Flood twin experiment for estimating the potential of satellite observations in shallow-water simulations

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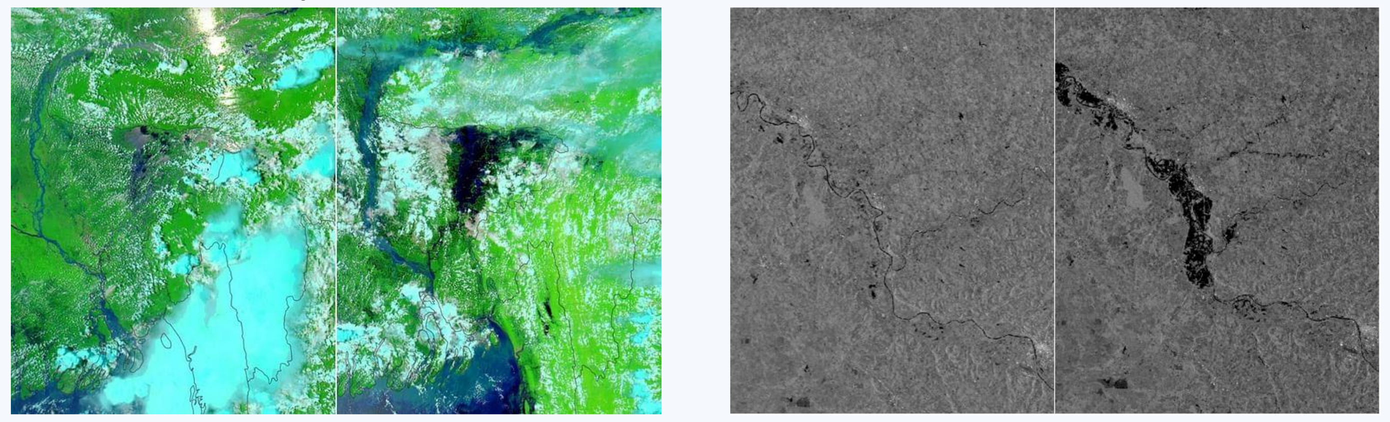
Motivations

The growing availability of distributed satellite observations in space and time is valuable information for improving flood modelling, as water surface areas can be detected from space.

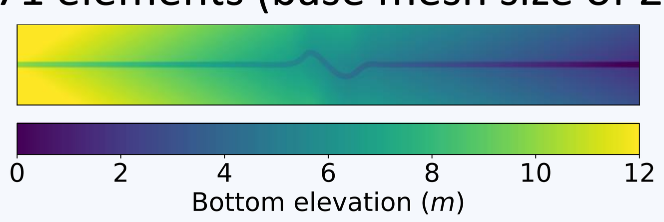


Examples of before / during flood events from satellite imagery.

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 sparsed point-wise measurements.
Our objective is to test data assimilation techniques to evaluate the potential of the backscattering intensity of SAR images.

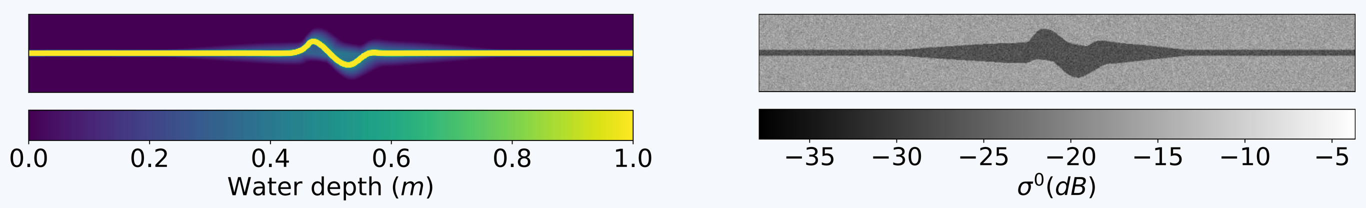
Case study

- **Twin experiment:**
- ➢ **Overland flow simulation:** 2D Shallow-Water Equations on TELEMAC-2D with finite-element
- ➢ **Geometry:** 10 km reach with unstructured triangular mesh containing 477 371 elements (base mesh size of 2 m)



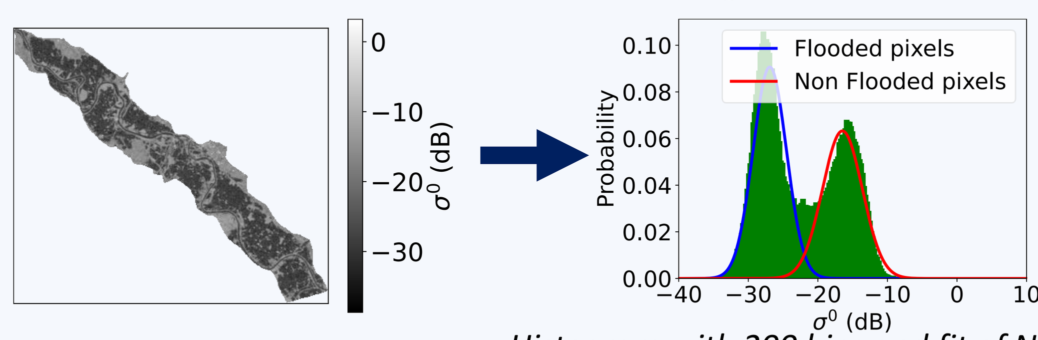
Bottom elevation of the test case geometry.

