Japan Uncertainty Modelling Project

Understanding and Interpreting Climate Model Ensembles

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JAMSTEC Japan Agency for Marine-Earth Science and Technology

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How can we use the (CMIP3) MME in probabilistic forecasting?

- MME samples some uncertainties in (physical) parameterisations
- Does it in some way "include" reality?
  - Is it too narrow?
  - Is it too broad?
- What do these statements mean, and how can we check them?

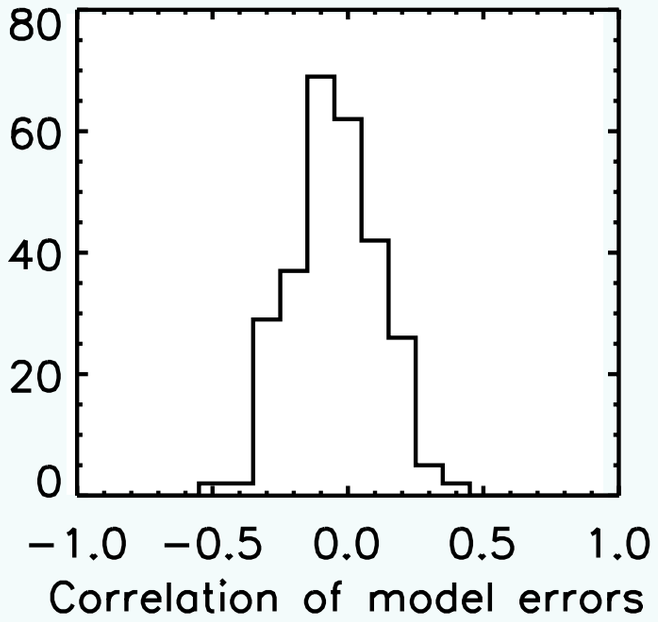
Paradigms for interpreting the CMIP3 "ensemble of opportunity"

(IPCC Expert Meeting, Boulder 2010)

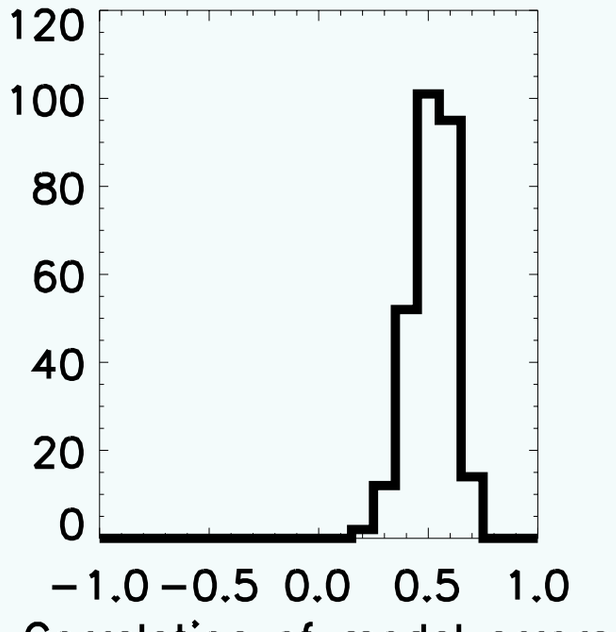
Truth-centred	**Statistically indistinguishable**
"each ensemble member is sampled from a distribution centered around the truth"	"each of the members is considered to be 'exchangeable' with the other members and with the real system"
$m_i = T + e_i \sim N(T,\sigma)$	$m_i = M + e_i \sim N(M,\sigma)$ $T = M + e_t \sim N(M,\sigma)$

