Decadal Prediction Research in Reading

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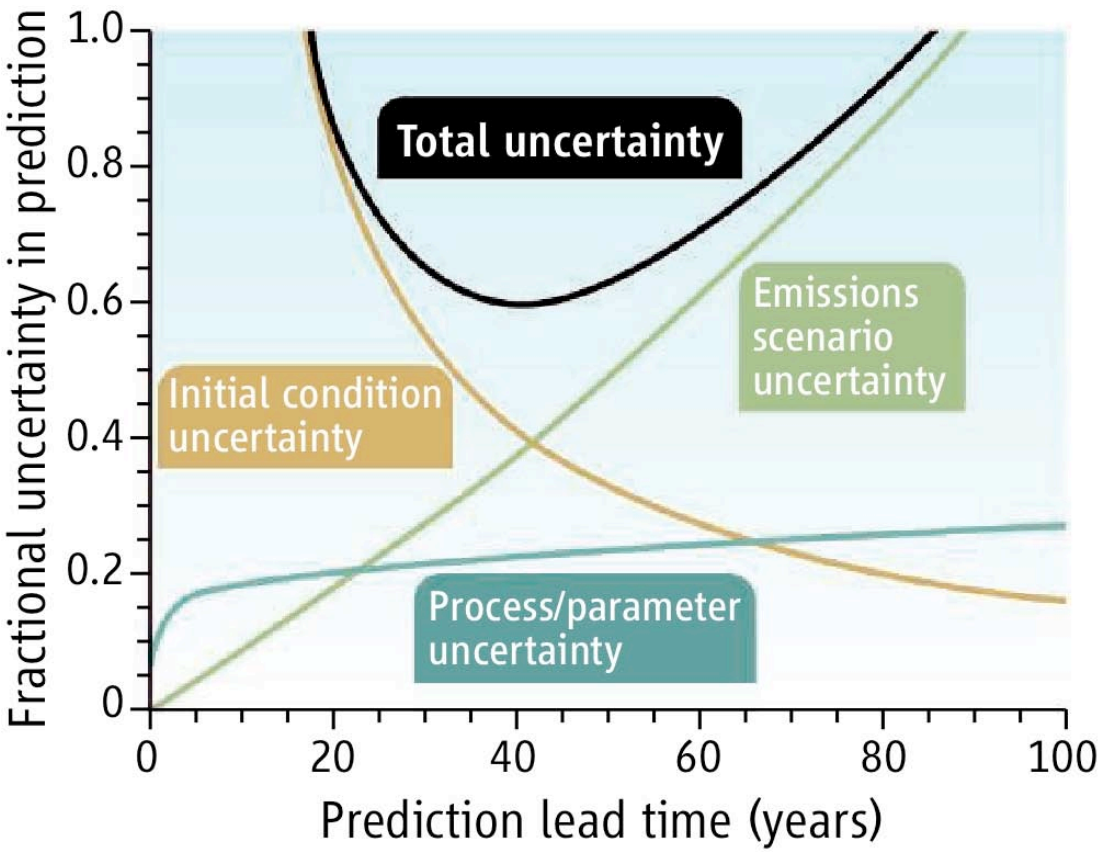
1. Analysis of sources of uncertainty in decadal climate predictions using CMIP data
   (Hawkins & Sutton, submitted to BAMS, 2008)
2. Estimation of Singular Vectors for Decadal Predictions
3. Analysis of UK Met Office Decadal Prediction system
4. Decadal predictability studies:
   - Sensitivity of predictability, for ocean and climate variables, to the initial ocean state
   - Potential predictability of rapid THC changes (Hawkins & Sutton, 2008, GRL)
   - Impact of higher resolution on simulation of decadal variability and predictability using UK-HiGEM model (~1 degree atmosphere, 1/3 degree ocean)

Will focus on 1 & 2 + 3 very briefly

1. Sources of uncertainty in decadal climate predictions

Motivation:

$$\frac{\sigma_{source}(t)}{T_{mean}(t)}$$



Cox & Stephenson, Science, 2007

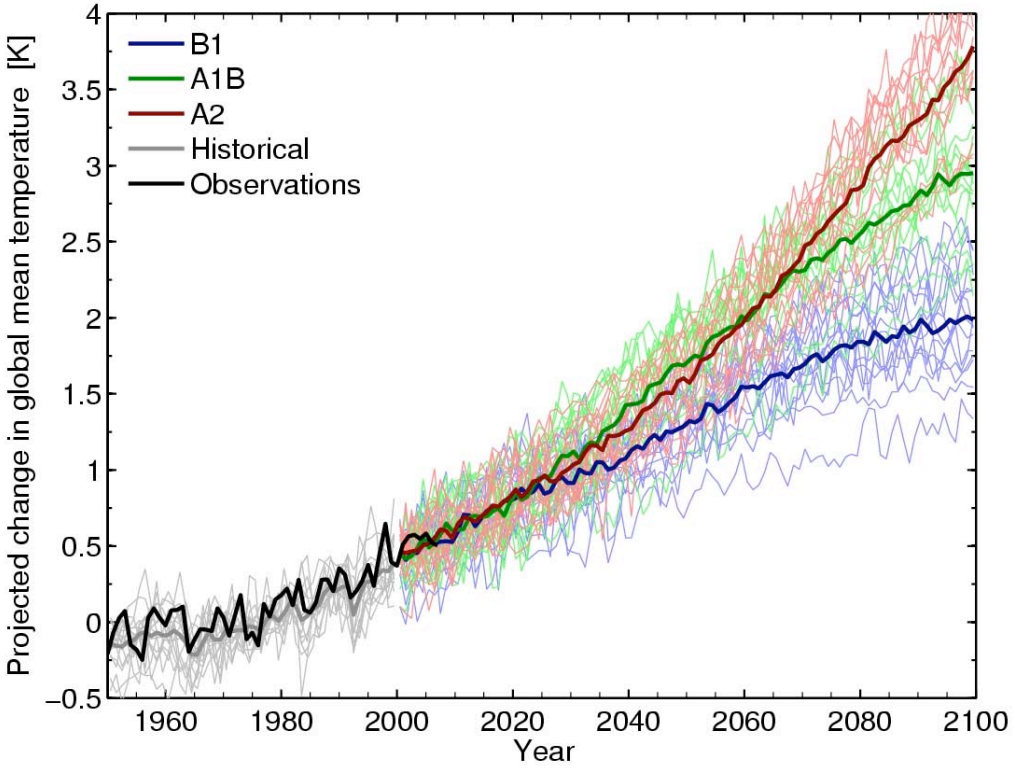
– using simple 1d climate model for global, decadal mean, surface temperatures

- Is this really correct? Is model uncertainty unimportant?
- What about on regional scales (which are much more relevant for decision making)?

