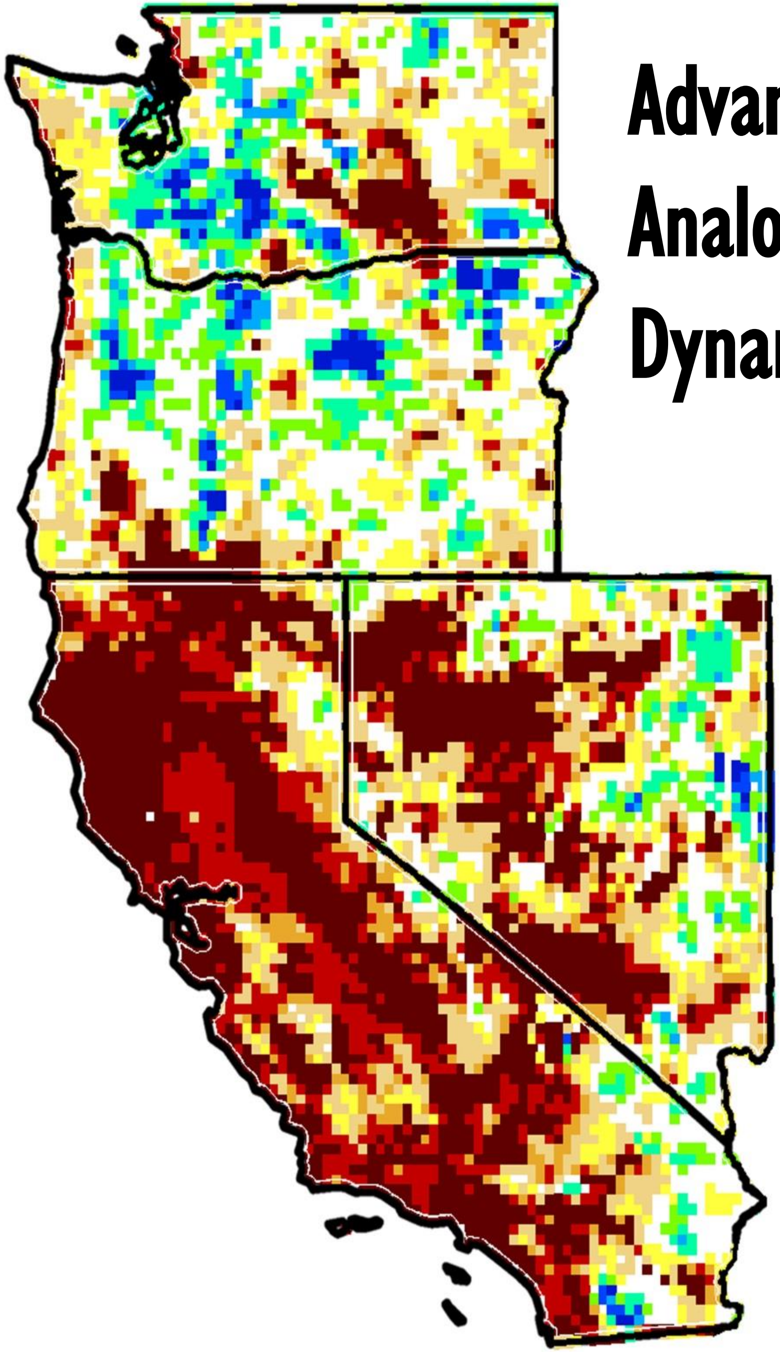


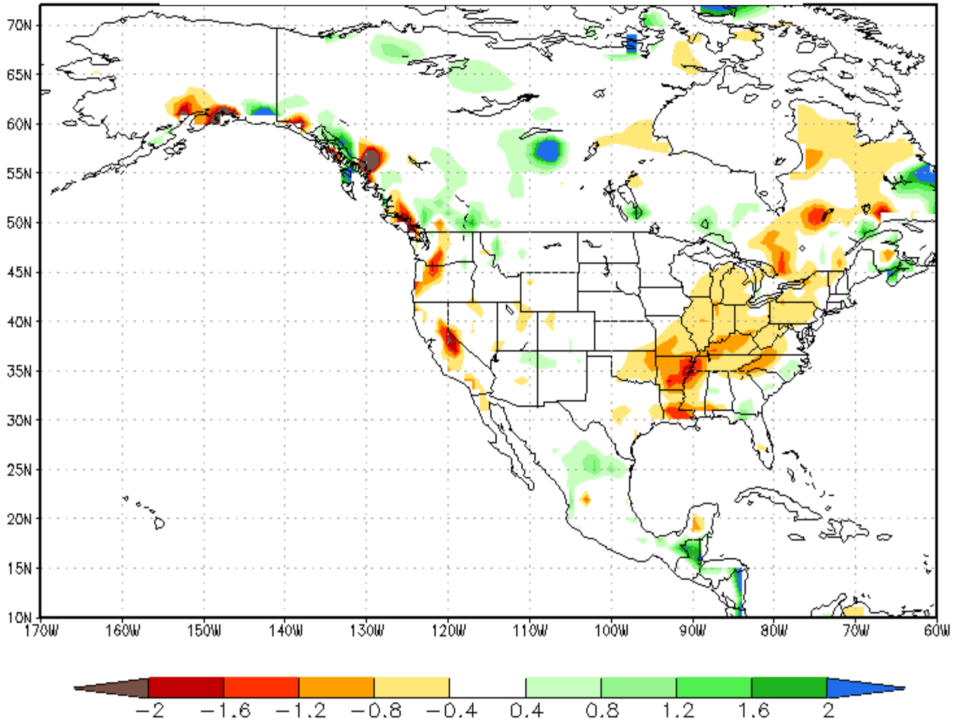
Advancing Drought Prediction Using an Analog-Year Model Combined with Dynamic Model Simulations

Shahrbanou Madadgar, Linyin Cheng, Shrad Shukla, Amir AghaKouchak

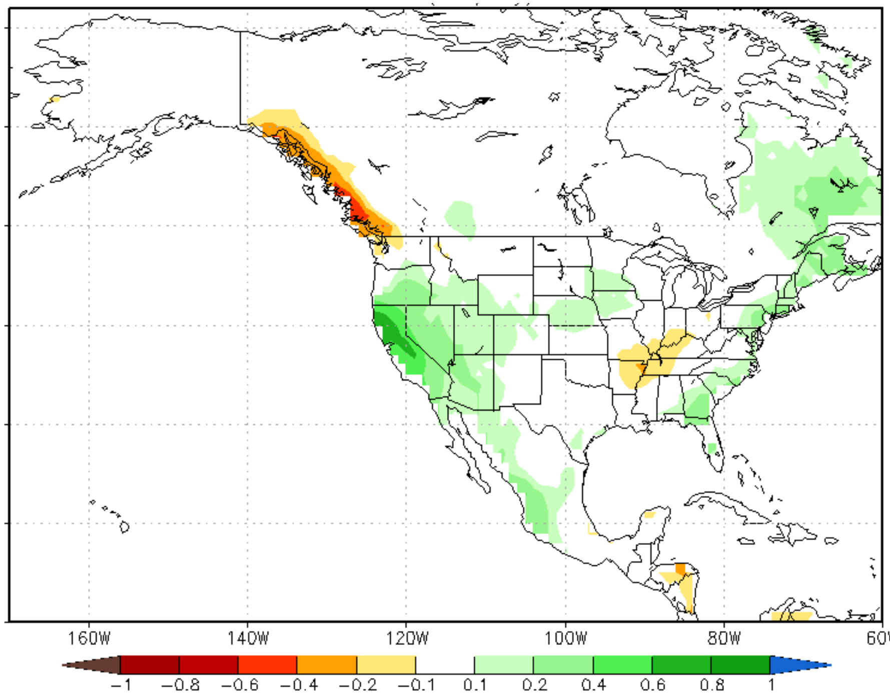
University of California, Irvine

Motivation

Observed Precipitation Anomaly DJF 2014

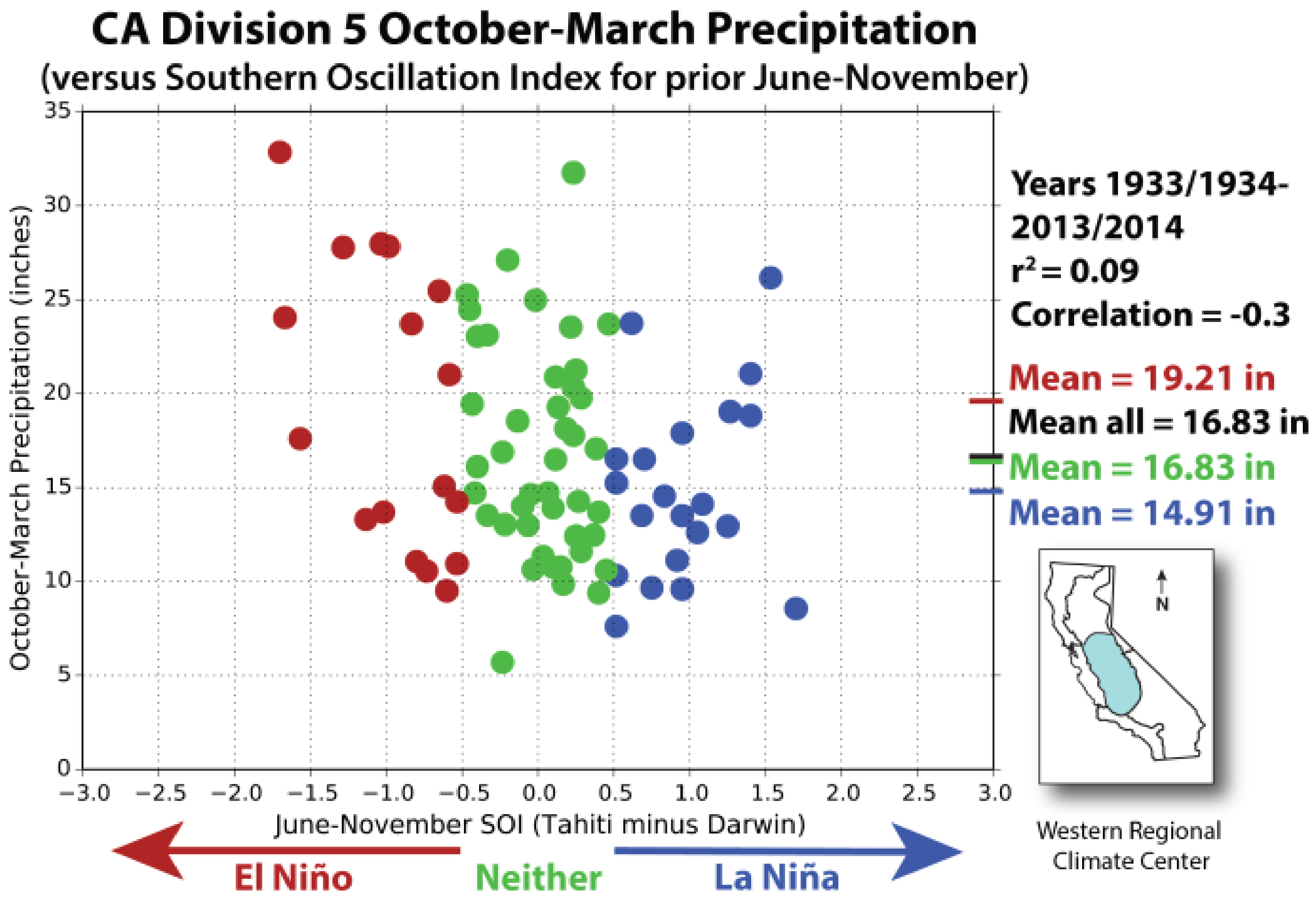


Predicted Precipitation Anomaly (mm/d) DJF 2014 (Initialized: November)



