**Statistically-based prediction approach for forecasting seasonal precipitation**

This study aims to evaluate the seasonal predictability of precipitation by utilizing the empirical linkages between Pacific sea surface temperature (SST) and seasonal precipitation (P) in western North America. Purely statistical prediction approach based on canonical correlation analysis (CCA) is used to identify temporally coupled and physically meaningful spatial modes in SST and P fields at appropriate lead times and, after considering their physical significance, use these coupled modes to construct a statistical forecasting model.

**Methodology at a glance**

**Predictor**: Antecedent observations of Pacific sea surface temperature (monthly average SST observed in previous months).

**Predictand**: Observed seasonal sum of precipitation in western US.

**Statistical model**:

1) Predictor and predictand fields are prefiltered with *p* principal components (PCs) each (same number of PCs for simplicity);

2) Patterns of variability in the predictor and predictand fields represented by their respective PCs (*p* of them) are related to each other via *k* canonical correlates derived from CCA. Thus, $k \leq p < T$, where T is the number of temporal observations available for model training;

3) The optimal statistical model is defined by considering cross-validated measures of skill for all reasonable combinations of *p* and *k* displayed on the skill optimization surface (SOS). The model complexity selection is strengthened by additional estimating root mean square error between time series of observed and predicted predictand fields, as well as their standard deviation. The PCs are recalculated for each ‘‘leave-one-out’’ cross-validation iteration.

**Forecast**: Antecedent SST field is observed at the appropriate lead time. A statistical forecast of seasonal precipitation sum is then constructed using the optimal model complexity.

**Model validation and skill optimization**: Prediction ability of the model is evaluated by using cross-validated application of the model to observed data. Skill is defined at each grid cell as the correlation coefficient between the time series of the observed and predicted predictand. Skill is optimized as follows. For each reasonable model complexity (i.e., *p*–*k* combination of PCs and CCs), field-averaged skill value is chosen to summarize seasonal skill for the entire spatial predictand field. This value is then displayed for each model complexity on a *p* –*k* plot. Such a display defines the SOS. Additionally, the root mean square error between time series of observed and predicted predictand fields, as well as their standard deviation, are calculated at each grid cell and averaged over the predictand field. These three metrics are then used to choose the optimal model complexity for the season (and predictor lead time) of interest.

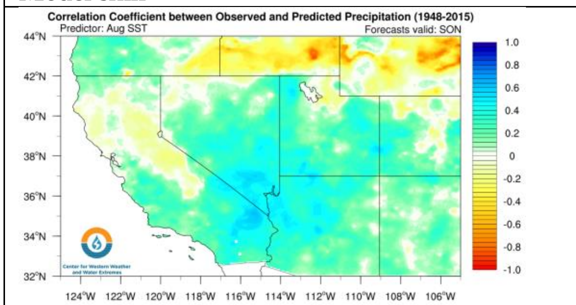
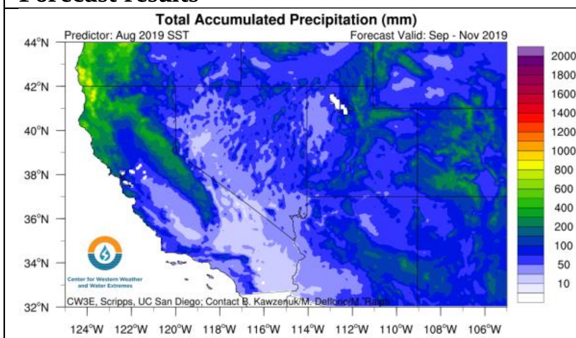
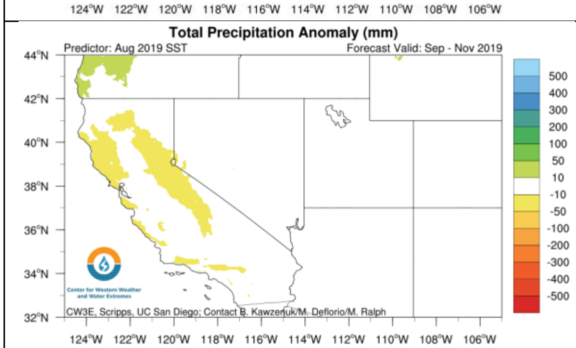
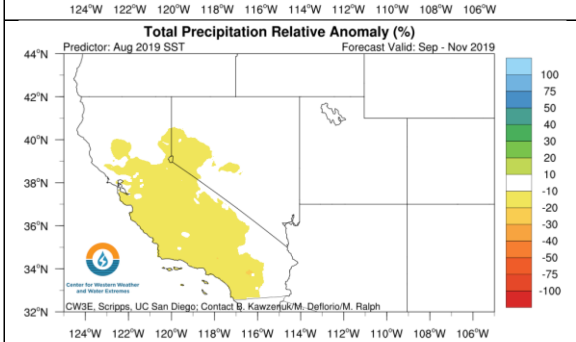
**Reference**:

Gershunov, A., and D.R. Cayan, 2003: Heavy daily precipitation frequency over the contiguous U.S. Sources of climatic variability and seasonal predictability. *J. Climate,* **16**(16), 2752-2765. *(69)*