Methods for IPCC data

- Fit polynomial to individual projections
  - Standard deviation of the residual is the internal variability component, assumed constant in time
- Scenario uncertainty is estimated as the standard deviation of the multi-model means (3 scenarios)
- Model uncertainty is mean of the standard deviation in each scenario (15 models)
  - models weighted by ability to reproduce global mean temperature increase at year 2000 above 1961-1990 baseline

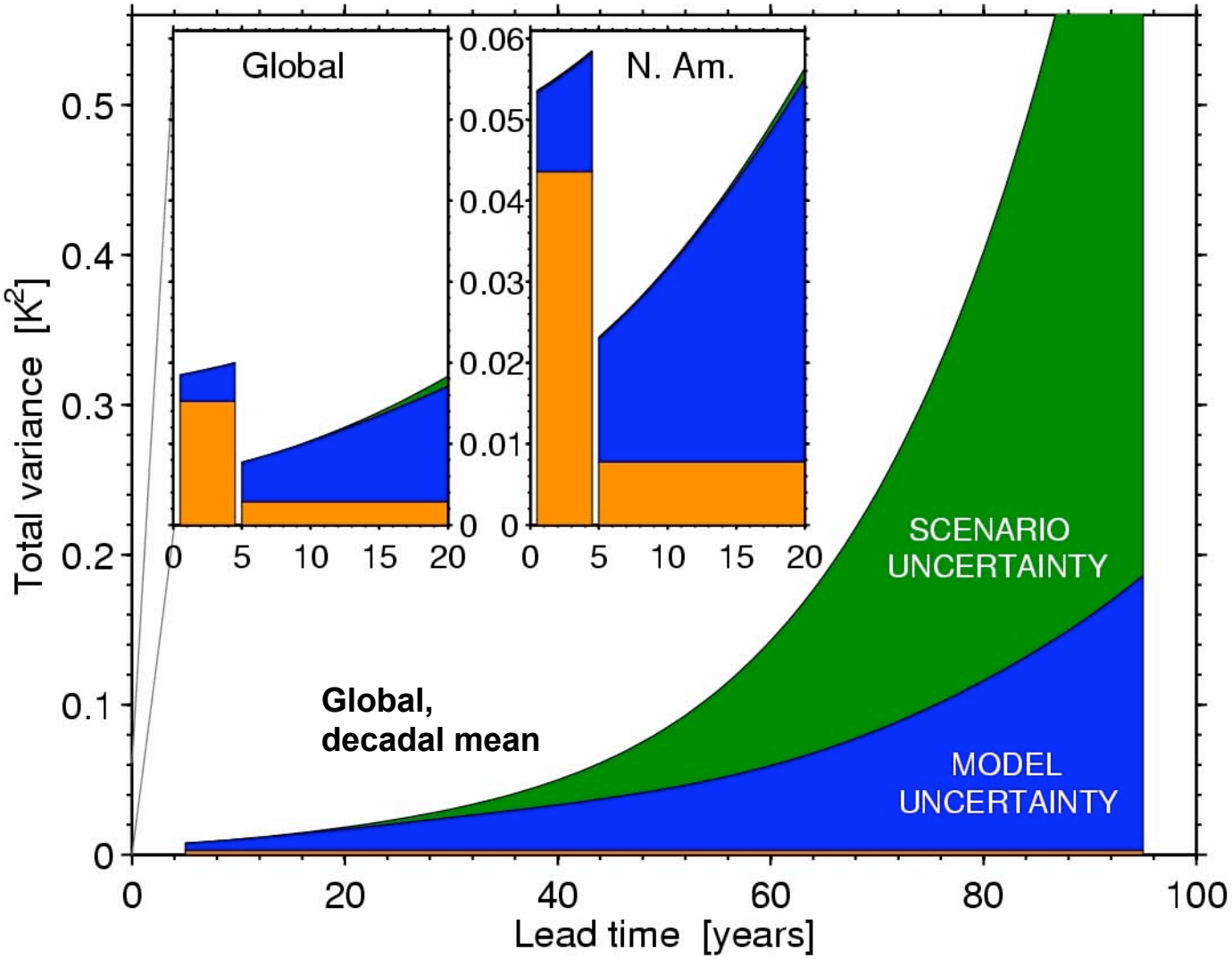
Global temperature projections from CMIP data



Can be repeated for different regions and temporal means

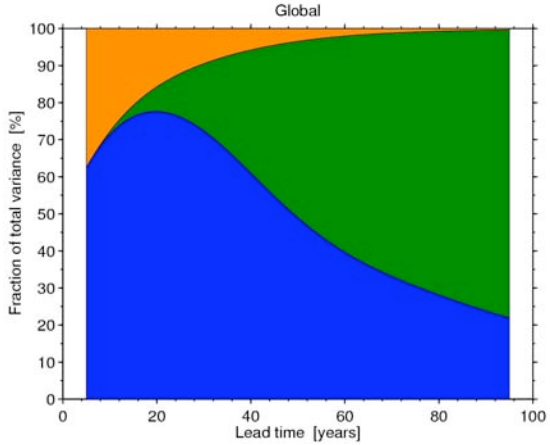
Uncertainty varies with spatial and temporal averaging, and lead time

