University of Colorado
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The Signal-to-Noise Error in Decadal Climate Modes

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Confronting Earth System Model Trends with Observations: The Good, the Bad, and the Ugly

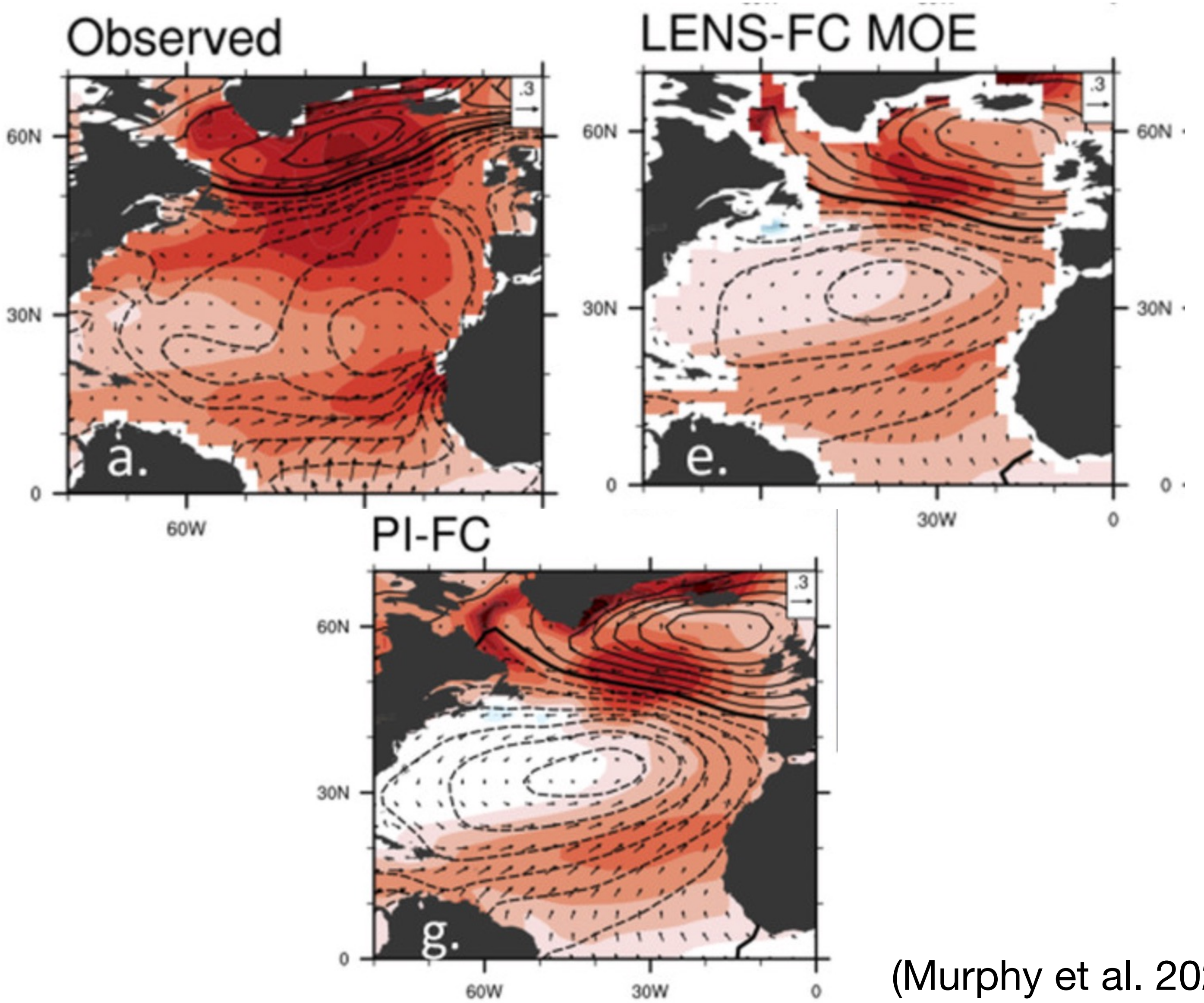
March 14, 2024

Outline

1. What are models doing well?
   - Models produce multidecadal modes with reasonably realistic spatial patterns and impacts
2. Where can models improve?
   - Observed variance is an outlier, relative to model ensemble spread
   - This is an error, caused by a S/N ratio that is too low in models
3. How can the S/N ratio be improved? What could rectifying this error teach us?
   - Potential sources of the S/N error
   - Implications of the S/N error

Models simulate internal patterns of variability

- Models produce multidecadal modes with reasonably realistic spatial patterns and impacts
  - **AMV**
  - NAO
  - PDO
- These internal modes produce have impacts similar to observations
  - MDR VWS; Sahel precipitation
  - Euro. Precipitation
  - SW US Precipitation



(Murphy et al. 2021)

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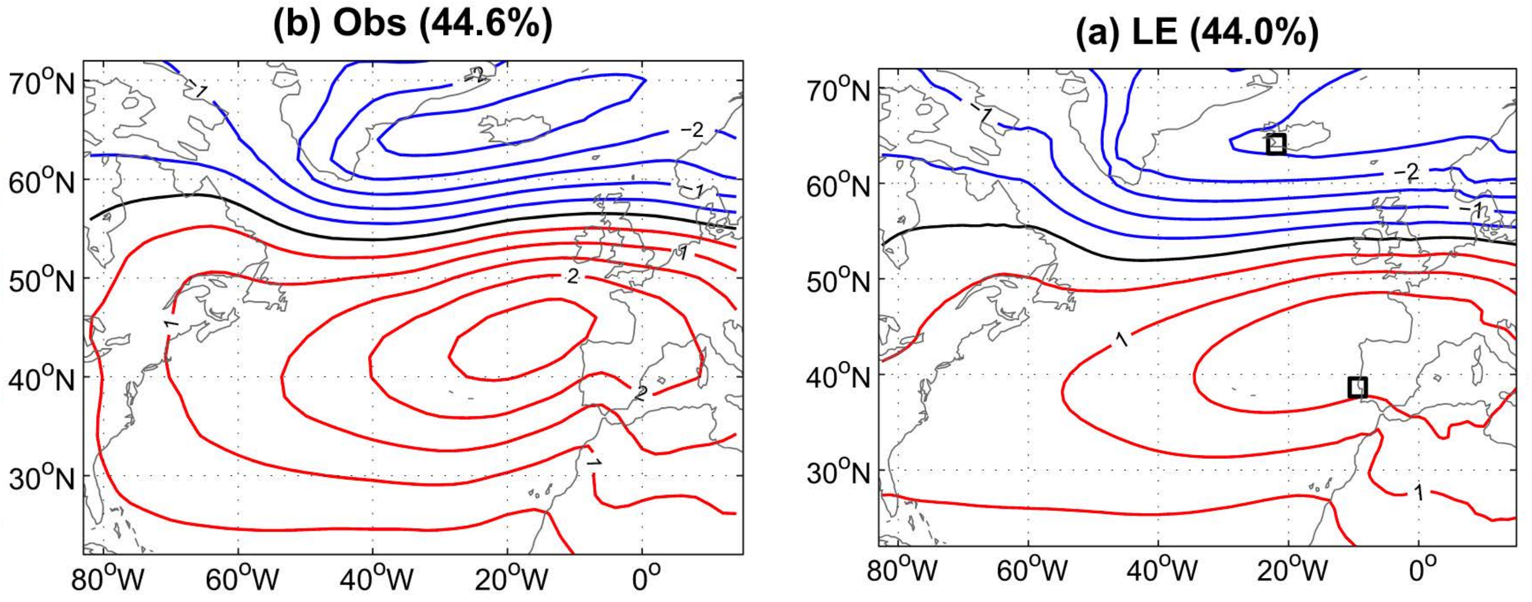

(Kim et al. 2018)

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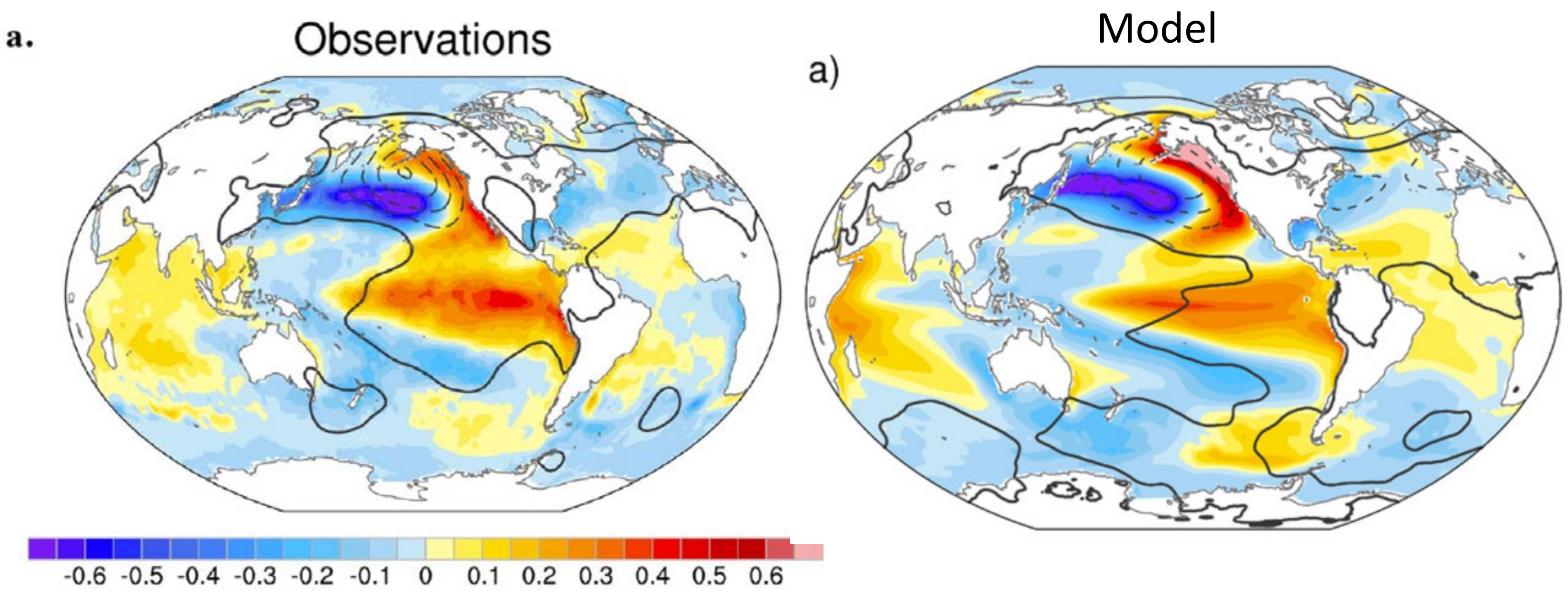

(Newman et al. 2016)

