Evaluating CMIP6 Model Fidelity at Simulating Non-Gaussian Temperature Distribution Tails

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Introduction

Changes in extreme temperature exceedances will be manifested in more complex ways in locations with non-Gaussian temperature distribution tails than if the distribution were Gaussian[1,2].

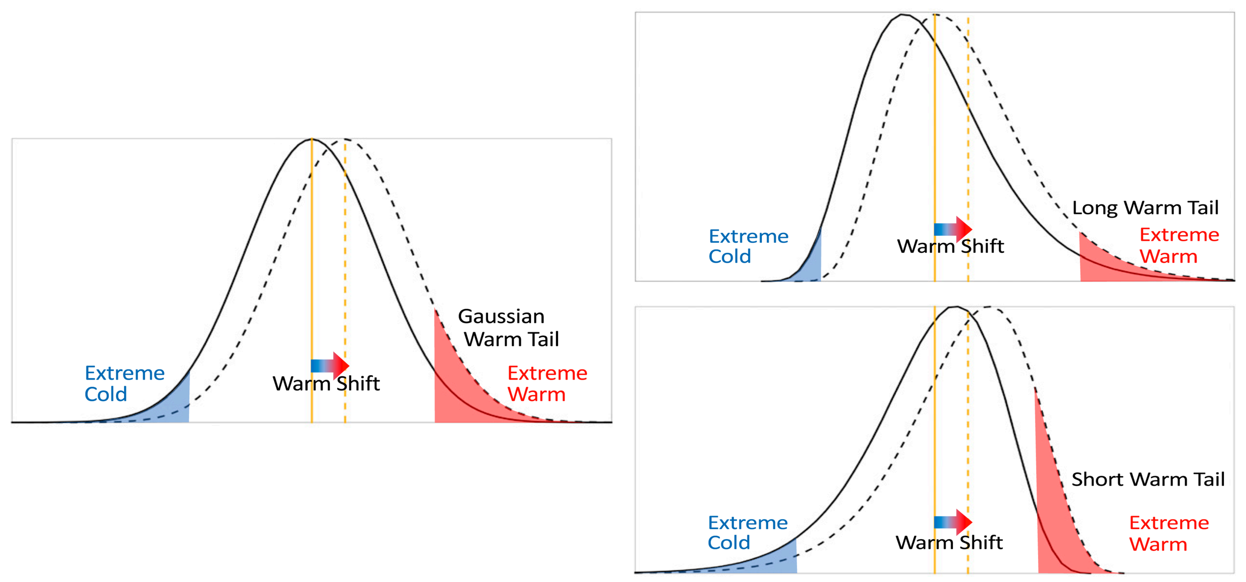

Figure 1: Schematic representing differences between Gaussian and non-Gaussian temperature distribution tail exceedances following a uniform warm shift. (*Adapted from Fig. 1 in Loikith and Neelin 2015*)[1]

To boost confidence in projections of future changes in extremes, it is therefore critical that climate models realistically simulate observed non-Gaussianity in temperature distribution tails.

We evaluate the ability of the new CMIP6 suite of models to capture temperature distribution tail shape

Methods

We use 2-m temperature data from the historical simulation of the recently released CMIP6 multi-model ensemble[3] and NASA's MERRA-2 reanalysis[4].

Datasets are regridded to a 1°x1° horizontal resolution.

Temperature anomalies are computed by subtracting the climatological mean and detrending linearly.

Temperature anomalies are analyzed over the period 1980–2014 for the seasons comprised of June, July, and August (JJA), and December, January, and February (DJF).

To determine CMIP6 model skill in simulating tail shape, **shift ratios** are computed as follows:

1. Shift the underlying daily temperature anomaly distribution uniformly by 0.5σ.
2. Tabulate the frequency of days that exceed a fixed threshold – warm-side threshold is the 95th percentile and cold-side is the 5th percentile.
3. Divide those threshold exceedances by the expected number of exceedances from shifting a Gaussian distribution.

