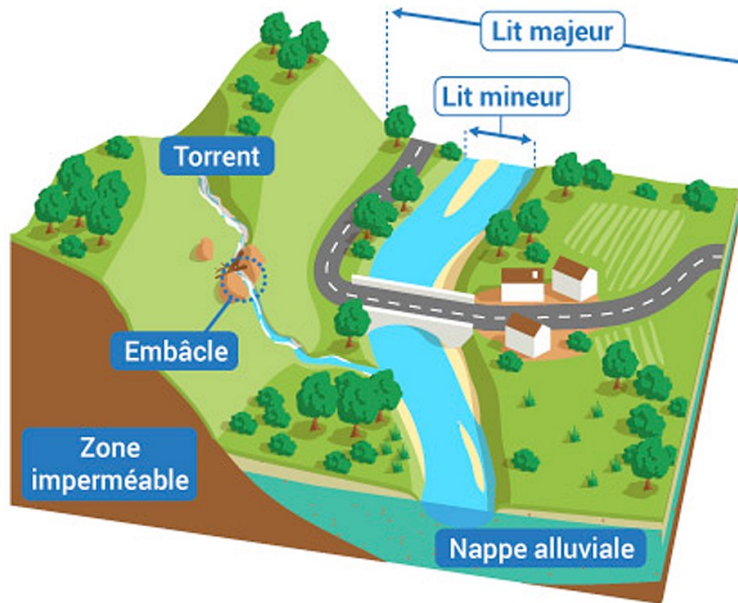


4th Workshop on Numérique en Terre Solide (GDR NuTS)

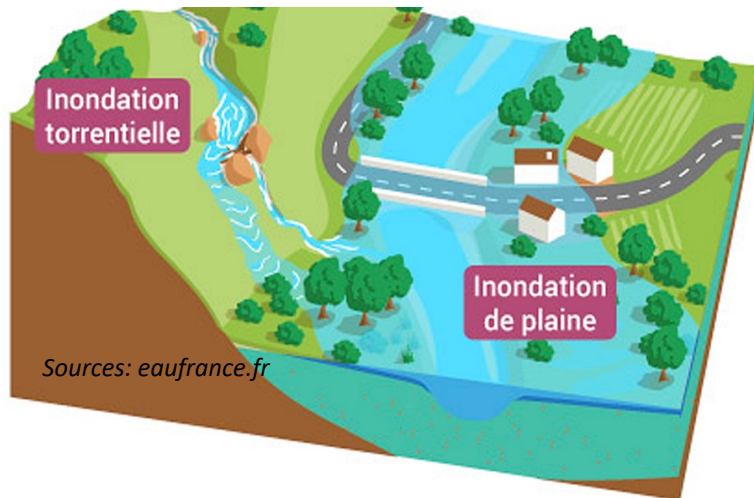
Ensemble-based data assimilation for high-fidelity flood forecasting with hydrodynamic models

Thanks to Ludovic Cassan, Andrea Piacentini, Quentin Bonassies, Théo Garin, Gabriel Besnard, Raquel Rodriguez Suquet (CNES), Thanh Huy Nguyen (LIST), Simon Munier (CNRM, MF), Telemac Consortium, ANR-SWIFT partners, AST Hydrologie Spatiale OMP, ...

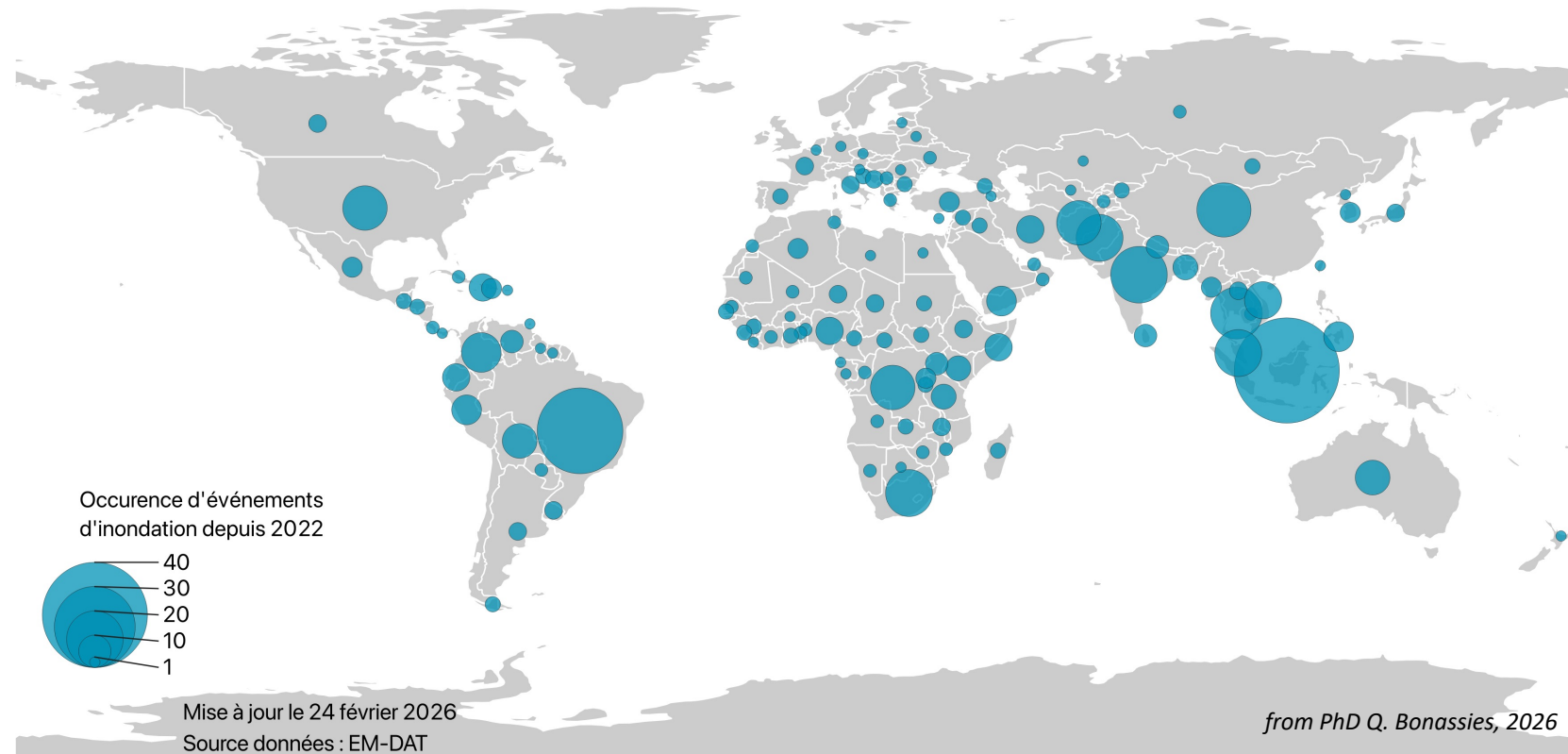
Hydrology: Flooding and Observations



River and flood plain dynamics



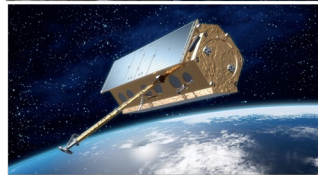
Worldwide flood events since 2022



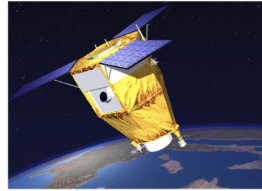
- ✓ Inondation : Major environmental risk (Emergency Events Database)
- ✓ Intensification of extreme events due to the impact of Climate Change

Hydrology: Flooding and Observations

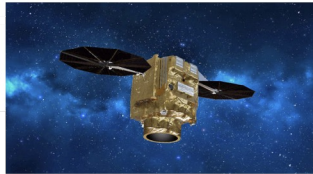
Sentinel 1&2 (ESA-Copernicus)
Synthetic Aperture Radar + Optical imagery for environmental Earth observation from space



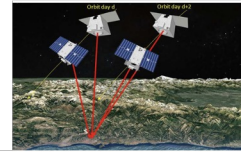
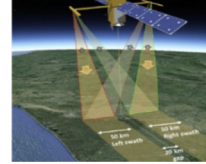
TerraSar-X
Tandem-X
X-band radar
sensor SAR



Pléiades/Pléiades-Néo
High-Resolution Optical Imaging Constellation
(CNES - Airbus DS)

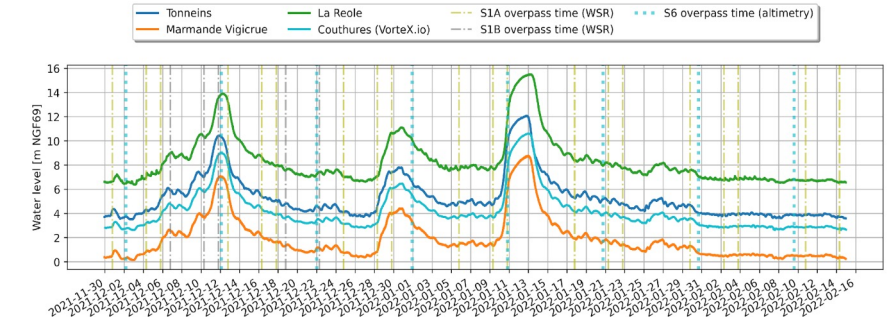


SWOT CNES-NASA
High resolution and global observation of
water level with Ka-Band Radar Interferometer

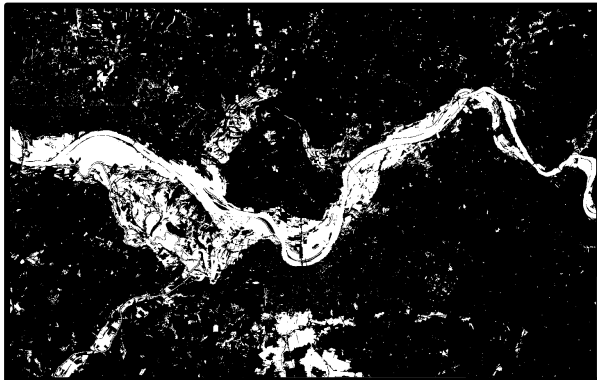


CO3D
High-Resolution Optical 3D
Imaging Constellation for DSM

In-situ network (water depth)

