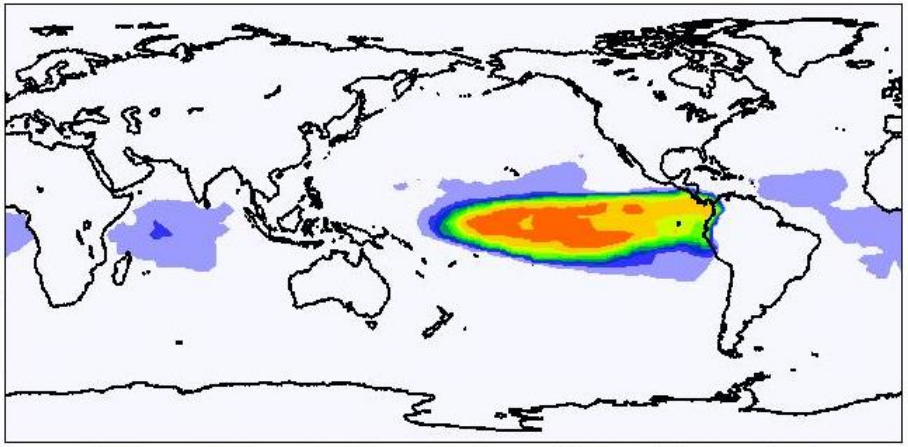


Climate networks: a large-scale perspective of the dynamics of our climate

Cristina Masoller

Universitat Politecnica de Catalunya

Cristina.masoller@upc.edu

www.fisica.edu.uy/~cris

UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH

Campus d'Excel·lència Internacional

Workshop on Critical and Collective Effects in Graphs and Networks (CCEGN)
Moscow Institute of Physics and Technology
April 2016

ICREA

GOBIERNO DE ESPAÑA

MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

UNIVERSITAT POLITÈCNICA
DE CATALUNYA
BARCELONATECH

Campus d'Excel·lència Internacional

Where are we?

1. Barcelona
2. Castelldefels
3. Igualada
4. Manresa
5. Mataró
6. Sant Cugat del Vallès
7. Terrassa
8. Vilanova i la Geltrú

Viernes, 25 de septiembre de 2009 **Diari de Terrassa**

El edificio Gaia centraliza grupos científicos consolidados y emergentes.

Attending this workshop,
also from Catalunya:

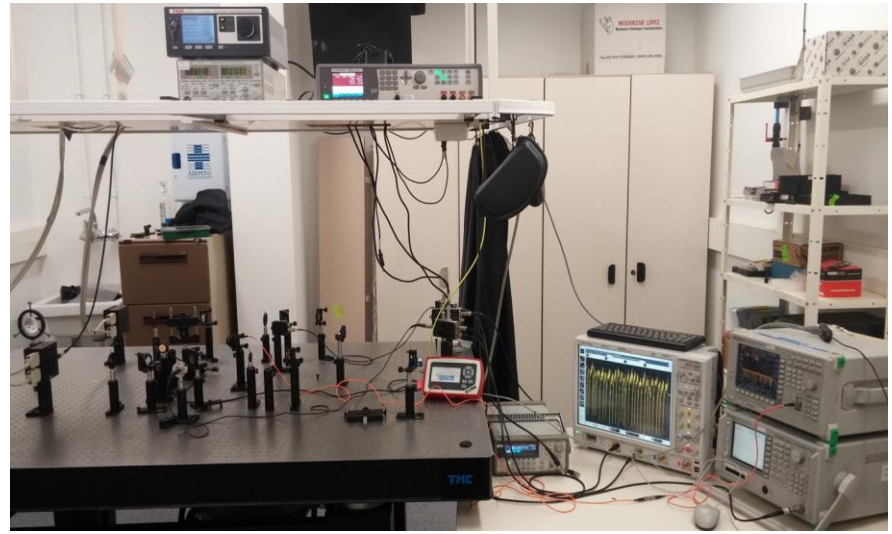
Who are we?

Research group on Dynamics, Nonlinear Optics and Lasers

UNIVERSITAT POLITÈCNICA
DE CATALUNYA
BARCELONATECH

Campus d'Excel·lència Internacional

What do we study?



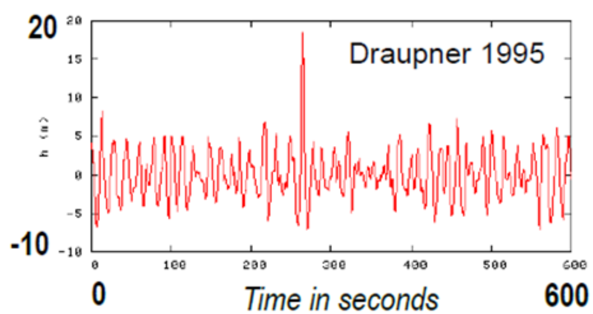
- Nonlinear phenomena in complex systems
  - Photonics (nonlinear dynamics of lasers, nonlinear optics)
  - Biophysics (excitability, coupled oscillators)
  - Data analysis (climate networks, biomedical signals)

Climate, lasers, networks??

- Optical systems allow recording long time-series under controlled conditions.
- This allows <u>testing novel analysis tools</u> (prediction, classification, etc.).

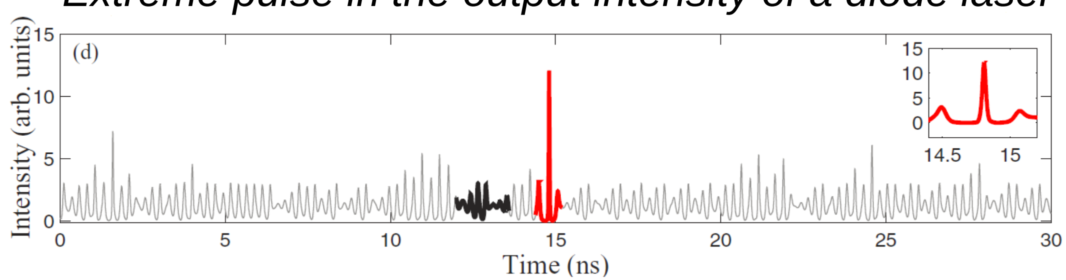
- Ocean rogue wave ⇒

Elevation of the sea surface (in meters)

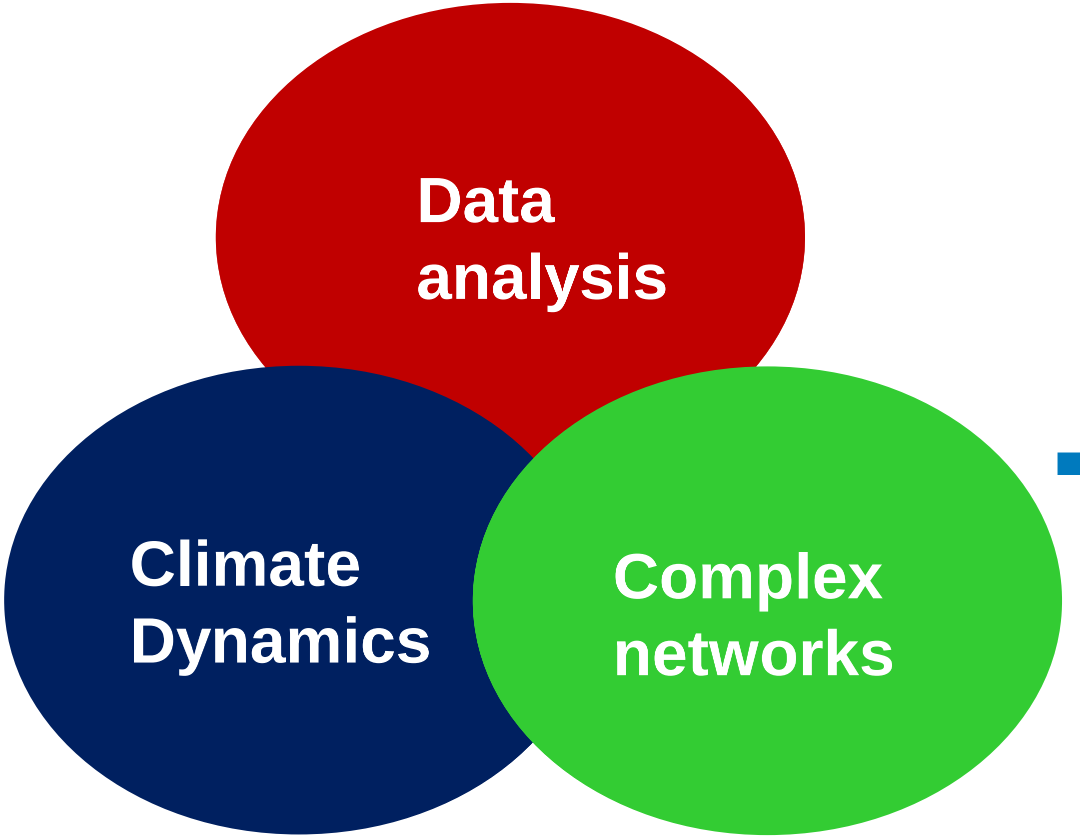


- Optical rogue wave ⇒

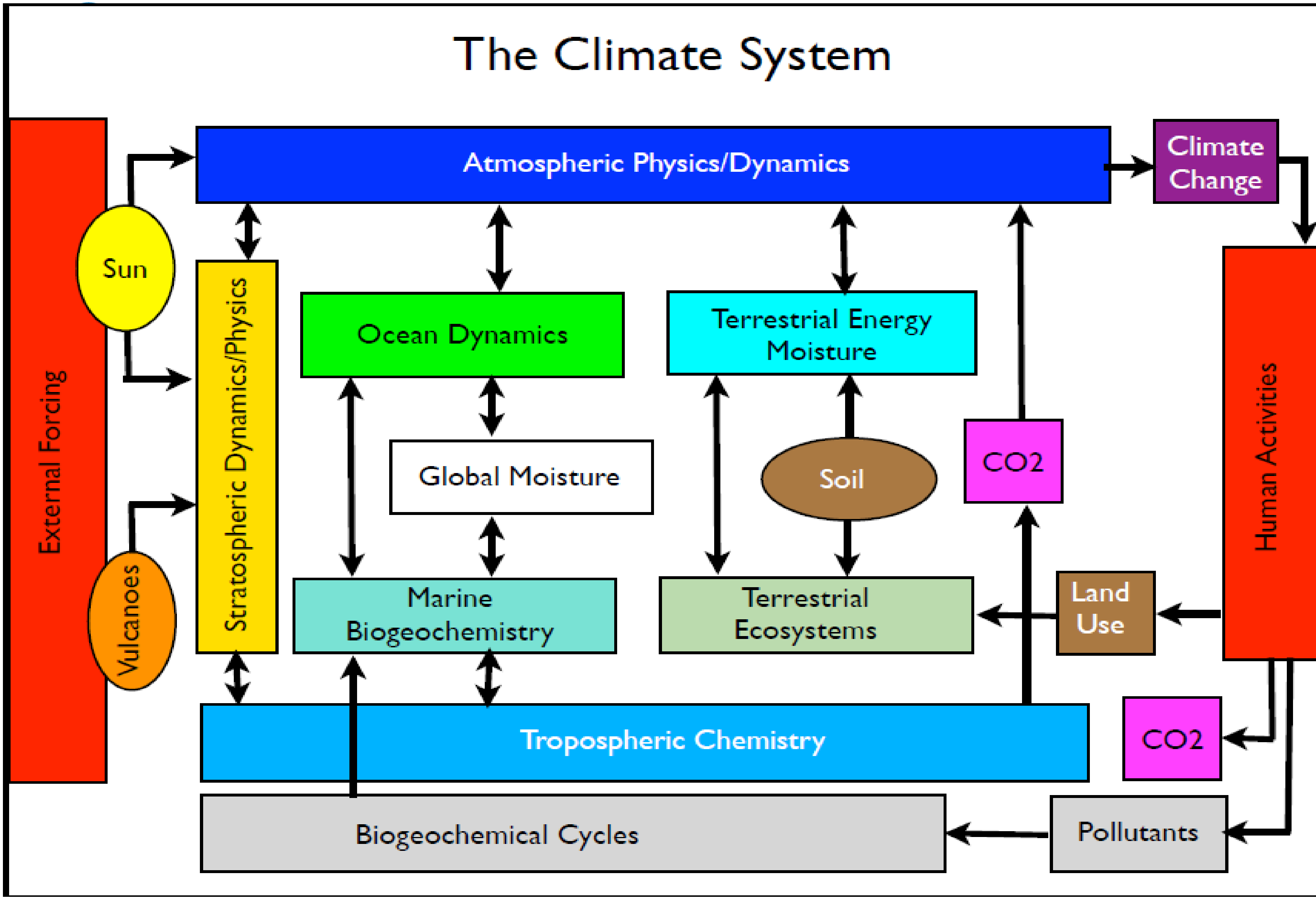
Extreme pulse in the output intensity of a diode laser



