# On near term climate (drought) prediction

T.J. O'Kane (CSIRO)

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# How is drought frequency and persistence associated with the LFV of the major climate modes?

## Consider rainfall trends in South Eastern Australia

- Risbey et al (2013) *"The existing literature is … somewhat contradictory, with some studies ruling out some of the processes that other studies have found to be a substantial cause"*

1. Increased (decreased) frequency of El Nino (La Nina) events (Cai & Cowan 2008, Gallant et al 2007) with an association to severe droughts (Nicholls 1988, Wang & Hendon 2007). ENSO-precipitation teleconnection varies with phase of the IPO (Power et al 1999, Arblaster et al 2002) i.e. is weaker during +ve IPO phase. Westra et al 2015 question the relationship between the ENSO-precipitation teleconnection and the IPO (Westra et al 2015). 1996-2009 drought not associated with ENSO (Murphy & Timbal 2008, Nicholls 2010, Timball & Hendon 2010)

2. Frequency of drought post 1950 with dry periods associated with an unusually high number of +ve IOD events (Cai et al 2009, Ummenhofer et al 2009, 2011). 1996-2009 drought not associated with the IOD (Verdon-Kidd and Kiem 2009, Nicholls 2010, Timball & Hendon 2011)

3. Positive trend in SAM leading to reduced autumn rainfall (Nicholls 2009). 1996-2009 drought not with SAM (Timbal 2009)

4. Poleward shift and reduced baroclinicity in the (winter) storm tracks (Frederiksen & Frederiksen 2007) driven by CO2 (Franzke et al 2015, Freitas et al 2015)

5. Regional effects such as pressure increases (Hope et al 2009) the subtropical ridge (Murphy & Timball 2008)

- Here we focus on ENSO as the paradigmatic problem of predicting inter annual climate extremes and their relationship to the phases of the background state namely the Interdecadal Pacific Oscillation (IPO)

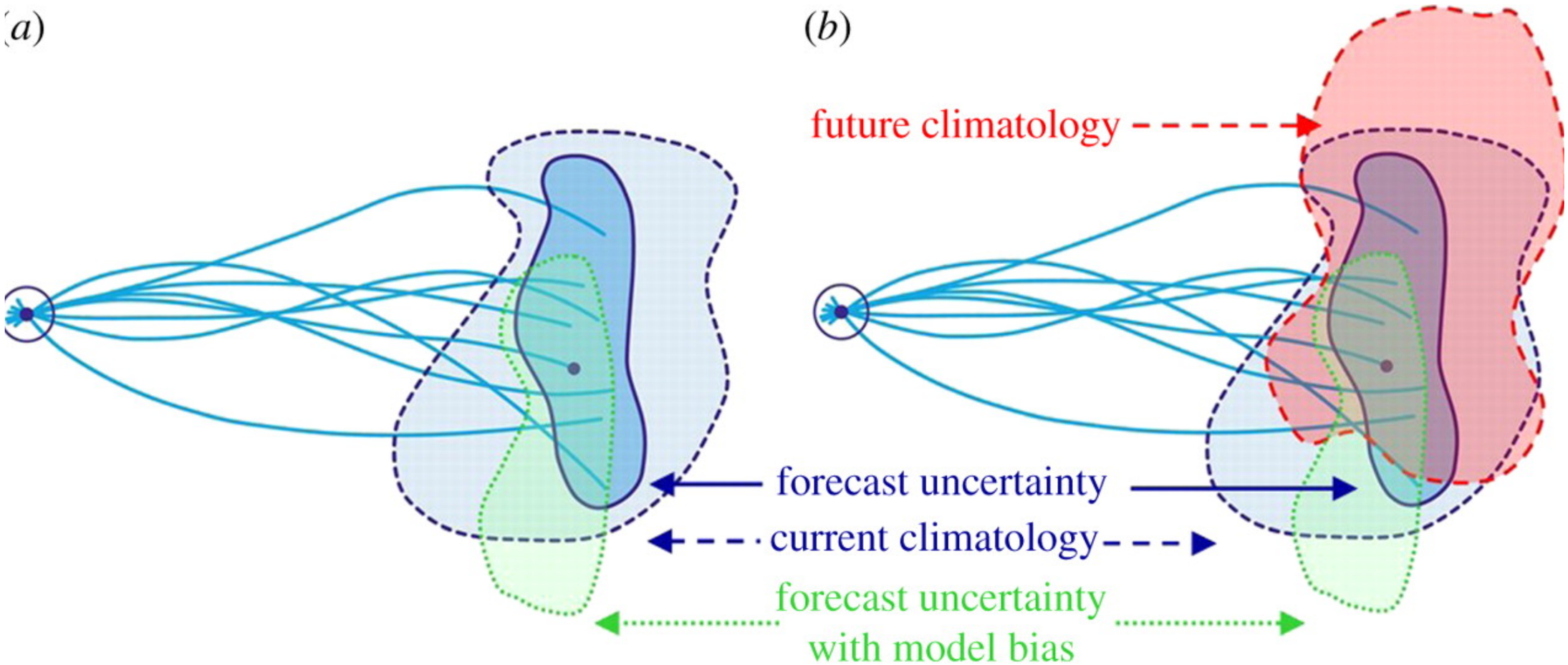
# Predictability in nonlinear, non-stationary and non-Gaussian systems

- Predictability and causality are fundamentally related via identification of an underlying stochastic model i.e. some slow manifold or local region in phase space whose dynamics capture the essential LFV of the climate system AND some noise process representative of fast processes at smaller spatial scales responsible for the initiation of transitions between regimes (phases of the respective climate modes).

- Prediction is the problem of projection onto the relevant dynamical vectors that span the relevant region of phase space (manifold) that determine the underlying dynamics of the climate modes and capture information about the instabilities (growing error modes) responsible for initiating transitions between metastable states (phases).

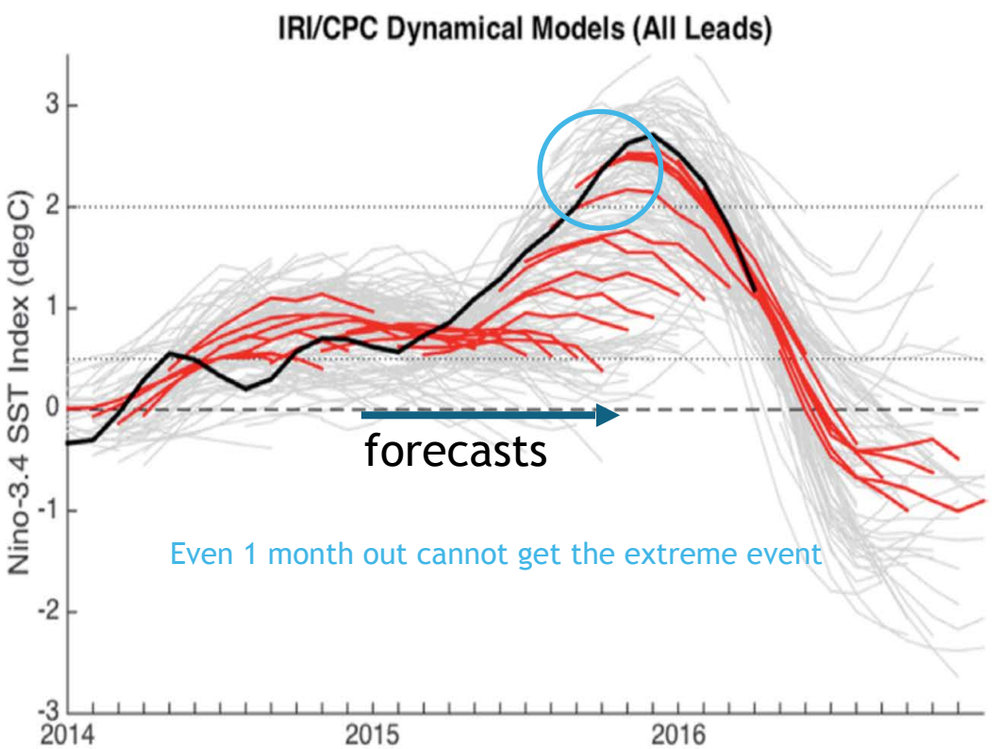
- A fundamental question is how to reduce the dimensionality of the problem and identify the relevant slow manifold and the form of the noise?

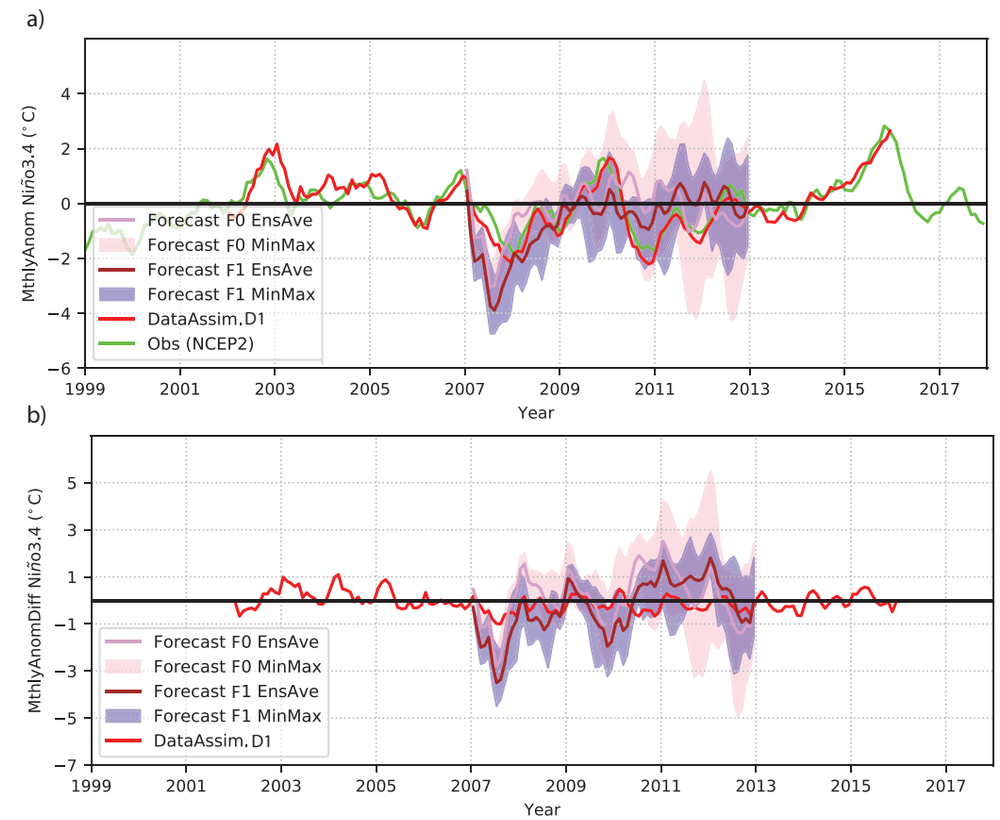
# Ensemble prediction




Schematic of ensemble prediction system on seasonal to decadal time scales showing (*a*) the impact of model biases and (*b*) a changing climate. The uncertainty in the model forecasts arises from both initial condition uncertainty and model uncertainty. (Slingo & Palmer (2011) DOI: 10.1098/rsta.2011.0161)

