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Probabilistic Seasonal Prediction of Drought Using long term precipitation and temperature data

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Content:

How can we use historical data to inform seasonal prediction of precipitation?

- We developed a probabilistic ensemble system for prediction of seasonal precipitation anomaly (e.g., drought) using "**available**" **long-term** indicators:
  - Precipitation
  - Surface air temperature,
  - ENSO (Nino 3.4),
  - and combination of them.

- Our method is an ensemble-learning method that relies on comparison to past data records to construct predictive distribution for precipitation anomaly.

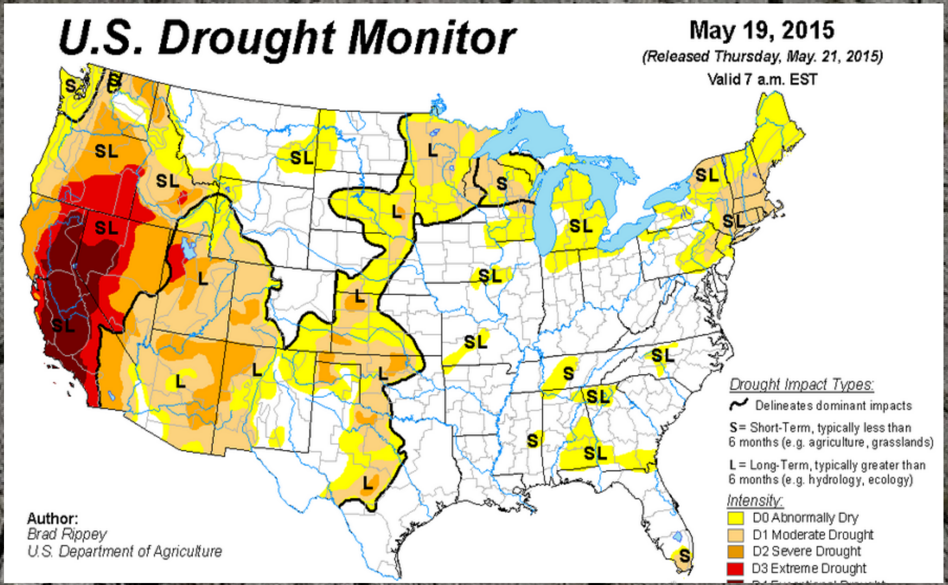
The study uses available long-term climate data records to address one of the goals of the NIDIS implementation plan (NOAA 2007):
the need for development of a more objective-based drought prediction approach that is transparent to the users and can generate probabilistic drought-related information for specific decision making needs.

Introduction:

- **Recently, we have experienced several severe droughts and we will have more. The challenge is how we can predict them?**
- **Clearly, improving seasonal climate forecast has significant socioeconomic benefits**
  - *For example, if ranchers and farmers know a severe drought is forming they can minimize potential economic losses by purchasing crop insurance or adjusting planting or grazing strategy.*
- **Forecasting can be done using dynamic models, statistical methods, or combination of the two.**

Here we focus on statistical model

We can also use them as a baseline for evaluation of dynamic models



Indicators

- **Precipitation: when precipitation variability is integrated over a range of time periods (e.g., from one month to few months) it can capture multiple aspects of hydrologic process**(e.g., soil moisture at different depth, river discharge, reservoir storage, ground water)

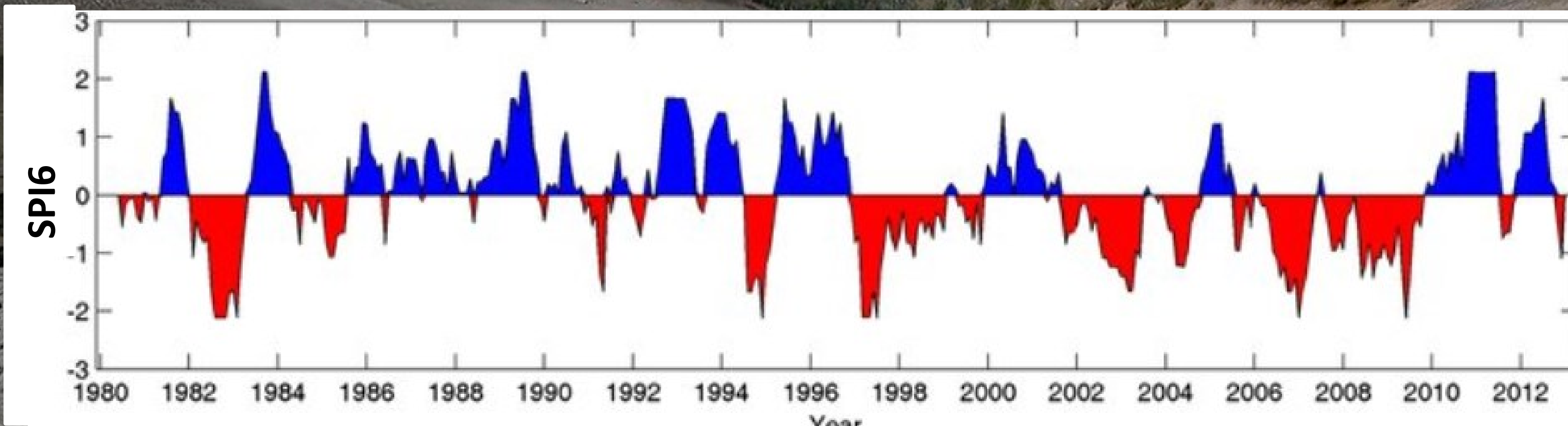
- **Temperature can impact precipitation characteristics**
  - Higher temperature => greater atmospheric demand for evapotranspiration => dryer land => influences convection initiation => changes rain pattern
  - The warmer climate may reduce frequency of rain (longer dry spells), but when it rains, it is expected to be more intense
  - Temperature has shown some leading signals compared to precipitation (e.g., signal of drought can show up earlier in temperature than precipitation)