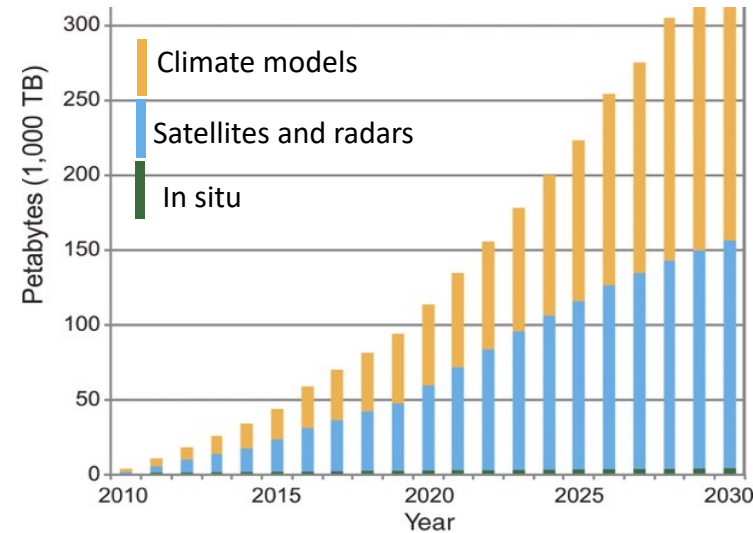


Earth Observation from space

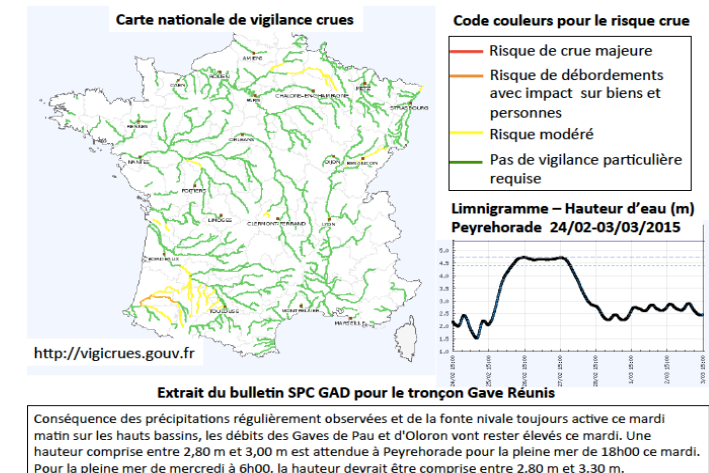


Binary flood map derived from Sentinel 1

A large volume of heteroneous imperfect data



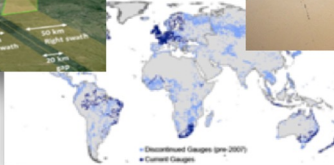
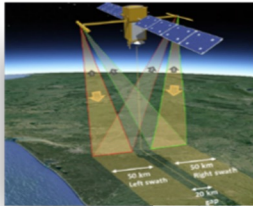
Operational monitoring and short term forecasting



Hydrology: Flooding and Observations

Operational issue

How to predict river discharge for flood forecasting and water balance estimation?



Observations

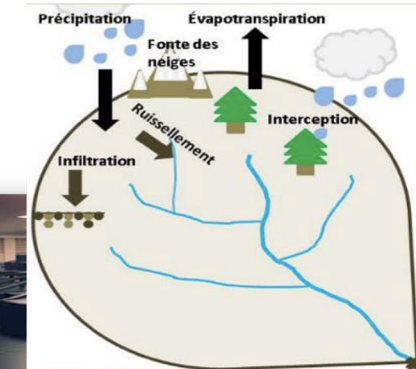
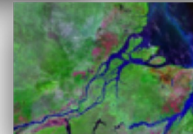
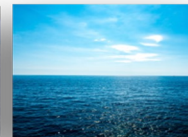
- in-situ : high frequency but sparse
- remote sensing : spatial coverage but low temporal coverage
- Various nature of errors



Data assimilation

Scientific issue

How to apply data assimilation to predict discharge and water level in rivers, estuaries and lakes ?

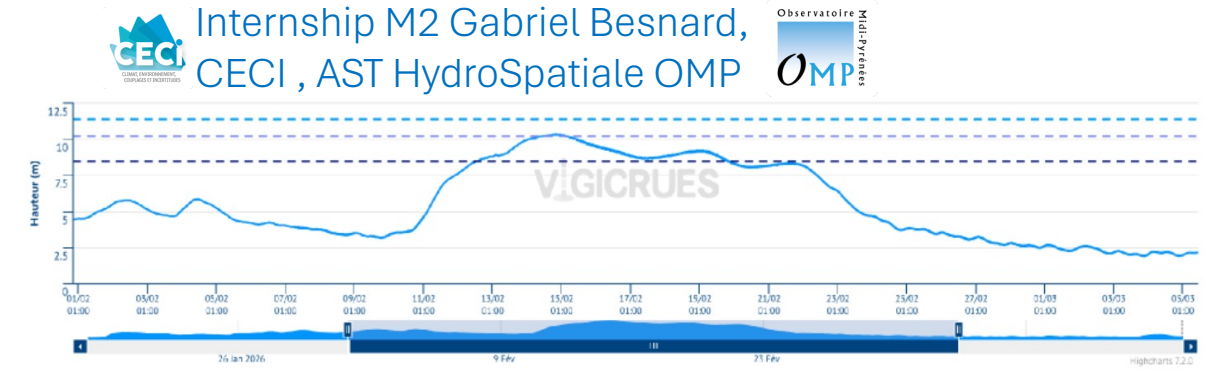
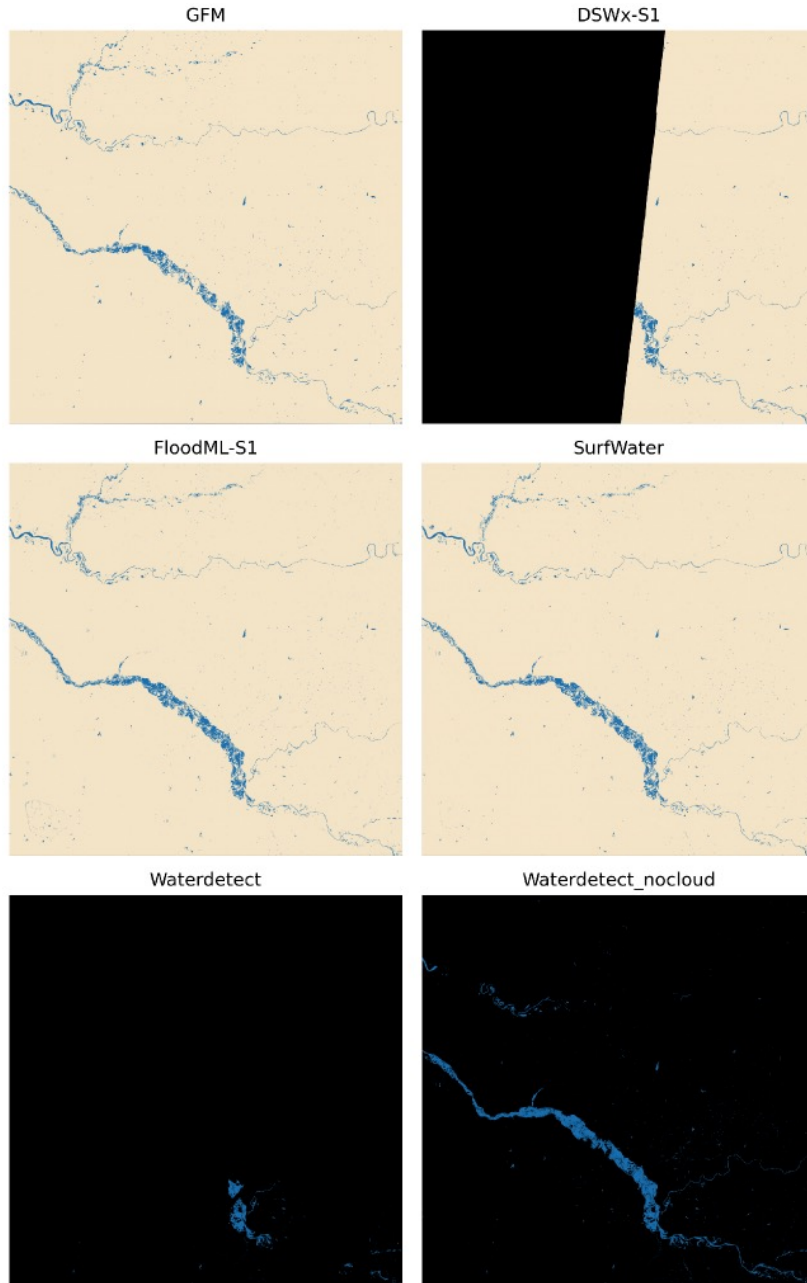


Numerical simulations

- Simplified Navier-Stokes equations 1D, 2D, 3D
- Limited information on bathymetry, topography, friction, hydrology, rainfall and maritime forcing

