trends that are lower than expected, possibly due to unresolved biases

Extra

PLS predictions versus actual tropical tropospheric warming.



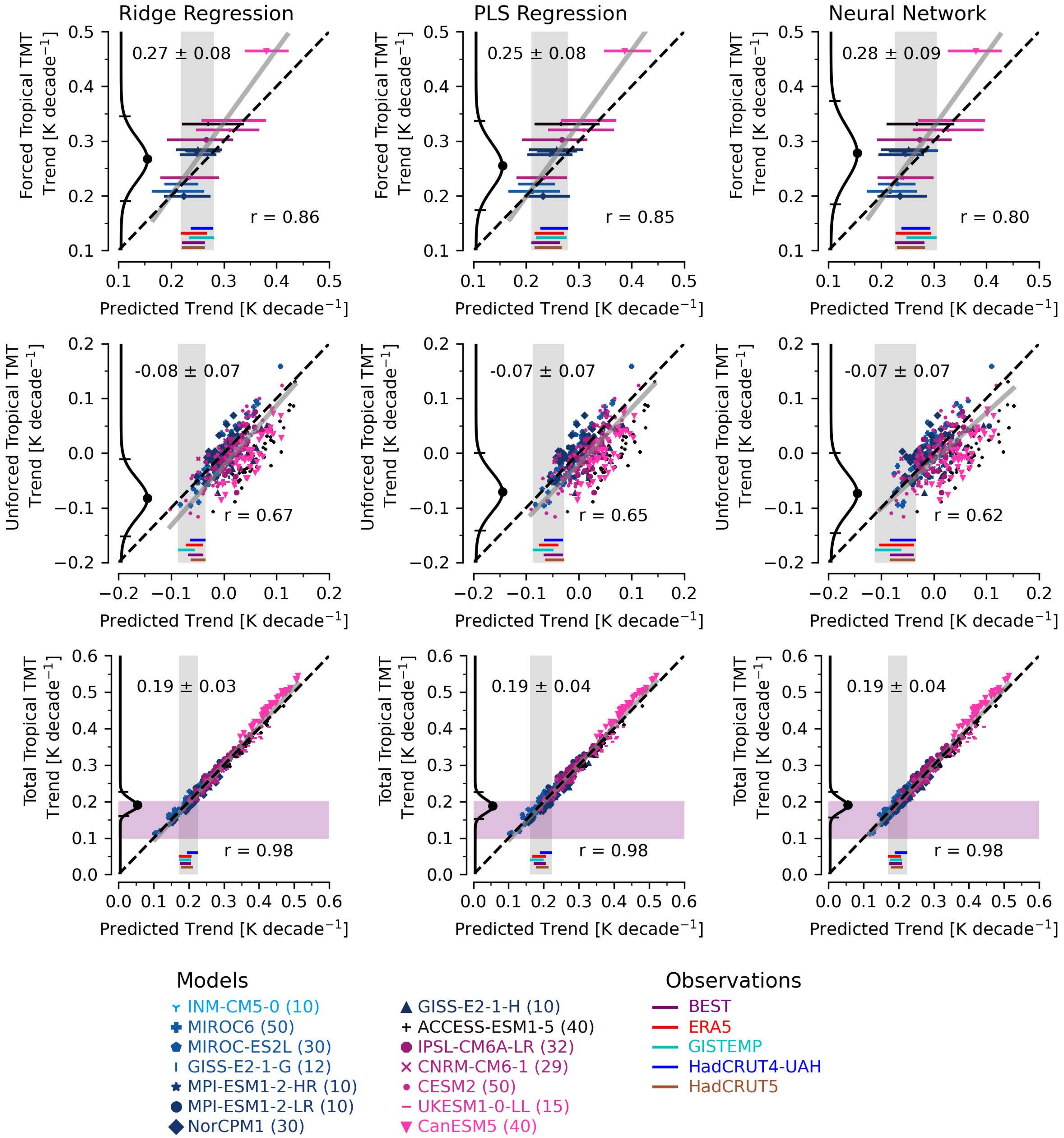
Fingerprint maps and observed warming.



