

# Nonlinear time series analysis

## Introduction

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Programa de Pós-graduação em Ecologia  
e Conservação da Universidade Federal  
do Paraná, July 2019

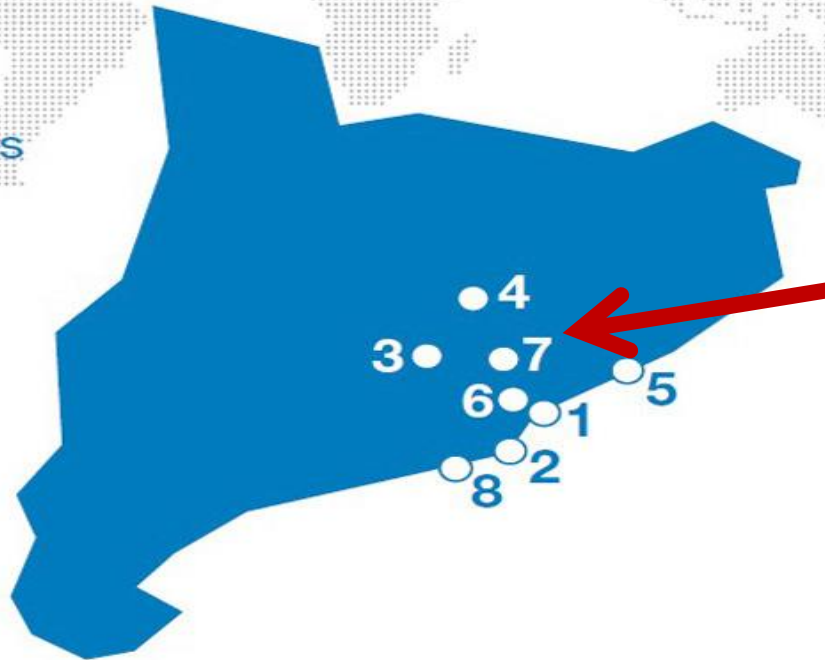
# Presentation

- Originally from Montevideo, Uruguay
- PhD in physics (lasers, Bryn Mawr College, USA)
- Since 2004 @ Universitat Politecnica de Catalunya.
- Professor in the Physics Department, research group on Dynamics, Nonlinear Optics and Lasers.



# 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 Gala centraliza grupos científicos consolidados y emergentes.

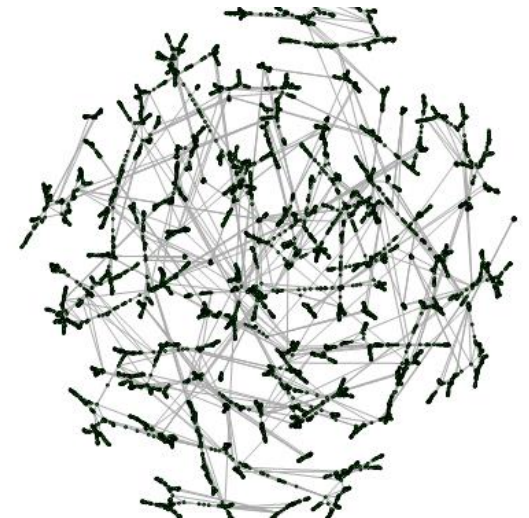
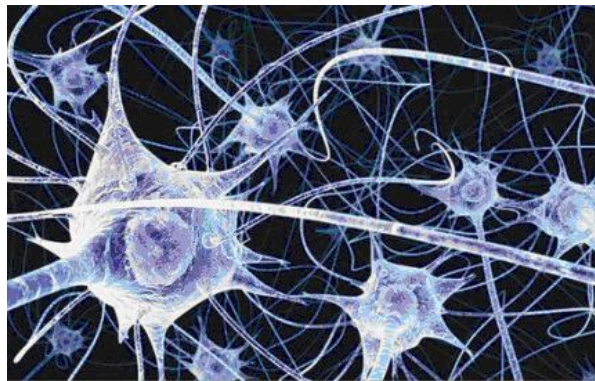
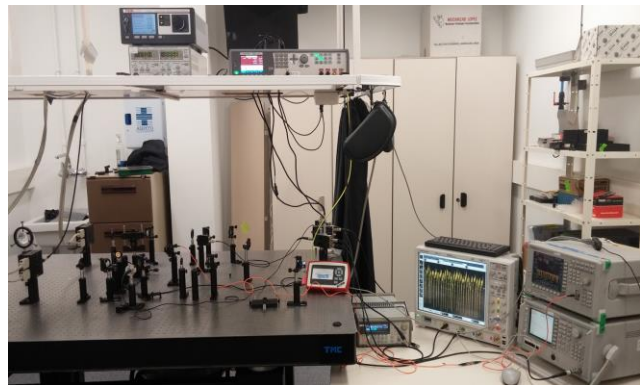
# What do we study?

- Nonlinear and stochastic phenomena
  - laser dynamics
  - neuronal dynamics
  - complex networks
  - data analysis (climate, biomedical signals)

**Data analysis**

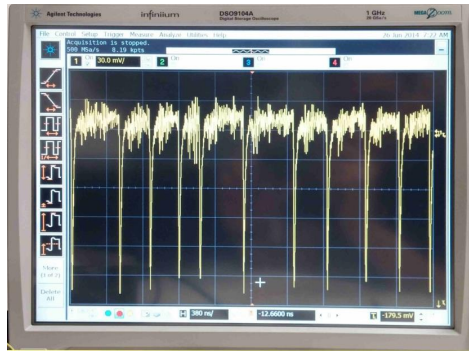
**Nonlinear  
dynamics**

**Applications**

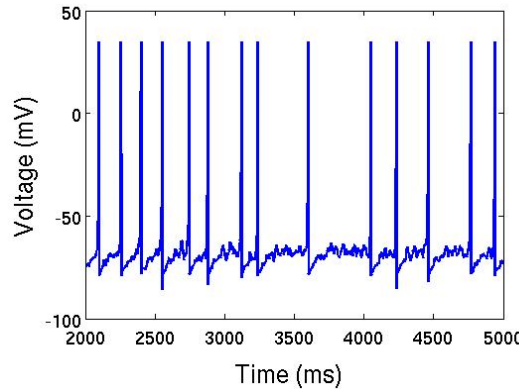


# Lasers, neurons, climate, complex systems?

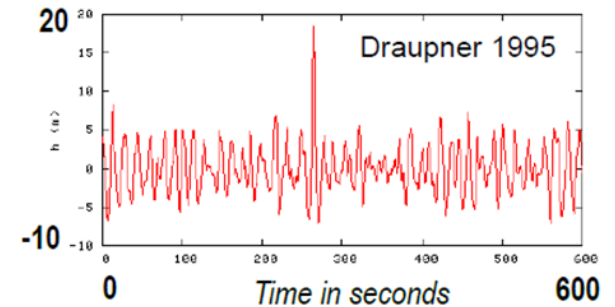
- Lasers allow us to study in a controlled way phenomena that occur in diverse complex systems.
- Laser experiments allow to generate sufficient data to test new methods of data analysis for prediction, classification, etc.



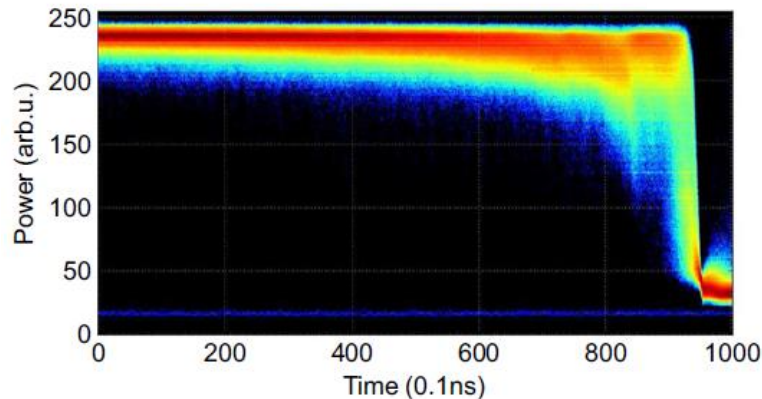
*Laser & neuronal spikes*



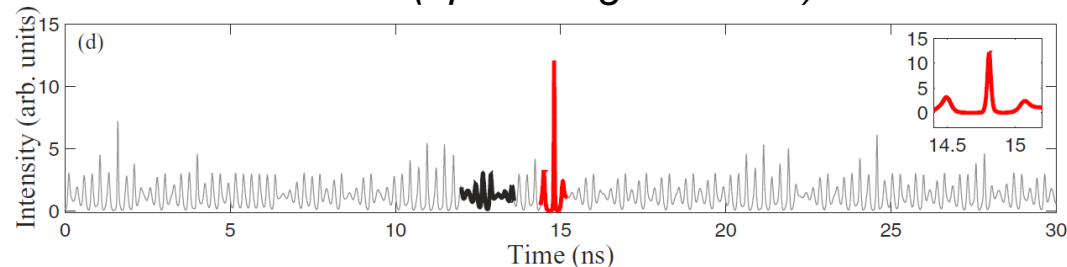
*Ocean rogue wave (sea surface elevation in meters)*



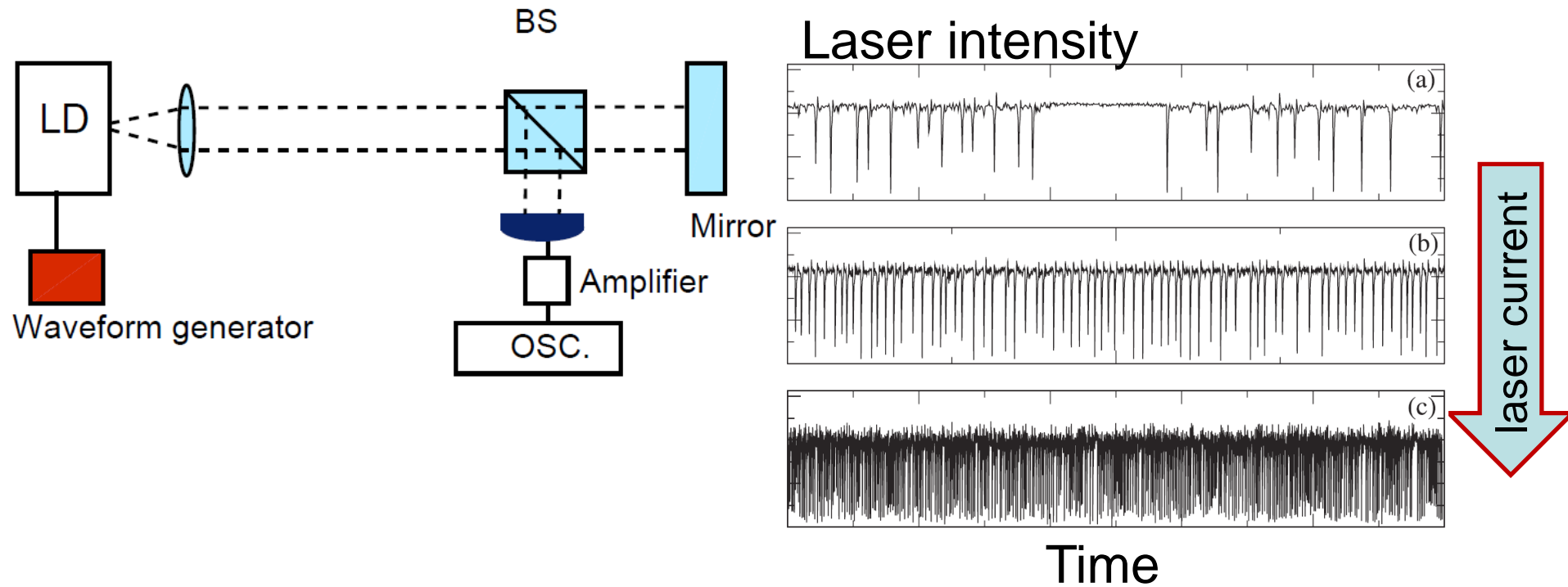
*Abrupt switching*



*Extreme events (optical rogue waves)*



**In complex systems dynamical transitions are difficult to identify and to characterize.  
Example: laser with time delayed optical feedback**



# How complex optical signals emerge from noise

## Quantitative identification of dynamical transitions in a semiconductor laser with optical feedback

Carlos Quintero, Jordi Tiana-Alsina, Jordi Roma,  
M. Carme Torrent, and Cristina Masoller.

