Improving Cool-Season Precipitation Forecasts Across CONUS and the West

CDWR/WSWC – May 17-19, 2022

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Dynamical Models and S2S

Priorities - including but not limited to:

- Reducing quantitative precipitation forecast (QPF) bias
- Improving storm structure
- Resolving pre-convective environment
- Enhancing forecasts of clouds, including ceiling & visibility (critical for aviation)
- Improving PBL inversion
- Reducing winter cold bias in the lower troposphere
- Improving track forecast of strong hurricanes (initial wind > 33 m/s) in the Atlantic

Dynamical Models and S2S

In the Physical Sciences Lab at NOAA:

- Lisa Bengtsson is working to improve organization of convective events. Ultimately, lead to better resolving precipitation and better forecasts.
- Juliana Dias is investigating: What if we get the forecasts in the tropics right/wrong? What does that mean for the extratropics (USA)?

The path that led me here

- About three years ago, I was working on trying to improve subseasonal precipitation forecasts.
- Internally at NOAA, Joe presented on a paper that showed some seasonal forecast skill of SWE that piqued my interest.
- I wanted to perform a comparative analysis, and that ultimately led me to focusing more exclusively on seasonal forecasts.

Outline of Today’s Talk

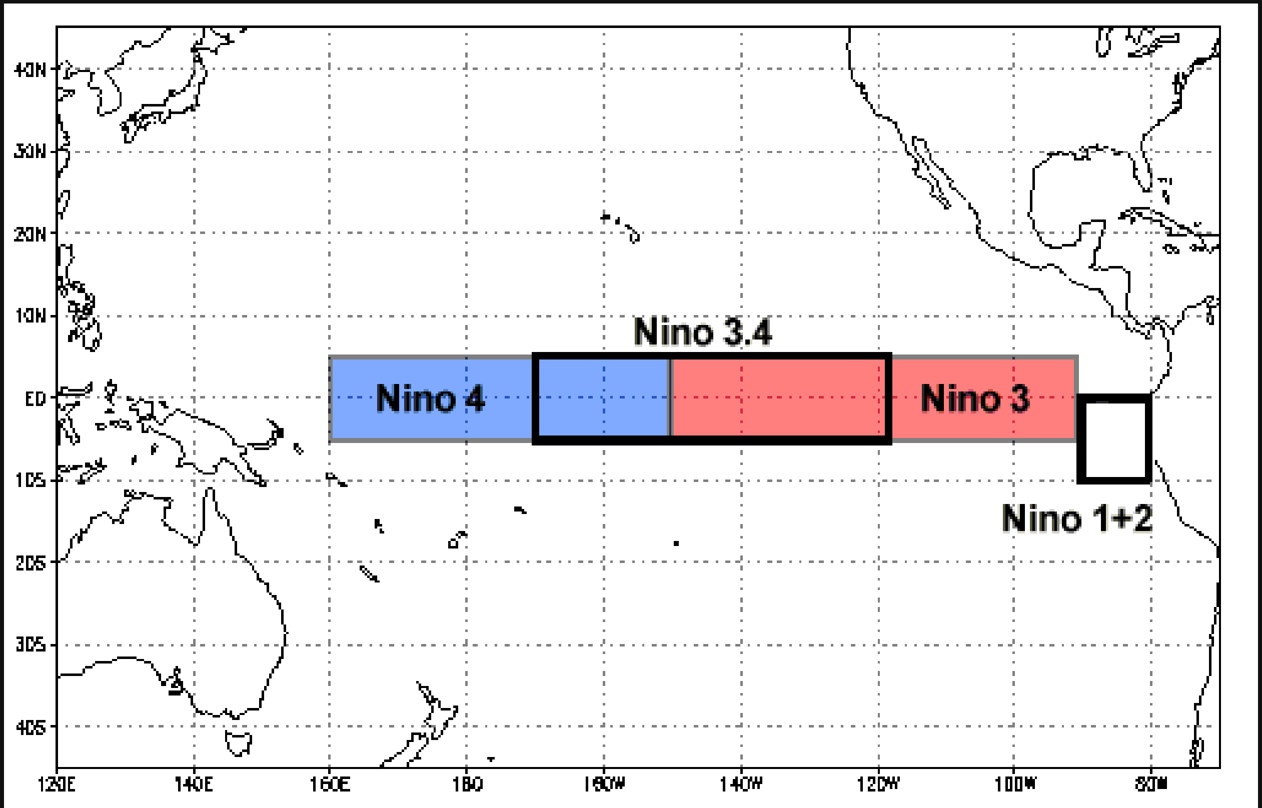
The Goal:

Make better forecasts of cool-season (Nov-Mar) precipitation. Re/forecasts are produced in October.

1. Some early results from a very simple model.

2. What have I been working on lately?

How much can we stretch the influence of ENSO?

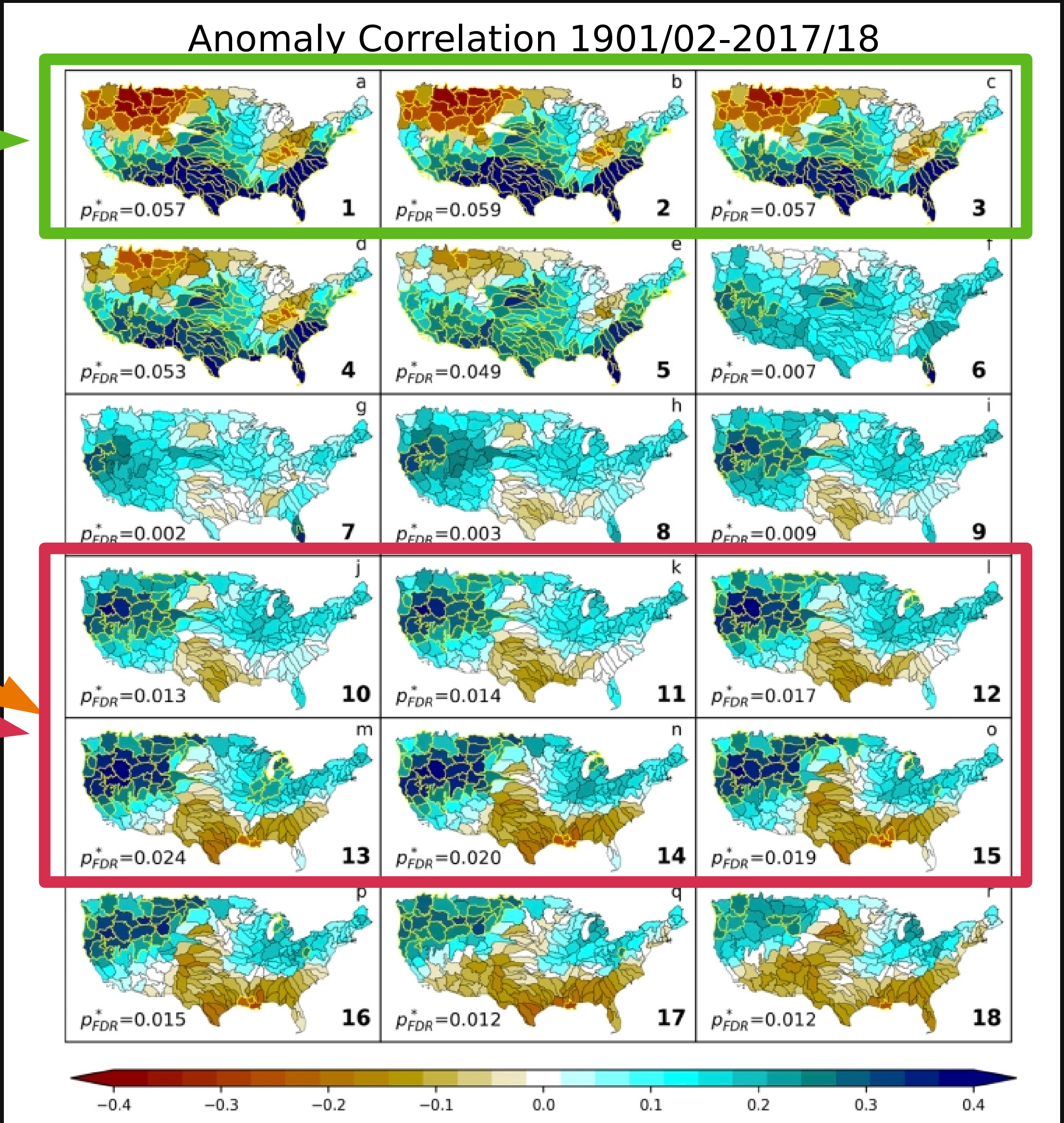


source: https://www.ncdc.noaa.gov/teleconnections/enso/indicators/sst/

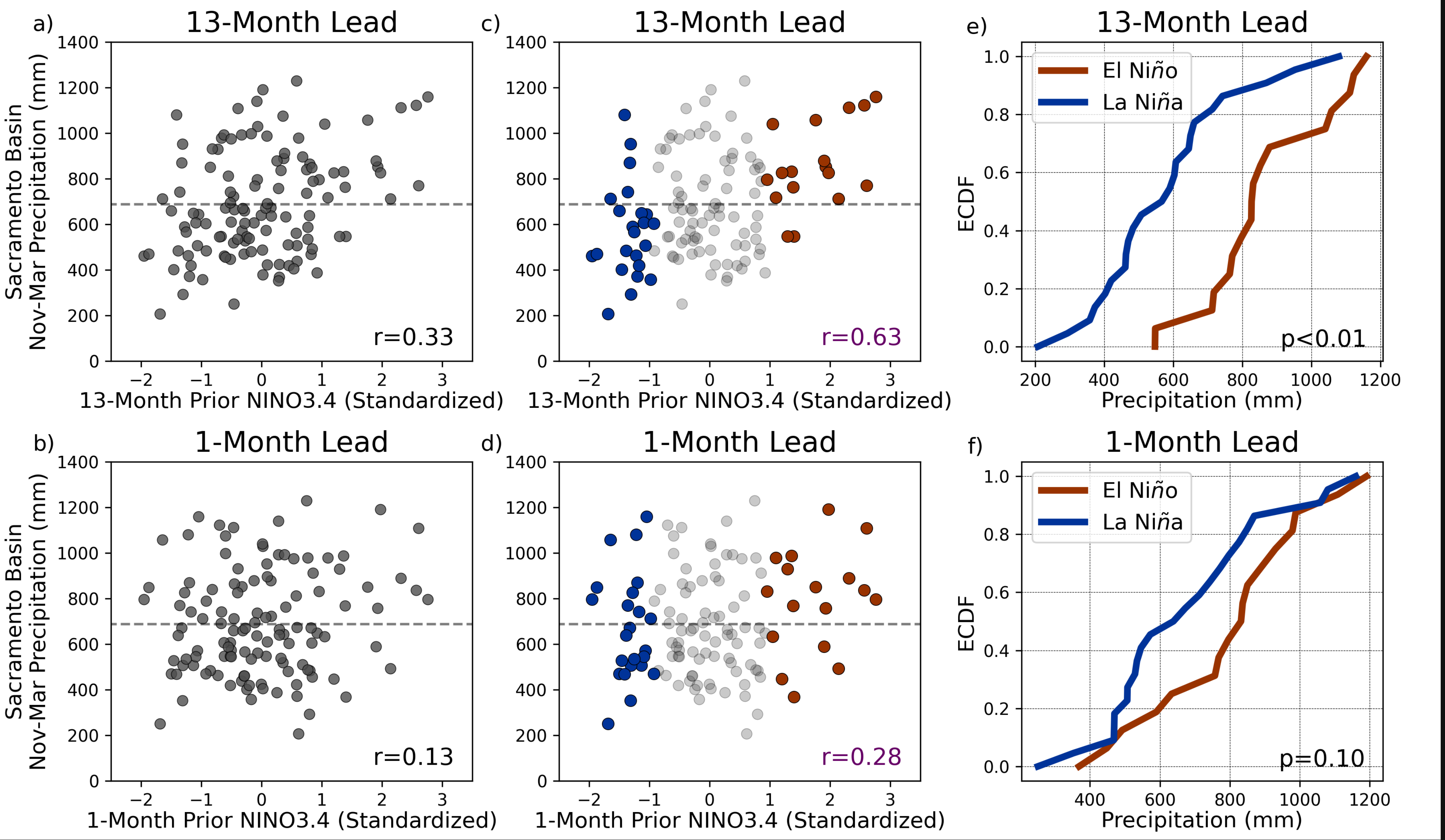
Short-lead time

This is robust and useful

Long-lead time



Switanek, M. B., Barsugli, J. J., Scheuerer, M., & Hamill, T. M. (2020). Present and past sea surface temperatures: a recipe for better seasonal climate forecasts. *Wea. Forecasting*, **54** , 6739–6756. doi: 10.1029/2018WR023153.



a)
13-Month Lead
Sacramento Basin
Nov-Mar Precipitation (mm)
13-Month Prior NINO3.4 (Standardized)
r=0.33
c)
13-Month Lead
13-Month Prior NINO3.4 (Standardized)
r=0.63
e)
13-Month Lead
El Niño
La Niña
ECDF
Precipitation (mm)
p<0.01
b)
1-Month Lead
Sacramento Basin
Nov-Mar Precipitation (mm)
1-Month Prior NINO3.4 (Standardized)
r=0.13
d)
1-Month Lead
1-Month Prior NINO3.4 (Standardized)
r=0.28
f)
1-Month Lead
El Niño
La Niña
ECDF
Precipitation (mm)
p=0.10

What have I been working on lately?

