

Inferring regional communities and time-scales of interactions in climate networks

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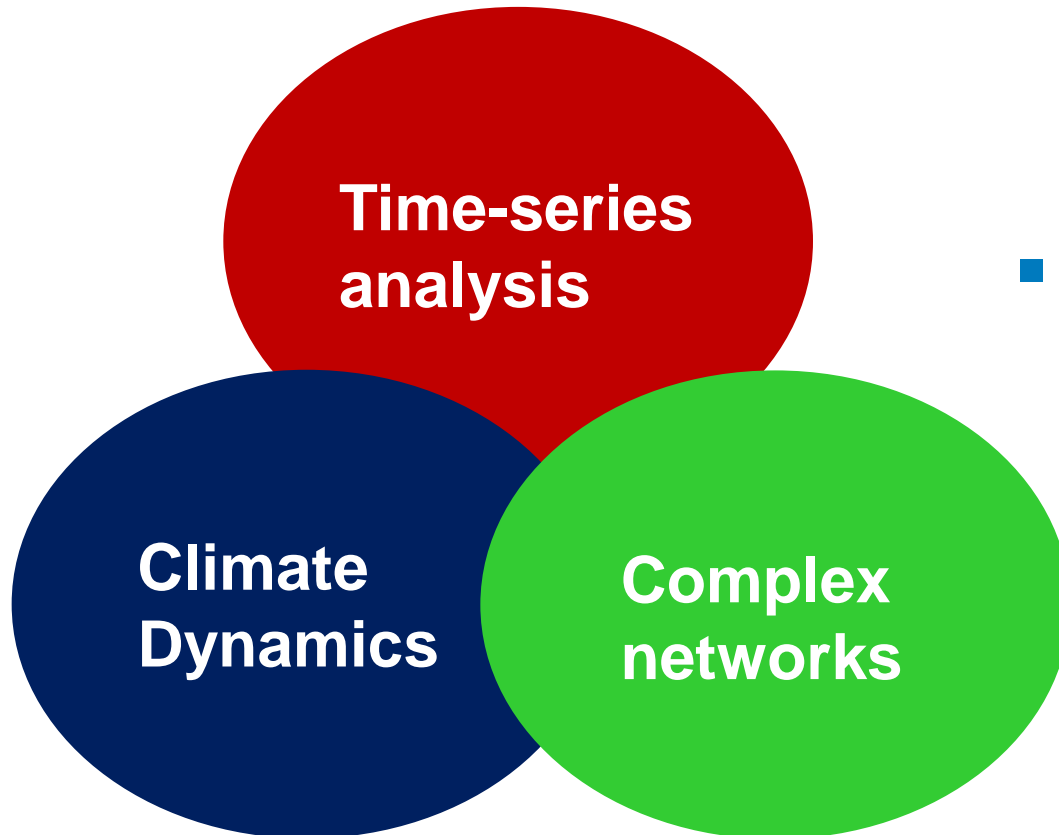
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Multistability and Tipping: From
Mathematics and Physics to
Climate and Brain

MPIPKS, Dresden, October 2016





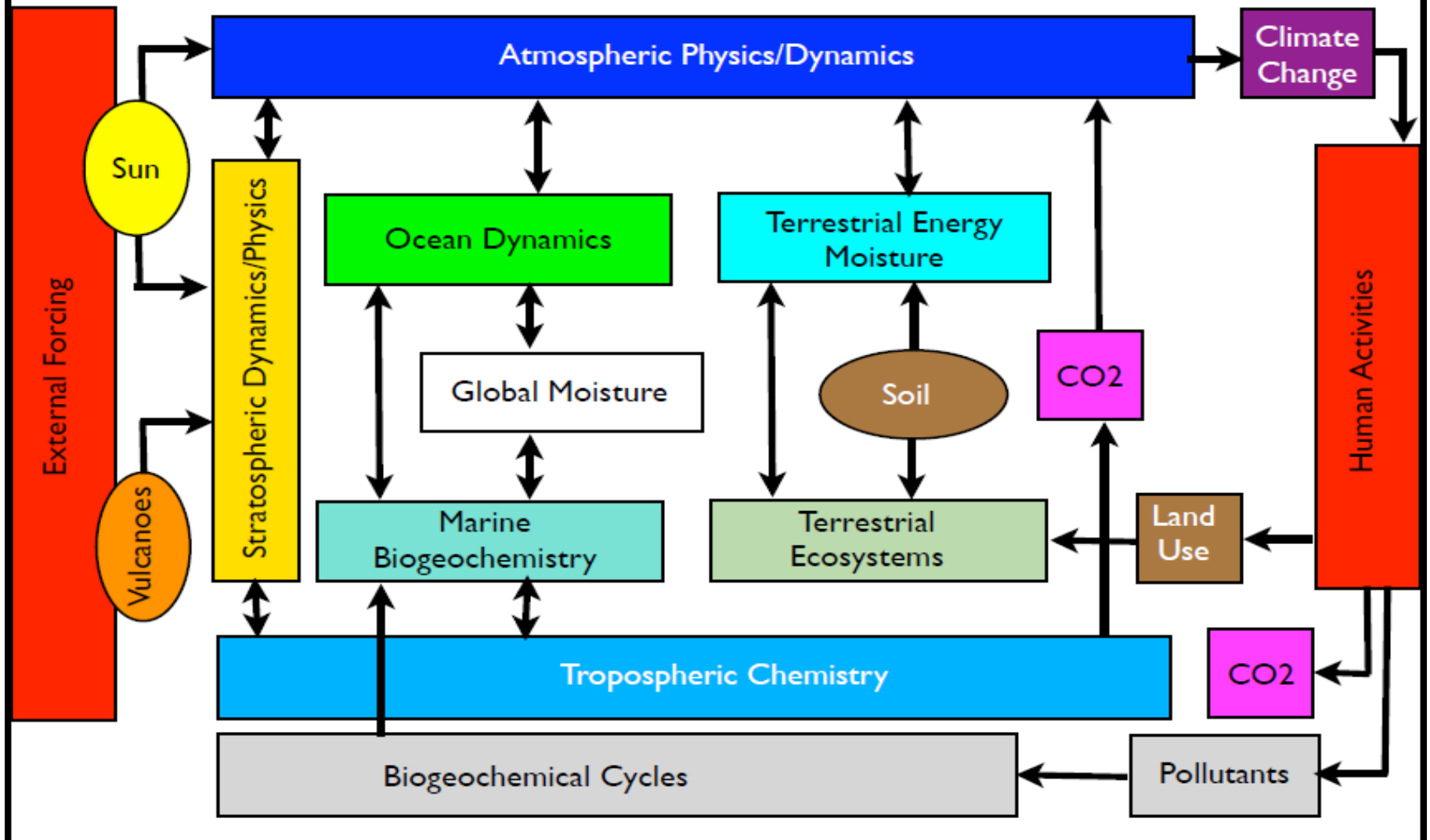
- Introduction
 - The climate system
 - Symbolic method of time-series analysis
- Results
 - Inferring the connectivity of the climate network
 - Inferring climate communities
 - Data analysis tools for detecting early signs of upcoming transitions
- Summary

WHAT DO NETWORKS HAVE TO DO WITH CLIMATE?

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

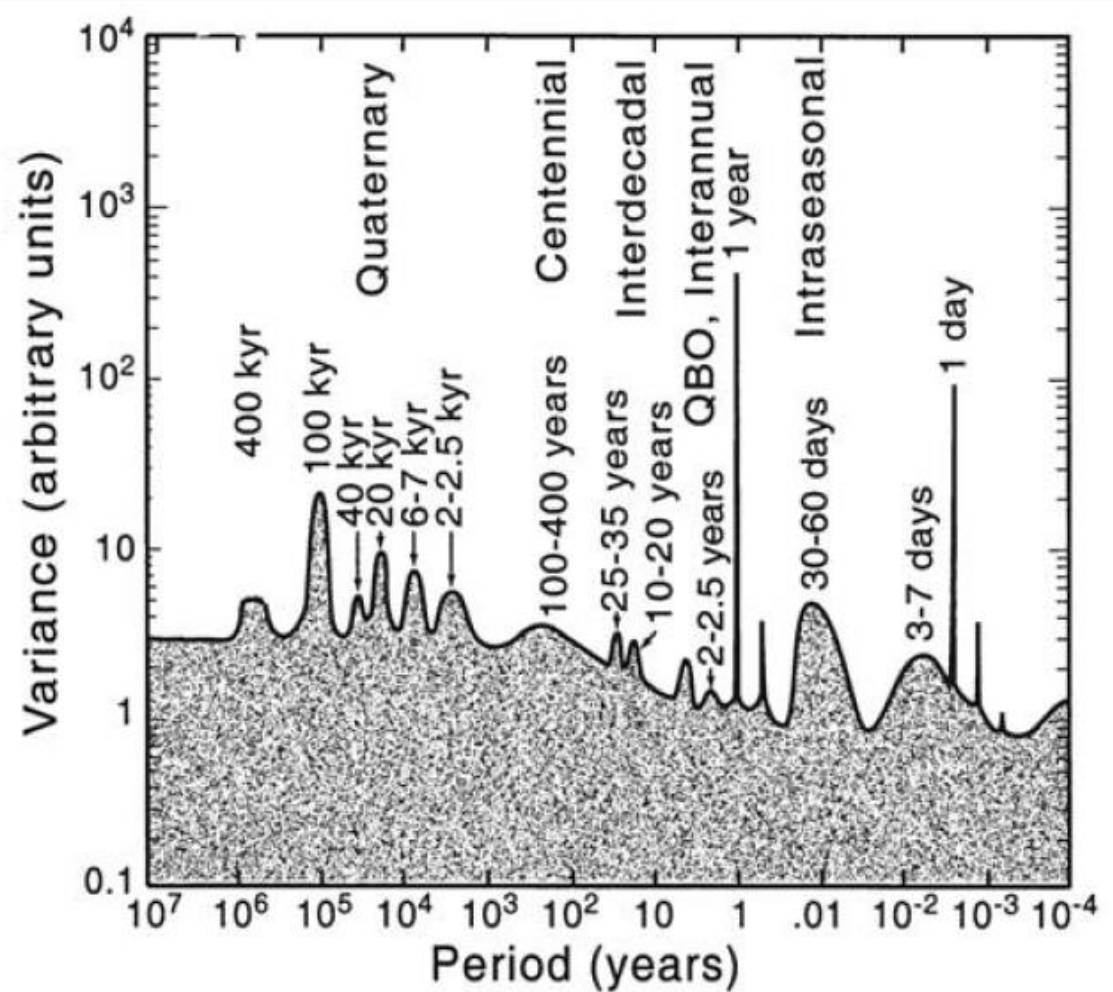
Advances in understanding coupling in complex networks offer new ways of studying the collective behavior of interactive systems and already have yielded new insights in many areas of science.

The Climate System



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

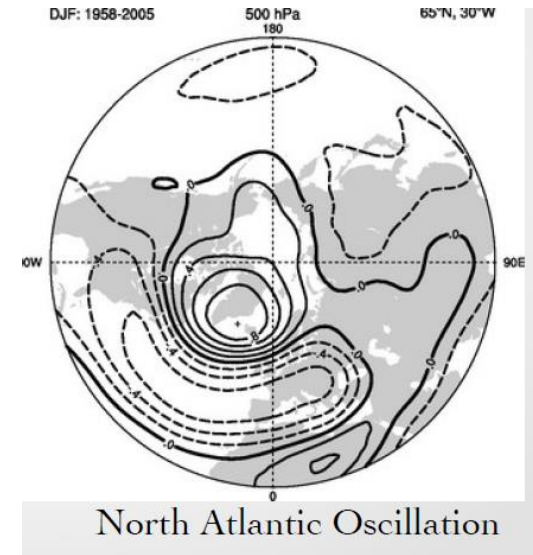
- hours to days,
- months to seasons,
- decades to centuries,
- and even longer...



