

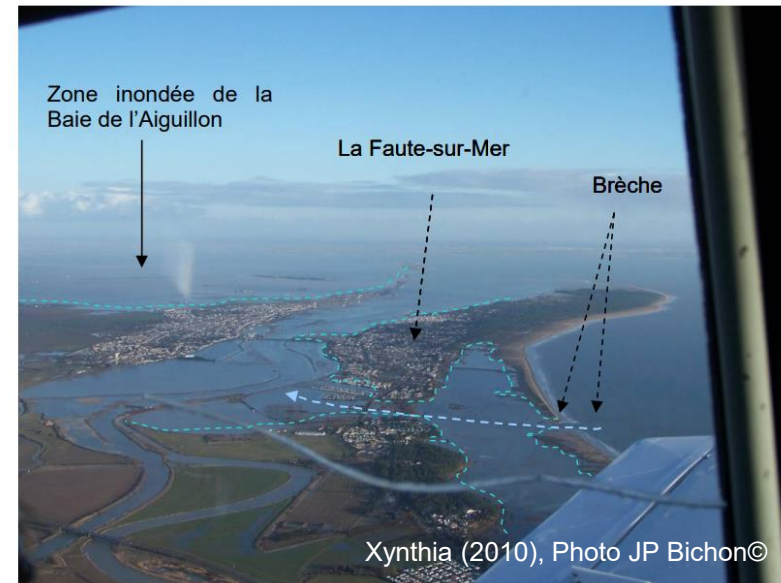
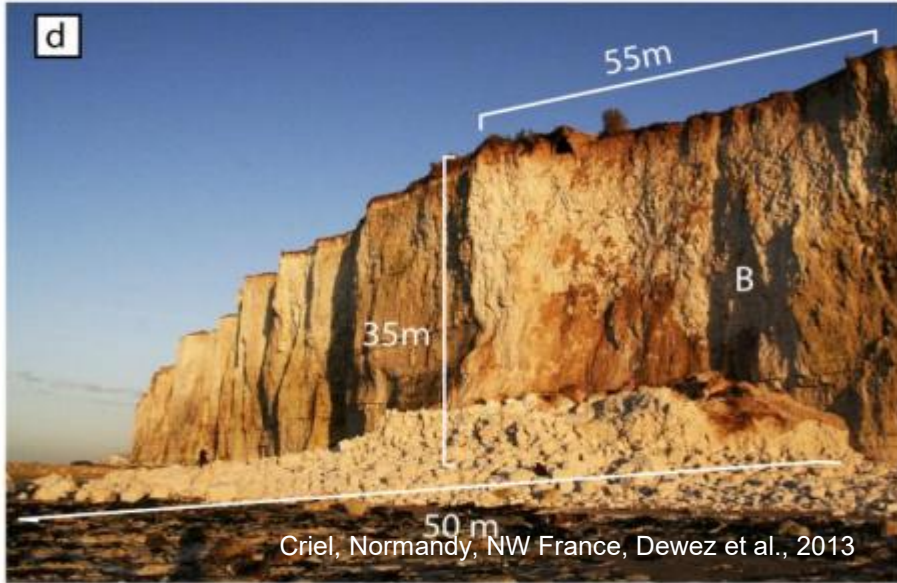


# Surrogate modelling for coastal hazard assessments

Jeremy Rohmer (BRGM, French geological survey)  
ANITI DAYS - 17 February 2026

Joint work with D. Idier, S. Lecacheux, R. Pedreros, A.G. Filippini, N. Valentini

# Coastal hazards



# The key role of computer codes

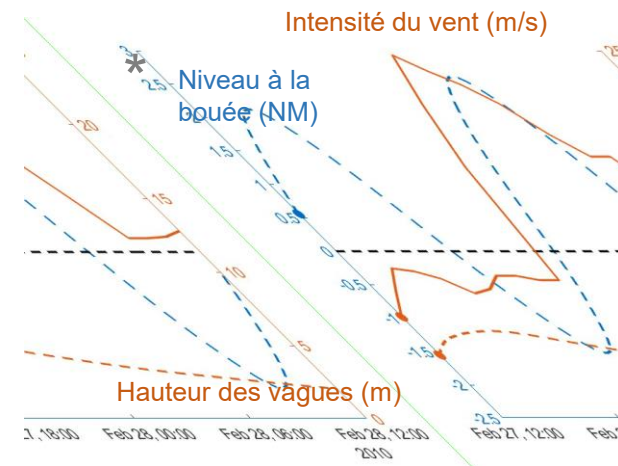
Computation time cost ~ 1 day even using a HPC architecture

Contact first author for the video



# Consequences of Xynthia storm at Arcachon

A. Filippini, R. Pedreros, S. Lecacheux



# A context of 'small data'... due to high computation time cost



SAPHIR HPC architecture at BRGM

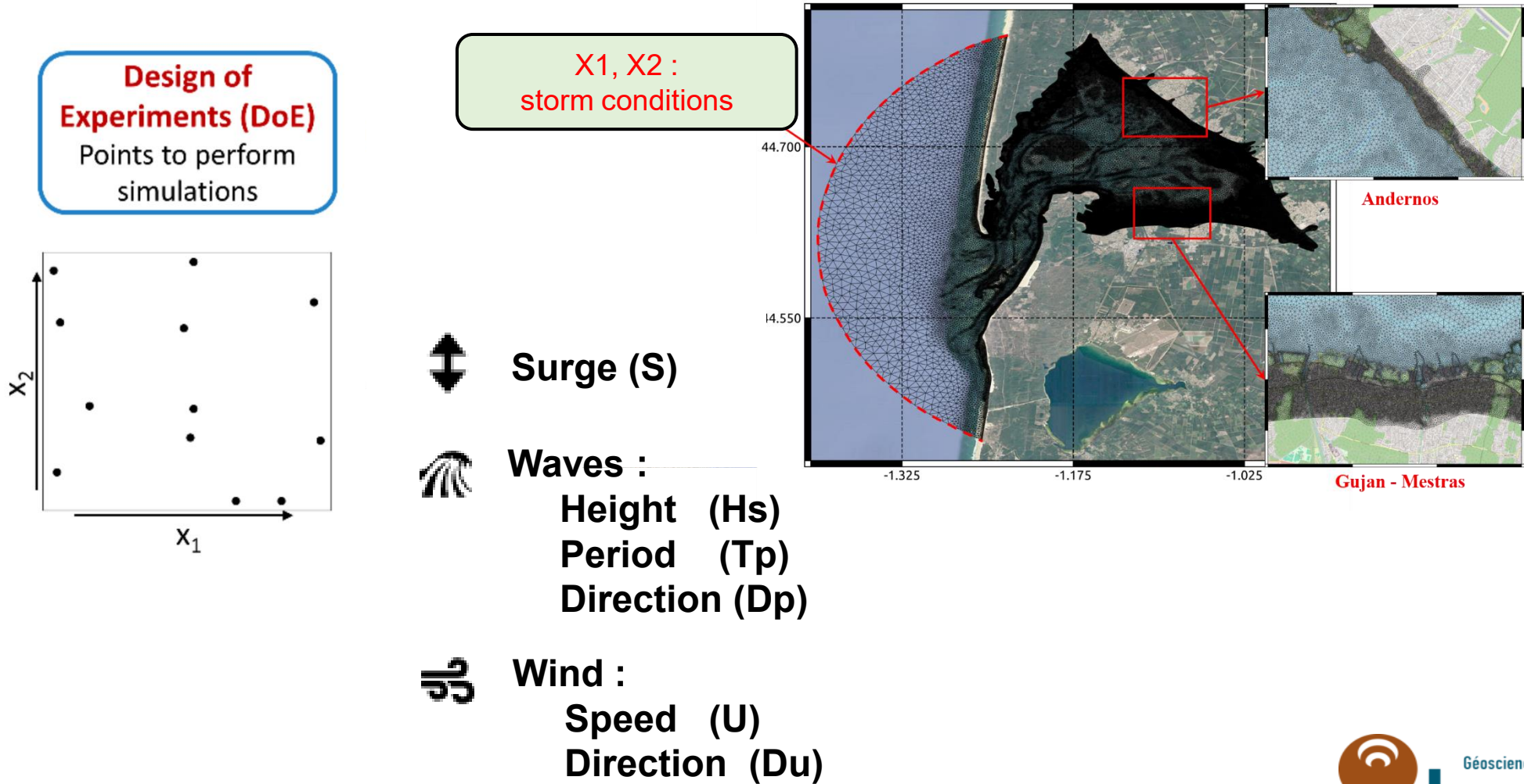
© BRGM - C. Boucley

❑ >2800 CPUs

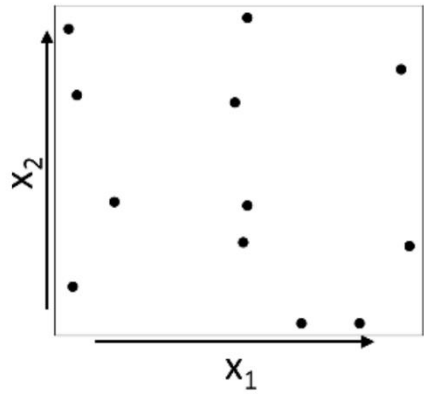
❑ If all of them were used, computation would last <1h30

❑ What about other sites, other storms?

