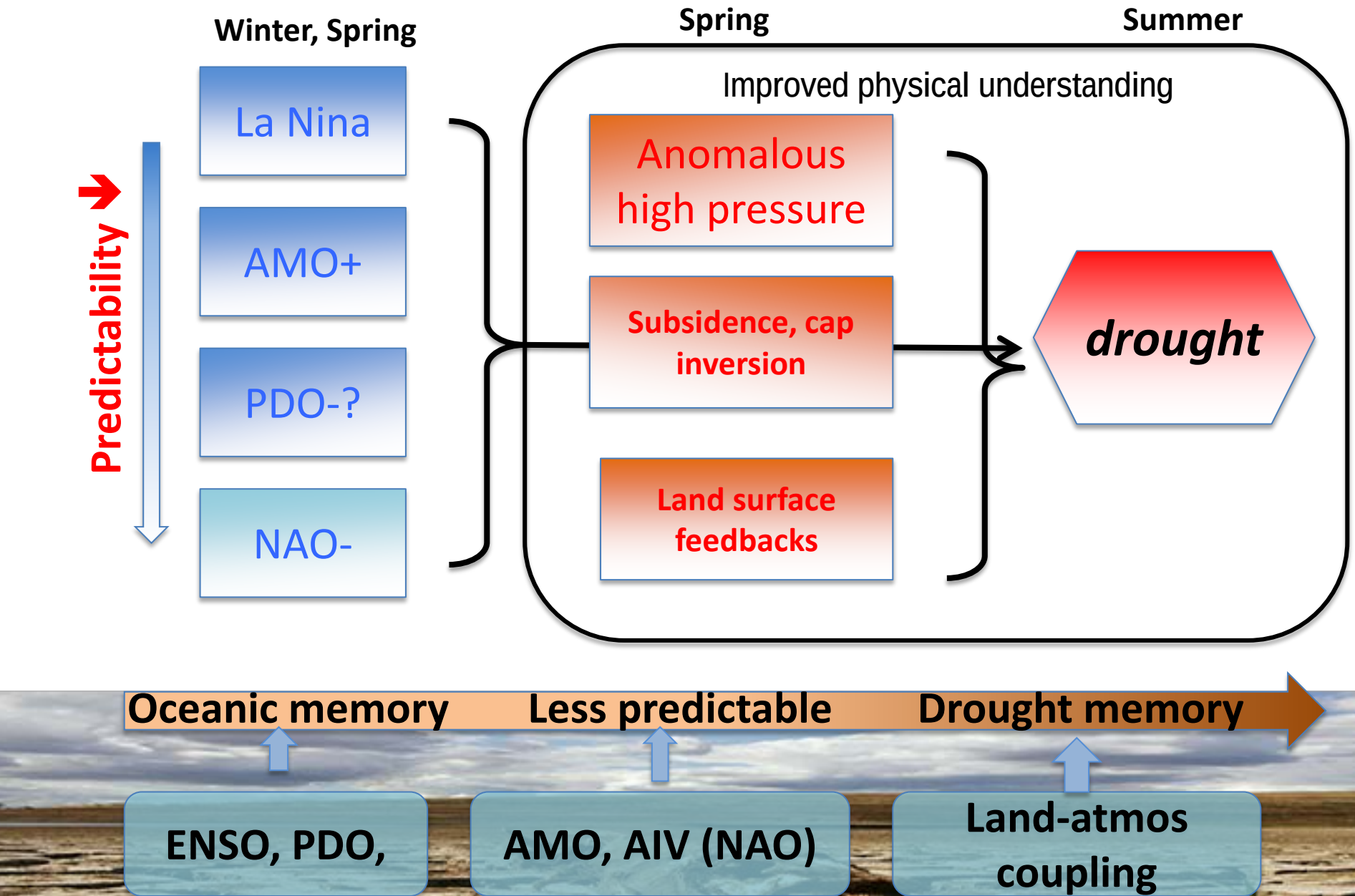
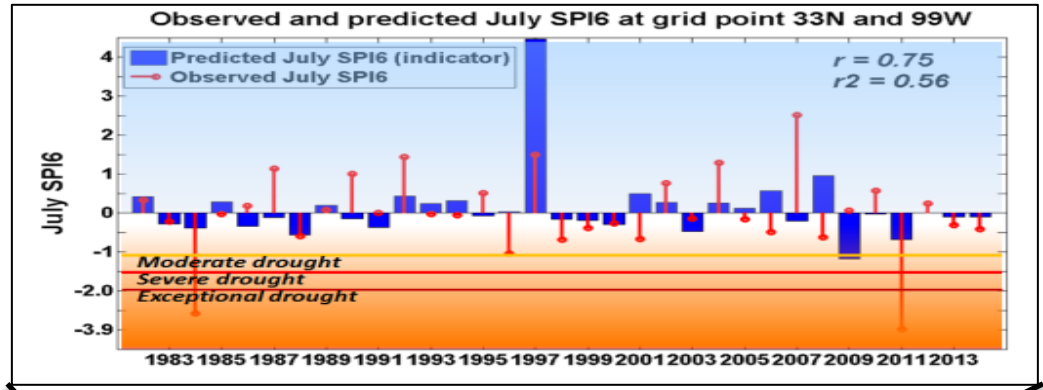
Main Points of the three slides:

