ASSIMILATION OF FLOOD MAPS DERIVED FROM SAR DATA INTO A FLOOD FORECASTING MODEL

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27/11/2019

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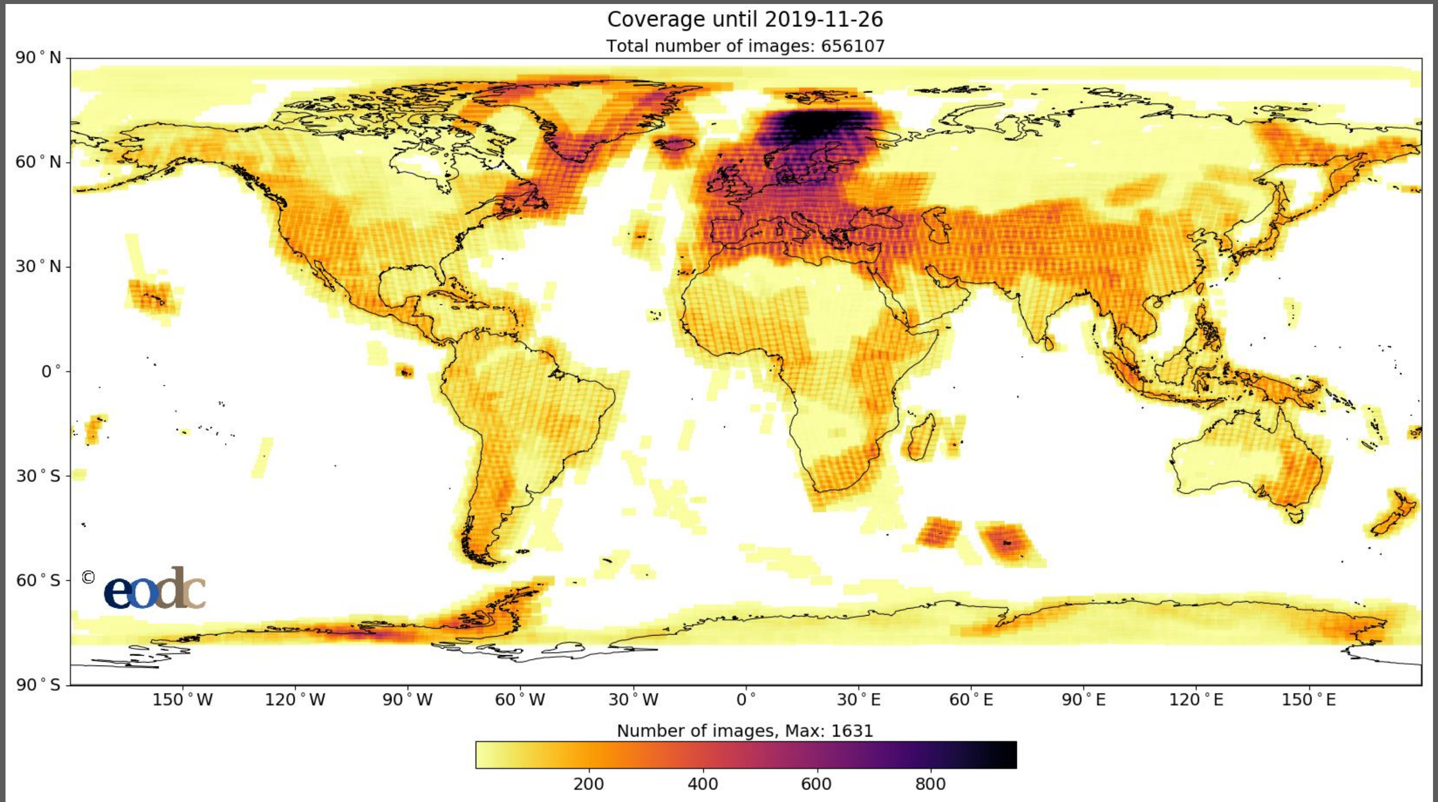
INTRODUCTION

Flooding surrounds Melk, Austria on June 3, 2013. (Roland Schlager/EPA)

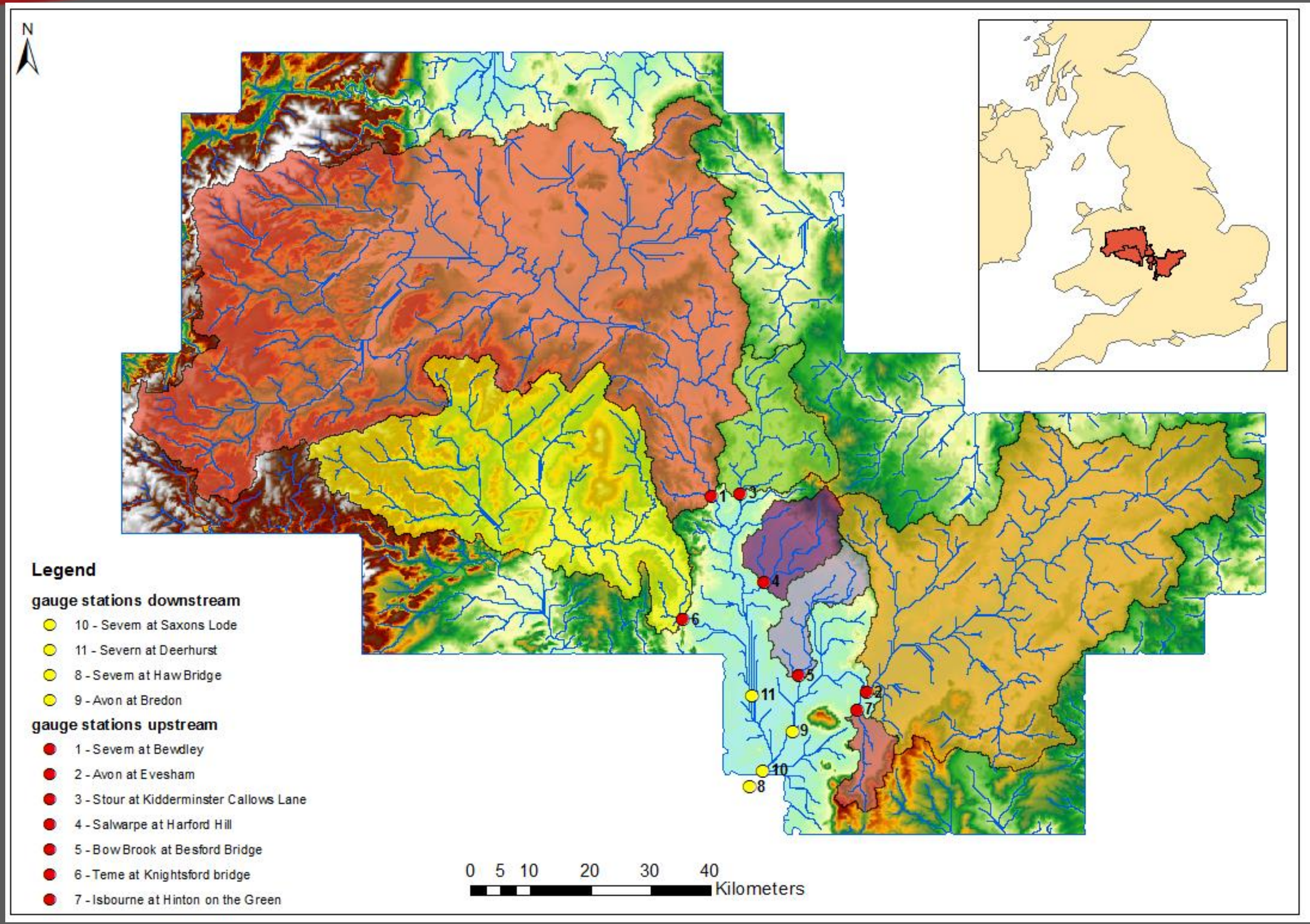
- To analyse/predict floods we use **hydrological and hydraulic** models.
- The **parameters**, the **initial and boundary conditions** and the **inputs** are sources of uncertainty.
- To reduce uncertainty in model predictions we traditionally use ***in situ*** **observations**.
- Limitation for poorly gauged or ungauged catchments.

