

Improving flood model predictions using satellite EO-derived flood extent maps

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SETTING THE SCENE

Objective

- To reduce uncertainties in numerical modelling-based flood forecasting

Traditional approach

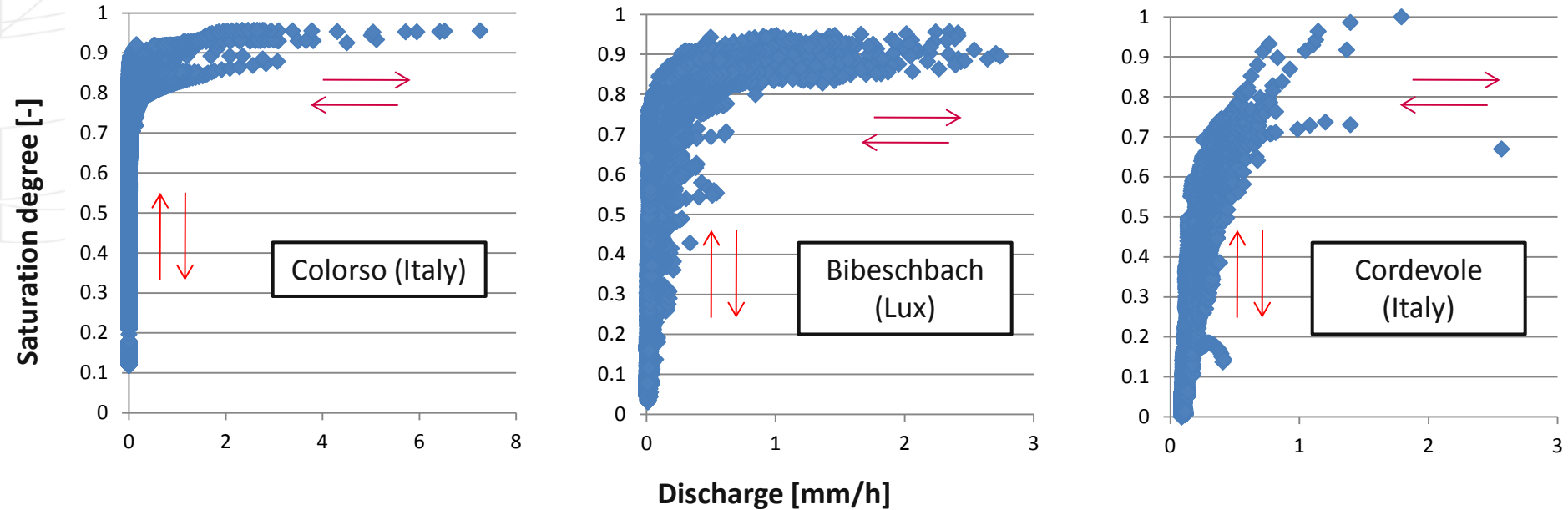
- To regularly control and correct the models by assimilating external observations (i.e. in situ river discharge measurements)

Limitations

- Problem of availability and representativeness of point measurements
- In situ measurements are not evenly distributed and networks globally tend to be in decline
- Uncertainties unknown or poorly understood
- Ground measurements difficult/dangerous to obtain during crises

Hence: There is a need for globally consistent and coherent high resolution observation data with known uncertainties that enable improved hydrological predictions at large scale

THE IMPORTANCE OF FLOOD EXTENT OBSERVATIONS



- Initiation of fast runoff is a threshold process that occurs when soil moisture rises above a critical threshold
- Soil moisture and water level variability are inversely correlated: potentially soil moisture and water level (or flood extent) observations are highly complementary

MICROWAVE REMOTE SENSING



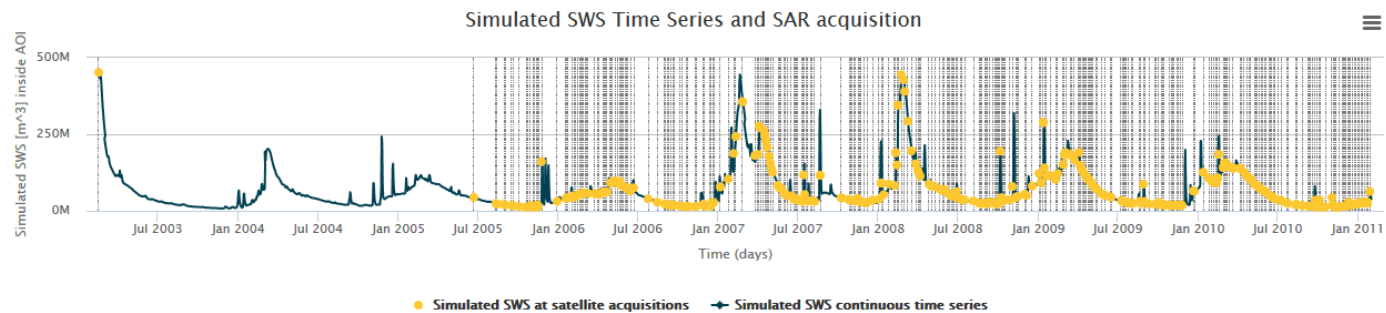
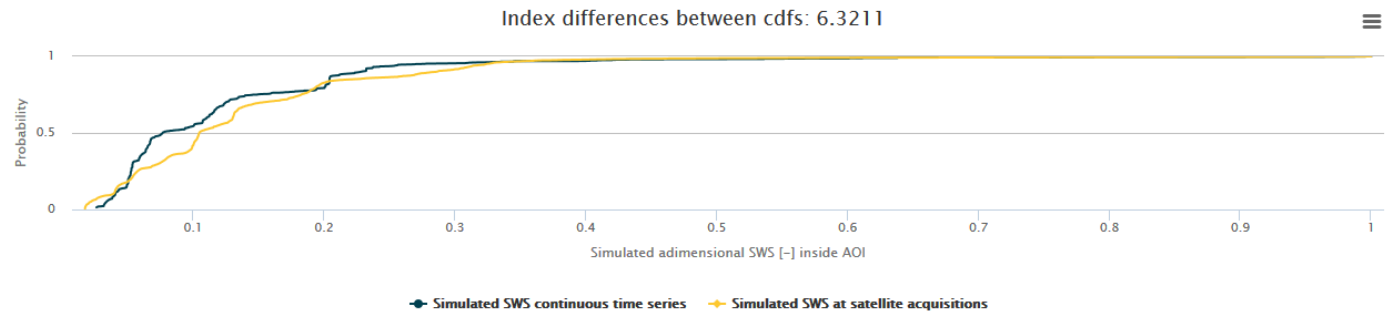
grid processing on demand

European Space Agency

SWS: Surface Water Storage

Advantages:

- Day/Night & all-weather observations
- Systematic observations of large scale flooding events
- High spatial and temporal resolutions



Research question: How to efficiently combine SAR remote sensing information with hydrologic-hydraulic models for improved predictions?

