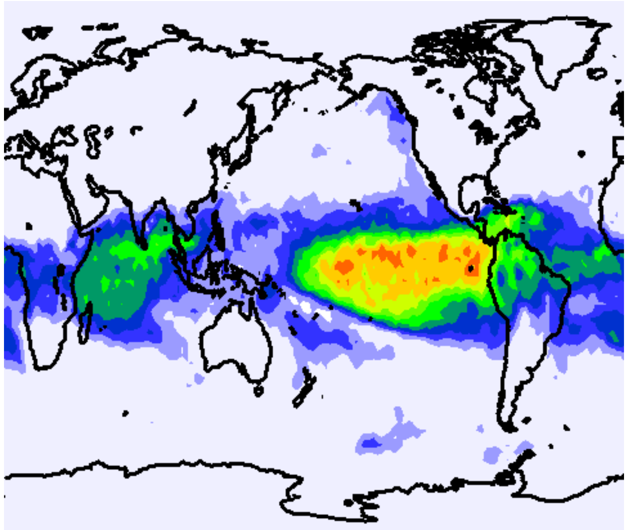

What have we learned about our climate by using networks and nonlinear analysis tools?

Cristina Masoller

Universitat Politecnica de Catalunya

www.fisica.edu.uy/~cris

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LINC conference
Wien, April 2015

"LINC" ITN
Learning about Interacting Networks in Climate

The LINC project

- Climatelinc.eu
- FP7-PEOPLE-2011-ITN-289447
- 6 academic partners + 3 companies
- 12 PhDs + 3 postdocs
- December 1st 2011 - November 30th, 2015
- Budget: 3.7 M€

Partners

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IMAU Institute for Marine and Atmospheric research Utrecht

IFISC

FACULTAD DE CIENCIAS UDELAR fcien.edu.uy

VORTECH BV THE SCIENTIFIC SOFTWARE ENGINEERS

climate risk analysis mudelsee

ambrosys

PIK POTSDAM INSTITUTE FOR CLIMATE IMPACT RESEARCH

Bar-Ilan University

LINC goals

- To train the researchers in the complete set of skills needed to undertake a career in physics and geosciences with expertise in climatology, complex systems and data analysis.

- To develop long-lasting collaborations.

Results

- About 25 published or accepted papers, available at climatelinc.eu

- The journals reveal the interdisciplinary nature of the LINC project: PRL, GRL, Nonlinear Processess in Geophys., Chaos, Entropy, etc.

- Software and database also available in our web page.

- 1 thesis completed (Ignacio Deza, UPC, 2/2015), several are scheduled for the next months.

Training Events

- First LINC school (Mallorca, Spain, September 2012)
- Second LINC school and Workshop 1 (The Netherlands, April 2013)
- Workshop 2 (Potsdam, Germany, November 2013)
- Workshop 3 (Montevideo, Uruguay, April 2014)
- Workshop 4 (Lucca, Italy, Sep. 2014 co-located with the European Conference on Complex Systems)
- Final Conference (Wien, April 2015, co-located with EGU)

Outline

- Ordinal analysis
- Results
- Summary
- Ongoing and future work

Co-authors

- Ignacio Deza (UPC)

- Giulio Tirabassi (UPC)

- Fernando Arismendi

UNIVERSIDAD DE LA REPÚBLICA
URUGUAY

- Marcelo Barreiro

UNIVERSIDAD DE LA REPÚBLICA
URUGUAY

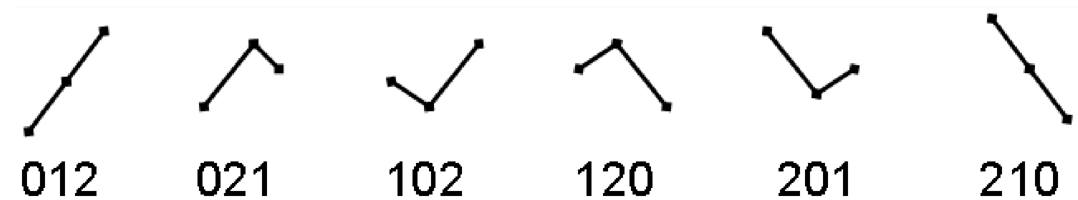
Universidad de la República,
Montevideo, Uruguay

Ordinal Analysis

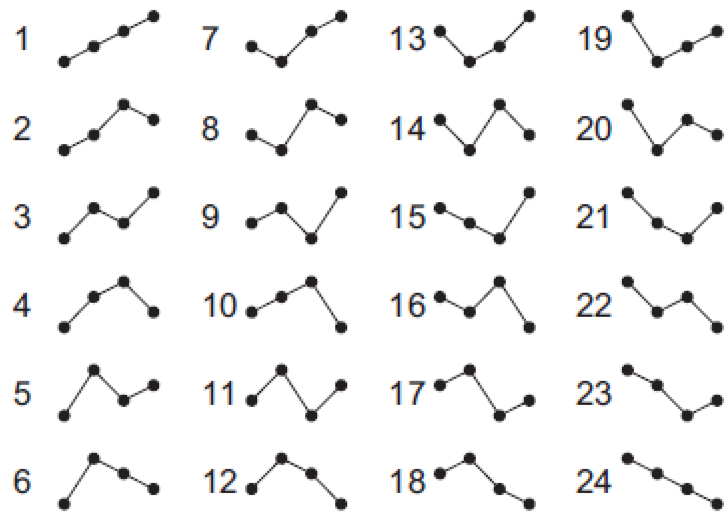
Brandt & Pompe PRL 88, 174102 (2002)

- Consider a time series $\{\ldots x_i, x_{i+1}, x_{i+2}, \ldots\}$ and compute the frequency of occurrence of patterns defined by the **order relation** among D values.

- For **D=3**



- For **D=4**



- **D=5** : 5! = 120

U. Parlitz et al. / Computers in Biology and Medicine 42 (2012) 319–327

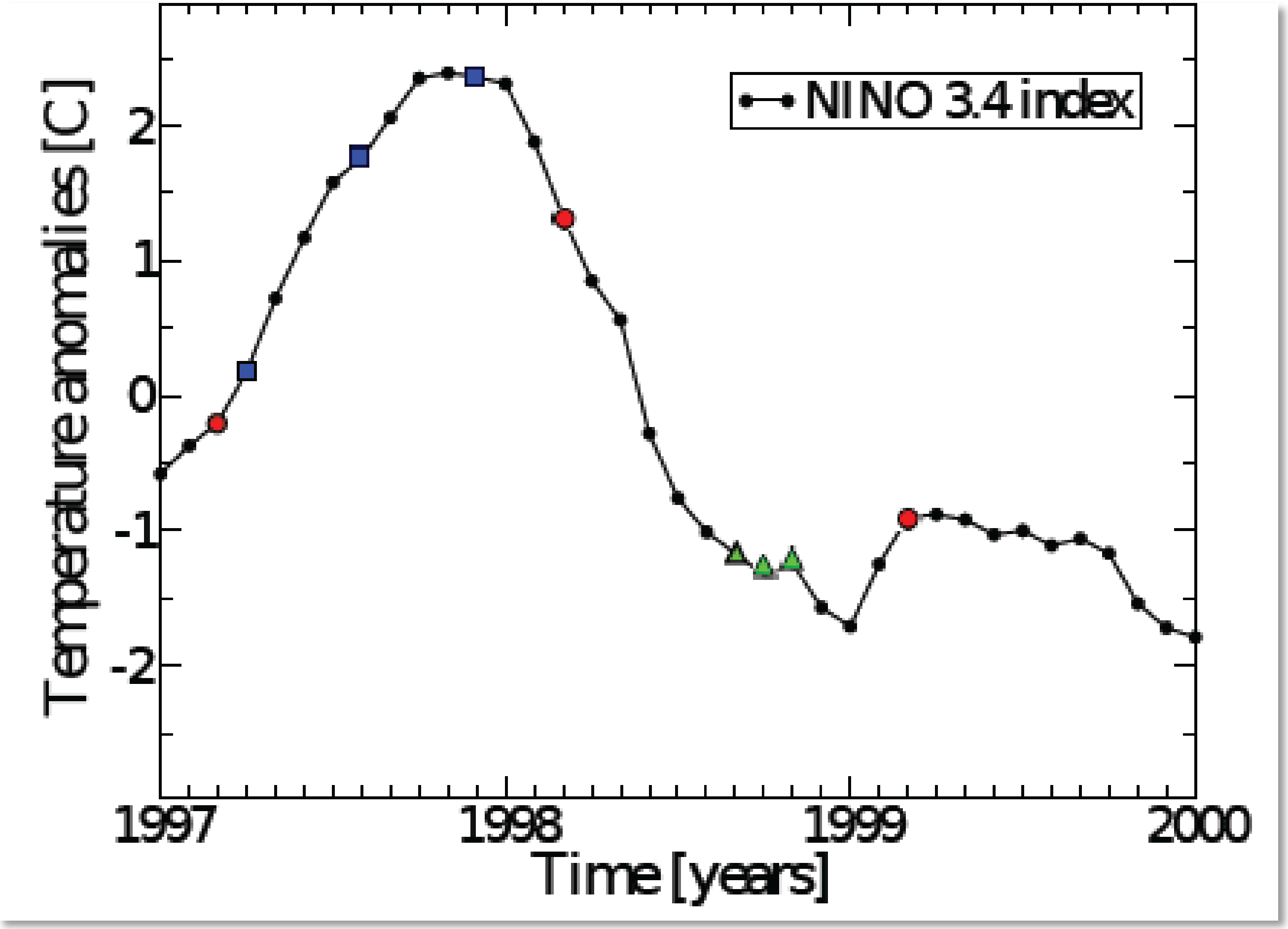
Time scales

Intra-season 102

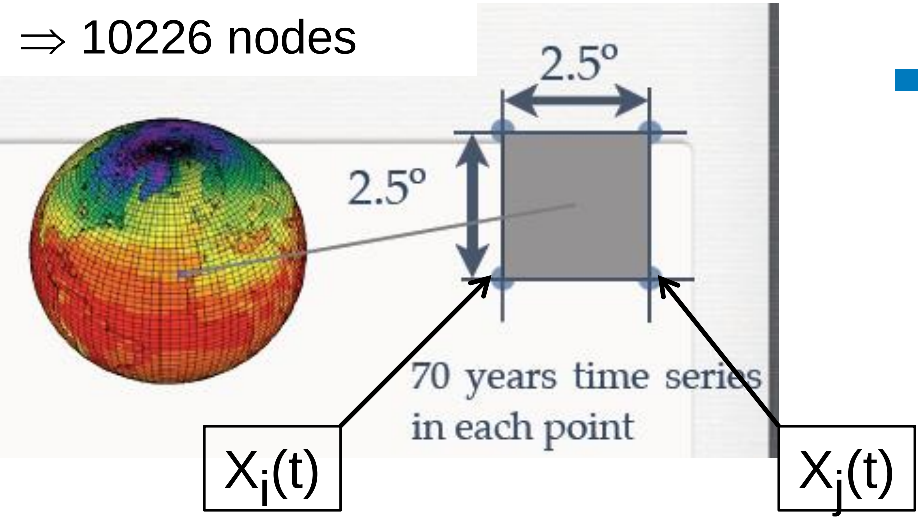
Intra-annual 012

Inter-annual 120

- Drawback: the actual values are not taken into account.



