

# Dynamical systems tools to study Neurosciences & Atmospheric Flows

D Faranda,

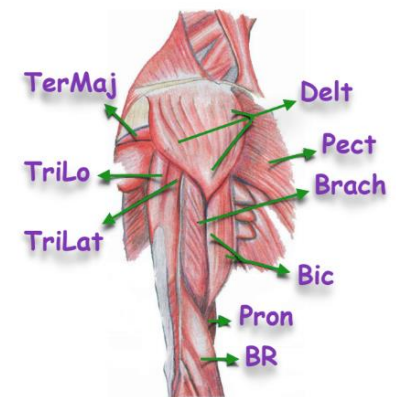
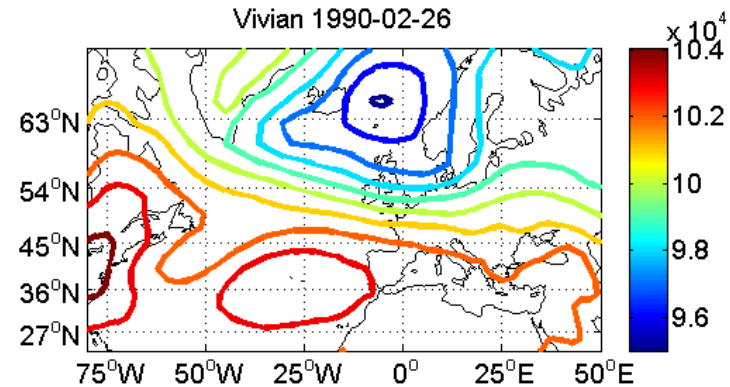
*with* MC Alvarez-Castro, S Cheng, D Rodrigues,  
G Messori, S Vaienti, M Vrac, T Caby, G Mantica,  
S Vannitsem, Y Sato, N Vercauteren, M D'Errico, G Carella,  
A. Hamid, D Battaglia, A Brovelli, P Yiou



# OBJECTIVES

Characterize the predictability of Configurations of systems

- *How recurrent?*
- *How rare and predictable?*
- *How persistent?*
- *Changes with parameters (age, greenhouse gases)*



# METHOD

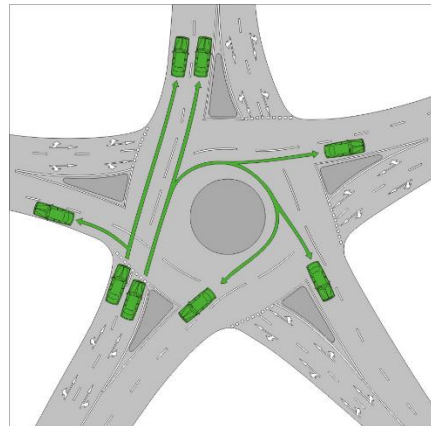
Compute Dynamical Systems metrics to characterize atmospheric states, verifying that a long series of observations sample the underlying attractor.

## Local Dimensions $d$

It is proportional to the number of possible configurations (**number of degrees of freedom**) originating and resulting from the atmospheric field analyzed.



~Number of possible exits  
in a roundabout



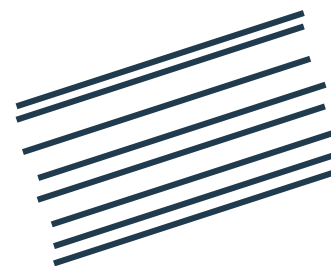
## Persistence $\Theta$

Its inverse tells for **how long the atmospheric field will look like the one under examination**. For the present analysis  $\Theta$  is an inverse number of persistence days.



~1/Time spent choosing a  
direction in a roundabout

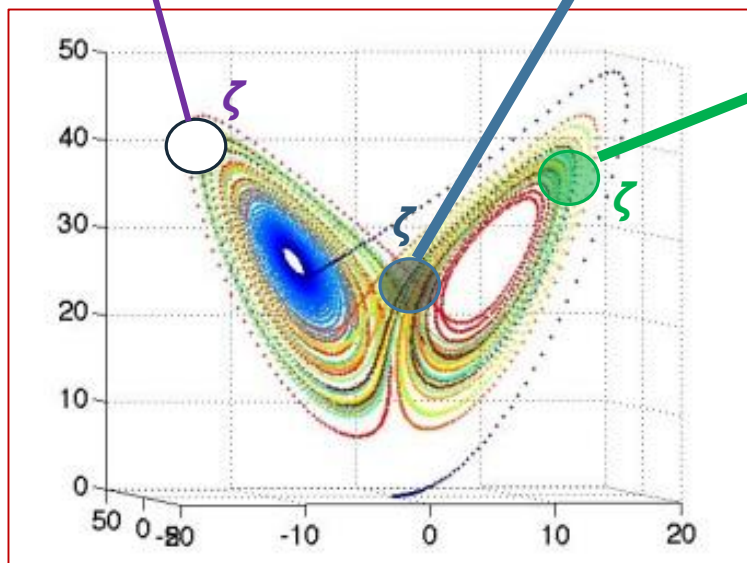
# METHOD – LOCAL DIMENSIONS



Line:  $d(\zeta)=1$

Patch:  $d(\zeta)=2$

Fractal:  $1 < d(\zeta) < 2$



The local dimension depends on the point of the attractor considered

**<= Example of trajectory in the Lorenz 1963 attractor**, the colors indicate the time of the simulations, thus the chaotic behavior

# METHOD – COMPUTE THE LOCAL DIMENSIONS

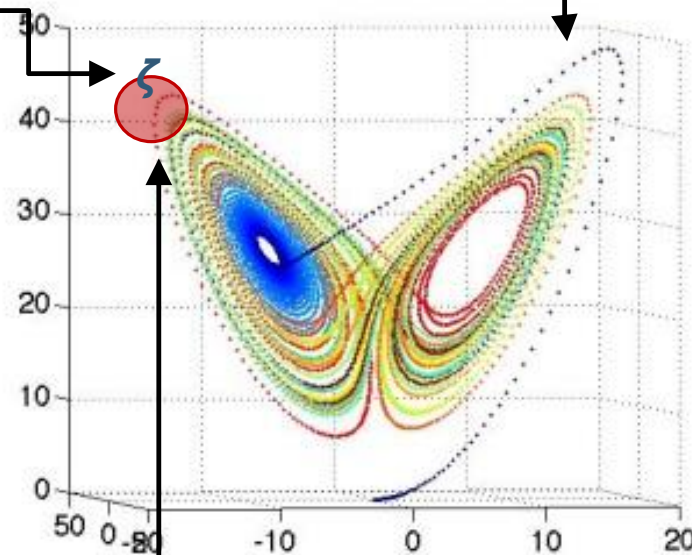
1) In a chaotic dynamical system, take a trajectory of the system:  $f^m(x)$

2) Rare events are recurrences of a state  $\zeta$ :

$$X_m(x) = g(\text{dist}(f^m(x), \zeta))$$

3) Then, chose observables such that the maxima of  $g$  correspond to minima of the distances with respect to  $\zeta$ :

$$g_1^m(\zeta) = -\log(\text{dist}(f^m(x), \zeta))$$



# METHOD – COMPUTE THE LOCAL DIMENSIONS

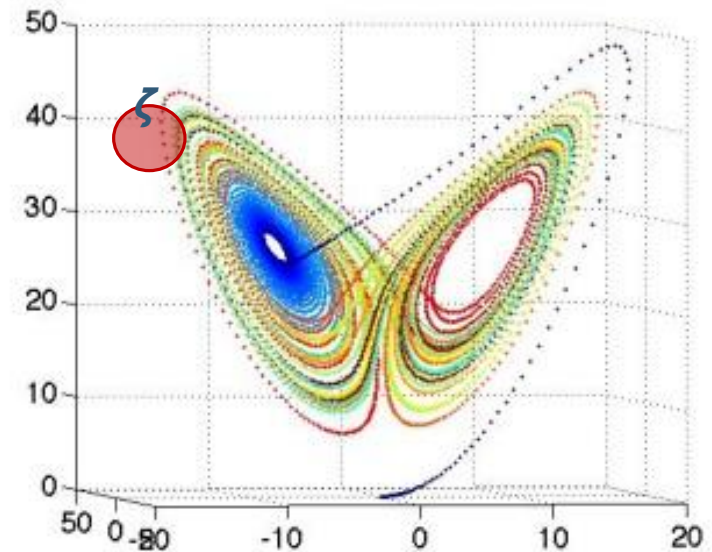
For any chaotic systems entering in a ball close to  $\zeta$ , is equivalent to study threshold exceedances of:

