Prospects for Continental Scale Decadal Prediction

Jagadish Shukla

Department of Atmospheric, Oceanic and Earth Sciences (AOES)
George Mason University (GMU)
Center for Ocean-Land-Atmosphere Studies (COLA)
Institute of Global Environment and Society (IGES)
Part I: (Ocean; DelSole, Tippett & Shukla, 2010)

1. Decadal Variability in unforced coupled models
2. Role of unforced decadal variability in global warming
3. Prospects for prediction of unforced decadal variability

Part II: (Land; Jia & DelSole, 2011, Jia, Ph.D. Thesis)

1. Predictable components of Land Surface Air Temp. (SAT)
2. Role of oceans in predictability over land
3. Forced and unforced predictable components of land SAT
Recent Papers (Decadal Predictability)

A significant Component of Unforced Multidecadal Variability in Twentieth Century Global Warming
Timothy DelSole, Michael K. Tippett, Jagadish Shukla
(J. of Climate, 2011, pp. 909-926)

Diagnosis of Multi-year Predictability on Continental Scales
Liwei Jia and Timothy DelSole
(J. Climate, 2011, in press)

Robust Multi-Year Predictability on Continental Scales
Liwei Jia
(Ph.D. Thesis, George Mason University, 2011)
Global average temperature 1850-2009
Based on Brohan et al. 2006

Annual average and 95% confidence range
Smoothed annual average and 95% confidence range

Anomaly (°C) wrt 1961-90
Global-mean Surface Temperature

On the Time-Varying Trend in Global-Mean Surface Temperature by Huang, Wu, Wallace, Smoliak, Chen, Tucker

EEMD: Ensemble Empirical Mode Decomposition; MDV: Multi Decadal Variability

Figure 4: Reconstruction of the raw GST time series (brown lines) using ST only (red lines) and ST + MDV (green lines).
Fingerprinting Method

Separating Forced and Un-Forced Patterns

Fit observed annual average SST to

\[ T_{obs}(x, y, t) = a_{for}(t)T_{for}(x, y) + a_{imp}(t)T_{imp}(x, y) + w(x, y, t) \]

- **Observed**
- **Forced Response**
- **Internal Pattern**
- **Random Noise**

- Define spatial response to external forcing \( T_{for}(x, y) \).
- Define spatial structure of IMP \( T_{imp}(x, y) \).
- Define statistics of internal variability (from 'control runs').
- Fit equation using generalized least squares:

**Detection:** Test hypothesis \( a_{for}(t) = 0 \).

**Attribution:** Test hypothesis \( a_{for}(t) = \) predicted amplitude.
Question

Is the observed multi-decadal variability externally forced (GHGs, aerosols, solar, volcanic, etc.)?

Or

Is this variability internally forced (atmosphere-ocean-land-cryosphere interactions)?
Find components that maximize the ratio of variances:

- Discriminant analysis (Fisher 1938)
- Seasonal Predictability (Straus et al. 2003)
- Decadal Predictability (Venzke et al. 1999)
- Climate Change (Ting et al. 2009) *(No IPCC Control Runs)*

Response pattern to climate forcing estimated by finding the pattern that maximizes the ratio

\[
\frac{\text{variance in twentieth century runs}}{\text{variance in pre-industrial control runs}} = \frac{\sigma^2_{20c3m}}{\sigma^2_{picntrl}}
\]

If forced response is additive, \(\sigma^2_{20c3m} = \sigma^2_{picntrl} + \sigma^2_{\text{forced response}}\)
Forced-to-Unforced Discriminant from Control Runs
How to Define:

- **Forced Response Pattern**
  - Signal to noise EOF for 20th century IPCC runs

- **Internal (Unforced) Pattern**
  - New Approach: IPCC pre-industrial controls
How to Define Patterns of Multidecadal Variability/Predictability?

EOF? Optimizes variance, not time scale.
EMD? Ignores spatial correlations, hence is suboptimal.
SSA? Ignores spatial correlations, hence is suboptimal.
EEOF? Not specifically optimized for multidecadal predictability.

New approach: Average Predictability Time (APT)
Identifying Internal Multidecadal Patterns (IMP)

Find a pattern that maximizes APT (unlike EOF which maximizes variance).

