

Implementation of the Chan-Vese distance in an Ensemble Kalman filter for the assimilation of SAR images as front-type data

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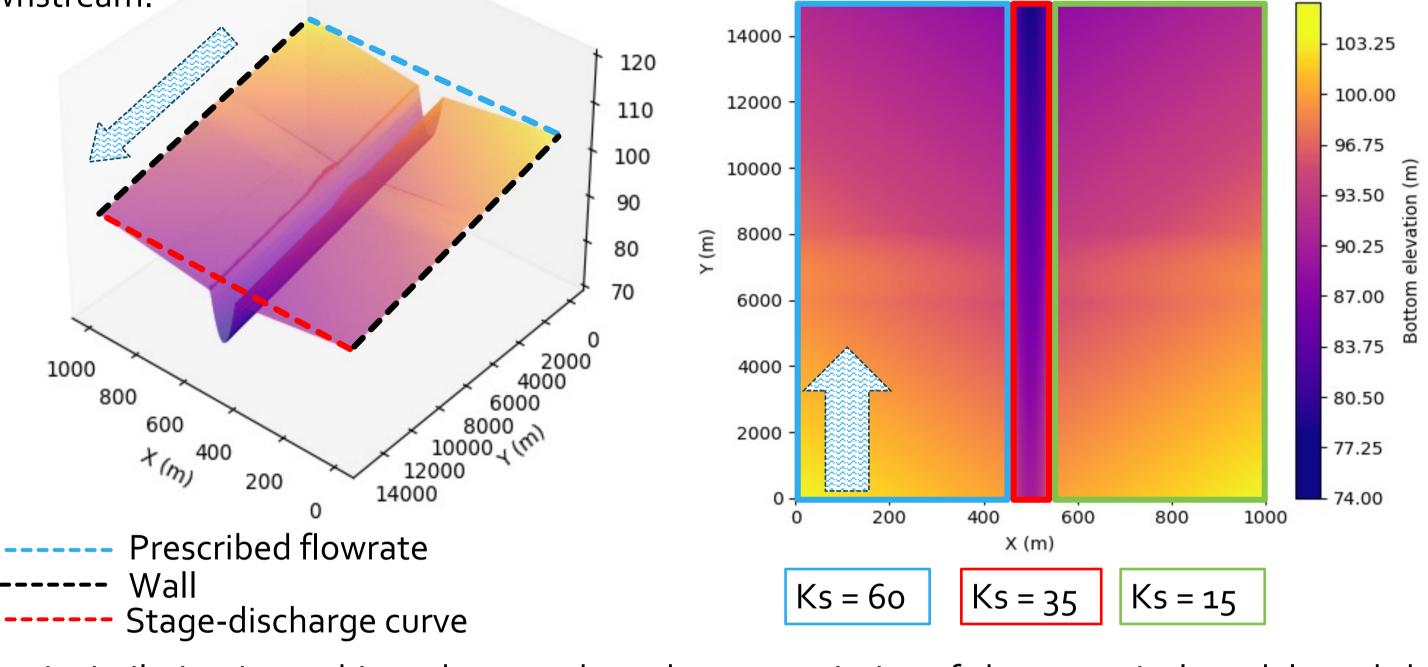
Objectives of the study

The study of flood event and inundation is crucial as it is the most common and devastating natural disasters in the world. The high uncertainty of numerical hydraulic models is a hindrance to their use. Data assimilation is used to reduce the uncertainty. In this work the position error of flood extent is search to be reduce.