Models underestimate the amplitude of variability

- Observed decadal variances are consistently on the edge/outside of ensemble spread
- If independent, this is an unlikely result
- Examples:
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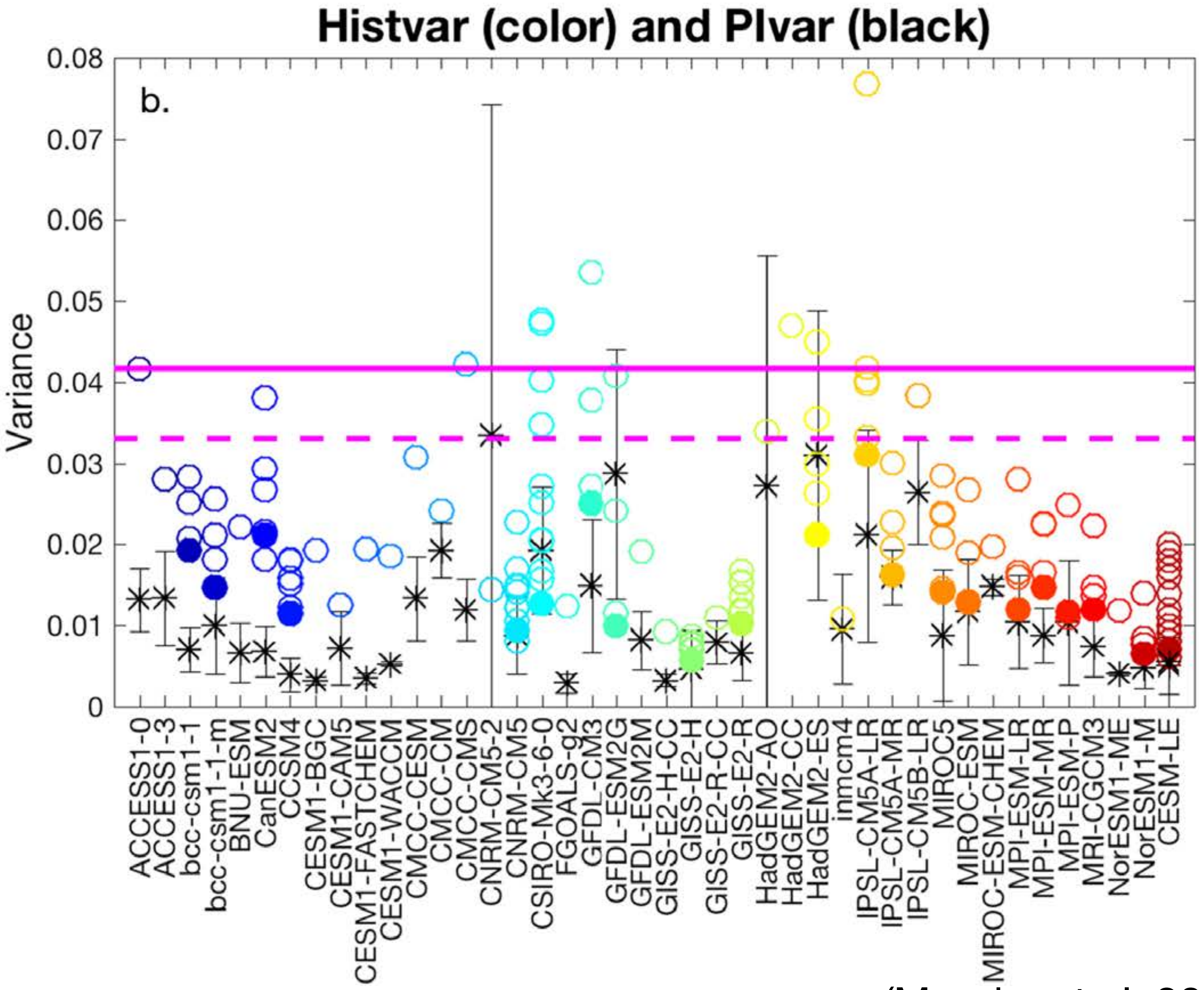
  - Sahel precipitation
  - Atlantic vertical wind shear
  - NAO/N. Euro. precip.
  - Western US precipitation



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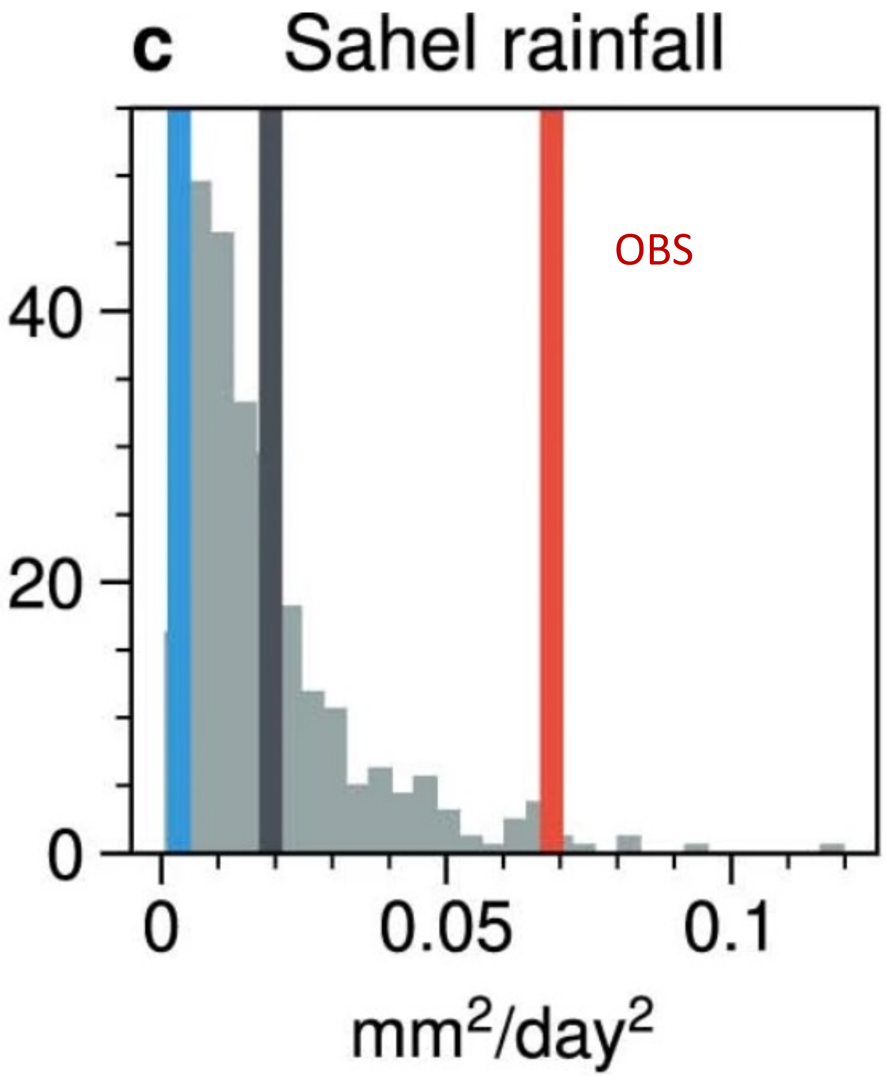

(He et al. 2023)

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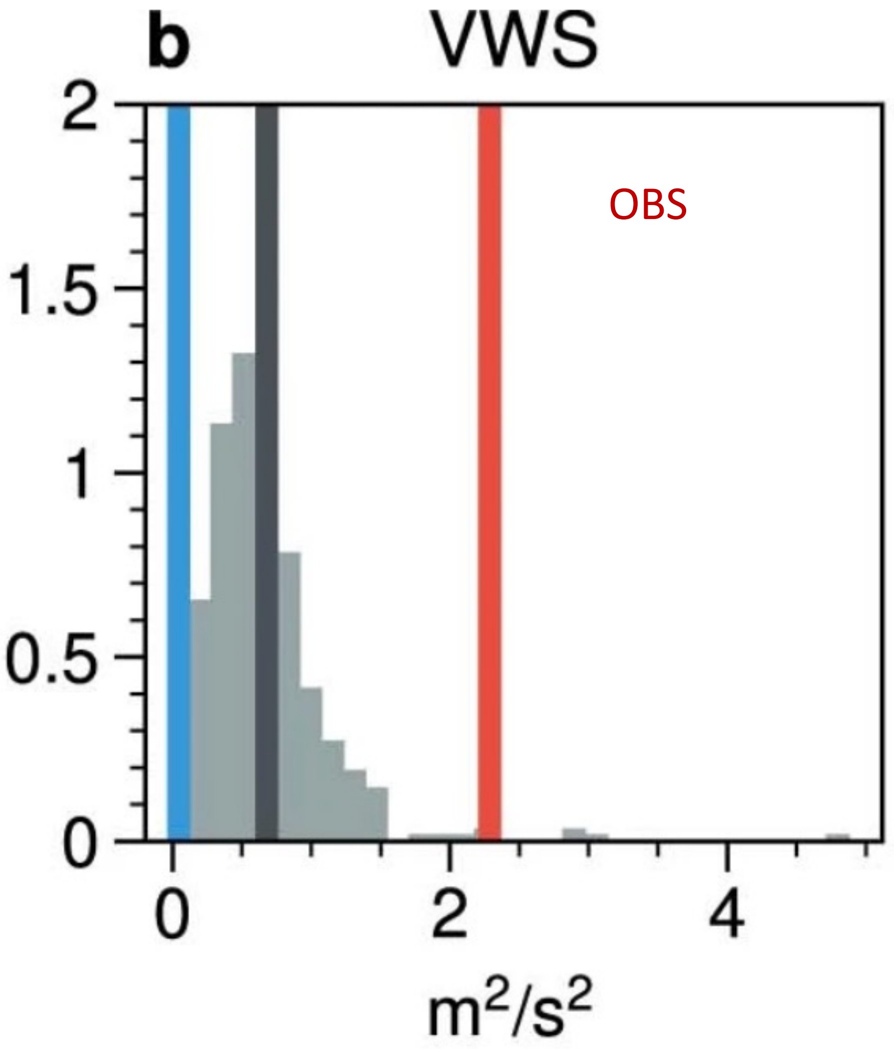

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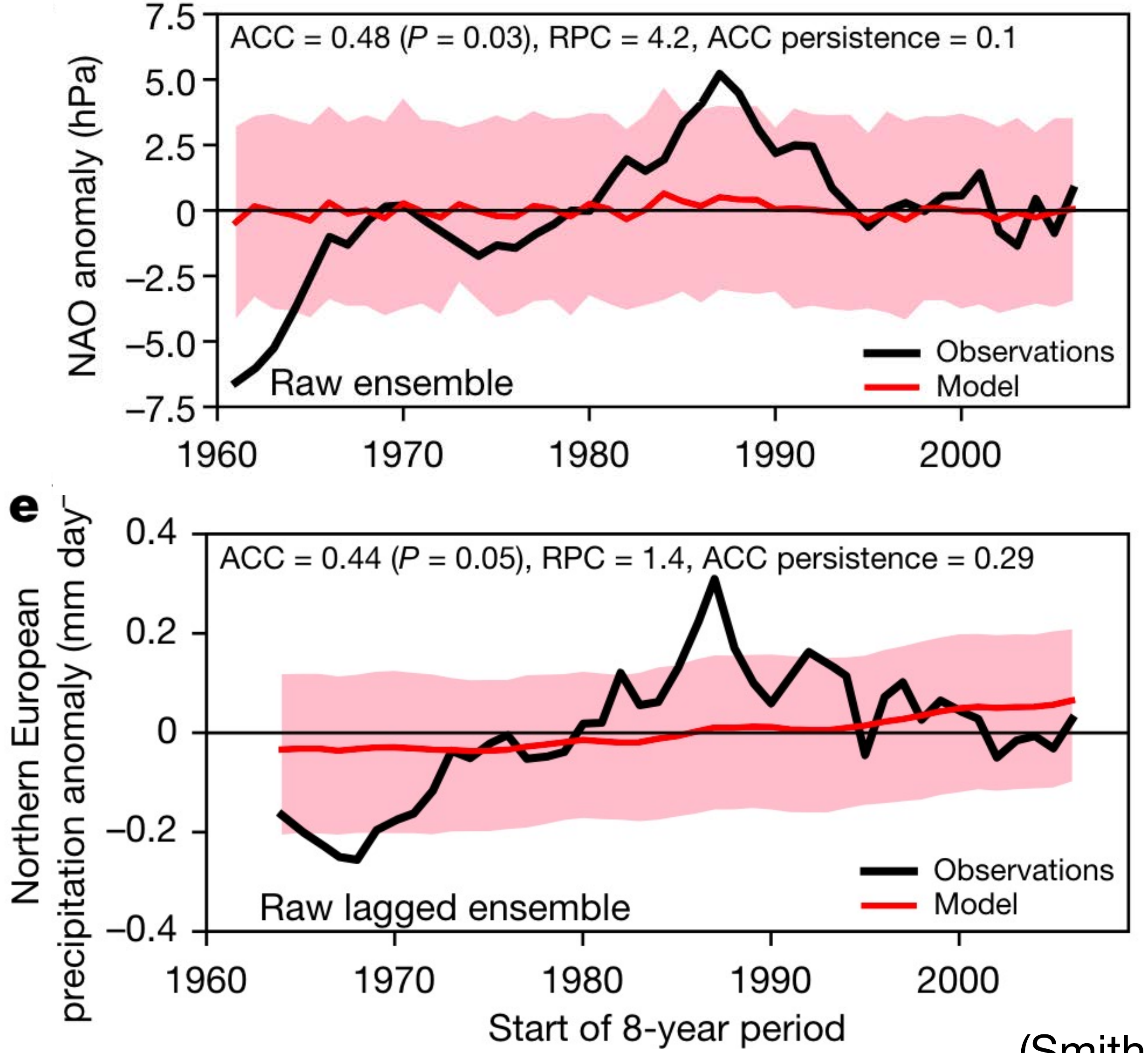

(Smith et al. 2020)

