REDES Y CLIMA (y métodos de análisis de datos)

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Slides:
http://www.fisica.edu.uy/~cris/enredando.pdf

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Presentacion

- Professor of Physics, Universitat Politecnica de Catalunya.
- Originally from Montevideo, Uruguay.
- PhD in physics (nonlinear laser dynamics, Bryn Mawr College, USA).
- Research group: Dynamics, Nonlinear Optics and Lasers

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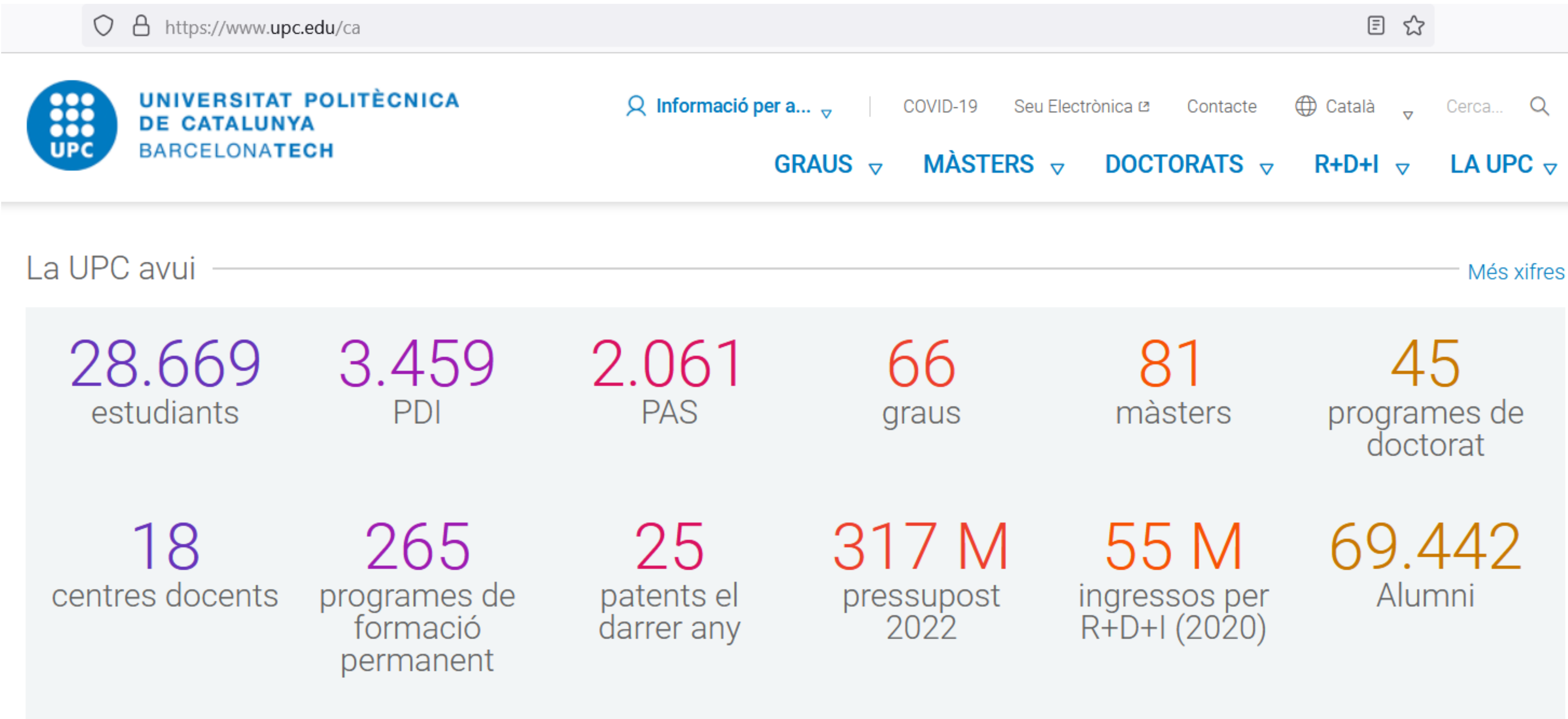
UPC: one of the largest technical universities in Spain



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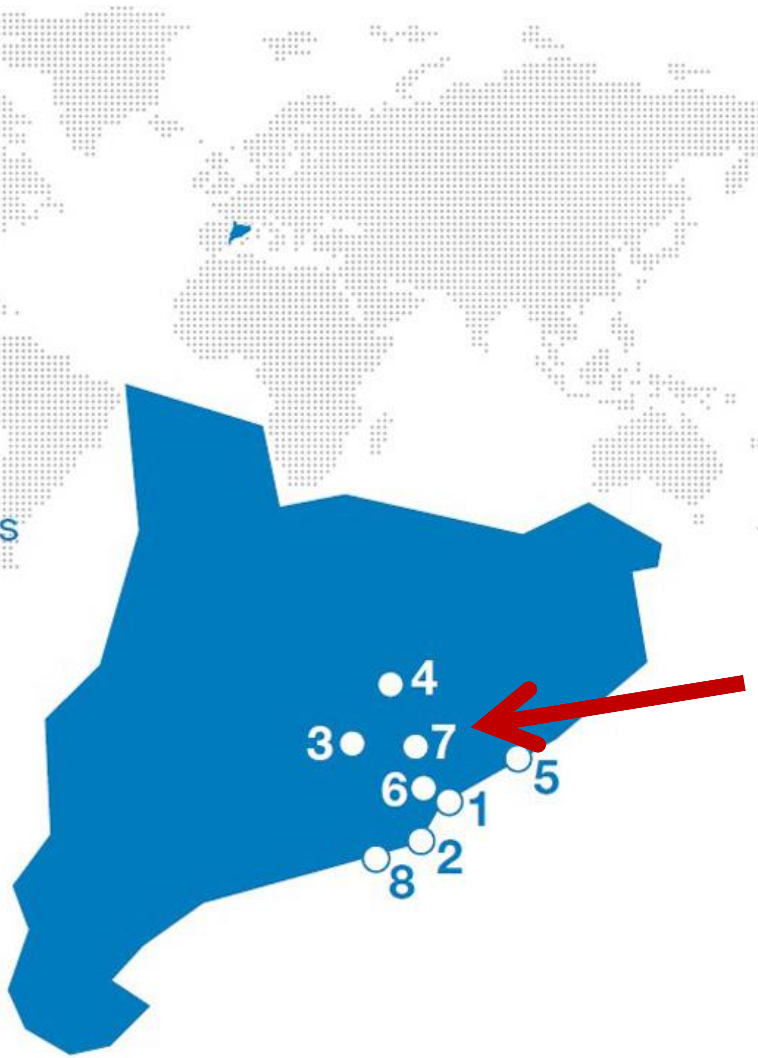
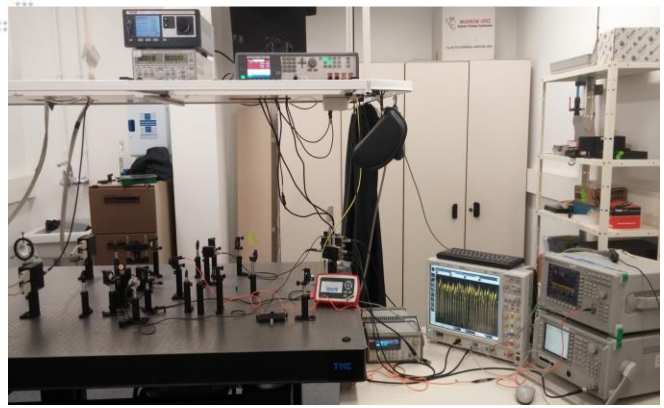
Where are we? UPC Campus Terrassa

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.



Laser lab in Gaia Building, UPC Campus Terrassa

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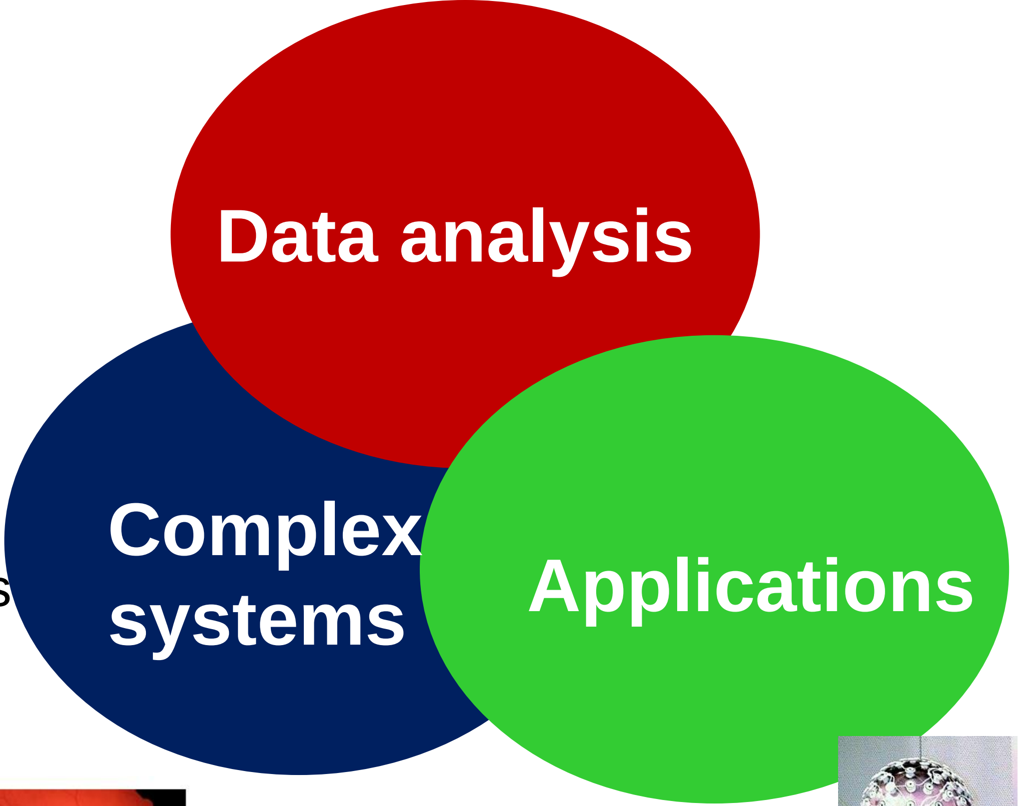
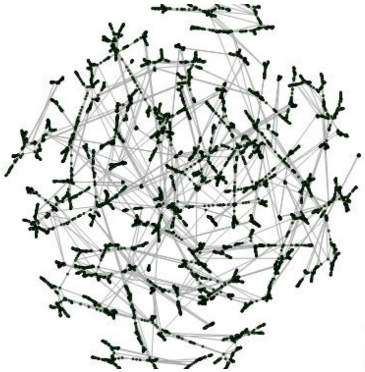
Research lines

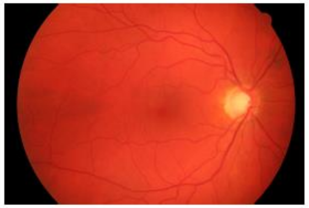
- Laser dynamics
- Neuronal dynamics
- Complex networks
- Data analysis

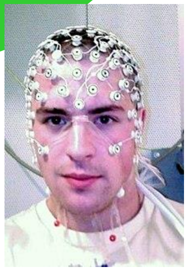
  climate and biomedical data

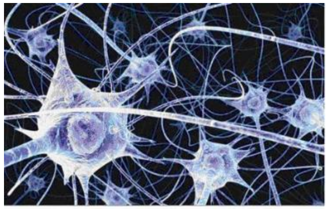
  tipping points, extreme events

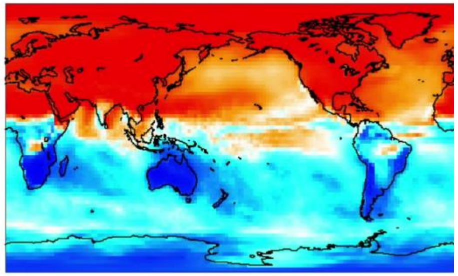


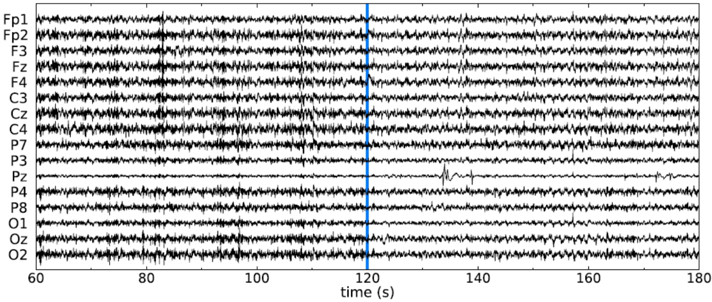












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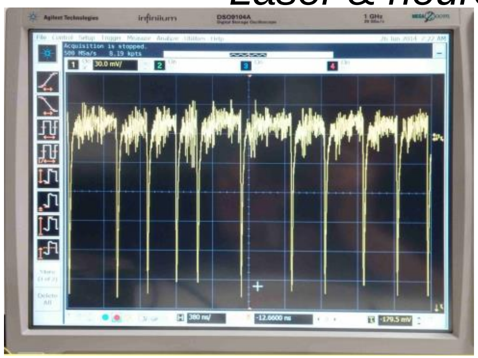
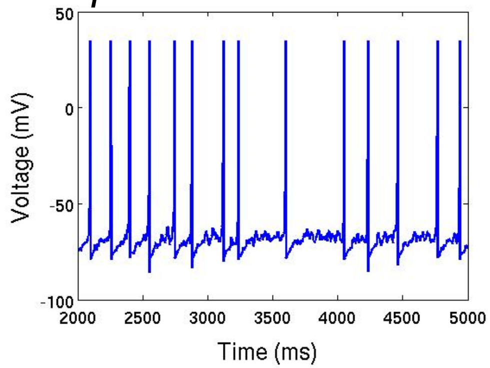
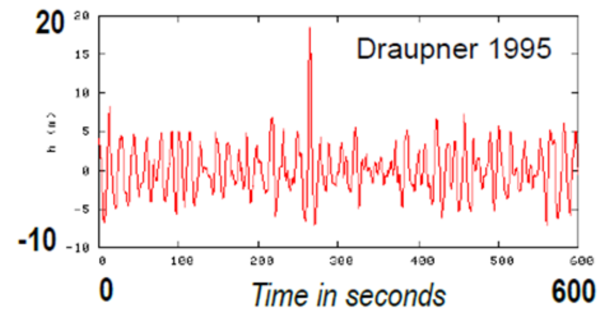
Lasers, neurons, climate, complex systems?