- Using subsurface ocean temperatures as predictors!

NCEP Global Ocean Data Assimilation System (GODAS)

Brief Description:

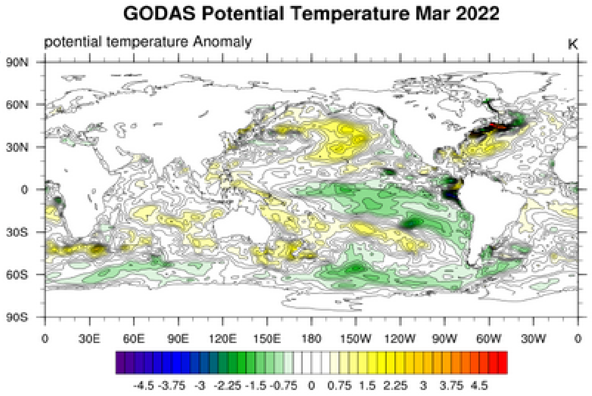
- High Resolution Multi-level ocean analysis from NCEP *More Details...*

Temporal Coverage:

- Monthly values for 1980/01 - 2022/03 .

Spatial Coverage:

- 0.333 degree latitude x 1.0 degree longitude global grid (418x360).
- 74.5S - 64.5N, 0.5E - 359.5E.
- 74.0S - 65.0N, 1.0E - 360.0E.

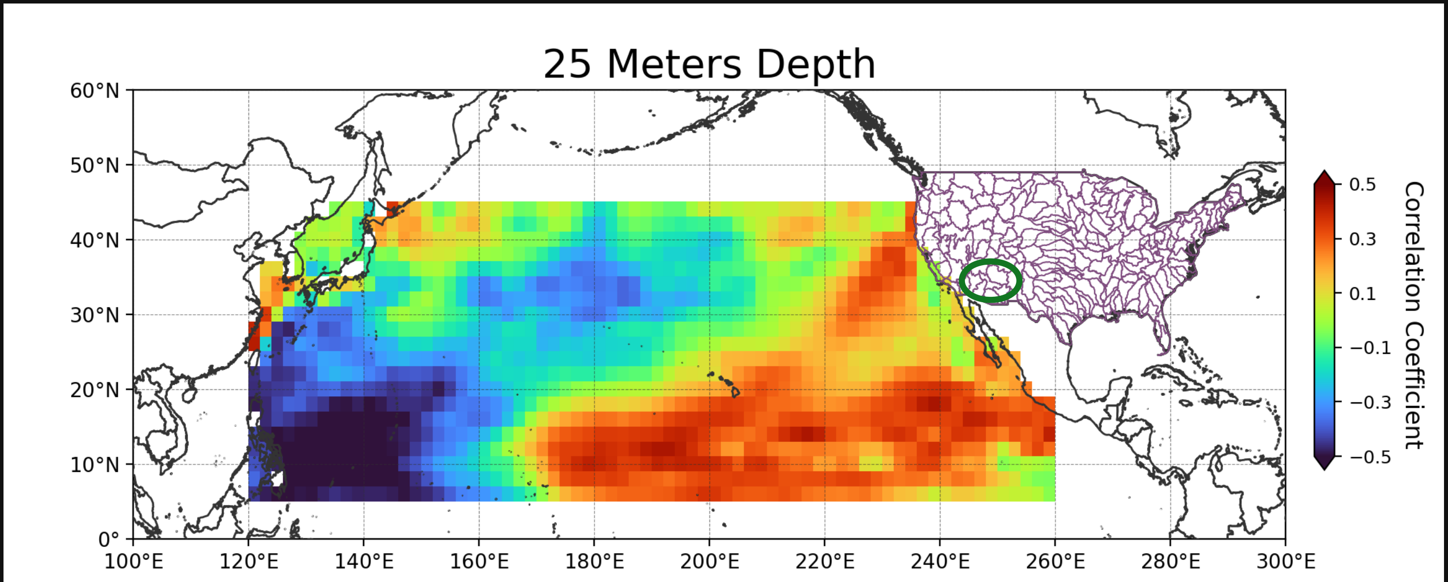


- Also, ocean reanalyses from ECMWF.

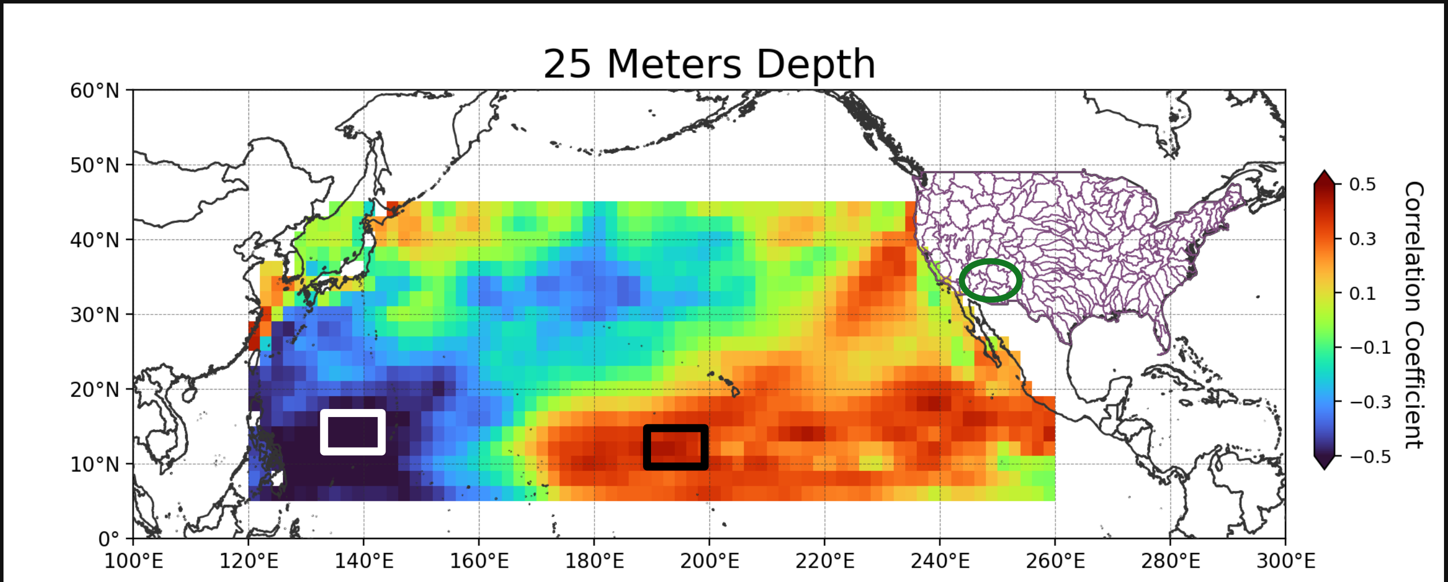
- Both data sets are updated with the prior month by about the 15th of the current month. So, in the middle of May, for example, they would update the data to include the prior April.

- Both data sets have coverage beginning in 1980, which gives us a sample size of 42 (1980/1981-2021/2022).

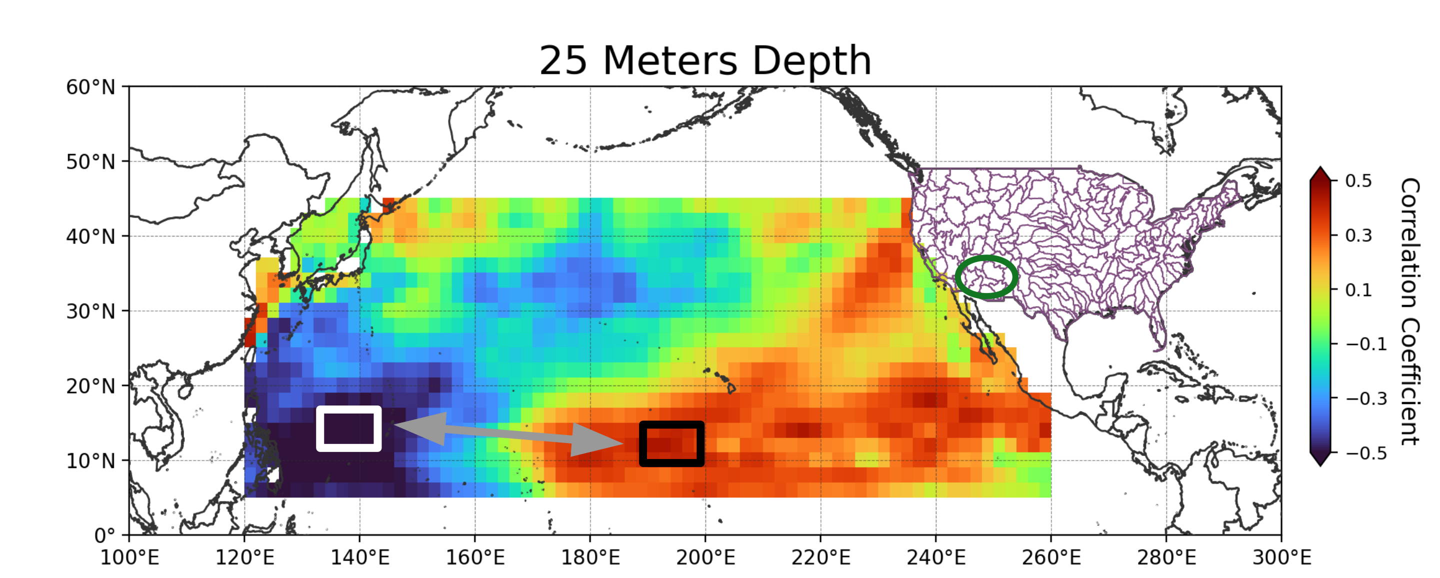
- My forecasting method relies on exploiting historical statistical relationships. More specifically, we have some precipitation time series, and we want to find a gradient that explains the greatest amount of variance.



Prior September ocean temperatures at 25 meters depth correlated with the following November-March precipitation in the Salt River Basin.

