

Climate data analysis

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ICTP SAIFR School, Sao Pablo, February 2018

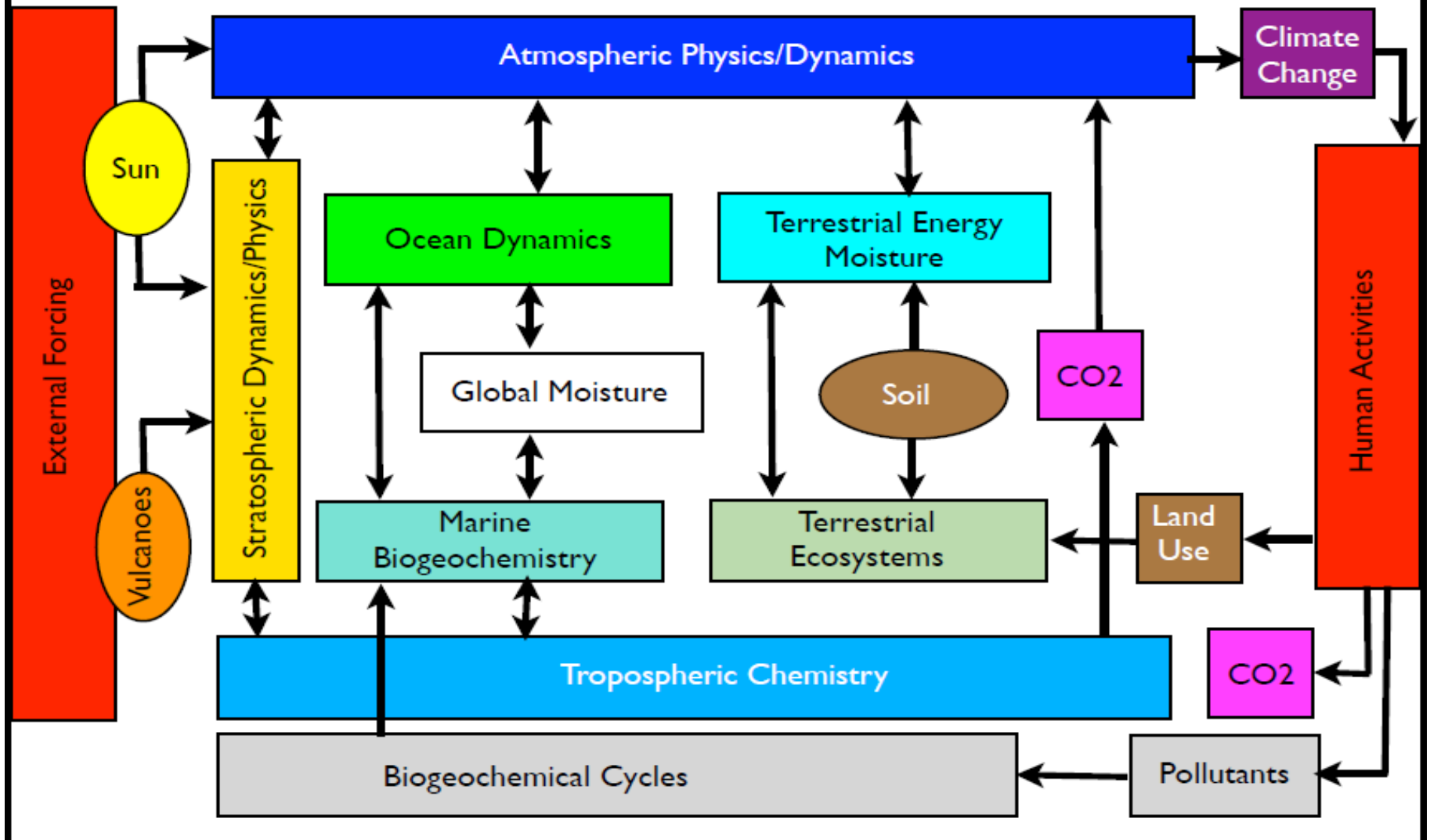
- Climate networks
- Assessing the direction of climate interactions
- Unravelling the community structure of the climate system
- Quantifying inter-decadal changes in climate dynamics

WHAT DO NETWORKS HAVE TO DO WITH CLIMATE?

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

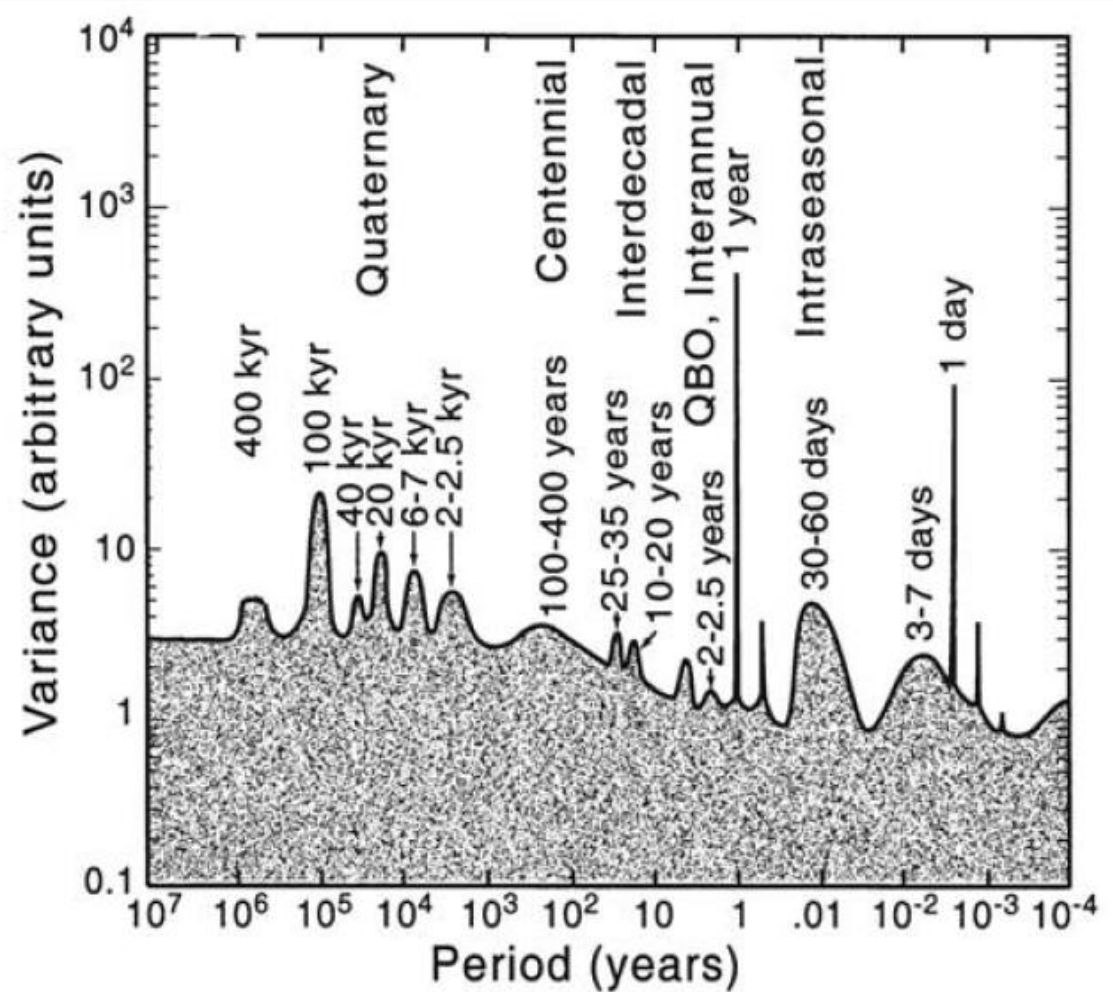
Advances in understanding coupling in complex networks offer new ways of studying the collective behavior of interactive systems and already have yielded new insights in many areas of science.

The Climate System



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

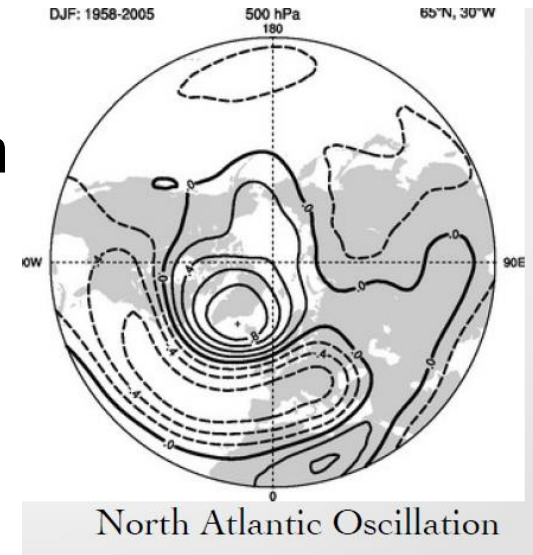
- hours to days,
- months to seasons,
- decades to centuries,
- and even longer...



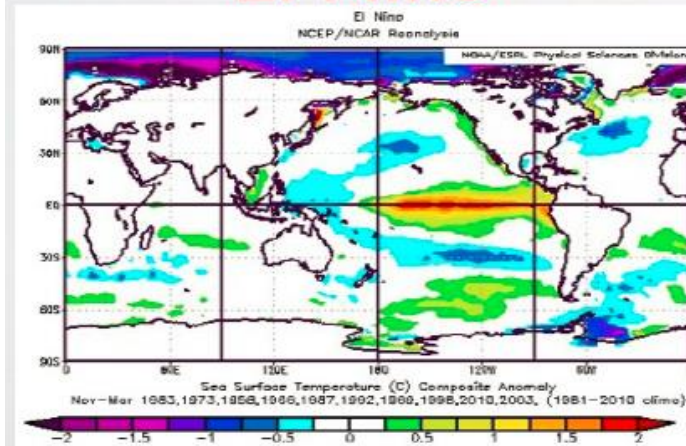
An “artist’s representation” of the power spectrum of climate variability (Ghil 2002).

And a wide range of spatial modes of variability

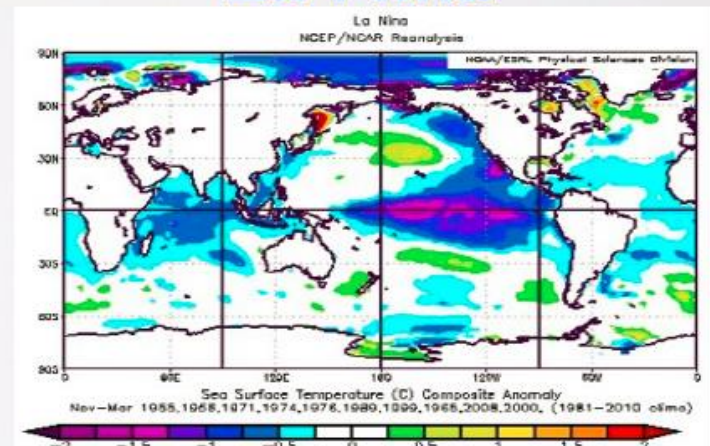
- ENSO
- The Atlantic multidecadal oscillation
- The Indian Ocean Dipole
- The Madden–Julian oscillation
- The North Atlantic oscillation
- The Pacific decadal oscillation
- Etc.



El Niño



La Niña



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?

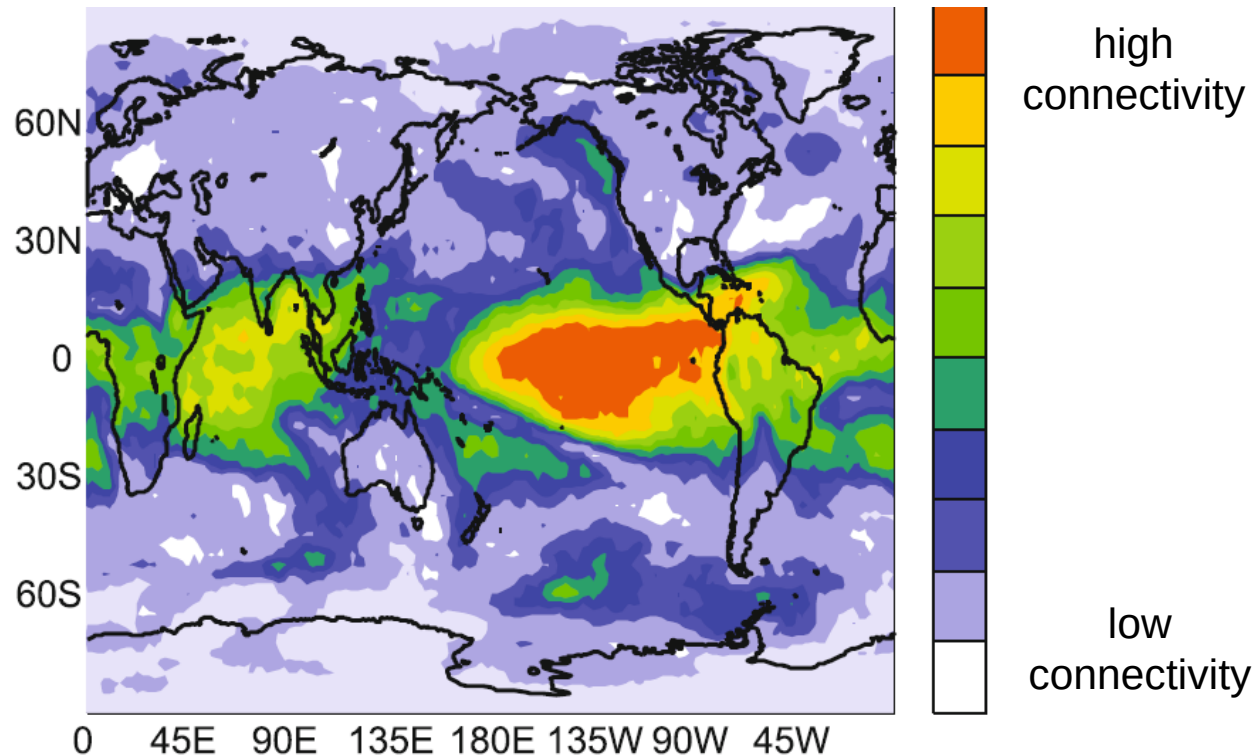
- National Center for Environmental Prediction, National Center for Atmospheric Research (NCEP-NCAR).
- Freely available.
- Reanalysis = run a sophisticated model of general atmospheric circulation and feed the model (data assimilation) with empirical data, where and when available.