# Idea: use results of high fidelity, high resolution numerical simulations already done to train a machine learning model

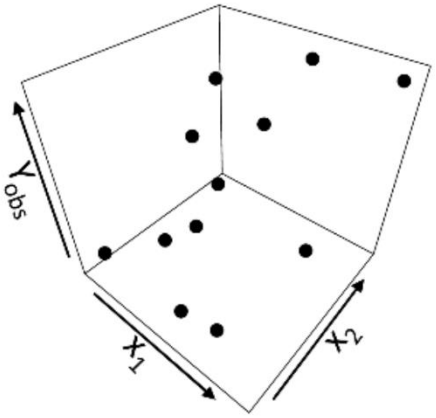


**Design of Experiments (DoE)**  
Points to perform simulations

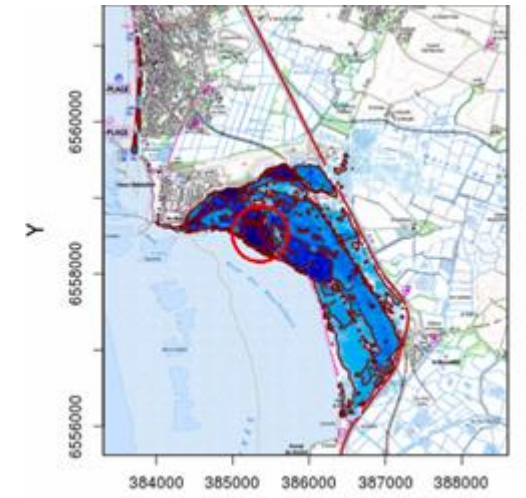


**Simulation**  
Performing simulations for the points of the DoE

Computer code

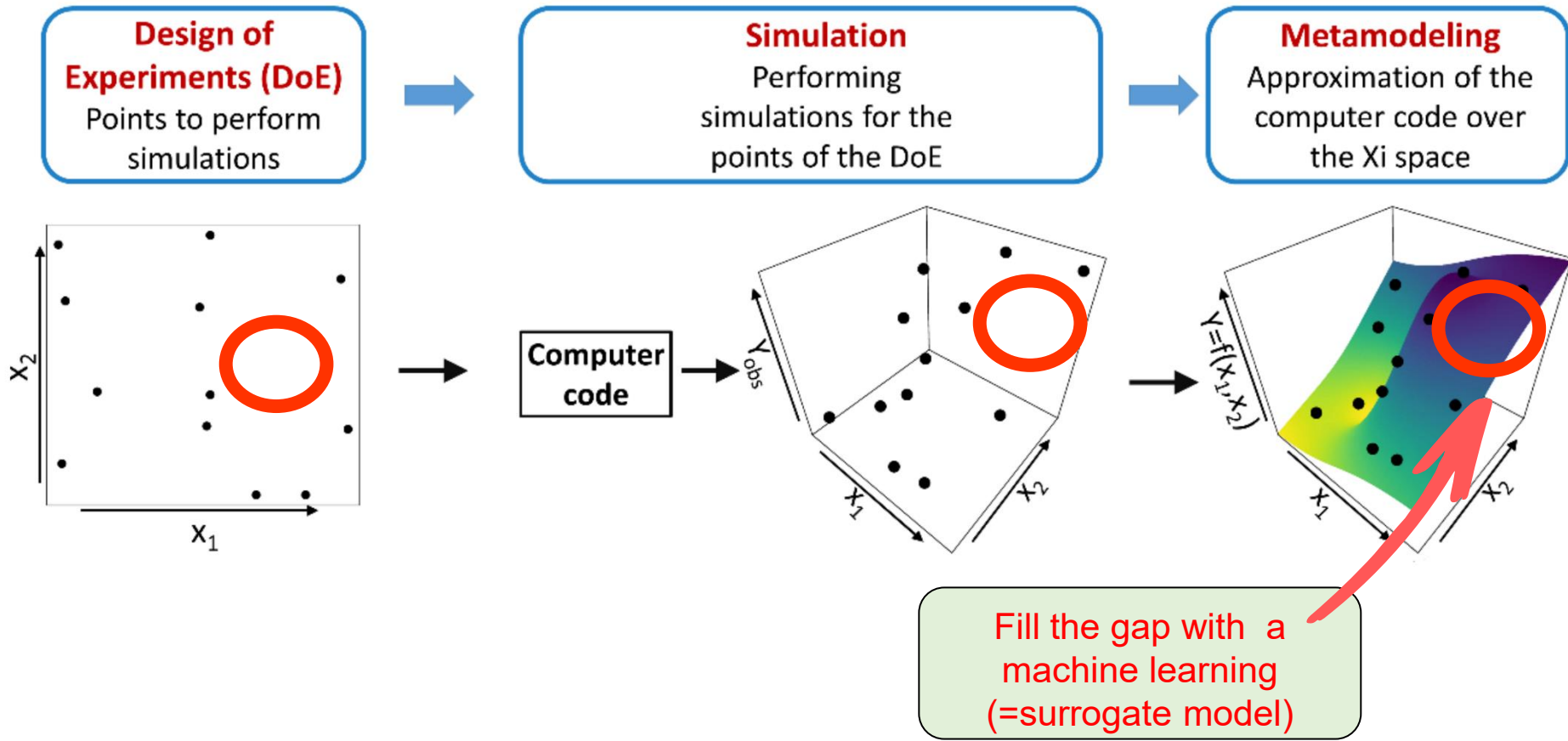


Computation time cost !!



$Y =$   
Local risk indicator e.g. flooded area, maps of water depths, spatiotemporal field of water velocity, etc.

Contact first author for the video



# A flexible surrogate model: Gaussian process (Gp) regression

[Williams and Rasmussen, 2006]

▪ **Objective:** predict  $Y_*$  for new storm conditions (inputs)  $x_*$   
**without** running the computer code

## ▪ Assumptions

- distribution of  $Y_*$  depends on  $n$  simulation results  $Y_n = \mathbf{y}$
- distribution of  $Y_* | \{Y_n = \mathbf{y}\}$  is Gaussian

Uncertainty  
quantification

## With parameters (simple kriging equations)

▪ Mean  $m = \mathbf{k}^{*t} \cdot \mathbf{K}^{-1} \mathbf{y}$

▪ Variance  $\sigma^2 = k(x_*, x_*) - \mathbf{k}^{*t} \cdot \mathbf{K}^{-1} \cdot \mathbf{k}^*$

