Dynamical ⇔ Statistical S2S Forecasts

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May 23, 2019

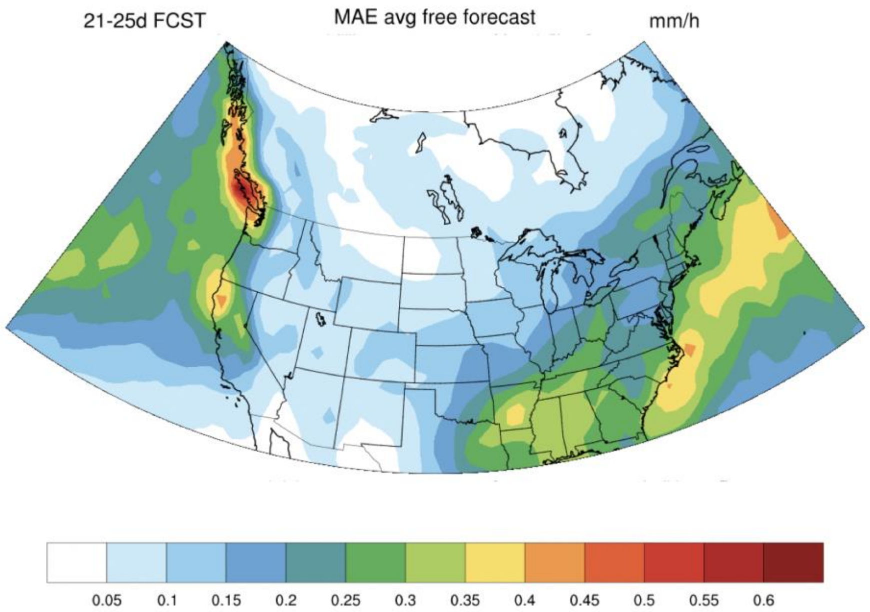
Update on my colleagues' research

1. Tropical nudging

2. Precipitation scheme and its influence on tropical convection and tropical waves

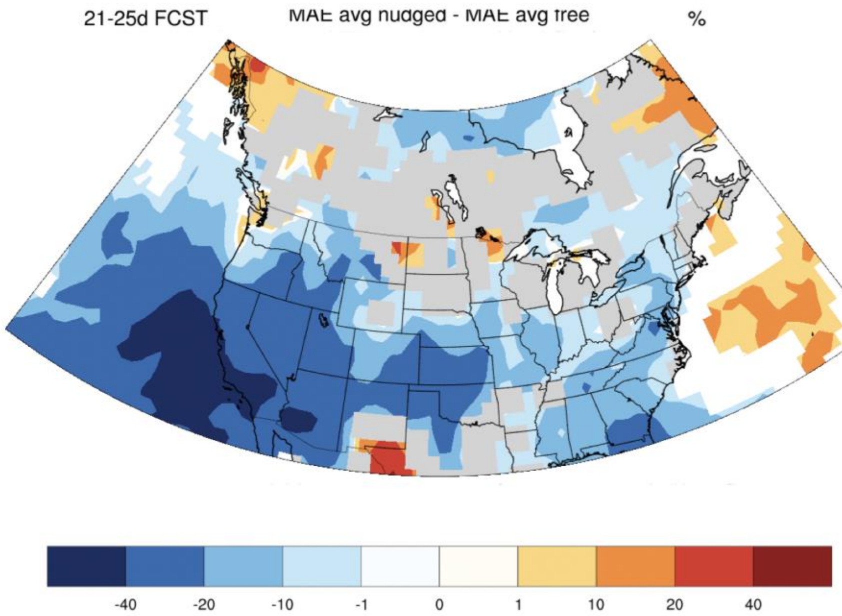
Tropical nudging experiments (J.Dias, S. Tulich, M. Gehne)

- Precipitation MAE (mm/hr) – forecast lead: Week 3



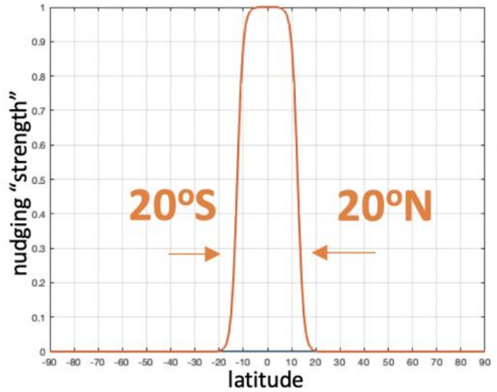
Jan-March 2016

- MAE difference between **tropical nudged** and free – forecast lead: Week 3



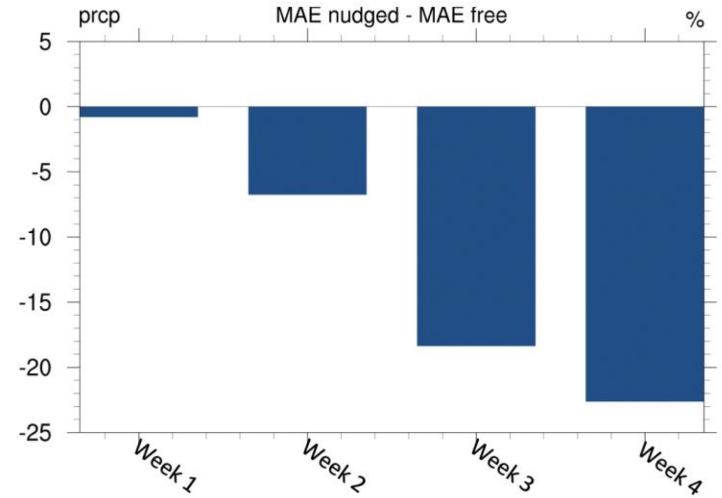
Blue means that errors are reduced when the tropical forecasts are "perfect"

- Nudging experiments are performed with FV3-GFS where the entire tropics are relaxed to GFS analysis

