Robust Changes in North America's Hydroclimate Variability and Predictability

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Robustness

Ability of a statistical method or modeling exercise to work well not only in ideal conditions, but in the presence of data and/or model updates, mild to moderate departure from assumptions, or both.

For example, for non-normal data and/or in the presence of large errors median is more robust statistics than mean.

Overview

- Introduction
- Soil moisture variability projections
- Reddened ENSO framework
- Projected change in hydroclimate predictability
- Changing drought and pluvial risks

Climate Modeling works!

When will Lake Mead go dry?

Tim P. Barnett[1] and David W. Pierce[1]

Received 27 November 2007; revised 22 January 2008; accepted 5 February 2008; published 29 March 2008.

[1] A water budget analysis shows that under current conditions there is a 10% chance that live storage in Lakes Mead and Powell will be gone by about 2013 and a 50% chance that it will be gone by 2021 if no changes in water allocation from the Colorado River system are made. This startling result is driven by climate change associated with global warming, the effects of natural climate variability, and the current operating status of the reservoir system. Minimum power pool levels in both Lake Mead and Lake Powell will be reached under current conditions by 2017 with 50% probability. While these dates are subject to some uncertainty, they all point to a major and immediate water supply problem on the Colorado system. The solutions to this water shortage problem must be time-dependent to match the time-varying, human-induced decreases in future river flow.

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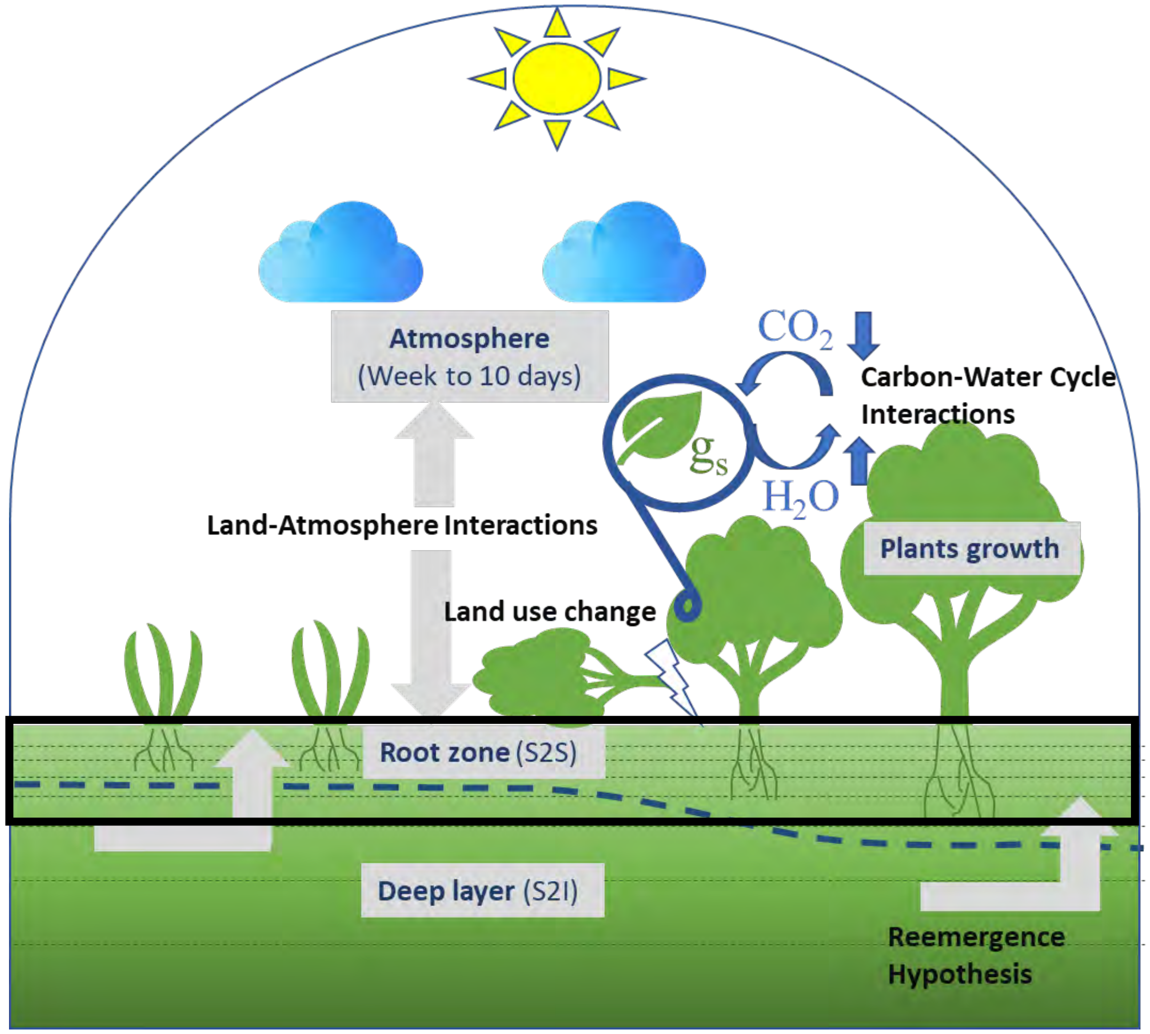
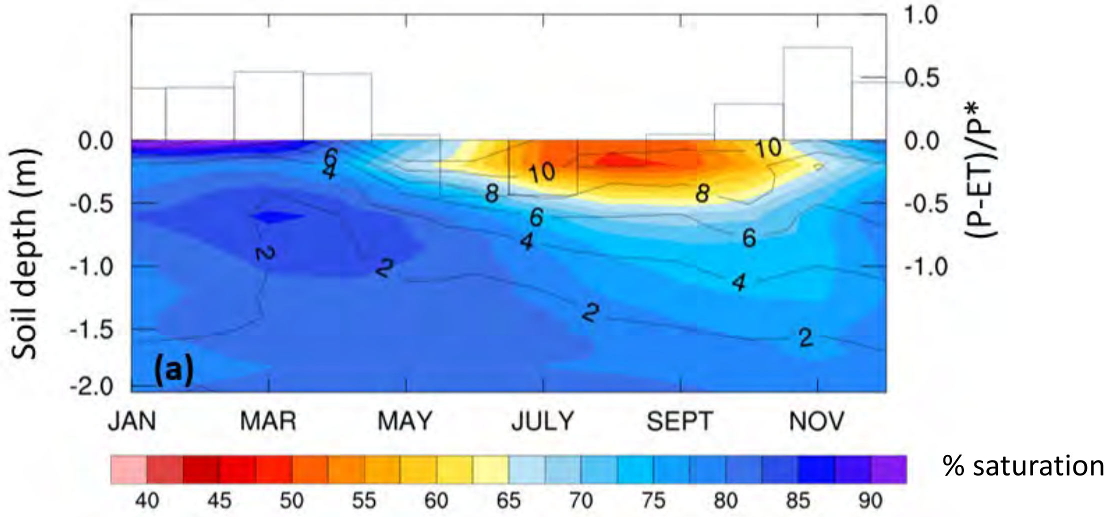
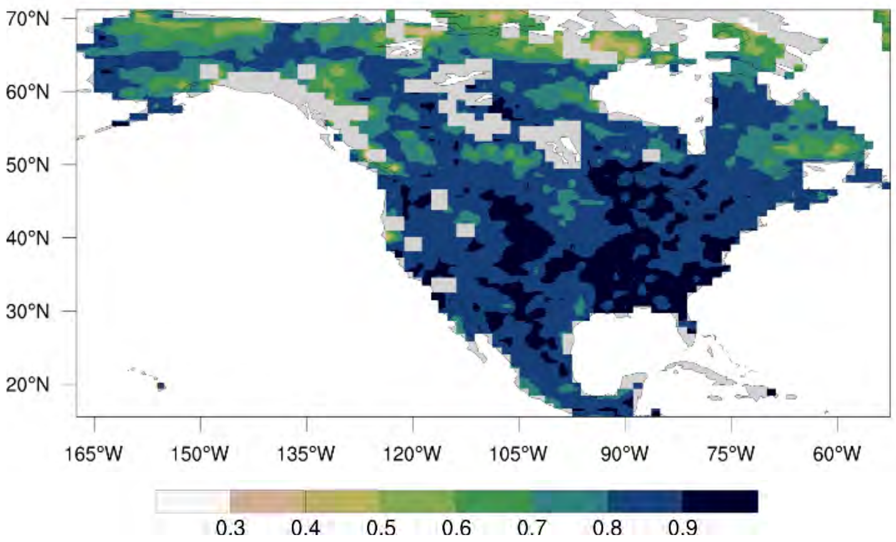
Soil Moisture

