



Center for Western Weather
and Water Extremes

SCRIPPS INSTITUTION OF OCEANOGRAPHY
AT UC SAN DIEGO



Jet Propulsion Laboratory
California Institute of Technology

EXPLORING AN EVOLUTION-CENTRIC STATISTICAL TECHNIQUE FOR IMPROVING SEASONAL PREDICTION

Western States Water Council S2S Workshop
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UC San Diego



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Outline

Part I: Hypotheses

Part II: Evolution-centric statistical forecast technique

Part III: Hindcast skill of winter precipitation over the western U.S.

Part IV: Verification of experimental seasonal forecast for winter 2021-22

Part V: Concluding remarks

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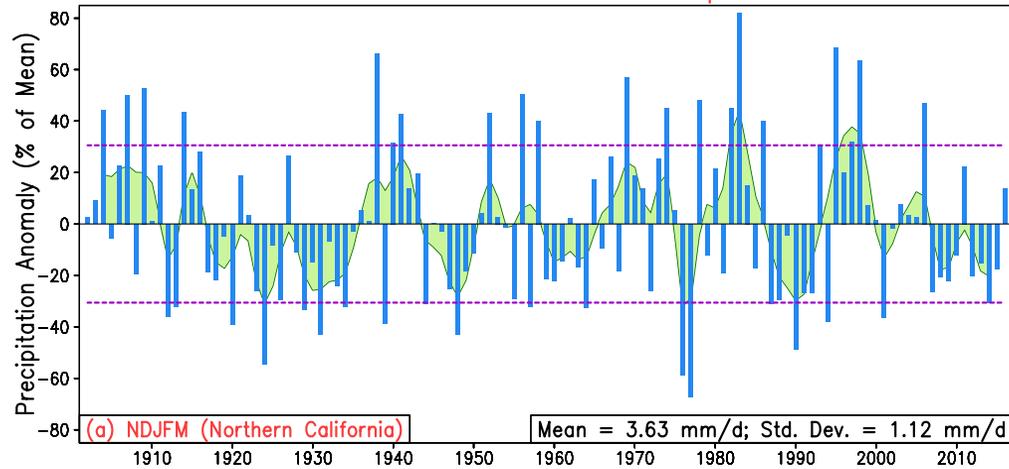
Part IV: Verification of experimental seasonal forecast for winter 2021-22

Part V: Concluding remarks

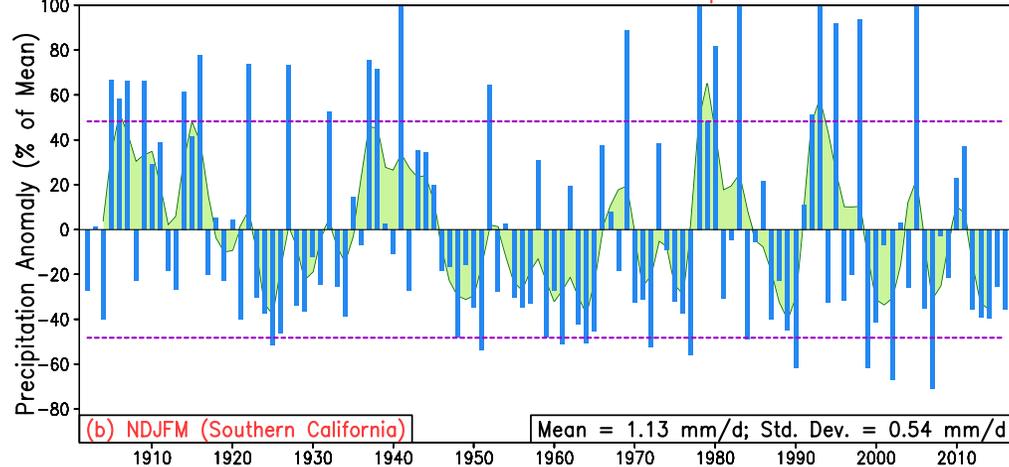
Hypothesis: Low-frequency variability in the forcing?

Observed Precipitation

Northern California NDJFM Precipitation

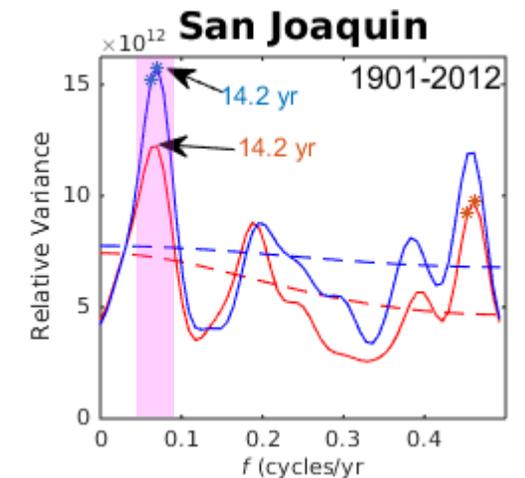
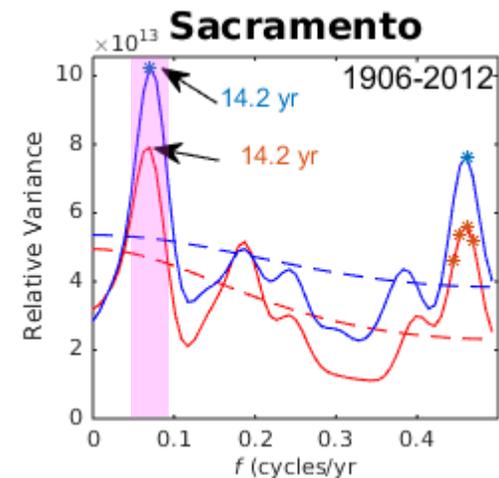
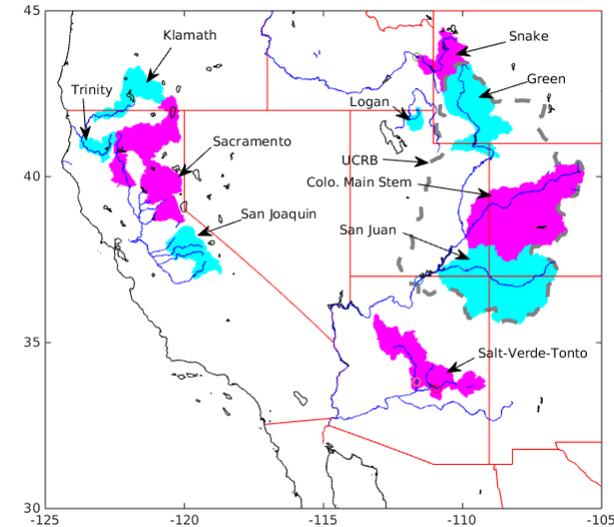


Southern California NDJFM Precipitation



- Besides *year-to-year* fluctuations, observed precipitation reveals prominent role of *slowly changing* recurrences.

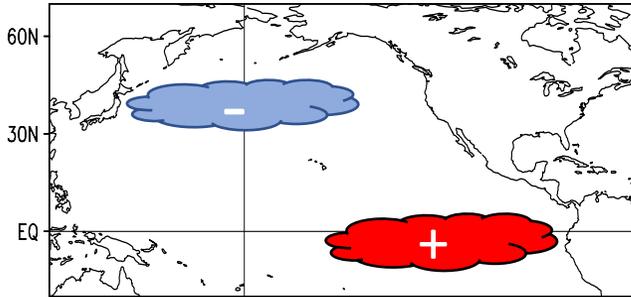
Tree-ring Records & Reconstructed Streamflow



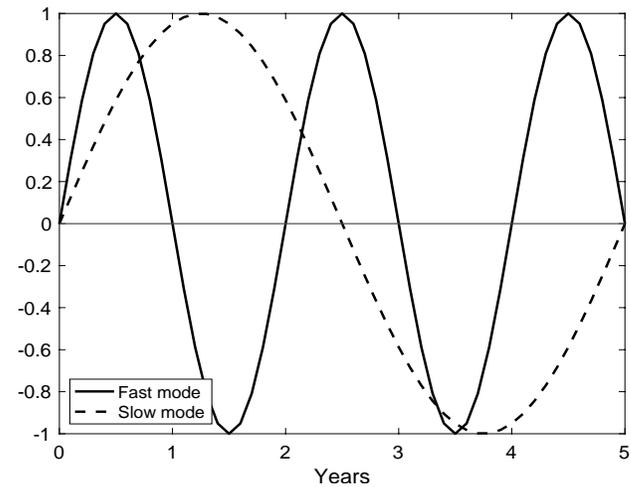
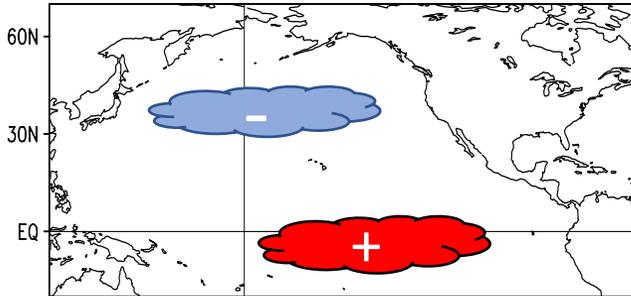
Reference: Meko, D.M., C.A. Woodhouse, and, E.R. Bigio. 2018. "Southern California Tree Ring Study." Final Report to California DWR.

