

Do quantitative decadal forecasts from GCMs provide decision-relevant skill?

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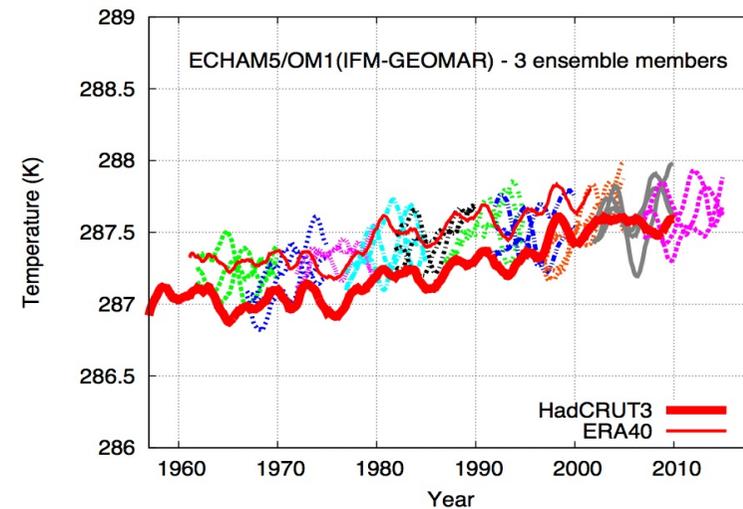
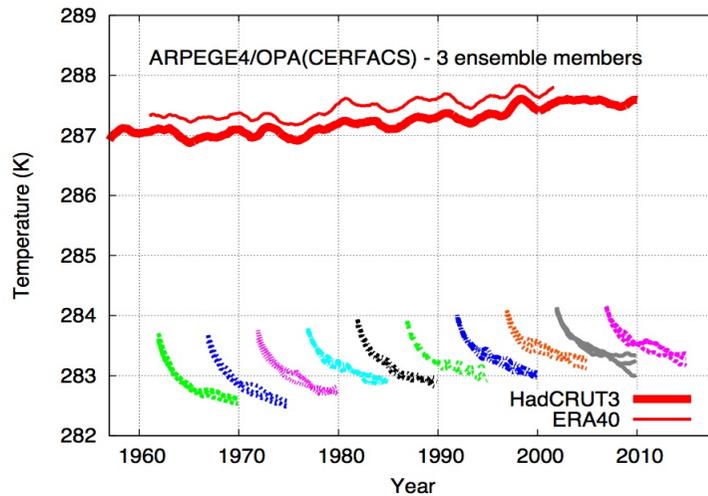
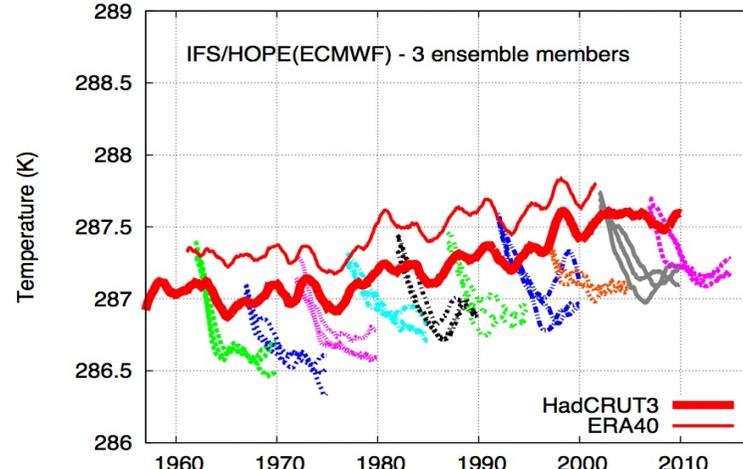
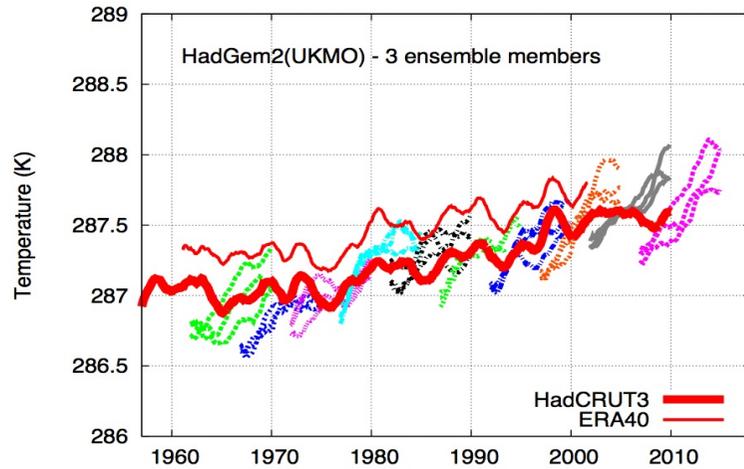
25th April 2012

Do decadal forecasts provide decision-relevant skill?

