Seasonal Predictability
OUTLINE

1. Predictability and Uncertainty
2. Sources of predictability
   Research for sources of predictability
3. Potential Predictability: Signal to Noise Ratio
   Optimal Estimation of Unpredictable Component using multi-model
4. Practical Predictability in the coupled model: Predictable Mode analysis
1. Predictability and Uncertainty
What is “Predictability?”

- “The extent to which a process contributes to prediction quality.”
- Literature provides variety of interpretations; committee agreed on qualitative approach.

**Key aspects of committee approach**

- Quantitative estimates of a *upper limit* of predictability for the real climate system are not possible.
- Verification of forecasts provide a *lower bound* for predictability.
- Traditional predictability studies (e.g., twin model studies) are qualitatively useful.
Aspects of Predictability

1. The concept of predictability stems from practice of prediction (Linkage to prediction).

2. Prediction of future climate states can never be perfect at any lead time due to turbulent nature of the atmospheric motion and intrinsic nonlinearity. (Hence the concept of predictability arises)

3. Predictability is a measure of the uncertainty that limits the accuracy of prediction. (or Predictability and uncertainty are complementary in nature and they might be used to describe theoretical upper limit of prediction).

4. Predictability is a function of state variables (temperature, winds, precipitation etc.) and varies with space, especially with the forecast lead time.
5. For a given variable and at a given place (air temperature at DC or Nino 3.4 SST for instance), the predictability (uncertainty) decreases (grows) with lead times. Hence, one way of measuring predictability is to use the maximum lead time at which the prediction becomes meaningless.

6. Predictability, however, can be also measured at any given lead time. Useful prediction must include information about the predictability (uncertainty). Probabilistic forecast may be considered as such a form of practice (recommended).
Aspects of Predictability

7. Predictability can be estimated, albeit imperfectly, by using observations limited by length of records or prediction tools (model systems) along with observations. (Pure model approach, for instance, the signal-to-noise ratio in forced AGCM response can be used, but the fidelity of the model must be established through validation against observations)

8. The optimal model system used for estimation of predictability should be able to predict future climate states as a whole, because any single variable at a given location is intimately linked to other fields at neighboring locations. Thus, CGCM is an ideal tool for this purpose. (Recommended)
Aspects of Predictability

9. Predictability that is estimated using a model system (the perfect model approach) is model-dependent; hence may be called practical predictability.

10. Predictability may be viewed as a limit of the practical predictability when the model system approaches ‘ultimate’ perfectness.
2. Sources of Predictability
Sources of predictability

Atmospheric internal dynamics

A-O interaction

A-L-I interaction

External forcing

- Aerosols
- Solar radiation fluctuations
- Green house gases
- ISV/Monsoon
- Mixed layer
- El Nino/La Nina
- Thermocline
- AMOC
- Thermohaline Conveyer Belt
- Global ocean
- Stratospheric polar vortex
- QBW
- MJO/MISV
- NAM/SAM/NAO/AO
- Snow cover
- Soil moisture
- Vegetation
- Land heat content
- Sea ice

Sources of predictability

- Blocking
- QBW
- MJO/MISV
- NAM/SAM/NAO/AO
- Stratospheric polar vortex
- QBO

Time scales (days)

- Synoptic: 5~20 dy
- Extended Range: 100 dy
- ISV: 10^1 ~ 10^2 yr
- AC: ~1 yr
- IAV: 2~7 yr
- IDV: 10~70 yr
- Centennial: 70~500 yr
- Millennial: 500~3000 yr
- Orbital: 10^7 yr
Example Sources of Predictability

Volcanic Eruptions

Soil Moisture

Rainfall

Soil Moisture

El Niño – Southern Oscillation (ENSO)
Many sources of predictability remain to be fully exploited by ISI forecast systems.