Sea surface temperature evolution: A key consideration in seasonal prediction

Fast mode

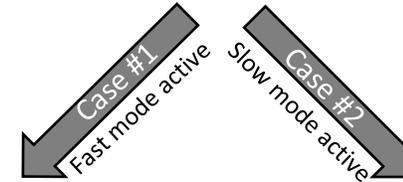
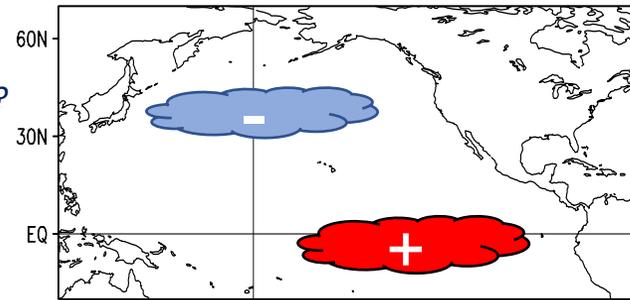


Slow mode

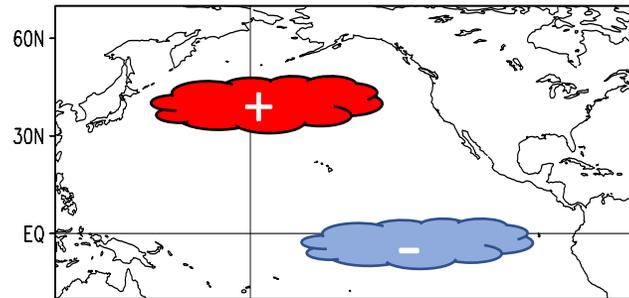


- Which of the two modes is active — the 5-year mode, or the 2-year one?
- Can we detect by simply looking at any single time point?

time, T

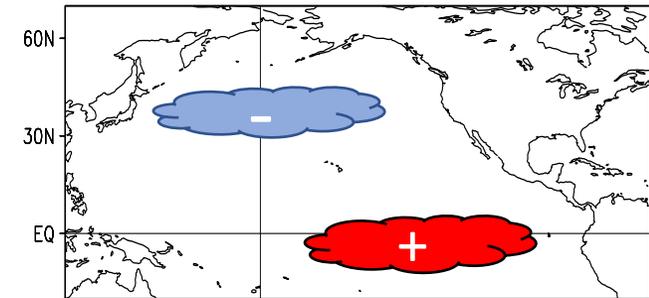


time, $T+2$ seasons



Negative phase of fast mode

time, $T+2$ seasons



Positive phase of slow mode

Hence, it becomes critical to focus on the past *multi-season* structure of the predictor instead of just the present season for an accurate attribution of the dominant mode.

Key questions and objectives

Key Questions



- ❑ Can predictor variables with large memory be mined for generating useful seasonal forecasts at longer lead times over the western U.S.?
- ❑ How can we optimize statistical methods to maximally utilize the influence of potential predictors of winter western U.S. precipitation?

Objectives

- ❑ Explore the viability of a statistical technique, which is rooted in the seasonal evolution of predictor variables, in context of winter precipitation forecasting
- ❑ Quantify the realized predictive skill from hindcasts in an independent period
- ❑ Generate experimental forecasts of seasonal winter precipitation, starting winter 2020-21

Outline

Part I: Hypotheses

Part II: Evolution-centric statistical forecast technique

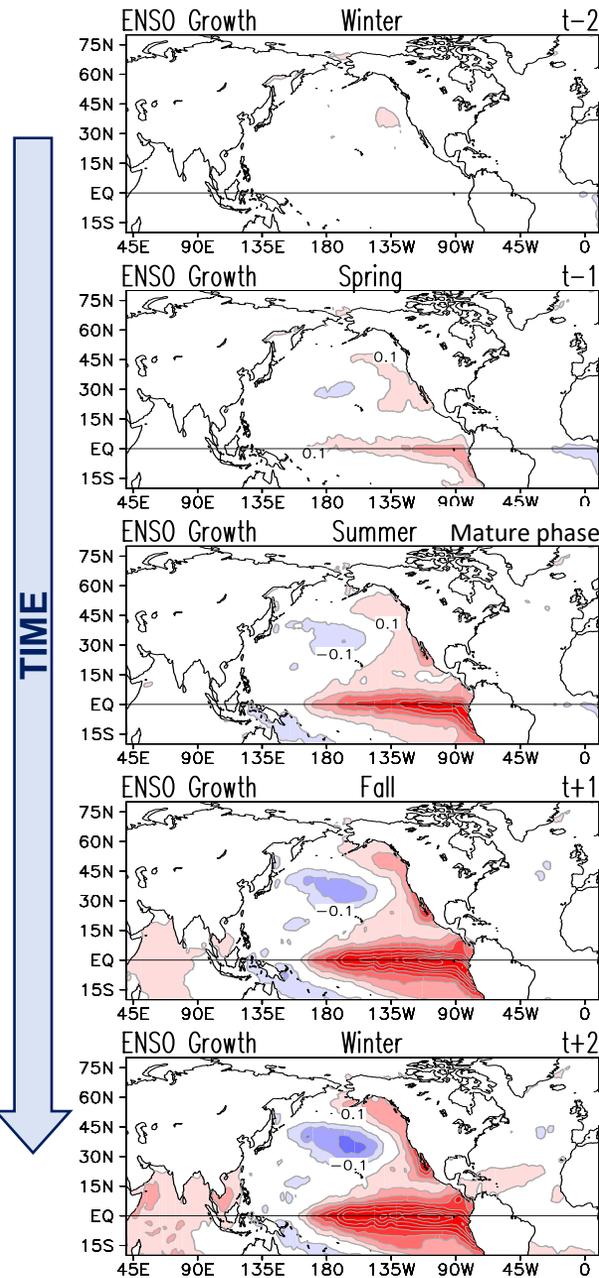
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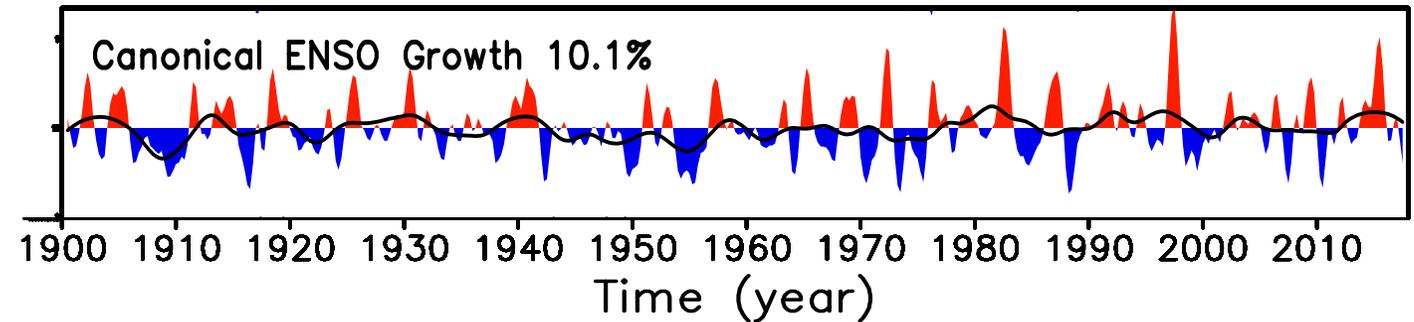
Predictors: *Multi-season sea surface temperatures*

- SSTs influence both regional and remote hydroclimate:
 - *Interannual variation*: ENSO impacts the North American hydroclimate, Indian summer monsoon
 - *Decadal variations*: Multi-year droughts, e.g., the 1930s 'Dust Bowl' over the Great Plains
- We analyze of 118 years of observed, seasonal SST anomalies
- Technique: Extended-Empirical Orthogonal Function (extended-EOF) analysis
- Eleven modes of global SST variability (natural variability and secular trend) extracted
- Each comprises of a sequence of maps (or, the extended-EOF pattern), and its related time series (principal component). For example,



C.I. for SST anomalies = 0.1 K

+



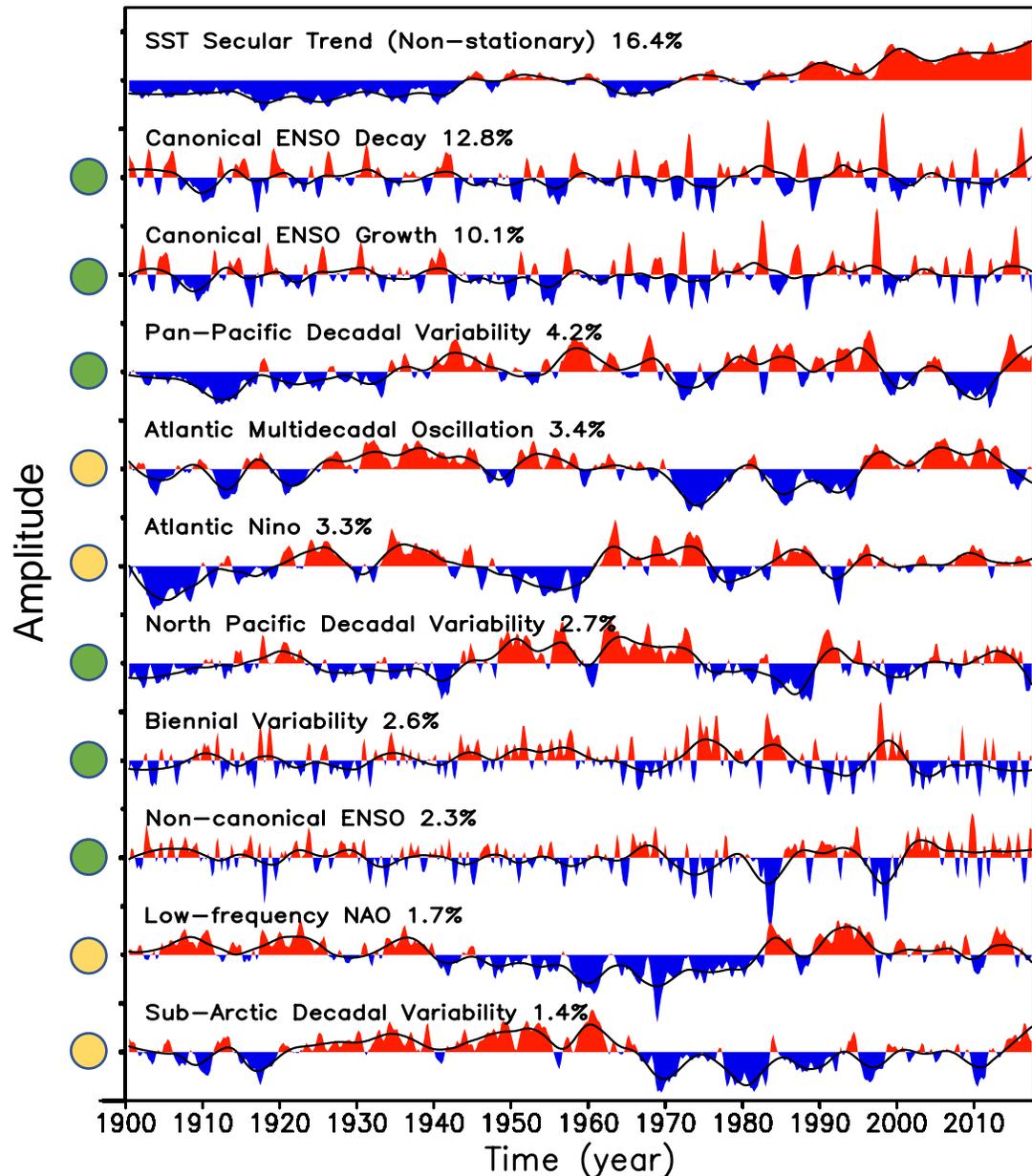
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Canonical ENSO Growth extended-EOF mode

