Climate prediction and its uncertainties
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Currents in climate prediction: Observationally-constrained *probabilistic* climate forecasts
- difficulties in pinning down sensitivity
- Monte Carlo approaches

Transient / “phase-out” scenarios as possible(?) alternatives to stabilization scenarios
- transient scenarios give us a warming rate
- maximum warming under a “phase out” scenario is much better constrained by observations than is sensitivity

Policy issues
Constraining climate sensitivity: probabilistic approaches

Attempting to constrain perturbed-physics ensembles with observational data.

- Observational constraints from ocean heat content changes.
- Observational constraints from Detection and Attribution studies.
- Physical constraints from perturbed-physics ensembles.
- Inferring probabilistic climate forecasts from these.
Uncertainty in climate sensitivity

Likelihood-weighted ensembles of climate models

- In ensembles of opportunity (CMIP etc.), individual models are tuned to agree with observations and with each other.
- In PPE (deliberately detuned models), results depend on the choice of parameter perturbations.

An example: energy balance model PPE constrained
  - by attributable warming (Stott & Kettleborough) data and
  - by ocean heat content (Levitus) data
  - uses GHG forcing diagnosed from HadCM3; doesn’t consider other contributions.
Comparing individual simulations with observations

- Use detection and attribution analysis to estimate attributable greenhouse warming, $\Delta T_{GHG}$ (linear trend 1900-2000), allowing for uncertainty in forcing. [Data from Stott & Kettleborough (2002).]

- Estimate effective heat capacity $c_{eff}$ from observed $\Delta Q_{1957-1994}/\Delta T_{1957-1994}$, allowing for uncertainty in both. [Data from Levitus et al (2005); CRU.]

- Sample sensitivity and heat capacity in a simple climate model.

\[
  c_{eff} \frac{d\Delta T}{dt} = F - \lambda \Delta T
\]
Sampling sensitivity and heat capacity in a simple climate model (Hansen et al, 1985)
Uniform sampling in sensitivity
Likelihood weighting

(a) Uniform prior in sensitivity

GHG warming (K/century)

Equivalent heat capacity, GJ/m²/K
Constraints implied by observations

(a) Uniform sensitivity

GHG warming (K/century)

Equivalent heat capacity, GJ/m²/K
Using a different prior gives a different result
Differences in the predictive distributions used to build the forecast gives the reported range in sensitivities.
Bertrand’s Paradox (1889)

- Bertrand intended to highlight problems with the classical definition of probability in the case of a problem with an infinity of possible outcomes.
- Depends strongly on the prior assumptions you use in setting up the problem.
- Many, equally plausible priors result from the underdetermined nature of “randomness”.
- We recommend using the principle of indifference over the forecast variable of interest to avoid claiming spurious “knowledge” from the prior alone.
- This amounts to choosing a uniform prior in the forecast variable of interest.
Hindcasts are quite closely related to (variants of) TCR because...
… Attributable GHG warming is linearly related to TCR

Figure from Jamie Kettlebrough

Oxford University
Summary

- So Attributable warming provides a particularly nice “observable” on which to condition our transient climate change experiments.

- Identifying such a nice “observable” for climate sensitivity is much harder.
Differences in the predictive distributions used to build the forecast gives the reported range in sensitivities.
The things we can observe scale with $\lambda$ not $S$. Since $S=1/\lambda$, this means that a Gaussian uncertainty on our observable leads to an inverse Gaussian on the distribution for $S$.

Paleoclimate studies potentially give us observables that scale with $S$, but in this case we know the temperature response better than the forcing, which causes trouble (since $S \sim \Delta T/F$): we get another inverse Gaussian.
Transient observables scale with $\lambda$ for large $S$

For large $S$ (small $\lambda$) or short times, response varies as...

So the first sensitivity-dependent term to appear in the transient response scales with $S^{-1}$ ($\lambda$), not $S$, (particularly for Pinatubo (Wigley et al, 2005)).
Have been claims that volcanoes provide a constraint on sensitivity (low heat uptake)
Have been claims that volcanoes provide a constraint on sensitivity (high heat uptake)
EBM responses to Pinatubo forcing

Also fitting ENSO, background climate and effective heat capacity
Paleo constraints

- We lack data to say what the global mean change is during LGM ("or any other period")
- Reconstructions flawed, MARGO suggests that results are proxy-dependent
- Forcing uncertainties are a problem

- Long time scales ✓
- Data constraints ❌
- Forcing uncertainties ❌
Are these high sensitivities ruled out by temperatures in the Last Glacial Maximum?

Forcing at Last Glacial Maximum

\[ \Delta F = -6.6 \pm 1.5 \text{W/m}^2 \]

\[ \Delta T = -5.5 \pm 0.5 \text{K} \]

Numbers courtesy of Stefan Rahmstorf and Gavin Schmidt, realclimate.org
climateprediction.net
No: symmetric uncertainty in past forcing $\rightarrow$ asymmetric, open-ended range for sensitivity
Monte Carlo Approaches

- Ideally we want to span the range of sensitivities using GCMs.
- BUT, GCMs are expensive to build, and every modelling group wants to build the “best guess” model.
- To span the range, we need to deliberately de-tune the models by perturbing the model physics within the ranges of uncertainty specified by the modellers.
The “cascade of uncertainty” in climate change prediction

- How do we find alternative, equally realistic, climate models to explore the full range of possible responses to increasing carbon dioxide?

