Predictability and Extremes

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Prediction on climate time scales

Progression from initial-value problems with weather forecasting at one end and multi-decadal to century projections as a forced boundary condition problem at the other, with climate prediction (sub-seasonal, seasonal and decadal) in the middle. Prediction involves initialization and systematic comparison with a simultaneous reference.

Adapted from Meehl et al. (2009)
Extremes in climate predictions

- Aim to predict statistics of unusual (not necessarily rare) events at specific, relatively short periods (e.g. number of tropical cyclones over a season), not the specific timing of the individual events.
- Traditionally, events are defined for small $p$, but not for $p \ll$. Sample sizes are small ($N \approx 30$), as are ensemble sizes ($M \approx 10-50$), and $p \approx 0.05-0.25$. Hence, no use of EVT from this point on.
- Examples: number of tropical cyclones, number of days a variable is above a given percentile, a percentile of a variable over a given period (a month, a season, etc).
- However, adequate use of the EVT might lead to interesting results for predictions of extreme events (although with large confidence intervals).
Extremes in climate predictions

- A fundamental aspect is the need to verify the forecasts, (verify events that actually occurred).
- However, measures of forecast quality typically degenerate to trivial values as the rarity of the predicted event increases. Alternatives are the “extremal dependence index”.

<table>
<thead>
<tr>
<th></th>
<th>Event observed</th>
<th>Nonevent observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Event forecast</td>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td></td>
<td>a+b</td>
<td></td>
</tr>
<tr>
<td>Nonevent forecast</td>
<td>c</td>
<td>d</td>
</tr>
<tr>
<td></td>
<td>c+d</td>
<td></td>
</tr>
<tr>
<td></td>
<td>a+c=pn</td>
<td>b+d=(1-p)n</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td></td>
</tr>
</tbody>
</table>

\[ H = \frac{a}{a+c} \text{ dashed, } F = \frac{b}{b+d} \text{ dotted, } OR = \frac{ad}{bc} \text{ solid } \]

Ferro and Stephenson (2011)
Seasonal forecasting

2014 ENSO predictions: July start date

Mid-Jul 2014 Plume of Model ENSO Predictions

IRI/CPC

- DYN AVG
- STAT AVG
- CPC CON

Dynamical Model:
- NCEP CFSv2
- NASA GMAO
- JMA
- SCRIPPS
- LDEO
- AUS/POAMA
- ECMWF
- UKMO
- KMA SNU
- ESSIC ICM
- CCLC CSM3
- MetFRANCE
- CS-IRI-VM
- GFDD CM2.1
- CMC CAN/PI
- GFDD CM2.5

Statistical Model:
- CPC MKOV
- CDC LIM
- CPC GA
- CPC CCA
- CSU CLIPR
- UBC NMET
- FSU REG
- UCLA-TCD
- UAH/CJC

Mid-Jul IRI/CPC Plume-Based Probabilistic ENSO Forecast

ENSO state based on NIN03.4 SST Anomaly
- Neutral ENSO: -0.5°C to 0.5°C

Probability (%)

Climate Probability:
- El Nino
- Neutral
- La Nina

Historical NINO3.4 Sea Surface Temperature Anomaly

WCRP-ICTP School on Attribution and Prediction of Extreme Events

Predictability and extremes

25 July 2014
Seasonal forecasting

2014 ECMWF System 4 temperature JJA seasonal forecast with May start date: upper quintile category.

ECMWF Seasonal Forecast
Prob(highest 20% of climatology) - 2m temperature
Forecast start reference is 01/05/14
Ensemble size = 51, climate size = 450

System 4
JJA 2014
Seasonal forecasting

2014 ECMWF System 4 hurricane or typhoon frequency seasonal forecast with July start date.

ECMWF Seasonal Forecast
Hurricane or typhoon Frequency
Forecast start reference is 01/07/2014
Ensemble size = 51, climate size = 300