$$P(g(x(t)) > q, \zeta)$$

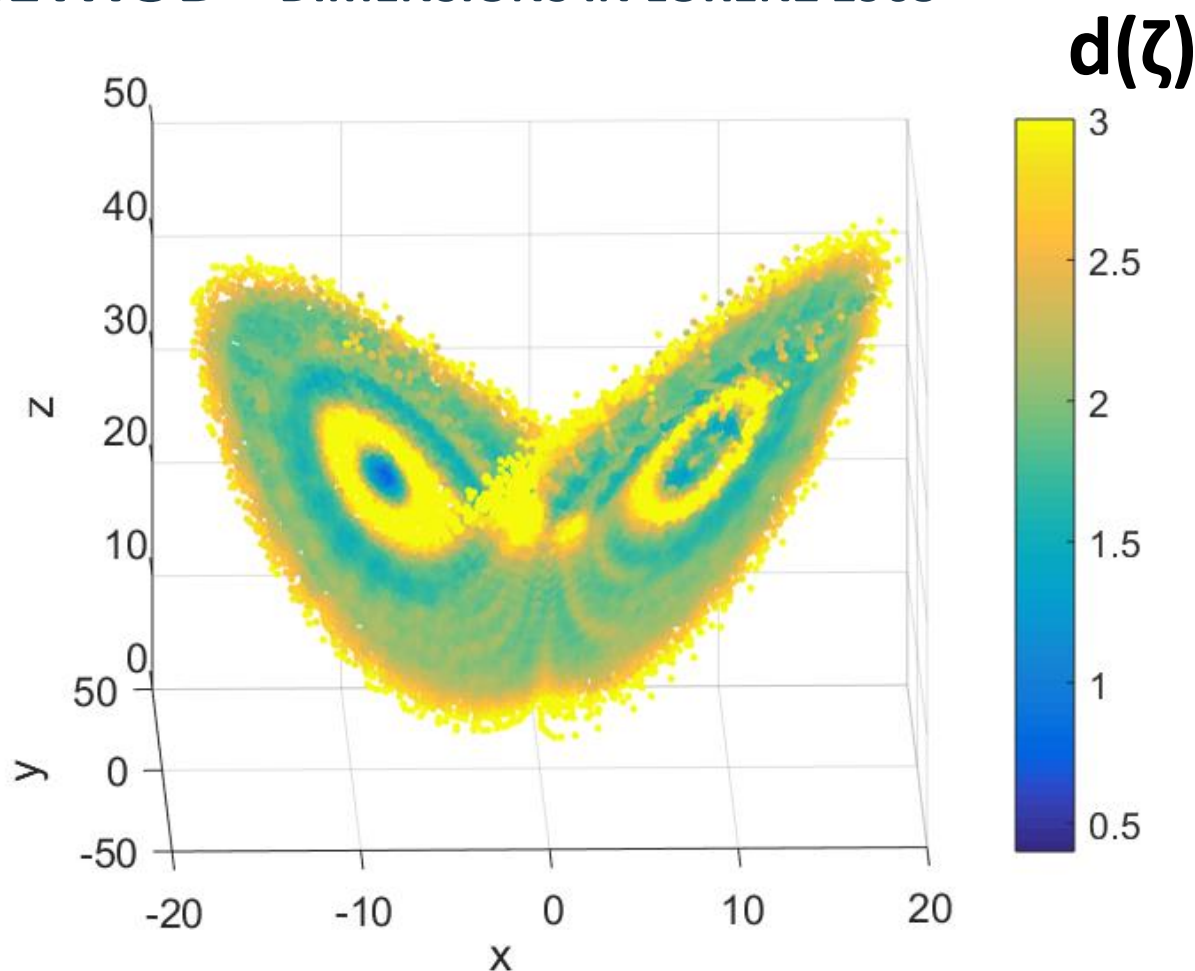
For the Freitas-Freitas-Todd theorem (2008)  $P$  converges asymptotically to an exponential function:

$$P(y, \zeta) = \exp(-[y - a(\zeta)]/\sigma(\zeta))$$

And the local dimension is  $d(\zeta) = 1/\sigma(\zeta)$



# METHOD – DIMENSIONS IN LORENZ 1963

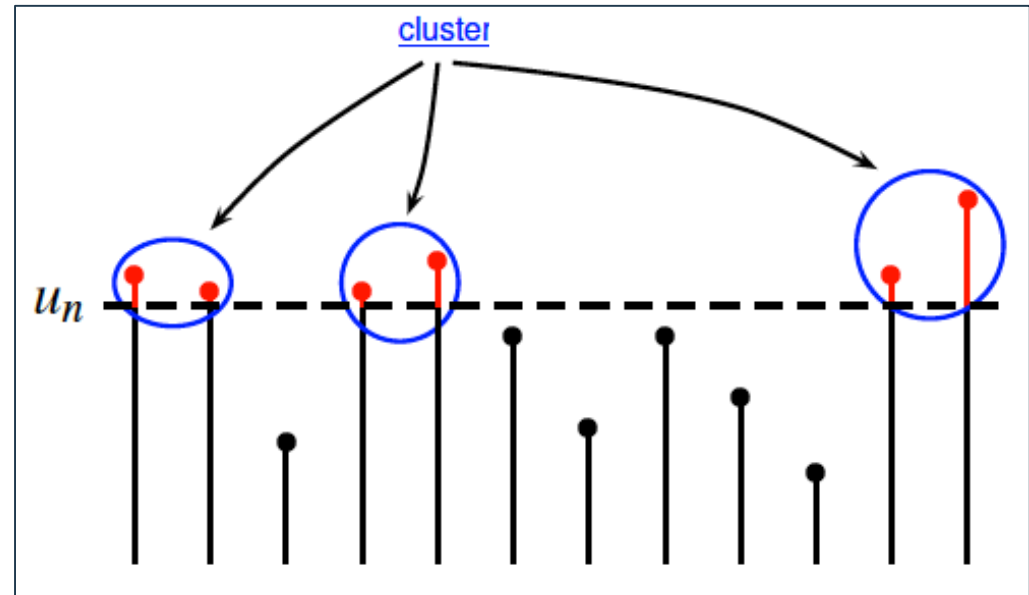
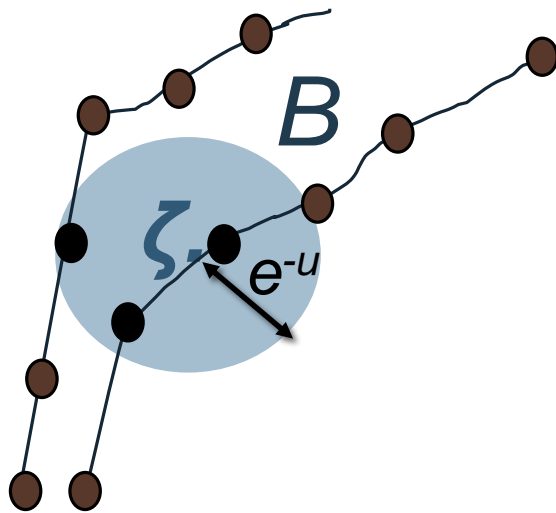


The average dimension  $\langle d(\zeta) \rangle_{\zeta} = 2.06$  is the same as classical estimates

*Faranda, Messori, Yiou. Scientific Reports 2017*



# METHOD – LOCAL PERSISTENCE

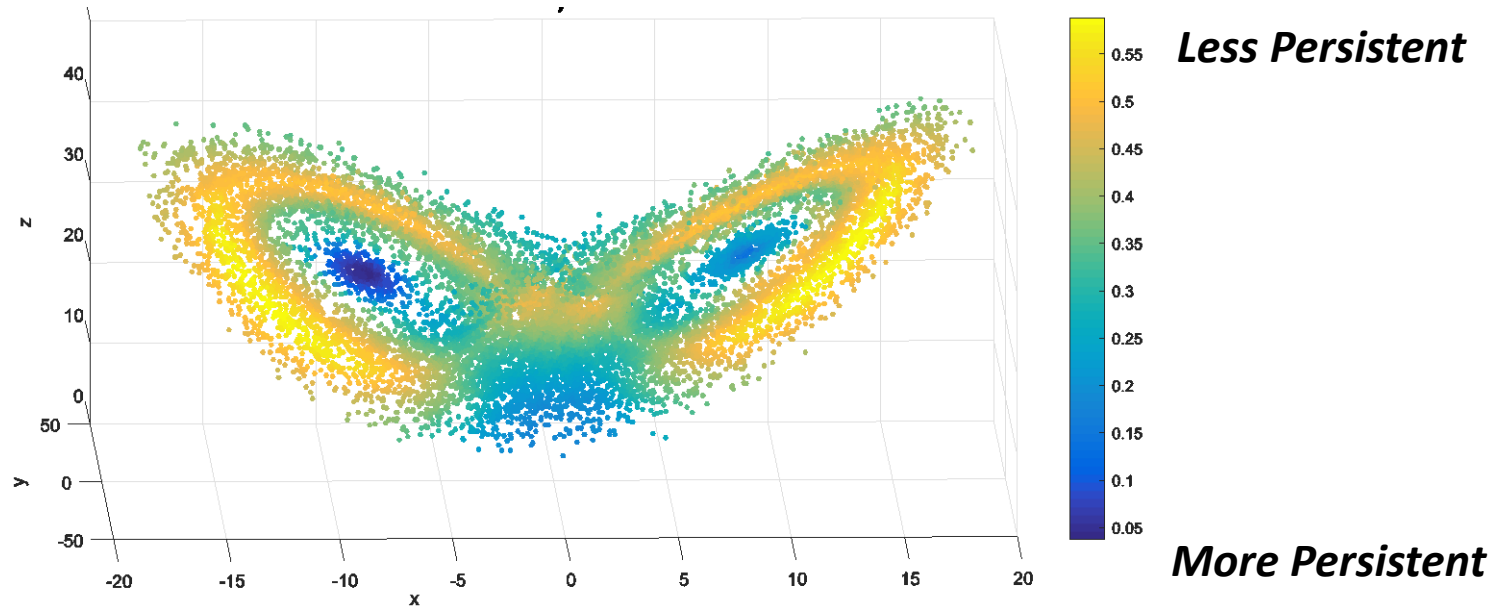


If a threshold  $u$  is applied to a series of observations  $x_1, x_2, \dots, x_S$ , the exceedances are those for which  $x_i > u$ . The **extremal index  $\theta$**  can then be thought of as the **average inverse time spent above  $u$** .