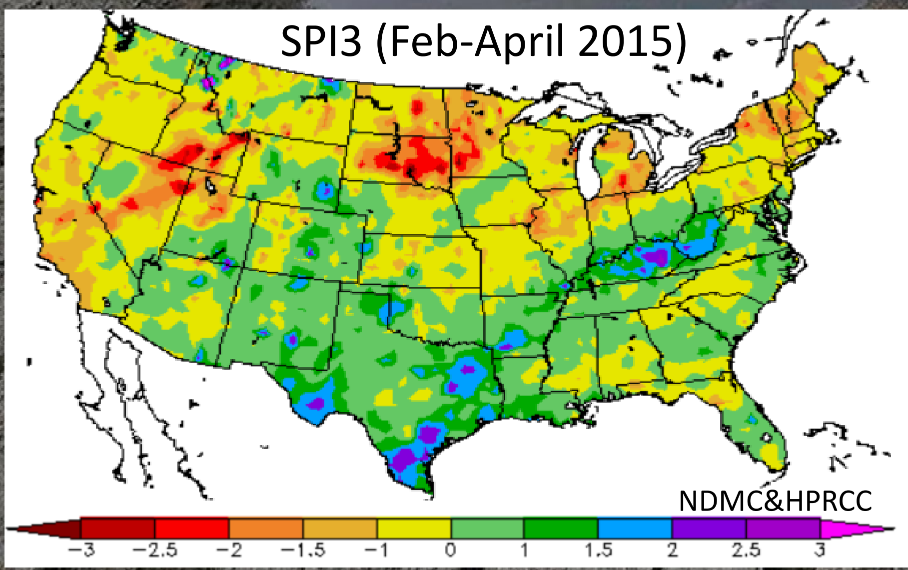
- **ENSO impacts precipitation characteristics**
  - ENSO / SST indices=> impact precipitation patterns and its regional variability

Standardized Precipitation Index (SPI)

Here we use SPI to represent precipitation anomaly

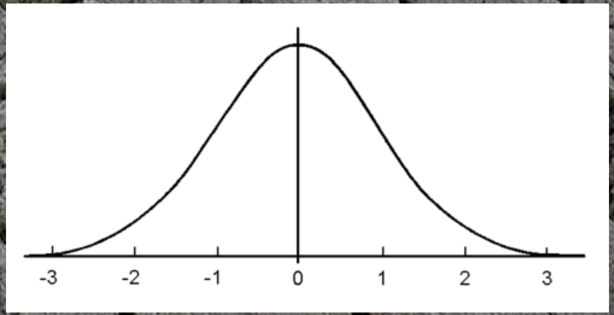
Time series of the 6 month (accumulation) Standardized Precipitation Index (SPI6)



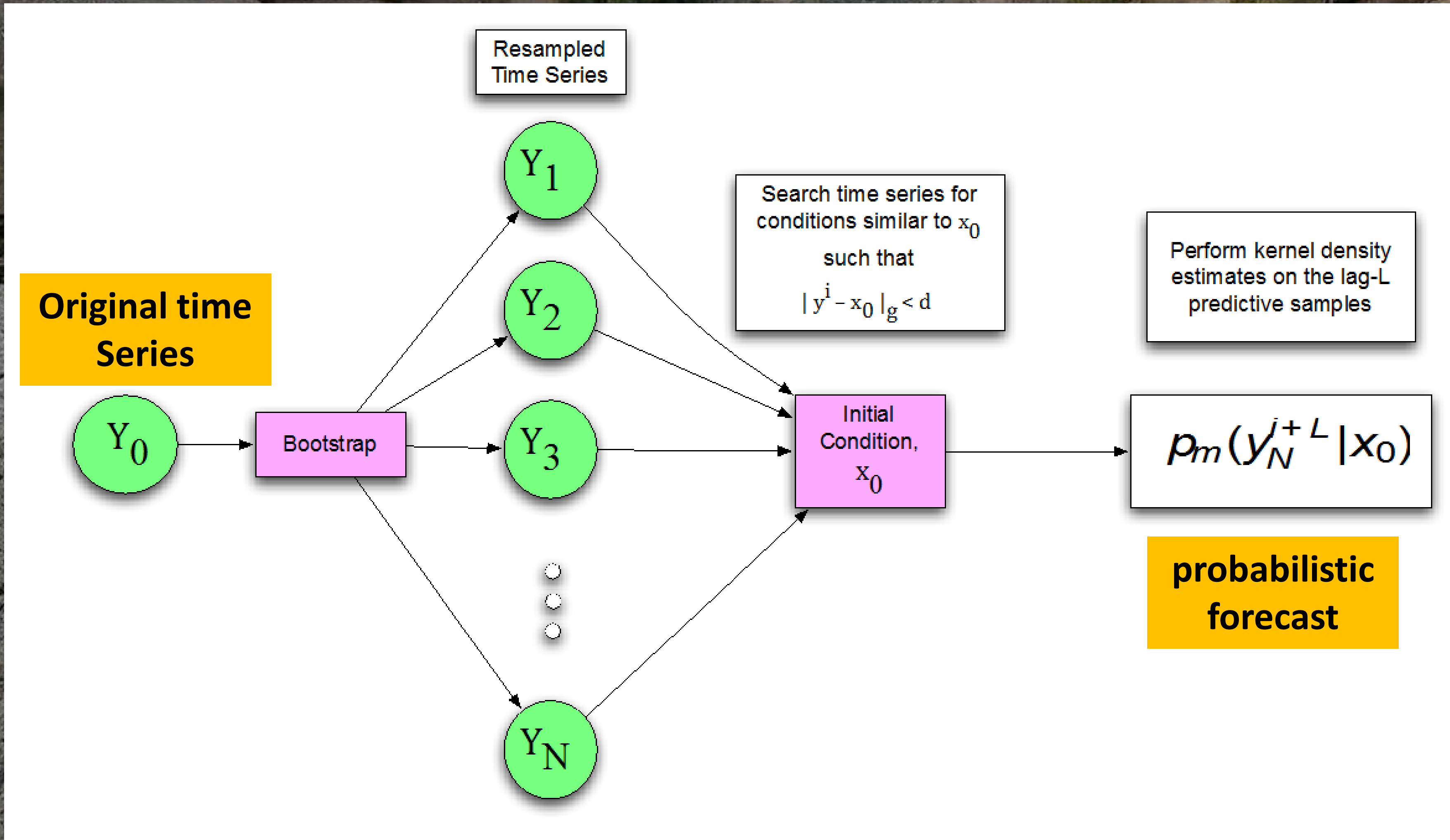


http://www.hprcc.unl.edu/maps/current

SPI Values	Drought Category
≤ -2.0	Extremely Dry
-2.0 to -1.5	Moderately Dry
-1.5 to -1.0	Dry
-1.0 to 1.0	Neutral
1.0 to 1.5	Wet
1.5 to 2.0	Moderately Wet
2.0 ≤	Extremely Wet