Laser & neuronal spikes

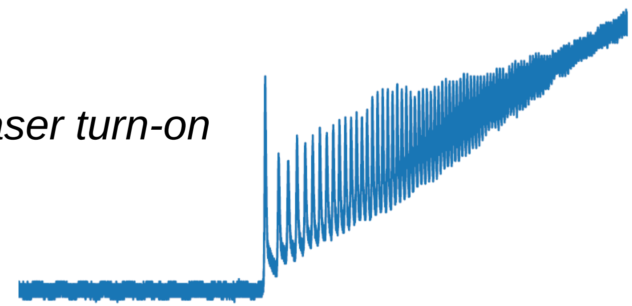




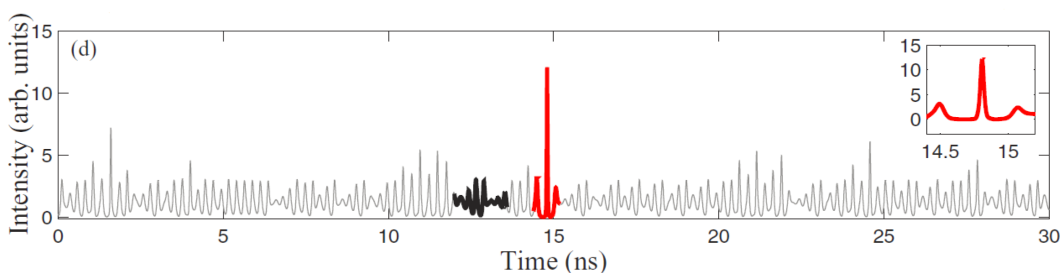
Ocean rogue wave (sea surface elevation in meters)



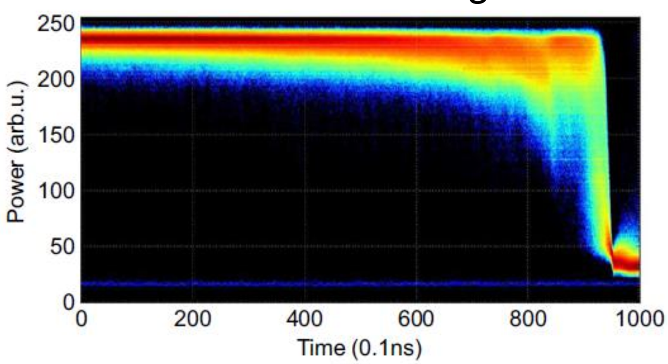
Laser turn-on



Extreme optical pulse (optical rogue wave)



Polarization switching



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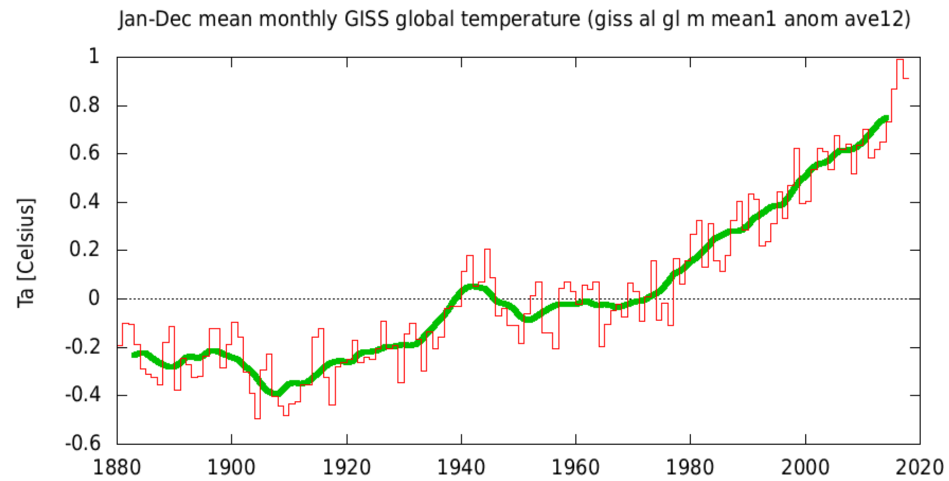
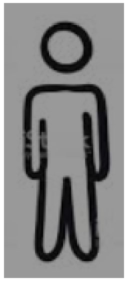
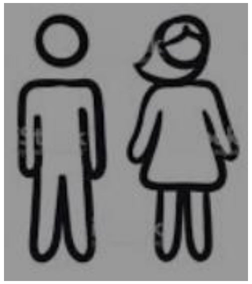
Methods of time series analysis $\{x_1, x_2, \ldots x_N\}$



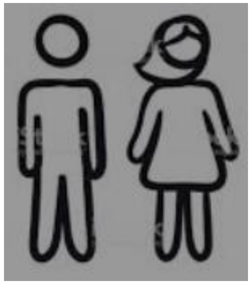
- Univariate analysis

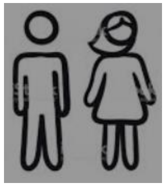


- Bivariate analysis



- Multivariate analysis
  - Complex networks





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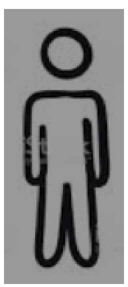
1) “Univariate” time-series analysis tool: Hilbert analysis

(for oscillatory time series)



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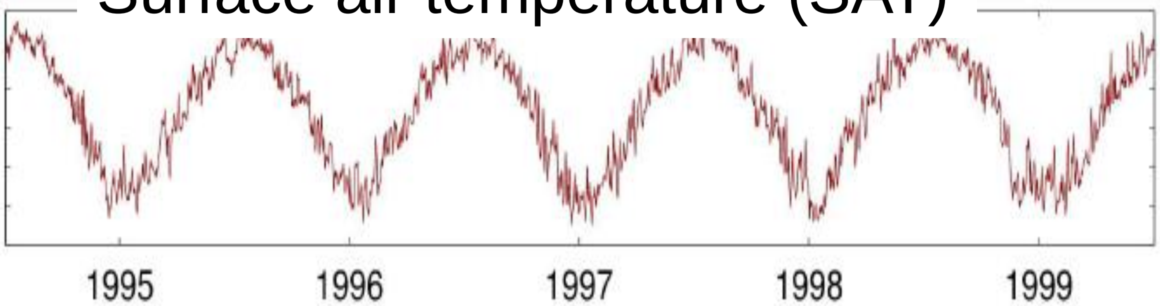
The Hilbert Transform (HT)

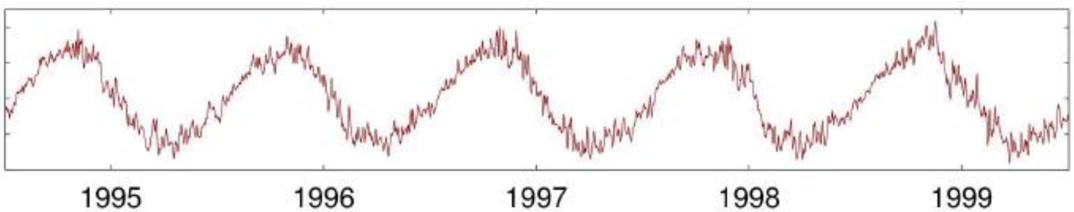
Surface air temperature (SAT)

x

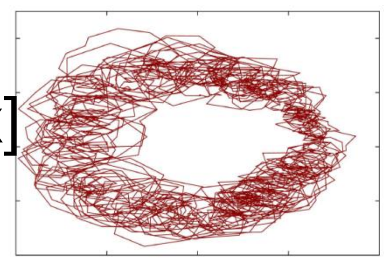


HT[sin(ωt)]=cos(ωt)

HT[x]



y=HT[x]



x

$$a(t) = \sqrt{[x(t)]^2 + [y(t)]^2}$$

$$\varphi(t) = \arctan[y(t)/x(t)]$$

$\omega(t) = d\varphi/dt$

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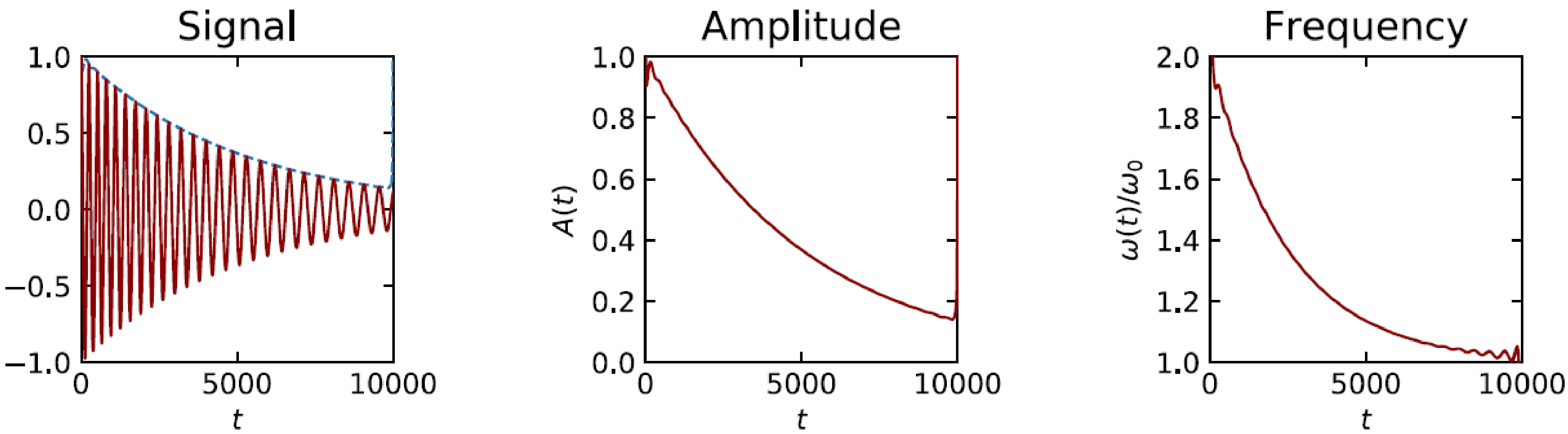
Example

$$x(t) = e^{-\alpha t} \cos\left[\left(1 + e^{-2\alpha t}\right) \omega_0 t\right].$$



A word of warning: only if *x(t)* is a "narrow-band" signal then *a(t)* and $\omega(t) = d\varphi/dt$ have clear physical meaning

- ***a(t)*** is the envelope of *x(t)*
- ***ω(t)*** is the main frequency in the Fourier spectrum

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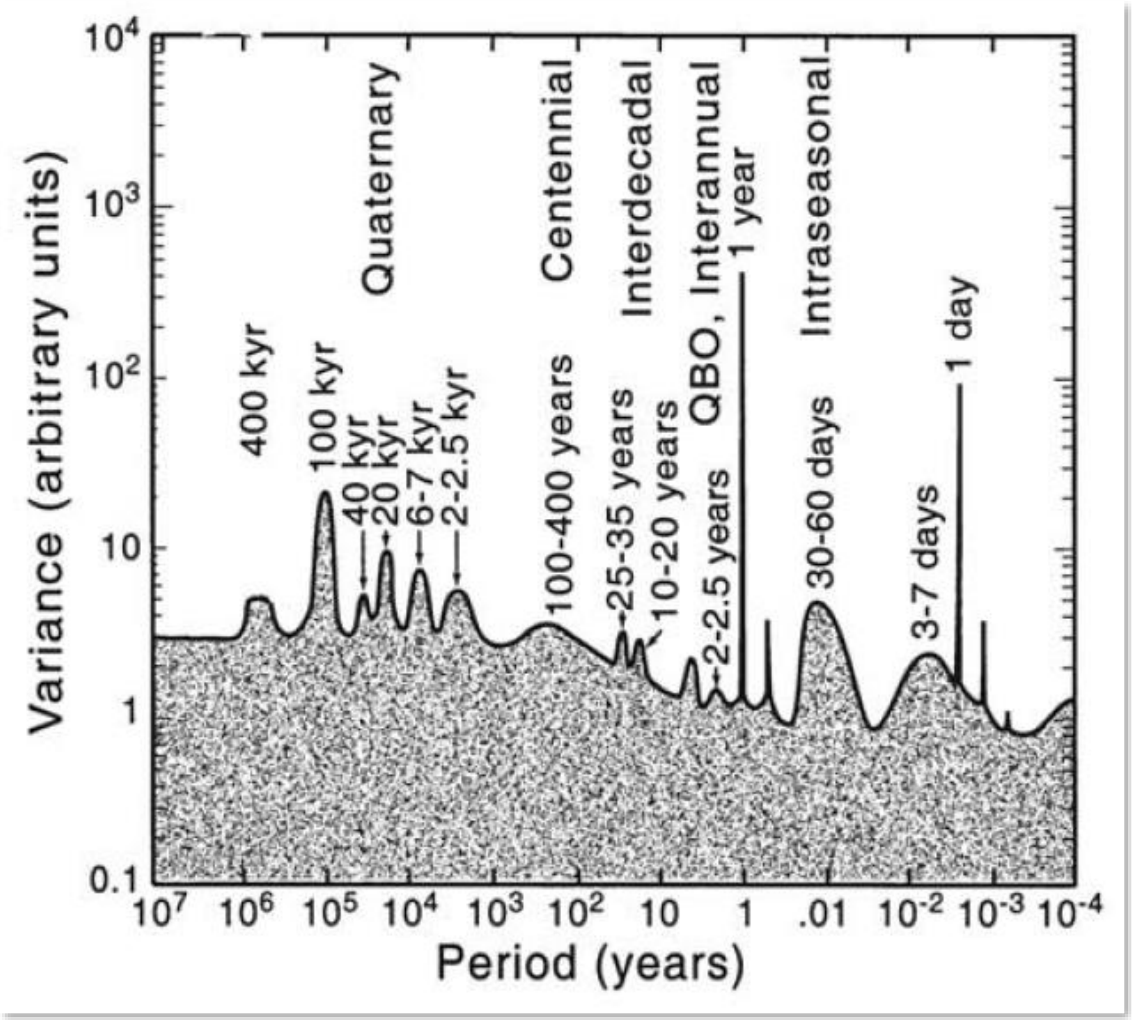
PROBLEM ! Climatic time series are NOT narrow-band.



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

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Solution ?

- Isolate a narrow frequency band (usual solution for EEG signals).

- However, I will show that HT directly applied to raw surface air temperature (SAT) returns meaningful results.

SAT data

- Spatial resolution $2.5^0 \times 2.5^0 \Rightarrow$ 10226 time series

- Daily resolution **1979 – 2016** $\Rightarrow$ 13700 data points

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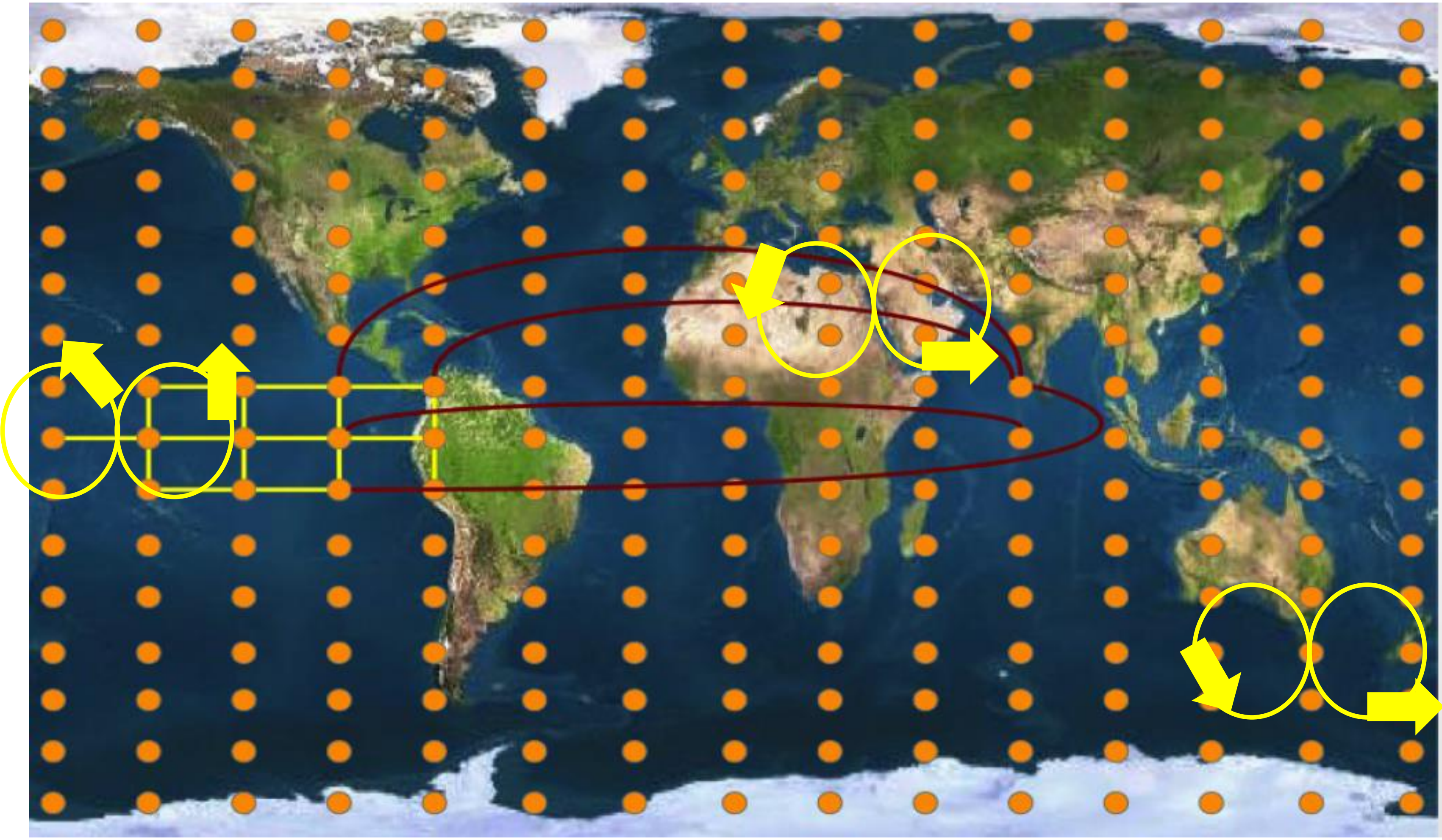
Oscillatory time series of 13700 data points in each "node" (more than 10000 nodes)



Credit: G. Tirabassi

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Where does the data come from?

- European Centre for Medium-Range Weather Forecasts (ECMWF).
- Freely available.
- <u>Reanalysis</u> = general atmospheric circulation model feed with empirical data, where and when available (data assimilation).