# METHOD – PERSISTENCE IN LORENZ 1963

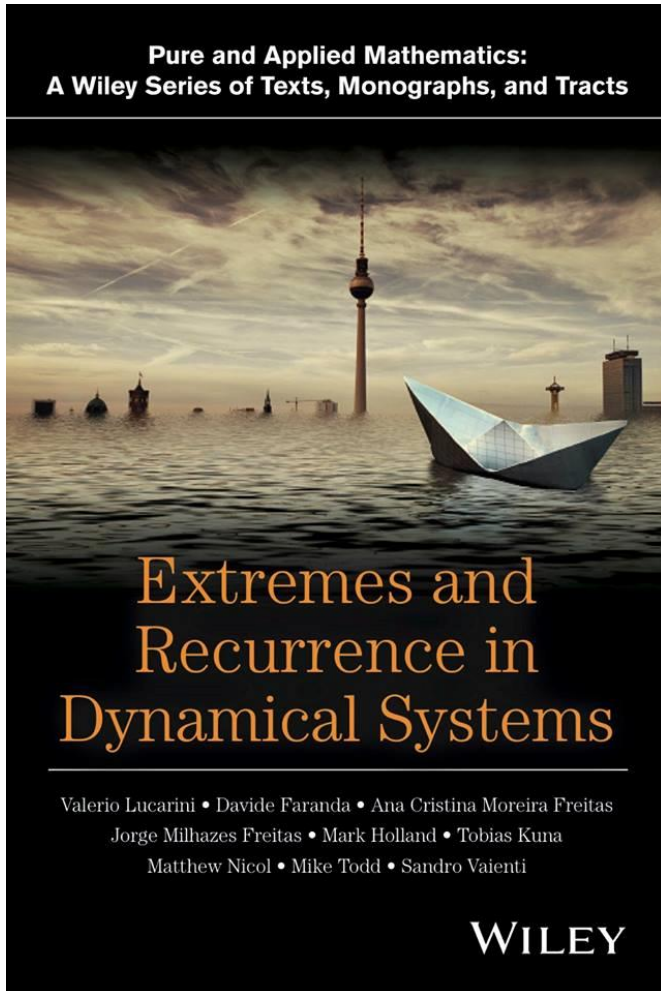
$$\theta(\zeta)$$



$\theta$  is a good proxy for **unstable fixed points of the system**

*Faranda, Messori, Yiou. Scientific Reports 2017*

# METHOD – REFERENCE

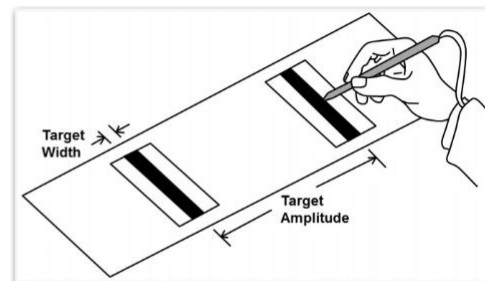
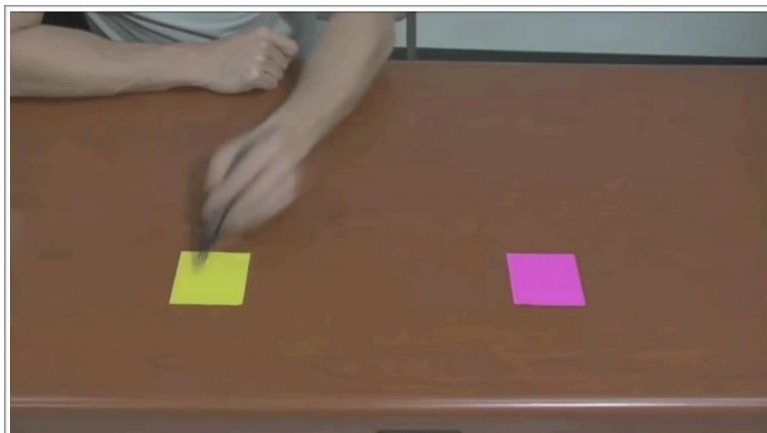


“Extremes and recurrence in Dynamical systems” contains new tools for estimating the local dimensions  $d(\zeta)$

*Book: Lucarini, Faranda et al. Wiley (2016)*

# RESULTS – BONUS TRACK: NEUROSCIENCES FIT TASK

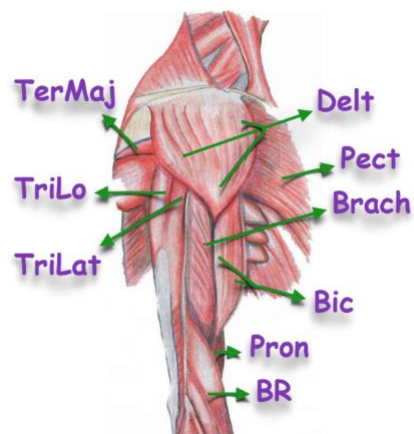
- TASK: Move the arm to target two different small region in space as fastest as possible
- DIFFICULTY: Target size reduce
- DIFFERENT SUBJECTS OF DIFFERENT AGES
- MEASUREMENTS: physical phase space (position speed) & 12 muscles EMG activity



**Braintime Project: with Demian Battaglia, Andrea Brovelli (La Timone, Marseille), Sandro Vaienti, Theo Caby (CPT)**

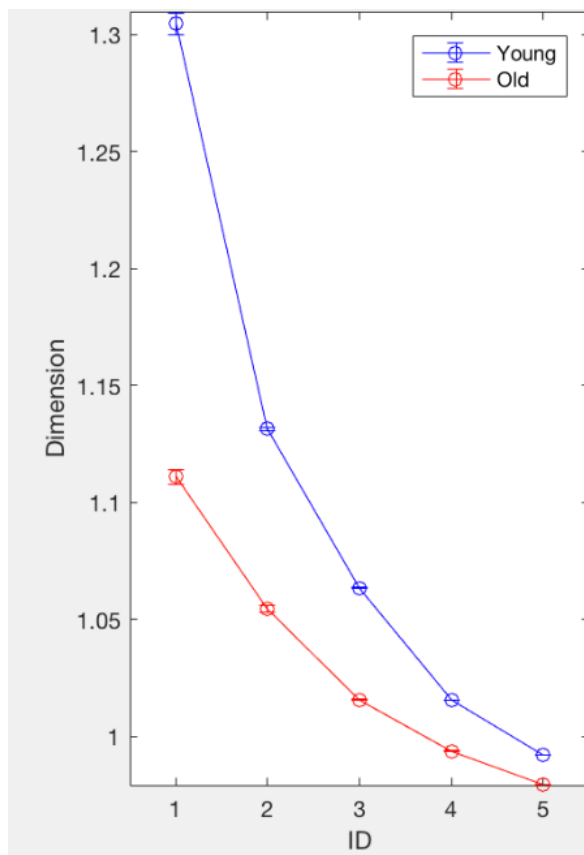
# RESULTS – BONUS TRACK: NEUROSCIENCES FIT TASK

- 1) how muscles respond to the difficulty of the task?
- 2) Differences between Old and young subjects?
- 3) Matching between physical phase space and muscles phase space?