North American Multi-Model Ensemble (NMME; Kirtman et al., 2014)

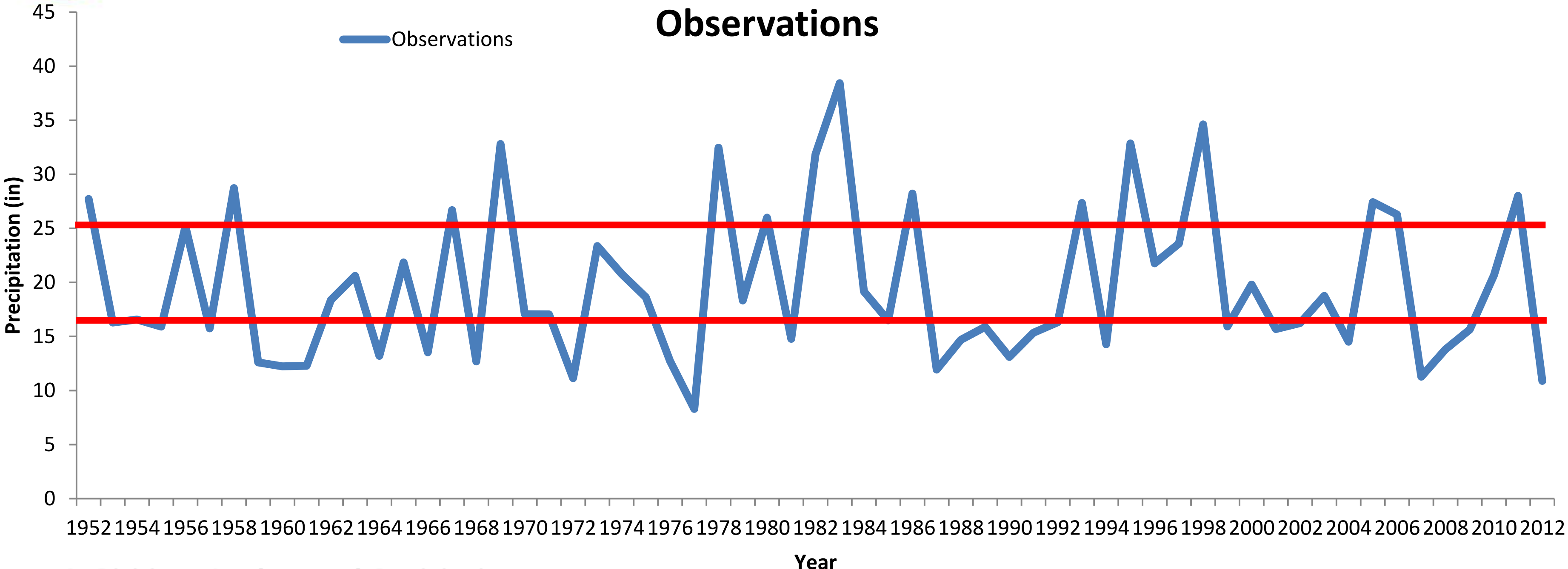
Low Predictability of Precipitation Forecasts in Dynamic Model Simulations

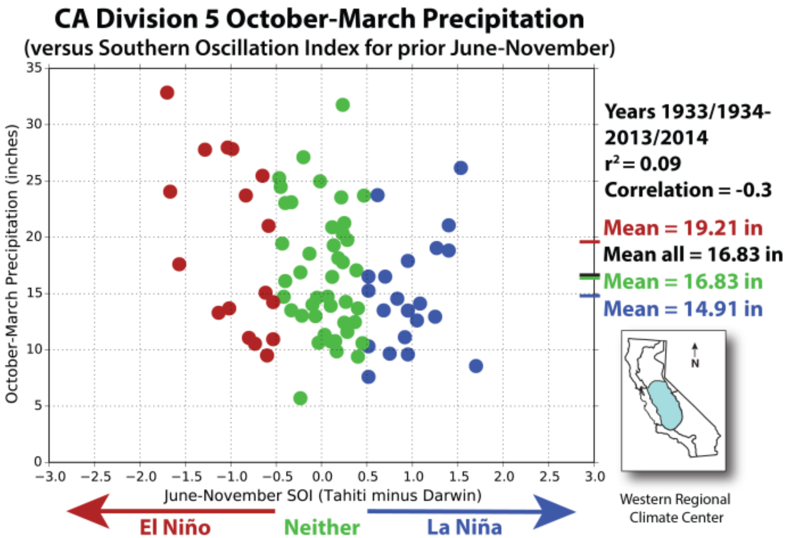


Analog-year based models also offer low predictability

Objective

Climate Division 5 Precipitation



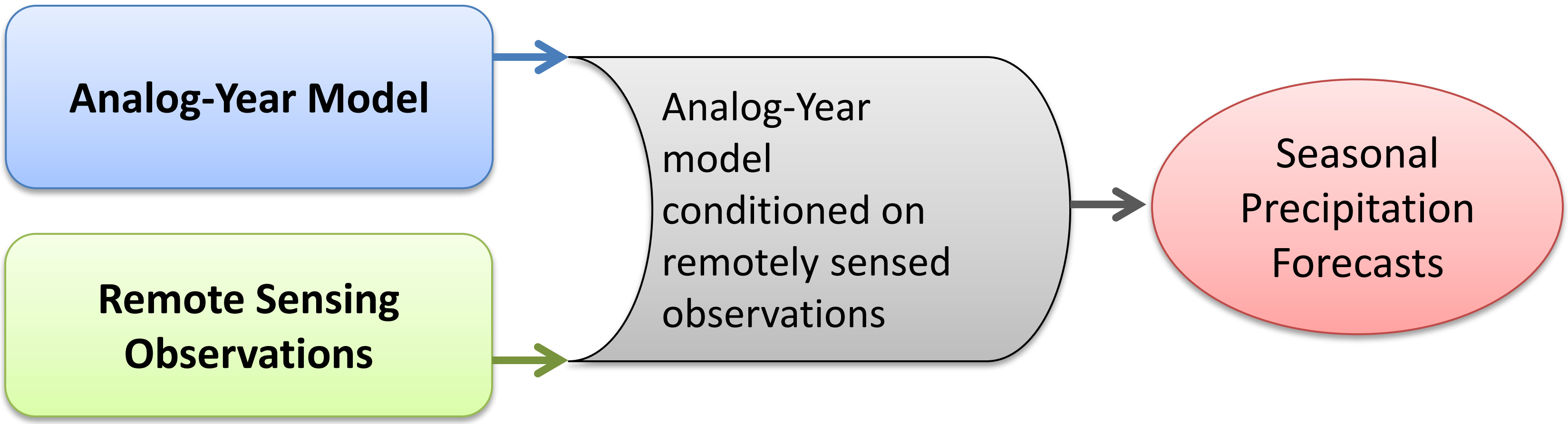


$$f(PDO, MEI, SOI, \ldots) \sim \begin{cases} \Pr(P > AN) \\ \Pr(P \sim NN) \\ Pr(P < BN) \end{cases}$$

AN: Above Normal (> 66th Percentile)
NN: Near Normal
BN: Below Normal (< 33th Percentile)