Regular grid
2.5º x 2.5º
⇒ 10226 nodes



- Data used: monthly-averaged SAT reanalysis
- Similarity measure: mutual information

$$M_{ij} = \sum_{m,n} p_{ij}(m,n) \log \frac{p_{ij}(m,n)}{p_i(m)p_j(n)}$$

- Network representation: area weighted connectivity (weighted degree)

$$\mathrm{AWC}_i = \frac{\sum_j^N A_{ij} \cos(\lambda_j)}{\sum_j^N \cos(\lambda_j)}$$

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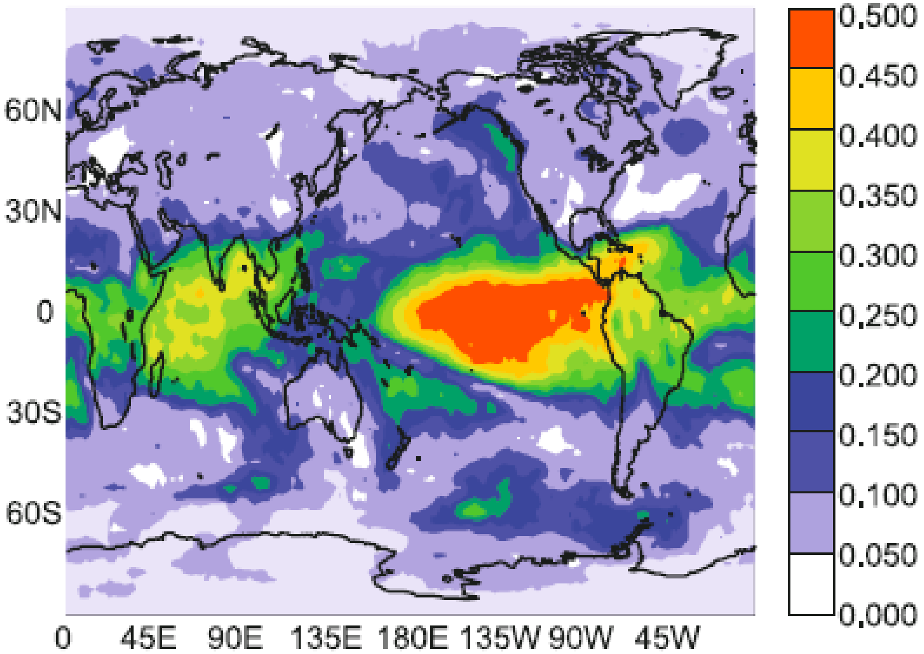
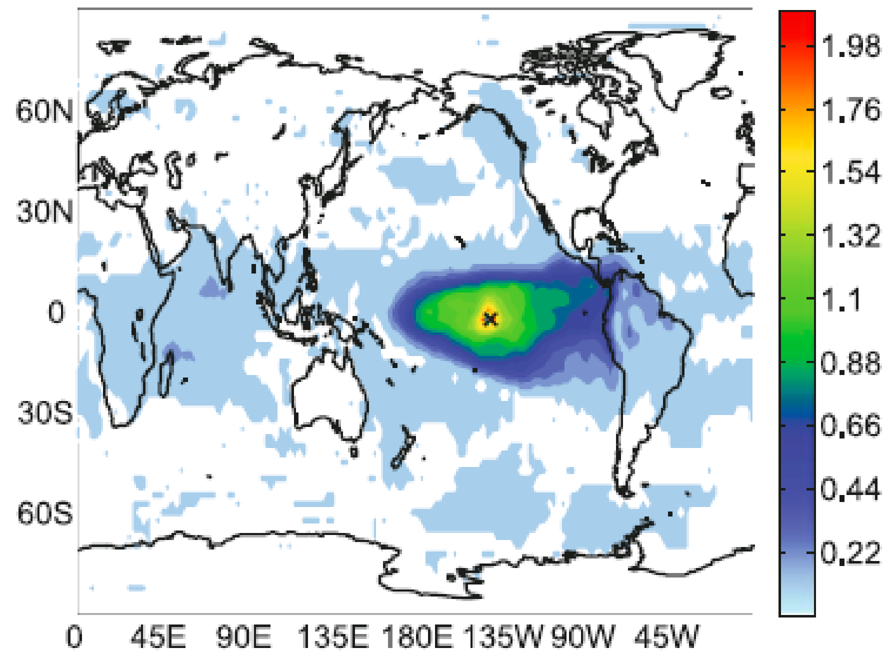
Inter-annual (3 consecutive years)

AWC



Links of a node in Central Pacific



J. I. Deza, M. Barreiro, and C. Masoller, Eur. Phys. J. Special Topics 222, 511 (2013)

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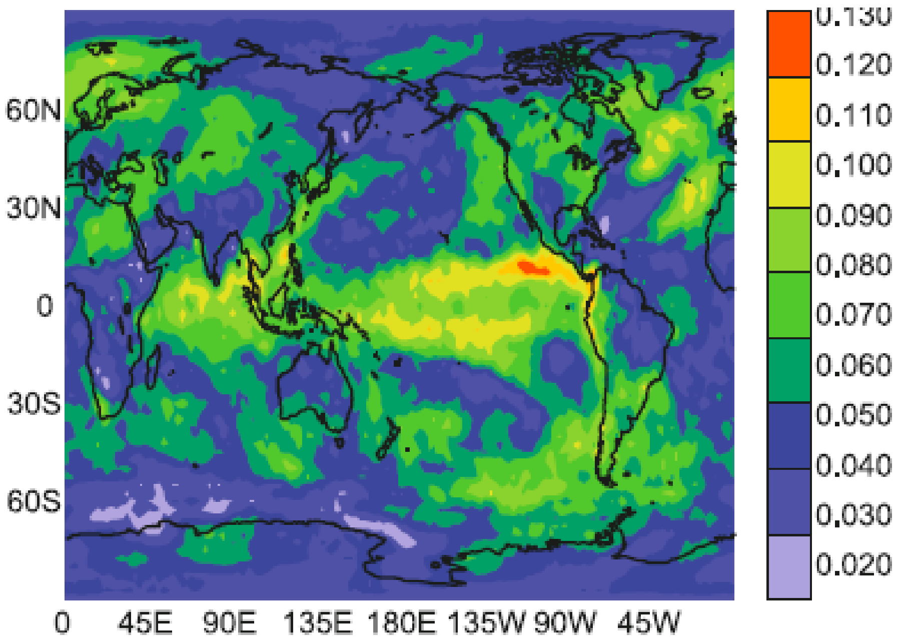
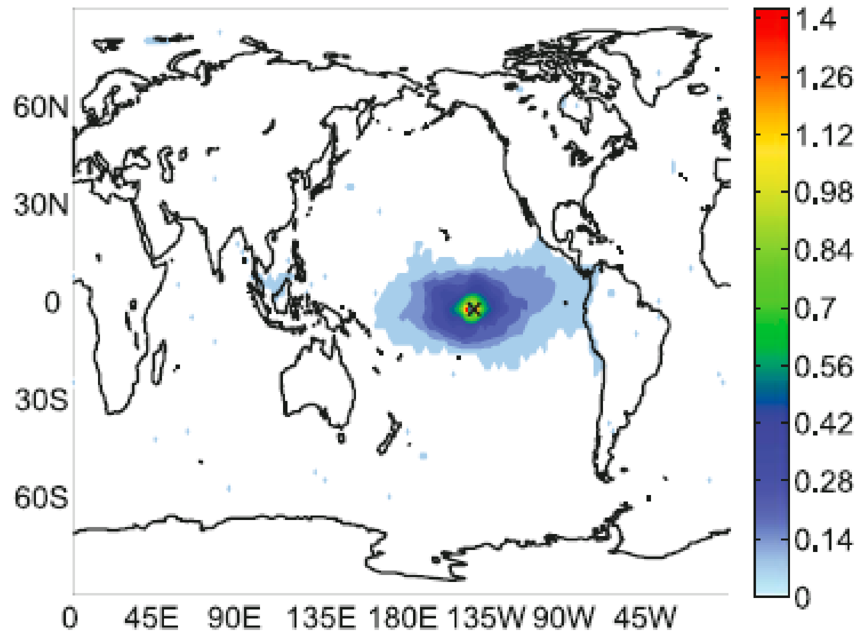
Intra-season (3 consecutive months)