Flood extent mapping from SAR images

Several state-of-the-art methods based on thresholding, region growing, change detection, segmentation...

→ but lack of efficient methods enabling probabilistic flood mapping that are necessary for data assimilation applications

Sequential assimilation in hydrologic/hydraulic models

Past studies only assimilate SAR image derived **water level (model state variable)**

→ Processing of images not straightforward and longer (issue for NRT applications + DEM consistency SAR/model)

Objective: directly assimilate flood extent observations into operational flood prediction model

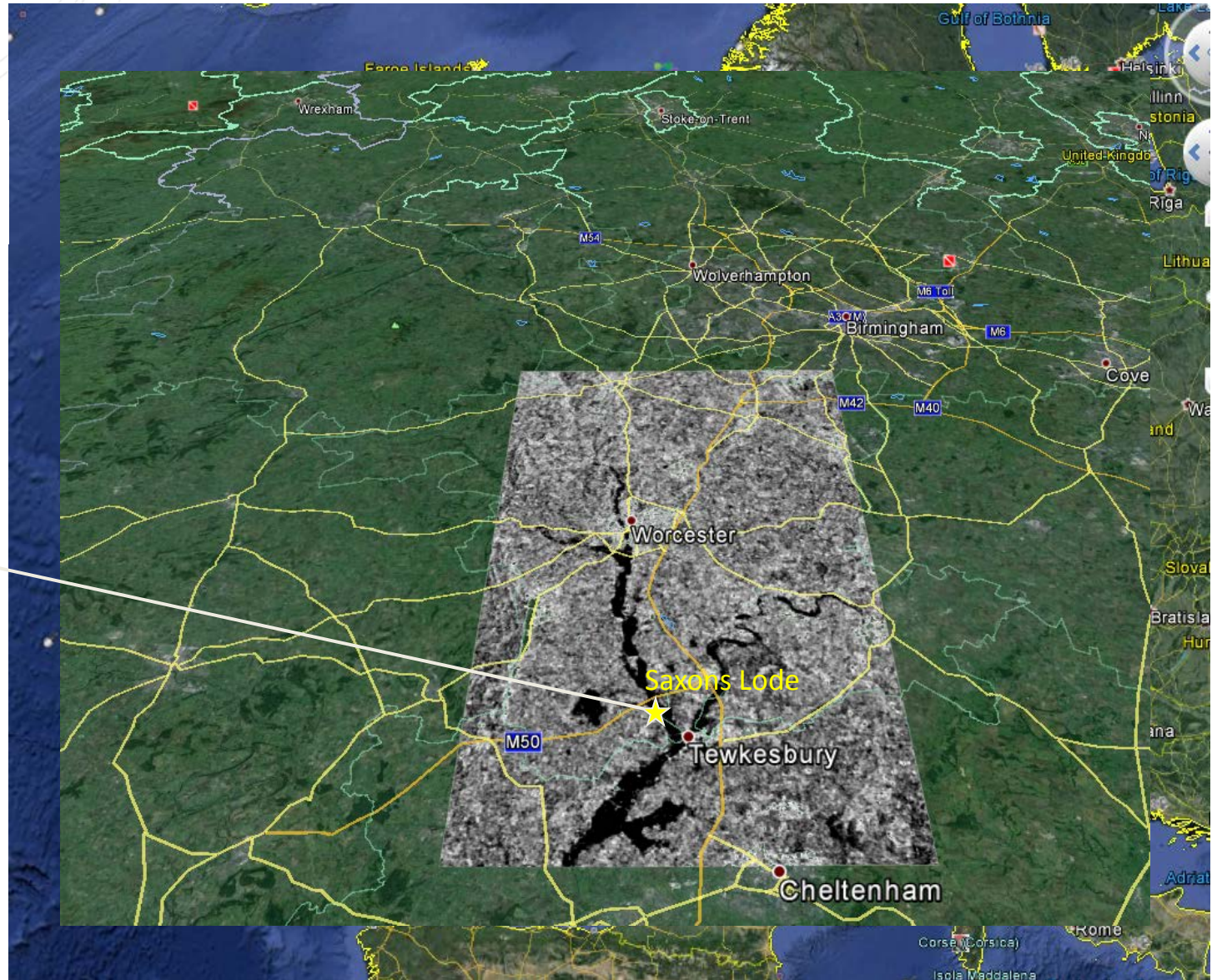
PROOF-OF-CONCEPT STUDY

July 2007 Flood event

2 Envisat WSM
images acquired
after flood peak

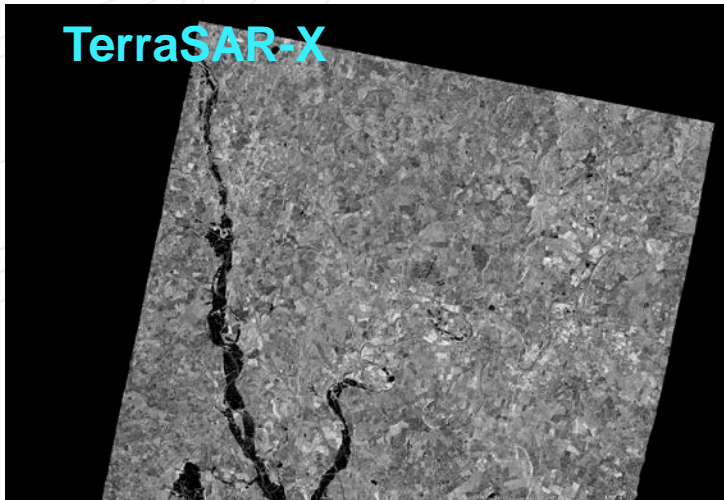
In situ WSE and Q
(control)

