

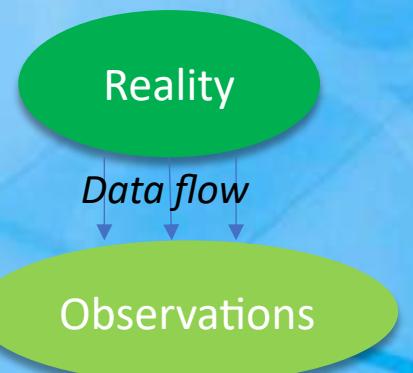
# Mathematical and Statistical Analysis of Data-Model Coupling

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Pierre AILLIOT

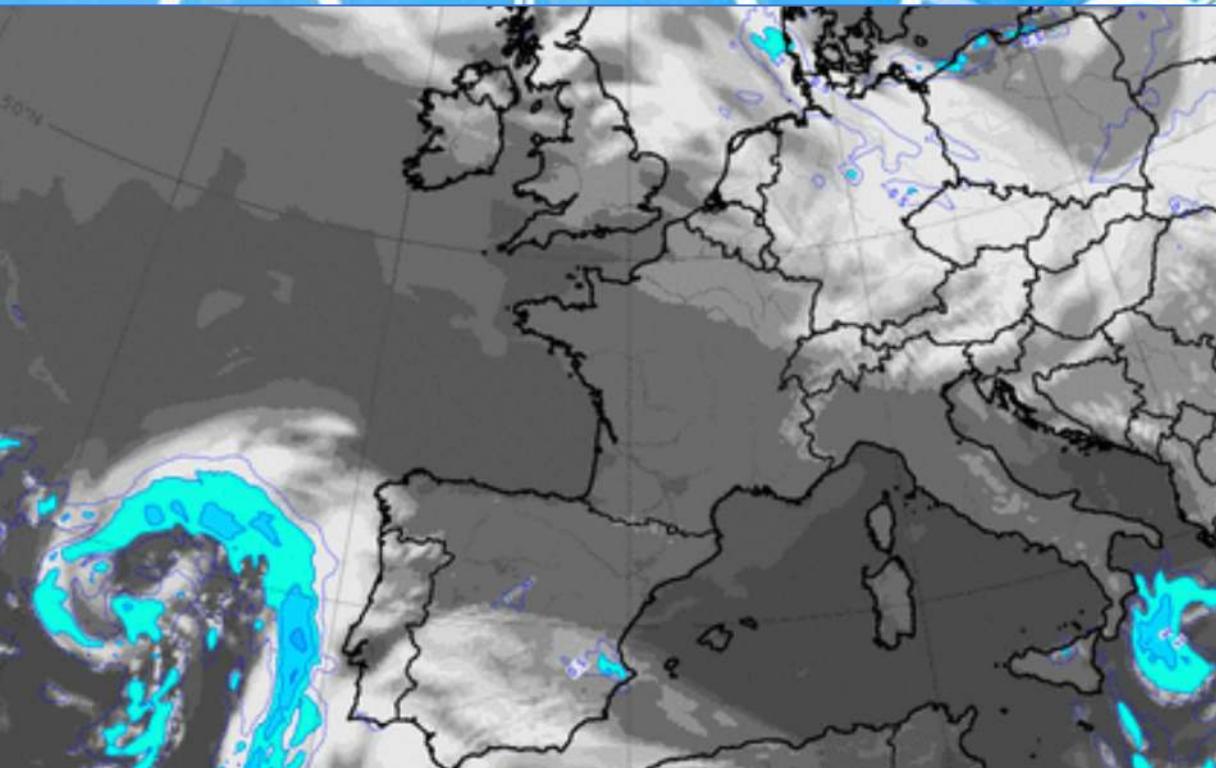


## DATA ASSIMILATION



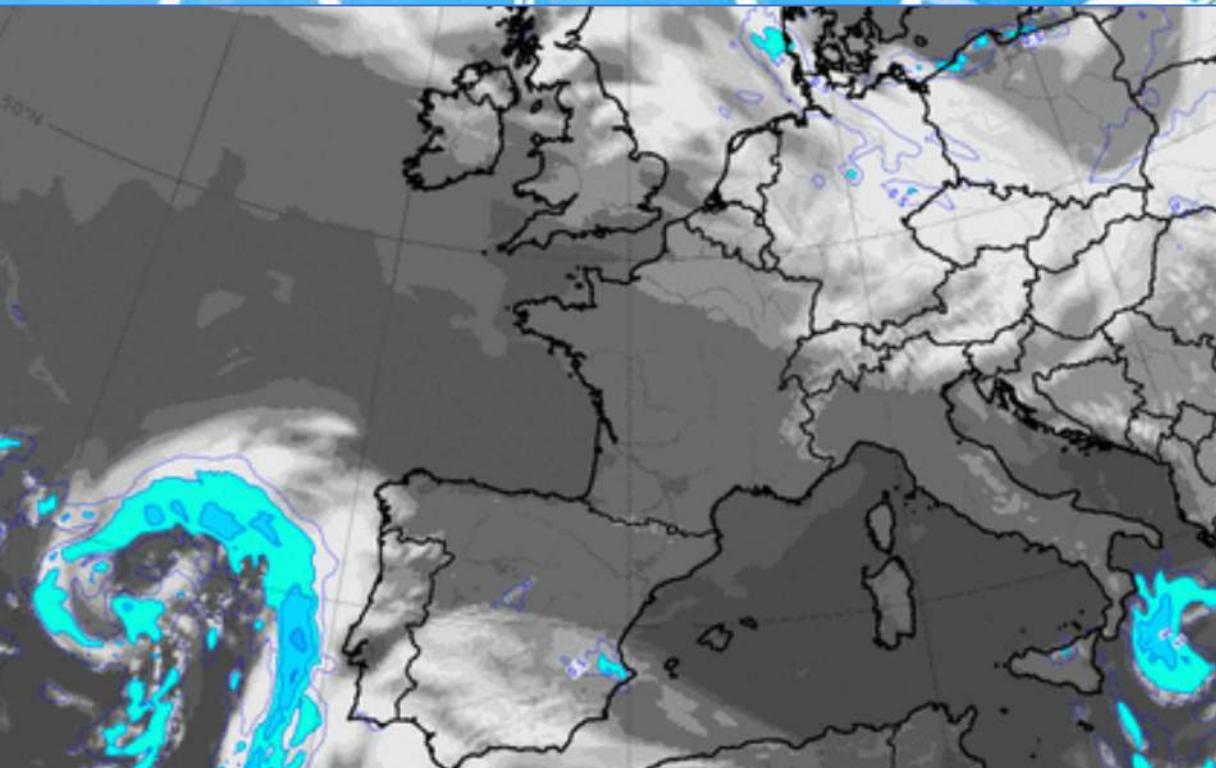
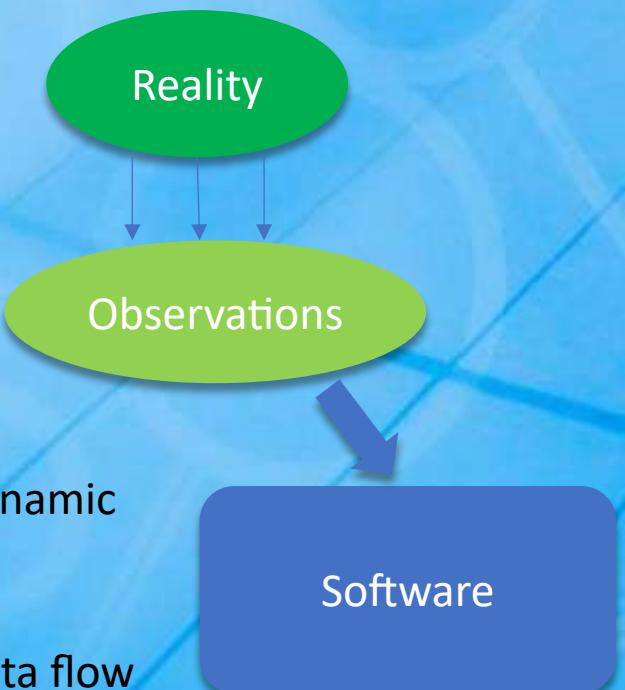
?