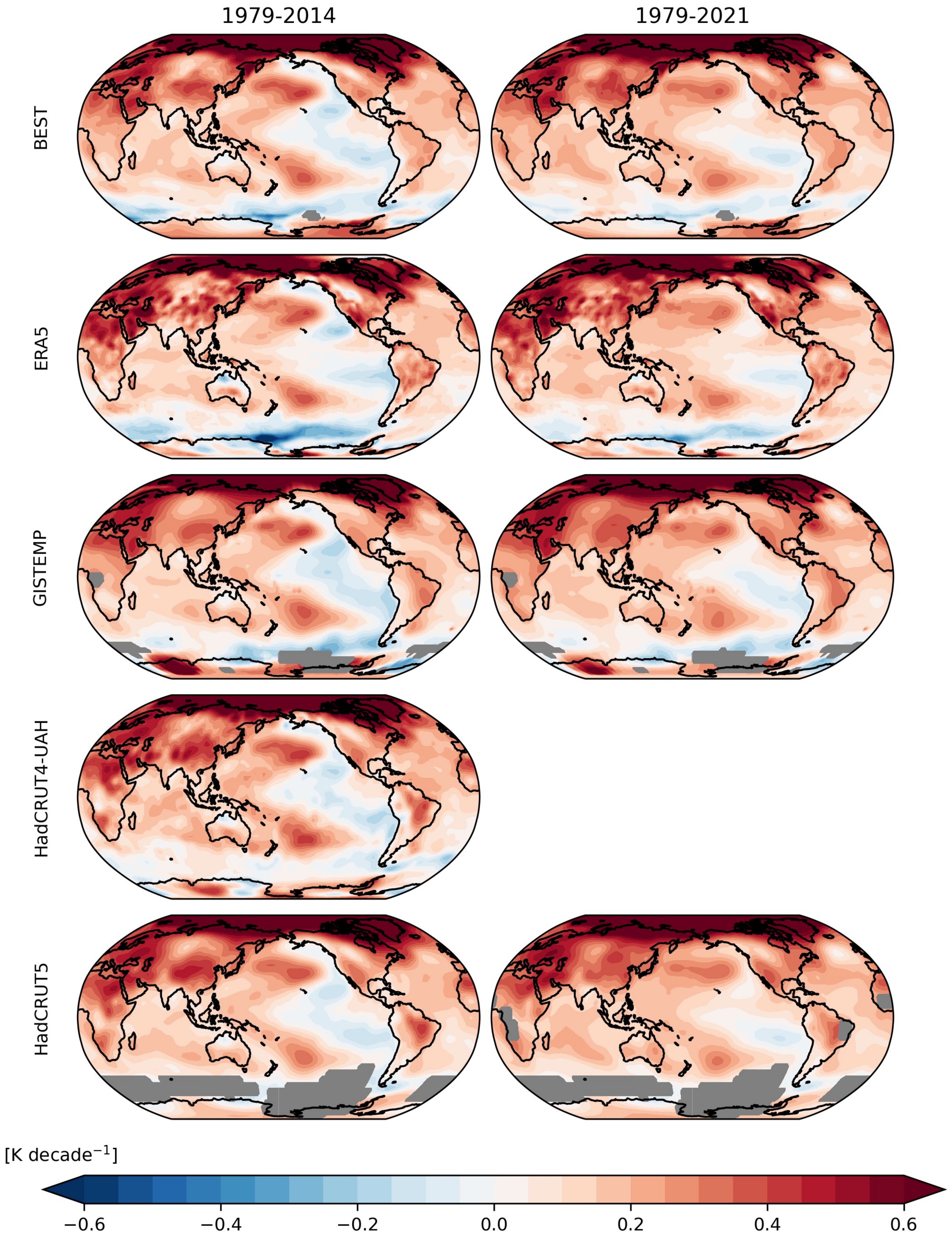
Contextualizing ML results with the total trend, the CMIP6 distribution, and ECS.