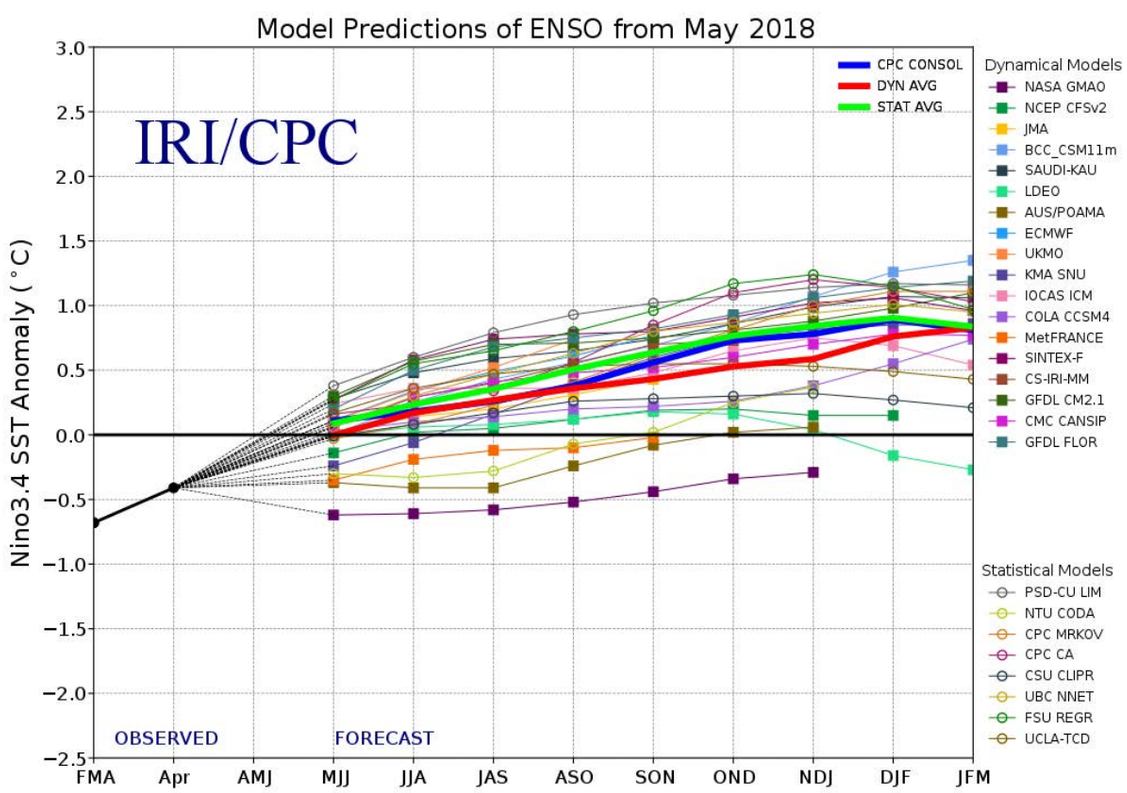
# ENSO forecast skill

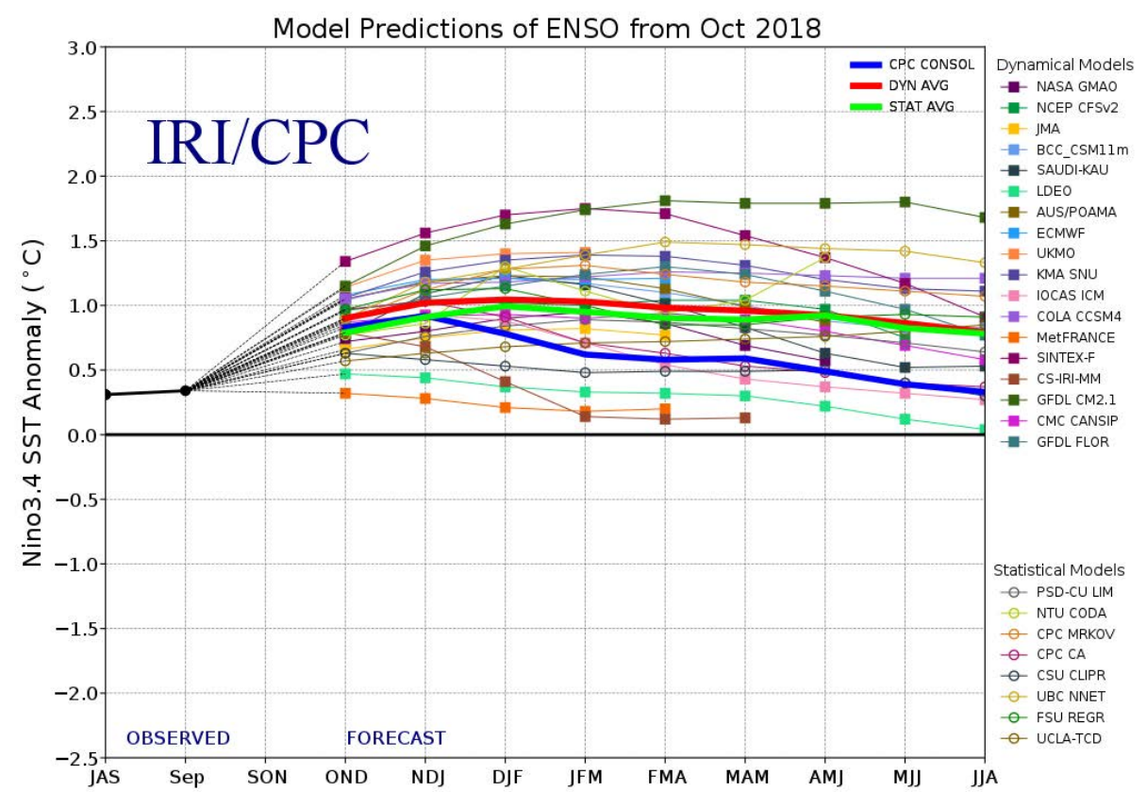


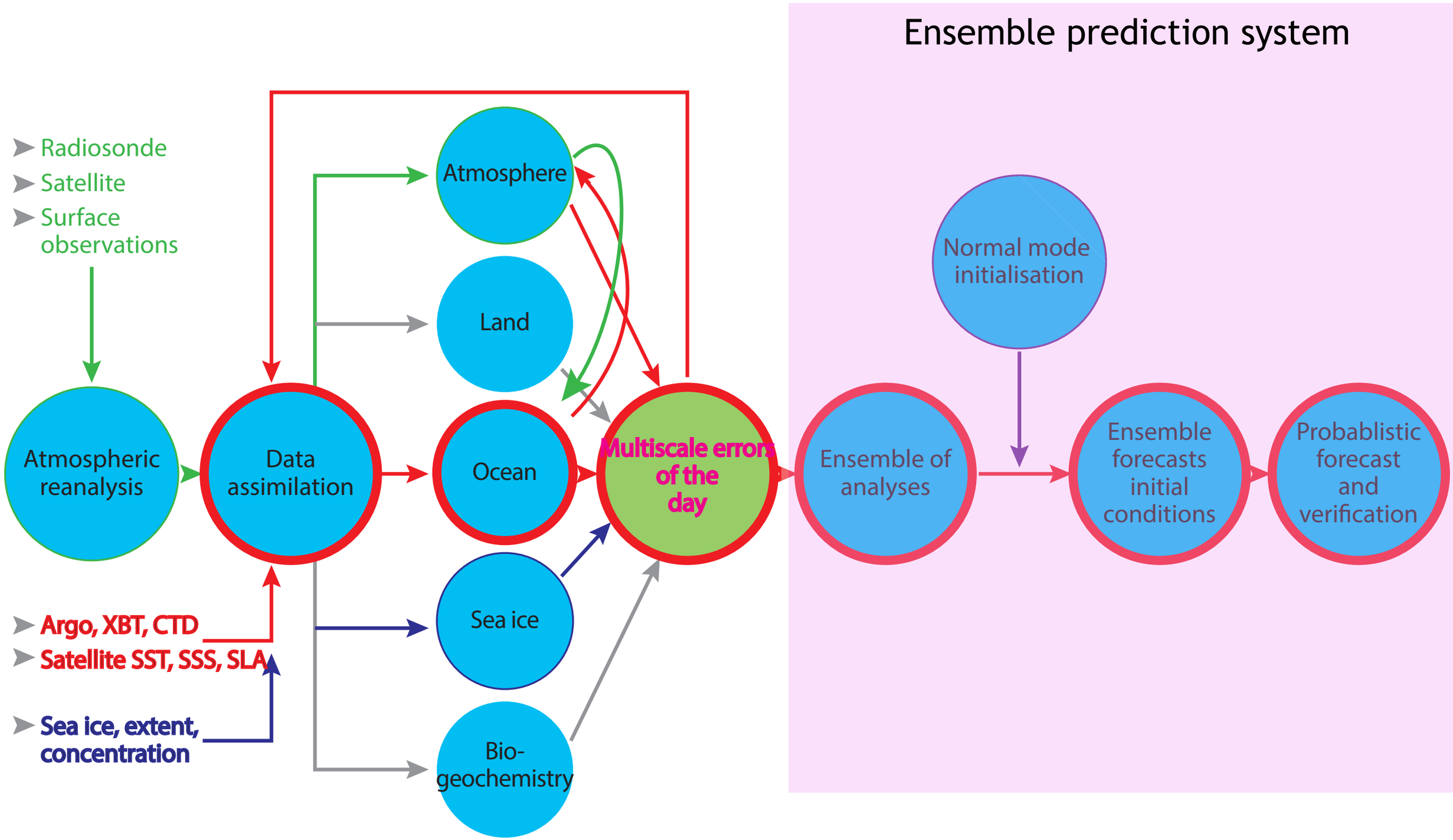

Bias corrected forecasts

CAFE raw hindcasts Jan 2007



# CAFE system version 2.0: DA + ensemble prediction system

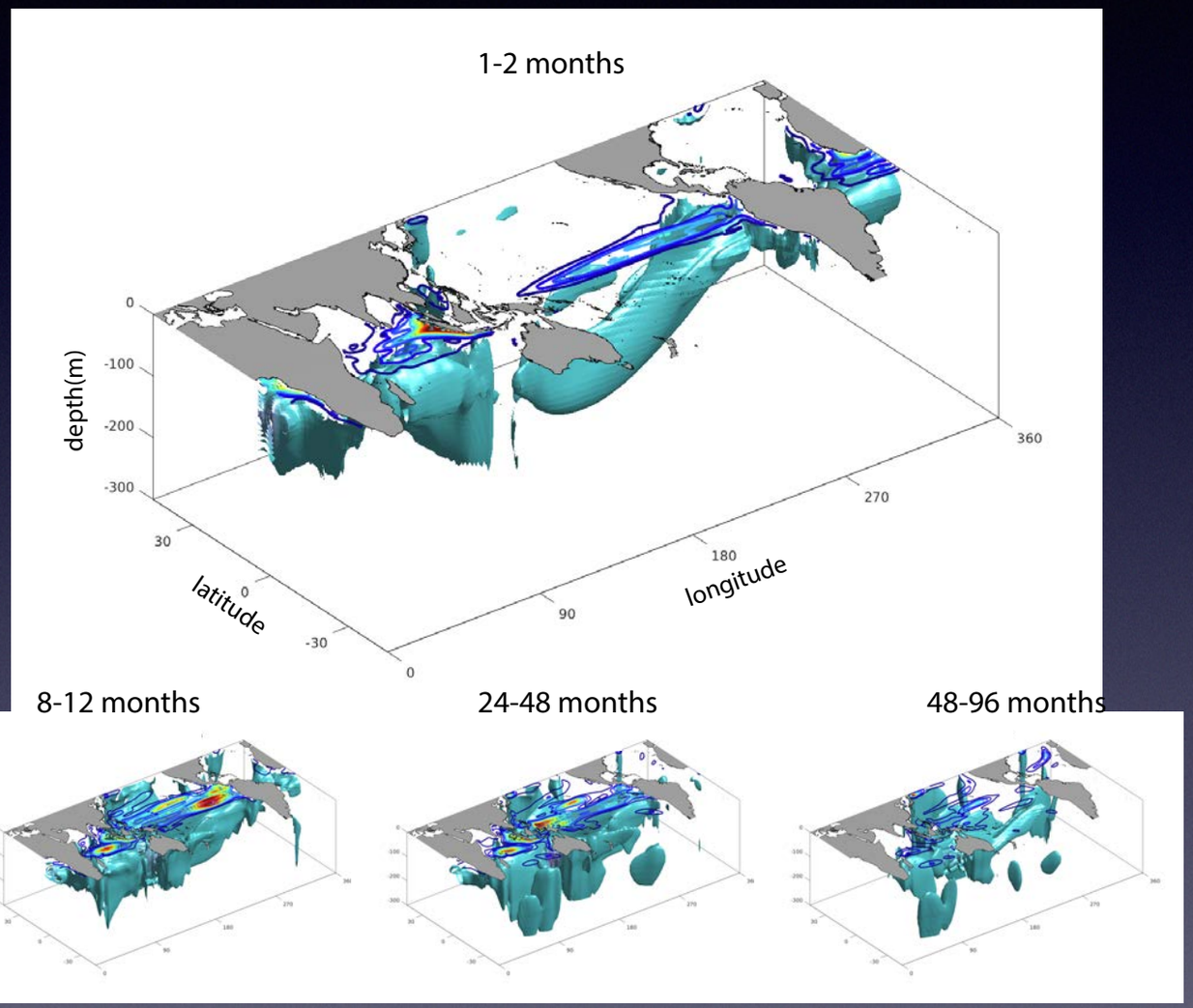




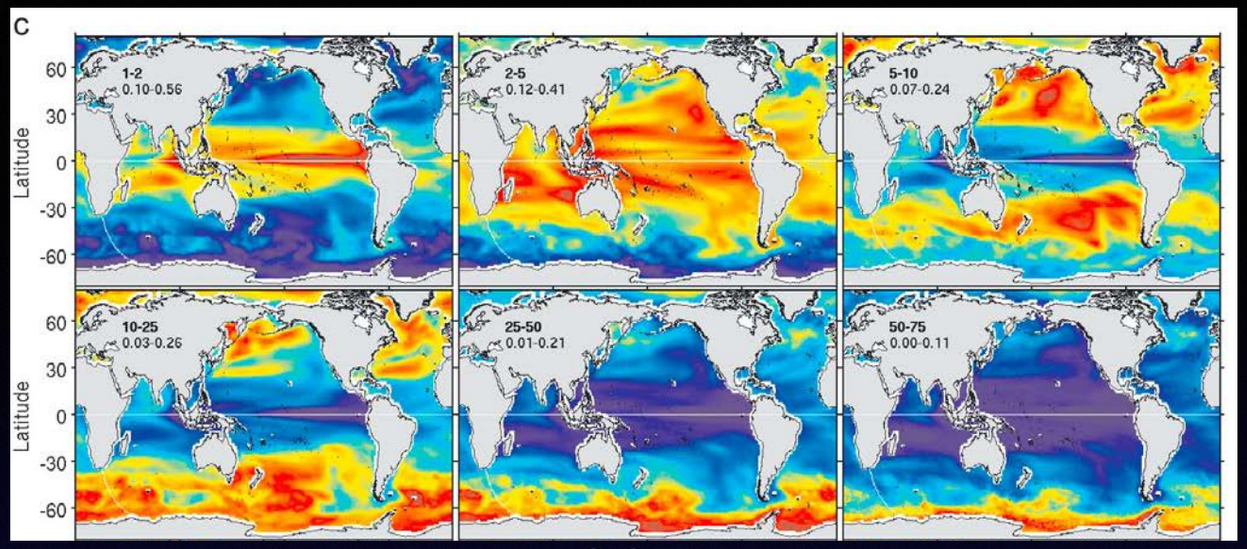

CLIMATE ANALYSIS FORECAST ENSEMBLE system

CSIRO