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)

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

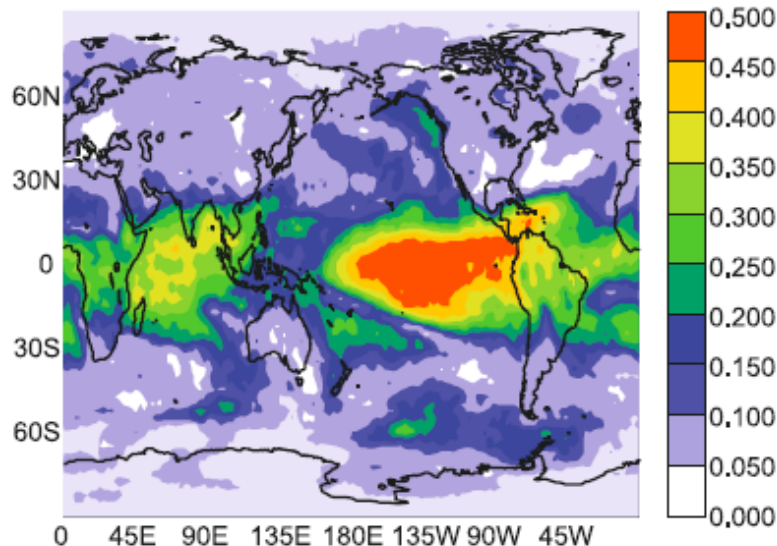


Deza, Barreiro and Masoller, EPJST 222, 511 (2013)

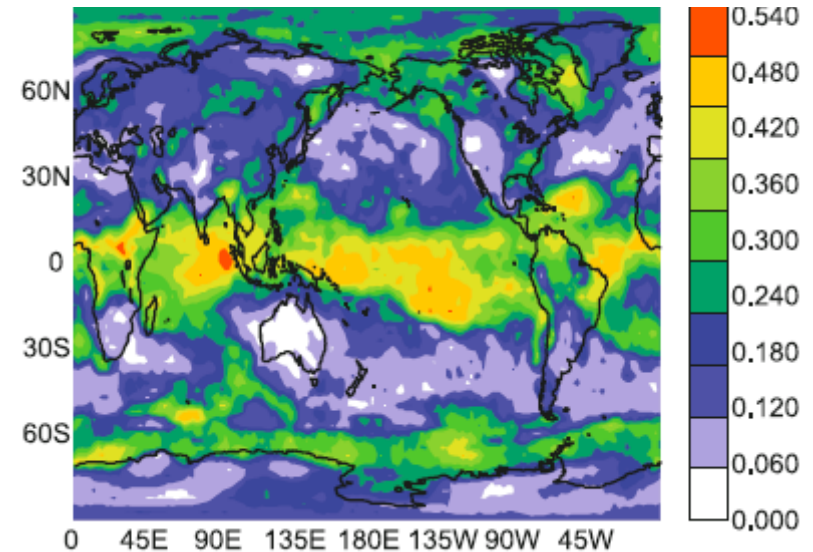
Contrasting two methods for inferring the climate network

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

Network when the probabilities are computed with ordinal analysis

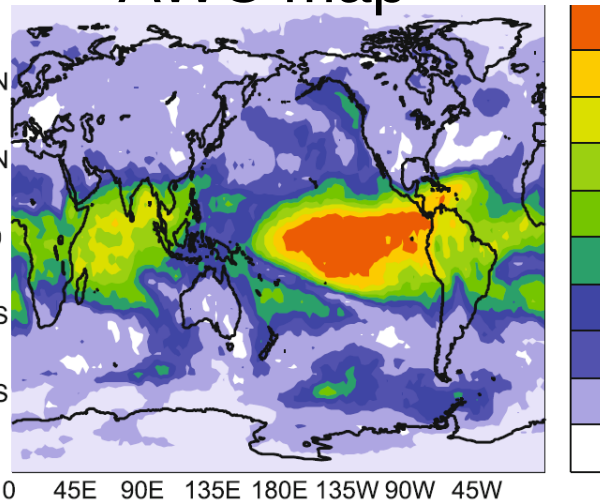


Network when the probabilities are computed with histogram of values

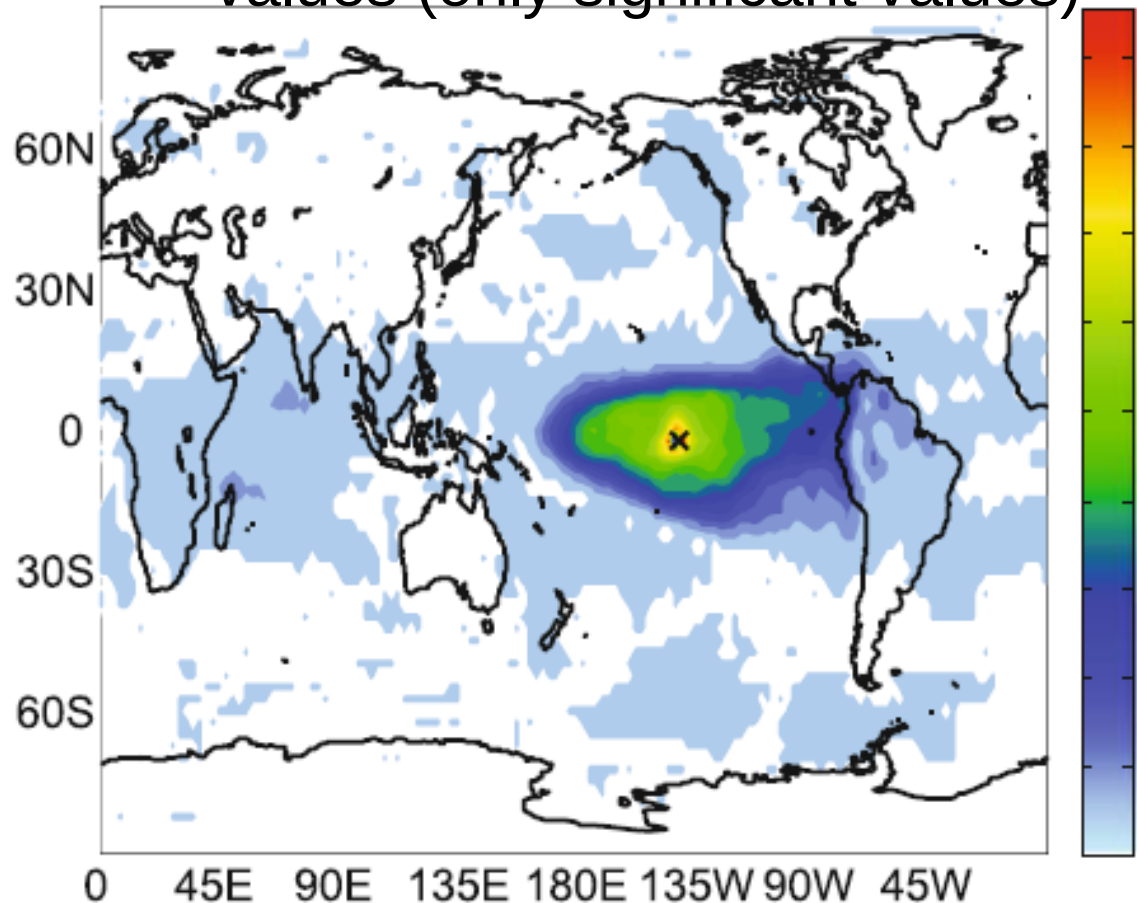


Who is connected to who?

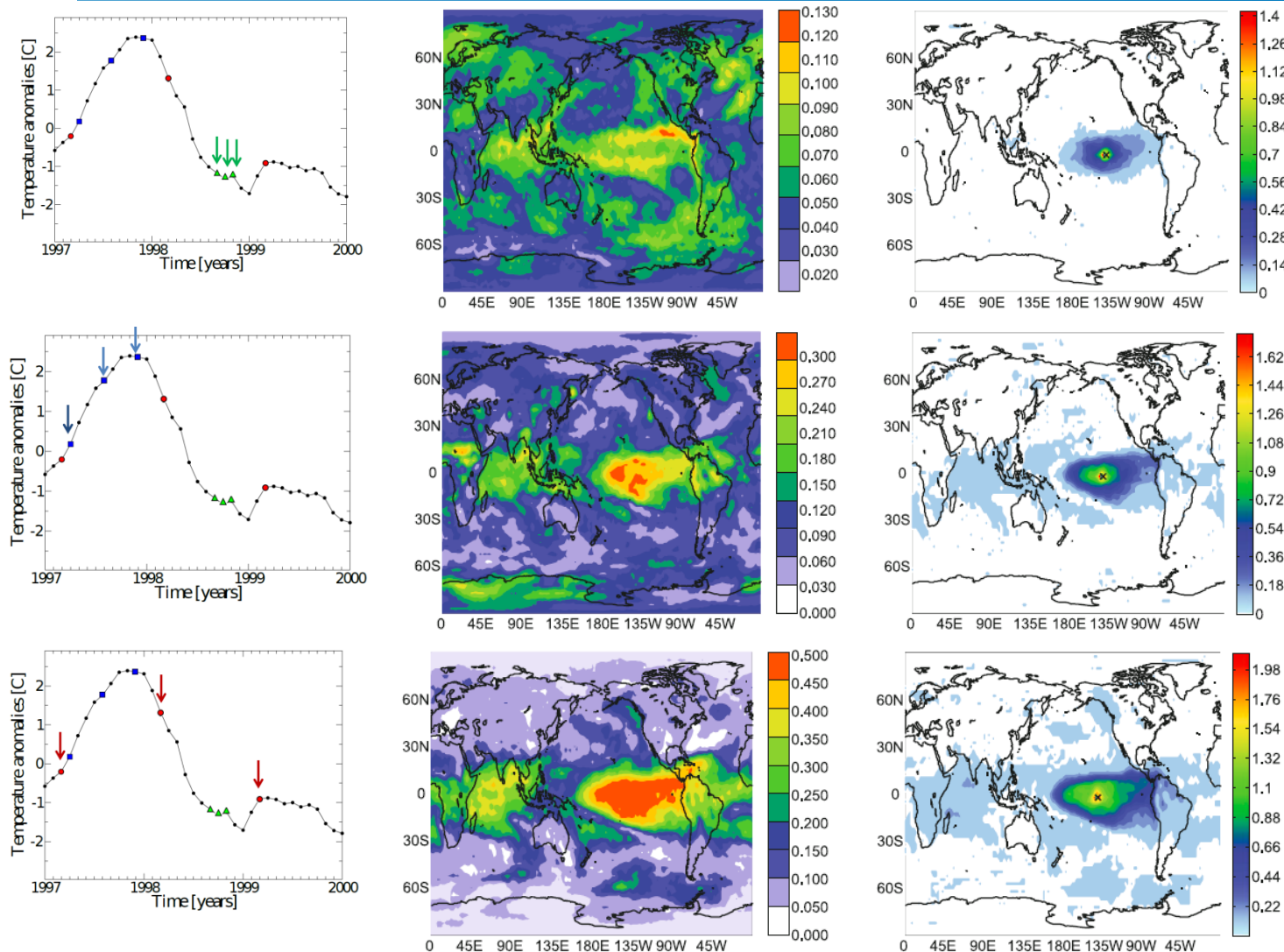
AWC map



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



Influence of the time-scale of the symbolic ordinal pattern



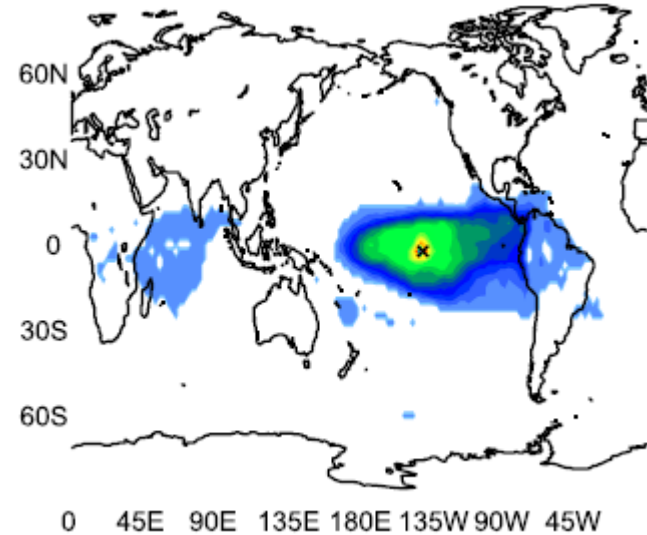
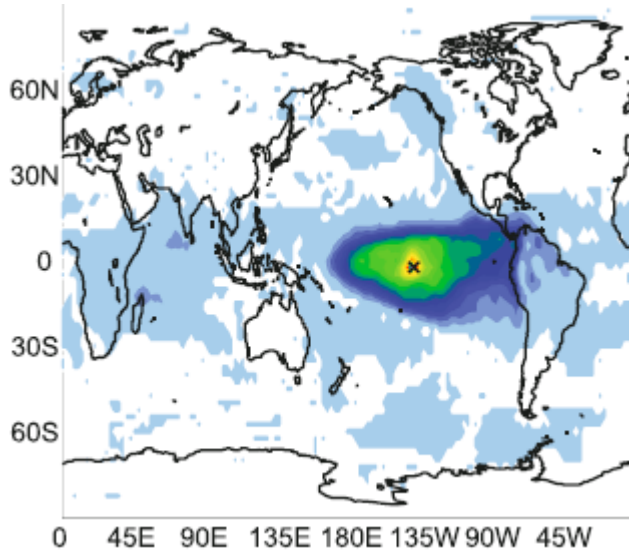
Longer time-scale $\Rightarrow$ increased connectivity

Are the links significant? Influence of the threshold

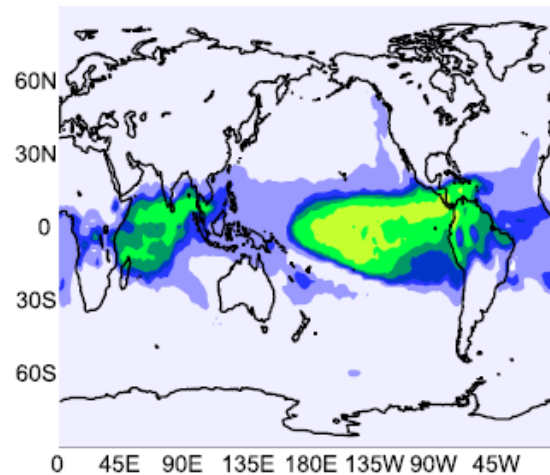
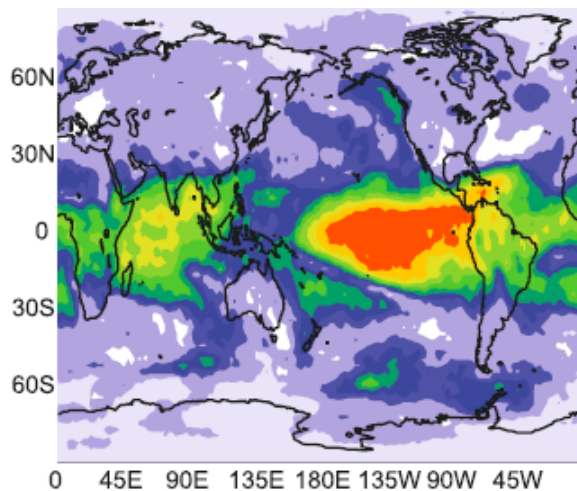
Low threshold (11% link density)

High threshold (3% link density)

Color
code:
MI



Color
code:
AWC



How to improve climate predictability?