A metric to examine land hydroclimate variability and predictability





Illinois soil moisture observations: mean (color shading) and variability (contour lines) (Kumar et al., 2019)



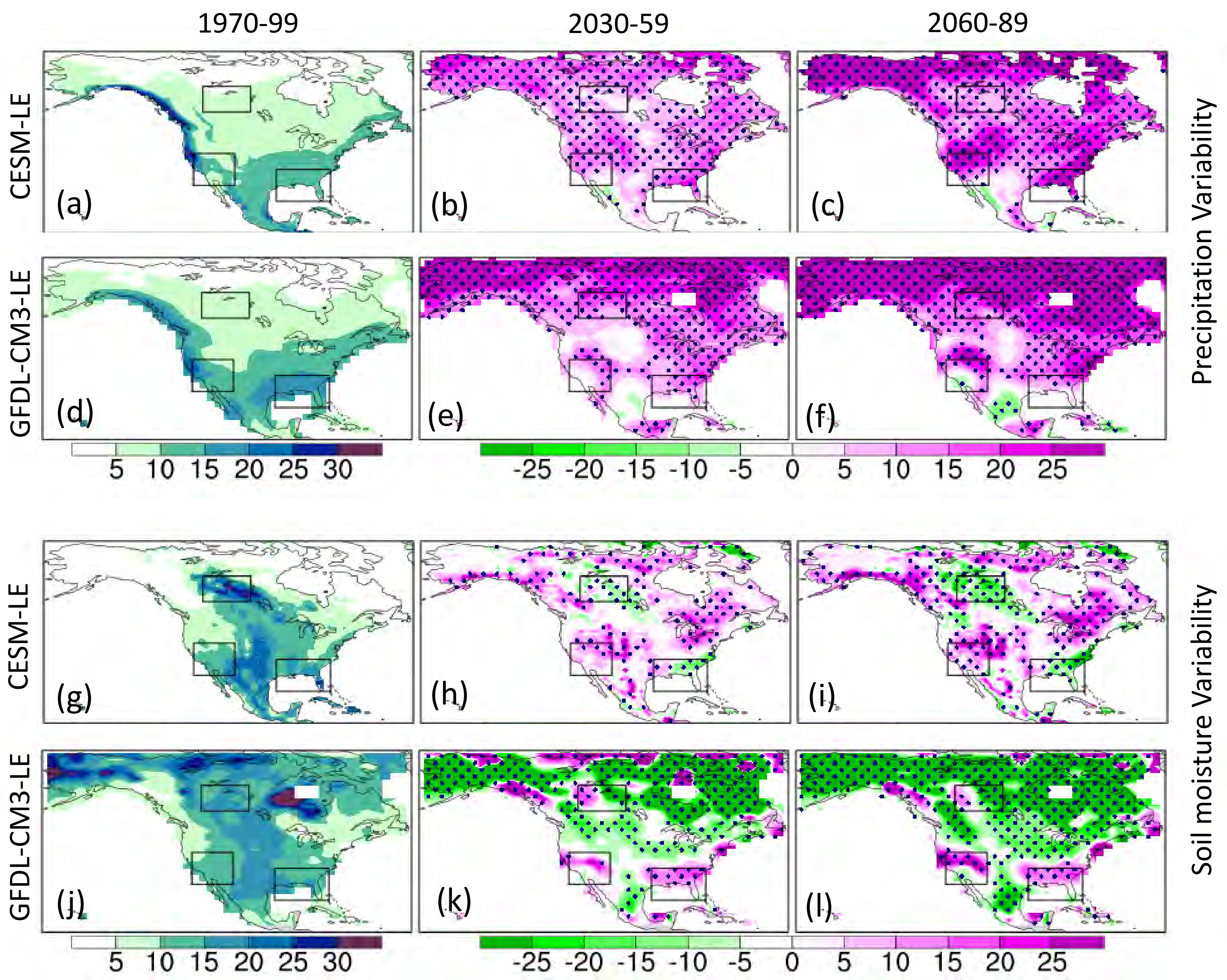
Soil moisture and PDSI correlation in climate model

Objectives

Investigate	Investigate projected change in soil moisture variability using the large ensemble data.
Understand	Understand drivers of changing soil moisture variability and predictability at inter-annual time scales.
Assess	Assess potential implications on drought and pluvial risks under changing climate.

Soil moisture variability changes are rather small or even decreases despite increase in precipitation variability

- Two large ensemble data: CESM-LE (40 members), and GFDL-CM3-LE (20 members).
- Historical and RCP8.5 (highest emission) climate projections
- Five climate period: 1940-69, 1970-99, 2000-2029, 2030-59, and 2060-89.
- Percentage change in variability relative to 1970-99 climate
- Statistical significance at 95% confidence level using f-test.



Reddened ENSO Framework

$$\boldsymbol{S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon}$$

- Modeling soil moisture variability at inter-annual time scales

- Soil moisture (S) in the current year (t) is modeled as a memory effect due to previous year soil moisture (t-1), and the current year ENSO (E) variability (major mode of SST variability in the tropical Pacific)

- Linear regression coefficients α (memory effect), and β (ENSO effect) are computed from climate model data, then ε (noise) is computed using the cross-validation techniques

- A similar model has been used to study multi-decadal variability in the north Pacific, although in that case, the memory term represents oceanic mixed layer processes (Newman et al., 2003)

- Time-averaging (12 month running mean) can allow us to represent a complex non-linear system using a linear set of equations (e.g., Huang et al. 2019).

Reddened ENSO Framework in observations

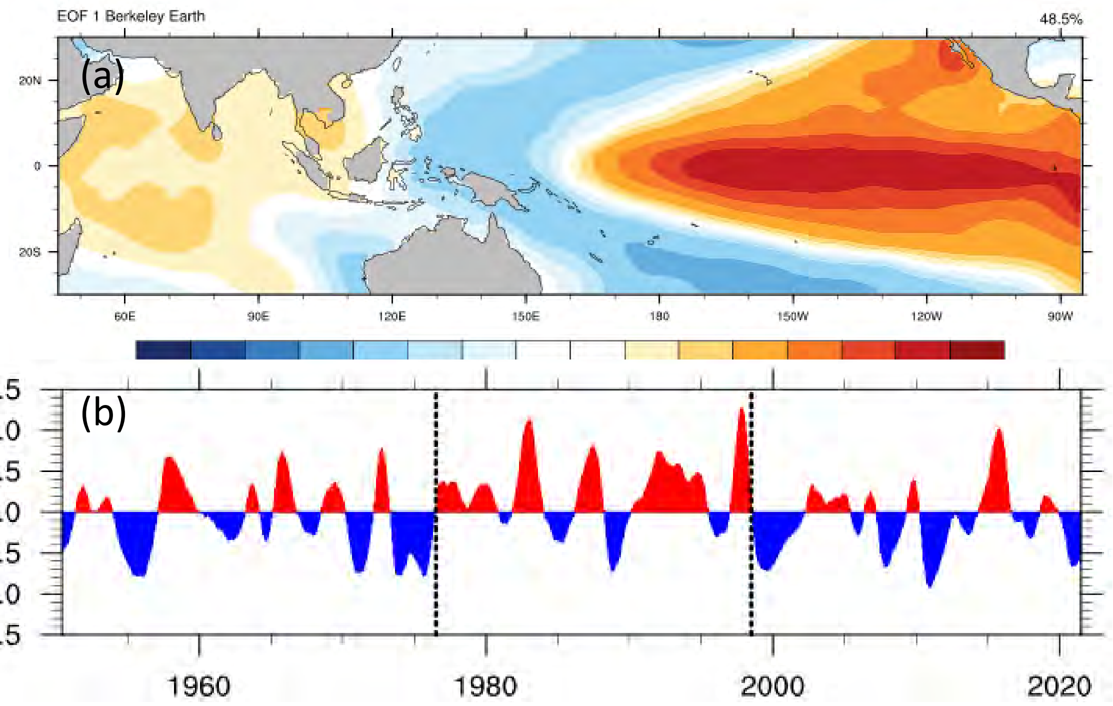
$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$