Aerial photos of
maximum flood
event

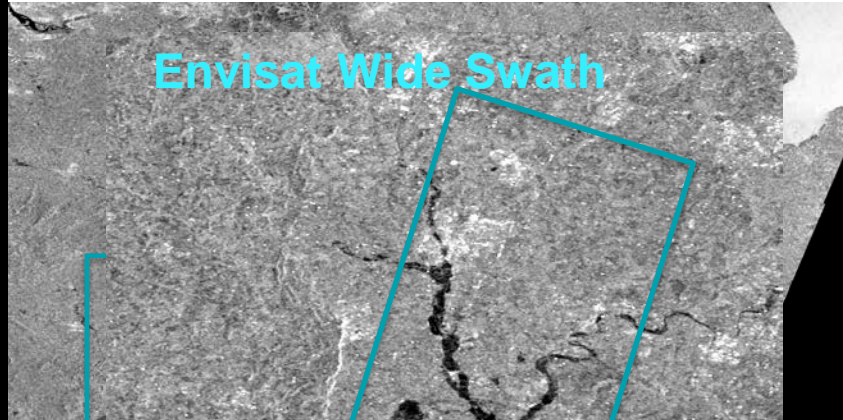


RETRIEVING FLOOD EXTENT

TerraSAR-X



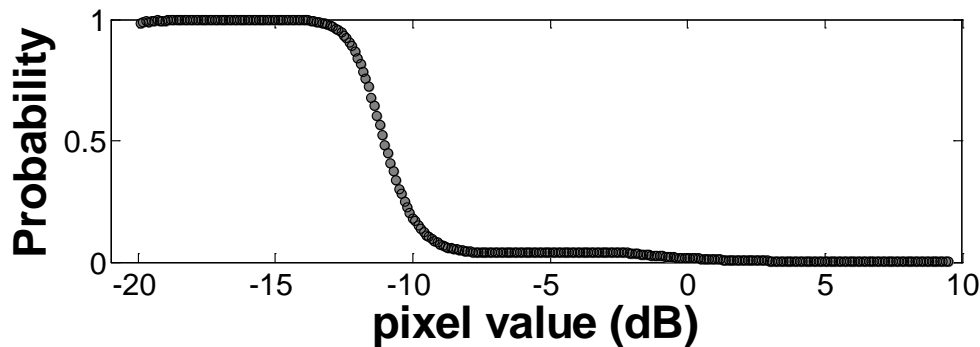
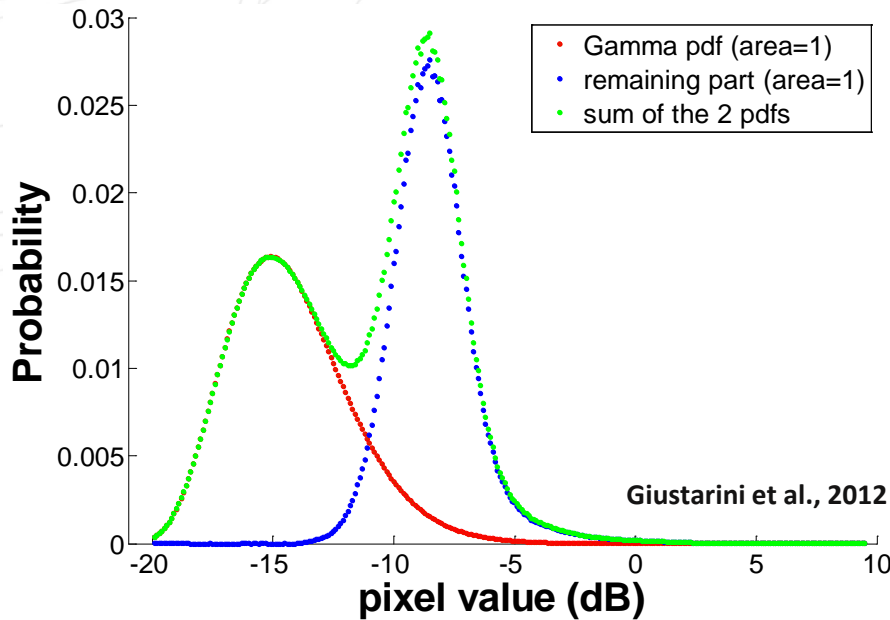
Envisat Wide Swath



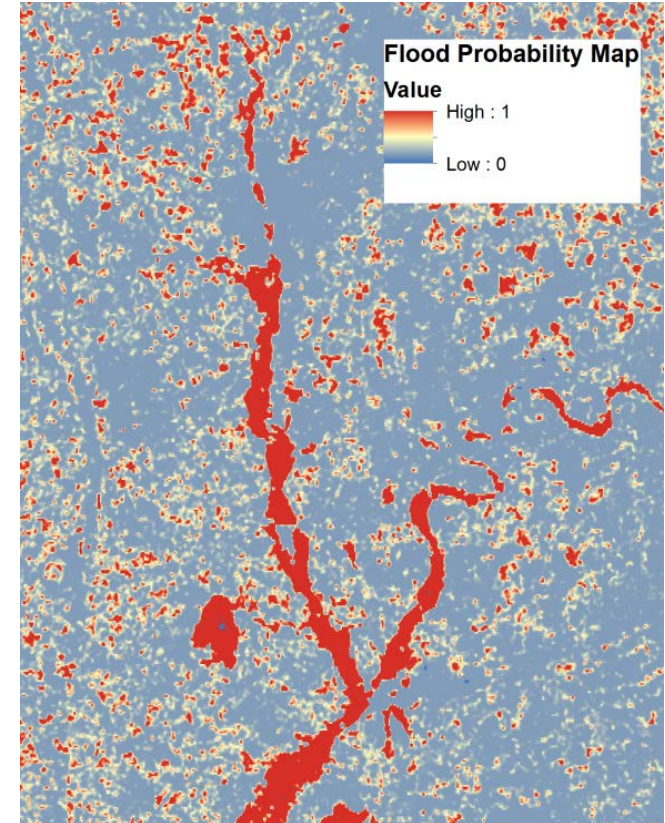
	Resolution (m)	Swath width (Km)	Wavelength (cm)	Flooded pixels
Envisat WS	150	400	5.6	0.05 % (5100x2850)
TerraSAR-X	3	30	3	2% (15135x21294)

RETRIEVING FLOOD EXTENT

Approach: to parameterize a distribution function of backscatter values attributed to water bodies



FLOOD EXTENT



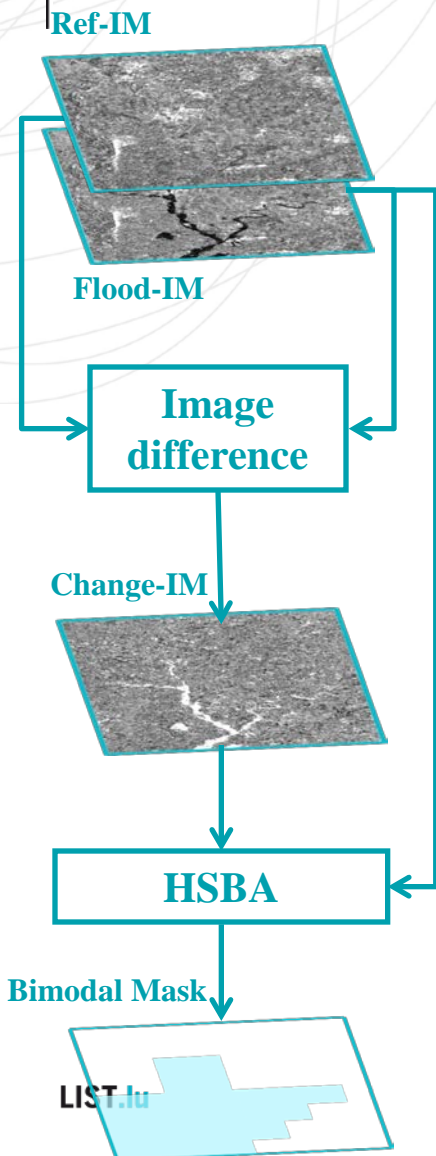
$$p(w|\sigma^0) = \frac{p(\sigma^0|w)p(w)}{p(\sigma^0|w)p(w) + p(\sigma^0|d)p(d)}$$