Comparison of behaviours

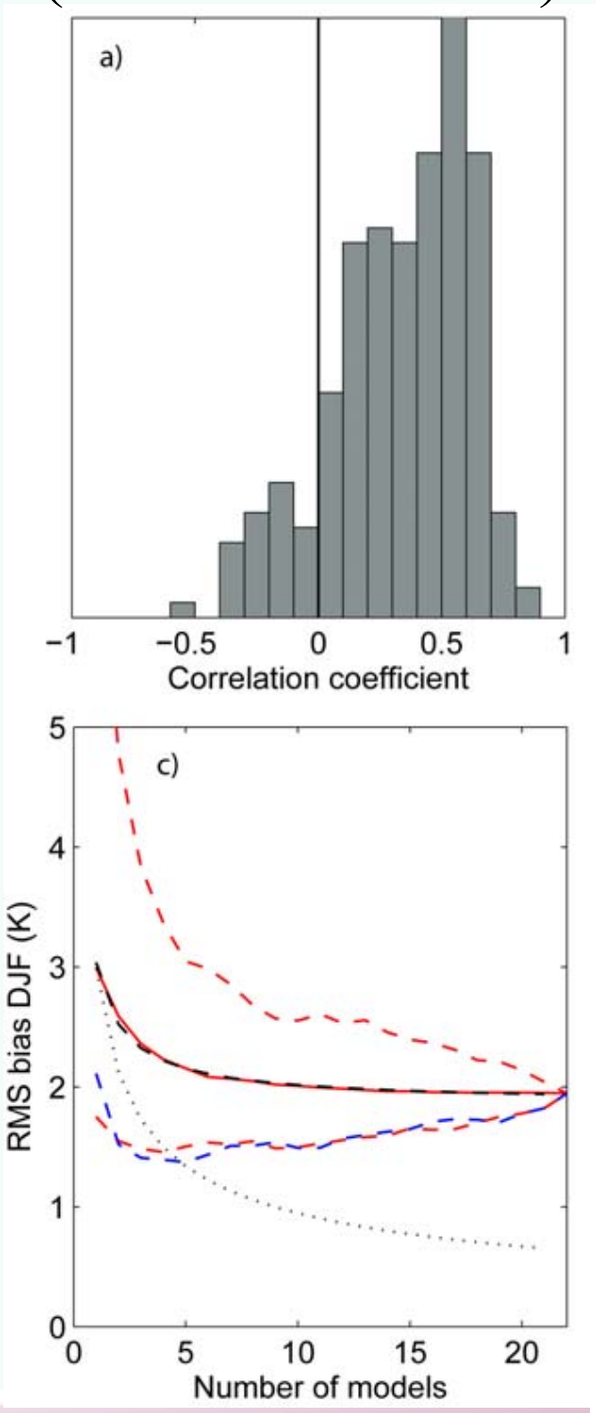
Synthetic
Truth-centred

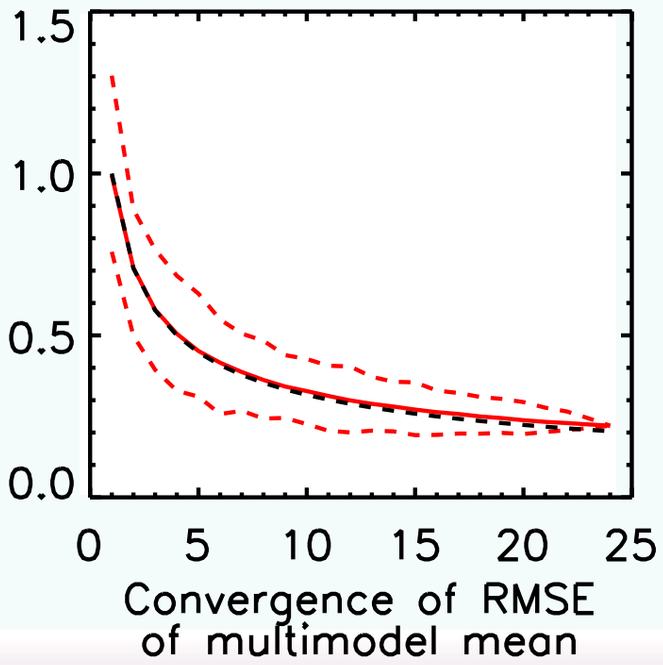


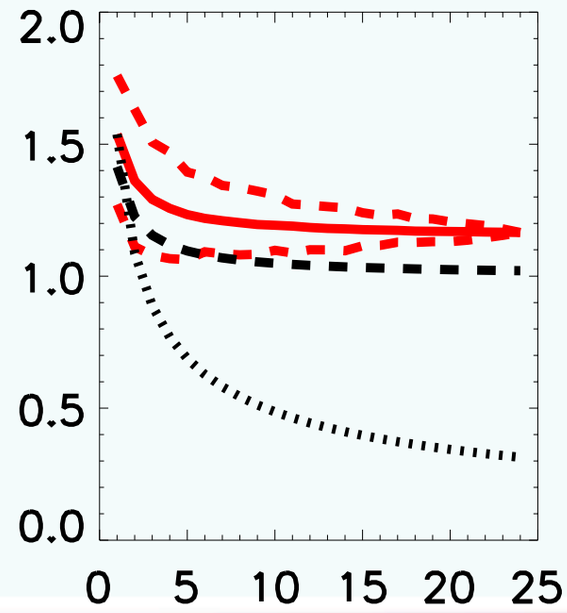
Statistically
Indistinguishable



CMIP3
(Knutti et al 2010)