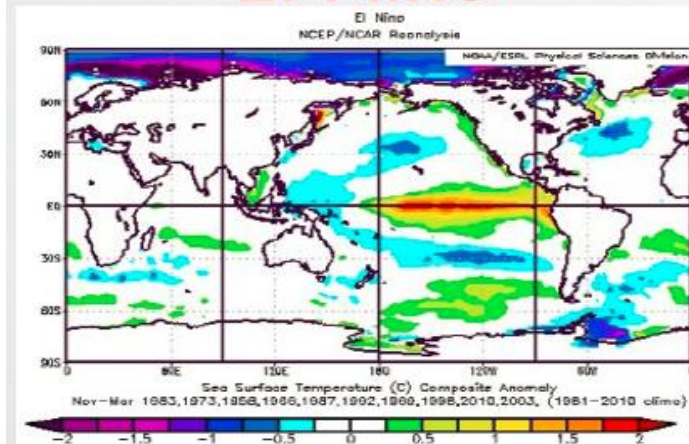
An “artist’s representation” of the power spectrum of climate variability (Ghil 2002).

And a wide range of spatial modes of variability

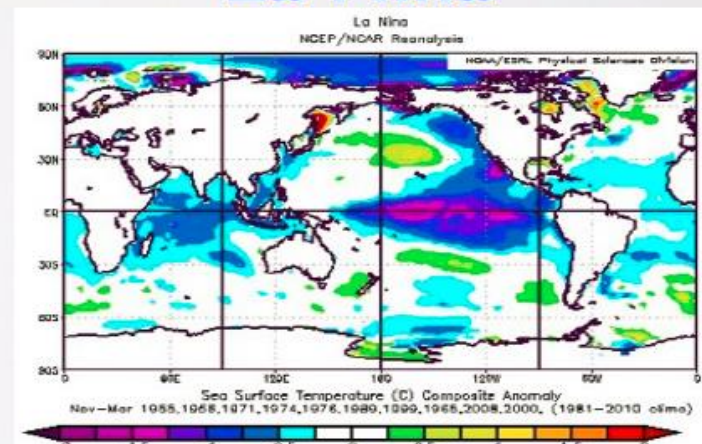
- ENSO
- The Atlantic multidecadal oscillation
- The Indian Ocean Dipole
- The Madden–Julian oscillation
- The North Atlantic oscillation
- The Pacific decadal oscillation
- Etc.



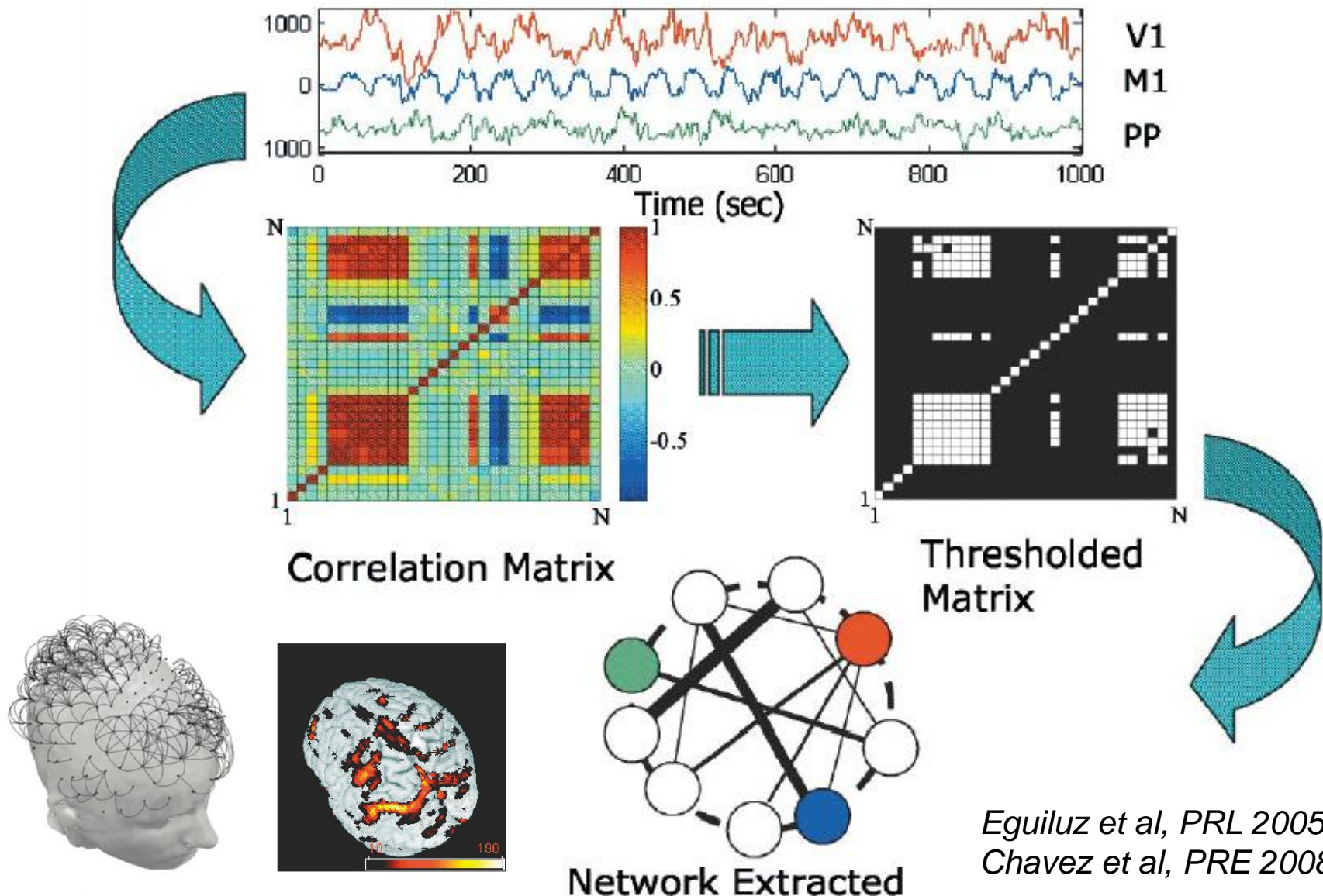
El Niño



La Niña

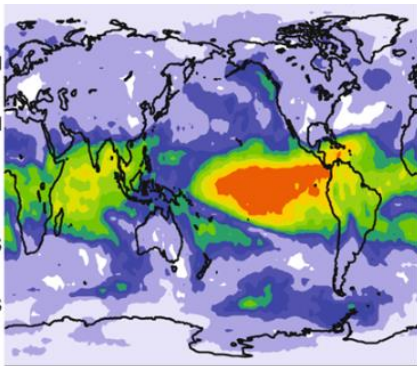


Brain functional network

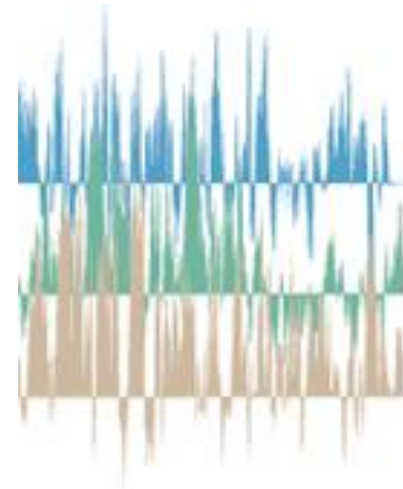
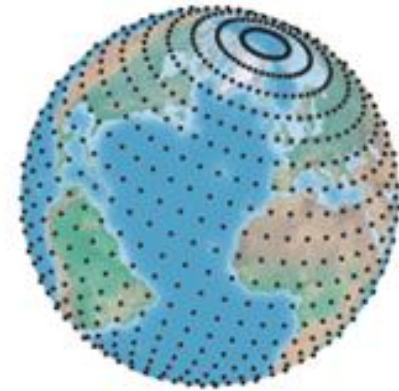


Climate networks

**Area-weighted
connectivity
(weighted degree)**



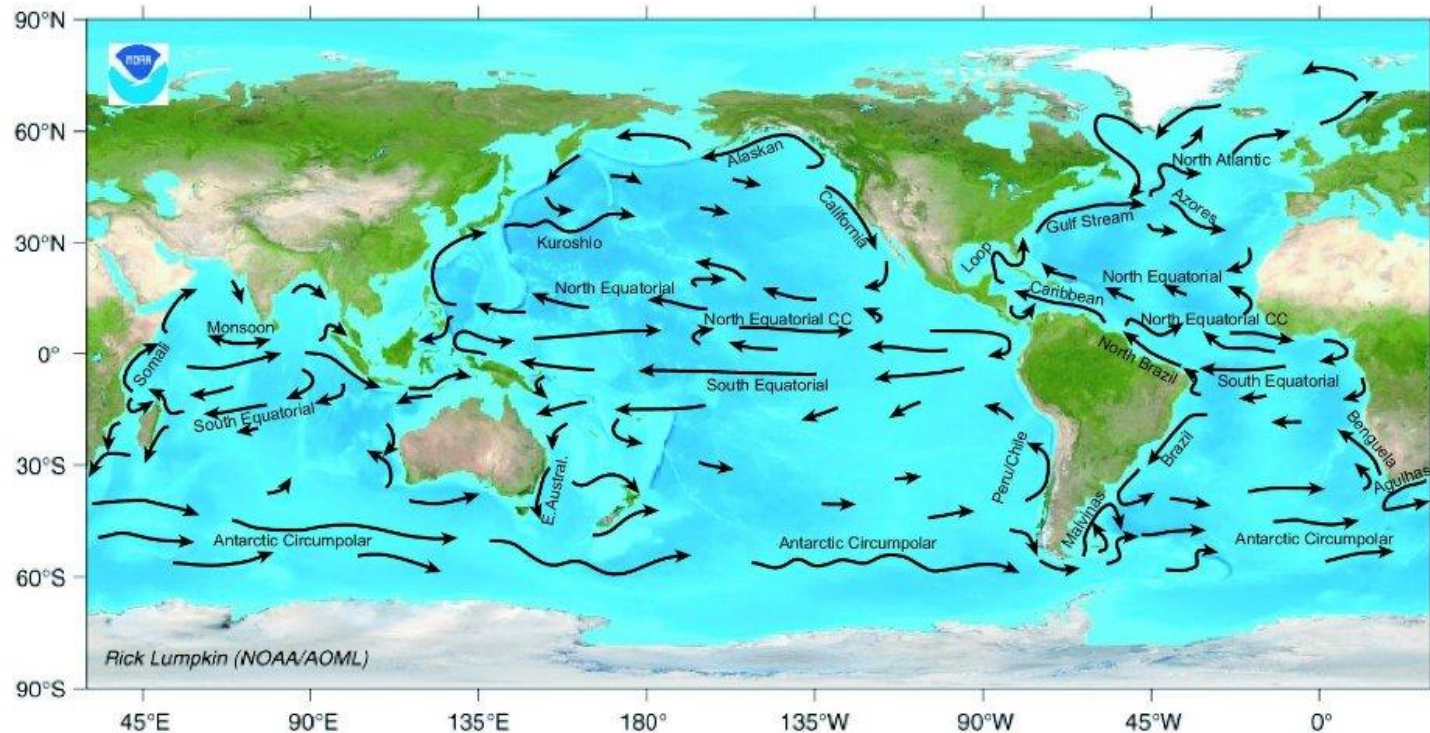
*Deza et al,
Chaos 2013*



*Donges et al,
Chaos 2015*

Physical mechanisms responsible for teleconnections

Winds, ocean currents and solar forcing.



Our way to construct the network: nonlinear in three aspects

- We use a **nonlinear measure** to quantify 'statistical interdependency' between the climate in different regions.