Applied mathematics algorithms: Data Assimilation to reduce uncertainties

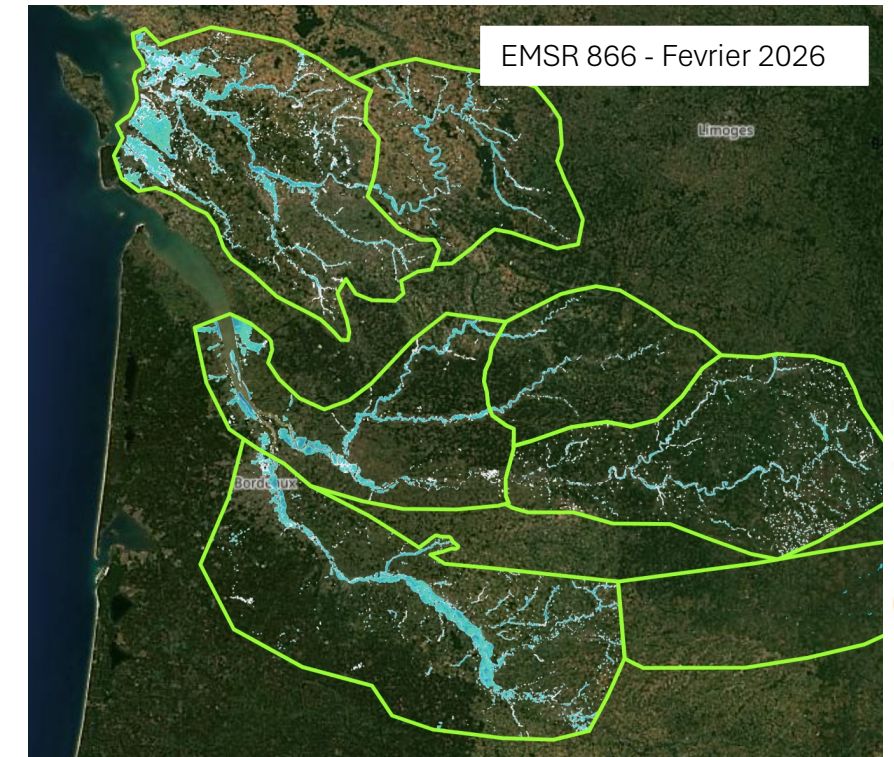
Remote sensing and automatic tools for FE generation from Sentinel images



Légende

—●— Marmande (Garonne) — — Crue du 23 juin 1875 - 11.39 m — — Crue du 5 février 2021 - 10.22 m — — Crue du 12 janvier 2022 - 8.48 m

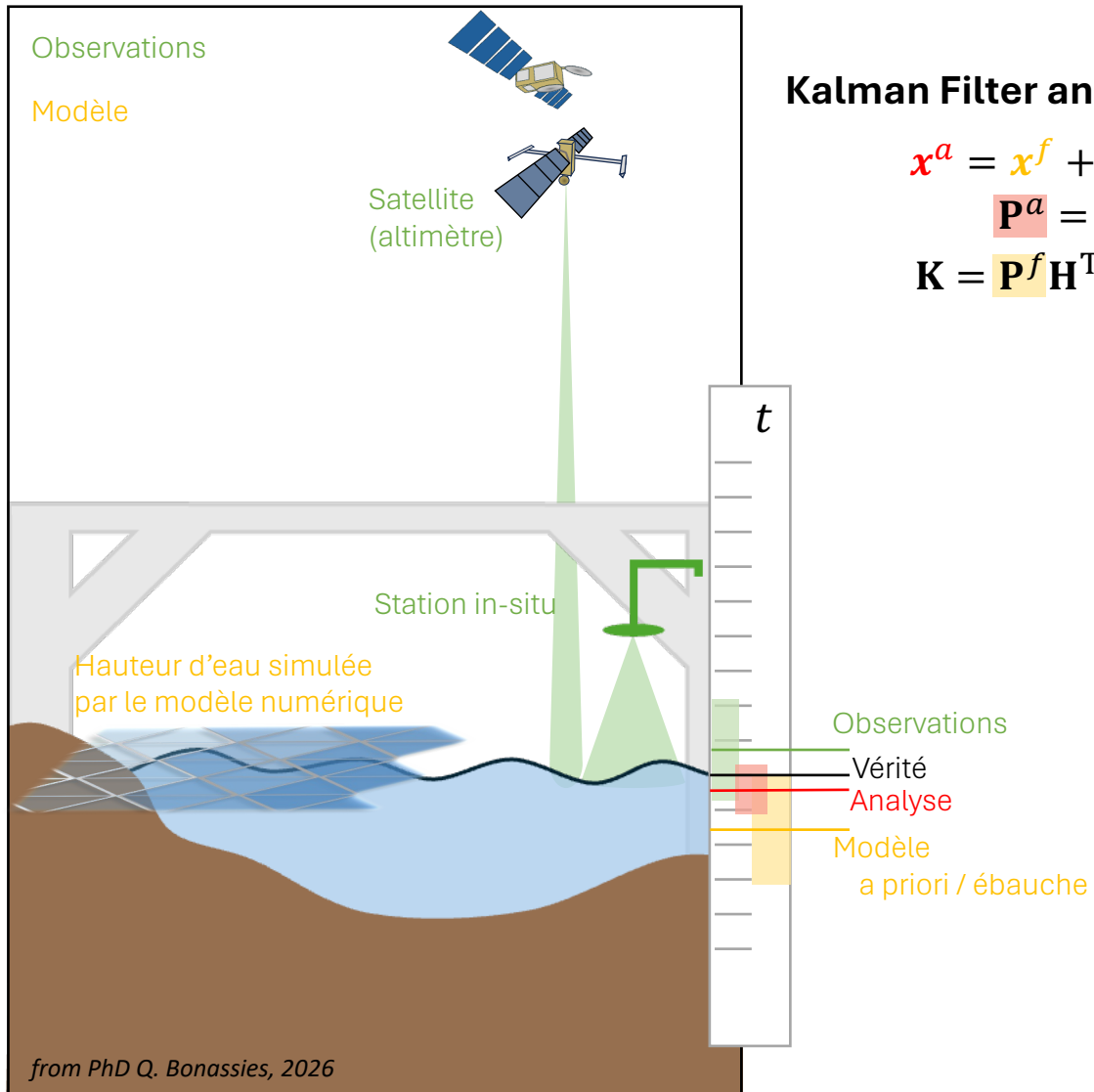
Emergency Management Service Rapid Mapping



PROGRAMME OF THE
EUROPEAN UNION



Data Assimilation in Hydrology



Kalman Filter analysis equations

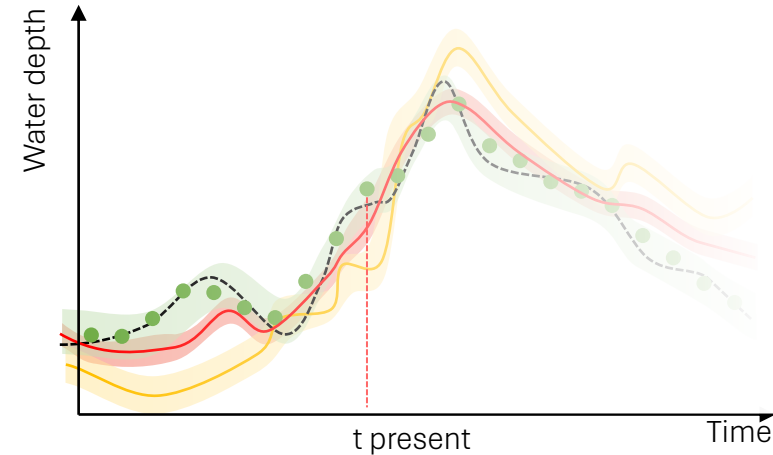
$$\mathbf{x}^a = \mathbf{x}^f + \mathbf{K} (\mathbf{y}^o - \mathcal{H}(\mathbf{x}^f))$$

$$\mathbf{P}^a = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}^f$$

$$\mathbf{K} = \mathbf{P}^f \mathbf{H}^T (\mathbf{H} \mathbf{P}^f \mathbf{H}^T + \mathbf{R})^{-1}$$

Kalman (1960)

Reduction of incertitudes and up date of model parametrers and states assimilating observations available up to present time t



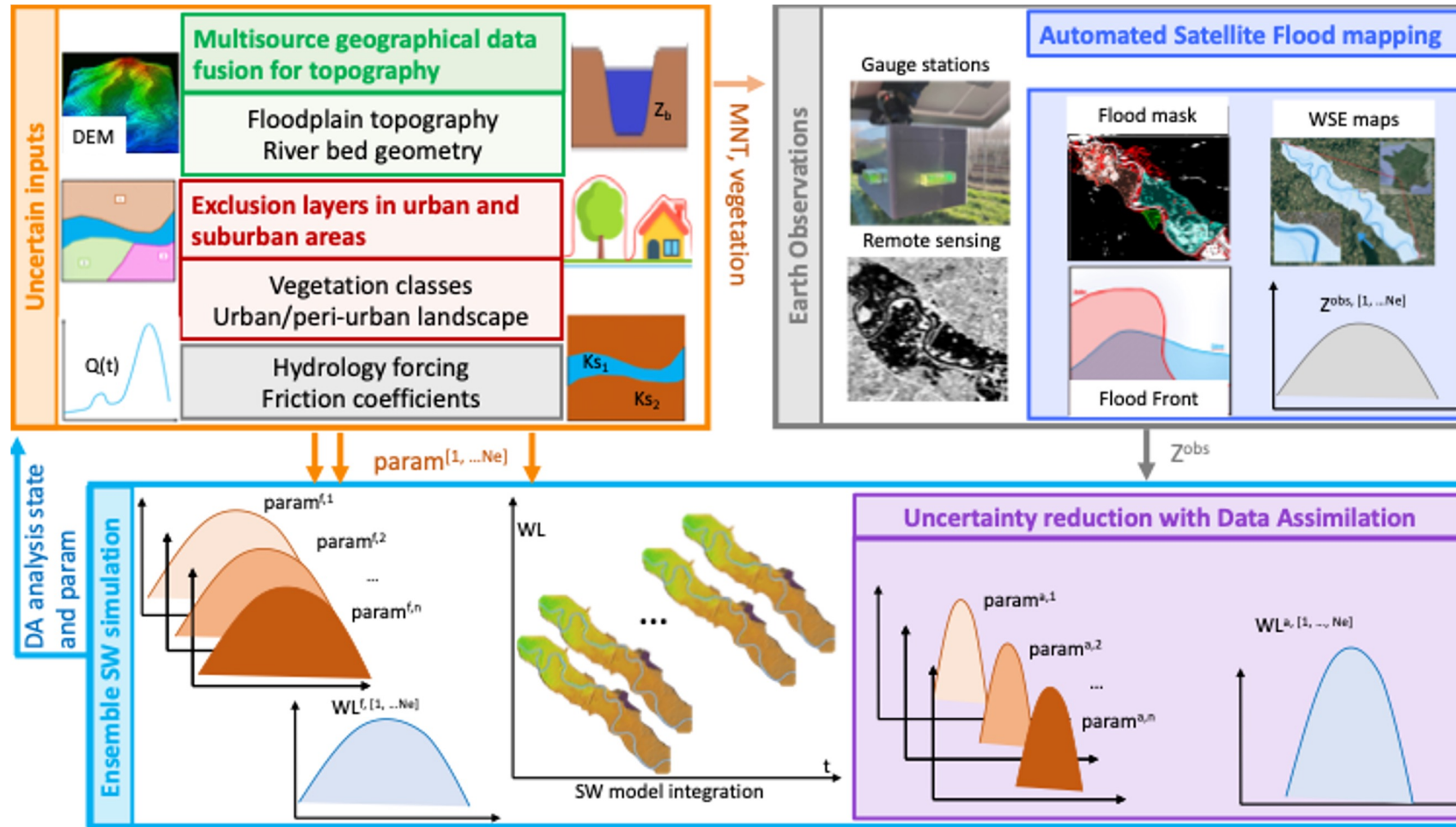
Data Assimilation in Hydrology – SWIFT ANR Project



Shallow Water modelling and satellite Imagery combination for improving Flood prediction

WP1: Produce an improved and high resolution DEM/DSM. Post treat RS images (Pléiades, CO3D) and make the most of the fusion of heterogeneous data to account for local structures (bridges, drains, weirs, ...) in DEM

WP2: Generate an exclusion map to restrain the SAR-derived flood extent to is area of reliability with an accurate classification of land cover



WP3: Develop an improved automated flood mapping system based on SAR and optical data (Sentinel, SWOT, ...)

