Addressing challenges in identifying trends in extremes to better compare models and observations

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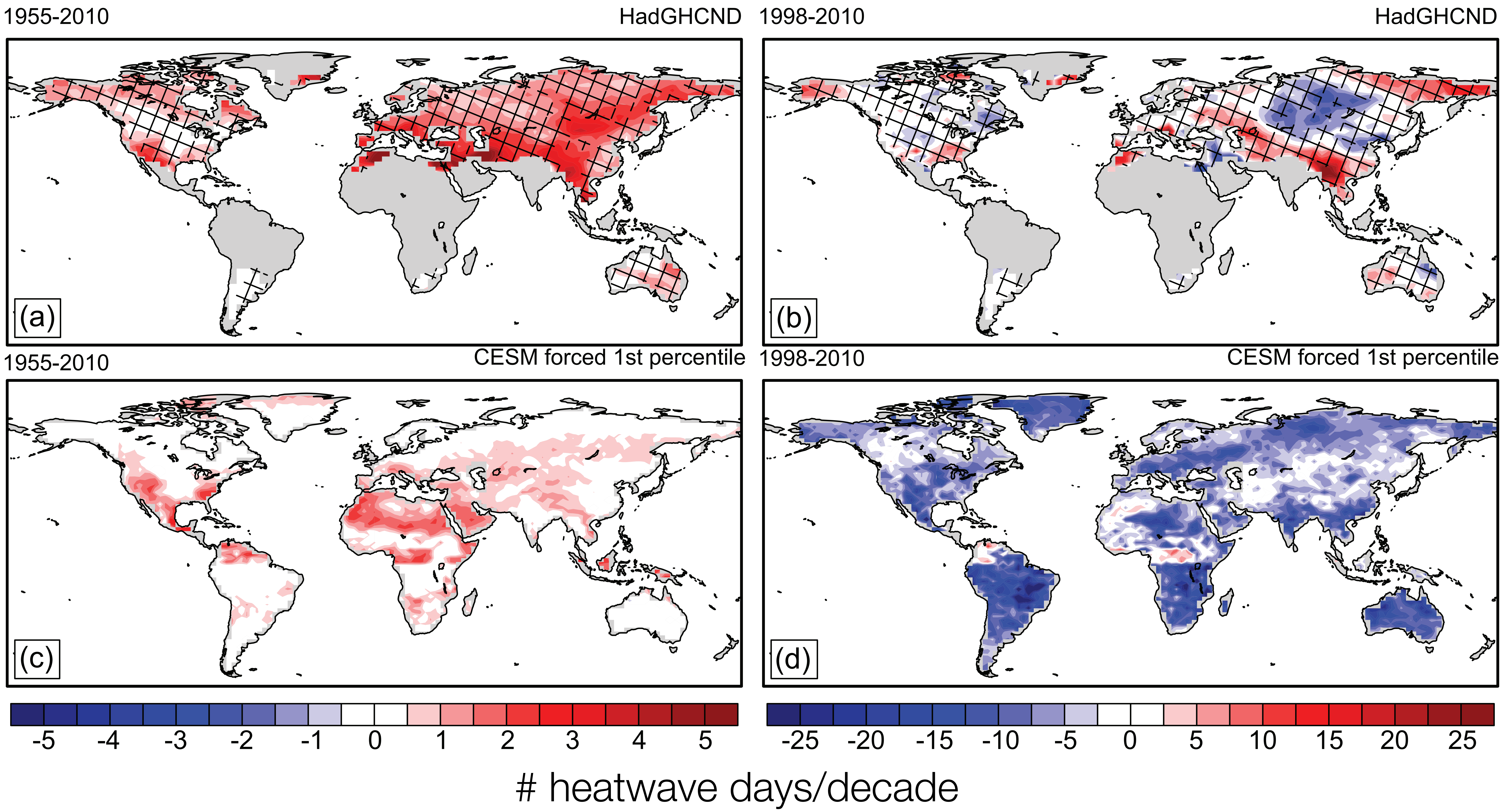
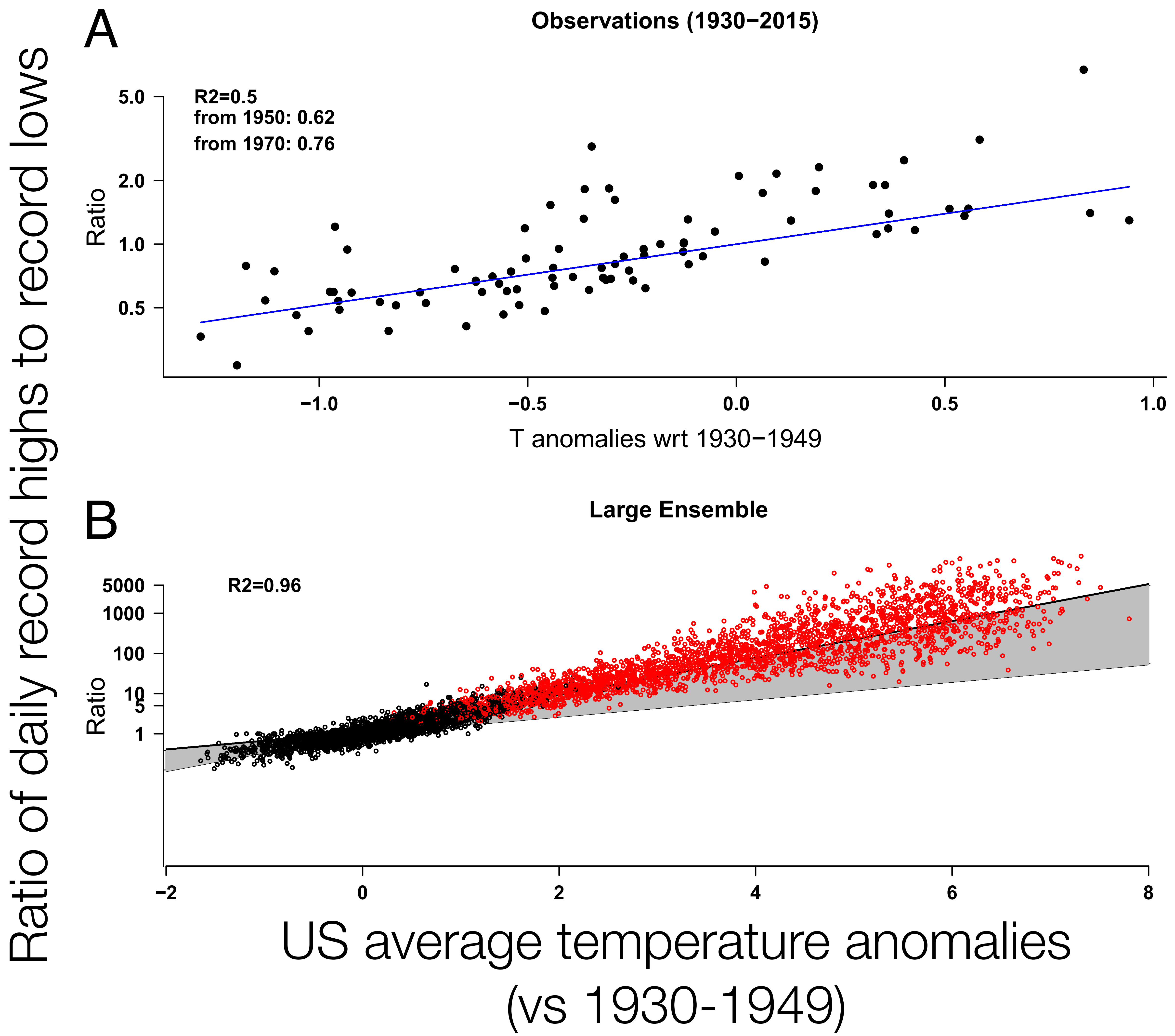
US CLIVAR Workshop on Confronting Earth System Model Trends with Observations: The Good, the Bad, and the Ugly

Directly comparing historical trends in heat extremes with model simulations is difficult due to influence of internal variability



Perkins-Kirkpatrick et al (2017) *ERL*

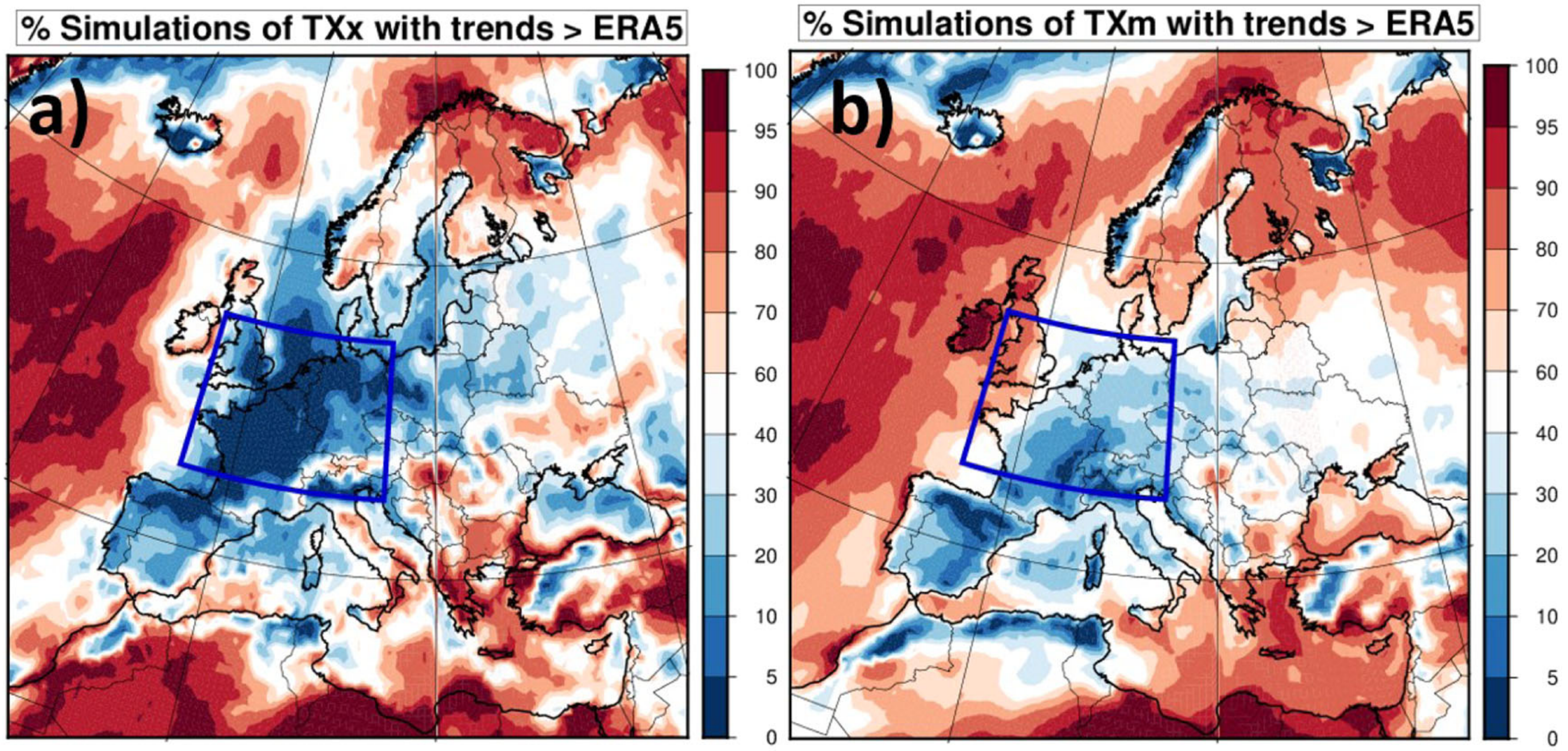
Signals in extremes get more clear through spatial aggregation. Hot extremes warm “too” fast in US in CCSM ensemble



hypothesized cause: decrease in precipitation and ET

Meehl et al (2016), *PNAS*

In contrast, western European heat extremes are warming faster than most models (1950-2022), difference greater than for mean