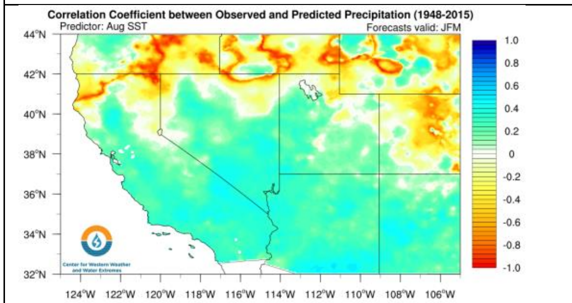
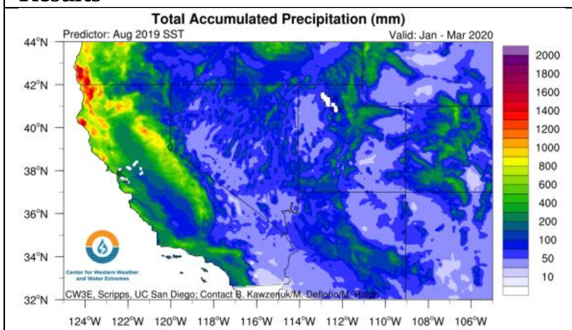
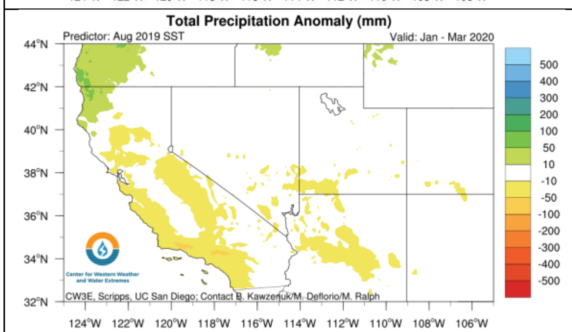
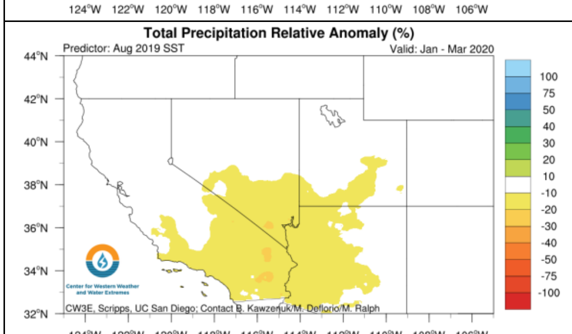
**Model results** (Example from September 2019)

**Predictor**: Monthly average data of sea surface temperature retrieved from NOAA Extended Reconstructed SST version 4 dataset over the Pacific Ocean [20S – 64N, 260-100S] cover time period 1948 – 2015. These data resolved on 2x2 degree spatial grid are used as predictor fields for the statistical forecast models.
**Predictand**: The predictand variable considered here is seasonal accumulations of total precipitation. Seasonal sum of precipitation retrieved from Livneh (2015) daily precipitation dataset over the California-Colorado states [32-44N, -124.5-105W] at 1948-2015 are used for model training.

**Task 1:** Construct a forecast field of total precipitation for September-November 2019 using August 2019 SST as a predictor.

<table>
<tr><td colspan="2">Model skill</td></tr>
<tr><td>
</td><td>Skill is defined as the correlation coefficient between the time series of observed and predicted seasonal precipitation at each grid cell using ‘‘leave-one-out’’ cross-validation iteration over September-November 1948-2015 and August SST forcing. Skill is obtained with the model complexity 3x3 (PCsxCCs), selected from SOS as optimal.</td></tr>
<tr><td colspan="2">Forecast results</td></tr>
<tr><td>
</td><td>Map of predicted total accumulated precipitation (mm) for September-November 2019 via August 2019 SST.</td></tr>
<tr><td>
</td><td>Map of predicted precipitation anomalies (mm) for September-November 2019 via August 2019 SST.</td></tr>
<tr><td>
</td><td>Map of predicted precipitation relative anomalies (%) for September-November 2019 via August 2019 SST.</td></tr>
</table>

**Task 2:** Construct a forecast field of total precipitation for January-March 2020 using August 2019 SST as a predictor.

<table>
<tr><td colspan="2">Model skill</td></tr>
<tr><td>
</td>
<td>Skill is defined as the correlation coefficient between the time series of observed and predicted seasonal precipitation at each grid cell using ‘‘leave-one-out’’ cross-validation iteration over January-March 1948-2015 and August SST forcing. Skill is obtained with the model complexity 2x2 (PCsxCCs), selected from SOS as optimal.</td></tr>
<tr><td>Results</td><td></td></tr>
<tr><td>
</td>
<td>Map of predicted total accumulated precipitation (mm) for January-March 2020 via August 2019 SST.</td></tr>
<tr><td>
</td>
<td>Map of predicted precipitation anomalies (mm) for January-March 2020 via August 2019 SST.</td></tr>
<tr><td>
</td>
<td>Map of predicted precipitation relative anomalies (%) for January-March 2020 via August 2019 SST.</td></tr>
</table>

**Reference:**


1. NOAA Extended Reconstructed SST V4: https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.ersst.v4.html
2. Livneh B., E.A. Rosenberg, C. Lin, B. Nijssen, V. Mishra, K.M. Andreadis, E.P. Maurer, and D.P. Lettenmaier, 2013: A Long-Term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States: Update and Extensions, Journal of Climate, 26, 9384–9392.
3. CW3E S2S-web