Boosting performance in Machine Learning of Turbulent and Geophysical Flows via scale separation

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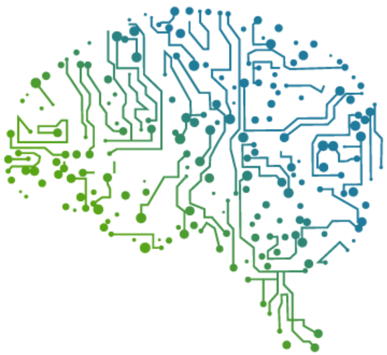
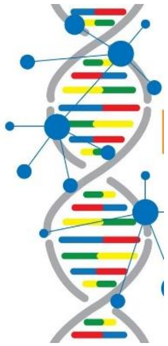
MACHINE LEARNING IN SCIENCE



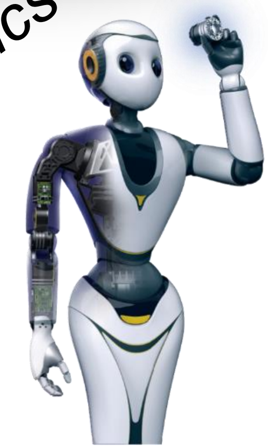
Neurosciences



Genomics

Traffic

Robotics



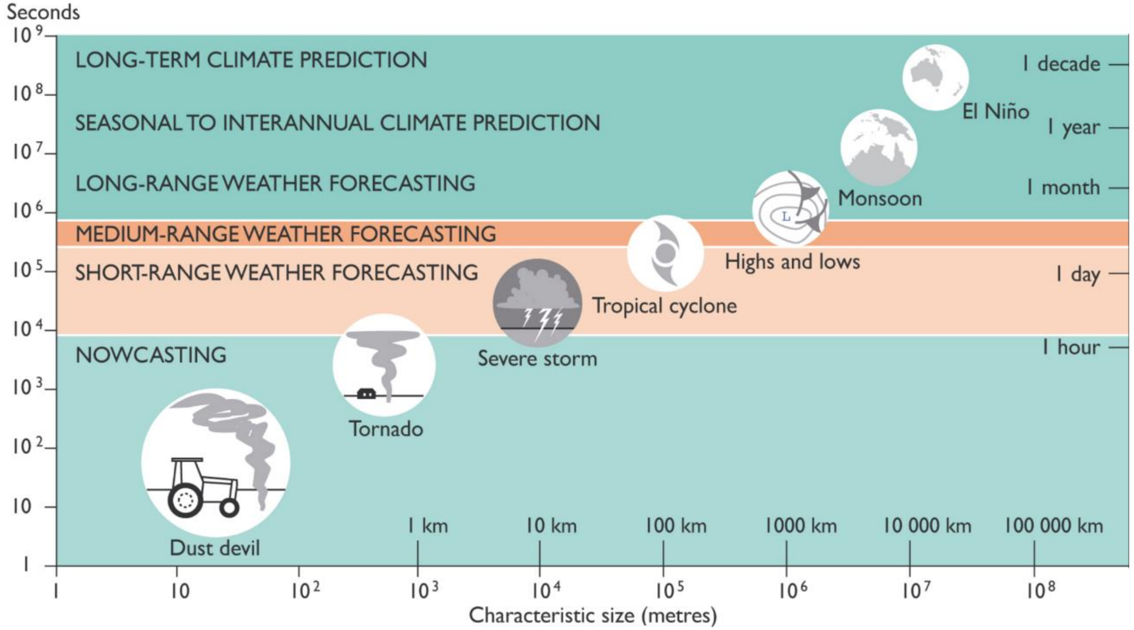
-**Complex** Systems

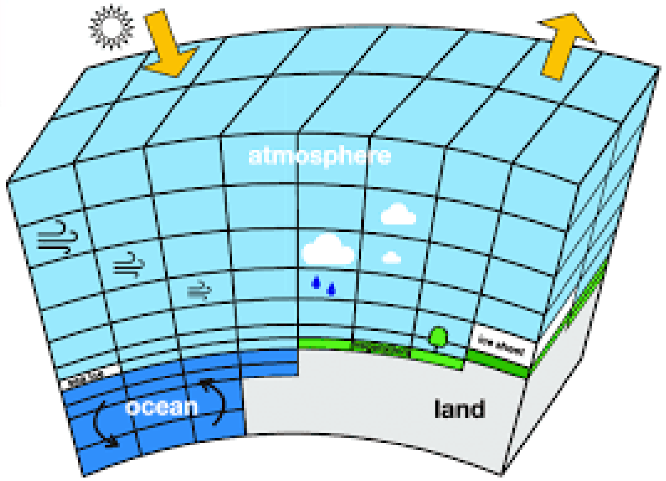
-Multiple **Spatial and time Scales**

-Large **Availability of Training Data**

-Missing Equations of State

MACHINE LEARNING IN CLIMATE SCIENCE





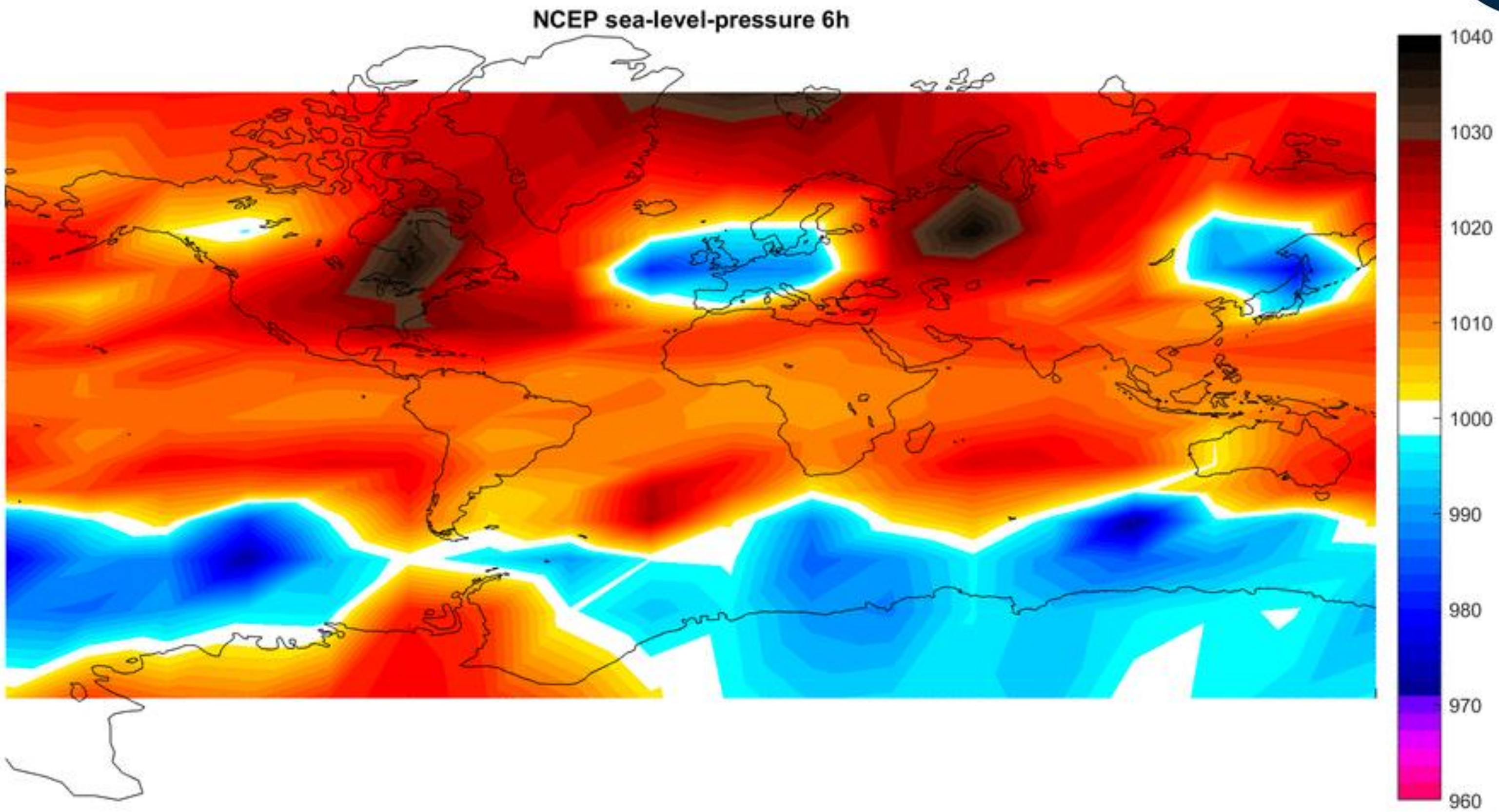