Criteria for identifying high-priority sources:

1) Physical principles indicate that the source has an impact on ISI variability and predictability.
2) Empirical or modeling evidence supports (1).
3) Identifiable gaps in knowledge/representation in forecasting systems.
4) Potential social value.
Research Goals for Sources of Predictability

1) Madden-Julian Oscillation (MJO)
   Develop model diagnostics. Expand process knowledge (e.g. MJO Task Force) regarding ocean-atmosphere coupling, convection, cloud processes
2) Stratosphere-troposphere interactions

Improve understanding of link between stratospheric processes and ISI variability. Successfully simulate/predict sudden warming events and subsequent impacts.
3) Ocean-atmosphere coupling
Understanding of sub-grid scale processes should be improved.
4) Land-atmosphere feedbacks

Investigate coupling strength between land and atmosphere. Continue to improve initialization of important surface properties (e.g., soil moisture).
5) High impact events (volcanic eruptions, nuclear exchange)

Develop forecasts following rapid, large changes in aerosols/trace gases.
6) Non-stationarity

Long-term trends affecting components of climate system (e.g., greenhouse gases, land use change) can affect predictability and verification techniques. Changes in variability may also be important.
3. Potential predictability

✓ Single Model
✓ Multi Models: Optimal Estimation of Unpredictable Component
In climate prediction, potential predictability is regarded as the predictability with full information of future boundary condition (e.g., SST). Thus, predictability is varied with similarity between the response of real atmosphere and prediction method to the same BC.

Establish “potentially” possible prediction skill with state-of-art prediction system

Courtesy of In-Sik Kang
**Potential Predictability (Signal to Noise Ratio)**

- **Total Variance** $\left( \sigma_{TOT}^2 \right) = \text{Signal Variance } \left( \sigma_{SST}^2 \right) + \text{Noise Variance } \left( \sigma_{INR}^2 \right)$

- **Signal Variance**: Square mean of the deviation of the ensemble means from the climatological mean and considering bias correction
  
  \[
  \sigma_{SST}^2 = \sigma_{EN}^2 - \frac{1}{n} \sigma_{INR}^2
  \]
  \[
  \sigma_{EN}^2 = \frac{1}{N-1} \sum_{i=1}^{N} (\bar{x}_i - \bar{x})^2
  \]
  \[
  \bar{x} = \frac{1}{(Nn)} \sum_{i=1}^{N} \sum_{j=1}^{n} x_{ij}
  \]
  \[\bar{x} \text{ is the climatological mean of ensemble mean}\]

- **Noise Variance**: 24-year mean variance of the deviations of 15 members from the ensemble mean of each year
  
  \[
  \sigma_{INR}^2 = \frac{1}{N(n-1)} \sum_{i=1}^{N} \sum_{j=1}^{n} (x_{ij} - \bar{x}_i)^2
  \]
  
  $x$ is the precipitation, $i$ indicates the individual year, $N=24$ and $j$ the ensemble member, $J=15$. $\bar{x}$ is the ensemble mean.

- **Signal-to-noise ratio** ($\rho$) = Signal Variance / Noise Variance

- **Theoretical Limit of Correlation Skill** ($R_{Limit}$) Kang and Shukla (2006)
  
  \[
  R_{Limit} = \sqrt{\frac{V(x_{S})}{V(x)}} = \sqrt{\frac{\rho}{\rho + 1}}
  \]
Potential Predictability: Single Model (NCEP CFS)

Observation

NCEP T1

JJA Precipitation

Signal (Ensemble Mean Variance with Bias Correction)

Noise (Ensemble Spread)

=> Inherent problem of monsoon prediction using one model
Each model shows different characteristics of signal-to-noise ratio.
Optimal Estimation of Predictability using Multi-Models

Predictability limits for seasonal climate variability depend on the fraction of external and internal variability. From the observed data alone, separation of the total seasonal variance into its external and internal components remains difficult and controversial issue.

**Kumar et al (2007, J Climate)**: Development of procedure for estimating atmospheric internal variability based on the expected value of the mean square error between the observed and the general circulation model simulated (or predicted) seasonal mean anomaly.

The expected value of Mean-Square Error (MSE) is the sum of three terms: the observed internal variability, the internal variability of the ensemble mean of model simulations, and a term that is the error in the model-simulated atmospheric response relative to the observed response to SSTs.

\[
MSE = (M - O)^2 = \sigma_{oi}^2 + \sigma_{mi}^2 + <(\mu_m - \mu_o)^2>
\]

The property of MSE can be considered as the estimate the internal variability of the observed seasonal variability because for large ensembles and an dynamical model with unbiased atmospheric response, MSE equals the observed internal variability. Using multi models, we can find the minimum value of MSE irrespective of which model it came from at each geographical location, and the spatial map of the minimum value of MSE is our best estimate for the observed internal variability.
# 13 Coupled Climate Models