Real state at  
each time t



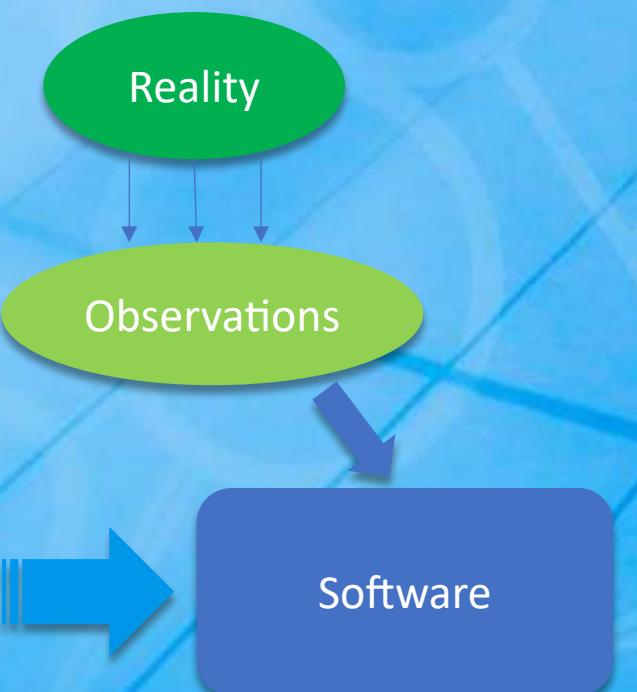
Satellite picture and expected rain  
(Arpege model) © Météo-France

