

A Mechanistic View of Prospects for Decadal Predictions

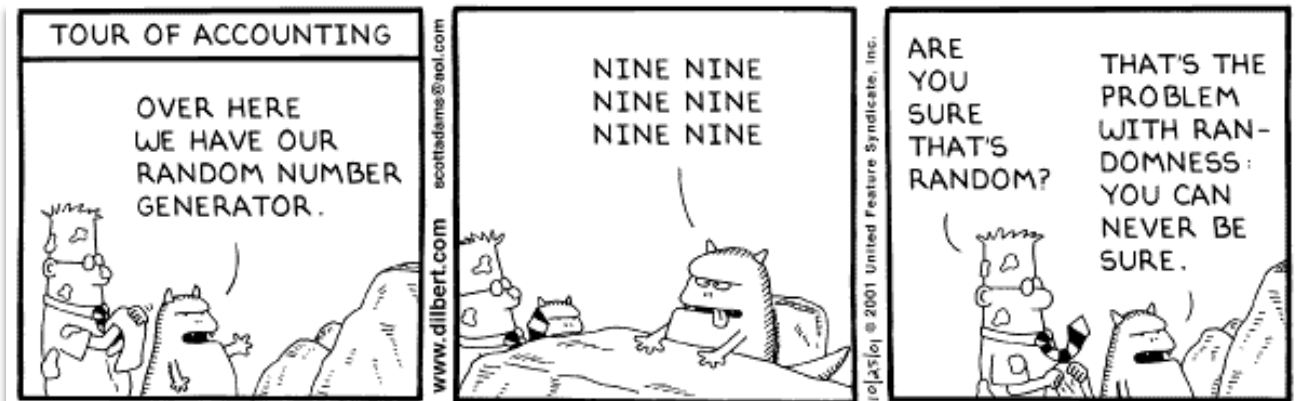
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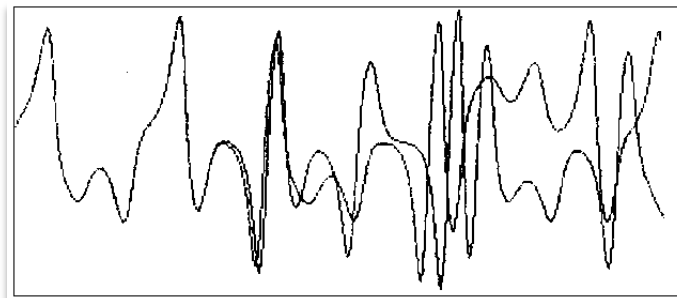
What is meant by the “mechanistic view” of decadal predictions?

- Beyond the physical process and mechanisms governing decadal variability, it is the signal and the noise that control the basic characteristics of decadal predictions, e.g., predictability, prediction skill, amount of effort one needs to realize predictability...

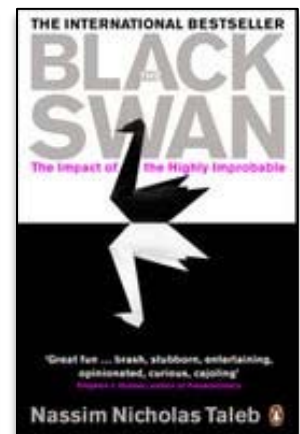


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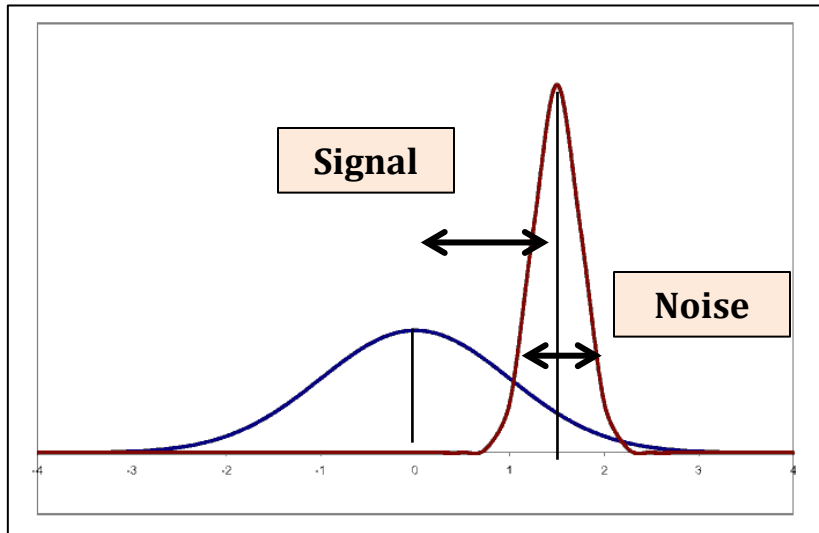
- Signal – Our ability to distinguish forecast outcomes from the climatological PDF
- Noise – Uncertainty (or non uniqueness) in forecast outcomes
 - Noise is a ubiquitous feature of non-linear dynamical systems and stems from sensitivity in the evolution of the future state to initial conditions