Background

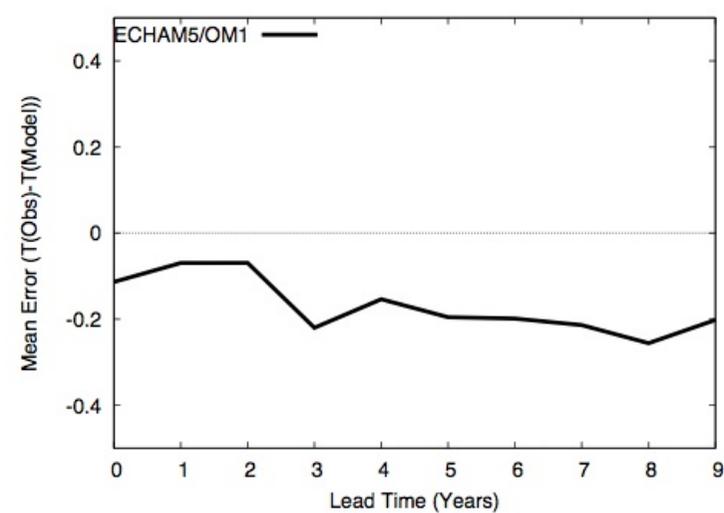
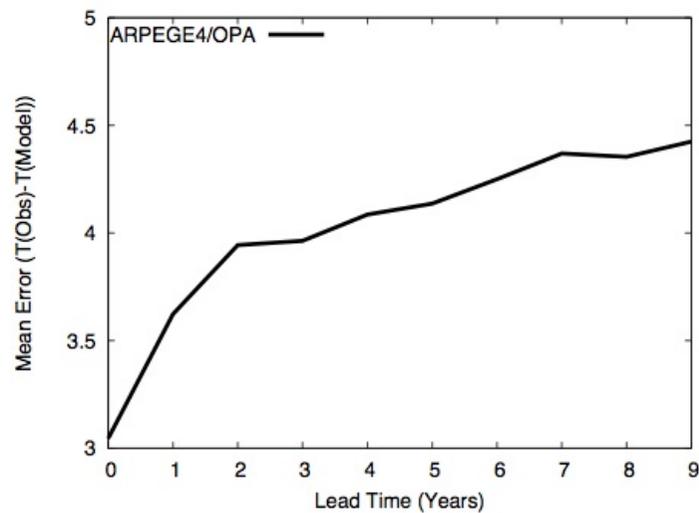
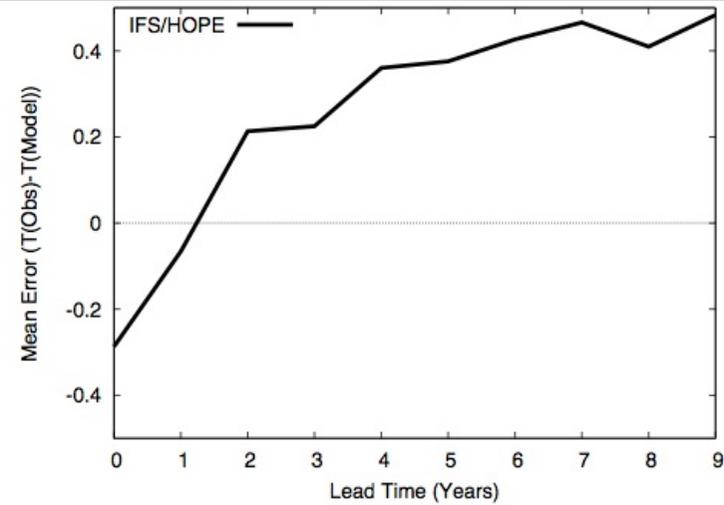
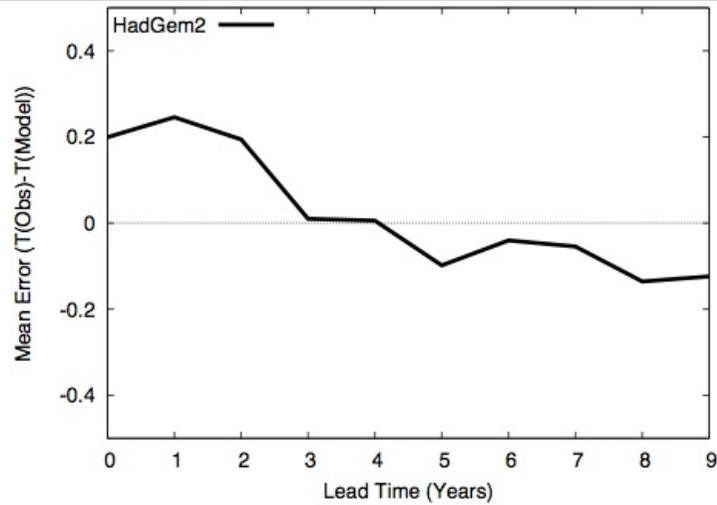
- 1. Decadal predictions potentially provide useful information for decision makers**
 - Adaptation to climate impacts
 - Flexible response planning
- 2. Decadal hindcast experiments and historical data archive allow standard forecast evaluation methods to be used**
 - Skillful hindcasts do not guarantee predictability into the future
 - Evaluation of hindcast skill can inform future experimental design and impacts studies
 - Knowing about a lack of skill is also useful to decision-makers
- 3. Initialised hindcast experiments are a focus for IPCC AR5**
 - What makes an appropriate benchmark to measure skill against for such forecasts?
- 4. Global mean temperature is the focus of this study**