Outline



- **Introduction**
  - Climate dynamics
  - Symbolic method of time-series analysis
- **Results: networks**
  - Connectivity of climate networks
  - climate communities
- **Summary & ongoing work**

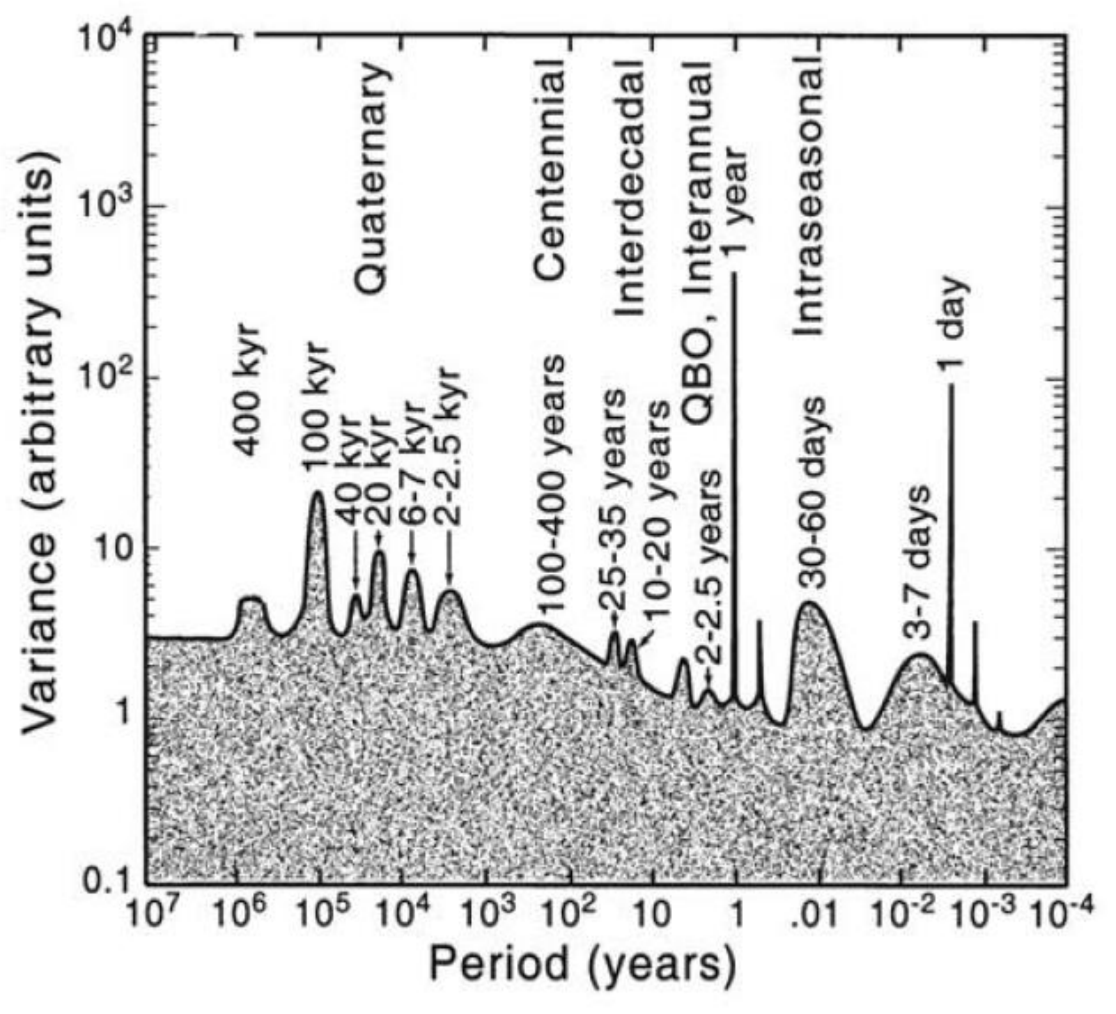


Courtesy of Henk Dijkstra (Ultrech University)

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH
Campus d'Excel·lència Internacional

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...



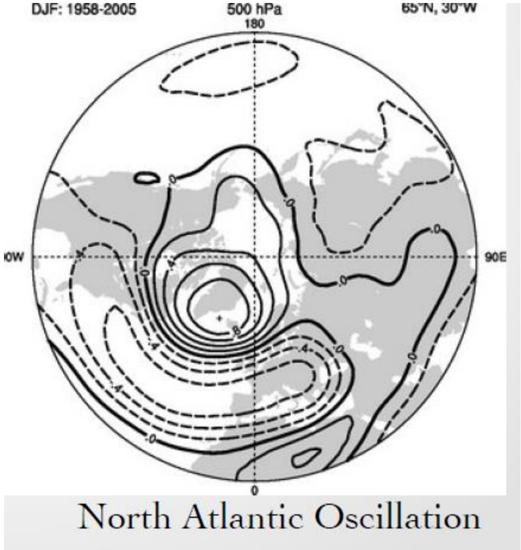
An "artist's representation" of the power spectrum of climate variability (Ghil 2002).

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

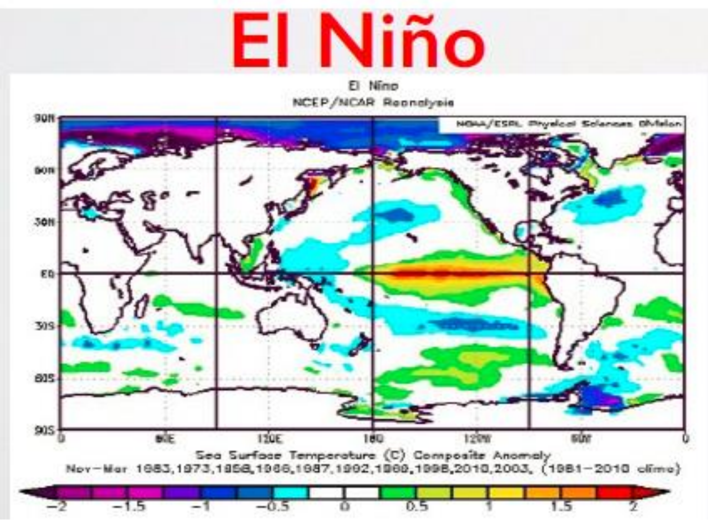
Campus d'Excel·lència Internacional

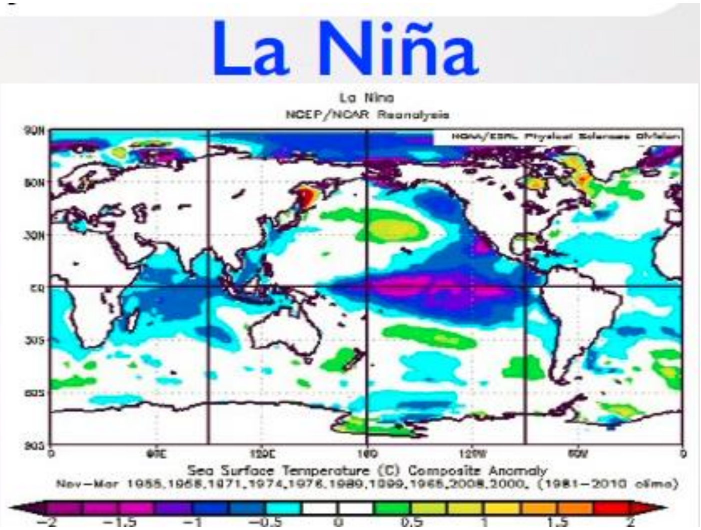
And a wide range of spatial modes of variability

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



North Atlantic Oscillation





WHAT DO NETWORKS HAVE TO DO WITH CLIMATE?

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

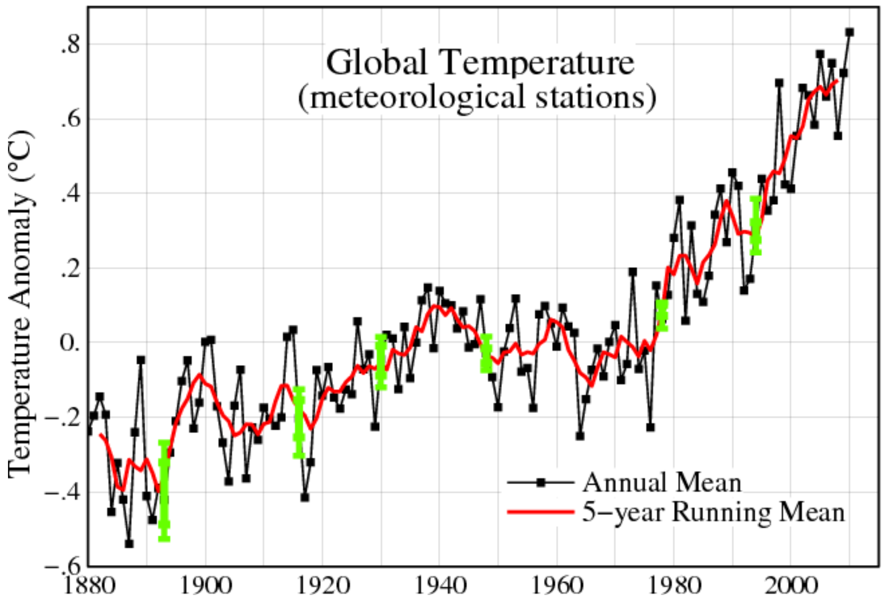
Advances in understanding coupling in complex networks offer new ways of studying the collective behavior of interactive systems and already have yielded new insights in many areas of science.

UNIVERSITAT POLITÈCNICA
DE CATALUNYA
BARCELONATECH

Campus d'Excel·lència Internacional

Time-scale of our analysis: weather vs. climate

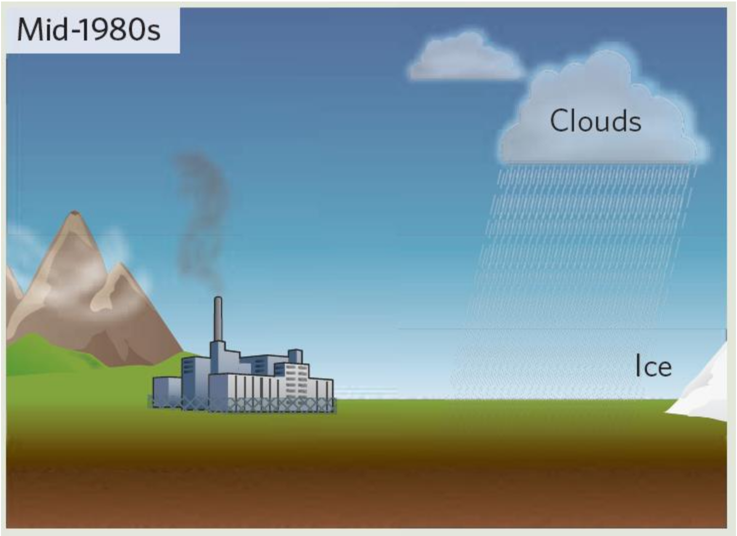
- weather = short-term variability
- climate = long-term trend

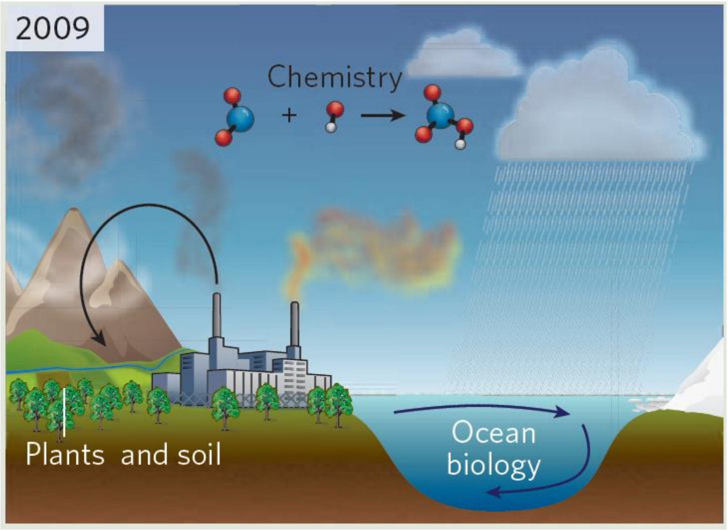


- Global warming

Monte Perdido (Spain)