System 4
ASONDJ 2014/15
Climate (initial dates) = 1990-2009

Not Significant
Significant at 5%
Seasonal forecasting

2014 ECMWF System 4 Niño3.4 seasonal forecast with May start date.
ECMWF forecasts (D+42) for the storm Lothar

<table>
<thead>
<tr>
<th>Deterministic prediction</th>
<th>Verification</th>
<th>Ensemble forecast (D+42)</th>
</tr>
</thead>
</table>

With a large enough ensemble size, the very rare event can be forecast with a probability of 9/50, i.e. ~20%
From ensembles to probability forecasts

Constructing a probability forecast from a nine-member ensemble

A threshold relative to the model climate (e.g. percentile)
From ensembles to probability forecasts

Constructing a probability forecast from a nine-member ensemble

A threshold relative to the model climate (e.g. percentile)
Systematic error: climatological pdf

Climatological PDF of DJF T2m (°C) for ERA-40/OPS and ECMWF System 3 computed over the period 1960-2005

For deterministic forecasts, compute anomalies with respect to the corresponding mean

For probabilistic forecasts, compute probabilities with respect to hindcast and reference thresholds (terciles)

Central Europe (50°N, 10°E)  
Equatorial Pacific (0, 180°)
Forecast quality for unusual events

Rank correlation of number of days maximum/minimum temperature is above/below the 90%/10% climatological percentile for the GloSea4 seasonal hindcasts over 1989-2009 (reference HadGHCND) using percentiles estimates from (left) daily data, (right) seasonal averages and (bottom) their difference. All seasons confounded. Dots for statistically significant correlations and differences (alpha=0.05).

Hamilton et al. (2012)
Composite precipitation differences (La Niña minus El Niño) based on years which observed seasonal mean Nino3.4 exceeds ±1 standard deviation over 1982-2009, from GPCP observations (left) and the CHFP ensemble at 1-month lead time (right), for JJA (top) and DJF (bottom).

Kirtman et al. (in prep.)
Forecast quality for unusual events

Anomaly correlation for 2-metre temperature CFSv2 forecasts as a function of lead time and target month for all (left) and extreme (right, 95th percentile) monthly mean anomalies with (bottom) and without (top) cross-validation in the calculation of the climatology.

Becker et al. (2013)
Forecast quality for unusual events

ROC area for near-surface temperature MAM (1-month lead time) predictions with ECMWF ENSEMBLES wrt NCDCv3 over 1979-2005: 75th (left) and 90th (right) percentile thresholds.
Hurricane frequency prediction

Average number of hurricanes per year estimated from observations and from the CMIP5 multi-model decadal prediction ensemble (forecast years 1-5). The correlation of the ensemble mean for the initialized, uninitialized and statistical predictions are shown with the 95% confidence intervals.

Caron et al. (2014)
An application: soil moisture impact

Difference in the correlation of the ensemble-mean near-surface temperature from two experiments, one using a realistic and another a climatological land-surface initialisation. Results for EC-Earth2.3 started every May over 1979-2010 with ERAInt and ORAS4 initial conditions and a sea-ice reconstruction.

**Skill difference for mean T**

**Skill difference for T max**

C. Prodhomme (IC3)
An application: soil moisture impact

GLACE2 Series 1 and Series 2 skill. Correlation of the ensemble-mean for temperature from experiments with realistic (dashed) and climatological (solid) land-surface initialisation. EC-Earth2.3 started in May with initial conditions from ERAInt, ORAS4 and a sea-ice reconstruction over 1979-2010.

C. Prodhomme (IC3)
Model improvement and extreme prediction


Weisheimer et al. (2011)
Model improvement and extreme prediction

Seasonal prediction with improved ECMWF system (changes in radiation, soil scheme and convection) for summer 2003 with May start date. Anomalies wrt period 1991-2005.

