Multi-year Predictability of Temperature and Precipitation Over Land

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NTU, Taiwan, 2012
Predictability of Land Surface Temperature

Guo, Dirmeyer and DelSole, *GRL*, 2012
Predictability of Land Surface Temperature

Can we find components over land that are predictable beyond seasons?

Guo, Dirmeyer and DelSole, GRL, 2012
Observed Land Surface Temperature Change

Global land-surface temperature anomalies, relative to 1961-1990 mean (IPCC AR4).
Previous Studies on Predictability

- Decadal predictability over oceans (Boer, 2004; Pohlmann et al., 2004; Collins et al., 2006, DelSole et al., 2011).

- Multi-year predictability over land on continental scales (Jia and DelSole, 2011).

Assess land predictability in new CMIP5 dataset.
Illustration of Unforced Predictability

\[ \text{var}(y_{t+} | x_t) \]

\[ \text{var}(E[y_{t+} | x_t]) \]

\[ \text{var}(y_{t+}) \]
Average Predictability Time

Measure of predictability:  

\[ STR(t) = \frac{\text{var}(E[y_{t+} | x_t])}{\text{var}(y_{t+})} \]

\[ APT = 2 \int_0^\infty STR(t) \, dt \]

DelSole and Tippett, *J. Atmos. Sci.*, 2009
Maximizing APT

• We seek a linear combination of variables that maximizes APT

\[ 2 \sum_{0}^{\text{signal}} q = \text{total} \]

• Eigenvalues give the APT values.
• Time series of a single component is \( q^T y \)
• Regression pattern of a component is \( p = \text{total} q \)
• Yields a complete, uncorrelated set of components, ordered by their contribution to APT.
Derive APT with One Ensemble Member

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

\[ y(t + t) = L x(t) + e(t) \]

- Derive multiple correlation for each component from regression model.

\[ APT = 2 \int_{0}^{\infty} R^2(t) \, dt \]
Model Data

- CMIP5 pre-industrial control runs with fixed external forcing.
- Reject model outliers in trends and variances.
- 10 models were selected.
- Model grids are interpolated to common grid (72 x 36).

- Last 300 years of annual mean temperature, precipitation.
- First 150 years as training, the second 150 years as verification.
- Selected model runs are pooled to create a multi-model data of 1500 years for training and verification separately.
- 20 PCs, 20-year time lags.
Most Predictable Component of SAT

Jia and DelSole, GRL, 2012
Predictable Components of SAT over Land

a) Component 1, APT = 2.18 years

b) Component 2, APT = 1.58 years

c) 

\[ R^2 \]

Time Lag (years)

- CanESM2
- MPI-ESM-LR
- CSIRO-Mk3.6.0
- MIROC-CCSM3
- IPSL-CM5A-LR
- IPSL-CM5A-MR
- NorESM1-M
- HadGEM2-ES
- GFDL-ESM2M

d) 

\[ R^2 \]

Time Lag (years)
Correlation of SAT over Oceans with Predictable Components

Ocean leads 3 yrs

Ocean leads 1 yr

Correlation map showing SAT over oceans with different lead times.
Correlation of SAT over Oceans with Predictable Components

Ocean leads 3 yrs

Ocean leads 1 yr
Predictable Components of Land Precipitation

(a) Component 1, APT = 1.54 years

(b) Component 2, APT = 0.874 years

(c) $R^2$ vs. Time Lag (years)

(d) $R^2$ vs. Time Lag (years)
Correlation of SAT over Oceans with Predictable Components

Ocean leads 2 yrs

Ocean leads 0 yr
Correlation of SAT over Oceans with Predictable Components

Ocean leads 2 yrs

Ocean leads 0 yr
Summary

• Explicitly identified space-time structure of predictable temperature and precipitation over land on multi-year scales.

• The leading 2 components of land temperature are predictable for 2-20 years depending on model.

• Predictability of land temperature arises from the persistence of temperature over oceans and ENSO.

• The leading 2 components of land precipitation are predictable for 2-4 years, and are correlated with ENSO.
Sensitivity of Predictability to Models
<table>
<thead>
<tr>
<th>Model</th>
<th>Institution</th>
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</thead>
<tbody>
<tr>
<td>CanESM2</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
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<tr>
<td>CSIRO-Mk3.6.0</td>
<td>Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queensland Climate Change Centre of Excellence (Australia)</td>
</tr>
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<td>IPSL-CM5A-LR</td>
<td>Institut Pierre-Simon Laplace (France)</td>
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<tr>
<td>IPSL-CM5A-MR</td>
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<td>HadGEM2-ES</td>
<td>Met Office Hadley Centre (UK)</td>
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<td>MPI-ESM-LR</td>
<td>Max Planck Institute for Meteorology (MPI-M) (Germany)</td>
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<td>MRI-CGCM3</td>
<td>Meteorological Research Institute (Japan)</td>
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<tr>
<td>CCSM4</td>
<td>National Center for Atmospheric Research (USA)</td>
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<tr>
<td>NorESM1-M</td>
<td>Norwegian Climate Centre</td>
</tr>
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<td>GFDL-ESM2M</td>
<td>Geophysical Fluid Dynamics Laboratory (USA)</td>
</tr>
</tbody>
</table>
Drivers for Multi-year variability

• Internal dynamics of climate system (e.g., air-sea interactions, slowly-varying climate components).
  - unforced predictability

• External forcing (e.g. CO2, volcano).
  - forced predictability
Correlation of SAT over Oceans with Predictable Components

Ocean leads 3 yrs  Ocean leads 2 yrs  Ocean leads 1 yr  Ocean leads 0 yr
Correlation of SAT over Oceans with Predictable Components

Ocean leads 3 yrs  Ocean leads 2 yrs  Ocean leads 1 yr  Ocean leads 0 yr