Climate modeling





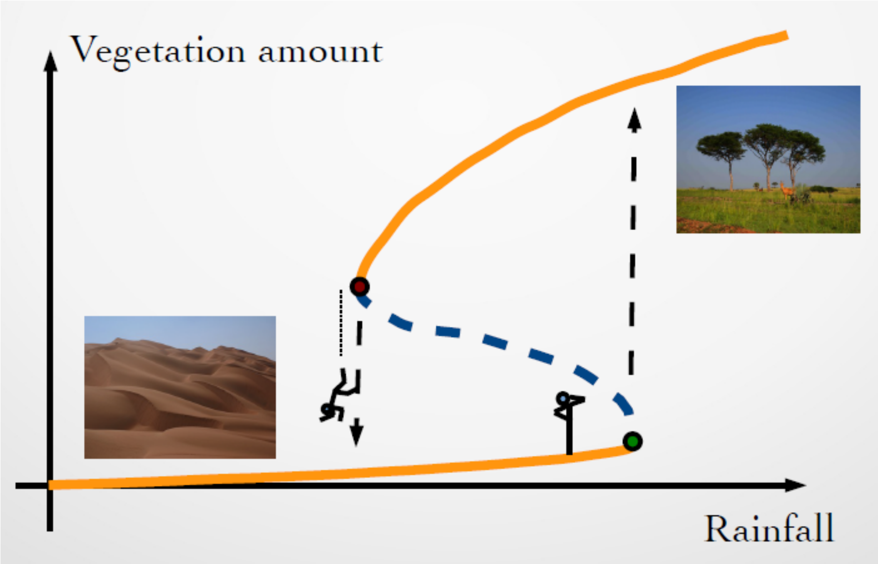
- Nowadays climate models capture many physical and biophysical processes.
- BUT many "feedback loops" (e.g., due to human adaptation activity) are poorly understood and not represented in models.
- Clear need of "data driven" studies.
- Clear need of reliable high-resolution spatio-temporal data.

Nature, February 2010

The importance of being nonlinear

- Methods of data analysis are dominated by linear thinking (example: expectations of continuity; extrapolation of trends).

- BUT in complex systems nonlinear thinking is crucial!
- Examples: accurate forecasts of critical transitions & extremes.

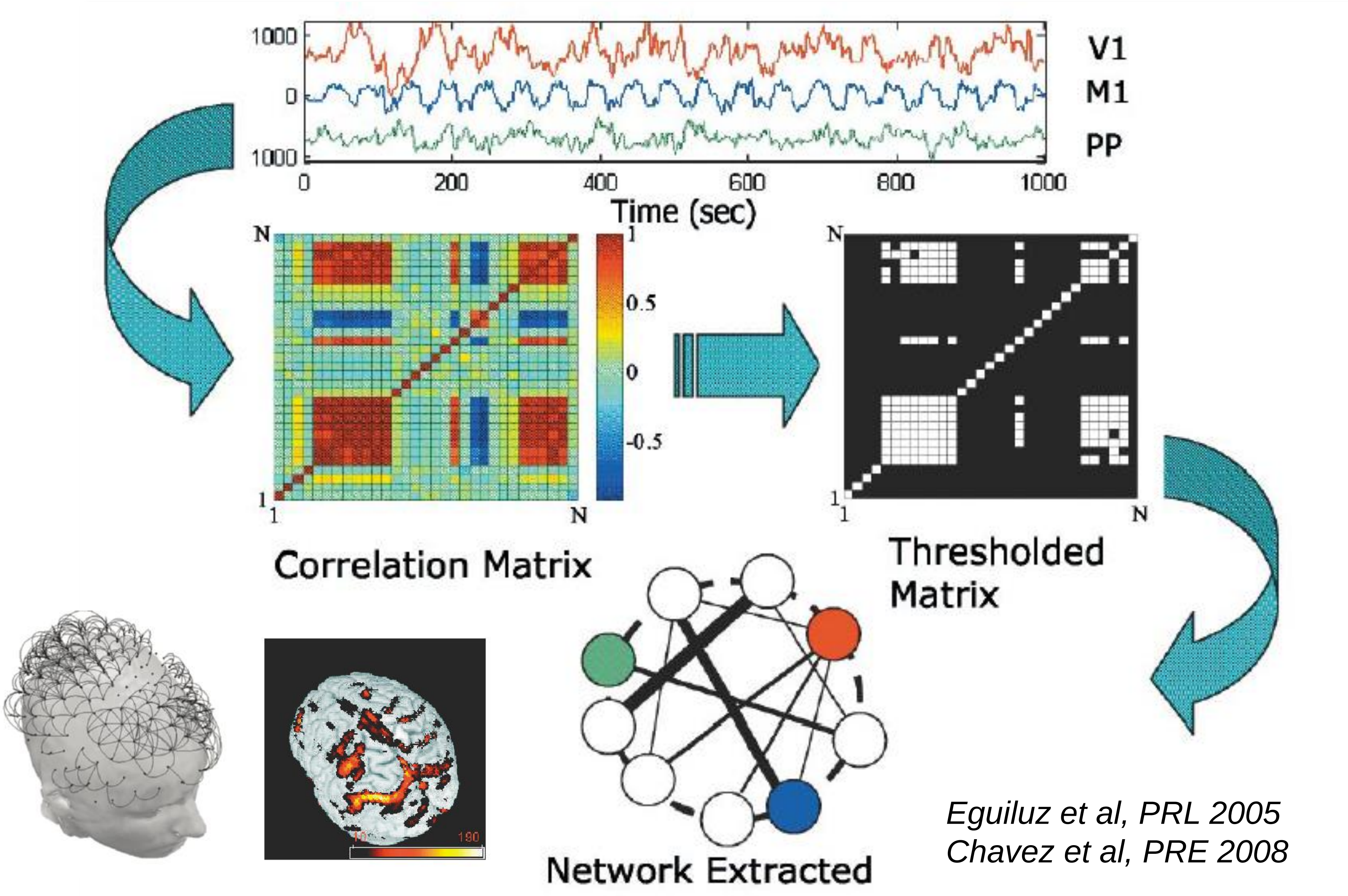


Bangladesh, Nature 2014

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

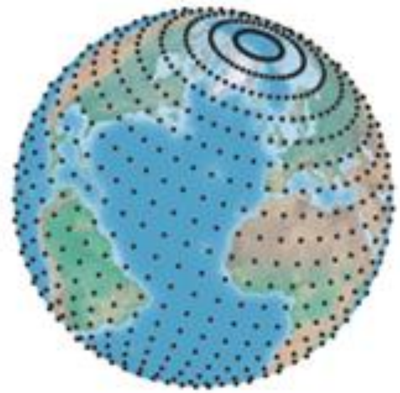
Campus d'Excel·lència Internacional

Brain functional network

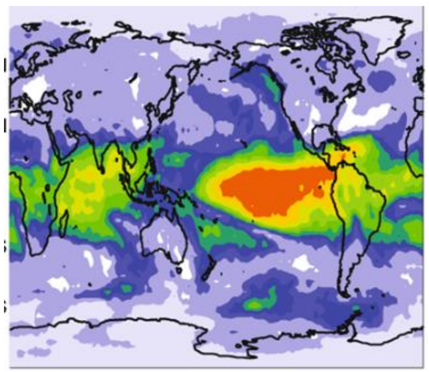


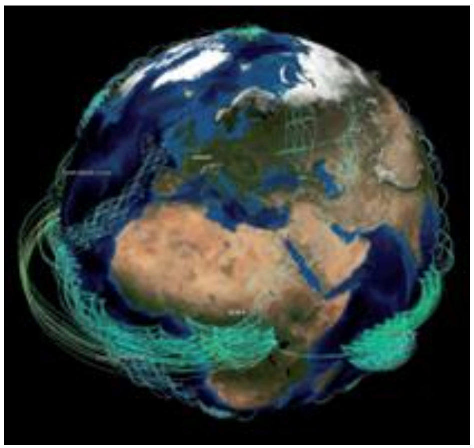
Eguiluz et al, PRL 2005
Chavez et al, PRE 2008

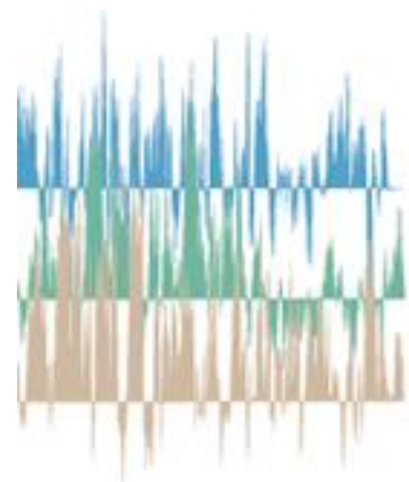
Climate networks



Area-weighted connectivity (weighted degree)





