"Real-Time" Simulations Methods for Flood Events and Data Assimilation

* A Computational Sciences Talk *

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Outline

▷Goal : simulations in seconds, including data assimilation.

▷Direction #1 : Models reduction by physics - machine learning approaches.
↪ Reduced order models (ROMs).

▷Direction #2 : Model calibration by Physics Informed Neural Networks (PINNs).
↪ Inverse problems - data assimilation.

▷Conclusion & Perspectives.

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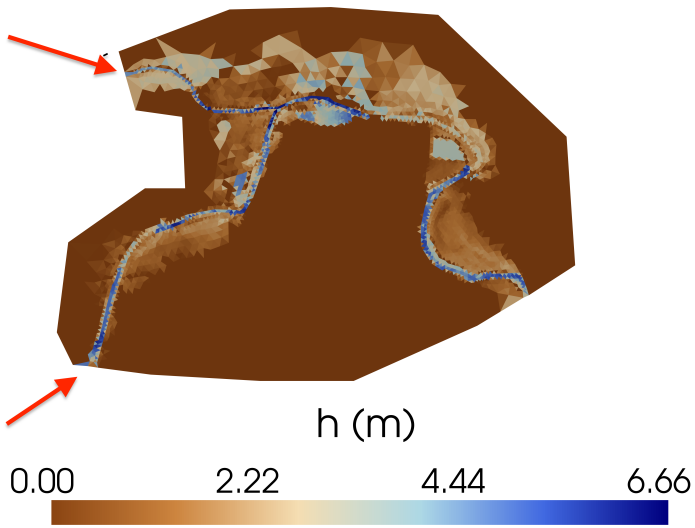
Goal : flood simulations in "real-time", with data assimilation

▷Goal.

High-resolution (HR) hydraulic model with data assimilation (DA) → Reduced order model (ROM) Simulations in seconds → Assimilation of new data on the fly

▷Example of a reduced model (2D shallow-water), here without DA : Aude-Fresquel rivers.

Results : M. Allabou's PhD (INSA-IMT, defended in 2026).
Data case : [Villenave et al., 2023], Vigicrues, SCHAPI-DGPR, Meteo-France.



Computational times, for a 52 000 **cells mesh.**

HR simulation	ROM
≈ 1h15mn (CPU)	≈ **10s** (CPU) / 10^{-2}**s** (GPU)

Laptop CPU, single-core mode, 11th Gen Intel Core i9-11950H processor (2.60 GHz) with 32 GB RAM.

Direction #1 :

Models reduction by physics - machine learning approaches.

$\hookrightarrow$ Reduced order models (ROMs)

High-Resolution (HR) model & Reduced Order Model (ROM)
Basic principles

▷**High-Resolution (HR) model : μ-parametrized PDEs**

Given the parameter $\mu \in \mathcal{P}$, $\mathcal{P} \subset \mathbb{R}^p$, find the state of the system $\mathbf{u}(\mu)(x,t)$ such that :

$$\mathcal{A}(\mu; \mathbf{u}(\mu))(x,t) = \mathcal{F}(\mu)(x,t)$$

For the 2D shallow water(SW) model, the state $\boxed{\mathbf{u} = (h, q_x, q_y)(x,t)}$.

μ can be : boundary value parameters (eg. hydrograph), source term parameters (eg. rain field), and so on.

▷**Reduced order model (ROM)** aims at providing an approximation of the HR solution at very low cost.

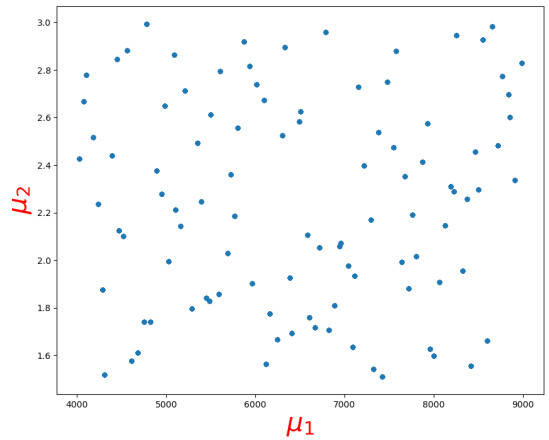
Challenge : Build a ROM cheap in computational-time, while preserving accuracy of the HR model.

Reduced Order Model (ROM) : **Offline phase**

▷**Compute $\mathcal{O}(10^p)$ HR simulations = "snapshots"**.

p potentially large, depending on $\dim(\mu)$.

Each snapshot $\mathbf{u}(x,t)$ corresponds to a different value of μ.



Plot : $\mu \in \mathbb{R}^2$

HR solutions

Snapshot matrix, $(N_s \times N_t) \times N_h$)

$$S = [\mathbf{u}(\mu_1, t), \ldots, \mathbf{u}(\mu_{N_s}, t)]$$

POD / PCA

Reduced eigenvectors basis

↪ Rectangular basis change matrix $N_h \times N_{rb}$

$$\mathbf{B_{rb}} = \left[\xi_1(x), \ldots, \xi_{N_{rb}}(x)\right]$$

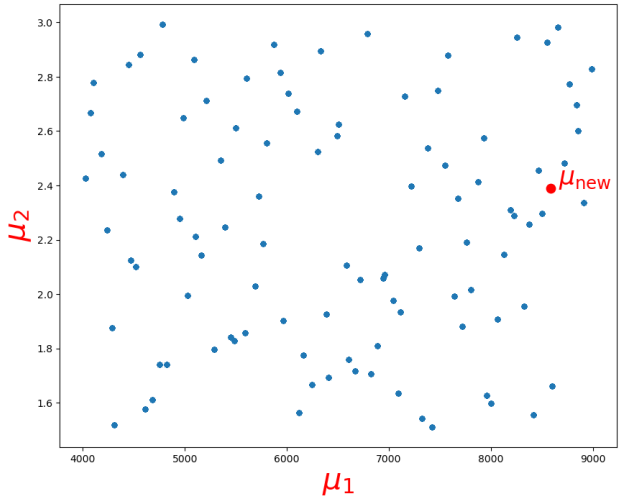
$$\mathbf{u}_{rb}(\mu)(x,t) = \sum_{i=1}^{N_{rb}} \underbrace{\alpha_i(\mu)(t)}_{\text{RB coeff.}} \xi_i(x)$$

For linear PDE models : standard POD reduction method.

Non-affine parametrization in μ ? Additional empirical interpolation techniques is required, see eg. [Quarteroni&Rozza's book].

Reduced Order Model (ROM) : **Online phase**

▷Given a new parameter value μ_{new}, compute the corresponding state $\mathbf{u}_{rb}(\mu_{new})$ in "real-time" ($\approx$ second).



Plot : $\mu \in \mathbb{R}^2$

Application of the reduction op. (fast) → Reduced basis solution $\mathbf{u}_{rb}(\mu_{new})$

Back to the HR space → Final approximation $\tilde{\mathbf{u}}_{rb}(\mu_{new})(x, t)$

▷In the end, do we have $\boxed{\tilde{\mathbf{u}}_{rb}(\mu_{new}) \approx \mathbf{u}(\mu_{new})}$?

