Sources of predictability beyond the deterministic limit

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(with thanks to Franco Molteni)

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Outline

Persistent anomalies in the tropics and extra-tropics: examples from the last two decades

Beyond deterministic predictability in non-linear, chaotic systems: the role of variability in surface conditions and energy/water fluxes

Coupled ocean-atmosphere variability - predictability on the weekly/monthly time scale arising from sub-seasonal tropical variability and teleconnections

A look at sea ice and the impact on predictions
Oct-Dec 1997: floods in East Africa

Rift Valley Fever outbreak

FIG. 45. (a, b) Accumulated observed precipitation (solid curve) and accumulated climatological precipitation (1961–90 base period) (dashed curve) beginning 1 October 1997 and ending 1 January 1998 at (a) Mombasa, Kenya and (b) Meru, Kenya. (c, d) Daily precipitation totals during October 1997–1 January 1998 at (c) Mombasa, Kenya and (d) Meru, Kenya. Green shading in (a, b) indicates the difference between the observed and normal accumulated rainfall.
July 2002: drought in India

All-India Rainfall time series
May - October
Summer 2003: European heat-wave
Winter 2009-2010: cold anomaly over N. Europe

7 Jan 2010
What limits deterministic prediction?

1. Size of the initial condition error
2. Error growth rate
3. Saturation value of the error

- Explains the seasonal, regional and hemispheric variations in NWP skill.
  - Winter more predictable than summer
  - Mid-latitudes more predictable than tropics
Limits of predictability

RMS error of 500 hPa height field
Northern Hemisphere

Initial state error
Model error growth
How can we forecast on long timescales?

Ocean – Magdalena
Sea ice
Land Surface - Bart
  • Soil moisture
  • Vegetation
  • Snow
Stratosphere – Andrew
Atmospheric composition
Solar
Climate forecasts are not crucially sensitive to the initial conditions. They are a mixed initial-boundary condition (forcing) problem in a chaotic system.
Observations

Forecast models extended range predictions
(All ensemble forecasts at ECMWF)

Data Assimilation

Coupled model

Forecast Products

current state of the atmosphere

atmospheric model

current state of the ocean

ocean model

Data Assimilation

Coupled model

Forecast Products

Observations
Seasonal forecasts aim to predict an anomaly from the default climatological probability.

Probability density distributions of a hypothetical climatology and forecast given an observation.

“Ideal” situation

“Real” situation
Edward Lorenz  (1917–2008)

\[
\begin{align*}
\dot{X} &= -\sigma X + \sigma Y + f \\
\dot{Y} &= -XZ + rX - Y + f \\
\dot{Z} &= XY - bZ
\end{align*}
\]

What is the impact of \( f \) on the attractor?
Add external steady forcing $f$ to the Lorenz (1963) equations

The influence of $f$ on the state vector probability function is itself predictable.
Mechanical analogue of preferred atmospheric circulation states
Preferred atmospheric circulation states: role of the forcing
Which regions are most predictable?

Use models to estimate predictable signal by comparing ensemble spread and ensemble mean

Variability of Z 200hPa in DJF from seasonal ensembles

Standard deviation from 11-member ensembles, DJF 1981/2005
Teleconnections with ENSO

Correlation of 700hPa height with
a) PC1 of Eq. Pacific SST
c) SOI index

Schematic diagram of tropical-extratropical teleconnections during El Niño

Horel and Wallace 1981
ENSO impacts: rainfall and temperature
The Pacific /North American (PNA) pattern

500-hPa height composites from Wallace and Gutzler 1981
The Indian Ocean Dipole (or I.O. Zonal Mode)

Saji et al. (1999)
Webster et al. (1999)
The North Atlantic Oscillation

Walker and Bliss (1932)
Van Loon and Rogers (1978)
MJO teleconnections in October-March

500 hPa height, MJO phase 3 + 10 days

2002 MOFC hindcasts

2011 MOFC hindcasts

ERA Interim

from Vitart 2014
Sea ice: Interaction of climate change and natural variability

Record minimum in Arctic sea-ice extent: 16/9/2012 (from NSIDC)
Impacts of Sea Ice

• Energy Fluxes:
  – Changes albedo of the region – solar heating of upper ocean
  – Thickness of the sea ice alters the surface heat fluxes
    • Winter; biggest effect – no sun and air colder than ocean
    • Leads in the ice are important (Badgerley, 1966)

