

Inferring the connectivity and the community structure of a complex system from observed data

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UNIVERSITAT POLITÈCNICA
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Dynamics Days Latin
America and the
Caribbean, Puebla,
Mexico, October 2016

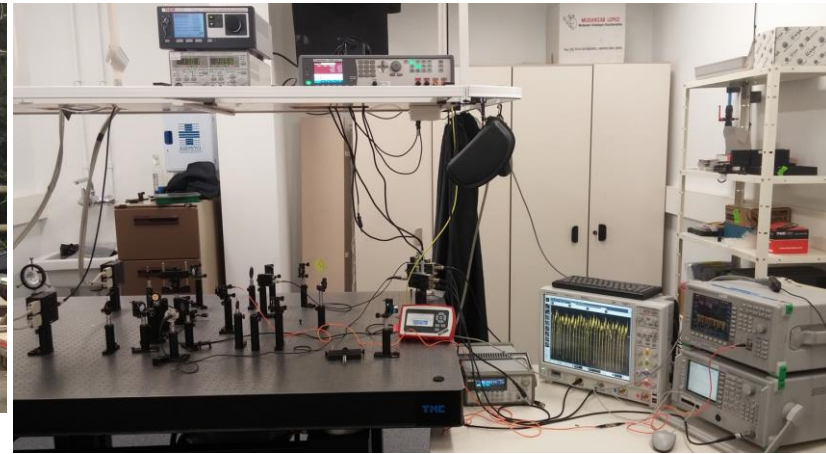


ICREA





Our research: nonlinear and stochastic phenomena in complex systems



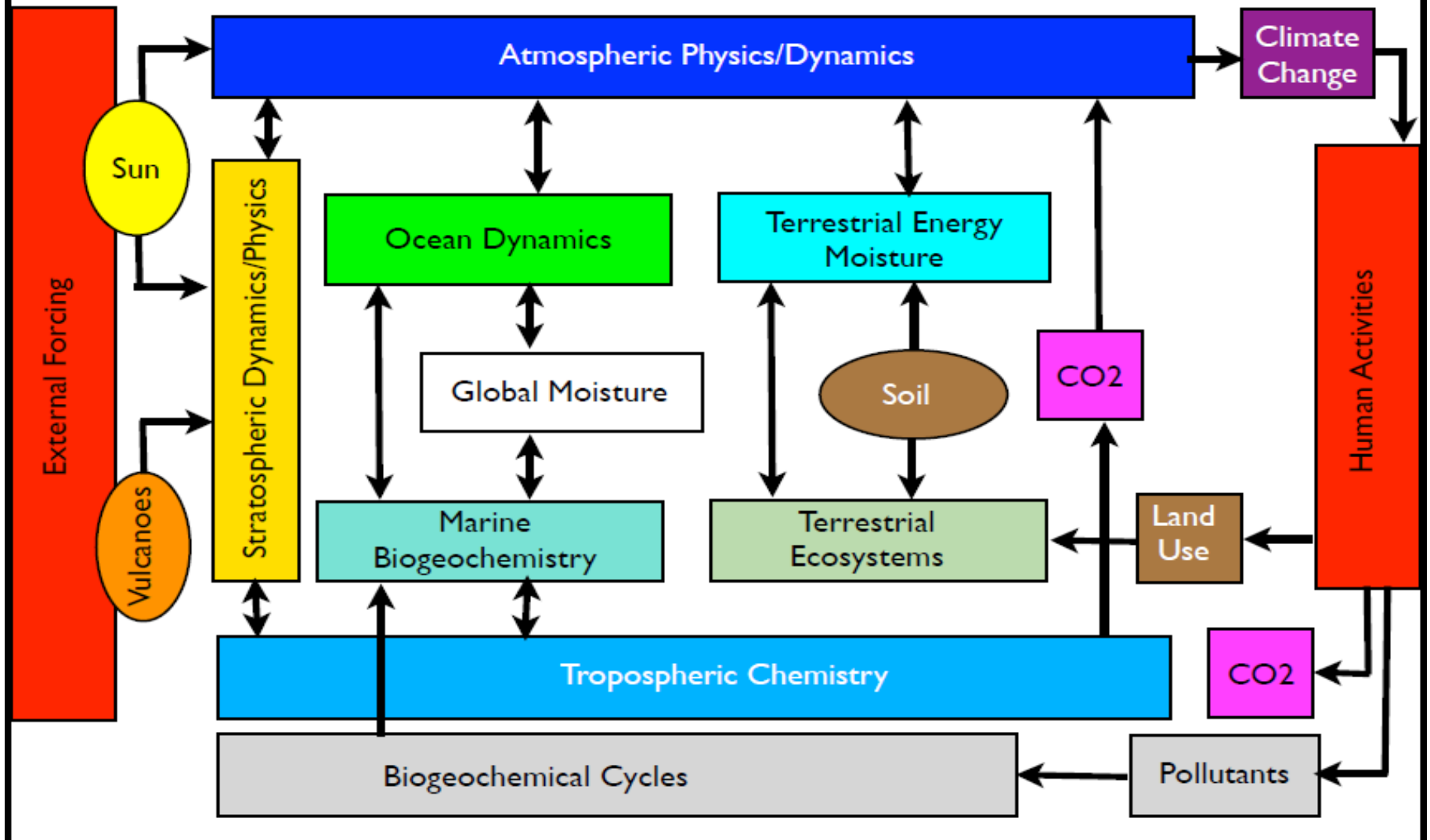
- Photonics (dynamics of laser, time-delay feedback),
- Biophysics (neuronal excitability, synchronization),
- Time series analysis (extreme events, tipping points and regime transitions, climate data analysis, biomedical signals),
- Complex networks (network inference, climate networks and communities).

WHAT DO NETWORKS HAVE TO DO WITH CLIMATE?

BY ANASTASIOS A. TSONIS, KYLE L. SWANSON, AND PAUL J. ROEBBER

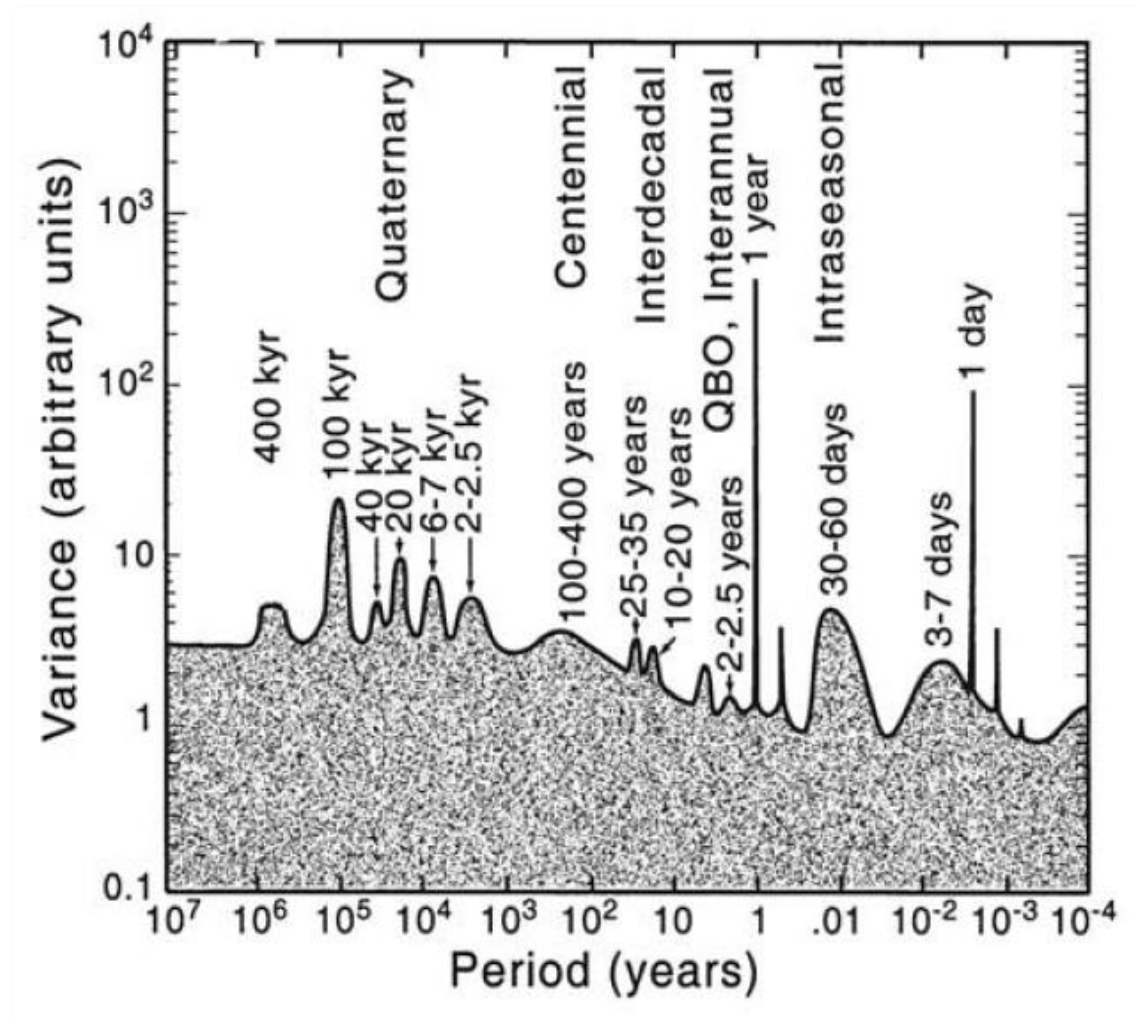
Advances in understanding coupling in complex networks offer new ways of studying the collective behavior of interactive systems and already have yielded new insights in many areas of science.

