A new statistical framework for analysing multi-model ensembles

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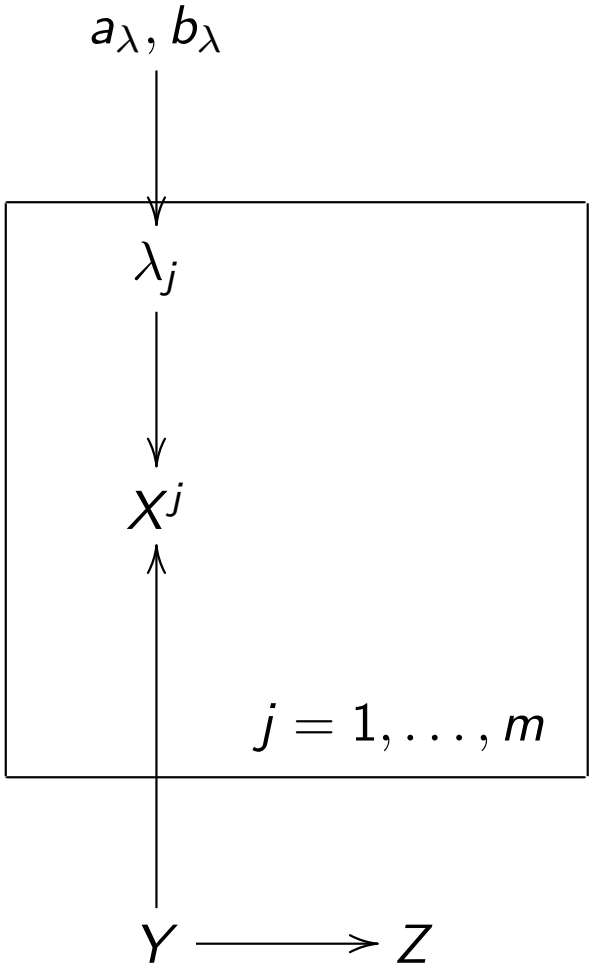
Edinburgh, IMSC 2010

