Discharge estimation from surface observables and ancillary data

by P.-A. Garambois (INSA-ICUBE), K. Larnier (CS - CNES), J. Monnier (INSA-IMT)
with A. Montazem (LEGOS-ICUBE), H. Roux (INPT-IMFT), J. Verley (CNES-IMT), S. Calmant (IRD-LEGOS).

Outline

Part 1) On the discharge estimation from 1D & 0.5D models (by J. Monnier)
Part 2) Numerical experiments and ancillary databases (by K. Larnier)
Part 3) Insight on river networks segmentation and hydraulic controls (by P.-A. Garambois)

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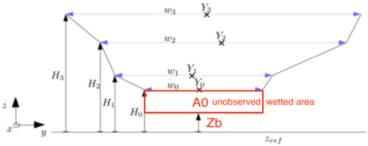
Outline

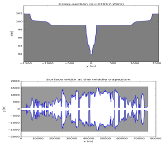
Discharge estimation from the 1D St-Venant model

The inverse model features

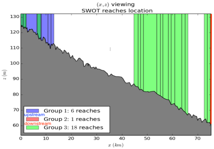
▷ Direct model : 1D St-Venant in (A, Q) variables (FV or FD scheme).



Effective wet-area : trapezium superimposition.



Width of middle trapeziums.



Simulator reaches.

▷ Variational Data Assimilation. Adjoint code fully automatic for the user.

DassFlow software [P. Brisset et al.] [J.Monnier et al.]. Stochastic tools possible by interfacing with OpenTurns.

▷ Identified parameters are :

- $Q_{in}(t)$ inflow discharge ; $K(h)$ varying Strickler coeff.
- Z_b effective topography elevation.
  and potentially $Z(Q)$ rating curve. Default outflow b.c. : normal depth.

An a-priori analysis

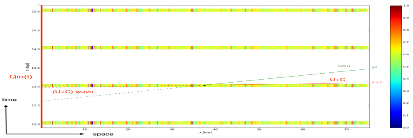
before the identification - model calibration

▷ Simulator like data, model outputs with Gaussian noise.
Reaches @ 200 m (RiverObs), noise $\sigma \sim 25$ cm (Garonne river, $\sim$ 80 km upstream portion).
Cal-Val repeat : 1 day with 377 reaches.
SWOT repeat ∼10 days with 25 reaches : not presented today, [Brisset et al.] in review.

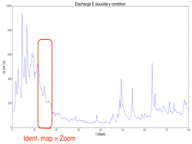
▷ **"Identifiability maps"** = model output read in the (x, t)-plane at obs times

$$\boxed{\left\{\begin{array}{ll}\dfrac{\partial S}{\partial t}+\dfrac{\partial Q}{\partial x} & = \\ \dfrac{\partial Q}{\partial t}+\dfrac{\partial}{\partial x}\left(\dfrac{Q^2}{S}+P\right) & =\end{array}\right.} \begin{array}{l} 0 \\ \boxed{g\int_0^h (h-z)\dfrac{\partial \tilde{w}}{\partial x}dz - gS[\dfrac{\partial z_b}{\partial x}+S_f]}\end{array}$$

Lines = wave propagation. Rectangle colors = misfit wrt equilibrium
= Manning's law residual.



(a) Cal-Val 1 day repeat



(b) The corresponding complete hydrograph

⇒ **Inference of reliable $Q_{in}(t)$ in the vicinity of the observation time,**

Identifiability time window sizes $\approx \dfrac{L}{(\bar{u}+\bar{c})} \approx$ day time scale

An a-priori analysis

before the identification - model calibration

▷ **"Identifiability maps"** = model output read in the (x, t)-plane at obs times

$$\boxed{\left\{\begin{array}{ll}\dfrac{\partial S}{\partial t}+\dfrac{\partial Q}{\partial x} & = \\ \dfrac{\partial Q}{\partial t}+\dfrac{\partial}{\partial x}\left(\dfrac{Q^2}{S}+P\right) & =\end{array}\right.}\begin{array}{l}0 \\ \boxed{g\displaystyle\int_0^h (h-z)\frac{\partial \tilde{w}}{\partial x}dz - gS[\frac{\partial z_b}{\partial x}+S_f]}\end{array}$$

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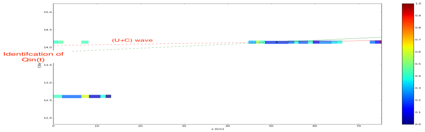
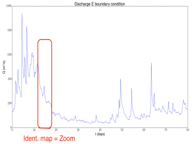


(c) SWOT (∼10 days, simulator swaths)



(d) The corresponding complete hydrograph

⇒ **Inference of reliable $Q_{in}(t)$ in the vicinity of the observation time**,

Identifiability time window sizes $\approx \dfrac{L}{(\bar{u}+\bar{c})} \approx$ day time scale.

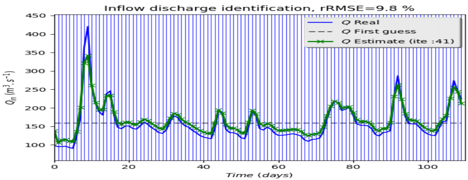
[P. Brisset et al.].

This is a rough analysis however confirmed by the numerical experiments.
VDA process is hopefully more complex and richer since least-square fitting in space - time and propagating of all the non-linear waves.

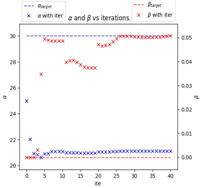
Discharge estimation & Model calibration

Garonne river (upstream). Cal-Val scenario.

VDA processes $\sim 15 - 50$ iterations of minimization. CPU time $\sim 10 - 100$mn on PC.



(e) Identified discharge $Q_{in}(t)$ Cal-Val SWOT data only, with outflow rating curve given.



(f) Optimisation iterations : friction coeff.

Computations : K. Larnier

▷ Two scenari related to the bathymetry :

Case 1) No prior information. 1st guess : Manning's law $(\bar{Q}^{(0)} = \bar{K}^{(0)} \cdot \Phi(Z_b^{(0)})) \Rightarrow Z_b^{(0)}$.

Case 2) One (1) in-situ depth value b_{ref} in the river section : low-Froude law $\Rightarrow Z_b^{(0)}$.

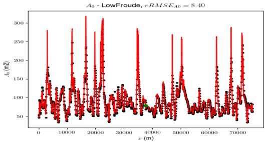
Case	1st guess required	1st guess $(\bar{Q}^{(0)}, \bar{K}^{(0)})$	RMSE $A_0^{(0)}$	RMSE $Q^{optim}(x,t)$
1)	$Q_{in}(t)$, K, Z_b	(30%, 30%) error	40%	9.8%
2)	$Q_{in}(t)$, K	$(\cdot, 30\%)$ error	8.5%	6.6%

On the bathymetry identification

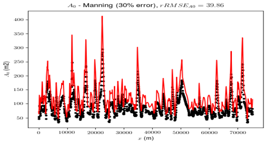
From the low-Froude model (0.5D)

▷ Case 1) While identifying the triplet $(Q_{in}(t), K(h), Z_b(x))$, without prior information the VDA process adjusts $Z_b(x)$ but not necessarily in the right way...
$\rightarrow$ Equifinality issue on the pair (K, Z_b).

▷ How to infer separately Z_b ?
A solution : the low-Froude relation (0.5D) with K constant + 1 ref. value b_{ref}.



(g) Lowest wetted section A_0 : infered value from the Low Froude eqn + 1 ref. value $\Rightarrow$ **RMSE $\sim$8.4%**



(h) A_0 inferred value from the Manning law with 30% errors on Q and K $\Rightarrow$ **RMSE $\sim$39.9%**. (Computations K. Larnier)

▷ Adopted strategy <u>if</u> one in-situ depth value b_{ref} is available in the section :
1) Infer the effective low-Froude bathymetry from the 0.5D model.
2) Perform the 1D VDA process to infer the pair $(Q_{in}(t), K(h))$.
$\Rightarrow$ The most accurate pair $(K(h), Z_b)$ (compared to those obtained if identifying the triplet).
$\Rightarrow$ A dynamic predictive model instead of a descriptive one only. [In prep.]

Summary

▷ 1D St-Venant model & VDA provide a good estimation of river portion discharges *at* $\sim$ *the "observation day"*, in $\sim$ an hour of computations - analyses.

Errors on $Q(x, t)$ at the observation times on the present example :
Cal-Val (1 day repeat) $\sim 8 - 10\%$, SWOT ($\sim$10 days partial repeat) $\sim 15 - 20\%$.

Synthetic data with noise, simulator scenari.

▷ The consequences of the equifinality issue on (K, Z_b) remains to be investigated more into details (from databases).

▷ The combination with regional databases can provide good bathymetry estimations, (in the sections with usable data) hence providing more accurate predictive models.

NB. The low complexity physical-based "discharge algorithms" *without additional information* (eg. GaMo, MetroMan etc) do not solve the equifinality issue.

▷ The low complexity inverse algorithms (AMHG, GaMo, MetroMan, MFG etc) are complementary. Moreover they can provide (near) real-time estimations (lower complexity...).

On-going & forthcoming studies

Forthcoming studies :

- Uncertainty Quantification within the model chain.
- Pursue the enrichment of our VDA algorithms to heterogeneous - multi-sources data and to the complete multi-dimensional - multi-scale modelling chain.

"DassFlow model" is based on the present hierarchical approach 0.5D-1D, including the 2D VDA model (not presented today).
Code sources are open to the community.

On-going studies :

- Combination of Regional Databases with the low complexity / 0.5D physical models :

  Low-Froude $\rightarrow$ Bathymetry
  Manning law $\rightarrow$ Discharge

  $\Rightarrow$ **See next part presented by K. Larnier.**

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On-going & forthcoming studies

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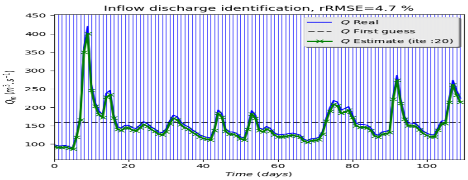

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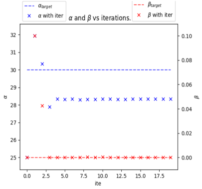

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Numerical results and ancillary databases

- Primary discharge algorithms tests (PEPSI dataset)
- Inversions with VDA and full Saint Venant
- Work on ancillary databases

Discharge algorithm

- Low complexity (Manning) equation
  - A0 assumed known
  - Computation of K using reference point(s):

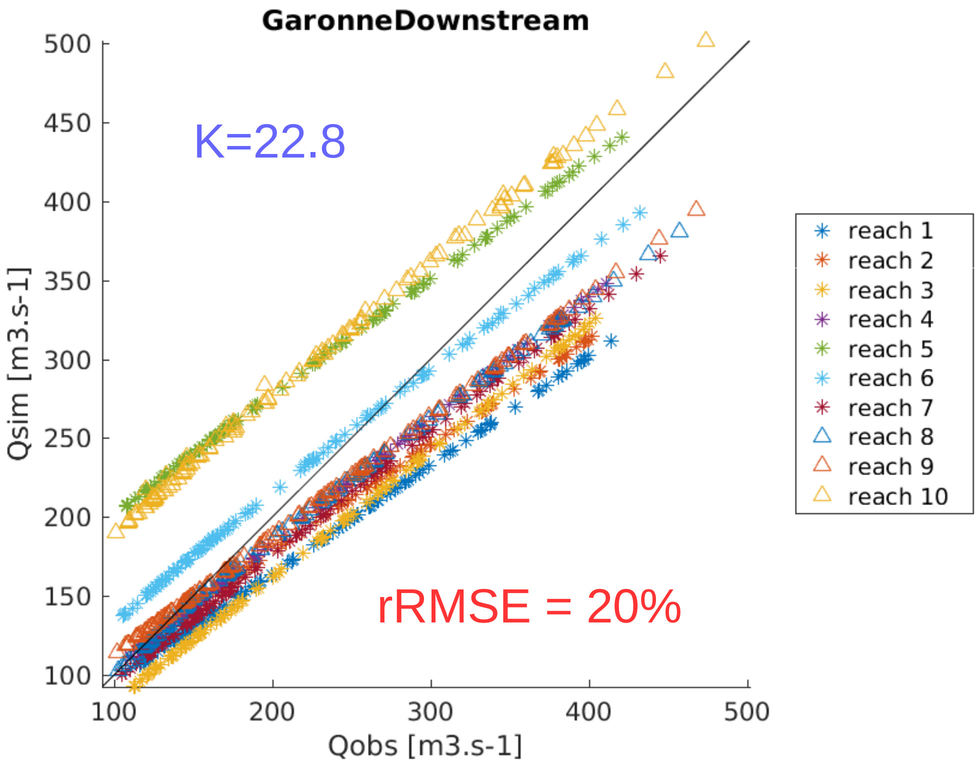
$$Q(x_{ref},t_{ref})=K(A_0+\partial A_{obs}(x_{ref},t_{ref}))^{(5/3)}.W_{obs}(x_{ref},t_{ref})^{(-2/3)}.\sqrt{S_{obs}(x_{ref},t_{ref})}$$