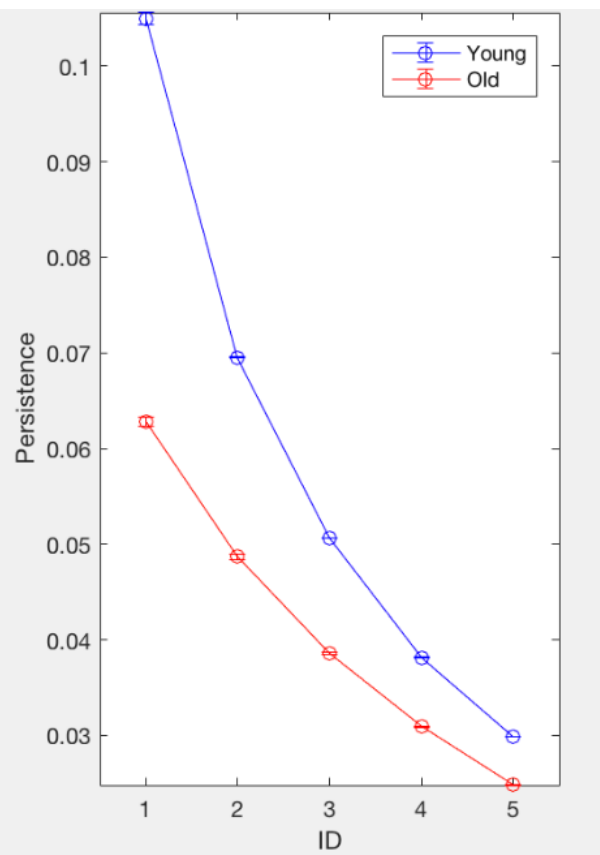


# RESULTS – PHYSICAL PHASE SPACE

## DIMENSION



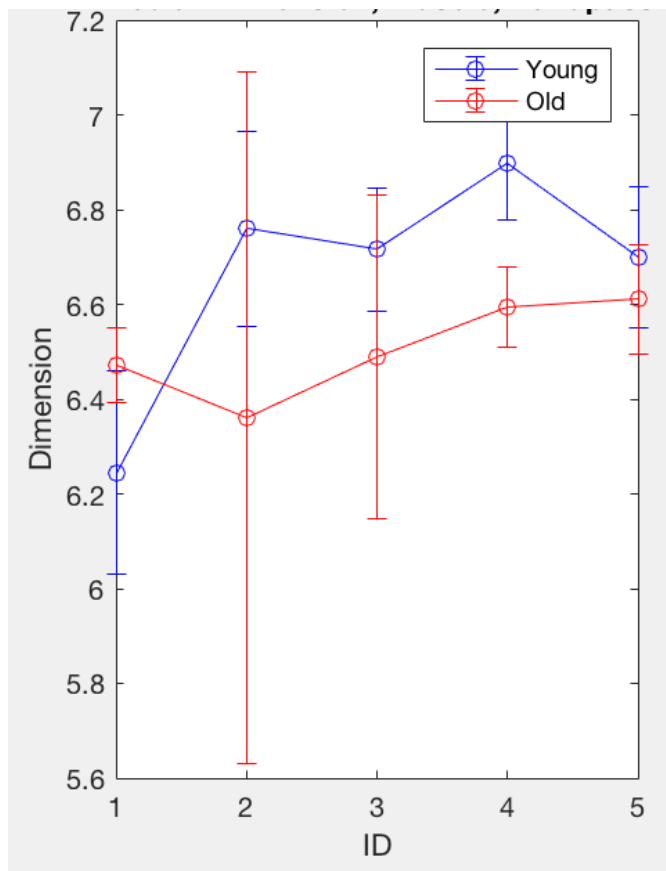
## INVERSE PERSISTENCE



**YOUNG/OLD threshold... 35 Years**

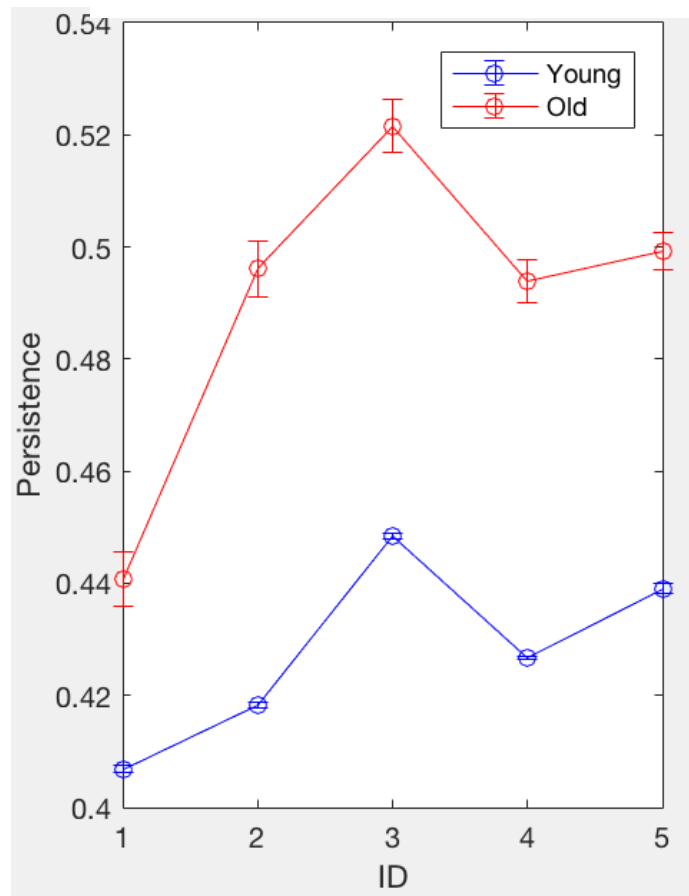
- **Young:** more movement freedom and faster
- **Old:** more careful but slower

# RESULTS – MUSCLE PHASE SPACE DIMENSION



YOUNG/OLD threshold... 35 Years

## INVERSE PERSISTENCE



- **Young:** can adapt the muscles to respond to the difficulty of the task
- **Old:** muscles less stable, « phase transitions » at diff=3

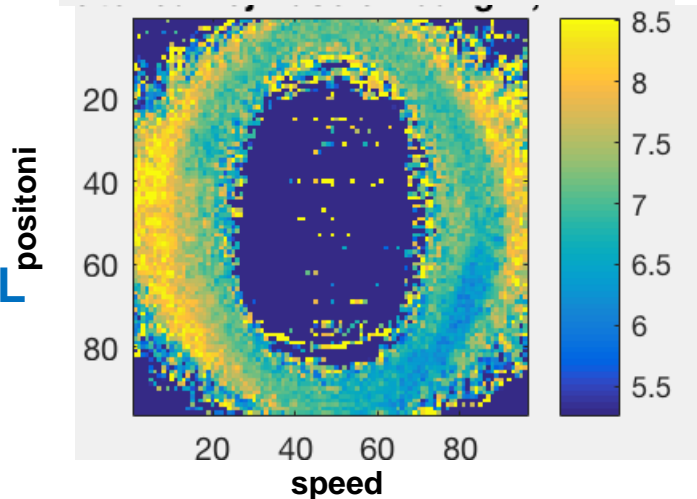
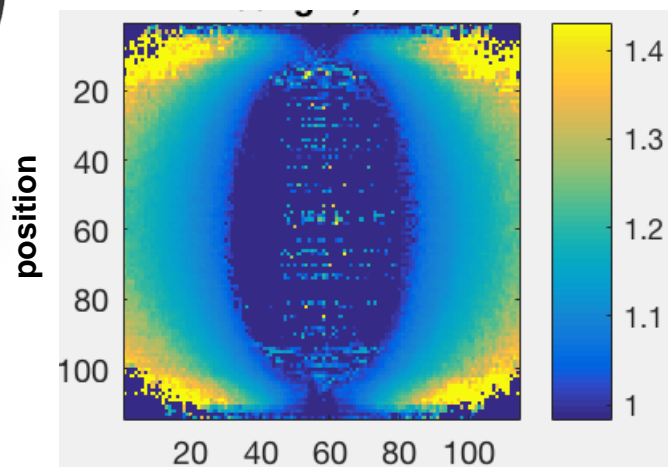
# RESULTS – DIM PERSISTENCE IN TRAJECTORY (SAURON'S EYE)



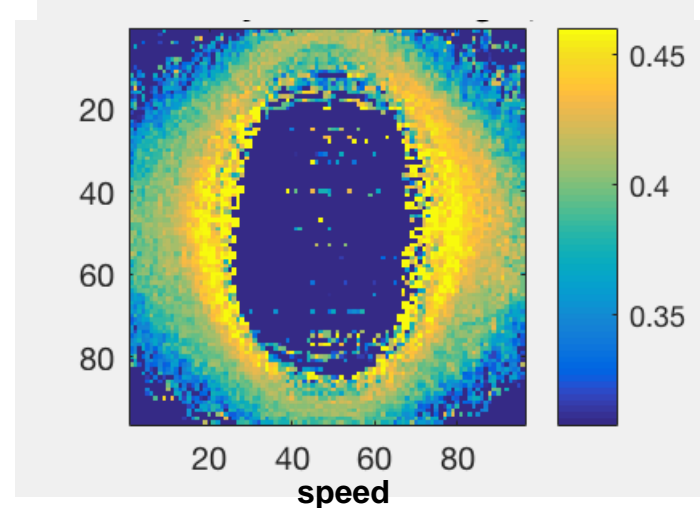
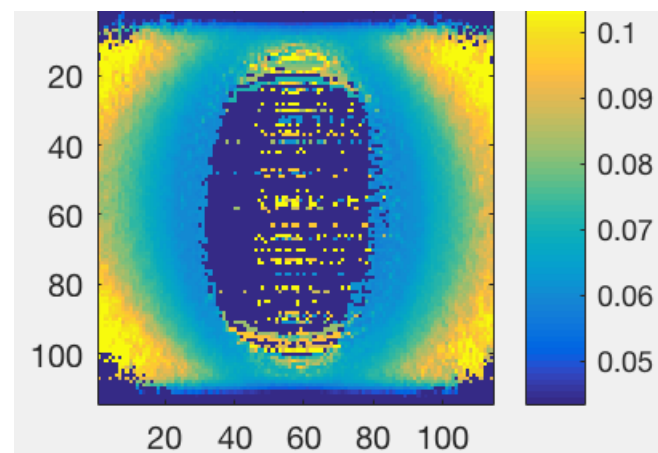
**PHYSICAL  
SPACE**