Matgen et al., PCE, 2011

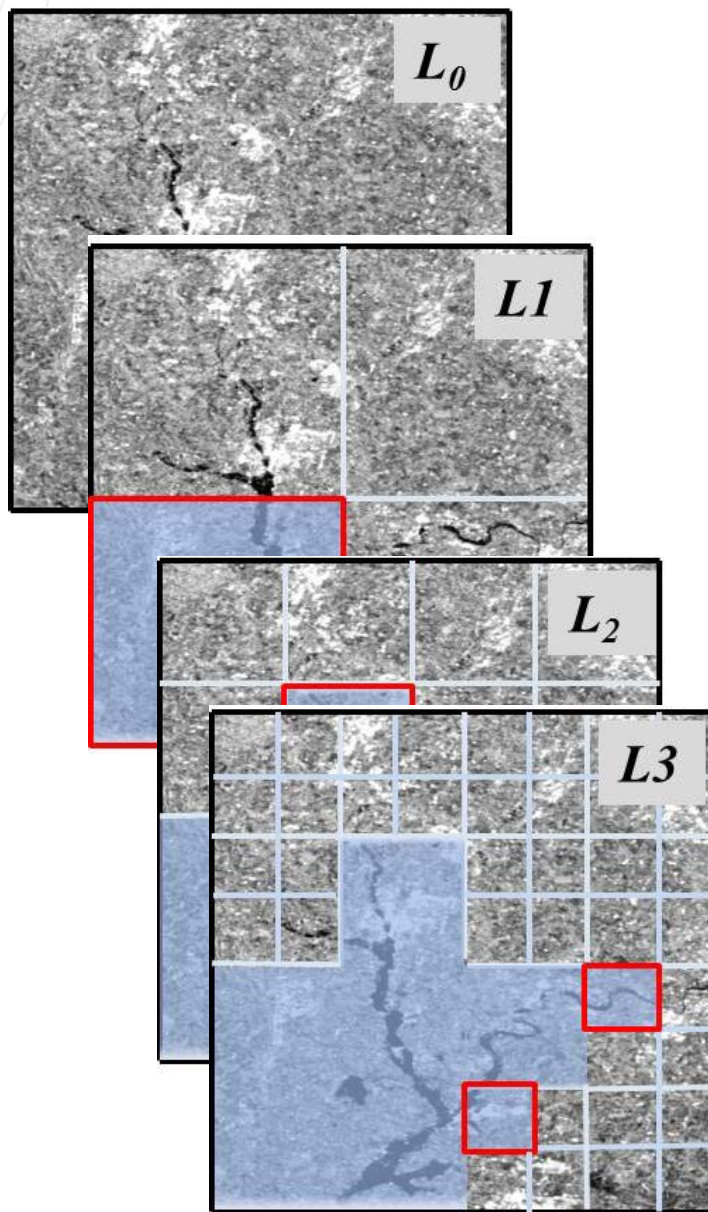
Giustarini et al., IEEE TGRS, 2016

RETRIEVING FLOOD EXTENT

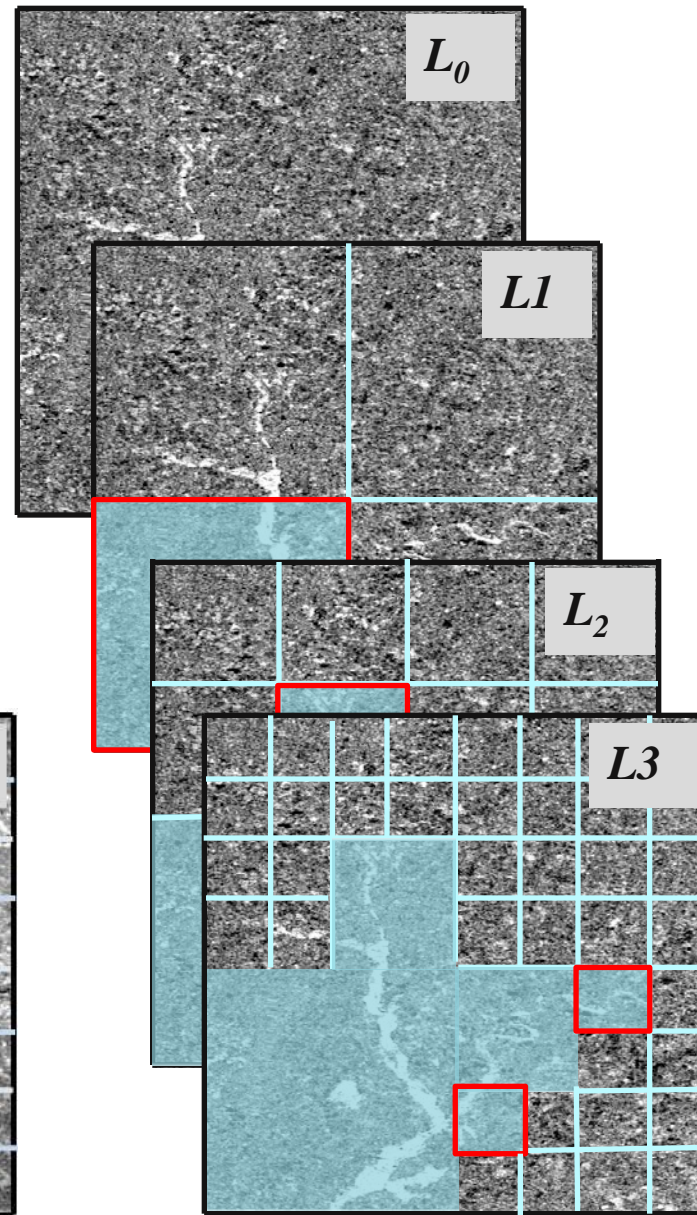
HSBA



Flood-IM