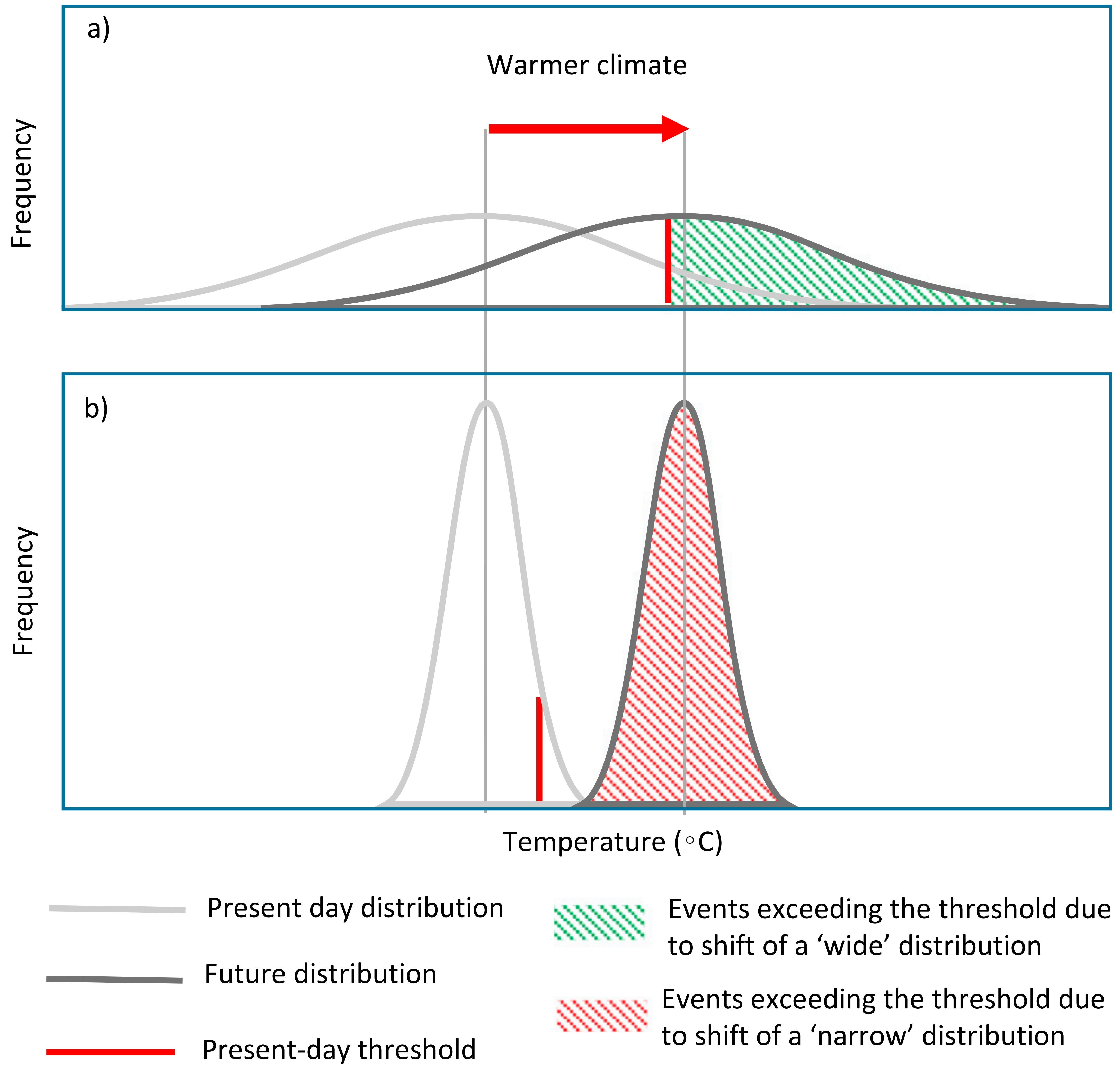
Vautard et al (2023) *Nature Communications*

Many metrics of changes in extremes are a strong function of the mean state.

Three examples.

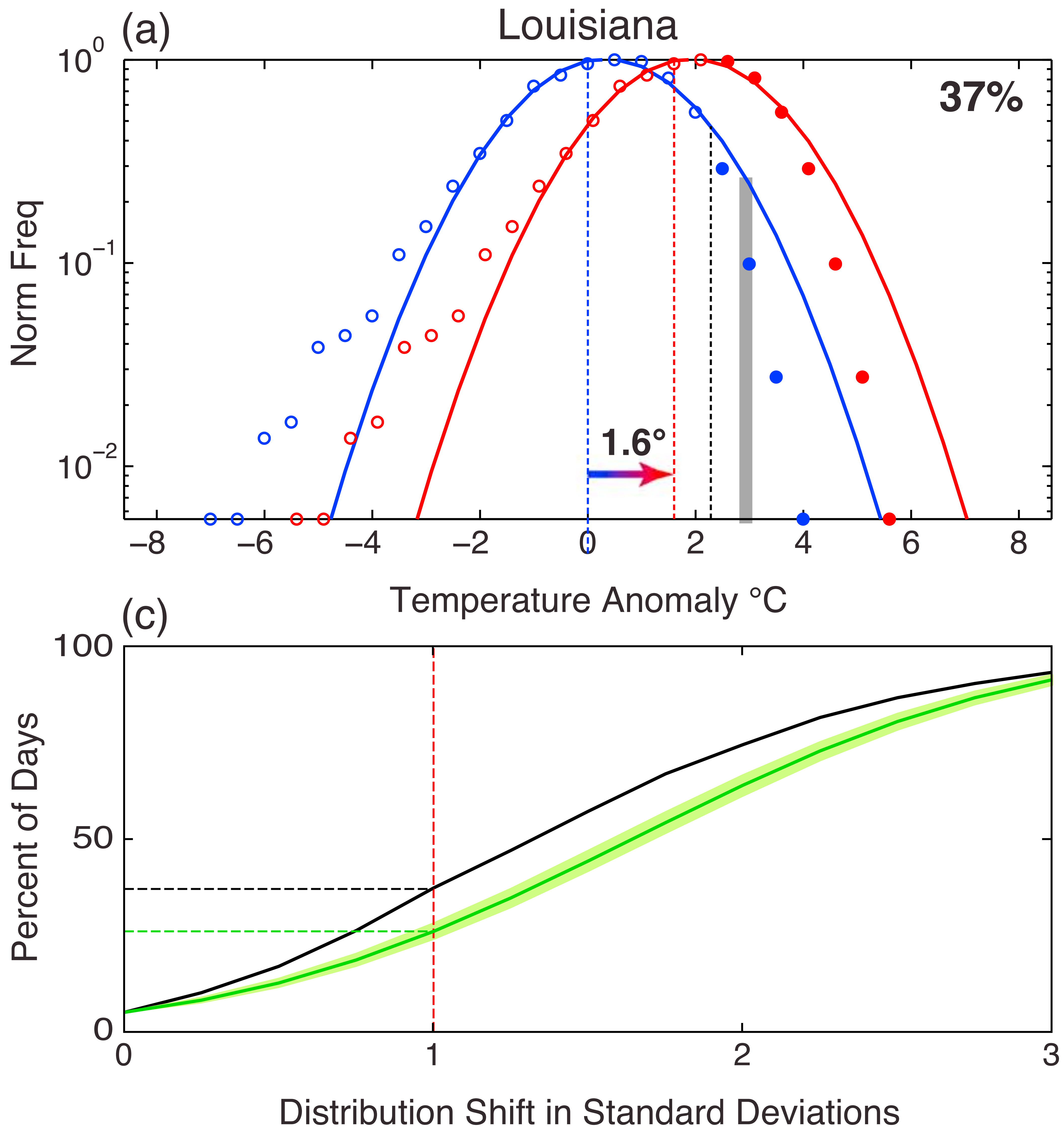
In all cases, the true climate change signal is a uniform warming across summertime temperatures.

The change of the number of days beyond a threshold depends on the width of the distribution: greater increases for narrow distributions



Borodina et al (2017) *JClim*

The change of the number of days beyond a threshold depends on the symmetry of the distribution: greater increases for short upper tails

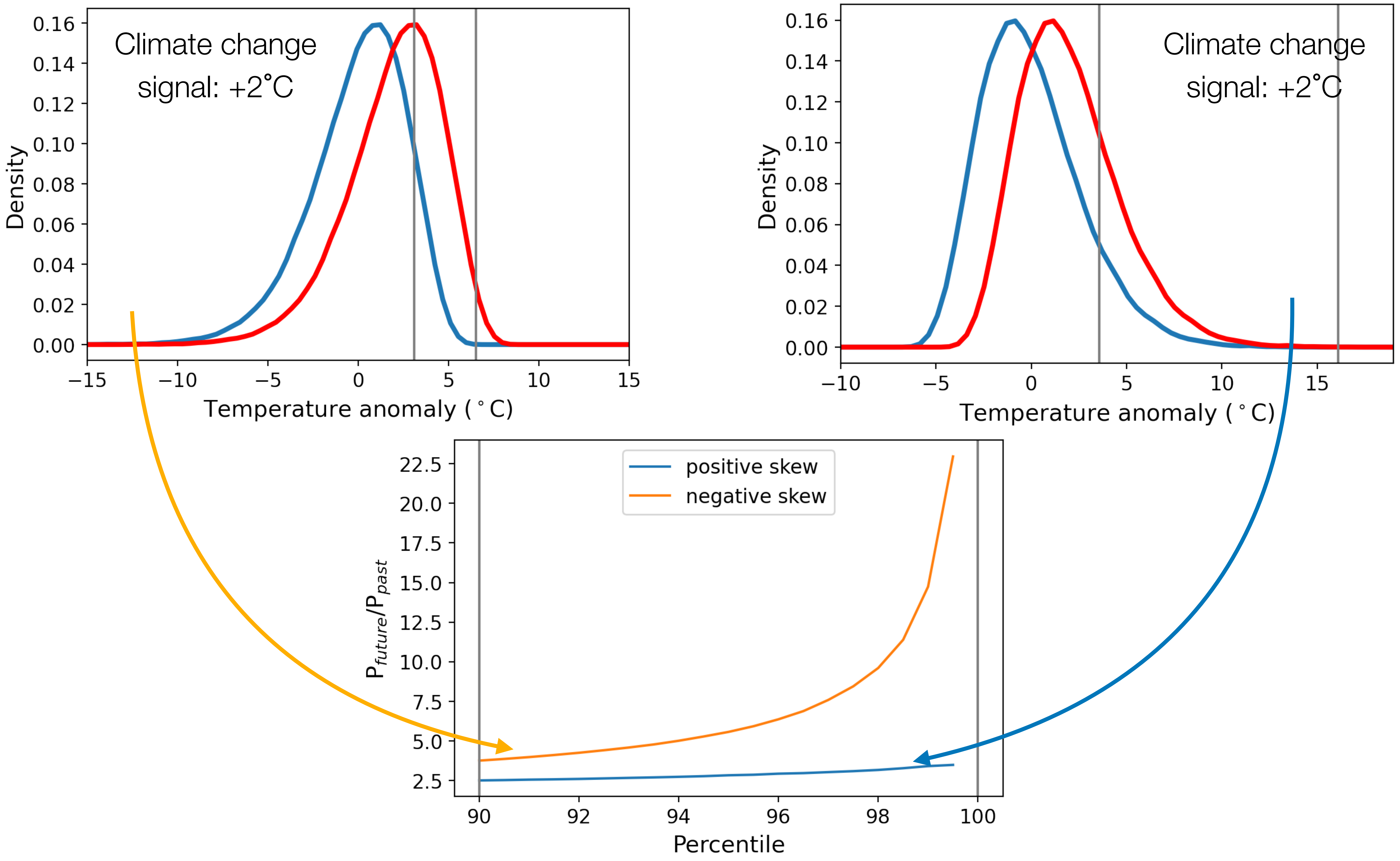


actual distribution

normal distribution

Loikith and Neelin (2015) *GRL*

The change in the probability of an event depends *non-linearly* on the threshold and the underlying distribution



