



The Abdus Salam
International Centre for Theoretical Physics



2160-5

Conference on Decadal Predictability

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Statistical decadal predictions and optimal observations

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Statistical decadal predictions and optimal observations

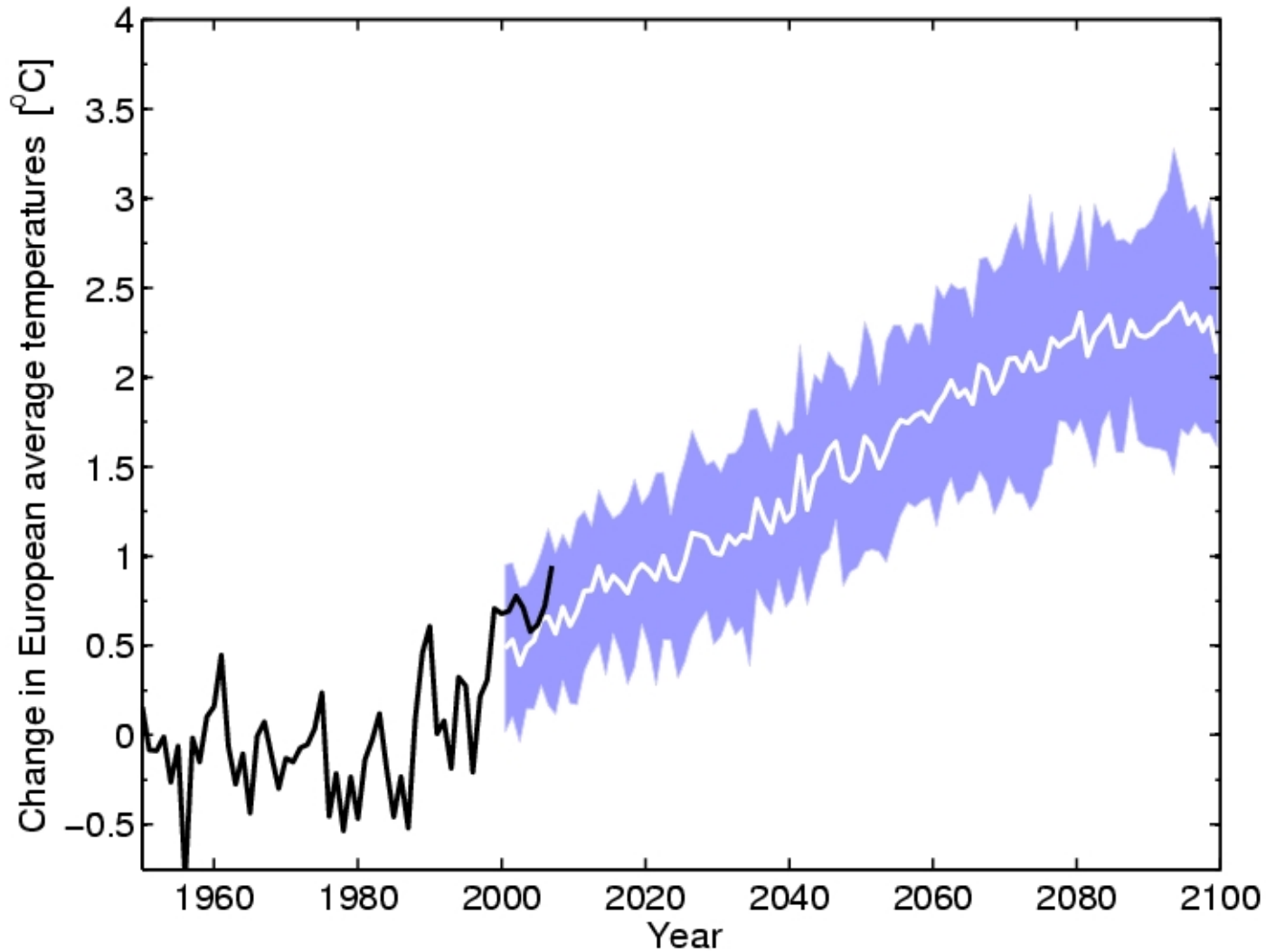
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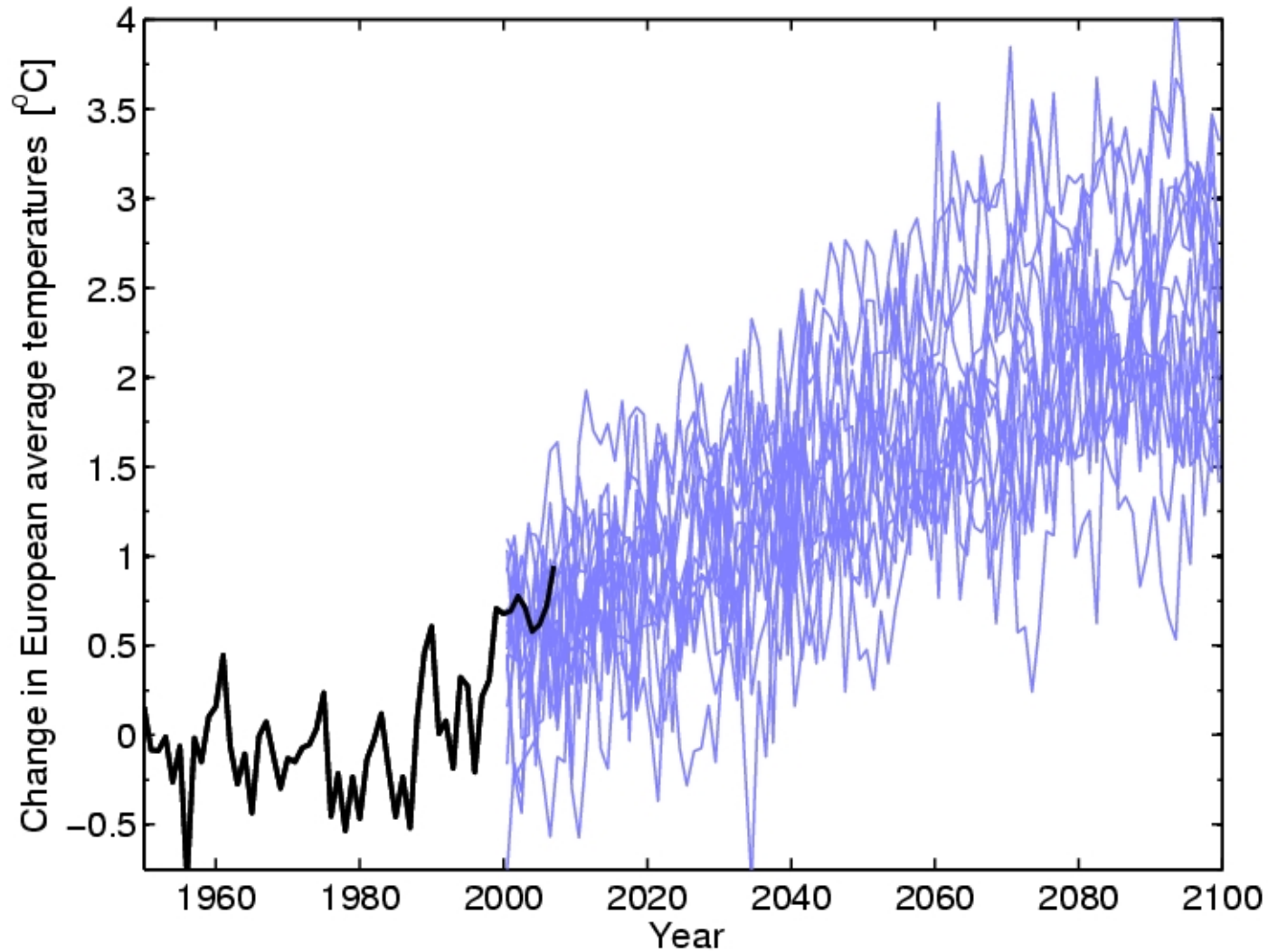
Thanks to:

Rowan Sutton, Jon Robson, Doug Smith, Noel Keenlyside,
Len Shaffrey and Fiona Underwood