• Impact on waves
• Salinity fluxes:
  – Production of brine (freezing) and freshwater (melting)

Maykut (1978), JGR
Impacts on the ocean

Deep convection:

- More important on longer time scales

- Impact on the Gulf Stream and the Thermohaline circulation – part of the feedback on the Arctic system
Impacts on the atmosphere

- Surface air temperatures
- Cloud
- Storm tracks
- Precipitation
- Large scale variability – NAO – seasonal timescale predictions
Summer sea ice impacts – Case study 2012

- Ensemble mean MSLP differences between experiments:

  2012 sea ice - sea ice climatology

Reanalysis

SST 2012

SST Clim

July MSLP anomaly
Era Interim 2012 - climatology
Summer SST impacts – Case study 2012

- Ensemble mean MSLP differences between experiments:

2012 SST - SST climatology

Reanalysis
Sea ice clim
Sea ice 2012

July MSLP anomaly
Era Interim 2012 - climatology
Results Sea Ice Predictability – July 2012

July MSLP anomaly
Era Interim 2012 - climatology

SST2012

SeaIce2012

SST: 2012-climatology

sea ice: 2012-climatology
Headline scores comparing ERA-I with: CNTL (persisted – climate ice) and LIM2

Rank probability skill score

Z500

Weekly periods
Northern Extratropics
87.5:30.0-180.0:180.0

100 cases – The vertical bars represent the 95% level of confidence
Headline scores comparing ERA-I with CNTL (persisted – climate ice) and LIM2

Rank probability skill score

Surface Temperature

Weekly periods
Northern Extratropics
87.5:30.0:180.0:180.0
Note of caution about increasing complexity

Keeley et al (2012) QJRMS
Conclusions

Regional anomalies in atmospheric flow and weather parameters may persist on time scales longer than the deterministic predictability limit, and have substantial societal impacts. The possibility of performing probabilistic predictions of these events arises from the interaction of the atmospheric flow with slowly varying anomalies in surface conditions, which modify the energy and water sources for the atmosphere. We need to initialise and model the coupled processes important for the atmosphere.

In the extratropics, persistent anomalies can be generated by (linear) teleconnections with tropical variability (eg ENSO) but also from the alternation of different (non-linear) flow regimes. Ensemble prediction systems provide an estimate of long-range predictability based on the ratio of ensemble spread and ensemble-mean variability.

Predictability over Europe: limited by strong internal variability during winter (but with significant teleconnections on the sub-seasonal scale), higher in other seasons when internal variability is reduced.
References


ECMWF
Extra slides
Prediction of tropical SST anomalies in Sys4

Nino3.4 DJF

IOD SON

cov (nino34, gh500)

cov (iod, gh500)
Prediction of tropical rainfall in Sys4: East Africa (SON)
Prediction of 2-m temperature in Sys4: Europe (DJF, JJA)
Prediction of 2-m temperature in Sys4: Europe (MAM)
Predictability varies with spatial and time scales

<table>
<thead>
<tr>
<th>Temperature 850 hPa</th>
<th>40-minute average</th>
<th>2-day average</th>
<th>8-day average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NH</td>
<td>SH</td>
<td>TR</td>
</tr>
<tr>
<td>T120 (170 km)</td>
<td>23.0</td>
<td>16.5</td>
<td>22.0</td>
</tr>
<tr>
<td>T30 (680 km)</td>
<td>24.0</td>
<td>17.0</td>
<td>23.0</td>
</tr>
<tr>
<td>T7 (3,000 km)</td>
<td>&gt; 32.0</td>
<td>23.0</td>
<td>26.5</td>
</tr>
</tbody>
</table>

Table 1 Forecast skill horizons for the probabilistic prediction of 850 hPa temperature over the northern hemisphere (NH), the southern hemisphere (SH) and the tropics (TR), for fields with increasingly larger spatial scales (T120, T30 and T7 spectral triangular truncation) and longer time averages (40-minute, 2-day and 8-day averages). The ‘greater than’ symbol (>) indicates that the forecast skill horizon is larger than the last time step that could be verified (i.e. 32 days for 40-minute average forecasts, 31 days for 2-day average forecasts and 28 days for 8-day average forecasts).