For non-linear models, challenge = construction of fast and accurate "reduction operators" (Parameter-to-RB solution operators)

$$\underbrace{\mu \in \mathcal{P} \subset \mathbb{R}^p}_{\text{parameter p-dim}} \mapsto \underbrace{{}^{\mathbf{T}}\mathbf{B}_{\mathbf{rb}}\mathbf{u}_h \in \mathbb{R}^{N_{rb}}}_{\text{solution in RB, } N_{rb}=\mathcal{O}(10)}$$

Reduction operators for **nonlinear** PDEs

A few recent approaches

▷**Basic method : POD-NN** (Neural Network) proposed by [Hesthaven et al. 2018].

Given N_s snapshots, the P2RB operator is learned as a NN $\boxed{\mathcal{N}_\theta : \mu \mapsto \mathbf{B_{rb}}^T \mathbf{u}_h}$.

Data=the snapshots $\mathbf{u}_h^{(s)}$. Loss function $\mathcal{L}(\theta) = \frac{1}{N_s} \sum_{s=1}^{N_s} \|\mathcal{N}_\theta(\mu^s) - \mathbf{B_{rb}}^T \mathbf{u}_h^{(s)}\|_2^2$. Training : $\min_\theta \mathcal{L}(\theta)$.

▷**Enriched version : Error-Aware** (EA - POD-NN) as proposed by [Allabou et al. 2024].

POD-NN approx.

$$u(\mu)(x,t) \approx \sum_{i=1}^{N_{rb}} \alpha_i(\mu)(t)\xi_i(\mathbf{x}) \quad \xrightarrow{\text{Add the projection error}} \quad u(\mu)(x,t) \approx \sum_{i=1}^{N_{rb}} \alpha_i(\mu)(t)\xi_i(\mathbf{x}) + \sum_{j=1}^{N_{er}} \beta_j(\mu)(t)\zeta_j(\mathbf{x})$$

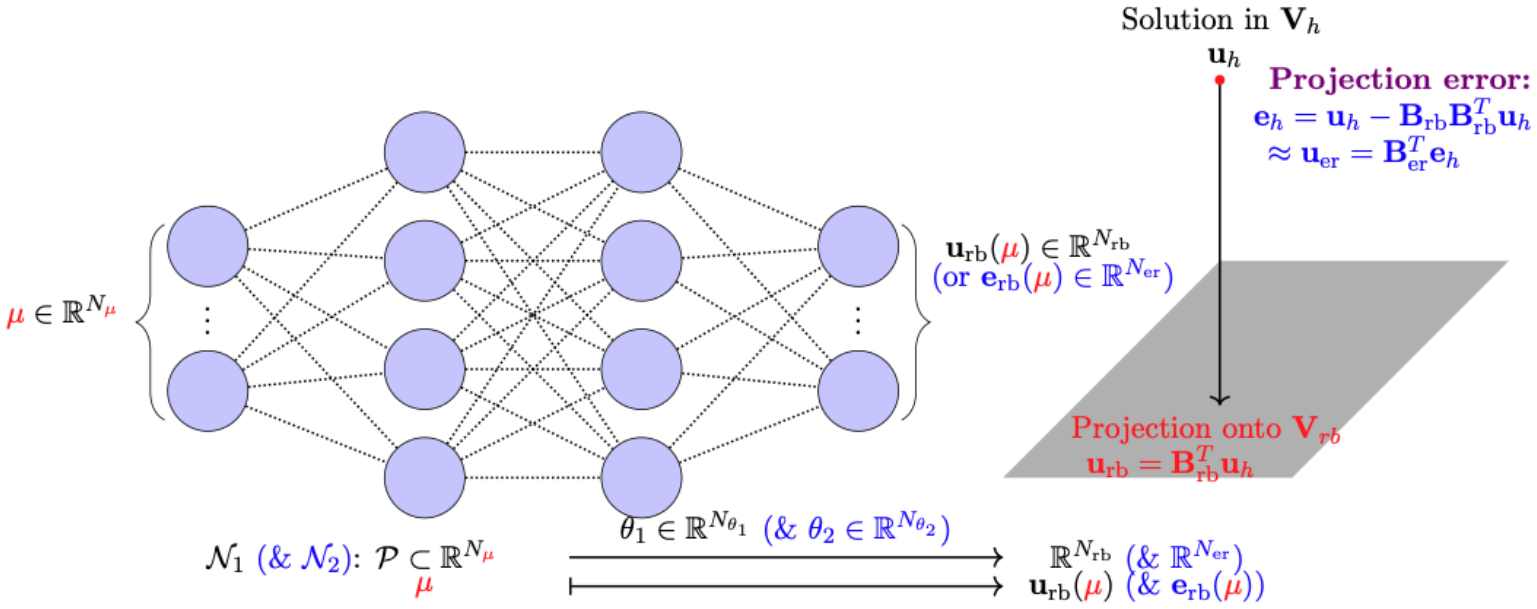
- **Online phase** : given a new parameter value μ_{new},

$$\mathbf{u_{rb}}(\mu_{new}) = (\mathbf{B}_{rb}\,\alpha + \underbrace{\mathbf{B}_{er}\,\beta}_{\text{corrective term}}) \text{ with } \mathbf{B}_{er} = \underbrace{[\zeta_1, \ldots, \zeta_{N_{er}}]}_{\text{POD of the proj. error}}$$

$\mathbf{B}_{er}$: a 2nd POD-based matrix of basis change, computable in parallel of $\mathbf{B}_{rb}$.

Reduction operators for **nonlinear** PDEs

The Error-Aware POD-NN method as proposed by Allabou's PhD



$$\mathcal{J}_1(\boldsymbol{\theta}_1) = \frac{1}{N_{train}} \sum_{s=1}^{N_{train}} \|\mathcal{N}_1(\boldsymbol{\theta}_1)(\mu_s) - \mathbb{B}_{rb}^T \mathbf{u}_h(\mu_s)\|_2^2 \quad ; \quad \mathcal{J}_2(\boldsymbol{\theta}_2) = \frac{1}{N_{train}} \sum_{s=1}^{N_{train}} \|\mathcal{N}_2(\boldsymbol{\theta}_2)(\mu_s) - \mathbb{B}_{er}^T \mathbf{e}_h(\mu_s)\|_2^2.$$

▷$\mathcal{N}_1$ is train to learn the projection of the snapshots (= the HR solutions = the learnt data) onto the reduced basis,
▷$\mathcal{N}_2$ is train to learn the error of the projection.
▷Basic idea $\sim$ multigrid-like approach.

Recall. These NNs are trained from the snapshots (=the HR solutions). They can be trained in parallel.