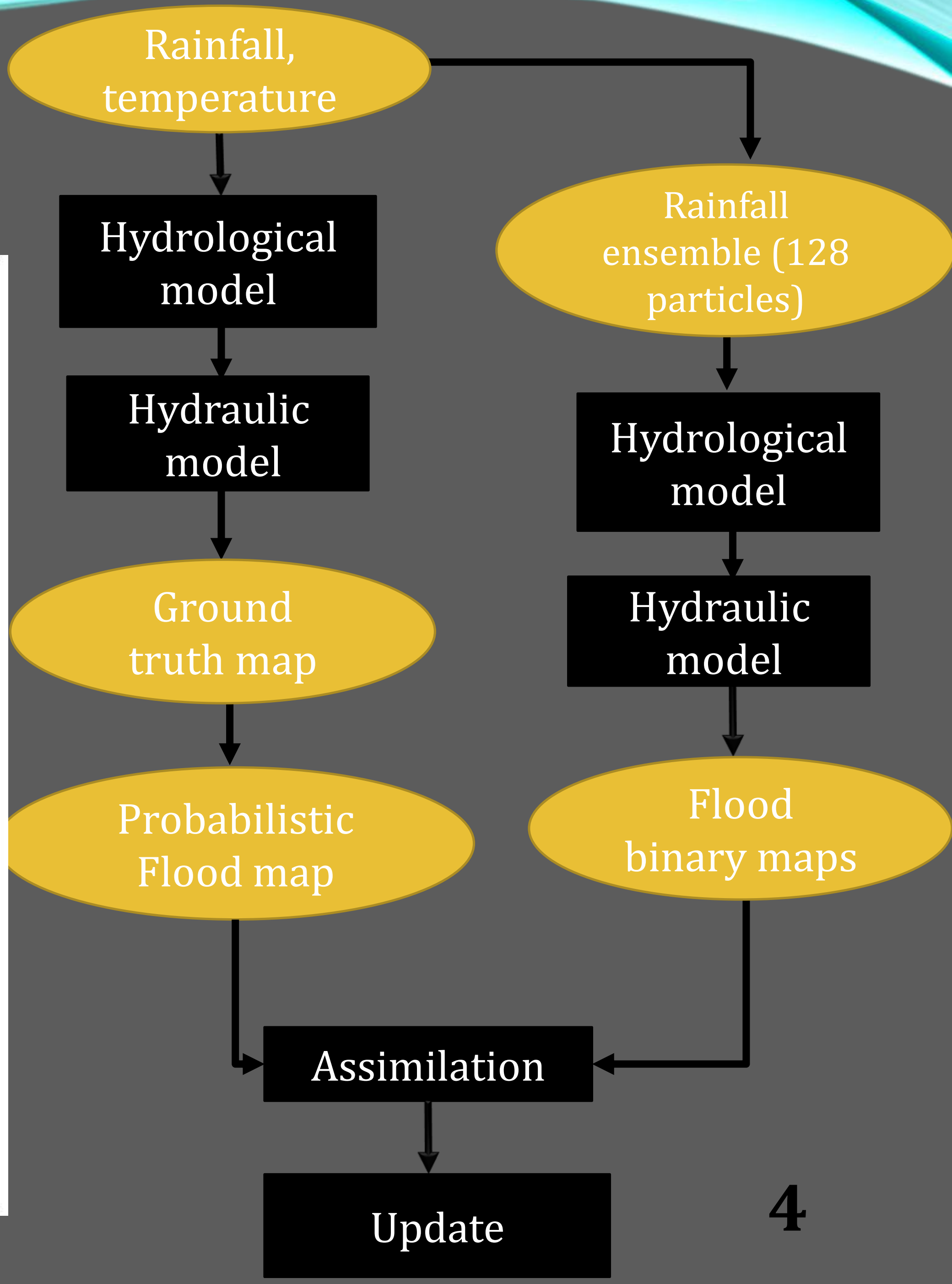
INTRODUCTION

- Synthetic Aperture Radar (SAR) data allows water bodies detection regardless of weather conditions and during day/night.
- Data assimilation of SAR derived information may improve flood predictions.
- SENTINEL-1 acquires high resolution satellite images every 2-3 days (over Europe).
- Objective: develop and validate an efficient and effective method for assimilation of flood extent map.



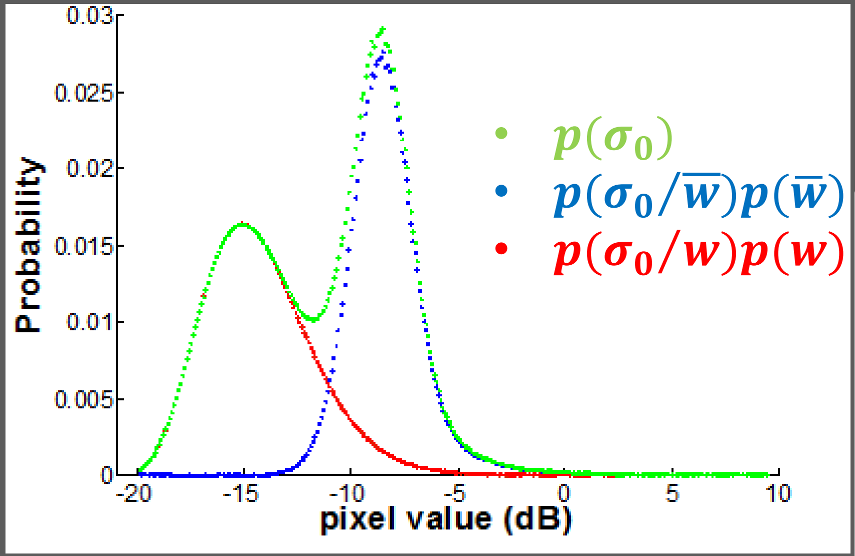
METHOD: SYNTHETIC EXPERIMENT





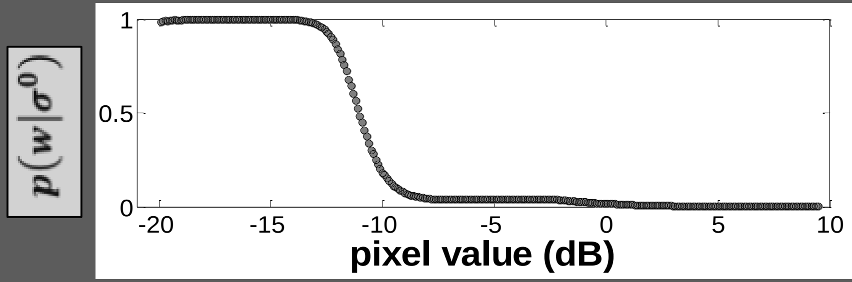
PROBABILISTIC FLOOD MAP (PFM)

- Probability of a pixel to be flooded $P(w/\sigma_0)$ knowing the backscatter σ_0.

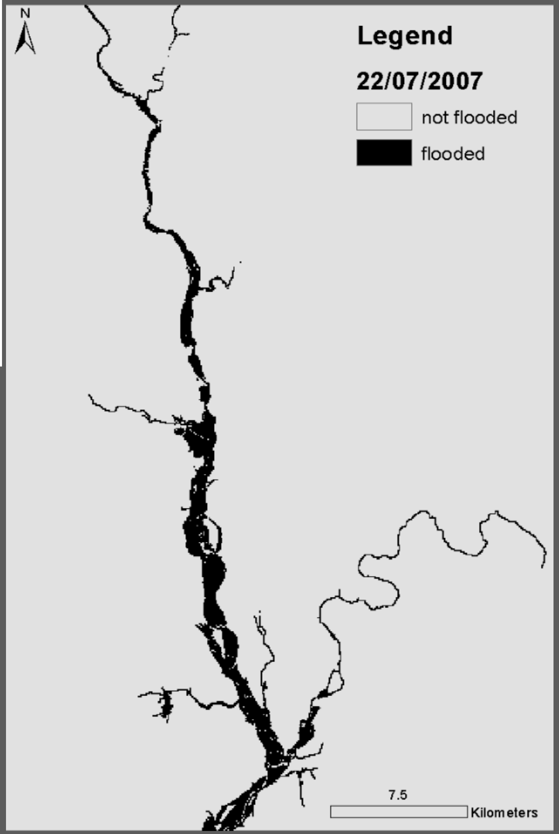


$$p(w|\sigma^0) = \frac{p(\sigma^0|w)p(w)}{p(\sigma^0|w)p(w) + p(\sigma^0|\overline{w})p(\overline{w})}$$

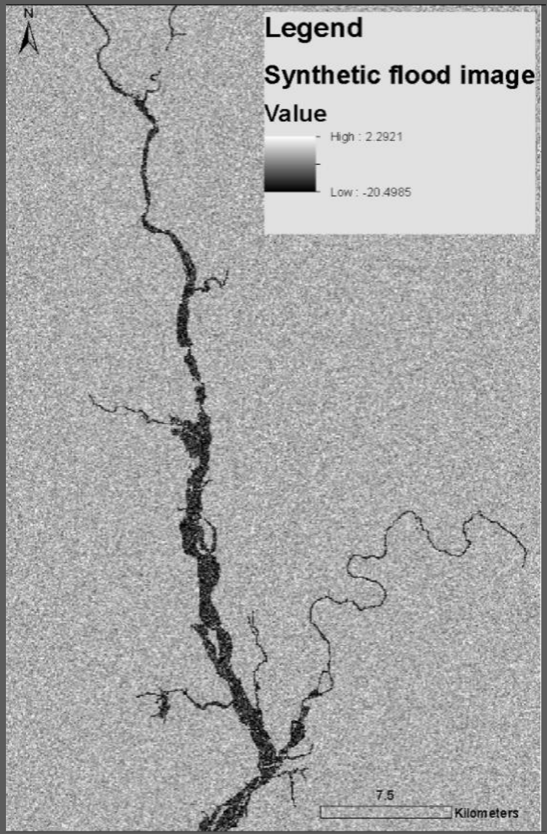
[Giustarini et al., IEEE TGRS, 2016]



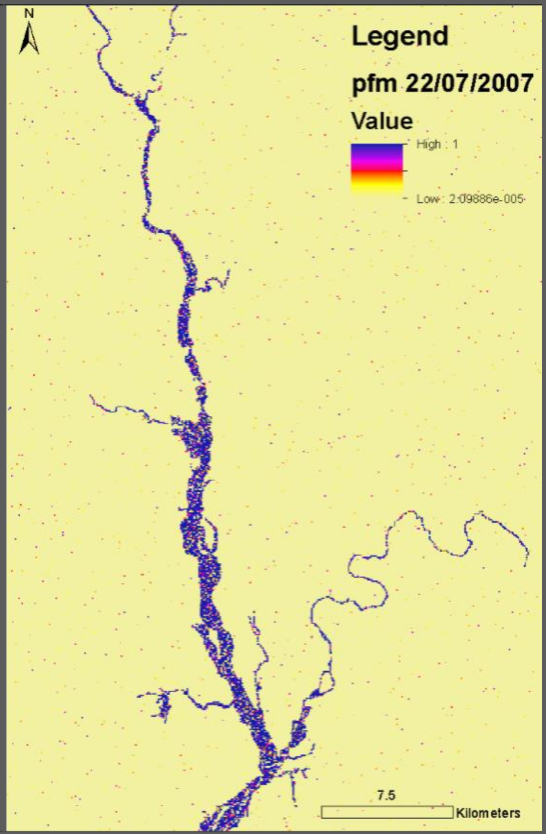
Simulated ground truth flood map



Synthetic SAR image



Synthetic PFM



PARTICLE FILTER

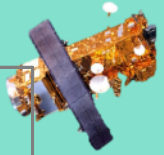
- Prior and posterior probability is approximated by a set of particles.
- Posterior probability is computed using ***weights.***

