Improving the temporal and spatial resolution of water level time series over Po River (Italy) obtained by satellite altimetry

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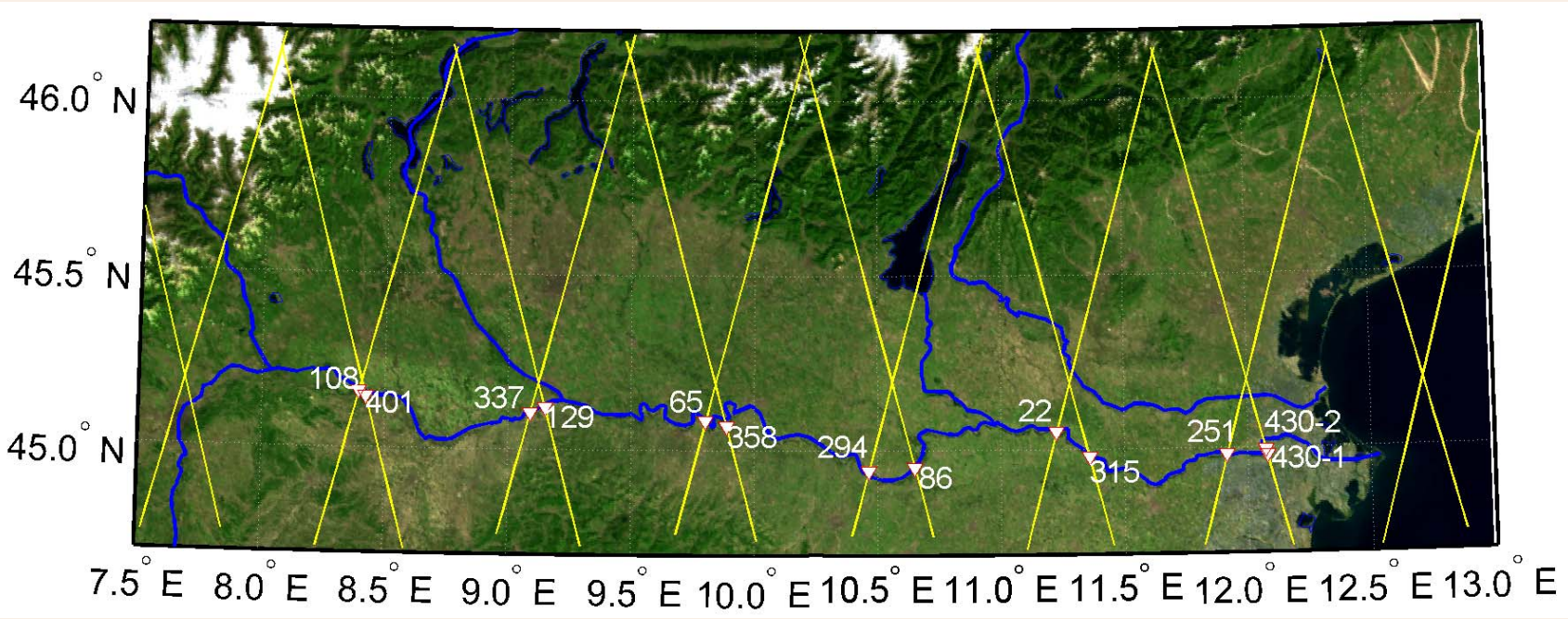
New frontiers of altimetry

27–31 October 2014, Lake Constance, Germany

GIS

Po River

ENVISAT



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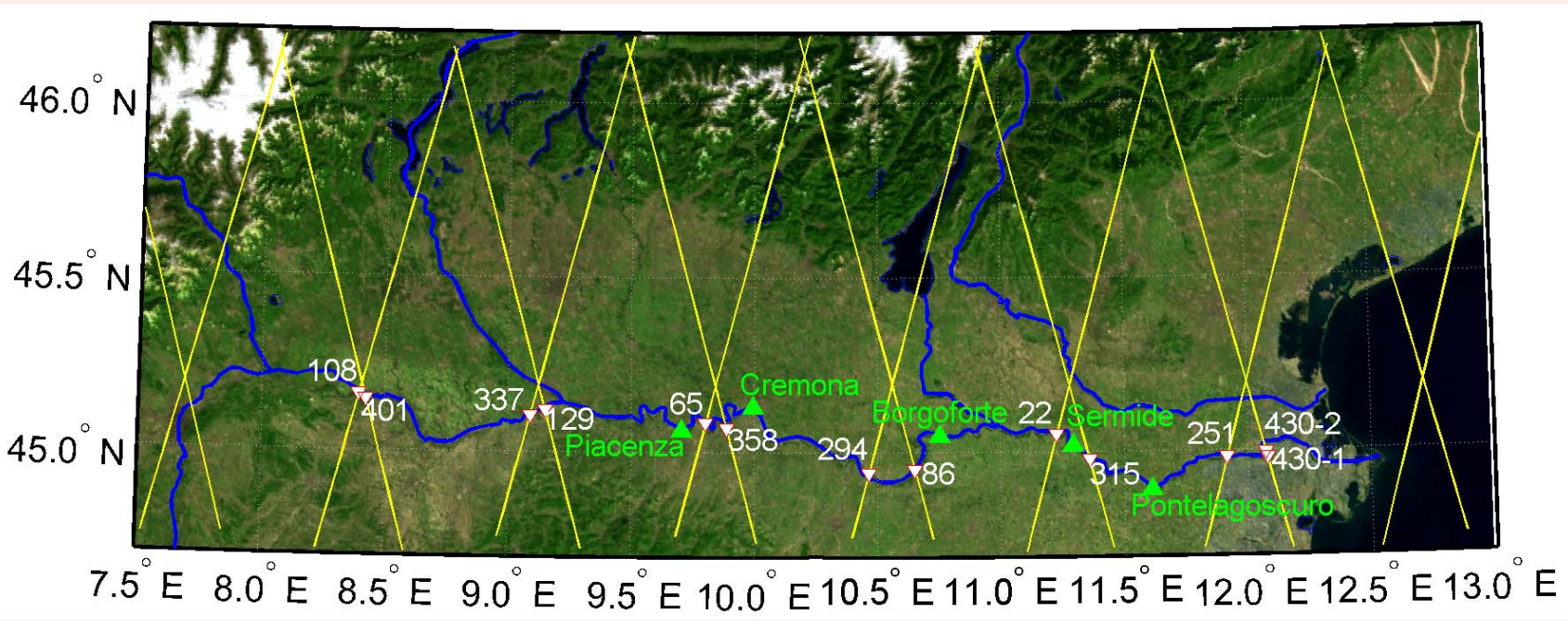
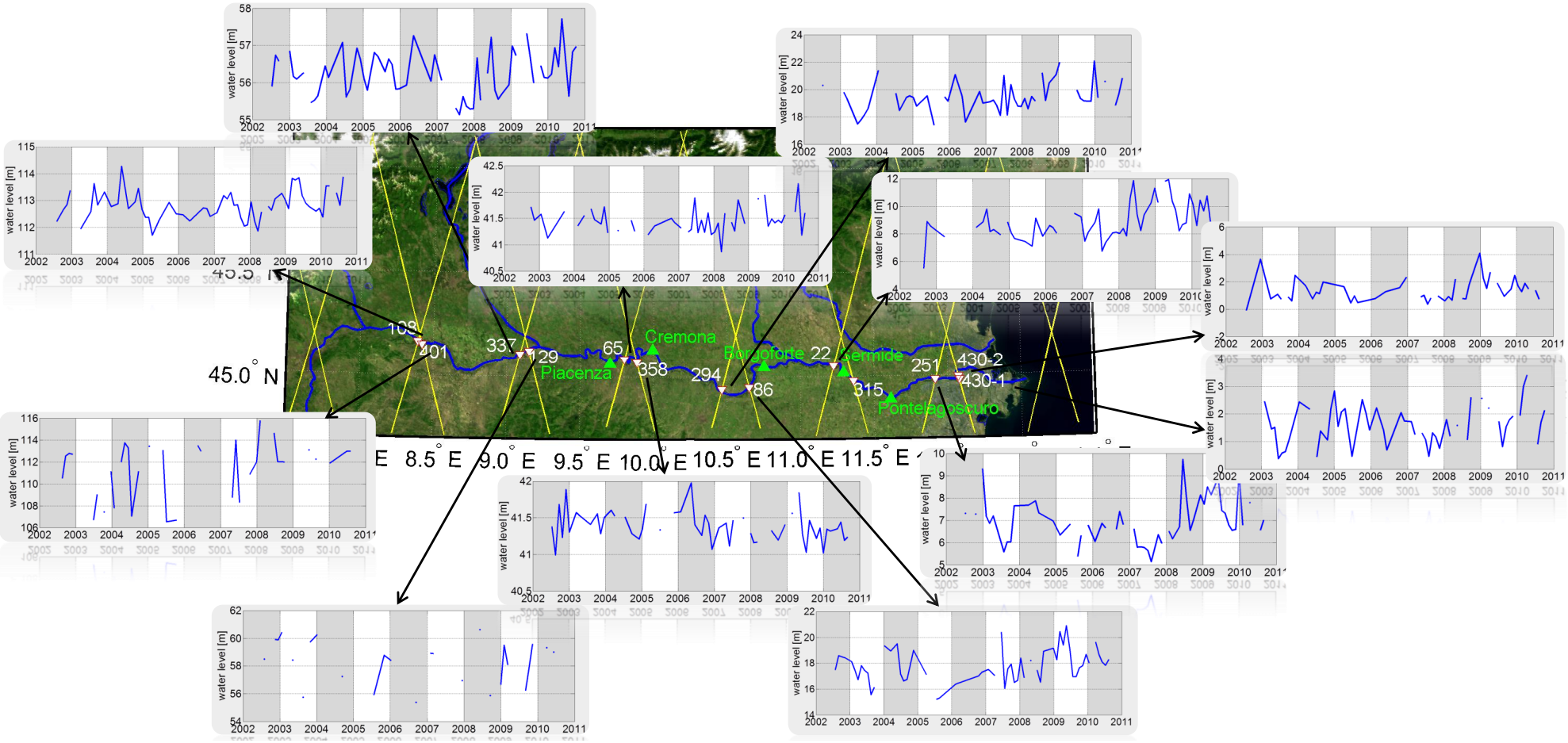