A modest proposal: measure change in extremes as the change in temperature for a given percentile (max = 100th percentile)

A hierarchy of controls on the change in extremes
(across models, or comparing models and observations)

Global mean temperature

A hierarchy of controls on the change in extremes
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Global mean temperature

Global land temperature

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Summer versus annual-mean temperatures

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Local summer average temperature

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A hierarchy of controls on the change in extremes (across models, or comparing models and observations)

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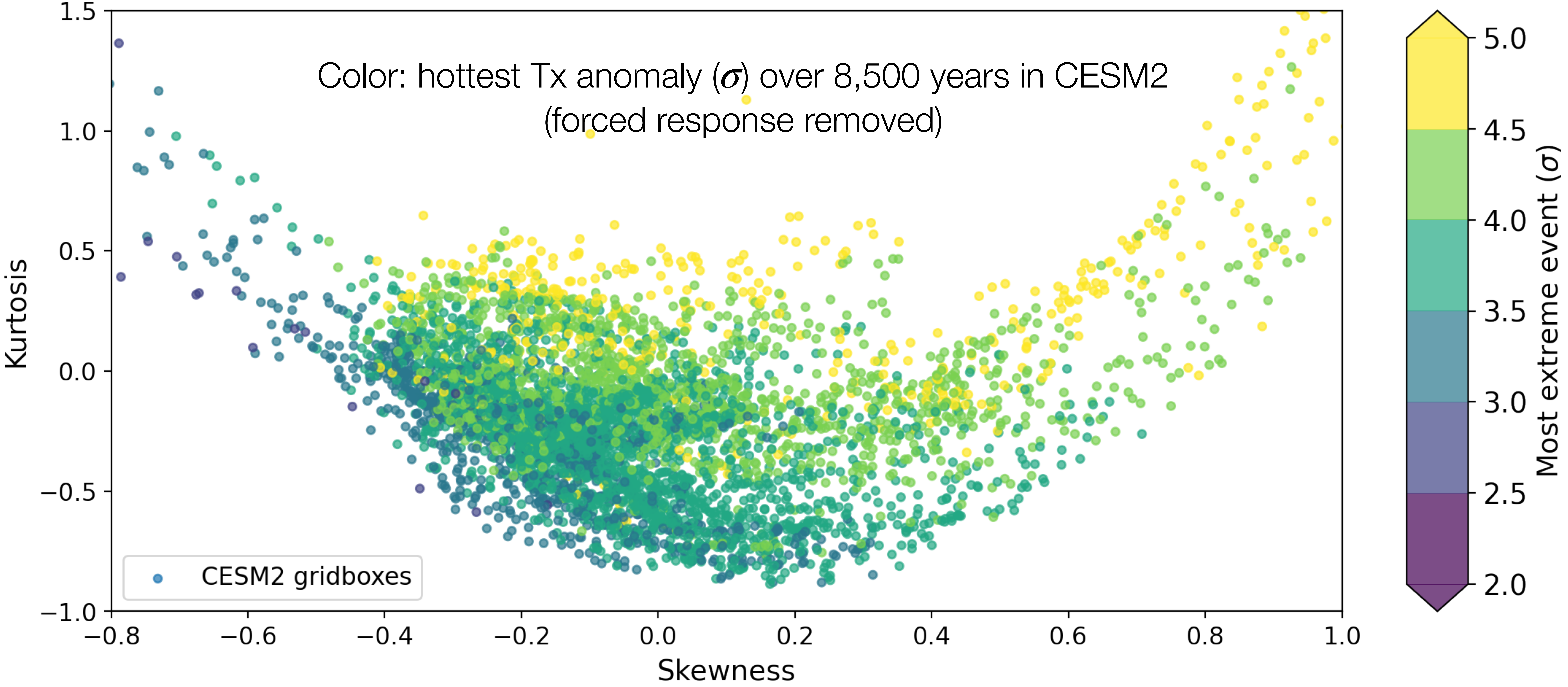
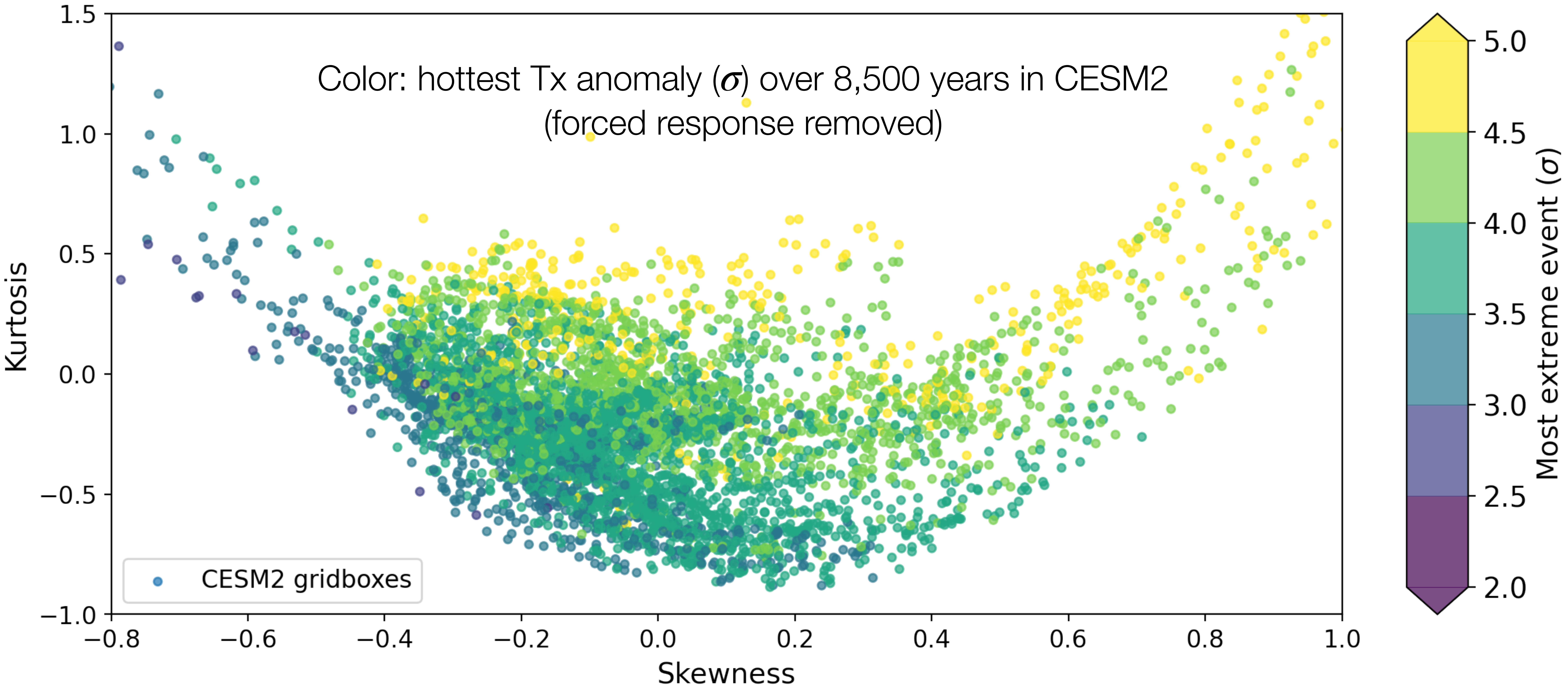
Local summer extreme temperature

The probability of very extreme events compared to the mean is higher for locations with positive skewness and/or kurtosis



McKinnon and Simpson (2022), *GRL;* see also Van Loon and Thompson (2023), *GRL*

This can lead to apparent trends in extremes from sampling alone



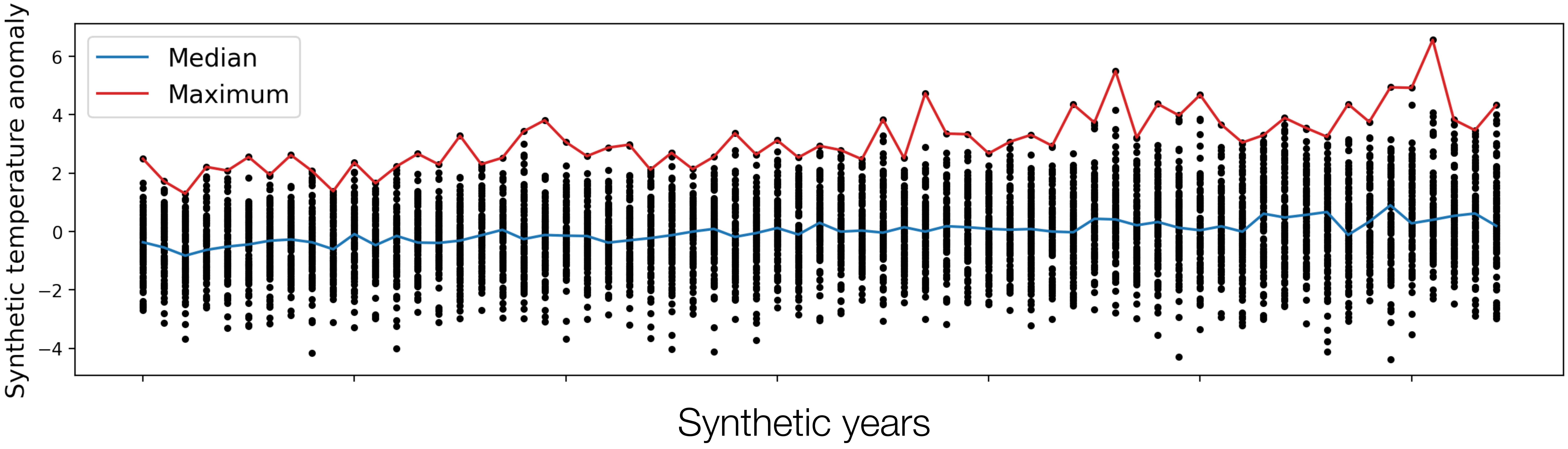
McKinnon and Simpson (2022), *GRL;* see also Van Loon and Thompson (2023), *GRL*

Two challenges:

1. The contribution of internal variability to trends in extremes is very large

2. The probability of a given extreme (e.g. a 3-sigma event) is spatially-variable due to non-normality in temperature distributions, so unclear how to average across space

Approach: spatial average of ranked difference between hot extremes and median



Synthetic data: normal distribution with an increasing variance

McKinnon, Simpson, and Williams (in prep)

