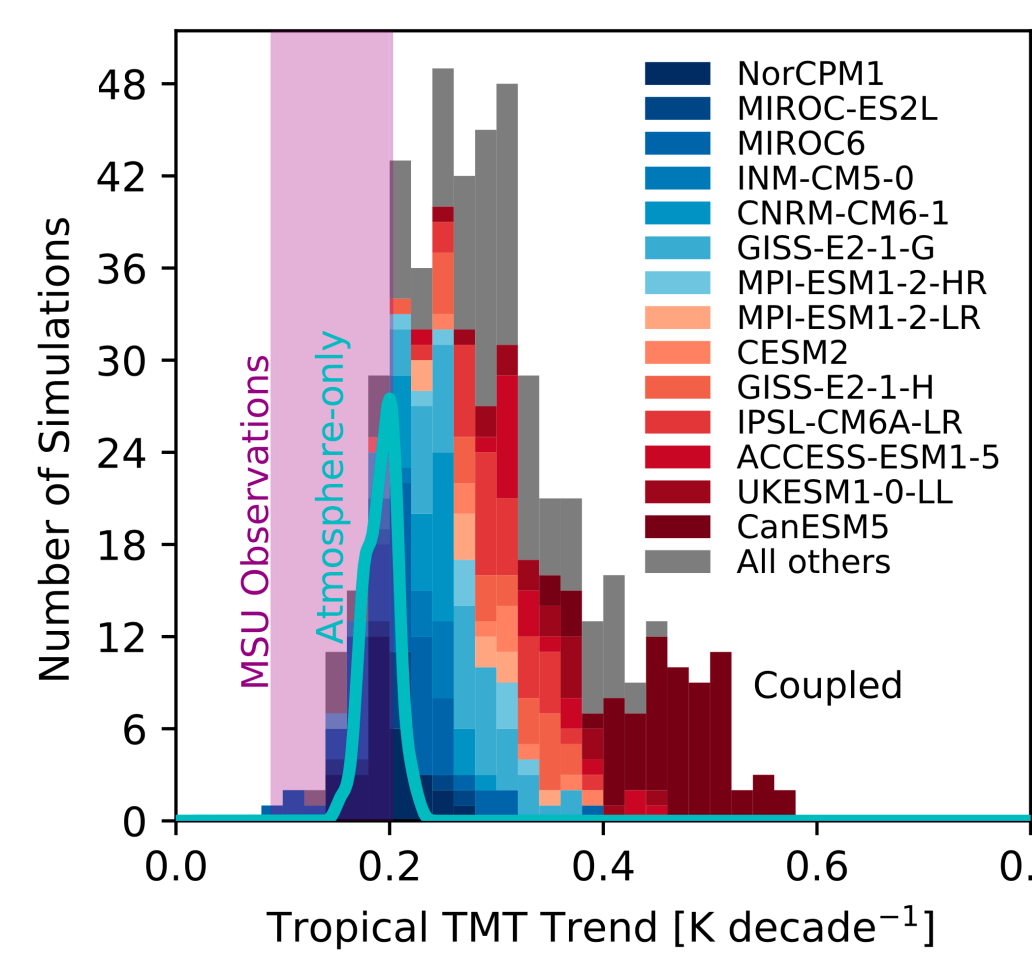


Internal variability influences model-satellite differences in the rate of tropical tropospheric warming

1. Introduction

- Several generations of climate model simulations exhibit substantially more tropical mid-tropospheric temperature (TMT) change compared to satellite observations^{1,2}.
- ~90% of CMIP6 simulations have larger TMT trends (1979 - 2014) compared to four satellite datasets (below). It has been suggested this model-observational discrepancy results from exaggerated model sensitivity to greenhouse gas changes².
- Recent analyses have demonstrated that multi-decadal internal climate variability has a substantial effect on the rate of warming and has likely slowed satellite-era warming^{1,3}.



Histogram of available CMIP6 tropical (20°N - 20°S) TMT trends (1979 - 2014) compared with the range of satellite observations (purple shading). Models with ≥ 10 simulations are color coded. A probability distribution function shows trends from prescribed SST simulations in teal. The multimodel average trend is $0.30 \text{ K decade}^{-1}$ whereas observed trends range from $0.10 - 0.20 \text{ K decade}^{-1}$. Figure from Po-Chedley et al. (2021).