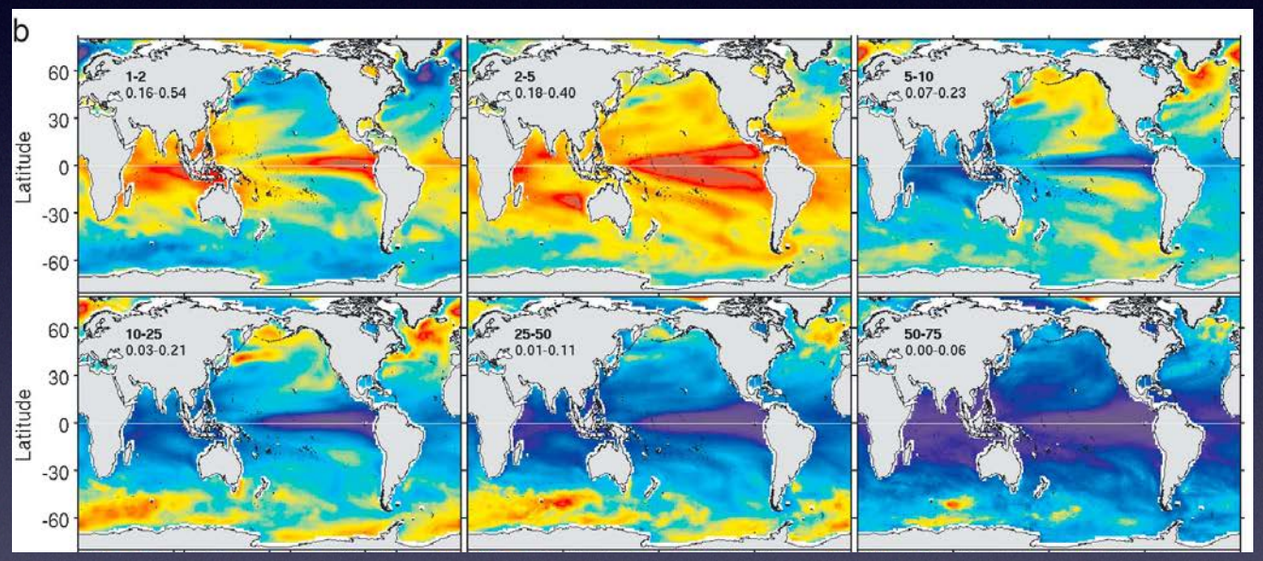
# Ocean variance distribution



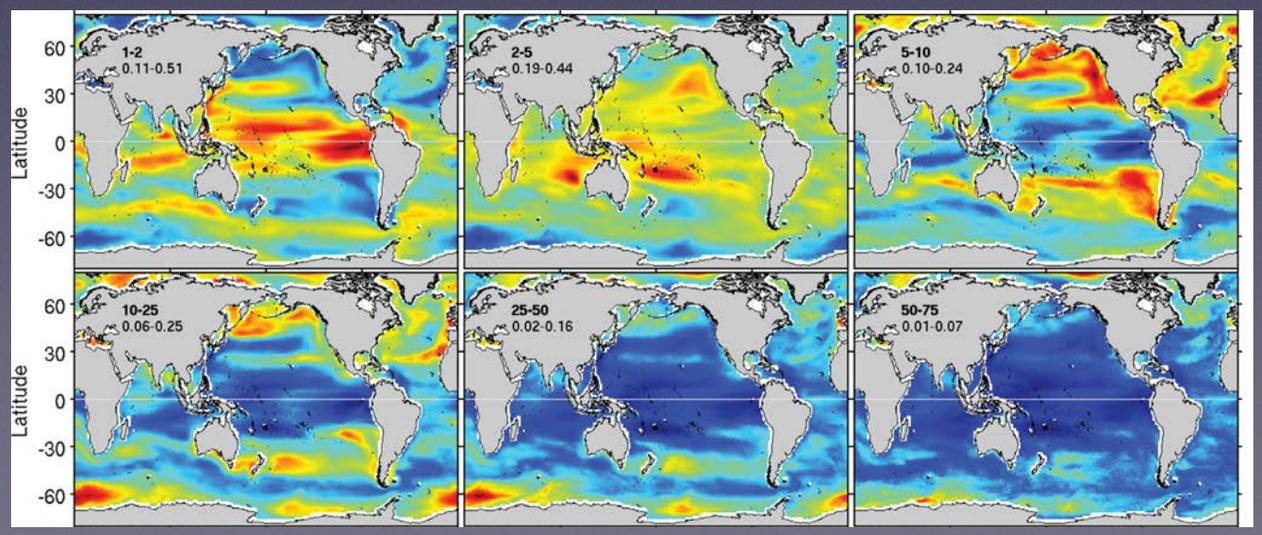

SLA




SST




SSS

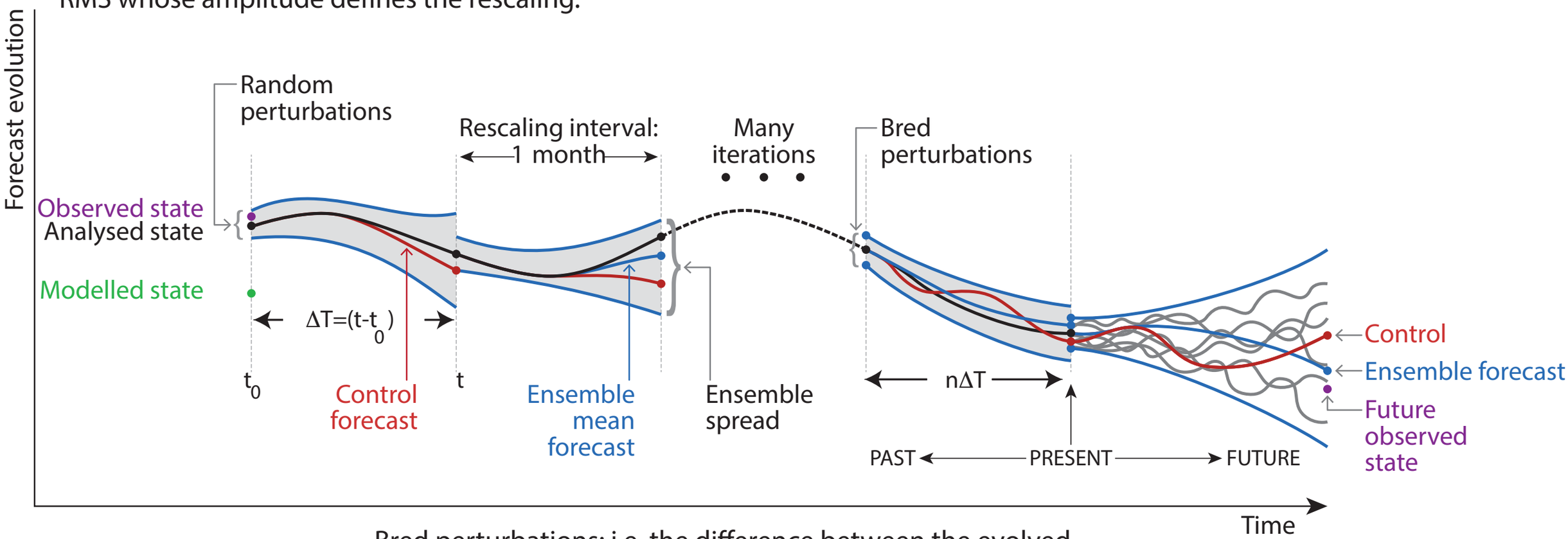



Monselesan et al GRL 2015
O'Kane et al JGR-oceans 2016

O'Kane et al J. Climate 2018

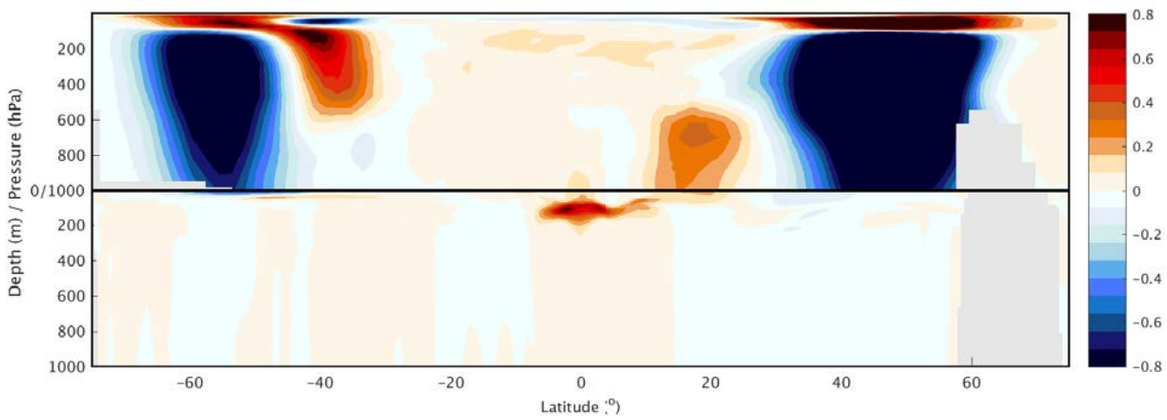
# CAFE ensemble generation

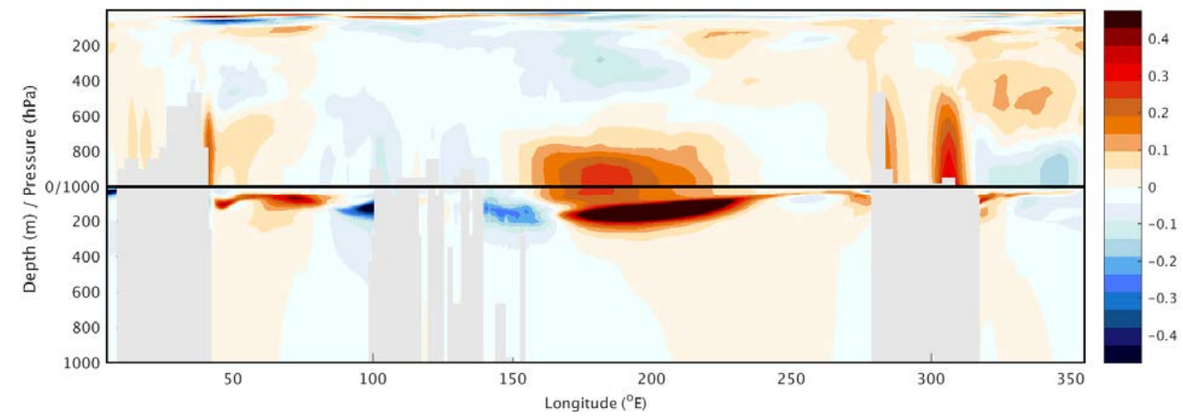