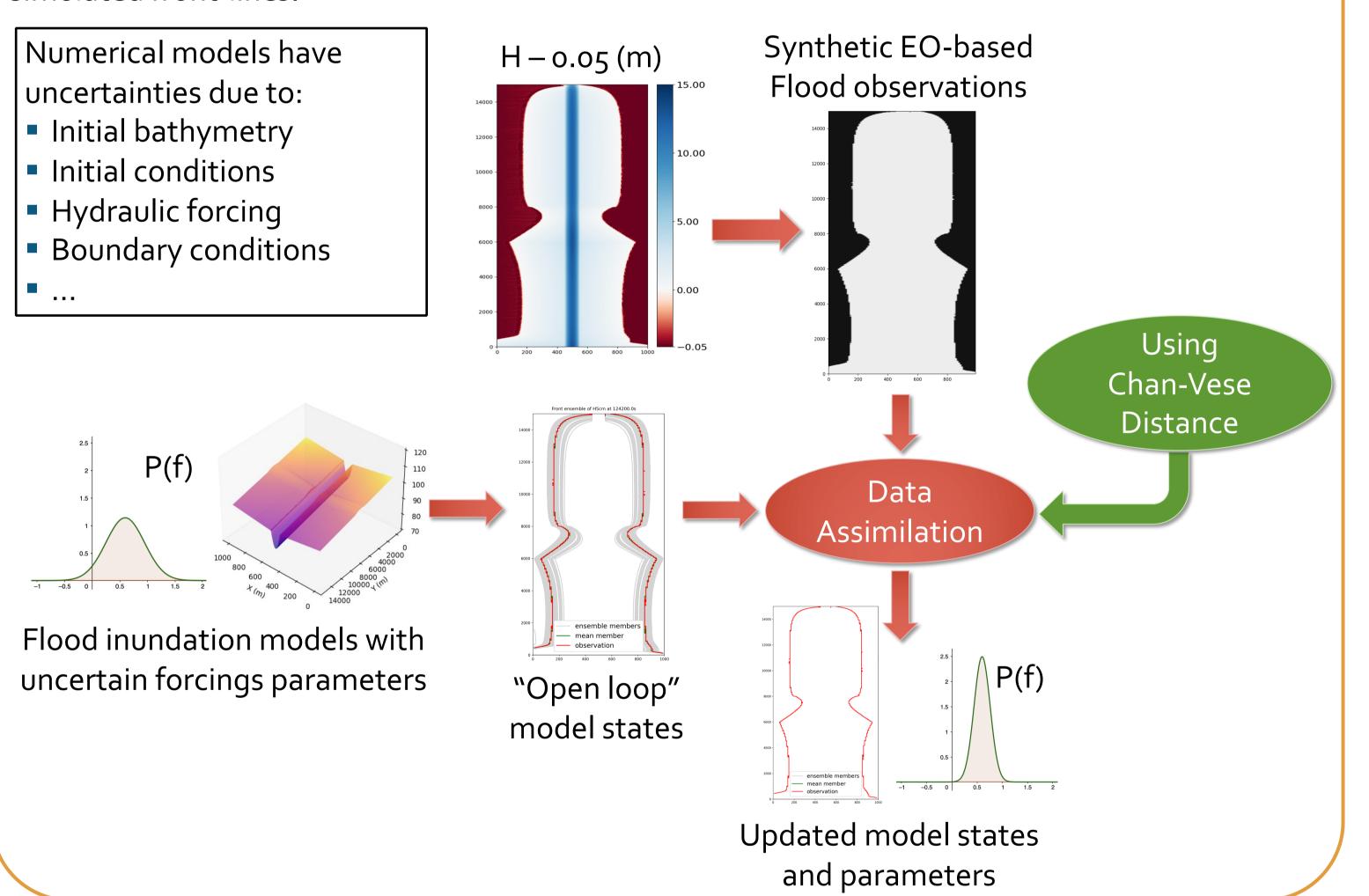
- Develop in Telemac-2D code the Chan-Vese distance within an Ensemble Transform Kalman Filter algorithm
- Create a simple Telemac-2D toy model
- III. Create two experiments to test the algorithm with the toy model

