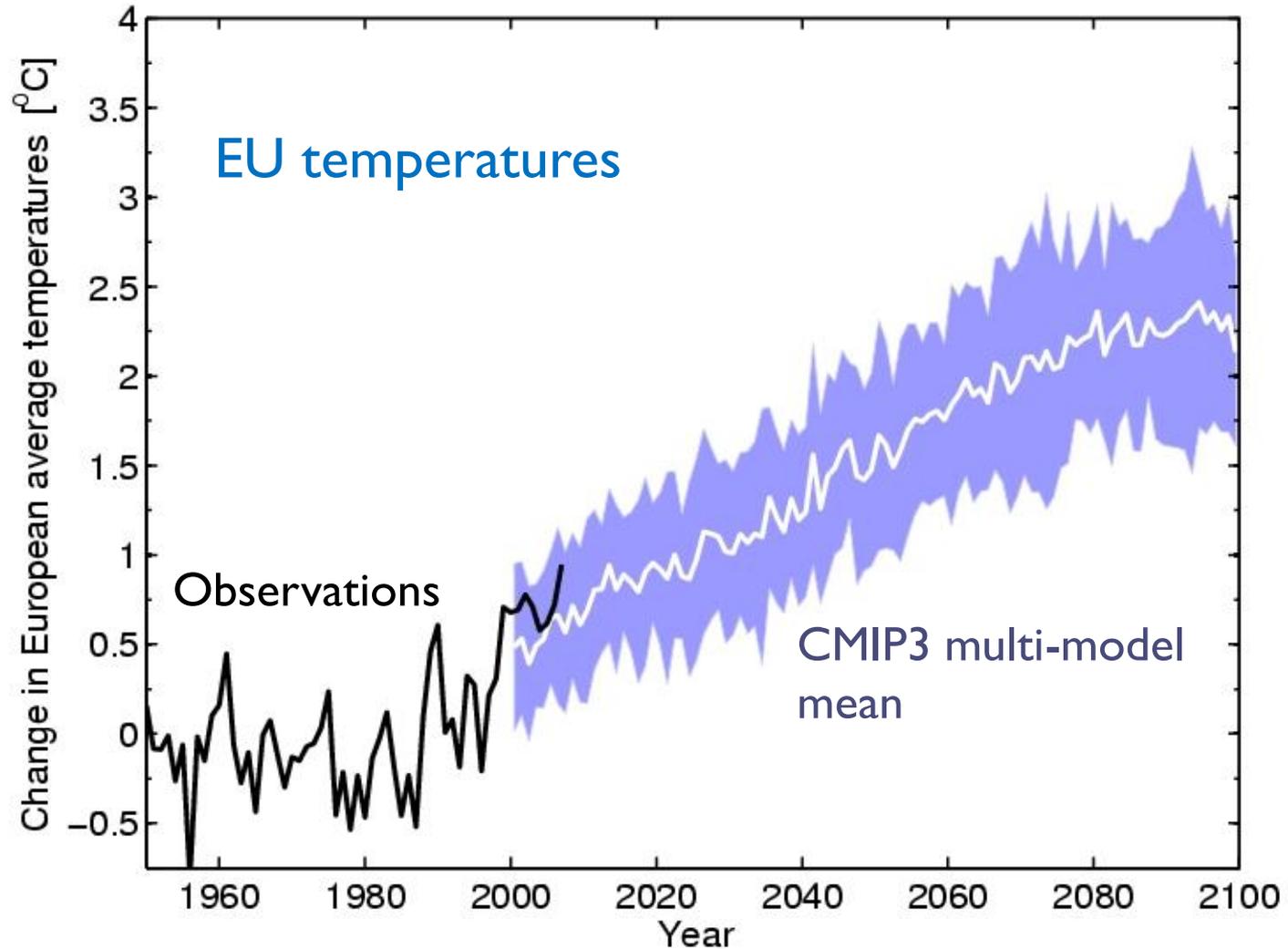


# The value of decadal predictions & links to the Arctic

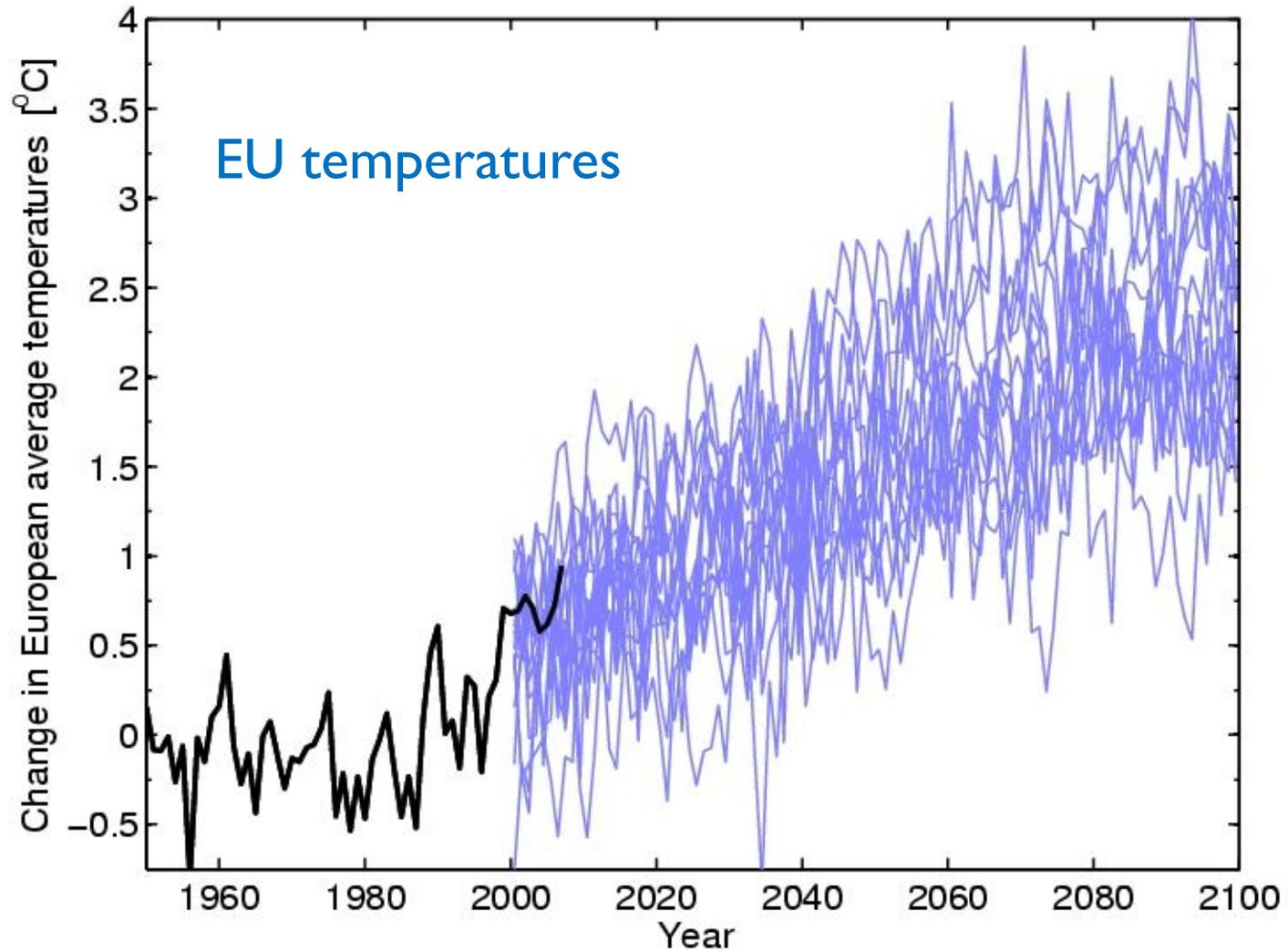
Ed Hawkins

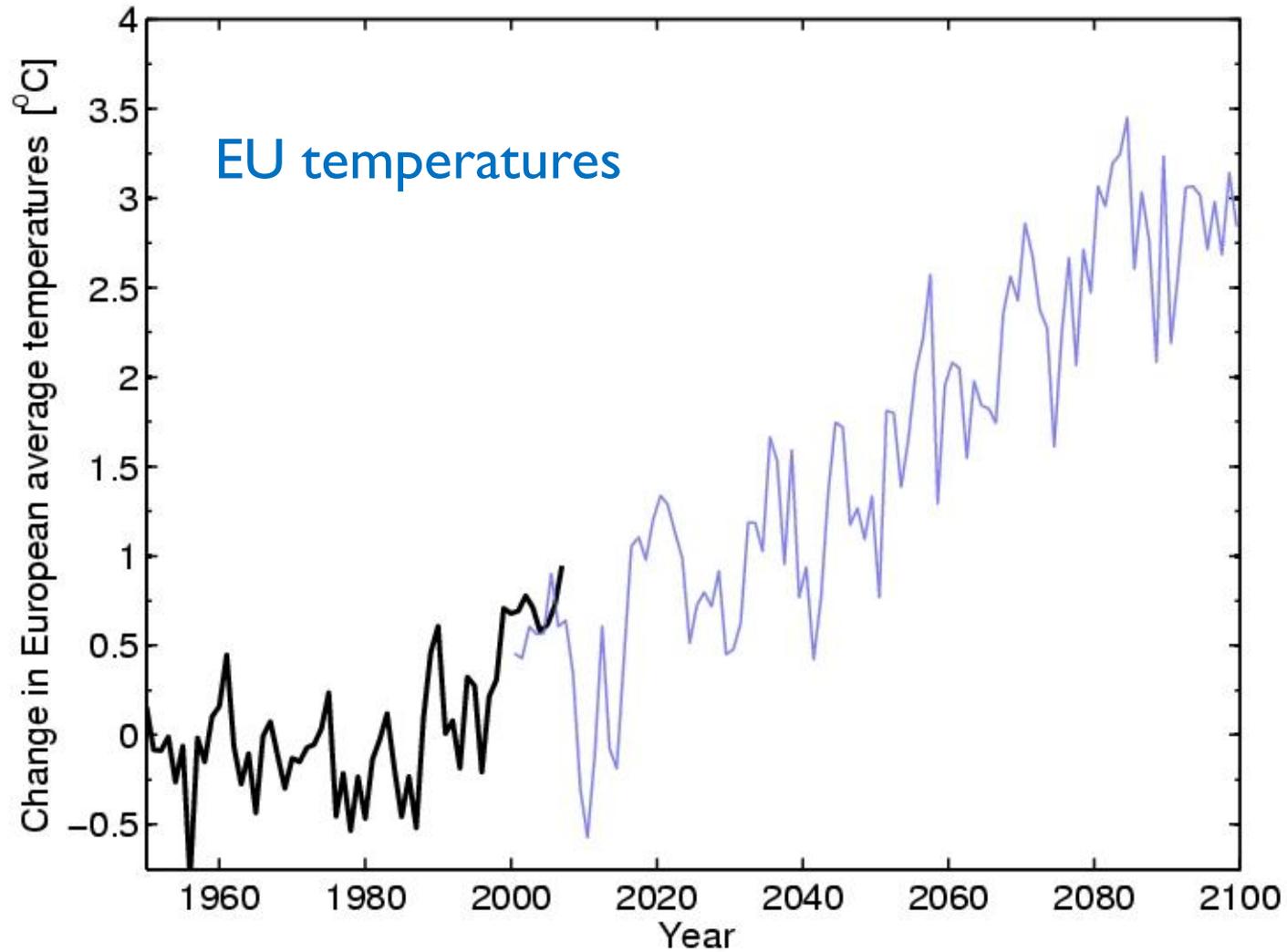
Thanks to: Rowan Sutton, Jon Robson, Buwen Dong, Sarah Keeley, Dan Hodson, Len Shaffrey