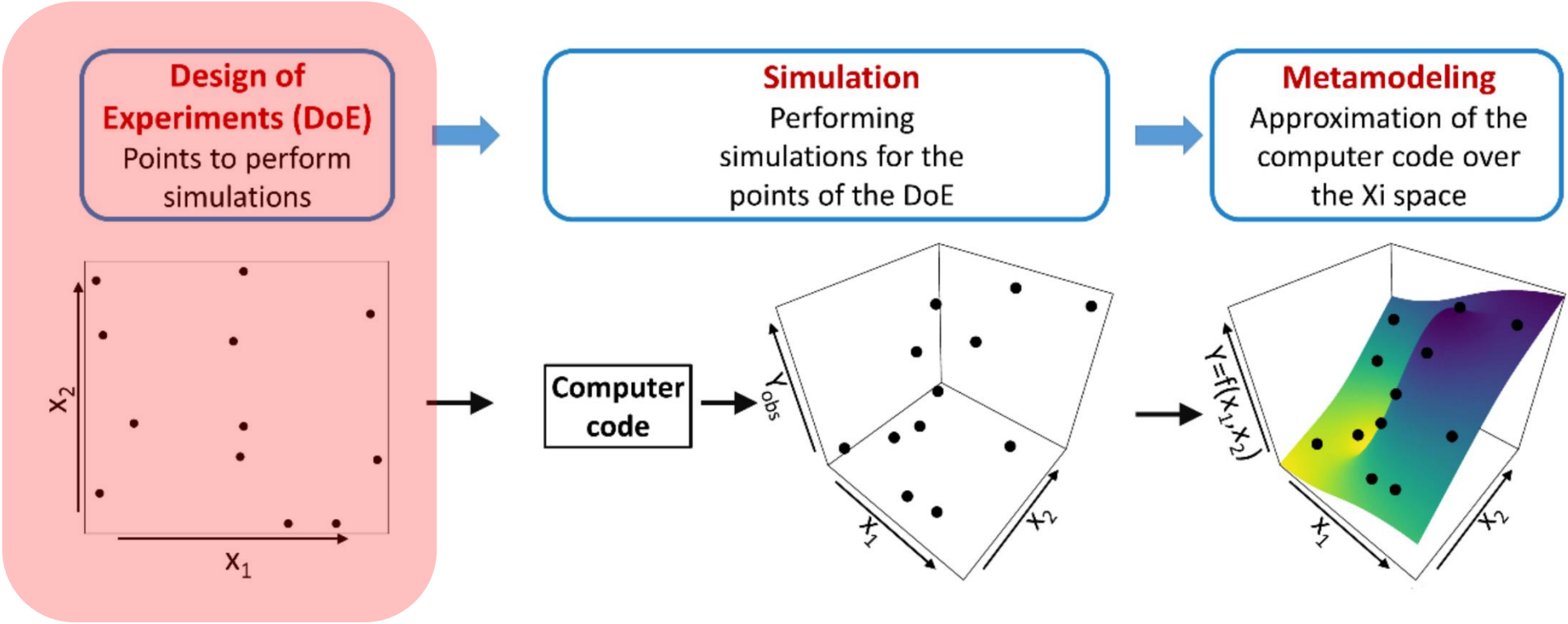
With

Covariance matrix  $\mathbf{K} = (k(x_i, x_j))_{1 \leq i, j \leq n}$

Covariance vector  $\mathbf{k}^* = (k(x_*, x_1), k(x_*, x_2), \dots, k(x_*, x_n))$

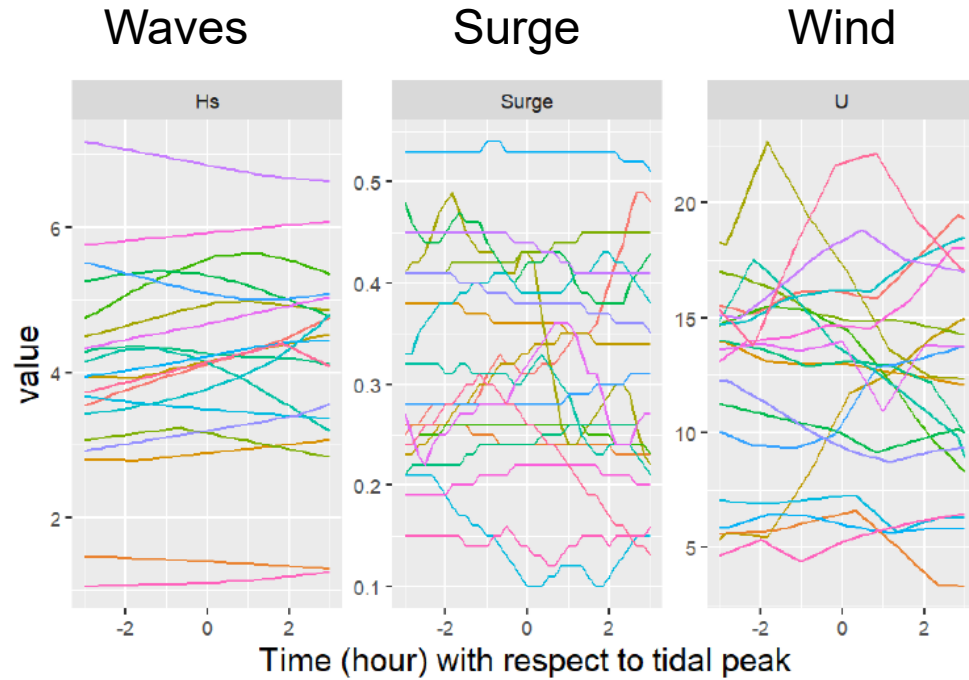
Flexibility via kernels

# Key challenges for coastal hazards



The inputs are  
**extreme time series**

# The inputs are **extreme time series**



Storm Goretti, 9/1/26 - T. CREUX / OUEST-FRANCE

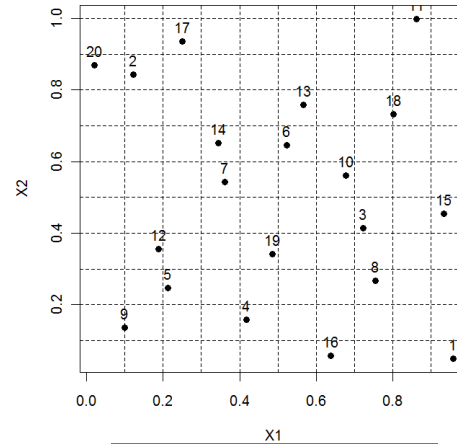


Storm Nils, close to Ajaccio (Corse-du-Sud), 12/2/26 - PASCAL POCHARD-CASABIANCA/AFP

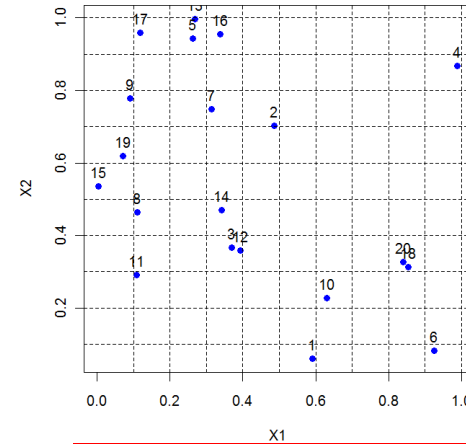
# Design Of Experiments (DOE)

## Objectives of 'classical' DOE

- Select a limited number of inputs' configurations
- Spanning a large range of values
- With space-infilling property

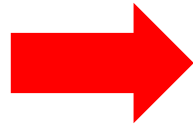


optimised



crude approach

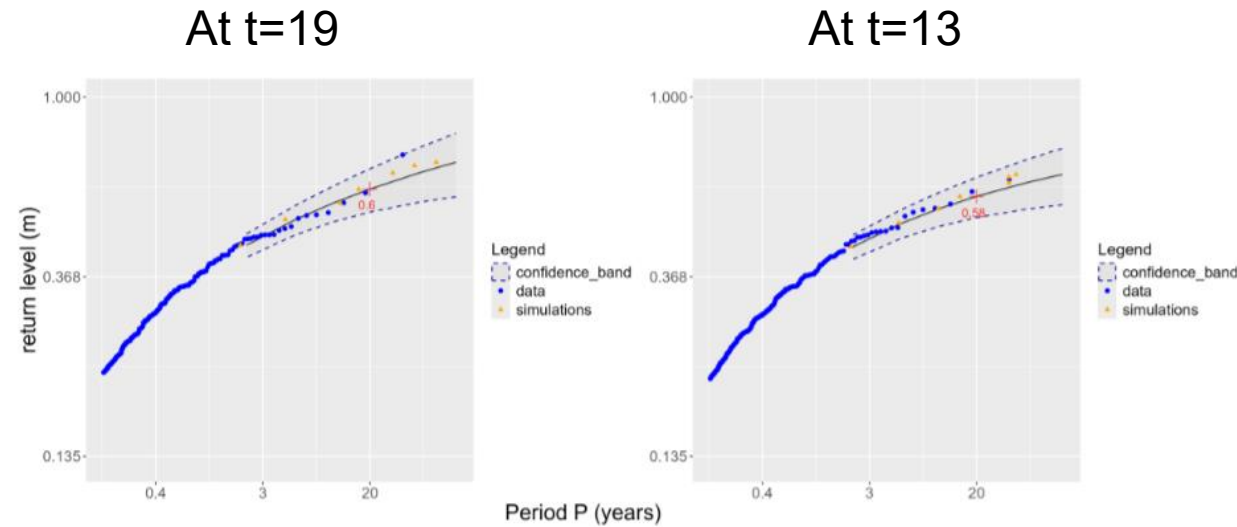
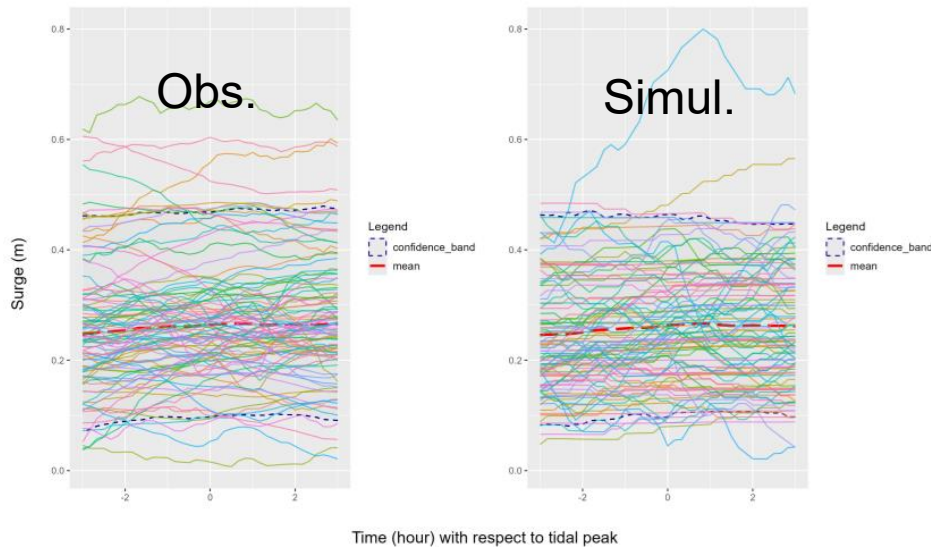
# DOE and extreme time series



Developments of an approach combining

- Stochastic simulation
- Multivariate extreme value theory
- Angular-radial decomposition
- ML-based validity check

See Nathan's poster this afternoon!



