

Doctoral Winter School

DATA RICH HYDROLOGY

2019 Edition

Remote sensing data and tools to foster inland water monitoring and flood modelling

Alessio Domeneghetti et al. (...many others)

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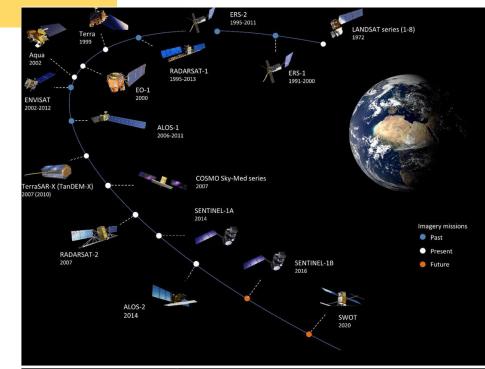
Remote sensing data and tools to foster...

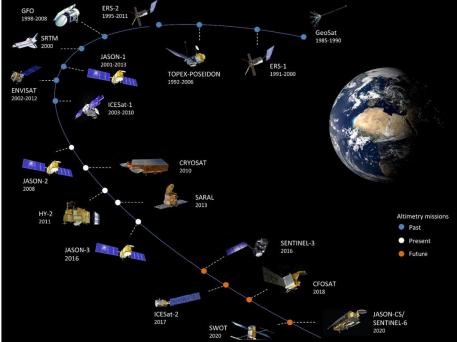
inland water monitoring

(e.g. satellite altimetry, SWOT)

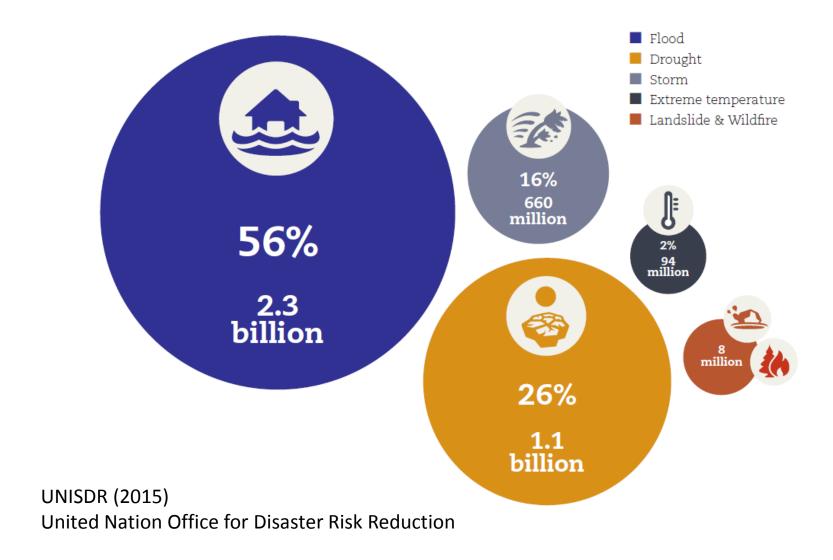
flood modeling

Available data and tools for flood hazard modelling

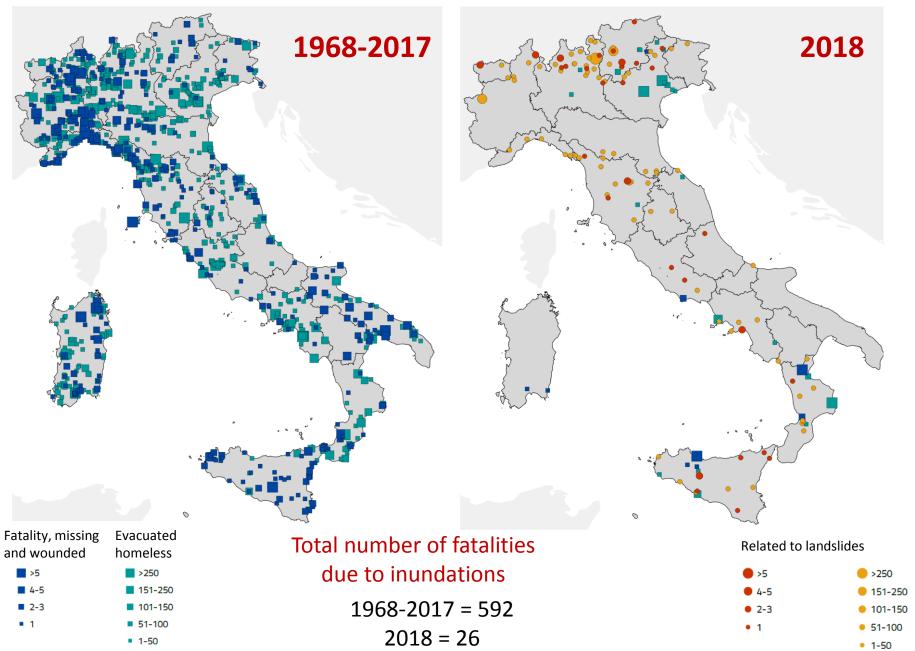




Number of people affected by weather-related disasters (1995-2015)



...in Italy?





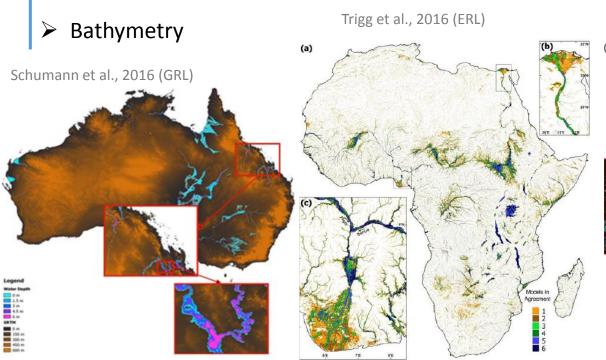
FLOOD HAZARD MODELING AT DIFFERENT (LARGE) SCALE AND IN POORLY SURVEYED AREAS

Main challenges

- Monitoring/modeling/predicting floods at the large (regional, continental or global) scale is challenging by nature
- Most hydrodynamic models were not developed for large scale applications
- Boundary data (river data, inflow, water level, floodplain topography, etc.) are lacking in many places or are inaccurate

Initiatives and concerns for global flood modeling

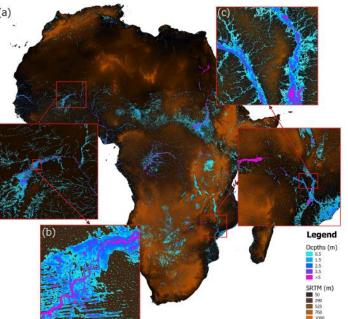
- River network characterization
- Model conditioning (precipitation, river flows, gauged information, etc.)
- Numerical model computationally efficient
- ➤ Model calibration and validation
- > Topography





Alfieri et al., 2014 (HP) Dottori et al., 2016

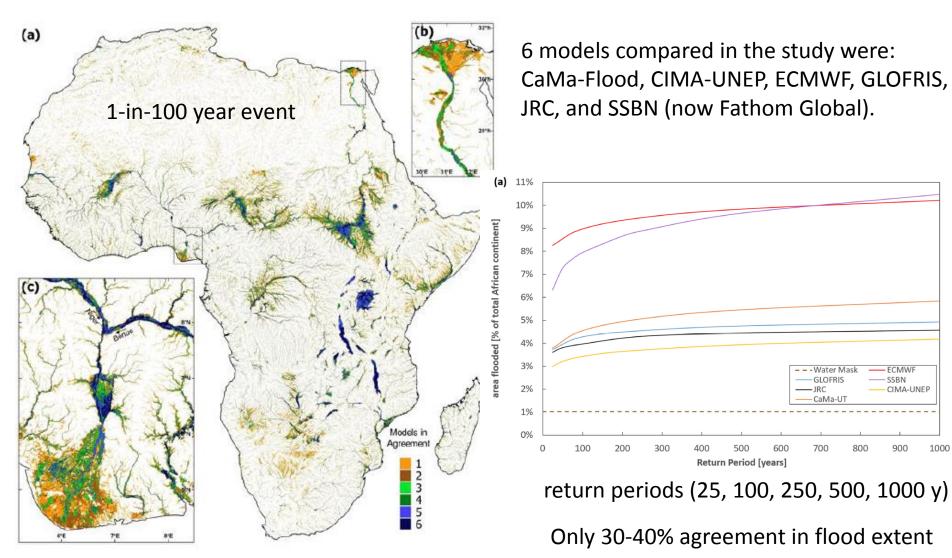
Sampson et al., 2015 (WRR)



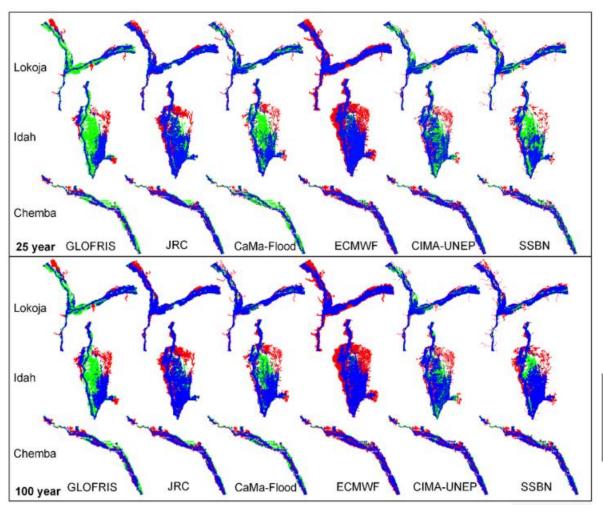
Initiatives and concerns for global flood modeling

"[...] fluvial (river) flood risk for much of the world is still 'unmapped', and even where mapping exists, it often uses different and inconsistent methodologies or datasets across countries and regions."

Trigg et al., 2016 (ERL)



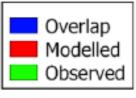
Initiatives and concerns for global flood modeling



Bernhofen et al., 2018 (ERL)

Events considered for the validation (2) are retrieved from the **Dartmouth Flood Observatory (DFO) archive**.

The DFO uses MODIS imagery to capture flood events globally, and stores them online in an open-access Archive (since 2000).



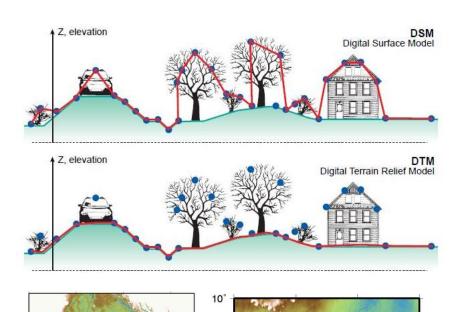
Overlap of individual global flood model extent for return period flows of 25 and 100 years and MODIS observed flood extent

Digital **E**levation **M**odel (DEM) is a fundamental baseline data for many geosciences analysis (hydrological modeling, flood modeling, land classification, terrain analysis, etc.)

... in most part of the world spaceborne DEM are usually the only source of topographic data

Error types in spaceborne DEMS

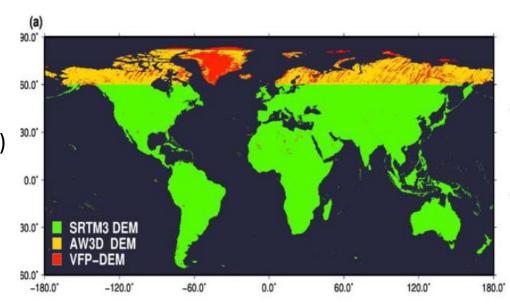
- Vegetation height bias/object bias
- Speckle noise (random noise due terrain reflection)
- Stripe noise (unrealistic terrain undulation)
- Absolute bias (overall shift)



31°

Common Global (semi-Global) DEMs

- SRTM3 DEM v2.1
 C-band radar interferometry, 90 m res.
 (Shattle Radar Topography Mission, 2000)
- AW3D-30m DEM (above 60N) optical stereoview.
- Viewfinder Panorama DEM digitized paper map to fill SRTM gap





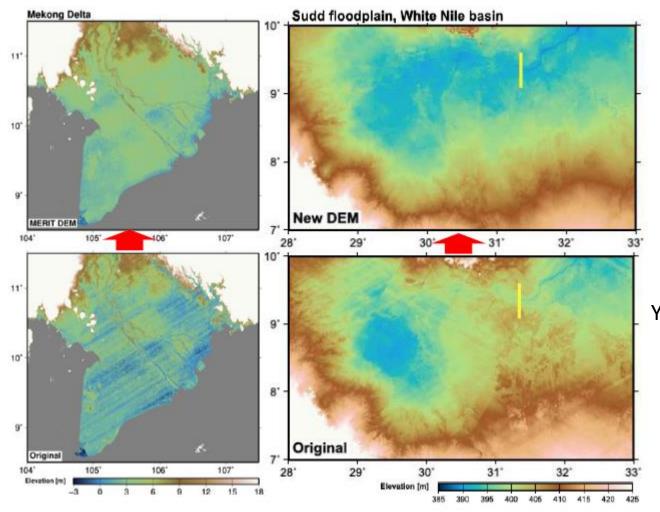
Overall vertical error might vary from 4.7 m up to 9 m in different continents [Rodriguez et al., 2006; Beck, 2014; Schumann et al., 2014; Yan et al., 2015].