"Reliability of the CMIP3 ensemble" GRL 2010

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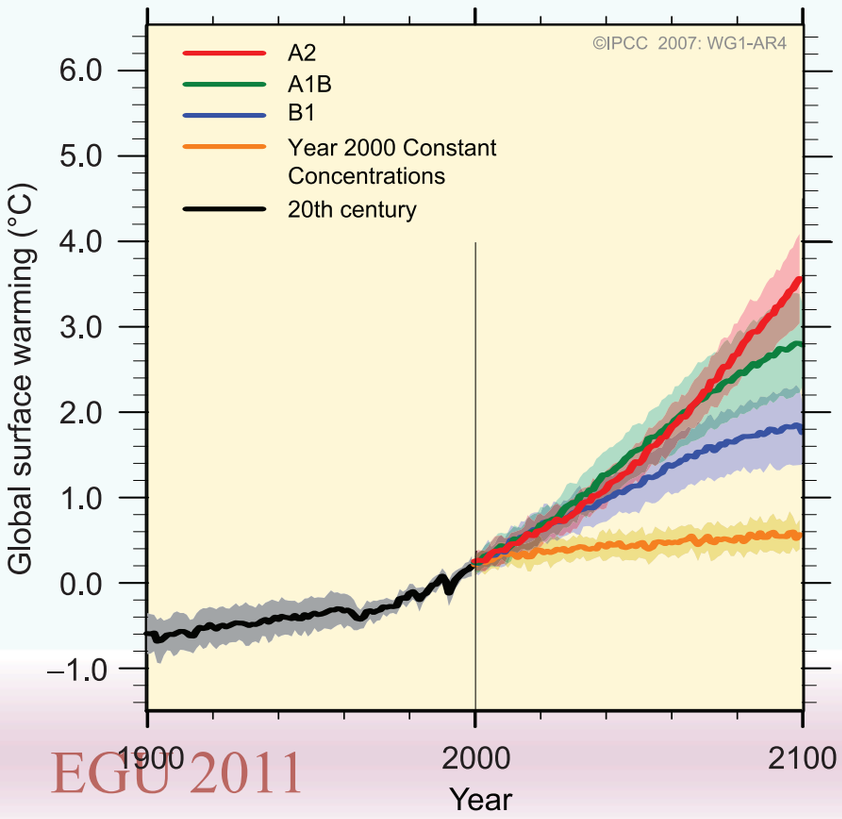
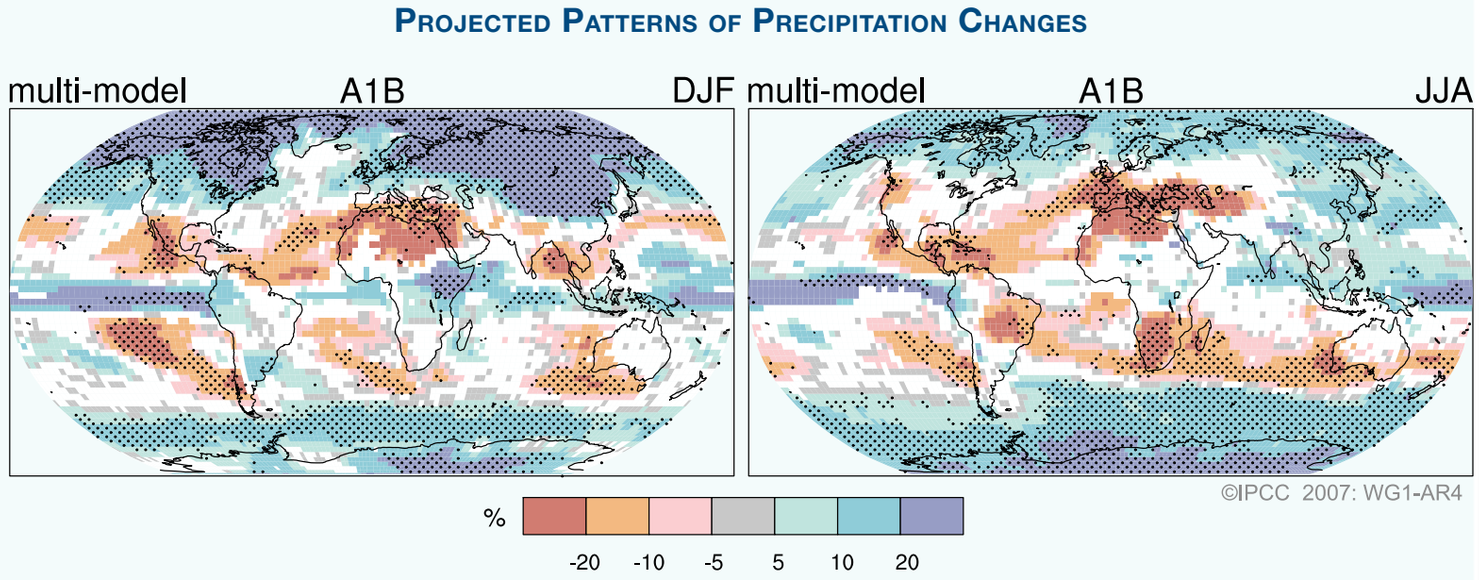
How can CMIP3 be understood within the statistically indistinguishable paradigm?