Stochastic simulation for extreme surge time series (Gorse et al., in review)



Physics-Informed Learning Methods for Continental Waters and Marine Risks

Olivier Roustant - Jérôme Monier

# Surrogate modelling and **time series**



Risk-based System  
For Coastal Flooding Early Warning

Collaboration  
IMT-BRGM

PhD thesis of Jose Betancourt (2017-2020)

Adapt standard kernels (e.g., Gaussian, Matérn)  
using a **dissimilarity measure adapted to  $df$  functions  $f, \tilde{f}$**

(Opt. 1) L2 norm for functions

$$\|f - \tilde{f}\|_{F, \theta_f} := \sqrt{\sum_{k=1}^{df} \frac{\int_{T_k} (f^{(k)}(t) - \tilde{f}^{(k)}(t))^2 dt}{(\theta_f^{(k)})^2}},$$

Length scales

(Opt. 2) Projection onto a new basis  $B$  of lower dimension  $p_k$

$$\|\Pi(f) - \Pi(\tilde{f})\|_{D, \theta_f} := \sqrt{\sum_{k=1}^{df} \frac{\int_{T_k} \left( \sum_{r=1}^{p_k} (\alpha_r^{(k)} - \tilde{\alpha}_r^{(k)}) B_r^{(k)}(t) \right)^2 dt}{(\theta_f^{(k)})^2}}.$$

Length scales

# Surrogate modelling and **time series**



Risk-based System  
For Coastal Flooding Early Warning

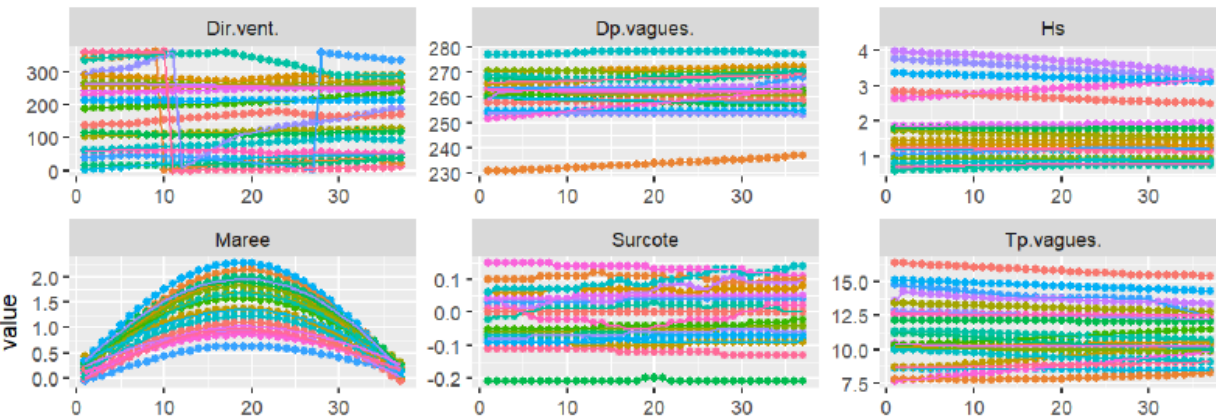
Collaboration  
IMT-BRGM

PhD thesis of Jose Betancourt (2017-2020)

## Application of Gp with adapted kernel at Gavres (French Brittany)

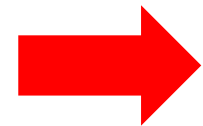
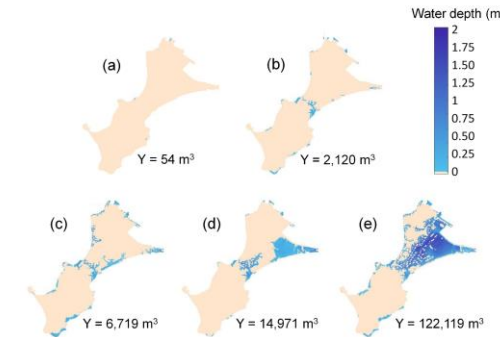
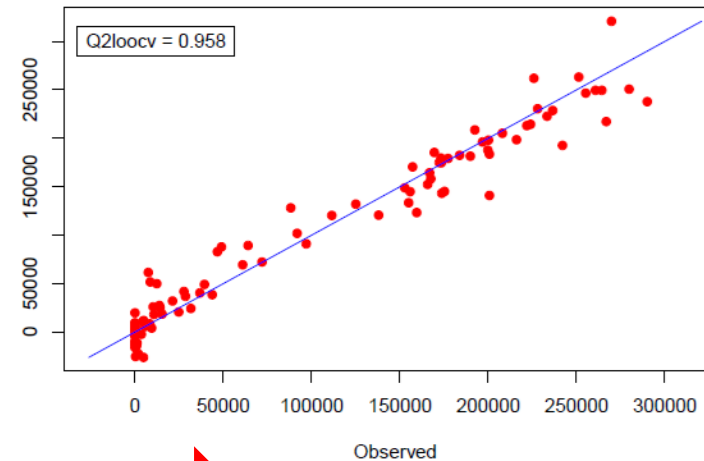
### Inputs

Sampling of 20 observations from 1979 to 2016



### Output: Flooded area (m<sup>2</sup>)

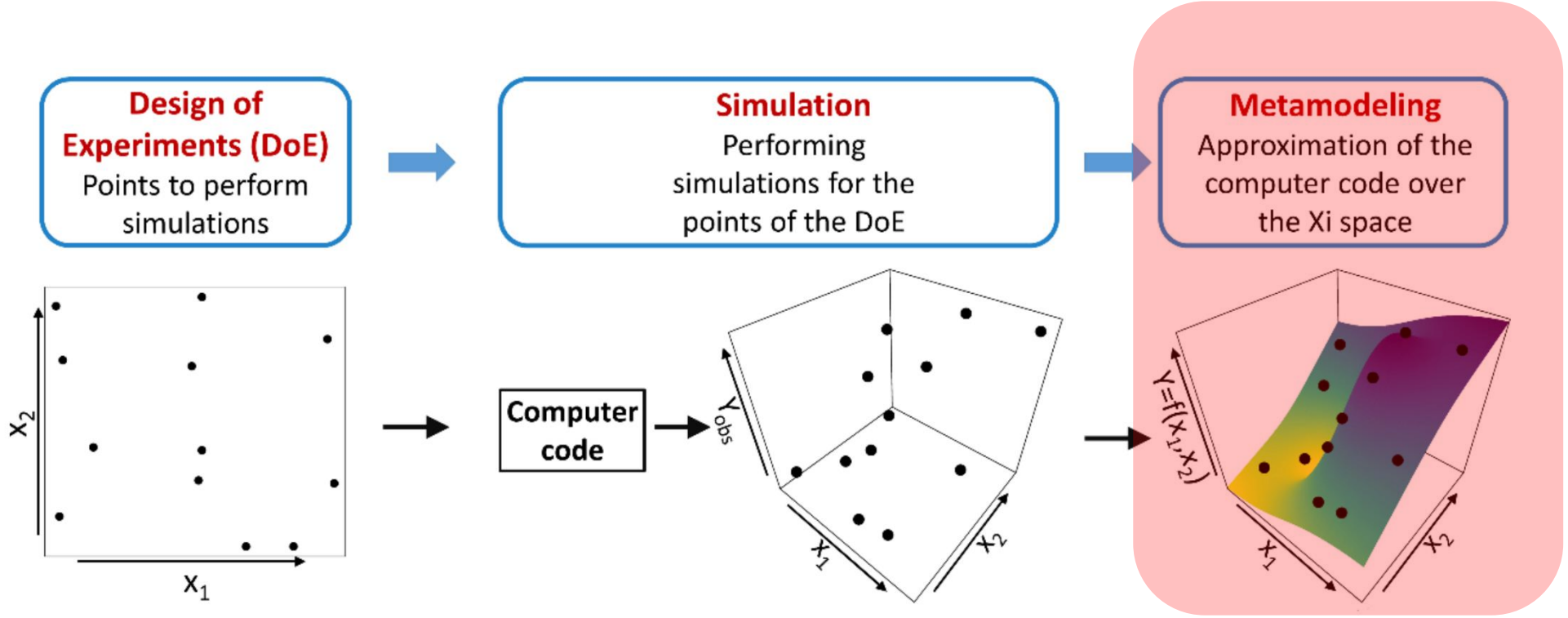
Model diagnostic by leave-one-out cross-validation