SRTM DEM



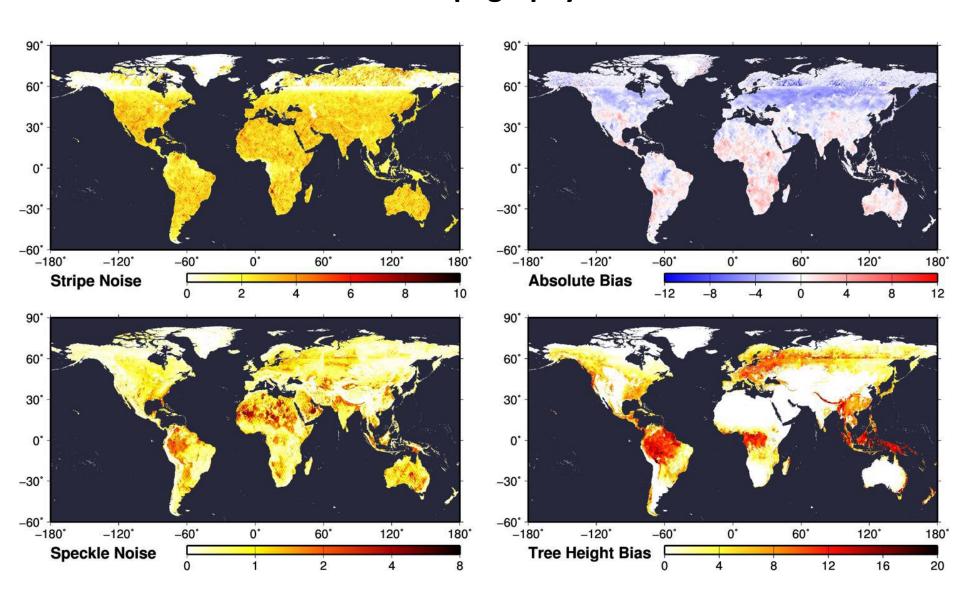
MERIT DEM (Multi-Error-Removed Improved-Terrain DEM)

Obtained by applying multi-component error removal to SRTM3 and AW3D



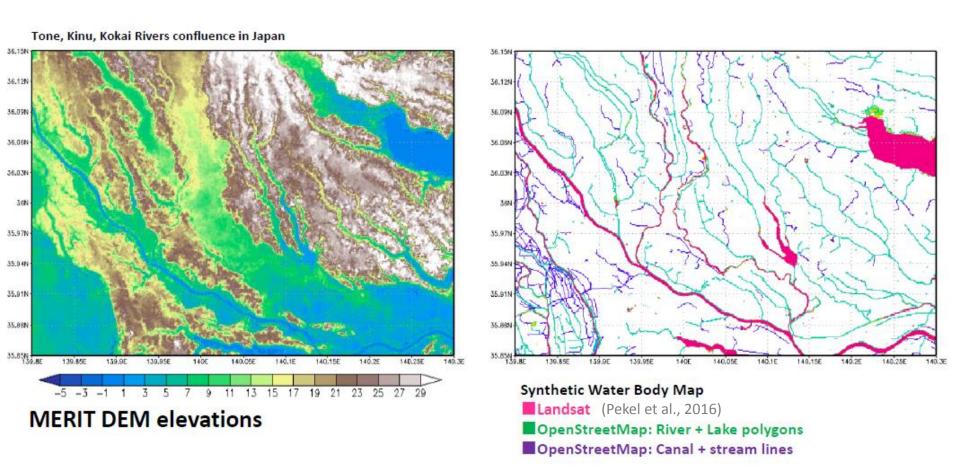
Yamazaki et al., 2017 (GRL)

http://hydro.iis.utokyo.ac.jp/~yamad ai/MERIT_DEM/

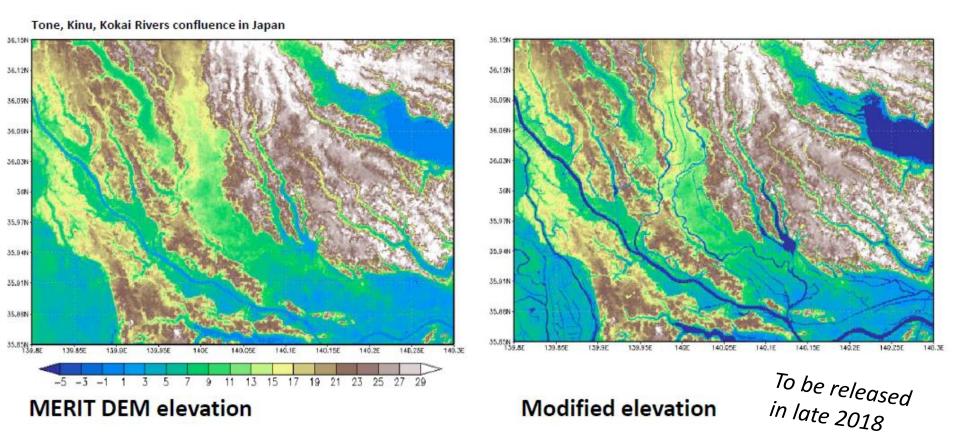


Yamazaki et al., 2017 (GRL)

Modified elevations of DEMS using multiple water body maps to ensure river connectivity and to represent small channels



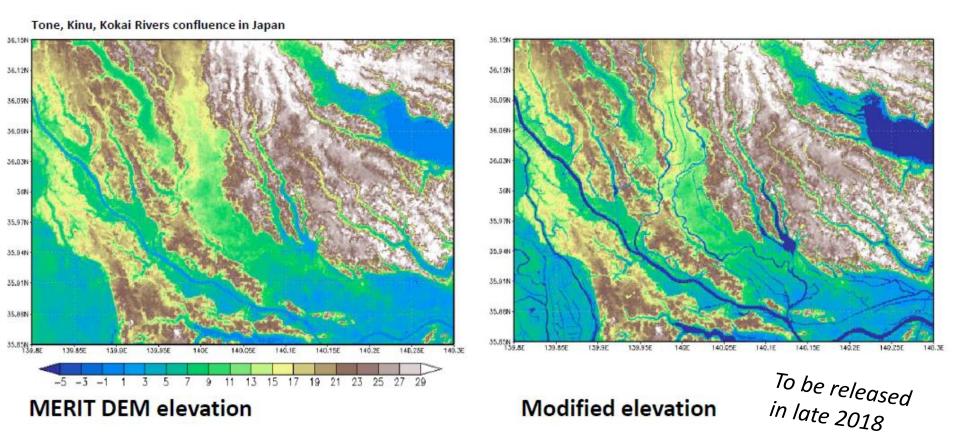
Modified elevations of DEMS using multiple water body maps to ensure river connectivity and to represent small channels



To further investigate:

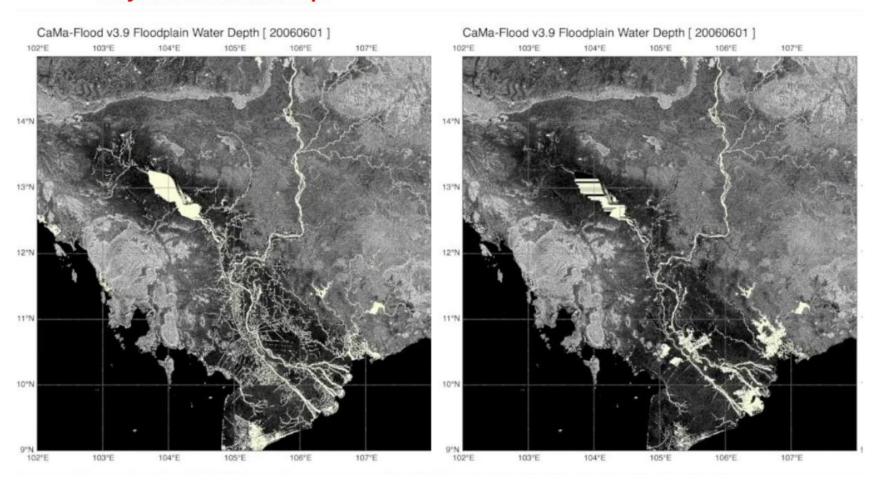
Global Flood Partnership

https://gfp.jrc.ec.europa.eu/about-us



[New] MERIT DEM + New hydrography + Synthetic water map

[Old] SRTM + HydroSHEDS



Credits to Dai Yamazaki – from his presentation at the Global Flood Partnership meeting – Delft 2018

OPEN CHALLENGES

- Missing dataset to improve global flood modelling

Global channel bathymetry Global levee height datasets Global reservoir, lakes datasets

- Local data integration

Possible integration of high-accuracy topography available locally

- Validation data, assimilation

Satellite Altimetry, multi-satellite flood extent (Landsat, MODIS, etc.)
Assimilation of these sources

RIVER BATHYMETRY ESTIMATION

The literature reports several attempts made to handle the absence of bathymetric information:

- **Geomorphic equations** relating river discharge, depth, and water surface width as proposed by Leopold and Maddock [1953];
- Using the original **SRTM assuming the knowledge of flow rates and concurrent water depth** during the SRTM acquisition [Alfieri et al., 2013];
- Considering bathymetry as an **additional model parameter** to be calibrated (Yan et al., 2015).
- By referring to local available data
- **Data assimilation** technique combines water surface elevation, h, with hydrodynamic models in order to estimate the flow depth and the river discharge at a given section [Andreadis et al., 2007; Durand et al., 2008, 2014; Oubanas et al., 2018];
- Referring to satellite images with the use of simplified flow resistance equation (Flow Resistance Equation-Based Imaging of River Depths –FREEBIRD- algorithm; Legleiter, 2015)
- by considering **concurrent water surface elevation**, h, **and width**, w, sensed from satellite [Mersel et al., 2013]



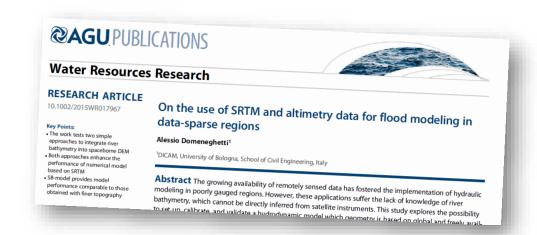
RIVER BATHYMETRY ESTIMATION

Channel Bankfull Method:

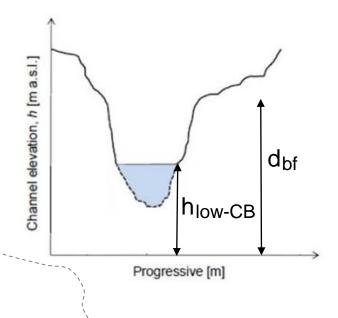
it estimates river depth using empirical relationship for a limited number of gauging stations [Leopold and Maddock, 1953]

Slope Break Method:

it exploits the linear relationship between water surface width and water surface elevation [Mersel et al., 2013]



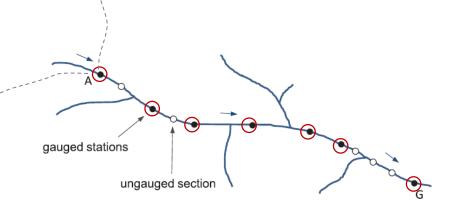
CHANNEL BANKFULL METHOD - CB

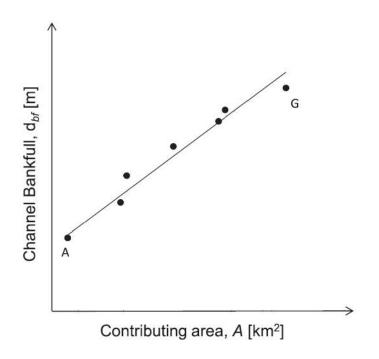


The CB approach investigates the possibility to enhance the description of the river geometry by exploiting the $A-d_{\rm bf}$ relationship.

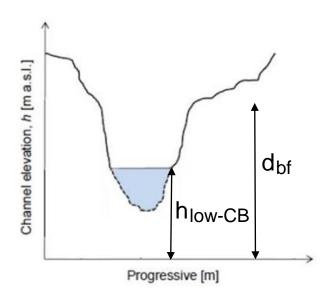
Firstly, the A-d_{bf} relationship is identified for gauged sections.

$$A \sim d_{bf}$$





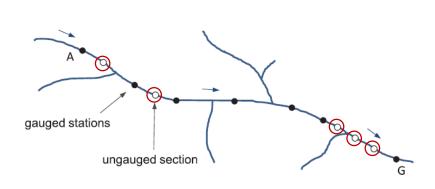
CHANNEL BANKFULL METHOD - CB

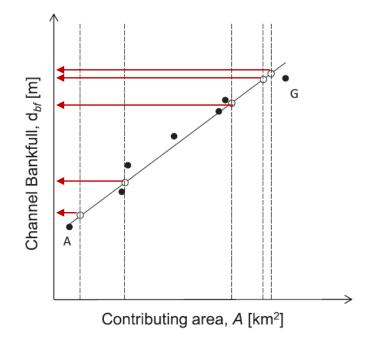


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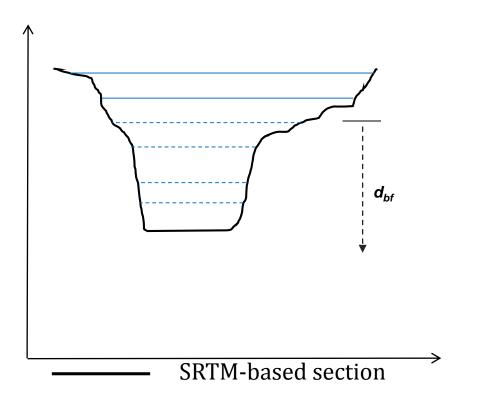
For all ungauged sections the contributing area is extracted, in order to find corresponding channel bankfull, exploiting previous linear relationship.