Local weights (pixel based)

Model results in pixels (prior)

1	0	1
0	1	1
1	0	0

Satellite observations (probability of being flooded)



$P_{1,1}$	$P_{1,2}$	$P_{1,3}$
$P_{2,1}$	$P_{2,2}$	$P_{2,3}$
$P_{3,1}$	$P_{3,2}$	$P_{3,3}$

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

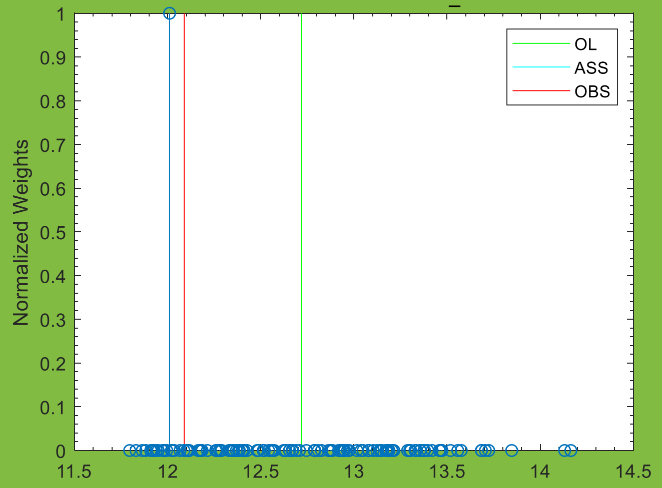
$w_{1,1}^{t,i}=P_{1,1}$ flooded pixel

$w_{3,3}^{t,i}=(1-P_{3,3})$ not flooded pixel

Global weights (particle based)

1. Standard method

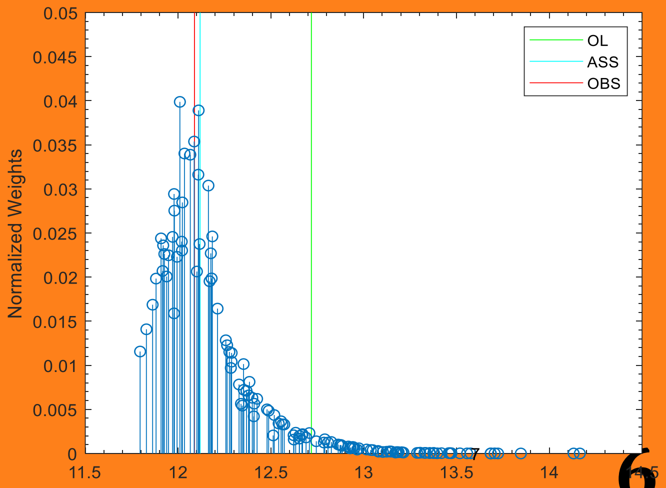
$$W_k^t = \frac{\prod_{i=1}^{n} w_{i,k}^t}{\sum \prod_{i=1}^{n} w_{i,k}^t}$$



2. Adapted method

$$W_k^t = \frac{\prod_{i=1}^{n} {w_{i,k}^t}^{\alpha}}{\sum \prod_{i=1}^{n} {w_{i,k}^t}^{\alpha}}$$

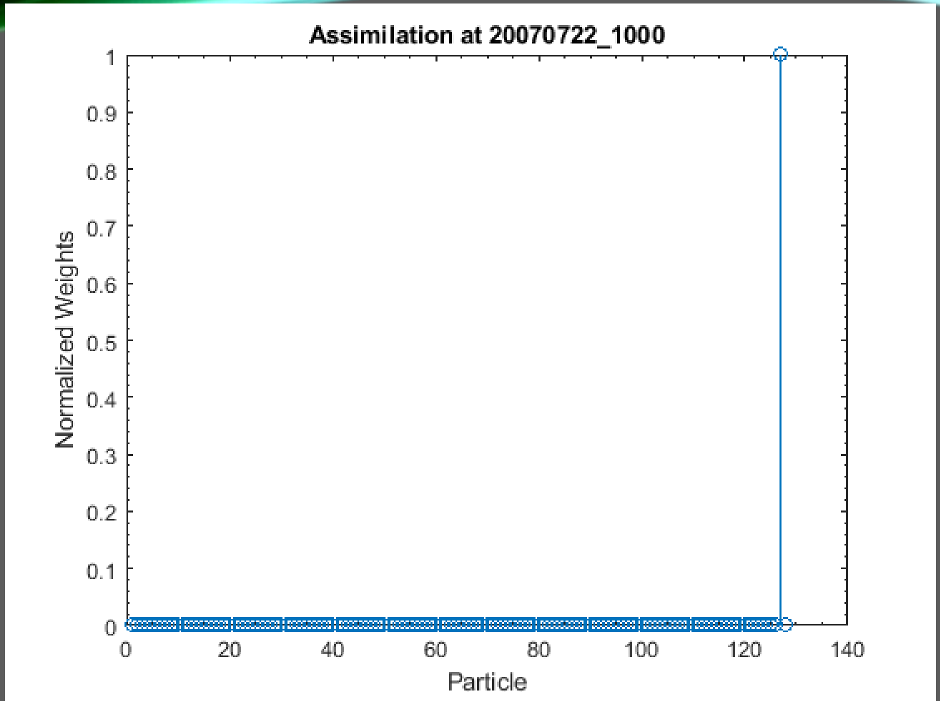
[Hostache et al., 2018]



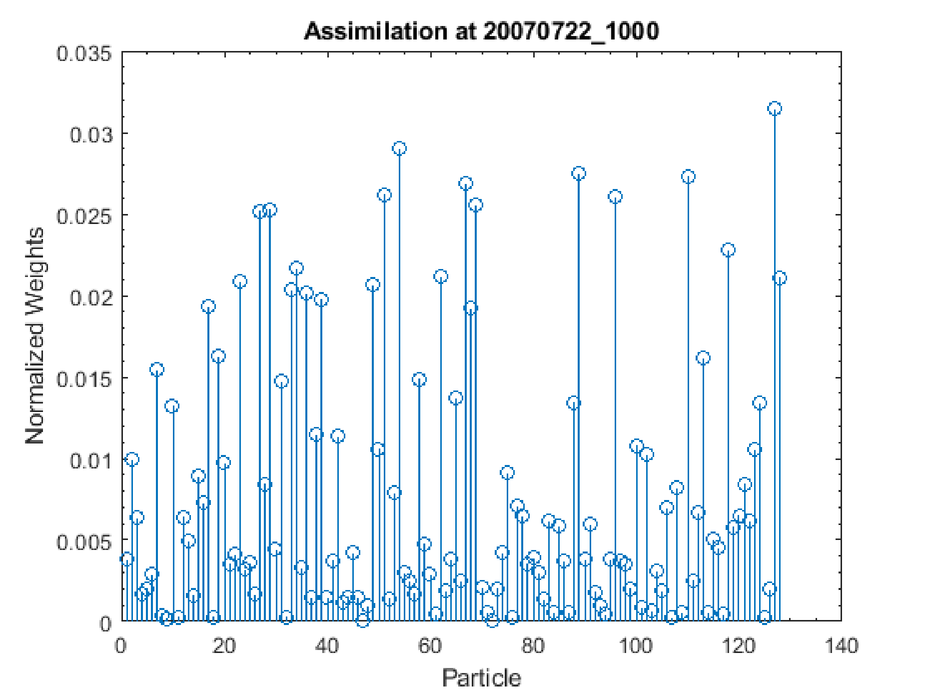
EFFECTIVE ENSEMBLE SIZE (EES)