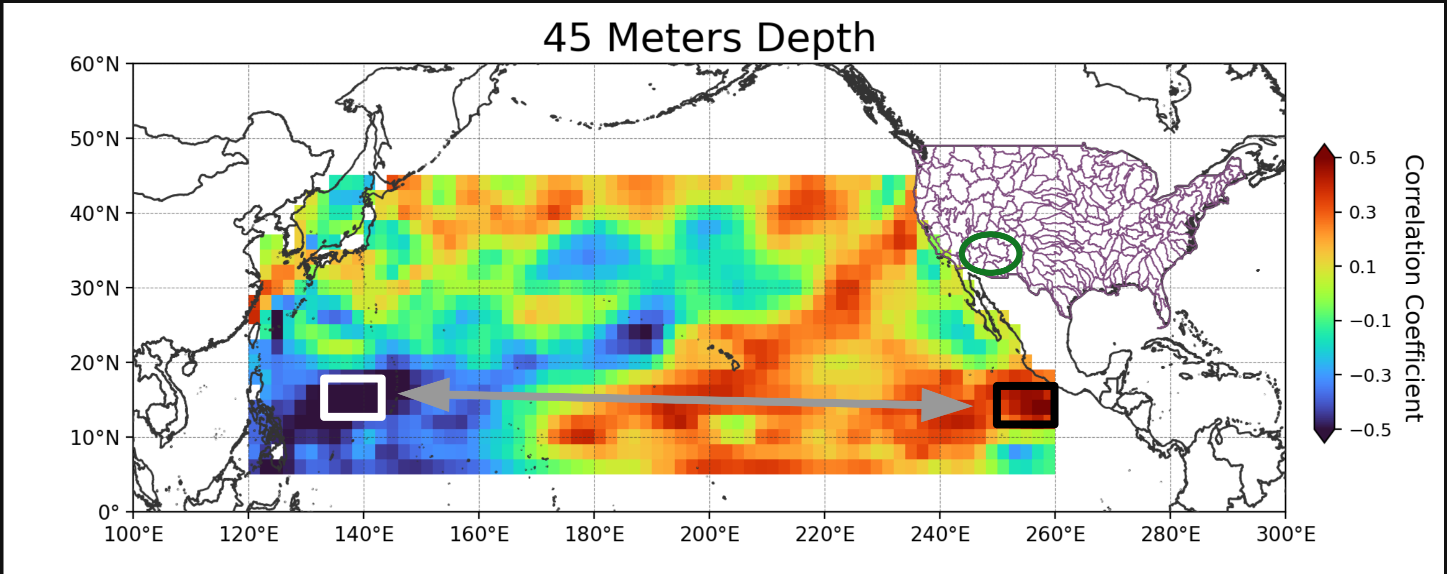


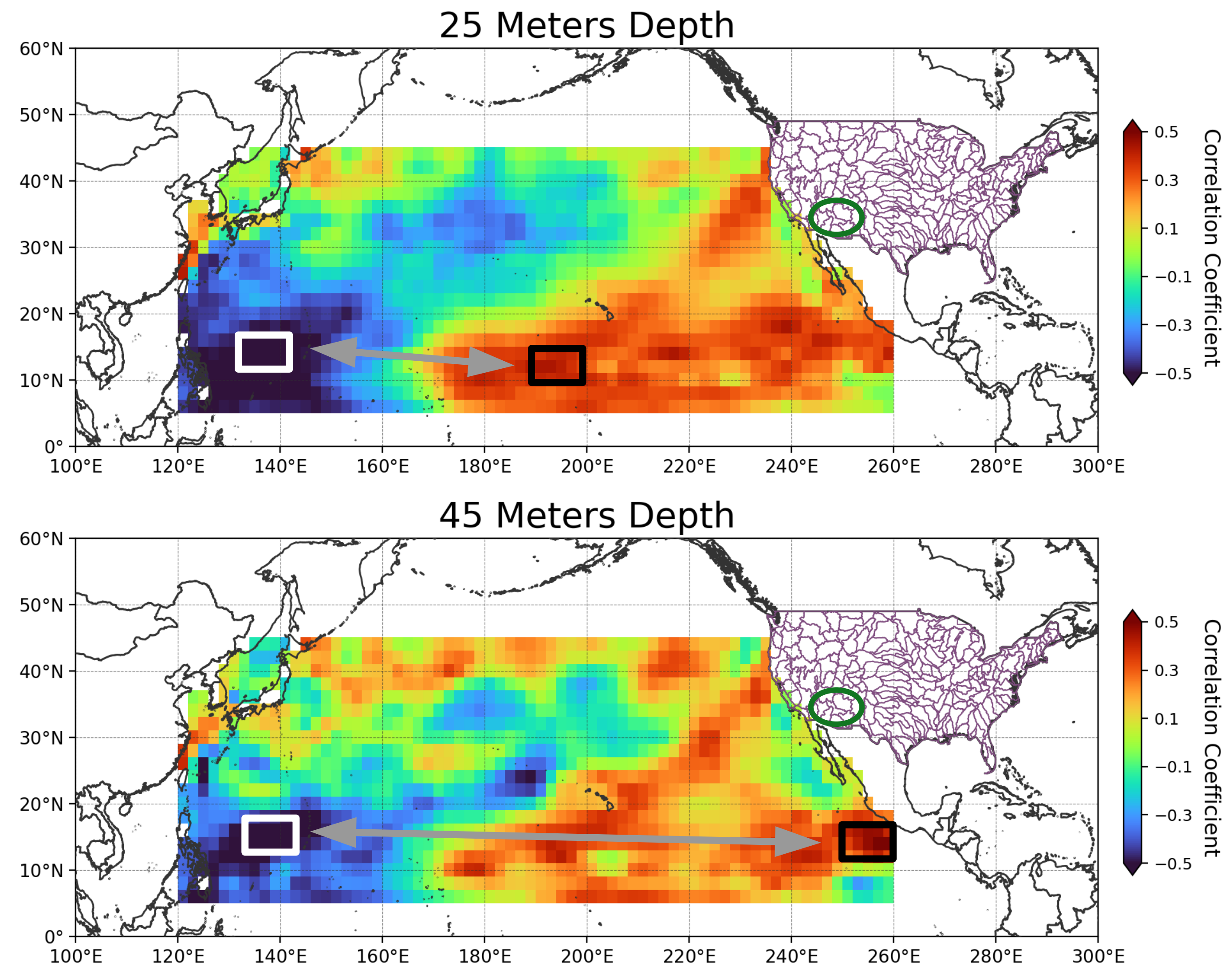
Prior September ocean temperatures at 25 meters depth correlated with the following November-March precipitation in the Salt River Basin.

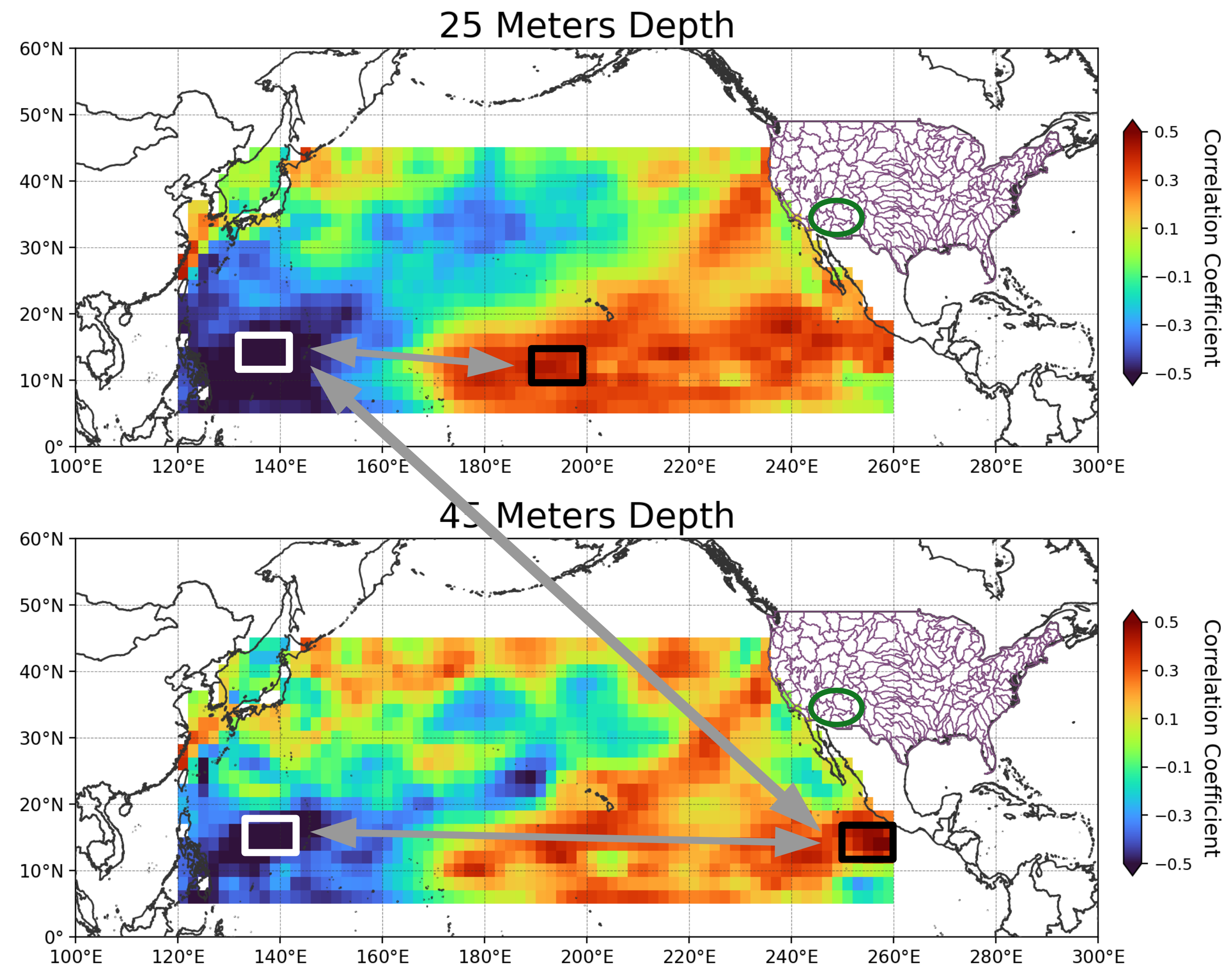


Prior September ocean temperatures at 25 meters depth correlated with the following November-March precipitation in the Salt River Basin.