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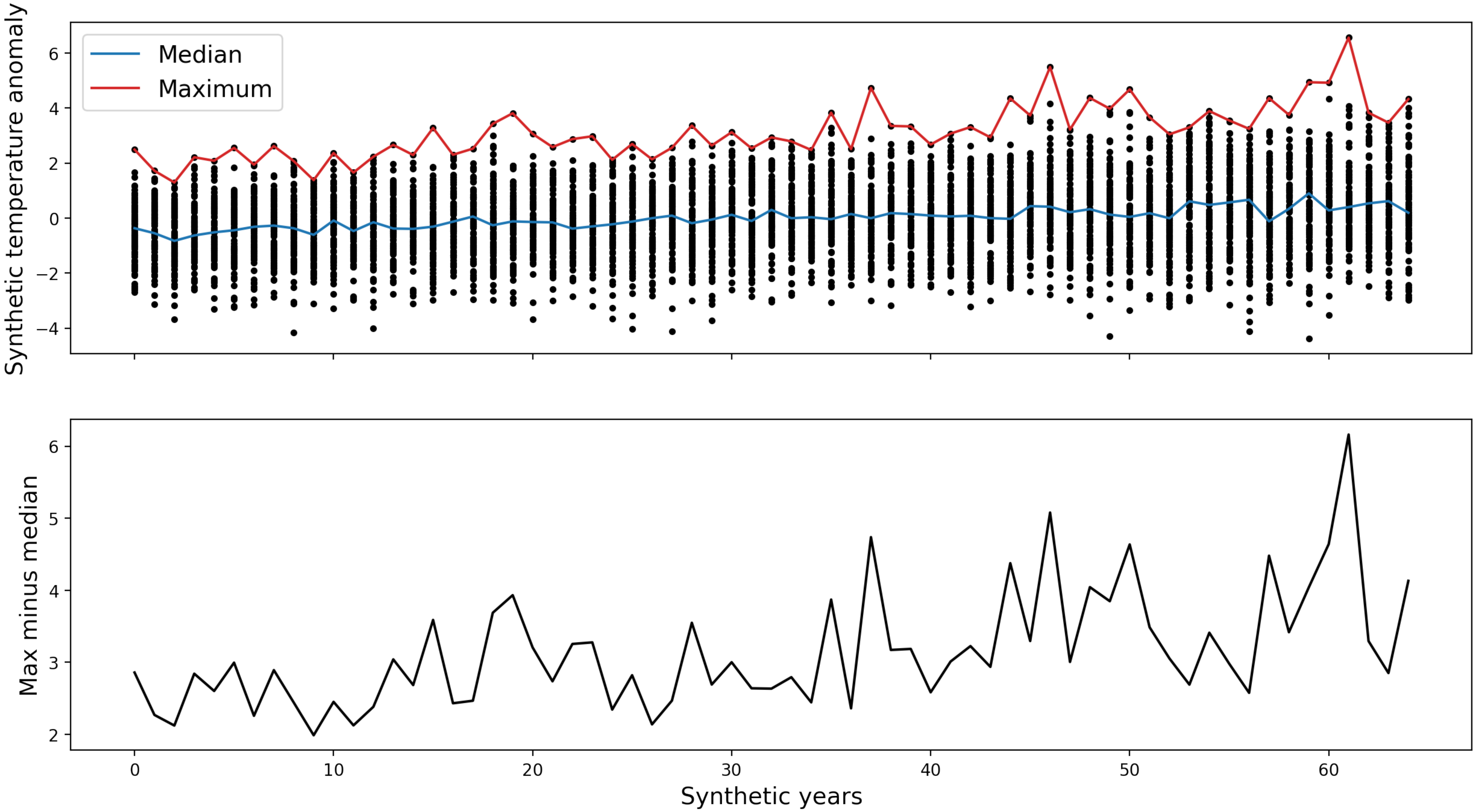

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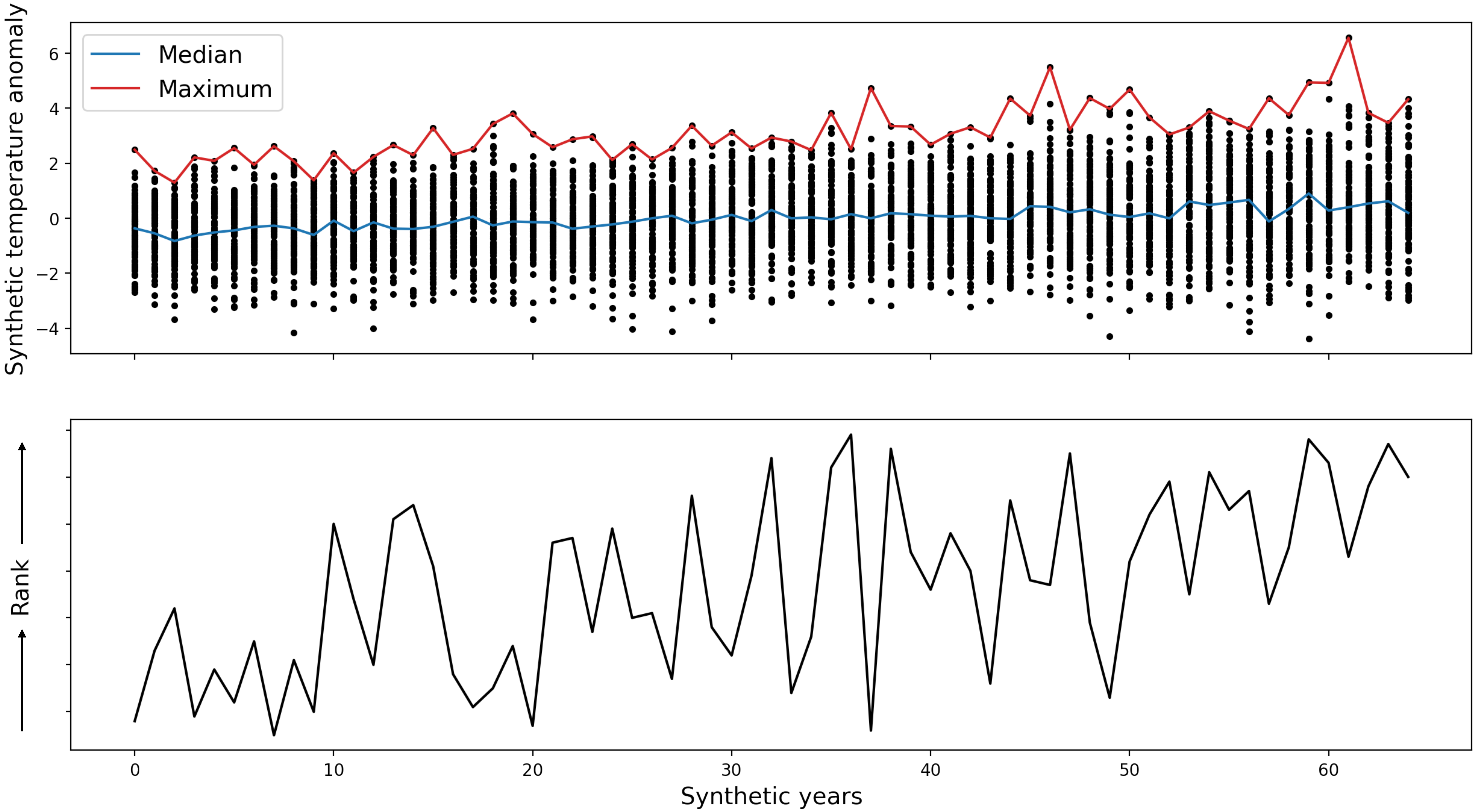

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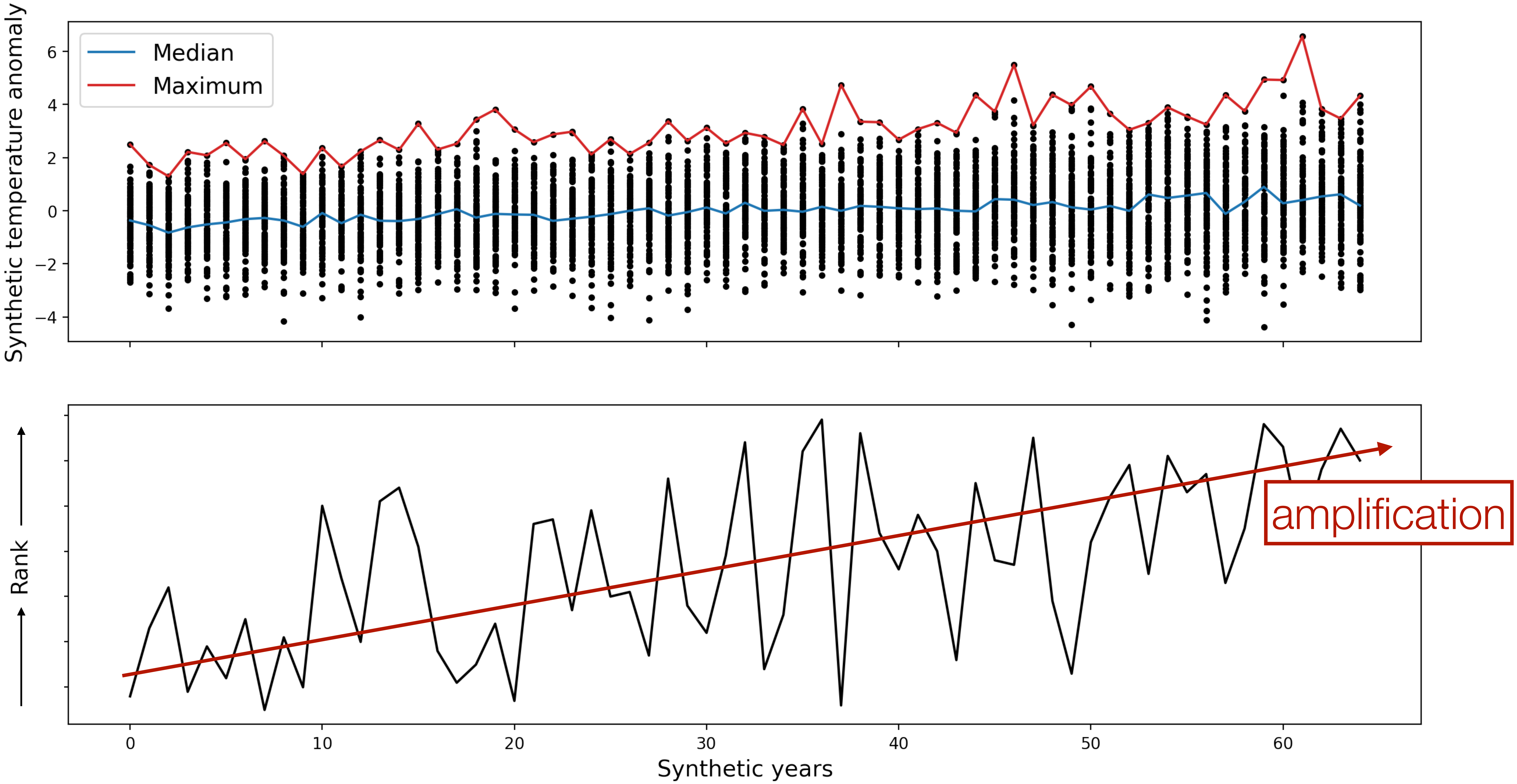

Advantages of a rank-based approach

- No dependence on the underlying distribution
- The expected rank across locations and time is known (33 for 65 years of data)
- Can combine information or inter-compare across different definitions of heatwaves