- ➢ **Simulated time:** 2h30 of physical time with a time step of 0.5 s
- **Synthetic observations:**
- ➢ **2 observations** at 1h15 interval



Water depth at second observation and transformation into backscattering intensities.

Based on probabilistic flood mapping [Giustarini, 2016] from a SAR image:



Flooded SAR image.

Histogram with 200 bins and fit of Normal distributions.

Dry pixels

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

Flooded pixels

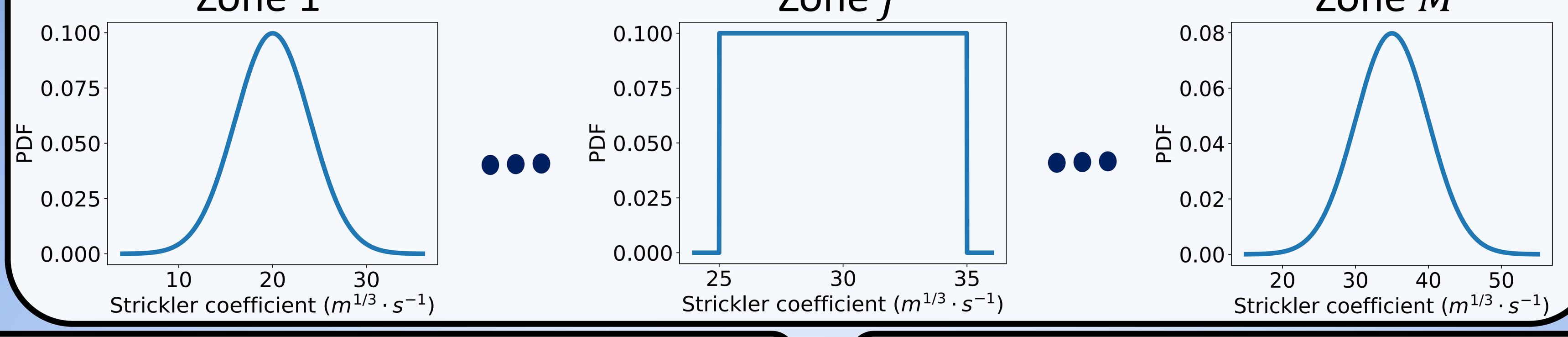
$\mathcal{N}(\mu_F, \sigma_F^2) = \mathcal{N}(-26.92, 5.74)$

Method: Parallel particle filtering

Goal: Estimate the posterior distribution of Strickler coefficients

Initialisation

Distributions for each Strickler zone based on literature and experts opinions



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

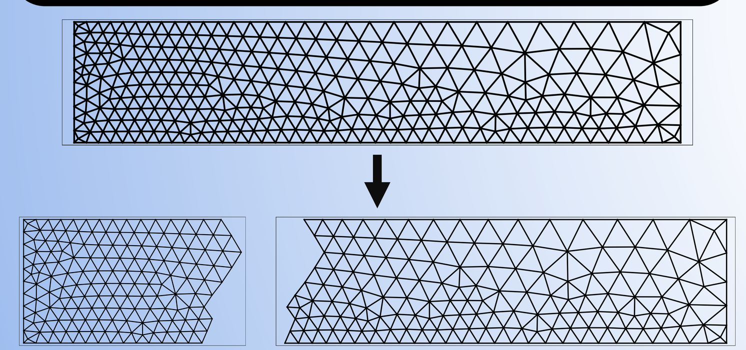
Consider uniform weights for all the particles $\boldsymbol{W} = [1/N, \dots, 1/N]$