Reddened ENSO Framework in observations

$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$

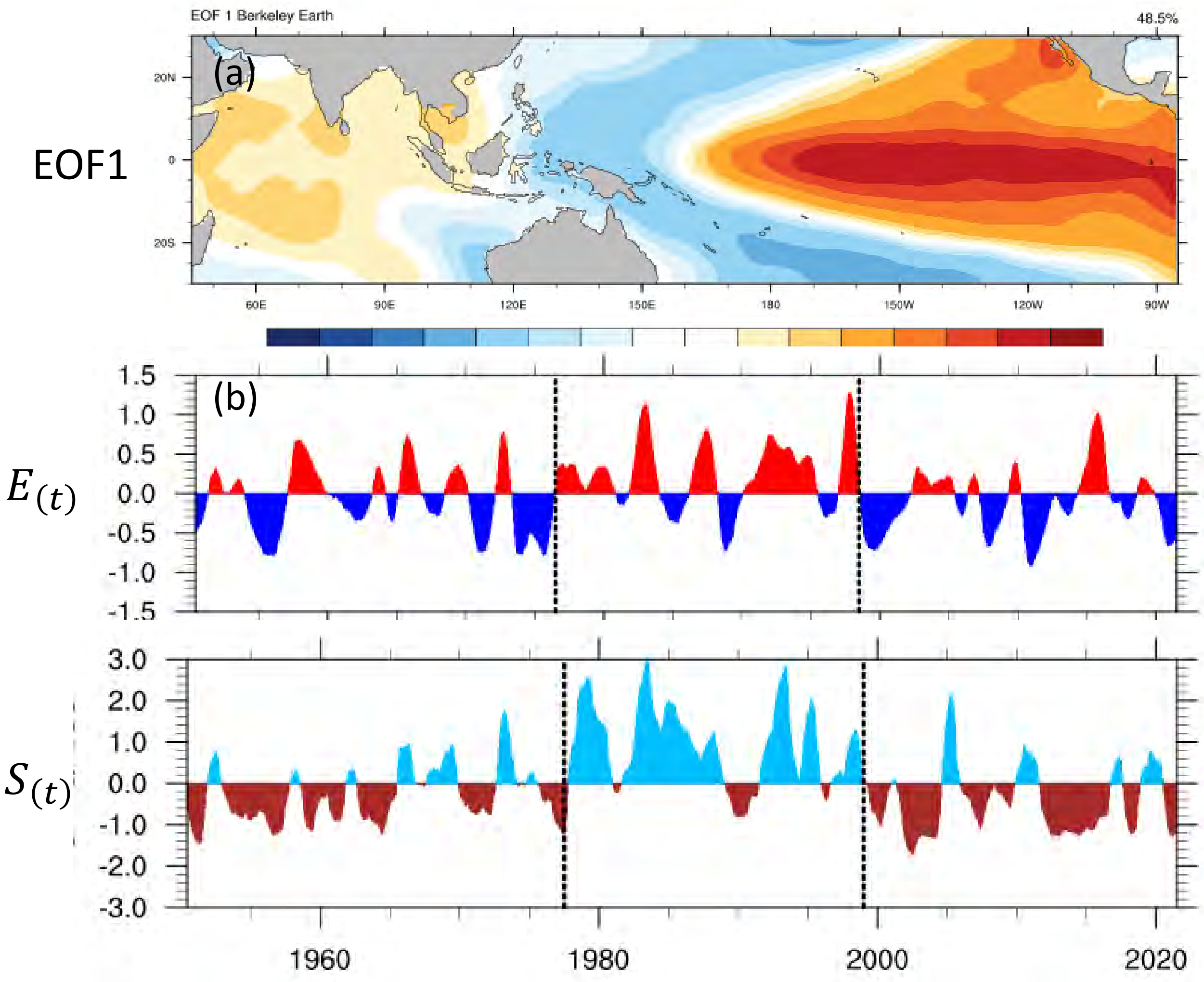
EOF1

$E_{(t)}$



Reddened ENSO Framework in observations

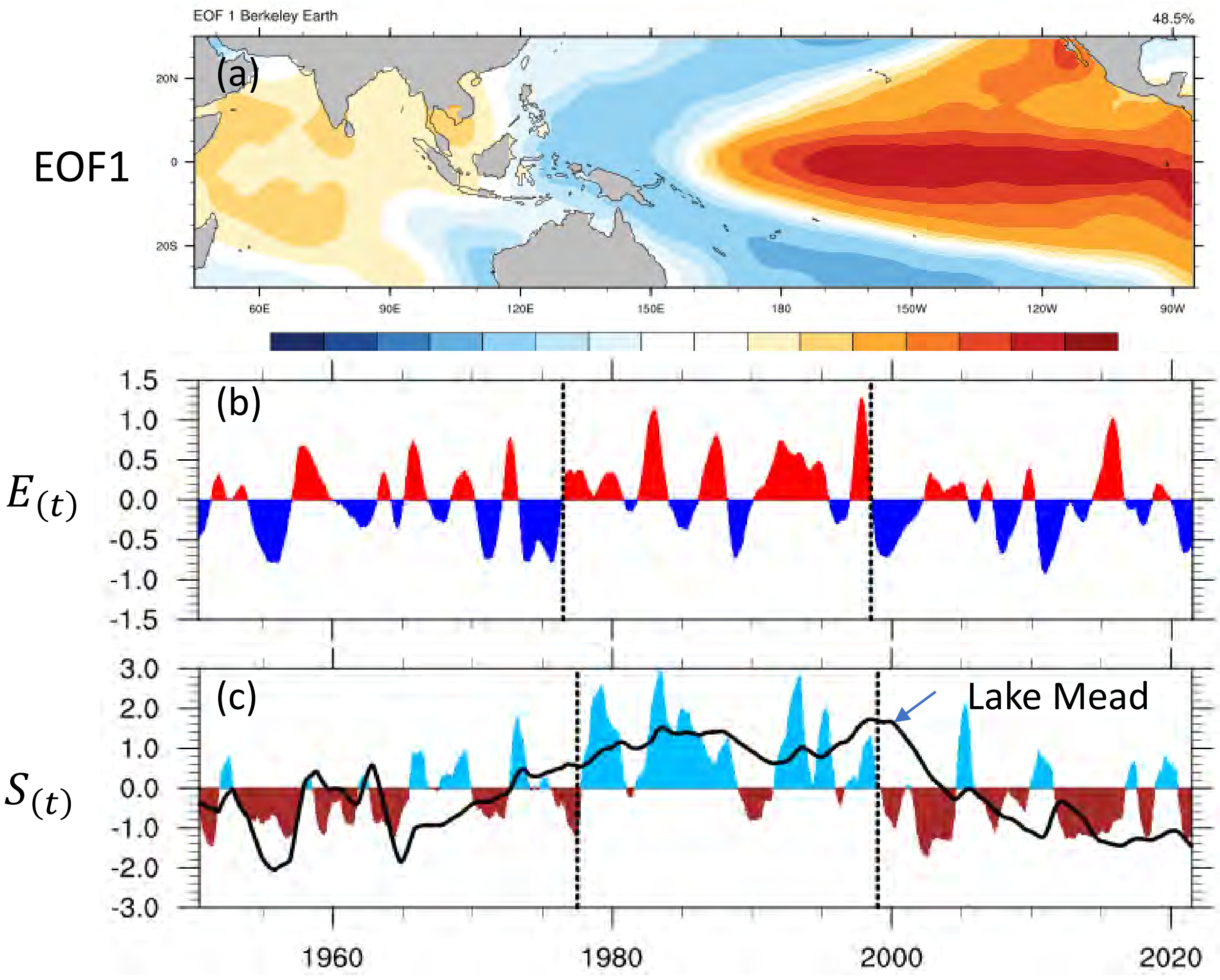
$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$



