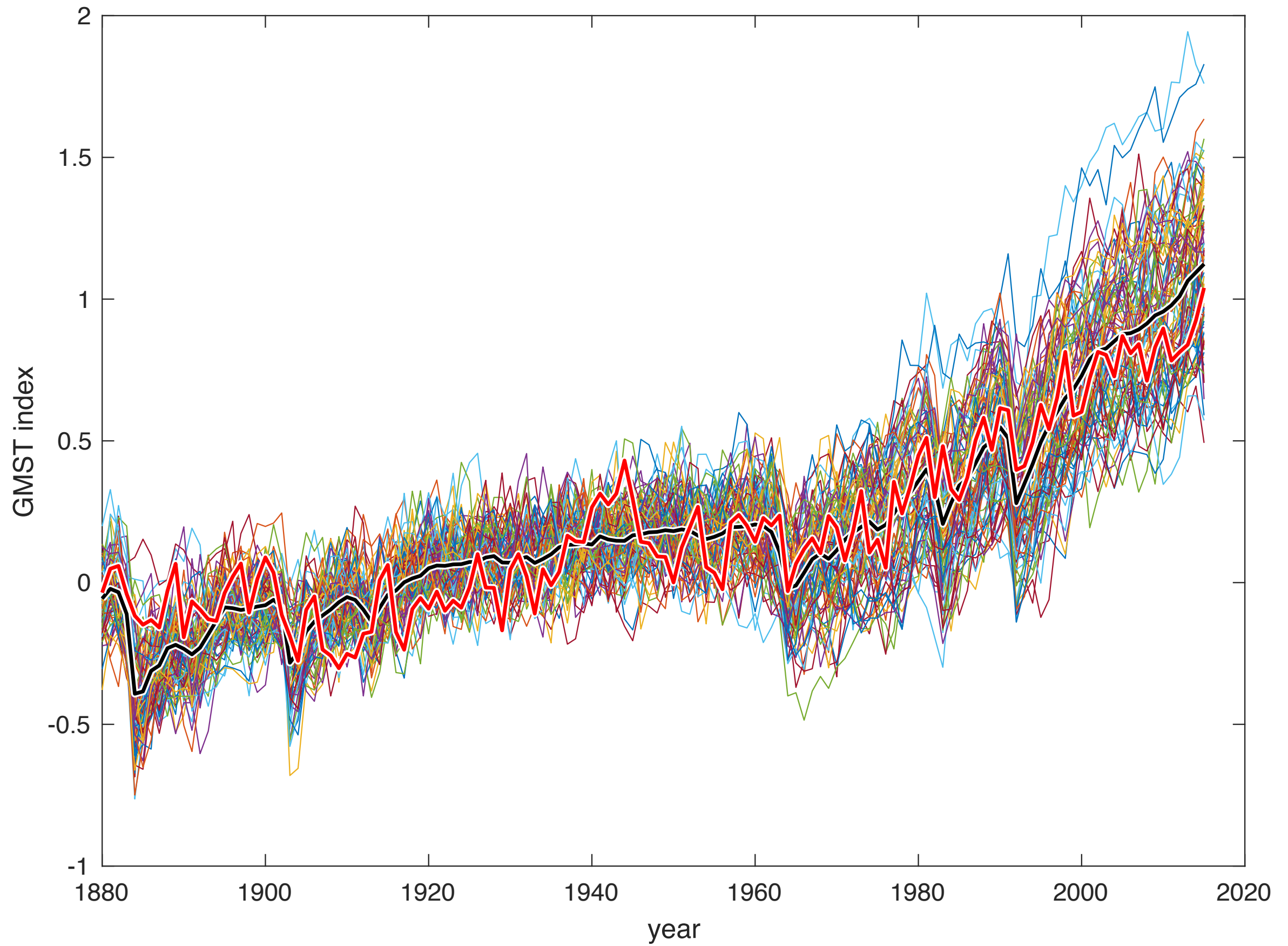


# On the Choice of Method for Estimating the Forced Signal in the Presence of Internal Variability

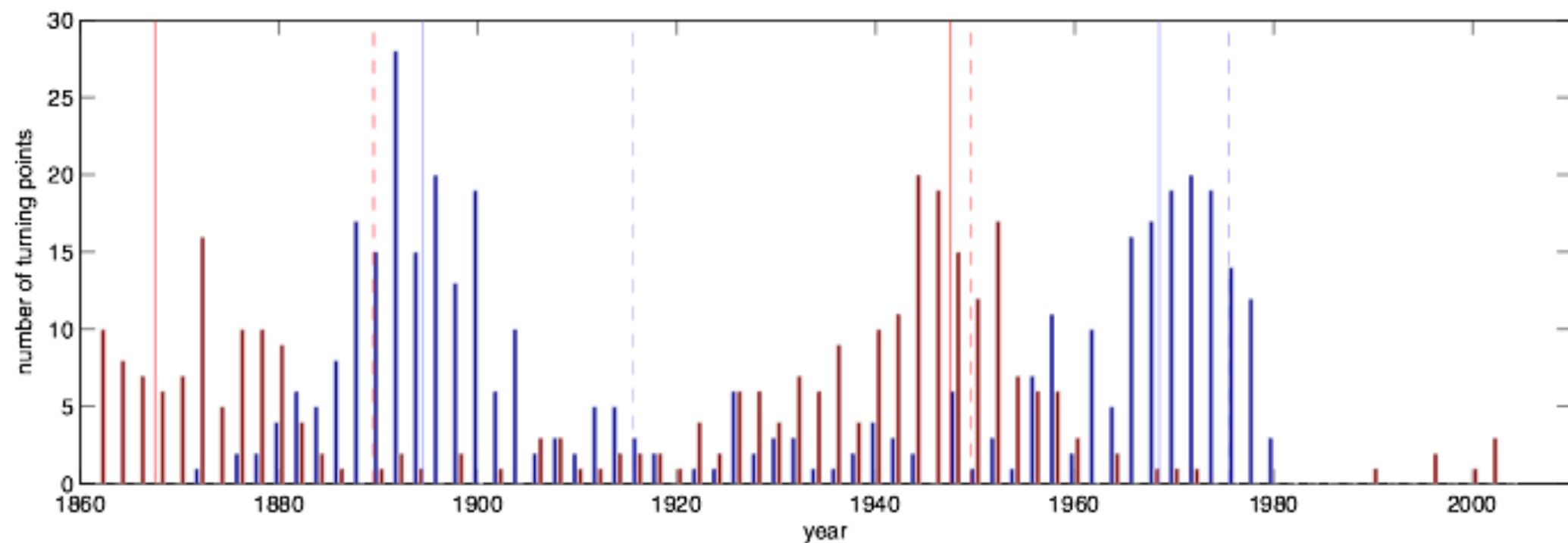
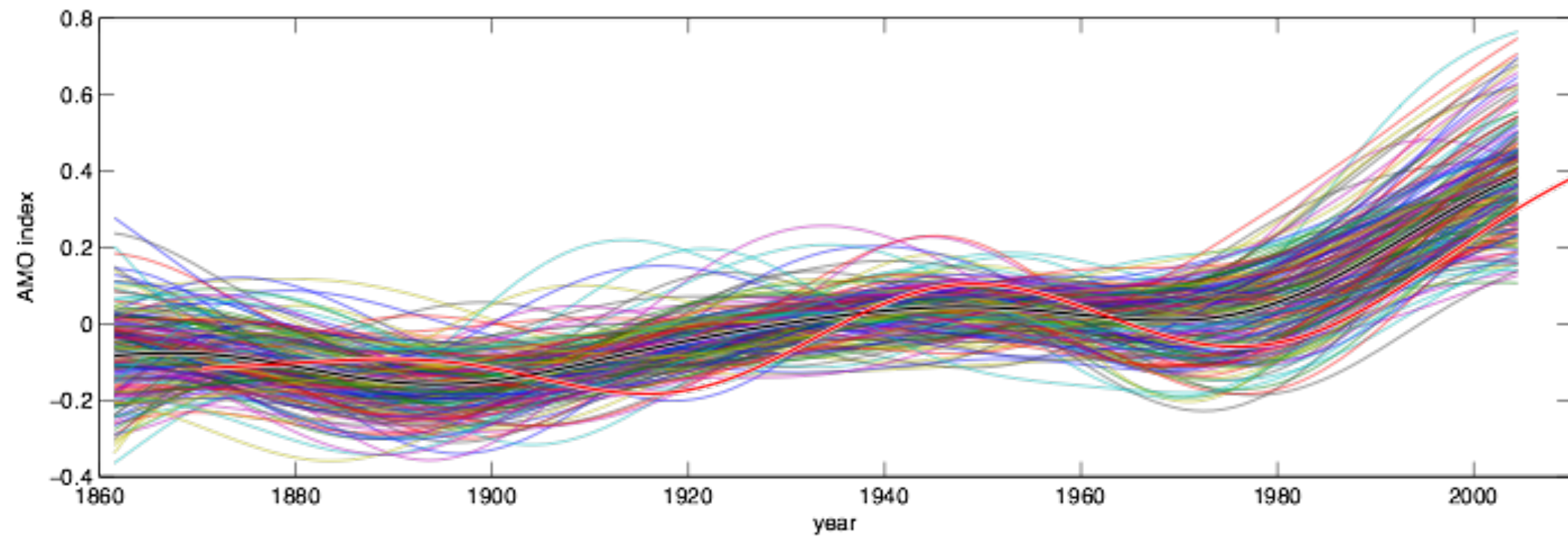
Leela Frankcombe

Matthew England, Jules Kajtar, Michael Mann and Byron Steinman



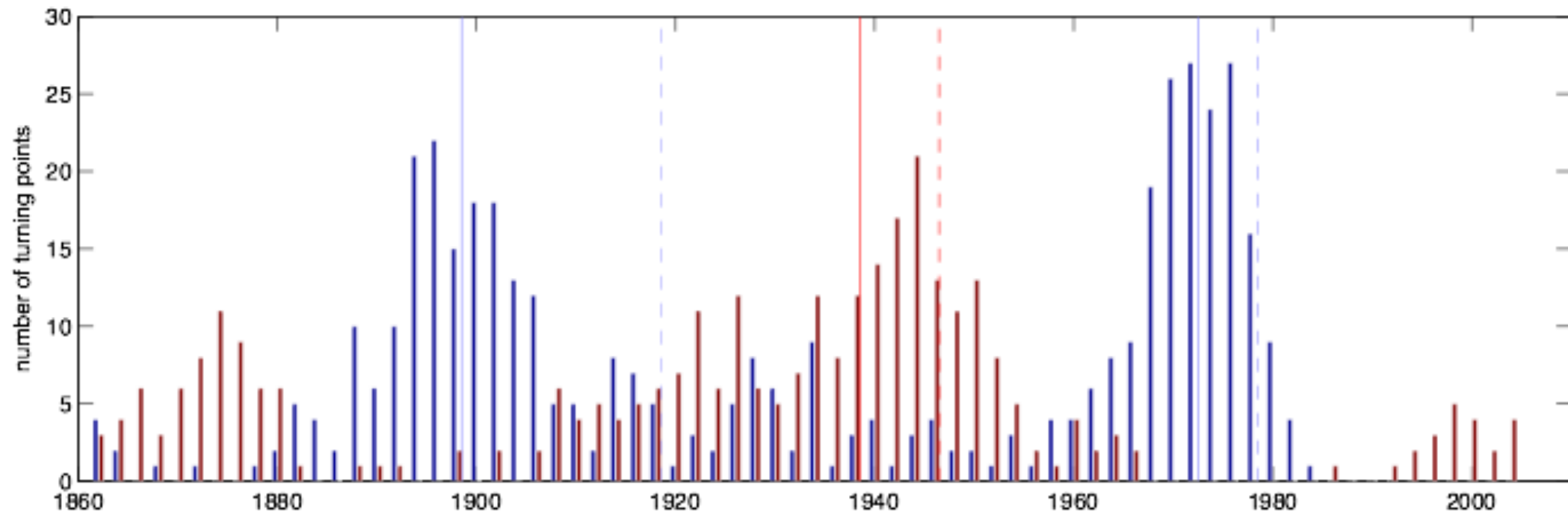
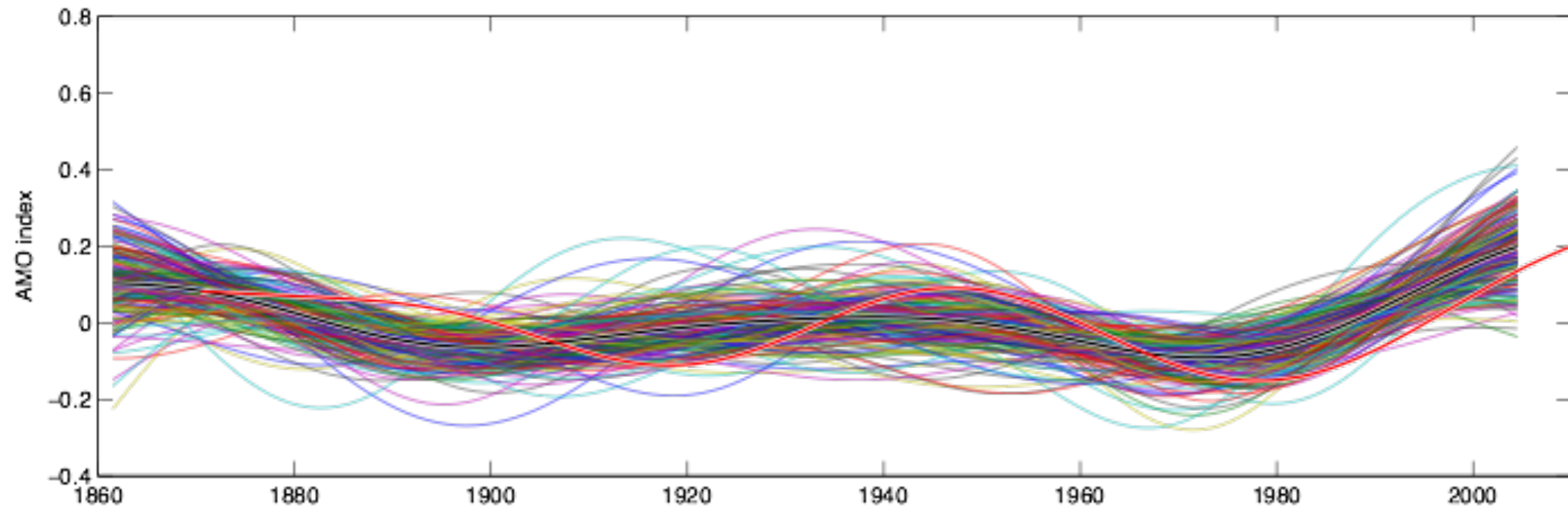
# Biases introduced by incorrect removal of forced signal

