REUNIÓN DE LA ASOCIACIÓN FÍSICA ARGENTINA
110ª RAFA
LA PLATA 2025
SEPTIEMBRE 15 - 18

Tercera Reunión Conjunta AFA-SUF
15-18 de septiembre de 2025
La Plata, Argentina

Sociedad Uruguaya de Física

Metodologías de análisis de datos no lineales para la investigación de sistemas complejos

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BARCELONATECH
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MINISTERIO DE CIENCIA E INNOVACIÓN

AIR FORCE OFFICE OF SCIENTIFIC RESEARCH
UNITED STATES AIR FORCE

Presentation (1/2)

- Bachelor and Master degrees in Montevideo, Uruguay (1986-1991).
- Master thesis co-supervised by Prof. Lilia Romanelli (UBA).

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URUGUAY

Physics Letters A 167 (1992) 185–190
North-Holland

PHYSICS LETTERS A

Regular and chaotic behavior in the new Lorenz system

C. Masoller, A.C. Sicardi Schifino
Instituto de Fisica de la Facultad de Ciencias, T. Narvaja 1674, Montevideo, Uruguay
and Instituto de Fisica de la Facultad de Ingenieria, J. Herrera y Reissig 565, CC30, Montevideo, Uruguay

and

Lilia Romanelli
Departamento de Fisica, F.C.E. y N. (U.B.A.), Ciudad Universitaria (1428), Buenos Aires, Argentina

Received 21 August 1991; revised manuscript received 11 May 1992; accepted for publication 13 May 1992

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Presentation (2/2)

- Bachelor and Master in Uruguay (1986-1991).

- PhD in Laser Physics (1999, Bryn Mawr College, PA, USA)

- Universitat Politecnica de Catalunya (2004 –to date; Prof. Catedratica since 2018)

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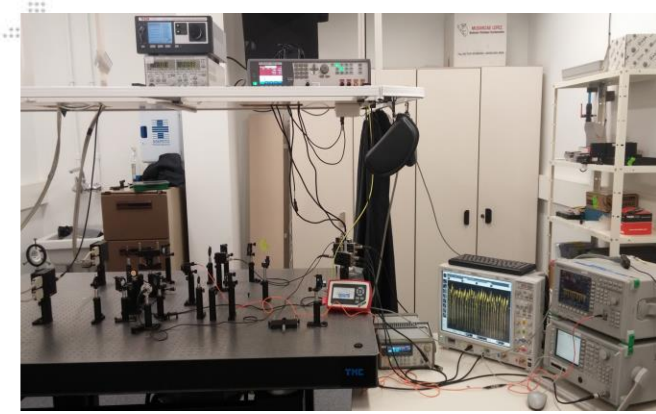
Where are we? Universitat Politècnica de Catalunya Campus Terrassa

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.



Semiconductor laser lab

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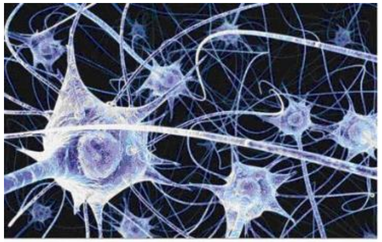
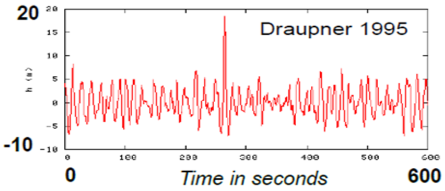
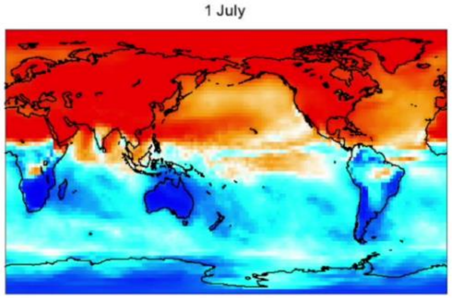
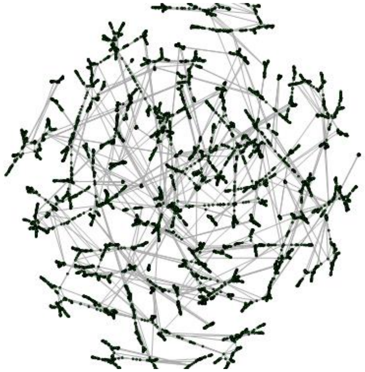
Research topics

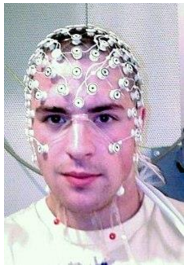
- Nonlinear laser dynamics
- Neuronal dynamics
- Synchronization
- Complex networks
- Extreme events
- Climate data analysis
- Biomedical data analysis

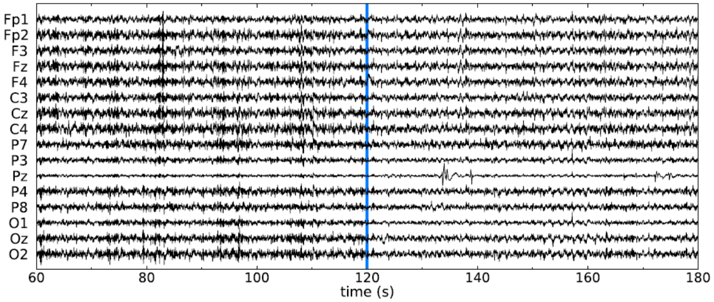












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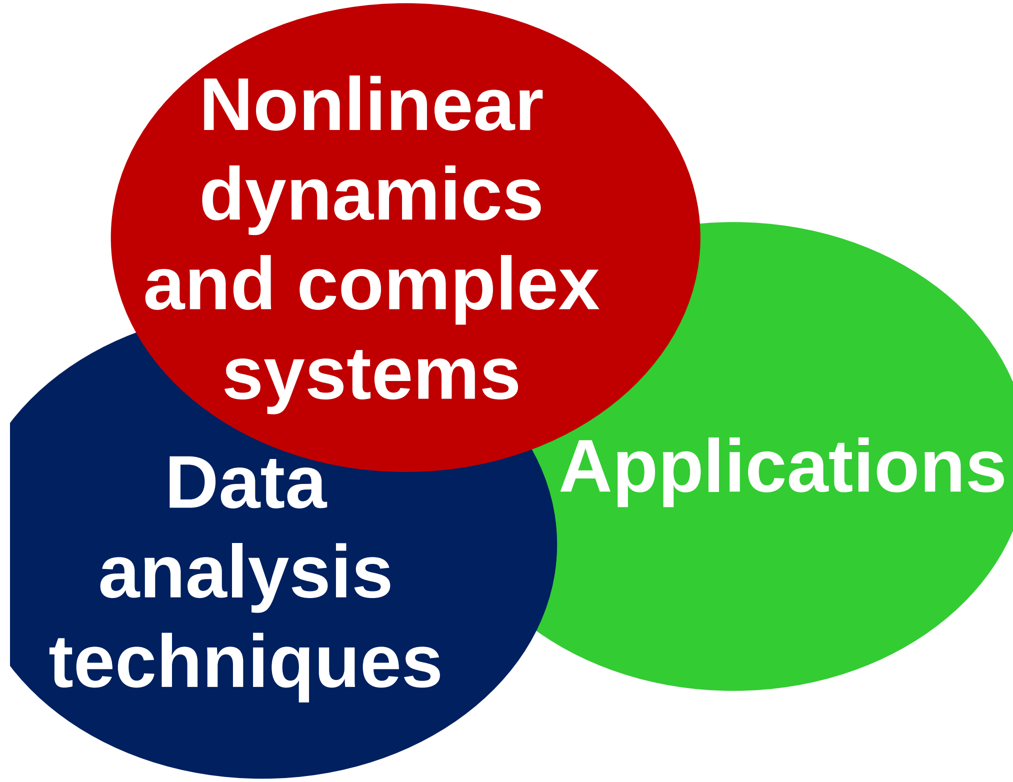
Research topics



https://shiny.rcg.sfu.ca/u/rdmorin/scholar_googler/

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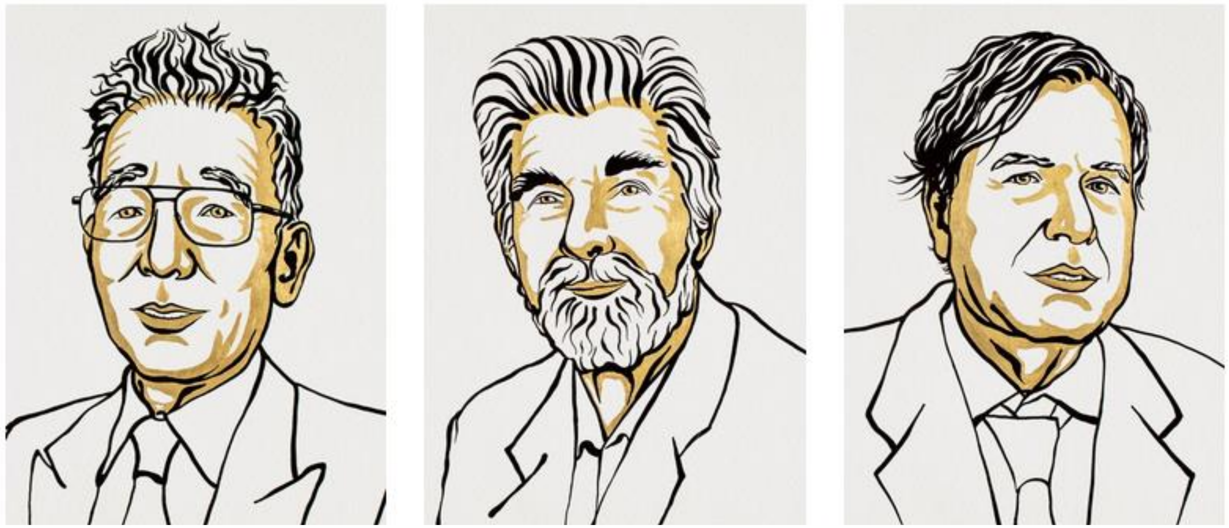
The Nobel Prize in Physics 2021



for groundbreaking contributions to our understanding of **complex systems**

½ Syukuro Manabe and Klaus Hasselmann ½ Giorgio Parisi

What is a complex system?

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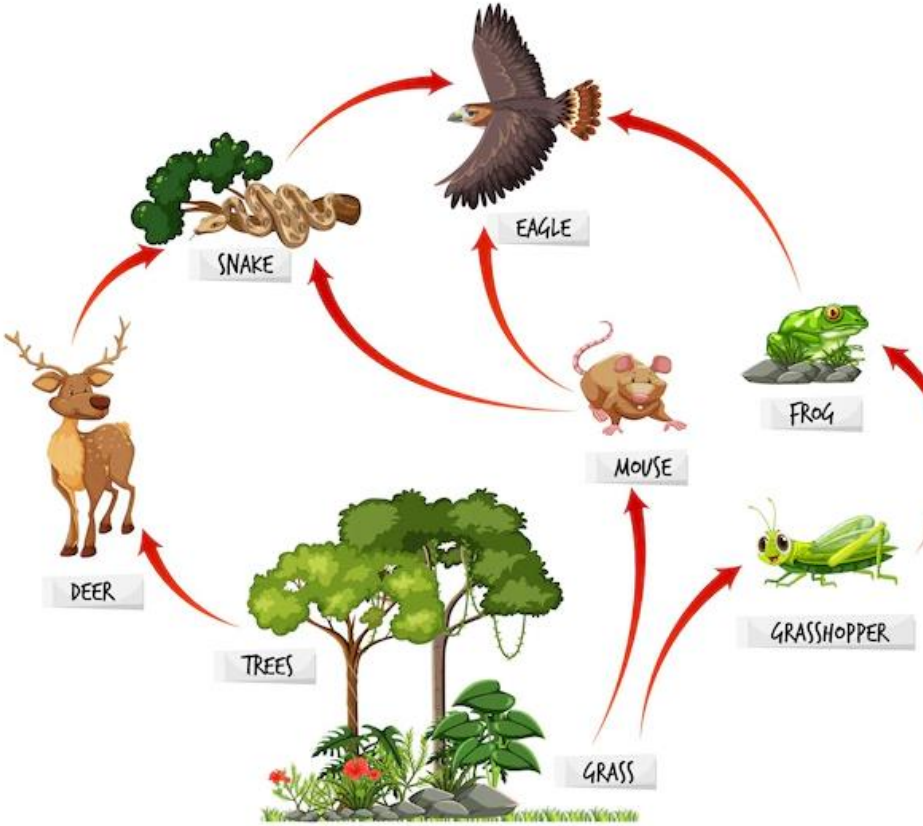
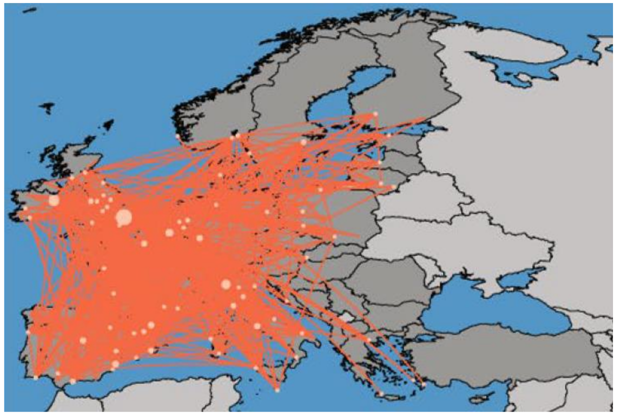
Complex systems are

- High-dimensional (huge number of variables or elements)
- Nonlinear (the elements and/or the interactions are nonlinear)
- Heterogeneous, multiscale, have memory and adapt
- Often modeled as complex networks / graphs





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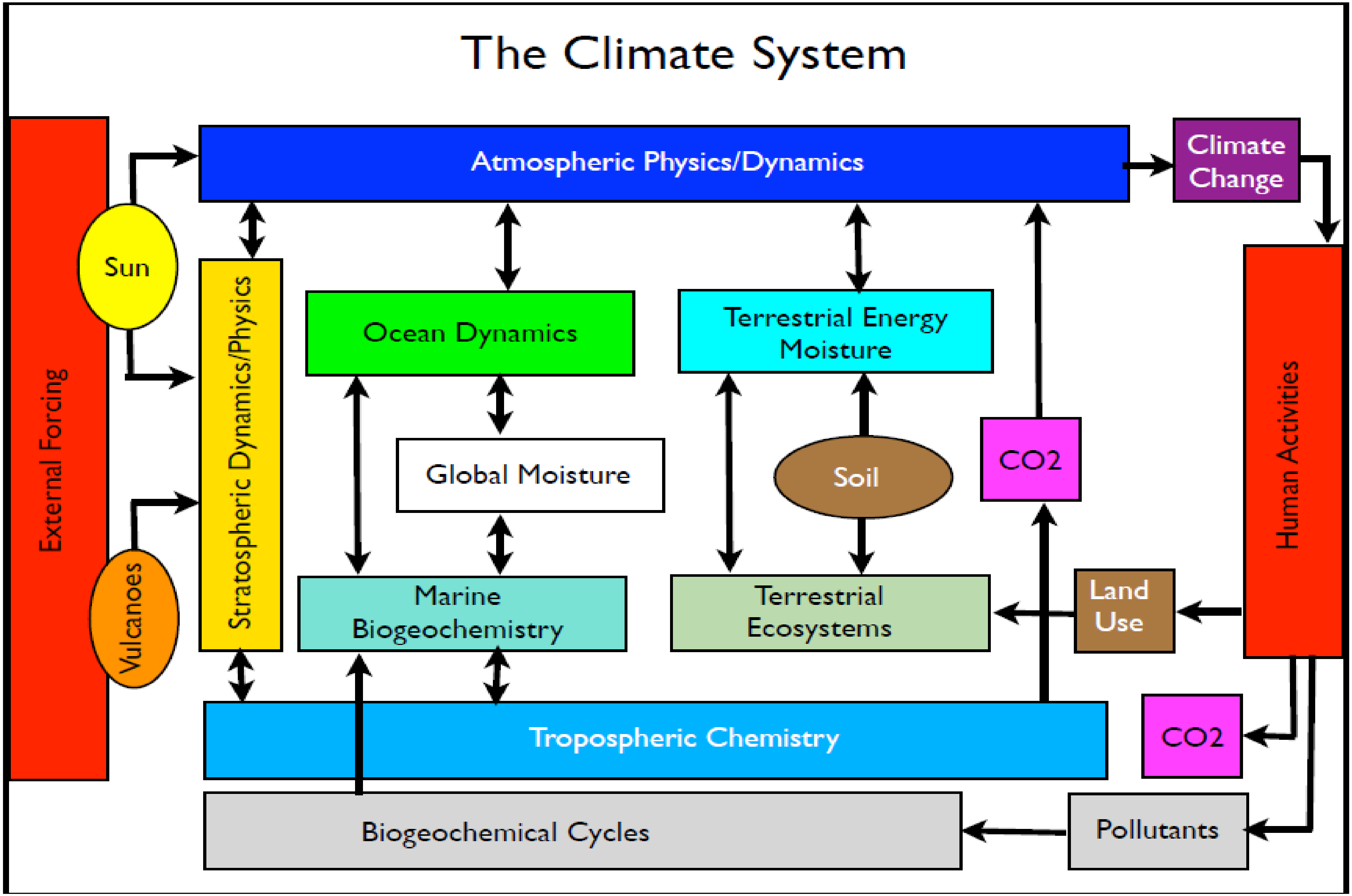

Courtesy of Henk Dijkstra (Universidad de Ultrech)

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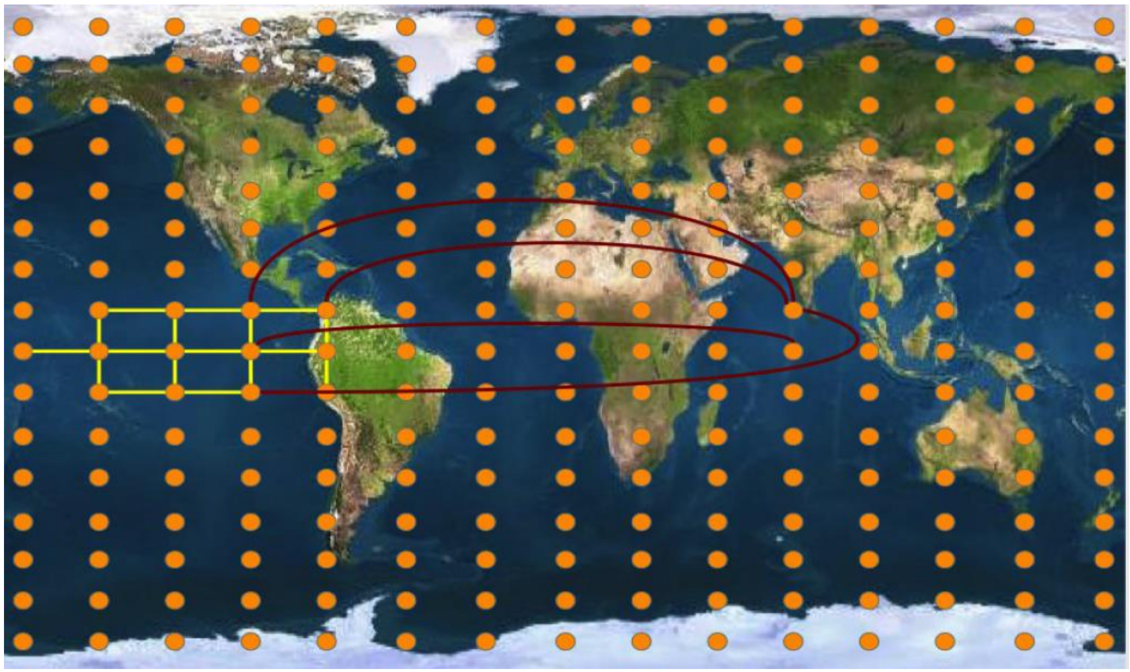
The analysis of interdependencies and causal interactions reveals networks of tele-connections



H. A. Dijkstra, E. Hernandez-Garcia, C. Masoller and M. Barreiro, "*Networks in Climate*", Cambridge University Press 2019

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Are extreme weather events becoming more extreme? More frequent?

