Assessing the skill of SEAS5

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Climate Change Service

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If you cannot predict the weather a week ahead, how can you predict the climate for the coming season?

Predictability of the first and second kind

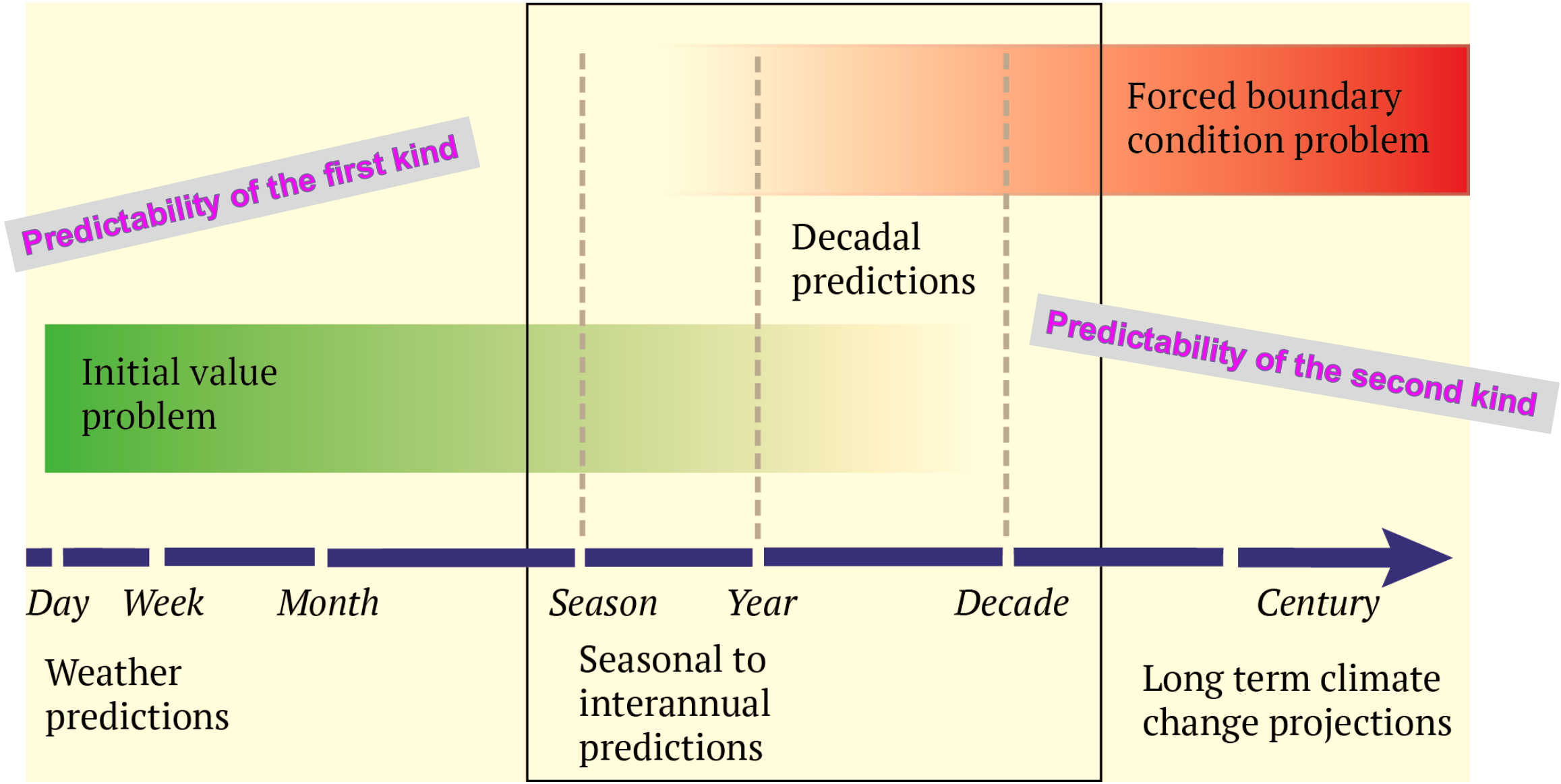
(Ed Lorenz: Climatic predictability, 1975)

- Numerical models used to predict weather and climate are based on the same physical principles
  e.g. Newton's laws of motion and the laws of thermodynamics

- However, forecasting the weather is a different problem to forecasting the climate

- **Weather prediction – *predictability of the first kind***
  - Predictability horizon is severely limited by the chaotic nature of the atmosphere → detailed evolution of the weather becomes unpredictable after *O*(10 days)
  - Predictability relies on sensitive dependence on initial conditions

- **Climate prediction – *predictability of the second kind***
  - Does not aim to forecast *individual weather* patterns
  - Rather, to forecast the *statistics* of the climate system averaged over time and space
  - Predictability relies on the sensitivity of the system to its boundary conditions (e.g. radiative forcing) and on the long memory of initial conditions of slowly evolving components of the climate system (e.g. the ocean, land surface)
  - Predictability horizon for climate forecasts is much longer than for weather forecasts


Predictability of the first kind
Forced boundary condition problem
Decadal predictions
Initial value problem
Predictability of the second kind
Day
Week
Month
Season
Year
Decade
Century
Weather predictions
Seasonal to interannual predictions
Long term climate change projections

Predictability in the Midst of Chaos: A Scientific Basis for Climate Forecasting

J. Shukla

The Earth's atmosphere is generally considered to be an example of a chaotic system that is sensitively dependent on initial conditions. It is shown here that certain regions of the atmosphere are an exception. Wind patterns and rainfall in certain regions of the tropics are so strongly determined by the temperature of the underlying sea surface that they do not show sensitive dependence on the initial conditions of the atmosphere. Therefore, it should be possible to predict the large-scale tropical circulation and rainfall for as long as the ocean temperature can be predicted. If changes in tropical Pacific sea-surface temperature are quite large, even the extratropical circulation over some regions, especially over the Pacific–North American sector, is predictable.

At the beginning of the 20th century it was hypothesized that it should be possible to predict weather by solving the mathematical equations that describe the physical laws that govern the motion of air. It took several decades to develop an appropriate set of

that aspects of the tropical atmosphere do not conform to the above definition of chaos. The tropical flow patterns and rainfall, especially over the open ocean, are so strongly determined by the underlying sea-surface temperature (SST) that they show little sensitivity to

predict large-scale changes in the winter season mean circulation over North America several months in advance, as indeed was the case for the 1997–1998 El Niño. However, the extent to which this apparent high potential predictability of the tropical and extratropical atmosphere can be realized in routine forecasting will depend on our ability to predict the SST itself.

The numerical model used in this research has been described (*3*). The dynamic equations and the numerical techniques used to integrate the model are the same as those used by the U.S. National Weather Service for routine weather prediction, and the accuracy of short-range weather forecasts made with this model is comparable to the state-of-the-art weather forecast models.

Two sets of simulations were carried out with the same prescribed SST but quite large differences in the initial conditions of the atmosphere. This simulation requires a selection of two very different initial conditions. Rather than choosing them arbitrarily, or constructing them artificially, atmospheric states observed during the past 50 years were chosen. The data show that the Southern Oscil-

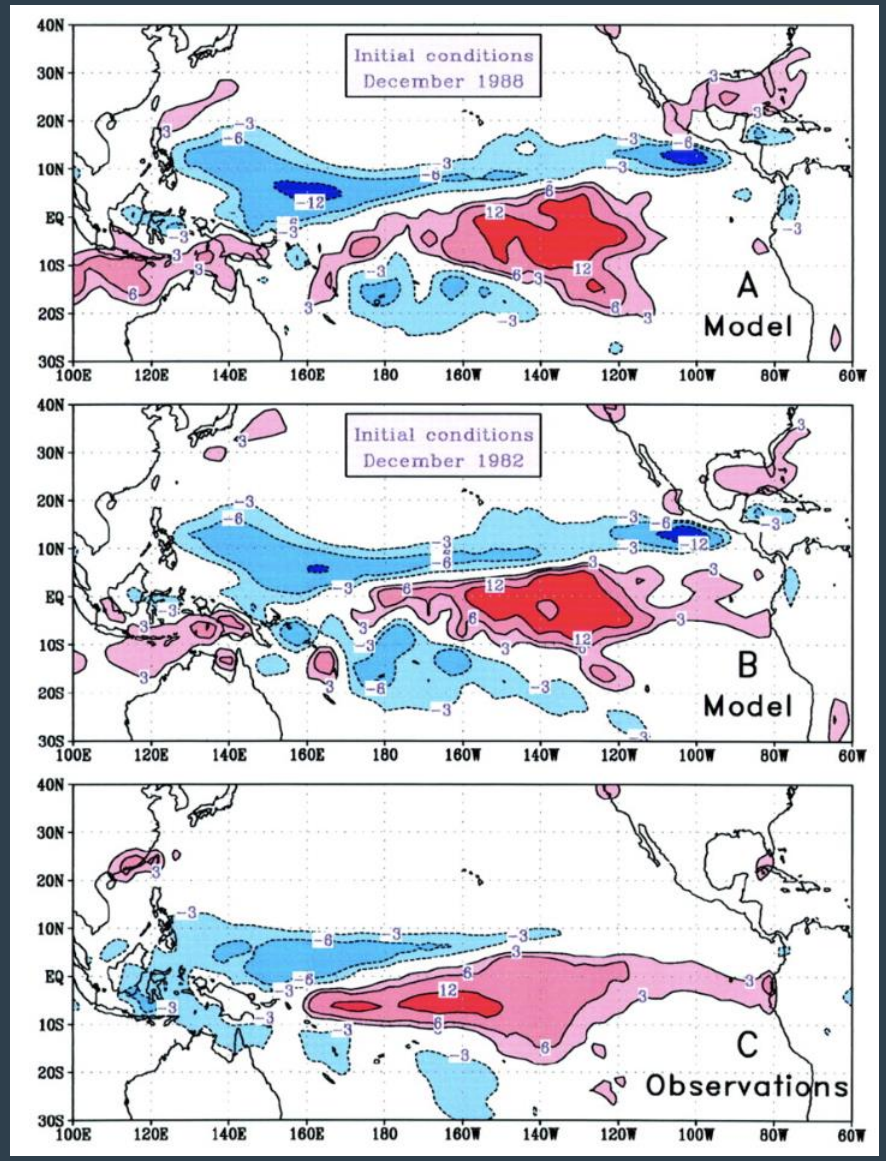
Science (1998)

Seasonal forecasting

- **Two numerical forecast experiments over ~100 days:**
  - identical prescribed observed SSTs of 1982/83
  - large differences in the initial conditions of the atmosphere: Dec 1988 (top) and Dec 1982 (middle)
  - Observations (bottom)
- **The two forecasts are remarkably similar despite the large difference in their atmospheric ICs**
- **Simulations converge to a solution uniquely determined by the boundary conditions of the SST**