Raw signal



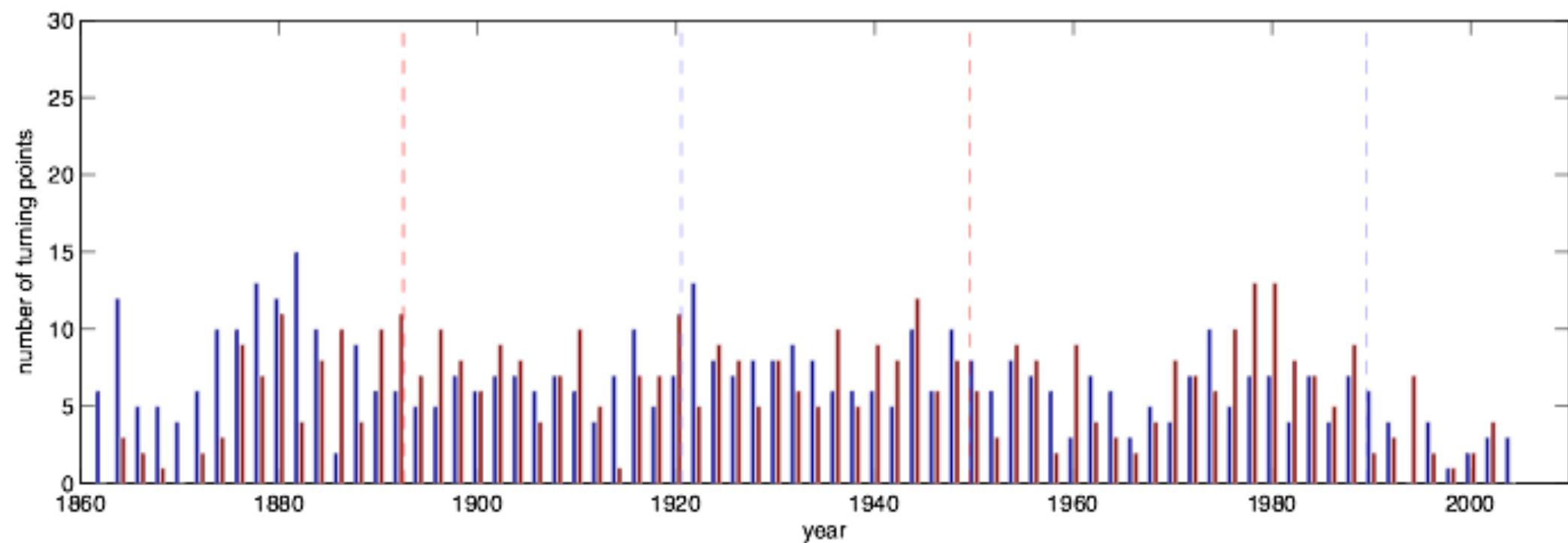
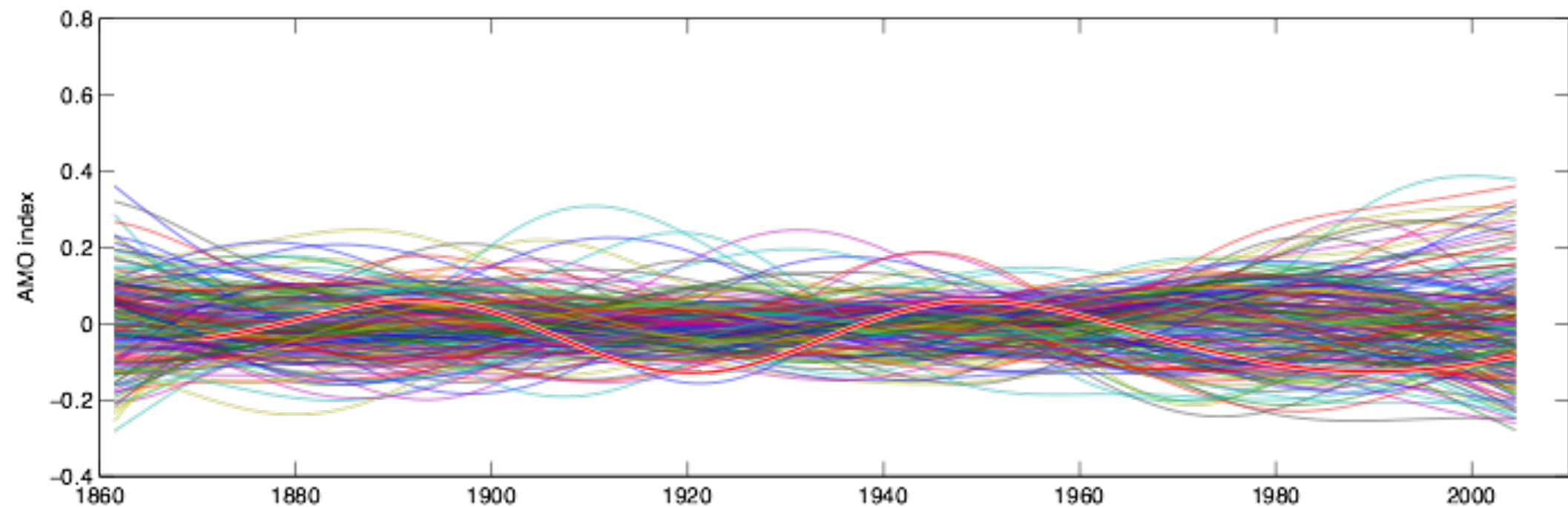
# Biases introduced by incorrect removal of forced signal

## Linear detrending



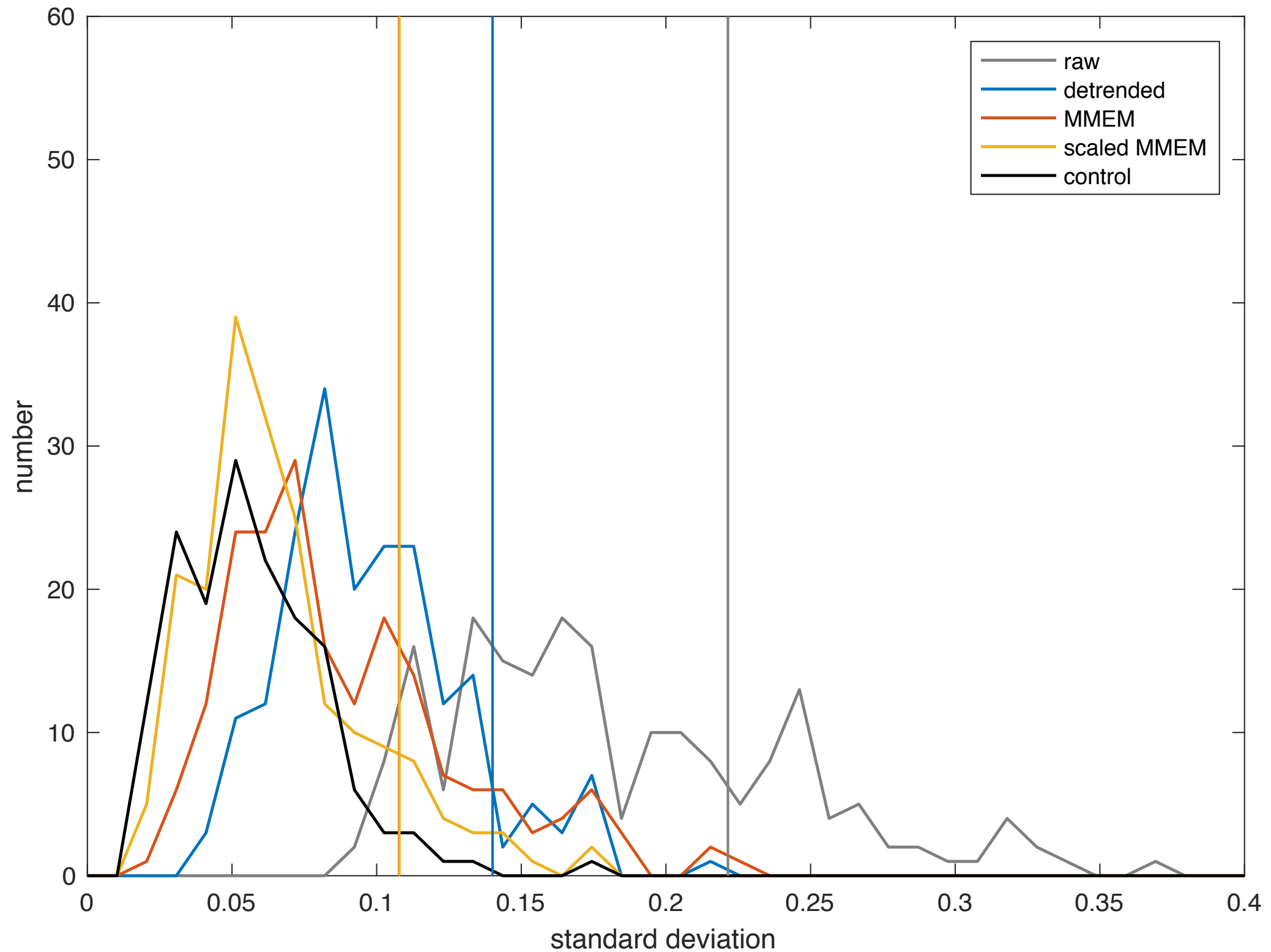
# Biases introduced by incorrect removal of forced signal