Drought Prediction Frameworks

Analog-Year Model Combined with Remote Sensing Observations



Drought Prediction Frameworks

Analog-Year Model Combined with Remote Sensing Observations

Analog-Year Model

Remote Sensing Observations

Analog-Year model conditioned on remotely sensed observations

Seasonal Precipitation Forecasts

Analog-Year Model Combined Dynamic Model Simulations

Analog-Year Model

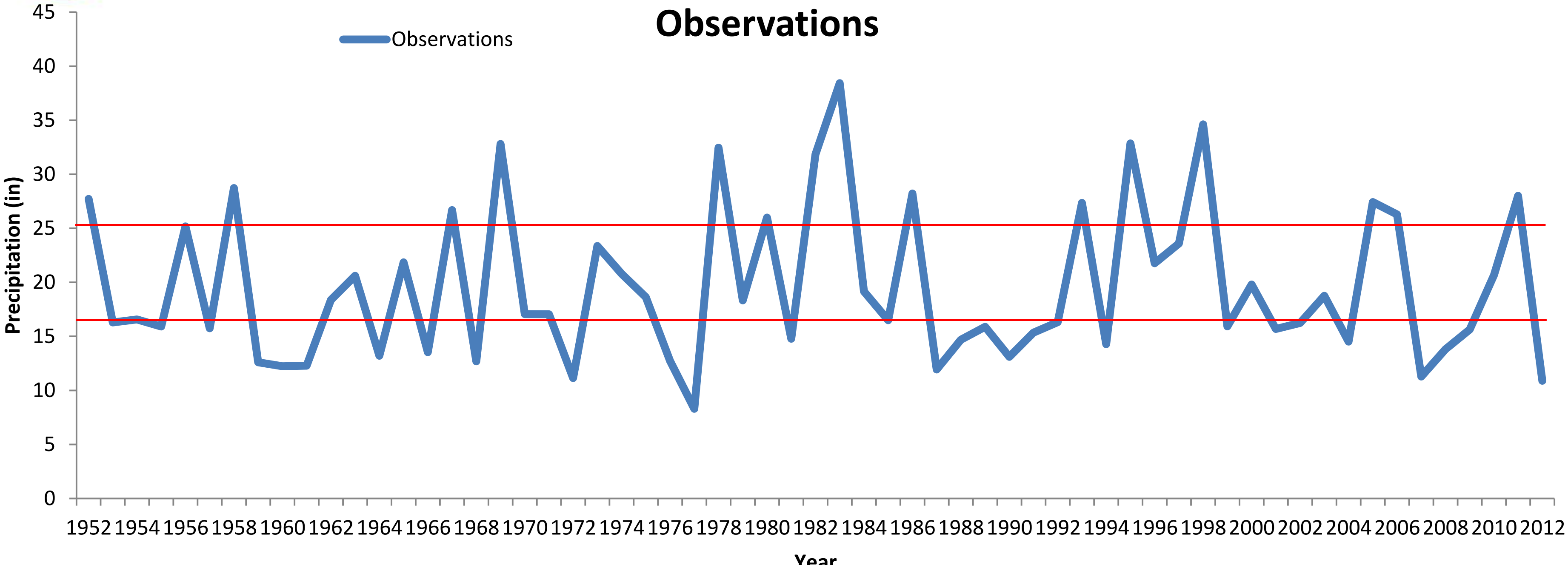
Dynamic Model Simulations

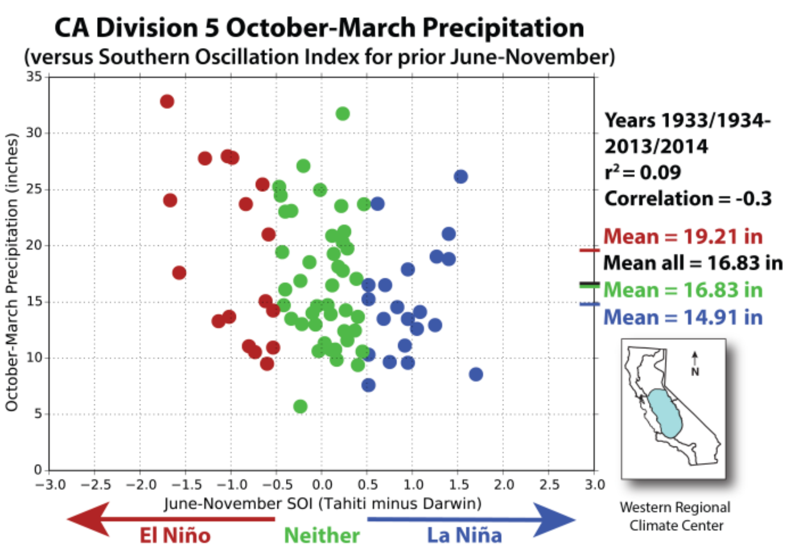
Multi-Model Assessment Using the Expert Advice Algorithm

Seasonal Precipitation Forecasts

Drought Prediction

Climate Division 5 Precipitation





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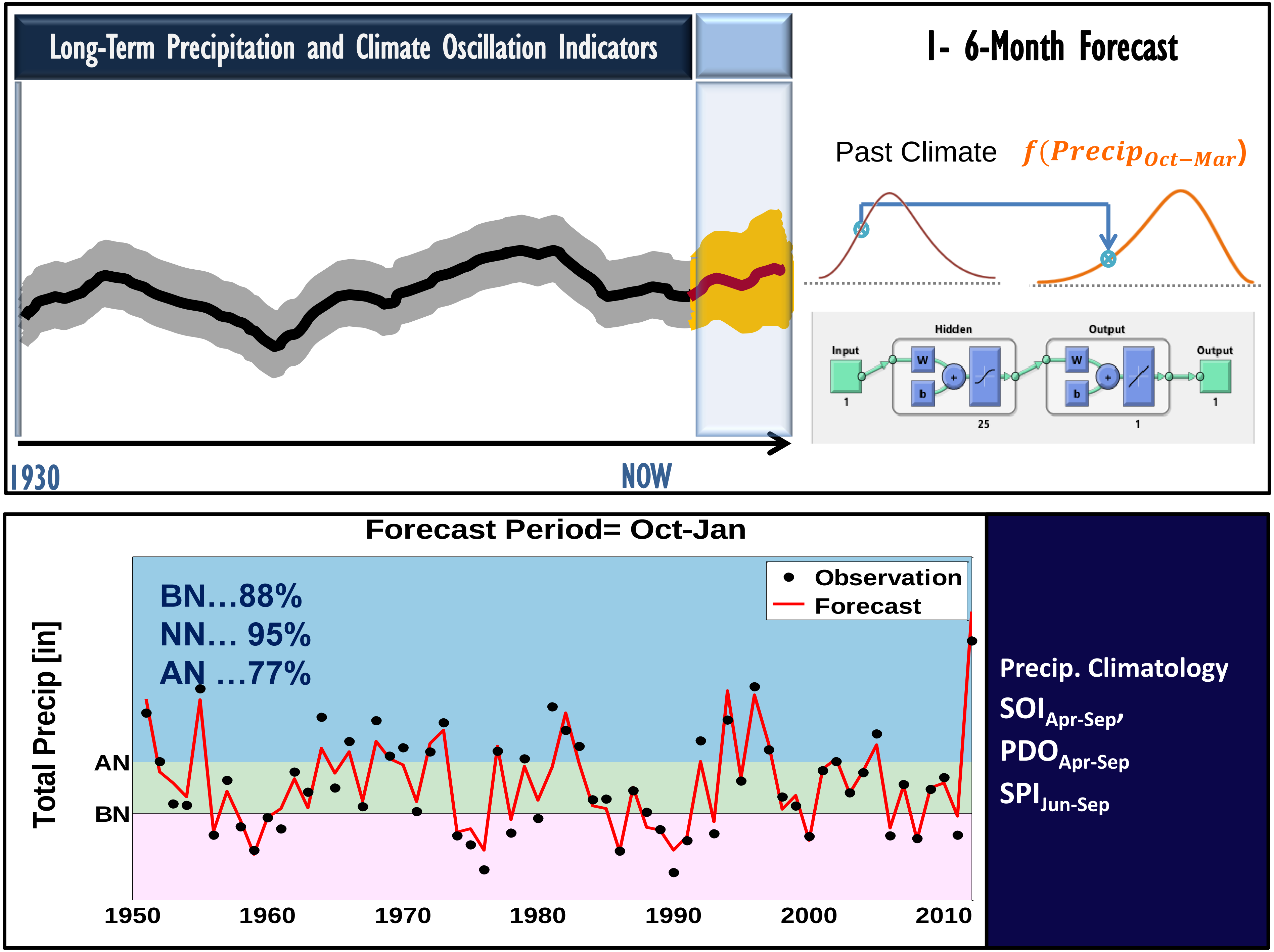
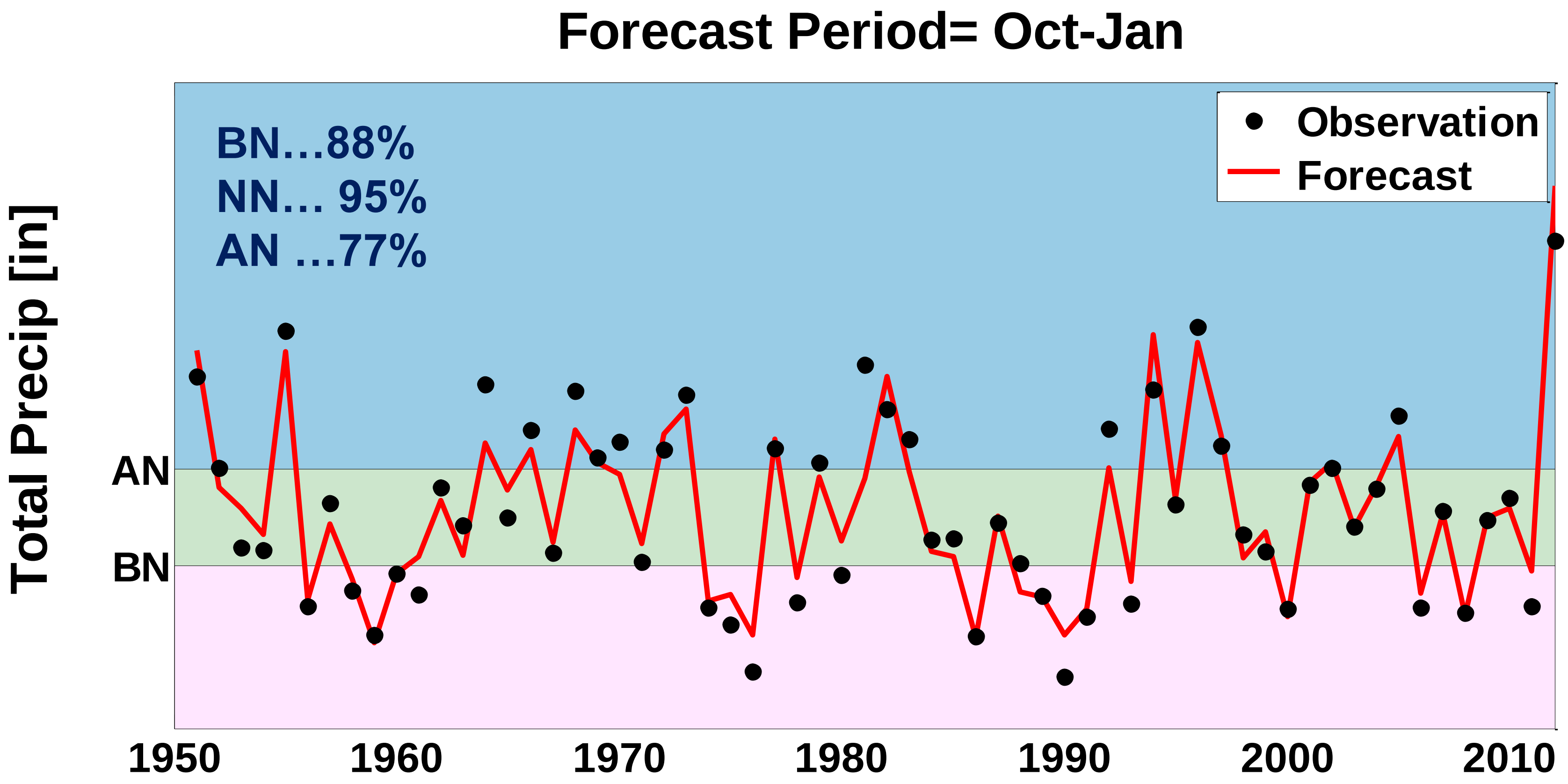


Long-Term Precipitation and Climate Oscillation Indicators
1930
NOW
1- 6-Month Forecast
Past Climate
$f(Precip_{Oct-Mar})$
Hidden
Output
Input
Output
W
b
W
b
1
25
1
1
Forecast Period= Oct-Jan
Observation
Forecast
BN…88%
NN… 95%
AN …77%
Total Precip [in]
AN
BN
1950
1960
1970
1980
1990
2000
2010
Precip. Climatology
$SOI_{Apr-Sep}$,
$PDO_{Apr-Sep}$
$SPI_{Jun-Sep}$