Variance in temperature projections

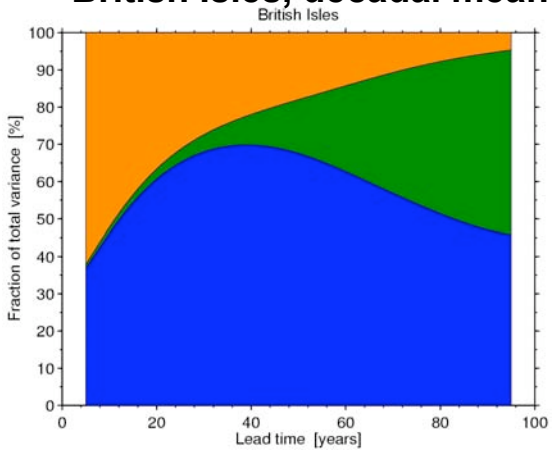


Fraction of total variance

Global, decadal mean



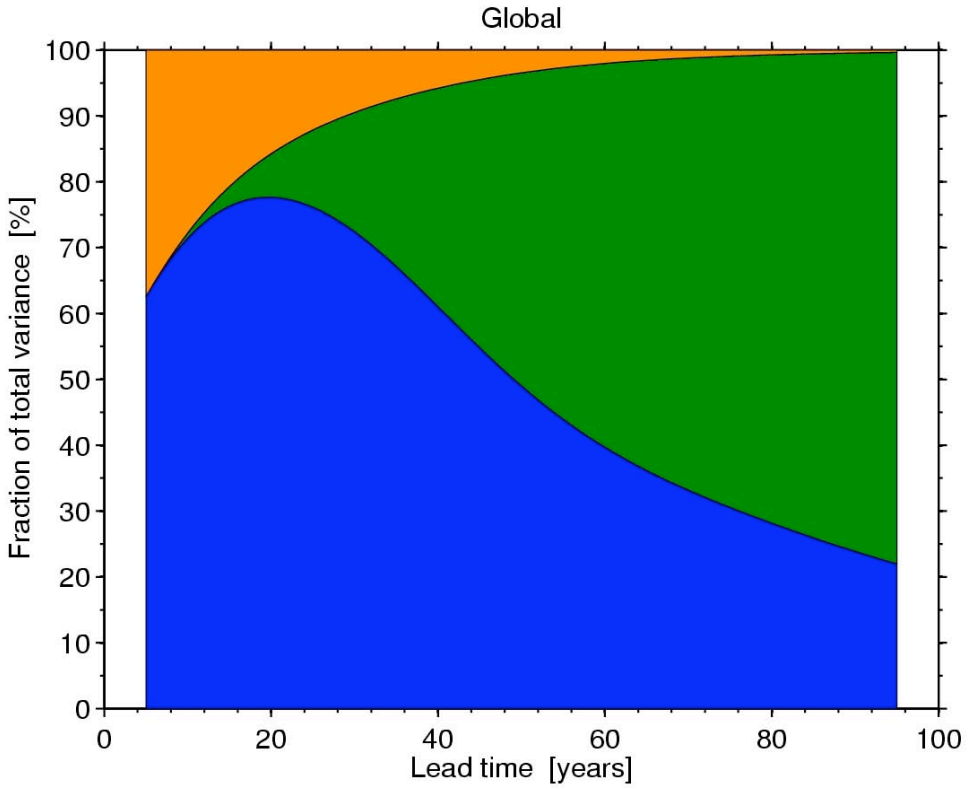
British Isles, decadal mean



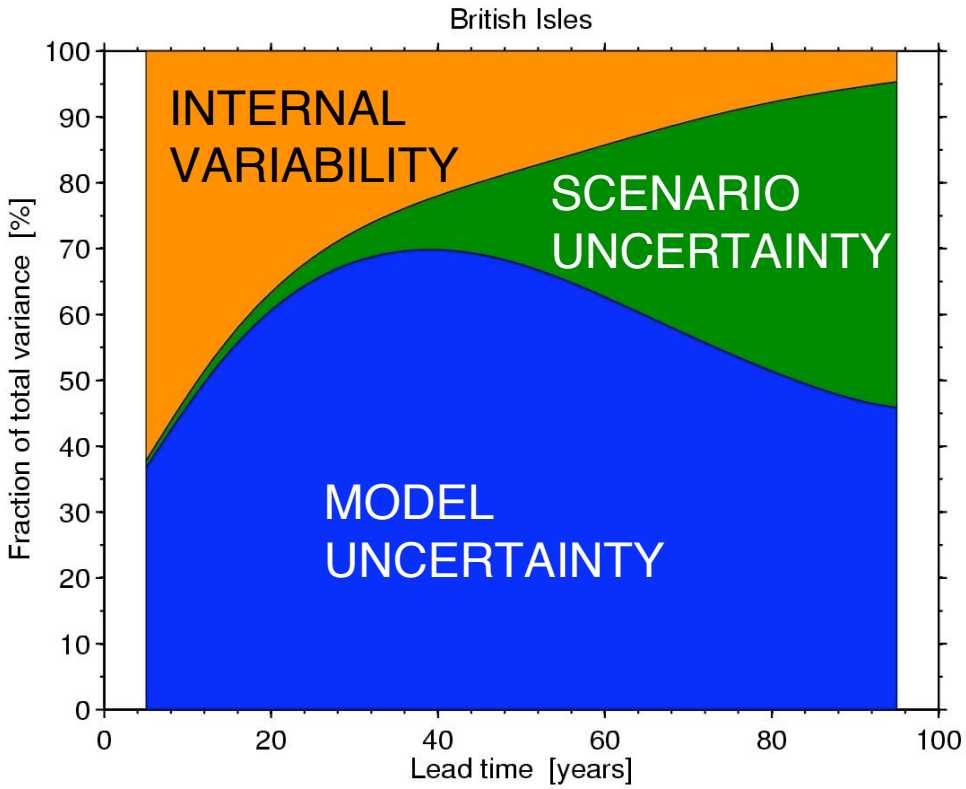
orange = internal variability

Uncertainty varies with spatial and temporal averaging, and lead time

Fraction of total variance