Most optimal model includes temporal effects (F)

	X1	X2	X3	X4	X5	X6	X7	X8	F1	F2	F3	F4	F5	F6	F7	Kern	Q2
1	x	x	x		x	x		x	x	x	x			x	x	gauss	0.970
2	x	x	x		x	x		x	x	x	x			x	x	gauss	0.968
3	x	x	x		x	x		x			x			x	x	gauss	0.968
4	x	x	x		x	x		x	x	x	x			x	x	gauss	0.968
5	x	x	x		x	x		x			x	x		x	x	gauss	0.966

# Key challenges for coastal hazards



The outputs are **high dimensional**



Forcing conditions

Flood map (max water depth)

$$\mathbf{x}^{(1)} = (S^{(1)}, T^{(1)}, t_0^{(1)}, t_+^{(1)}, t_-^{(1)})$$



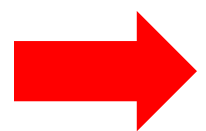
$$\mathbf{x}^{(2)} = (S^{(2)}, T^{(2)}, t_0^{(2)}, t_+^{(2)}, t_-^{(2)})$$



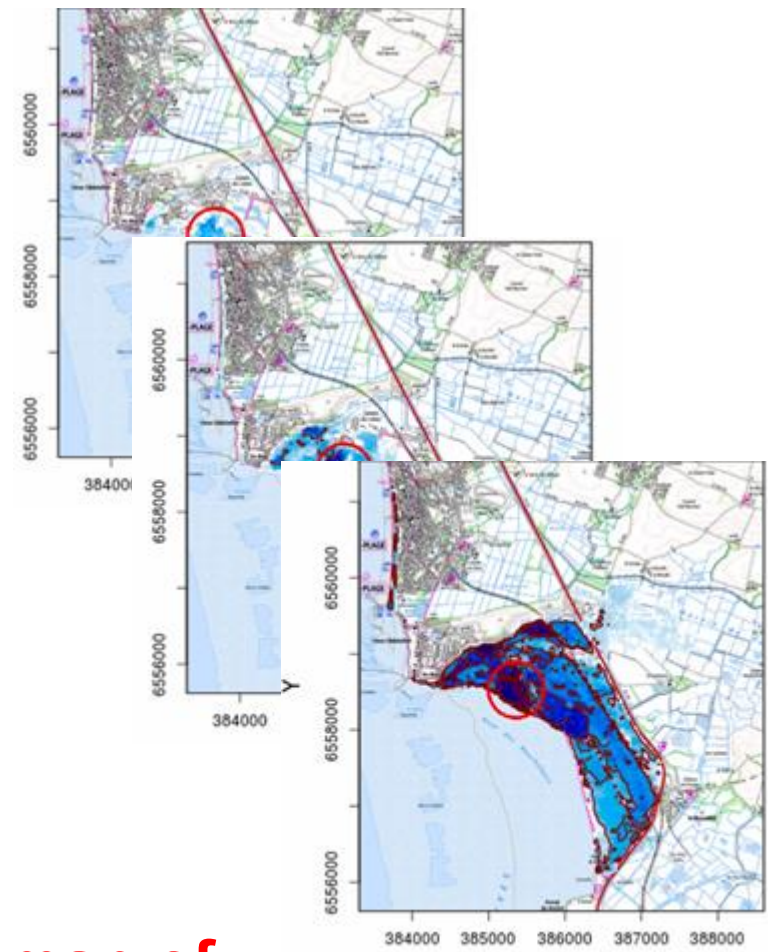
$$\mathbf{x}^{(3)} = (S^{(3)}, T^{(3)}, t_0^{(3)}, t_+^{(3)}, t_-^{(3)})$$



Etc...



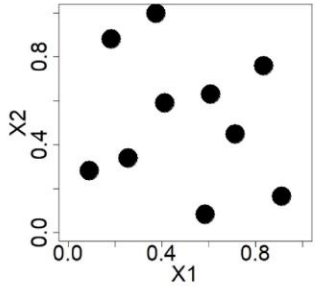
Flood map of >10,000 of pixels



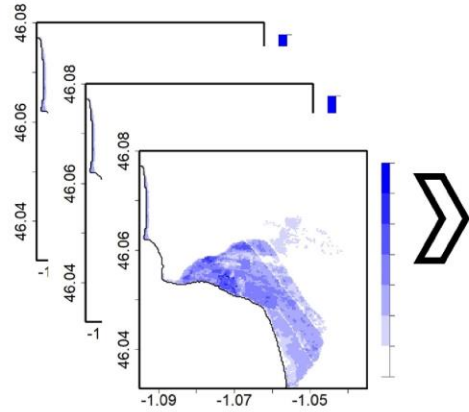
# A combined Dimension Reduction – Surrogate Modelling approach

PhD thesis of Elodie Perrin – collaboration Mines St Etienne – CCR - BRGM

Step 1. Design of experiments



Step 2. Numerical simulation



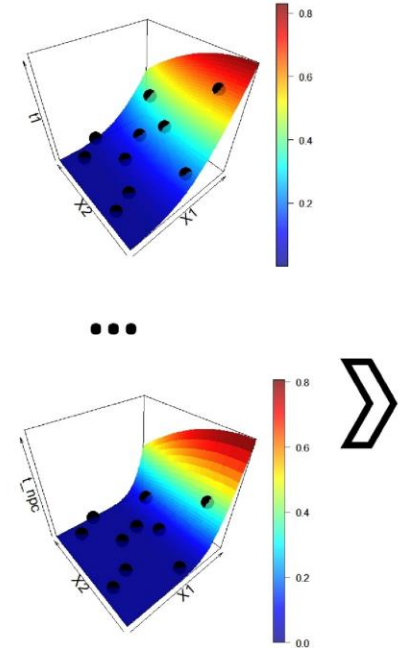
Set of  
**High dimensional**  
flood maps of size  $N$

Step 3a. Dimension reduction

$$\begin{pmatrix} Z_1 \\ Z_2 \\ \dots \\ Z_{n_{pc}} \end{pmatrix}$$

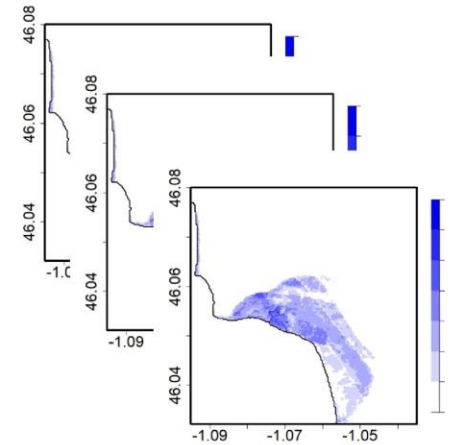
Set of  
latent  
variables of size  
 $n_{pc} \ll N$

