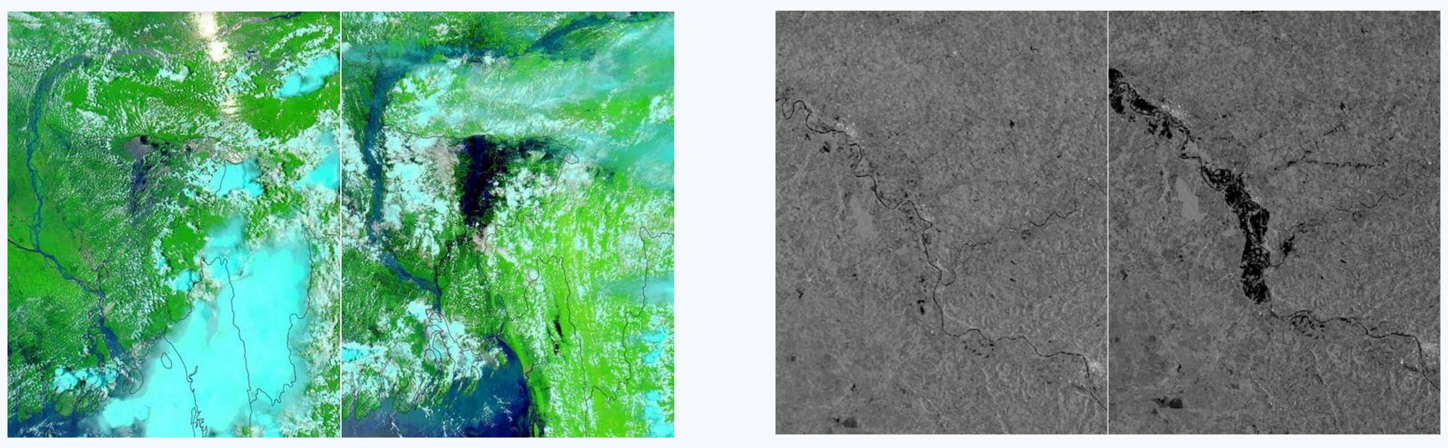
Flood twin experiment for evaluating the potential of satellite data in shallow-water simulations

Jean-Paul TRAVERT[1,2], Cédric GOEURY[1,2], Vito BACCHI[1], Fabrice ZAOUI[1], Sébastien BOYAVAL[2,3]

[1]National Laboratory for Hydraulics and Environment, EDF R&D, France; [2]Saint-Venant Laboratory for Hydraulics, France; [3]MATHERIALS, INRIA, France

Motivations

The growing availability of distributed satellite observations in space and time is valuable information for improving flood modelling.

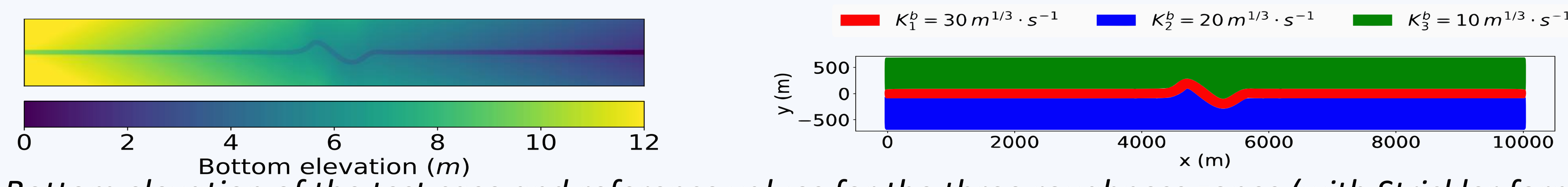


Examples of before / during flood events from satellite imagery.

For 2D hydraulic modelling, roughness is one of the most forcing parameters. It is especially the case for large floods on floodplains, and these parameters are based on experts' opinions and sparse point-wise measurements. Our objective is to test data assimilation techniques to evaluate the potential of the backscattering intensity of SAR images for estimating this parameter.

