

ASSIMILATING SATELLITE SOIL MOISTURE AND FLOOD EXTENT MAPS INTO A FLOOD PREDICTION MODEL.

—
Renaud Hostache, Patrick Matgen, Peter-Jan van Leeuwen,
Nancy Nichols, Marco Chini, Ramona Pelich, Carole Delenne



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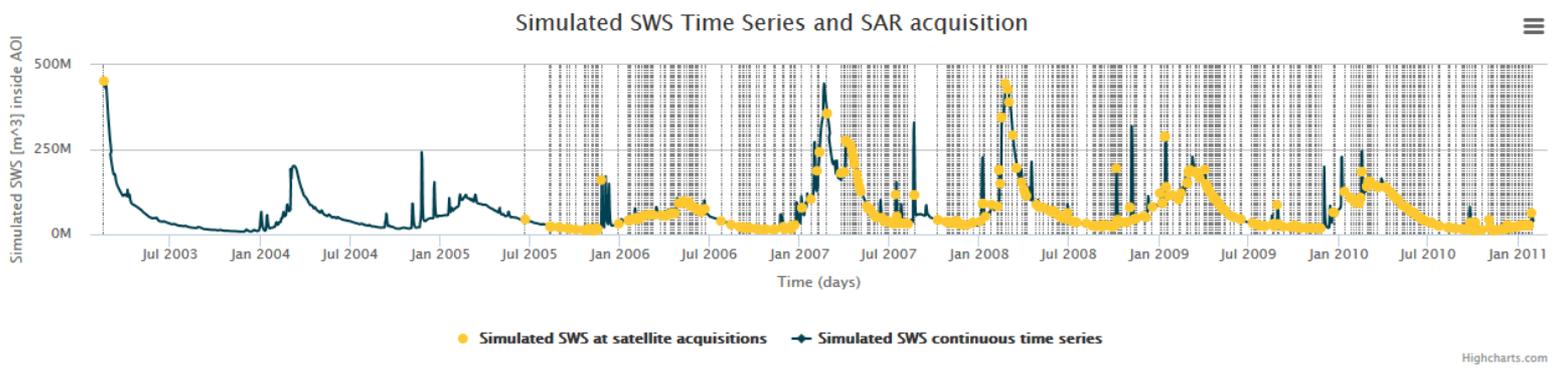
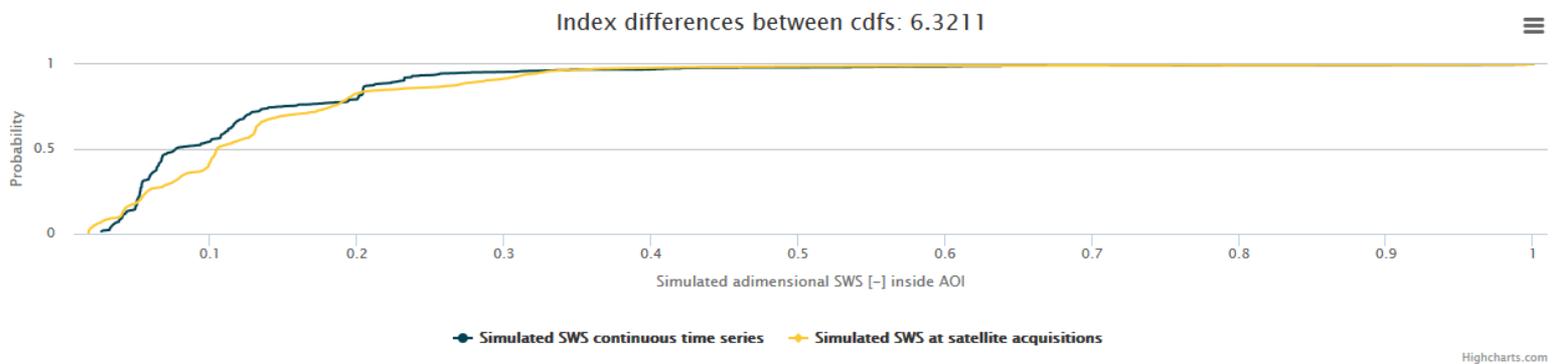
MORE AND MORE READILY AVAILABLE (RADAR) OBSERVATIONS



