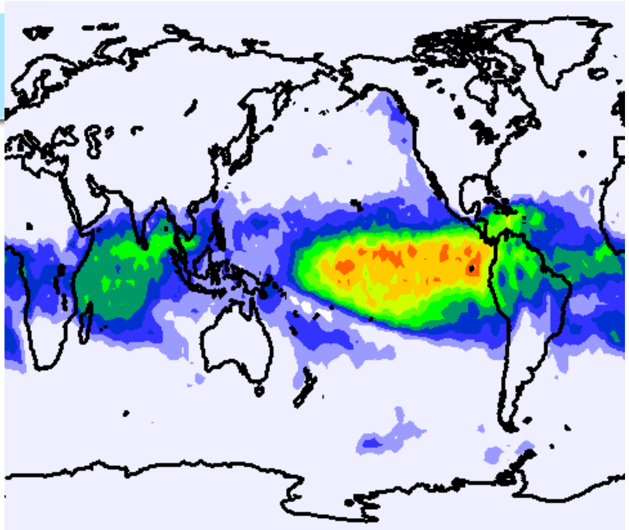
"LINC"
Learning about Interacting Networks in Climate



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

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Analysis of Dynamic Networks and data driven Modeling of the climate (DyNeMo-Clim)
Potsdam, October 2015

analysis of Dynamic Networks and data driven Modelling of the Climate

"LINC"

Learning about Interacting Networks in Climate

Climatelinc.eu

- Call: FP7-PEOPLE-2011-ITN
- December 1st 2011 - November 30th, 2015
- Budget: 3.7 M€
- Goals:
  - To train 15 young researchers (12 PhDs + 3 postdocs) in the complete set of skills needed to undertake a career in physics and geosciences (climatology, complex systems, computer science, data analysis).
  - To develop long-lasting collaborations among the partners.

Partners: 6 academic + 3 companies
Spain, Germany, The Netherlands, Uruguay and Israel

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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

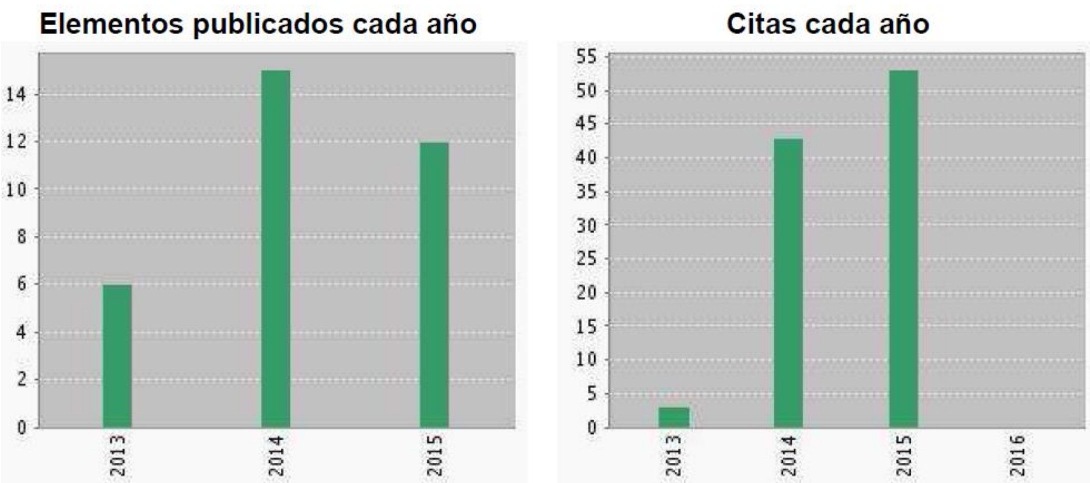
Results

Informe de citas: 33

(de Colección principal de Web of Science)

Buscó: **Entidad financiadora:** (linc) *AND* **Número de concesión:** (289447) **...Más**

Este informe refleja las citas de los elementos origen indexados dentro de Colección principal de Web of Science.
elementos no indexados dentro de Colección principal de Web of Science.



- <u>Interdisciplinary</u> journals (PRL, GRL, Nonlinear Processes in Geophys., Chaos, Entropy, etc.)

- Many available at climatelinc.eu
- 5 PhD theses completed, several are scheduled for the next months.
- Software and database also available in our web page.

Training Events

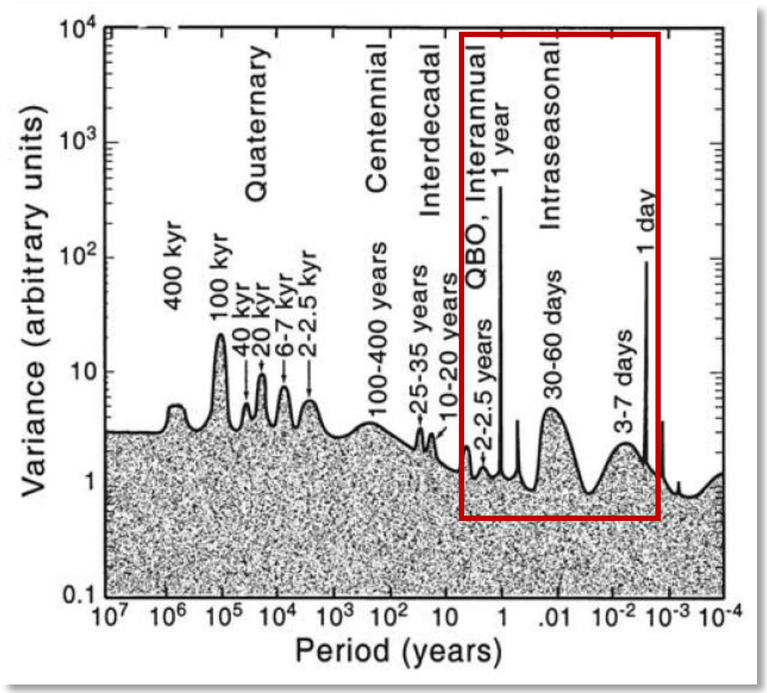
- First school (Mallorca, Spain, September 2012)
- Second school and Workshop 1 (The Netherlands, April 2013)
- Workshop 2 (Potsdam, November 2013)
- Workshop 3 (Montevideo, Uruguay, April 2014)
- Workshop 4 (Lucca, Italy, Sep. 2014 co-located with ECCS)
- Final Conference (Viena, April 2015, co-located with EGU)

Outline

- Introduction to nonlinear tools for climate data analysis (motivation and methodology)
- Results
- Summary
- Ongoing and future work

Motivation

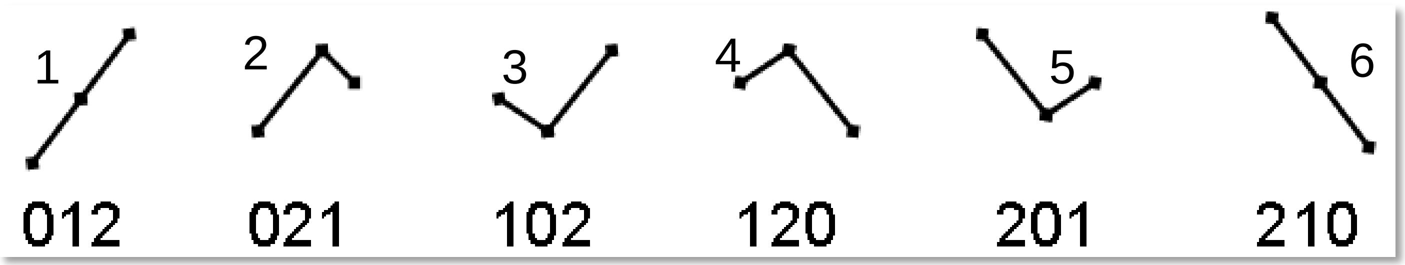
- Improving our understanding of climate dynamics requires the identification of <u>recurrent patterns</u> and their underlying causes.
- Wide range of time-scales.
- Methods of data analysis remain dominated by linear thinking (e.g., extrapolation of trends).
- Nonlinear thinking is important (e.g., for identifying precursors of extreme events and regime shifts).

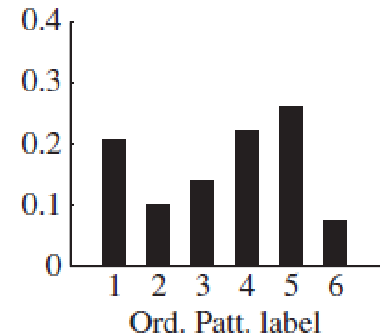


Method of time-series analysis: ordinal patterns

Brandt & Pompe, PRL 88, 174102 (2002)

- $X = \{\ldots x_i, x_{i+1}, x_{i+2}, \ldots\}$





The OP probabilities allow to identify <u>frequent patterns in the *ordering*</u> of the data points

- Drawback: the *values* of the data points are not considered.
- Advantages:
  - We take into account temporal correlations.
  - We can select specific time-scales.