ECMWF datacenter,
Reading, UK, March 2022
Meeting of EU project CAFE

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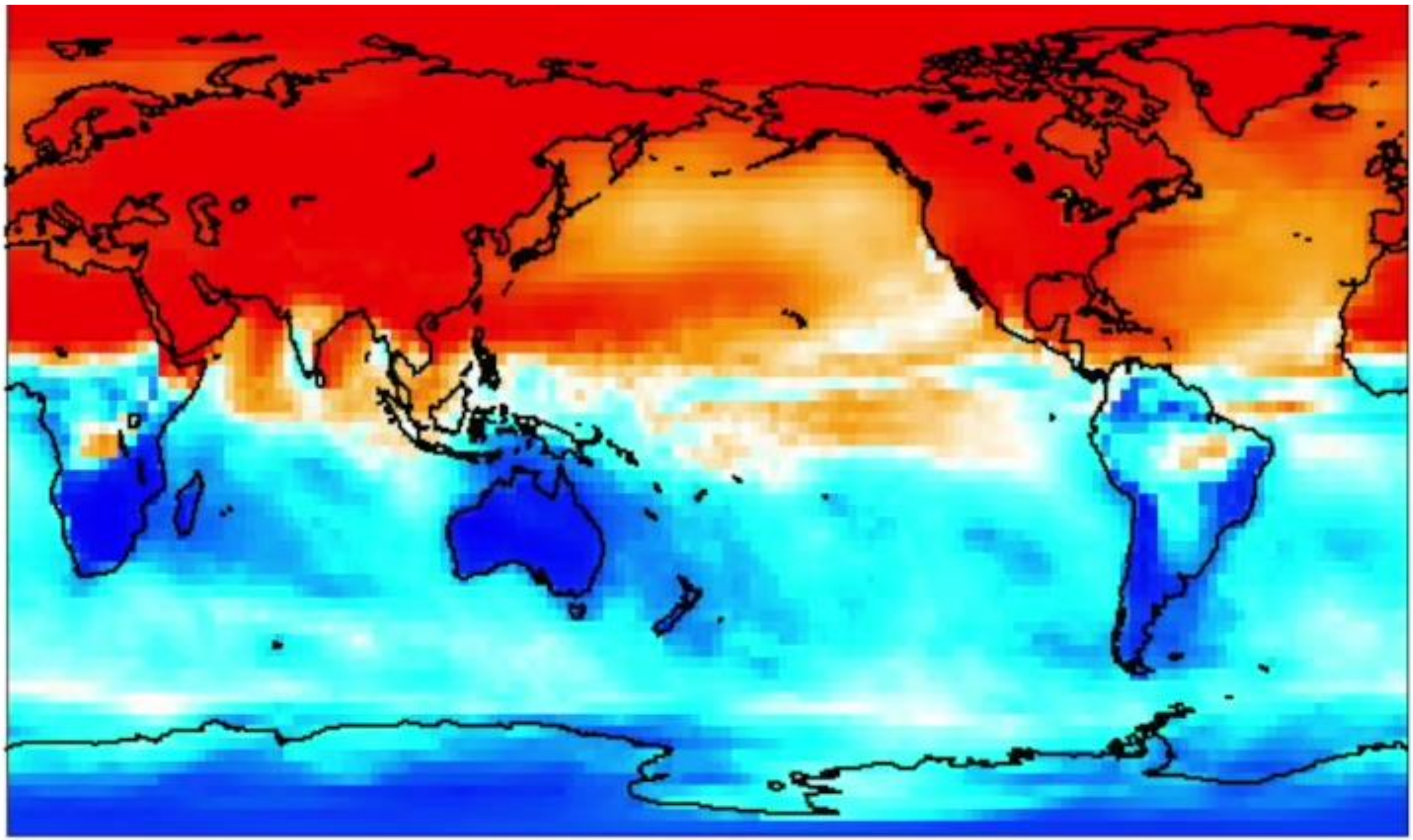
Which information carries the Hilbert phase?

In color code the cos(φ) averaged over all **July 1** in the period 1979 – 2016.



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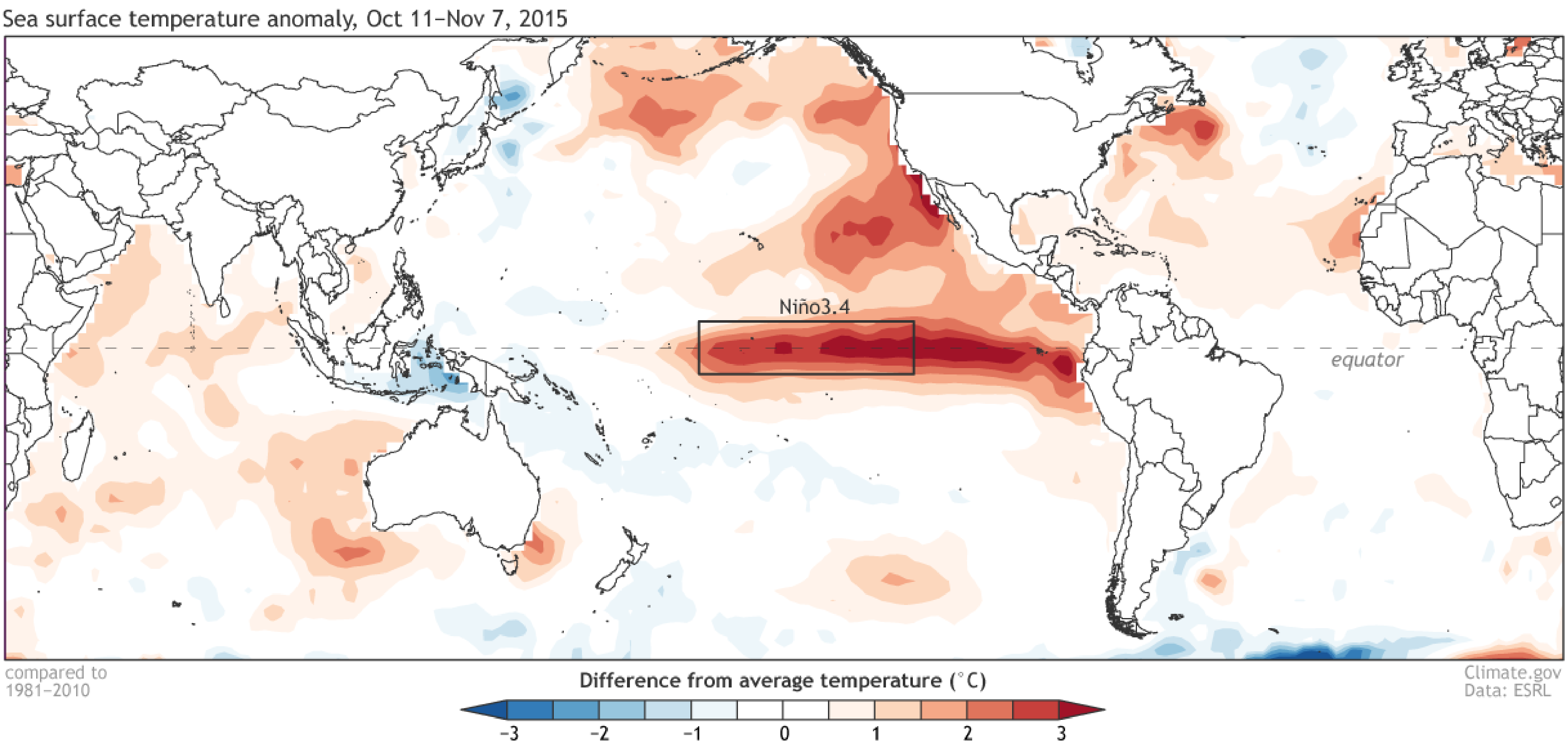
ENSO (El niño / southern oscillation)



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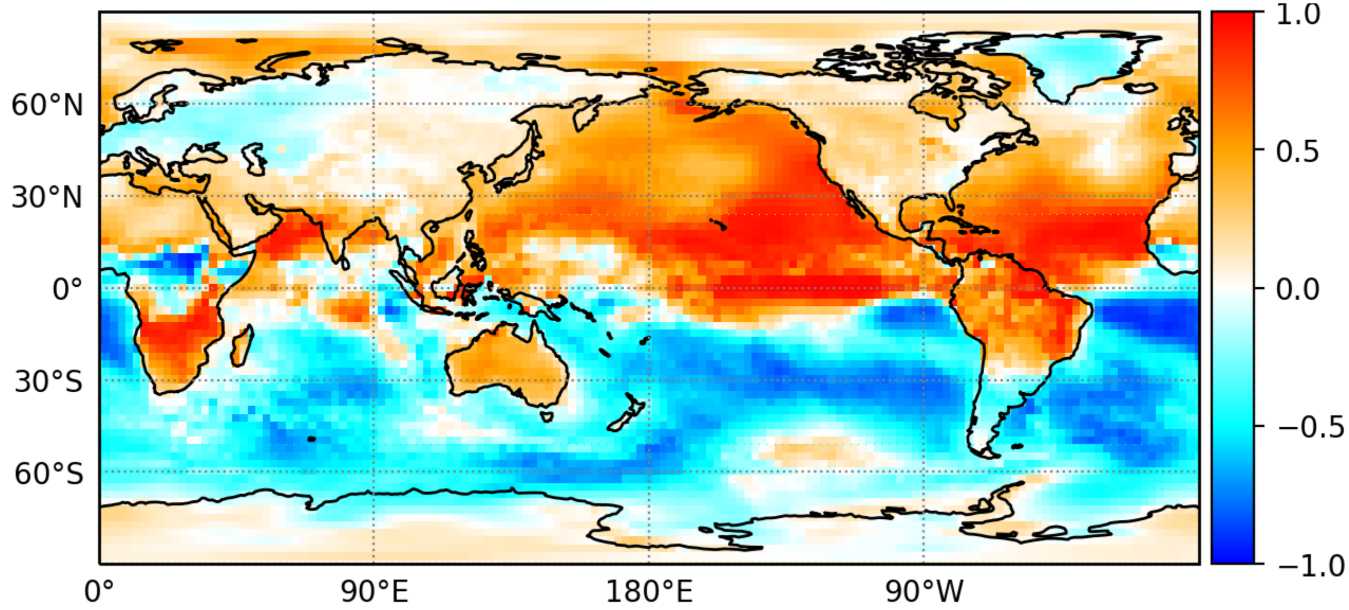
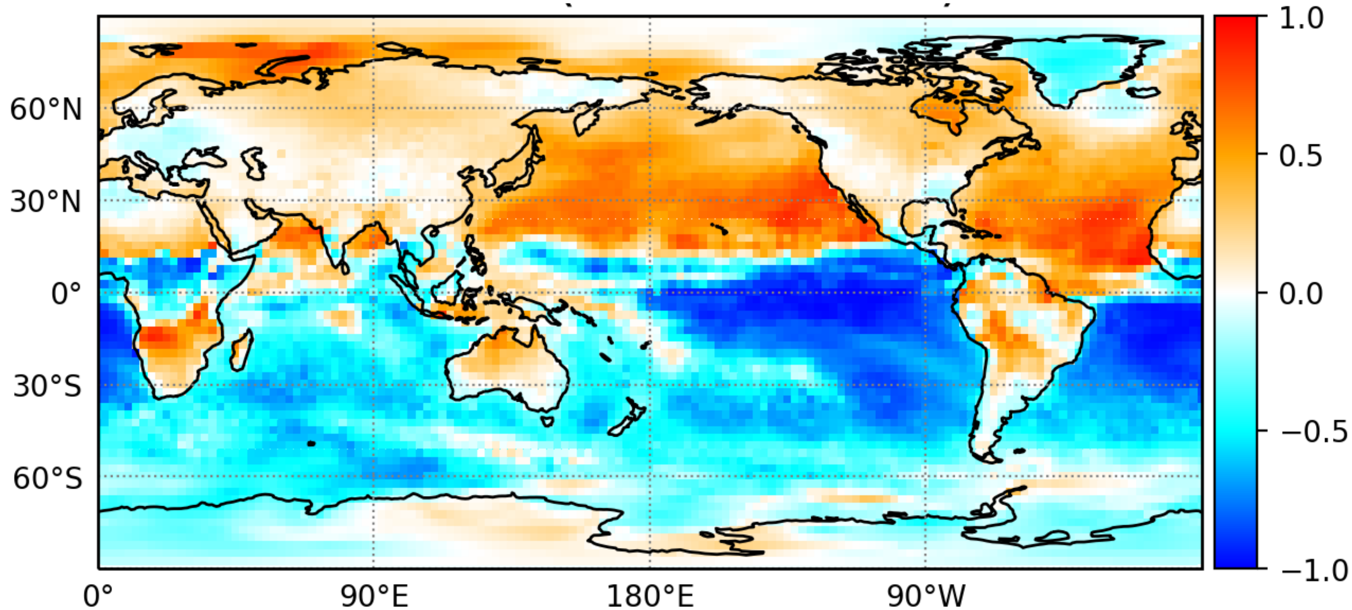
El Niño period
(October 2015)



La Niña period
(Octubre 2011)



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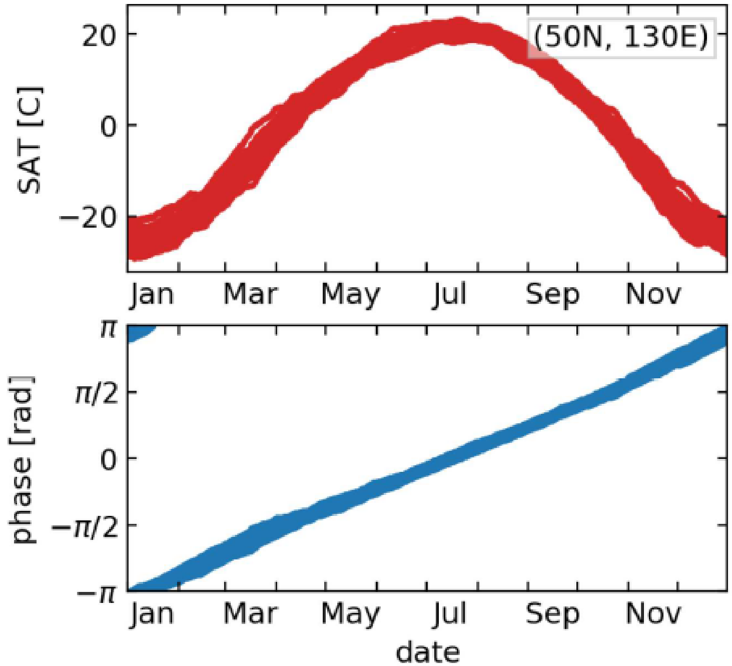
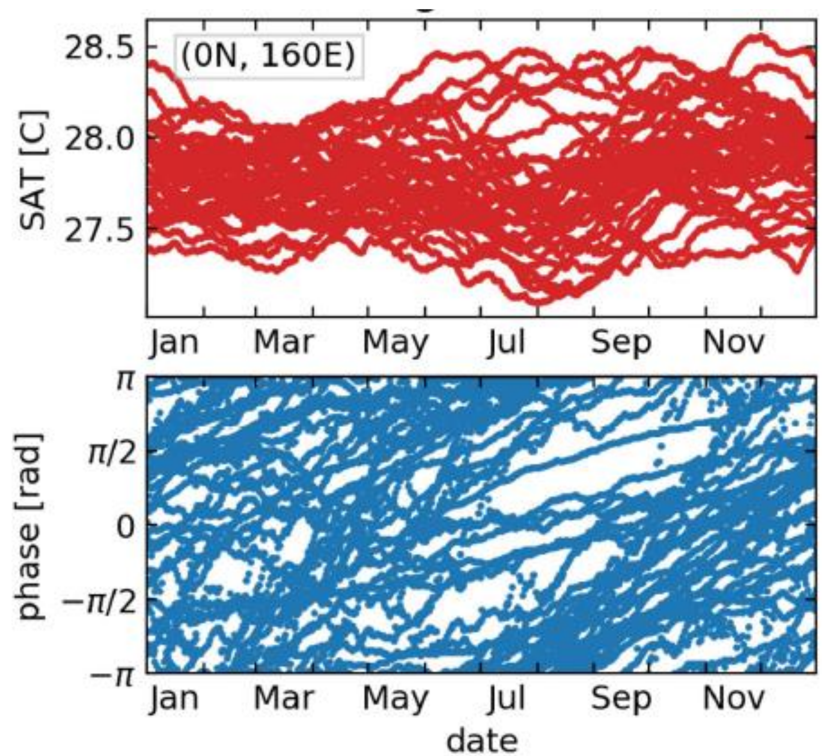
Hilbert phase vs day of the year (1979 – 2016)



in a continental
“regular” region / node



And in an irregular region?