-**Complex** Systems

-Multiple **Spatial and time Scales**

-Large **Availability of Training Data**

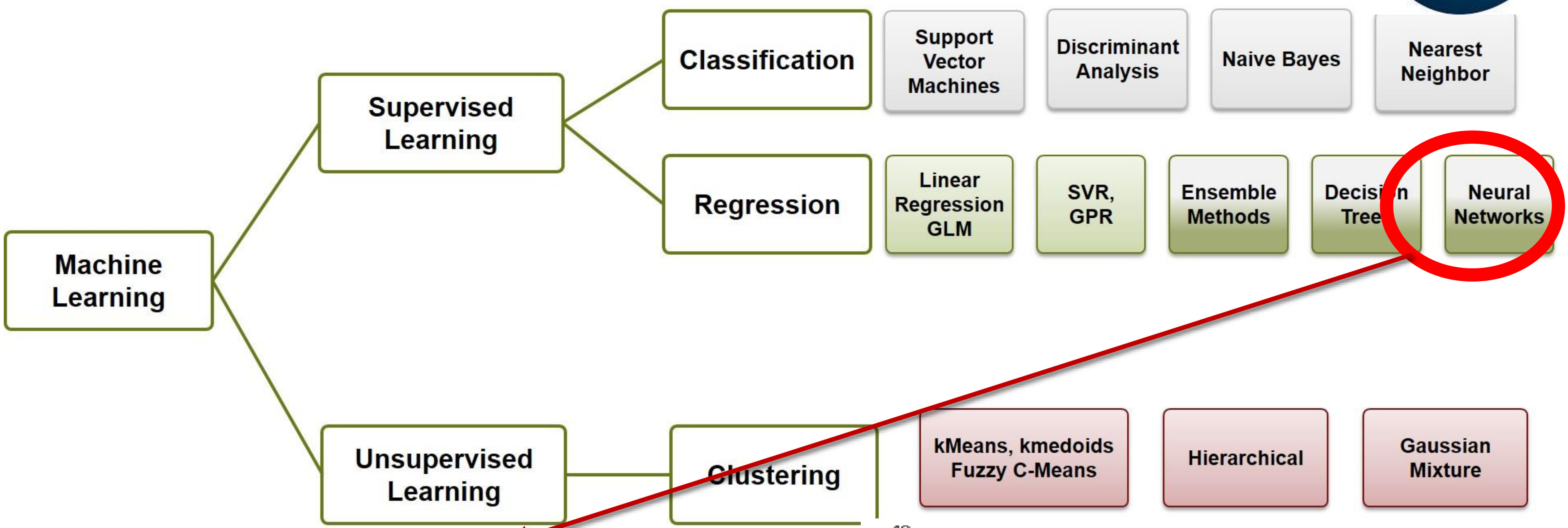
~~-Missing Equations of State~~ **(we have Navier-Stokes eqs.)**

WHICH SCIENTIFIC PROBLEM?



Task: forecast and generate a sea-level pressure forecast and its long term statistics to mimic that of the NCEP reanalysis.

WHICH TECHNIQUE?

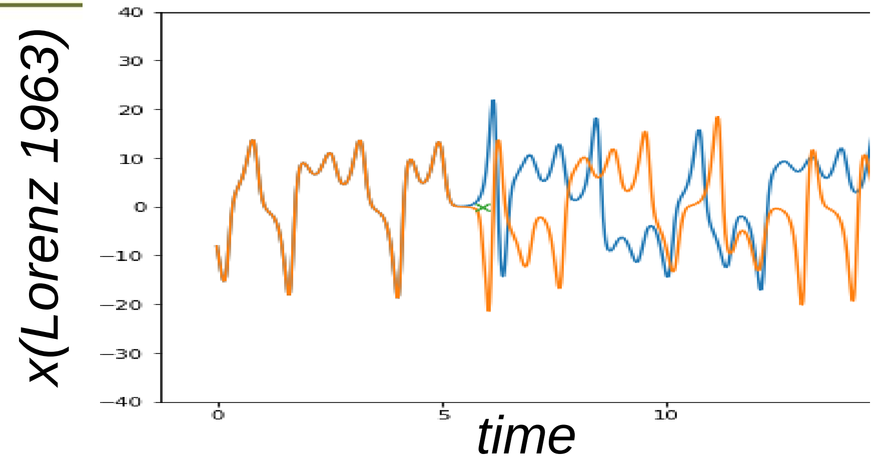


Pathak et al.– Phys. Rev. Lett. 2018

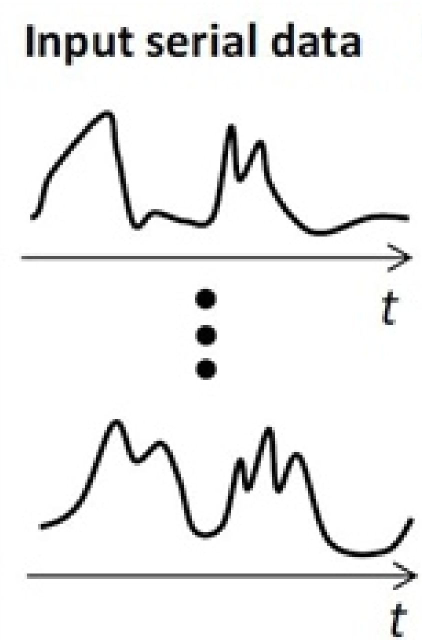
-Echo State Network for chaotic Systems

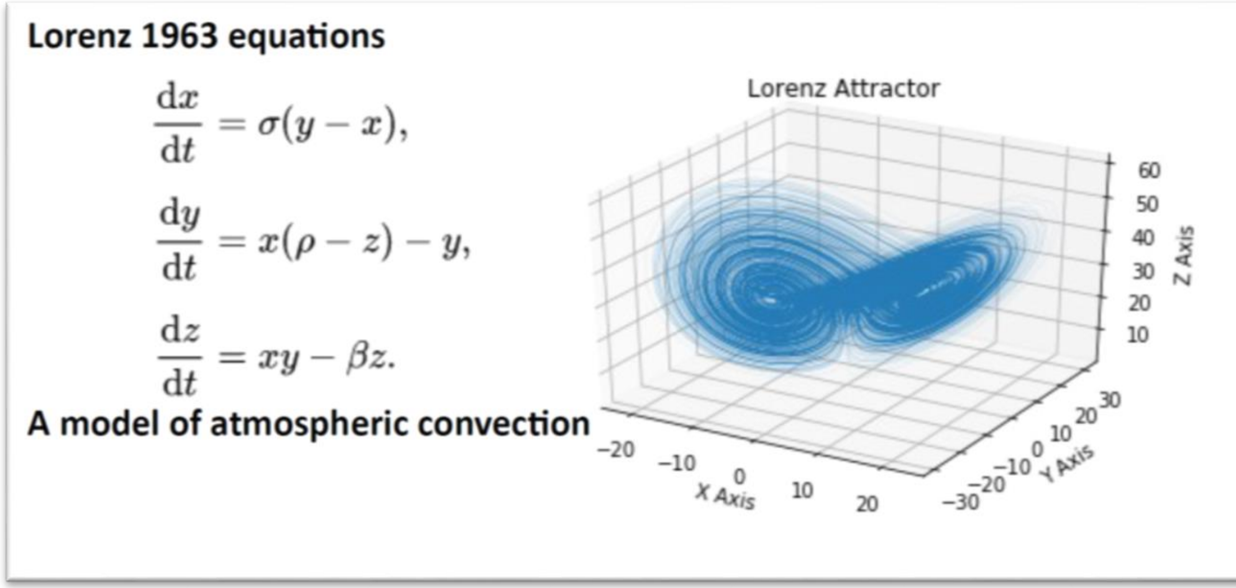
-Forecasts beyond the Lyapunov time!