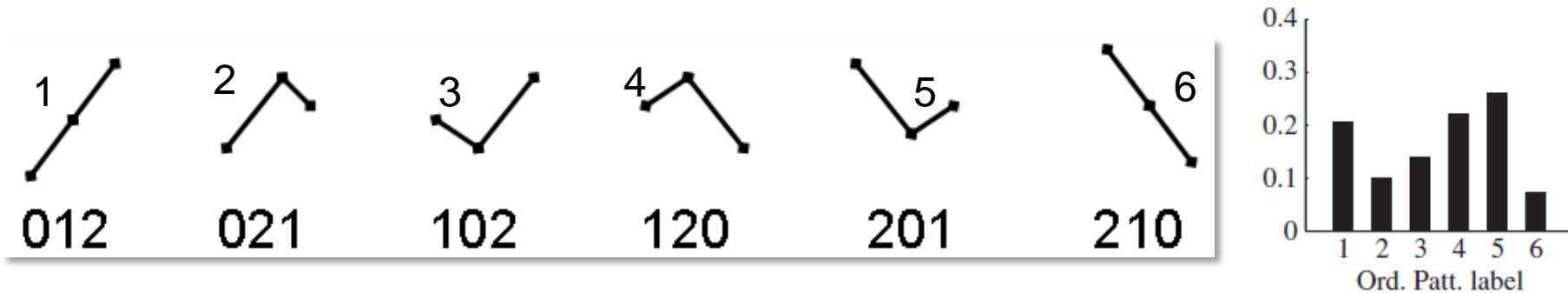
$$M_{ij} = \sum_{m,n} p_{ij}(m,n) \log \frac{p_{ij}(m,n)}{p_i(m)p_j(n)}$$

- We use a **threshold** to select the significant M_{ij} values (contrasting M_{ij} values obtained from original time-series with M_{ij} values obtained from surrogates).
- We use **symbolic** time-series analysis (ordinal patterns) to compute the probabilities.

Method of **symbolic** time-series analysis: ordinal patterns

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

Brandt & Pompe, PRL 88, 174102 (2002)



The OP probabilities allow to identify frequent patterns in the *ordering* of the data points

Random data
⇒ OPs are
equally probable

- Advantage: the probabilities uncover temporal correlations.
- Drawback: we lose information about the actual values.

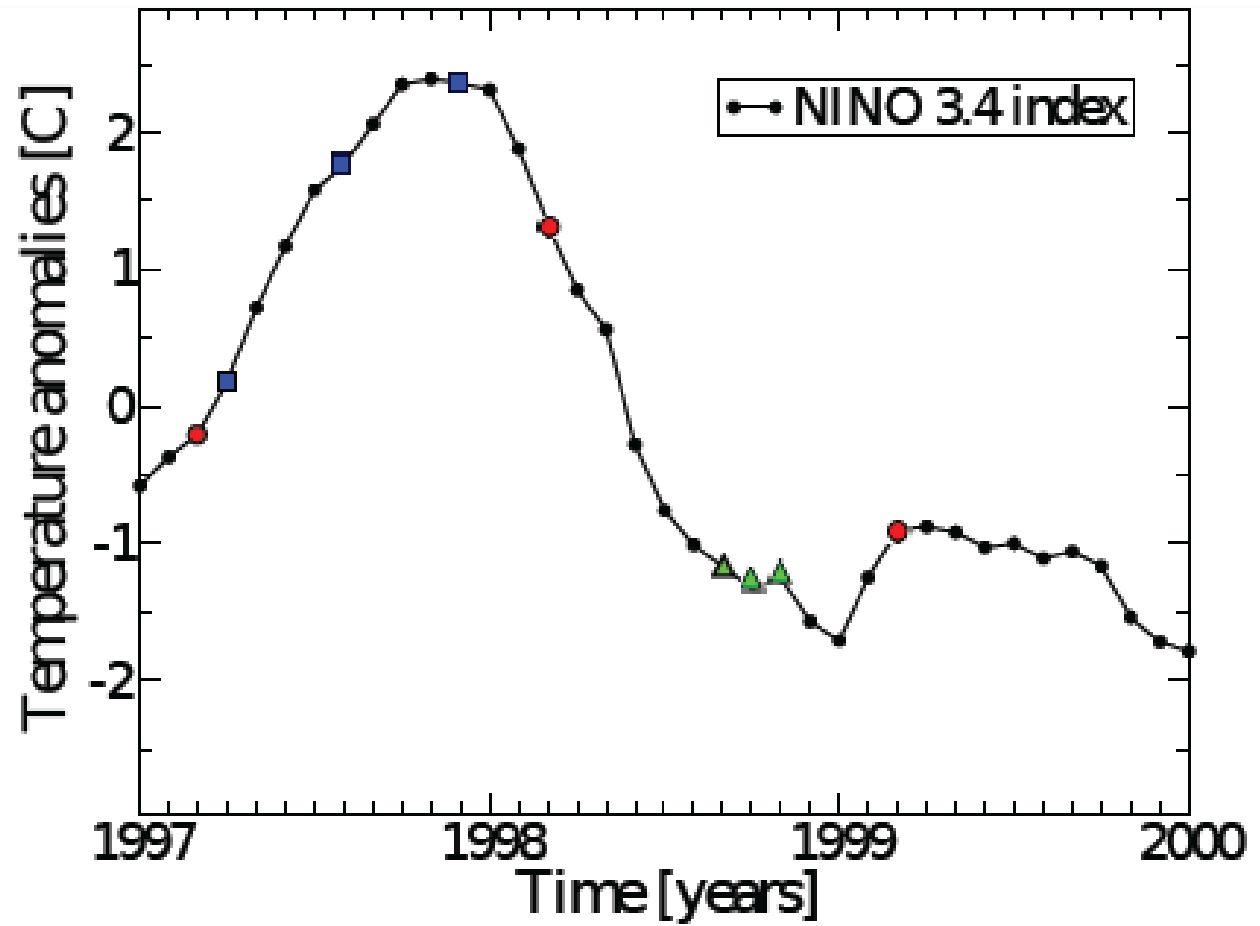
$$M_{ij} = \sum_{m,n} p_{ij}(m,n) \log \frac{p_{ij}(m,n)}{p_i(m)p_j(n)}$$

Ordinal analysis allows selecting the time scale of the analysis

**Intra-
season 102**

**Intra-
annual 012**

**Inter-
annual 120**



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?

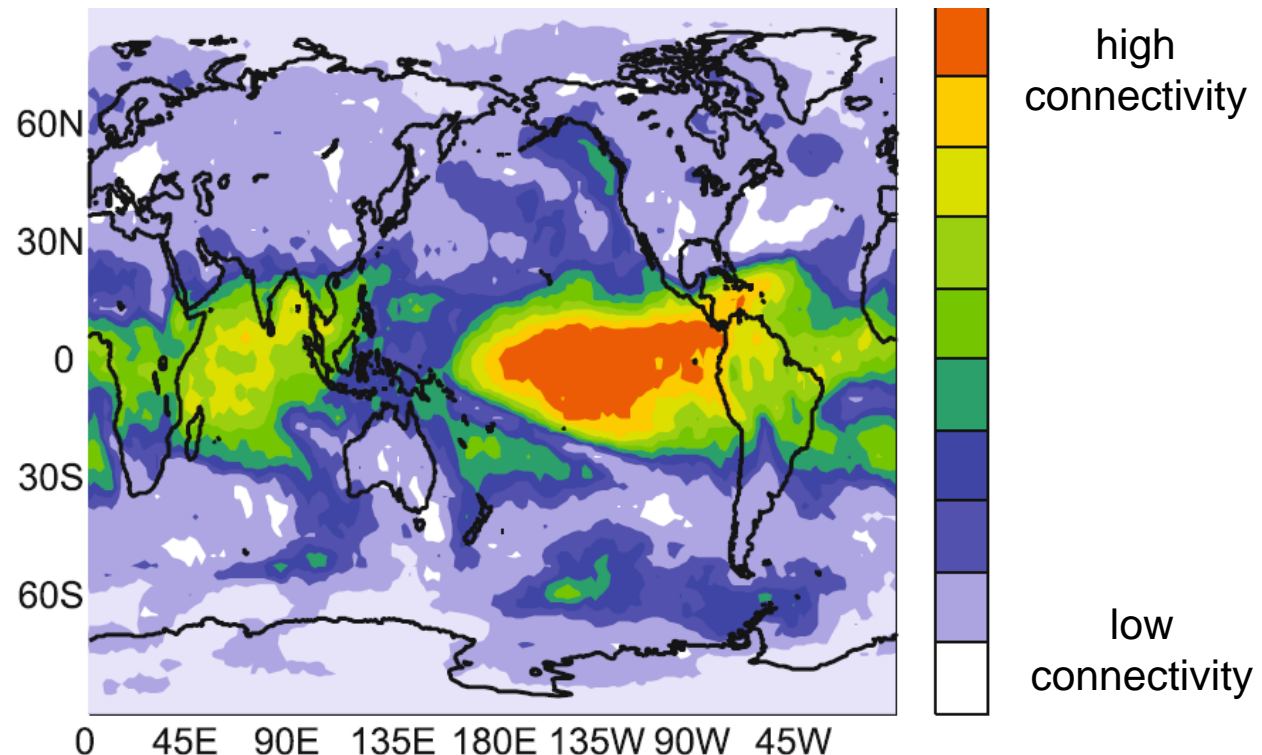
- National Center for Environmental Prediction, National Center for Atmospheric Research (NCEP-NCAR).
- Freely available.
- Reanalysis = run a sophisticated model of general atmospheric circulation and feed the model (data assimilation) with empirical data, where and when available.
- This process restricts the solution of the model to one as close to reality as possible in regions/times where there are data available, and to a solution physically “plausible” in regions/times where no data is available.

Graphical representation of the climate network

Network obtained with ordinal patterns, inter-annual time-scale: 3 consecutive years.

*The color-code
indicates the Area
Weighted Connectivity
(weighted degree)*

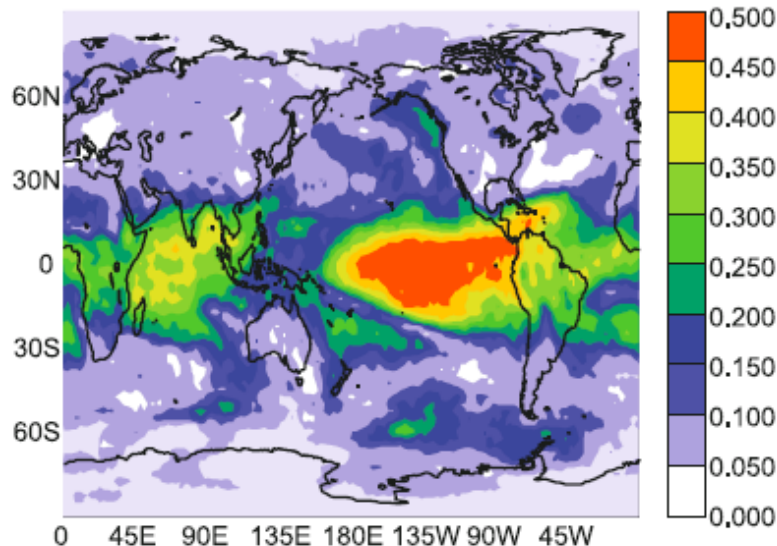
$$AWC_i = \frac{\sum_j^N A_{ij} \cos(\lambda_j)}{\sum_j^N \cos(\lambda_j)}$$



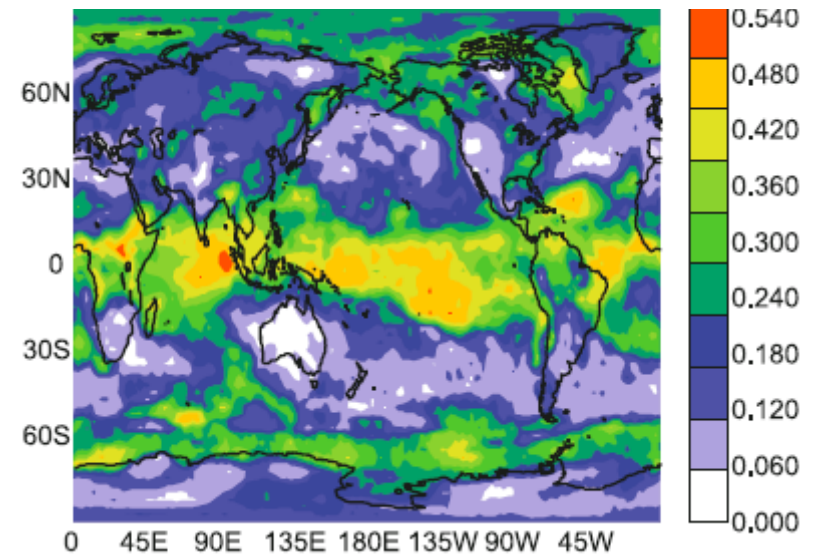
Contrasting two methods for inferring the climate network