ERA5 soil moisture variability in the US Southwest

Reddened ENSO Framework in observations

$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$



ERA5 soil moisture variability in the US Southwest and Lake Mead Water Level

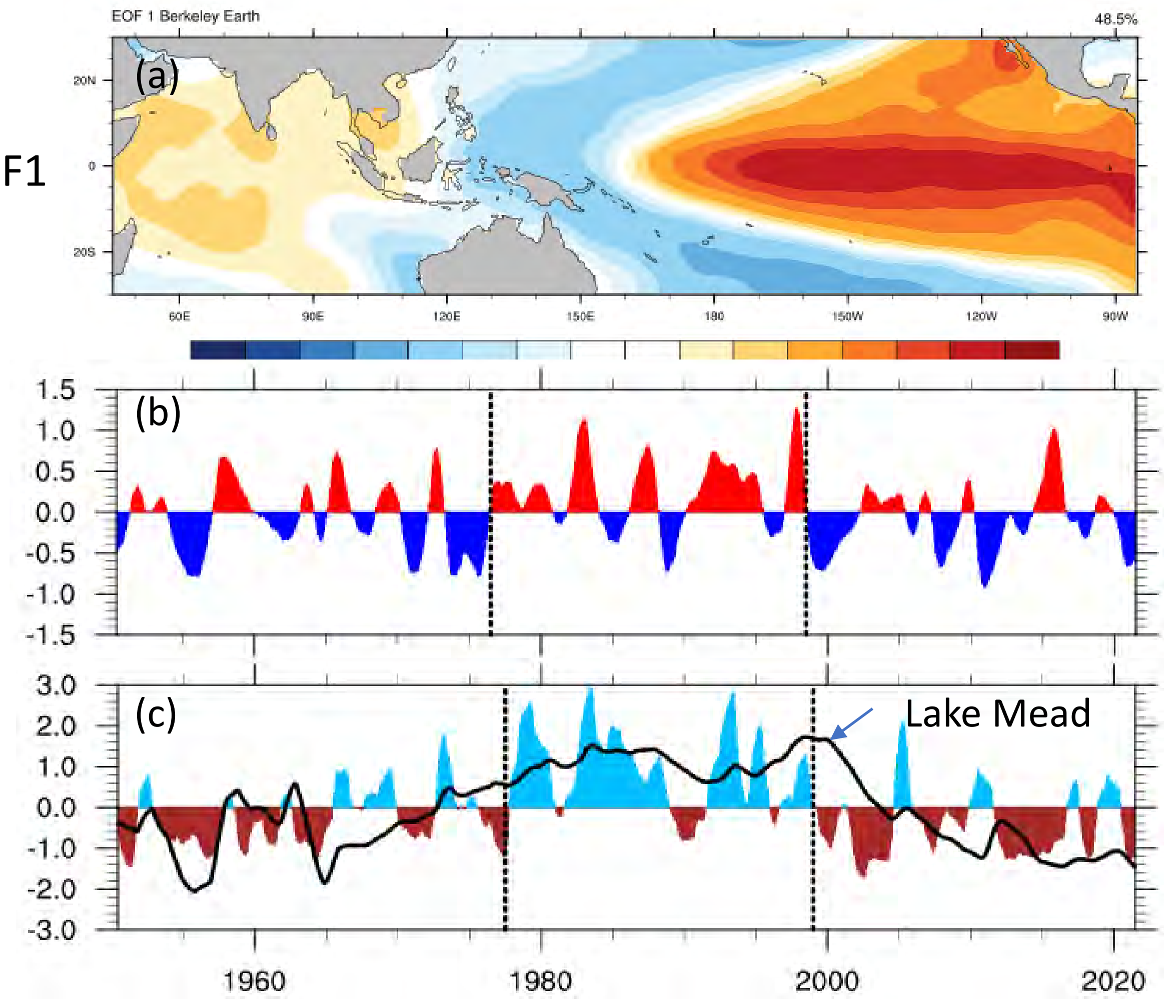
Reddened ENSO Framework in observations

$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$

EOF1

$E_{(t)}$

$S_{(t)}$



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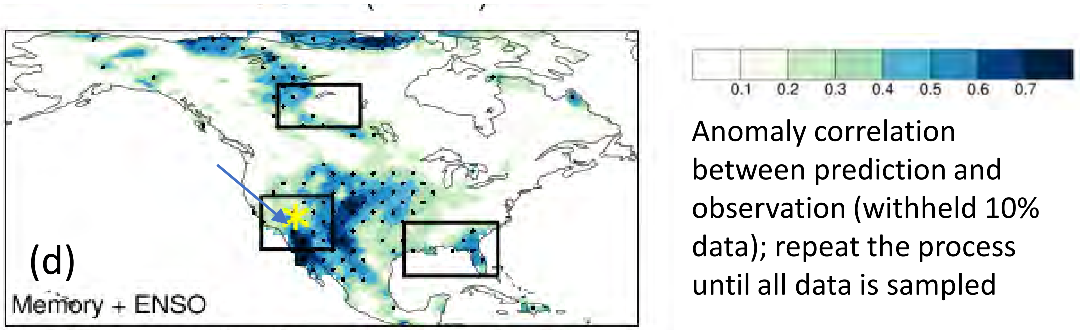

Anomaly correlation between prediction and observation (withheld 10% data); repeat the process until all data is sampled