WP4: Implement ensemble-based DA algorithms to reduce errors in hydrology-hydrodynamic models' input parameters and state making the most of in-situ and Remote Sensing data

Data Assimilation in Hydrology – Short summary on EnKF

$\mathbf{x}$ is the control vector, it spans in the control space and contains

- ▶ the state vector $\mathbf{x}_t$ at time t ,
- ▶ the state vector $\mathbf{x}_0$ at time t_0 ,
- ▶ the model parameters λ ,
- ▶ the boundary conditions $f(t, \mathbf{z})$, function of time and space

$\mathbf{y}$, is the model equivalent in the observation space

- ▶ observations in time
- ▶ observations in space.

$\mathcal{G}$ is the observation operator that maps $\mathbf{x}$ onto the observation space: $\mathbf{y} = \mathcal{G}(\mathbf{x})$

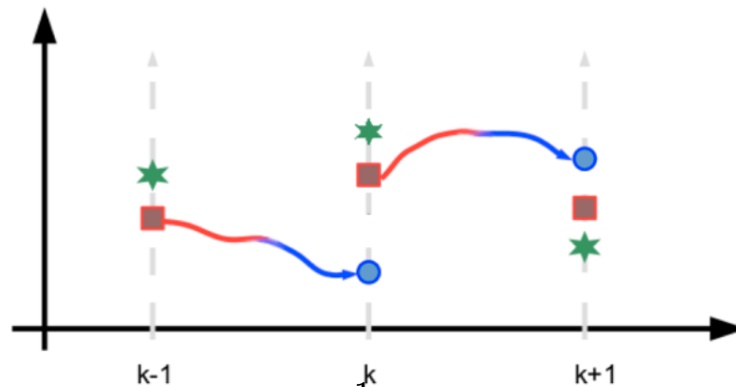
- ▶ $\mathcal{G} = \mathcal{S}$ is a selection matrix (linear) if $\mathbf{x} = \mathbf{x}_t$
- ▶ $\mathcal{G} = \mathcal{S} \circ \mathcal{M}$ is the generalized observation operator composed of the integration of the model over time and the selection matrix $\mathcal{S}$.

Evensen, 1994

Data Assimilation in Hydrology – Correction of model state at time t with EnKF

- ▶ Propagation for cycle k : $\mathbf{x}_k^b = \mathcal{M}(\mathbf{x}_{k-1}^a)$
The analysis step contains the model integration over $[t, t + T]$

- ▶ Analysis for cycle k : $\mathbf{x}_k^a = \mathbf{x}_k^b + \mathbf{K} [\mathbf{y}_k^o - \mathcal{G}(\mathbf{x}_k^b)]$



$\mathbf{x}^a$: analysis vector
 $\mathbf{x}^b$: background vector
 $\mathcal{G}(\mathbf{x}^b)$: in obs. space
 $\mathbf{y}^o$: obs. vector

$\mathbf{K} = \mathbf{B}_{xy} (\mathbf{B}_{yy} + \mathbf{R})^{-1}$: Kalman gain

$\mathbf{R}$: Observation error covariance matrix

$\mathbf{B}_{yy}$: Covariance matrix for background state error in observation space

$\mathbf{B}_{xy}$: Covariance matrix for background error on the entire state and the state at observation point.

- ▶ Propagation for cycle k between $[t, t + T]$:
 $\lambda_k^b = \mathcal{P}(\lambda_{k-1}^a)$
with $\mathcal{P}$ the model parameter evolution model (persistence, random walk, inflation, ...)
- ▶ Analysis for cycle k between $[t, t + T]$:
 $\lambda_k^a = \lambda_k^b + \mathbf{K} [\mathbf{y}_k^o - \mathcal{G}(\lambda_k^b)]$
with $\mathcal{G}(\lambda_k^b) = \mathcal{S} \circ \mathcal{M}_{t,t+T}(\lambda_k^b)$

The analysis step contains the model integration over $[t, t + T]$

$\mathbf{B}_{\mathbf{xy}}$: Covariance matrix between background model parameter error and model parameter equivalent in observation space.

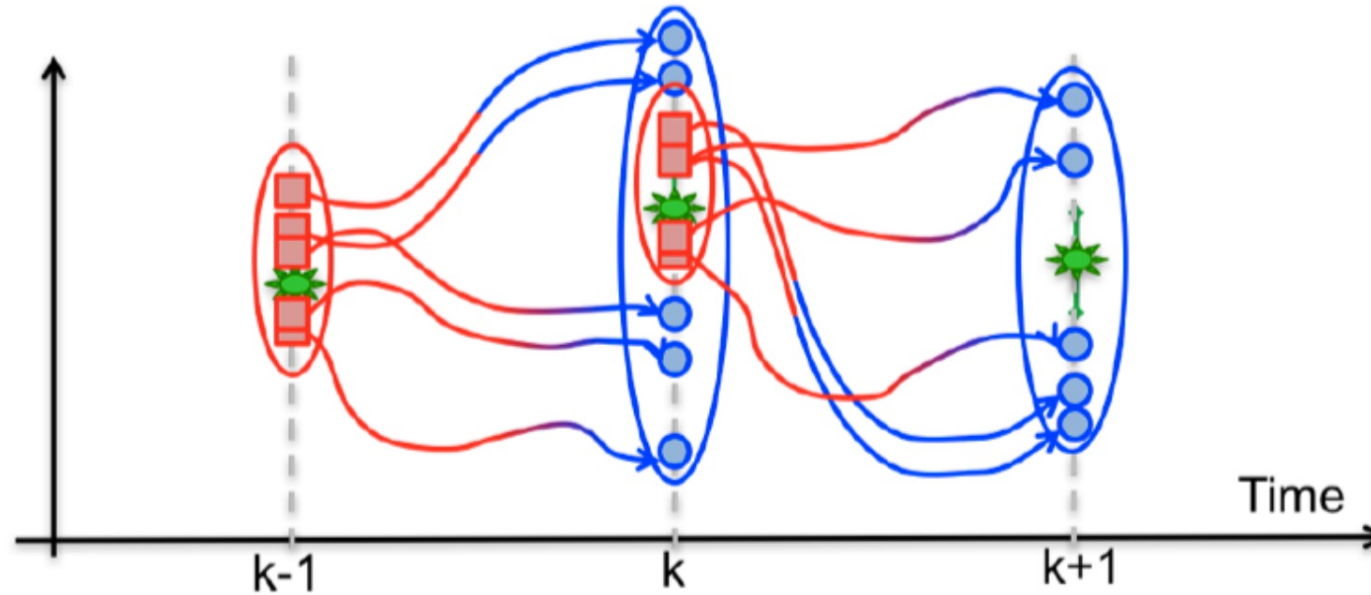
Issues for the Kalman Filter:

Compute $\mathbf{y}^b = \mathcal{G}(\mathbf{x}^b)$ with $\mathcal{H}$ complex and non-linear

Compute $\mathbf{B}_{yy}$, $\mathbf{B}_{xy}$

To use an Ensemble of Kalman Filters

Monte Carlo sampling with N_e members



Generate the ensemble with perturbations $\delta^{(r)}$ for each member

$$\mathbf{x}_{k-1}^{a(r)} = \bar{\mathbf{x}}_{k-1}^a + \delta^{(r)}$$

Integrate the model to obtain

$$\mathbf{x}_k^{b(r)} = \mathcal{M} \left(\mathbf{x}_{k-1}^{a(r)} \right)$$

$$\mathbf{y}_k^{b(r)} = \mathcal{G} \left(\mathbf{x}_{k-1}^{a(r)} \right)$$

Calculate stochastically (index k has been dropped)

$$\mathbf{B}_{yy} = \frac{1}{R-1} \sum_{i=1}^R \left(\mathbf{y}^{b(r)} - \bar{\mathbf{y}}^b \right) \left(\mathbf{y}^{b(r)} - \bar{\mathbf{y}}^b \right)^T$$

Calculate stochastically (exponent (k) has been dropped)

$$\mathbf{B}_{xy} = \frac{1}{R-1} \sum_{i=1}^R \left(\mathbf{x}^{b(r)} - \bar{\mathbf{x}}^{b(r)} \right) \left(\mathbf{y}^{b(r)} - \bar{\mathbf{y}}^b \right)^T$$

Observation and modeling of flooding area – Garonne Marmandaise

Model provided by EDF

- 50-km river reach
- Downstream from the Garonne-Lot confluence
- High flood risk impacting urban area
- Topo. and bathy. provided by IGN

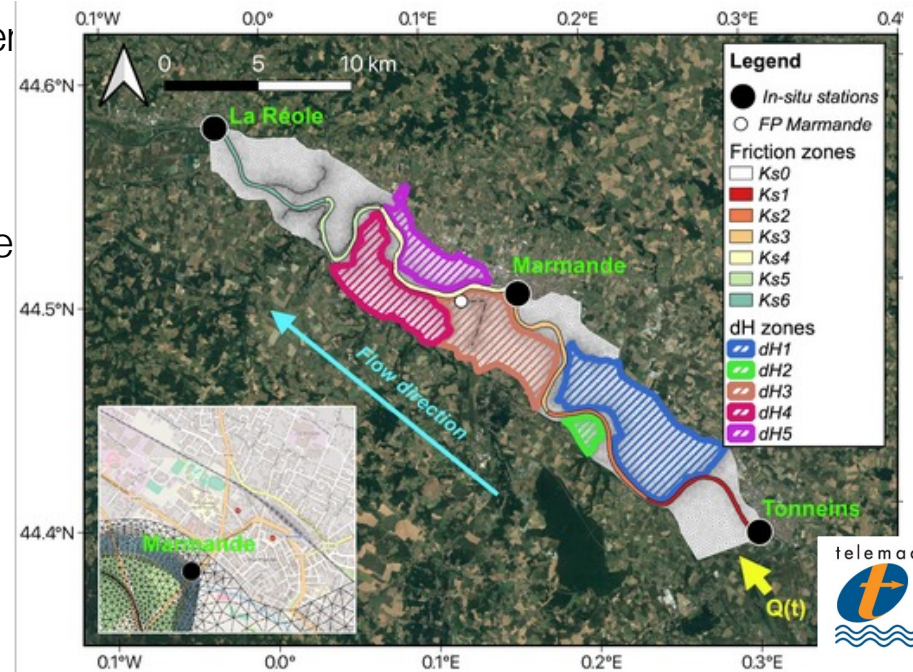
Mesh (41K nodes) with different triangle size among riverbed, floodplain and dykes.

