Decadal variability, predictability and prediction: progress, challenges and opportunities

Rowan Sutton, Ed Hawkins, Dan Hodson, Jon Robson
National Centre for Atmospheric Science (Climate division)
Department of Meteorology, University of Reading

Doug Smith
Met Office Hadley Centre
The potential to narrow uncertainty in decadal climate predictions

Model uncertainty and initialisation

Evaluation & a case study in decadal climate prediction

Optimal perturbations for decadal climate predictions

[Statistical decadal predictions]

[VALOR project on the exploitation of RAPID array observations for decadal predictions]
Sources of uncertainty in decadal climate predictions

Contributions estimated from the CMIP3 ensembles

Decadal mean surface air temperature

Hawkins & Sutton, 2009, 2010
Fraction of total variance explained by internal variability for predictions of the first decade ahead

Fraction of total variance explained by model uncertainty for predictions of the second decade ahead

Decadal mean surface air temperature

Hawkins & Sutton, BAMS, 2009
Sources of uncertainty in decadal climate predictions

Hawkins & Sutton, 2009, 2010
Signal-to-noise ratio for decadal predictions

Signal = change in decadal mean temperature relative to 1961-90
Noise = sqrt(total prediction variance)

Third decade ahead

- Signal-to-noise is consistently highest in tropics, and larger than 1 almost everywhere for all lead times
- Almost all regions show a maximum in signal-to-noise at a lead time of some decades

Hawkins & Sutton, 2009
Predictability of natural internal climate variability

Low resolution “perfect model” studies suggest predictability:

- up to a decade for large scale climate variables (heat content, salinity, AMOC)
- is state dependent (forecasts of opportunity)
- very rarely exceeds 2 years at most for surface climate variables over land (regional scales)

- So why are 30 year initialised hindcasts included in CMIP5?

- Need more work to understand mechanisms responsible for predictability, including state dependence + robustness e.g. at higher resolution.
Model uncertainty also “infests” internal variability...

North Atlantic decadal variability in coupled GCMs

Evolution in the subspace of the leading 3D EOFs of T and S (after Hawkins & Sutton, 2007)

MPI  HadCM3  GFDL CM2.1
Model uncertainty: sensitivity to resolution

HiGEM (1/3° ocean)

1500-3000m density regressed on MOC @ 40N
Model uncertainty: sensitivity to resolution

HadGEM (1° ocean)

Kg/m³/Sv

1500-3000m density regressed on MOC @ 40N
The potential to narrow uncertainty in decadal climate predictions

- Uncertainty in decadal predictions is dominated by internal variability and **model uncertainty**

- Both contributions are potentially reducible through progress in climate science, but there are fundamental (predictability) limits on the potential to narrow the uncertainty arising from internal variability

- **Reducing model uncertainty is the top priority**

- The economic value of reducing uncertainty in predictions is potentially very large (cheaper adaptation).

- *Initialisation of predictions* has important potential to contribute to understanding and reducing model uncertainty (as well as for predicting a fraction of natural variability).
Addressing model uncertainty ( & errors)

- Fundamental to increasing the value and trustworthiness of climate models and predictions
- CMIP-style ensembles of opportunity do not provide a reliable measure of model uncertainty
- Model consensus is not a reliable basis for trust

Need to build confidence that models capture all the relevant processes with sufficient accuracy:
- Testing models with observations, at a process level, is fundamental
Increasing the trustworthiness of climate models and predictions

A hierarchy of evidence:

1. Model consensus
   - Weak role for observations

2. Detection and attribution
   - Tests response to specific forcings; model errors may lead to false attribution

3. Initialised decadal hindcasts
   - Test full evolution of the system on timescale of the predictions we want to use
The role of Detection and Attribution in decadal climate prediction

- D&A is a key approach for testing consistency of models and observations (wrt response to radiative forcings)
- Can be used to provide observationally constrained decadal predictions
- Scope for wider application to oceans, especially using a more process-based approach

Detection & Attribution of Atlantic salinity changes, P. Stott, R. Sutton, D. Smith, GRL, 2008

(Allen et al, 2000)
Initialisation usually motivated by the need/opportunity to predict aspects of internal variability (e.g. AMO).

Arguably it will - in time - prove more important as a tool to address model uncertainty, by identifying errors.

Analysis of error growth provides a powerful new way to test models and prediction systems at a process level, and thereby improve them.