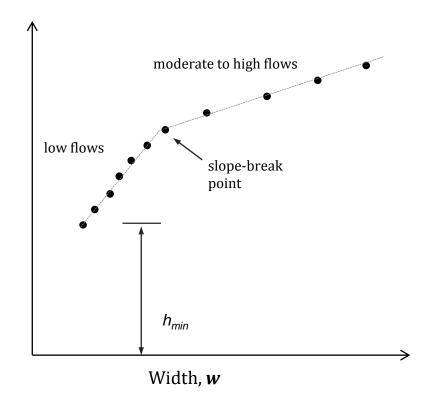




SLOPE BREAK METHOD - SB

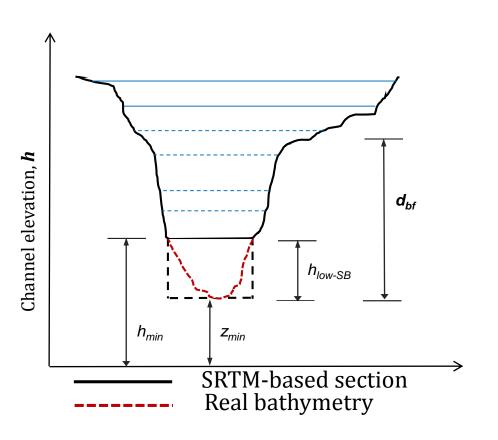
 \rightarrow Linear relationships among the water surface width, w, and water surface elevation, h

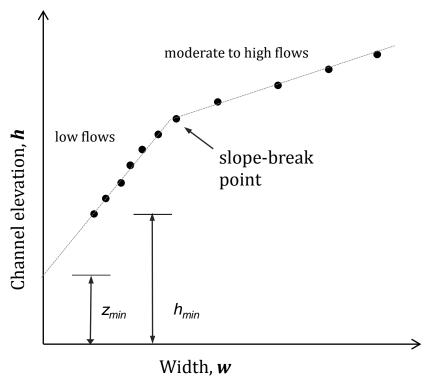




SLOPE BREAK METHOD - SB

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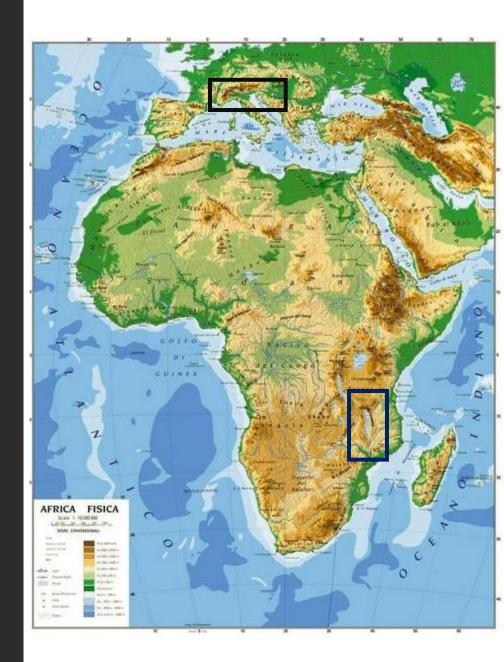


SURVEY AREAS

Po River, Italy (132 km)
Limpopo River, Mozambique (164 km)

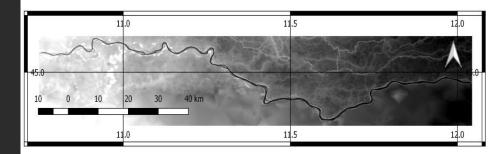
Case study characteristics

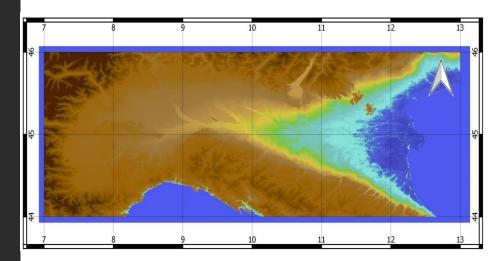
- 1. Mono-corsual stretch
- 2. River width greater than DEM resolution
- 3. Availability of in-situ measurements



PO RIVER: AVAILABLE DATA

- LiDAR DEM (resolution 2 m integrated with in-situ bathymetry measurements)
- SRTM 90
- Mean daily water level and discharge at gauged stations
- Altimetry series (ERS and ENVISAT)
- Reference hydraulic model (quasi-2D)







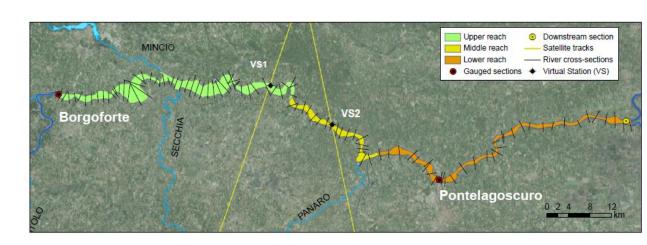
DATA & BENCHMARK MODEL

- 2 m LiDAR for the overall study area
- 104 river cross-sections
- Mean daily discharge at the upstream section

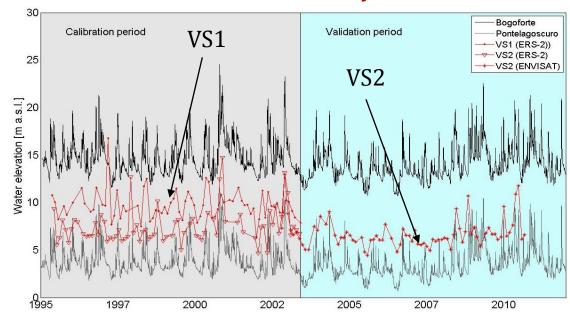
Mean daily waterelevation at Pontelagoscuro

ERS-2: June 1995-May 2003

ENVISAT: Oct. 2002- Aug. 2010



- Satellite altimetry datasets:



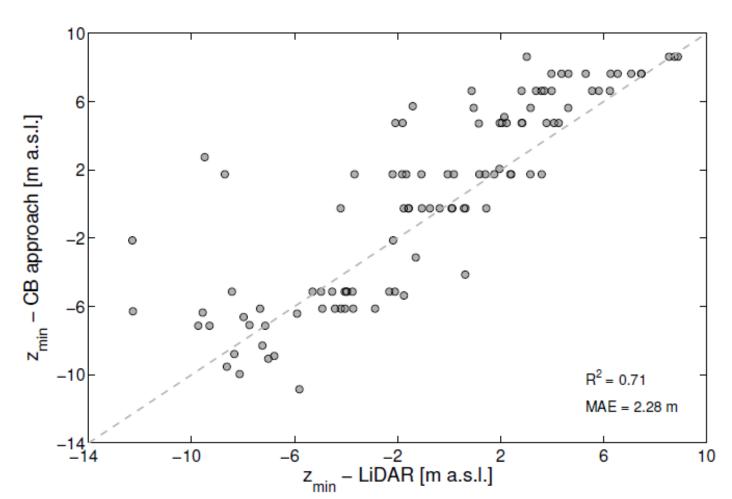
CHANNEL BANKFULL METHOD - CB

Linear relationship identified among

River thalweg: LiDAR vs CB-approach

$$A \sim d_{bf}$$

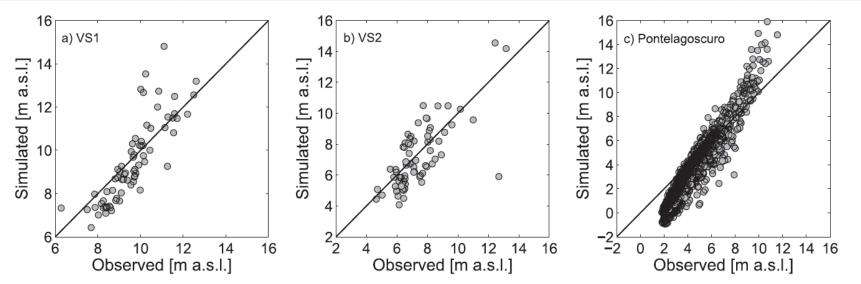
Lowering values: $4.37 \div 7.13 \text{ m}$



 $R^2 = 0.71$ ME = 1.18 m MAE = 2.28 m

CHANNEL BANKFULL METHOD -CB

Configuration	River Portion	Manning's coefficient (s m-1/3)	NS	MAE (m)	RMSE (m)
CB-model	Upper reach (VS1)	0.049	0.23	0.86	1.09
	Middle reach (VS2)	0.045	0.34	1.10	1.44
	Lower reach (PonteLS)	0.052	0.17	1.18	1.38
LiDAR-model	Upper reach (VS1)	0.044	0.43	0.70	0.93
	Middle reach (VS2)	0.042	0.34	0.76	1.08
	Lower reach (PonteLS)	0.025	0.95	0.28	0.35



The image shows the comparison between simulated water levels from CB-model and observed ones for VS1, VS2 and Pontelagoscuro, respectively.

SLOPE BREAK METHOD - SB

River cross-sections extraction

01

- DEM reading (SRTM-MERIT)
- extract river cross sections: the user can exploit a shapefile or makes the code generate perpendicular equidistant cross sections respect with a given channel center line.

River **B**athymetry **E**stimation from **S**a**T**ellite (Ri-BEST) is a Matlab software for river bathymetry evaluation applying the Slope-Break Method

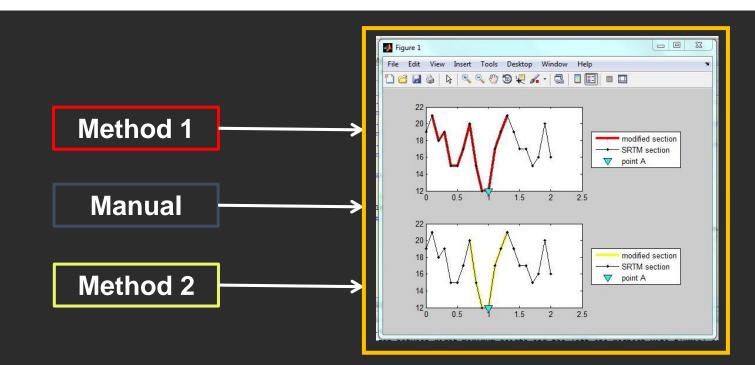


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River channel selection

02

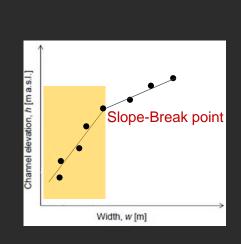
- Method 1 isolates cross section portion between left maximum height and right one;
- Method 2 identifies the part for which each point has a greater elevation than the previous one (on left and right side respectively).
- Using "Manual" method the user can see both two selections and choose the best one.

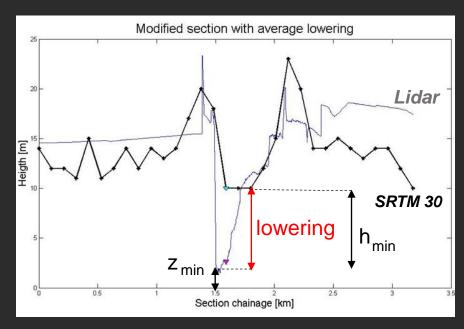


Average lowering estimation

03

Only cross sections that have at least 5 points under slopebreak point are used to estimate the river bathymetry.

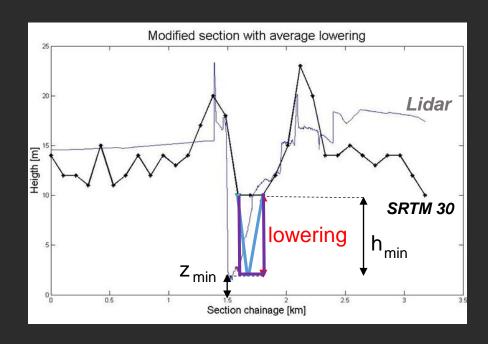




04

Cross section geometry modification

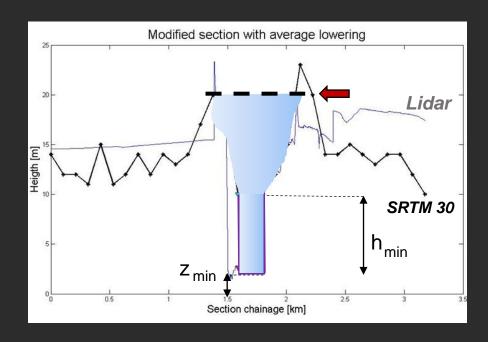
SRTM profile is corrected with two different approach: triangular and rectangular modification.



05

Estimation of flow area and wetted perimeter

Imposing a water level, flow area and wetted perimeter are estimate for the new modified cross section.



PO RIVER RESULTS: bathymetry

SRTM 90	Equidistant sections			Historical sections		
Channel selection method	Manual Method	Method 1	Method 2	Manual Method	Method 1	Method 2
Average lowering* [m]	8.3	8.8	8.9	8.7	8.5	8.6

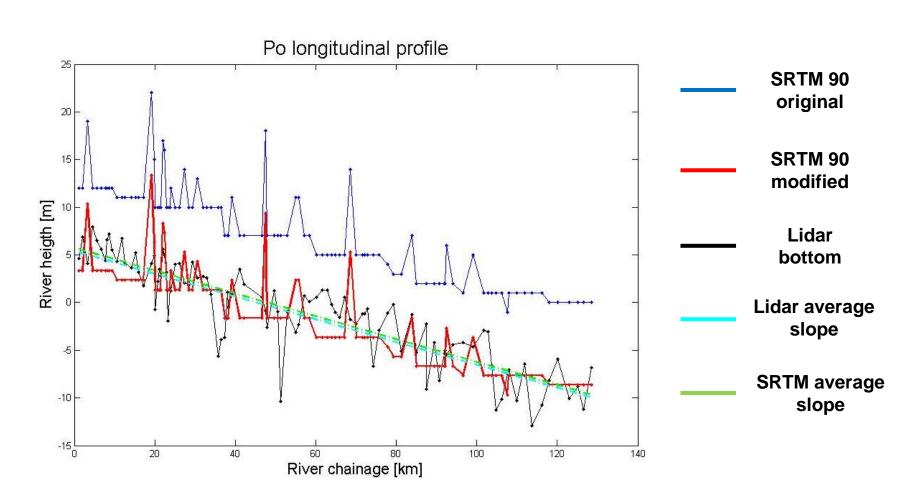
	SRTM 90	SRTM 90 mod**				
		Manual Method	Method 1	Method 2		
ME [m]	8.34	-0.32	-0.15	-0.22		
RMSE [m]	9.02	3.45	3.44	3.44		
MAE [m]	8.34	2.8	2.75	2.77		

^{*} Average lowering is the different between LiDAR and SRTM bottoms

^{**} SRTM 90 mod are referred to cross sections modified with Ri-BEST tool

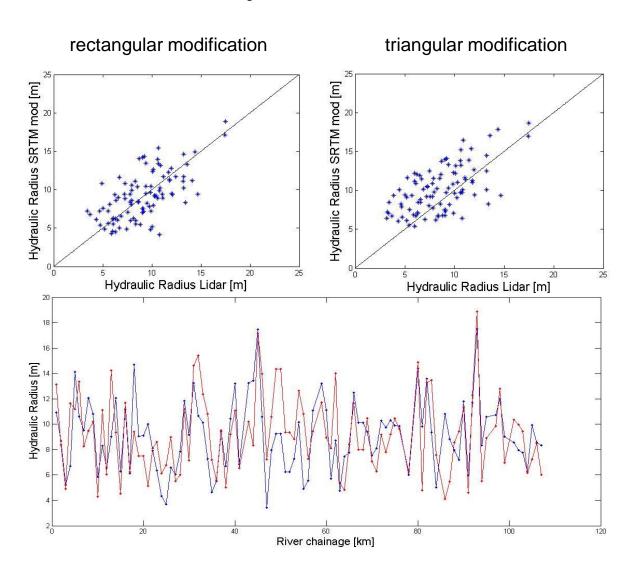
PO RIVER RESULTS:

Longitudinal profile



PO RIVER RESULTS:

Hydraulic radius

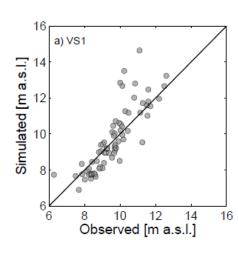


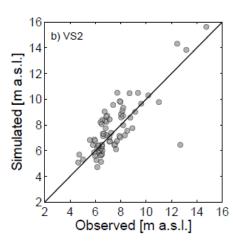
PO RIVER RESULTS:

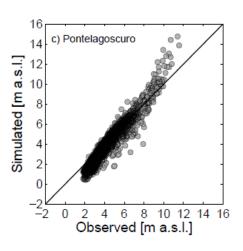
Hydraulic model



Configuration	River Portion	Manning's coefficient (s m-1/3)	NS	MAE (m)	RMSE (m)
SB-model	Upper reach (VS1)	0.044	0.38	0.68	0.97
	Middle reach (VS2)	0.042	0.49	0.97	1.13
	Lower reach (PonteLS)	0.040	0.79	0.55	0.70
LiDAR-model	Upper reach (VS1)	0.044	0.43	0.70	0.93
	Middle reach (VS2)	0.042	0.34	0.76	1.08
	Lower reach (PonteLS)	0.025	0.95	0.28	0.35







Reference model

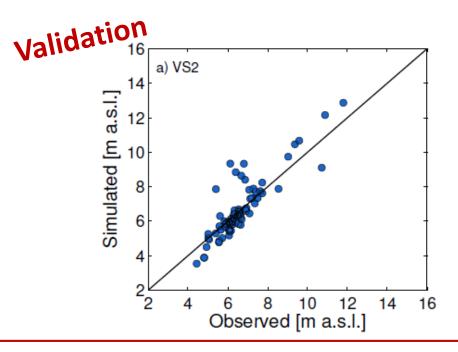
Calibration

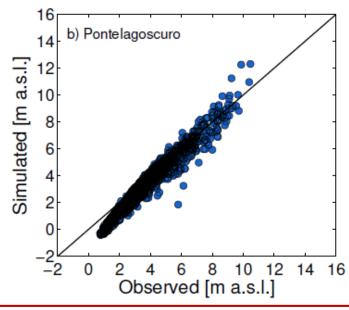
$$\Delta NS = -0.16$$
 $\Delta MAE = 0.27$ m $\Delta RMSE = 0.35$ m

PO RIVER RESULTS:

Hydraulic model







LiDAR model

NS = 0.76RMSE = 0.66 m NS = 0.96RMSE = 0.32 m

Reference model

SB-model

NS = 0.57RMSE = 0.87 m NS = 0.83RMSE = 0.60 m

Main findings

- ➤ Both CB and SB approaches can enhance the bathymetry description of the original SRTM
- ➤ SB does not require in-situ data and is more reliable than CB approach for the reconstruction of the river geometry (MAE = 2.28 m and 1.75 m for CB and SB approach, respectively)
- ➤ Calibrated friction coeff. of the SB-model are physically meaningful and reproduce the real characteristics of the river
- > SB-model performances are of the same order of magnitude of the benchmark model based on LiDAR (max Δ MAE = \sim 0.30 m)



Next steps?

Utilizing Flood Inundation Observations to Obtain Floodplain Topography in Data-Scarce Regions

Apoorva Shastry^{1,2*} and Michael Durand^{1,2}

¹ School of Earth Sciences, The Ohio State University, Columbus, OH, United States, ² Byrd Polar and Climate Research Center, The Ohio State University, Columbus, OH, United States



"Spaceborne remote sensing observations of inundation extent contain indirect information about floodplain topography." Shastry and Durand 2019

Main idea → Because two-dimensional flood models encapsulate floodplain processes, it is natural to attempt to use such models to help extract topographic information from inundation. So, the idea is to infer floodplain topography using inundation maps, while flood models do the inverse: predict inundation using floodplain topography

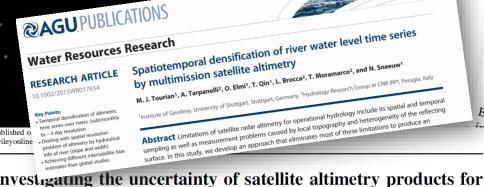


Inverse problem solved with Data Assimilation technique

Great potential in the light of the upcoming **SWOT mission** (see later on)



THE USE OF REMOTE **SENSING-DERIVED WATER** SURFACE DATA FOR HYDRAULIC **MODELING**

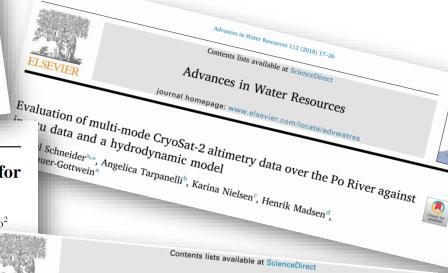


hydrodynamic modelling

Alessio Domeneghetti, 1* Attilio Castellarin, 1 Angelica Tarpanelli 2 and Tommaso Moramarco 2

¹ DICAM—University of Bologna, School of Engineering, Viale del Risorgimento, 2, Bologna, Italy ² Research Institute for Geo-Hydrological Protection, National Research Council, Via Madonna Alta 126, 06128 Perugia, It





Journal of Hydrology

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

Research papers

River discharge estimation at daily resolution from satellite altimetry

M.J. Tourian ^{a,*}, C. Schwatke ^b, N. Sneeuw ^a



HYDROLOGY

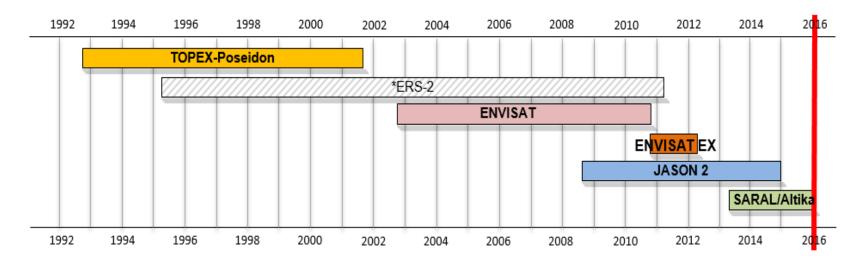


Graphical illustration of past, current and future satellite altimetry missions for the monitoring of the world's rivers, lakes and reservoirs.

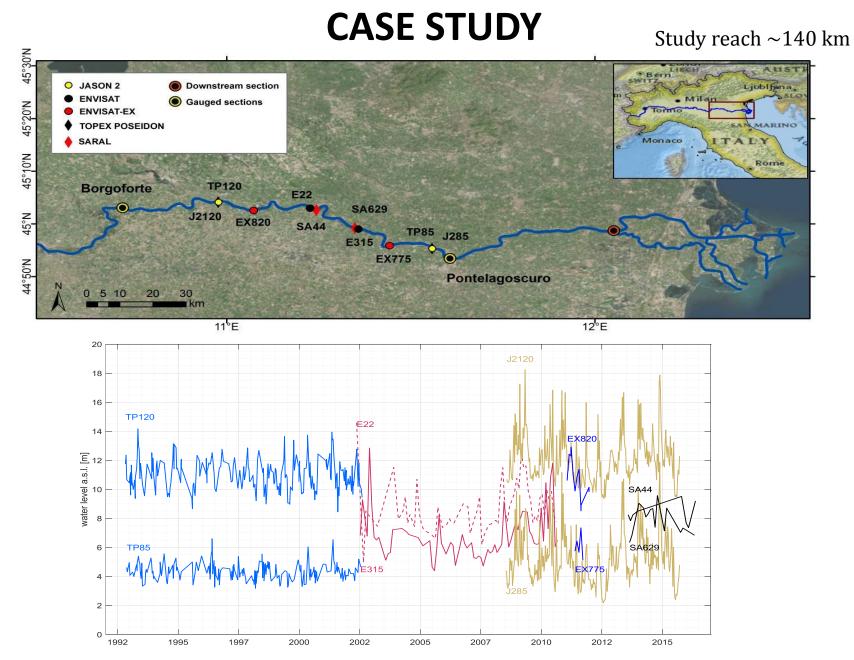
Monitoring of freshwater represents the base for the management of global water resources. However, the high cost related to the set-up and maintenance of traditional monitoring networks makes the density of observed data very limited in vast parts of the globe. On the contrary, the last decades have seen a great evolution on the capability to acquire remotely sensed observations, providing an increasing availability of spatially distributed data to be used for monitoring inland water.

ON THE POTENTIAL OF ALTIMETRY DATA FOR THE CALIBRATION OF HYDRAULIC MODELS: A COMPARISON OF DIFFERENT PRODUCTS AND MULTI-MISSION SERIES

- → the effect of satellite record length (i.e. number of available measurements) on the calibration of the hydraulic model;
- → the impact of the uncertainty of altimetry data on the accuracy of model calibration;
- → comparison of different satellite altimetry products;
- → the benefit of multi-mission series, which overcome the low satellite temporal resolution.



Temporal distribution of all satellite altimetry missions available up to 2016 (red line): TOPEX/Poseidon, Envisat, Envisat EX, JASON-2, SARAL/AltiKa (*ERS-2 data are shown for completeness but not explicitly considered in the study).



Synoptic view of altimetry series at the virtual stations identified along the river stretch of interest

CASE STUDY



Mission	Abbreviations	Version	Retracker	Observation period	Temporal resolution [day]
TOPEX/Poseidon	ТР	MGDR-B	onboard	1992–2002	10
Envisat	E	GDR	ICE-1	2002–2010	35
Envisat XT	EX	GDR	ICE-1	2010–2012	35
SARAL/AltiKa	SA	GDR-t	onboard	2013–2016	35
JASON 2	J2	GDR	ICE-3	2008–2015	10
Multi-mission	MM			1995–2016	3

Satellite sensors and altimetry series considered in this study

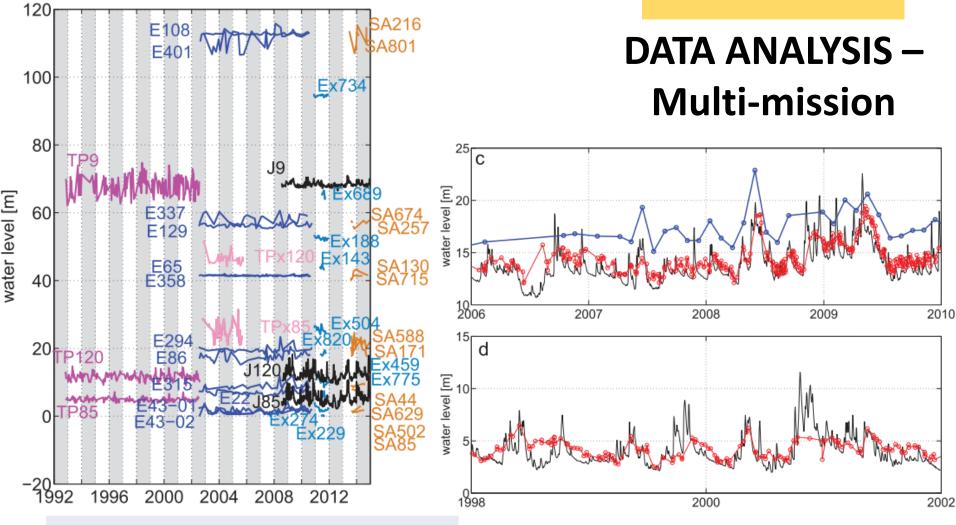


Table 4. Mean Water Level Time Series Obtained From Different Missions Over the Northern Part of the Adriatic Sea Against Tide Gauge

Mean Water Level (m)	Number	
0.48 ± 0.03	516	
0.41 ± 0.05	164	
0.52±0.06	148	
0.55±0.06	21	
0.61 ± 0.04	363	
0.55±0.04	255	
-1.19±0.05	114	
0.42±0.05	22	
	0.48 ± 0.03 0.41 ± 0.05 0.52 ± 0.06 0.55 ± 0.06 0.61 ± 0.04 0.55 ± 0.04 -1.19 ± 0.05	

in situ water level
original altimetric water level from ENVISAT
densified altimetric water level

Tourian et al., 2016 (WRR)

DATA ANALYSIS – single mission

$$\varepsilon(x,t) = h_{sat}(x,t) - h_{obs}(x,t)$$

Estimated at VS by linearly interpolating concurrent water elevation measured at the gauging stations

EX775 and SA44 are particularly limited in the number of measurements.

Jason 2 outperforms all the other satellite products.