ECMWF

Credit: Richard Williams, North Wales, UK

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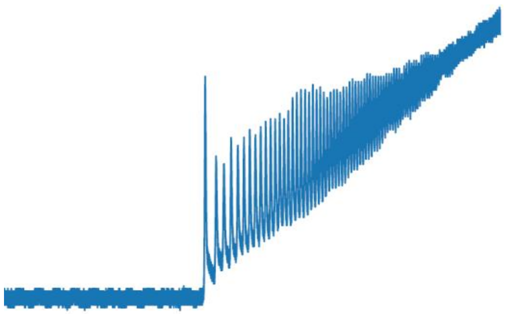
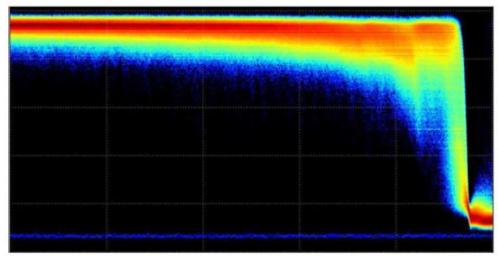
Complex systems typically display:

- Emergent phenomena synchronization
- Gradual or abrupt transitions
- Extreme fluctuations



Time



Time

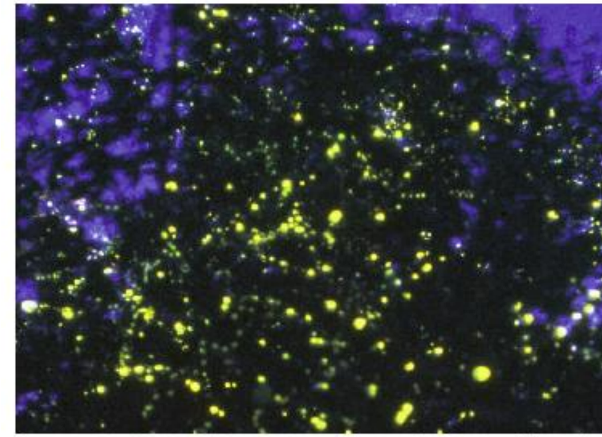
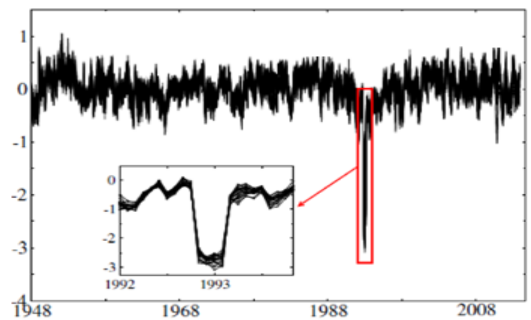
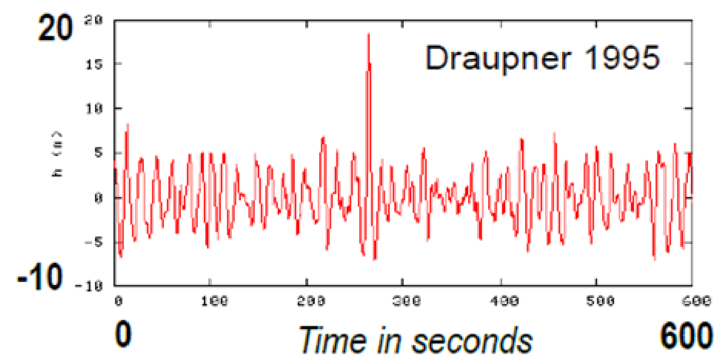


Figure 1 | Fireflies, fireflies burning bright. In the forests of the night, certain species of firefly flash in perfect synchrony — here *Pteroptyx malaccae* in a mangrove apple tree in Malaysia. Kaka *et al.*[2] and Mancoff *et al.*[3] show that the same principle can be applied to oscillators at the nanoscale.





For the sake of clarity, what is NOT, in my view, a complex system:

Any linear system (no matter how big).

Low dimensional system.

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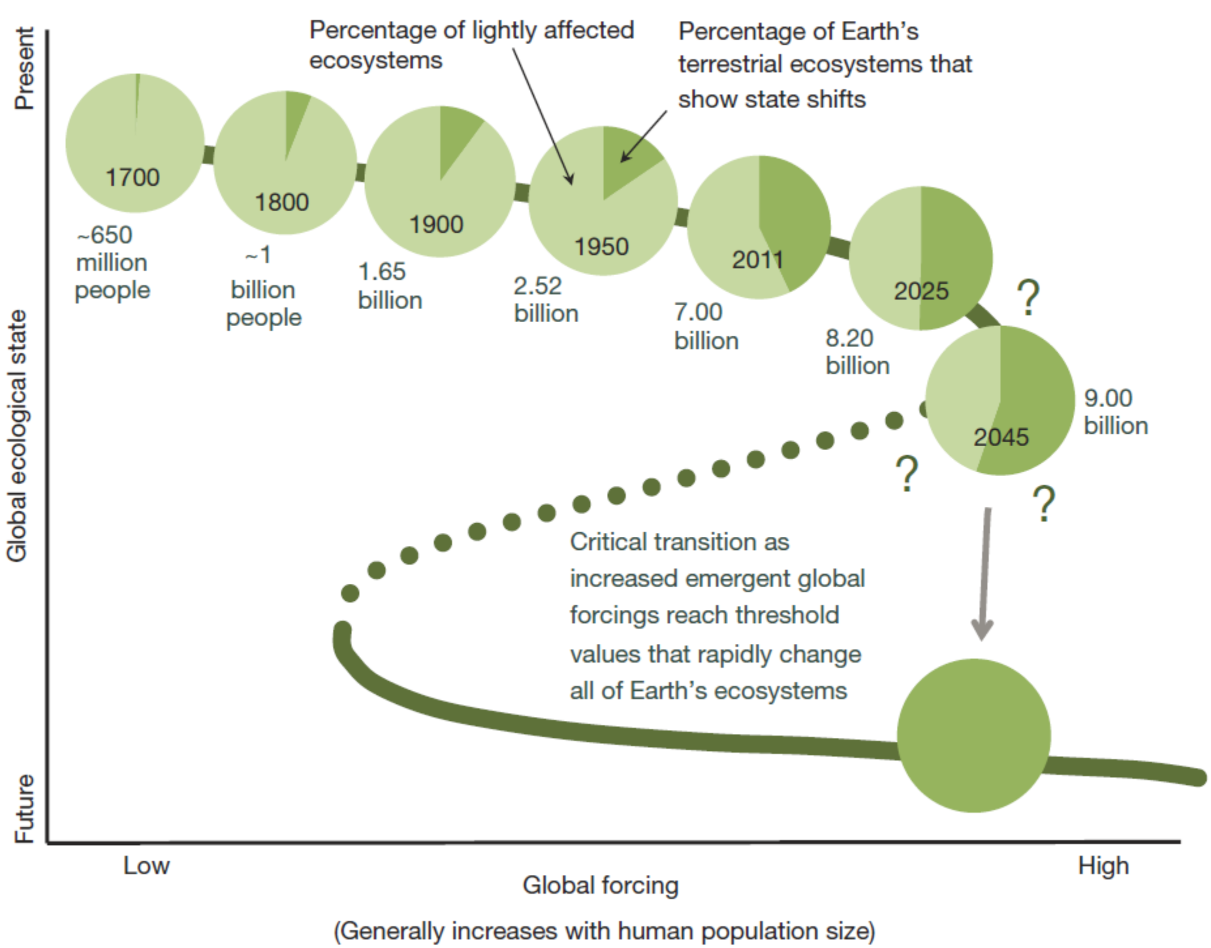
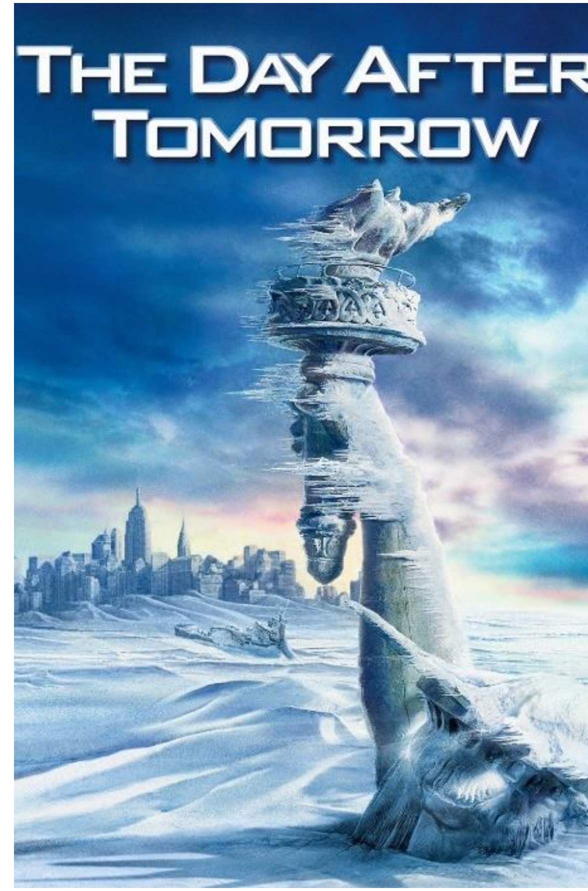
A lot of research of "early warning signals" of critical transitions

Are we approaching a planetary-scale critical transition?





A. D. Barnosky et al, "*Approaching a state shift in Earth's Biosphere*", Nature 52, 486 (2012).

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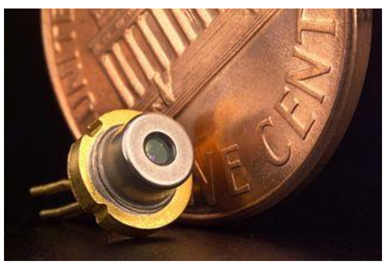
Controlled experiments with complex systems are rare

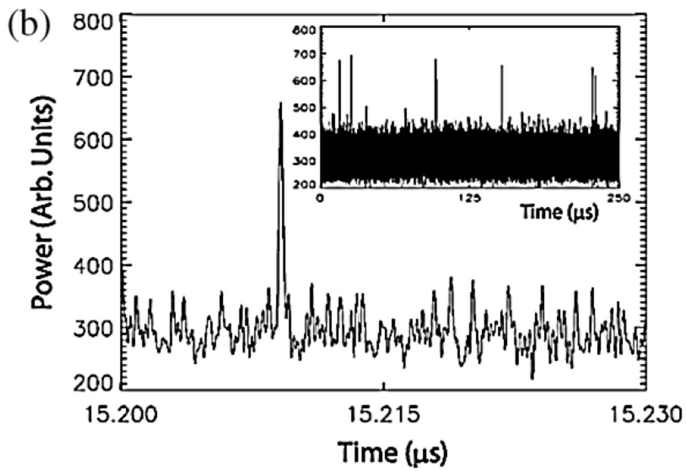
Time scales of photonic systems allow recording long data sets in short time.

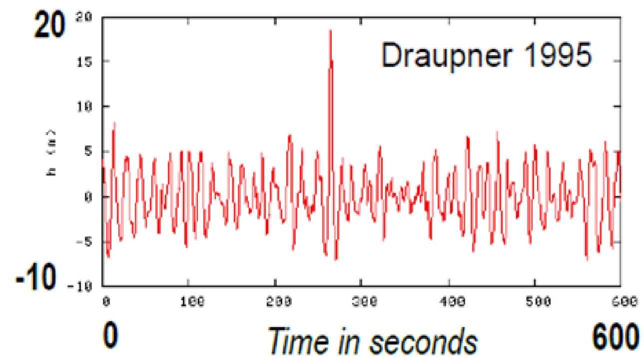
The power of analogies

NATURE PHOTONICS | VOL 8 | JANUARY 2014 |

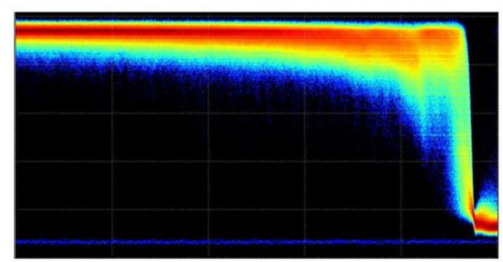
Black holes, gravitational lenses, turbulence, chaotic flow and rogue waves are just a few examples of complex physical phenomena that can be conveniently modelled using photonics.







C. Bonatto et. al, Phys. Rev. Lett. 107, 053901 (2011)



Time (0.1 µs)

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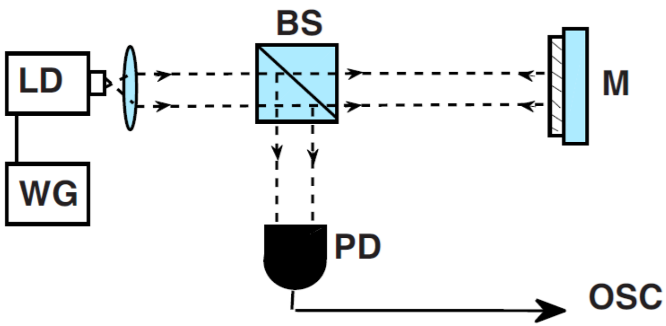
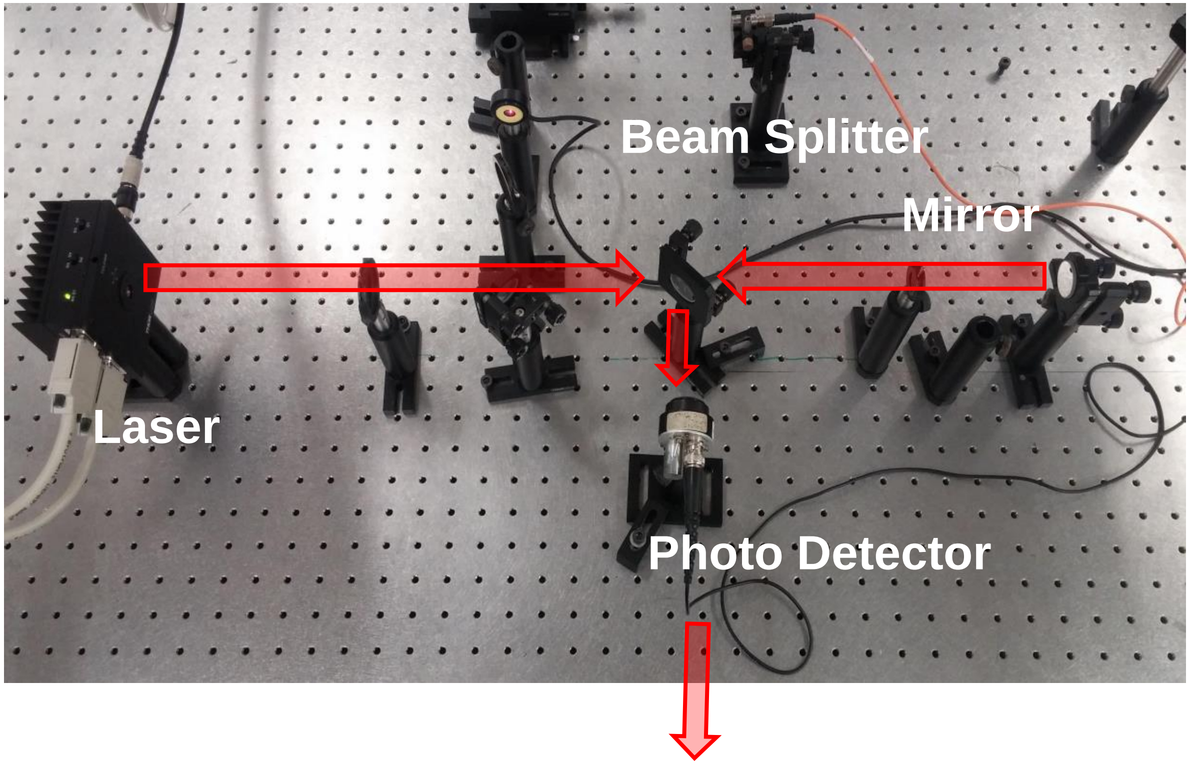
In our lab: experiments with diode lasers with optical feedback





WG: wave generator used to modulate the laser current.