Assessing the directionality of the links

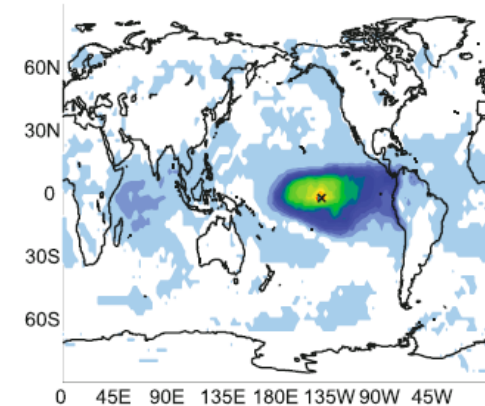
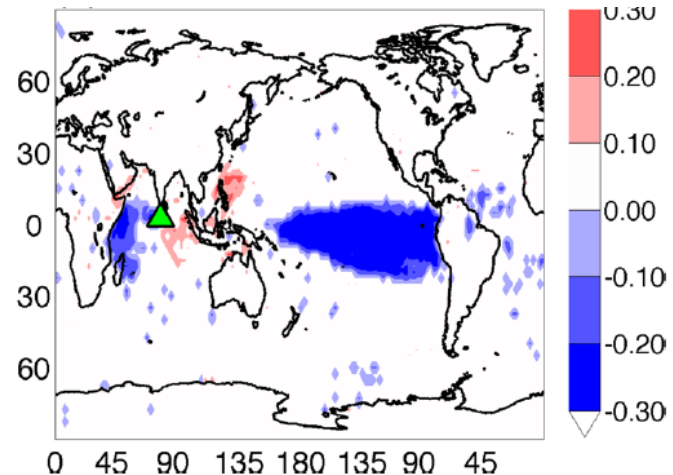
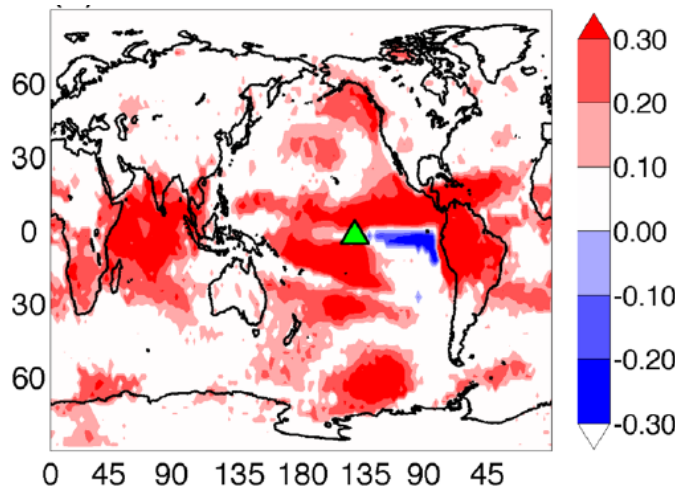
$$D_{XY}(\tau) = \frac{I_{XY}(\tau) - I_{YX}(\tau)}{I_{XY}(\tau) + I_{YX}(\tau)}$$

$x \rightarrow y$
 $x \rightarrow z$ $y \leftrightarrow z$?

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

A. Bahraminasab et al, PRL **100**, 084101 (2008)

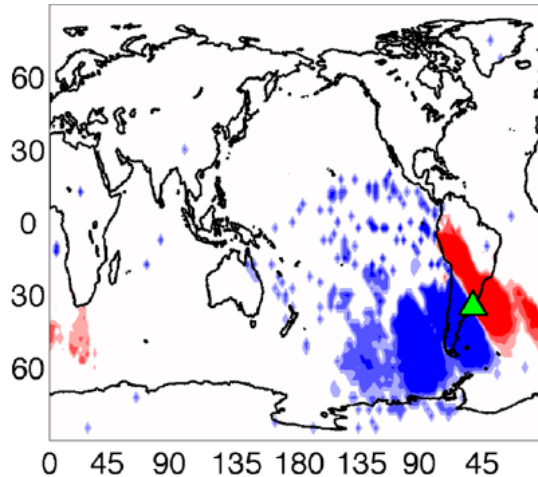
- Data: daily SAT anomalies
- PDFs: histograms of values
- $\tau=30$ days
- MI and D are both significant ($>3\sigma$, bootstrap surrogates)

 MI D 

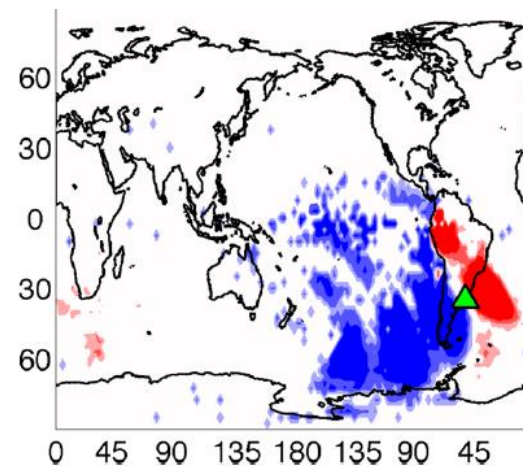
Deza, Barreiro and Masoller, Chaos 25, 033105 (2015)

Time-scale of interactions

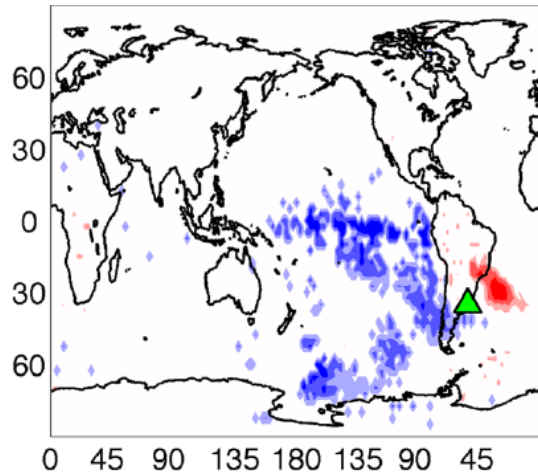
$\tau=1$
day



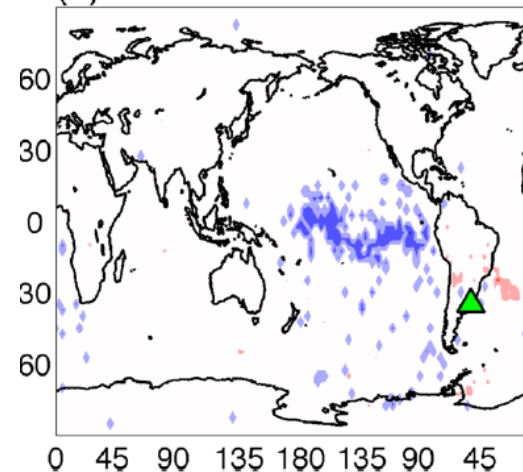
$\tau=3$ days



$\tau=7$
days



$\tau=30$ days



DI reveals wave trains propagating from west to east

[Video: directionality in reference point along the equator](#)

Unravelling the community structure of the climate system

How to identify geographical regions with similar climate?

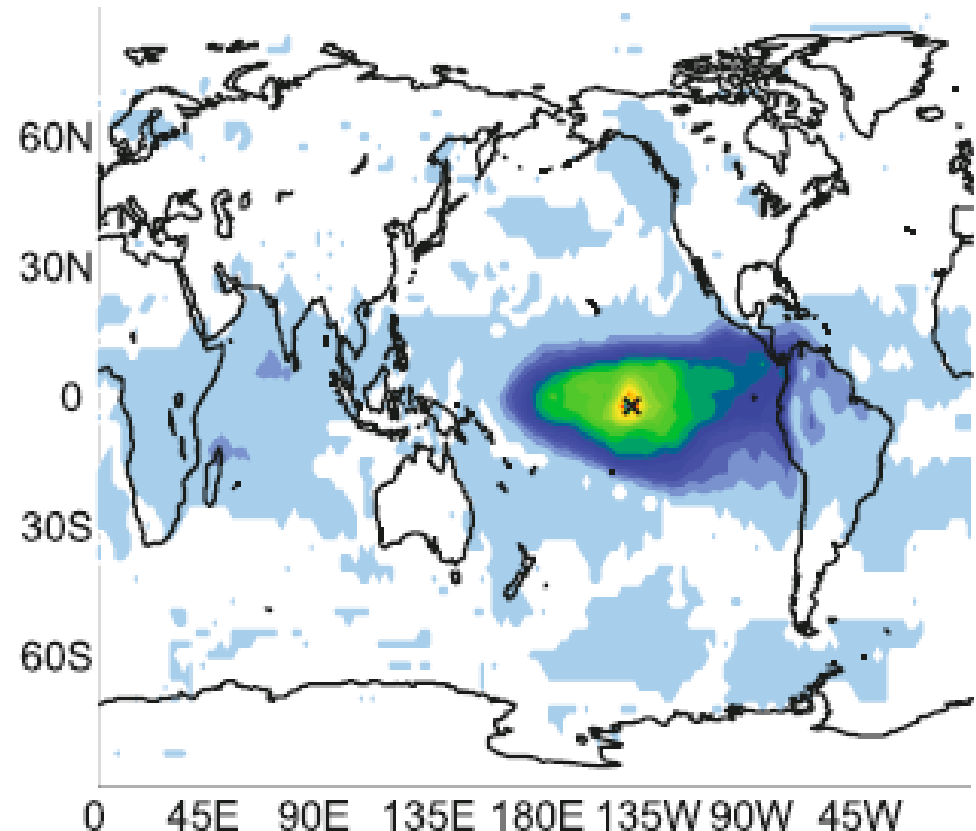


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Problem: the spatial embedding of the network

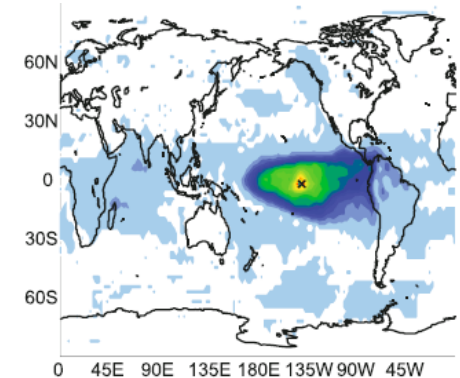
- Due to the **physical proximity**, the links (defined via thresholding similarity measure – cross correlation, mutual information) are mainly between neighboring nodes $\Rightarrow$ **long distance links are scarce**.



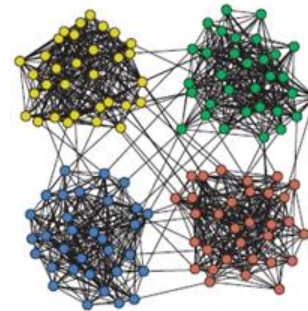
Cross correlation of surface
air temperature anomalies
(seasonal cycle removed)

Climate “communities”

- A first solution: construct the climate network and run a community detection algorithm.
- Regions with similar climate (rainforests, dry and arid regions, maritime regions, etc.) should belong to the same “community”.
- Problem: the spatial embedding of the network.
- Due to the **physical proximity**, the links are mainly between neighboring nodes $\Rightarrow$ **long distance links are scarce**.
- **No direct North – South links.**

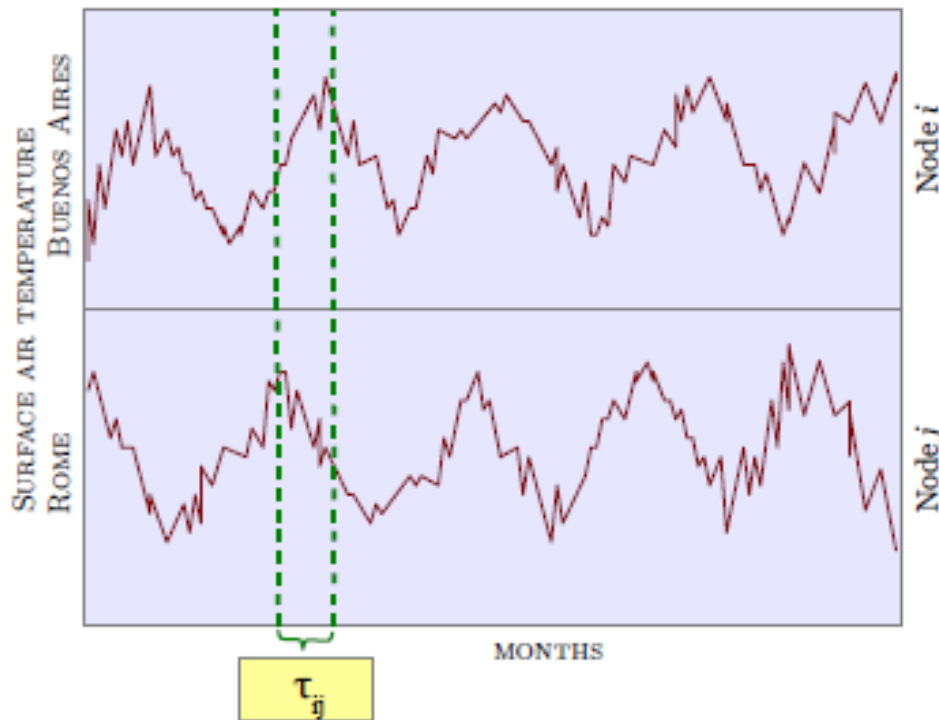


Cross correlation of SAT anomalies



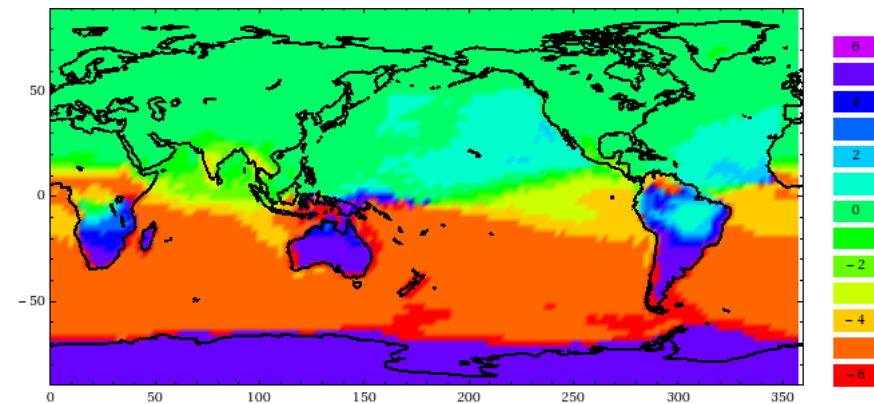
How to identify geographical regions with similar climate?

