Statistical methods for managing uncertainty in complex models and their application to global change science

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Two of the principal challenges for global change science involve specifying $L$ and assessing $P(Y_{1:t}(d))$. 

We use models to assist with both. Simplifying, let $Y = (Y_H, Y_F)'$. We observe climate with error $Z_H = Y_H + e_H$. If we can find $P(Y)$ and we know the distribution of $e_H$, we can easily derive $P(Y_F|Z_H)$. Enter climate models. We have a selection of climate models $f_i(x|[i], \theta)$ used to try to predict $Y$ under forcing $\theta$. How can information from the $f_i$'s get us to $P(Y)$?
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- How can information from the $f_i$’s get us to $P(Y)$?
Statistical modelling

One model approach:

- Each model is informative for $Y(\theta)$, but there is structural discrepancy left over:

$$Y(\theta) = f_i(x^*_{[i]}, \theta) + \eta_i(\theta)$$

- We can get Monte Carlo samples from $P(Y(\theta))$ if we can sample from

$$P(f_i(x^*_{[i]}, \theta)|x^*_{[i]})P(x^*_{[i]})P(\eta_i(\theta))$$

Statistical modelling

Multi-model approach:

- The models are exchangeable and \( Y(\theta) \) relates to the collection: E.g.

\[
f_i(x^*_i, \theta) = \mathcal{M}(\theta) + R_i(\theta); \quad Y(\theta) = \alpha \mathcal{M}(\theta) + U(\theta)
\]

- We observe \( f_1(x^t_{[1]}), \ldots, f_n(x^t_{[n]}) \) and we can get Monte Carlo samples from \( P(Y(\theta)) \) if we can sample from

\[
P(U(\theta))P(\alpha, \mathcal{M}(\theta)) \prod_{i=1}^k P(f_i(x^*_i) | f_i(x^t_{[i]}), x^*_i, \mathcal{M}(\theta))P(x^*_i)
\]

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Current practice: What lurks in the conditioning?

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Example

- The CMIP GCMs are run at $x_{[i]}^t \neq x_{[i]}^*$. I.e. they are not optimally tuned.
- But this is rarely not addressed. In fact, we act as if $x_{[i]}^t = x_{[i]}^*$. 
- Now $P(x_{[i]}^*)$ is gone and $P(f_i(x_{[i]}^t, \theta))$, has no code uncertainty!
- Hence we obtain samples from internal variability only and can get to $P(Y(\theta)|x_{[i]}^* = x_{[i]}^t)$.
- Is this a called-off bet that we know is already called off?
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We build a statistical model for the simulator that gives, for any $x$:

1. A prediction at $x$
2. Uncertainty on the prediction at $x$. 

If you've heard of Pattern Scaling, it is essentially a special case of an emulator (without 2 and with restrictions on the types of predictions allowed).

25 years of statistical methods for complex models: an introduction

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Emulators let us cheaply sample from $P(f_i(x^*_i, \theta)|x^*_i)P(x^*_i)$.

They also allow us to improve tuning (reducing uncertainty in $P(x^*_i)$) to make models more informative.

This happens by history matching:

$$I(x)^2 = \frac{(Z - E[f(x)])^2}{\text{Var}[Z - E[f(x)]]}.$$

A point $x_0$ is ruled out of parameter space if $|I(x_0)| > a$ for some threshold $a$.

Policy support: Beyond Pattern Scaling

- $P(Y(\theta)) = P(Y|\theta)$.

- Can we get to $P(Y)$ or $P(Y|\theta^*)$?

- How do we make inference and provide decision support beyond the RCPs/SSPs?

- Emulation can help AND carry through the uncertainty!
Critical future research directions

- Huge interdisciplinary challenges include:
  - Parametrisation of scenarios and GCM emulation in scenario space.
  - Including parameter uncertainty in CMIP based uncertainty/policy studies.
  - Understanding, modelling and quantifying model discrepancy.
  - Quantifying uncertainty in observations ($Z = Y + e$).
  - Decision support using all of the above.
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- ISBA - EnviBayes / RSS - ESS
References

• Tebaldi, C., Sanso, B. (2009), Joint projections of temperature and precipitation change from multiple climate models: A hierarchical Bayesian approach. JRSSA , 172, 83-106.