The Climate System



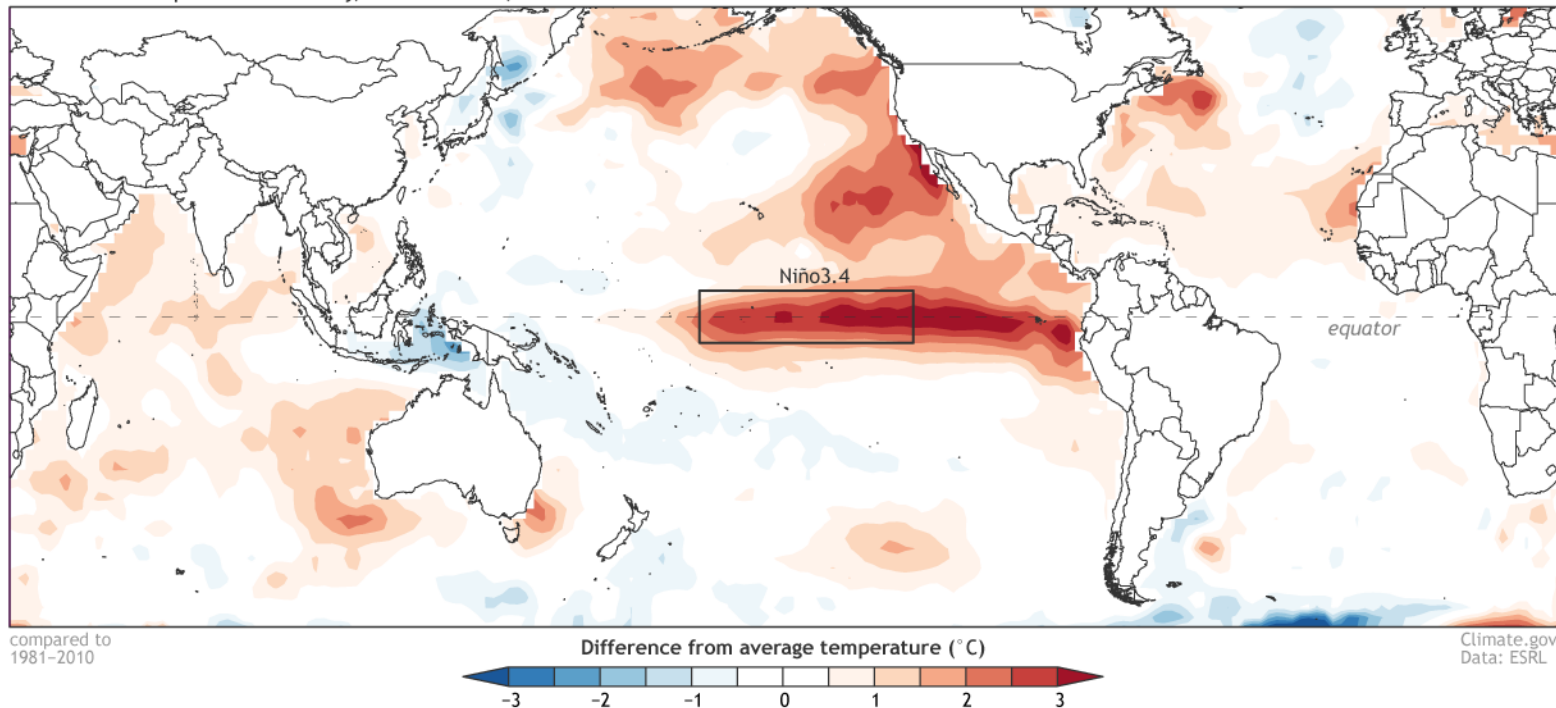
The climate system: a complex system with a wide range of time-scales

- hours to days,
- months to seasons,
- decades to centuries,
- and even longer...



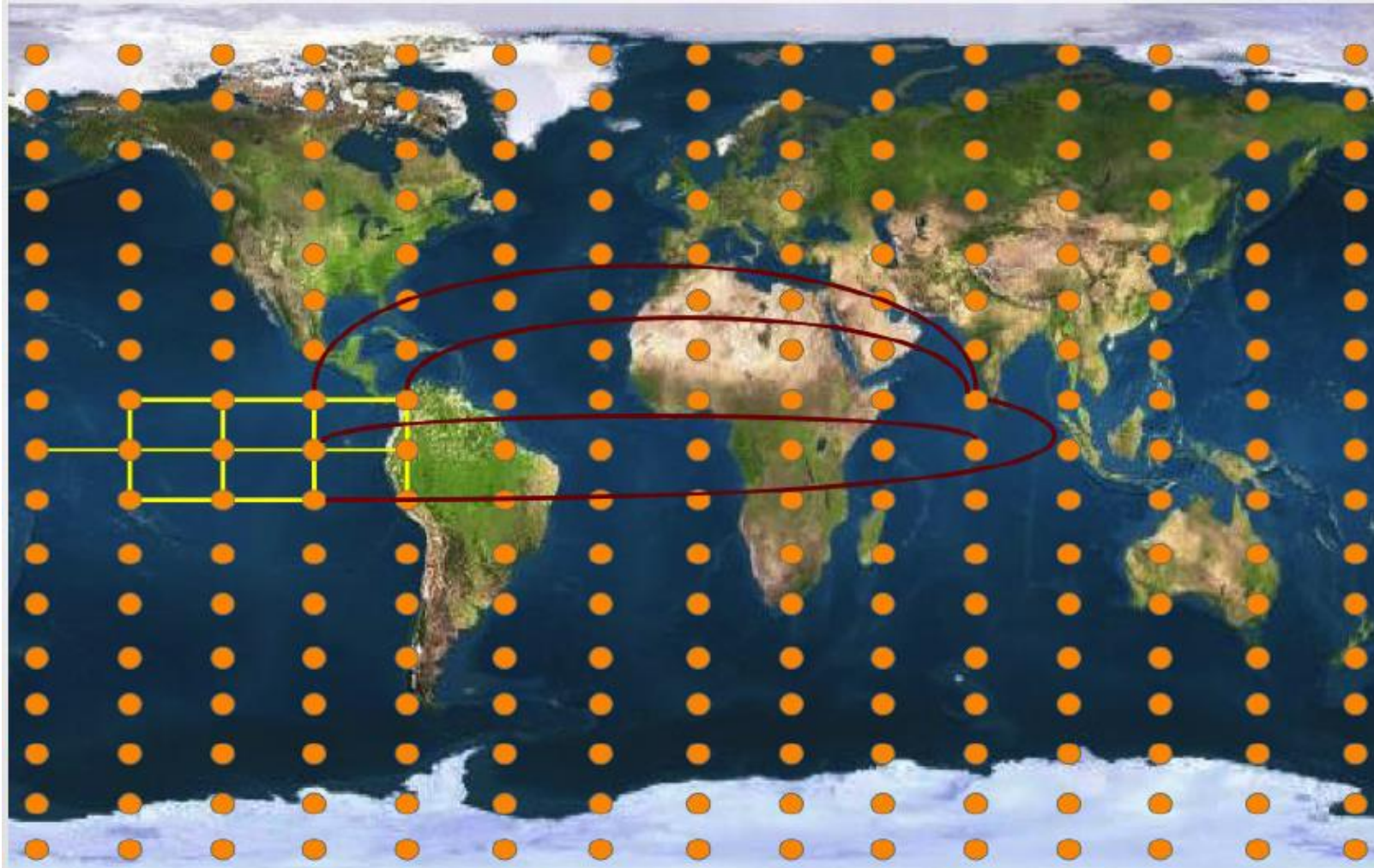
An “artist’s representation” of the power spectrum of climate variability (Ghil 2002).

Sea surface temperature anomaly, Oct 11–Nov 7, 2015



- ENSO
- The Atlantic multi-decadal oscillation
- The Indian Ocean Dipole
- The Madden–Julian oscillation
- The North Atlantic oscillation
- The Pacific decadal oscillation
- Etc.

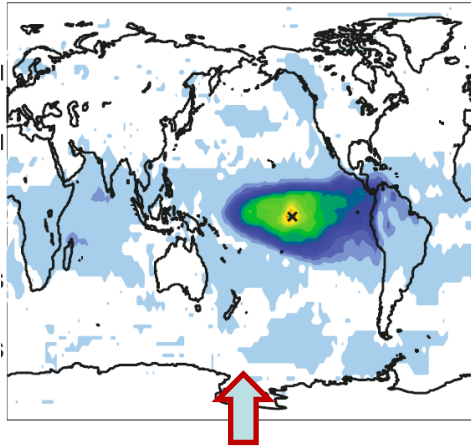
Nodes and links of the climate network



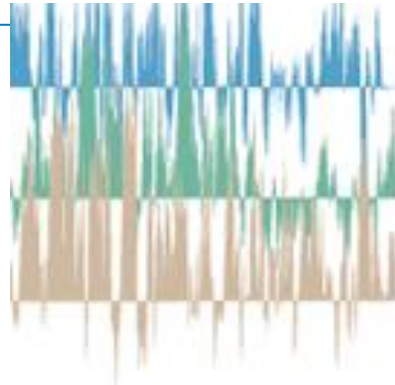
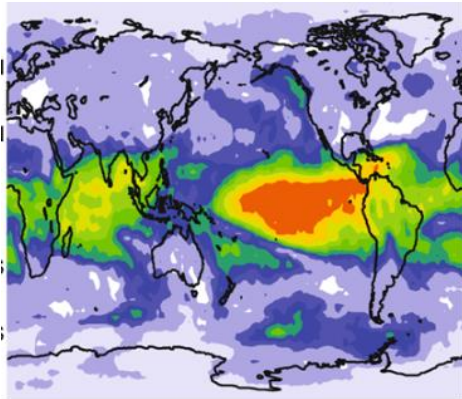
Time series of a climate variable (air temperature, wind, precipitation, etc.)

Similarity measure (correlation, mutual information, etc.)

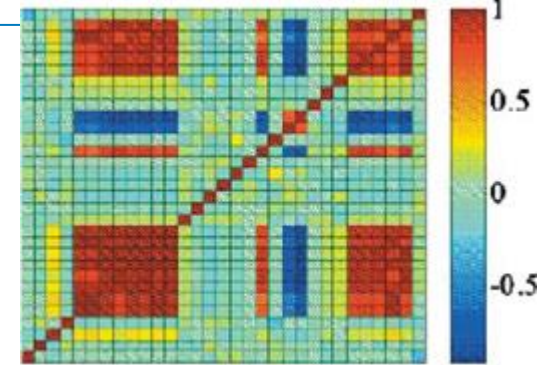
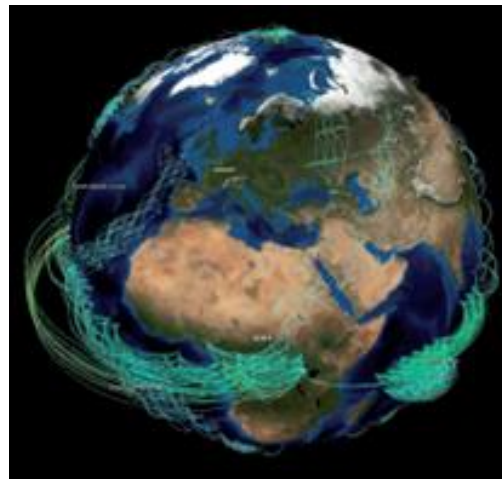
Statistically significant similarity values (links)



Area-weighted connectivity (degree)