- Our first approach: lag-times between seasonal cycles (bivariate correlation analysis of Surface Air Temperature)

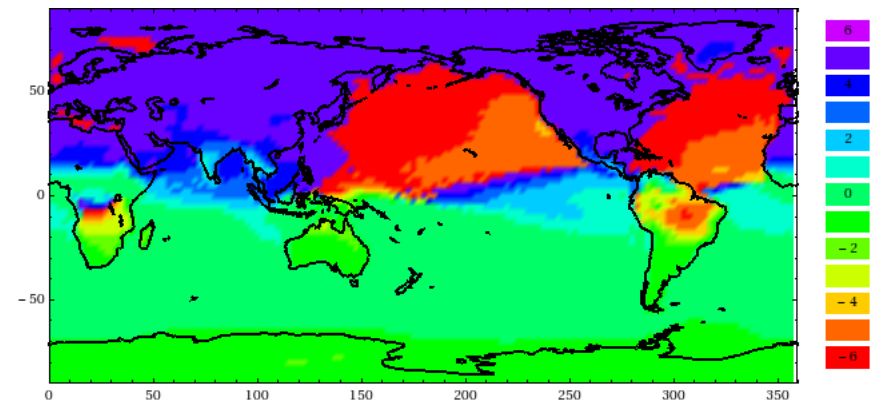


[Tirabassi and Masoller, Sci. Rep. 6:29804 \(2016\)](#)

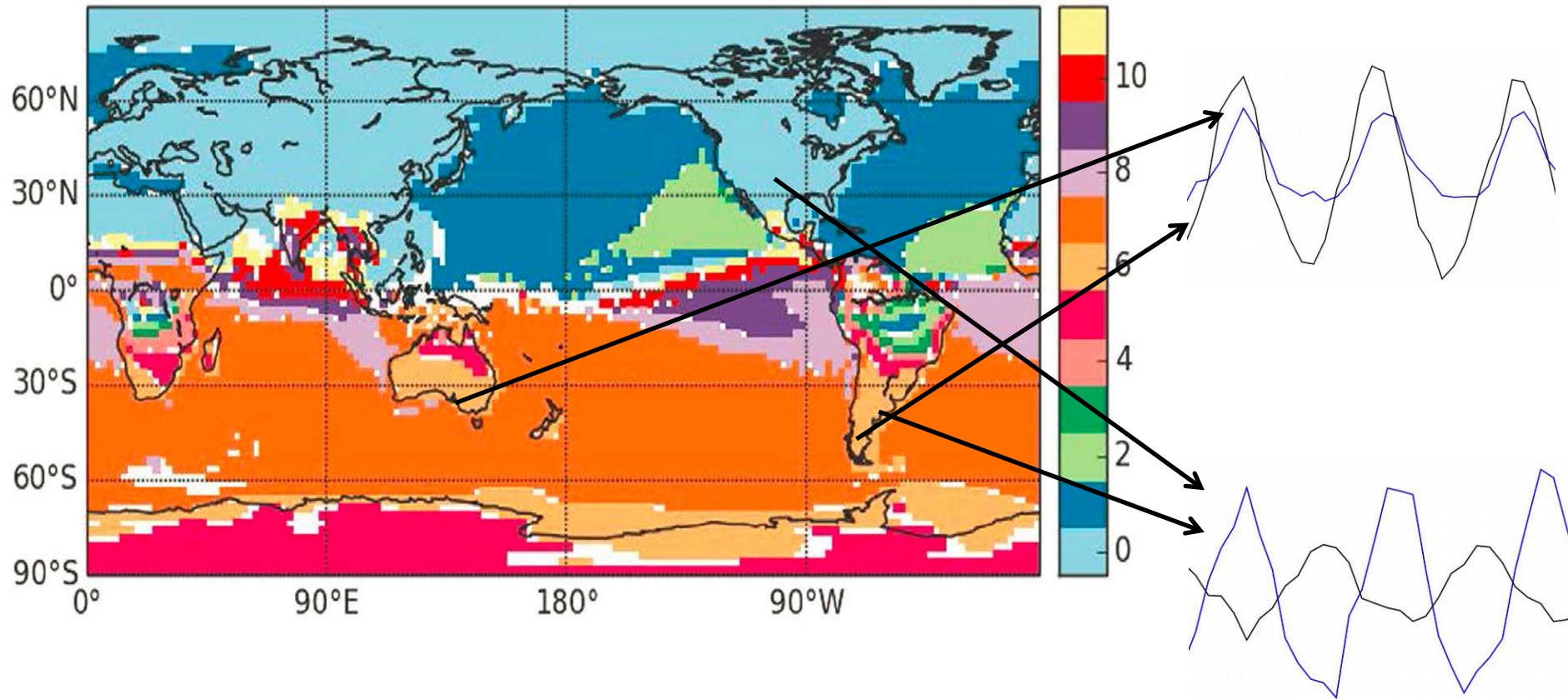
Rome



Buenos Aires



Geographical regions with synchronous (inphase) seasonal cycles

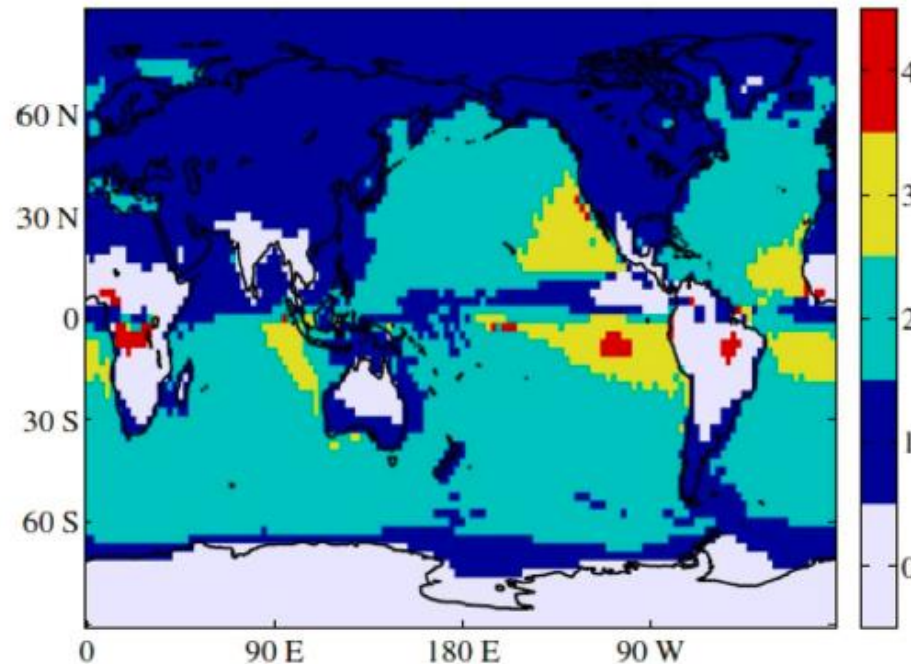


- Six-month lag between the two hemispheres.
- Oceans have a one-month lag with respect to the landmasses

[Tirabassi and Masoller, Sci. Rep. 6:29804 \(2016\)](#)

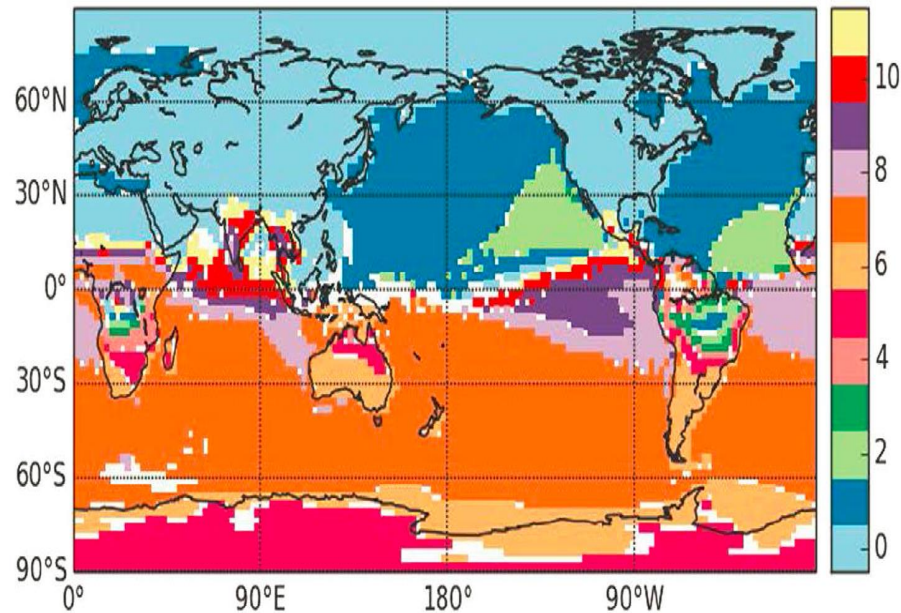
Our second approach

- Lag-time between surface air temperature seasonal cycle and the isolation (local top-of-atmosphere incoming solar radiation)
- computed by minimizing the distance between the time-series.



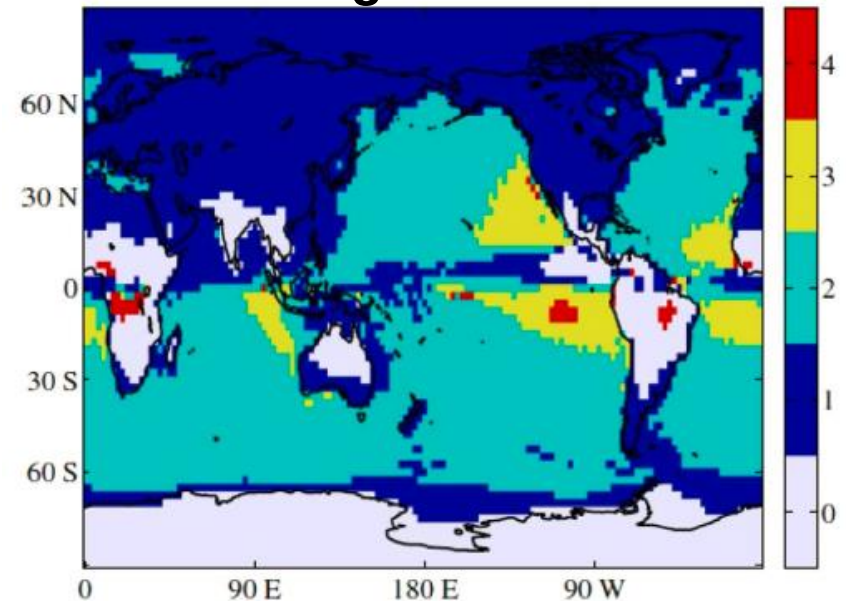
[Arizmendi, Barreiro and Masoller, Sci. Rep. 7, 45676 \(2017\)](#)

Regions with inphase (synchronized) surface air temperature seasonal cycle



G. Tirabassi and C. Masoller,
Sci. Rep. 6:29804 (2016)

Lag between surface air temperature seasonal cycle and incoming solar radiation



F. Arismendi, M. Barreiro and C. Masoller,
Sci. Rep. 7, 45676 (2017)

Third method: network 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

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

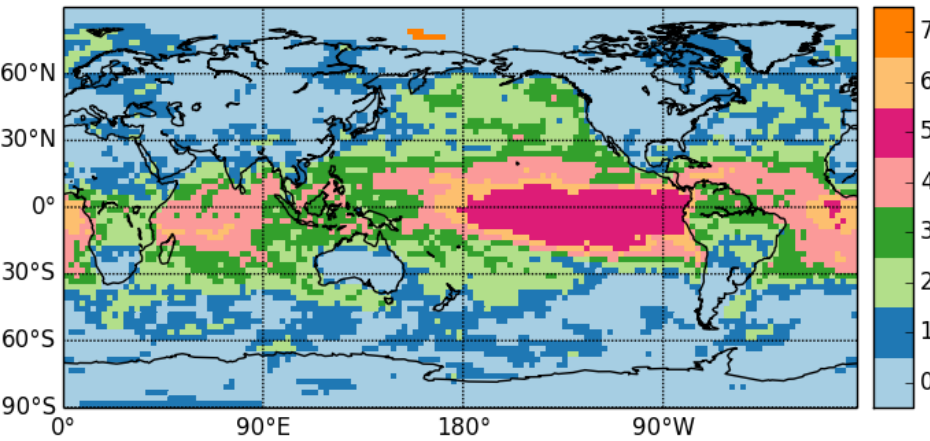
- Step 3: define the weights

$$w_{ij} = \frac{1}{\sum_{\alpha\beta} (TP^i_{\alpha\beta} - TP^j_{\alpha\beta})^2}$$