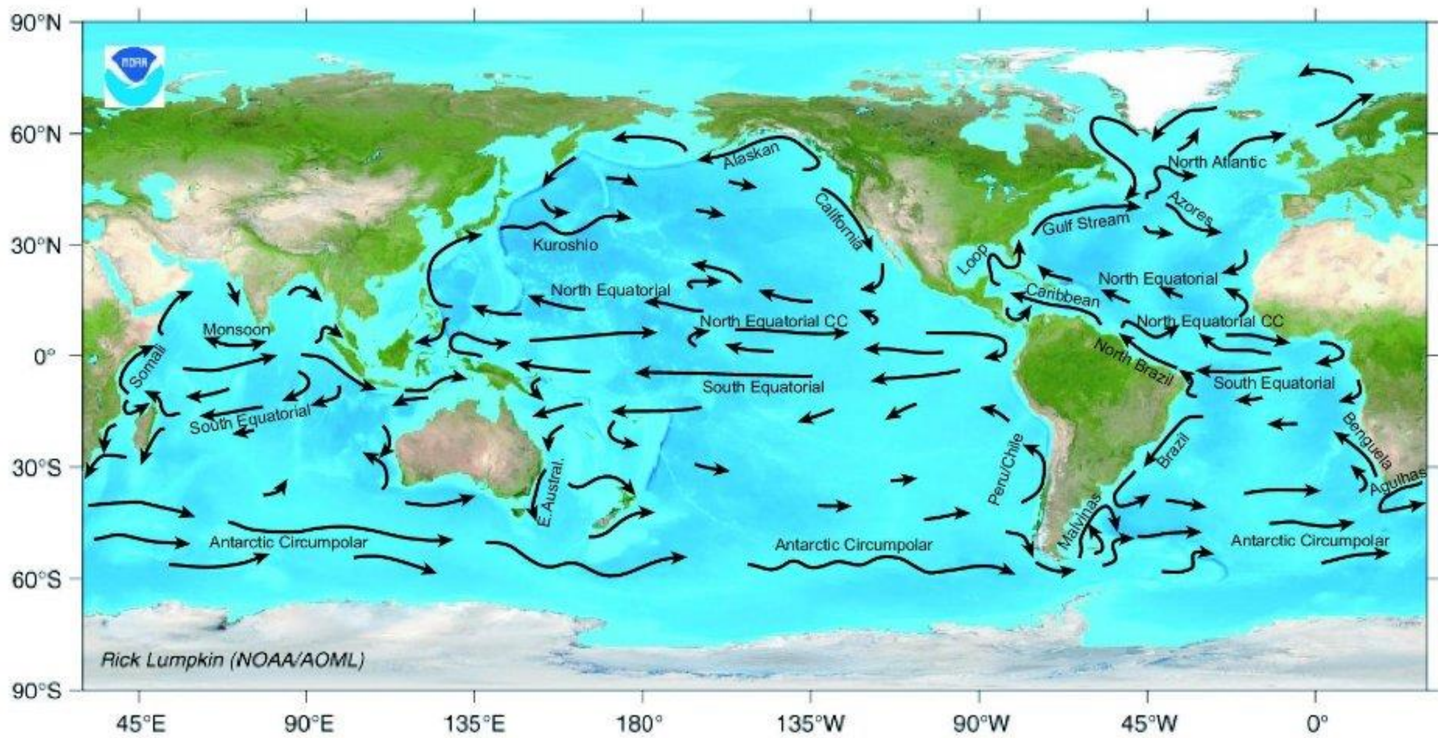


Deza et al, Chaos 2013

Donges et al, Chaos 2015

Physical mechanisms responsible for teleconnections

Winds, ocean currents, solar forcing…



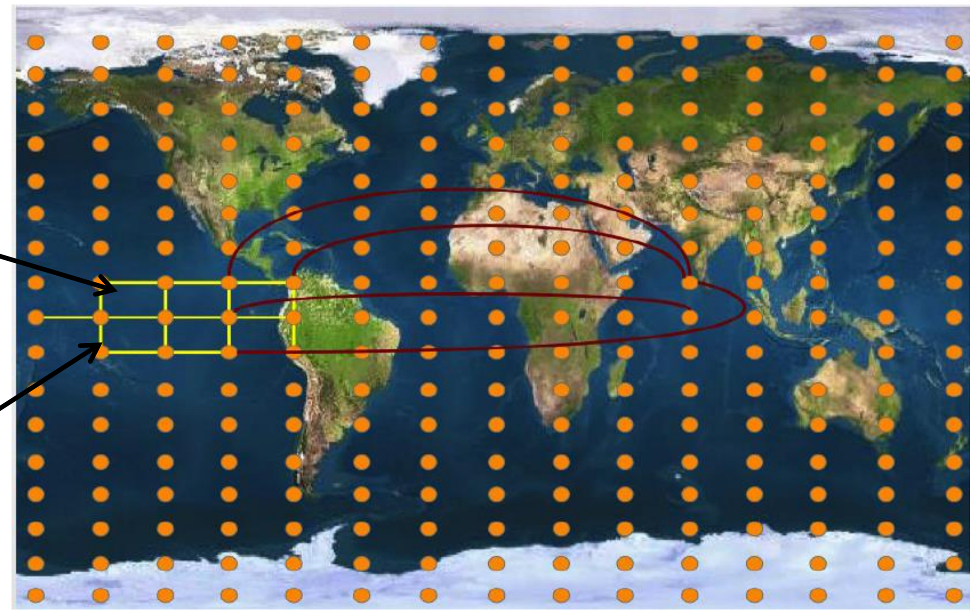
http://www.aoml.noaa.gov

Climate networks

Regular grid
2.5º x 2.5º
⇒ 10226 nodes

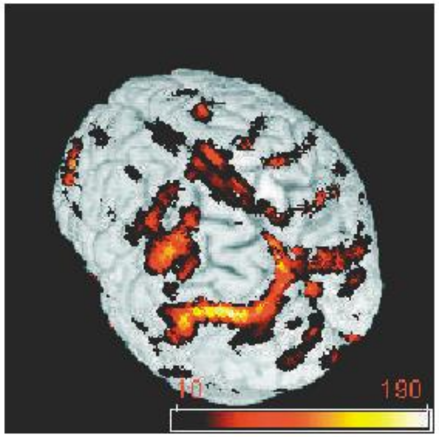
$X_i(t)$

$X_j(t)$

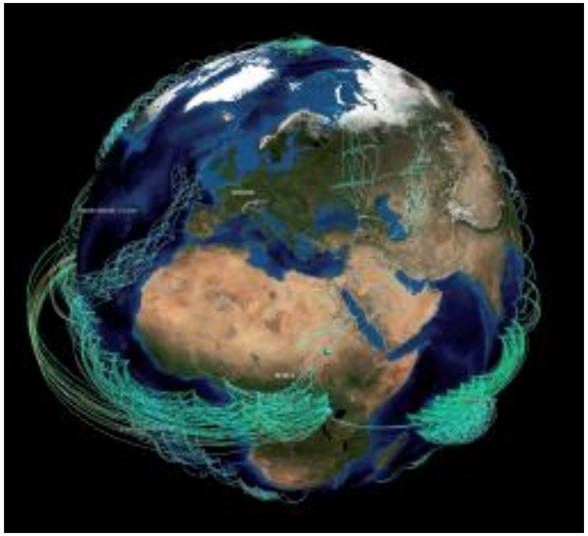


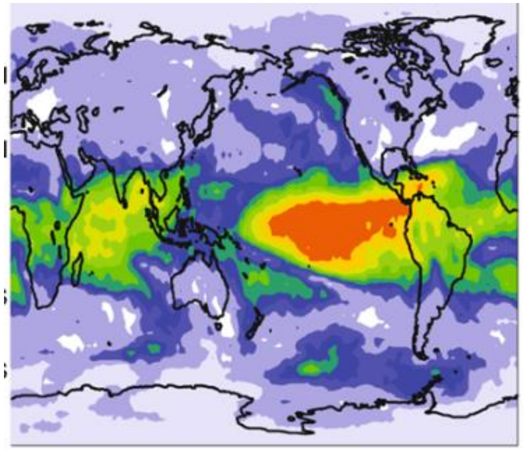
- CNs constructed from an **interdependency/causality** analysis of a climate variable.
- Which climate variable? **surface air temperature, surface sea temperature, wind velocity, precipitation, etc.**
- Interdependency measure: usually **cross-correlation or mutual information.**
- Causality measure: **conditional mutual information or Granger estimator**

Brain network



Climate network



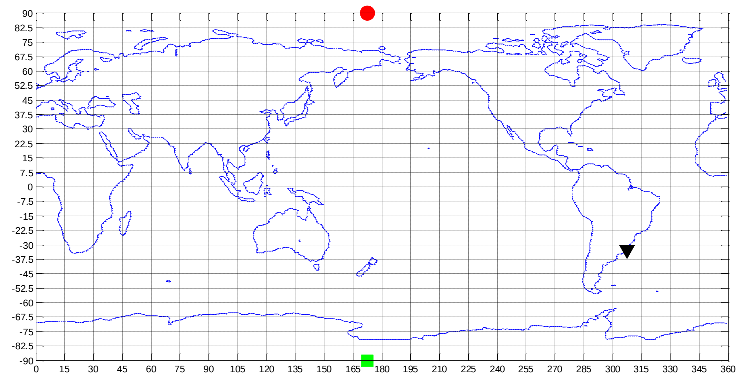


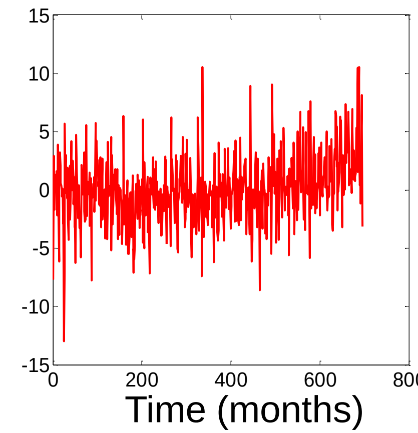
The data: monthly surface air temperature (SAT) 1949-2013

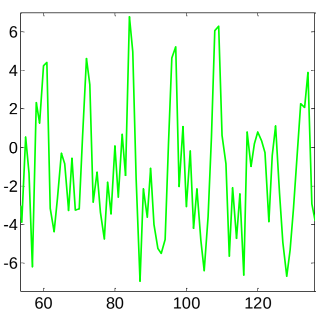
Anomalies = <u>annual solar cycle removed</u>

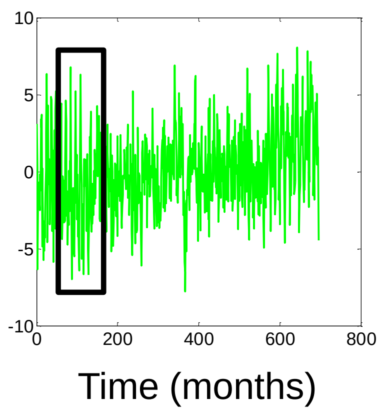
In each of the 10226 nodes ≈700 data points (60 years x 12 months)

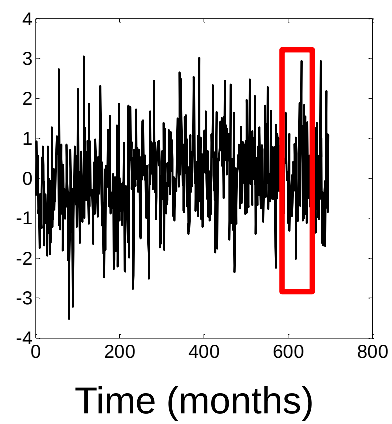
How does the data look like?

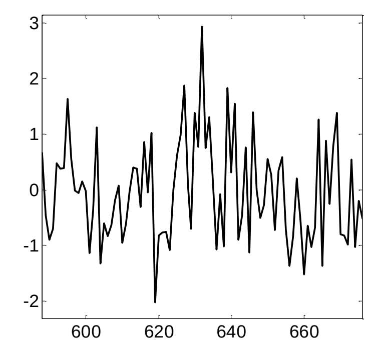












Where does the data come from?

- 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.

Our analysis: 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.

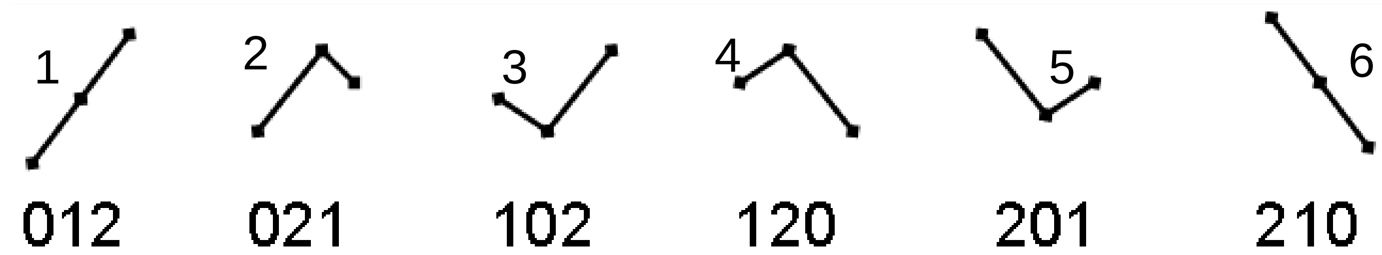
UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH

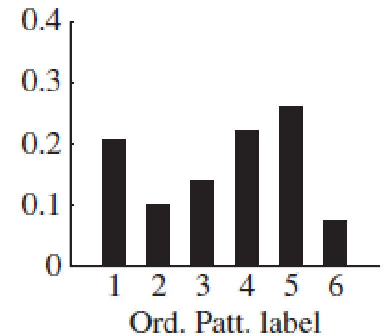
Campus d'Excel·lència Internacional

Method of symbolic time-series analysis: ordinal patterns

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

Brandt & Pompe, PRL 88, 174102 (2002)





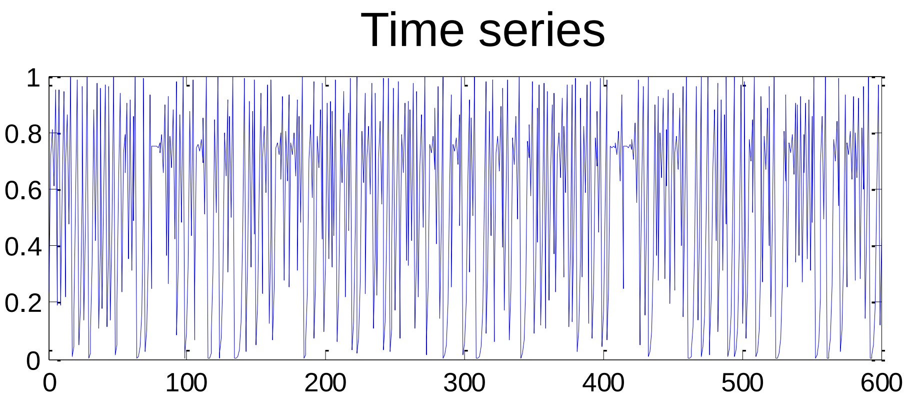
The OP probabilities allow to identify frequent patterns in the *ordering* of the data points