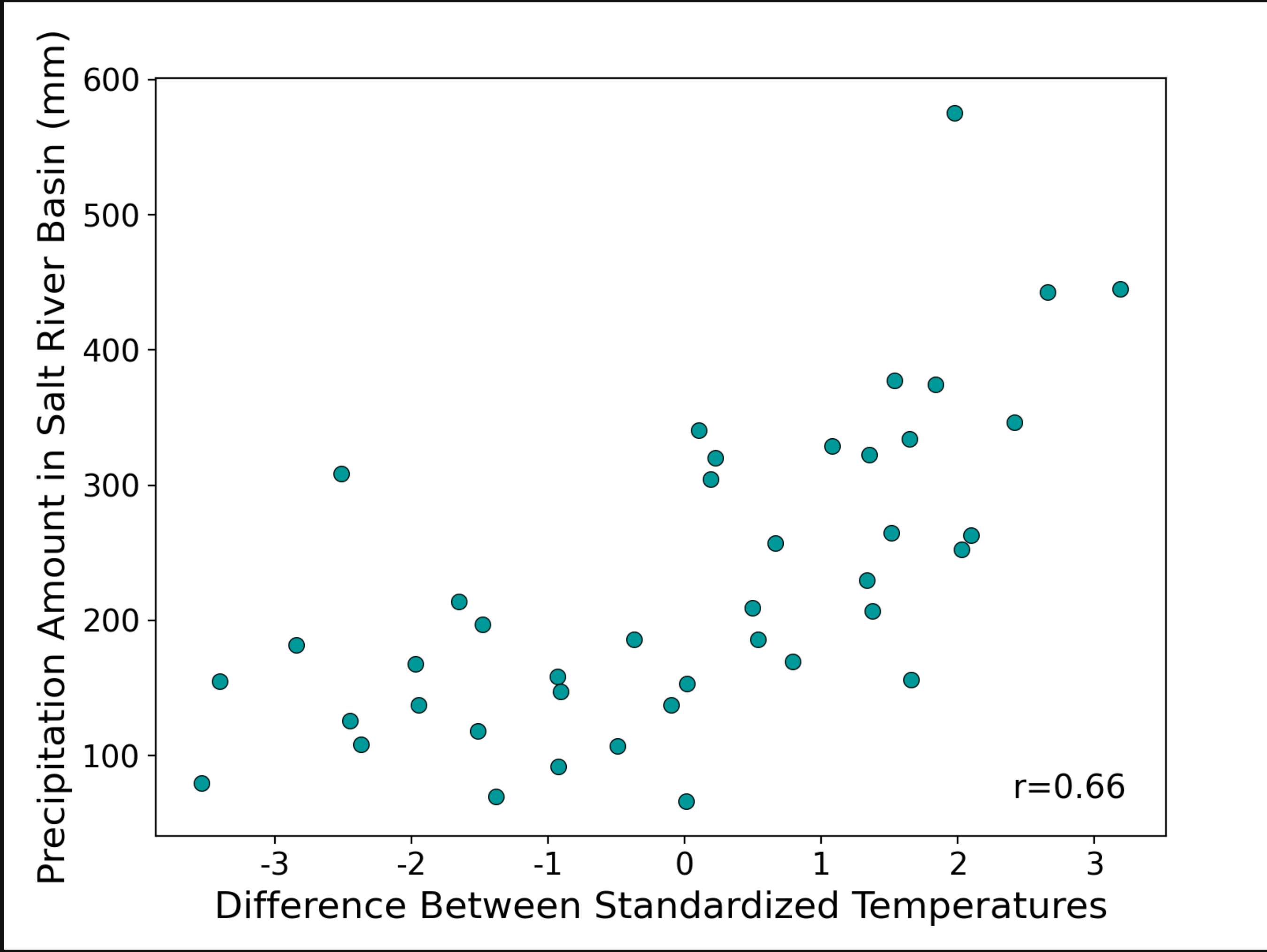
Prior September ocean temperatures at 45 meters depth correlated with the following November-March precipitation in the Salt River Basin.




25 Meters Depth
60°N
50°N
40°N
30°N
20°N
10°N
0°
100°E
120°E
140°E
160°E
180°E
200°E
220°E
240°E
260°E
280°E
300°E
0.5
0.3
0.1
−0.1
−0.3
−0.5
Correlation Coefficient
45 Meters Depth
60°N
50°N
40°N
30°N
20°N
10°N
0°
100°E
120°E
140°E
160°E
180°E
200°E
220°E
240°E
260°E
280°E
300°E
0.5
0.3
0.1
−0.1
−0.3
−0.5
Correlation Coefficient


25 Meters Depth
45 Meters Depth
60°N
50°N
40°N
30°N
20°N
10°N
0°
100°E
120°E
140°E
160°E
180°E
200°E
220°E
240°E
260°E
280°E
300°E
0.5
0.3
0.1
−0.1
−0.3
−0.5
Correlation Coefficient

Statistical relationship over the entire period of record.



A few points to consider:

1. In terms of actual forecasting, the statistical relationships must be robust enough to hold up in a cross-validated framework.

2. To that end, the process that I outlined in the previous few slides is illustrative, and not exactly what is being done.

So, what is being done?

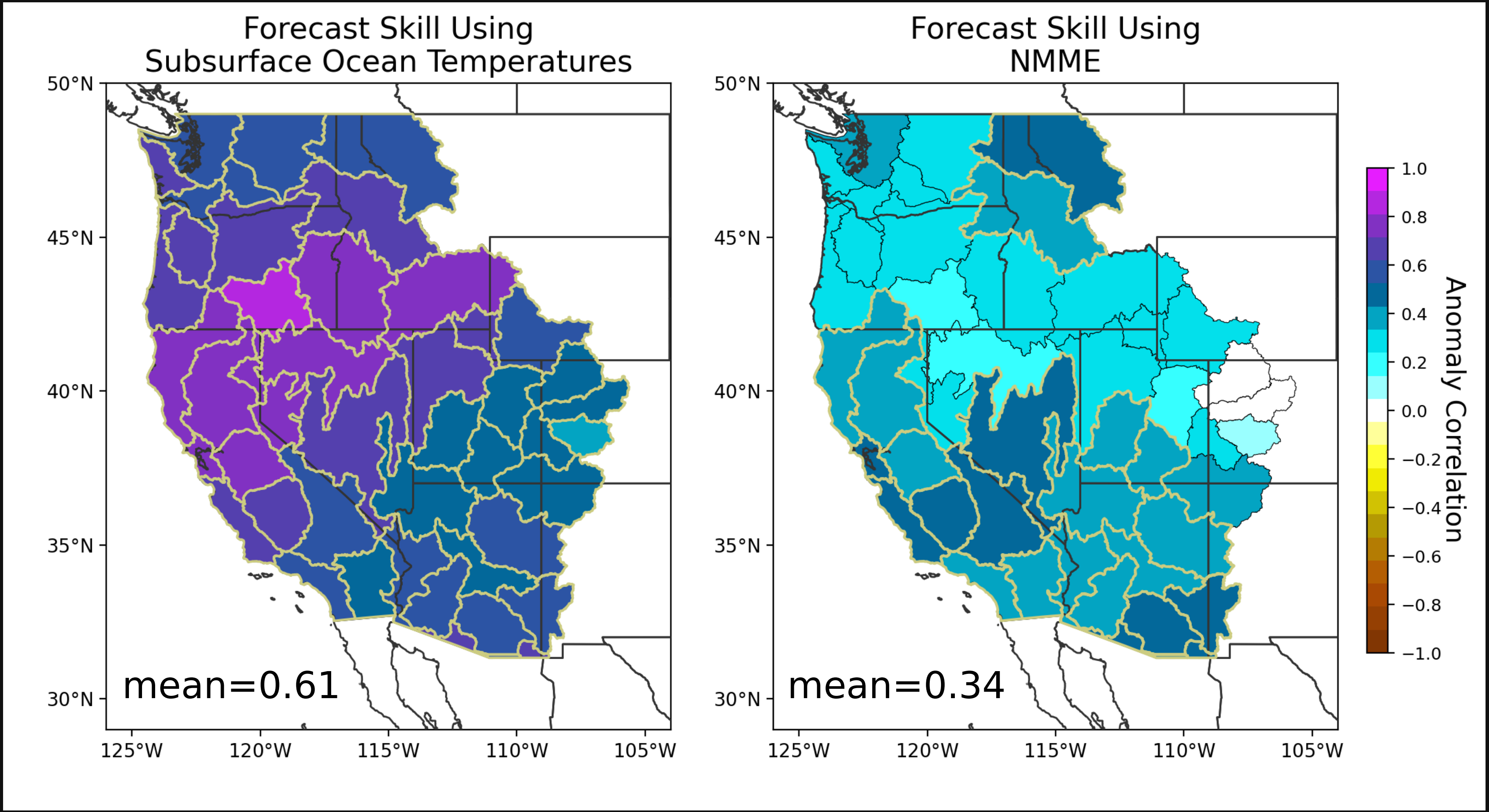
- Reduce the dimensionality of the data, reduce the noise.
- Apply some averaging of the predictor subsurface ocean temperature fields.
- Need to make cross-validated forecasts. That is, we cannot use the data from 2021/2022, for example, to fit the model in order to make a forecast of that year.

Cross-validation: First Case

Leave-one-season-out cross-validation.

For example, use data for the years 1980/1981-2020/2021 to forecast the year 2021/2022. We always use 41 years worth of data to forecast the current left-out year.

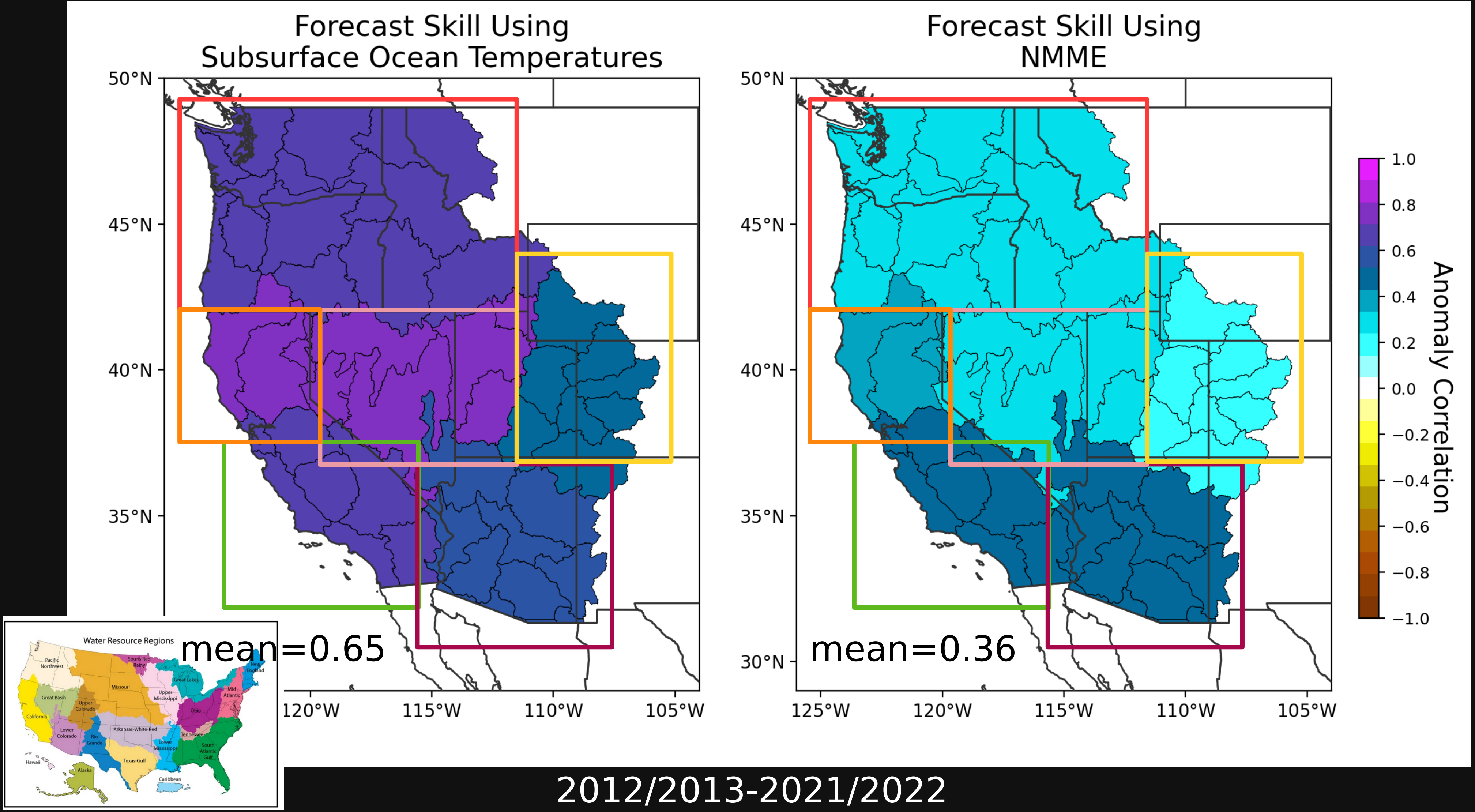
Validation period 1991/1992-2021/2022. This is the time period of the current set of NMME reforecasts.



