Combining the strength of satellite altimetry and imagery to estimate river discharge

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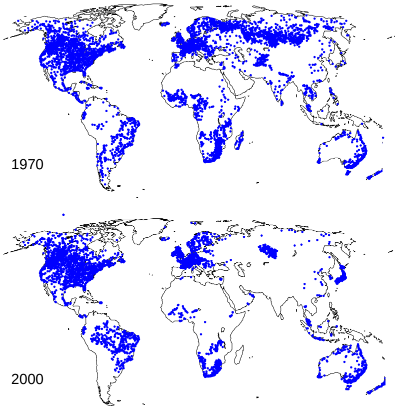
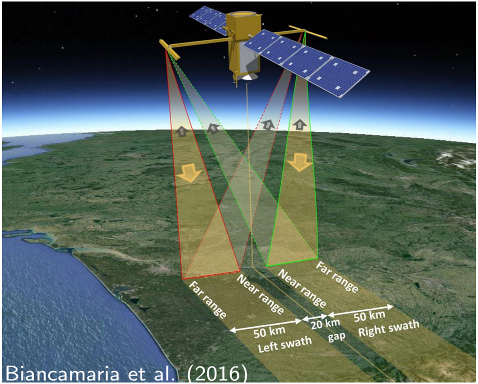
Problem



- The spatiotemporal coverage of in situ discharge databases is surprisingly poor
- Catchments with limited observations after 2002 cover an area of more than 11,500,000 km^2 comprising freshwater discharge of more than 125,000 m^3/s!

SWOT mission, a remedy?



Height accuracy
<10 cm for water area >1 km
<25 cm for 0.6 km^2 <water area<1 km^2

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

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SWOT-based discharge will never be a replacement for in situ discharge measurements (Durand et al. 2016)

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- It can provide discharge estimates at continental scale
- It monitors ungauged river
- It will complement river discharge modeling

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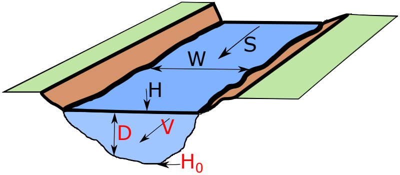
A serious question for the community

How to estimate discharge from SWOT observables H, W, S?



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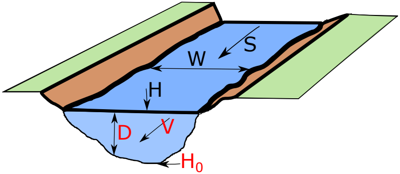

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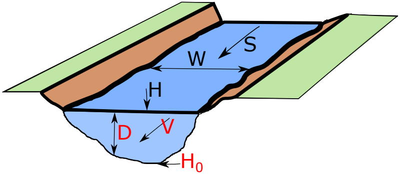

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Goal

Assessing the performance of different discharge estimation methods using H and S from altimetry and W from imagery

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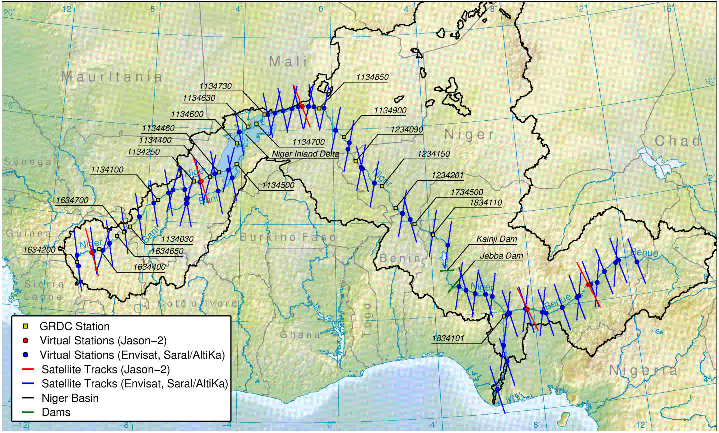
GIS

