Probabilistic climate prediction in the presence of model error.

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Aim:

Probabilistic Climate prediction.

Two main uncertainties:

Uncertainty in forcing scenario

Uncertainty in climate response to forcing
Method:

Climate scientists choose their model physics carefully but there remains a major source of uncertainty in the values of many of the parameters. Objective methods for tuning the model parameters and simultaneously providing error estimates on the tuning have the potential for providing probabilistic climate prediction estimates.

Changing parameterisations is a more technically difficult problem because of discontinuity.
Outline of talk

- Perfect model assumption
  - THC change for GW scenarios using C-GOLDSTEIN

- The effect of model error and how to deal with it
  - study using the Lorenz model

- Including estimates of model error.
  - THC change for GW scenarios using C-GOLDSTEIN

- Coping with subjectivity
  - Validation using paleoclimates - study of climate sensitivity using CCSR/NIES/FRCGC AGCM
  - An alternative approach - futures market
Tuning C-GOLDSTEIN to present day climatology

• **Model**
  Intermediate complexity AOGCM, C-GOLDSTEIN
  Frictional geostrophic 3D ocean, EMBM 2D atmosphere.
  Additional hydrological response to global warming

• **Data**
  Levitus ocean temperature and salinity
  NCEP atmospheric temperature and humidity
  THC estimates/observations

• **Assimilation**
  Ensemble Kalman Filter (EnKF);
  54 member ensemble.
  12 parameters tuned.
C-GOLDSTEIN ensembles compared to CMIP

Two tunings: 1. Present day climatology (blue); 2. Present day climatology plus THC estimates (cyan).
Global warming experiments with tuned ensemble

Enhanced hydrological response based on Rahmstorf and Ganopolski (1999). Additional freshwater flux north of 50N, $\Delta F = k\Delta T_{NH}$.

Experiments:

- Rapid CO$_2$ rise to 3.3x present day – fast recovery
- Rapid CO$_2$ rise to 3.3x present day – slow recovery
- Rapid CO$_2$ rise to 3.3x present day – stabilisation

$k$ is adjusted to give a maximum freshwater anomaly of about 0.1 Sv at maximum warming for experiment 3.
Maximum Atlantic overturning for 3.3x$CO_2$ with slow recovery to 1.5x$CO_2$. 
Sensitivity of the fate of the THC to CO$_2$ recovery rate. Maximum Atlantic overturning for 3.3x CO$_2$: left plot with fast CO$_2$ recovery; right plot stabilisation at 3.3 CO$_2$. 
Response of the North Atlantic THC to global warming in C-GOLDSTEIN.

- No abrupt change - THC collapse takes 100s of years
  - Tuning model to higher THC increases stability
  - Increasing freshwater to N. Atlantic decreases stability
  - Quicker recovery of CO$_2$ increases stability

- Initial conditions matter - even if the model is closely tuned to the observations the THC is not predictable

- Which ensemble is "correct"? We don’t know, and yet two ensembles are almost disjoint, which suggests we have overtuned the model.
A closer look at the nature of the problem we have been solving

An imperfect model study using Palmer’s forced Lorenz model

\[
\begin{align*}
    x' &= \sigma(y - x) + f \cos 70^\circ \\
    y' &= rx - y - xz + f \sin 70^\circ \\
    z' &= xy - bz
\end{align*}
\]

‘Climate sensitivity’ = mean\(x\) for forcing \(f = 2\).

True system has \(\sigma = 11, r = 28\). Our imperfect model has \(r = 28.5\). Can we tune \(\sigma\) in our imperfect model using observations of the true unforced system so as to predict the climate sensitivity?
Climate sensitivity depends strongly on $\sigma$
Tuning $\sigma$ under the standard perfect model assumption

Ensemble centred on ML, plus obs errors
A horrible forecast
Some alternative ensembles based on fewer observations

Ensembles are **disjoint**, method must be **wrong**!
What should we do?