AWC



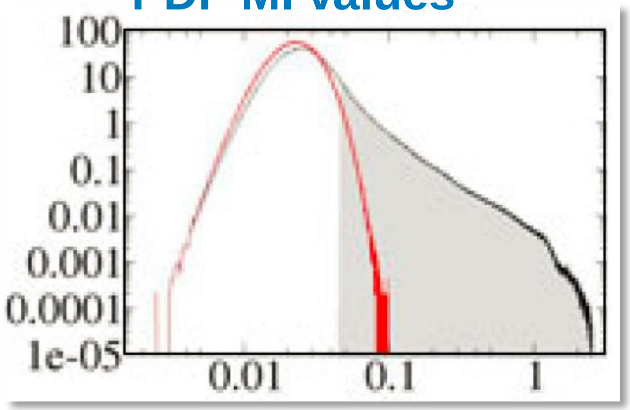
Links of a node in Central Pacific



J. I. Deza, M. Barreiro, and C. Masoller, Eur. Phys. J. Special Topics 222, 511 (2013)

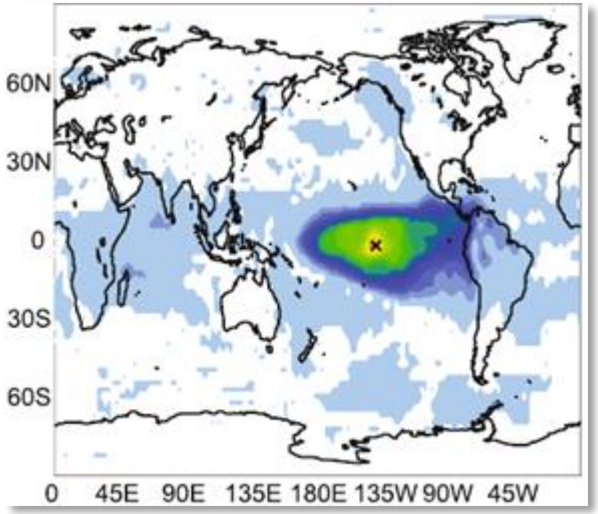
Significance test

PDF MI values

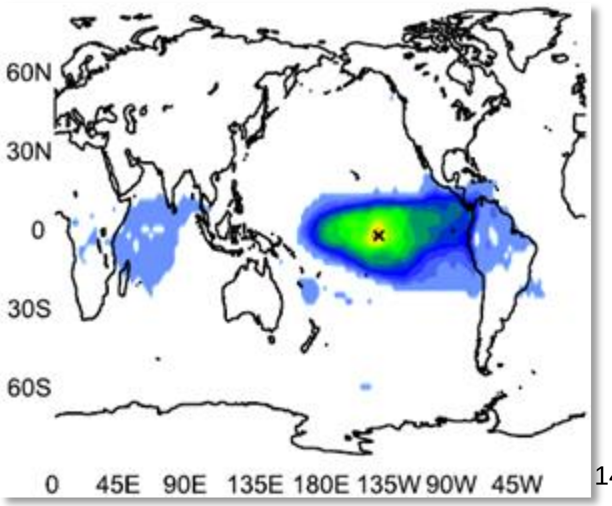


Surrogated data
Original data

Low threshold



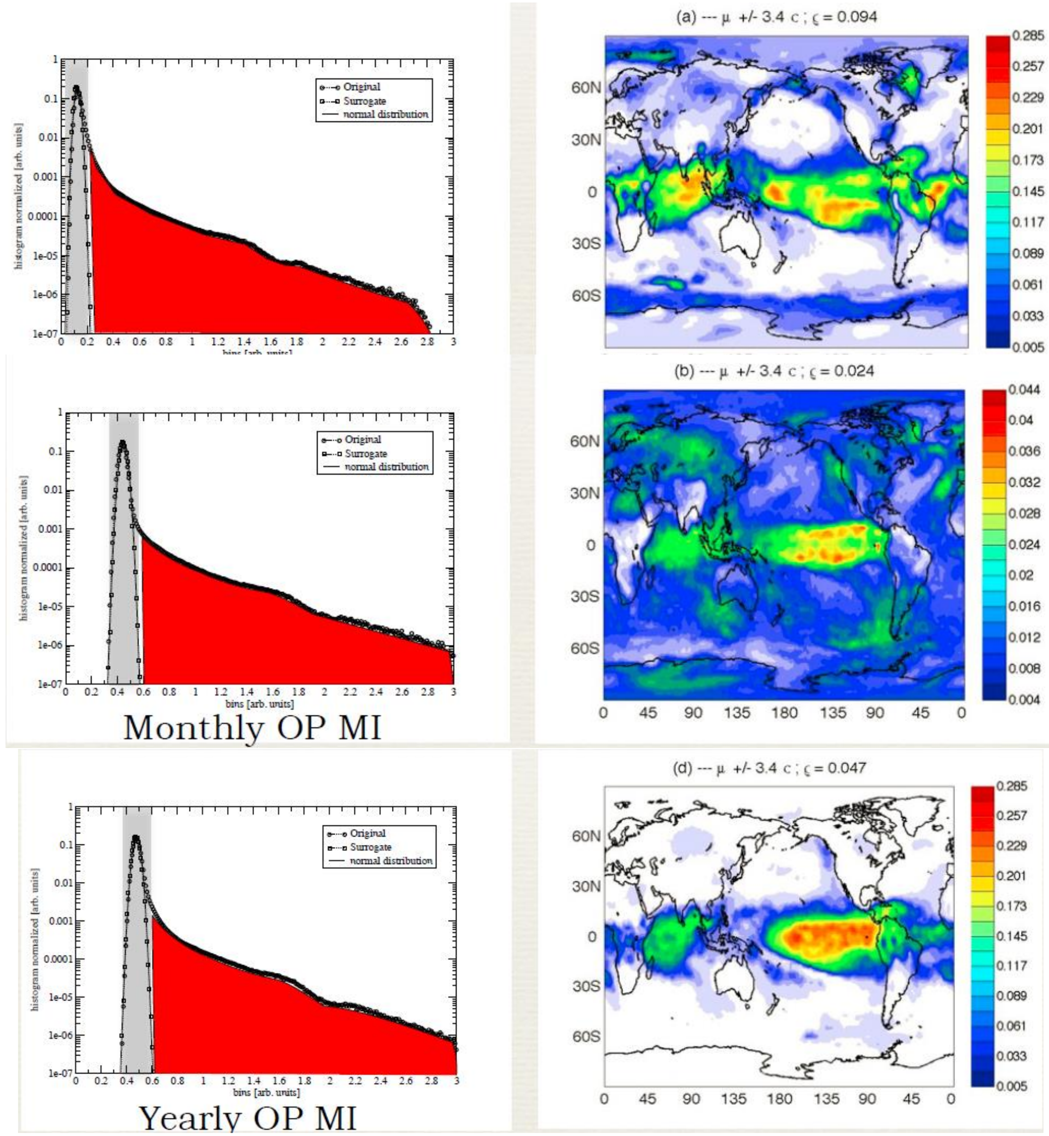
Higher threshold



Comparison AWC maps

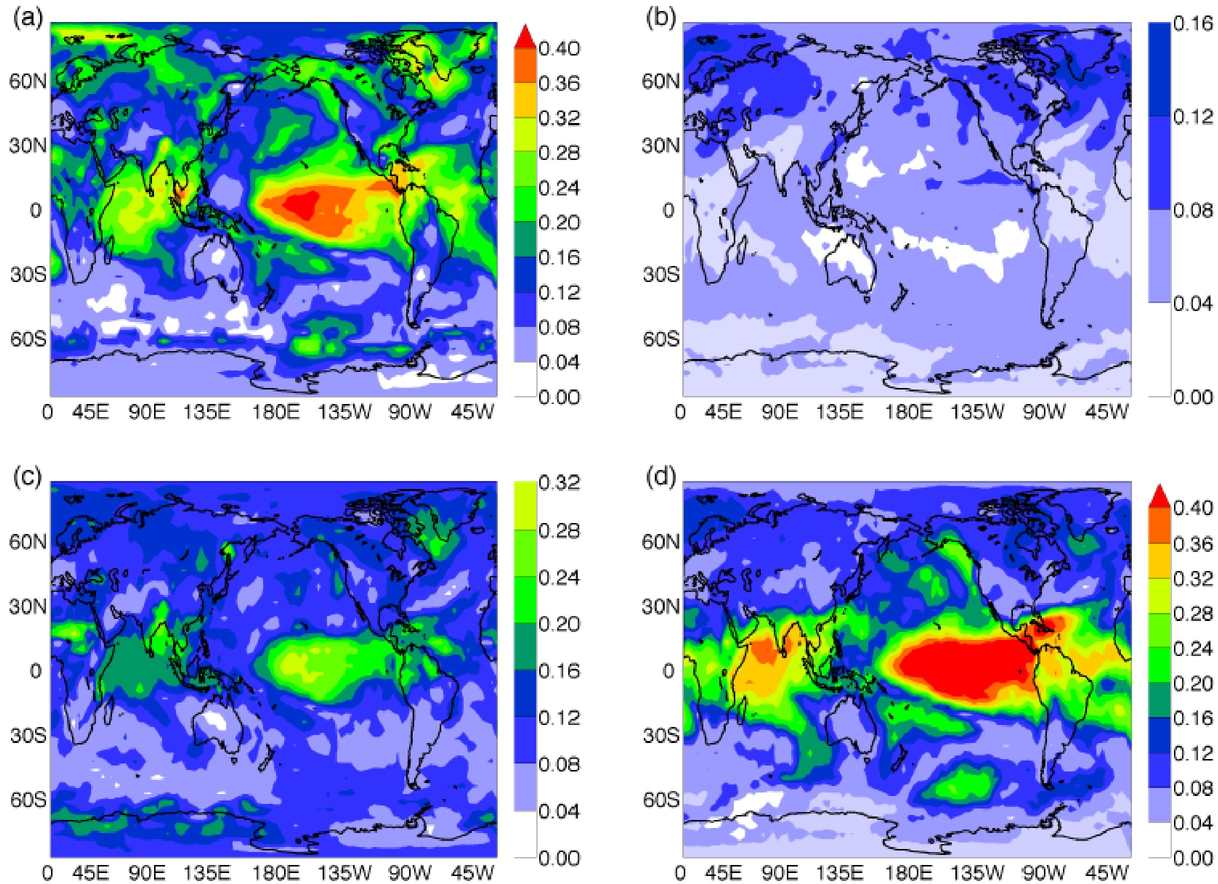
Link density

- MIH — 0.094
- Intra-season (4 months) — 0.024
- Inter-annual (4 years) — 0.047



Comparison AWC maps

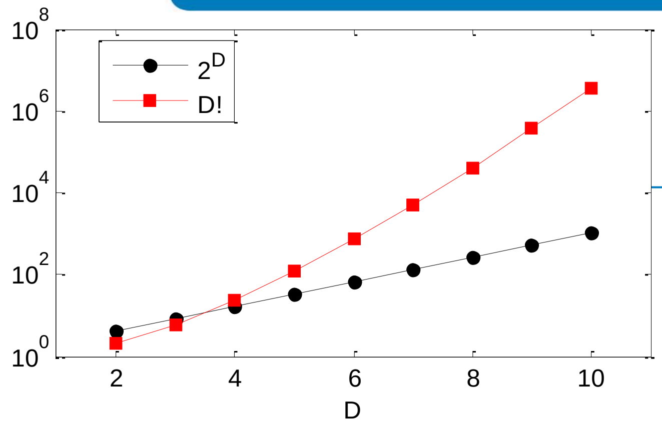
- MIH
- Intra-annual
- Intra-season (3 months)
- Inter-annual (3 years)



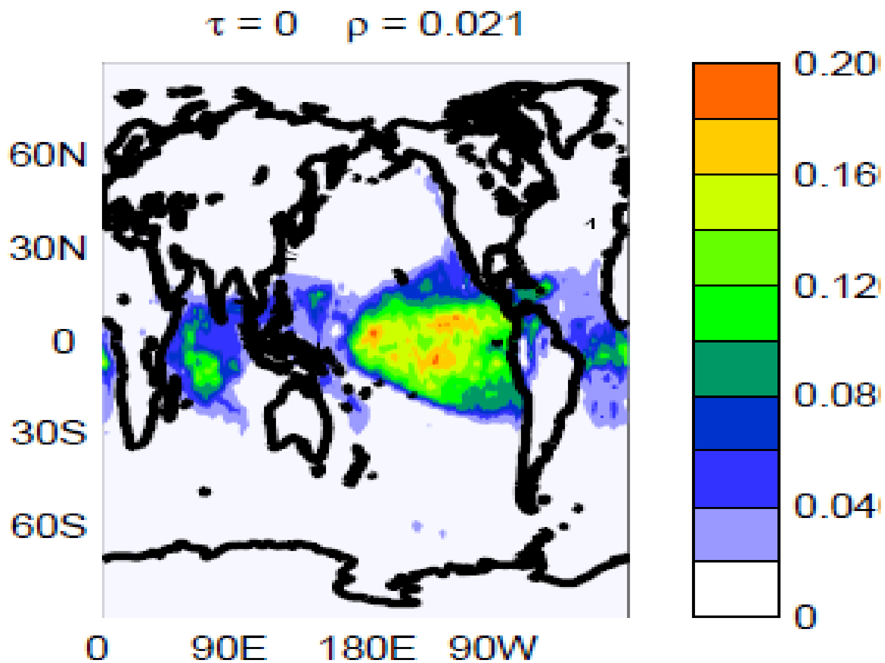
The color scale is the same in the four panels

Deza et al, Nonlin. Processes Geophys., 21, 617–631, 2014

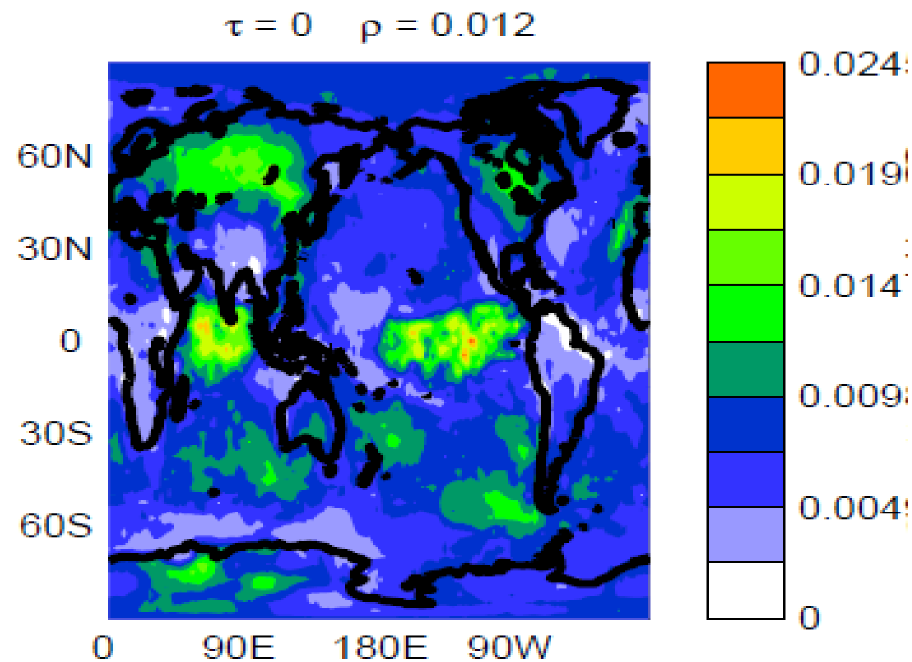
Binary transformation



5 consecutive years



5 consecutive months



Barreiro et al, Chaos, 21 (2011) 013101.