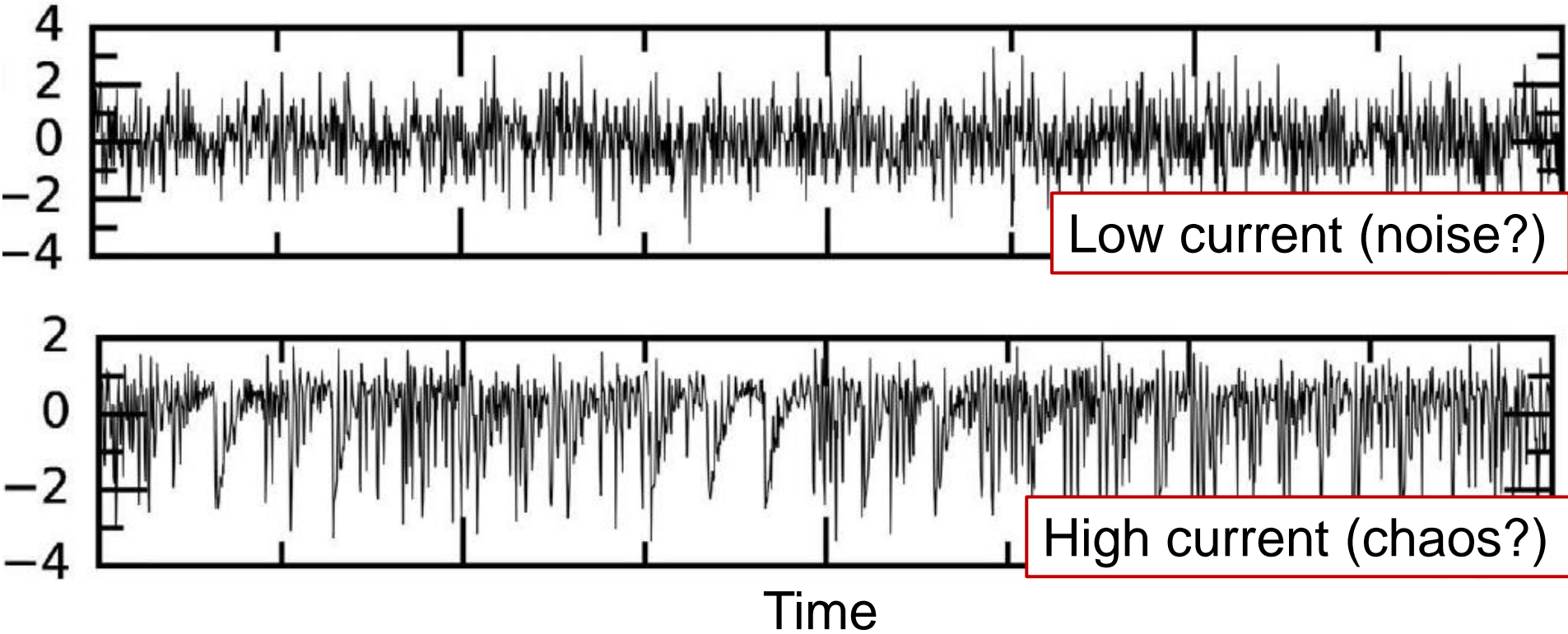


Grup de Recerca en Dinàmica No Lineal, Òptica No Lineal i Làsers  
UNIVERSITAT POLITÈCNICA DE CATALUNYA

Dinàmica i Òptica No Lineal i Làsers (DONLL)  
Dept. Física, Terrassa, Barcelona, Spain

Video: [how complex optical signals emerge from noisy fluctuations](#)

Laser output intensity



Can differences be quantified? With what reliability?

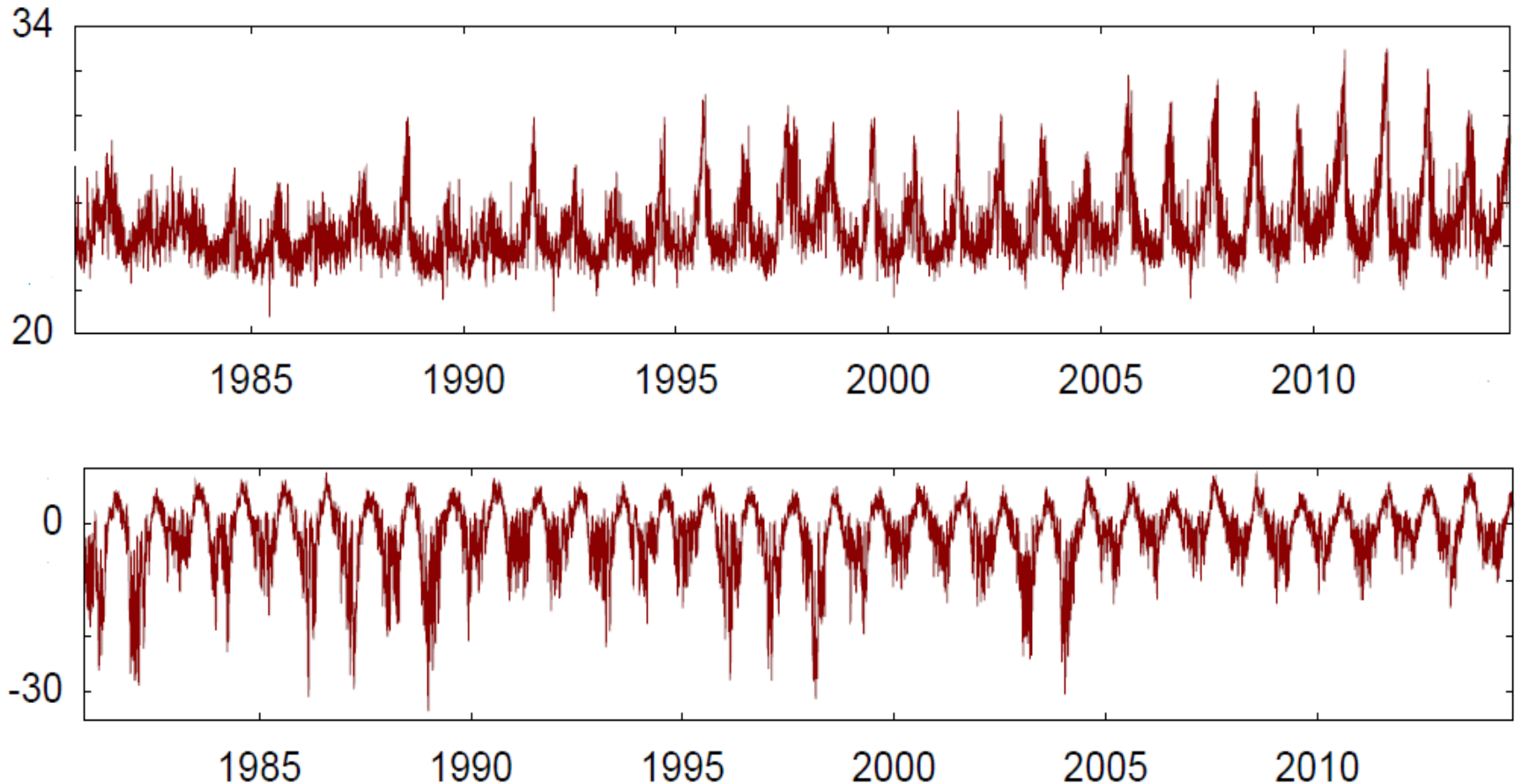


# Are weather extremes becoming more frequent? more extreme?



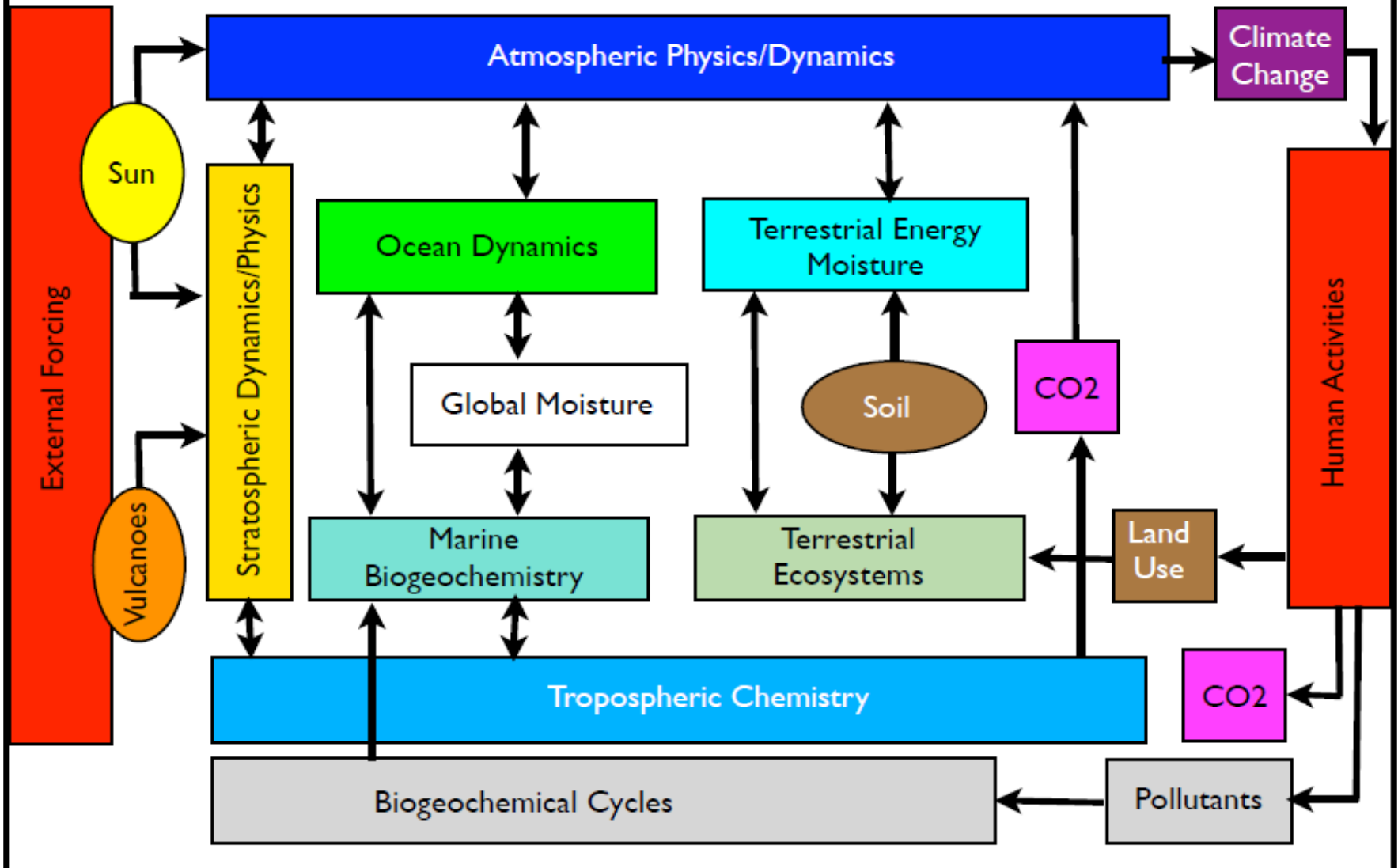
Credit: Richard Williams, North Wales, UK

# Surface air temperature in two different regions



Can changes be quantified? With what reliability?

# The Climate System is a “complex system”

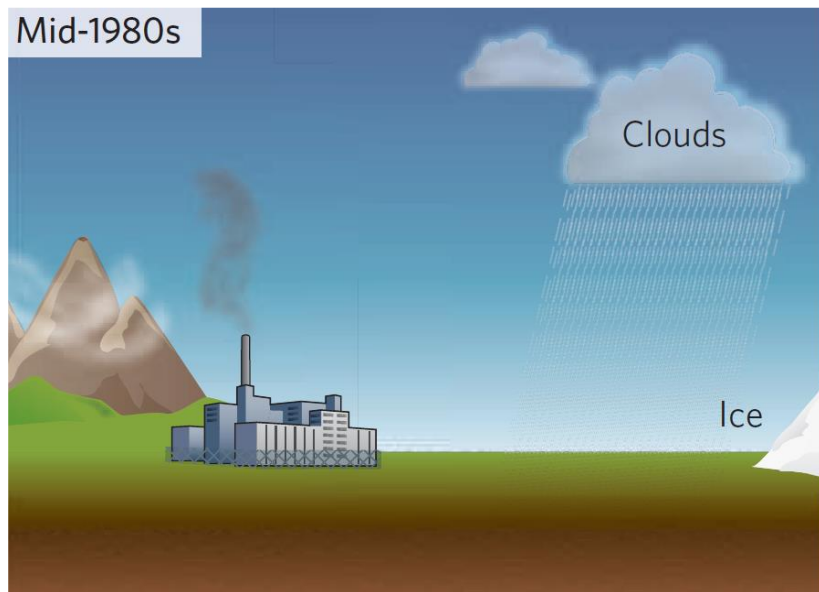


Courtesy of Henk Dijkstra (Utrecht University)

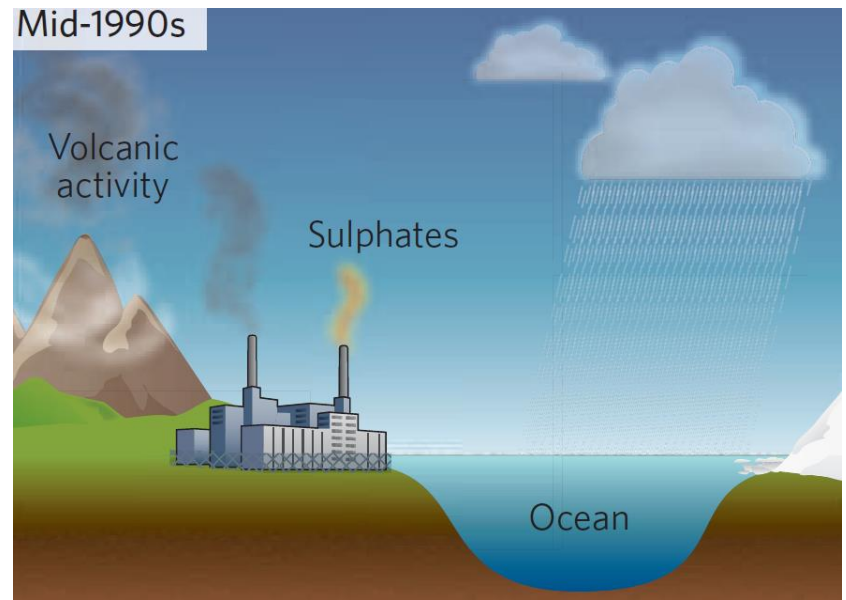
**Thanks to advances in computer science, global climate models allow for good weather forecasts**