Dense water level from altimetry



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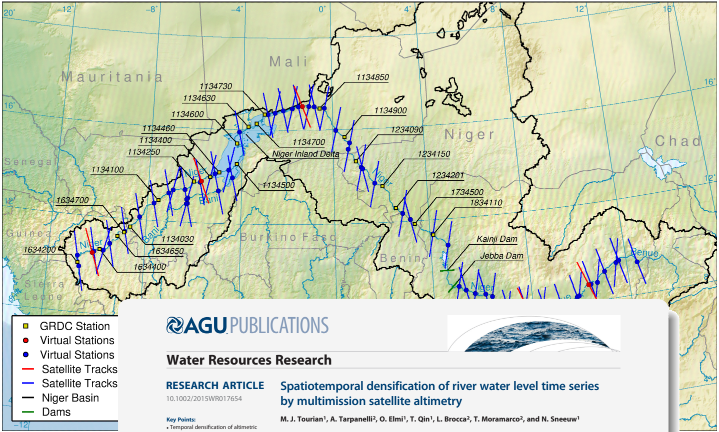

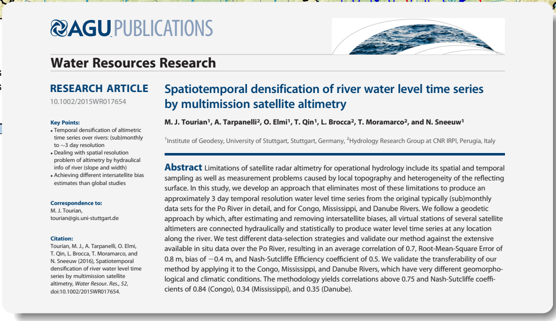

AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

10.1002/2015WR017654

Spatiotemporal densification of river water level time series by multimission satellite altimetry

M. J. Tourian[1], A. Tarpanelli[2], O. Elmi[1], T. Qin[1], L. Brocca[2], T. Moramarco[2], and N. Sneeuw[1]

[1]Institute of Geodesy, University of Stuttgart, Stuttgart, Germany, [2]Hydrology Research Group at CNR IRPI, Perugia, Italy

Key Points:
- Temporal densification of altimetric time series over rivers: (sub)monthly to ~3 day resolution
- Dealing with spatial resolution problem of altimetry by hydraulical info of river (slope and width)
- Achieving different intersatellite bias estimates than global studies

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M. J. Tourian,
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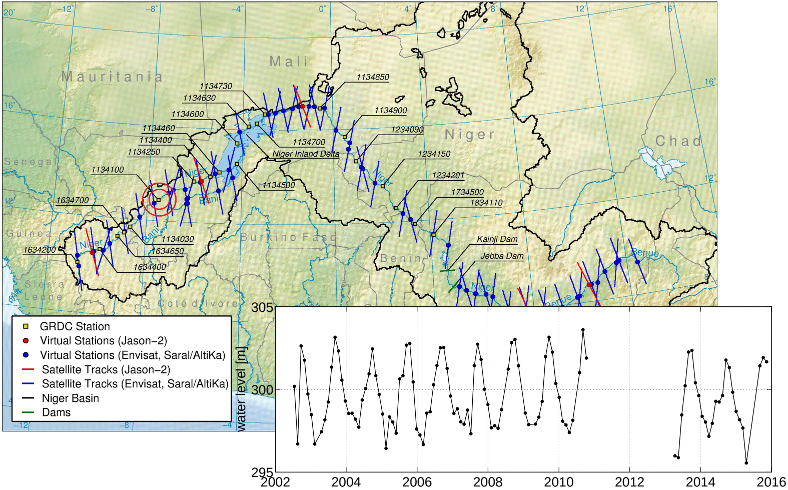
Citation:
Tourian, M. J., A. Tarpanelli, O. Elmi, T. Qin, L. Brocca, T. Moramarco, and N. Sneeuw (2016), Spatiotemporal densification of river water level time series by multimission satellite altimetry, *Water Resour. Res.*, 52, doi:10.1002/2015WR017654.