Effect of biomass burning aerosol bias on tropospheric warming.

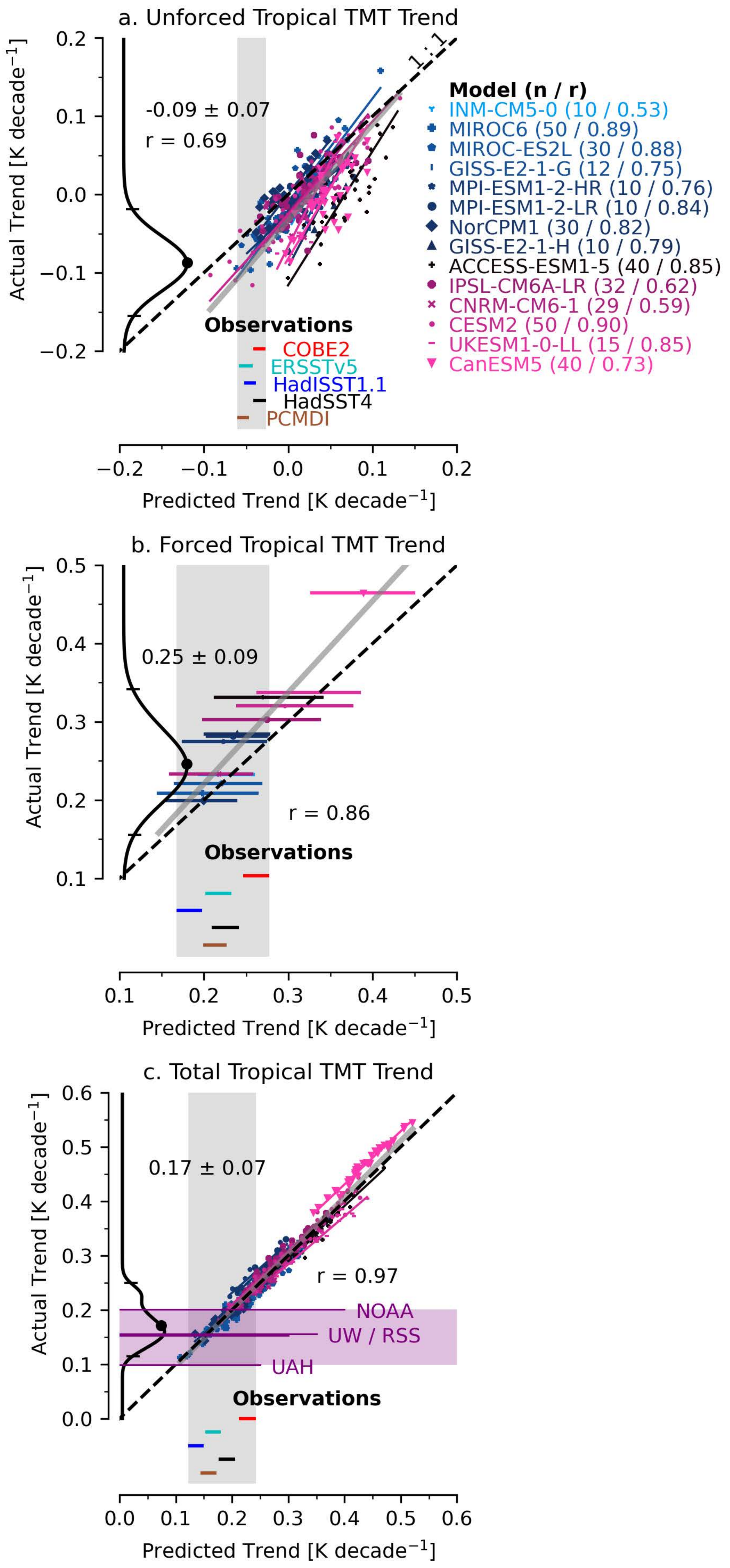
Results across methods.