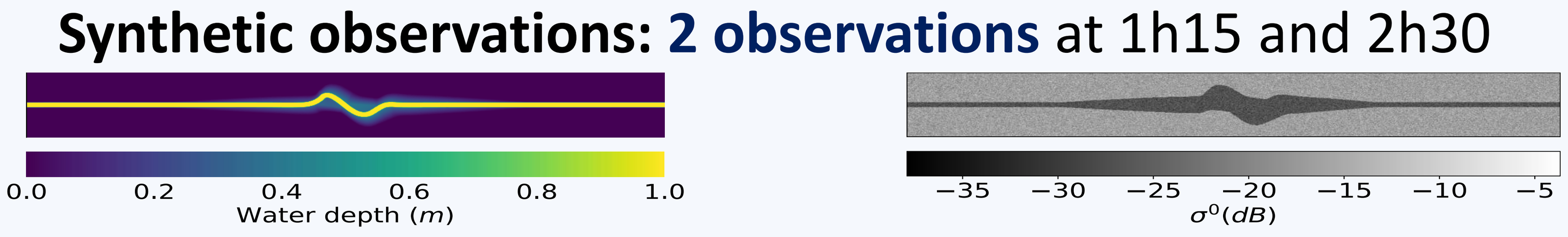
Case study

- 2D Shallow-Water Equations on TELEMAC-2D with finite element
- **Geometry:** Unstructured triangular mesh containing 477 371 elements (base mesh size of 2 m) with three roughness zones



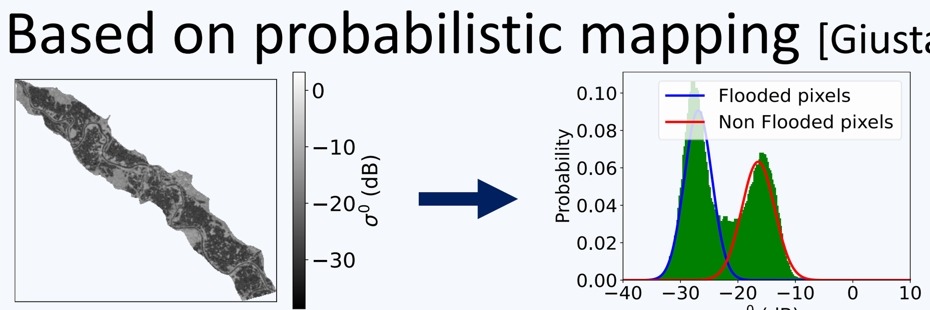
Bottom elevation of the test case and reference values for the three roughness zones (with Strickler formula)

- **Synthetic observations: 2 observations** at 1h15 and 2h30



Water depth at second observation and transformation into backscattering intensities.

Based on probabilistic mapping [Giustarini et al., 2016] from a SAR image:



Dry pixels

$$\mathcal{N}(\mu_D, \sigma_D^2) = \mathcal{N}(-16.48, 8.24)$$

Flooded pixels

$$\mathcal{N}(\mu_F, \sigma_F^2) = \mathcal{N}(-26.92, 5.74)$$

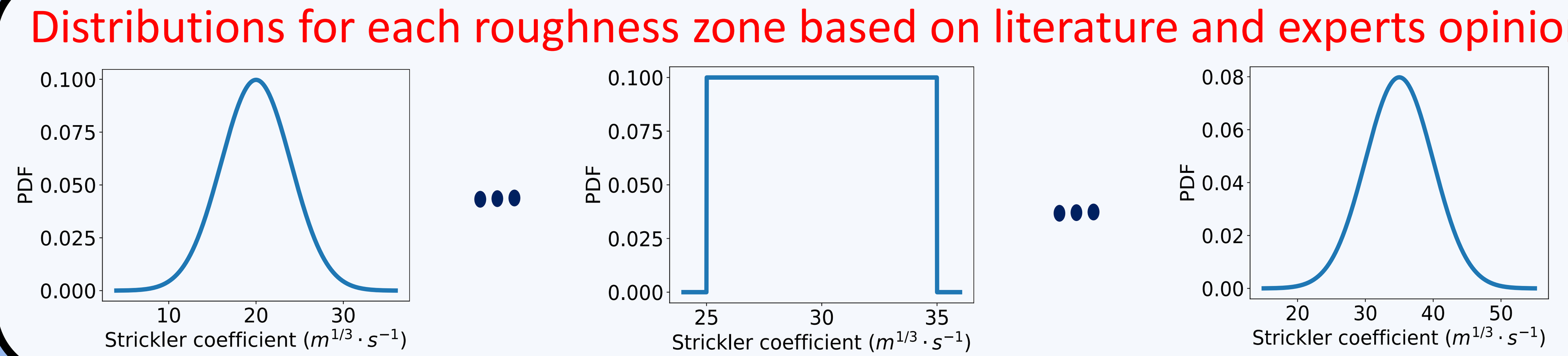
Flooded SAR image. Histogram of σ^0 and fit of Normal distributions.