$$\mathbf{EES} = \frac{1}{\sum (W_k^t)^2}$$

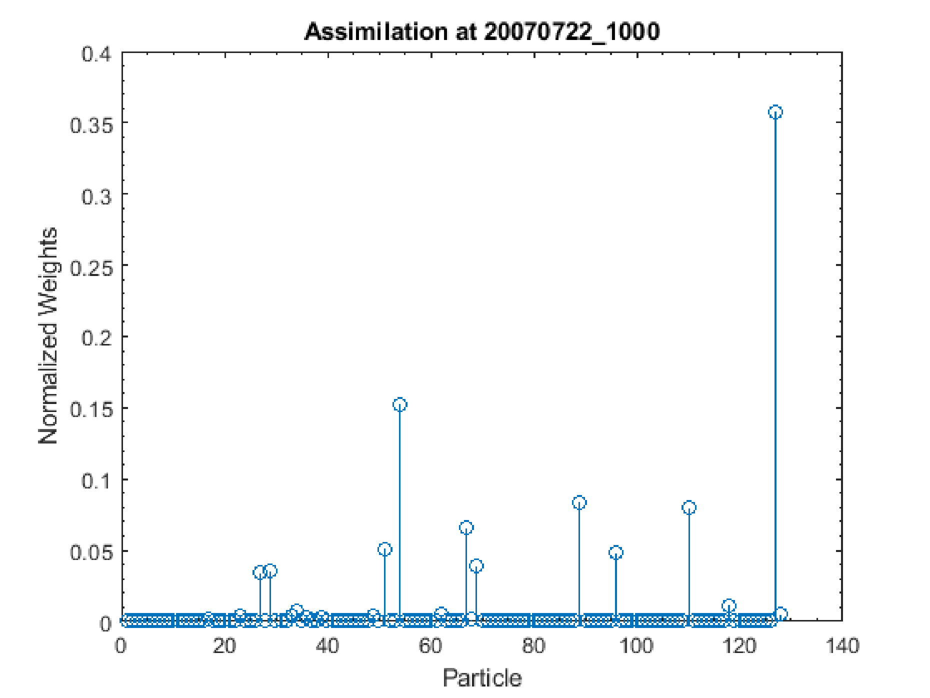
Low EES indicates severe degeneracy



Standard method

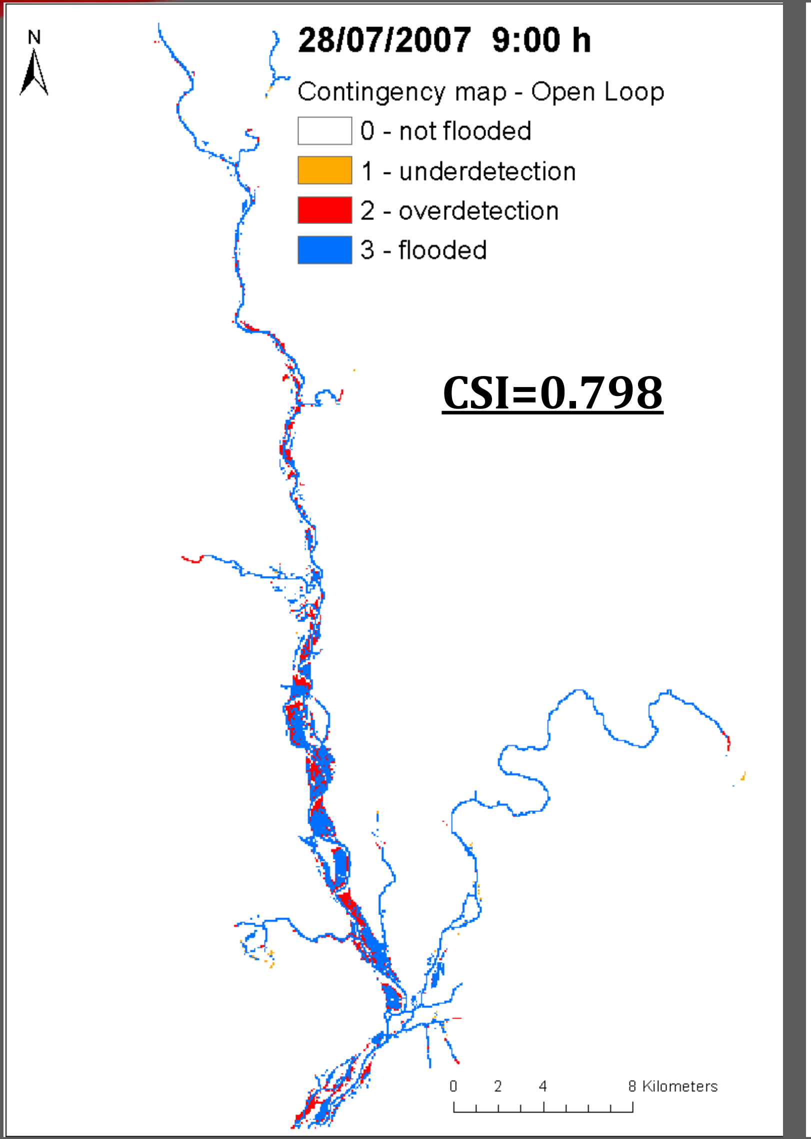


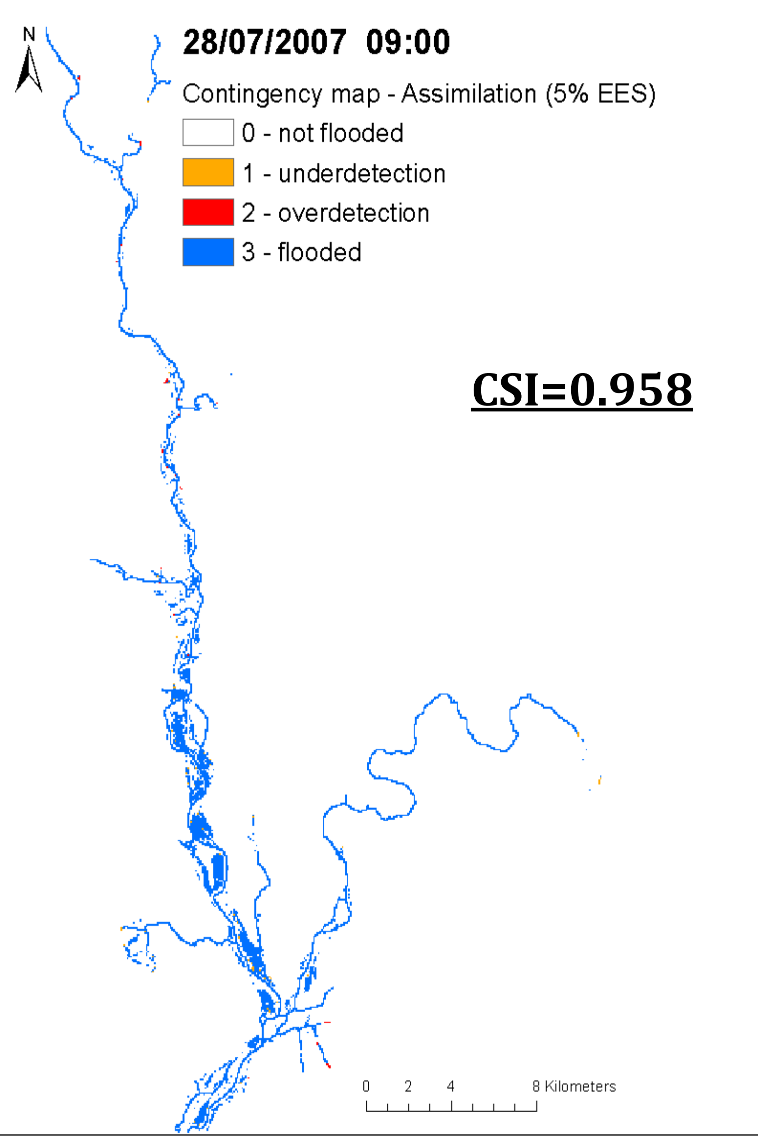
Adapted method EES is 50% of the ensemble

