Seasonal to Decadal Prediction

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Seasonal to Decadal Prediction

• **Recent Seasonal Predictability and Prediction Assessments**
  – Current Forecast Capability (ENSO, Global $T_{2m}$, P)
  – Maximum Predictability Not Achieved

• **Improving Prediction Quality**
  – Untapped Sources of Predictability
  – Improving the building blocks of forecast systems

• **Decadal: Prediction and Predictability**

• **Lessons Learned Outstanding Issues**
1st WCRP Seasonal Prediction Workshop

Kirtman and Pirani (2009)

Assessment of Intraseasonal to Interannual Climate Prediction and Predictability

US National Academies

Maximum Predictability has Not been Achieved

http://www.nap.edu/catalog.php?record_id=12878
Predictability - “The extent to which a process contributes to prediction quality”

Many sources of predictability remain to be fully exploited by ISI forecast systems

- Land Interactions (e.g., Soil Moisture, Snow Cover; Vegetation changes)
- Sea-Ice Interactions (i.e., atmosphere-ice; ocean-ice)
- Troposphere-Stratosphere Interactions
- Sub-Seasonal Variability (e.g., MJO)
Improving Forecast System
Building Blocks

• Sustaining and Enhancing Observing Systems

• Improving Data Assimilation Systems (component wise and the coupled system)

• Quantifying Sources of Uncertainty

• Reducing Model Errors
ENSO Prediction: Current Status

- Observations by TAO/TRITON have been critical to progress in understanding and simulation.
- Dynamical models are competitive with statistical models.
- MME mean outperforms individual models
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Seasonal Forecast ROC Scores for $T_{2m}$ and Precipitation

ROC scores for tercile categories Jan/Feb/Mar/: Issued Oct. above-normal 2m temperature

ROC scores for tercile categories Jan/Feb/Mar/: Issued October above-normal precipitation

below-normal 2m temperature

below-normal precipitation
Multi-Model vs. Single Model

Results collected over:
- all regions
- all start dates
- all lead times

MM wins: 1778 (99.2%)
SM wins: 14 (0.8%)

Events:
- ▼ <-0.43 sigma
- ▲ < 0
- △ > 0
- □ > +0.43 sigma

CERFACS: MM/SM wins: 255 / 1
INGV: MM/SM wins: 254 / 2
LODYC: MM/SM wins: 253 / 3
MPI: MM/SM wins: 253 / 3
CNRM: MM/SM wins: 255 / 1
UKMO: MM/SM wins: 255 / 1
ECMWF: MM/SM wins: 253 / 3

2m Temperature, RPSS over Northern Extratropics
Forecast start month and years: May / 1987-1999
Average over 4-6 months FC (ASO)

Large Ensemble vs. Multi-Model
### Brier Skill Score for Lower/Upper tercile (1980-2001)

#### Temperature and Precipitation

<table>
<thead>
<tr>
<th>Region</th>
<th>2m Temperature</th>
<th>Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>JJA</td>
<td>DJF</td>
</tr>
<tr>
<td></td>
<td>$E_T^*(x)$</td>
<td>$E_T^{+}(x)$</td>
</tr>
<tr>
<td></td>
<td>$E_T^*(x)$</td>
<td>$E_T^{+}(x)$</td>
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<tr>
<td>Australia</td>
<td>10.7</td>
<td>10.1</td>
</tr>
<tr>
<td>Amazon Basin</td>
<td>14.4</td>
<td>9.1</td>
</tr>
<tr>
<td>Southern South America</td>
<td>8.5</td>
<td>8.2</td>
</tr>
<tr>
<td>Central America</td>
<td>12.1</td>
<td>9.9</td>
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<tr>
<td>Western North America</td>
<td>6.5</td>
<td>7.7</td>
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<tr>
<td>Central North America</td>
<td>-4.1</td>
<td>-3.6</td>
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<tr>
<td>Eastern North America</td>
<td>0.6</td>
<td>5.7</td>
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<tr>
<td>Alaska</td>
<td>3.0</td>
<td>2.1</td>
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<tr>
<td>Greenland</td>
<td>3.6</td>
<td>4.2</td>
</tr>
<tr>
<td>Mediterranean Basin</td>
<td>7.6</td>
<td>10.7</td>
</tr>
<tr>
<td>Northern Europe</td>
<td>-4.4</td>
<td>-4.2</td>
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<tr>
<td>Western Africa</td>
<td>10.4</td>
<td>11.8</td>
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<tr>
<td>Eastern Africa</td>
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<tr>
<td>Southern Africa</td>
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<tr>
<td>Sahara</td>
<td>7.6</td>
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<td>Southeast Asia</td>
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<tr>
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<td>13.1</td>
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<tr>
<td>Central Asia</td>
<td>0.8</td>
<td>3.8</td>
</tr>
<tr>
<td>Tibet</td>
<td>10.7</td>
<td>10.1</td>
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Climate Historical Forecast Project (CHFP)

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- Sub-Seasonal Variability (e.g., MJO)
- Initialization is a challenge due to spatial and temporal heterogeneity in soil moisture

- Procedures for measuring of land-atmosphere coupling strength are still being developed

- Land Data Assimilation Systems (LDAS) coupled with satellite observations could contribute to initialization

- Further evaluation and intercomparison of models are necessary
Conclusions of First GLACE-2 Analysis

1. Almost all of the expected GLACE-2 submissions are in.

2. The individual models vary in their ability to extract forecast skill from land initialization (not shown). In general,
   -- Low skill for precipitation
   -- Moderate skill (in places) for temperature, even out to two months.