Random initial perturbations with prescribed RMS whose amplitude defines the rescaling.




Bred perturbations: i.e. the difference between the evolved perturbed forecasts and the control, renormalised via the norm defined by the RMS of the initial perturbations and the length of the rescaling interval.

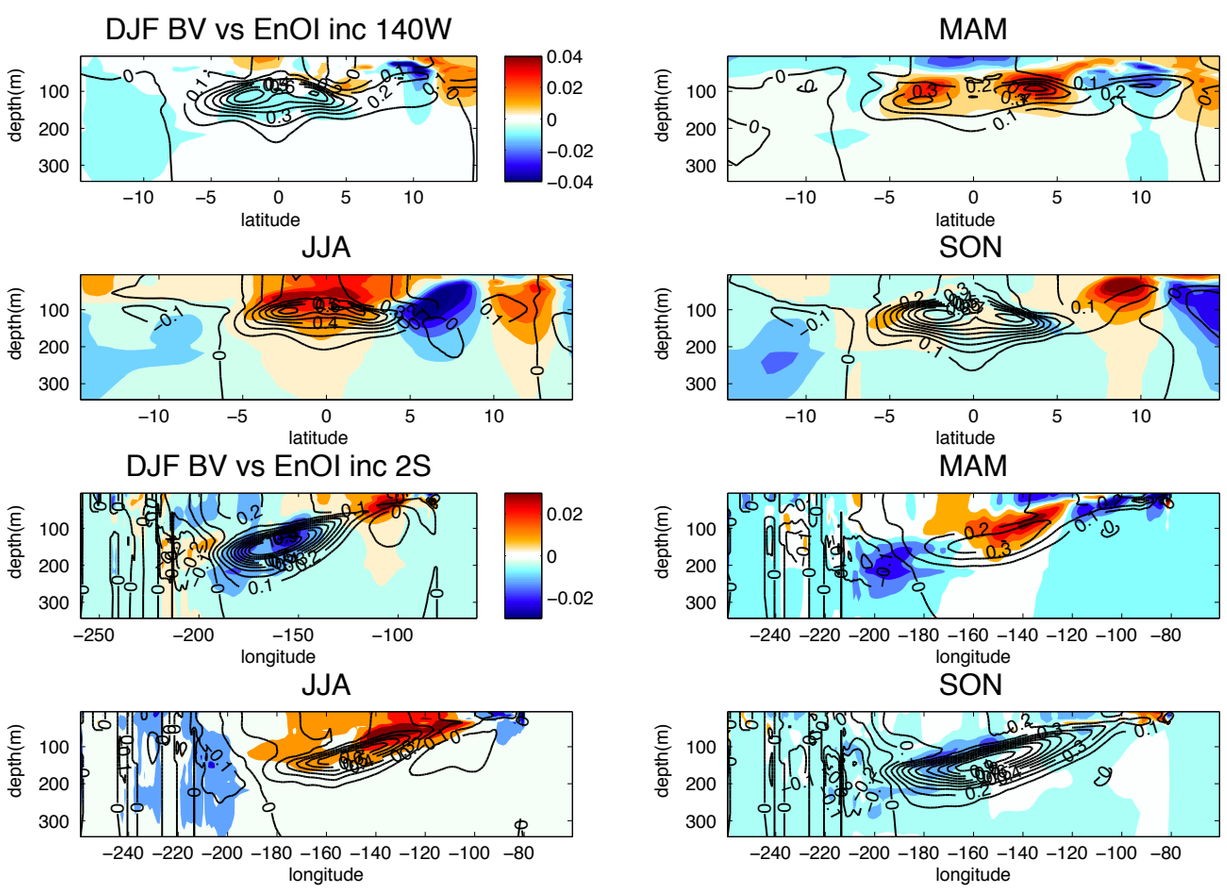
# Mean summer DJF cross covariance between ocean observations and atmosphere Along 140E and 2S