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

Network when the probabilities are computed with ordinal analysis

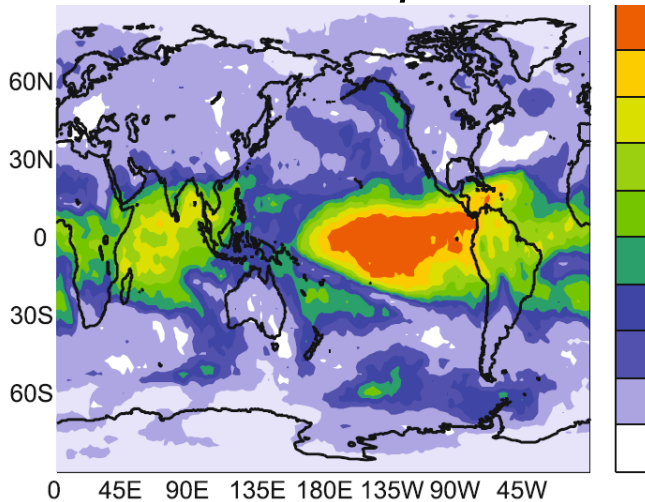


Network when the probabilities are computed with histogram of values

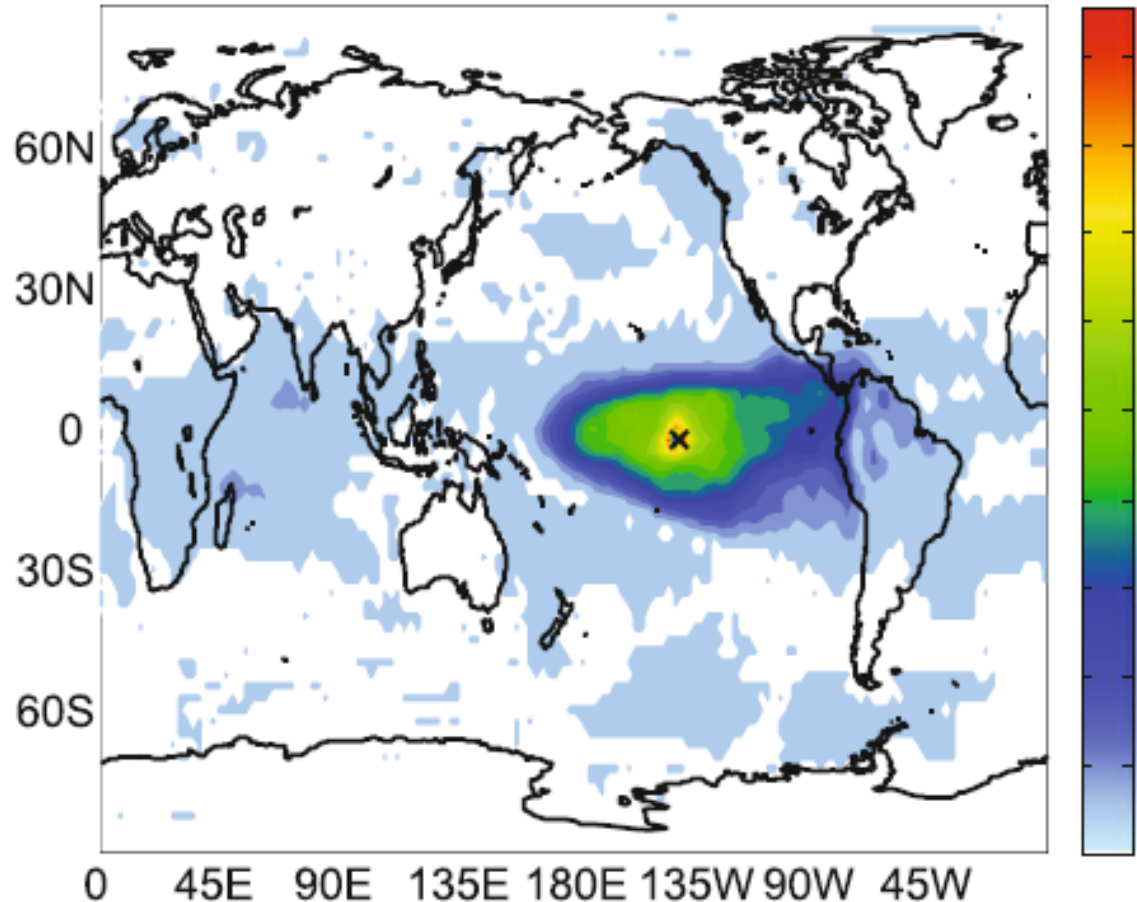


Who is connected to who?

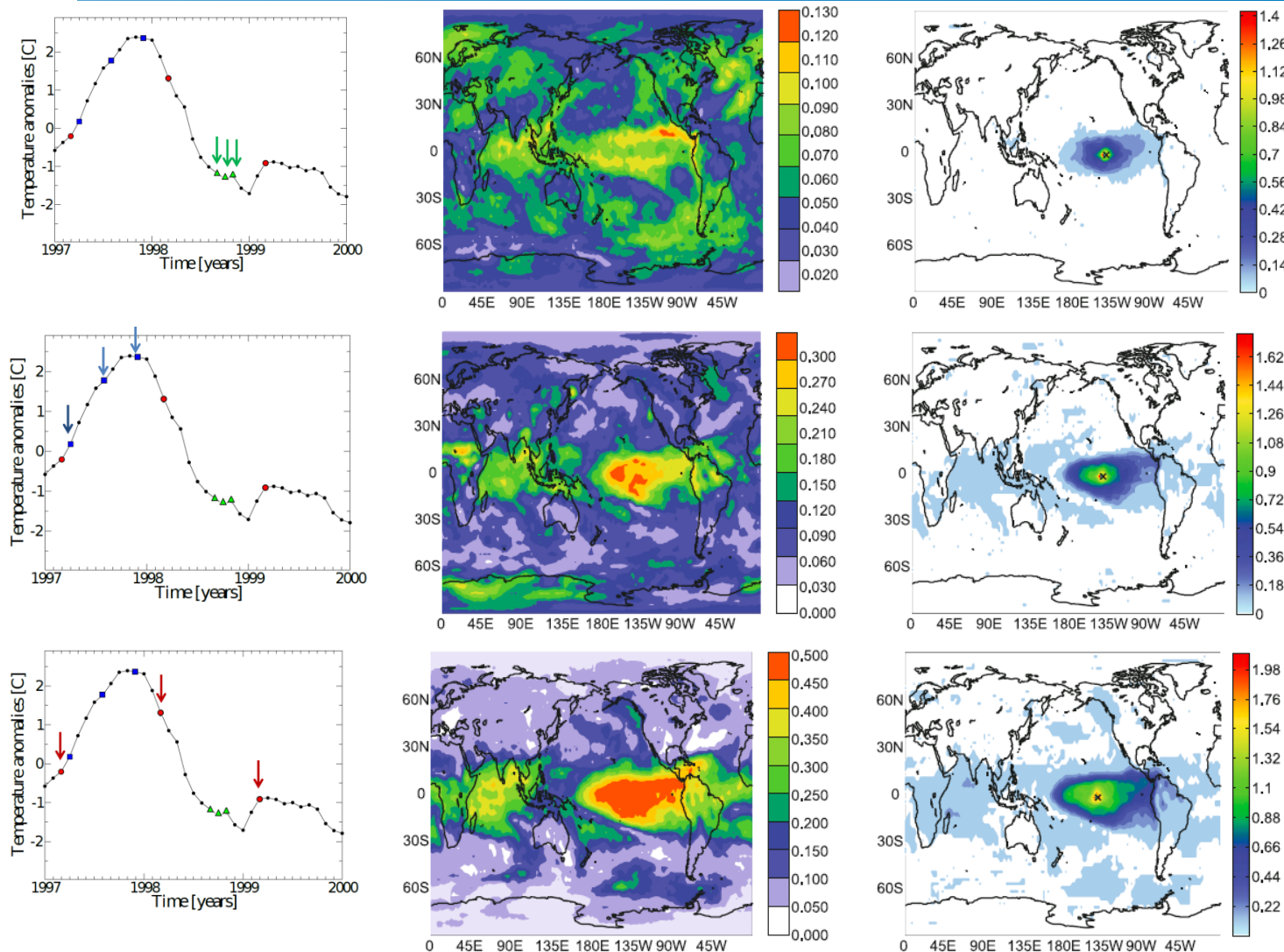
AWC map



color-code indicates the MI values (only significant values)



Influence of the time-scale of the symbolic ordinal pattern



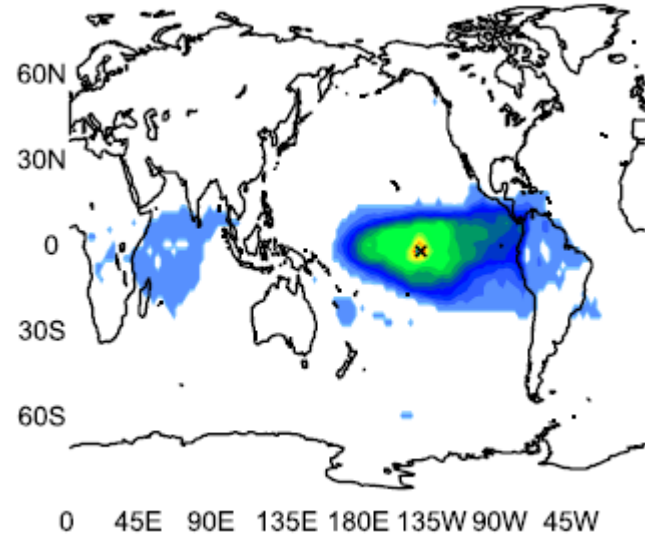
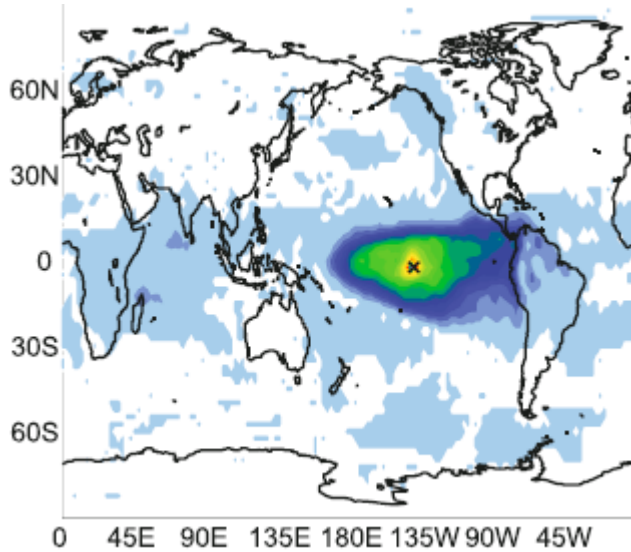
Longer time-scale \Rightarrow increased connectivity

Are the links significant? Influence of the threshold

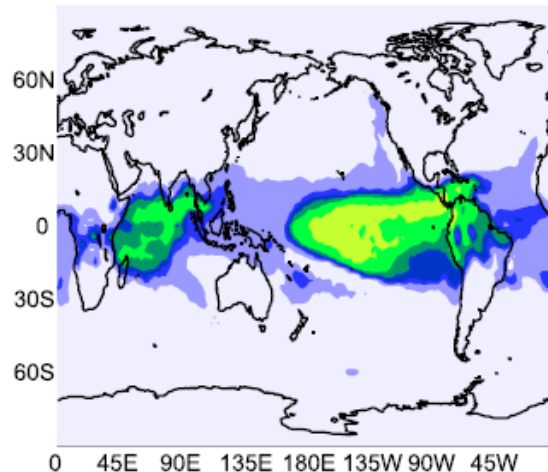
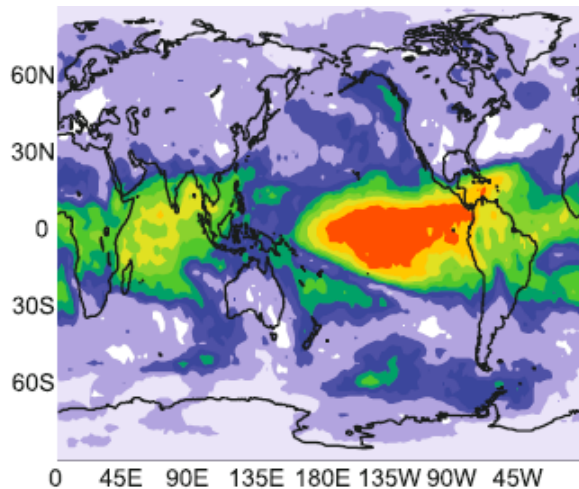
Low threshold (11% link density)

High threshold (3% link density)

Color code:
MI



Color code:
AWC



How to improve climate predictability?