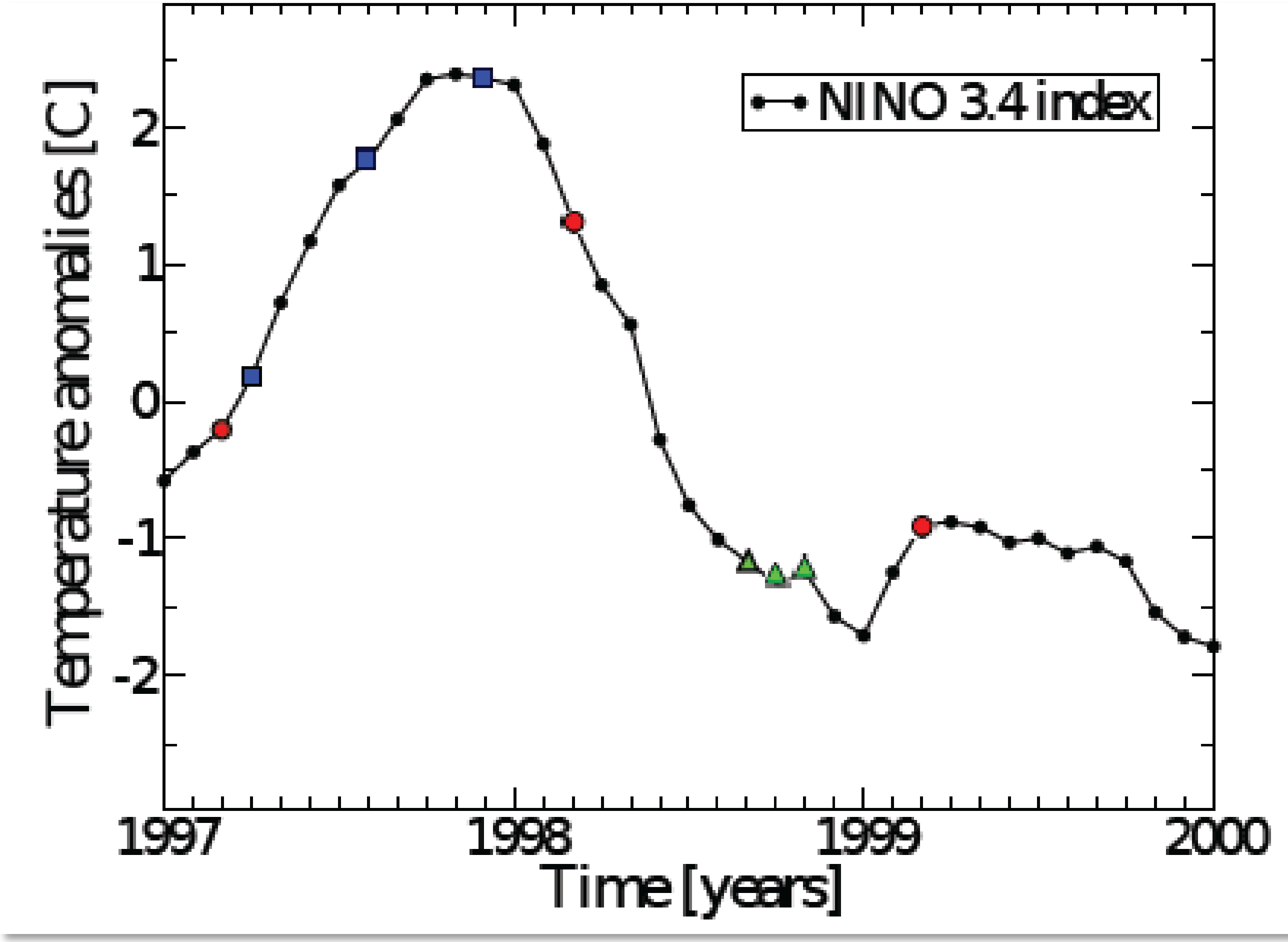
Time scales

- Monthly data

Intra-season 102

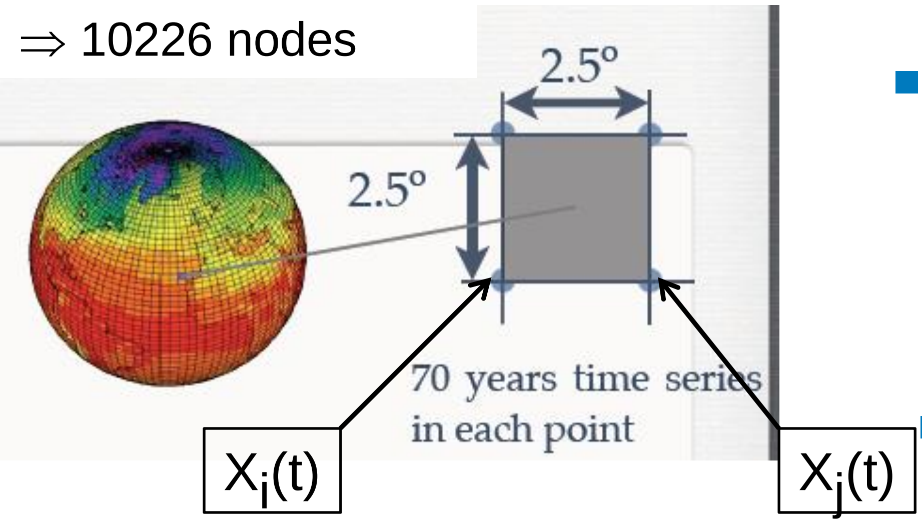
Intra-annual 012

Inter-annual 120



Climate networks: construction and visualization

Regular grid
2.5º x 2.5º
⇒ 10226 nodes



- Data: monthly SAT **anomalies** NCEP/NCAR reanalysis
- Similarity measure: mutual information

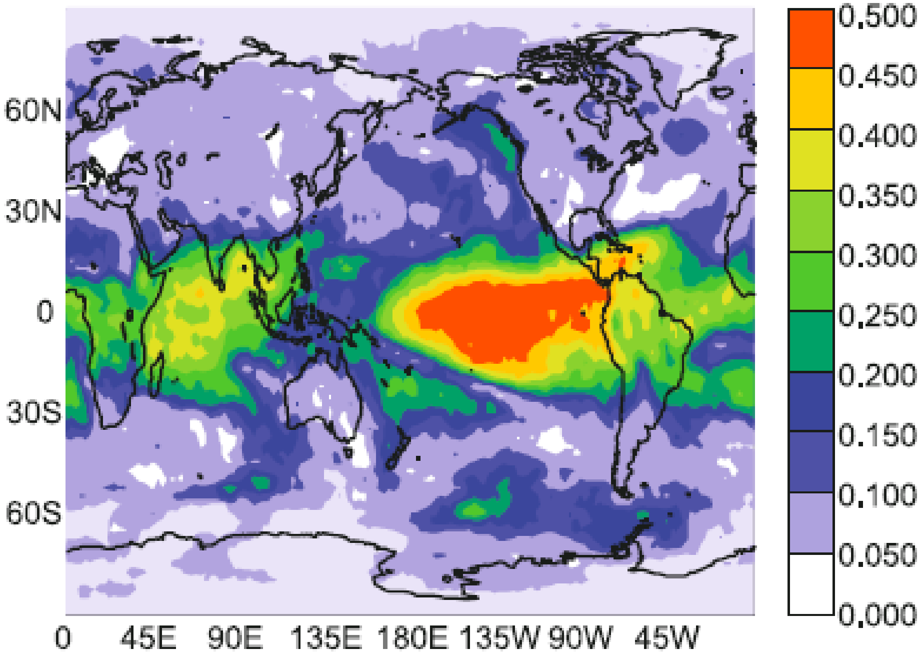
$$M_{ij} = \sum_{m,n} p_{ij}(m,n) \log \frac{p_{ij}(m,n)}{p_i(m)p_j(n)}$$

- Visualization: area weighted connectivity (weighted degree)

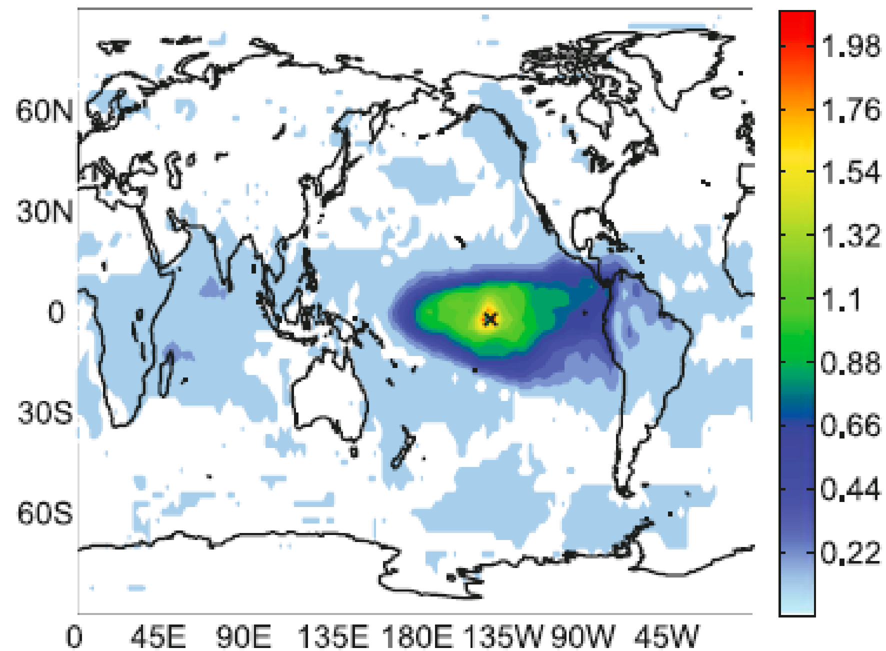
$$\mathrm{AWC}_i = \frac{\sum_j^N A_{ij} \cos(\lambda_j)}{\sum_j^N \cos(\lambda_j)}$$

Results: inter-annual OPs (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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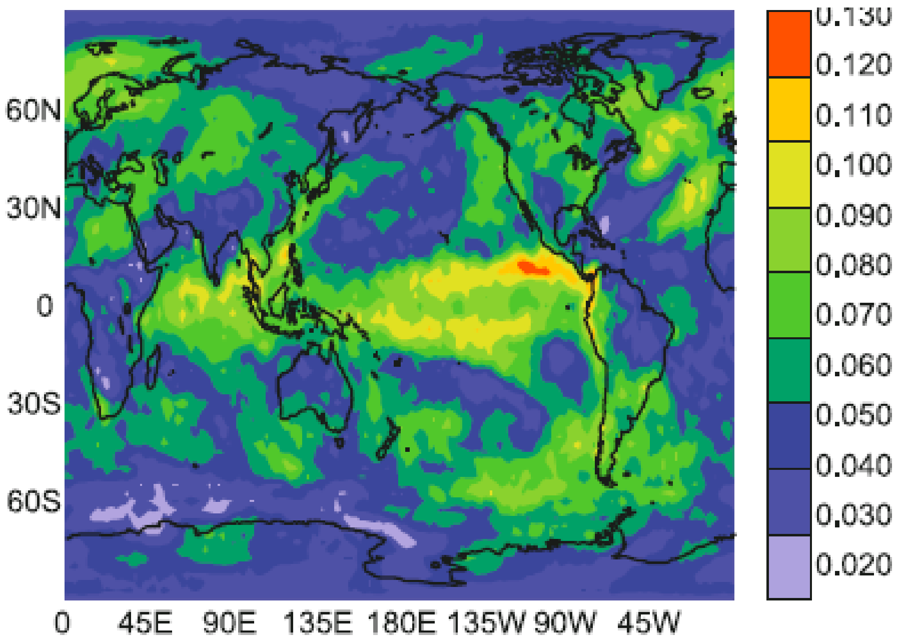
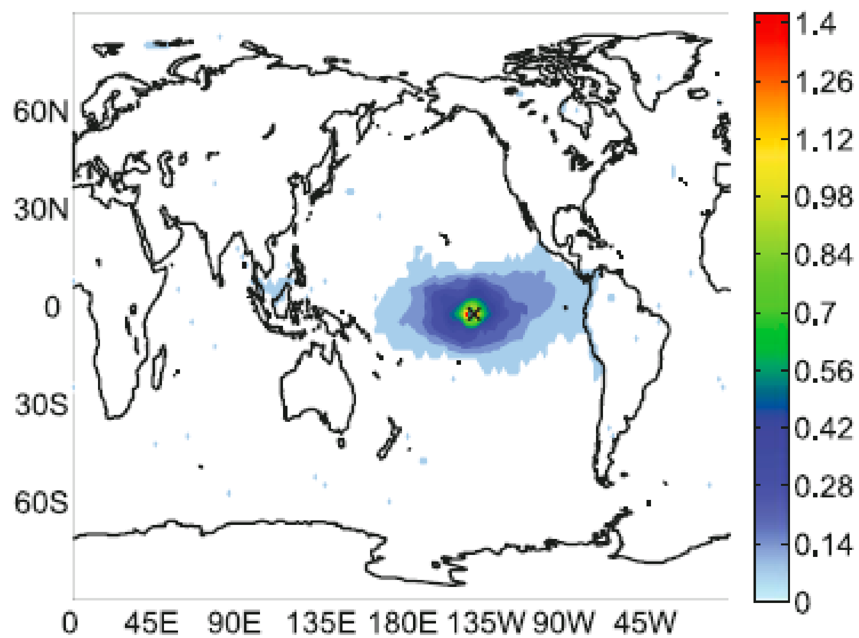
Intra-season (3 consecutive months)

AWC



Links of a node in Central Pacific



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

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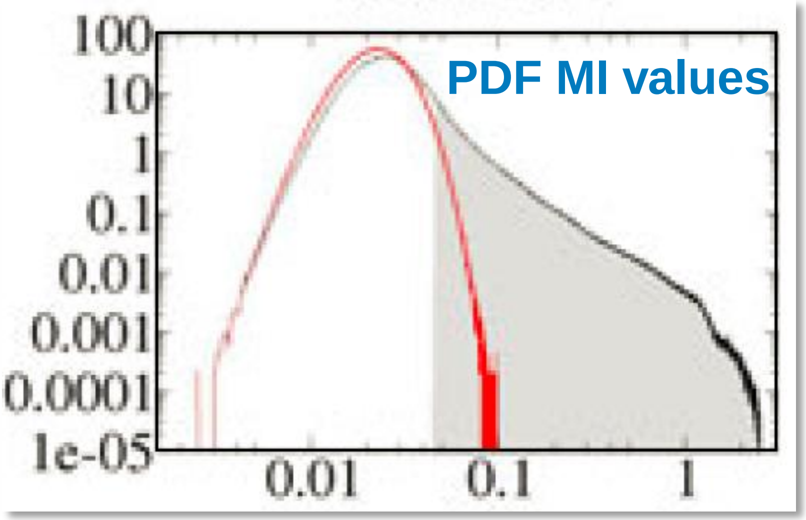
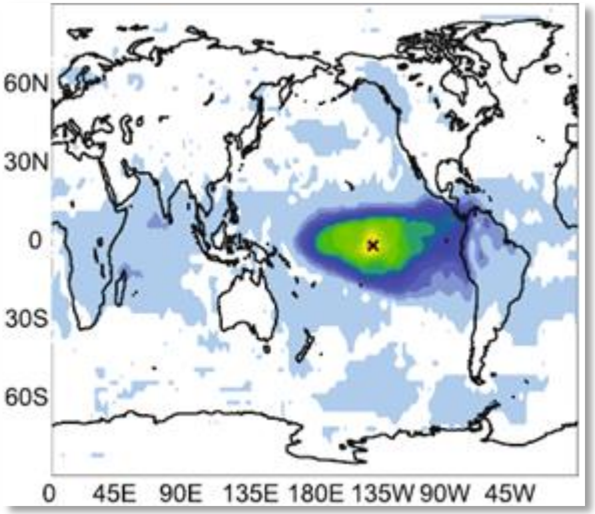
Significance test