European Space Agency

Day-Night-All weather acquisitions

Synoptic view of large areas



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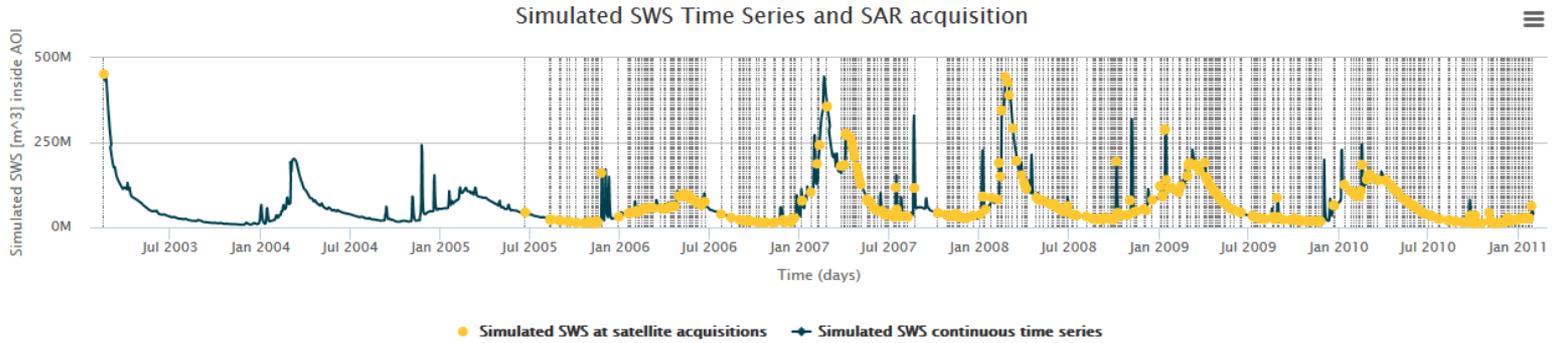
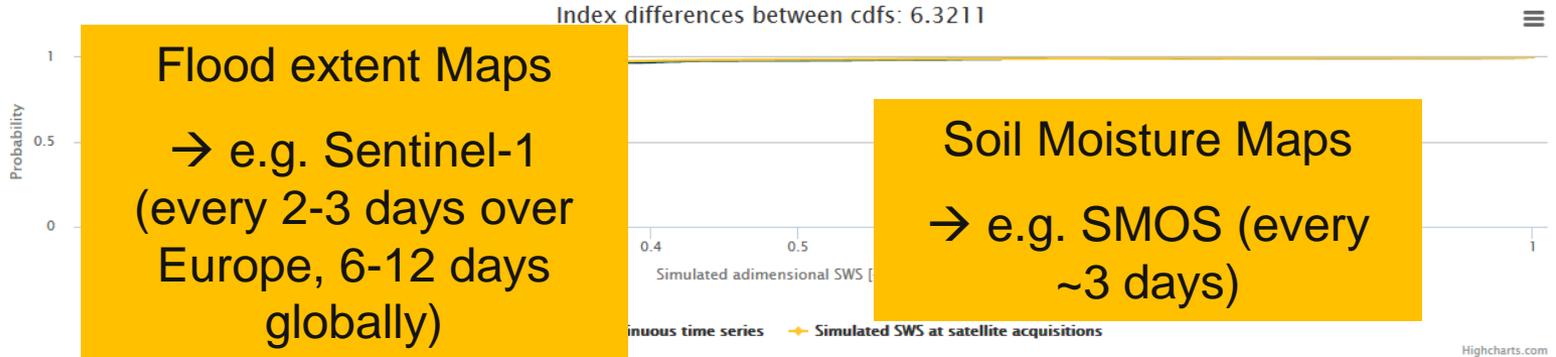
European Space Agency

Day–Night–All weather acquisitions

Synoptic view of large areas

Flood extent Maps
 → e.g. Sentinel-1
 (every 2-3 days over Europe, 6-12 days globally)

Soil Moisture Maps
 → e.g. SMOS (every ~3 days)



Research question: Are these EO datasets sufficient for calibrating a distributed conceptual hydrological model ?