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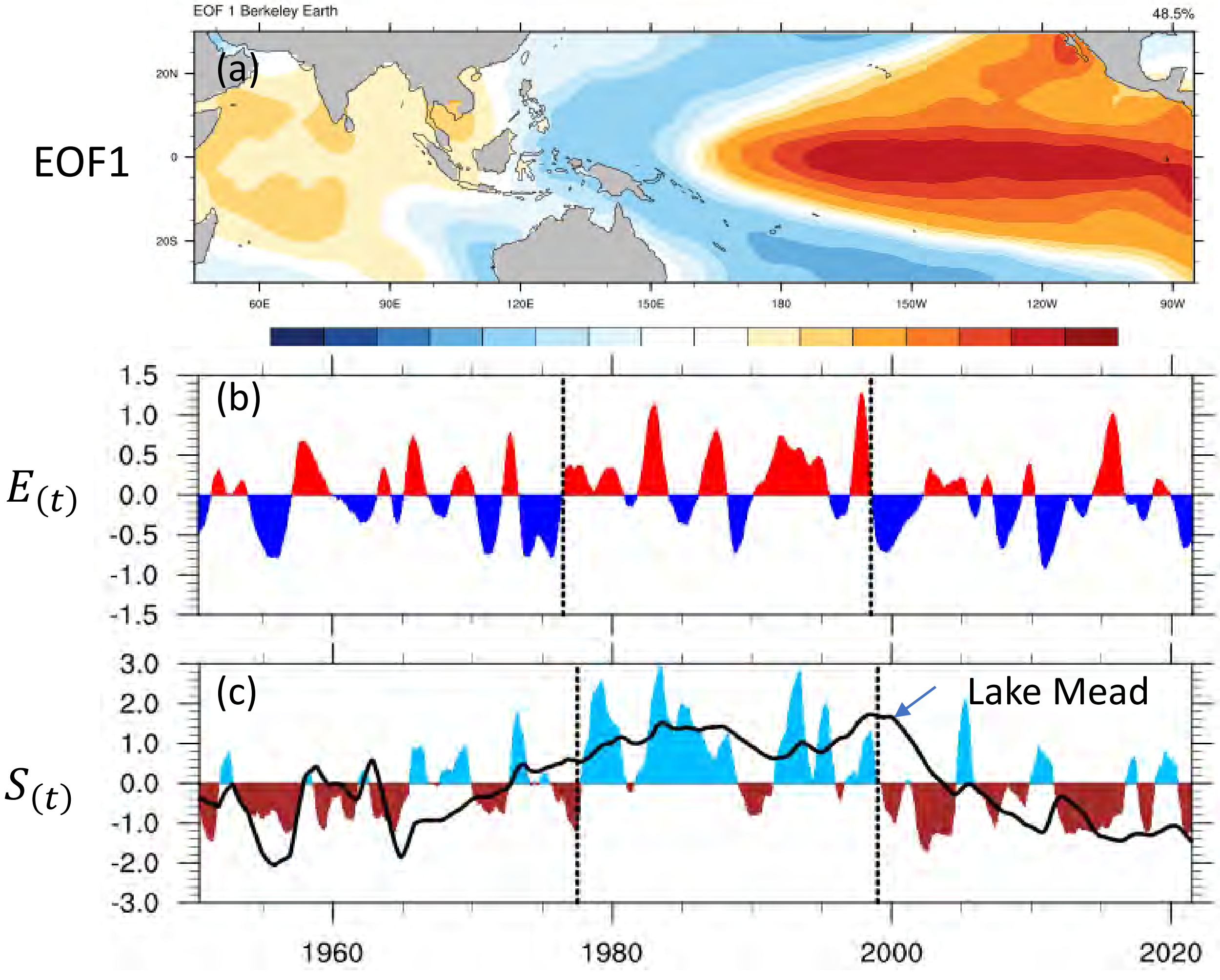
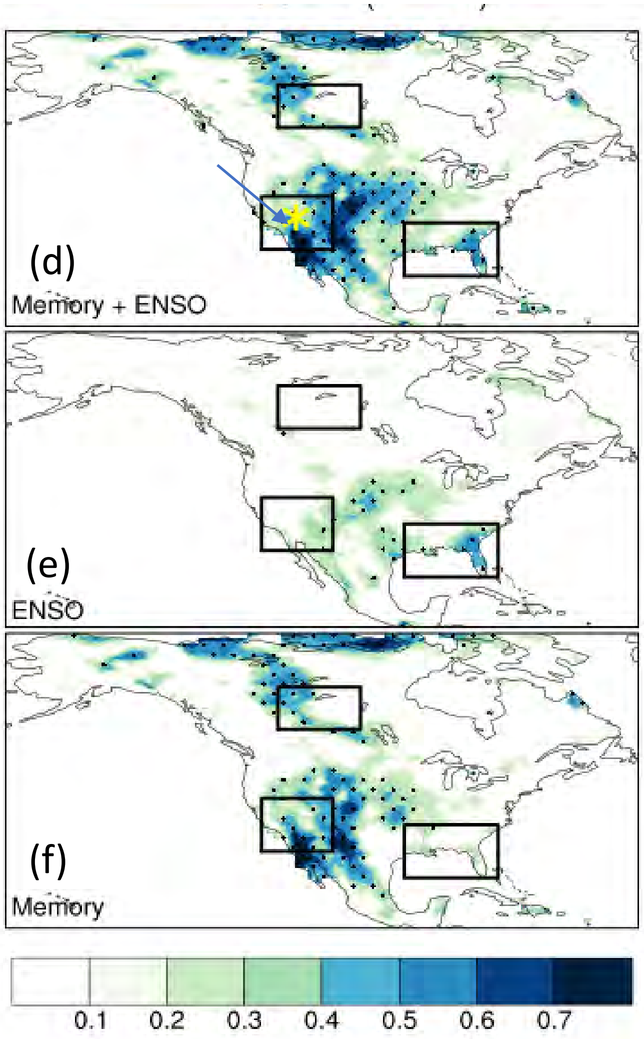


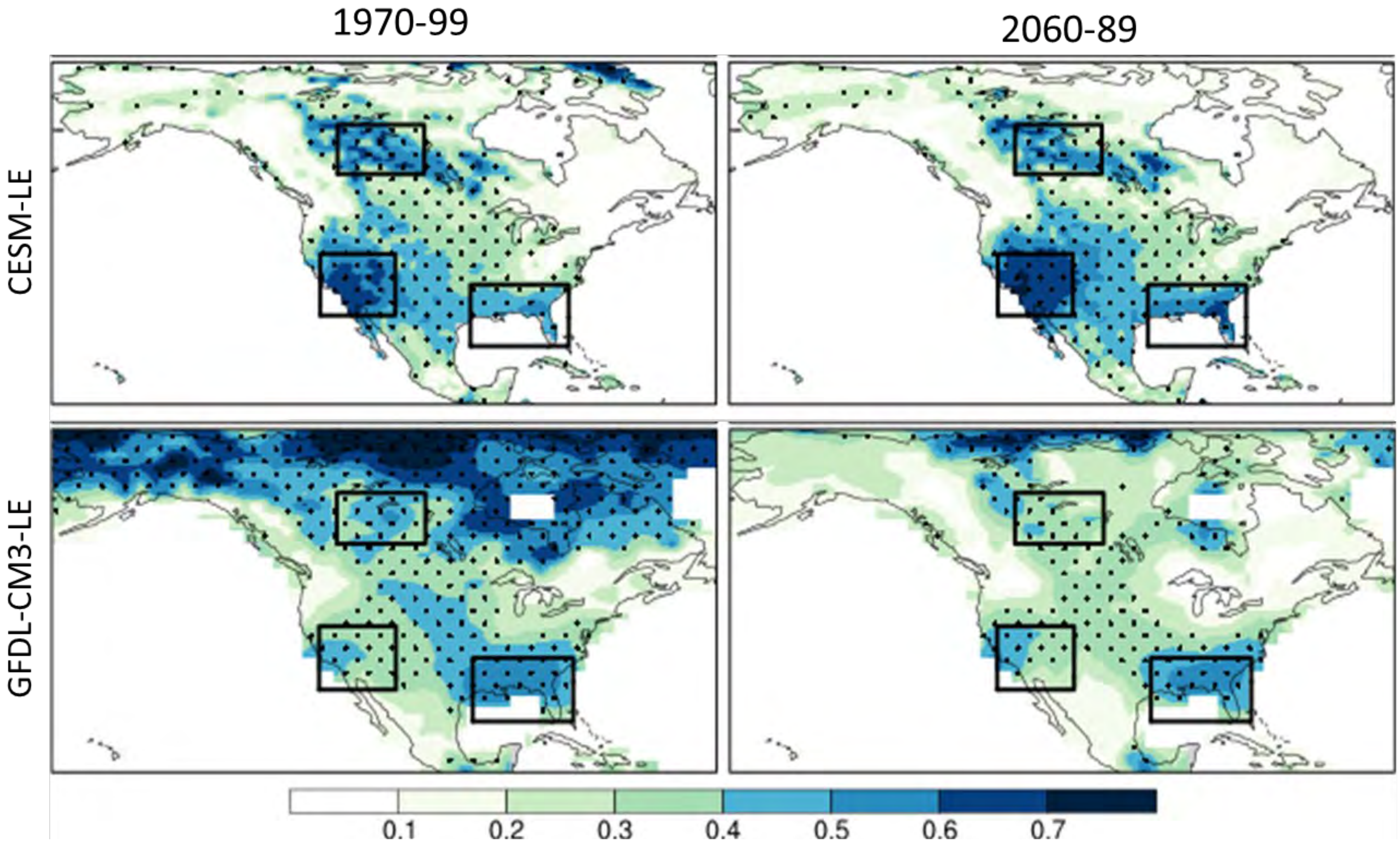
ERA5 soil moisture variability in the US Southwest and Lake Mead Water Level



Anomaly correlation between prediction and observation (withheld 10% data); repeat the process until all data is sampled

Hydroclimate Predictability in Changing Climate

A reduction in high-latitude, e.g., Canadian Plains, and an increase in the US Southwest