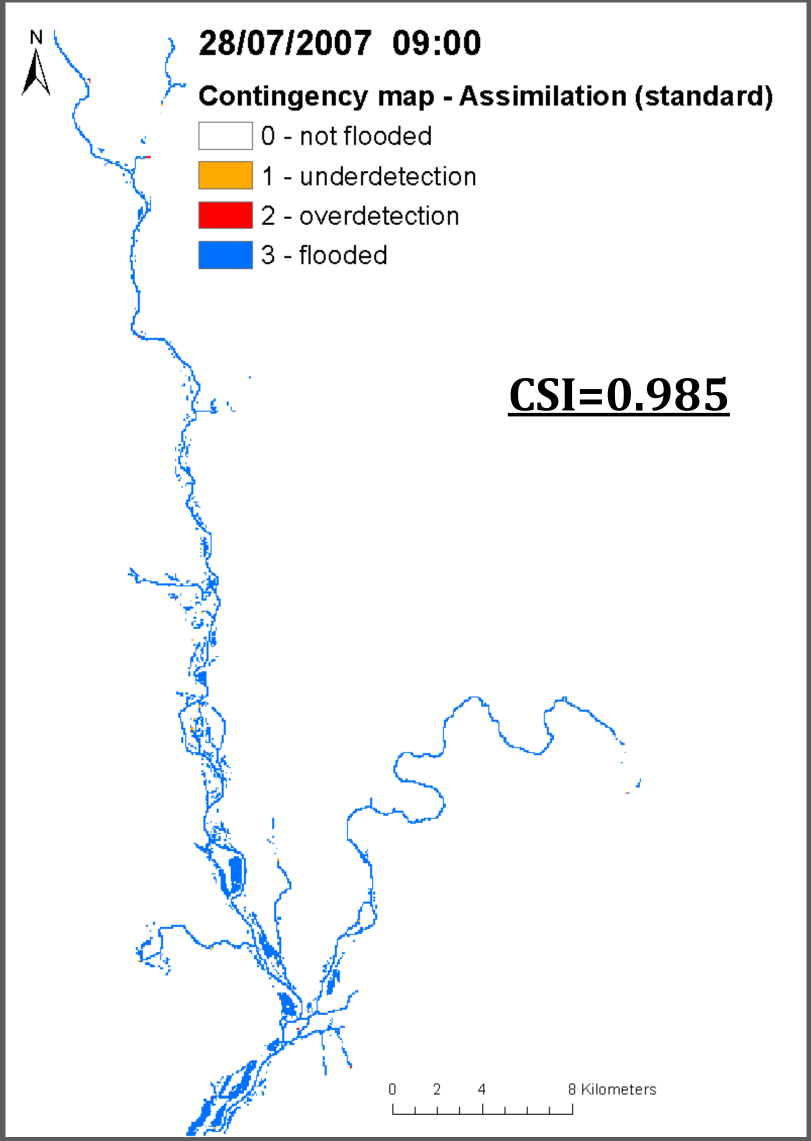


Adapted method EES is 5% of the ensemble

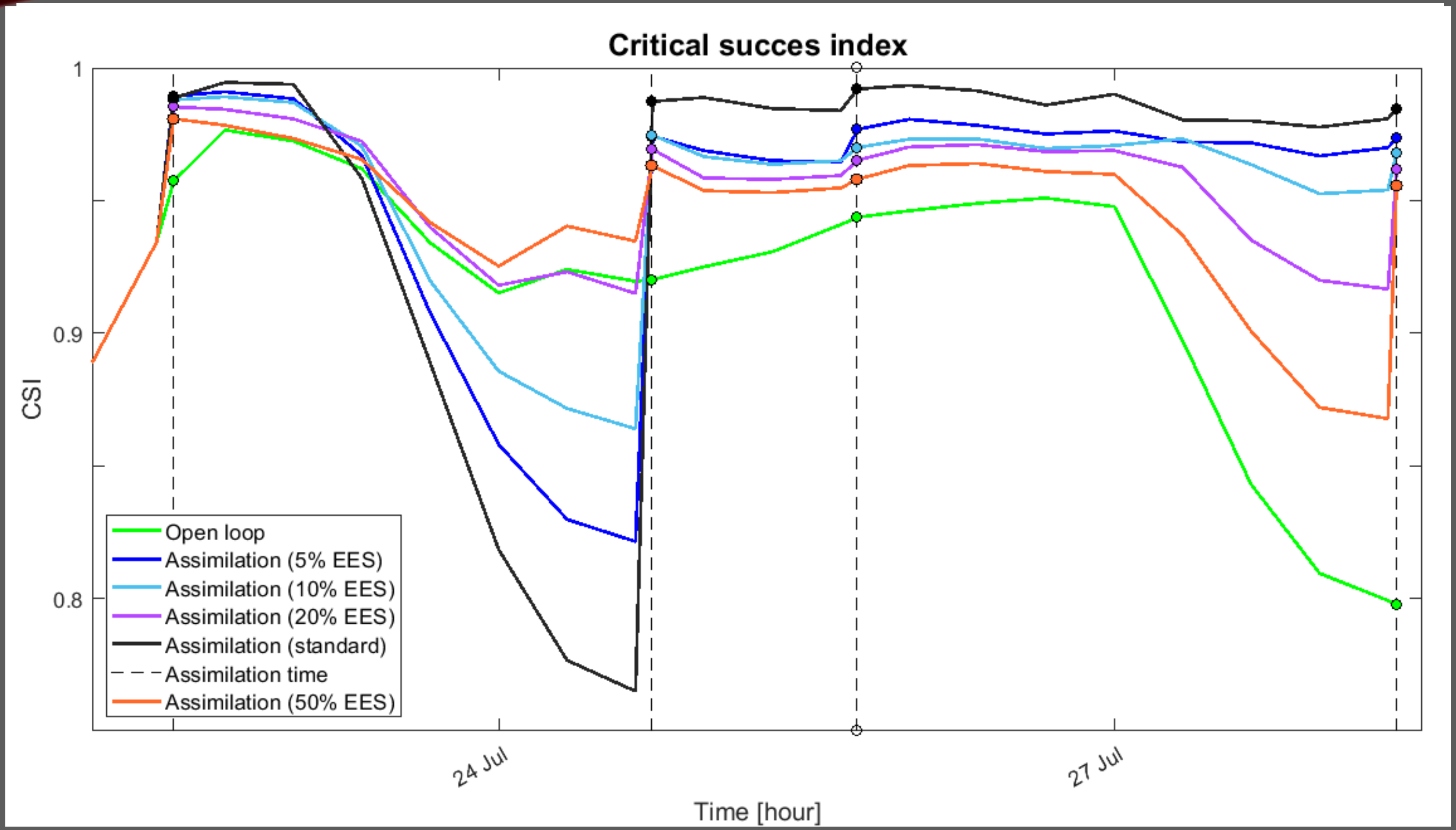
RESULTS: CONTINGENCY FLOOD MAP







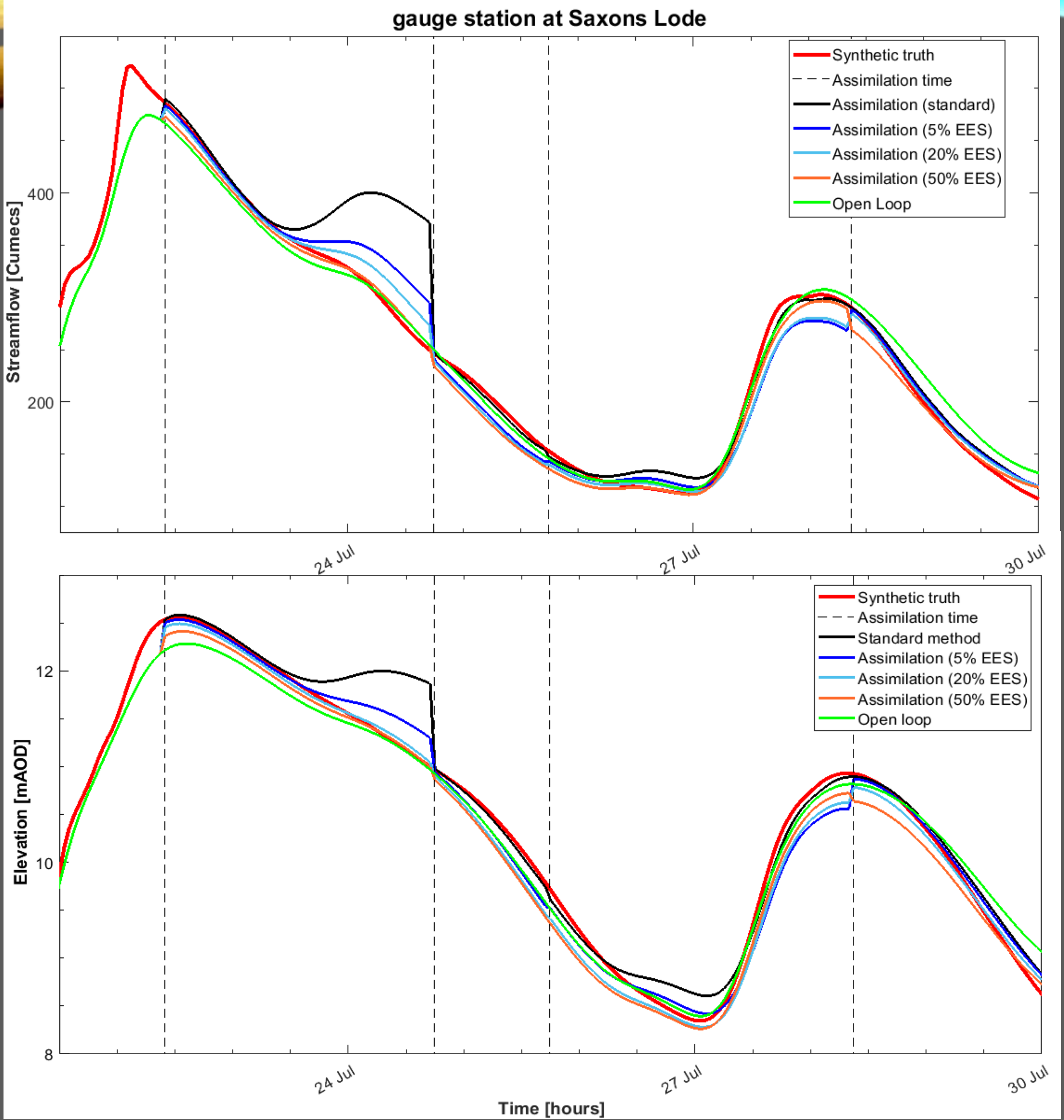
RMSE OF WATER LEVELS & CRITICAL SUCCESS INDEX



- CSI: number of flooded pixels improves with assimilation.
- Improvements are time window limited.
- RMSE: assimilation is beneficial for the prediction of the water levels over the entire domain.

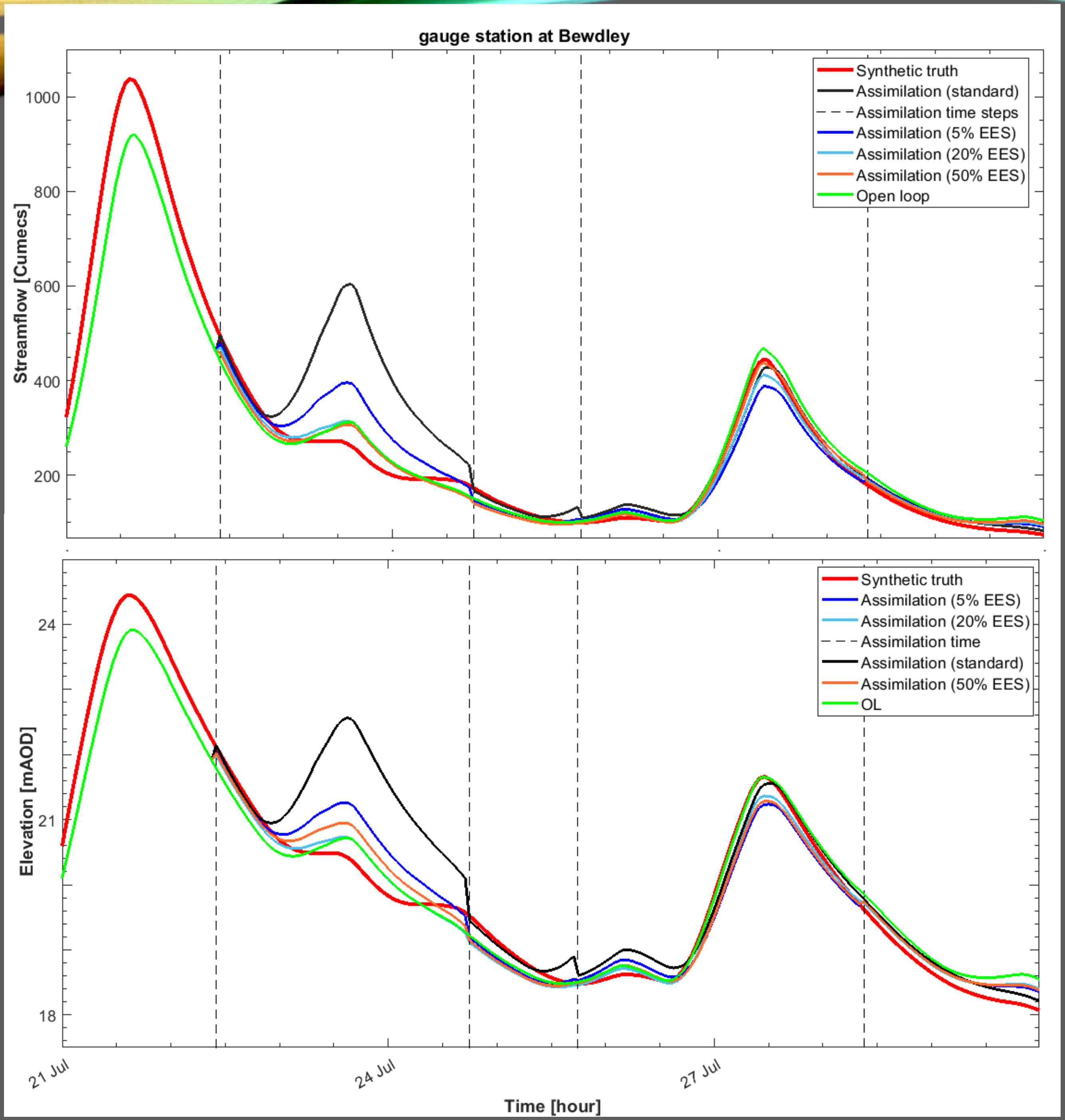
- Data assimilation improves the estimation of streamflow and water elevation at the gauge station **downstream** at the assimilation times.