Reduction operators for **nonlinear** PDEs

Another version : the Non-Linear Compressive (NLC) method as proposed by [Cohen et al., CRM 2023]

Based on mathematical estimations related to the Gelfand width concept, extension of the Kolmogorov width concept, see eg. [Cohen et al., CRM 2023],

Basic POD approx.

$$\mathbf{u}_{rb}(\mu)(x,t) = \sum_{i=1}^{N_r} \alpha_i(\mu)(t)\xi_i(\mathbf{x})$$

Add further terms

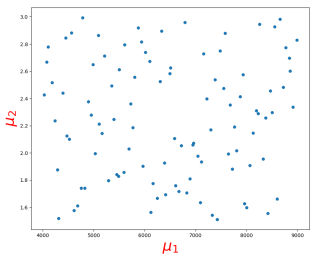
$$\mathbf{u}_{rb}(\mu)(x,t) = \sum_{i=1}^{N_{er}} \alpha_i(\mu)(t)\xi_i(\mathbf{x}) + \sum_{j=N_{er}+1}^{N} \underbrace{\alpha_j\left(\underline{\alpha}\right)(t)}_{\text{nonlinear approx.}} \xi_j(\mathbf{x})$$

with $\underline{\alpha} = (\alpha_1, \ldots, \alpha_{N_{er}})$.

▷Basic idea $\sim$ multi-scale approach.

Nonlinear prediction of the $(N - N_{er})$ missing coefficients from the N_{er} POD-based retained modes.

▷**Using NNs as non-linear predictors**, (this could be e.g. random forests, decision tree too)



HR sol. → Snapshot matrix $S = \left[\mathbf{u}(\mu_1), \ldots, \mathbf{u}(\mu_{N_s})\right]$ → POD → Reduced Basis RB $\{\xi_1, \ldots, \xi_{N_{rb}}\}$ → 1st NN as before $\mathcal{N}_\theta^1 : \mu \mapsto (\alpha_1, \ldots, \alpha_{N_{er}})$

2nd NN is now $\mathcal{N}_\theta^2 : \underline{\alpha} = (\alpha_1, \ldots, \alpha_{N_{er}}) \mapsto \hat{\alpha} = (\alpha_{N_{er}+1}, \ldots, \alpha_N)$

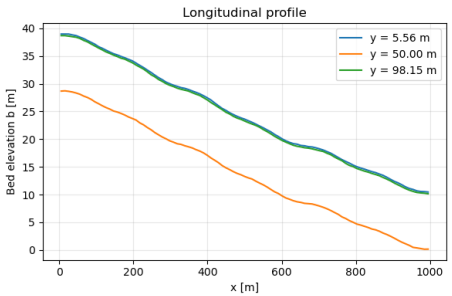
The loss function for $\mathcal{N}_\theta^2$ is : $\mathcal{L}_2(\theta) = \frac{1}{N_s} \sum_{s=1}^{N_s} \|\mathcal{N}_\theta^2(\mu^s) - \hat{\alpha}^s\|_2^2$.

Reduced Order Model (ROM)

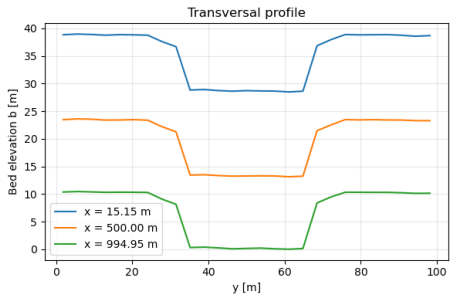
A basic academic case

$\mu \in \mathbb{R}^3$: single inflow discharge parametrization $(Q_{\max}, t_{\max}) \in \mathbb{R}^2 \oplus t_s$.

Bathymetry & cross-sections profiles : main channel + overbank areas

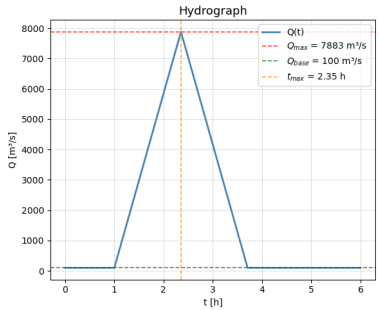


Longitudinal profiles



Transversal profiles

Inflow discharge $Q_{in}(t)$ example



Boundary conditions

Left side : inflow discharge $Q_{in}(t)$ parameterized by $Q_{\max}$ and $t_{\max}$.

Right side : imposed water level.

Numerical parameter values

Variables	**Values**
Q_{min}	$100\ m^3/s$
Q_{max} range	$[4000, 9000]\ m^3/s$
Final simulation time	$6\ h$
t_{rise}	$1\ h$
t_{max} range	$[1.5, 2.4]\ h$
N_t	33
N_s **snapshots**	$10^2 \times 33 = 3\ 300$

Simple academic channel case
The flow at a given instant

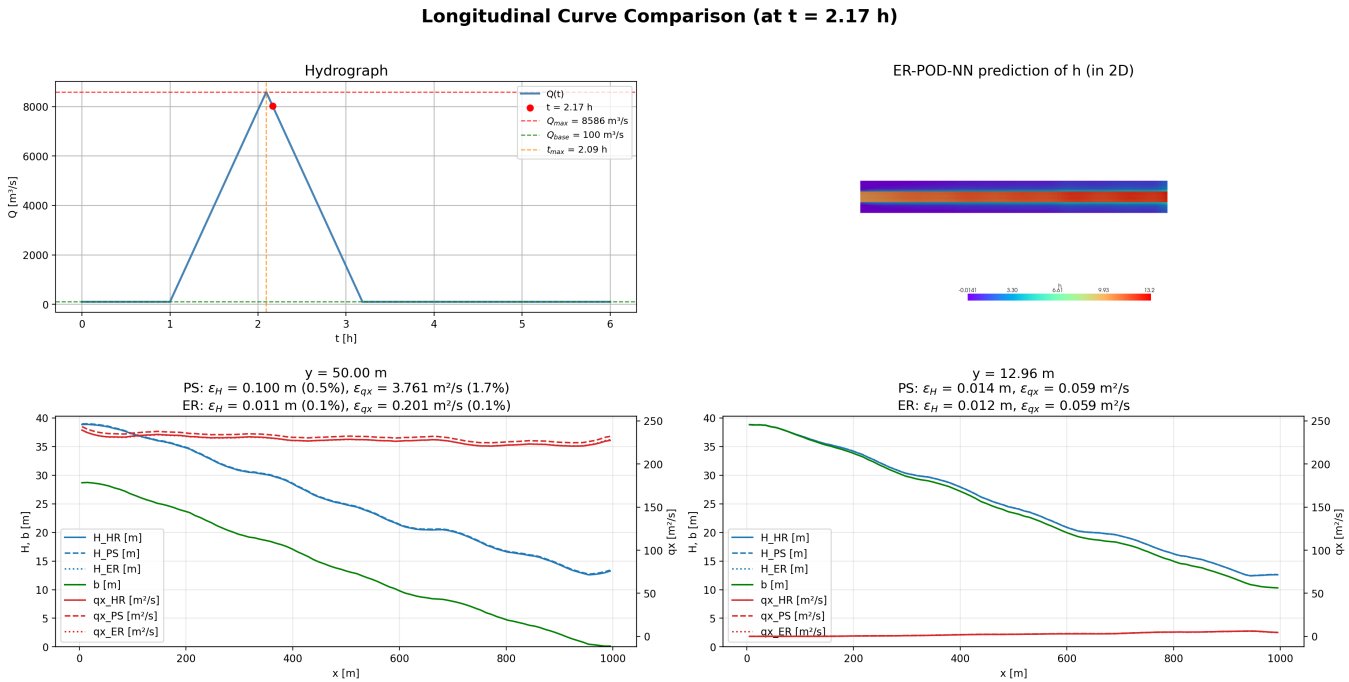
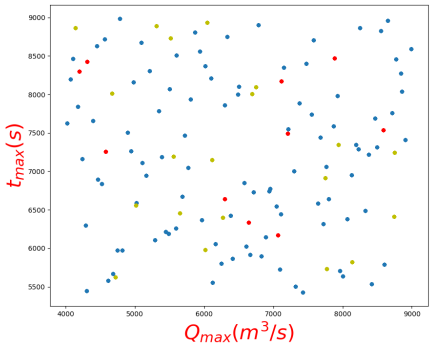
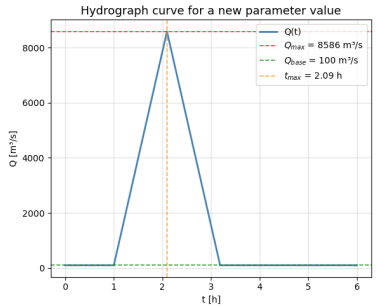