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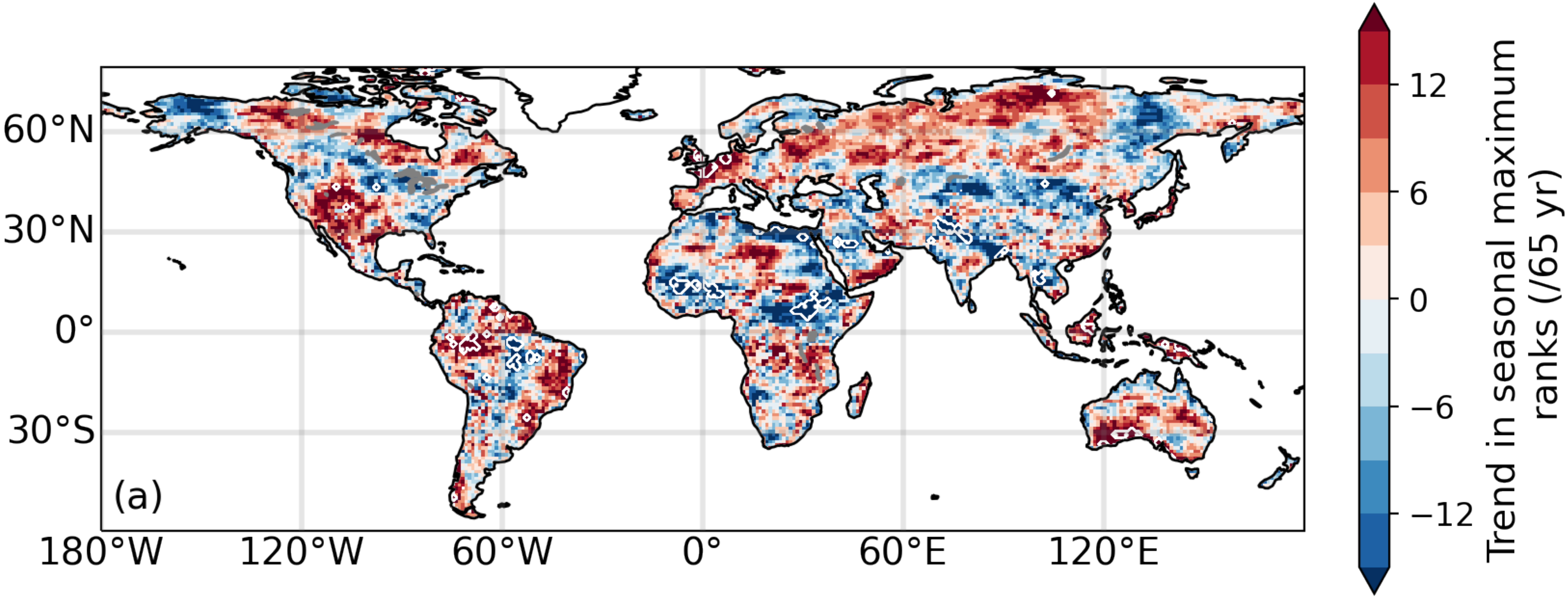
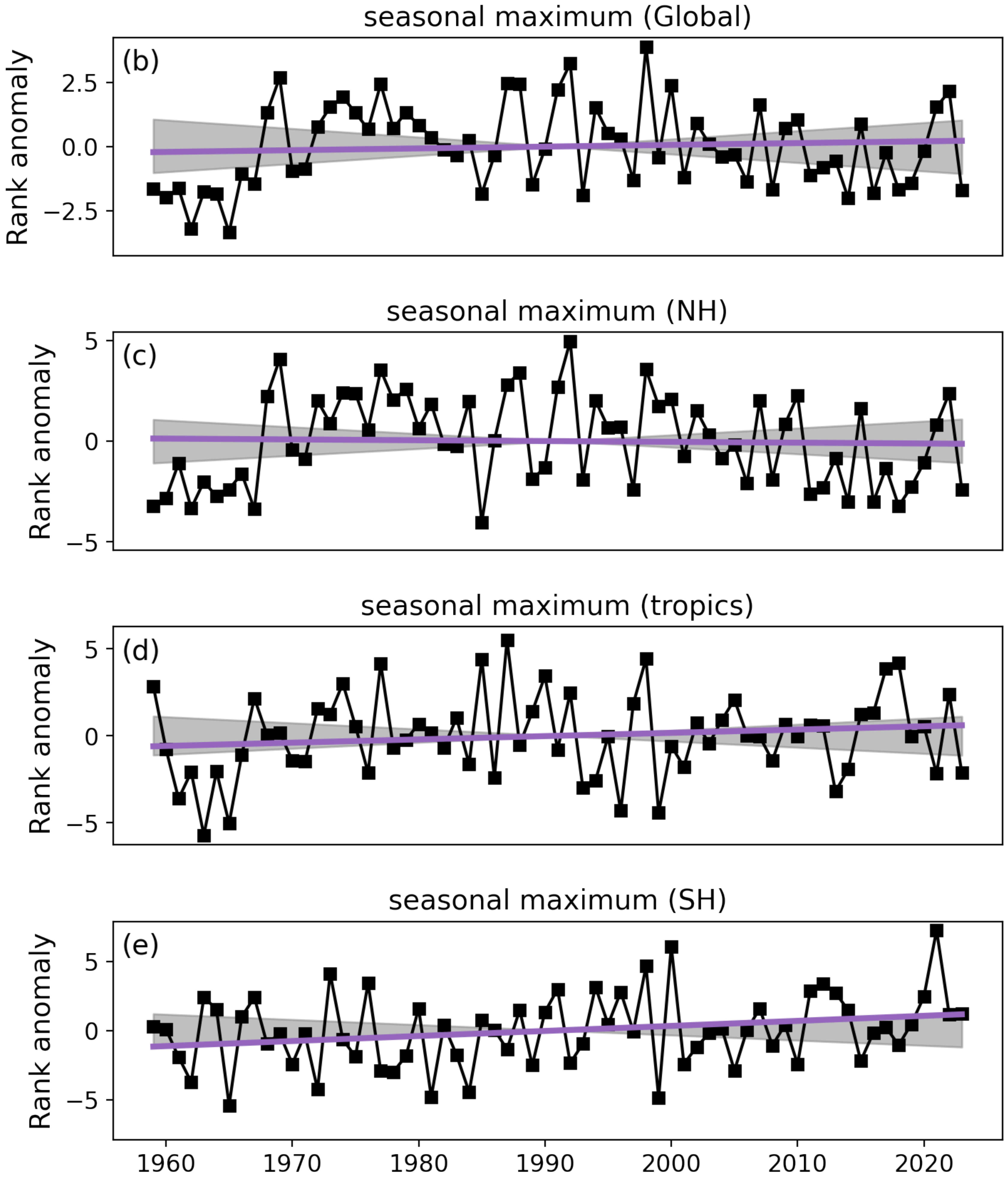
Data: ERA5, daily maximum (Tx), 1959-2023

Spatial heterogeneity in trends of amplification in ERA5, very few trends are locally significant ($\alpha_{FDR} = 0.05$)