Assessing the directionality of the links

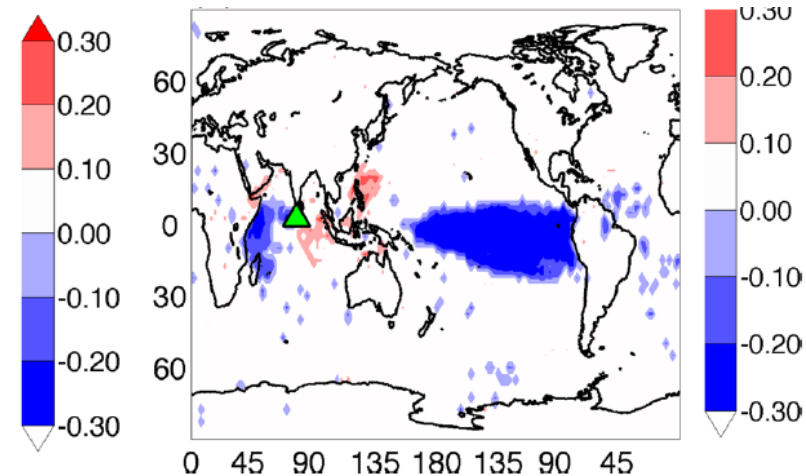
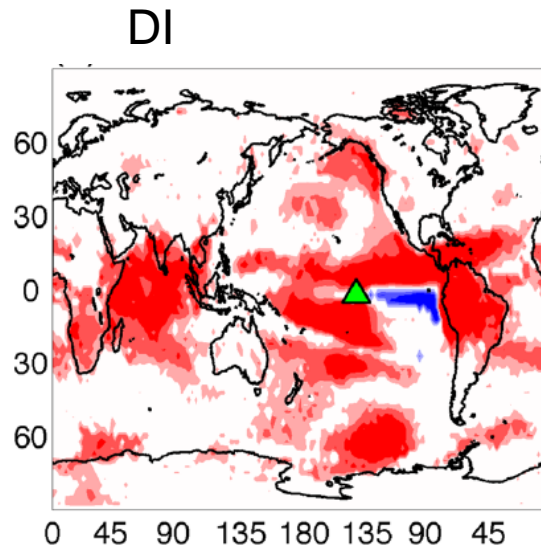
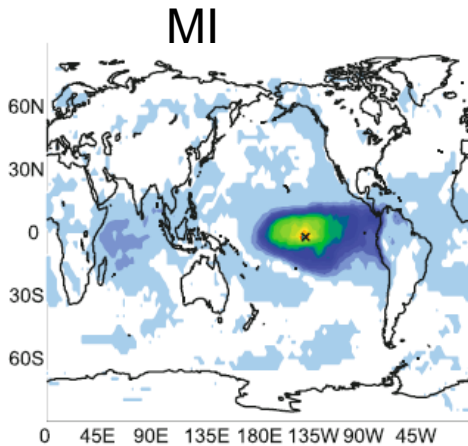
- $I_{xy}(\tau)$: conditional mutual information
- τ : *time-scale* of information transfer
- D : net direction of information transfer

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

$x \rightarrow y$

$x \rightarrow z$

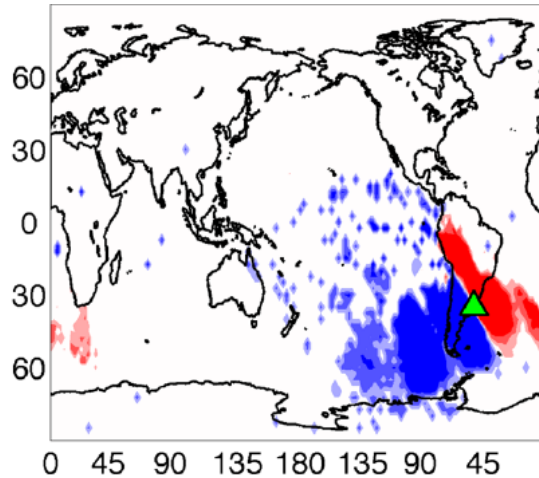
$y \leftrightarrow z ??$



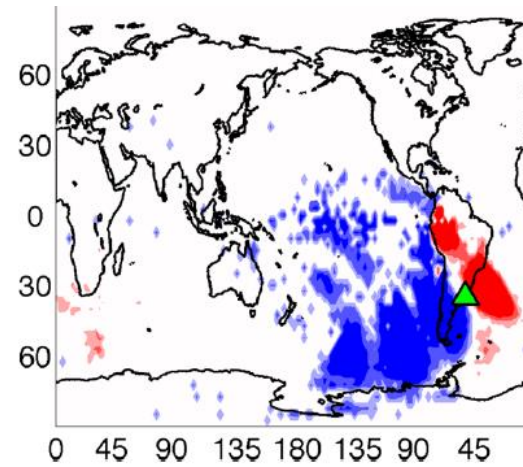
Computed from daily SAT anomalies, PDFs estimated from histograms of values.
MI and DI are both significant ($>3\sigma$, bootstrap surrogates), $\tau=30$ days.

Time-scale of interactions

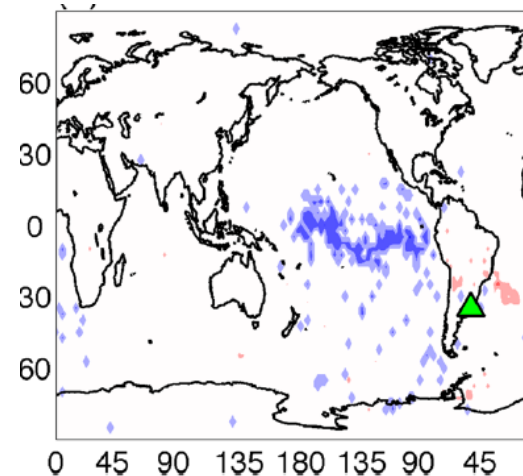
$\tau=1$ day



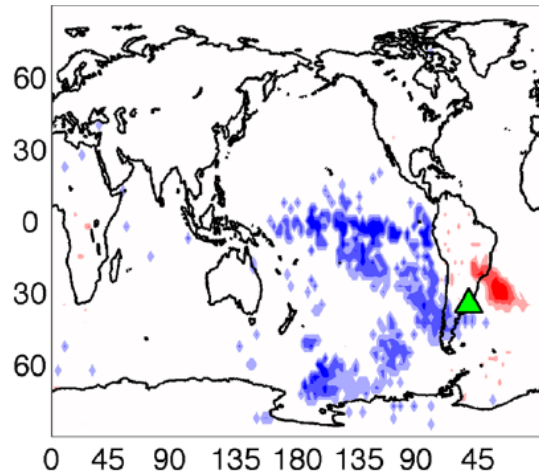
$\tau=3$ days



$\tau=30$ days



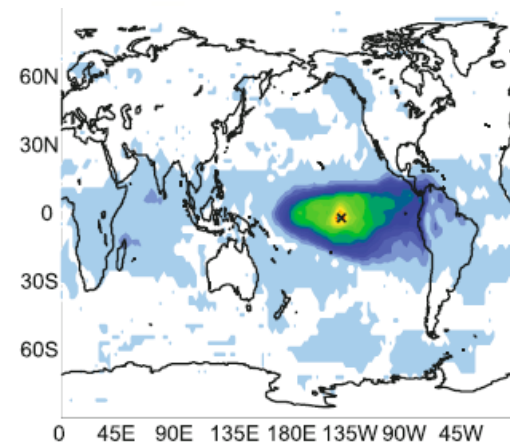
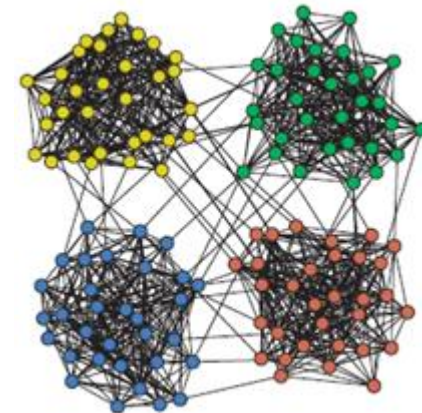
$\tau=7$ days



Link directionality reveals wave trains propagating from west to east

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

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

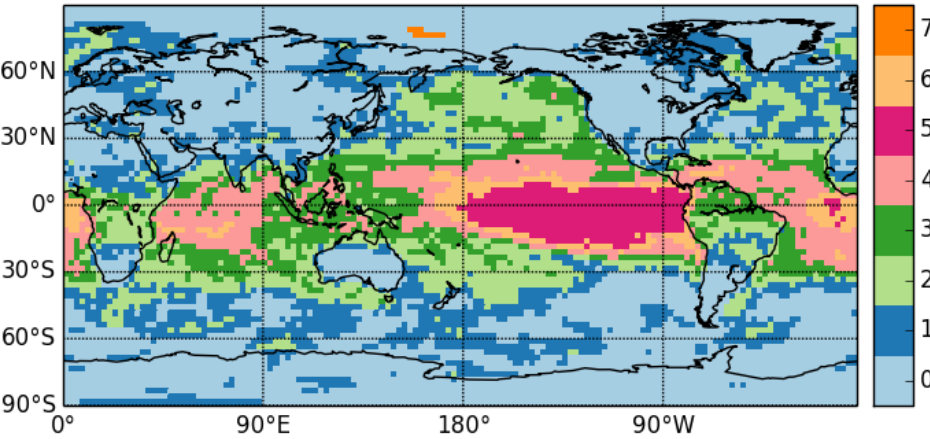
- Step 3: define the weights

$$w_{ij} = \frac{1}{\sum_{\alpha\beta} (TP_{\alpha\beta}^i - TP_{\alpha\beta}^j)^2}$$