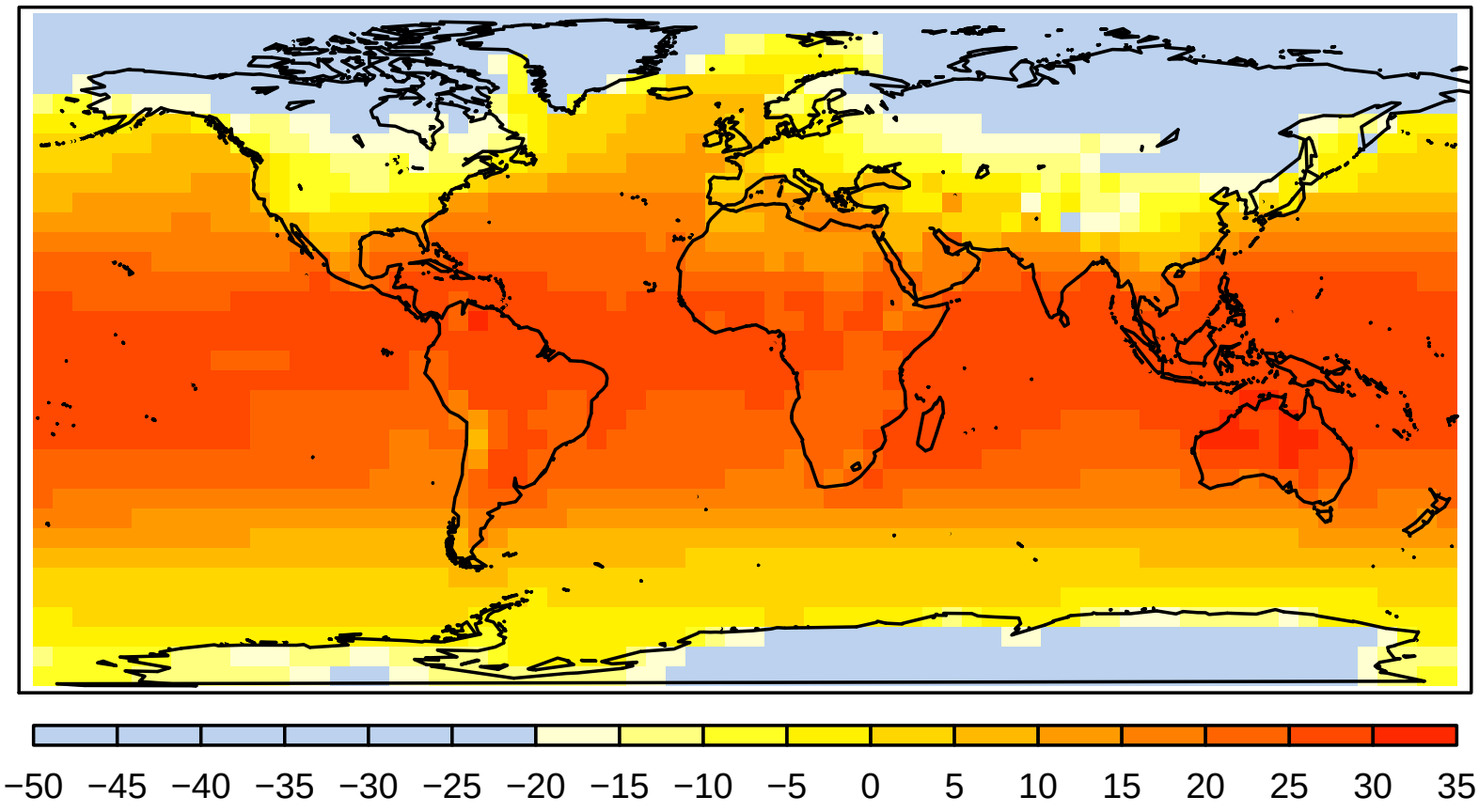
Two factorisations



Standard approach (e.g. Smith et al, 2009, JASA)

X^j = model j; Y = actual climate; Z = climate observations.

HadCM3, DJF atmospheric temperature, 1980−1999



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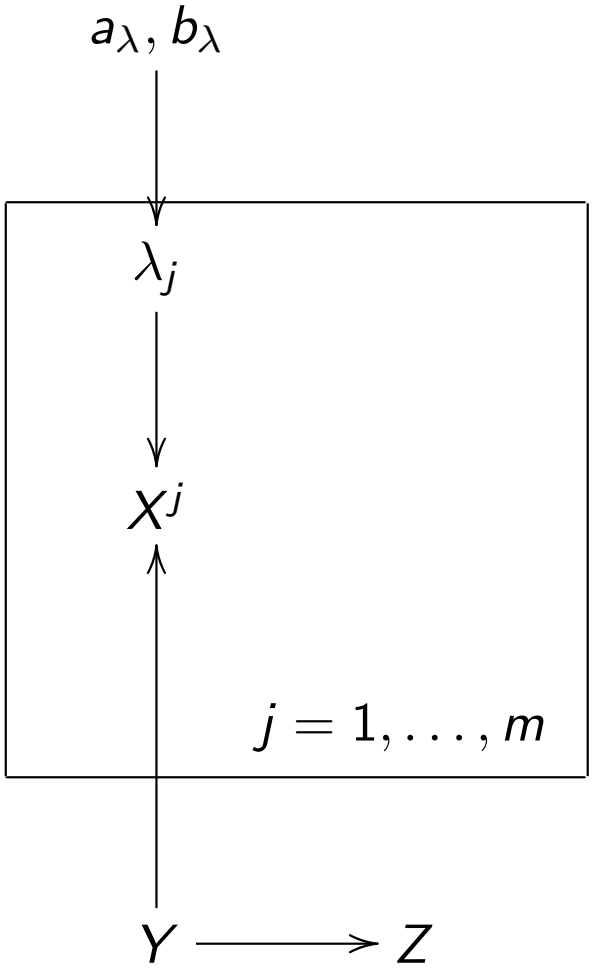