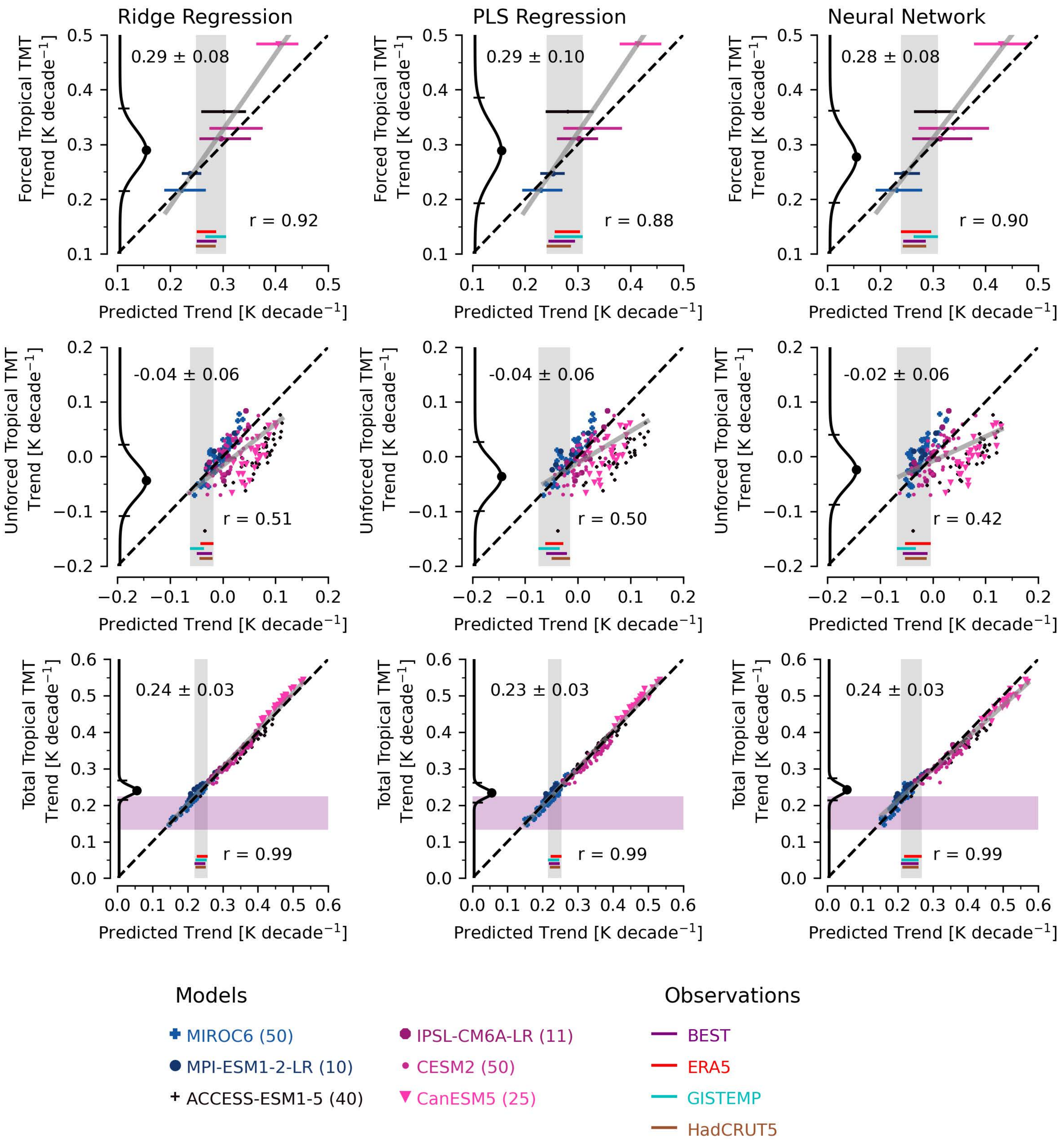
Observed warming.