Climate network



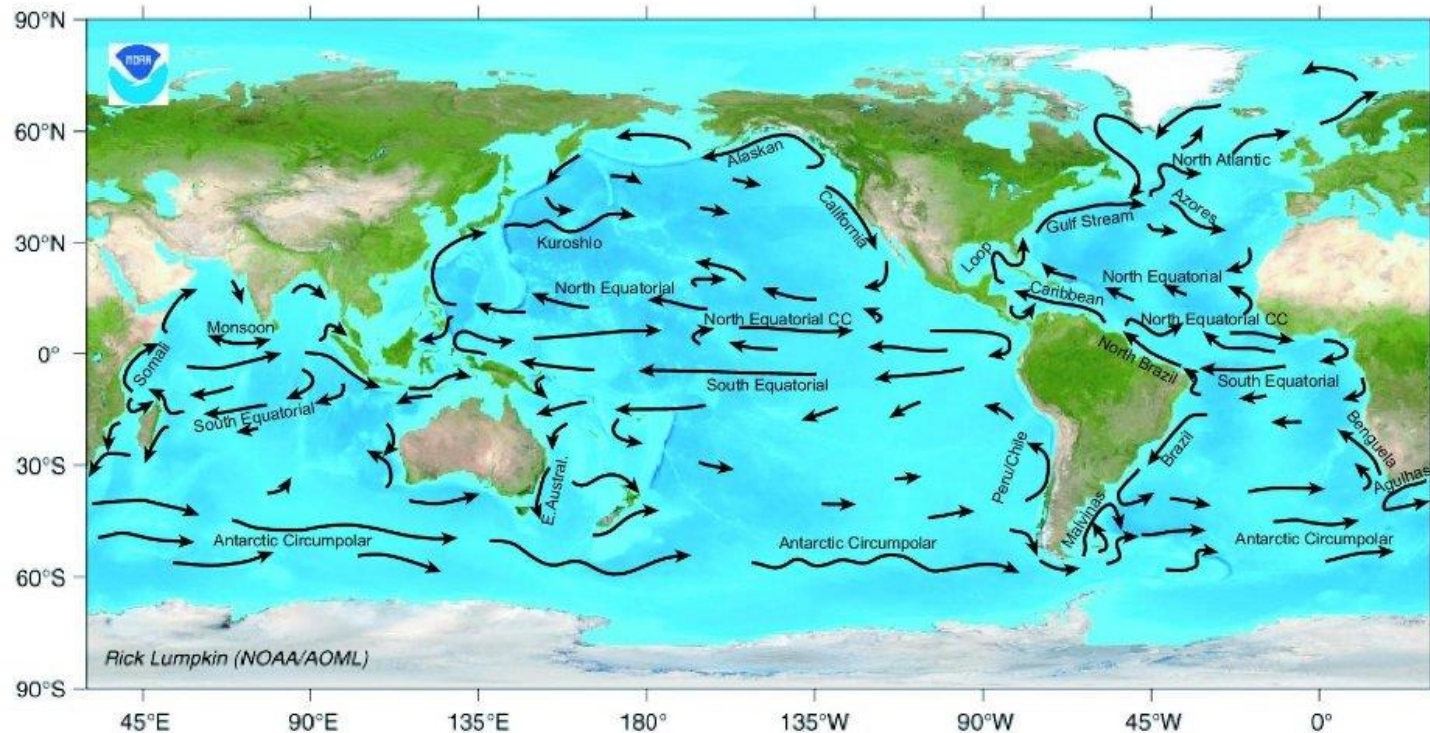
Thresholded matrix (adjacency matrix)



Eguiluz et al, PRL 2005
Deza et al, Chaos 2013
Donges et al, Chaos 2015

Physical mechanisms responsible for teleconnections

Winds, ocean currents and solar forcing.



The data: surface air temperature

- Anomalies = annual solar cycle removed
- Spatial resolution $2.5 \times 2.5 \Rightarrow 10226$ nodes
- Daily / monthly 1949 - 2013 $\Rightarrow 23700 / 700$ data points

Where does the data come from?

- National Center for Environmental Prediction, National Center for Atmospheric Research (NCEP-NCAR).
- Free!
- Reanalysis = run a sophisticated model of general atmospheric circulation and feed the model (data assimilation) with empirical data, where and when available.

Statistical similarity measure

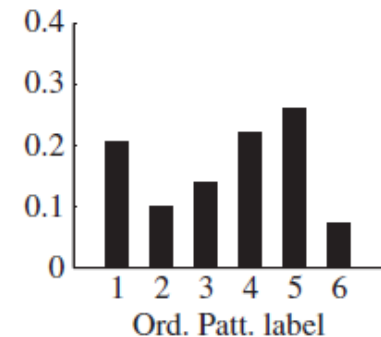
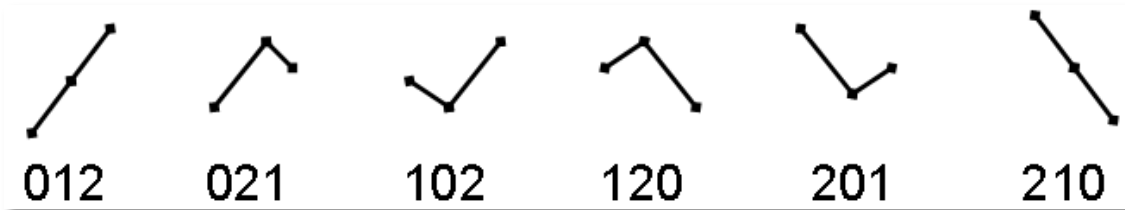
- Mutual information

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

$$p_{ij}(m,n) = p_i(m)p_j(n) \Leftrightarrow M_{ij} = 0$$

- We use **ordinal symbolic** time-series to compute the probabilities.

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



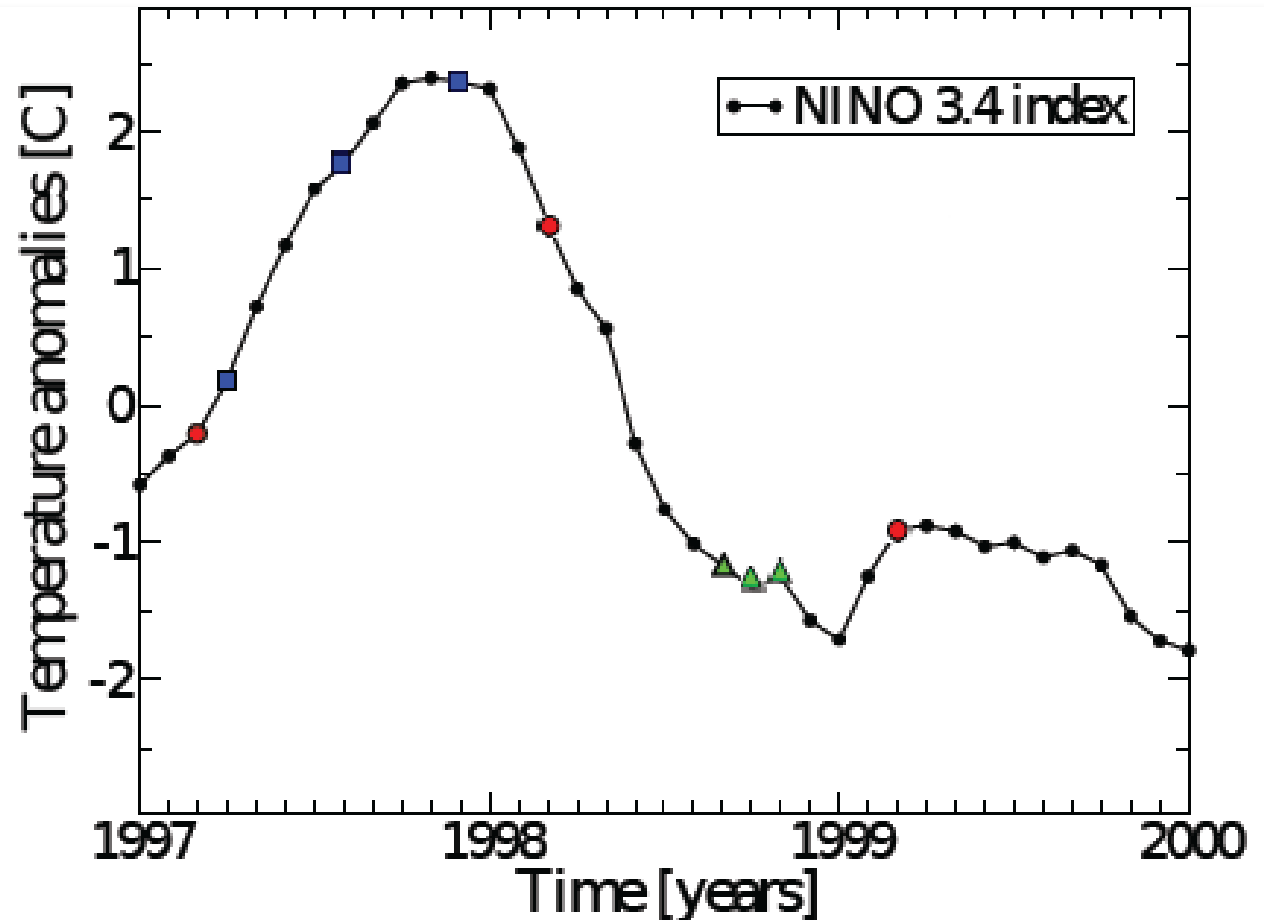
- Drawback: we lose information about the actual values.
- Advantage: we can select the time scale of the analysis.