Removing CMIP5 ensemble mean

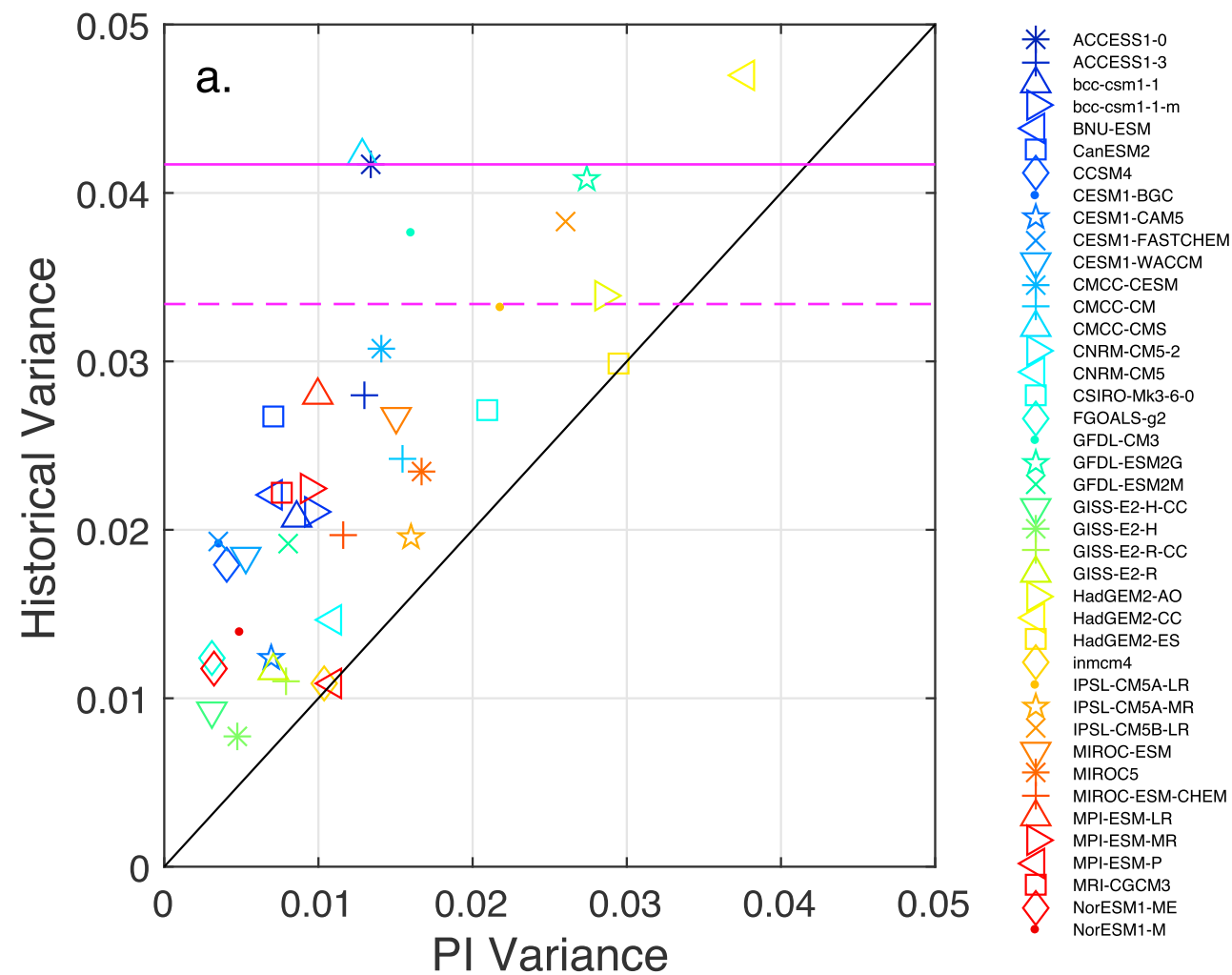




# Scaling the MMEM

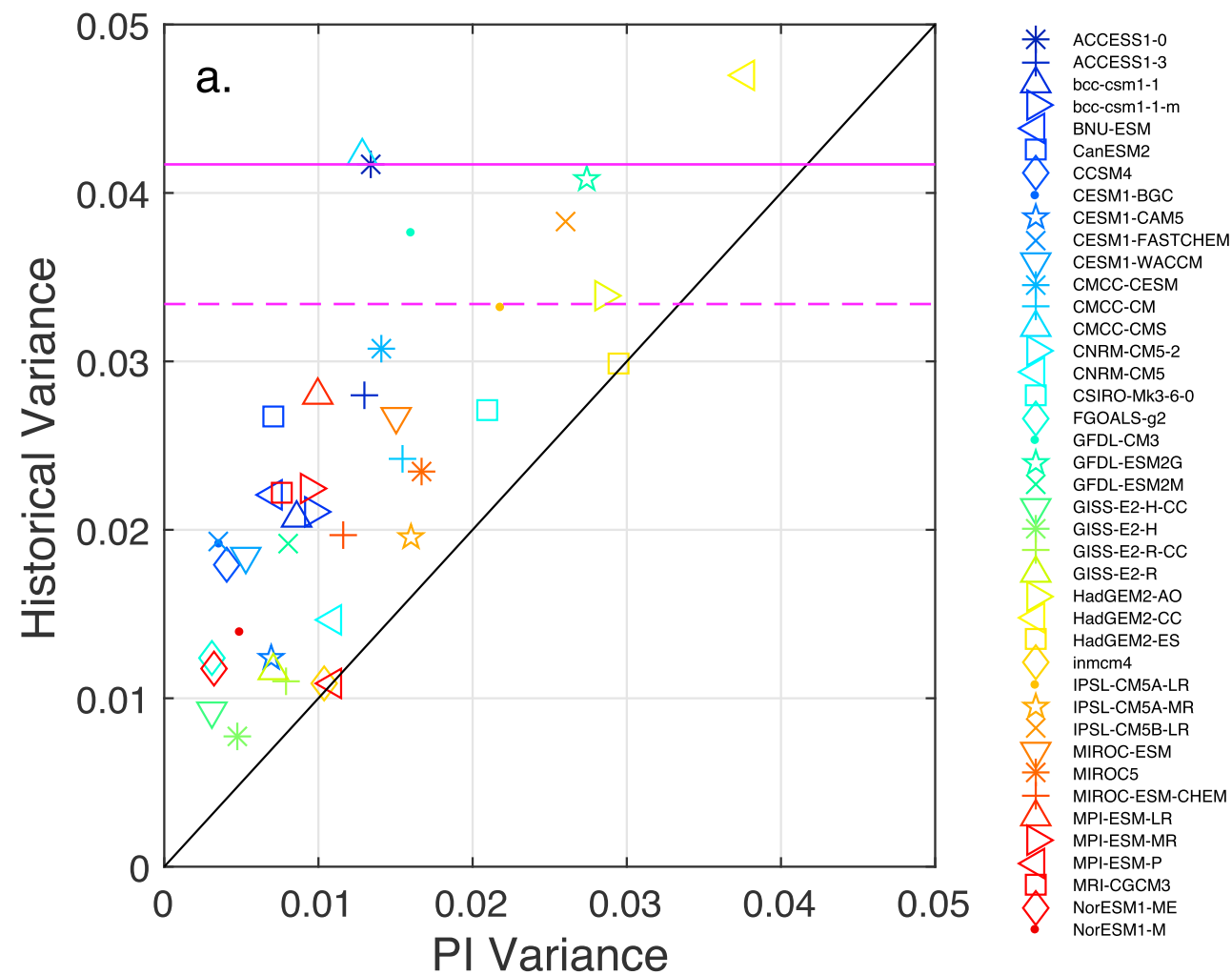


# What could possibly go wrong?

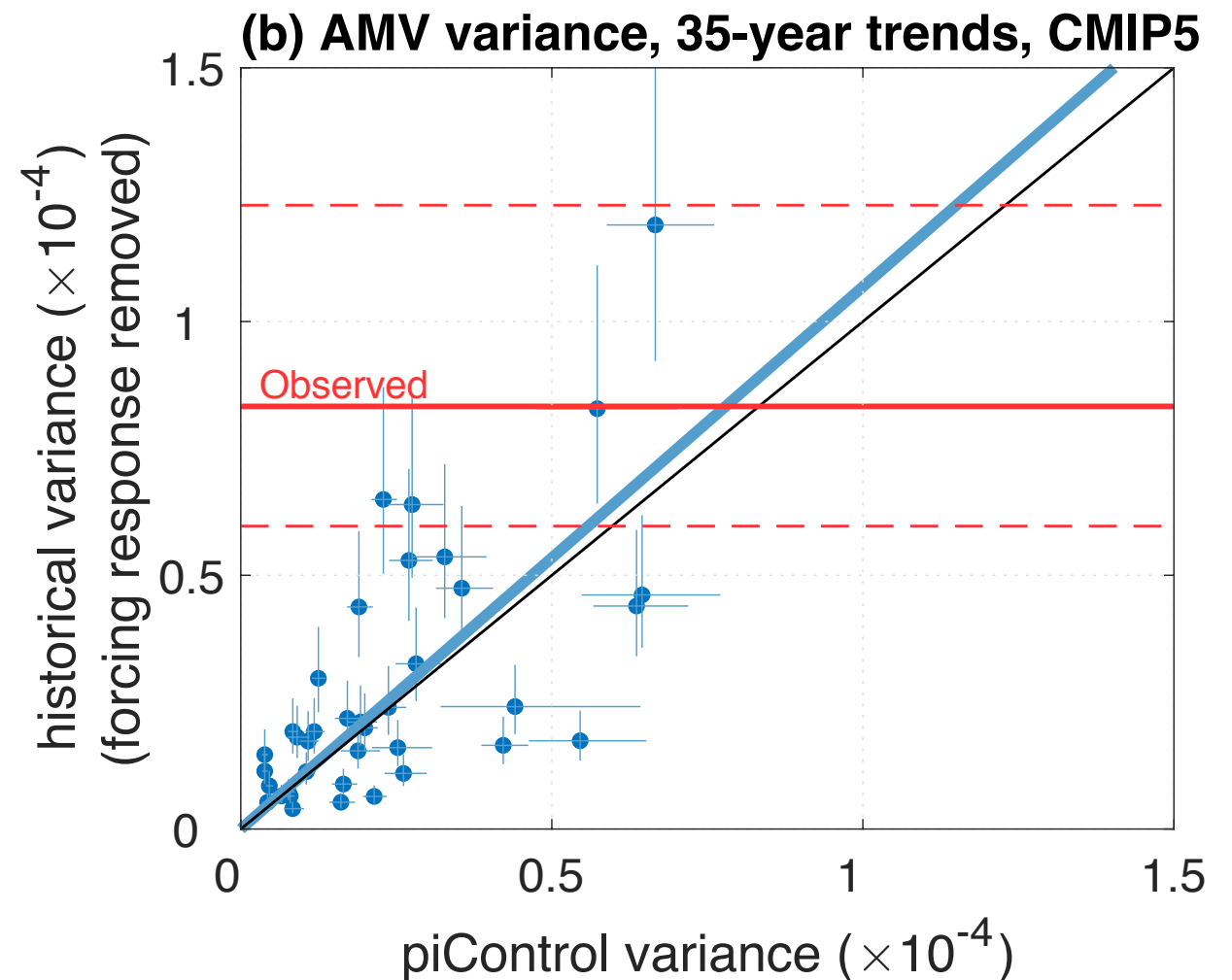


**Murphy et al., GRL, 2017**  
**(used linear detrending)**

# What could possibly go wrong?



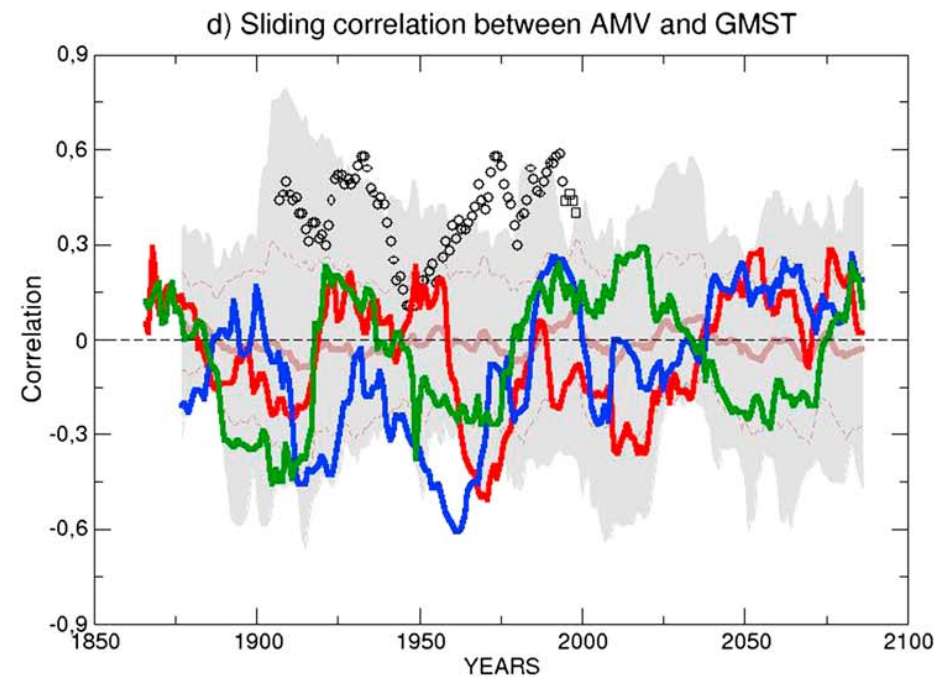