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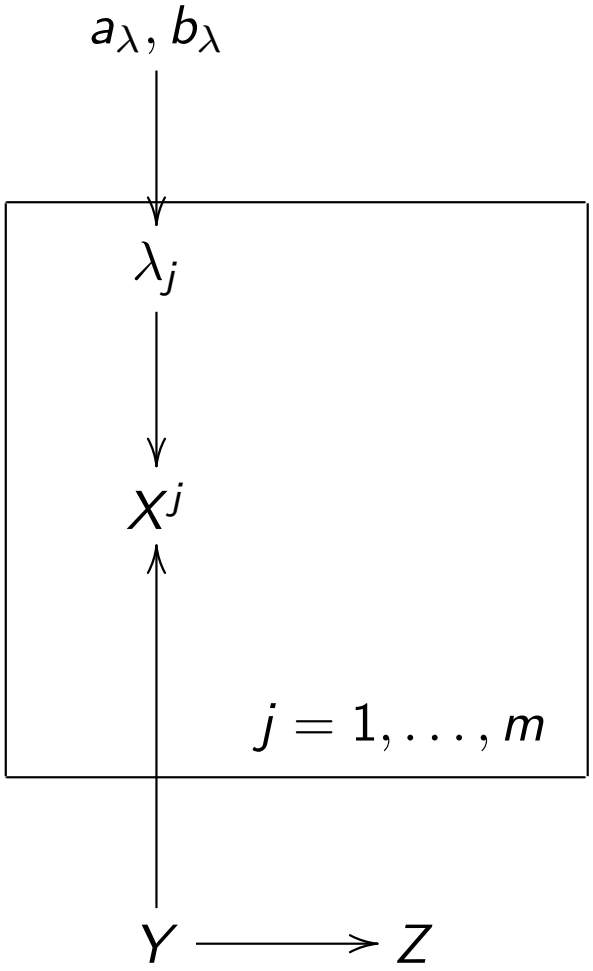

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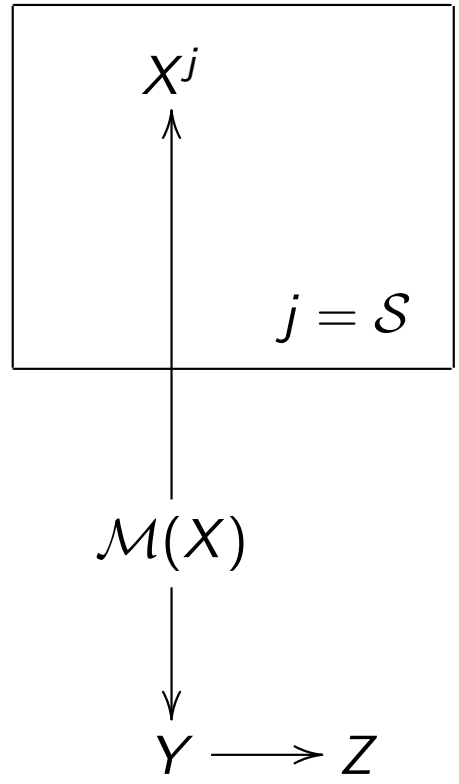

Cool new approach,
$\mathcal{S} \subseteq \{1, \ldots, m\}$.

X^j = model j; Y = actual climate; Z = climate observations.

Structural statistical principle

There is a subset $\mathcal{S}$ of the simulators which we are prepared to treat as second-order exchangeable, and actual climate respects exchangeability with these simulators.

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Consequences

$$X^j = \mathcal{M}(X) + \mathcal{R}^j(X) \qquad j \in \mathcal{S}$$
$$Y = A\mathcal{M}(X) + U$$

where $\mathcal{M}(X)$ is the 'representative' simulator and $\mathcal{R}^j(X)$ and U are 'residuals'.