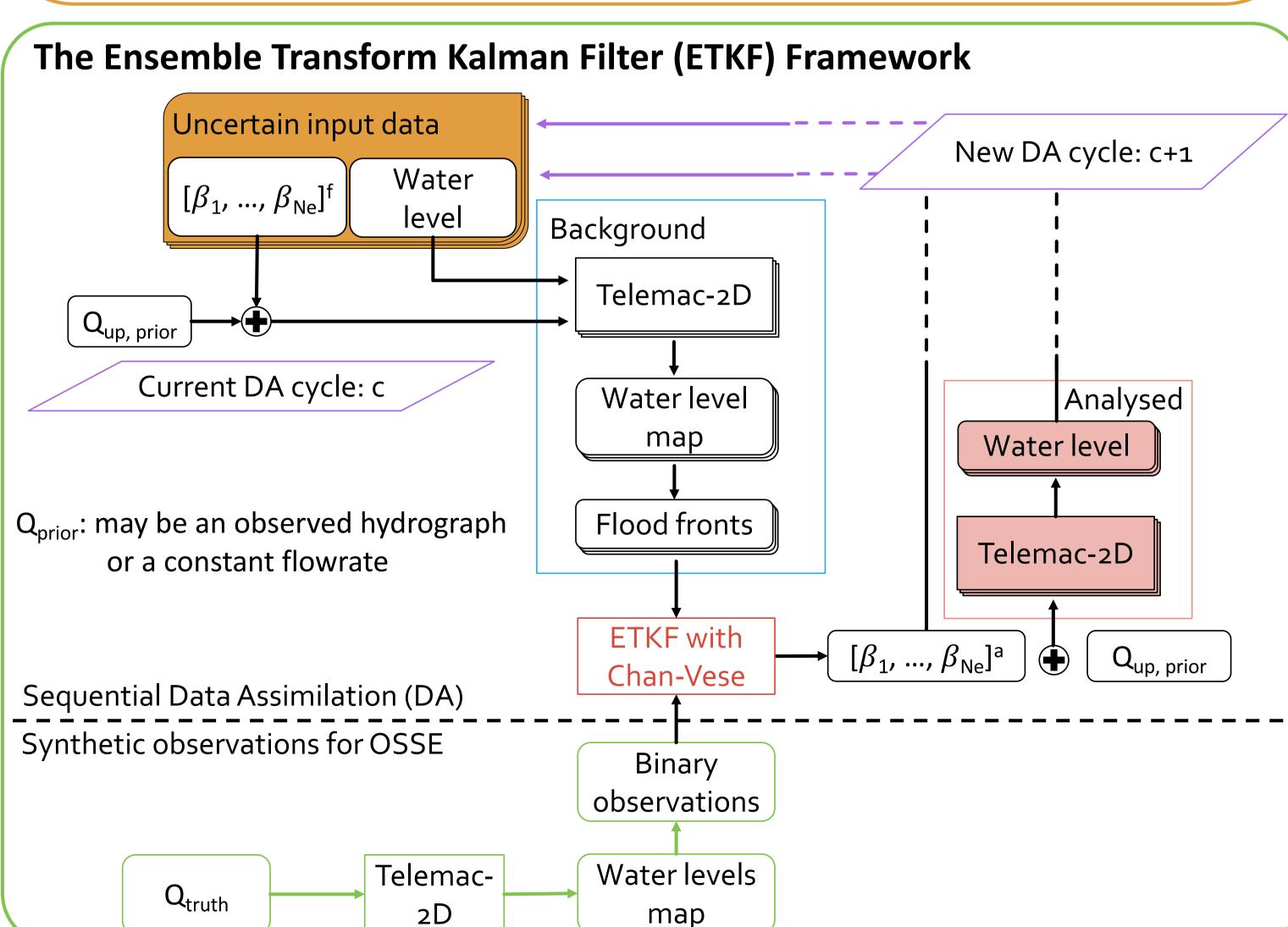
Telemac-2D (T2D) and the Valley test case

The T2D numerical model represent a straight channel of 15km length and 1km width with two floodplains at each side of the channel. The mesh is composed of around 115,000 nodes. There three Strickler coefficients, one in the riverbed and two for each floodplains. The model is composed of two liquid boundaries: a prescribed flowrate upstream and a stage-discharge curve (a) Bottom downstream.