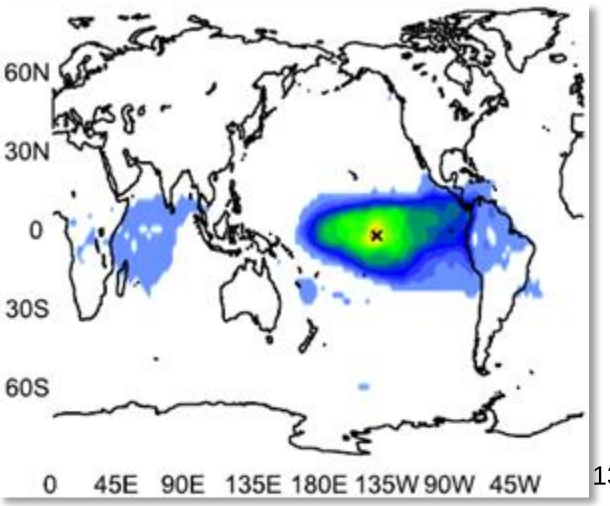
Surrogated data

Original data

Low threshold



Higher threshold



Network comparison

Link density

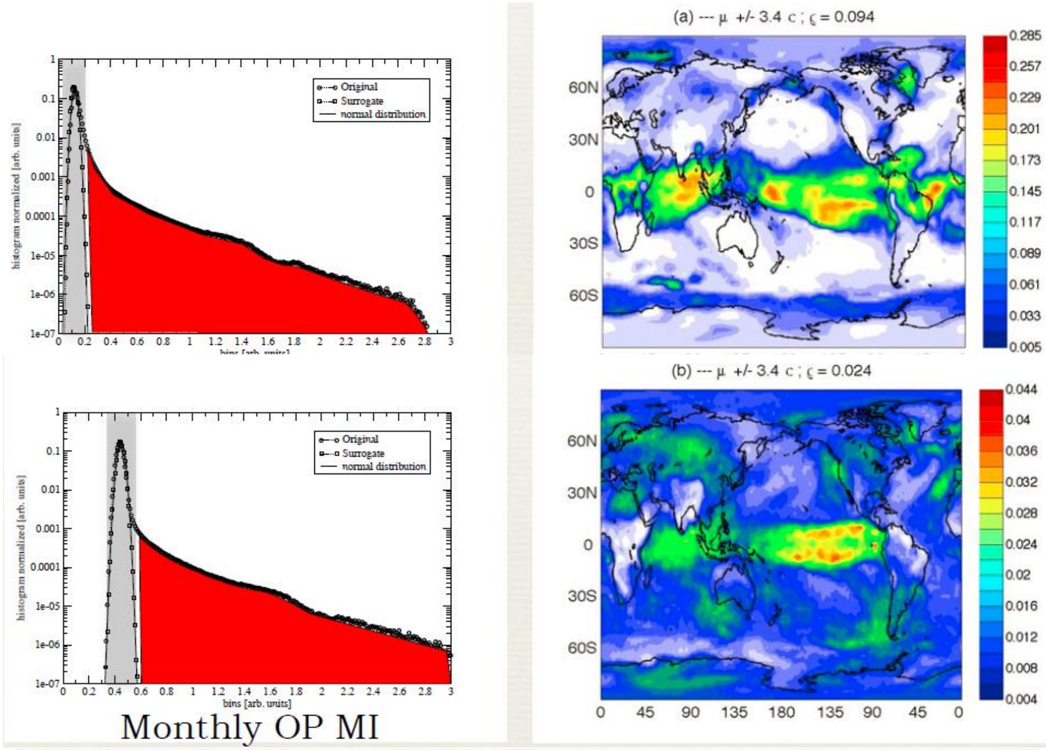
- MIH

0.094

- Intra-season

(4 months)

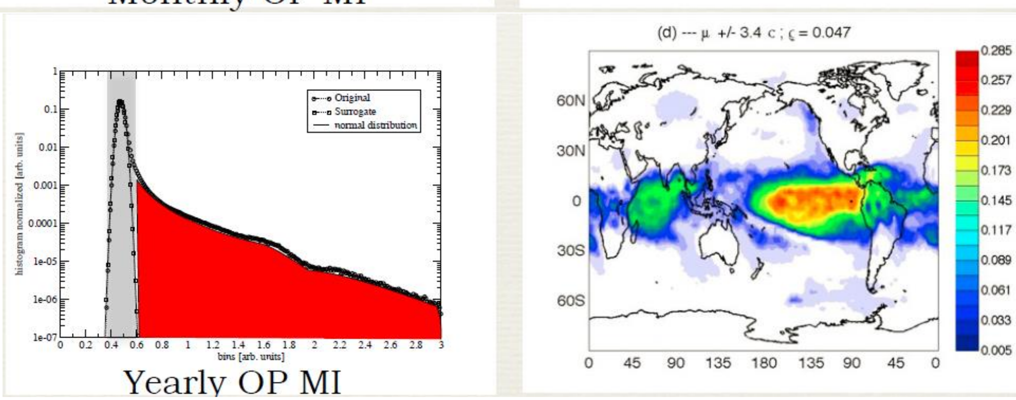
0.024



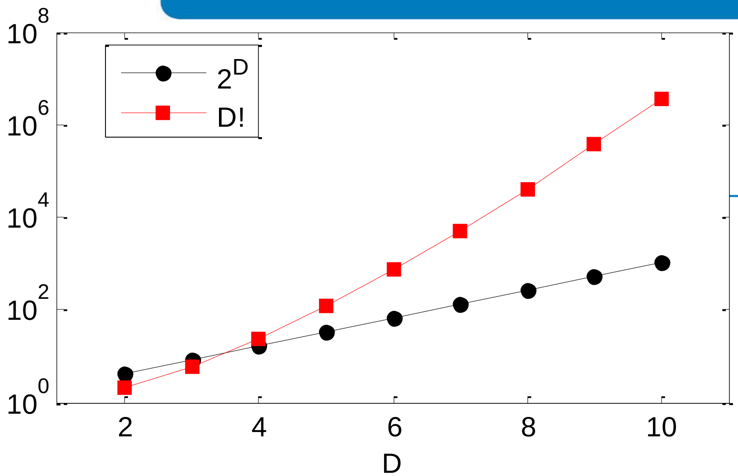
- Inter-annual

(4 years)