References:

- Nigam, S., A. Sengupta, and A. Ruiz-Barradas, 2020, *J. Climate*, 33(13), 5479-5505.
- Nigam, S. and A. Sengupta, 2021, *Geophysical Research Letters*, 48(3), <https://doi.org/10.1029/2020GL091447>.

SST Analysis: Principal components (PCs) of Global SSTs



Modes obtained are:

- Non-stationary SST Secular Trend
- ENSO (Growth, Decay, Non-Canonical, Biennial mode)
- Pacific Decadal Variability (North Pacific, Pan-Pacific)
- Atlantic (AMO, Atlantic Nino, Low-frequency NAO, Subarctic Decadal Variability)

- Pacific mode
- Atlantic mode

References:

- Nigam, S., A. Sengupta, and A. Ruiz-Barradas, 2020, *J. Climate*, 33(13), 5479-5505
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Statistical forecast technique

This analysis leverages observational variables with large thermal inertia (e.g., SSTs) for skillful seasonal prediction.

Unique characteristics of our approach:

- use of multi-season, antecedent predictor information instead of utilizing just the preceding one season
- improved characterization of the evolution of the recurrent variations, i.e., both the *spatial and temporal* recurrence
- additional consideration of *lower-frequency* sources of natural variability in addition to interannual variability

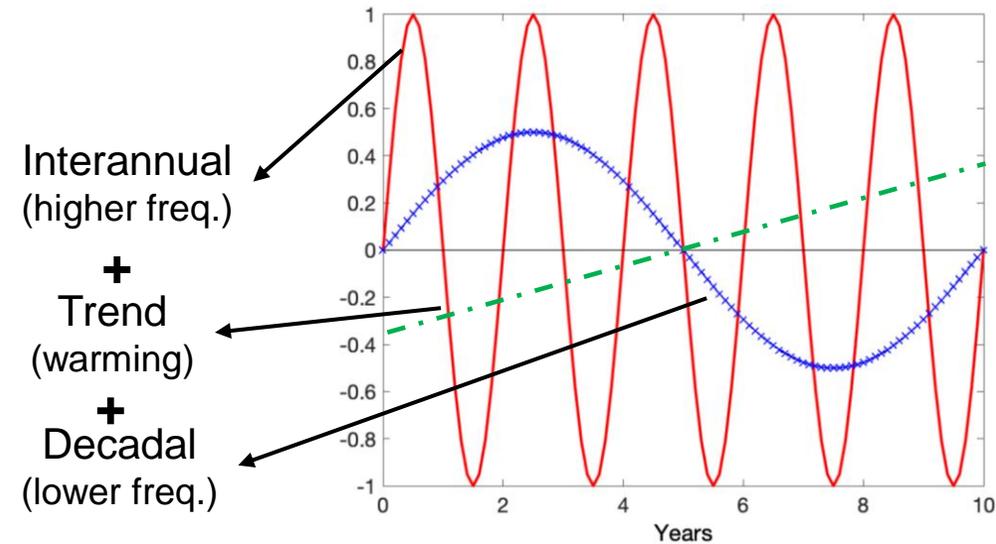
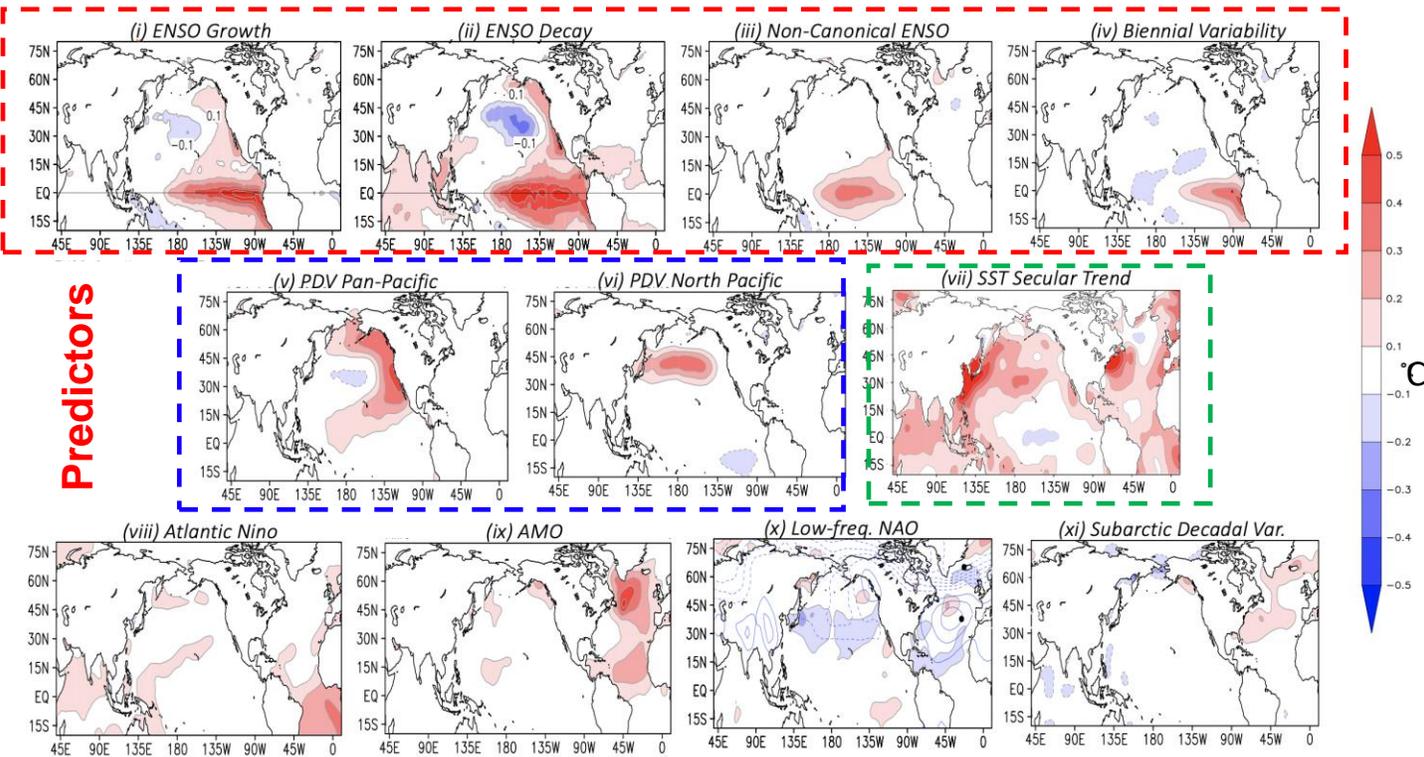


Figure (left) Leading modes of global SST variability – ENSO (top row), Pacific Decadal Variability and Secular Trend (middle row), Atlantic modes (bottom row) informing seasonal prediction of precipitation. (right) Idealized representation of the frequency of SST modes