Shukla (1998)

winter (JFM) mean rainfall



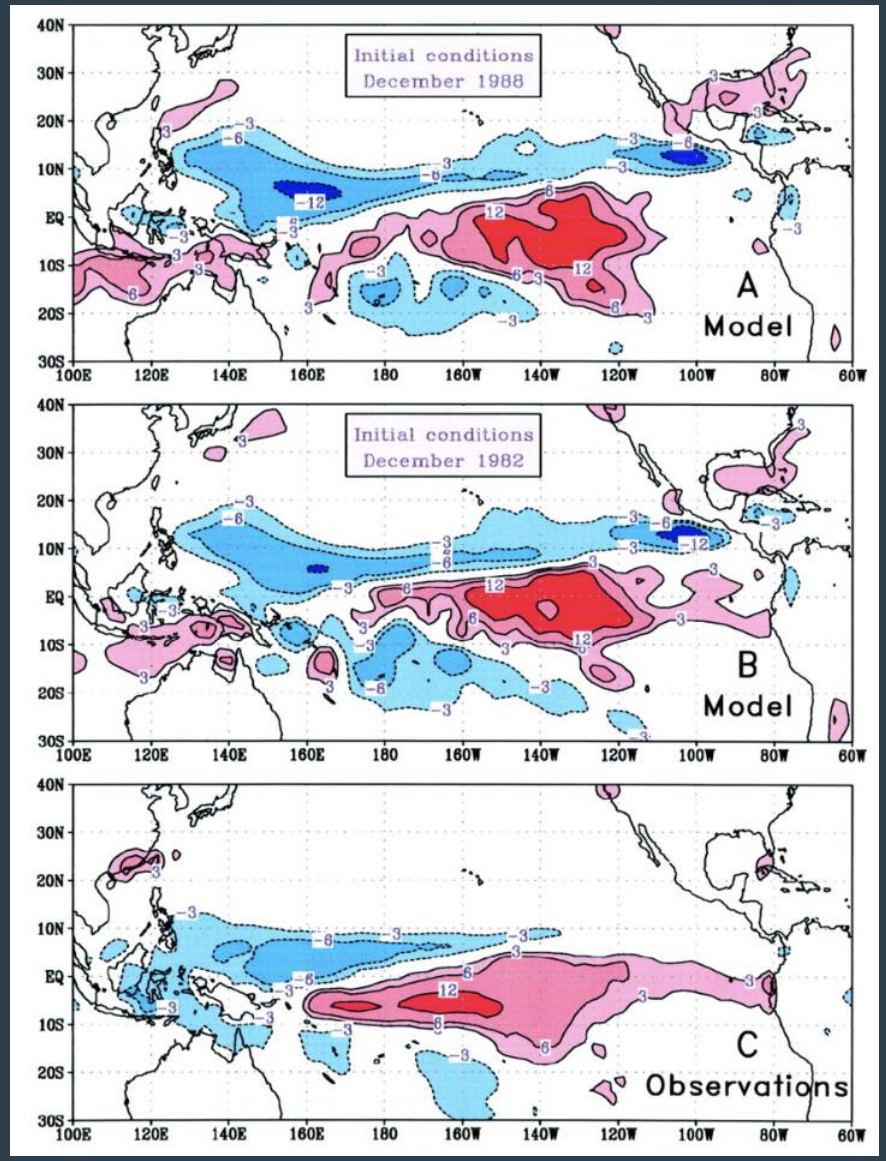
Seasonal forecasting

- **Two numerical forecast experiments over ~100 days:**
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  - Observations (bottom)
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- **Simulations converge to a solution uniquely determined by the boundary conditions of the SST**

As long as the ocean temperature can be predicted, it should be possible to predict the large-scale tropical circulation and rainfall, sometimes even the extratropical circulation over some regions, especially the Pacific-North America sector.

Shukla (1998)

winter (JFM) mean rainfall



Aspects of the tropical atmosphere *do not* follow the deterministic chaos paradigm:

- Tropical flow and rainfall patterns, especially over the ocean, are strongly coupled to the underlying SSTs which show little sensitivity to initial conditions of the atmosphere
- Even with very large changes in the atmospheric IC (as large as the climatological variability), the resulting large-scale wind and rainfall pattern in certain tropical regions do not diverge

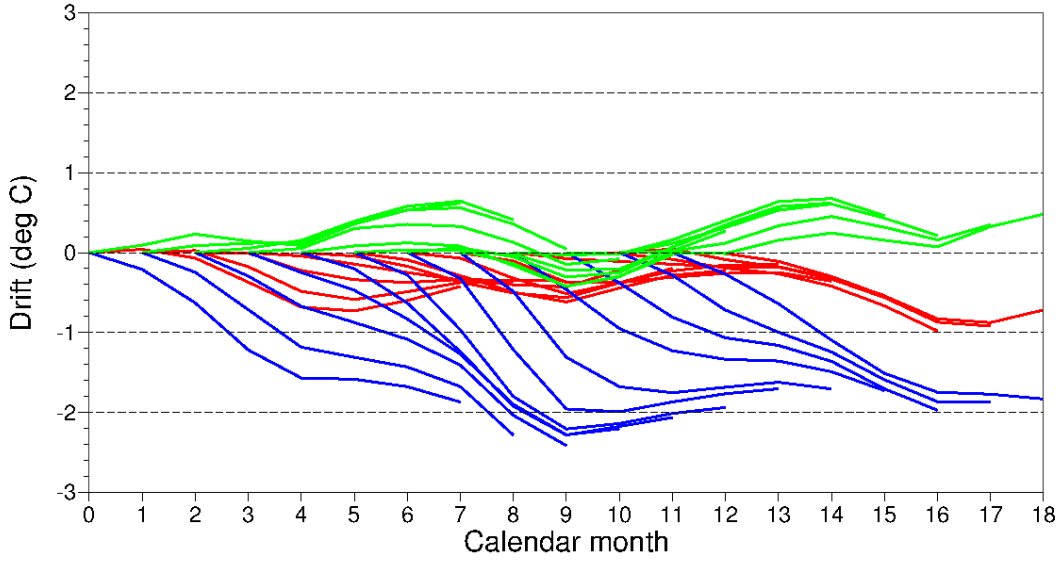
A unique and fundamental property of the tropical atmosphere:

Tropical large-scale seasonal circulation and rainfall are almost completely determined by the boundary conditions of SSTs.

1. It should be possible to predict the large-scale seasonal tropical circulation and precipitation for as long as the SSTs can be predicted
2. Tropics act as a source of e.g. Rossby waves which can propagate into the distant extra-tropics → *Predictability in the Midst of Chaos*

The extent to which this high predictability in the atmosphere can be realized depends on our ability to predict the SST itself.

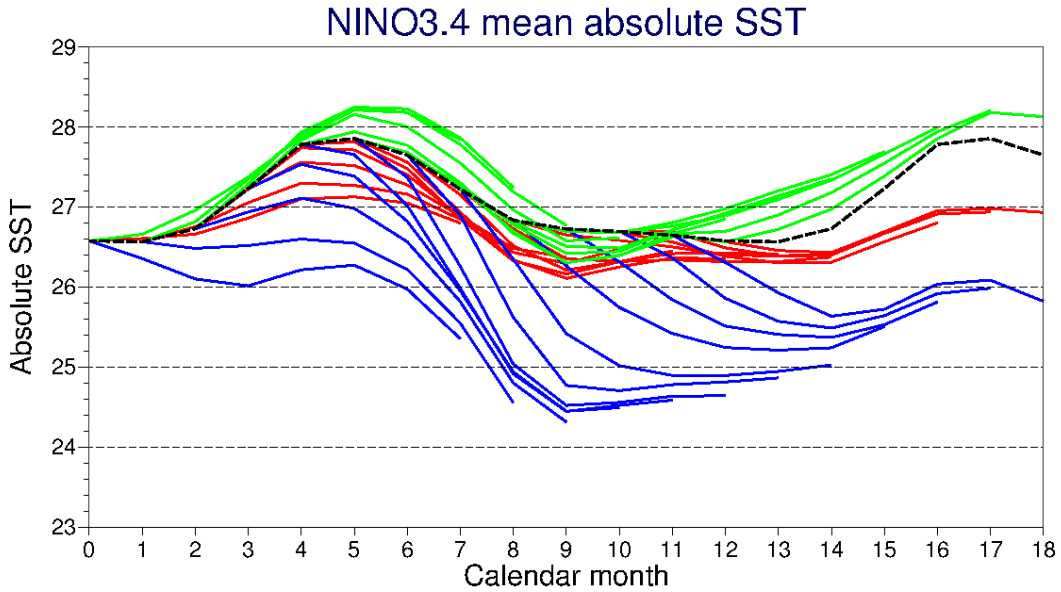
Assessing the skill of SEAS5



Nino3.4 SST drift

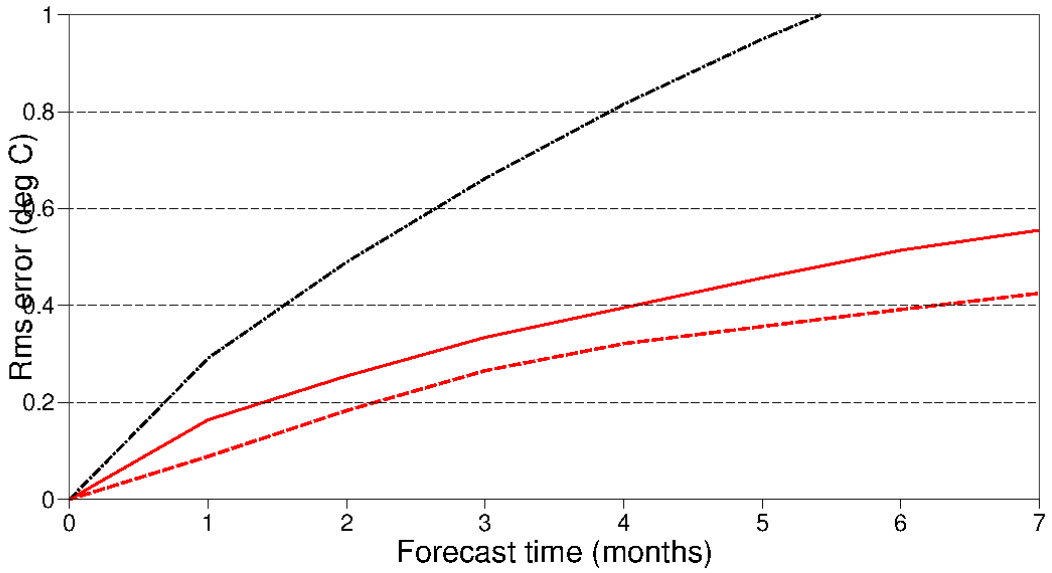
Local SST bias is a function of

- **lead time**
- **season**



System 5 (Nov 2017 onwards)
System 4 (Nov 2011 - Oct 2017)
System 3 (March 2007 - Nov 2011)

Nino3.4 SST forecast error and ensemble spread: lead-time dependence (all seasons)