1991/1992-2021/2022

LOSO Cross-Validation

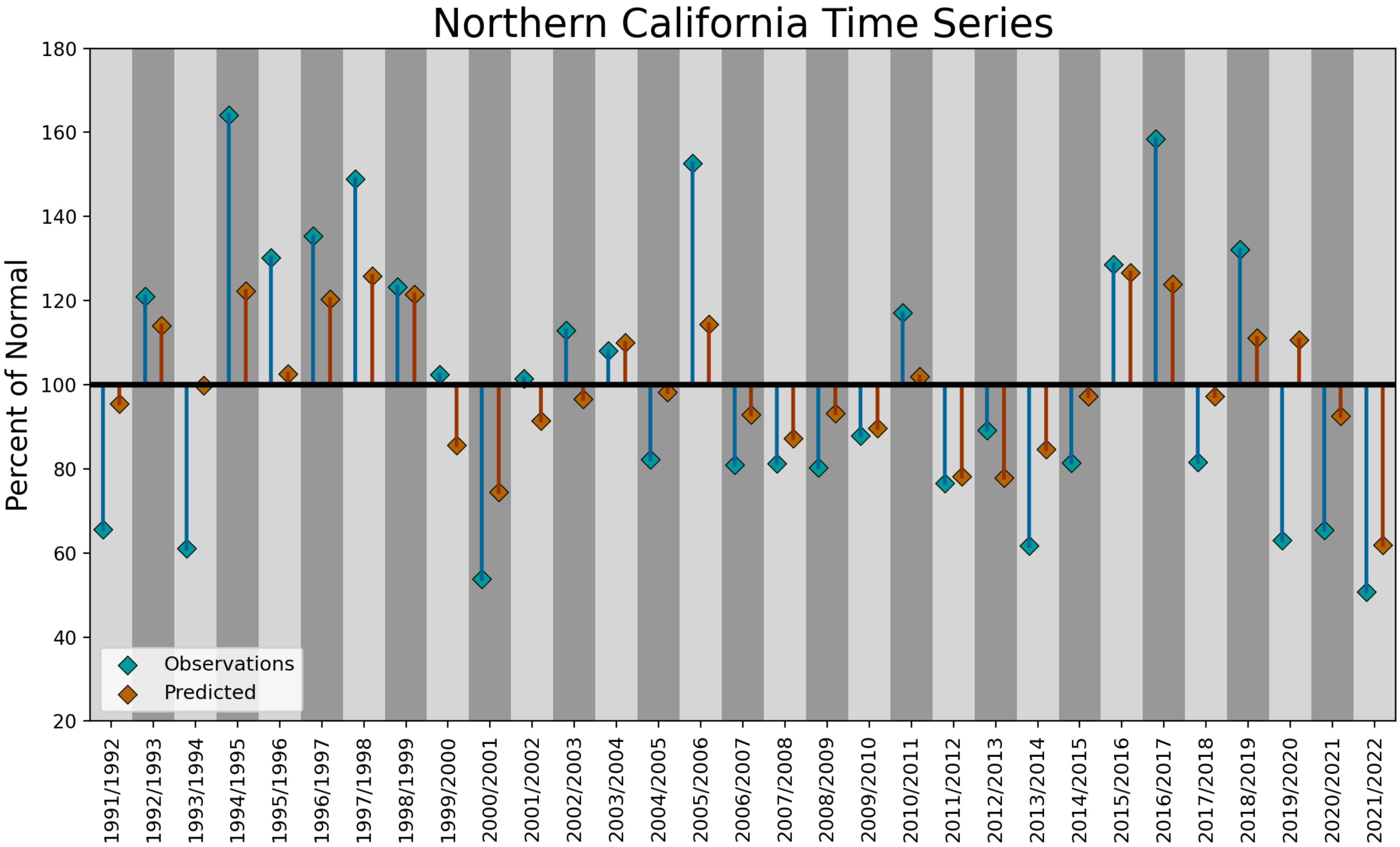
Split Cross-Validation



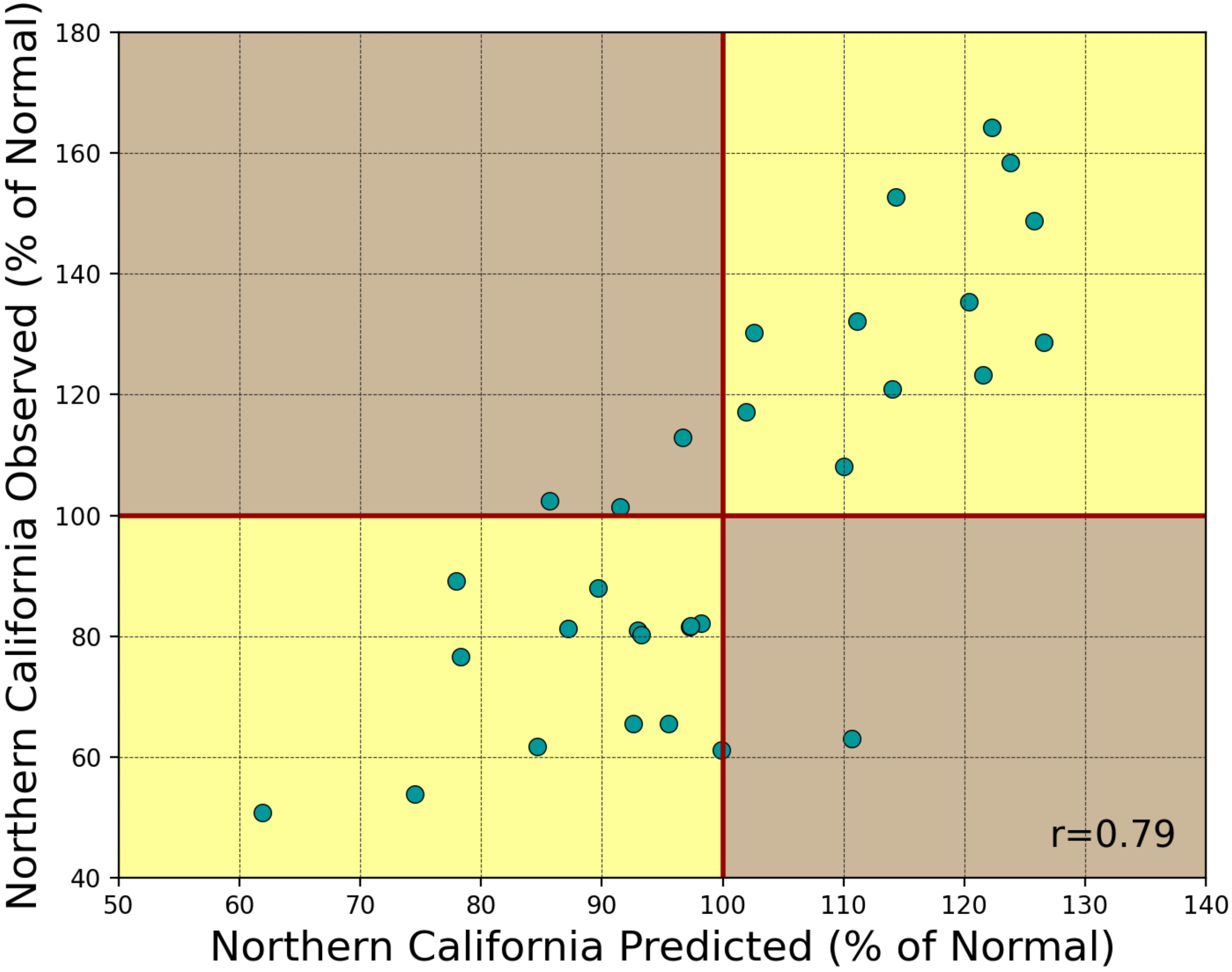
2012/2013-2021/2022

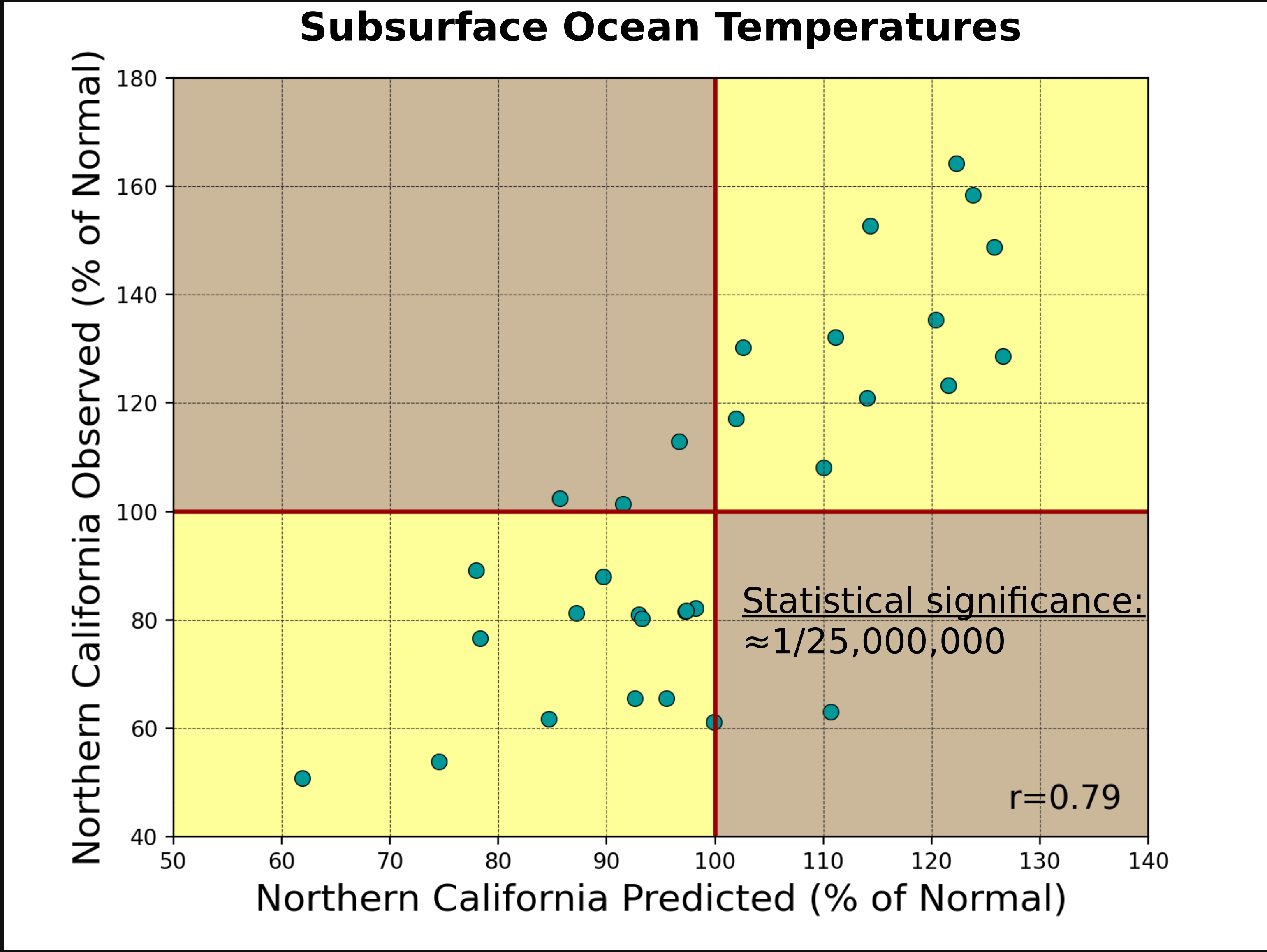
What do the cross-validated forecasts and observations look like for Northern California?

