HiGEM: The 97/98 El Nino

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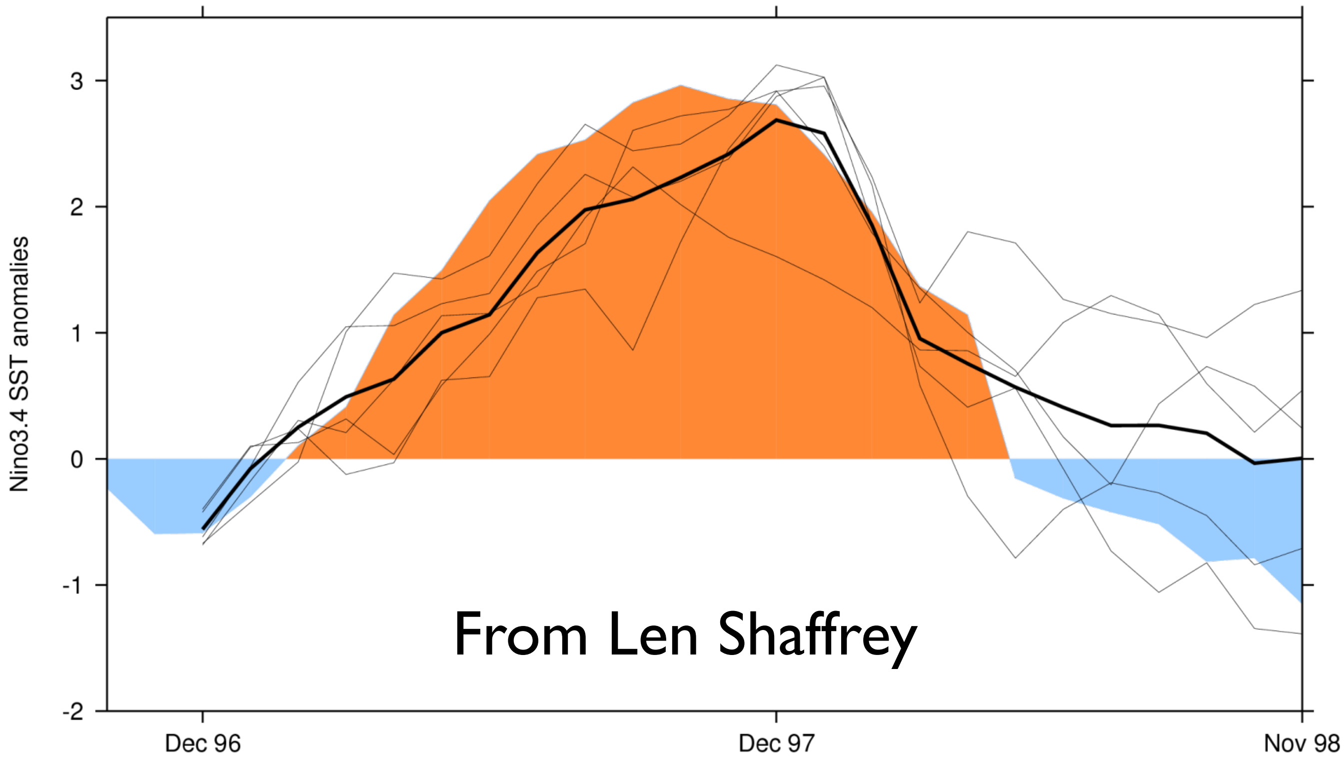
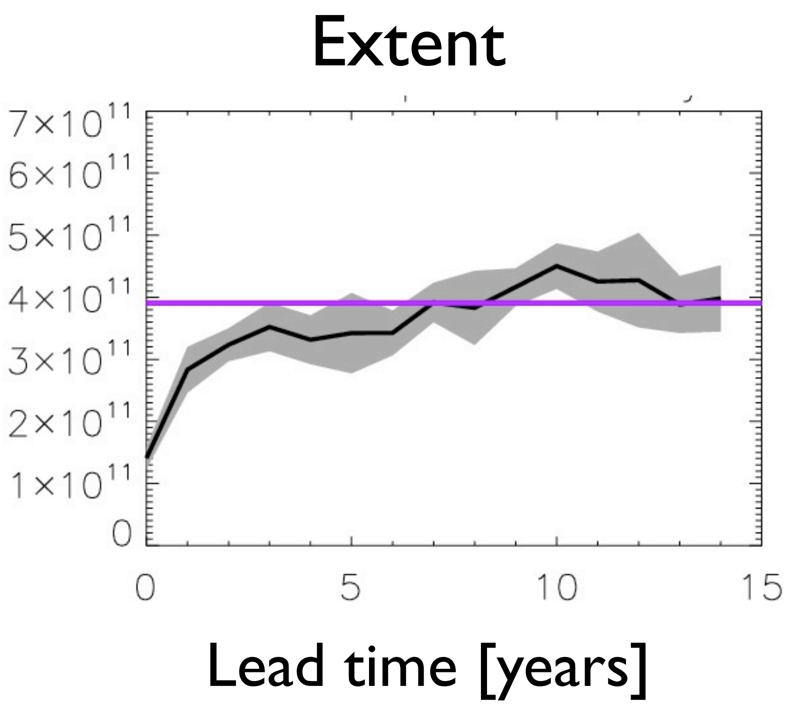
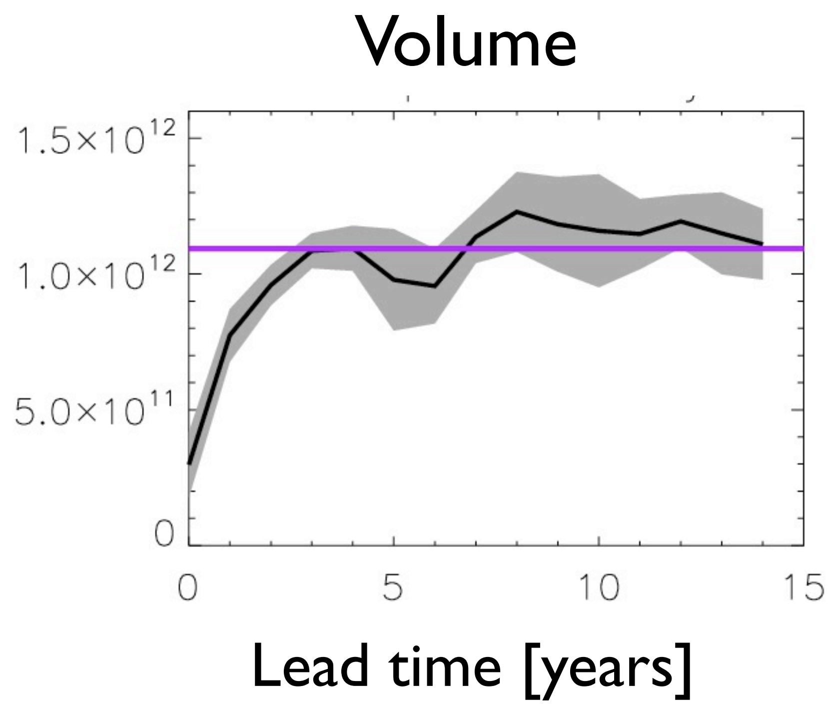
HiGEM GCM:

- based on HadGEM1, but higher resolution
- 1/3°x1/3° ocean & ~1° atmosphere
- CMIP5 decadal predictions underway – using anomaly initialization



RMS Error in DJF Arctic sea-ice from perfect model predictability experiments





Thanks to Sarah Keeley

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Comparing statistical and dynamical predictions of SSTs

Ed Hawkins, John Ho

NCAS-Climate, University of Reading

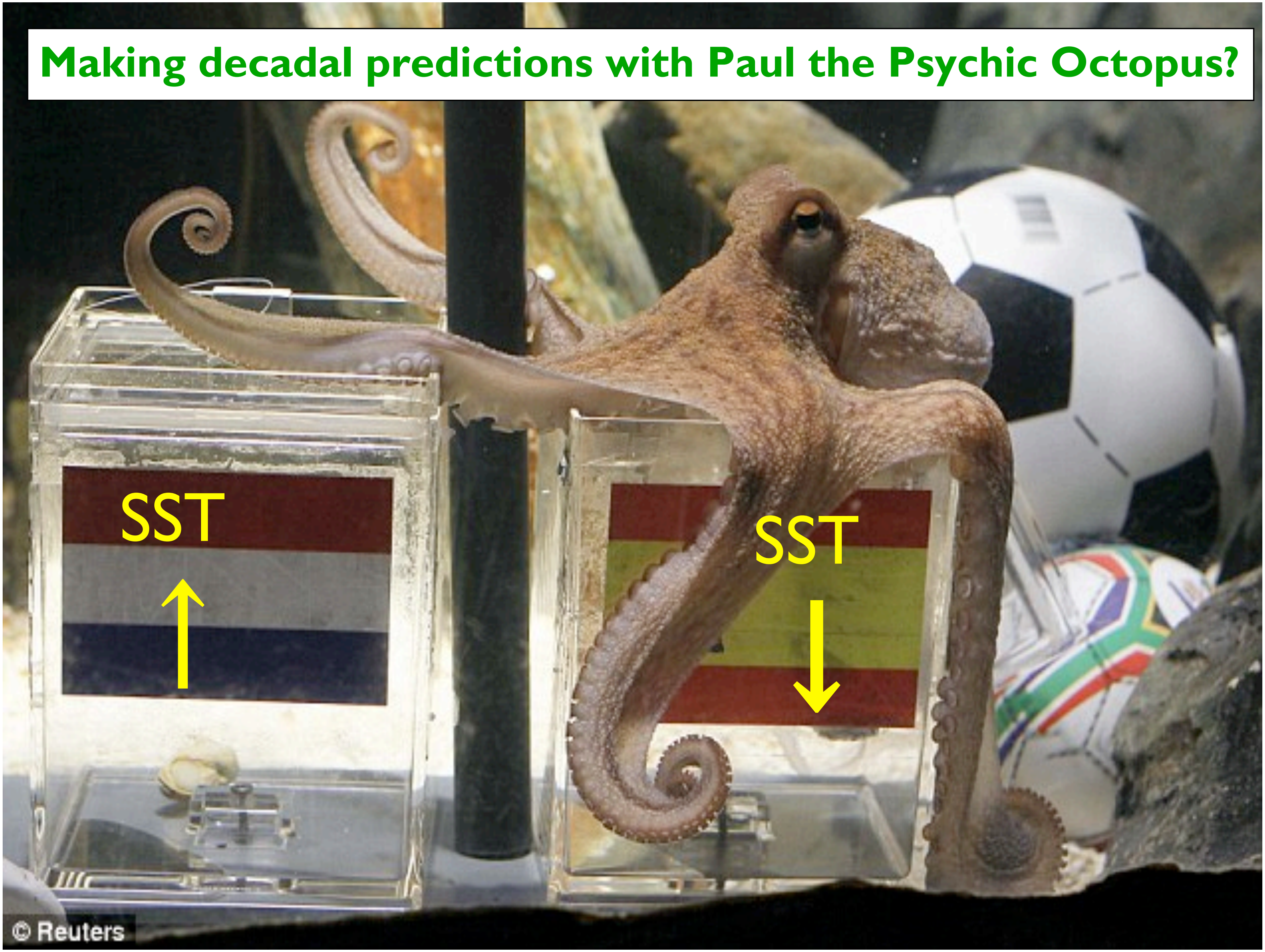
Thanks to:

Nick Dunstone, Sarah Keeley, Len Shaffrey, Fiona Underwood, Jon Robson, Rowan Sutton, Doug Smith, Noel Keenlyside

University of Reading

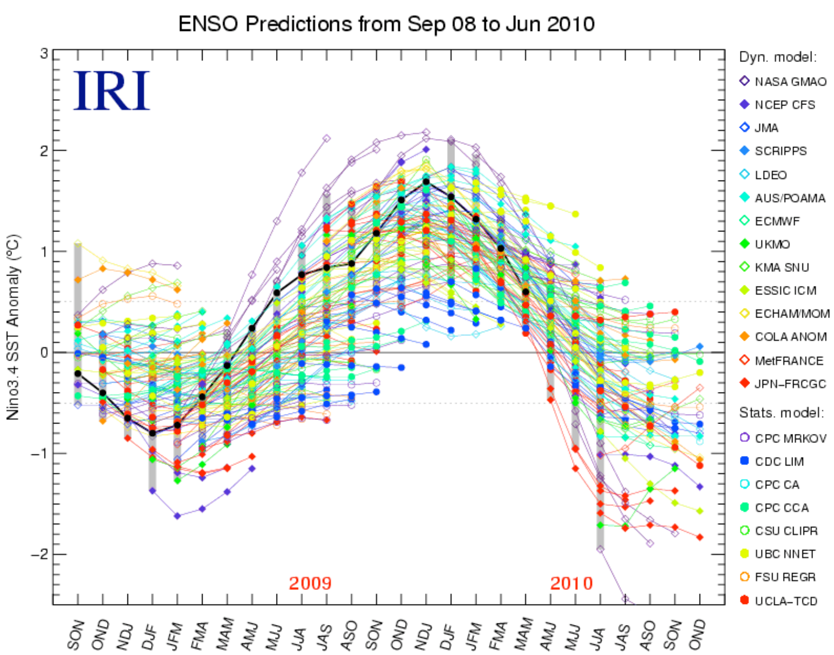
Walker INSTITUTE

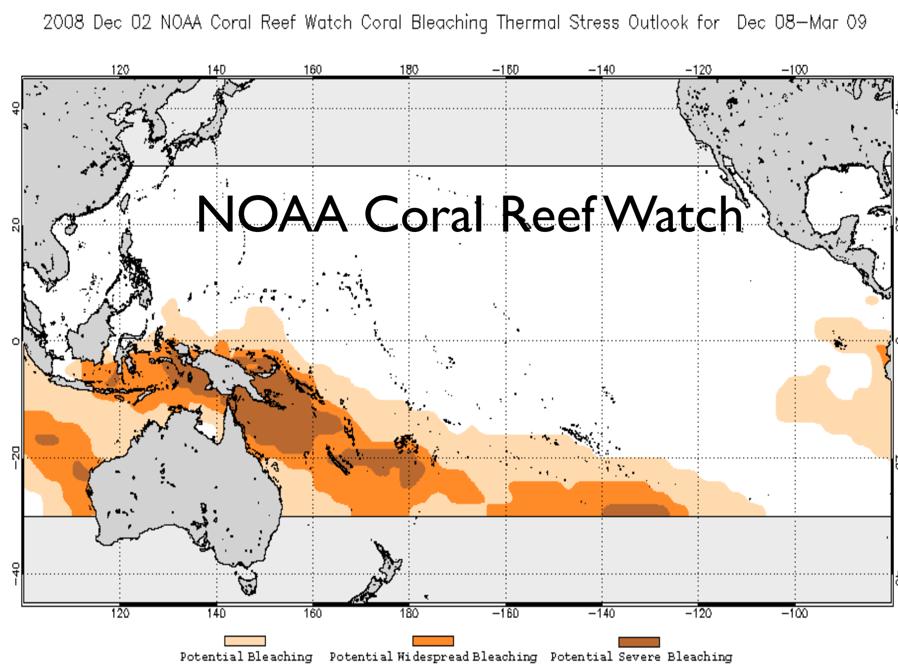
Making decadal predictions with Paul the Psychic Octopus?



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)





Motivation and key questions

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

Questions:

1) How well can we statistically predict SSTs a decade ahead?

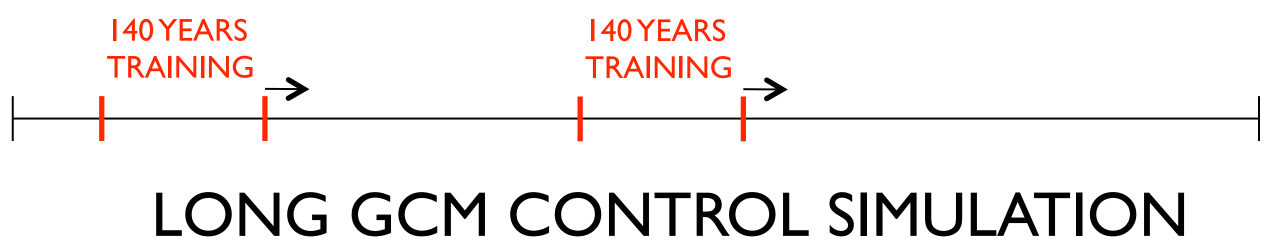
2) Do we have enough historical observations to train a statistical model to match or better the skill of GCM predictions?

First steps – an idealised case

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 various statistical methods on data from two GCMs
- focus on Atlantic where decadal variability is relatively large and historical observations are better
- use 140 years of annual means as training data



Hawkins et al., in press, Clim. Dyn.

Methods for predictions

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Grid-point independent estimates:

$$\begin{aligned}
\text{Climatology}: &\quad x(t_0+\tau) = 0, \\
\text{Persistence}: &\quad x(t_0+\tau) = x(t_0), \\
\text{Lagged correlation}: &\quad x(t_0+\tau) = \beta(\tau)x(t_0),
\end{aligned}$$

τ: lead time

x: SST anomalies

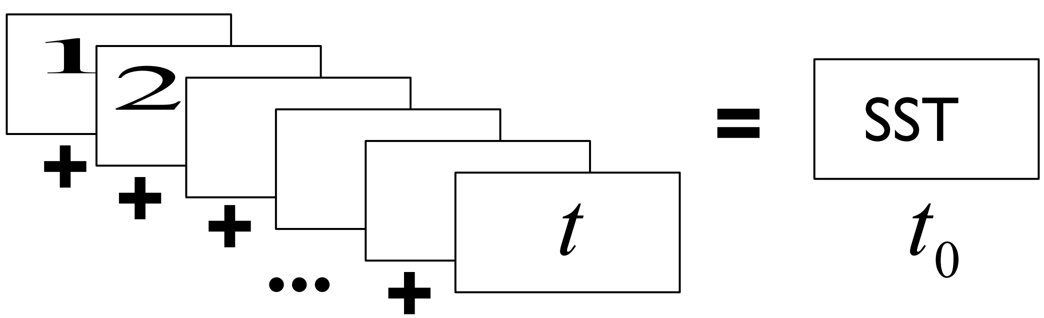
Spatial methods:

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

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

x: EOFs of SST

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



Example from HadCM3

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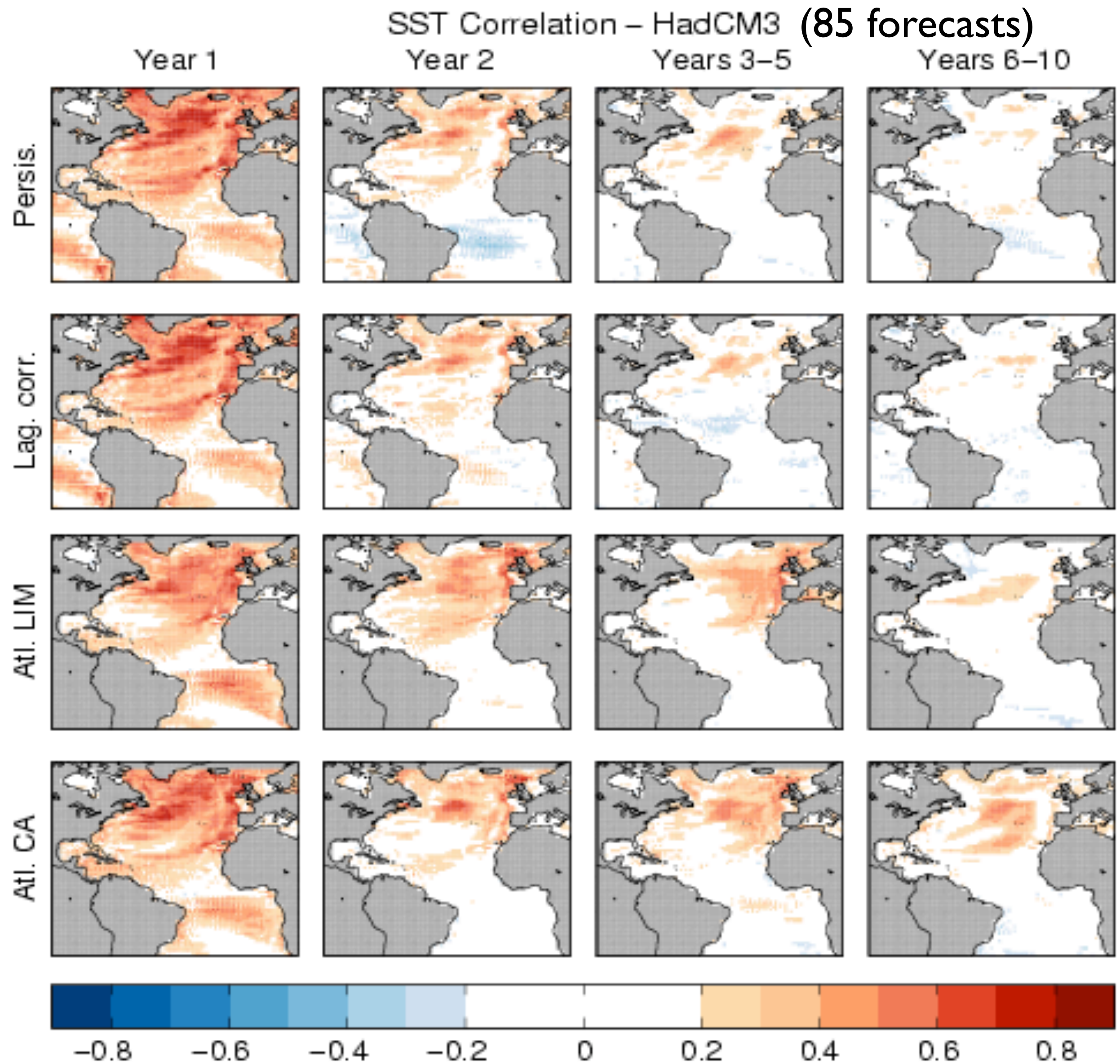