Global, decadal mean



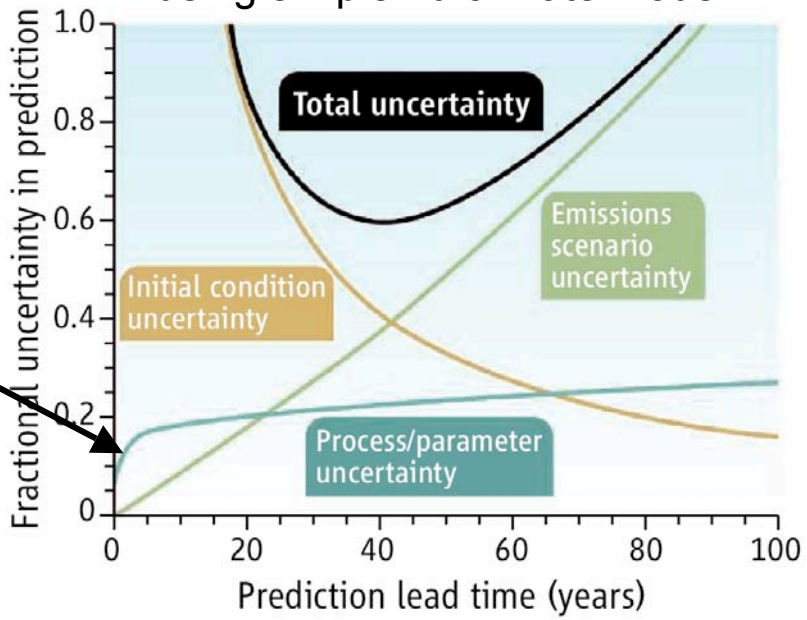
British Isles, decadal mean

Fractional uncertainty in projections of global mean decadal mean temperature

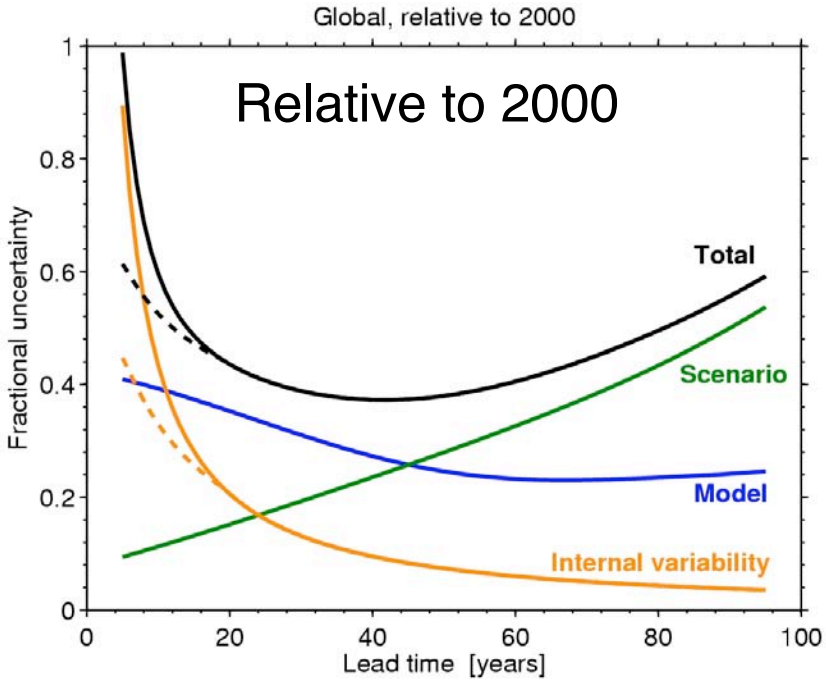
Cox & Stephenson, Science, 2007
– using simple 1d climate model

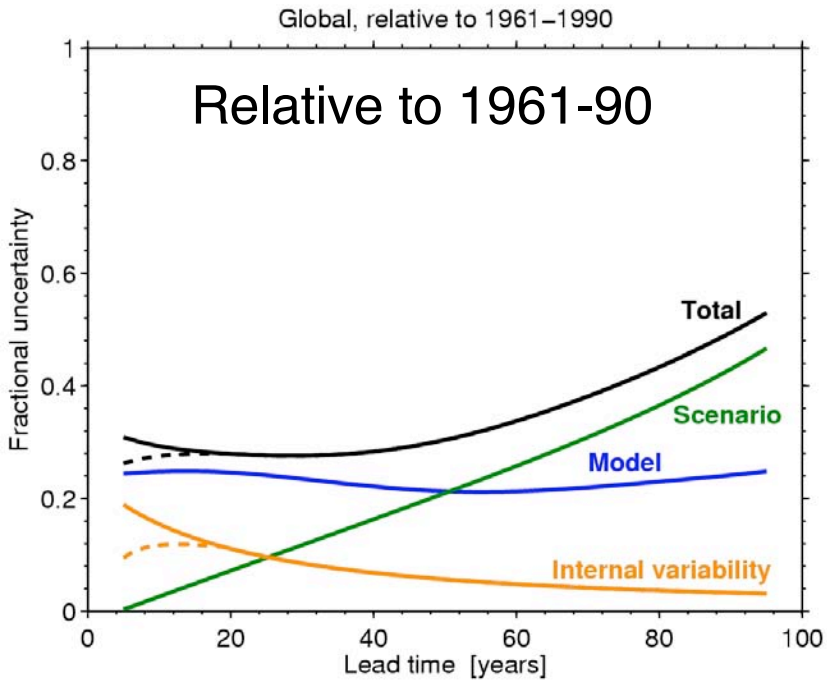
$$\frac{\sigma_{source}(t)}{T_{mean}(t)}$$