**MUSCLE  
SPACE  
MAPPED  
TO PHYSICAL  
SPACE**

**DIMENSION**

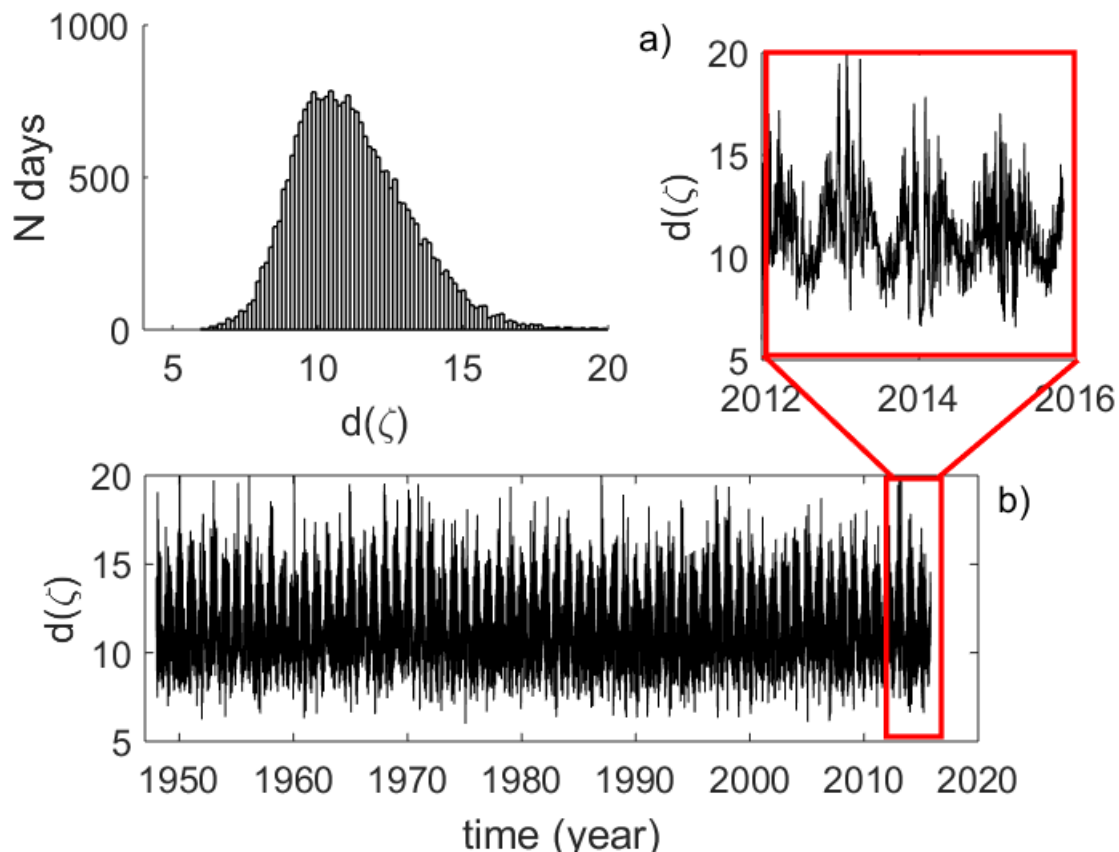


**INVERSE PERSISTENCE**



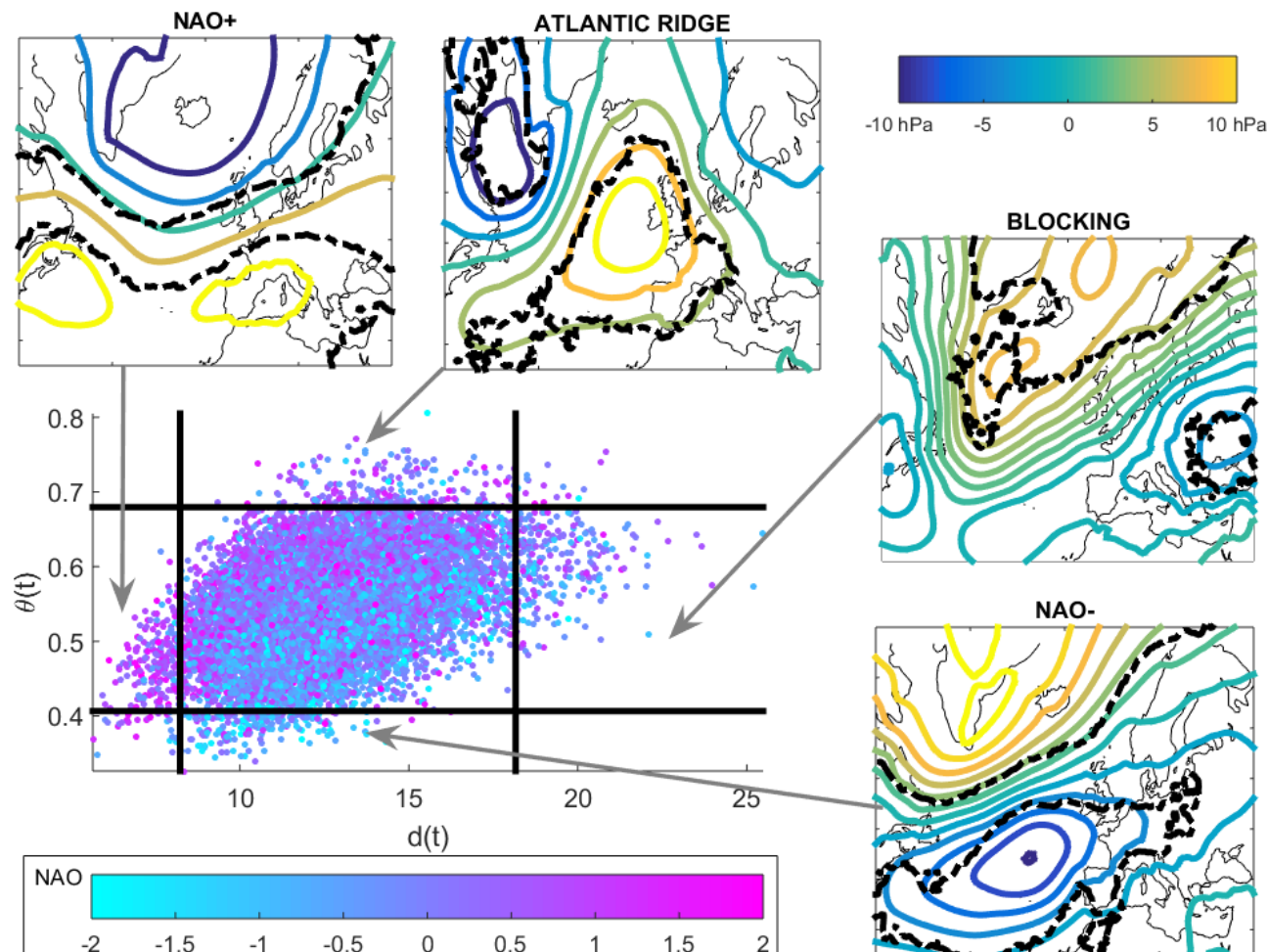


# RESULTS – LOCAL DIMENSION IN NCEP 1948-2015



The instantaneous dimensions  $d$  (y-axis) versus the years of the database shows an interesting seasonal cycle. Extremes are found in wintertime, where sharp transitions occur between maxima and minima.