Step 3b. Metamodelling



Set of  
Surrogate models,  
one for each of the  
 $n_{pc}$  latent variables

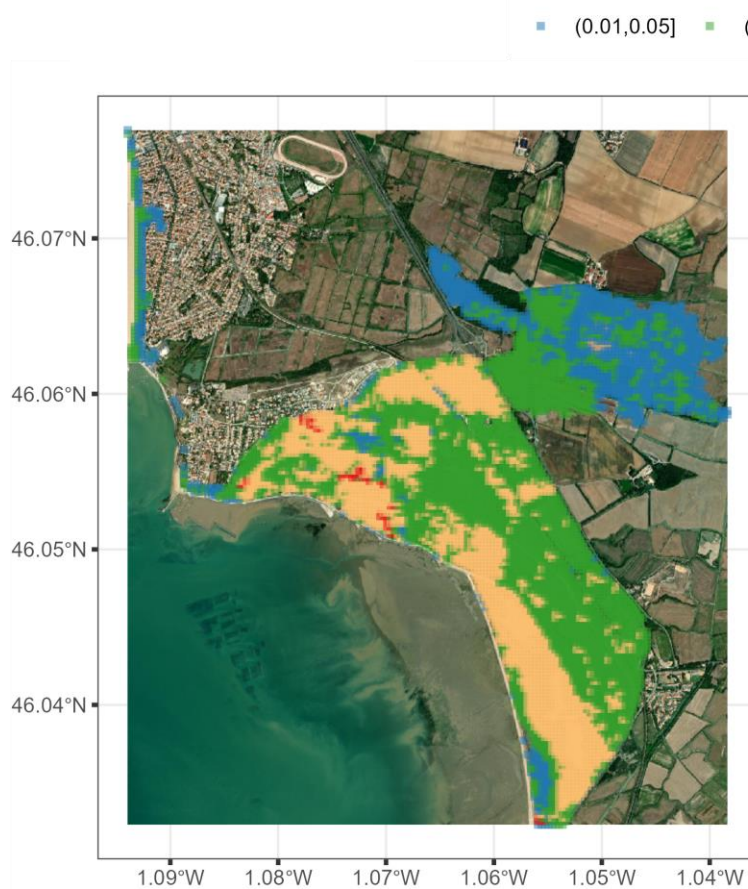
Step 3c. Reconstruction



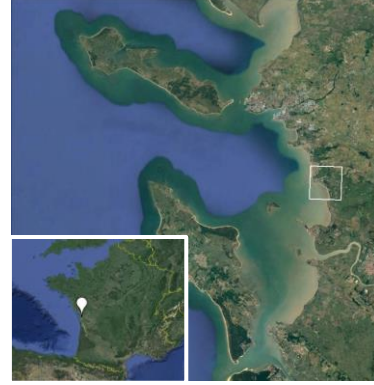
For prediction

# Application at Boucholeurs [1]

5-fold cross validation **prediction error (RMSE)**

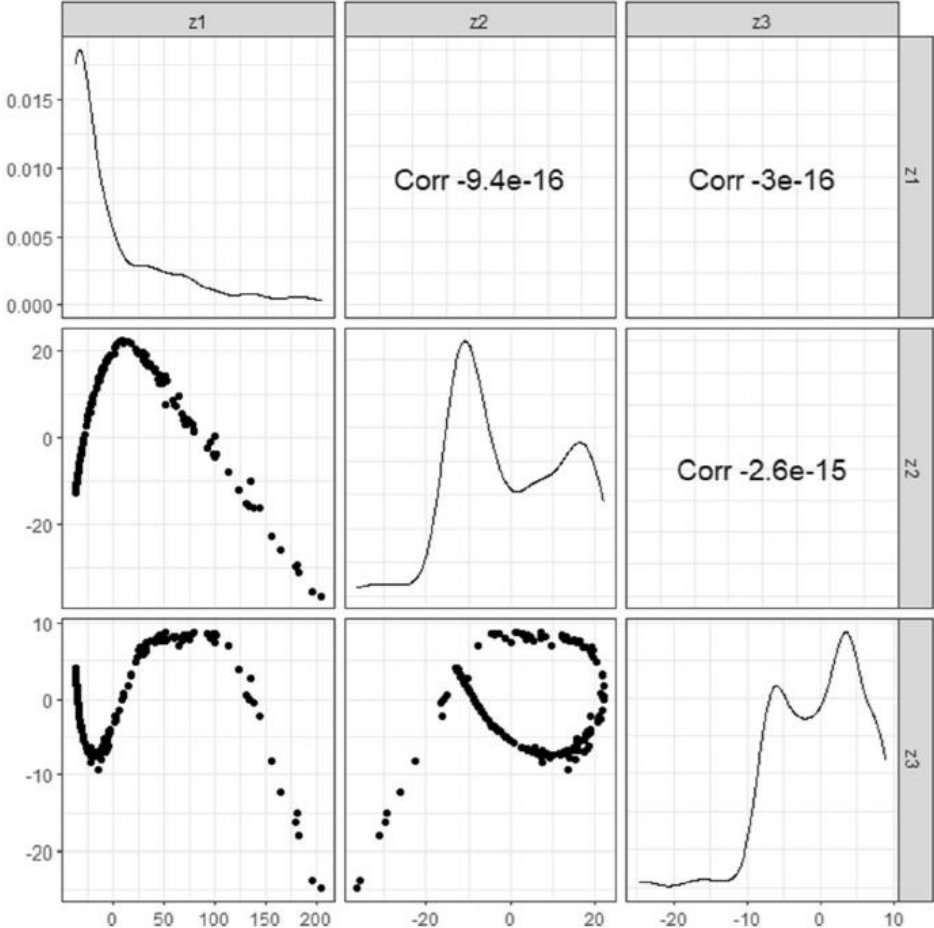


- Training dataset of 200 flood maps of size  $N = 256 \times 256$
- Dimension reduction using Principal Component Analysis
- $n_{pc} = 2$  : 95% of explained variance
- Used of  $n_{pc} = 2$  independent Gp models (Matérn 5/2 covariance, linear trend, no nugget)



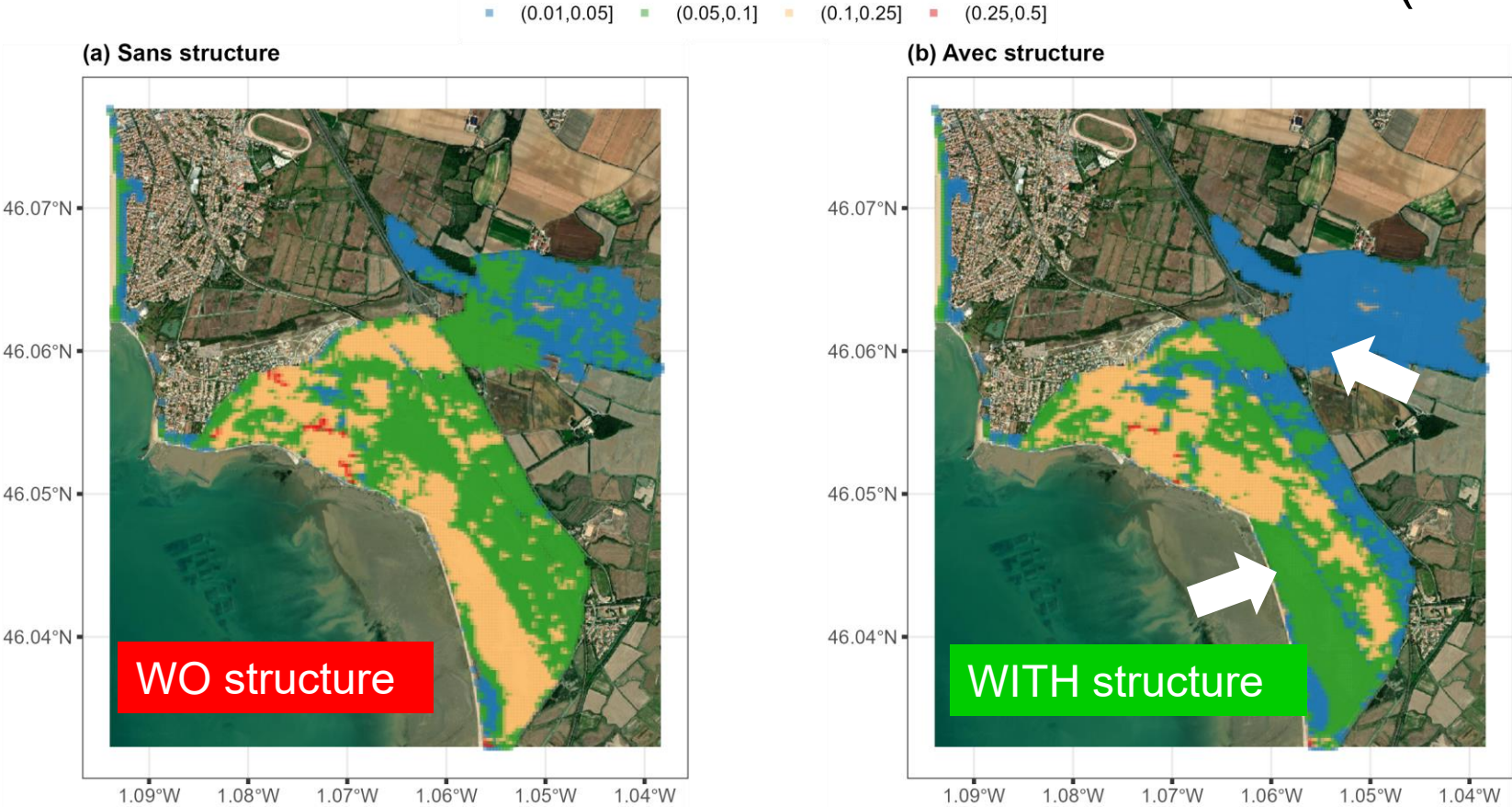
# Improvement #1 [ROH23]

Dependence structure of the latent variables after applying PCA to the 200 flood maps