## DATA ASSIMILATION

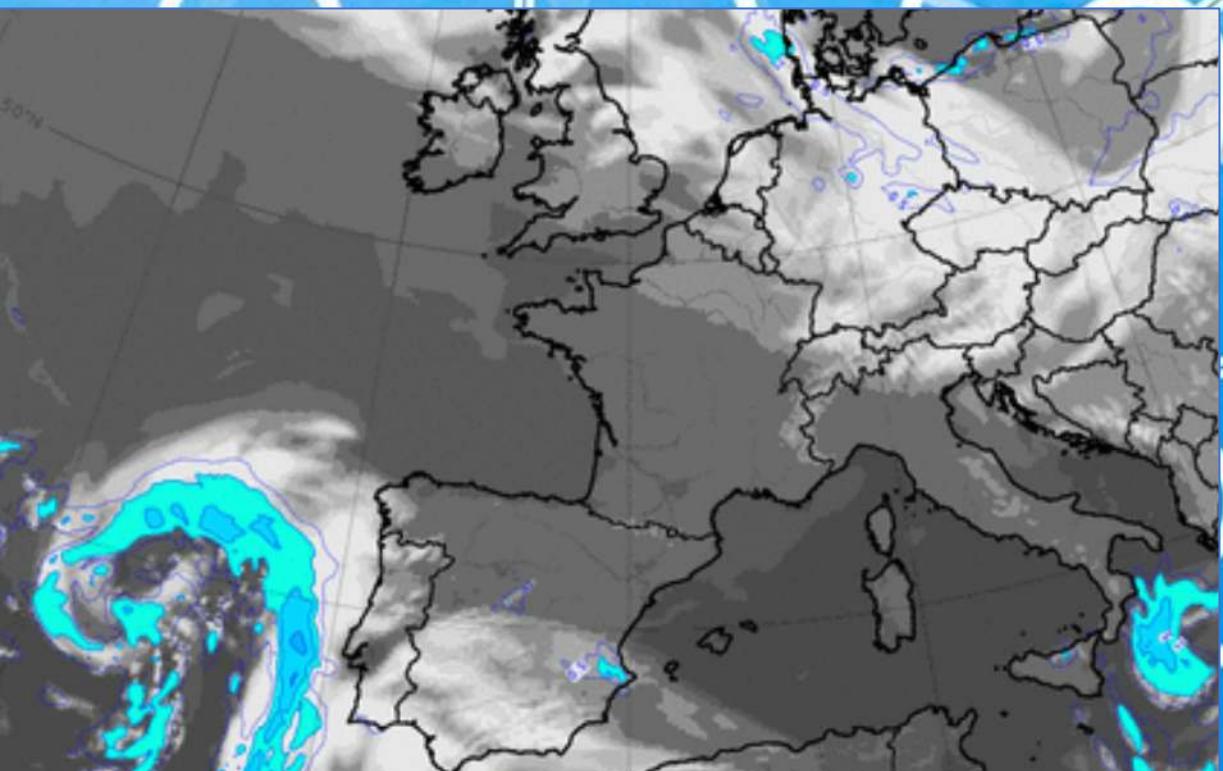


*Satellite picture and expected rain  
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## DATA ASSIMILATION