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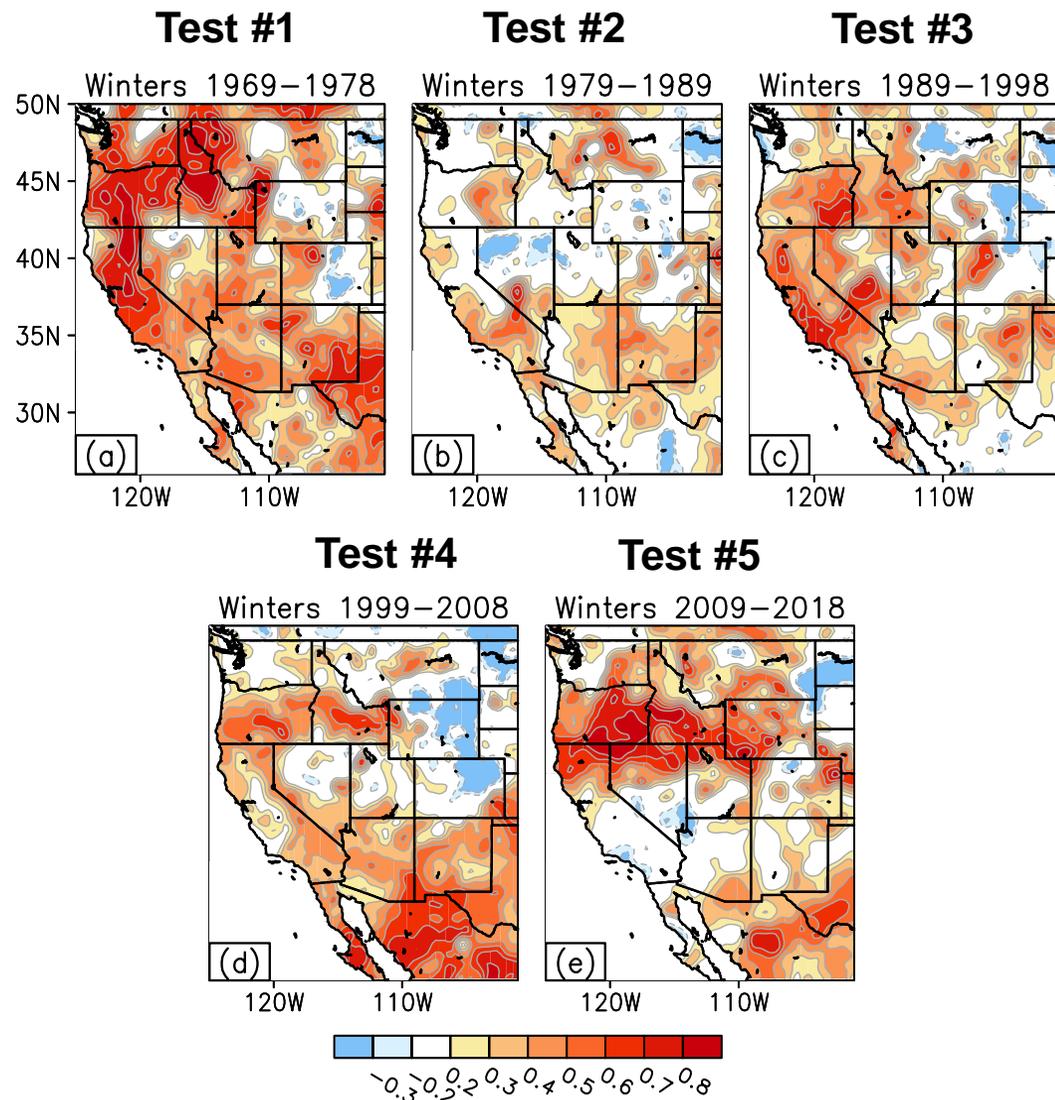
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Precipitation hindcast skill

Model hindcast skill during the past five decades



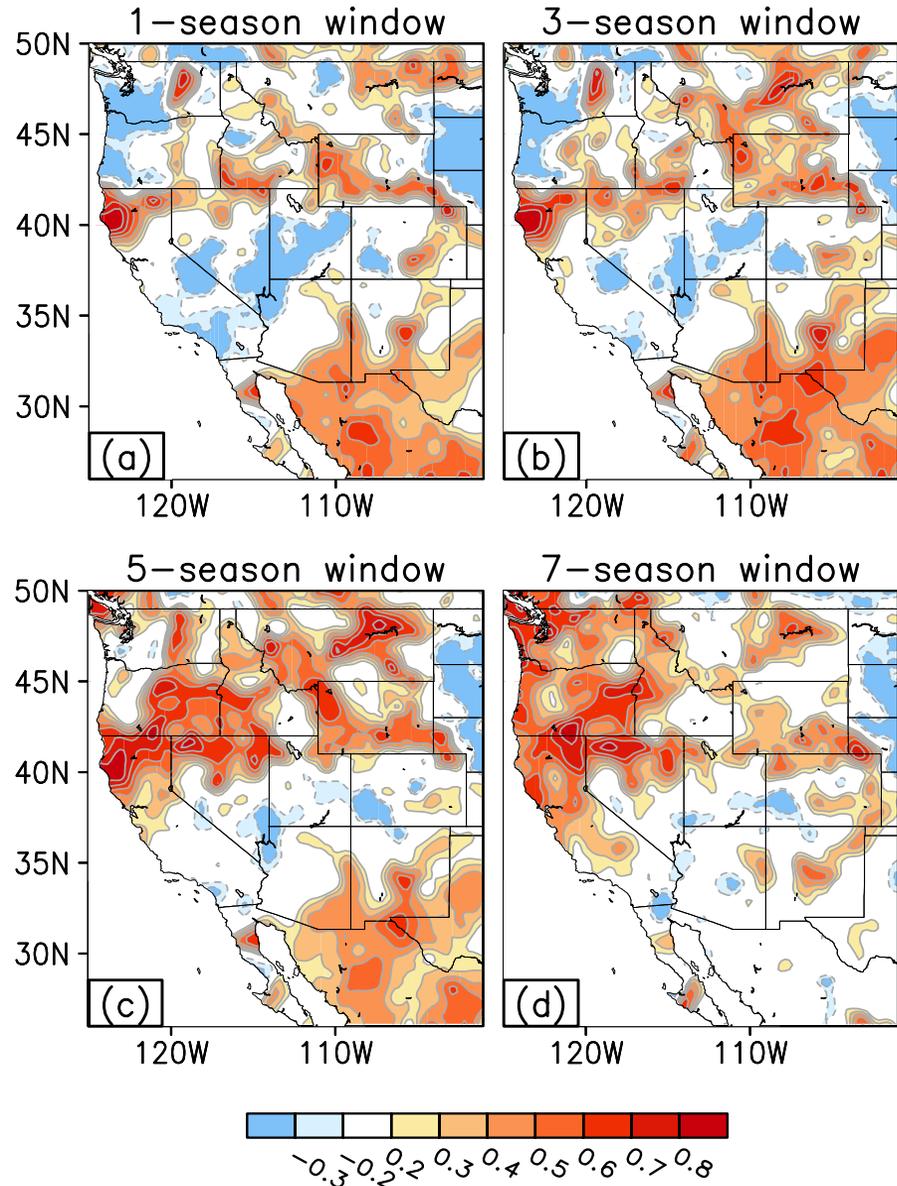
- Hindcast skill is assessed via *n-fold cross-validation* over winters (Nov-Mar).
- The model is fit iteratively *n* times, each time training the data on *n-1* folds and evaluating on the the validation set.

Test #1	1949-58	1959-68	1969-78	1979-88	1989-98	1999-08	2009-18
Test #2	1949-58	1959-68	1969-78	1979-88	1989-98	1999-08	2009-18
Test #3	1949-58	1959-68	1969-78	1979-88	1989-98	1999-08	2009-18
Test #4	1949-58	1959-68	1969-78	1979-88	1989-98	1999-08	2009-18
Test #5	1949-58	1959-68	1969-78	1979-88	1989-98	1999-08	2009-18

Testing set
 Training set

- Correlation coefficients between the hindcast and observed precipitation anomalies are displayed over individual test sets.

Skill score with change in length of predictor window



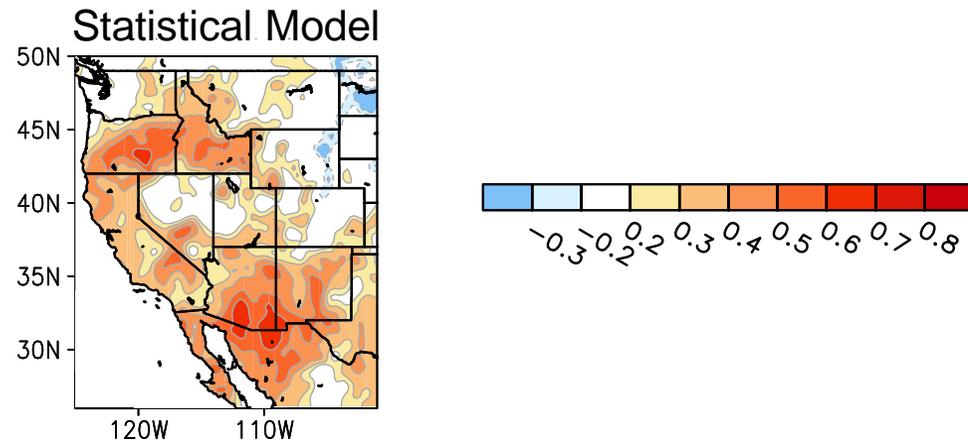
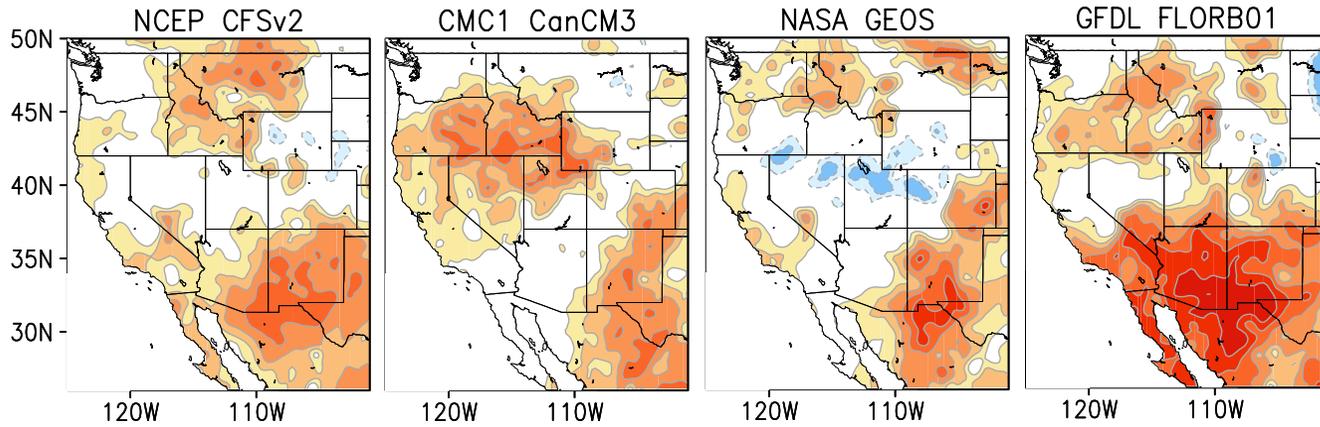
Precipitation hindcast skill

- Hindcast skill is assessed as a function of the length of temporal sampling window employed in an extended-EOF analysis.