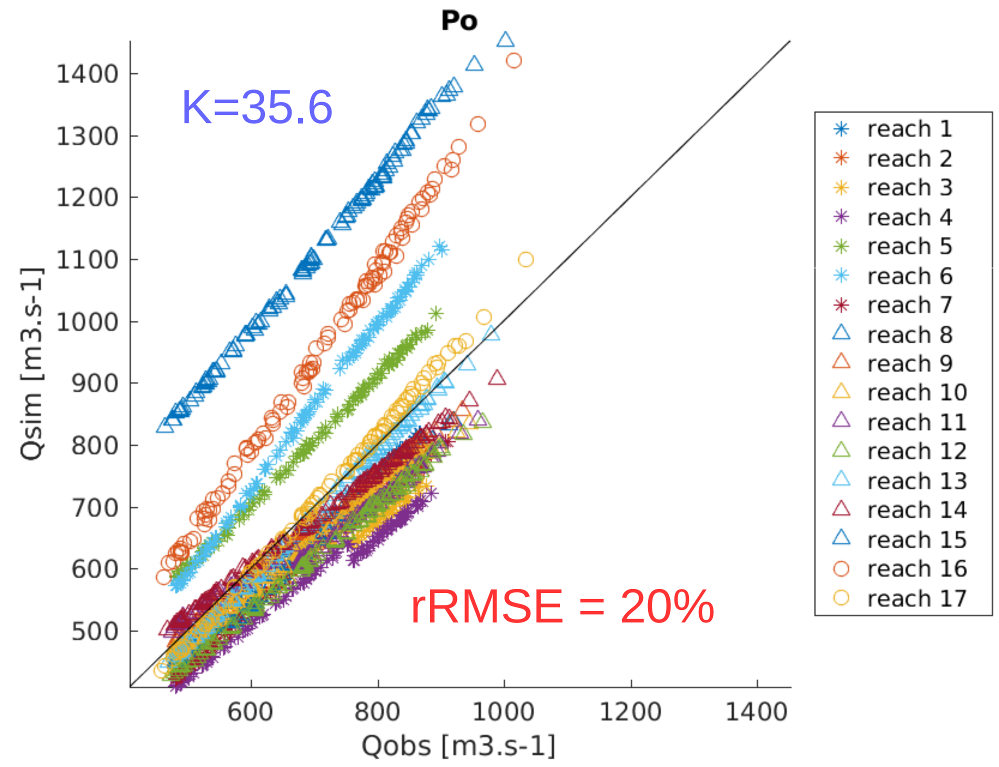
$$Q(x_{ref},t)=K(A_0+\partial A_{obs}(x_{ref},t))^{(5/3)}.W_{obs}(x_{ref},t)^{(-2/3)}.\sqrt{S_{obs}(x_{ref},t)}$$