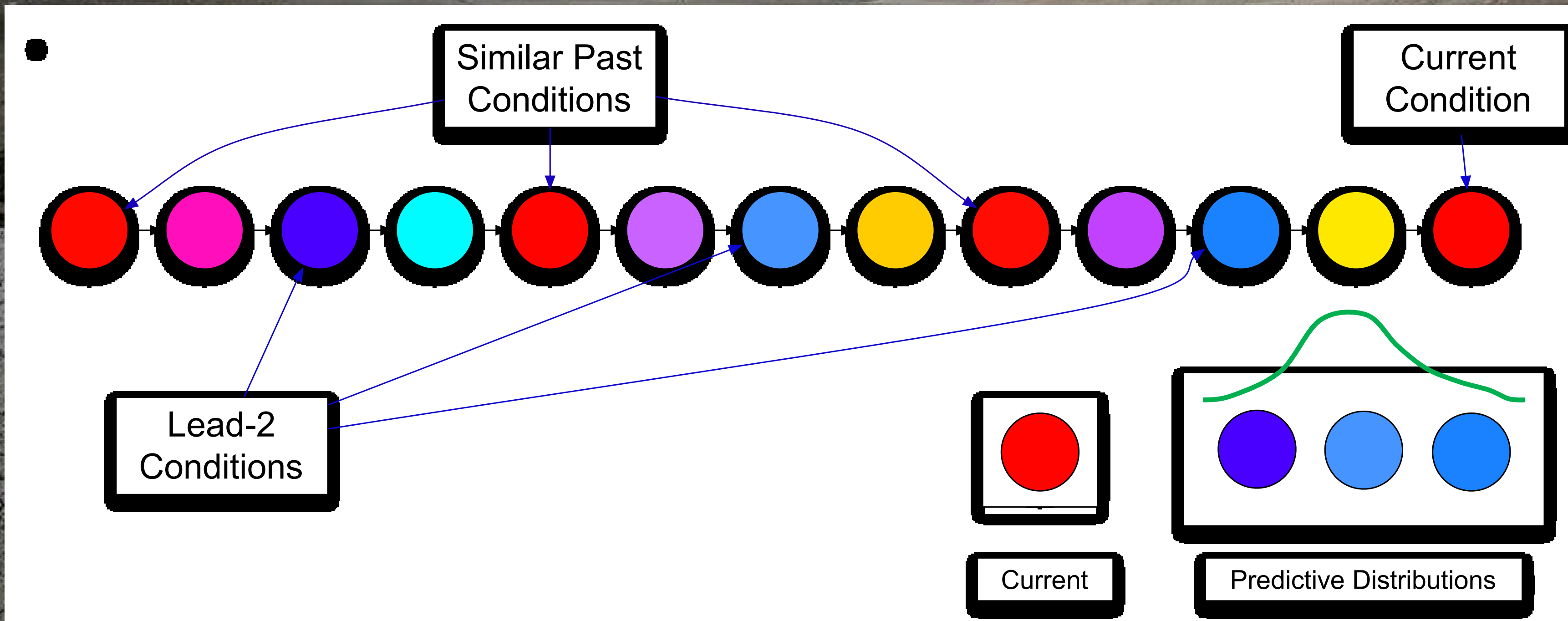


Simplified description of the prediction method



The original time-series is given in Y_0, which allows for generation of multiple realizations via the bootstrap. The predictive distribution given x_0 is obtained at the end via a kernel density estimate.

Illustration of comparison to past records



Prediction scenarios:

Which combination of indicators gives the best prediction?

- SPI3
- SPI6
- Air temperature
- ENSO
- Month of year

Potentially these indicators should help refine the ensembles used to predict future precipitation anomaly

Evaluating the accuracy of probabilistic predictions

We choose to use a **logarithmic skill score (LSS)**(Bickel, 2007). , which has the following form:

Data at prediction location

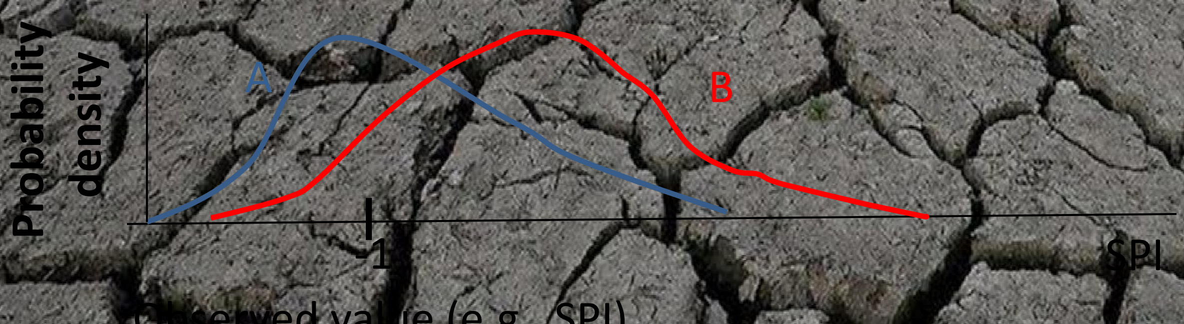
$$LSS = \sum_{l=1}^{n-L} \log(p_m(y_v^{l+L} | y_v^{l}))$$