Abstract Limitations of satellite radar altimetry for operational hydrology include its spatial and temporal sampling as well as measurement problems caused by local topography and heterogeneity of the reflecting surface. In this study, we develop an approach that eliminates most of these limitations to produce an approximately 3 day temporal resolution water level time series from the original typically (sub)monthly data sets for the Po River in detail, and for Congo, Mississippi, and Danube Rivers. We follow a geodetic approach by which, after estimating and removing intersatellite biases, all virtual stations of several satellite altimeters are connected hydraulically and statistically to produce water level time series at any location along the river. We test different data-selection strategies and validate our method against the extensive available in situ data over the Po River, resulting in an average correlation of 0.7, Root-Mean-Square Error of 0.8 m, bias of −0.4 m, and Nash-Sutcliffe Efficiency coefficient of 0.5. We validate the transferability of our method by applying it to the Congo, Mississippi, and Danube Rivers, which have very different geomorphological and climatic conditions. The methodology yields correlations above 0.75 and Nash-Sutcliffe coefficients of 0.84 (Congo), 0.34 (Mississippi), and 0.35 (Danube).

Dense water level from altimetry



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GIS

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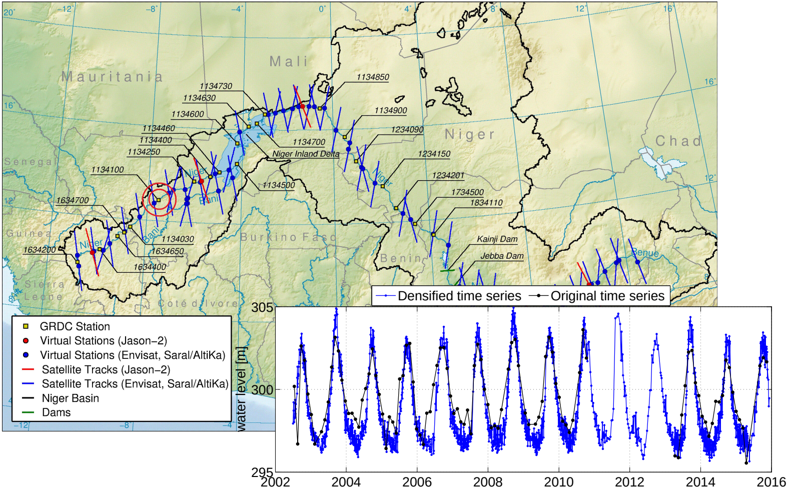

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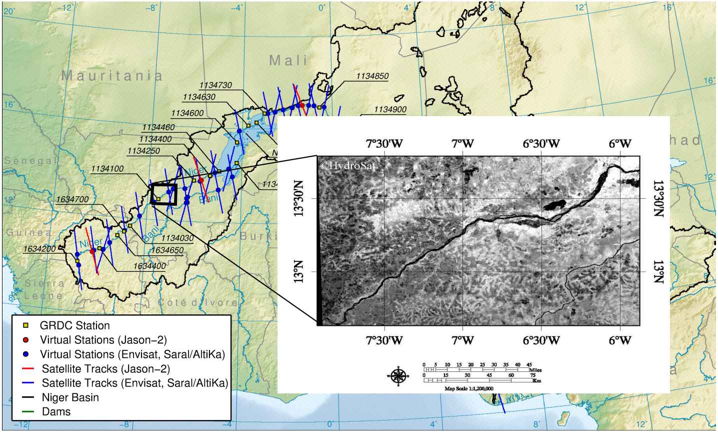
Effective river width from imagery