- Our ensemble represents our uncertain beliefs about the system
  - Ensemble is centred on our "mean beliefs" (not reality)
- If our uncertainty (ie ensemble range) is well-calibrated relative to error in the mean, then reality and models will be a similar distance from the mean
- Corollary: natural "counting" interpretation will be *reliable*





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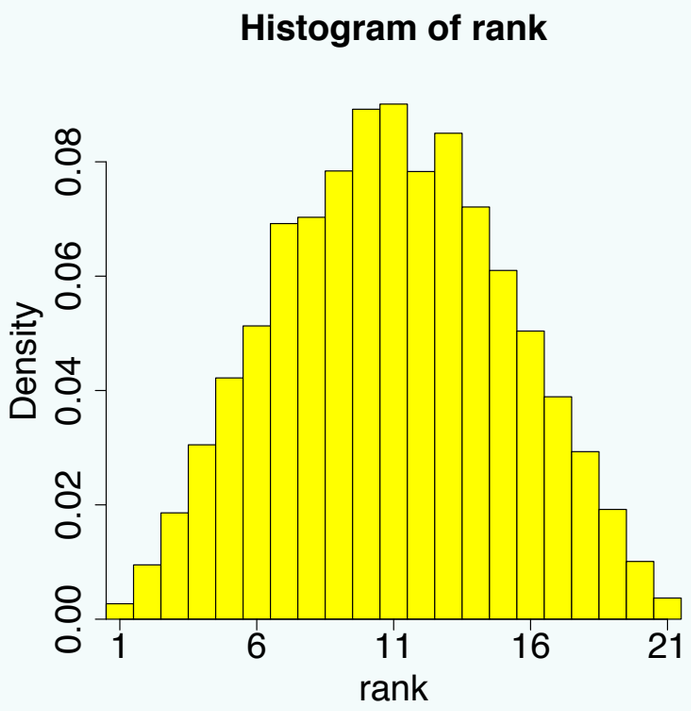
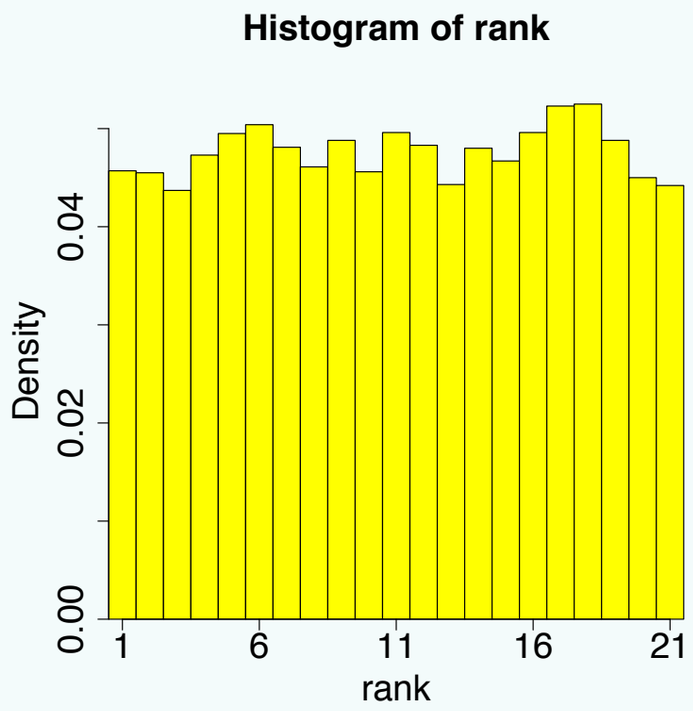
Evaluating reliability with the Rank Histogram (Talagrand diagram)

