Estimation of Natural Variability and Detection of Anthropogenic Signal in Summertime Precipitation in La Plata Basin

Marcelo Barreiro – Stefanie Talento

Talento and Barreiro (2012)

Facultad de Ciencias
Universidad de la República, Uruguay

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Background

- Decision makers need information on 20-30 years time scale.
- Most CC studies tend to focus on changes for the end of the 21st century.
  - Main reason: internal climate variability obscures radiatively forced signal.
- We need to develop methodologies that allow to attribute a certain change to forcing.

Quantification of Natural Variability

3 approaches:

- Analysis of Instrumental Records
  Short time series,contamination by anthropogenic signals, not available in every region of the planet, etc.

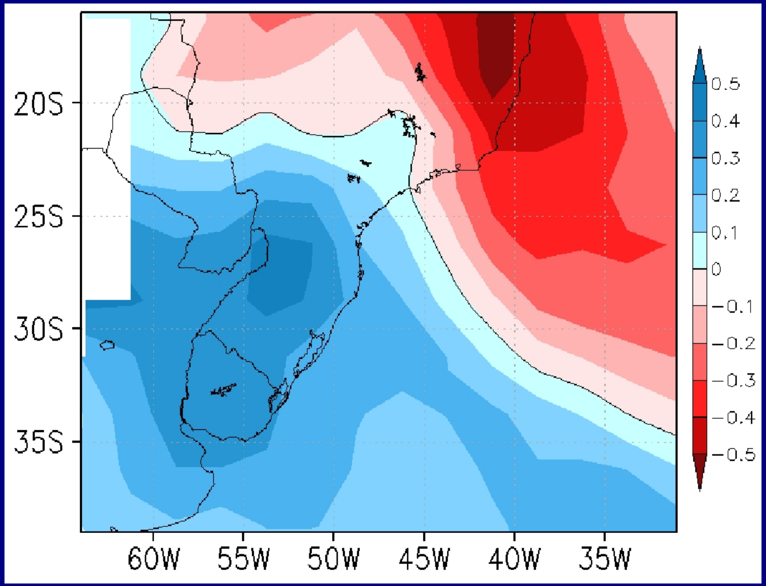
- Analysis of paleoclimate proxies
  Lack of accuracy, not available in every region, etc.

- Analysis of climate models
  - Different initial conditions
  - Operated in a control-run mode (without anthropogenic forcing)

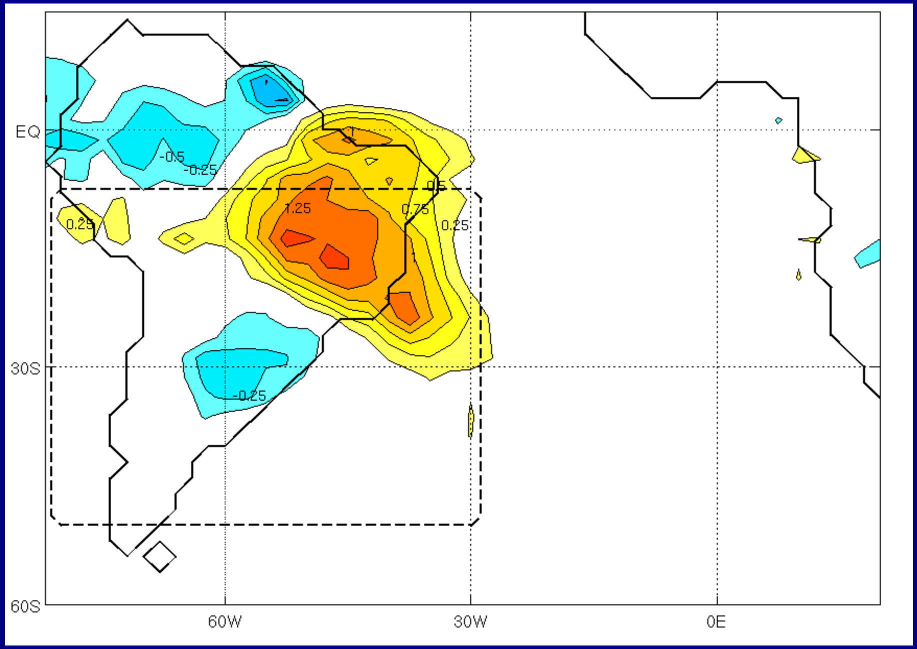
    Are they able to reproduce the low-frequency variability in the variable and region of interest?

Case study

Under radiative forcing summertime precipitation in South America will change characterized by a dipole structure (CMIP3, CMIP5).



That rainfall change pattern has been related to a change in the occurrence of the positive and negative phases of the leading summertime pattern of interannual variability (Junquas et al. 2011).



Question

When does the forced CC signal raise above the internal variability?

Or

When does the pdf change?

Data

Observations:

- Sea Surface Temperature (SST): NOAA_ERSST_V3.
- Precipitation: Arkin-Xie, 1979-2009.

HadCM3 model:

HadCM3 IPCC-AR4:

- Pre-industrial
- 20th century
- SRES A1B scenario: 21st and 22nd centuries

Methodology:

1. Determination of pattern of study:

   EOF1: Obtained as the first EOF of DJF precipitation in South America, in the HadCM3 20th century run.

2. Model validation:

   Comparison of EOF1 against observed analogous.