FIGURE – Longitudinal profiles : (L) along the main channel ; (R) along the overbank.
Curves : bathymetry $b(x)$, surface elevation $H(x)$ and $q_x(x)$ from (HR & reduced) models.

Simple academic channel case
Comparisons of 4 ROM for tiny mesh and dim(μ)



Parameter distribution (t_{max}, Q_{max}) used for snapshot generations



Inflow discharge $Q_{in}(t)$ corresponding to the new parameter value μ_{new}, $\mu_{new} \in \mathbb{R}^2 \oplus t_s$.

▷**Computational time comparison** for 2 673 cells. Computations on a single NVIDIA RTX 2000 Ada Generation GPU (8 GB VRAM, 60 W TDP), running CUDA 13.0.

Method		**POD-NN**	**Error Aware (EA)** -POD-NN	**Non Linear Compressive (NLC)**	**Extra Residual (ER)** -POD-NN
Offline phase	Generation of each snapshot (CPU-time) (same time for all methods)	158.2 *s*	158.2 *s*	158.2 *s*	158.2 *s*
	RB construction - POD (GPU-time)	2.4 *s*	3.8 *s*	2.4 *s*	2.4 *s*
	NN trainings (GPU-time)	31.8 *s*	98.5 *s*	46.8 *s*	980.1 *s* including the 100 residuals evaluation at each epoch.
Online phase (GPU time)		139 μs	281 μs	286 μs	273 μs

▷**Accuracy** (relative 2-norm errors wrt the reference HR solution).

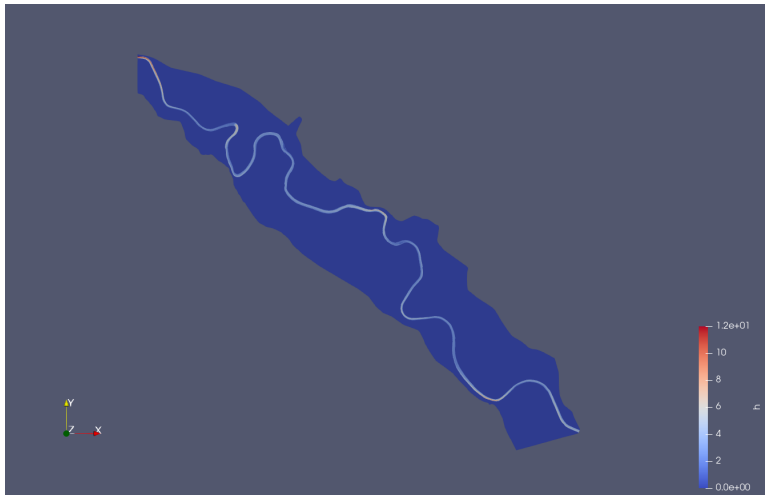
Method	**POD-NN**	**EA-POD-NN**	**NLC**	**ER-POD-NN**
depth h	0.97 %	0.91 %	0.91 %	0.39 %
longitudinal discharge q_x	1.17 %	1.15 %	1.15 %	0.30 %
cross-discharge q_y	8.69 %	4.82 %	3.34 %	8.56 %

Garonne river case (Marmande-la Reole station)

Real-like data

▷Configuration : same as the academic test case.

- Triangle hydrograph parametrized by $(Q_{max}, t_{max}) \Rightarrow \mu \in \mathbb{R}^2 \oplus t_s$.
- $N_s = (10^2 \times 43)$ snapshots.
  (= the training database).
- Mesh of 123 960 cells.
  Bathymetry data from IMFT [Roux et al.].
  DassFlow2D computations by T.-V. Nguyen, IMT-INSA.



Water height h.

Computation times

		Non Linear Compressive (NLC)
Offline phase	Generation of **each snapshot (CPU-time)**	$\approx 1h\,30$
	RB construction - POD (GPU-time)	$20\,s$
	NN trainings (GPU-time)	$55\,s$
Online phase (GPU time)		$3\,ms$

Accuracy vs the HR solution

	NLC
height h	0.69 %
discharge q_x	1.28 %
discharge q_y	1.25 %

Reduction operators for **nonlinear** PDEs

Conclusion of this part

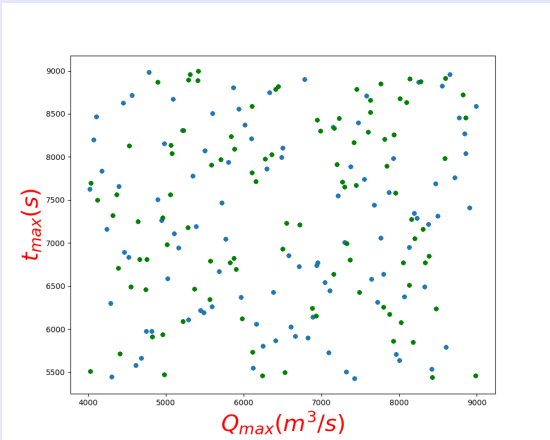
▷**Recalls :**
The data used for training are the snapshots.
Each snapshot is a finely tuned and expensive HR space-time simulation.
And, the parameter space $\mathcal{P} \subset \mathbb{R}^p$ needs to be covered by the snapshots...

⊕ **The good news.**

- **Reduction of the 2D shallow water model** in real-world geometries (nonlinear hyperbolic system with complex wave interactions) is **possible with good accuracy** *[M. Allabou's PhD 2026, T.-V. Nguyen On-Going]*.
- The methods aforementionned enables parallel training of the NNs ($\mathcal{N}_\theta^1$ and $\mathcal{N}_\theta^2$).