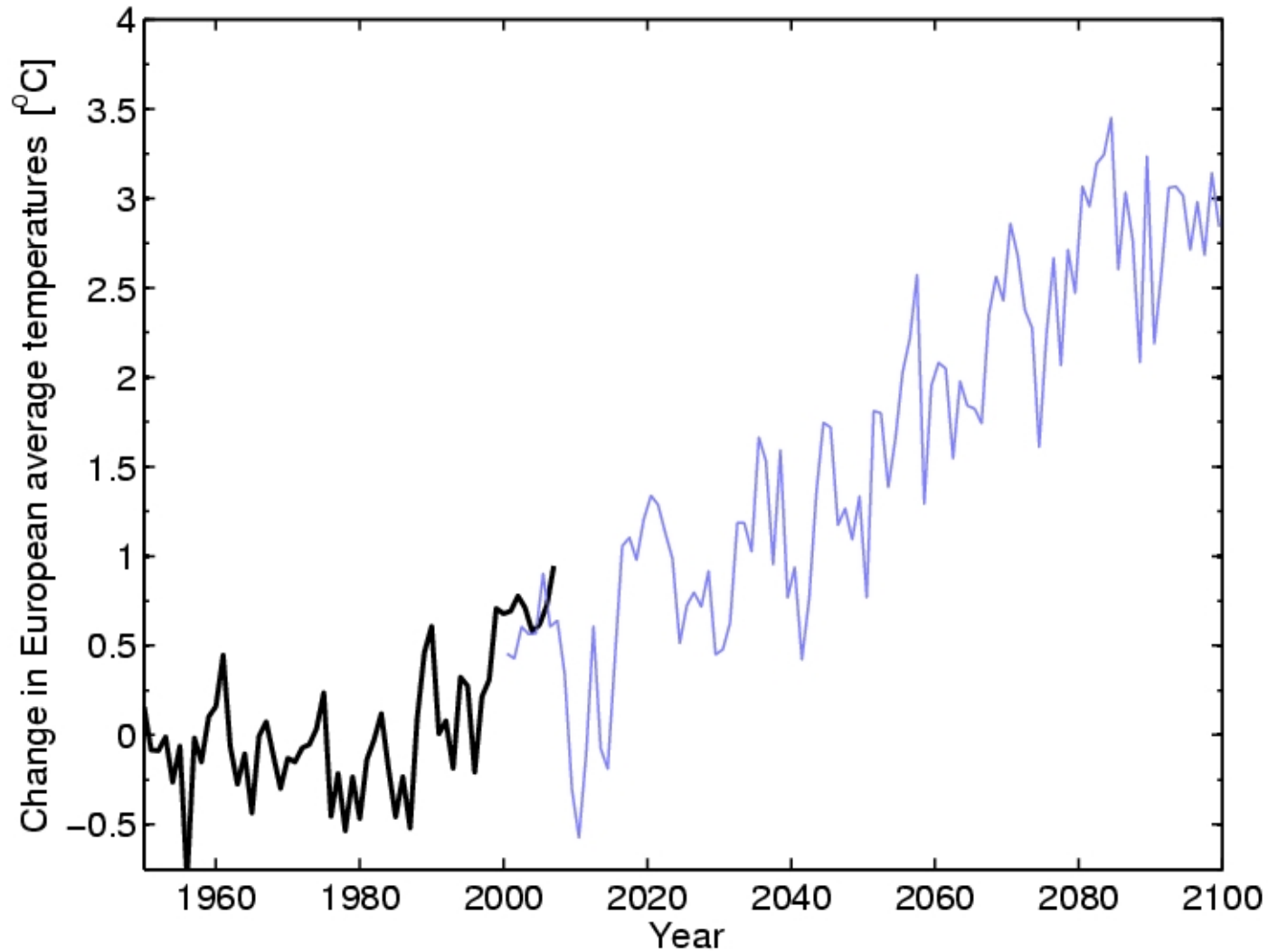
Decadal variability



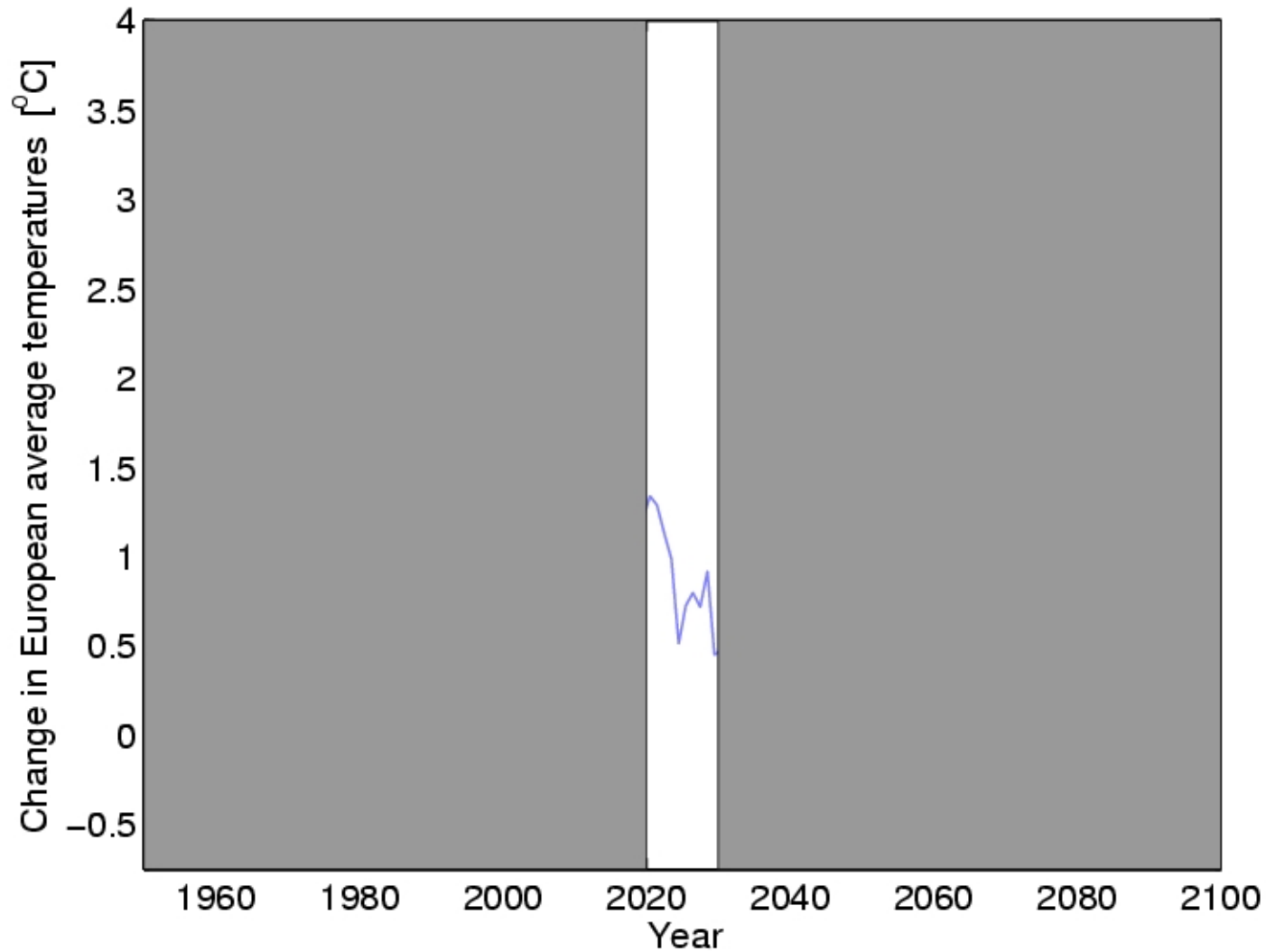
Decadal variability



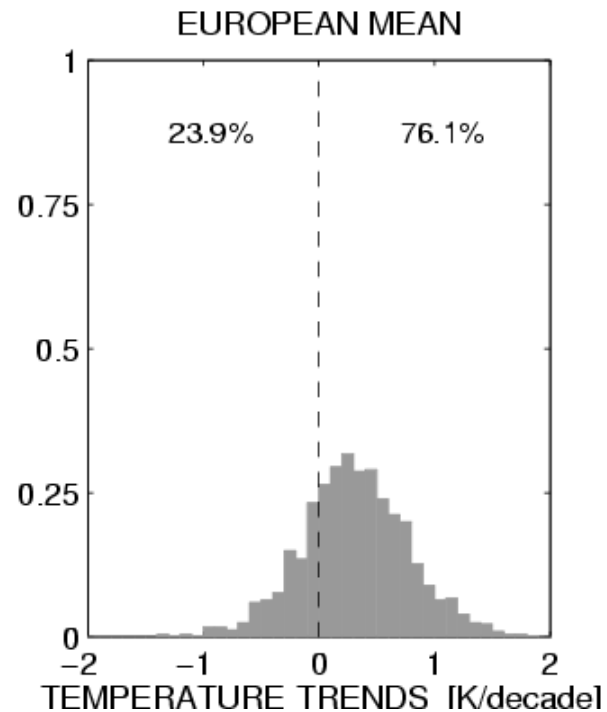
Decadal variability



Decadal variability



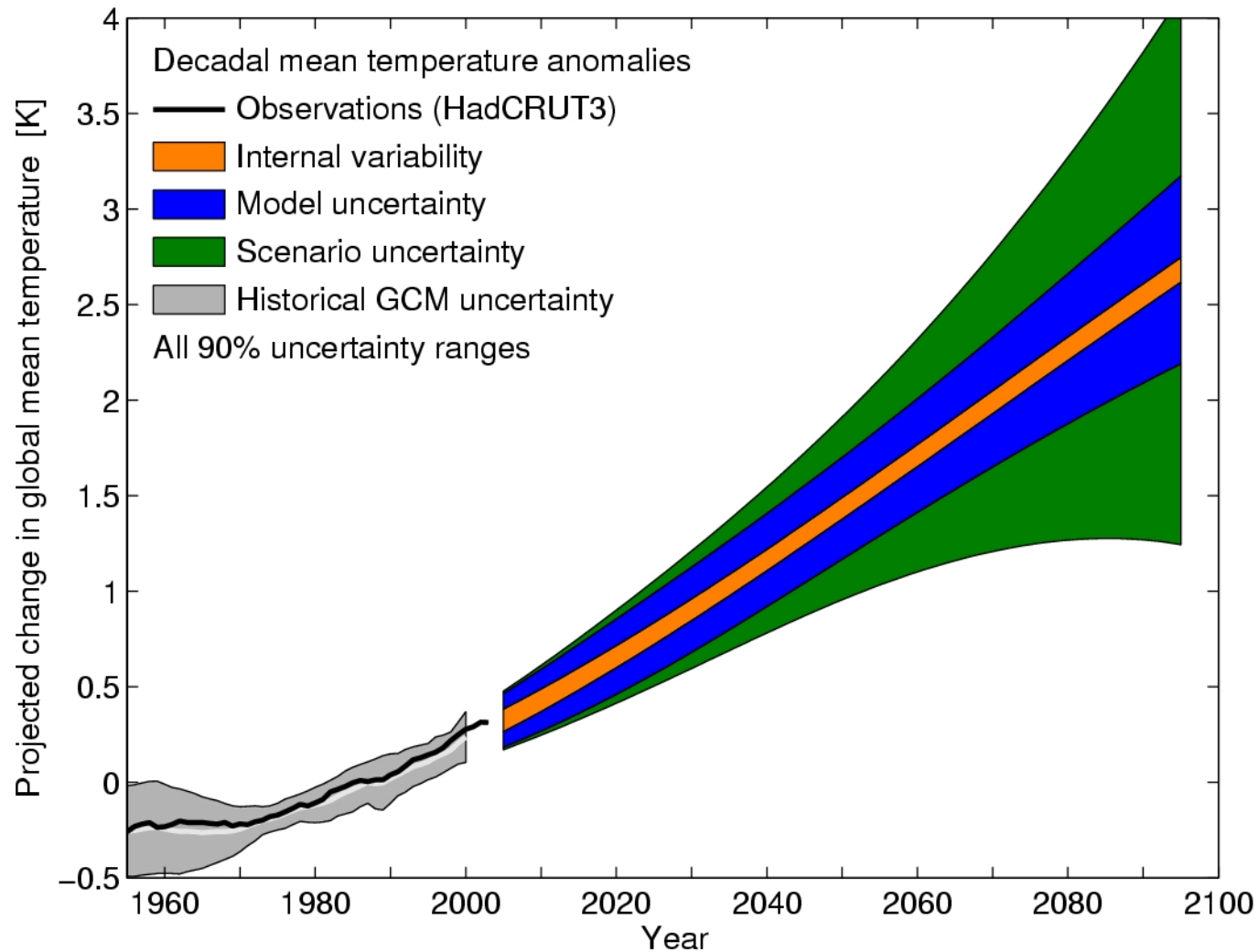
SRES A1B 21st century decadal trends



Also see Easterling &
Wehner (2009)