0.047

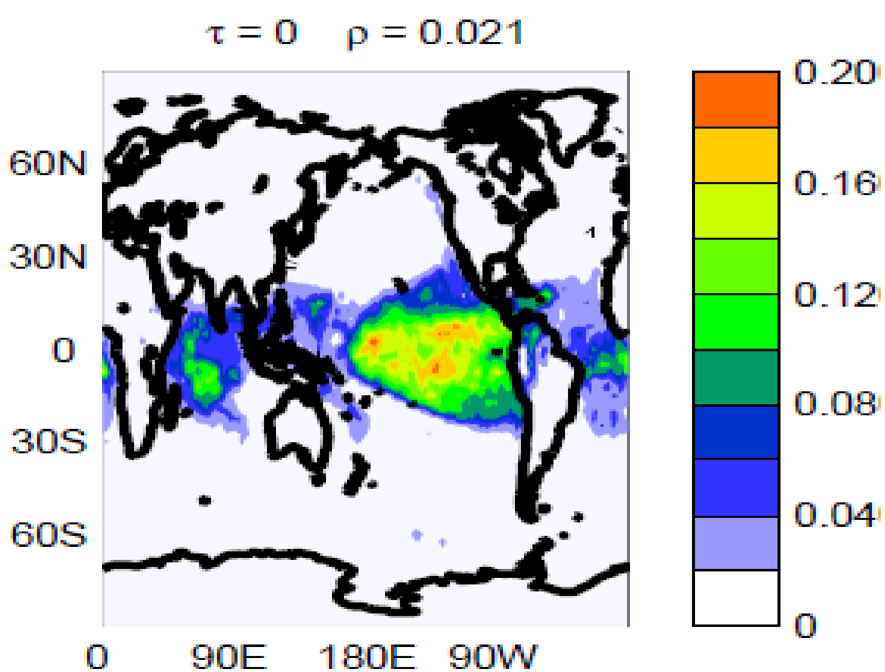


Longer time intervals: binary representation

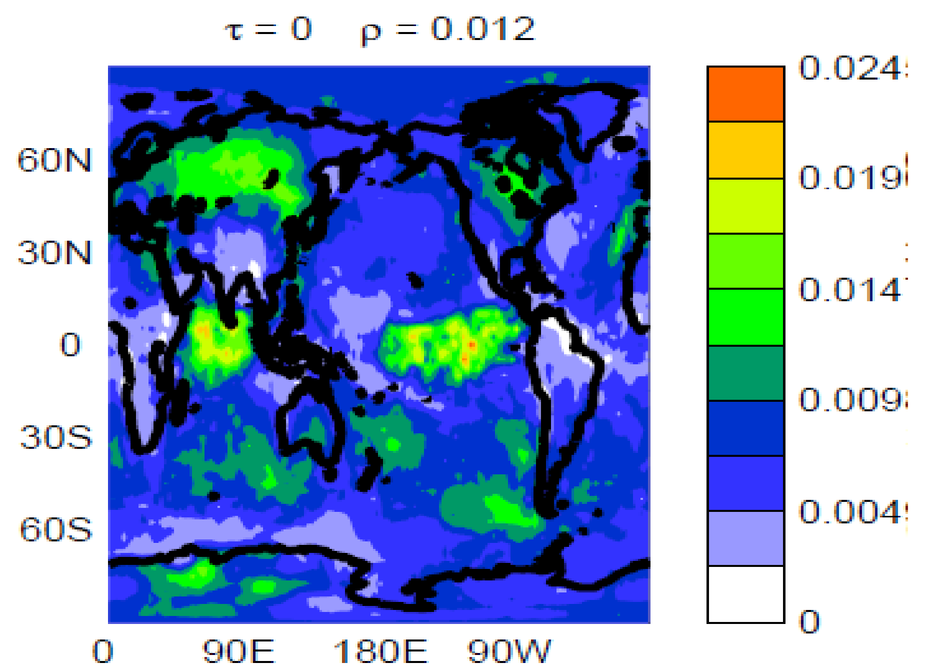


- $X = \{\ldots x_i, x_{i+1}, \ldots, x_{i+D}, \ldots\}$

5 consecutive years

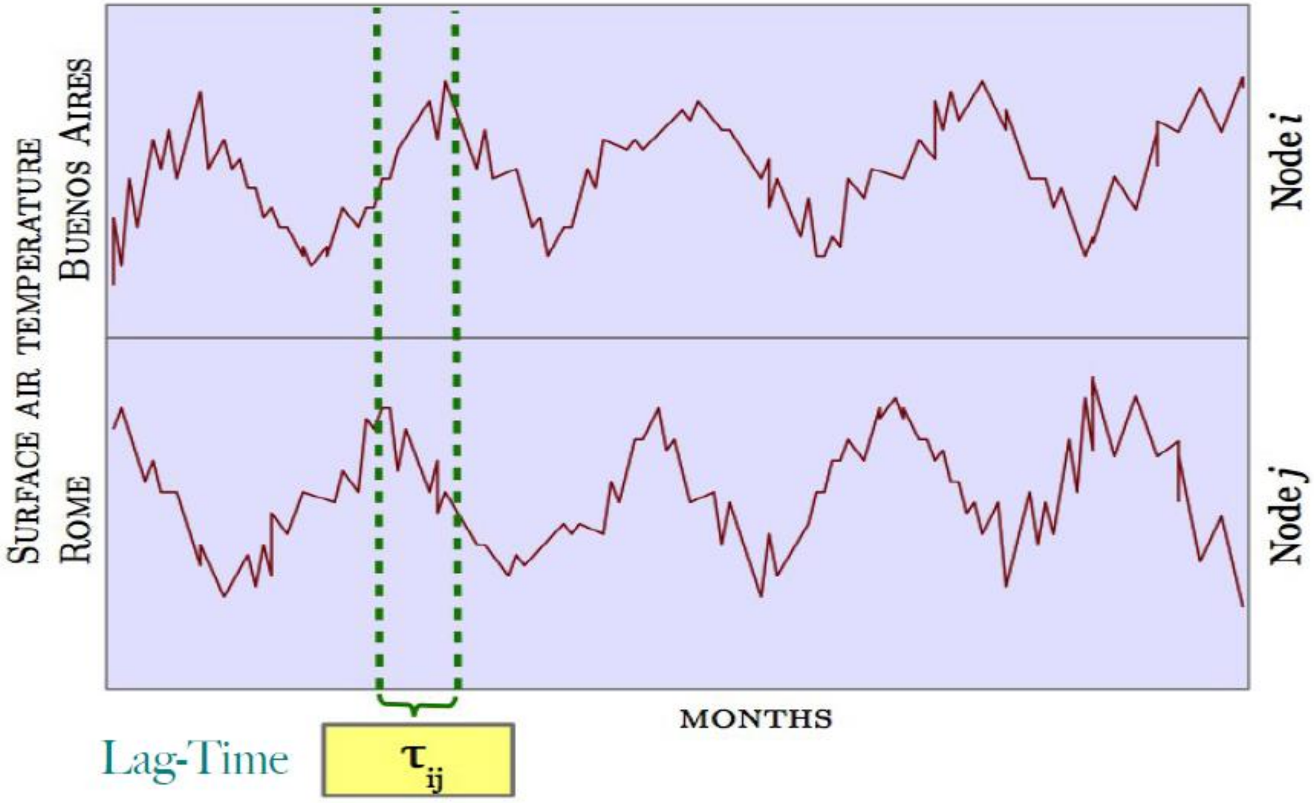


5 consecutive months

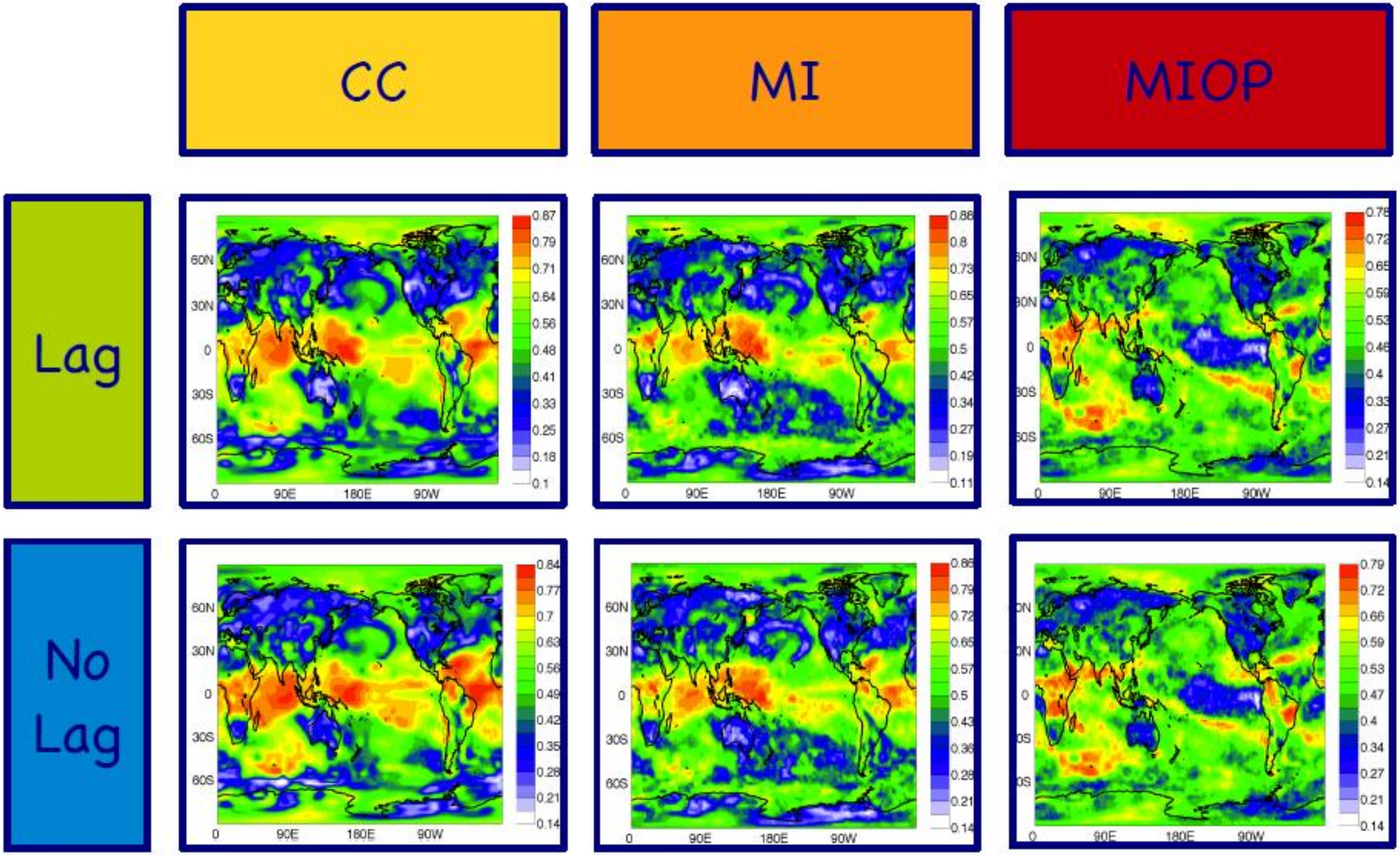


Barreiro et al, Chaos, 21 (2011) 013101.