Oscilloscope

What do we see in the oscilloscope?
(with 1 GHz resolution)

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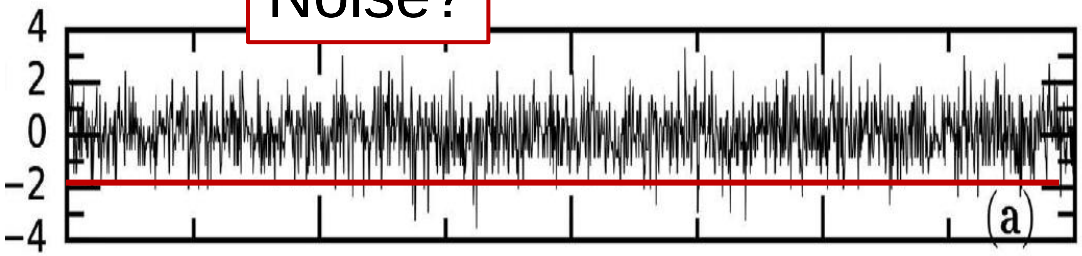
By counting the number of “threshold crossings” we can distinguish dynamical regimes

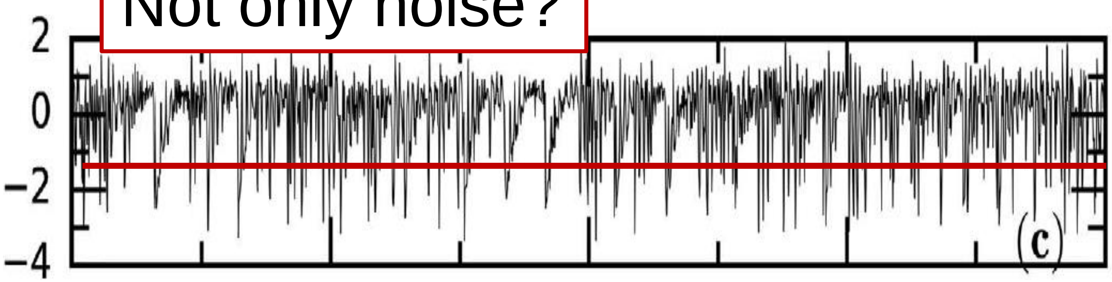
$$Z = \frac{X - \mu}{\sigma}$$

Noise?



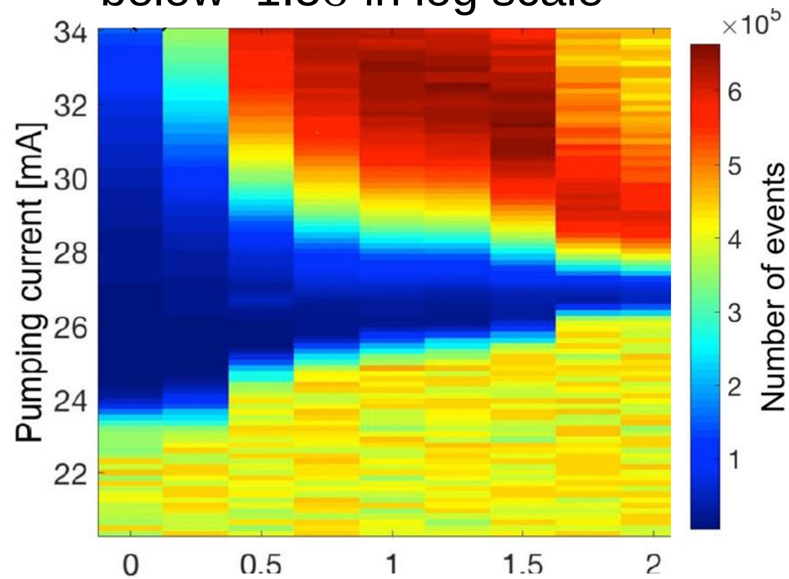
Time

Not only noise?



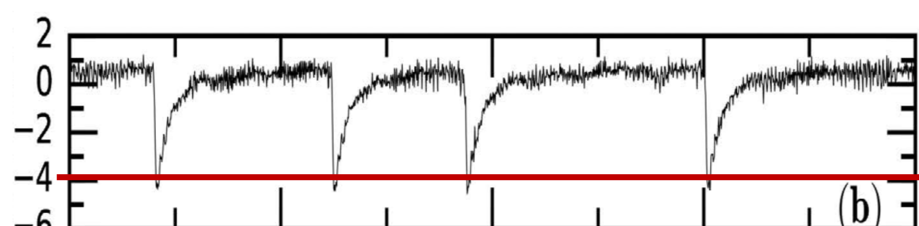
Time

Number of crossings below -1.5σ in log scale



Feedback strength (a.u.)

Blue region? Optical Spikes



Time

M. Panozzo et al, Chaos 27, 114315 (2017).

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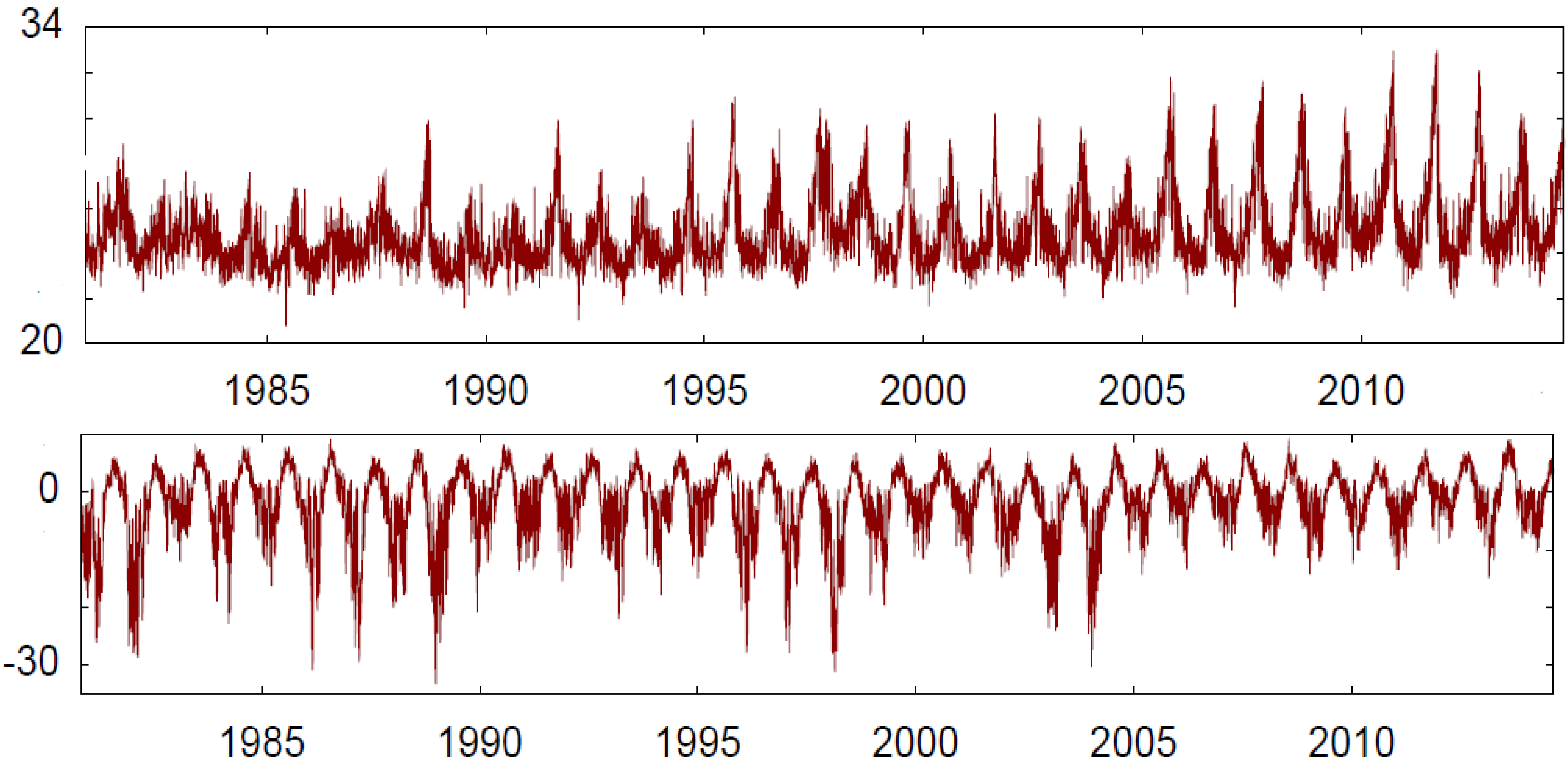
An example of a gradual change in behavior: Surface Air Temperature (SAT) in two geographical regions



How to quantify the differences?

Dario A. Zappala, M. Barreiro and C. Masoller, Earth Syst. Dynam. 9, 383 (2018)

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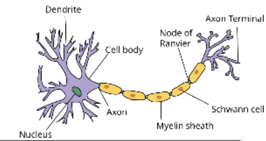
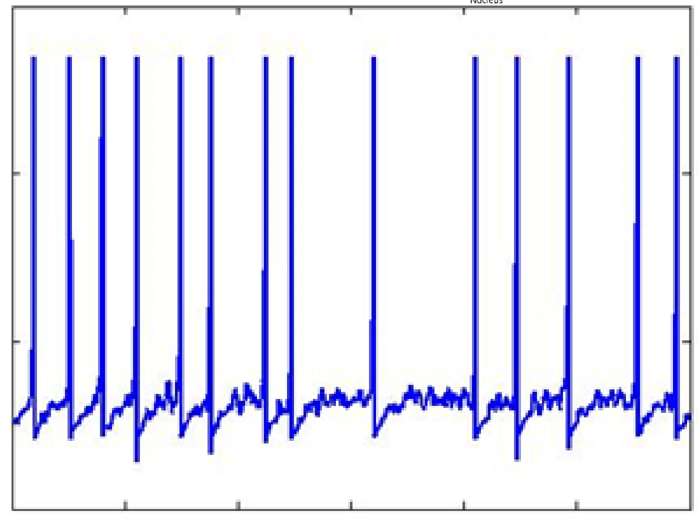
Intensity emitted by a diode laser and simulated spikes

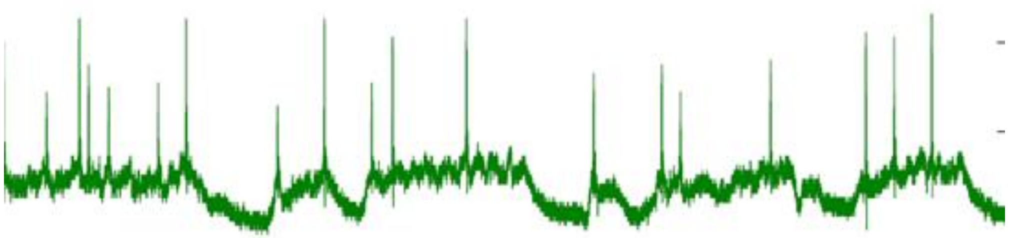




Time 10^{-9} s

Time 10^{-3} s

How neurons encode information?



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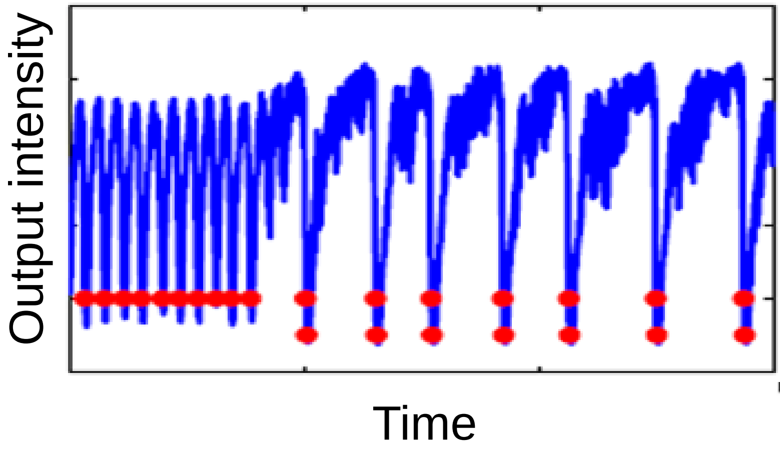
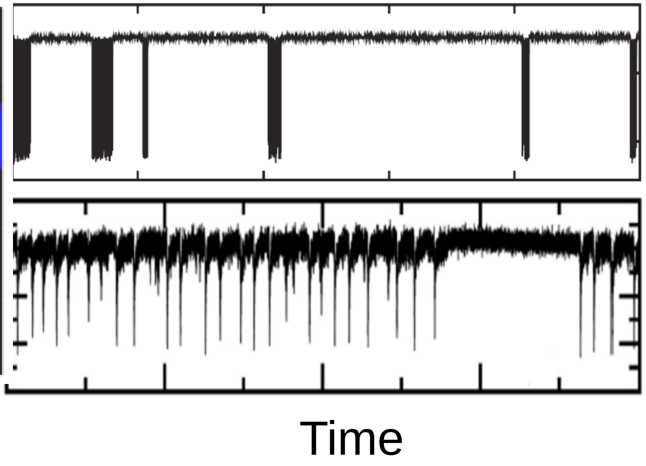
Uncovering similarities between neuron and lasers… Interesting but relevant?

- Data centers, AI and HPC systems consume a lot of power.
- Big concern in the context of climate change.
- The human brain works with only 20 Watts.
- **Laser-based neurons** should work as neurons, but
  - Much faster
  - With much less energy consumption.





Statistically similar to neurons?

A. Aragoneses et al., Sci. Rep. **4**, 4696 (2014).
C. Quintero-Quiroz et al., Sci. Rep. **6** 37510 (2016).

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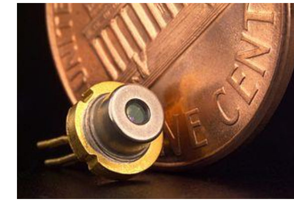
Why photonic neurons with semiconductor diode lasers?



- They are inexpensive, compact and energy-efficient.
- They emit a wide range of wavelengths.
- Nanolasers emit ultra low powers; large arrays can be integrated on chips (photonics integrated chips =PICs).
- There are several configurations in which a diode laser emits (“fires”) well-defined pulses of light (“optical spikes”).

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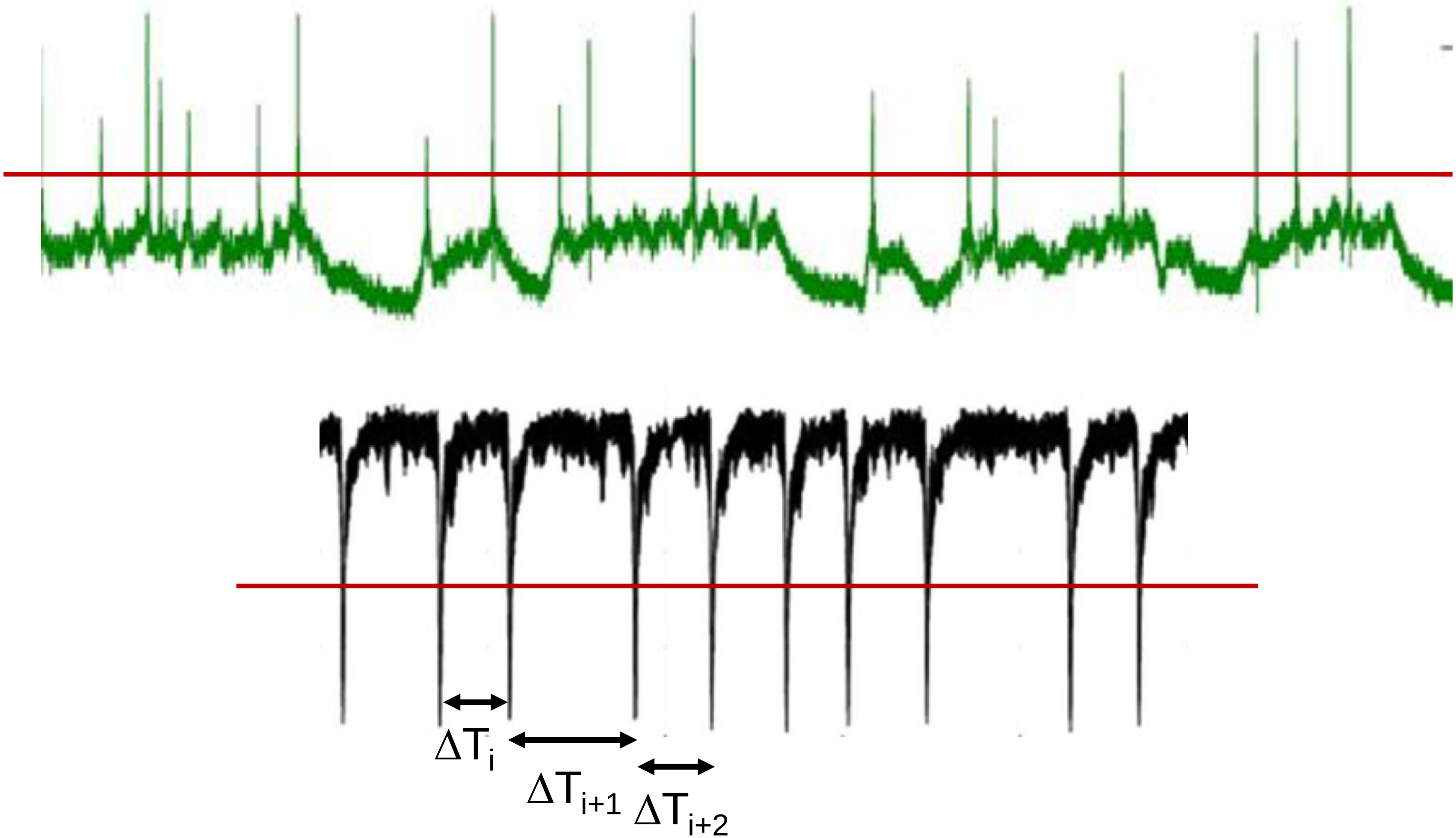
Thresholding detects the spike times $\Rightarrow$ Point Process $\Rightarrow$ sequence of inter-spike-intervals (ISIs)



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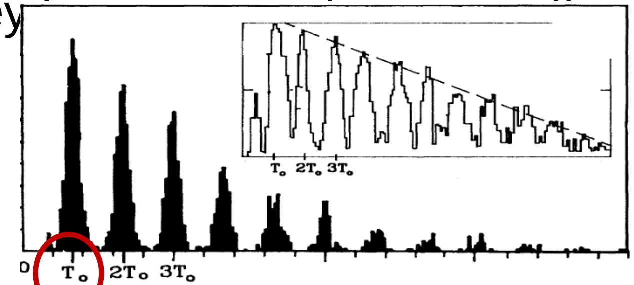
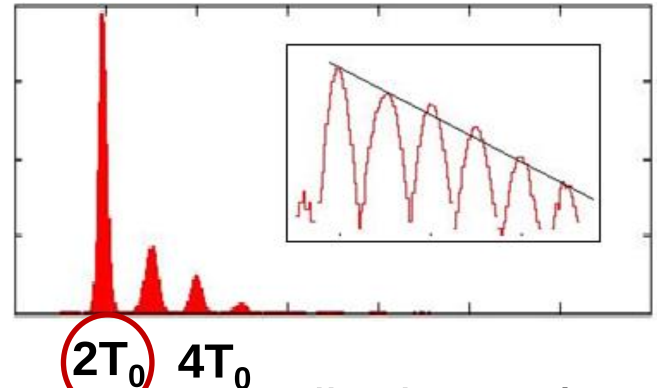
Neuron inter-spike-intervals (ISI) distribution

(spikes in the auditory nerve when a monkey

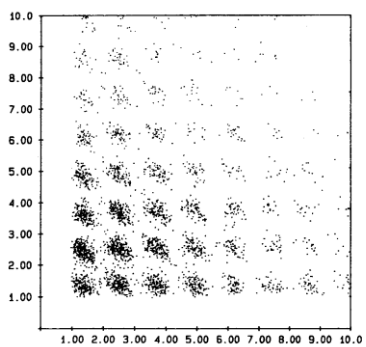


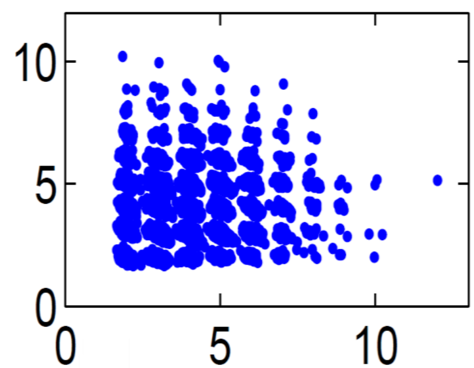
Diode laser ISI distribution

(when the laser is sinusoidally modulated)



Auditory nerve when a cat hears a pure tone sound:





How to detect similar temporal order in the ISI sequences?