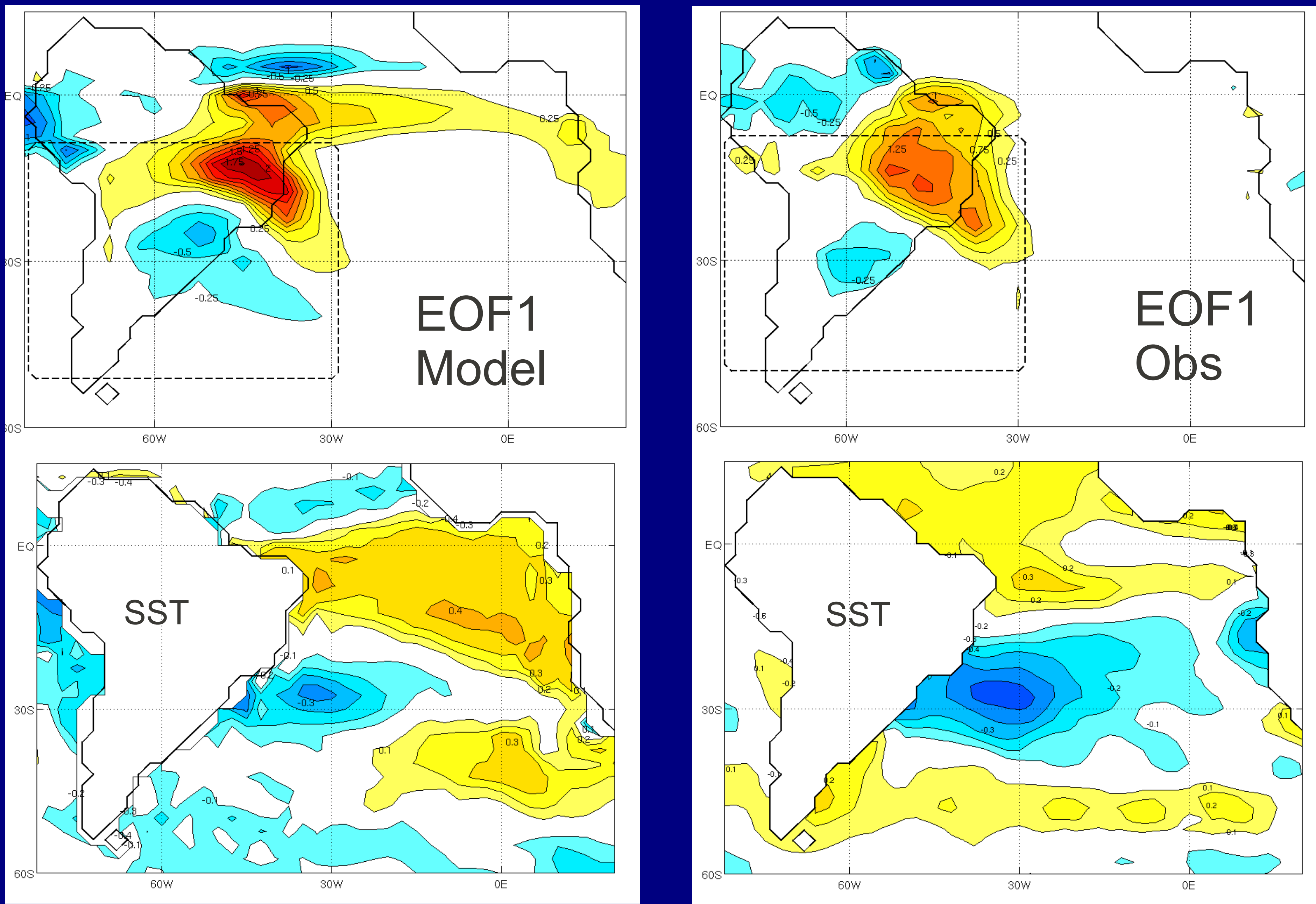
3. Quantification of EOF1 variability under NO external forcing:

   Project HadCM3 pre-industrial (NO external forcing) precipitation anomalies onto EOF1 spatial pattern.

4. Detection of Anthropogenic Signal

   Project HadCM3 A1B scenario precipitation anomalies onto EOF1 spatial pattern.

1. - 2. Model validation: EOF1 and correlation with SST.



3. Quantification of EOF1 variability under NO external forcing: Pre-industral run

Project HadCM3 pre-industrial (NO external forcing) precipitation anomalies onto EOF1 spatial pattern.

- **341 years time-series**
- **PDF (Probability Density Function) Analysis**

Climate System:

Nonlinear dynamical system with multiple states.

Shift between states: stochastic forcing

$$dz = -U'(z)dt + \sigma dW,$$

z: Climatic Variable (time series of EOF1)
W: Standard random walk process
U: Potential
σ: Noise

Under stationary conditions:

One-to-one correspondence between U and the pdf (p_d):