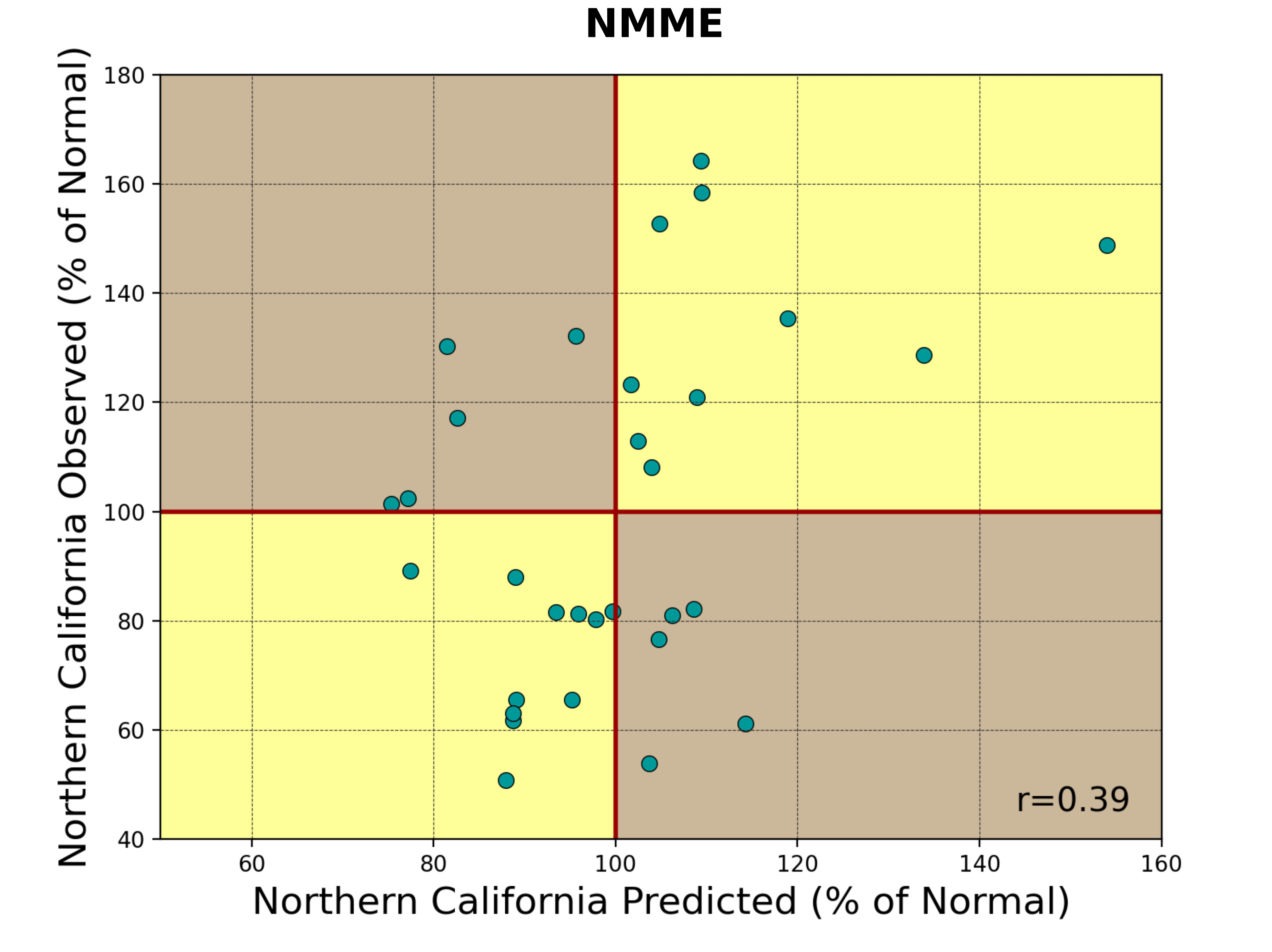
Subsurface Ocean Temperatures

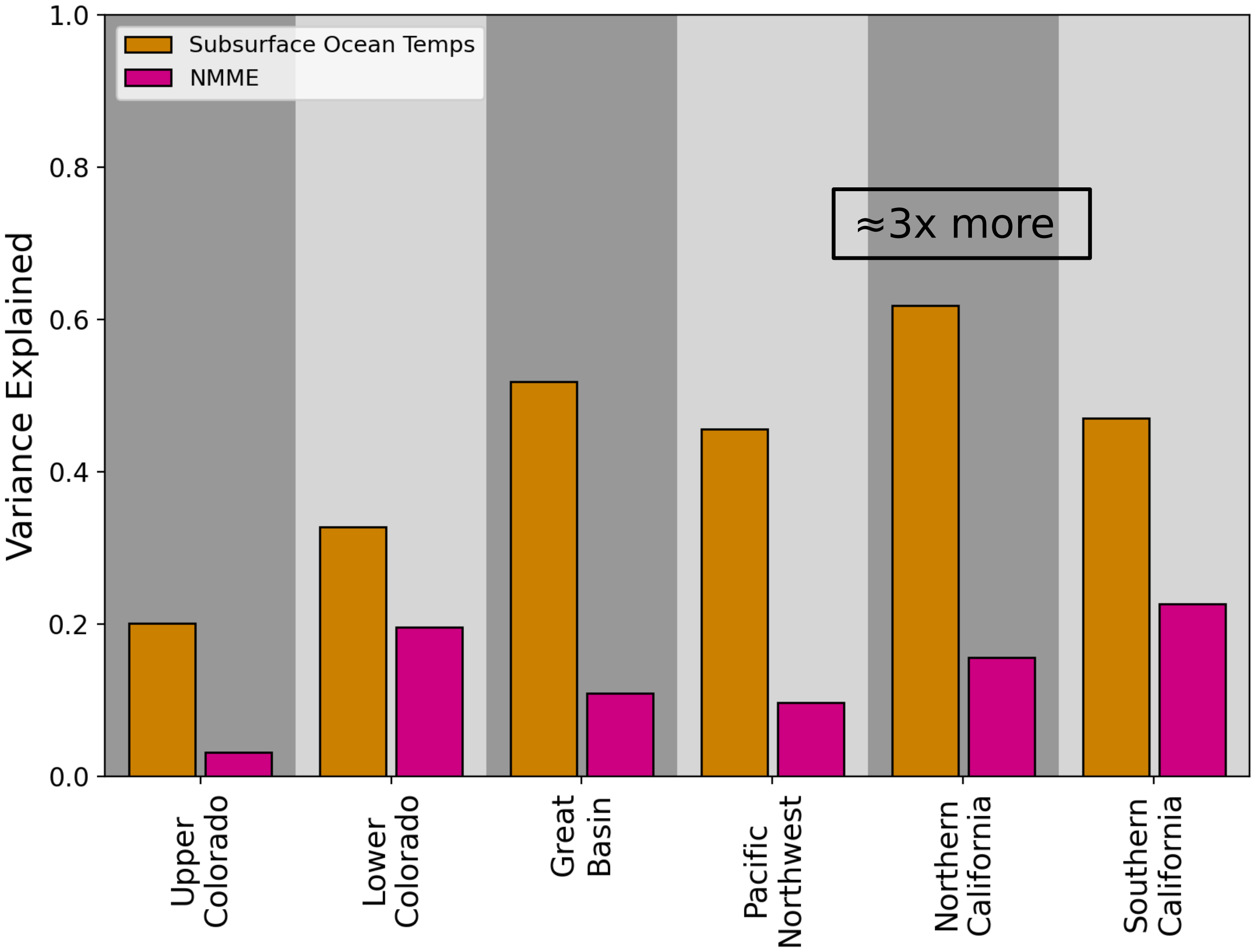


Subsurface Ocean Temperatures




Subsurface Ocean Temperatures
Northern California Observed (% of Normal)
Northern California Predicted (% of Normal)
Statistical significance:
≈1/25,000,000
r=0.79
180
160
140
120
100
80
60
40
50
60
70
80
90
100
110
120
130
140


NMME
Northern California Observed (% of Normal)
Northern California Predicted (% of Normal)
r=0.39
180
160
140
120
100
80
60
40
60
80
100
120
140
160



Subsurface Ocean Temps
NMME
≈3x more
Variance Explained
1.0
0.8
0.6
0.4
0.2
0.0
Upper Colorado
Lower Colorado
Great Basin
Pacific Northwest
Northern California
Southern California

Conclusions

1. We can produce much more skillful cross-validated cool-season precipitation forecasts using a statistical model that relies on subsurface ocean temperatures, than what we can obtain from NMME.

2. Anomaly correlation, and variance explained, does not capture everything that is, or is not, a good forecast. For example:
    - Is the mean of your forecasts biased?
    - Ultimately, we would produce probabilistic forecasts.

3. How might climate change and/or decadal-to-multidecadal variability affect the forecast skill?

More Conclusions

4. **Processes?** Statistical or machine learning methods exploit relationships in the data, but why are some of these relationships so robust?
    - There is not a direct physical interface between ocean temperatures below the sea surface and what plays out in the atmosphere. Are the temps a proxy for something else, and do they act as a filter?
    - I have had some discussions with some oceanographers at our lab, but these are ongoing questions.

Collaboration??? I am very excited about these results, and we are currently working on a manuscript. However, I believe that these results can further be strengthened by providing some reasonable process-based hypotheses. To that end, if anyone wants to contact me, please do so.

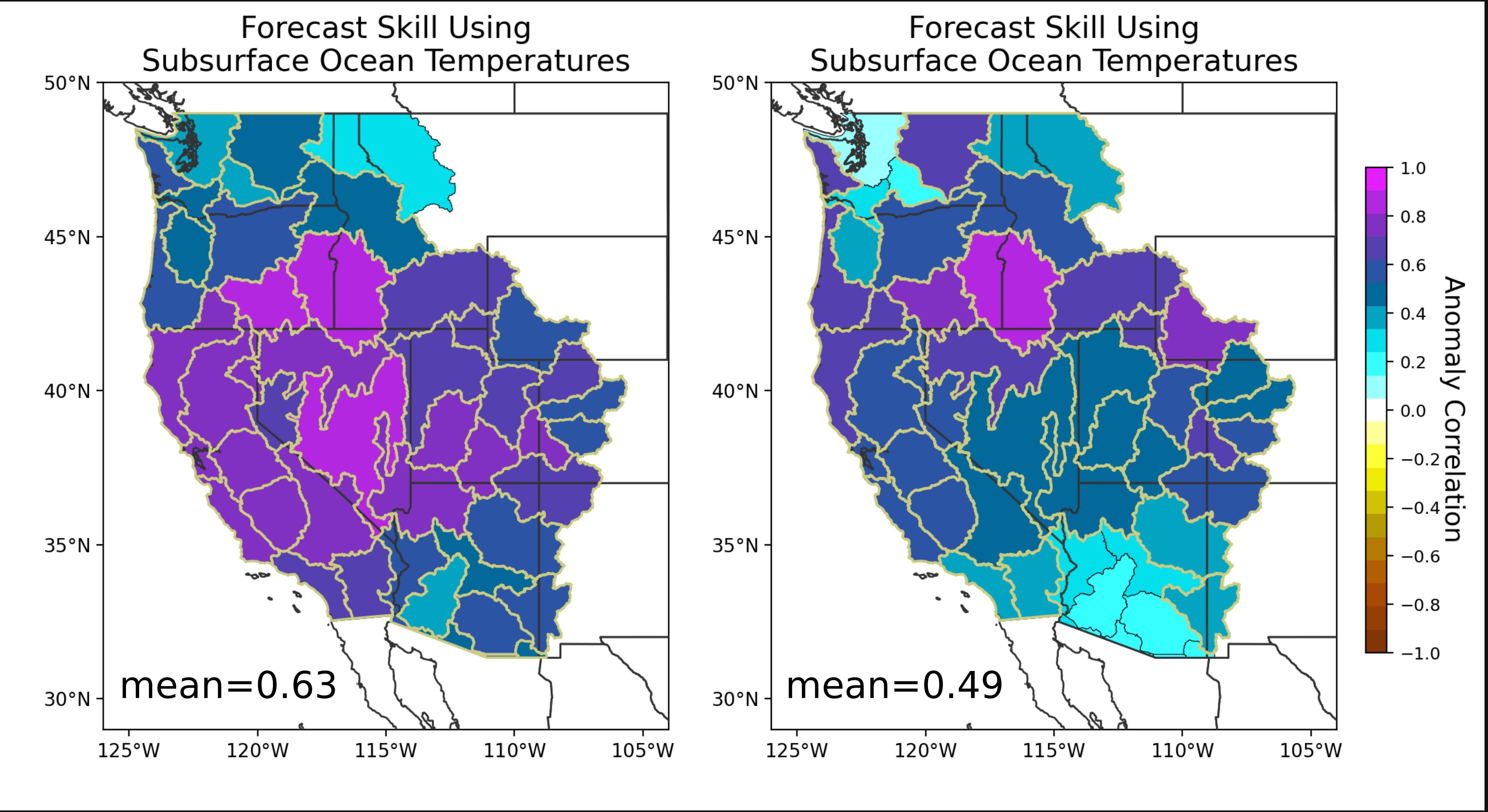
Thank You!!!