Ordinal analysis allows selecting the time scale of the analysis

**Intra-
season 102**

**Intra-
annual 012**

**Inter-
annual 120**

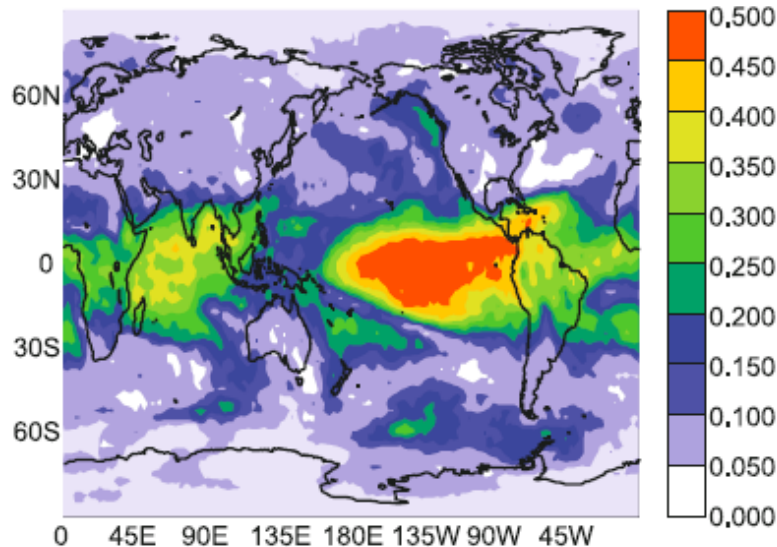


Contrasting two methods for inferring the climate network

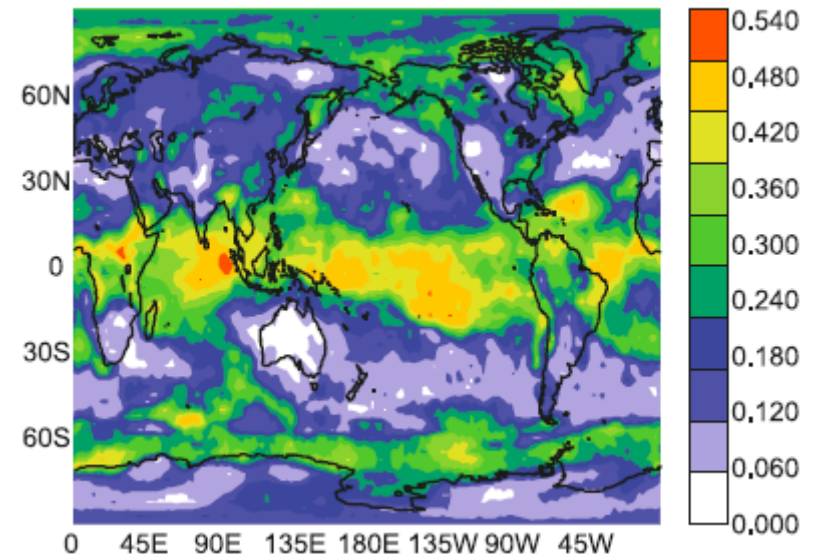


$$M_{ij} = \sum_{m,n} p_{ij}(m,n) \log \frac{p_{ij}(m,n)}{p_i(m)p_j(n)}$$

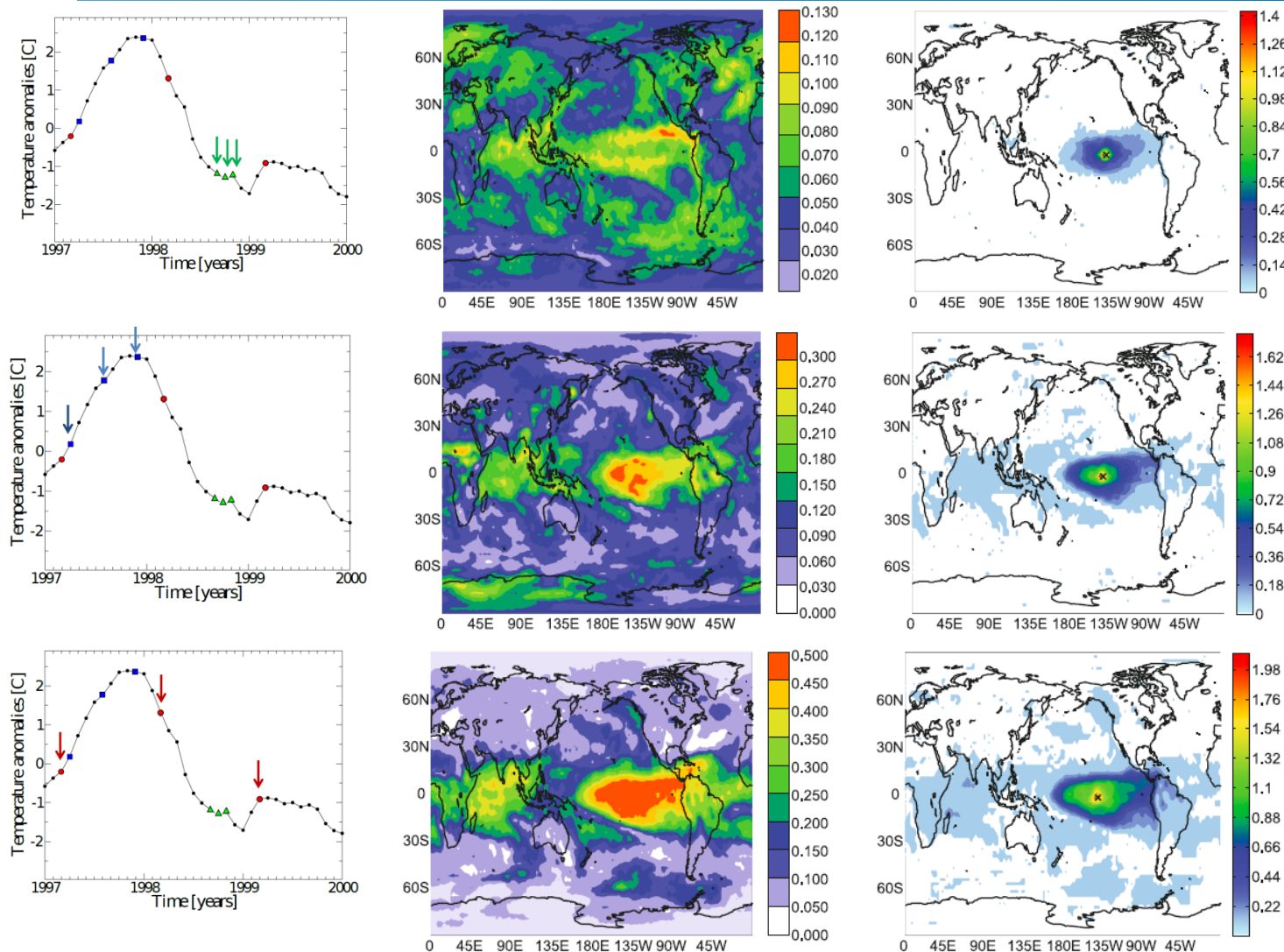
Network when the probabilities are computed with ordinal analysis



Network when the probabilities are computed with histogram of values



Influence of the time-scale of the symbolic ordinal pattern

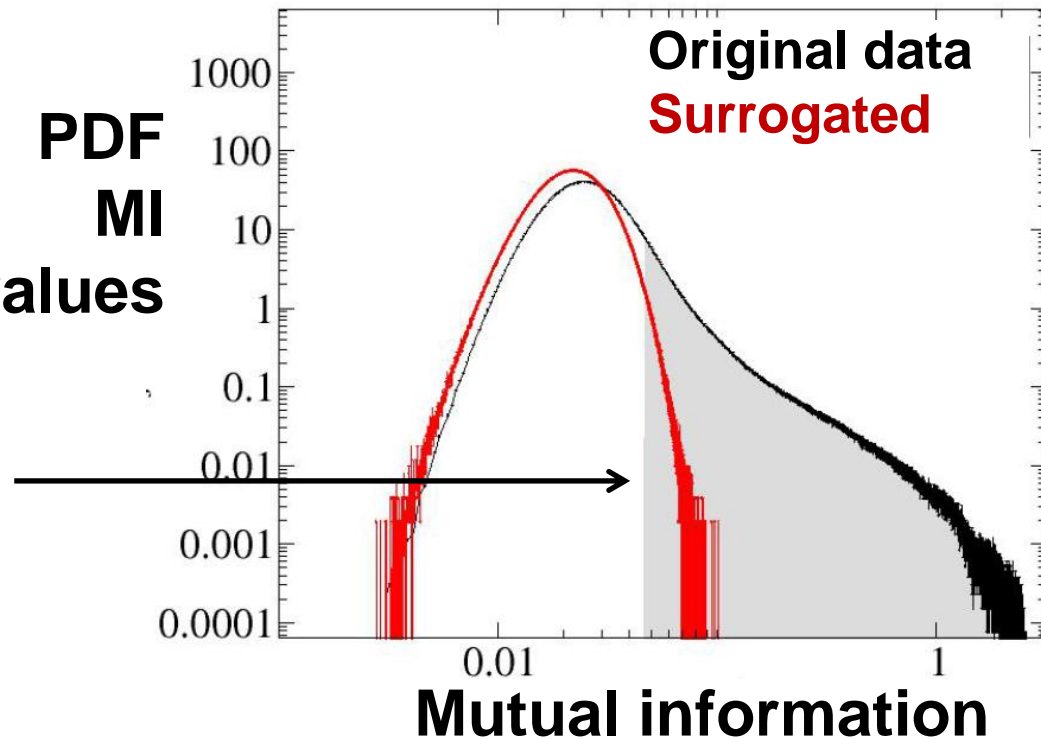


How do we assess the significance of the links?



PDF
MI
values

$$TH = \langle MI \rangle + 3\sigma$$

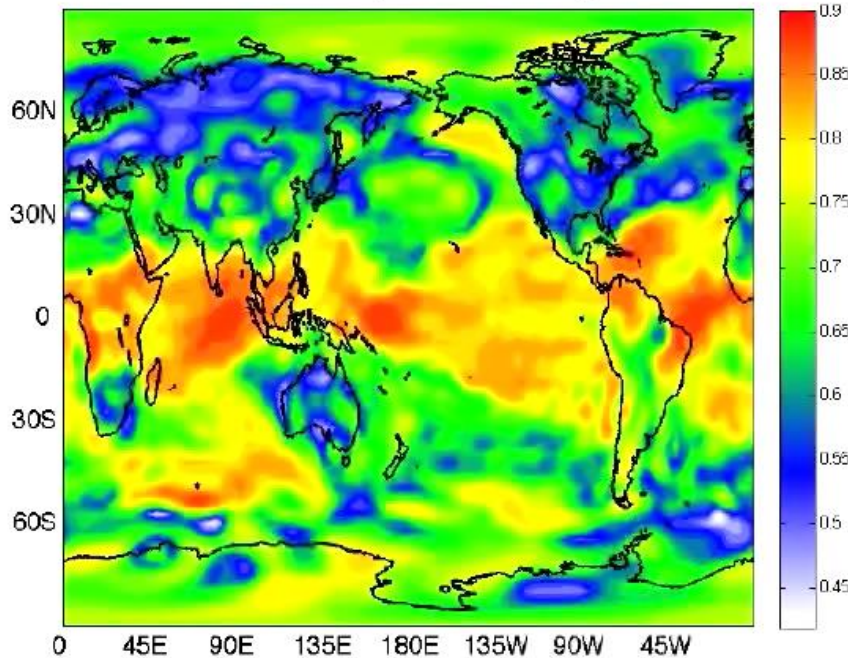


99.87% confidence level that the links have MI values that are not consistent with random values.