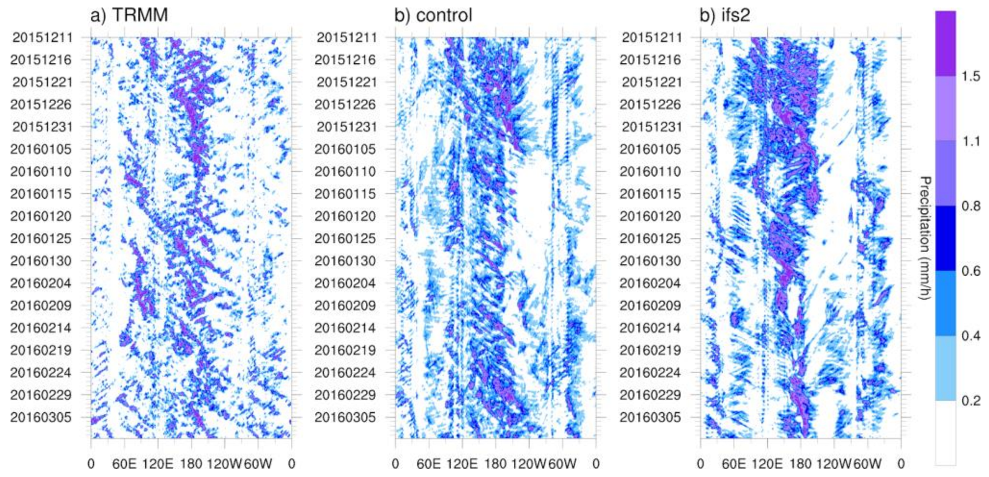


Tropical nudging region

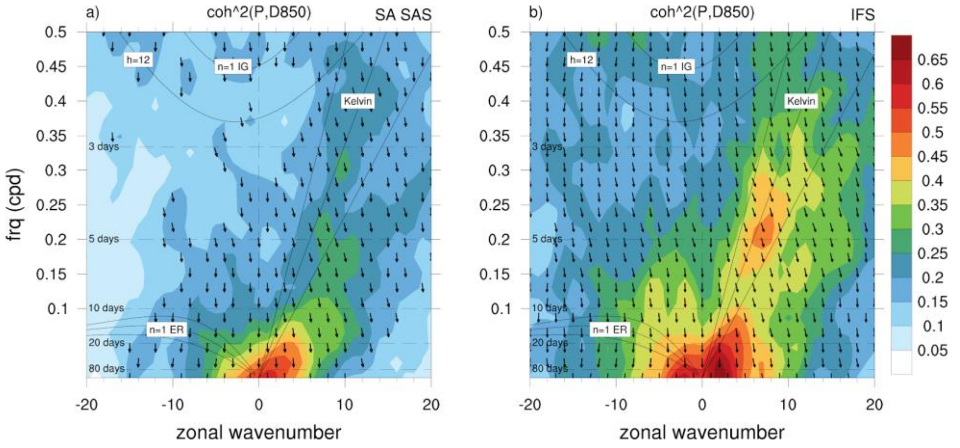
- MAE percentage reduction over CA



Convectively coupled equatorial wave simulations using the ECMWF IFS and the NOAA GFS cumulus convection schemes in the NOAA GFS model



Hovmöller diagram of 6-hourly precipitation initialized December 11th, 2015 for a) TRMM, b) GFS with SASAS, and c) GFS with IFS convection. 5S to 5N.



Frequency-wavenumber coherence-squared spectra 15°S to 15°N between 850hPa divergence and precipitation. Phase angles are shown where the coherence-squared is significant at the 95% level. a) SASAS b) IFS convection.

- Consistent treatment between PBL and convection is necessary in order to reproduce the tendency profiles from the ECMWF IFS model.
- The IFS convection scheme produces much more organized convection in the tropics, and tends to generate tropical waves that propagate more coherently than the GFS in its standard configuration, and has better simulated interaction between low level convergence and precipitation.
- The IFS convection scheme triggers deep convection to a much larger extent than the SASAS scheme, whereas the SASAS scheme triggers shallow convection more frequently.
- The IFS convection scheme moistens the PBL to a much larger extent than the SASAS scheme.

Sub-seasonal forecasts of precipitation (Weeks 3-4)

Objectives

1. Extract the most skill from the long-range forecasts made by ECMWF. Next step is to compare to the FV3-GFS when the long-range forecasts become operational.

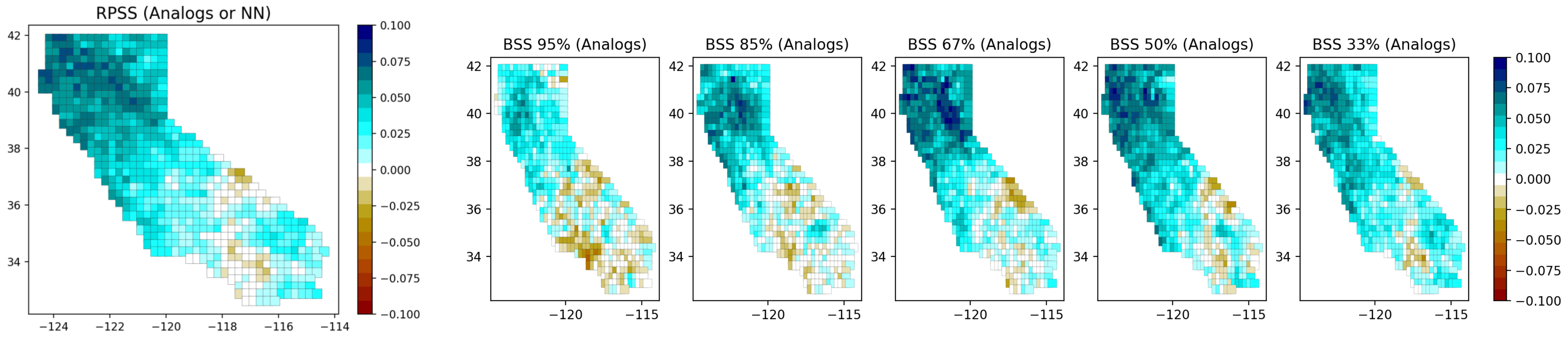
Data

1. Long-range forecasts made by ECMWF.
   - We focus on forecasts for the outlook time between 15-28 days. The retrospective forecasts are made twice a week for the period 1997-2016.

Sub-seasonal forecasts of precipitation (Nov-Mar)

An analog method is used to make probabilistic forecasts of precipitation across California. Brier skill scores (BSS) and ranked probability skill scores (RPSS) are shown spatially. These scores are averages across the winter period for the period 1997-2016. An RPSS value of 0.1 can be thought of, deterministically, as an anomaly correlation on the order of 0.3.

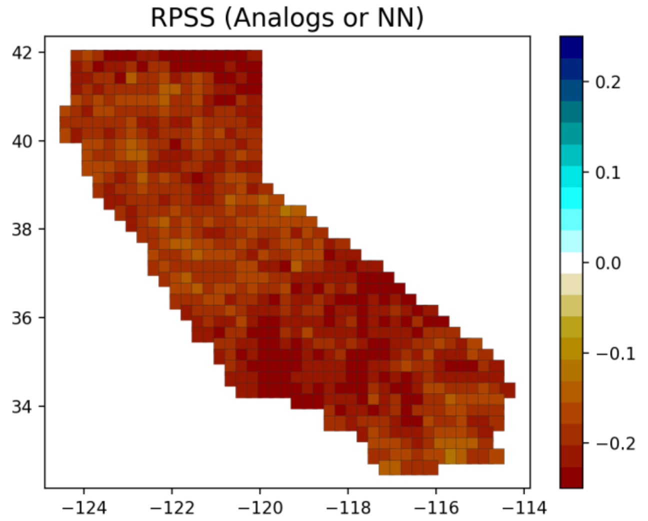
Week 3-4

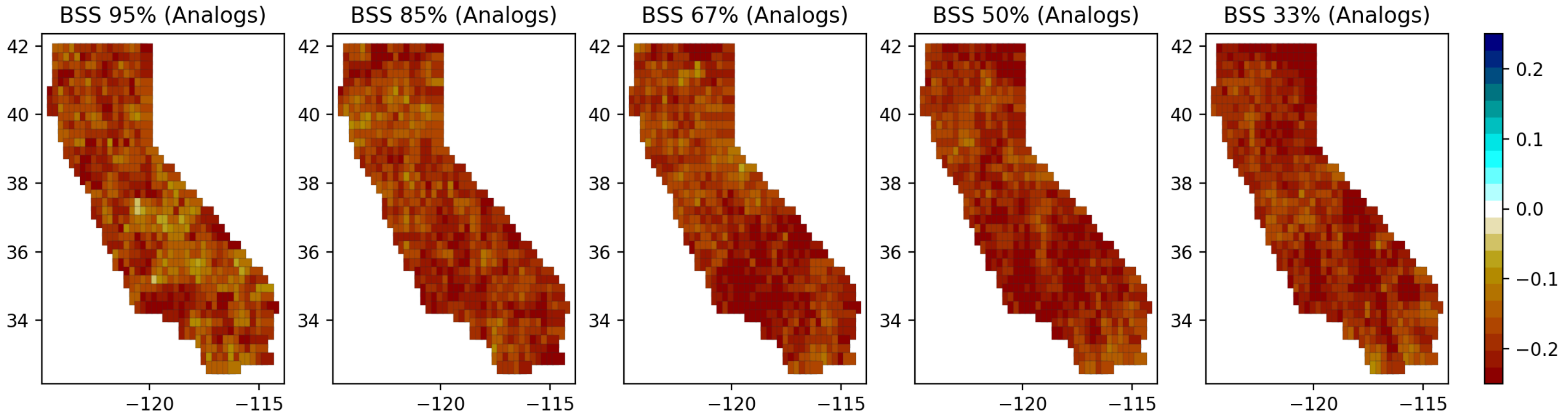


Sub-seasonal forecasts of precipitation (Nov-Mar)