VS	n° data	r ² [-]	μ [m]	σ [m]
TP120	174	0.77	-0.42	0.75
TP85	158	0.60	0.08	0.70
E22	61	0.85	0.05	0.87
E315	65	0.97	0.30	0.43
EX820	12	0.91	0.50	0.57
EX775	5	-0.35	1.17	1.40
J2-120	261	0.99	0.17	0.30
J2-85	259	0.98	0.19	0.37
SA44	8	0.92	0.14	0.55
SA629	15	0.96	0.40	0.30

DATA ANALYSIS – multi-mission

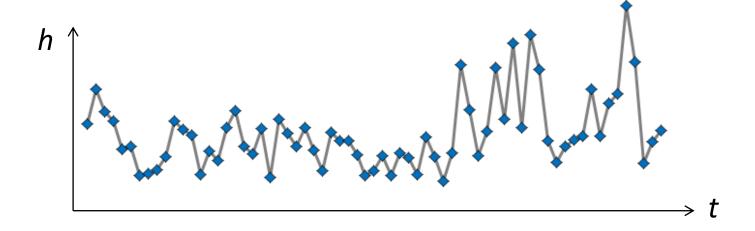
$$\varepsilon(x,t) = h_{mm}(x,t) - h_{obs}(x,t)$$

All multi-mission series reports a considerable number of observations

VS	n° data	r ² [-]	μ [m]	σ [m]
MM120	1411	0.77	0.91	0.96
MM820	1237	0.77	-0.01	0.85
MM22	1235	0.78	0.20	0.89
MM44	1411	0.78	0.14	0.89
MM629	1411	0.78	0.36	0.87
MM315	1236	0.78	0.39	0.87
MM775	1236	0.77	0.79	0.93
MM85	1413	0.77	0.99	0.99

Multi-mission series (MM) algorithm connects all VSs hydraulically and statistically and densifies the water level time series obtaining a temporal density on average equal to **3 days**

DATA ANALYSIS

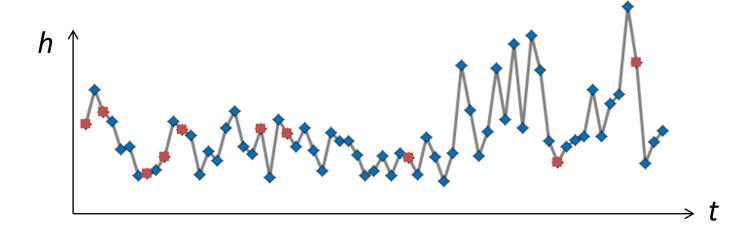


 L_{tot} = total record length of the original satellite dataset (total number of observations) m = generic record length;

$$\begin{aligned} & \boldsymbol{h_{sat,m}}(x) = [h_{sat,m}(x,t_1),h_{sat,m}(x,t_2),...,h_{sat,m}(x,t_{m-1}),h_{sat,m}(x,t_m)] \quad \forall \, m = 3,...,L_{tot} \\ & \boldsymbol{h_{obs,m}}(x) = [h_{obs,m}(x,t_1),h_{obs,m}(x,t_2),...,h_{obs,m}(x,t_{m-1}),h_{obs,m}(x,t_m)] \end{aligned}$$

 $1000 \; h_{sat,m}(x)$ subsets for each m value

DATA ANALYSIS



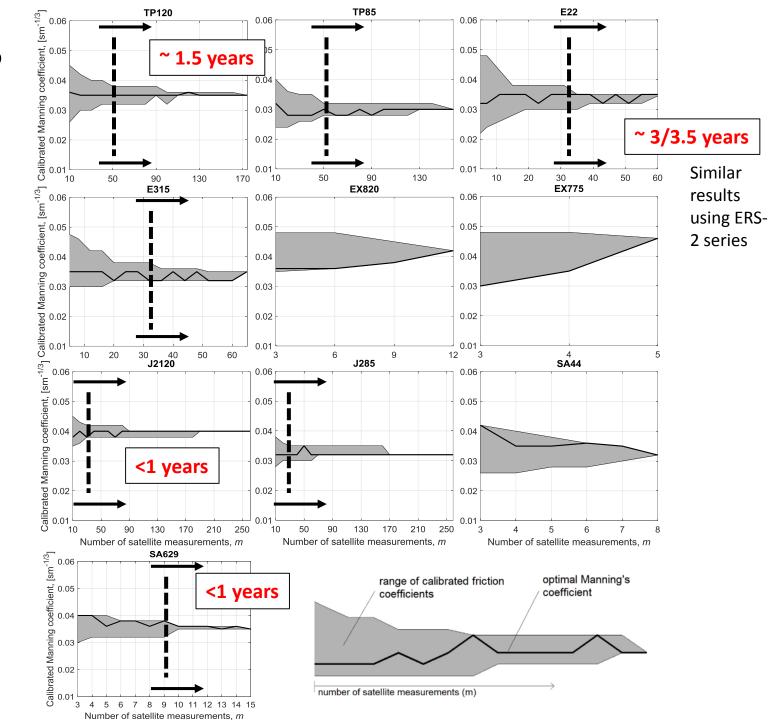
 L_{tot} = total record length of the original satellite dataset m = generic record length;

$$\begin{aligned} & \boldsymbol{h_{sat,m}}(x) = [h_{sat,m}(x,t_1),h_{sat,m}(x,t_2),\dots,h_{sat,m}(x,t_{m-1}),h_{sat,m}(x,t_m)] \ \forall \ m = 3,\dots,L_{tot} \\ & \boldsymbol{h_{obs,m}}(x) = [h_{obs,m}(x,t_1),h_{obs,m}(x,t_2),\dots,h_{obs,m}(x,t_{m-1}),h_{obs,m}(x,t_m)] \end{aligned}$$

 $1000 \; h_{sat,m}(x)$ subsets for each m value

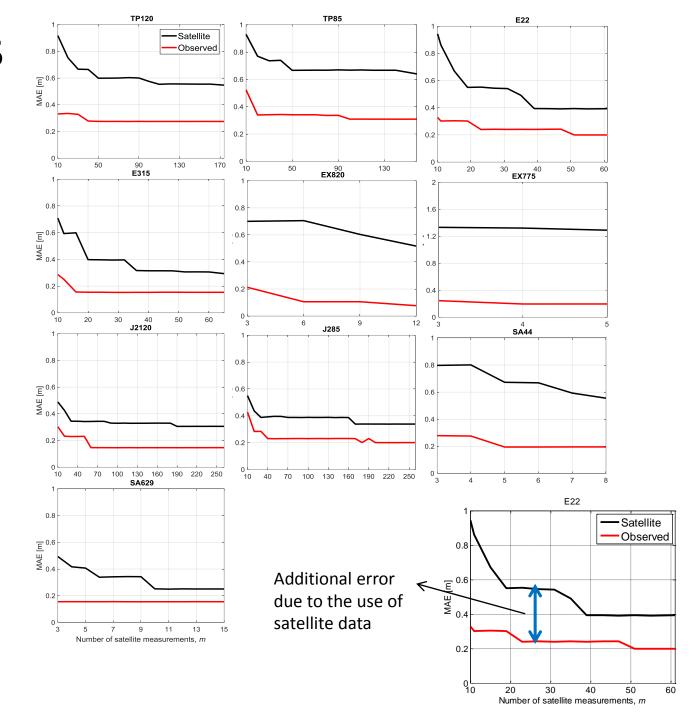
RESULTS

Calibration results for different altimetry series length: range of calibrated roughness coefficient (grey areas) and optimal Manning's value (black line) as a function of the number of satellite measurements, m.

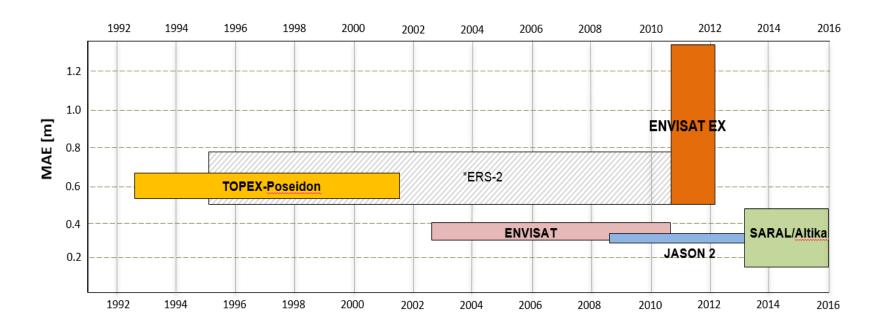


RESULTS

Maximum mean absolute error (MAE) obtained calibrating the numerical model with satellite altimetry data (black line) and in situ water levels (red line) as a function of data length, m.



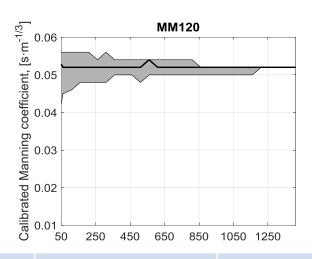
RESULTS Single mission

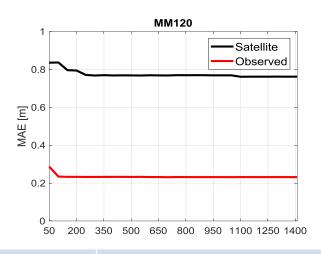


Synoptic view of the maximum mean absolute error (MAE) of each satellite mission in time (*ERS-2 is a recall from a previous investigation): the vertical height of each box is defined as the range of the MAE obtained from the calibration considering $m = L_{tot}$

RESULTS – Multi-mission

Example of results obtained using Multi-mission series

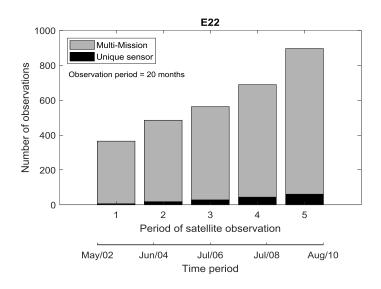


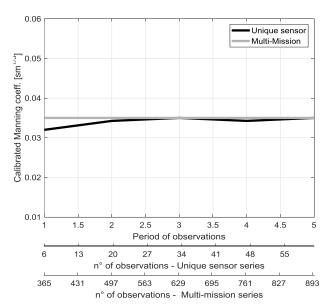


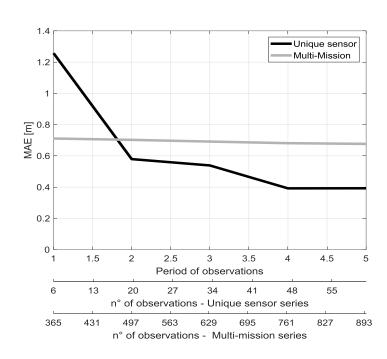
	r	MM series		Original altimetry series $\Delta = MM - Orig.$		Original altimetry series $\Delta = MM - Orig.$			
VS	n	RMSE	MAE	n [m ^{1/3} s ⁻¹]	RMSE	MAE [m]	Δn	Δ-RMSE [m]	Δ-ΜΑΕ
	[m ^{1/3} s ⁻¹]	[m]	[m]		[m]		[m ^{1/3} s ⁻¹]		[m]
MM -E22	0.035	0.94	0.68	0.035	0.83	0.39	0.00	0.11	0.29
MM-E315	0.035	0.89	0.64	0.035	0.46	0.29	0.00	0.43	0.35
MM-EX820	0.038	0.92	0.65	0.042	0.61	0.52	-0.004	0.31	0.13
MM-EX775	0.043	0.96	0.70	0.046	1.53	1.29	-0.003	-0.57	-0.59
MM-TP120	0.052	1.07	0.76	0.035	0.75	0.55	0.017	0.32	0.21
MM-TP85	0.043	1.02	0.73	0.030	0.79	0.64	0.013	0.23	0.09
MM-SA44	0.032	0.96	0.69	0.034	0.72	0.56	-0.002	0.24	0.13
MM-SA629	0.035	0.90	0.65	0.035	0.29	0.25	0.00	0.61	0.4
MM-J2-120	0.052	1.07	0.76	0.040	0.40	0.31	0.012	0.67	0.45
MM-J2-85	0.043	1.02	0.73	0.032	0.48	0.34	0.011	0.54	0.39

Calibration results: optimal calibrated Manning's coefficient (n), root mean square error (RMSE) and mean absolute error (MAE) obtained from the calibration process performed adopting the MM and original altimetry series ($m = L_{tot}$).

RESULTSSingle Vs. Multi-mission

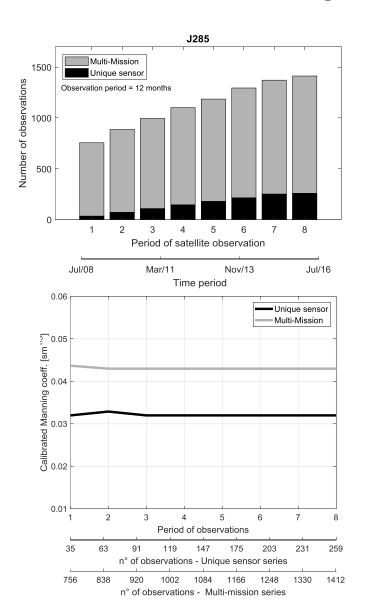


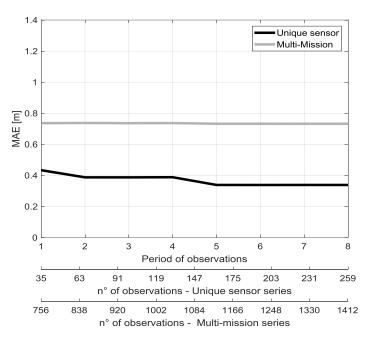




ENVISAT Vs. Multi-mission

RESULTSSingle Vs. Multi-mission





JASON-2 Vs. Multi-mission



INLAND WATER MONITORING THE **SWOT** MISSION AND ITS CAPABILITIES FOR LAND HYDROLOGY

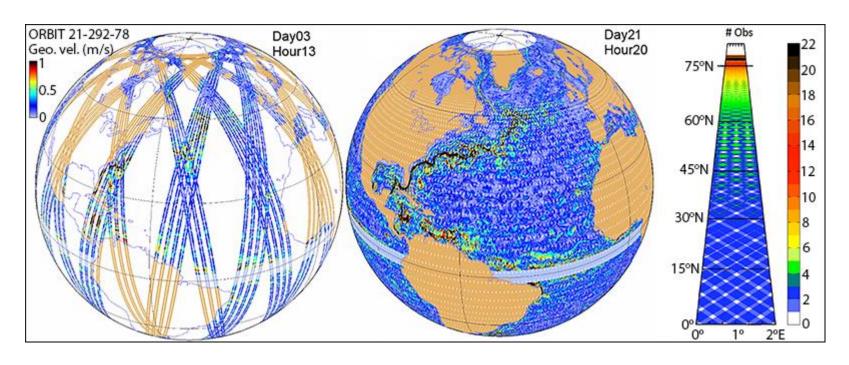
SWOT: **S**urface **W**ater and **O**cean **T**opography

NASA, French, Canadian and United Kingdom Space Agencies

To be launched on Sept. 2021, SWOT will completely cover the world's oceans and freshwater bodies with repeated high-resolution elevation measurements.

https://swot.jpl.nasa.gov/

Spatial and temporal coverage



SWOT's nominal coverage during its 3-year science orbit will include measurements between 78°N and 78°S collected over a period of 21 days. Maps show the **coverage after 3 days (left)** and the **full 21 days (center)** of a complete cycle. The graphic at the far right illustrates the number of **observations at a given latitude during the 21-day repeat period**.

Credits: C. Ubelmann, CLS (left, center) and JPL/NASA (right)

Science requirements and goals

Observed areas	All observed water areas detected by SWOT will be provided to end users, but: errors will be <i>evaluated</i> for $(250 \text{ m})^2$ (= 62,500 m ²) water bodies and 100 m (width) × 10 km (long) river reaches or higher errors will be <i>characterized</i> for $(100 \text{ m})^2$ to $(250 \text{ m})^2$ water bodies and 50 m to 100 m (width) × 10 km (long) river reaches
Height accuracy	<10 cm when averaging over water area >1 km ² <25 cm when averaging over (250 m) ² <water <1="" area="" km<sup="">2</water>
Slope accuracy	1.7 cm/km for evaluated river reaches when averaging over water area >1 km ²
Relative errors on water areas	<15 % for evaluated water body and river reaches <25 % of total characterized water body and river reaches
Mission lifetime	3 months of fast sampling calibration orbit $+$ 3 years of nominal orbit
Rain/layover/frozen water flag	68 % or more of the contaminated data should be correctly flagged
Data collection	>90 % of all ocean/continents within the orbit during 90 % of operational time

Rodrìguez E. (2015) Surface Water and Ocean Topography mission (SWOT), Science Requirements Document. JPL document D-61923. https://swot.jpl.nasa.gov/files/swot/SRD 021215.pdf.