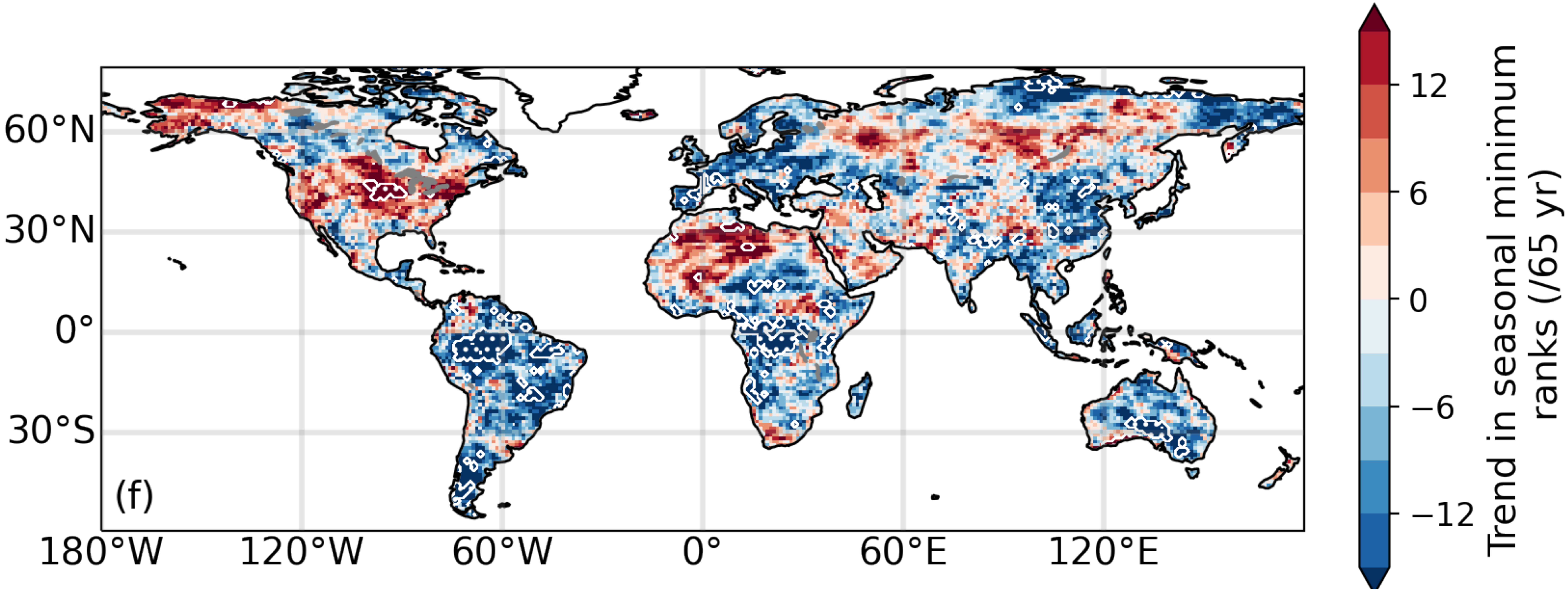


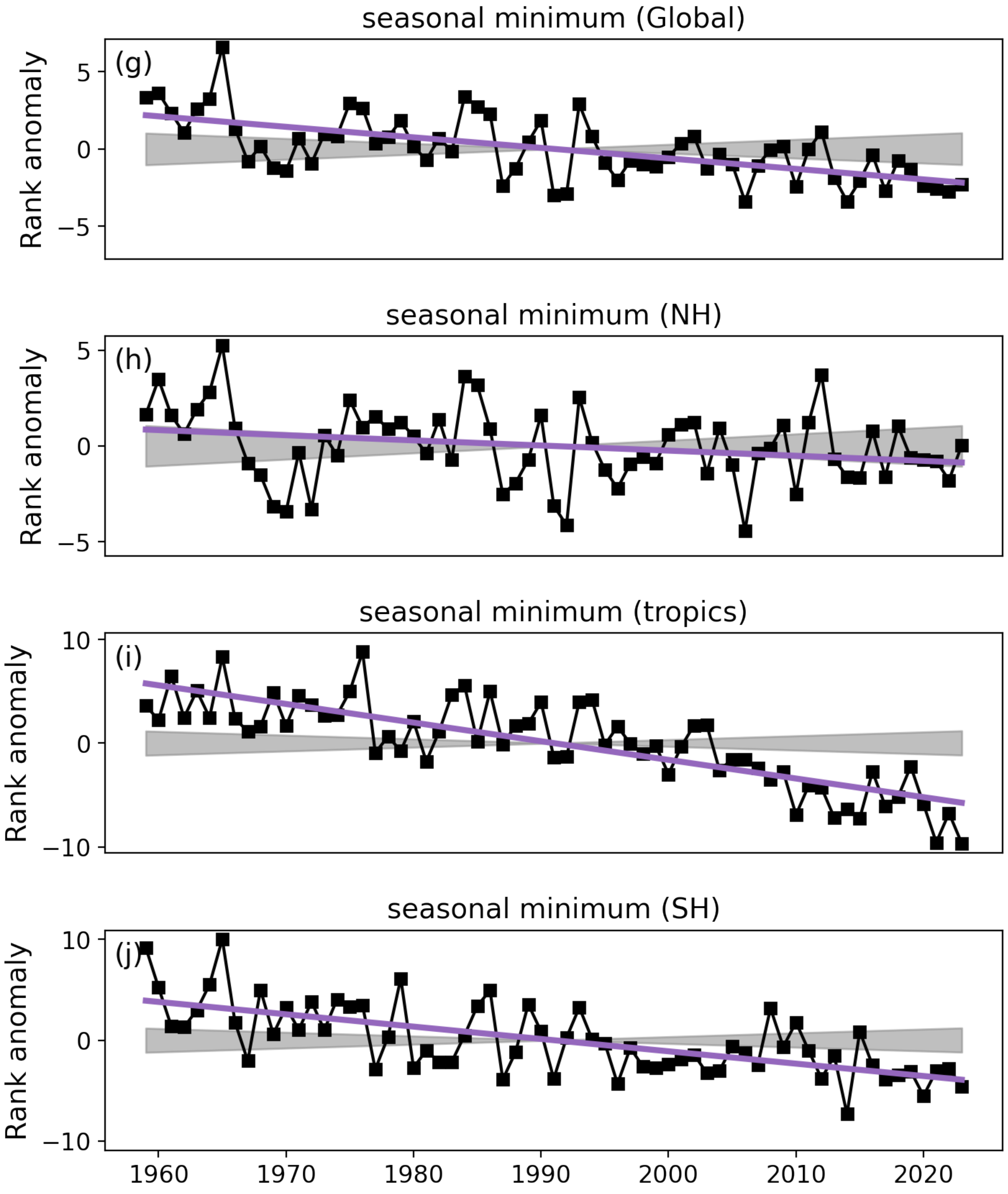
significance indicated by white contours / stippling



No significant trends at the global or hemispheric/tropical scale

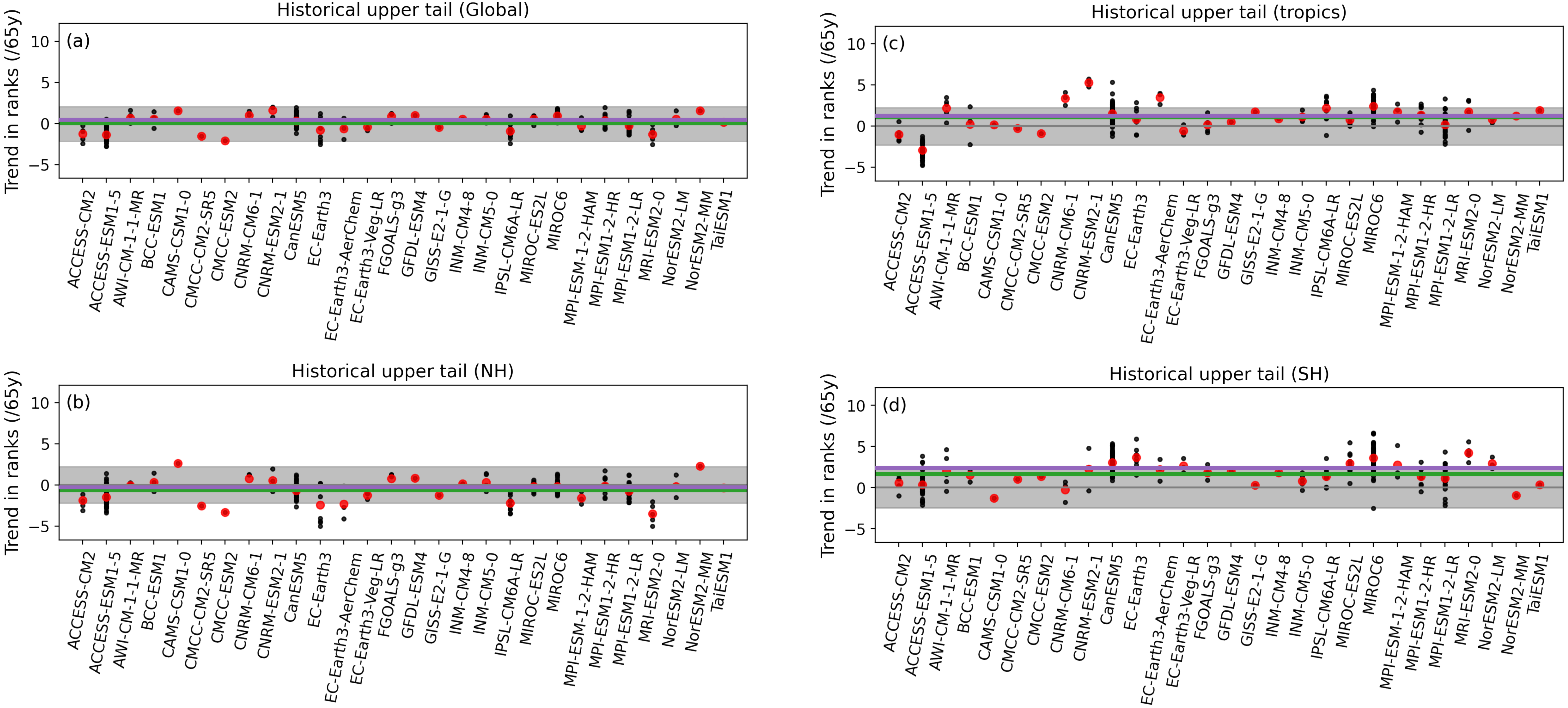
What about cold summertime temperatures (still Tx though)?
In most regions of the world, they are warming *less* than the median