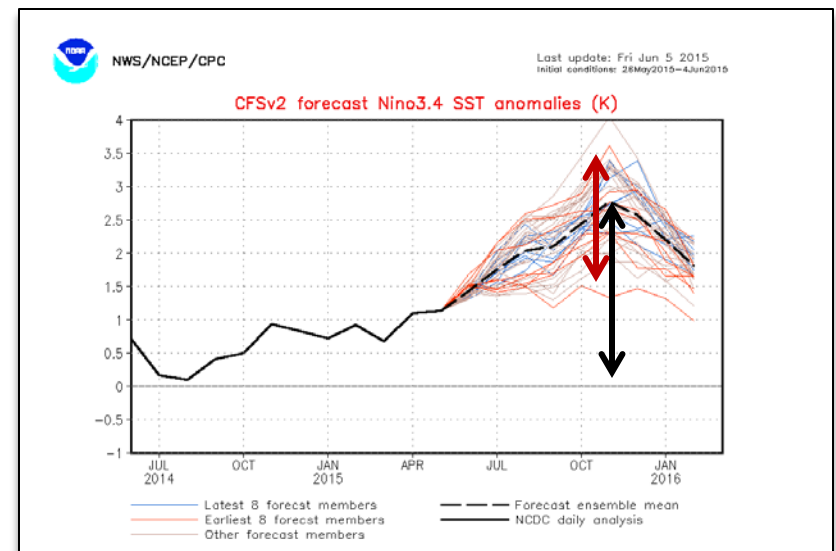
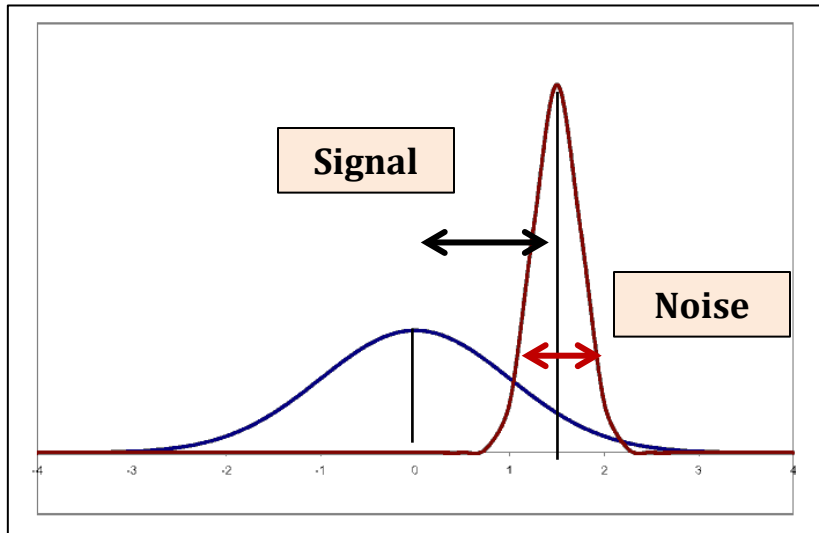
the signal and the noise and the noise and the noise and the noise why so many predictions fail – but some don't and the noise and the noise and the noise nate silver noise



- An illustration of signal and noise in the context of probability density functions (PDFs)