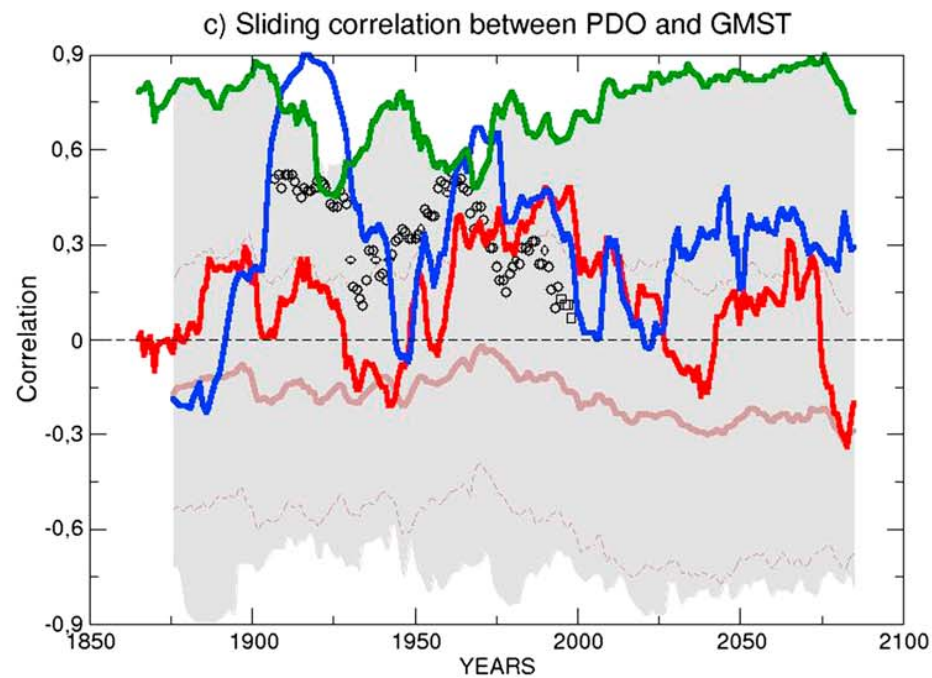
**Murphy et al., GRL, 2017**  
(used linear detrending)



**Kajtar et al., GRL, 2019**

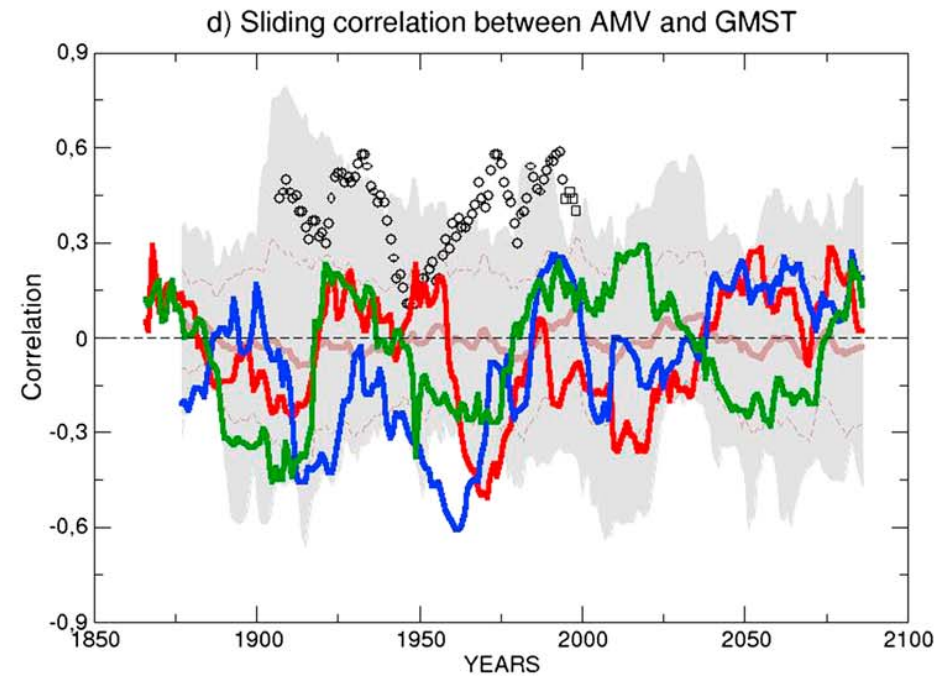
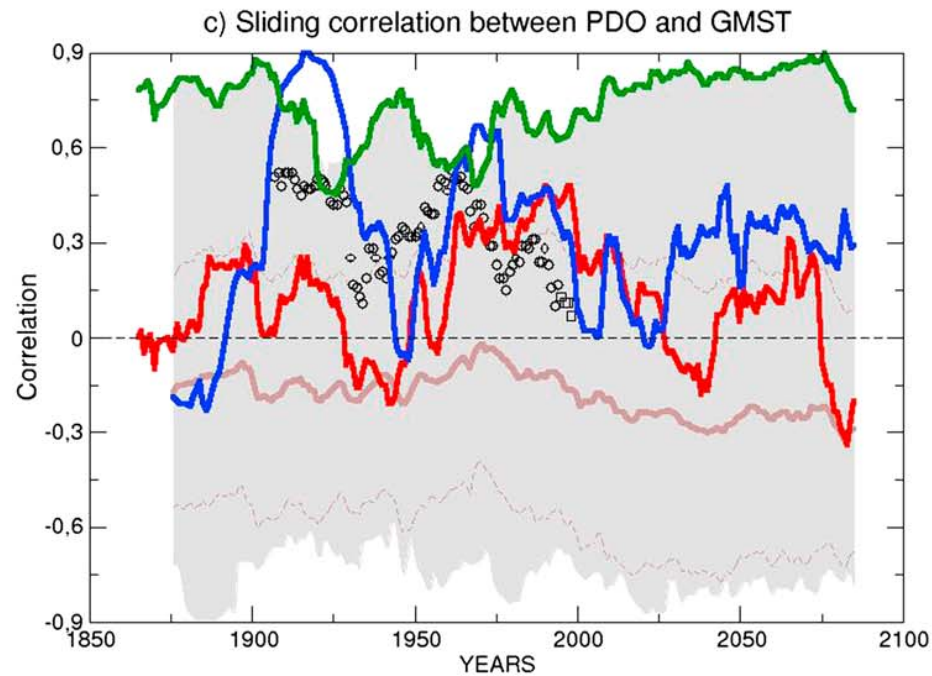


# What could possibly go wrong?

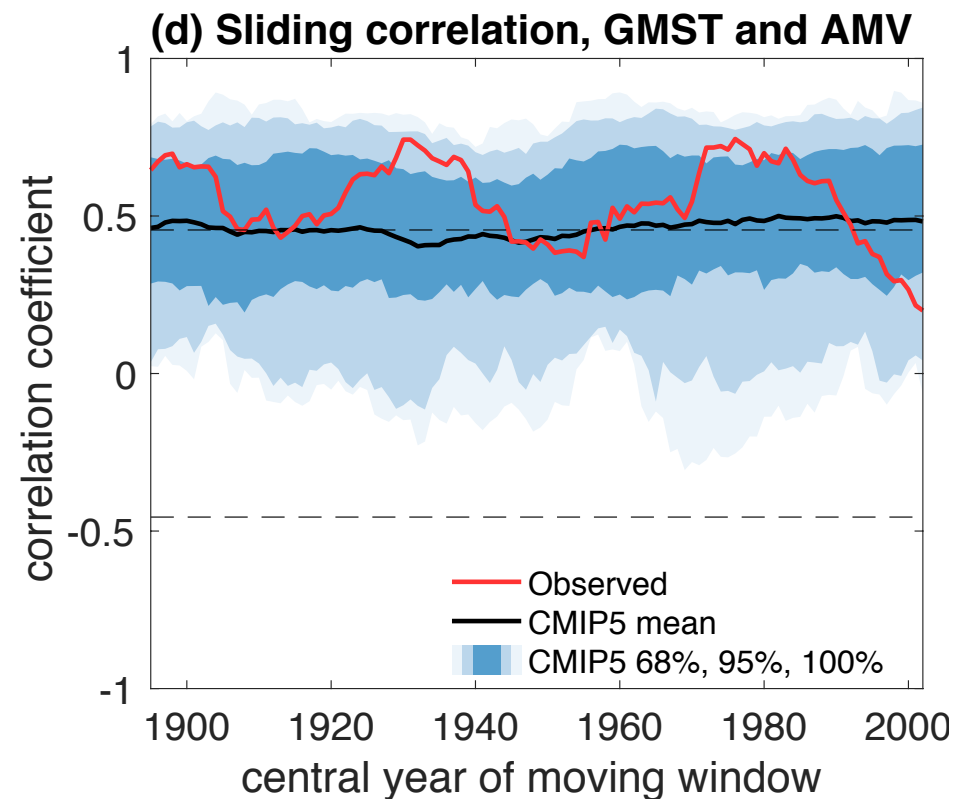
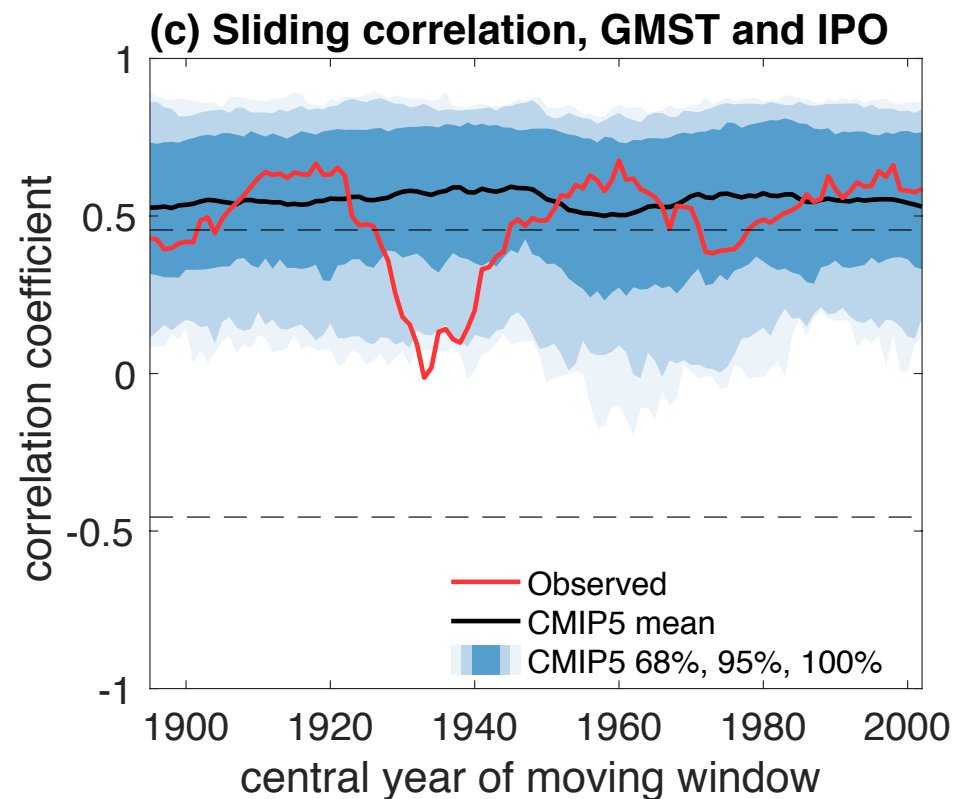