Compare to raw forecasts

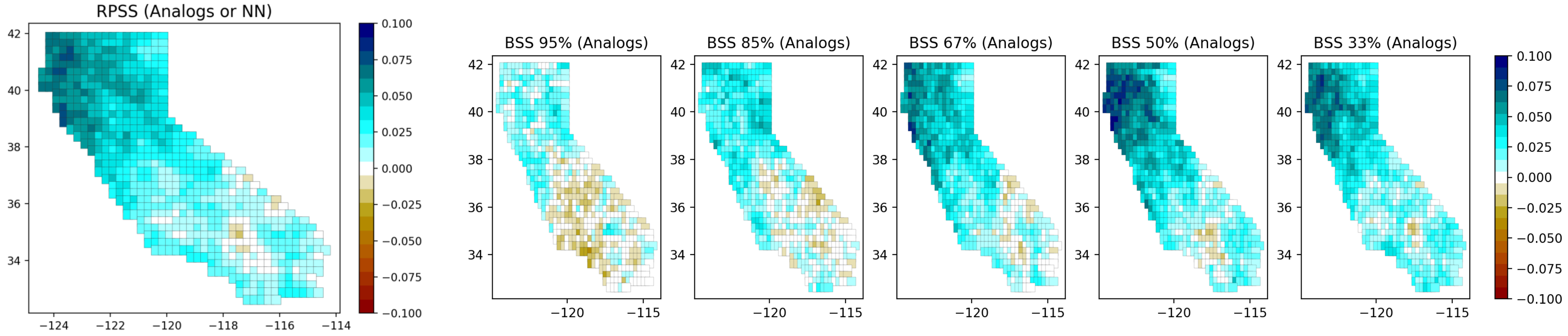
Week 3-4





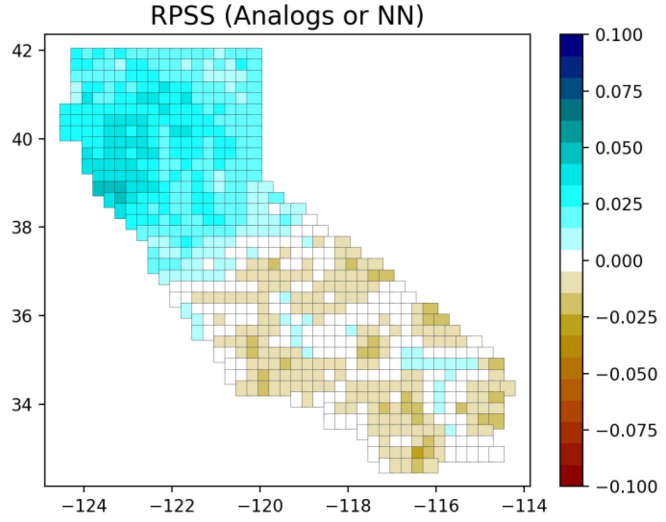
Sub-seasonal forecasts of precipitation (Nov-Mar)

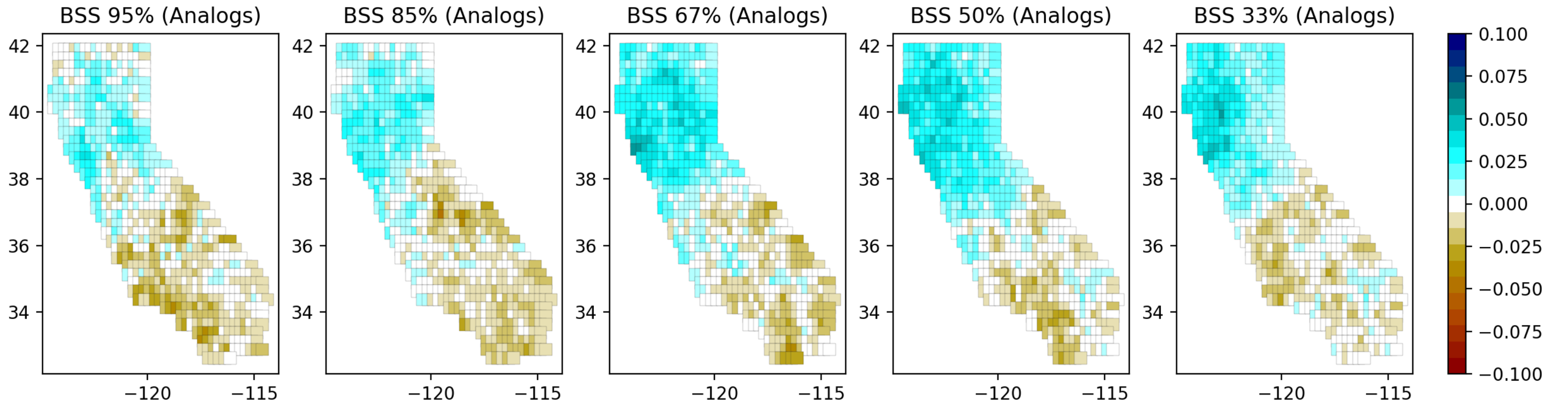
Week 3



Sub-seasonal forecasts of precipitation (Nov-Mar)