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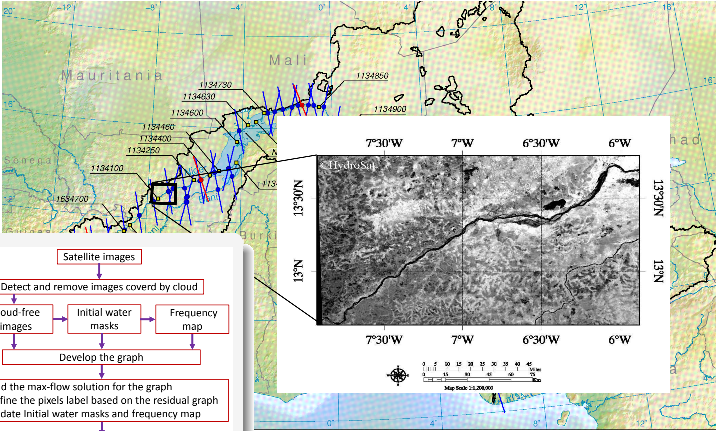

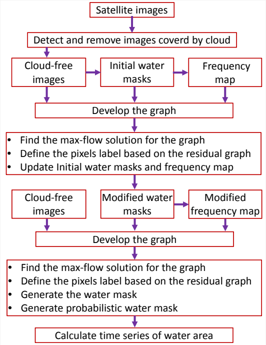

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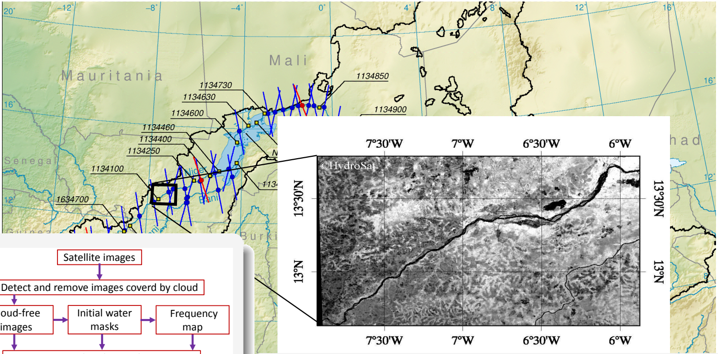
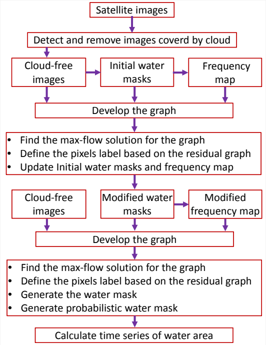
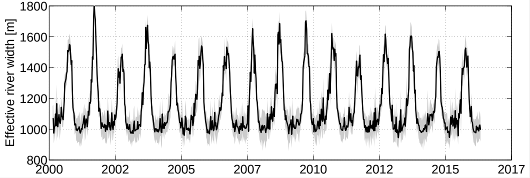
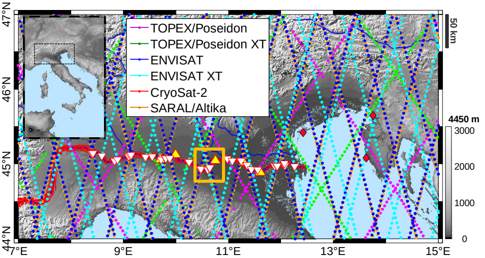


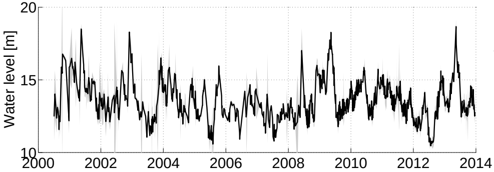


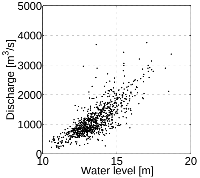


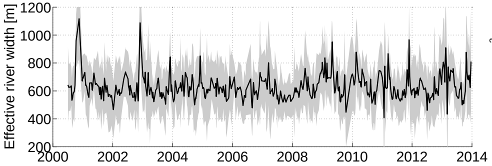
Elmi et al. (2016) Dynamic river masks from multi-temporal satellite imagery: an automatic algorithm using graph cuts optimization, Remote Sensing, under review