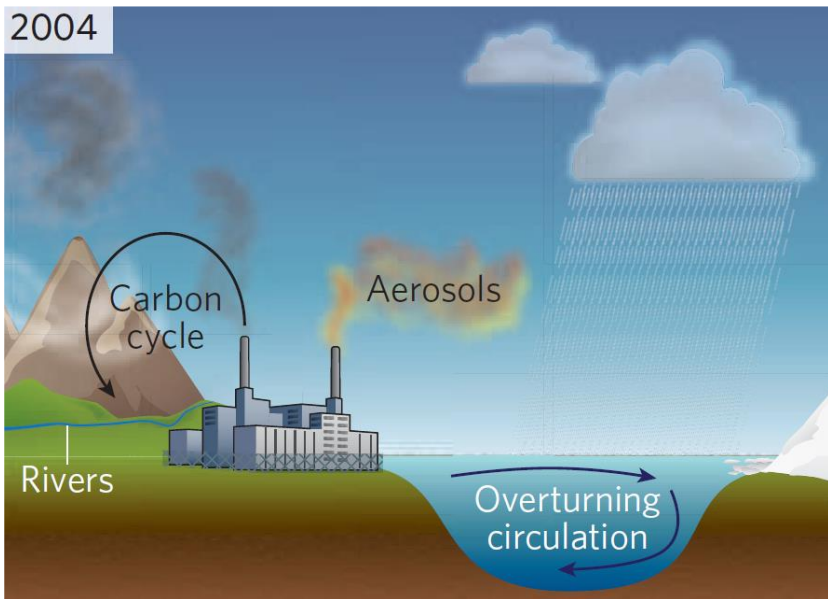
Mid-1980s



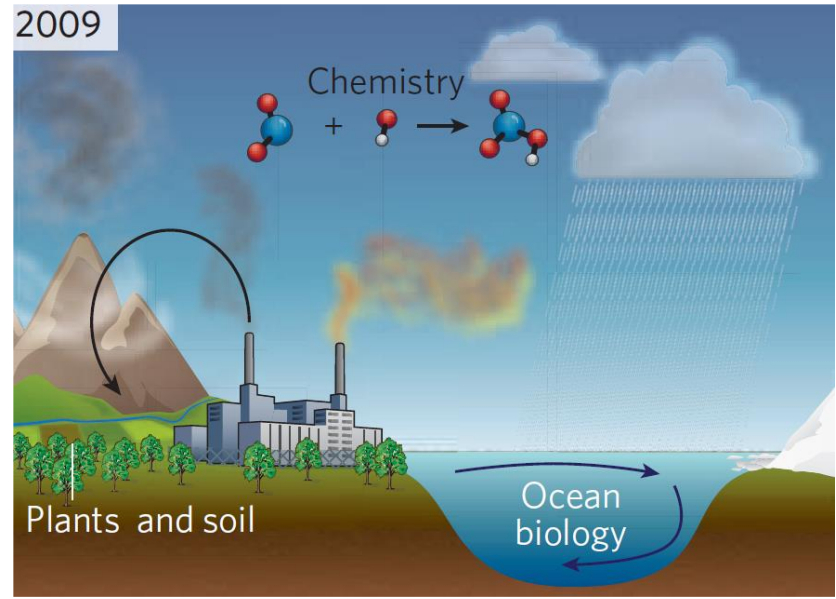
Mid-1990s



2004



2009



# But global climate models are not very useful for improving our understanding

- But “over-simplified models” do not always provide useful information.

In early summer, 1996, milk production at a Wisconsin dairy farm was very low. The farmer wrote to the state university, asking help from academia. A multidisciplinary team of professors was assembled, headed by a theoretical physicist, and two weeks of intensive on-site investigation took place. A few weeks later, a physicist phoned the farmer, "I've got the answer," he said, "But it only works when you consider spherical cows in a vacuum. . . ."

*Source:*

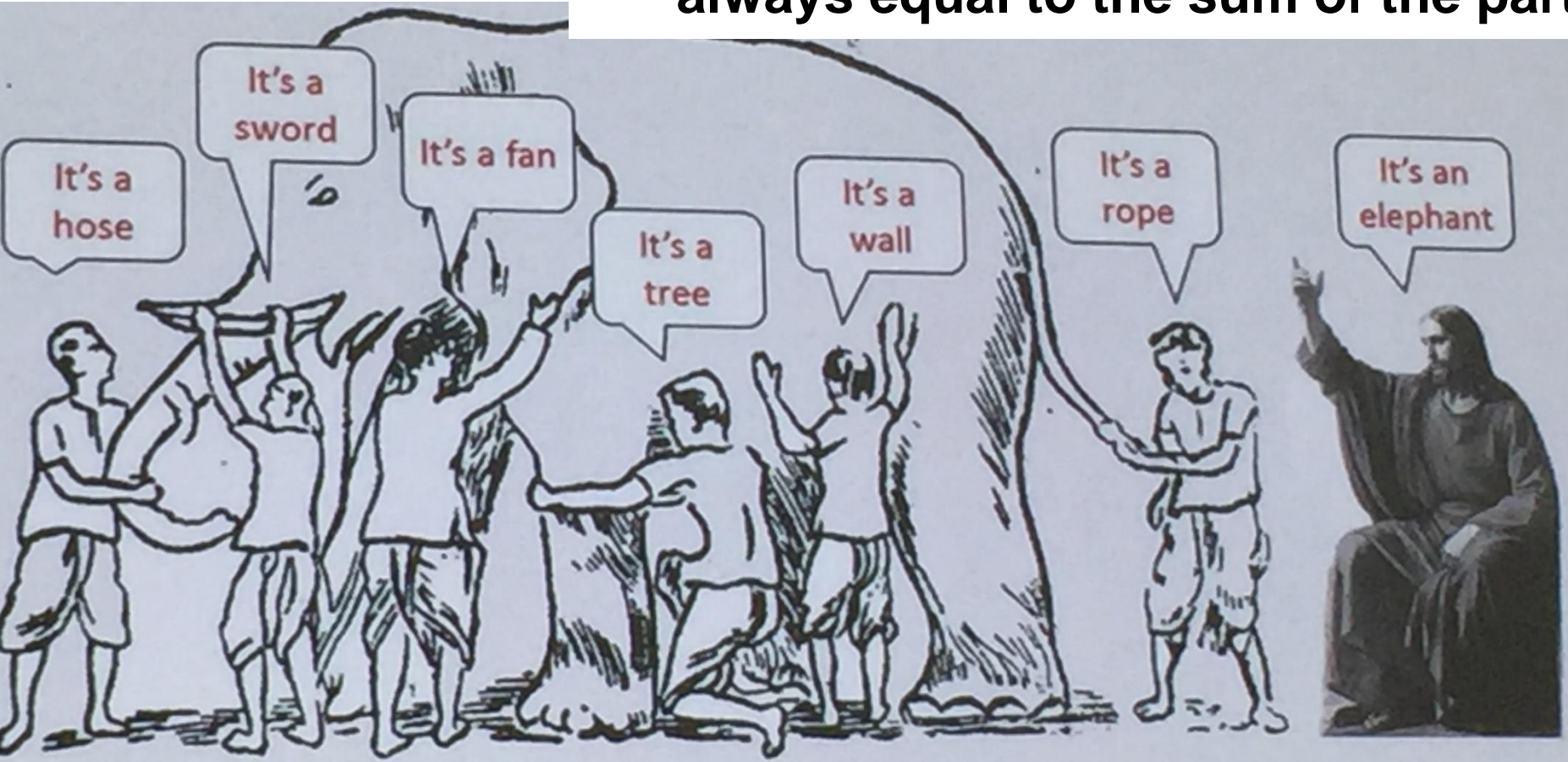
*[https://mirror.uncyc.org/wiki/Spherical\\_Cows](https://mirror.uncyc.org/wiki/Spherical_Cows)*



**Strong need of nonlinear methods to  
extract reliable information from data**

**Why nonlinear ?**

Because in nature the whole is not always equal to the sum of the parts





## ■ Introduction

- Historical development: from dynamical systems to complex systems

## ■ Univariate analysis

- Methods to extract information from a time series.
- Applications.

## ■ Bivariate analysis

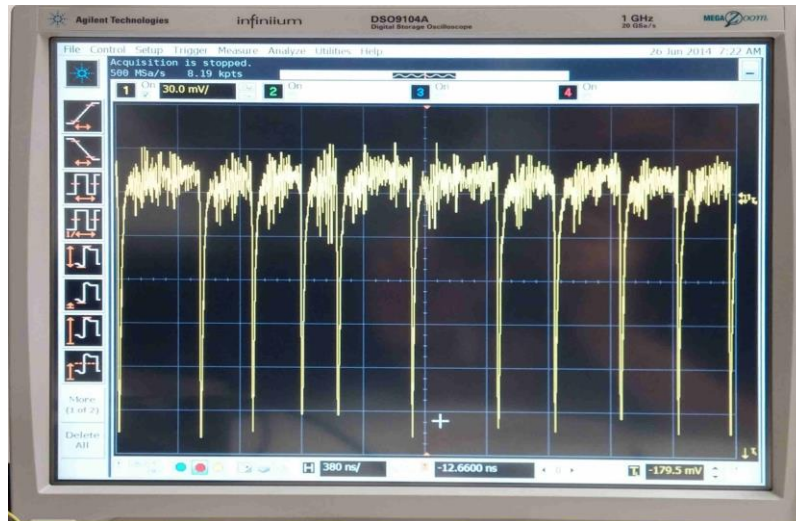
- Correlation, directionality and causality.
- Applications.

## ■ Multivariate analysis

- Many time series: complex networks.
- Network characterization and analysis.
- Applications.

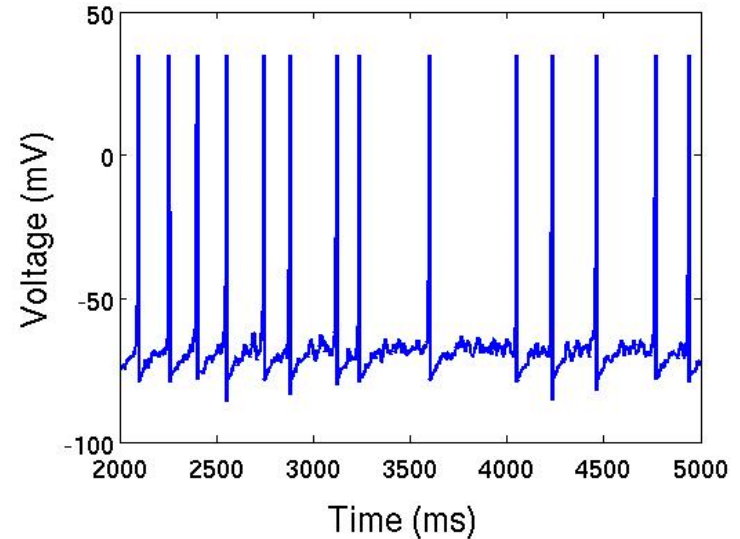
# Time Series Analysis: what is this about?

## Optical spikes



Time ( $\mu\text{s}$ )

## Neuronal spikes

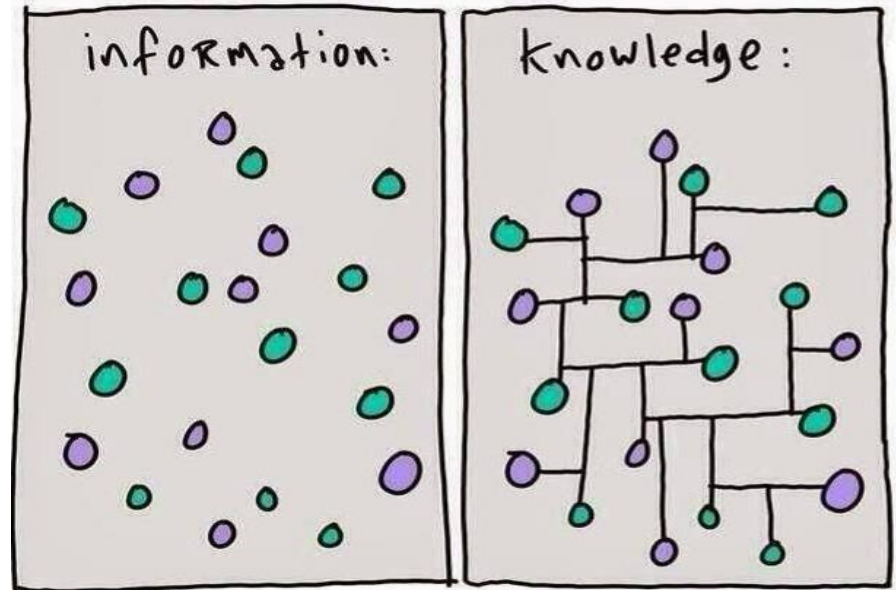


- Similar dynamical systems generate these signals?
- Ok, very different dynamical systems, but maybe similar statistical properties?
- Time series analysis finds “hidden similarities” in very different systems.

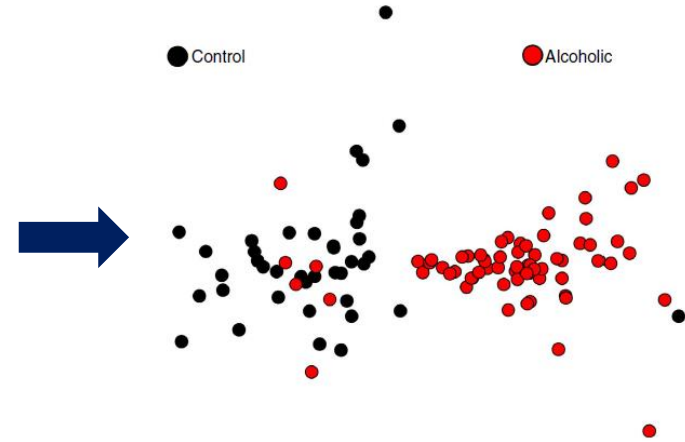
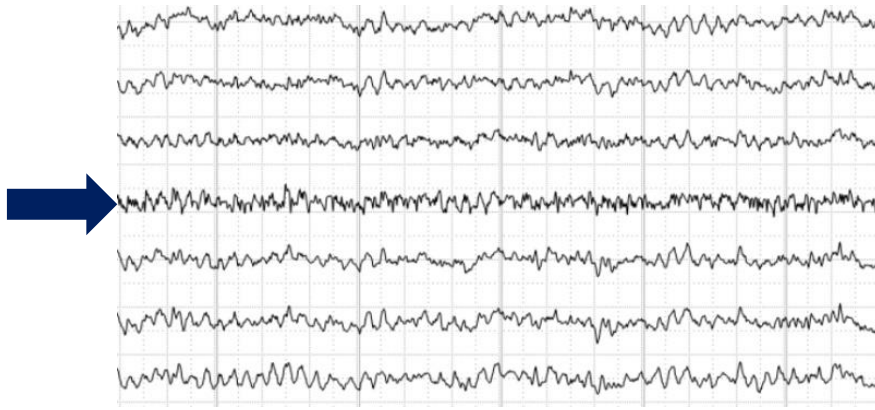
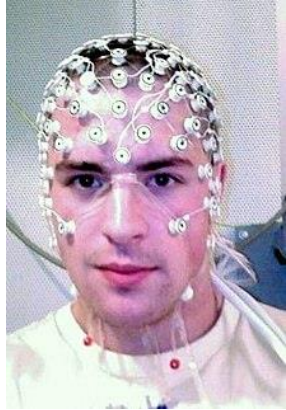
# Main goal of Time Series Analysis: to extract meaningful information

What for?