<table>
<thead>
<tr>
<th>Institute</th>
<th>AGCM</th>
<th>Resolution</th>
<th>OGCM</th>
<th>Resolution</th>
<th>Ensemble Member</th>
<th>Reference</th>
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<td>BMRC POAMA1.5</td>
<td>BAM 3.0d</td>
<td>T47 L17</td>
<td>ACOM3</td>
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<td>Kug et al. (2005)</td>
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<td>Kug et al. (2005)</td>
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<td>ARPEGE</td>
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<td>OPA8.2</td>
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<td>IFS</td>
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<td>HOPE-E</td>
<td>1.4x0.3-1.4 L29</td>
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<td>MPI</td>
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<td>Pope et al. (2000) Gordon et al. (2000)</td>
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<td>2.5x3.75 L19</td>
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<td>1.25x0.3-125 L40</td>
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Optimal Estimate of Predictability for Seasonal 2m Air Temperature
Using 13 models in CliPAS and DEMETER

JJA

Estimated Var_Int

Estimated Var_Ext

Estimated SN Ratio

DJF

Estimated Var_Int

Estimated Var_Ext

Estimated SN Ratio

Var: [x0.5°C²]
Predictability vs Prediction Skill for Seasonal 2m Air Temperature
Using 13 models in CliPAS and DEMETER

JJA

Fractional Variance of Estimated External Variance

DJF

Temporal Correlation Skill of MME prediction

Predictability limit in current MME system
Optimal Estimate of Predictability for Seasonal Precipitation

Using 13 models in CliPAS and DEMETER

JJA

Estimated Var_Int

60\degree N
30\degree N
EQ
30\degree S

Estimated Var_Ext

60\degree N
30\degree N
EQ
30\degree S

Estimated SN Ratio

0 60E 120E 180 120W 60W 0

DJF

Estimated Var_Int

Estimated Var_Ext

Estimated SN Ratio

Var: [mm² day⁻²]

0 60E 120E 180 120W 60W 0
Predictability vs Prediction Skill for Seasonal Precipitation
Using 13 models in CliPAS and DEMETER

JJA
Fractional Variance of Estimated External Variance

DJF
Temporal Correlation Skill of MME prediction
Optimal Estimate of Predictability for Seasonal 850 hPa Streamfunction

Using 13 models in CliPAS and DEMETER
Predictability vs Prediction Skill for Seasonal 850 hPa Streamfunction
Using 13 models in CliPAS and DEMETER

JJA
Fractional Variance of Estimated External Variance

DJF
Temporal Correlation Skill of MME prediction
4. Practical Predictability in the coupled model: Predictable Mode analysis

✓ Determination of the Major Modes of Variability
✓ Determination of the Predictable Modes
✓ Determination of Predictability
Predictability of Seasonal Precipitation over Global Tropics in Coupled Climate Models

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J. Shukla, George Mason University, USA
C.-K. Park and Saji Hameed, APCC, Korea
Climate scientists have made tremendous advances in understanding and modeling the variability and predictability of the climate system. As a result, the prediction of seasonal-to-interannual climate variations and the associated uncertainties using multiple coupled models has become operational. However, how to determine the predictability in the coupled climate system, where no atmospheric lower boundary forcing given, remains an unresolved issue.

We propose one method to quantify predictability of global precipitation which relies on identification of the “predictable” leading modes of the observed interannual variations. The predictability is quantified by the fractional variance accounted for by these “predictable” leading modes.

Questions

- How to determine the major modes of variability for precipitation over global Tropics [30S-40N]?
- How many modes of interannual variability of global precipitation are predictable in coupled MME system?
- How large fractional variance can be accounted for by the “predictable” leading modes?
- How good is the prediction skill of the MME in terms of the “predictable” part?
(1) How to determine the major modes of variability for precipitation over global Tropics (30S-40N)?

**Season-Reliant EOF (SEOF)**
(Wang and An 2005 (GRL), Wang et al 2007 (Clim Dyn))

- **Physical consideration**
  Anomalous climate (ENSO, monsoon) is regulated by the *seasonal march of the solar radiation forcing (annual cycle)*. Season-Reliant EOF (SEOF) analysis detects *seasonal evolving major modes of climate variability*.

- **Method**
  Construct a covariance matrix that consists of a sequence of seasonal anomalies within a “Monsoon year” (Meehl 1987, Yasunari 1991)

<table>
<thead>
<tr>
<th>JJA (o)</th>
<th>SON (o)</th>
<th>DJF (o/1)</th>
<th>MAM (1)</th>
</tr>
</thead>
</table>

IAV in each monsoon year
2) How many modes are predictable

Percentage Variance

- The first two SEOF modes are very well predicted. The third are also reasonably well predicted. But all other higher modes are not predictable as shown by the insignificant correlation skill in the spatial structures and temporal variation.
- We defined the first three modes are predictable part of the interannual variation using the current coupled MME prediction system.