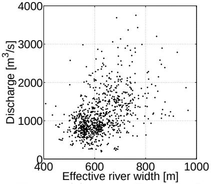
A challenging river, Po



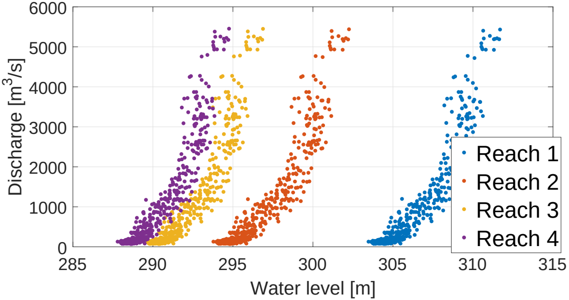


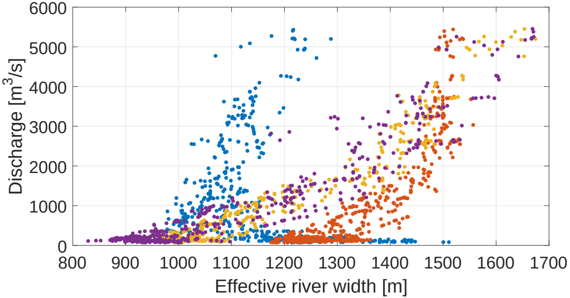






Discharge models





GIS

Discharge models

Niger: training period 2002–2004, validation period 2004–2006
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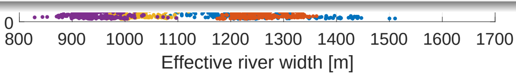

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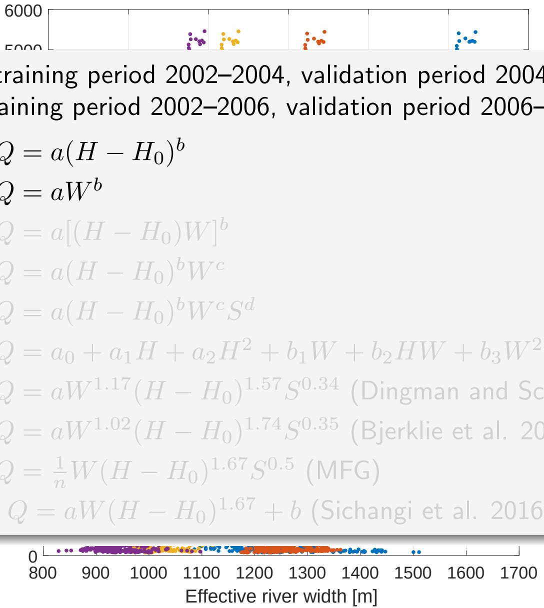

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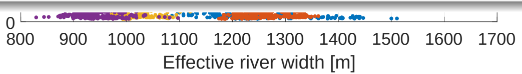

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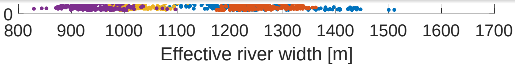

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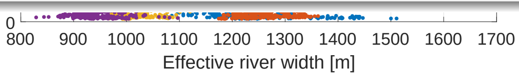

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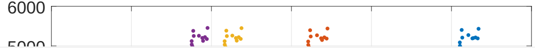

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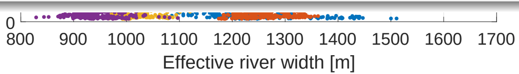

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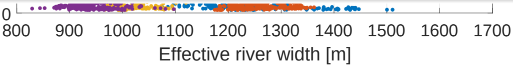