- *Equations* *VS* *machine learning*



ECHO STATE NETWORKS + RECURRENCE



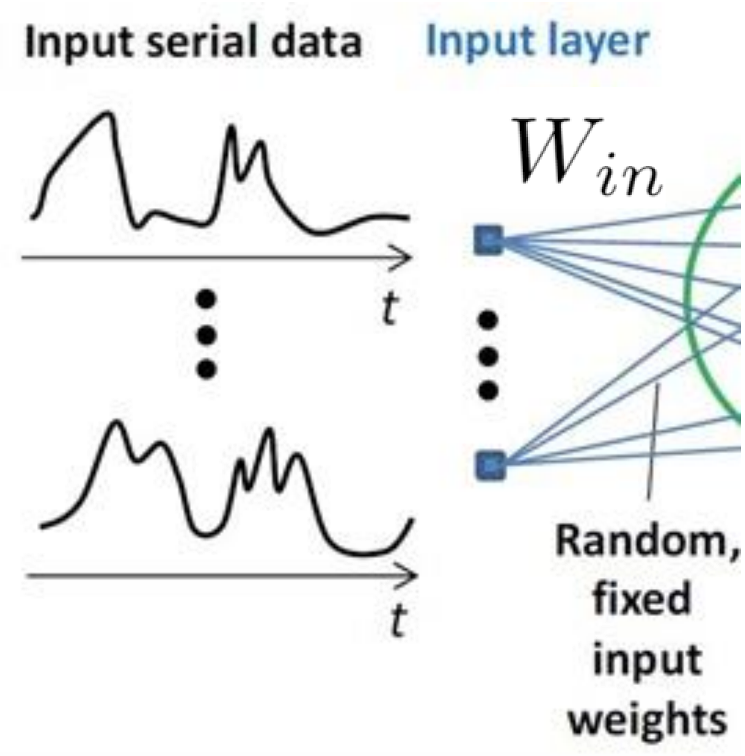


X(t) is a L dimensional vector

-Variables need to be standardized

$$x(t) \xrightarrow{\text{ECHO STATE NETWORK}} x(t+dt)$$

ECHO STATE NETWORKS + RECURRENCE



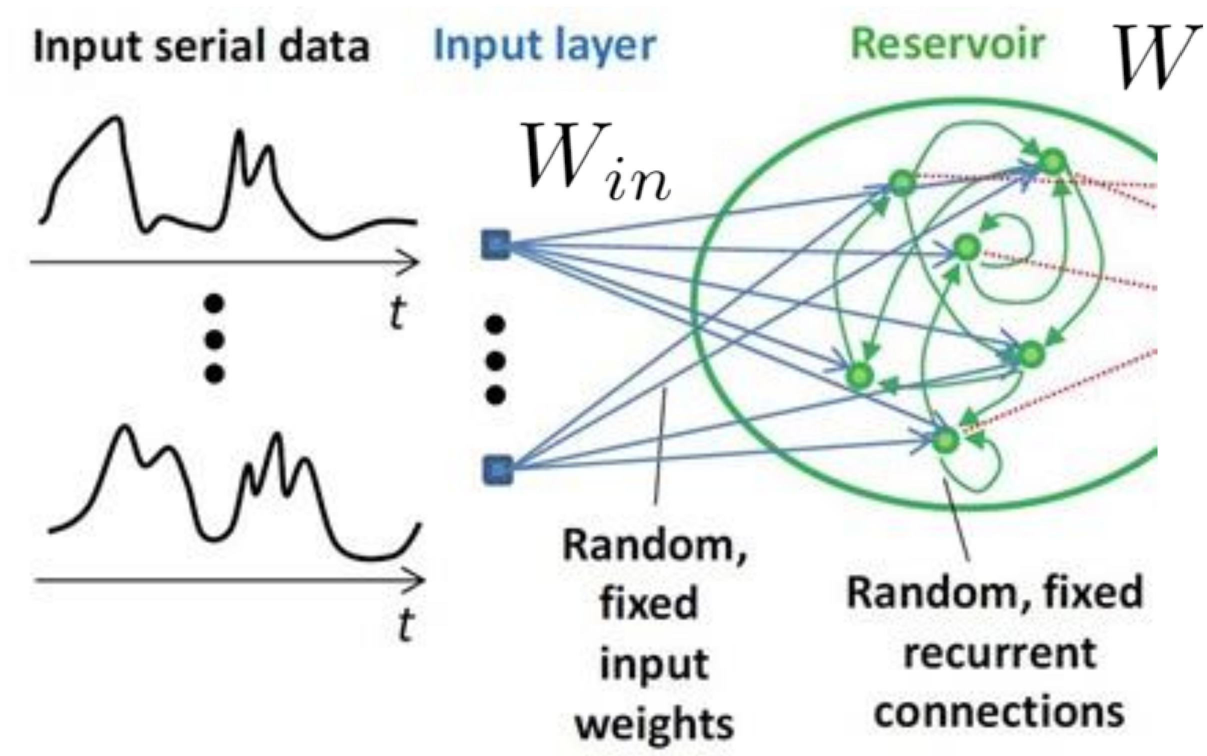
W_{in} is a matrix LxN

-*L* is the number of variables.
-*N* is the network size

Each lines consists of random weights uniform in [0.5 0.5]

$x(t)$ —ECHO STATE NETWORK→ $x(t+dt)$

ECHO STATE NETWORKS + RECURRENCE



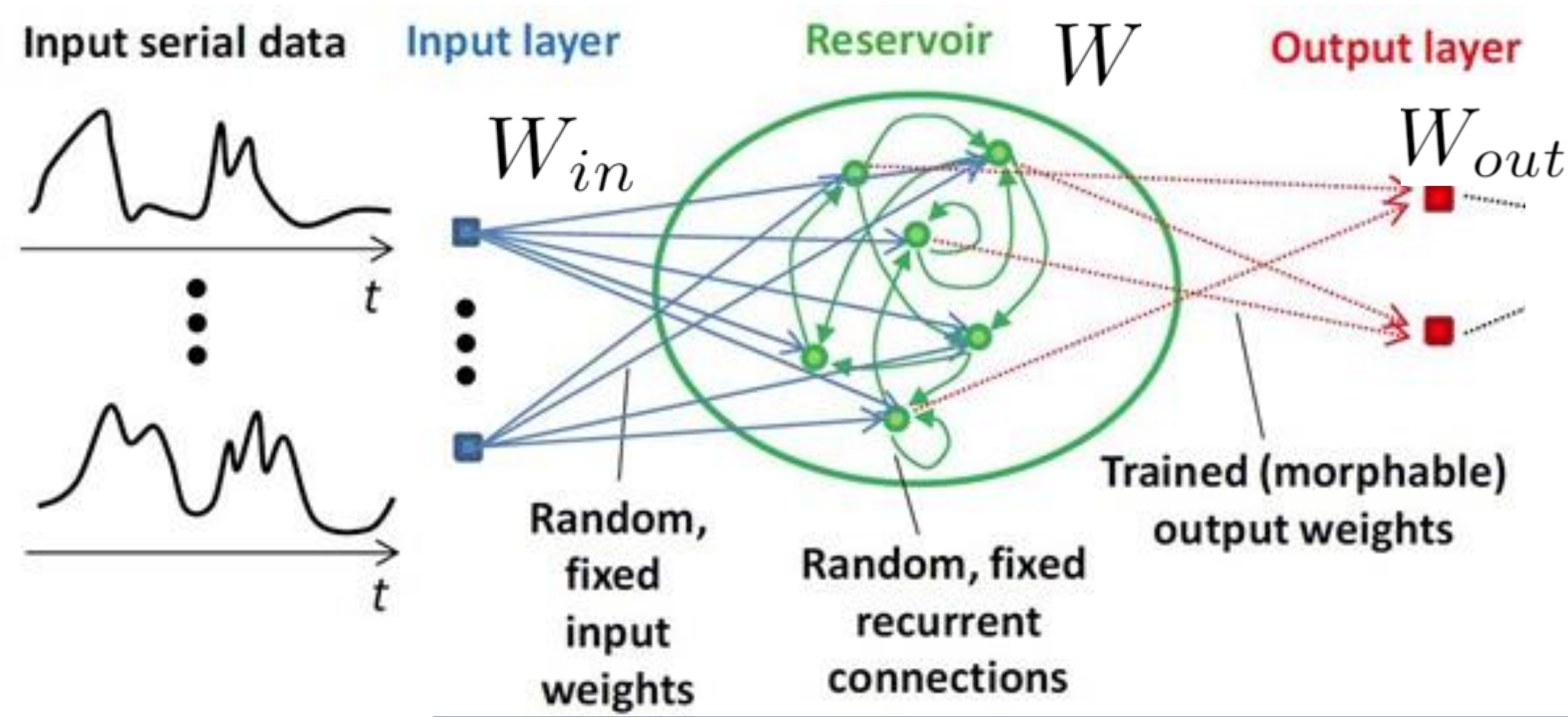
W is NxN matrix

-*N* is the network size
-Activation function is tanh

Each lines consists of random weights uniform in [0.5 0.5]