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

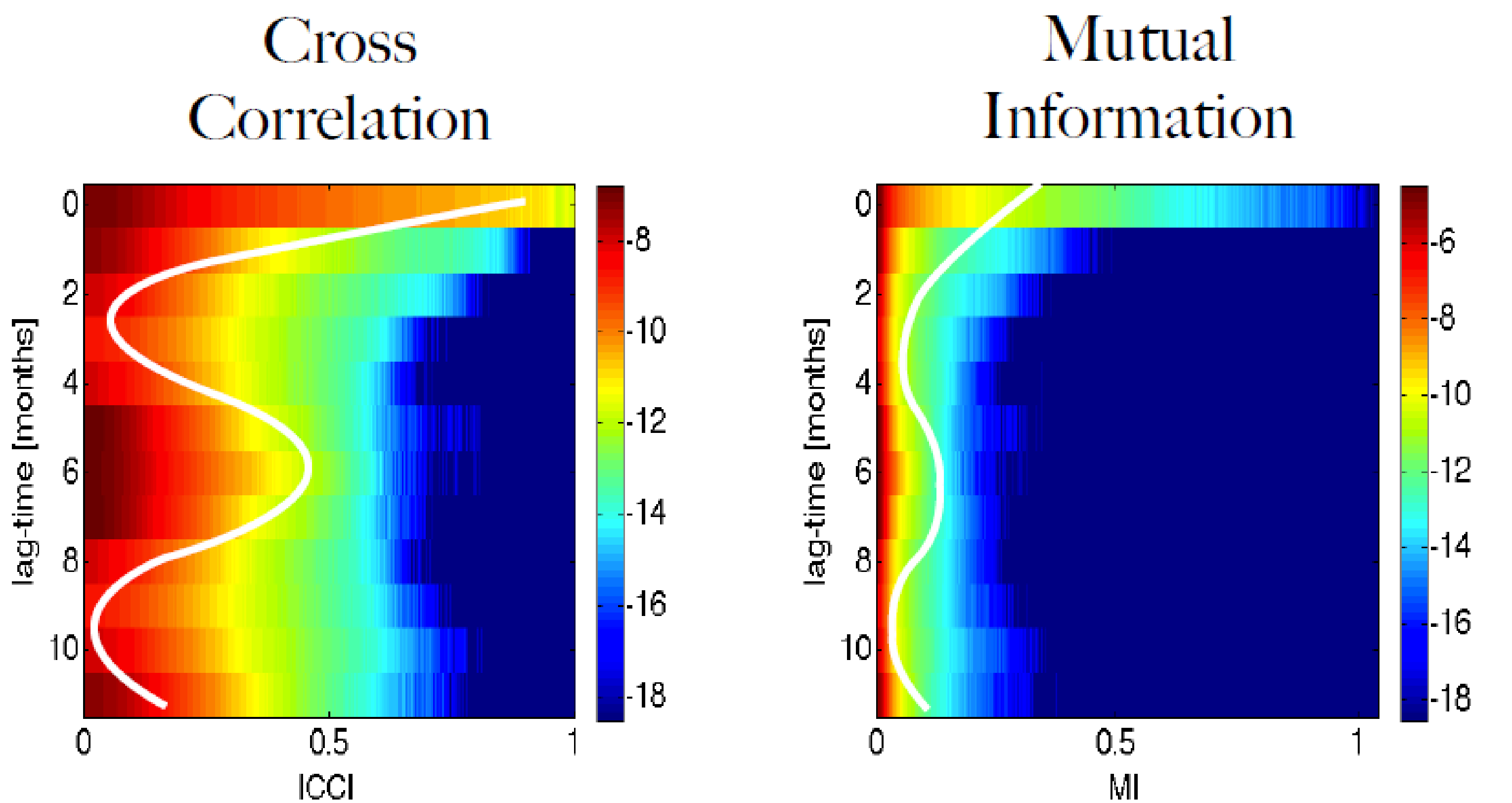


AWC with 50% strongest links

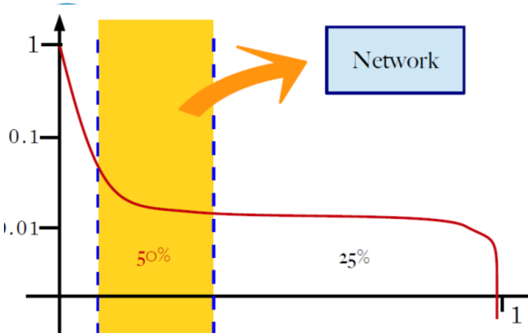


Tirabassi and Masoller, EPL, 102 (2013) 59003

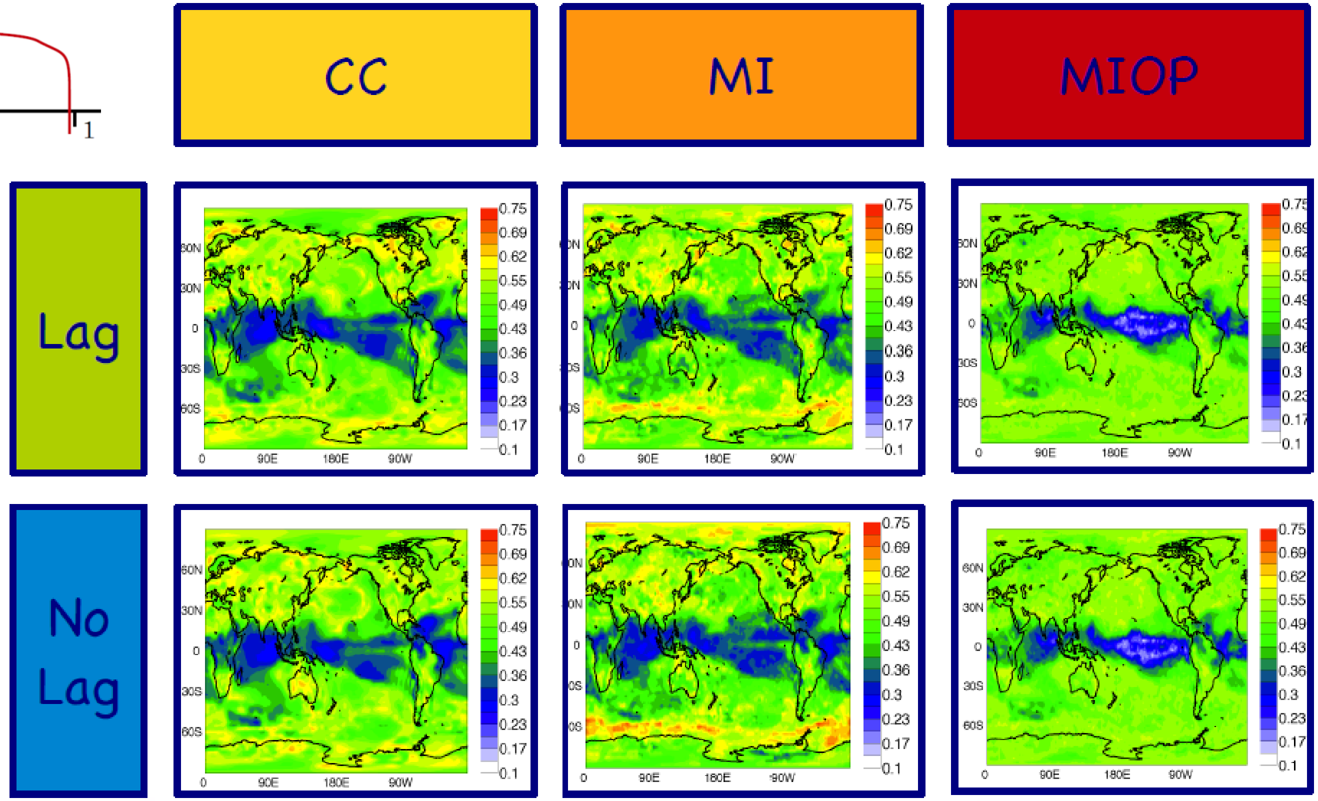
Links: distribution of strengths and lag-times



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

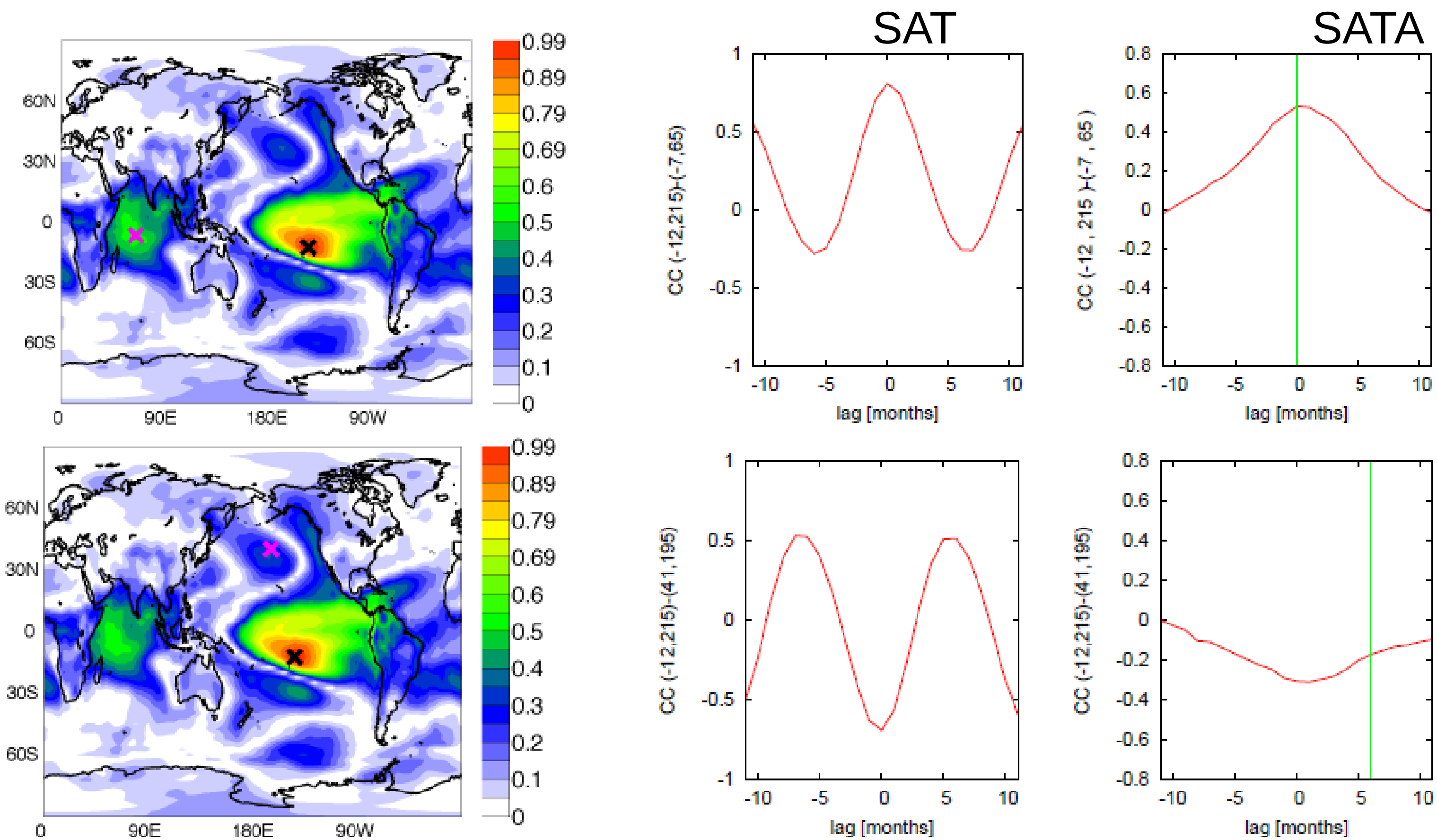


AWC density 50%, the strongest and the weakest links are removed



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

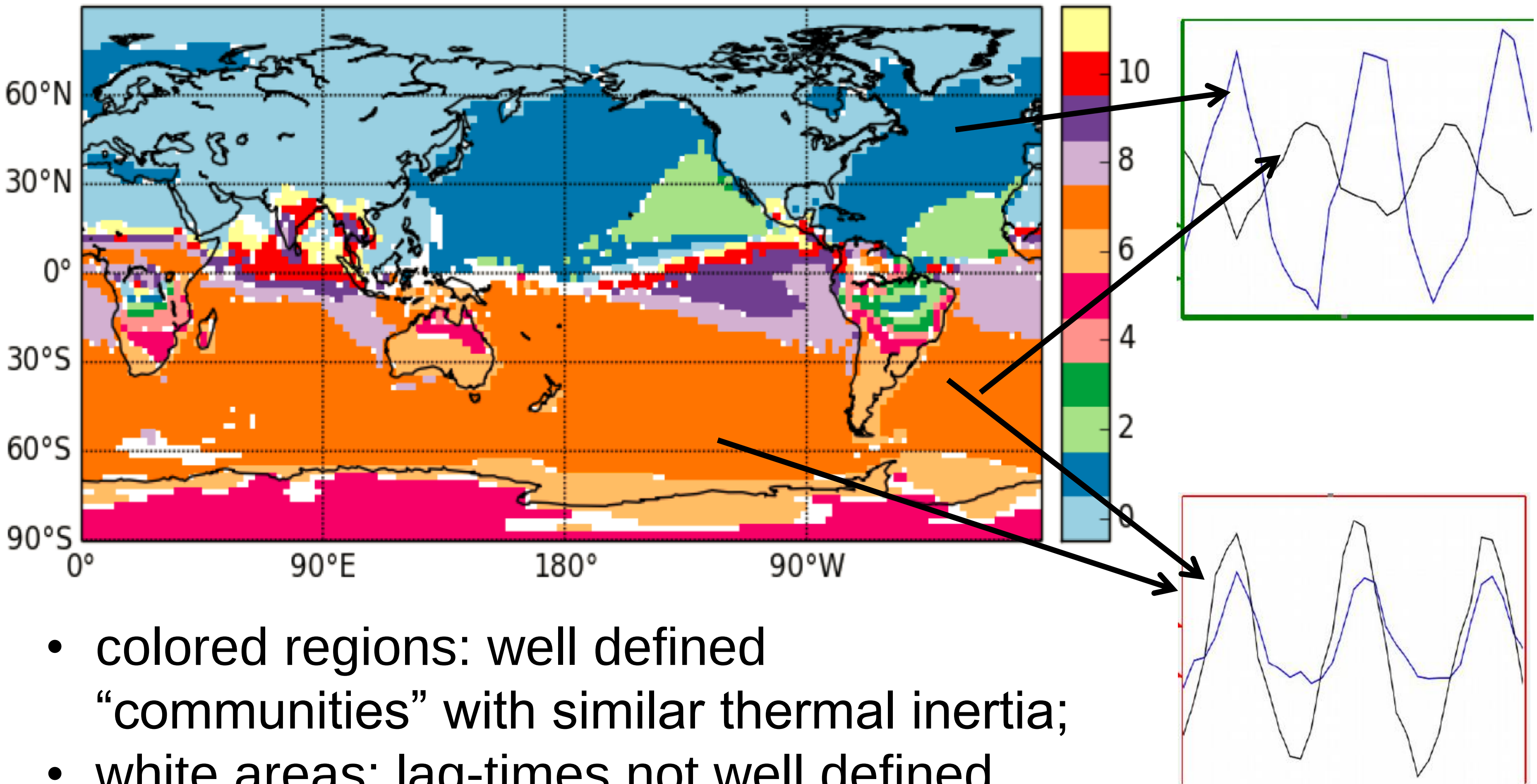
Why there is no effect?



Links with non-zero lags: the time-shifting changes their weight.
But, these changes appear to be random $\Rightarrow$ effects are washed out in the AWC.

Lag-times useful to identify regions with in-phase cycles

$$\ell_{ij} = (\ell_{ik} + \ell_{kj}) \bmod 12$$



- colored regions: well defined "communities" with similar thermal inertia;
- white areas: lag-times not well defined.

To further understand the role of annual solar forcing

- 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** and **SAT anomalies** to quantify atmospheric nonlinearity and stochasticy.