Predictive model

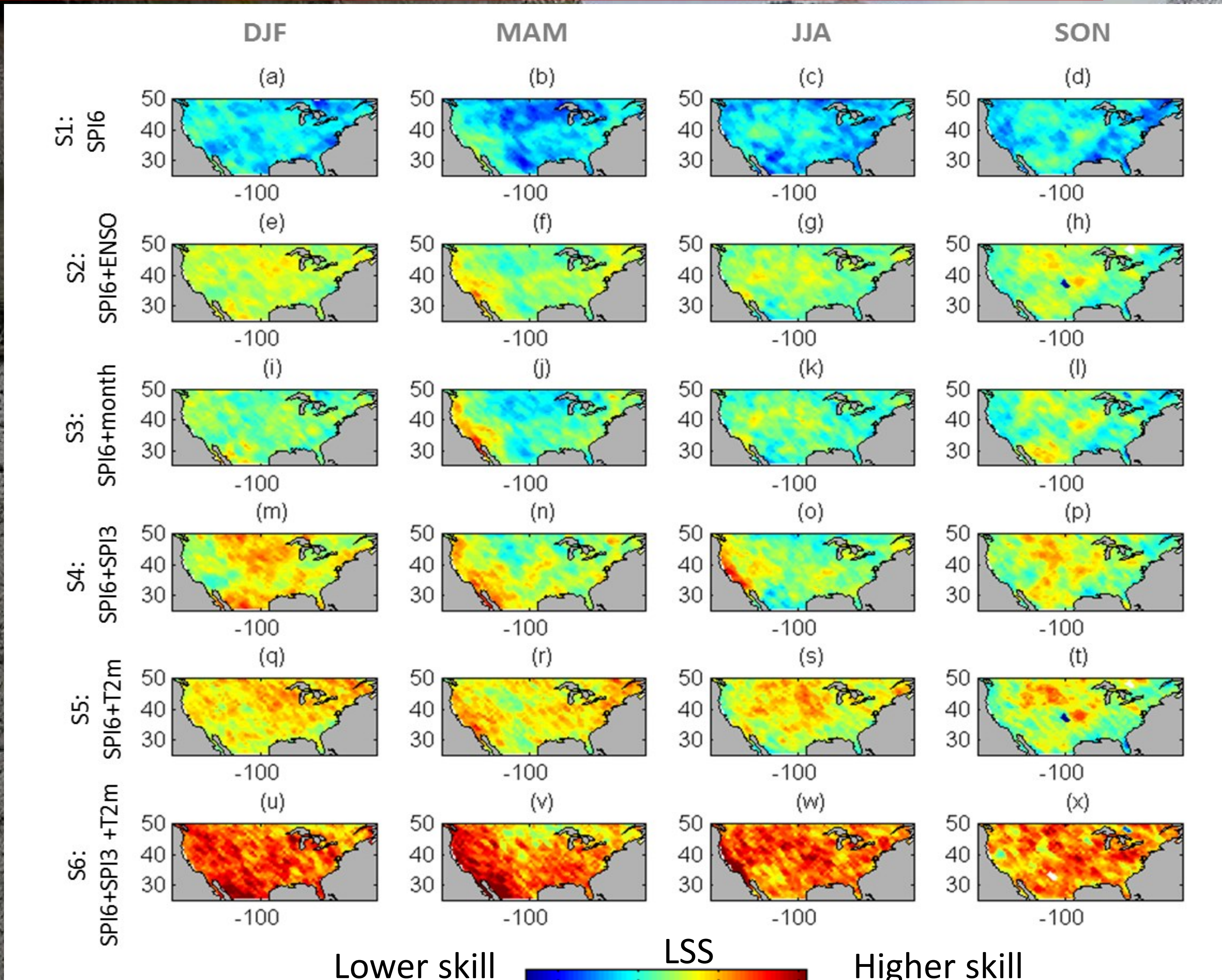
Past data

The LSS is a measure of the predictive skill of the models. The LSS score can be derived as a sum of the log-likelihood of the observed data given that the prediction model is correct.

- The PDFs constructed 1901-1990 data, evaluation is performed using 1991-2010 data.
- This approach evaluates the entire continuous predictive PDF against the actual observed value and produces a quantitative assessment of the prediction accuracy.
- **The higher the LSS is, the better the predictive performance.**