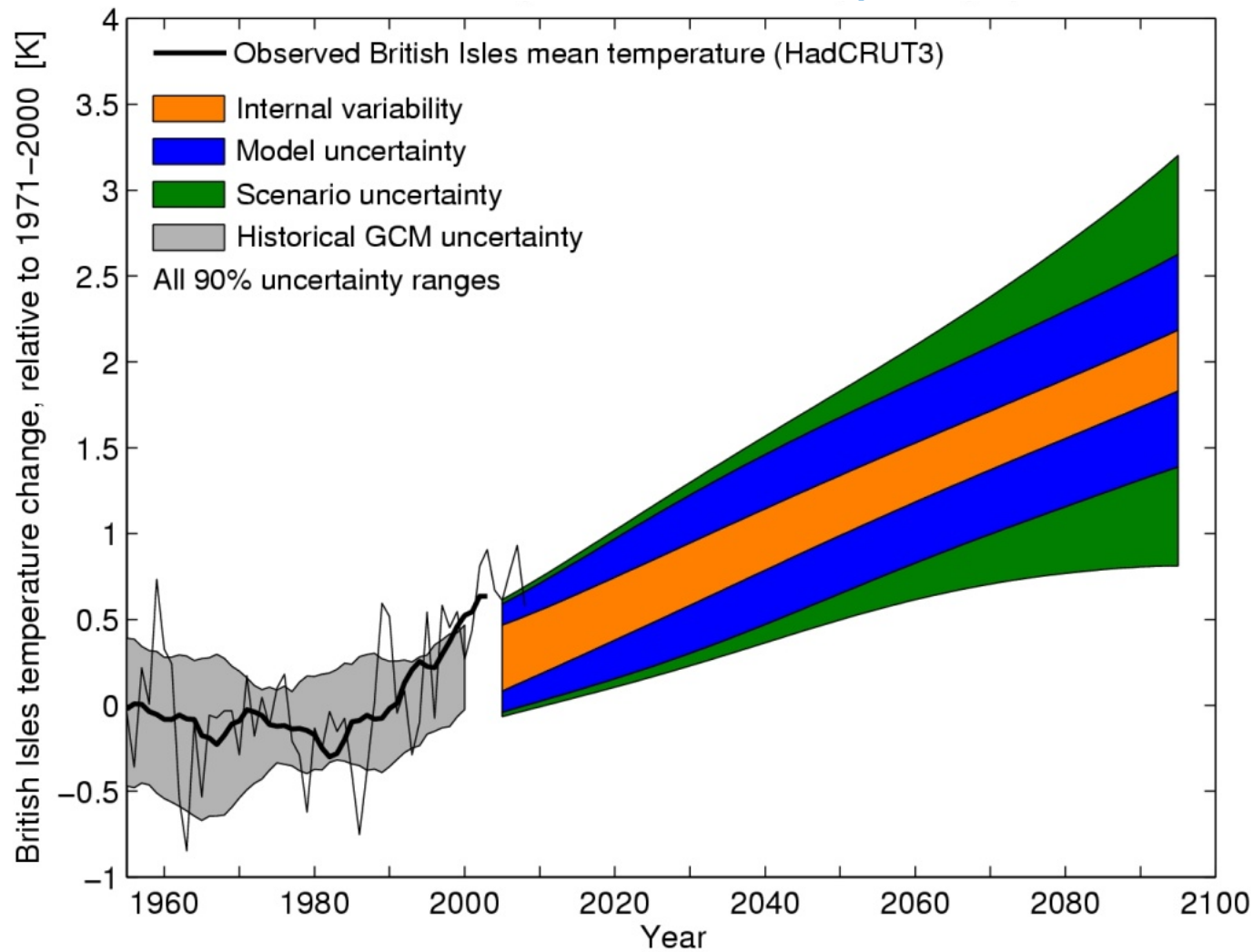
Sources of uncertainty in projections

Global mean temperature



Sources of uncertainty in projections

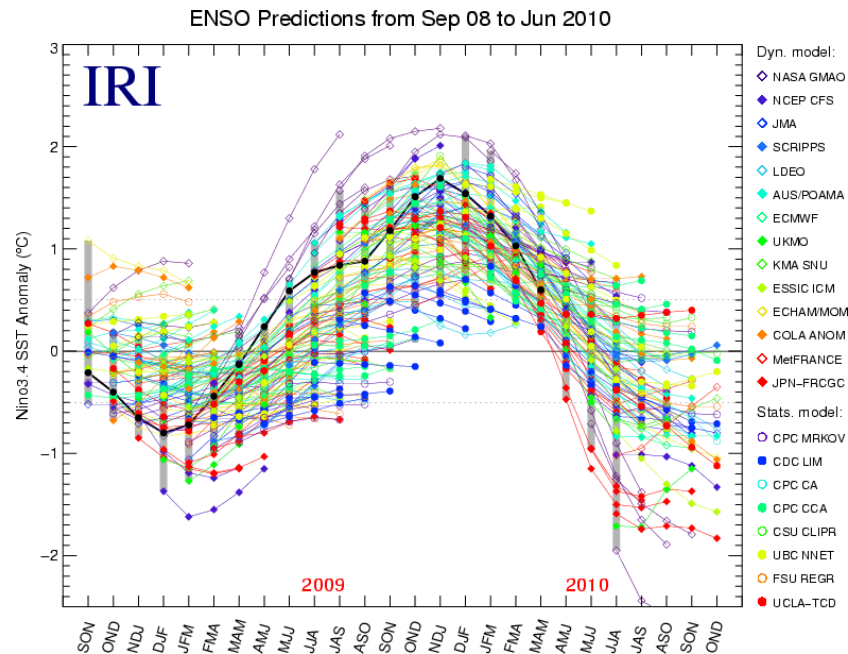
British Isles mean temperature



- ⊙ Long ‘memory’ in the ocean provides potential predictability on decadal timescales
- ⊙ Decadal climate predictions are now being made
 - initialised from ocean state to try and predict both the response to radiative forcings *and* the internal variability
 - what about statistical methods for predicting SSTs? [Part 1]
- ⊙ Large uncertainties in current ocean state analyses
 - need to efficiently sample uncertainty in initial ocean state
 - where would extra observations help improve predictions?
 - adapt methods used in weather prediction for climate [Part 2]

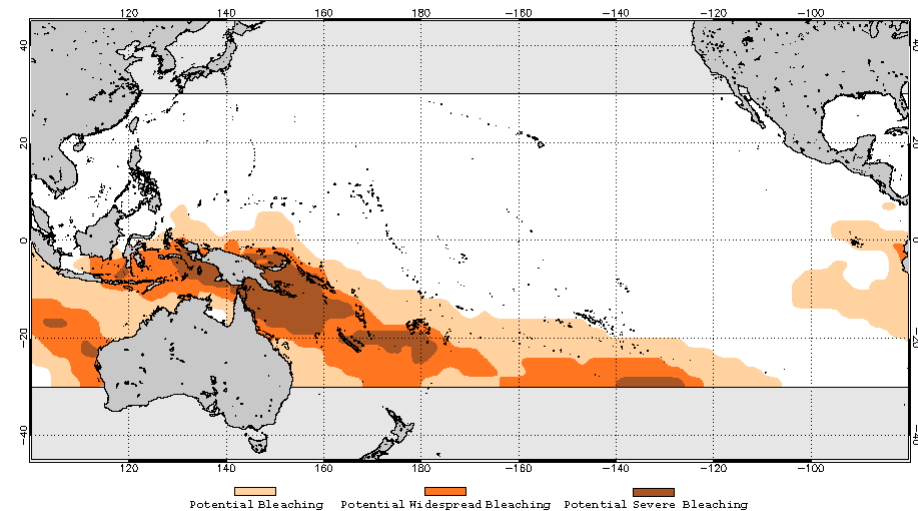
Motivation and key questions

- Statistical predictions of seasonal SSTs have proved useful
 - to help benchmark GCM predictions of ENSO
 - to inform policymakers (e.g. coral bleaching predictions)
 - what about decadal timescales?



NOAA Coral Reef Watch

2008 Dec 02 NOAA Coral Reef Watch Coral Bleaching Thermal Stress Outlook for Dec 08–Mar 09



Need to assess the potential for statistical decadal SST predictions before trying to use the (complicated) observations

First steps:

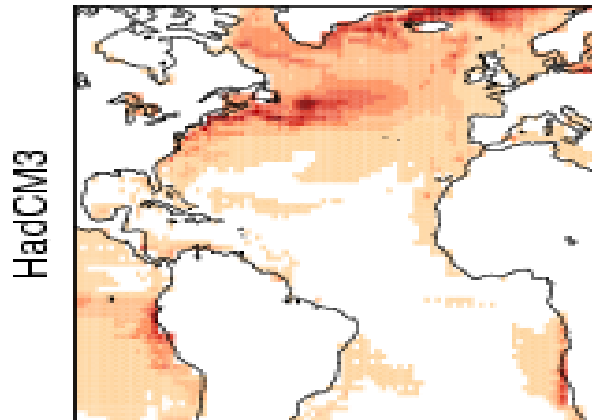
- use 'perfect GCM' approach to assess potential skill
- use data from more than one GCM to examine robustness
- use more than one statistical method
- focus on Atlantic where decadal variability is relatively large and historical observations are better
- use 140 years of annual means as training data



Potential predictability of SSTs

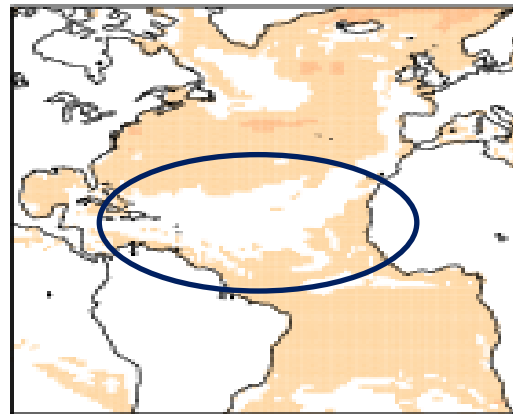
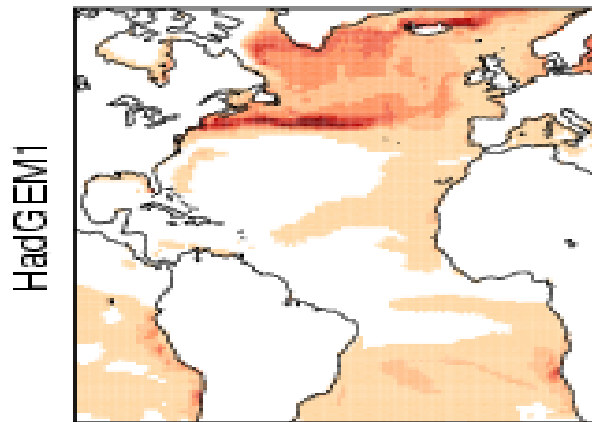
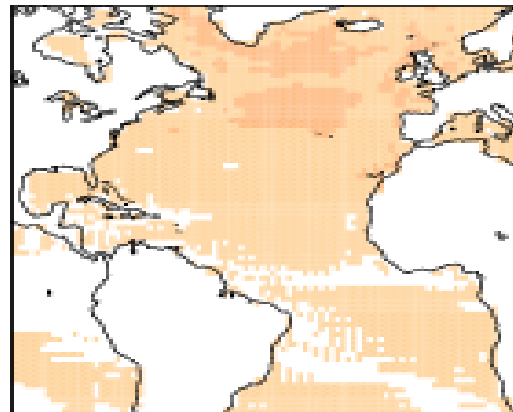
Inter-annual variability

$$\sigma_1$$

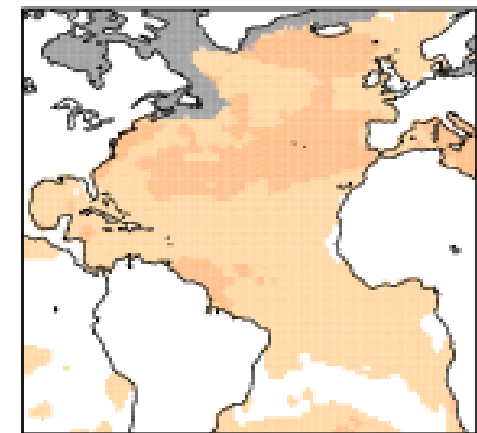


Potential predictability

$$\sigma_{10}/\sigma_1$$



$$\sigma_{10}/\sigma_1$$



OBSERVATIONS
(HadISST)



Is most persistent pattern the most predictable?

e.g. Boer 2000, 2004

Grid-point independent estimates:

Climatology : $x(t_0 + \tau) = 0,$

Persistence : $x(t_0 + \tau) = x(t_0),$

Lagged correlation : $x(t_0 + \tau) = \beta(\tau)x(t_0),$

τ : lead time

x : SST anomalies

t_0 : start time

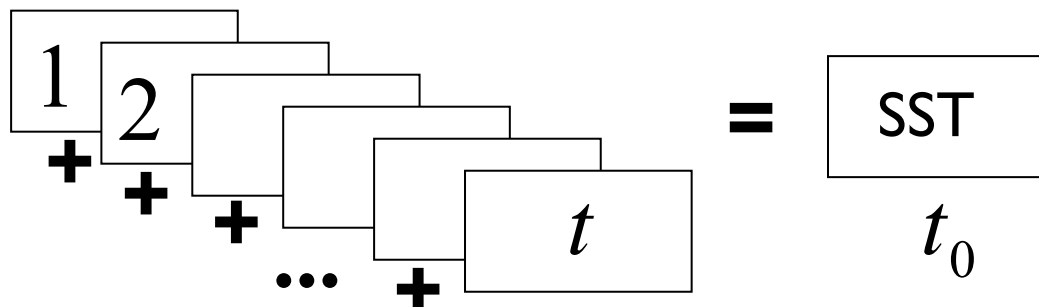
Spatial methods:

- Linear Inverse Modelling (LIM) (Penland & Magorian 1993)

$$\mathbf{x}(t_0 + \tau) = \mathbf{P}(\tau)\mathbf{x}(t_0)$$

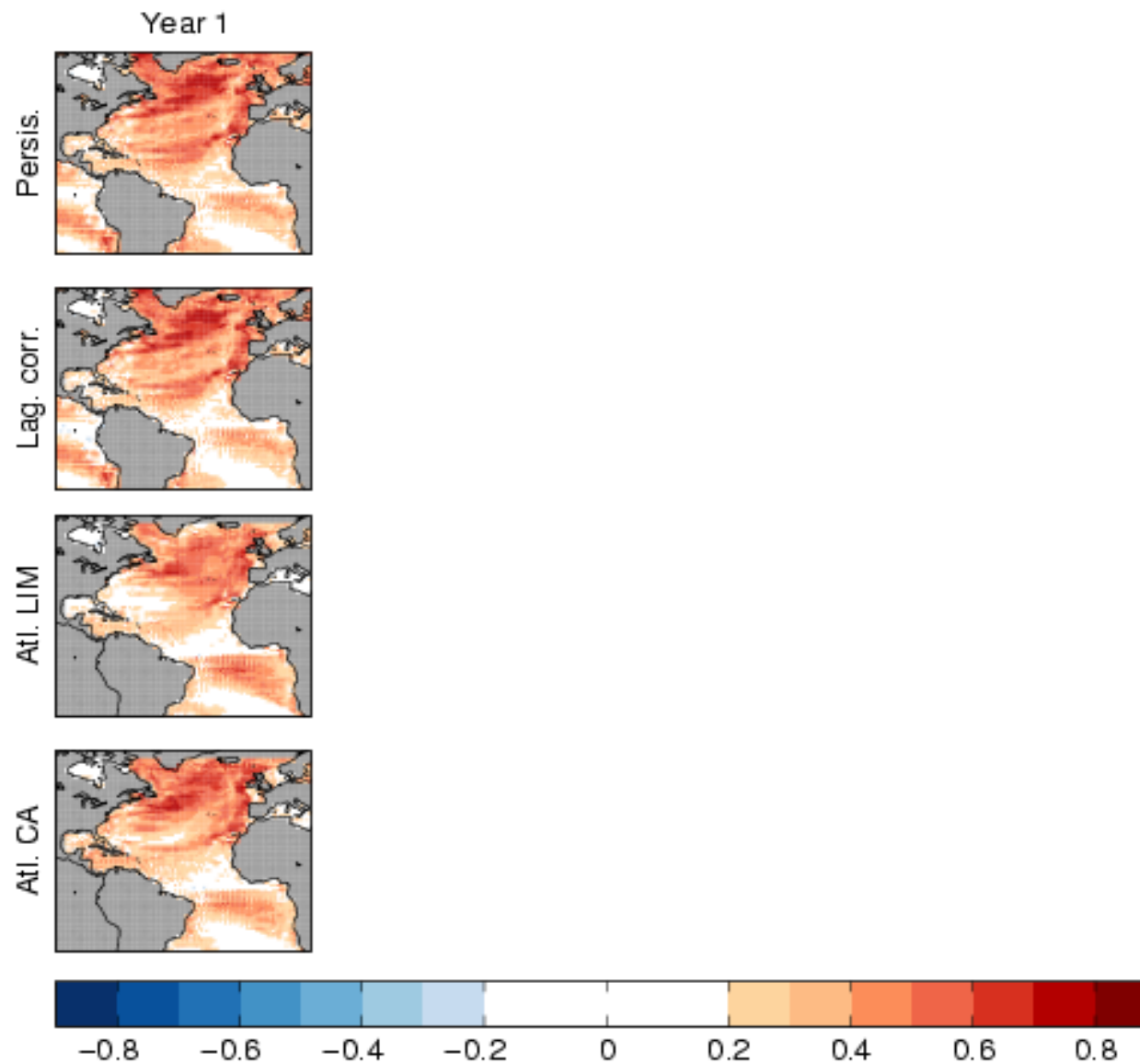
\mathbf{x} : EOFs of SST

- Constructed Analog (CA) (van den Dool 1994)