- An example of signal and noise in the context of PDFs

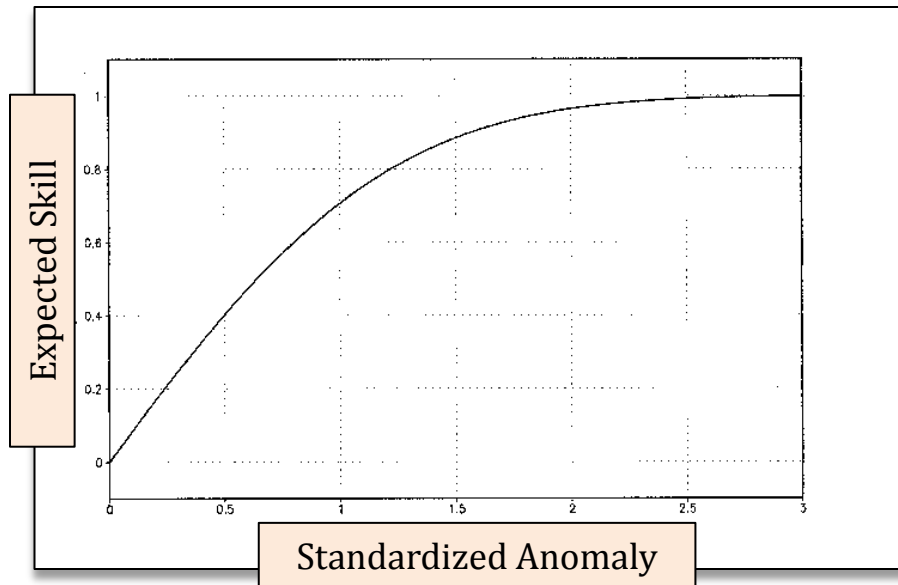


- The relative amplitude of signal-to-noise determines
 - Expected skill of prediction
 - Influence of ensemble size on skill
 - Influence of the length of verification time series on estimate of skill
 - ...