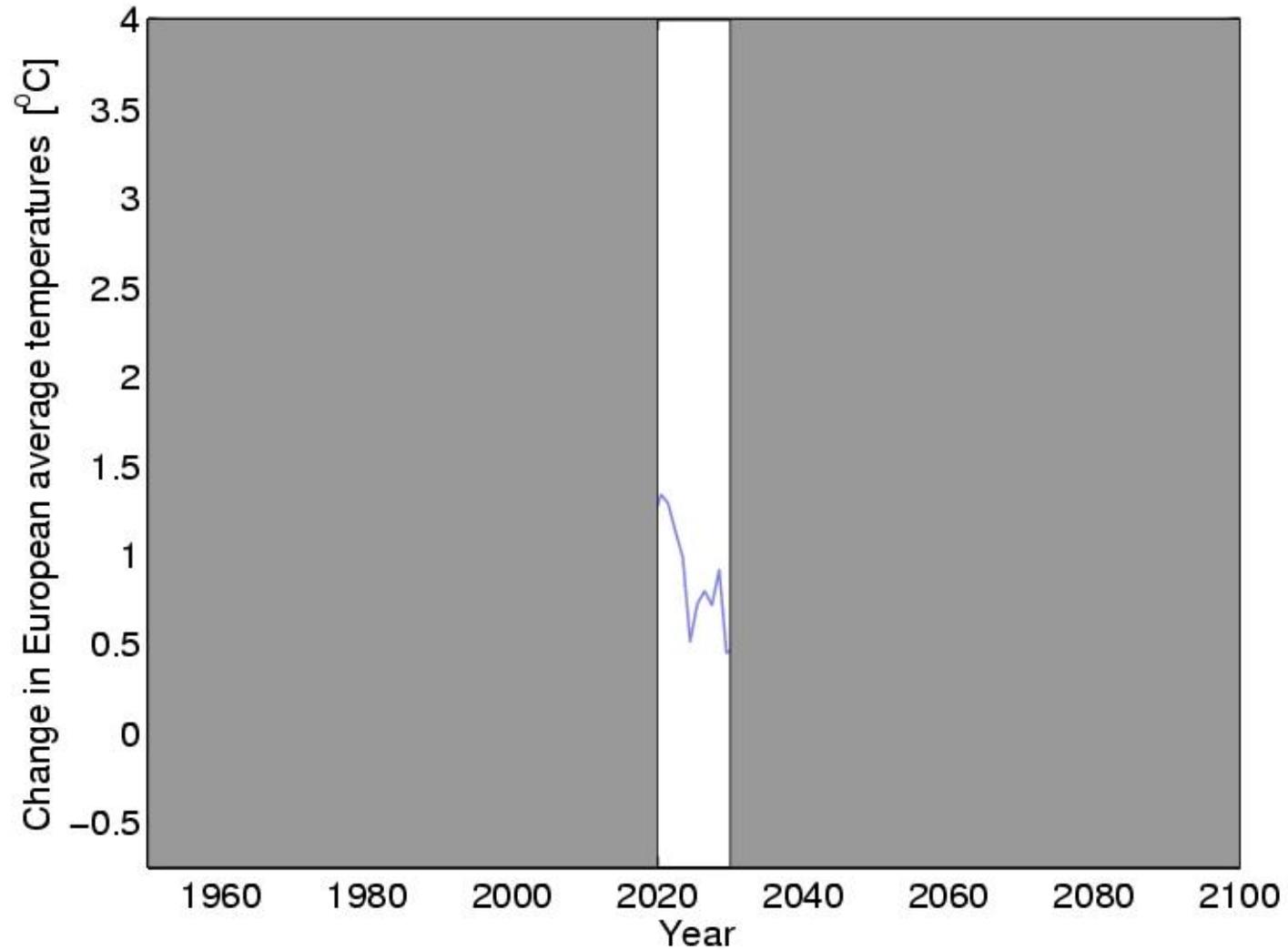
*NCAS-Climate, University of Reading*

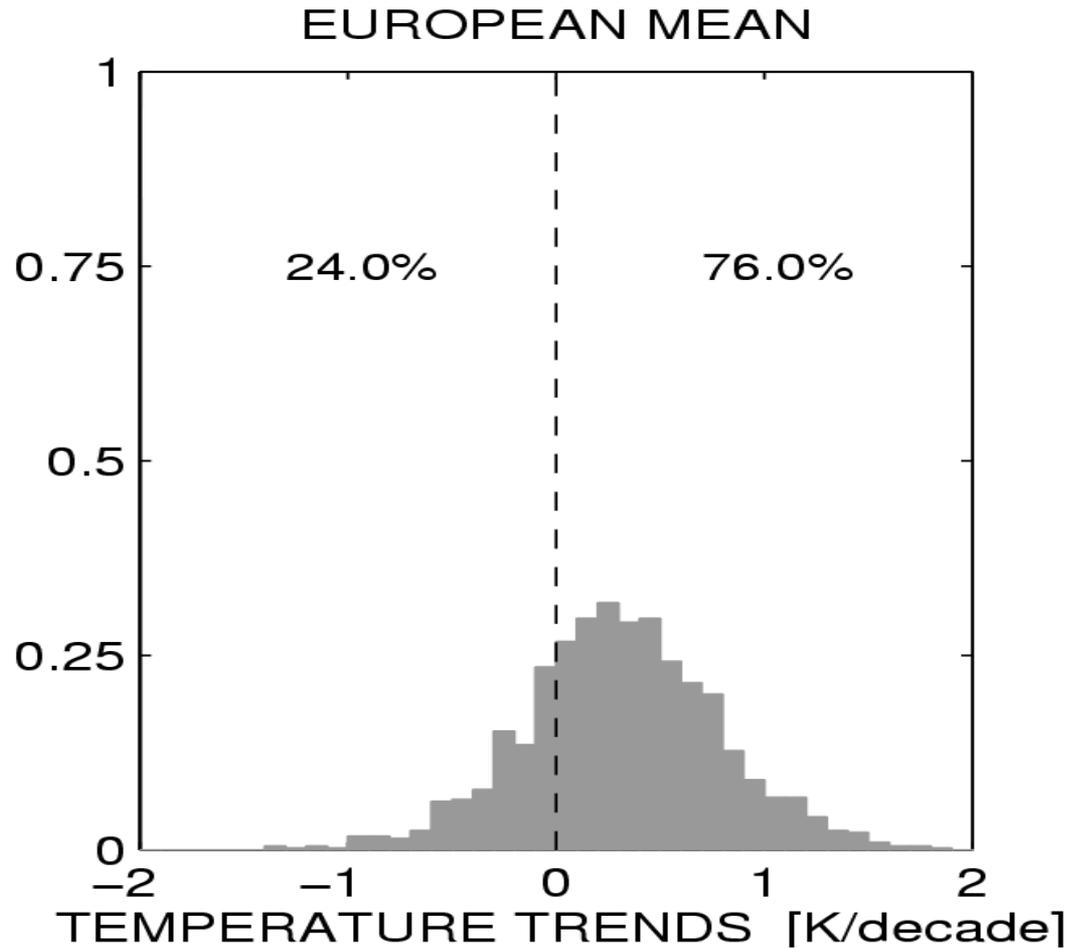


# Decadal variability









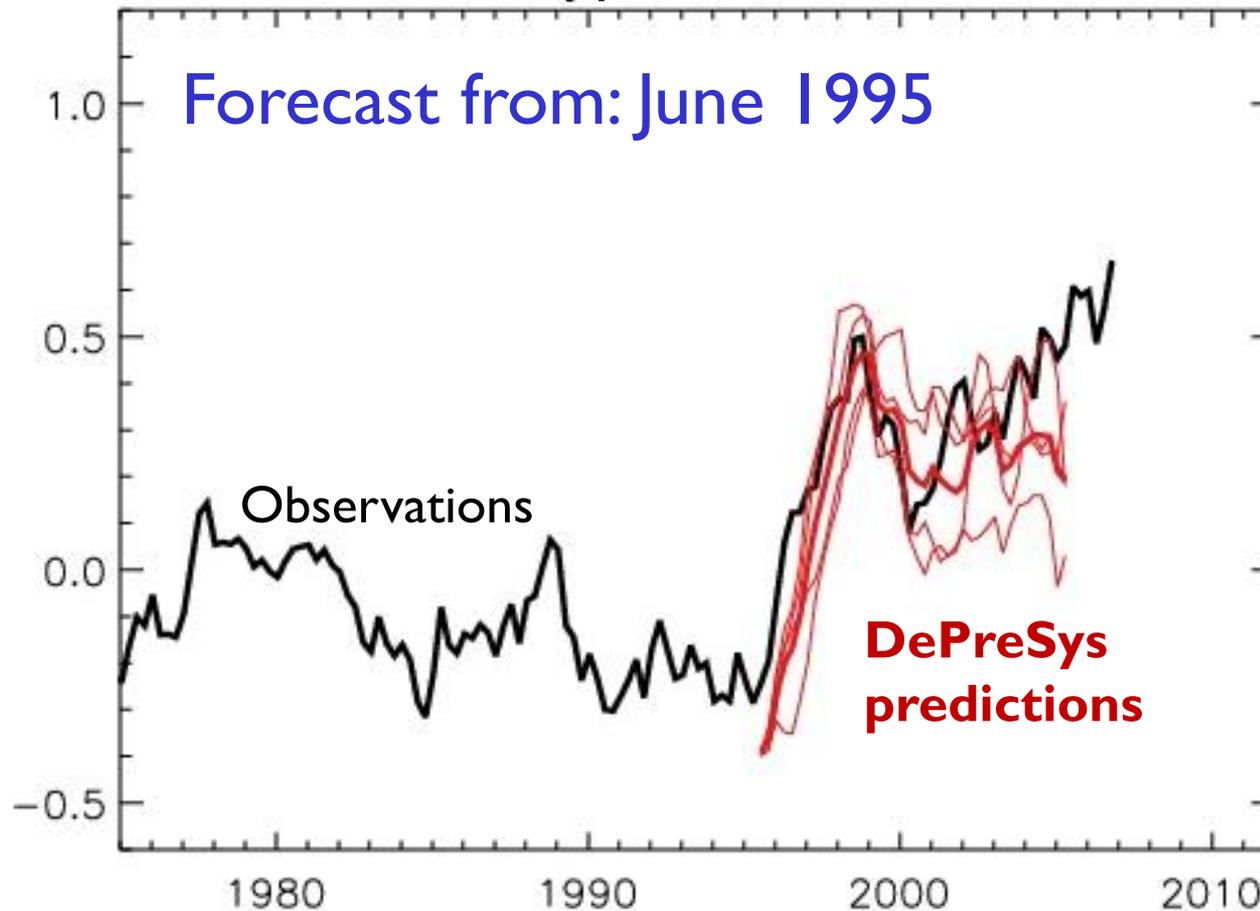
21<sup>st</sup> century EU  
decadal temperature  
trends

CMIP3 SRES A1B



- ◎ The value of decadal predictions
  - The case study approach