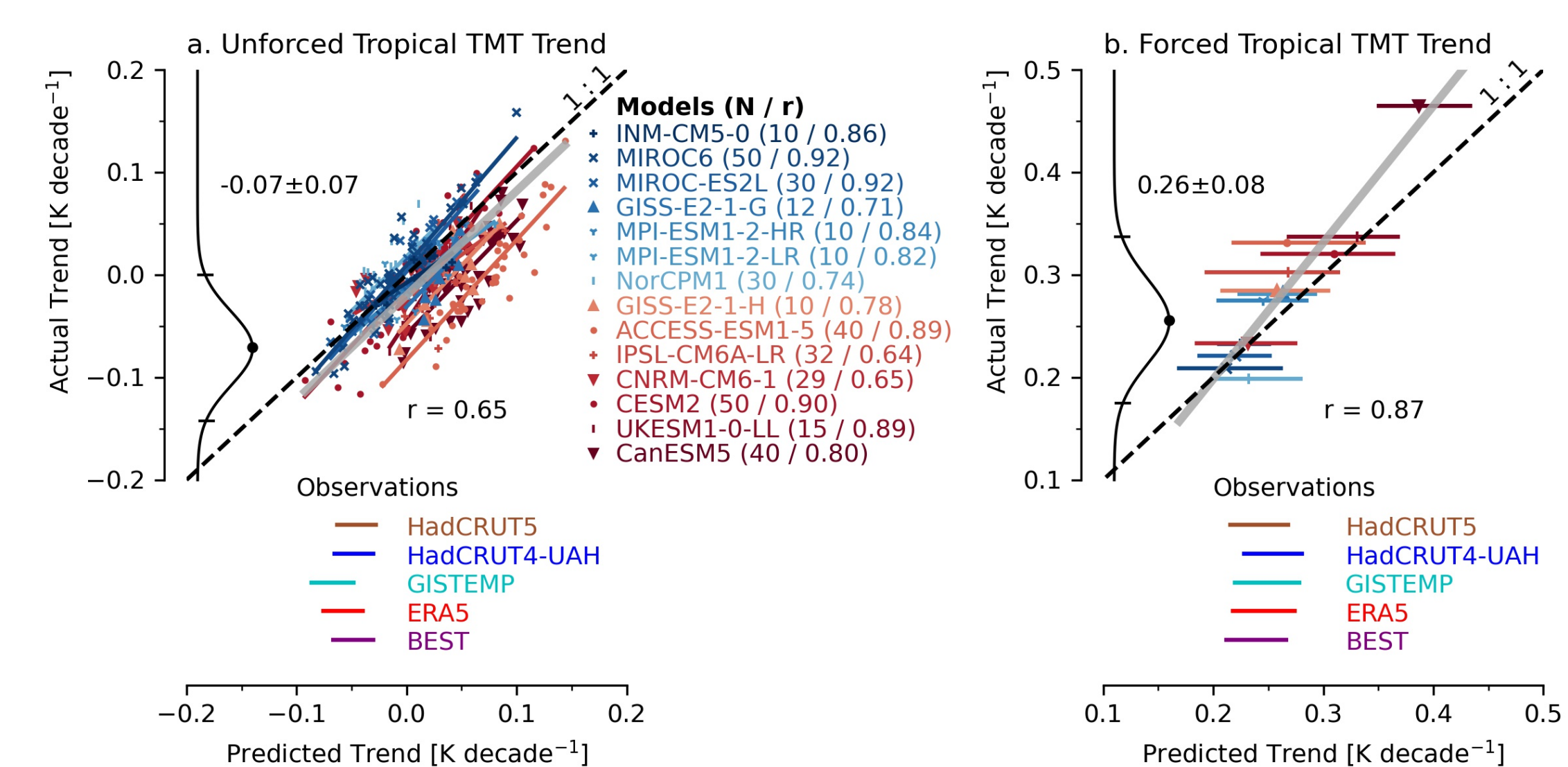
- Here we apply machine learning (ML) to disentangle and quantify the components of tropical tropospheric temperature change due to external climate forcing and internal variability.

2. Method

- Our overarching approach is to try to predict the magnitude of tropical ($30^\circ\text{N} - 30^\circ\text{S}$) TMT change (1979 - 2014) that results from a) internal variability and b) external forcing using the surface temperature trend map as a predictor ($2.5^\circ \times 2.5^\circ$ grid).
- We train our ML algorithms using climate model data: we sample 25 periods (P) from each model simulation, 10 model simulations (N), and 14 models (M). This yields 3,250 samples (see right).
- For each surface trend map, we calculate the corresponding values of the forced (ensemble average) and unforced (deviation from ensemble average) component of the tropical TMT trend.
- We utilize partial least squares (PLS) Regression, training on 13 models and testing on the 14th climate model (iteratively, see right).
- Last, we use observed surface temperature trend maps (1979 - 2014) to predict the unforced and forced components of observed TMT change.