Influence of the threshold

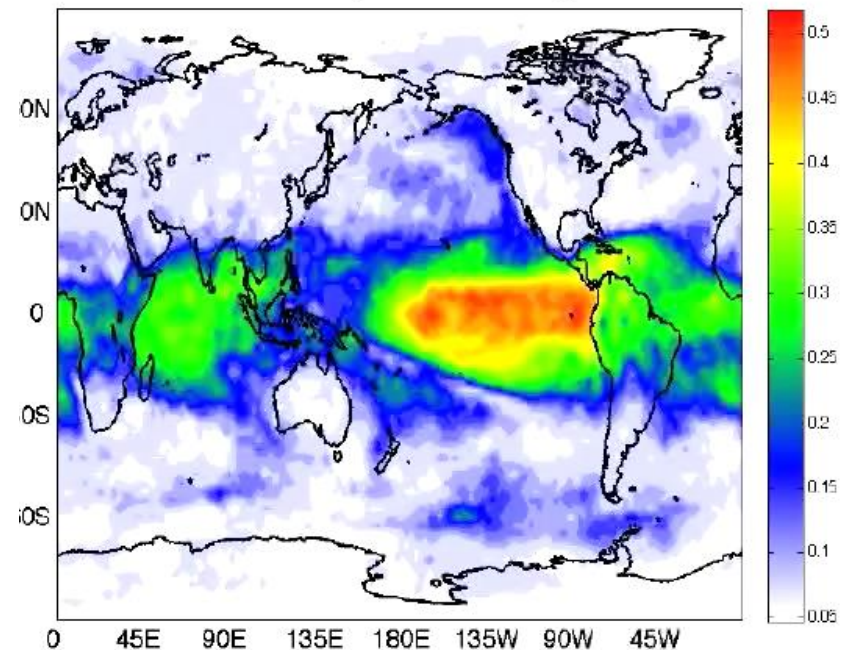
Network constructed from Cross-Correlation (CC) analysis

$\rho = 0.69593$; mean ± 1 sigma



Network constructed from Mutual Information (MI ordinal analysis, annual time scale)

$\rho = 0.1191$; mean ± 2 sigma



Can we test the method used to infer the links?

- Simulations of Kuramoto oscillators with known random coupling topology.
- Experiments with chaotic electronic circuits.





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

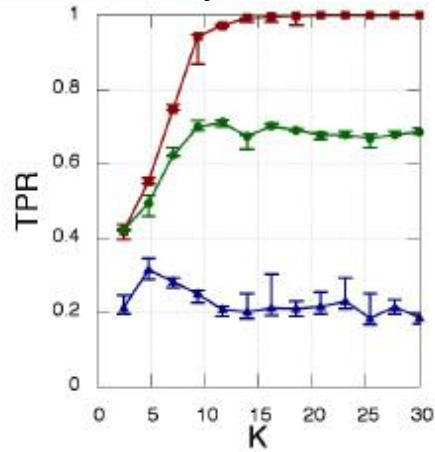
- A_{ij} is a **known symmetric random matrix**
- $N=12$ oscillators.
- Performed 100 simulations (10^4 data points each) with different oscillators' frequencies, random matrices, noise realizations and initial conditions.
- For each value of K , the threshold was varied to obtain optimal reconstruction.

Phases (θ)

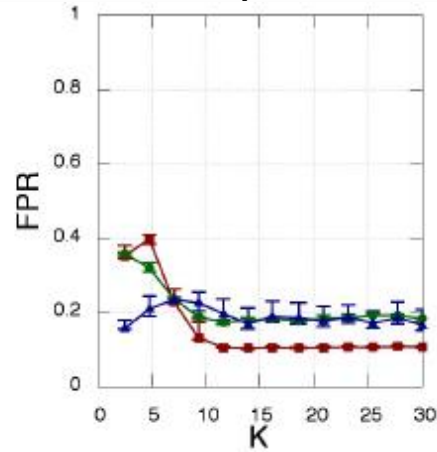
CC **MI** **MIOP**

"Observable" $Y=\sin(\theta)$

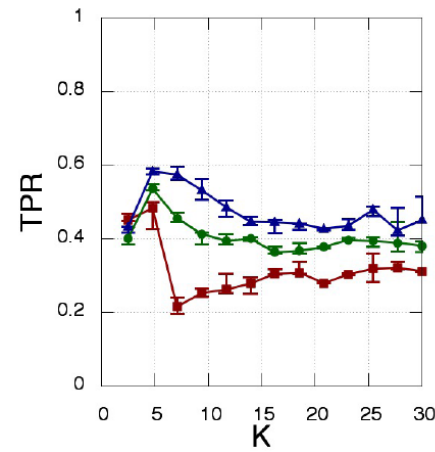
True positives



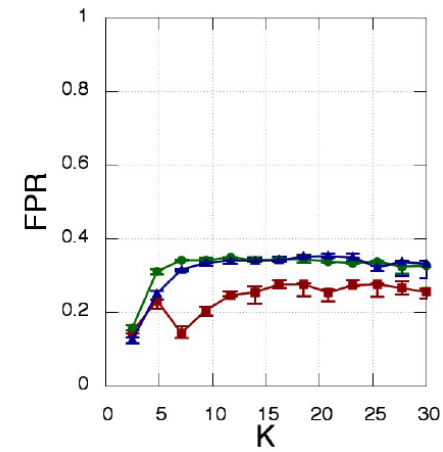
False positives



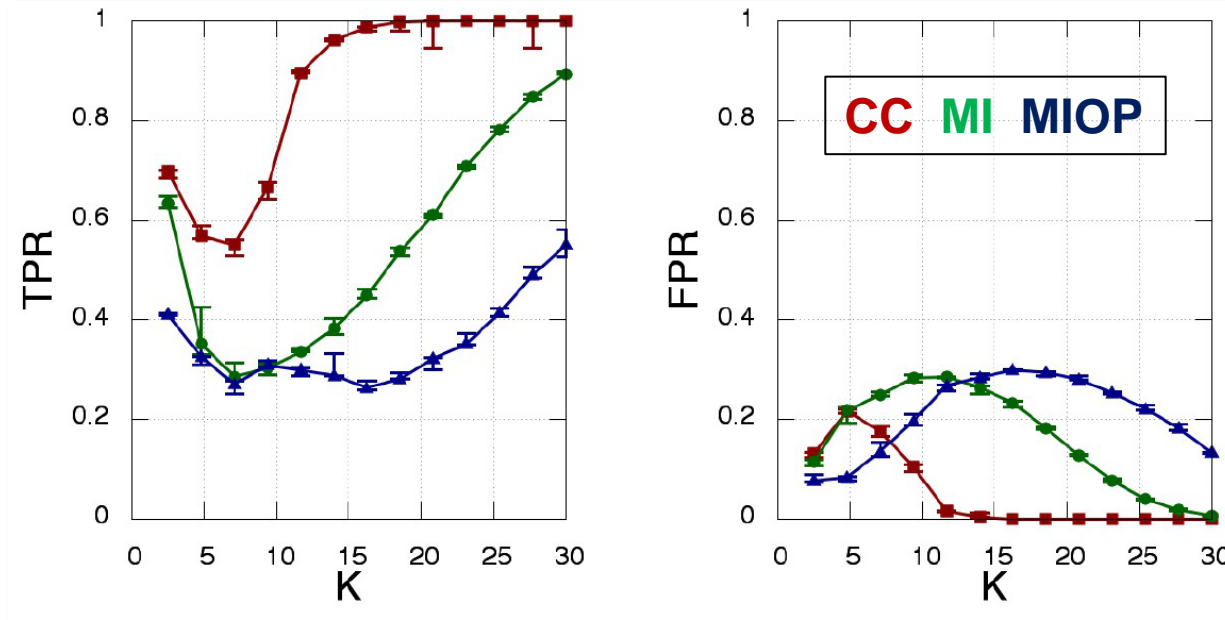
True positives



False positives



Instantaneous frequencies ($d\theta/dt$)