Long used in NWP; arguably the big opportunity in climate prediction.
Evaluation of decadal hindcasts

Smith et al, 2007

RMSE of 9-year mean anomalies
Impact of bias correction

Jon Robson
A case study in initialised decadal climate prediction

- Average skill scores of limited use for decadal prediction:
  - Short observational record
  - Non-stationarity of the observing system
  - Non-stationarity of the climate
  - State dependent predictability

- Case studies offer an alternative / complementary focus for testing (& improving) the performance of a decadal prediction system

- Of particular interest is potential to predict the unexpected …
Rapid warming of the North Atlantic in the mid 1990s: a case study in decadal climate prediction

Subpolar gyre 500m heat content

Jon Robson, Doug Smith
What is the cause of the problem?

Anomaly assimilation method is based around a model climatology

Hypotheses (focussing on initialisation)

1. Problem with the model climatology
2. Errors in assimilated density anomalies arising from non-linearities in the equation of state

\[ \begin{array}{c} \mathbf{x}' = \mathbf{x} \left( \overline{T} + T', \overline{S} + S', P \right) \end{array} \]
The effect of correcting density errors

Subpolar gyre 0-500m
Temp

Observations

Unperturbed

Perturbed salinity

2nd year SST forecast difference control – perturbed Salinity.

Control – Perturbed Salinity
overturning stream function

Nortward HEAT Transport diff between control and pert S
Conclusions:

- Anomaly assimilation approach is subject to errors arising from non-linearities, e.g. in the equation of state
- Results can also be sensitive to the model climatology
- Case study approach valuable way to test a decadal prediction system
Optimal perturbations for decadal predictions

- forecast perturbations which grow most rapidly, averaged over weather ‘noise’, for a specified lead time.

**Motivation:**
- identifying & understanding the processes that limit predictability
- identifying regions where *additional* observations would be most valuable to improve predictions
- efficient design of ensembles
We have been using two different methods:

1. Linear Inverse Modelling (LIM)  
   e.g. Penland & Sardeshmukh 1995  
   • computationally inexpensive  
   • initial condition independent  
   • multi-model analysis underway as part of EU THOR project  
     (Hawkins & Sutton, J. Climate, 2009)

2. Climatic Singular Vectors (CSVs)  
   e.g. Kleeman et al. 2003  
   • expensive to estimate  
   • calculated for each initial condition separately  
   • just HadCM3 considered so far  
     (Hawkins & Sutton, J. Climate, in press, 2010)
Linear Inverse Modelling:

- fit a statistical model to the evolution of the ocean state
- reduce dimensionality by representing ocean variability using leading 3d EOFs of T, S
- using control run data, and a focus on Atlantic/Arctic domain

\[
\frac{dy}{dt} = F(y) \quad \text{GCM:}
\]

\[
\frac{dx}{dt} = Bx + ! \quad \text{LIM:}
\]

\( y \) represents ocean data

\( x(t + !) = P_1 x(t) \)

\( x \) represents leading PCs

- From \( P \), the optimal perturbations can be found
Multi-model amplification
HadCM3 decadal amplification

Temperature

Year: 0

15 m: 3.1381
136 m: 5.6337
438 m: 3.7065
989 m: 2.2471
1486 m: 2.6761
2120 m: 0.7941
Growth profiles

Growth from shallow anomalies in subpolar gyre to deeper ocean in tropics

Hawkins & Sutton, J. Clim., 2009

HadCM3
Does the predicted amplification occur?

Projection onto initial state vector
(10 years later)

Projection onto final state vector
(10 years later)
GFDL decadal amplification

Year: 0

Temperature
Climatic Singular Vectors (CSVs)

Build a propagator matrix (P) from a series of ensemble runs from a single initial condition

- control ensemble
- 8 EOF perturbed ensembles
- 16 members each
- run for 40 years
- further ensembles to test optimal perturbations

Total: >7000 years with HadCM3, or 20 CPU-years
Leading CSV in HadCM3

Optimal perturbation

Predicted state 10 years later

Note changed colour scales!
Does the CSV work?
Does the CSV work?