A. Longtin et al. PRL (1991), IJBC (1993).

A. Aragoneses et al. Opt Express (2014).

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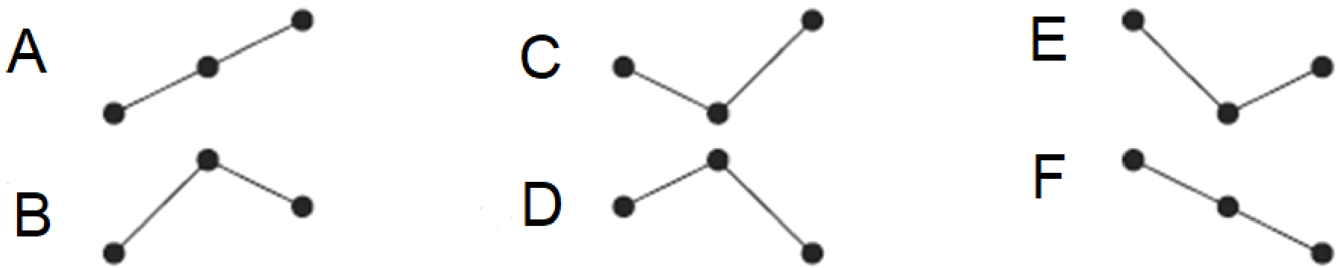
First analysis method: ordinal analysis

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

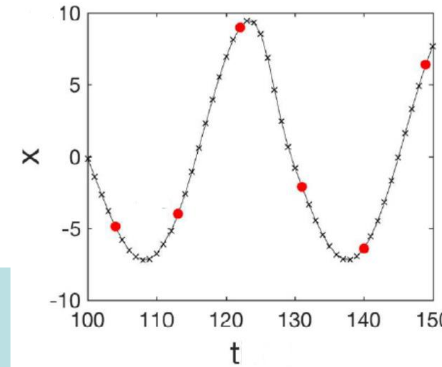
Possible order relations among three numbers (e.g., 2, 5, 7)

{…2, 5, 7…}   {…5, 2, 7…}   {…7, 2, 5 …}



{…2, 7, 5…}   {…5, 7, 2…}   {…7, 5, 2…}

Which is the code?



A B F C

C. Bandt and B. Pompe, Phys. Rev. Lett. 88, 174102 (2002).

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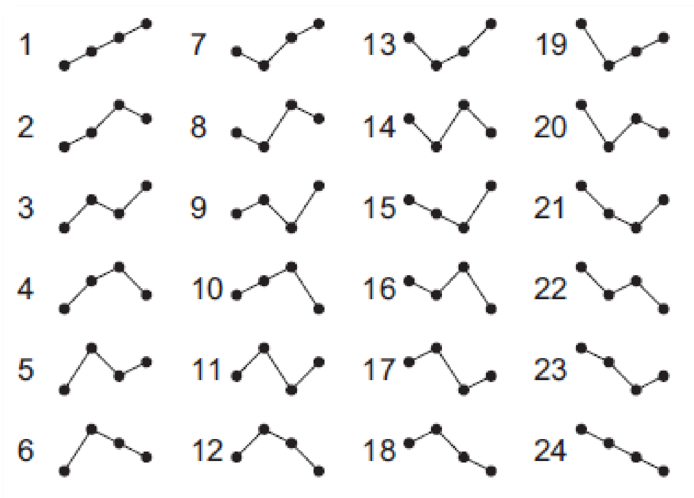
Drawbacks

1. Information about the data values is lost.
(5,7,2) and (5,70,2) are both represented by the same symbol.

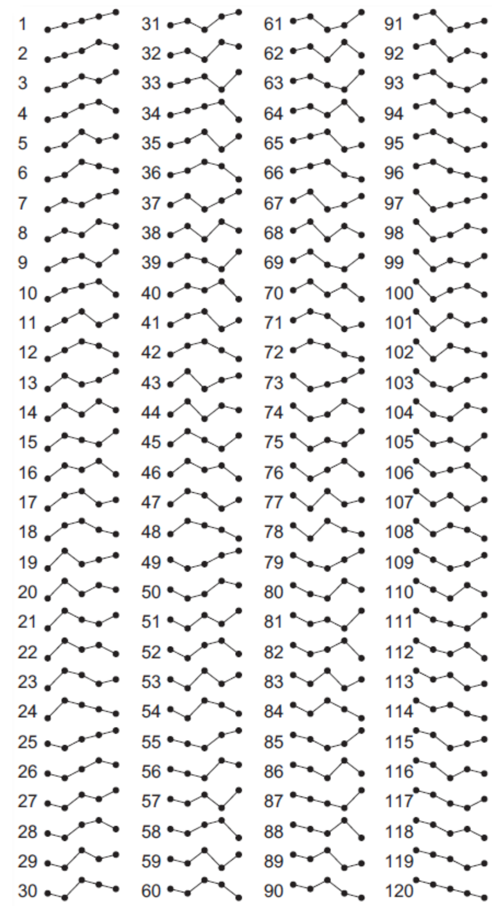
2. The number of possible patterns (N)
grows with the length (D) of the pattern as D!

D=3

D=4



D=5



U. Parlitz et al. / Computers in Biology and Medicine 42 (2012) 319–327

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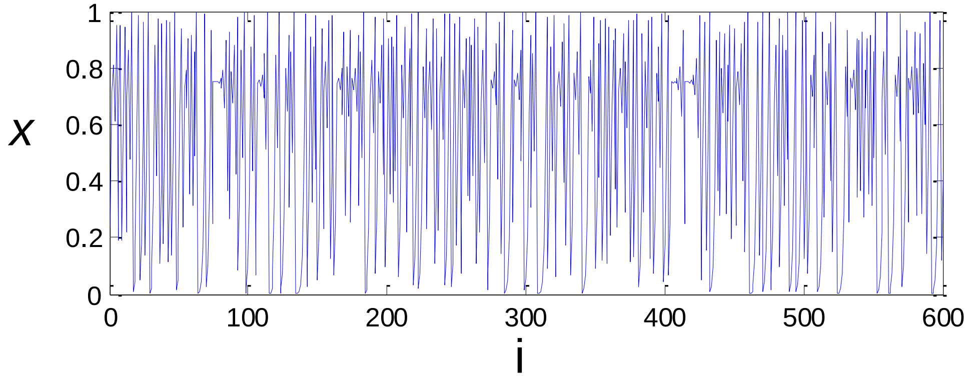
Example: chaotic time series generated with the Logistic map

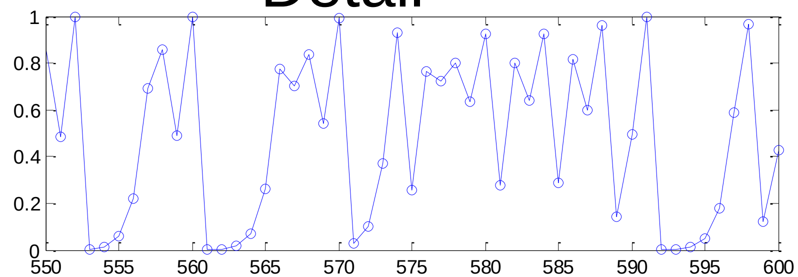
$$x(i+1) = r\, x(i)[1 - x(i)]$$

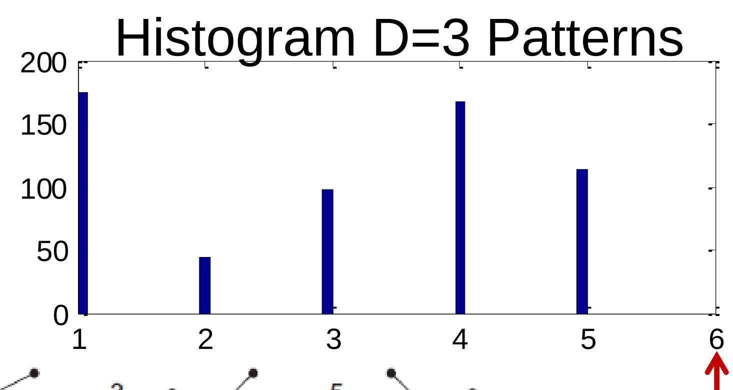
$x(1) \in (0,1)$

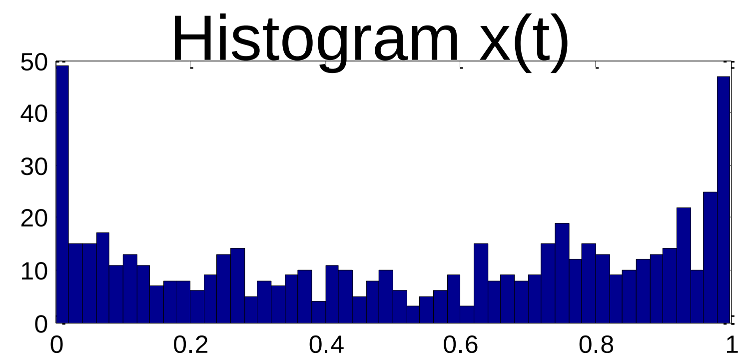
r=3.99

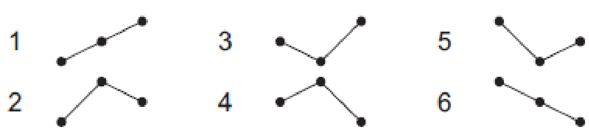


Detail









forbidden

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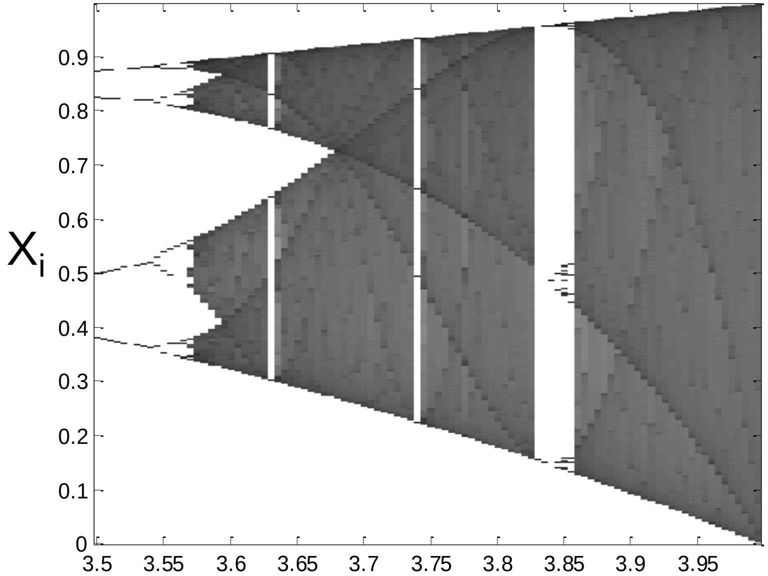
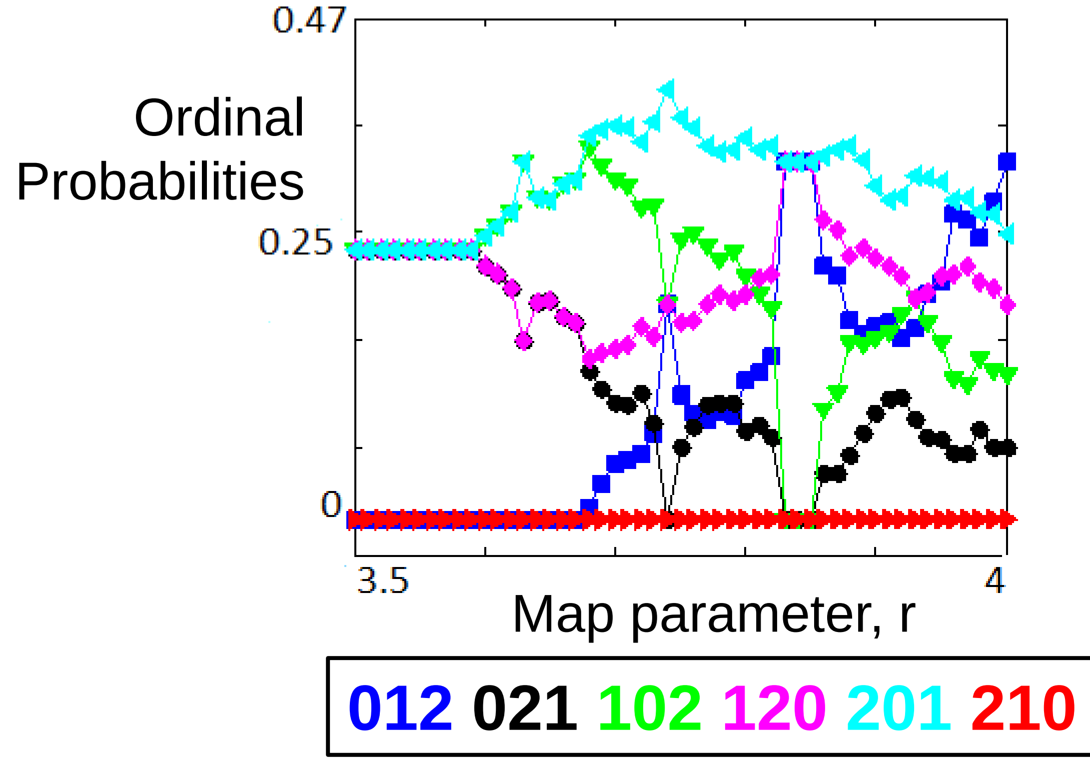
“Normal” and “Ordinal” bifurcation diagrams of the Logistic map

$$x(i+1) = r\,x(i)[1 - x(i)]$$

Normal bifurcation diagram



Ordinal diagram with D=3



Pattern **210** is always forbidden; pattern **012** becomes more probable as r increases

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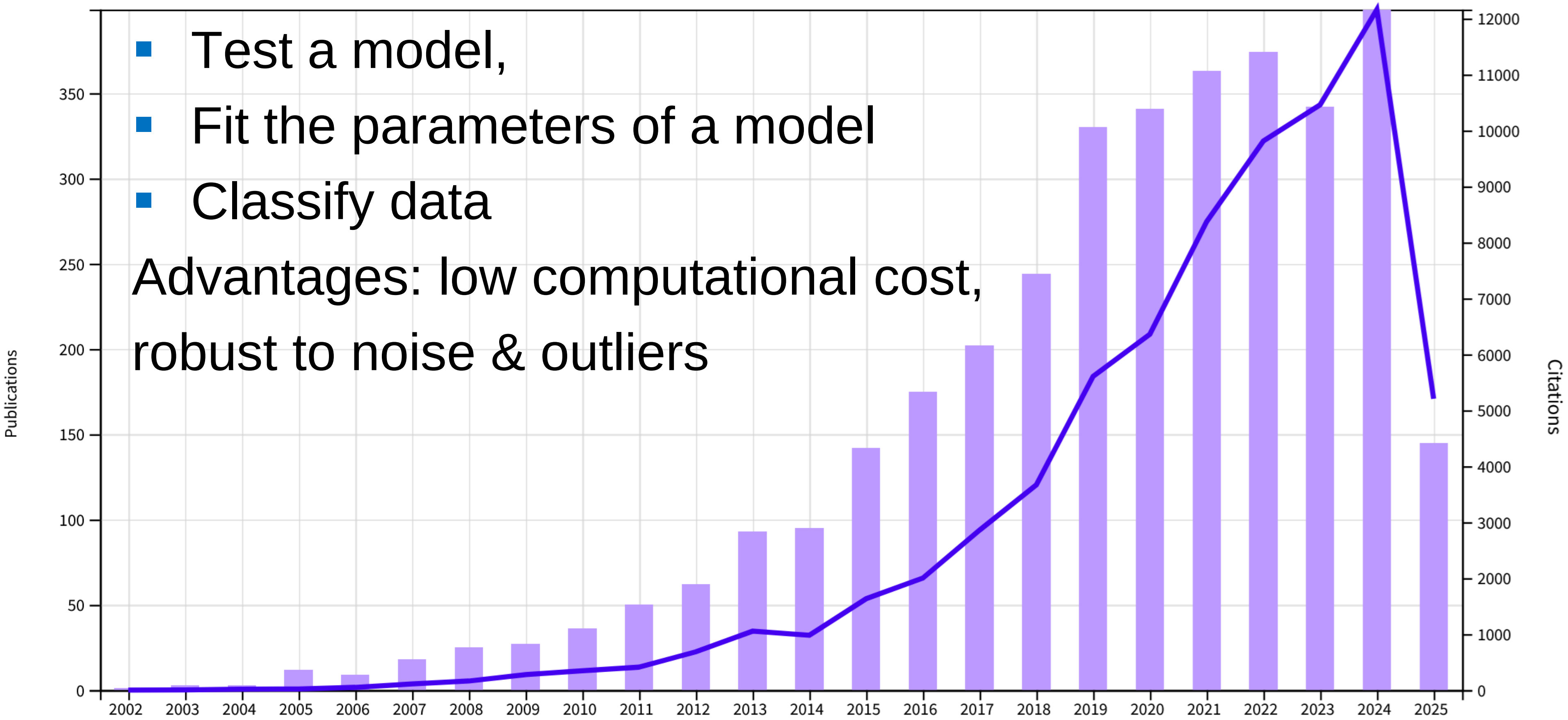
Ordinal analysis is a popular technique to:

- Test a model,
- Fit the parameters of a model
- Classify data

Advantages: low computational cost, robust to noise & outliers



I. Leyva, J. M. Martinez, C. Masoller, O. A. Rosso, M. Zanin, *“20 Years of Ordinal Patterns: Perspectives and Challenges”,* EPL 138, 31001 (2022).