- Improvements are time window limited.

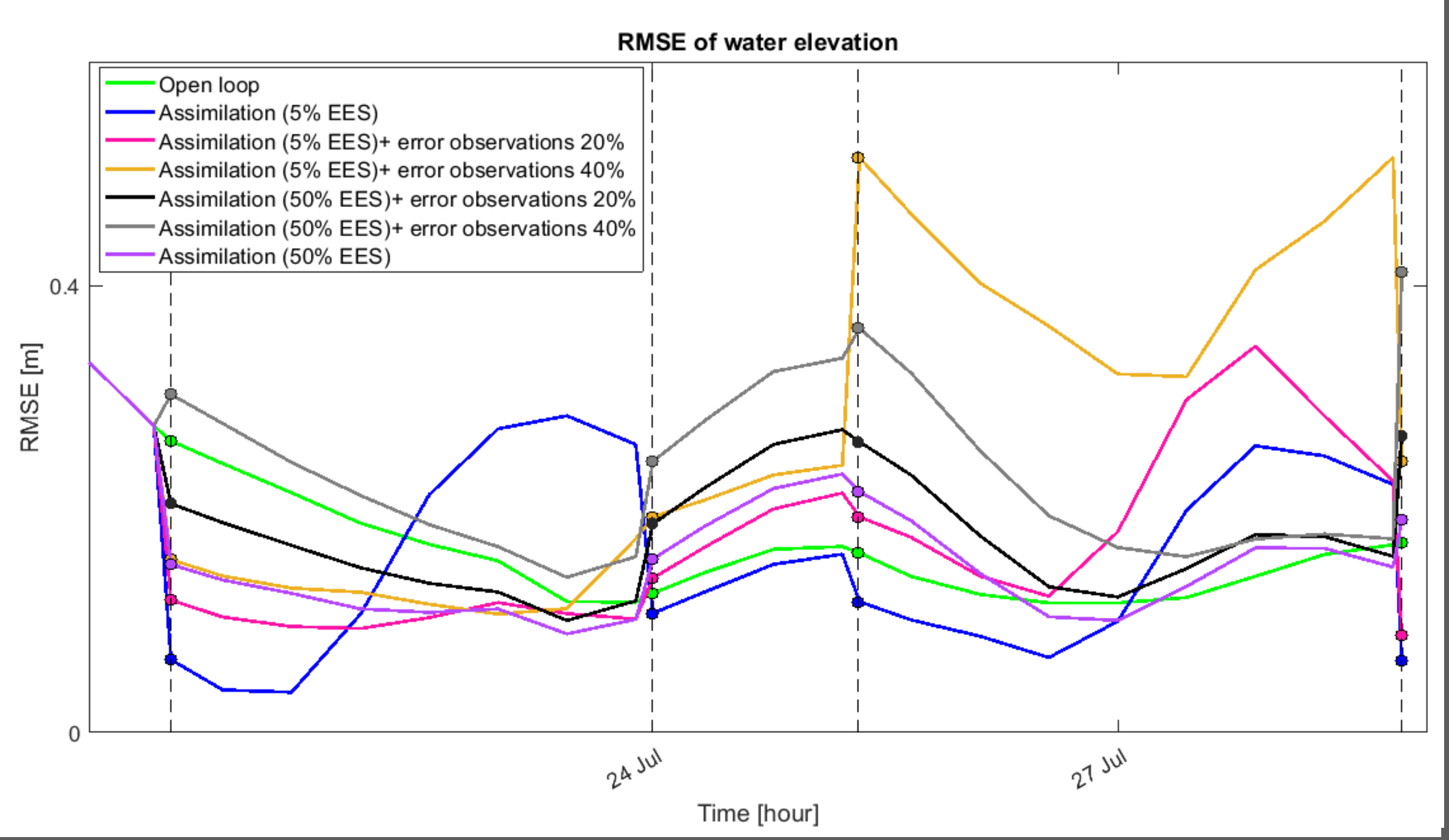


- Data assimilation improves the estimation of streamflow and water elevation at the gauge station **upstream** at the assimilation times.

- Improvements are time window limited.



RMSE OF WATER LEVELS & CRITICAL SUCCESS INDEX



- Errors in the observations are due to limitations of radar flood mapping in vegetation and urban areas, or in particular meteorological condition.

CONCLUSIONS

In this proof of concept with the rainfall and SAR-derived flood extent as the only source of uncertainty:

- Data assimilation of PFM into a flood forecasting model leads to improvements of discharge, water elevation and flood extent simulations.

LIMITATIONS:

- Accuracy in the estimation of water level depends on the location.
- Standard method and DA where the EES is low are more efficient at the assimilation time steps but results are limited in time.

WHAT'S NEXT?

- Introduction of other sources of uncertainties in the model.
- Improvement of the DA framework with the other variance of PF as the "tempered PF".
- Application to different real case studies.

THANK YOU!