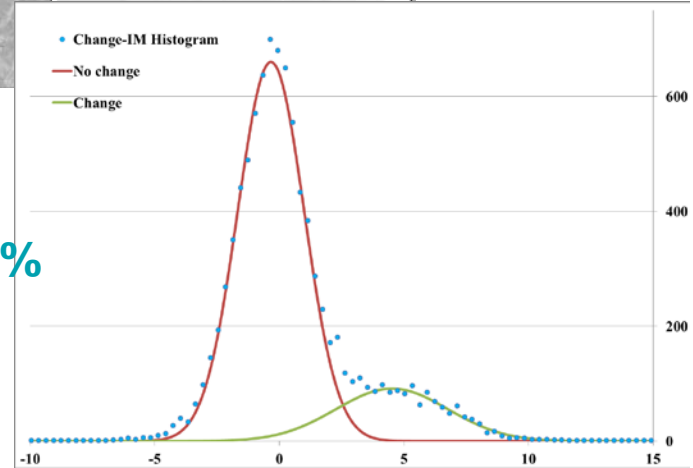
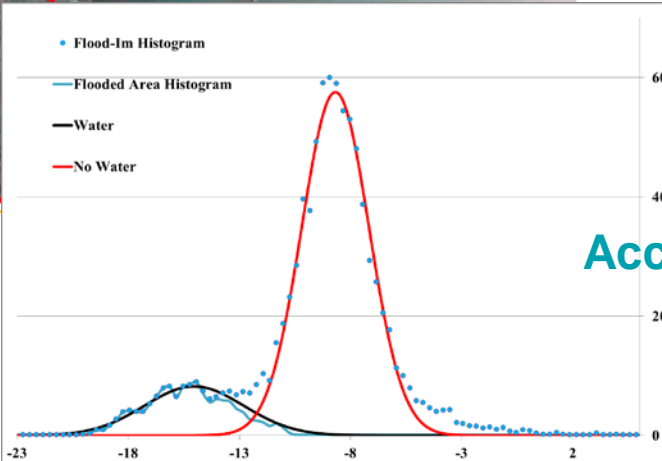
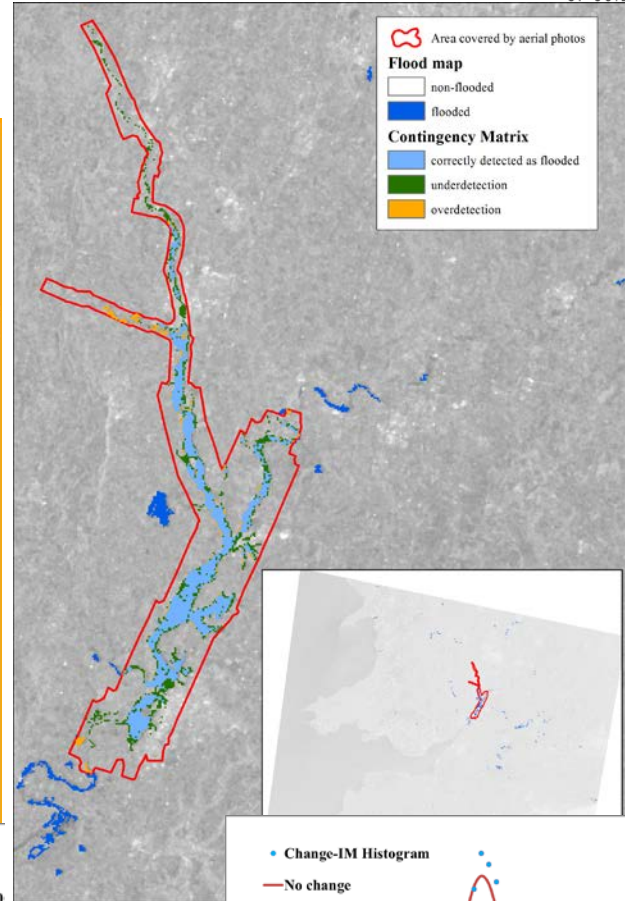
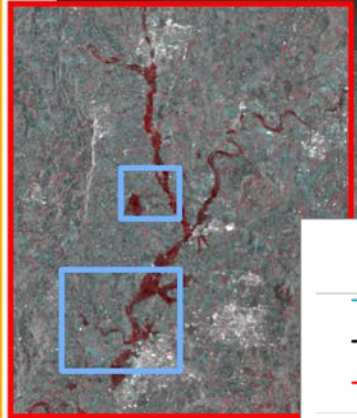
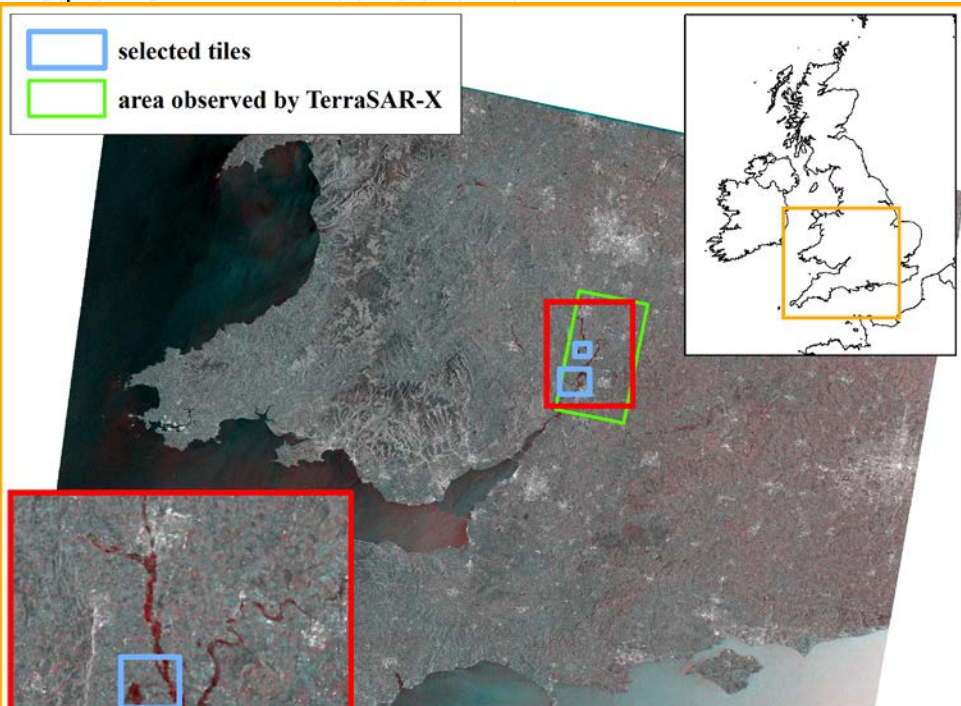
Change-IM