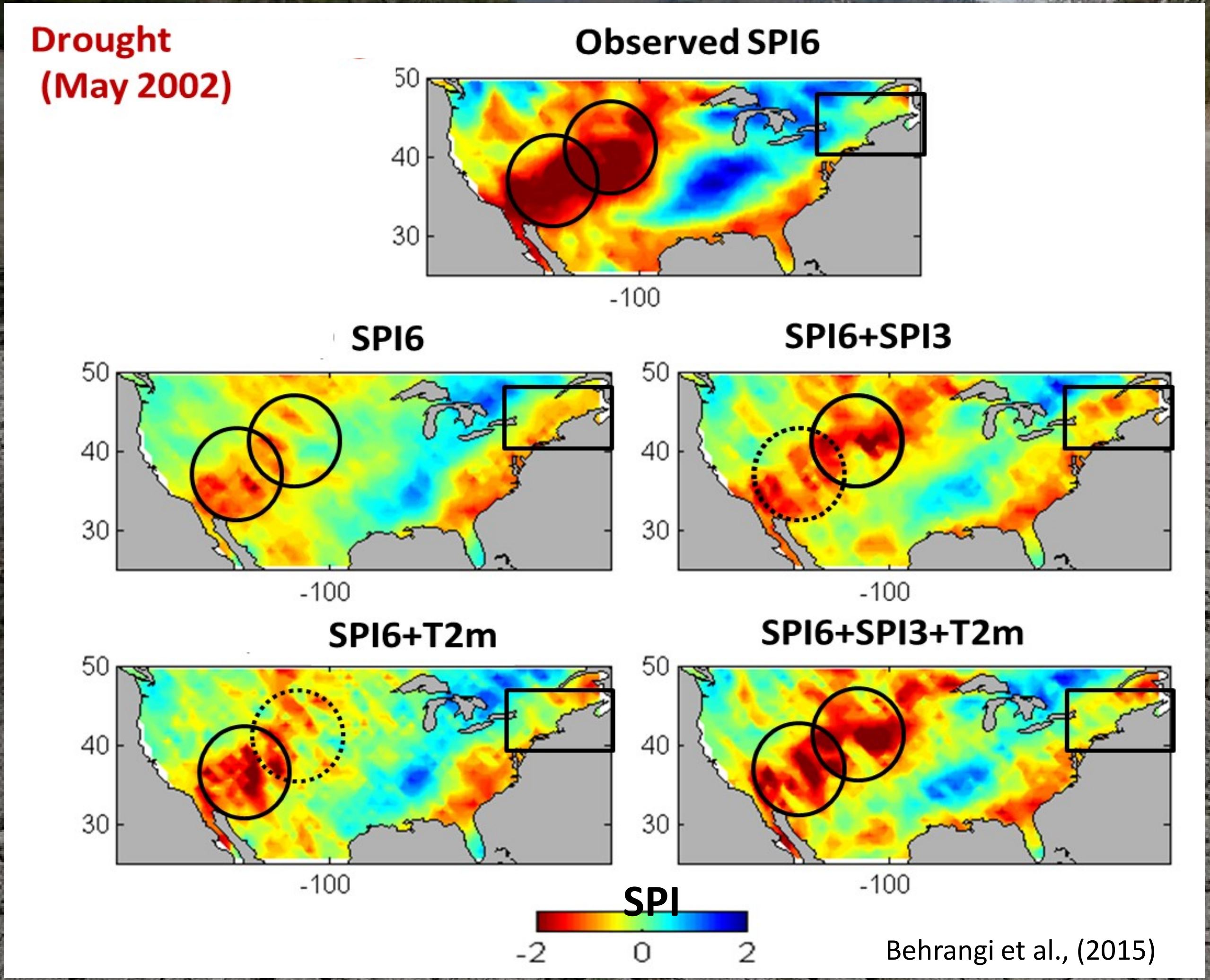


LSS (skill) for SPI6 prediction with 2-month lead time



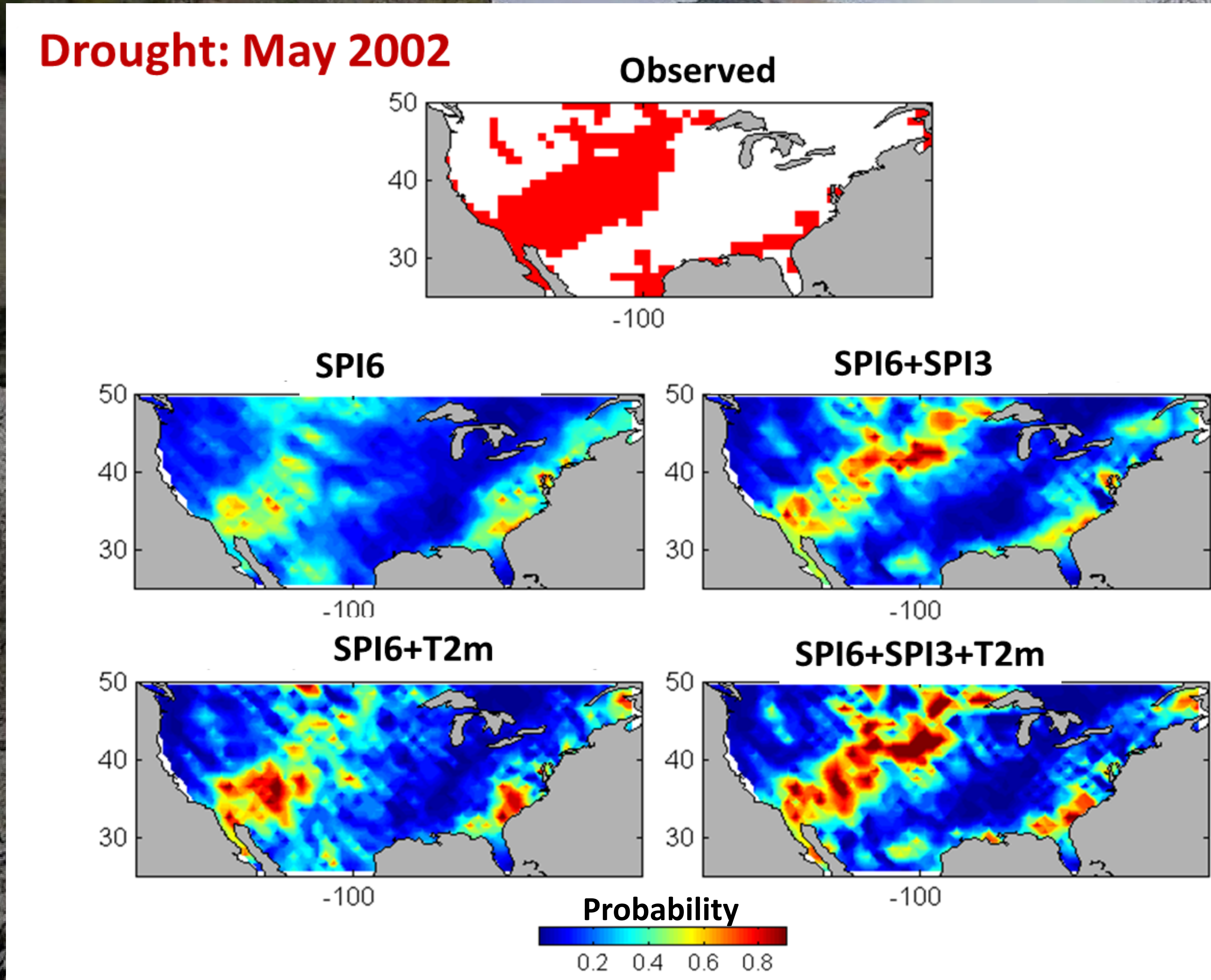
Entire evaluation dataset is used (1990-2010).