$$x(t) \xrightarrow{\text{ECHO STATE NETWORK}} x(t+dt)$$

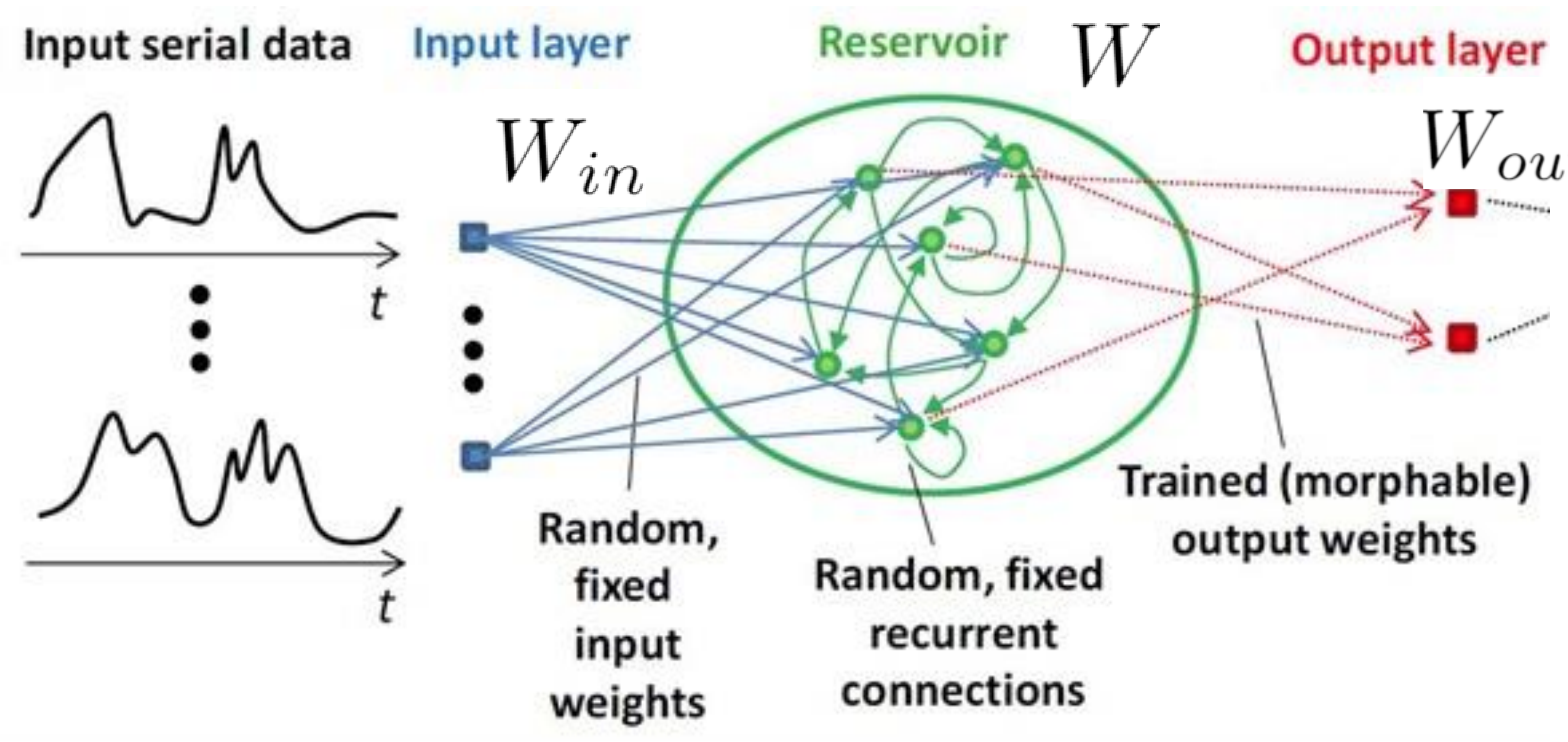
ECHO STATE NETWORKS + RECURRENCE



W_{out} is a matrix NxL

-Optimized during the training with a ***Ridge regression*** *so that the output matches x(t+dt)*

ECHO STATE NETWORKS + RECURRENCE

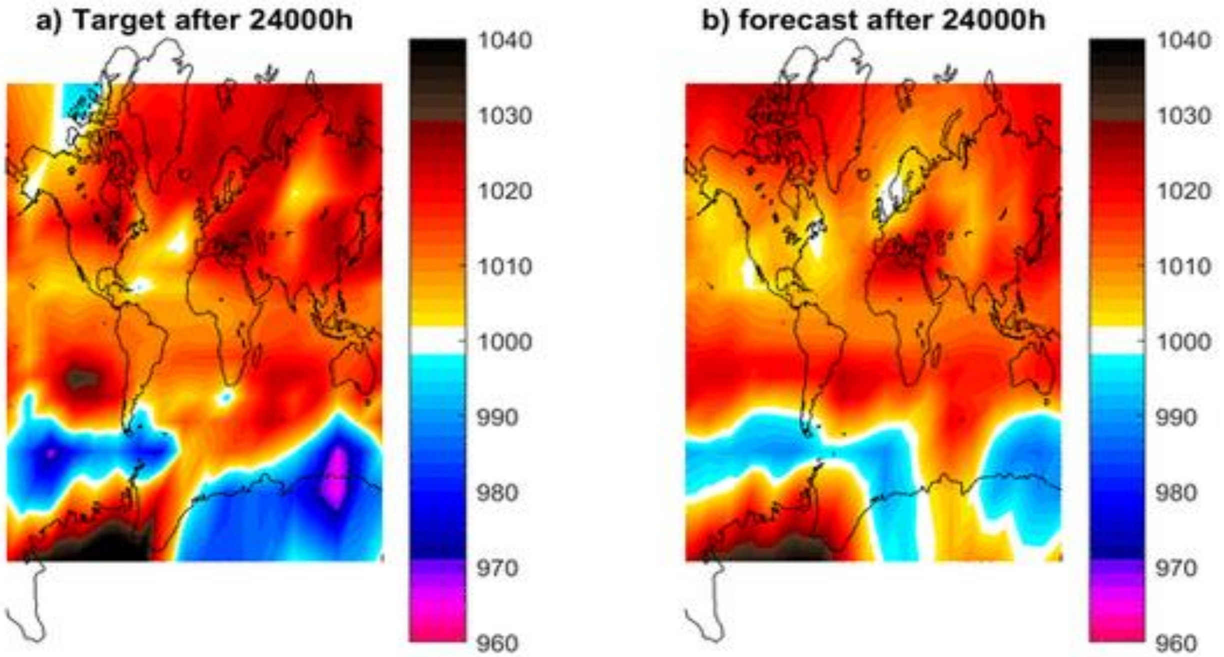


$$x(t+dt) = \tanh(Wx(t) + W_{in}W_{out}x(t))$$

FIRST TRIALS ON SEA-LEVEL PRESSURE

Network Size= 200 Neurons, Learning Time = 10 years Forecast Length = 10 years

At long time, the dynamics is stuck, it does not look realistic anymore (independently on the chosen parameters)



Similar results: Scher & Messori (2018,2019), Dueben & Bauer (2018)

=> We need to take one step back to assess what is wrong

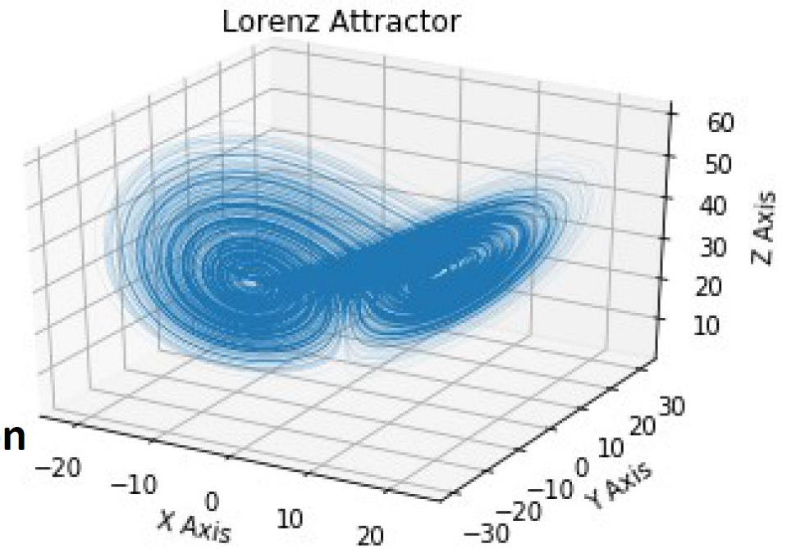
TEST SYSTEMS

Lorenz 1963 equations

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \sigma(y - x),$$

$$\frac{\mathrm{d}y}{\mathrm{d}t} = x(\rho - z) - y,$$

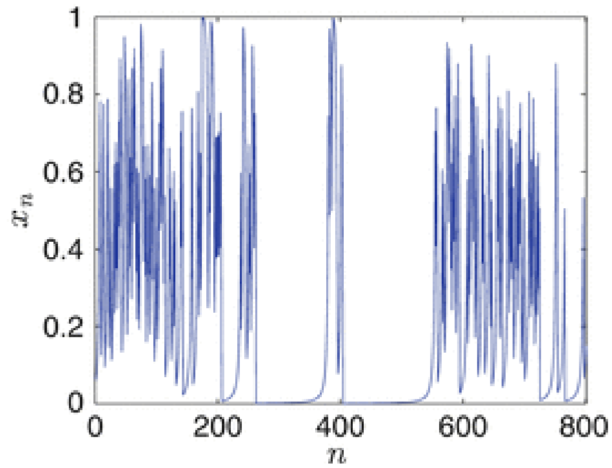
$$\frac{\mathrm{d}z}{\mathrm{d}t} = xy - \beta z.$$