RMSE forecast error
Ensemble spread
RMSE of persistence

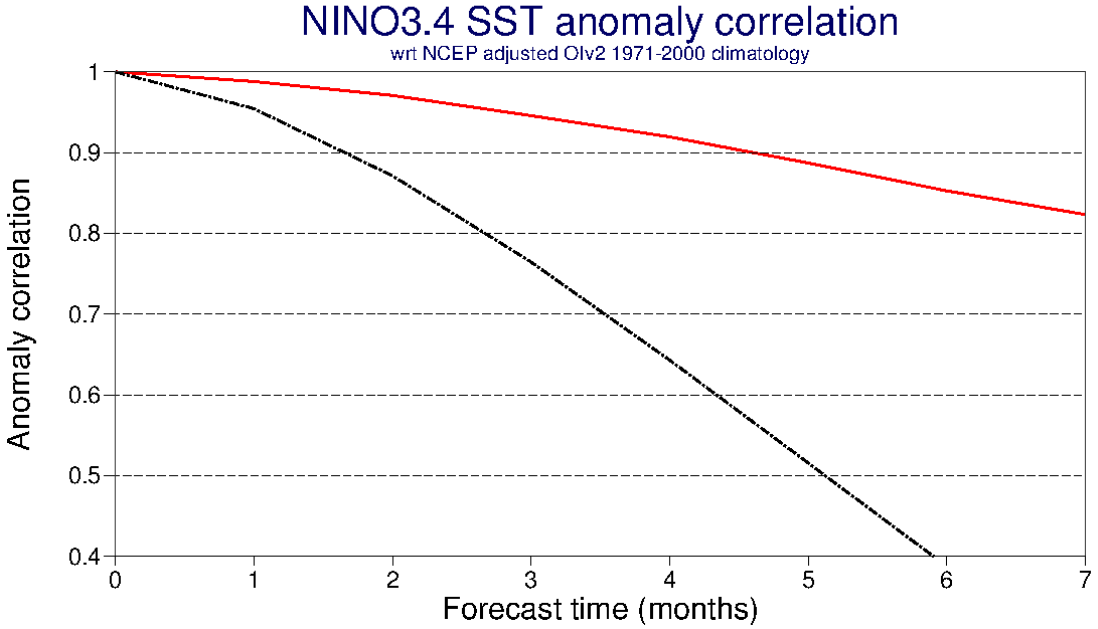
In a *perfect model*:

RMSE ≃ ensemble spread

In *SEAS5*:

actual RMS errors > "perfect model" errors

or ensemble spread too small (overconfidence)



forecast anomaly correlation
persistence anomaly correlation

What is a perfect model ensemble?

- Perfect sampling of the underlying probability distribution of the true state
- Over a large number of forecasts, the statistical properties of the truth are identical to the statistical properties of a member of the ensemble
- I.e., the truth is indistinguishable from the ensemble
- Time-mean RMSE of the ensemble mean equals the time-mean ensemble spread

→ spread is an indication of perfect model error

From Palmer et al. (2006)

Box A The relationship between spread and ensemble mean RMS error in a perfect ensemble

In a perfect ensemble, i.e. a perfect sampling of the underlying probability distribution of truth, then, over a large number of ensemble forecasts, the statistical properties of the true value X_T of X are identical to the statistical properties of a member of the ensemble, X_e (when that member is removed from the ensemble). For the following analysis of spread and skill, we assume that the ensemble size N is sufficiently large that removing one member from the ensemble does not materially affect the results. Hence, for example, the mean squared distance of the J-th member $X_e(J)$ from the ensemble mean $\langle X_e \rangle$ is identical to the mean squared error of the ensemble mean

$$\overline{\left\| X_e(J) - \langle X_e \rangle \right\|^2} = \overline{\left\| X_T - \langle X_e \rangle \right\|^2} \qquad \text{(A1)}$$

where $\langle \ldots \rangle$ denotes the expectation value with respect to a particular ensemble forecast, and $\overline{\ldots}$ denotes an average over many such ensemble forecasts. Equation (A1) holds for any J and it can be applied to a scalar quantity X or to a vector $\boldsymbol{X}$. In the latter case, $\| \ldots \|$ should be understood as the Root Mean Square (RMS) or the Euclidean norm. Taking the expectation $\langle \ldots \rangle$ of Equation (A1) yields

$$\overline{\left\langle \left\| X_e - \langle X_e \rangle \right\|^2 \right\rangle} = \overline{\left\| X_T - \langle X_e \rangle \right\|^2} \qquad \text{(A2)}$$

Equation (A2) implies that the time-mean ensemble spread about the ensemble-mean forecast, should equal the time-mean RMS error of the ensemble-mean forecast.

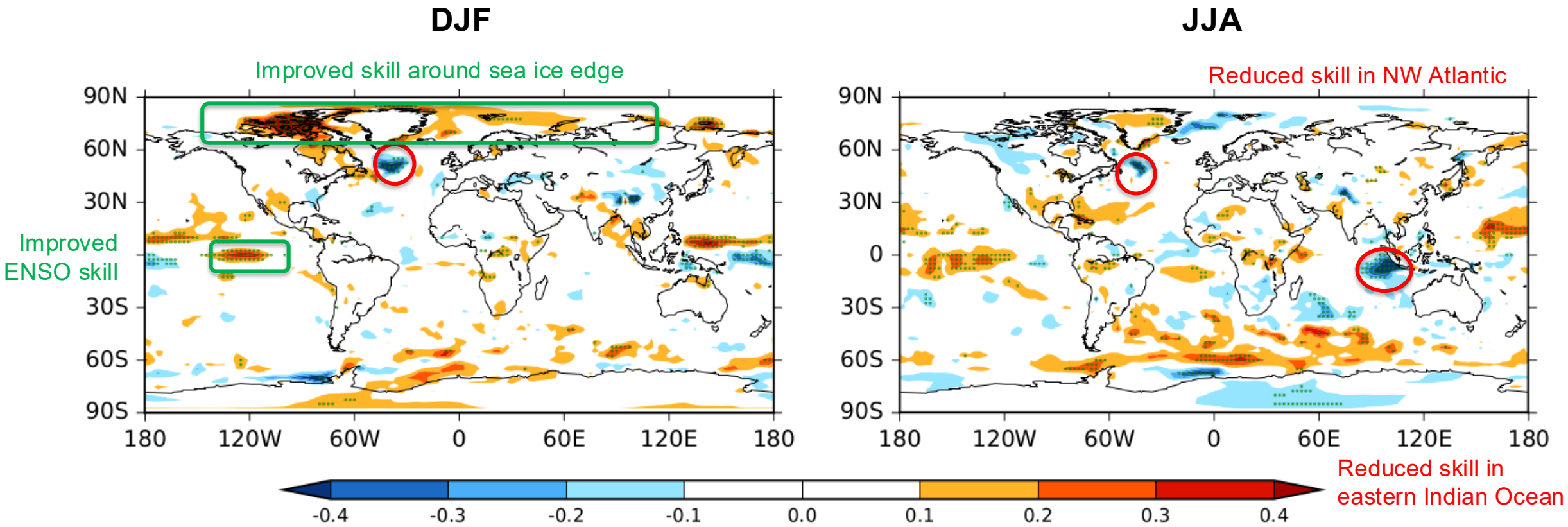
System 4 vs SEAS5

	System 4 Introduced: 2011	SEAS5 Introduced: 2017
Atmosphere	Cycle 36r4 T_L255 L91	Cycle 43r1 T_{Co}319 L91
Ocean	NEMO v3.0 ORCA 1.0-L42	NEMO v3.4 ORCA 0.25-L75
Sea ice model	Sampled climatology	LIM2
Atm. initial conditions	ERA-Interim/Ops	ERA-Interim/Ops
Ocean and sea ice initial conditions	OCEAN4	OCEAN5

SEAS5 documentation: Johnson et al. (2019)

Global 2m temperature skill differences

$CRPSS_{SEAS5}$ - $CRPSS_{SEAS4}$

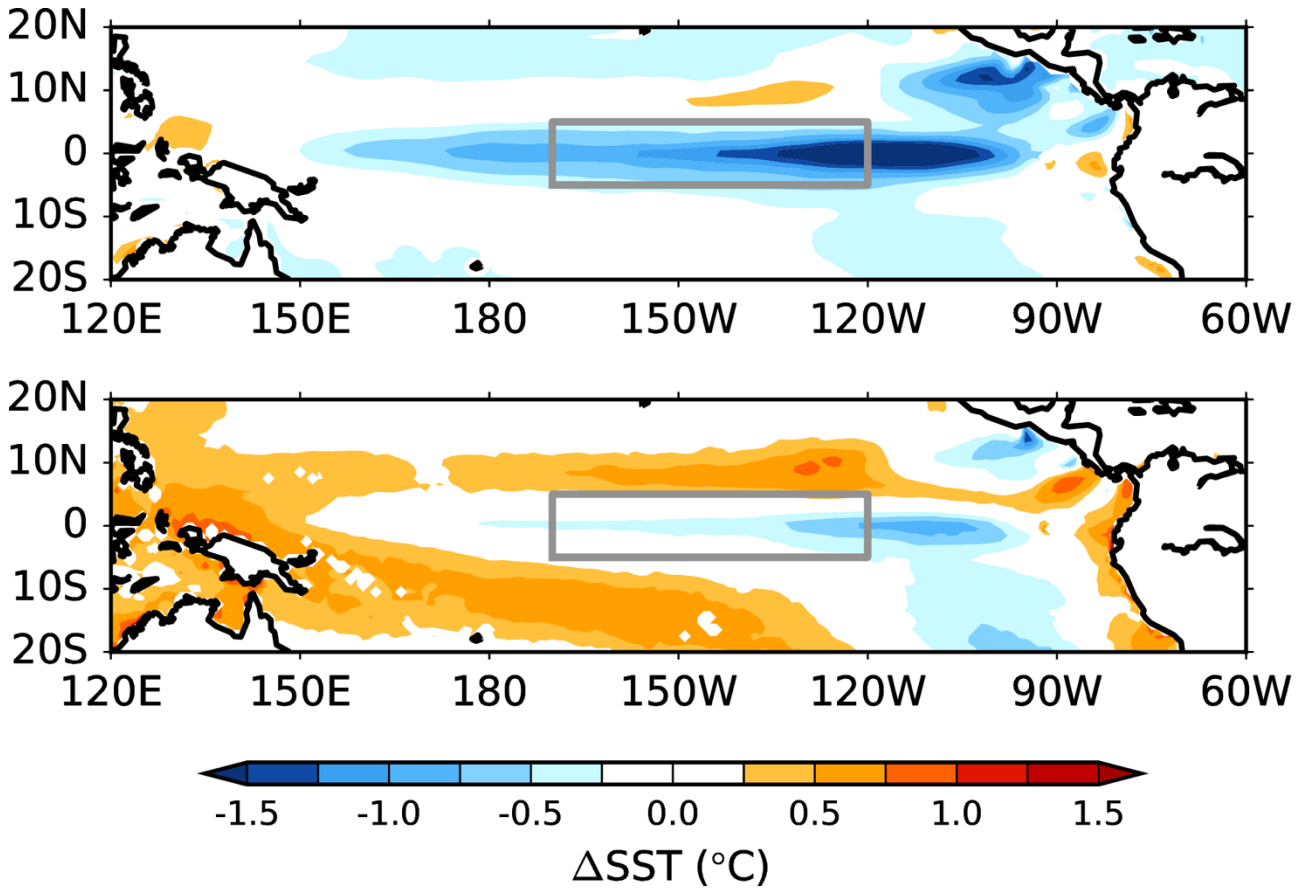


All plots show seasonal means at one month forecast lead (i.e. month 2 to 4 of the forecast) and using 25 ensemble members, unless stated otherwise