D. A. Zappala, M. Barreiro, C. Masoller, Chaos 29, 051101 (2019).

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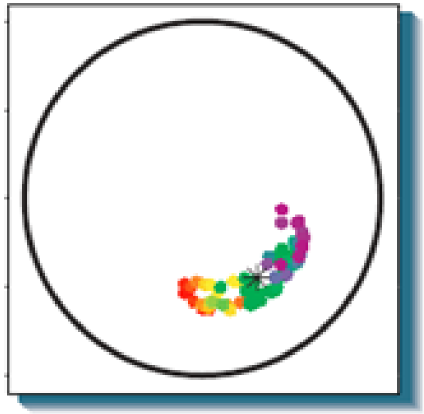
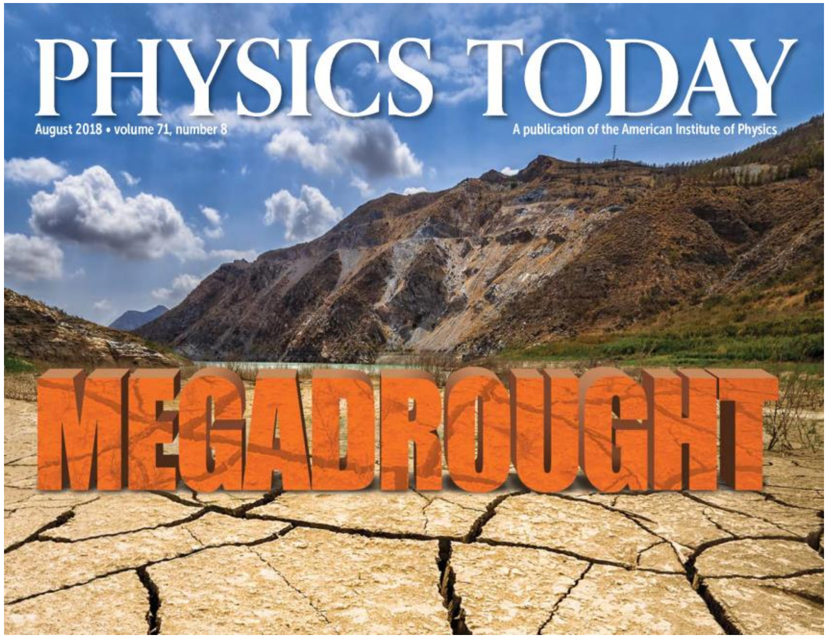
Questions?

1) Can we use the Hilbert amplitude, phase, frequency, to identify and quantify regional "climate change"?

2) Can we identify and quantify synchronized oscillations?





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Relative decadal variations in each region ("node")

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

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

Relative variation is considered **significant** if:

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

100 "surrogates"

G. Lancaster et al, "Surrogate data for hypothesis testing of physical systems", Physics Reports 748, 1 (2018).

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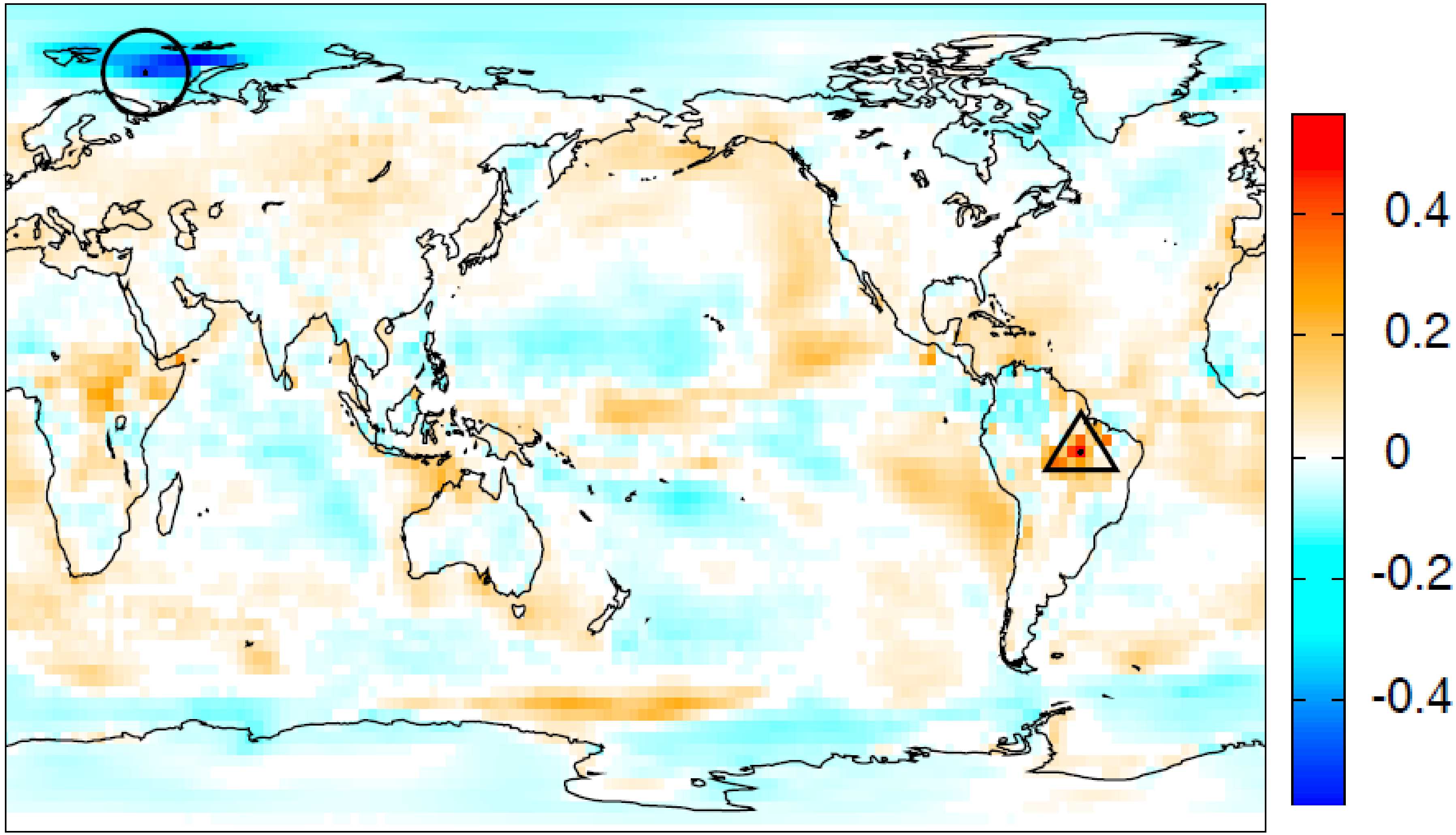
Relative decadal variations



D. A. Zappala, M. Barreiro, C. Masoller, Earth Syst. Dynamics 9, 383 (2018)

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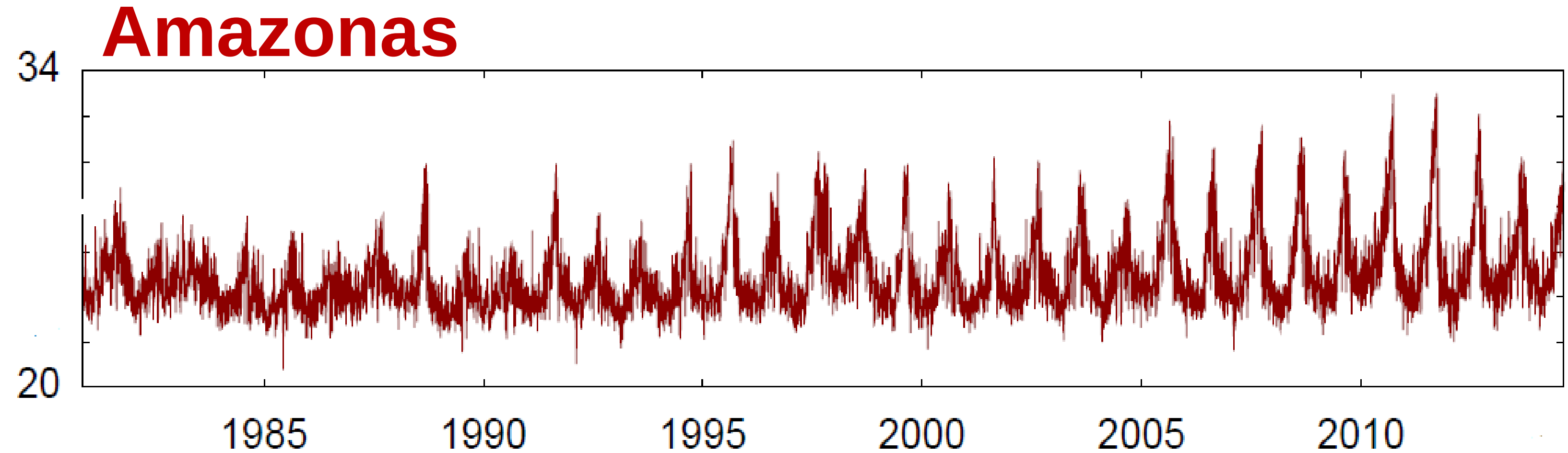

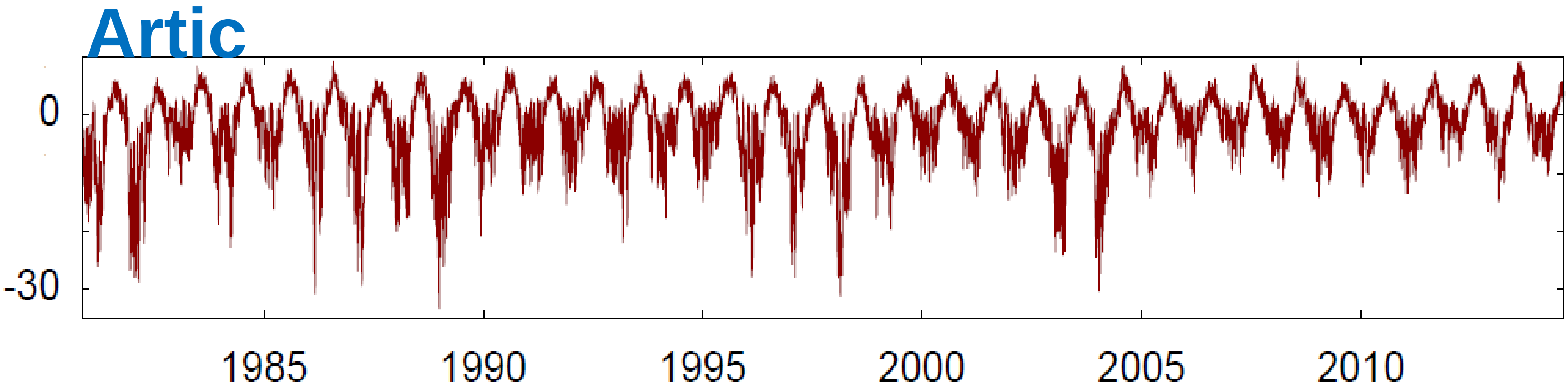

- **Decrease of precipitation**: the solar radiation that is not used for evaporation is used to heat the ground.

- **Melting of sea ice**: during winter the air temperature is mitigated by the sea and tends to be more moderated.

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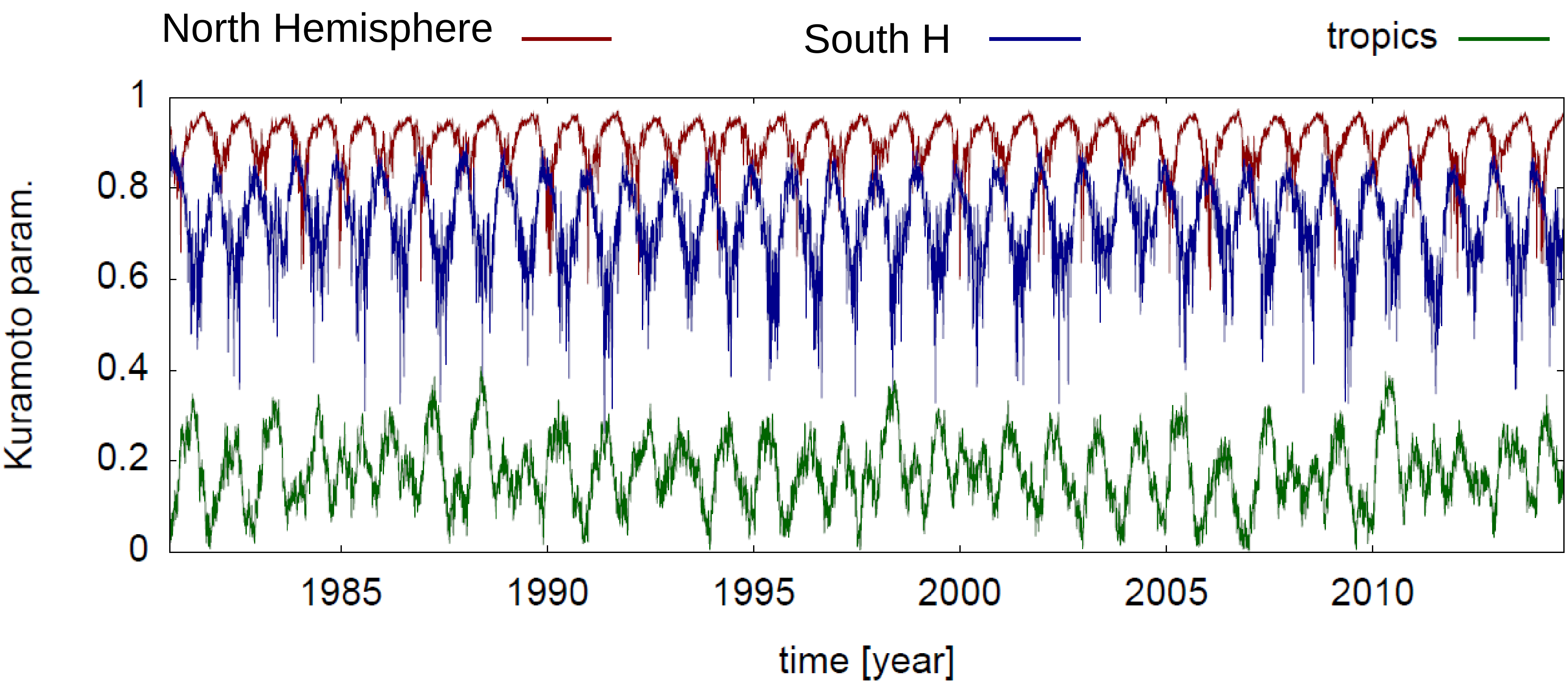
Quantifying synchronization of air temperature oscillations

Kuramoto order parameter

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



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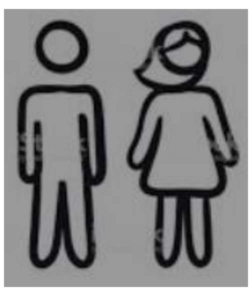
2) “Bivariate” time-series analysis tool: pseudo Transfer Entropy (pTE)



- For time series with a distribution of values that is approximately Gaussian
- It provides “causal” information (whether or not knowledge of Y improves the forecast of X)

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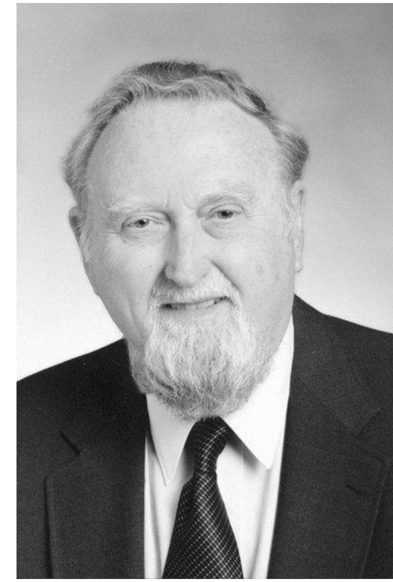
Granger Causality



Hypothesis: X_1 and X_2 can be described by autoregressive linear models

past of X_1 — Residual error

$$X_1(t) = \sum_{j=1}^{p} A_{11,j}\, X_1(t-j) \qquad + E_1(t)$$

past of X_1 — past of X_2 — Residual error

$$X_1(t) = \sum_{j=1}^{p} A_{11,j}\, X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + E'_1(t)$$

If $\langle E'_1(t)\rangle < \langle E_1(t)\rangle$ ➡ $X_2 \rightarrow X_1$

Granger, C. W. J. *Investigating causal relations by econometric models and cross-spectral methods*. *Econometrica* 37, 424–438 (1969).

Software: Fulton, C, https://github.com/statsmodels/statsmodel (2020)

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Entropy (disorder) and information

HIGH entropy LOW information

LOW entropy HIGH information

https://imgur.com/gallery/Otg97

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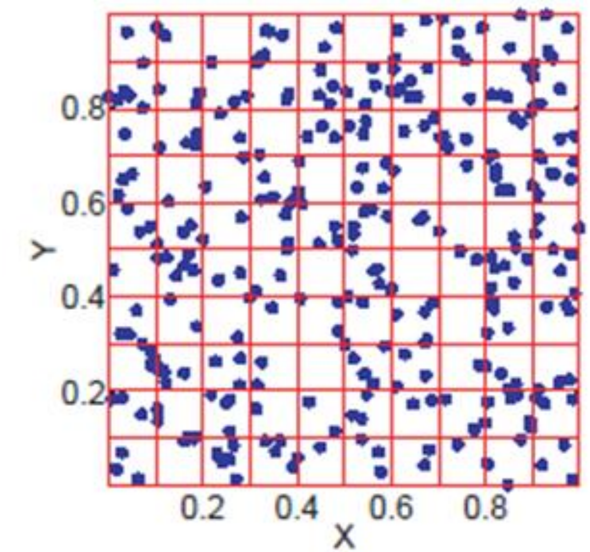
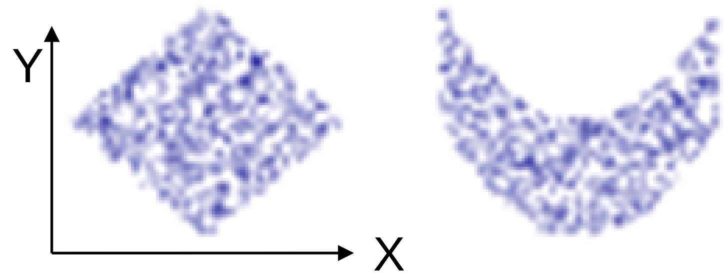
Mutual Information (MI)



Quantifies the reduction in uncertainty of one variable by knowing the other variable.