Boundary conditions:

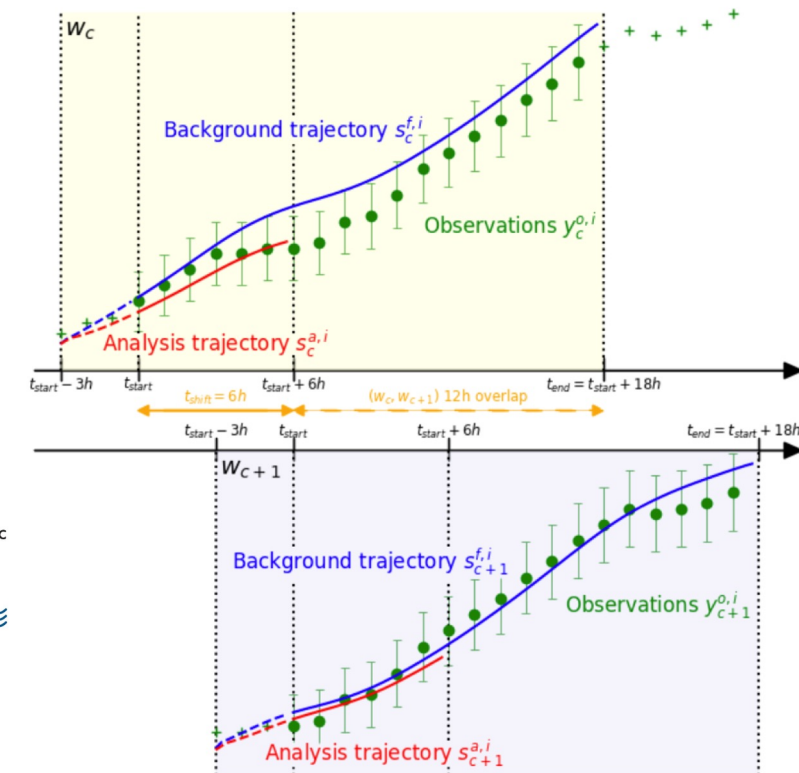
- Upstream hydrograph $Q_{up}(t)$ at Tonneins
- Downstream rating curve $Z(Q)$ at La Réole

Observations:

- In-situ data: 3 VigiCrue observing stations
- Remote sensing WSR observations in 5 subdomains of the floodplain
- Five defined hydraulic state correcting zones dH1-5 in the floodplain



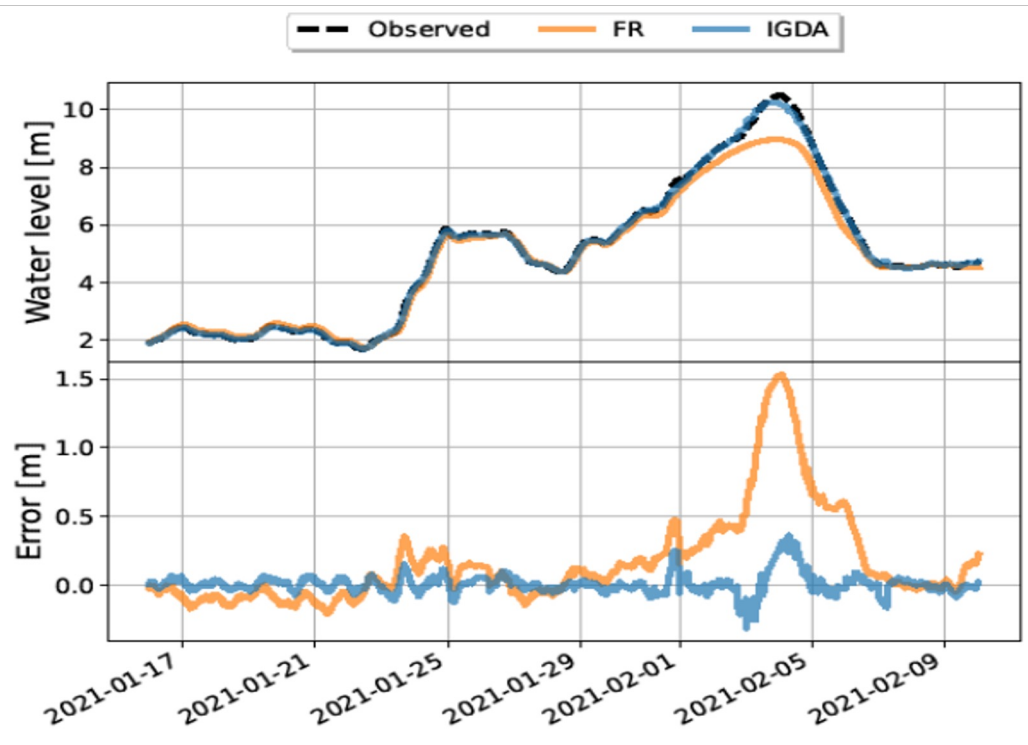
Sequential data assimilation



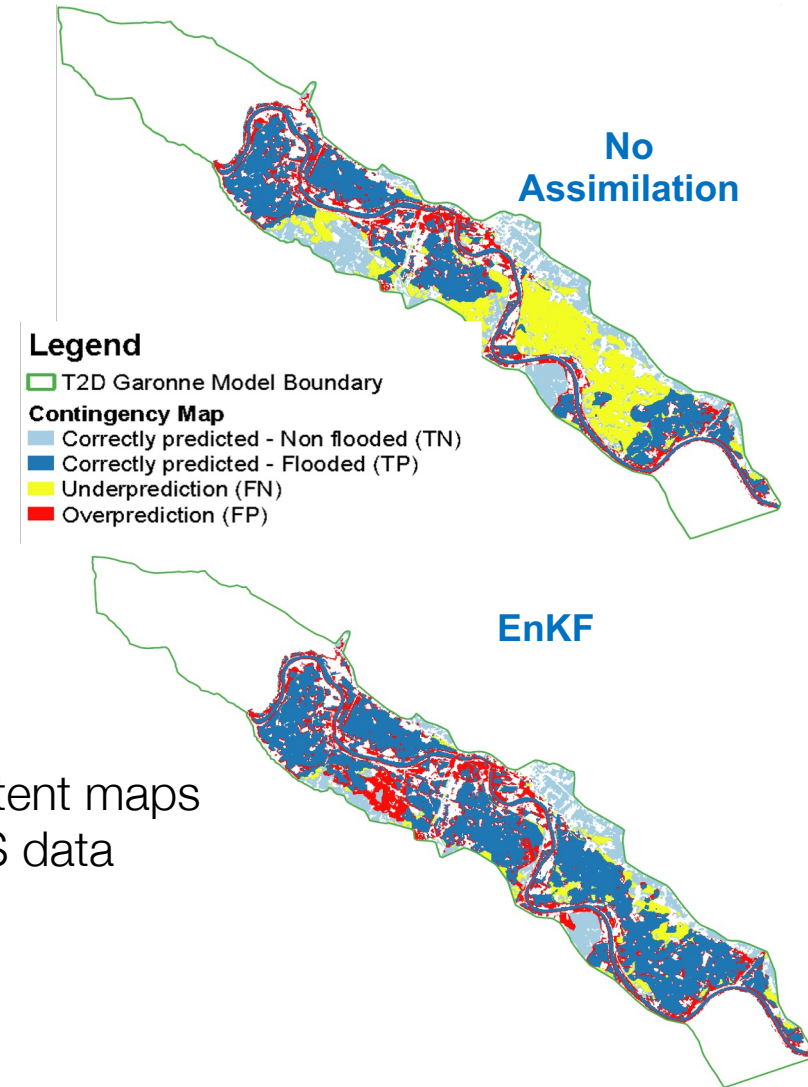
Nguyen et al., WRR 2026

Assimilation of in-situ and remote sensing S1-derived data

Simulated vs. observed water level



Simulated vs. observed flood extent maps



Clear improvement of simulated flood extent maps using Data Assimilation of in-situ and RS data

Hydrodynamic model : Telemac 2D
FR : Free run simulation
ASSIM-IGDA: FR simulation with Data assimilation of in-situ and remote sensing observations