Nino3.4 SST bias in DJF

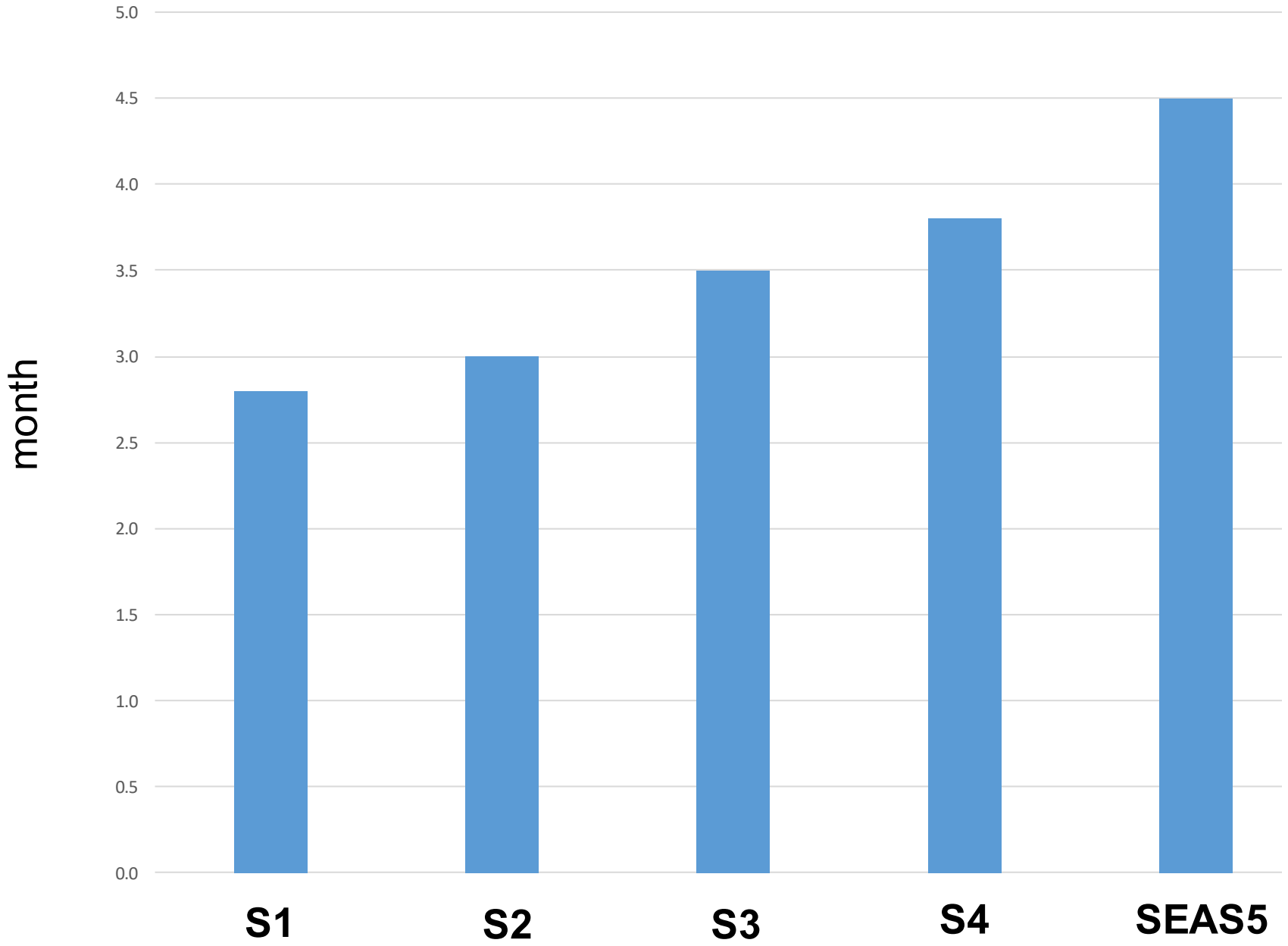
System 4

SEAS5

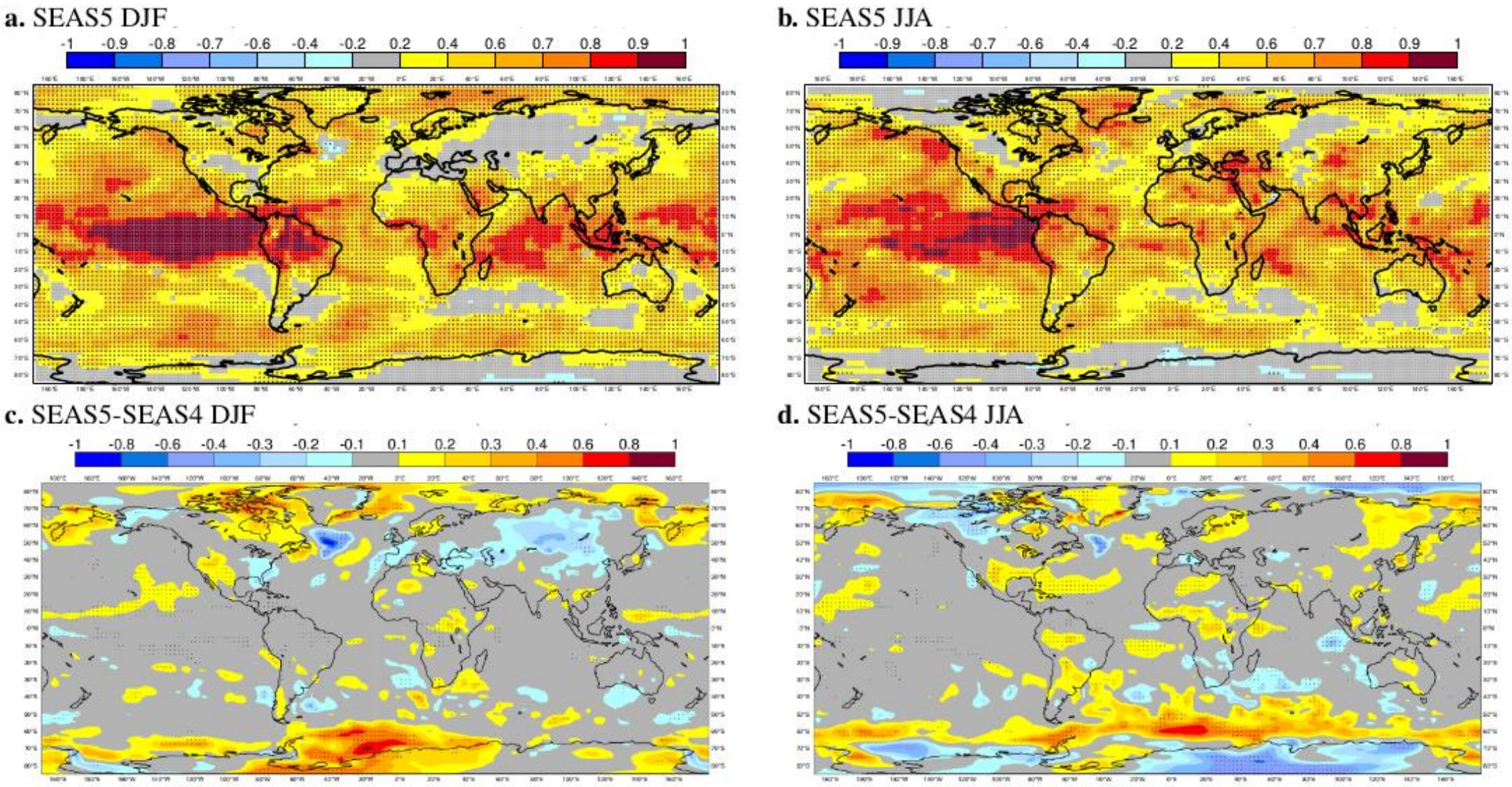


Large improvement in equatorial cold tongue bias

Forecast lead time when ACC (NINO3.4) < 0.9

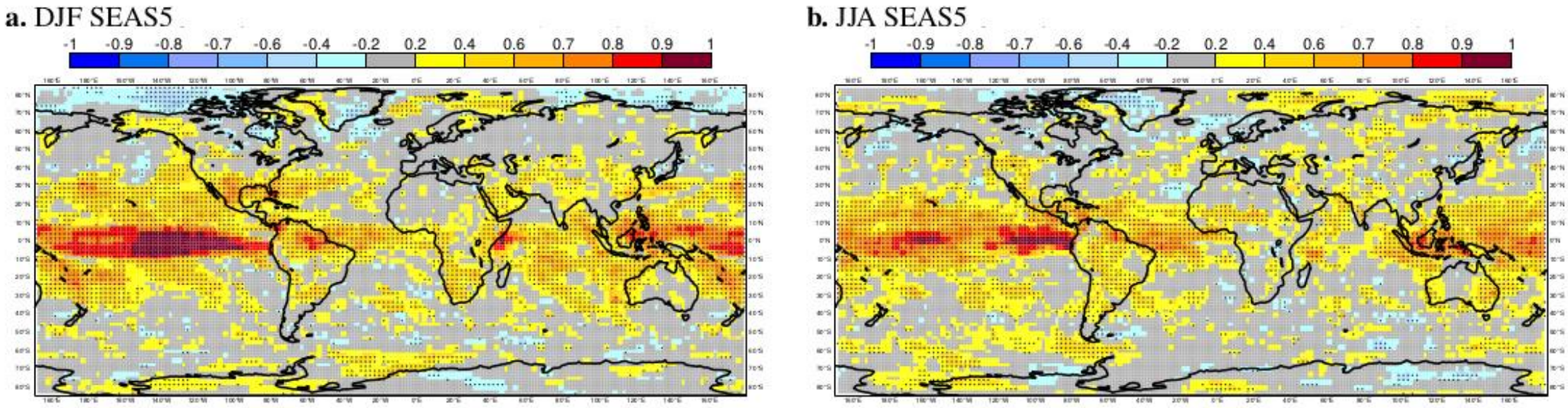


Ensemble mean correlation skill for 2m temperature



From Johnson et al. (2019)