  - Learning about model bias and ocean monitoring
  - How about statistical decadal predictions?
- ◎ What about the Arctic?
  - Quantifying uncertainty
  - Potential predictability

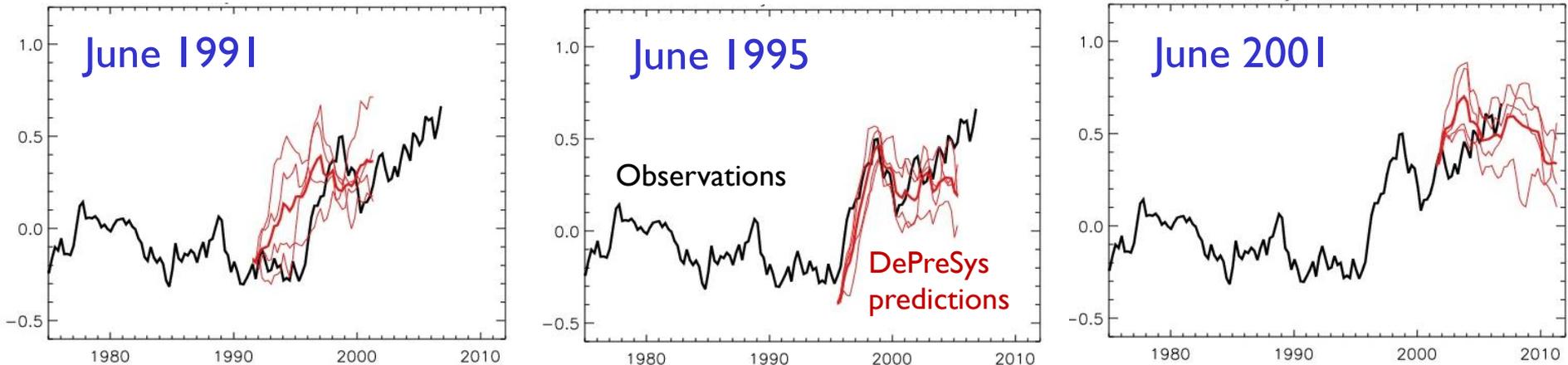
## North Atlantic upper ocean heat content



Hypotheses:

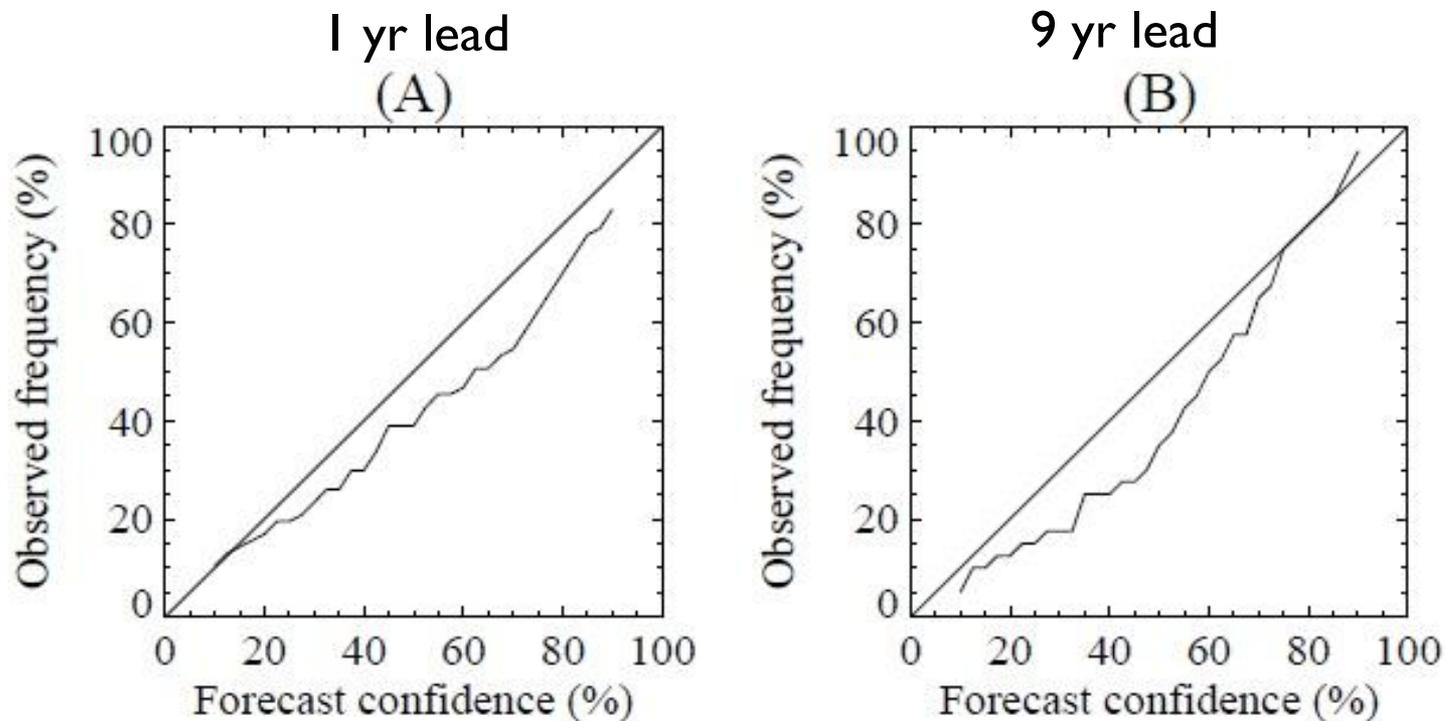
was the rapid warming because of the MOC or the NAO?