Problem

temporal resolution



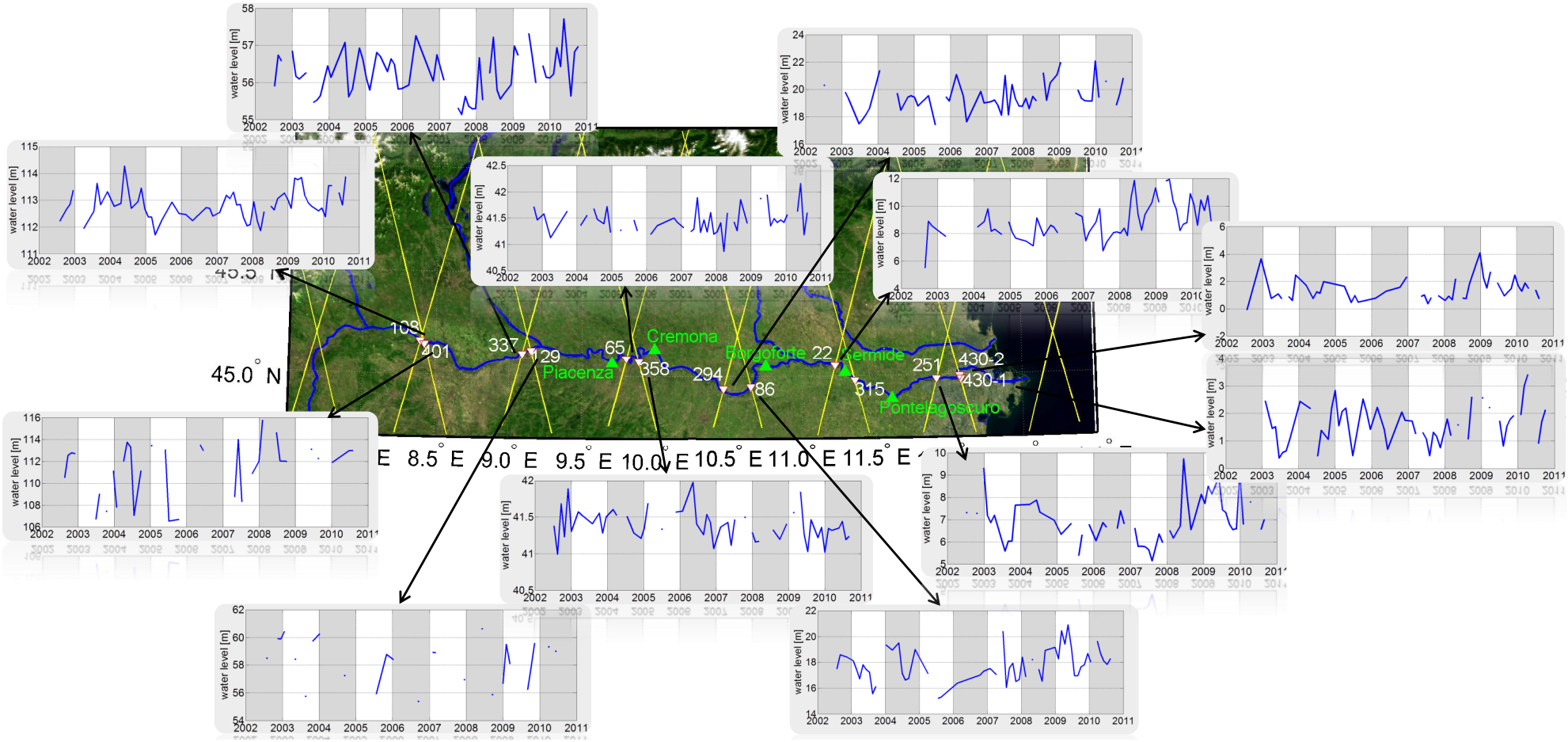
positive aspects

river is a dynamic system

asynchronous tracks

Problem

temporal resolution



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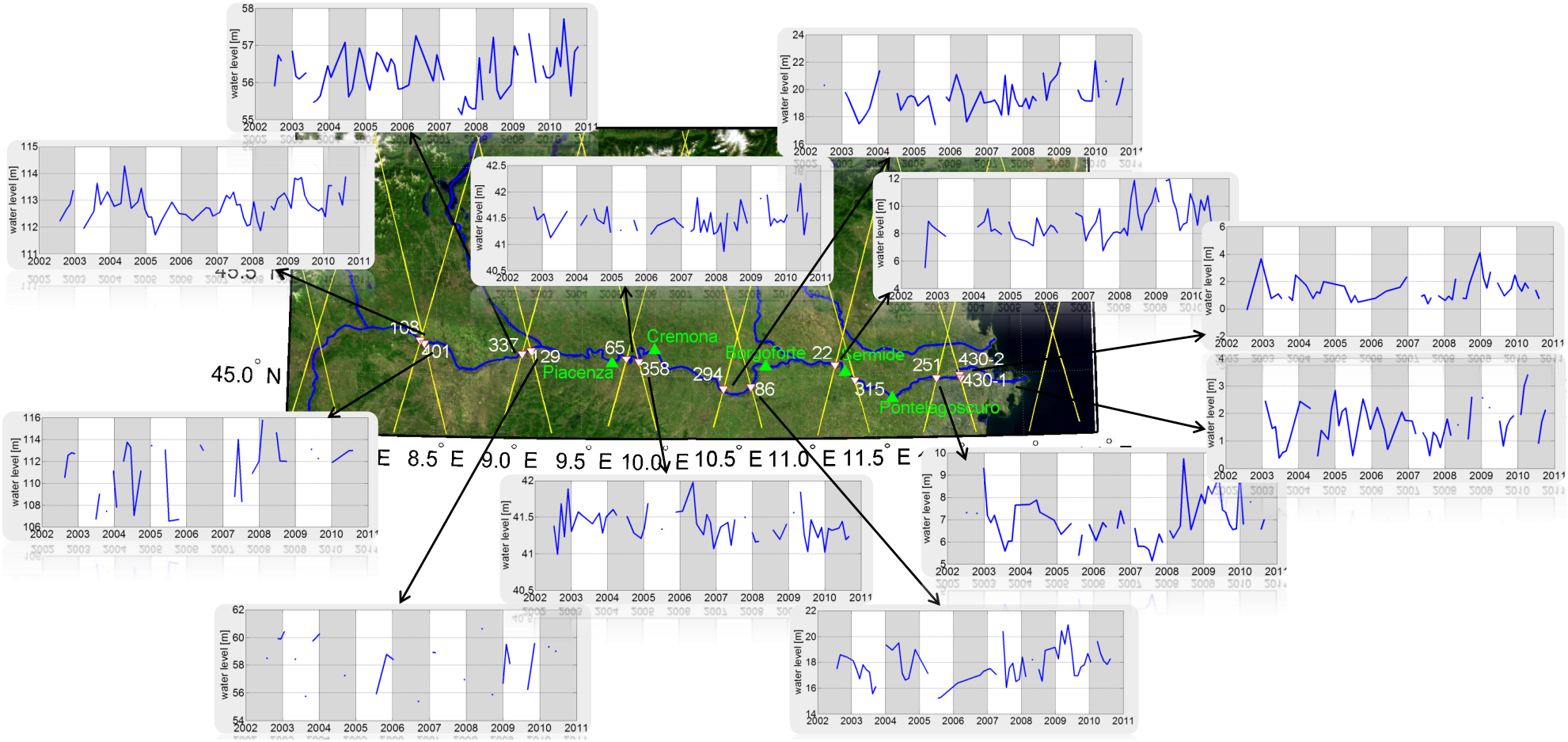
Problem

temporal resolution **spatial resolution**



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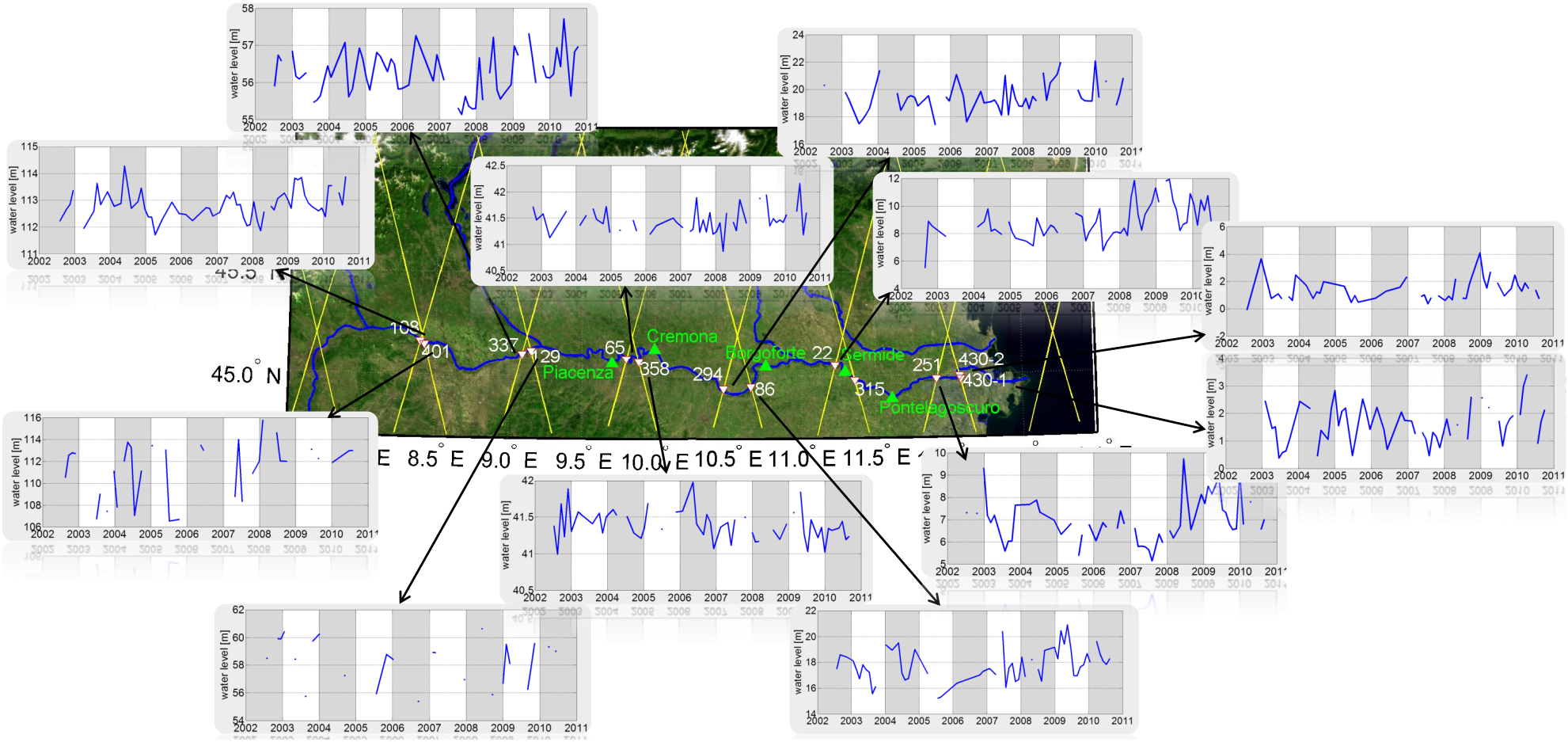
temporal resolution **spatial resolution** **consistency**