# Growth of disturbances due to associated with initial ocean forecast perturbations

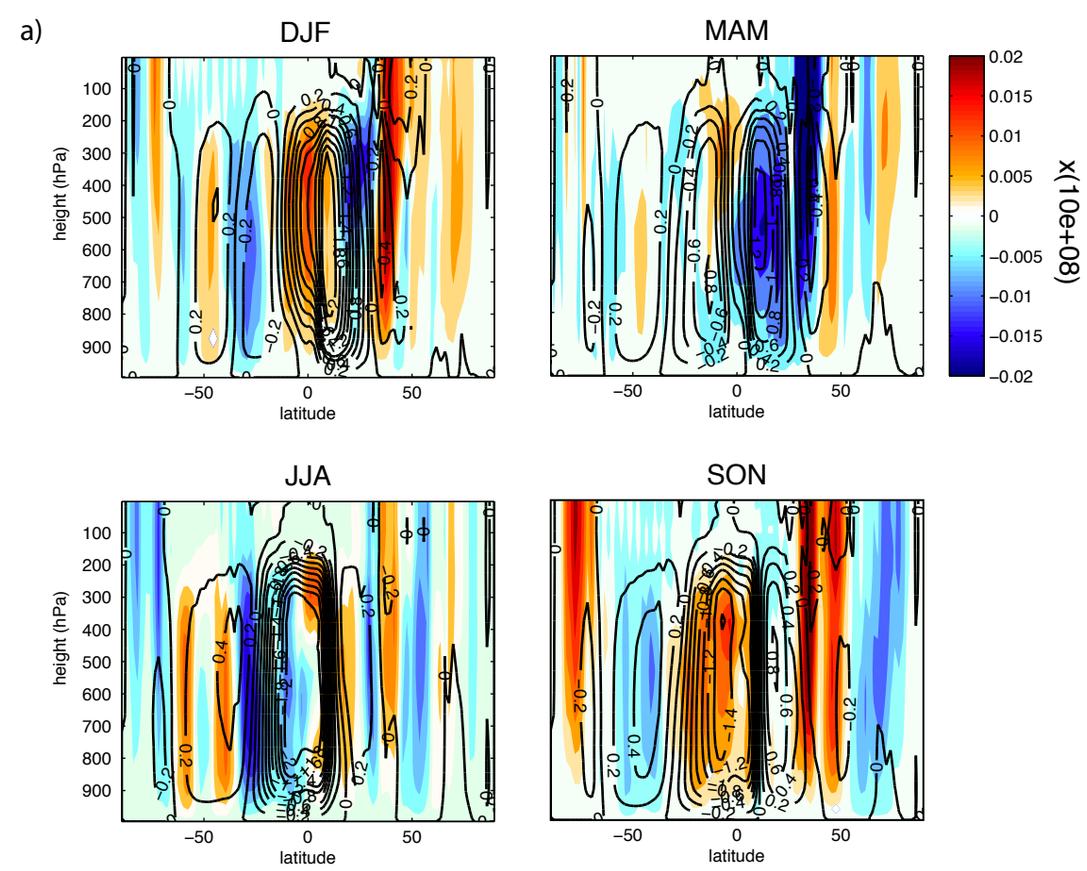
Temperature




Zonal mean meridional mass stream function

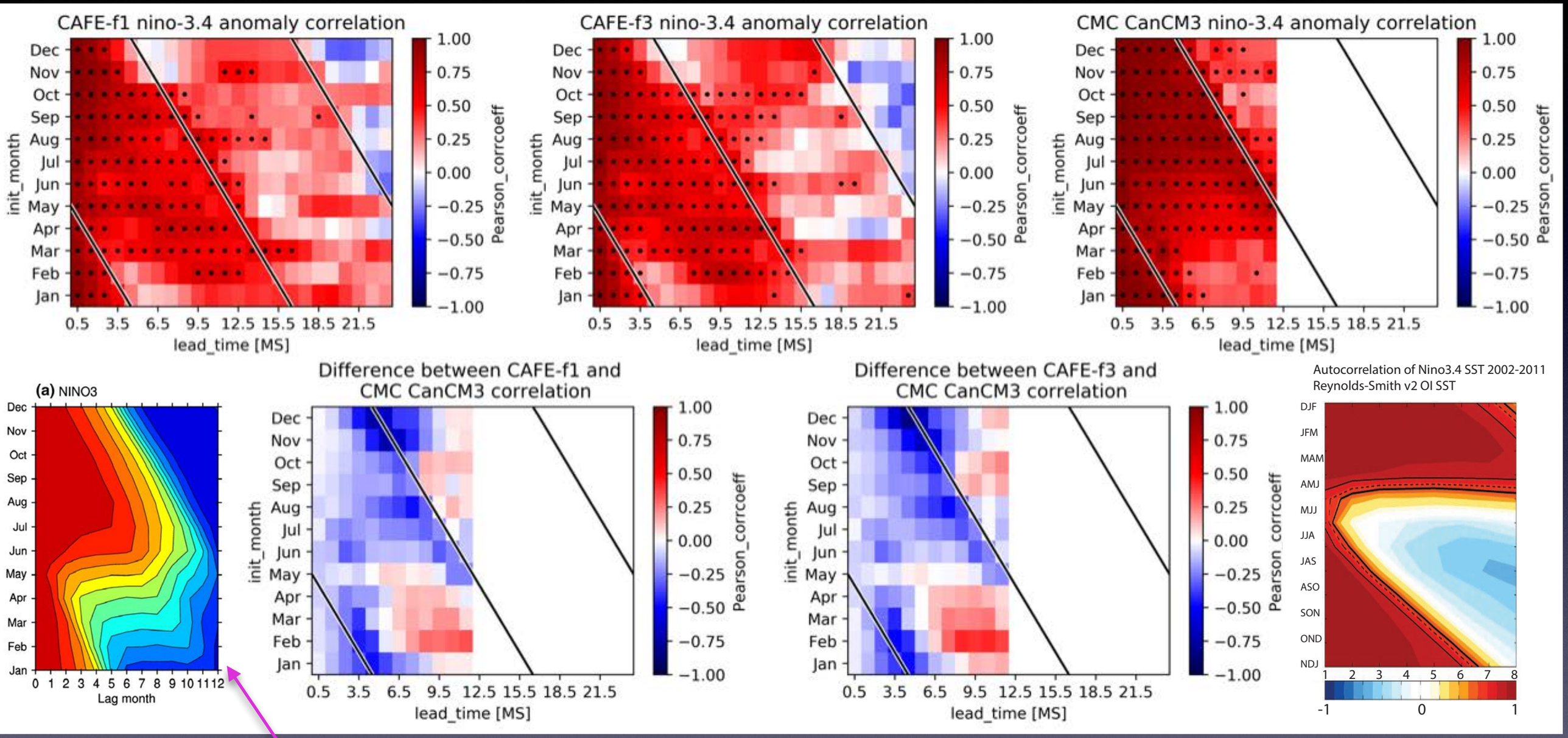
Cntrl (contours) vs BV avg (shaded)

20S-20N



# ENSO skill comparison

## Nino 3.4 anomaly correlation coefficients for CAFE BV and CanCM3 forecasts




Lagged auto-correlation coefficients of monthly Nino SST based on100 years of control simulation

Projection onto only those disturbances relevant to the Eq. Pacific thermocline enhances long range ENSO prediction

# ENSO-precipitation teleconnection and the IPO

Westra et al (J. Climate 2015): Examined issues when using smoothed data as a covariate to predict seasonal and annual precipitation. They looked at the apparent modulation of the ENSO-precipitation relationship by the IPO considering

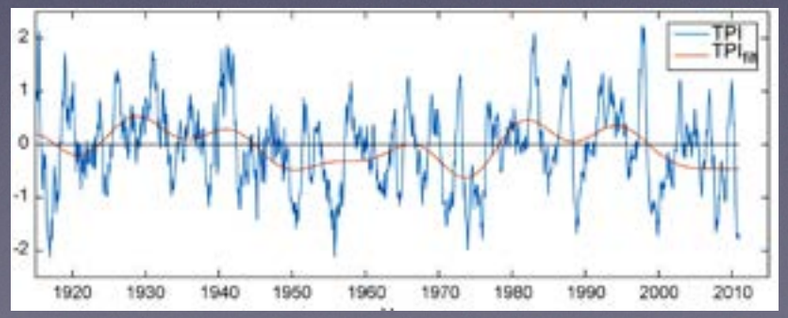
1. Artefacts introduced when using a predictor along with its smoothed version in developing predictor–response relationships,
2. stratifying according to the ENSO phase when the true ENSO– precipitation relationship is in fact continuous, and
3. assuming that a linear ENSO–precipitation relationship is modulated by the IPO when the true ENSO– precipitation relationship is nonlinear.
4. Identified correlations / regressions must be dynamically reasonable (see for example the PSA-ENSO teleconnection: O'Kane et al 2017 MWR)

*In the absence of the identification of a physical mechanism of how the IPO modulates the ENSO–precipitation relationship, the IPO index is not recommended as the basis for statistical modelling of seasonal or annual precipitation because of the potential for statistical artefacts when stratifying and using smoothed series to simulate the ENSO–precipitation relationship.*

*IS THE IPO THE BACKGROUND STATE OF ENSO?*

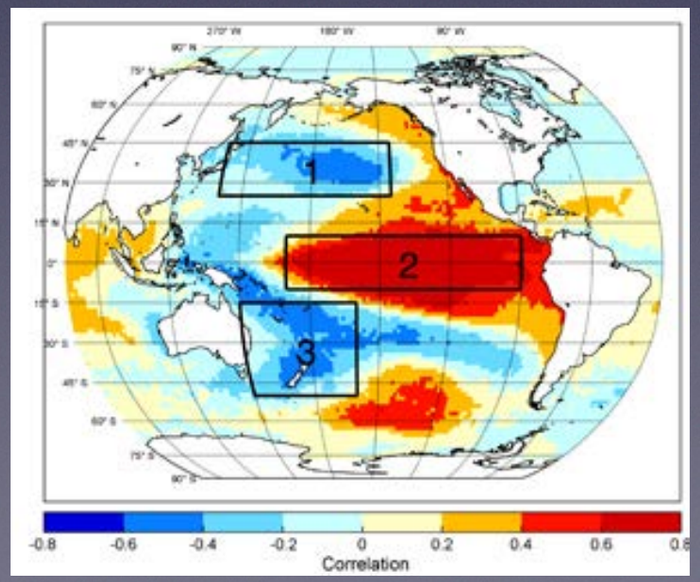
*IF YES ONE WOULD EXPECT SOME RELATIONSHIP BETWEEN DROUGHT FREQUENCY AND INTENSITY AND THE PHASE OF THE IPO.*

*IS THE IPO REALLY A PHYSICAL MODE OF VARIABILITY?*




TPI=T2 - 0.5(T1+T3)

Henley et al (2017)



# Drought and the IPO

MAJOR DROUGHTS IN AUSTRALIA http://www.abs.gov.au/

**1958 - 68**

**This drought was most widespread and probably second to the 1895-1903 drought in severity.**

**For more than a decade from 1957, drought was consistently prominent and frequently made news head-lines from 1964 onwards.**

**1982-83**

**This extensive drought affected nearly all of eastern Australia, and was particularly severe in south eastern Australia.**

**Lowest ever 11 month rainfall occurred over most of Victoria and much of inland New South Wales and central and southern Queensland.**

**2001-2009**

Millenium drought.