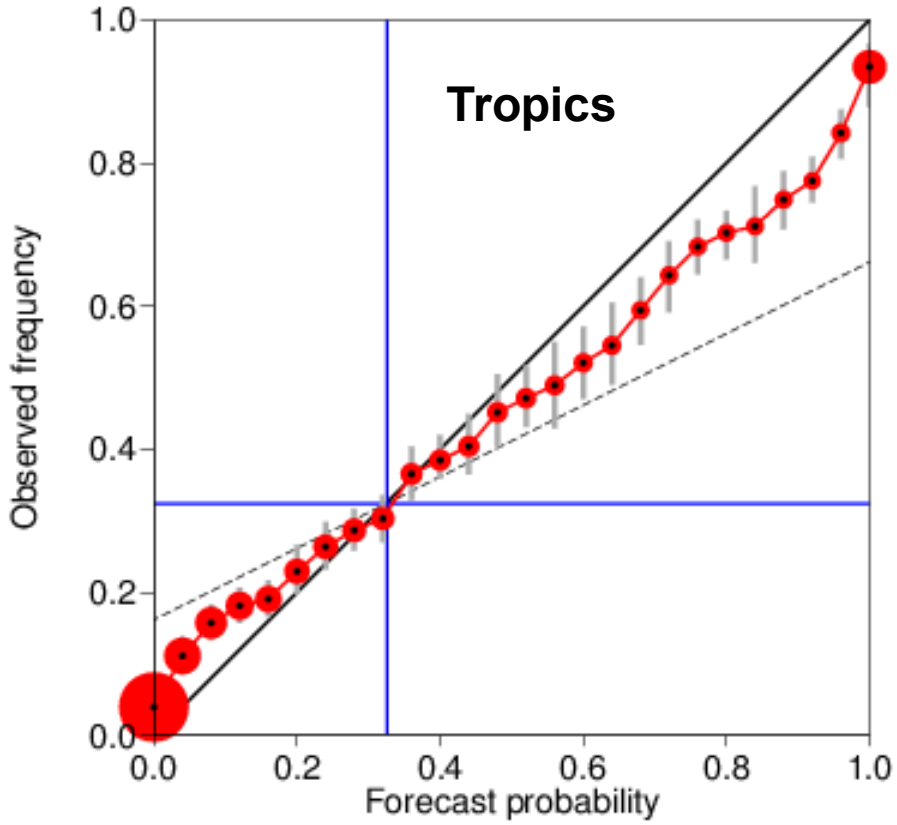
Ensemble mean correlation skill for precipitation

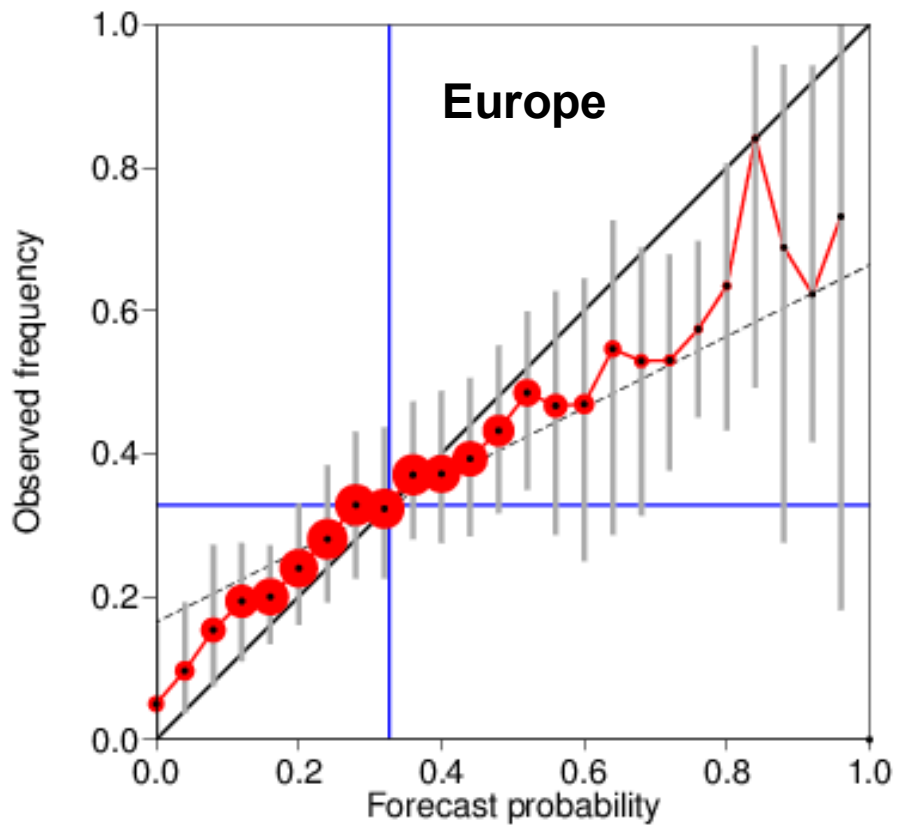


From Johnson et al. (2019)

Reliability diagrams

2m temperature upper tercile events in DJF





Overconfident forecasts

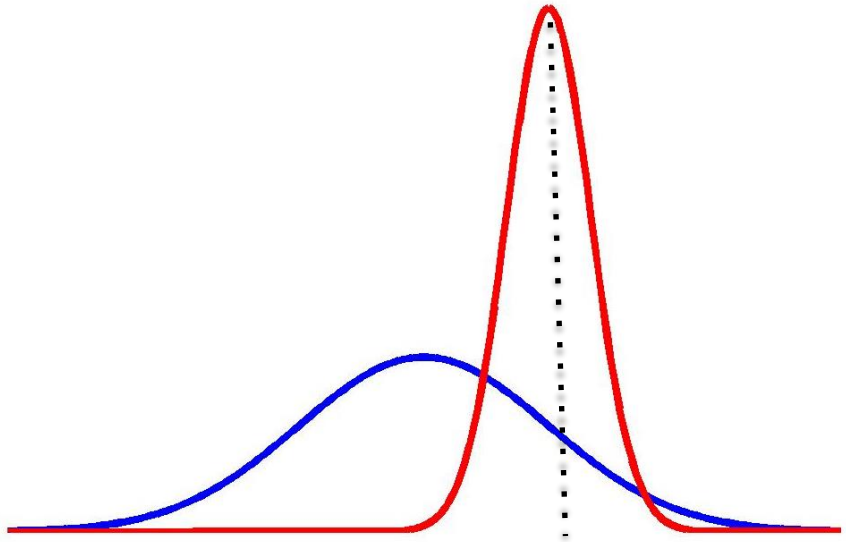
From Johnson et al. (2019)

Seasonal forecasting: challenges

Aim: forecast distribution that sufficiently discriminates the interannual signal from the historical background distribution

"Ideal" situation (tropics)

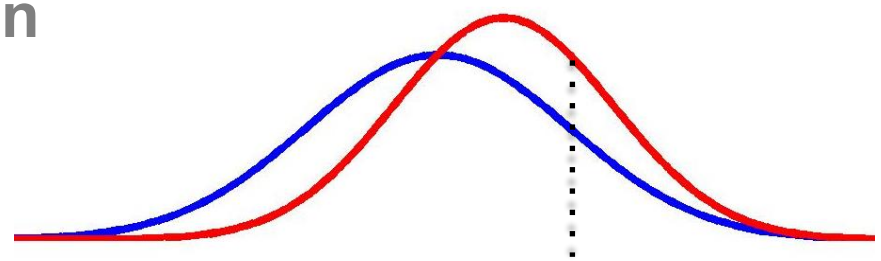
"Real" situation (extra-tropics)



Climatology

Forecast

Observation



A crucial component of any (seasonal) forecasting system is its retrospective forecasts.

Reforecasts are used for:

- ✓ **Calibration of real-time forecasts**

  e.g., mean-state bias corrections, variance inflations

- ✓ **Skill estimation to assess confidence in real-time forecasts**

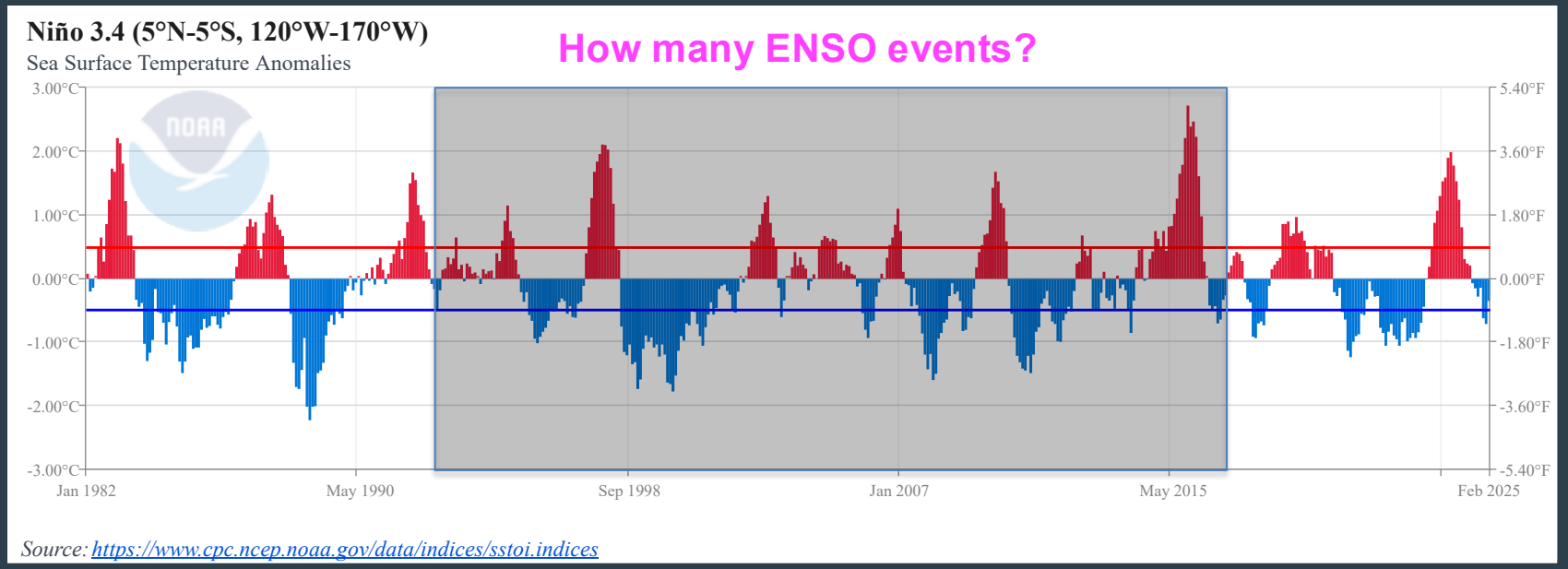
Re-forecasts in C3S cover the 24-year period 1993-2016.

SEAS5 has re-forecasts over the 36-year period 1981-2016.