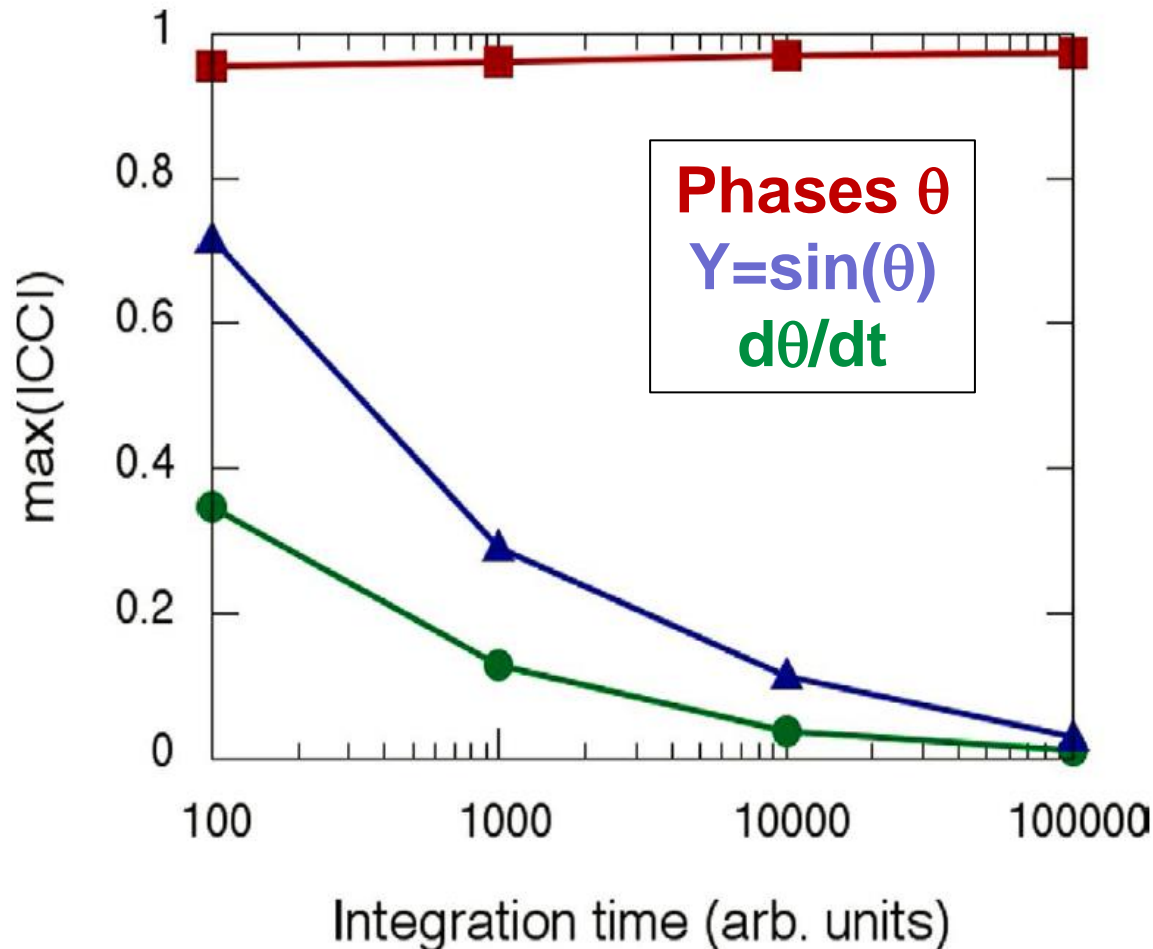


For strong enough coupling K perfect inference is possible!
BUT

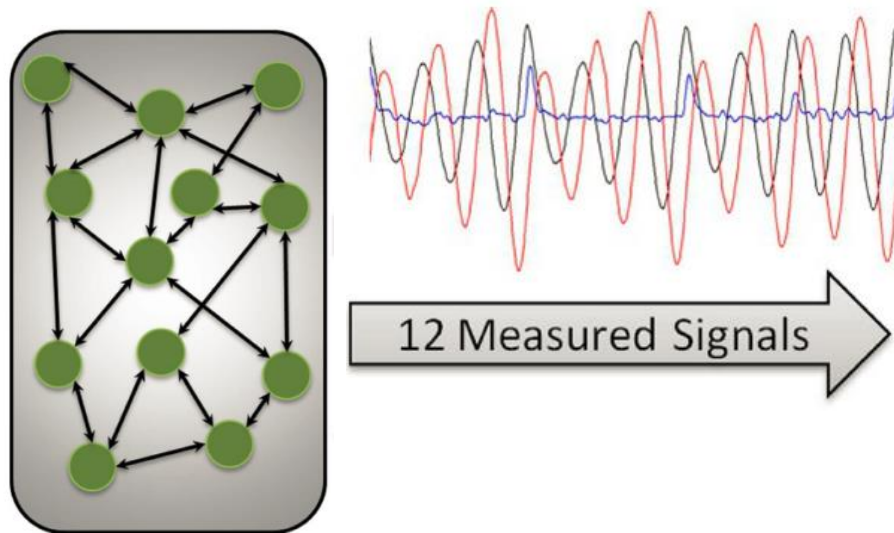
- the number of oscillators is small (12),
- the coupling is symmetric (\Rightarrow only 66 possible links) and
- the data sets are long (10^4 points)

Why the frequencies are better than phases and “observables”?

Correlation analysis of two UNCOUPLED oscillators ($K=0$)



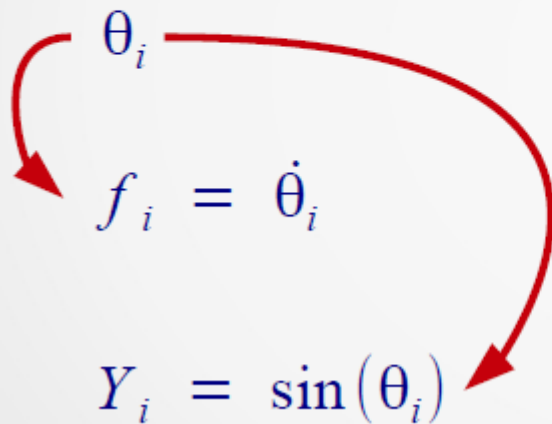
We also analyzed experimental data: 12 chaotic Rössler electronic oscillators (symmetric and known random coupling)



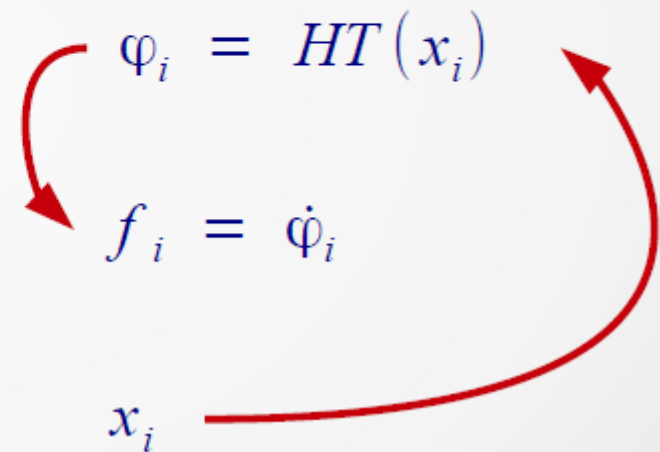
The Hilbert Transform
was used to obtain
phases from
experimental data

*Experiments performed by Javier Buldu (Universidad Rey Juan Carlos, Madrid)
and Ricardo Sevilla-Escoboza (Universidad de Guadalajara, México)*

- Kuramoto Oscillators' Network



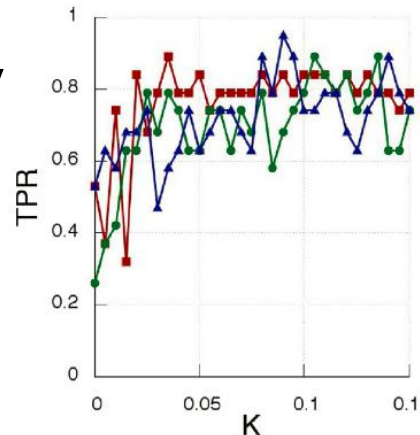
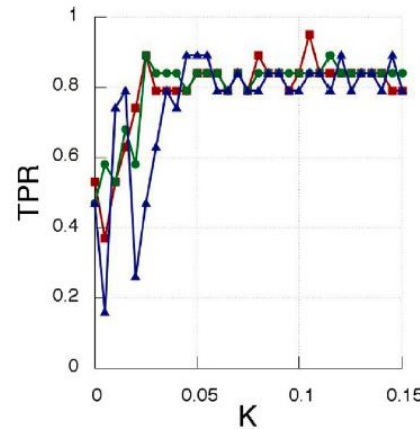
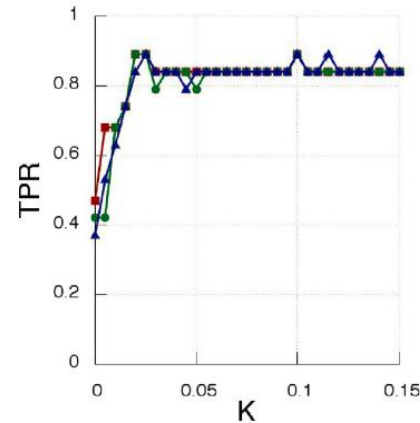
- Rössler Oscillators' Network



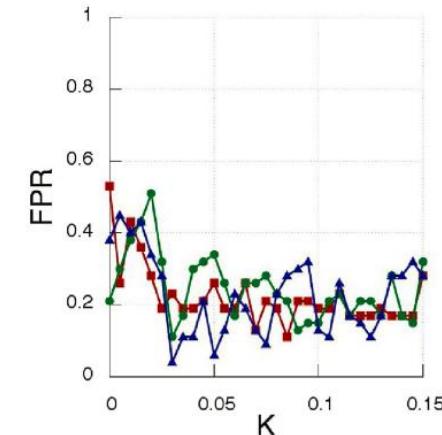
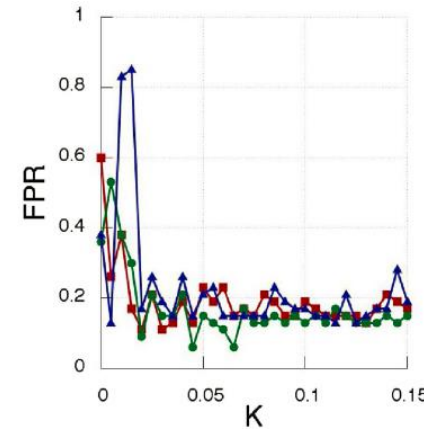
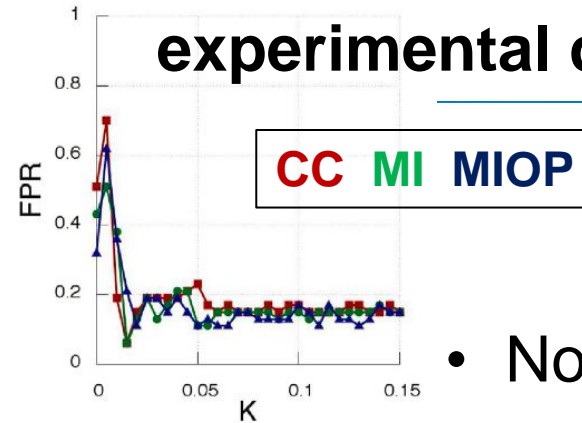
Observed
variable (x)

Hilbert phase

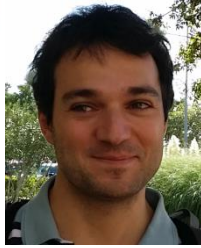
Hilbert frequency



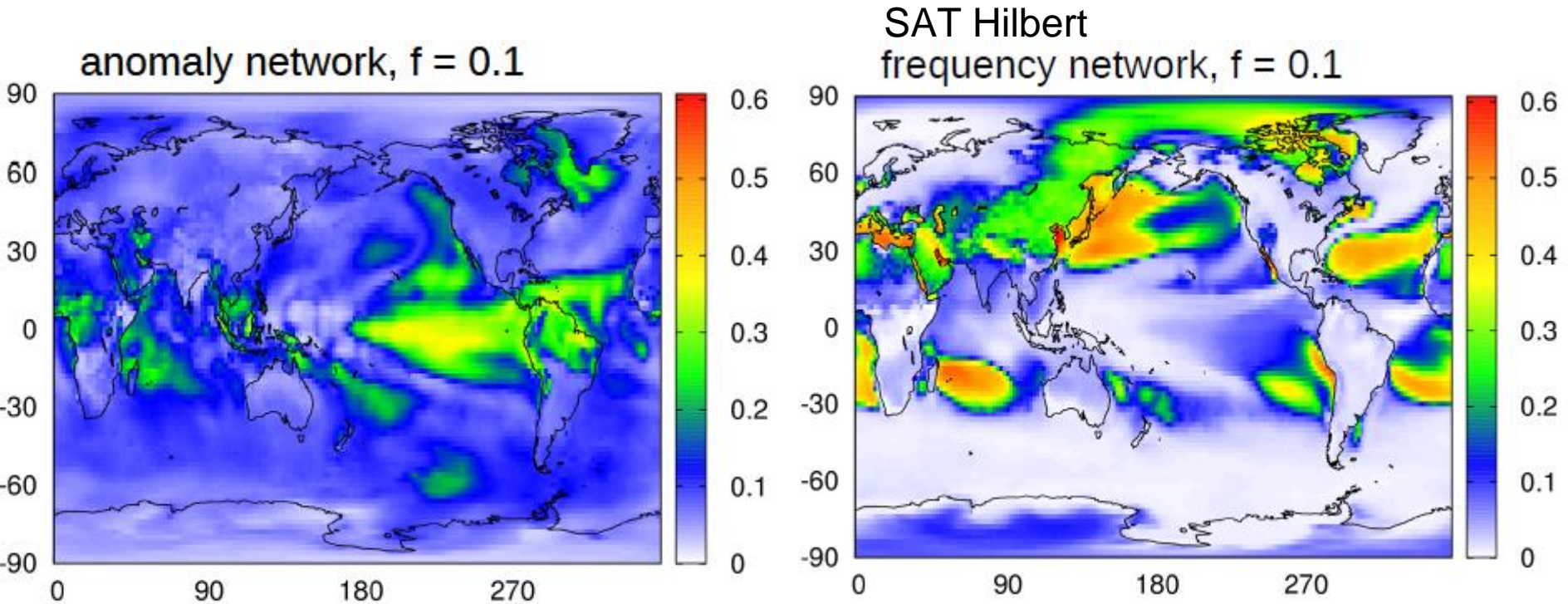
Results obtained with experimental data



- No perfect reconstruction
- No important difference among the 3 methods & 3 variables