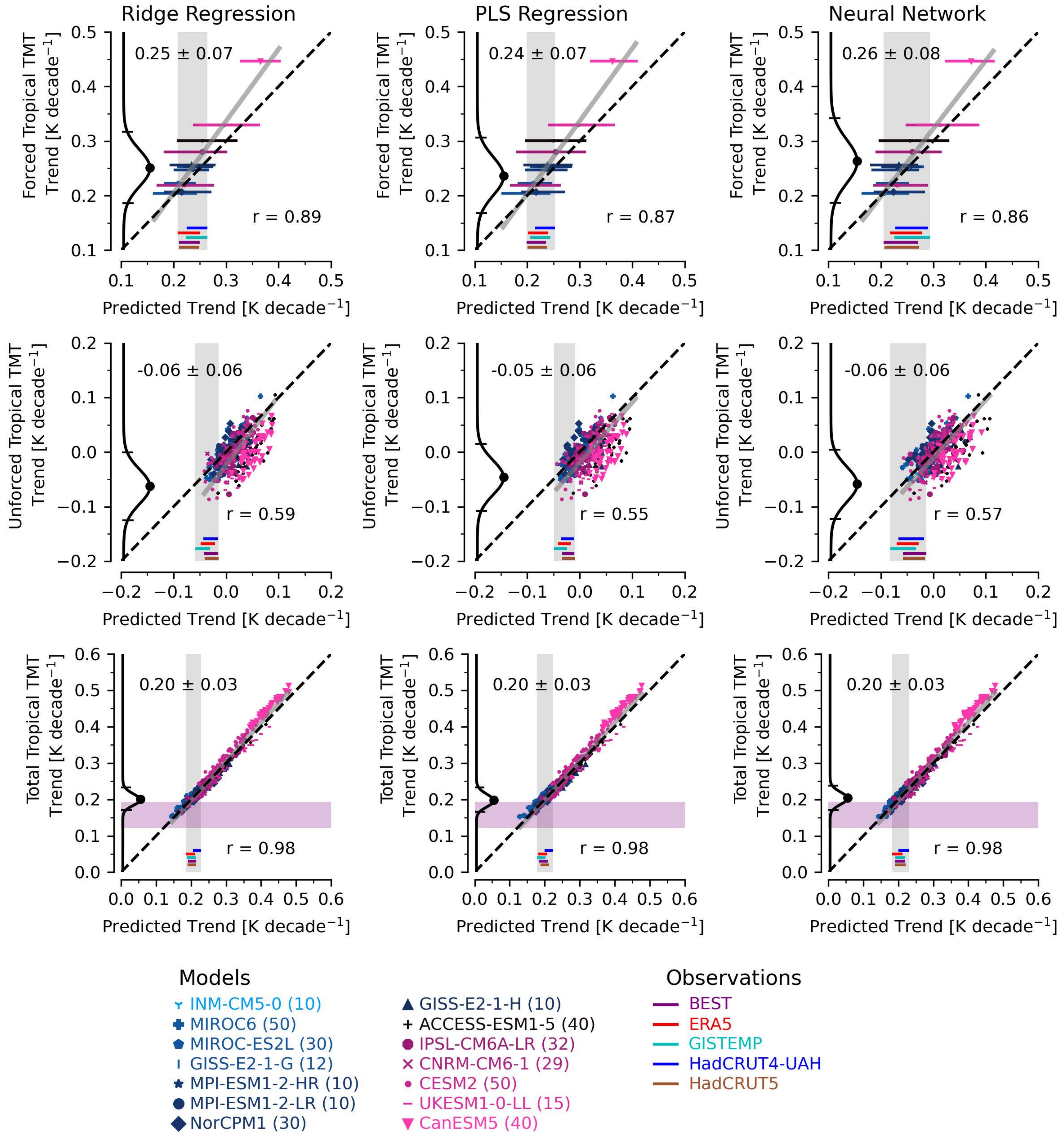
Results with SST trends as predictors.