Week 4





Seasonal forecasts of precipitation and temperature

Objectives

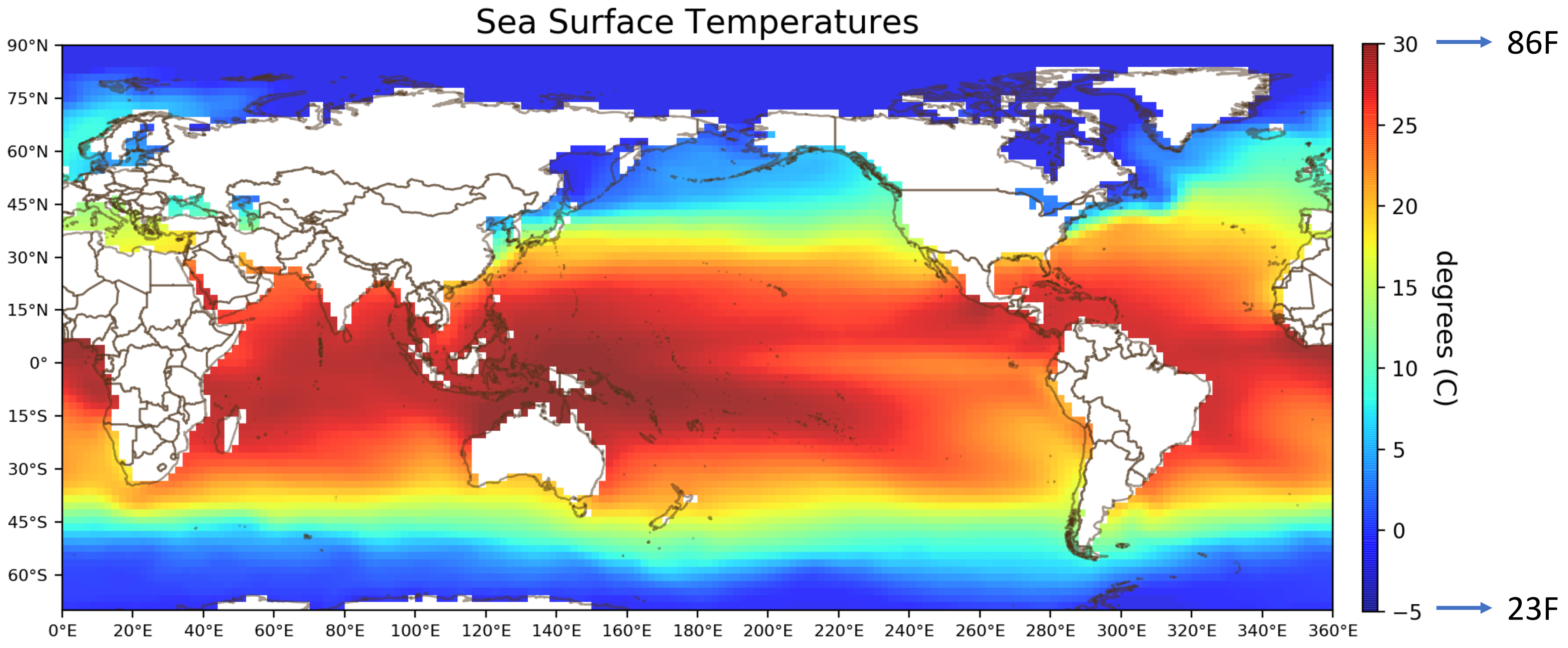
1. Develop a relatively simple and improved statistical baseline model for seasonal climate forecasts
   - For my project, in particular, improve forecasts of precipitation in Northern California
   - What information can we transfer from seasonal timescales to sub-seasonal timescales? How quickly are long-range weather prediction models reverting to the mean seasonal forecast (e.g., week 3, 4, …)?

Data

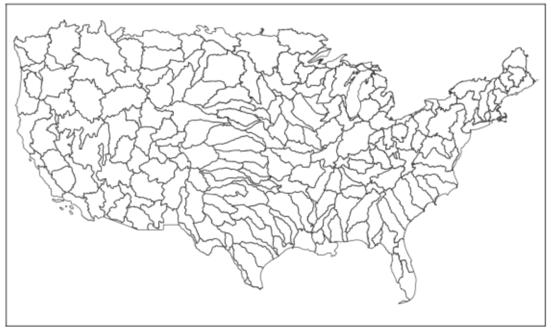
1. NOAA SST Extended Reconstruction (version 5)

2. PRISM (precipitation and mean temperature)
   - Focus on extended winter season that has a large impact on water resources of the mountainous western United States. Aggregate data for NDJFM.

SSTs and seasonal forecasts of precipitation and temperature



Focus on precipitation



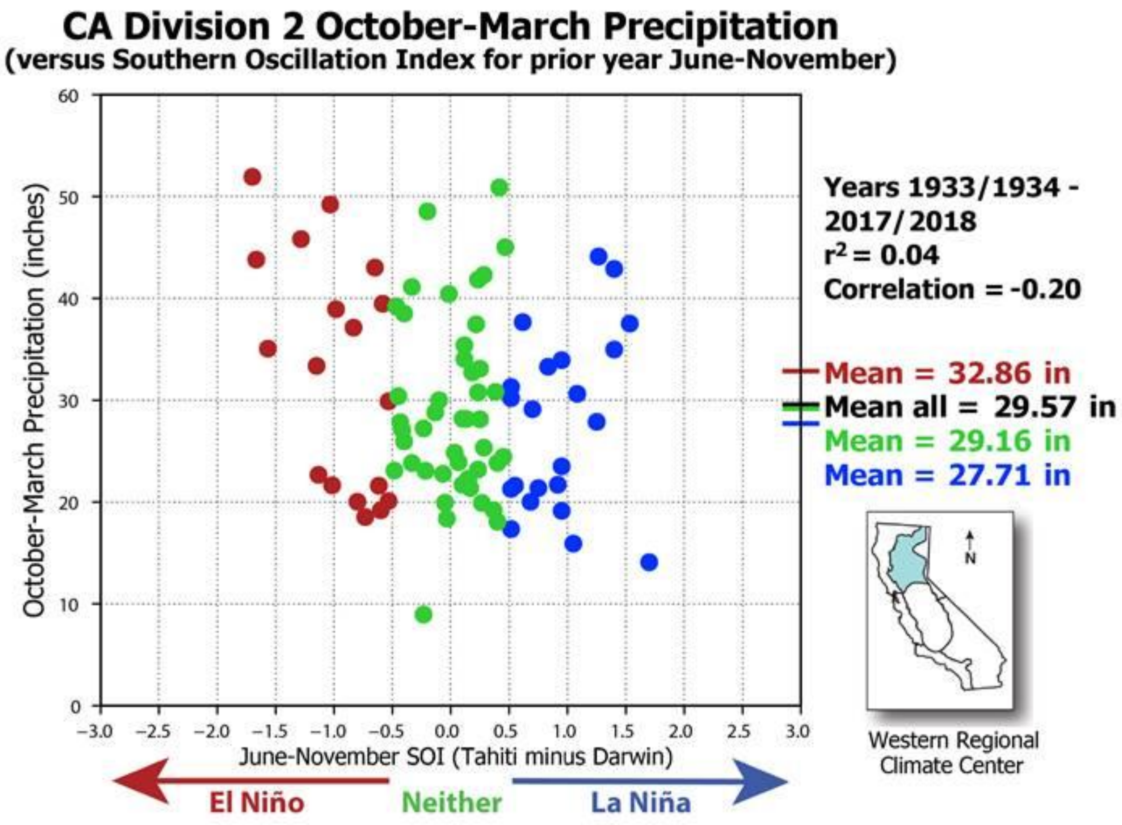
1. Detrend and normalize the SST time series
    - Do this separately for each month
    - Means, standard deviations and trends are all established from the period 1901-1980, then applied to the entire time series 1901-2018.

2. Get the broader winter (NDJFM) accumulations for each of the 202 Hydrologic Unit Code (division 4). However, the methodology can easily be implemented using gridded data.

3. Predict the leading principal components of our precipitation and temperature data sets, then regress these back into real space. This ensures consistency of regression coefficients across space, and it is faster. Train on 1901-1980, validate on 1981-2017.