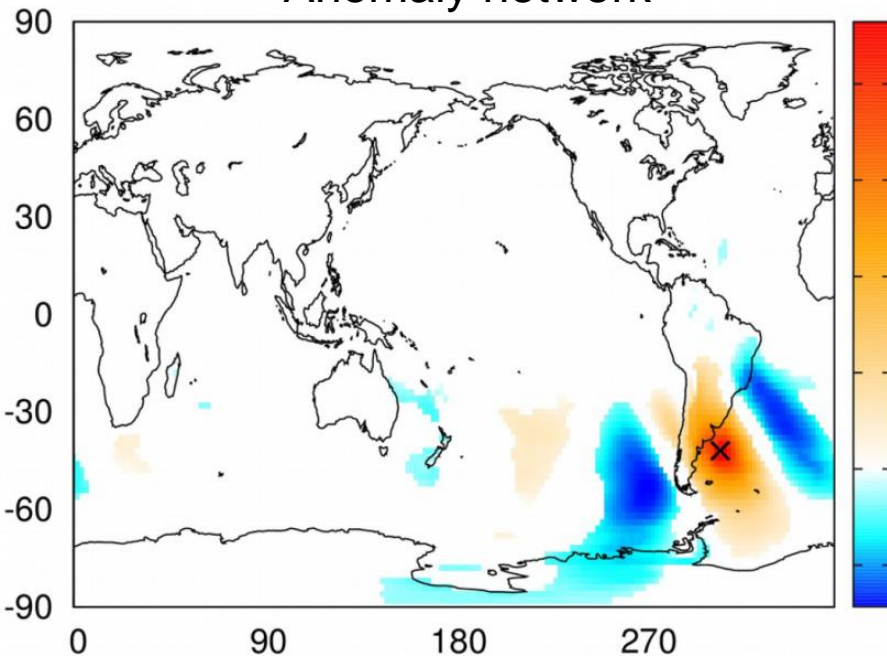
Climate network built from zero-lag CC analysis



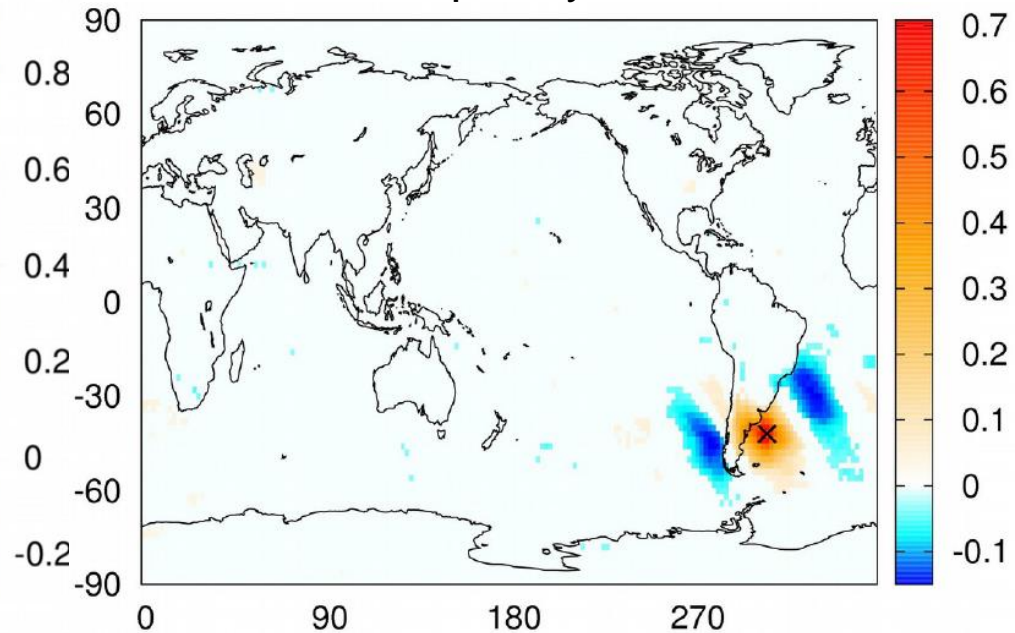
D. Zappala et al, in preparation.

Connectivity maps

Anomaly network

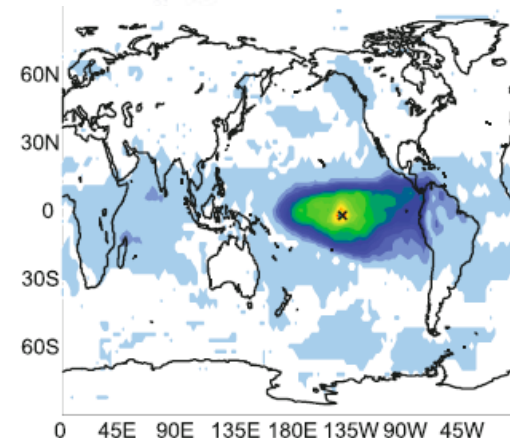
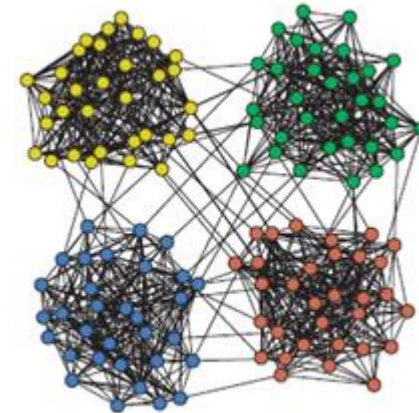


Hilbert frequency network



How to identify regions with similar climate?

- Goal: to construct a network in which regions with similar climate (e.g., continental) are in the same “community”.
- Problem: not possible with the “usual” method to construct the network because NH and SH are only indirectly connected.



Network construction based on similar symbolic dynamics



- Step 1: transform SAT anomalies in each node in a sequence of symbols (we use ordinal patterns)

$$s_i = \{012, 102, 210, 012, \dots\} \quad s_j = \{201, 210, 210, 012, \dots\}$$

- Step 2: in each node compute the transition probabilities

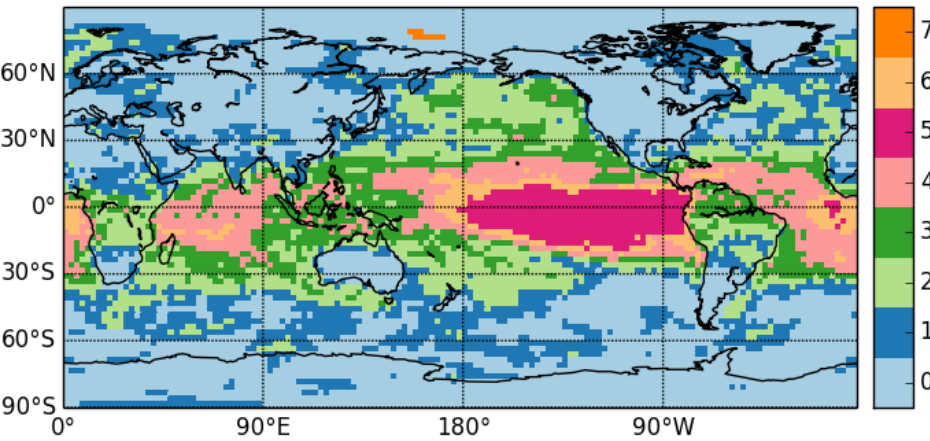
$$TP_{\alpha\beta}^i = \#(\alpha \rightarrow \beta) / N$$

- Step 3: define the weights $w_{ij} = \frac{1}{\sum_{\alpha\beta} (TP_{\alpha\beta}^i - TP_{\alpha\beta}^j)^2}$
- Step 4: threshold w_{ij} to obtain the adjacency matrix.

High weight
if similar
symbolic
“language”