- *MI is calculated from probability distributions, p(X), p(Y) and p(X,Y)*
- *If X, Y are independent, MI = 0*, else ***MI >0***
- For Gaussian distributions: MI = $-1/2 \log(1-\rho^2)$

where ρ is the cross-correlation coefficient.

K. Hlaváčková-Schindler et al. / Physics Reports 441 (2007) 1–46

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Transfer Entropy (TE) and Directionality Index (DI)

- TE: is the Conditional Mutual information, given the "past" of one of the variables.

$$TE\ (x,y) = MI\ (x,\ y|x_{\tau})$$

$$TE\ (y,x) = MI\ (y,\ x|y_{\tau})$$

- MI (x,y) = MI (y,x) but TE (x,y) $\neq$ TE(y,x)

- Directionality Index: TE(x,y)-TE(y,x)

K. Hlaváčková-Schindler et al. / Physics Reports 441 (2007) 1–46

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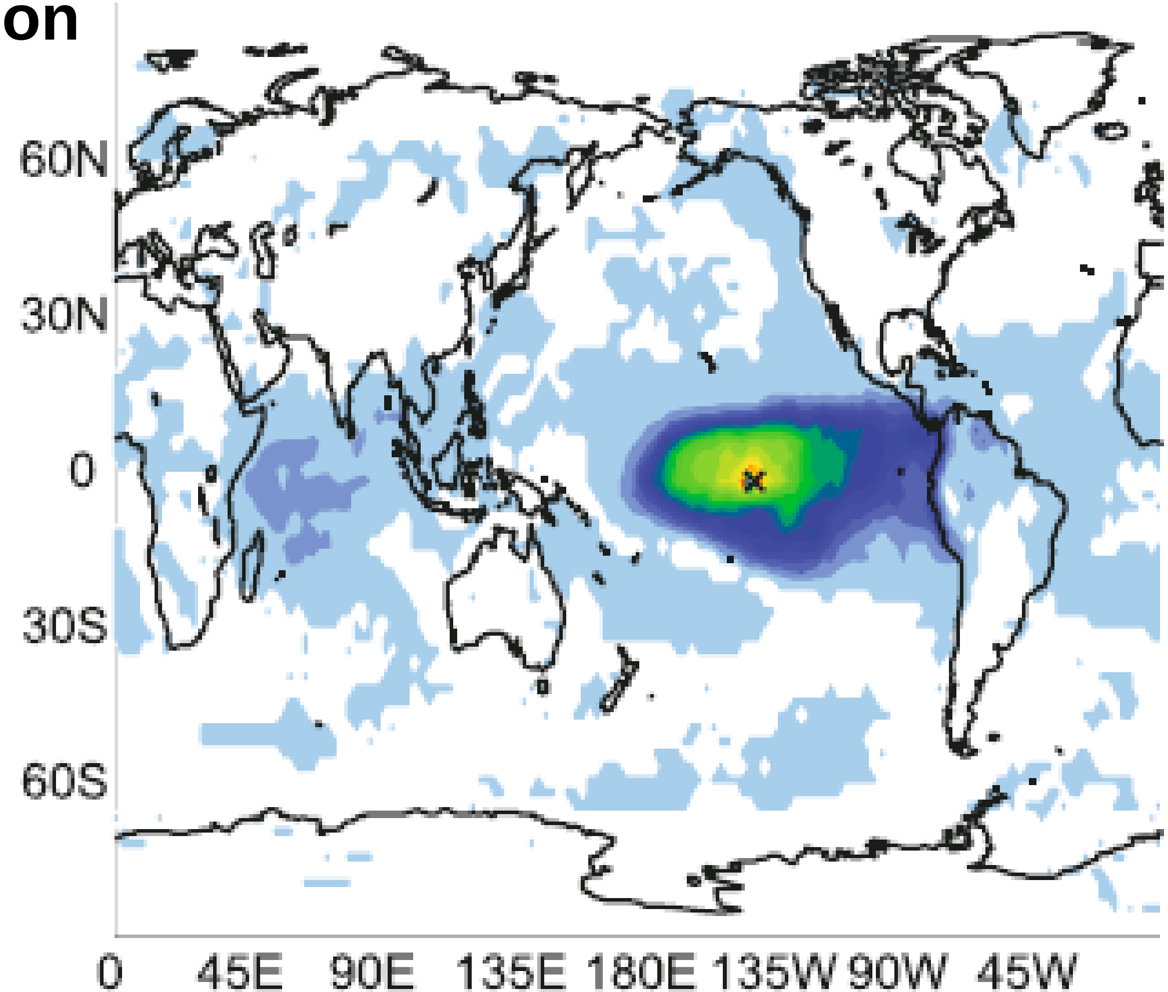
Analysis of surface air temperature anomalies: Mutual Information



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).

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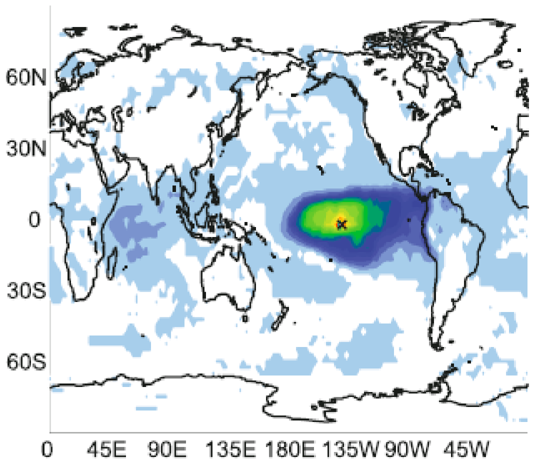
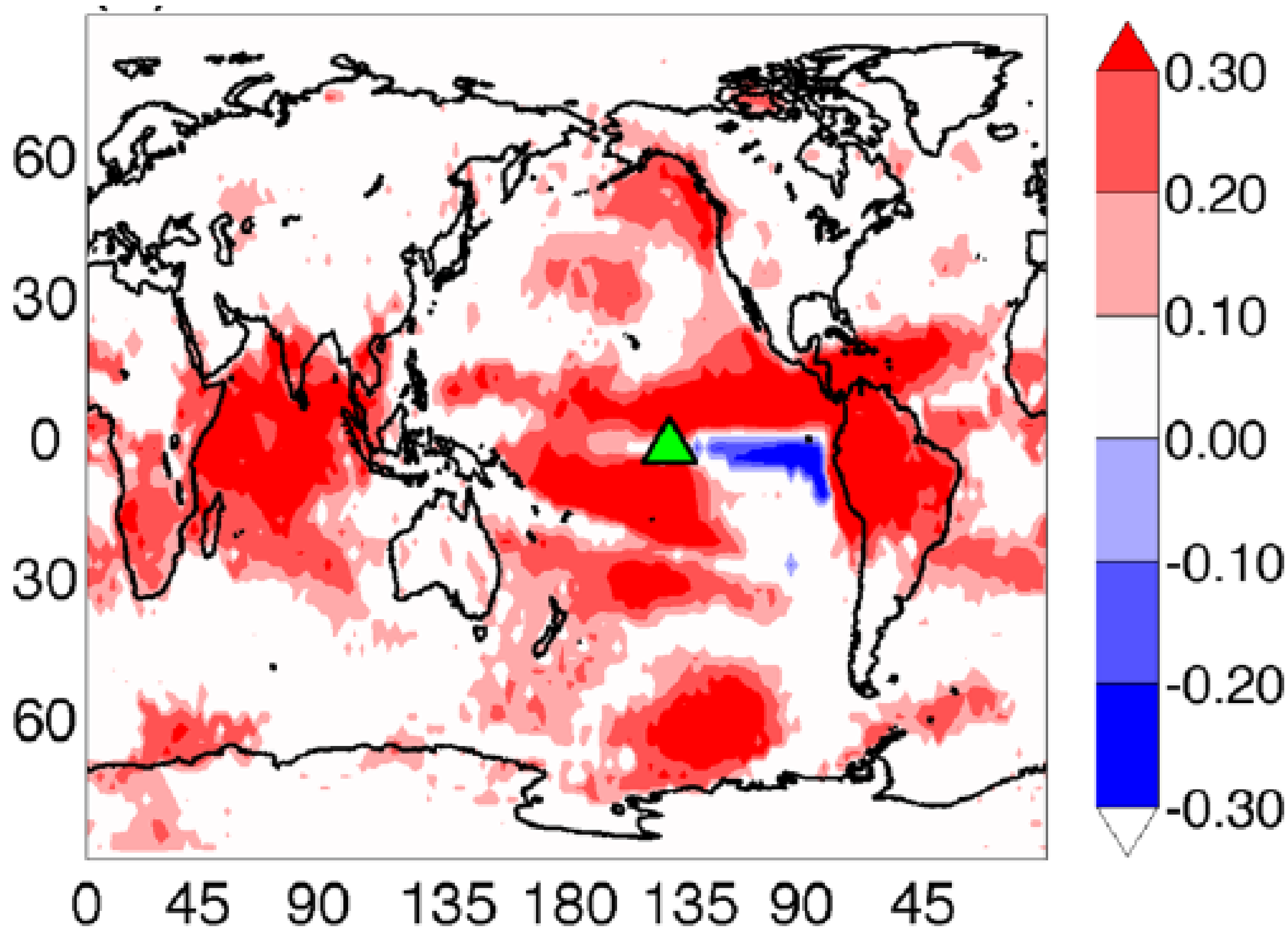
Analysis of surface air temperature anomalies: Directionality Index





J. I. Deza, M. Barreiro, and C. Masoller, Chaos 25, 033105 (2015).

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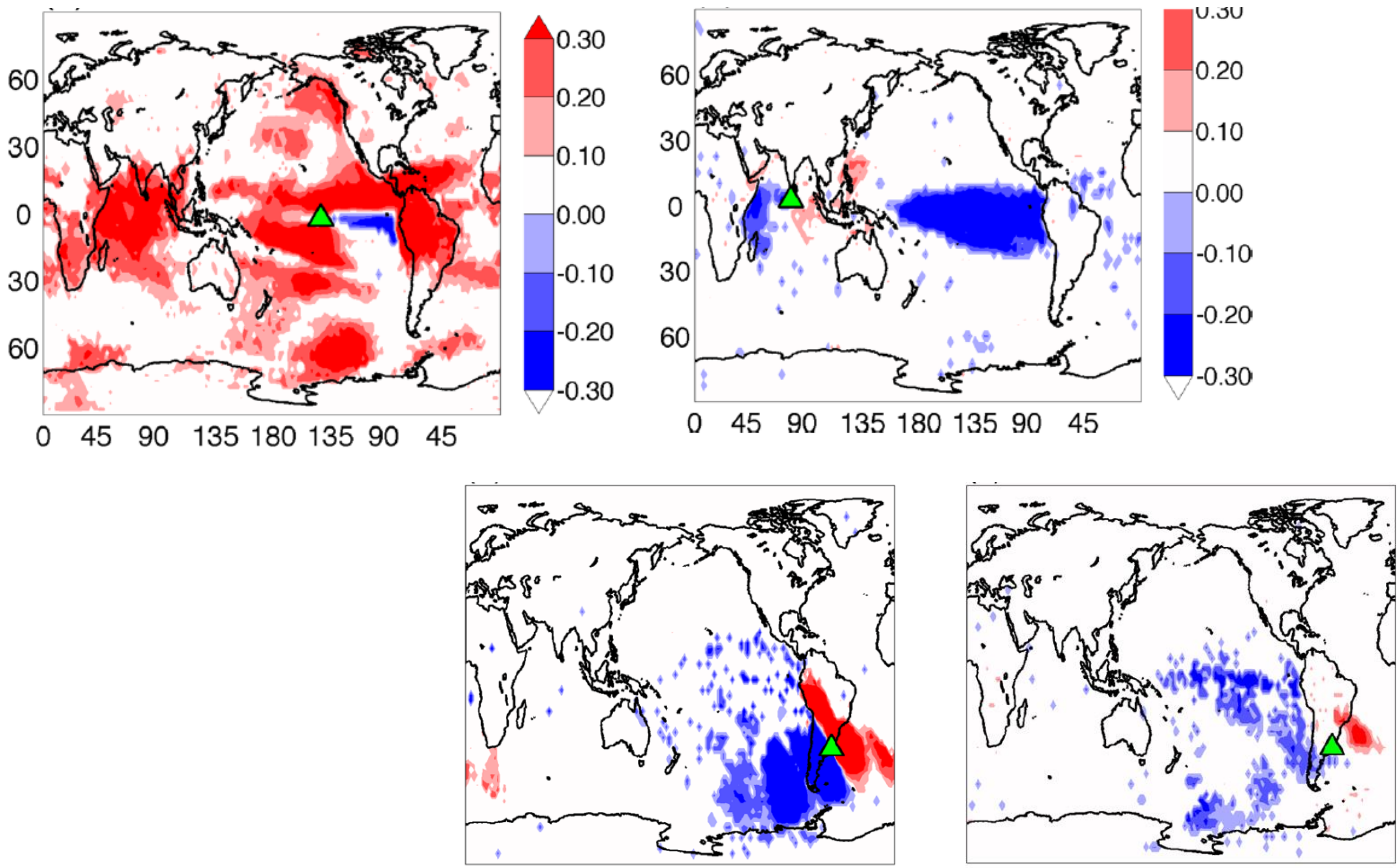
Analysis of surface air temperature anomalies: Directionality Index



J. I. Deza, M. Barreiro, and C. Masoller, Chaos 25, 033105 (2015).

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Problem: Transfer Entropy is computationally demanding

"simple" solution: use the expression that is valid for Gaussian distributions [MI = $-1/2 \log(1-\rho^2)$]

Does this work? Check it out:

scientific reports

Check for updates

OPEN **Fast and effective pseudo transfer entropy for bivariate data-driven causal inference**

Riccardo Silini & Cristina Masoller

https://doi.org/10.1038/s41598-021-87818-3

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Data Generating Processes and Performance Quantification

Power: True Positives

Size: False Positives

	Model	
Y X	M0 M1 M2	$x_t = (0.01 + 0.5\, x_{t-1}^2)^{0.5} + E_{1t}$ $\quad y_t = 0.5\, y_{t-1} + E_{2t}$
Y → X	M3 M4 M5 M6 M7 M8 M9 M10 M11 M12	$x_t = 0.6\, x_{t-1} + 0.5\, y_{t-1} + E_{1t}$ $\quad y_t = 0.5\, y_{t-1} + E_{2t}$
Y ⇆ X	M13 M14	$x_t = 0.15\, x_{t-1} + 0.7\, y_{t-1} + E_{1t}$ $y_t = 0.1\, y_{t-1} + 0.8\, x_{t-1} + E_{2t}$

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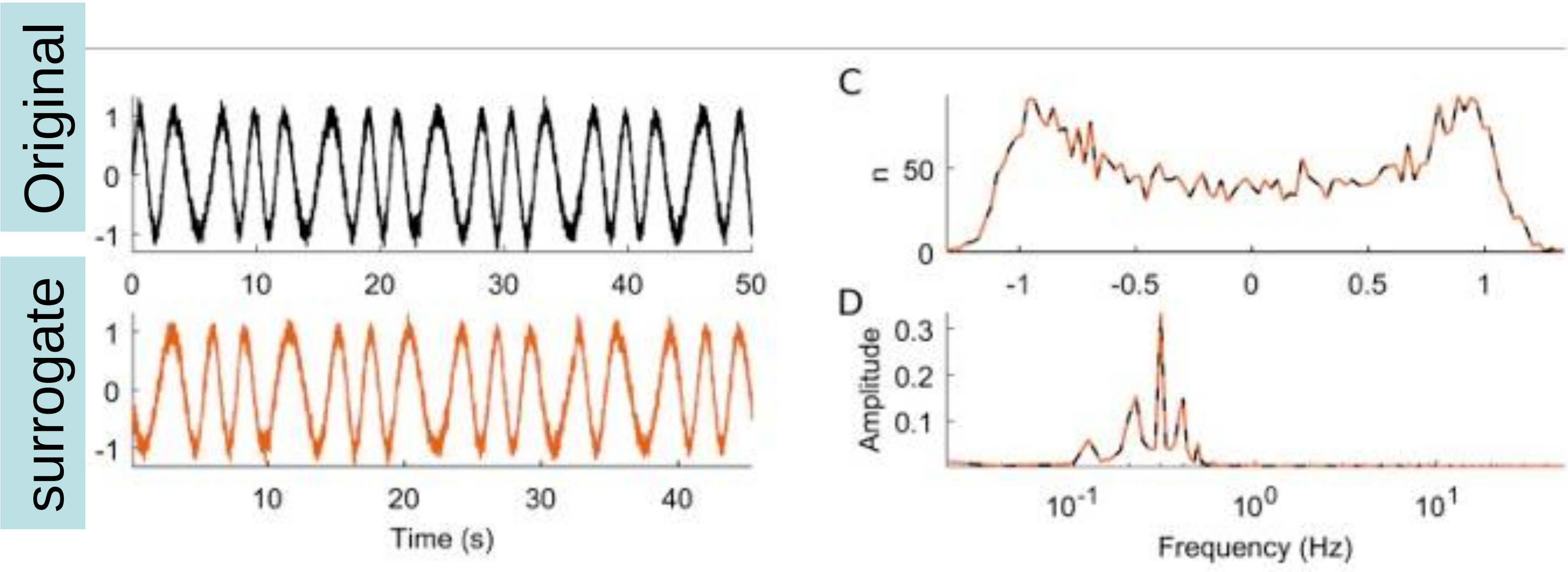
Time-shifted surrogates: “cheap” option for causality testing