Results

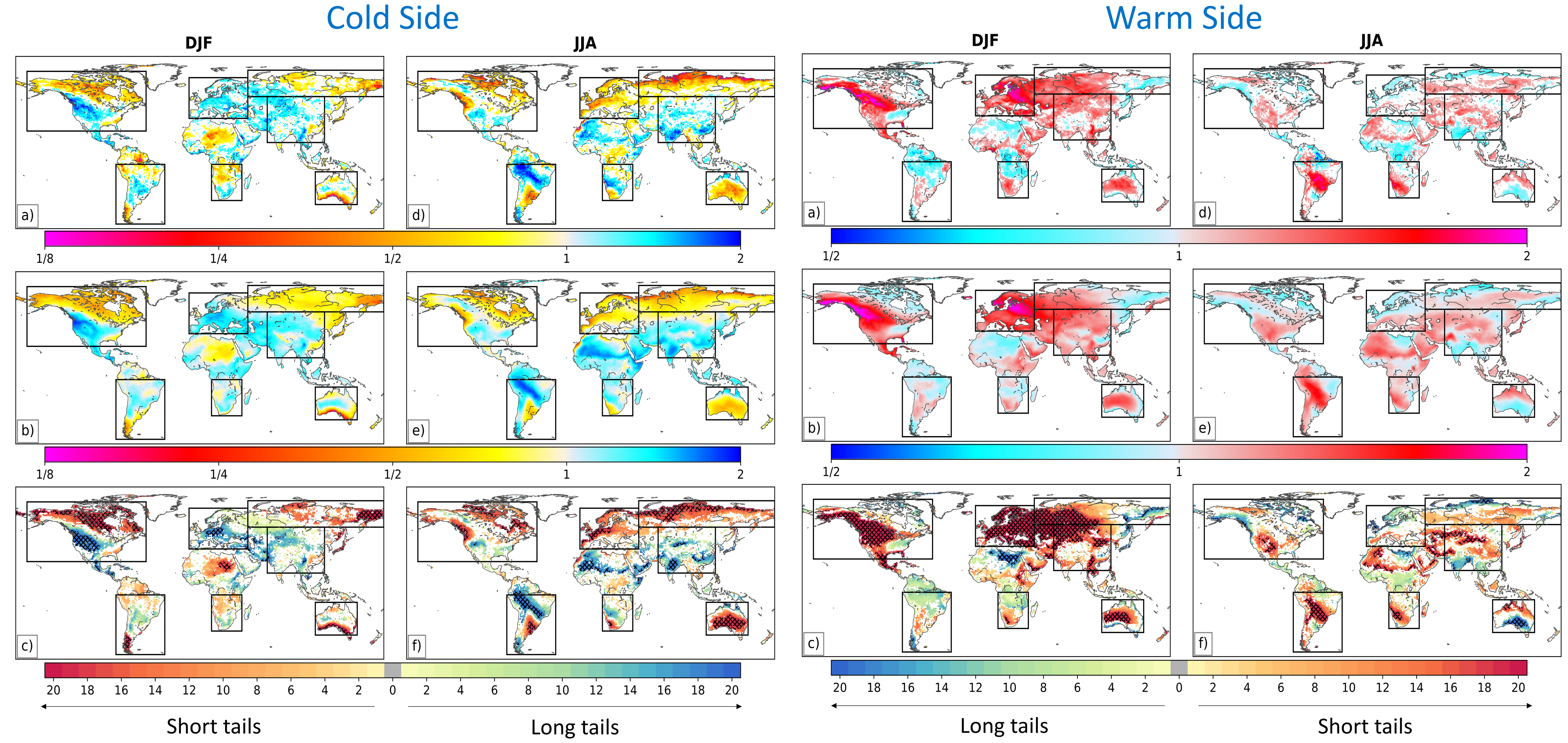

Figure 2: (a,d) MERRA-2 shift ratios for cold-side and warm-side tails, shaded where the tail deviates from Gaussian with statistical significance at the 95% confidence level. (b,e) CMIP6 ensemble mean shift ratios. Hatching indicates where at least 85% of CMIP6 models (≥ 17) agree with MERRA-2 on tail significance and shape. (c,f) Number of models in agreement with MERRA-2 (gray = all models disagree). Boxes denote sub-regions, labeled as NAM, EUR, NAS, SEA, AUS, SAF, and SAM moving clockwise from the upper left corner.

- CMIP6 ensemble mean shift ratios broadly capture the principal spatial patterns of both shorter- and longer-than-Gaussian tails in MERRA-2.
- There is robust (≥ 85%) model agreement over coherent non-Gaussian areas in all sub-regions.
- Nearly all models adequately simulate broad sections of significantly shorter-than-Gaussian warm tails during DJF.
- Most models mischaracterize tail shape over areas in Russia (NAS), South America (SAM), and South Africa (SAF), implying potential biases in the large-scale circulation producing temperature extremes[5].