Decadal hindcast experiments - ENSEMBLES

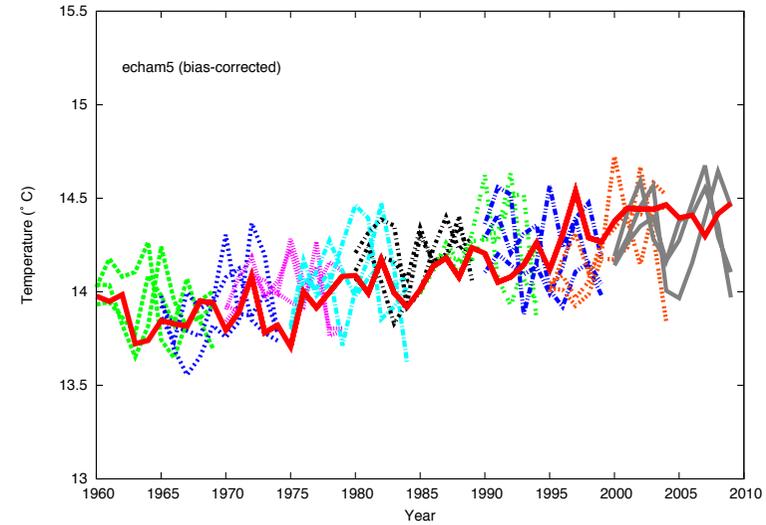
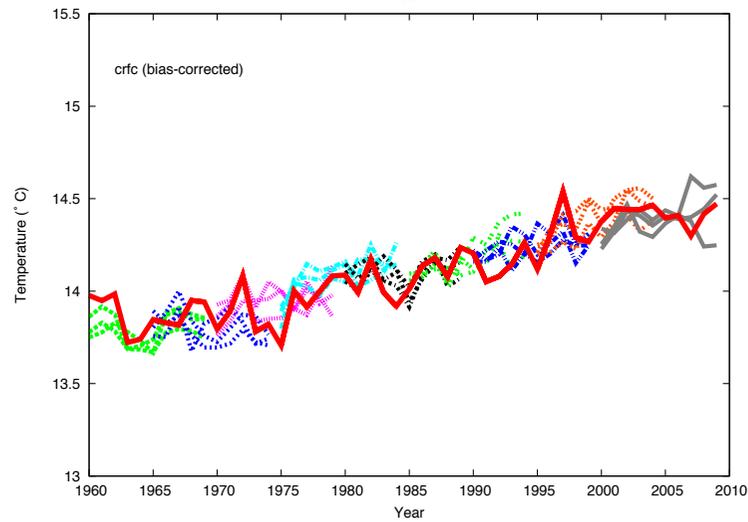
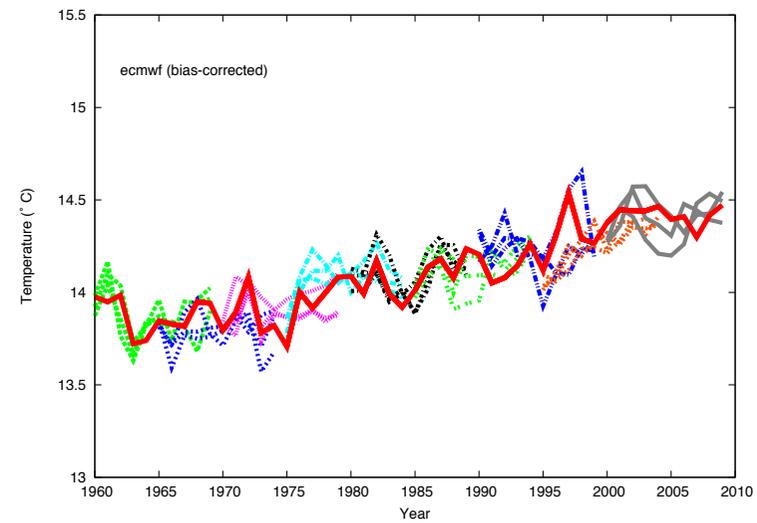
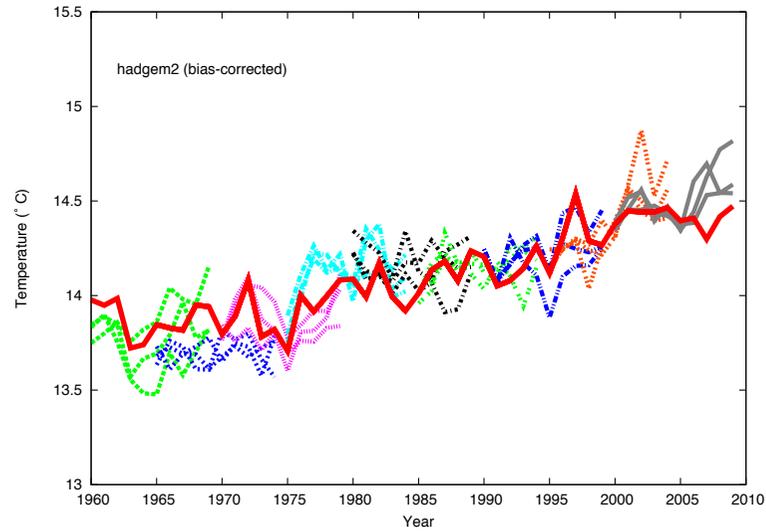


F. J. Doblas-Reyes et al. *Technical Memorandum ECMWF*, 621 (2010).

Decadal hindcast experiments – model bias



Decadal hindcast experiments after bias correction



From ensembles to predictive distributions

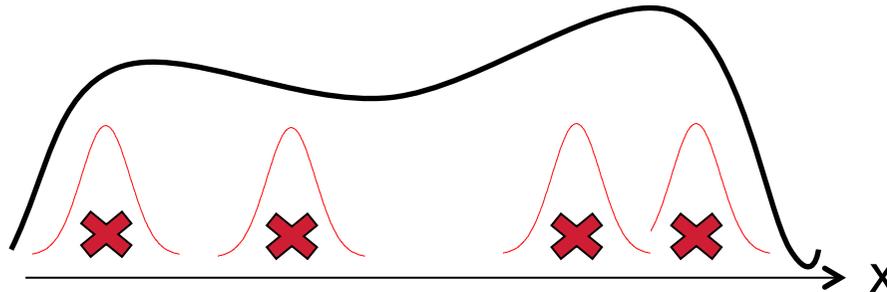
Kernel Dressing

The model-based component of the density, with N ensembles

$$p(y : x, \sigma) = \frac{1}{N\sigma} \sum_{i=1}^N K\left(\frac{y - (x^i + \mu)}{\sigma}\right)$$