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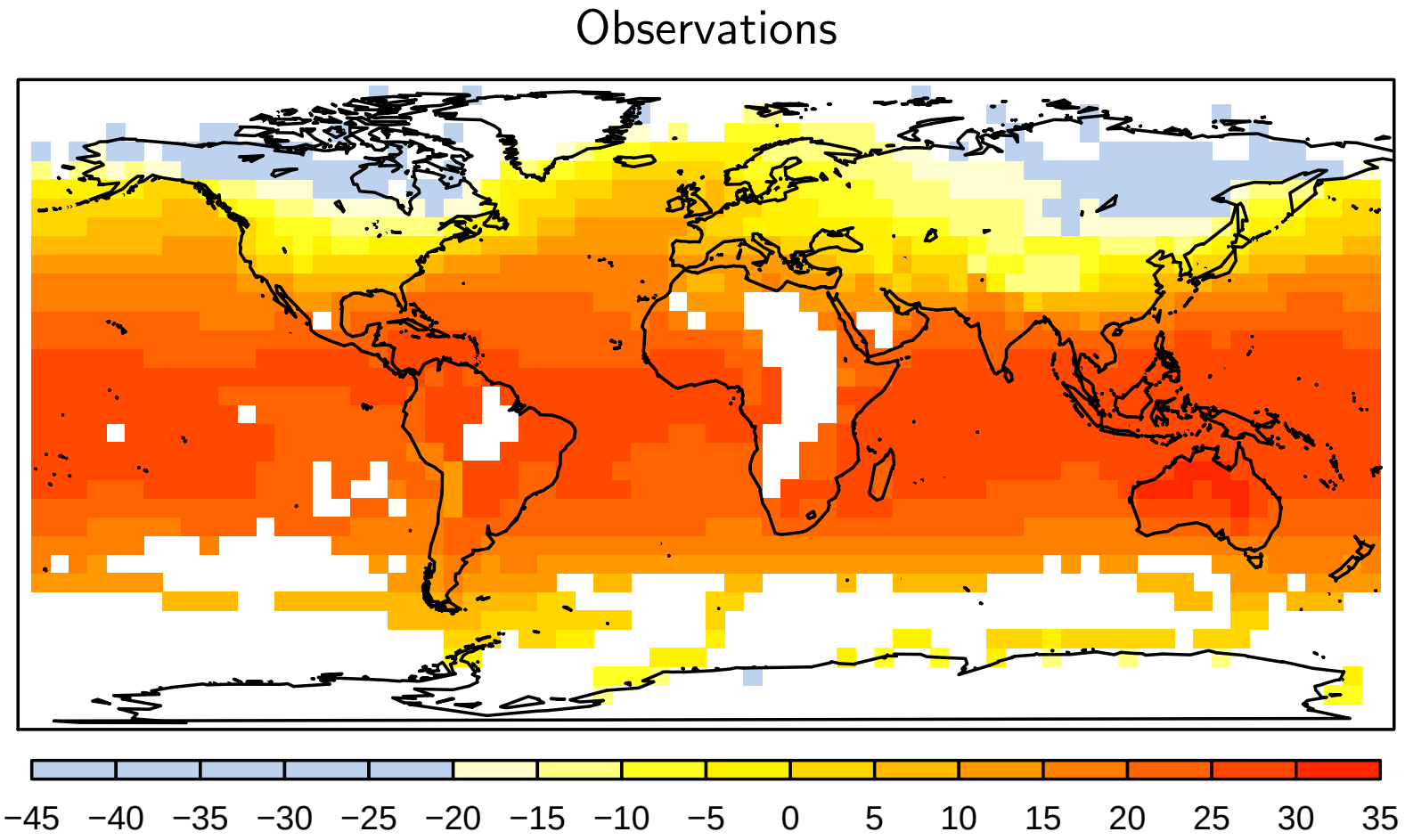
Objects

We take $A = I$ and then need to specify:

1. $E\{\mathcal{M}(X)\}$ and $\mathrm{Var}\{\mathcal{M}(X)\}$;
2. $\mathrm{Var}\{\mathcal{R}(X)\}$, same for all $j \in \mathcal{S}$;
3. $\mathrm{Var}(U)$, the *discrepancy variance*.