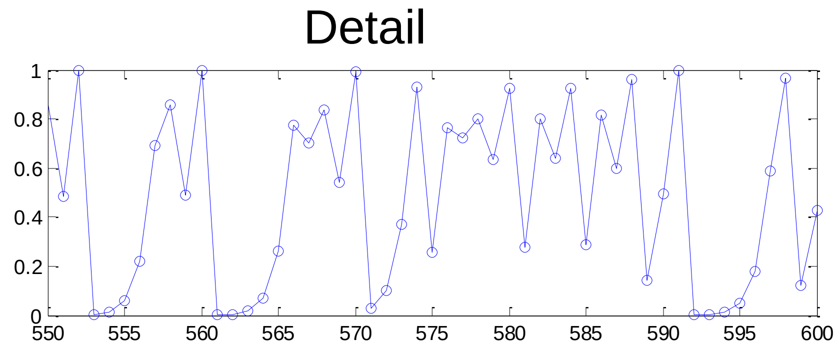
Random data $\Rightarrow$ OPs are equally probable

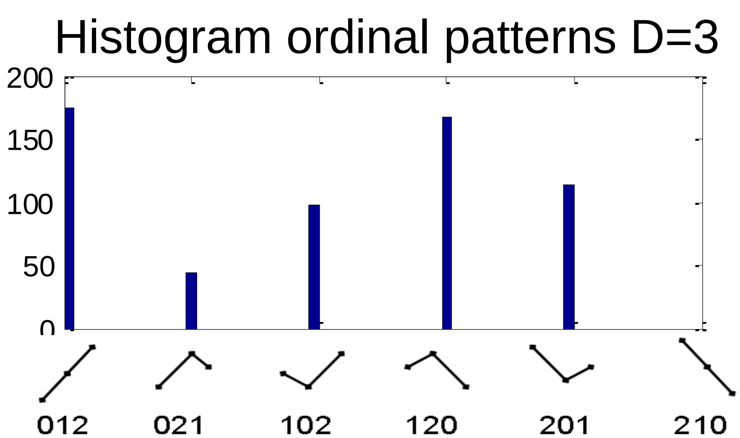
– Advantage: the probabilities uncover temporal correlations.

– Drawback: we lose information about the actual values.

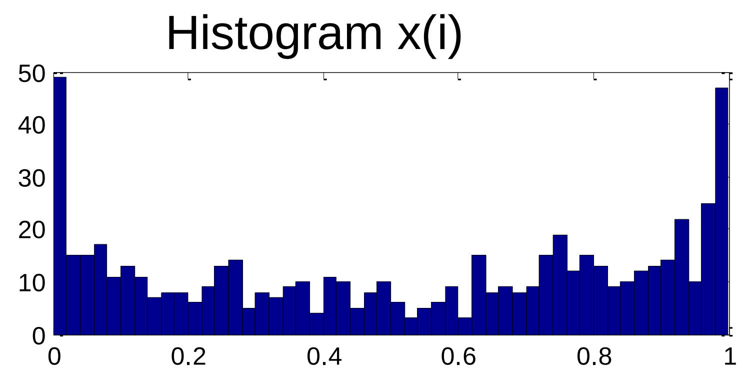
Example: the logistic map $x(i+1)=4x(i)[1-x(i)]$







Forbidden pattern



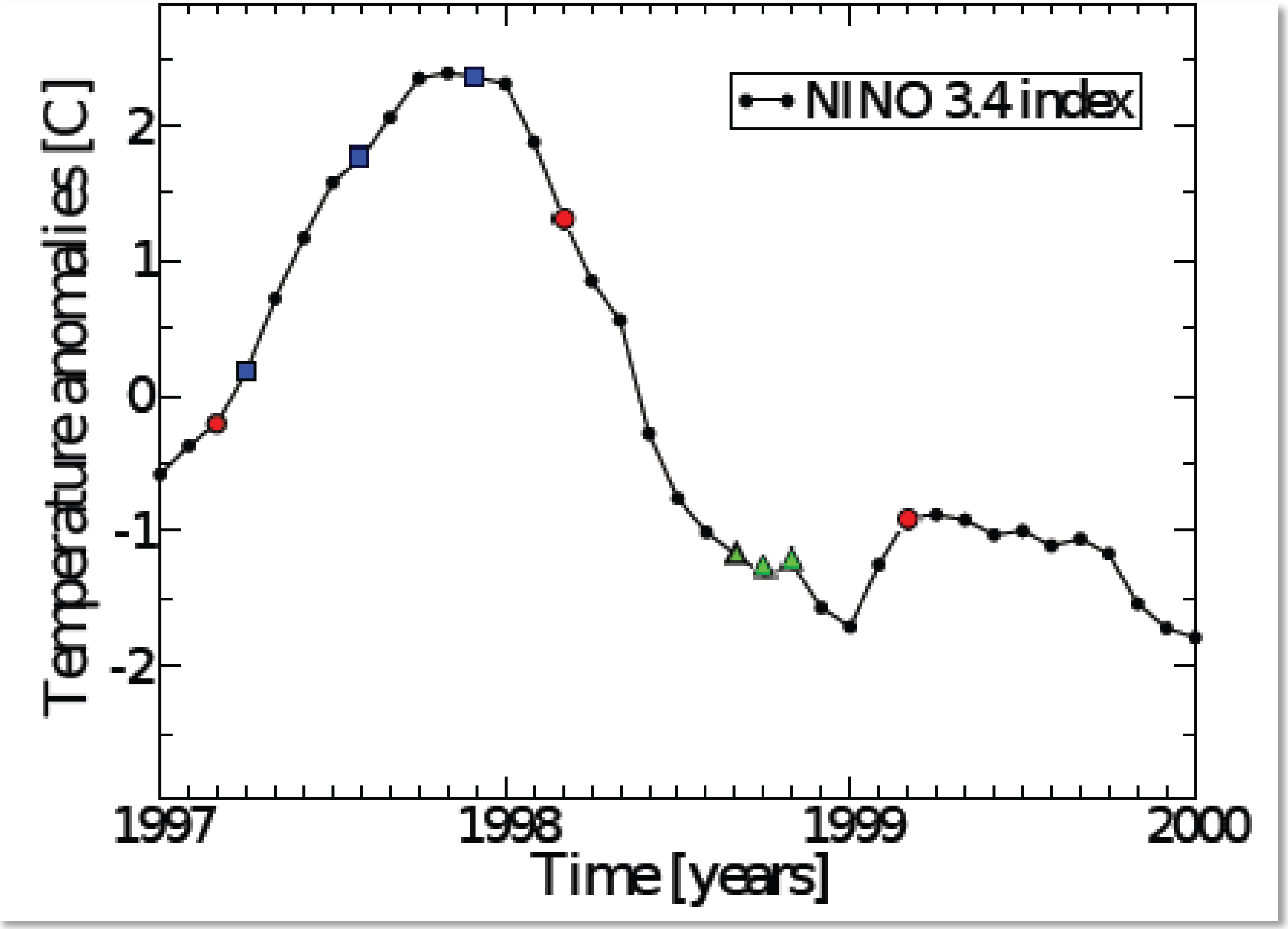
Ordinal analysis provides complementary information.

Ordinal analysis allows selecting the time scale of the analysis

Intra-season 102

Intra-annual 012

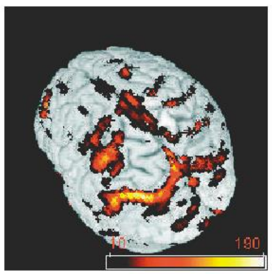
Inter-annual 120

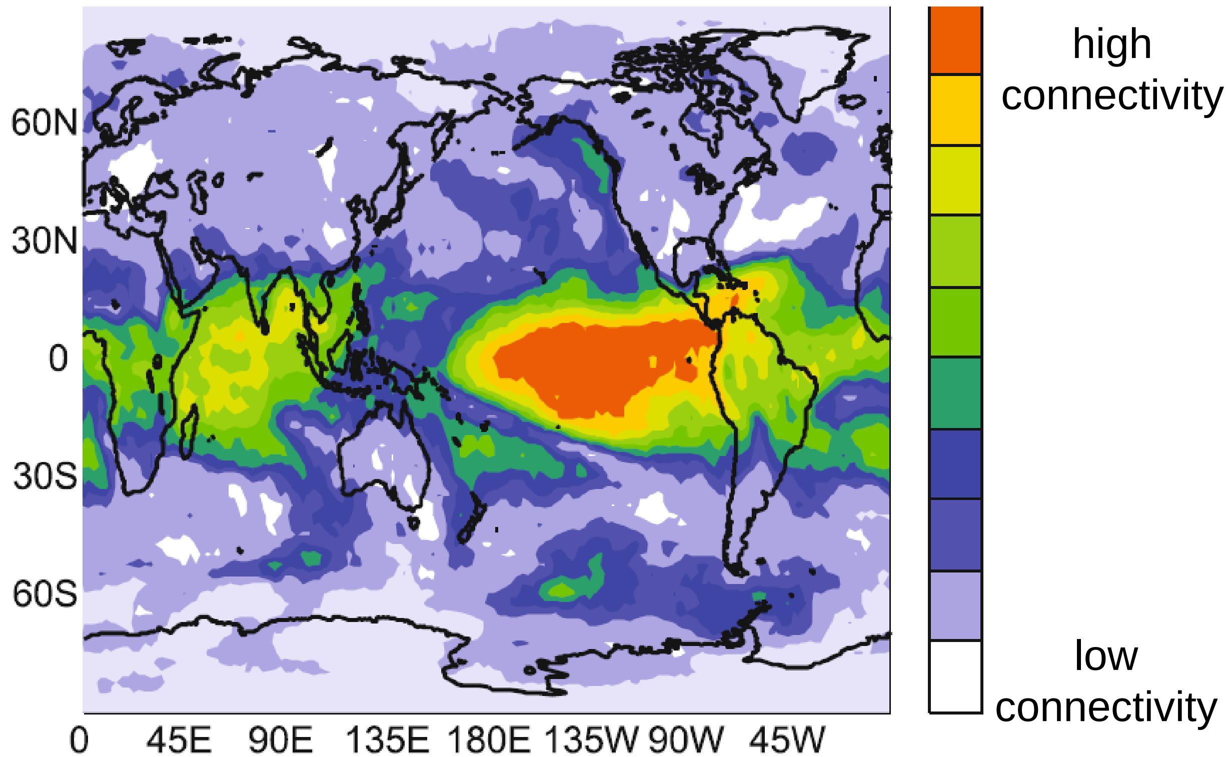


Graphical representation of the climate network

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

Network obtained with ordinal analysis using <u>inter-annual</u> time-scale (3 consecutive years). The color-code indicates the Area Weighted Connectivity (weighted degree)





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

El Niño/La Niña-Southern Oscillation (ENSO)

Is the most important climate phenomena on the planet

- Occurs across the tropical Pacific Ocean with ≈ 3-6 years periodicity.
- Variations in the surface **temperature** of the tropical eastern Pacific Ocean