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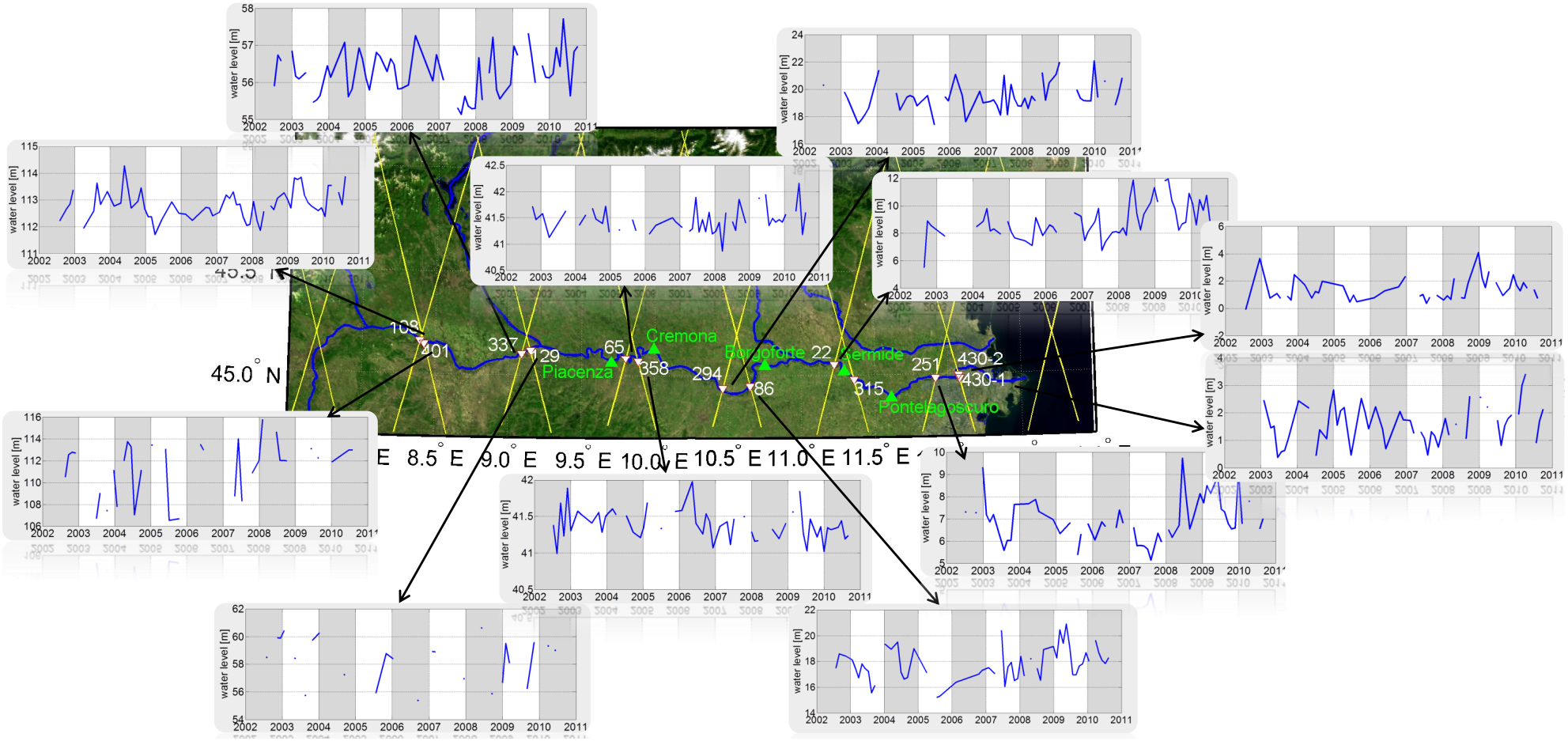

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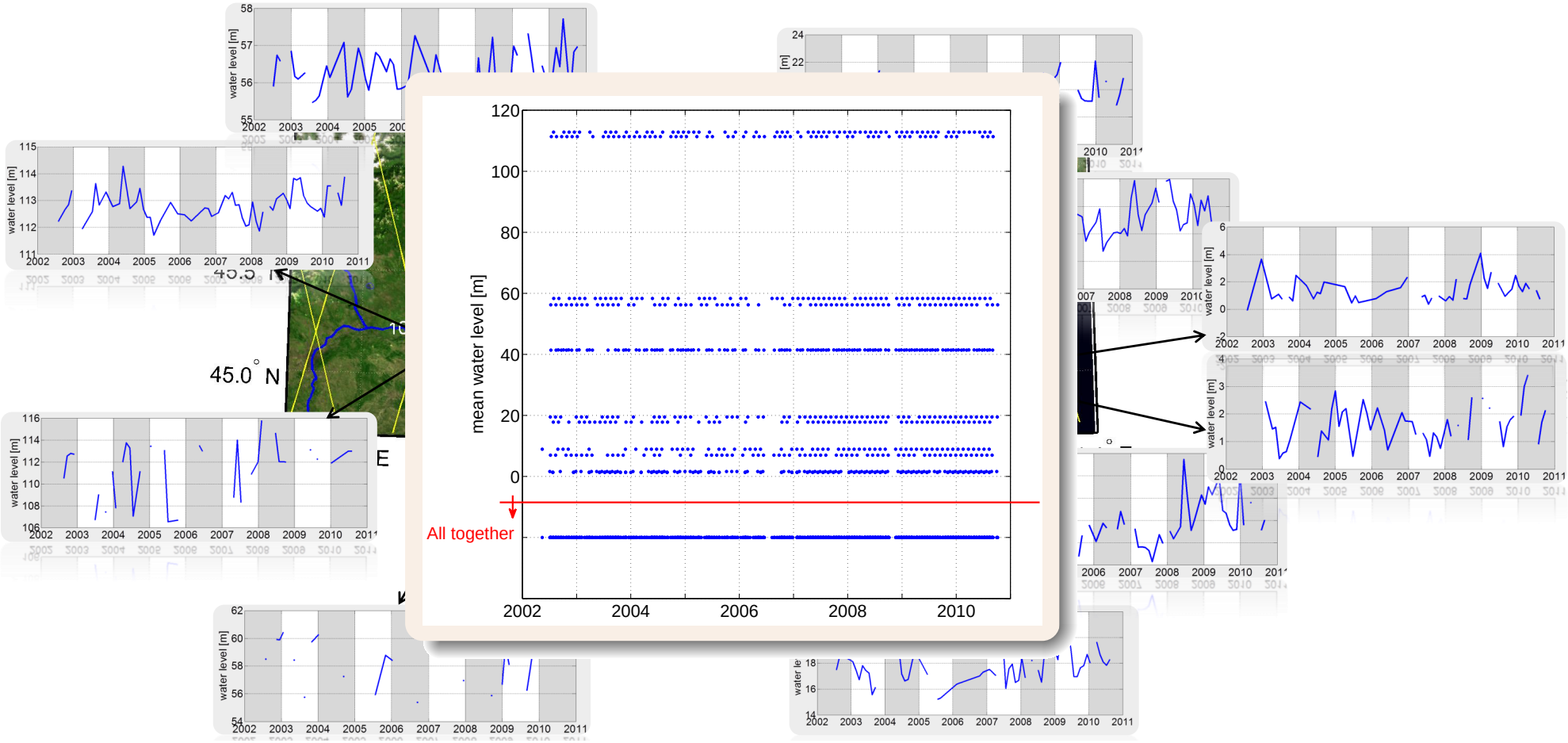

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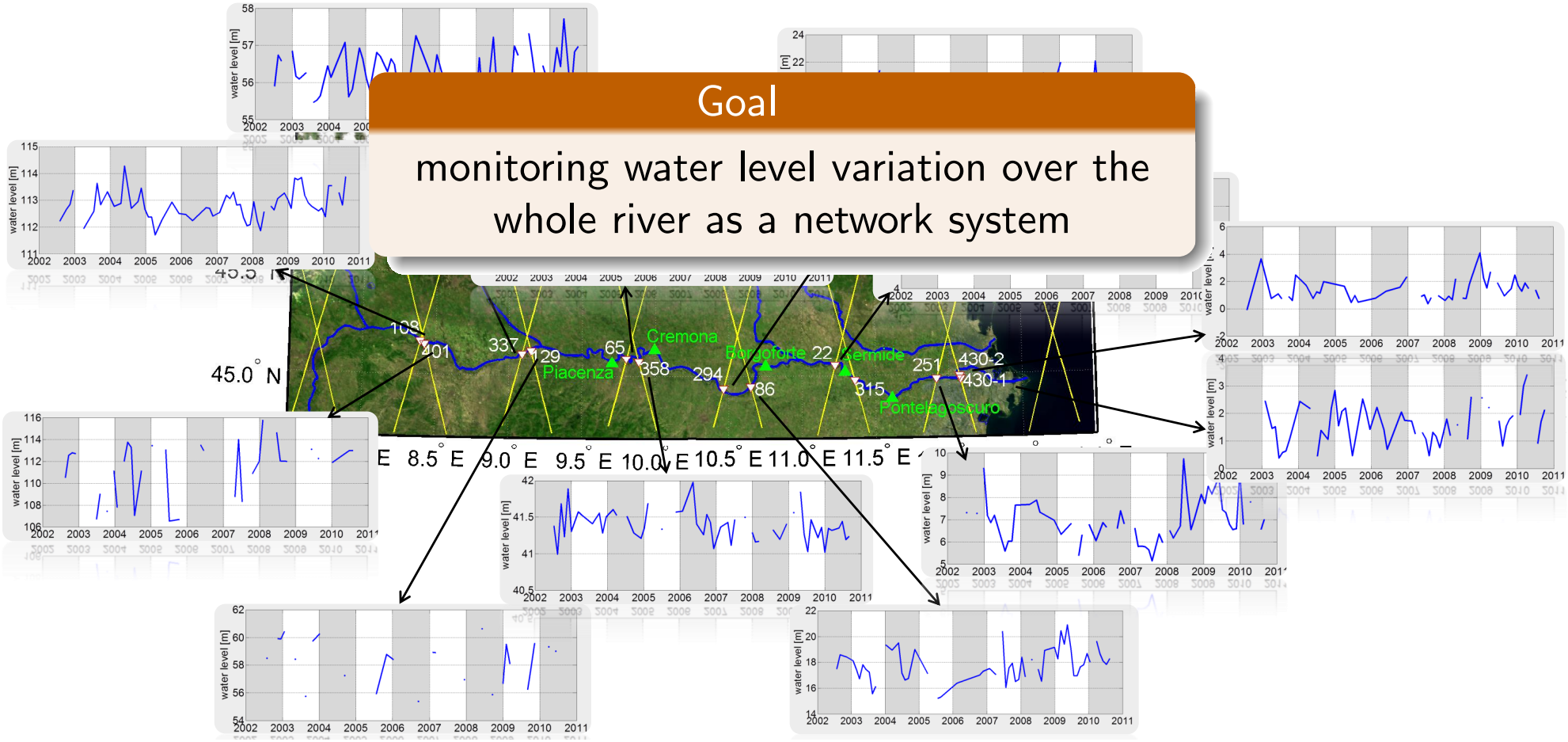
river is a dynamic system **asynchronous tracks**