## Retrospectively predicting North Atlantic upper ocean heat content



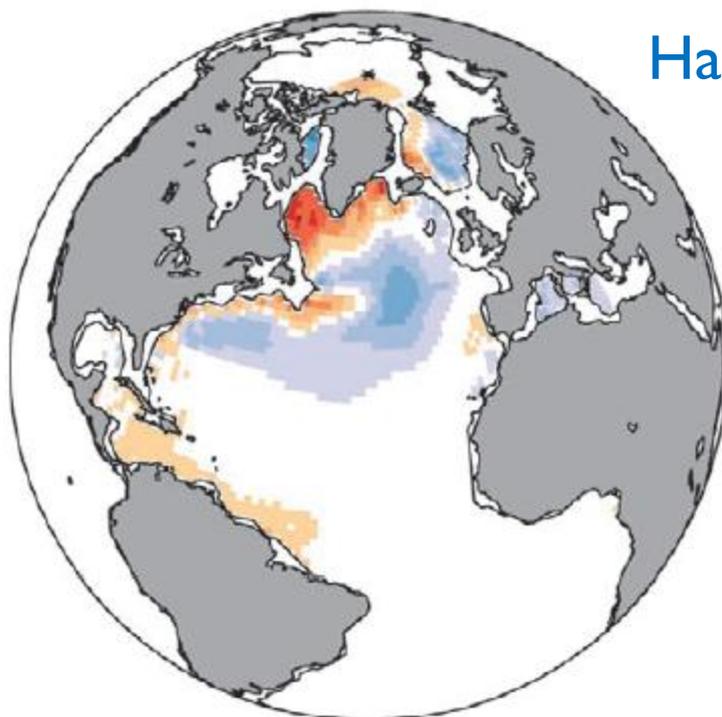
### Decadal predictions allow:

- building trust in GCMs for making predictions and projections,
- the understanding of mechanisms causing variability,
- to identify processes causing forecast errors



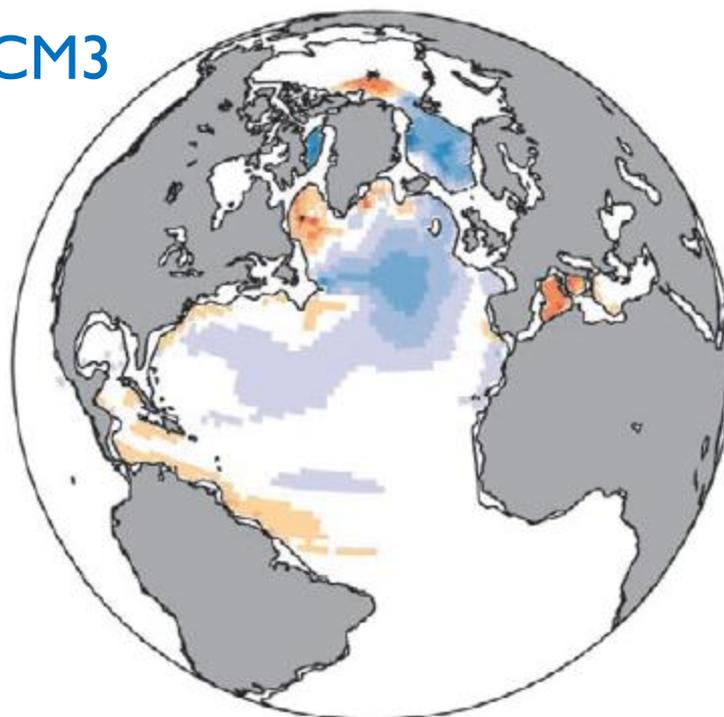
For global temperature, the DePreSys hindcasts are slightly overconfident, suggesting the need for greater spread in the predictions.

Integrated Temperature



HadCM3

Integrated Salinity



→ Learning about predictability and optimal observations

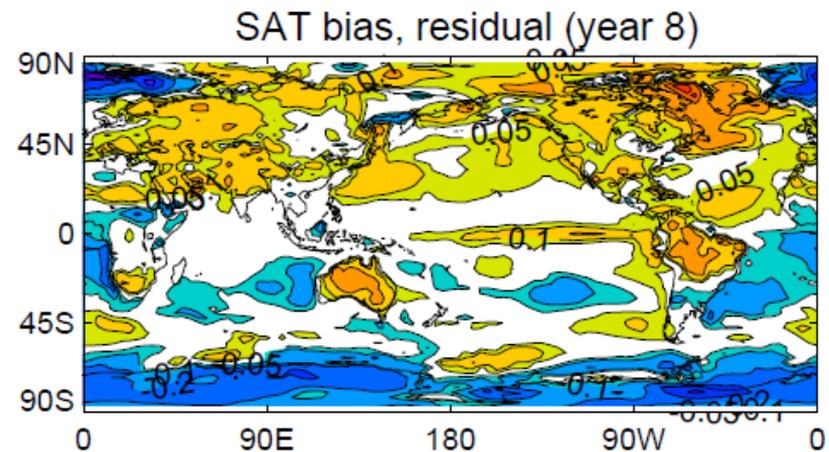
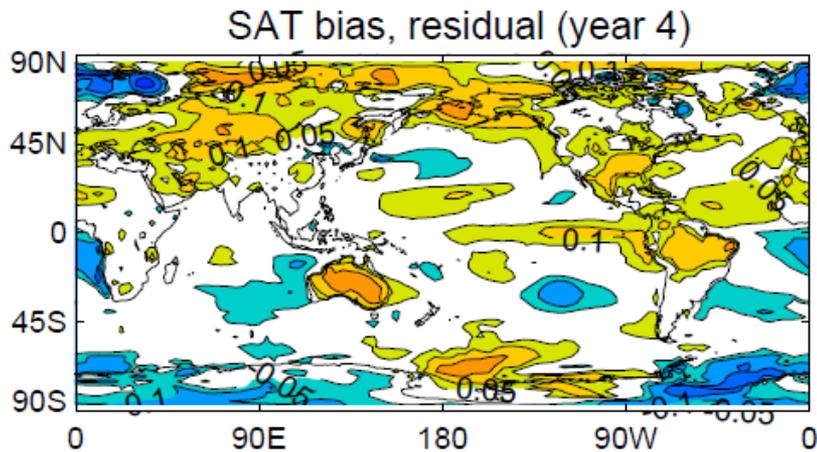
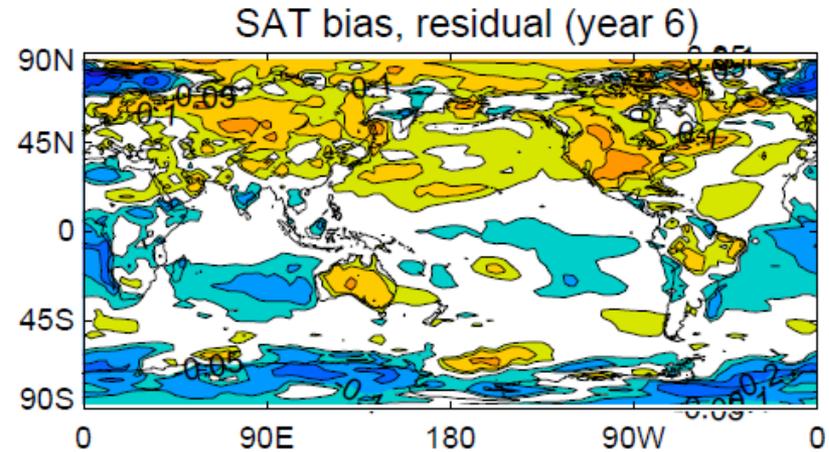
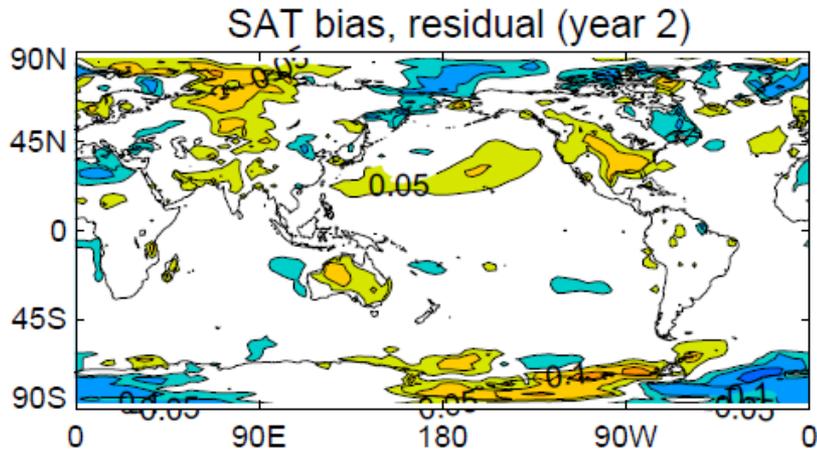
See Tziperman et al. 2008, Hawkins & Sutton 2009, 2010