- Classification
- Prediction
- Model verification
- Parameter estimation
- Etc.

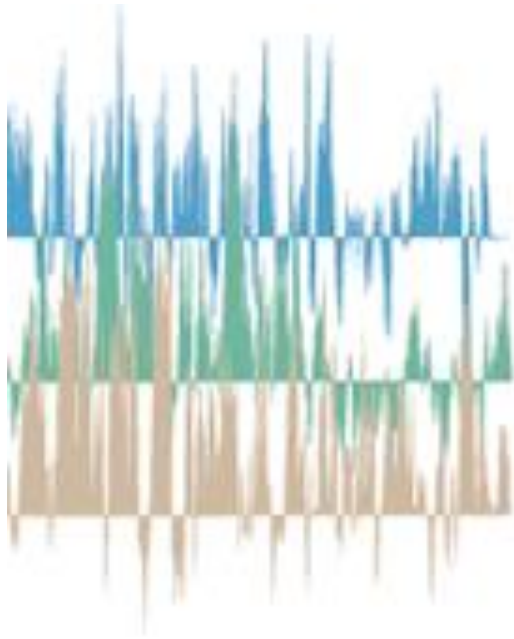


# Example: analysis of EEG signals allows to distinguish control from alcoholic subjects



[T. A. Schieber et al, Nat. Comm. 8:13928 \(2017\).](#)

# Example: inferring climatic interactions

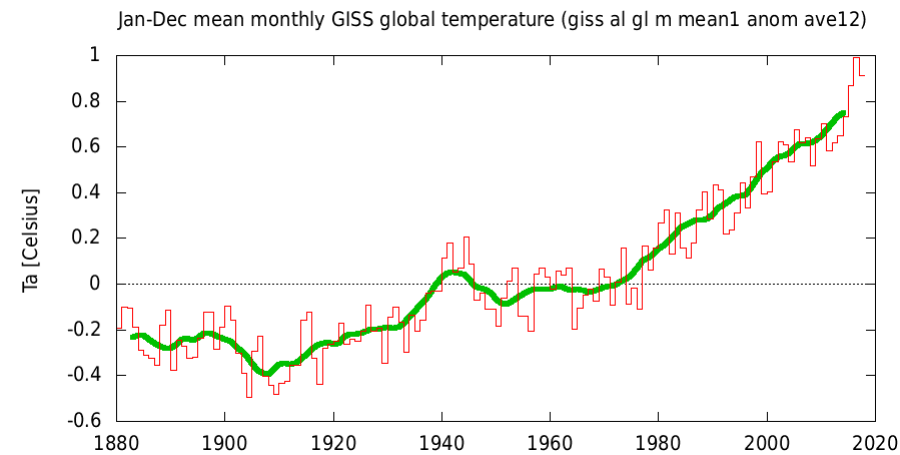


Surface Air Temperature  
Anomalies in different  
geographical regions

*Donges et al, Chaos 2015*

# Methods

- Many methods have been developed to extract information from a time series  $(x_1, x_2, \dots, x_N)$ .
- The method to be used depends on the characteristics of the data
  - Length of the time series;
  - Stationarity;
  - Level of noise;
  - Temporal resolution;
  - etc.



- **Different methods provide complementary information.**

# Where the data comes from?

- Modeling assumptions about the **type of dynamical system** that generates the data:
  - Stochastic or deterministic?
  - Regular or chaotic or “complex”?
  - Stationary or non-stationary? Time-varying parameters?
  - Low or high dimensional?
  - Spatial variable? Hidden variables?
  - Time delays? Etc.
- Good results depend on the *knowledge* of the system that generates the time series.



**Brief historical tour, from  
dynamical systems to  
complex systems**



# The start of dynamical systems theory

- Mid-1600s: Ordinary differential equations (ODEs)
- **Isaac Newton**: studied planetary orbits and solved analytically the “two-body” problem (earth around the sun).
- Since then: a lot of effort for solving the “three-body” problem (earth-sun-moon) – Impossible.



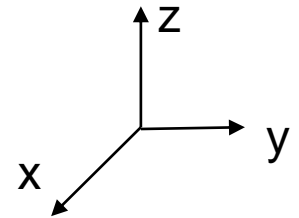


- **Henri Poincaré** (French mathematician).

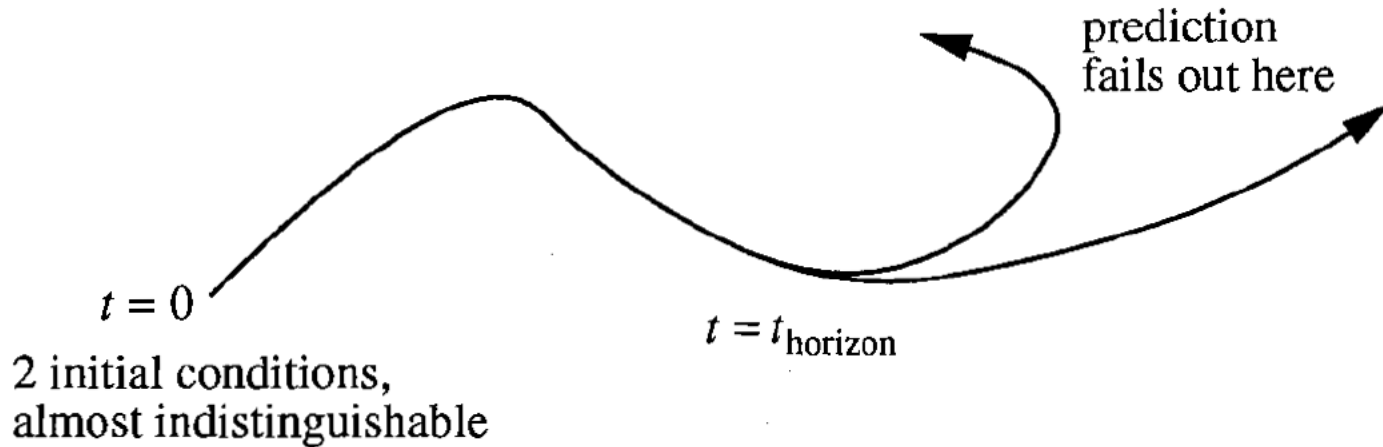
Instead of asking “*which are the exact positions of planets (trajectories)?*”

he asked: “*is the solar system **stable** for ever, or will planets eventually run away?*”

- He developed a **geometrical** approach to solve the problem.
- Introduced the concept of “phase space”.
- He also had an intuition of the possibility of **chaos**.



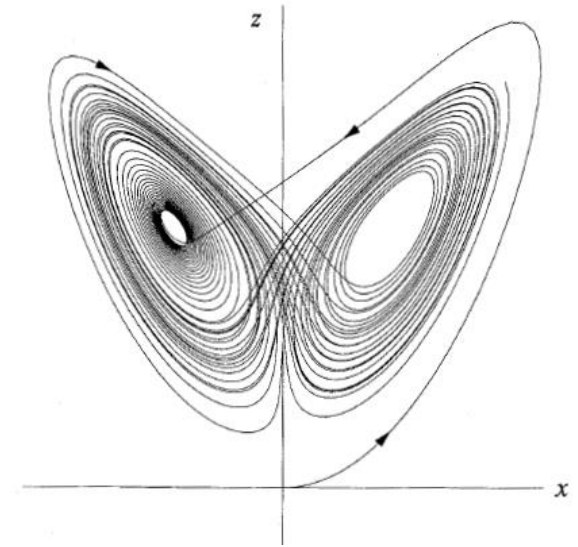
Poincare: “The evolution of a **deterministic** system can be aperiodic, unpredictable, and strongly depends on the initial conditions”



Deterministic system: the initial conditions fully determine the future state. **There is no randomness but the system can be unpredictable.**

# 1950s: First computer simulations

- Computes allowed to experiment with equations.
- Huge advance in the field of “*Dynamical Systems*”.
- 1960s: **Eduard Lorentz** (American mathematician and meteorologist at MIT): simple model of convection rolls in the atmosphere.
- **Chaotic** motion.



# Order within chaos and self-organization

- **Ilya Prigogine** (Belgium, born in Moscow, Nobel Prize in Chemistry 1977)
- Thermodynamic systems far from equilibrium.
- Discovered that, in chemical systems, the interplay of (external) **input of energy** and **dissipation** can lead to “self-organized” patterns.



# The study of spatio-temporal structures has uncovered striking similarities in nature



Honey bees do a spire wave to scare away predators

<https://www.youtube.com/watch?v=Sp8tLPDMUyg>



Rotating waves occur in the heart during ventricular fibrillation



Hurricane Maria (Wikipedia)

<https://media.nature.com/original/nature-assets/nature/journal/v555/n7698/extref/nature26001-sv6.mov>

# Spiral vegetation patterns in high-altitude wetlands

Cristian Fernandez-Oto\*, Daniel Escaff, Jaime Cisternas

*Complex Systems Group, Facultad de Ingeniería y Ciencias Aplicadas, Universidad de los Andes, Av. Mon. Alvaro del Portillo, 12455 Santiago, Chile*

Ecological Complexity 37 (2019) 38–46



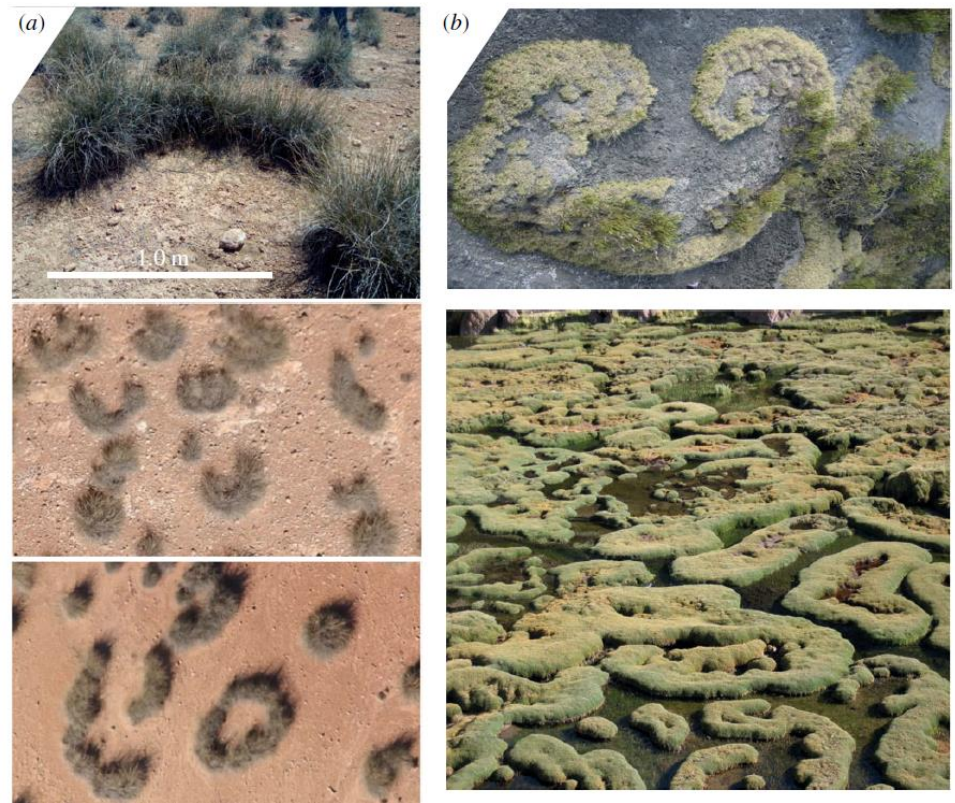
Spiral vegetation patterns in San Pedro de Atacama, Chile



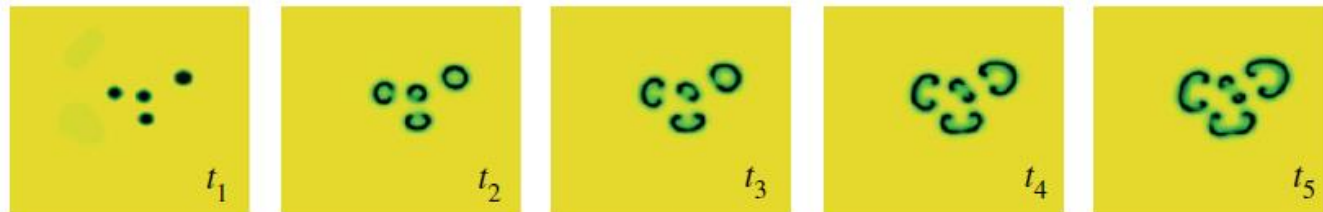
# Observation and modelling of vegetation spirals and arcs in isotropic environmental conditions: dissipative structures in arid landscapes