Comparing with 'perfect dynamic model'

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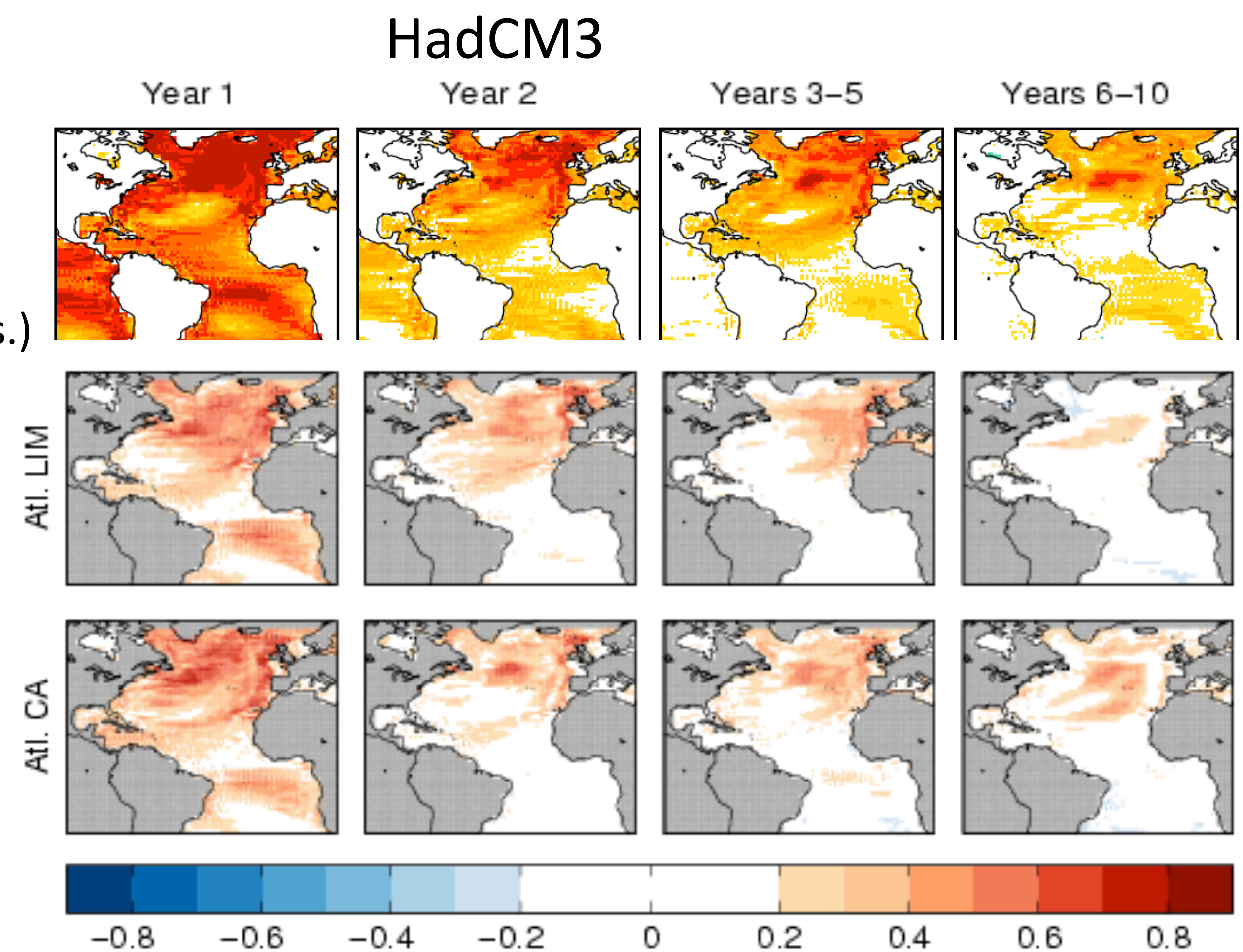
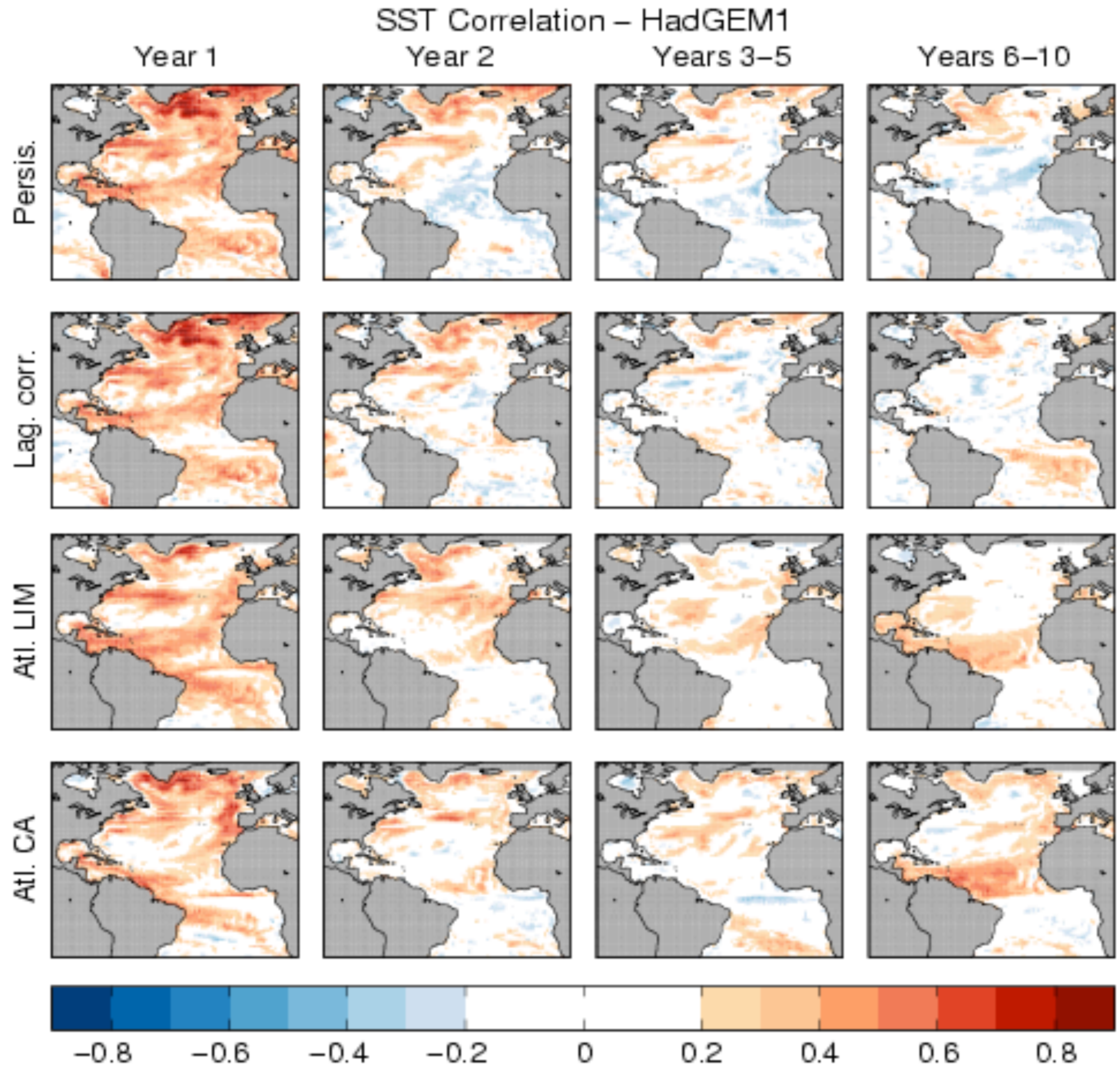
PERFECT DYNAMICAL PREDICTABILITY, USING 3D NUDGING
(26 start dates, 5 mems.)