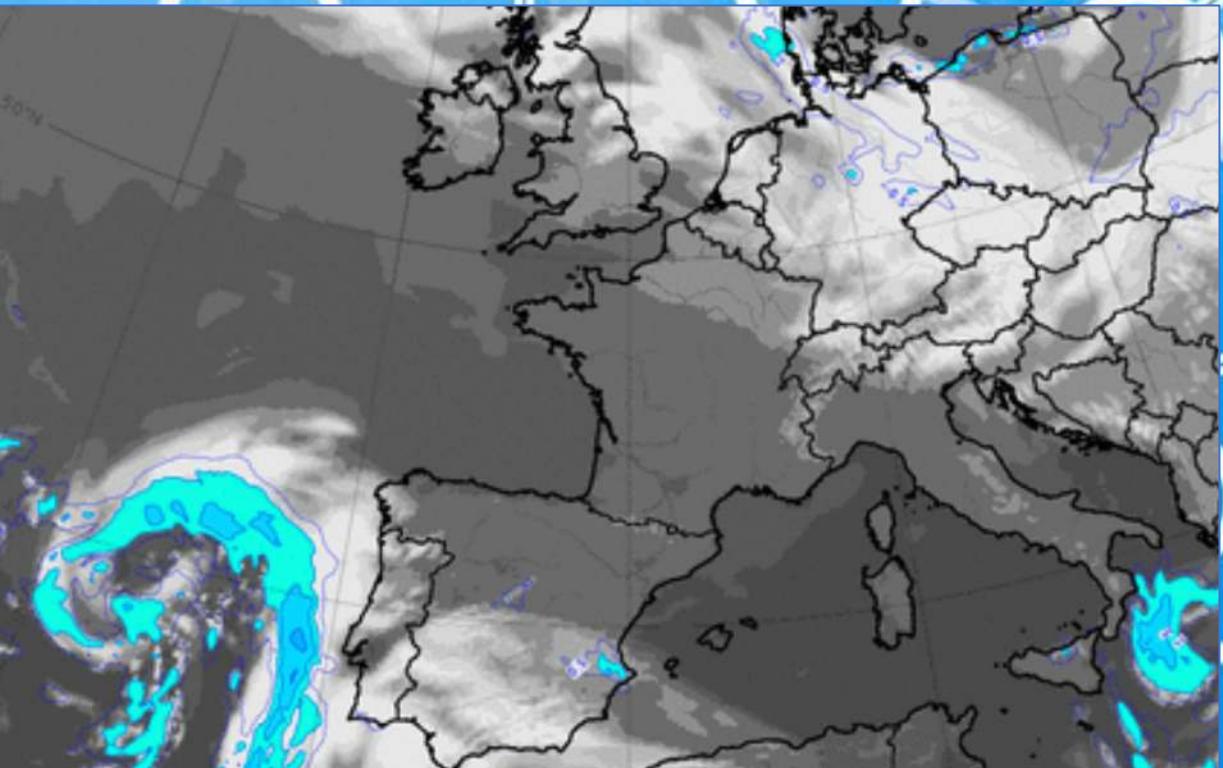
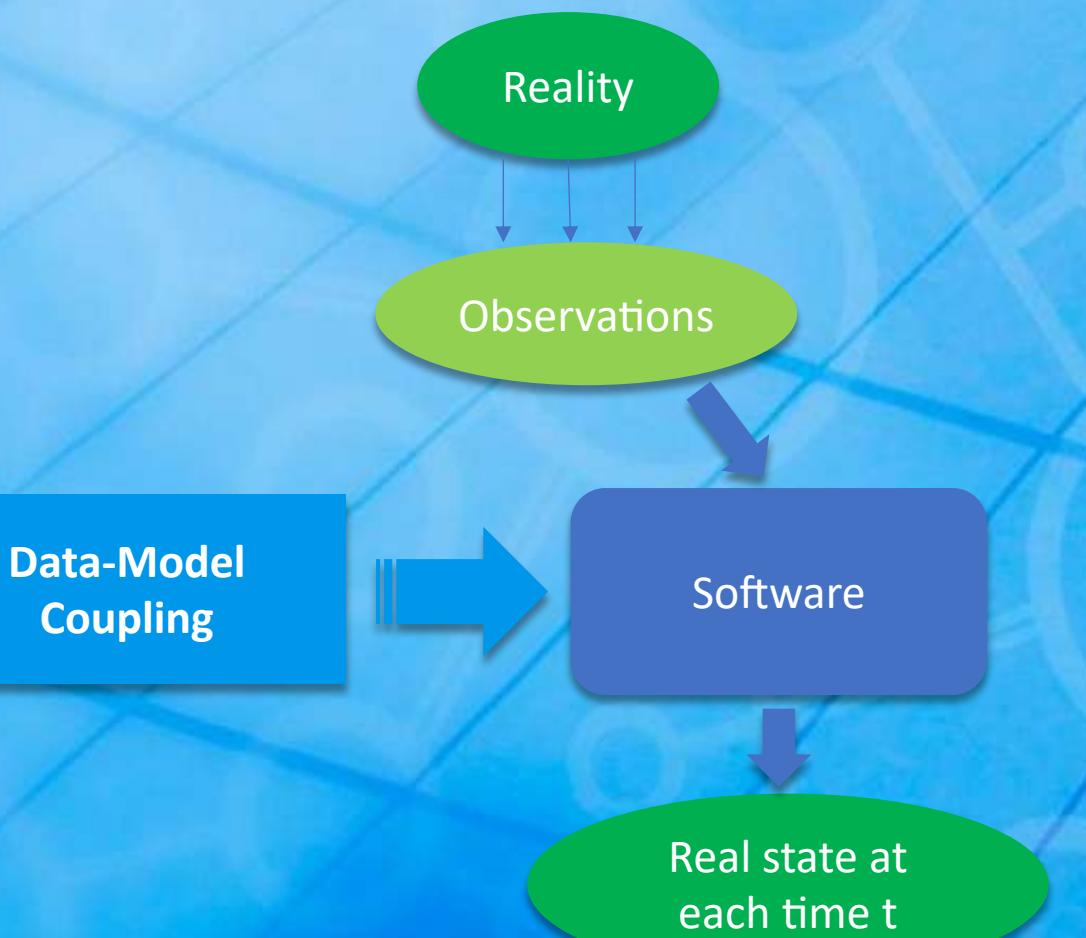