Quiroga R.Q., Kraskov A., Kreuz T., Grassberger P. *Performance of different synchronization measures in real data: A case study on electroencephalographic signals,* Phys. Rev. E, 65 (4) (2002)

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Results

	Model	pTE	
		$Y \rightarrow X$	$X \rightarrow Y$
	M0	3.8	3.9
Y X	M1	2.3	2.6
	M2	4.2	4.7
	M3	100	4.5
	M4	80.7	3.8
	M5	100	2.2
	M6	100	1.8
	M7	100	2.8
$Y \rightarrow X$	M8	100	4.5
	M9	100	0.1
	M10	62.6	3.1
	M11	46.1	43.1
	M12	99.9	1.0
	M13	100	100
$Y \leftrightarrows X$	M14	100	100

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Comparison with Granger Causality and Transfer Entropy

	Model	pTE		GC		TE		DI		
		$Y \to X$	$X \to Y$	$Y \to X$	$X \to Y$	$Y \to X$	$X \to Y$	pTE	GC	TE
	M0	3.8	3.9	5.1	5.0	4.4	4.4	−0.01	0.01	0.00
Y X	M1	2.3	2.6	3.3	3.1	100	100	−0.06	0.03	0.00
	M2	4.2	4.7	5.5	5.9	4.7	4.9	−0.06	−0.04	−0.02
	M3	100	4.5	100	4.8	70.2	5.6	0.91	0.91	0.85
	M4	80.7	3.8	84.2	4.9	96.0	4.7	0.91	0.89	0.91
	M5	100	2.2	100	3.1	100	3.8	0.96	0.94	0.93
	M6	100	1.8	100	2.8	100	4.3	0.96	0.95	0.92
	M7	100	2.8	100	3.4	100	4.0	0.95	0.93	0.92
$Y \to X$	M8	100	4.5	100	5.6	100	100	0.91	0.89	0.00
	M9	100	0.1	100	0.1	100	100	1.00	1.00	0.00
	M10	62.6	3.1	67.3	4.3	12.2	4.5	0.91	0.88	0.46
	M11	46.1	43.1	53.1	49.8	37.8	45.0	0.03	0.03	−0.09
	M12	99.9	1.0	100	0.9	100	0	1.0	1.0	1.0
	M13	100	100	100	100	100	100	0.00	0.00	0.00
$Y \leftrightarrows X$	M14	100	100	100	100	100	100	0.00	0.00	0.00

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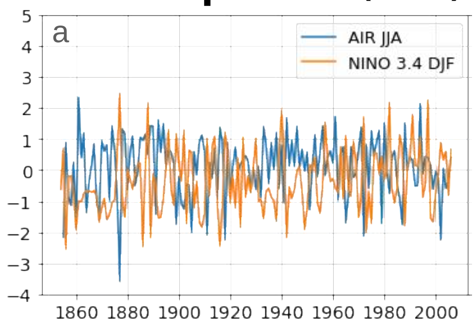
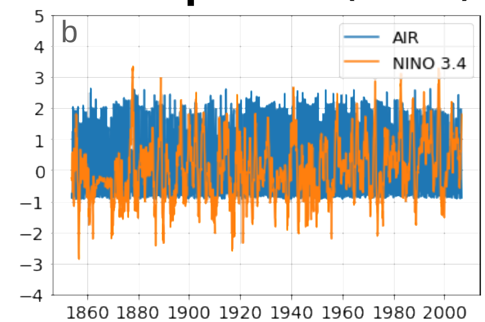
Application to real data NINO3.4 ← → All India Rainfall

Yearly sampled (152)



Monthly sampled (1836)



IAAF

	Yearly sampled (152)	Monthly sampled (1836)
pTE	**NINO3.4 ⟶ AIR** 0.04 s	**NINO3.4 ⟵ AIR** 0.5 s
GC	**NINO3.4 ⟶ AIR** 0.4 s	**NINO3.4 ⟵ AIR** 0.9 s
TE	**NINO3.4 ⇆ AIR** 1 s	**NINO3.4 ⇆ AIR** 68 s

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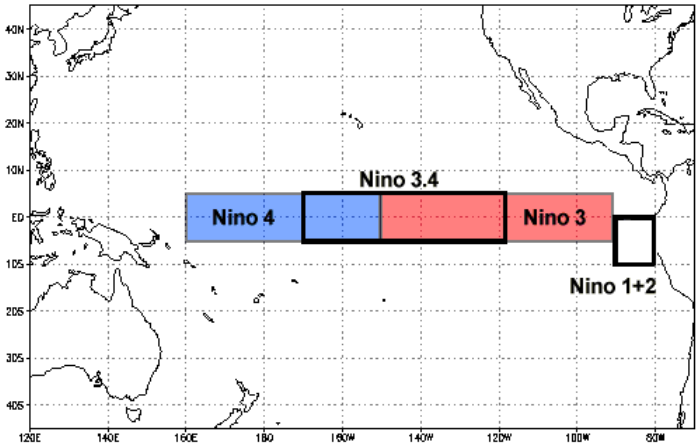
How much time can we save?

For two time-series of 500 data points (1 data point per month, 40 years):

TE:**112 ms** but pTE: **4 ms**



8000 grid points (high resolution)

$\Rightarrow$ 64 x 10^6 pairs

$\Rightarrow$ **829 days** (TE) vs. **29 days** (pTE).

(without “surrogate” analysis)

But, there is a price to pay, no “free lunch”.

https://github.com/riccardosilini/pTE

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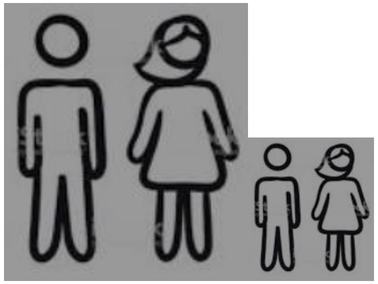
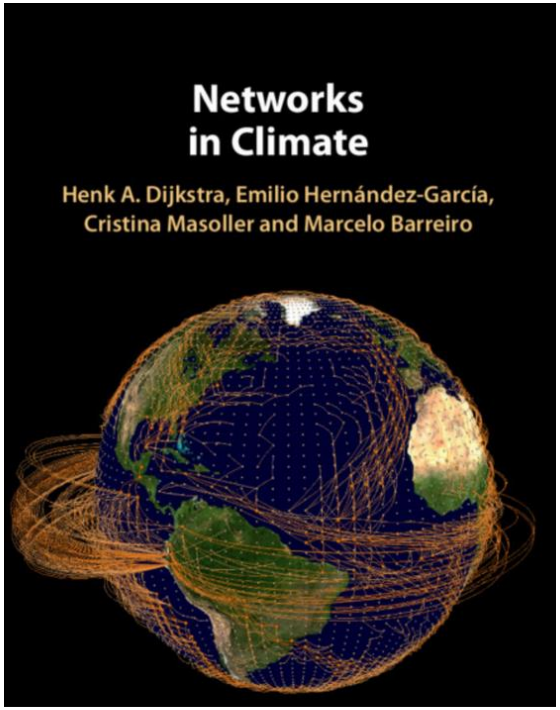
3) "Multivariate" time-series analysis





Cambridge University Press 2019

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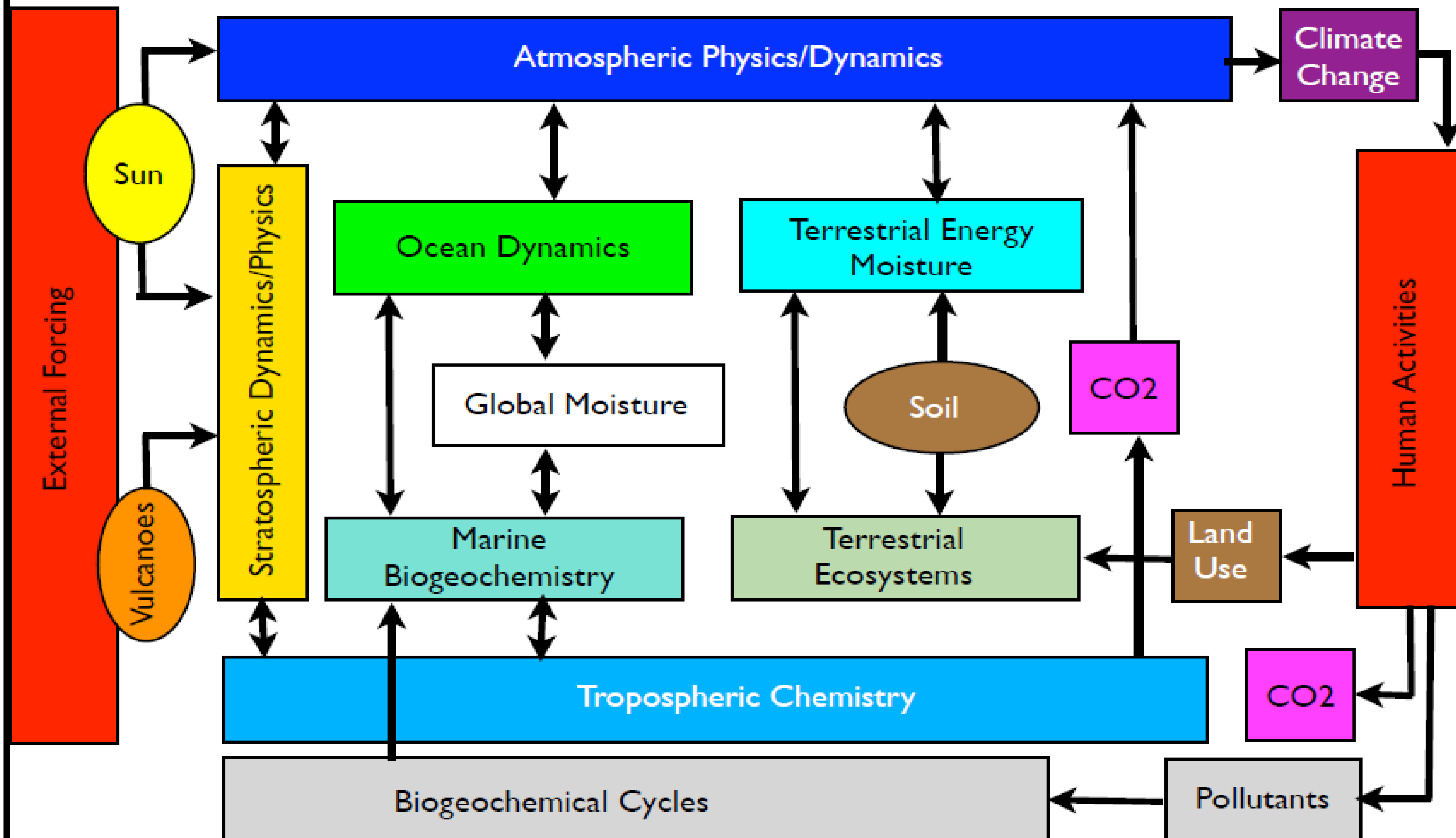
The Climate System



Courtesy of Henk Dijkstra (Ultrech University)

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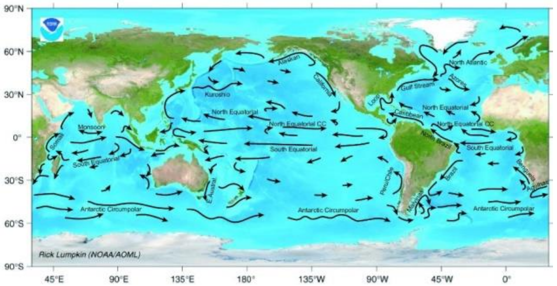
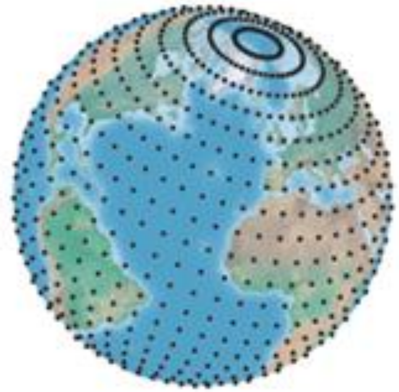
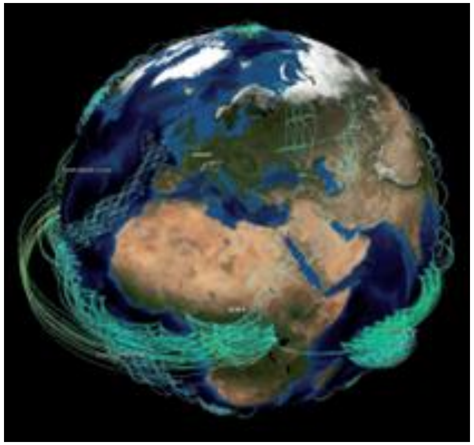
Complex network representation of the climate system

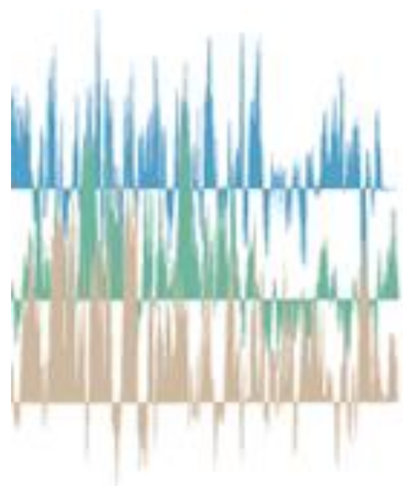




More than 10000 nodes.

Back to the climate system: interpretation (currents, winds, etc.)