Initial minimum is an artefact of calculation method



Hawkins & Sutton, submitted – using IPCC data

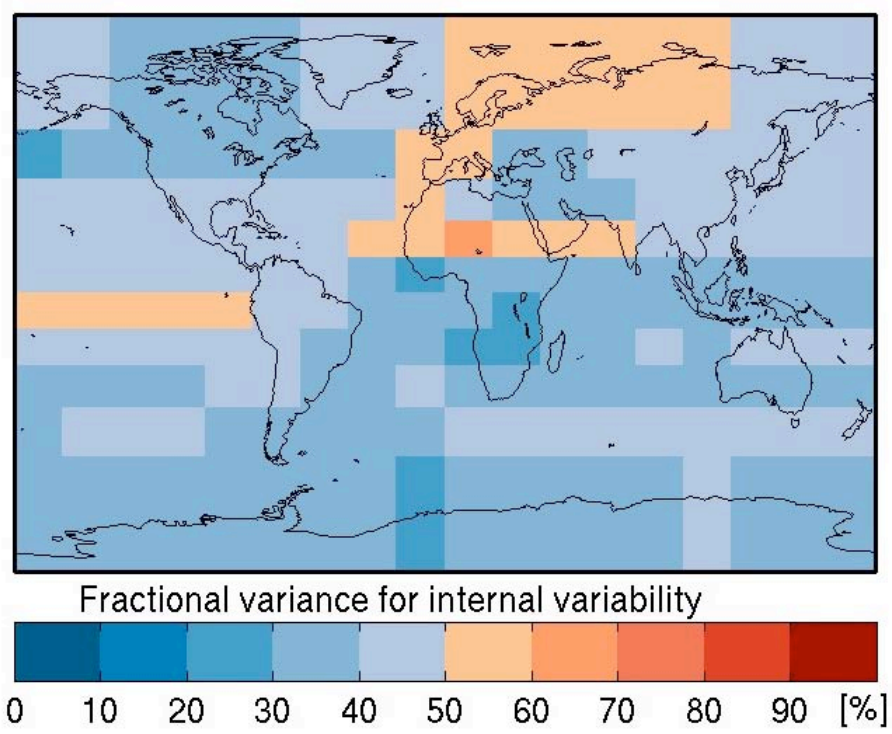




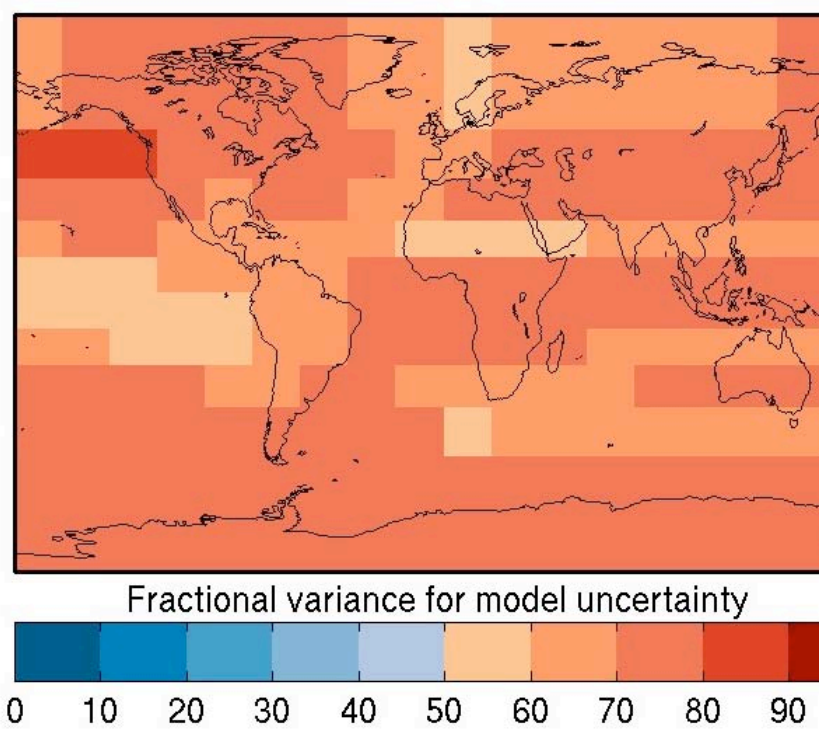
- Using IPCC data, model uncertainty is clearly the dominant contribution for decadal predictions
- Importance of initial condition uncertainty appears to have been *greatly* overestimated by Cox & Stephenson
- Existence and character of any minimum in total uncertainty is sensitive to choice of reference period

Sources of uncertainty in projections of *regional* decadal mean temperature

Fraction of total variance explained by internal variability for predictions of the first decade ahead



Fraction of total variance explained by model uncertainty for predictions of the second decade ahead



- For projections of the first decade ahead internal variability and model uncertainty account for a similar fraction of the total variance
- For projections of the second or third decade ahead, model uncertainty is by far the dominant contribution

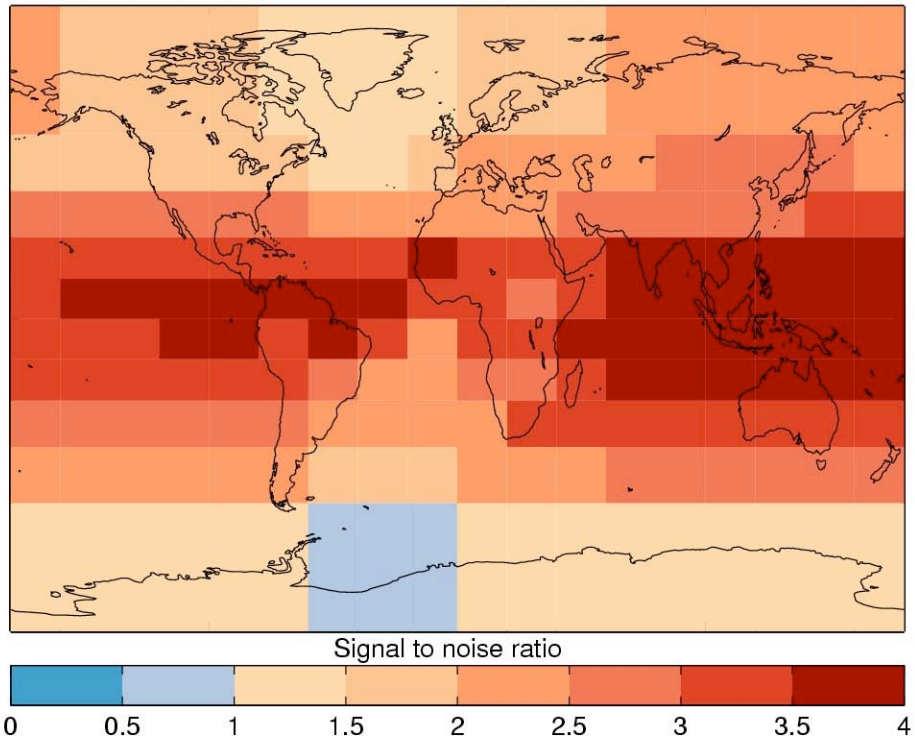
Hawkins & Sutton, submitted

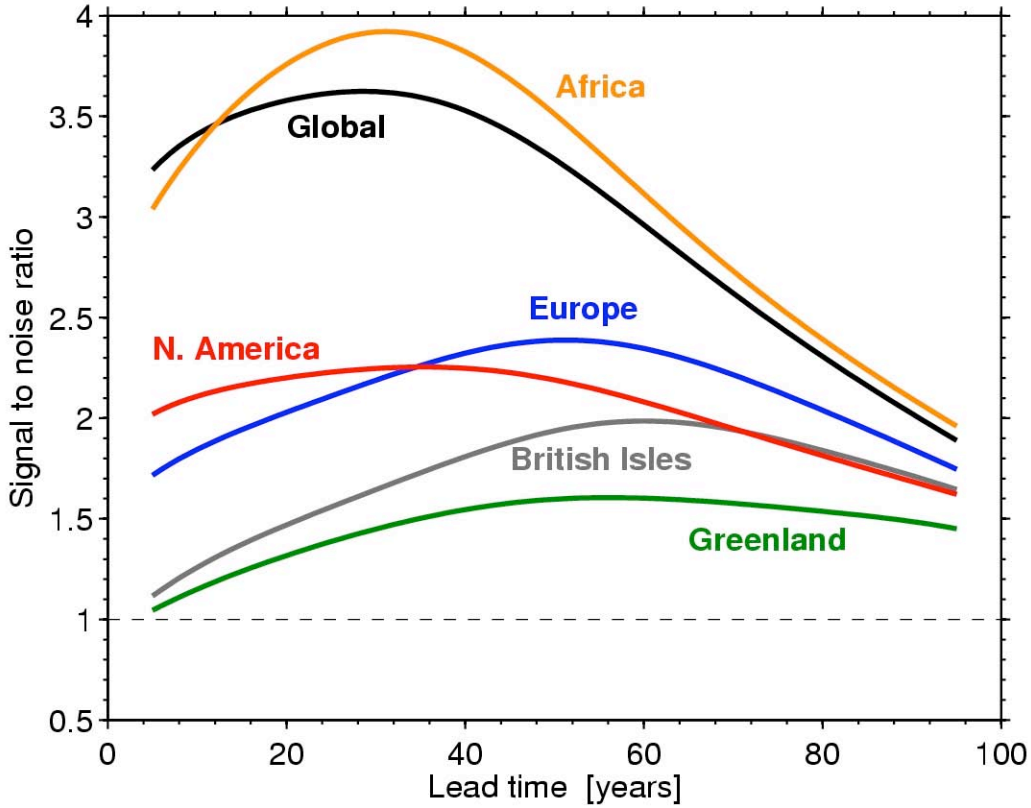
Signal-to-noise ratio

Signal = change in decadal mean temperature relative to 1961-90

Noise = sqrt(total prediction variance)