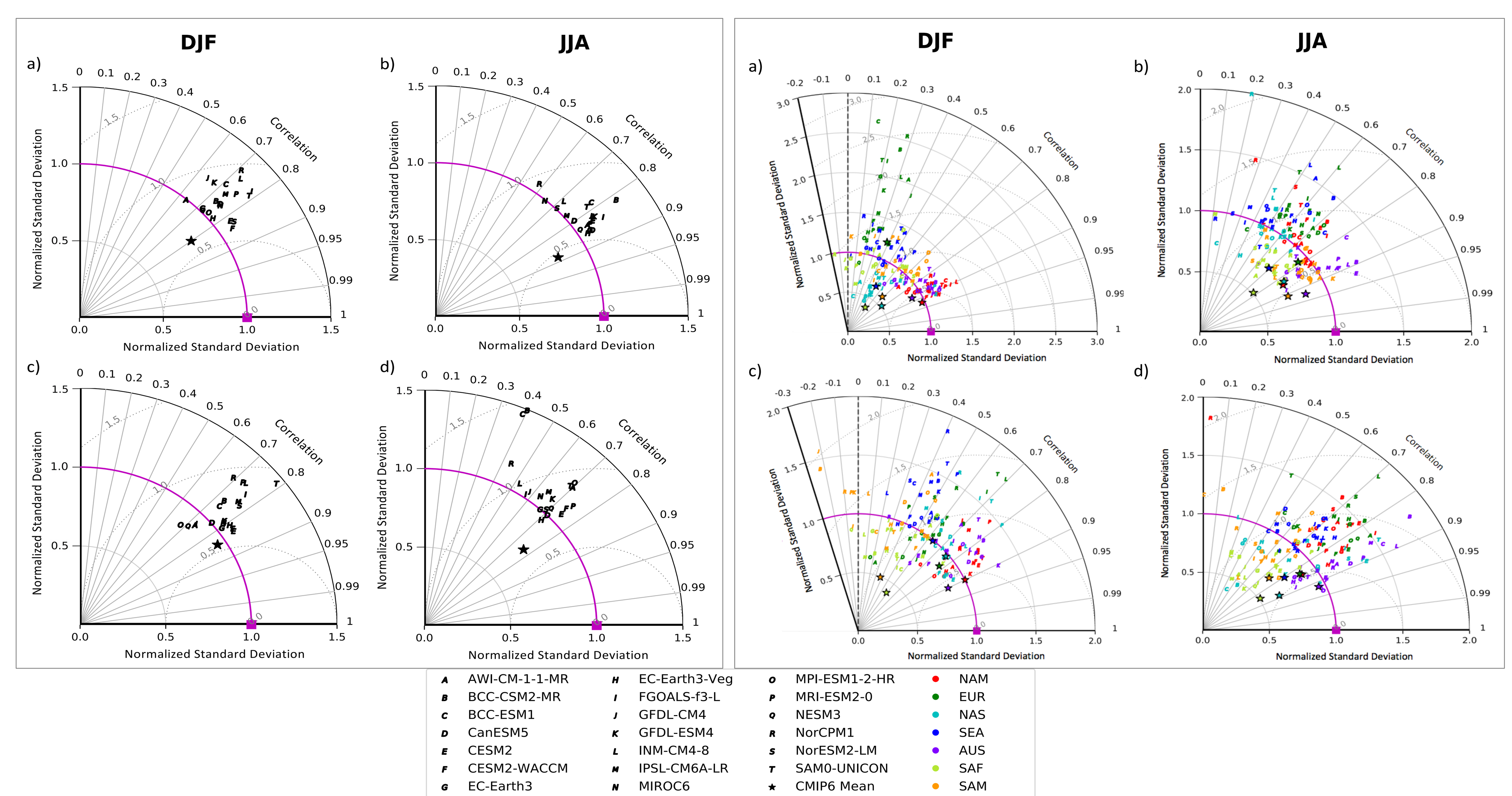

Figure 3: Taylor diagrams for (left) global and (right) regional shift ratios of (a,b) cold and (c,d) warm tails. Radius is normalized standard deviation (magenta = MERRA-2), angle is correlation coefficient, and dotted gray circles are normalized centered root mean squared difference.

- CMIP6 models generally capture the MERRA-2 global shift ratio patterns with reasonable skill.
- Multi-model mean patterns are generally closer to reanalysis than individual models, with higher correlation values but lower variance compared with MERRA-2.
- Some models (e.g. CESM2, CESM2-WACCM) exhibit higher skill, whereas others (e.g. NorCPM1, BCC-ESM1) are outliers in many sub-regions and scenarios.
- Models perform well over Australia (AUS) in all scenarios, whereas performance over other sub-regions varies depending on season and tail.

Conclusions

- The CMIP6 ensemble captures the principal coherent spatial regions of non-Gaussian 2-m temperature distribution tails.
- Individual models exhibit high skill in global shift ratio patterns compared with MERRA-2, indicating models simulate extreme temperatures for plausible physical and dynamical reasons.
- Understanding regional differences in model skill requires further research.

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References

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