CASE STUDY

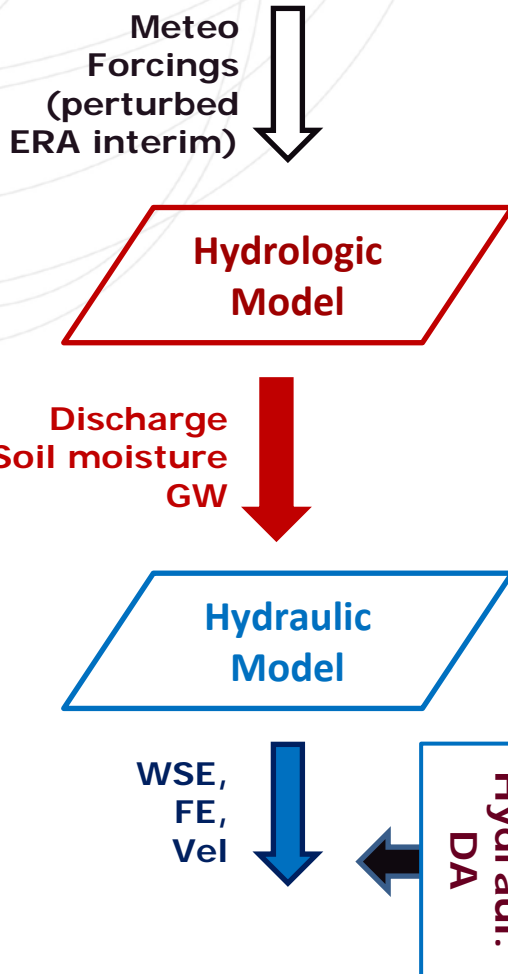
Envisat WS

 selected tiles
 area observed by TerraSAR-X

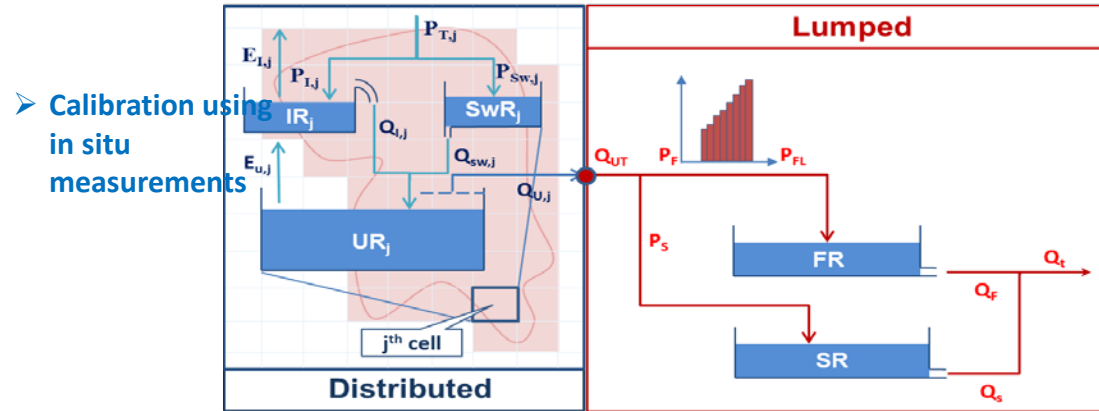


Accuracy: 89%

CASCADE OF NUMERICAL MODELS

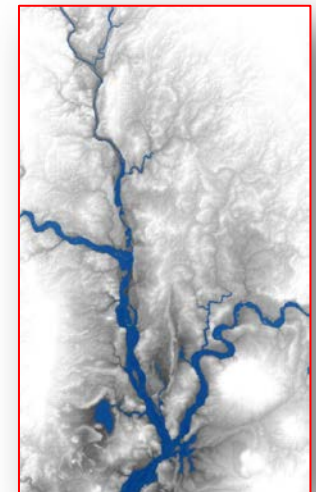


Model set up: SuperFlex (Fenicia et al., WRR, 2010)

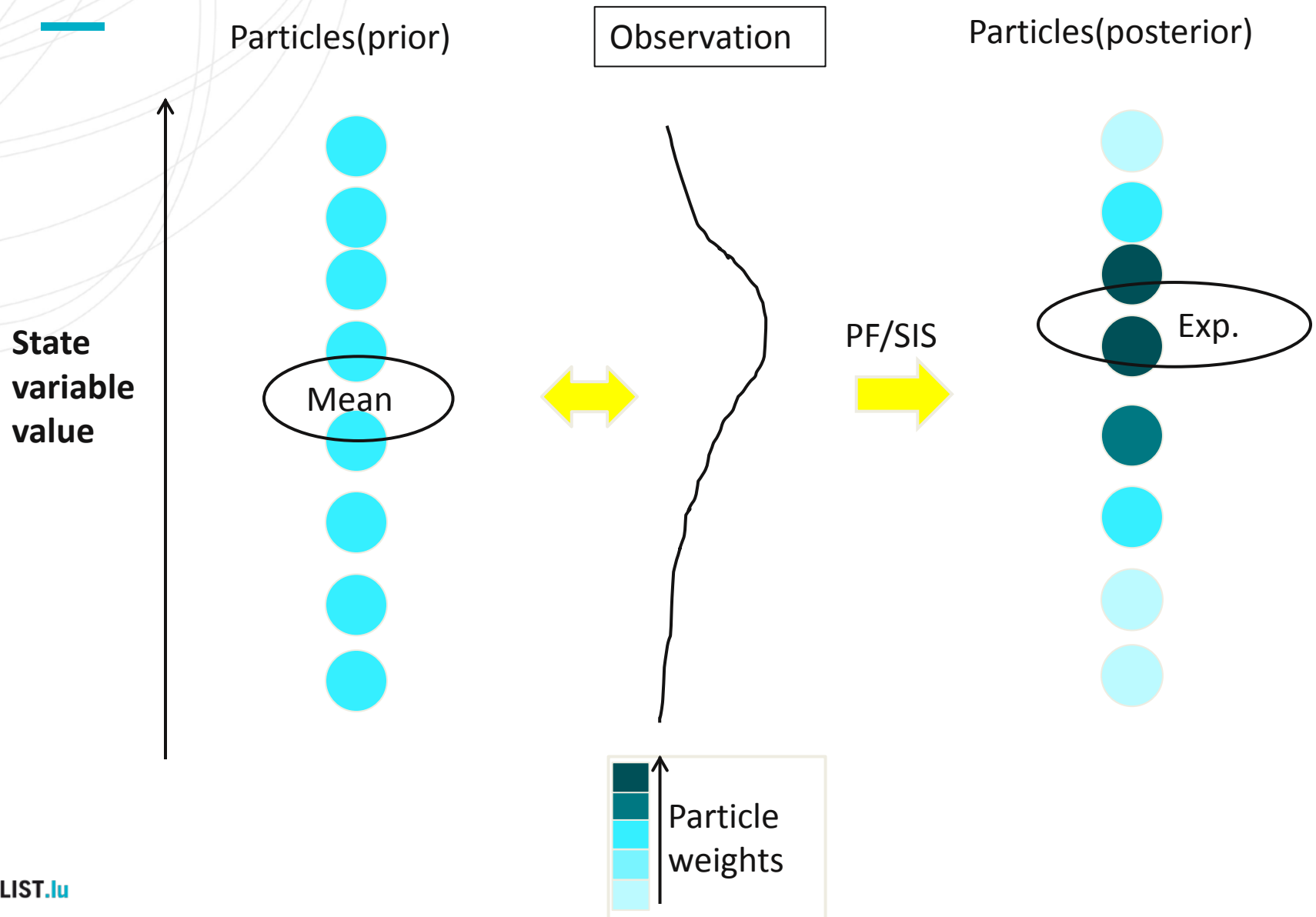


LISFLOOD-FP SubGrid (Neal et al 2012)