High weight
if similar
symbolic
“language”

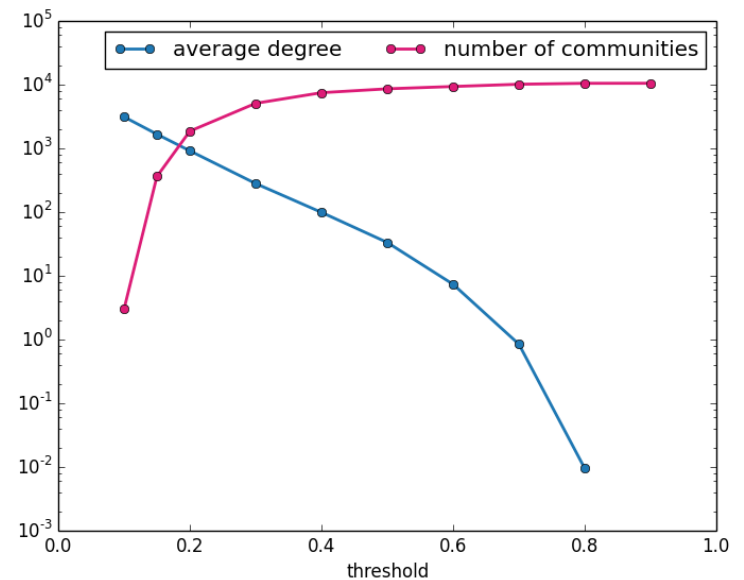
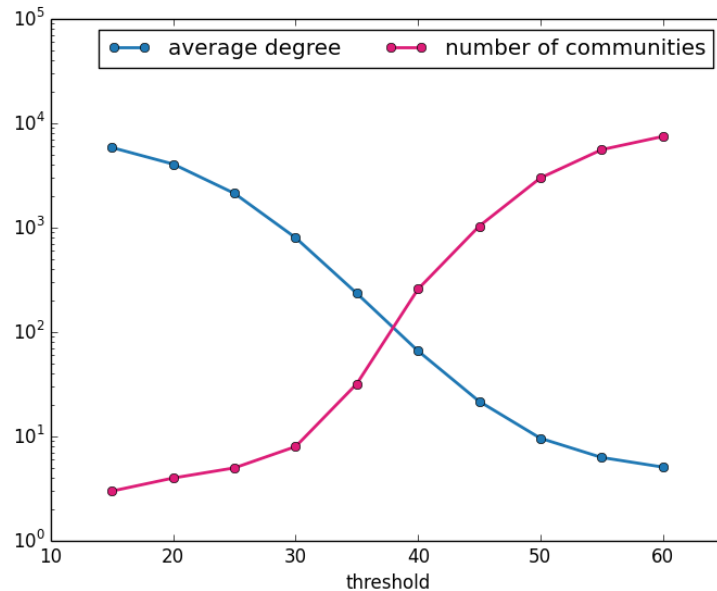
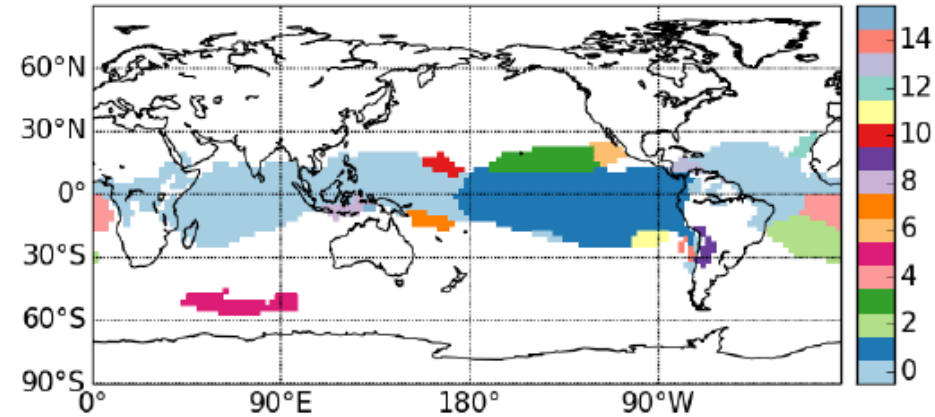
- Step 4: threshold w_{ij} to obtain the adjacency matrix.
- Step 5: run a community detection algorithm (Infomap).

TP Network



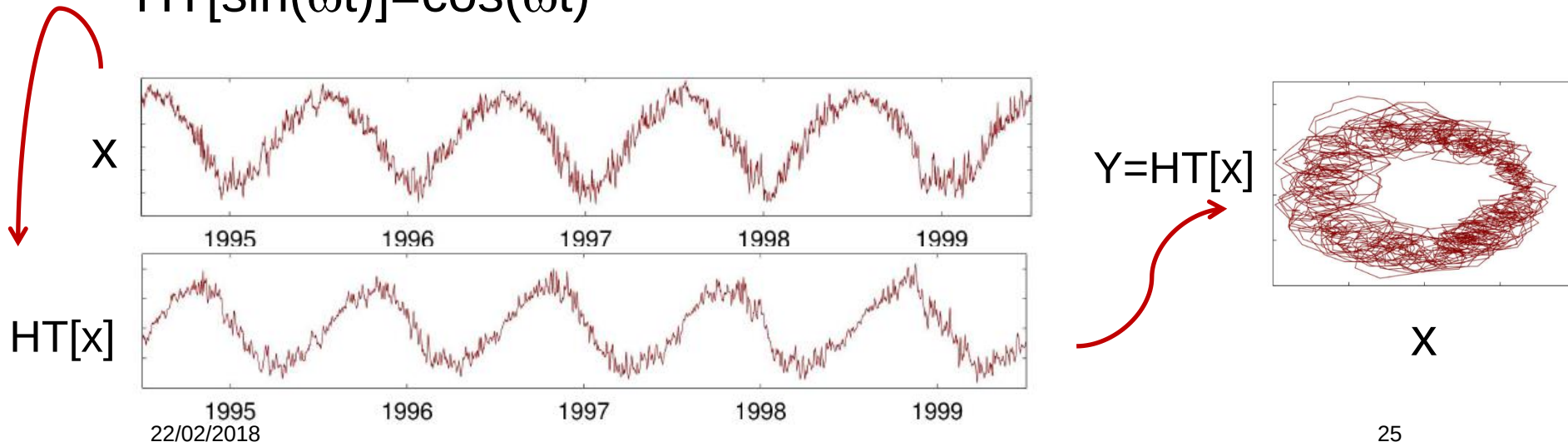
CC Network

(only the largest 16)

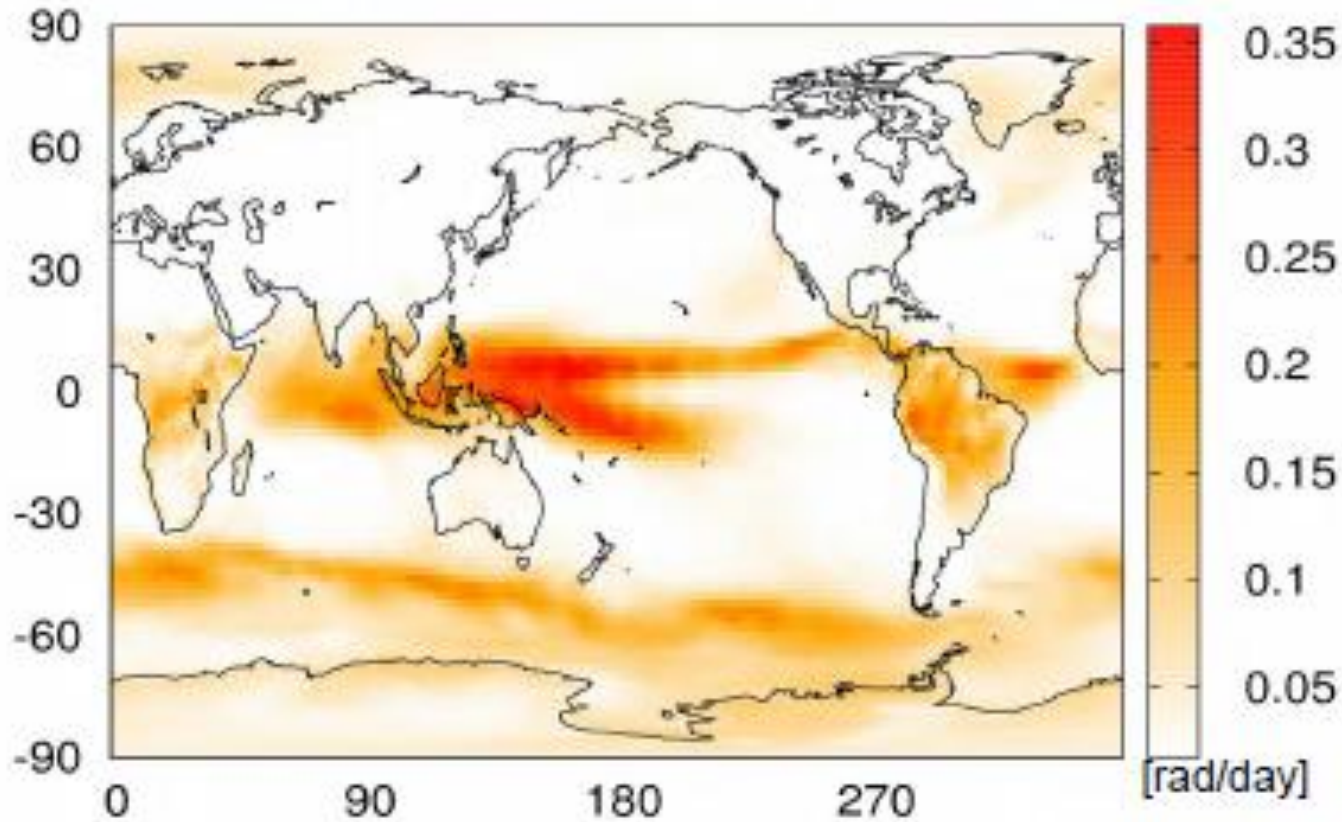


How to identify regions with similar climate dynamics?

- Hilbert Transform of a real **oscillatory** signal.
- Allows to calculate, **for each data point** in the time series, the instantaneous
Amplitude **$a(t)$** Phase **$\varphi(t)$** Frequency **$\omega(t)=d\varphi(t)/dt$**
- $HT[\sin(\omega t)] = \cos(\omega t)$

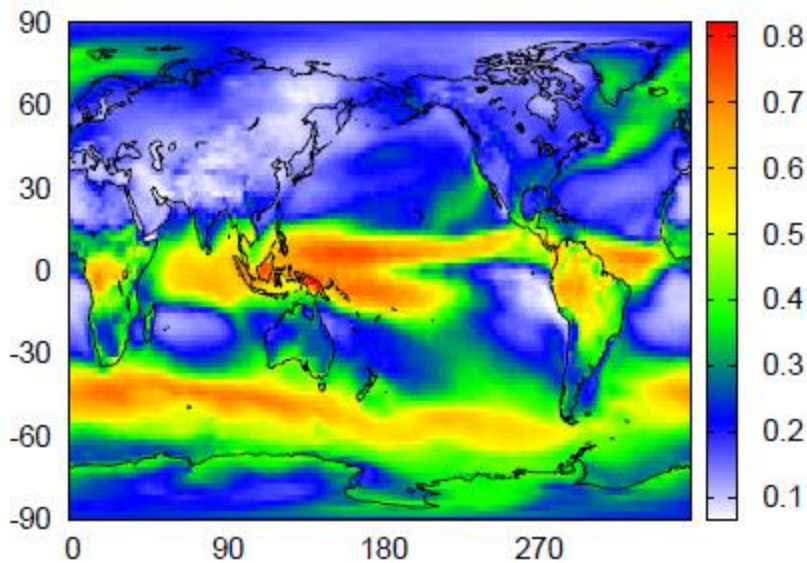


Average frequency

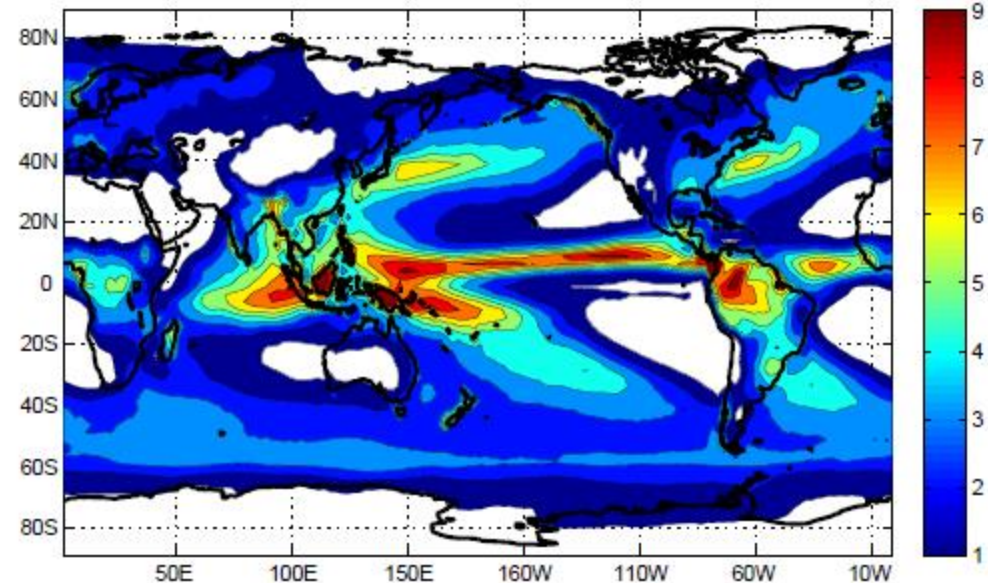


- The expected average frequency (one complete cycle in one year) is 0.017 rad/day