Spring (t-6)	Summer (t-5)	Fall (t-4)	Winter (t-3)	Spring (t-2)	Summer (t-1)	Fall (t)	Winter (t+1)
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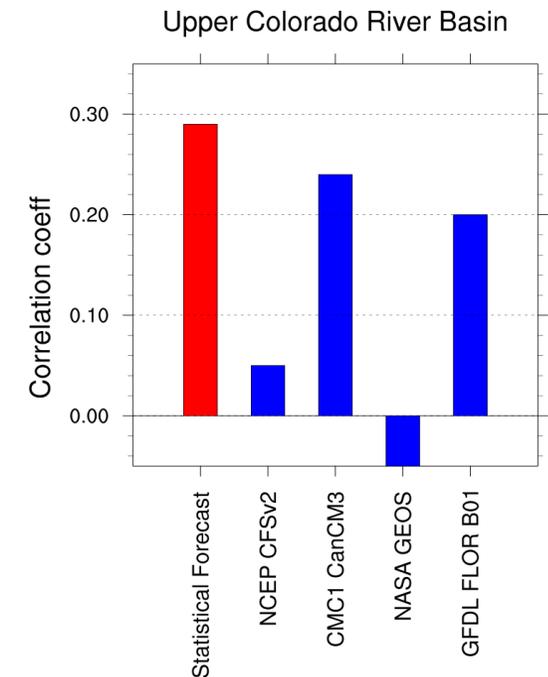
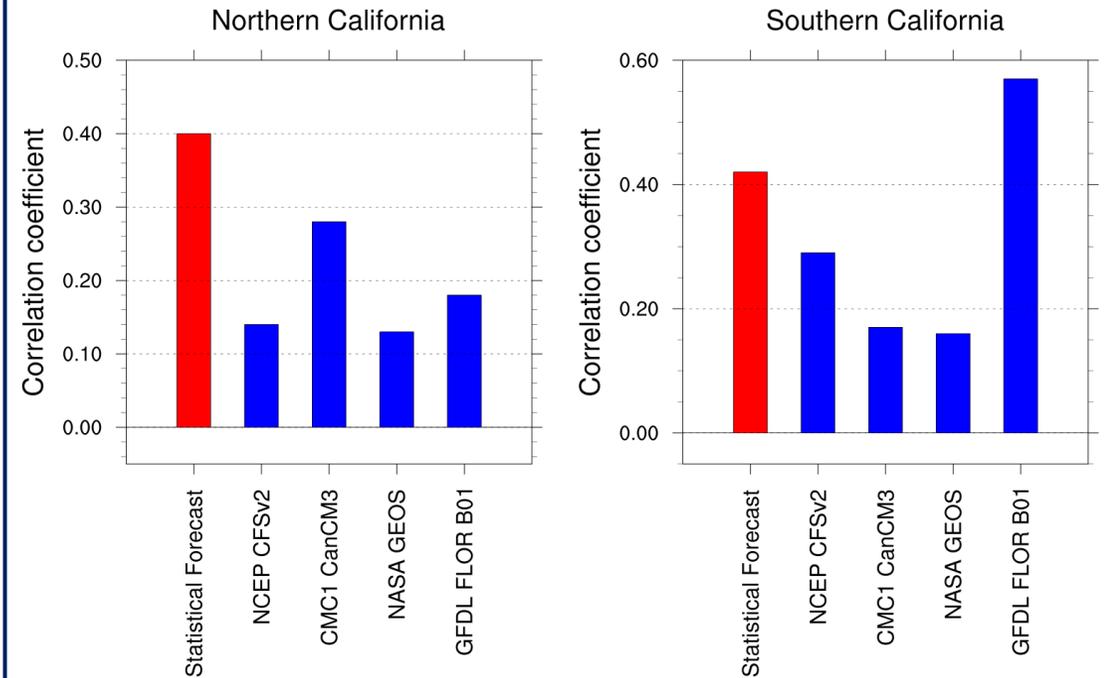
- Skill assessment based on correlation coefficients values vis-à-vis observations
- Training period: 1948-2008 winters
- Validation period: 2009-2018 winters
- Using a longer temporal sampling window of predictors leads to better forecast skill

Comparison with dynamical model skill



Correlations between model hindcasts and observed from 1982-83 to 2010-11 winters (NDJFM)

- NCEP-CFSv2 (24 ensemble members)
- CMC1-CanCM3 (10 ensemble members)
- NASA-GEOS2S (4 ensemble members)
- GFDL-FLOR-B01 (12 ensemble members)



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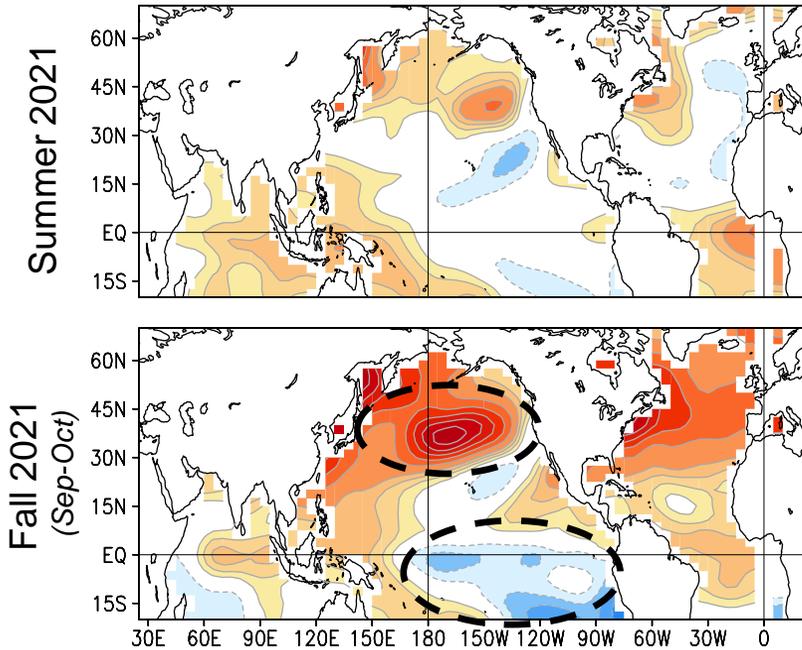
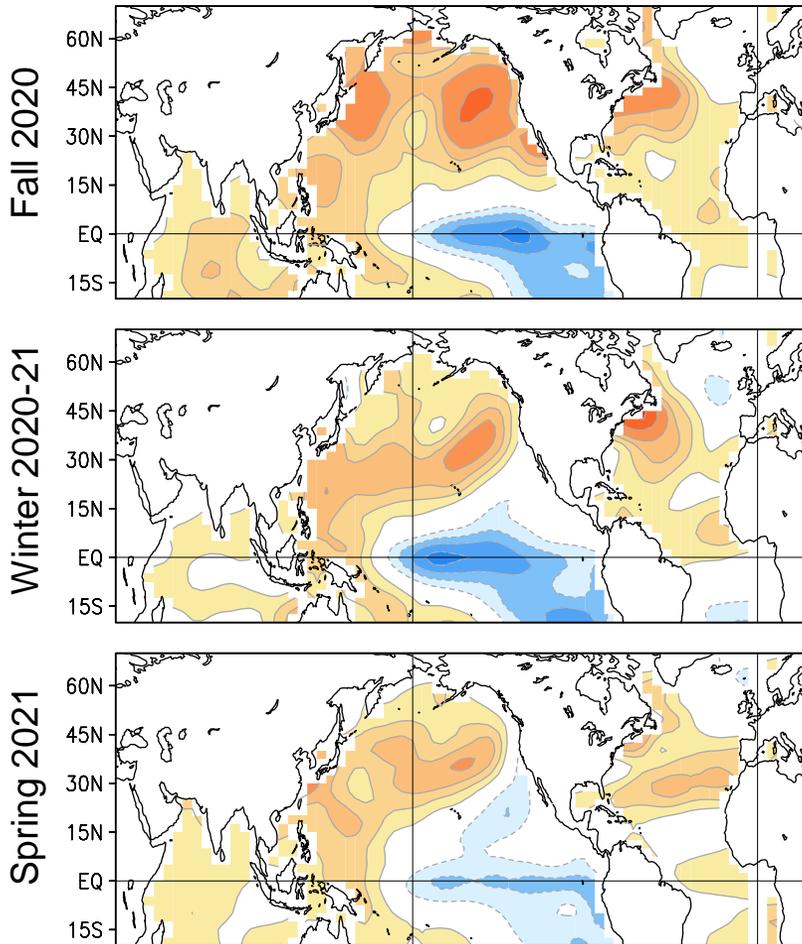
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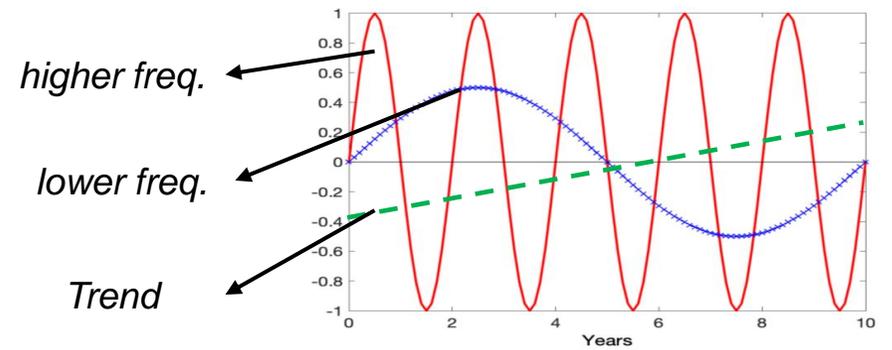
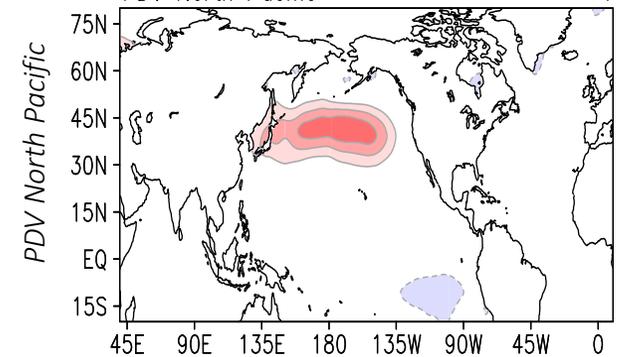
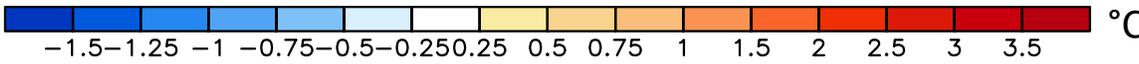
Part V: Concluding remarks