M. Tlidi<sup>1</sup>, M. G. Clerc<sup>2</sup>, D. Escaff<sup>3</sup>, P. Couteron<sup>4</sup>,  
M. Messaoudi<sup>5</sup>, M. Khaffou<sup>5</sup> and A. Makhoute<sup>5</sup>

*Phil. Trans. R. Soc. A* **376** 20180026 (2018)



Morocco



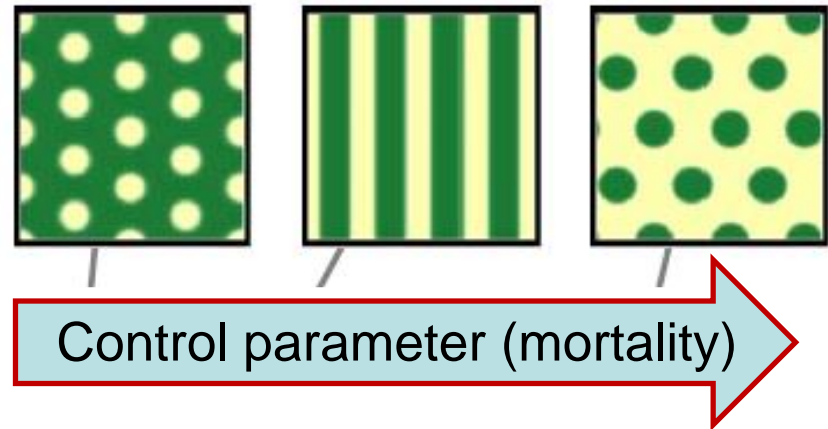
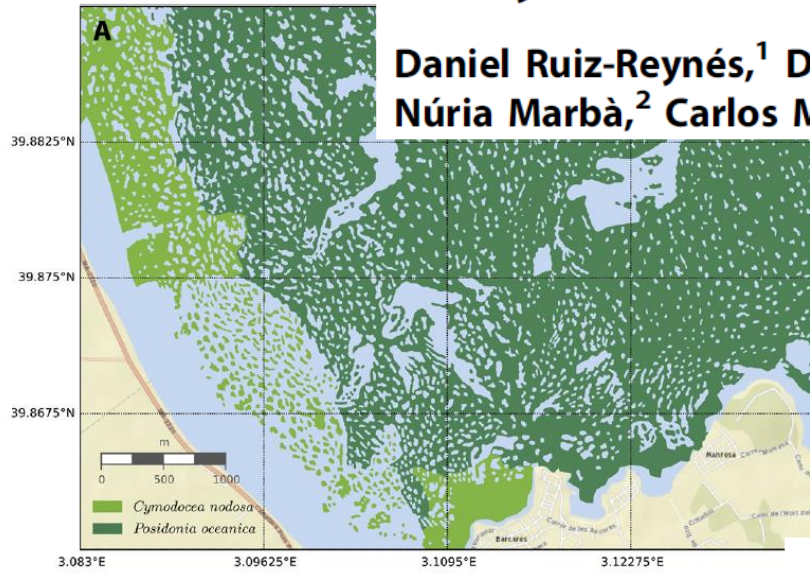
Model simulation showing the temporal transition from localized patterns to arcs and spirals.



# Fairy circle landscapes under the sea

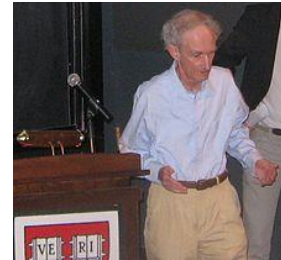
Daniel Ruiz-Reynés,<sup>1</sup> Damia Gomila,<sup>1\*</sup> Tomàs Sintes,<sup>1</sup> Emilio Hernández-García,<sup>1</sup>  
Núria Marbà,<sup>2</sup> Carlos M. Duarte<sup>3</sup>

Ruiz-Reynés *et al.*, *Sci. Adv.* 2017;**3**:e1603262 2 August 2017



**Fig. 1. Examples of fairy circles and spatial patterns in Mediterranean seagrass meadows.** (A) Side-scan image of a seagrass meadow in Pollença bay (Mallorca

- **Robert May** (Australian, 1936): population biology
- "Simple mathematical models with very complicated dynamics“, *Nature* (1976).



$$x_{t+1} = f(x_t)$$

$$\text{Example: } f(x) = r x(1 - x)$$

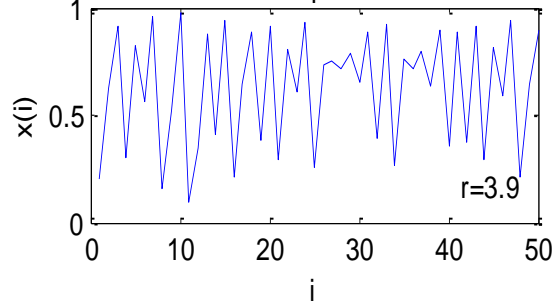
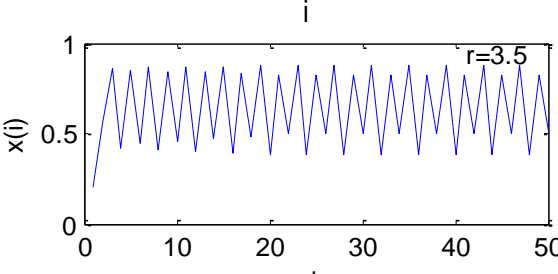
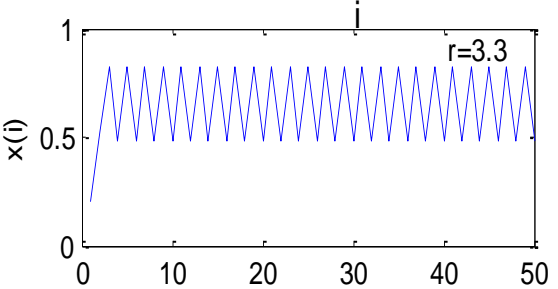
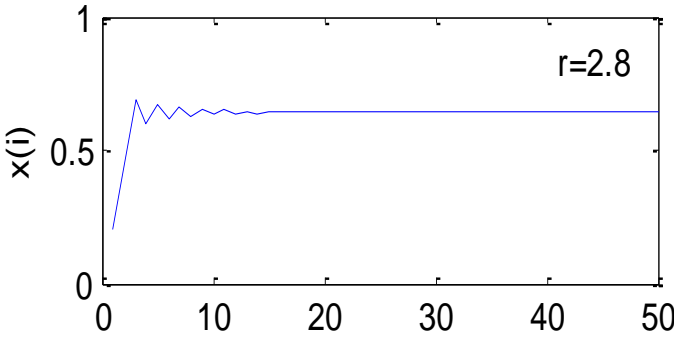
- Difference equations (“iterated maps”), even though simple and deterministic, can exhibit different types of dynamical behaviors, from **stable points**, to a bifurcating hierarchy of **stable cycles**, to **apparently random fluctuations**.

# The logistic map

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

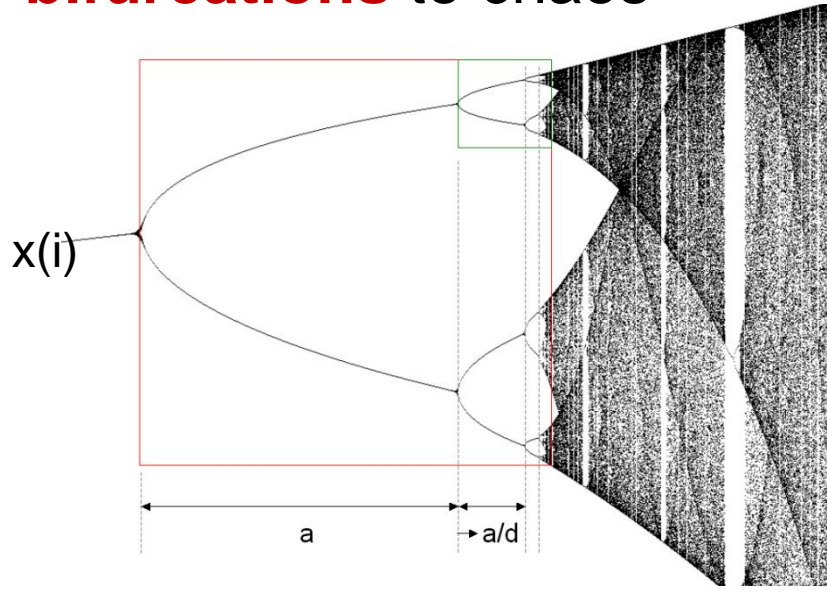
$r=2.8$ , Initial condition:  $x(1) = 0.2$

Transient relaxation  $\rightarrow$  long-term stability



Transient dynamics  $\rightarrow$  stationary oscillations (regular or irregular)

“period-doubling” bifurcations to chaos



Parameter  $r$

# Universal route to chaos

- In 1975, **Mitchell Feigenbaum** (American mathematician and physicist 1944-2019), using a small HP-65 calculator, discovered the scaling law of the bifurcation points

$$\lim_{n \rightarrow \infty} \frac{r_{n-1} - r_{n-2}}{r_n - r_{n-1}} = 4.6692\dots$$

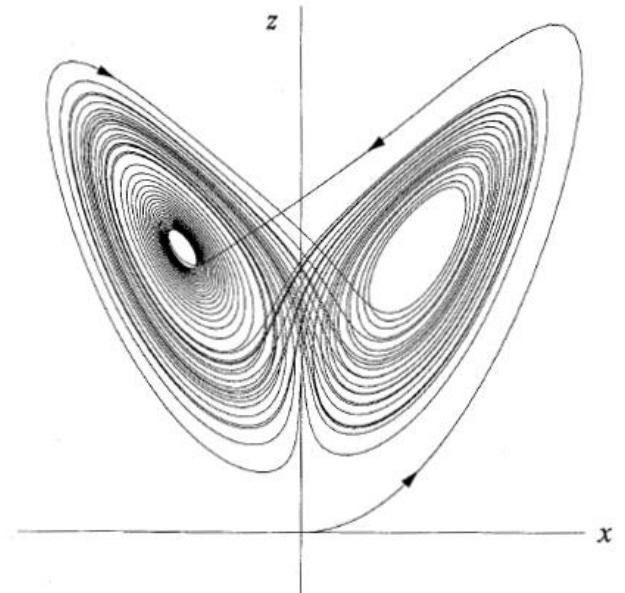
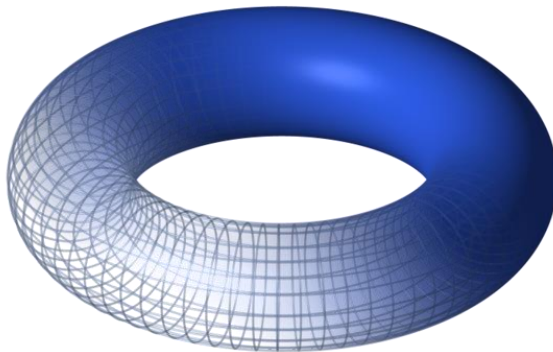
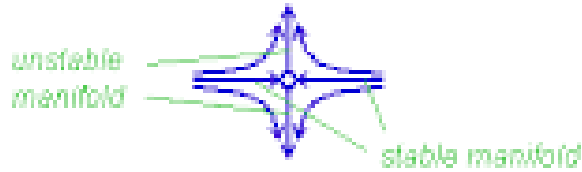
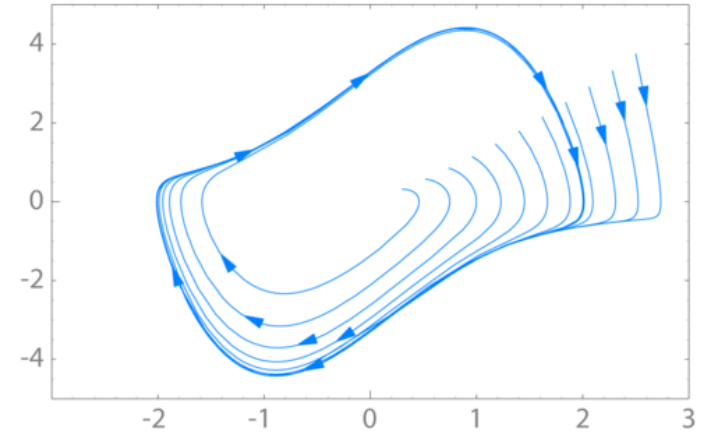
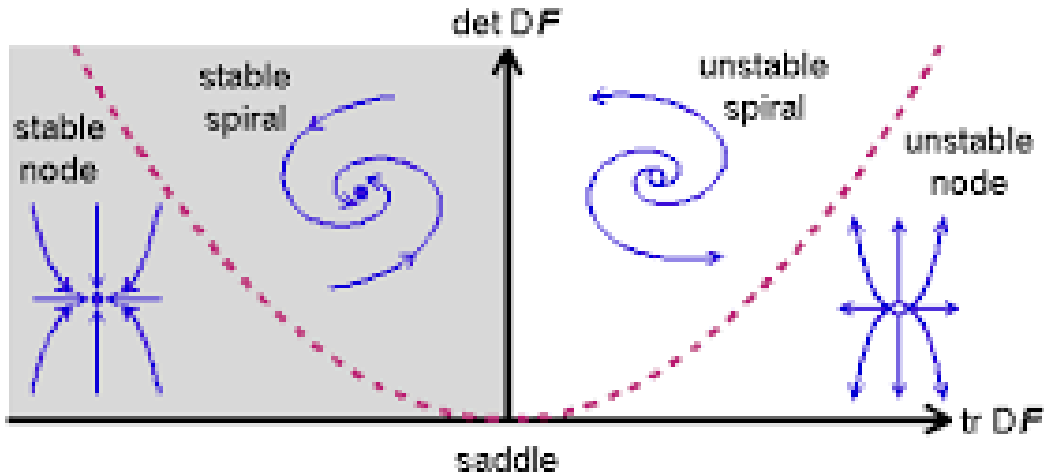
- Then, he showed that the same behavior, with the same mathematical constant, occurs within a wide class of functions, prior to the onset of chaos (**universality**).