**Theory:**

**State after 10 years**

**Actual:**
Demonstrated two methods for estimating optimal perturbations for decadal climate predictions

In HadCM3, both methods show significant amplification
  - maximum growth after ~35 years
  - largest growing perturbations located in far North Atlantic
  - other models show similar features (e.g. Tziperman et. al. 2008)

Multi-model analysis shows diverse range of variability and growth - to be explored further. Other regions to be considered also.

These approaches have valuable potential to guide development of:
  - efficient ensemble decadal forecasting systems
  - optimal ocean observing systems
Statistical decadal predictions

- Valuable benchmark for dynamical predictions & can give insight into mechanisms

![SST Correlation - HadGEM1](image)

Ed Hawkins
Correlation skill of SST predictions
Optimal regions for observations?

SST Correlation – HadGEM1 – lead 6–10 years

Correlation skill of SST predictions
Optimal regions for observations?

SST Correlation – HadGEM1 – lead 6–10 years

Correlation skill of SST predictions
Suggests remote influences on tropical N Atlantic SSTs
Optimal regions for observations?

SST Correlation – HadGEM1 – lead 6–10 years

LIM

CA

All Atl.

No tropical N. Atl.

Correlation skill of SST predictions
How should we use the RAPID array observations for:
- Evaluating predictions?
- Initialising predictions?

- U. Reading, NOC, Met Office, ECMWF
- DePreSys & NEMO workstreams
VALOR Aims

1. To use the RAPID observations as independent data to evaluate the representation of the AMOC in ocean analyses, and to assess the skill of AMOC predictions.  
   Evaluation

2. To develop and evaluate strategies for including RAPID observations in ocean syntheses, thereby generating new, improved, ocean analyses.  
   Synthesis

3. To determine the impact of assimilating RAPID and other ocean observations on predictions of the AMOC and climate.  
   Predictions

4. To develop and evaluate strategies for sampling the initial condition and model-related uncertainty in ensemble predictions of the AMOC and its impacts of climate.  
   Ensemble design
Responses to short-lived changes in radiative forcing (e.g., Volcanos) may give greater predictive information than that arising from internal variability.

Need to understand processes...
Ocean response to Volcanic forcing

Alan Iwi, Leon Hermanson, Keith Haines
Biases in DePreSys and NoAssim

- Both DePreSys and NoAssim exhibit a lead dependent bias with respect to observations.

Causes of bias:

- Sampling uncertainty, for both observations and model, due to: finite climatology period; finite hindcast period; finite hindcast ensemble size
- Drift in transient model runs especially, but not only at depth
- Rapid adjustment in DePreSys
- Errors in model and/or radiative forcing (interaction with offset between climatology period and hindcast period)

Biases affect RMSE of DePreSys relative to NoASSIM

Whether biases should be removed depends on cause
Impact of bias correction on comparison of DePreSys and NoAssim

Some of the improvement of DePreSys over NoAssim is attributable to correction of the mean bias rather than prediction of low frequency variability
Impact of bias correction on comparison of DePreSys and NoAssim
Implications

- Conclusions about the skill of DePreSys and NoAssim are sensitive to the presence of mean bias, which may in turn be sensitive to a range of choices (climatology period, hindcast period, number of transient runs & how spun up, number and spacing of hindcasts,...)

- Important to understand, minimise and quantify the causes of mean bias:
  - Reducing and characterising drift
  - Attention to initial imbalance / rapid adjustment
  - Attention to sampling uncertainties

- Compare bias corrected as well as “raw” hindcasts.

- Correction for non-linear density errors?
Model uncertainty: sensitivity to resolution

HiGEM

MOC Boundary Density

HadGEM

Density Integrated 1500-3000m
Evaluating the potential for statistical predictions of Atlantic SSTs

Ed Hawkins

*NCAS-Climate, University of Reading*

Thanks to:
Jon Robson, Rowan Sutton, Doug Smith, Noel Keenlyside, Len Shaffrey and Fiona Underwood
Motivation and key questions

- Statistical predictions of seasonal SSTs have proved useful
  - to help benchmark GCM predictions of ENSO
  - to inform policymakers (e.g. coral bleaching predictions)
  - what about decadal timescales?

Enso predictions from Sep 08 to Jun 2010

NOAA Coral Reef Watch

2008 Dec 02 NOAA Coral Reef Watch Coral Bleaching Thermal Stress Outlook for Dec 08–Mar 09
Potential predictability of SSTs

Inter-annual variability

Potential predictability

\( \sigma_1 \)

\( \sigma_{10}/\sigma_1 \)

OBSERVATIO NS (HadISST)

e.g. Boer 2000, 2004
Need to assess the potential for statistical decadal SST predictions before trying to use the (complicated) observations.