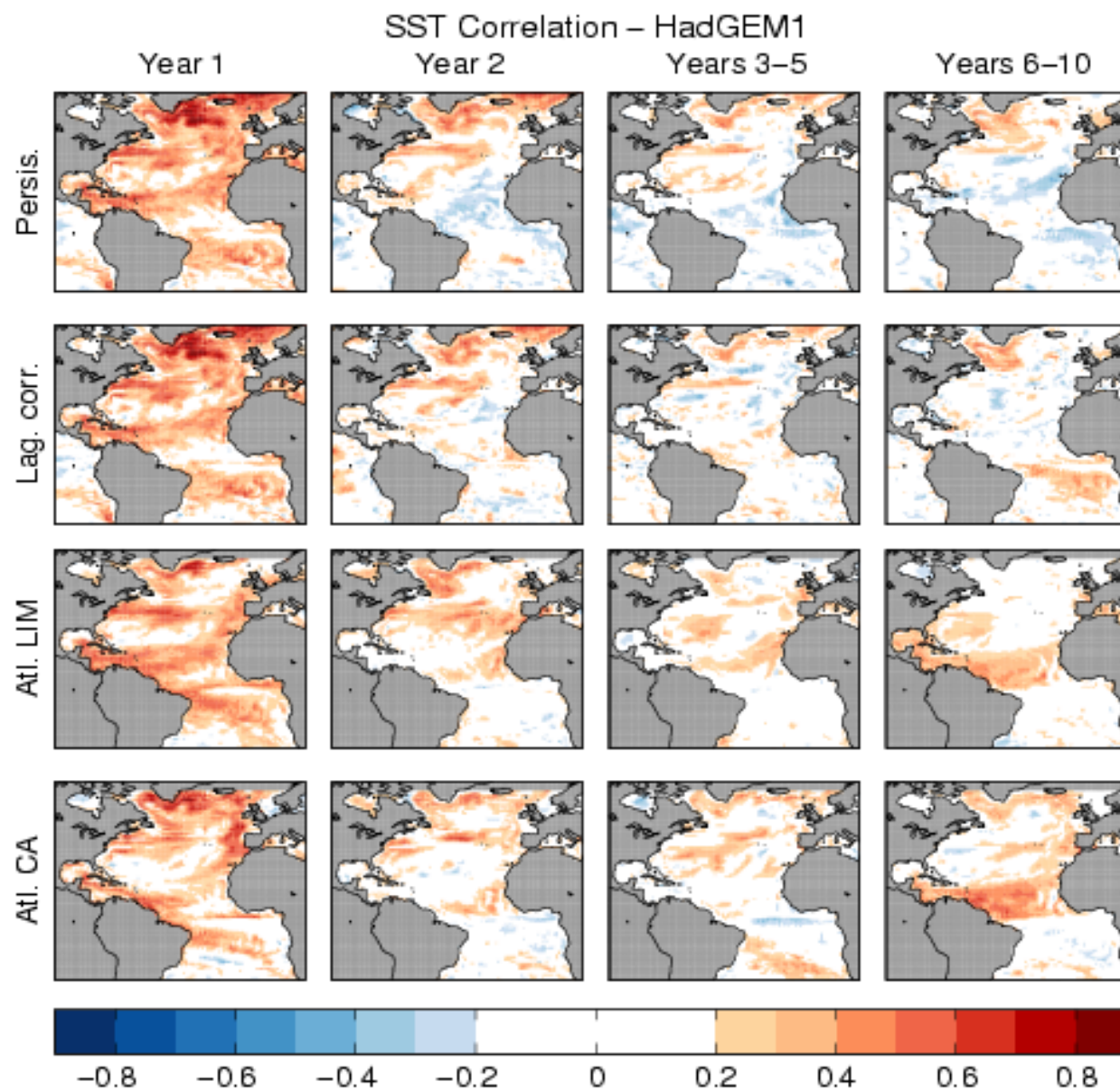


Example from HadCM3

SST Correlation – HadCM3



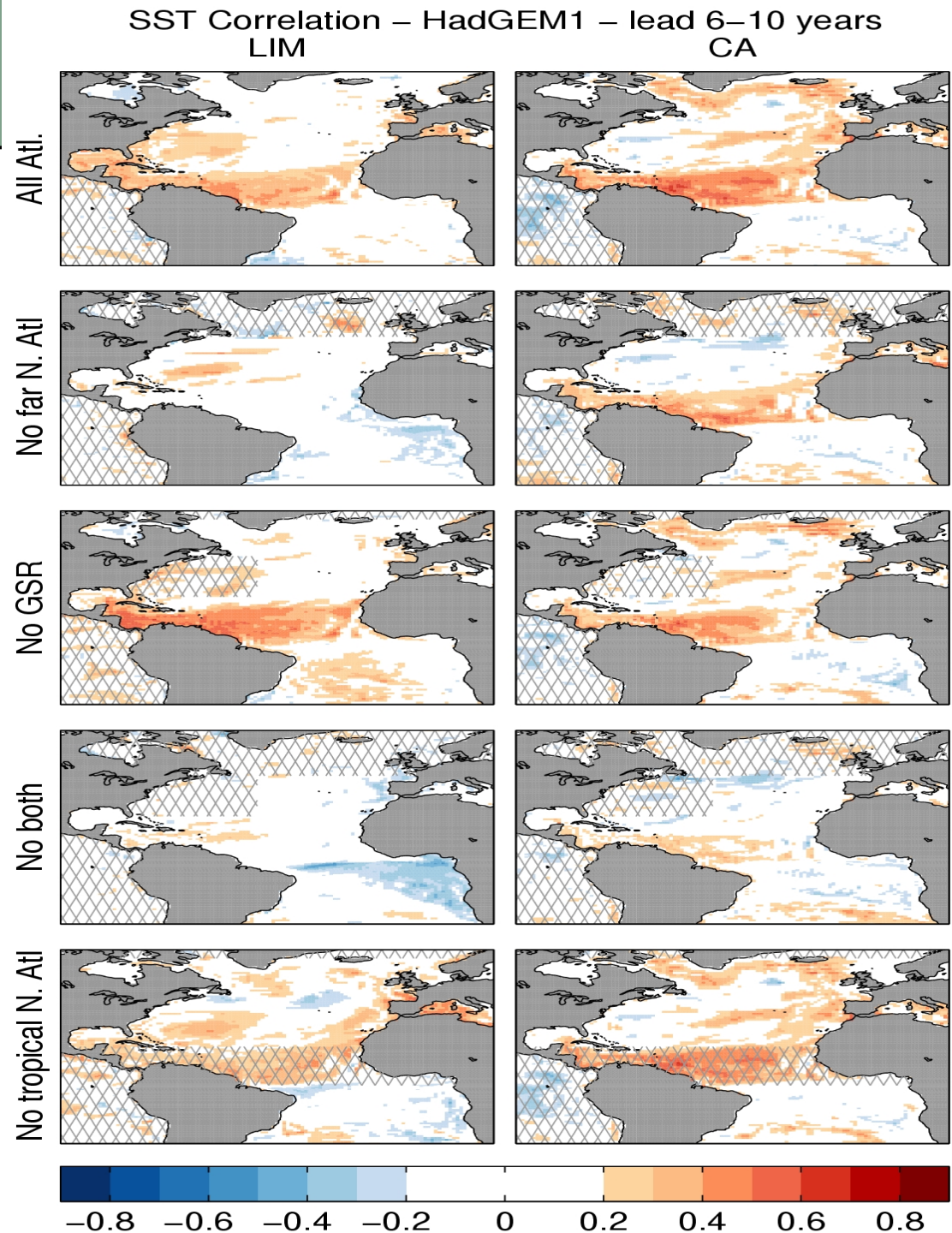
Example from HadGEM1

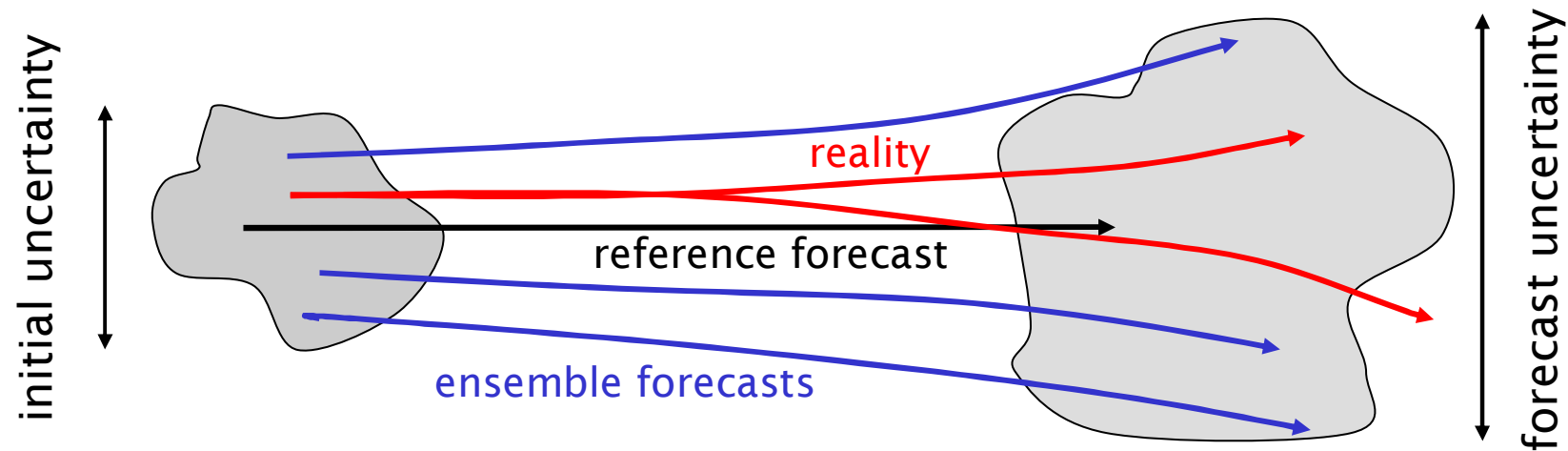


Optimal regions for observations?

Where does this long lead time skill come from?
Not the most persistent pattern

» SST observations in far North Atlantic important for tropical skill (using HadGEM1)





Optimal perturbations for decadal climate predictions are:

- ⦿ perturbations which grow most rapidly
- ⦿ consistent with the observational uncertainties
- ⦿ average over weather 'noise'
- ⦿ useful for:
 - efficient perturbations in ensemble forecasts
 - identifying regions where *additional* observations would be most valuable to improve predictions

Using two different methods:

1. Linear Inverse Modelling (LIM) e.g. Penland & Sardeshmukh (1995)
 - computationally cheap, initial condition independent
 - also see Tziperman et al 2008, Hawkins & Sutton 2009
2. Climatic Singular Vectors (CSVs) e.g. Kleeman et al. (2003)
 - expensive, estimated for each initial condition separately
 - not shown here – paper to appear in J. Climate

Focus here on Atlantic domain

Reduce dimensionality by representing ocean variability (T & S) in **control run** with leading 3d EOFs:

$$\text{GCM: } \frac{dy}{dt} = F(y)$$

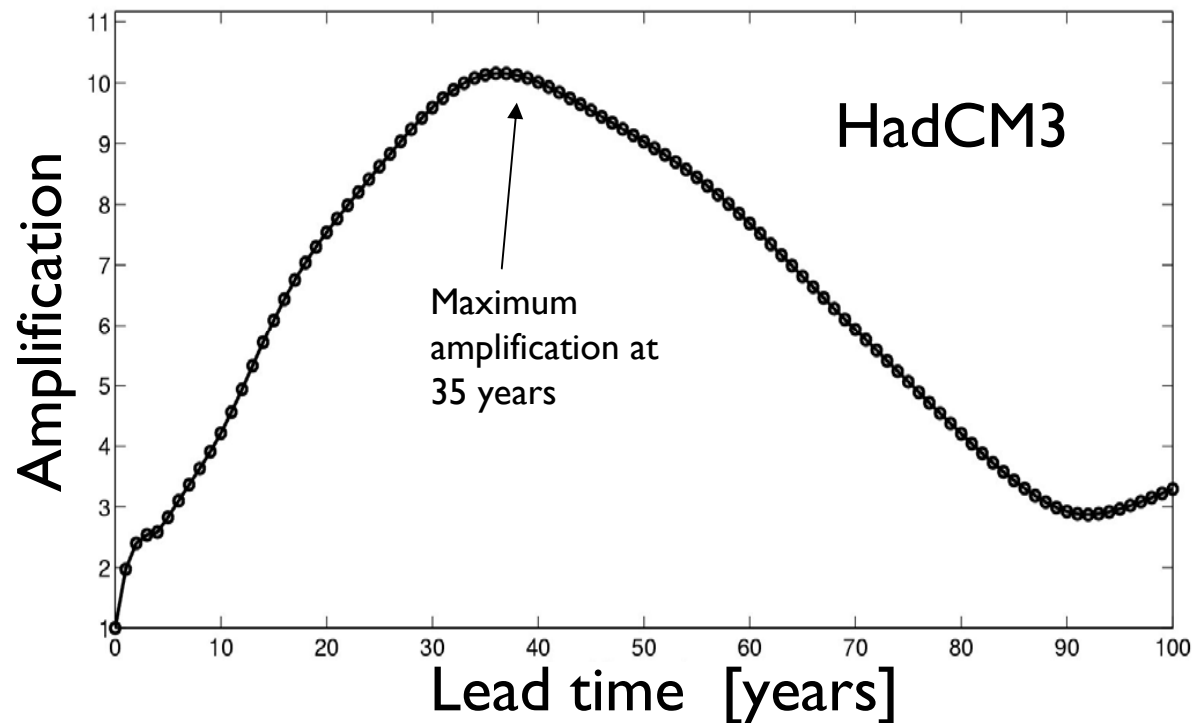
y represents ocean data

$$\text{LIM: } \frac{dx}{dt} = \mathbf{B}x + \xi$$

x represents leading PCs

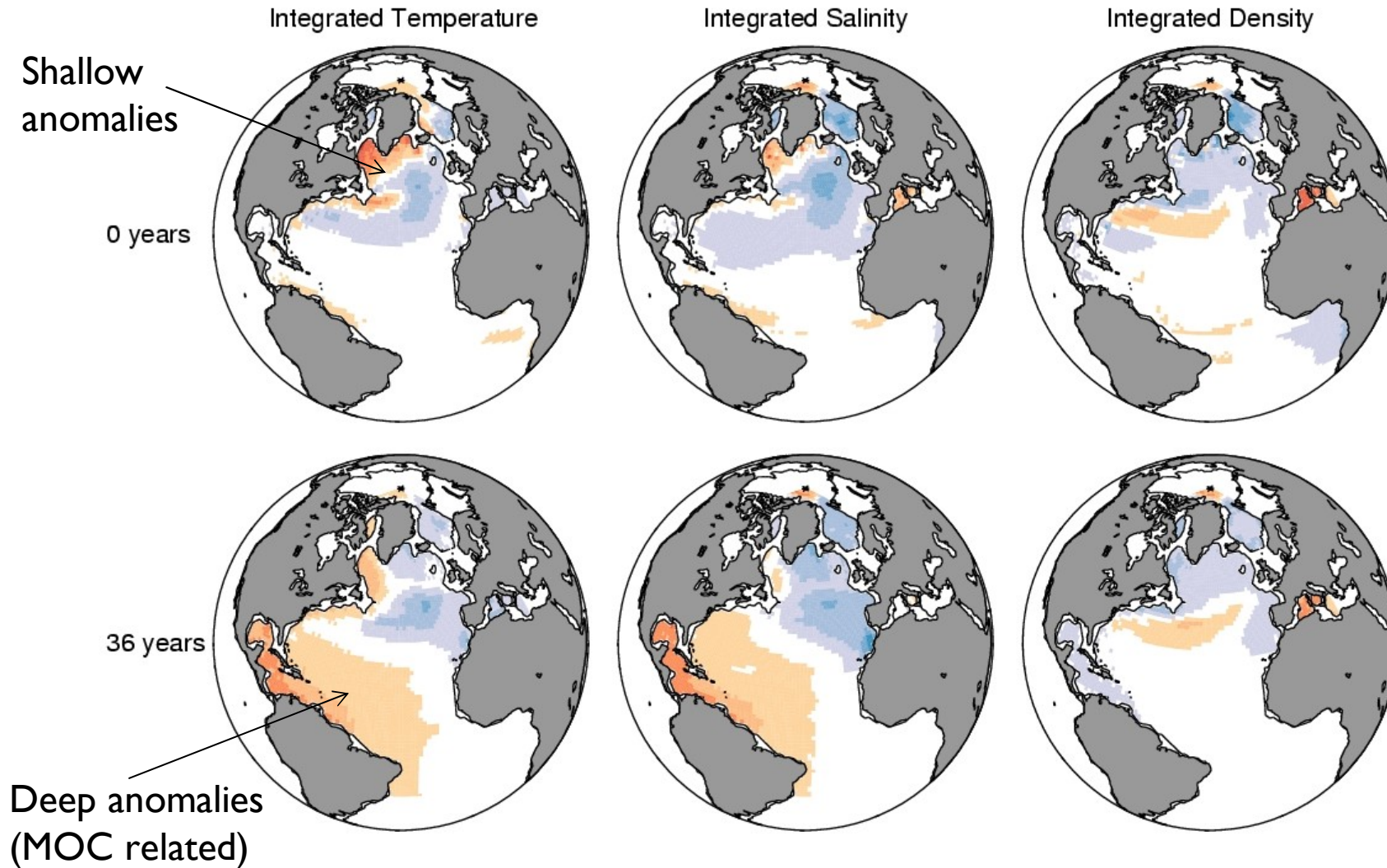
LIM forecast model:

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

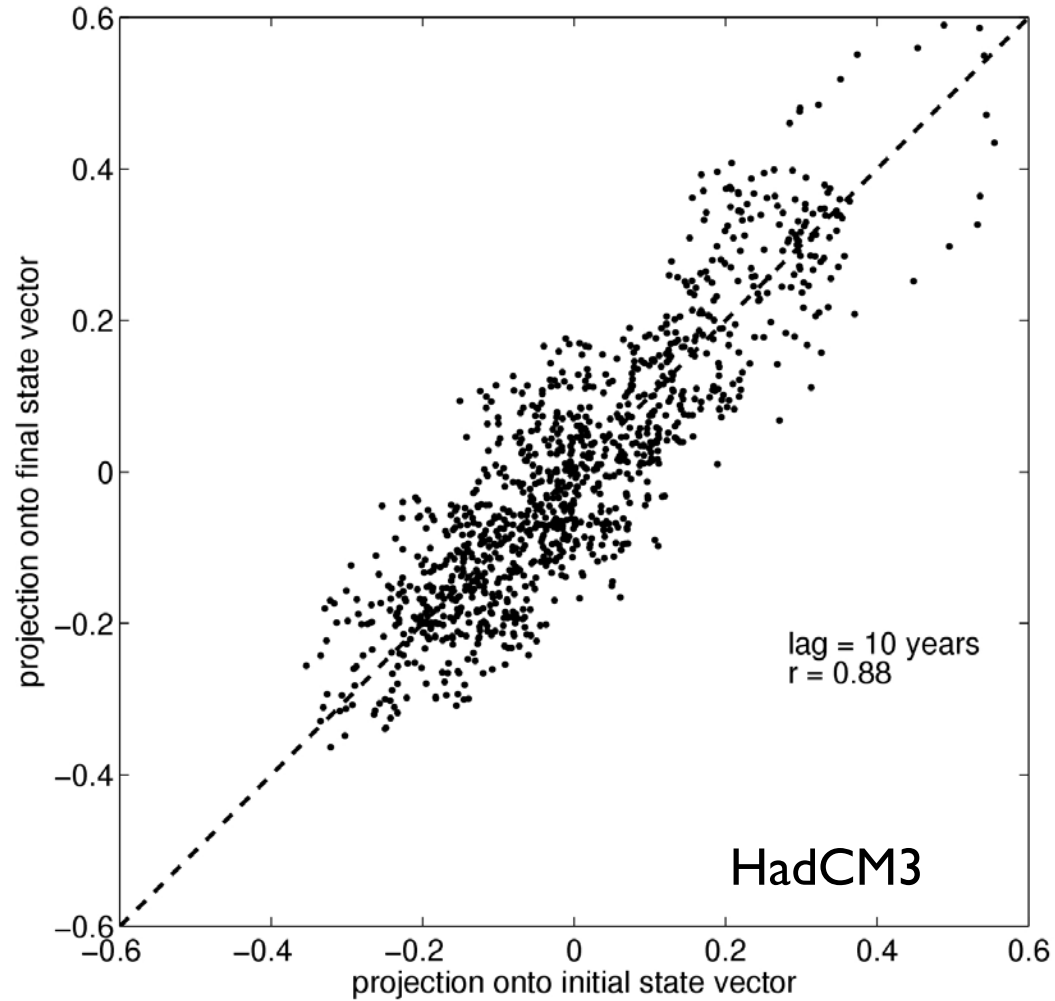


Growth of optimal perturbations

Ocean variables integrated to 1500m depth



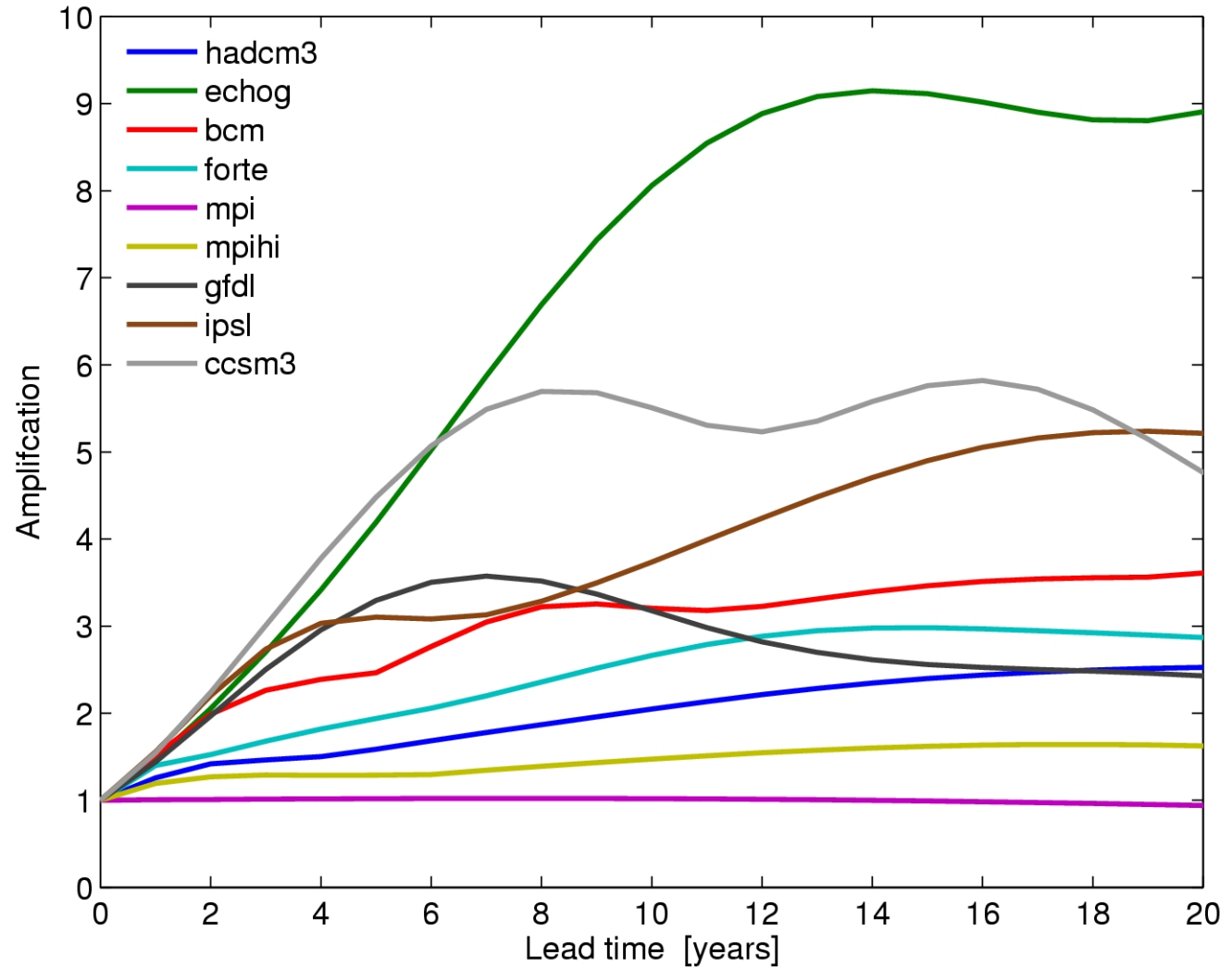
Does the linear model work?



» predictability

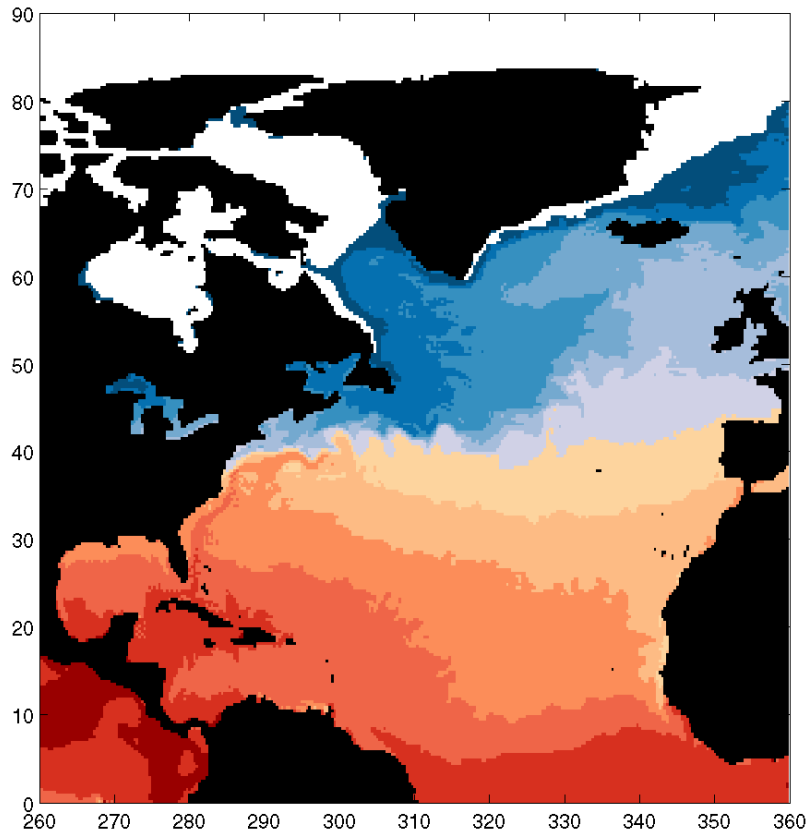
Multi-model amplification

In progress...



- Statistical predictions of SSTs are *potentially* feasible to match the skill of GCM predictions for far cheaper cost
- Potential predictability is not always the same as actual prediction skill
- Demonstrated methods for estimating optimal perturbations for decadal predictions
- These approaches have great potential to guide development of:
 - efficient decadal forecasting systems
 - ocean observing systems
- NCAS-Climate will make decadal predictions for CMIP5 with HiGEM

Going to higher resolution



Atlantic SST and sea ice

HiGEM:

- based on HadGEM1
- ocean: $1/3^\circ \times 1/3^\circ$, 40 levels
- atmos: NI44, 38 levels