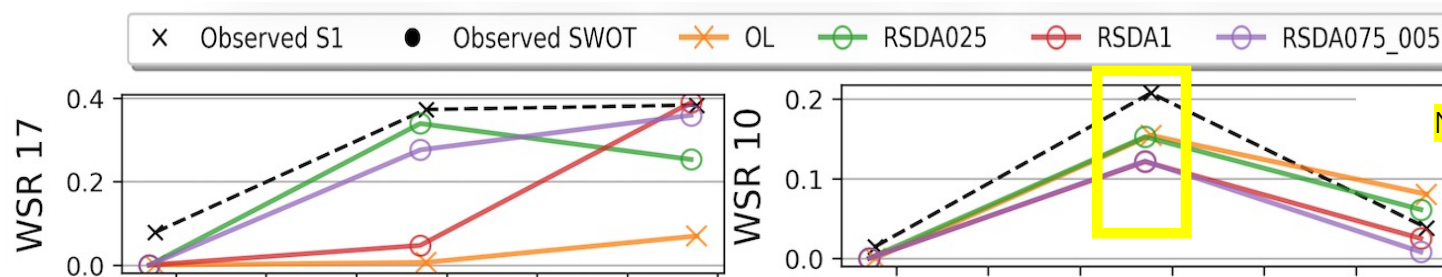
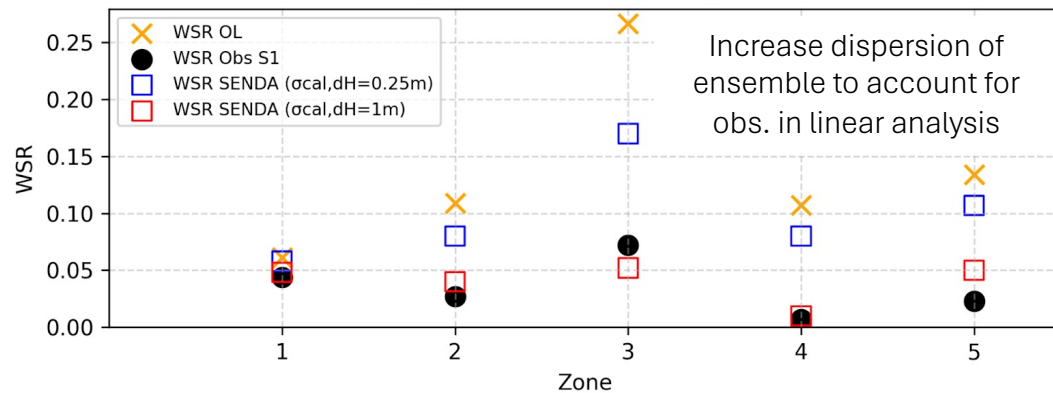
EnKF T2D assimilation of S1-derived Water Surface Ratio for Ohio River

Conf. RiverFlow 2026

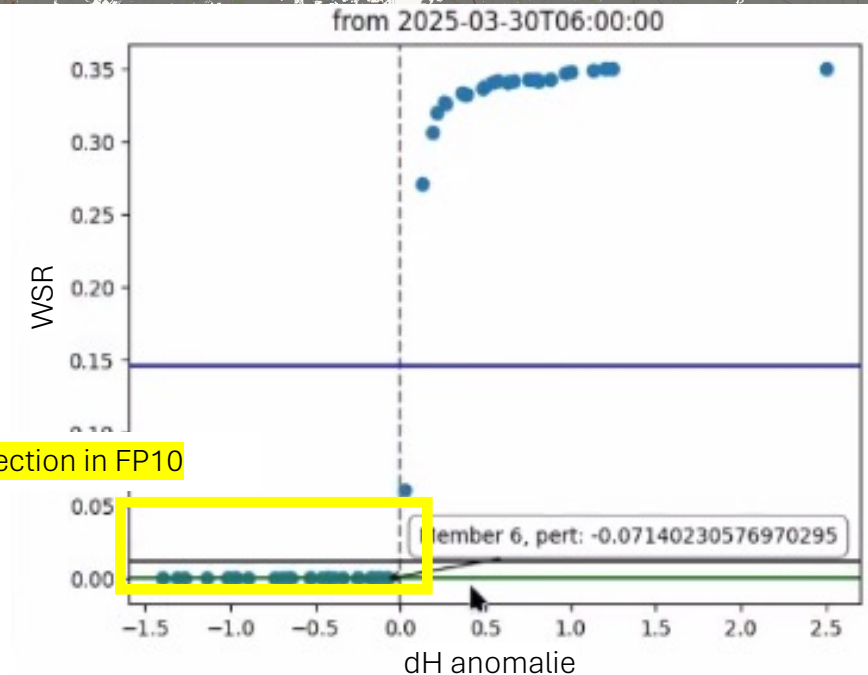
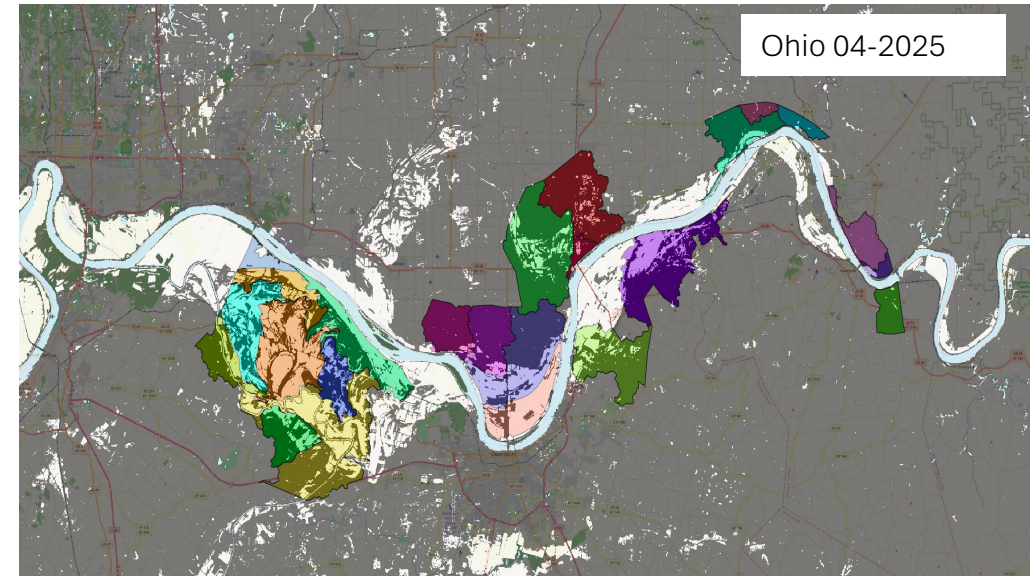
Challenges :

- Definition of disconnected subdomains (automatic)
- Investigation of ensemble dispersion and obs. errors (RF2026)
- Suboptimality of the filter due to dH perturbations response (dry areas)
- Filtering of forest + urban pixels : need for improved FE product with associated uncertainty (EGU2026)

Impact of WSR obs. error



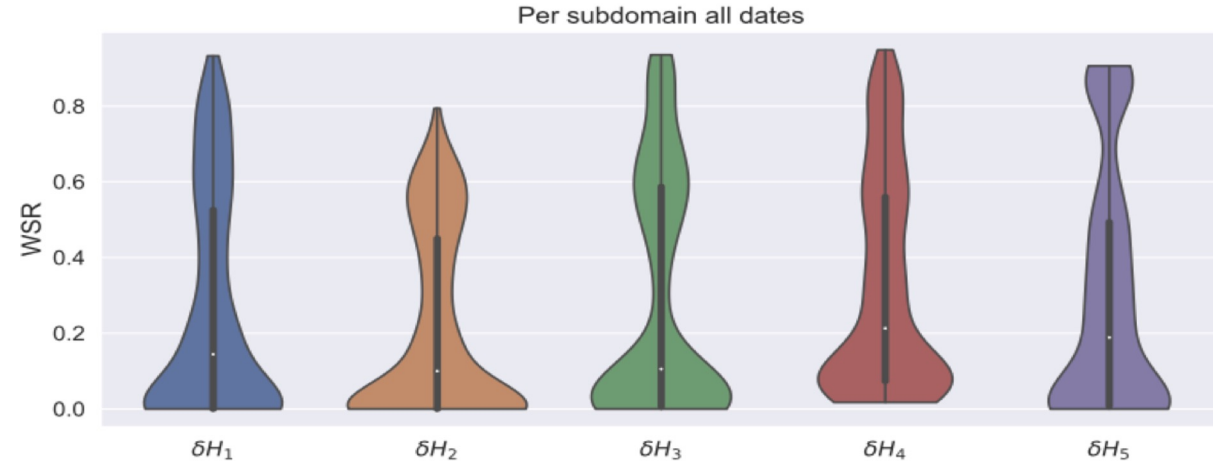
S. Ricci, NuTS, 26/05/2026



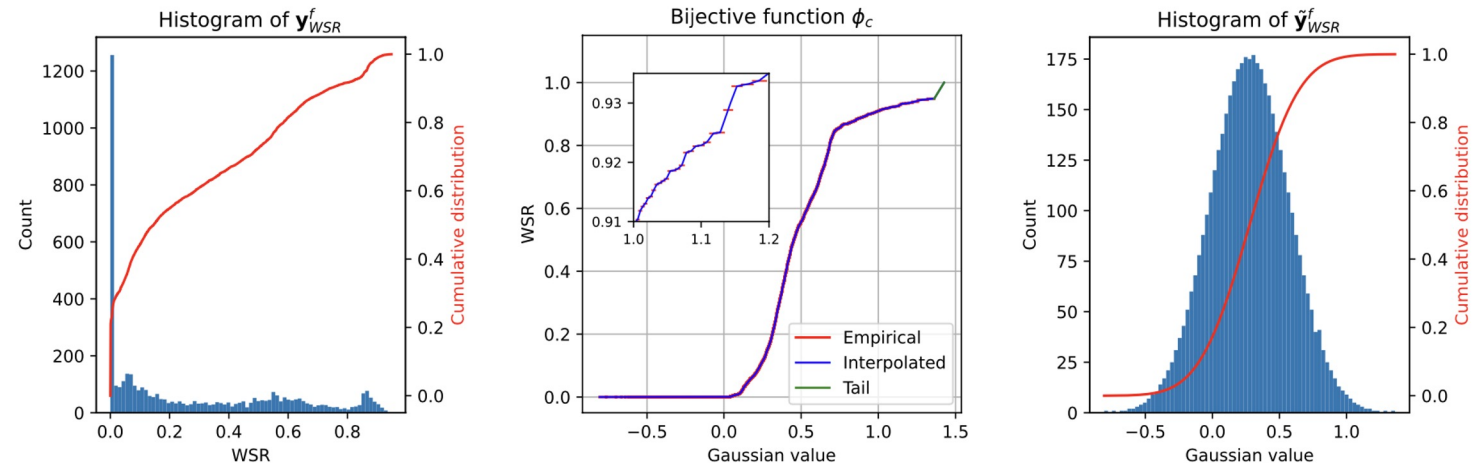
Treatment of non-gaussian observation errors with EnKF