Case study of observed versus predicted SPI6:



The predictions are based on initial conditions in February 2002 (**3 month lead**).

Case study of predicted probability of SPI6< -0.8 :



The predictions are based on initial conditions in February 2002 (**3 month lead**).

Concluding remarks :

- A probabilistic ensemble method using the bootstrap is developed to predict the future state of the precipitation anomaly using historical data (e.g., Precipitation, air temperature , ENSO)

- Seasonal drought prediction using combination of SPI6, SPI3, and T2m suggests that the three predictors collectively yield complementary information.

- Investigating other indicators is planned (e.g., SST driven indices, humidity, etc.). They may also help forecast with longer lead time

- Estimating the severity of drought remains as a prediction weakness which is related to the typical problem with ensemble prediction and the inherent averaging effect that depresses the extremes.

- Numerical models will continue to play a critical role in the seasonal drought prediction, especially when an ensemble of model predictions is used. Efforts are planned to quantify gains from the numerical model (compared to the statistical methods).

- We need to know more about what is **"needed"** by **decision makers** so we can improve our analysis accordingly.

Thanks !

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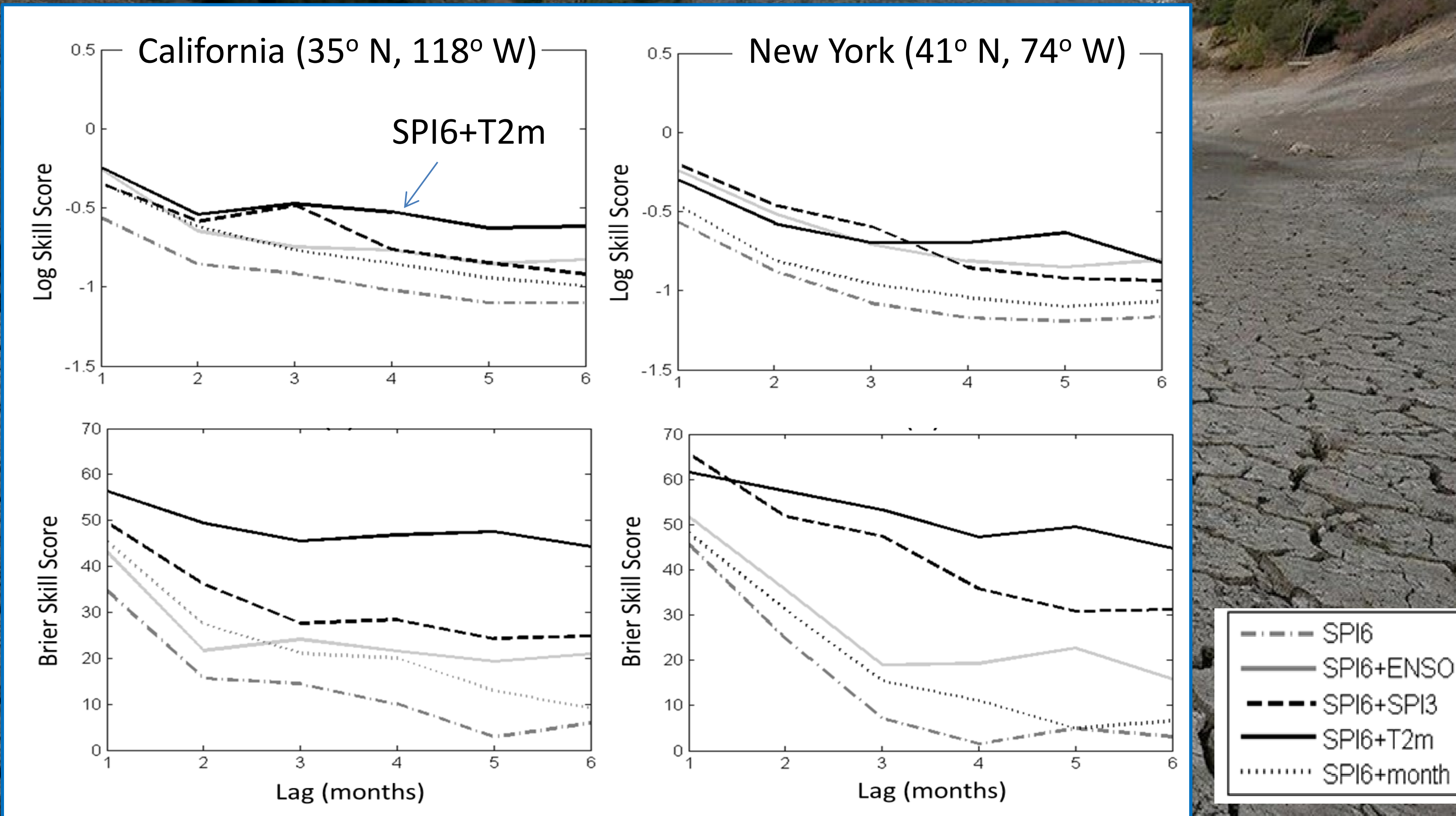
Example:



Cross comparison of the prediction skills of the 5 studied scenarios as a function of the lead time for two grids in California and New York. For BSS a threshold of -0.8 is used for converting the continuous PDFs into binary categorical predictions.

Ensemble prediction (review):

- There are many ways of capitalizing on the auto-correlation of a single variable to estimate the predictive distribution for some future time:

- Lyon et al. (2012): A parametric method : estimating a normal predictive distribution using observed climatology data for the predictive mean and the autocorrelation for the predictive standard deviation.

This is a parametric approach with several Gaussian assumptions.

- Day 1985: suggests historical observations can be used to empirically find pairs of observations separated by the desired prediction length where the first value belongs within some small range of desired initial value

This approach is data dependent and does not assume any particular parametric class for the predictive distribution. However, building a robust predictive PDF requires a substantial number of observations.