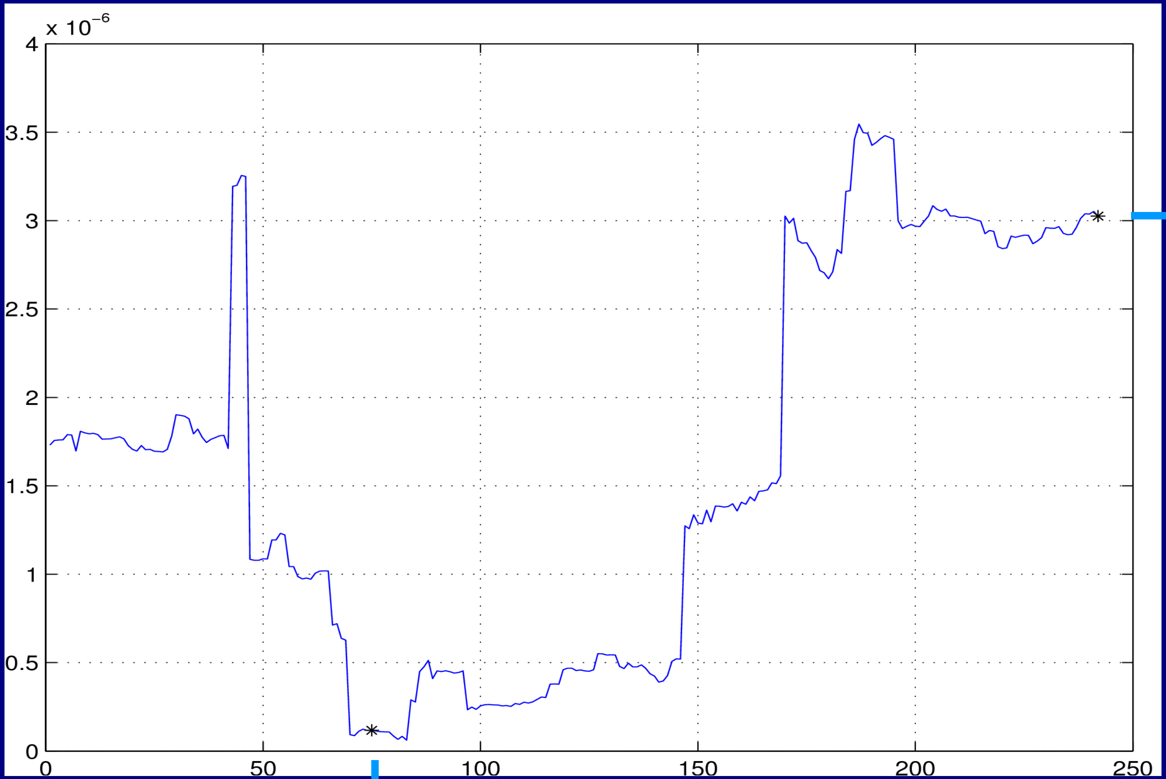
$$U = \frac{-\sigma^2}{2} \log p_d,$$

[Livina et. al, 2010]

3. Quantification of EOF1 variability under NO external forcing: Pre-industral run

We assume U can be expressed as a 4th-order polynomial (with no independent term).

4th order coefficient of pdf potential, considering 100-years window.



Period with large 4th order coefficient

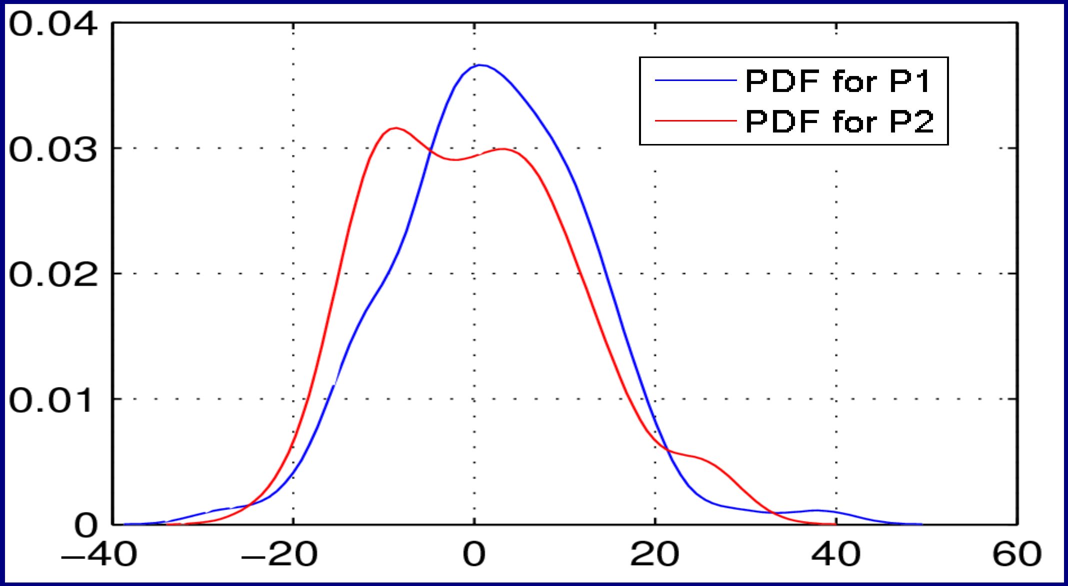
Period with small 4th order coefficient

3. Quantification of EOF1 variability under NO external forcing: Pre-industrial run

We identify 2 periods of different behaviour:

P1: years 75-174: EOF1 has Unimodal distribution

P2: years 242-341: EOF1 has Bimodal-wide distribution

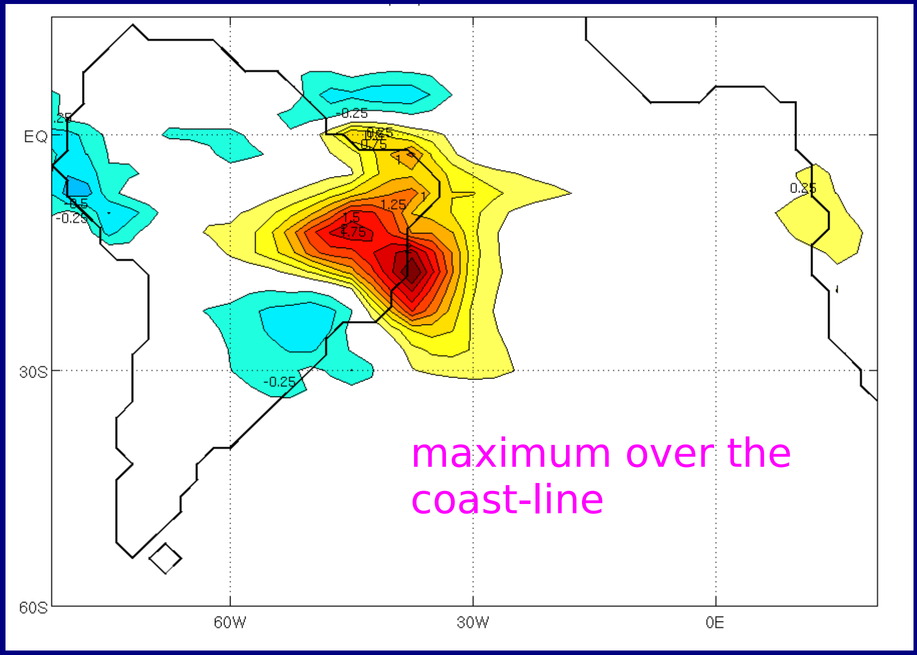


The distributions in P1 and P2 are statistically different according to a Kolmogrov test (10% level of confidence).