Limitations of re-forecasts

- **Balance of re-forecast size and computational costs**
- **Uncertainties due to sample size constrain**:

  → evaluation of sporadic natural drivers, e.g., ENSO, MJO, SSW



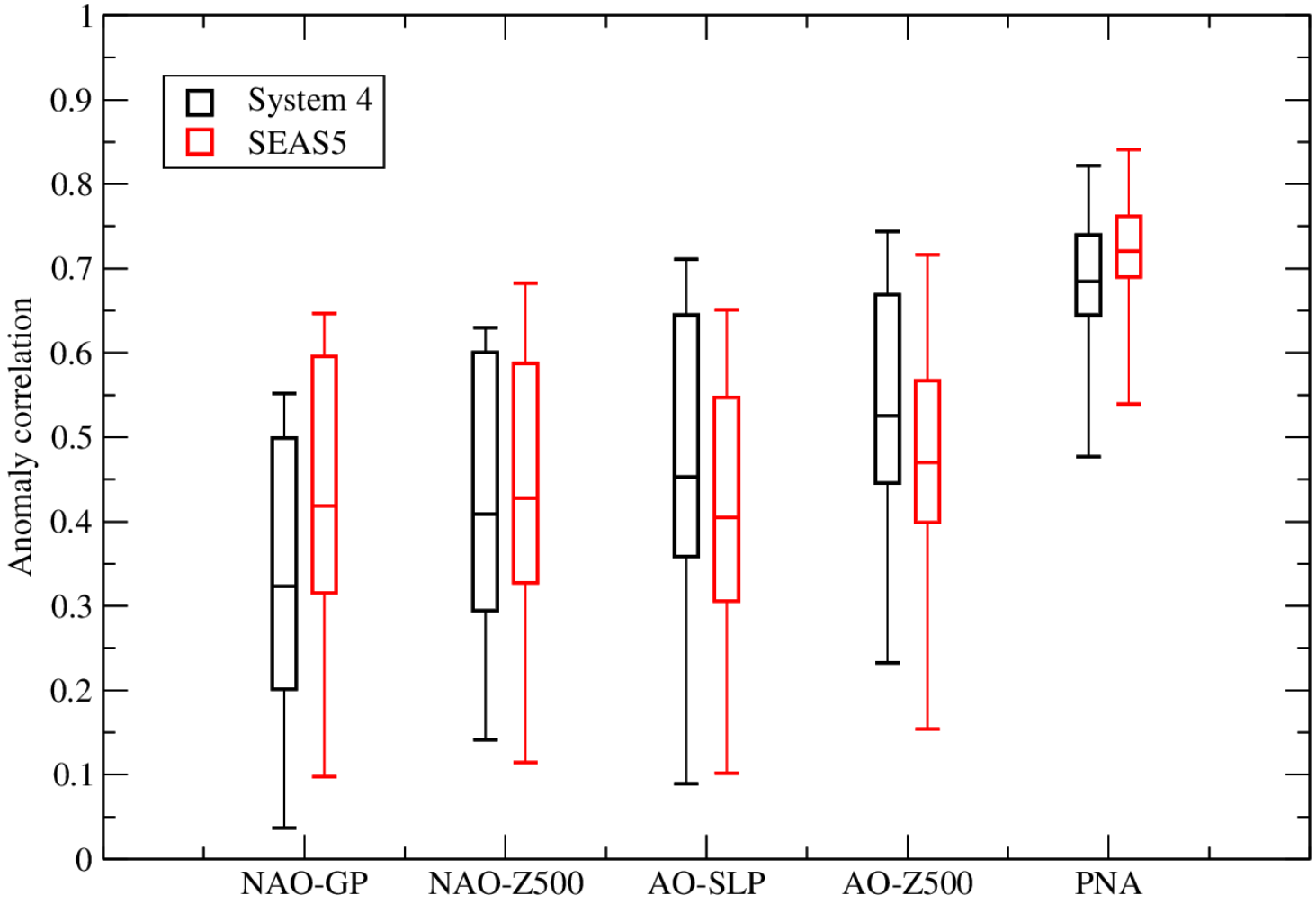
Limitations of re-forecasts

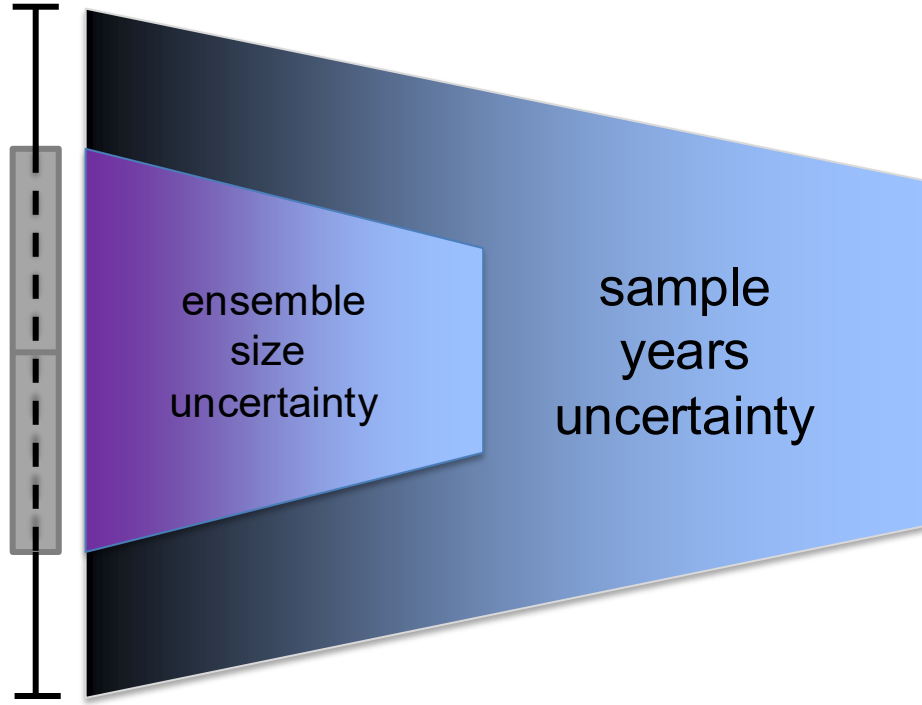
- **Balance of re-forecast size and computational costs**
- **Uncertainties due to sample size constrain**:

  → skill estimation in regions of large interannual variability, e.g., Euro-Atlantic

Hindcast skill of the NAO, AO and PNA in DJF

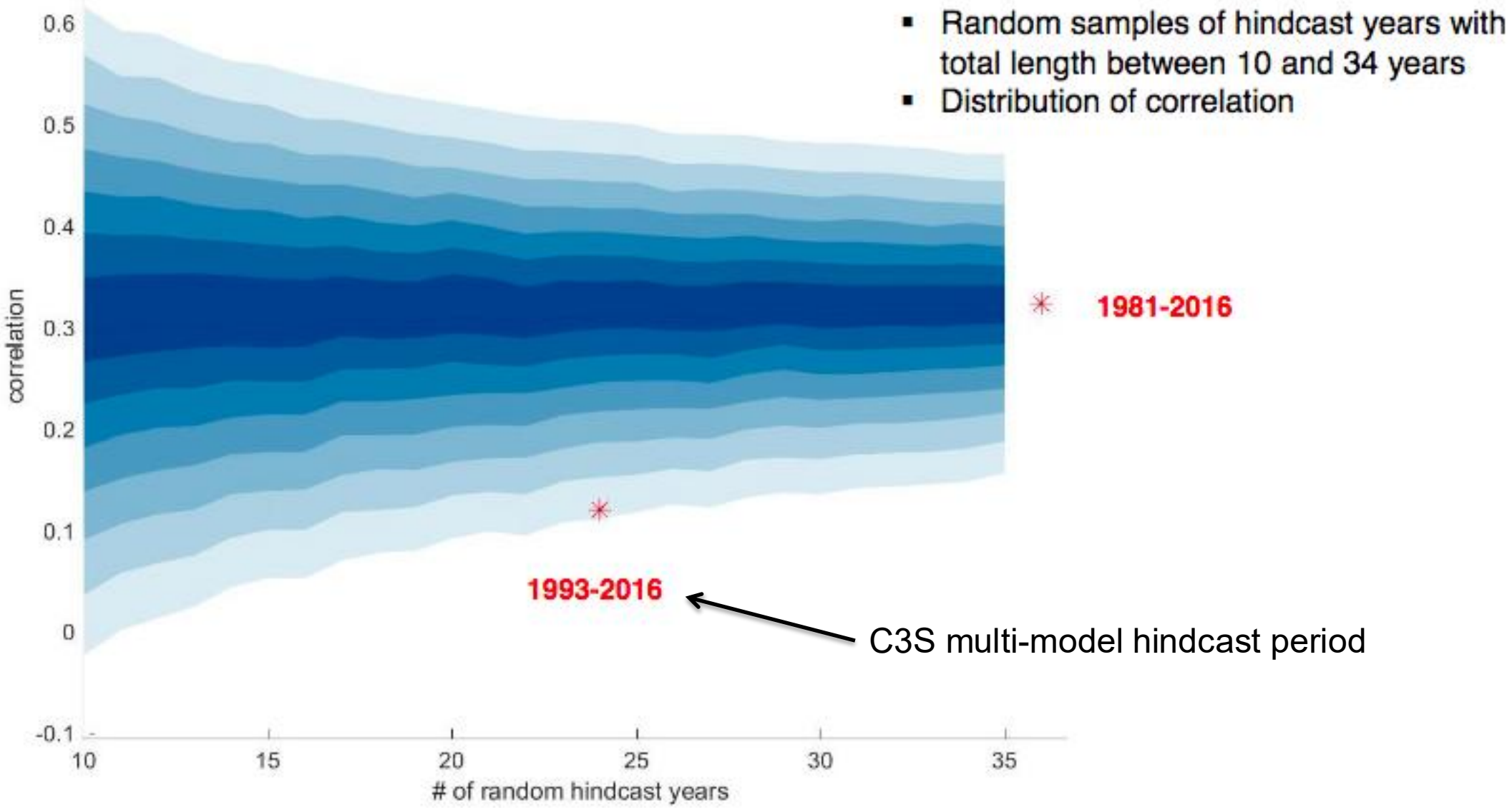
Nov start dates 1981-2016, 51 ensemble members





Two types of sampling uncertainty

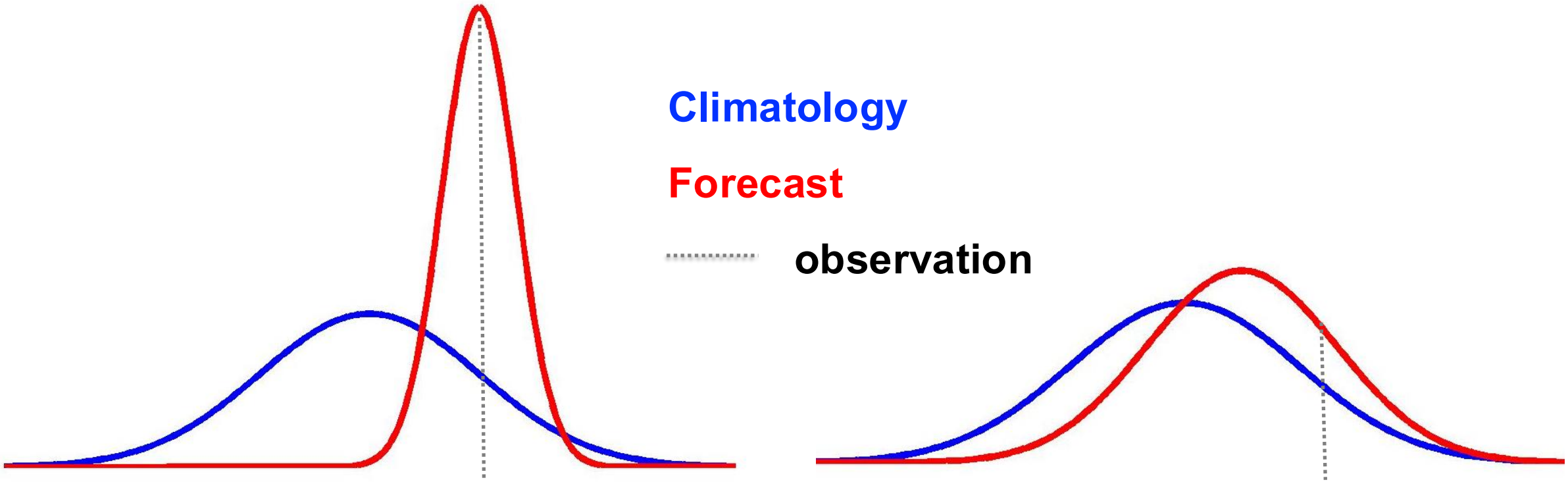
NAO hindcast skill in SEAS5 – how (un)lucky are we?