Daily resolution: more than 13000 data points in each time series

J. F. Donges et al, Chaos 25, 113101 (2015).

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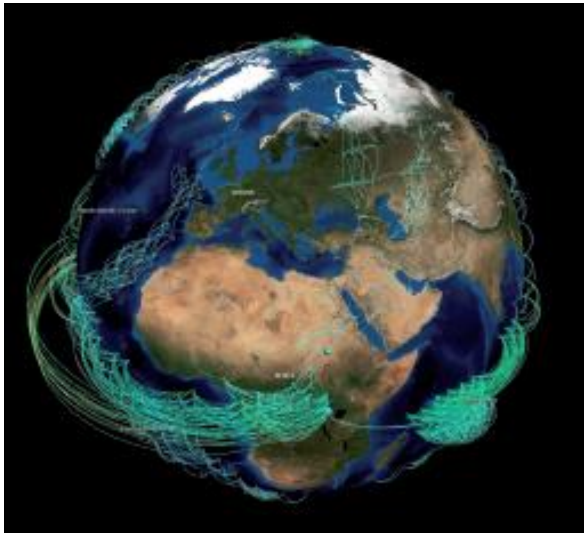
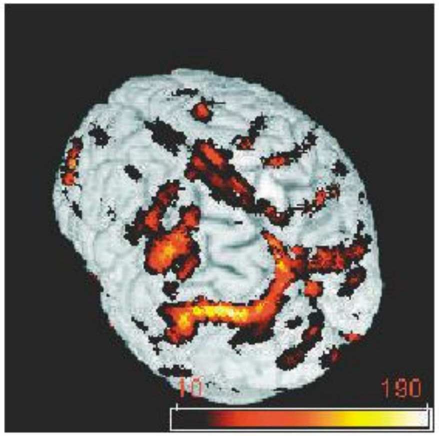
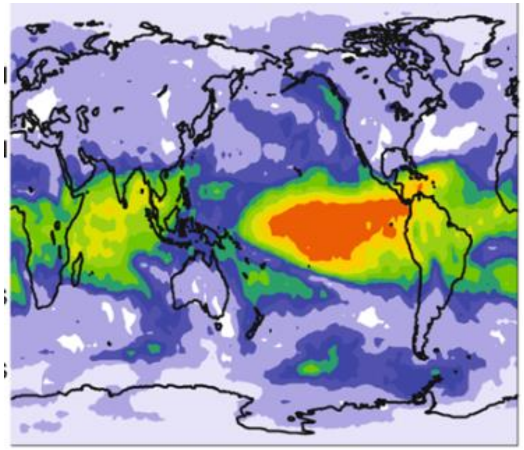
Brain network

Climate network





“Degree”
(number of links)



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In the analysis of climate data, depending on temporal resolution, lags need to be taken into account

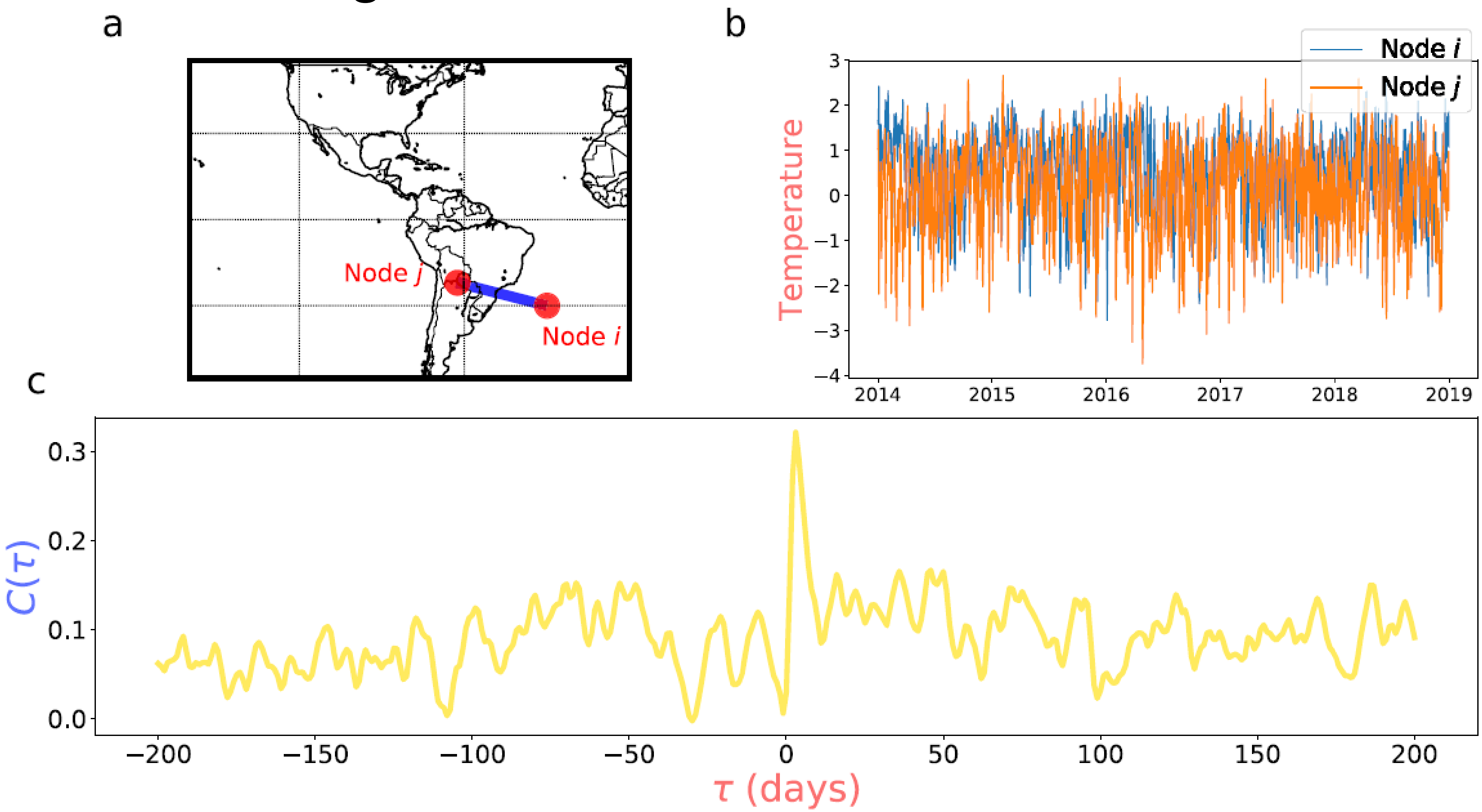

Fig. 6. Typical weighted and directed link in a Pearson Correlation Climate Network. (a) Node i is located on the Southwest Atlantic and node j is in the South American continent. (b) The near surface daily air temperature anomalies for the period [2014,2018]. (c) The cross-correlation function between the time series shown in (b). The direction of this link is from j to i with weight $W^{+}_{i,j} = 5.71$.

J. Fan, J. Meng, J. Ludescher et al. Physics Reports 896, 1 (2021).

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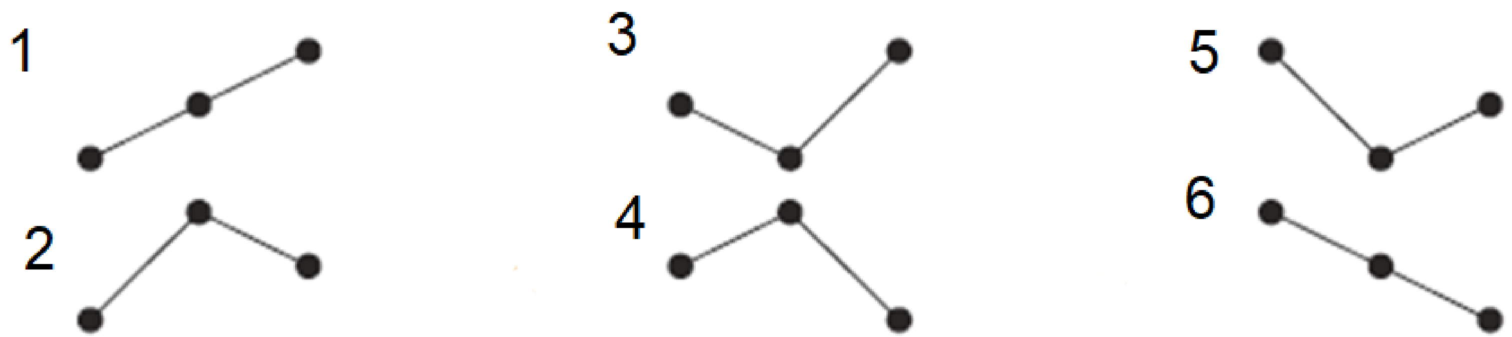
Ordinal analysis provides a nonlinear way to consider lags

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

How can three data points (let's say 2, 5, 7) be ordered?

{…2, 5, 7…} {…5, 2, 7…} {…7, 2, 5 …}



{…2, 7, 5…} {…5, 7, 2…} {…7, 5, 2…}

Bandt and Pompe: Phys. Rev. Lett. 2002

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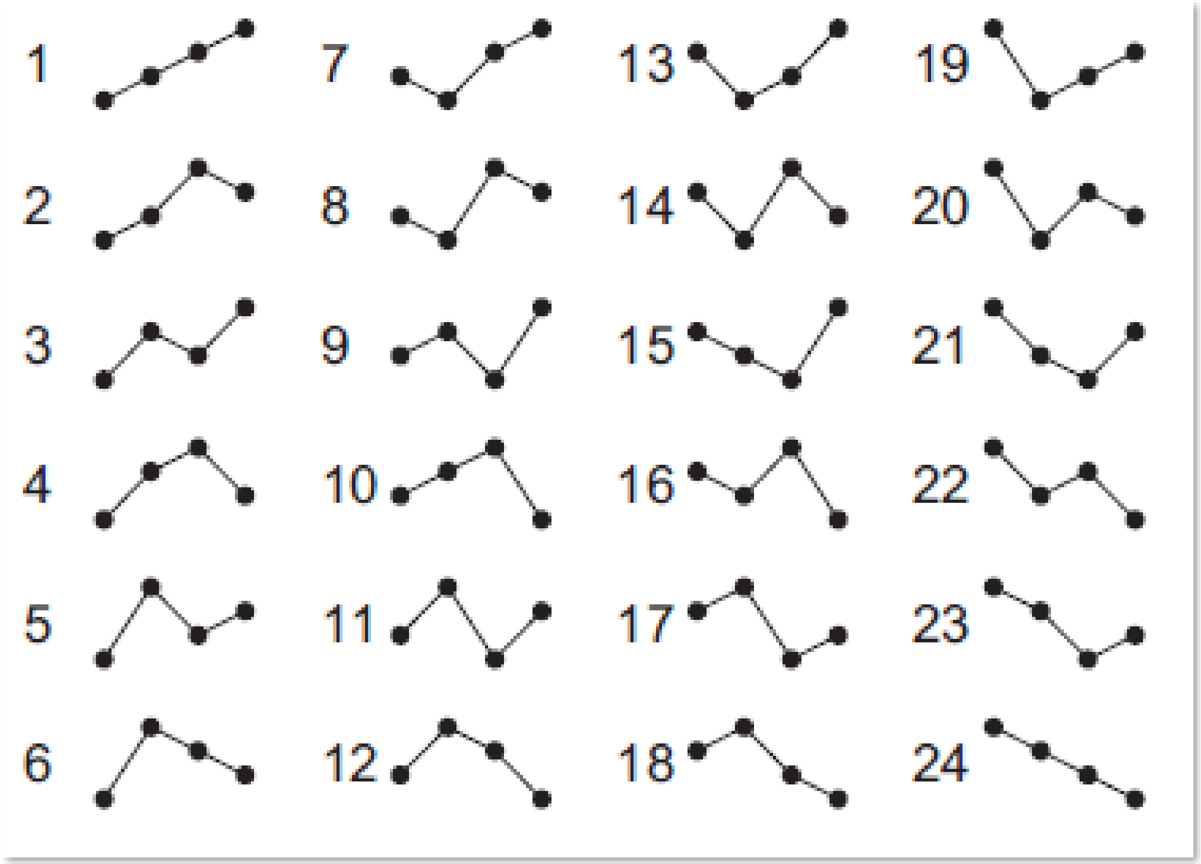
How many possibilities for ordering four data points ?
$\{\ldots x_i, x_{i+1}, x_{i+2}, x_{i+3}, \ldots\}$



Python and Matlab codes for computing the ordinal pattern index available at:
U. Parlitz et al. Computers in Biology and Medicine 42, 319 (2012)

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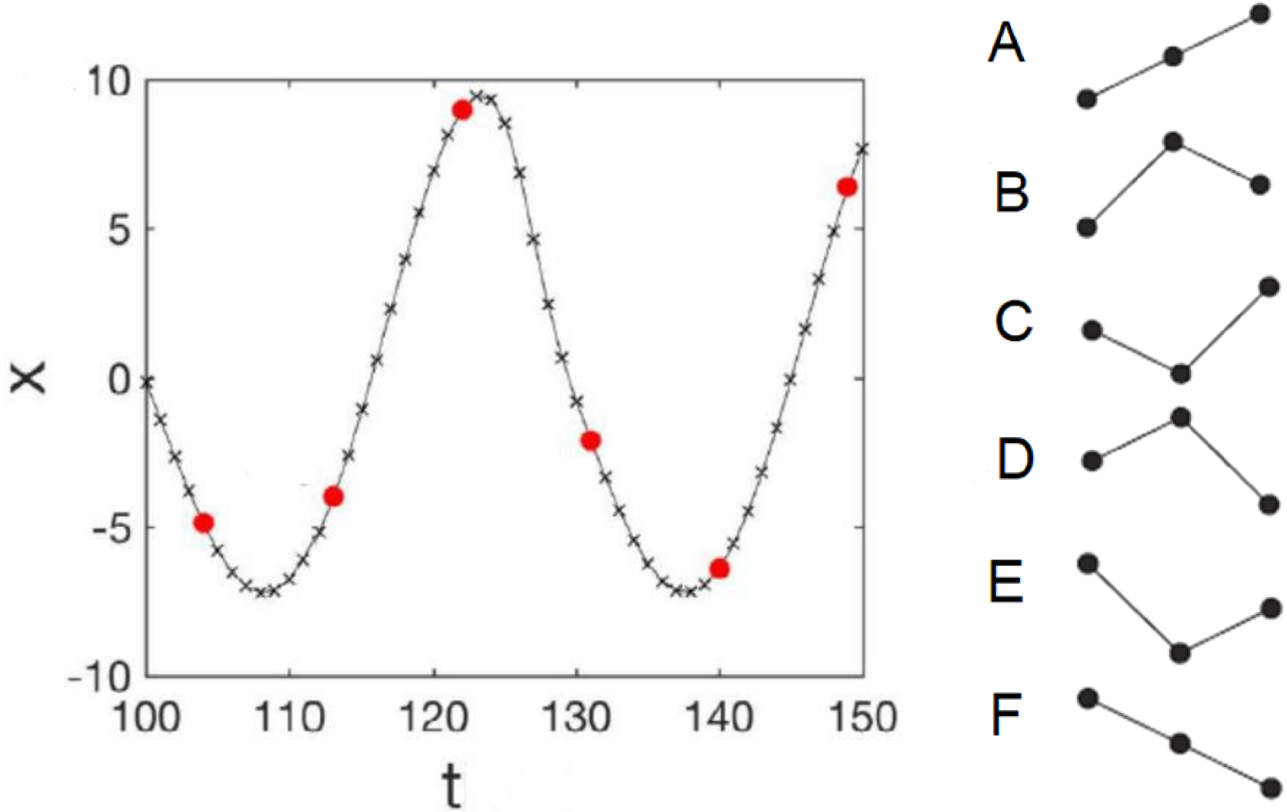
Which is the "message" "encoded" in the red dots?

s={A, B, F, C}



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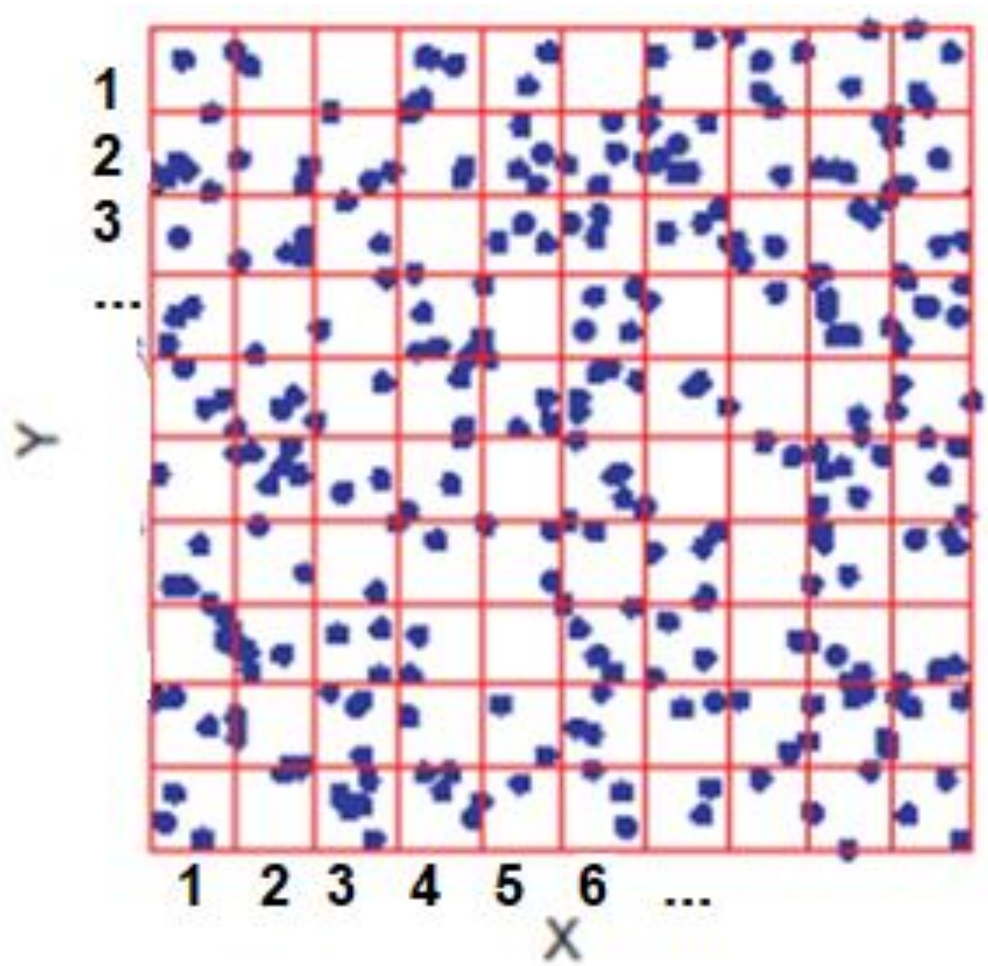
Given two time series, X and Y, we can compute each sequence of "ordinal" patterns, s_x and s_y, and then, their mutual "ordinal" information.