# RESULTS – PERSISTENCE/DIMENSION DIAGRAM

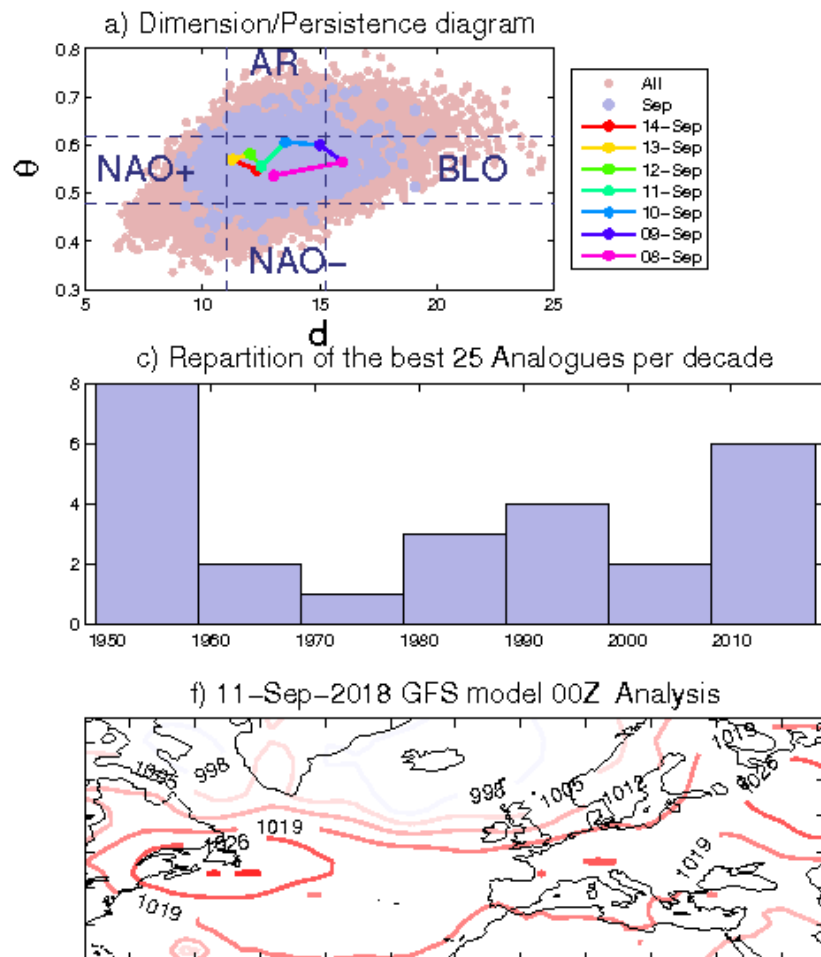


The scatter plot displays the daily values of the instantaneous dimension  $d$  - the higher  $d$ , the more unpredictable is the atmospheric circulation - and the persistence  $\theta$  - the lower  $\theta$  the more stable is the atmospheric circulation - of the sea level pressure field (in hPa) extracted from the NCEP Database. The colorscale represents the North Atlantic Oscillation (NAO) index.

Faranda, Messori, Yiou. *Scientific Reports* 2017

# RESULTS – PERSISTENCE/DIMENSION DIAGRAM - TODAY

DINAMICAL SYSTEMS ANALYSIS AND FORECAST FOR: 11-Sep-2018

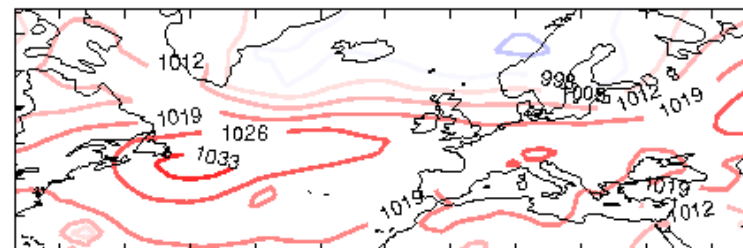


b) Weather Regimes last 30 days and September Climatology

d) Days of Sep with lower d than today

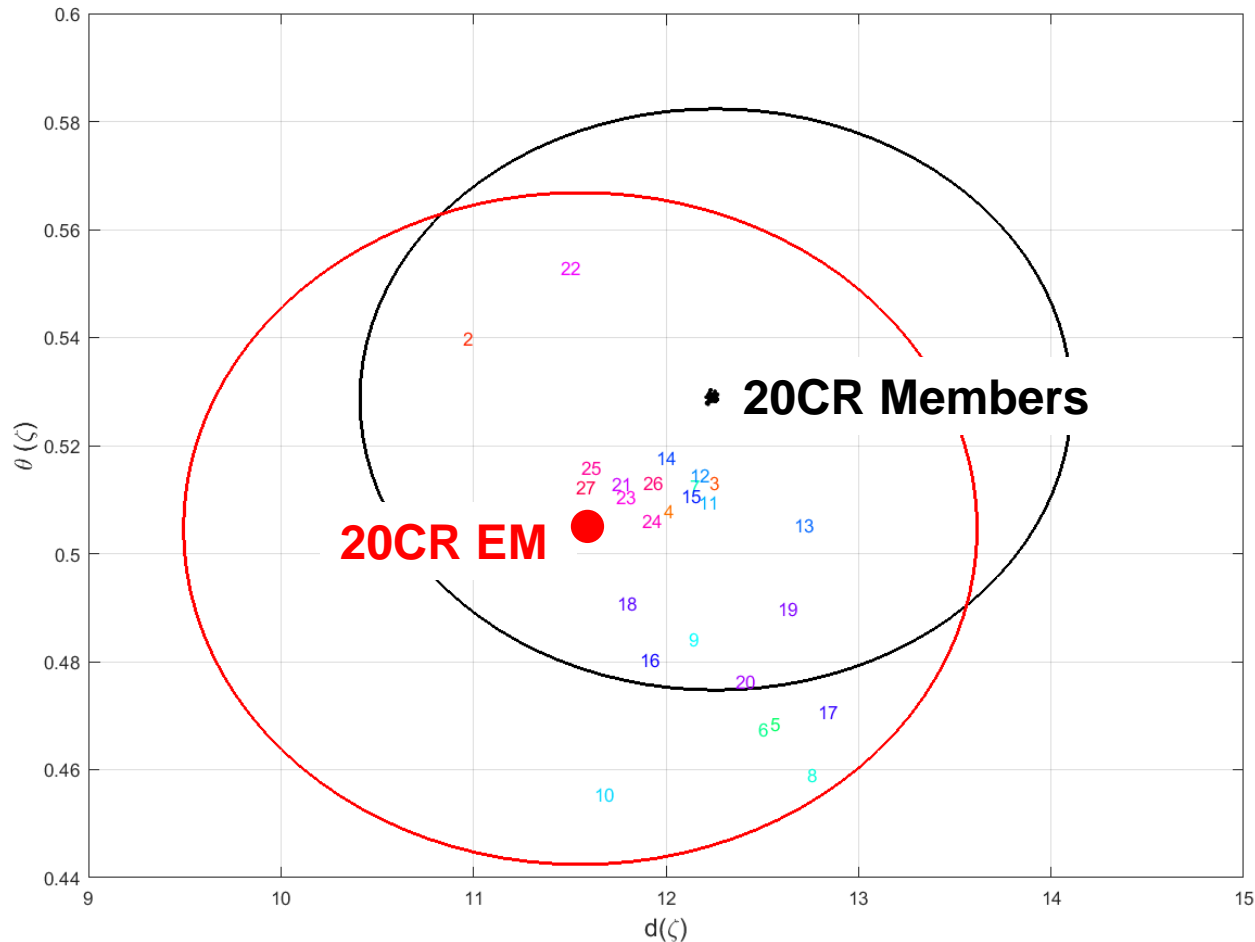
e) Days of Sep with lower  $\theta$  than today

+24h Forecast (hPa)