Application: reconstructing mean DJF atmospheric temperature, 1980-1999



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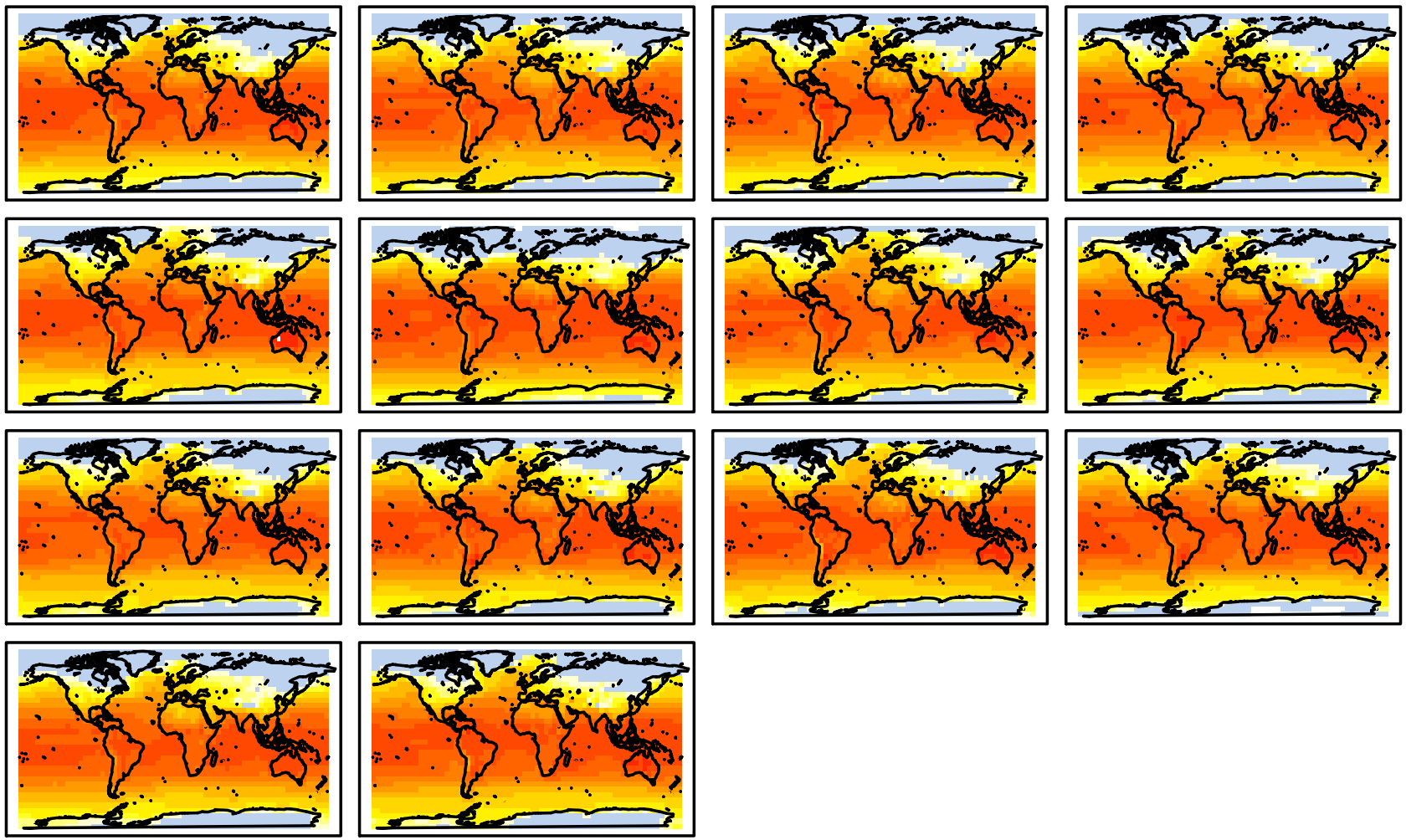
Exchangeable ensemble