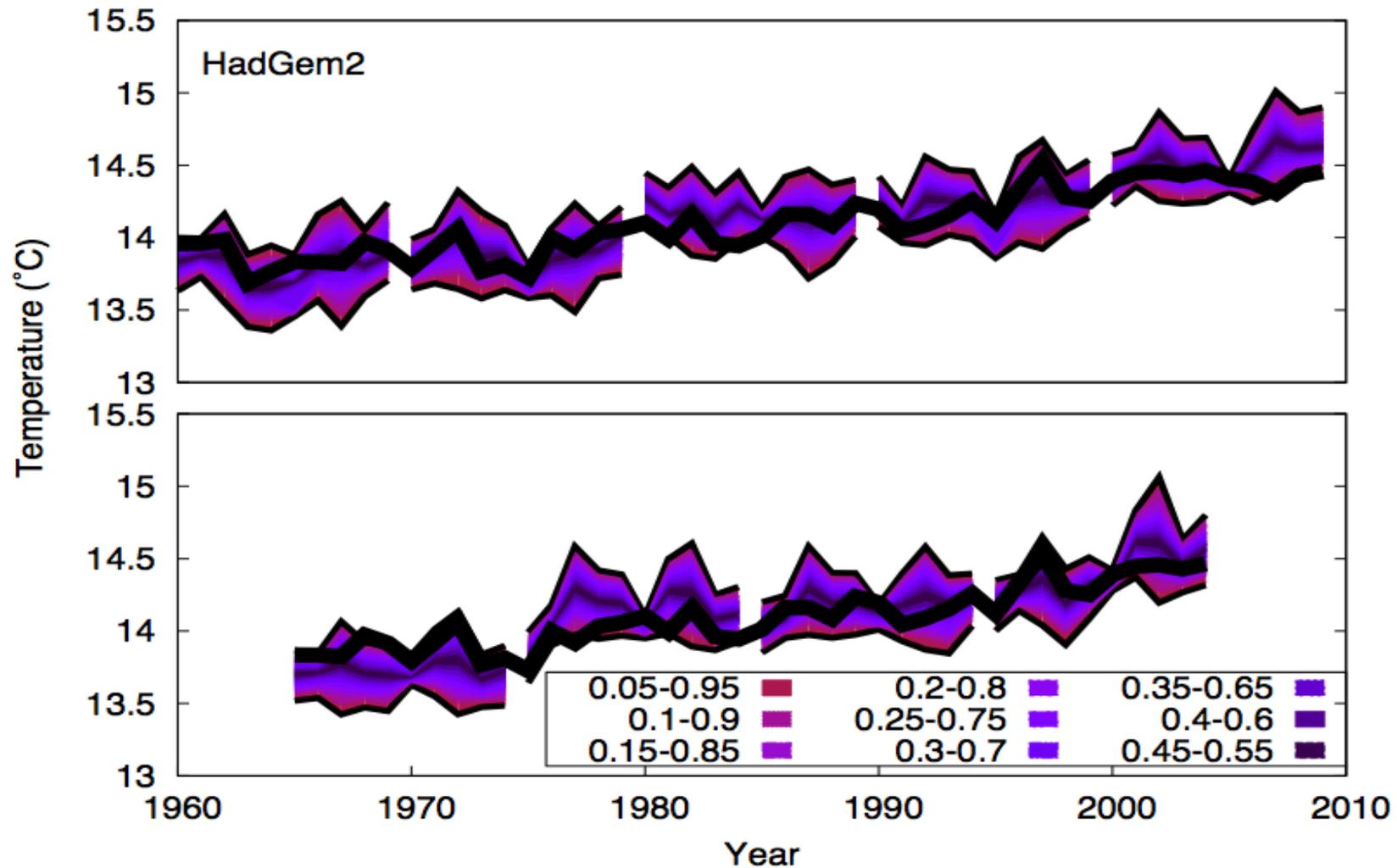
Kernel, K , is a normalised Gaussian

- Parameters, μ (kernel mean plus bias correction) and σ (kernel spread), are varied to minimise the skill score (Ignorance, CRPS, quadratic)
- Cross-validation method important in evaluation



J. Bröcker and L. A. Smith, *Tellus A*, 60(4):663-678 (2007).

GCM decadal forecast distributions (GMT)



Defining 'zero skill' with empirical models

Dynamic climatology

1. Evaluating forecast performance involves computing skill relative to a benchmark that defines 'zero skill'

- Empirical models quantify our ability to predict without knowing the laws of physics
- Climatology, persistence, statistical models serve as empirical benchmark models
- But what makes an appropriate 'zero skill' model?