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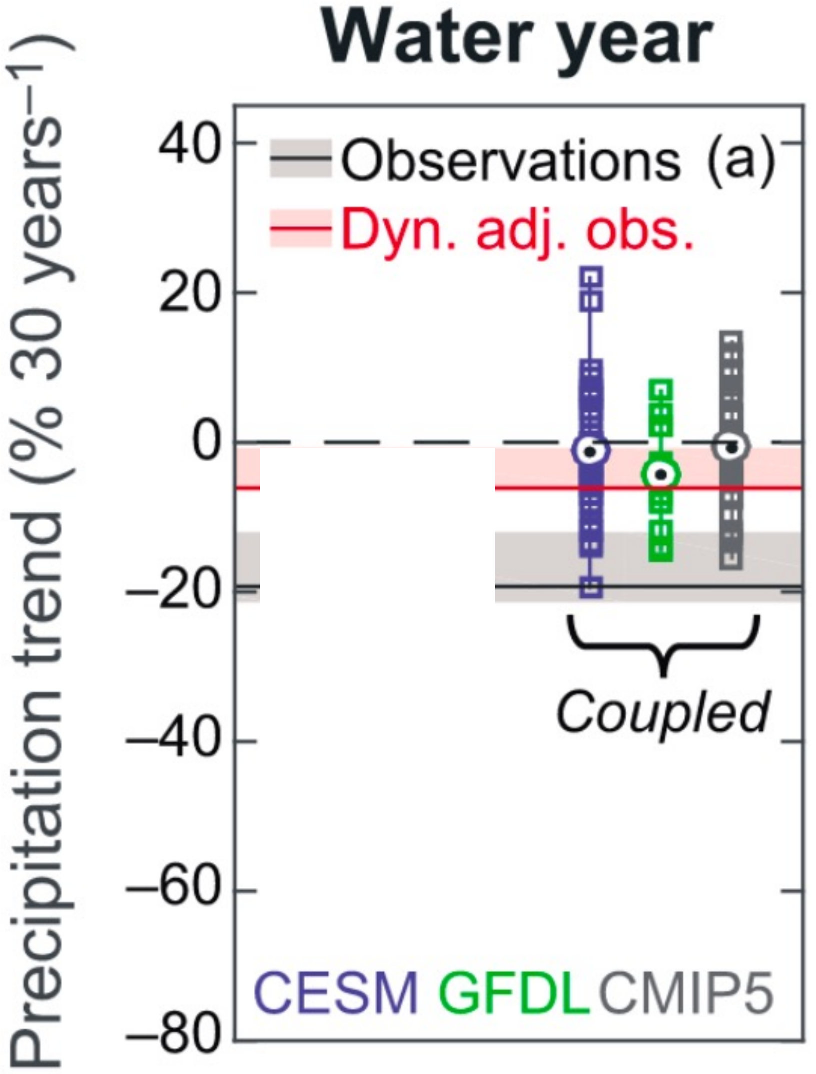


(Lehner et al. 2018)

Large ensembles of climate models

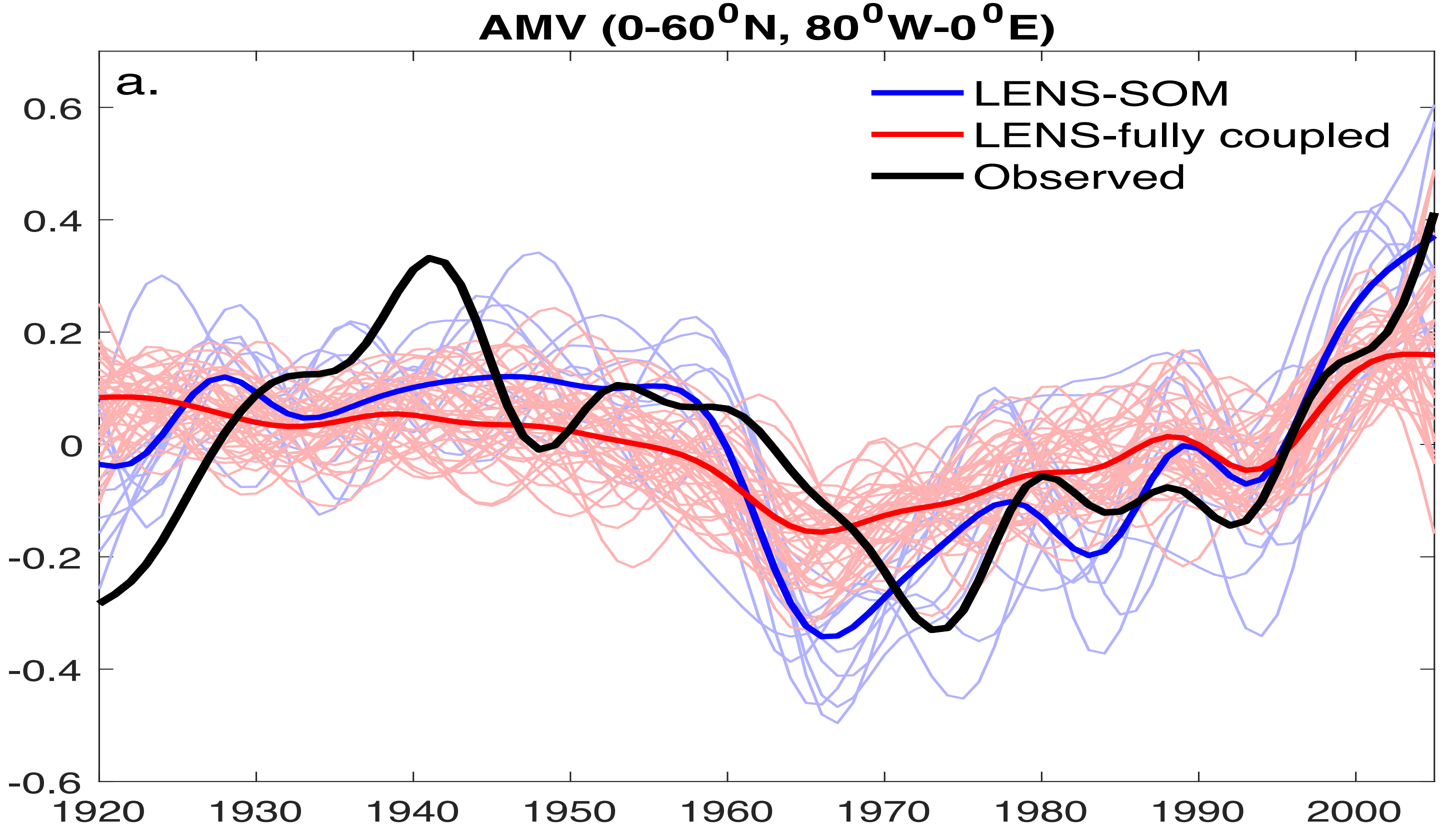
- Either we live at the edge of many pseudo-independent distributions OR there is a problem with models
- If there is a problem in models, either:

  1. Models underestimate interval variability (ensemble spread is too small)
  2. Models underestimate the response to external forcing (ensemble mean too weak)

- Use large ensembles of climate models to evaluate these possibilities

Ensemble means highly correlated with obs.

- Ensemble mean indices are surprisingly highly correlated with observations
  - **AMV ($R^2 \approx 0.75$)**
  - NAO ($R^2 \approx 0.60$)
  - PDO ($R^2 \approx 0.50$)
  - Still a role for internal variability!
- And these high correlations are unlikely from internal variability alone



(Murphy et al. 2021)

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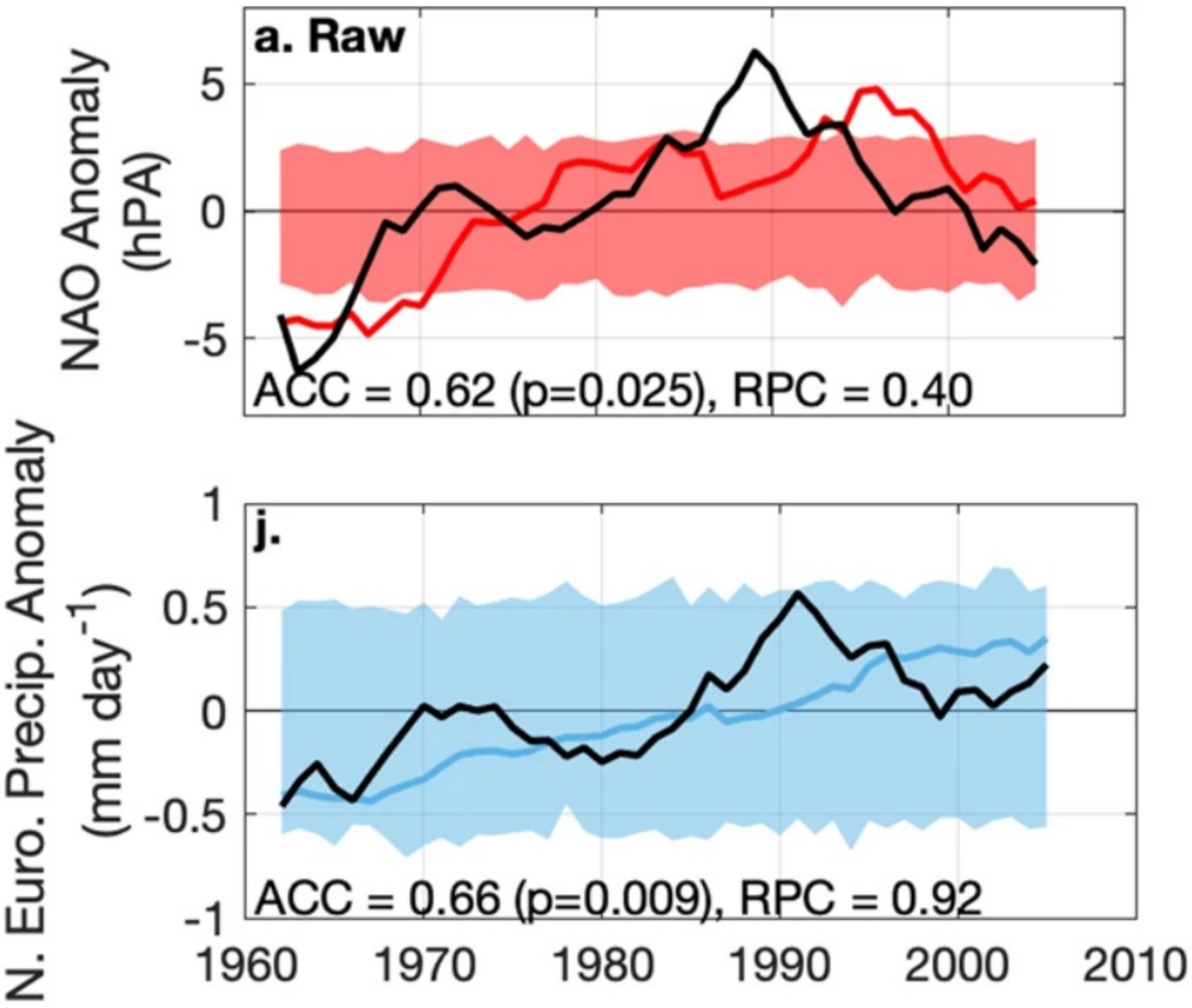

(Klavans et al. 2021)