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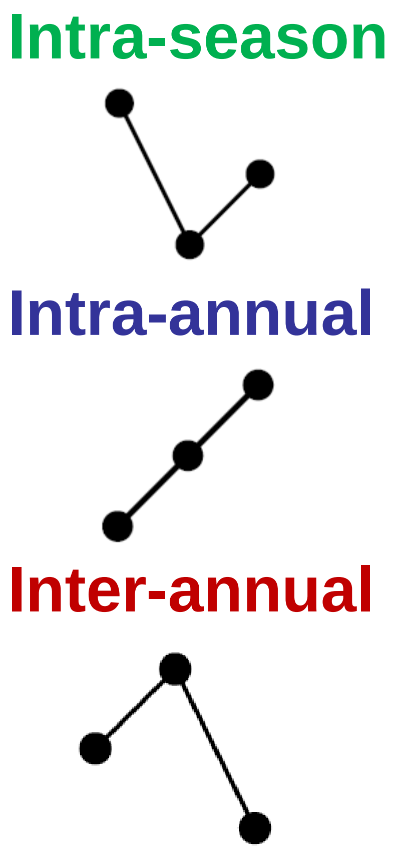
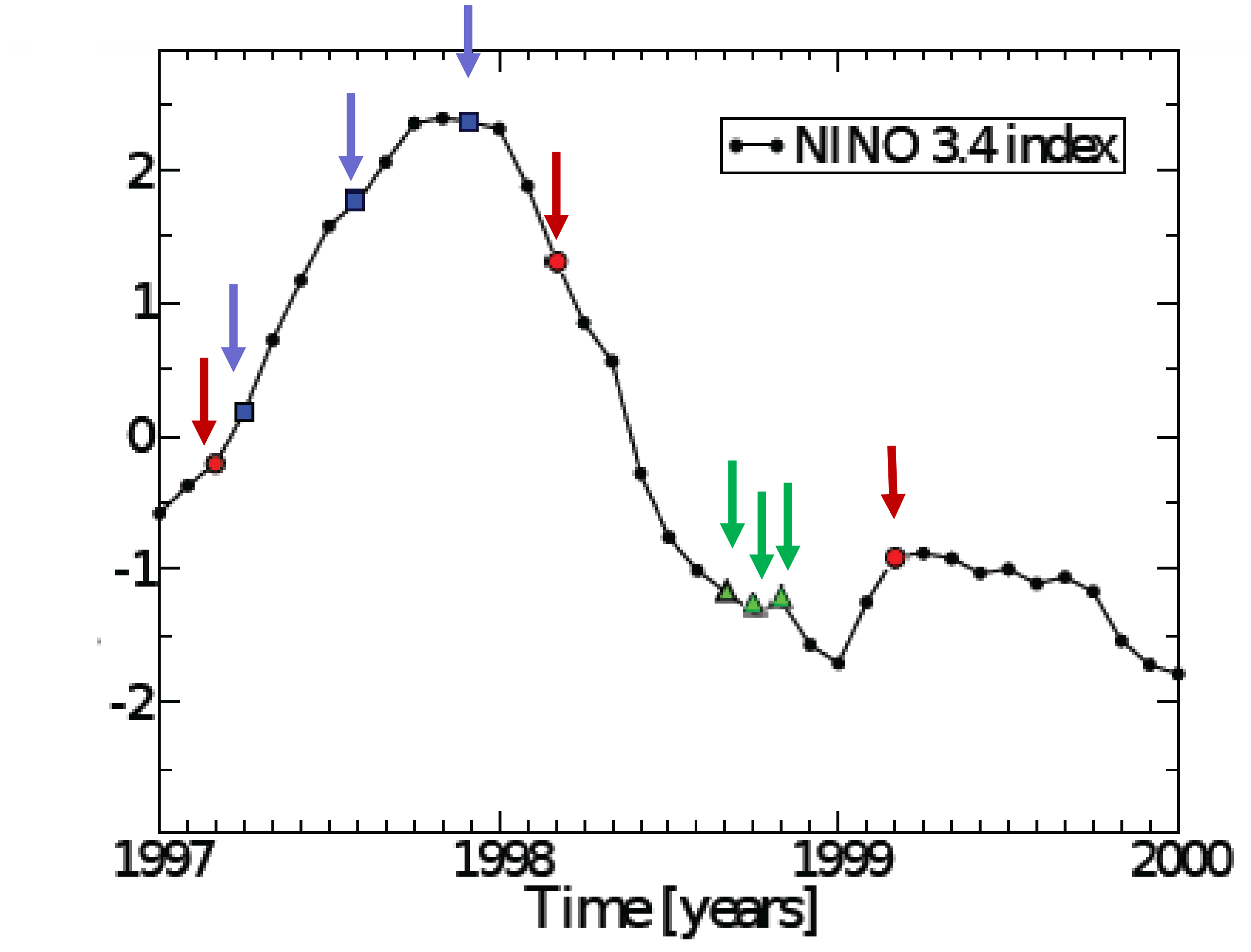
Using lagged points to define the patterns allows to select the time scale of the analysis, useful for climatological data





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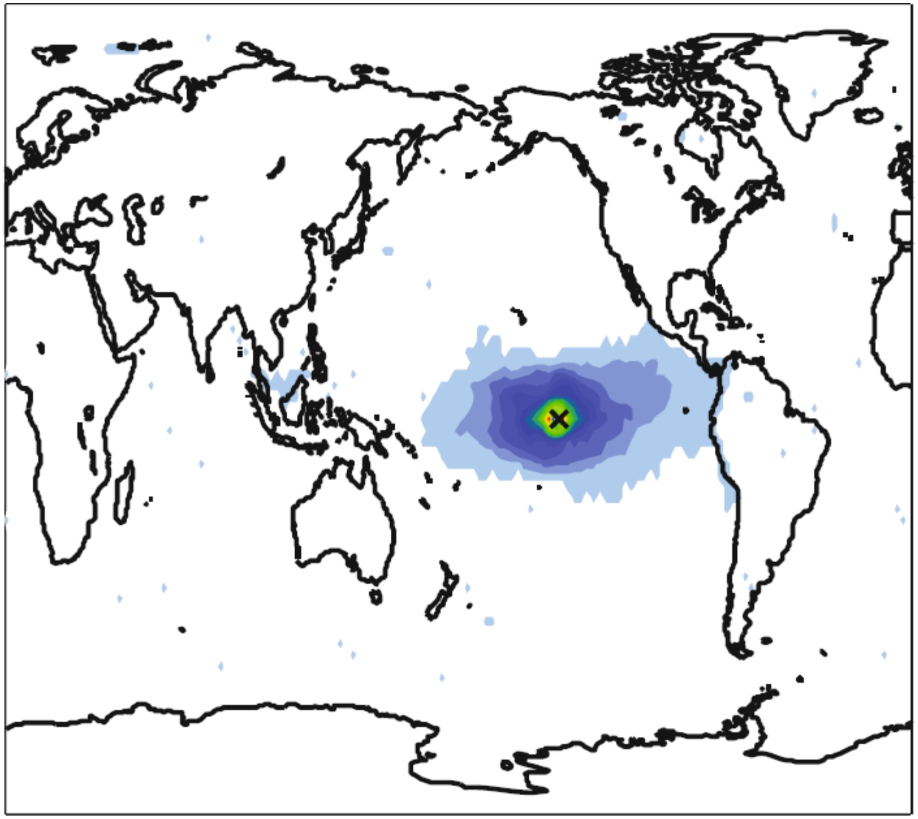
Mutual Information (color code) from probabilities of ordinal patterns (white: MI not significant)

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

MI from probabilities of ordinal patterns defined by values of **surface air temperature anomalies** in 3 consecutive months.



Juan Ignacio Deza, M. Barreiro, C. Masoller, Eur. Phys. J. ST 222, 511 (2013).

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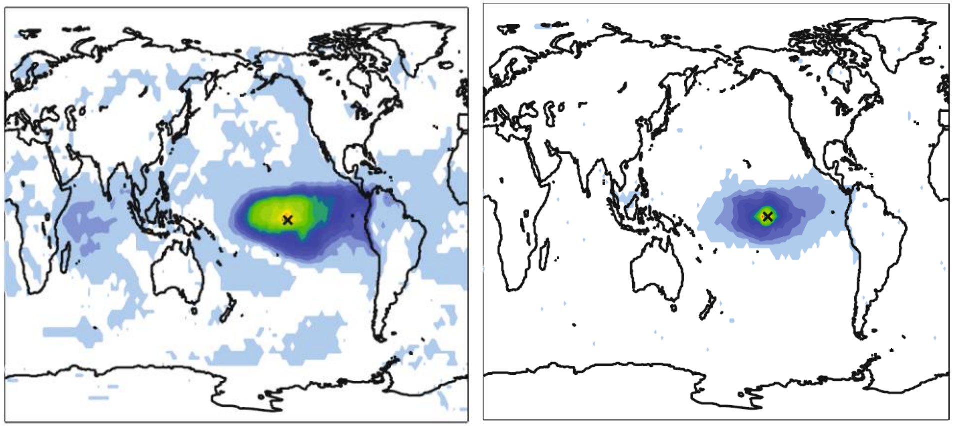
Comparison

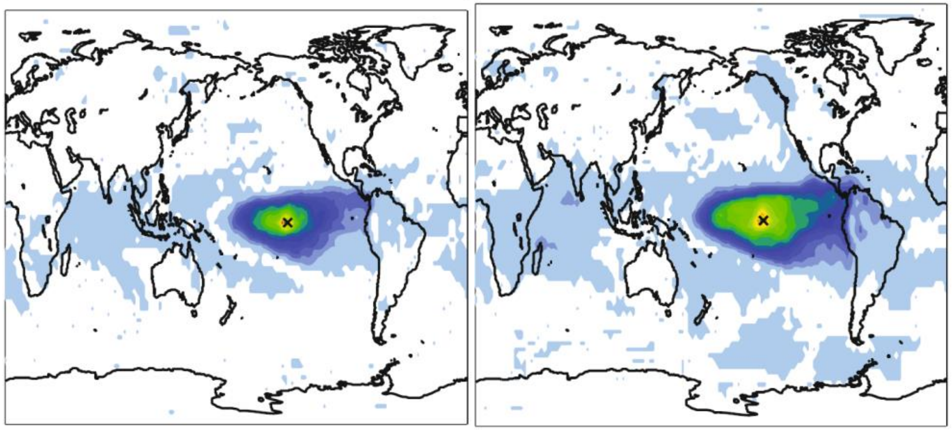
$$M_{ij} = \sum_{m,n} p_{ij}(m,n) \log \frac{p_{ij}(m,n)}{p_i(m)p_j(n)}$$

Probabilities of data values



Probabilities of ordinal patterns defined by values in 3 consecutive months.

Probabilities of patterns defined by 3 values within a year.



Probabilities of patterns defined by values in 3 consecutive years.

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

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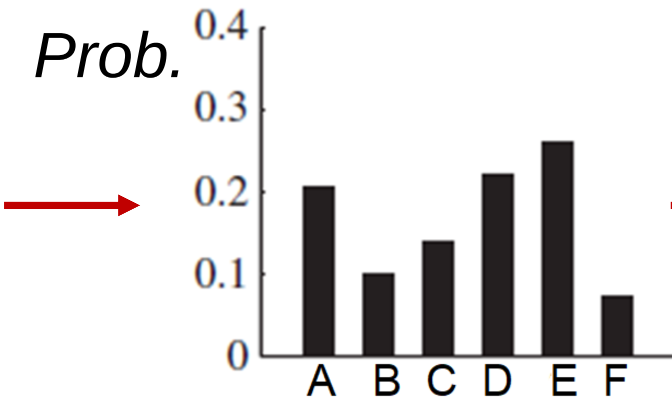
From a sequence of data points, by counting the different patterns we can estimate the “ordinal probabilities”



?

What to do next?

1. Permutation Entropy:

$p_i = p_j$ for all $i, j \Rightarrow H=1$

$p_i = 1$, $p_j = 0$ for all $j \neq i \Rightarrow H=0$

$$\boxed{H = -\frac{1}{\ln N!}\sum_{i=1}^{N} p_i \ln p_i}$$

(Nonlinear dimensionality reduction)

2. Analyze all the probabilities (features for machine learning algorithms)

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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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Shannon entropy

$$\boxed{H = -\sum_{i=1}^{N} p_i \ln p_i}$$

$$\sum_{i=1}^{N} p_i = 1$$

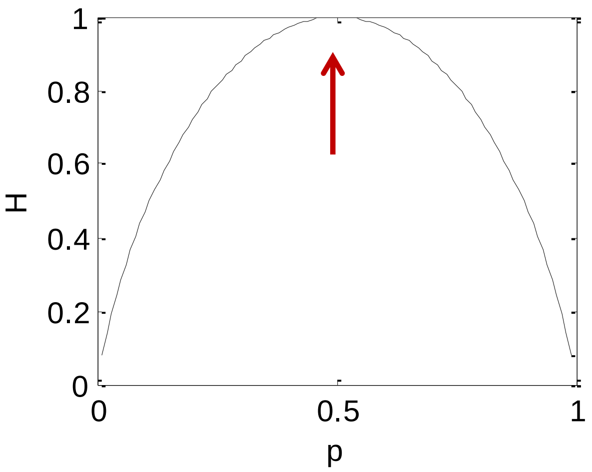
- Interpretation: "*quantity of* ***surprise*** *one should feel upon reading the result of a measurement* ".

- Example: a random variable takes values 0 or 1 with probabilities:

  p(0) = p, p(1) = 1 − p.

  H = −p ln(p) − (1 − p) ln(1 − p).

  $\Rightarrow$ p=0.5: Maximum **unpredictability.**



C. Shannon, "A Mathematical Theory of Communication", Bell System Technical Journal. 27 (3): 379–423 (1948). Bell System Technical Journal. 27 (4): 623–656 (1948).

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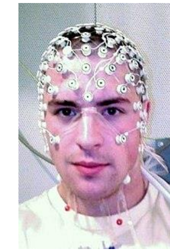
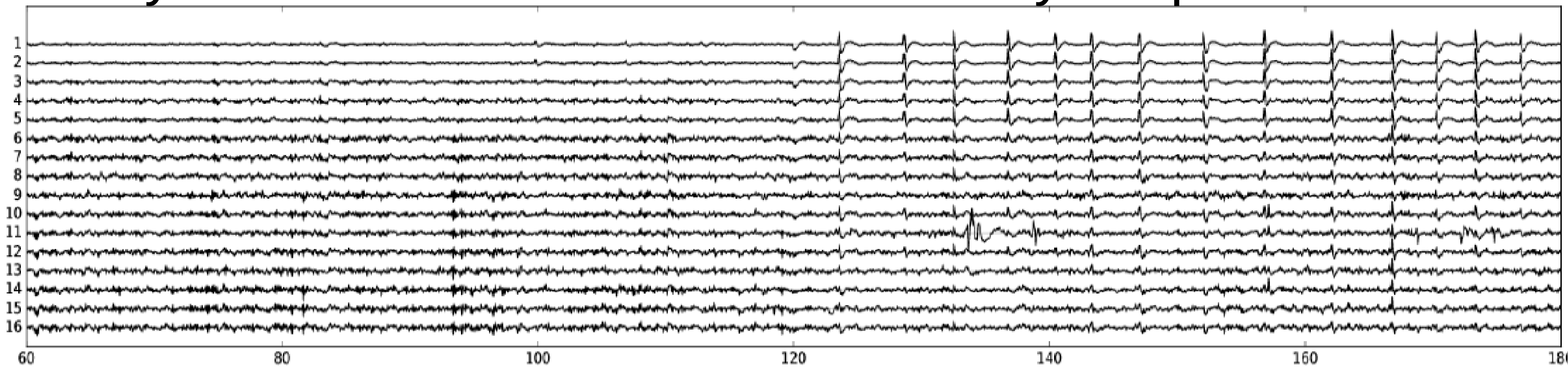
First example: entropy analysis of EEG recordings can distinguish eyes-closed and eyes-open states?



Eyes closed   Eyes open



Time (seconds)

TABLE I. Description of the datasets used.