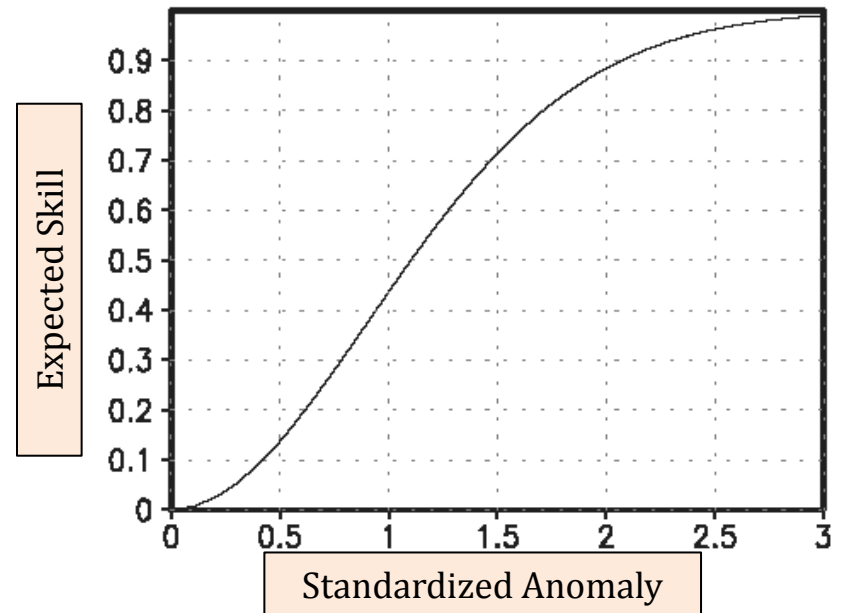
Expected skill and signal-to-noise

- Expected skill and SN

AC

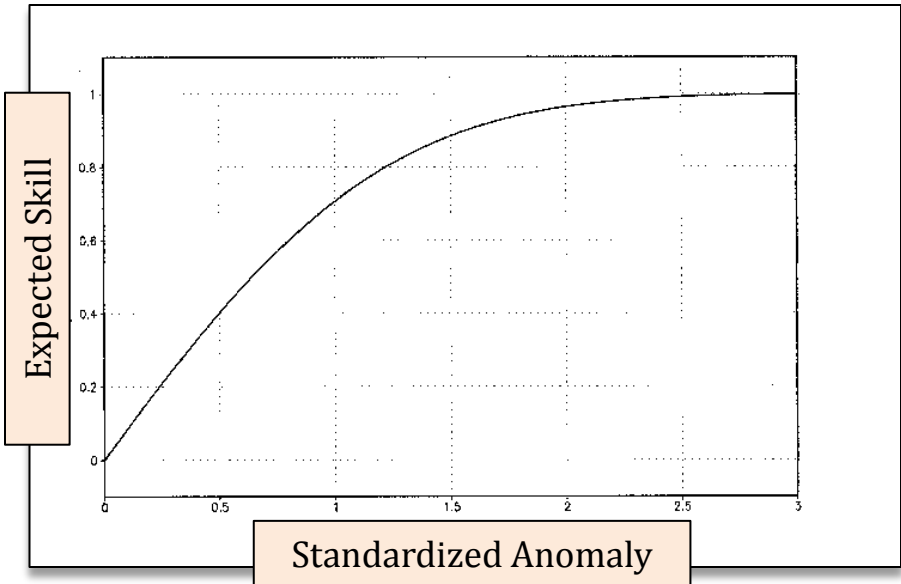


RPSS

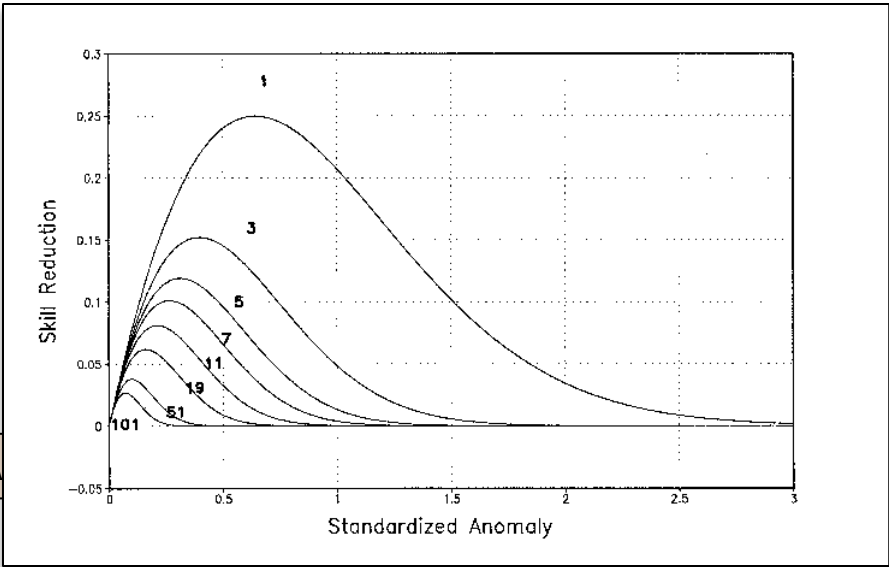


Influence of ensemble size and signal-to-noise

Expected Skill

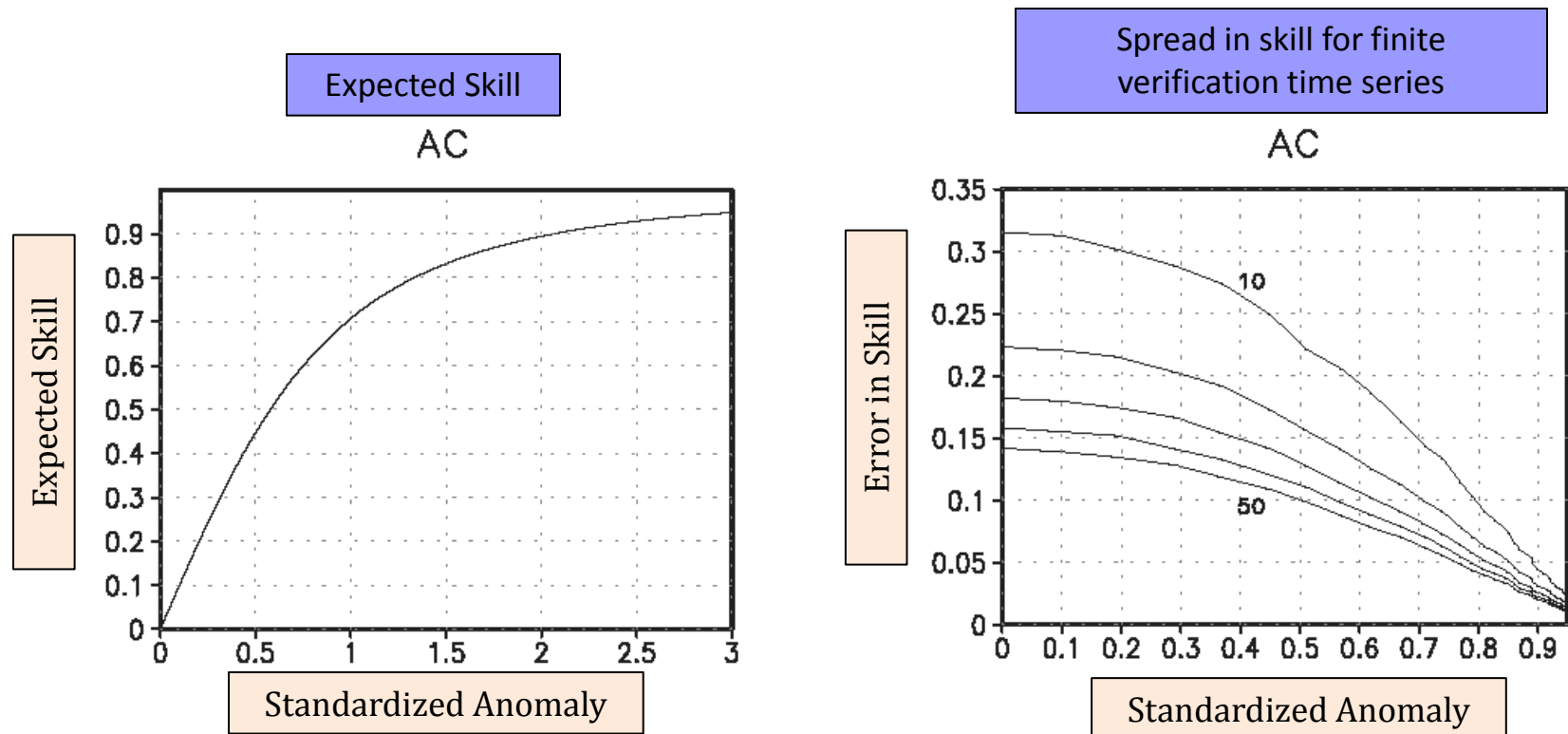


Reduction in skill for finite ensemble size



- High SN do not need large ensembles
- Low SN large require large ensembles, but...

Influence of the length of verification time series on skill estimate and signal-to-noise



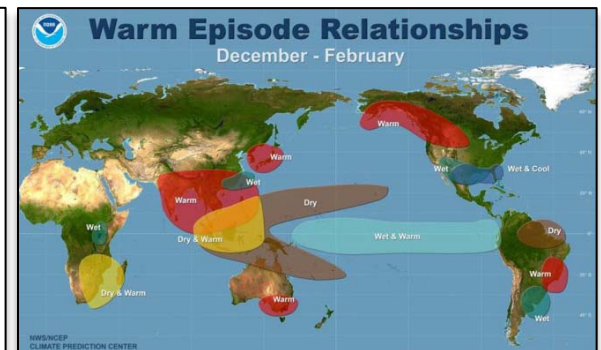
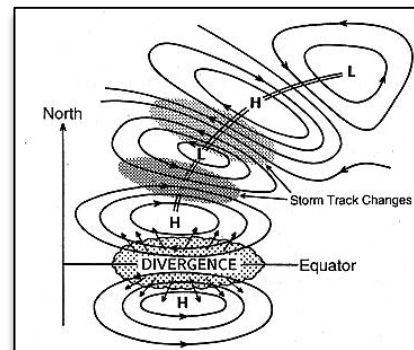
- High SN do not need long verification time-series
- Low SN do need long verification time-series, but...

Ensemble size, predictability, and complementarity

- There is a complementarity between the predictability (and the level of skill one can achieve) and ensemble size one thinks one should have
 - High predictability requires small ensemble size; skill is high
 - Low predictability requires much larger ensemble size, but skill is still low
 - The very need for ensembles implies an upper limit in skill, and

Ensemble size, predictability, and complementarity

- The very perception for the need to having larger ensembles (or larger verification time series) to quantify decadal predictability is pointing of low predictability
- Harder you have to work, lower is the predictability!
- The fact the we need massive experiments may be implying that predictability is low!