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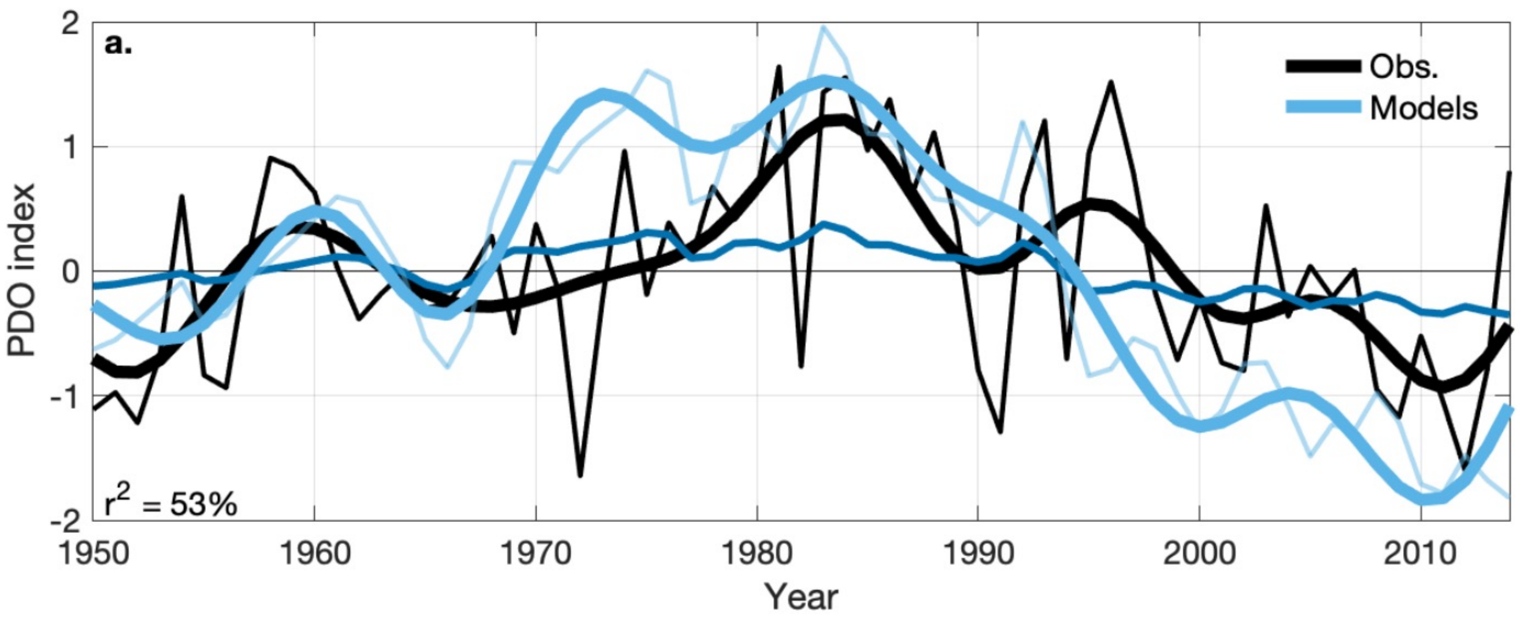

(Klavans et al. *In Review*)

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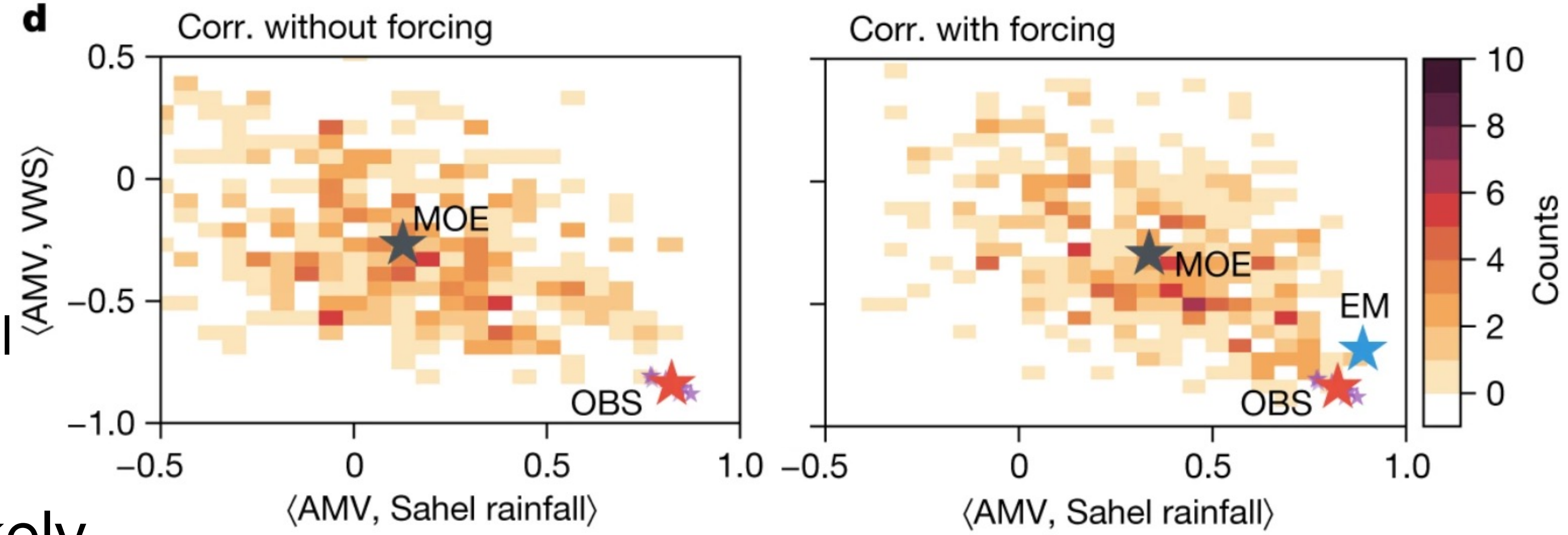

(He et al. 2023)

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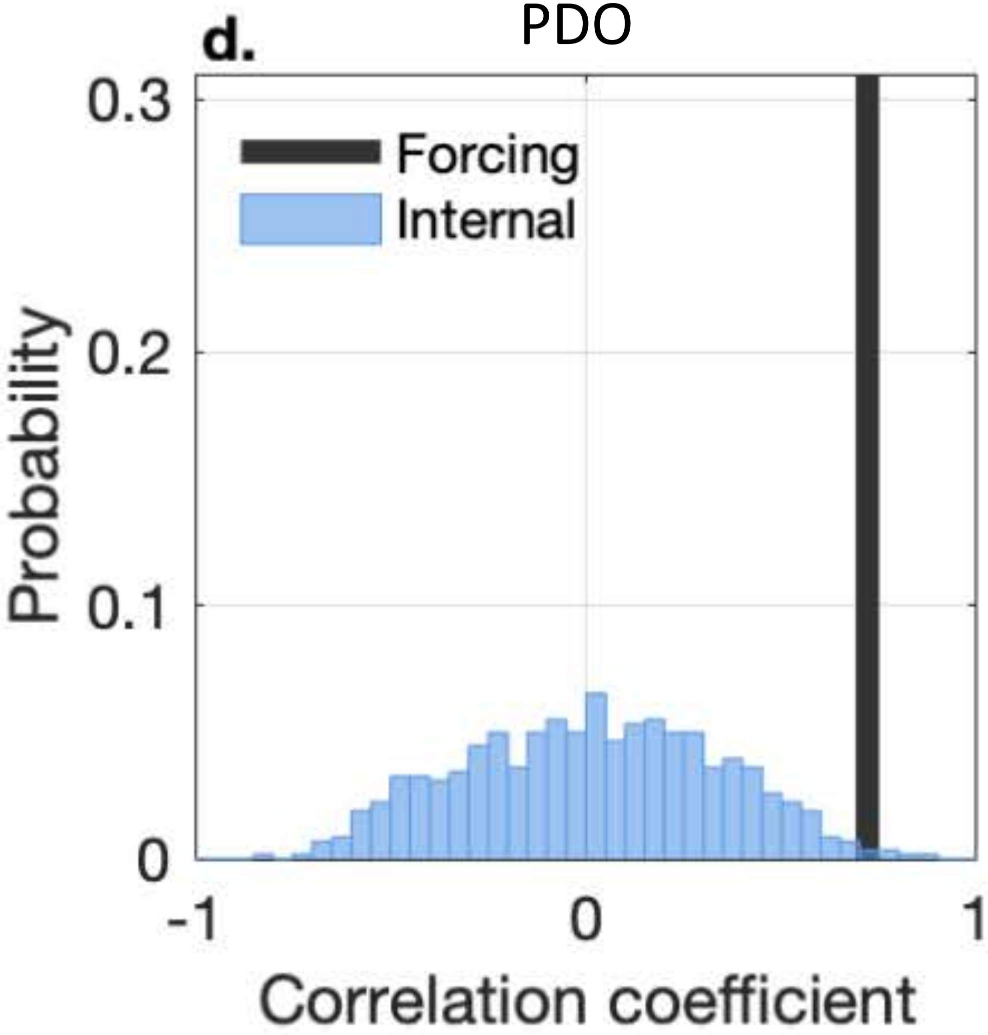
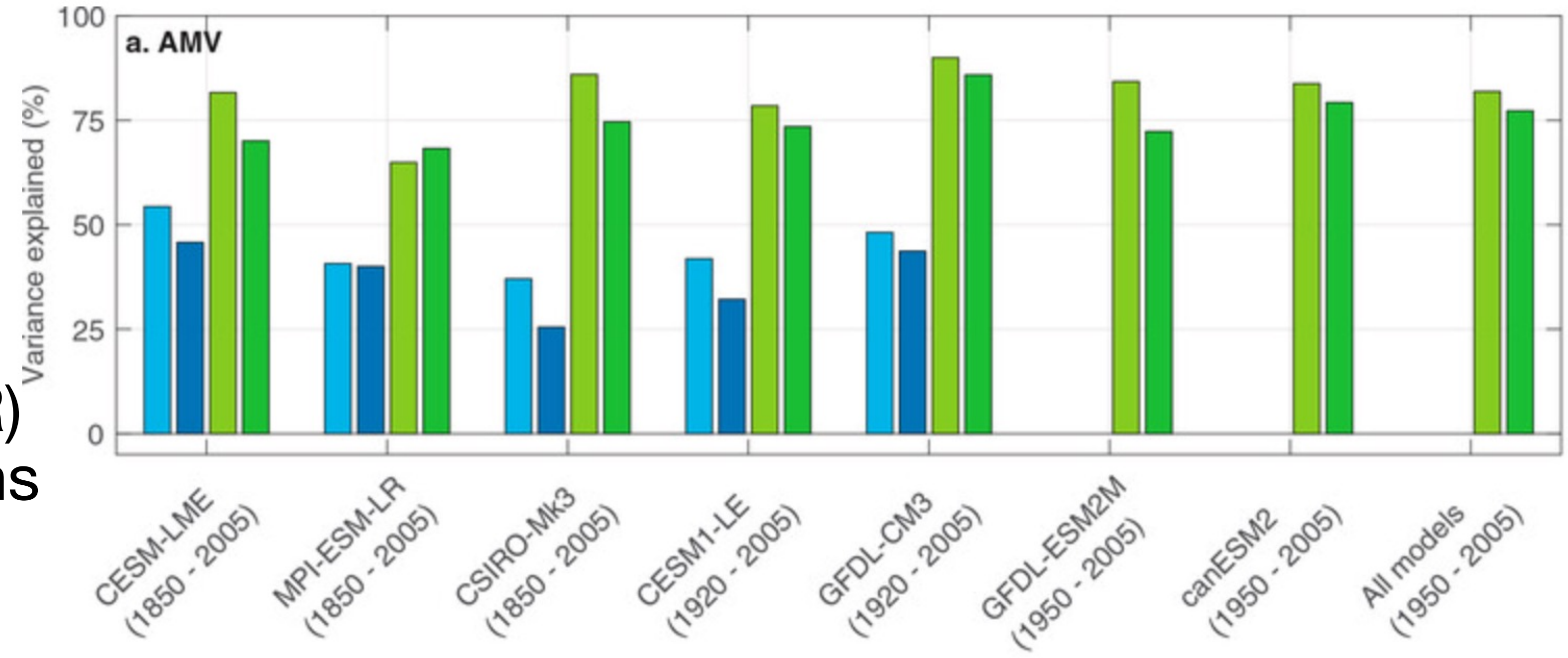
PDO



(Klavans et al. *In Review*)

Assorted evidence for the role of forcing

- Role of forcing increases as anthropogenic forcing increases (AMV, PDO, NAO)
  - Correlation
  - Variance
- Single-forcing (GHG, AER) runs have high correlations during appropriate time periods
- Ensemble mean spatial patterns bear strong similarity to observations (not always perfect)