Problem

temporal resolution **spatial resolution** **consistency**

Goal

monitoring water level variation over the whole river as a network system



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...previous activities

- **No study** dedicated to this purpose so far
- As a collateral results, though, we have

- Calmant et al. (2013) developed two regression models to link the altimetric level at virtual station to the nearby gauge
- Birkinshaw et al. (2010) proposed a statistical method for outlier rejection considering all contemporaneous altimetry data

Calmant et al. (2013), Detection of Envisat RA2/ICE-1 retracked radar altimetry bias over the Amazon basin rivers using GPS, Advances in Space Research, 51(8): 1551–1564. doi: 10.1016/j.asr.2012.07.033

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$$N_A(t_i) - W(t_i) = b + \left[s_0 + A \sin\left(2\pi \frac{DOY_i}{365} + \varphi\right)\right] \times \Delta_i, \tag{4.a}$$

$$N_A(t_i) - W(t_i) = b + \left[s_0 + s_1 \times \Delta_i + A \sin\left(2\pi \frac{DOY_i}{365} + \varphi\right)\right] \times \Delta_i. \tag{4.b}$$

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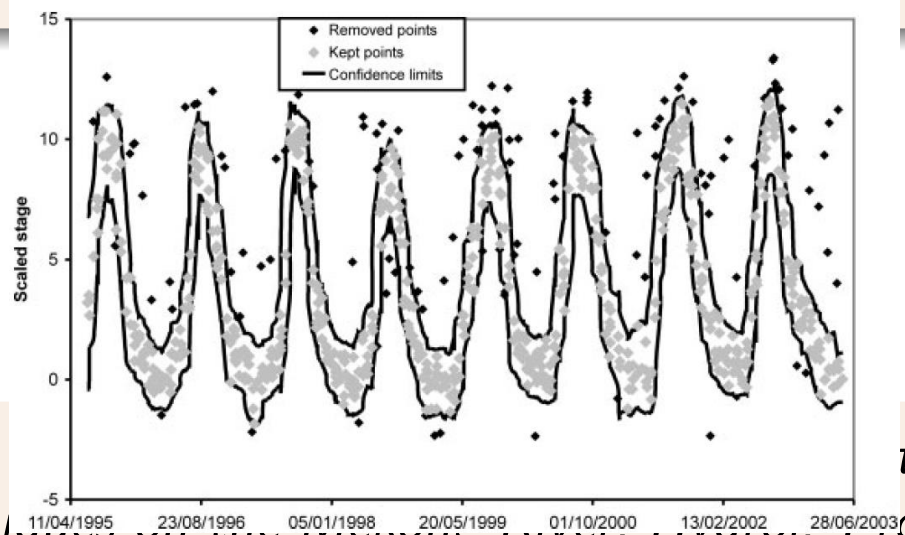

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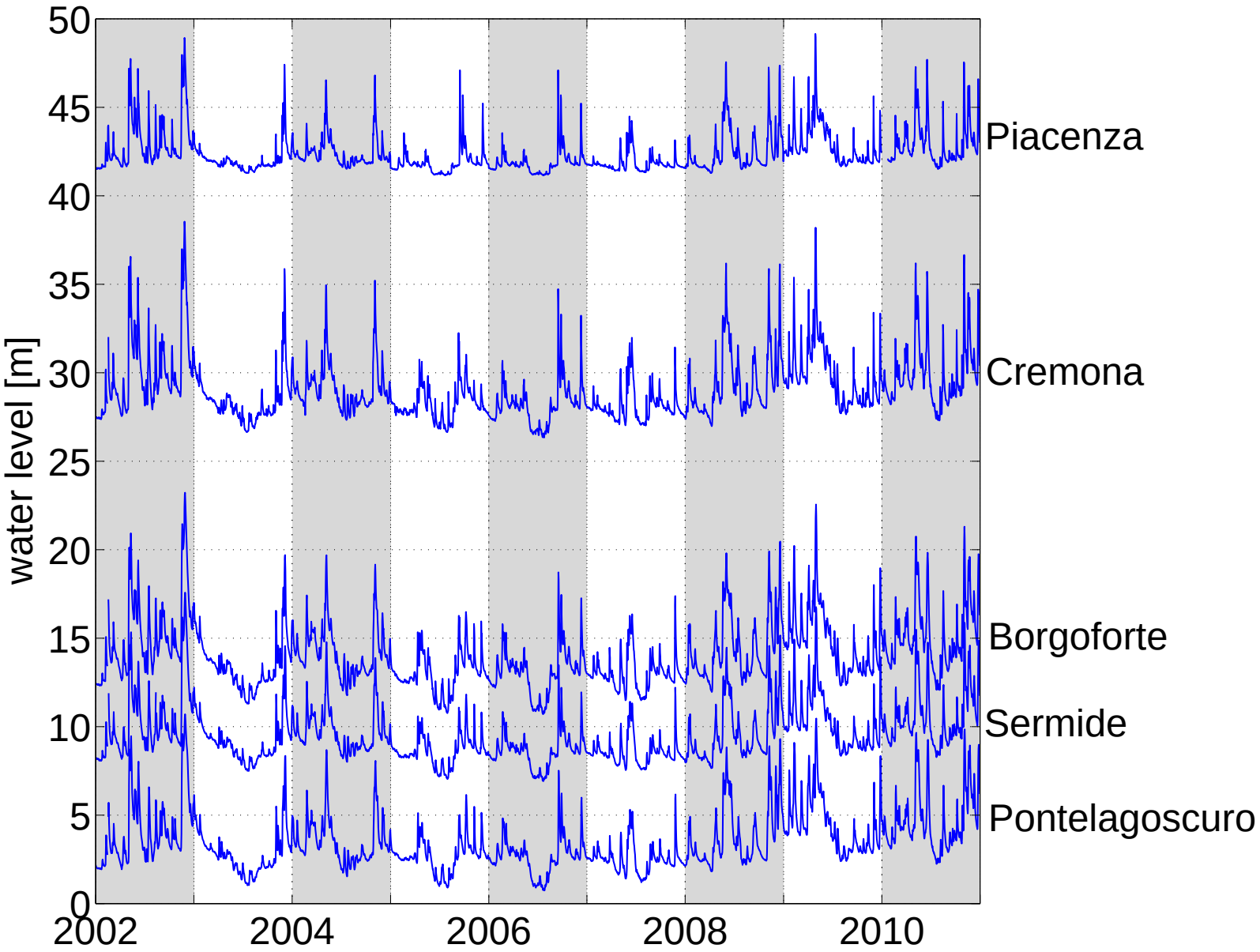
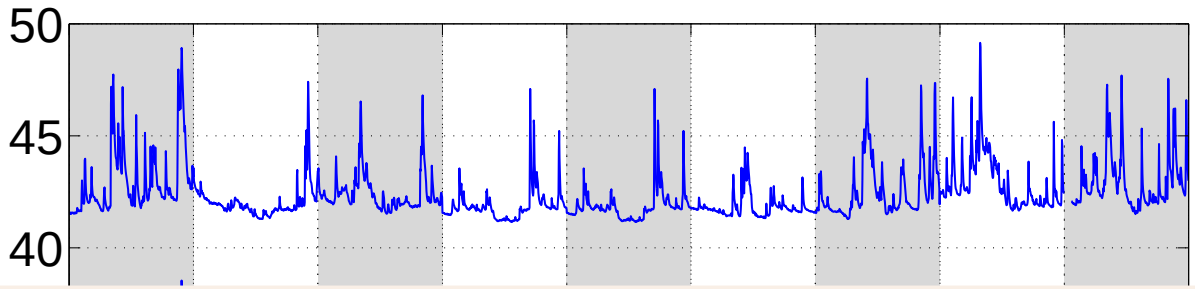
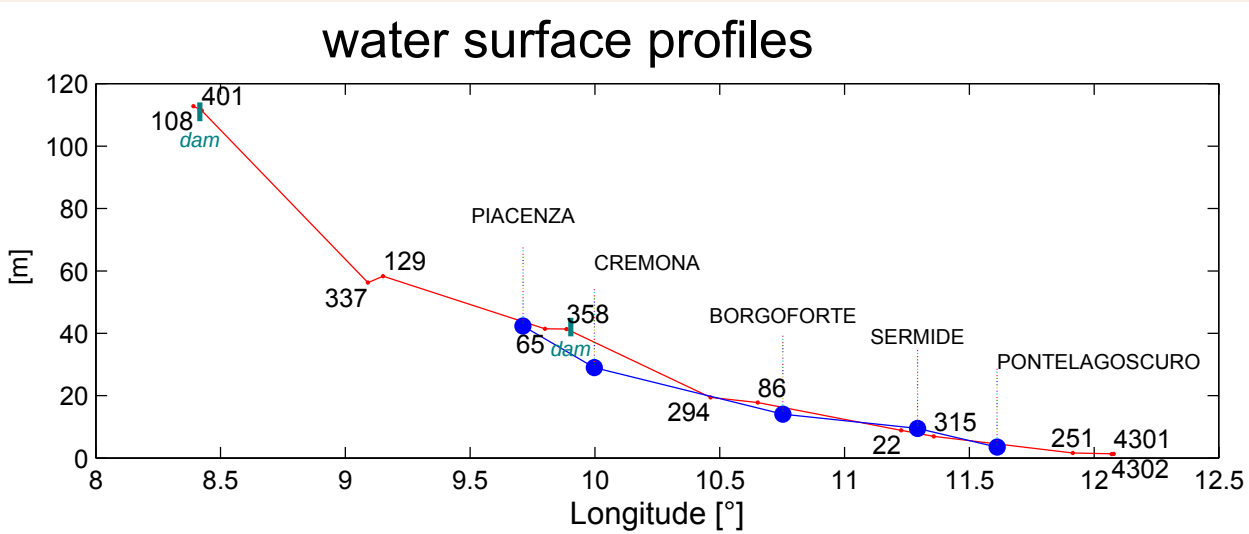
Gauge data


water level [m]
50
45
40
35
30
25
20
15
10
5
0
2002
2004
2006
2008
2010
Piacenza
Cremona
Borgoforte
Sermide
Pontelagoscuro