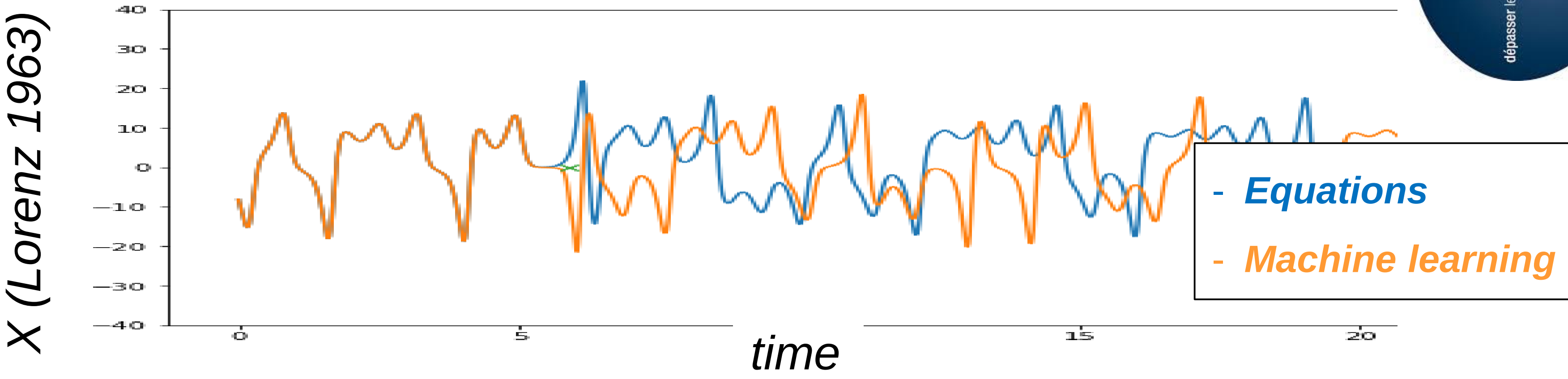
A model of atmospheric convection

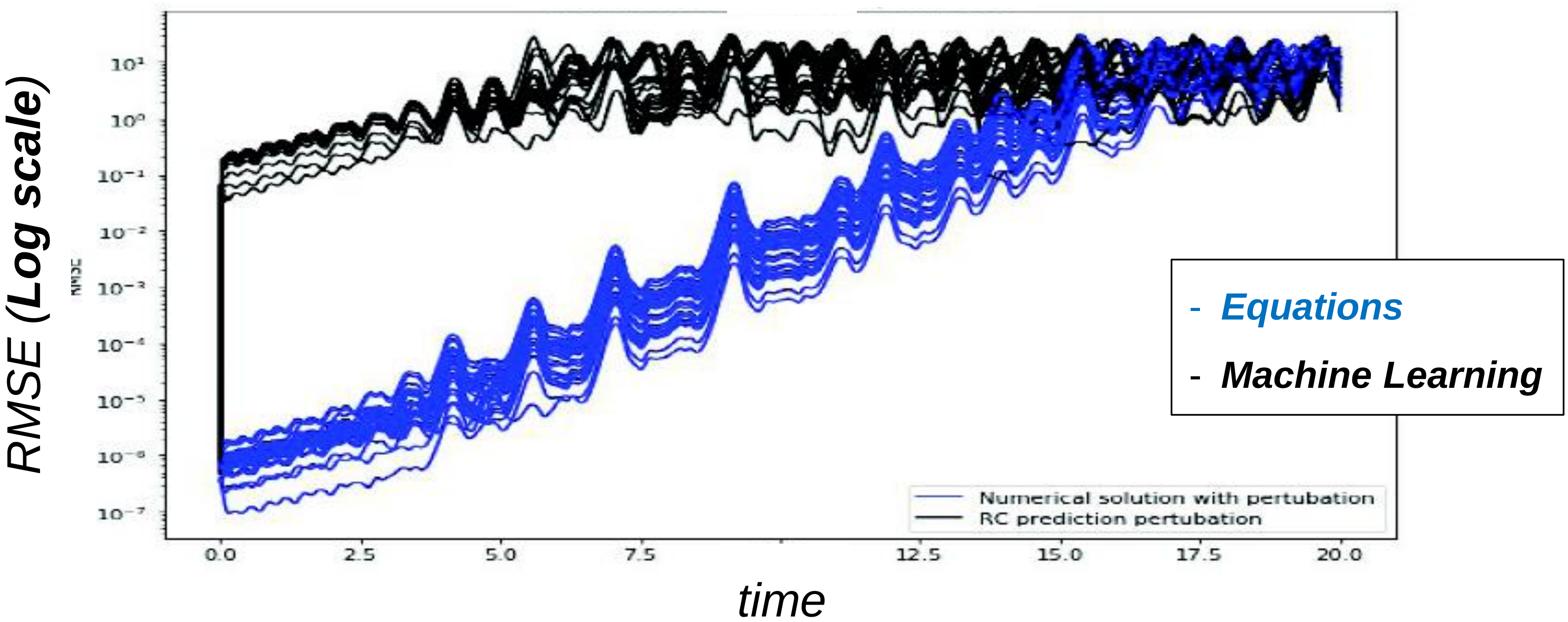
Pomeau Manneville intermittent map

$$x_n = x_{n-1}(1 + 2^{\beta} \mathrm{x}_{n-1}) \quad \text{if } x_n < .5$$
$$x_n = 2x_{n-1} - 1 \quad \text{if } x_n > .5$$