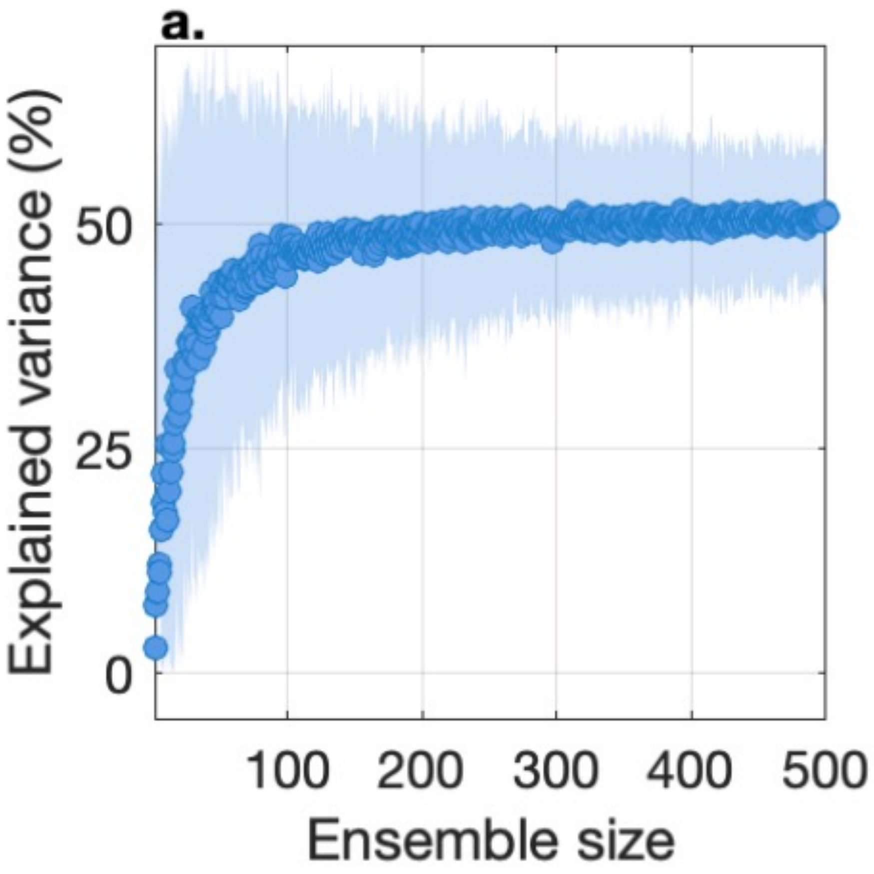
1850/1920 – 2005

1950 - 2005

(Klavans et al. 2022)

The need for large ensembles

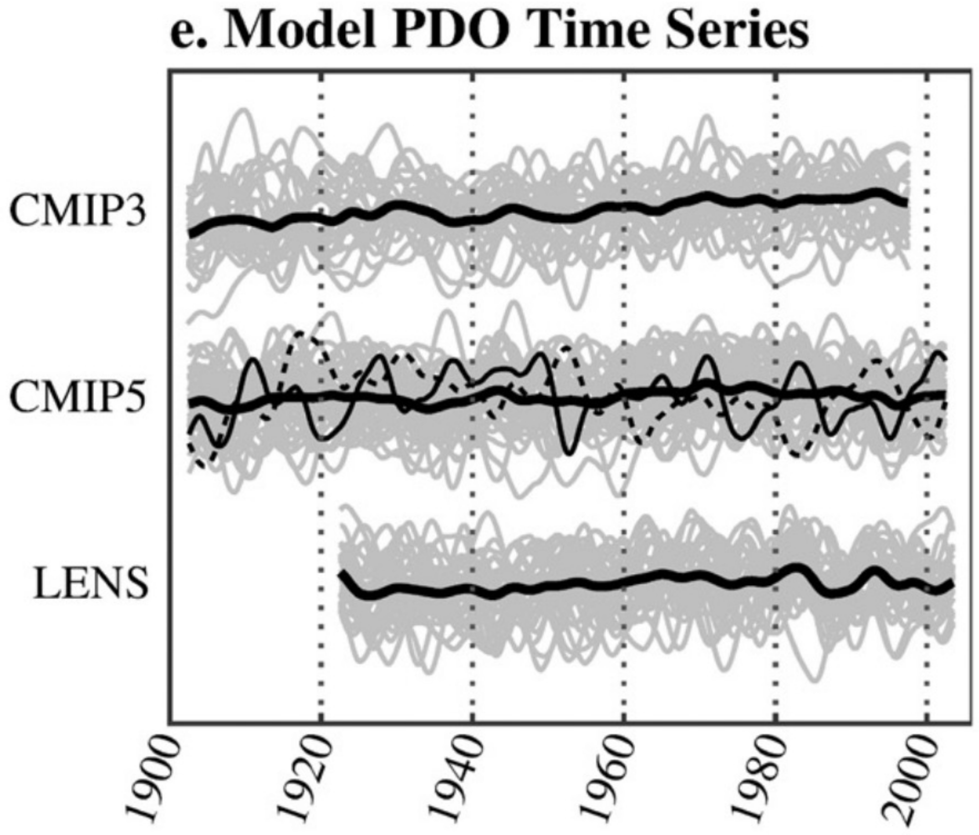
- These high correlations could only be unearthed with very large ensembles of climate models
  - **PDO**, NAO, AMV, impacts
  - More members to isolate NAO, fewer to isolate AMV
- Amplitude of the forced signal is too small, overwhelmed by internal noise



(Klavans et al. *In Review*)

The need for large ensembles

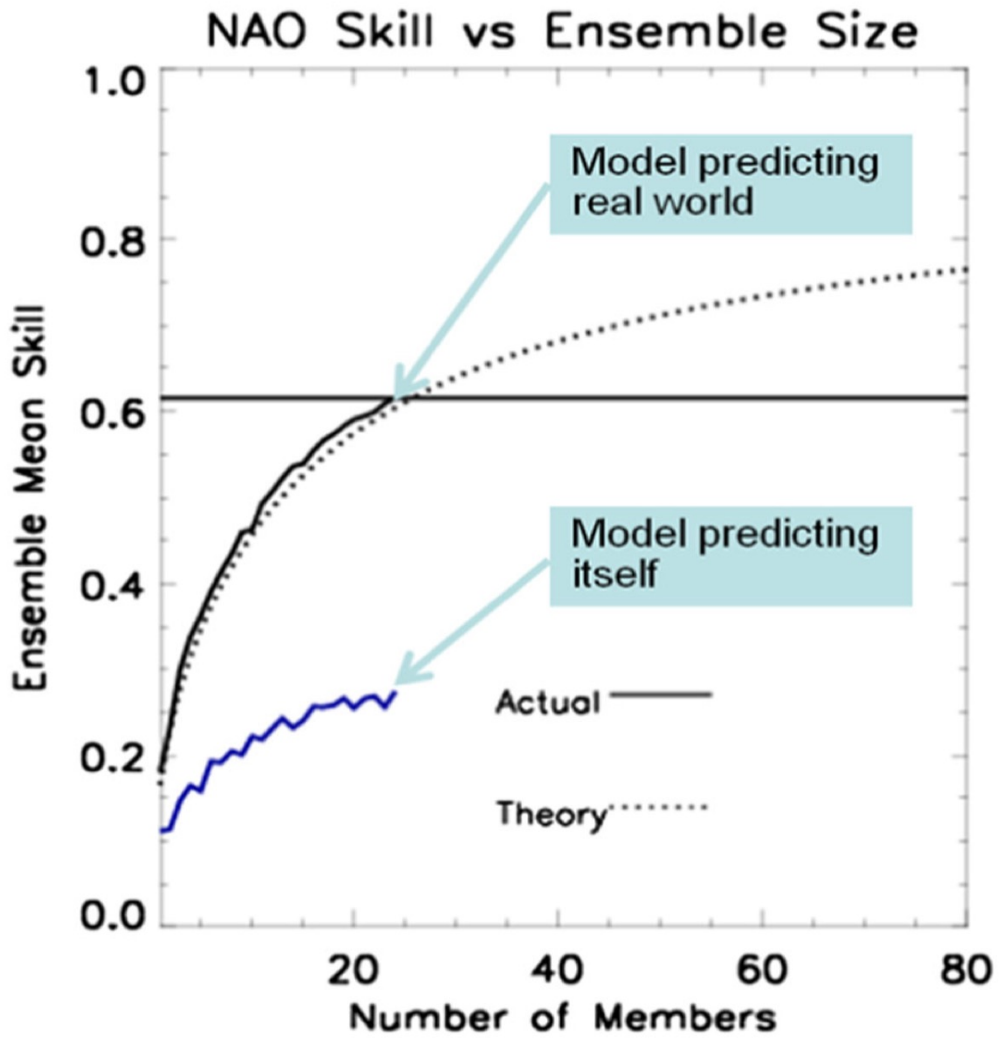
- Forced amplitude is so weak it was very easy to overlook
- Example using the PDO index:
  - In a 40-member ensemble, the R^2 from 1920 – 2005: 5%
  - In a 472-member ensemble, the R^2 from 1950 – 2005: 53%
- The externally forced signal to internally generated noise ratios in models is too weak



(Newman et al. 2016)

Aside: the signal-to-noise paradox

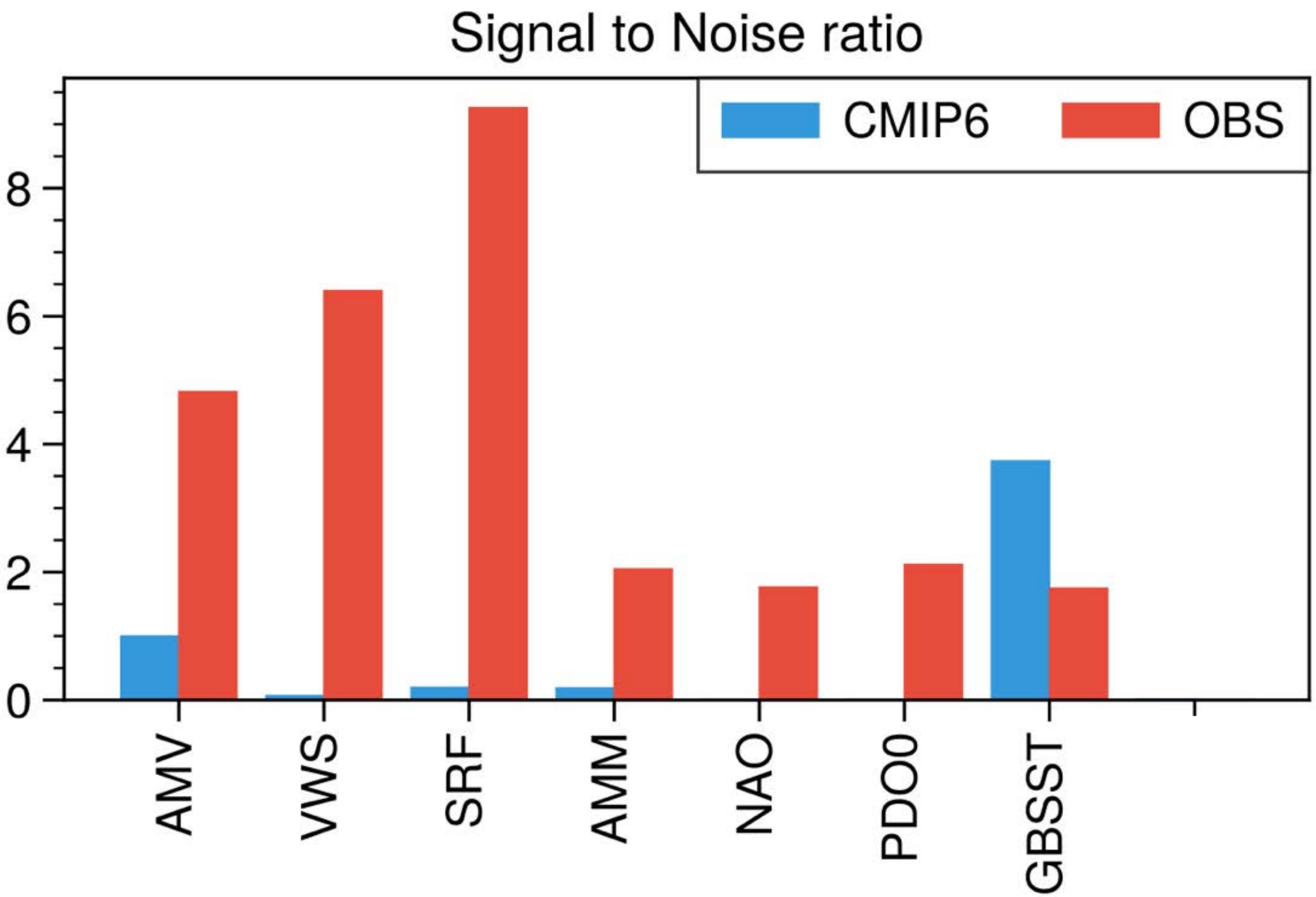
- What we've presented so far is a narrowing of the signal-to-noise paradox (Eade et al. 2014; Dunstone et al. 2016; Smith et al. 2020; and many others)
- Comparing initialized and uninitialized ensembles shows the error at decadal signal primarily associated with the forced signal (Klavans et al. 2022)