Gauge data

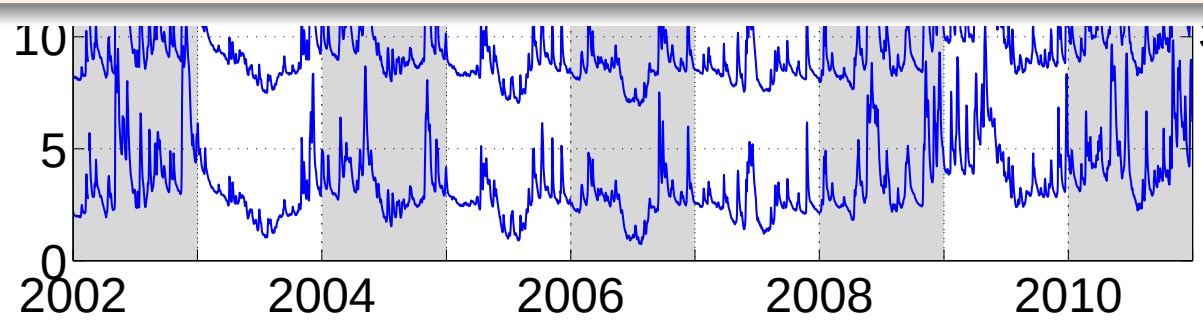


Piacenza



mona

goforte



Sermide

Pontelagoscuro

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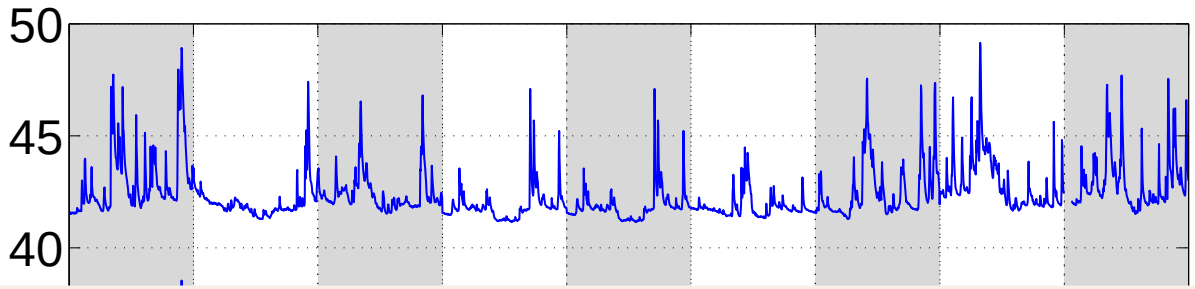

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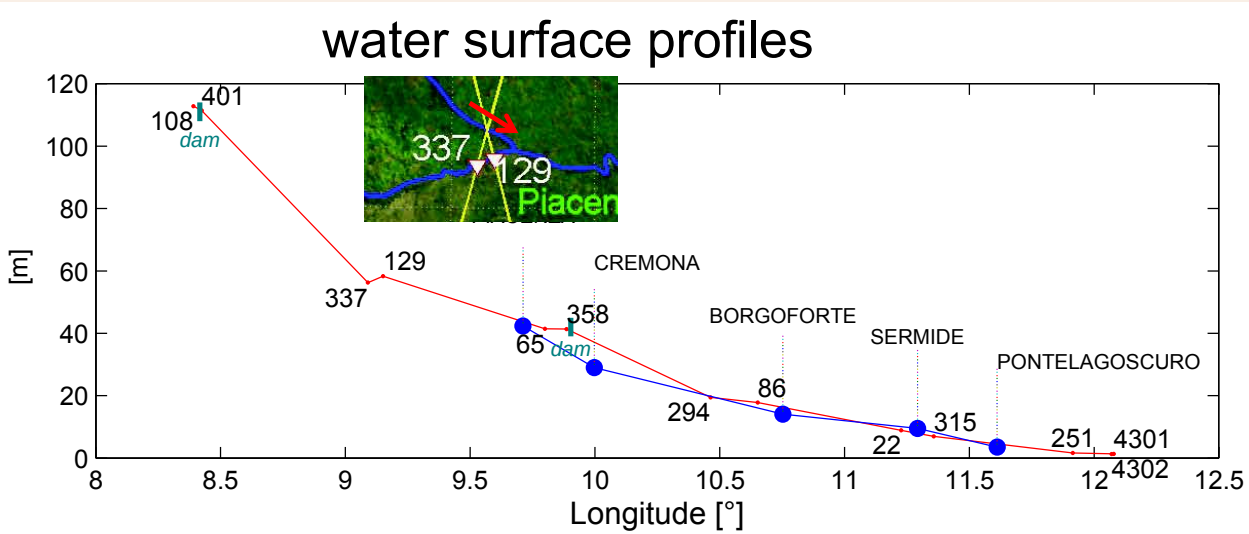

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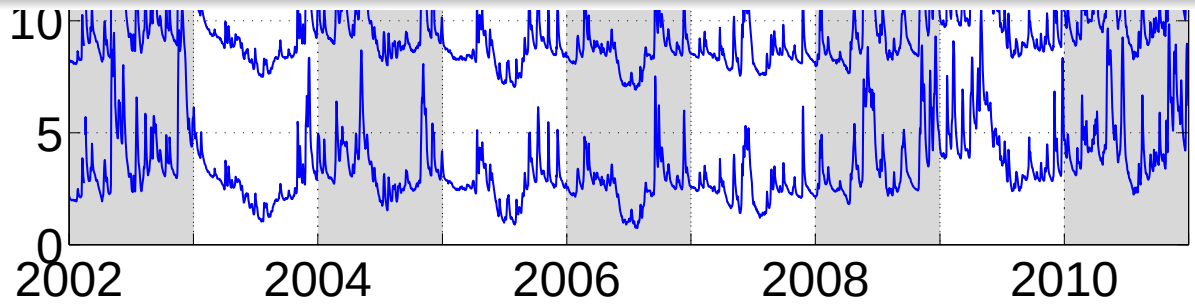


Sermide

Pontelagoscuro

Algorithm

1. time lag determination with respect to the considered VS
2. normalization of time series
3. confidence limit definition
4. outlier identification and rejection
5. scaling (back) the measurements at the considered VS
6. constructing the time series

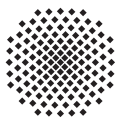
GIS

Step 1: time lag determination

- **flow velocity estimation**

Bjerklie et al. (2005), Tommy S.W. Wong (2003)

W	channel width	attained by the nearest cross-section information
S	slope	computed through the mean water level at virtual station
L	reach length	between two virtual stations
$\overline{V}$	local velocity	$\overline{V} = 2.3W^{0.8}S^{0.4}$
c	celerity	$c = \frac{5}{3}\overline{V}$
T	time lag	$T = \frac{L}{c}$



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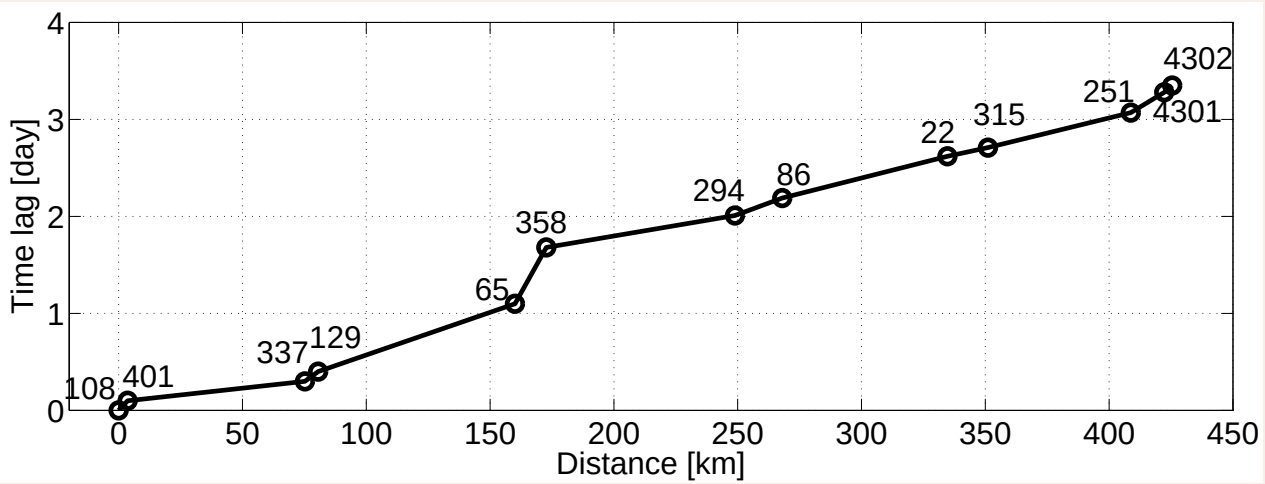
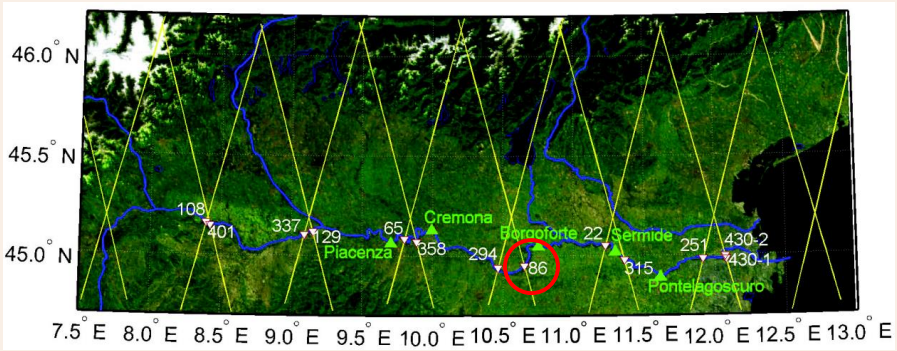
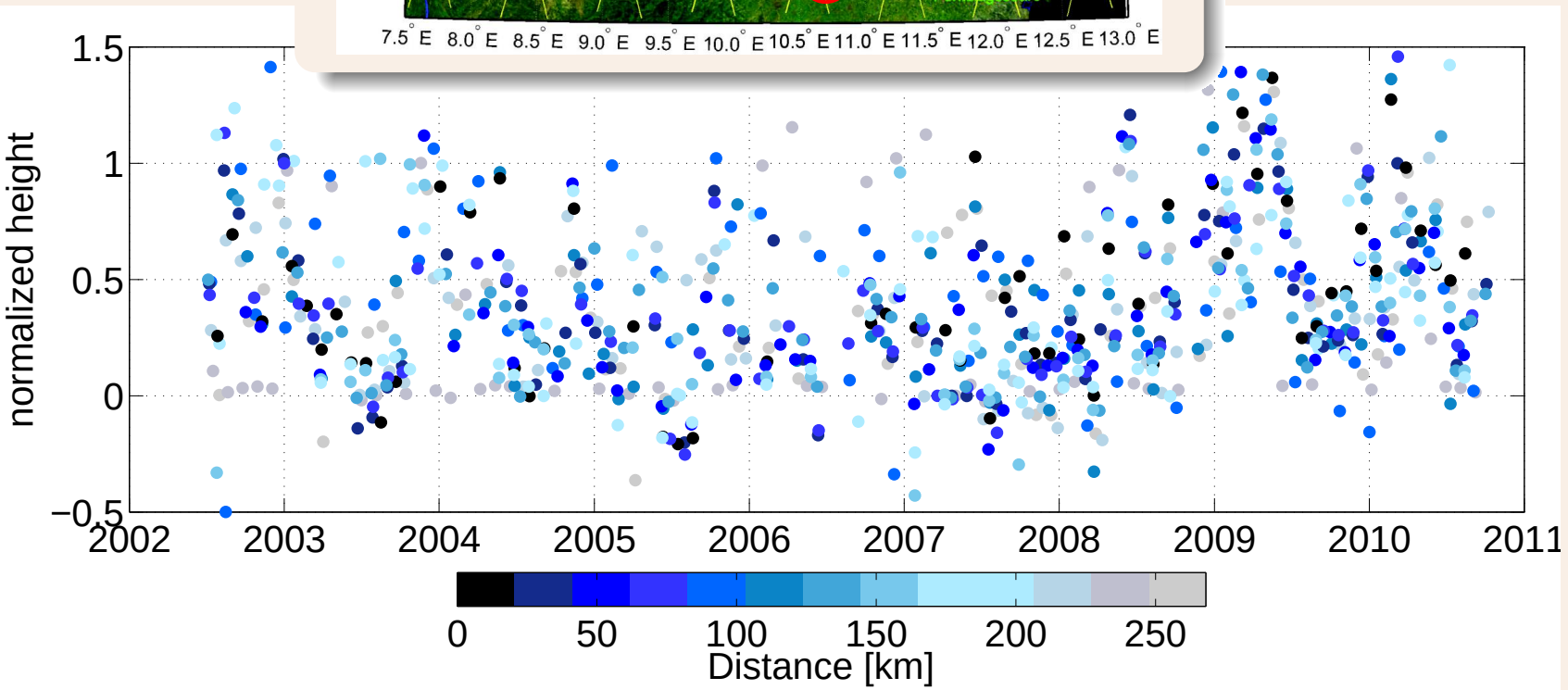