Third decade ahead





• Signal-to-noise is consistently highest in tropics, and larger than 1 almost everywhere for all lead times

• Almost all regions show a maximum in signal-to-noise (minimum in fractional uncertainty) at a lead time of some decades

Hawkins & Sutton, submitted

Conclusions: Opportunities to improve regional decadal predictions

- Reducing model related uncertainty is the top priority
- Reducing the uncertainty that arises from predictable components of internal variability is important for the first decade ahead.
- Both these components of uncertainty should be reducible through progress in climate science.
- Initialisation of climate predictions can potentially contribute to reducing both components of uncertainty (but the major focus so far has been on the internal variability component).
- The economic value of reducing uncertainty in predictions is potentially very large (cheaper adaptation), and offers an important motivation for the necessary investments.

Note: interactive analysis tool at: www.met.reading.ac.uk/~ed/ipcc

2. Estimation of Singular Vectors for Decadal Predictions

Motivation:

- An initialised decadal prediction system requires observations of the ocean state and ensembles for sampling the uncertainty in initial conditions (and the choice of model)
- Key questions include:
  - Which observations are most valuable for predictions, and where should any new observations be targeted?
  - How can we design ensembles that sample uncertainty efficiently (i.e. with as few members as possible)?
- Optimal perturbations such as Singular Vectors can address both these questions

Singular Vectors – method 1

- Linear Inverse Modelling (e.g. Penland & Sardeshmukh 1995)

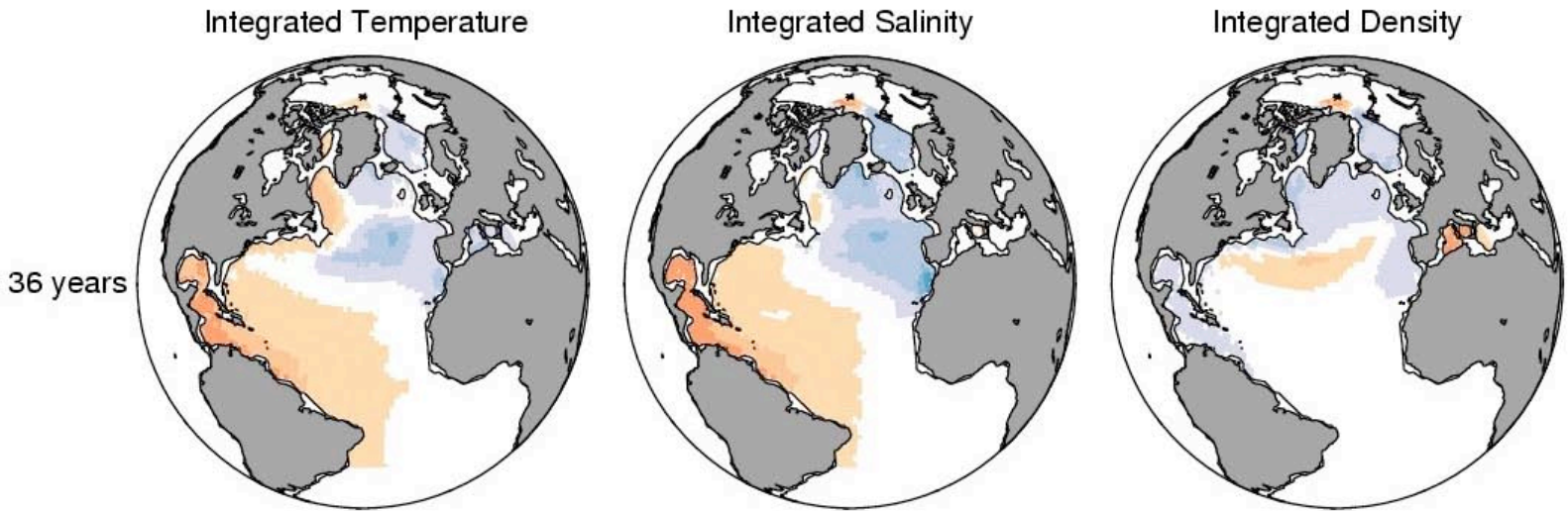
• Represent ocean variability in HadCM3 control run with leading **3d** EOFs to reduce dimensionality:

LIM: $$\frac{d\mathbf{x}}{dt} = \mathbf{B}\mathbf{x} + \xi$$ $\mathbf{x}$ represents leading PCs

LIM forecast: $$\mathbf{x}(t+\tau) = \mathbf{P}_\tau \mathbf{x}(t)$$

• Eigenvectors of: $$\mathbf{P}^{\mathrm{T}}\mathbf{P}\mathbf{x}_0 = \lambda \mathbf{x}_0$$

are the optimally growing perturbations

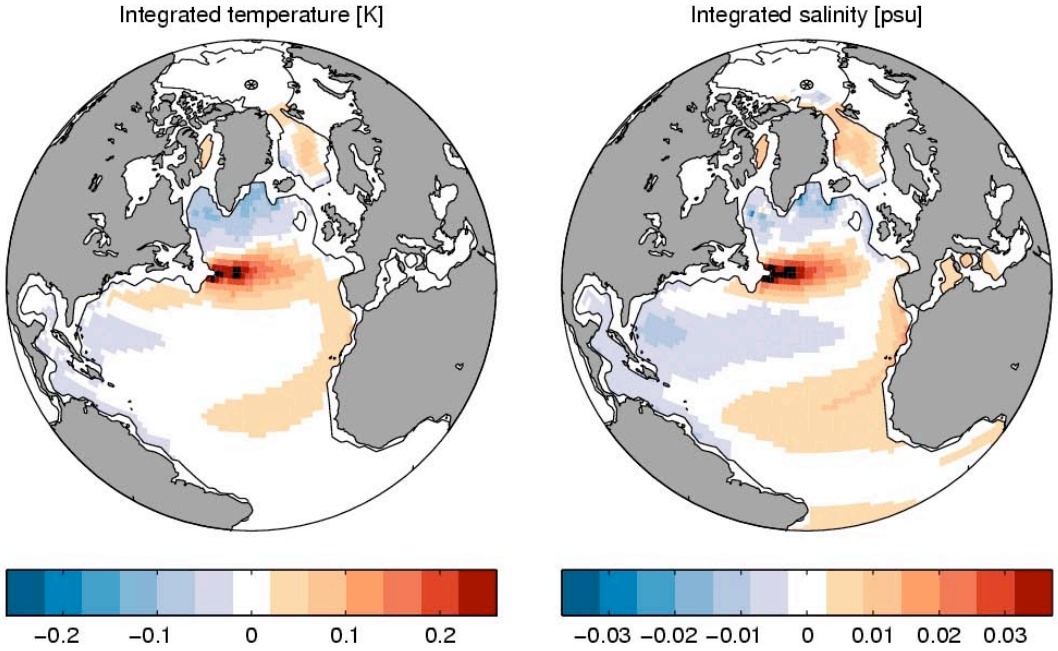


Singular Vectors – method 2

- Climatic Singular Vectors (CSVs) (e.g. Kleeman et al. 2003)
  - Propagator matrix $(\mathbf{P})$ estimated from a series of ensemble runs from one initial condition