**High weight
if similar
symbolic
“language”**

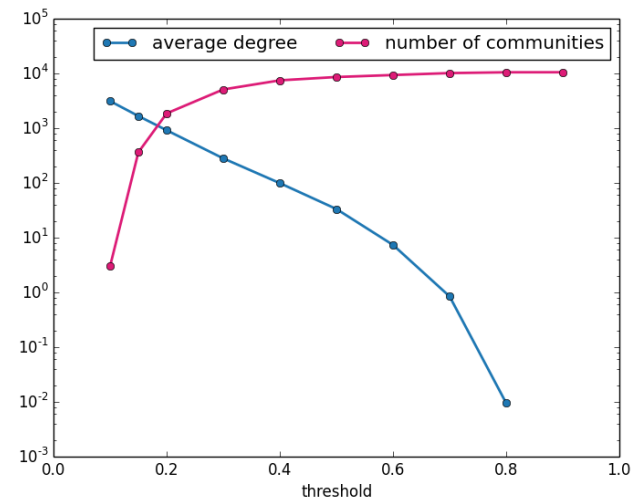
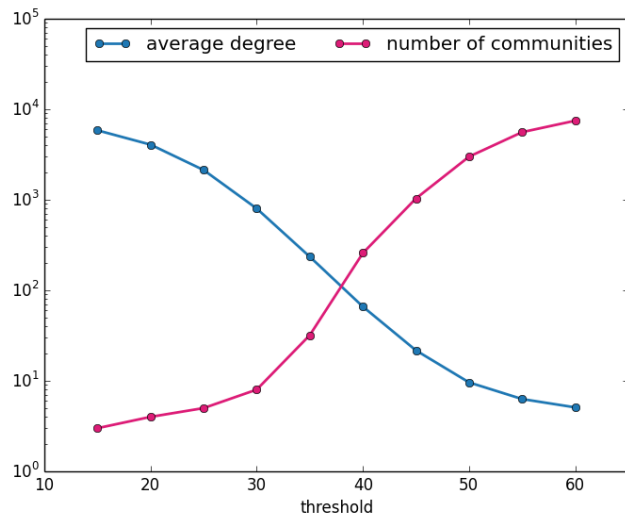
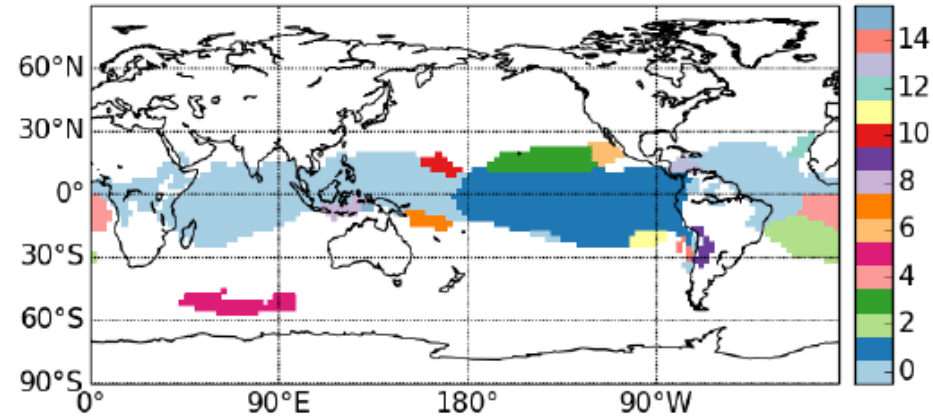
- Step 4: threshold w_{ij} to obtain the adjacency matrix.
- Step 5: run a community detection algorithm (Infomap).

TP Network

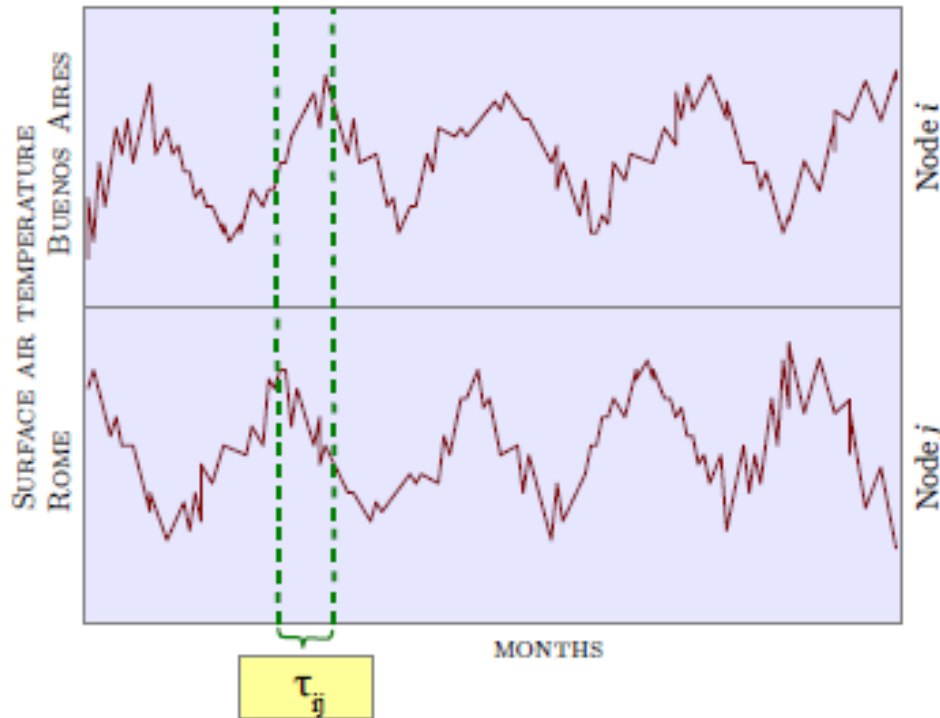


CC Network

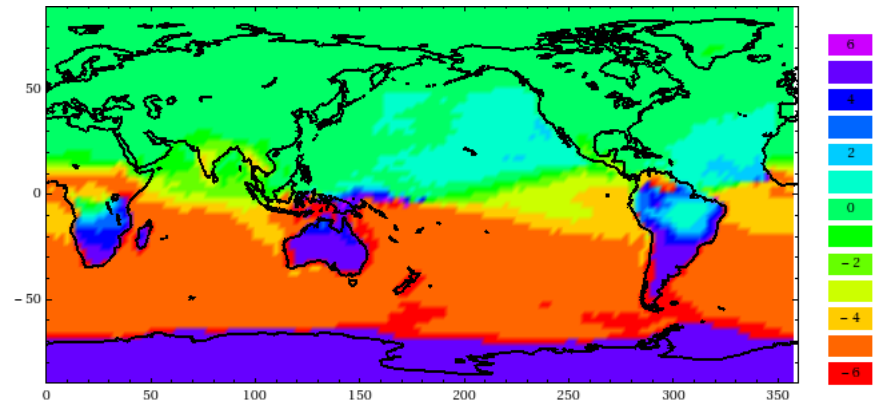
(only the largest 16)



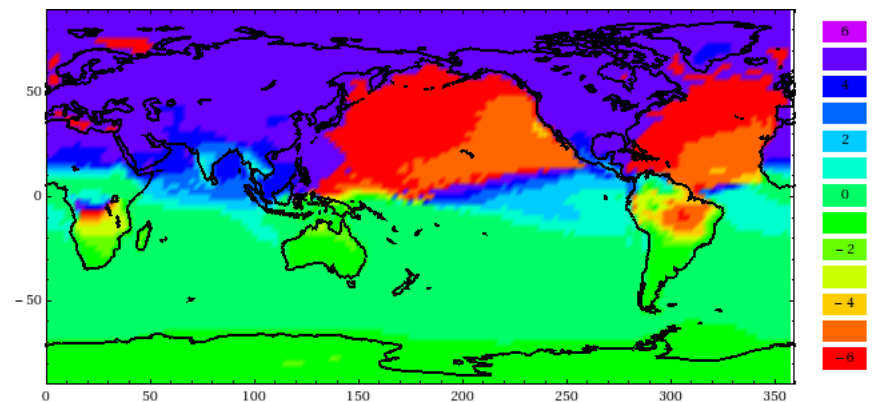
Another way to identify climate communities: lag-times between seasonal cycles



Rome

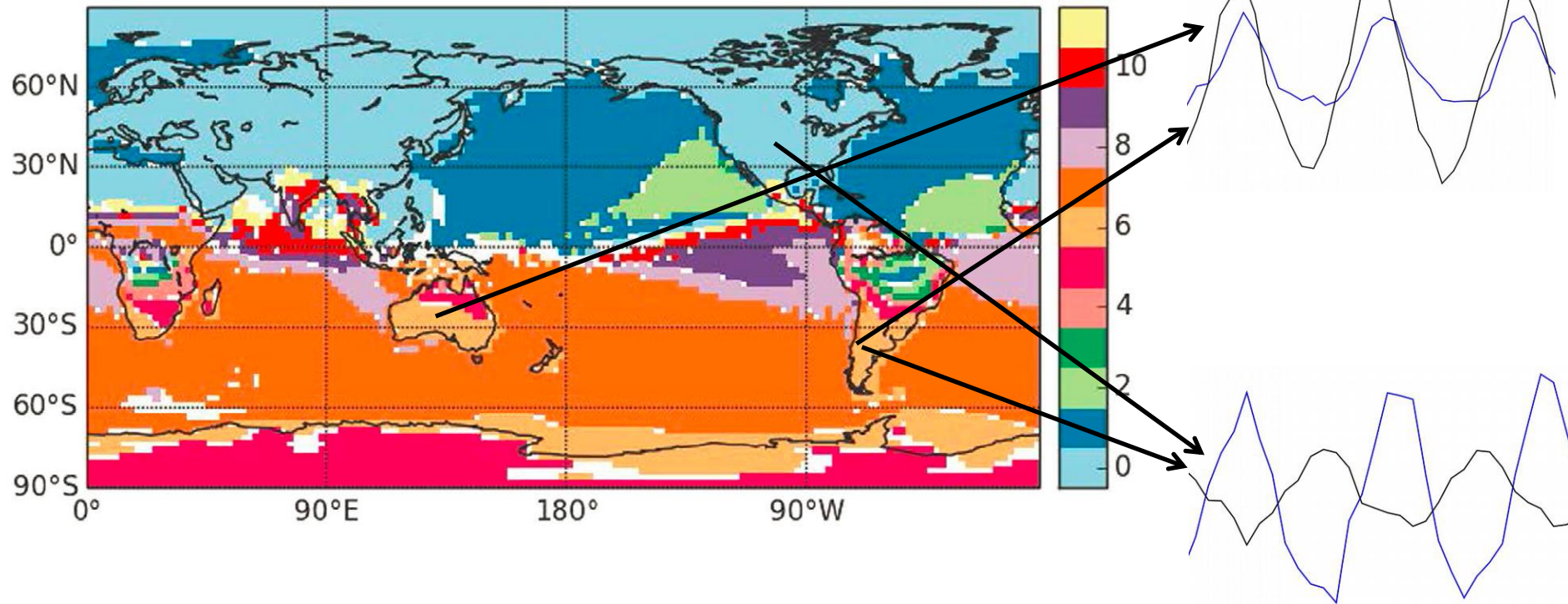


Buenos Aires

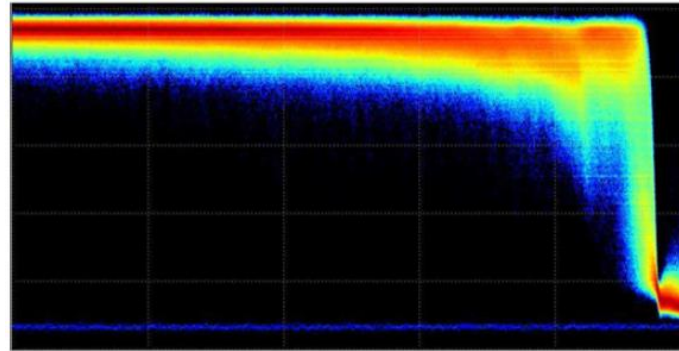


Climate communities: geographical regions with inphase seasonal cycles

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



- Six-month symmetry between the two hemispheres.
- Ocean areas have a one-month delay with respect to the landmasses



Identifying early signs of upcoming transition

- controlled experiments with laser systems provide data that allows testing diagnostic tools