**Douville et al.,  
GRL, 2015  
(subtracted each  
ensemble members'  
global mean SST)**

# What could possibly go wrong?

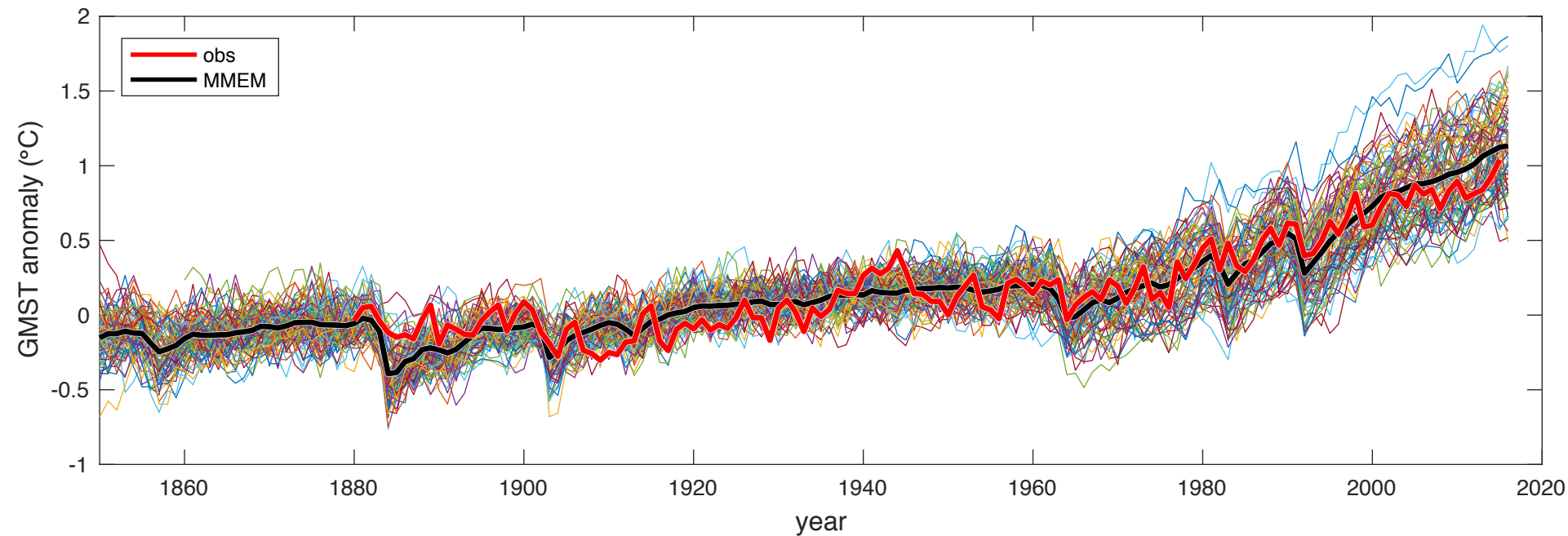


**Douville et al.,  
GRL, 2015**  
(subtracted each  
ensemble members'  
global mean SST)

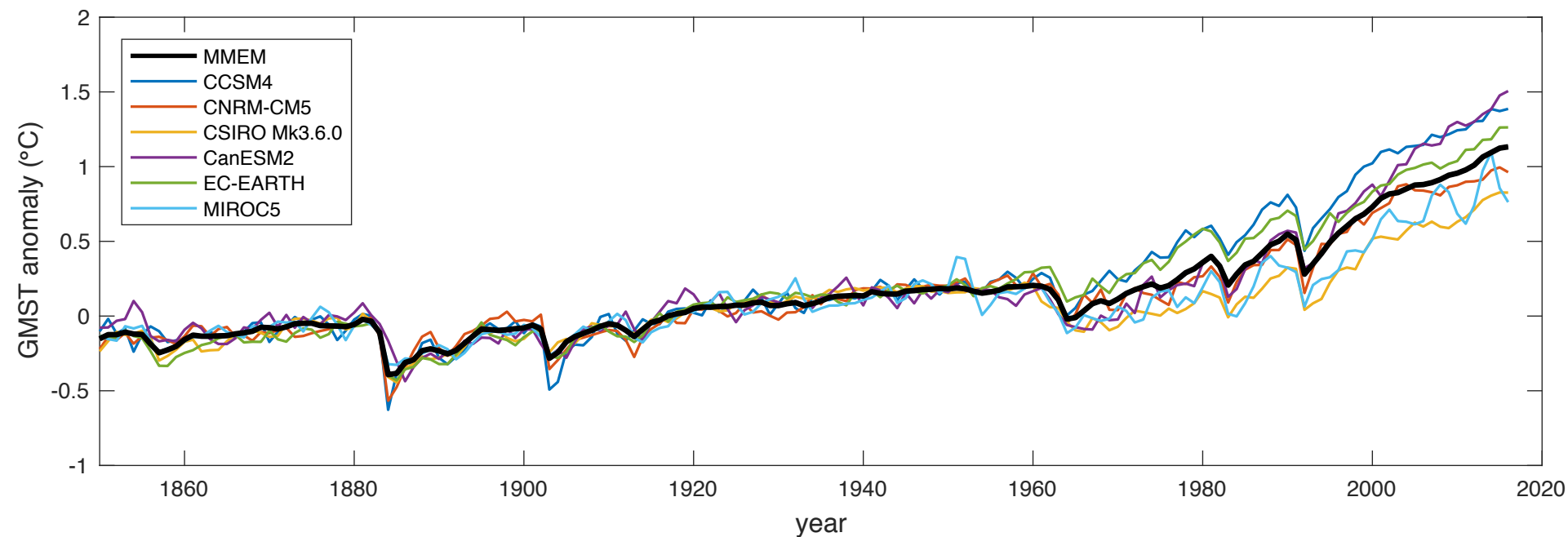


**Kajtar et al.,  
GRL, 2019**

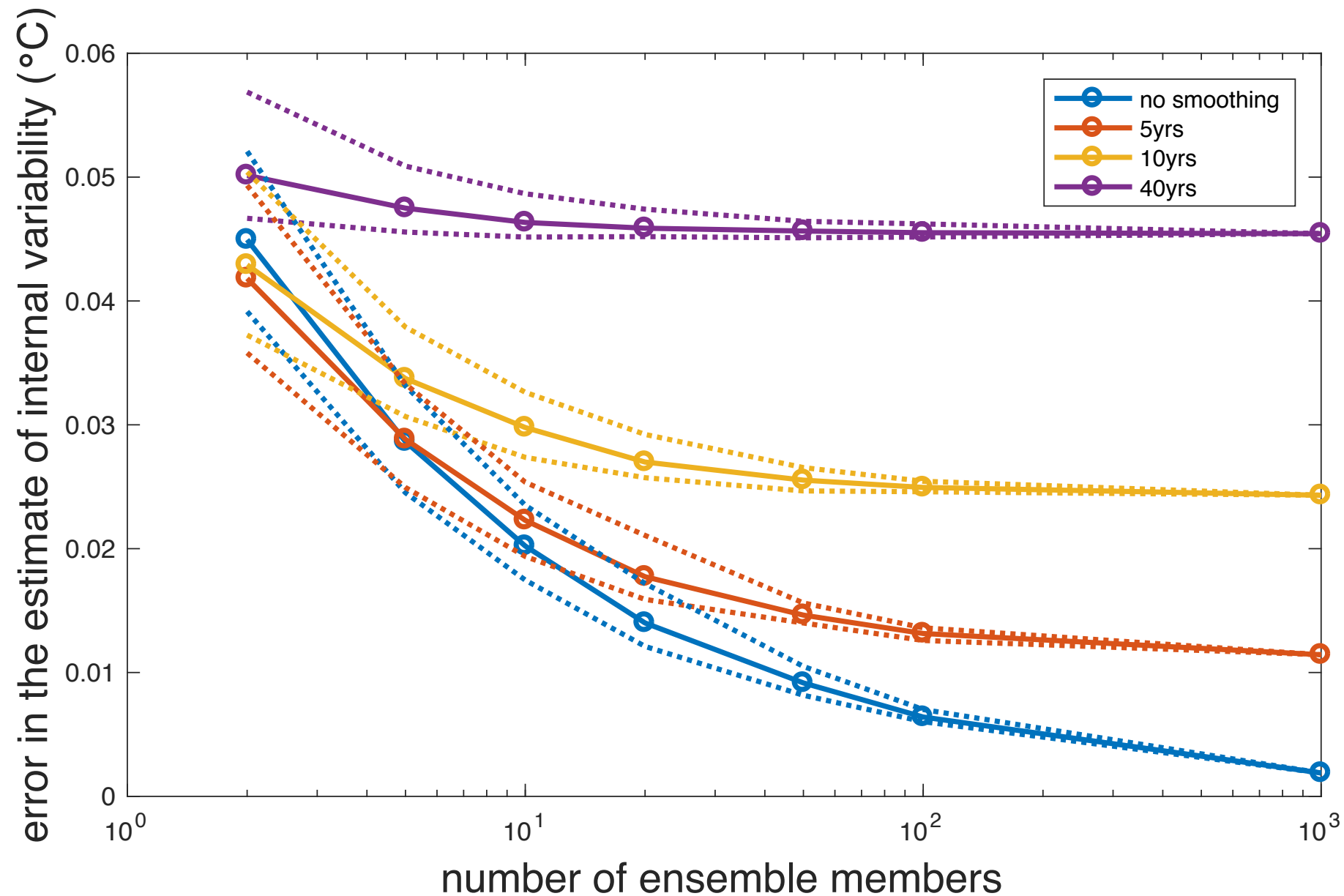
# Using single model ensemble means



- How many ensemble members are required?