- control ensemble
- 8 EOF perturbed ensembles
- 16 members, each run for 40 years
- further ensembles to test optimal perturbations

(Total: >7000 years with HadCM3)



Optimal perturbation

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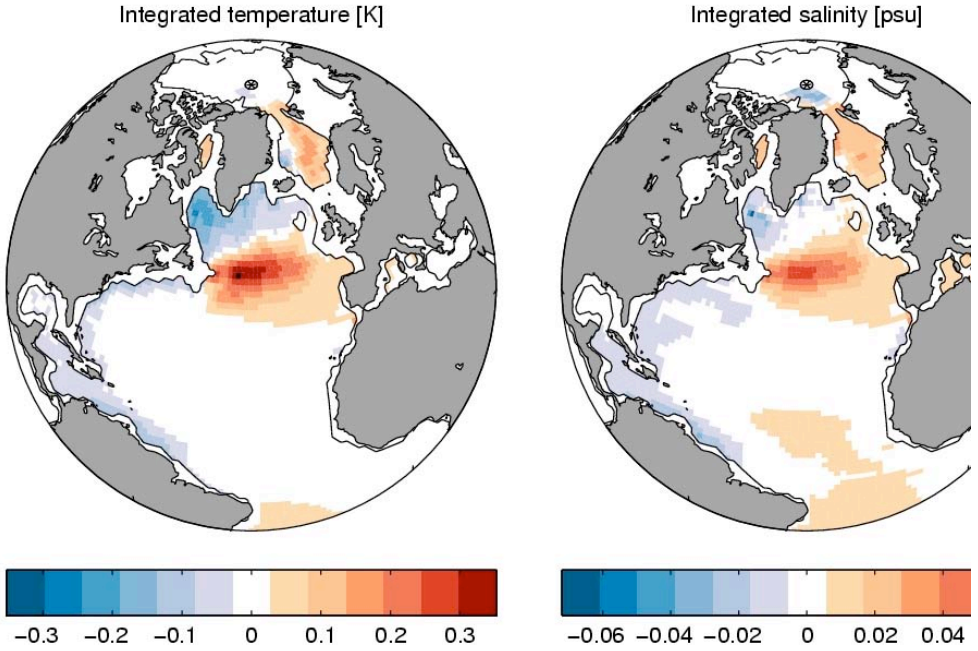


10 years later

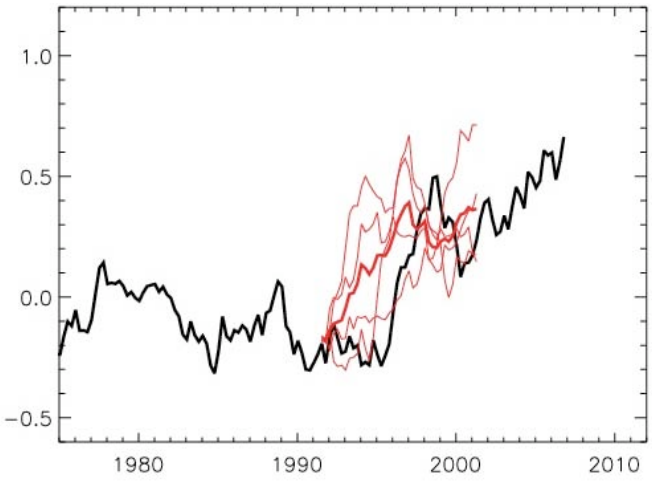
Conclusions: Design of efficient decadal forecast ensembles

- Two methods have been used to estimate optimal perturbations in HadCM3.
- Both show that the far North Atlantic is the most sensitive region to small perturbations and optimal for targeted observations

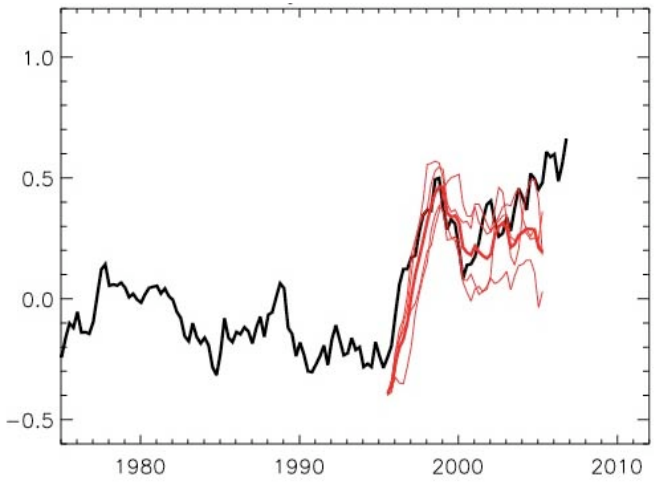
- Future extensions: (EU THOR project)
  - Use similar methods on different models
  - Compare properties of SVs and random perturbations

3. Analysis of UK Met Office Decadal Prediction system

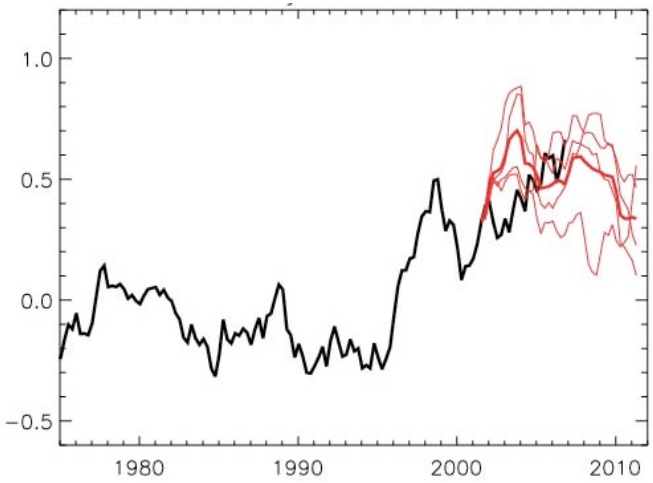
- N. Atlantic sub-polar gyre: upper ocean heat content hindcasts



June 1991



June 1995



June 2001

Work in progress aimed at understanding hindcast successes and failures, impact of model bias etc, using a case study approach.