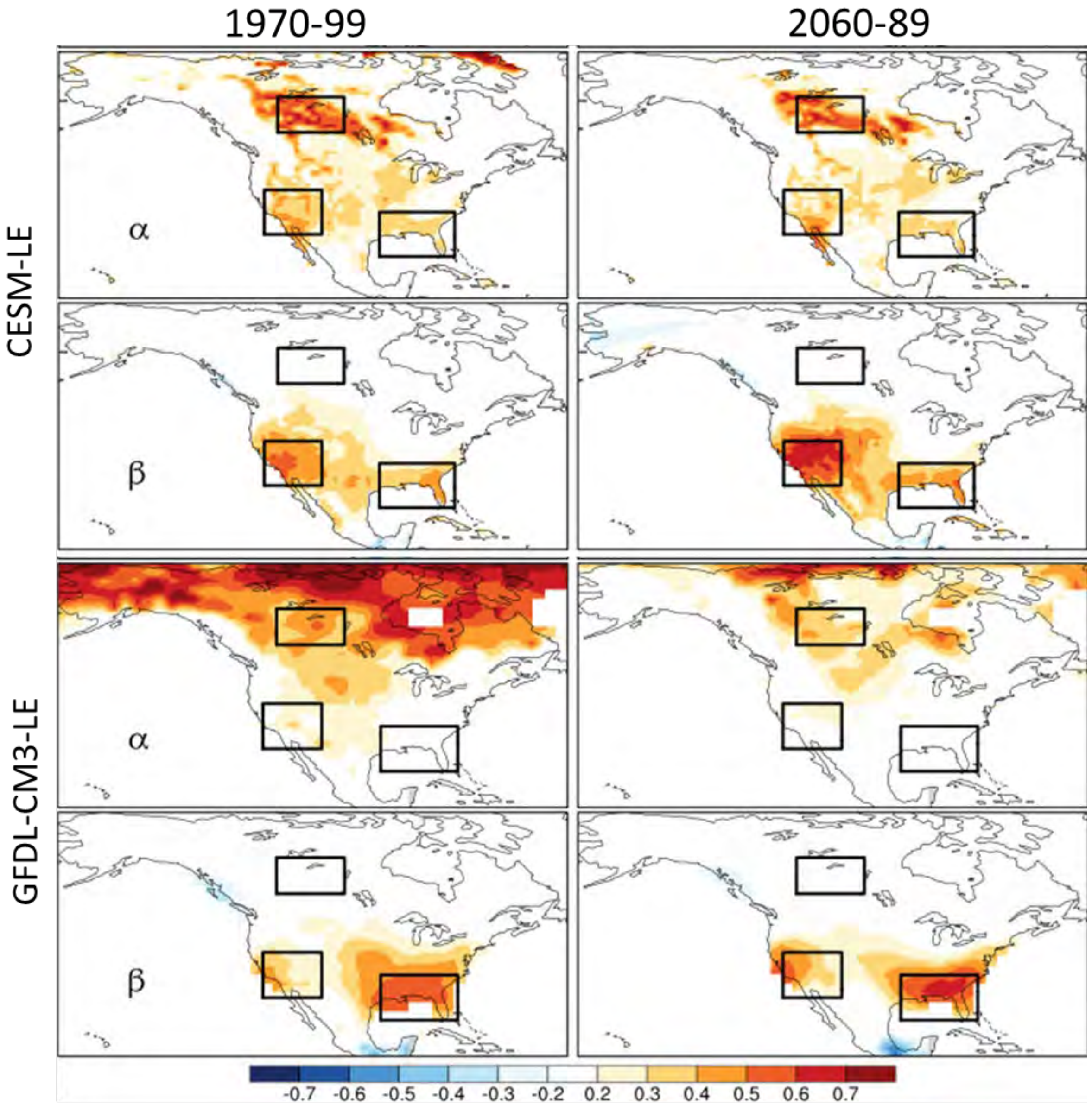


$$\frac{signal}{signa + noise}$$

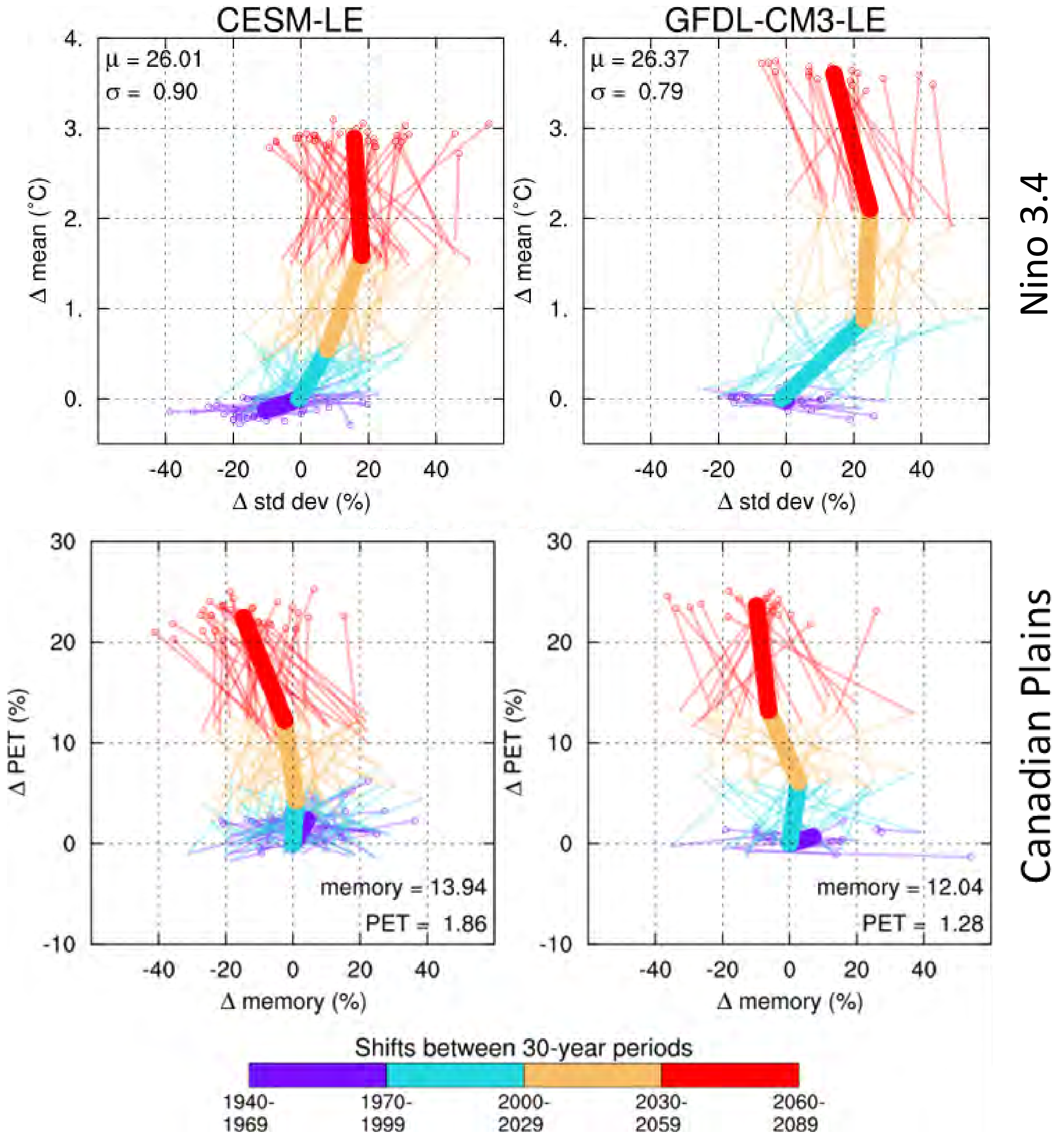
Understanding changing hydroclimate variability and predictability