**Diagram:**
- Standard model set-up
  - Vary model parameters
  - Vary initial conditions
  - Vary external drivers
- Overall Grand Ensemble

**Model Versions**
- 10000s

**Simulations**
- 10s
- 10s

climateprediction.net
Climateprediction.net: an example of a Grand Ensemble of GCMs

~30,000 active volunteers, 130 countries, ~110,000 full runs

Upload servers
Members of the public download and run a full 3-D climate model on their personal computers.
Software provided for school and undergraduate projects
Exploration of parameter space, focussing on identifying non-linear interactions

- Perturbations to 21 atmospheric/surface parameters
- Three values each, including combinations
- Initial exploration of 6 parameters (clouds and convection)
Time-evolving distribution: red=dense

Remove models that are unstable in the control.

Few remaining negatively drifting 2xCO₂ model versions are an unrealistic consequence of using a slab ocean.
Not The Day After Tomorrow: why we got some negative sensitivities…

climatemodelsuppfigure2

Annual Mean Surface Temperature for Run 0316_000066991, 2xCO2 Phase

Annual Mean Surface Temperature Anomaly Field for Run 0316_000066991
47334 simulations passing initial quality control

![Graph showing climate sensitivity with traditional range highlighted.](image-url)
Result was a double edged sword…

That's how much hotter scientists believe the world will get … and it will be worse in Britain.
PPE generates high sensitivity models that are hard to rule out

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Stainforth et al, 2005

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CMIP-2 coupled models

Original model

Single perturbations

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Oxford University

climateprediction.net
Perturbations add non-linearly
Initial results

- On-going task to compare models against observations (Piani et al.)
- Building on CMIP-II’s experience
- Models that give us high sensitivities not yet ruled out by observations
- There are a number of interesting models that give us a range of sensitivities (<2K to >11K) that do not appear to be worse climate models than HadCM3
Next steps, analysis

- Systematic quality control process
  - Models vs physics, vs other models
  - Models vs observations
- More full analysis of the entire ensemble
- Several subprojects already suggested
  - New variables (precip, mslp, etc.)
  - Regional analyses
- Ultimately want this to become a dataset like CMIP-II or a satellite dataset – a community resource (we just have to build the infrastructure, first!)
Next steps, experimental development

- **Sulphur cycle experiment**
  - Perturbations to the S-cycle, sensitivity experiment to changes in aerosols, similar to current experiment

- **Coupled model spinups**
  - Perturbations to ocean to give range of Kv, thermohaline behaviours

- **Coupled model hindcast experiment**
  - Run 1950-2000 using historical forcings as a test of the models from the slab phase(s)

- **Coupled model 21st century experiment**
  - Run 2000-2100 using range of future forcings, having run the hindcast and found models which are both interesting (phase 1) and good (phase 2)
  - Predictive experiment with the goal of a “probabilistic” forecast
Exploiting the TCR in “scenario” design

- The equilibrium response is NON-linearly related to past (attributable) warming
- The transient response is linearly related to past (attributable) warming

- Consider maximum warming under emissions scenarios in which emissions drop back to zero** by 2300.
  - **Zero basically means within the uncertainties associated with the carbon cycle (by 2300)
Policy possibilities using the TCR?

- May allow us to exploit
  - linear relation between TCR, Attributable warming
  - Not completely unreasonable assumptions about carbon futures
  - Lagged nature of the emissions/response in the climate system

- To develop tighter confidence intervals for inputs into IAMs, etc. Most suitable for problems in which the observational constraint problem is relevant.

- Potentially leading to better constrained ideas about the price of carbon (very early in this analysis).
TCR phase out scenarios

- The exact path (timing of the peak) may not matter as much as the total amount of carbon
- Emissions scenarios:
  - peaking early
  - peaking for 550ppm in 2100
  - peaking late
  - +20% (dashed)
  - -20% (dash-dotted)
- Investigating this with MAGICC
- Emissions → 0 in 2300.
Phase out concentrations

- Concentrations are strongly dependent on the carbon cycle model used.
- This analysis uses Nordhaus’s 1991 approach, such that:
  \[ Q(t) = (1 - \lambda) Q(t-1) + \varphi e(t-1) \]
  - where:
    » \( Q \) = carbon stock,
    » \( e \) = emissions
    » \( \lambda = 1/120, \Phi = 0.64 \)
- Not exactly a comprehensive carbon cycle model…
Forcing under phase outs
Remaining neutral in observable quantities
Maximum warming under phase outs
Some doubts about Article 2 of the Rio Convention

- Article 2 of the Rio Convention commits the parties to take actions to “stabilise greenhouse gas concentrations at a level (TBD) to avoid dangerous interference” in the climate system.

- Is stabilisation of GHG a sensible way to think about “avoid[ing] dangerous interference” in the climate system, given that it is
  - impossible to observe directly
  - difficult to construct a reliable pdf?

- It’s probably worthwhile considering alternatives, such as phase-out scenarios, which are better constrained by observations.