Nguyen et al., TGRS 2024

WSR observation errors non-gaussian,
which triggers the optimality of the filter



The anamorphosis function is a non-linear bijective function the maps WSR physical space to Gaussian space

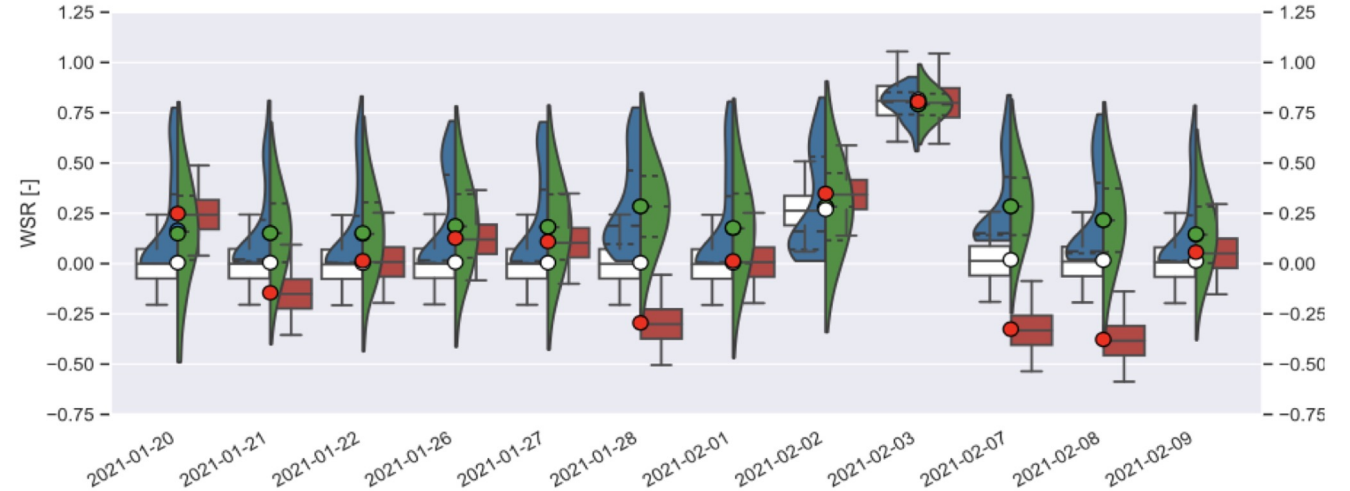
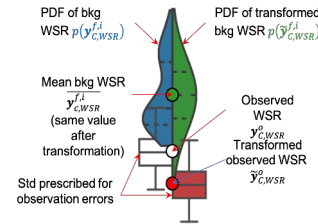


$$\tilde{\mathbf{y}}_{c,WSR}^{o,i} = \phi_c \left(\mathbf{y}_{c,WSR}^{o,i} \right), \quad \tilde{\mathbf{y}}_{c,WSR}^{f,i} = \phi_c \left(\mathbf{y}_{c,WSR}^{f,i} \right)$$

Treatment of non-gaussian observation errors with EnKF

Nguyen et al., TGRS 2024

Result of the anamorphosed vector for the equivalent of the WSR observations



- ★ This comes to redefining the observation operator that maps the hydraulic state onto the transformed space

$$\tilde{\mathbf{y}}_c^{f,i} = \tilde{\mathcal{H}}_c(\mathbf{s}_c^{f,i}) = \phi_c(\mathcal{H}_c(\mathbf{s}_c^{f,i}))$$

- ★ The EnKF analysis is now carried out in the transformed Gaussian space

$$\mathbf{x}_c^{a,i} = \mathbf{x}_c^{f,i} + \mathbf{K}_c(\tilde{\mathbf{y}}_c^{o,i} - \tilde{\mathbf{y}}_c^{f,i})$$

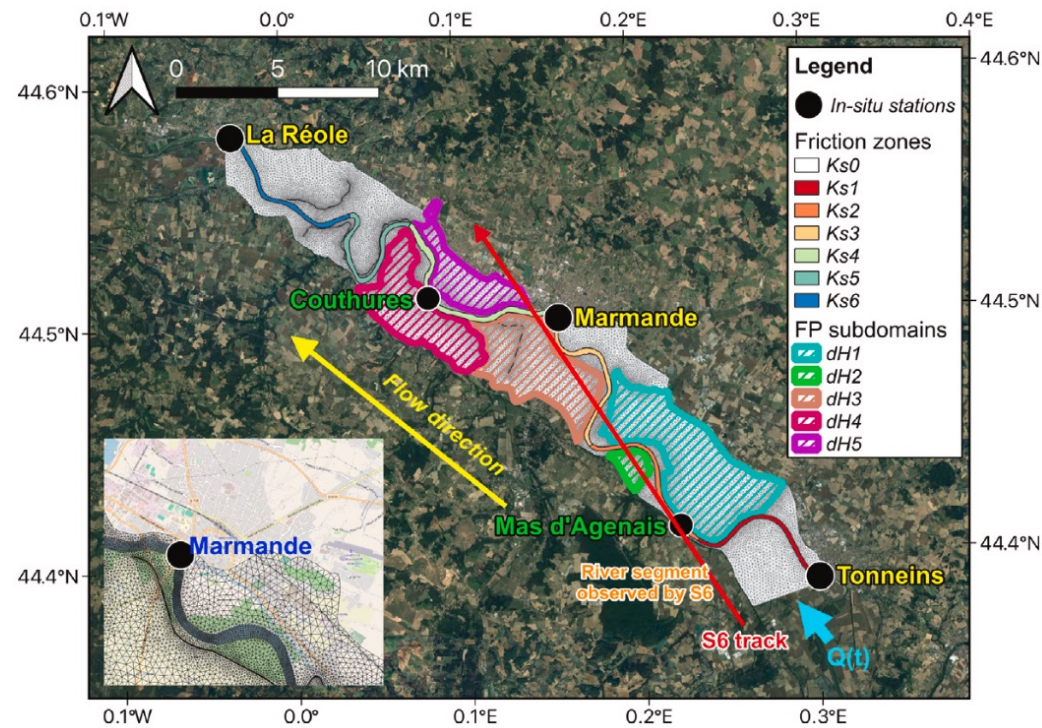
with the stochastic estimation of the covariance using the transformed observed vector Gaussian space

$$\mathbf{K}_c = \mathbf{P}_c^{\mathbf{x},\tilde{\mathbf{y}}}[\mathbf{P}_c^{\tilde{\mathbf{y}},\tilde{\mathbf{y}}} + \mathbf{R}_c]^{-1}$$