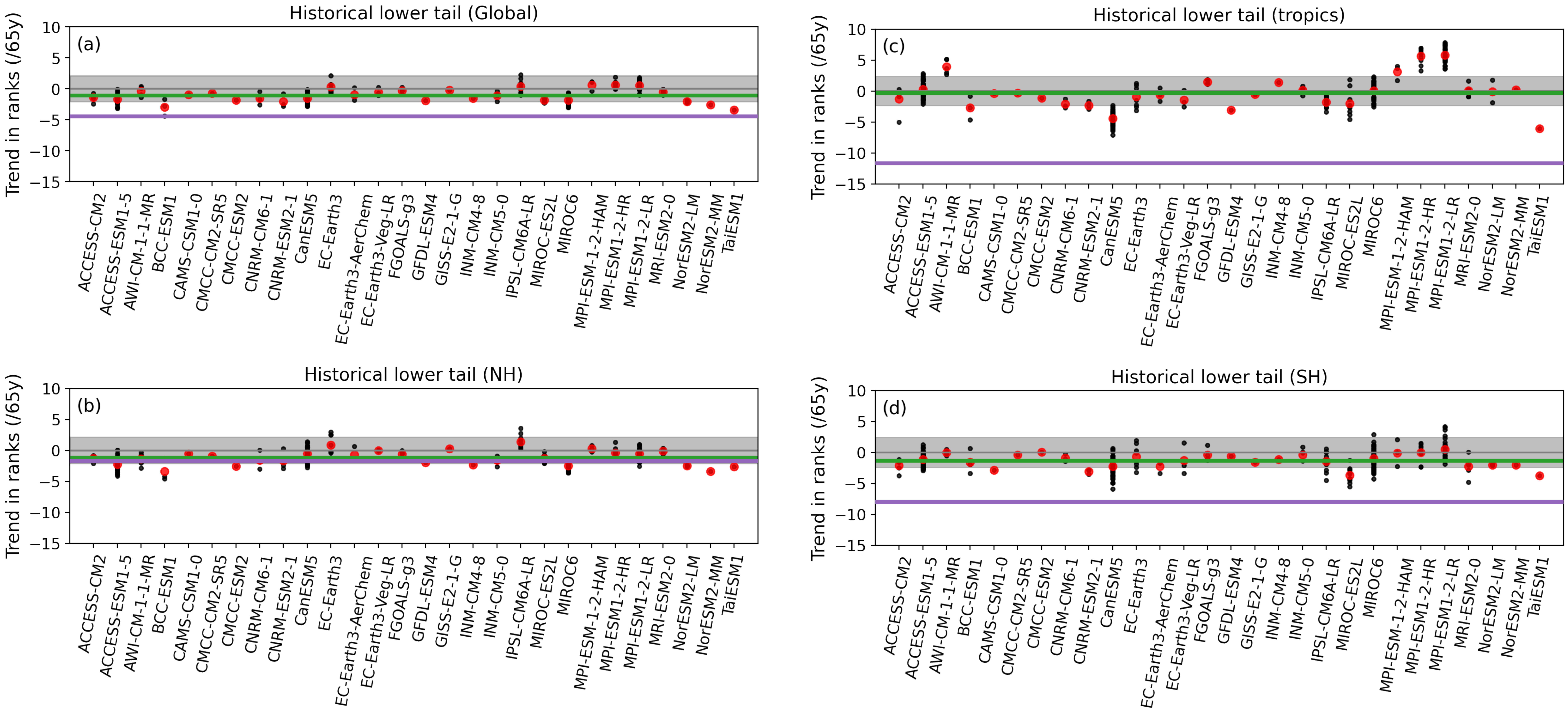


Significant trends (except in NH) towards *damped* warming of the lower tail

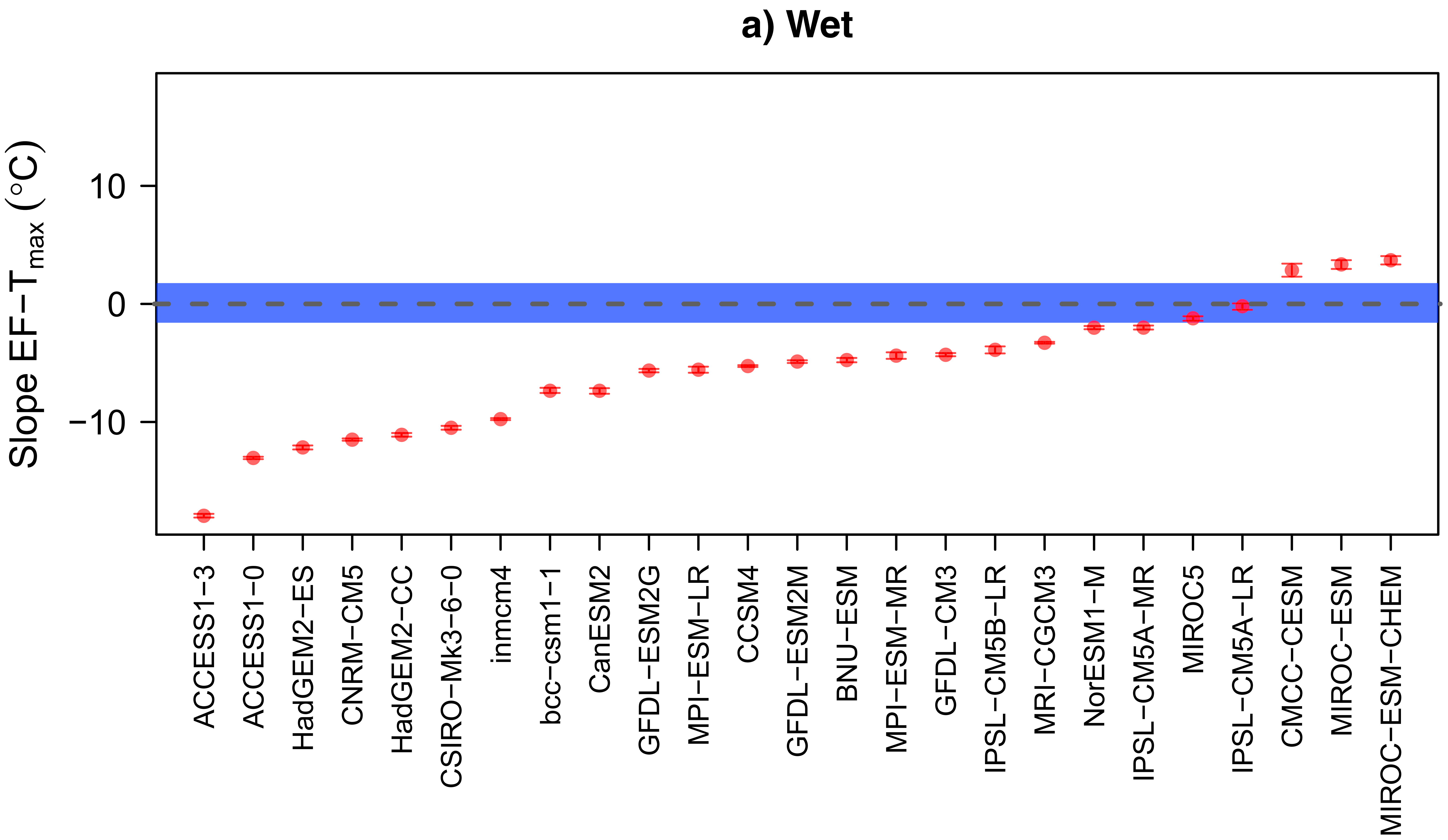
CMIP6 simulations tend to agree with observations of no historical, significant amplification of heat extremes



But they miss the observed damping of the cold tail in the tropics and Southern Hemisphere, perhaps related to precipitation changes



Consistency between models and observations in terms of lack of hot day amplification does not preclude model errors



observations: Tmax in "wet" regions is insensitive to evaporative fraction -> lack of land/atmosphere coupling

most models (CMIP5): Tmax is higher when the evaporative fraction is lower (drier conditions) -> existence of land/atmosphere coupling

How do mean state errors affect (or not) trends?

Ukkola et al (2018) *GRL*

Trends in extremes are strongly affected by internal variability, so can be difficult to intercompare with models.

Many trend metrics are a strong function of the underlying distribution, which should be considered before interpretation.

The probability of extremes is spatially-variable due to non-normality. We propose a rank-based analysis. Heat extremes are not warming faster than the median at large scales in models or observations, but the models miss the damped warming of the lower tail.

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website

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THE David & Lucile Packard Foundation

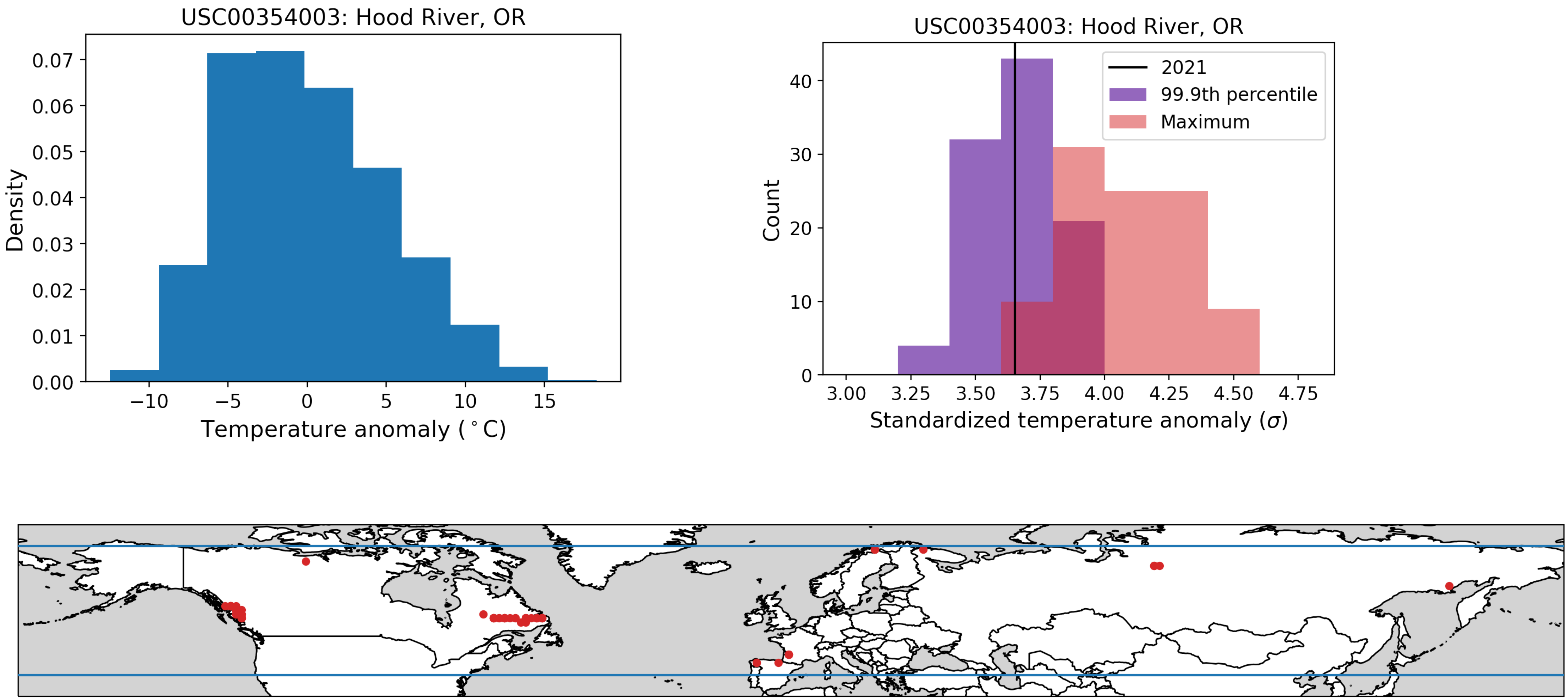
NSF

Be in touch if you want to join the group to work on these topics! Post-docs (now) and PhD students (next season)

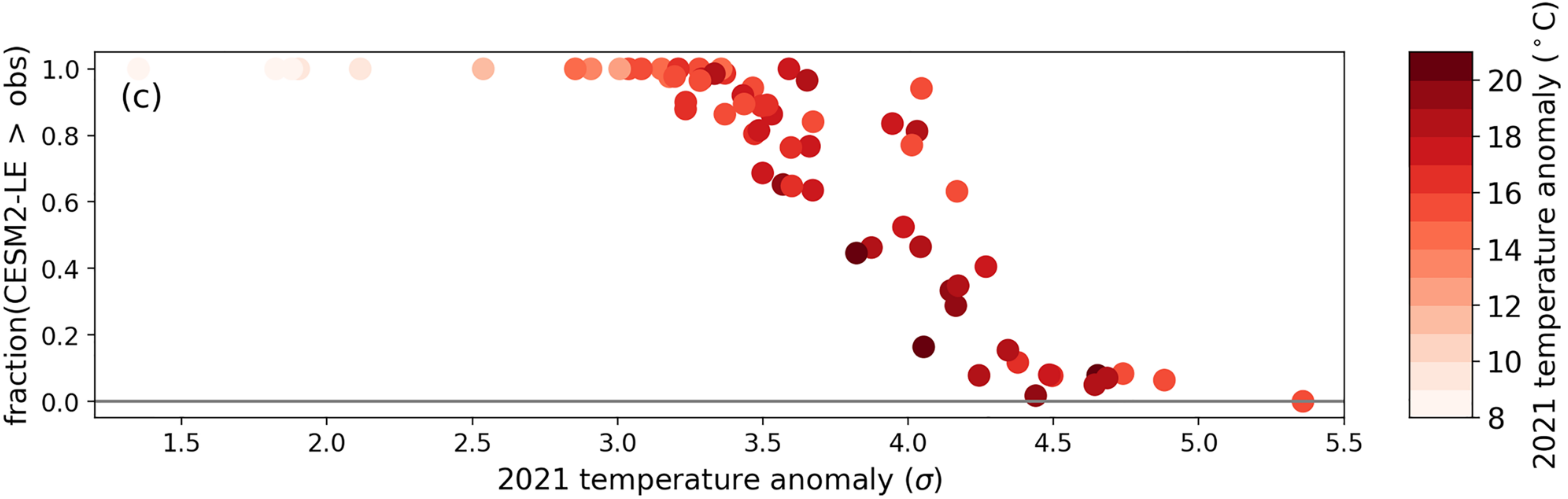
website

Extras


(a) Individual ranks, Change in mean only
(b) Individual ranks, Change in variance only
(c) Individual ranks, Change in mean and variance
(d) Averaged ranks, Change in mean only
(e) Averaged ranks, Change in variance only
(f) Averaged ranks, Change in mean and variance
Change in mean
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
Fractional change in variance
0.1
0.2
0.3
0.4
0.5
Fraction of nulls rejected
0.00
0.15
0.30
0.45
0.60
0.75
0.90


USC00354003: Hood River, OR
Density
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
−10
−5
0
5
10
15
Temperature anomaly (∘ C)
USC00354003: Hood River, OR
Count
40
30
20
10
0
2021
99.9th percentile
Maximum
3.00
3.25
3.50
3.75
4.00
4.25
4.50
4.75
Standardized temperature anomaly (σ)

“Analog locations” (similar skewness and kurtosis) in CESM2 produce heatwaves as large and larger than we saw in 2021