Thanks to Nick Dunstone, Hadley Centre

Example from HadGEM1



Using observations

Global mean temperature

MAEs (MdAEs) for forecasting 1–4 years ahead

	Method	1983–2005
Horizon 1–4	Naïve	0.116 (0.100)
	Single ES	0.106 (0.101)
	Holt ES	0.084(0.082)
	Damped trend ES	0.098 (0.089)
	AR	0.113 (0.097)
	NN-univariate	0.094 (0.080)
	NN-multivariate	0.098 (0.093)
	Combination	0.092 (0.091)
	Smith (DePreSys)	**0.067** (**0.048**)

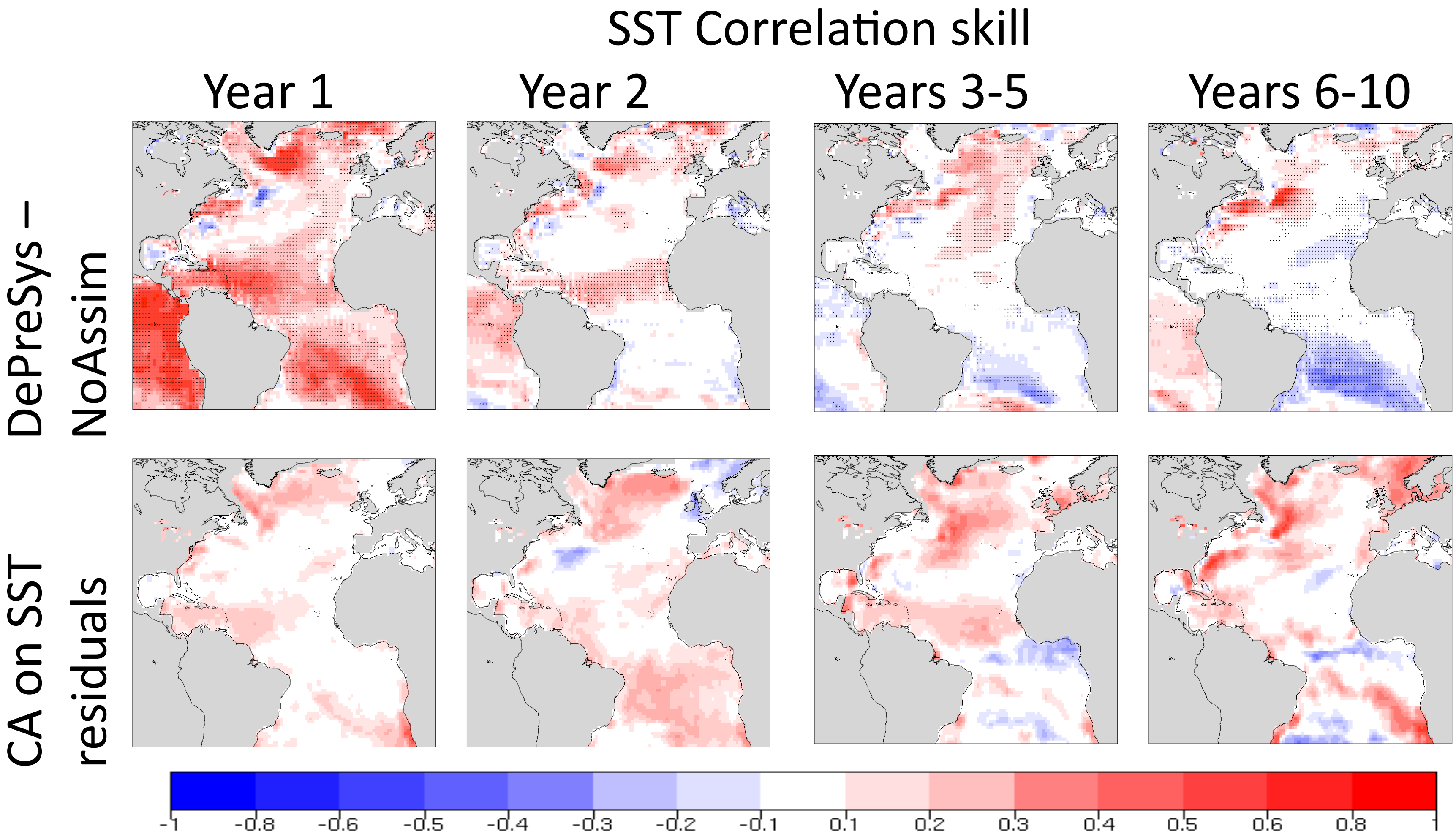
From Fildes & Kourentzes, in press, IJoF

Global mean temperature

Method	MAEs (MdAEs) for forecasting 10 and 20 years ahead		
	Hold-out sample period		
	Horizon 10		
	1948–2007	1968–2007	1992–2007
Naïve	0.152 (0.142)	0.155 (0.142)	0.202 (0.198)
Single ES	0.156 (0.130)	0.168 (0.160)	0.220 (0.242)
Holt ES	0.184 (0.146)	0.136 (0.125)	**0.088** (0.084)
Damped trend ES	0.158 (0.134)	0.161 (0.145)	0.195 (0.189)
AR	0.140 (0.122)	0.131 (0.119)	0.169 (0.156)
NN-univariate	0.136 (0.091)	**0.106** (**0.087**)	0.098 (0.079)
NN-multivariate	0.154 (0.136)	0.131 (0.099)	**0.088** (**0. 058**)
Combination	**0.133** (**0.113**)	0.118 (0.110)	0.133 (0.131)
Smith (DePreSys)	–	–	0.127 (0.127)

From Fildes & Kourentzes, in press, IJoF

Using observations (HadISST)



Start dates: every year from 1960-2005

DePreSys/NoAssim: PPE, 9 member ensemble mean

SST correlations with HadISST

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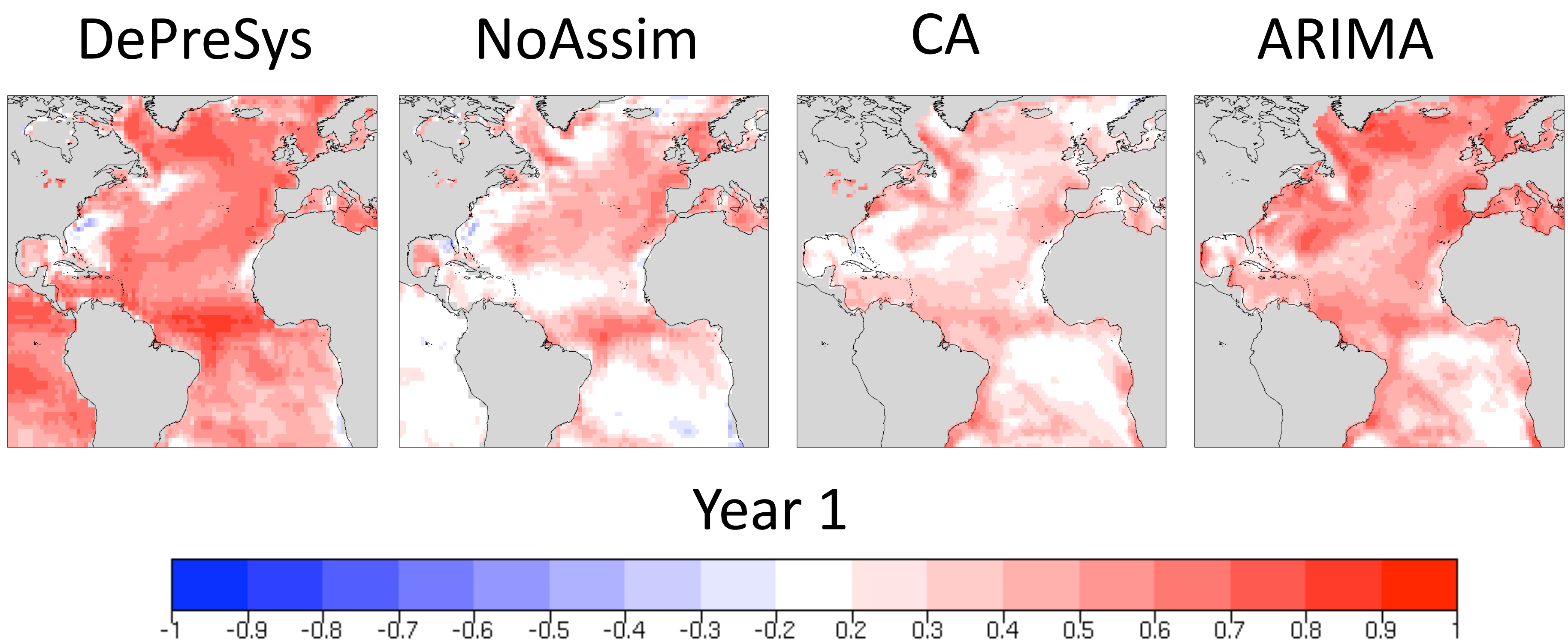

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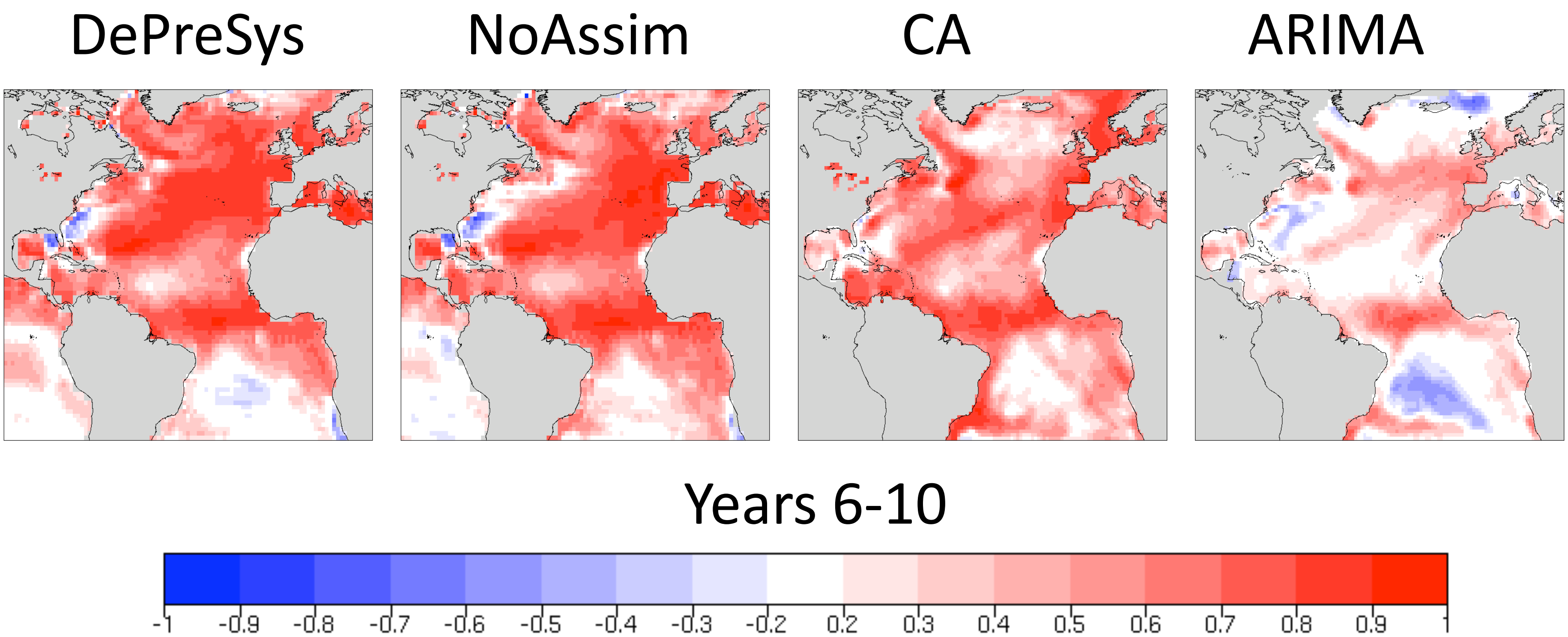