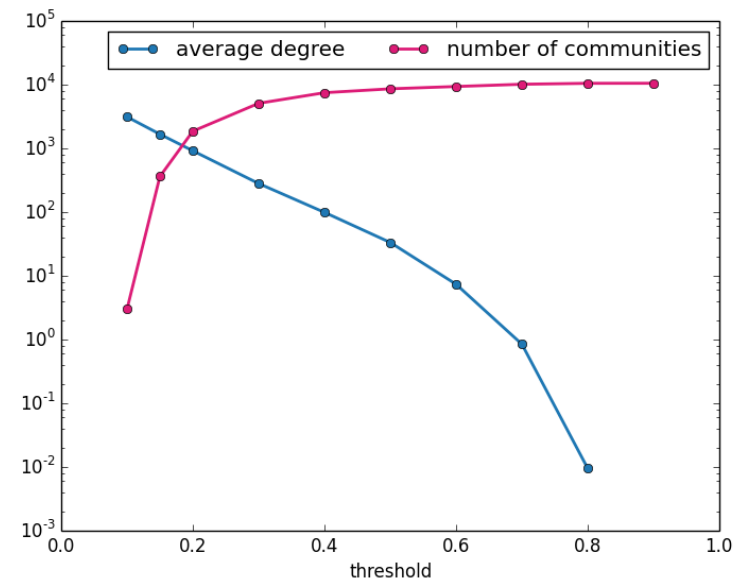
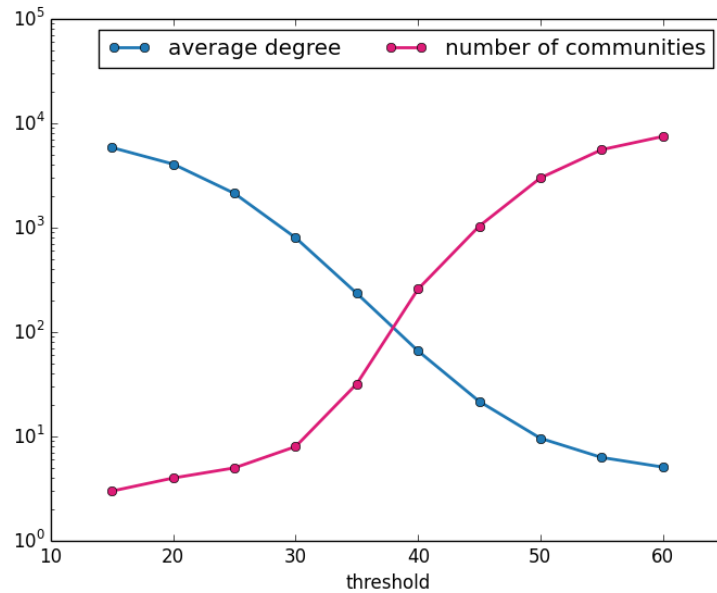
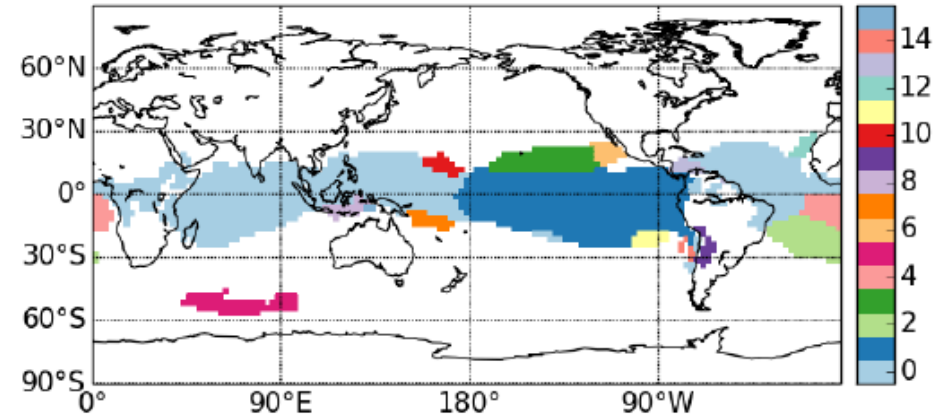
- Step 5: run a community detection algorithm (Infomap).

TP Network

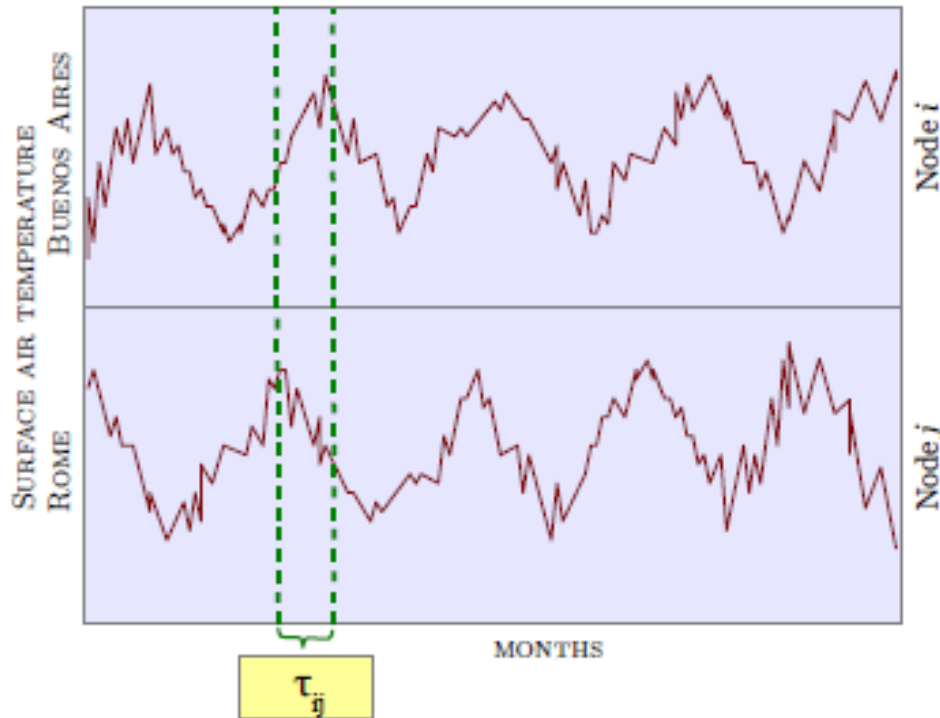


CC Network

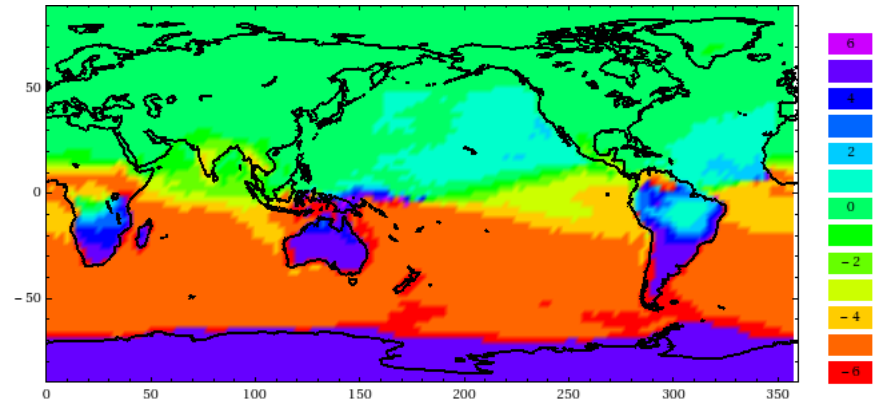
(only the largest 16)



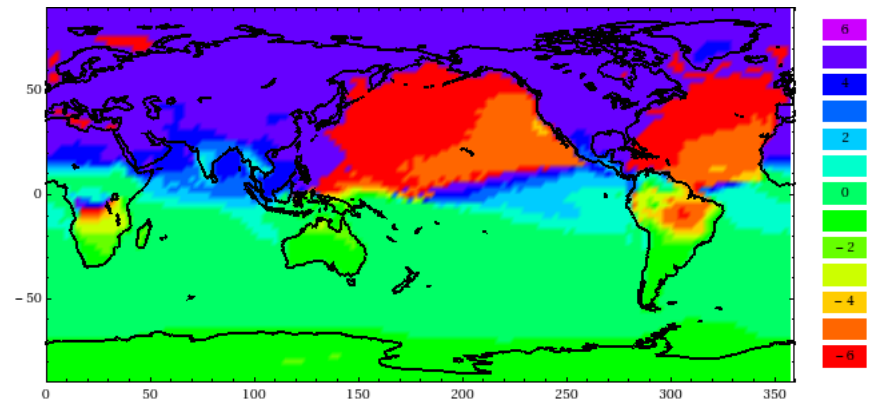
Another way to identify communities: lag-times between seasonal cycles



Rome

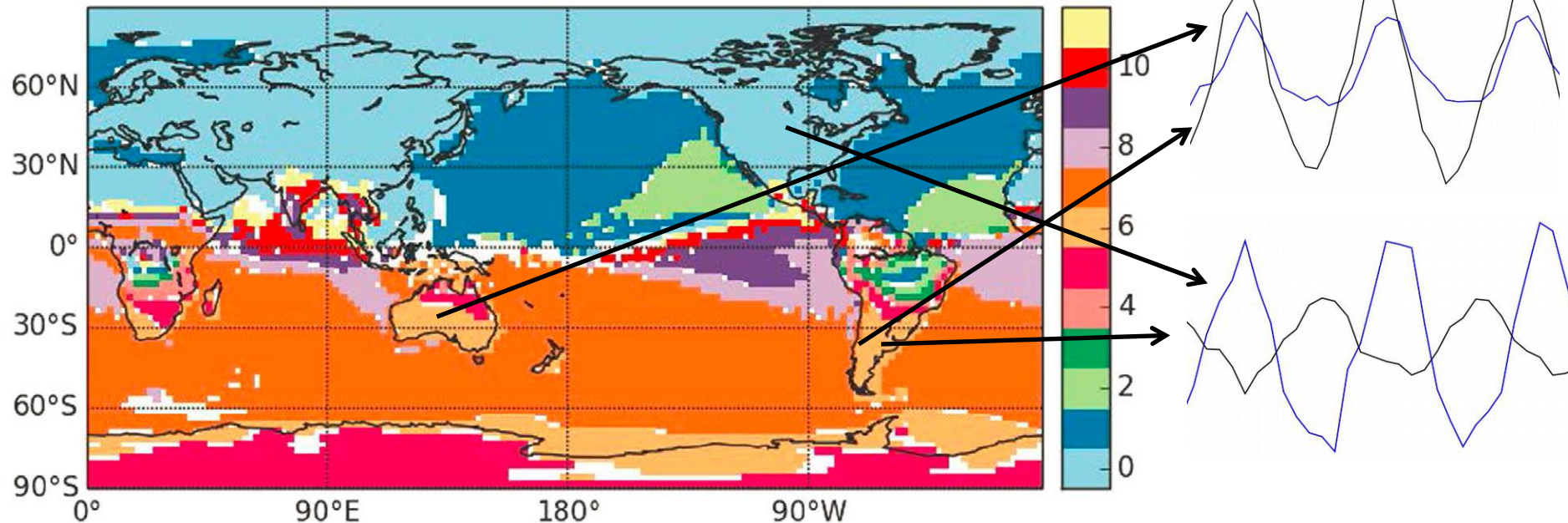


Buenos Aires



Climate communities: regions with inphase seasonal cycles

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



- Oceans tend to have a one-month delay with respect to the landmasses.
- Well defined long-range spatial patterns.



- Take home message: network tools and symbolic ordinal analysis provide an opportunity for advancing understanding and predictability of our climate.
- Ordinal analysis allows identifying time-scales of climate interactions and climate communities.
- In small synthetic networks, under appropriate conditions, perfect network inference is possible.

Papers at <http://www.fisica.edu.uy/~cris/>

- J. I. Deza et al, Eur. Phys. J. Special Topics 222, 511 (2013).
- G. Tirabassi et al, Sci. Rep. 5, 10829 (2015).
- G. Tirabassi and C. Masoller, Sci. Rep. 6, 29804 (2016).

60 two-year postdoctoral research positions
in the Catalan science and technology
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Thank you for your attention!

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