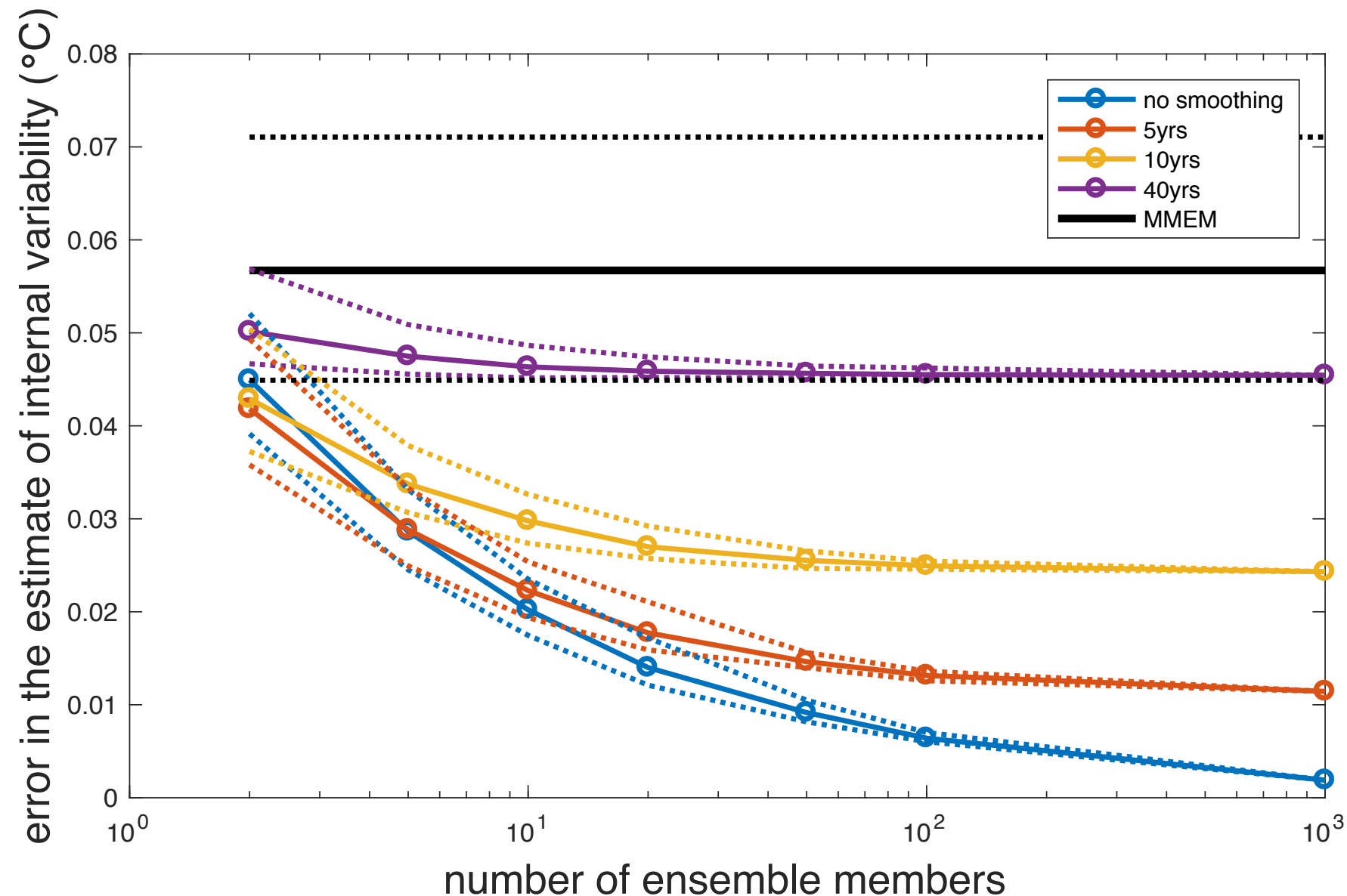


# How many ensemble members?



- Smoothing the ensemble mean is ineffective

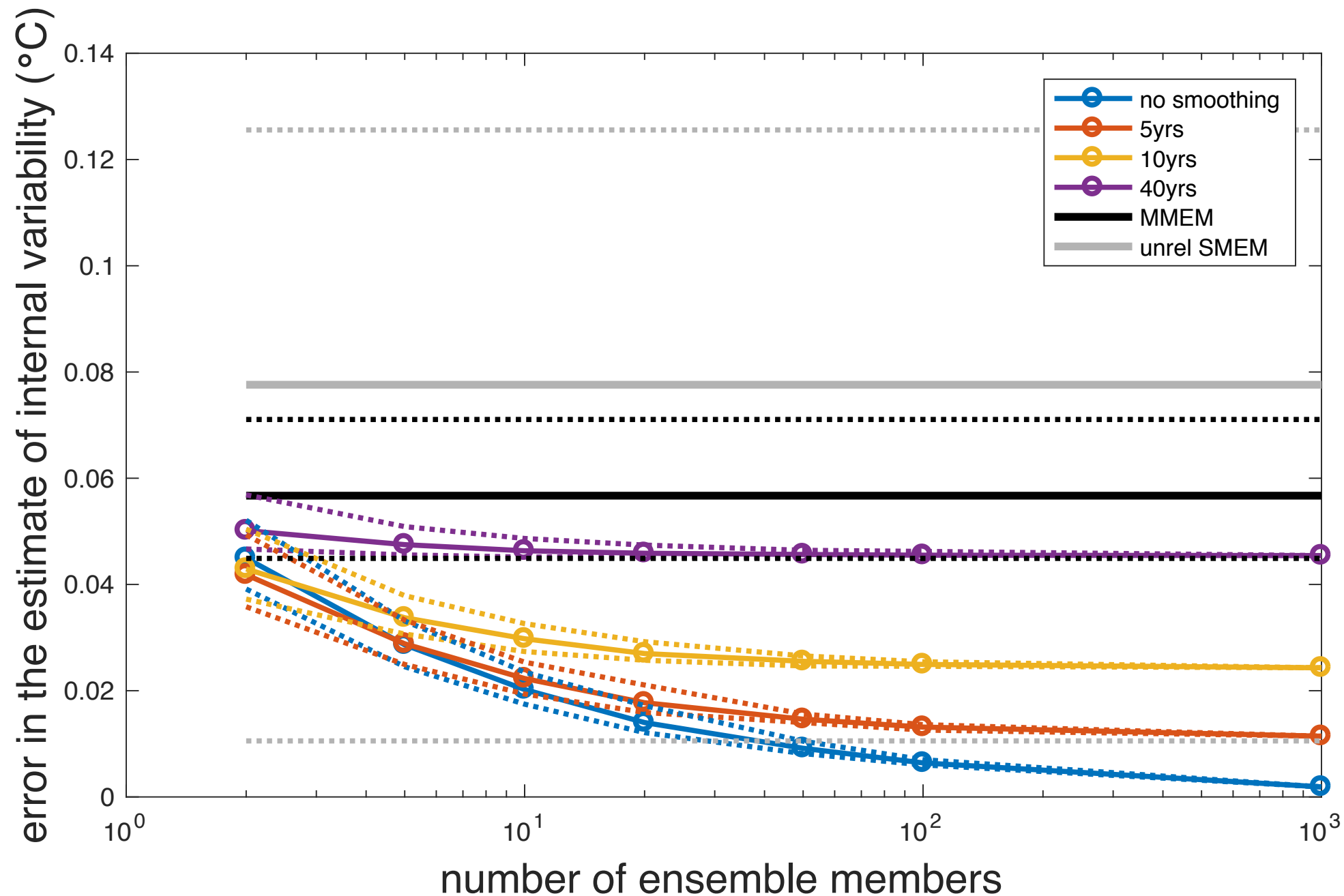
# How many ensemble members?



- Even two ensemble members can be more accurate than using the multi-model ensemble mean



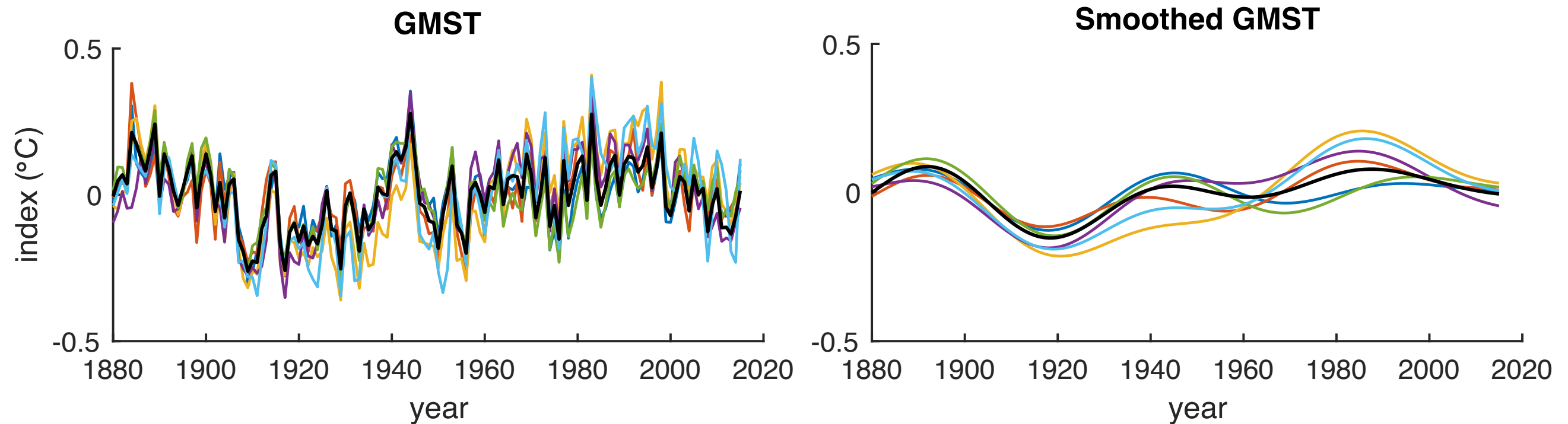
# How many ensemble members?



- Using the MMEM is better than using the wrong SMEM



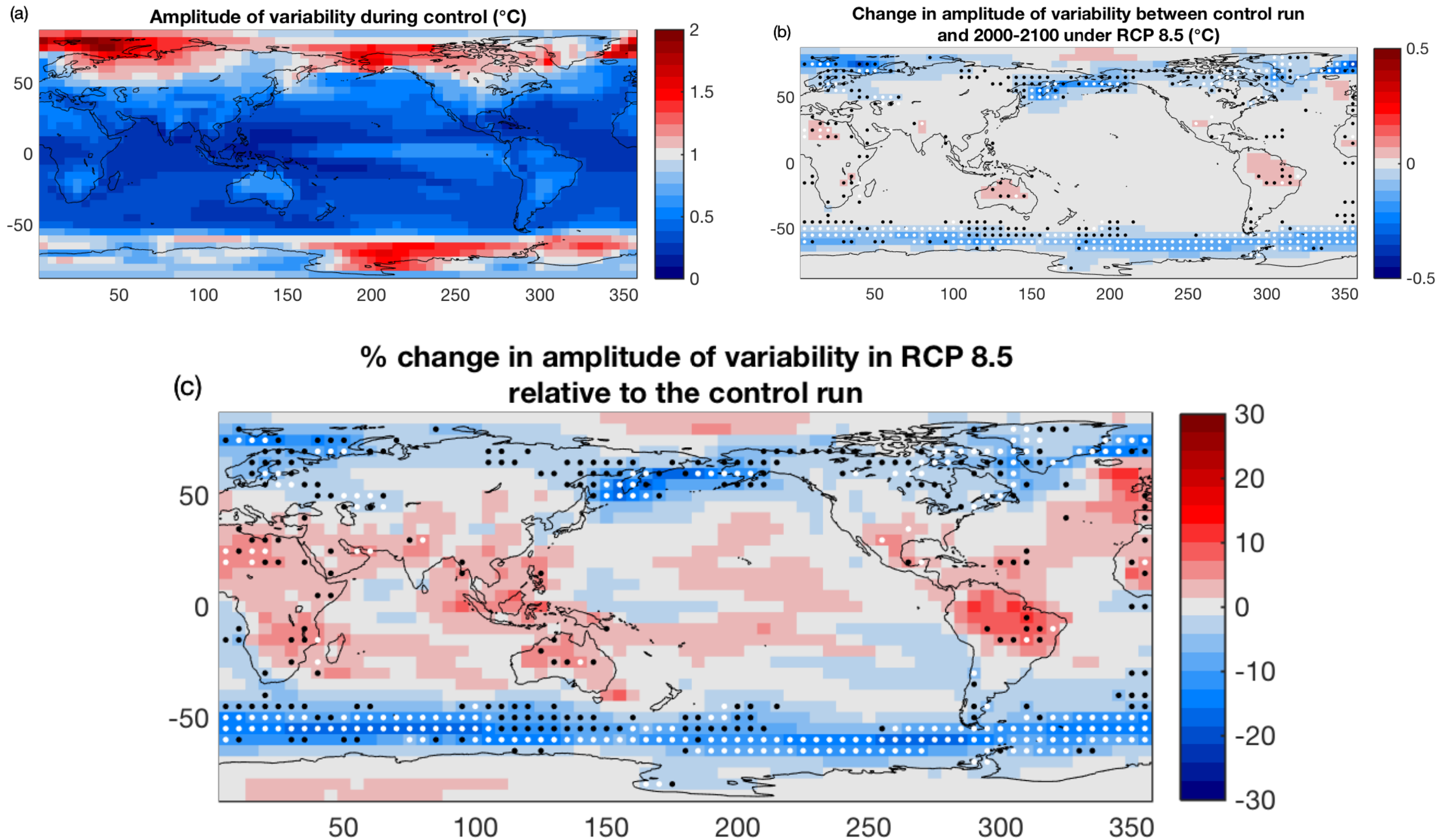
# Multiple estimates of internal variability from observations