Start dates: every year from 1960-2005
DePreSys/NoAssim: PPE, 9 member ensemble mean

Analysing DePreSys PPE ensemble spread

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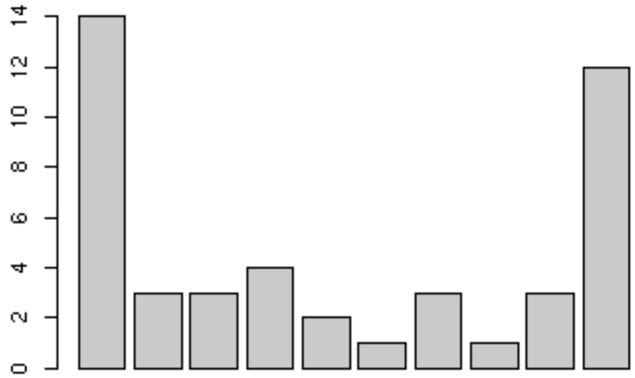
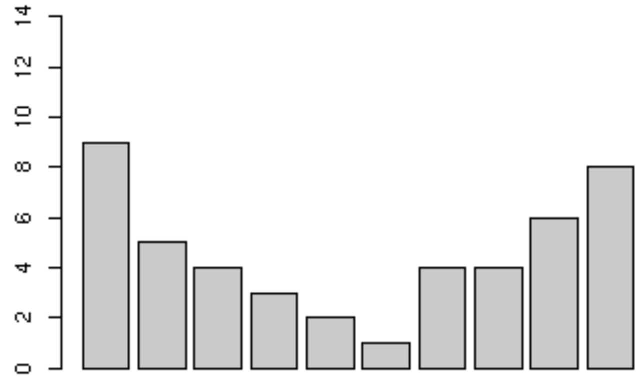
43.125N 46.25W year 1

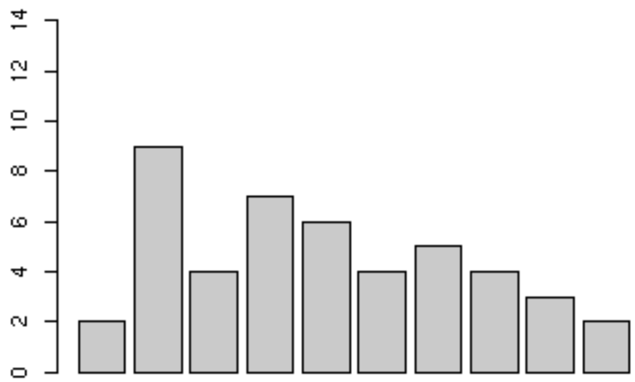


43.125N 46.25W year 2

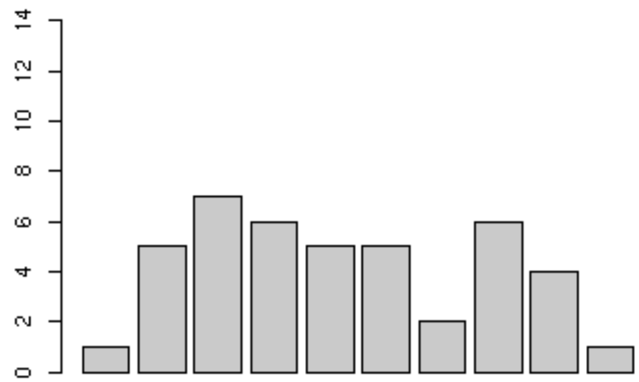


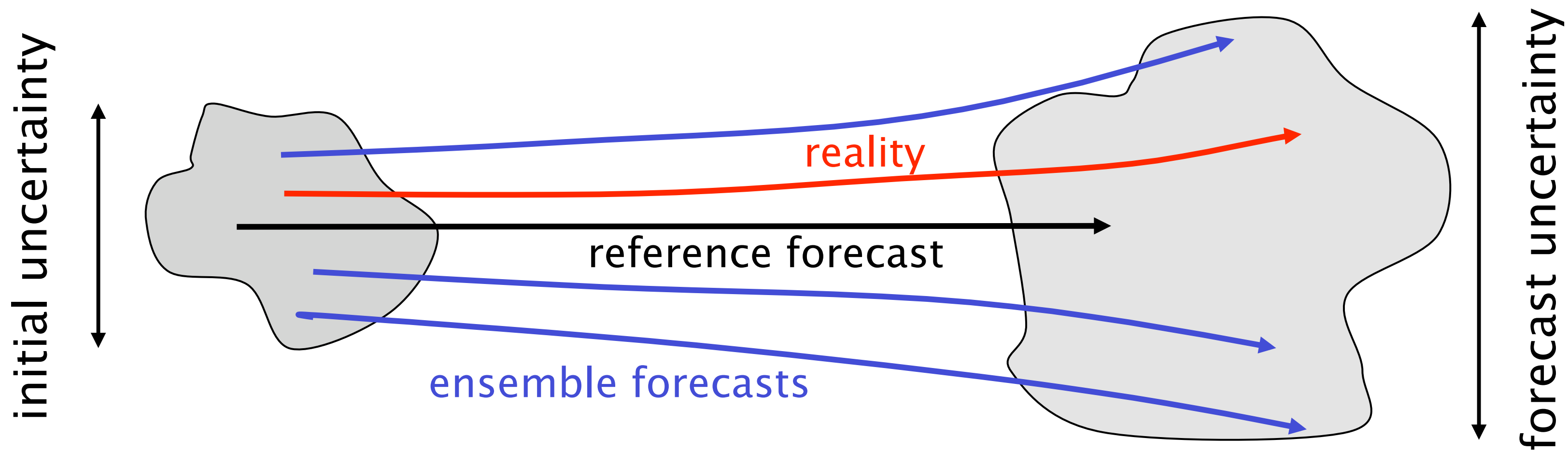
Rank histograms

43.125N 46.25W years 3-5



43.125N 46.25W years 6-9





Optimal perturbations:

- design of efficient, reliable ensembles,
- learn about mechanisms of error growth,
- inform on optimal regions for observations

e.g. Hawkins & Sutton 2009, 2011

Optimal perturbations

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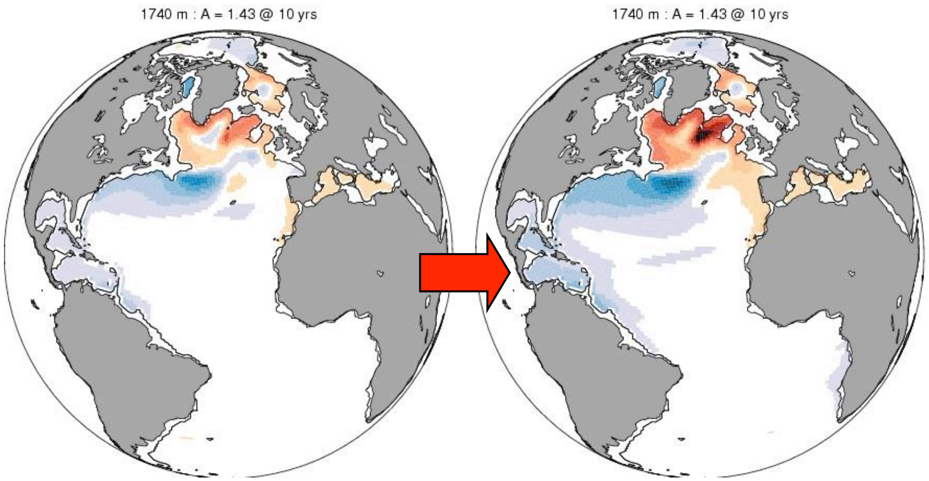
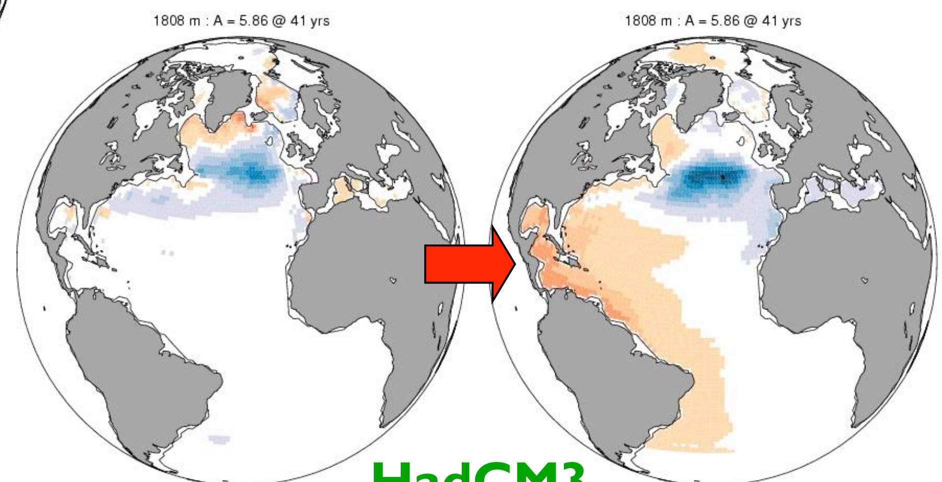
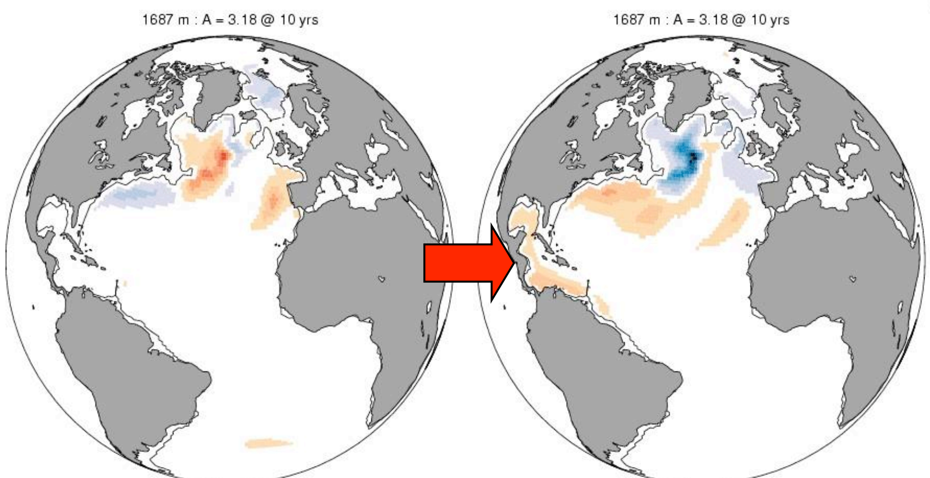