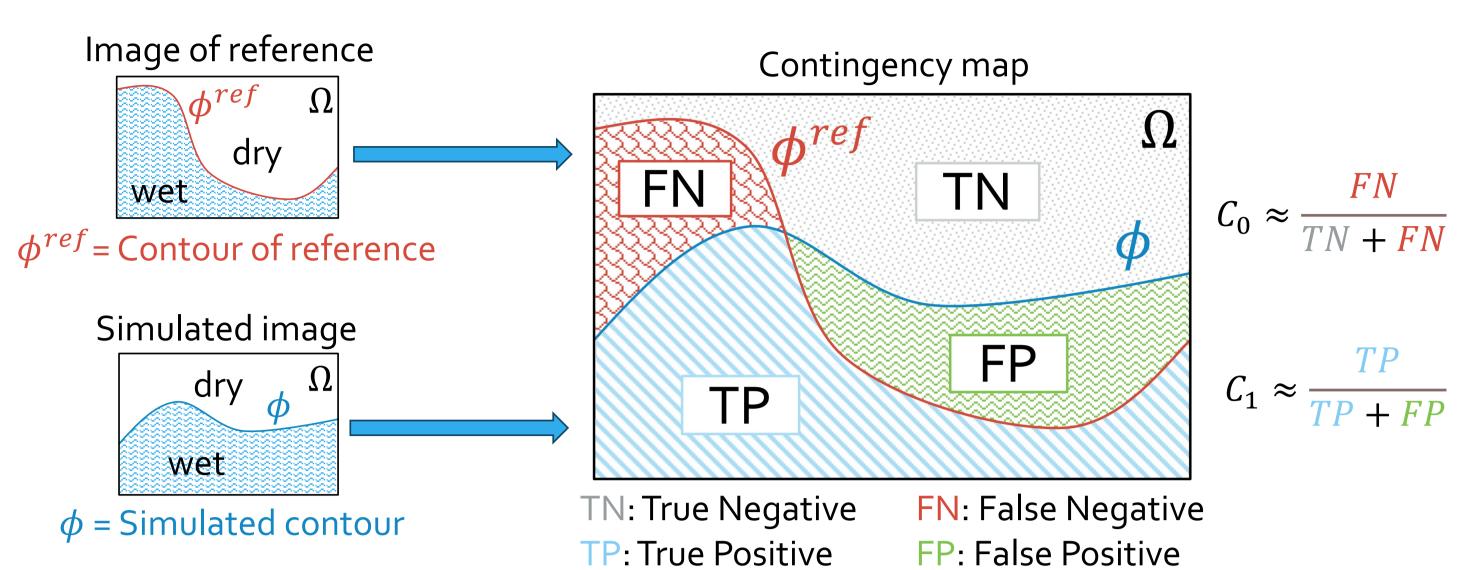
Data Assimilation is used in order to reduce the uncertainties of the numerical models and the observations. The test setting uses an Ensemble Transform Kalman Filter (ETKF) algorithm combined with the Chan-Vese distance to compare the observed front-lines and the ensemble of simulated front-lines.





The Chan-Vese distance

The Chan-Vese distance is based on the principle of contingency maps which defined four areas in the image: False positive, True positive, False negative and False positive. From those areas, two scalars are defined to compute the Chan-Vese distance.