(Scaife and Smith 2018)

The signal-to-noise ratio in models is too low

- We can estimate the signal-to-noise ratio in models and observations
- Large ensembles
  - Ensemble mean / internal variability
- Observations
  - $OBS = \beta_1 EM + \varepsilon$
- Could observed internal variability be correlated with the forced signal by chance? Unlikely across many pseudo-independent modes



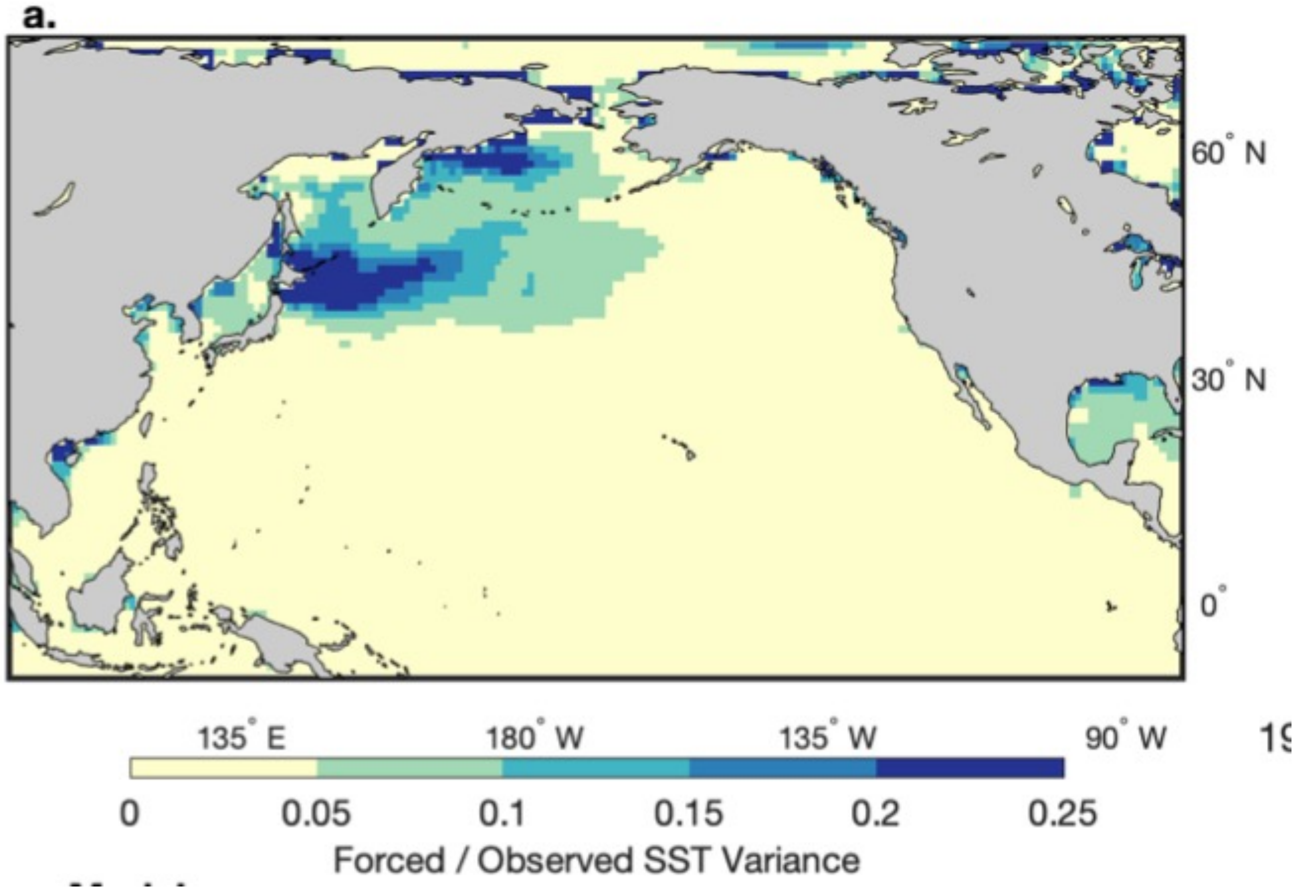
(Chengfei He - does good work, go to his poster!)

Summary

1. What are models doing well?
   - Models produce multidecadal modes with reasonably realistic spatial patterns and impacts
2. Where can models improve?
   - Observed variance is an outlier, relative to model ensemble spread
   - Ensemble mean is highly correlated with observations – but it's amplitude is too weak
   - The forced signal to internally generated noise ratio is too low in models
3. How can the S/N ratio be improved? What could rectifying this error teach us?

How can the S/N ratio be improved?

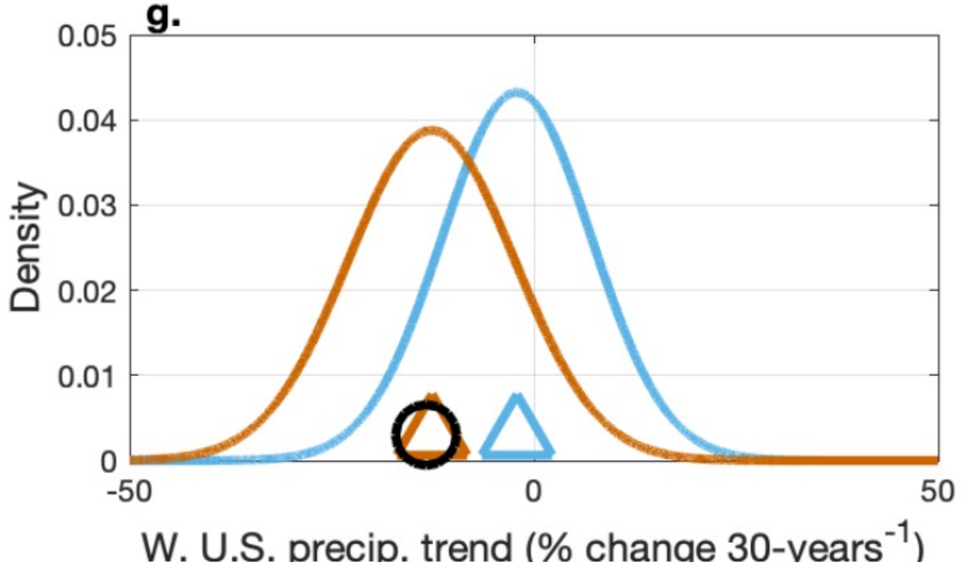
- Some proposed causes of the S/N error:
  - Air-sea coupling (Smirnov et al. 2015; Kim et al. 2018)
  - Upper ocean damping (Murphy et al. 2021)
  - Model resolution (Scaife et al. 2019)
  - Ocean front resolution (Kirtman et al. 2017)

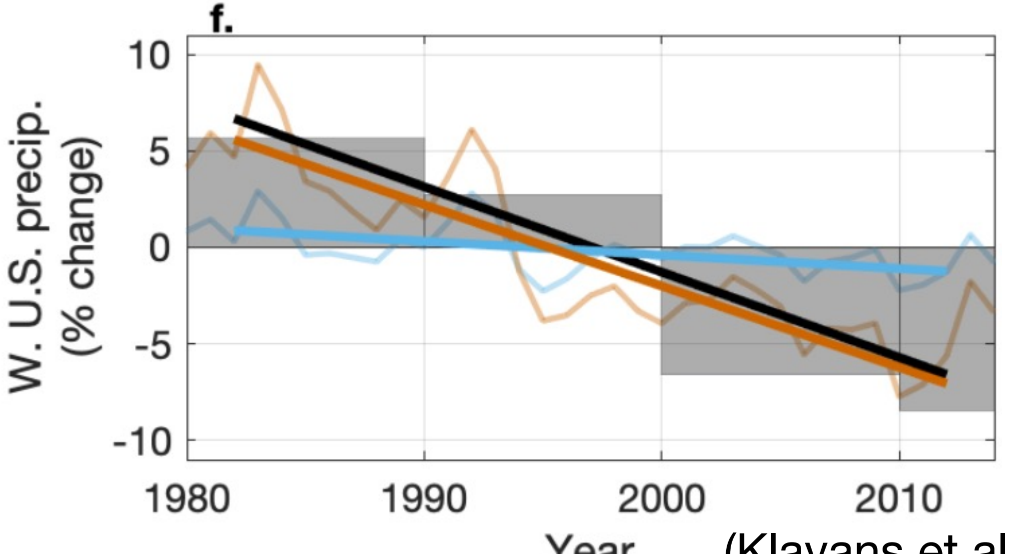


(Klavans et al. *In Review*)

What could rectifying this error teach us?

- Models may be underestimating climate risk while overestimating uncertainty
- Increasing the S/N ratio to match observations suggests that observations are an average response
- External forcing is predictable in the near-term

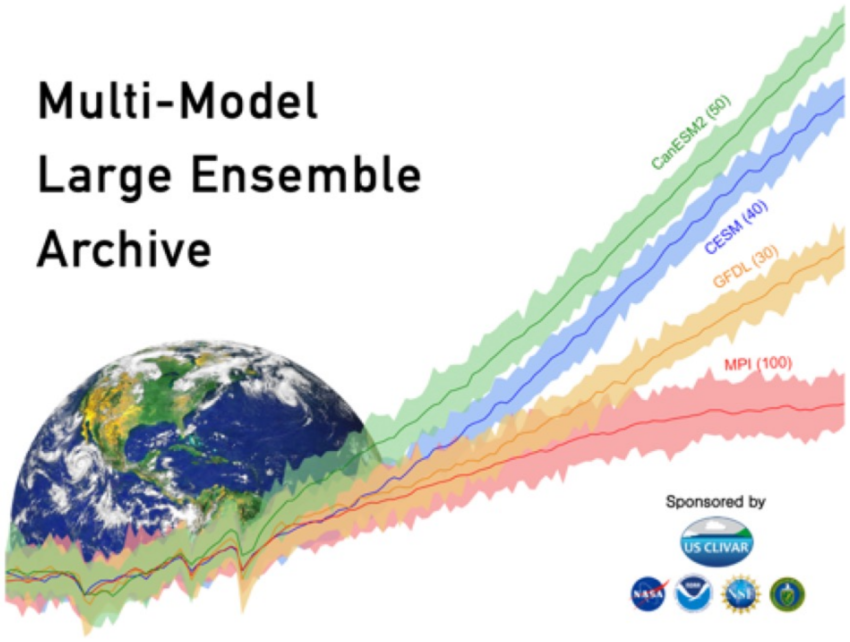




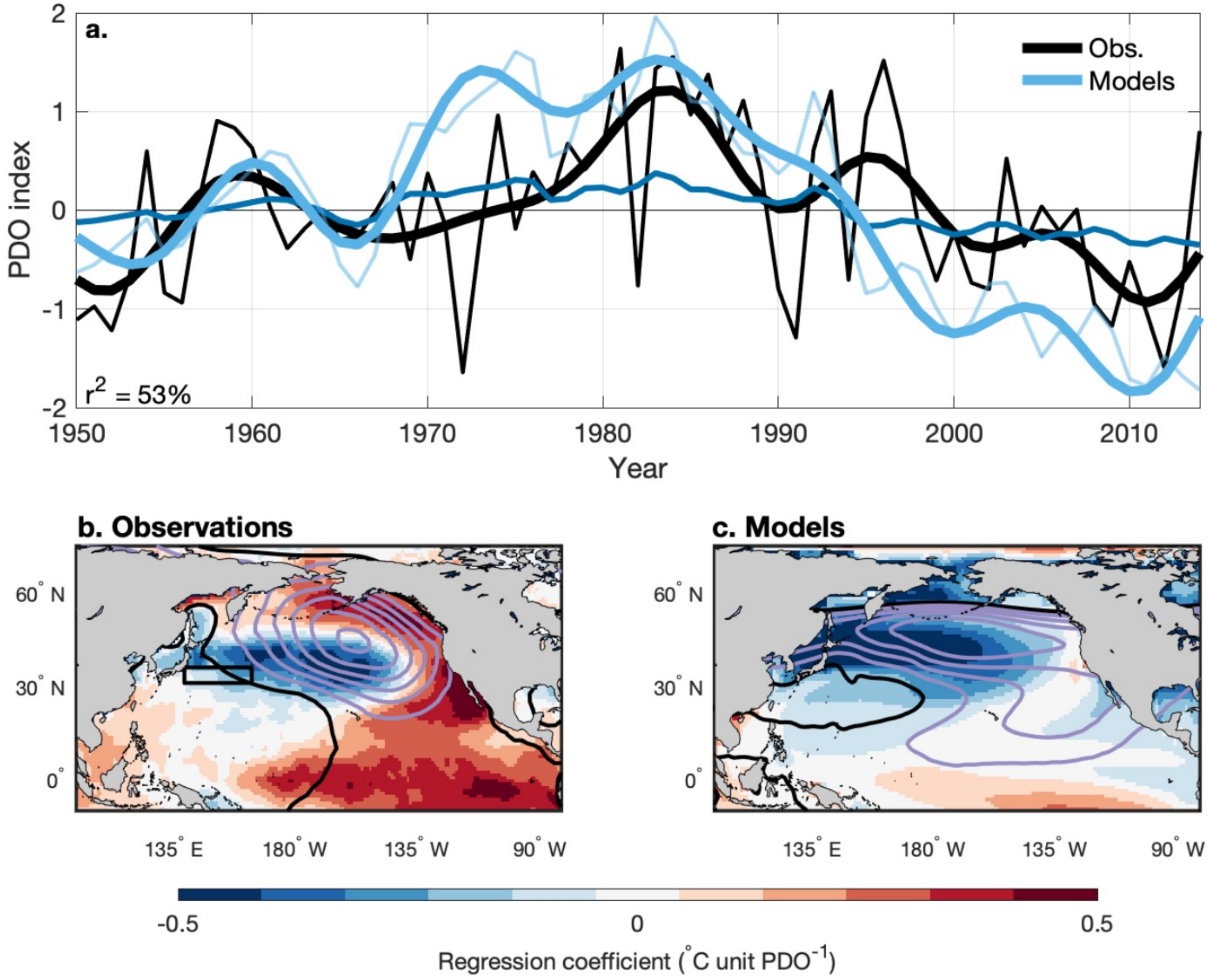
(Klavans et al. *In Review*)