EC-EARTH

Growth of integrated temperature anomalies



HadCM3



GFDL CM2.1

→ different mechanisms of growth of perturbations

After Hawkins & Sutton, 2009

Small increase in SST ensemble spread

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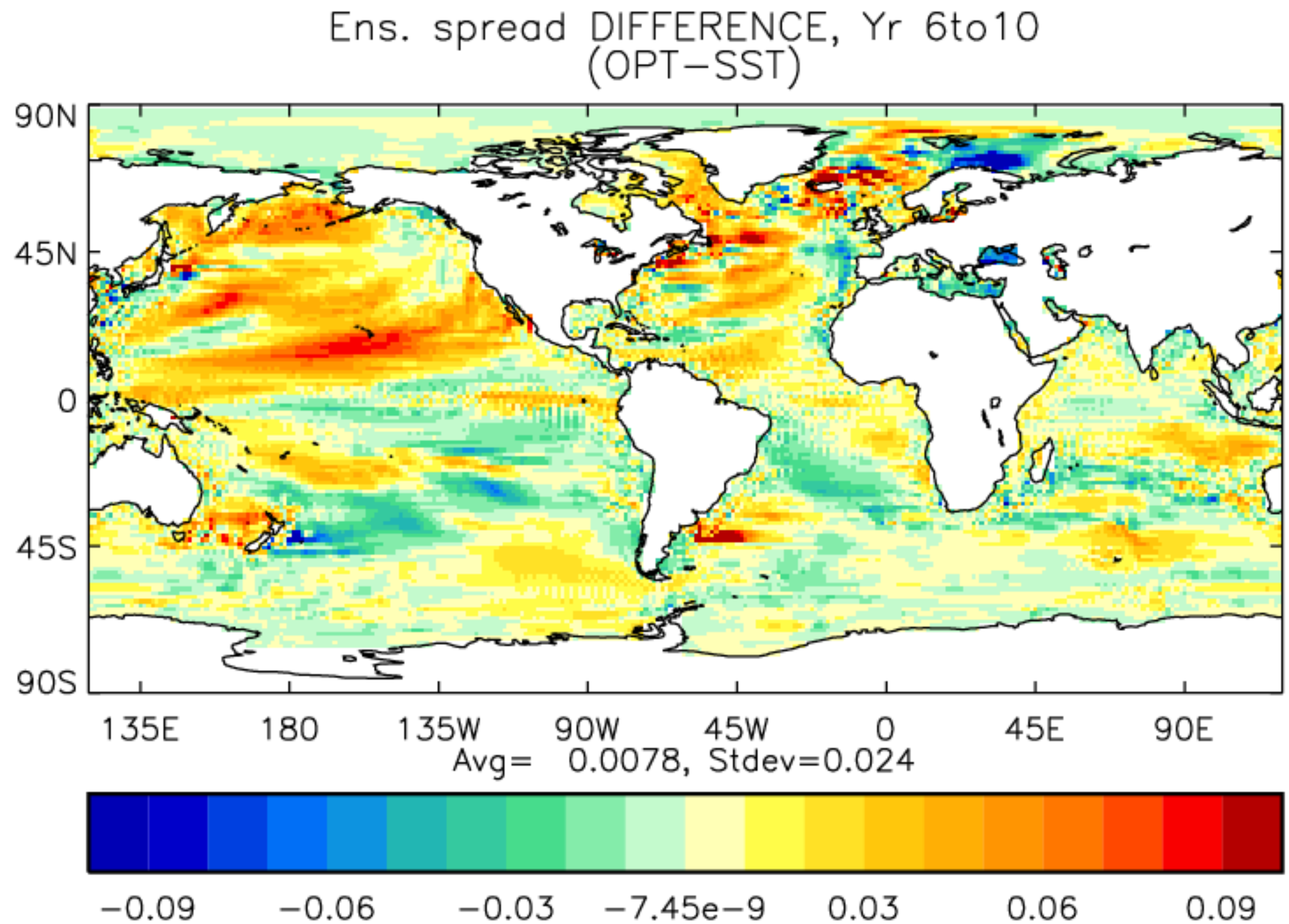

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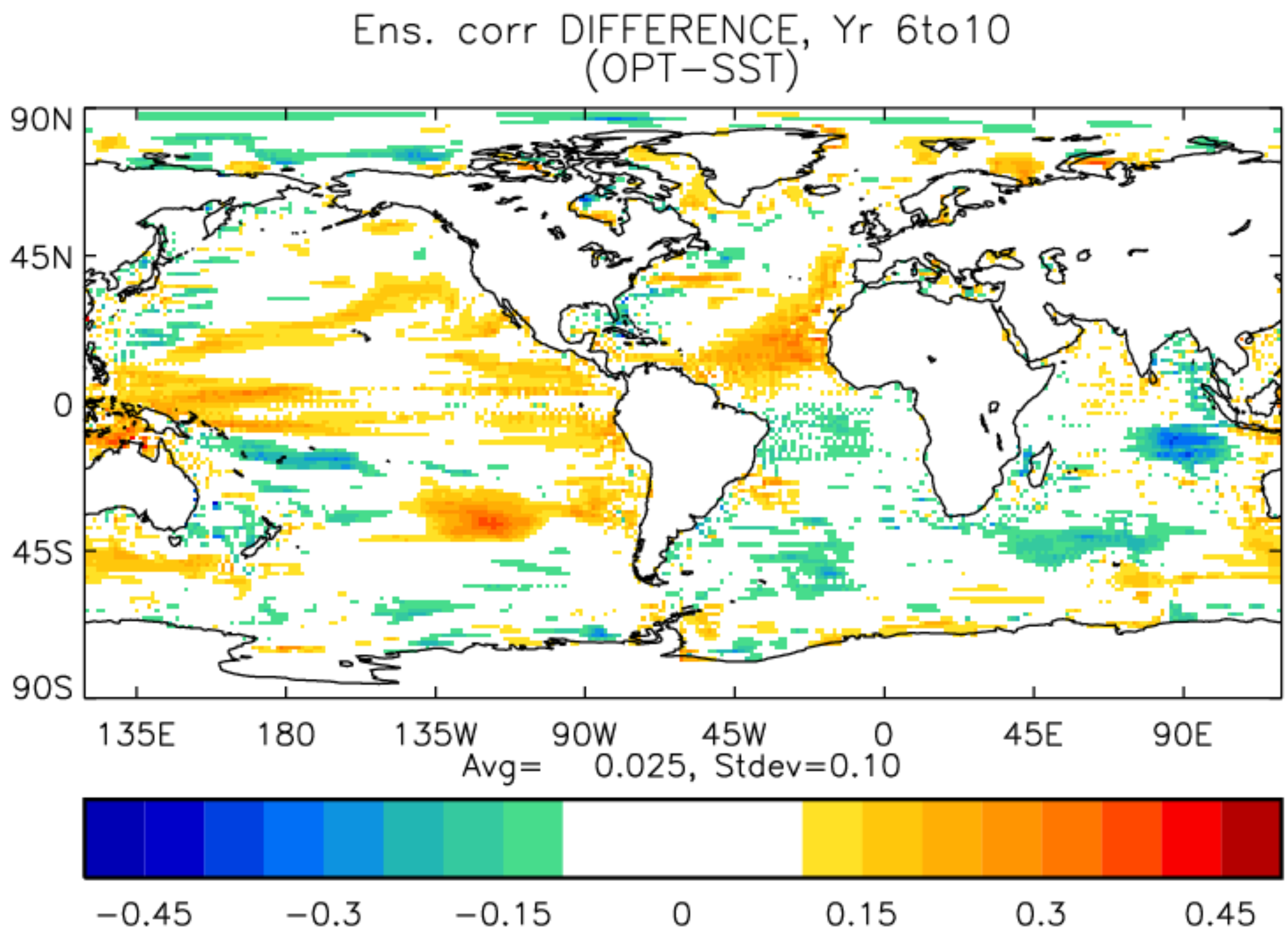
Small increase in SST ensemble spread