- Designed for modeling flood flows in large catchments as well.
- Uses DEM file as geometry.
- Models 1D- 2D dimensional flows.
- Calibration using in situ measurements and archived flood extent observations



DATA ASSIMILATION



DATA ASSIMILATION

Assumption : binomial pdf

$$p(k, n \mid \Theta) = \binom{n}{k} \Theta^k (1 - \Theta)^{n-k}$$

$k = \# \text{ successes}$
 $n = \# \text{ trials } (n=1)$

MOD_{t,i}

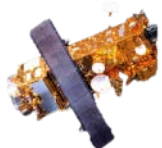
1	0	1
0	1	1
1	0	0

$$W_{1,1}^{t,i} = \Theta_{1,1}$$

Simulated Water pixel
(k=1)

$$W_{3,3}^{t,i} = 1 - \Theta_{3,3}$$

Simulated Dry
pixel (k=0)



Satellite
observation

$\Theta_{1,1}$	$\Theta_{1,2}$	$\Theta_{1,3}$
$\Theta_{2,1}$	$\Theta_{2,2}$	$\Theta_{2,3}$
$\Theta_{3,1}$	$\Theta_{3,2}$	$\Theta_{3,3}$



$W_{1,1}^{t,i}$	$W_{1,2}^{t,i}$	$W_{1,3}^{t,i}$
$W_{2,1}^{t,i}$	$W_{2,2}^{t,i}$	$W_{2,3}^{t,i}$
$W_{3,1}^{t,i}$	$W_{3,2}^{t,i}$	$W_{3,3}^{t,i}$

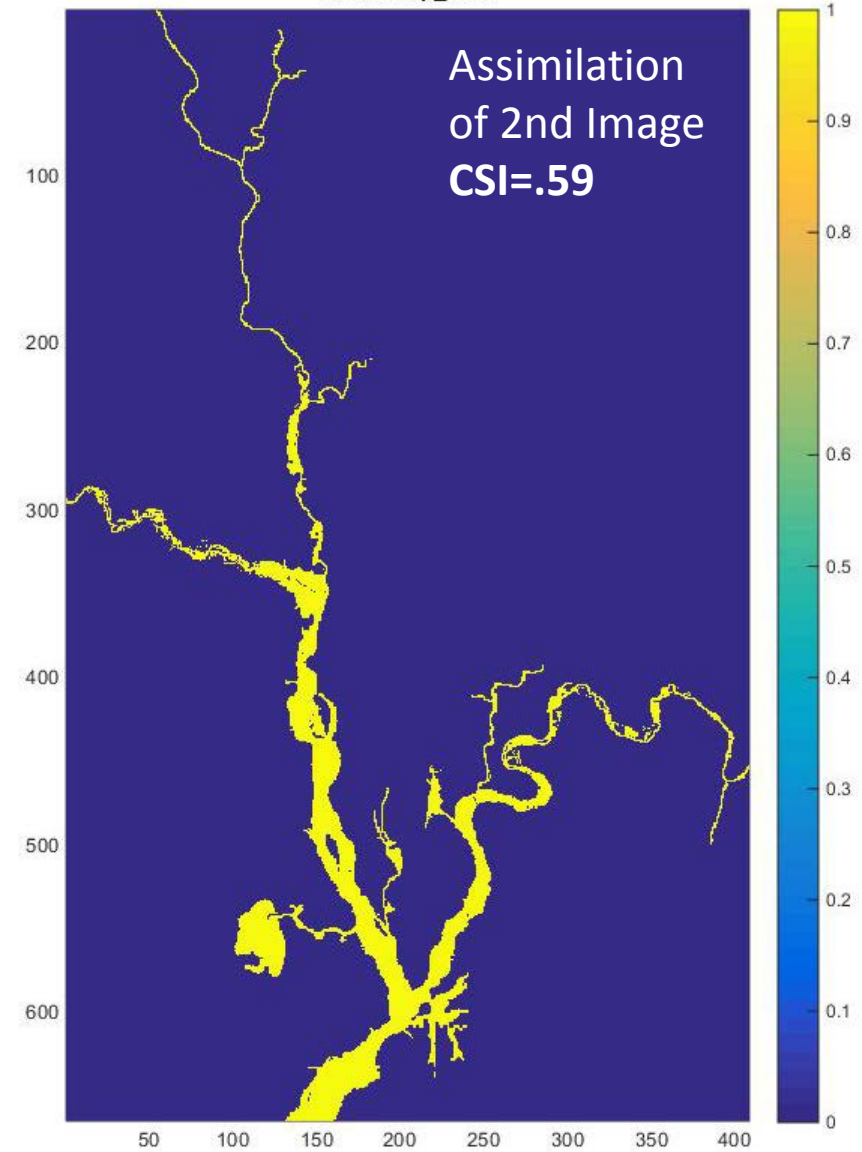
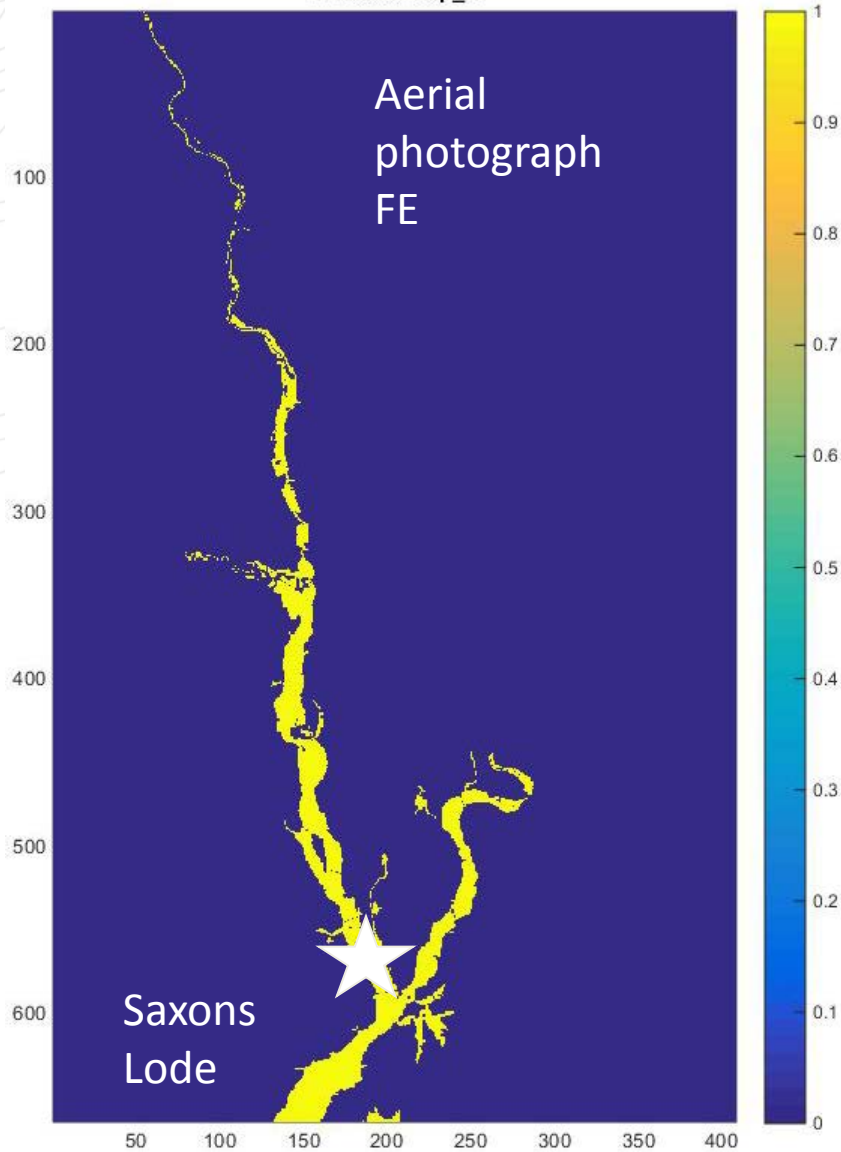
Spatial Weights aggregations