⊖ **What can be an issue.**

- The number of necessary snapshots is related to $\dim(\mu)$, therefore potentially large... Say $O(10^p)$ with p related to $\dim(\mu)$...



On-going improvements :
densify the parameter space using residuals of the model only (vs additional snapshots).
T.-V. Nguyen's PhD, INSA-IMT, ANITI-CNES funds, started in 2026.

Direction #2 :

Model calibration in "real-time" ?
Using Physics Informed Neural Networks (PINNs) ?

$\hookrightarrow$ Inverse problems - data assimilation topics...

Ref. [H. Boulenc's PhD 2026], INSA-IMT.
ANR fund. Collaboration INRAe Aix.
[Boulenc et al., Inverse Problems 2025].

Example : calibration of the infiltration coefficient K_i in a watershed.

Model : 2D shallow water with rainfall-runoff - infiltration source terms.

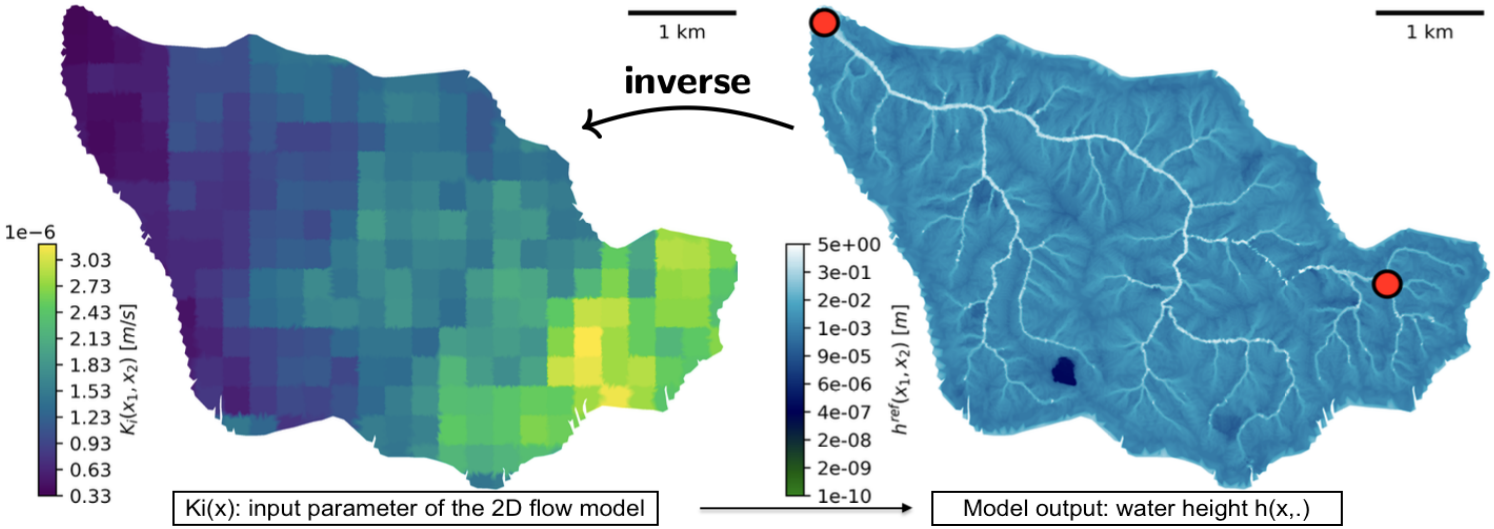


FIGURE – (Left) The spatially distributed infiltration coefficient $K_i(x)$ (Green-Ampt) (here, 279 coeffs). (Right) Water height $h(x, \cdot)$.

Case Réal-Colobrier provided by CEREMA - INRAe Aix-en-Provence. DassFlow2D computations.

▷Calibration by the standard Variational Data Assimilation (VDA) method [DassFlow2D et al.] is effective : see [Pujol et al. AWR 2025]. Eg. given hydrographs at stations ⊕ ..., infer $K_i(x)$.

Question : Can we achieve similar accuracy and robustness as VDA with much lighter computations, and a simpler methodology as well ?

Inversion - calibration by Machine Learning
Learning of the complete parameter-to-state operator

▷k-parametrized direct model : $\boxed{\mathcal{M} : k(x,t) \mapsto \mathbf{y}(k;(x,t))}$.

For the 2D shallow-water model, the state of the system $\mathbf{y} = (h, q_x, q_y)$.

▷**Inverse problems** : given data/observations $\mathbf{z}^{obs}$ to be compared to $\mathbf{y}$, **infer** $k(x,\cdot)$.

▷A potentially simple and efficient approach : **brute-force operator learning** as

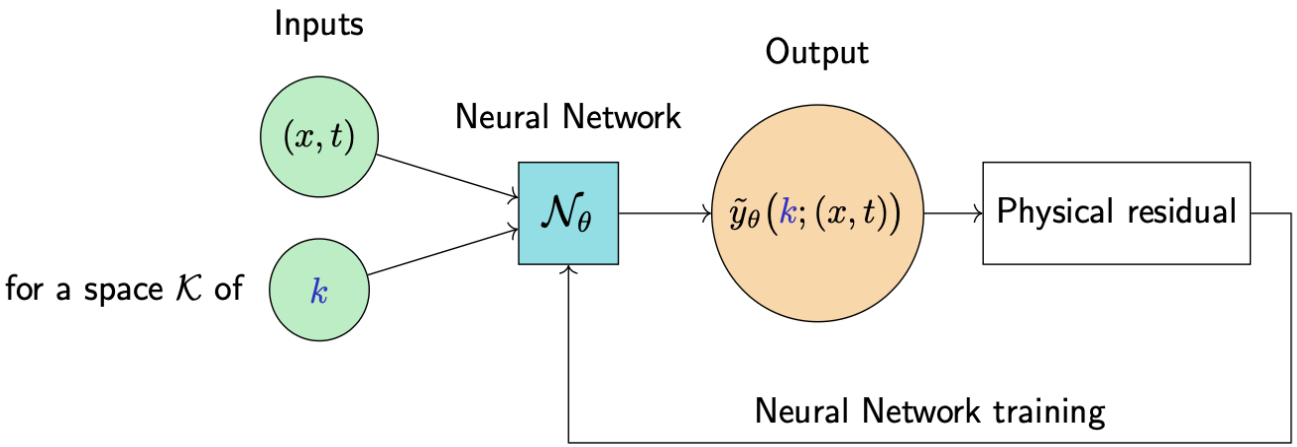


FIGURE – Operator learning by PINNs-like methodology. Residual $= \|\mathcal{A}(k;y) - \mathcal{F}(k)\|^2_{\Omega\times(0,T)}$

▷**First limitation** : dimension of the parameter k must be small (dim $\approx$ 5 max.).