Sea surface temperatures during the prior seasons

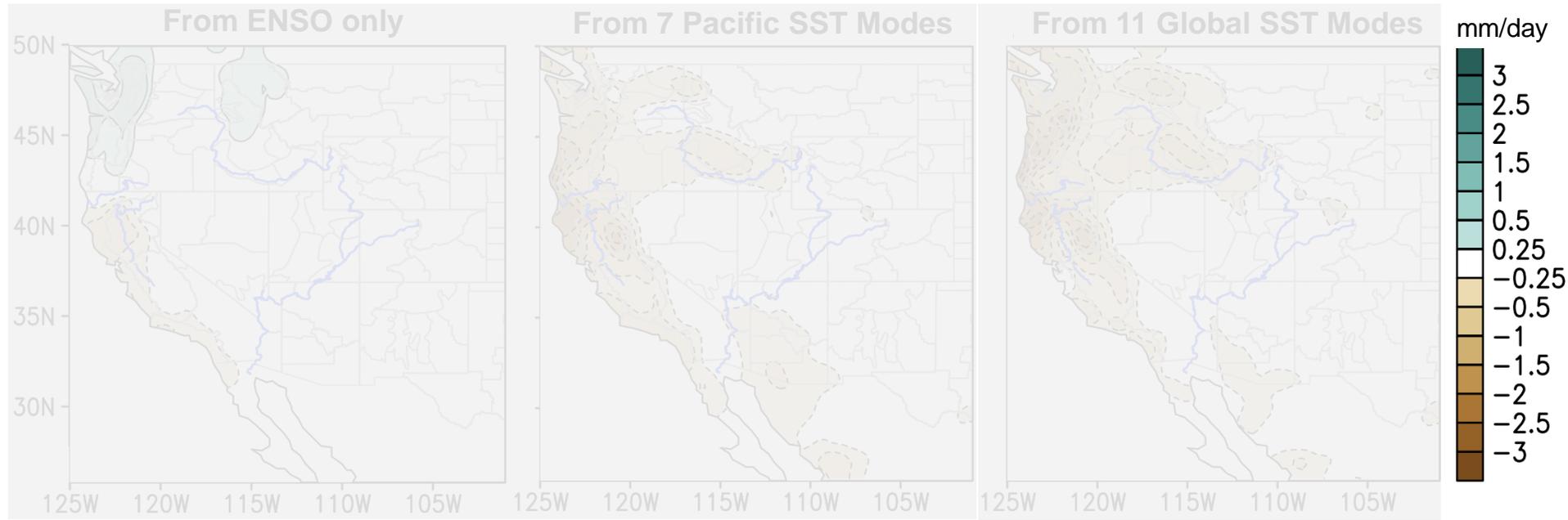
TIME



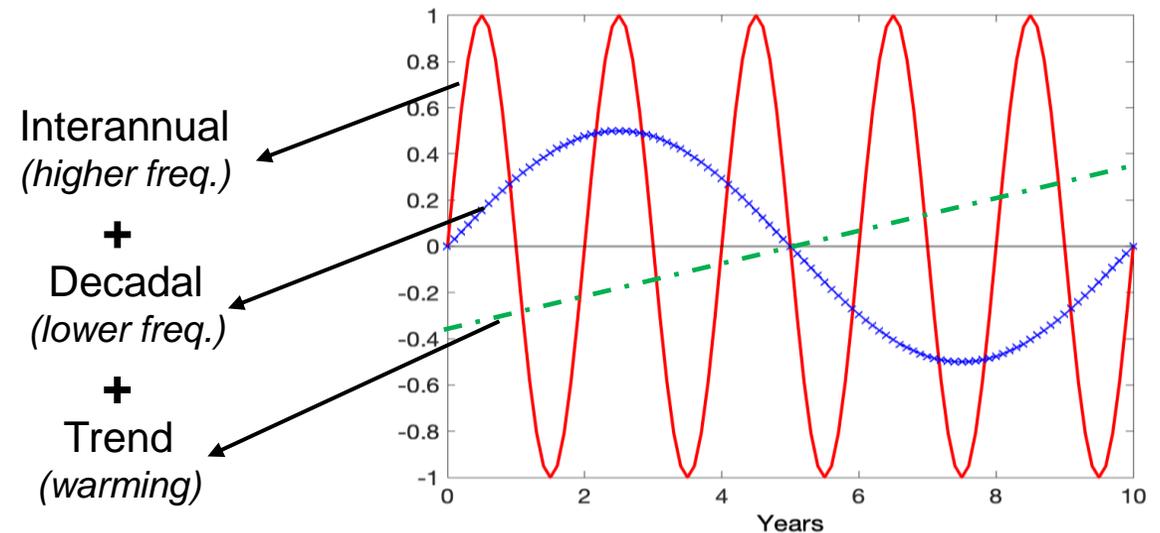
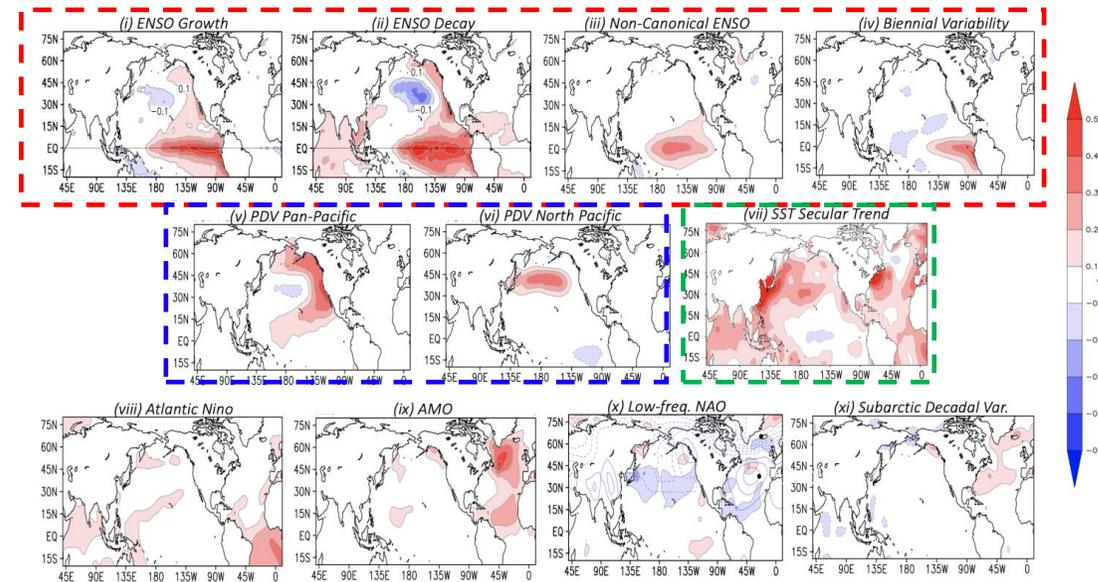
- ❑ Equatorial SSTs were below normal across most of the central and eastern Pacific Ocean.
- ❑ Persistent warm SSTs in the northern Pacific Ocean across multiple seasons.
- ❑ Interesting resemblance to the Pacific Decadal Variability: North Pacific mode (low frequency)



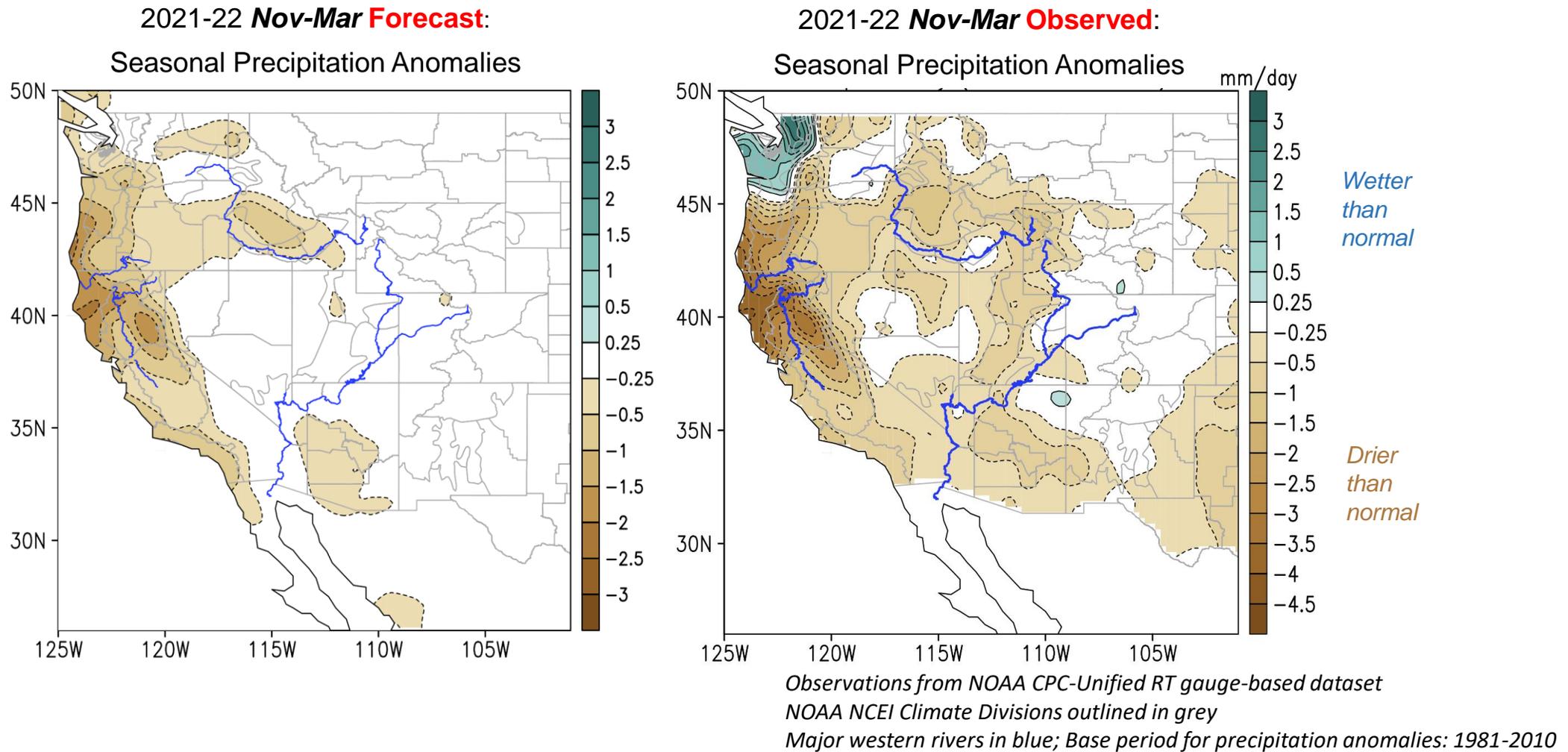
Modal attribution to the seasonal forecast