Forecasting winter precipitation

"It's a shotgun plot, 'nuff said' ☺"



p = 0.066

Forecasting winter precipitation

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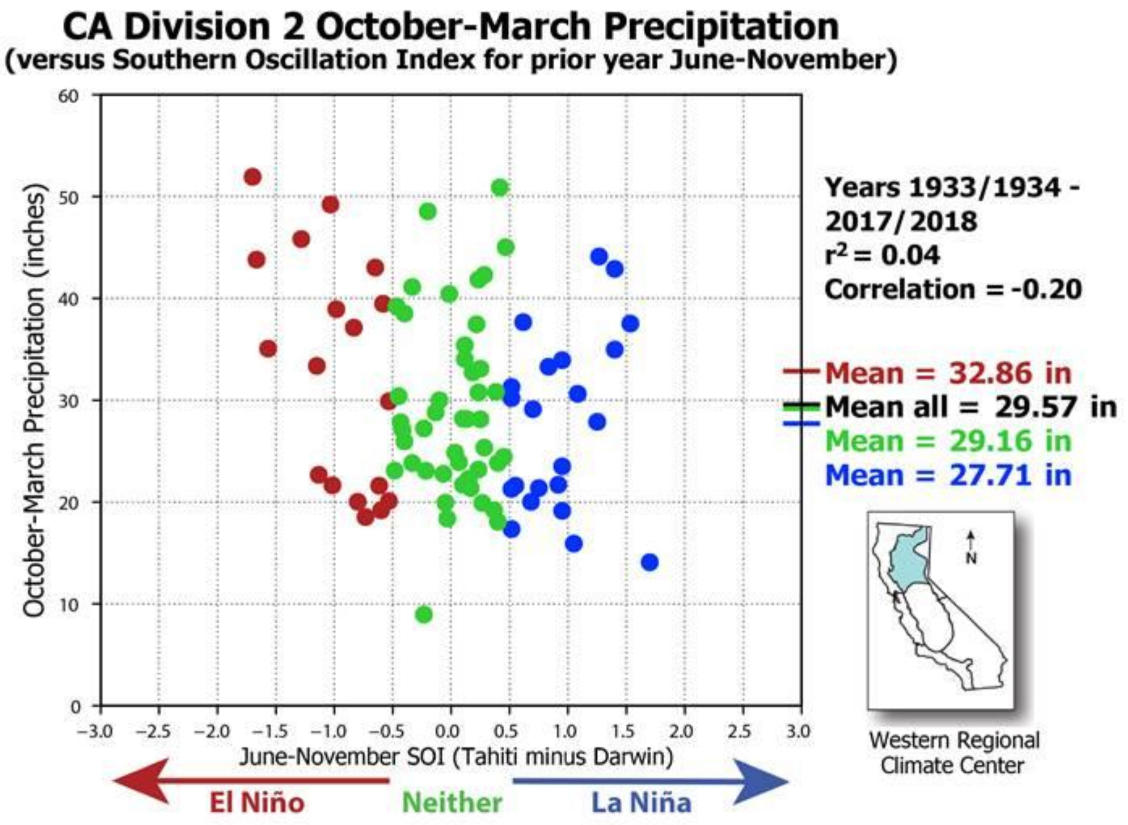
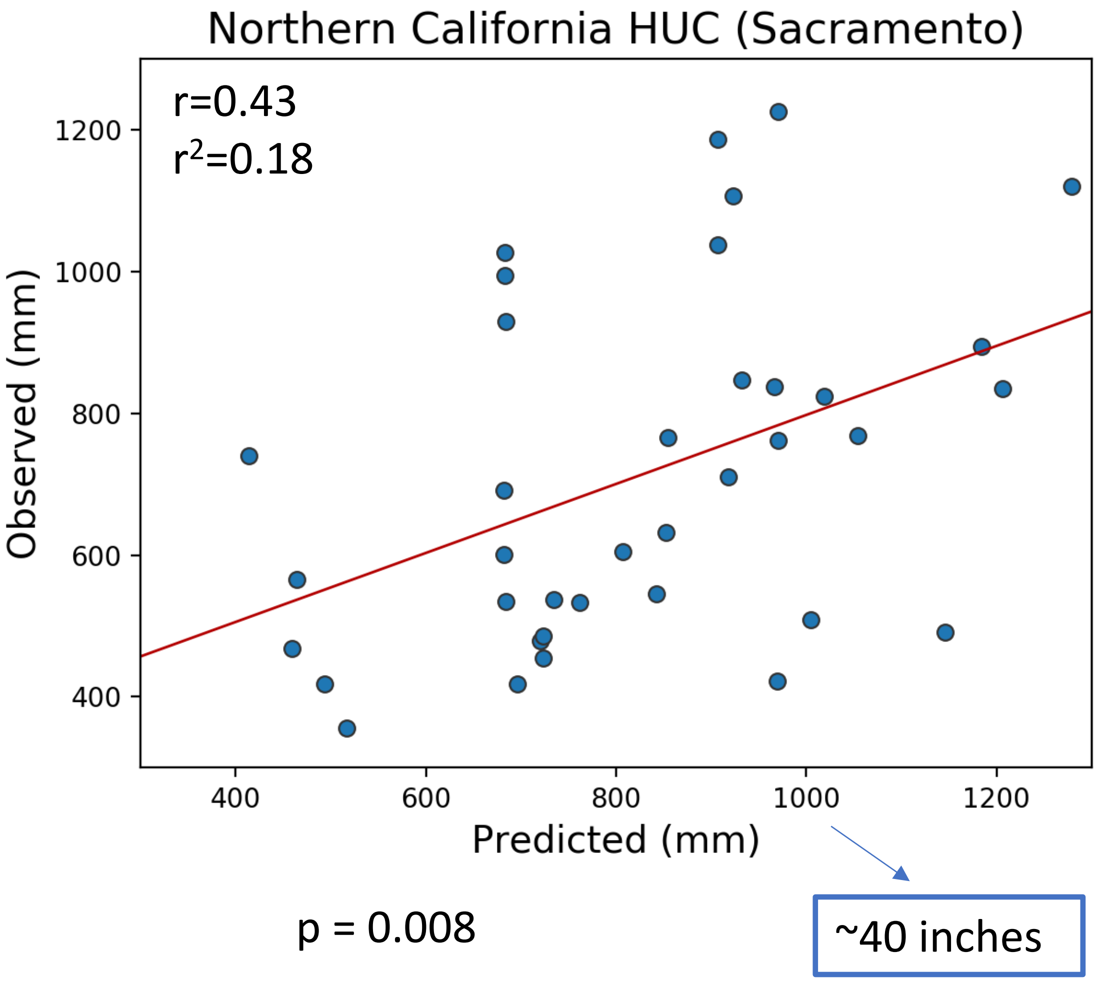