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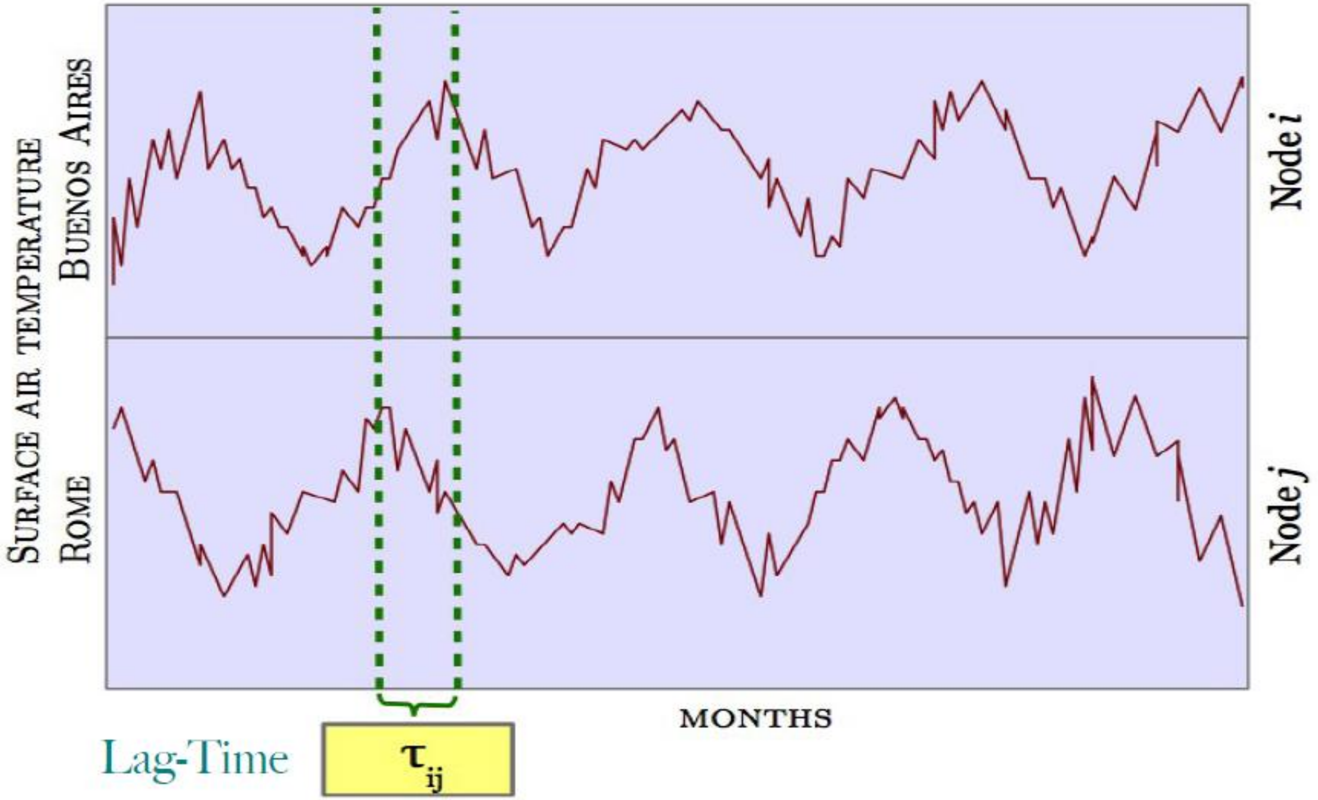
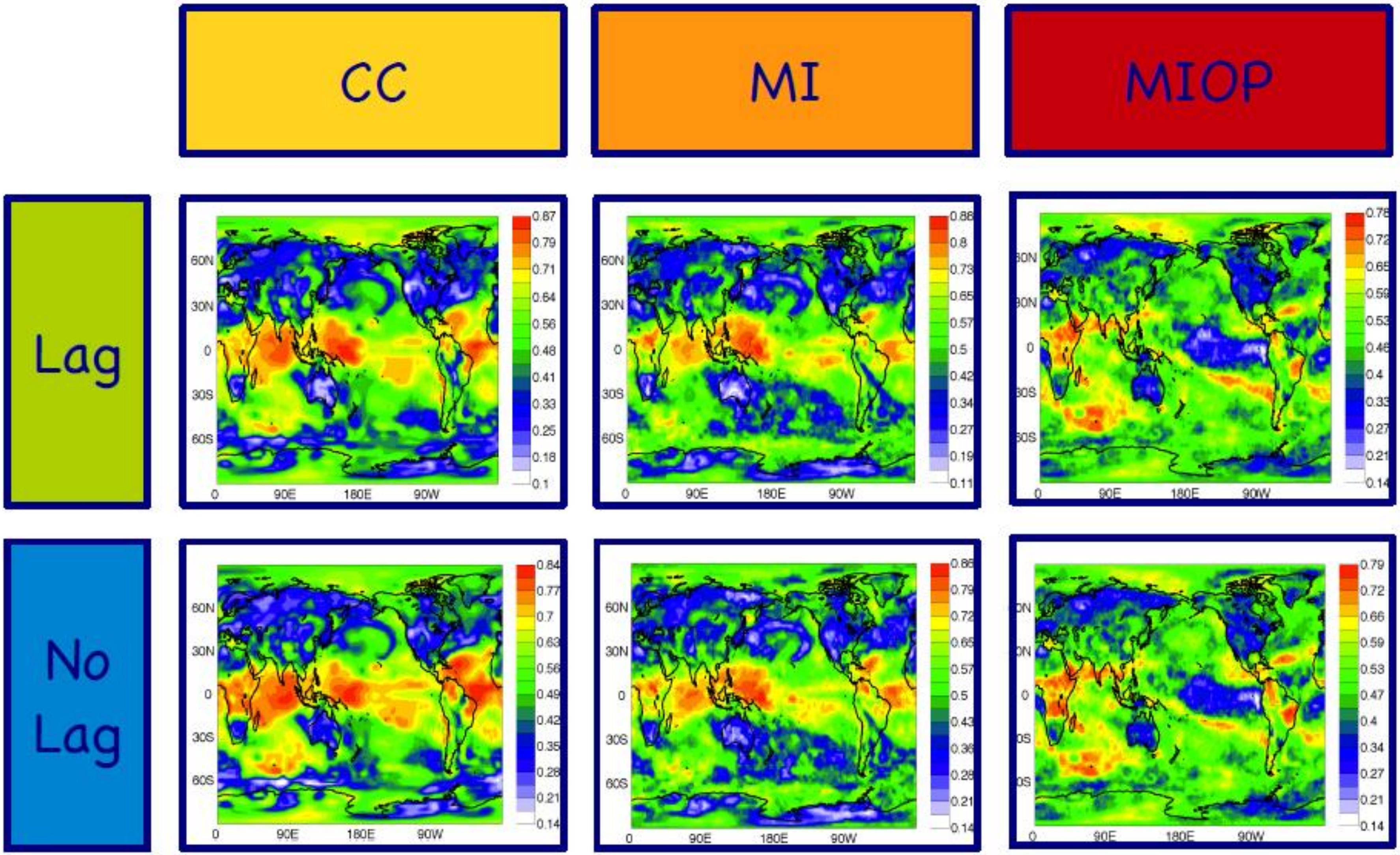
Question: can the average connectivity increase if the cycles are synchronized?

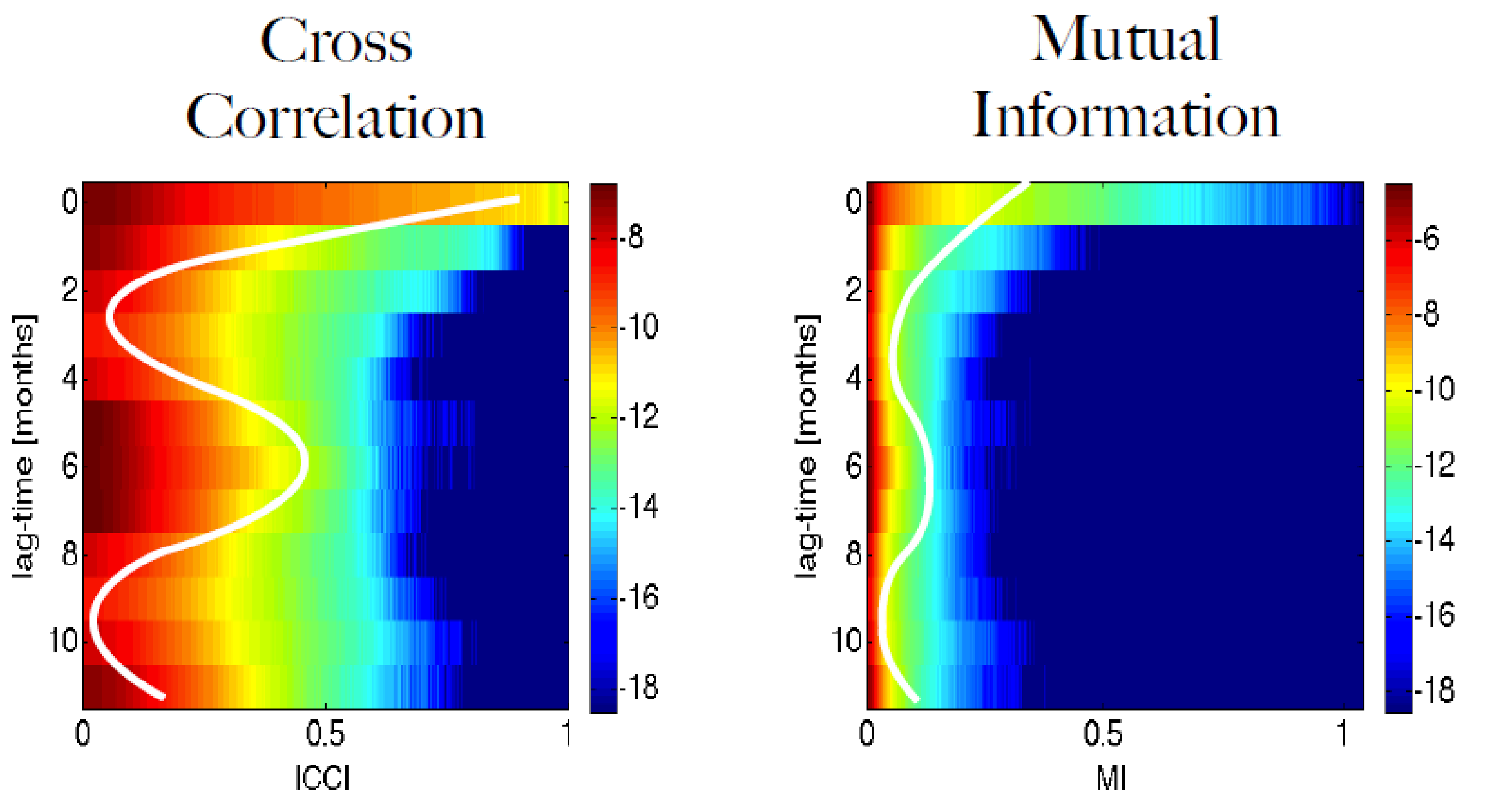


AWC with 50% strongest links



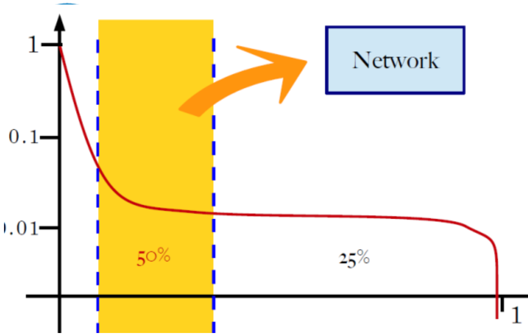
Tirabassi and Masoller, EPL, 102 (2013) 59003

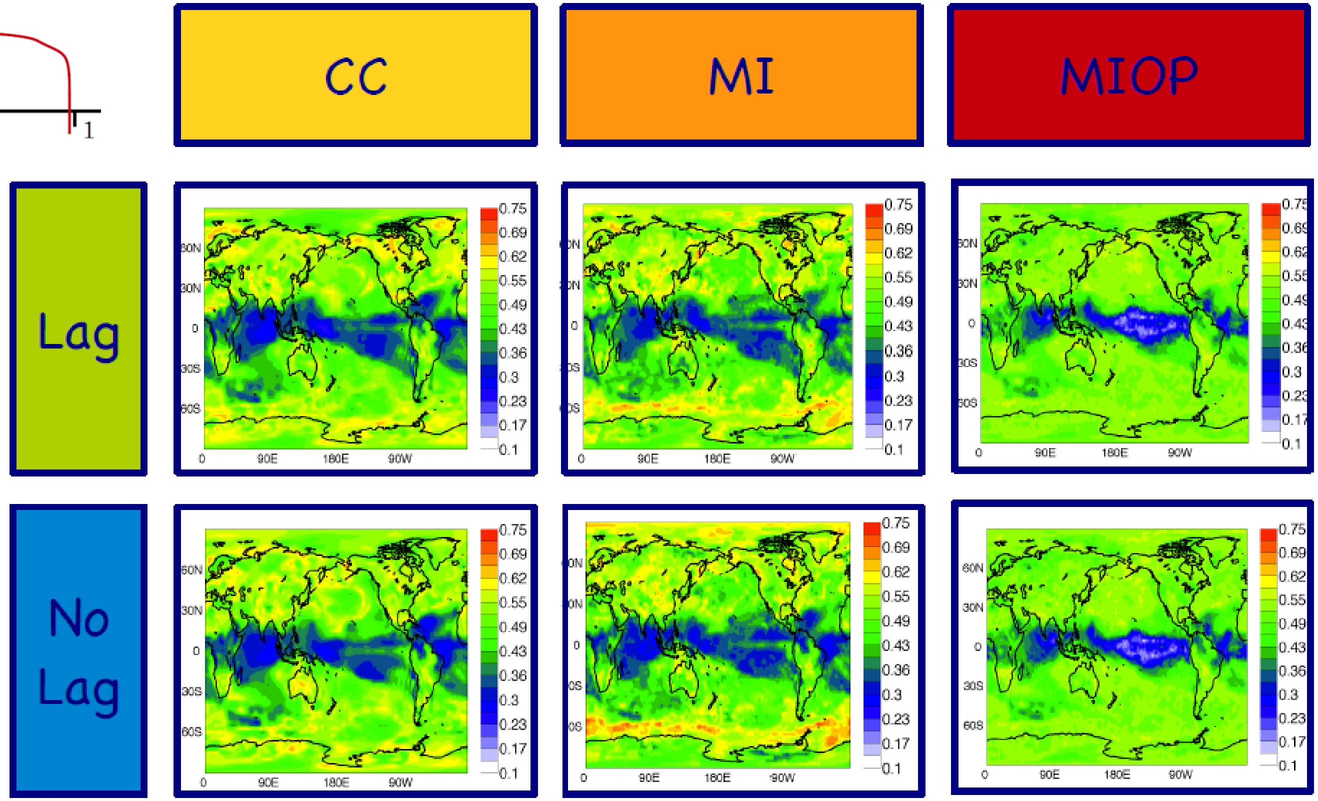
Links: distribution of strengths and lag-times



Strongest links have lag-time = 0; most of the links with non-zero lags are weak

AWC density 50%, the strongest and the weakest links are removed





For links with non-zero lags, the time-shifting changes their similarity values; however, these changes appear to be random and the effects are washed out when computing the AWC.