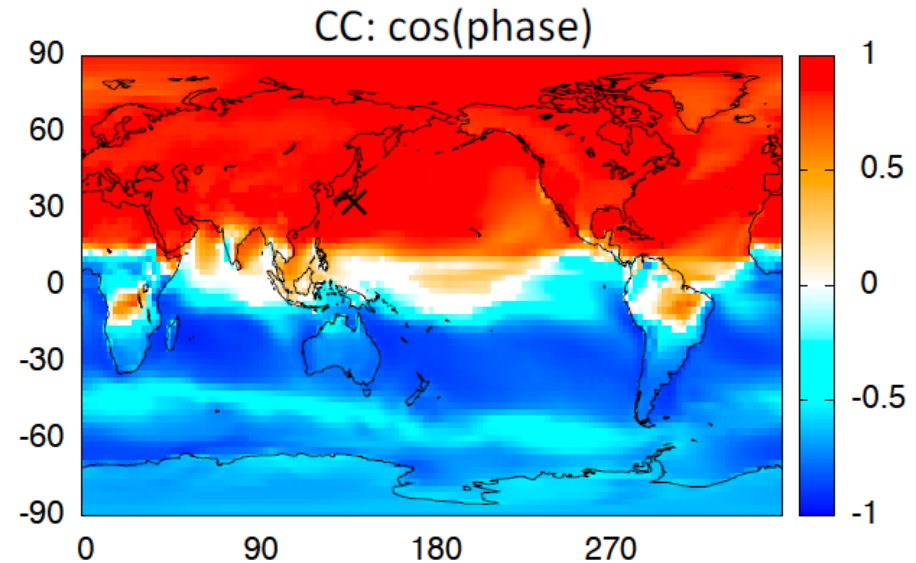
Standard deviation of frequency fluctuations



Annual mean precipitation (mm/day)



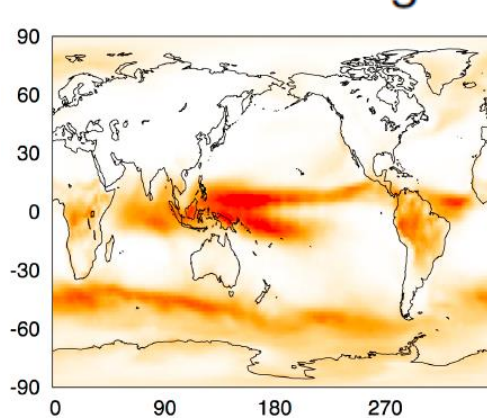
- Cos(phase) –typical year
- Cos(phase) –El Niño year



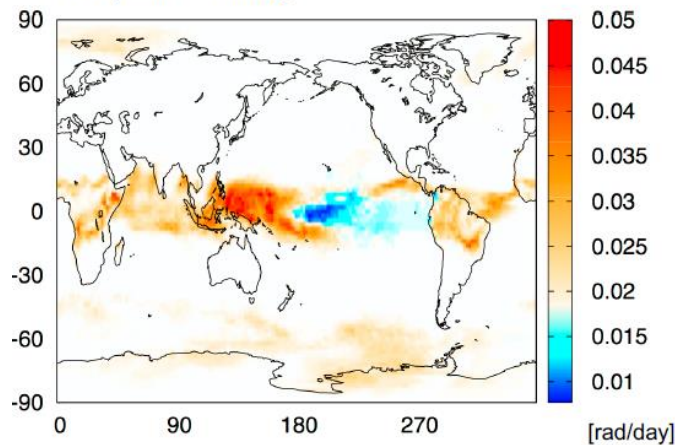
Influence of filtering the data

- SAT $\rightarrow$ average in a window of D days $\rightarrow$ Hilbert

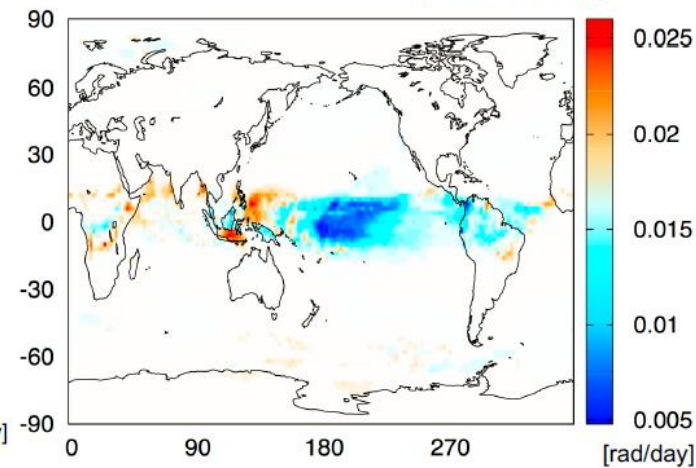
no smoothing



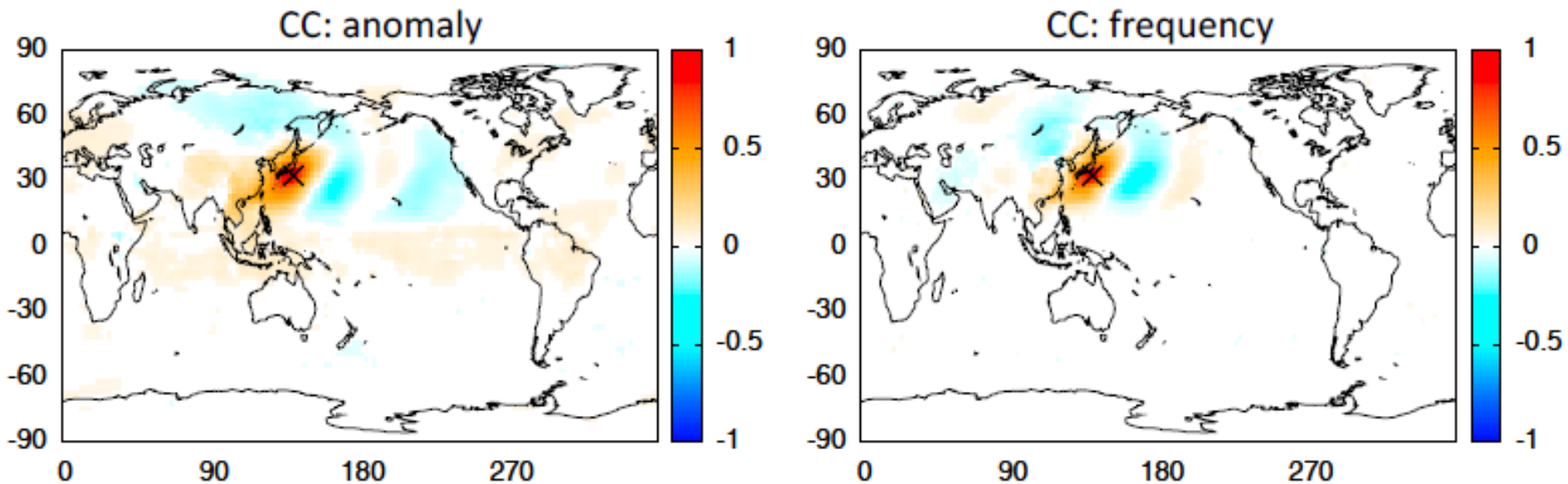
31-day smoothing



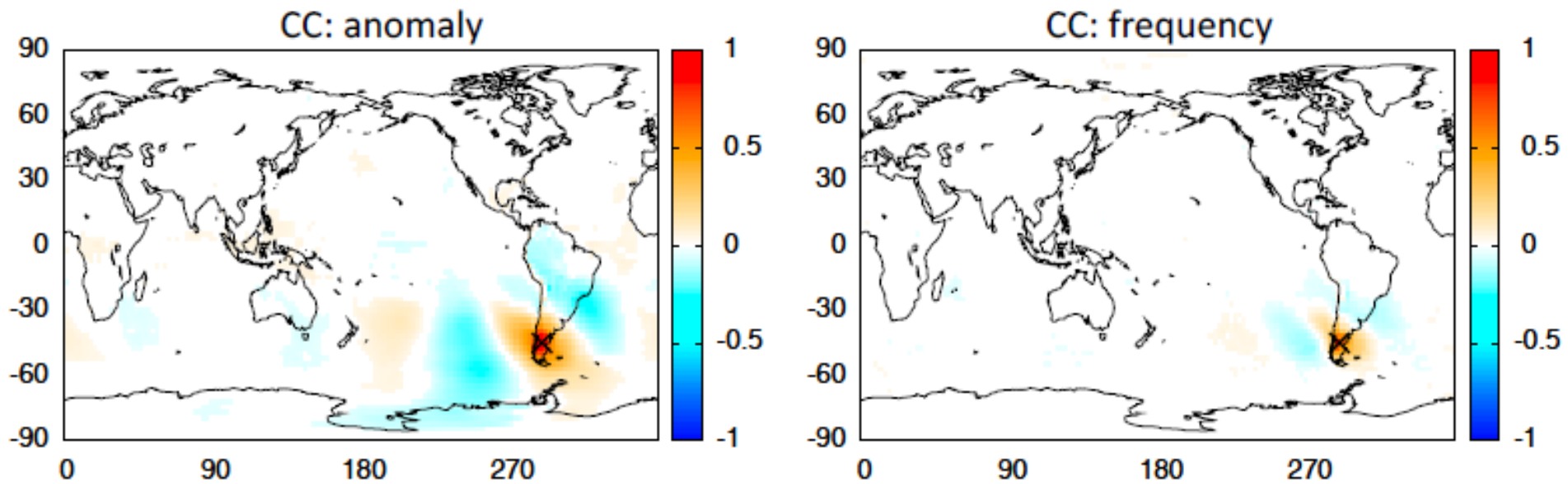
99-day smoothing



Bivariate analysis: extra-tropics

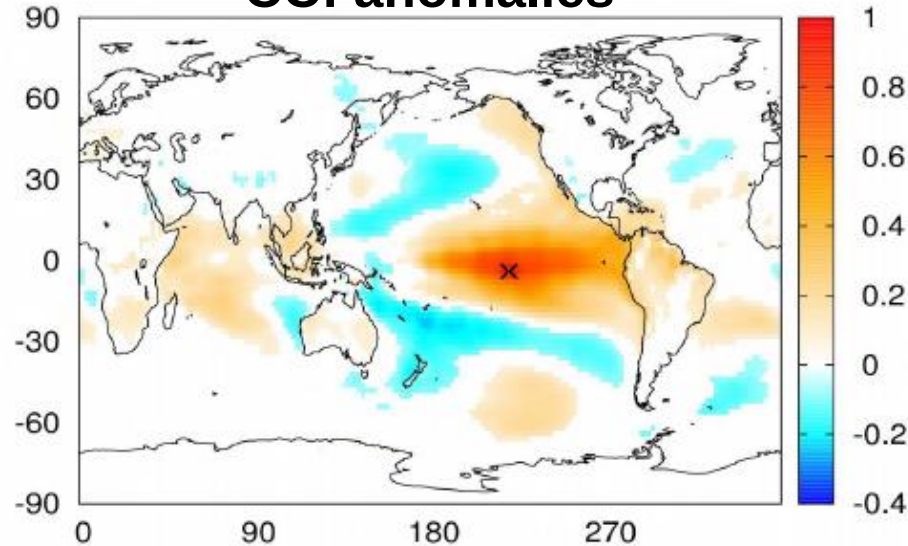


Significance: 100 surrogates (anomaly TS or Hilbert TS), then use 3σ confidence level