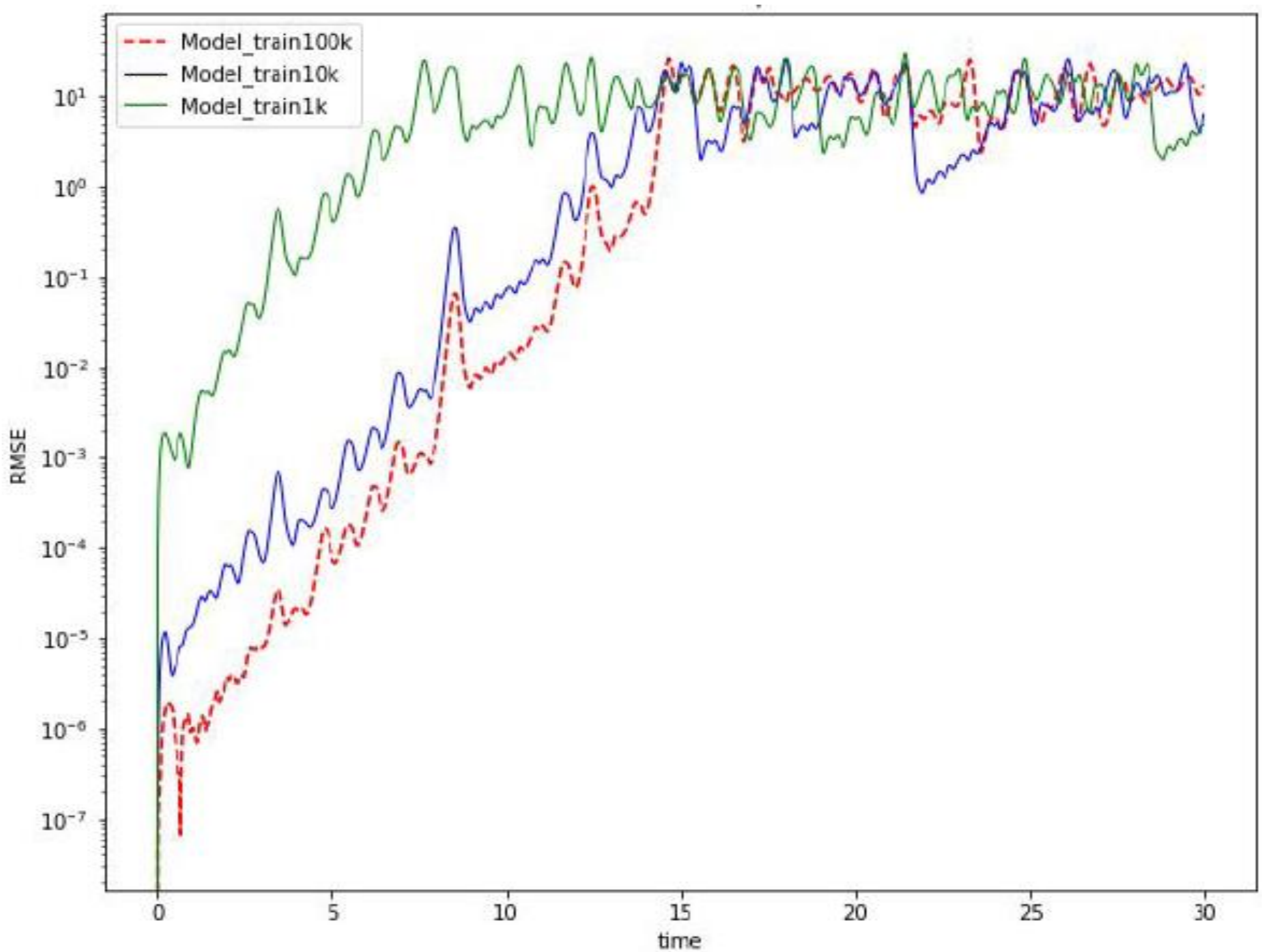


DANGER #1: LEARNING TIME





DANGER #1: LEARNING TIME

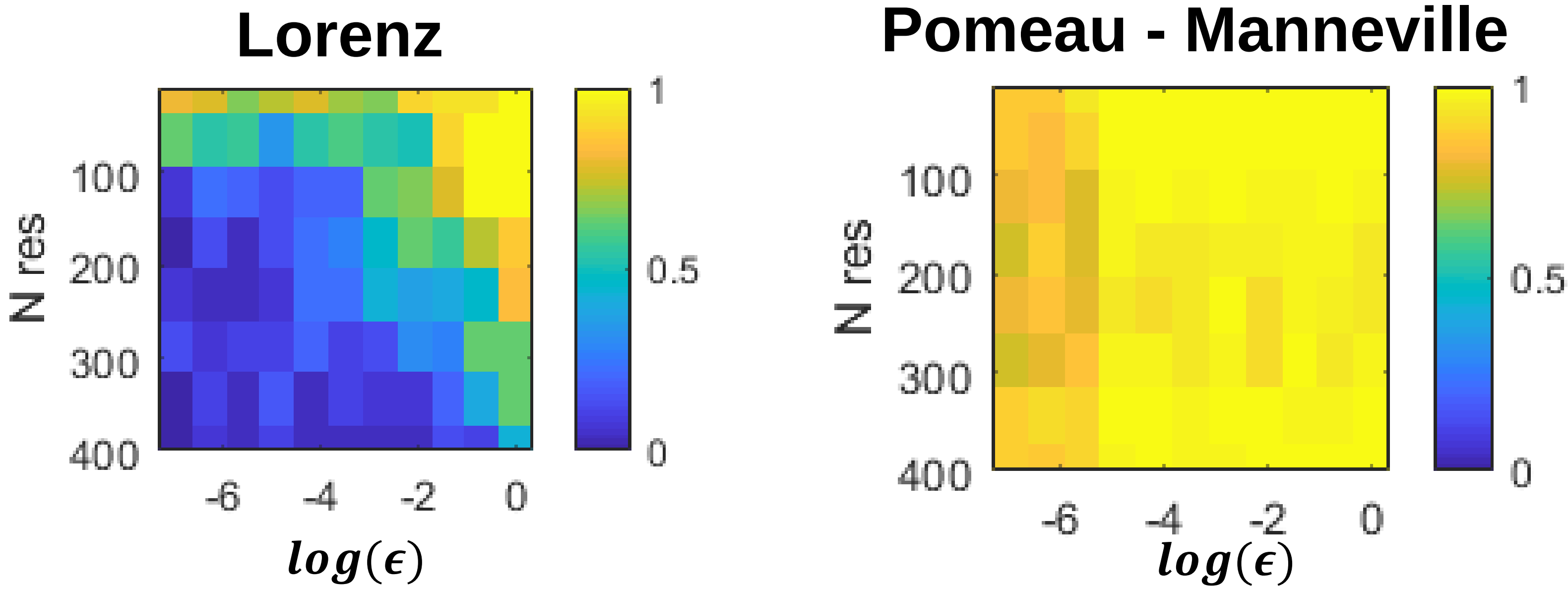


DANGER #2 NOISE & INTERMITTENCY

Additive noise to the Lorenz 1963 equations & Pomeau-Manneville Intermittent map:

$$x(t+dt) = f\big(x(t)\big) + \epsilon\xi(t)$$

where $\xi(t)$ is a random variable uniform in [-0.5 0.5]



Percentage of failure in reproducing the attractor

(0 means never fail,   1 means always fail)

POSSIBLE SOLUTION: SCALE SEPARATION

1) **Filter the noise**

There are countless methods, but we use the simplest possible one:

Moving Average filter *with window size:*

$$ws \ll \tau$$

where τ is the Lyapunov time

2) **Apply Echo State Network to the filtered system only**

3) **Add back the residual to the forecast**

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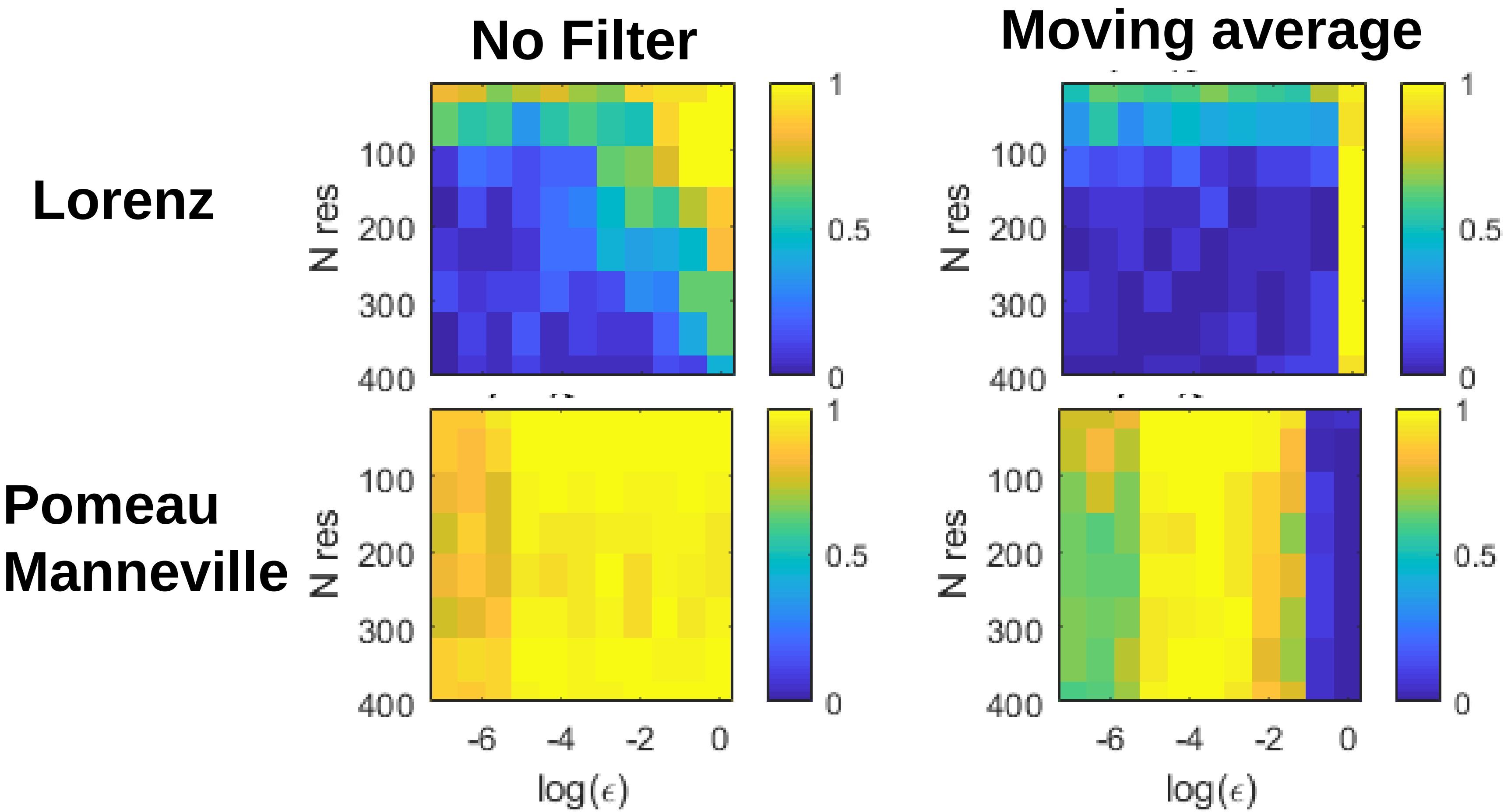
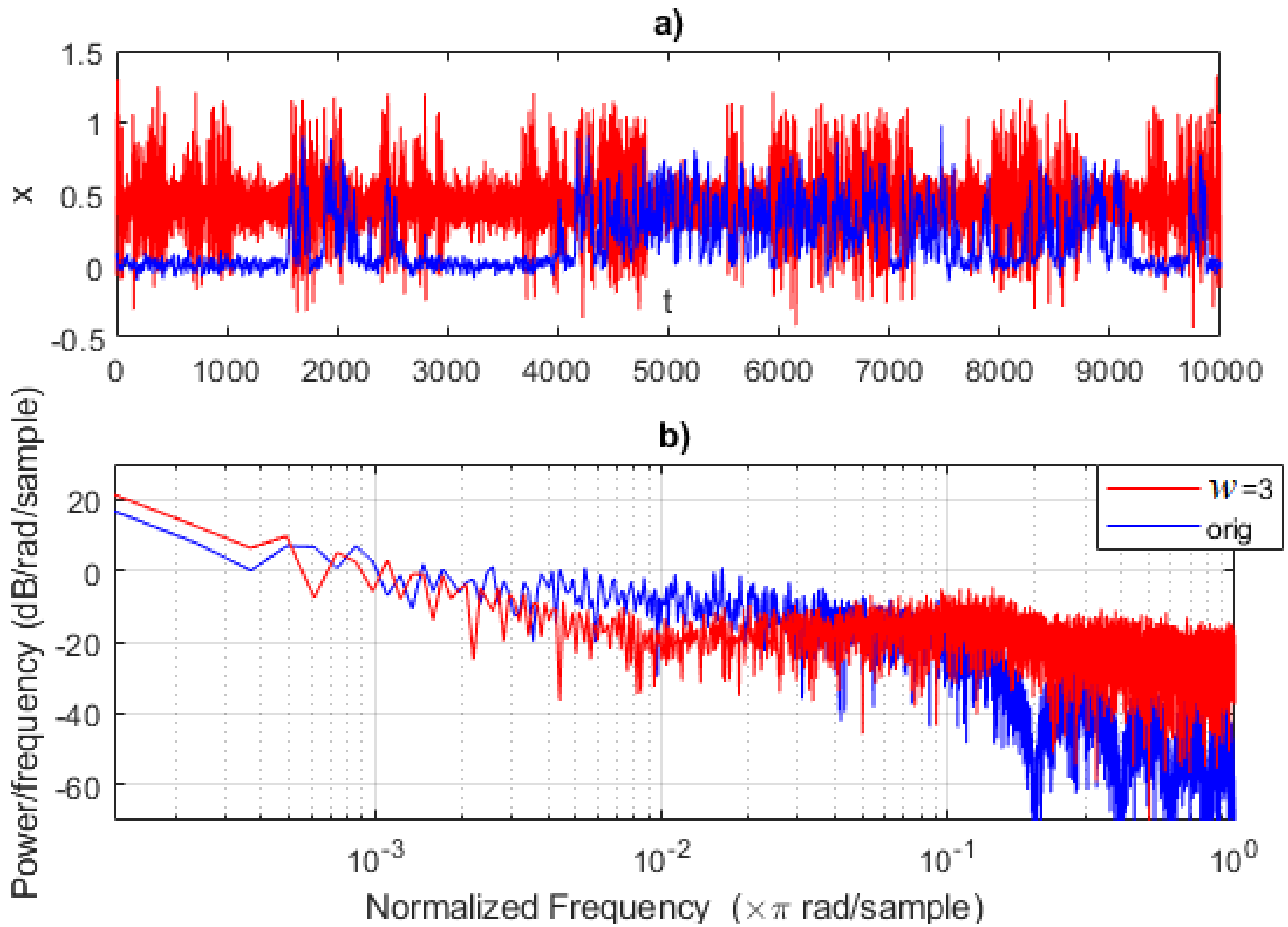
IMPROVEMENTS FOR LOW D SYSTEMS