  - K constant and uniform

Discharge algorithm

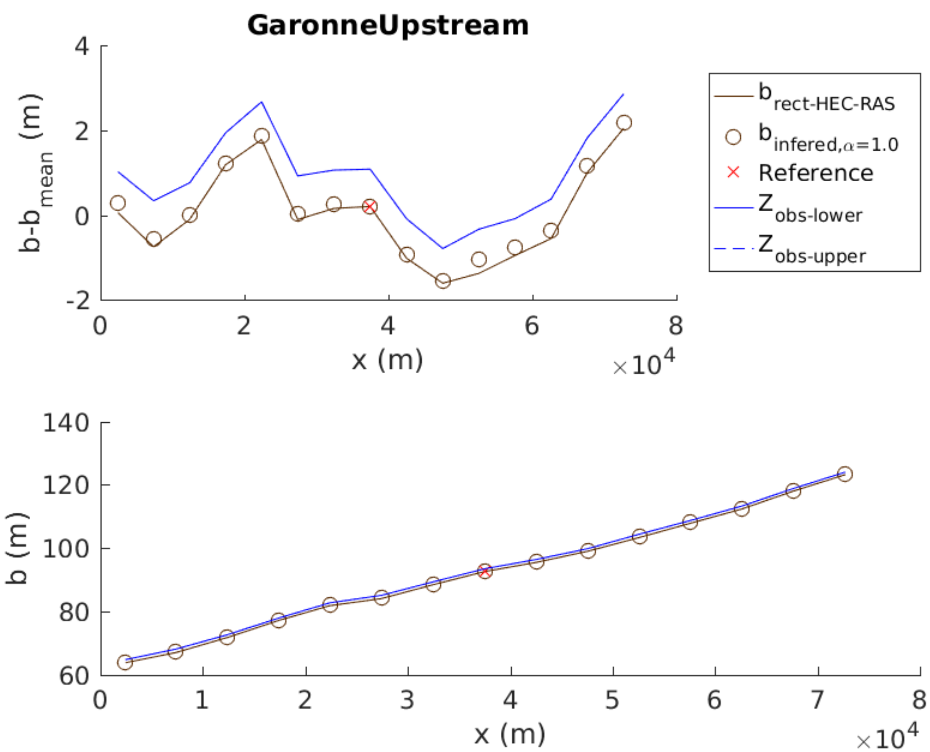
- Low complexity (Manning) equation

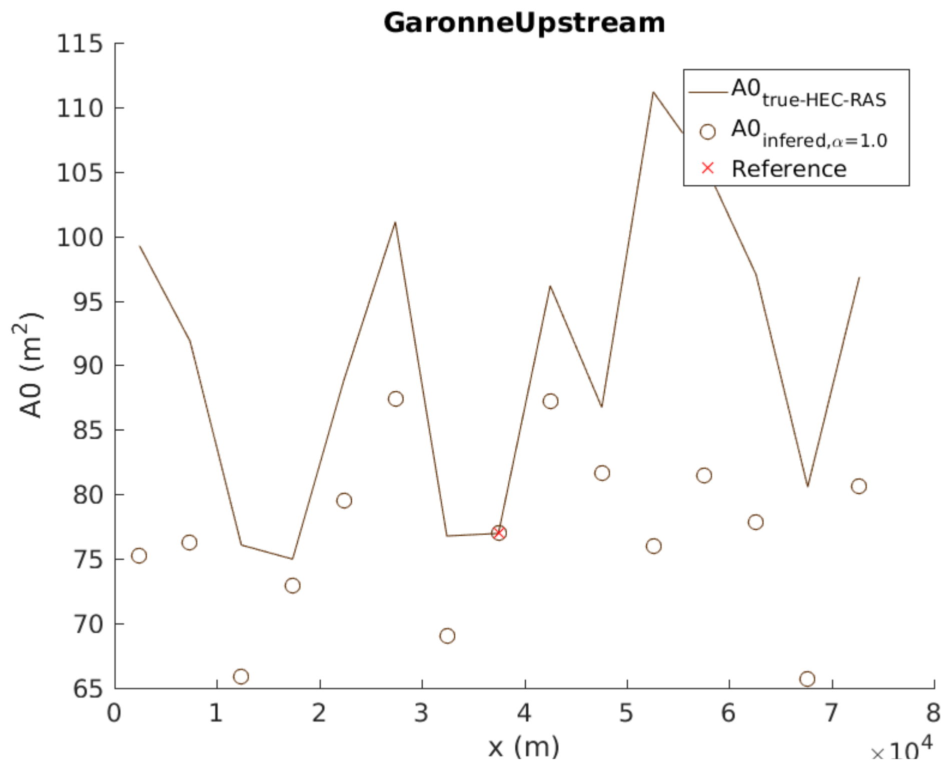


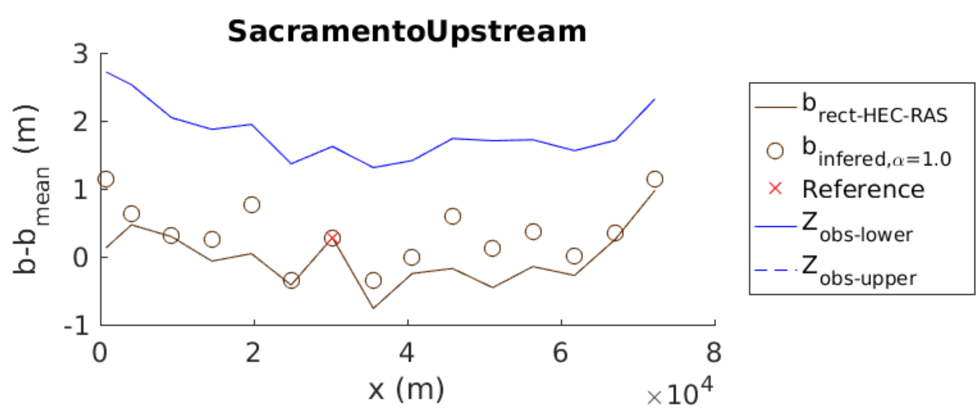


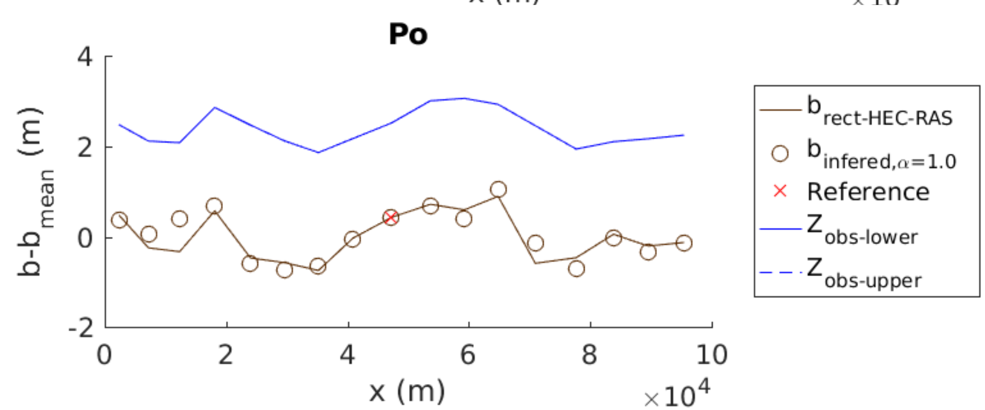
Bathymetry inference

- Low Froude model









Bathymetry inference

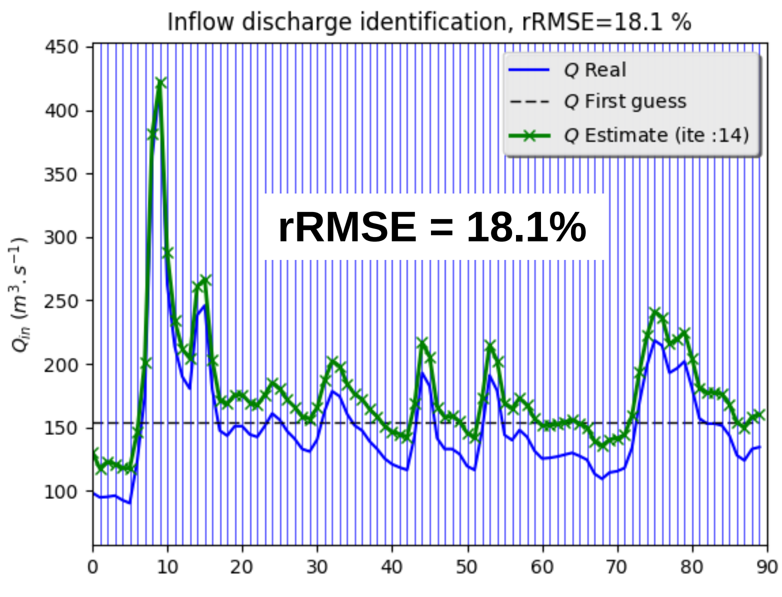
- Low Froude model
  - PEPSI rivers

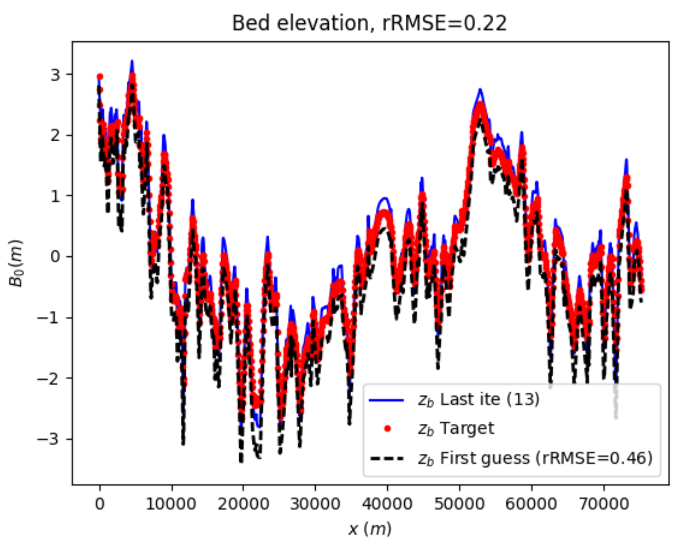
RIVER	RRMSE (%) GaMo	$AO(x)$	$Q(x,t)$
Connecticut	**29.2**	90.3	39.4
Cumberland	47.9	56.9	**36.6**
Ganges	279.8	53.3	**37.0**
GaronneDownstream	128.8	63.4	**37.7**
GaronneUpstream	**28.9**	44.9	34.6
Kanawha	**46.7**	19.3	49.9
MississippiDownstream	35.7	60.4.2	**11.8**
MississippiUpstream	35.1	25.6	**15.4**
Ohio	**42.7**	54.8	54.4
Platte	347.7	46.7	**65.1**
Po	**29.8**	21.2	46.4
SacramentoDownstream	26.8	20.3	**25.1**
SacramentoUpstream	69.1	31.2	**26.6**
Seine	**22.5**	20.9	38.7
Severn	**17.6**	16.6	24.9
Wabash	146.1	95.8	**50.6**

Good accuracy using a combination of L*ow Froude* + *in-situ* discharge value(s)
Primary equations, real-time computation

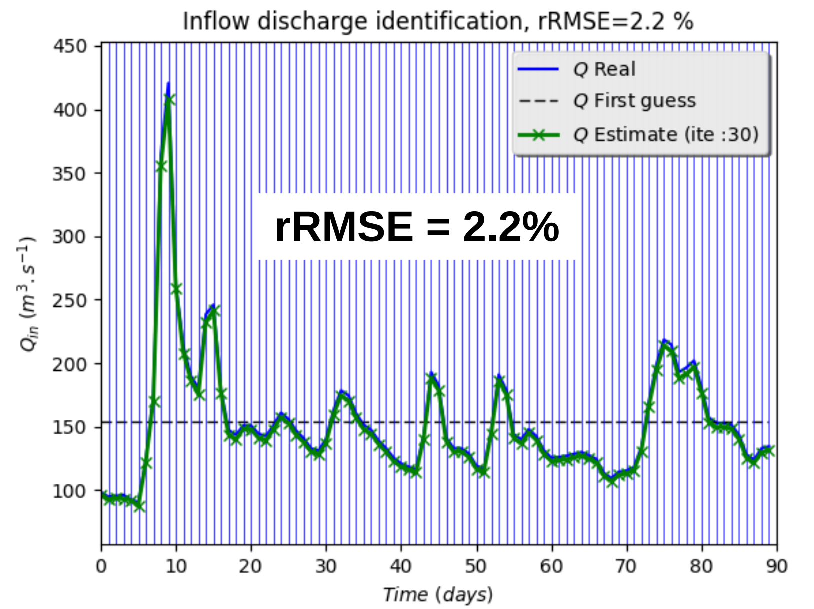
Variational Data Assimilation

- DassFlow 1D – Twin Experiment





Unknowns: (Q,K,B)
1st guess on B: Manning



Unknowns: (Q,K)
1st guess on B: Low Froude

Garonne Upstream
CAL/VAL-like

Variational Data Assimilation

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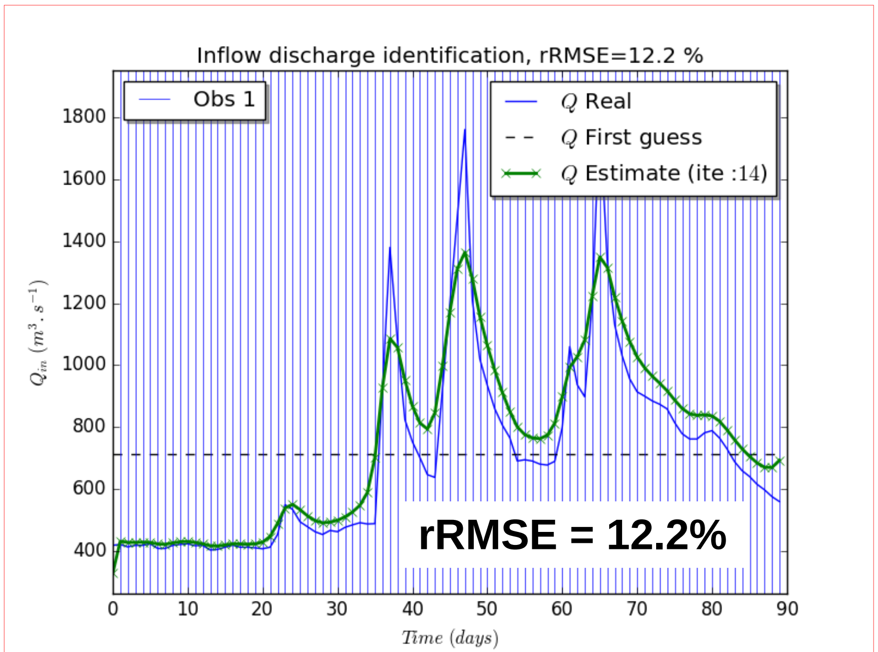

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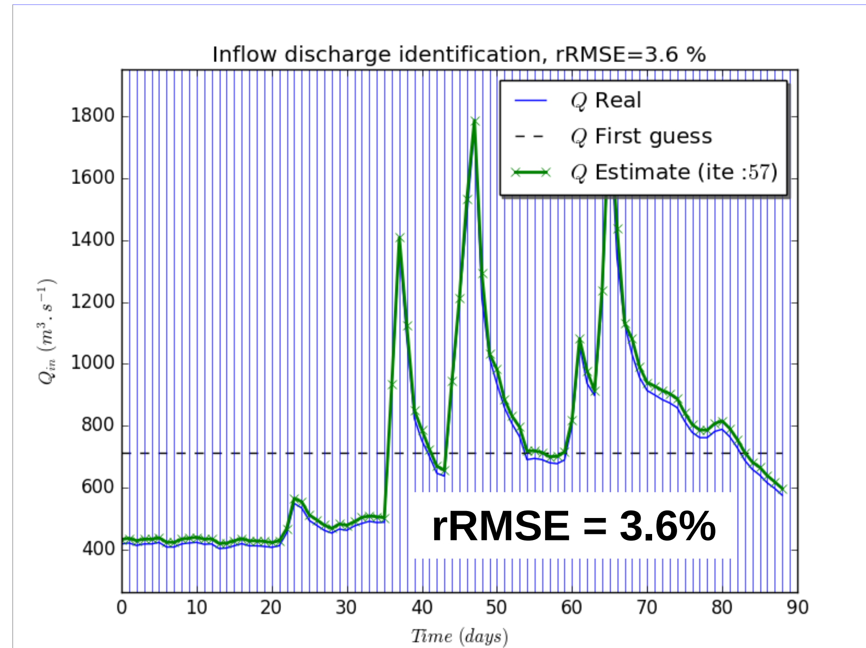


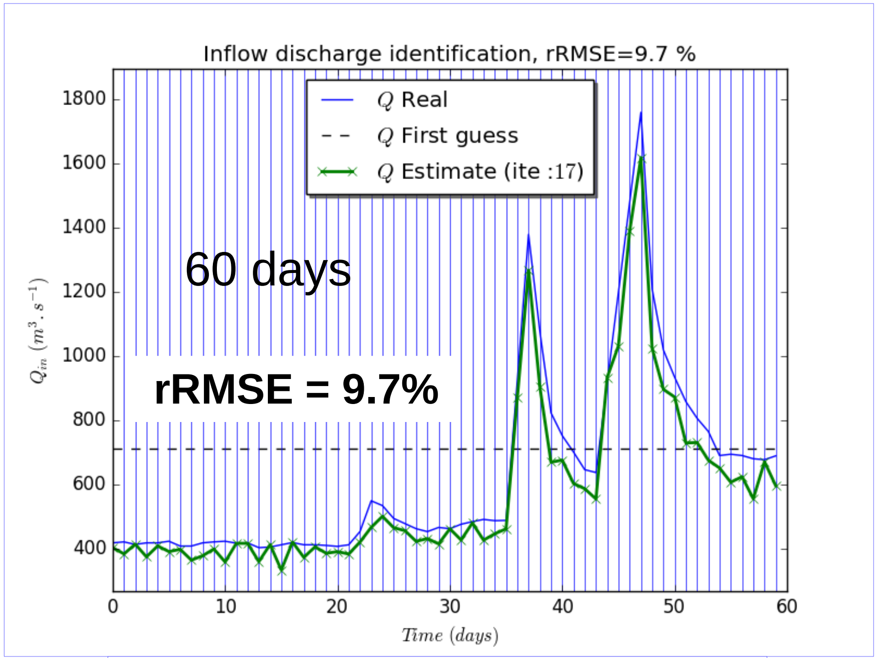
Unknowns: (Q,K)
1st guess on B: Low Froude

Po River
CAL/VAL-like

Equifinality K,B
High accuracy using *Low Froude* bathymetry, equifinality tackled

Validation

- VDA + rerun low-complexity
  - Model outputs (HEC-RAS) + 30 cm error on Z



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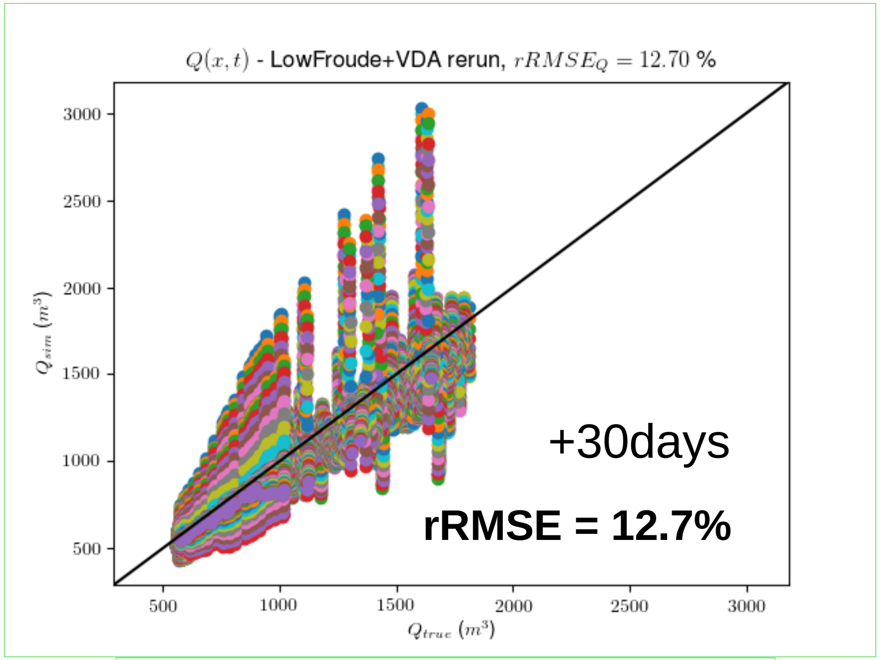
Po River CAL/VAL-like