# Conclusions so far...

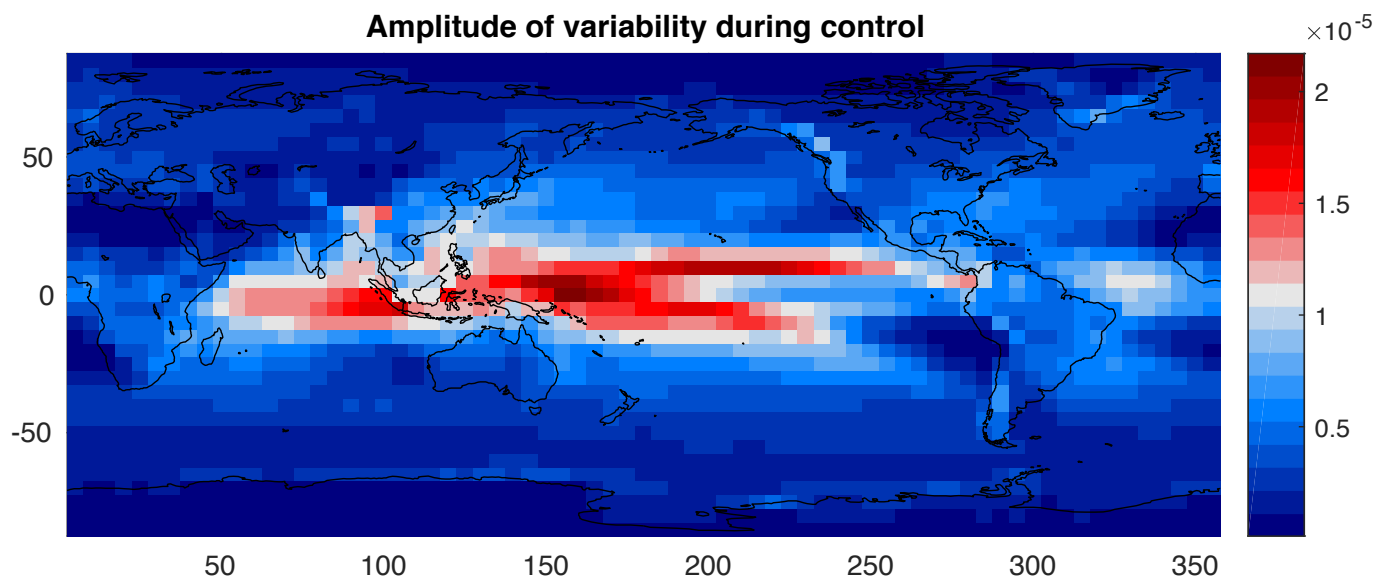
- Using an unsuitable method to remove the forced trend can result in large biases in estimates of internal variability.
- Useful single model ensemble means can be constructed with surprisingly few ensemble members.
- The (scaled) multi-model ensemble mean is still the best estimate for observations.
- **What about spatial patterns of variability?**

# SAT

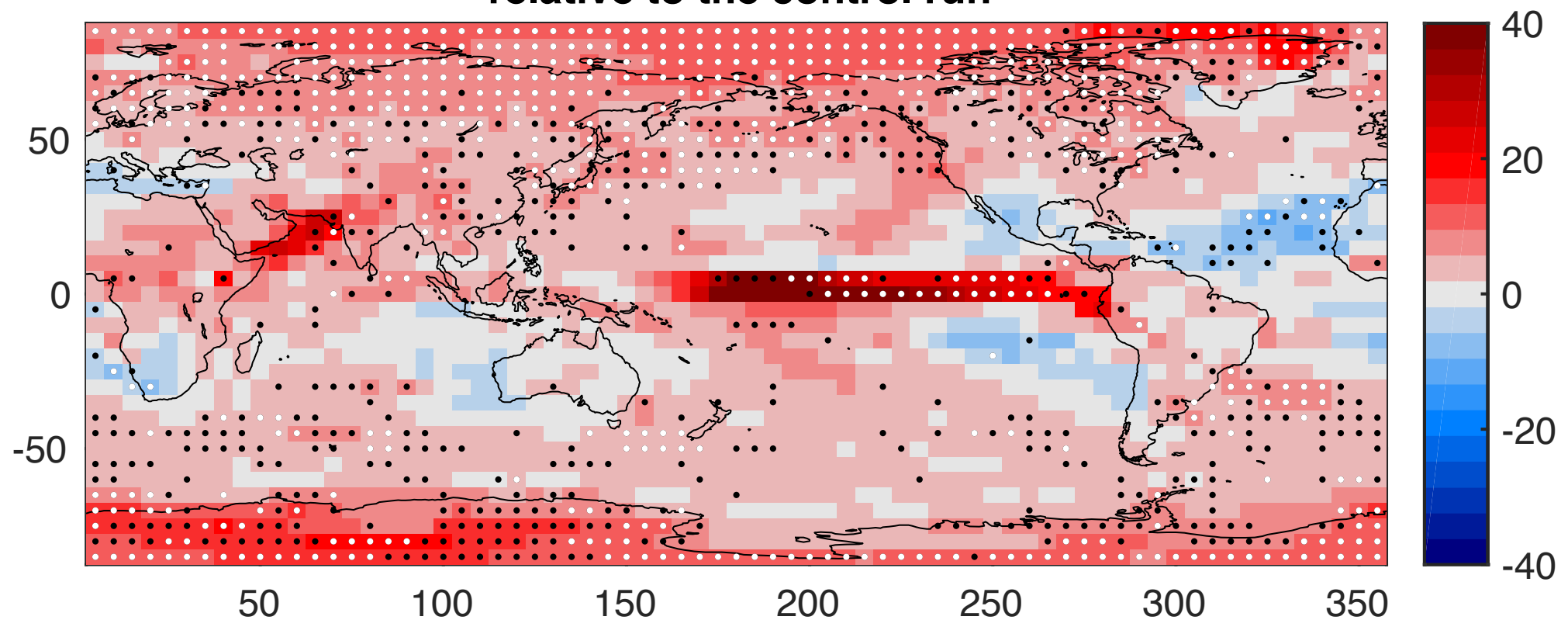


# Precipitation

Amplitude of variability during control

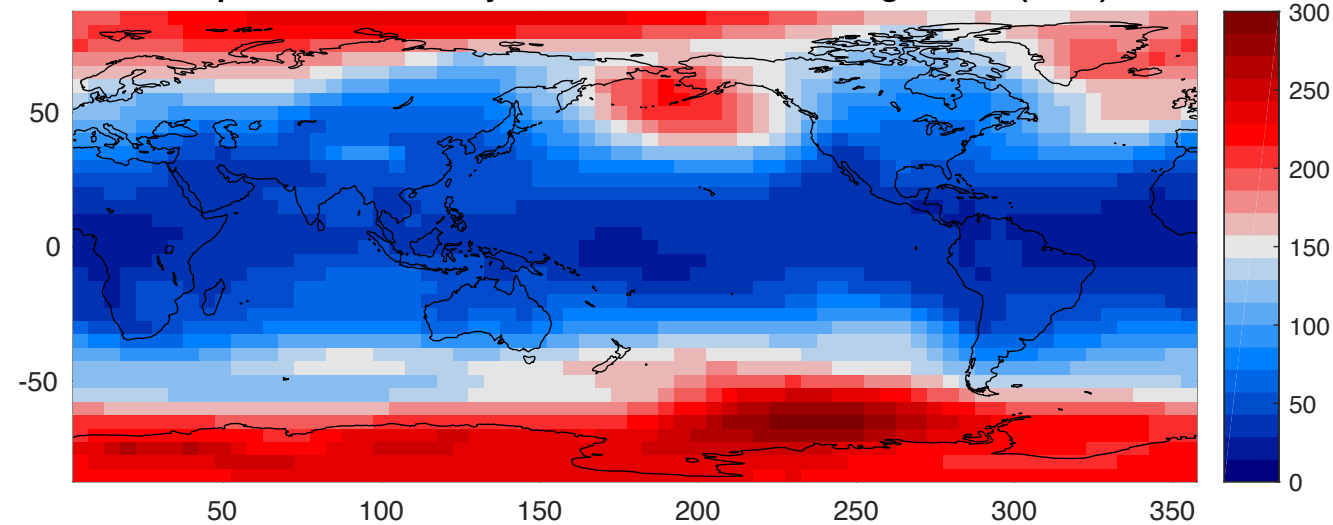


% change in amplitude of variability in RCP 8.5  
relative to the control run



# SLP

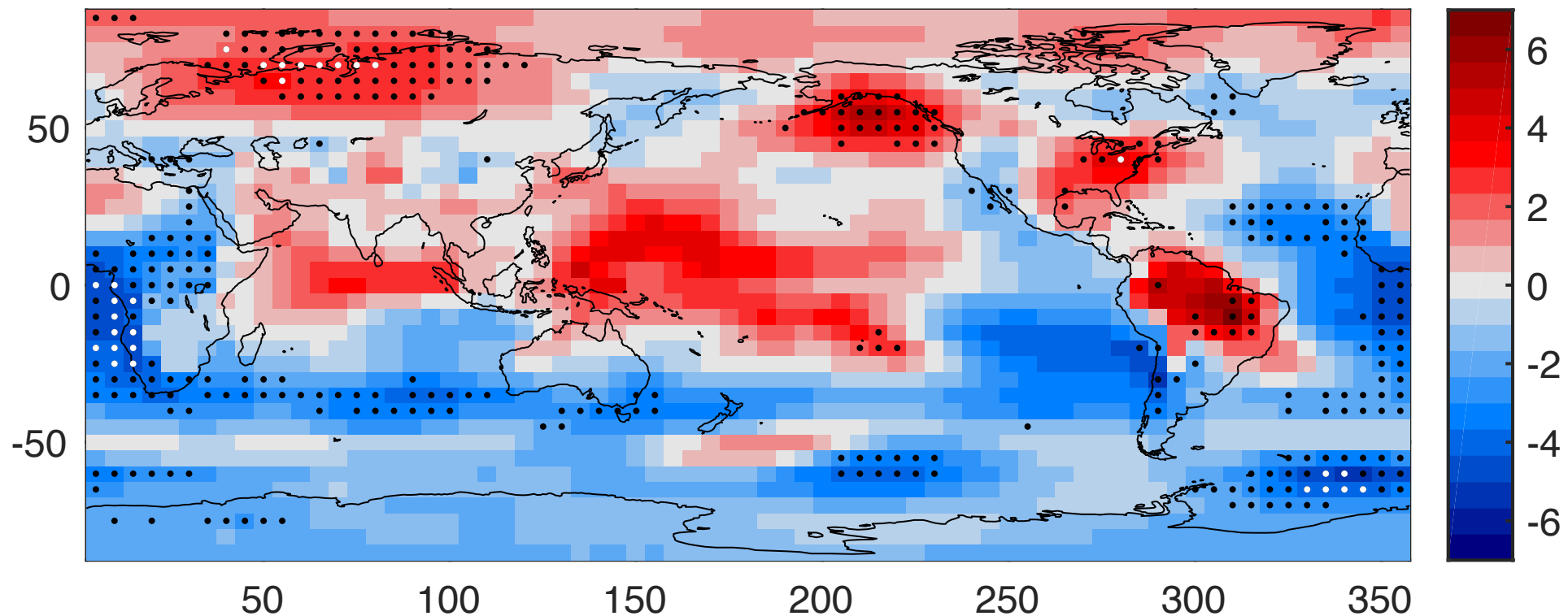
Amplitude of variability of annual mean SLP during control (in Pa)



Barnes and Polvani (2013):

- Jet variability is a function of jet latitude, with jets closer to the equator exhibiting more meridional shifting.
- In the SH and NA, jets shift poleward in future climates.
- Opposite in the NP.