Chan-Vese contour fitting distance is defined as:

$$D(\phi^{\text{ref}}, \phi) = D^{+}(\phi^{\text{ref}}, \phi) + D^{-}(\phi^{\text{ref}}, \phi)$$

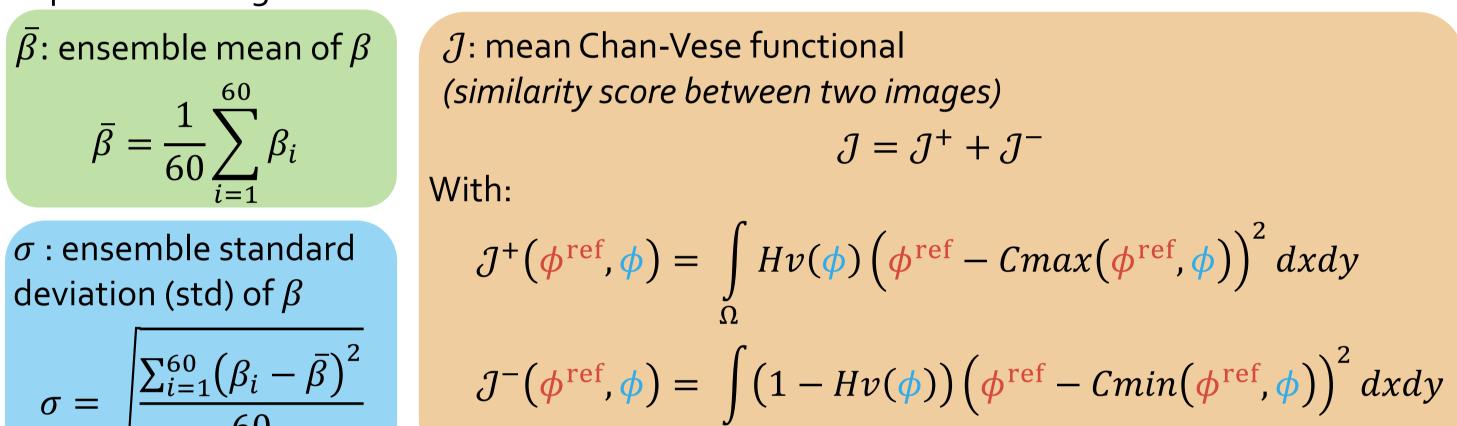
Where:

$$D^{+}(\phi^{\text{ref}}, \phi) = Hv(\phi) \left(\phi^{\text{ref}} - Cmax(\phi^{\text{ref}}, \phi)\right)$$
$$D^{-}(\phi^{\text{ref}}, \phi) = \left(1 - Hv(\phi)\right) \left(\phi^{\text{ref}} - Cmin(\phi^{\text{ref}}, \phi)\right)$$