	DTS1	DTS2
Sampling rate (Hz)	256	160
Time task (seg)	120	60
Total points	30 720	9600
Number of electrodes	16	64
Number of subjects (healthy)	71	109

DTS1: Bitbrain (Zaragoza)
DTS2: Physionet

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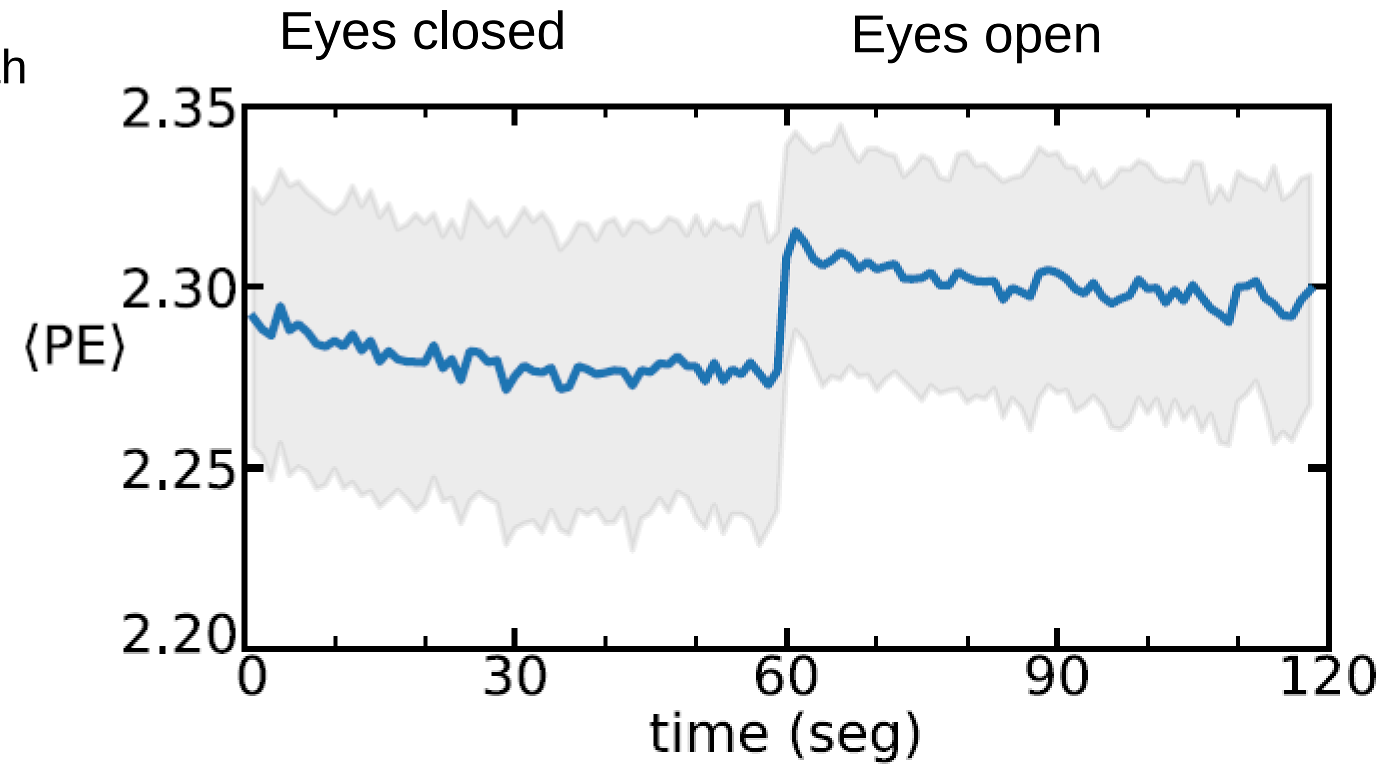
The Permutation Entropy increases in the eyes open state

$$\langle \mathrm{PE} \rangle = \frac{1}{N[\mathrm{electrodes}]} \sum_i \mathrm{PE}^i$$

PE was calculated with patterns of length 4 (# of possible patterns 24) in time windows containing >4000 patterns



Gray region: Standard deviation of ⟨PE⟩ across subjects

C. Quintero-Quiroz et al., *“Differentiating resting brain states using ordinal symbolic analysis”,* Chaos 28, 106307 (2018).

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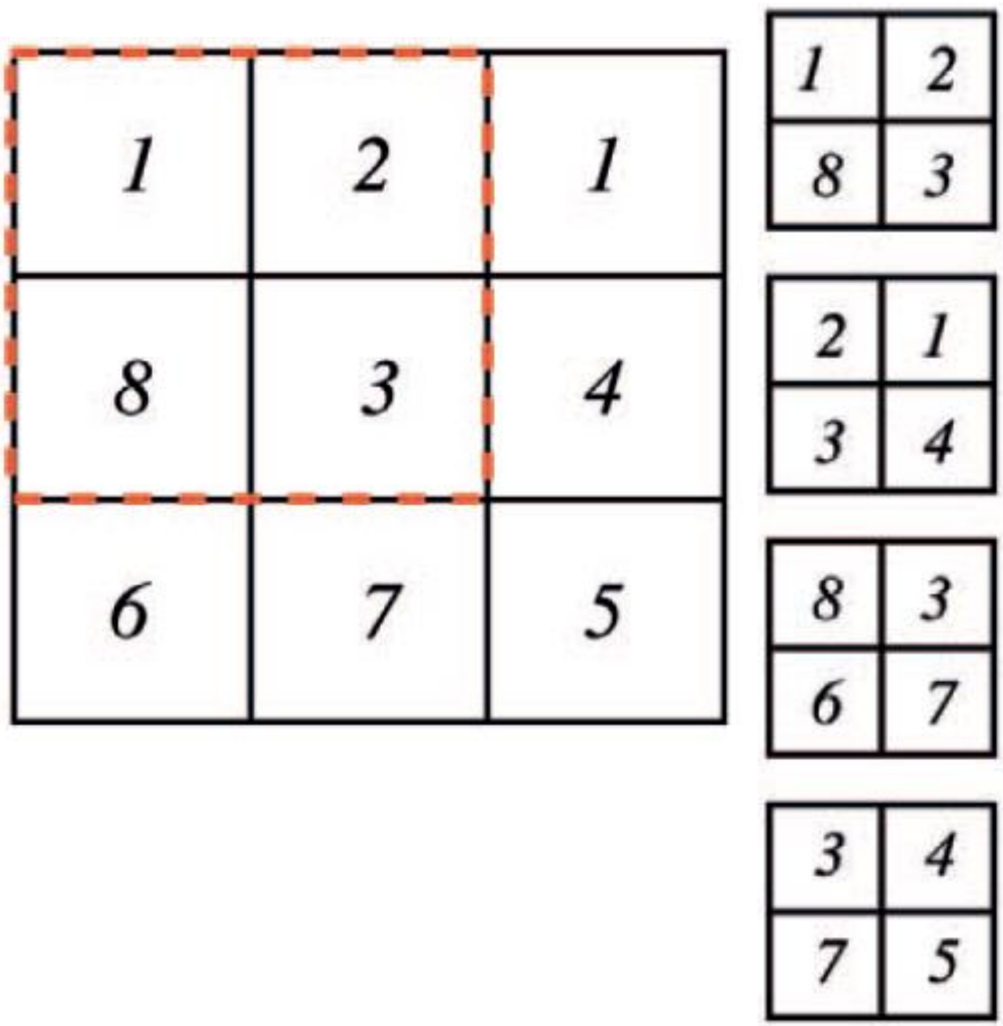
Spatial data ⇒ Spatial Permutation Entropy (SPE)



1283 ⇒0132

2134 ⇒1023

8367 ⇒3012

3475 ⇒0132

$$\boxed{H = -\frac{1}{\ln N!}\sum_{i=1}^{N} p_i \ln p_i}$$

2x2 pixels:
24 possible
patterns

*Haroldo Ribeiro, **Luciano Zunino** and coworkers, PLoS ONE 7, e40689 (2012)*

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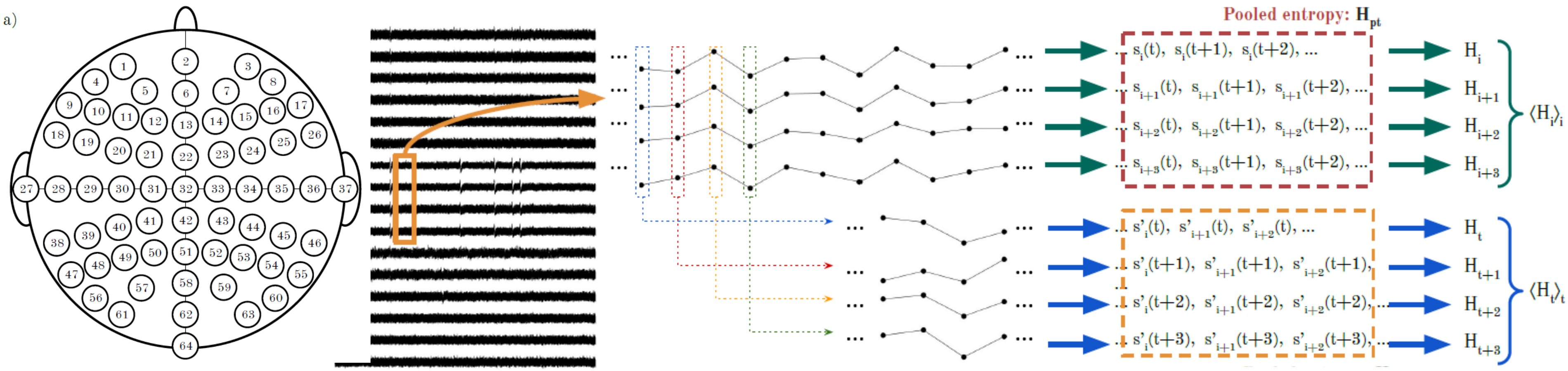
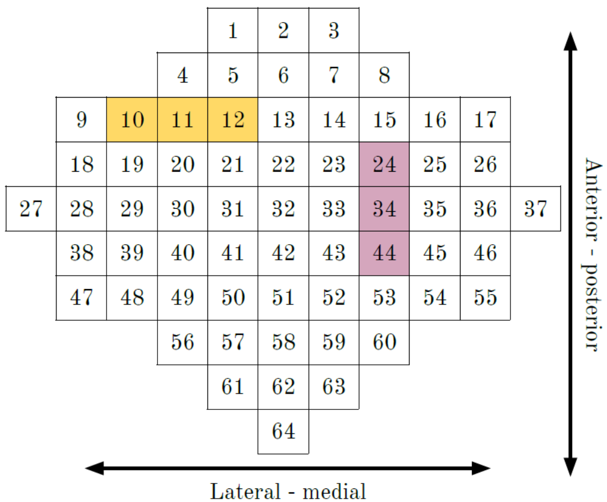
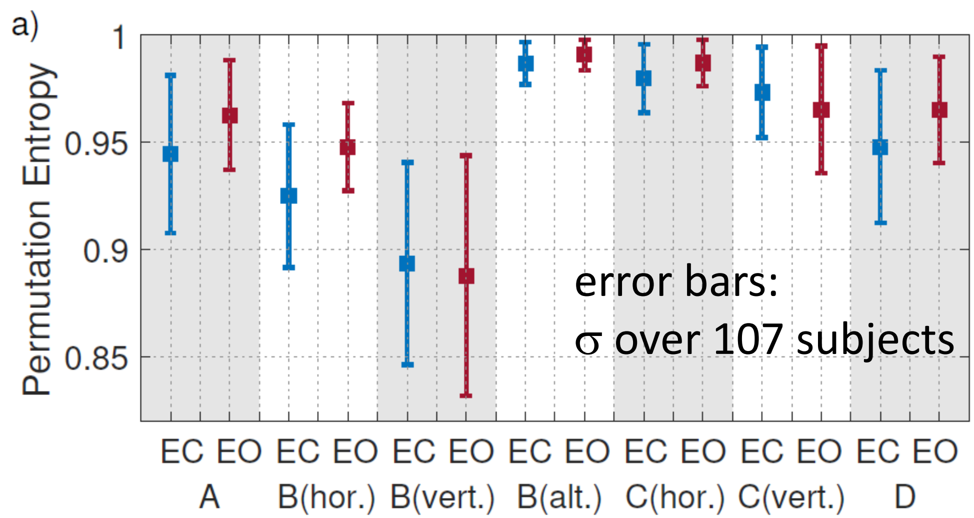
Different approaches to calculate permutation entropy







A: temporal coding
B: spatial coding (horizontal, vertical, alt.)
C: spatial pooling (horizontal and vertical symbols)
D: temporal pooling

J. Gancio, C. Masoller, G. Tirabassi, Chaos 34, 043130 (2024).

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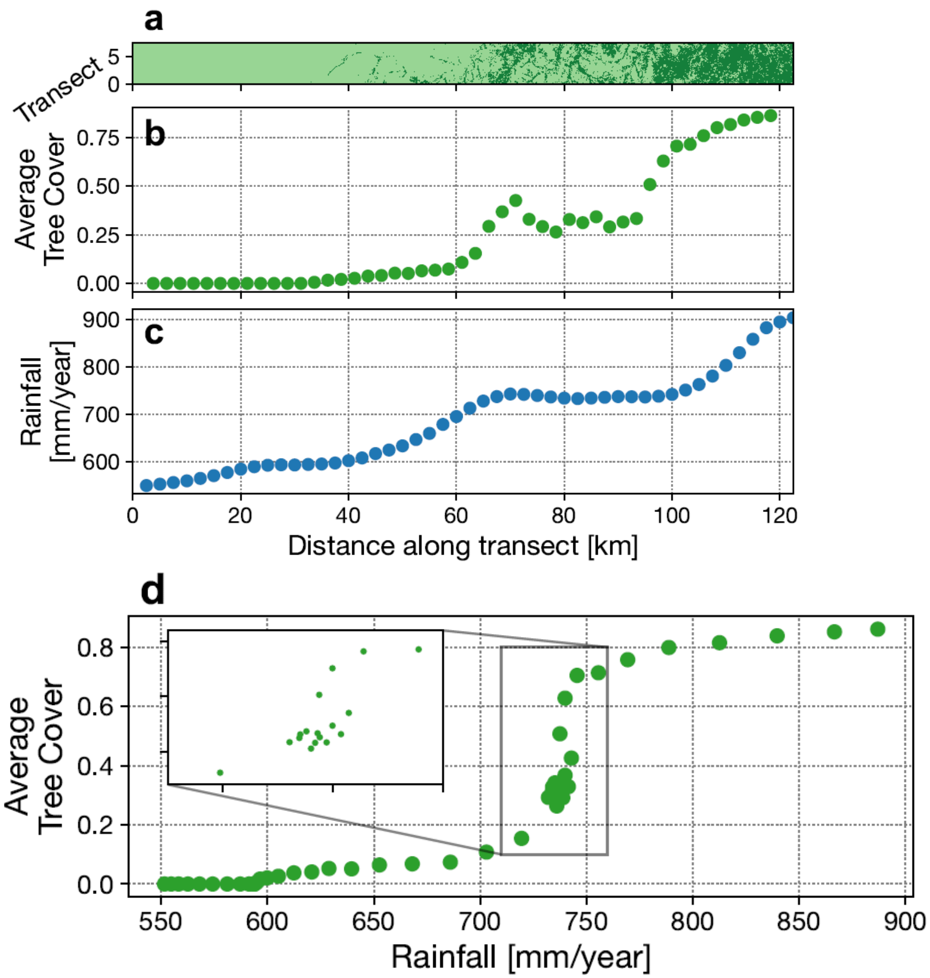
The spatial permutation entropy (SPE) can be an early indicator of a vegetation transition (tipping point)



Giulio Tirabassi and C. Masoller, "*Entropy-based early detection of critical transitions in spatial vegetation fields*", PNAS 120, e2215667120 (2023).

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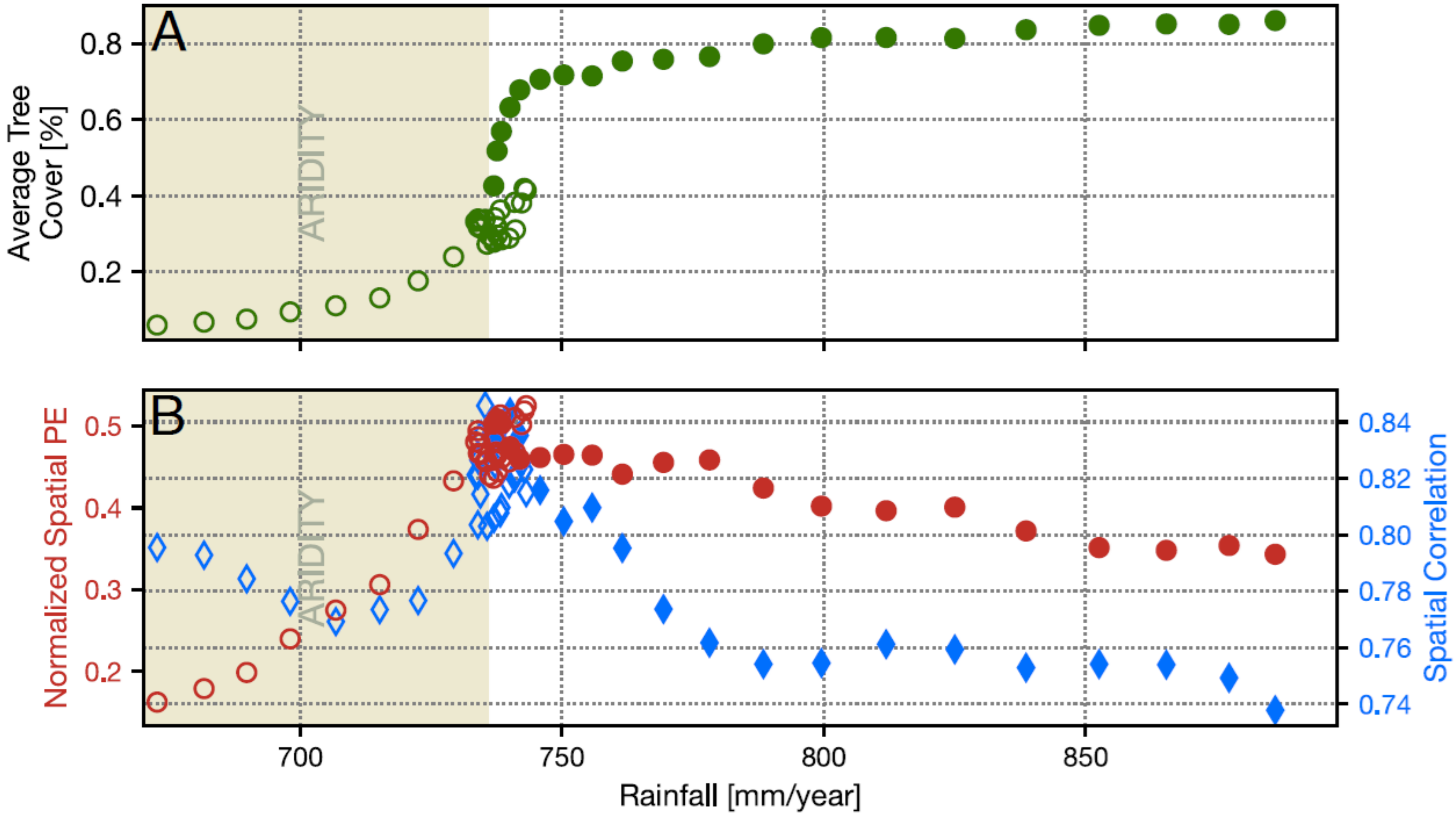

Can we test this indicator in controlled experimental data?

Giulio Tirabassi and C. Masoller, "*Entropy-based early detection of critical transitions in spatial vegetation fields*", PNAS 120, e2215667120 (2023).