$$W^{t,i} = \prod_{j,k} W_{j,k}^{t,i}$$

Applicable for independent observations

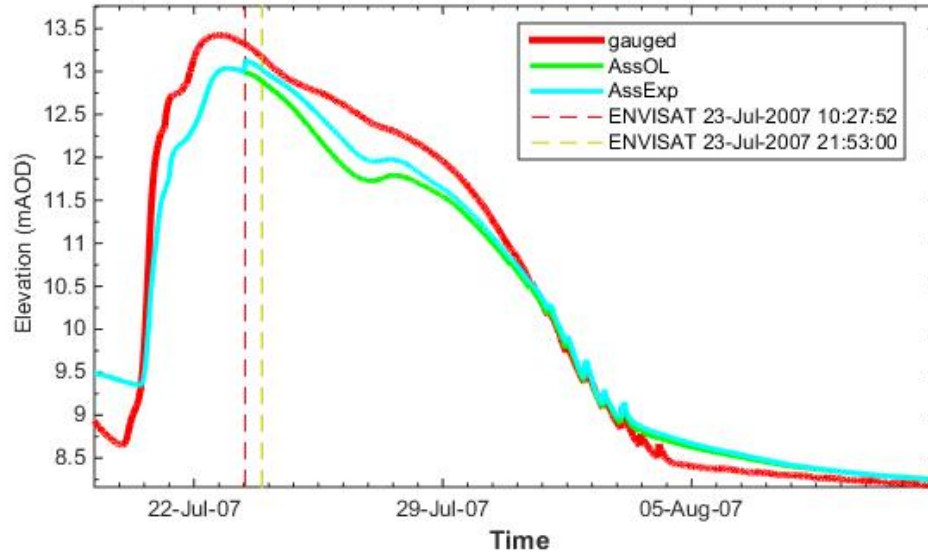
$$\sum_i \left(\prod_{j,k} W_{j,k}^{t,i} \right)$$

RESULTS



RESULTS

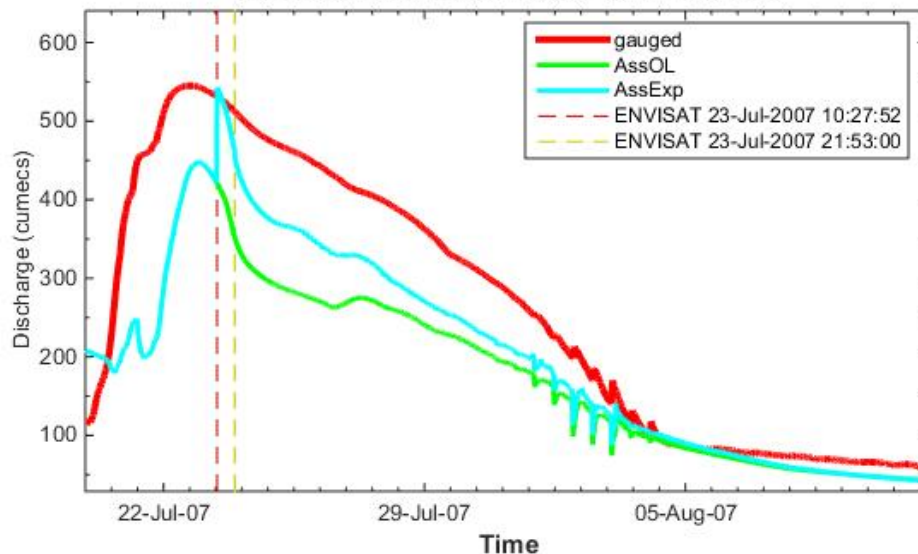
SaxonsLode Water elevation (all models)



RMSE (WSE) [cm]

1. Open loop: 31 cm
2. 1st image assimil.: 23 cm
3. 2nd image assimil.: 21 cm

SaxonsLode Discharge (all models)



NSE(Q) [-]:

1. Open loop: .64
2. 1st image assimil.: .88
3. 2nd image assimil.: .86

SUMMARY & PERSPECTIVES

We introduce a new method for assimilating in NRT SAR-derived flood extent maps into hydrological-hydraulic models:

→ To exploit continuously growing satellite image collections with faster repeat times and processing

First results:

- The approach improves simulated flood extent over several time steps
- The approach further improves simulated discharge and water surface elevation hydrographs over several time steps

Perspectives:

- Not restricted to NRT sequential assimilation, but potentially useful for improved reanalyses over many years (using catalogue of historic flood extent obs.)
- Further testing in operational context
- Investigate complementarity of various satellite EO data sets (flood extent, soil moisture, ET, snow water equivalent, etc.)
- Critical to reduce data latency!