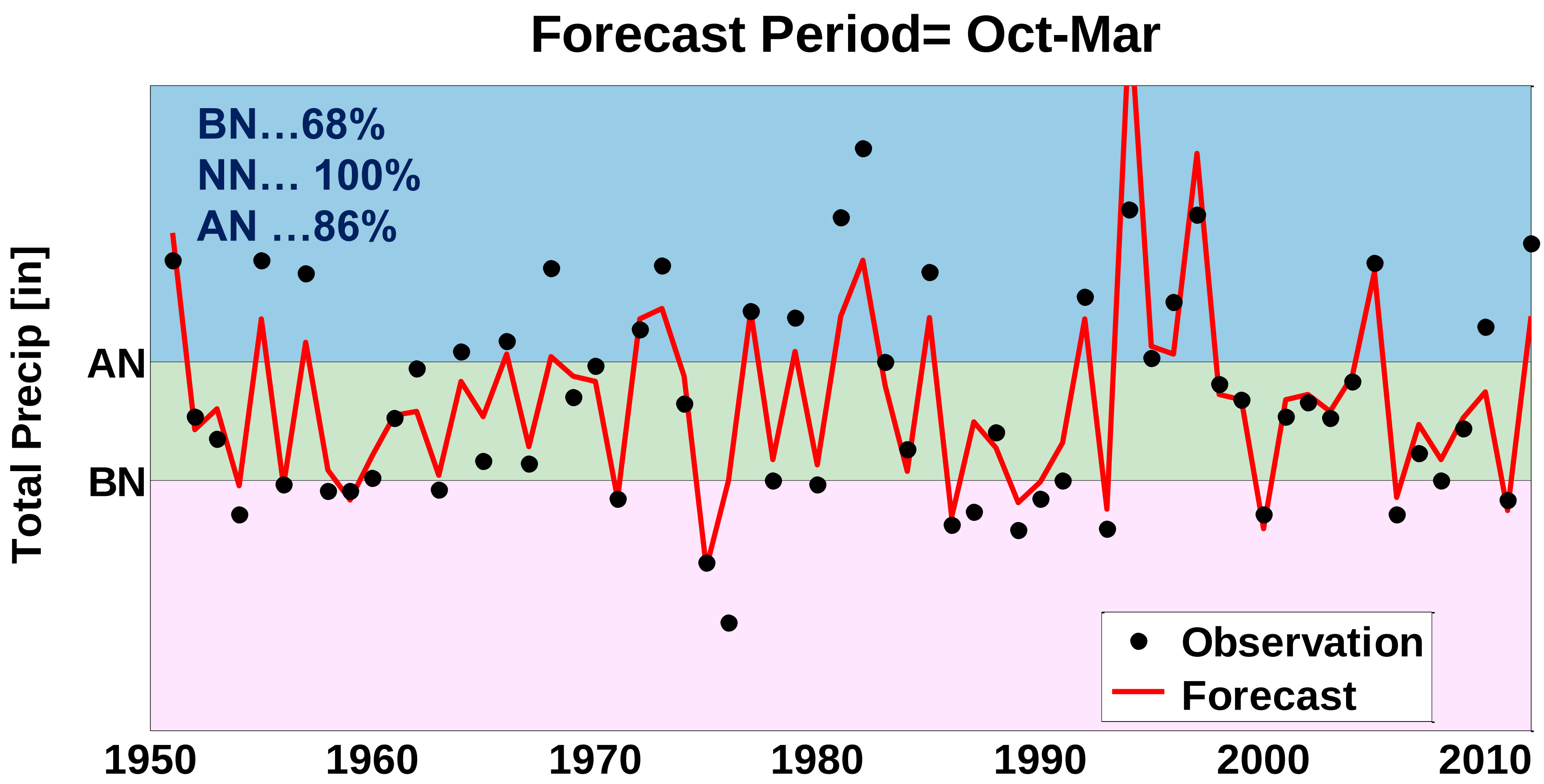
Preliminary Results

- **Climate Index: $SOI_{Apr\text{-}Sep}$, $PDO_{Apr\text{-}Sep}$**
- **$SPI_{Jun\text{-}Sep}$**