PDF of EOF1 in P1 (years 75-174) and in P2 (years 242-341).

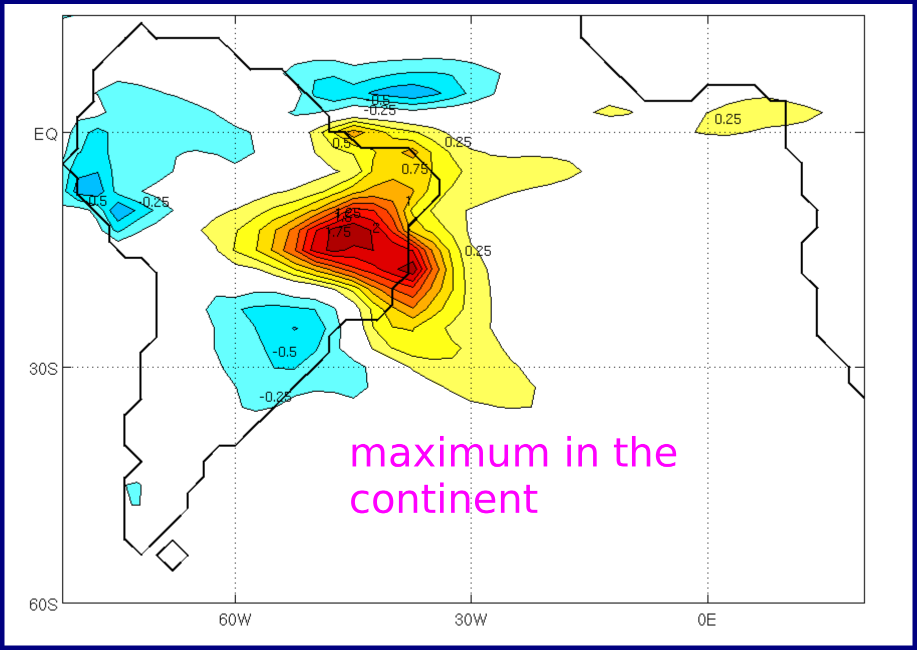
3. Quantification of EOF1 variability under NO external forcing: Pre-industral run

EOF1, HadCM3 pre-industrial P1



EOF1 pattern during P1.
Contour interval: 0.25 mm/day.

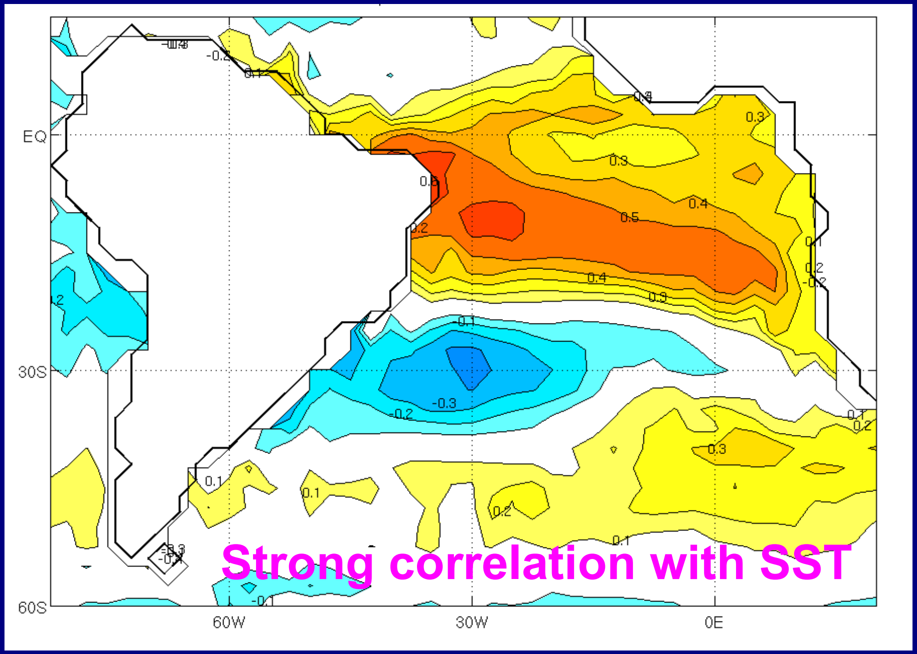
EOF1, HadCM3 pre-industrial P2



EOF1 pattern during P2.
Contour interval: 0.25 mm/day.

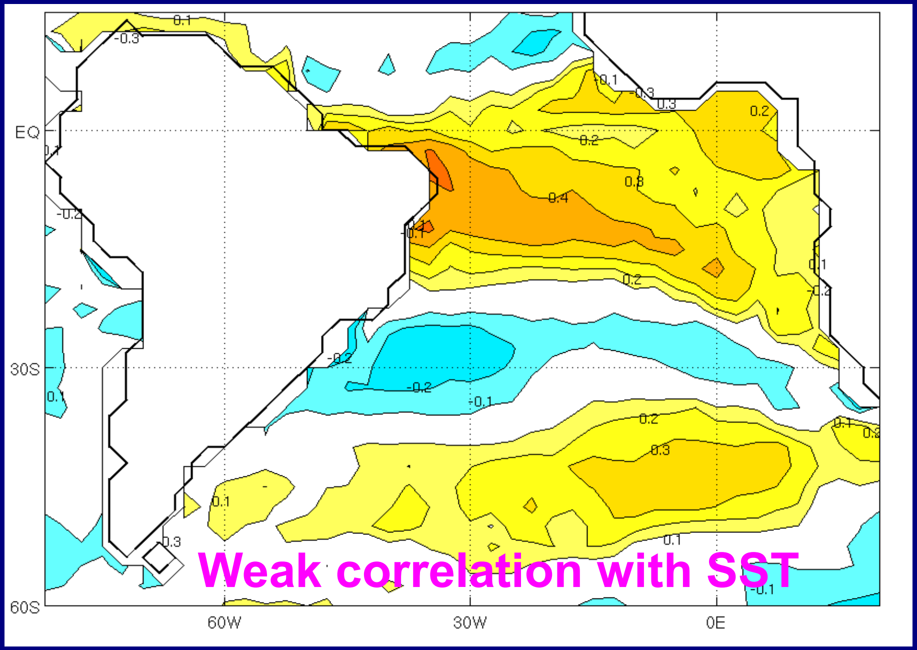
3. Quantification of EOF1 variability under NO external forcing: Pre-industrial run