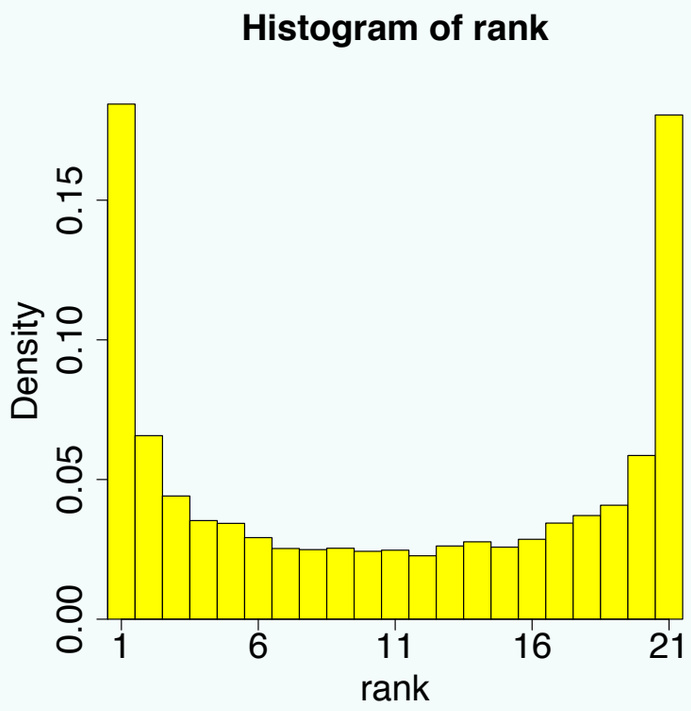
- For a reliable ensemble, the truth lies equiprobably at each position in the rank ordering of ensemble plus truth
- Histogram of ranks of observations should be flat



Wide ensemble: spread is too large, observation is near the centre.



Reliable: ensemble represents our uncertainty.



Narrow ensemble: observation is too often outside ensemble range.

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Real data and models - MMEs and SMEs

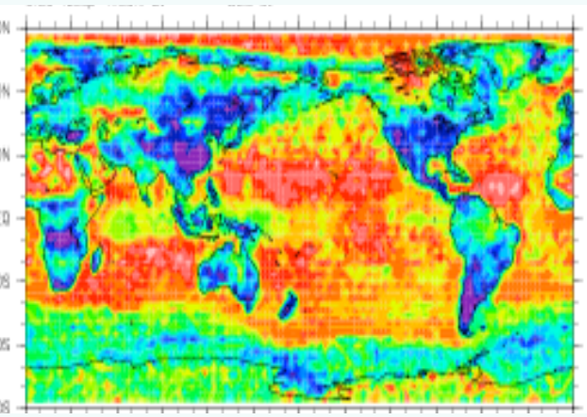
(Yokohata et al submitted - see poster XL115 today)

- Reliability of CMIP3 MME and several single model ensembles
  MIROC, HadCM3/SM3, NCAR CAM3

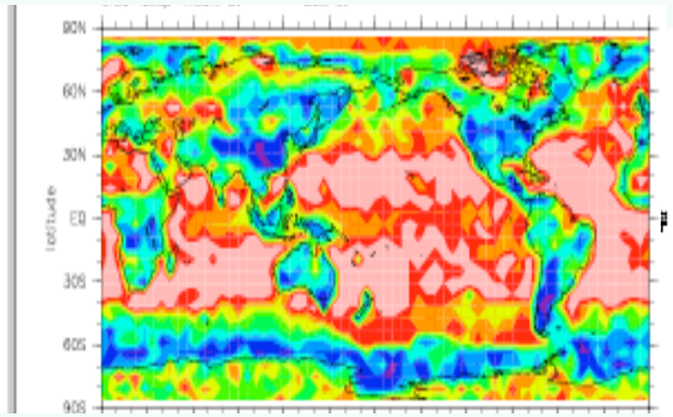
- Many observations relating to radiation balance and clouds