- Parameterized PDEs
- Database



*Satellite picture and expected rain  
(Arpege model) © Météo-France*

## DATA ASSIMILATION

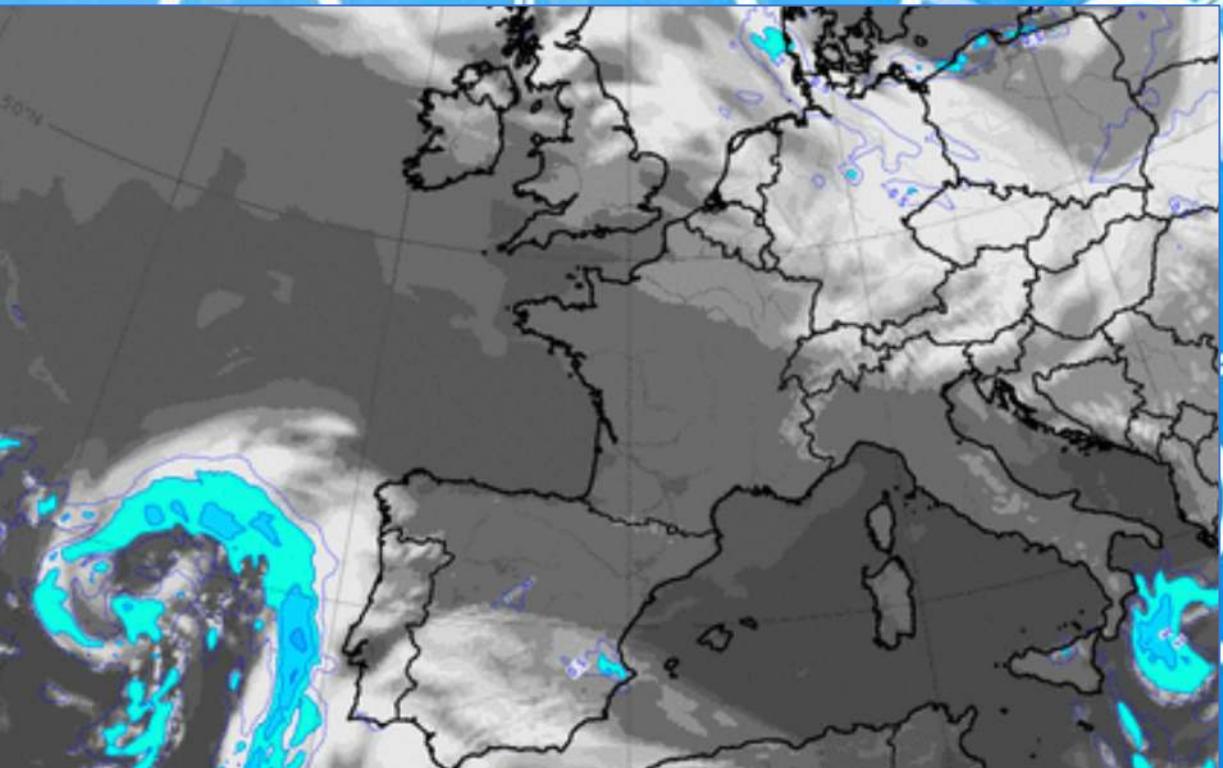


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## Other definition of Data Assimilation :

$$\begin{cases} x(t) = M[x(t-1)] + \eta(t) \\ y(t) = H[x(t)] + \varepsilon(t) \end{cases}$$

- $t$  the discrete time
- $x$  the real state
- $y$  the associated observation
- $M$  the model
- $H$  the observation operator
- $\eta$  the model uncertainty
- $\varepsilon$  the observation error



*Satellite picture and expected rain  
(Arpege model) © Météo-France*

## State of the art:

- ❖ **H. Flourent, E. Frénod & V. Sincholle** (preprint). *An Innovating Statistical Learning Tool Based on Partial Differential Equations, Intending Livestock Data Assimilation.*
- Simulation and prediction methods of biological data
- ❖ **R. Lguensat, P. Tandeo, P. Ailliot, M. Pulido & R. Fablet** (2017). *The analog data assimilation. Monthly Weather Review, 145(10), 4093-4107.*
- Data assimilation methods, based on the nearest neighbors



## Food for thought:

- Use of the **maximum likelihood** for learning.
- Modeling with **non linear PDEs**.
- **Deep learning** : construction of an initial state for a deep Neural Network from PDEs.



## Fields of application:

- A.I
- Meteorology
- Smart Farming
- Industry
- Bank
- SMEs



Thank you for  
your attention !