EnKF T2D Multi-mission remote sensing DA for flood modeling with Sentinel 6

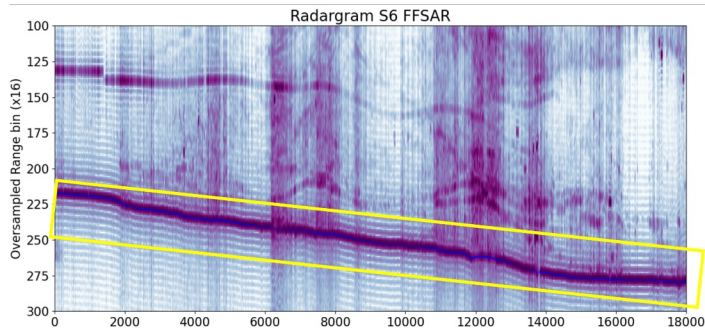
Nguyen et al., JoH 2026

Garonne Marmandaise

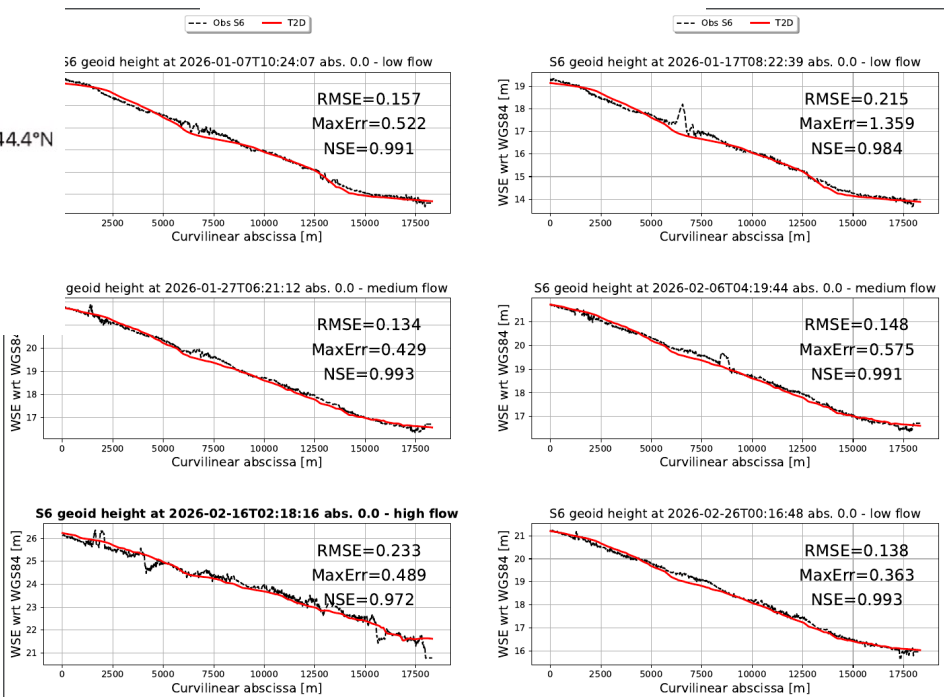


Flood Event Dec2021-Jan2022

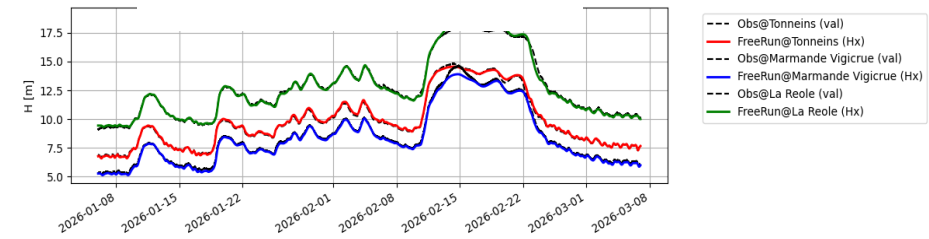
Altimetry data from Sentinel 6



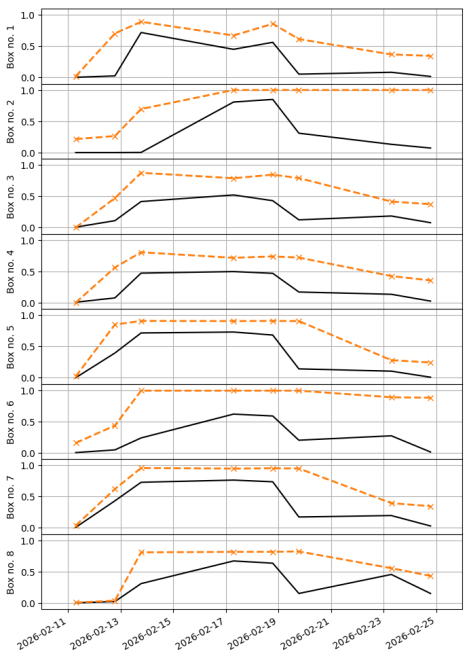
WSE T2D OL versus S6



Flood event Feb. 2026

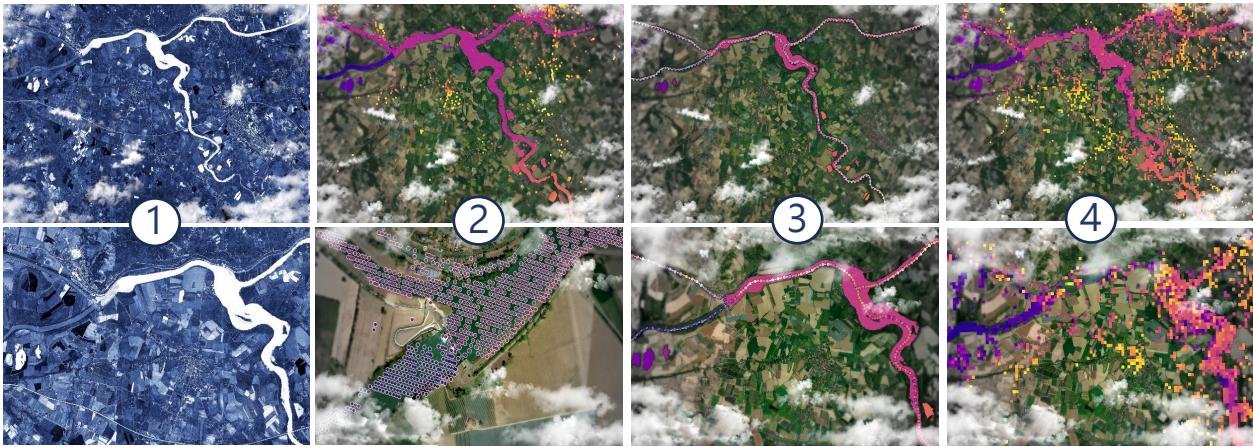


WSR T2D OL versus S1



EnKF T2DiSurf SWOT-nodes RiverSP WSE remote sensing data assimilation for flooding

Bonassies et al., JSTAR 2026

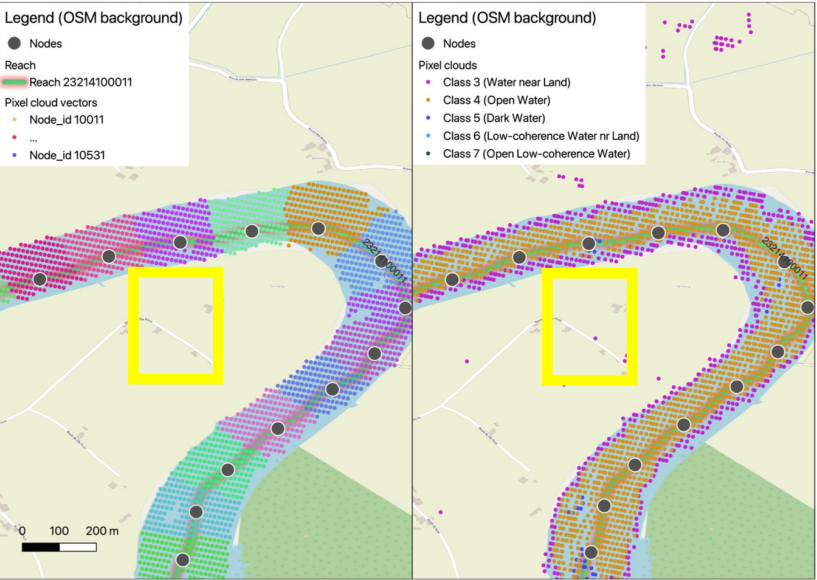


Source: N. Gasnier, EGU2024

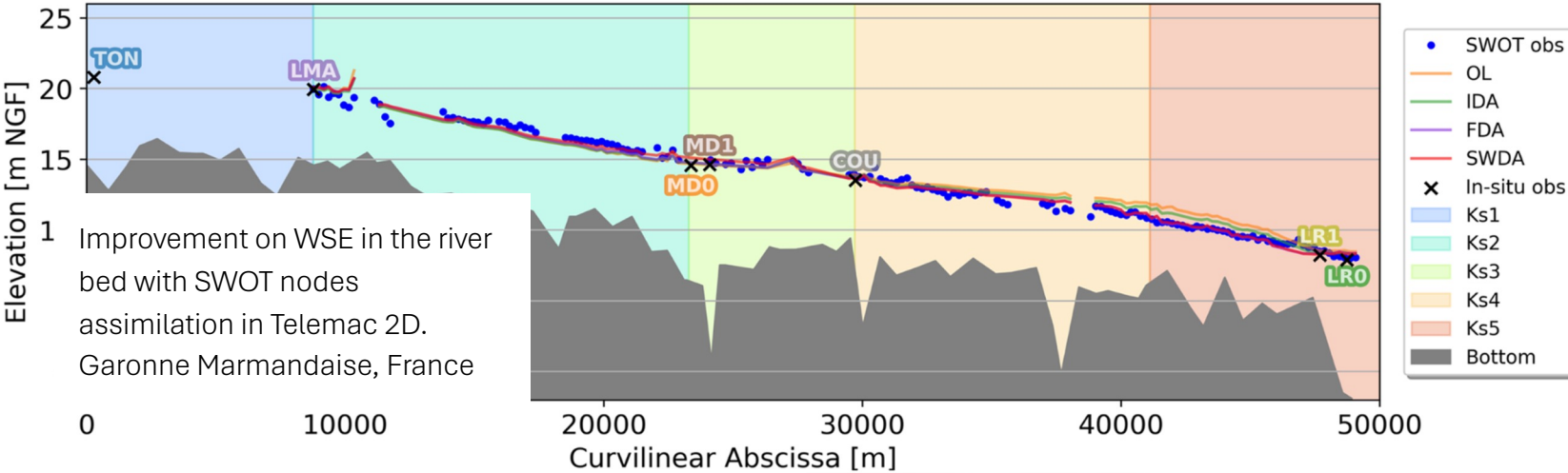
The swot HR products for hydrology:

- Level-1b HR Single Look Complex (only available on PO.DAAC)
- Level-1 HR Pixel Cloud (and Pixel Cloud Vector companion product)
- Level-2 HR Single Pass (River Reach/Node, Lake)
- Prior Observed/Unassigned)
- Level-2 HR Average (River, Lake)
- Level-4 HR Raster 100m/250m

L2 RiverSP WSE at SWOT-Nodes along river center line



Assimilation of L2 RiverSP WSE at SWOT-Nodes along river center line – 2024-02-18



Improvement on WSE in the river bed with SWOT nodes assimilation in Telemac 2D. Garonne Marmandaise, France



Assimilation de données des étendues des inondations obtenues par télédétection pour la prévision des inondations : Apports des données issues du satellite SWOT

Thèse soutenue par Quentin Bonassies

21 avril 2026

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M. Ludovic CASSAN, Directeur de thèse, UMR CECI, CERFACS
M. Christophe FATRAS, Co-directeur de thèse, CLS

Membres invités:
M. Santiago PENA LUQUE, co-encadrant, CNES
Mme Sophie RICCI, co-encadrante, UMR CECI, CERFACS

Logos: IRD, cnrs, Université de Toulouse, CECI, cnes, CLS, CERFACS

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journal homepage: www.elsevier.com/locate/rse

A comprehensive study of Surface Water and Ocean Topography (SWOT)
Pixel Cloud data for flood extent extraction

Quentin Bonassies^{a,d}, Christophe Fatras^b, Santiago Peña-Luque^c, Pierre Dubois^b, Andrea Piacentini^d, Ludovic Cassan^{a,d}, Sophie Ricci^{a,d}, Thanh Huy Nguyen^e

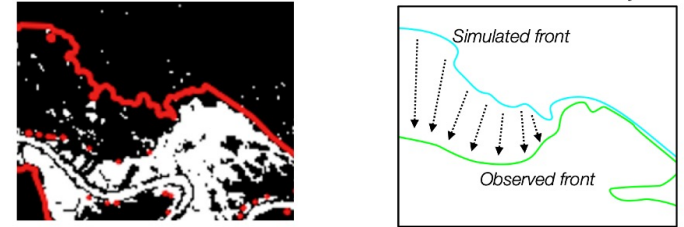
7024 IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 19, 2026

Assimilation of SWOT Altimetry Data for Riverine Flood Reanalysis: From Synthetic to Real Data

Quentin Bonassies^a, Thanh Huy Nguyen^a, Member, IEEE, Ludovic Cassan^a, Andrea Piacentini^a, Sophie Ricci^a, Charlotte Emery^a, Christophe Fatras^a, Santiago Peña Luque^a, and Raquel Rodríguez Suquet^a

Exploration of novel forms of data: assimilation of front-type features with Chan Vese metrics (image segmentation) and ETK

From pixel analysis... ... To a flood front analysis





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