Cost function should really be

\[ J = \frac{1}{2} \begin{pmatrix} m - b \end{pmatrix}^T (R + T)^{-1} \begin{pmatrix} m - b \end{pmatrix} \]

where \( T \) is the uncertainty of the model error.

Since \( T \gg R \), we just plug it straight in to the estimation algorithm. NB \( T \) is highly subjective, at least \textit{a priori}. 
A better attempt including model error
A valid forecast
Another go with GOLDSTEIN - results submitted to AR4

- New tactic - widest ensemble that is physically reasonable for the present day.
- A multitude of experiments
  - 3402 runs (1000-3000y); 21 CO₂ scenarios; 3 climate sensitivities (1.5, 3 and 4.5 °C)
- A few examples; results
C-GOLDSTEIN results

![Graph showing relative density vs. Max North Atlantic Overturning (Sv)]
CO$_2$ stabilisation experiments, 450ppm, 750ppm, CS, 1.5 and 4.5 °C
Results

- For these (more realistic?) scenarios, <20% ensemble members prone to collapse.

- Higher climate sensitivity is less stable.

- Collapse dependent on duration of perturbation, so rapid increase and decrease both increase stability.

- We still don’t know if this is a realistic prediction, because we do not know what the error is, or even if the model is capable of providing a valid prediction.
Validation using paleoclimate

- **Model:**
  CCSR/NIES/FRCGC AGCM; T21L20 with slab ocean
  Run on Earth Simulator

- **Data:**
  Seasonal present day climatology; 2D fields of 15 data types from ERA40, CMAP, ERBE.
  LGM data for validation from PMIP (Tropical SST from alkenones): 3 estimates for the range of acceptable models
• **Data assimilation:**
  EnKF; 25 parameters; 40 member ensembles
  4 ensembles:
  – 3 different model error assumptions
  – Direct sampling from prior

• **Experiments:**
  2XCO₂
  Last Glacial Maximum
Climate sensitivity and gain for the 4 ensembles

Climate Sensitivity

Tight

Medium

Loose

Prior

Climate Sensitivity (°C)
Climate sensitivity vs. LGM Tropical SST

The graph shows a scatter plot with the x-axis representing Tropical SST, LGM – present day (°C), and the y-axis representing Climate sensitivity (°C). The data points are distributed across a range of values, indicating a relationship between the two variables. The graph includes a linear regression line and dashed lines indicating the range of the relationship.
Constraining the high end of climate sensitivity

Fraction of ensemble with climate sensitivity greater than x-axis value; original results and 3 constraints using observed LGM tropical SST.
Validation using paleoclimates

The prediction did not validate!

But using the LGM information we can place an upper limit on climate sensitivity of about $6^\circ C$, under the assumption that our LGM/$2xCO_2$ relationship is reasonable.

Multi-models required to both span the range of possibilities and (in)validate our conclusions.
Where does this leave us?

Fundamentally subjective decisions required which make objective probabilistic prediction difficult even for non-abrupt changes such as climate sensitivity calculations. Scientists have to understand and acknowledge the assumptions (implicit and explicit) in their methods that make their “probabilities” actually little more than wild guesses.

Validation with independent data is an important component of (in)validating assumptions.

Making real predictions - A Climate Futures market.
A market in climate futures

Why?

• Subjectivity is fundamental, so it is better to deal with it openly than brush it under the carpet.

• A futures market (prediction market) allows all to participate according to their confidence rather than media presence. It is a highly inclusive mechanism.

• Those who are (or feel) vulnerable can use the market to hedge their risks.
The story so far:

No-one is prepared to bet against continued warming at the IPCC-predicted rate (0.1-0.2C/decade for the next few decades). All the noisy sceptics go very quiet when asked to put their money where their mouths are. Eg Lindzen: probability of warming v cooling over 20 years is “roughly 50-50” but he won’t bet unless he gets odds of 50:1!

Draw your own Conclusions!