Tirabassi and Masoller, EPL, 102 (2013) 59003

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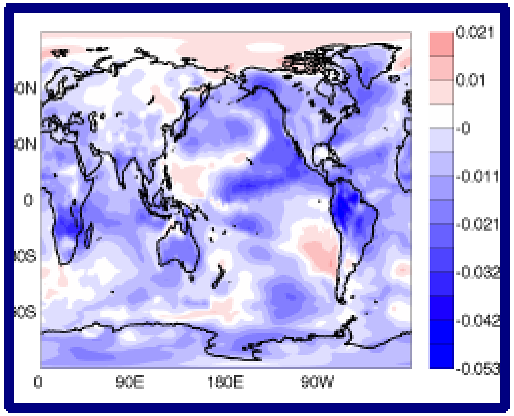
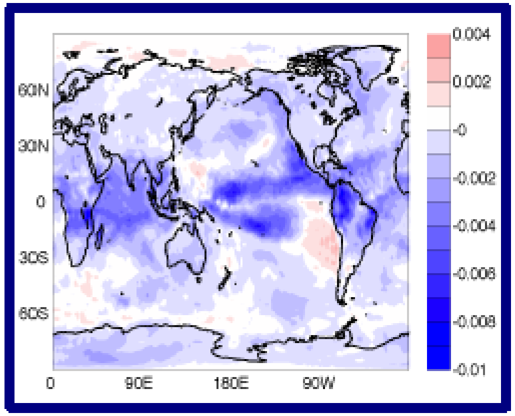
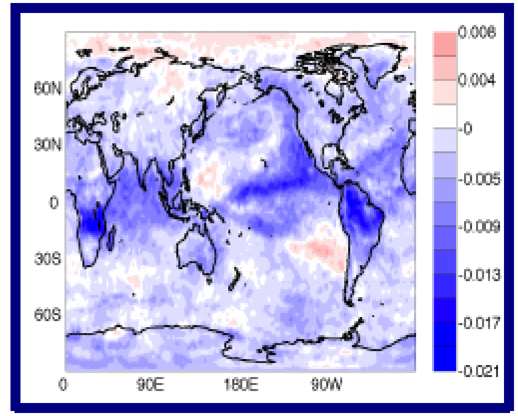
Increase of connectivity?

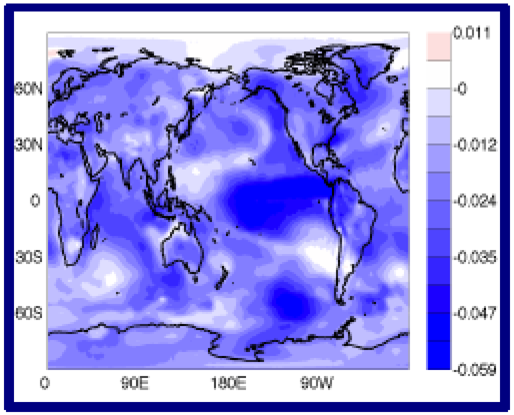
ΔCC	ΔMI	ΔMIOP(4)

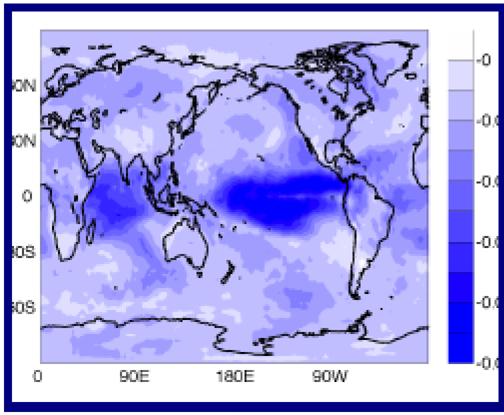


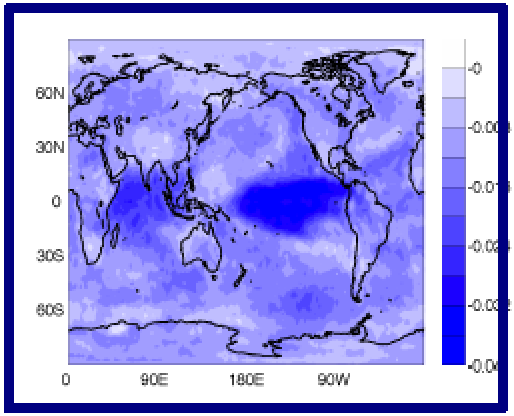




Ran. Lag

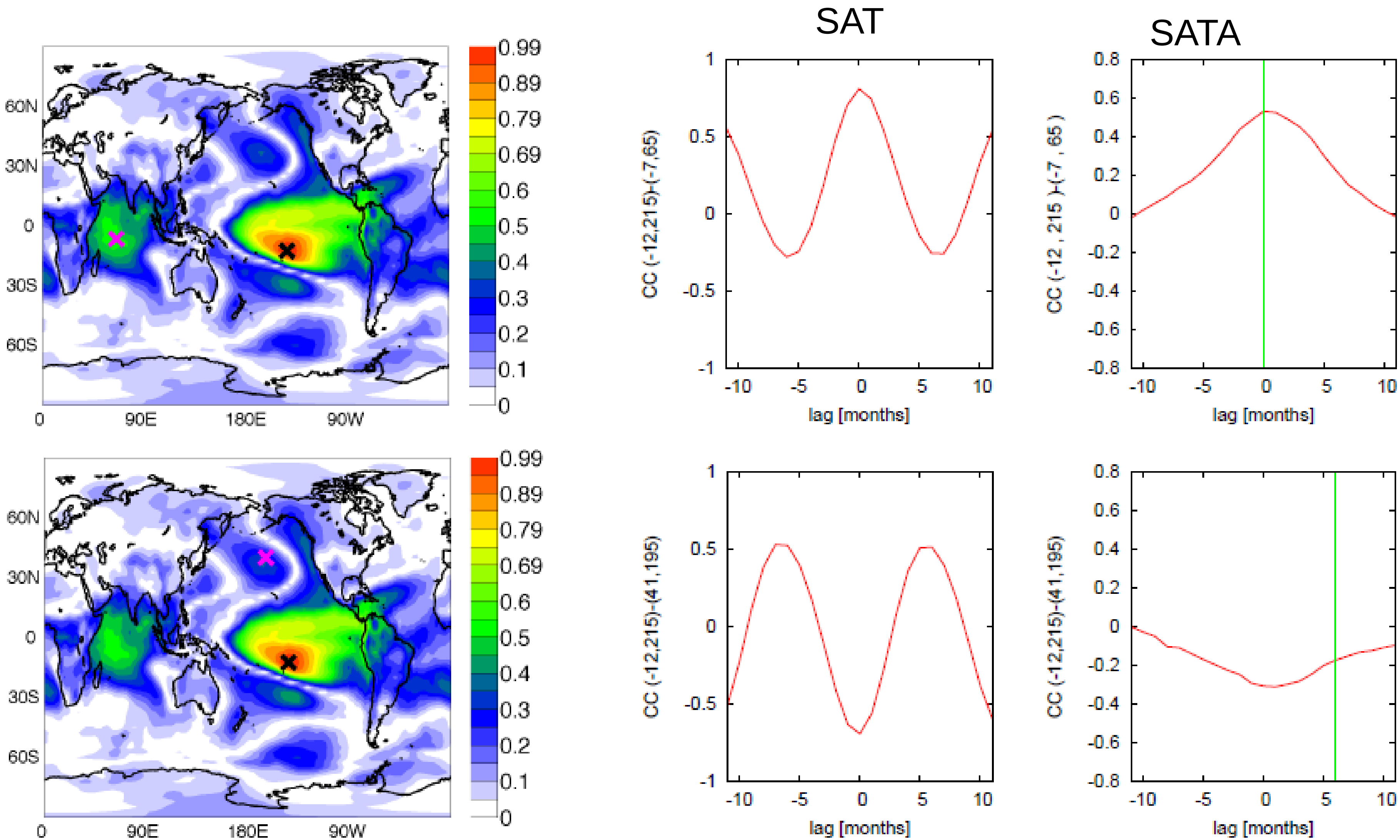






Why?

$$C_{ij}(\tau) = \sum_{t=1}^{N} x_i(t+\tau)\, x_j(t)$$



To further understand the role of the annual solar cycle

- where are the regions with strongest nonlinear climate?
- where are the regions where the climate is more stochastic?
- A first step: univariate analysis of monthly SAT data to quantify atmospheric nonlinearity and stochasticy.

Quantifying atmospheric nonlinearity and stochasticity

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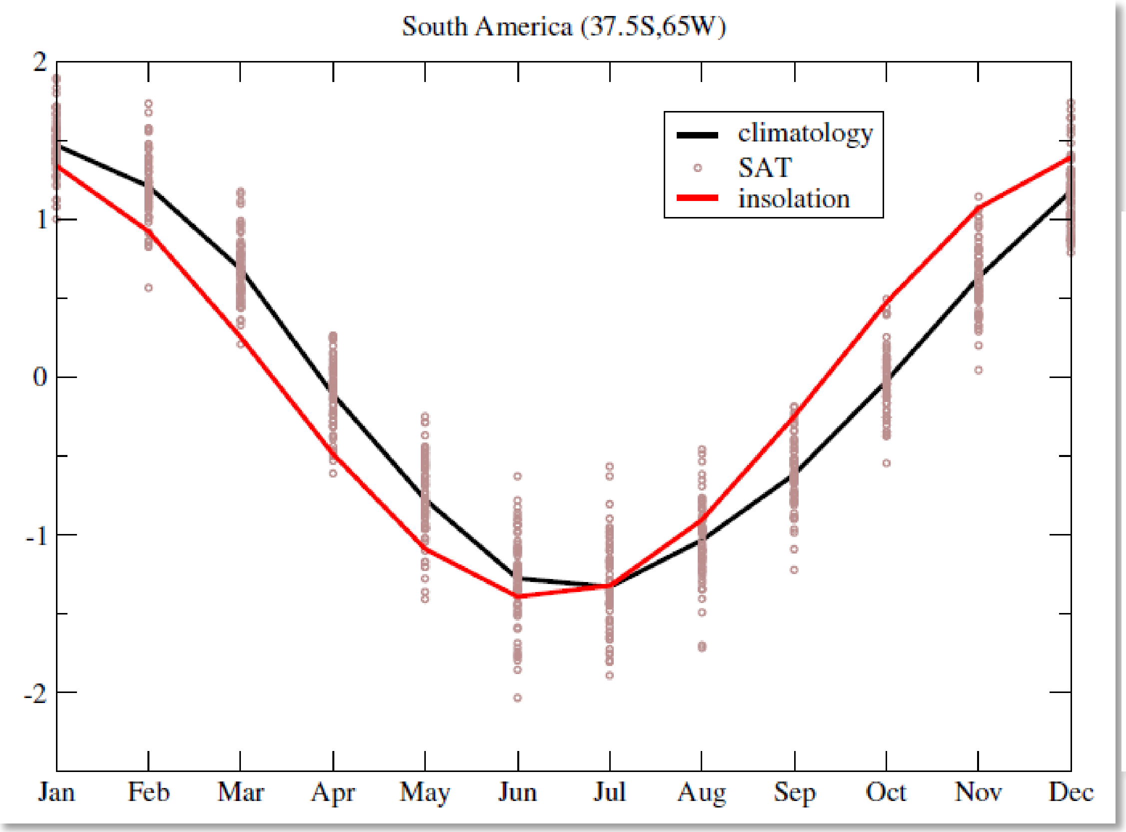
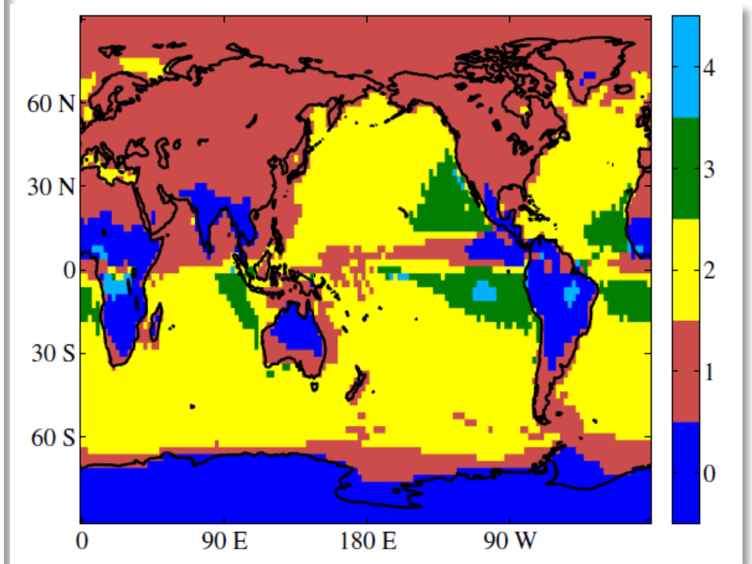