p = 0.066

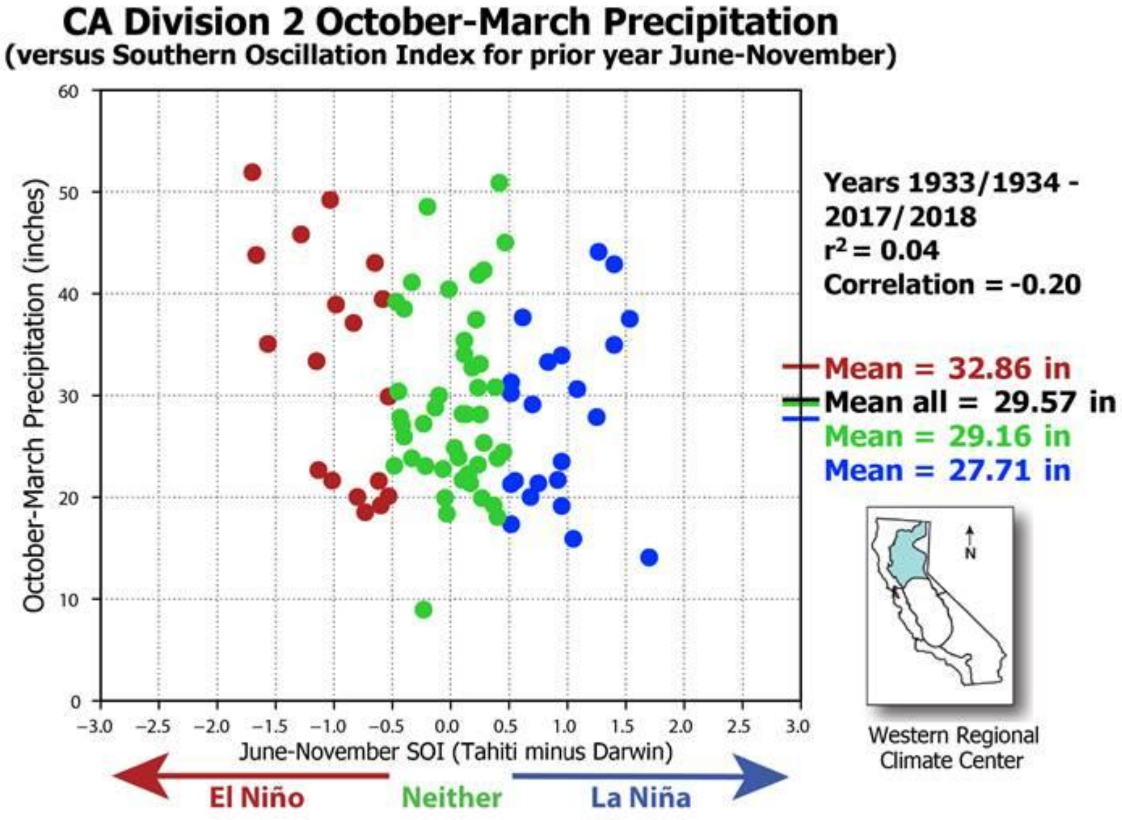
Last 37 years (1981-2017)



p = 0.008

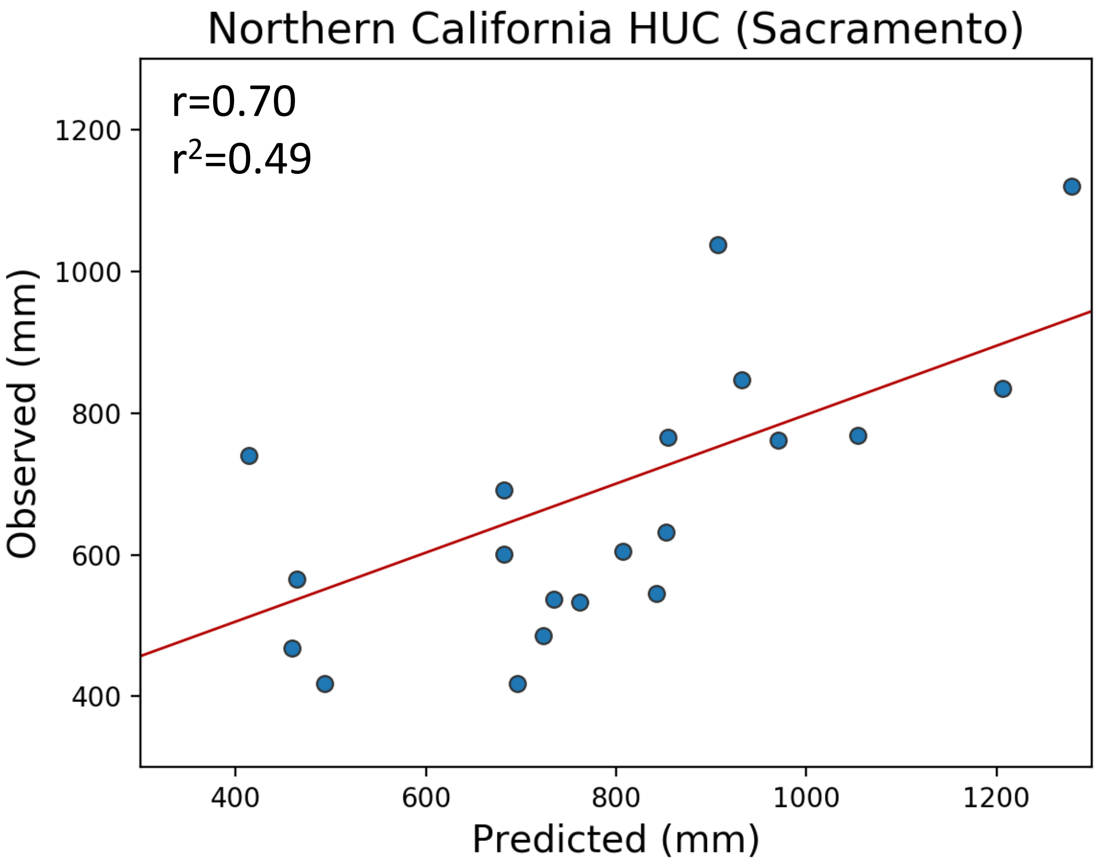
Forecasting winter precipitation

"It's a shotgun plot, 'nuff said' ☺"



$p = 0.066$

Last 20 years (1998-2017)