## Model based on PDEs for biological data

Annex 1

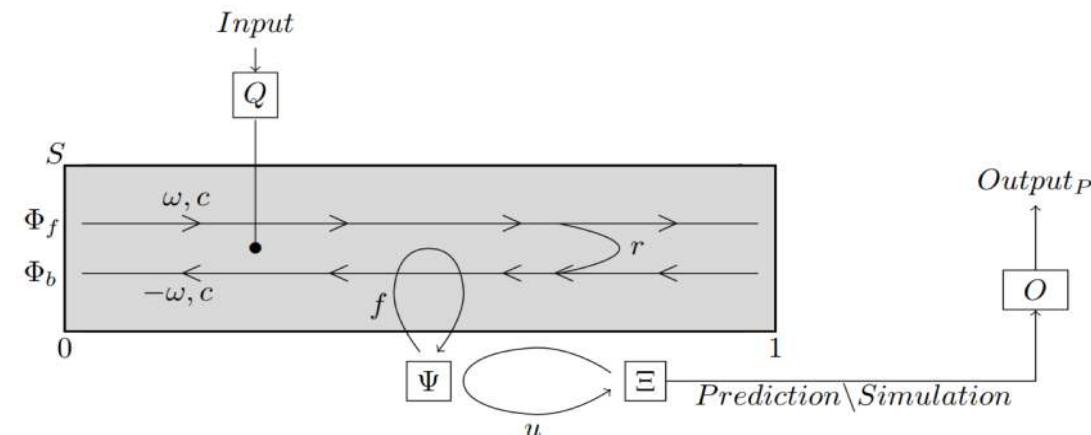
$$\begin{aligned} \frac{\partial \{\Phi_f(d)\}}{\partial t}(t, \mathbf{x}) + \omega_d \frac{\partial \{\Phi_f(d)\}}{\partial \mathbf{x}}(t, \mathbf{x}) - \frac{\partial \left[ c_d \chi \frac{\partial [\{\Phi_f(d)\} + \{\Phi_b(d)\}]}{\partial \mathbf{x}} \right]}{\partial \mathbf{x}}(t, \mathbf{x}) \\ = \frac{1}{2} \{Q(d)\}(t, \mathbf{x}) - f_d \{F(d)\}(\mathbf{x}) \{\Phi_f(d)\}(t, \mathbf{x}) - r_d \{\Phi_f(d)\}(t, \mathbf{x}) \quad (1) \end{aligned}$$

$$\begin{cases} \mathbf{x}(t) = \mathbf{M}[\mathbf{x}(t-1)] + \boldsymbol{\eta}(t) \\ \mathbf{y}(t) = \mathbf{H}[\mathbf{x}(t)] + \boldsymbol{\varepsilon}(t) \end{cases}$$

$$\begin{aligned} \frac{\partial \{\Phi_b(d)\}}{\partial t}(t, \mathbf{x}) - \omega_d \frac{\partial \{\Phi_b(d)\}}{\partial \mathbf{x}}(t, \mathbf{x}) - \frac{\partial \left[ c_d \chi \frac{\partial [\{\Phi_f(d)\} + \{\Phi_b(d)\}]}{\partial \mathbf{x}} \right]}{\partial \mathbf{x}}(t, \mathbf{x}) \\ = \frac{1}{2} \{Q(d)\}(t, \mathbf{x}) - f_d \{F(d)\}(\mathbf{x}) \{\Phi_b(d)\}(t, \mathbf{x}) + r_d \{\Phi_f(d)\}(t, \mathbf{x}) \quad (2) \end{aligned}$$

$$\frac{\partial \{\Psi(d)\}}{\partial t}(t, \mathbf{x}) = f_d \{F(d)\}(\mathbf{x}) \left[ \{\Phi_b(d)\}(t, \mathbf{x}) + \{\Phi_f(d)\}(t, \mathbf{x}) \right] - u_d \{\Psi(d)\}(t, \mathbf{x}) \quad (3)$$

Mathematical model:



## Example of prediction methods by the nearest neighbors

Annex 2