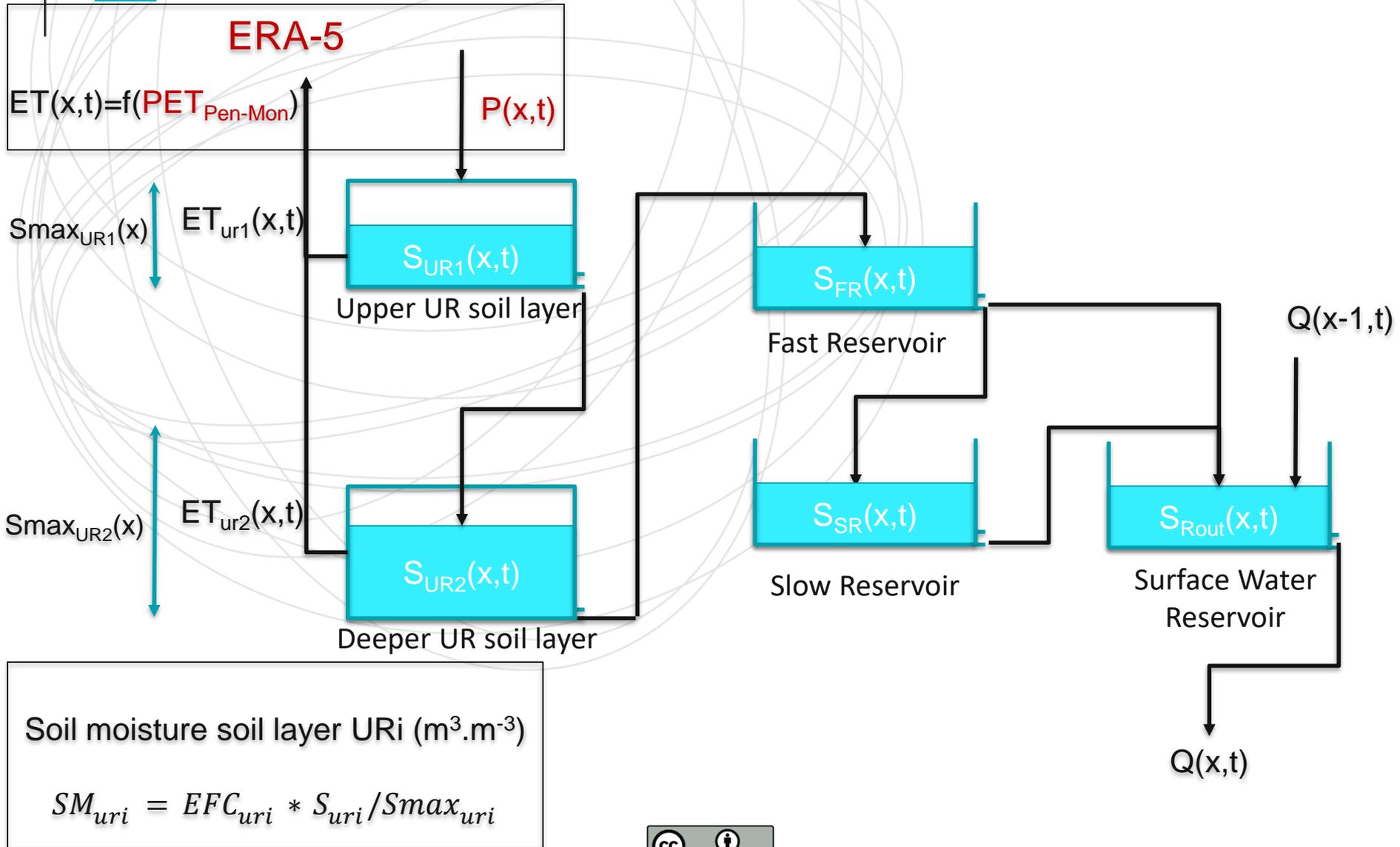
THE CONCEPTUAL HYDROLOGICAL MODEL



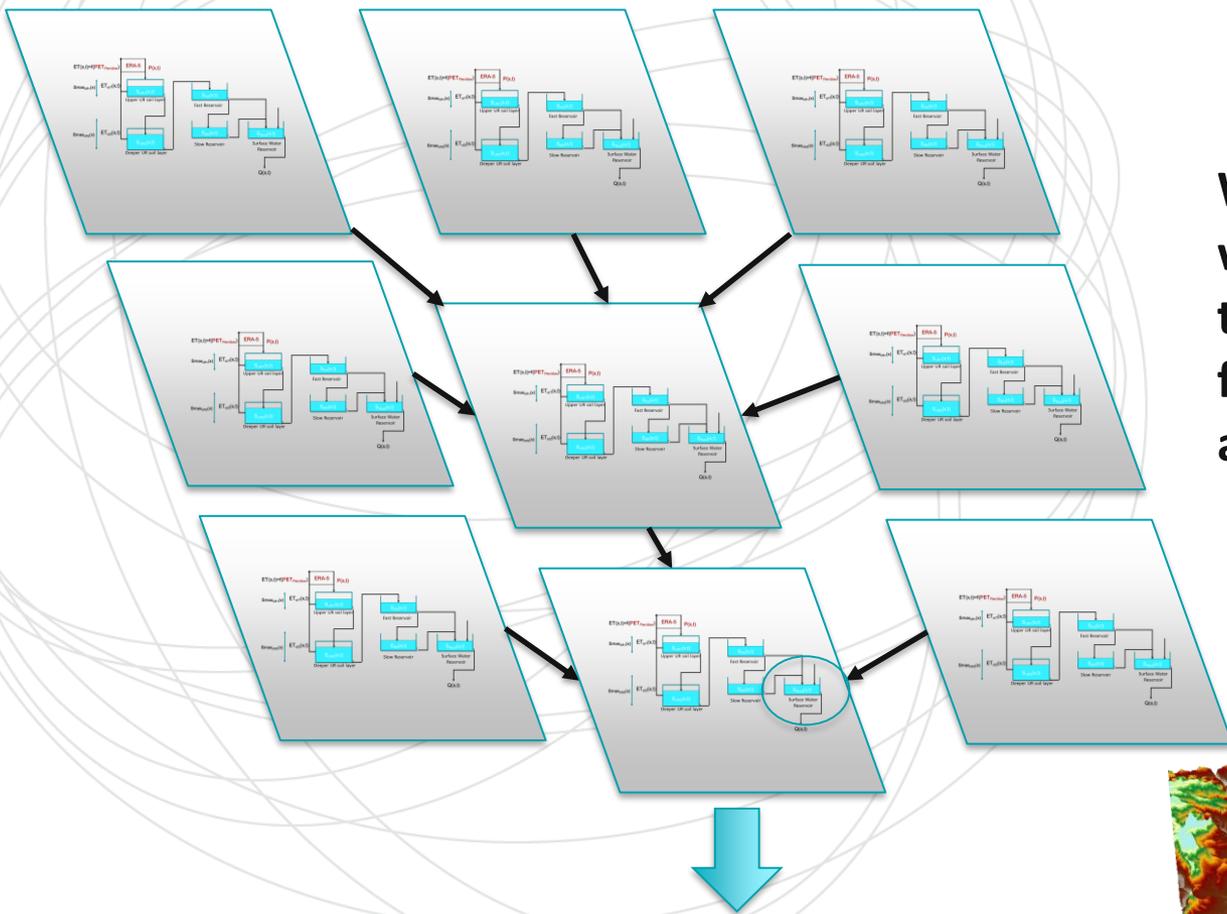
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THE MODEL STRUCTURE