<https://www.lsce.ipsl.fr/Pisp/davide.faranda/>

# RESULTS – CMIP5 ANALYSIS – AVERAGES 1850-2100

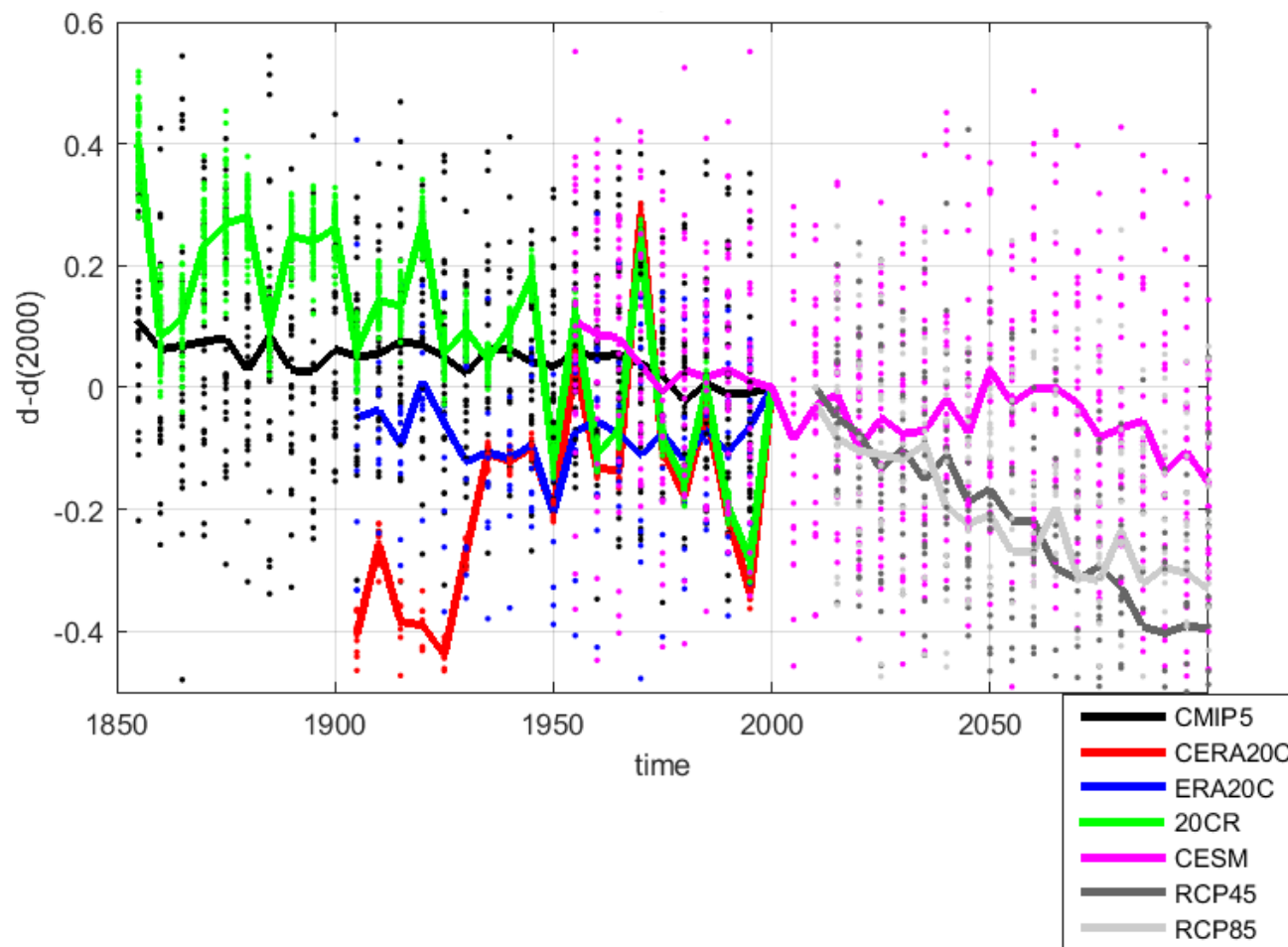


- 02-CMCC-CESM
- 03-CanESM2
- 04-MIROC-ESM-CHEM
- 05-MIROC-ESM
- 06-BCC-CSM1-1
- 07-IPSL-CM5B
- 08-NorESM1-M
- 09-FGOALS-S2
- 10-MPI-ESM-P
- 11-MPI-ESM-LR
- 12-CSIRO-MK3-6-0
- 13-CMCC-CMS
- 14-MPI-ESM-MR
- 15-IPSL-CM5A
- 16-INM-CM4
- 17-ACCESS '1.0
- 18-MIROC5
- 19-CNRM-CM5
- 20-MRI-ESM1
- 21-BCC-CSM1-M
- 22-MRI-CGCM3
- 23-EC-EARTH
- 24-CESM1-FAST
- 25-CESM1-CAM5
- 26-CESM1-BGC
- 27-CCSM4

**Median values of local dimensions  $d$  and the persistence  $\theta$ .** Semiaxes of each ellipse represent one standard deviation of  $d$  and  $\theta$ .

*Rodrigues et al. Journal of Climate 2018*

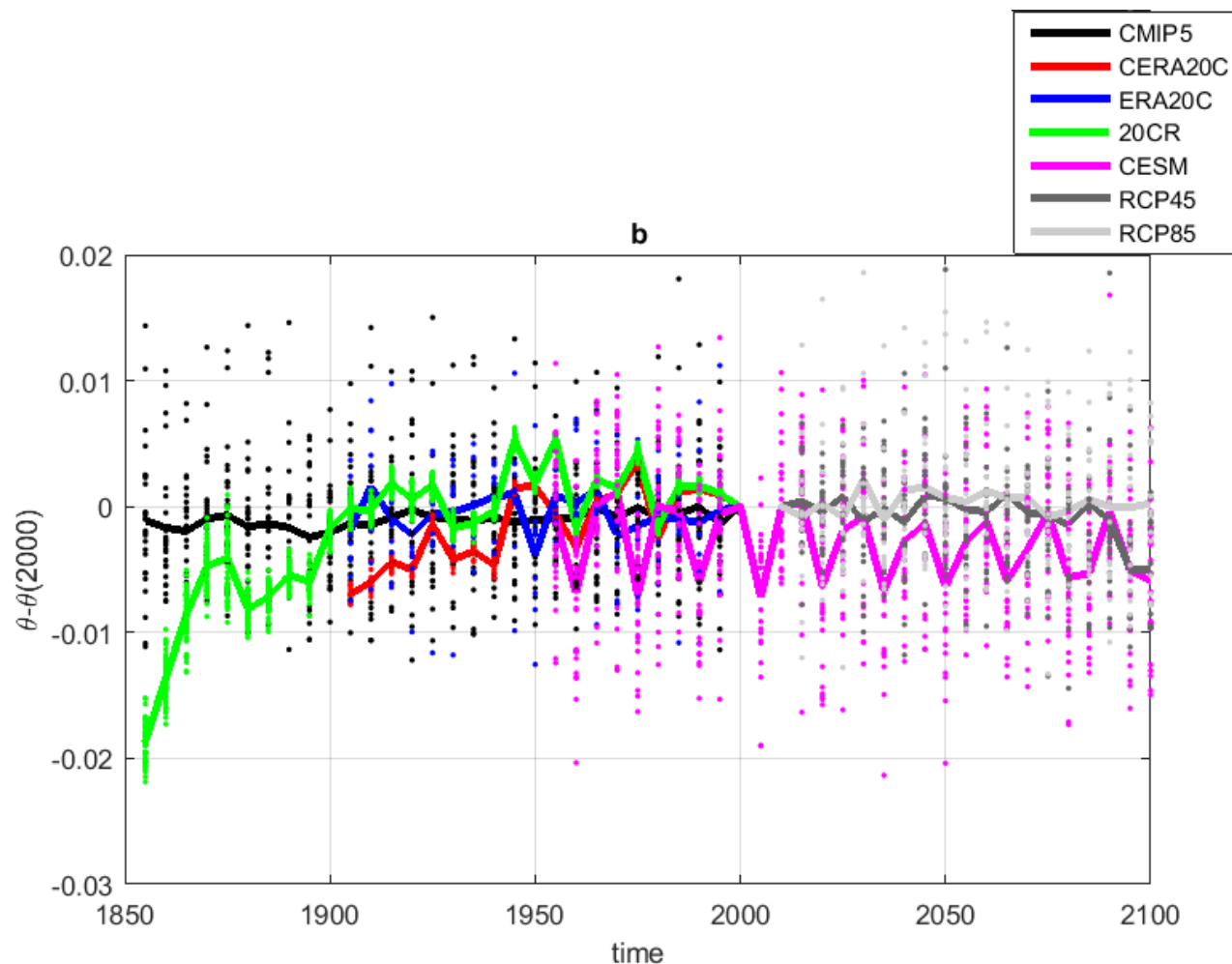
# RESULTS – CHANGES OF DIMENSION IN TIME