3. Land initialization impacts on skill increase dramatically when conditioned on the size of the initial local soil moisture anomaly.

   If you know the local soil moisture anomaly at time 0 is large, you can expect (in places) that initializing the land correctly will improve your temperature forecast significantly, and your precipitation forecast slightly, even out to 2 months.

4. The results highlight the potential usefulness of improved observational networks for prediction.
Additional Predictability Likely Associated with Stratospheric Dynamics

Stratosphere resolving HFP

Goal: Quantifying Skill Gained Initializing and Resolving Stratosphere in Seasonal Forecast Systems

- Parallel hindcasts from stratosphere resolving and non-resolving models
- Action from WGSIP-12: Endorse as subproject of CHFP
- SPARC to recommend diagnostics
Dynamical forecast

(Christiansen 2005)

Dynamical forecast + 70hPa stat fcast

(Christiansen 2005)

Surface wind at 60N

(Ineson and Scaife, 2009)

QBO teleconnection

(Marshall and Scaife 2009)

ENSO teleconnection

(Ineson and Scaife, 2009)
Links across WCRP

Explore Seasonal Predictability Associated with Sea-Ice

• Sea-Ice Initialization Experiment:
  • Follow CHFP Protocols for Other Components, Data
  • Initializing with observed Sea-Ice vs. Climatology
    • 1 May, 1 November 1996 and 2007
    • 8 Member Ensembles
• Spring snow melt into soil moisture and influence on spring temperature anomalies
Several areas of potential collaboration on intraseasonal time-scales:

- Investigate how much ocean-atmosphere coupling impacts skill
- Role of resolution on skill
- Multi-Scale interactions
- Ensemble techniques
- Intraseasonal Variability (e.g., MJO)
Forecasting of MJO is relatively new; many dynamical models still represent MJO poorly.
Improving Forecast System Building Blocks

• Sustaining and Enhancing Observing Systems

• Improving Data Assimilation Systems (component wise and the coupled system)

• Quantifying Sources of Uncertainty

• Reducing Model Errors
Bias Removed

Bias Included
Improvements to Building Blocks
Initializing the Coupled Modes of the Coupled Model
Coupled Data Assimilation

Nino34 SSTA Evolution

- CFS Control
- Initialized Coupled Modes
- GODAS
What do we need to do?

WCRP Priority Tasks (7)

Develop and test next generation climate models: First decadal climate prediction

Fundamentals: coupled climate model run including the oceans.

Smith et al., Science 10.08.2007
Potential predictability of temperature for 2010-20 (“next decade”)

- percentage of total variance over decade
  - associated with forced component
  - associated with internal variability
- $p_\Omega$ and $p_\nu$ tend to be inverses of one another so $p = p_\Omega + p_\nu$ is more uniform than either

Boer 2008
Predictability Estimate:
Forecast Spread as a Fraction of Saturation
Blue $\rightarrow$ High Predictability
Red $\rightarrow$ Low Predictability

One-year Lead

Four-year Lead
CMIP5 Experiment Design

“Near-Term”
(decadal)

prediction &
predictability

CORE
(initialized
ocean state)

TIER 1

“Long-Term”
(century & longer)

“realistic”
diagnostic

CORE

TIER 1

TIER 2
Decadal forecast results to 2015

ANN SCREEN TEMPERATURE GLOBAL (K)
annual means

- HadCRUT3
- 95% conf.int.
- ensemble mean
- +/-2 stand.dev.

Volcano forcing

CCCma
Global Trends:

Hindcasts
Observations
Uninitialized
Hindcast Annual Mean SSTA Correlation Coefficient

Lead-Time 8-years

Southern Tropics (30S-2S) Lead-Times 1-10 years
Exchange of Decadal Prediction Information

GFDL – Tony Rosati  MRI-JMA – Kimoto Masahide
SMHI – Klaus Wyser, Colin Jones  KNMI – Wilco Hazeleger
IC3 – Francisco Doblas-Reyes  MPI – Daniela Matei
RSMAS – Ben Kirtman  CCCMA-EC – George Boer
IfM-GEOMAR - Mojib Latif  CERFACS – Laurent Terray

Adam Scaife and Doug Smith
WGSIP July 2010
We plan to keep initial exchange very simple:

Global Annual Mean Temperature

One file for each year, each member

Exchanged once per year around October

Example diagnostics:
Lessons Learned

• One-Tier Systems have more Skill then 2-tier systems
• Probabilistic Problem
• Multi-Model Useful
• No-Cheating Testing of Prediction Systems
• Sample Size Issues
• Statistical and Dynamical Techniques are Complementary
Outstanding Issues

- **Quantifying Forecast Uncertainty Due to Uncertainty in Model Formulation**
  - Multi-Model Helps, but Ad-Hoc; Need Models of Model Error (e.g., Stochastic physics)

- **Quantifying Forecast Uncertainty Due to Uncertainty in Observational Estimates**
  - Initial Condition Problem

- **Model Error**
  - Need for International Coordinated Effort at Improving Models
    - Multi-Model is Not an Excuse for Neglecting Model Improvement; Resolution

- **Data Assimilation (Coupled Assimilation) and Forecast Initialization**

- **Sustained and Enhanced Observing Systems**

- **Climate System Component Interactions**
  - Coupled Ocean-Land-Ice-Atmosphere; External Forcing vs. Natural Variability

- **Quantifying the Limit of Predictability**
  - Identifying Sources and Mechanisms for Predictability
Rainfall: HRC, and LRC

Rainfall: Observational Estimate