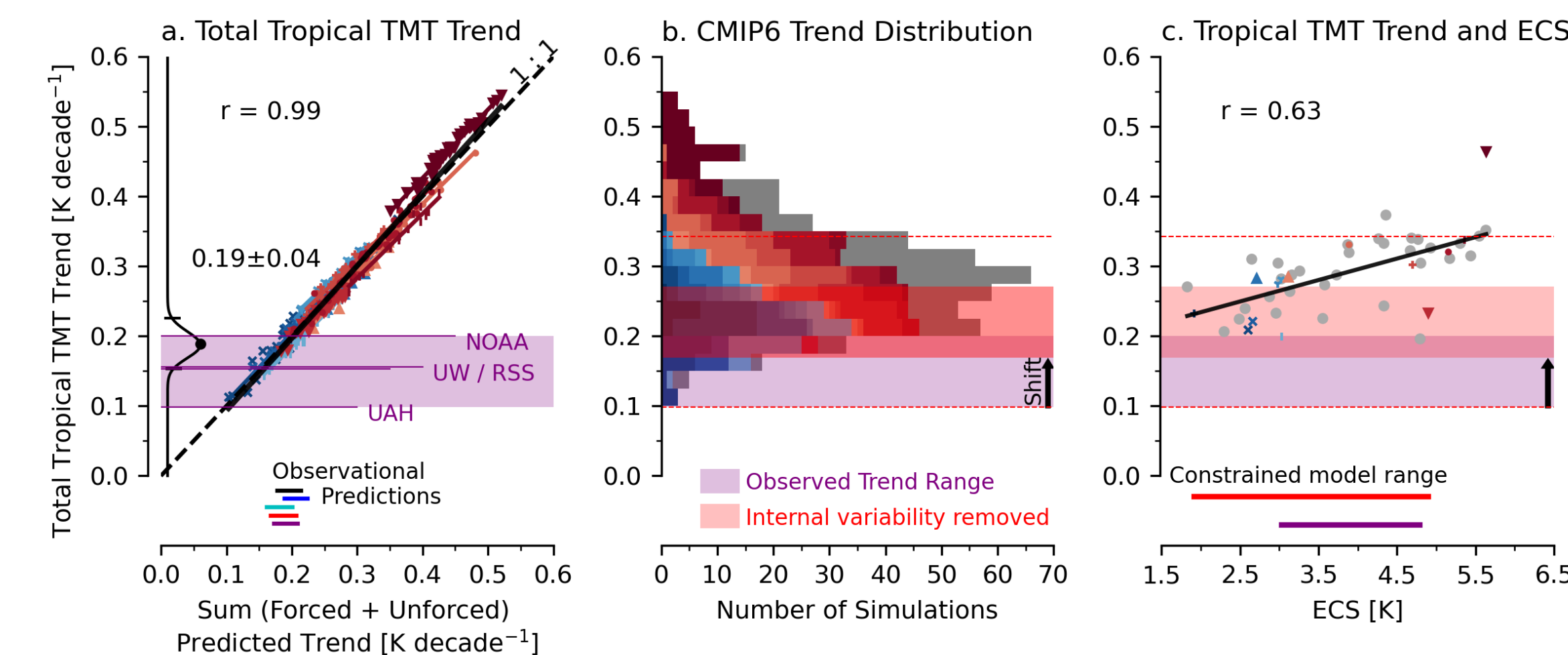
3. Results

ML skill in disentangling forced and unforced components of TMT change



Left: Predicted versus actual (a) unforced and (b) forced tropical TMT change for different climate models (see legend). The predicted values for observations are shown as horizontal lines. These predictions are convolved with the model scatter plot to produce a bias-corrected estimate of the forced and unforced tropical TMT trend (PDF along y-axis). Right: "Fingerprint" coefficient maps for the (a) unforced and (b) forced components of tropical TMT change. We also show the (c) observed surface temperature change over 1979 - 2014.

Internal variability contributes to model-versus-satellite warming differences



Left: (a) as in the figure above but for the forced + unforced (total) tropical TMT change. The purple shading denotes the range of observed tropical TMT trends. (b) Histogram of CMIP6 tropical TMT trends compared to the observed range (purple shading). The red shading shows the observed range with internal variability removed. (c) Tropical TMT trends versus ECS. The purple and red shading are the same as panel (b). The range of model ECS values consistent with the observations are denoted with horizontal bars.

4. Summary

- Only about ~10% of CMIP6 simulations are within the range of satellite observed tropical TMT trends. Past work suggests decadal variability contributes to this apparent model-satellite disagreement.
- We apply ML to disentangle and quantify the forced-versus-unforced component of tropical TMT change.
- Applying ML to model simulations shows that this approach has skill. In applying ML to observations we find that internal variability reduced the forced component of tropical TMT change ($0.26 \pm 0.08 \text{ K decade}^{-1}$) by $0.07 \pm 0.07 \text{ K decade}^{-1}$.
- Our results also suggest that observed tropical tropospheric warming is at the upper end of the range of satellite dataset trends.
- Models with both small and large ECS values are consistent with satellite observations (before and after internal variability is accounted for).
- Our results suggest that the difference between CMIP6 multimodel average tropical TMT warming ($0.30 \text{ K decade}^{-1}$) and observed warming ($\sim 0.15 \text{ K decade}^{-1}$) is exacerbated by internal climate variability.

Acknowledgements: This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344. S.P. and C.J.W.B. were supported by the Regional and Global Model Analysis Program of the Office of Science at the US Department of Energy.

References: 1: Po-Chedley et al. (2021)
2: McKittrick and Christy (2020)
3: Mitchell et al. (2020)