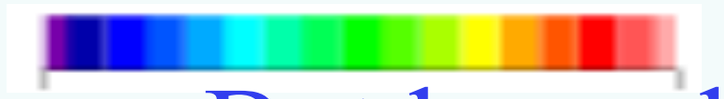
Clear sky SW Radiation

CMIP3-AOGCM

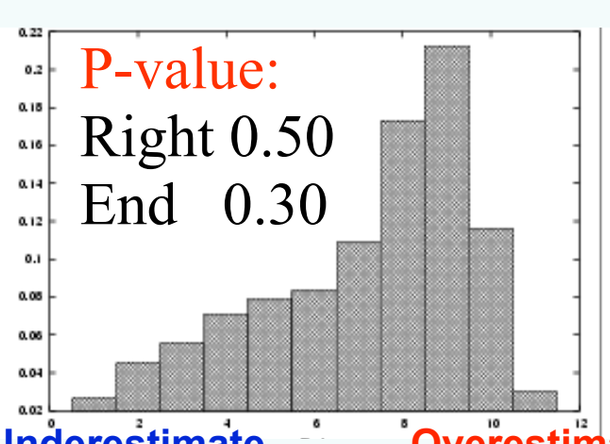


CMIP3-ASGCM

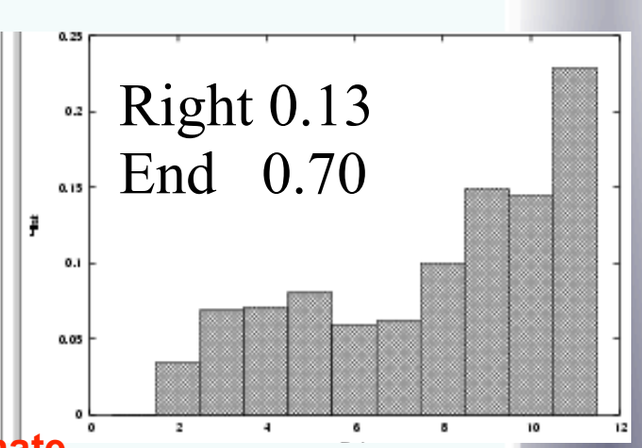




CMIP3-AOGCM



CMIP3-ASGCM



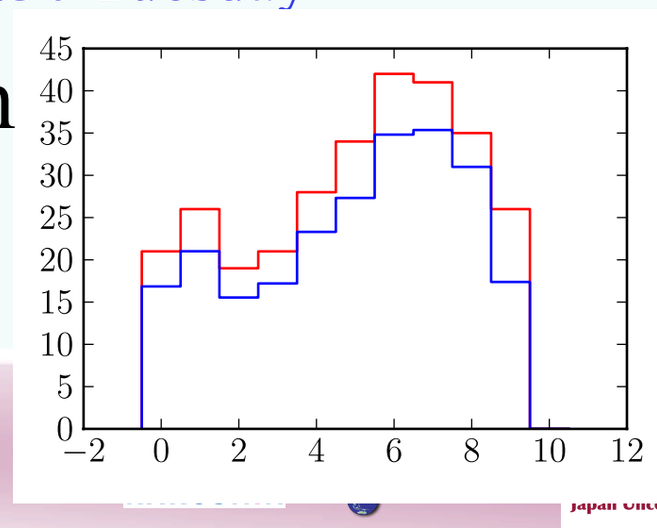
Underestimate Overestimate

But how about climate *change*?

Hargreaves et al submitted - see talk, CL1.2 15:30 Tuesday

Climate change at the Last Glacial Maximum

Rank Histogram of temperature anomalies
MARGO vs PMIP2



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"But if the ensemble isn't centred on the truth, why is the multi-model mean so good?"

$$(1/n)\sum||m_i-O||^2 = (1/n)\sum||m_i-M||^2 + ||O-M||^2$$

Average of model errors = Ensemble spread + Error of multi-model mean
(eg Stephenson and Doblas-Reyes 2000, Epstein 1969, Leith 1974)