Percentage of failure in reproducing the attractor
(0 means never fail,   1 means always fail)



IMPROVEMENTS FOR LOW D SYSTEMS

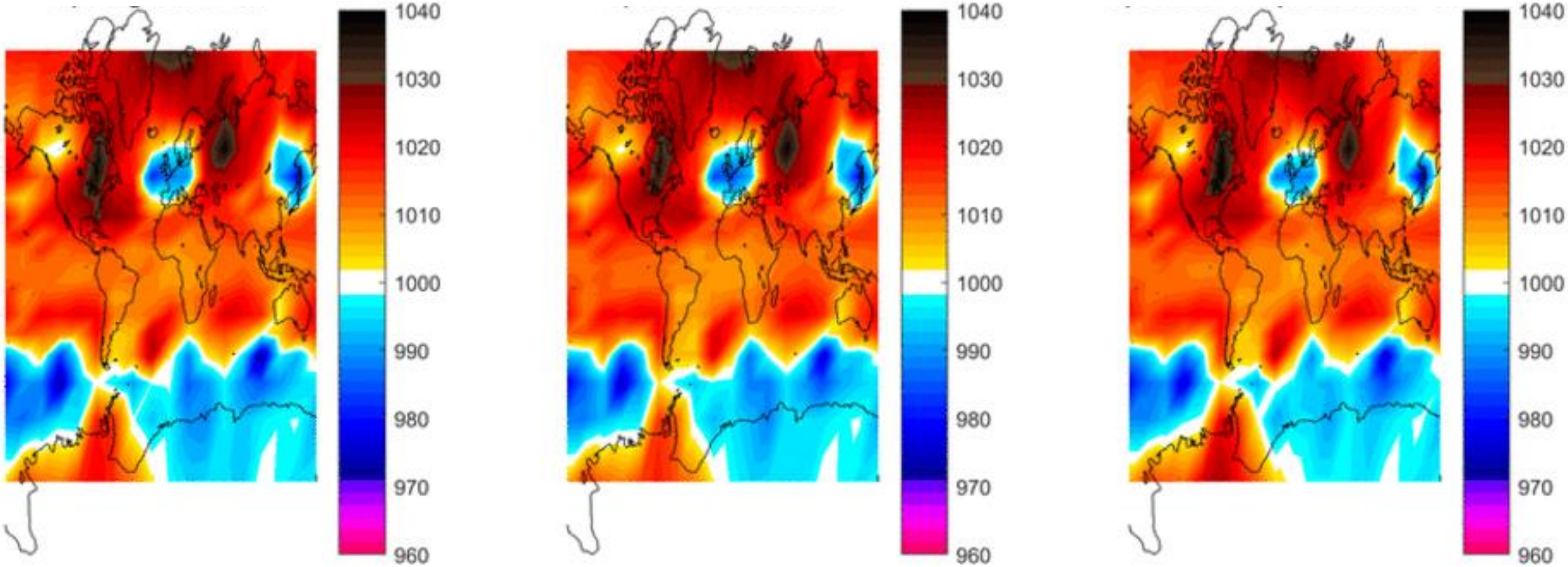
Pomeau Manneville



TEST ON NCEP SEA-LEVEL PRESSURE

Network Size= 200 Neurons, Learning Time = 10 years Forecast Length = 10 years

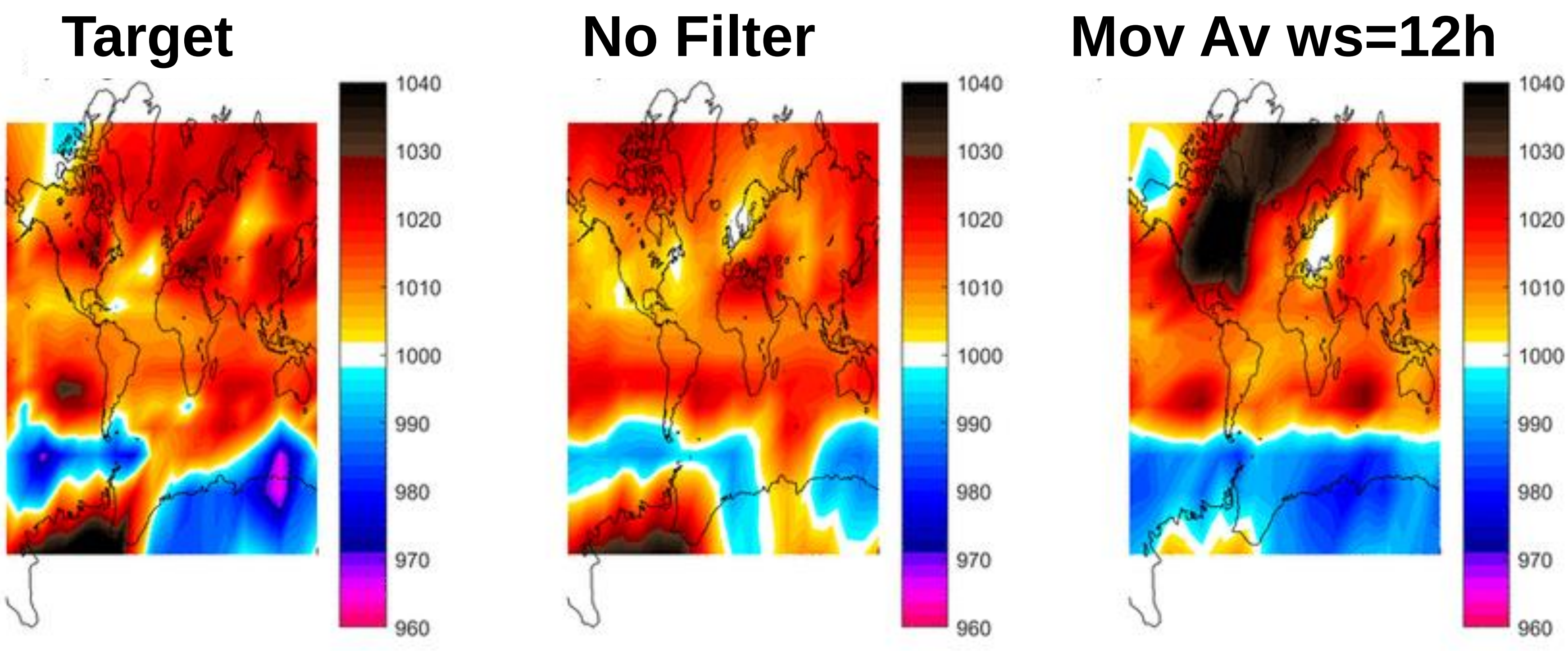
Target | **No Filter** | **Mov Av ws=12h**