SEVERE DROUGHTS IN SOUTH-EASTERN AUSTRALIA

**1972-73**

**Most of Victoria, western and central New South Wales, South Australia and north eastern Tasmania**

**1996-2009**

**Reduced rain per frontal system, reduced cutoff rainfall associated with weaker blocking systems**

DROUGHTS IN AUSTRALIA OF LESSER SEVERITY

**1951 - 52**

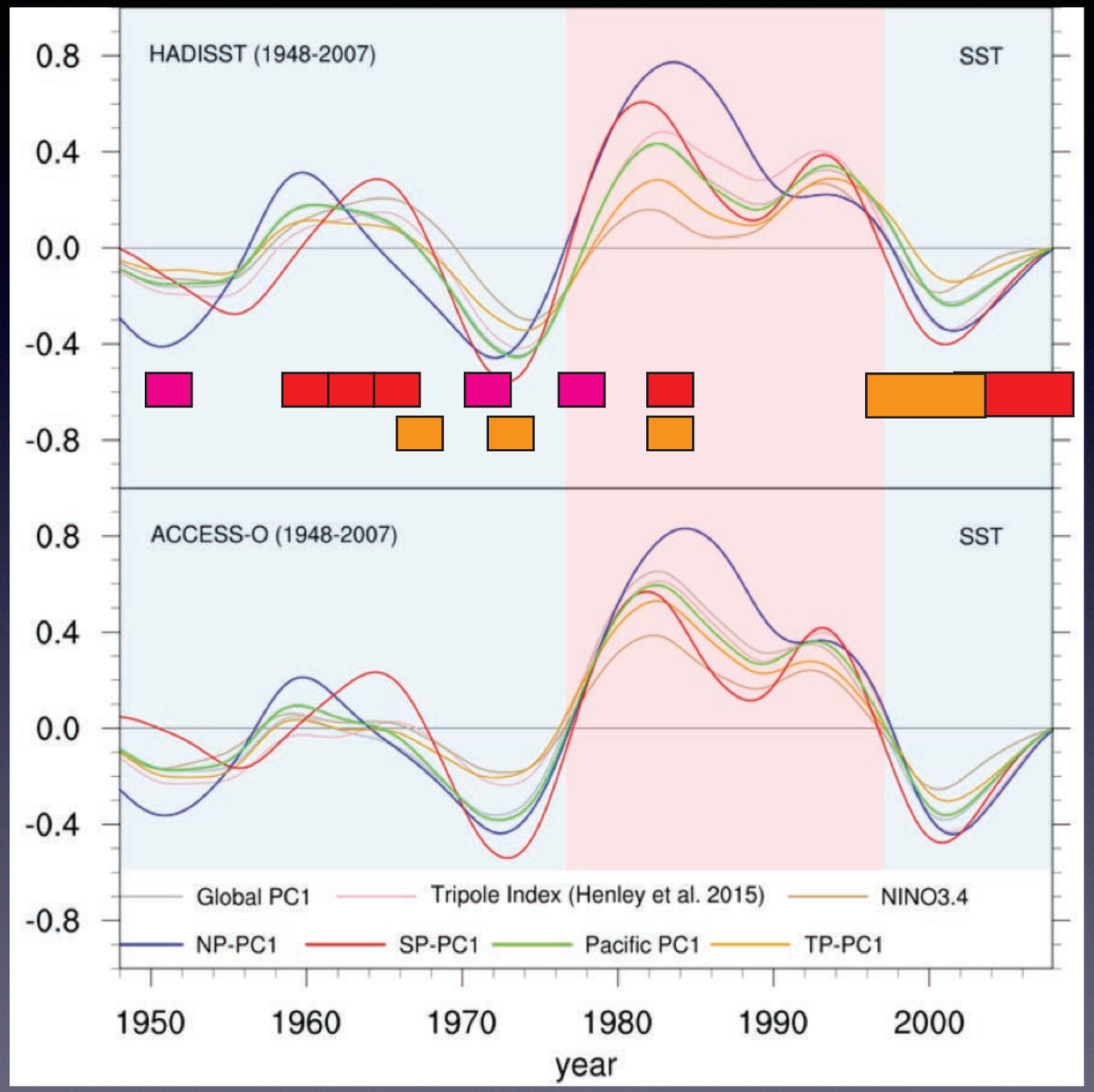
**Queensland and Northern Territory; and Western Australia, especially pastoral areas (1951-54).**

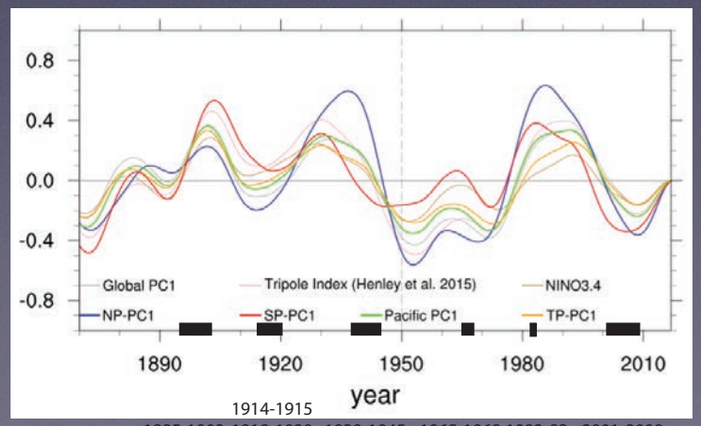
**1970 - 73**

**Prolonged drought over the north-eastern goldfields of Western Australia and adjacent areas.**

**1976**

**Western New South Wales, most of Victoria and South Australia due to failure of aut**umn-winter rains.




1914-1915

1895-1903 1918-1920 1939-1945 1965-1968 1982-83 2001-2009

Prediction of the changes in phase of the major climate teleconnections is hard!
We first need to understand the causal relationships between them.

We can develop models based on observational data or reanalysis to develop predictive linear stochastic models.

Such approaches are needed in addition to help advance forecast systems.

# Stochastic models is one approach

AR(n) models
(multi-) Linear regression
POPs / LIMs

BUT we need
Non-stationary nonparametric methods that can be applied to high dimensional data capable of identifying meta-stable states and the external covariates responsible for secular (regime) behaviour

**VARX – stochastic model** Horenko 2011, O'Kane et al 2013, 2015, 2017

The FEM-BV-VARX approximates dynamical processes by a stochastic model of the form:

$$x_t = \mu_t + A(t)\phi_1(x_{t-\tau}, \ldots, x_{t-m\tau}) + B(t)\phi_2(u_t) + C(t)\varepsilon_t \tag{1}$$

where $\Theta(t) = (\mu(t), A(t), B(t), C(t))$ is the vector of time dependent model parameters with mean $\mu(t)$. $\phi_1$ is in general a nonlinear function connecting present and past observations $(x_{t-\tau}, \ldots, x_{t-m\tau})$, but here we take it to be the linear autoregressive factor model. $\phi_2(u_t)$ is an external factor function, and $C(t)$ couples the non-parametric, independent and identicallly-distributed (i.i.d.) noise process $\varepsilon_t$ to the analysed time series (hereby modelling the impact of unresolved subgrid-scale effects). Time dependence of the model parameters $\Theta(t)$ is also induced by the influence of the unresolved scales and leads to regime transitions in many realistic systems.

# On Inference and Validation of Causality Relations in Climate Teleconnections

*Illia Horenko, Susanne Gerber, Terence J. O'Kane,*
*James S. Risbey and Didier P. Monselesan*