Step 2: normalization

Normalize the data from each virtual station
the 10th percentile falls on 0 and the 90th percentile on 1





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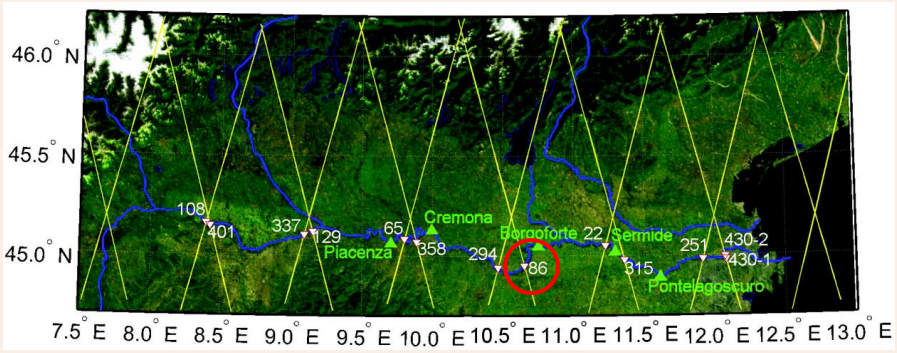
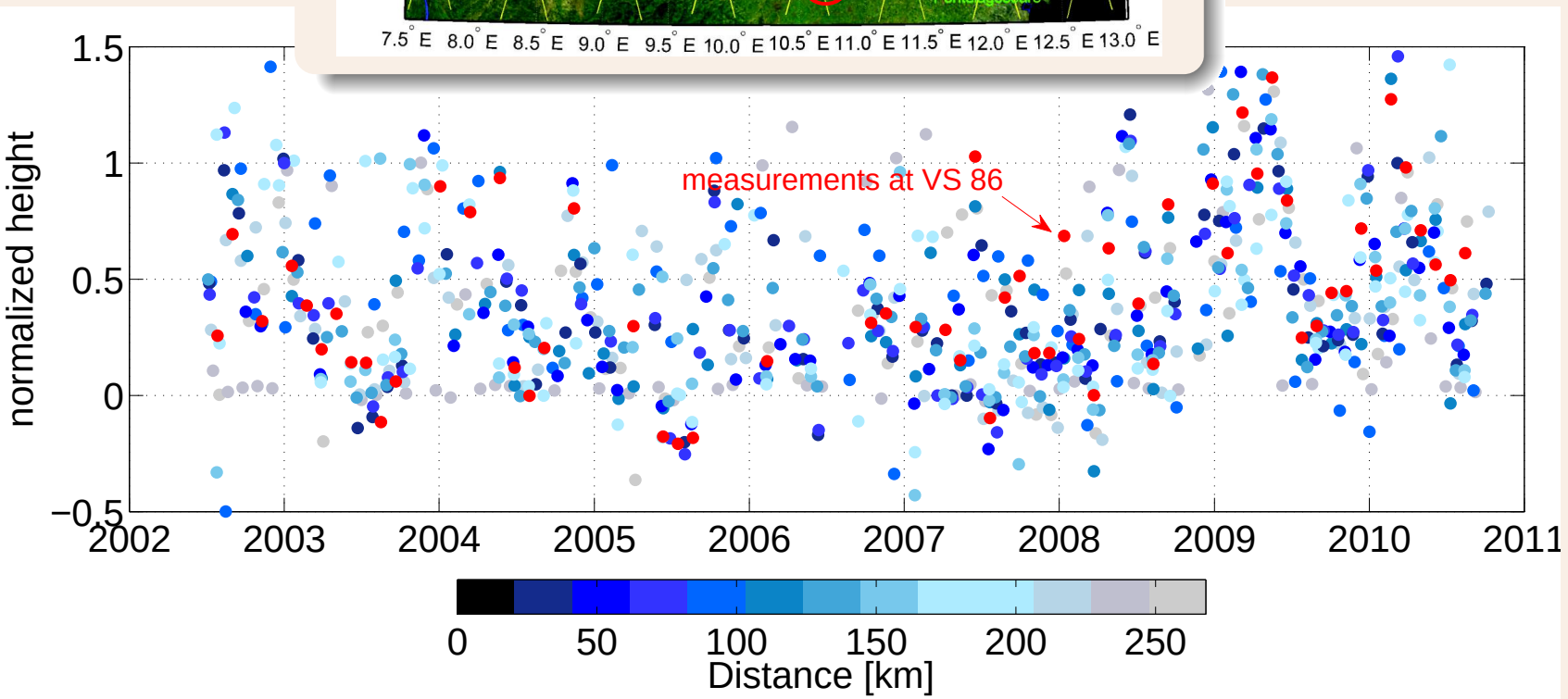
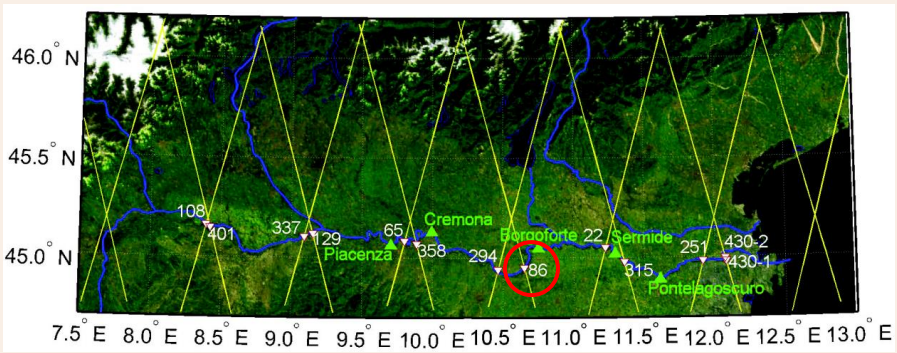
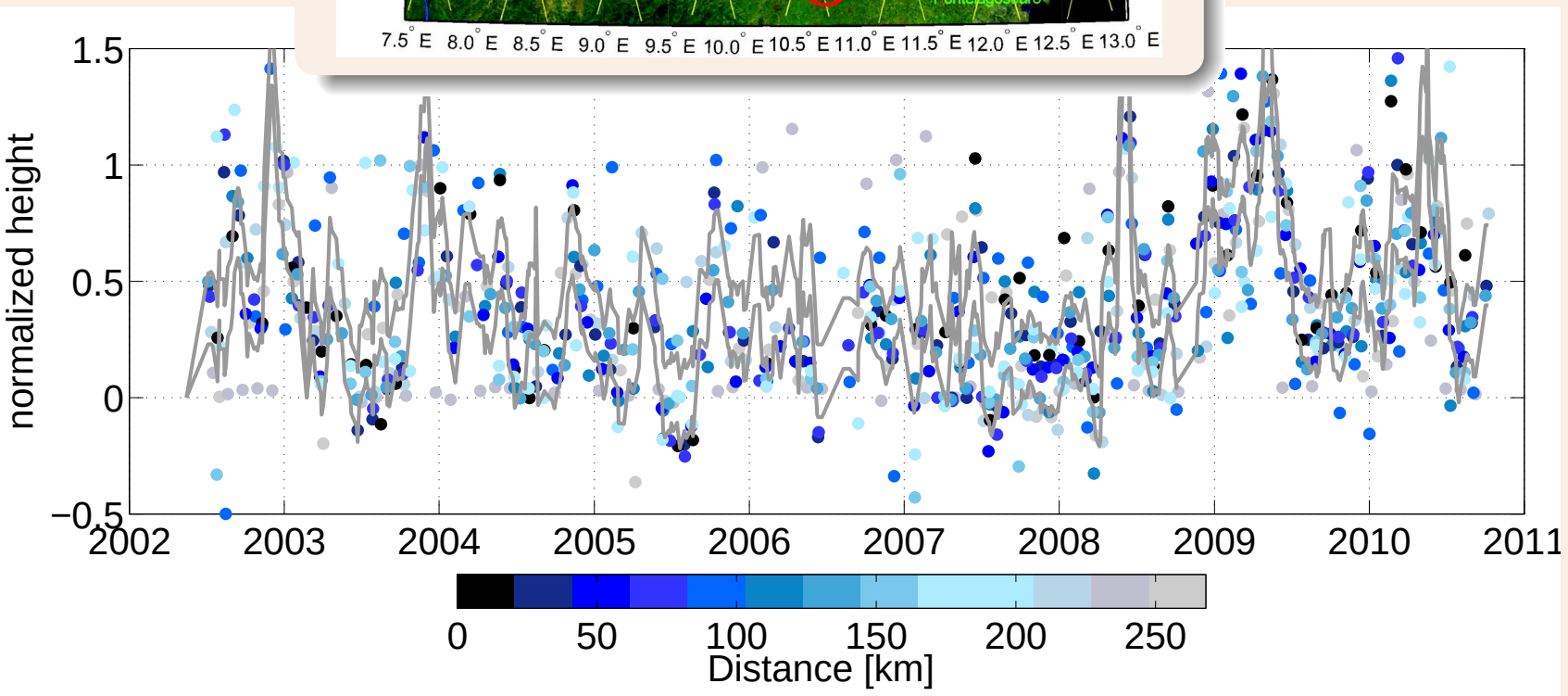