*For the **short term forecast**, there is no much improvement*

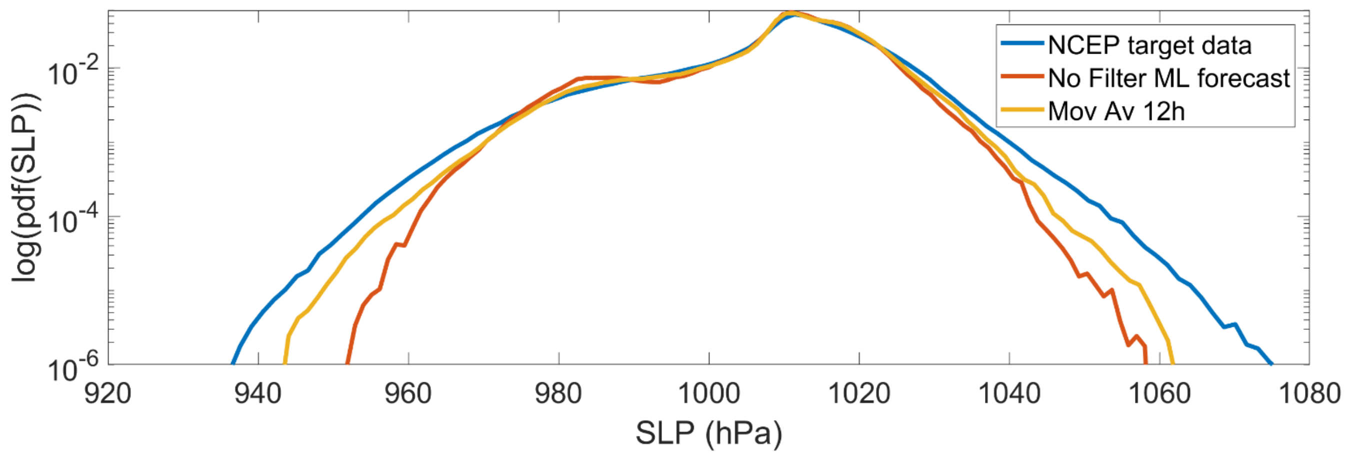
TEST ON NCEP SEA-LEVEL PRESSURE

Network Size= 200 Neurons, Learning Time = 10 years Forecast Length = 10 years

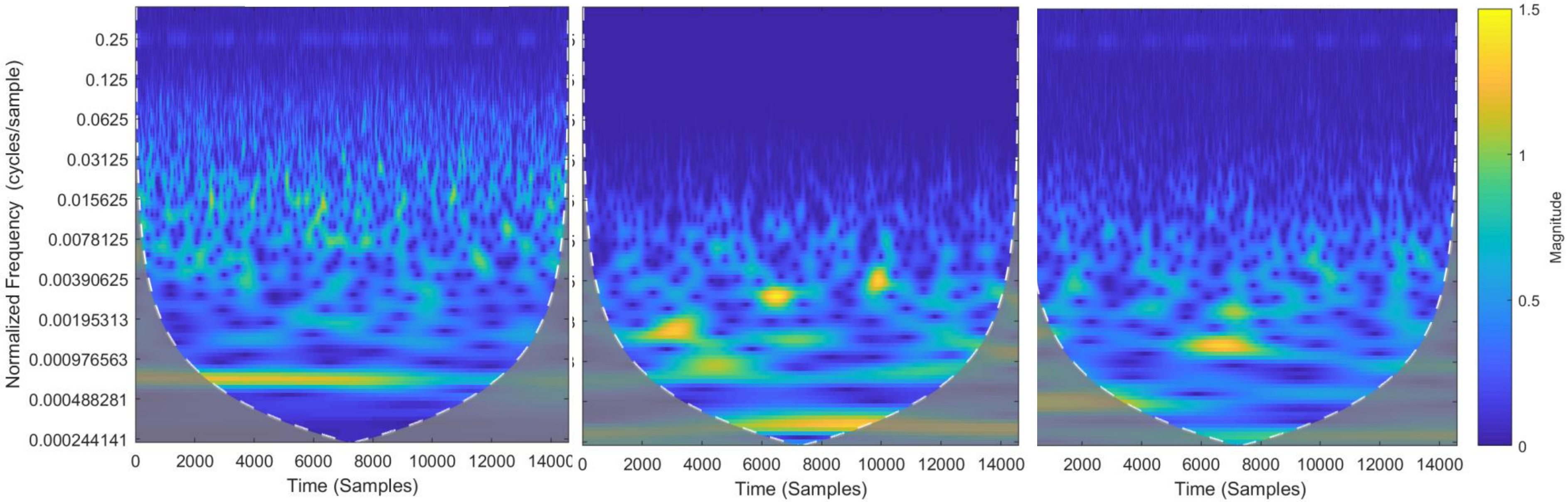


*If we look at the **long term behavior**, it is evident that the simulation with moving average is more realistic*

SPACE TIME STATISTICS



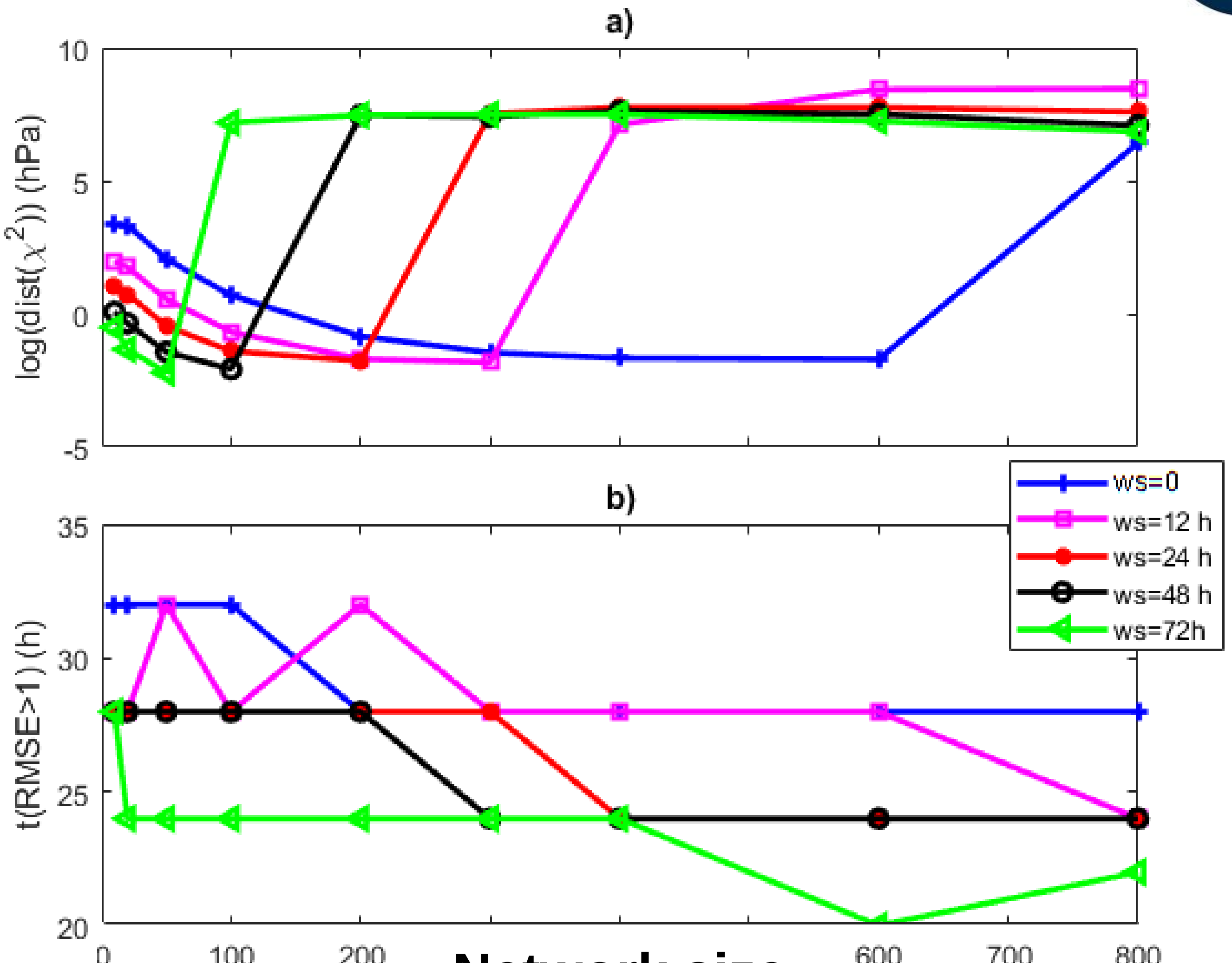
Target **No Filter** **Mov Av ws=12h**



A MORE QUANTATIVE ASSESSMENT

Distance from the NCEP data

Predictability horizon (in hours)



Network size

CONCLUSIONS

1) **It is not straightforward to apply Machine Learning techniques to geophysical flows: turbulence and intermittency worsen the performance**

2) **Partial predictability can be recovered by separating large from small scale dynamics (e.g moving average, PCA, wavelets)**

3) **Possible developments will largely benefit from interactions with the stochastic dynamical systems community**

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REFERENCES

[1] J. Pathak, B. Hunt, M. Girvan, Z. Lu, and E. Ott, Model free prediction of large spatiotemporally chaotic systems from data: A reservoir computing approach, Physical review letters 120, 024102 (2018)

[2] S. Scher and G. Messori, Weather and climate forecasting with neural networks: using general circulation models (gcms) with different complexity as a study ground, Geoscientific Model Development 12, 2797 (2019)

[3] D. **Faranda**, M. Vrac, P. Yiou, F.M.E. Pons, A. Hamid, , G. Carella, C.G. Ngoungue Langue, S. Thao, V Gautard. Boosting performance in Machine Learning of Turbulent and Geophysical Flows via scale separation. Phys Rev Letters (in review) (2019)

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Thank You for the Attention