2m temperature over Southern Europe (land)

Weisheimer et al. (2011)
SPECS FP7

SPECS will deliver a new generation of European climate forecast systems, including initialised Earth System Models (ESMs) and efficient regionalisation tools to produce quasi-operational and actionable local climate information over land at seasonal-to-decadal time scales with improved forecast quality and a focus on extreme climate events, and provide an enhanced communication protocol and services to satisfy the climate information needs of a wide range of public and private stakeholders.
Seasonal forecasts for malaria warning

Precipitation composites for the five years with the highest (top row) and lowest (bottom row) standardised malaria incidence for DJF DEMETER (left) and CMAP (right)

Quartiles define extreme events (outbreaks) for malaria prediction

Thomson et al. (2006)
Malaria warning with climate information

Probabilistic predictions of standardised malaria incidence quartile categories in Botswana with five months lead time

<table>
<thead>
<tr>
<th>ROC Score</th>
<th>Precipitation</th>
<th>Incidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Event</td>
<td>DEMETER</td>
<td>CMAP</td>
</tr>
<tr>
<td>Very low</td>
<td>0.95</td>
<td>1.00</td>
</tr>
<tr>
<td>Very high</td>
<td>0.52</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Available in March

Available in November

Very low malaria

Very high malaria
Communicating extreme predictions

**Alarm in Europe:** 2013’s summer predicted as the closest to 1816, the year without summer. Canal Météo used external sources.

Le Parisien, 28 May 2013

Canal Météo, 25 May 2013
Attribution: The 2012 sea-ice minimum

Spain + Portugal + France + Italy + Swiss + Germany + Netherlands + Belgium + Poland + Austria + Czech Republic + England + Scotland

Extent (Million km²)

- 1.5 x the area of Spain
- 7 million km²
- 3.61 million km²
- ±2 standard deviation

NSIDC

15 Sep 2012

25 July 2014
The 2012 sea-ice minimum

Arctic sea-ice area from calibrated NEMO-LIM simulations forced by ERAInt (left); NSIDC data in black and 5-member ensemble experiments in red. (Right) Attribution of the 2012 sea-ice minimum to several factors: the storm of 5-8 August (STORM), initial conditions (MEMORY), air temperature and humidity (WARM) and initial conditions and air temperature (M-W).

Guemas et al. (2013)
CMIP5 near-term projections: verification

Time series of global-mean decadal mean surface temperature anomalies (relative to preindustrial conditions) from CMIP3 experiments (black solid), after pattern scaling (black dashed) and observations (diamonds). Yellow diamonds for annual observations.

Allen et al. (2013)
CMIP5 simulations

Time series of global-mean annual mean surface air temperature anomalies (relative to 1986–2005) from CMIP5 simulations (yellow lines). An ensemble of forecasts of global annual mean temperature initialized in 1998 is plotted as thin purple lines (average, green line). The grey areas along the axis indicate the presence of external forcing associated with volcanoes.

IPCC AR5 WGI (2013)
The hope to predict

The sources of uncertainty include the internal variability, model differences and scenario spread. The internal variability is an uncertainty source particularly important for the near term that could be reduced, especially at regional scales.

IPCC AR5 WGI (2013)
Predictions and projections

Annual-mean global-mean temperature predictions and projections from CMIP5.

IPCC AR5 WGI (2013)
Attribution of the XXI\textsuperscript{st} century hiatus

Predictions of the recent global-temperature slow down with EC-Earth 2.3. Global-mean SST from observations (ERSST) and simulations, three-year averages. The experiments suggest an important role of the internal variability, especially increased capture of heat in the ocean, in the hiatus.

Guemas et al. (2013)
Attribution of the XXI\textsuperscript{st} century hiatus

Predictions of the recent global-temperature slow down with EC-Earth 2.3. OHC for the top 800 m ($10^9$ J, excluding the mixed layer) for the ORAS4 reanalysis and the initialised hindcasts, three-year average at the onset of the hiatus. The hiatus is associated with an increased ocean heat absorption, especially in the Pacific. This is captured by the Init experiment. ORAS4

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![Map showing ocean heat content for ORAS4 reanalysis and initialised hindcasts](attachment:image.png)