Inversion - calibration by Machine Learning
Learning of the "semi-parametrized" parameter-to-state operator

▷Same k-parametrized direct model : $\boxed{\mathcal{M} : k(x,t) \mapsto \mathbf{y}(k;x,t)}$

▷**Inverse problems** : given data/observations $\mathbf{z}^{obs}$ to be compared to $\mathbf{y}$, **infer** $k(x,\cdot)$.

▷Another simple approach : learning of the **"semi-parametrized" operator (=PINNs)**

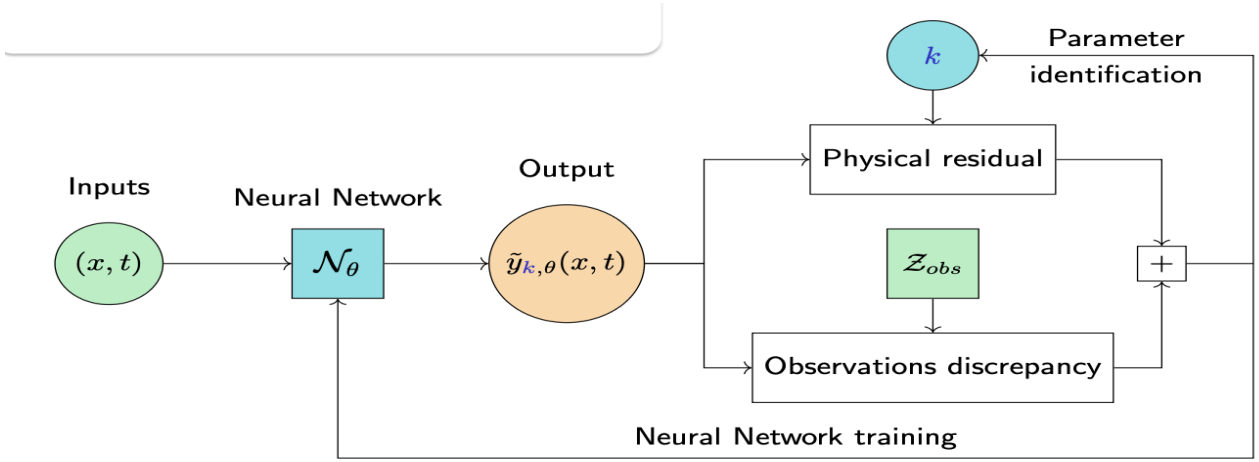


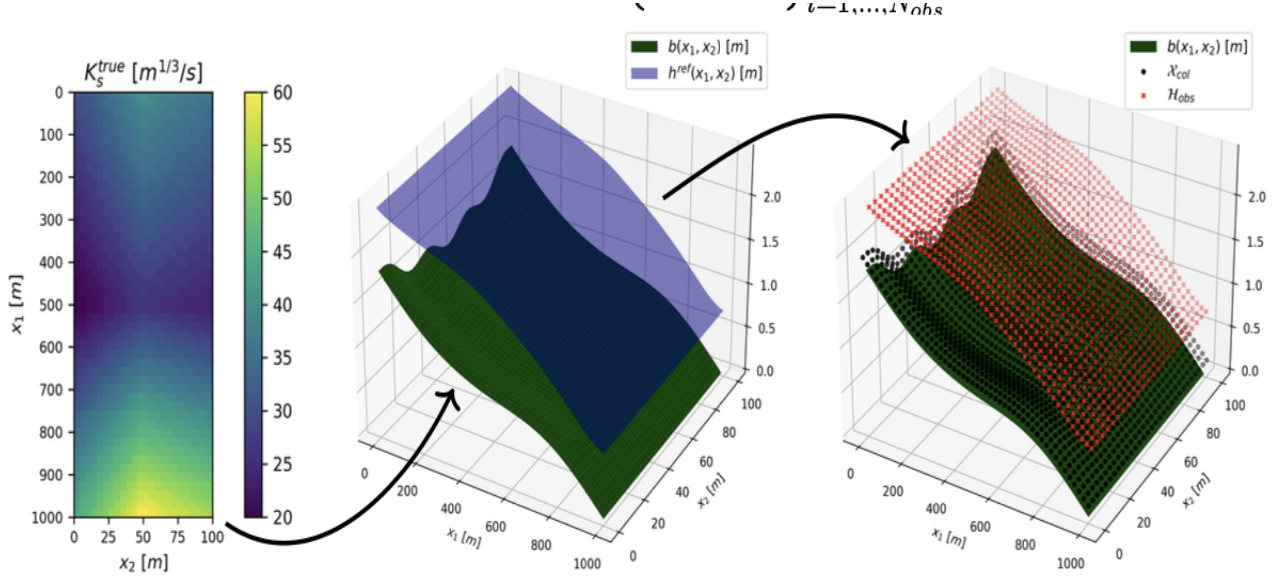
FIGURE – Operator learning by PINNs methodology. Residual $= \|\mathcal{A}(k;y) - \mathcal{F}(k)\|^2_{\Omega\times(0,T)}$.

Here, simultaneous learning of the state $\mathbf{y}$ and k from the data (data assimilation).
▷**Advantage :** Semi-Parametrized version $\Rightarrow$ $\dim(k)$ can be large e.g. $O(10^3)$.
▷**Issue :** Minimizing an equation residual does not necessarily imply an accurate approximation of the solution $y(x,t)$... Here $\mathbf{y} = (h, q_x, q_y)$.

Inversion - calibration by PINNs

A toy test case with extremely dense observations

▷Calibration of the friction coefficient $K_s(x)$, given the (quasi-complete) knowledge of the surface elevation $H(x, \cdot)$:
(48×24) surface data with (48×24) values of $K_s(x)$ to identify.

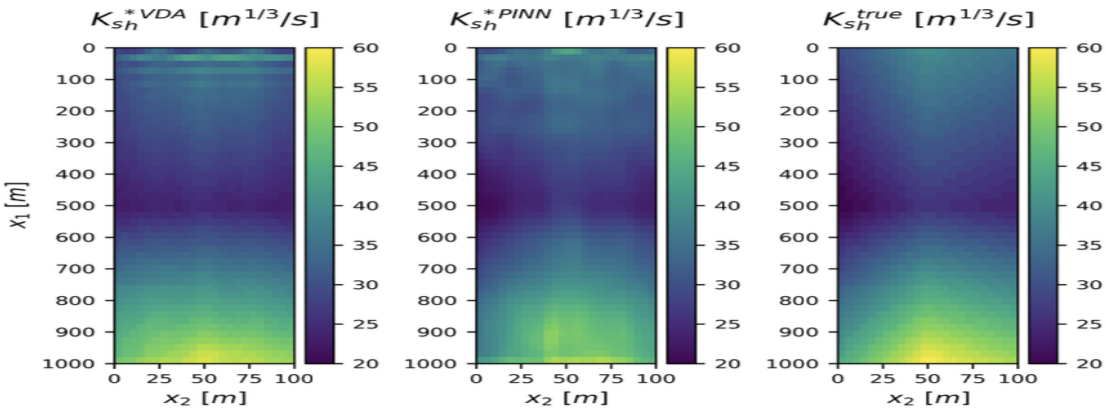


$K_s{}^{true}(x)$ (48×24), $b(x)$ and $h^{ref}(x)$ $(t = 21\,600\ s)$, col. (50×30) and obs. (48×24) points.