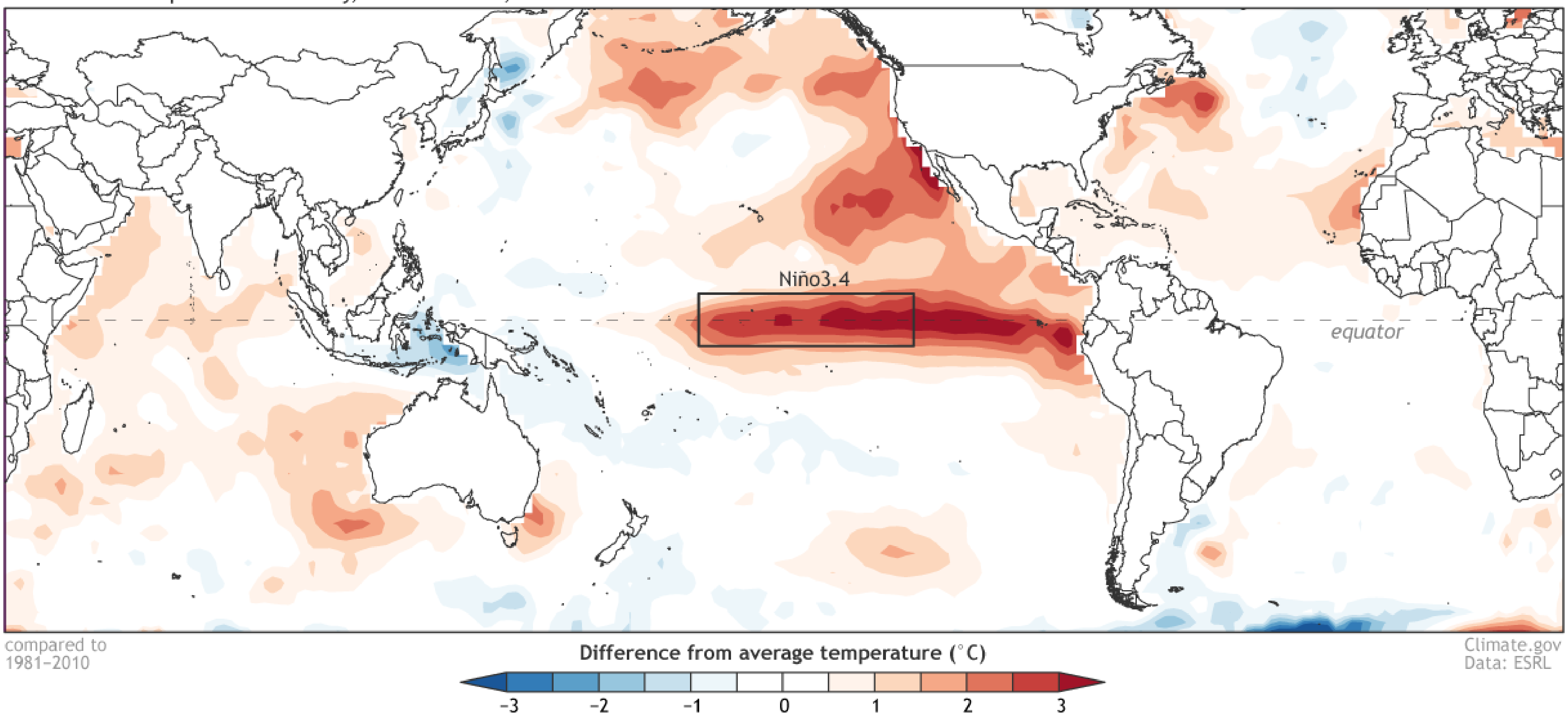
  (warming: El Niño, cooling: La Niña)
- Variations in the air surface **pressure** in the tropical western Pacific (the Southern Oscillation).
- These two variations are coupled:
  - **El Niño** (ocean warming) -- high air surface pressure,
  - **La Niña** (ocean cooling) -- low air surface pressure.

UNIVERSITAT POLITÈCNICA
DE CATALUNYA
BARCELONATECH

Campus d'Excel·lència Internacional

Oct.-Nov. 2015: how ocean surface temperature differed from average

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



World-wide impact of El Niño

A few examples:

- Extreme rainfall in South America: malaria outbreaks (tornados?).
- Devastating forest fires in Indonesia.
- Dry conditions in South Africa: stress in water availability.
- Enhanced hurricane season in the Pacific.
- etc. etc. etc.

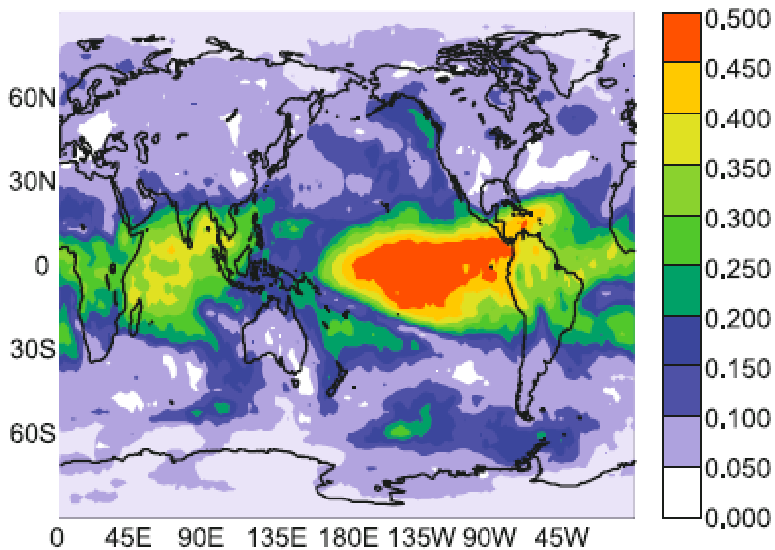
A lot of work to forecast El Niño evolution.

Dolores, Uruguay, a few days ago.

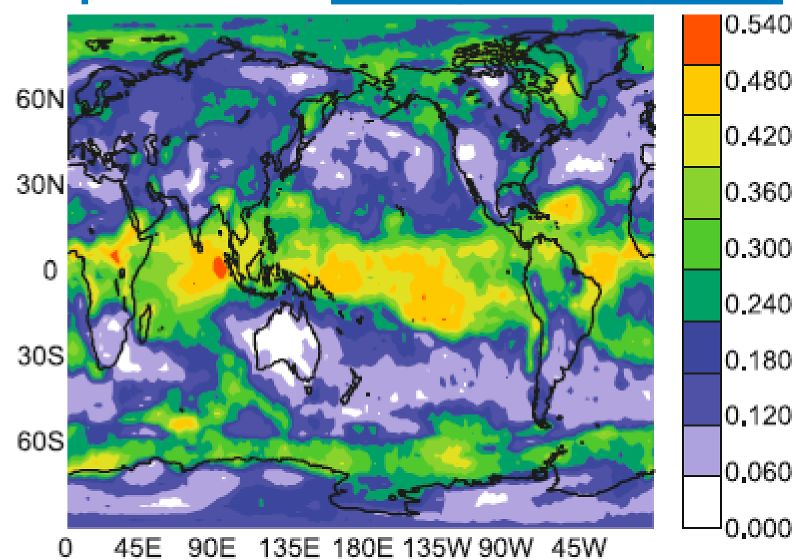
Contrasting two methods for inferring the climate network

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

Network when the probabilities are computed with ordinal analysis



Network when the probabilities are computed with histogram of values

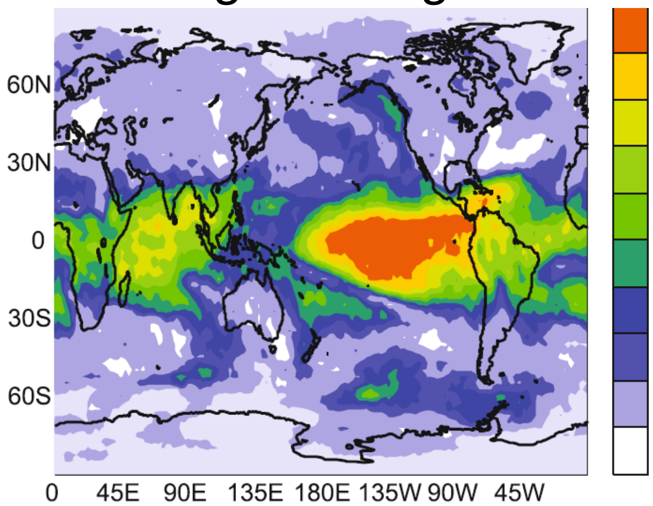


UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

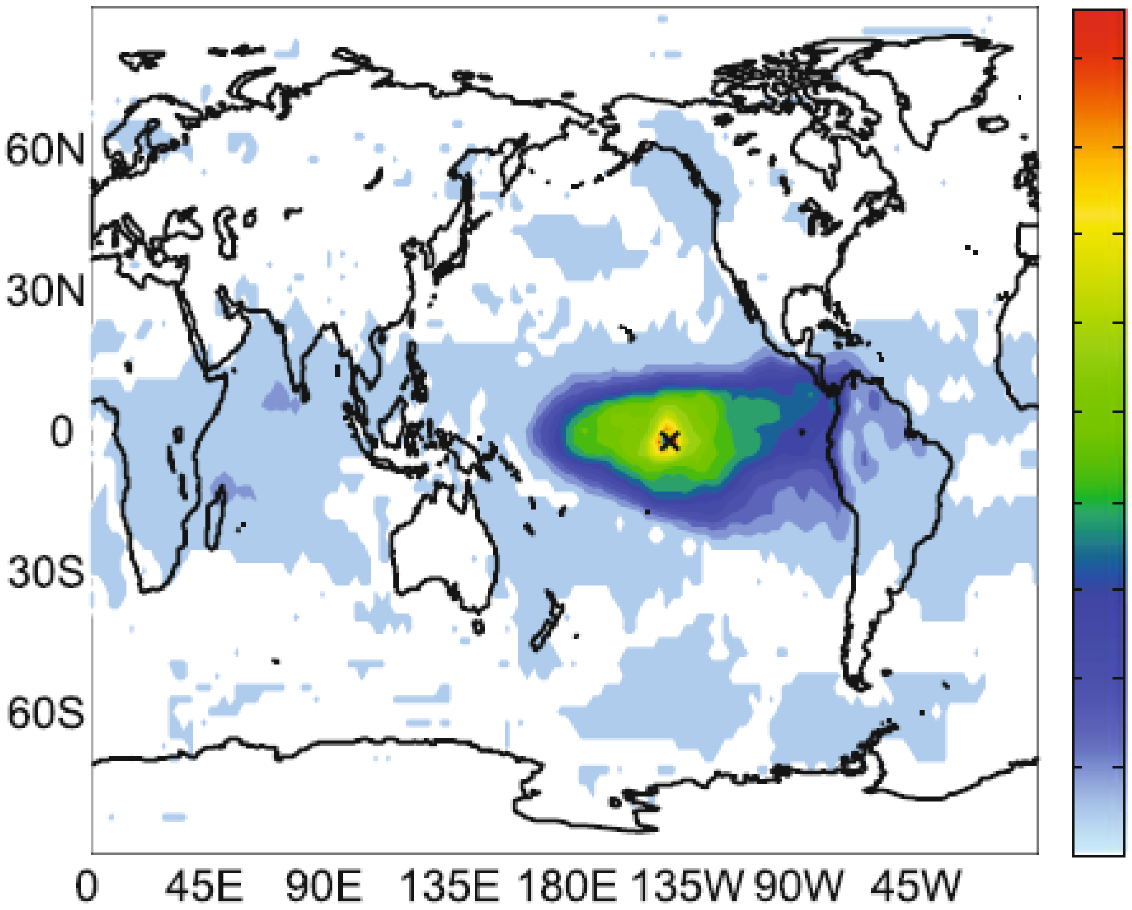
Campus d'Excel·lència Internacional

Who is connected to who?