HiGEM

Shaffrey et al. 2009

High resolution decadal predictions using HiGEM for CMIP5

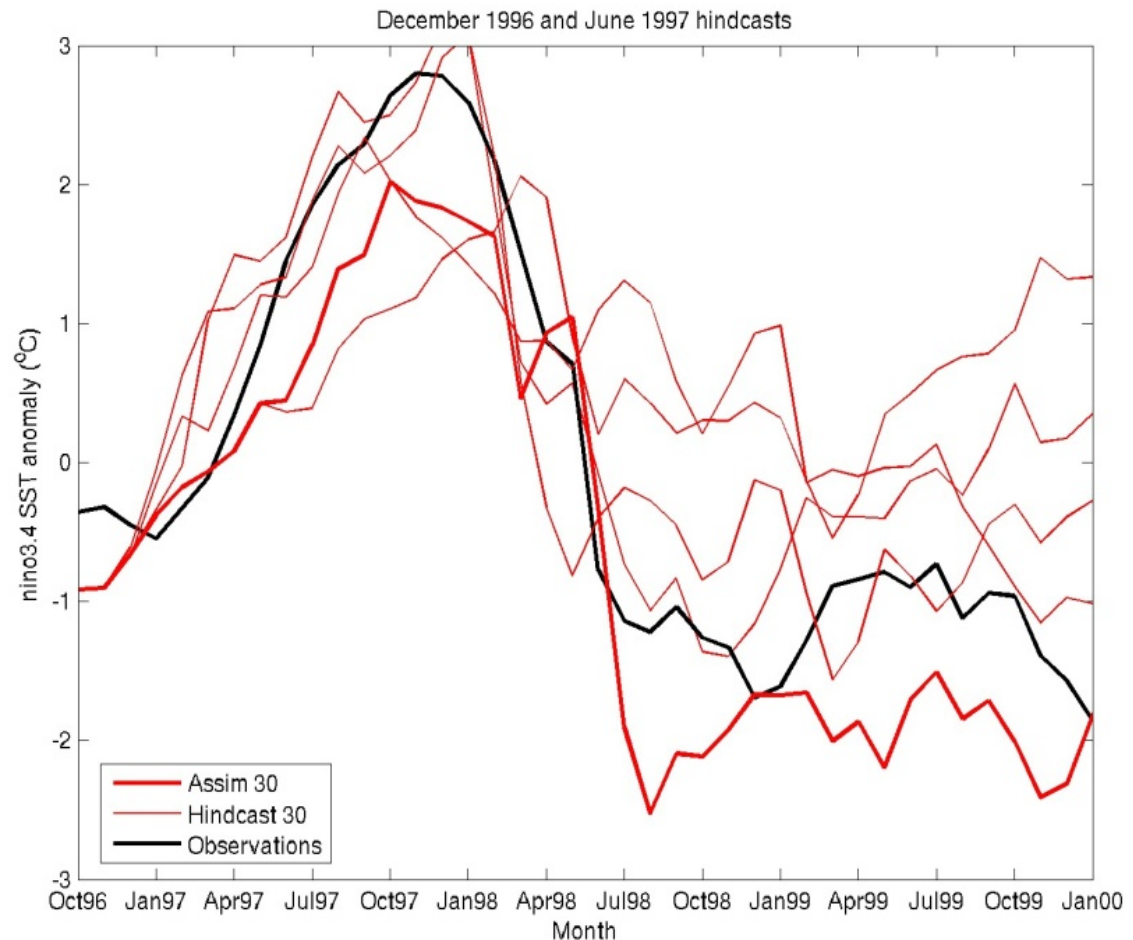
Len Shaffrey¹, Pier Luigi Vidale¹, Rowan Sutton¹, Ed Hawkins¹, Ian Stevens², Dave Stevens², Doug Smith³

¹NCAS, University of Reading

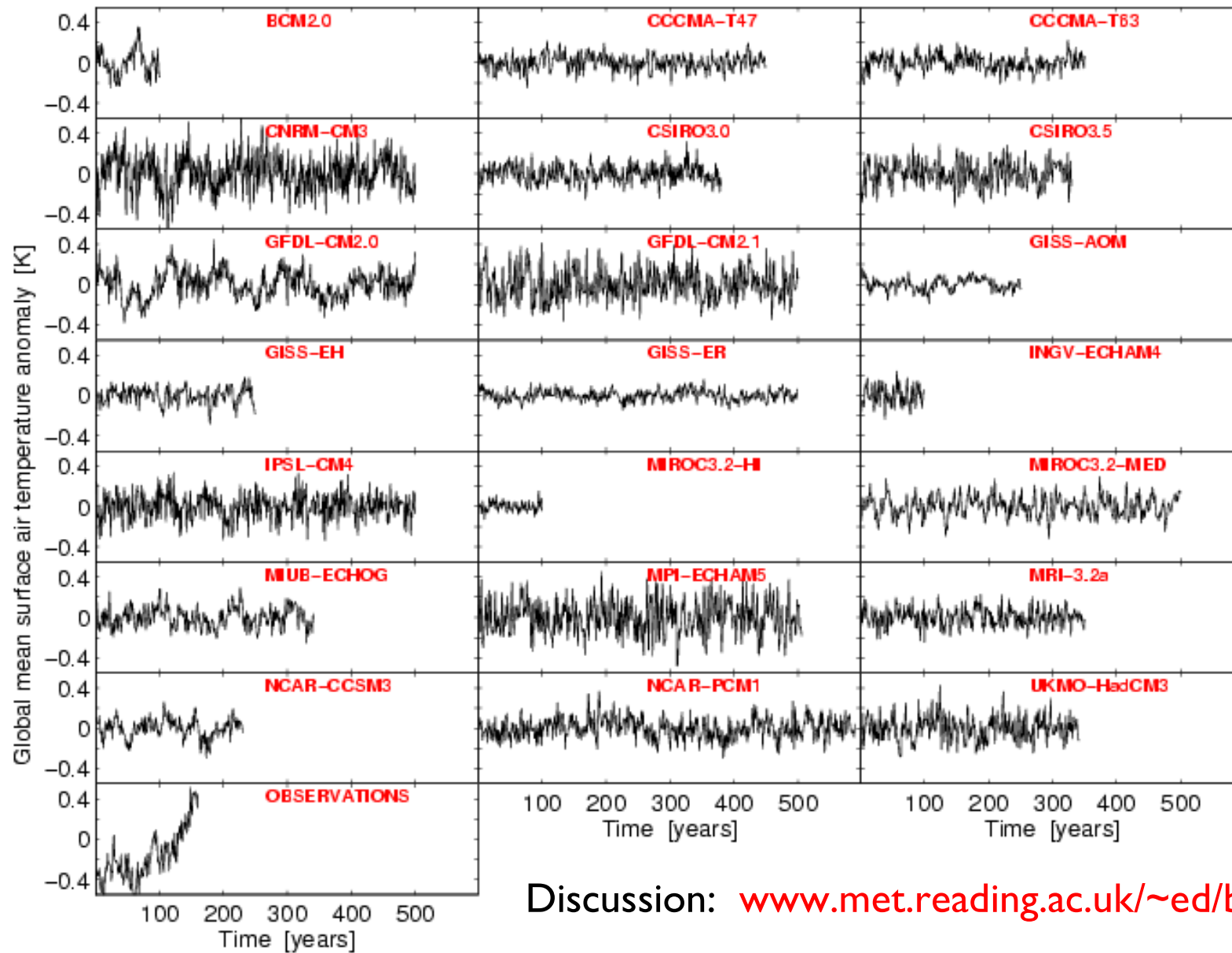
²University of East Anglia

³Met Office

HiGEM test 1997 El Nino forecast. Nino3.4 SST observations (black), assimilation run (thick red) and an ensemble of HiGEM hindcasts (thin red) initiated on 1st Dec 1996

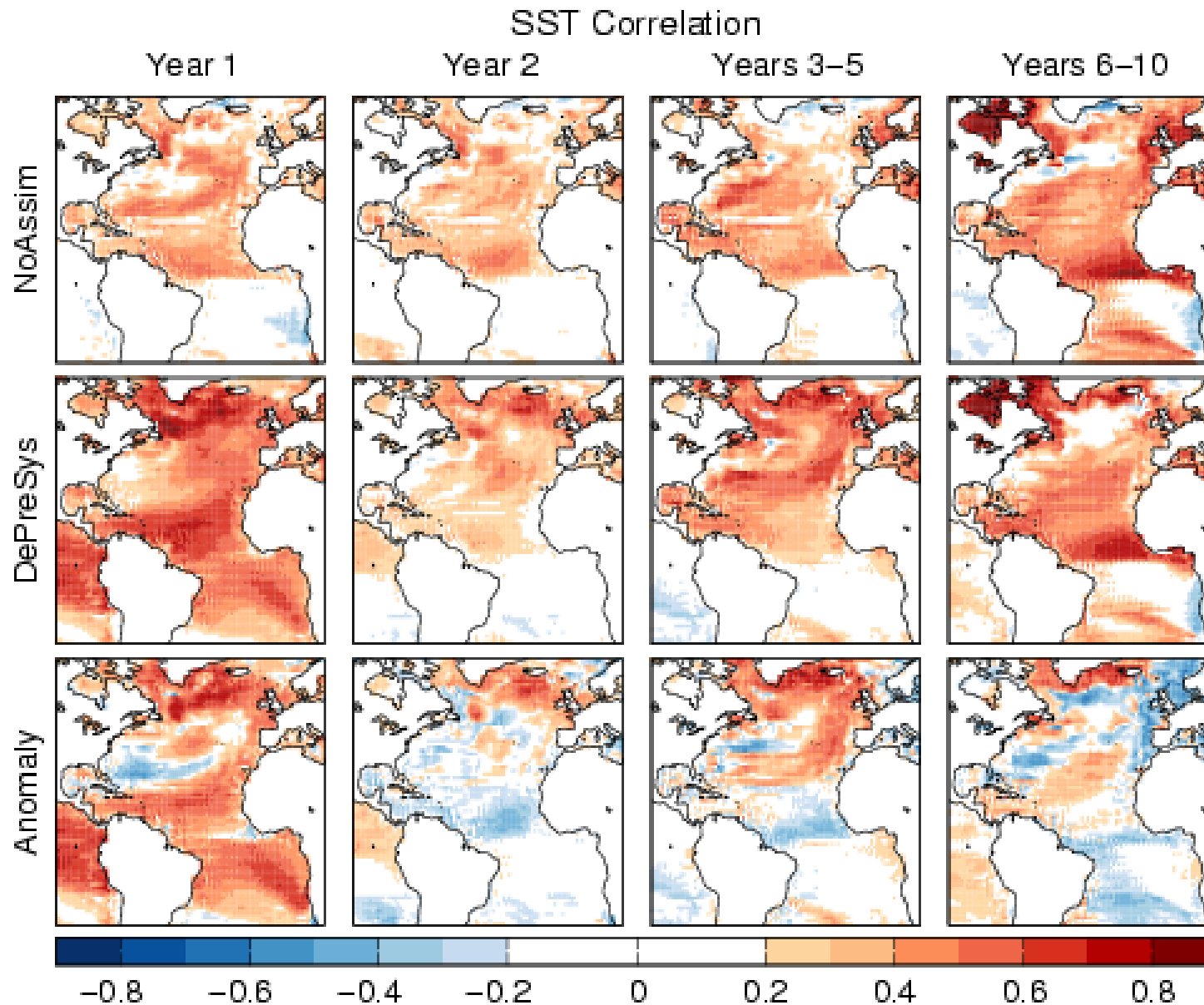


Internal variability in CMIP3 GCMs



Discussion: www.met.reading.ac.uk/~ed/blog

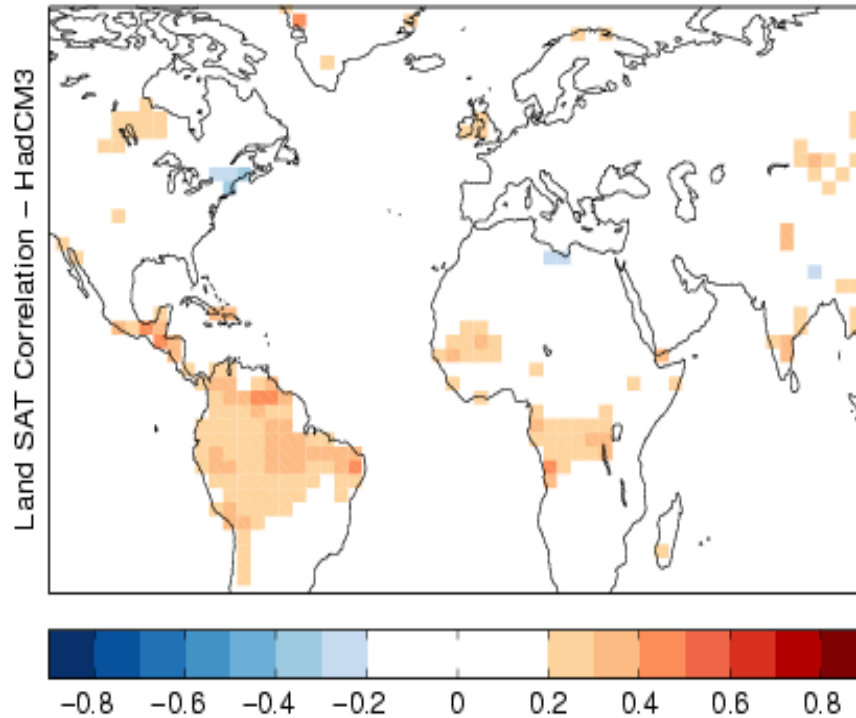
UKMO operational GCM decadal predictions (DePreSys)



Skill in temperatures over land?