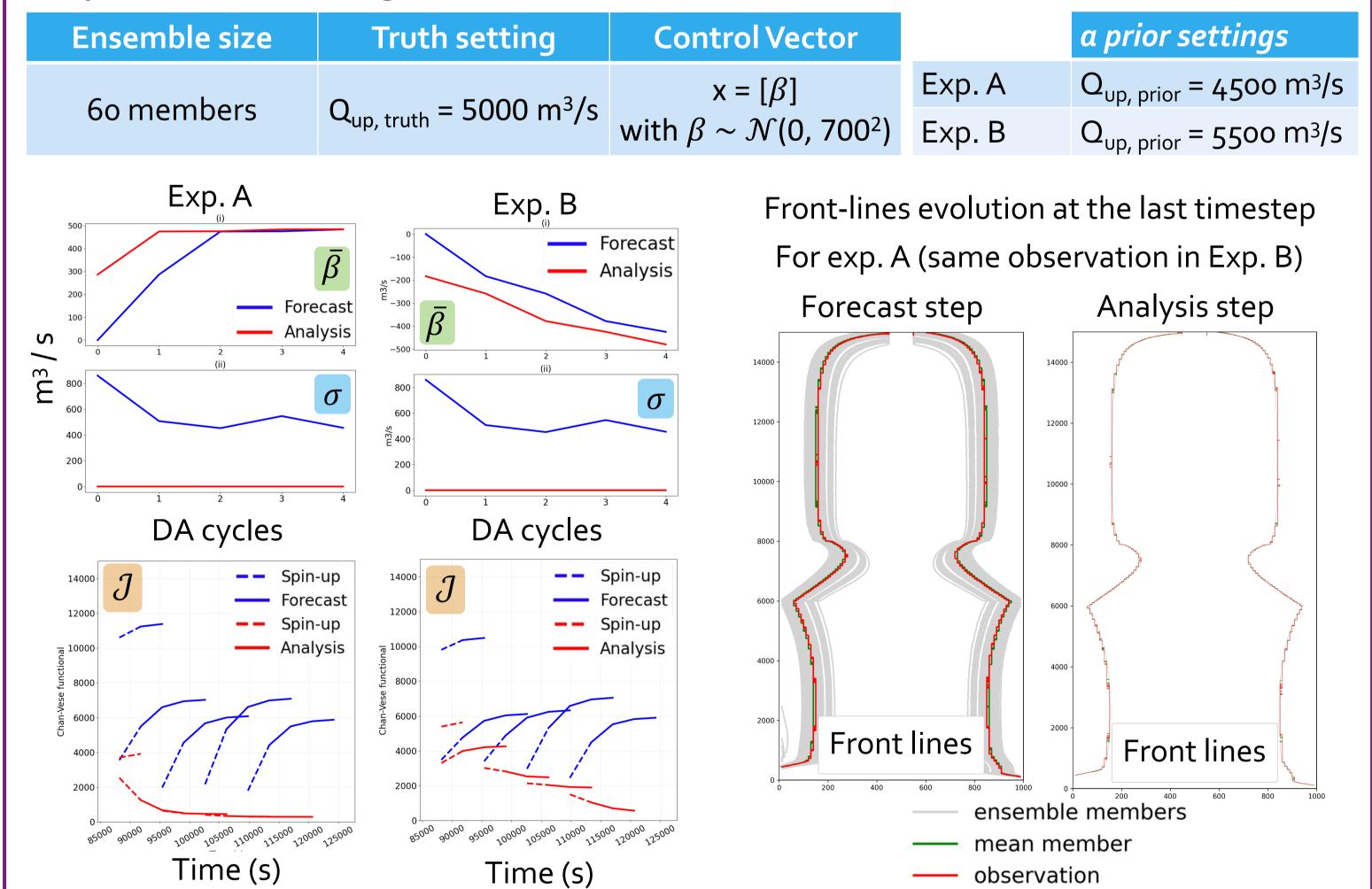
Hv is a Heaviside function returning 1 if the pixel is flooded, 0 elsewhere. Cmax and Cmin are respectively the max and min of the scalar C_0 and C_1 .

Analytical metrics

Three metrics are used to analyse the results. The first two moments of the control vector are the first metrics: the mean and standard deviation. The last one is the Chan-Vese functional which compare two images.



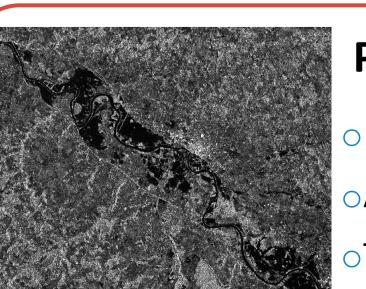
Experimental settings and results



For both experiment, $\bar{\beta}$ is reaching a value that, added to the prior setting goes to the truth value of the upstream flow. \mathcal{J} show similar result, it is reducing with the simulation.

After the analysis steps, σ is reduced to zero. This mean that the ensemble collapse to one value.

The front-lines evolutions is comforting with $ar{eta}$ and ${\mathcal J}$ evolutions.



Perspectives on Chan Vese-ETKF work

- •New experiment with an observation created with a different topography;
- Add spatial control vector;
- Test with a more realistic synthetic SAR observation;
- Test on the Garonne catchment model on 2019/2021 flood events.



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