Weighted degree

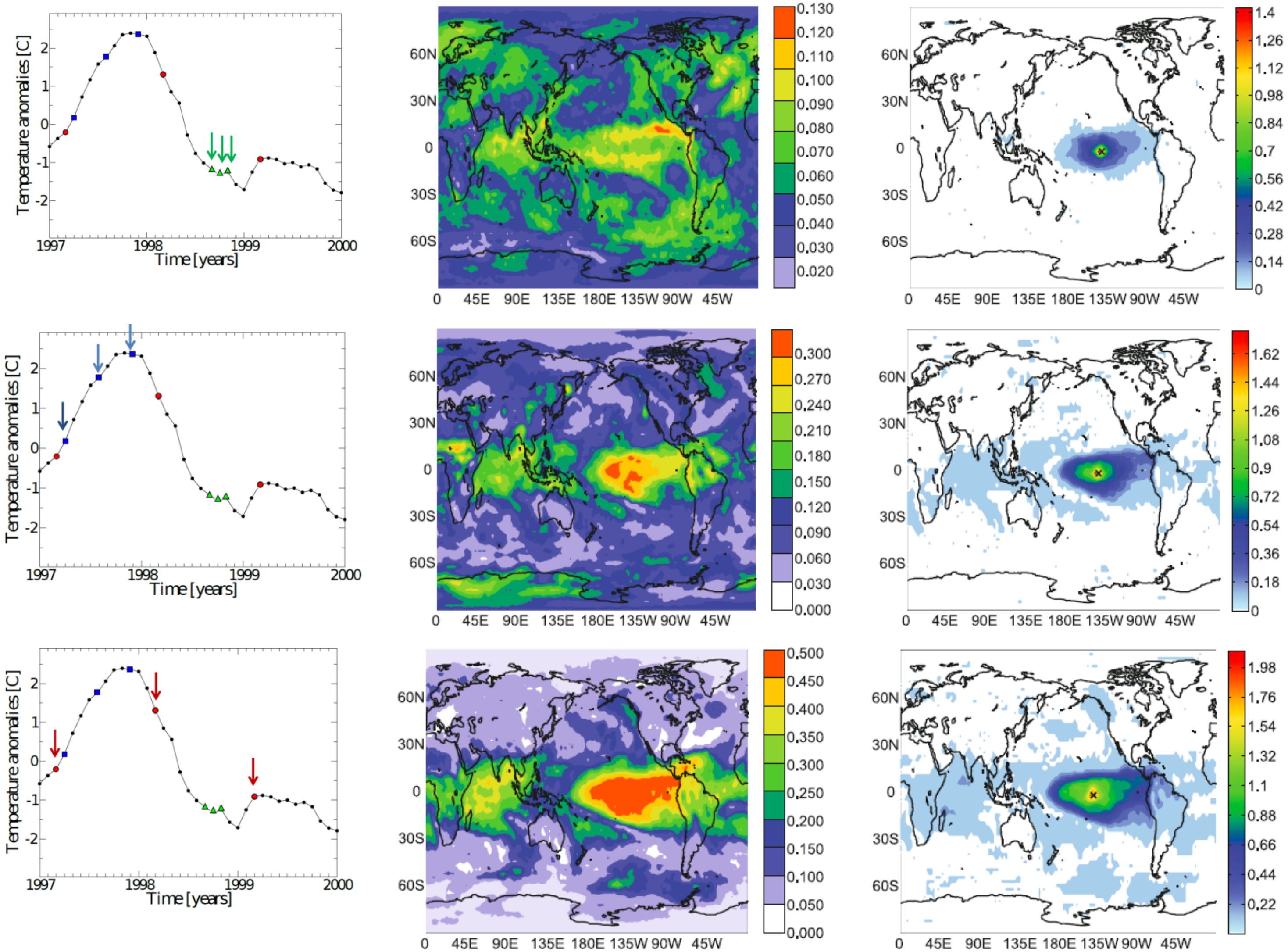


color-code indicates the MI values (only significant values)



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

Influence of the time-scale of the symbolic ordinal pattern



Longer time-scale ⇒ increased connectivity

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Campus d'Excel·lència Internacional

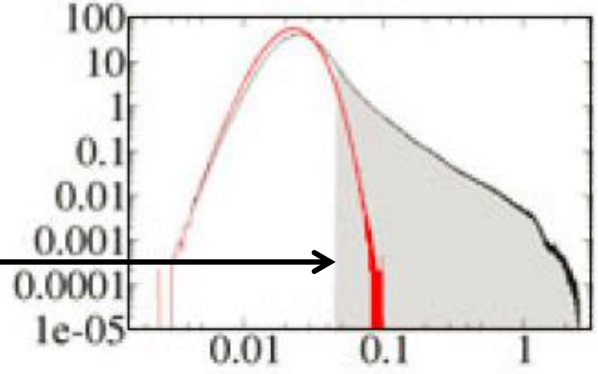
How do we assess the significance of the links?

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

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

PDF MI values

$$\tau = \mu + 3\sigma$$



Original data

Surrogated

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

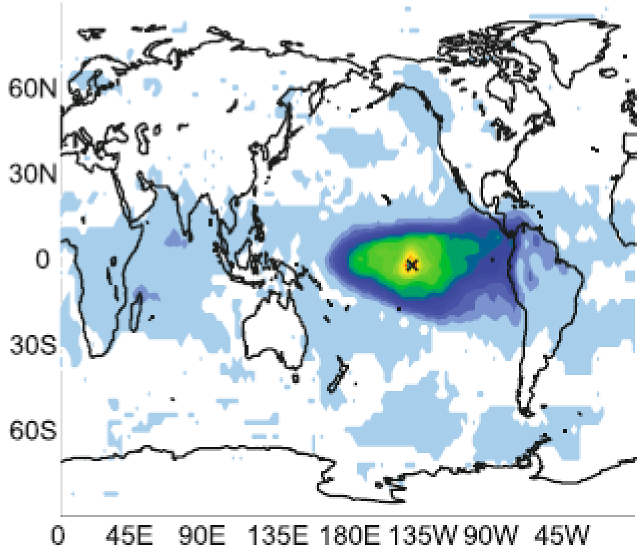
J. I. Deza, M. Barreiro, and C. Masoller, Eur. Phys. J. Special Topics 222, 511 (2013)

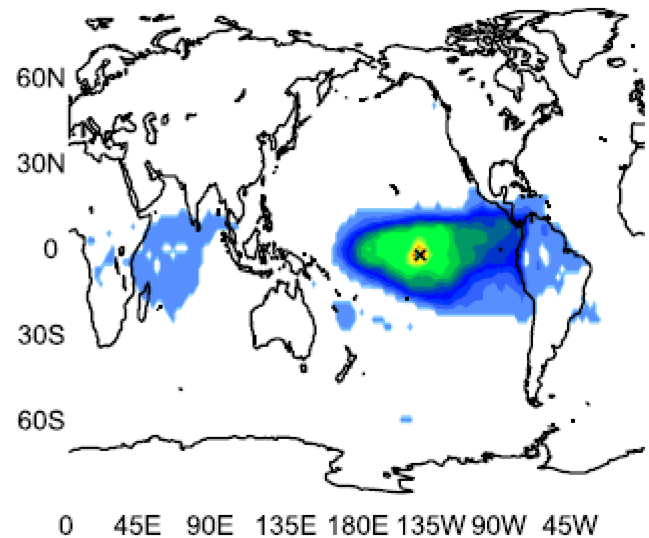
Are the links significant?
Influence of the threshold

3σ threshold *(11% link density)*

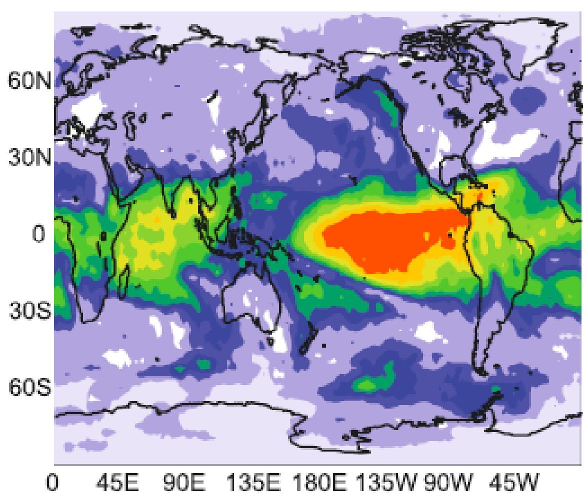
High threshold *(3% link density)*

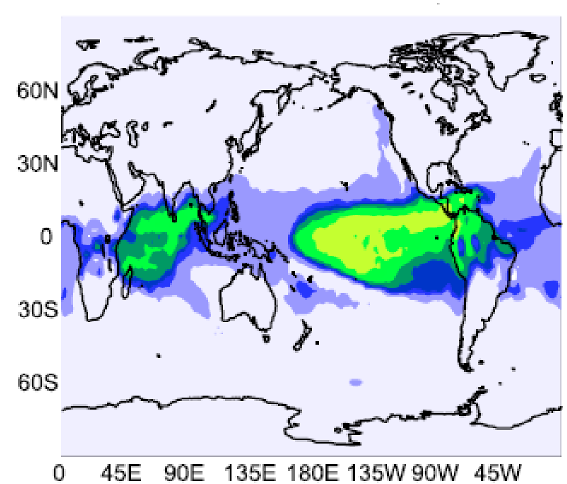
Color code: MI





Color code: weighted degree





How to improve climate predictability?

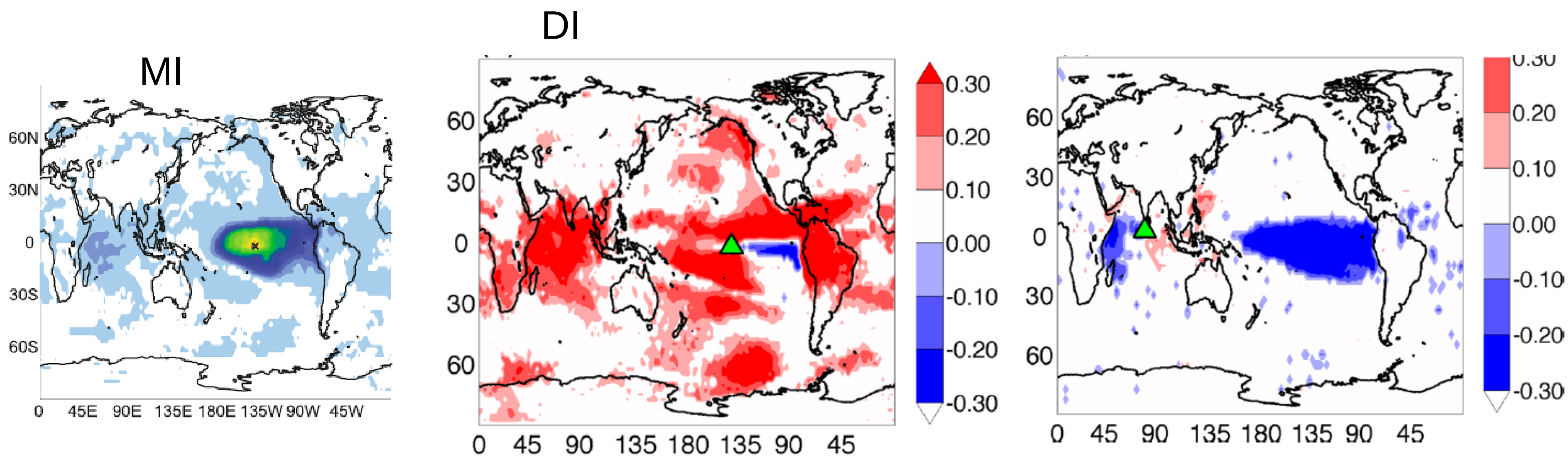
Assessing the directionality of the links

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

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

x → y
x → z

y ↔ z ??



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, Barreiro and Masoller, Chaos 25, 033105 (2015)

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Campus d'Excel·lència Internacional