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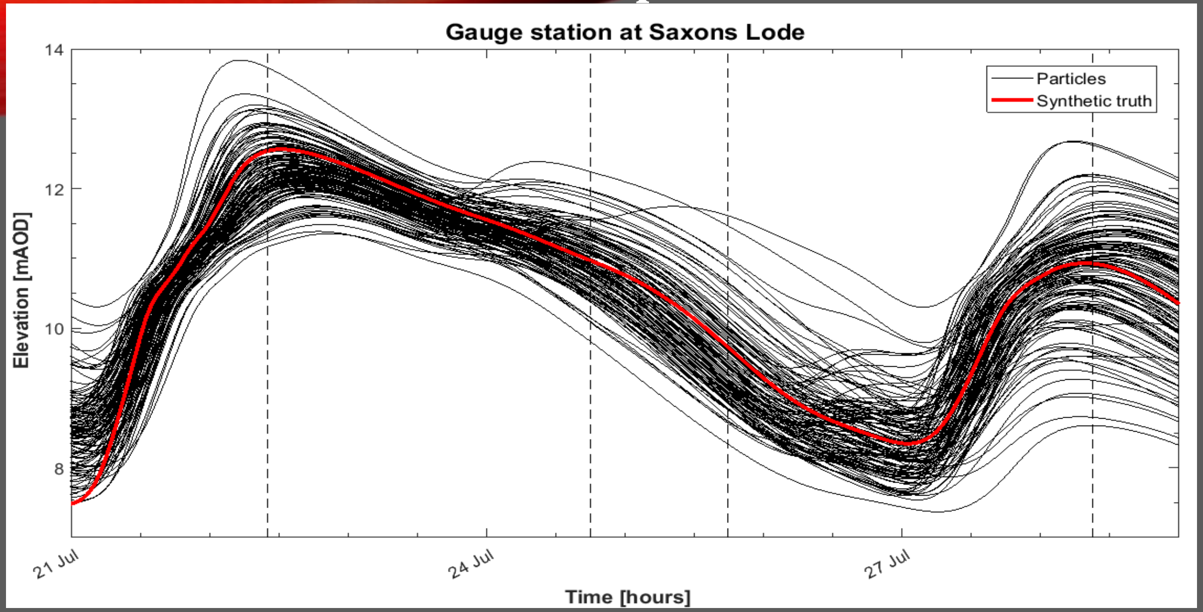
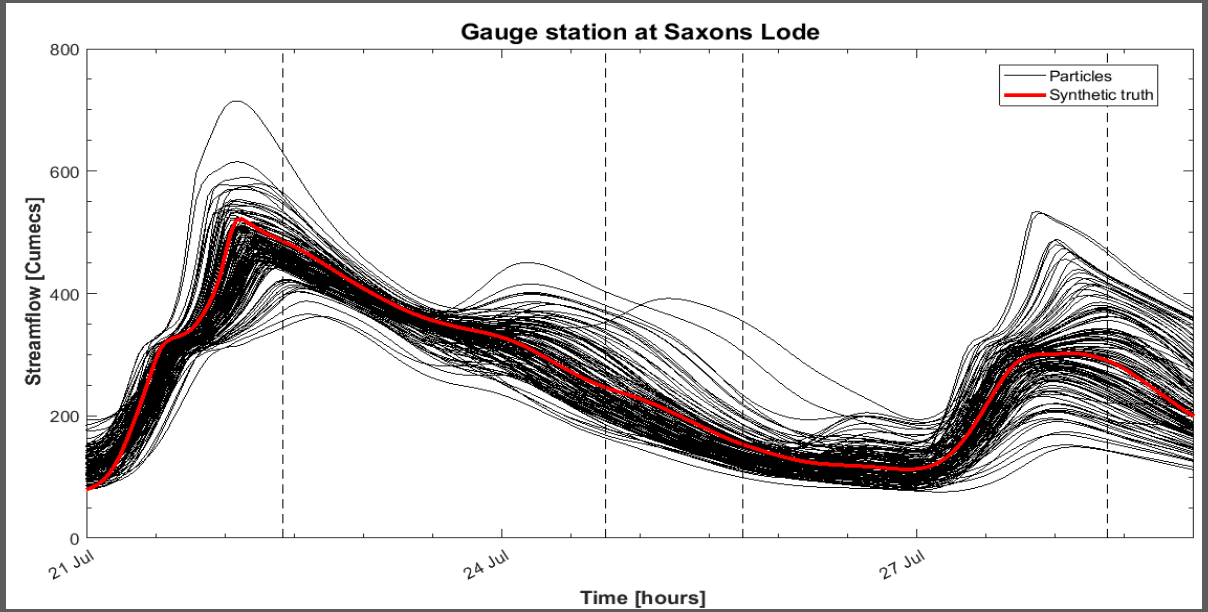
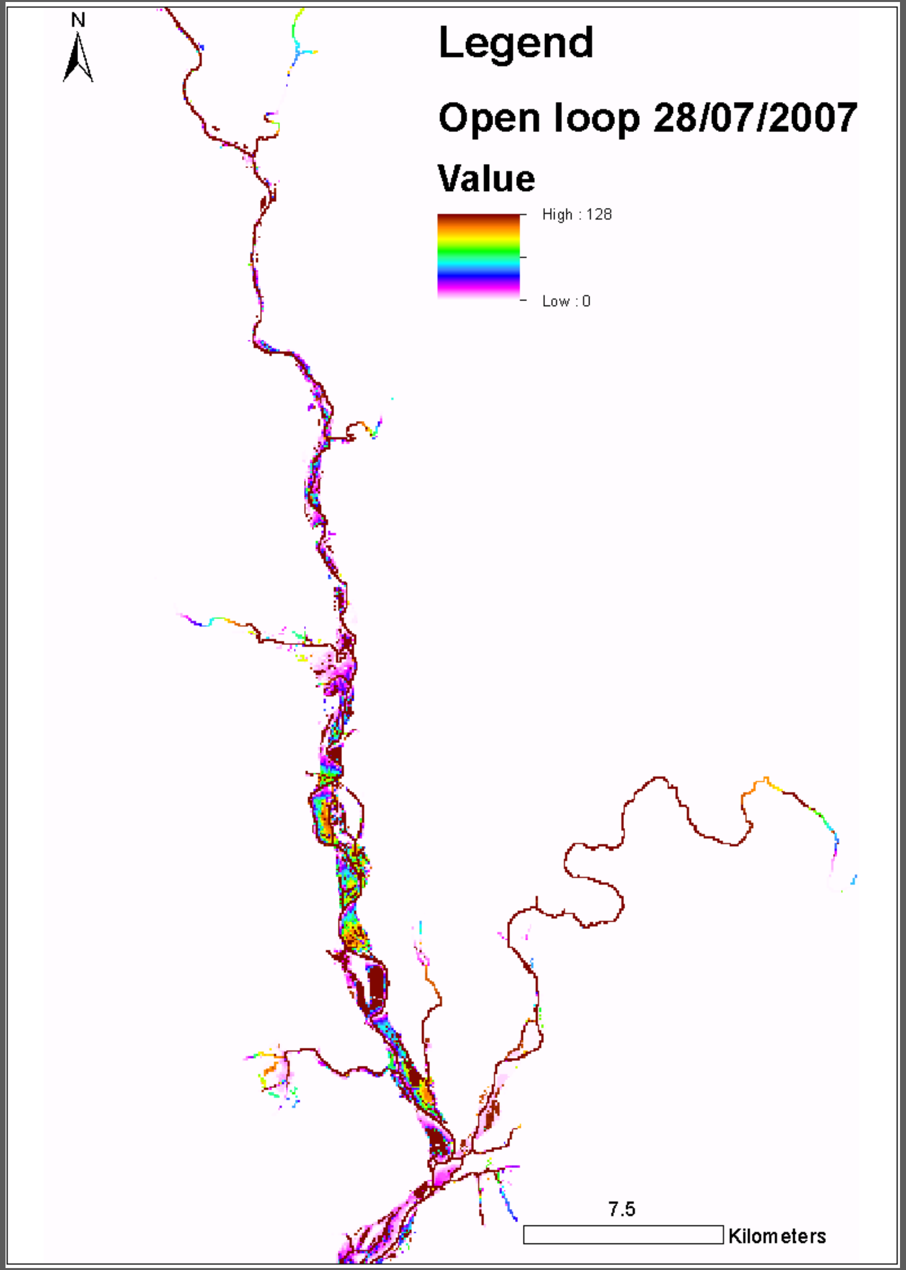
ENSEMBLE

- Generation of 128 particles





Open loop of the ensemble flood maps



DATA ASSIMILATION OF FLOOD EXTENTS

Authors	Technique
Revilla-Romero et al. (2016)	Ensemble Kalman Filter (EnKF)
Lai et al.(2014)	Variational data assimilation (4D Var)
Hostache et al. (2018)	Particle Filter

Assumption: rainfall is the only source of uncertainty.

- Proof of concept with a synthetic experiment

VERIFICATION MEASUREMENTS ENSEMBLE (1)

- To verify the quality of the ensemble discharge the following verification measurements have been used.

$$\bar{x}_i = \frac{1}{N}\sum_{k=1}^{N} \widehat{x_{i,k}}$$ **Ensemble mean**

$$ensp_i = \frac{1}{N}\sum_{k=1}^{N} (\widehat{x_{i,k}} - \widehat{\bar{x}_i})^2$$ **Ensemble spread**

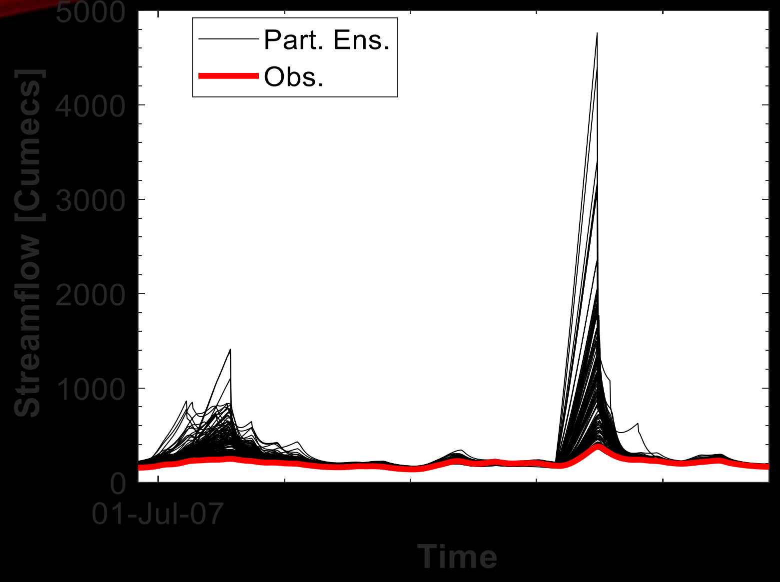
$$mse_i = \frac{1}{N}\sum_{k=1}^{N} (\widehat{x_{i,k}} - y_i)^2$$ **Mean squared error**

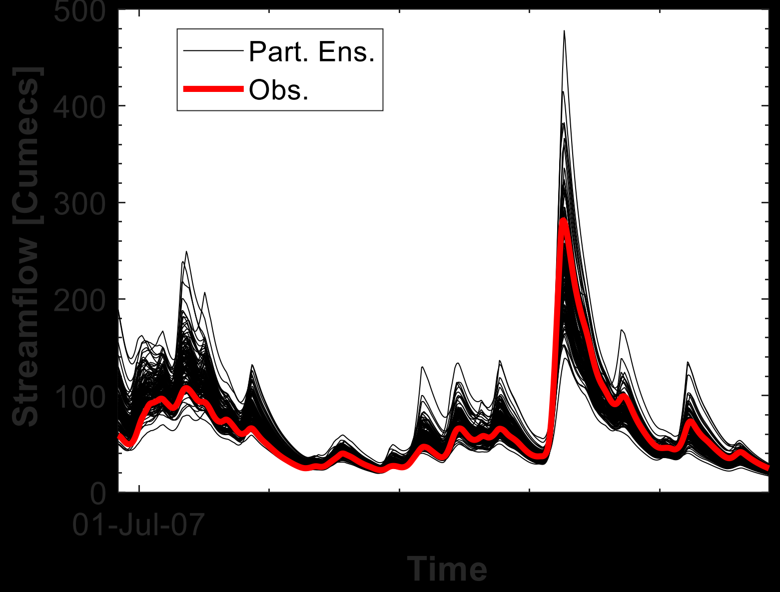
$$ensk_i = (\widehat{\bar{x}_i} - y_i)^2$$ **Ensemble skill**

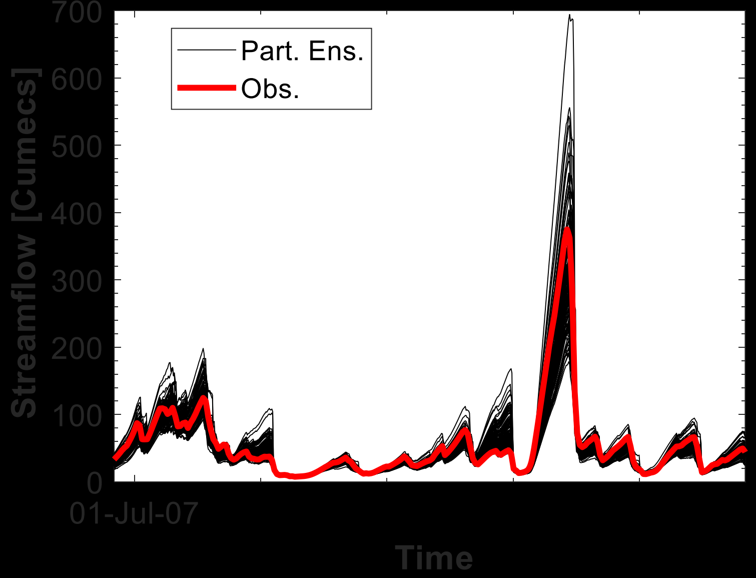
$$\mathrm{VM}_1 = \frac{\langle ensk \rangle}{\langle ensp \rangle} \cong 1$$

$$\mathrm{VM}_2 = \frac{\langle \sqrt{ensk} \rangle}{\langle \sqrt{mse} \rangle} * \sqrt{\frac{(N+1)}{2N}}^{\,-1} \cong 1$$