# LEARNING FROM MODEL FORECAST BIAS

Thanks to Buwen Dong

## The growth of forecast bias in HadCM3

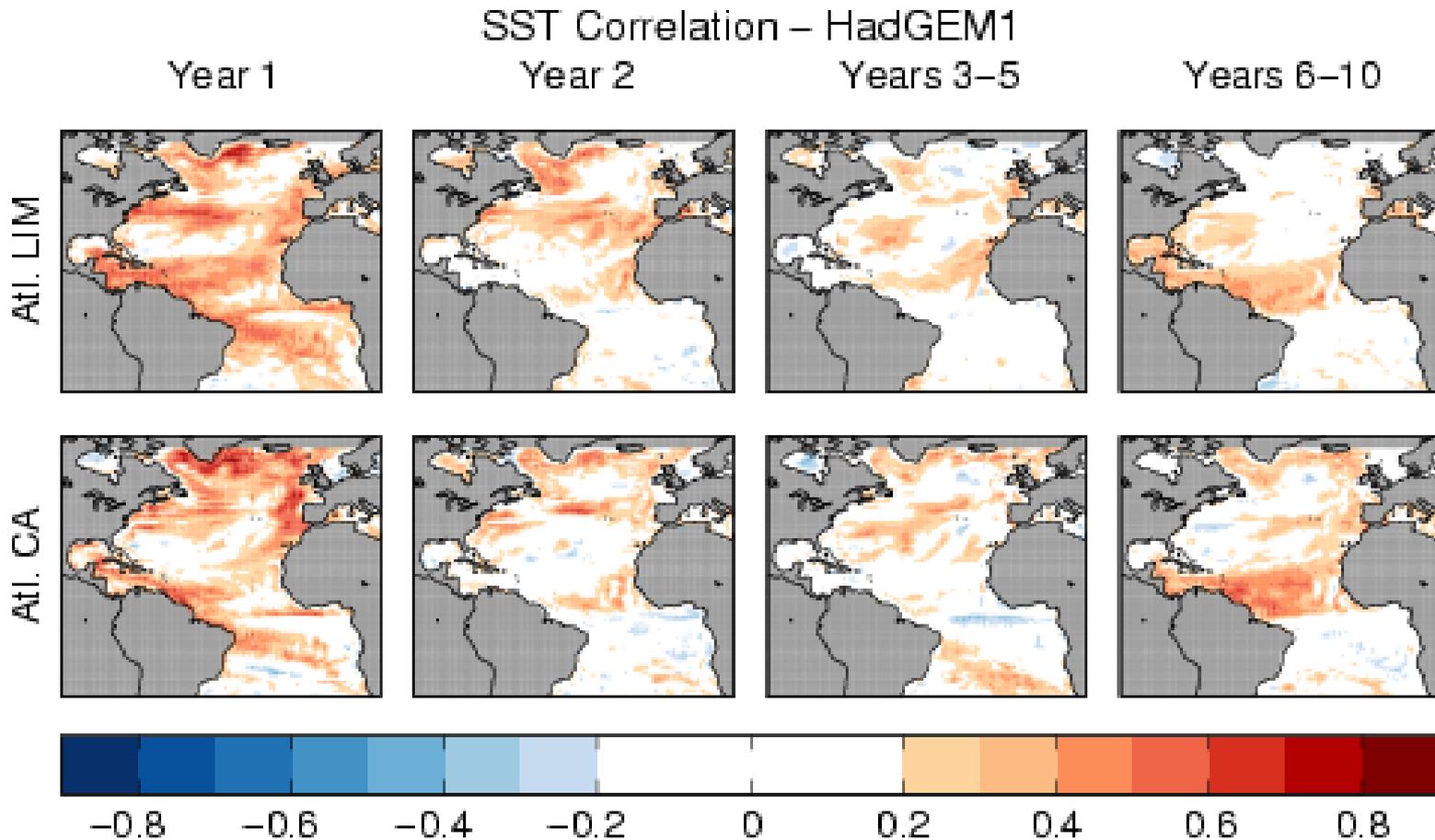


→ future projections constrained by the past



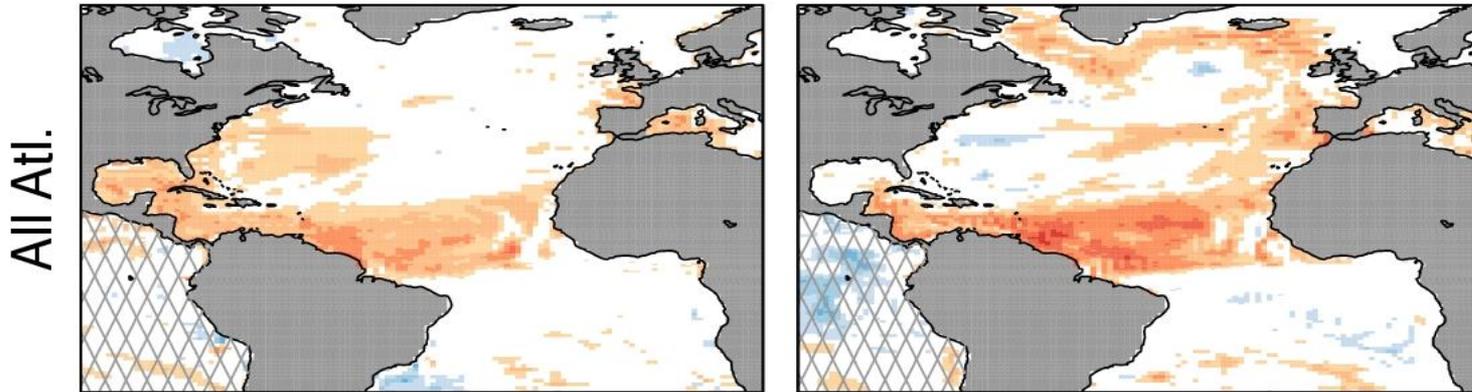
# LEARNING FROM STATISTICAL DECADAL PREDICTIONS OF SSTs

Statistical methods



Correlation skill of idealised SST predictions  
(perfect model framework, control run)

SST Correlation – HadGEM1 – lead 6–10 years  
LIM CA



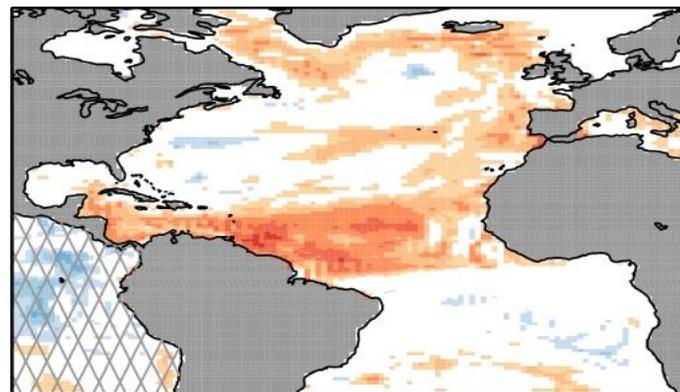
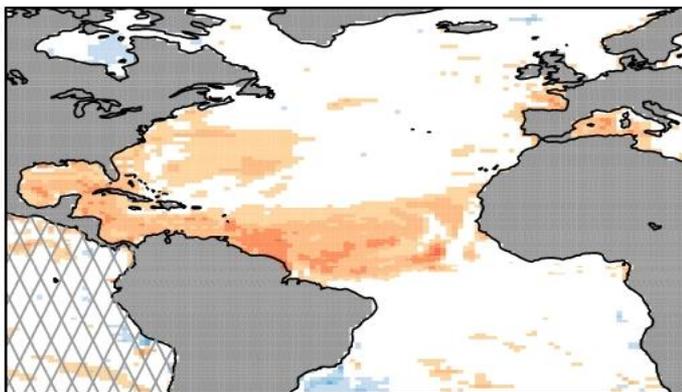
Correlation skill of SST predictions

## SST Correlation – HadGEM1 – lead 6–10 years

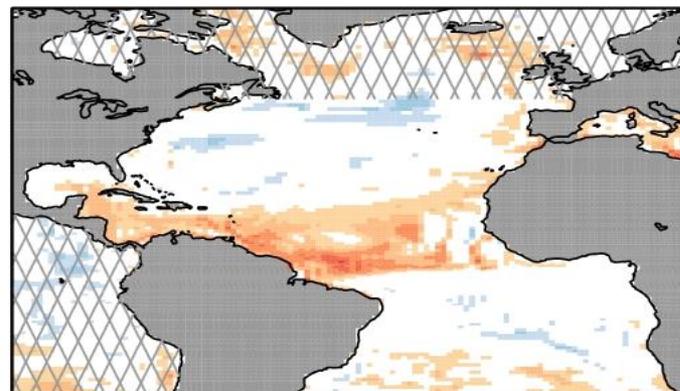
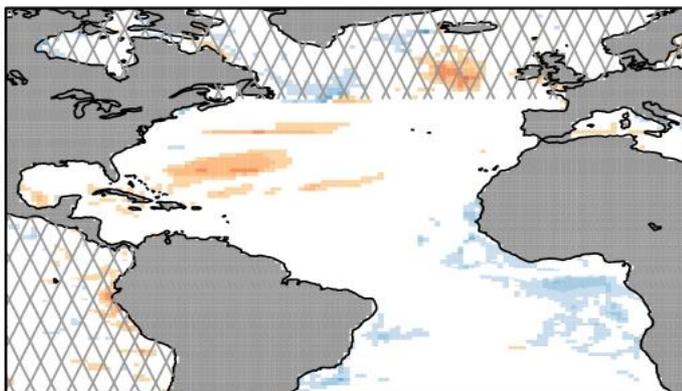
LIM

CA

All Atl.