EOF1, HadCM3 pre-industrial P1



Correlation between EOF1 time series and SST during P1. Contour interval: 0.1.

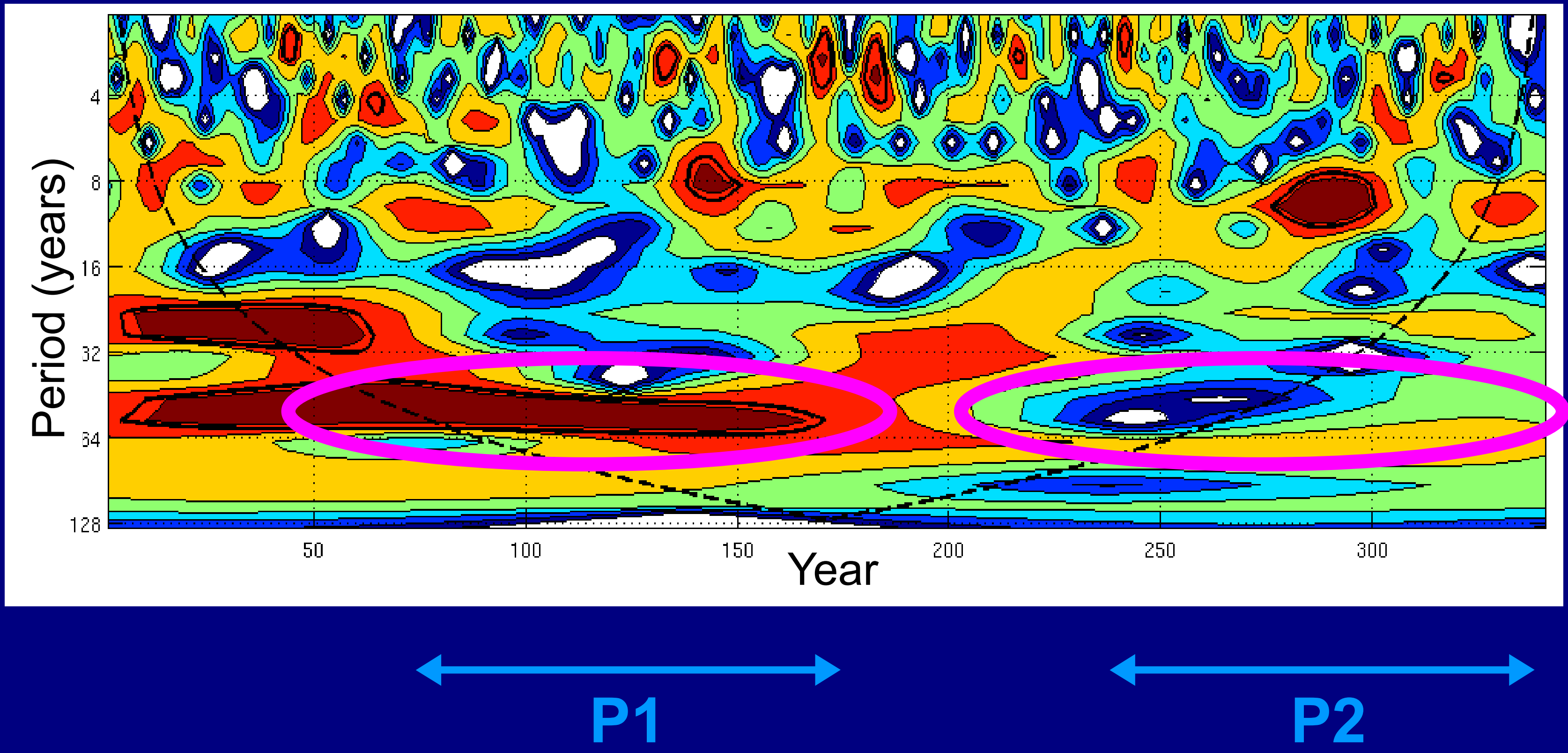
EOF1, HadCM3 pre-industrial P2



Correlation between EOF1 time series and SST during P2. Contour interval: 0.1.