VERIFICATION MEASUREMENTS ENSEMBLE (2)



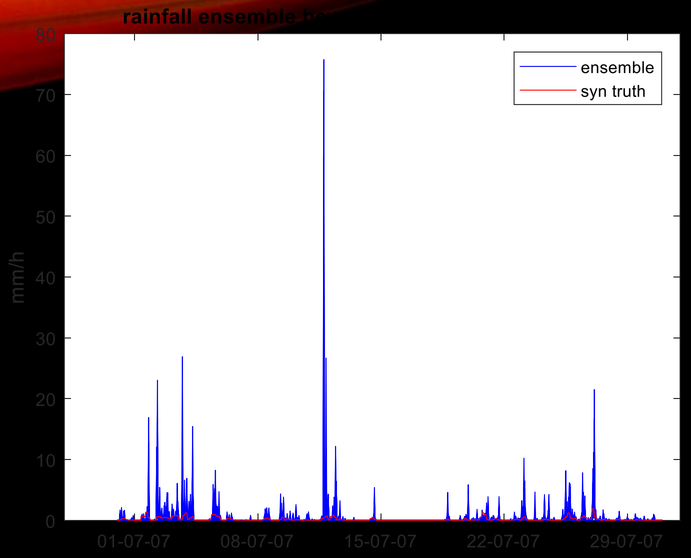




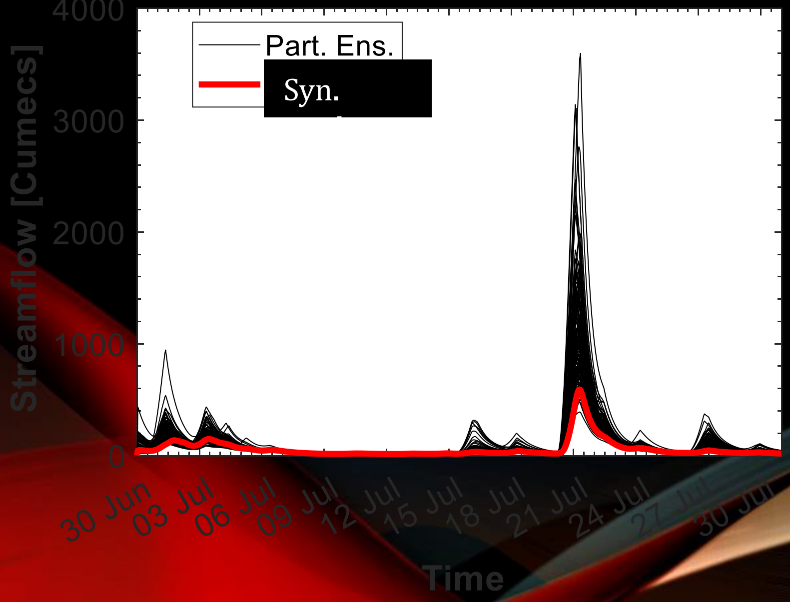
GAUGE STATIONS	$VM1_Q$	$VM2_Q$
Bewdley	0.7845	0.9513
Besford	0.7437	0.8217
Evesham	0.7405	0.8287
Harford	1.0666	0.8933
Hinton	0.7109	0.7963
Kidder	1.1510	0.8266
Knightsford	0.7895	0.8801

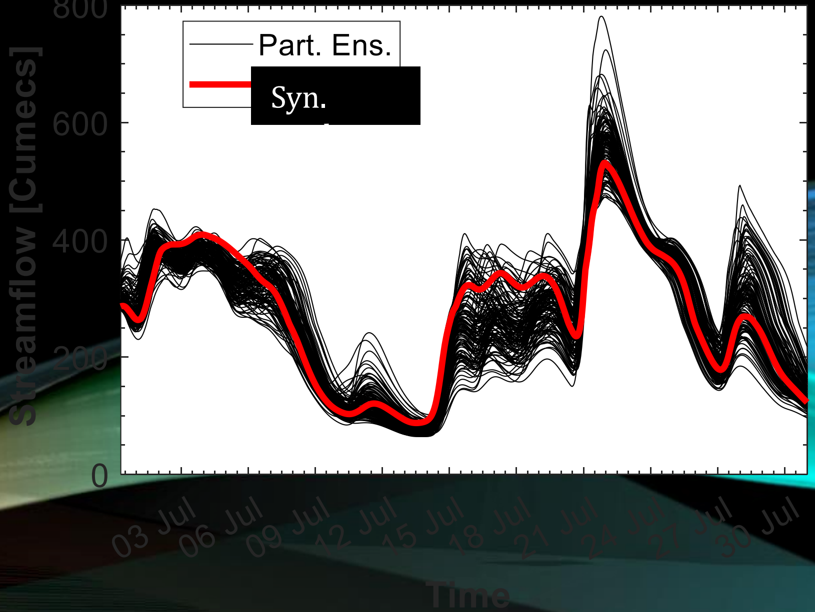
Only discharge time-series having verification metrics≥0.7 have been taken into account.

The rainfall & inflow ensemble

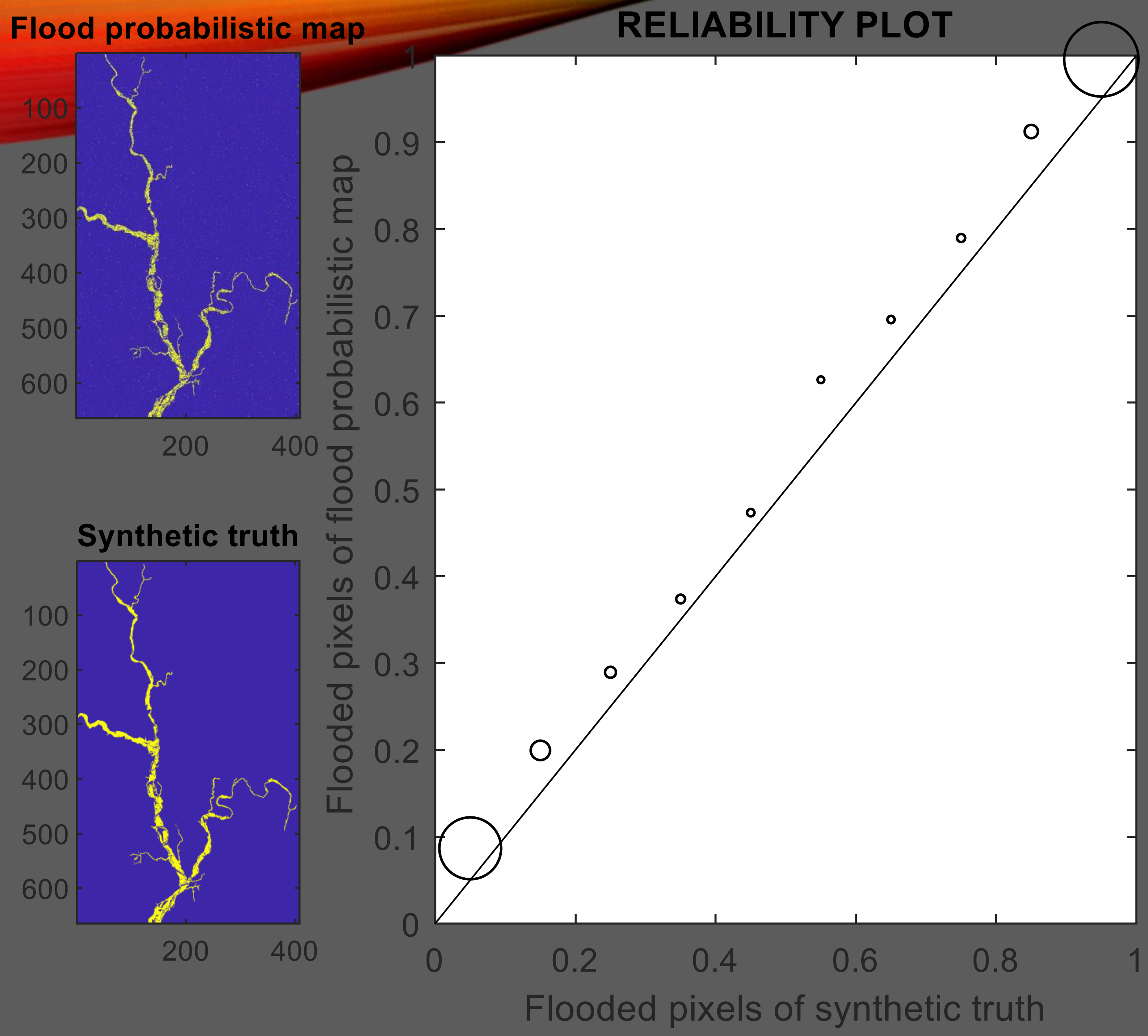


- Rainfall has been perturbed using a log-normal noise distribution
- Different values of standard deviations have been used.
- Statistical verification measurements [De Lannoy et al. 2006] have been used.





RELIABILITY ASSESSMENT OF SYNTHETIC PROBABILISTIC FLOOD MAPS



- Evaluation of the SAR-derived probabilistic map against the synthetic binary ground truth map.
- Flood probability maps generated in accordance with the frequency of acquisition of SENTINEL1.
- 10 probabilistic flood maps assimilated.