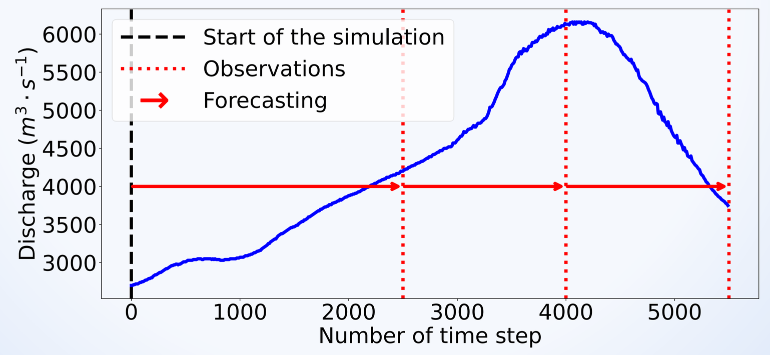
Call Ncsize processors

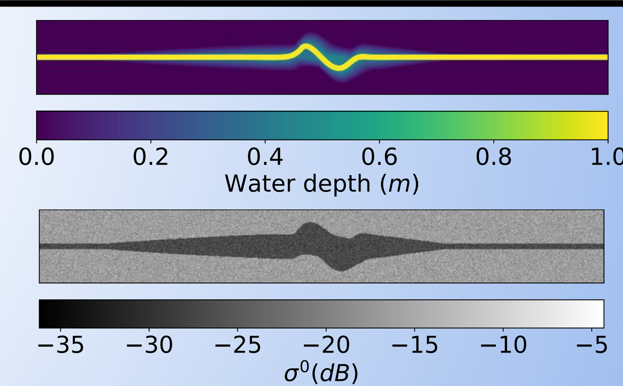
Forecasting

Run groups of Ncsize/Runsize particles until all N particles are launched

Partition each run with Runsize processors → Continue TELEMAC-2D computation until the next observation → Simulated water level / Transformation 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, 2018], and $w_{(k,j)}^i$ local weight at **each pixel** between observed and simulated backscattering intensities.

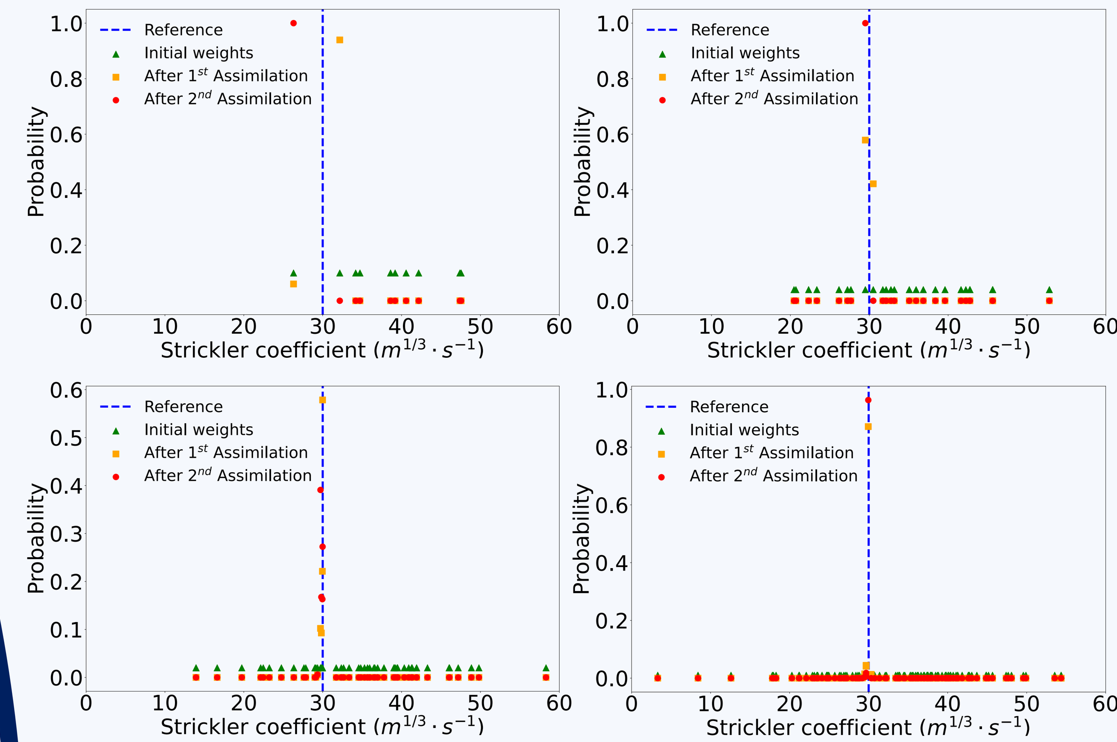
Observed flooded pixels: $w_{(k,j)}^i = \frac{1}{\sigma_F\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{sim_{k,j}^i - obs_{k,j}^i}{\sigma_F}\right)^2}$ **Dry pixels:** $\sigma_F \to \sigma_D$

Broadcast the weights to all processors

Normalise weights and go back to the forecasting step if an observation is available

Results

- Reference simulation with a Strickler of $\boldsymbol{30\ m^{\frac{1}{3}} \cdot s^{-1}}$ with **2 observations** at 1h15 and 2h30 by converting water depth map into backscattering intensities with a resolution of 10 m × 10 m
  - **Prior distribution** $\boldsymbol{K_s \to \mathcal{N}(\mu = 34, \sigma = 10)}$
  - Particle convergency:



Particle filter for N=10 (top left), N=25 (top right), N=50 (bottom left) and N=100 (bottom right).

- Encouraging results with N>25 particles

Conclusion and perspectives

- Functional parallel implementation of particle filter
- The methodology allows retrieving Strickler coefficients on simple controlled test cases
- Add more roughness zones, and compare with other likelihood measures as the one in [Dasgupta, 2021]
- Add a resampling step for the particles
- Application on an operational case

References

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,57(2) :e2020WR027859.

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, 54(12):6958–6969.

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,54(8):5516–5535.

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