3. Quantification of EOF1 variability under NO external forcing: Pre-industrial run

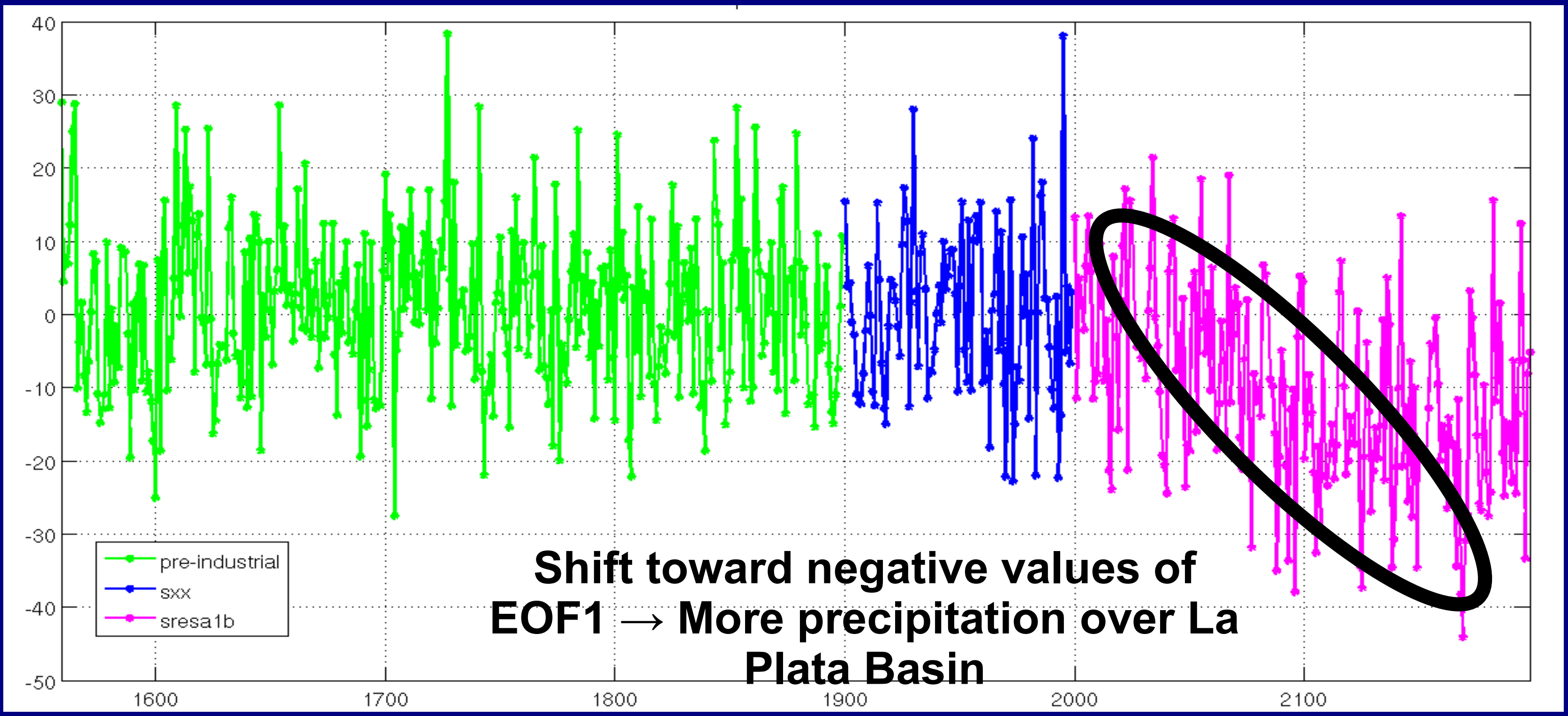
Wavelet frequency analysis: EOF1 in pre-industrial era



Period P1 coincides with a period of low frequency variability (also seen in the ocean) → consistent with maximum over ocean.
Period P2 shows no preferred time scale → consistent with maximum over land.

4. Detection of Anthropogenic Signal: A1B Scenario

Evolution of EOF1 in HadCM3



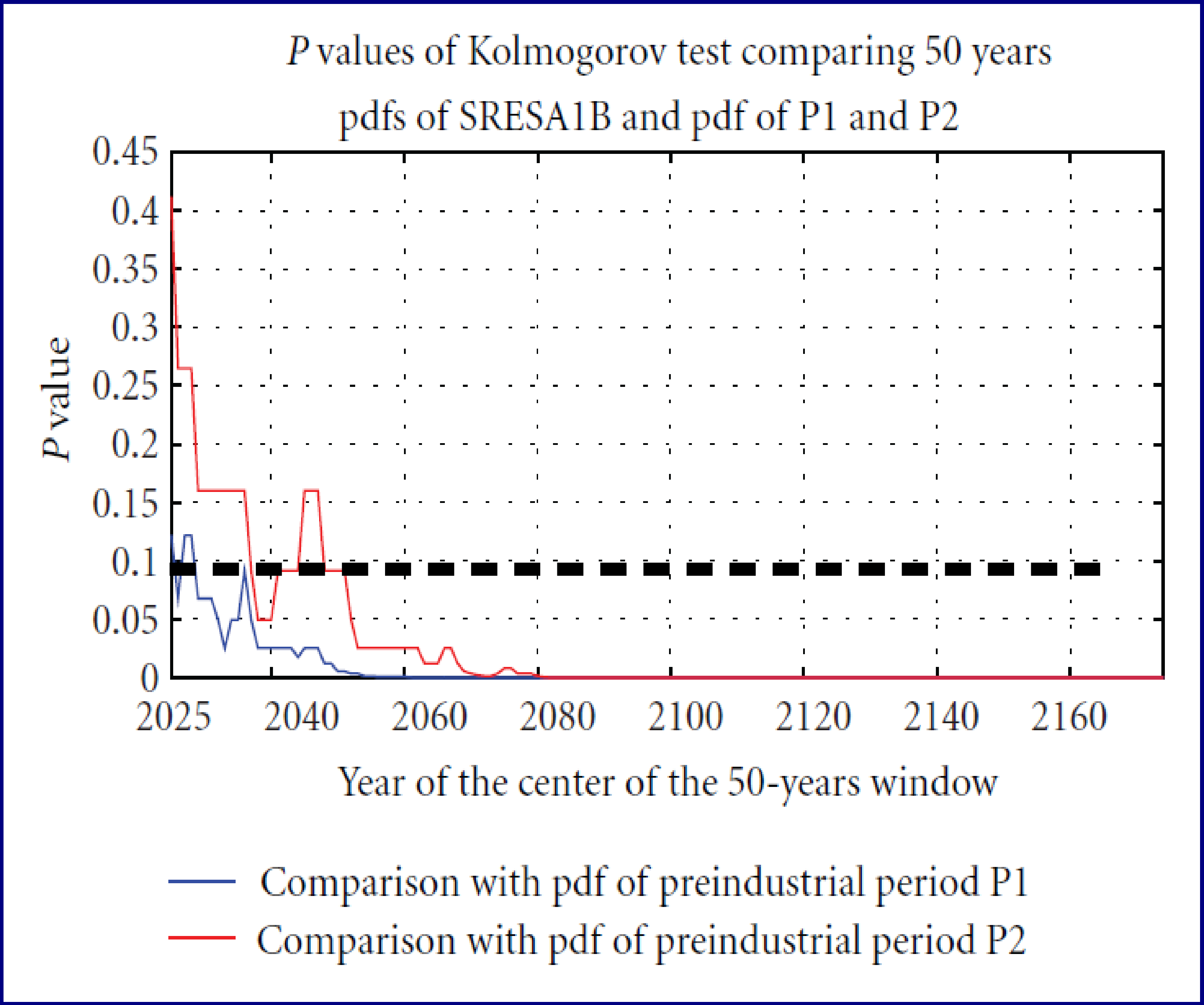
4. Detection of Anthropogenic Signal: A1B Scenario