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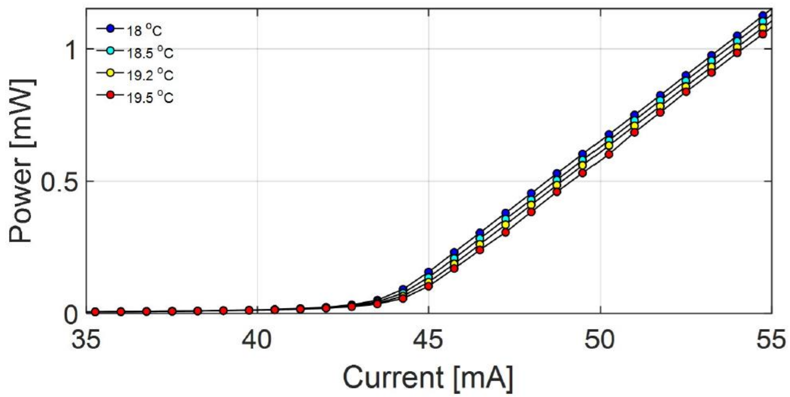
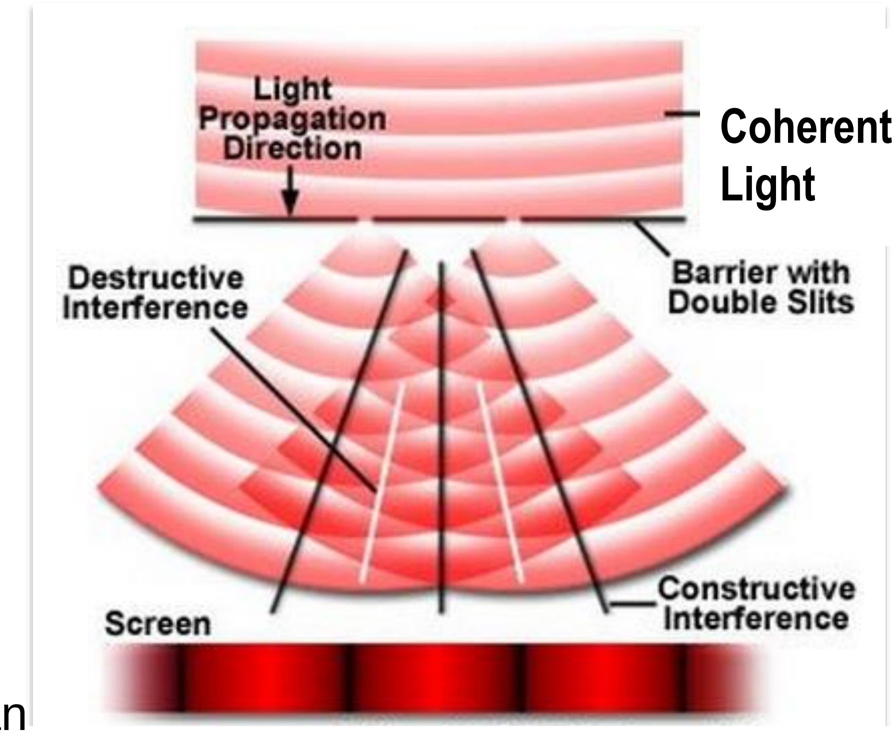
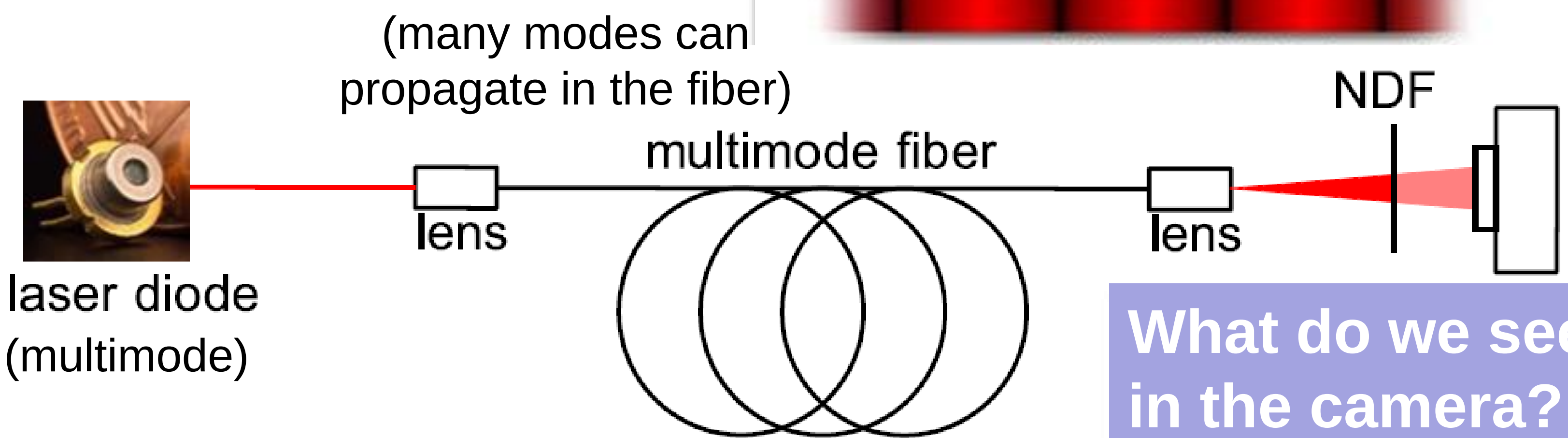
Quick reminder: laser threshold and interference of coherent waves







What do we see in the camera?

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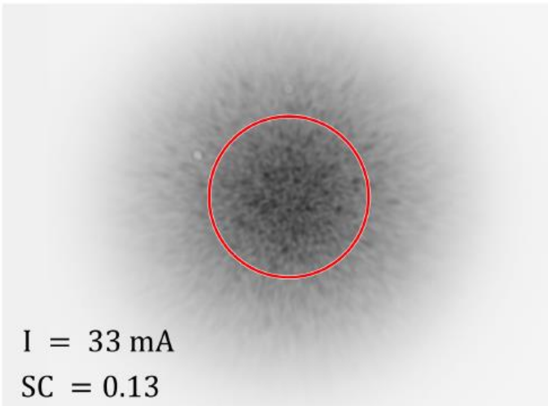
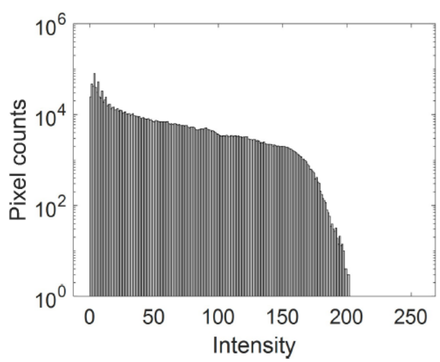
Speckle pattern

Below lasing threshold

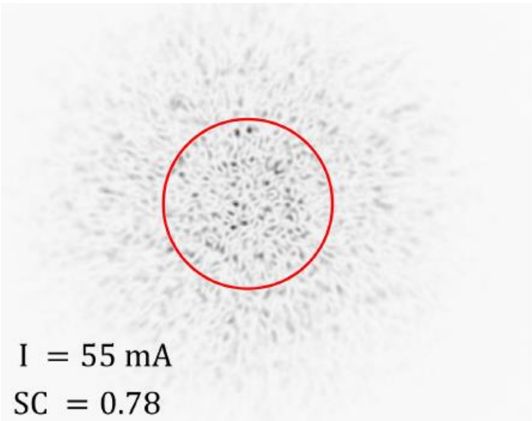
Low coherence → low speckle contrast

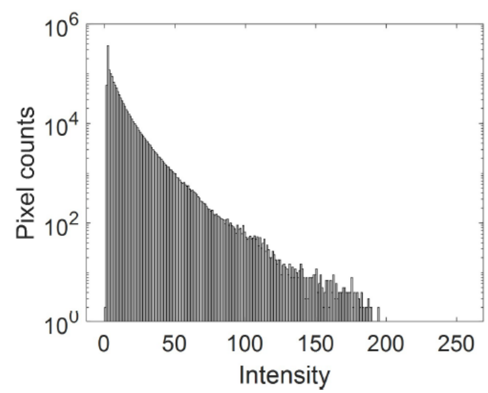




Above lasing threshold

High coherence→ high speckle contrast





How to quantify the degree of speckle?

Speckle contrast
(coefficient of variation, CV)

$$\boxed{SC = \sigma/\langle I \rangle}$$

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Can we identify, from the entropy of the patterns, the laser threshold? and infer which medium generated the speckles?

$$\text{PE} = -\frac{1}{\ln N!}\sum_{i=1}^{N} p_i \ln p_i$$

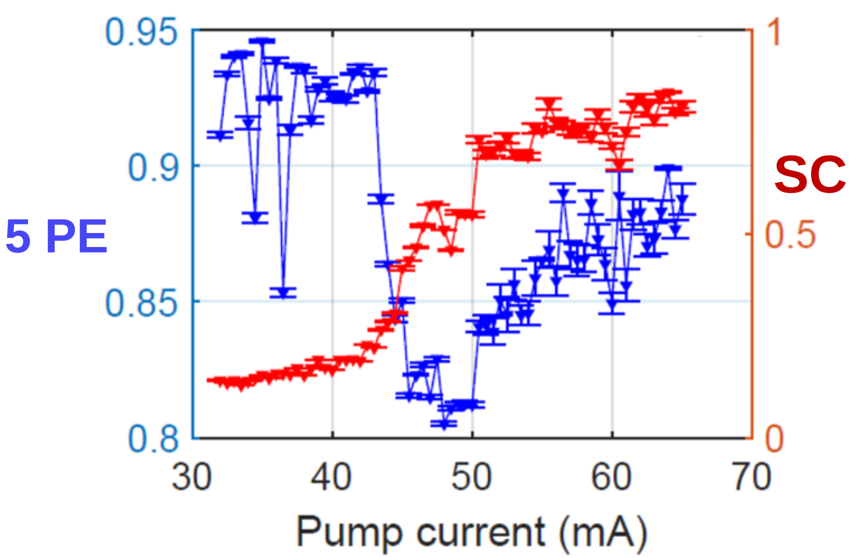
$$\text{SC} = \sigma/\langle I \rangle$$

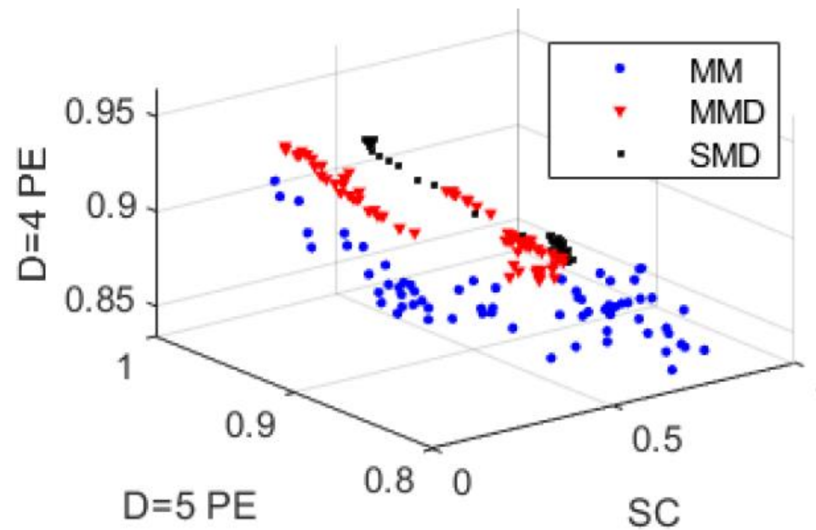
4 PE : x x
x x

5 PE : x
x x x
x

Diffusive Medium that generates speckle:

- Multimode fiber
- Multimode fiber and diffuser
- Single mode fiber and diffuser





Accuracy of the random forest classifier: 99.4 % ± 0.4 %

Giulio Tirabassi et al., APL Photonics 8, 126112 (2023).

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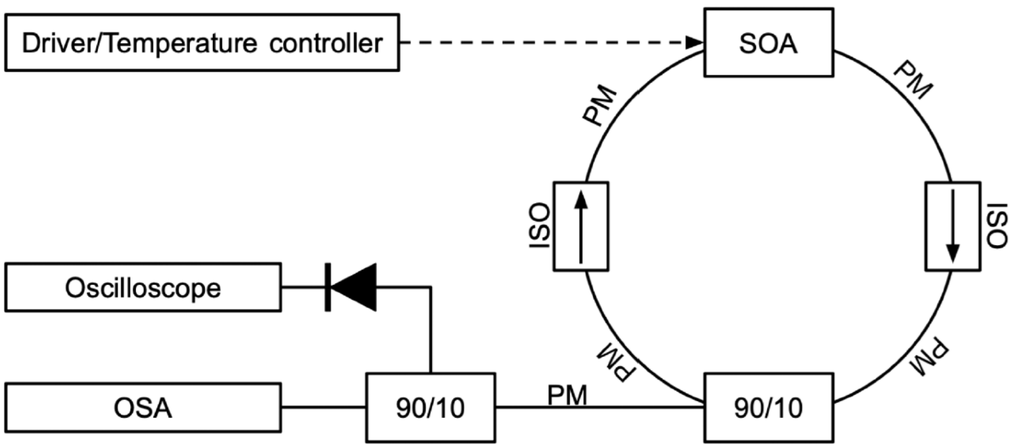
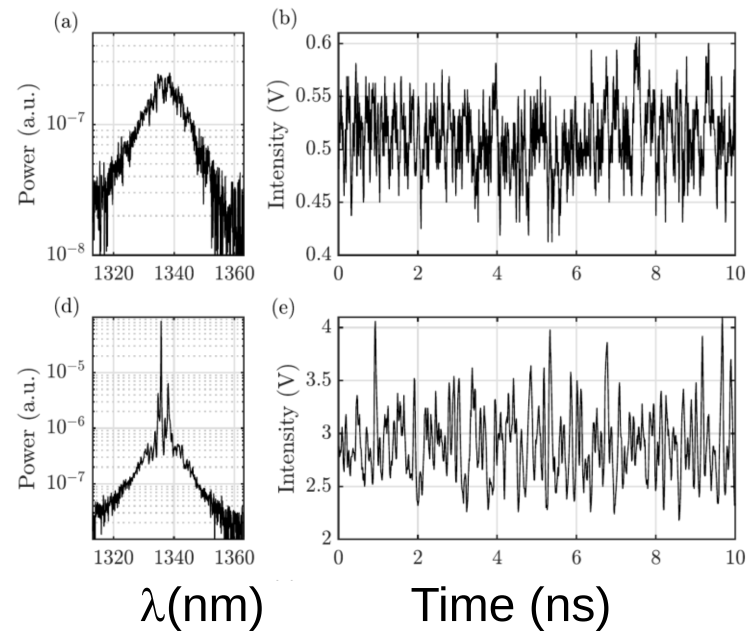
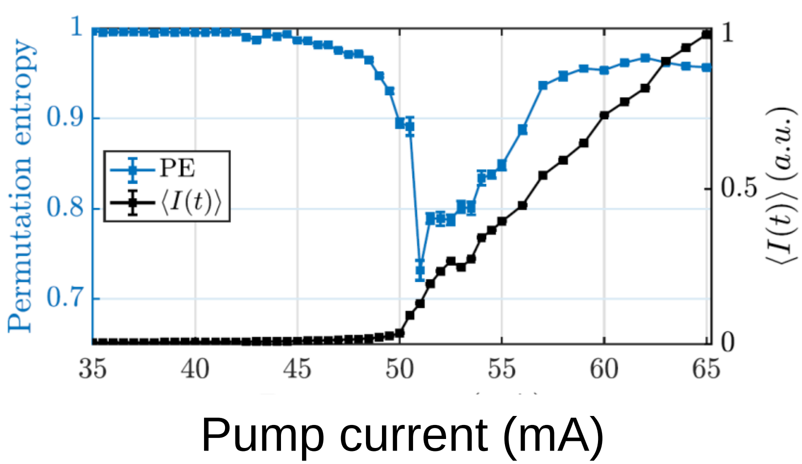
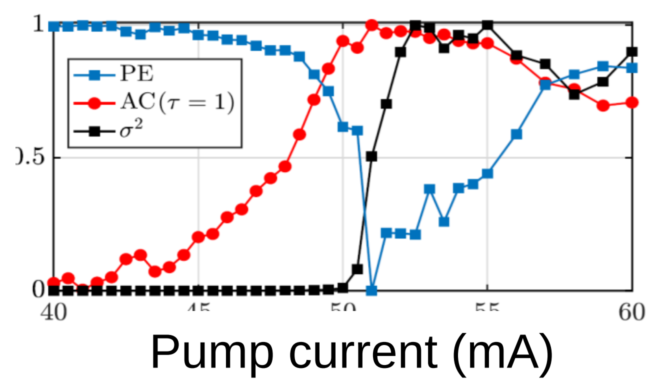
Another example: the turn-on of a highly multimode laser









J. Gancio, C. Masoller, M. Marconi, "*Identifying and anticipating the threshold bifurcation of a complex laser with permutation entropy*", Phys. Rev. Lett. 135, 093802 (2025).

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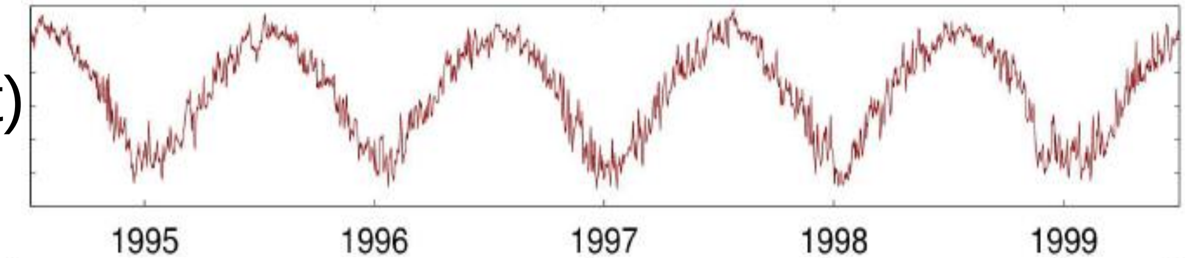
Second data analysis method: Hilbert analysis

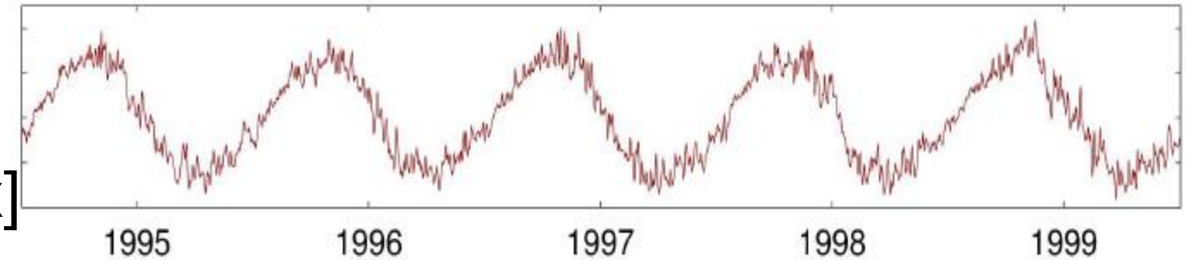
Surface Air Temperature (SAT) in a region

x(t)

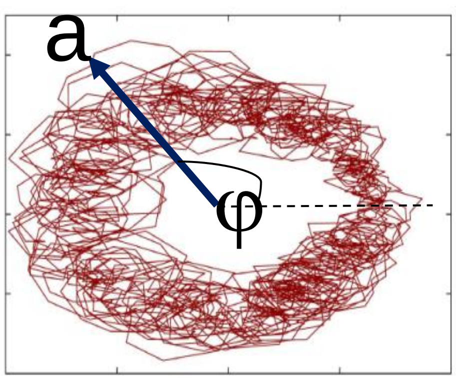


HT[sin(x)]=cos(x)

y(t)= HT[x]



y



x

Instantaneous amplitude and phase

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

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

Clear physical meaning only if *x(t)* is a narrow-band signal. Then, *a(t)* coincides with the envelope of *x(t)* and $\omega(t)=d\varphi/dt$, coincides with the main frequency in the spectrum.