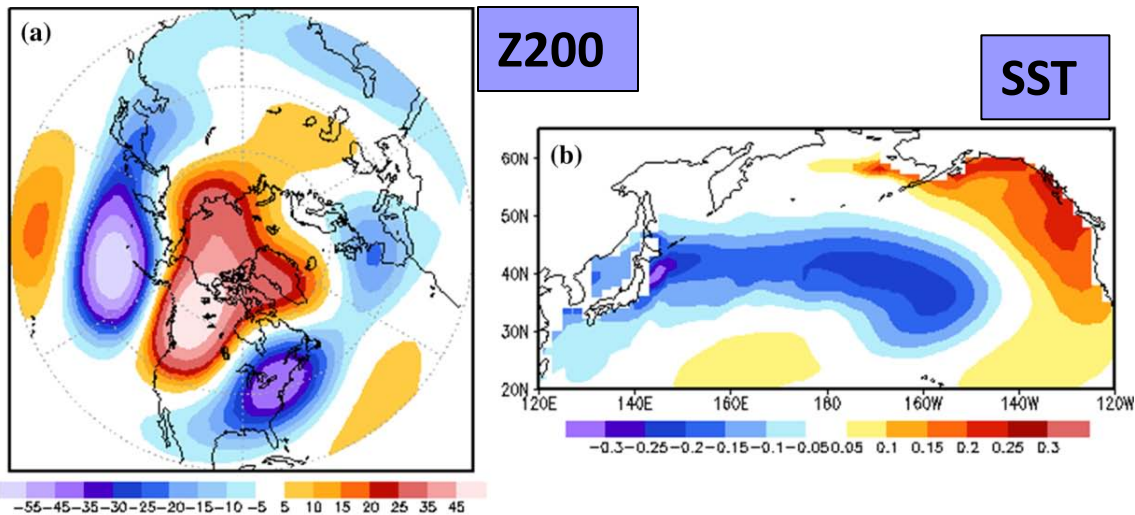
Signal-to-Noise and actual vs. potential skill (for anomaly correlation measure)

- Model variability \sim Observed variability
- However, spilt between signal and noise could be different resulting in a lack of relationship between actual and potential skill
- $\text{Signal}_m > \text{Signal}_o$; $\text{Noise}_m < \text{Noise}_o$
 - $AC_m > AC_o$
- $\text{Signal}_m < \text{Signal}_o$; $\text{Noise}_m > \text{Noise}_o$
 - $AC_m < AC_o$

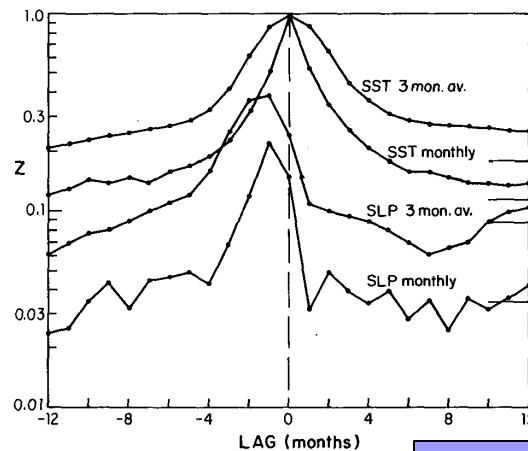
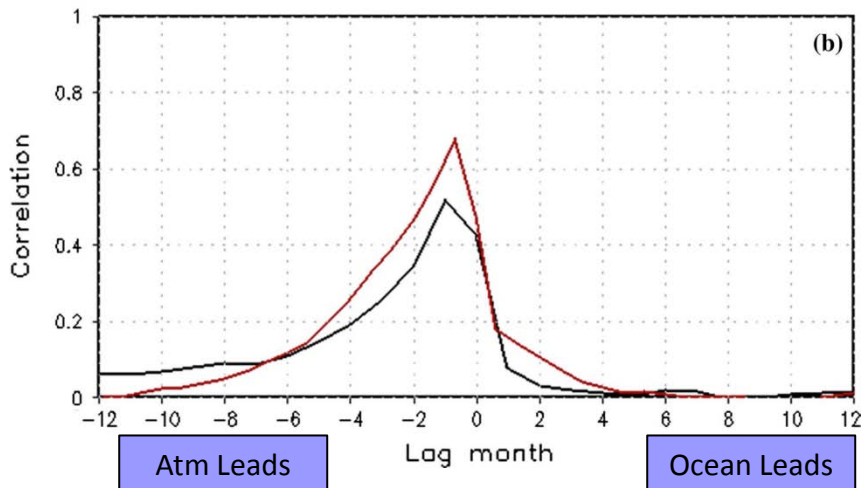
Potential for extratropical SSTs for improving prediction skill