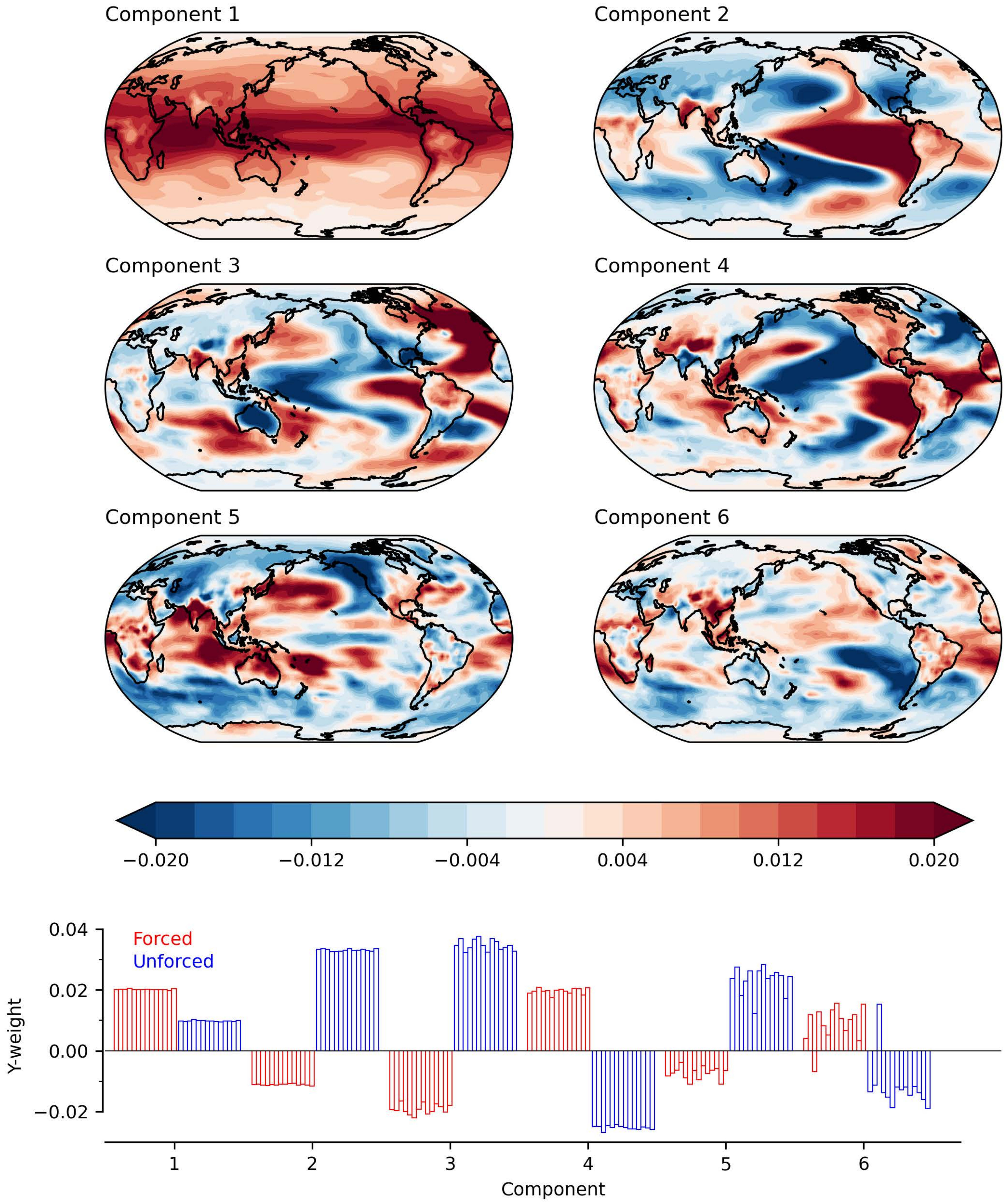
Results over 1979 - 2021.