2. Dynamic climatology (DC) is a more appropriate benchmark for near-term (initialised) climate forecasts

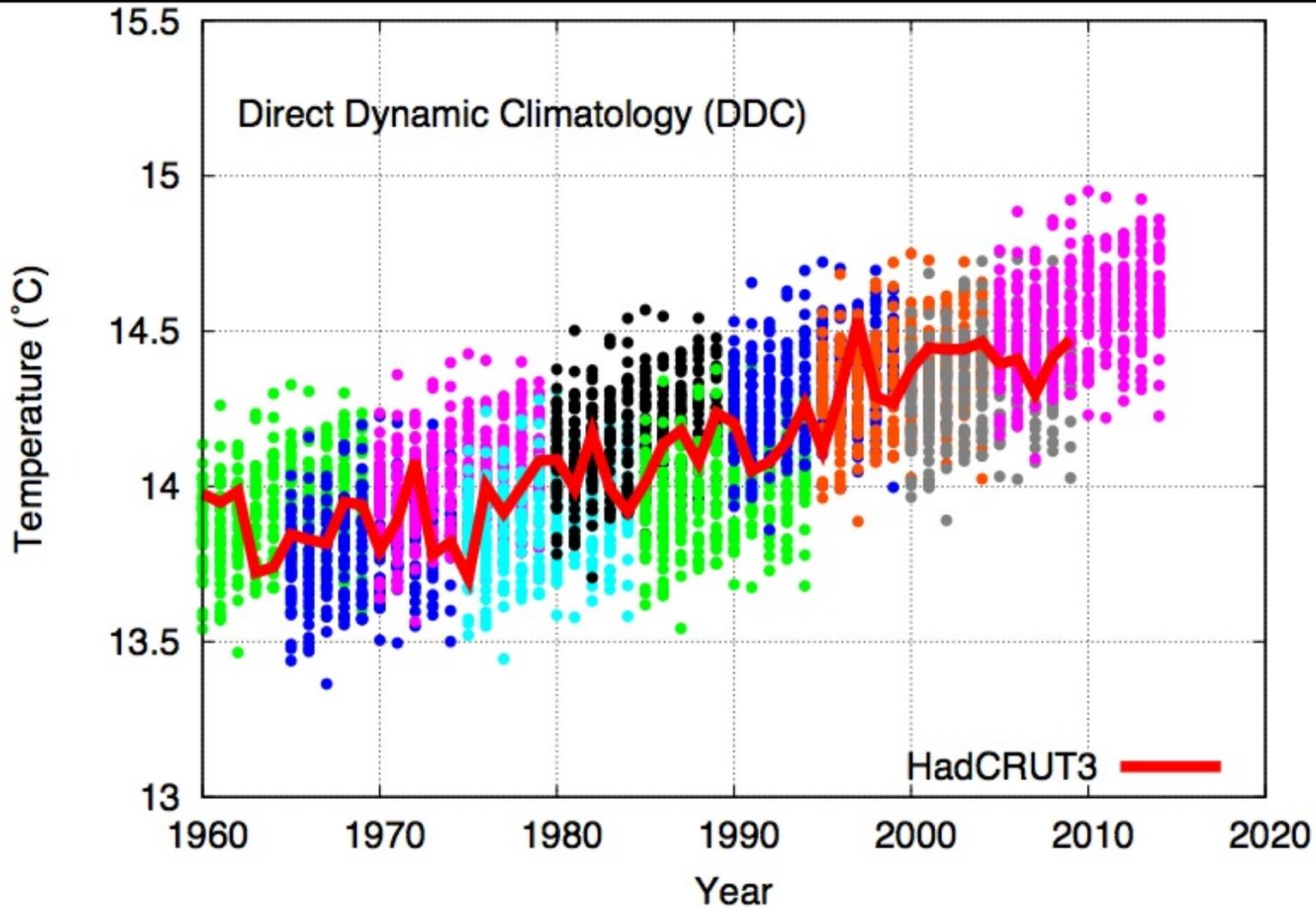
- A conditional climatology, initialised at launch and built from the historical archive
- Ensemble members are composed of analogues of the current state, mapped forward in time
- Analogues defined in terms of l th differences in observed record