Acknowledgments: Jon Robson, Doug Smith

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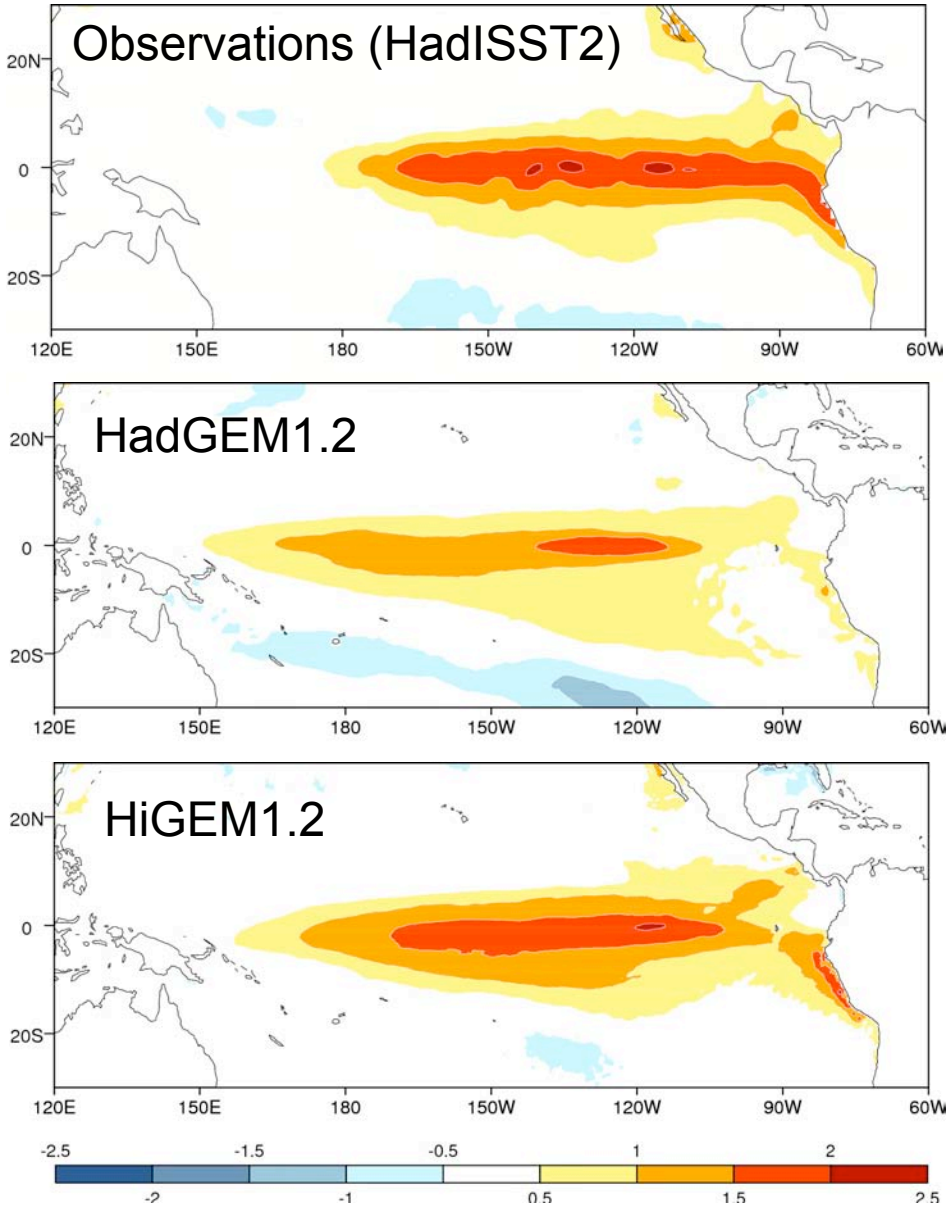
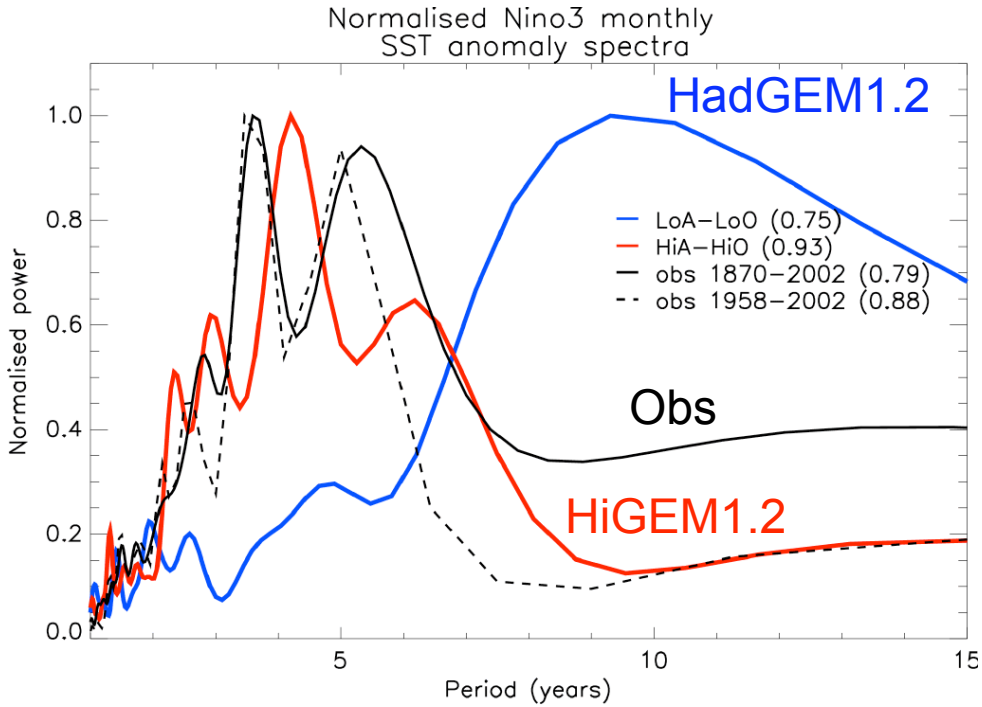
Impact of higher resolution: improved ENSO

(Malcom Roberts, Len Shaffrey et al)

DJF Sea Surface Temperature Anomalies - El Nino Composites





Impact on decadal variability and predictability is under investigation in Reading