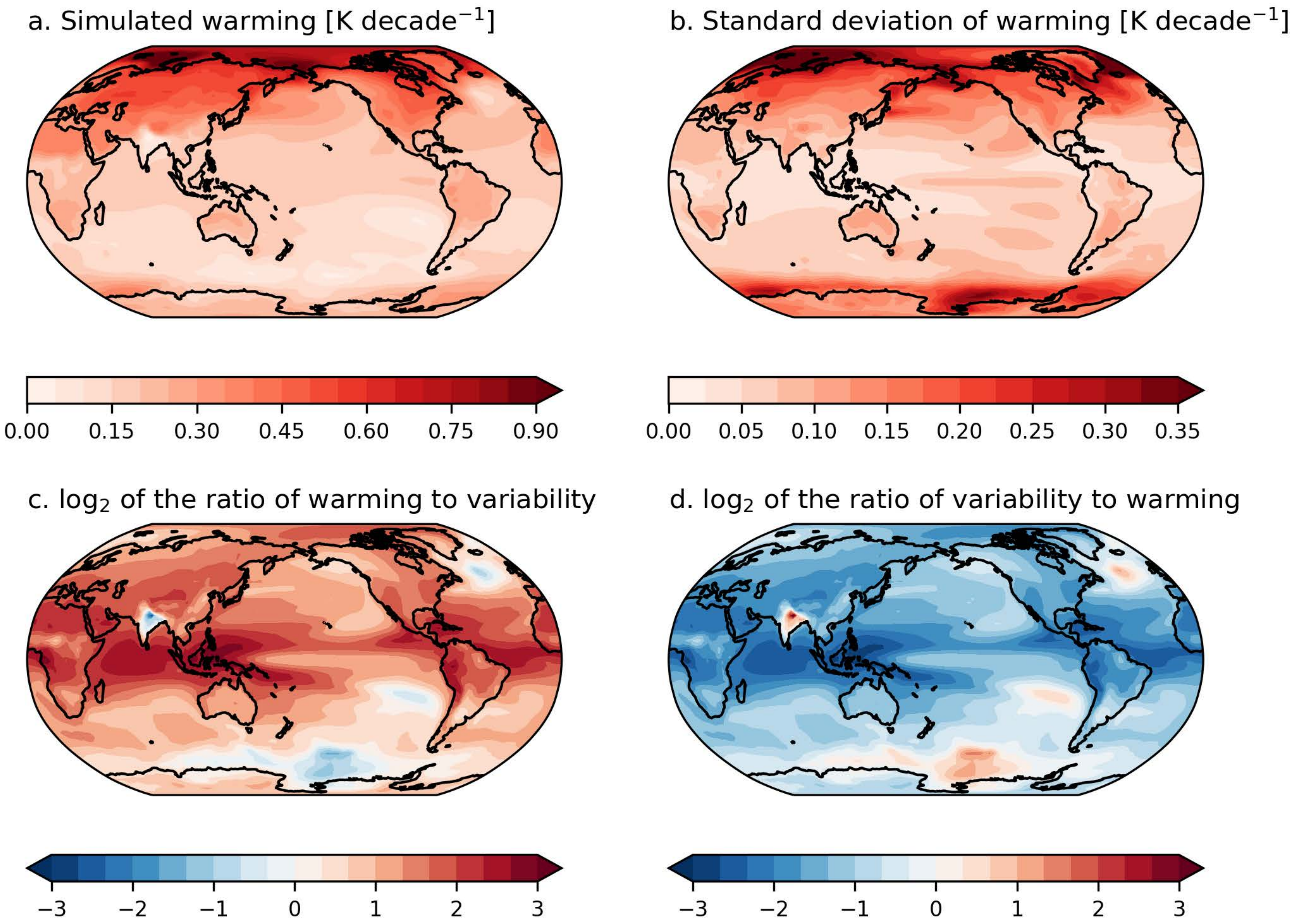
Results on global scale.



PLS Regression components.



Model warming relative to variability.