# Improvement #1 [ROH23]

## 5-fold cross validation prediction error (RMSE)



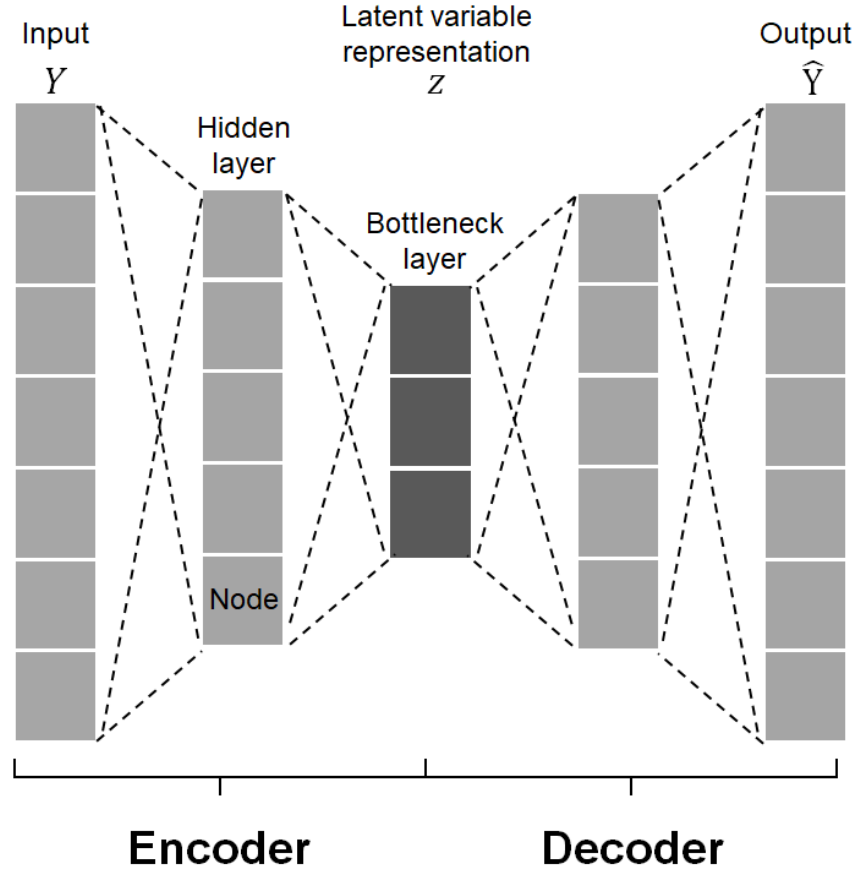
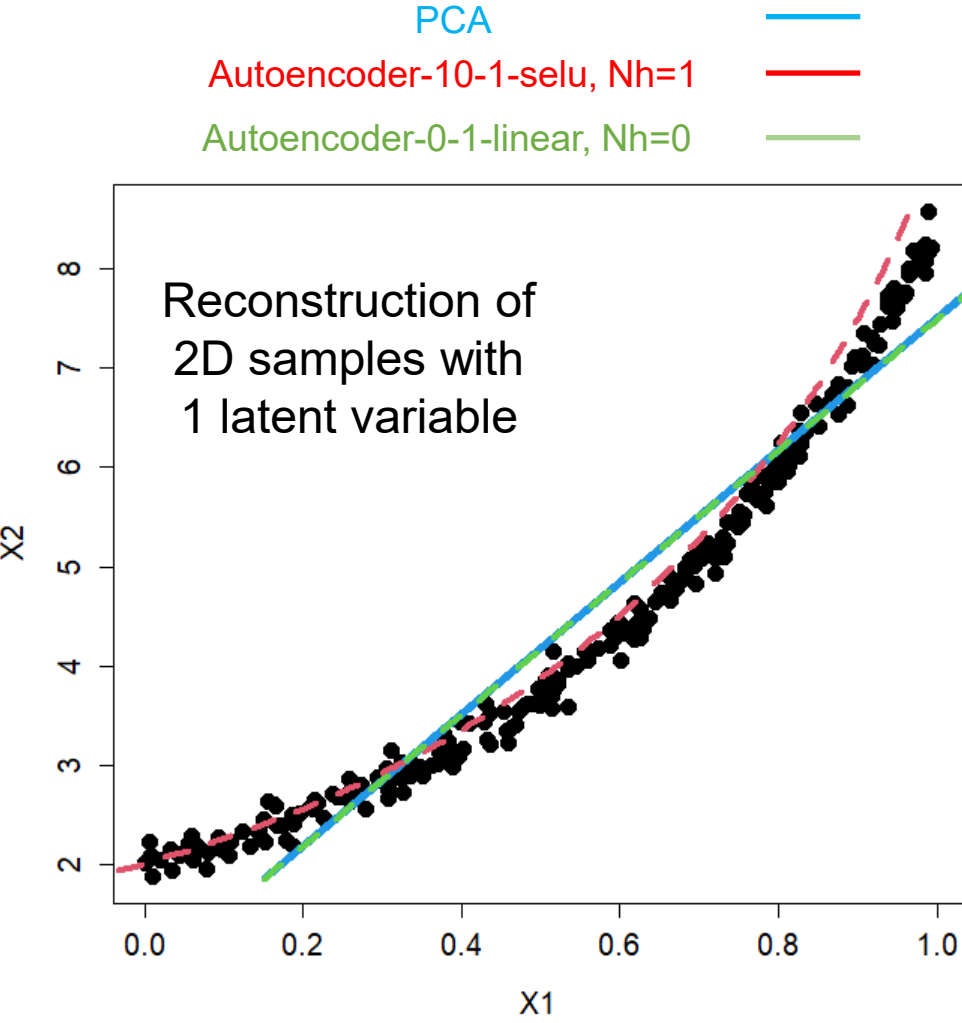
Approach via independent Gps

Approach via Multi-output MoGp



[ROH23] Rohmer et al., SERRA, (2023)

# Improvement #2 [ROH24]



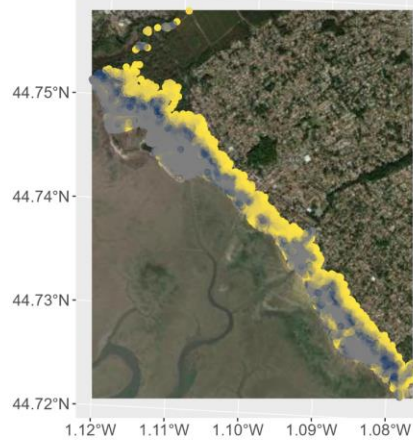
[ROH24] Rohmer et al., Symhydro, (2024)

# Improvement #2 [ROH24]

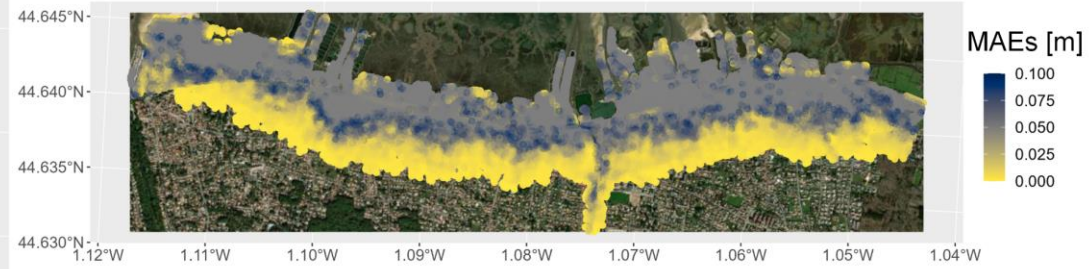
Mean absolute reconstruction error  
(5-fold cross-validation  
over 250 flood maps)