- The very basic dynamics in extratropics is that atmosphere drives the ocean
- Atmosphere is chaotic
- Initialized prediction starts from a snapshot of ocean and atmosphere
- The evolution of the atmosphere is highly chaotic but the hope is that the near term evolution of the ocean will ALSO constrain the evolution of the atmosphere
- The constrain will determine how large an ensemble is required to get atmospheric response, and prediction skill of surface temperature and precipitation
- An implication of weak constraint is that the association between ocean and atmosphere seen in individual realization may not be prominent on ensemble mean basis

Ocean and atmospheric fingerprints of PDO



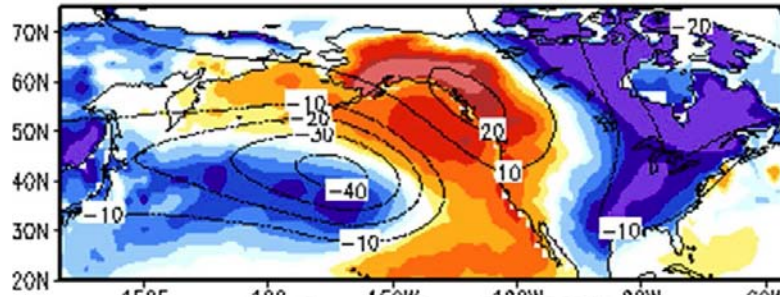
Lead-lag correlation



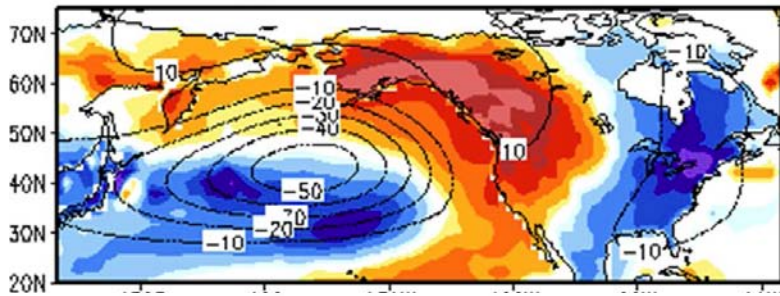
Davis, 1976

Individual Runs

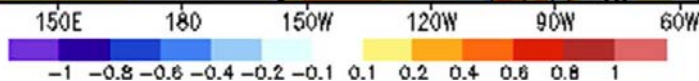
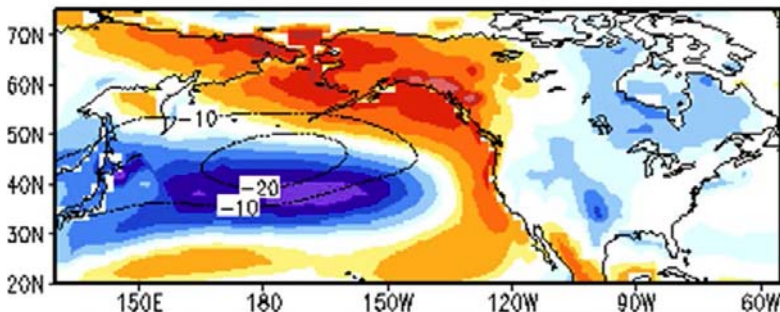
(a) 0-mon Lead NOV