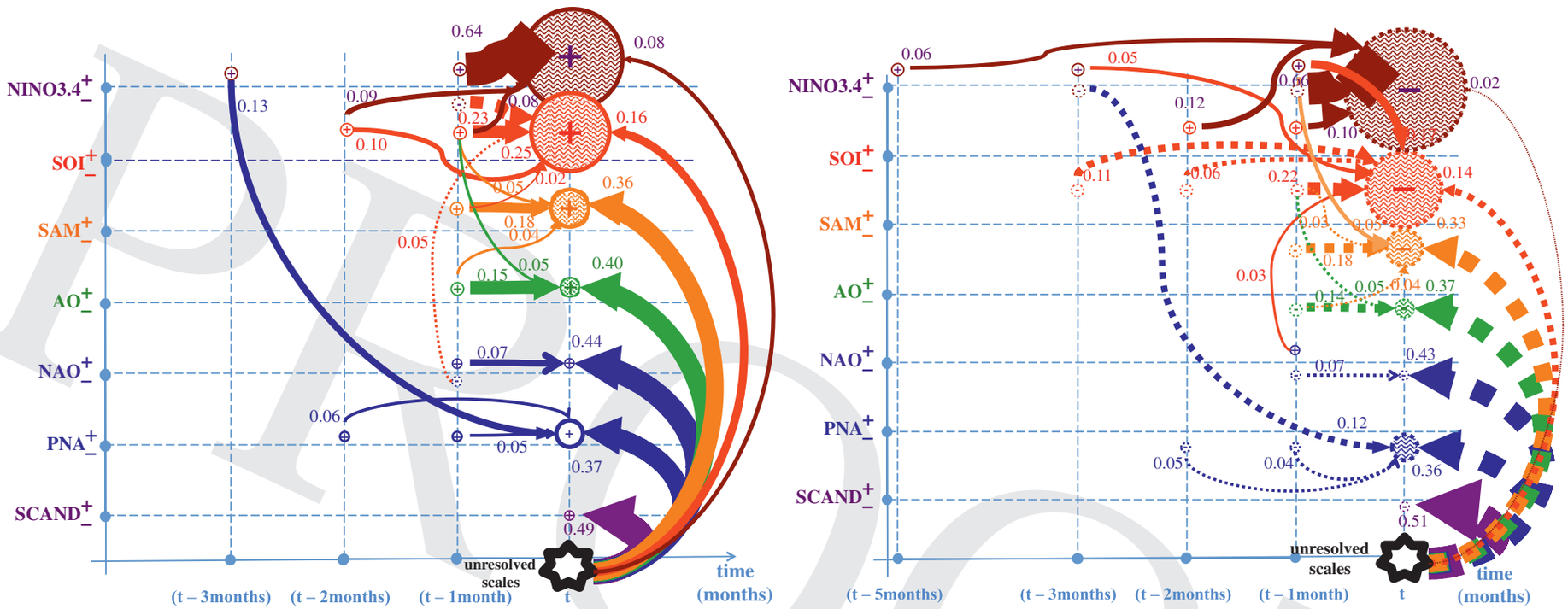
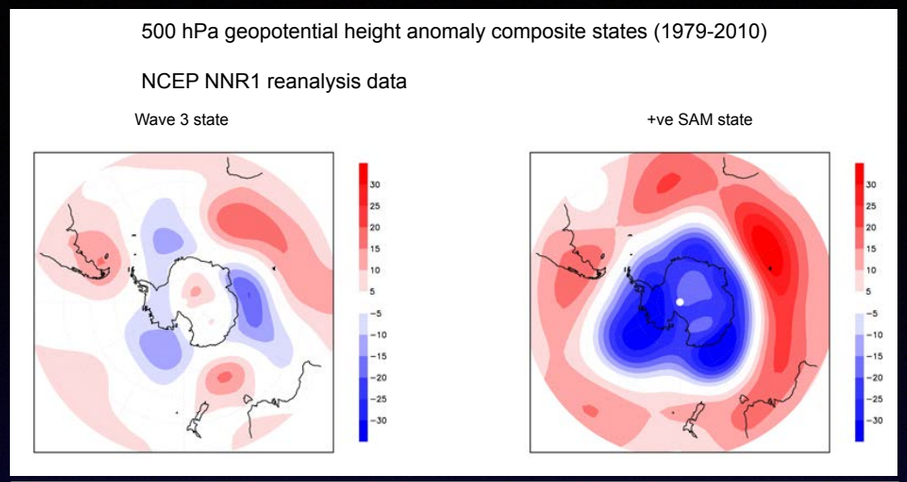
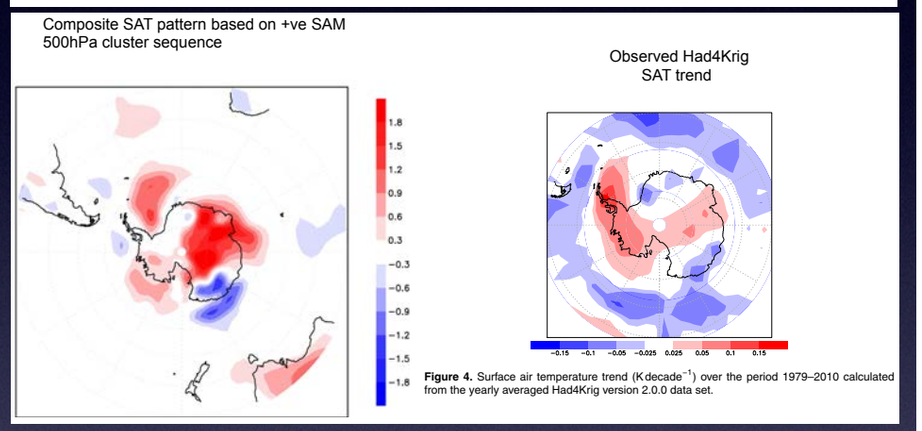
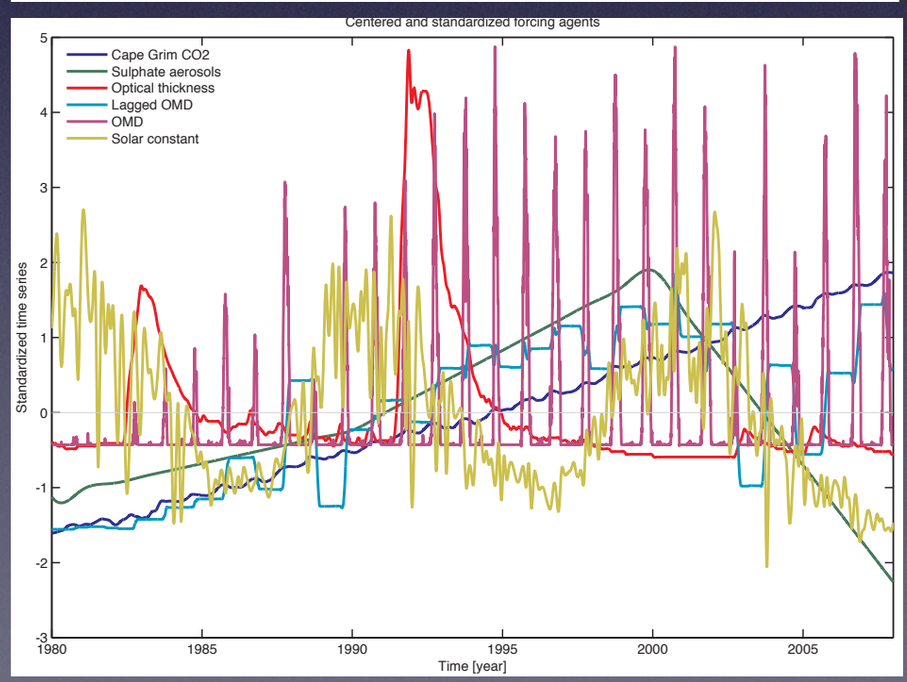



Figure 7.1 Optimal causality networks for explaining the positive (upper panel) and negative (lower panel) phases of the leading seven atmospheric teleconnections at time $t$ based on observations in the previous months. Bayesian causality relations induced by the positive teleconnection phases are shown as solid lines whereas causalities coming from the negative phases are marked as dotted lines. Presence of arrows in the graph means a presence of statistically significant Bayesian causality relations – for example a blue arrow from NINO3.4(+) to PNA(+) means a statistically significant conditional probability dependence of the form $\Lambda_{\mathrm{NINO3.4}^+(t-3)\rightarrow\mathrm{PNA}^+(t)} = \mathbb{P}\left[\mathrm{PNA}^+ \text{ at t} \mid \left(\mathrm{NINO3.4}^+ \text{at (t-3 months) and } u^t\right)\right] = 0.13$. Absence of arrows going from other edges in the past (e.g. from NINO3.4$^+$ at (t-1months)) to some particular edge at time $t$ (e.g. to PNA$^+$at t) means that this particular relation is not significant and that the observed dynamics of PNA$^+$at t can be completely explained without this information, e.g. without knowledge about NINO3.4$^+$at (t-1 months). Two essential sub-graphs of the positive phase network (the first sub-graph describing the relations for SOI($t$) and NINO3.4($t$), the second one for five other teleconnections) are shown in Fig. 7.4 (Appendix A7.2).

# SH Circulation changes coincident with change of IPO phase

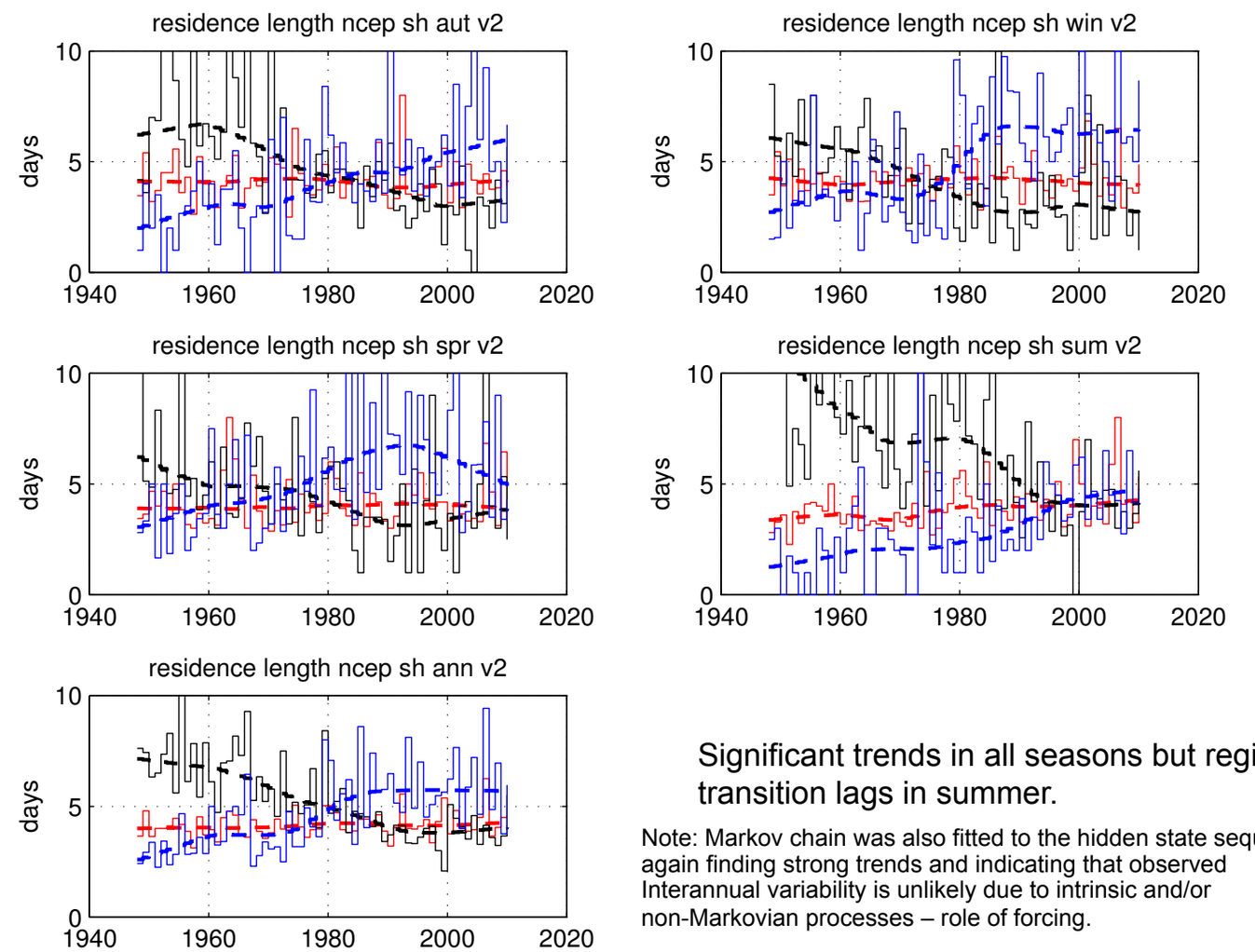



Residence length in blocked (black), SAM (blue) or transition (red) states: 500hPa NCEP reanalysis (5 day running average)

The dashed lines are LOESS smoothed fits to the time averaged data. The values of the yearly averaged data are shown by the solid lines.