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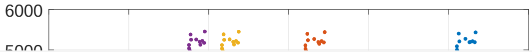

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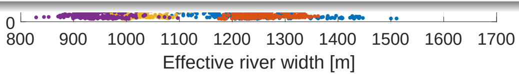

Discharge models

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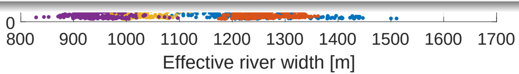
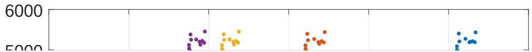
Po: training period 2002–2006, validation period 2006–2014

- Model 1: $Q = a(H - H_0)^b$
- Model 2: $Q = aW^b$
- Model 3: $Q = a[(H - H_0)W]^b$
- Model 4: $Q = a(H - H_0)^b W^c$
- Model 5: $Q = a(H - H_0)^b W^c S^d$
- Model 6: $Q = a_0 + a_1 H + a_2 H^2 + b_1 W + b_2 HW + b_3 W^2$
- Model 7: $Q = aW^{1.17}(H - H_0)^{1.57} S^{0.34}$ (Dingman and Schrama 1997)
- Model 8: $Q = aW^{1.02}(H - H_0)^{1.74} S^{0.35}$ (Bjerklie et al. 2003)
- Model 9: $Q = \frac{1}{n} W(H - H_0)^{1.67} S^{0.5}$ (MFG)
- Model 10: $Q = aW(H - H_0)^{1.67} + b$ (Sichangi et al. 2016)



GIS

Discharge models



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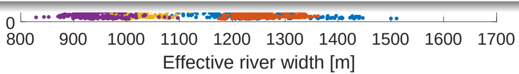
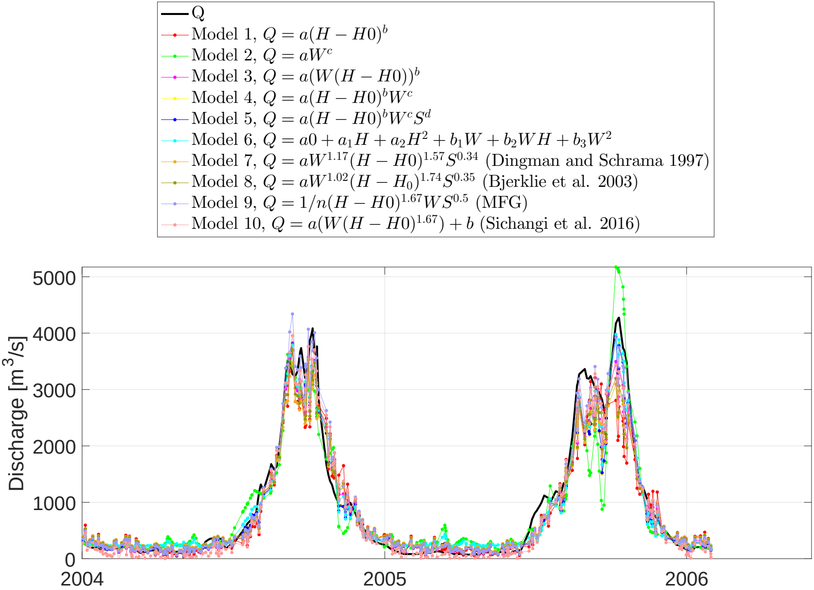
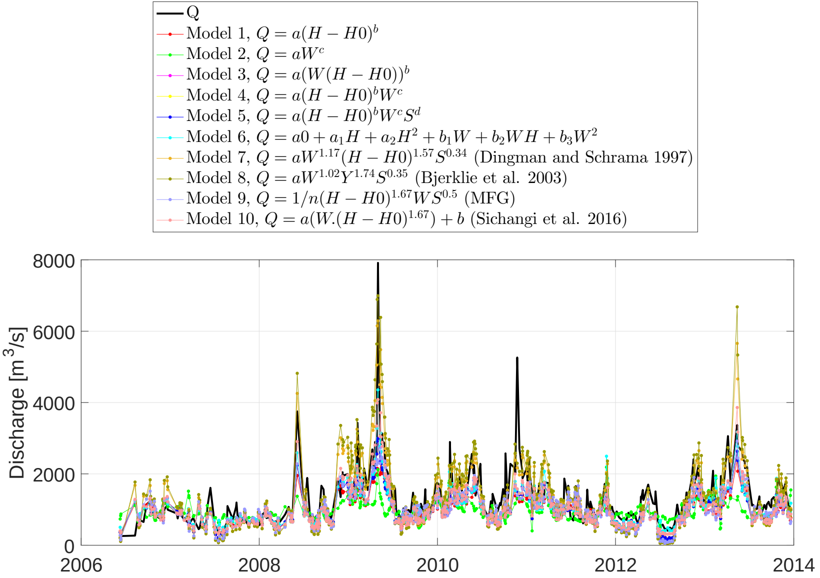