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Summary

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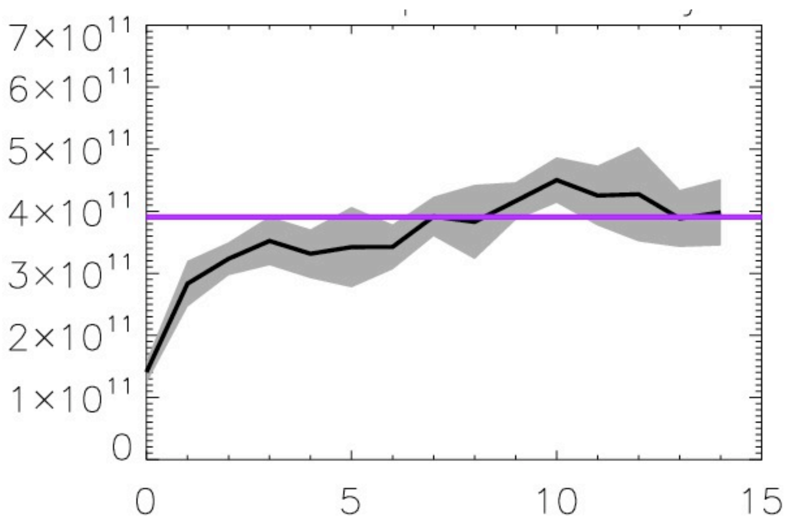
- Statistical decadal predictions of SSTs are feasible and show some skill
- DePreSys PPE currently more skilful than empirical hindcasts for most of the Atlantic
- Optimal perturbations can potentially help to improve *reliability* of dynamical forecasts

Work underway:

- Use multiple SST datasets
- Use other forecasting methods
- Consider ensembles of statistical predictions
- Consider other possible skill scores
- Consider other variables

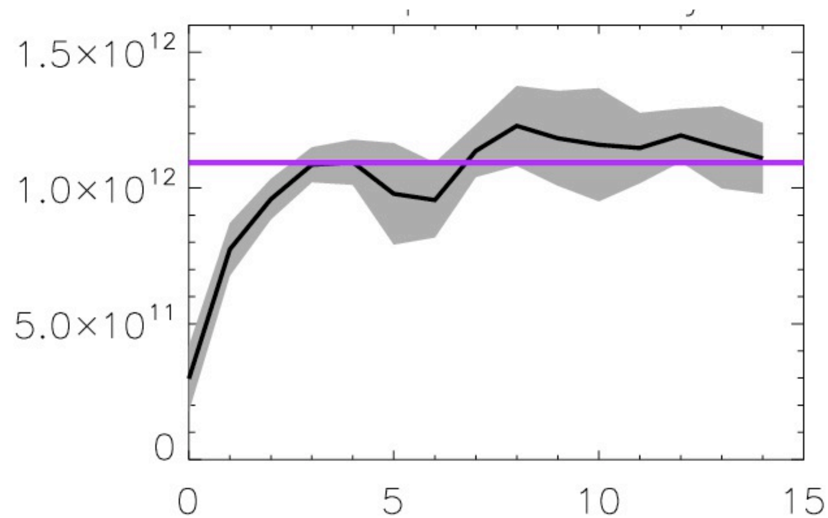
RMS Error in DJF Arctic sea-ice from perfect model predictability experiments

Extent



Lead time [years]

Volume



Lead time [years]

Thanks to Sarah Keeley

Potential predictability of SSTs

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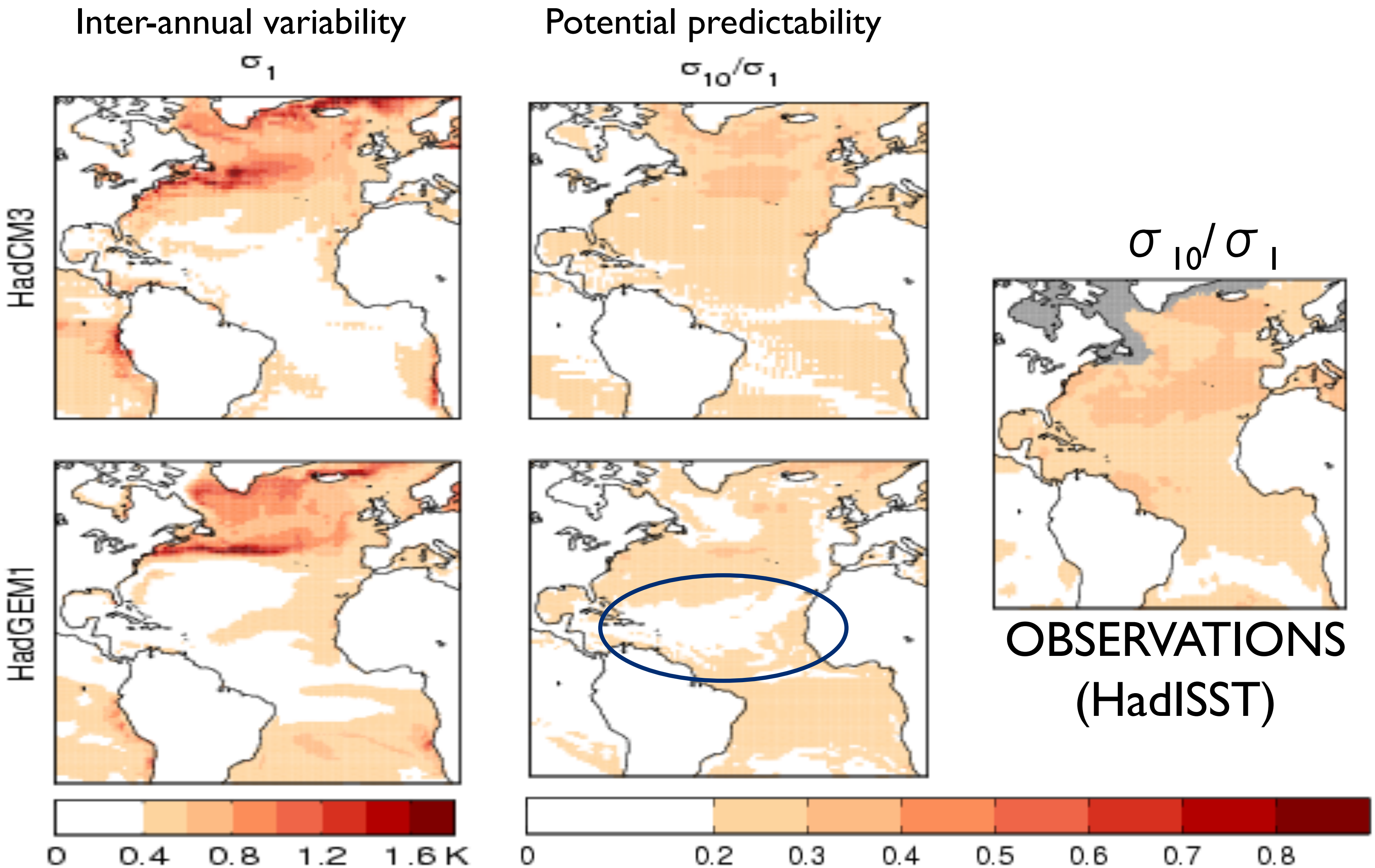
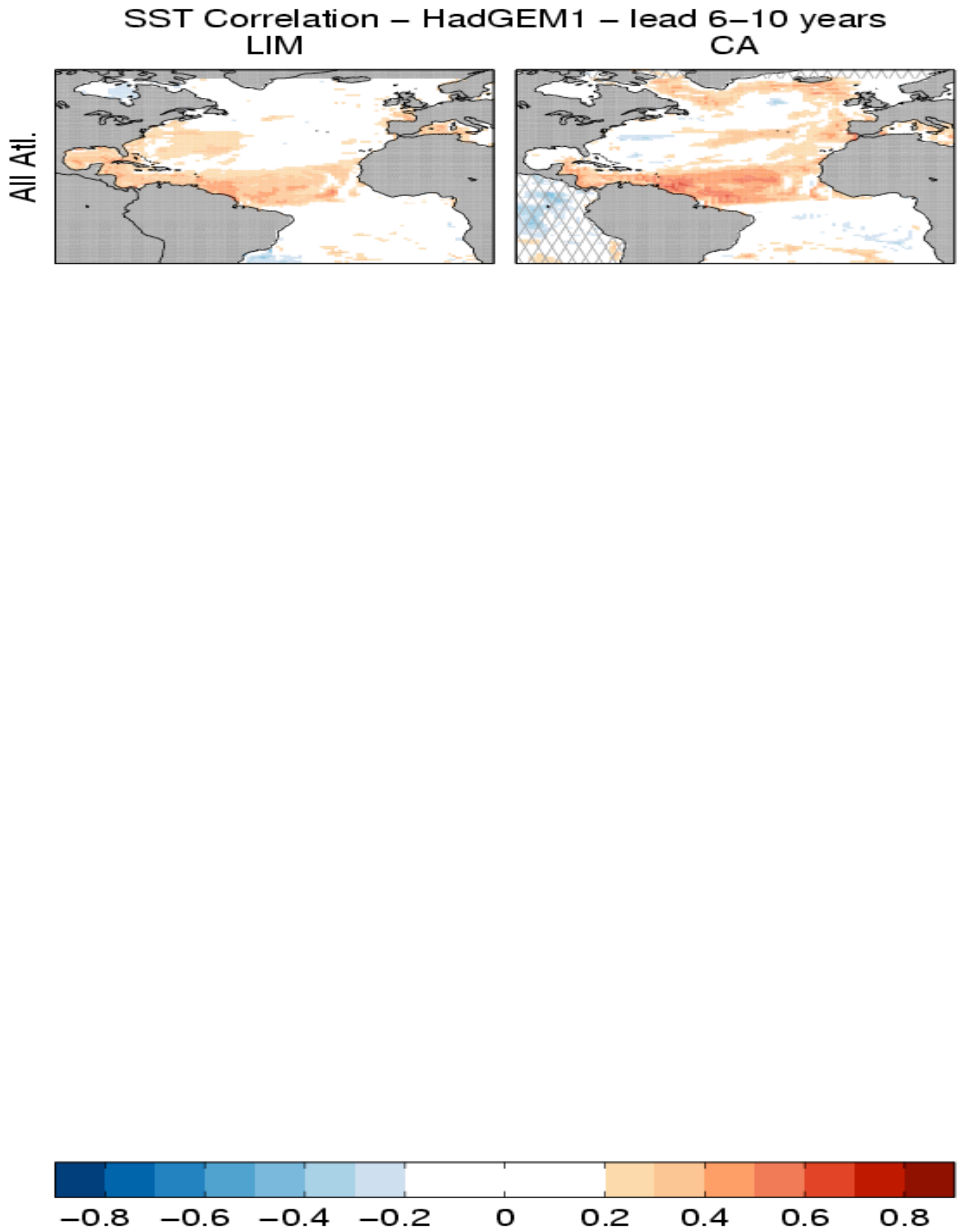