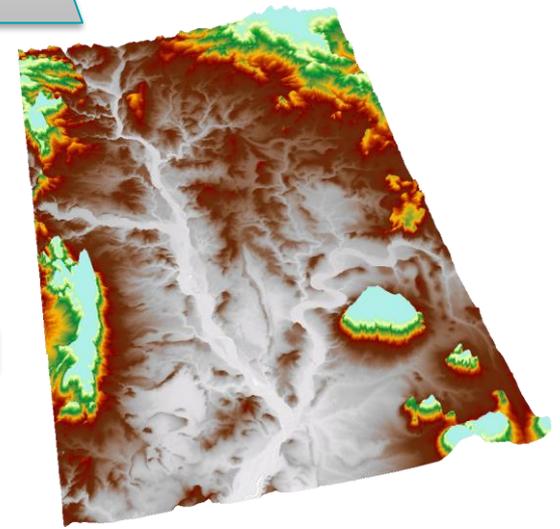


THE MODEL STRUCTURE

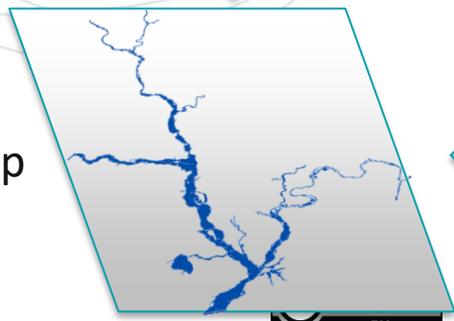


We distribute Surface water volume over topography to obtain flood extent maps and flooded area