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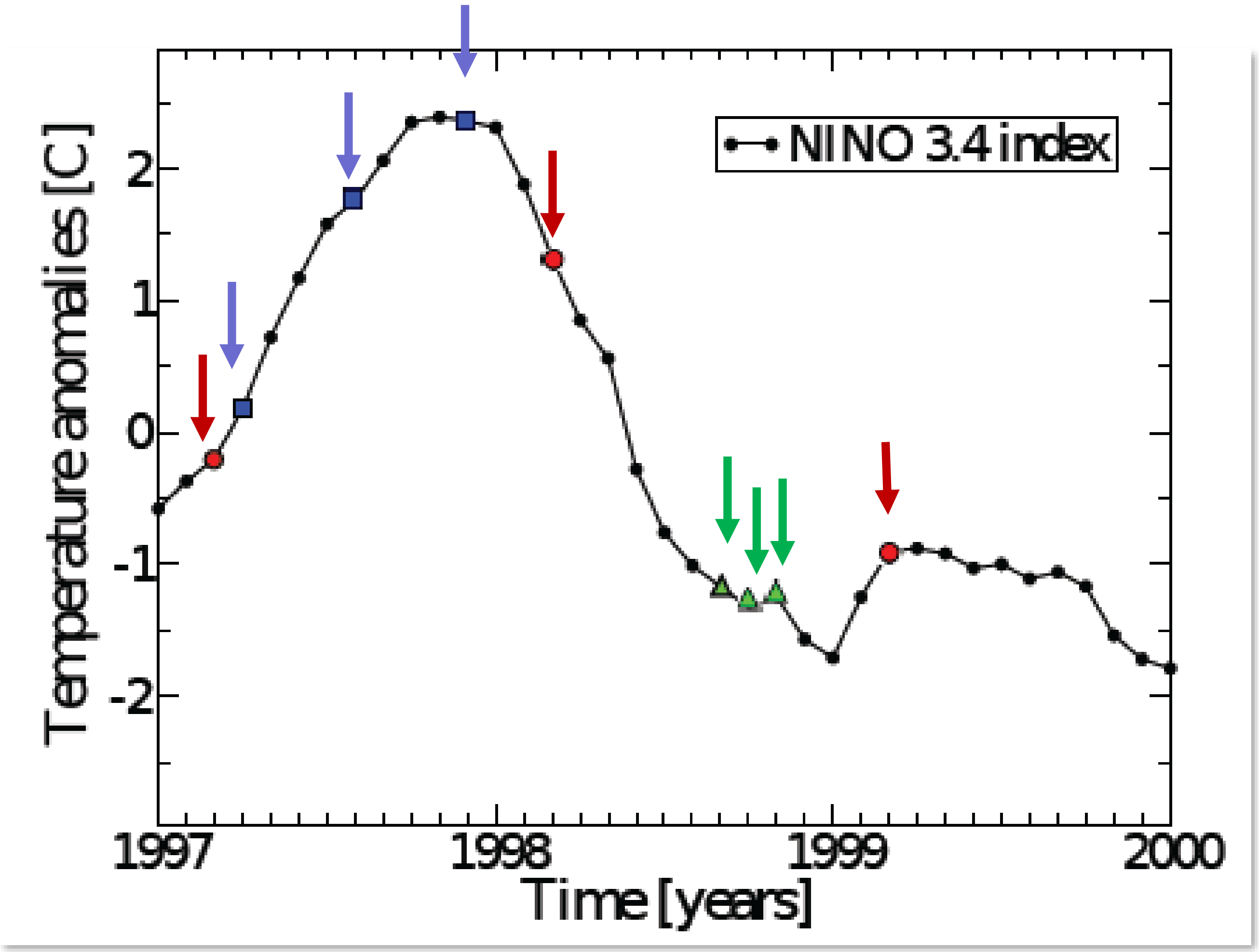
Ordinal analysis allows to study different time scales

Intra-season
102

Intra-annual
012

Inter-annual
120



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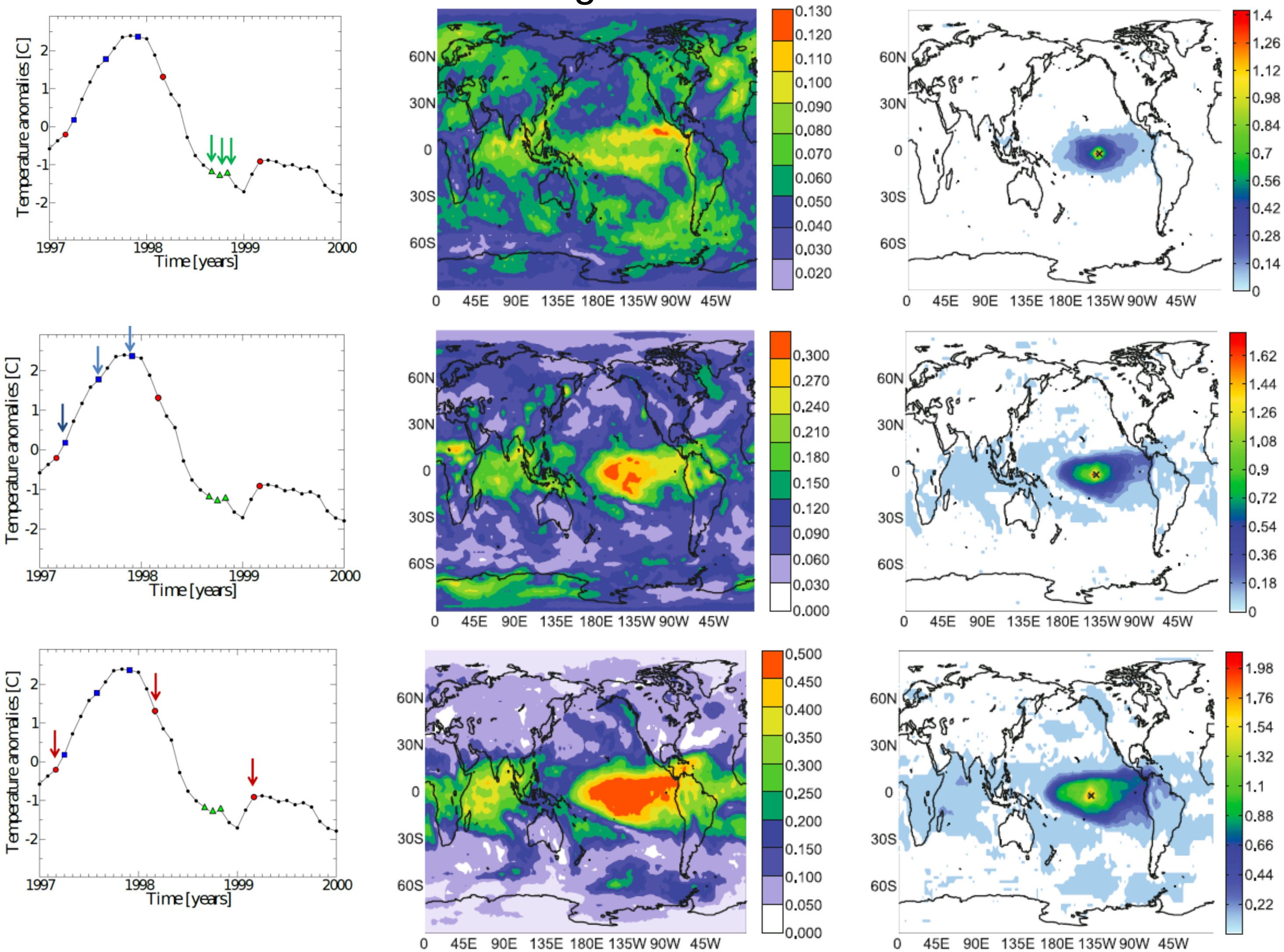
Ordinal analysis detects teleconnections with different “time-scales”

Degree

Links of a node in El Niño area



Longer time-scale ⇒ increased connectivity

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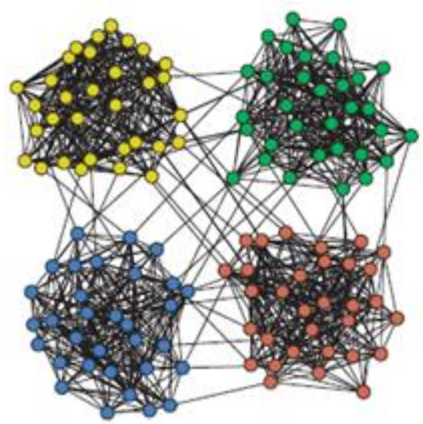
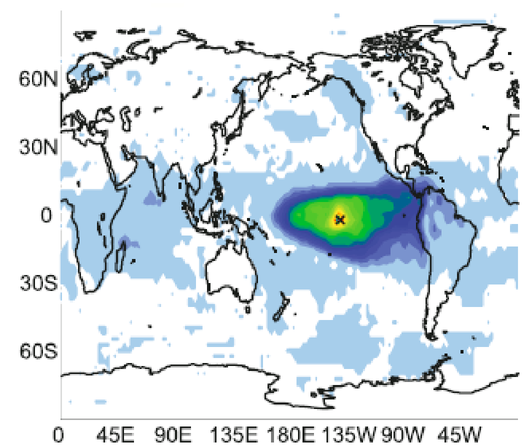
Climate "communities"

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" correlation-based method to construct the network because NH and SH are only indirectly connected.



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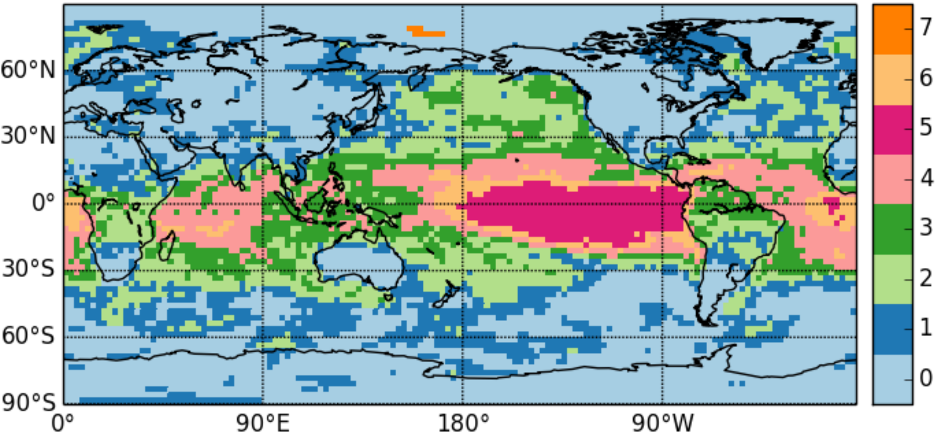
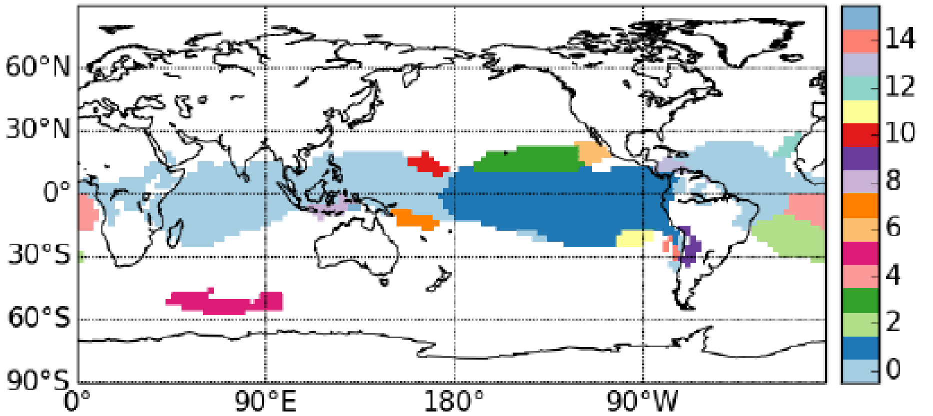
Results

Ordinal Network



Correlation network

(only the largest 16 communities)



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).

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Summarizing

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Take home messages

- Many measures are available to uncover inter-relationships in datasets.
- Each dataset has its own peculiarities.
- Different measures can uncover different properties.
- Hidden variables, hidden “nodes”, common “drivers” can make impossible to understand the network structure.
- Network science: many applications and challenges!

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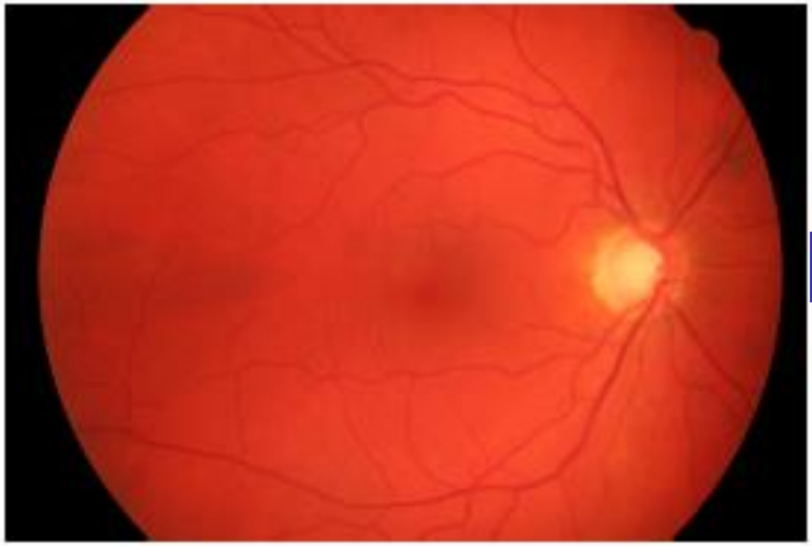
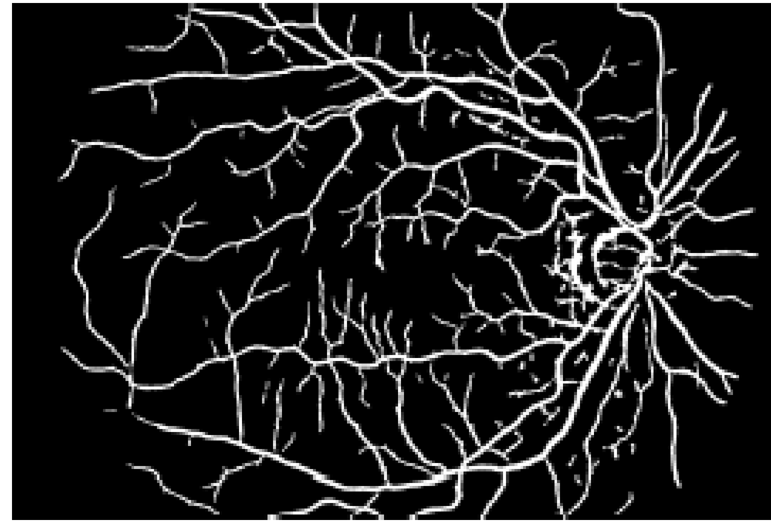
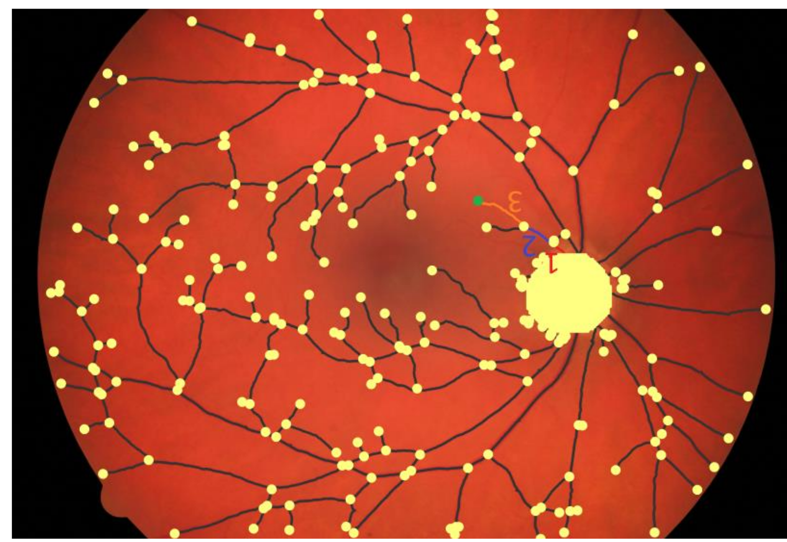
“Extra bonus”: application of network science to fundus image analysis







P. Amil et al., PLoS ONE 14, e0220132 (2019).

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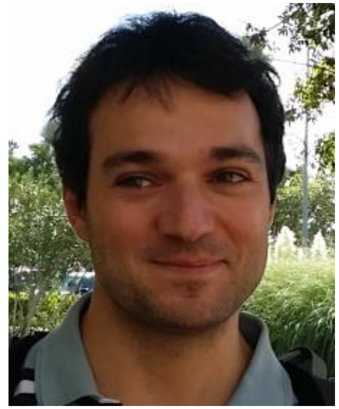
THANKS TO

Ignacio Deza

Giulio Tirabassi



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Thank you for your attention

Slides: http://www.fisica.edu.uy/~cris/enredando.pdf

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