**Very different systems (in chemistry, biology, physics, etc.) go to chaos in the same way, quantitatively.**



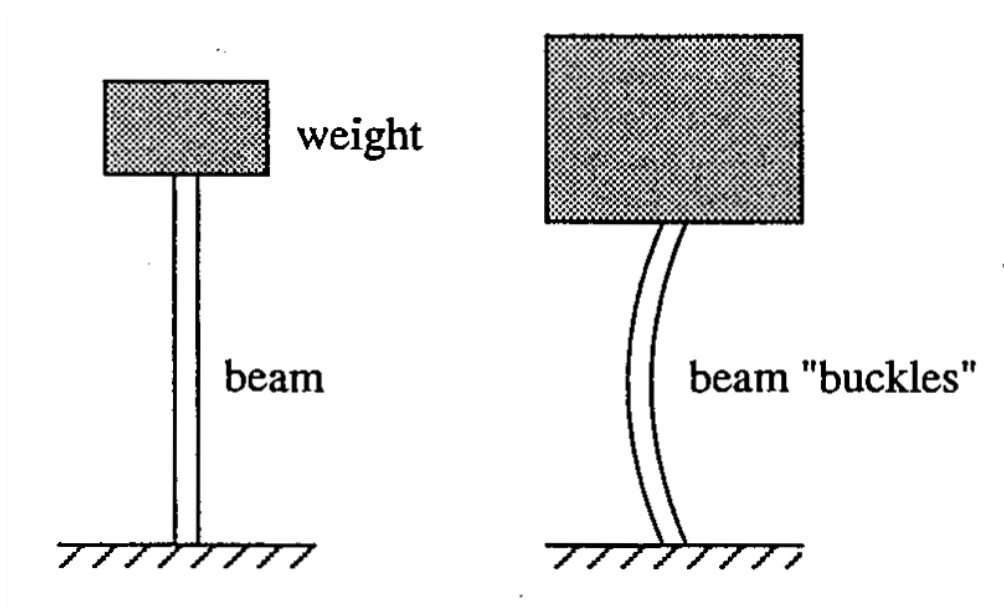
HP-65 calculator: the first magnetic card-programmable handheld calculator

# Attractors: fixed points, limit cycles, torus, chaotic (strange) attractors



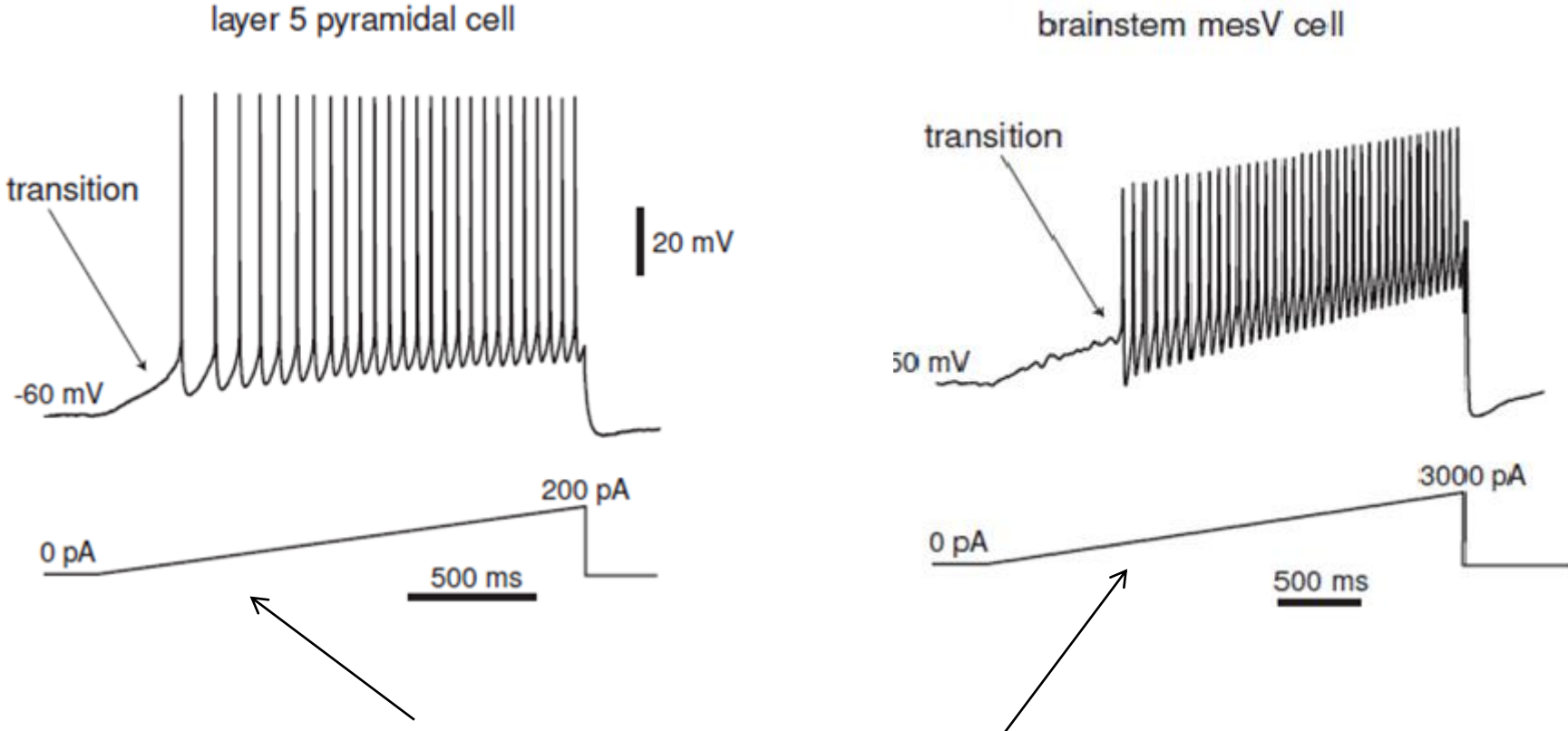
# Brief introduction to bifurcations

- A qualitative change (in the structure of the phase space) when a **control parameter is varied**:
  - Attractors can be created or destroyed
  - The stability of an attractor can change
- There are many examples in physical systems, biological systems, etc.



Further reading: Strogatz, *Nonlinear dynamics and chaos*

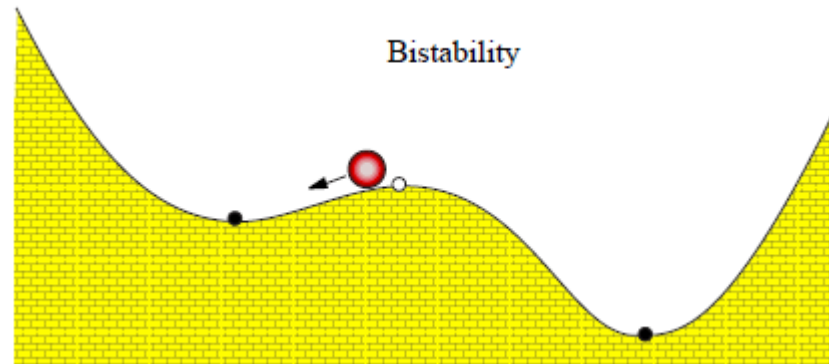
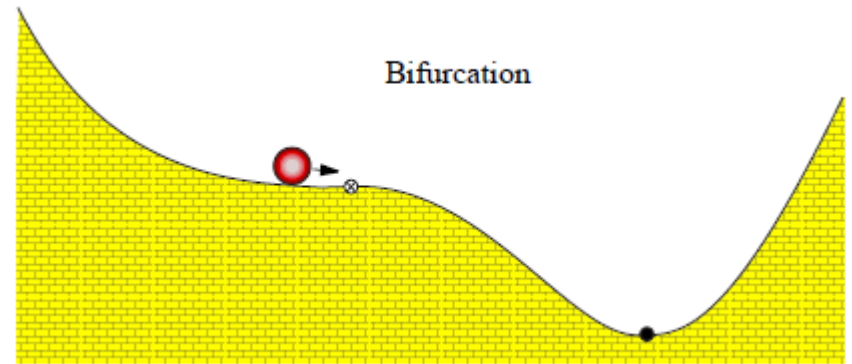
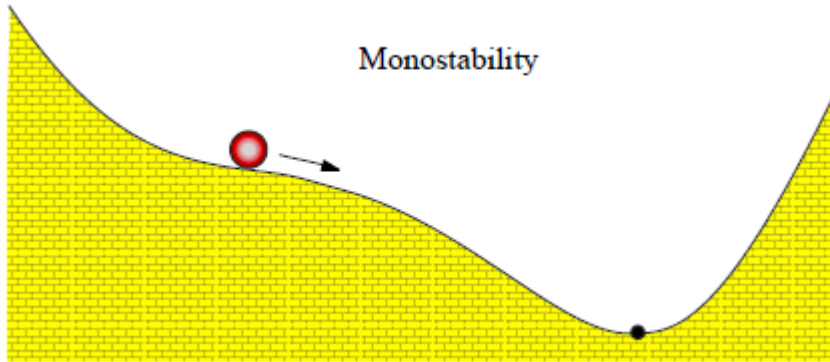
# Example: neuronal spikes



Control parameter increases in time

Further reading: Eugene M. Izhikevich, *Dynamical Systems in Neuroscience*

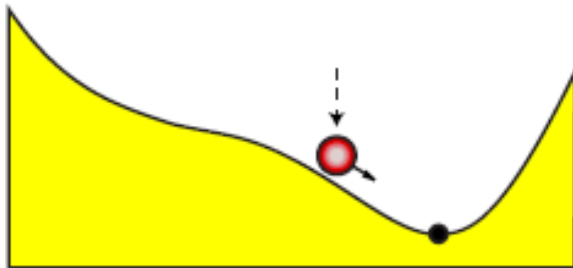
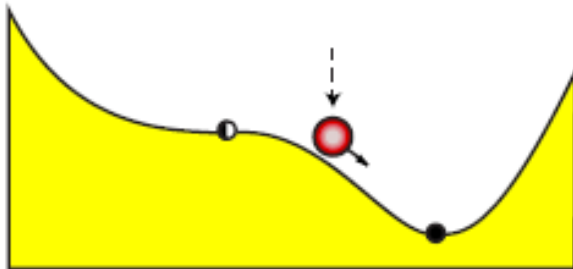
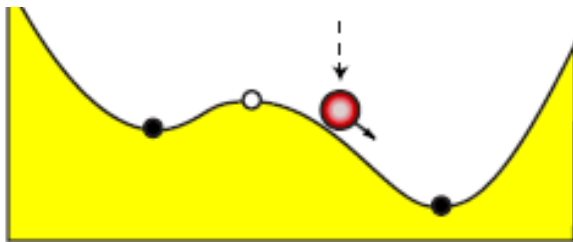
# Physical interpretation of a bifurcation



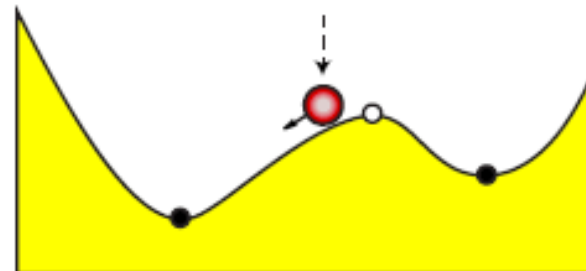
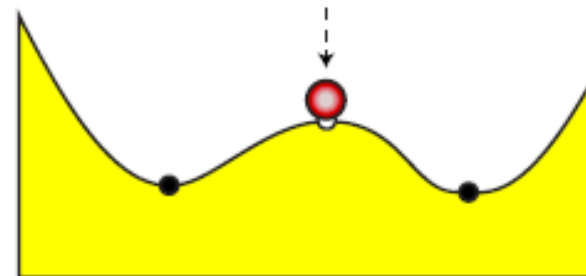
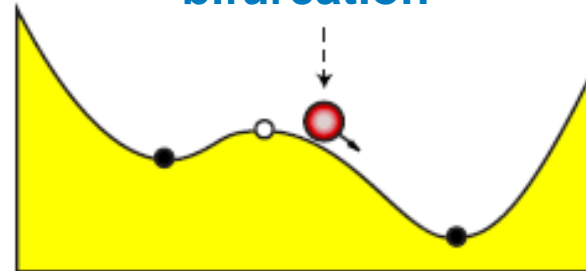


# Bifurcations are not the same a qualitative change of behavior

Bifurcation but no change of behavior

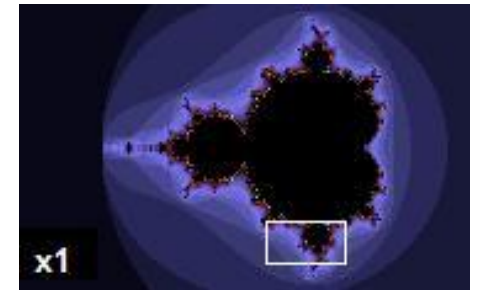


Change of behavior but no bifurcation



## The late 1970s

- **Benoit Mandelbrot** (Polish-born, French and American mathematician 1924-2010): “self-similarity” and **fractal objects**:
  - each part of the object is like the whole object but smaller.
- Because of his access to IBM's computers, Mandelbrot was one of the first to use **computer graphics** to create and display fractal geometric images.



# Fractal objects

- Are characterized by a “fractal” dimension that measures roughness.