ENSO increases and memory decreases

$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$



Large Ensemble provides a robust assessment



ENSO Index (Nino 3.4) mean (y-axis) and variability (x-axis) changes

Soil moisture memory (x-axis) and potential evapotranspiration (PET) changes

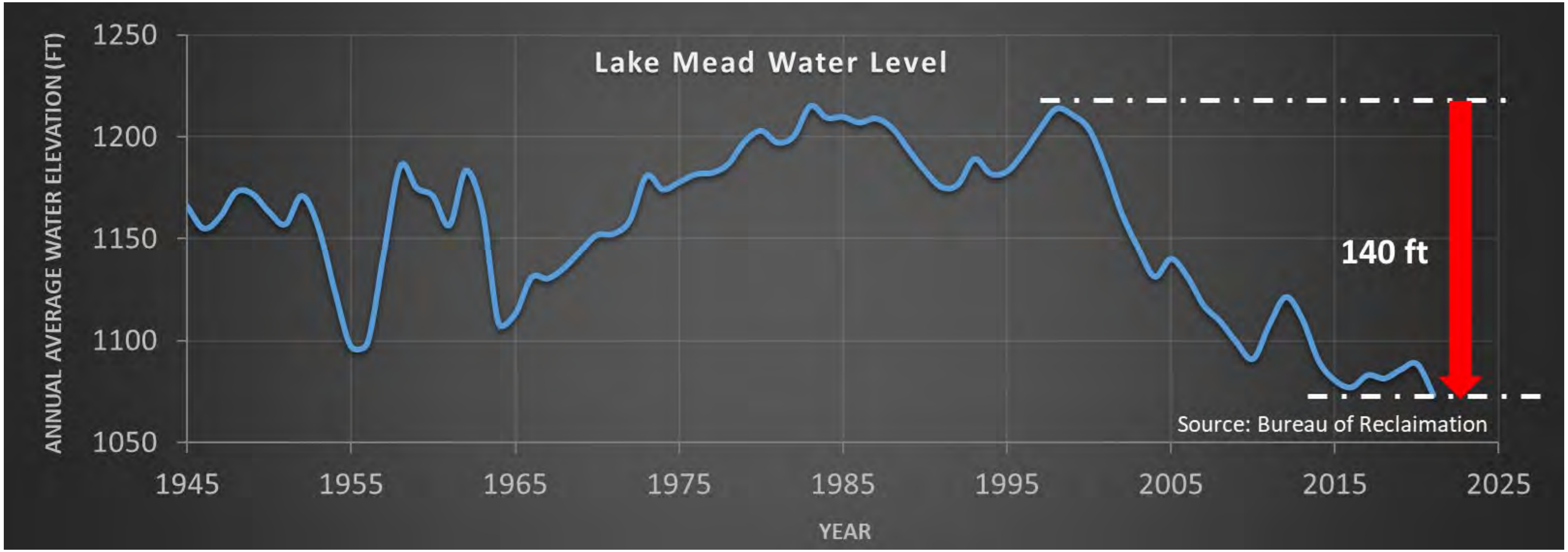
$$\frac{ds}{dt} = -\left({}^{1}/_{\tau}\right)s + \varepsilon$$

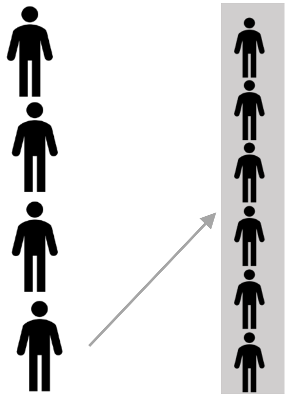
$$\Delta S = \; -ET + (P - R)$$

ET = f(s)* PET

As PET ⇧ τ ⇩

Hydroclimate Extremes
A limited sample size problem in observations and climate model





4 X 6 = 24
person height

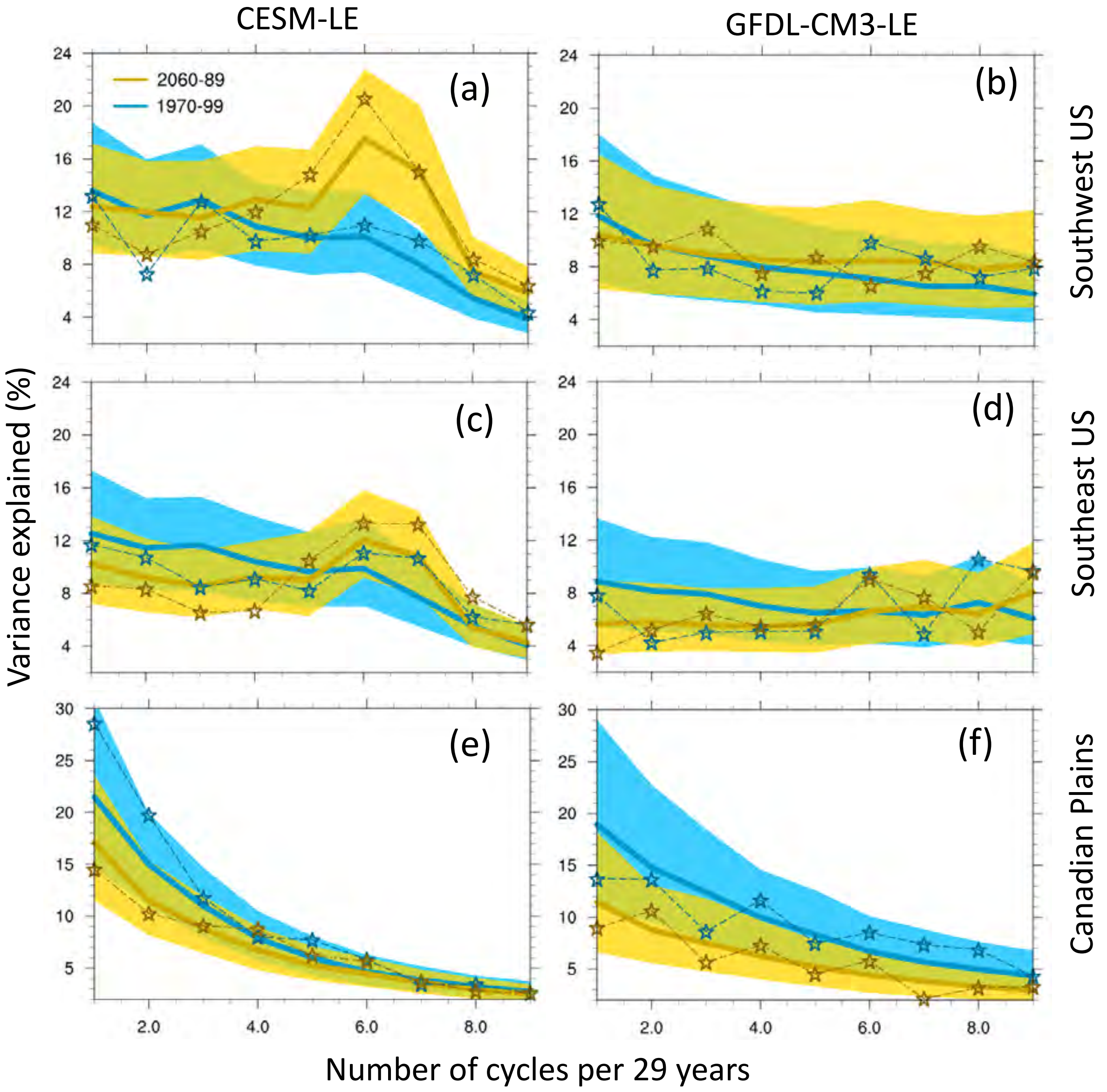
Annual average water level in Lake Mead at Hoover Dam (Source: Bureau of Reclamation).