$p = 0.0007$

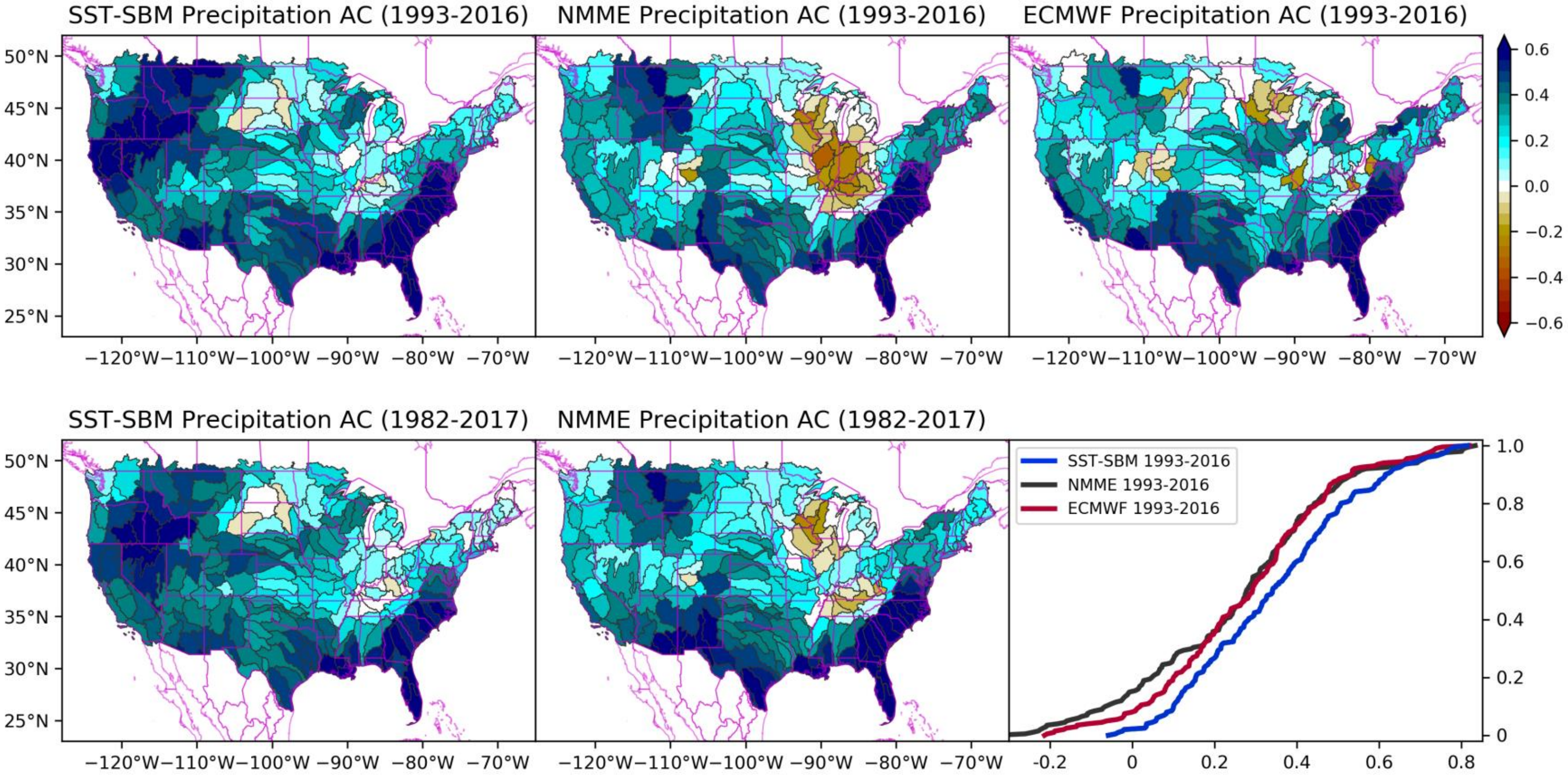
NMME and ECMWF SEAS5

- NMME is the ensemble average of 7 models, each with multiple runs for the years 1982-2017

- ECMWF makes seasonal forecasts with 15 ensemble members using 2 different “systems” for the years 1993-2016

Anomaly Correlation Skill of precipitation forecasts

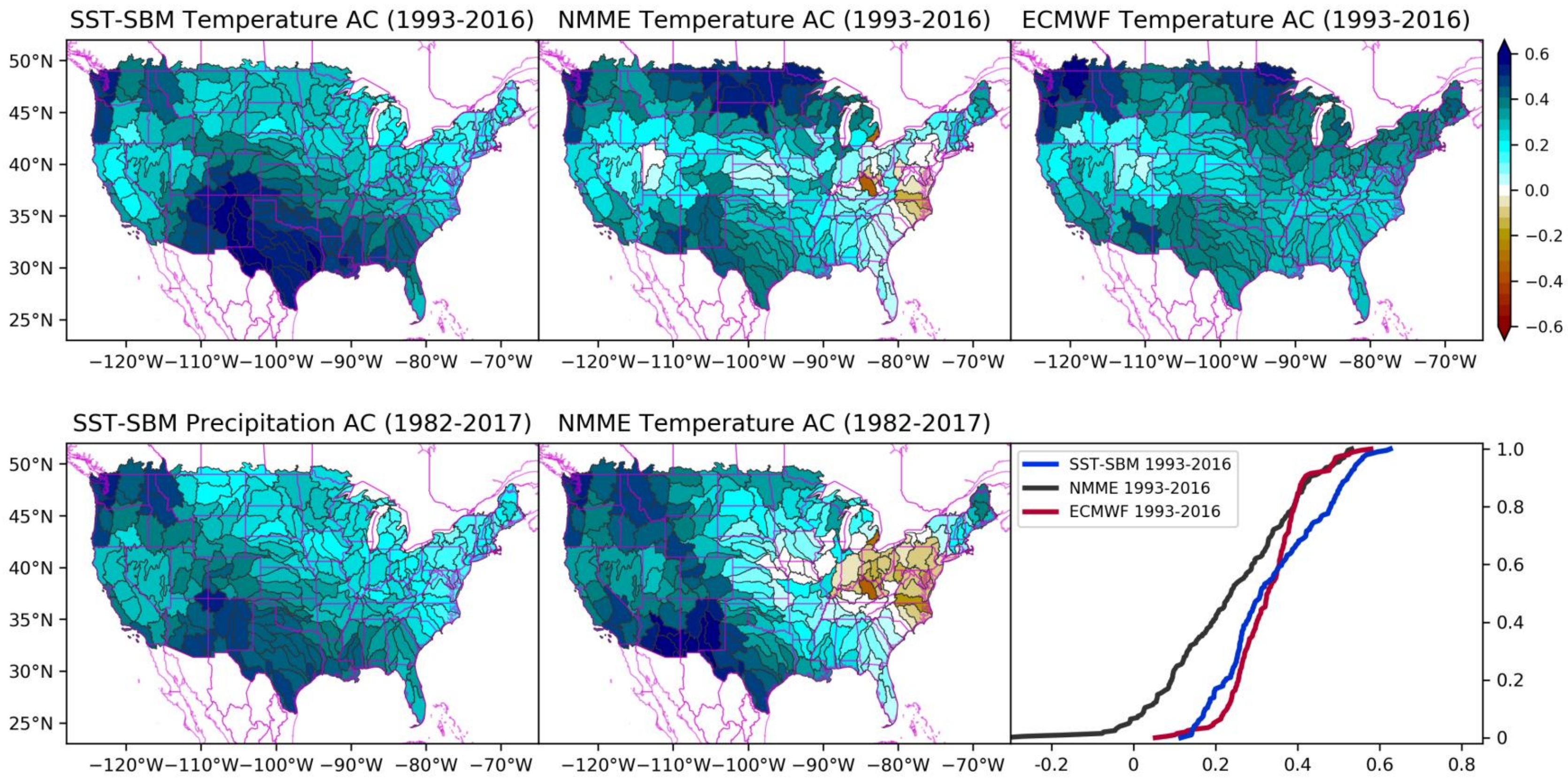
Mean=0.35 Mean=0.26 Mean=0.28



Mean=0.31 Mean=0.28

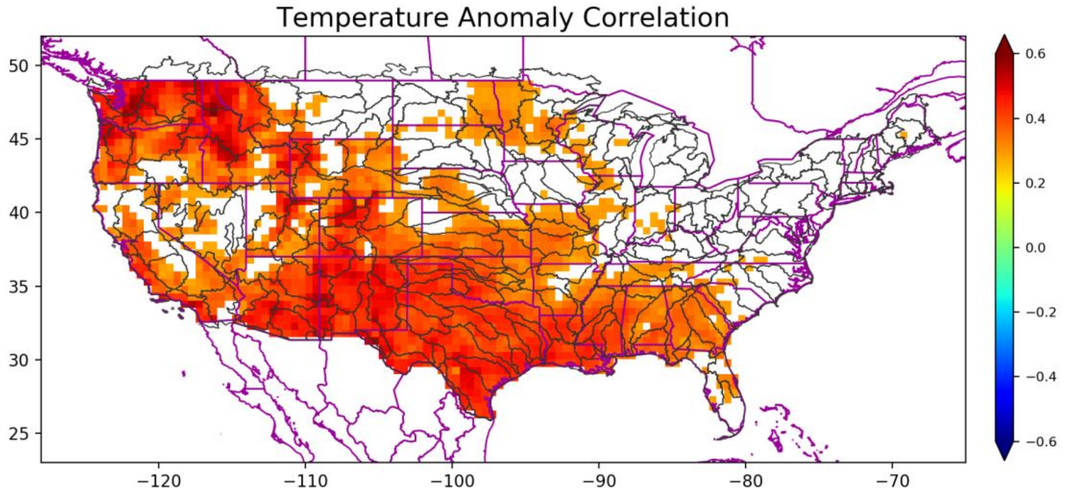
Anomaly Correlation Skill of temperature forecasts