Questions, Comments, and/or Suggestions

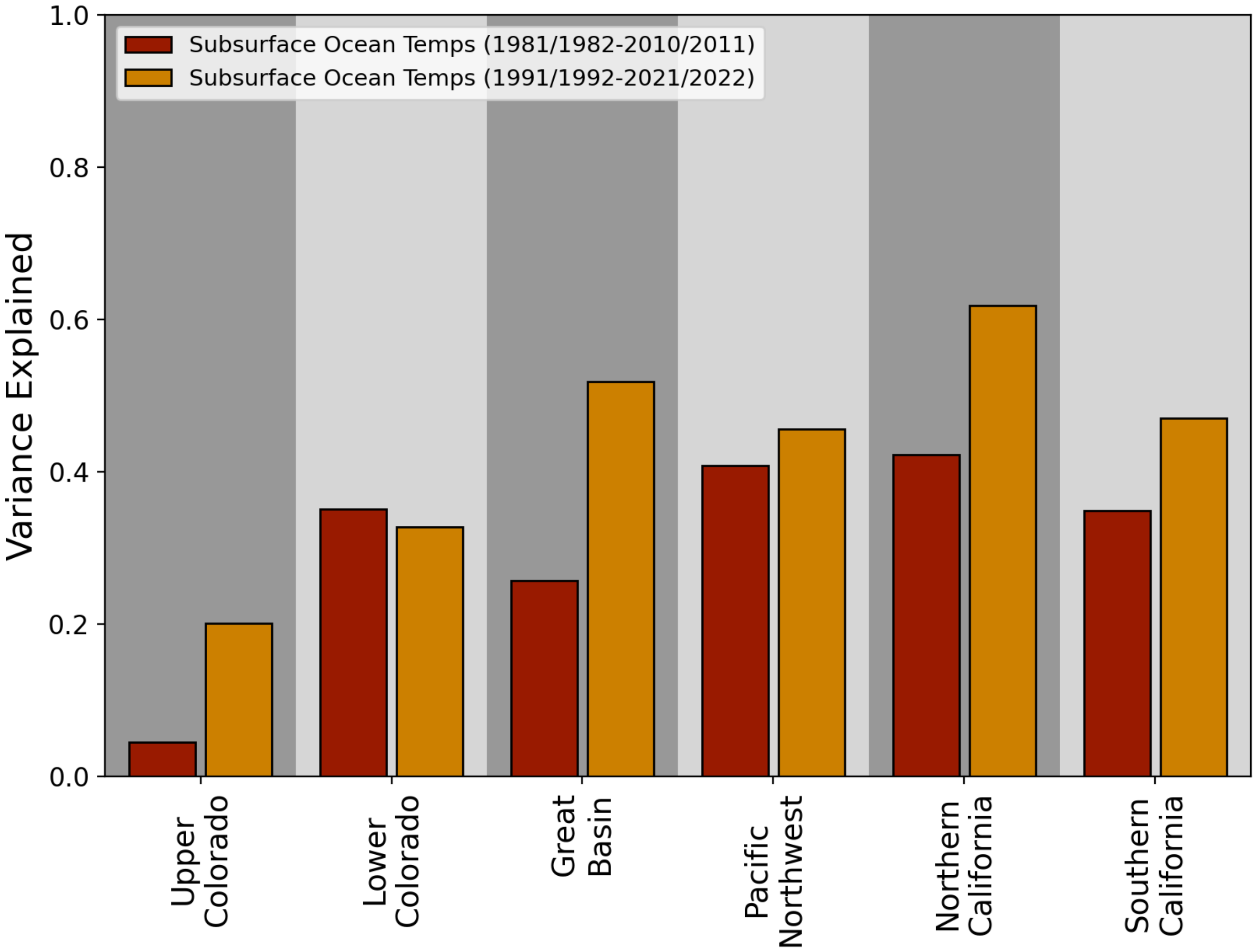
matt.switanek@noaa.gov (next 3 months)

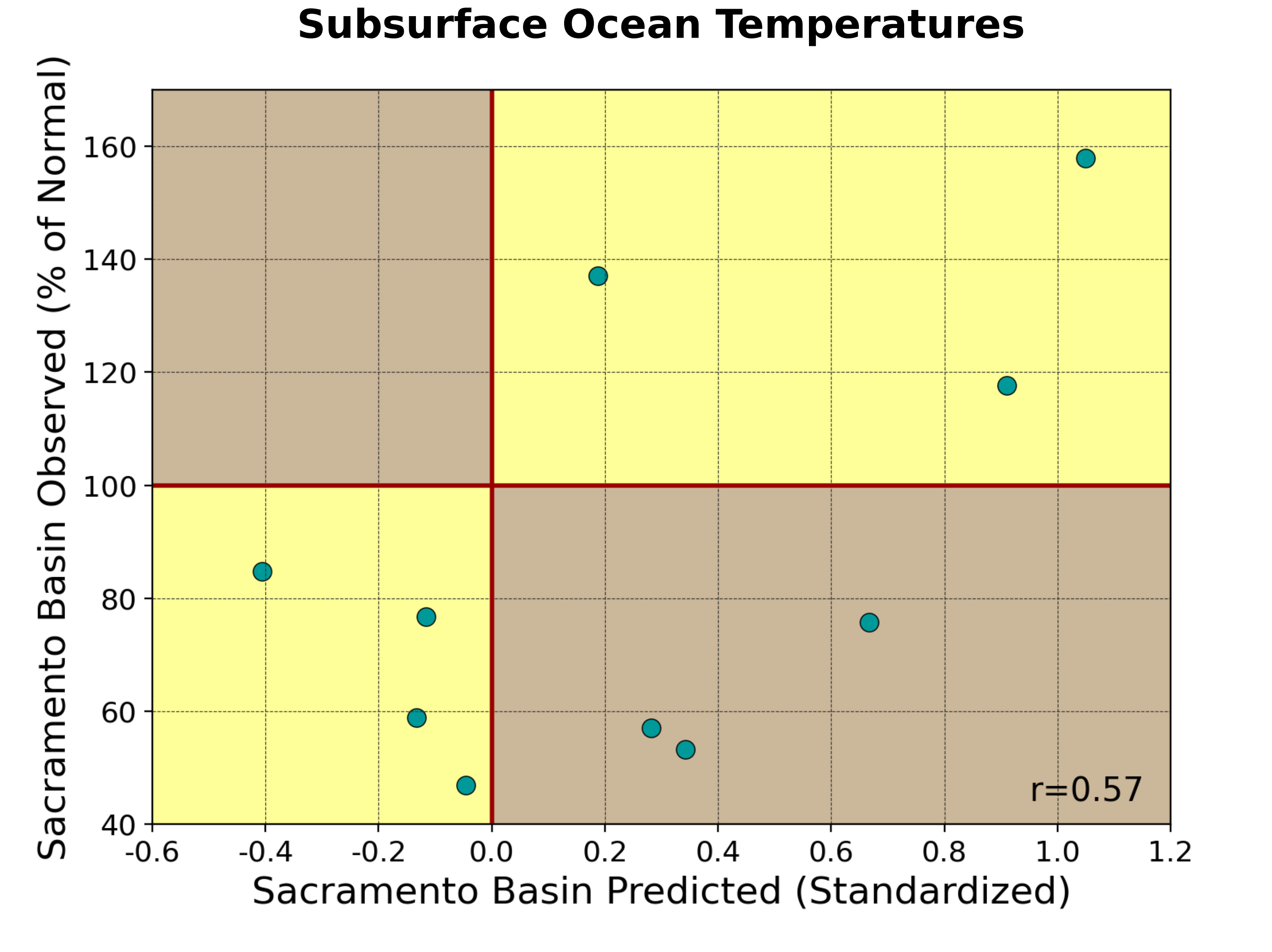
LOSO Cross-Validation

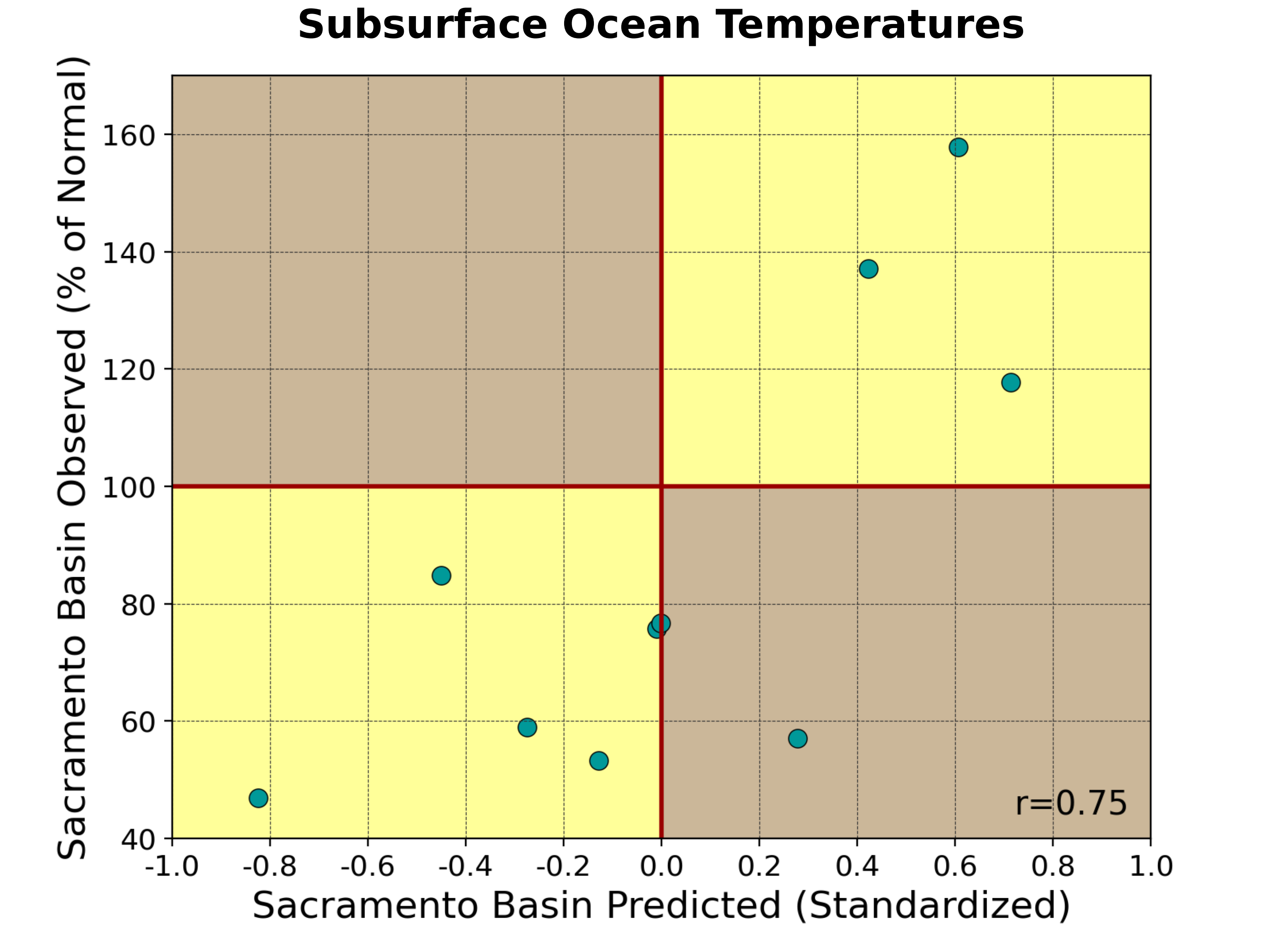
Split Cross-Validation



2012/2013-2021/2022


Subsurface Ocean Temps (1981/1982-2010/2011)
Subsurface Ocean Temps (1991/1992-2021/2022)
Variance Explained
1.0
0.8
0.6
0.4
0.2
0.0
Upper Colorado
Lower Colorado
Great Basin
Pacific Northwest
Northern California
Southern California