**% change in amplitude of variability of annual mean SLP  
in RCP 8.5 relative to the control run**

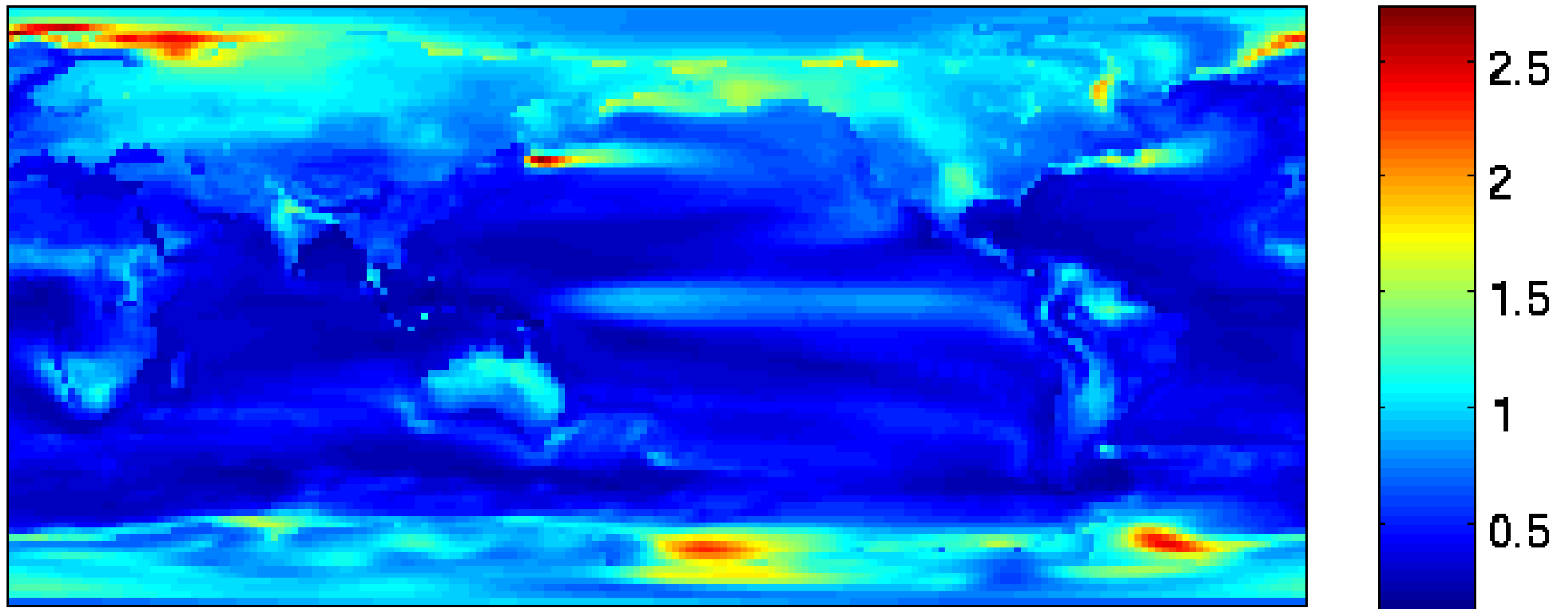


# Changing spatial variability

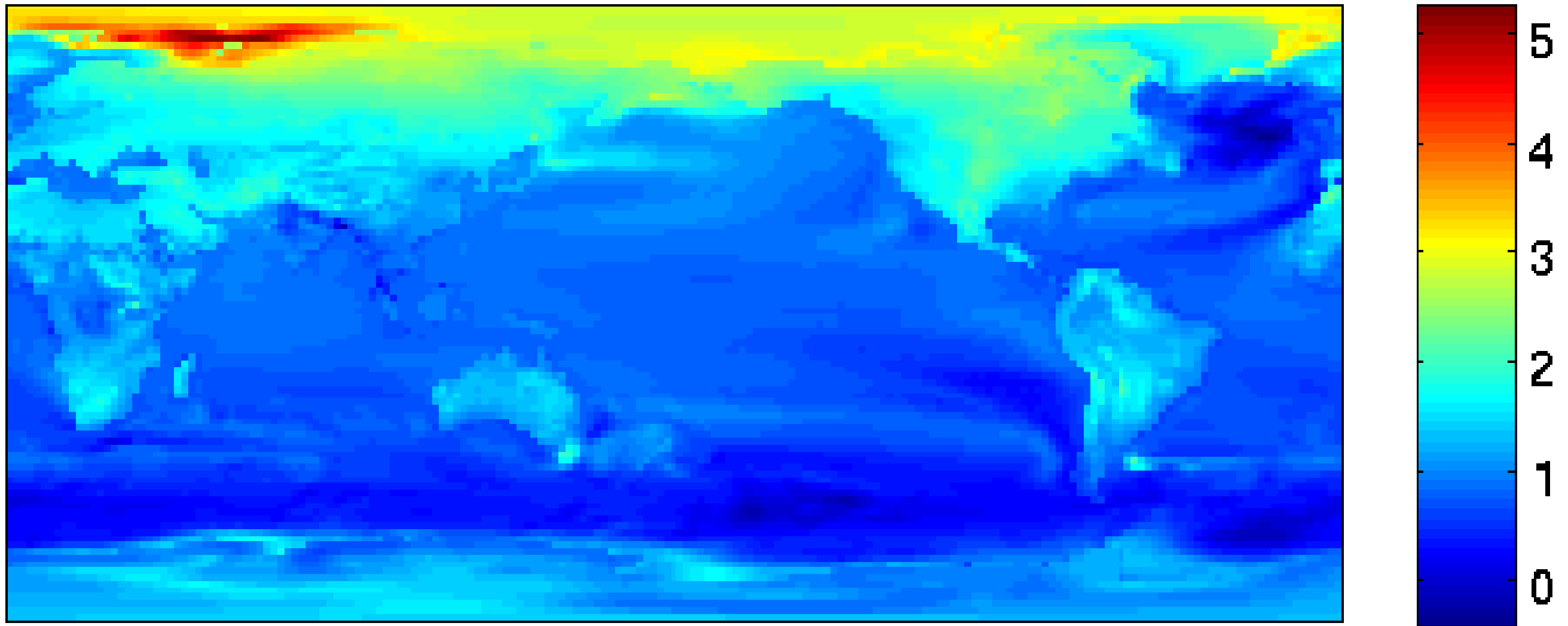
- Internal variability of SAT is projected to decrease along sea ice edges and increase over land at low latitudes.
- Variability of precipitation will increase, particularly at high latitudes.
- SLP variability is projected to decrease in the Southern Hemisphere and the North Atlantic and increase in the North Pacific.
- **Can we learn anything from comparing local and global responses?**



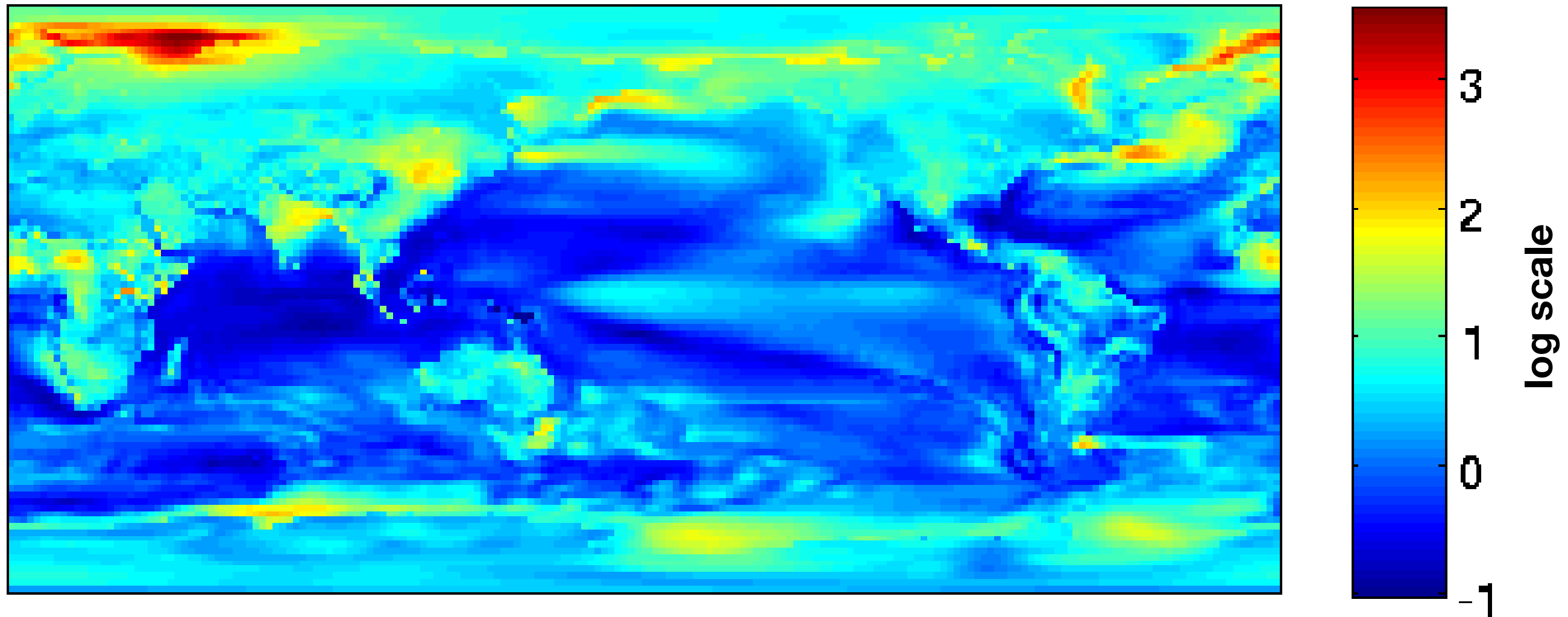
# Amplitude of variability



# Spatial variation of scaling coefficient

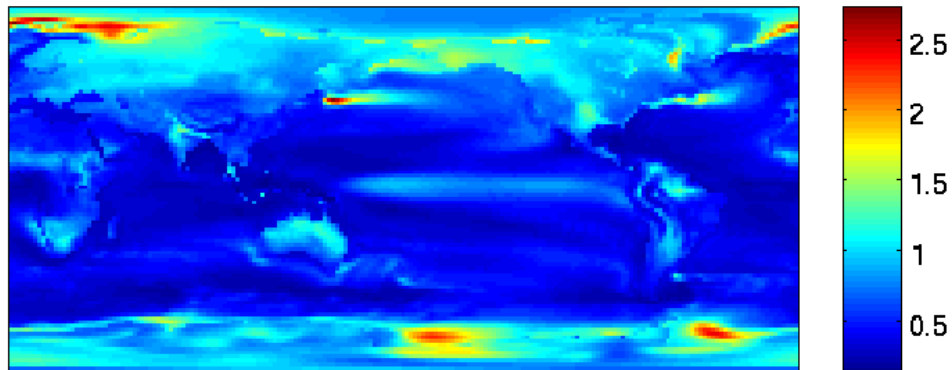


# Error in local estimate of forced signal

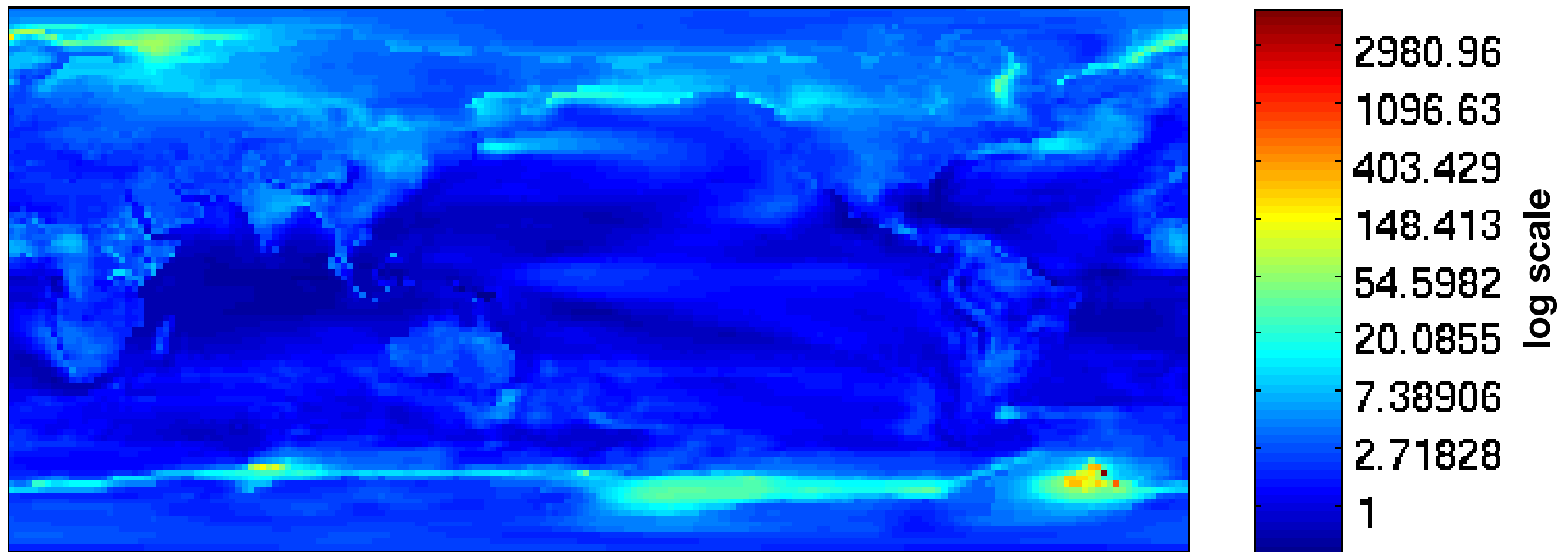


# Error in estimate of variability

Amplitude



Error



# Conclusions

- Using an unsuitable method to remove the forced trend can result in large biases in estimates of internal variability.
- Useful single model ensemble means can be constructed with surprisingly few ensemble members.
- The (scaled) multi-model ensemble mean is still the best estimate for observations.
- We can make predictions about future changes in variability, but only using models with a sufficient number of ensemble members.
- There are regions where the local forced signal differs considerably from the global mean (work in progress...).

# References

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