Method: Parallel particle filter

Goal: Estimate the posterior distribution of roughness coefficients

Initialisation

Distributions for each roughness zone based on literature and experts opinions



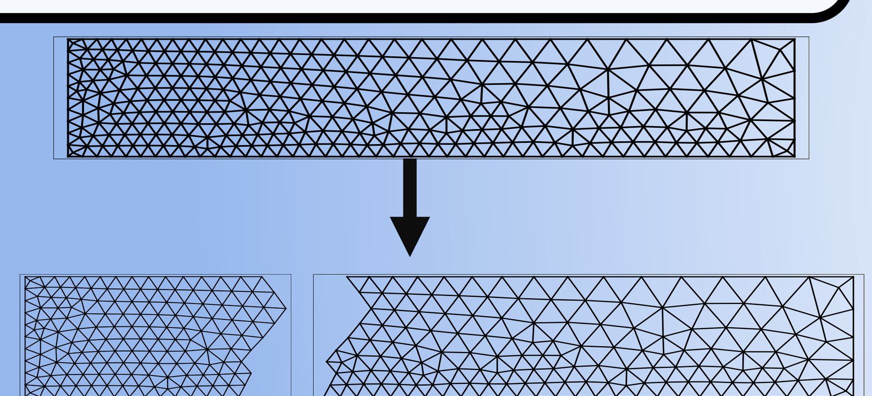
N particles from the prior distributions $\boldsymbol{x} = [\boldsymbol{x}^1, \ldots, \boldsymbol{x}^N]$ with $(\boldsymbol{x}^i)_{1\le i\le N} \in \mathbb{R}^M$

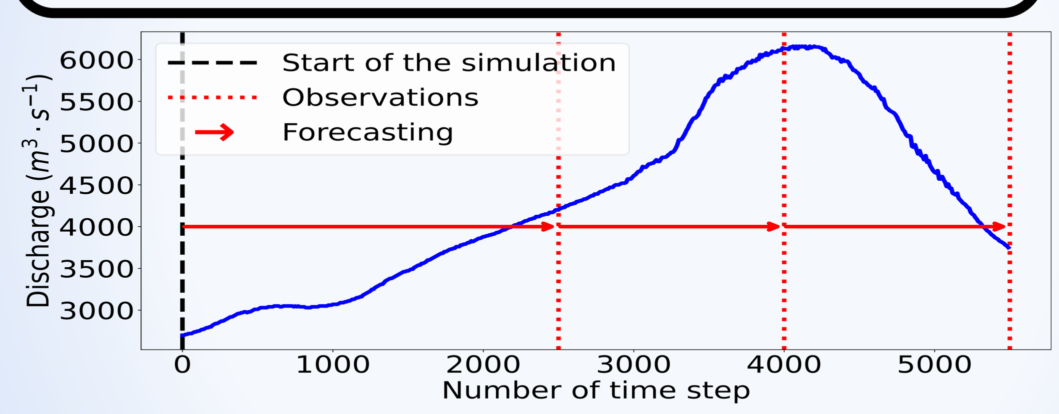
Uniform weights for all the particles $\boldsymbol{W} = [1/N, \ldots, 1/N]$

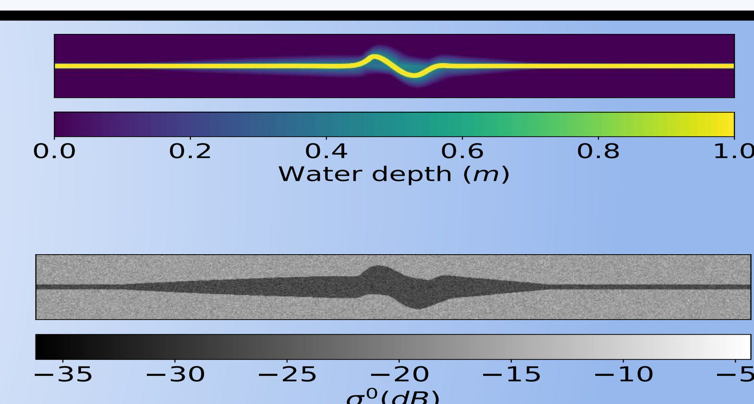
Forecasting

Launch all the particles on Ncsize processors in parallel on a cluster and make them communicate at each time step

Partition each run with Runsize processors → Continue TELEMAC-2D computation until the next observation → Simulated water level / Transformed into backscattering intensities







Wait for all the particles to be propagated

Analysis

Particle weight 1 ••• Particle weight i ••• Particle weight N

$W_k^i = W_{k-1}^i \Pi_{j=1}^{N_p} \left(w_{(k,j)}^i\right)^\alpha$ with W_k^i the global weight of particle i at time k, N_p the number of assimilated pixels, α an hyperparameter [Hostache et al., 2018], and $w_{(k,j)}^i$ local weight at **each pixel** between observed and simulated backscattering intensities.