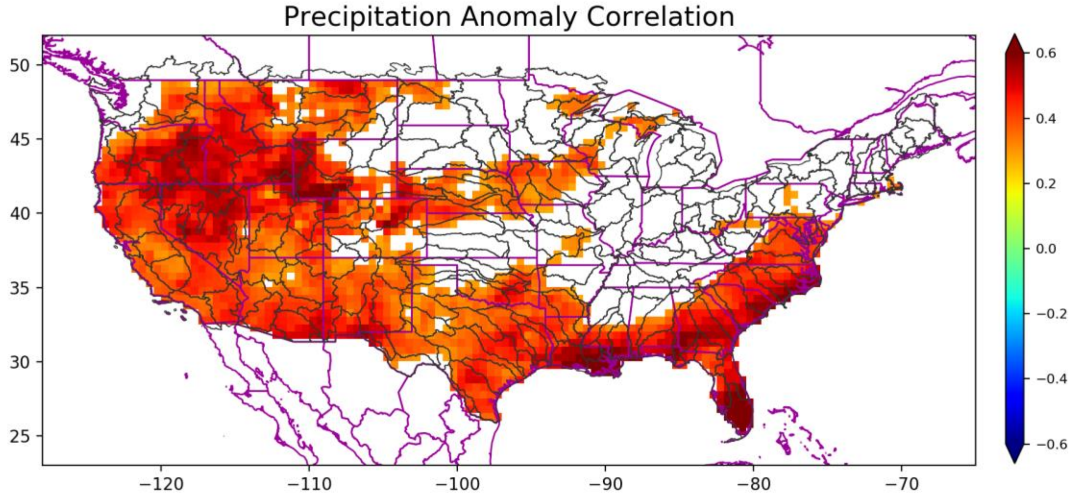
Mean=0.34 Mean=0.23 Mean=0.33

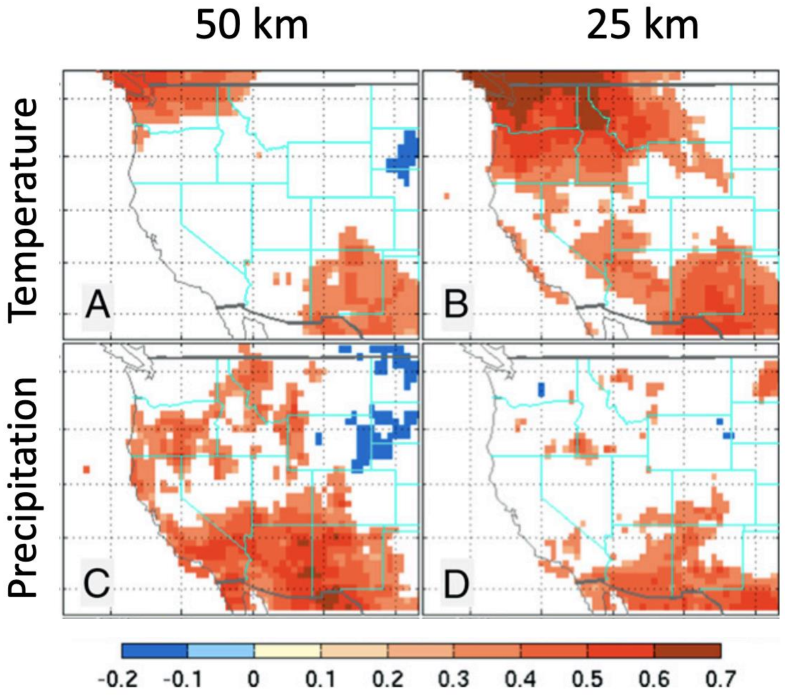


Mean=0.30 Mean=0.23

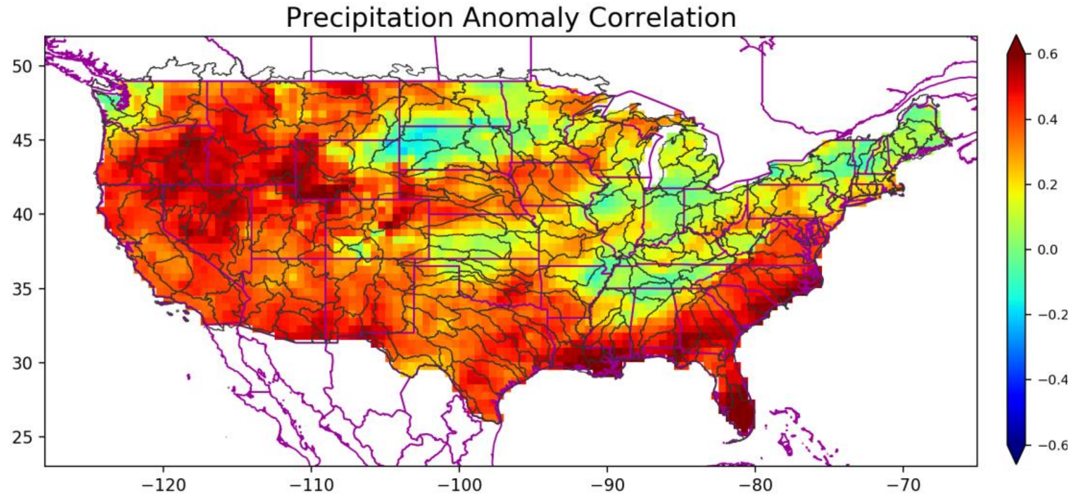
Comparing skill to the Kapnick et al. (2018) paper

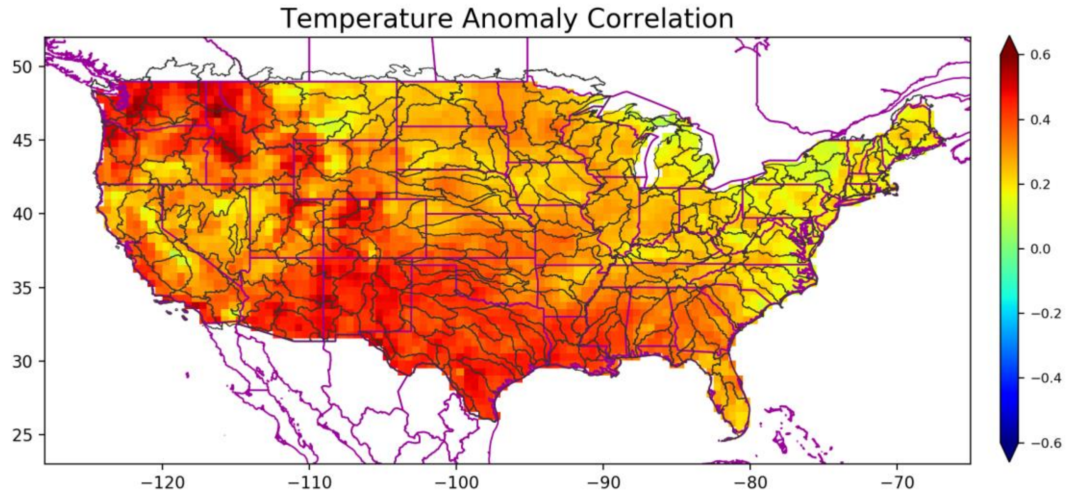






Comparing skill to the Kapnick et al. (2018) paper





What next?

- Gain a better understanding of the physical mechanisms driving the improved skill with respect to the dynamical models. In particular, why do we see such an improvement in a region like northern California?
- How useful can seasonal forecasts be when applied to the sub-seasonal (e.g., weeks 3-4)?

Questions, comments, suggestions