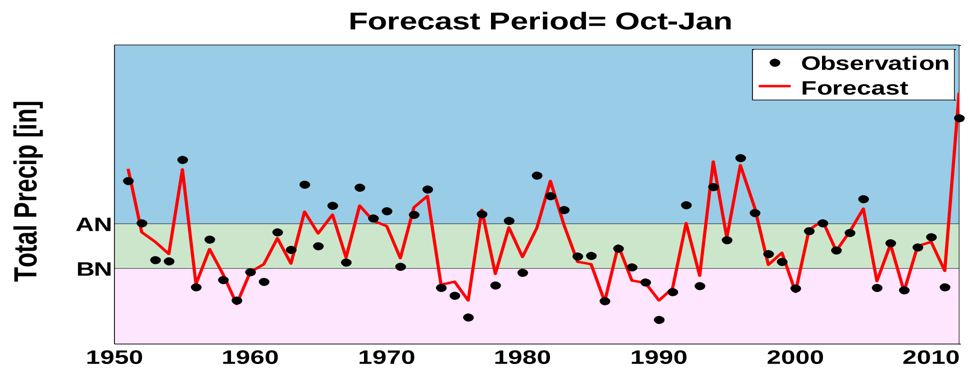


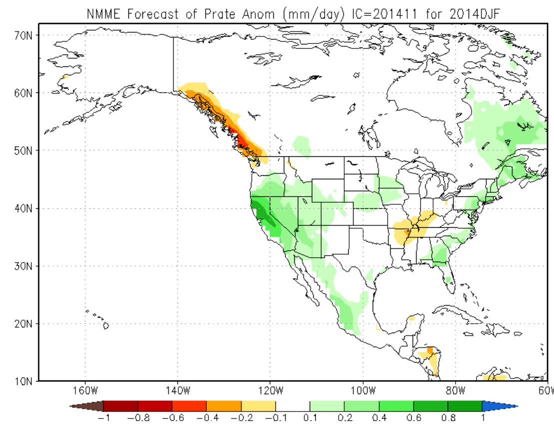
Preliminary Results

- Climate Index: $SOI_{Apr-Sep}$, $PDO_{Apr-Sep}$
- $SPI_{Jun-Sep}$



Drought Prediction Frameworks



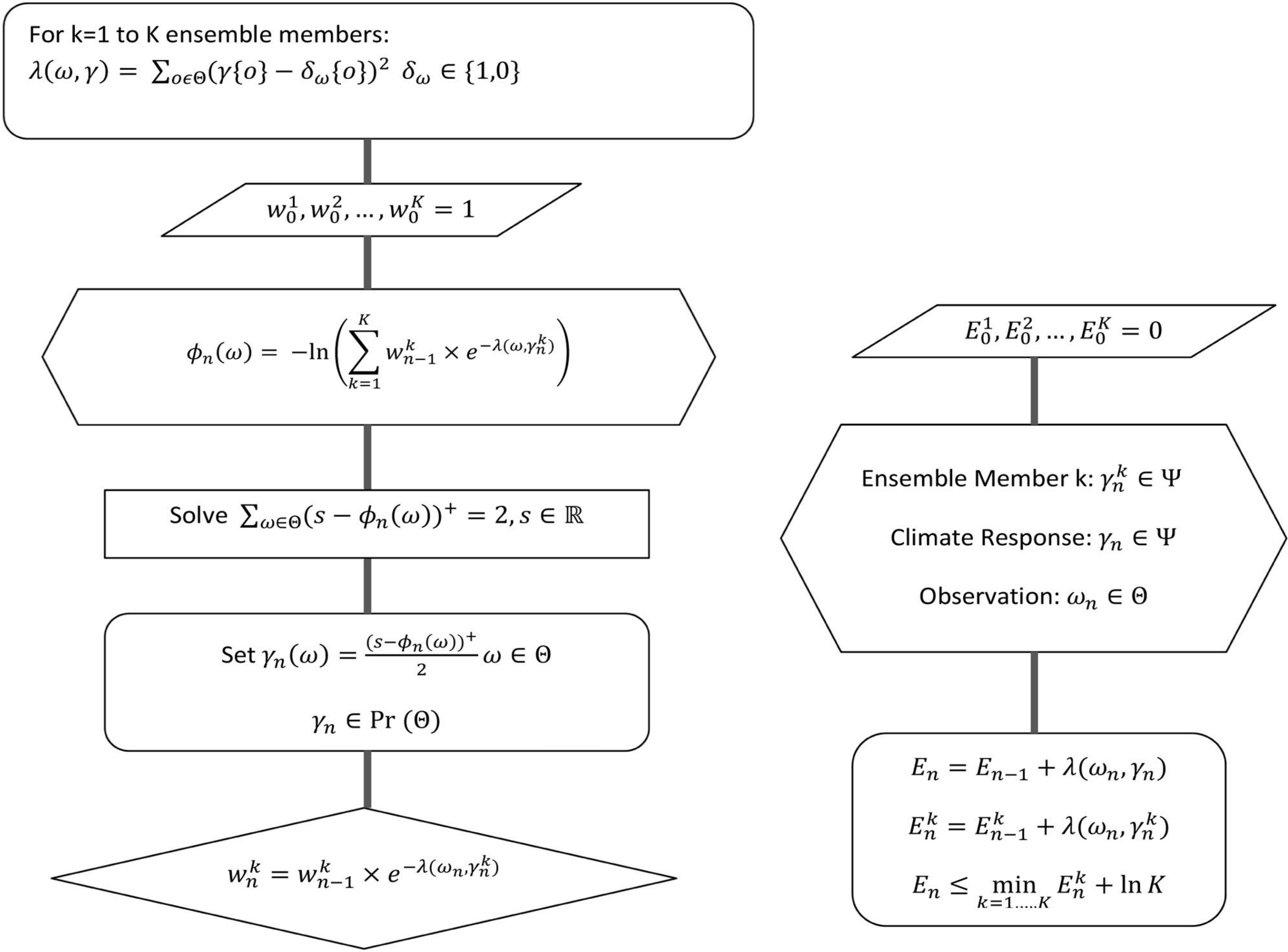


Analog-Year Model

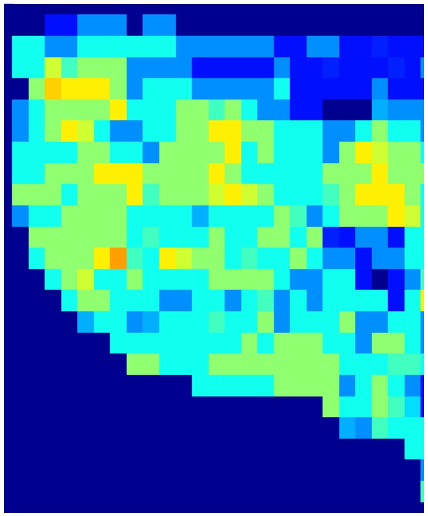
Dynamic Model Simulations

Multi-Model Assessment Using the Expert Advice Algorithm

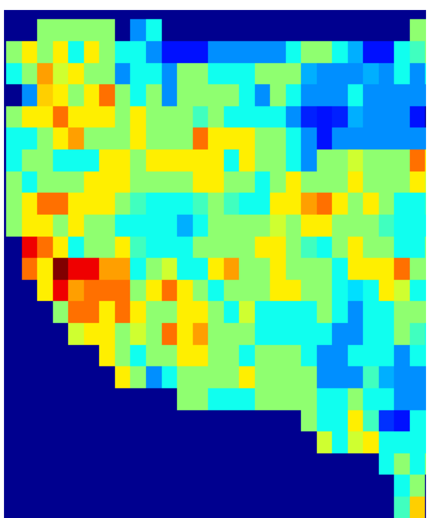
Seasonal Precipitation Forecasts


For k=1 to K ensemble members:
$\lambda(\omega,\gamma) = \sum_{o\epsilon\Theta}(\gamma\{o\} - \delta_\omega\{o\})^2 \;\; \delta_\omega \in \{1,0\}$
$w_0^1, w_0^2, \dots, w_0^K = 1$
$\phi_n(\omega) = -\ln\left(\sum_{k=1}^{K} w_{n-1}^k \times e^{-\lambda(\omega,\gamma_n^k)}\right)$
Solve $\sum_{\omega\in\Theta}(s - \phi_n(\omega))^+ = 2, s \in \mathbb{R}$
Set $\gamma_n(\omega) = \frac{(s-\phi_n(\omega))^+}{2} \omega \in \Theta$
$\gamma_n \in \Pr(\Theta)$
$w_n^k = w_{n-1}^k \times e^{-\lambda(\omega_n,\gamma_n^k)}$
$E_0^1, E_0^2, \dots, E_0^K = 0$
Ensemble Member k: $\gamma_n^k \in \Psi$
Climate Response: $\gamma_n \in \Psi$
Observation: $\omega_n \in \Theta$
$E_n = E_{n-1} + \lambda(\omega_n,\gamma_n)$
$E_n^k = E_{n-1}^k + \lambda(\omega_n,\gamma_n^k)$
$E_n \leq \min_{k=1.....K} E_n^k + \ln K$

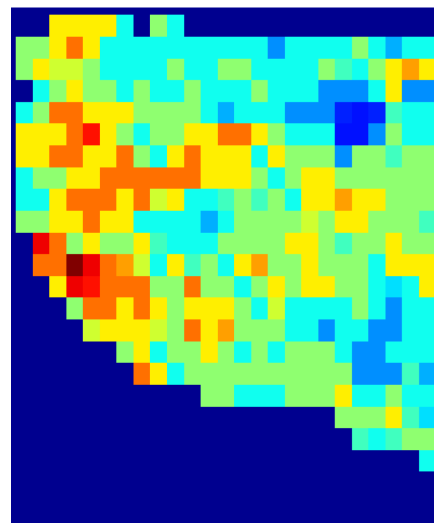
NMME (Ensemble Mean)

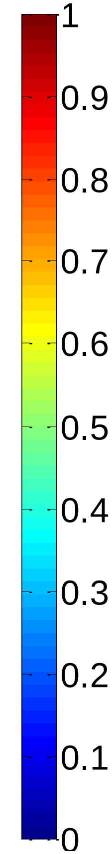


NMME + AE



NMME + Analog-Year + AE

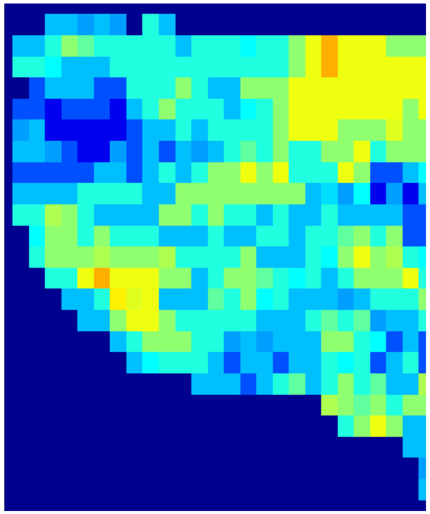




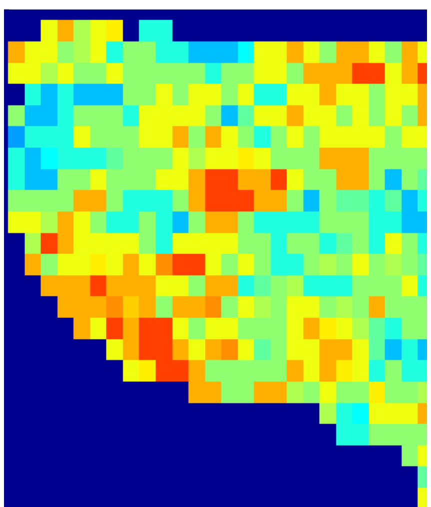
DJF Precipitation Forecasts - Percentage of captured Below Normal events

Drought Prediction

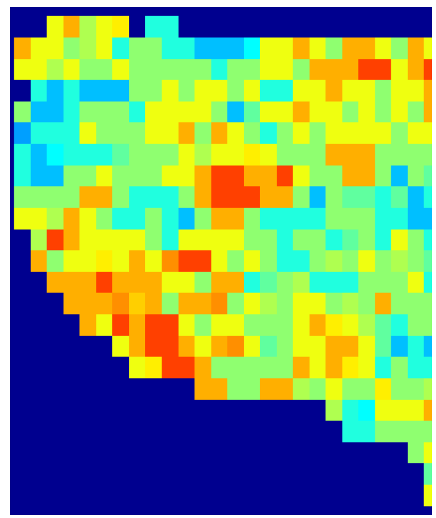
NMME (Ensemble Mean)

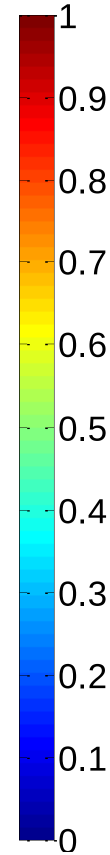


NMME + AE



NMME + Analog-Year + AE

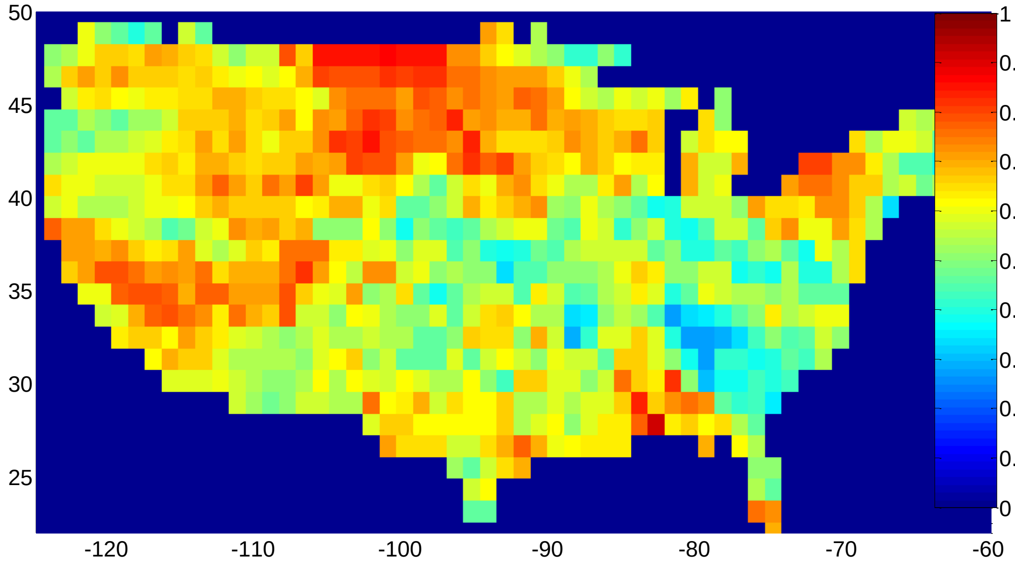




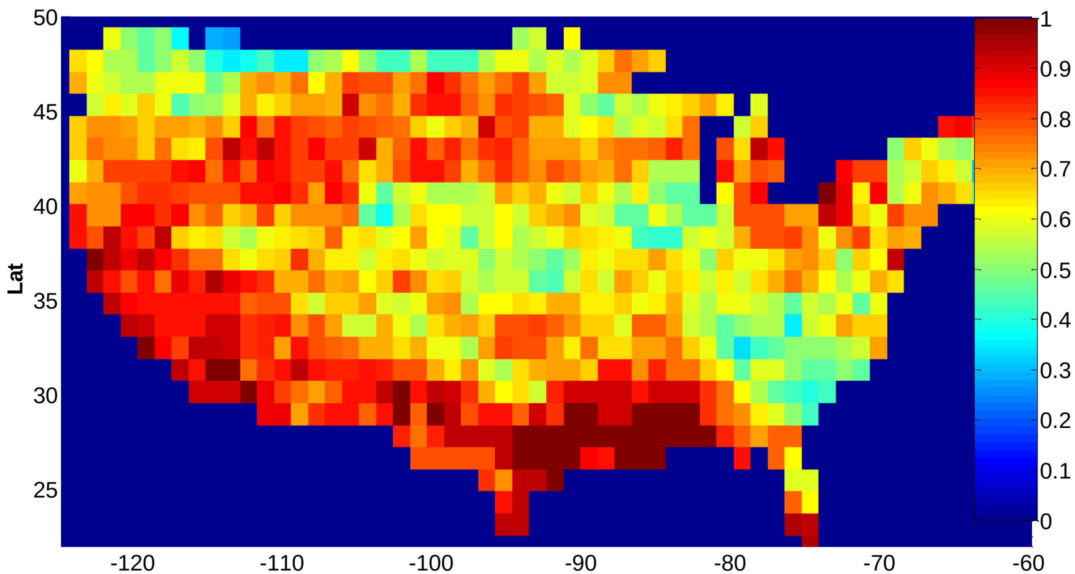
DJF Precipitation Forecasts - Percentage of captured Above Normal events

Drought Prediction

NMME (Ensemble Mean)