$$d_i(\varphi_i) = \frac{1}{T}\sum_{t=1}^{T}\left|x_i(t) - I_i(t+\varphi_i)\right|$$

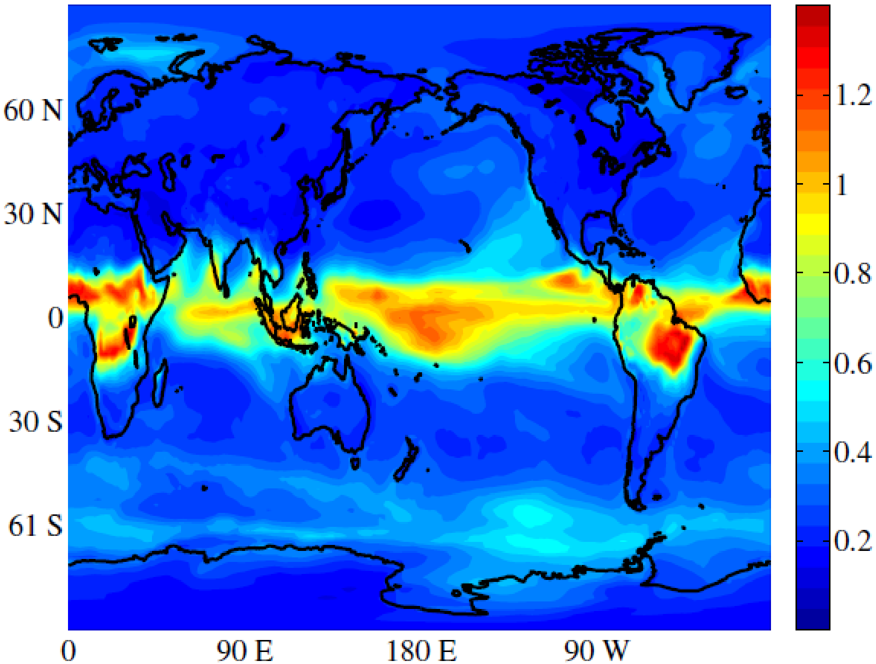


shift in [0-4 months] that minimizes d_i

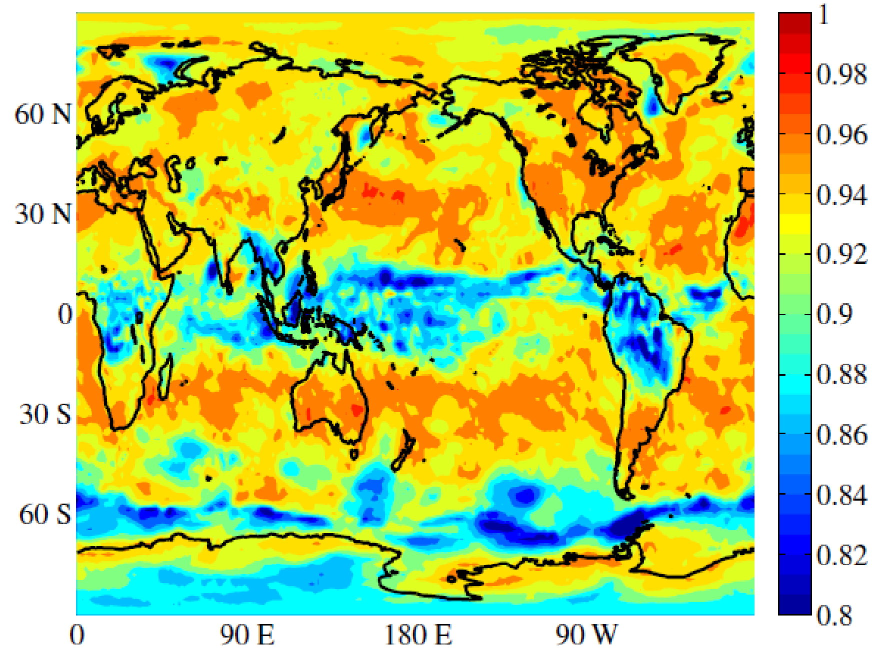
Computed from SAT anomalies

$$H = -\int p(x)\log p(x)dx$$

Nonlinear measure



Anomaly Entropy

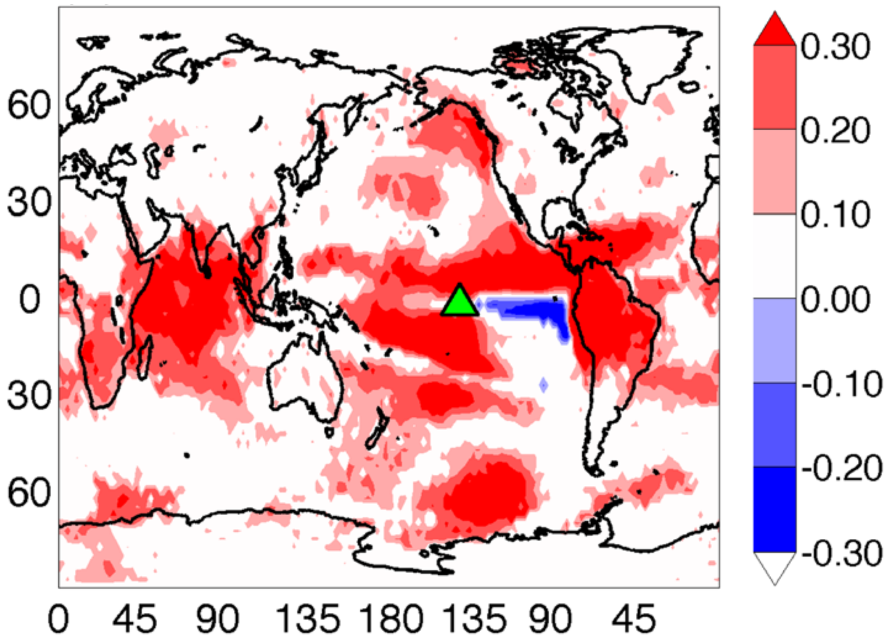


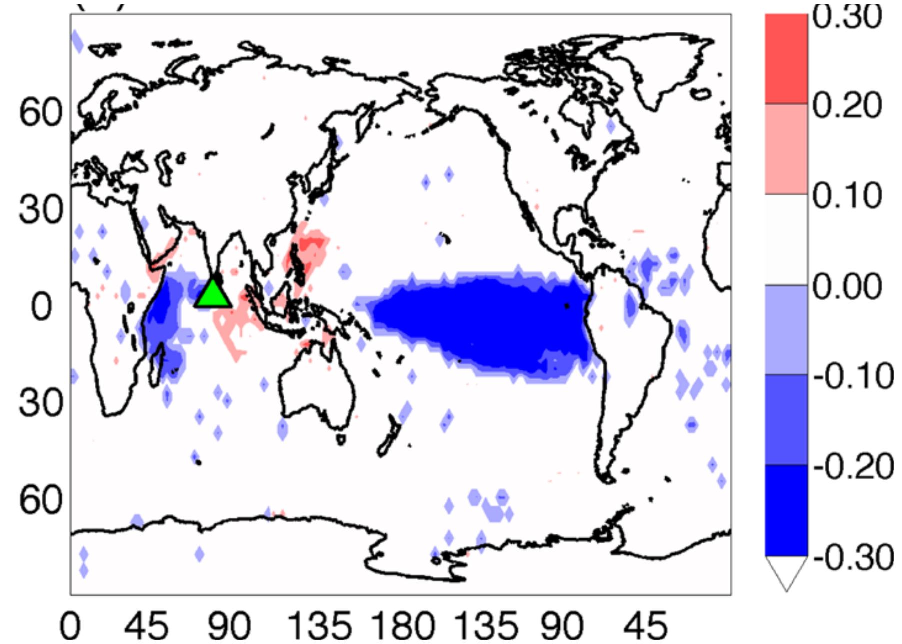
F. Arismendi et al, submitted (2015)

Link directionality

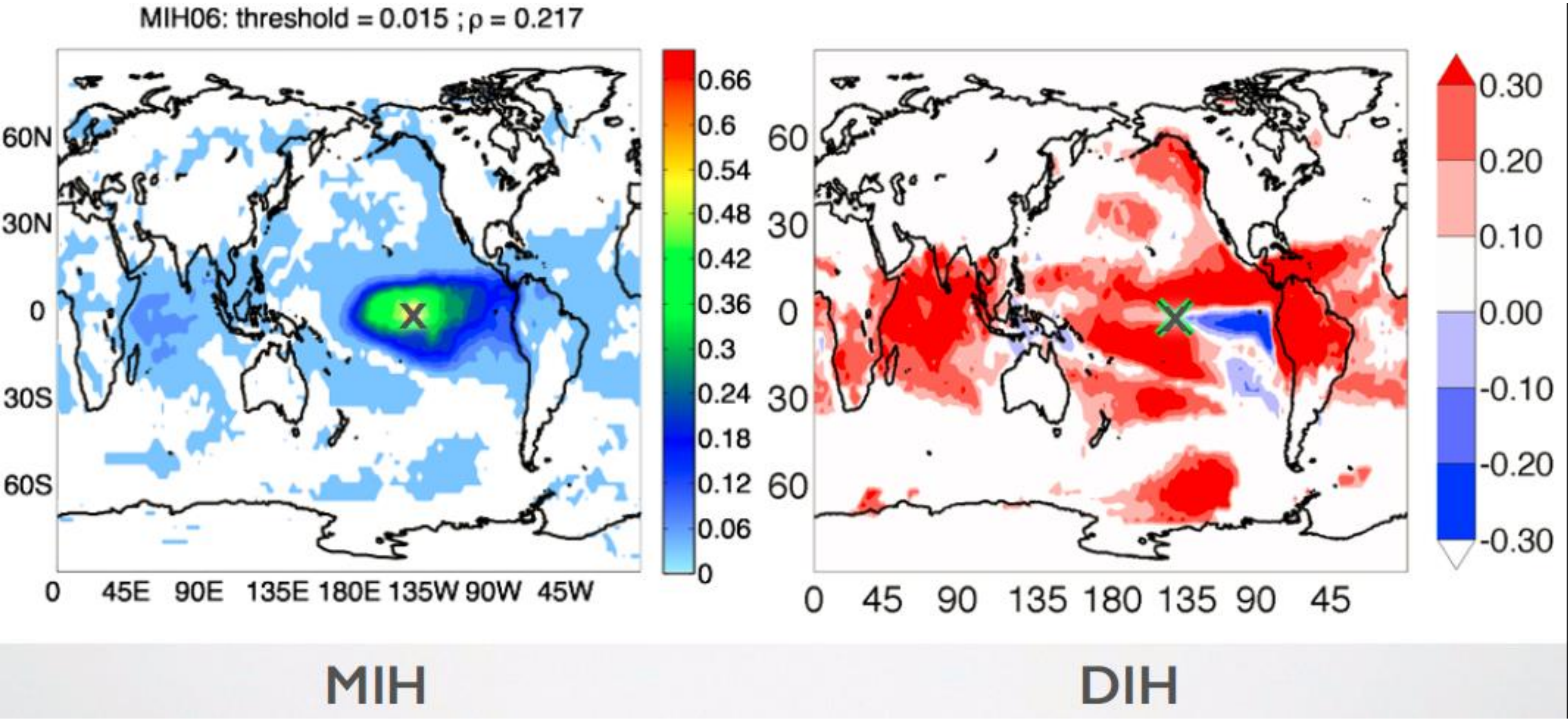
- $I_{xy}(\tau)$: *conditional* mutual information
- *D*: *net* direction of information transfer