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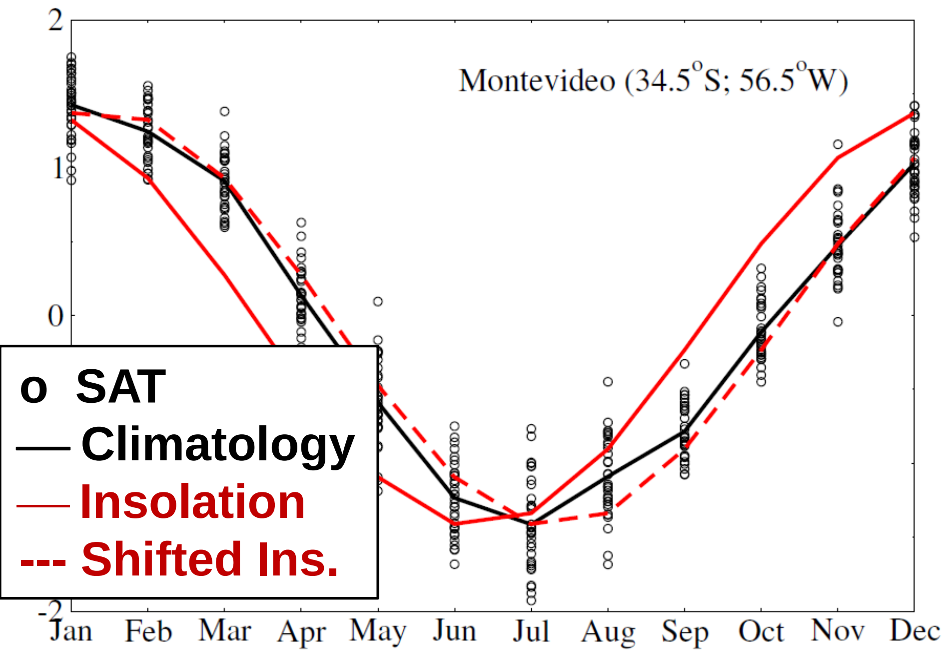
Quantifying atmospheric nonlinearity and stochasticity

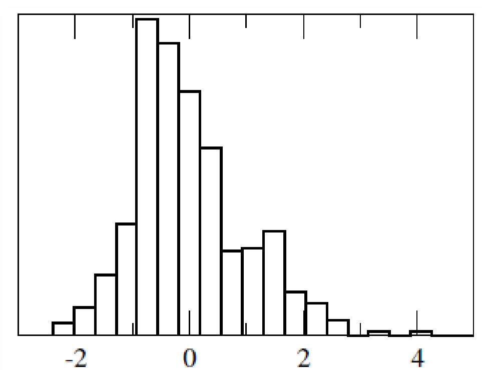


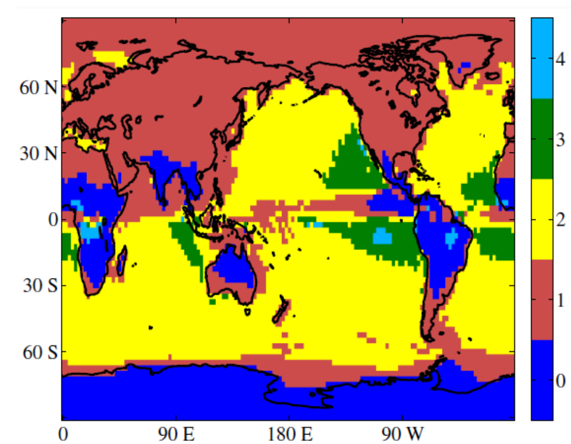
$$D_i(\varphi_i) = \frac{1}{T}\sum_{t=1}^{T}\left|x_i(t) - I_i(t+\varphi_i)\right|$$

I_i = insolation at node *i* (top-of-atmosphere incoming solar radiation)
x_i = climatology at node *i*
x_i and I_i are both normalized to zero mean and σ=1.

φ_i = in [0-4 months] minimizes D_i.

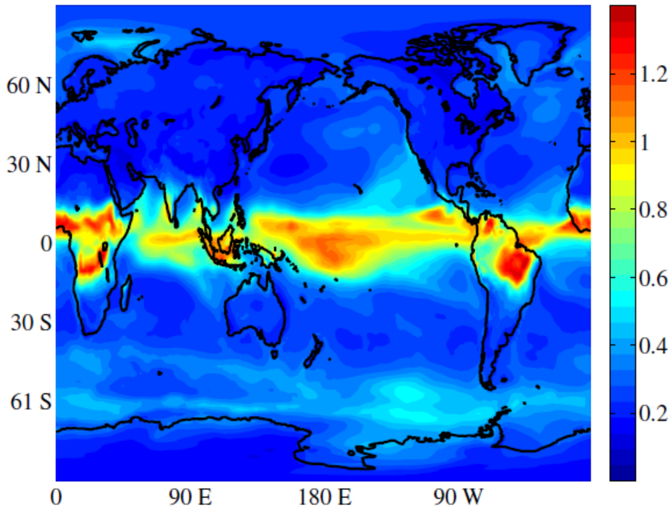
The entropy is computed from the PDF of SAT anomalies



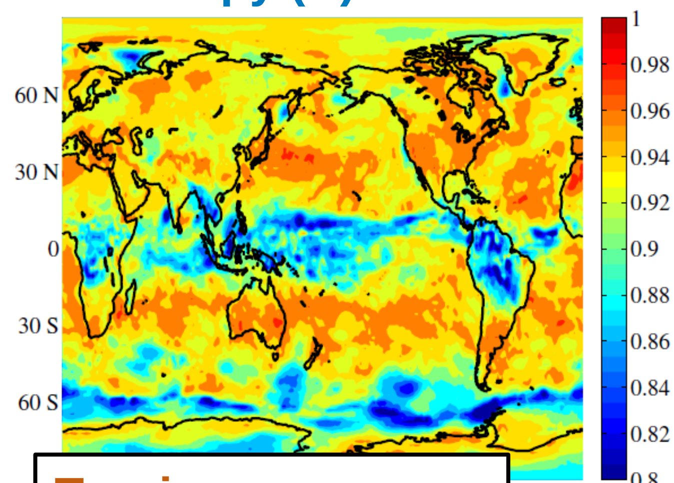


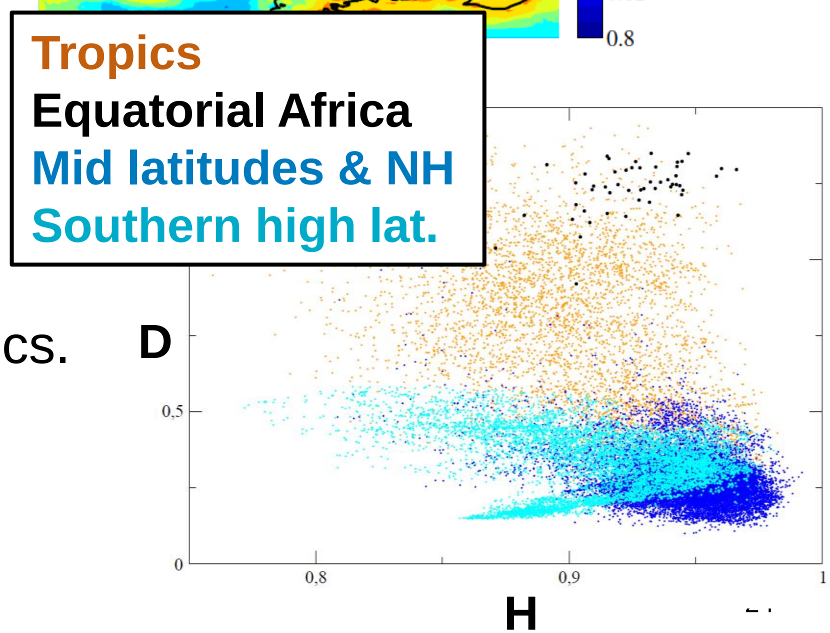
Results

Nonlinear measure (D)



Entropy (H)





- Regions with high nonlinearity: tropics.
- Extratropics: high entropy & low nonlinearity

F. Arismendi et al, submitted (2015)

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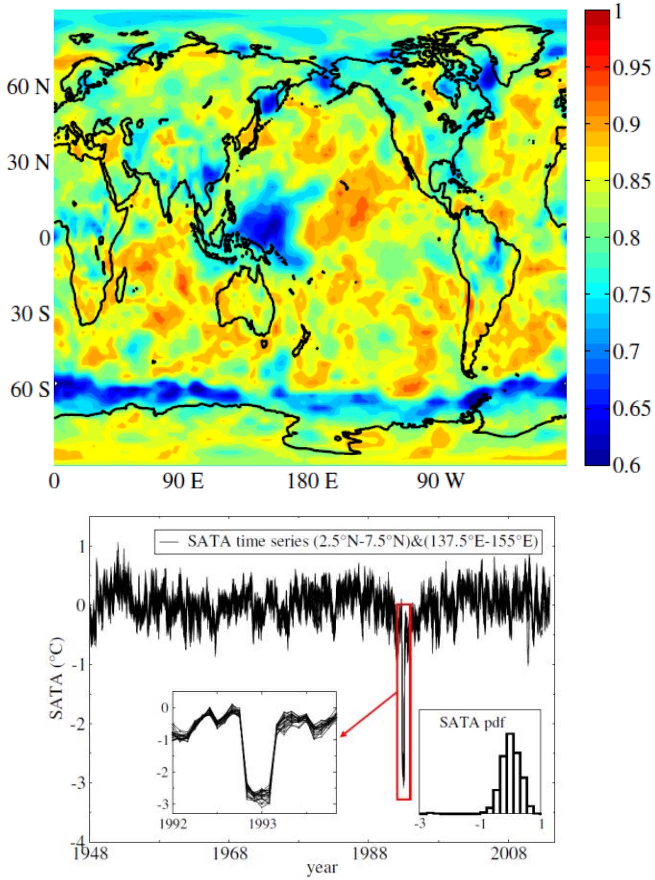
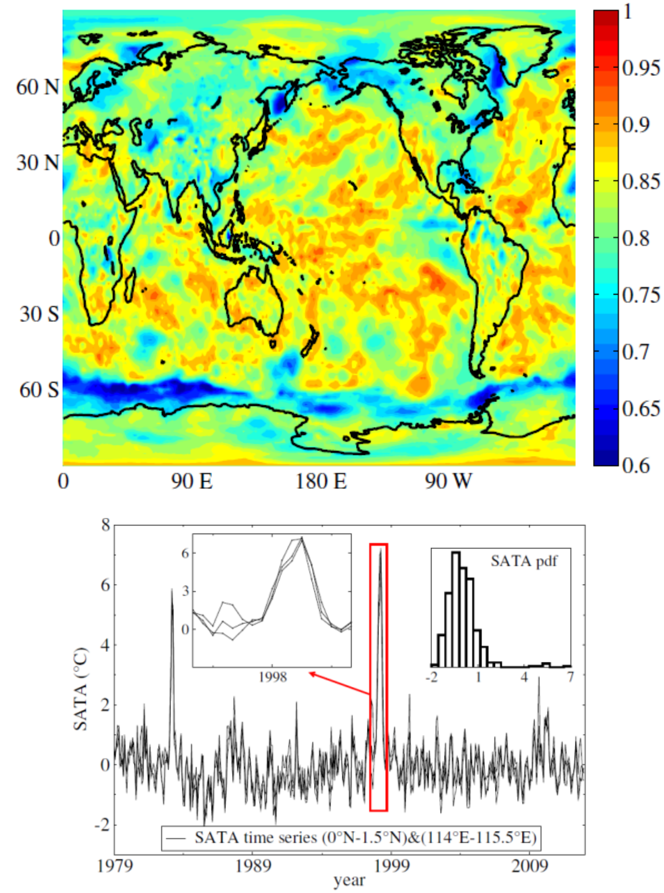
Dataset comparison

NCEP CDAS1



ERA Interim



In both cases, the extreme values do not appear in the other dataset

Identifying regions with similar climate

- Goal: to construct a network in which regions with similar climate (e.g., continental) are in the same "community".
- "Usual" way not doable: NH and SH are indirectly connected.