Biancamaria et al., 2016 (SG)

Science requirements and goals

Orbit			
Altitude	890.5 km		
Inclination	77.6°		
Repeat period	20.86 days		
KaRIn (core payload)			
One swath extent (total swaths: 2)	50 km		
Distance between the two swaths outer edges	120 km		
Distance between the two swaths inner edges ("nadir gap")	20 km		
Radar frequency/wavelength	35.75 GHz/8.6 mm (Ka-band)		
Distance between the two antennas (baseline)	10 m		
Instrument azimuth pixel size (radar projection)	6–7 m		
Instrument range pixel size (radar projection)	From 60 m (near range, incidence angle $\sim 0.6^{\circ}$) to 10 m (far range, $\sim 3.9^{\circ}$)		
Additional science payload			
Nadir altimeter	Similar to the dual-frequency (Ku/C) Poseidon-3 nadir altimeter on Jason-2		
Precise orbit determination system	Laser retroreflector DORIS receiver GPS receiver		
Radiometer (usable only over oceans)	Three-frequency (18, 23 and 34 GHz) radiometer, similar to advanced microwave radiometer on Jason-2		

SWOT mission characteristics

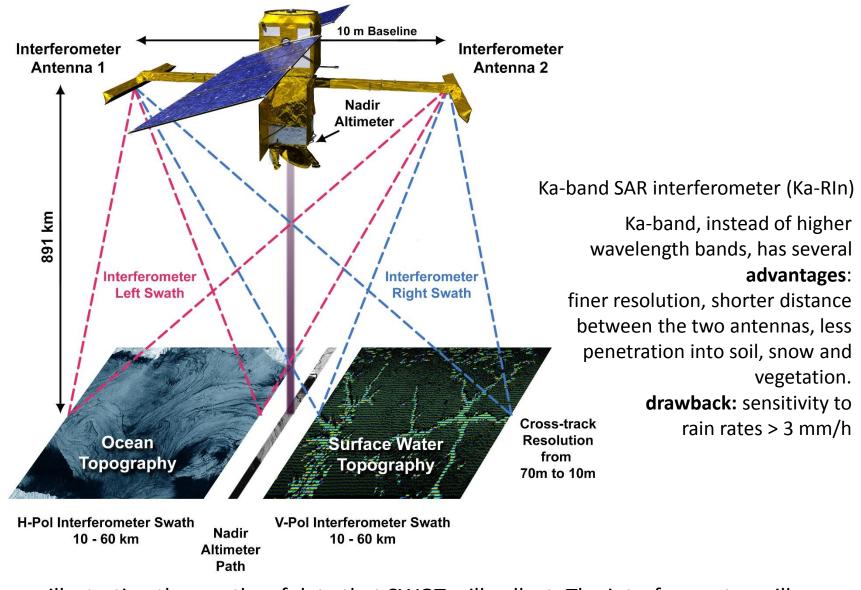
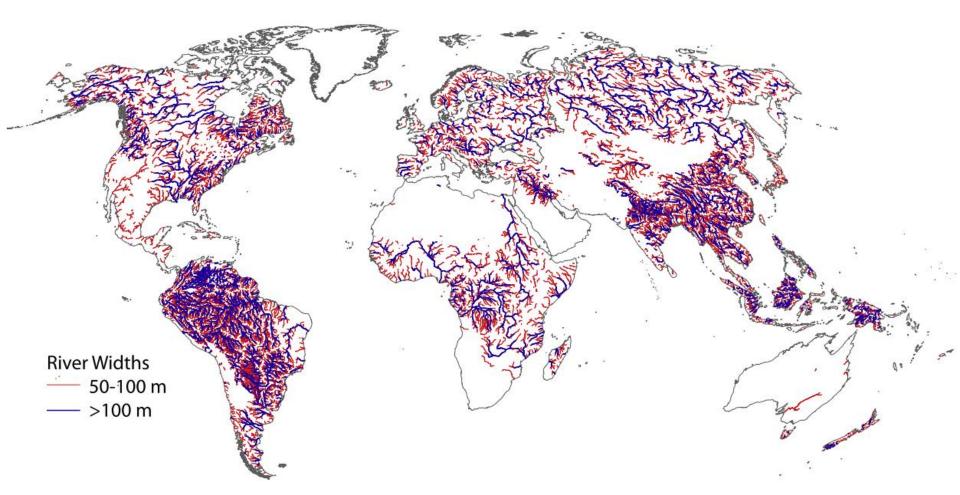


Diagram illustrating the swaths of data that SWOT will collect. The interferometer will produce two parallel tracks, with a Nadir track from a traditional altimeter in the gap between the swaths. The overall width of the swaths will be approximately 120 km.

Global river coverage

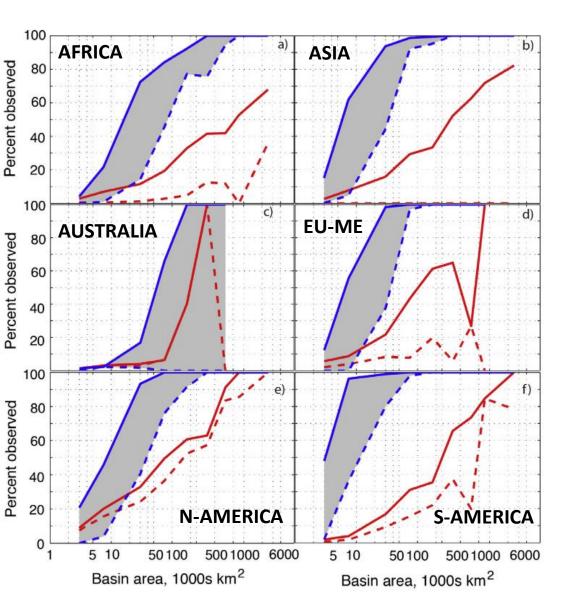
Pavelsky et al., 2014 (JH)



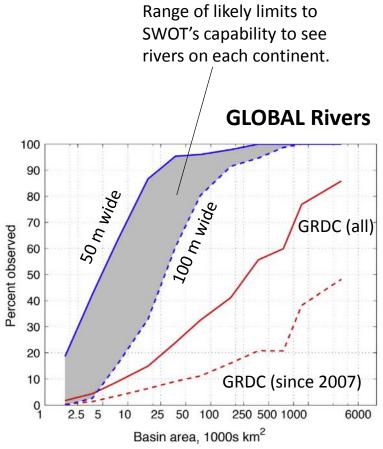
Map of global river database used in this study (GRDC).

Allen, G. H., & Pavelsky, T. M. (2018). Global extent of rivers and streams. Science.

Global river coverage



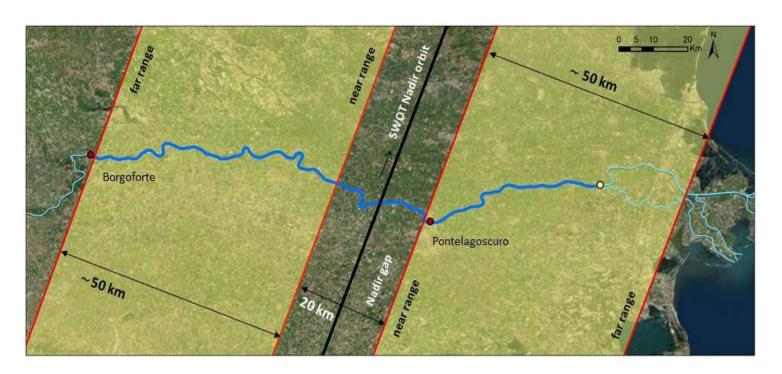
Pavelsky et al., 2014 (JH)



SWOT would observe more than 60 % of the global sub-basins with an area of 50,000 km2 given the ability to observe rivers wider than 100 m. If SWOT can meet the goal of observing 50-m-wide rivers, more than 60 % of sub-basins with an area of 10,000 km2 would be observed.

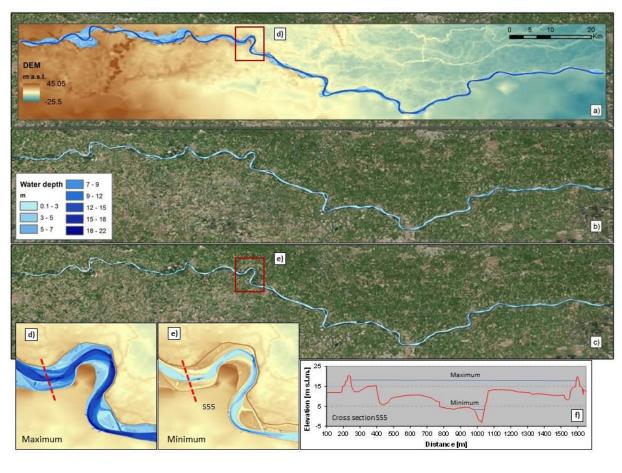
SWOT Hydrology Simulator developed by JPL

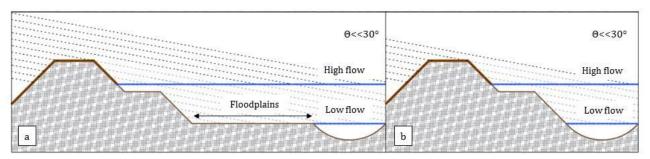
The simulation assumes a backscatter coefficient (σ_0) of -5 dB for land and 10 dB for water.



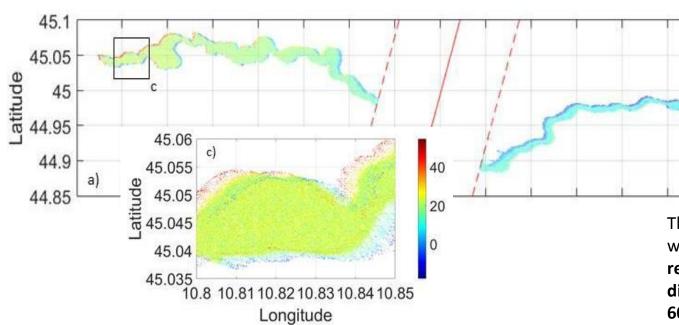
Example of a SWOT orbital pass over the study area: satellite swath (yellow areas), Po river reach considered in the study (dark blue), flowing from the gauging station (red points) of Borgoforte to the beginning of the river delta (yellow point).

Input datasets for the SWOT simulator: 2D water depth coverage simulated for (a) high, (b) mean and (c) low river flow conditions (blue scale) and 2 m resolution DEM for river bathymetry and flood prone areas (from brown to green). Red boxes identify the same area used to show the different flood extents for (d) high and (e) low flow events, which may correspond to very different water depths at a given crosssection (e.g., cross-section S55; panel (f)).





Layover illustration for embanked river in case of incidence angles <<30° and in case of (a) large or (b) absent lateral floodplains (modified from Fjortfot *et al.*, 2014).



Mean error (m) of water surface elevation for different point classifications.

	Point classification					
	All points	Interior water	Water near land edge	Land near water edge	Land	
High flow	0.040	-0.0016	0.378	0.773	0.059	
Mean flow	-0.354	-0.157	-1.249	-1.489	-0.197	
Low flow	-0.51	-0.218	-1.365	-1.588	-0.47	

The Ka-band sensor will observe water bodies with a ground pixel resolution of nearly 6 m in the direction of the satellite, and from 60 m to 10 m (near and far range, respectively) in the direction perpendicular to the satellite track.

40

20

0

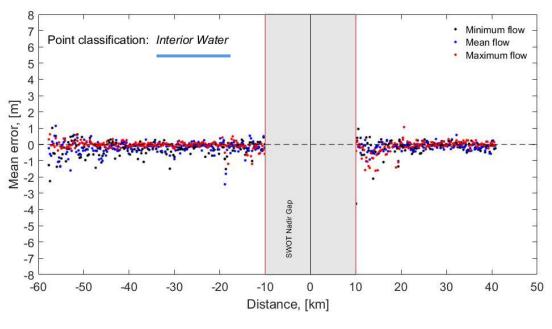
Some spatial averaging is required:

pixel cloud → a collection of
intrinsic pixels plotted with
reference to a geographical
coordinate system

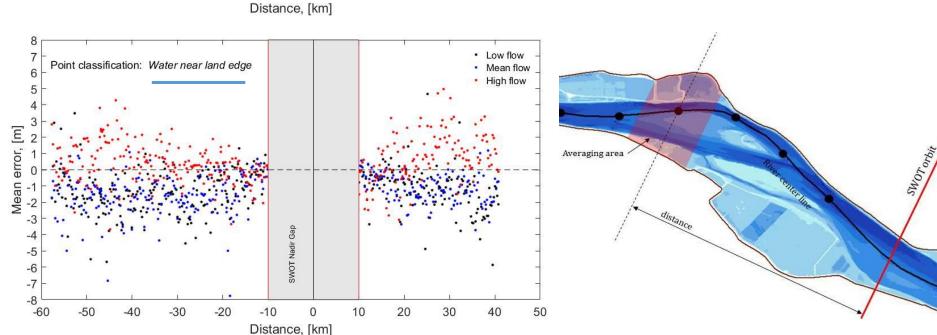
Mission Requirements - Height accuracy:

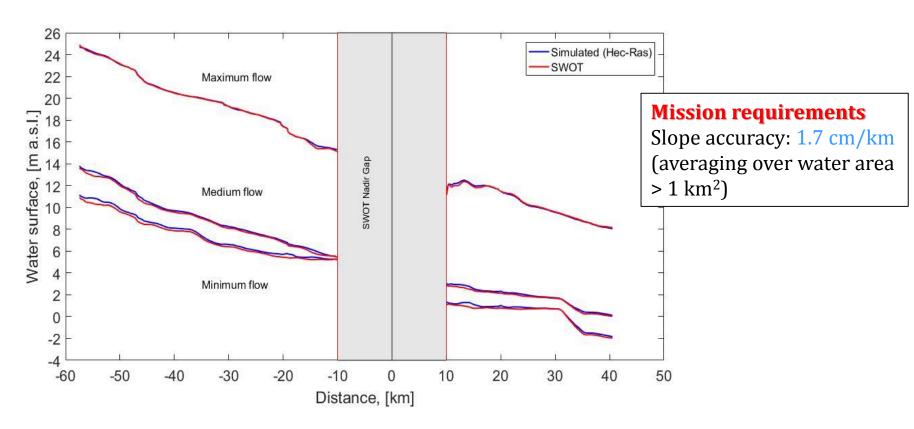
< 10 cm; area > 1 km²

 $< 25 \text{ cm}; (250 \text{ m})^2 < \text{water area} < 1 \text{ km}^2$



Mean error (ME) on water surface elevation for interior water (upper panel) and water near land edge (lower panel) points; points are shown in relation to the distance from the Nadir orbit (negative distances indicate the left swath).