Average Predictability Time (APT)

Average predictability can be characterized in a way that is independent of lead time by integrating the predictability metric, which always decreases with time. For example, the rate of decay is much slower and enhance the integral is much higher for decadal variation than seasonal variation.

(DelSole & Tippett, 2009, JAS)
Average Predictability Time (APT)

APT = integral of 2P over all lead times

\[ APT = 2 \int_{0}^{\infty} \left( \frac{\sigma_c^2 - \sigma_f^2}{\sigma_c^2} \right) d\tau \]
Optimize APT in Control Runs

- Use IPCC AR4 data set (also called CMIP3).
- Last 300 years of PICNTRL are used.
- Model grids interpolated onto HadSST2 grid.
- Only “well-observed” grid points in the model are analyzed.
- Annual averaged sea surface temperature.
- Each model’s climatology subtracted out.
- All runs pooled to compute “total EOF” and “total APT.”
- The “outliers” IAP, GISS-EH, GISS-ER were omitted.
- 14 models, effective time series length = 4200 years.
- 40 EOF truncation, 20-year maximum maximum lag for APT.
- No Detrending
- Null hypothesis: white noise when sampled every 2 years.
Leading Predictable Component (APT)
Internal Multi-decadal Pattern (IMP)

tos.ann.terp.glo apt(5.92yr) Mode-1 (40EOFs; 300yrs; 20yr Lag)
Leading Predictable Component (APT): Internal Multi-decadal Pattern (IMP)
Separating Forced and Un-Forced Patterns

Fingerprinting Method

Fit observed annual average SST to

\[ T_{obs}(x, y, t) = a_{for}(t) T_{for}(x, y) + a_{imp}(t) T_{imp}(x, y) + w(x, y, t) \]

- Define spatial response to external forcing \( T_{for}(x, y) \).
- Define spatial structure of IMP \( T_{imp}(x, y) \).
- Define statistics of internal variability (from 'control runs').
- Fit equation using generalized least squares:

  **Detection:** Test hypothesis \( a_{for}(t) = 0 \).

  **Attribution:** Test hypothesis \( a_{for}(t) = \) predicted amplitude.
Internal Multi-decadal Pattern (IMP)

shaded area: 66% confidence interval of IMP in observations.

red line: Observed Atlantic Multidecadal Oscillation (AMO) index.
Separating Forced and Un-Forced Patterns
Fingerprinting Method

Fit observed annual average SST to

$$T_{\text{obs}}(x, y, t) = a_{\text{for}}(t) T_{\text{for}}(x, y) + a_{\text{imp}}(t) T_{\text{imp}}(x, y) + w(x, y, t)$$

- Defined spatial response to external forcing $T_{\text{for}}(x, y)$.
- Define spatial structure of IMP $T_{\text{imp}}(x, y)$.
- Define statistics of internal variability (from 'control runs').
- Fit equation using generalized least squares:

Detection: Test hypothesis $a_{\text{for}}(t) = 0$.
Attribution: Test hypothesis $a_{\text{for}}(t) =$ predicted amplitude.
Forced Pattern

**shaded area:** 95% confidence interval of forced pattern in observations.

**blue line:** Ensemble mean amplitude of forced pattern in models
Amplitude of Forced and Unforced Patterns

Signal-to-Noise-EOF of IPCC Models
Twentieth Century Forced Runs

- **Shading:** $\pm \sigma$ Fingerprint Amplitude
- **Blue Solid Line:** Signal-to-noise PC
- **Blue Dashed Line:** Major Volcanic eruptions

Internal Multidecadal Pattern (IMP)

- **Shading:** $\pm \sigma$ Fingerprint Amplitude
- **Blue Solid Line:** AMO Index
Leading Predictable Component (APT): Internal Multi-decadal Pattern (IMP)
Scientific Basis for Decadal Predictability

Squared Autocorrelation of Predictable Component –1

- rho-squared
- Time Lag (years)

Legend:
- cccma_cgcm3_1
- cccma_cgcm3_1_t63
- cnrm_cm3
- csiro_mk3_0
- csiro_mk3_5
- gfdl_cm2_0
- gfdl_cm2_1
- inmcm3_0
- ipsl_cm4
- miroc3_2_medres
- miub_echo_g
- mri_cgcm2_3_2a
- ncar_ocsm3_0
- ukmo_hadcm3
- Multimodel
Scientific Basis for Decadal Predictability

- **Slowly varying climate components**

- **Atmosphere-ocean interactions** (Pohlmann et al., 2006; Stouffer et al., 2006, 2007; Latif and Barnett, 1996; Held et al., 2005; Knight et al., 2006; Zhang and Delworth, 2006).