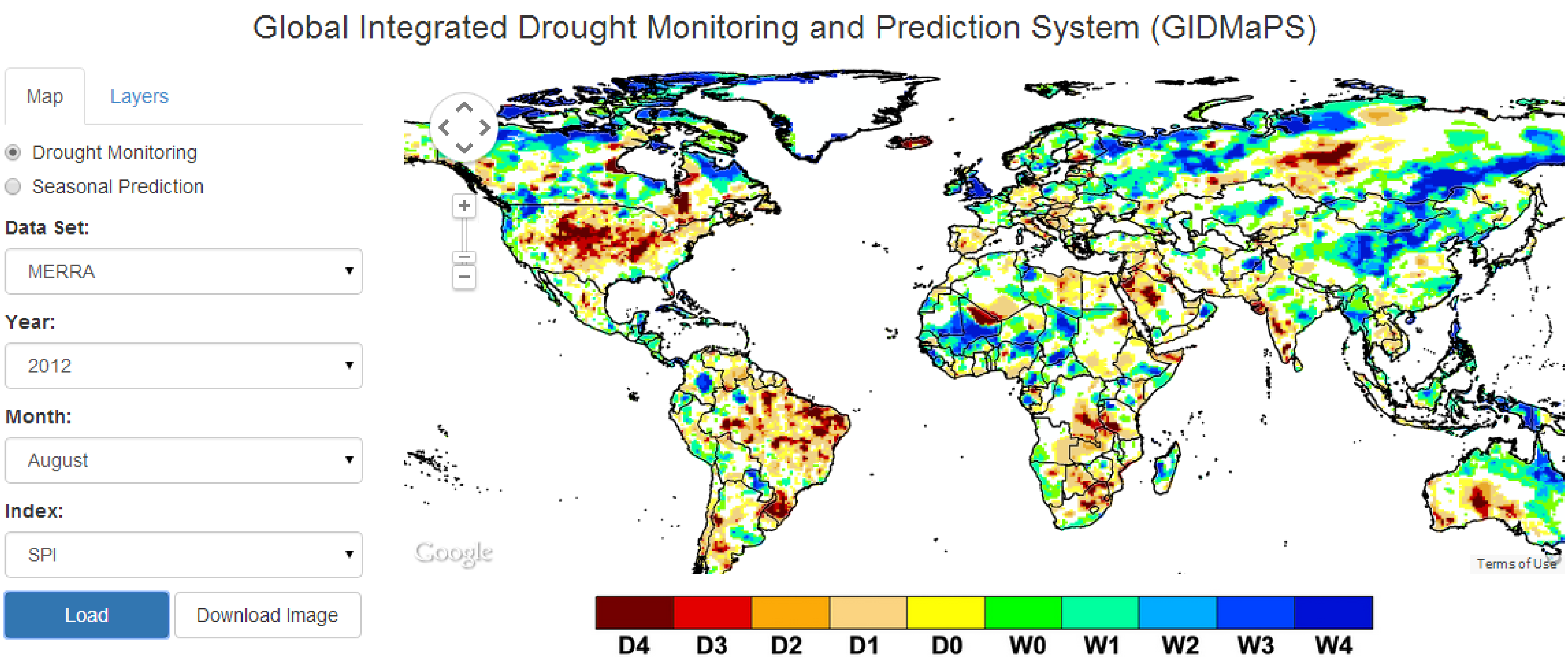
NMME + Analog-Year + AE



DJF Precipitation Forecasts - Percentage of captured Negative Anomaly

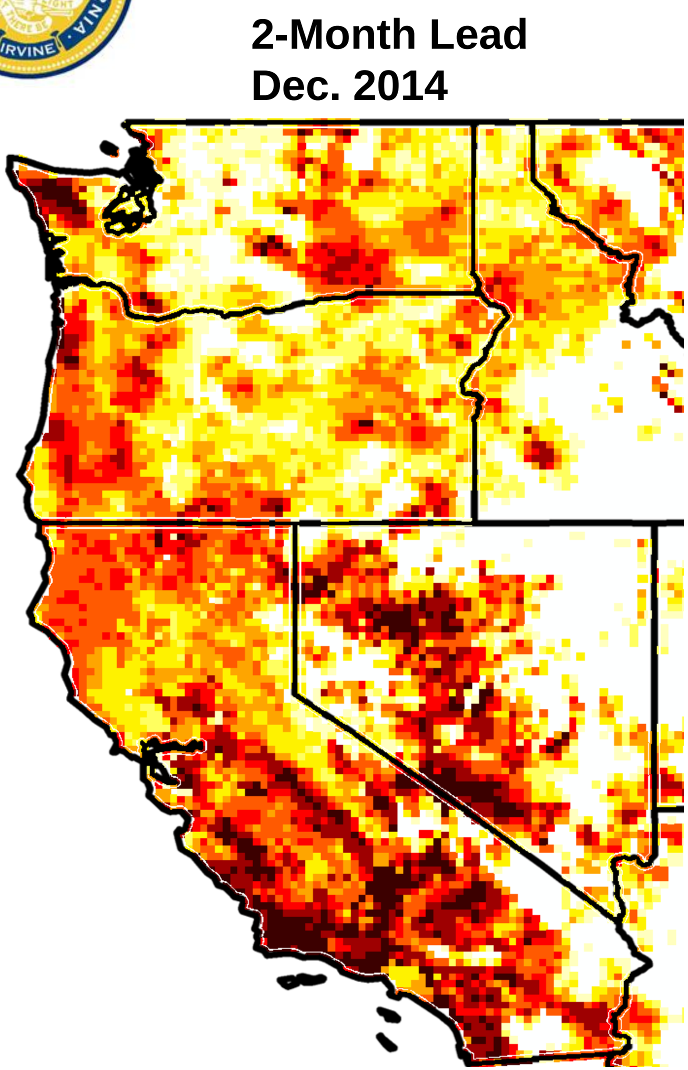
GIDMaPS: Global Integrated Drought Monitoring and Prediction System

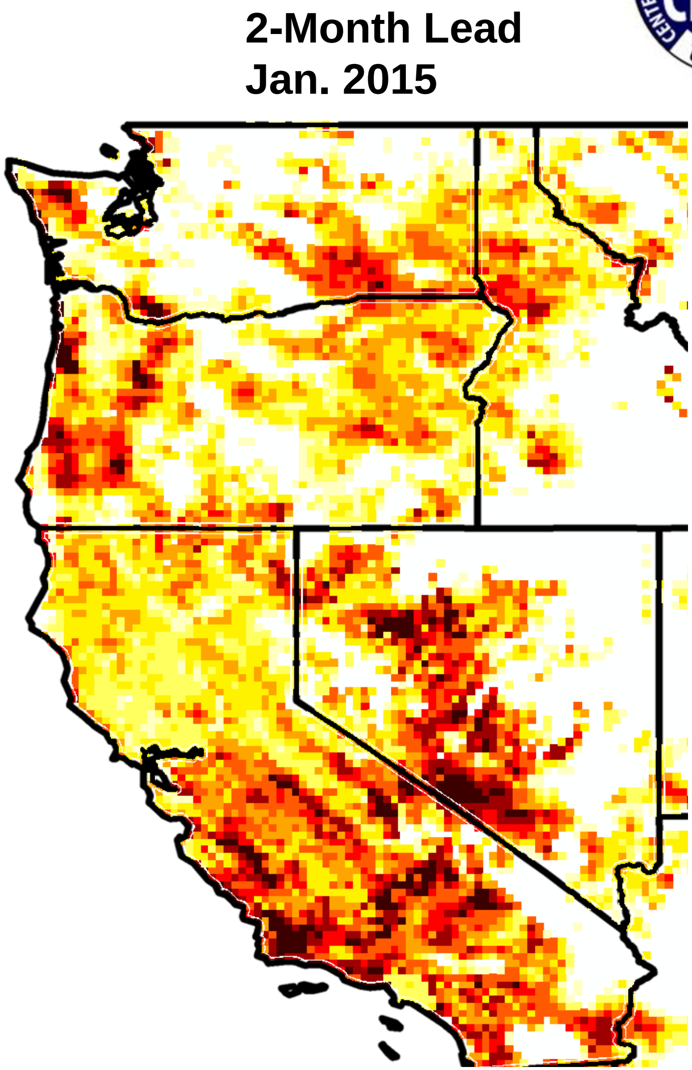
http://drought.eng.uci.edu/

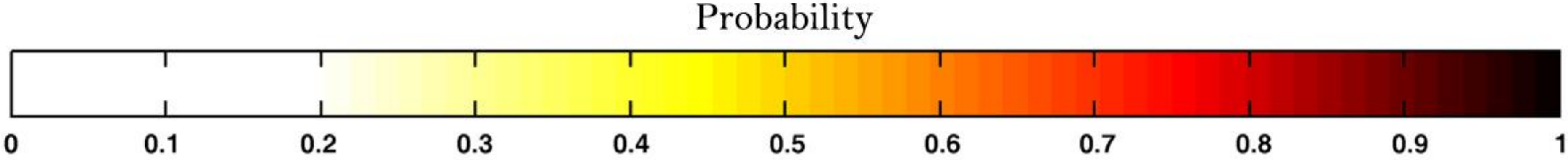


Hao Z., AghaKouchak A., Nakhjiri N., Farahmand A., 2014, Global Integrated Drought Monitoring and Prediction System, *Scientific Data*, 1:140001, 1-10, doi: 10.1038/sdata.2014.1. http://www.nature.com/articles/sdata20141