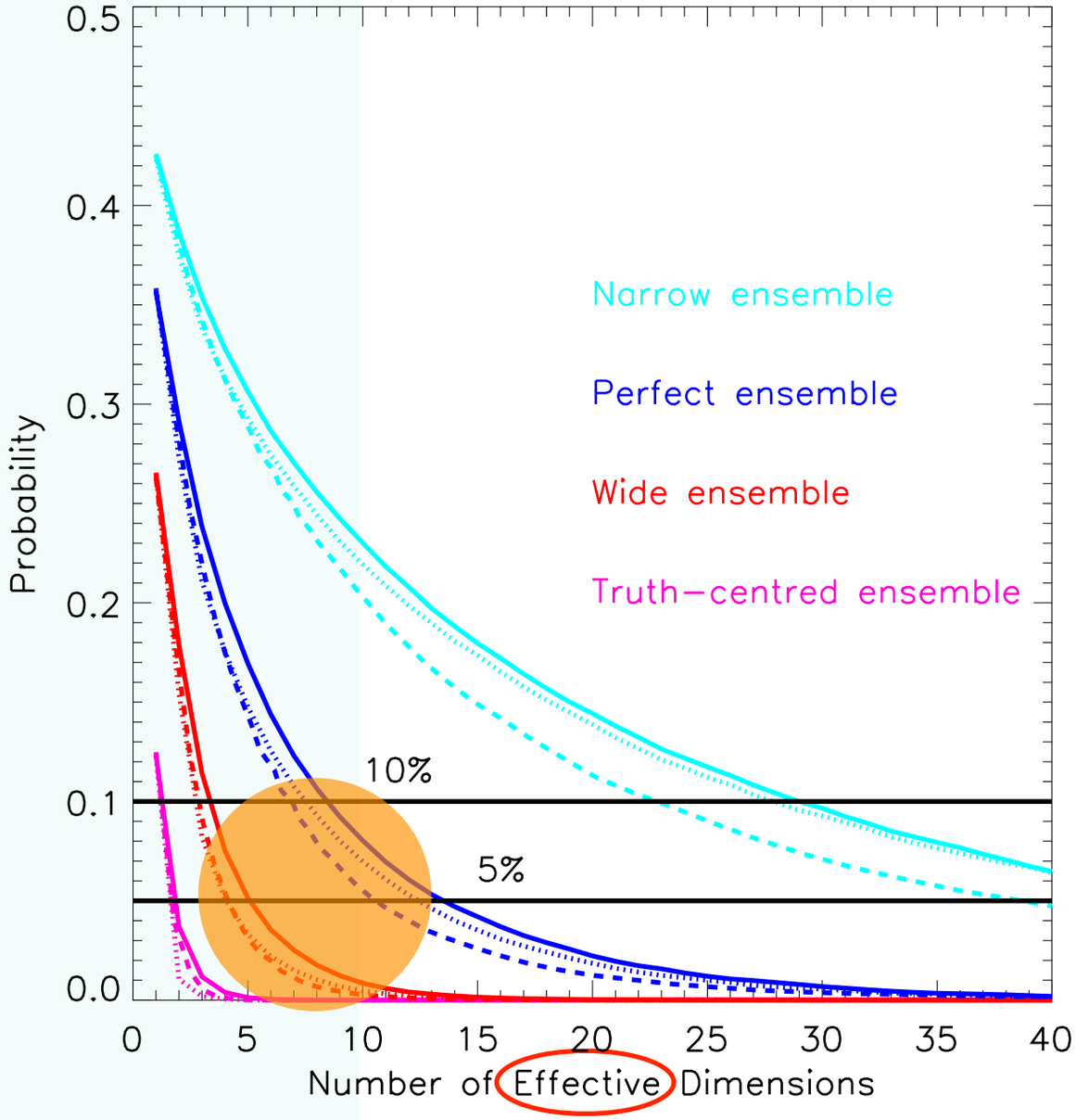
Where the m_i are the models, $M=(1/n)\sum m_i$ is their mean and O are the obs

Follow-up: When is the mean better than the *best* model, and why?

(Annan and Hargreaves, J Clim in press)

- Lambert and Boer 2001 Cli Dyn: "the mean model is generally the best model"
- Glecker et al 2008 JGR : "in most cases the mean and median models score best"
- Pierce et al 2009 PNAS: "Although MM's superiority has been found in previous studies focusing on the mean climate, the reasons for this have not generally been elucidated"
- Statistically Indistinguishable paradigm can provide some insights

Probability of a given model being better than the mean



Solid: Isotropic (spherical) Gaussian
Dotted: exponential eigenvalues
Dashed: 1/√i distribution

(T.Palmer, ECMWF Newsletter #106)