Step 3: confidence limit definition

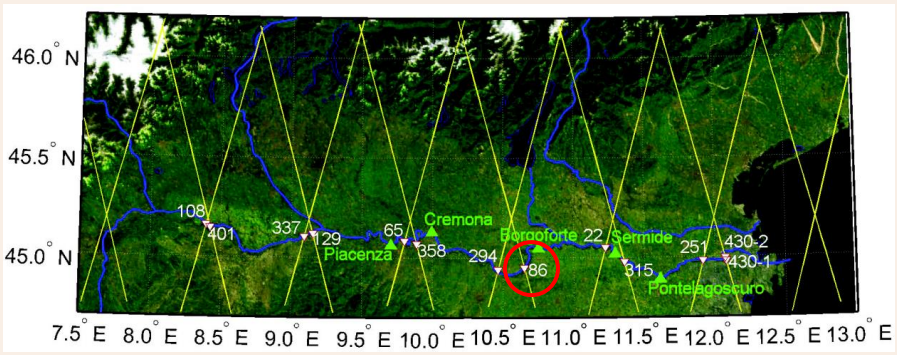
Definition of confidence limits of 99% using Student's t-test for a sliding 1-month time window

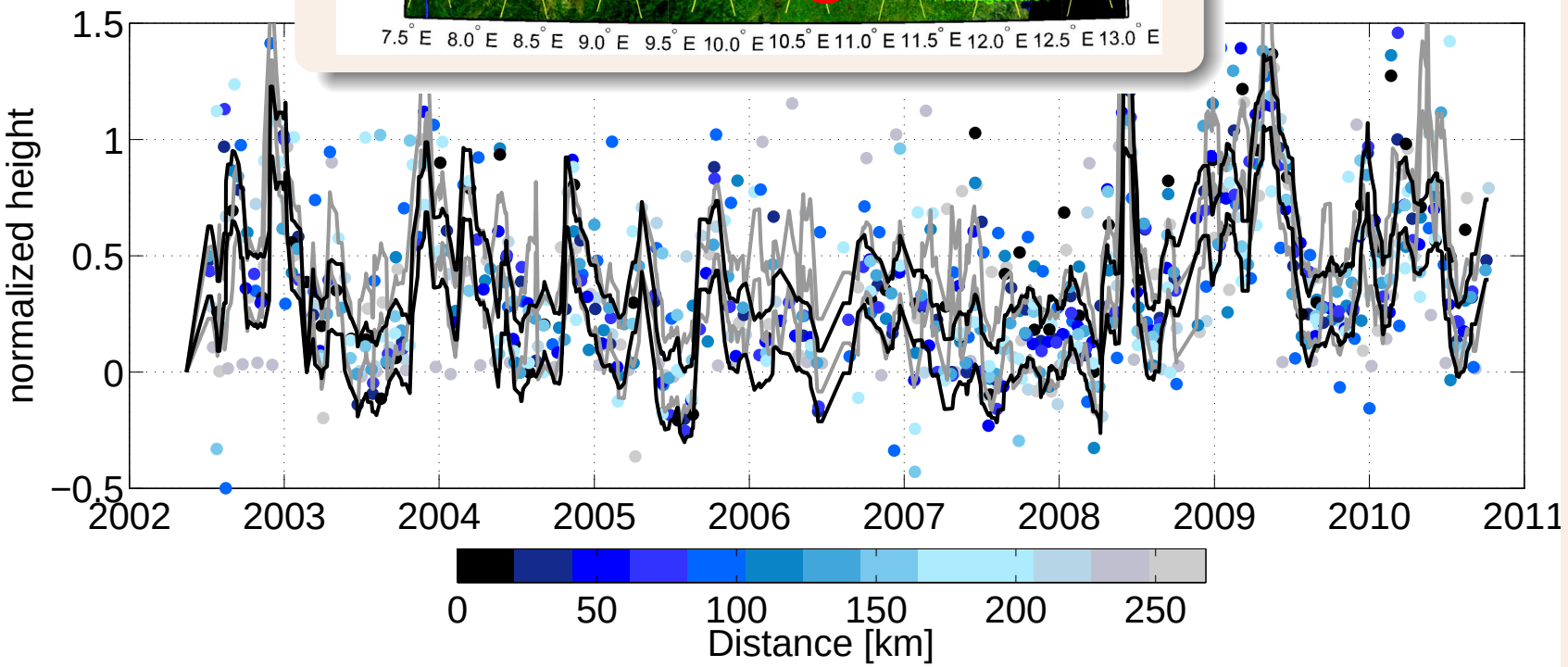




Step 4: outlier identification & rejection

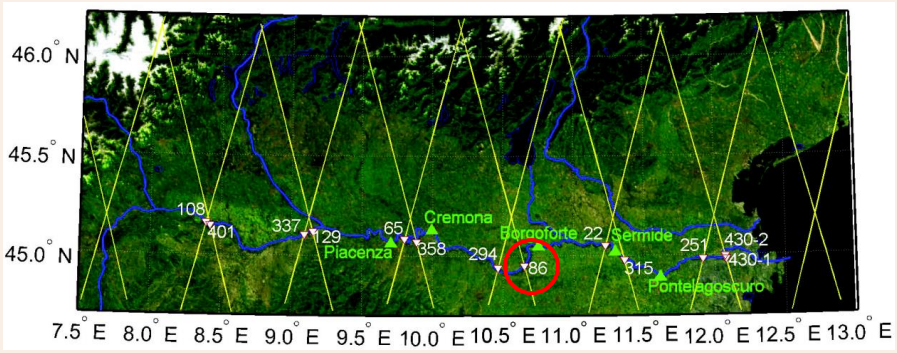
Iterative data snooping and updating the confidence limits

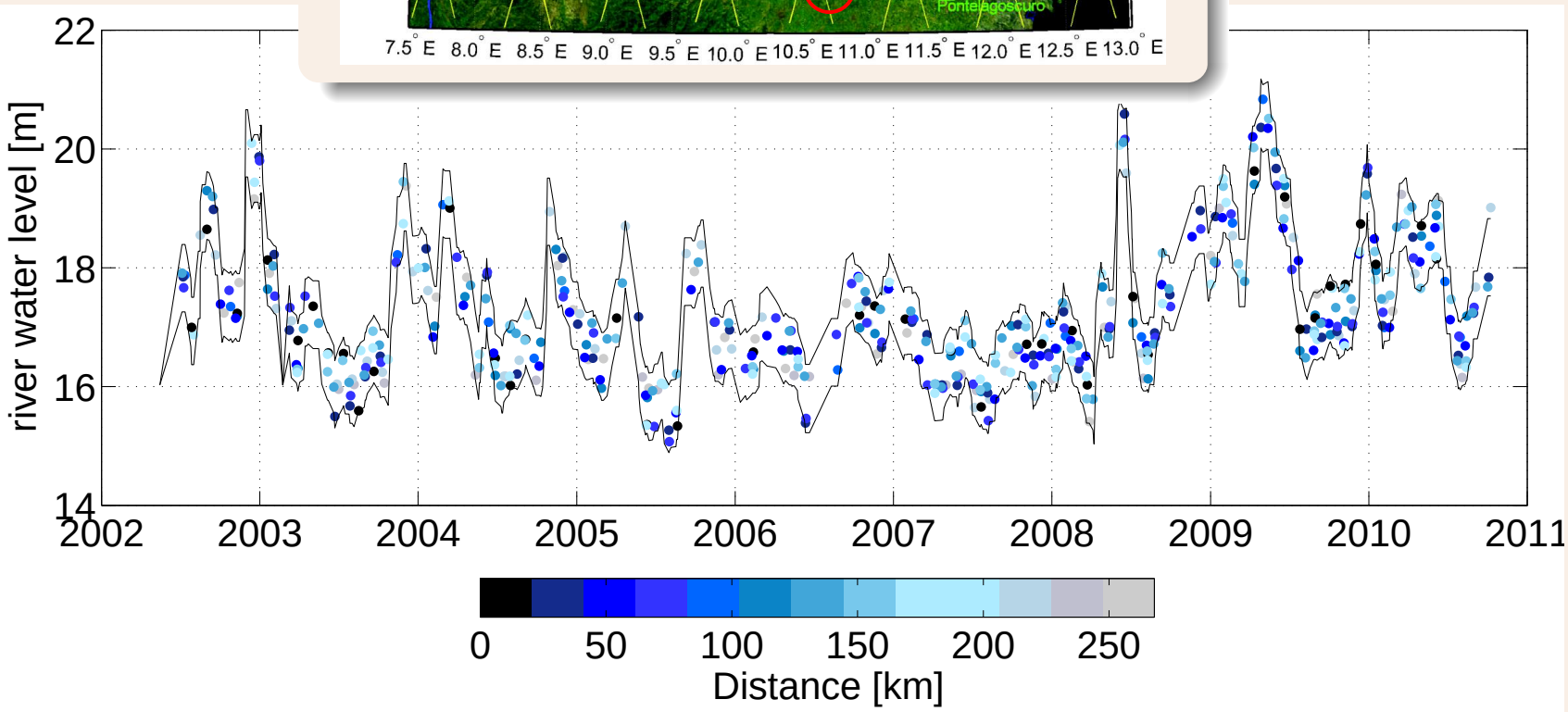




Step 5: scaling (back)

Rescaling the combined altimetric measurements to the considered virtual station

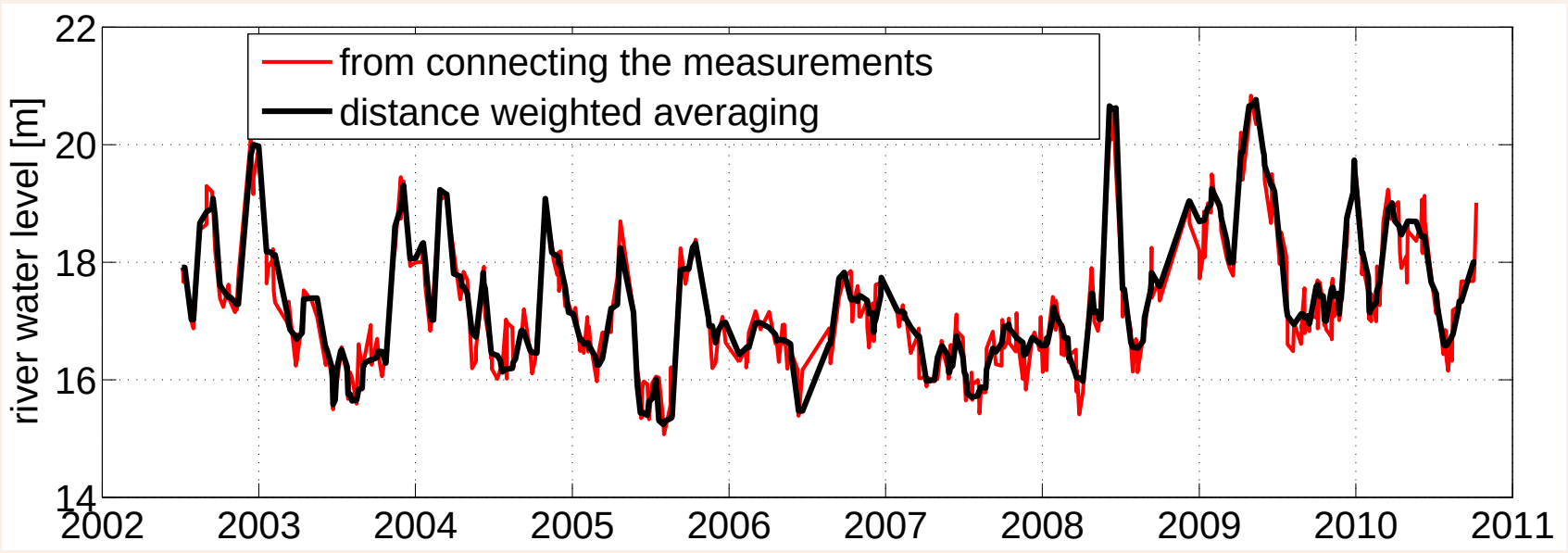




Step 6: constructing the time series

two options:

1. simply connecting the measurements
2. 3-point moving average, distance weighted



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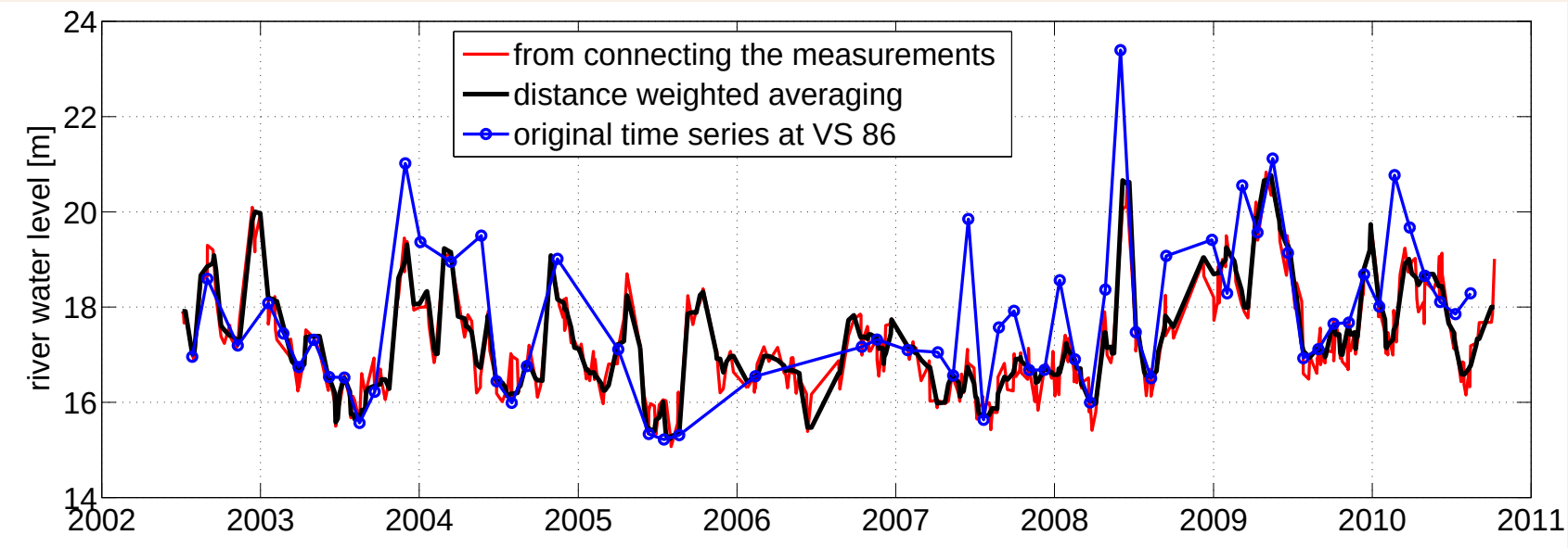
long-term mean is removed...



Validation

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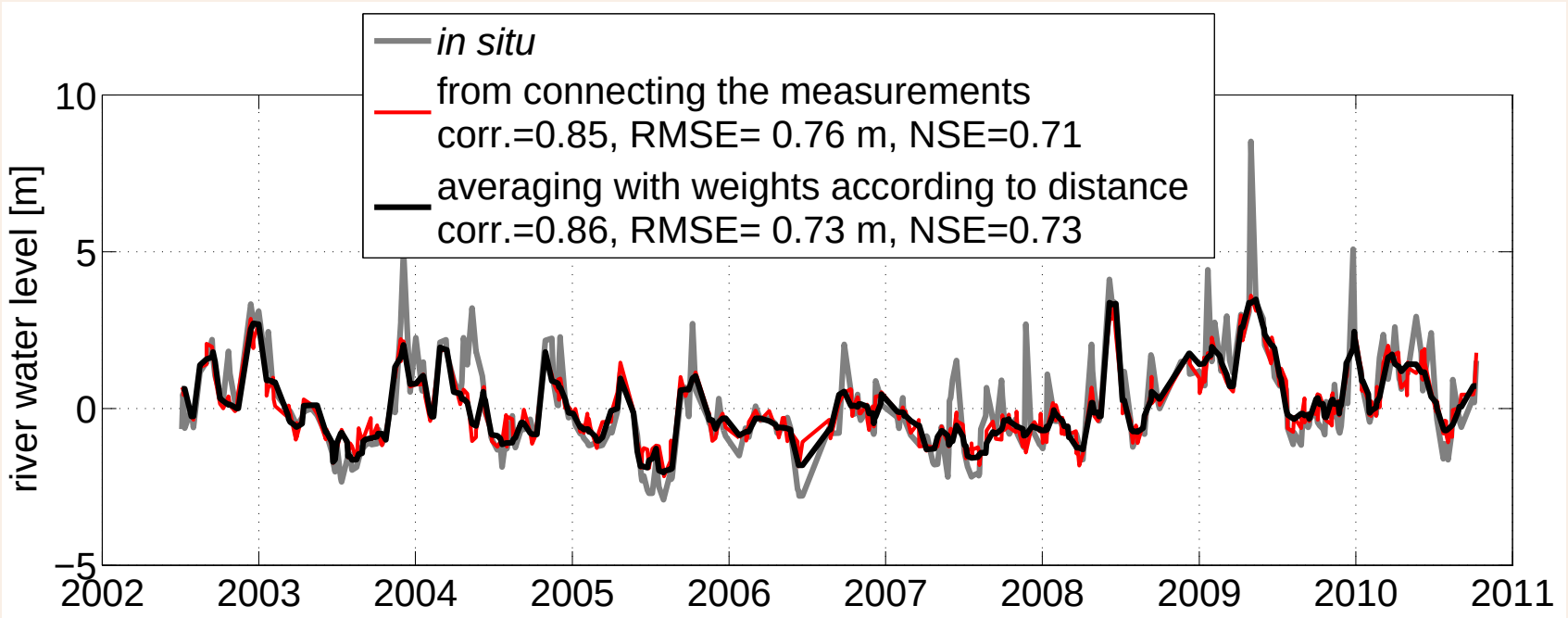
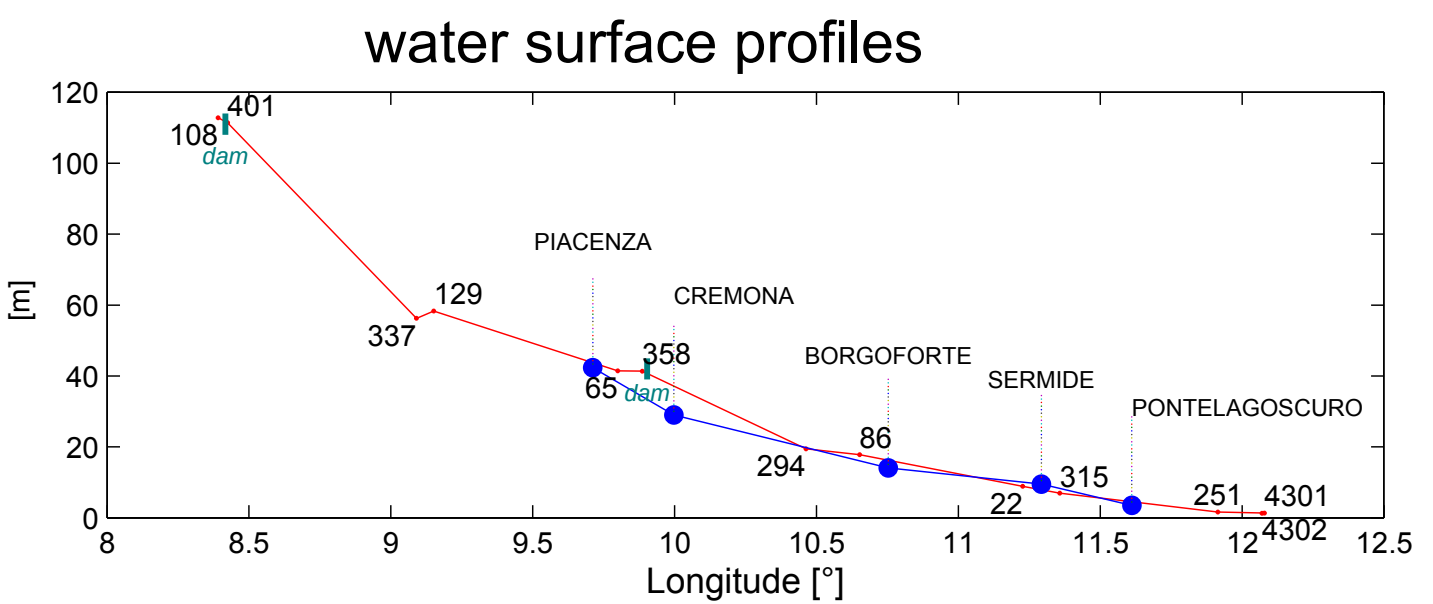


Validation



VS at	RMSE [m]	Correlation	NSE
Piacenza	0.63	0.71	**0.36**
Cremona	1.16	0.80	**0.20**
Borgoforte	0.73	0.86	**0.73**
Sermide	0.56	0.86	**0.75**
Pontelagoscuro	0.62	0.86	**0.74**

Summary and conclusion

- we investigated the water level time series over Po River at different virtual stations as a dynamic system
- the time lag between virtual stations is estimated
- the time series of individual VS are normalized and combined to each other
- outliers are removed using data snooping
- the time series are scaled back to the considered VS and a new time series is constructed by distance weighted averaging
- temporal resolution is improved from 35 day to an effective temporal resolution of $\sim$ 5 day
- water level time series can be obtained at any location along the river using this approach
- we validate our results against daily in situ water level, we obtain Corr.= 0.85, RMSE =0.6 m and NSE = 0.7 for the unmanaged part of the river

GIS

Still open for future work

- bringing more hydraulic information into the modeling
- time variable slope consideration for time lag estimation
- improving the method over the managed part of river (before and after dam)
- multi-mission altimetry would definitely improve the temporal resolution
- bias consideration in case of multi-mission

GIS

Thank you

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