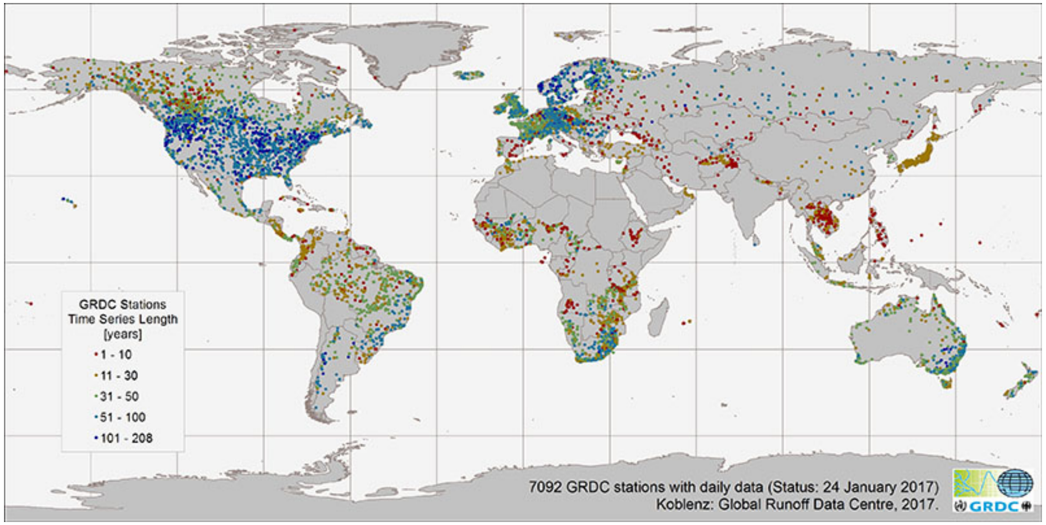


Unknowns: (Q)
K from VDA
1st guess on B: Low Froude

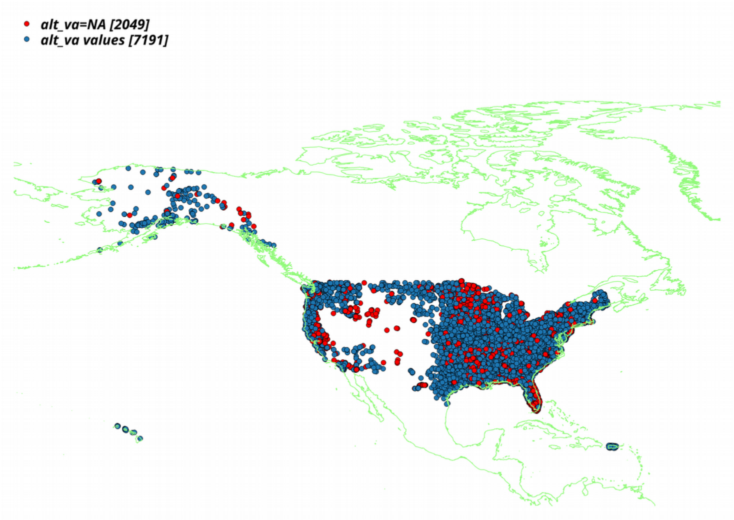
Better accuracy with complete toolchain
Low Froude bathymetry + VDA (Q,K) + discharge algorithm

Ancillary databases

- Key idea: develop rating curve
  - In-situ databases
  - Altimetry data
- Inverse discharge algorithm to infer parameters
  - Manning/Strickler
  - Bathymetry



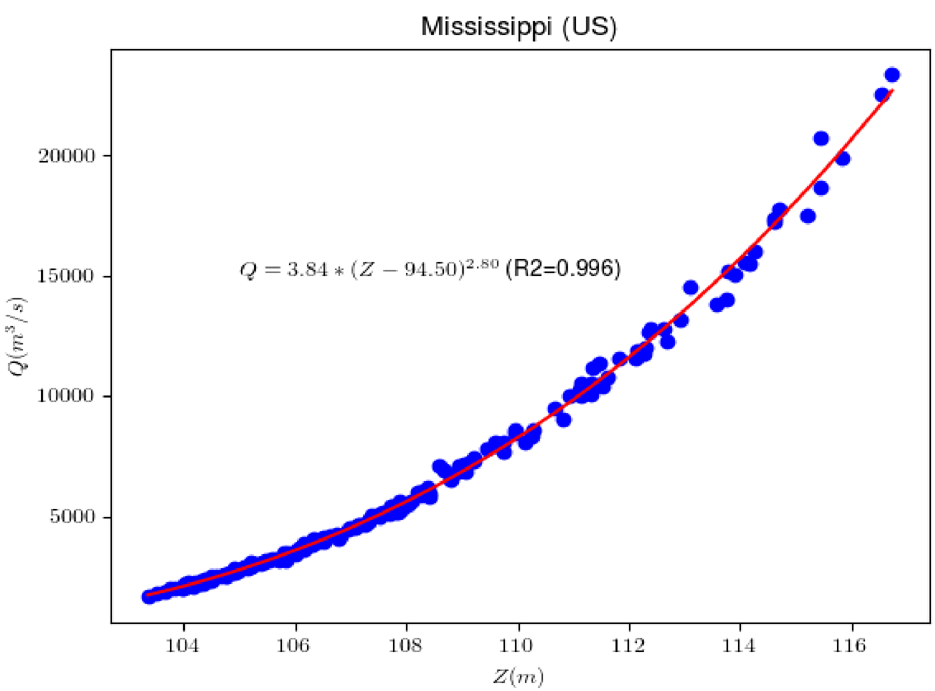
GRDC stations with daily data

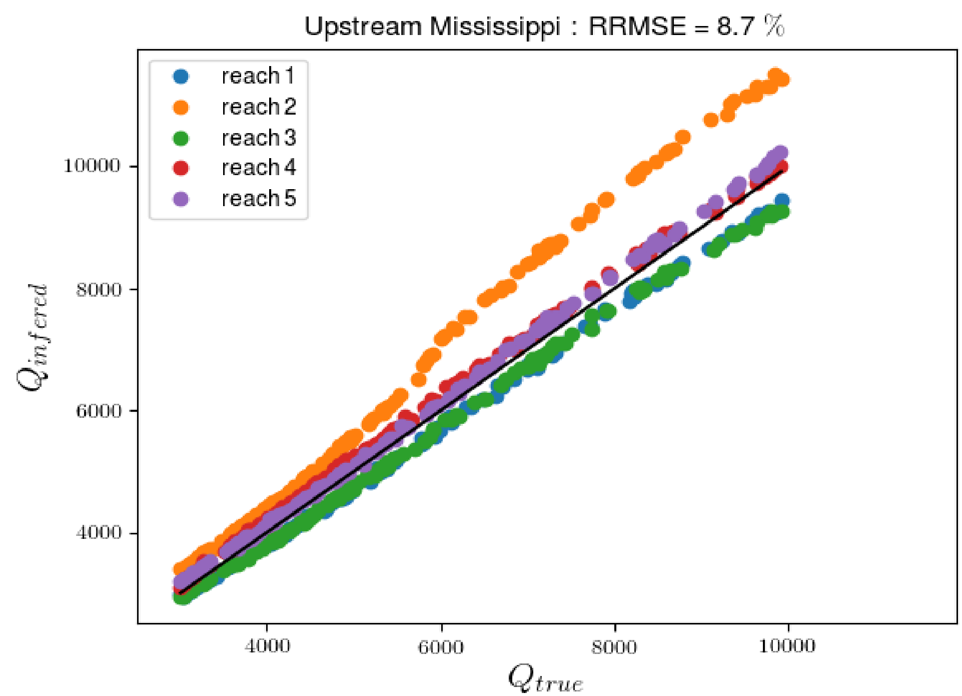


HYDRoSWOT (USGS) stations

Ancillary databases

- HYDRoSWOT (USGS)
  - Rating curve + low-complexity inversions
  - Uniform manning



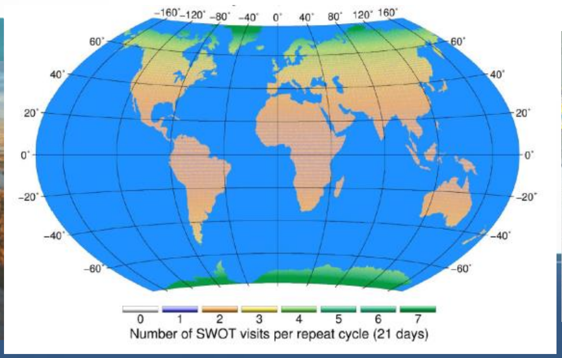


High accuracy using *in-situ* flux measurements
Towards databases over Europe, Amazon, …

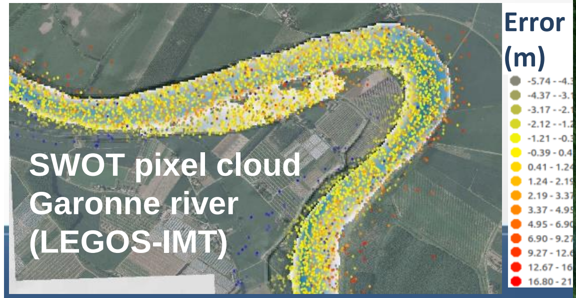
Insight on physical river networks segmentation and hydraulic controls

(A. S. Montazem phD (LEGOS – ICUBE), S. Calmant, P. A. Garambois)

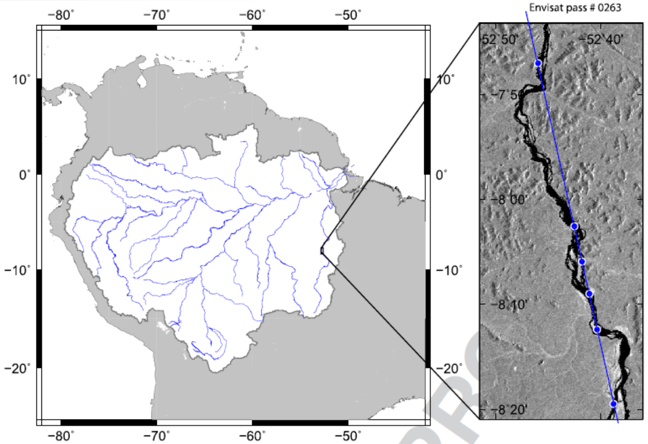
- General context :
  - Study of continental hydrosystems from multisource data (satellites + in situ)
  - Discretization required for signal processing, hydrodynamic modeling, data assimilation, data diffusion
- Problematics: How to represent and discretize river networks effectively at the global scale for discharge estimation with SWOT data?
  - Spatio-temporal variabilities of: hydrological forcing, free surface flows, River morphology,



Biancamaria et al. 2016



Hydraulic visibility from altimetric observations



Study site: Xingu River reach within the Amazon watershed, virtual stations SV#12 to SV#1 from south to north

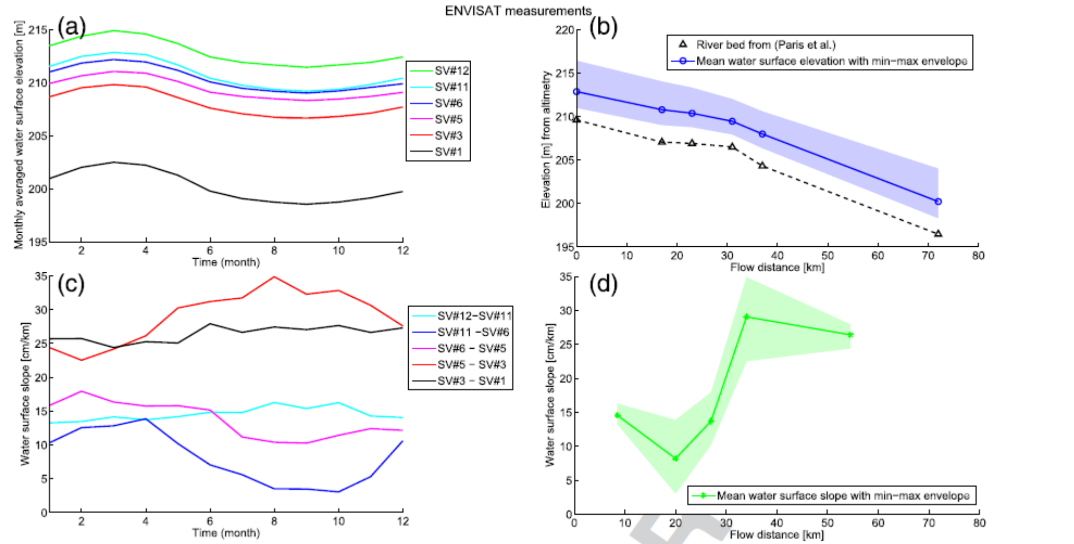
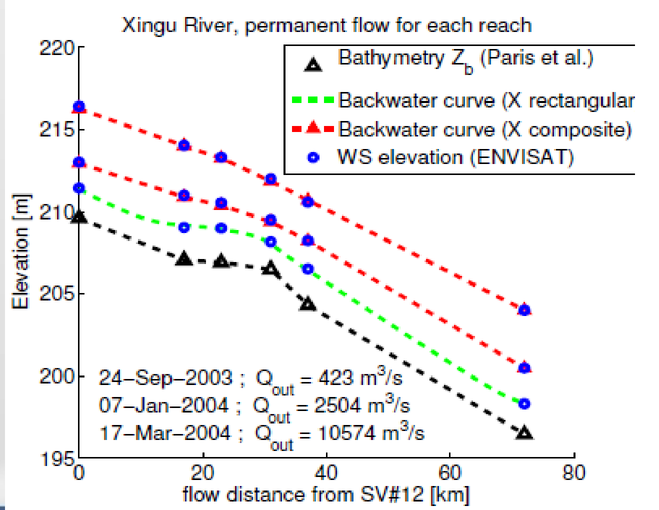