Similar toy experiments can be performed to infer spatially-distributed infiltration coefficients $K_i(x)$.

Inversion - calibration by PINNs

Toy test case with extremely dense observations : very efficient



Left: VDA after 200 M1QN3 ite. Middle: SP-PINN after 1500 L-BFGS ite. Right: $K_s{}^{true}$.

Comparison with the traditional Variational Data Assimilation method.

[H. Boulenc's PhD].

	SP-PINN	VDA
Global relative RMSE on $K_s{}^*$	5.9%	6.2%
Computation time on 1 CPU	$\sim 70\ s$	$\sim 30\ h$
Computation time in parallel	$\sim 35\ s$	$\sim 5\ h$

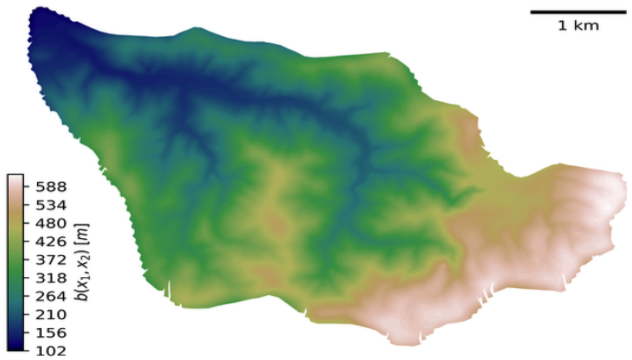
$\times\ \mathcal{O}(500)$

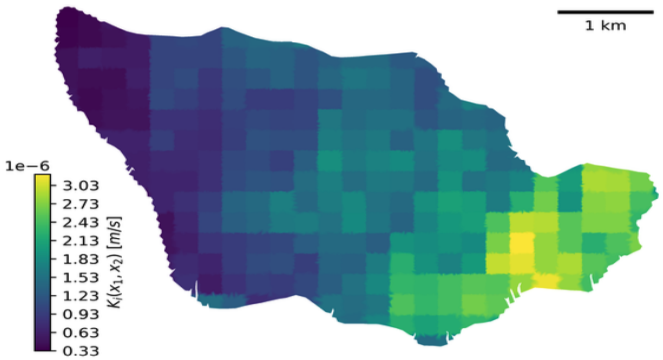
Parallel computing refers to GPU with 4096 CUDA cores and 6 GB of memory for the SP-PINN and 6 CPU threads for VDA.

Inversion - calibration by PINNs

Back to the Réal-Colobrier test case

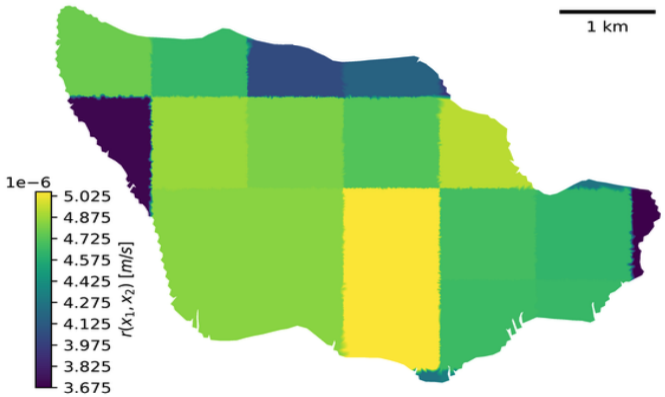
▷2D shallow-water flow, steady-state, DassFlow2D code, 53 967 cells.





Bathymetry and infiltration coefficient for the Malière test case with $dim(K_i{}^{true}) = 279$.

reference water height (log scale).

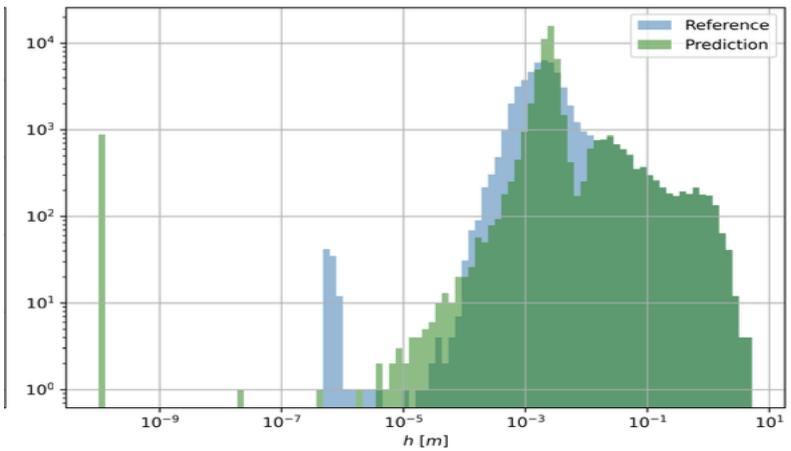


ed rain for the Malière test case.

Inversion - calibration by PINNs
Back to the Réal-Colobrier watershed case

▷2D shallow-water flow, steady-state, DassFlow2D code, 53 967 cells.
▷Given the complete knowledge of the flow, $(h, q_x, q_y)(x)$, the PINNs is trained to learn the steady-state flow. Optim. algorithms (ADAM + L-BFGS), during 60 000 iterations.

Fig. : Comparaison of h in **log scale**, *after training (green) vs the reference one (blue).*