- Based on contribution from ENSO only, we have the classical dipole in precipitation footprint.
- However, our analysis emphasizes the need to consider modes of variability across a wide range of timescales.

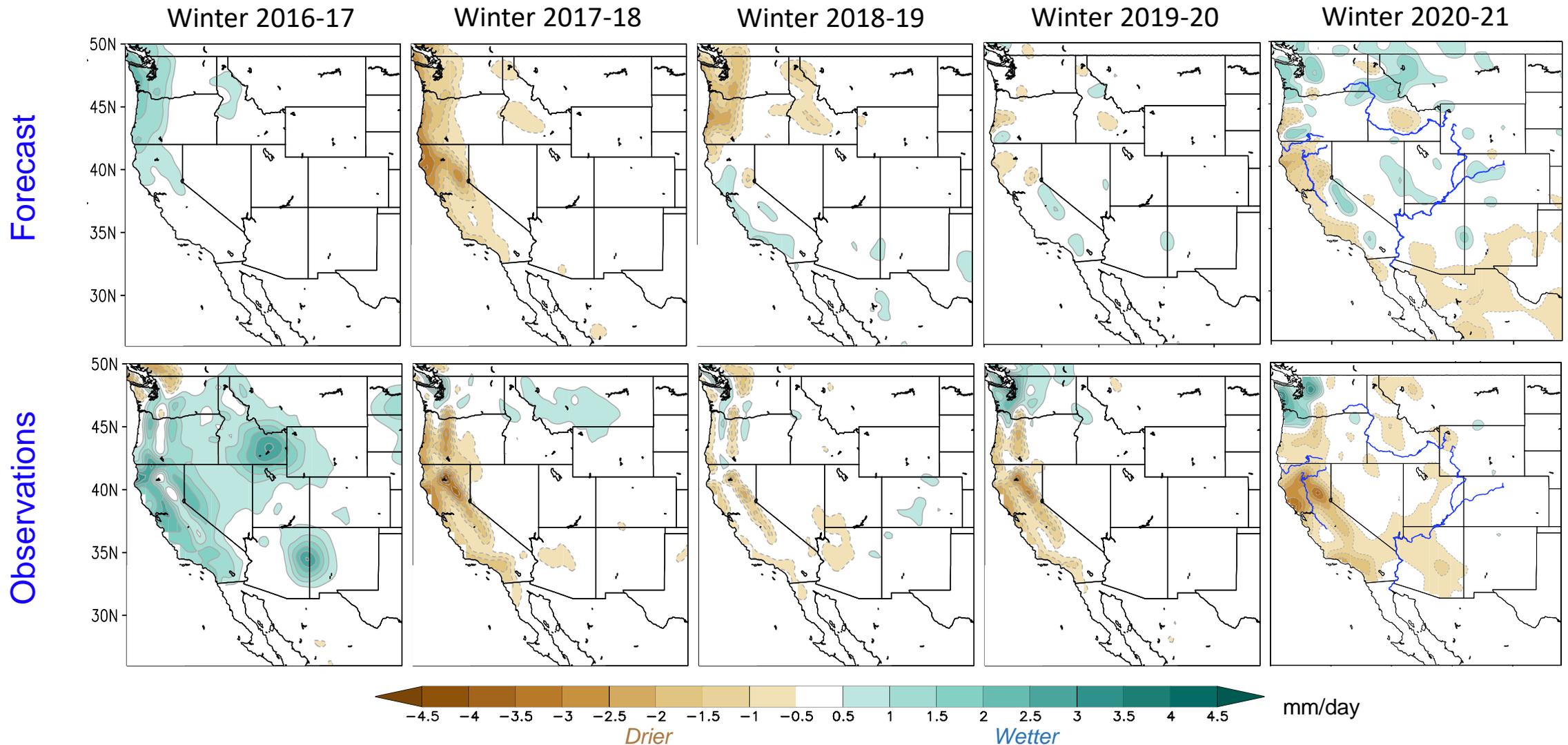


Verification of experimental seasonal forecast (Nov-Mar 2021-22)



- Our experimental forecast favored *drier-than-normal* conditions in northern and southern California
- *Near-normal* rainfall was forecasted in the Upper Colorado river basin.

Past winter precipitation forecasts and verification



- ❑ Observed vs. predicted winter (December-February) precipitation anomalies over the Western U.S.
- ❑ Forecasts are generated from the modal contributions of Pacific SST PCs using a 5-season predictor window

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Concluding remarks

- ❑ The observational record (including paleoclimate proxies) over the Western U.S. is characterized by prominent *low-frequency variability*.
- ❑ We demonstrate the need to accommodate the sources of predictability ranging from interannual to decadal-multidecadal timescales in context of longer lead seasonal forecasting.
- ❑ Regional hydroclimate predictions at longer lead times benefit from characterization of the *evolution* of the nascent and mature phases of variability.
- ❑ Based on the retrospective forecasts, thus far, global and basin-scale modes of SST variability are shown to be viable predictors of wintertime precipitation over the Western U.S.

Thank you for listening!

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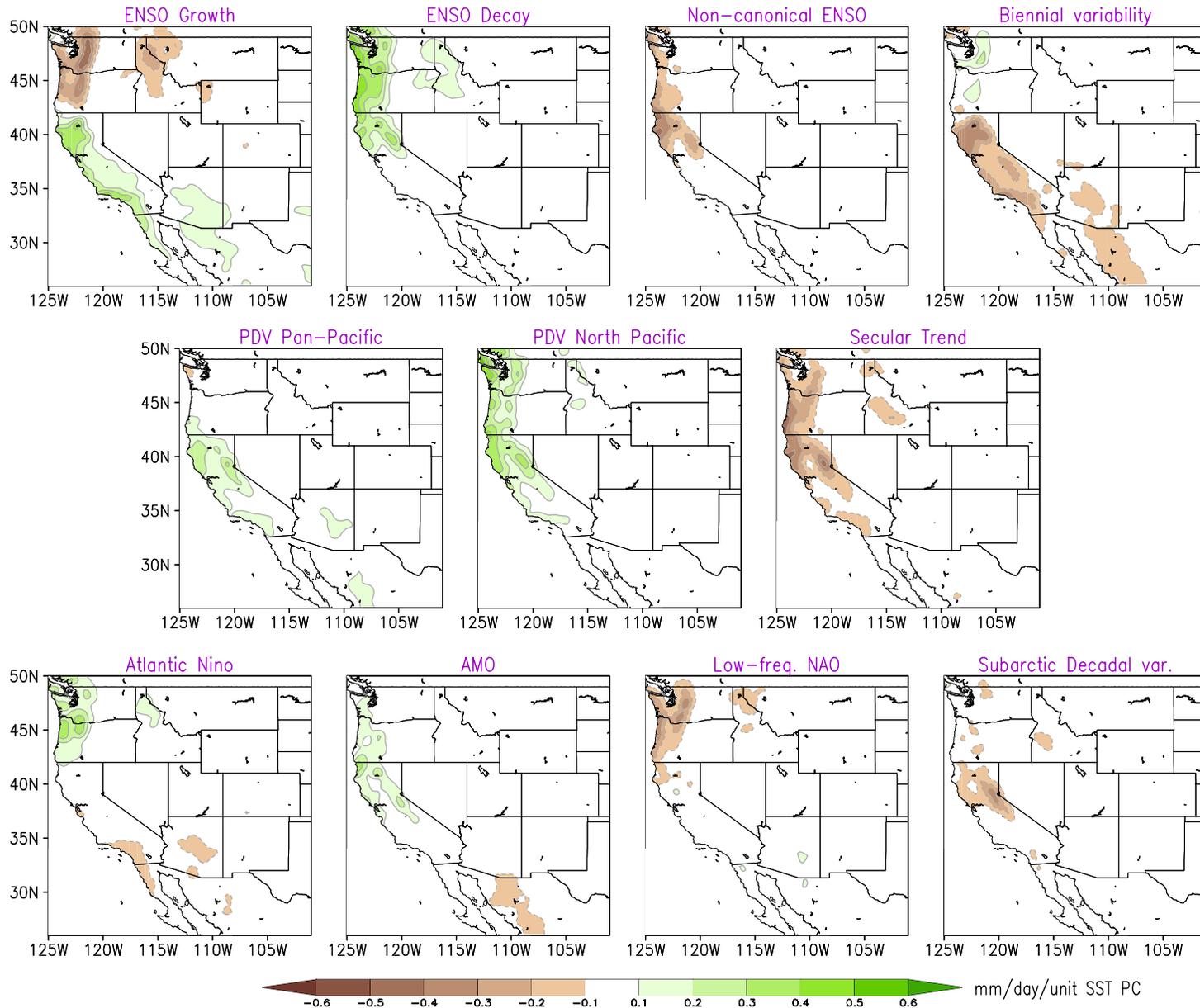