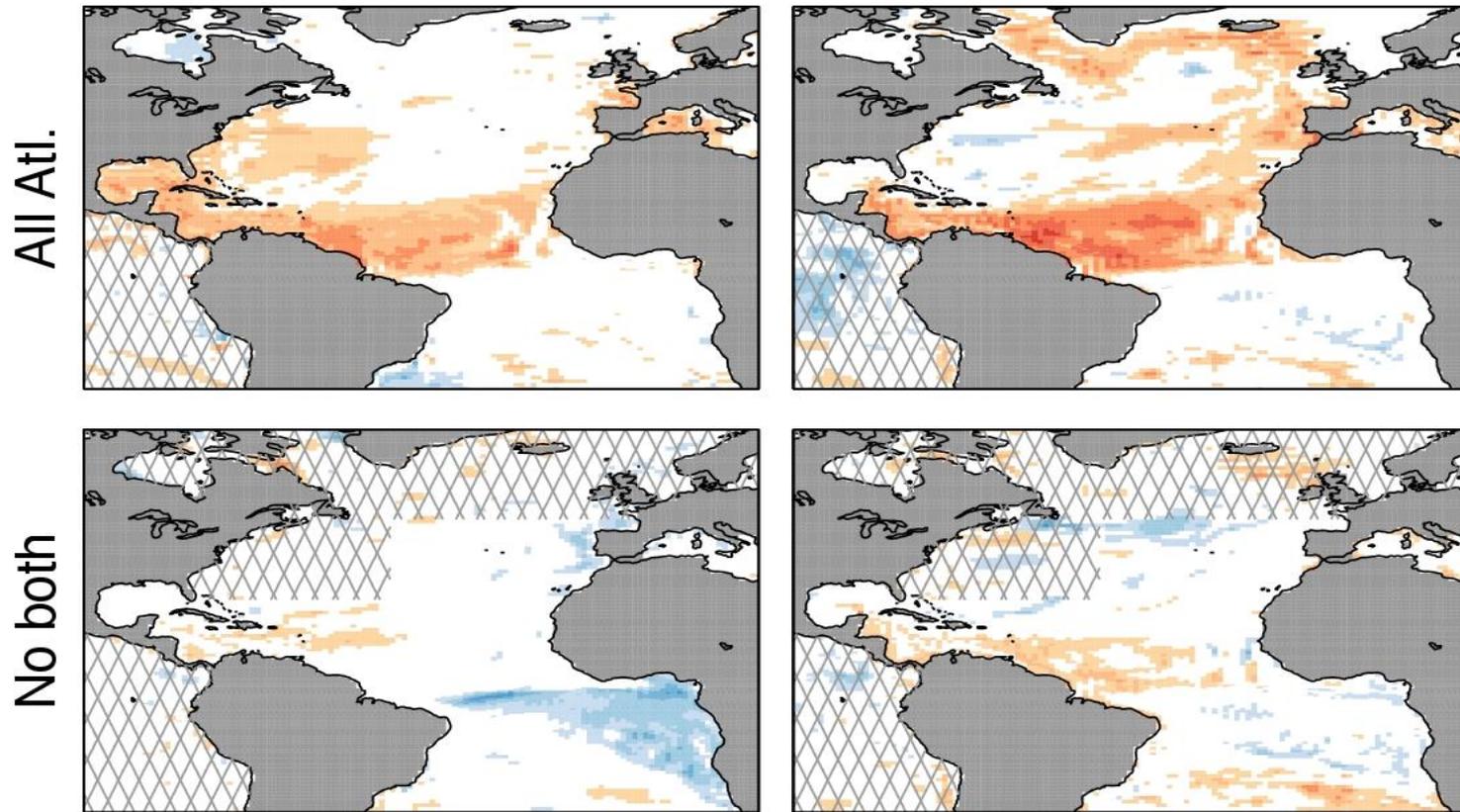


No far N. Atl.