(c) 4-mon Lead MAR

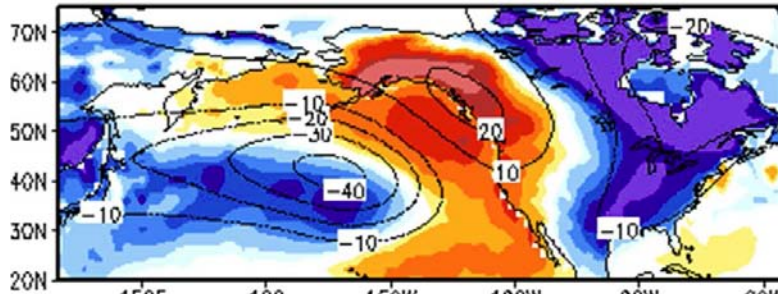


(e) 8-mon Lead JUL

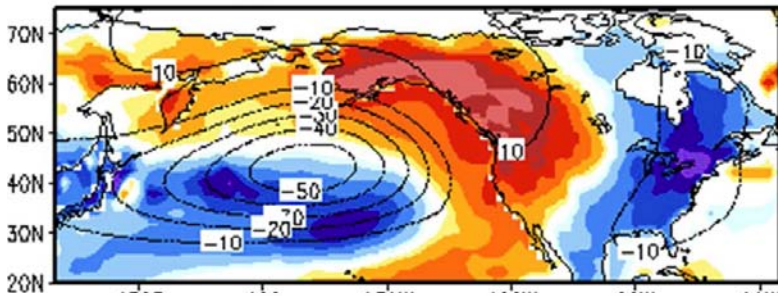


Individual Runs

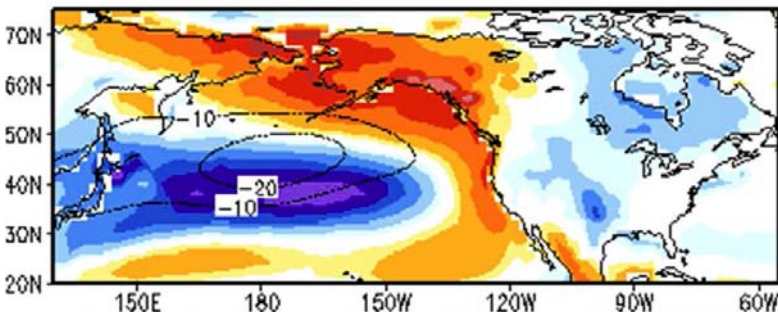
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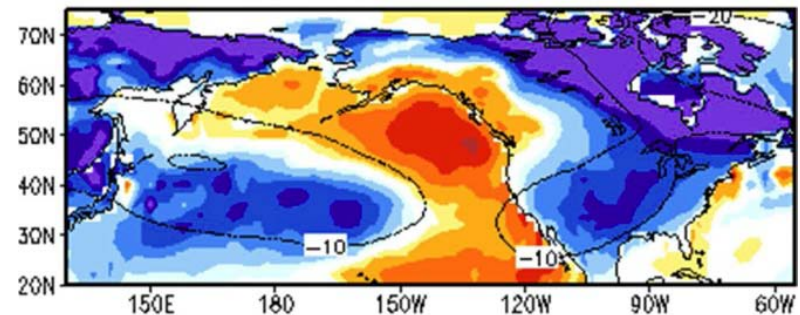
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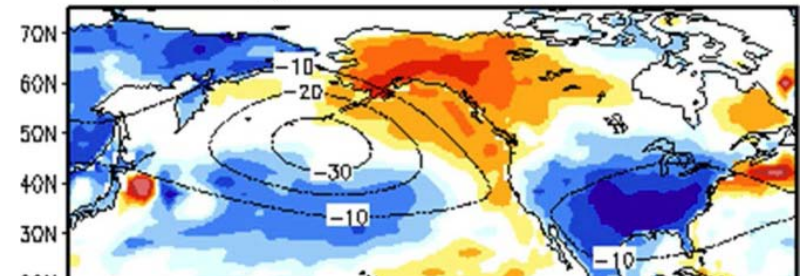
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Ensemble Means

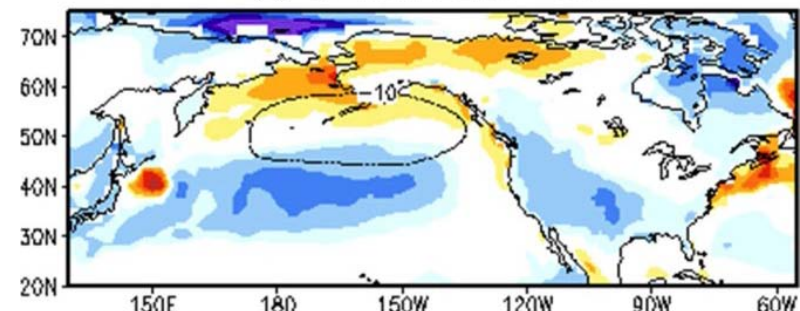
(a) 0-mon Lead NOV



(c) 4-mon Lead MAR



(e) 8-mon Lead JUL



-1 -0.8 -0.6 -0.4 -0.2 -0.1 0.1 0.2 0.4 0.6 0.8 1

Further Reading

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