Significant trends in all seasons but regime transition lags in summer.

Note: Markov chain was also fitted to the hidden state sequence again finding strong trends and indicating that observed Interannual variability is unlikely due to intrinsic and/or non-Markovian processes – role of forcing.

O'Kane et al 2013, 2015, 2017; Franzke et al 2015

Prediction must be based on identification of causal relationships between climate modes and projection onto the relevant error modes that determine predictability.

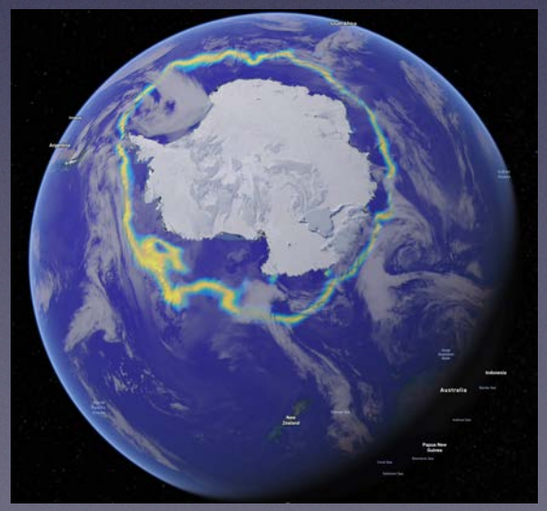
Our lack of predictive capability of the causal relationships between the major climate teleconnections, even taking into account model deficiencies, is the primary limitation on longer term forecast skill for drought.

CAFE88 coupled ensemble reanalysis:

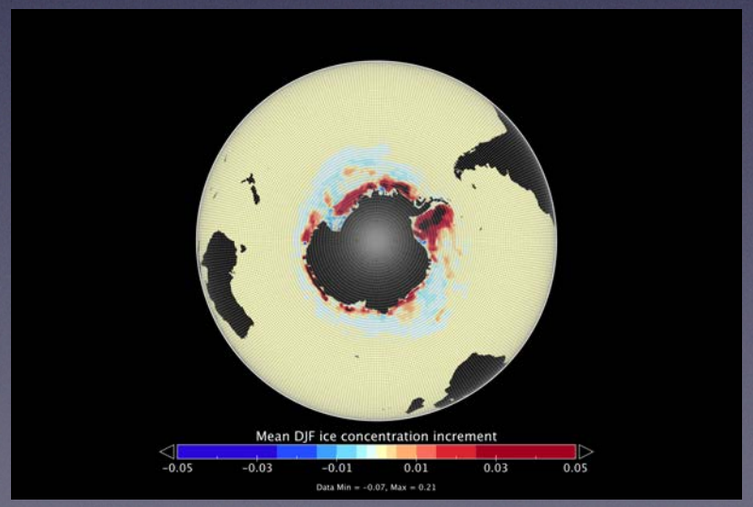
ETKF 96 members
1988-2018 Daily resolution
Assimilation of ocean - sea ice - atmosphere - BGC observations
Ensemble saved for all 2D AND 3D variables
comprehensive error statistics w.r.t. observations

Aim: to provide a probabilistic state estimation whose statistics come from a dynamically consistent data set for understanding climate variability and extremes.

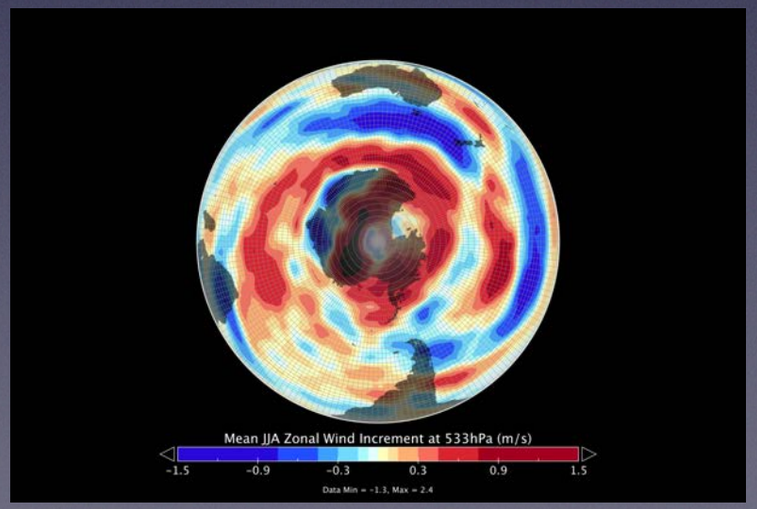
Aim: to provide initial conditions for assessing forecast skill and model biases over the near term climate.



ensemble spread 2014-06-06

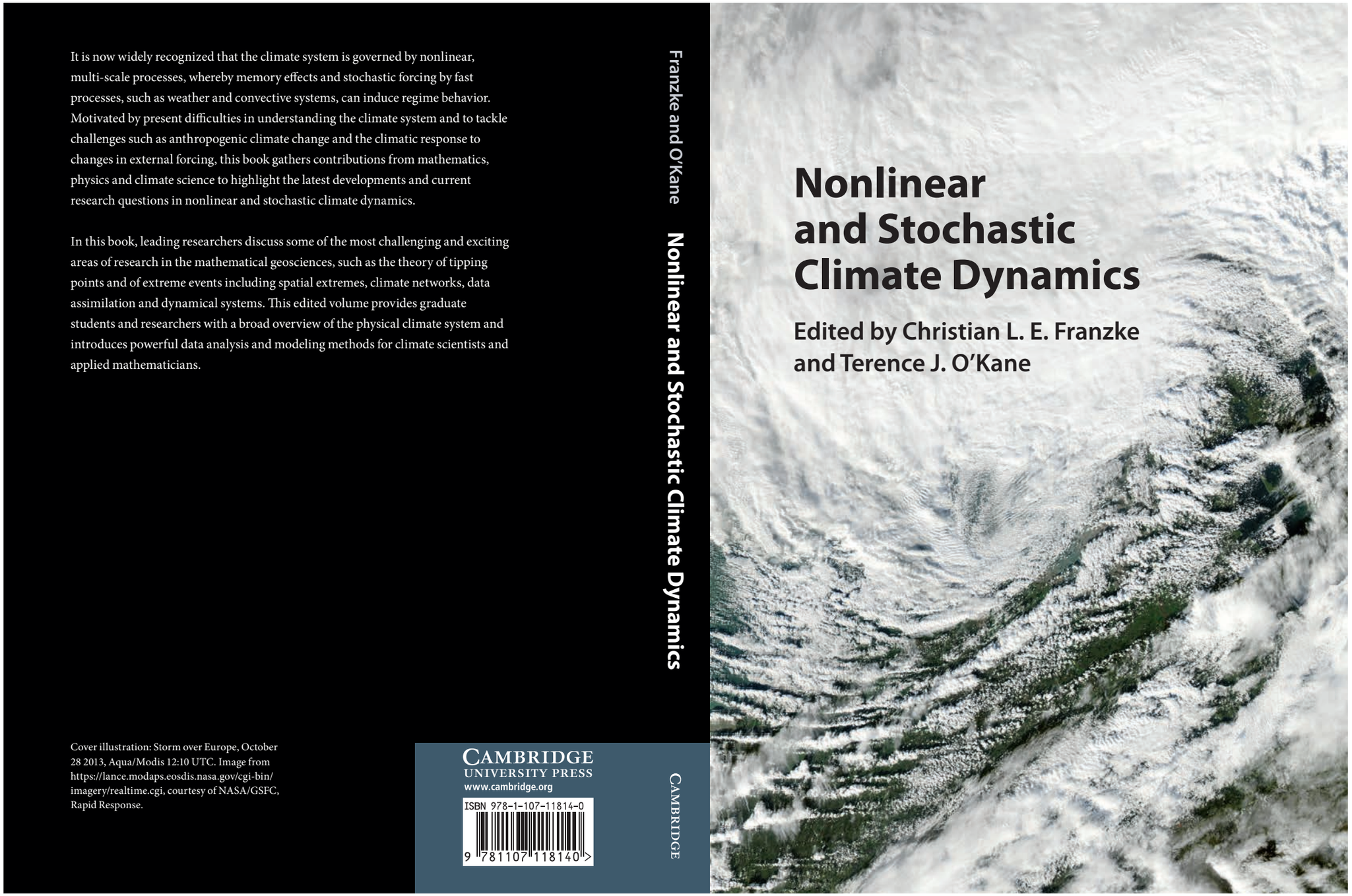



**Mean DJF ice concentration increment**




**Mean JJA zonal wind increment**

# Thank you



It is now widely recognized that the climate system is governed by nonlinear, multi-scale processes, whereby memory effects and stochastic forcing by fast processes, such as weather and convective systems, can induce regime behavior. Motivated by present difficulties in understanding the climate system and to tackle challenges such as anthropogenic climate change and the climatic response to changes in external forcing, this book gathers contributions from mathematics, physics and climate science to highlight the latest developments and current research questions in nonlinear and stochastic climate dynamics.

In this book, leading researchers discuss some of the most challenging and exciting areas of research in the mathematical geosciences, such as the theory of tipping points and of extreme events including spatial extremes, climate networks, data assimilation and dynamical systems. This edited volume provides graduate students and researchers with a broad overview of the physical climate system and introduces powerful data analysis and modeling methods for climate scientists and applied mathematicians.

Cover illustration: Storm over Europe, October 28 2013, Aqua/Modis 12:10 UTC. Image from https://lance.modaps.eosdis.nasa.gov/cgi-bin/imagery/realtime.cgi, courtesy of NASA/GSFC, Rapid Response.

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Franzke and O'Kane

Nonlinear and Stochastic Climate Dynamics

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