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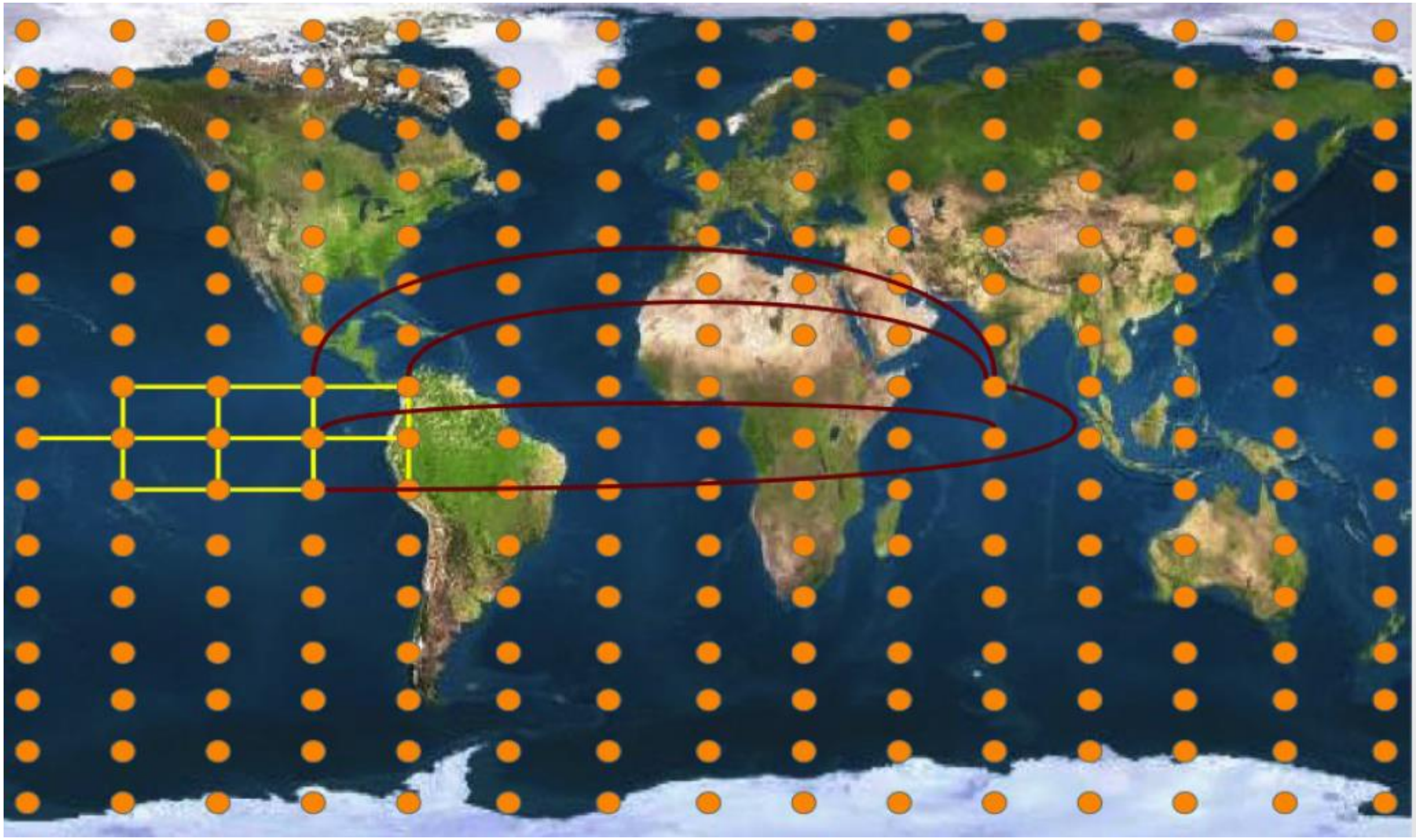
Using the HT we analyzed "re-analysis data" from the *European Centre for Medium-Range Weather Forecasts*, with high spatial and temporal resolution in the period 1979-2016



73 x 144 = 10 512 geographical sites, in each site the SAT time series has 13696 days

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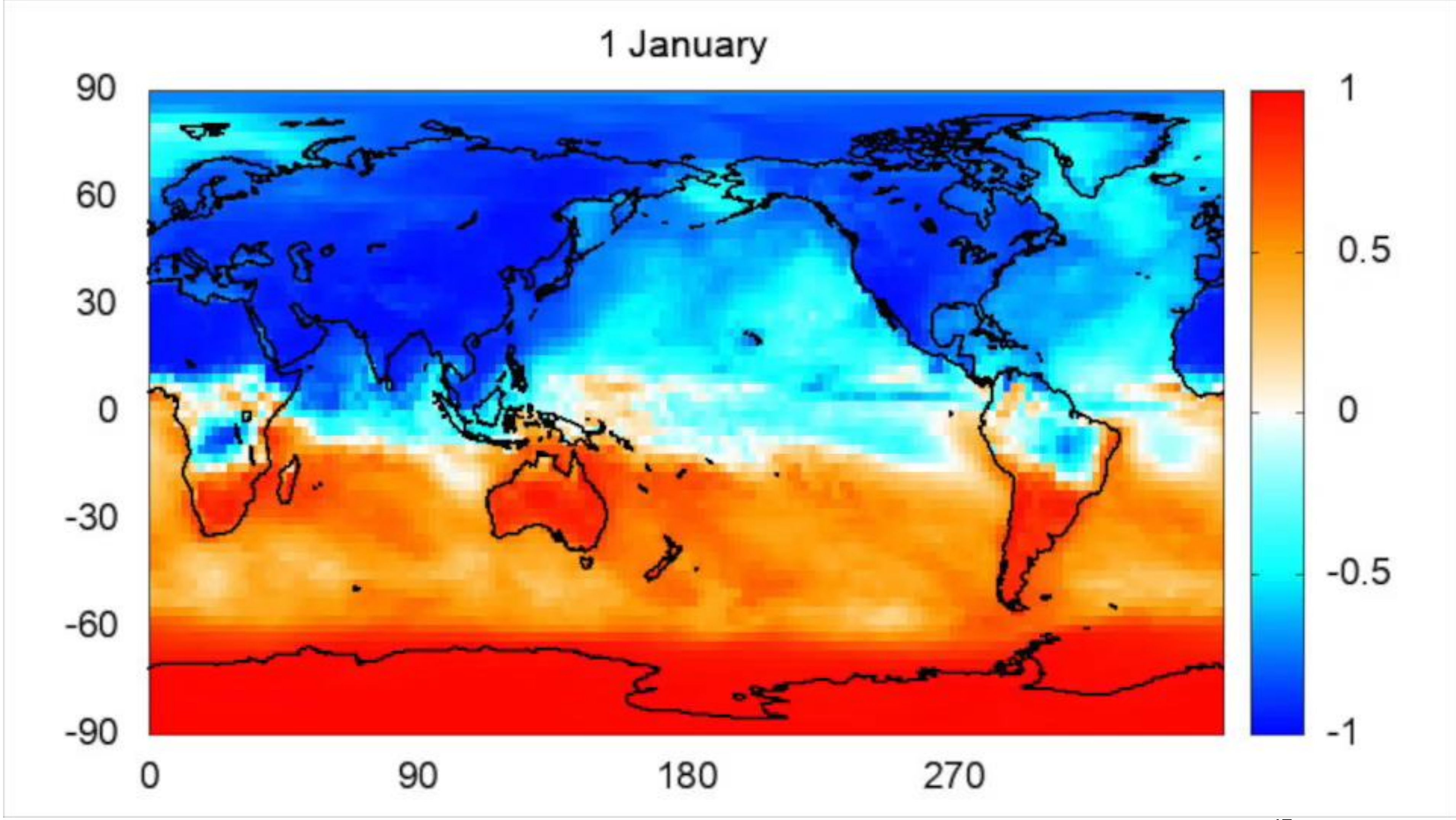
Average of the cosine of Hilbert phase of surface air temp.

Can we visualize the passing of the seasons?



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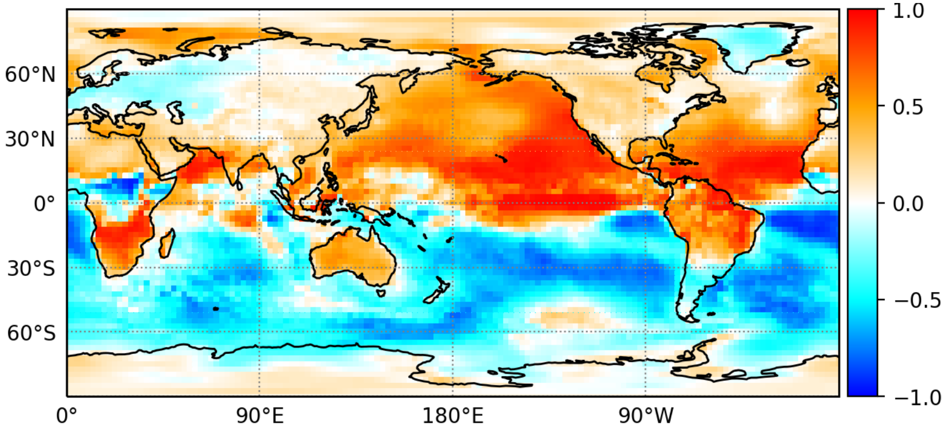
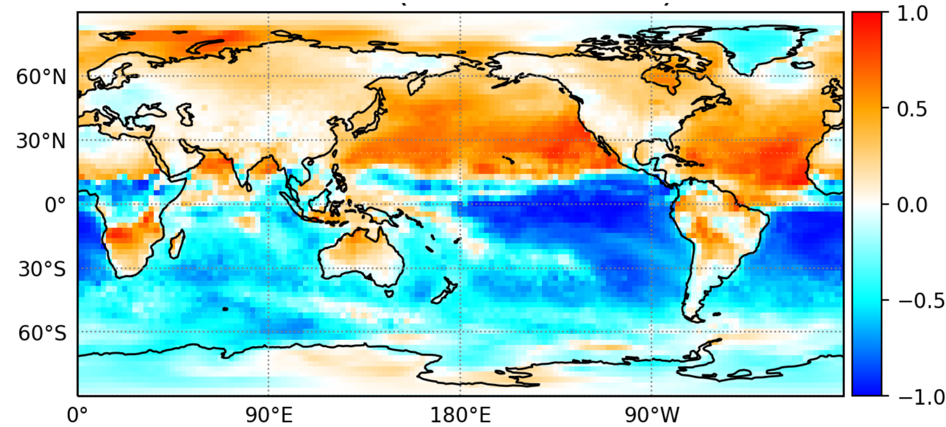
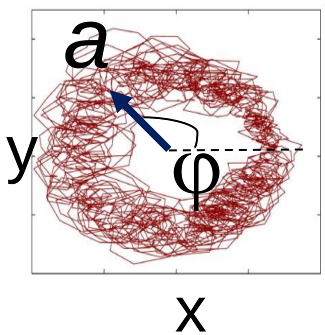
Cosine of Hilbert phase during an *El Niño* year



Cosine of Hilbert phase during a *La Niña* year



Can we detect significant changes in the last decades in the amplitude of the oscillations of surface air temperature?



In each grid point we calculate:

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

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

Significant if: $\dfrac{\Delta a}{\langle a \rangle} \geq \langle . \rangle_s + 2\sigma_s$ or $\dfrac{\Delta a}{\langle a \rangle} \leq \langle . \rangle_s - 2\sigma_s$

(100 surrogates)

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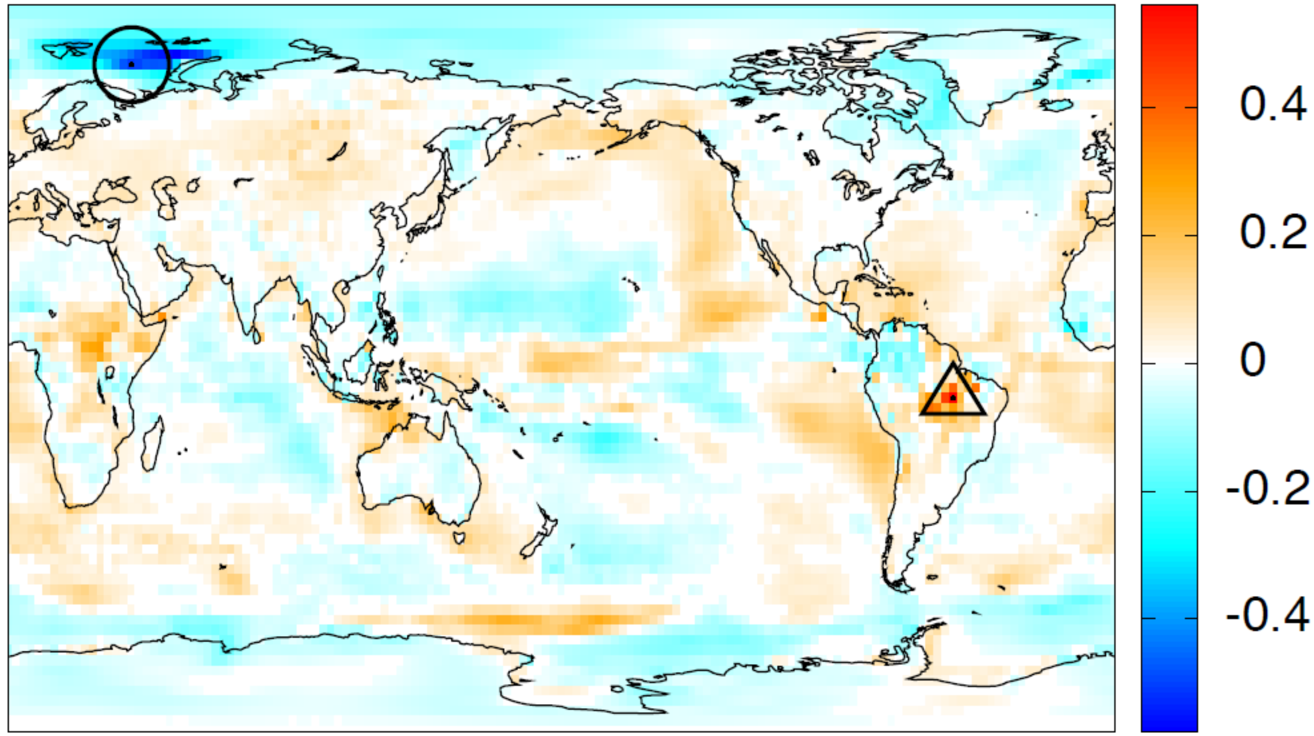
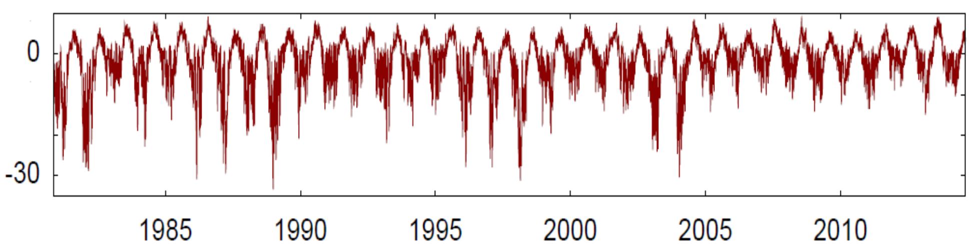
Color code:

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

White: not significant

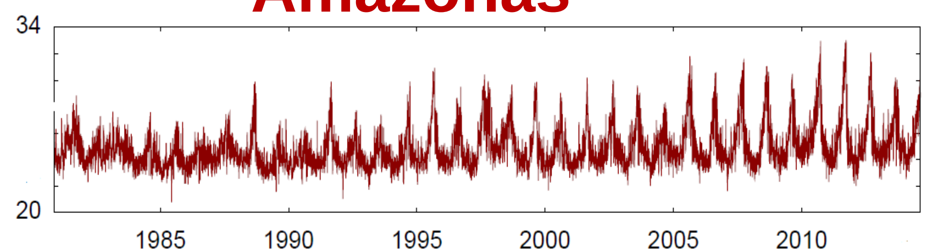


Artic



Sea ice melting

Amazonas



Deforestation

Dario A. Zappala, M. Barreiro and C. Masoller, Earth Syst. Dynam. 9, 383 (2018).

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Take home messages

- Nonlinear data analysis techniques are useful to uncover patterns and relationships in data generated by complex systems.
- Different methods often provide *complementary* information.
- “Surrogate” tests are needed to analyze statistical significance.
- Even when the data does not meet the mathematical or algorithmic requirements, the results can give useful info.
- Prof. Holger Kantz: “*Every data set bears its own difficulties: data analysis is never routine*”.

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Funding and references

- B. R. R. Boaretto, E. E. N. Macau, C. Masoller, "*Characterizing the spike timing of a chaotic laser by using ordinal analysis and machine learning*", Chaos 34, 043108 (2024).
- J. Gancio, C. Masoller, G. Tirabassi, "*Permutation entropy analysis of EEG signals for distinguishing eyes-open and eyes-closed brain states: Comparison of different approaches*", Chaos 34, 043130 (2024).
- G. Tirabassi and C. Masoller, "*Entropy-based early detection of critical transitions in spatial vegetation fields*", PNAS 120, e2215667120 (2023).
- D. A. Zappala et. al, "*Quantifying changes in spatial patterns of surface air temperature dynamics over several decades*", Earth Syst. Dy. 9, 383 (2018).
- J. Gancio, C. Masoller, M. Marconi, "*Identifying and anticipating the threshold bifurcation of a complex laser with permutation entropy*", Phys. Rev. Lett. 135, 093802 (2025).

Muchas gracias por su atención!

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