$$f(l) = \sum_{i=1}^N O(t=0) + \Delta_i O(l_i)$$

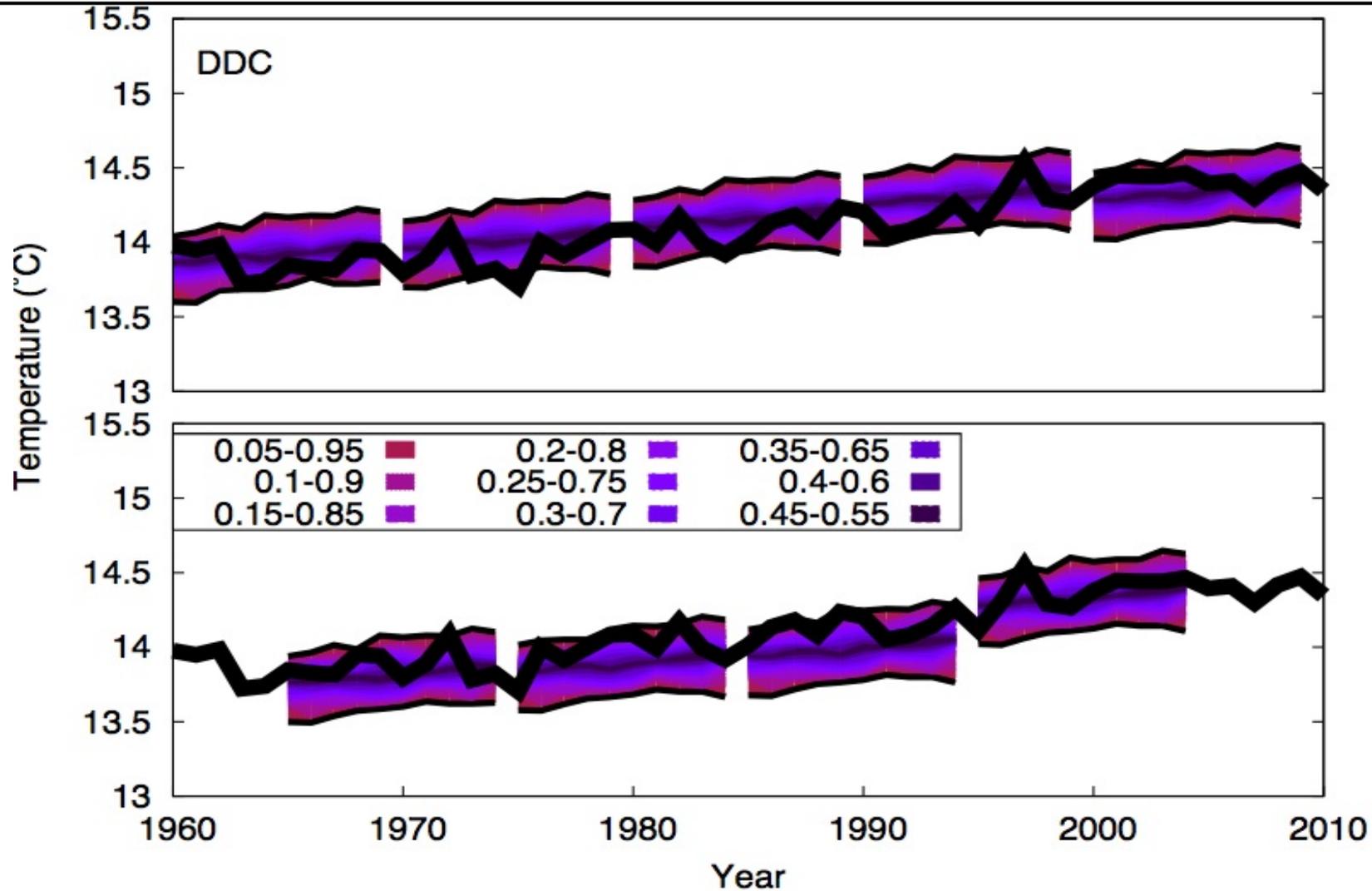
- Choosing analogues:
 - Use full set of available analogues (dynamic climatology)
 - Define nearest neighbours and sample (random analogue prediction)

L. A. Smith, *Nonlinearity in Geophysics and Astrophysics*, CXXXIII:177-246 (1997).

Dynamic climatology as a 'zero skill' benchmark

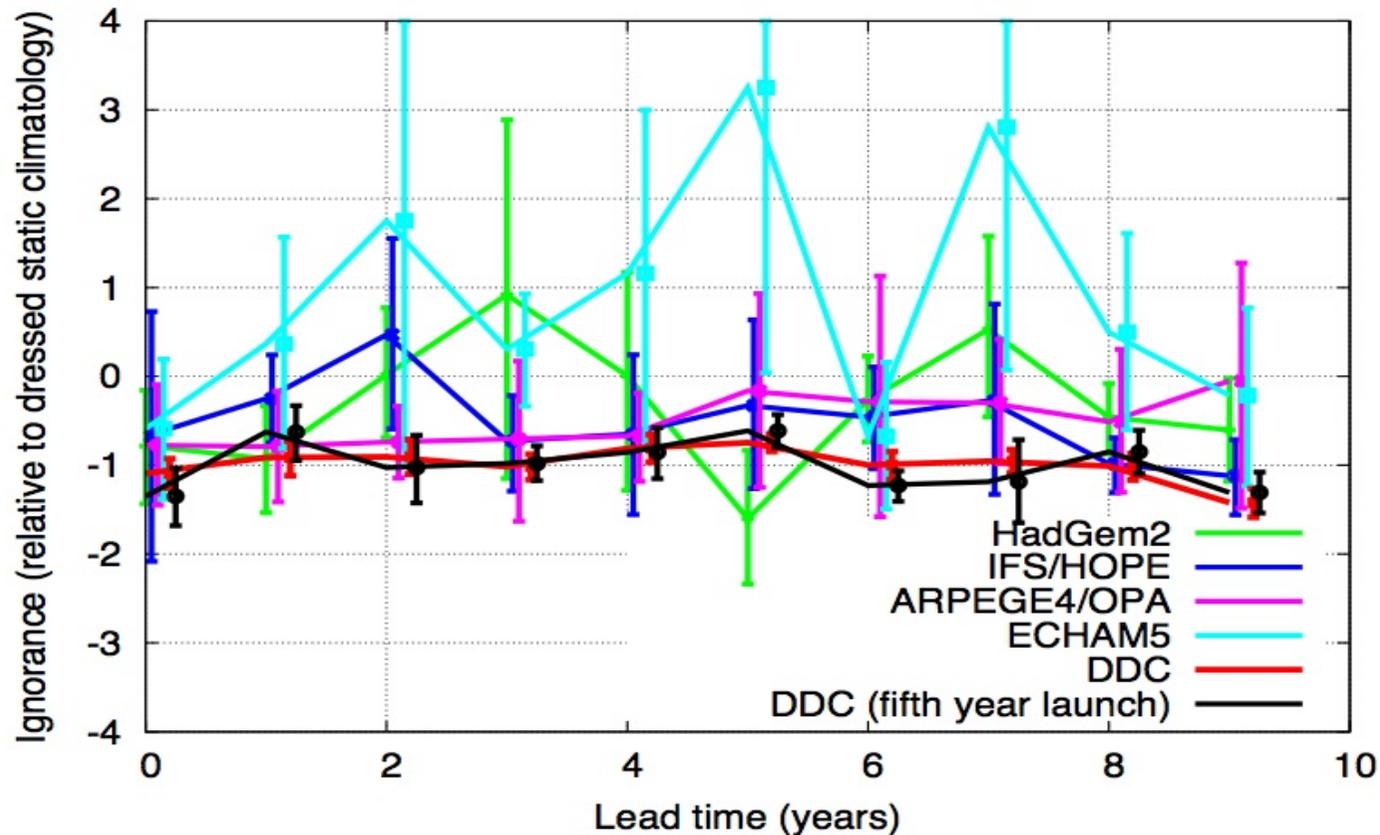


Dynamic climatology forecast distribution (GMT)