FIGURE 4 Analysis of ENVISAT data: (a) monthly average for water surface elevation at each virtual stations (VS); (b) mean, minimum, and maximum (blue envelope) water surface elevation with river bed elevation Z_0 according to Paris et al. (2016); (c) monthly average for the water surface slope for each reach between two VS; and (d) mean, minimum and maximum (green envelope) water surface slope

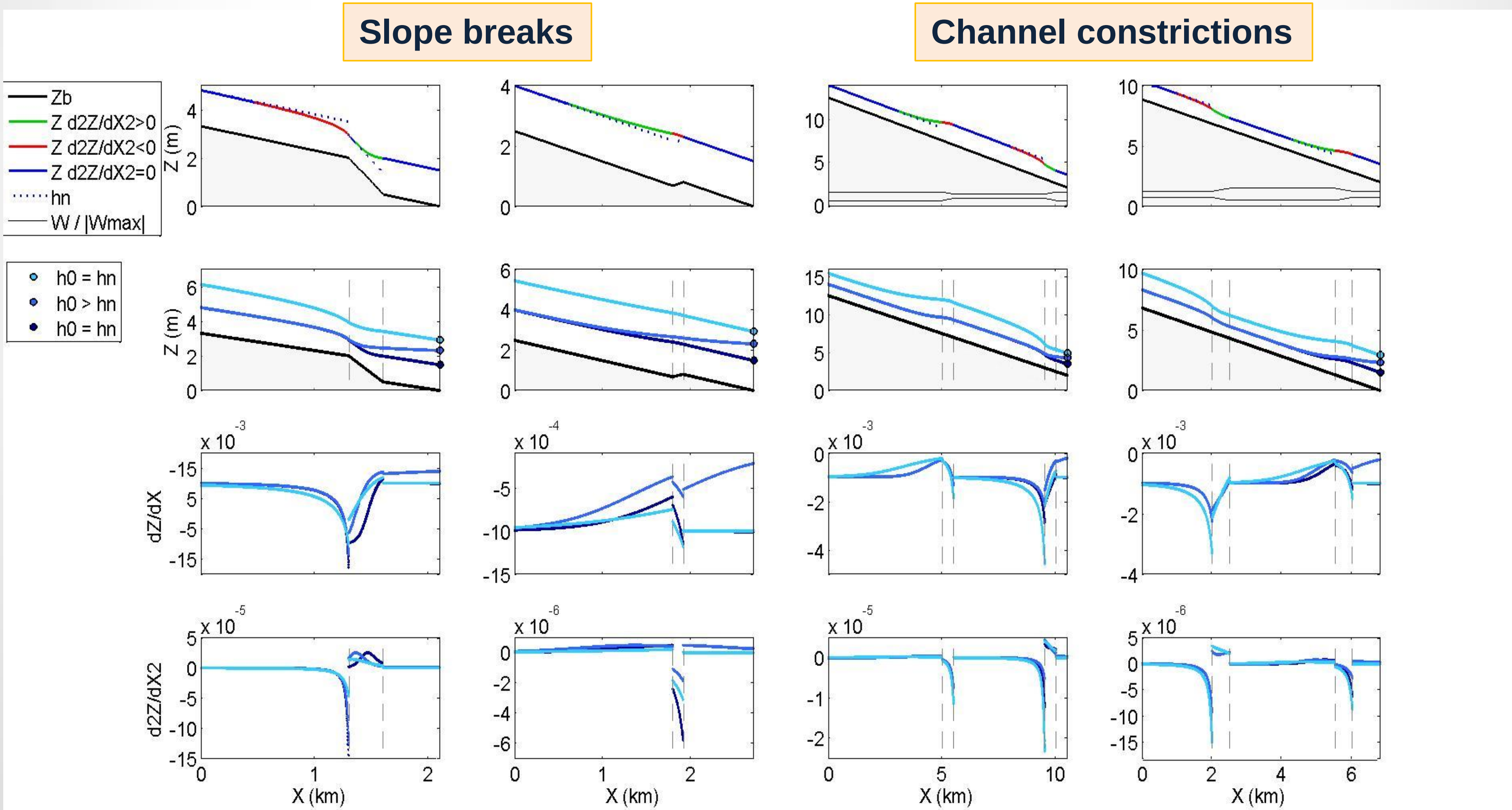
« SWOT like data » : Xingu River (amazone tributary) cross cut mroe than 6 times by a single ENVISAT track



- d_xZ(x,t) → 3 reach behaviours identified from ENVISAT altimetric measurements (riffles, pools, control sections)
- Simple effective roughness- geometry model (K(Z)) of this braided river reach
- Important physical proxy determined: water surface slope and curvature (space – time)

(Garambois, Calmant et al. 2016) HP

Quantification of Water surface deformations induced by hydraulic controls



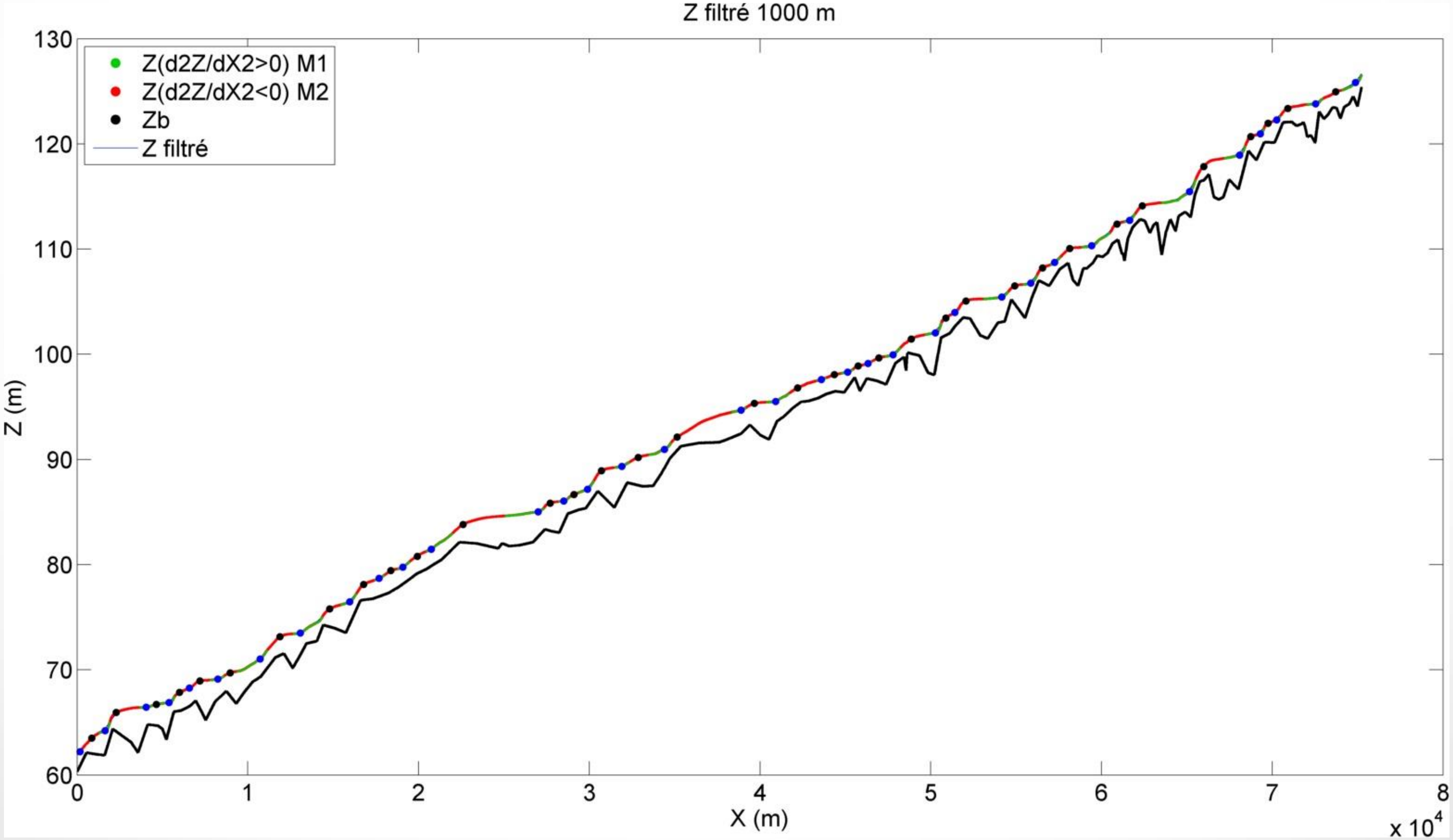
→ WS slopes and curvatures quantified for a range of synthetic rivers and control types
→ Backwater length, masking effects also quantified

Montazem, Garambois, Calmant et al. (final redaction)

Signal filtering and river segmentations (Garonne Upstr.)

Method:

- **Water surface elevation filtering at different length**
- **Segmentation following curvature (around control points)**



Signal filtering and river segmentations (Garonne Upstr.)

Method:

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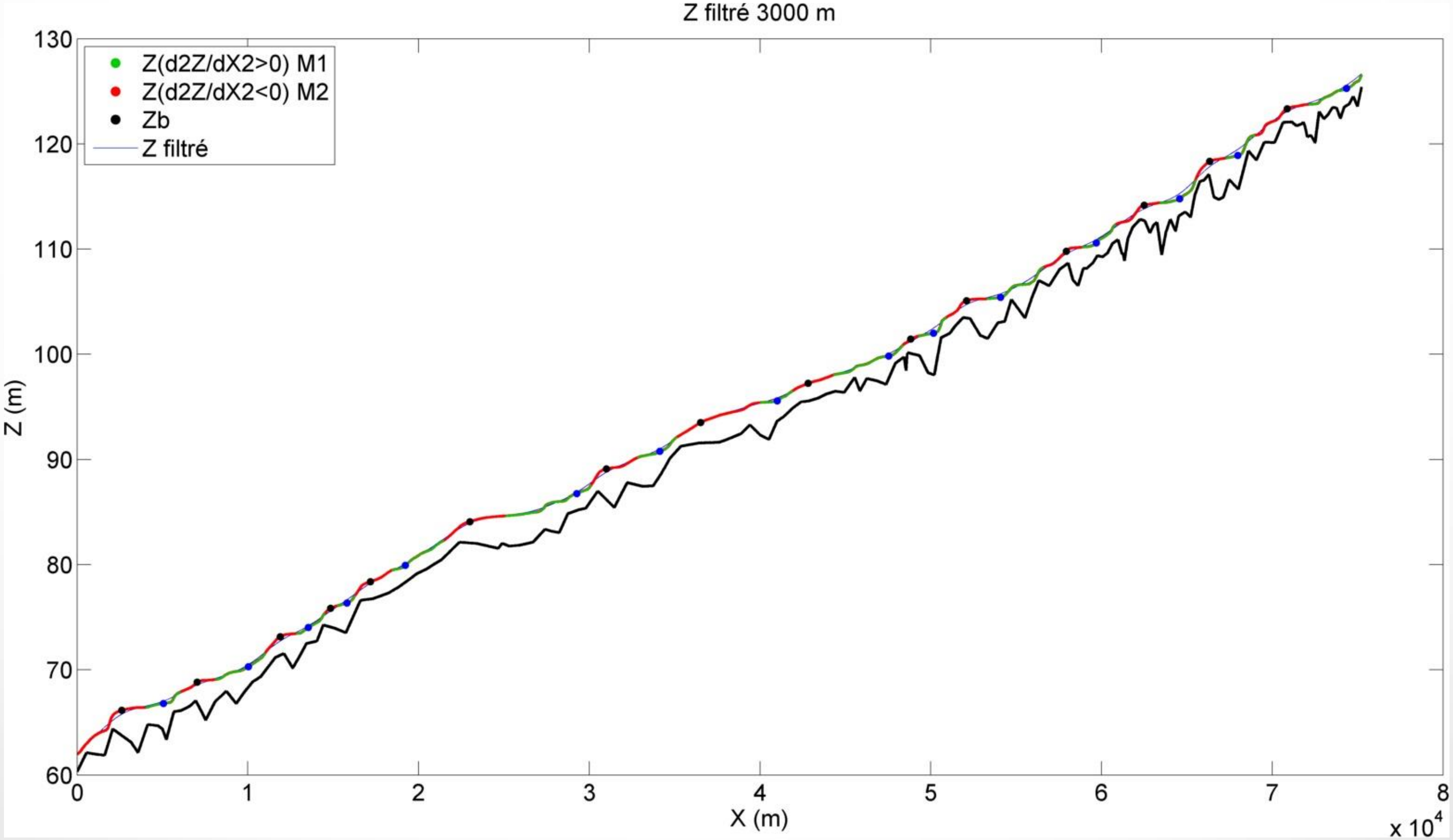