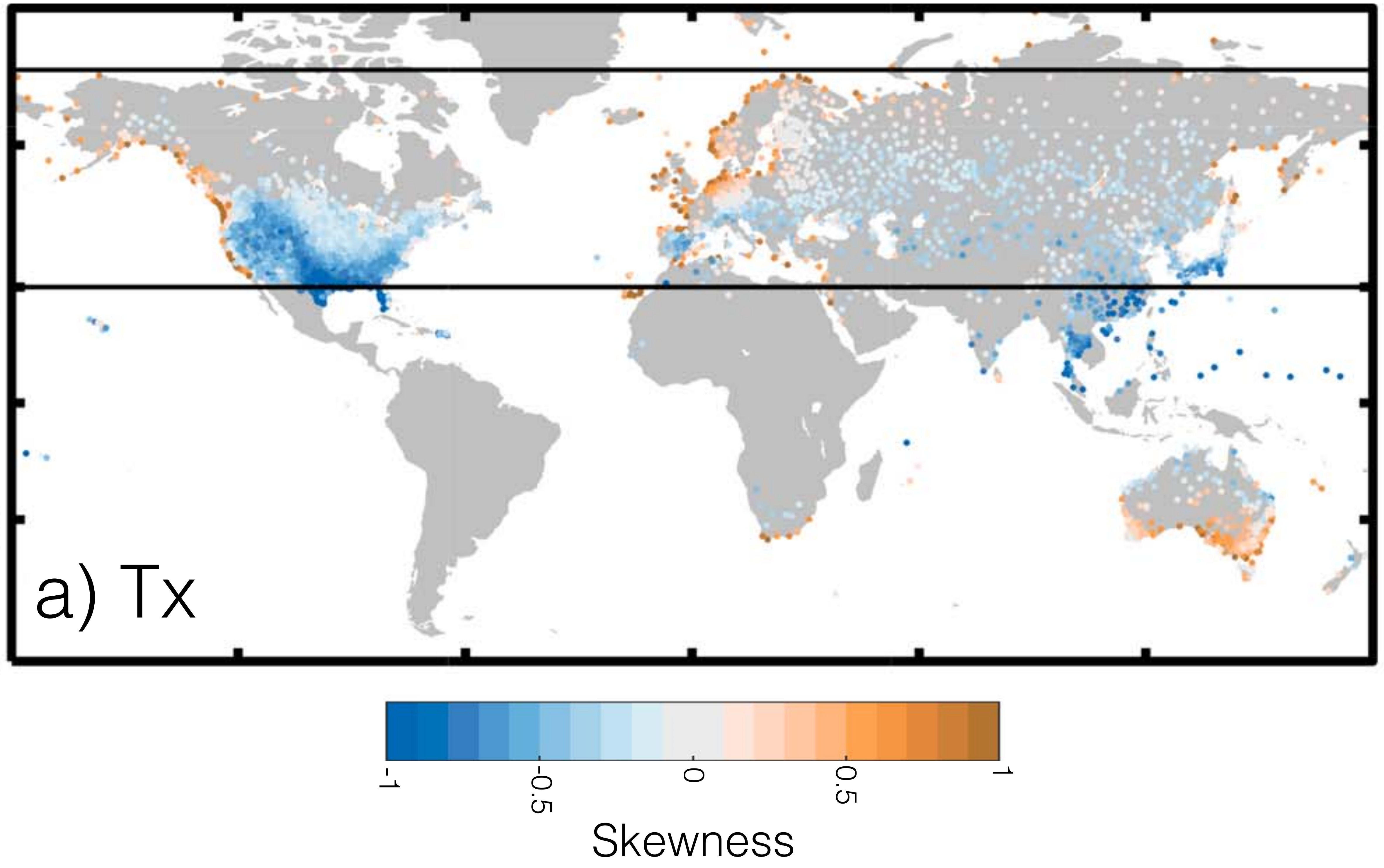


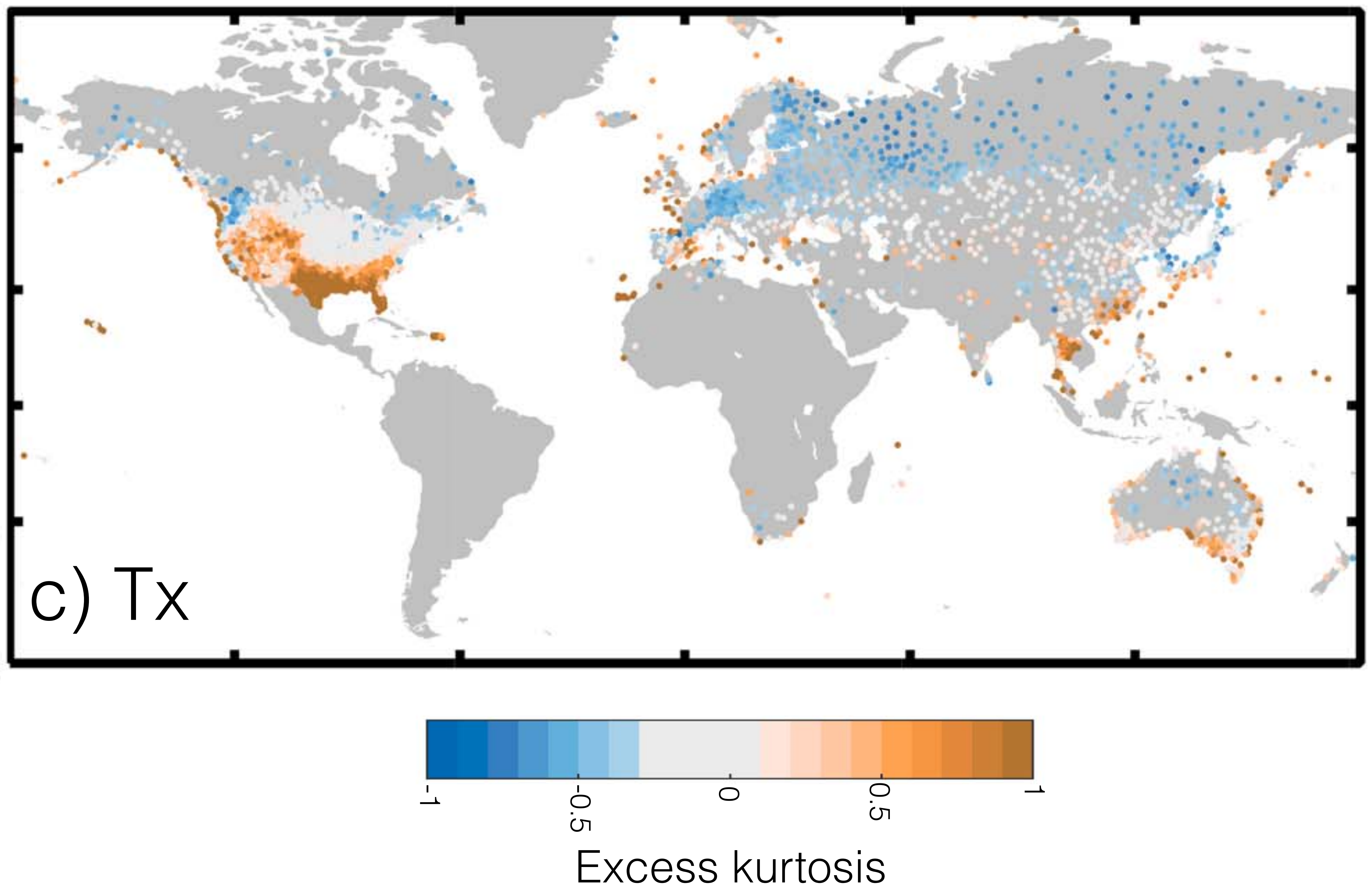
But comparable events are rare:
the maxima across 171 years x 50 ensemble members

After accounting for warming of the mean, a large climate model ensemble detects significant trends of the *most* extreme events, although their probabilities remain small

Data: CESM2 large ensemble

Daily temperature data is typically non-Gaussian, so insufficient to only assess changes in the mean and variance

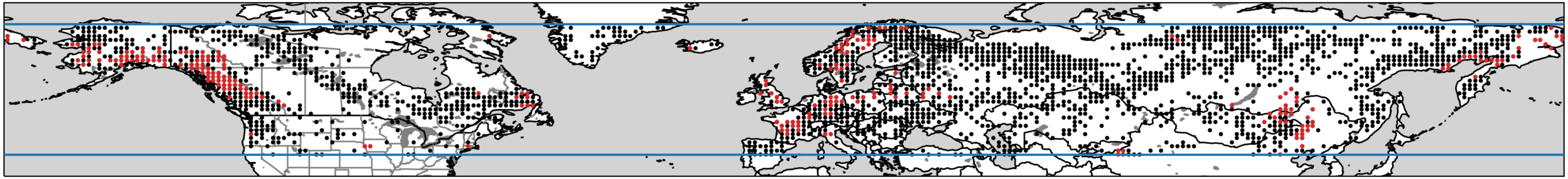




Data: GHCND (weather) stations

Black: all analog locations

Red: both observations and CESM2 had greater than 4 sigma event



Hot days largely follow the median; some places have warmed *a lot*

Relatively small differences between percentiles, limited significance

Qualitatively similar results with the 1959-2023 ERA5 analysis

Assuming climate change has mostly *shifted* the temperature distribution, do we expect that the climate system can produce heat waves as large as the 2021 event?

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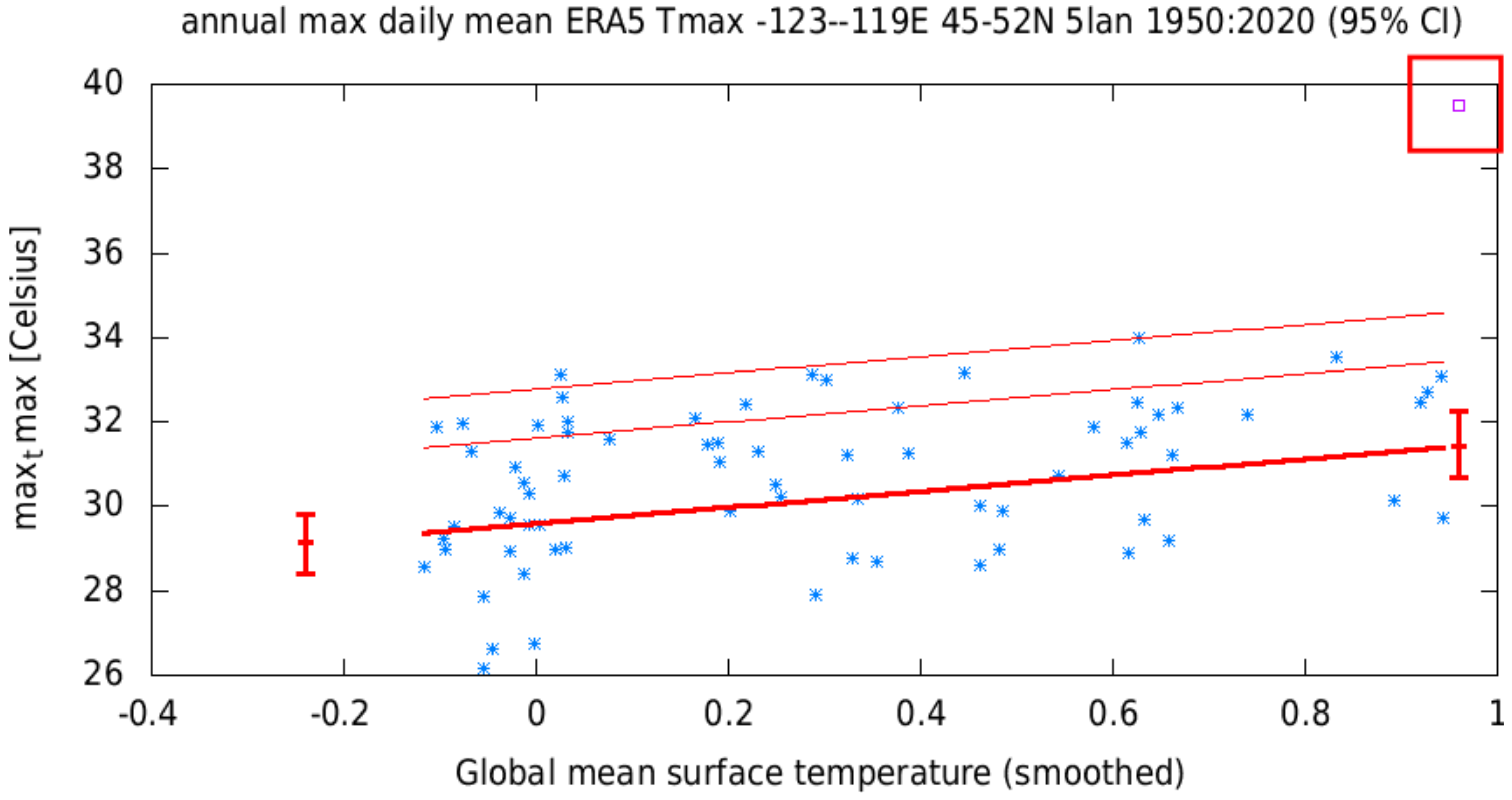

Philip et al (2022) *ESD*