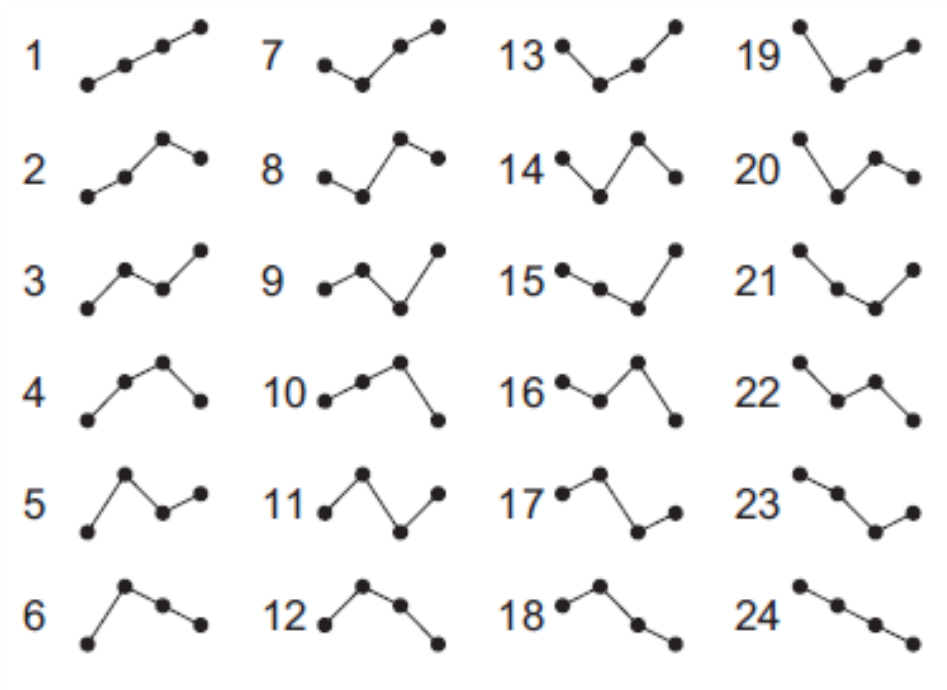


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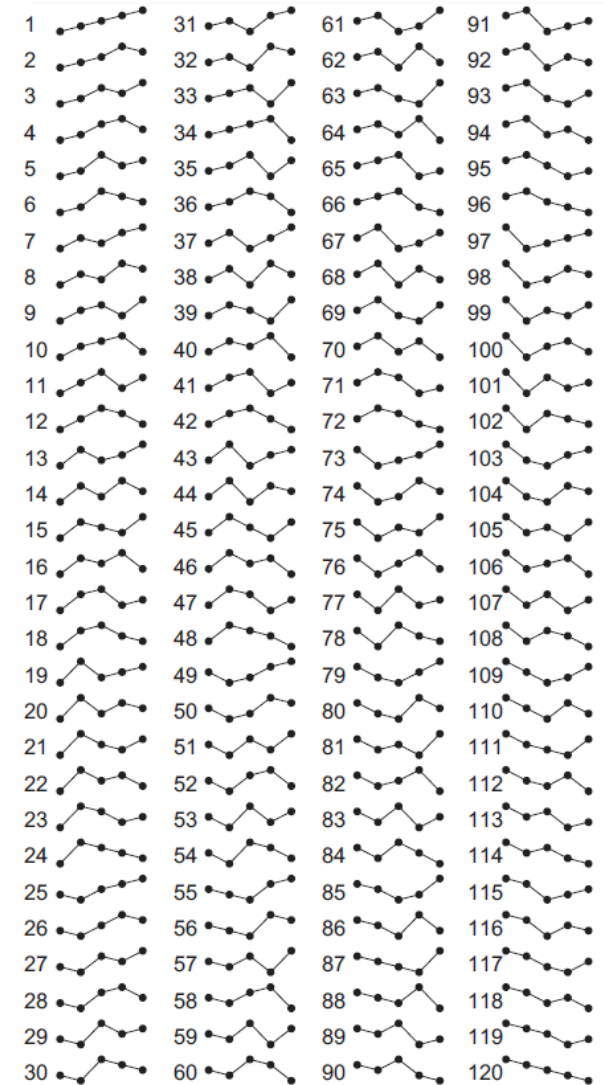
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Experimental data from INLN & Bangor University
(S. Barland & Y. Hong)

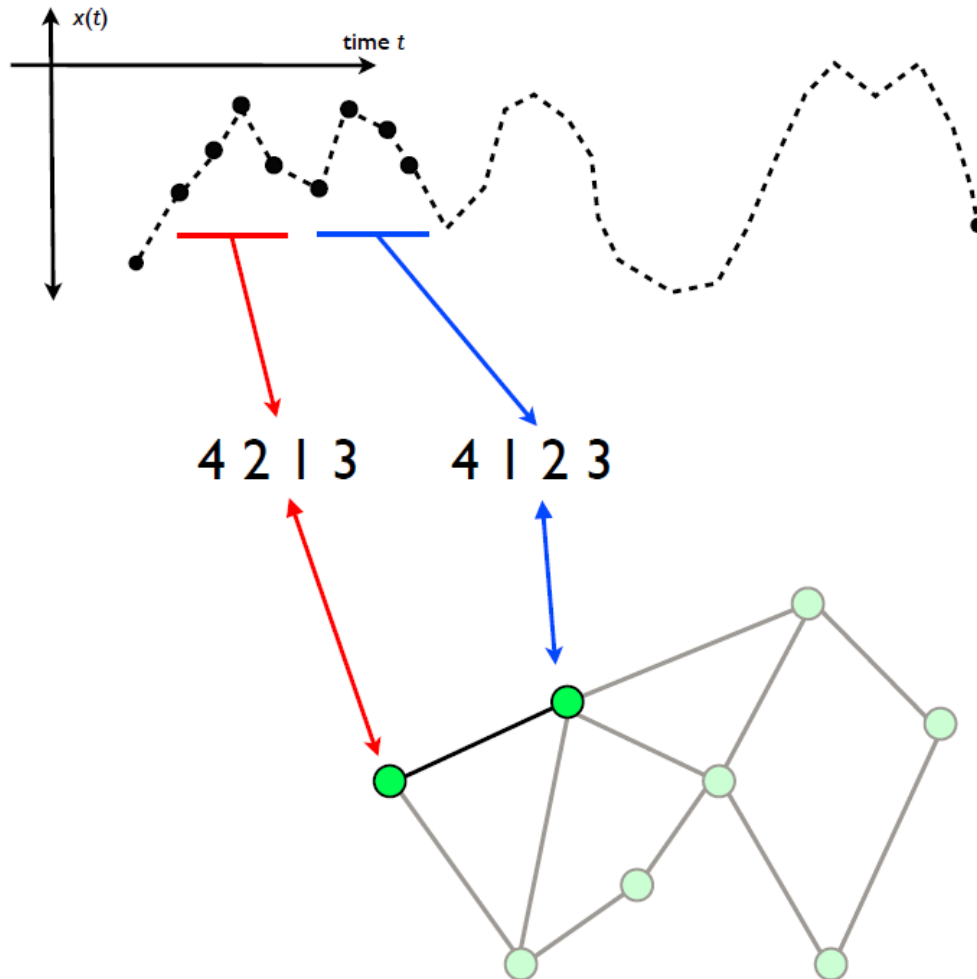
The number of patterns increases as D!



Opportunity: turn a time-series into a network by using the patterns as the “nodes” of the network.



The nodes are the “ordinal patterns”, and the links?



- The links are defined in terms of the probability of pattern “ β ” occurring after pattern “ α ”.
- Weighs of nodes: the probabilities of the patterns ($\sum_i p_i = 1$).
- Weights of links: the probabilities of the transitions ($\sum_j w_{ij} = 1 \forall i$).

\Rightarrow **Weighted and directed network**

Three network-based diagnostic tools

- Entropy computed from the weights of the nodes (**permutation entropy**)

$$s_p = -\sum p_i \log p_i$$

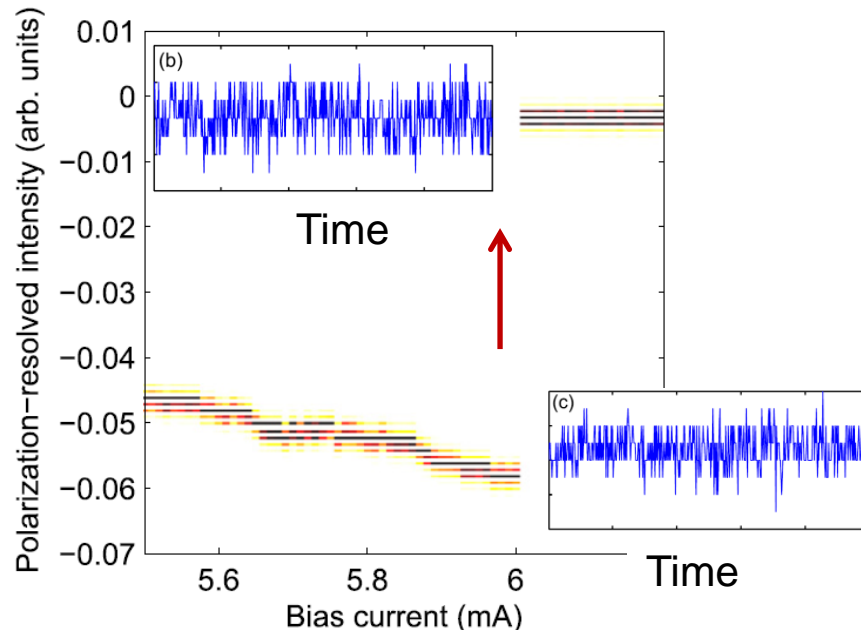
- Entropy computed from weights of the links (**transition probabilities**, '01'→'01', '01'→'10', etc.)
- Asymmetry coefficient: normalized difference of transition probabilities, $P('01' \rightarrow '10') - P('10' \rightarrow '01')$, etc.

$$a_c = \frac{\sum_i \sum_{j \neq i} |w_{ij} - w_{ji}|}{\sum_i \sum_{j \neq i} (w_{ij} + w_{ji})}$$

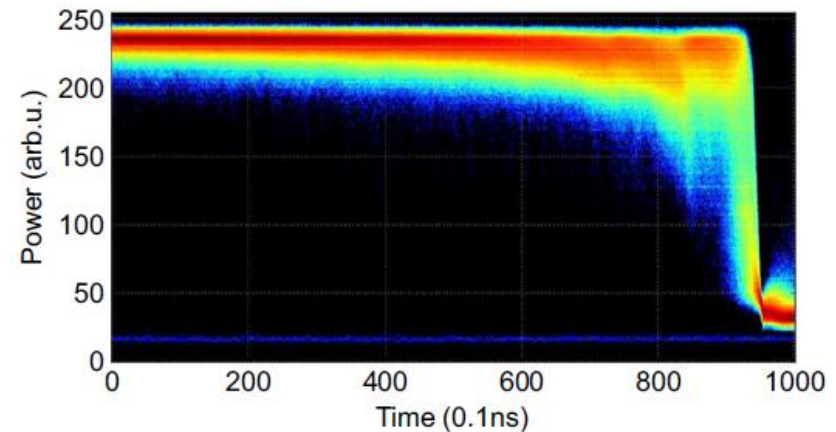
(0 in a fully symmetric network;
1 in a fully directed network)

VCSEL polarization-resolved intensity: two sets of experiments

- Time series recorded with pump current constant in time.
- Record the turn-on of the orthogonal mode.