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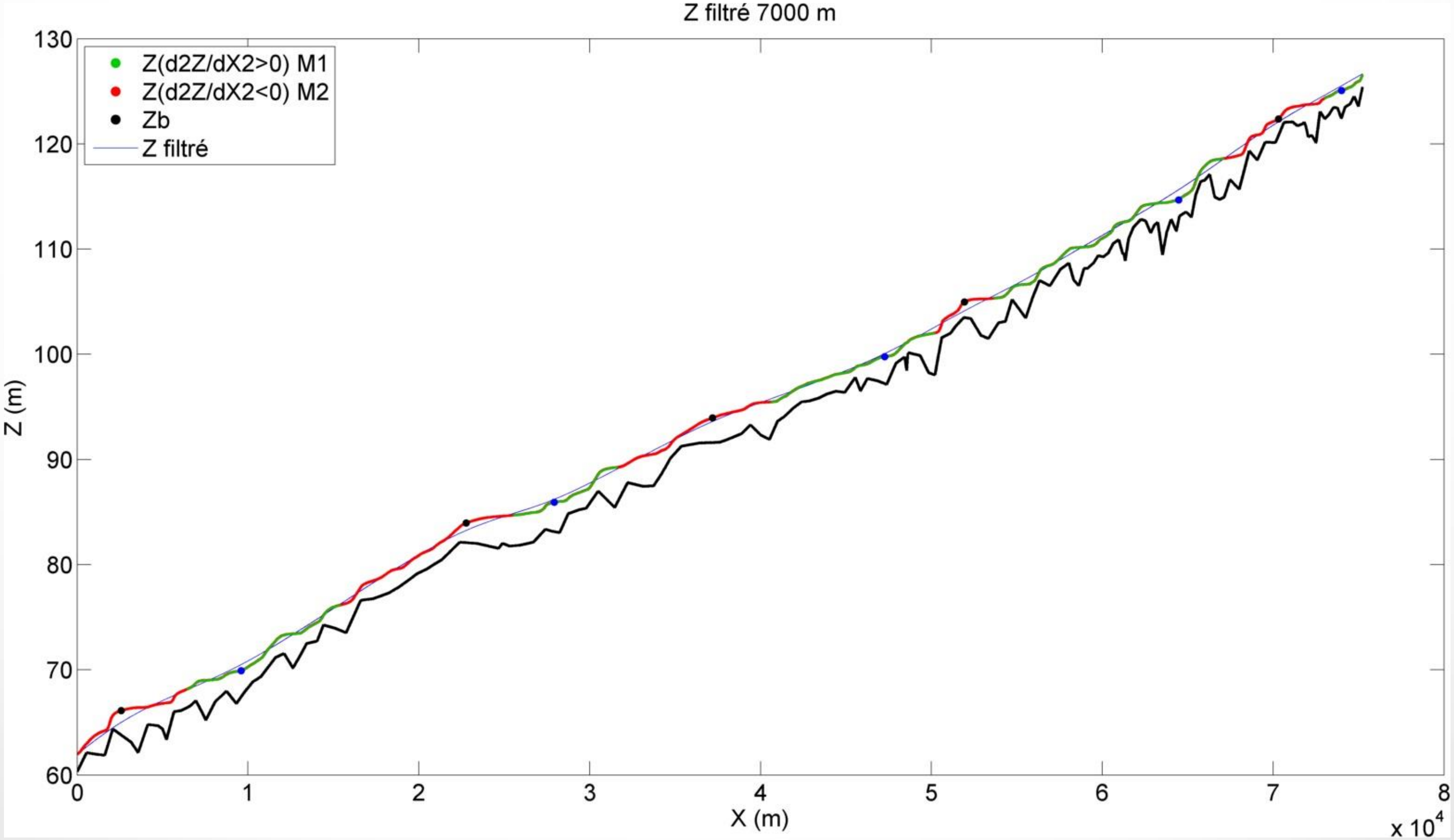

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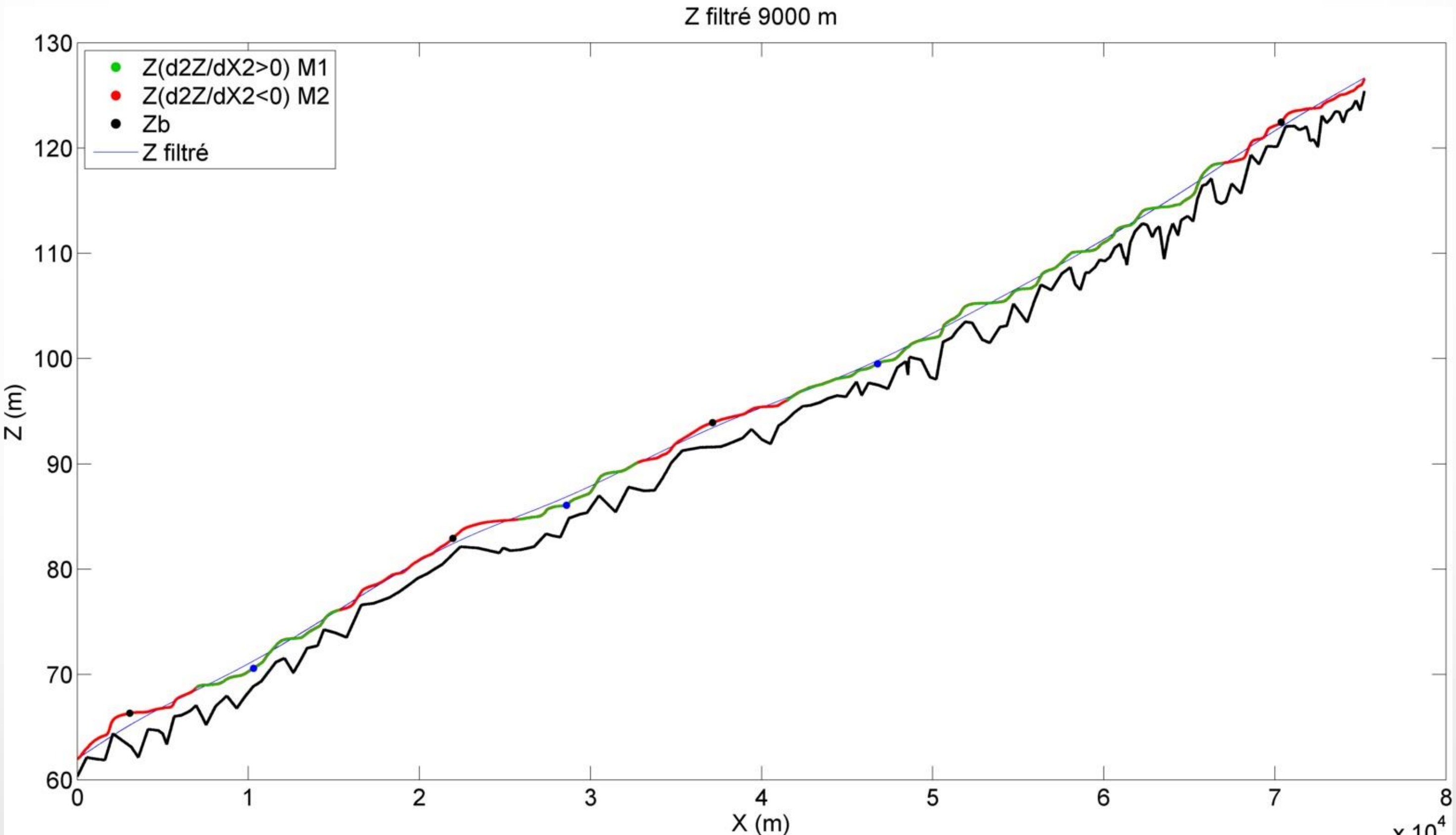
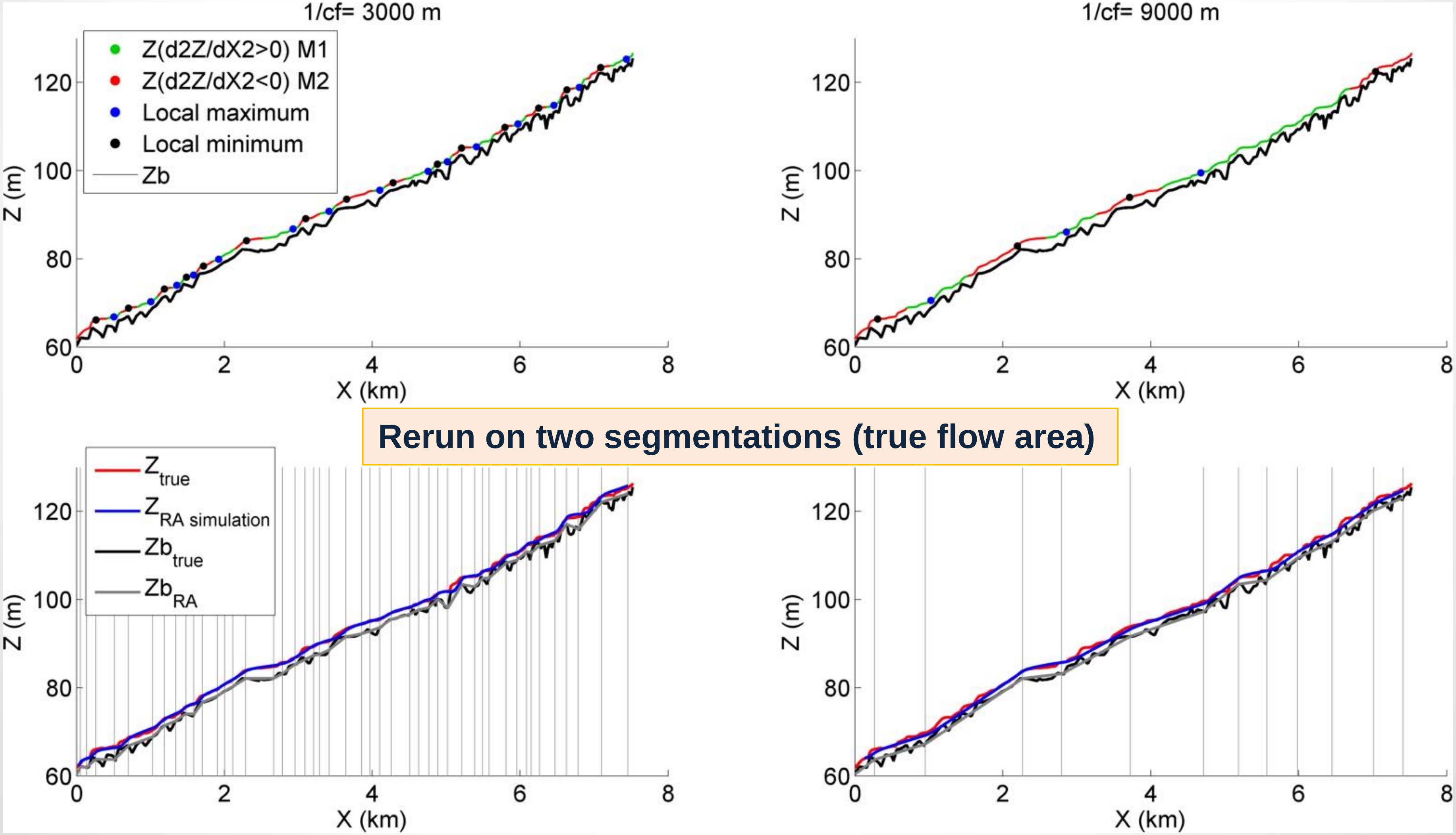