Observed flooded pixels: $w_{(k,j)}^i = \frac{1}{\sigma_F\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{sim_{k,j}^i - obs_{k,j}^i}{\sigma_F}\right)^2}$ **Dry pixels:** $\sigma_F \to \sigma_D$

Broadcast the weights to all processors

Normalise weights and **Resampling step with Kernel Density Estimation** and going back to forecasting step

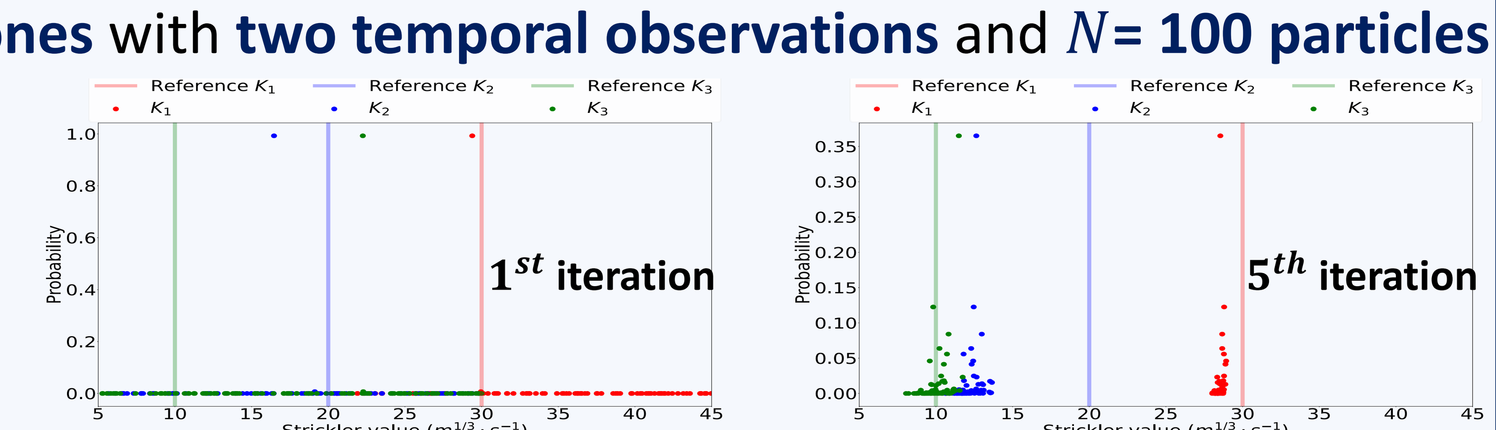
Results

- **Three roughness zones** with **two temporal observations** and **N= 100 particles**
- Priors:

$K_1 \to \mathcal{U}(20;\ 45)$

$K_2 \to \mathcal{U}(5;\ 30)$

$K_3 \to \mathcal{U}(5;\ 30)$



- Poor identification of floodplains coefficients without resampling (1^{st} iteration)
- Resampling is essential to identify floodplains roughness distributions (5^{th} iteration)
- Unable to identify K_2, because of low sensitivity in regards to the likelihood measure

Conclusions and perspectives

- Functional parallel implementation of particle filter
- The methodology allows retrieving roughness coefficients on simple controlled test cases
- Compare with other likelihood measures as the one in [Dasgupta et al., 2021]
- Need to test on other test cases with the flooded area being more sensible to roughness coefficients
- Application on an operational case

1. [Dasgupta et al., 2021] Dasgupta, A., Hostache, R., Ramsankaran, R., Schumann, G. J.-P., Grimaldi, S., Pauwels, V. R., and Walker, J. P. (2021). A mutual information-based likelihood function for particle filter flood extent assimilation. Water Resources Research
2. [Giustarini et al., 2016] Giustarini, L., Hostache, R., Kavetski, D., Chini, M., Corato, G., Schlaffer, S., and Matgen, P. (2016). Probabilistic flood mapping using synthetic aperture radar data. IEEE Transactions on Geoscience and Remote Sensing
3. [Hostache et al., 2018] Hostache, R., Chini, M., Giustarini, L., Neal, J., Kavetski, D., Wood, M., Corato, G., Pelich, R.-M., and Matgen, P. (2018). Near-real-time assimilation of sar-derived flood maps for improving flood forecasts. Water Resources Research

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