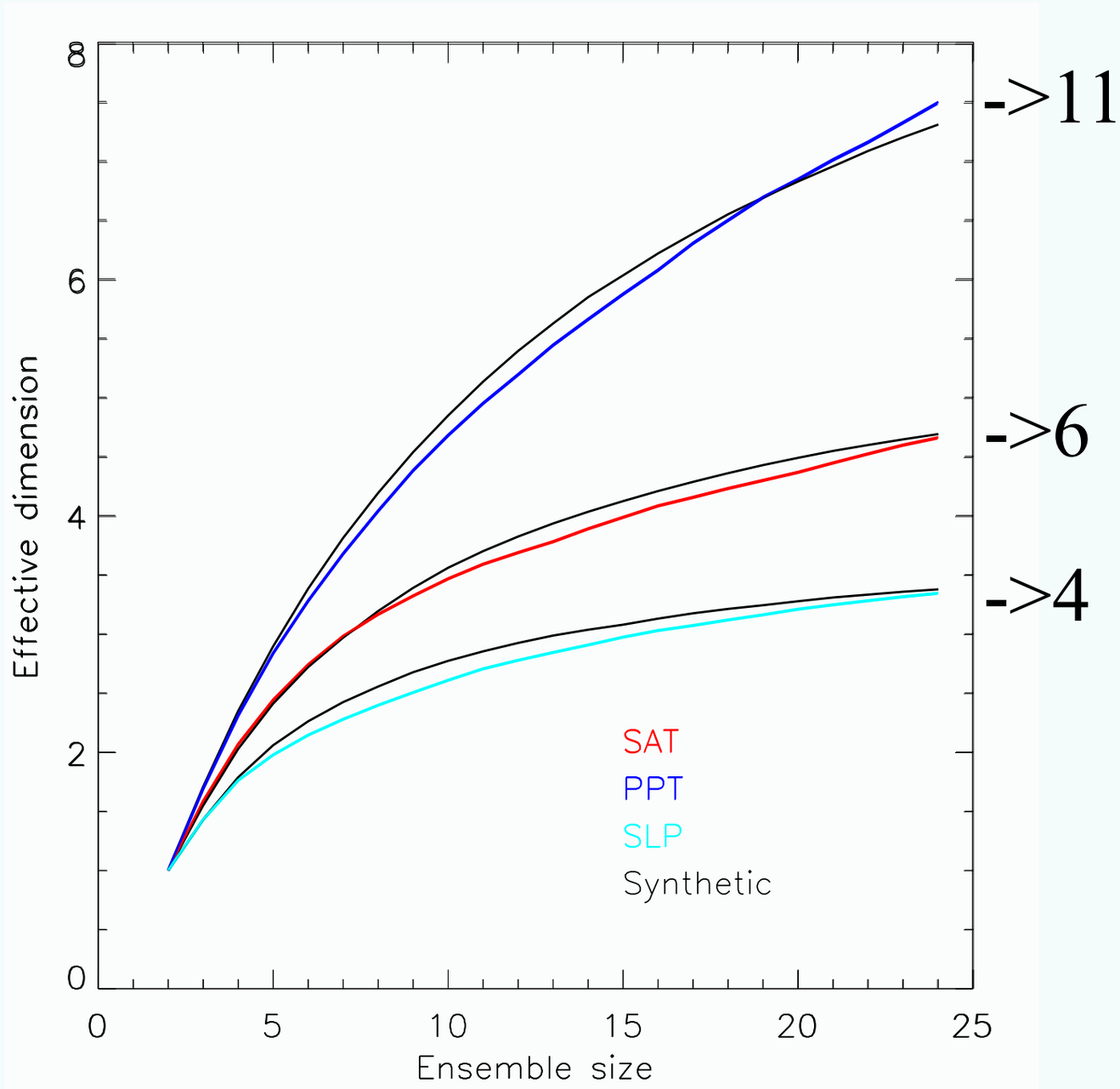
CMIP3 results (2D fields)

- Strongly depends on relative width and effective dimension
- Doesn't depend on shape of distribution

How many effective dimensions are there?

- We've seen this is critical for analysing CMIP3 behaviour
  - Annan and Hargreaves GRL 2010:
    N_{ef} = 40 (NWP) or 5 (cross-validation)
  - These imply very different interpretations of the results
- CMIP3 ensemble: N_{ef} = 4.6, 7.5 and 3.4 (SAT, PPT, SLP)
  (based on Bretherton et al EOF approach, supported by cross-validation)
- Finite sample gives lower N_{ef} than infinite ensemble from same distribution
  - More models will sample more dimensions

Test subsets of models



Comparison with synthetic data of known effective dimension

Summary

- Multi-model ensemble fits the statistically indistinguishable paradigm fairly well.
- ...Even for out of sample data (PMIP and the LGM).
- Many properties of the ensemble can be easily explained within this framework.
- “Reliability” is a key concept in evaluating the MME.
- Provides a basis for use of the MME in probabilistic prediction.
- Ensemble size is far from saturated

Bibliography

- J.C. Hargreaves “Skill and uncertainty in climate models” WIRES 2010
- J.D. Annan and J.C. Hargreaves, “Reliability of the CMIP3 ensemble”, GRL 2010
- J.D. Annan and J.C. Hargreaves “Understanding the CMIP3 multi-model ensemble”, In Press, J Clim
- T. Yokohata et al, “Reliability of structurally different perturbed physics and multi-model ensembles”, submitted to Climate Dynamics
- J.C. Hargreaves et al, Are the PMIP climate models consistent with the MARGO data synthesis for the Last Glacial Maximum? Clim Past Discussions.

All papers are online: Google “James Annan”, and go to his work page.

The End