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Influence of multi-season long SST predictors on winter precipitation

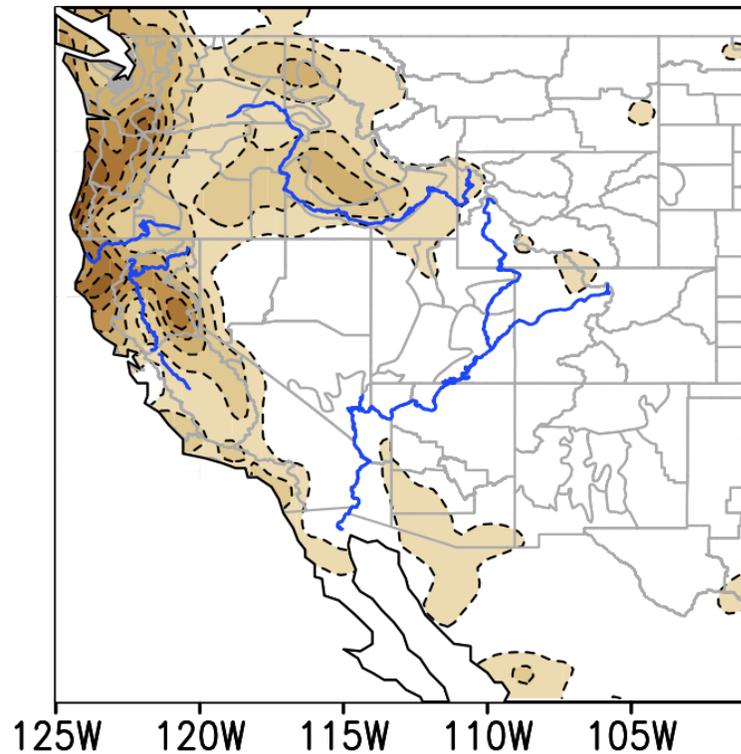


- Temporally-lagged regressions of winter precipitation on antecedent (5-season long) SSTs
- Notable precipitation surplus associated with canonical ENSO, AMO, and the Pacific decadal variability patterns
- Impressive deficits noted for the biennial variability, secular trend, Atlantic Nino, low-frequency NAO, and the Subarctic decadal variability

Verification of experimental seasonal winter precipitation forecast (Dec-Feb)

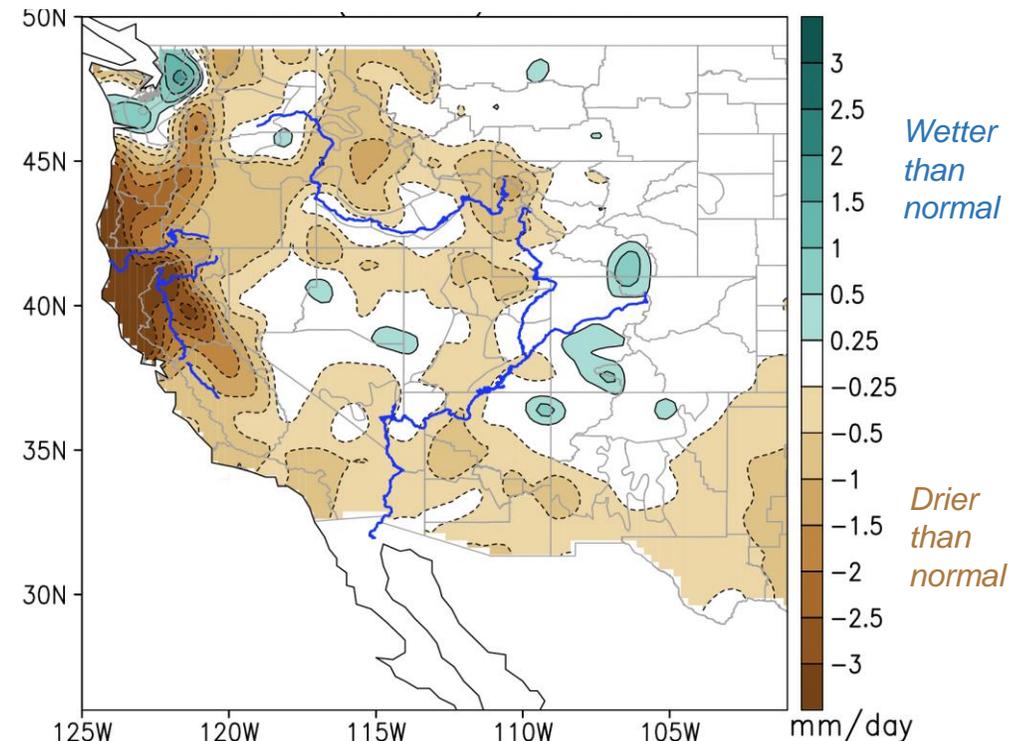
2021-22 **Dec-Feb Forecast** (issued 7 Nov '21):

Seasonal Precipitation Anomalies



2021-22 **Dec-Feb Observed:**

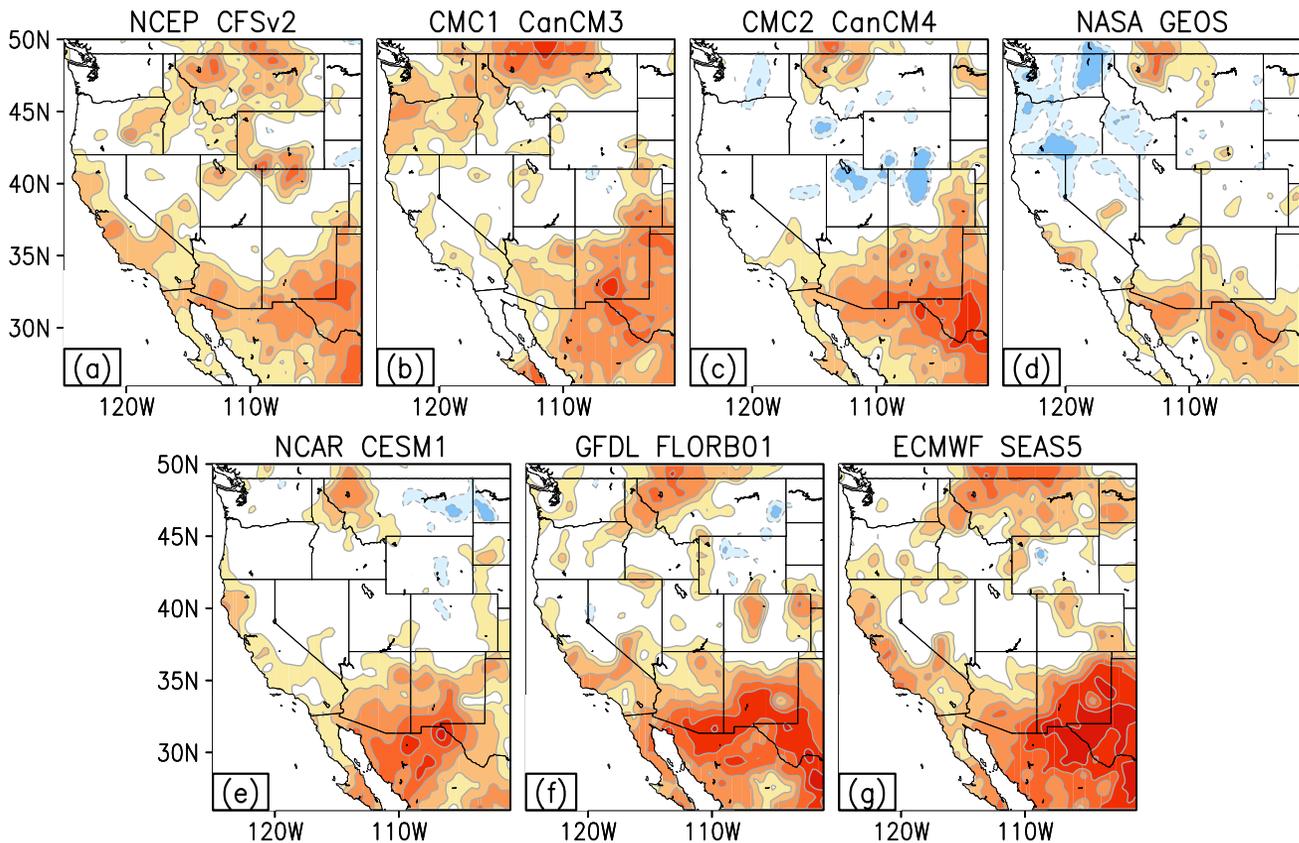
Seasonal Precipitation Anomalies



based on NOAA CPC Unified RT dataset
(base period: 1981-2010)

- Our experimental forecast favored *drier-than-normal* conditions in northern and southern California.
- *Near-normal* rainfall was forecasted in the Upper Colorado river basin.

Dynamical prediction skill



Correlations between model hindcast and observed

-0.3 0.2 0.3 0.4 0.5 0.6 0.7 0.8

- NCEP-CFSv2 (24 ensemble members)
- CMC1-CanCM3 (10 ensemble members)
- CMC2-CanCM4 (10 ensemble members)
- NASA-GEOS2S (4 ensemble members)
- NCAR-CESM1 (10 ensemble members)
- GFDL-FLOR-B01 (12 ensemble members)
- ECMWF-SEAS5 (25 ensemble members)

Validation of hindcasts from dynamical models for 1982-83 to 2010-11 winters (DJF)