Topography information



Simulated flood extent map



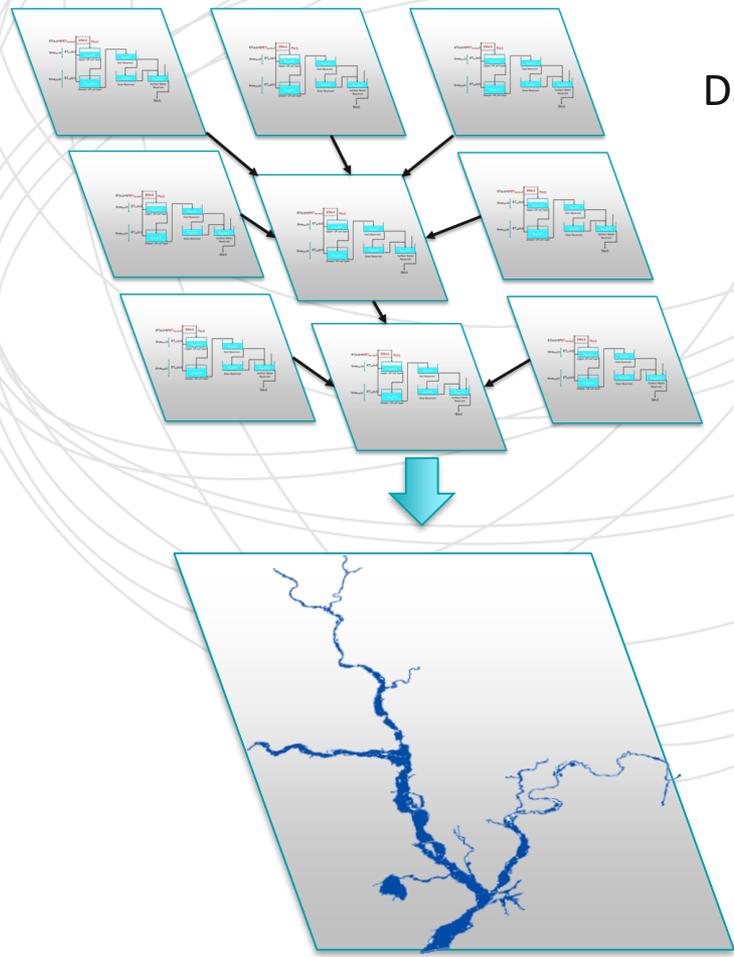
ASSIMILATION DESIGN



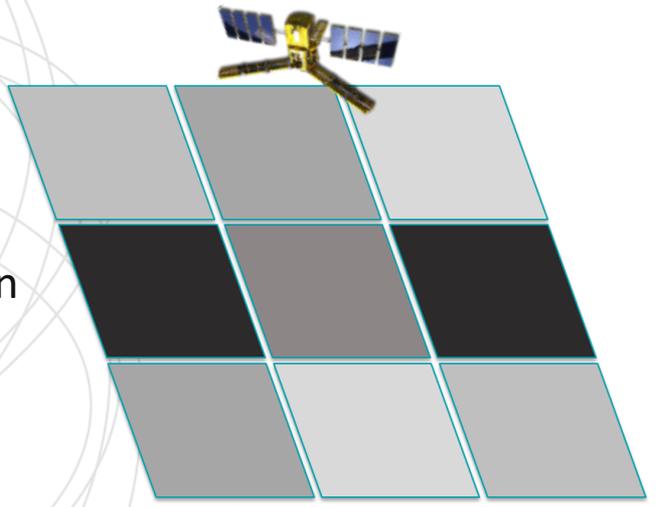
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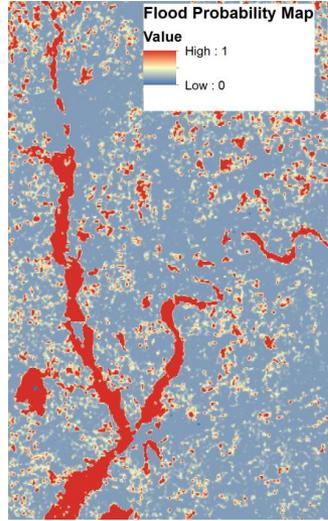
ASSIMILATION DESIGN: THE OBSERVATION