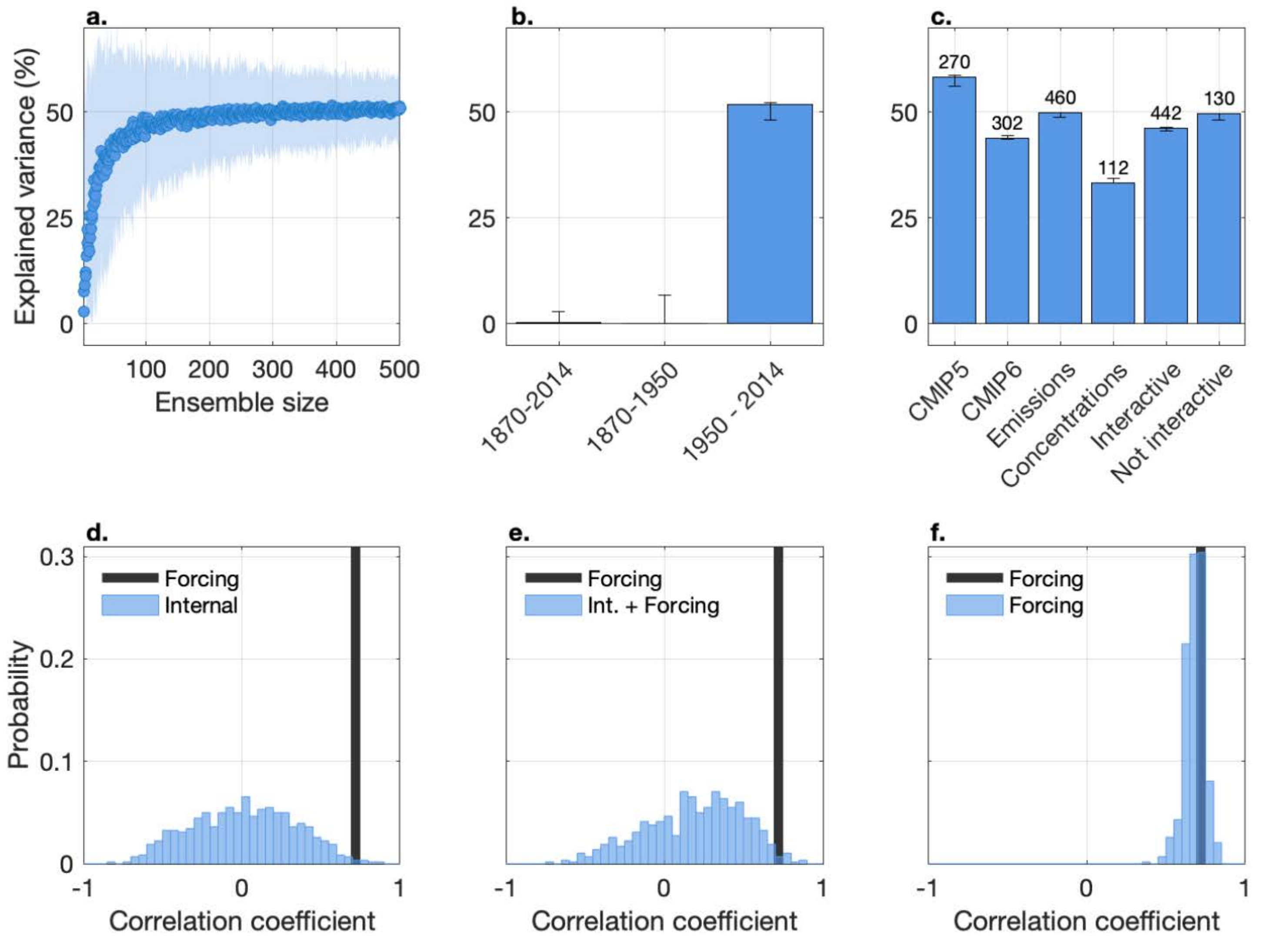
What could rectifying this error teach us?

- Paleoclimate: Is climate model response to solar/orbital forcing too weak? (Victoria Todd and Tim Shanahan)
- Internal variability: how does internal noise change when the signal increases? Some evidence signal and noise are additive
- Until the S/N error in models is fixed, large ensembles are a required tool for understanding regional climate change

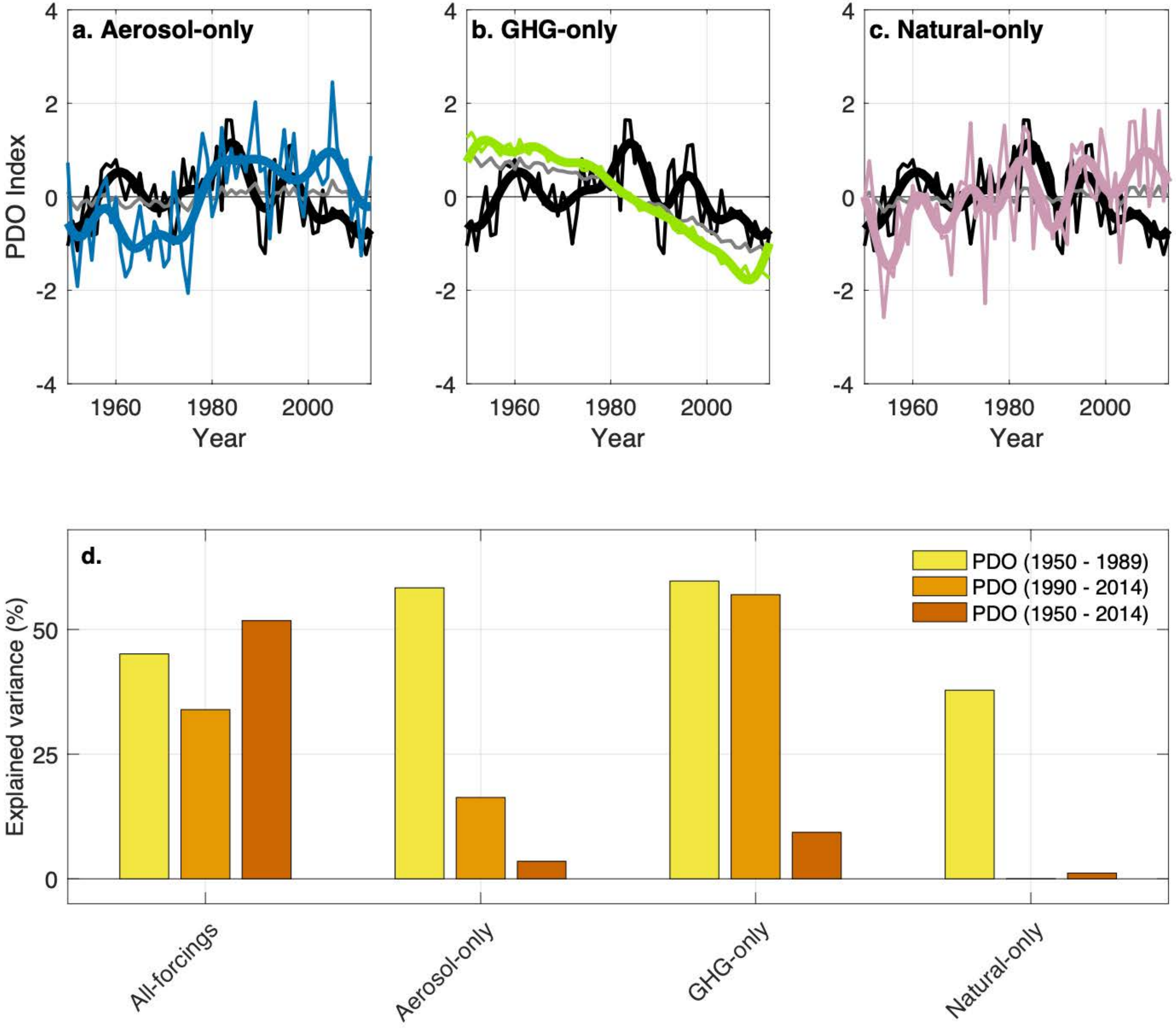


More slides!


a.
Obs.
Models
PDO index
Year
r² = 53%
2
1
0
-1
-2
1950
1960
1970
1980
1990
2000
2010
b. Observations
c. Models
60° N
30° N
0°
135° E
180° W
135° W
90° W
-0.5
0
0.5
Regression coefficient (°C unit PDO⁻¹)