Broccoli  
 $D=2.66$



Human lung  
 $D=2.97$



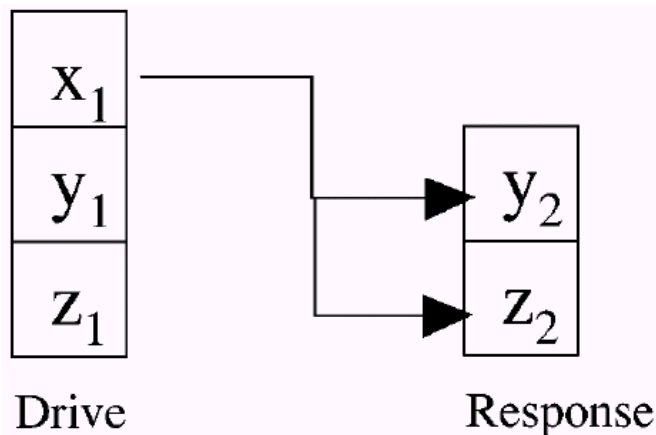
Coastline of  
Ireland  
 $D=1.22$

A lot of research is focused on detecting fractal objects underlying real-world signals.

# The 1990s: **synchronization** of chaotic systems

Pecora and Carroll, PRL 1990

Unidirectional coupling of two chaotic systems: one variable, 'x', of the response system is **replaced** by the same variable of the drive system.



$$t \rightarrow \infty \quad |y_2 - y_1| \rightarrow 0, \quad |z_2 - z_1| \rightarrow 0$$

# First observation of synchronization: mutual *entrainment* of pendulum clocks

In mid-1600s **Christiaan Huygens** (Dutch mathematician) noticed that two pendulum clocks mounted on a common board synchronized with their pendulums swinging in opposite directions (in-phase also possible).

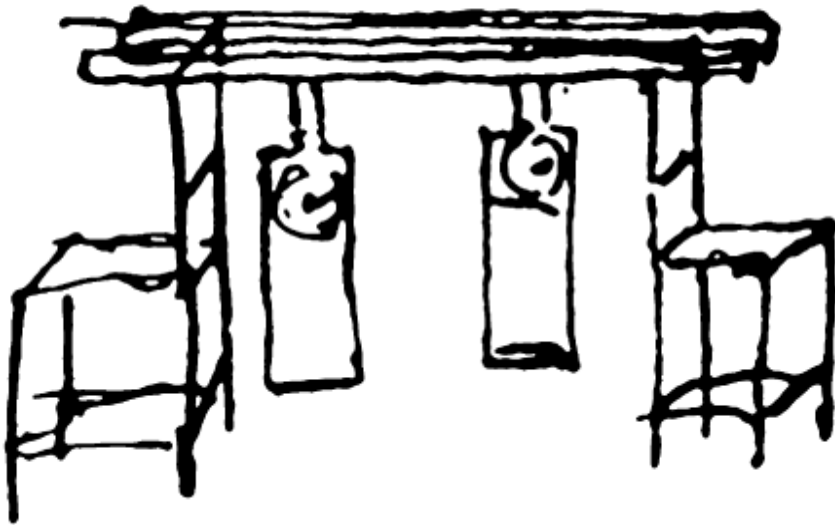
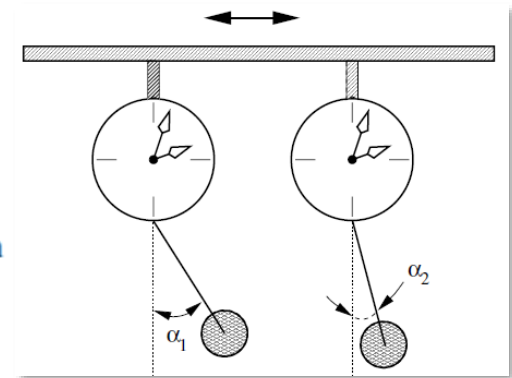


Figure 1.2. Original drawing of Christiaan Huygens illustrating his experiments with two pendulum clocks placed on a common support.



<http://www.youtube.com/watch?v=izy4a5erom8>

# Different types of synchronization

$$dx_1 / dt = F(x_1)$$

$$dx_2 / dt = F(x_2) + \alpha E(x_1 - x_2)$$

- Complete:  $x_1(t) = x_2(t)$  (identical systems)
- Phase: the phases of the oscillations synchronize, but the amplitudes are not.
- Lag:  $x_1(t + \tau) = x_2(t)$
- Generalized:  $x_2(t) = f(x_1(t))$  ( $f$  can depend on the strength of the coupling)

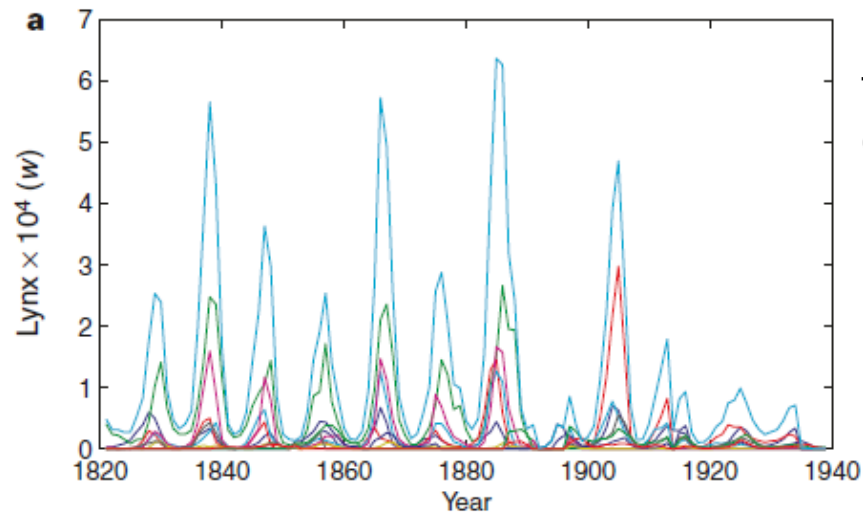
A lot of research is focused on detecting synchronization in real-world signals.

# Complex dynamics and phase synchronization in spatially extended ecological systems

NATURE | VOL 399 | 27 MAY 1999

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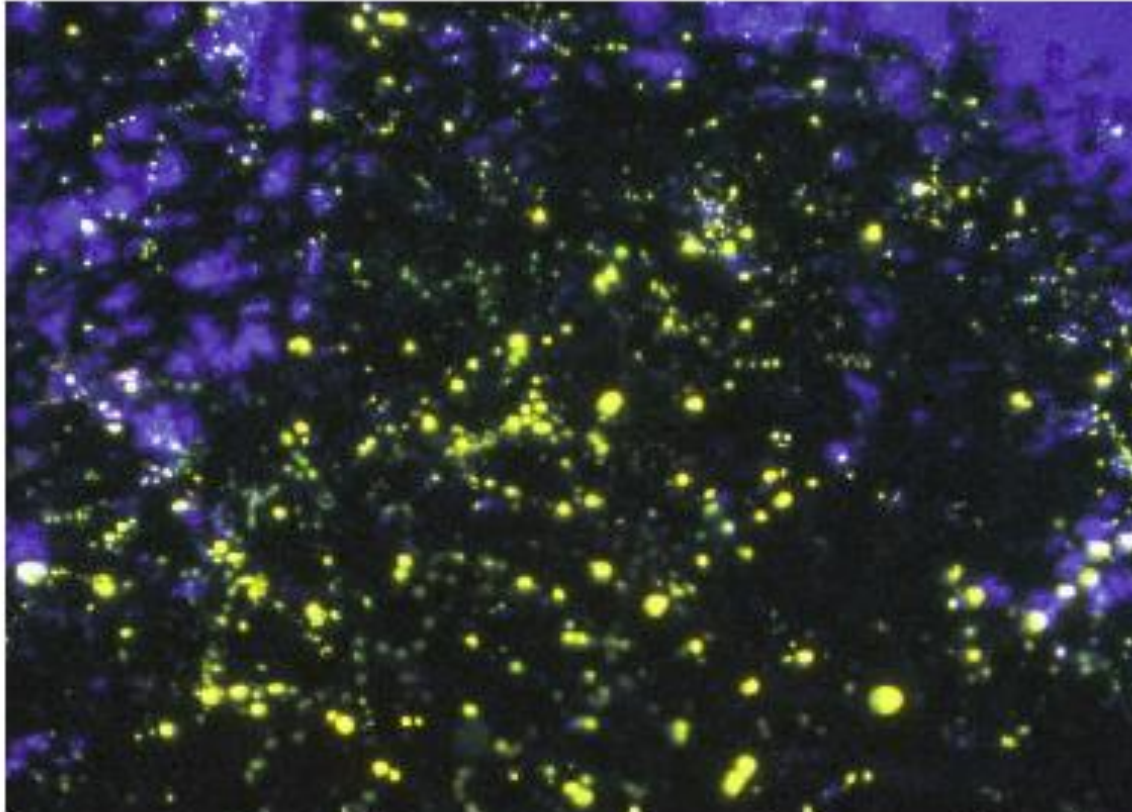


Lynx abundances from six regions in Canada



Lynx populations oscillate regularly and periodically in **phase**, but with irregular and chaotic peaks in abundance.

# Synchronization of a large number of coupled oscillators



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

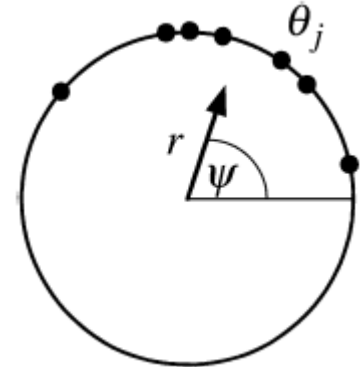


# Kuramoto model

(Japanese physicist, 1975)

Model of **all-to-all** coupled **phase oscillators**.

$$\frac{d\theta_i}{dt} = \omega_i + \frac{K}{N} \sum_{j=1}^N \sin(\theta_j - \theta_i) + \xi_i, \quad i = 1 \dots N$$



$K$  = coupling strength,  $\xi_i$  = stochastic term (noise)

Describes the emergence of collective behavior

How to quantify?

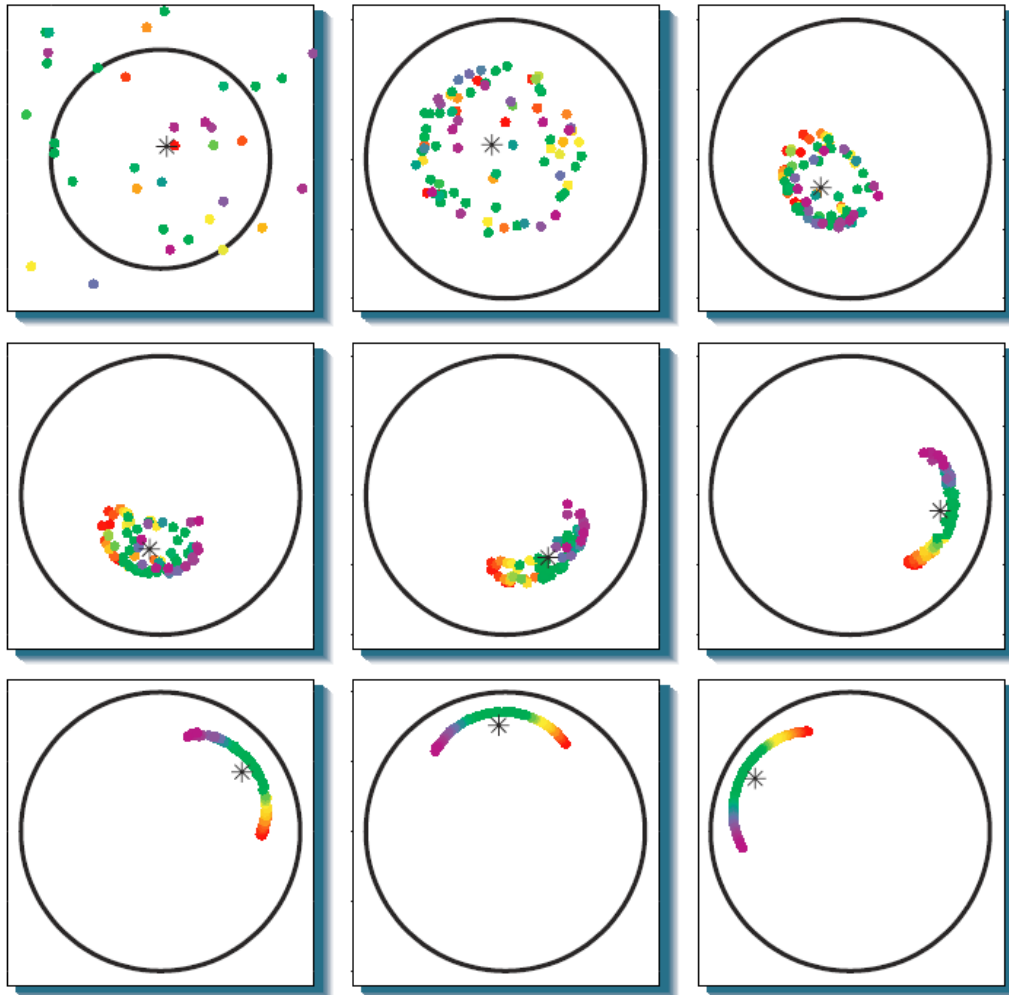
With the **order parameter**:

$$r e^{i\psi} = \frac{1}{N} \sum_{j=1}^N e^{i\theta_j}$$

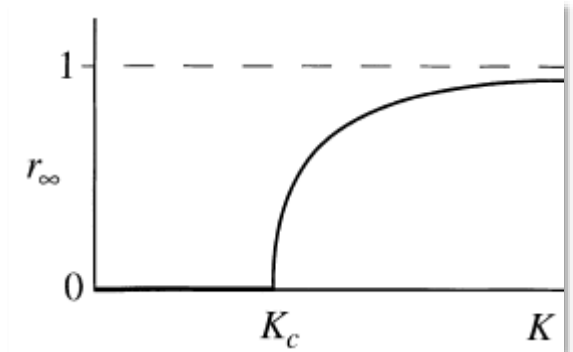
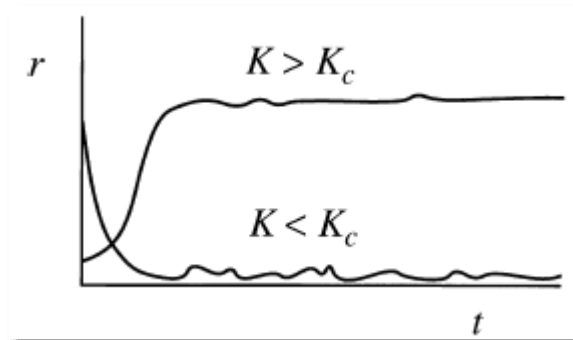
$r = 0$  incoherent state (oscillators scattered in the unit circle)