- *The three slides intend to show that the scientific basis, skills and application that is already used to support decisions for the state drought preparedness in 2014.*
- *Slide one: previous drought prediction depends on oceanic forcing such as ENSO. However, lower climate predictability in spring and large uncertainty in modeled processes that control drought memory causes large uncertainty in drought prediction. Our process-based empirical drought early warning is designed to reduce this gap in drought prediction.*
- *Slide two: this slide show the 3-months lead time hindcasts made by the empirical drought prediction vs. dynamic hindcasts made by the national multi-model ensemble prediction. The hindcasts skills (described in the next slides) suggest that the empirical drought early warning matches with observation for more than 50% times (outperform random guess) and outperform (the National Multi-model Ensemble prediction) NMMN hindcasts.*
- *The drought early warning indicator prediction (left panel.) we provided to the Texas Water Development Board (TWDB) was used by the agency to brief the state drought preparedness council in May 1st, 2014 to support stakeholder drought management. The middle panel shows the summer rainfall anomalies predicted by NMME, the right panel shows the observed rainfall anomalies. This indicator will be formally introduced to stake holders by TWDB through press release in a day or two.*

Physical basis for the drought early warning indicator:

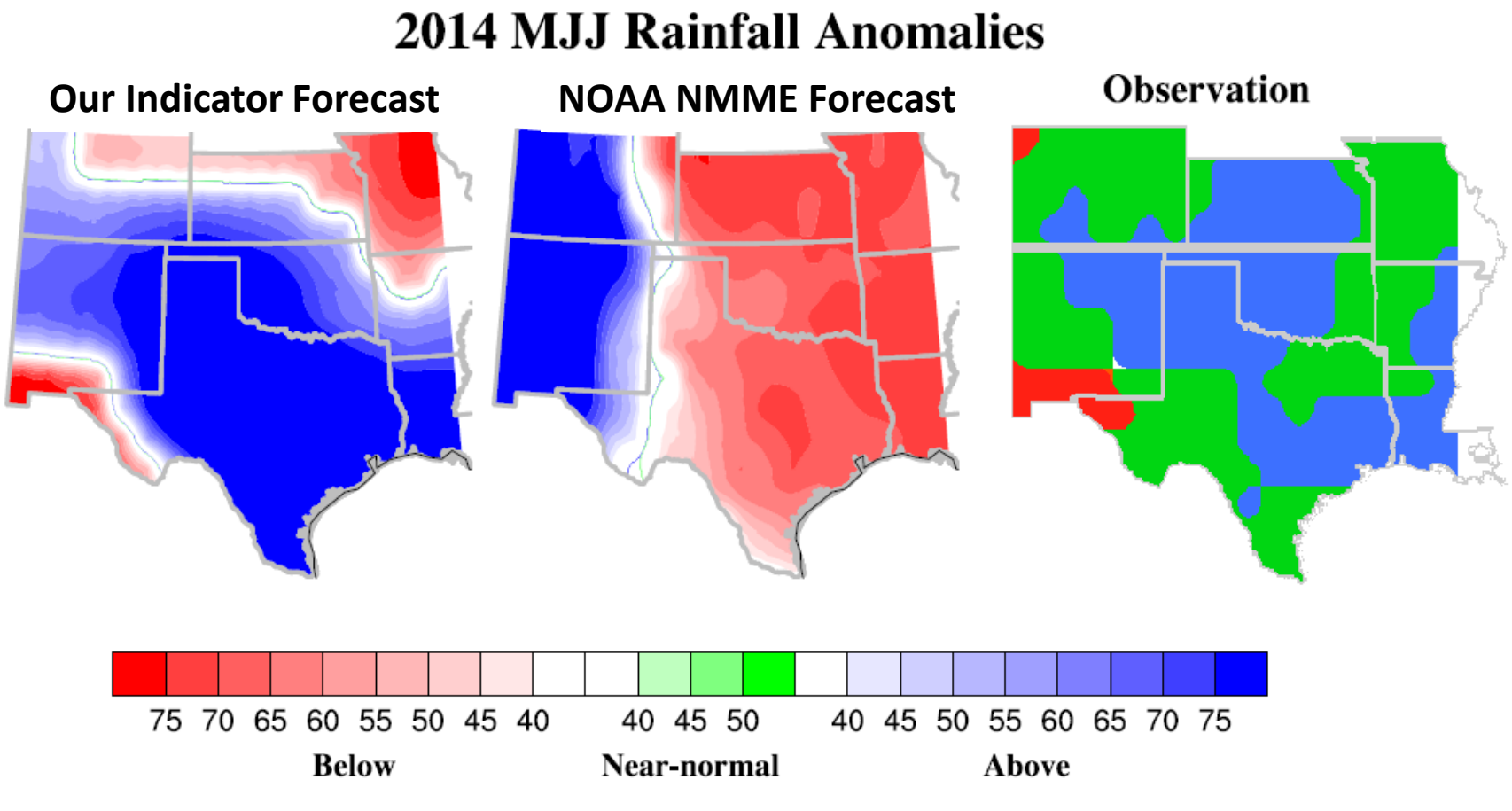


- ***Our drought early Indicator out-performs random guess and state-of-art NMME ensemble seasonal prediction for 1982-2013.***



e Forecast Skill for July SPI6
Indicator vs NMME

Prediction for summer 2014 used by the TWDB in briefing the state drought preparedness council



Layer-2: How well does this summer drought early warning indicator work in general?

Forecast verification:

- The 2 alternative forced choice (2AFC): This approach compare all possible sets of two forecast–observation pairs, asking the same question each time, and calculating the proportion of times that the question is answered correctly. Each time the question is asked, there is a 50% chance of picking the correct observation in the absence of any useful information, but if the forecasts are skillful, the proportion of correctly picked observations will exceed 50%, and the better the forecasts are the closer the proportion will be to 100%. This is known as the probability of a correct decision (Green and Swets 1989; Mason and Graham 2002, Mason and Weigel 2009).
- The **receiver operating characteristic** (**ROC**): This approach measures the rate of true positive prediction rate vs. the false positive prediction rate in a ROC space, defined by FPR and TPR as *x* and *y* axes respectively. The best possible prediction method, or a perfect classification, would yield a point in the upper left corner or coordinate (0,1) of the ROC space, representing 100% sensitivity (no false negative) and 100% specificity (no false positive). A completely random guess would give a point along the diagonal line (the line of no-discrimination) from the left bottom to the top right corners. A example of random guess is a decision based on flipping coins (heads or tails). If you repeat this many times, this random classifier's ROC points migrates towards (0.5,0.5) in the ROC space (source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic). A better than random guess prediction will provides points to the upper-left of the line of non-discrimination.
- Pearson correlation coefficient: Covariance of the two variable divided by the product of their standard deviation. It measures linear correlation between the predicted values and observed values. The correlation is significant if the correlation coefficient is greater than the critical value for statistical significance, which depends on the number of effective samples. defined as the