SEOF Modes for Precipitation over Global Tropics

- [0-360E, 30S-40N] Prediction skill of each mode

- The first two SEOF modes are very well predicted. The third are also reasonably well predicted. But all other higher modes are not predictable as shown by the insignificant correlation skill in the spatial structures and temporal variation.
- We defined the first three modes are predictable part of the interannual variation using the current coupled MME prediction system.

The first three modes: 54.3% (CMAP), 83% (MME)
MMEs are highly correlated with CMAP

MMEs underestimate QB Peak and total variances

MME capture ENSO-MNS relation

It is found that those predictable modes are significantly related with ENSO variability with different lead-lag relationship, especially in the 1st and 2nd modes.
S-EOF 1 of CMAP: 33%  
Quasi-Biennial (QB)

S-EOF 2 of CMAP: 15%  
Quasi-Quadrennial (QQ)
(3) How large fractional variance can be accounted for by the “predictable” leading modes

The fractional variance is obtained from the ratio of the variance associated with a single SEOF mode to the total variance (Wang and An 2005). If we take these three predictable modes together, about 53% of the total variance can be captured by those observational modes. In observation, the fractional variance accounted for by the “predictable part” exhibits large spatial and seasonal variance. The MME prediction exaggerates the fractional variance of predictable modes, suggesting that the MME does not capture the higher modes.
4) How good is the prediction skill of the MME in terms of the “predictable” part?

Temporal Correlation Skill/ Precipitation

(a) All Modes  (b) Predictable Modes  (c) The Residual Modes

- JJA
- SON
- DJF
- MAM

Figure b shows the correlation skill for the reconstructed precipitation just by using the three predictable modes of MME prediction. The similarity between (a) and (b) indicates that the MME prediction skill basically comes from the first three leading modes of seasonal precipitation.
Predictability in Coupled Models

Upper limit of predictability if there is no other prediction source in MME system

0.4 correlation is correspondent to 16% of fractional variance. (d) will be same as (a) If there is no systematic anomaly errors for the “predictable modes” in MME prediction.

We can quantify the “predictability” by the fractional variance that is accounted for by the “predictable” leading modes in the observations. Such “predictable” modes can be determined by examining models’ hindcast results.
Predictability vs Prediction Skill in Coupled Models

Correlation Skill for JJA Precipitation Prediction

(a) Practical Skill

(b) Skill Limit for Predictable Mode

(c) Theoretical Limit

(d) Practical Skill with Downscaling

Forecast Limit in terms of predictable modes

Practical MME skill

Theoretical limit in terms of signal-to-noise ratio

Practical MME skill with statistical downscaling
Summary

How to measure the predictability in coupled climate system, where no atmospheric lower boundary forcing given, is an open issue. We have shown that the prediction skill of the coupled model MME basically comes from the skill in prediction of the first three major modes of interannual variations in the global tropical precipitation.

The three modes together account for about 53% of the total interannual variance averaged over the tropics in observations. This portion of the variation may be considered as practically predictable part of the precipitation variability, because the MME can capture these three major modes reasonably well but cannot capture the rest higher modes.

This result leads to a new approach to estimate the practical predictability of the tropical seasonal precipitation in the coupled climate models; i.e., we can quantify the “predictability” by the fractional variance that is accounted for by the “predictable” leading modes in the observations. Such “predictable” modes can be determined by examining models’ hindcast results.
Thank You!
Sources of predictability

Source of Predictability

Solar Radiation Fluctuations
Green House Gases
Land Use

Aerosols
Volcanoes

ENSO
Sea Ice

Monsoon-WPO/IDO/ZM

Water Table
Vegetation

Soil Moisture
Snow Cover

Land Heat Content

QBO
Oceanic Waves

MJO/MISV
NAM/SAM/NAO/AO
Blocking/Strat-polar vortex

TIW
CCEW

10^0 10^1 10^2 10^3 10^4 10^5 10^6 10^7 (days)
synoptic 5~20d 20~100d ISV 1 yr AC 2~7 yr IAV 8~70 yr IDV 70~500 yr Centennial 500~3000yr Millennial Orbital

Atmosphere-ocean internal dynamics

A-L interaction A-O interaction External forcing