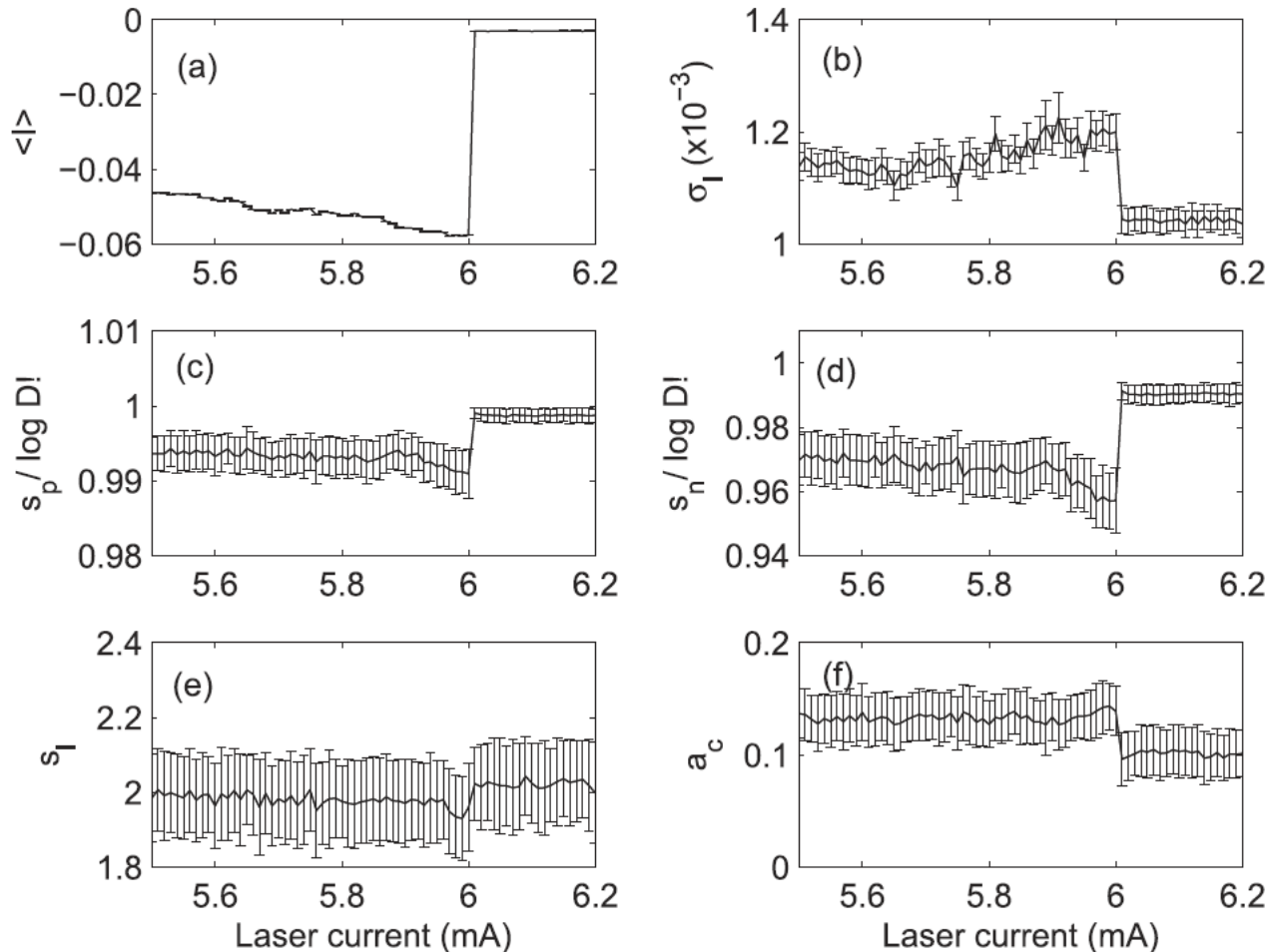
- Time series recorded with pump current varying in time.
- Record the turn-off of the fundamental mode.



Is it possible to anticipate the PS?

No if the mechanisms that trigger the PS are fully stochastic.

Results for constant pump current & turn-on of the orthogonal mode

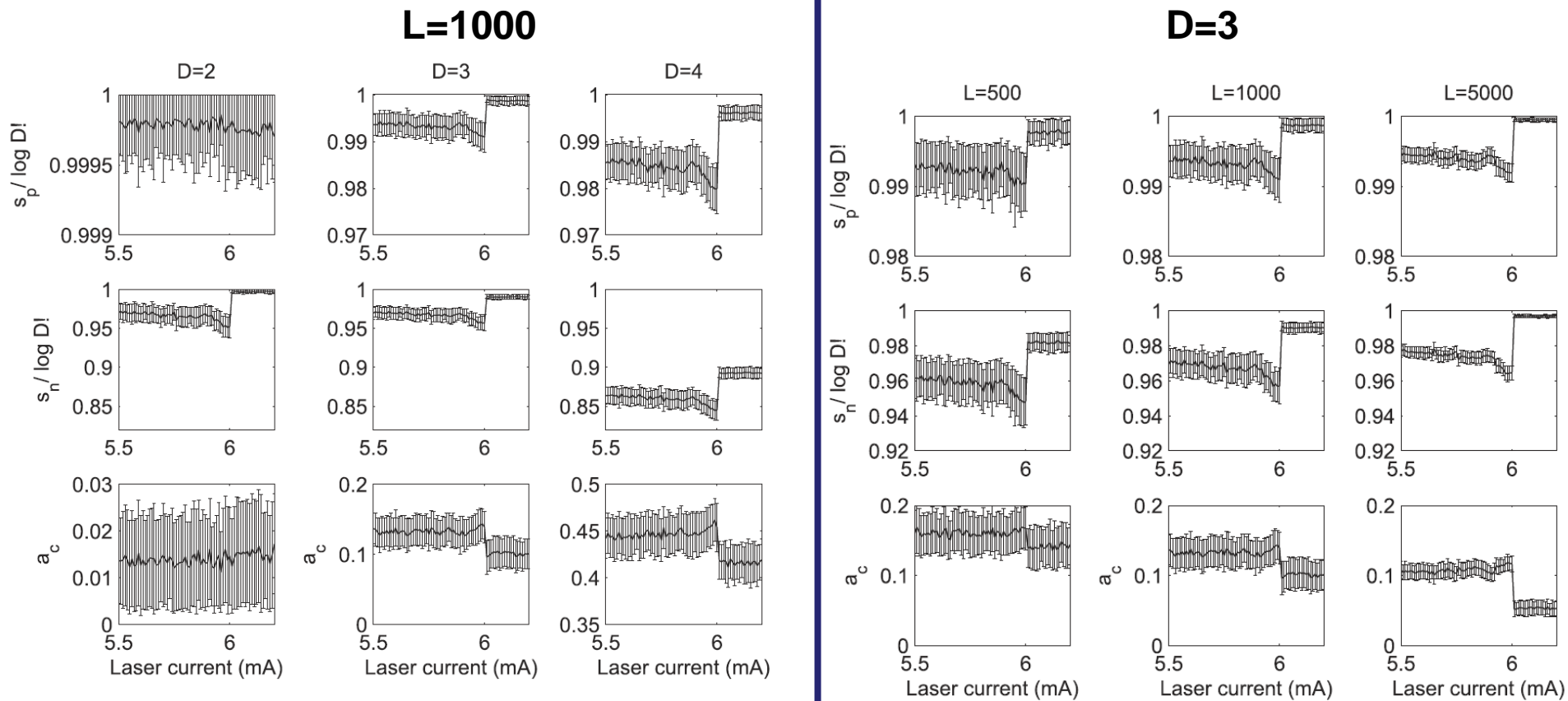


⇒ Despite of the stochasticity of the time-series, the measures “anticipate” the PS.

⇒ Deterministic mechanisms involved.

Error bars computed from 100 non-overlapping windows with $L=1000$ data points each. Length of the pattern $D=3$.

Influence of the length of the pattern (D) and of length of the time-series (L)

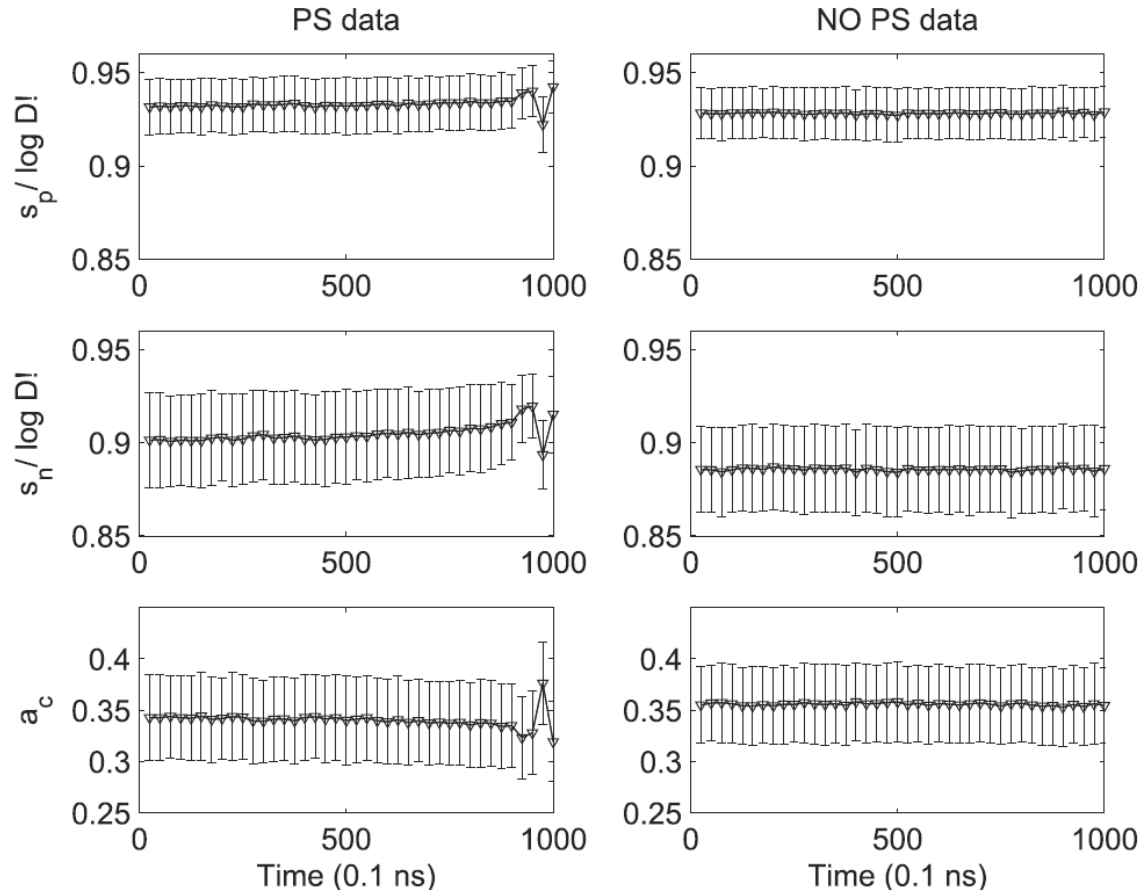


⇒ Transition detected even for short dataset ($L=500$ with $D=3$).
Open issues: How to quantify performance? Optimal D depends on L ?

Results for time-varying pump current & turn-off of the fundamental mode

Slightly different optical feedback conditions result in PS or no PS.

Analysis done with $D=3$, error bars computed with 1000 time series $L=500$.



Another open issue: comparison with other diagnostic tools

- Introduction
- Results
- **Summary**

■ Take home message:

- Symbolic ordinal analysis and network tools provide an opportunity for advancing understanding and predictability of our climate.

■ A few specific conclusions:

- Ordinal analysis allows identifying different **time-scales** of interactions.
- Tools for detecting the **net direction** of interactions and identifying **communities** validated: the uncovered structure is consistent with known climate phenomena.
- Tools for identifying **early-warning signs** of upcoming transition validated.

■ Ongoing/future work:

- Potential of Hilbert transform to gain more information from climate data?
- Quantify the performance of the PS diagnostic tools & application to real-world data.

■ Climate networks

- Ignacio Deza
- Giulio Tirabassi
- Marcelo Barreiro (Universidad de la República, Uruguay)

■ Early warning of polarization switching

- Toni Pons
- Sergio Gomez (URV, Tarragona)
- Alex Arenas (URV, Tarragona)
- Experimental data from INLN (S. Barland) and Bangor University (Y. Hong)



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THANK YOU FOR YOUR ATTENTION !

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

- C. Masoller et al, “*Quantifying sudden changes in dynamical systems using symbolic networks*”, New J. Phys. 17, 023068 (2015).
- J. I. Deza, M. Barreiro and C. Masoller, “*Assessing the direction of climate interactions by means of complex networks and information theoretic tools*”, Chaos 25, 033105 (2015).
- G. Tirabassi and C. Masoller, “*Unravelling the community structure of the climate system by using lags and symbolic time-series analysis*”
Sci. Rep. 6:29804 (2016).