Forecast skill relative to static climatology

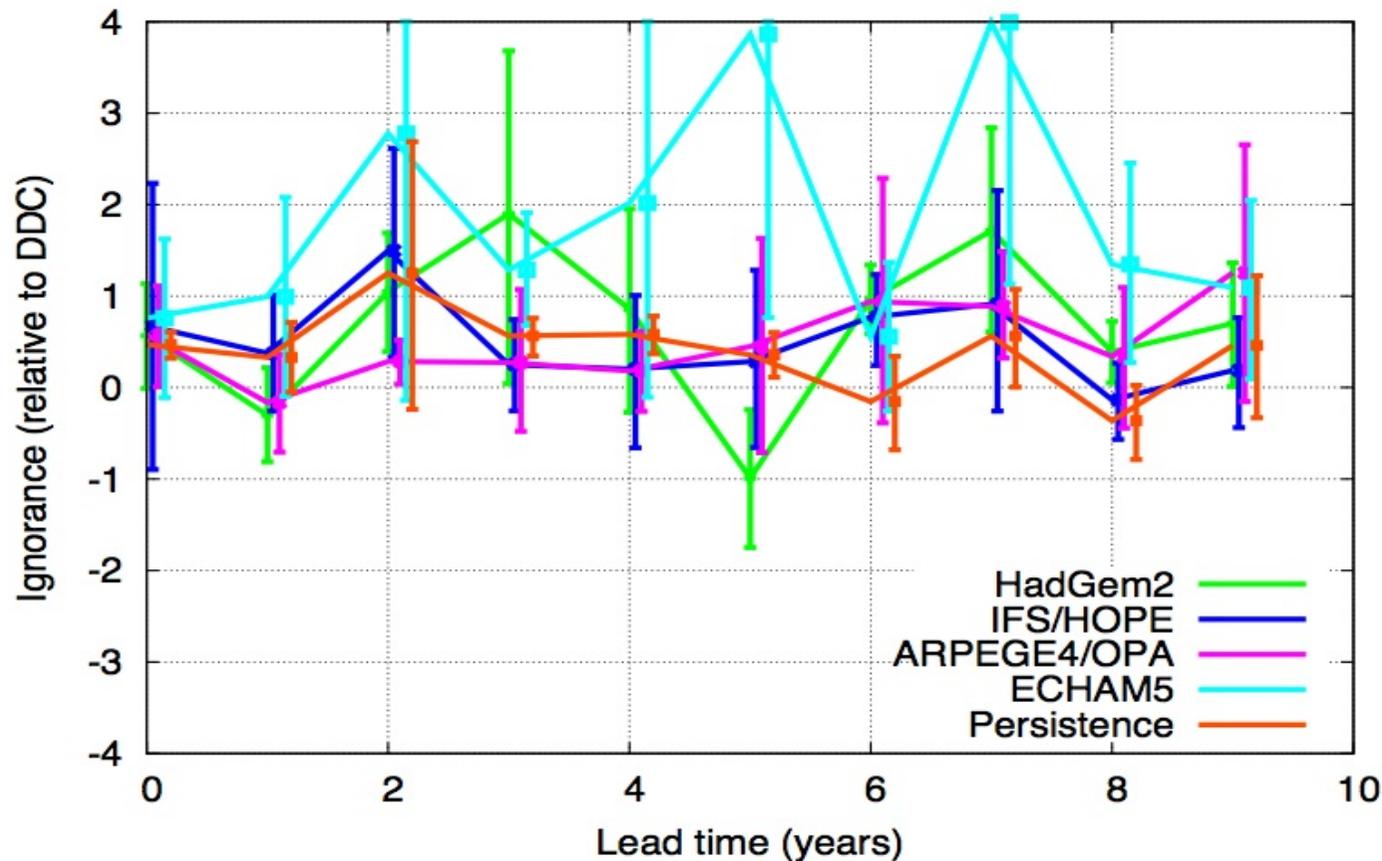
Most models (including benchmark) show skill against static climatology



Ignorance skill score:
$$S_{rel}(p(y), Y) = \frac{1}{F} \sum_{i=1}^F -\log_2 \left[\frac{p_i(Y_i)}{p_{ref}(Y_i)} \right]$$