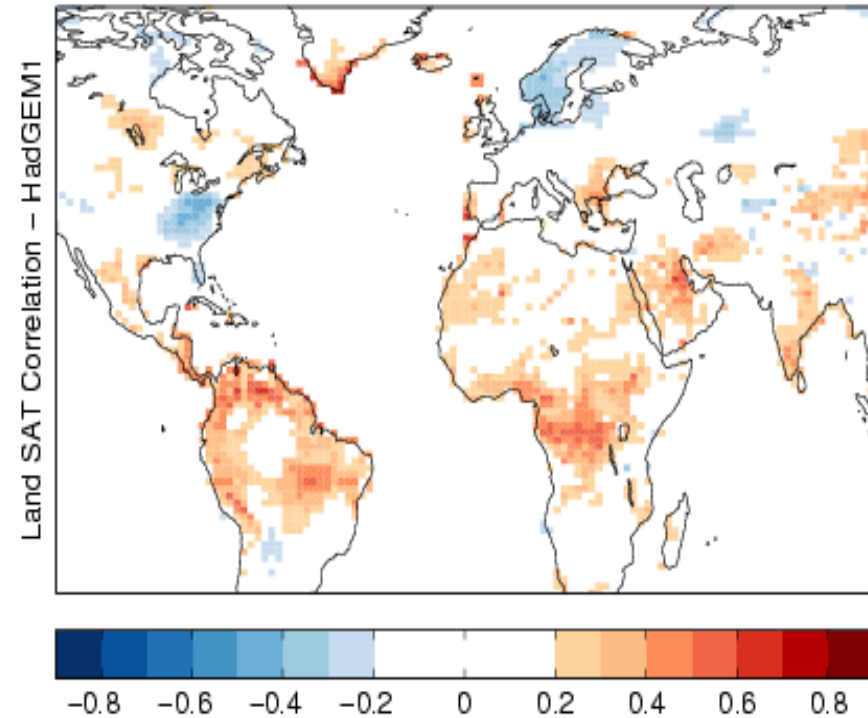
HadCM3

Year 1



HadGEM1

Year 1



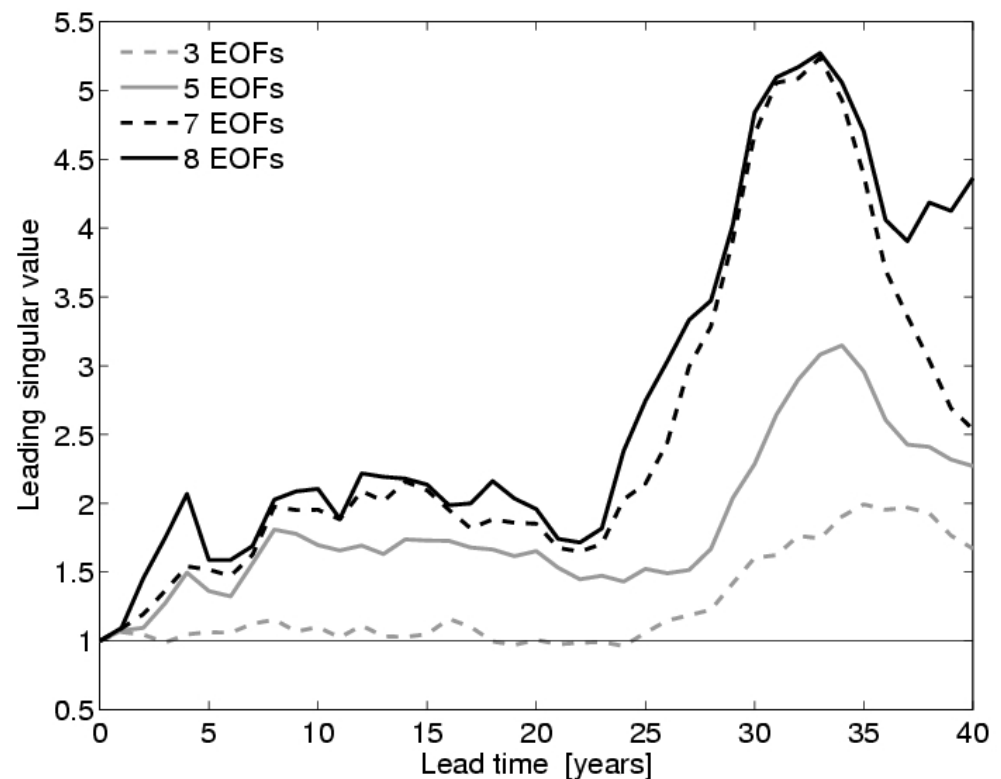
- Using CA method, can also predict other climate variables, e.g. temperature over land (above)

Climatic Singular Vectors (CSVs)

Build a propagator matrix (**P**) from a series of ensemble runs from a single 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)

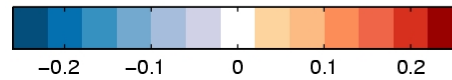
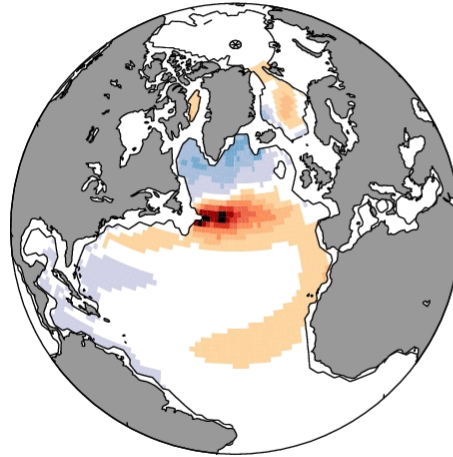
Amplification



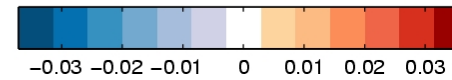
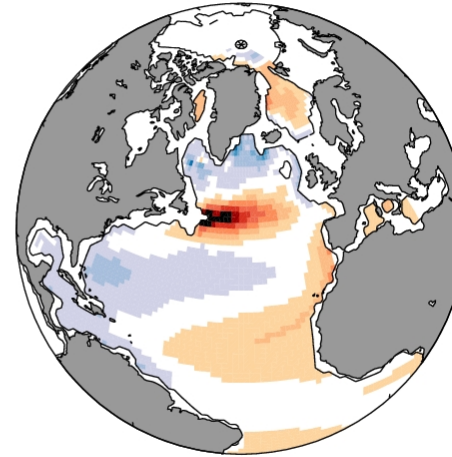
Leading CSV in HadCM3

Optimal
perturbation

Integrated temperature [K]

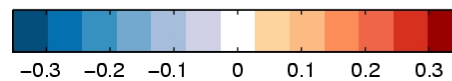
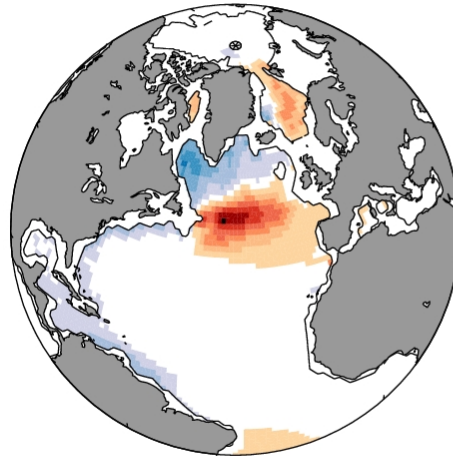


Integrated salinity [psu]

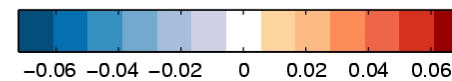
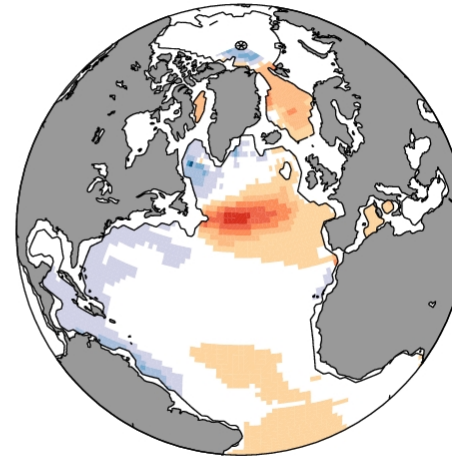


Predicted
state 10
years later

Integrated temperature [K]



Integrated salinity [psu]

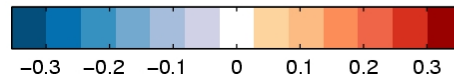
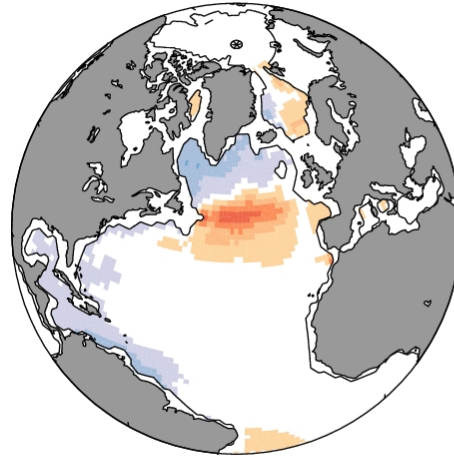


Note changed
colour scales!

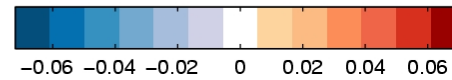
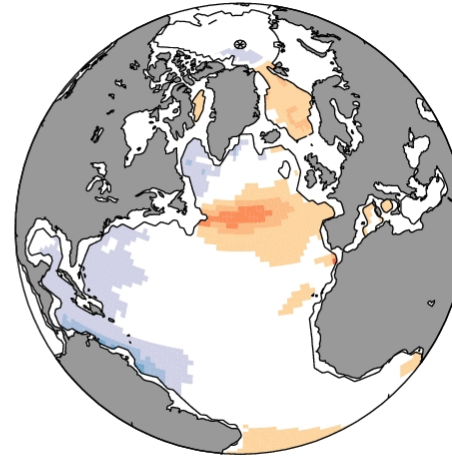
Leading CSV in HadCM3

Actual
state 10
years later

Integrated temperature [K]

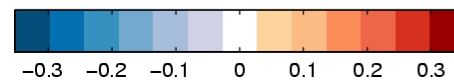
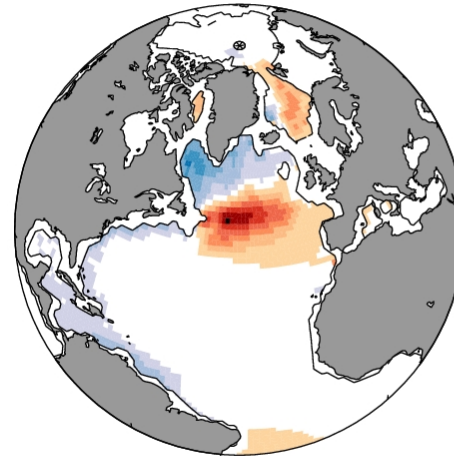


Integrated salinity [psu]



Predicted
state 10
years later

Integrated temperature [K]



Integrated salinity [psu]