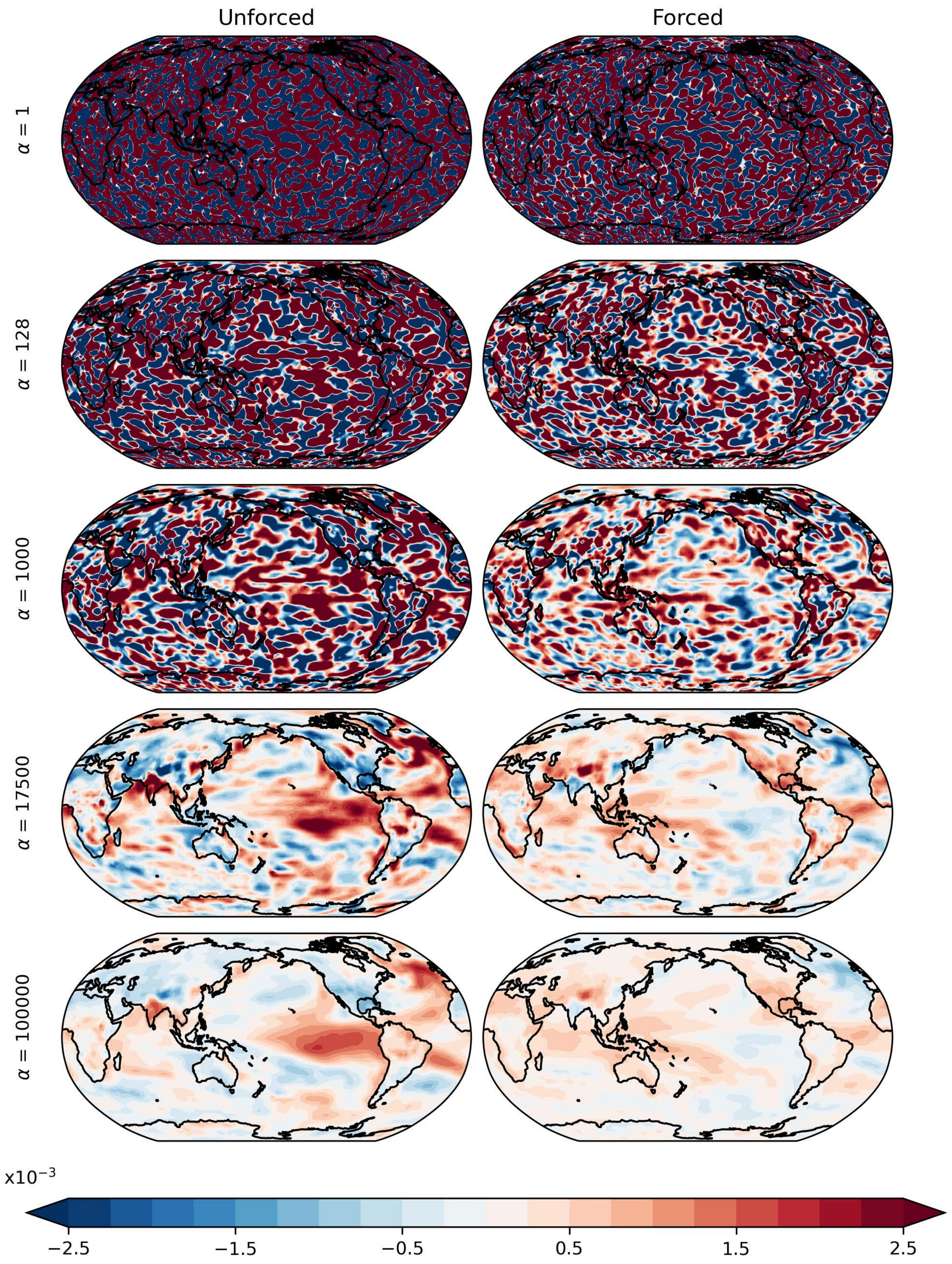


Mean squared error across parameter space.

Results across parameter space.

Ridge regression fingerprint maps.

Ridge regression alpha sensitivity.



Estimated internal variability compared to historical and piControl variability distributions.