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Network Construction

- Step 1: transform SAT anomalies in each node in a sequence of ordinal patterns

  s_i = {012, 102, 210, 012…} s_j = {201, 210, 210, 012, …}

- Step 2: compute <u>transition probabilities</u>

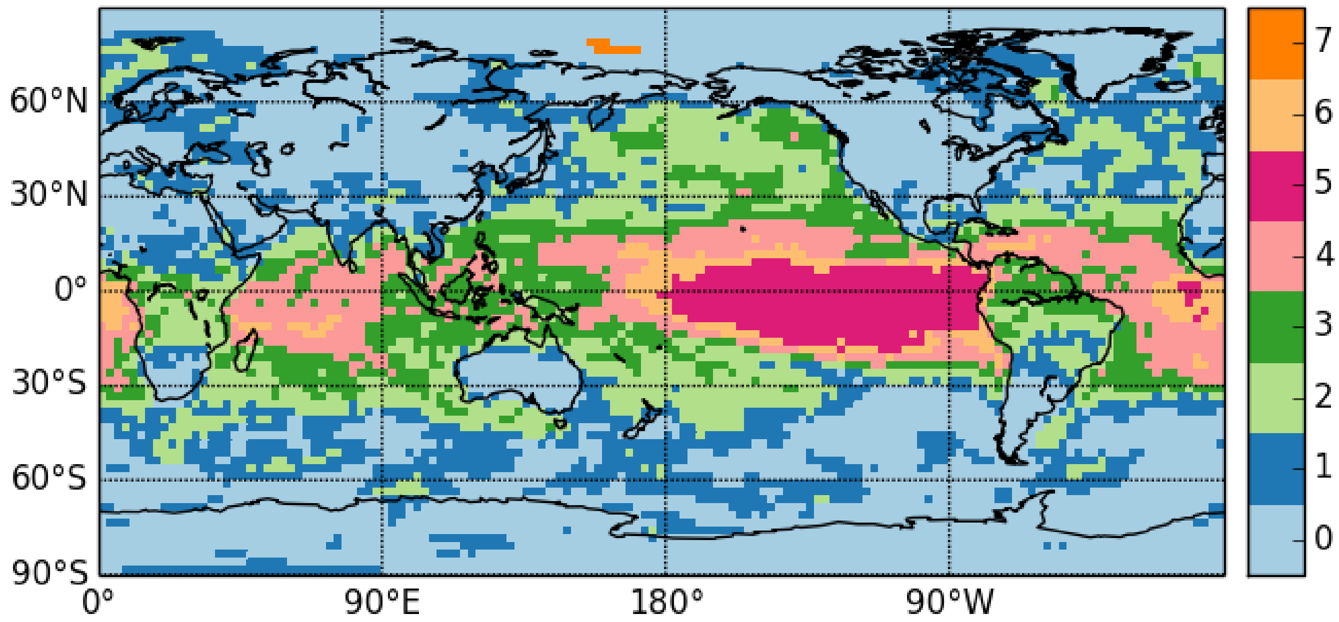
  $TP^{i}_{\alpha\beta} = \#(\alpha \rightarrow \beta)/N$

- Step 3: define the weights $$w_{ij} = \frac{1}{\sum_{\alpha\beta}\left(TP^{i}_{\alpha\beta} - TP^{j}_{\alpha\beta}\right)^2}$$

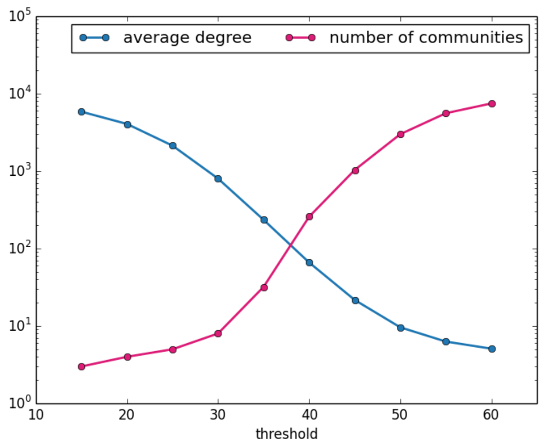
- Step 4: threshold w_{ij} to obtain the adjacency matrix.

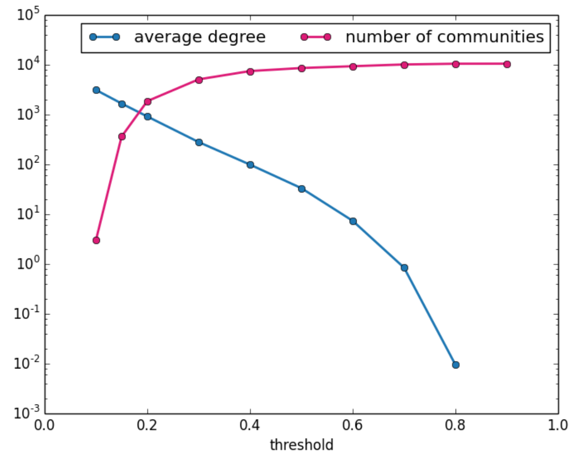
- Step 5: run a community detection algorithm.

Results



TP Network





CC Network

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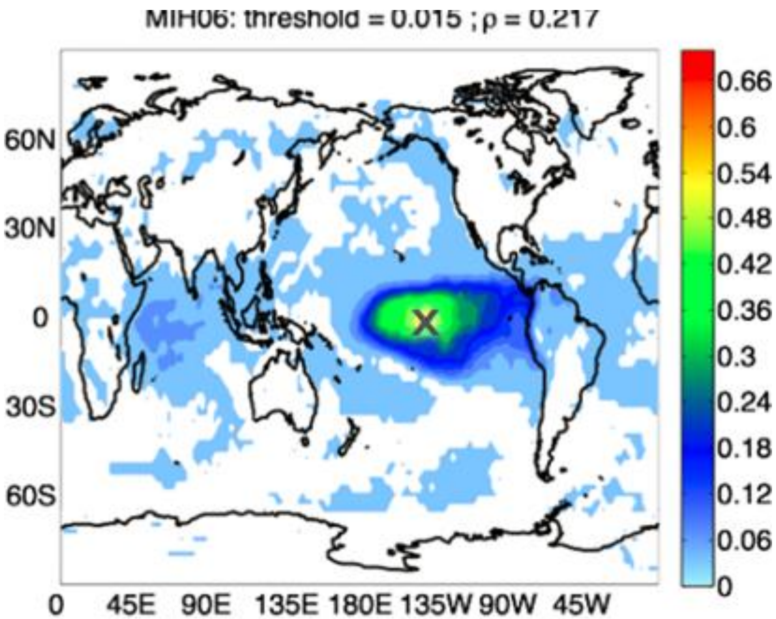
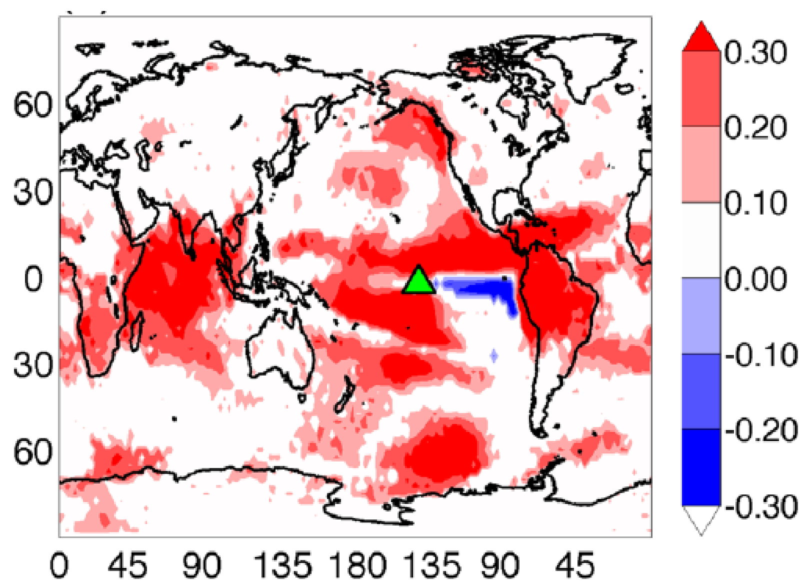
Link directionality

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

(Prof. Palus' talk)

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

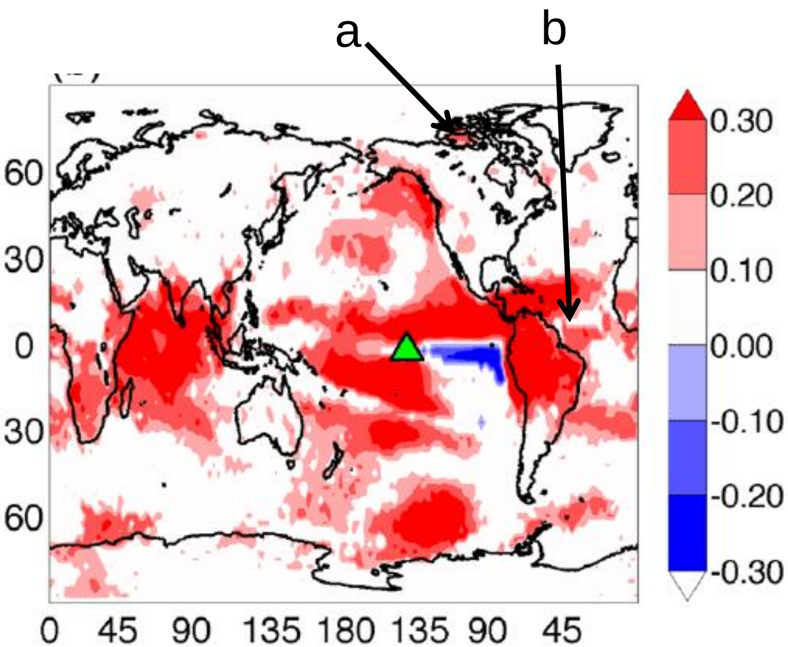


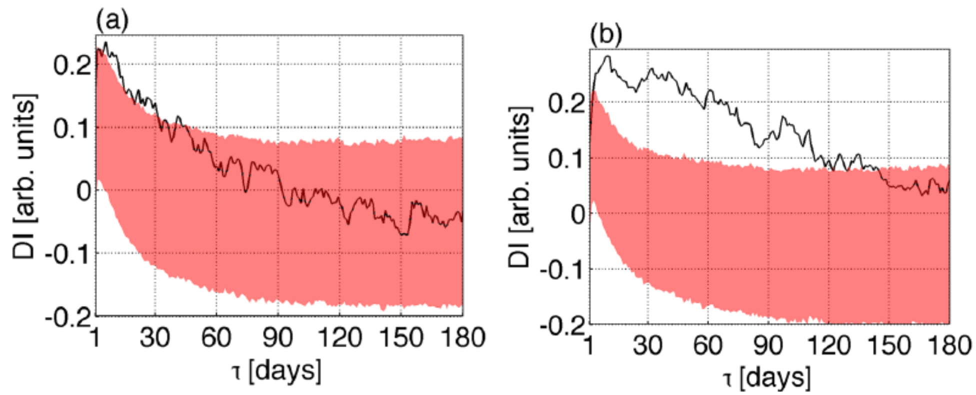


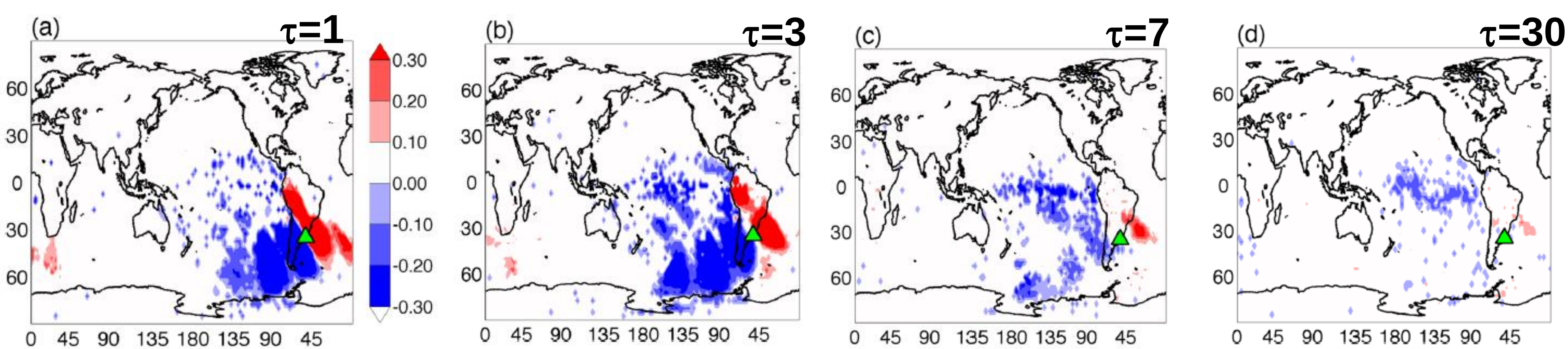
Computed from daily SAT anomalies, PDFs estimated from histograms of values.
MI and DI are <u>*both significant*</u> (>3σ, bootstrap surrogates), τ=30 days.