Water surface profiles for the three considered scenarios: (blue) Hec-Ras and (red) SWOT water profiles estimated considering an averaging area of 1 km² and a ten-point moving average filter

	HR-slope (m/km)	SWOT- slope (m/km)	Δ slope SWOT-HR (cm/km)
Max flow	0.172	0.175	0.2573
Mean flow	0.0954	0.0855	0.9942
Min flow	0.0948	0.0608	3.394

SWOT will provide measurements of surface water elevation, slope, and water mask

SWOT level-2 data products will (likely) **include**:

- For each pass a water mask with point cloud product with water elevation (and uncertainty)
- Once every repeat cycle: a global water mask following shorelines of observed water bodies in vector format (+ e.g., water elevation, wetted area, slope)
- Global one-dimensional vector product with estimated discharge along river reaches (wider than 50 m)
- Cross-sectional map of all observed water bodies derived from time-varying water elevations (yearly)

...in addition to this product SWOT will be able to characterize *changes in cross-sectional area*, as well as *channel morphology* through indices such as *sinuosity, meander length, and radius*, whereas the remaining variables, i.e., **velocity and depth, will have to be estimated**.

No real-time consideration for provision of SWOT data product

→ Derived product are expected to be provided within 60 days of their collection

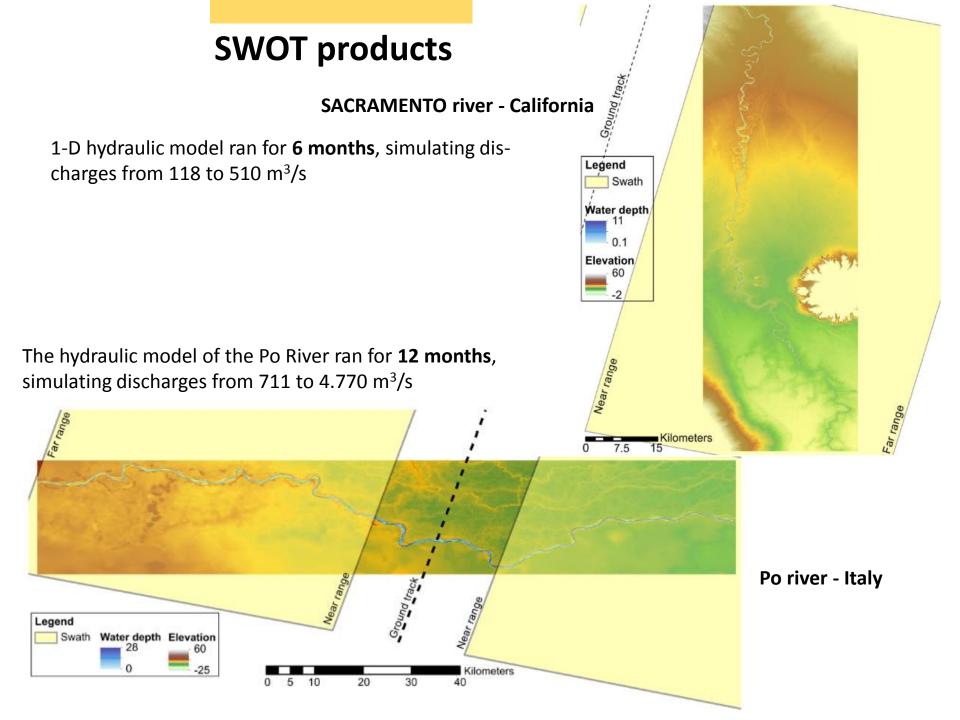
There are still many challenges regarding how to manage and process the observations.

What is the best river reach definition strategies?
How does this choice impacts on product accuracy?
What is the accuracy on discharge estimation?

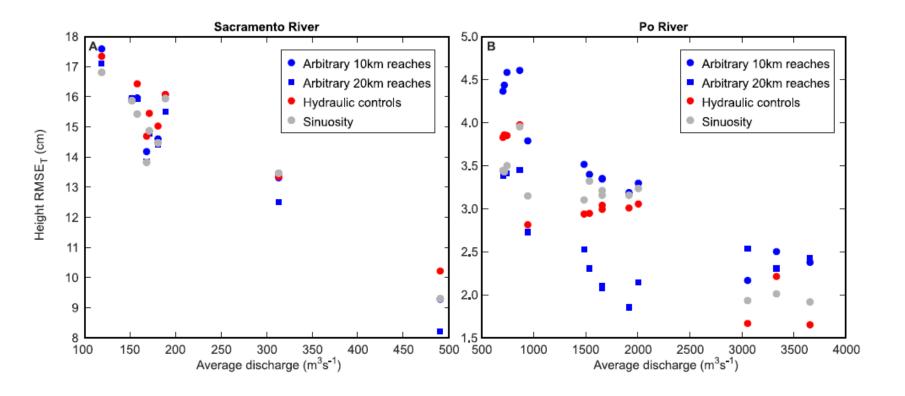


- Arbitrary lengths (es. 10km, 15km, etc.)
- River sinuosity
- Inflection points on the water surface profile

How do height, width and slope errors propagate to discharge estimation?

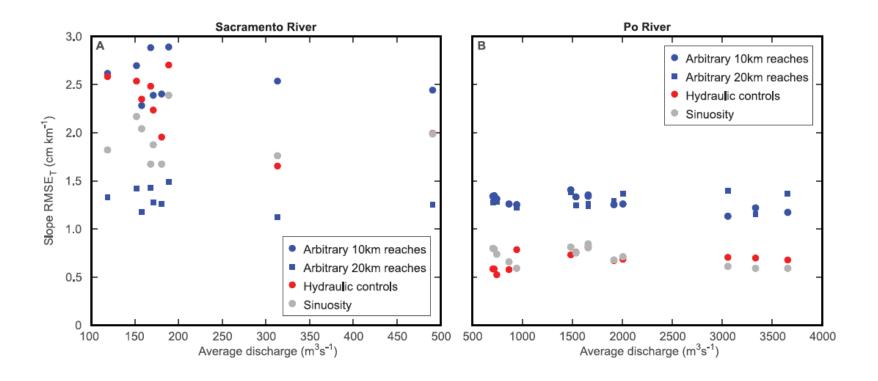


SWOT will provide an estimate of discharge by means of slope, river width and height



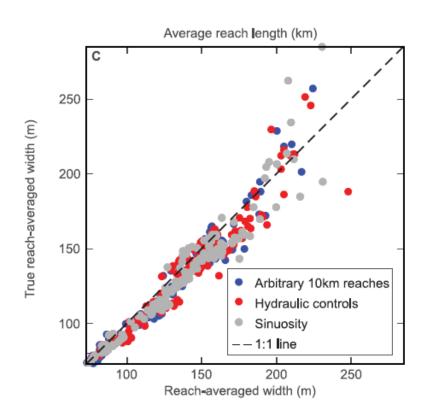
SWOT products

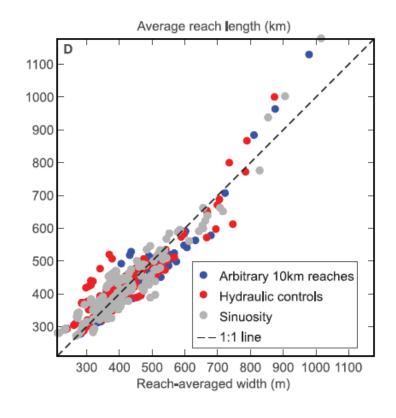
SWOT will provide an estimate of discharge by means of slope, river width and water surface elevation



SWOT products

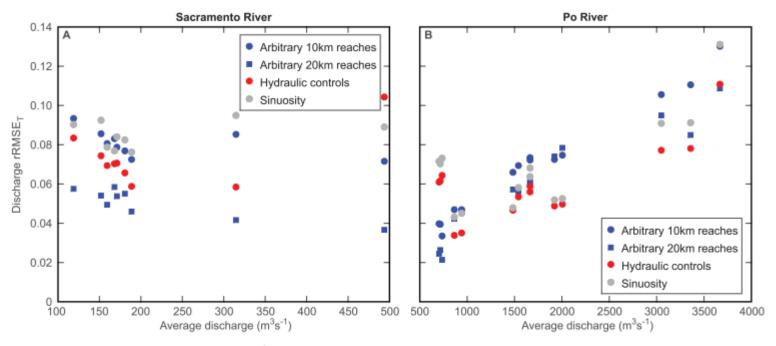
SWOT will provide an estimate of discharge by means of slope, river width and water surface elevation





SWOT products

Estimated discharge errors caused by the propagation of height, width, and slope errors through the discharge equation were often smaller for sinuosity (on average 8.5% for the Sacramento and 6.9% for the Po) and hydraulic control (Sacramento: 7.3% and Po: 5.9%) reaches than for arbitrary reaches of comparable lengths (Sacramento: 8.6% and Po: 7.8%).

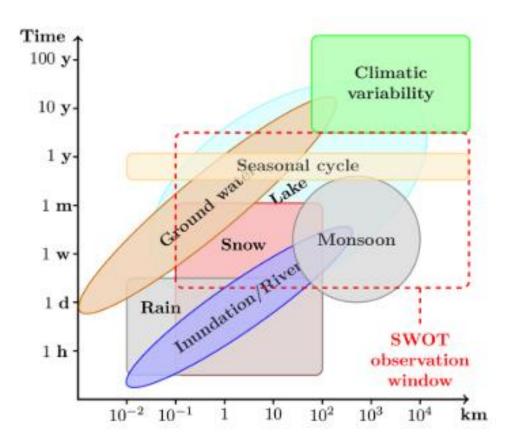


Hydraulic control method often leads to smaller discharge errors than arbitrary 10 km reaches, whereas the sinuosity method, despite its shorter reach lengths, led to discharge errors that were comparable to the arbitrary 10 km reaches.

For the Po River, both sinuosity and hydraulic control methods outperformed the arbitrary 20 km reaches in 9 out of the 14 evaluated overpasses

Biancamaria et al., 2016 (SG)

APPLICATIONS



"Time-space diagram of continental water surface processes and SWOT observation window."

- Discharge
- lakes and reservoirs
- Transboundary rivers
- Impact of human activities on hydrological cycle.
- Data for calibration and validation
- Stream-aquifer interactions
- Estuaries dynamics

To further investigates



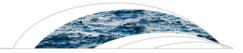
Algorithm Development for SWOT River Discharge Retrievals

https://swot.jpl.nasa.gov/project-wood.htm

Discharge estimation

The literature provides a number of different methodologies to estimate the river discharge using different variables combinations and assumptions...few examples: Smith et al., 1996; Smith, 1997; Bjerklie et al., 2003, 2005; Kouraev et al., 2004; Dingman and Bjerklie, 2006; Bjerklie, 2007; Birkinshaw et al., 2010; Michailovsky et al., 2012, Durand et al., 2016, Hagemann et al., 2017, ...





Water Resources Research

RESEARCH ARTICLE

10.1002/2015WR018434

Key Points:

- SWOT discharge algorithms were tested on synthetic observations for 19 rivers
- Algorithms accurately characterized temporal dynamics of river discharge
- At least one algorithm estimated discharge to <35% relative RMSE on 14/16 of nonbraided rivers

An intercomparison of remote sensing river discharge estimation algorithms from measurements of river height, width, and slope

M. Durand¹, C. J. Gleason², P. A. Garambois³, D. Bjerklie⁴, L. C. Smith⁵, H. Roux^{6,7}, E. Rodriguez⁸, P. D. Bates⁹, T. M. Pavelsky¹⁰, J. Monnier¹¹, X. Chen¹², G. Di Baldassarre¹³, J.-M. Fiset¹⁴, N. Flipo¹⁵, R. P. d. M. Frasson¹, J. Fulton¹⁶, N. Goutal¹⁷, F. Hossain¹⁸, E. Humphries¹⁰, J. T. Minear¹⁹, M. M. Mukolwe²⁰, J. C. Neal⁹, S. Ricci²¹, B. F. Sanders²², G. Schumann^{9,23}, J. E. Schubert²², and L. Vilmin¹⁵

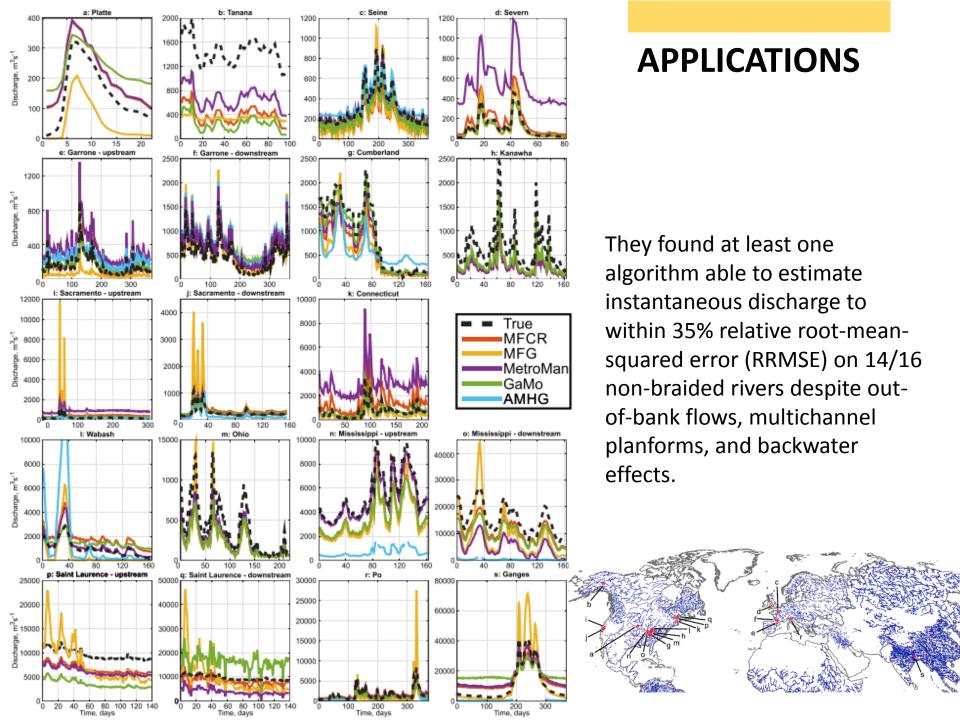
1) at-many-stations hydraulic geometry (AMHG) method [Gleason and Smith, 2014; Gleason et al., 2014]; 2) GaMo [Garambois and Monnier, 2015], 3) MetroMan [Durand et al., 2014], and 4) the novel mean flow and geomorphology (MFG) and 5) the mean flow and constant roughness (MFCR) algorithms, in addition to 6) an ensemble median product.