Dataset:

- **2m surface air temperature** from the University of Delaware Air Temperature dataset (V3.01) from 1901-2010.
- **Precipitation** observation is obtained from the Global Precipitation Climatology Center (GPCC) monthly global gridded analyses (V6) at 0.5^{o} longitude x 0.5^{o} latitude spatial resolution (1901–2010). GPCC used in GPCP.
- The commonly used **NINO3.4** index- the average sea surface temperature anomaly in the region bounded from 5°N to 5°S and from 170°W to 120°W- is utilized. Nino 3.4 was obtained from climate prediction center (CPC) since 1950.

Ensemble prediction using bootstrap:

- We consider the observed data to be a single realization of some process,
- Bootstrap allows us to construct many realizations of the same process.
- The ensemble of bootstrap realizations would then allow us to construct more accurate and more robust predictive PDF.

Details :

- Given a detrended N-dimensional vector of data that is regularly spaced in time called y_0 ; $\boldsymbol{y}_0 = (y^1, y^2, \dots, y^N)'$,
- A resampled dataset is constructed by taking randomly sampled 'blocks' of the original data $\boldsymbol{y}_0$ and to construct M new datasets $\boldsymbol{y}_i$, $i = 1, \dots, M$.
- **Method can easily be extended to multi-variate inputs, which makes it attractive for exploring the interactions between different geophysical processes for drought prediction.**

For example : *The construction of the predictive PDF can be done similarly by selecting pairs of bivariate vectors where the initial condition x_0 and historical data are similar (i.e., $|y^i - x_0|_g < d$ for some distance d and vector norm g).*

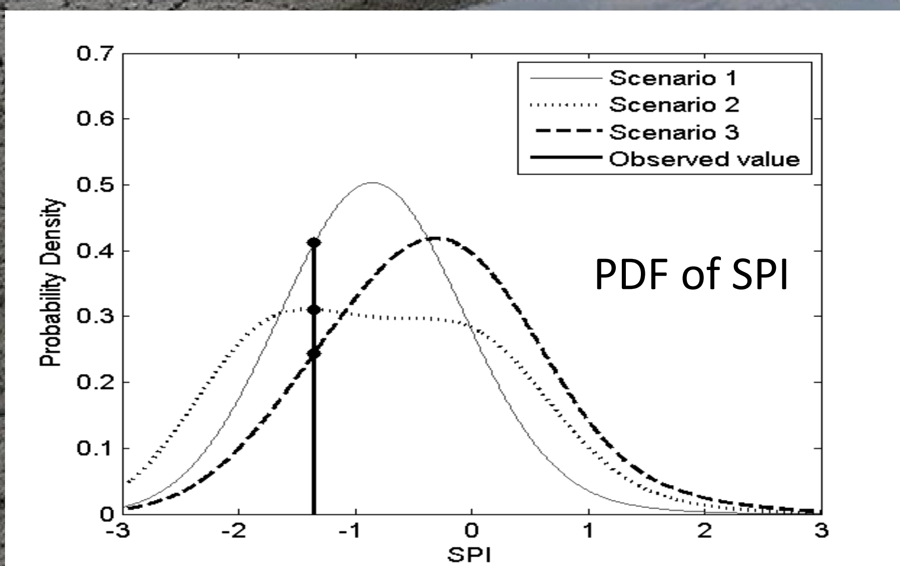
- **Continuous prediction PDF is constructed using a probability density kernel smoother,** which estimates the probability density function of a random variable from finite data samples using non-parametric methods (Wand and Jones, 1995).

Evaluating the accuracy of probabilistic predictions

We choose to use a **logarithmic scoring score (LSS),** which has the following form:

$$LSS = \sum_{I=1}^{n-L} \log(p_m(y_v^{i+L}\,|y_v^i\,))$$

The logarithmic skill score is simply the sum of the log of the probability density of the observed data y_v^{i+L} from the predictive PDF. The advantage of LSS is that it evaluates the entire continuous predictive PDF against the actual observed value and produces a quantitative assessment of the prediction accuracy.