Probabilistic Drought Prediction

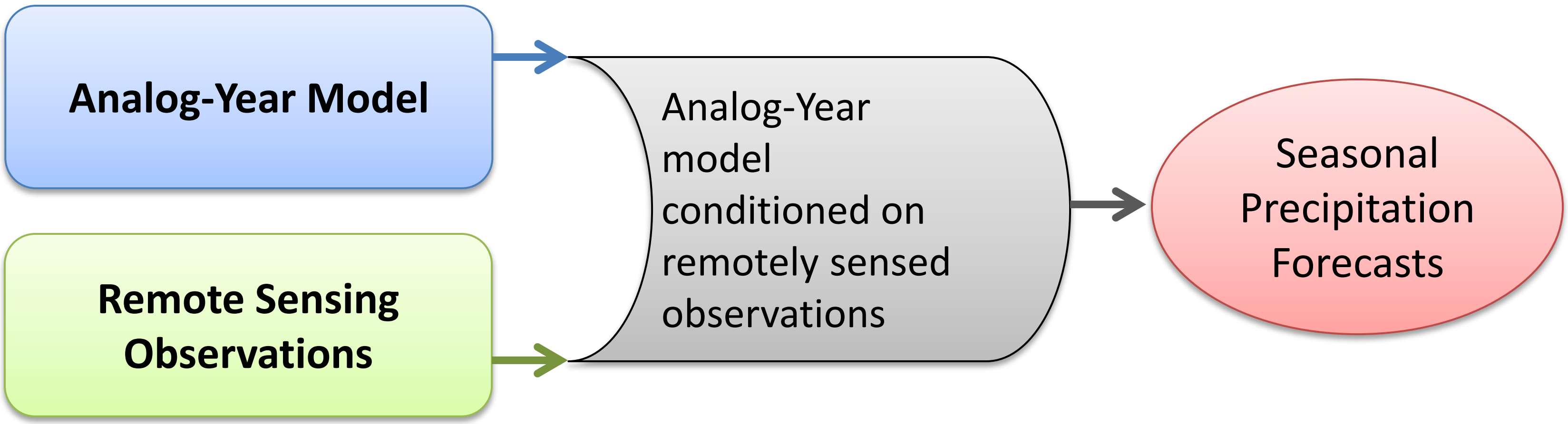




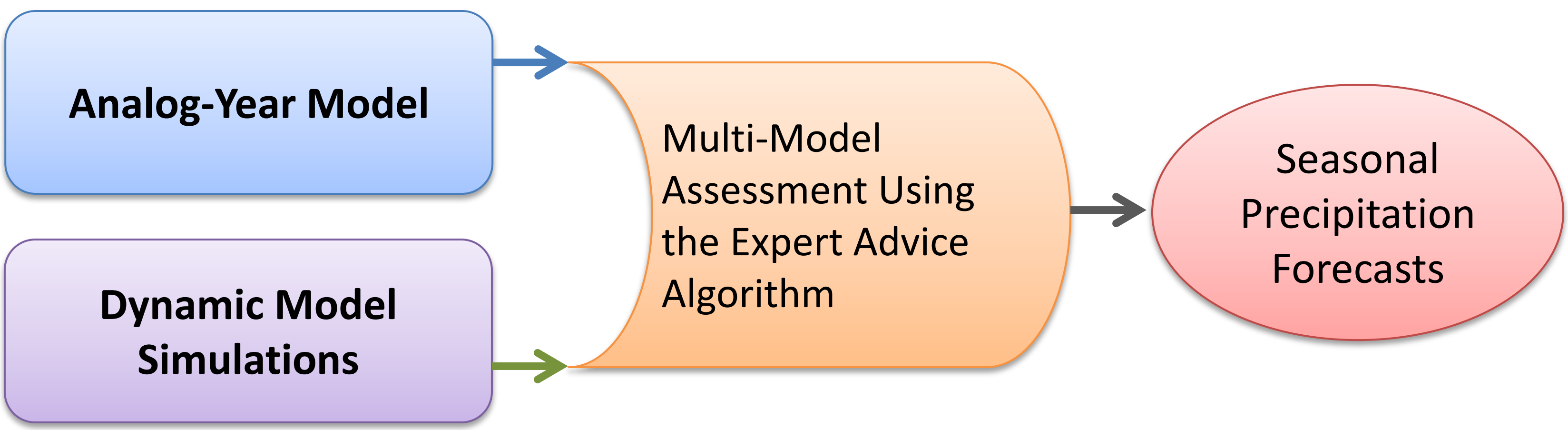


Drought Prediction Frameworks

Analog-Year Model Combined with Remote Sensing Observations



Analog-Year Model Combined Dynamic Model Simulations



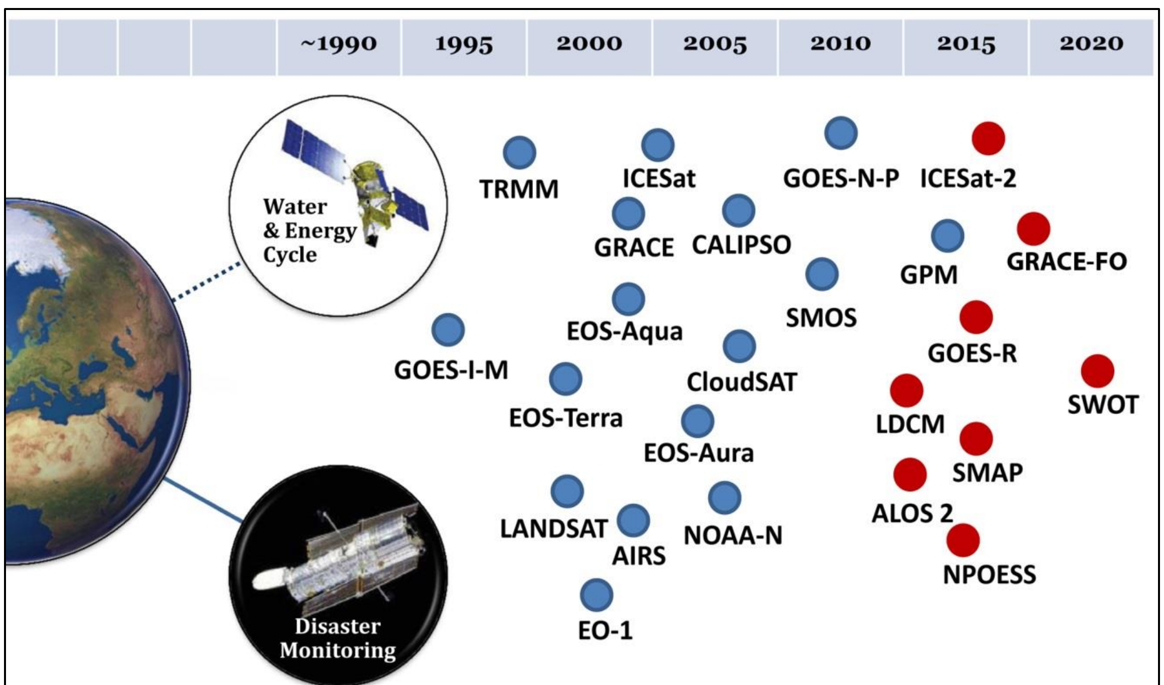
Analog-Year Model Combined with Remote Sensing Observations

Analog-Year Model

Remote Sensing Observations

Analog-Year model conditioned on remotely sensed observations

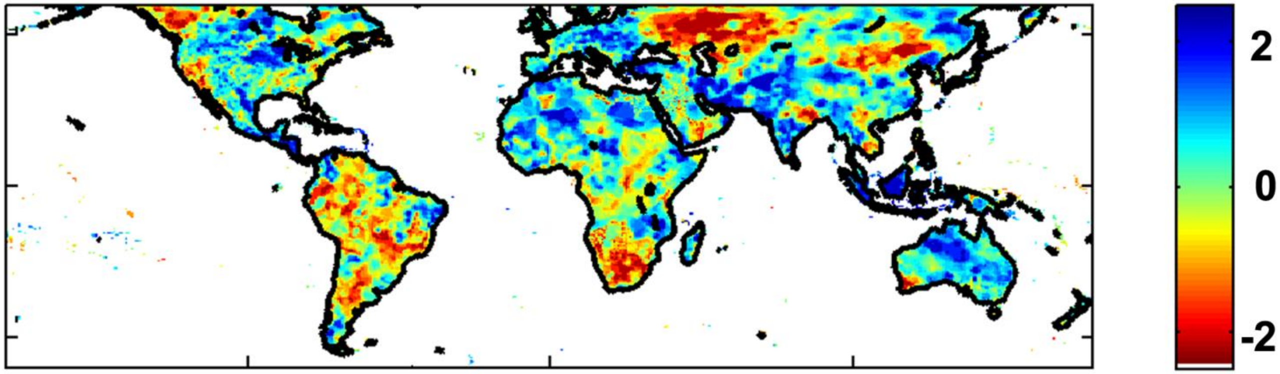
Seasonal Precipitation Forecasts



Integration of AIRS Data into GIDMaPS

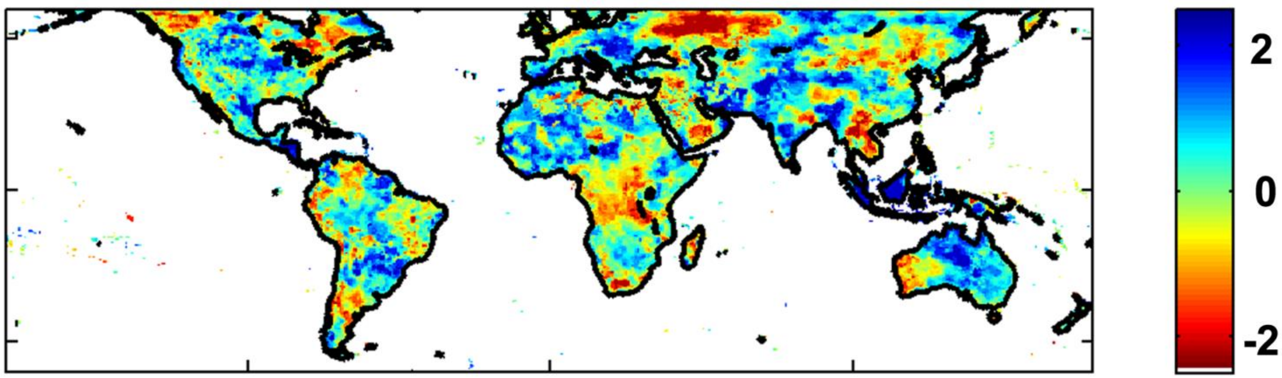
3-month SPI August 2010

Precipitation (MERRA)



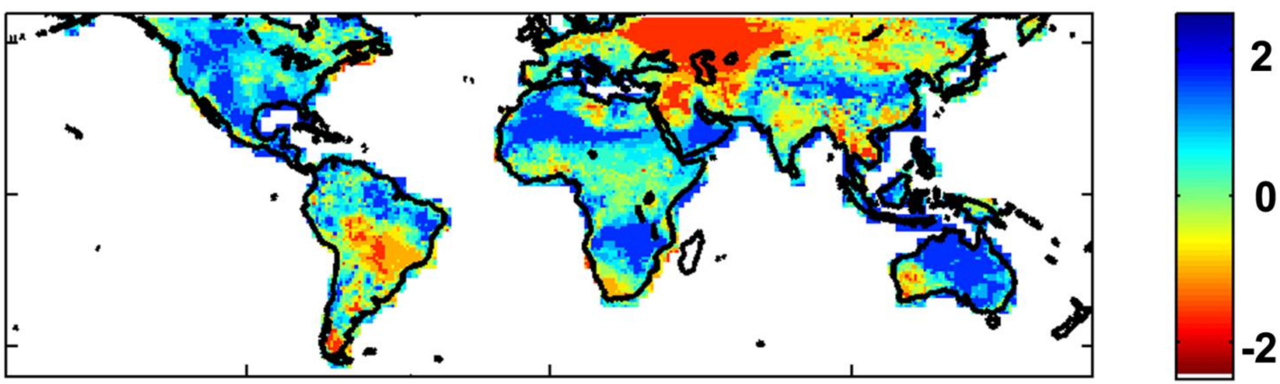
3-month SSI August 2010

Soil Moisture (MERRA)