Different scales of curvature exist
Increasing reaches number unsurprisingly reduces the number of control points detected
This method likely preserves the 'strongest' controls (slightly shifted…)

On the impact of signal filtering and river segmentations

Case of the Garonne Upstream

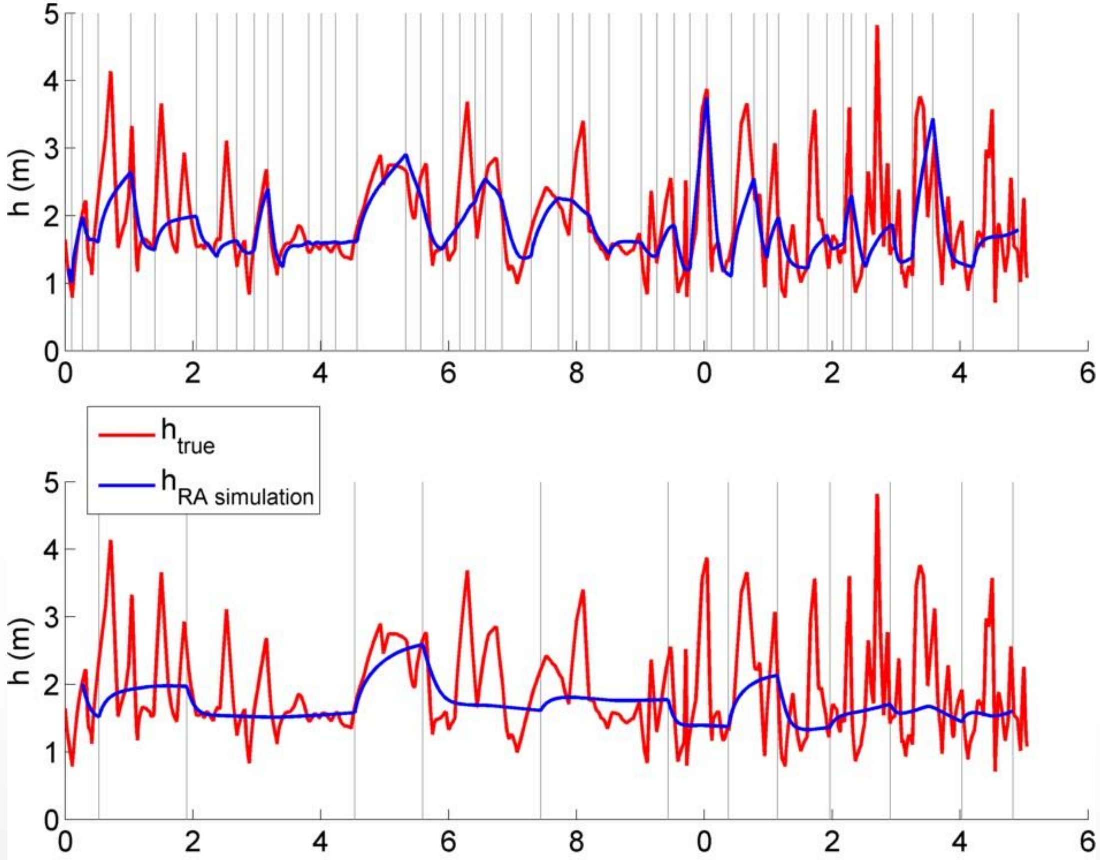


Rerun on two segmentations (true flow area)

On the impact of signal filtering and river segmentations

Case of the Garonne Upstream

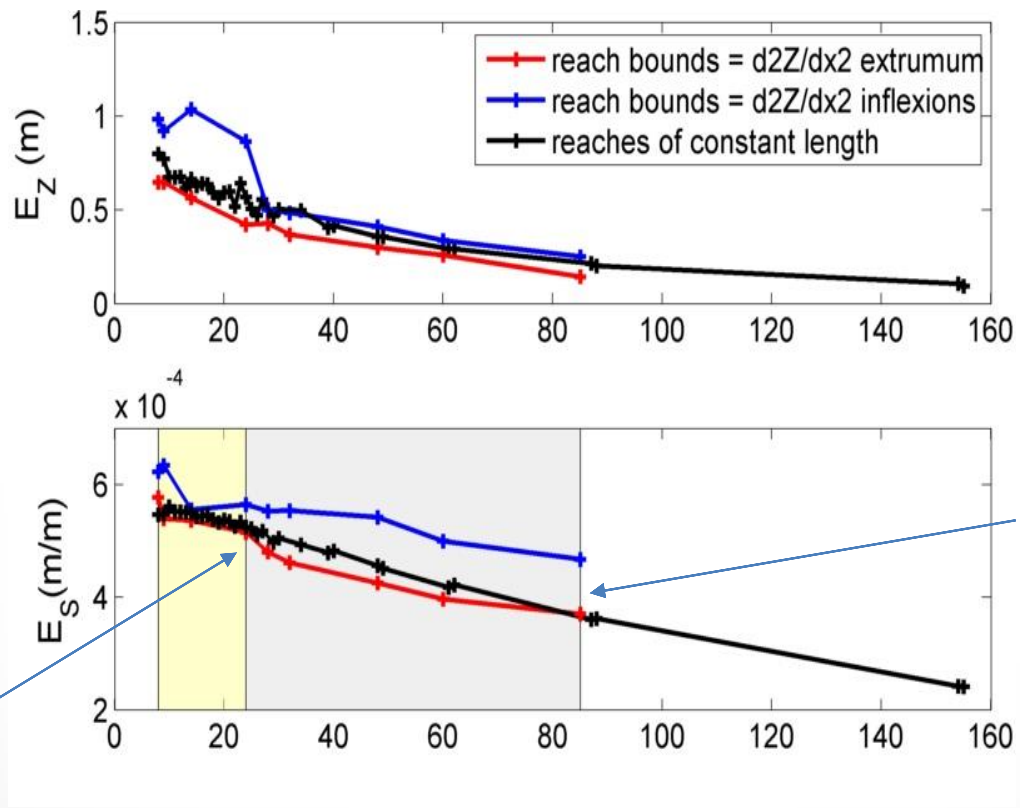
Rerun on two segmentations (true flow area)



Physical signal segmentation ensures less errors on WS slope on the testes cases for large to small reaches length

Signal filtering and river segmentations (Garonne Upstr.)

Rerun on two segmentations, Garonne Up (true flow area)



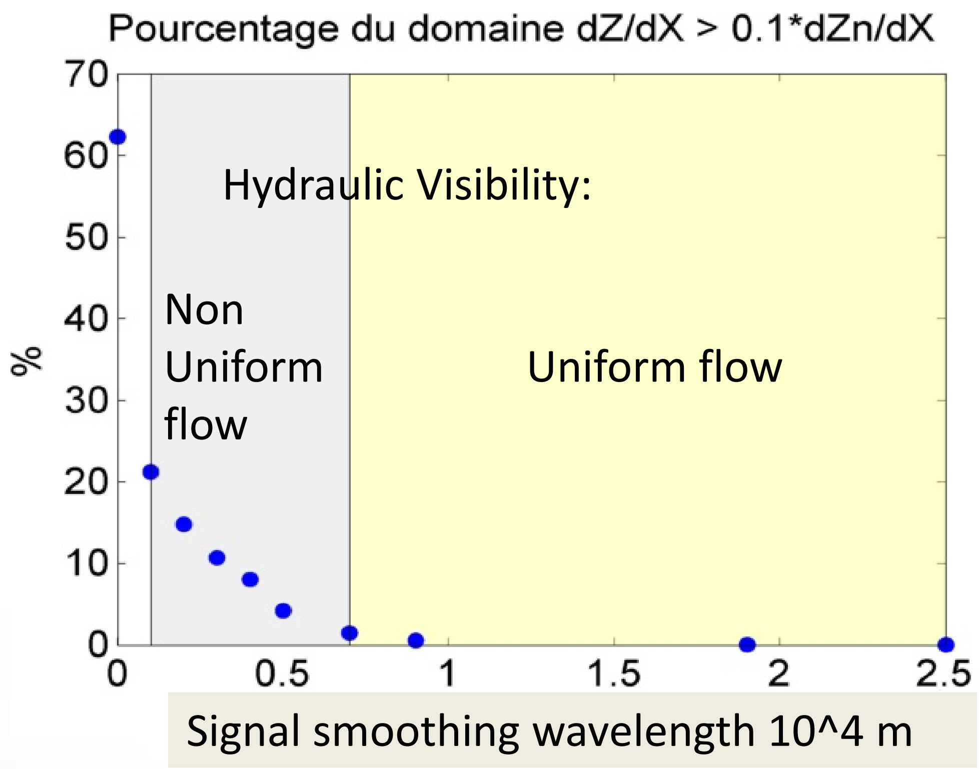
« Small scale variabilities »

« Geomorphological bound »

Physical signal segmentation ensures less errors on WS slope on the testes cases for large to small reaches length

Signal filtering and river segmentations (Garonne Upstr.)

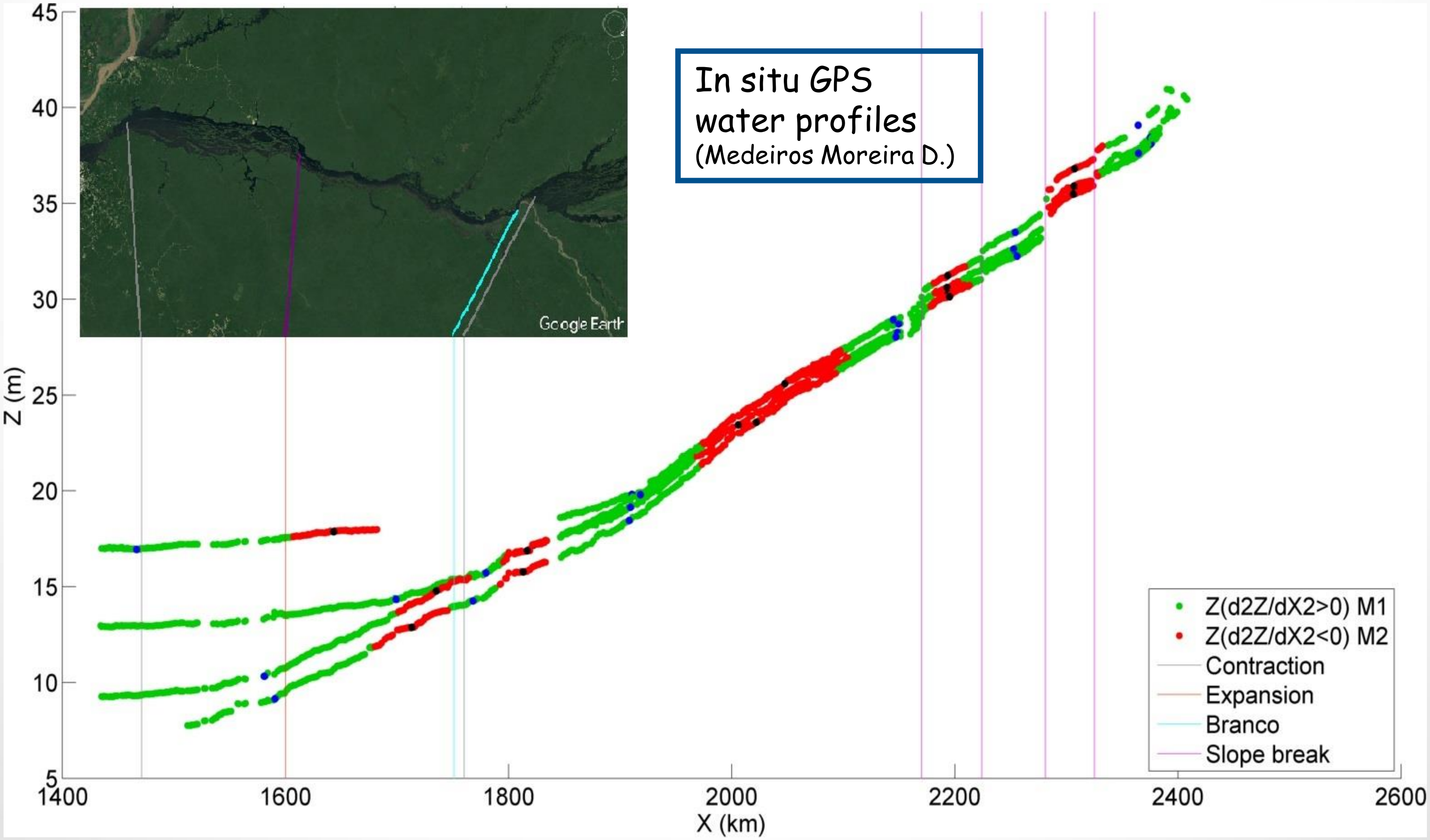
Rerun on two segmentations, Garonne Up (true flow area)



For long reach length only (permanent) uniform flows visible!
→ What is the importance of depicting spatial nonlinearities of flow lines?