$r = 1$  all oscillators are in phase ( $\theta_i = \theta_j \forall i, j$ )

# Synchronization transition as the coupling strength increases



**Strogatz** and others, late 90'



Strogatz, Nature 2001

Video: [https://www.ted.com/talks/steven\\_strogatz\\_on\\_sync](https://www.ted.com/talks/steven_strogatz_on_sync)

**The synchronization  
transition can be explosive**

# Rossler oscillators

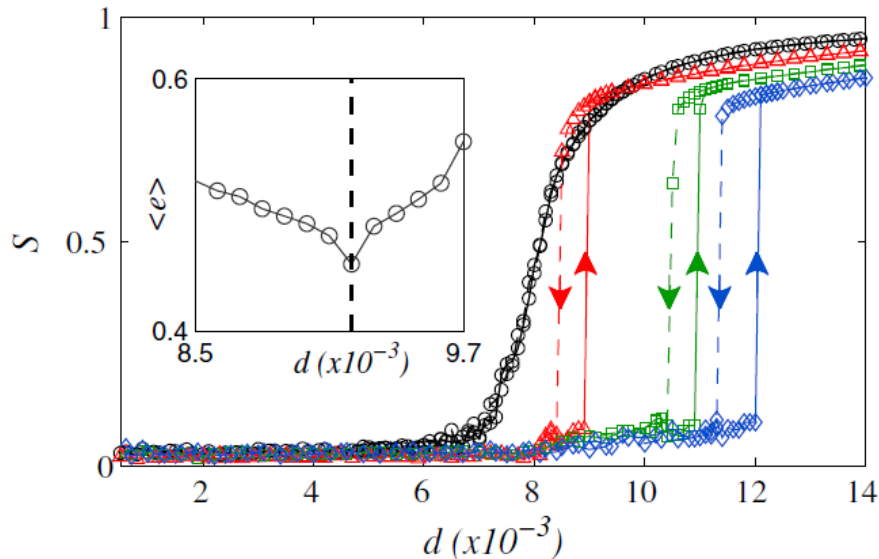
$$\dot{x}_i = -\alpha_i \left[ \Gamma \left( x_i - d \sum_{j=1}^N a_{ij} (x_j - x_i) \right) + \beta y_i + \lambda z_i \right],$$

$$\dot{y}_i = -\alpha_i (-x_i + \nu y_i), \quad \dot{z}_i = -\alpha_i [-g(x_i) + z_i],$$

$$\phi_i(t) = \arctan[y_i(t)/x_i(t)].$$

$$S = \left\langle \left| \frac{1}{N} \sum_{j=1}^N e^{i\phi_j(t)} \right| \right\rangle_t$$

## Simulations



## Experiments (chaotic circuits)

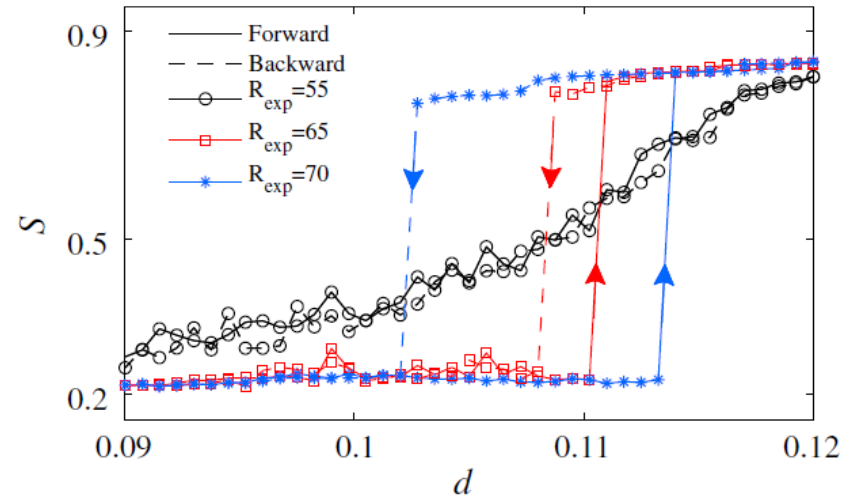


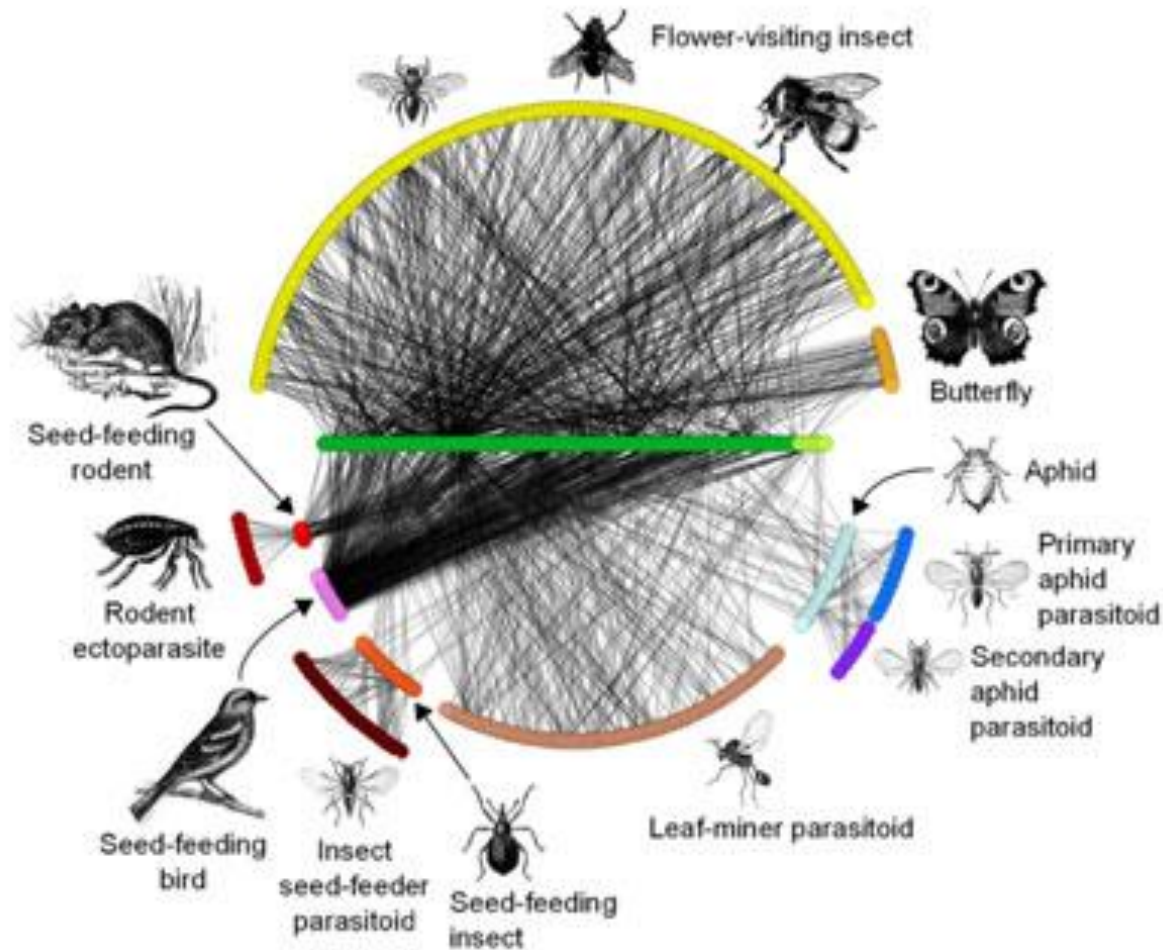
FIG. 1 (color online). Phase synchronization degree  $S$  as a function of the coupling strength  $d$  for different SF networks of size  $N = 1000$ , and average degree  $\langle k \rangle = 6$ . The networks are

## End of 90's - present

- Interest moves from chaotic systems to complex systems (small vs. very large number of variables).
- Networks (or graphs) of interconnected systems
- **Complexity science**: dynamics of emergent properties
  - Epidemics
  - Rumor spreading
  - Transport networks
  - Financial crises
  - Brain diseases
  - Etc.

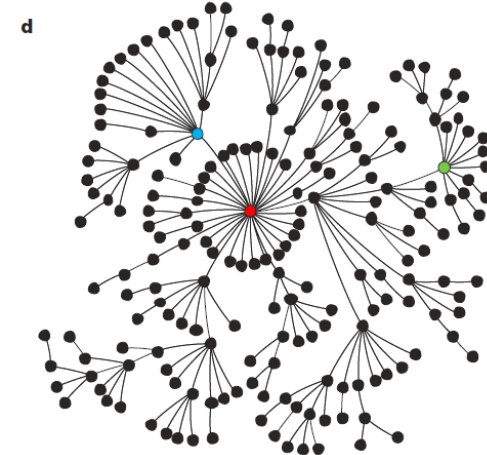
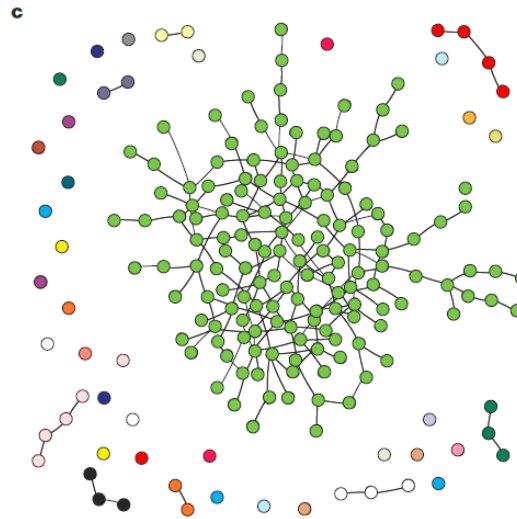
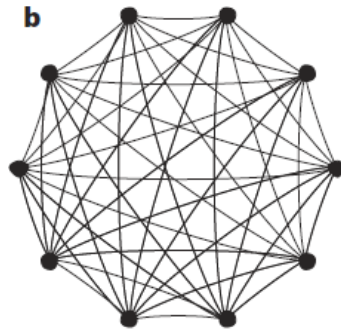
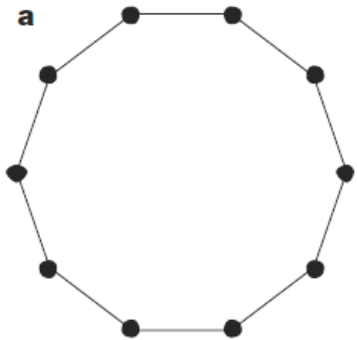
# Networks in ecology

- species (nodes) are connected by pairwise interactions (links)



# Network science

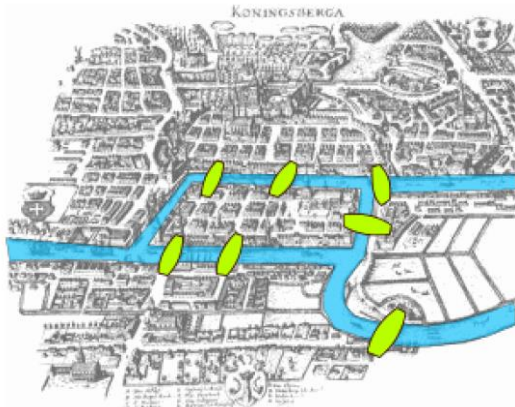
The challenge: to understand how the network **structure** and the **dynamics** (of individual units) determine the collective behavior.



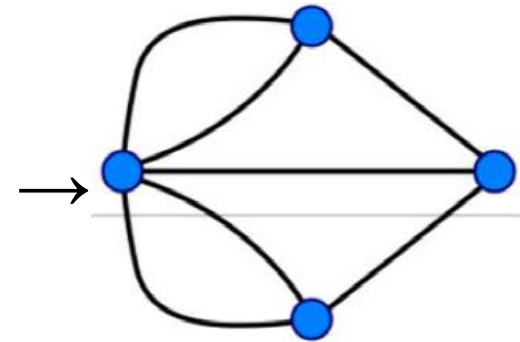
Source: Strogatz  
Nature 2001

# The start of Graph Theory: The Seven Bridges of Königsberg (Prussia, now Russia)

- The problem was to devise a walk through the city that would cross each of those bridges once and only once.



Source: Wikipedia



- By considering the number of odd/even links of each “node”, **Leonhard Euler** (Swiss mathematician) demonstrated in 1736 that is impossible.





# Summary

- Dynamical systems allow to
  - understand low-dimensional systems,
  - uncover patterns and “order within chaos”,
  - characterize attractors, uncover universal features
- Synchronization: emergent behavior of interacting dynamical systems.
- Complexity and network science: emerging phenomena in large sets of interacting units.
- Time series analysis develops tools to characterize complex signals.
- Is an interdisciplinary research field with many applications.



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