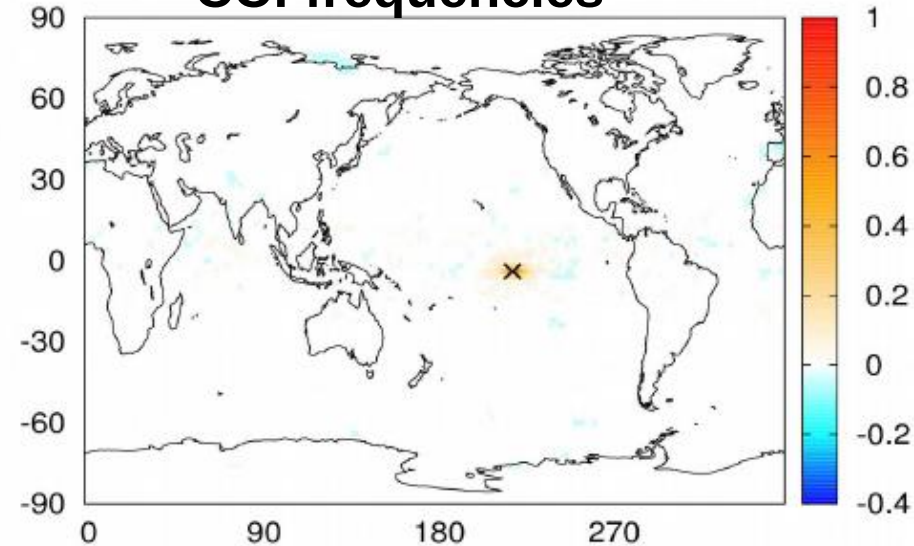


But in the El Niño region

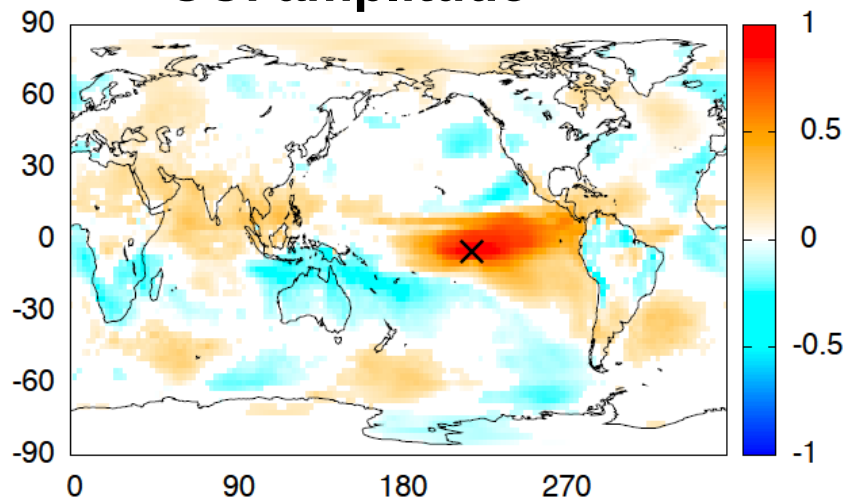
CC: anomalies



CC: frequencies

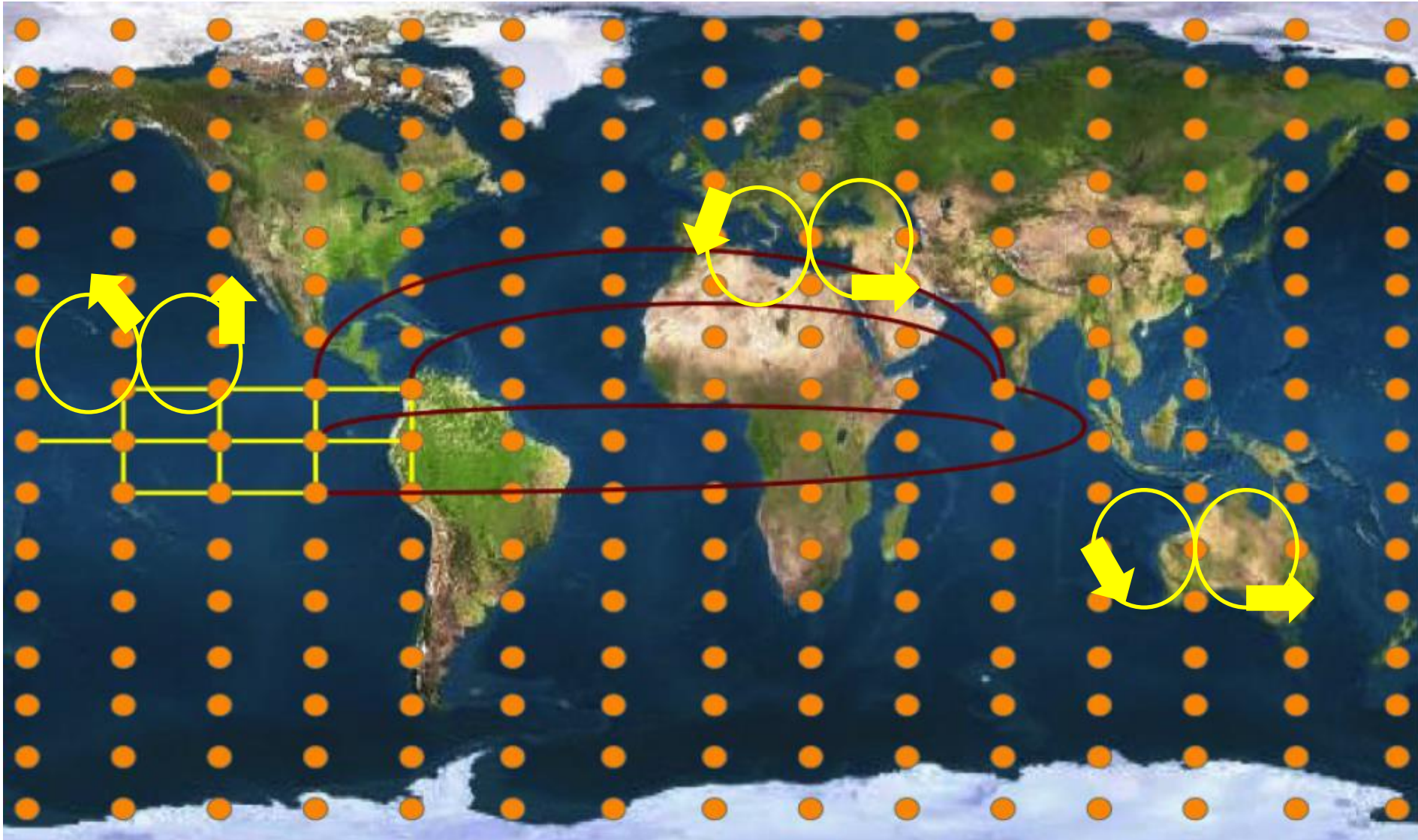


CC: amplitude



⇒ Frequency dynamics in the tropics is very different from frequency dynamics in the extra-tropics

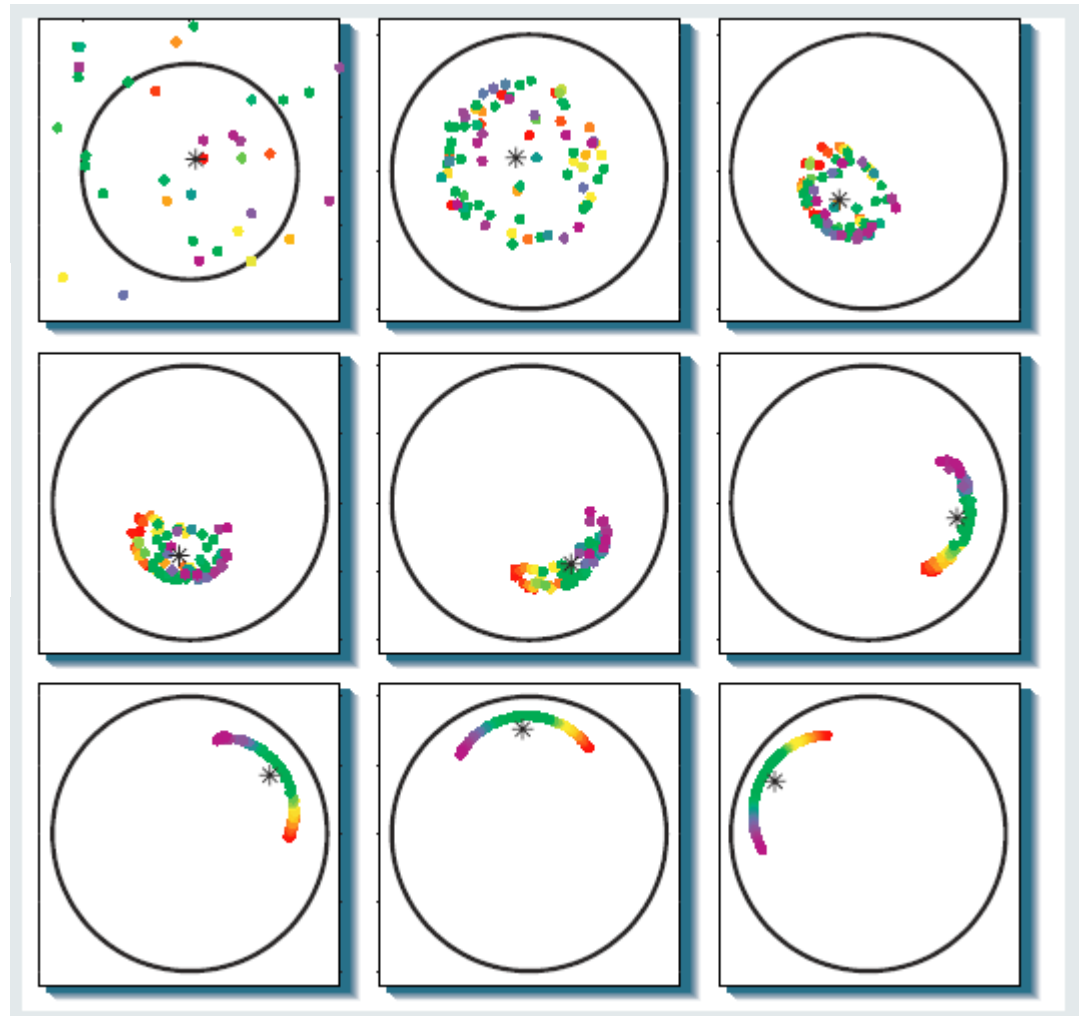
Network of individual oscillators

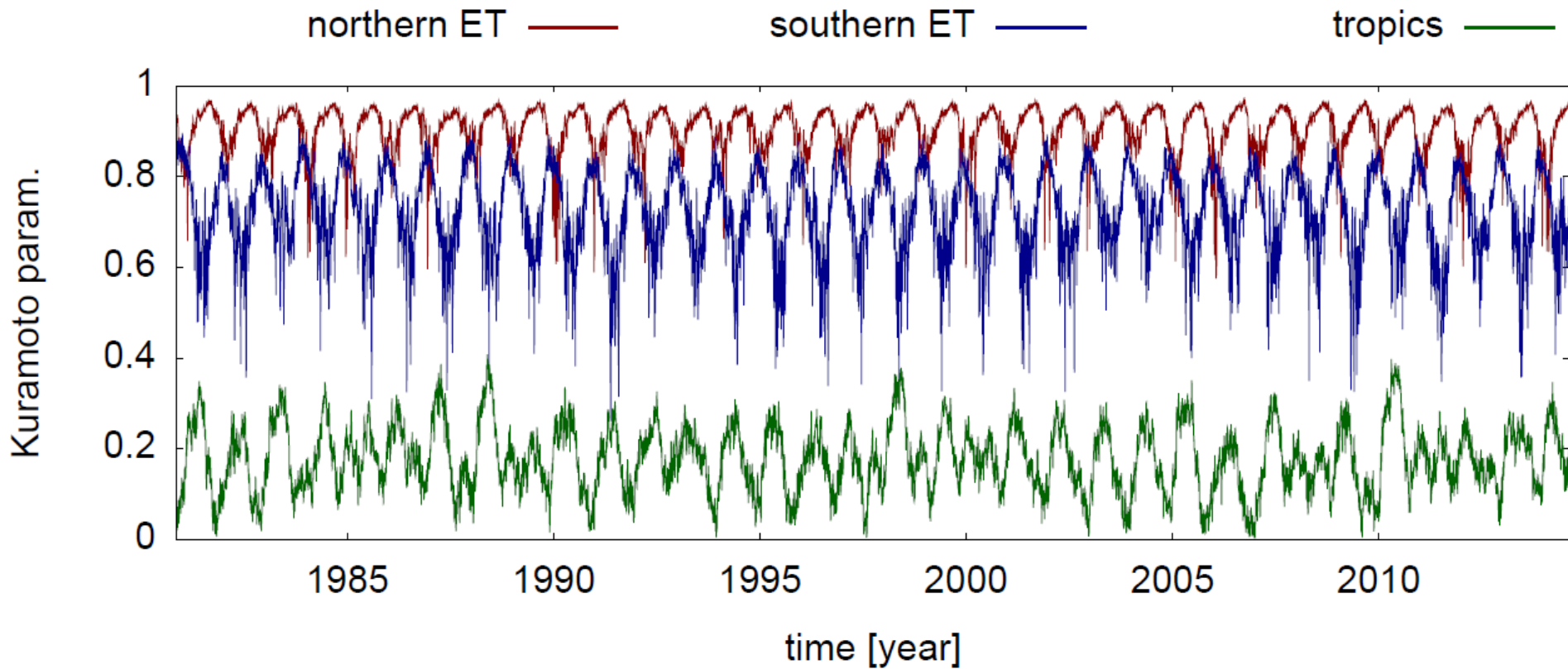


Quantifying phase synchronization

- Kuramoto order parameter

$$r(t) = \left| \frac{1}{N} \sum_{j=1}^N e^{i\theta_j(t)} \right|$$





Quantifying inter-decadal changes in climate dynamics

-can amplitude and frequency variations be used as a quantitative measure of regional climate change?



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Relative inter-decadal variation (ERA-Interim, 37 years)

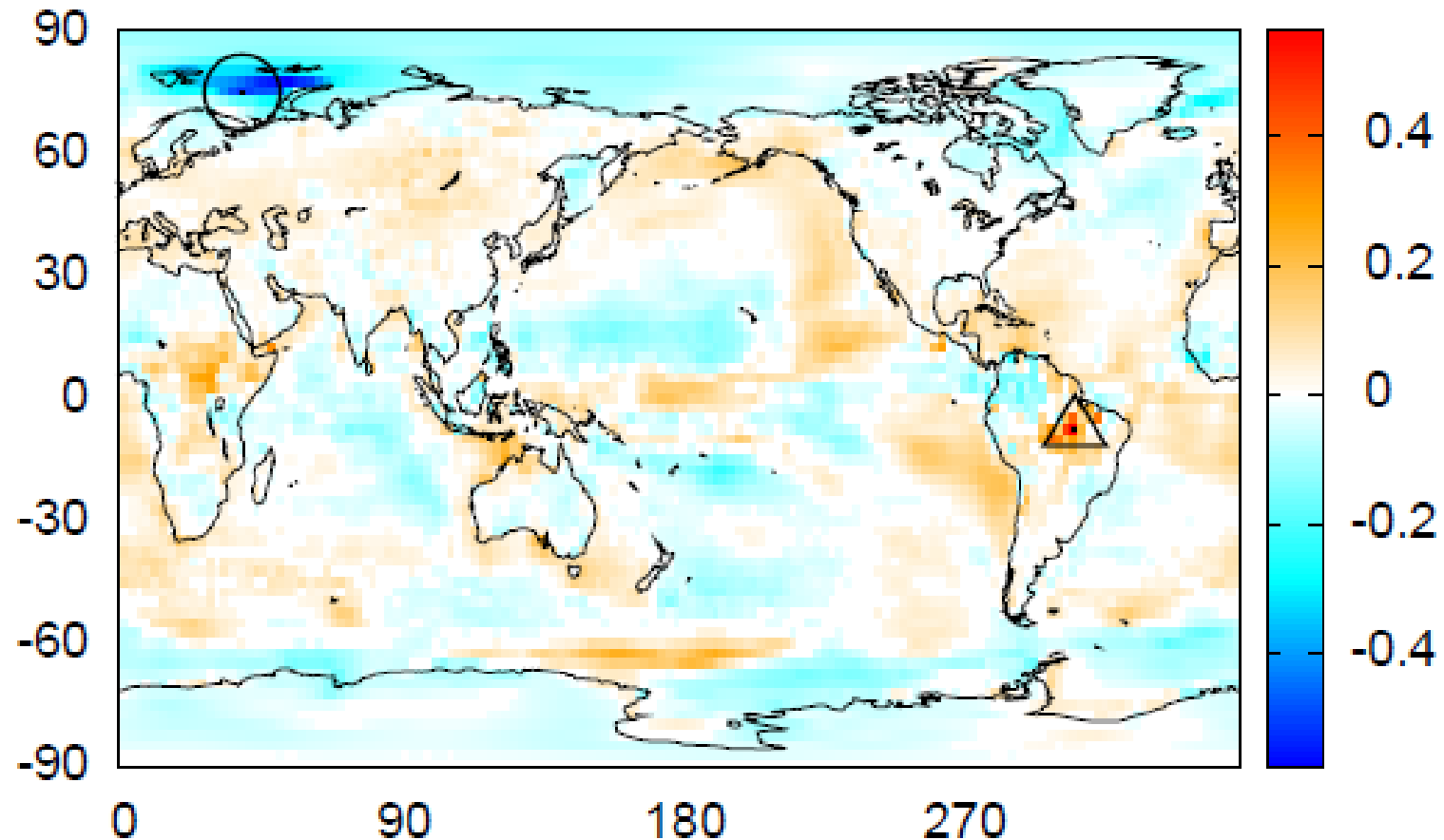
$$\Delta a = \langle a \rangle_{2016-2007} - \langle a \rangle_{1988-1979}$$

$$\frac{\Delta a}{\langle a \rangle_{2016-1979}}$$

Significance analysis: For each amplitude time series 100 shuffle surrogates were generated, and the relative change is significant if:

$$\frac{\Delta a}{\langle a \rangle} \geq \langle \cdot \rangle_s + 2\sigma_s \quad \text{or} \quad \frac{\Delta a}{\langle a \rangle} \leq \langle \cdot \rangle_s - 2\sigma_s$$