Seasonal forecasting in the extra-tropics
with low signal-to-noise ratios

“ideal” situation

“real” situation



Seasonal forecasts of the winter NAO

THE TIMES
Science

April 2014

News | Opinion | Business | Money | Sport | Life | Arts | Puzzles | Papers | Irish news

Welcome to your preview of The Times

Forecasters crack formula to predict long-range weather

Article | Pictures | Catalysts for change



Daffodils were blooming in Whitegate, Cheshire Christopher Furlong/Getty Images

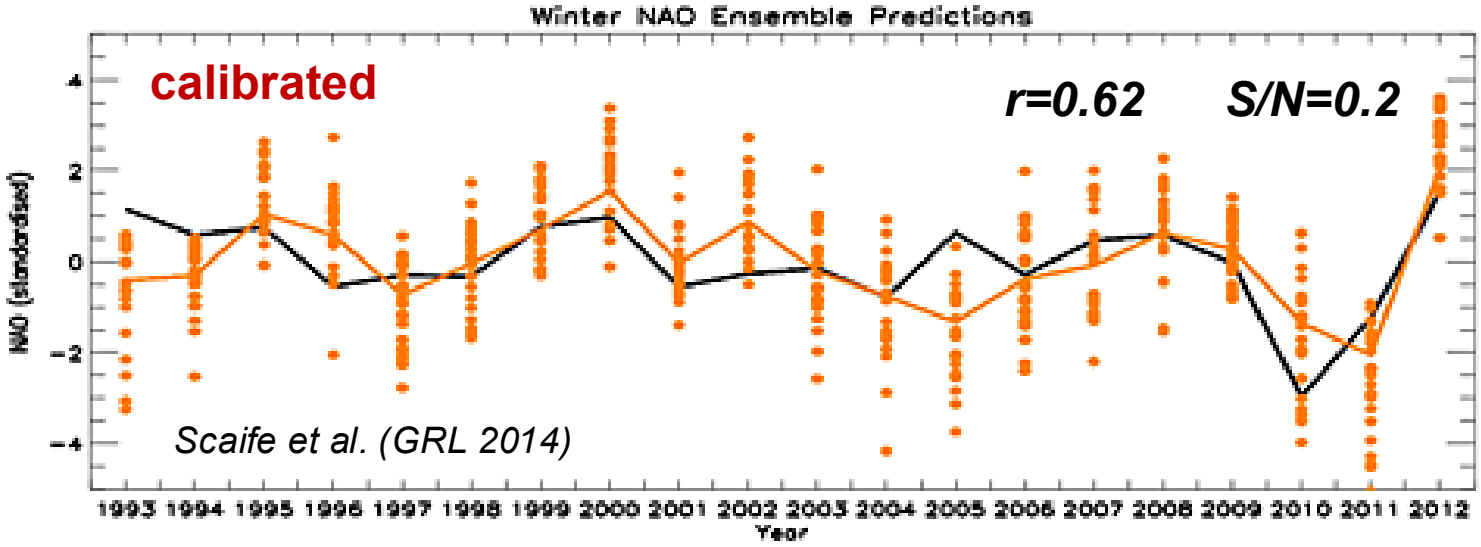
Paul Simons and Hannah Devlin
Last updated at 12:01AM, April 2 2014

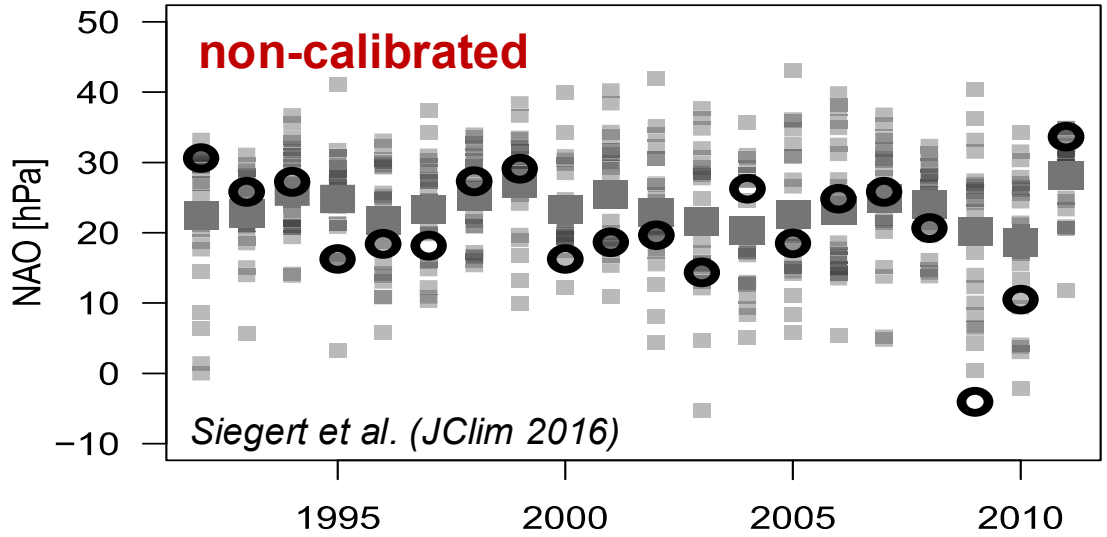
Extreme winters will be predicted with greater reliability than before after the world's best long-term weather forecast model was developed by British scientists, the Met Office said.

The breakthrough may have a substantial impact on the economy, allowing power companies and wind farms to anticipate energy demands while airports and councils can estimate how much grit and anti-freeze is likely to be required.

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Ensemble hindcasts of the NAO index 1993-2012
with the Met Office model (GloSea GA3)





The Ratio of Predictable Components (RPC)

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2014GL061146

Key Points:
- Model members can be too noisy and not potential realizations of the real world
- Predictability may be underestimated by idealized experiments and skill measures
- Can achieve skilful and reliable forecasts using large ensembles to reduce noise

Do seasonal-to-decadal climate predictions underestimate the predictability of the real world?

Rosie Eade[1], Doug Smith[1], Adam Scaife[1], Emily Wallace[1], Nick Dunstone[1], Leon Hermanson[1], and Niall Robinson[1]

[1]Met Office Ha

Abstract s

$$RPC = \frac{PC_{obs}}{PC_{model}} \geq \frac{r(obs, ens\ mean)}{\sqrt{VAR_{signal}/VAR_{total}}}$$

Predictable Components (PCs) … predictable part of the total variance

observed PC_{obs} … estimated from explained variance = $r^2(obs, ensmean)$

model PC_{model} … estimated from ratio of signal variance to total variance

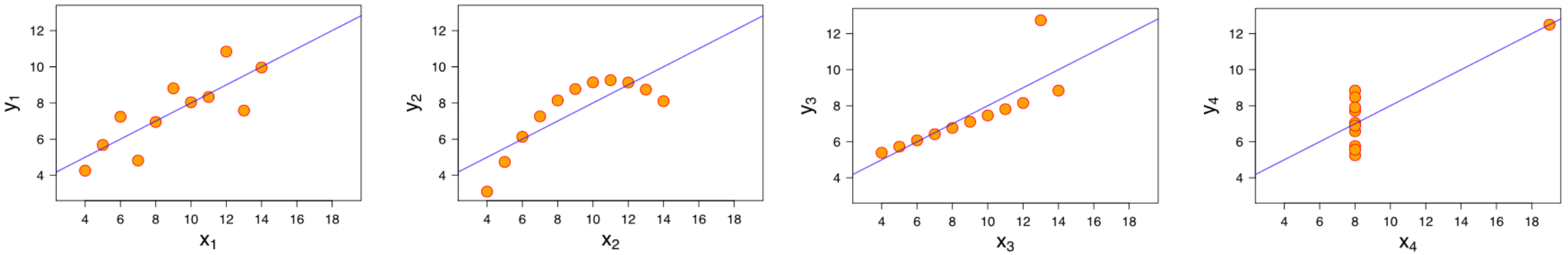
Properties of a perfect model ensemble

- Time-averaged ensemble spread *approx. equals* RMSE of ensemble mean forecast
- Correlation skill (aka potential skill): correlation(ensemble mean, ensemble member)
- Observed correlation ≤ perfect model correlation
- RPC of a perfect ensemble *approx. equals* 1

Illustrative example of correlation drawbacks after Anscombe (1973):

- Four pairs of x-y variables
- The four y variables have the same mean (=7.5), variance (=4.1) and **correlation (=0.82)**
- However, distributions of variables are very different

Anscombe's quartet



Normally distributed, "well behaved"