Specification

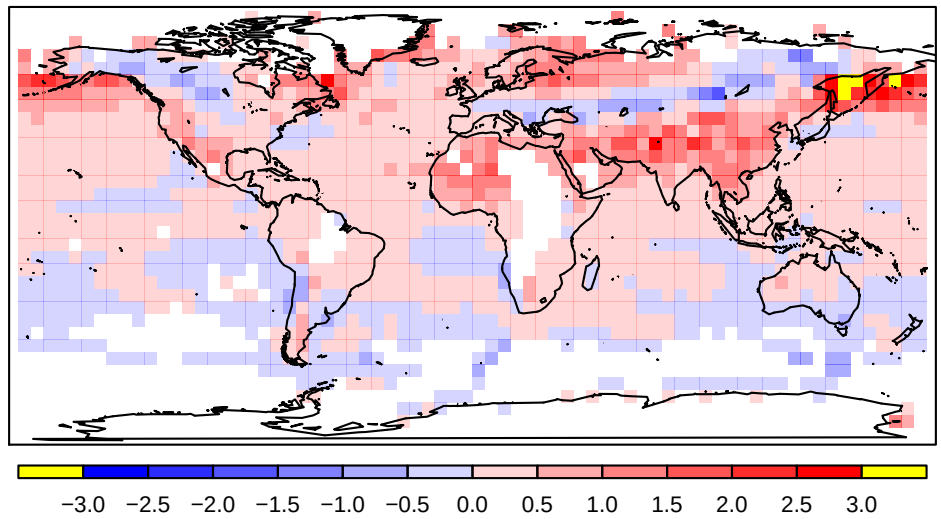
`REM: all variances must be coherent on the 2-sphere!`

1. $E\{\mathcal{M}(X)\}$: specified for zonal means using an EBM
2. $\mathrm{Var}\{\mathcal{M}(X)\}$: $\pm 10^{\circ}$C for the zonal means
3. $\mathrm{Var}\{\mathcal{R}(X)\}$: mainly the sample variance of the ensemble
4. $\mathrm{Var}(U)$: judgements of simulator quality for zonal means

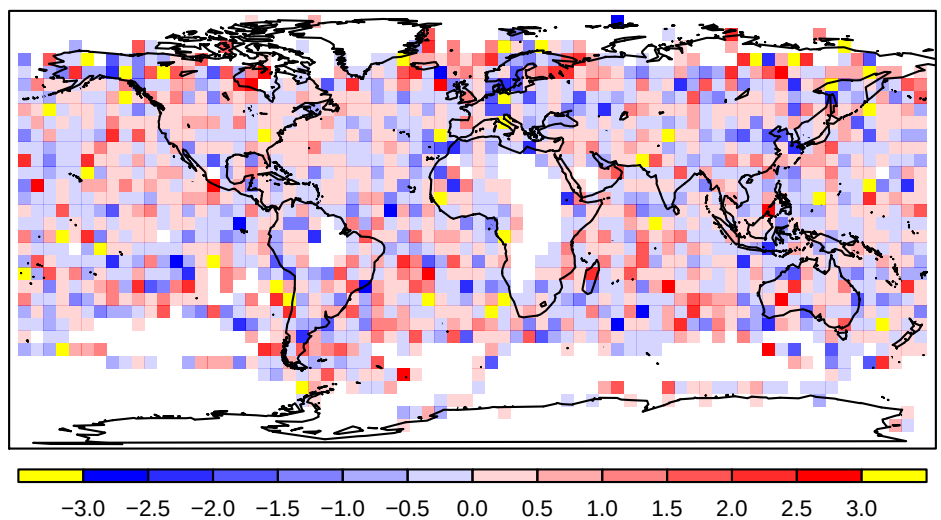
Diagnostics

Example: Mean and variance of the observations, adjusted by the MME $X^{\mathcal{S}}$.