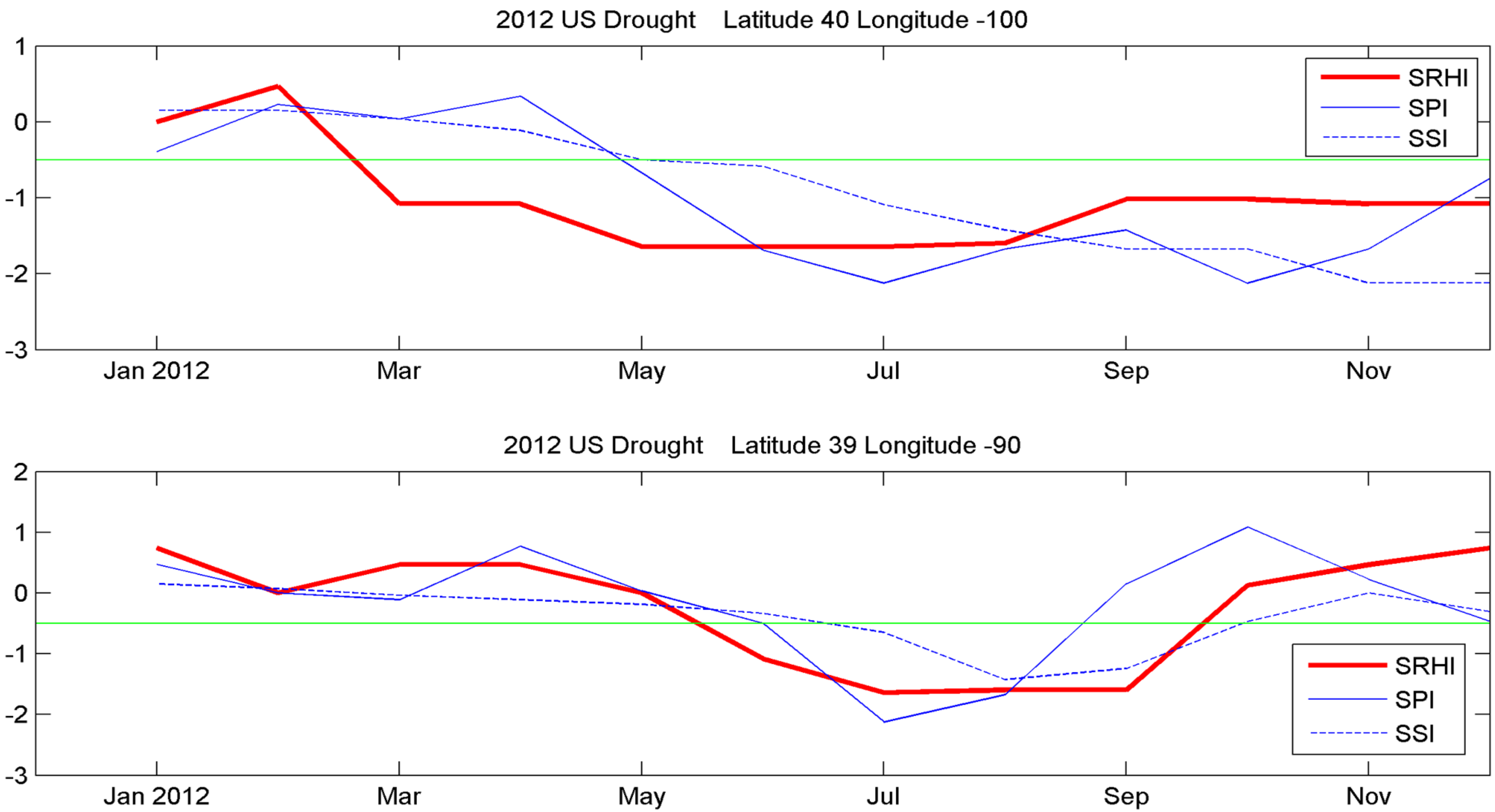


3-month SRHI August 2010

Relative Humidity (AIRS Data)



Integration of AIRS Data into GIDMaPS



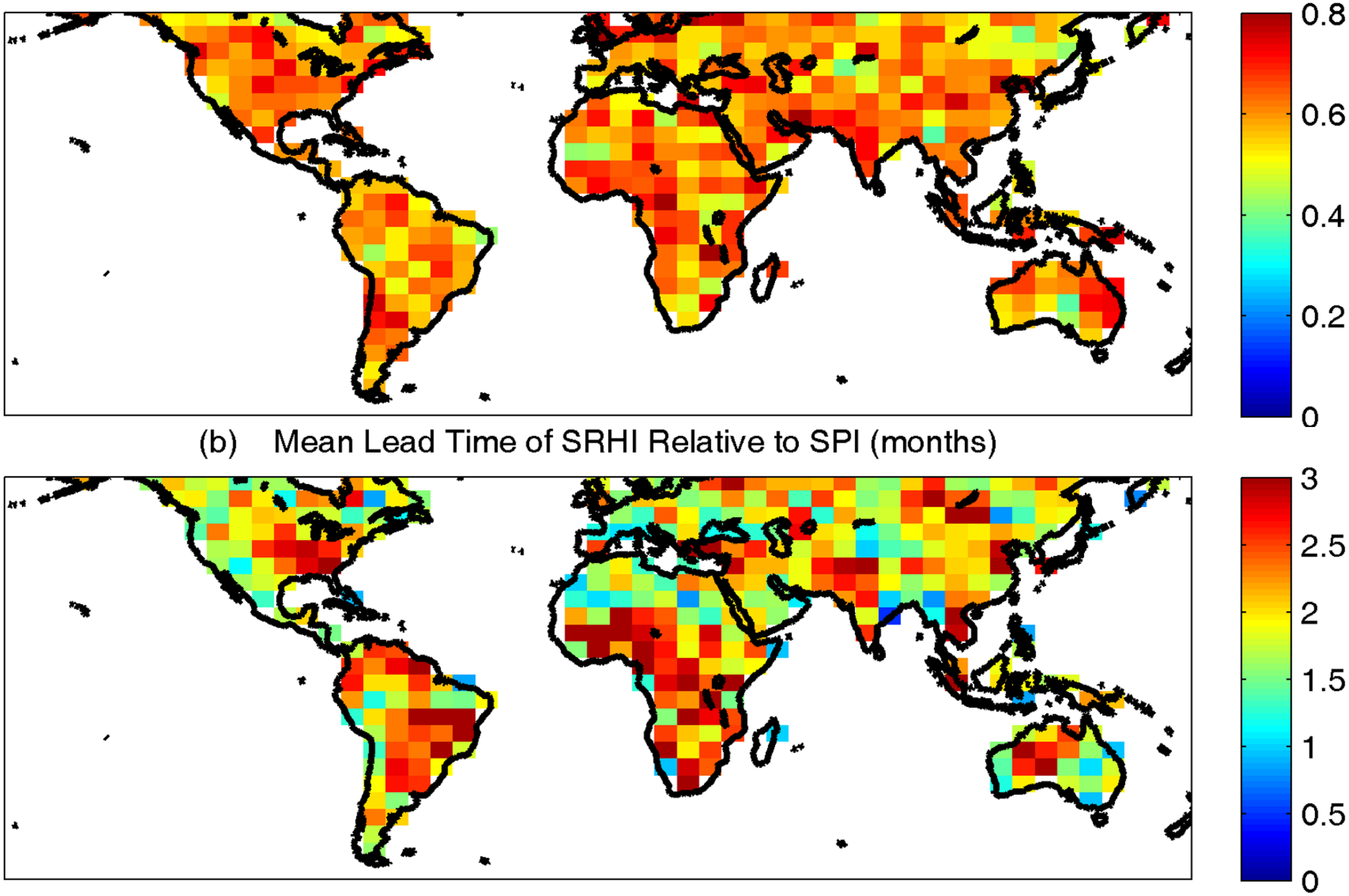
Farahmand et al. 2015; http://www.nature.com/srep/2015/150225/srep08553/full/srep08553.html

Integration of AIRS Data into GIDMaPS

Probability of drought detection (i.e., fraction of detected drought) when Drought Onset (DO) based on SRHI is less or equal to that of SPI (a), mean lead time based on SRHI relative to SPI (months)(b).

(a) $POD_{SRHI} \mid DO_{SRHI} \leq DO_{SPI}$

(b) Mean Lead Time of SRHI Relative to SPI (months)



Farahmand et al. 2015; http://www.nature.com/srep/2015/150225/srep08553/full/srep08553.html

Drought Prediction

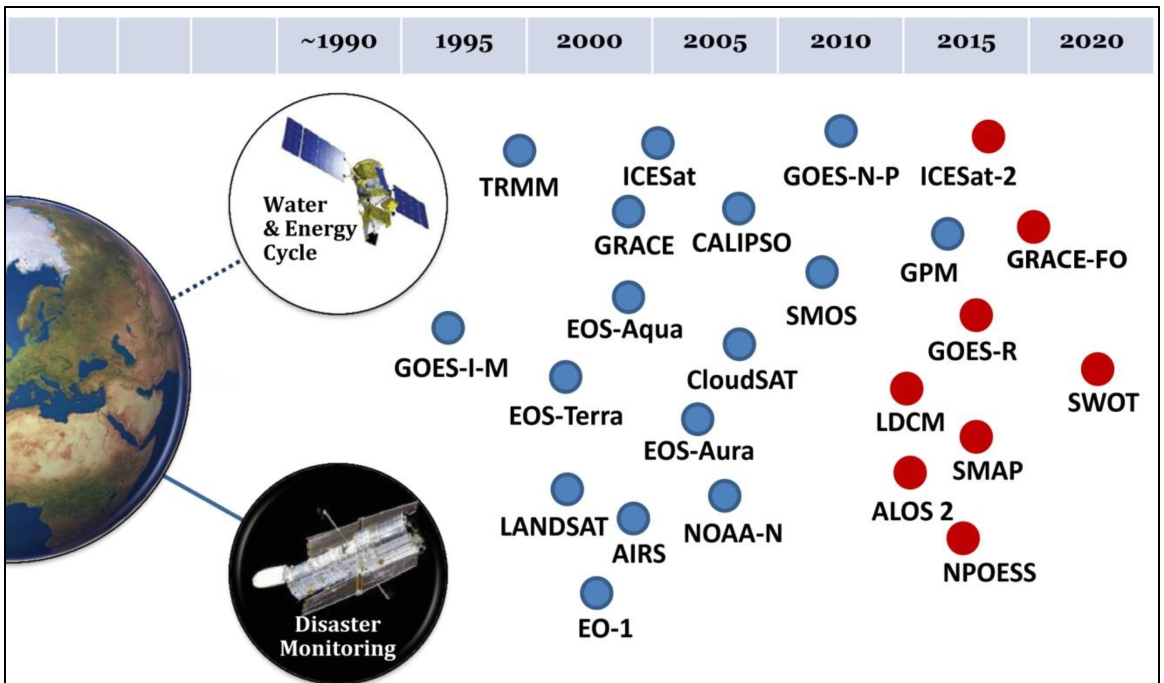
Analog-Year Model Combined with Remote Sensing Observations

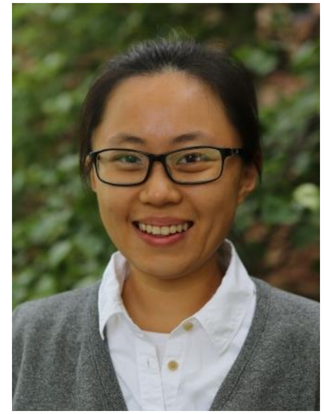
Analog-Year Model

Remote Sensing Observations

Analog-Year model conditioned on remotely sensed observations

Seasonal Precipitation Forecasts





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NASA, NOAA, NSF, JPL

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University of California, Irvine

Email: amir.a@uci.edu

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