Not normally distributed, non-linear relationship

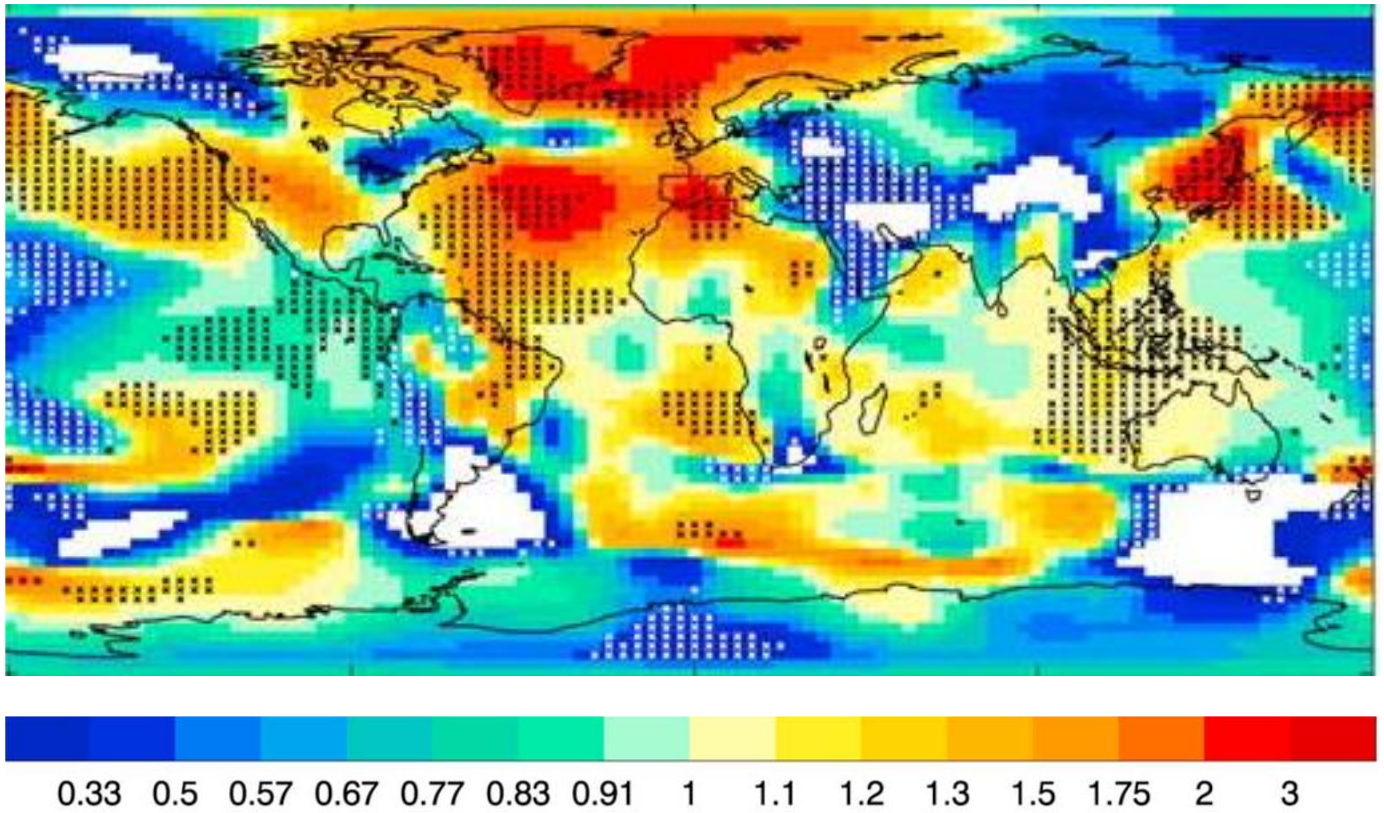
Perfect linear relationship, Except for one outlier

No relationship with one outlier

Anscombe (Amer. Statist. 1973)

The signal-to-noise “conundrum” or “paradox”

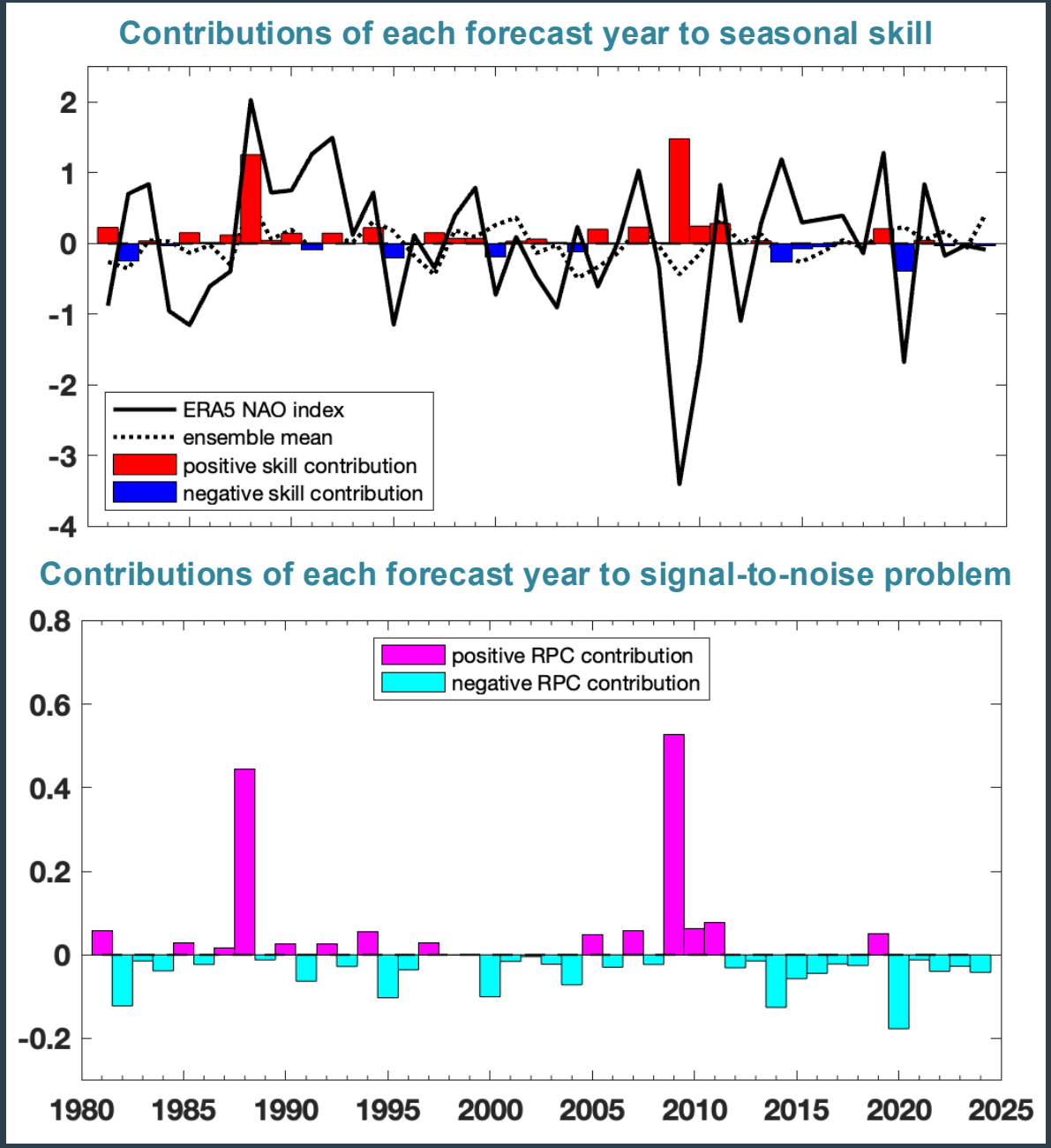
RPC of DJF MSLP in GloSea5 $\left(\mathrm{RPC} = \frac{\mathrm{PC_{obs}}}{\mathrm{PC_{model}}}\right)$



Eade et al. (GRL 2014)

The real world seems to have higher predictability than the model

Intermittency of winter NAO forecast skill in SEAS5



Thank you!

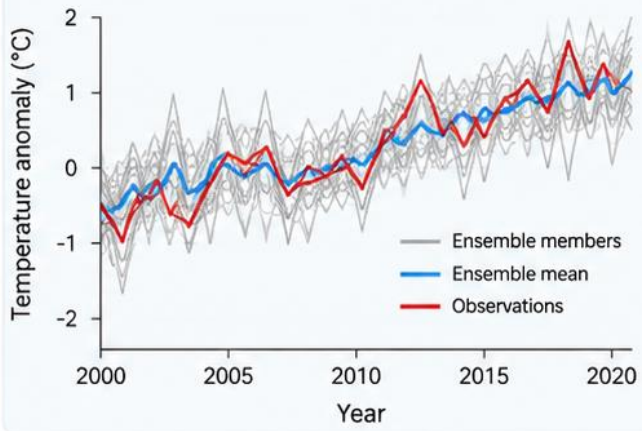
The Signal-to-Noise Paradox in Climate Forecasting

Ensemble-mean forecasts can be more skillful (more correlated with reality) than the ensemble members are with each other.

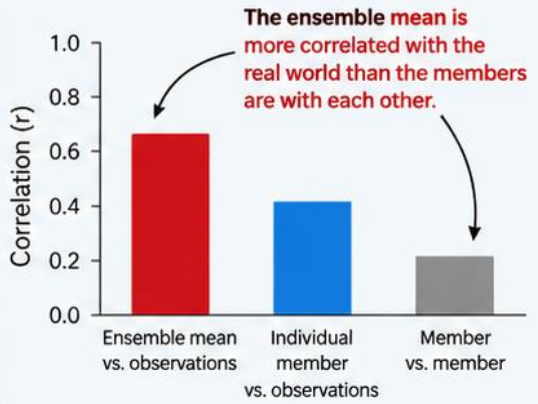
What is the paradox?

- In many climate forecast systems, the **ensemble-mean forecast correlates better with observations** than the individual ensemble members correlate with each other.
- This is paradoxical because if ensemble members realistically represent the same climate signal, we would expect them to be at least as similar to each other as they are to the real world.

Schematic example



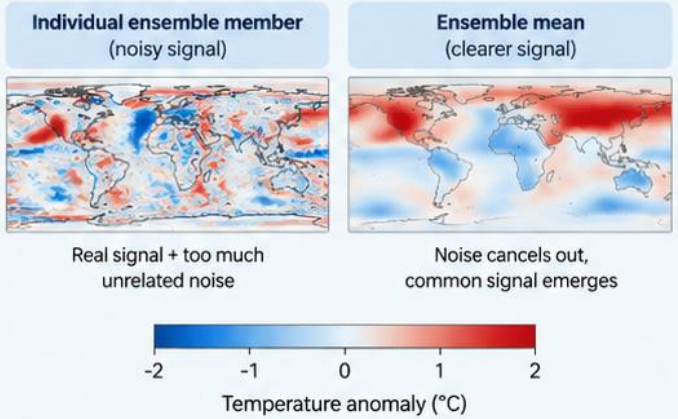
Typical correlations
(seasonal-to-decadal forecasts)



Why does it happen?

1. **Models capture real-world signals**
   Ensemble members share a common, realistic response to external forcings (e.g., ENSO, volcanic eruptions, greenhouse gases).
2. **Excess internal variability in models**
   Each member includes too much uncorrelated disorder ("noise") compared to the real climate, making members less similar to each other.
3. **Error cancellation in the ensemble mean**
   Averaging reduces uncorrelated model noise, revealing the common signal and leading to higher skill relative to observations.

Conceptual illustration



Implications for forecasting

1. **Models may underestimate predictable signals**
   The real world appears more signal-rich (less noisy) than simulated by current models.
2. **Larger ensembles increase skill**
   More members help **average out** excessive **model noise**.
3. **Calibration and uncertainty**
   Ensemble spread may be too large, leading to overly conservative uncertainty estimates.
4. **Useful skill exists**
   Despite the paradox, **the ensemble mean** provides valuable, skill**ful forecasts**, especially on seasonal-**to-decadal** timescales.

Key takeaway

The signal-to-noise paradox highlights that climate models often have the **right signal but too much noise**.
Improving the realism of internal variability and increasing ensemble sizes can lead to more confident and skillful climate forecasts.

References

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