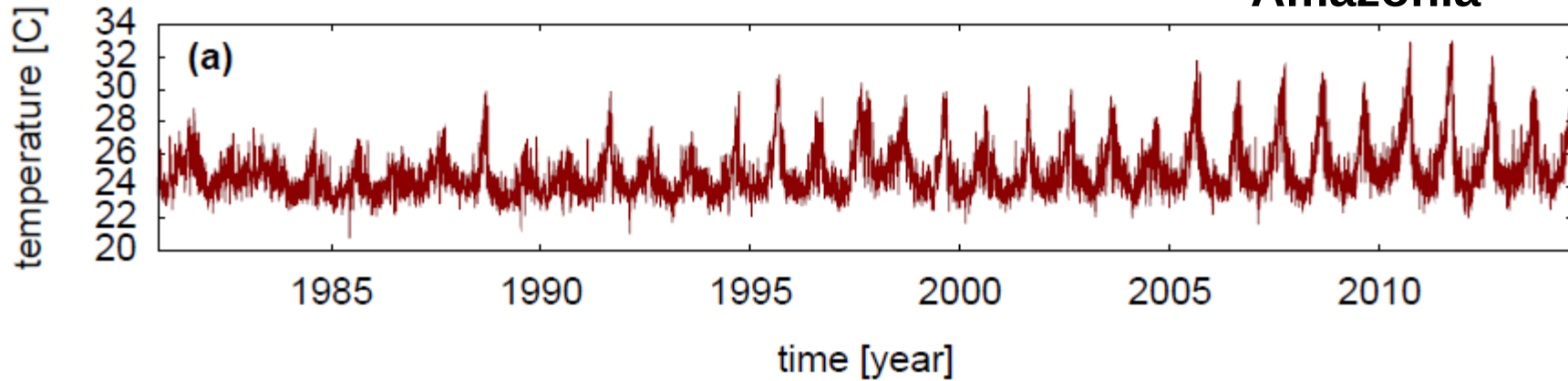
Relative change of time-averaged Hilbert amplitude



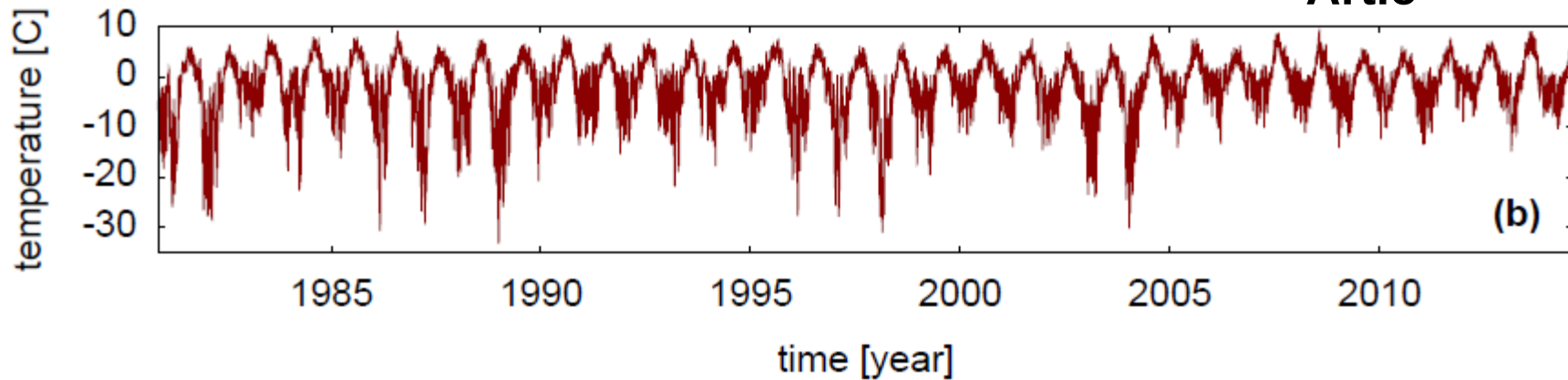
Melting of sea ice: during winter the air temperature is mitigated by the sea and tends to have more moderated values

Decrease of precipitation: the solar radiation that is not used for evaporation is used to heat the ground.

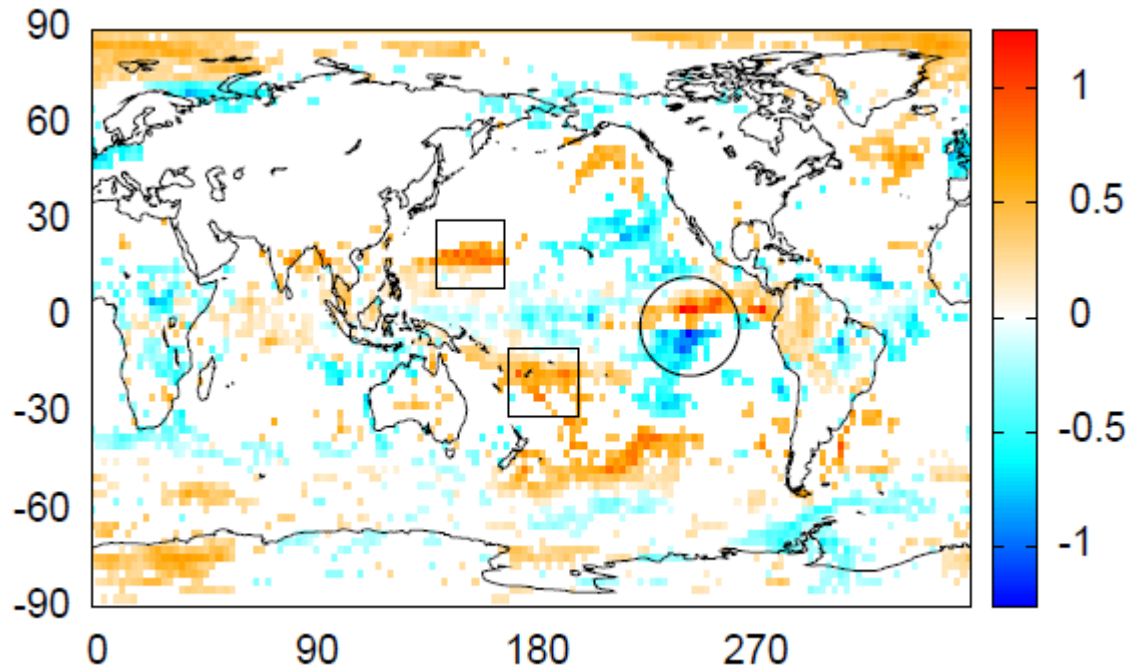
Amazonia



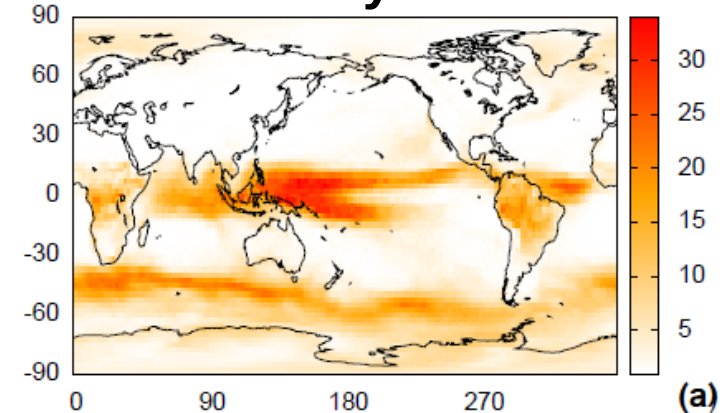
Artic



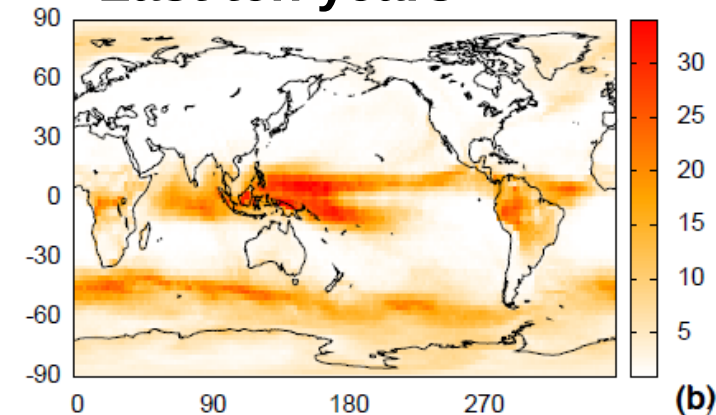
Relative change of time-averaged Hilbert frequency



First ten years



Last ten years

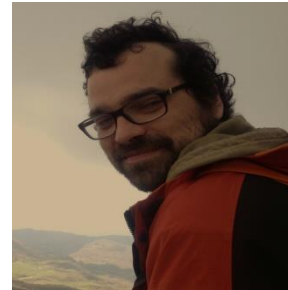
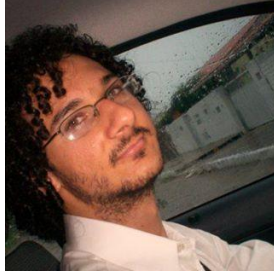


- ⇒ Consistent with a **shift towards north and a widening of the ITCZ**
- ⇒ Consistent with variation in the number of zero-crossings

What did we learn?

- Ordinal analysis allows inferring time-scales of interactions.
- Climate “communities” identified with different methods.
- Hilbert analysis applied to raw data can be useful for investigating synchronization and regional climate changes.
- High phase synchronization in the NH, lower in the SH, and even lower in the tropics.
- Large variations of Hilbert amplitude interpreted as due to ice melting (Arctic) or precipitation decrease (in Amazonia).
- Large variations of Hilbert frequency interpreted as due to a shift and enlargement of the ITCZ.

- [Deza, Barreiro and Masoller, EPJST 222, 511 \(2013\)](#)
- [Deza, Barreiro and Masoller, Chaos 25, 033105 \(2015\)](#)
- [Tirabassi and Masoller, Sci. Rep. 6:29804 \(2016\)](#)
- [Zappala, Barreiro and Masoller, Entropy 18, 408 \(2016\)](#)
- [Arizmendi, Barreiro and Masoller, Sci. Rep. 7, 45676 \(2017\)](#)



- Maria Masoliver, Pepe Aparicio Reinoso (*neurons*)
- Taciano Sorrentino, Carlos Quintero, Jordi Tiana, Came Torrent (*laser lab*)
- Andres Aragoneses, Laura Carpi (*data analysis, networks*)
- Ignacio Deza, Giulio Tirabassi, Dario Zappala, Marcelo Barreiro (*climate*)

<https://networkscied.wordpress.com/about/>

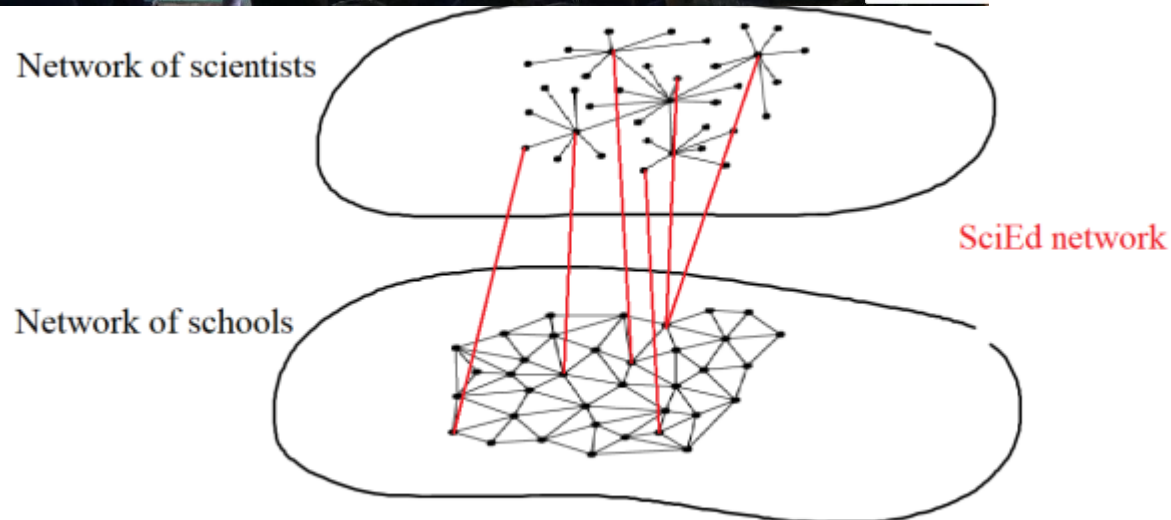


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<crisrina.masoller@upc.edu>

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



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