First steps:

- use ‘perfect GCM’ approach to assess potential skill
- use data from more than one GCM
- use more than one statistical method
- focus on Atlantic where decadal variability is relatively large and historical observations are better
- use 140 years of annual means as training data

140 YEARS TRAINING

LONG GCM CONTROL SIMULATION

Hawkins et al. 2010, submitted
Need to assess the potential for statistical decadal SST predictions before trying to use the (complicated) observations

First steps:
- use ‘perfect GCM’ approach to assess potential skill
- use data from more than one GCM
- use more than one statistical method
- focus on Atlantic where decadal variability is relatively large and historical observations are better
- use 140 years of annual means as training data

Hawkins et al. 2010, submitted
Methods for predictions

Grid-point independent estimates:

- Climatology: \( x(t_0 + \tau) = 0, \)
- Persistence: \( x(t_0 + \tau) = x(t_0), \)
- Lagged correlation: \( x(t_0 + \tau) = \beta(\tau) x(t_0), \)

\( \tau: \) lead time
\( x: \) SST anomalies

Spatial methods:

- Linear Inverse Modelling (LIM) (Penland & Magorian 1993)
  \[ x(t_0 + !) = P(!) x(t_0) \]
  \( x: \) EOFs of SST

- Constructed Analogue (CA) (van den Dool 1994)
Example from HadCM3

SST Correlation – HadCM3

- Years 1
- Years 2
- Years 3–5
- Years 6–10

- Persis.
- Lag. corr.
- Atl. LIM
- Atl. CA

Color scale:
- -0.8 to 0.8
Example from HadCM3

<table>
<thead>
<tr>
<th>DePreSys</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Years 3–5</th>
<th>Years 6–10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag. corr.</td>
<td><img src="image1.png" alt="Map" /></td>
<td><img src="image2.png" alt="Map" /></td>
<td><img src="image3.png" alt="Map" /></td>
<td><img src="image4.png" alt="Map" /></td>
</tr>
<tr>
<td>Atl. LIM</td>
<td><img src="image5.png" alt="Map" /></td>
<td><img src="image6.png" alt="Map" /></td>
<td><img src="image7.png" alt="Map" /></td>
<td><img src="image8.png" alt="Map" /></td>
</tr>
<tr>
<td>Atl. CA</td>
<td><img src="image9.png" alt="Map" /></td>
<td><img src="image10.png" alt="Map" /></td>
<td><img src="image11.png" alt="Map" /></td>
<td><img src="image12.png" alt="Map" /></td>
</tr>
</tbody>
</table>

SST Correlation – HadCM3

Temperature range: -0.8 to 0.8
Example from HadGEM1

SST Correlation – HadGEM1

Year 1  Year 2  Years 3–5  Years 6–10

Persis.

Lag. corr.

Atl. LIM

Atl. CA

-0.8  -0.6  -0.4  -0.2  0  0.2  0.4  0.6  0.8
Example from control run of HadGEM1

Correlation skill of SST predictions
Correlation skill of SST predictions
Optimal regions for observations?

SST Correlation – HadGEM1 – lead 6–10 years

LIM

CA

All Atl.

No far N. Atl.

Correlation skill of SST predictions
Optimal regions for observations?

SST Correlation – HadGEM1 – lead 6–10 years

LIM

CA

All Atl.

No both

Correlation skill of SST predictions
Optimal regions for observations?

SST Correlation – HadGEM1 – lead 6–10 years

LIM  CA

All Atl.

No tropical N. Atl.

Correlation skill of SST predictions
• Statistical predictions of SSTs are potentially feasible to match the skill of GCM predictions for far cheaper cost

• ‘Potential predictability’ not necessarily the same as ‘actual predictability’

• Prediction skill can come from remote regions, possibly informing where observations might be most valuable to improve predictions

• These techniques will soon be applied to the historical observations

e.hawkins@reading.ac.uk
Signal-to-noise ratio

Estimated Signal-to-noise ratio for decadal mean surface air temperature change

Fourth decade ahead

Signal-to-noise is lower for other variables
Aside... the MPI model

Temperature evolution in PC1-PC2 space