- **Decadal predictability in oceans** (Griffies and Bryan, 1997; Collins and Sinha, 2003; Collins et al., 2006, Msadek et al., 2010, DelSole et al., 2010).

- **Potential predictability of temperature, precipitation, sea level pressure** (Collins, 2002; Boer, 2004; Boer and Lambert2008; Pohlmann et al., 2004, 2006, Smith et al., 2007; Keenlyside et al., 2008).

- **Predictable external forcing** (Hegerl et al., 2007).
Example of Unforced Predictability Study

Percent of potential predictable variance of 5-yr


Little to no predictability over land!
Limitations of Previous Studies

- Univariate (noise dominates on grid scales).
- No decomposition in terms of distinct spatial patterns with associated time series.
- Mixed predictable patterns, thus is hard to interpret physically.
- Time averaging (e.g., 5- or 10-yr means).
Regression coefficients between the leading component of SST and SAT (K per unit predictable component) and precipitation (mm/day per unit predictable component).
Interim Summary

1. Land surface temperature and precipitation over continents have no correlation with the most predictable global optimized SST pattern.

2. Land surface temperature and precipitation have no intrinsic predictability of their own.

3. Question: Does optimized regression between global SST and land surface temperature produce predictable patterns?
Predictability over Land in IPCC Pre-Industrial Control Runs (SST effect)
Measures of Predictability

- Signal-to-noise ratio
- Mean square error
- Correlation between ensemble members
- Multiple correlation
- Autocorrelation

These measures are fundamentally equivalent to STR.

signal-to-total ratio (STR):

\[
\frac{\text{var}(E[y_{t+\tau} | y_t])}{\text{var}(y_{t+\tau})}
\]
Average Predictability Time (APT)

\[ APT = 2 \int_{0}^{\infty} STR(\tau) d\tau \]

For discrete time:

\[ APT = 2 \sum_{\tau=1}^{\infty} STR(\tau) \Delta \tau \]
Derive APT with One Ensemble Member

- Project data on the first few principal components.
- Construct a linear regression model.

\[ y(t + \tau) = L_{\tau}y(t) + \varepsilon(t) \]

- Derive signal variance \( \text{var}(E[y_{t+\tau} | y_t]) \) and total variance \( \text{var}(y_{t+\tau}) \).
Time Scales of Predictability

- Weather
- Seasonal
- Multi-year
- Decadal

Graph showing the STR (Lead time) over time (days) for different time scales.
Model Data

- Output of CMIP3 pre-industrial control runs with fixed external forcing from multiple models.
- Reject models based on outliers in trends and variances.
- Model grids are interpolated into common grid (72 x 36).
- Last 300 years of annual mean SAT, precipitation, SST.
  - SAT: surface air temperature
  - SST: sea surface temperature
- Selected model runs are pooled to create a multi-model data. This gives robust results.
- 30 PCs, 20-year time lags.
## Selected Models

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Institute/Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. GFDL-CM2.0</td>
<td>(GFDL, USA)</td>
</tr>
<tr>
<td>2. GFDL-CM2.1</td>
<td>(GFDL, USA)</td>
</tr>
<tr>
<td>3. IPSL-CM4</td>
<td>(France)</td>
</tr>
<tr>
<td>4. MIROC3.2(medres)</td>
<td>(Japan)</td>
</tr>
<tr>
<td>5. ECHO-G</td>
<td>(Germany/Korea)</td>
</tr>
<tr>
<td>6. MRI-CGCM2.3.2</td>
<td>(Japan)</td>
</tr>
<tr>
<td>7. CCSM3</td>
<td>(NCAR, USA)</td>
</tr>
<tr>
<td>8. UKMO-HadCM3</td>
<td>(UK)</td>
</tr>
</tbody>
</table>
Revised Regression Model for APT

Old: \[ y(t + \tau) = L\tau y(t) + \varepsilon(t) \]

Revised: \[ y(t + \tau) = L\tau x(t) + \varepsilon(t) \]

- \( x = \text{SST} \)
- \( y = \text{land temperature or precipitation} \)