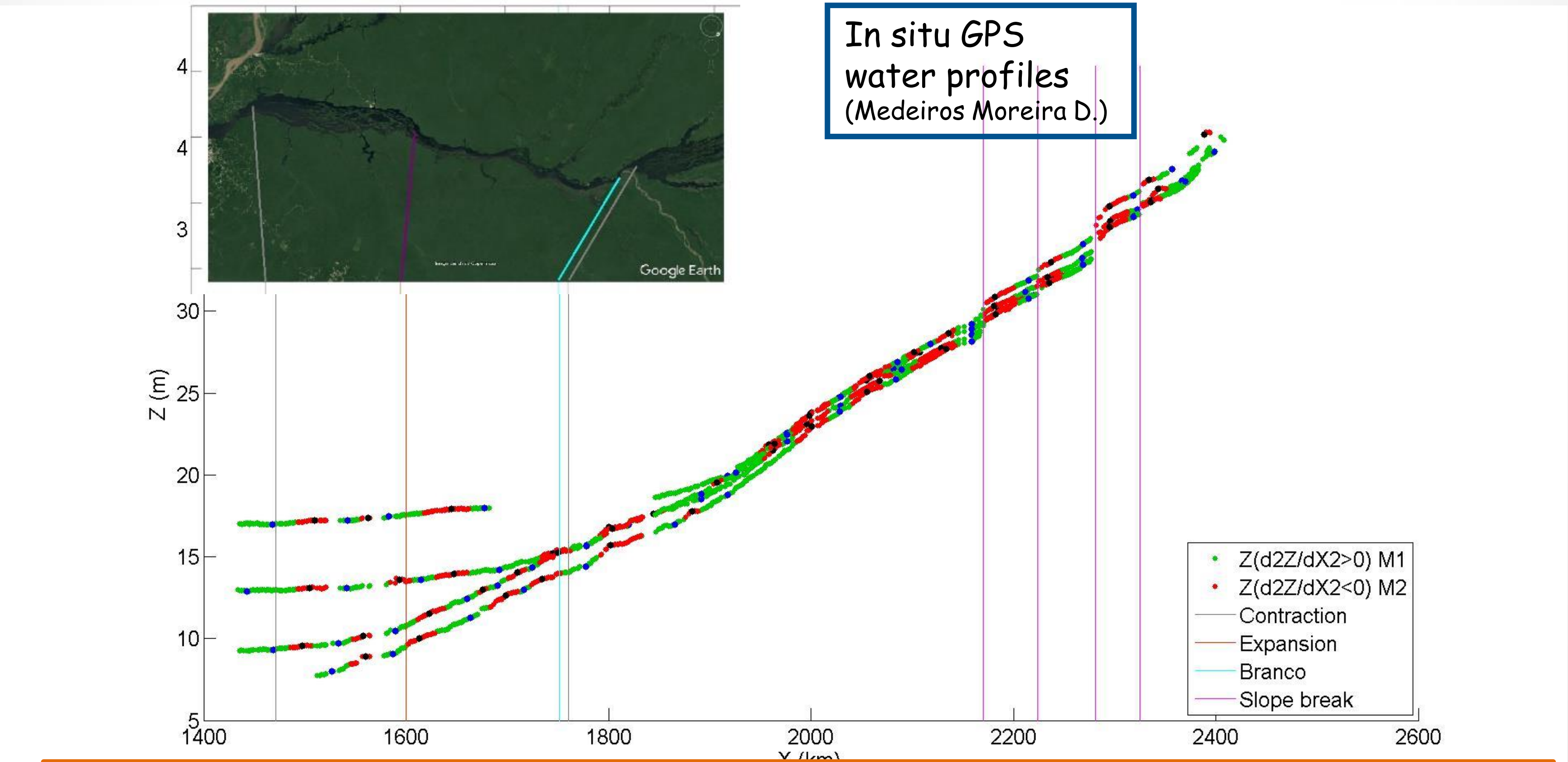
In situ flow lines a large amazonian River: the Rio Negro (in situ GPS)

Large scale segmentation (cutoff 100 km)



Water surface measurements on the Rio Negro (in situ GPS)

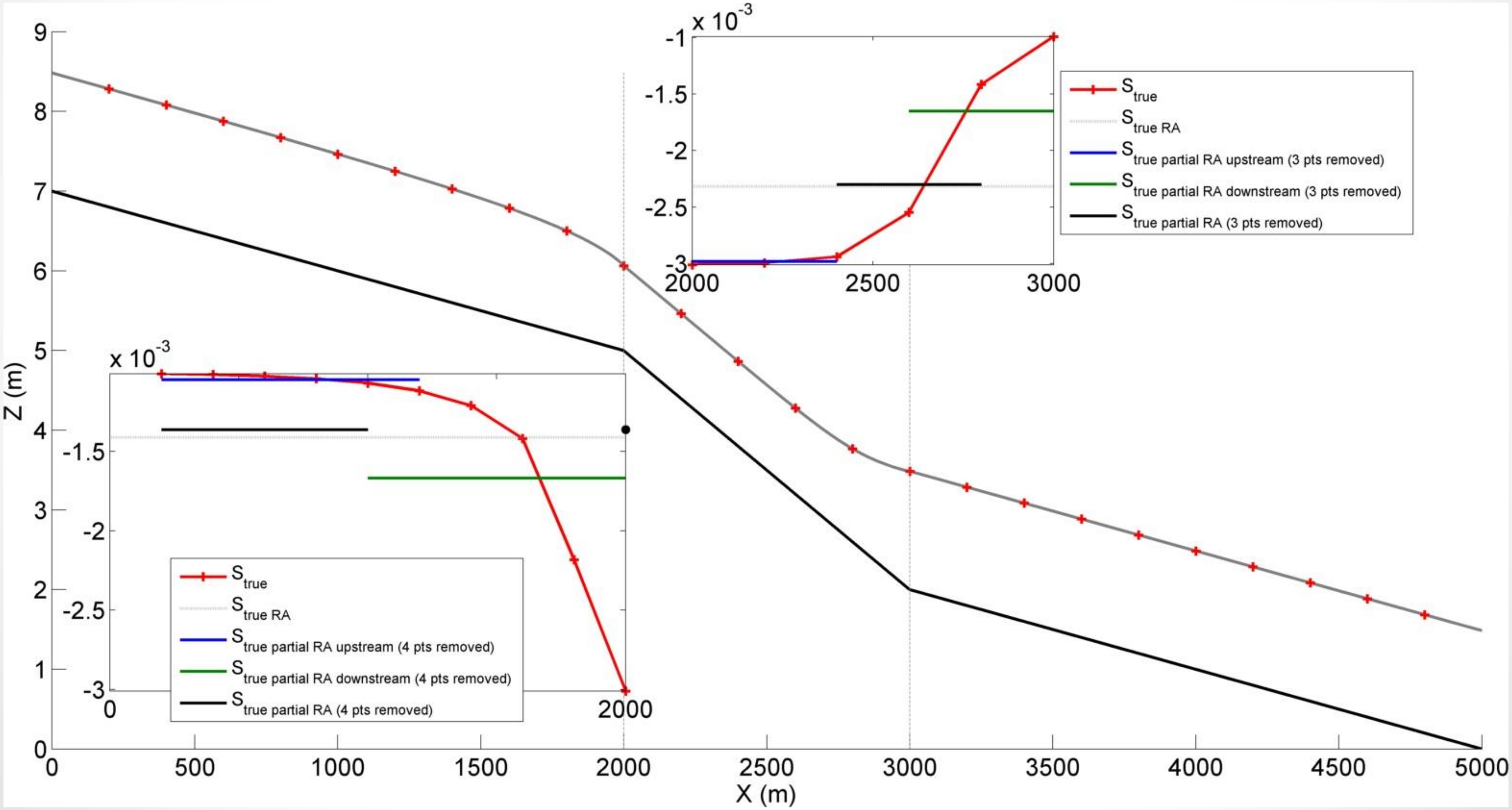
Smaller scale segmentation (cutoff xx km)



Geomorphologic scales, hydrologic variabilities characterized
Which river segmentation and for wich (modeling) objectives?

Montazem, Garambois, Calmant et al. (final redaction)

Partially Observed Reaches?

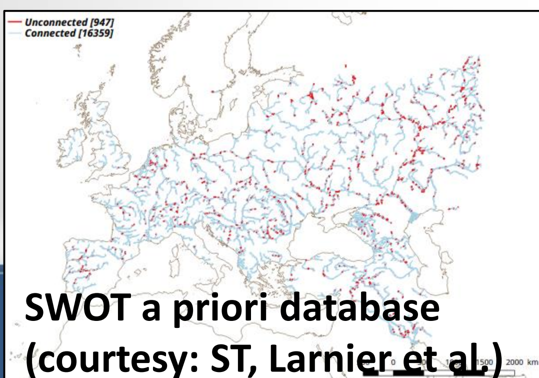


What is an « observed river reach », for which objective?
→ Importance of water surface slopes variability within a reach

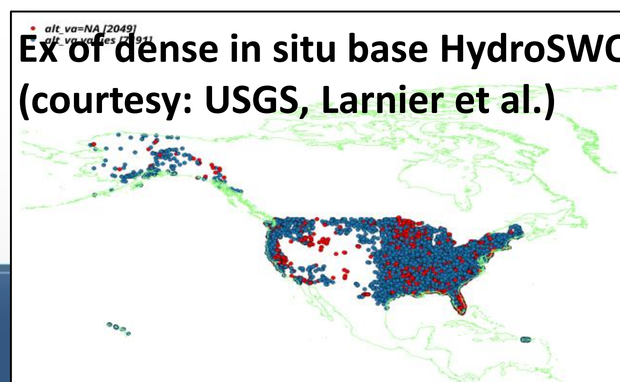
Ongoing and forthcoming studies on physical river network segmentation and satellite data assimilation

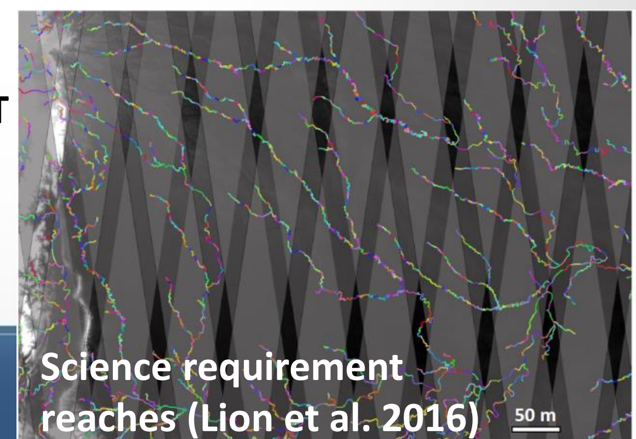
- Test river segmentation on other river cases and data types
- Analysis from altimetry datasets, river width (JERS, Peckel, …) over the Amazone basin (and others ?)
- Geomorphology aspects, human structures
- Assess influence of river segmentation on:
  - « full » inverse problems (DA-PEPSI ?),
  - Bayesian altimetric rating curves,

Towards extended databases



SWOT a priori database (courtesy: ST, Larnier et al.)


Ex of dense in situ base HydroSWOT (courtesy: USGS, Larnier et al.)



Science requirement reaches (Lion et al. 2016)