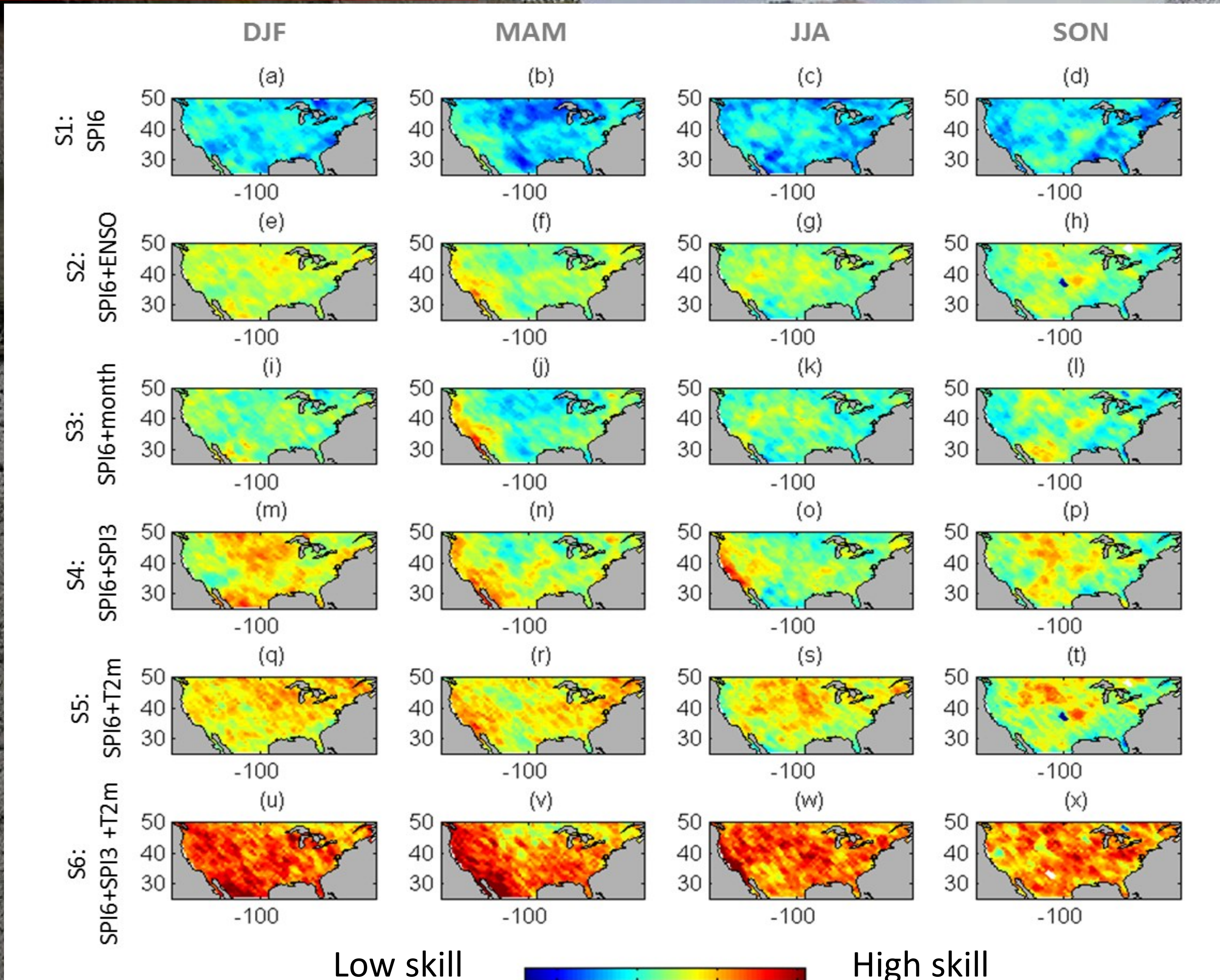


- **The intersection values (y-axis) is probability density: the higher the probability density, the more prediction skill**

Schematic display of the log-likelihood skill score (LSS)

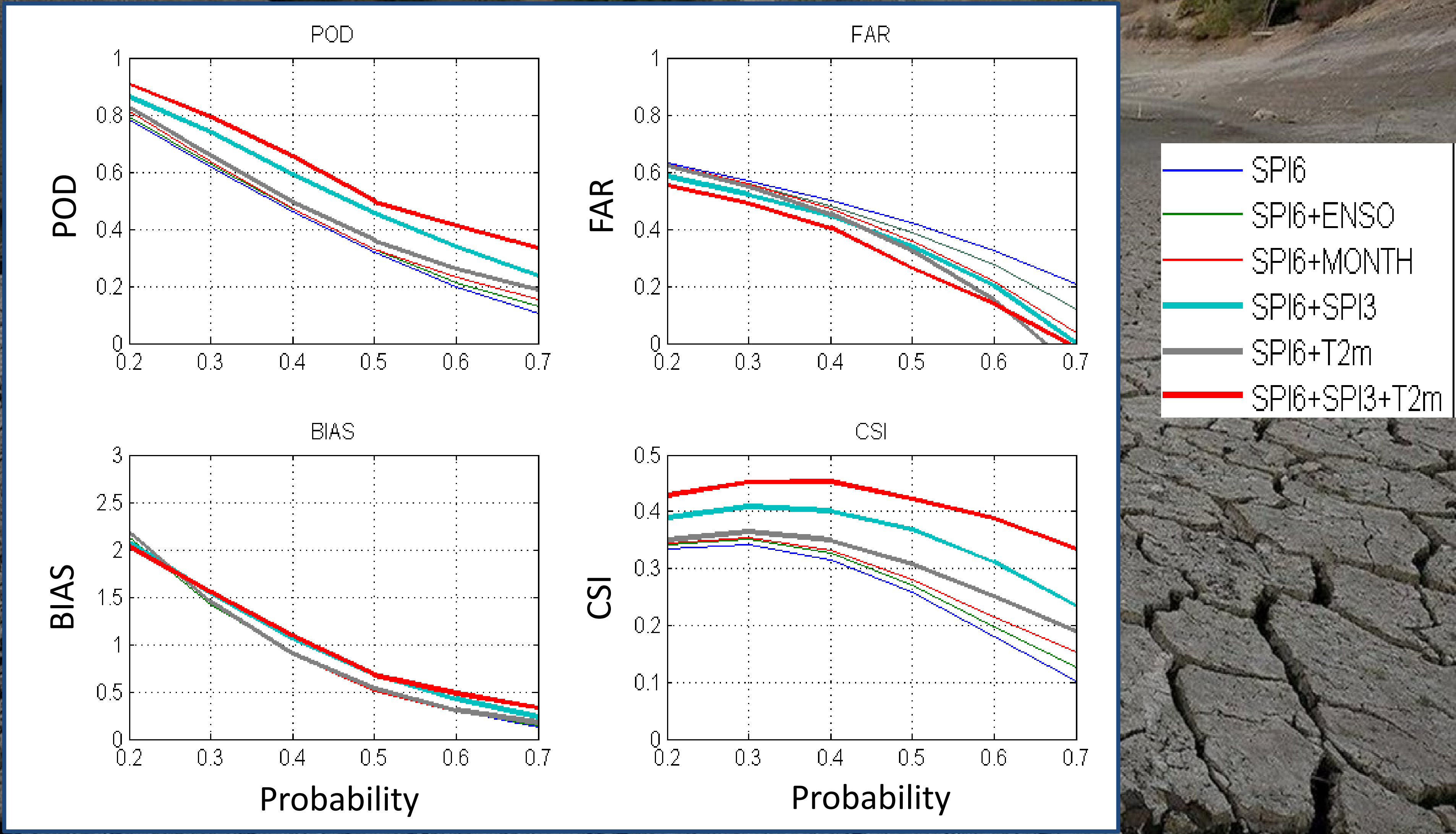
- The PDFs constructed 1901-1990 data; evaluation is performed using 1991-2010 data.
- **This approach evaluates the entire continuous predictive PDF against the actual observed value and produces a quantitative assessment of the prediction accuracy.**

Geographical map of LSS



Geographical maps of the LSS for 2 month lead seasonal prediction of SPI6. Entire evaluation dataset is used.

Detection of Drought: Binary scores (yes/no)



Detecting drought defined by SPI6<-.6 over the CONUS (3-month lead time)