PCA  
99%  
explained  
variance

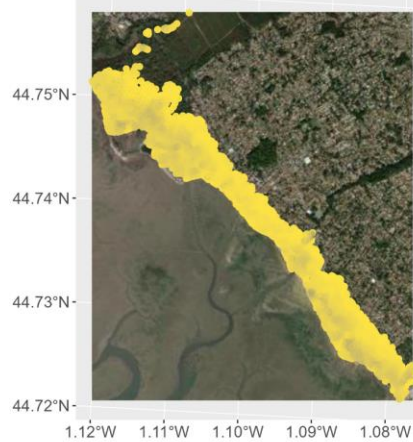
Andernos – PCA



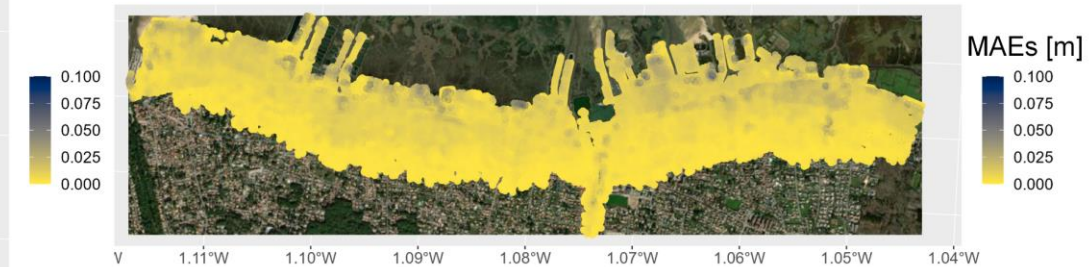
Gujan-Mestras – PCA



Andernos – AE



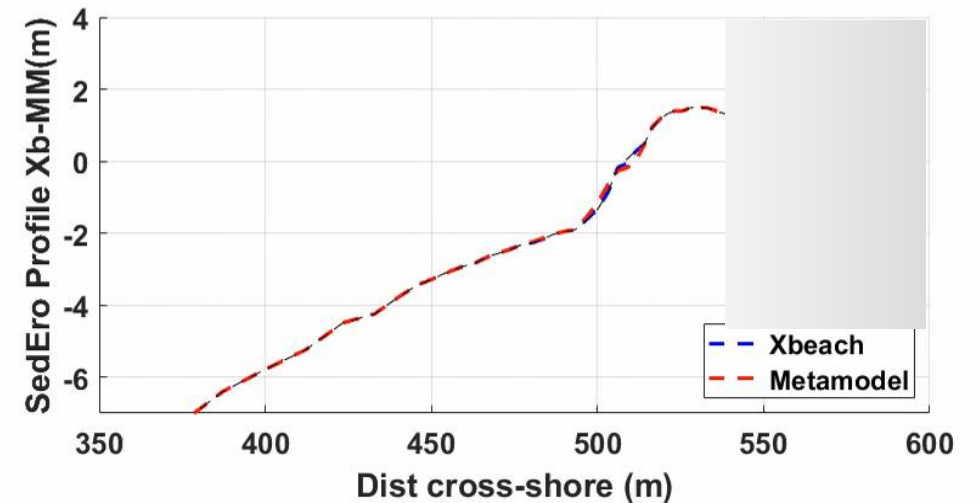
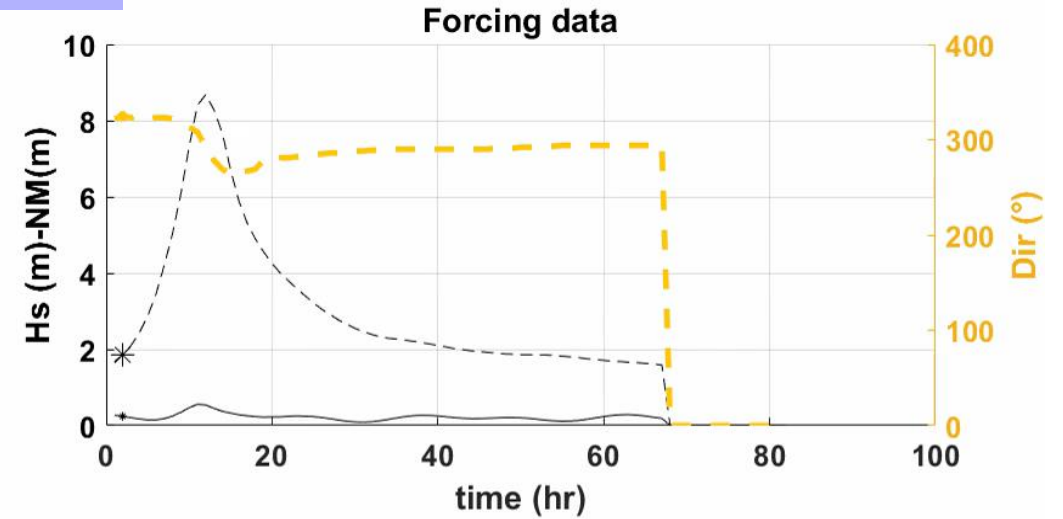
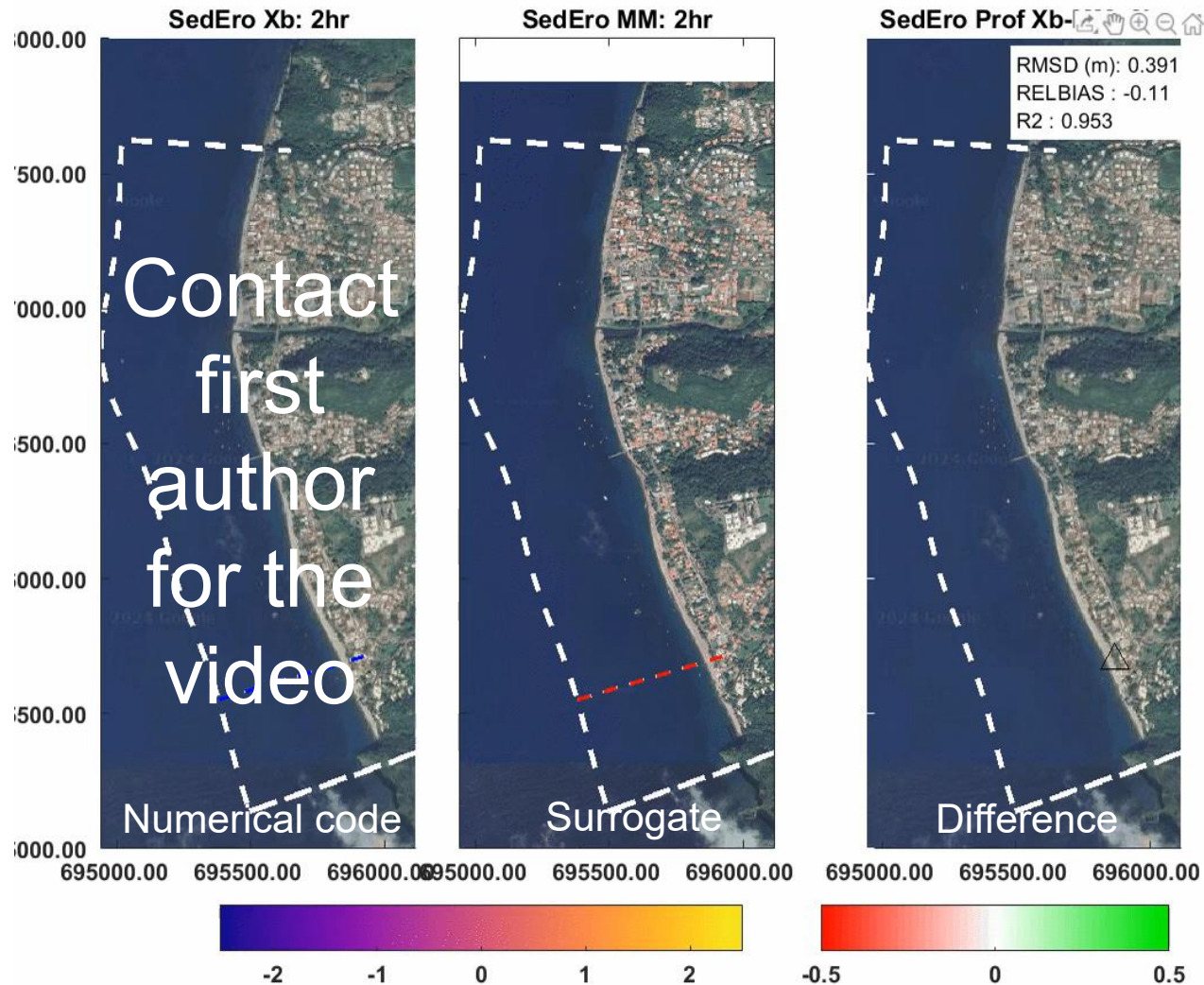
Gujan-Mestras – AE



Auto-  
Encoder

# Improvement #3 [VAL25]

Prediction of beach morphodynamic **spatio-temporal** response to tropical storms using **ConvLSTM**-based metamodels



# Summary

- Successful application of machine-learning based on surrogate modelling in **multiple coastal environments** (Arcachon, Gavres, Boucholeurs, Antilles)
- **Collaboration with IMT Toulouse** enabled us to overcome the '*curse of dimensionality*' (time varying inputs and spatial outputs)
- On-going developments for **DOE adapted to functional extreme inputs** (N. Gorse's PhD within ANITI PILearnWater)
- The integration of **high dimensional spatiotemporal** variables (e.g., evolving bathymetry, space-time evolution of water depth, etc.) = **open question**

>> **More coming soon for wave models** with Antoine Jarry's PhD thesis (start 02/2026) - collab. ISAE-SUPAERO, INSA, BRGM



# Merci pour votre attention!

Merci aux projets ANR ORACLES, ANR RISCOPE, ANR SHORECAST, Chaire PILearnWater



Risk-based System  
For Coastal Flooding Early Warning

ANITI