Subsurface Ocean Temperatures
Sacramento Basin Observed (% of Normal)
Sacramento Basin Predicted (Standardized)
r=0.57
160
140
120
100
80
60
40
-0.6
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2

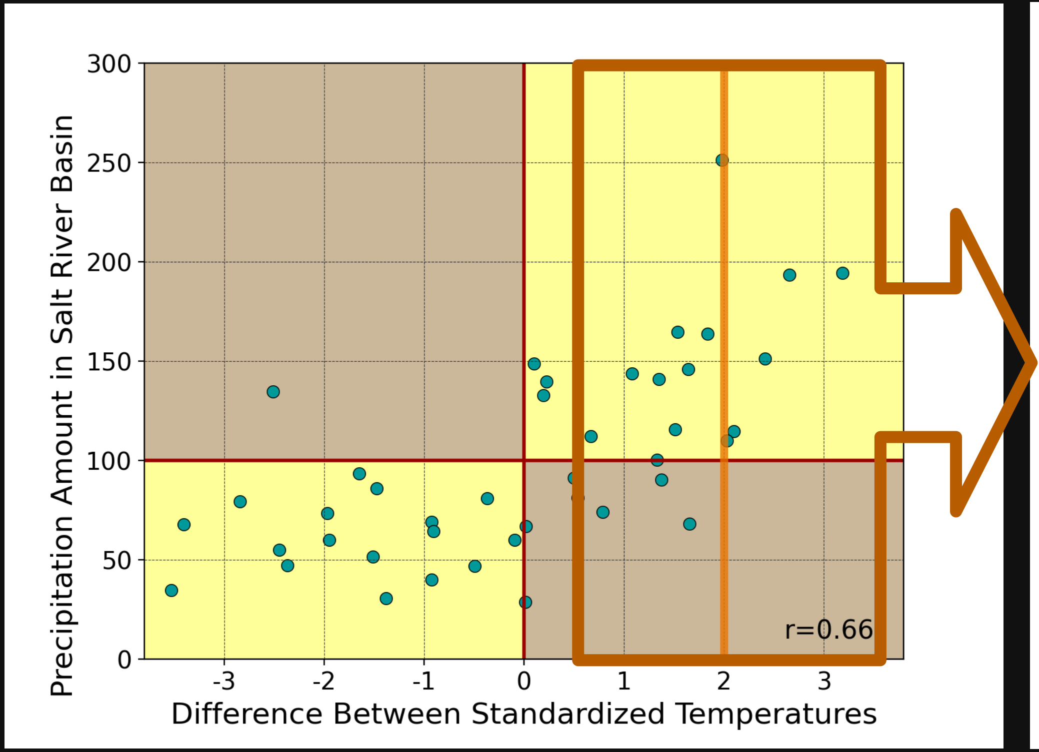

Subsurface Ocean Temperatures
Sacramento Basin Observed (% of Normal)
160
140
120
100
80
60
40
-1.0
-0.8
-0.6
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
r=0.75
Sacramento Basin Predicted (Standardized)

What does this mean?

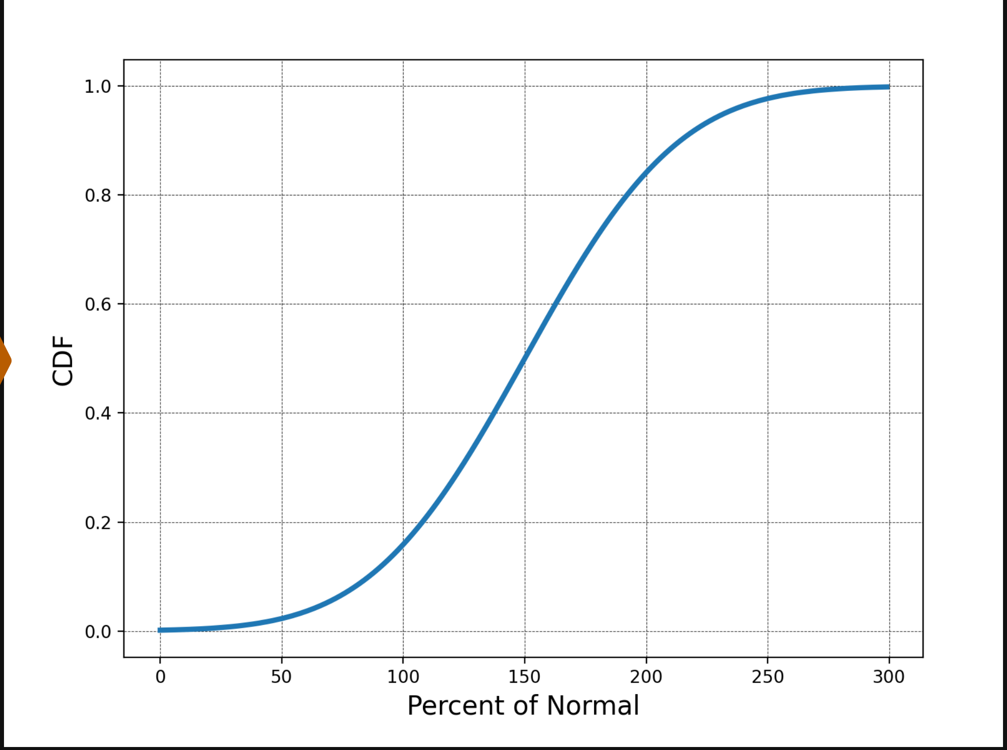
1. Having a larger sample size is better.

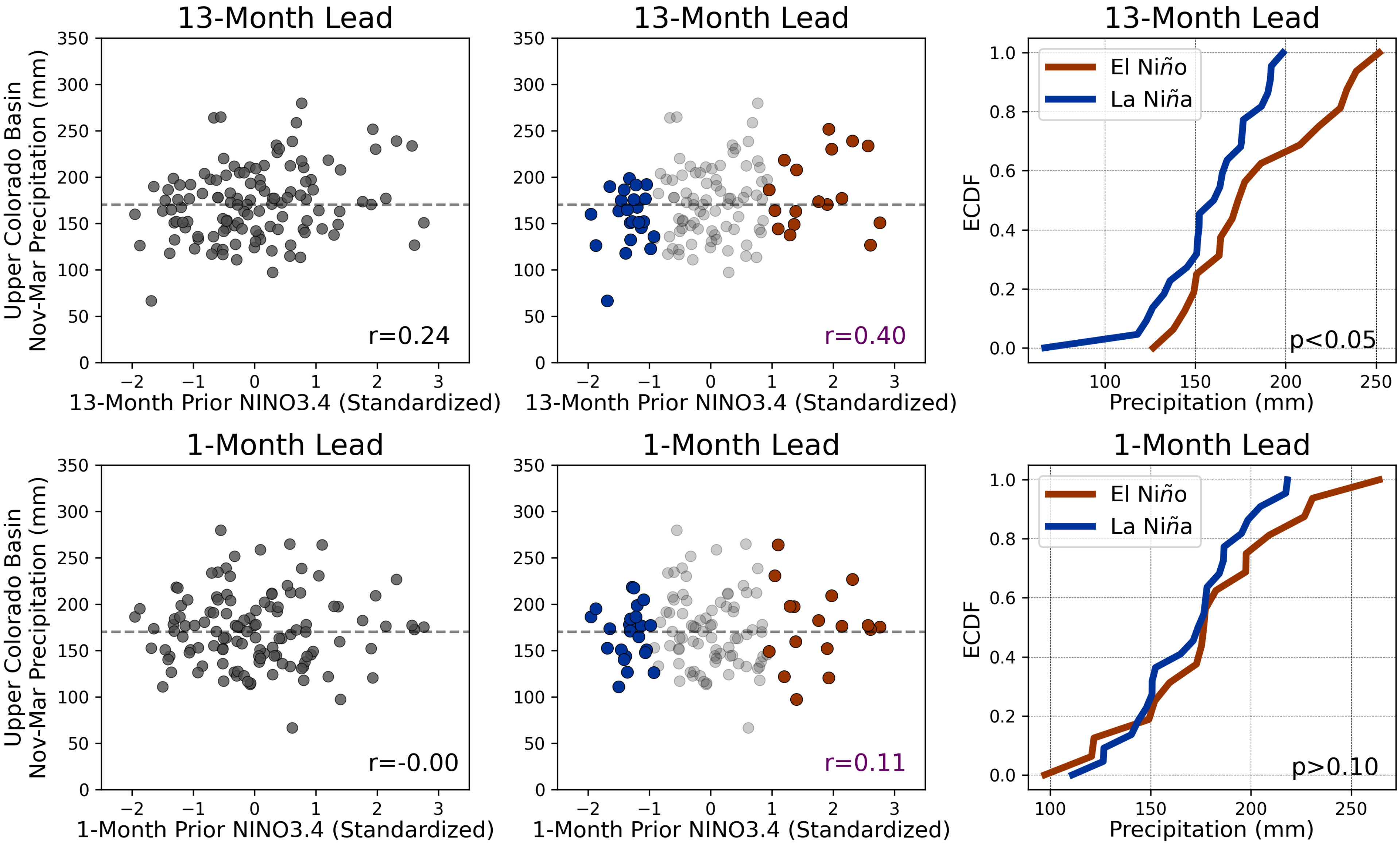
2. Variable trends in the different gradient components can shift the forecasts to the left or right. This will result in creating a mean bias in long-term forecasts.

Normalized (Percent of Normal)



Probabilistic Forecast





13-Month Lead
Upper Colorado Basin Nov-Mar Precipitation (mm)
r=0.24
13-Month Prior NINO3.4 (Standardized)
13-Month Lead
r=0.40
13-Month Prior NINO3.4 (Standardized)
13-Month Lead
El Niño
La Niña
ECDF
p<0.05
Precipitation (mm)
1-Month Lead
Upper Colorado Basin Nov-Mar Precipitation (mm)
r=-0.00
1-Month Prior NINO3.4 (Standardized)
1-Month Lead
r=0.11
1-Month Prior NINO3.4 (Standardized)
1-Month Lead
El Niño
La Niña
ECDF
p>0.10
Precipitation (mm)

Our forecast for this cool-season (Nov-Mar 2021/2022)