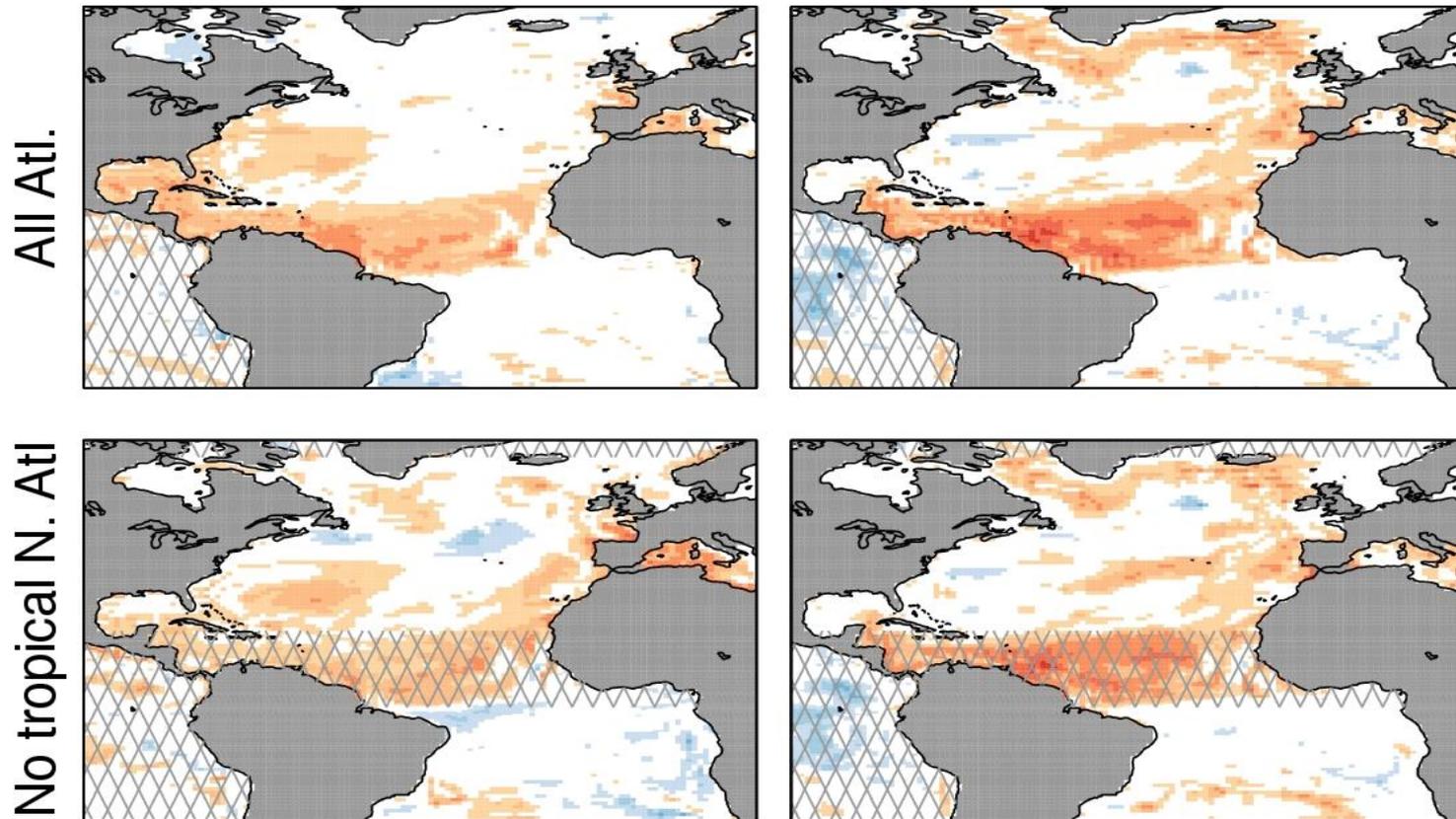
Correlation skill of SST predictions

## SST Correlation – HadGEM1 – lead 6–10 years



Correlation skill of SST predictions

## SST Correlation – HadGEM1 – lead 6–10 years



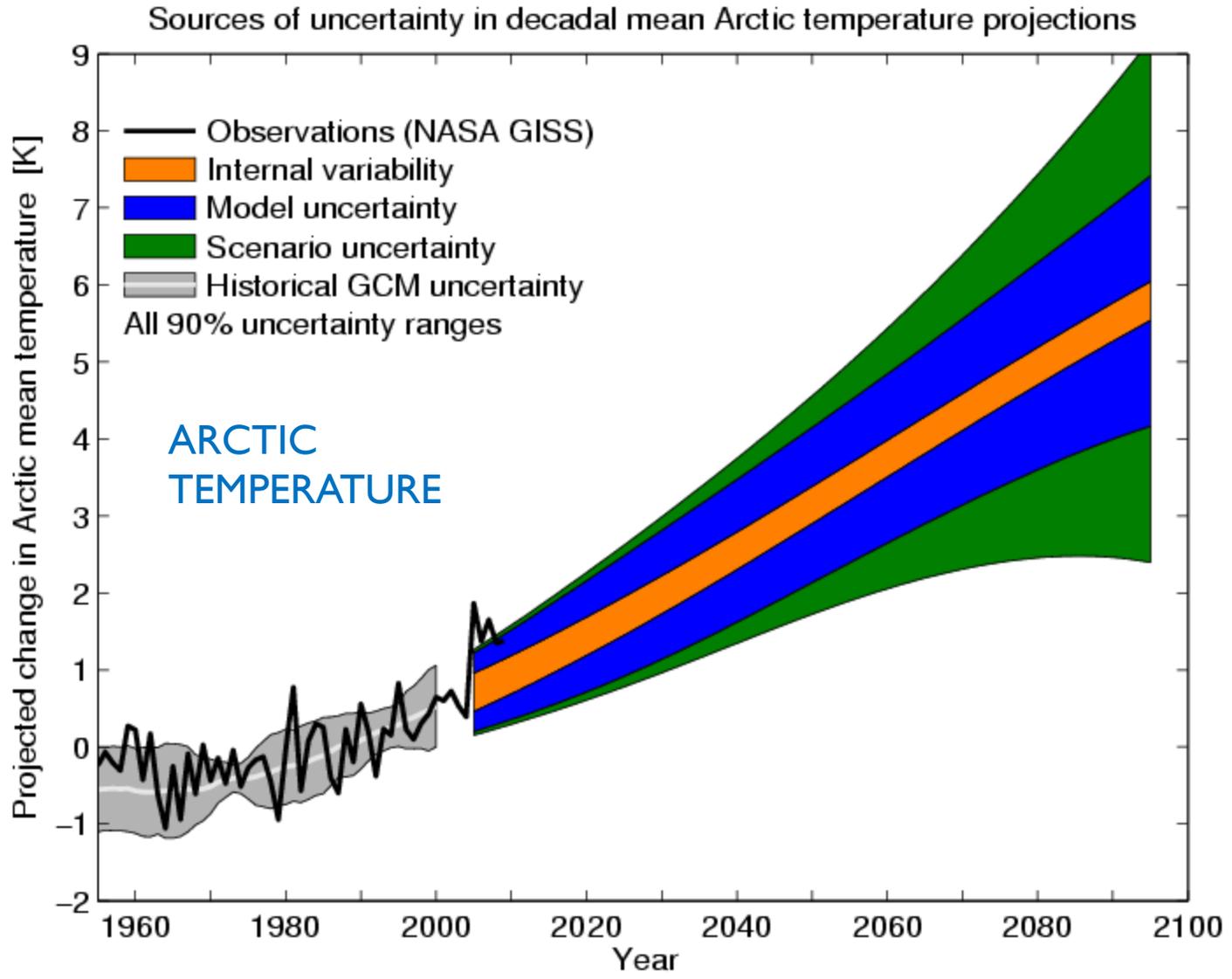
Correlation skill of SST predictions

→ methods to be extended to analyse observations

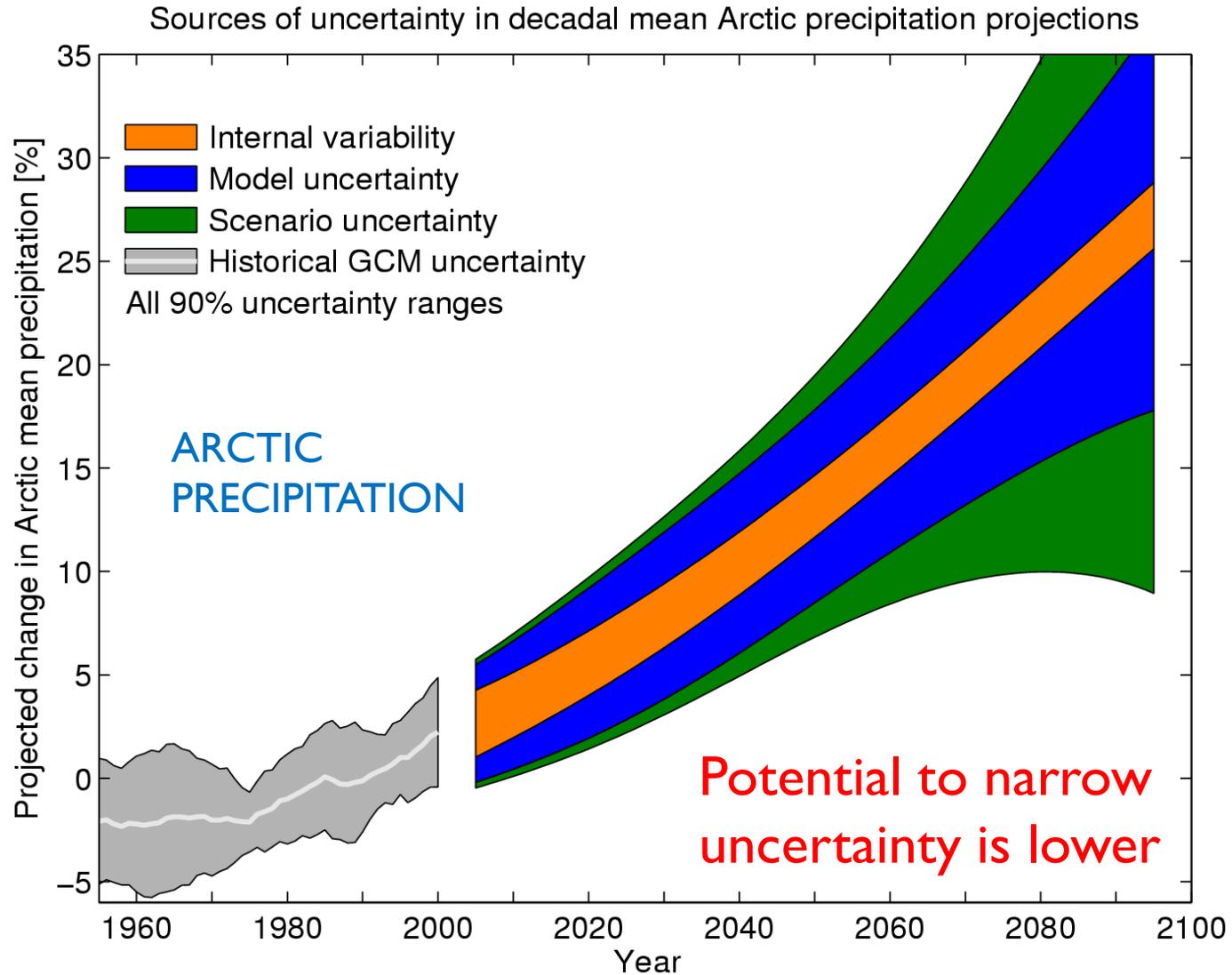


# LINKS TO THE ARCTIC

# Sources of uncertainty in Arctic projections



# Sources of uncertainty in Arctic projections



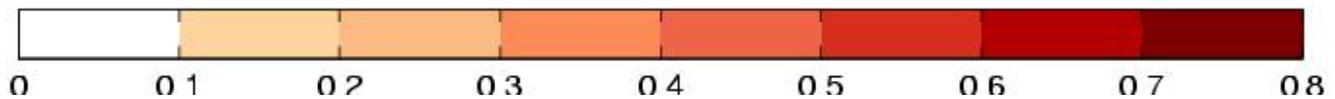
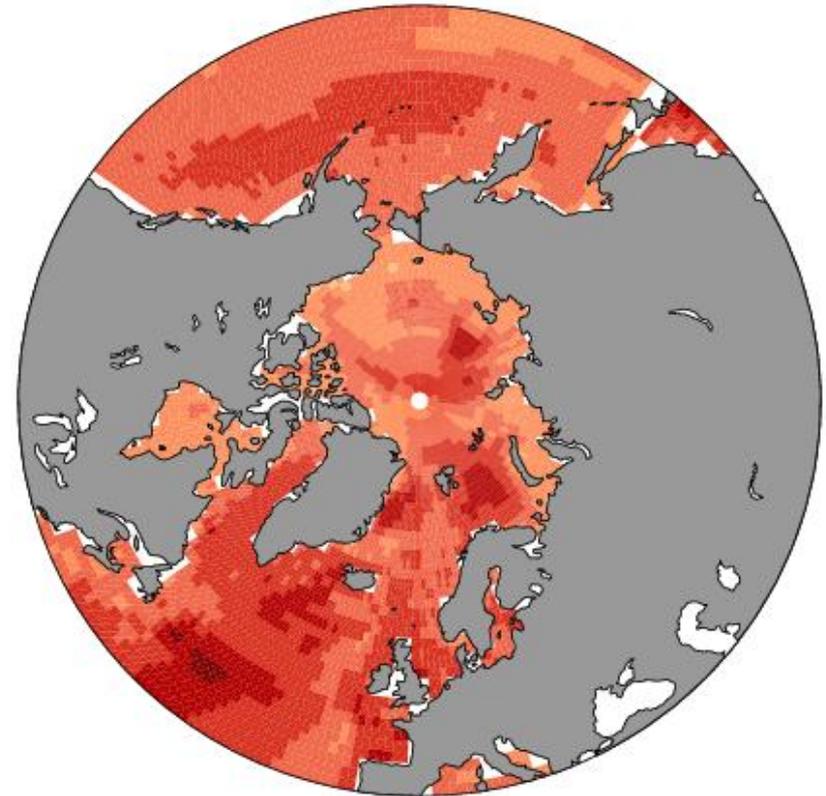
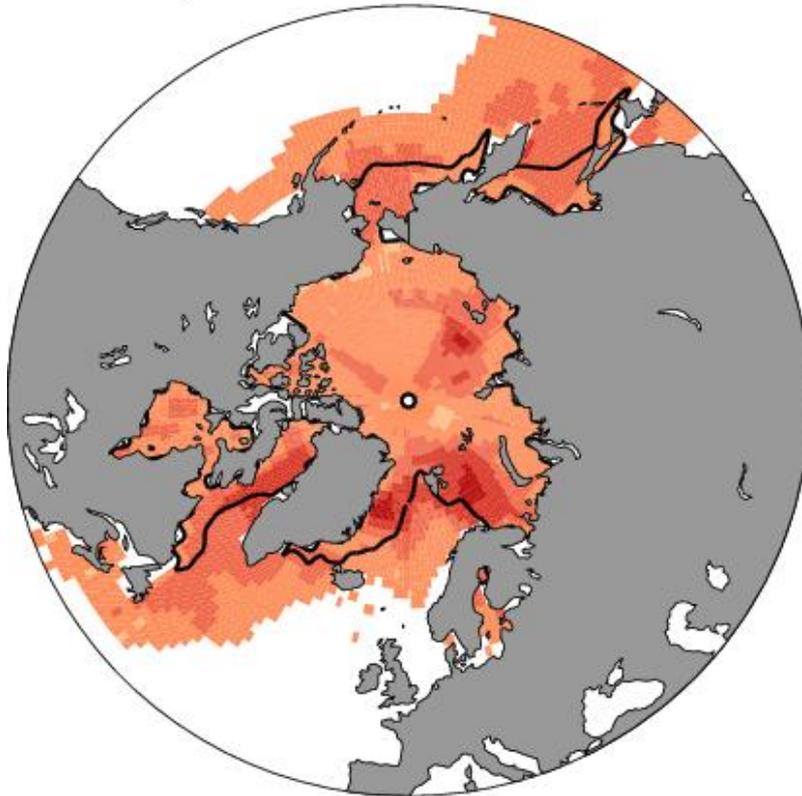
# Potential predictability (PP)

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

HadCM3

Potential predictability of sea ice concentration

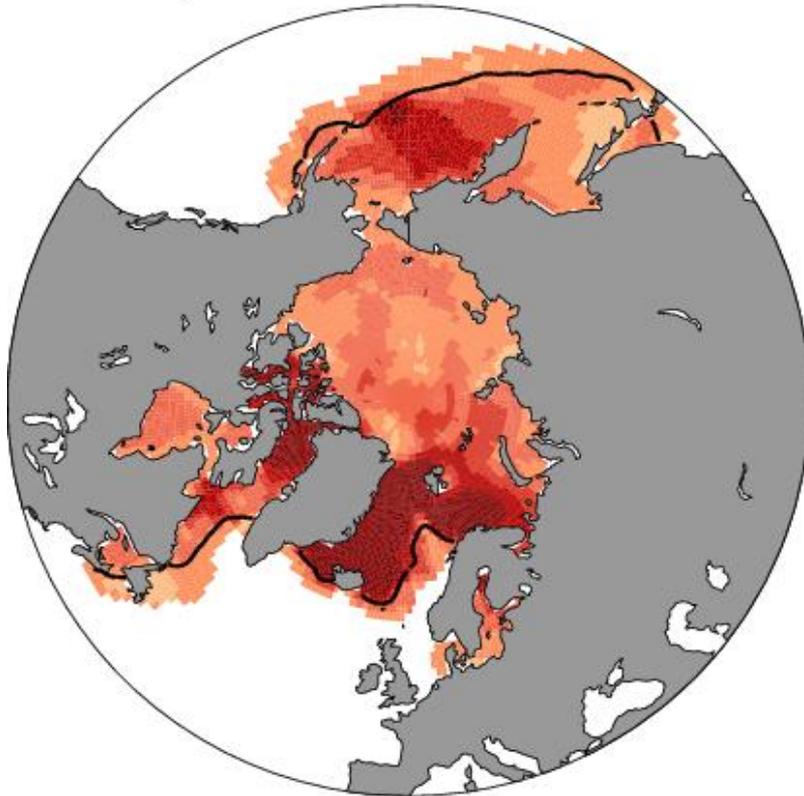
Potential predictability of SSTs



# “Potential predictability”

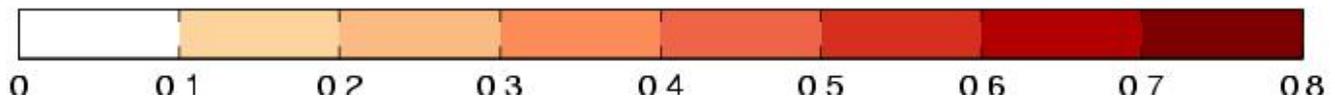
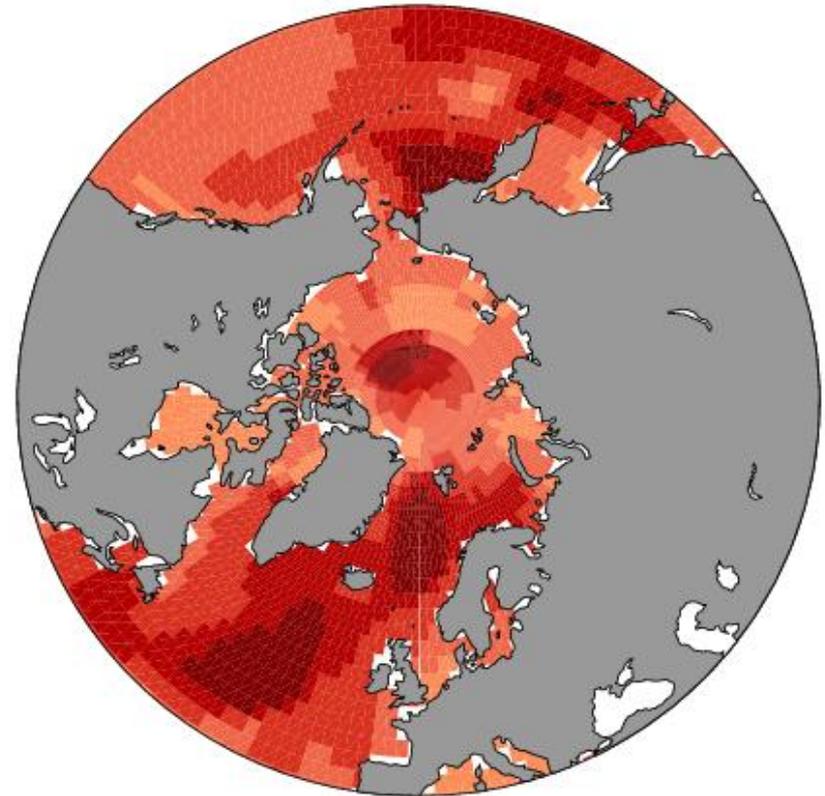
$$PP = \sigma_{10} / \sigma_1$$

Potential predictability of sea ice concentration



Bergen CM

Potential predictability of SSTs



## Initialised (decadal) climate predictions are not just about improving forecast skill

- They have the potential to:
  - help build trust in climate model projections
  - learn about model bias and climate variability
  - learn about physical processes leading to forecast error
  - inform model development and improvements
  - inform design of effective climate monitoring systems
- “Decadal” = anything longer than seasonal
- Need to test Arctic predictability in idealised GCM settings as well as (or before?) tackling real predictions



- Case study approach useful
- HadCM3 weakly too sensitive, mainly over land  
→ constrained projections?
- Statistical decadal predictions also potentially possible as a benchmark or source of skill
- Targeted observations in far North Atlantic should be beneficial for predictions
- Arctic sea ice shows significant decadal variability in (some) GCMs