Discharge estimation (Niger)



Discharge estimation (Po)



Validation (Niger)

Model 1: $Q = a(H - H_0)^b$
Model 2: $Q = aW^b$
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Average over 3 river reaches of the Niger River

Model	Corr. [ ]	RMSE %	NSE [ ]	Bias %
1	0.95	29	0.87	10
2	0.96	25	0.90	7
3	0.97	24	0.91	10
4	0.98	21	0.93	10
5	0.98	20	0.94	9
6	0.97	21	0.93	5
7	0.97	28	0.88	8
8	0.96	25	0.90	8
9	0.97	20	0.94	-1
10	0.96	24	0.91	16

Validation (Po)

Model 1: $Q = a(H - H_0)^b$
Model 2: $Q = aW^b$
Model 3: $Q = a[(H - H_0)W]^b$
Model 4: $Q = a(H - H_0)^b W^c$
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Model 10: $Q = aW(H - H_0)^{1.67} + b$ (Sichangi et al. 2016)

Average over 3 river reaches of the Po River

Model	Corr. [ ]	RMSE %	NSE [ ]	Bias %
1	0.79	36	0.39	23
2	0.30	48	−0.08	21
3	0.75	36	0.41	19
4	0.79	34	0.45	20
5	0.80	34	0.46	21
6	0.78	33	0.50	16
7	0.79	34	0.45	2
8	0.80	37	0.36	−2
9	0.78	33	0.48	18
10	0.80	31	0.54	16

Summary and conclusion

- A densification process has been employed to generate water level time series from satellite altimetry with temporal resolution of 3 days
- Time series of effective river width with the corresponding uncertainty have been generated from satellite imegary using graph cuts optimization
- 10 different discharge models have been tested over Niger and Po River
- The models with width and height outperform the models with height or width only
- The empirical model with slope (Model 5) shows better performance in comparison to other empirical models
- The MFG model with channel roughness quantity leads to high NSE and low bias

Still open for future work

- Implementing GaMo and Metropolis-Manning (MetroMan) algorithms

Thank you

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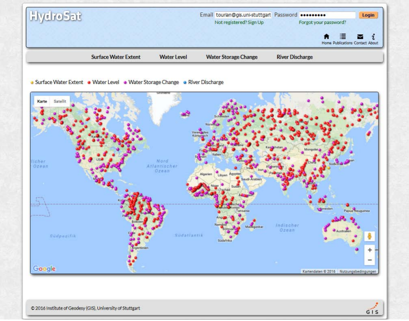

Tourian et al. (2016), Spatiotemporal densification of river water level time series by multimission satellite altimetry, Water Resour. Res., 52, doi:10.1002/2015WR017654.

Elmi et al. (2016) Dynamic river masks from multi-temporal satellite imagery: an automatic algorithm using graph cuts optimization, Remote Sensing, under review

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