How do we determine when certain variability is not natural?

Comparing against the variability found in the pre-industrial run.

Problem: Should we compare with the variability found in P1 or P2?

4. Detection of Anthropogenic Signal: A1B Scenario



PDFs calculated using 50-years sliding windows

With P1: Differences are detected after 2029

With P2: Differences are detected only after 2048!!

Summary

The proposed methodology allows to determine horizon of detection of CC above internal climate variability.

The existence of two possible internal variability regimes (and pdfs) in the model results in different time horizons of when the anthropogenic signal will become evident.

Having estimations of the natural internal variability of the system is extremely important in order to determine the impacts of anthropogenic forcing, particularly on horizons of 20-50 years.

To conclude...

Deser et al (2012): “As climate models improve, decision-makers' expectations for accurate climate predictions are growing. Natural climate variability, however, poses inherent limits to climate predictability and the related goal of adaptation guidance in many places, as illustrated here for...” South America.

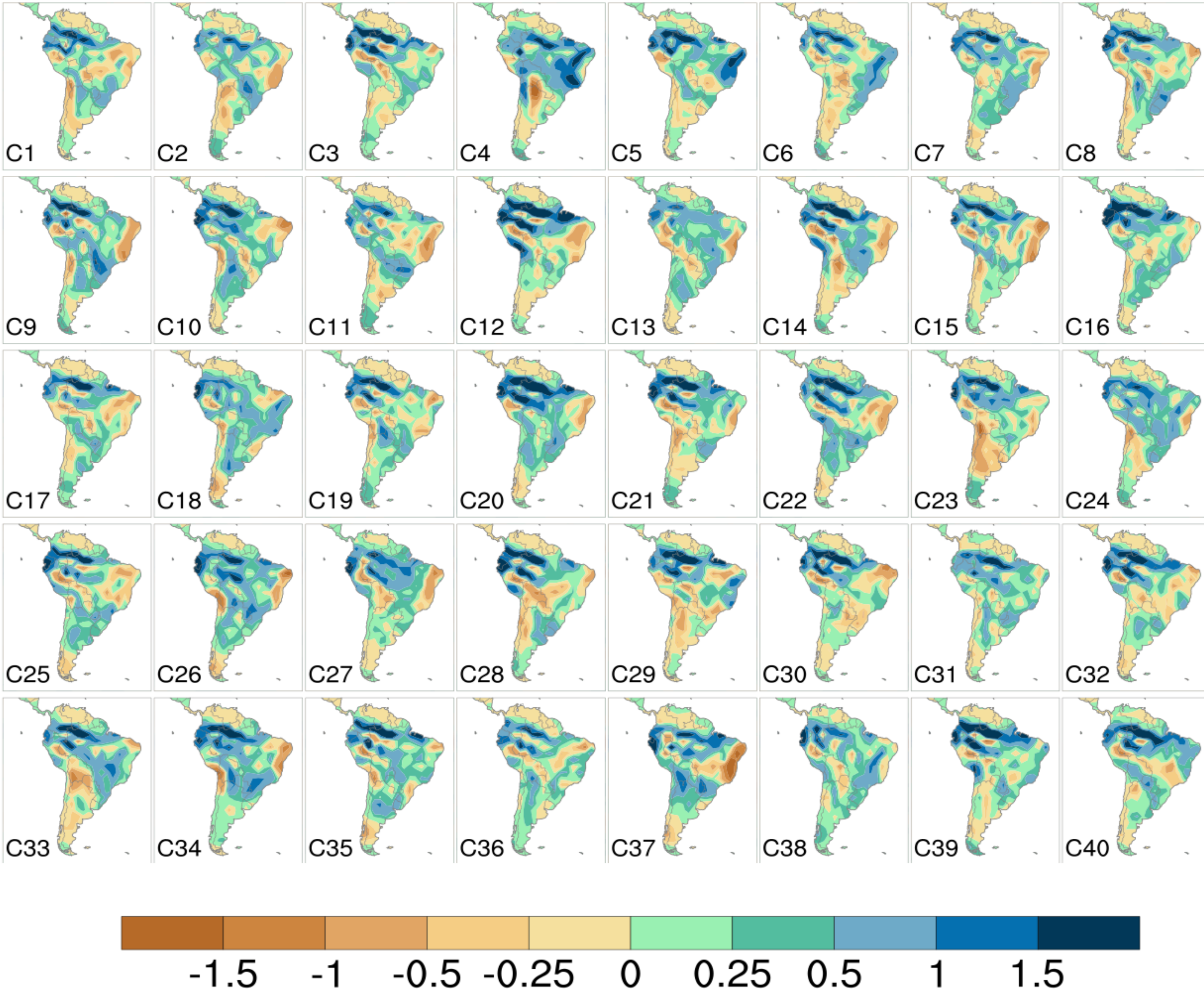
Experiment:

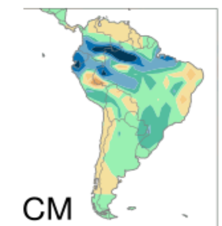
40 member ensemble, CCSM3, A1B.