**5 years averaged values of local dimensions  $d$**

*Faranda et al. Submitted 2018*

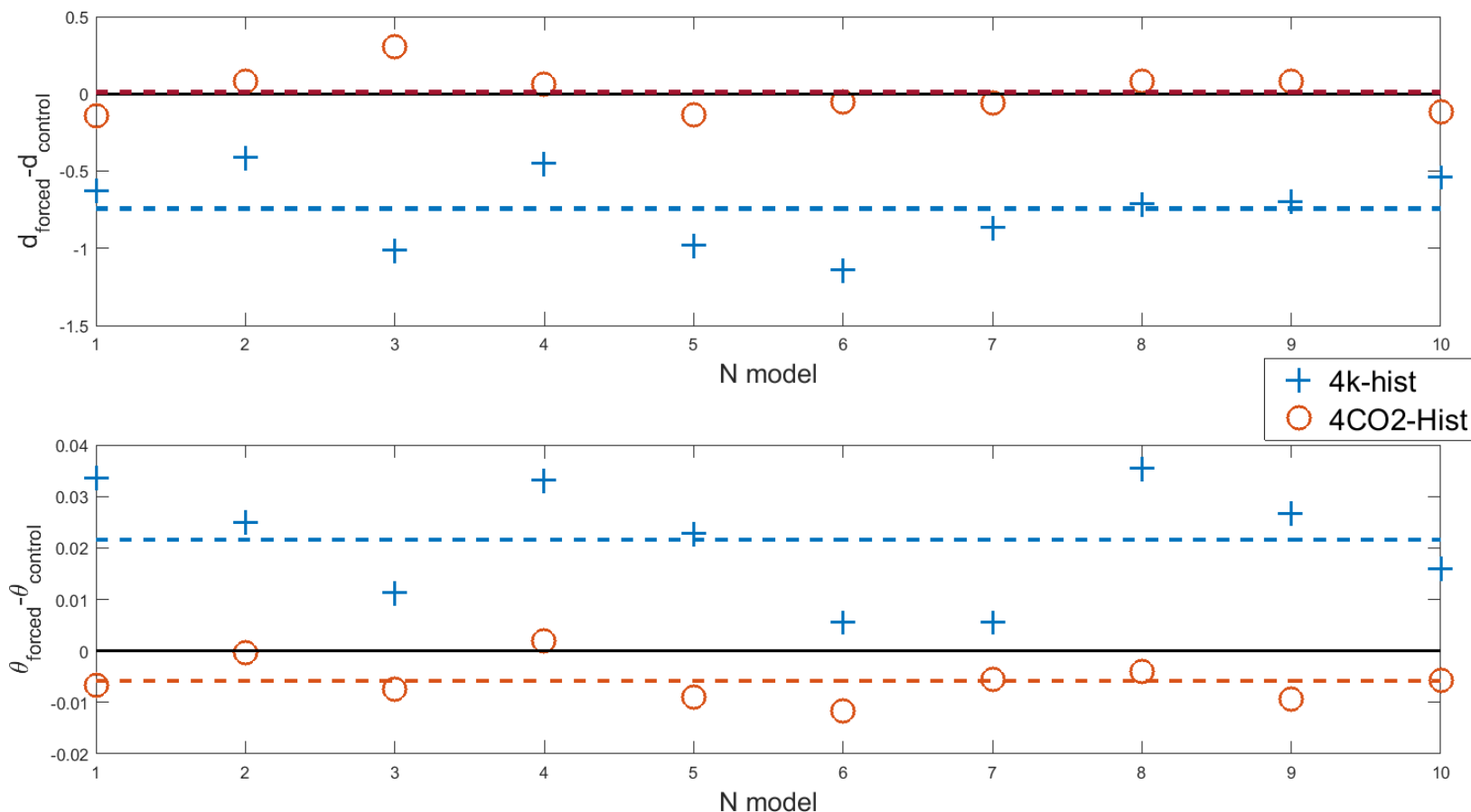
# RESULTS – CHANGES OF PERSISTENCE IN TIME



**5 years averaged values of the persistence  $\theta$ .**

*Faranda et al. Submitted 2018*

# RESULTS – HOW TO EXPLAIN THE DECREASE OF D



**Ocean's inertia effects reduce the dimension of North Atlantic circulation when ocean temperature is increased**



# OUTLOOK: INDICATORS AND SWG

**Sheng Cheng postdoc: provide both a theoretical framework and a numerical tool to build conditional Stochastic Weather Generators (SWG) driven by dynamical systems properties.**

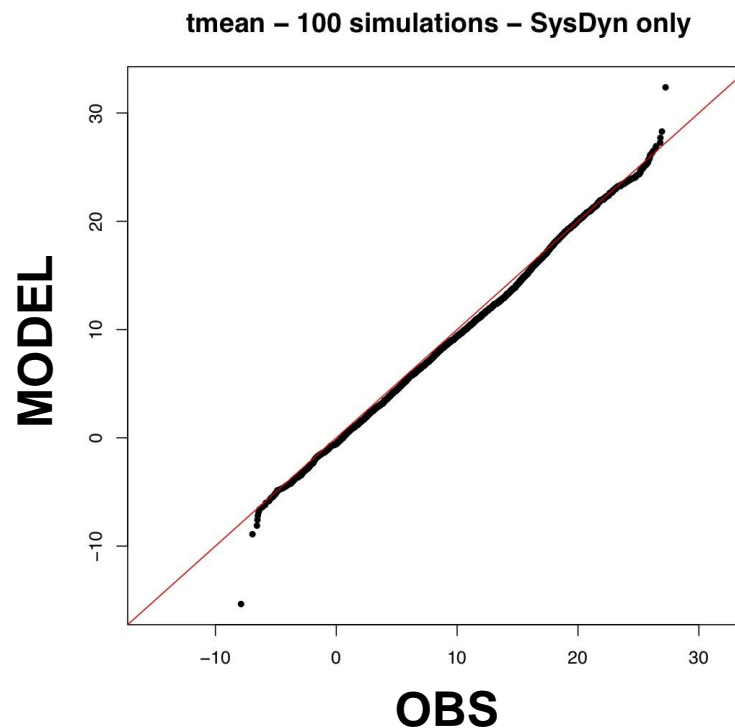
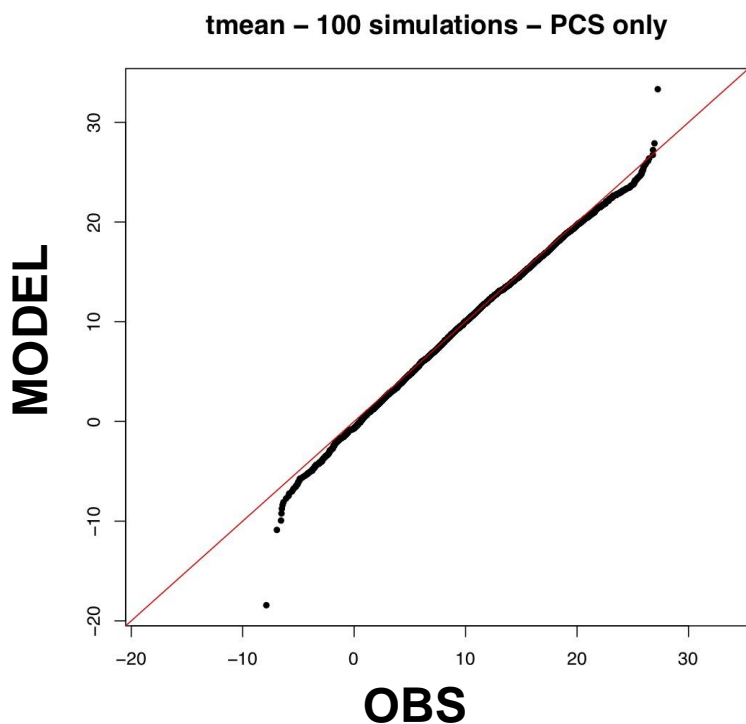
1/ Introduce **the indicators in simple autoregressive models** to mimic the dynamical properties of univariate time series  $X_t$  of climate variables and simple dynamical systems.

$$X_{t+1} = \phi(\theta(X_t))X_t + \epsilon(d(X_t))\xi(t)$$

Where  $\phi$  is the autoregressive coefficient depending on the persistence index and  $\epsilon$  is the noise amplitude ( $\xi(t)$  is a random variable drawn from a normal distribution at each time)

2/ Those **state-dependent indicators introduces nonlinearities** . We use them to condition progressively more sophisticated SWGs (e.g., Vrac et al., 2007), up to spatial models (i.e., simulating field) for climate variables as wind, temperature or precipitation.

# OUTLOOK: EXAMPLE QQ PLOT



**Data: daily temperature mean over Ile de France 1979-2018;**

**Left** using 20 **principal components (PCS)** for Sea Level pressure fields over the North Atlantic as predictor for SWG.

**Right** using system **dynamical indicators** computed for sea level pressure fields over the North Atlantic as predictor for SWG.

# CONCLUSIONS



From an innovative application of recent results in dynamical system theory, we obtain that:

- The distribution of the local dimensions **capture the features of mid-latitude circulation dynamics**.
- Extremes of local dimensions **correspond to real-life extreme weather** (storms and blocking).
- There is a robust decrease in the dimension with greenhouse forcing, which implies a more predictable atmosphere. **This could be explained by the larger inertia feedback on atmospheric motions given by a warmer ocean.**

# REFERENCES



- [1] Davide Faranda, Gabriele Messori and Pascal Yiou. Dynamical proxies of North Atlantic predictability and extremes. **Scientific Reports**, 7-41278, **2017**.
  
- [2] Valerio Lucarini, Davide Faranda, Ana Cristina Gomes Monteiro Moreira de Freitas, Jorge Miguel Milhazes de Freitas, Mark Holland, Tobias Kuna, Matthew Nicol, Mike Todd, Sandro Vaienti. Book: **Extremes and Recurrence in Dynamical Systems**. ISBN 978-1-118-63219-2, 312 pages, **Wiley**, **2016**.
  
- [3] David Rodrigues, M Carmen Alvarez-Castro, Gabriele Messori, Pascal Yiou, Yoann Robin , Davide Faranda. Changes in the dynamical properties of the North Atlantic atmospheric circulation in the past 150 years. Accepted in ***Journal of Climate***, **2018**