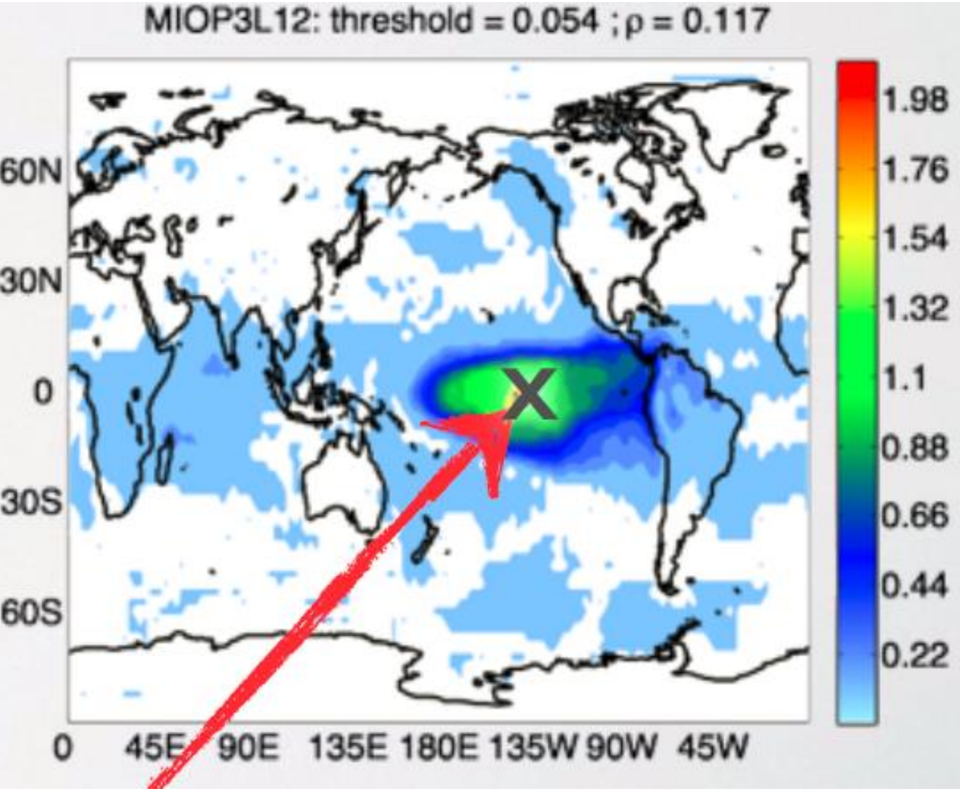
$$D_{XY}(\tau) = \frac{I_{XY}(\tau) - I_{YX}(\tau)}{I_{XY}(\tau) + I_{YX}(\tau)}$$

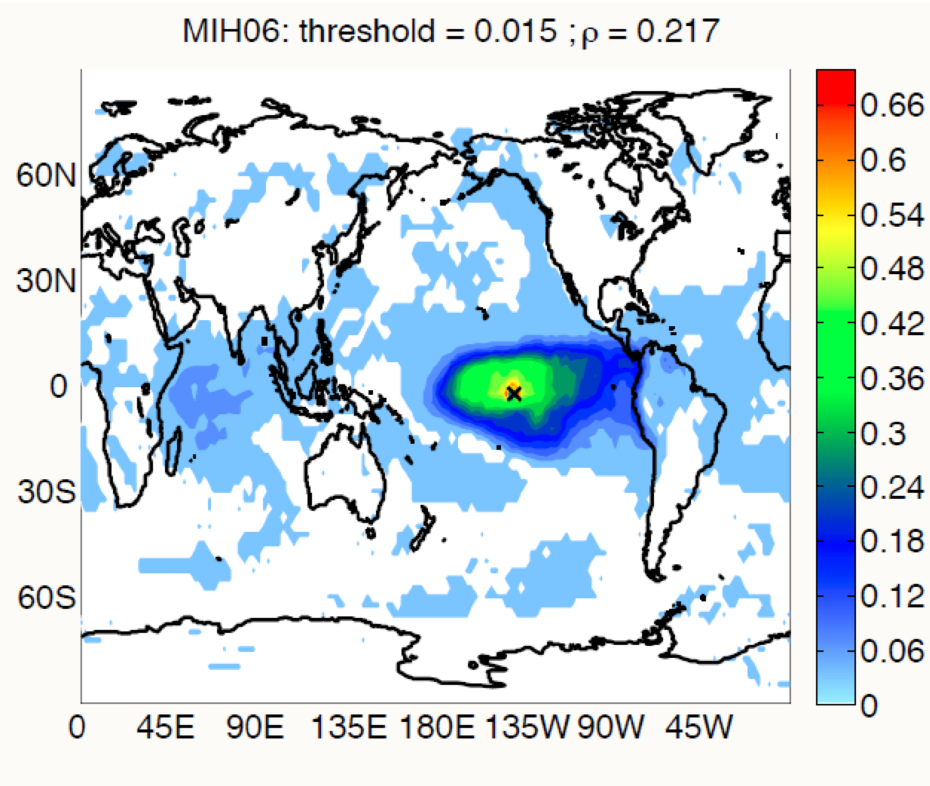




Deza et al, Chaos 25, 033105 (2015)


MIH06: threshold = 0.015 ; ρ = 0.217
60N
30N
0
30S
60S
0 45E 90E 135E 180E 135W 90W 45W
0.66
0.6
0.54
0.48
0.42
0.36
0.3
0.24
0.18
0.12
0.06
0
60
30
0
30
60
0 45 90 135 180 135 90 45
0.30
0.20
0.10
0.00
-0.10
-0.20
-0.30
MIH
DIH


MIOP3L12: threshold = 0.054 ; ρ = 0.117
60N
30N
0
30S
60S
0
45E
90E
135E
180E
135W
90W
45W
1.98
1.76
1.54
1.32
1.1
0.88
0.66
0.44
0.22
X


MIH06: threshold = 0.015 ; ρ = 0.217
60N
30N
0
30S
60S
0
45E
90E
135E
180E
135W
90W
45W
0.66
0.6
0.54
0.48
0.42
0.36
0.3
0.24
0.18
0.12
0.06
0

Assessing link directionality via Granger causality: analysis of the SACZ region

South Atlantic Convergence Zone (South America Monsoon)

When SACZ is active (summer) heavy precipitation over Amazonas and low precipitation over Uruguay.

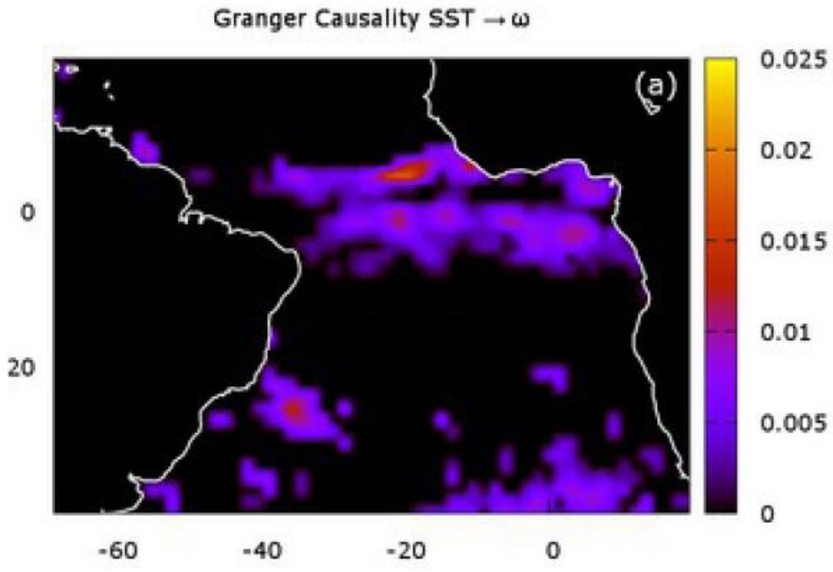
Also possible the opposite (heavy precipitation over Uruguay and low precipitation over Amazonas).

Question: how atmospheric circulation patterns associated with SACZ are influenced by surface ocean conditions?

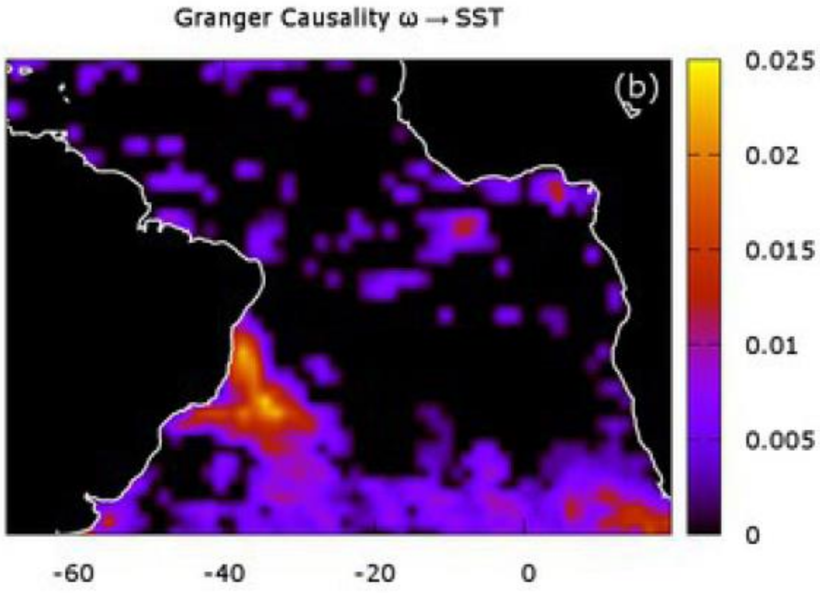
- Sea surface temperature (SST)
- Vertical wind velocity at 500 hPa (ω, "proxy" for rainfall)