Identical initial conditions in the oceans, land and sea ice.

Slightly different initial conditions in atmosphere.

DJF Precip Trend 2010-2060



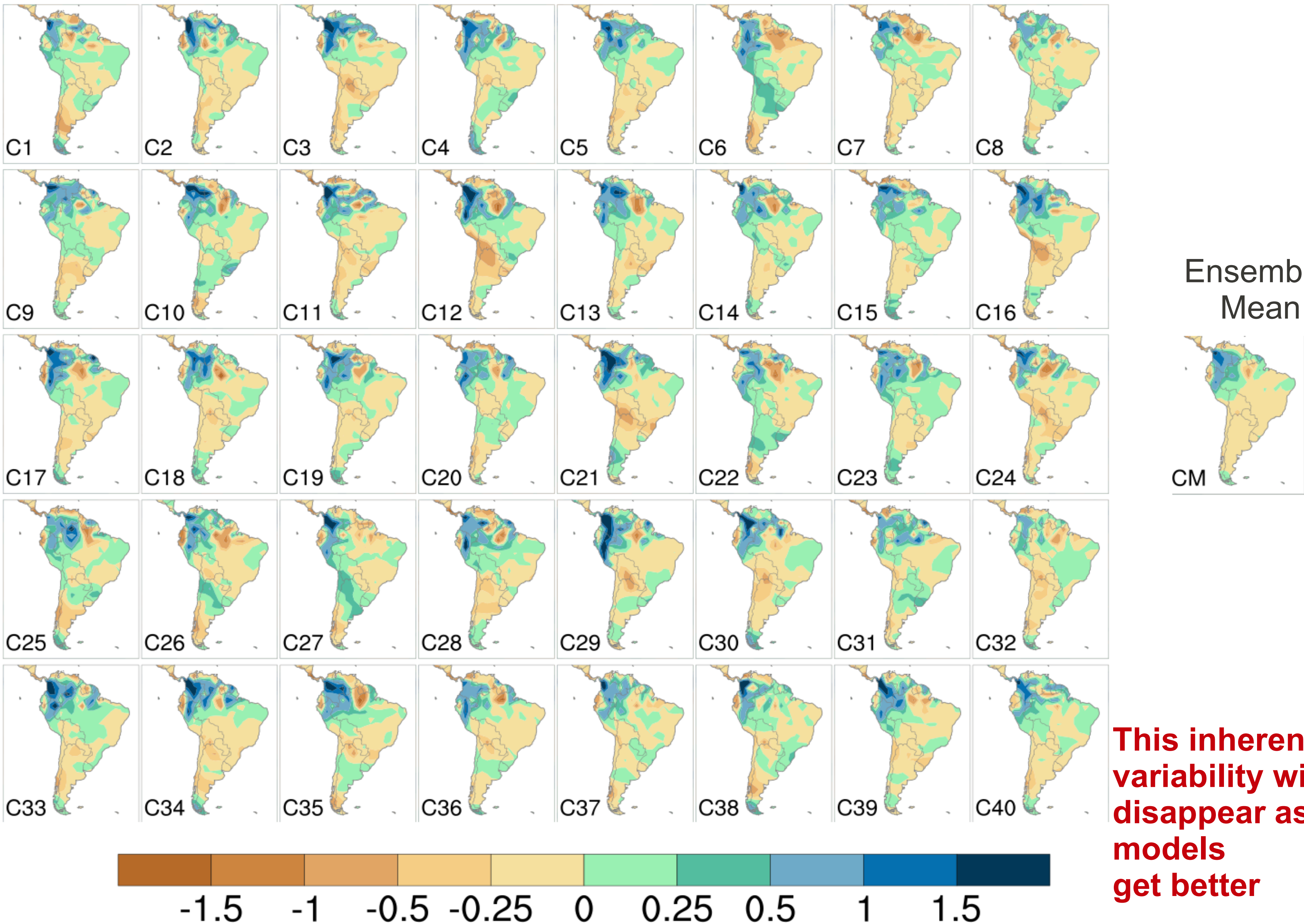


Ensemble Mean

Individual realizations can look very differen from the E.M.

Courtesy: C. Deser, NCAR

JJA Precip Trend 2010-2060



This inherent variability will not disappear as models get better

Courtesy: C. Deser, NCAR

Premonition?
Mafalda in yesterday's El Comercio

"Fantastic!"

"A meteorological observatory in England has electronic machines to forecast weather!"

"Great! Finally they have been able to automatize to make a fool of themselves!"

Mafalda is from the 1960s...

We really need to focus on impact studies on seasonal time scales, because it allows regular comparison with observations → only way to improve!

Quantification of EOF1 variability under NO external forcing: Pre-industral run

Physical mechanism explaining differences in pre-industrial EOF1 distributions in P1 and P2:

Periods of high EOF1-SST correlation (P1):

The SACZ maximum is over the Ocean

→ Increased cloudiness induces negative SST anomalies south of 15ºS

→ SST anomalies force oceanic part of SACZ

→ Negative feedback

→ Bounded anomalies

→ Unimodal PDF for EOF1.

Periods of weak EOF1-SST correlation (P2):

Absence of SST negative feedback

→ The anomalies can reach higher amplitudes

→ Wider PDF → Bimodal PDF for EOF1.