e.g. Boer 2000, 2004

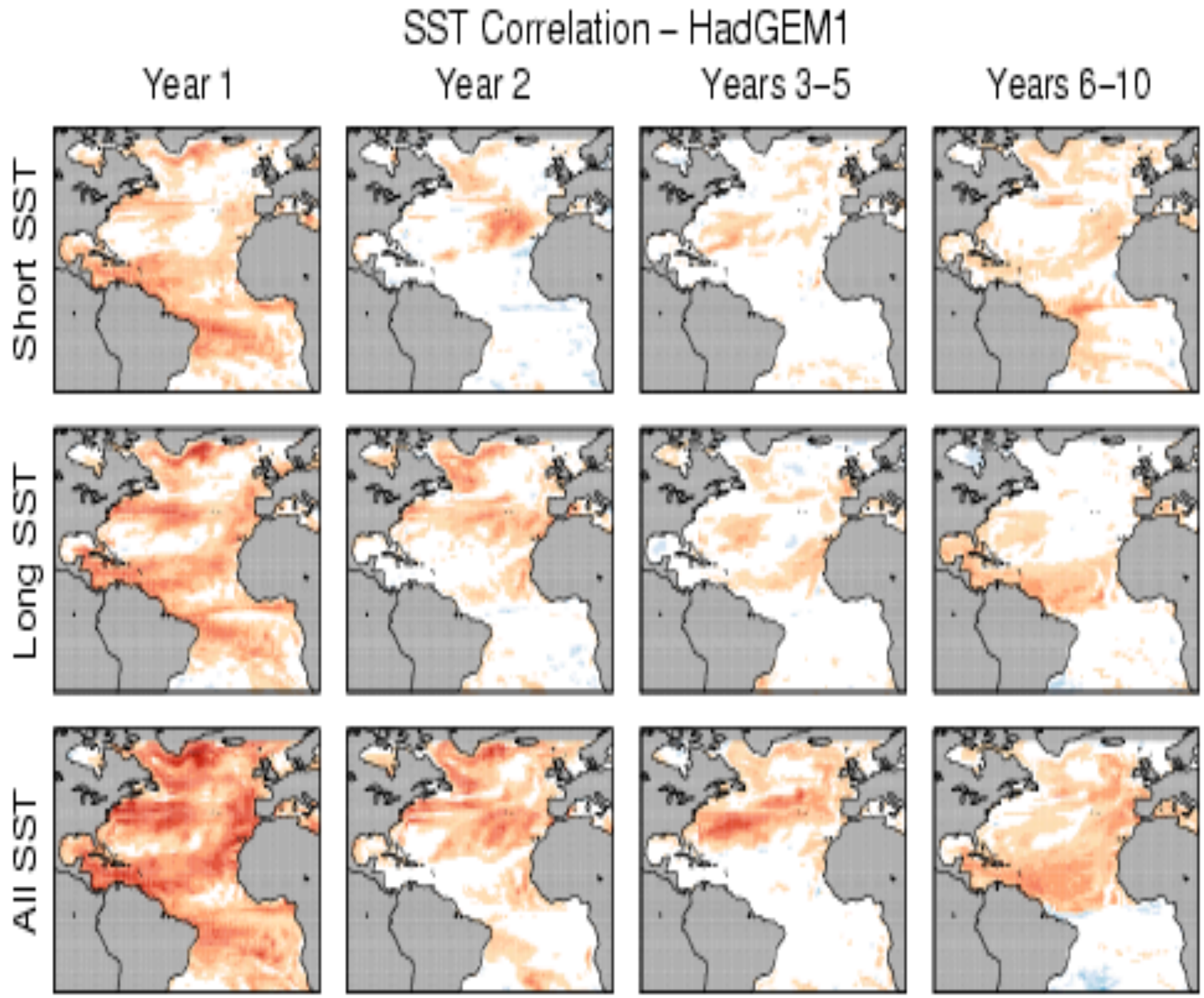
Optimal regions for observations?



Where does this long lead time skill come from?

LIM method

Can adding more data help?



Skill in temperatures over land?

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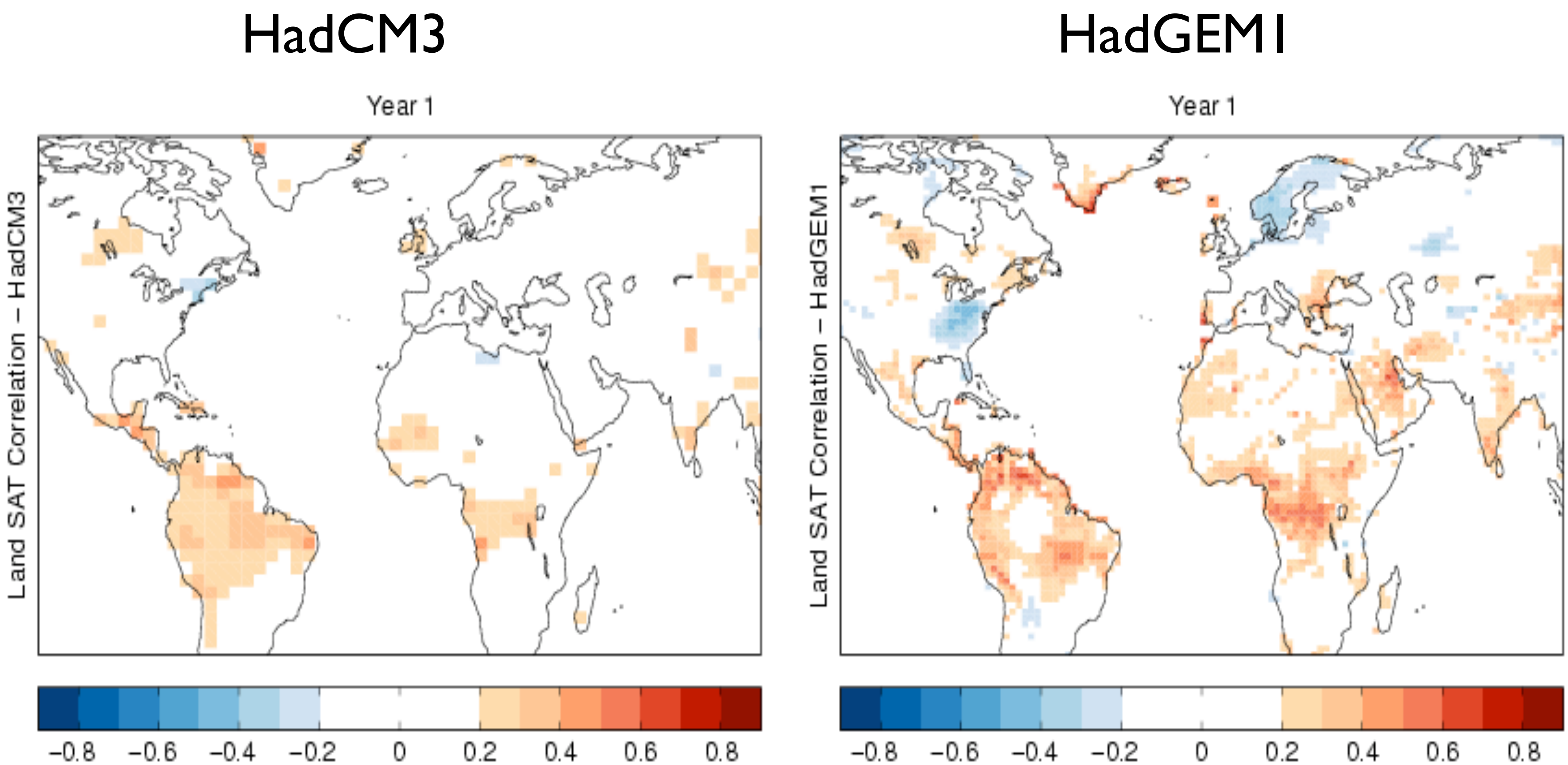

- Using CA method, can also predict other climate variables, e.g. temperature over land (above)

DePreSys ensemble spread

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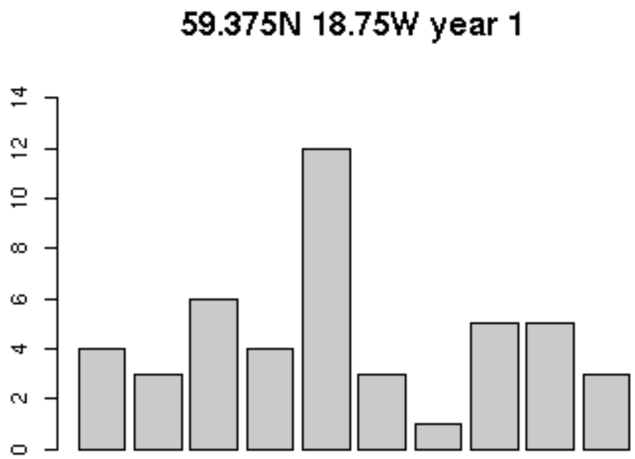

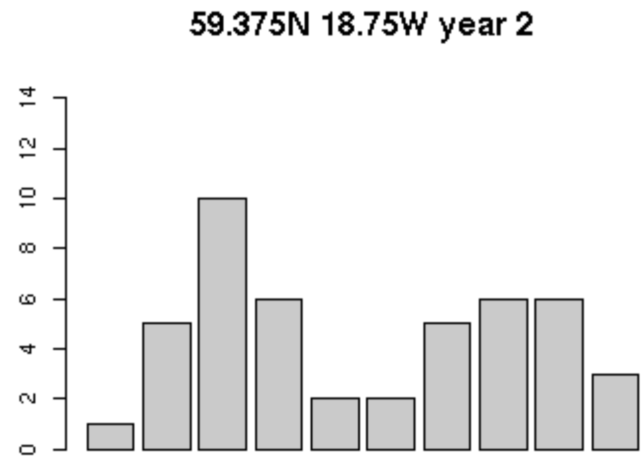

Rank histograms