Granger Causality Estimator: Local analysis

Ocean → wind

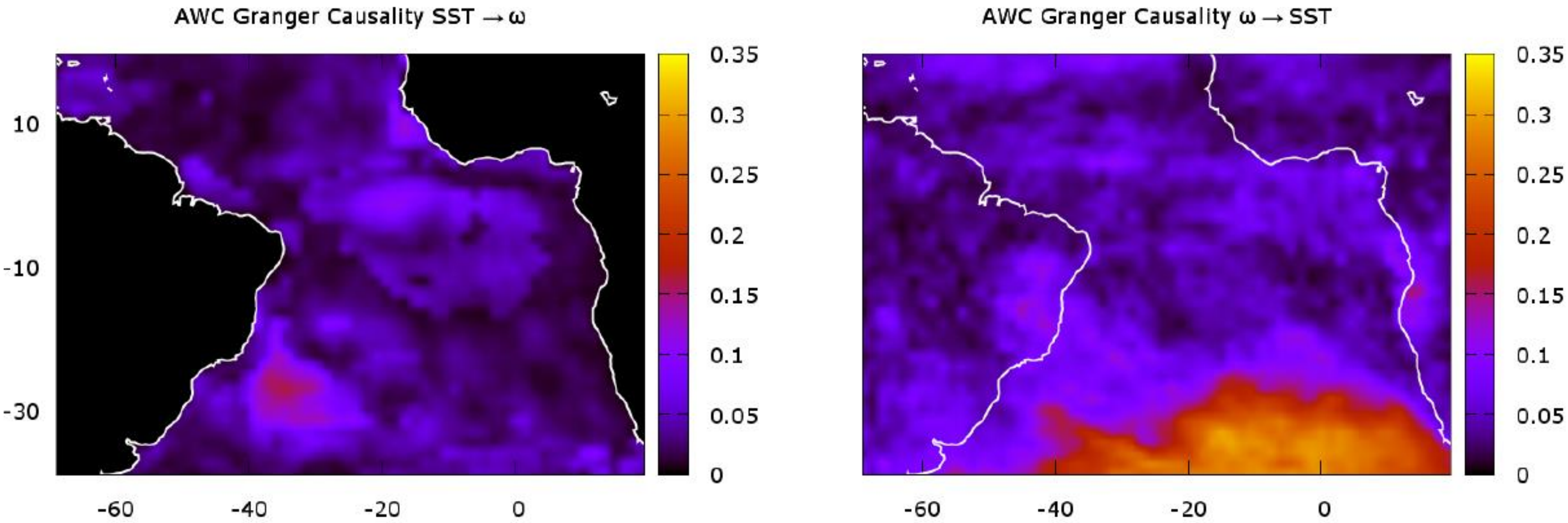


Wind → ocean



Tirabassi et al, Int. J. of Climatology 2014 DOI: 10.1002/joc.4218

Granger Causality Estimator: Bilayer network



Tirabassi et al, Int. J. of Climatology 2014 DOI: 10.1002/joc.4218

Contrasting structural and functional connectivity

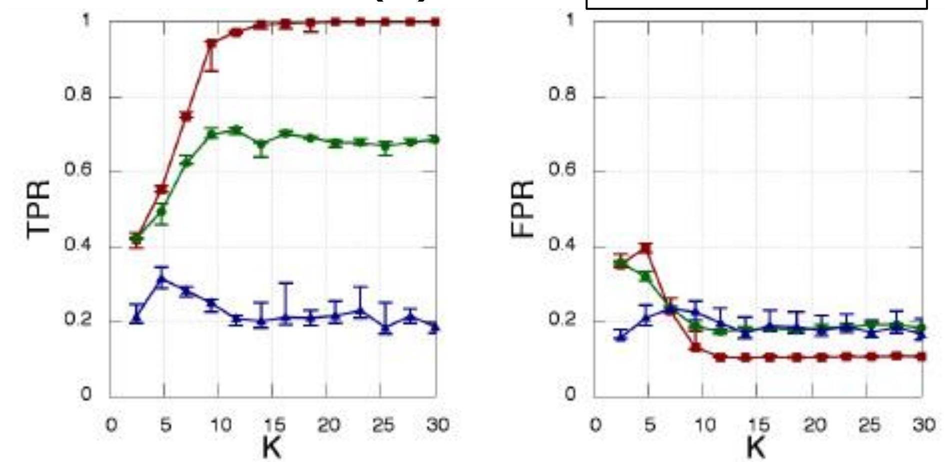
Goal: to test the method of network inference on Kuramotto oscillators with known coupling topology (A_{ij})

$$\mathrm{d}\theta_i = \omega_i \mathrm{d}t + \frac{K}{N}\sum_{j=1}^{N} A_{ij}\sin(\theta_j - \theta_i)\mathrm{d}t + D\ \mathrm{d}W_t^i$$

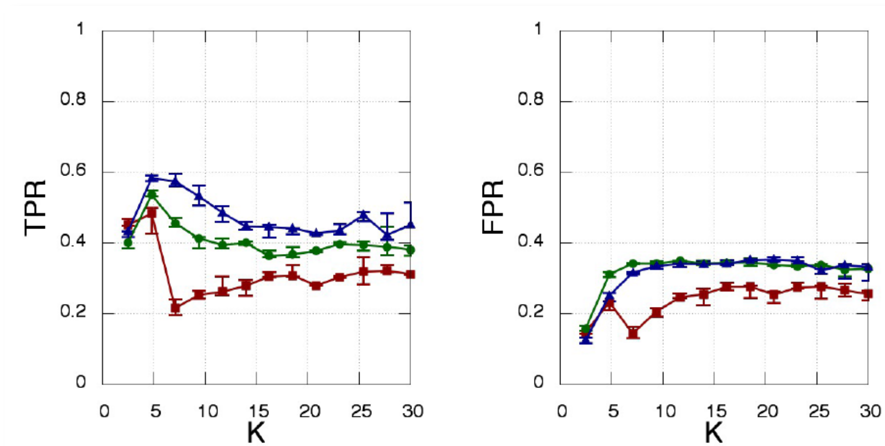
N=12 time-series with 10^4 data points

Phases (θ)

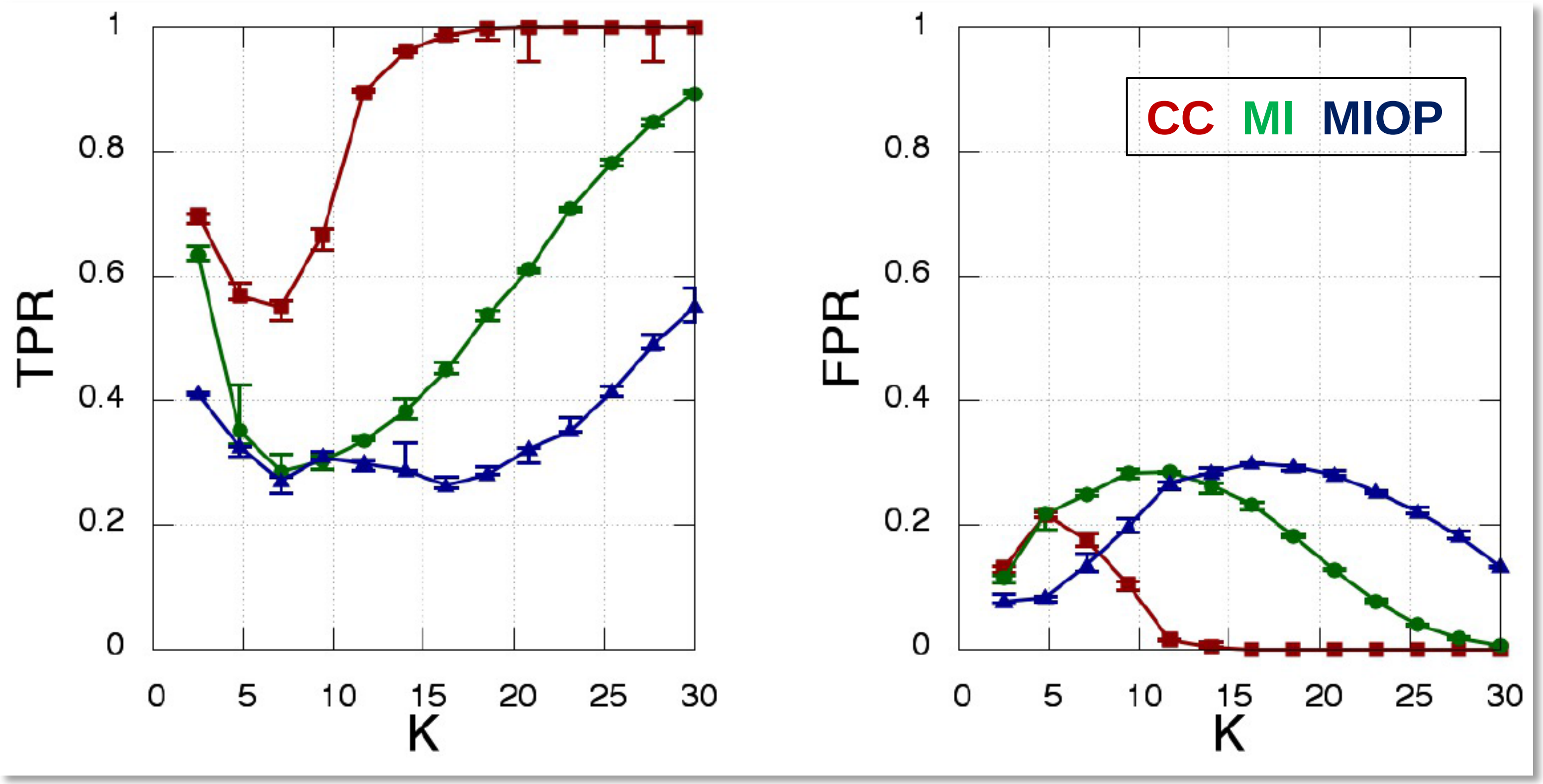
CC MI MIOP



"Observables" Y=sin(θ)



Instantaneous frequencies (dθ/dt)



Tirabassi et al submitted (2015)

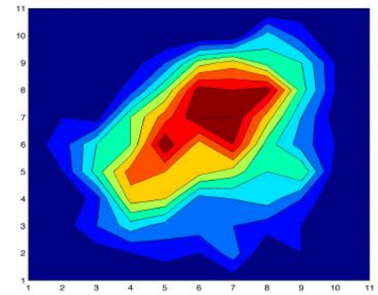
Summary: what did we learn?

- Ordinal analysis allows to identify characteristic time-scales of teleconnections, consistent with well-known climate phenomena.
- No increase of connectivity was obtained by taking into account lag-times between annual solar cycles. This was interpreted as due to the fact that lags produce small, apparently random changes that are washed out when calculating the AWC.
- Regions with strong atmospheric nonlinearity have, in general, low anomaly entropy.
- The Directionality Index allowed to identify the net direction of teleconnections and the time-scale of information transfer.
- Granger Causality Estimator allowed to disentangle air-ocean interactions in the South Atlantic Convergence Zone.
- In a small synthetic network, the cross-correlation analysis of the instantaneous frequencies allowed perfect network inferrence.

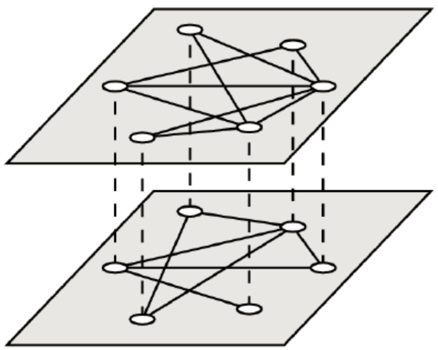
Ongoing and Future work

- "missing" / improbable patterns in climate dynamics?
- Quantifying climate similarities via Transition Probabilities.

$$w_{ij} = \frac{\sum_{t=1}^{L-1} n\left[s(t) = i,\, s(t+1) = j\right]}{\sum_{t=1}^{L-1} n\left[s(t) = i\right]}$$



- Symbolic analysis & multiplex networks:
  - in different seasons (winter, summer) or years (El Niño / La Niña)
  - from different fields (pressure, wind velocity, etc.)



- Networks in shorter time-scales (weather, sub-seasonal).
- Networks constructed from "frequencies" (Hilbert transform).

Ongoing and future work

New J. Phys. 17 (2015) 023068

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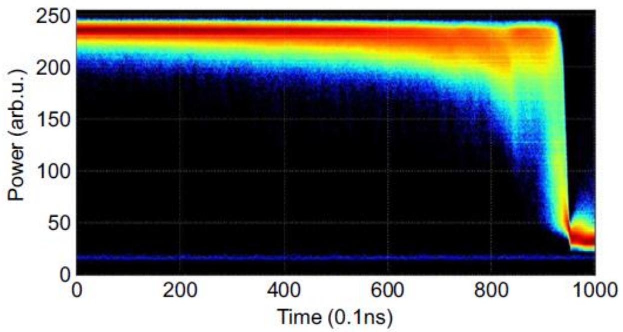

PAPER

Quantifying sudden changes in dynamical systems using symbolic networks

Cristina Masoller[1], Yanhua Hong[2], Sarah Ayad[3], Francois Gustave[3], Stephane Barland[3], Antonio J Pons[1], Sergio Gómez[4] and Alex Arenas[4]

- Symbolic network representation for identifying
  - early warning indicators of climate transitions
  - precursors of extreme events
  - synchronization periods.
- Directionality analysis of SST and relation with Lagrangian Networks.

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THANK YOU FOR YOUR ATTENTION !

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Learning about Interacting Networks in Climate