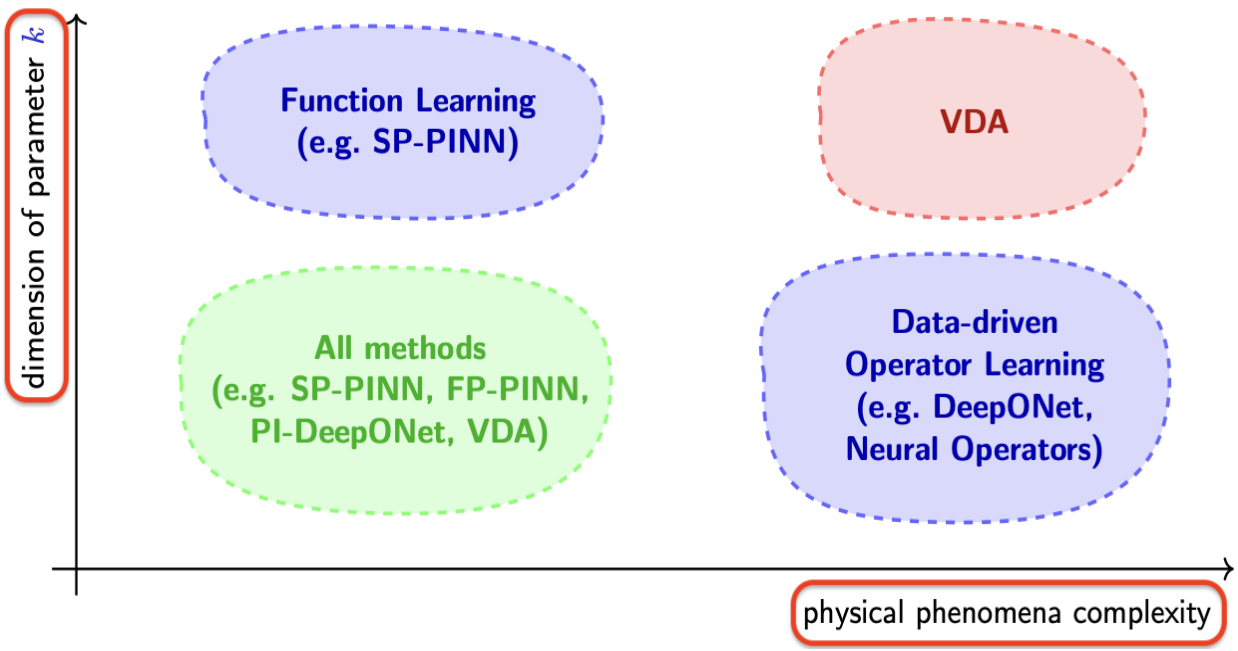


▷The PINN fails to accurately represent the wide range of magnitudes for h.
even if using area descriptors, recent techniques from image reconstruction and so on.

▷Minimizing the residual $\|\mathcal{A}(k; y) - \mathcal{L}(k)\|$ does not necessarily implies a small error $\varepsilon(y) = \|y - y_{ref}\|$...
↪ PINN solvers vs accurate Finite Volume solvers...

Inversions - Model calibration from data
Brief outline of methods & Conclusion of this part

▷For complex non-linear wave interactions like those appearing in the 2D shallow-water models / flood dynamics,
- using PINNs only, we did not manage to set up **accurate** calibrated 2D shallow water based flow models...
- on the contrary if using variational data assimilation (VDA), [DassFlow2D et al.].



General conclusion

▷Given a "good" numerical model, simulations corresponding to a new configuration, that is from μ_{new}, can be performed in **less than 1 second with acceptable accuracy**.

The basic simulations can be based on your favorite hydrodynamics software.

They were here based on DassFlow2D, which includes data assimilation capabilities.

▷For a **large dimensional input parameter μ, a preliminary reduction is required** :

- For hydrographs, a very efficient compressing method has been elaborated in [M. Allabou's PhD 2026].

- For rain signals, on-going work by [D. Gomez, PhD INSA-IMT / CS Lab - Sopra-Steria].

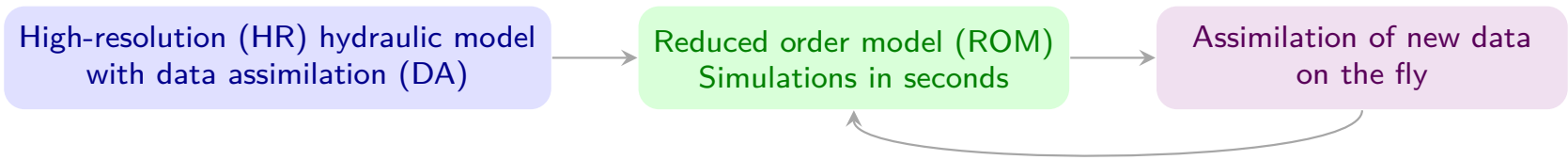
▷Concerning **data assimilation on the fly, in "real-time"**,

-PINNs have not provided the expected results.

Further fundamental (math structures of the system) investigations seem necessary.

- On the contrary, **Data Assimilation methods applied to ROMs constitute a promising approach**.

Our investigations based on the aforementioned understandings (ROMs-PINNs) are still active (3AI ANITI chaire), in particular through T.-V. Nguyen's PhD (INSA-IMT, ANITI-CNES funds) started in 2025.



Perspectives & Other on-going investigations

▷Uncertainty quantification (UQ) for the aforementioned ROMs & other types of ROMs.

On-going studies with [O. Roustant Prof. INSA-IMT & I. Henderson Prof. ISAE-SupAero, Toulouse] in the context of our 3IA ANITI chaire "PiLearnWater" (Physics-Informed Learning Methods for Continental Waters and Marine Risks).

▷Our mathematical - computational sciences - algorithm know-hows (VDA, hybrid modeling, inverse problems analyses, PINNs, ROMs, codes) have been and are still directly transferred to our partners.

In particular INRAe Aix ([P.A. Garambois et al.]), SERTIT-Icube ([L. Pujol et al.]), etc, in particular for watershed river networks / H&H coupled models.

▷Application to peri-urban and urban flood dynamics.

On-going investigations with [D. Gomez's PhD INSA-IMT / CS Lab-Sopra-Steria, 2026-2x] with / CEREMA et al.. 3AI ANITI Chaire context.

***

Recall, for ROMs, the basic simulations can be based on your favorite hydrodynamics software. Here, they were based on DassFlow2D, which includes high-dimensional data assimilation capabilities, as well as various features for urban flow modeling, fluids with nonlinear rheology (muds), etc.

Talk's publications

- M. Allabou, R. Bouclier, P.-A. Garambois, J. Monnier, "Reduction of the shallow water system by an error aware POD-neural network method : Application to floodplain dynamics". CMAME 2024.

- H. Boulenc, R. Bouclier, P.-A. Garambois, J. Monnier, "Spatially-Distributed Parameter Identification by Physics-Informed Neural Networks illustrated on the Shallow-Water Equations". Inverse Problems, 2025.

- M. Allabou, PhD thesis, "Reduced-Order Modeling of the Shallow-Water Equations via an Error-Aware POD-Neural Network : Application to Flood Dynamics", INSA-Université de Toulouse, 2026.

- H. Boulenc, PhD thesis, "Solving inverse problems by physics-informed machine learning for flood dynamics", INSA-Université de Toulouse, 2026.

- T.V. Nguyen, R. Bouclier, J. Monnier. "Model reduction methods based on physics informed machine learning". *In preparation*

Key References

- A. Quarteroni, G. Rozza. "Reduced Order Methods for Modeling and Computational Reduction". Springer, 2014.
- J. S. Hesthaven, S. Ubbiali. "Non-intrusive reduced order modeling of nonlinear problems using neural networks". Journal of Computational Physics, 2018.
- A. Cohen, C. Farhat, Y. Maday, A. Sommacal, "Nonlinear compressive reduced basis approximation for PDE's". Comptes Rendus. Mécanique, 2023.

Links

- ANITI chaire, PILearnWater ("PiLearnWater Physics-Informed Learning Methods for Continental Waters and Marine Risks") :
https ://aniti.univ-toulouse.fr/en/physics-informed-learning-methods-for-continental-waters-and-marine-risks/
- DassFlow software : https ://github.com/DassHydro
- MathHydroNum team-project.

Thank you for your attention.

Any questions ?