Forecast skill relative to benchmark model

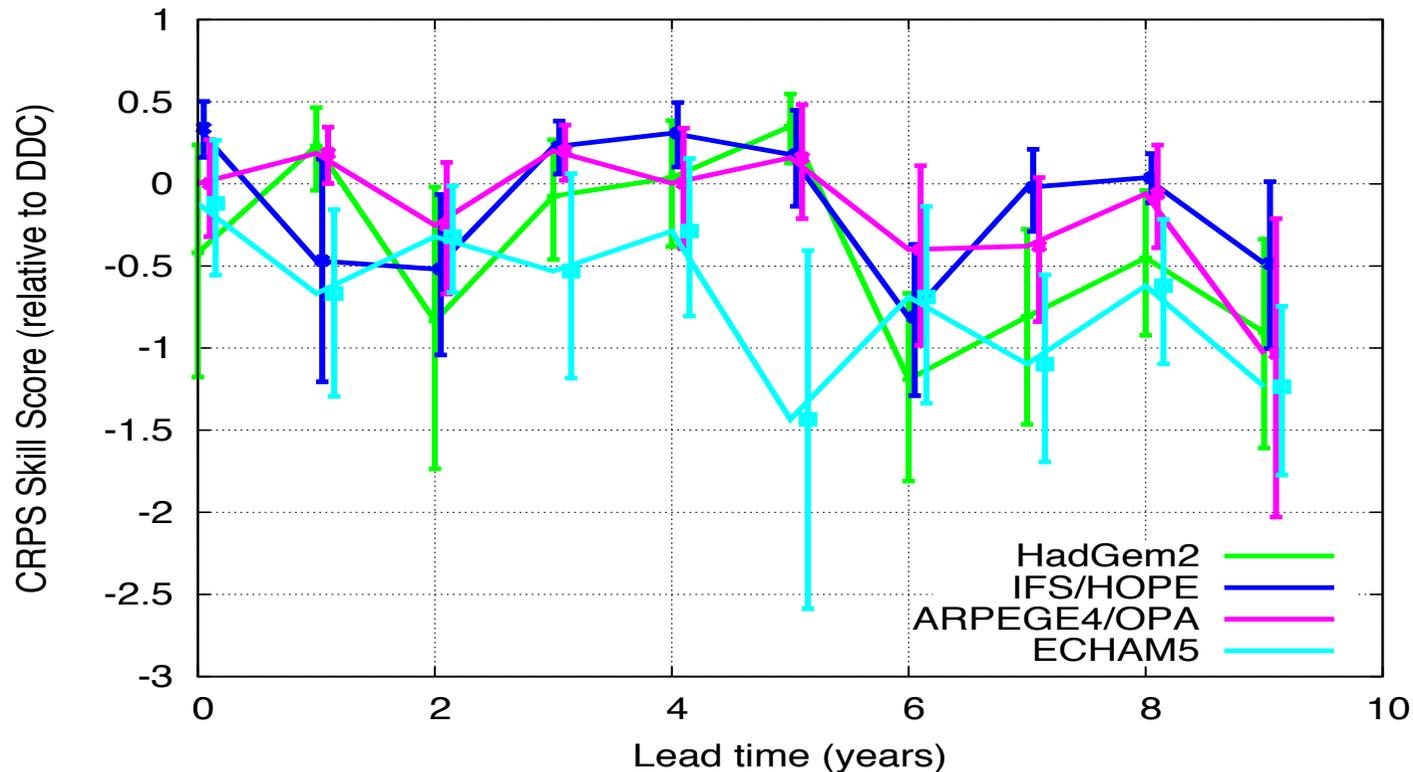
No evidence of significant skill above the statistical benchmark



Similar results have been demonstrated over each of the Giorgi regions for surface air temperature at annual lead times

Evaluation of skill using CRP skill score

Result is robust across skill scores



Continuous ranked probability score: $CRPS = \int_{-\infty}^y G(x)^2 dx + \int_y^{\infty} [G(x) - 1]^2 dx$

Skill score: $SS = 1 - \frac{CRPS_{forecast}}{CRPS_{reference}}$

Do decadal forecasts provide decision-relevant skill?

Summary

- 1. A robust and transparent forecast evaluation procedure is desirable**
 - Important because of decision-relevance
 - Forecast skill is necessary, but not sufficient to establish value to a user
 - Evaluation and post-processing methods need to be made clear in advance
 - Appropriate measures of skill and value evaluated
- 2. A framework for in-sample skill evaluation of ensemble prediction systems is demonstrated**
 - Approach addresses the value added compared to a 'zero skill' benchmark model
- 3. Significant skill is not found for any of the ENSEMBLES GCMs against a simple data-based model**
 - Demonstrated at GMT and Giorgi region scale for ENSEMBLES models
 - Small sample size is part of the problem – results should inform future design
 - How do we use scientific insight given low model skill?

E. B. Suckling and L. A. Smith, Do decadal predictions from GCMs yield decision-relevant skill?
in preparation.

Do decadal forecasts provide decision-relevant skill?

Methodology - Summary

1. Bias correction

- Evaluation framework allows different bias correction approaches to be tested
- Variational method seeks post-processing parameters that produce minimised score

2. Kernel dressing

- Predictions for decision-making are generally given out as probabilistic forecasts
- Evaluating post-processed forecasts provides a better basis for decision-makers

3. Scoring rule

- Evaluating proper scoring rules provides most robust measures of skill
- All scoring rules applied in this case led to the same conclusion

4. Benchmark model

- Dynamic climatology is a more appropriate 'zero skill' model against initialised decadal hindcasts
- Differences (changes) are chosen rather than absolute values and care is taken to not over fit or cheat by leaving out period being forecasted/evaluated
- More sophisticated methods to choose analogues could be applied
- Initialised DDC forecast for the next decade is based on differences over last decades

Thank You!

Contact Me

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Related posters and talks

CL3.3/NP5.4: Insightful measures of predictive skill in seasonal forecasts
H. L. Du, F. Niehörster & L. A. Smith (Hall Z #83 – 17.30)

Skill scores for probabilistic climate and weather prediction
T. Maynard, E. B. Suckling & L. A. Smith (Hall Z #84 – 17.30)

AS1.2: Gradient descent assimilation for the point-vortex model
E. B. Suckling and L. A. Smith (Room 14 - 09.30)

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