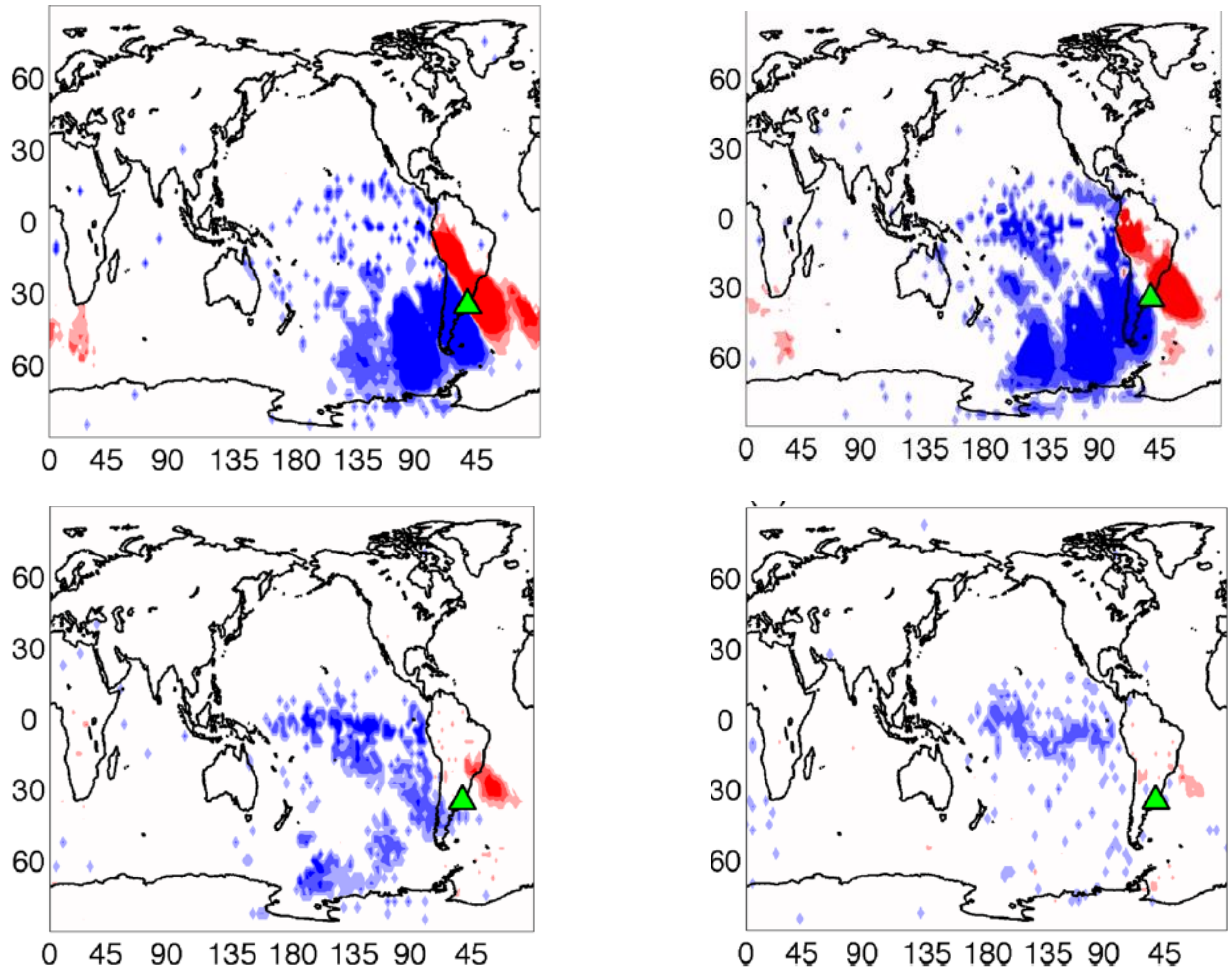
Time-scale of interactions

τ=1 day

τ=3 days

τ=7 days

τ=30 days



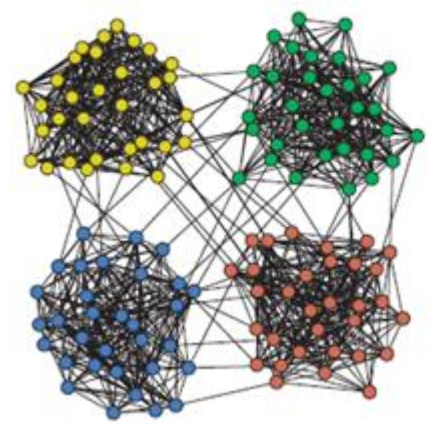
Link directionality reveals wave trains propagating from west to east

Deza, Barreiro and Masoller, Chaos 25, 033105 (2015)

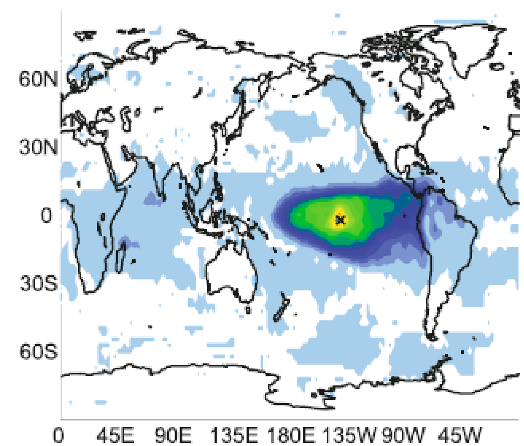
Climate "communities"

How to identify regions with similar climate?

- Goal: to construct a network in which regions with similar climate (e.g., continental climate) are in the same "community".



- Problem: not possible with the "usual" correlation method to construct the network because NH and SH are only indirectly connected.



UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Campus d'Excel·lència Internacional

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…} s_j = {201, 210, 210, 012, …}

- Step 2: in each node compute the transition probabilities

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

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

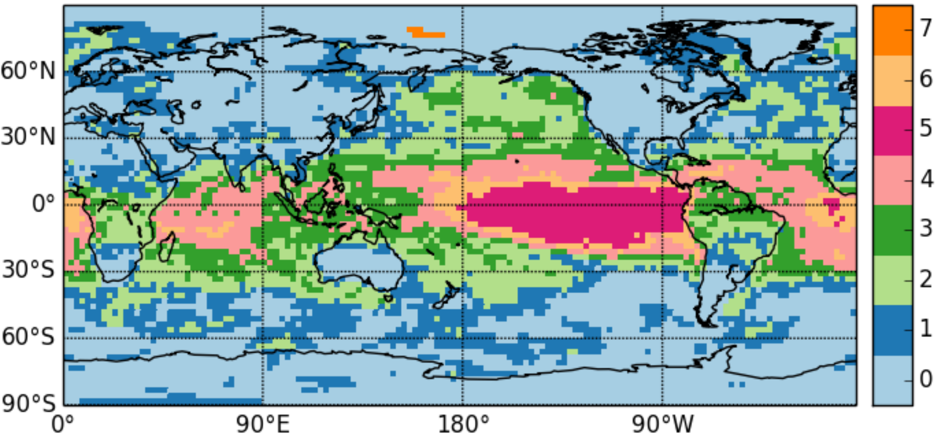
  High weight if similar symbolic "language"

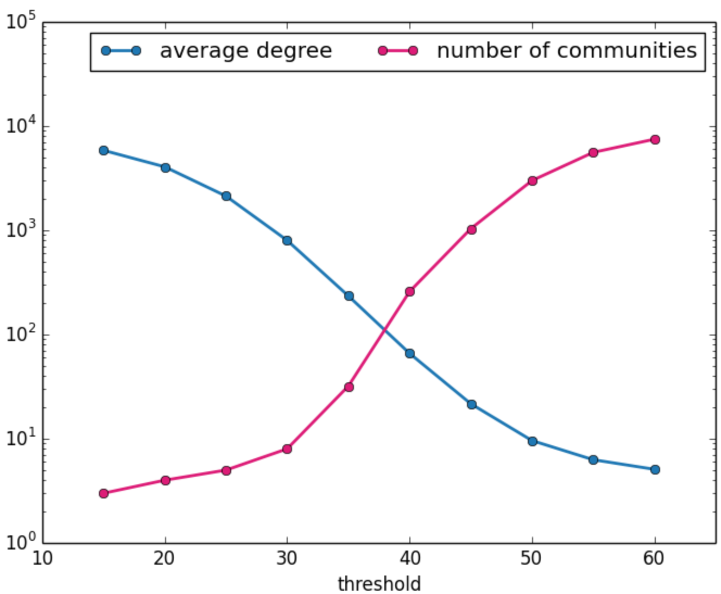
- Step 4: threshold w_{ij} to obtain the adjacency matrix.

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

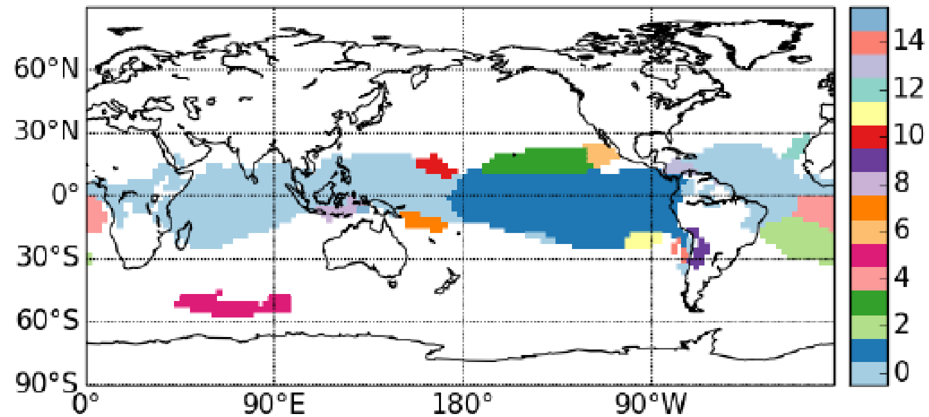
Results

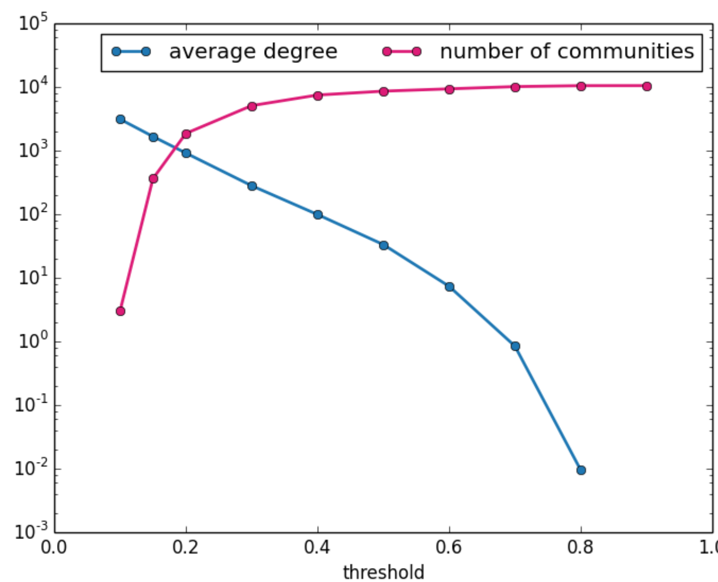
TP Network





CC Network (only the largest 16)





Outline

- Introduction
- Results
- **Summary**

What did we learn?

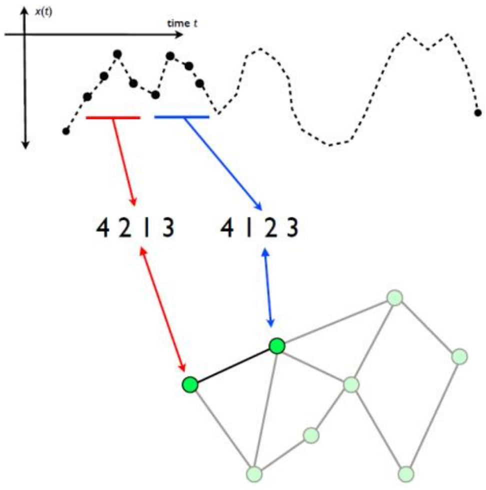
- Take home message:
  - The network perspective offers an opportunity for improving our understanding of climate phenomena.
  - The challenge: can we use networks to improve climate predictability?
- A few specific conclusions:
  - Ordinal analysis allows identifying specific time-scales of climate interactions.
  - Conditional mutual information allows identifying the net direction of climate interactions.
  - A new method to construct the network (using symbolic transition probabilities) allows identifying geographical regions with similar climate (communities).

Ongoing and future work

- In climate data, can we obtain useful information from Hilbert phases and frequencies?
- Are there favored / infrequent symbolic patterns in the climate dynamics?
- Potential for advancing sub-seasonal predictability?

- By mapping a time-series to a network:

  can we predict *El Niño* "symbolic" dynamics?



M. Small, Univ. W. Australia

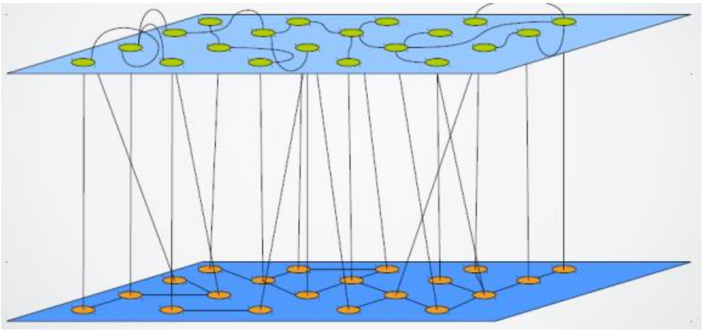
Ongoing and future work

- Novel measures for graph comparison allow to study time-evolving networks.

    potential to uncover / anticipate regime transitions in our climate?

- Multilayer networks (Granger causality analysis of air-ocean interactions in the South America Convergence Zone – SACZ)

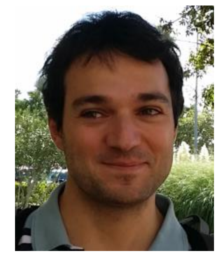
SST, pressure, wind, precipitation, etc.



SAT

Collaborators & funding

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



ITN LINC
FP7-289447

ICREA

GOBIERNO DE ESPAÑA
MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

THANK YOU FOR YOUR ATTENTION !

<cristina.masoller@upc.edu>

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

- M. Barreiro et al, Chaos 21, 013101 (2011).
- J. I. Deza et al, Eur. Phys. J. Special Topics 222, 511 (2013).
- G. Tirabassi and C. Masoller, submitted (2016).