Reddened ENSO Framework can enlarge the sample size to 1000 by randomly generating the noise (from estimated parameters of normal distribution), and soil moisture initial condition, and taking ENSO sequence from the climate model

$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$

Power spectra of changing soil moisture variability

A strengthening of ENSO variability and wakening of low frequency variability (memory reduction effect)

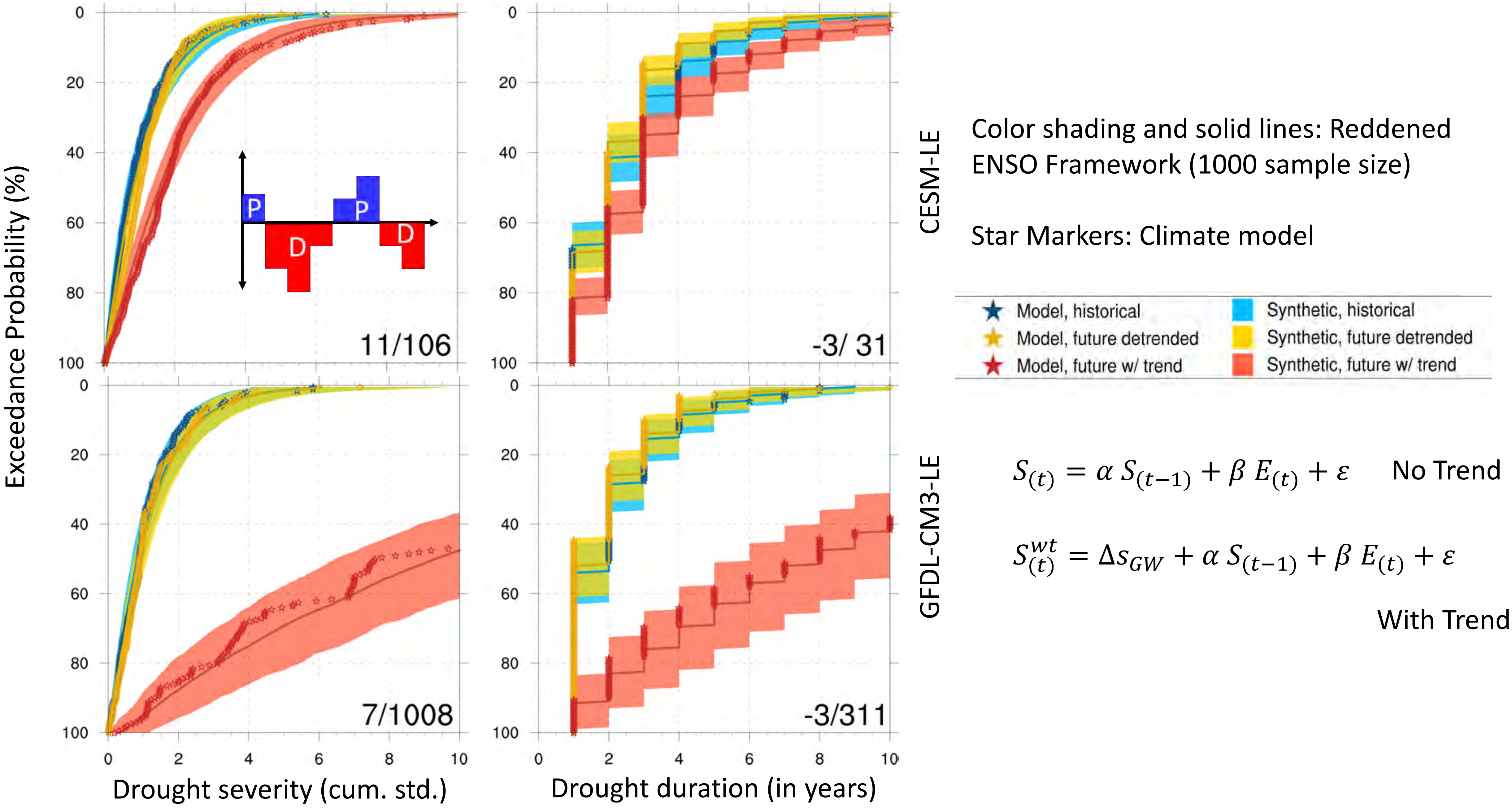


Color shading and solid lines: Reddened ENSO Framework (1000 sample size)

Star Markers: Climate model

ENSO Frequency: 6-7 cycles per 29 years

Changing risk of Drought in US Southwest: Mean state changes drive future drought risks



Color shading and solid lines: Reddened ENSO Framework (1000 sample size)

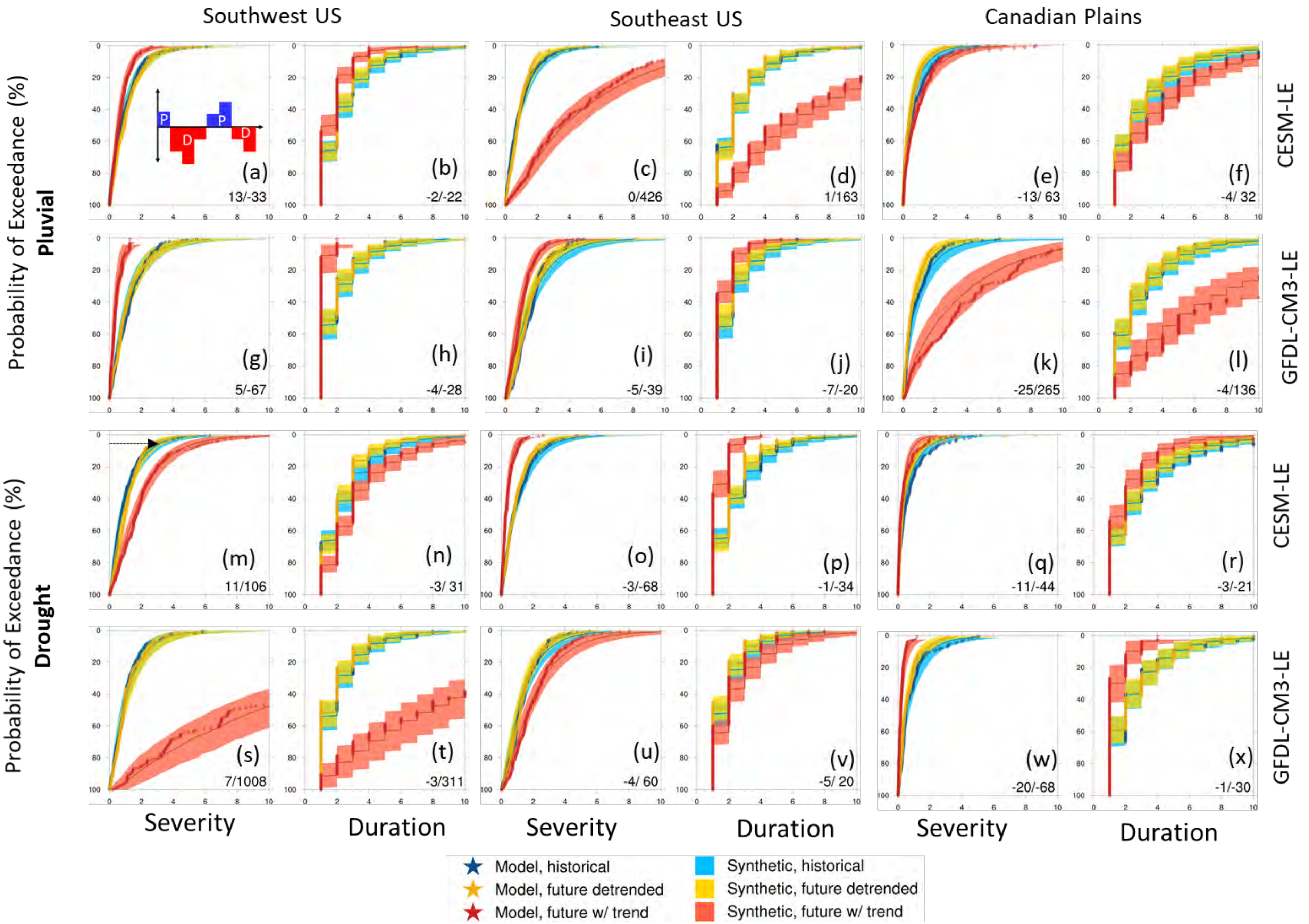
Star Markers: Climate model

$$S_{(t)} = \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$ No Trend

$$S_{(t)}^{wt} = \Delta s_{GW} + \alpha\, S_{(t-1)} + \beta\, E_{(t)} + \varepsilon$$

With Trend

Mean state changes drive future drought and pluvial risks



Conclusions

1. North America’s hydroclimate is changing
2. Changes in soil moisture variability is rather small or even decrease despite increase in precipitation variability.
3. Increasing ENSO variability, and decreasing soil moisture memory affect land hydroclimate variability and predictability
4. Future drought and pluvial risks are primarily driven by changes in the mean state suggesting infrastructure planning can incorporate robust mean state changes despite uncertainty in the variability projections.