Deza et al, Chaos 25, 033105 (2015)

Time-scale of interactions







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Contrasting structural and functional connectivity

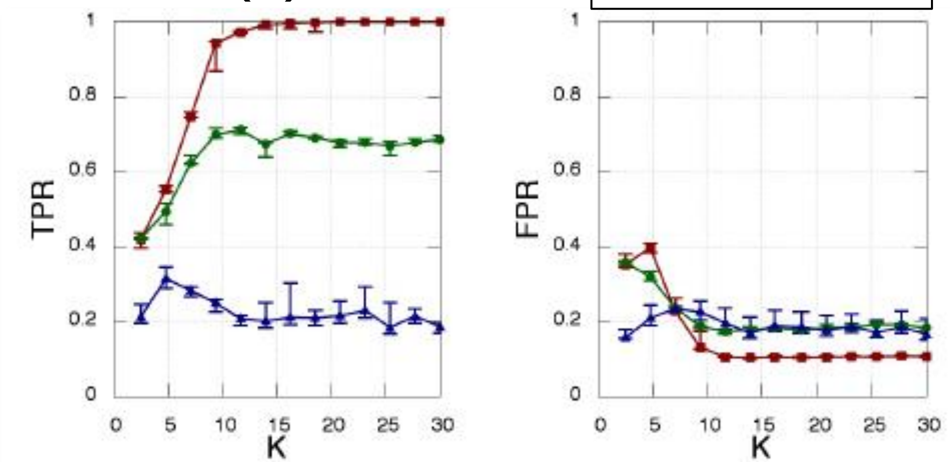
Goal: to test the method of network inference on Kuramoto oscillators with known coupling topology (A_{ij})

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

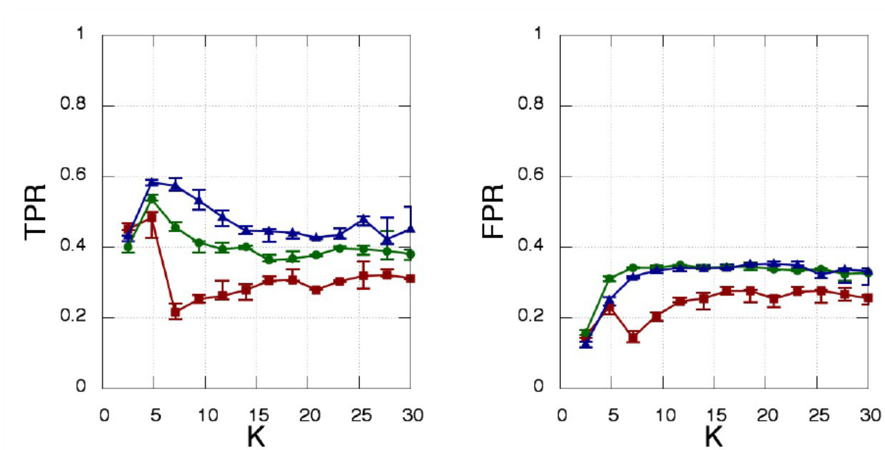
N=12 time-series with 10^4 data points

Phases (θ)

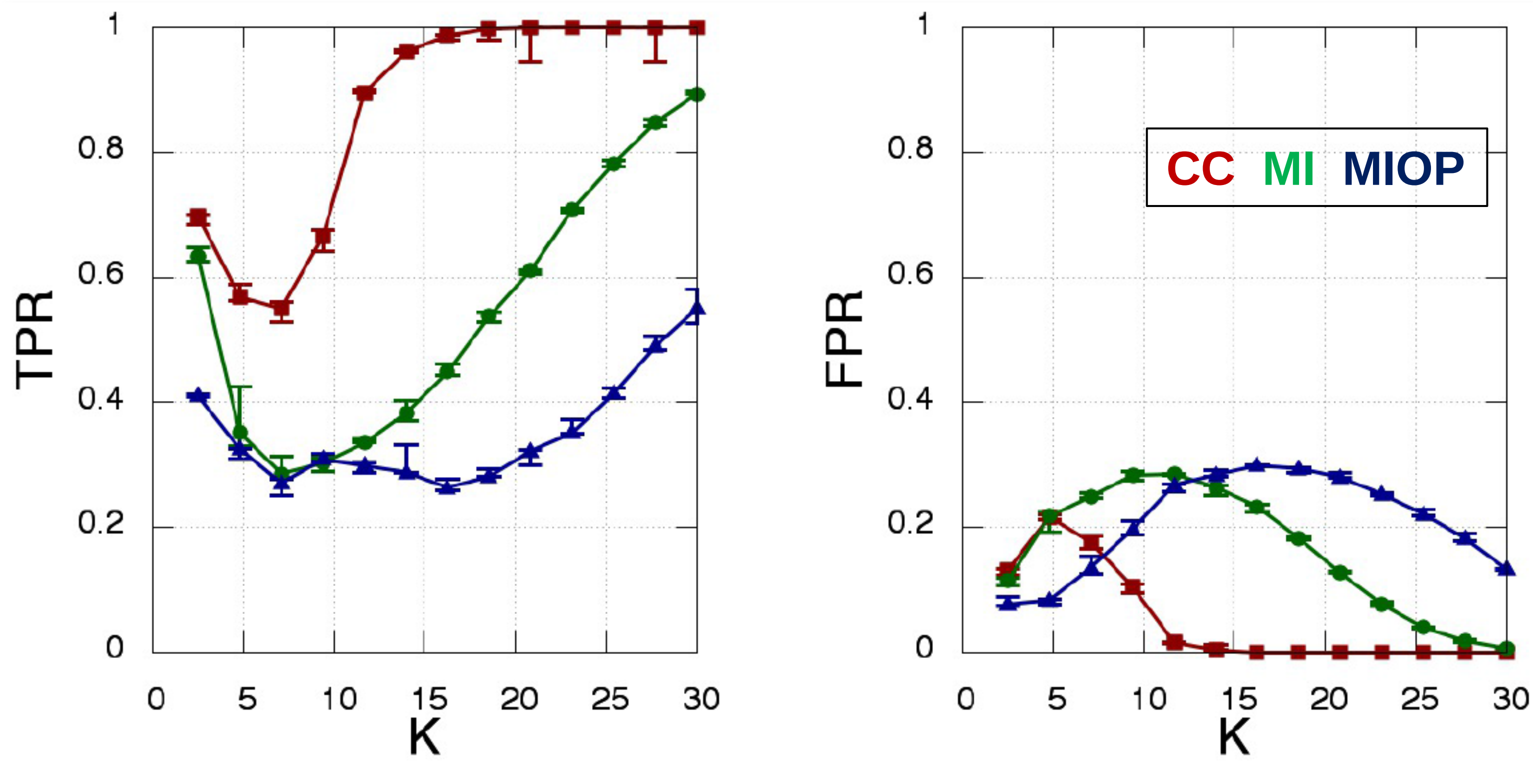
CC MI MIOP



"Observables" Y=sin(θ)



Instantaneous frequencies (dθ/dt)

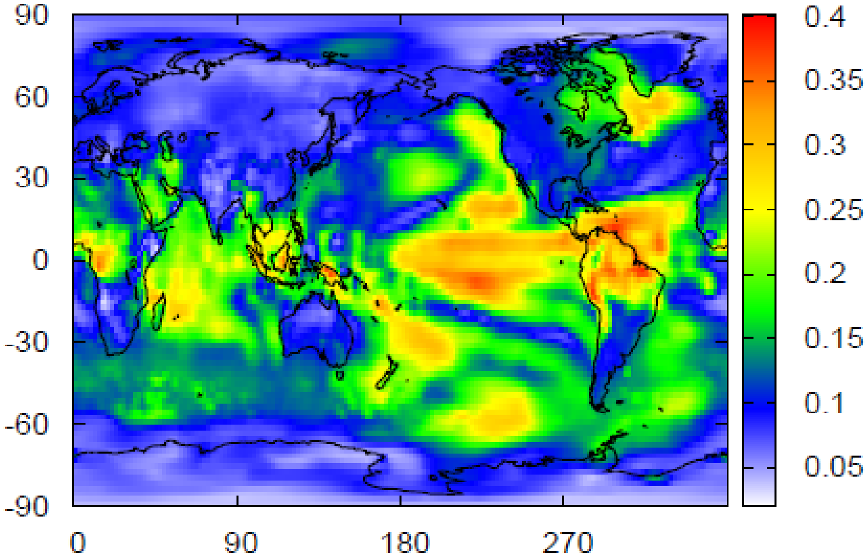


Also analyzed empirical data from coupled electronic chaotic circuits: results in good agreement with synthetic Kuramoto data.

Tirabassi et al, Sci. Rep. **5** 10829 (2015)

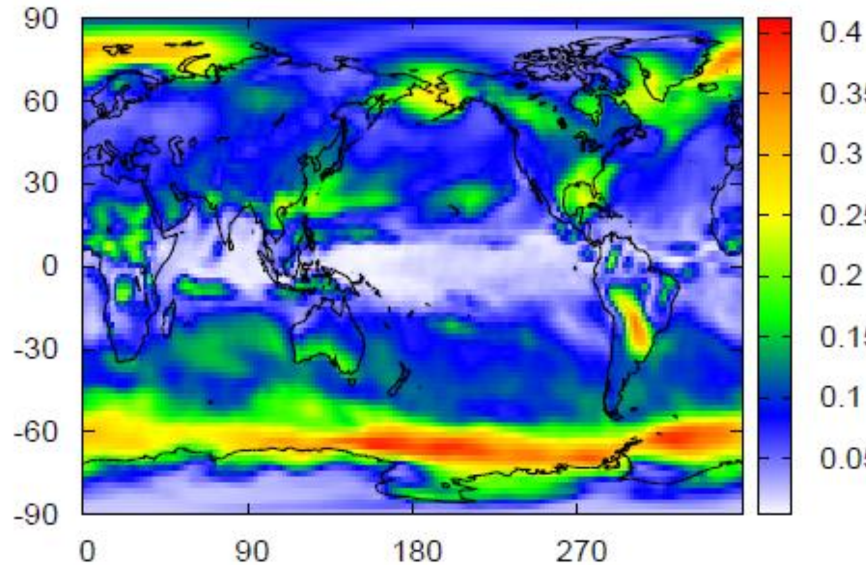
Ongoing work

Climate network constructed from CC analysis of SATA data



(a) Data anomaly. $p = 10^{-4}$; $d = 0.13$

CC analysis of Hilbert frequencies computed from SAT data



(b) Frequency. $p = 10^{-3}$; $d = 0.13$

Details in Dario Zappala's poster

Summary: what did we learn?

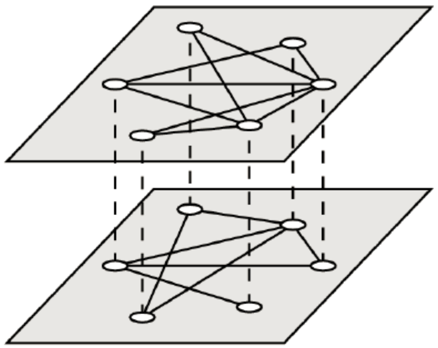
- Take home message: nonlinear time-series analysis unveils relevant information about our climate dynamics, consistent with well-known climate phenomena.

- A few conclusions:
  - No increase of connectivity obtained when taking into account lag-times between annual solar cycles.
  - Atmospheric stochasticity & nonlinearity: nonlinearity mainly in the tropics; possible application: model inter-comparisons.
  - Climate communities: regions with similar thermal inertia or dynamics.
  - DI identifies the net direction & time-scale of information transfer.
  - In a small synthetic network, CC analysis of the instantaneous frequencies allowed perfect network inference.

Ongoing and future work

- Favored / infrequent patterns in climate dynamics?
- Quantifying time-evolving networks via a novel network dissimilarity measure (poster by Laura Carpi).

- Ordinal 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 (sub-seasonal).

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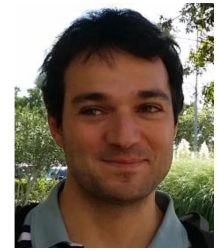


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THANK YOU FOR YOUR ATTENTION !

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