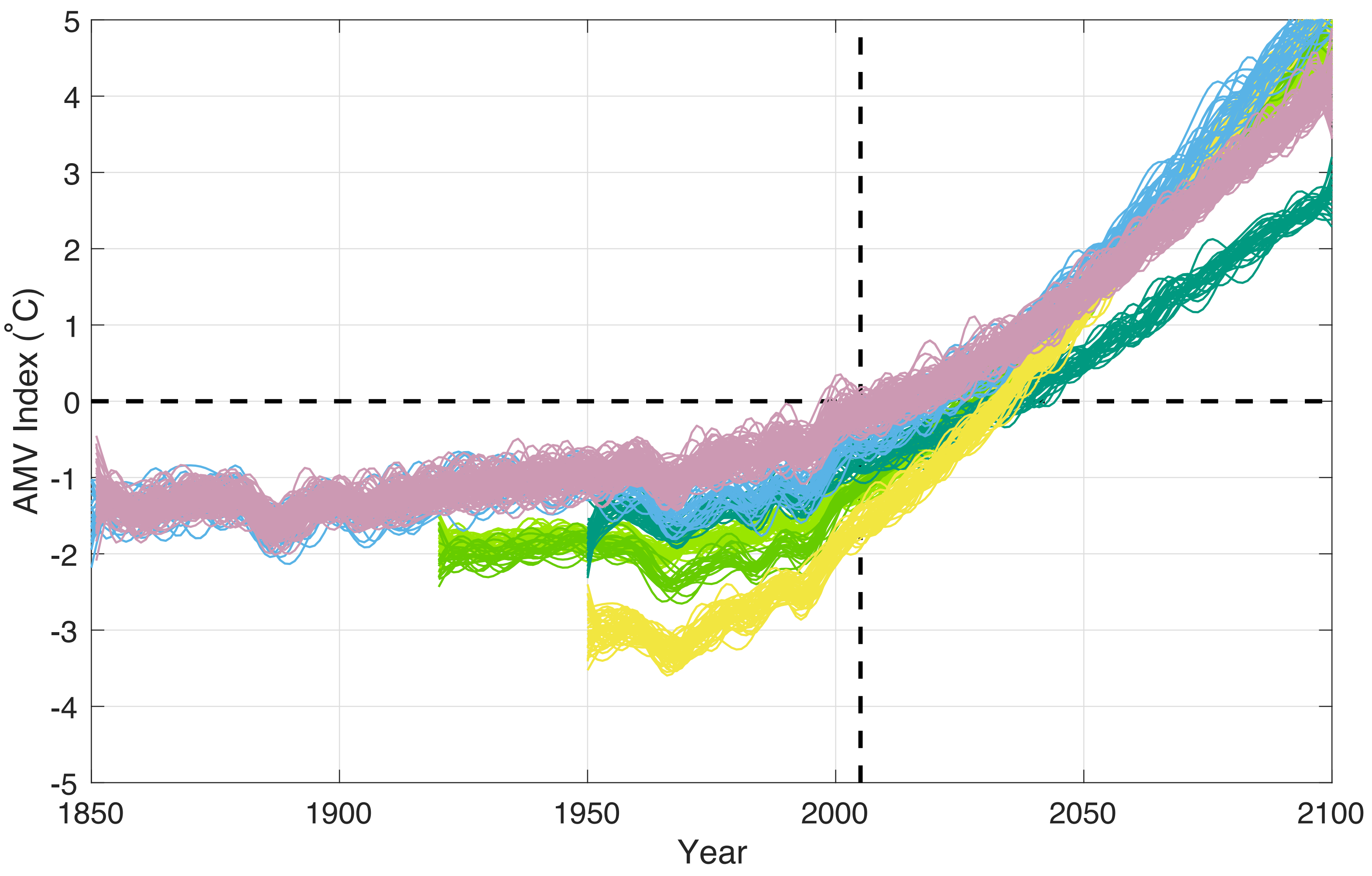


a.
Explained variance (%)
Ensemble size
b.
1870-2014
1870-1950
1950 - 2014
c.
270
302
460
112
442
130
CMIP5
CMIP6
Emissions
Concentrations
Interactive
Not interactive
d.
Forcing
Internal
Probability
Correlation coefficient
e.
Forcing
Int. + Forcing
Correlation coefficient
f.
Forcing
Forcing
Correlation coefficient

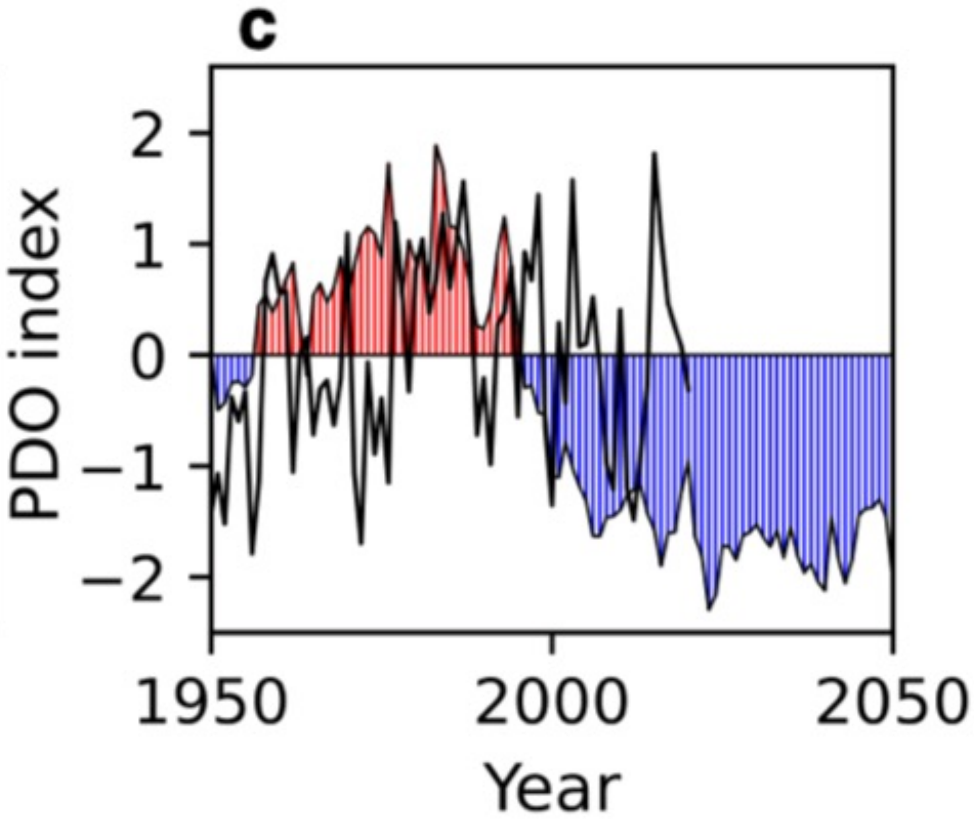


a. Aerosol-only
b. GHG-only
c. Natural-only
PDO Index
4
2
0
-2
-4
1960
1980
2000
Year
d.
PDO (1950 - 1989)
PDO (1990 - 2014)
PDO (1950 - 2014)
Explained variance (%)
50
25
0
All-forcings
Aerosol-only
GHG-only
Natural-only

Future AMV

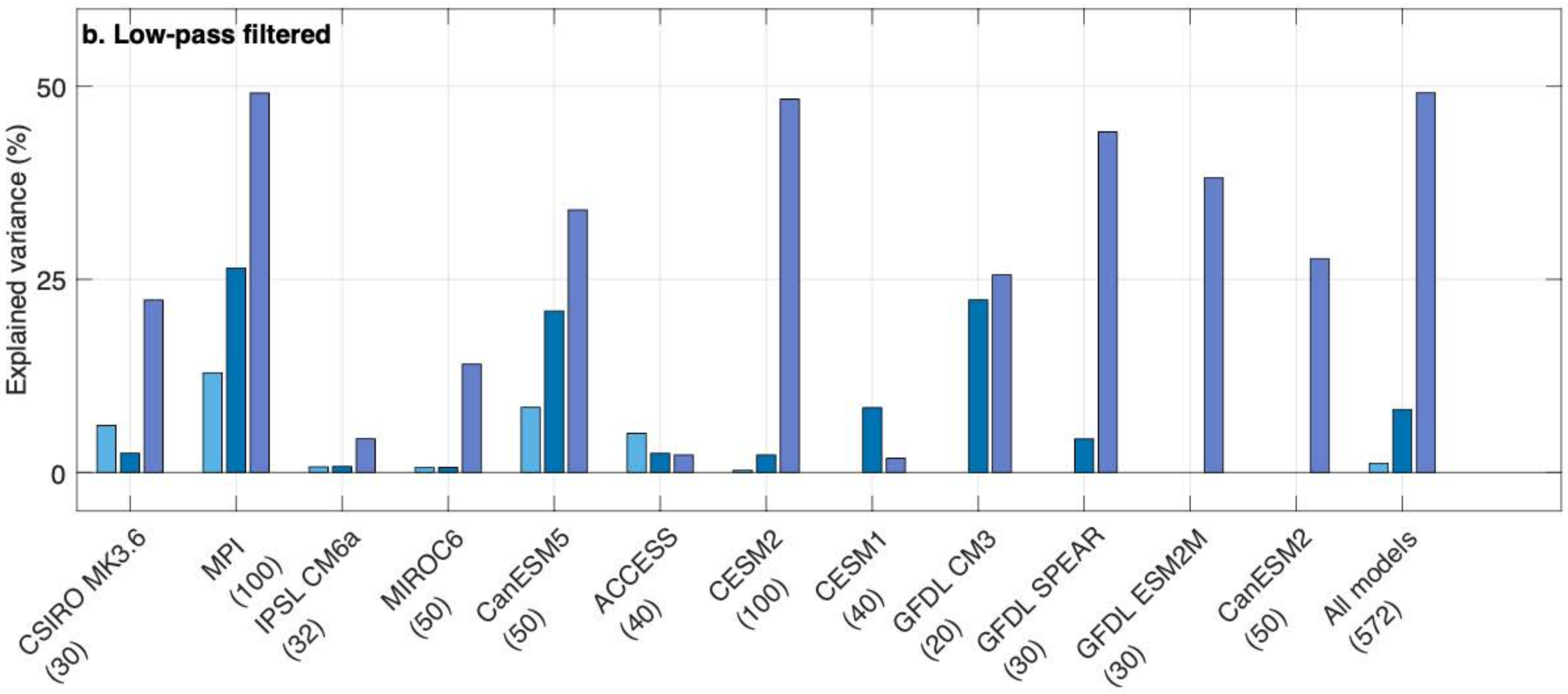


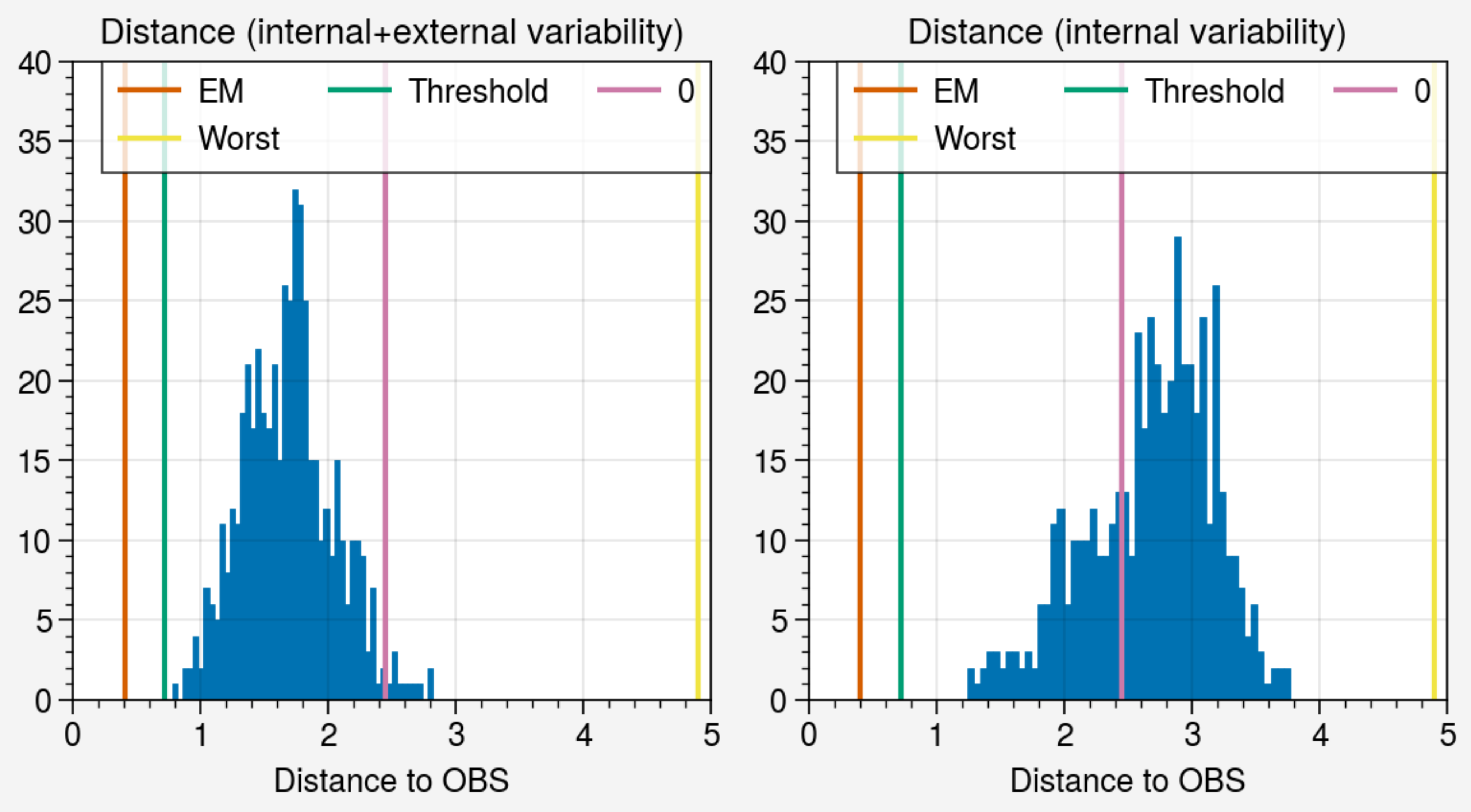
Future PDO



PDO Exp. Var

1850 – 2014, 1920 – 2014, 1950 - 2014




Distance (internal+external variability)
EM
Threshold
0
Worst
Distance to OBS
Distance (internal variability)
EM
Threshold
0
Worst
Distance to OBS