Marginal standardised prediction errors



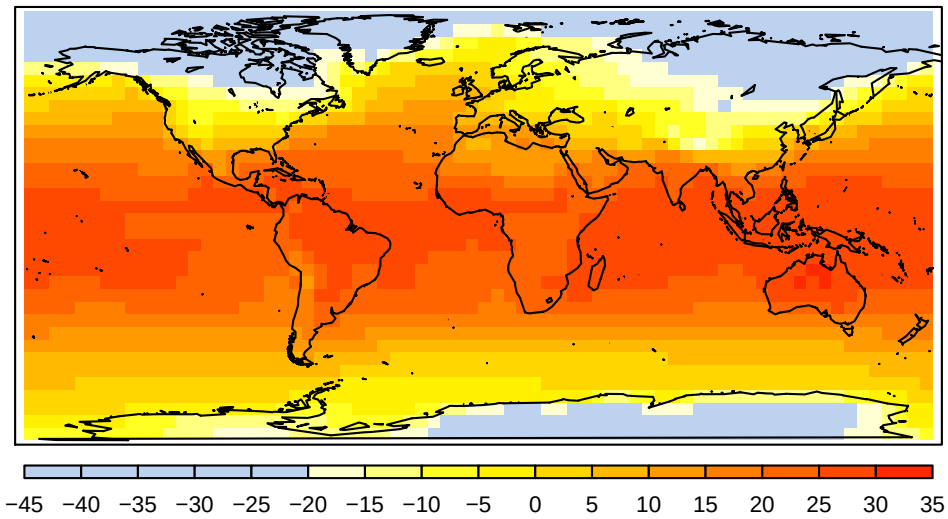
Joint standardised prediction errors



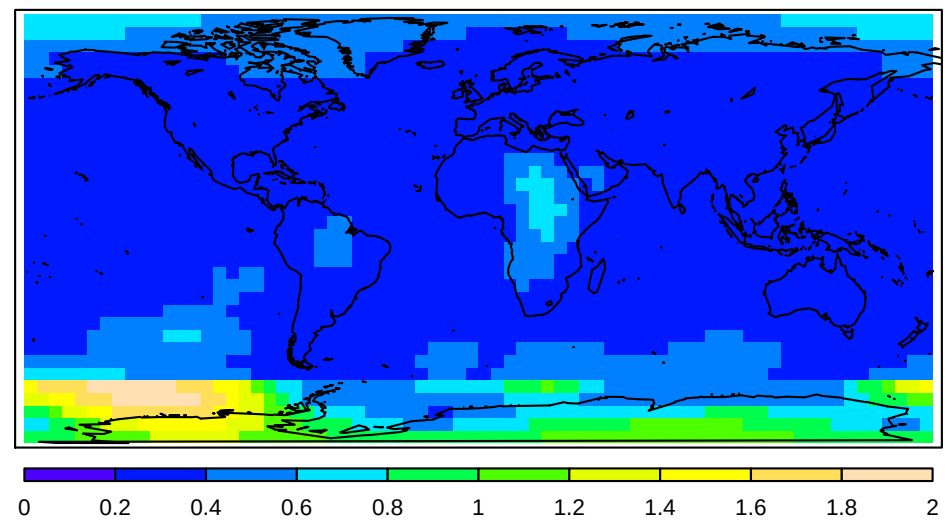
Reanalysis results

Example: Mean and std dev. adjusted by the MME $X^{\mathcal{S}}$ and the observations Z.

Mean surface temperature field (degrees Celcius)



Std dev. surface temperature field (degrees Celcius)



Summary

- A strong case based on common practice can be made for specifying judgements about climate *conditionally* on the results of climate simulator evaluations.
- We have based our statistical model on this, and on the notion of second-order exchangeability in the simulator ensemble.
- The resulting framework requires us to make explicit (non-vague) judgements about the ensemble and about the relationship between the ensemble and actual climate: this is surely a good thing!
- Highly tractable second-order calculations allow for very detailed diagnostic testing, even in large problems with $\sim$2500 components to predict and 14 climate simulators to assimilate.

Further reading: J.C. Rougier, M. Goldstein, and L. House, Assessing climate uncertainty using evaluations of several different climate models, available shortly, please contact `j.c.rougier@bristol.ac.uk`.