Data:
- First half (150 yrs) data are **training data**
- Second half (150 yrs) are **verification data**
- 30 PCs, 20-year time lags
Domain of Six Continents

NA  |  Europe  |  Asia
SA  |  Africa  |  Australia
APT Values of Land Temperature

Graphs showing APT values for different land regions:
- NA (North America)
- Asia
- SA (South America)
- Africa
- Europe
- Australia
Pattern of the Leading Component
Time Lagged $R^2$

- $R$ is correlation between $y$ and the best linear prediction of $y$.
- $R^2$ is the fraction of variance explained by predictors.
- $R^2$ is the signal to total ratio for a linear prediction of $y$.
- If $R^2$ is insignificant, $y$ is statistically unpredictable.
a) APT values.

b) Pattern of the leading component.

c) $R^2$ in independent data.
Unforced Leading Predictable Pattern

a) APT values. 
b) Pattern of the leading component. 
c) $R^2$ in independent data.
Lagged Correlation Between SST & PC 1 of SAT
APT Values of Land Precipitation

NA Asia

SA Africa

Europe

Australia
Patterns of Prc1 for Land Precipitation
$R^2$ of Precipitation in Independent Data
Lagged Correlation Between SST & PrC1

SST lead 2 years

SST lead 1 year

SST lead 0 year
Lagged Correlation Between SST & PrC 1

SST lead 2 years

SST lead 1 year

SST lead 0 year
Summary of Unforced Predictability (1)

Identified unforced predictable components of land surface temp. (SAT) and precip. using a optimization method.

- SAT is predictable for 3-6 years.
- Precipitation is predictable for 1-3 years.

- Since it is **optimized**, it is difficult to find additional predictability
- Is there a scientific basis for multi-decadal prediction of unforced variability over land?
Summary of Unforced Predictability (2)

- Predictability of land SAT arises from ENSO and persistent SST near the land region.
- Predictability of precipitation arises from ENSO.

- Virtually all land predictability can be explained by SST.
- Realistic ENSO simulation is required for prediction over continents.
Identification of Forced Predictability over Land

(IPCC runs with 20th century forcings)
Model Data

- Output of CMIP3 20th-century runs and control runs.
  - 20th-century runs initialized from a point in control runs and forced by historic natural and anthropogenic forcing
- The same 8 models as in APT analysis.
- Maximum 5 ensemble members in each model.
- Pooled ensembles to create a multi-model data.
- Multi-model annual mean SAT and precipitation.
- 30 PCs.
Discriminant Analysis

- Variance of 20th-century runs: \( \sigma_{20C}^2 = \sigma_U^2 + \sigma_F^2 \)

- Variance of control runs: \( \sigma_{\text{control}}^2 = \sigma_U^2 \)

\[
\phi = \frac{\sigma_{20C}^2}{\sigma_{\text{control}}^2} = \frac{\sigma_U^2 + \sigma_F^2}{\sigma_U^2} = 1 + \frac{\sigma_F^2}{\sigma_U^2}
\]

The larger the ratio, the more forced response.
Variance Ratio of Land SAT
Pattern of the Forced PrC1 of SAT
a) Pattern of the “forced” predictable component in the 20th century runs.
b) Pattern of the leading “unforced” component in control runs.
c) Variance ratio between “forced” and “unforced” runs.
a) Pattern of the “forced” predictable component in the 20th century runs.
b) Pattern of the leading “unforced” component in control runs.
c) Variance ratio between “forced” and “unforced” runs.
Variance Ratio of Precipitation over Land
Summary of Forced Predictability

- Maximizing ratio of forced to internal variability produces only one forced pattern in continental surface air temperature (SAT).
- It is not possible to attribute changes in annual mean SAT to different forcings.
- Forced and unforced patterns are similar.
- No significant forced pattern in land precipitation.
  (Possibly contradicts previous studies)
Limitations

- Results may depend on selected models
- Miss “nonlinear” predictability
- Space-only patterns
- Missing values in observations
Summary

• Identified unforced predictable components of surface air temperature (SAT) and precipitation on continental scales forced by SST. (Land SAT: 3-6 yrs; Precip.: 1-3 yrs)

• Identified forced predictable components of land surface air temperature (SAT).

• No forced predictable components for Precip.

• The forced response of annual mean SAT could not be clearly detected in observation.
THANK YOU!

ANY QUESTIONS?