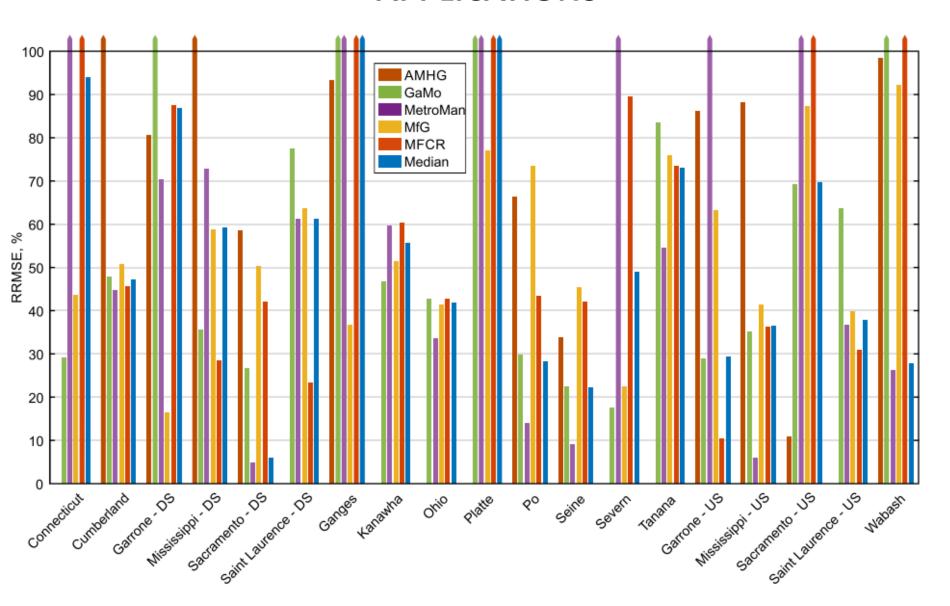
Durand et. al., 2016 (WRR)

Other
methodologies (not
considered here) are
available. Among
those: DataAssimilation (DA)
[Oubanas et al., 2018
(WRR)], «inverse
routing» [Pan and
Wood, 2013 (HESS)],
Bayesian AMHG
[Hagemann et al., 2017
(WRR)].

Table 3. Summary of Discharge Algorithms				
Algorithm	Theoretical Basis	Applied Variables From Observation	Estimated Variables	Variable Estimation Method
AMHG	At-many-stations hydraulic geometry	Water surface width (W)	a, b	 a and b are optimized to preserve continuity between stations using a genetic algorithm
GaMo	Manning flow resistance equation (equation (4))	Change in cross-sectional area of flow (δA) computed from the mean width and change in water surface height (δH , stage), water surface slope (δ) for several reaches	Flow resistance (n) and cross-sectional area of channel at zero flow (A ₀)	A ₀ and n are both optimized to preserve continuity between the observed reaches using a constrained, nonlinear steepest-descent optimization
MetroMan	Manning flow resistance equation (equation (4))	Change in cross-sectional area of flow (δA) computed from the mean width and change in water surface height (δH) , stage), water surface slope (S) for several reaches	Flow resistance (n) and cross-sectional area of channel at zero flow (A ₀)	A ₀ and n are both optimized to preserve continuity between the observed reaches (must be three or more) using the Metropolis algorithm
MFG	Manning flow resistance equation (equation (5))	Water surface width (<i>W</i>), water surface slope (<i>S</i>), and water surface height (<i>H</i> , stage) for the reach	Flow resistance (<i>n</i>) and height (stage) of zero flow (B)	n is estimated from an empirical relation between its mean value and slope, and then adjusted based on an empirical relation between the change in river cross section. B is calibrated to an estimate of the mean annual discharge for the time series
MFCR	Manning flow resistance equation (equation (4))	Water surface width, water surface slope, water surface height (stage) for the reach	Cross-sectional area of channel at zero flow (A_0)	Flow resistance is assumed constant at 0.03, an estimate of the mean annual discharge is used to calibrate A_0 for the time series

Tested on 19 rivers worldwide spanning a range of hydraulic and geomorphic conditions (data extracted from hydraulic models)





remote sensing Flow Duration Curve from Satellite: Potential of a

Lifetime SWOT Mission

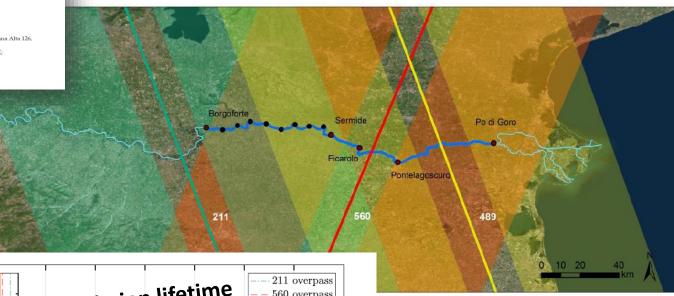
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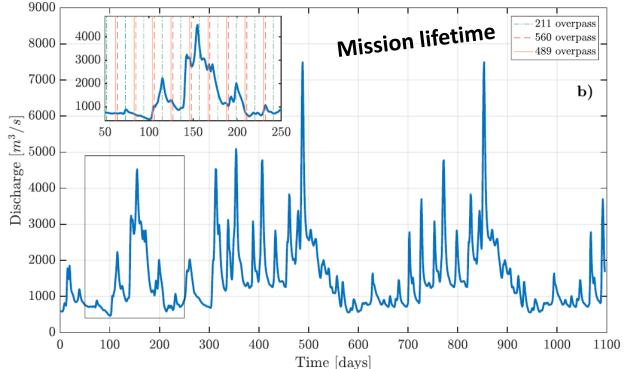
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total number of satellite overpasses: 52, 53, and 52 referring to orbit 489, 560 and 211, respectively

APPLICATIONS





MDPI

Flow hydrograph at the gauging station of Sermide (blue lines) in the period 2008–2010: vertical lines represent an example of the timing of the SWOT overpasses during a short period.

Discharge estimation

$$Q_{ij} = \frac{1}{n} A_{ij}^{5/3} w_{ij}^{-2/3} S_{ij}^{1/2}$$

Manning equation

- J (friction slope) = S (surface slope)
- Large rectangular shape
- j = j-th day of SWOT pass
- i = i-branches of length Δx

average value of the minimum wet areas recorded for the i-th branch during the entire period of study

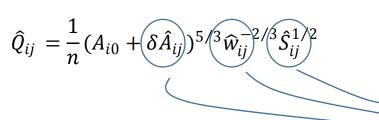
Wetted Area, A $A_{ii} = A_{i0} + \delta A_{ii}$

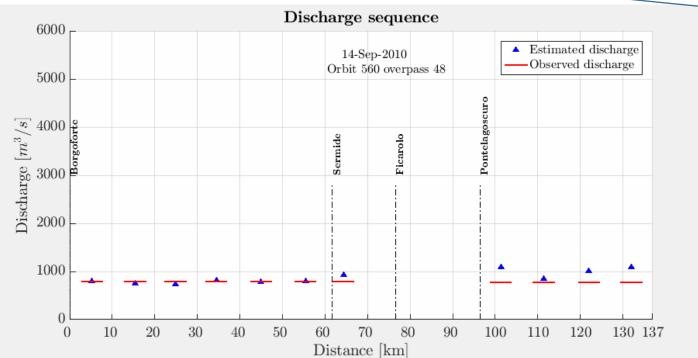
$$A_{ij} = \frac{w_{i0} + w_{ij}}{2} (y_{ij} - y_{i0})$$

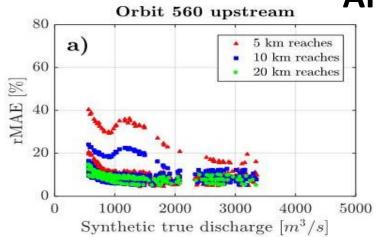
Surface Slope, S

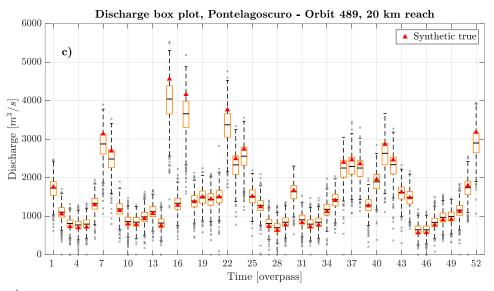
$$y = S \cdot x + x_0$$

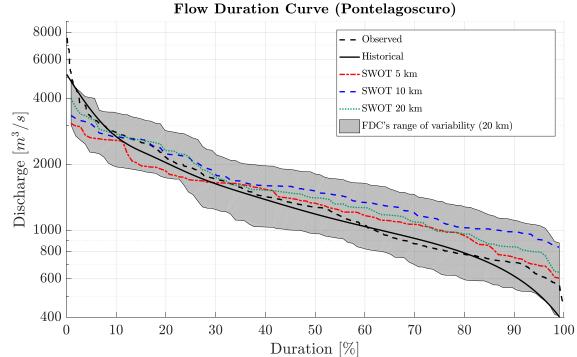
Values corrupted with Gaussian random errors (mission requiremetns)







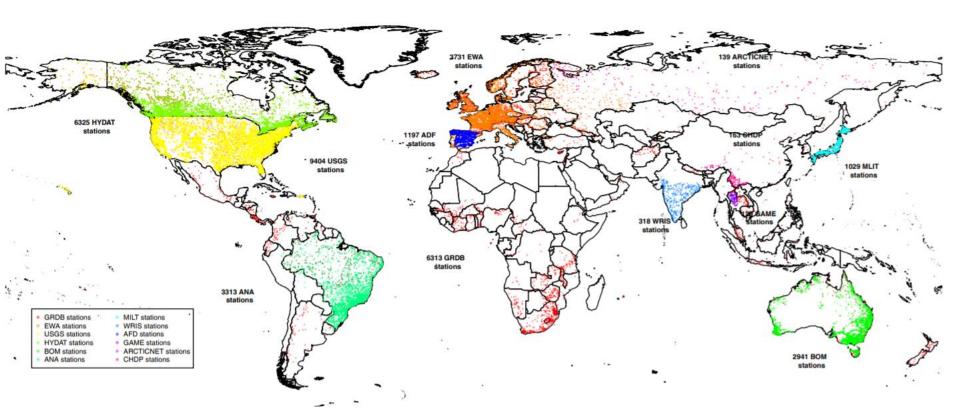




FDCs at the gauging station of Pontelagoscuro for the three-year period based on observed daily data (black dashed line) and estimated from SWOT-like observations, considering different river discretizations; grey area represents the 90% confidence interval of streamflow estimation with $\Delta x = 20$ km; black solid lines show FDCs based on historical data recorded at the gauging stations.

Many hydrologic dataset (global or nearly global) are getting available

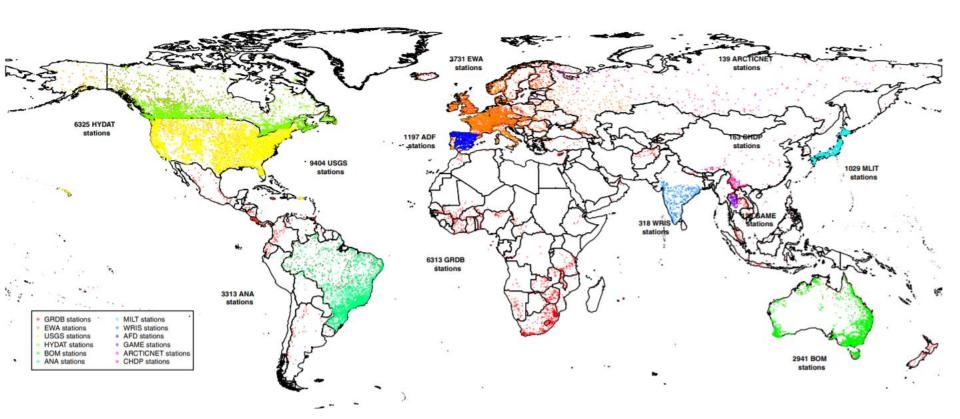
Global Streamflow Indices and Metadata Archive (GSIM) – Part 1 and Part 2



PART 1: station name, river name, coordinates, elevation, drainage area, catchment boundary, catchment metadata such as land cover type, soil type, and climate and topographic characteristics

The Global Streamflow Indices and Metadata Archive (GSIM) – Part 1: The production of a daily streamflow archive and metadata. Hong Xuan Do, Lukas Gudmundsson, Michael Leonard and Seth Westra1





PART 2: a collection of daily streamflow observations at more than 30000 stations around the world. Part 2 introduces a set of quality controlled time-series indices representing (i) the water balance, (ii) the seasonal cycle, (iii) low flows and (iv) floods

7.4

Gudmundsson, L., Do, H. X., Leonard, M., and Westra, S.: The Global Streamflow Indices and Metadata Archive (GSIM) – Part 2: Quality control, time-series indices and homogeneity assessment, Earth Syst. Sci. Data, 10, 787-804, https://doi.org/10.5194/essd-10-787-2018, 2018.

Many hydrologic dataset (global or nearly global) are getting available

Global Streamflow Indices and Metadata Archive (GSIM) – Part 1 and Part 2 Global extent of rivers and streams (Allen, G. H., & Pavelsky, T. M., 2018). Global river slope: A new geospatial dataset and global-scale analysis (Cohen et al., 2018 JH)

More accurate and "hydrologically meaningful" topographic data are coming out (see MERIT and HydroMERIT)

...the same for observations useful for model calibration and validation (see e.g., rainfall patterns, altimetry, satellite-derived inundation extent...)

...new models with higher computational efficiency

But with some drawbacks... in terms of uncertainties and accuracy in both data and large scale model results



THANKS FOR YOUR ATTENTION



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