Data Assimilation



Satellite soil moisture maps

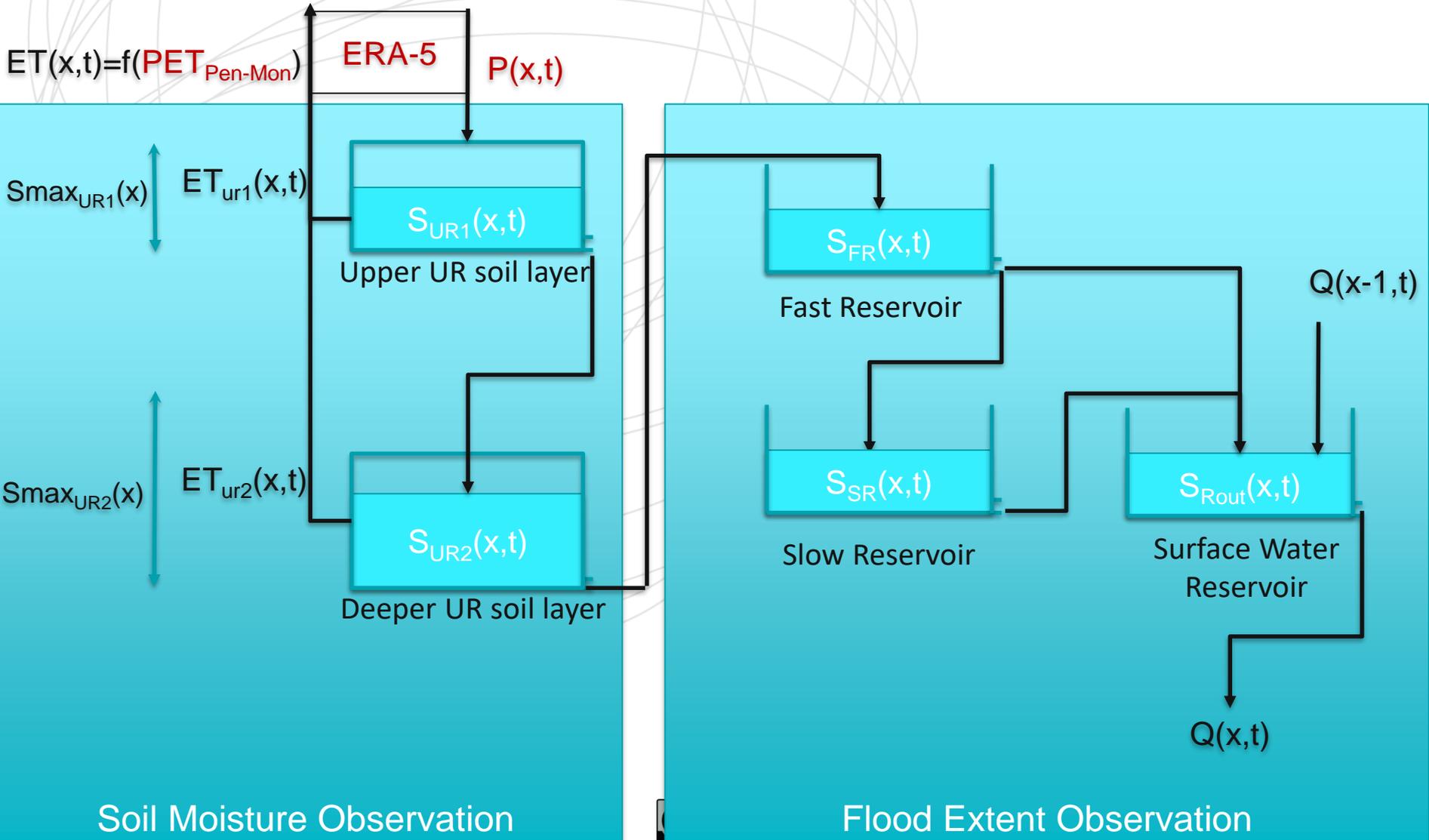


Data Assimilation



Satellite flood extent maps

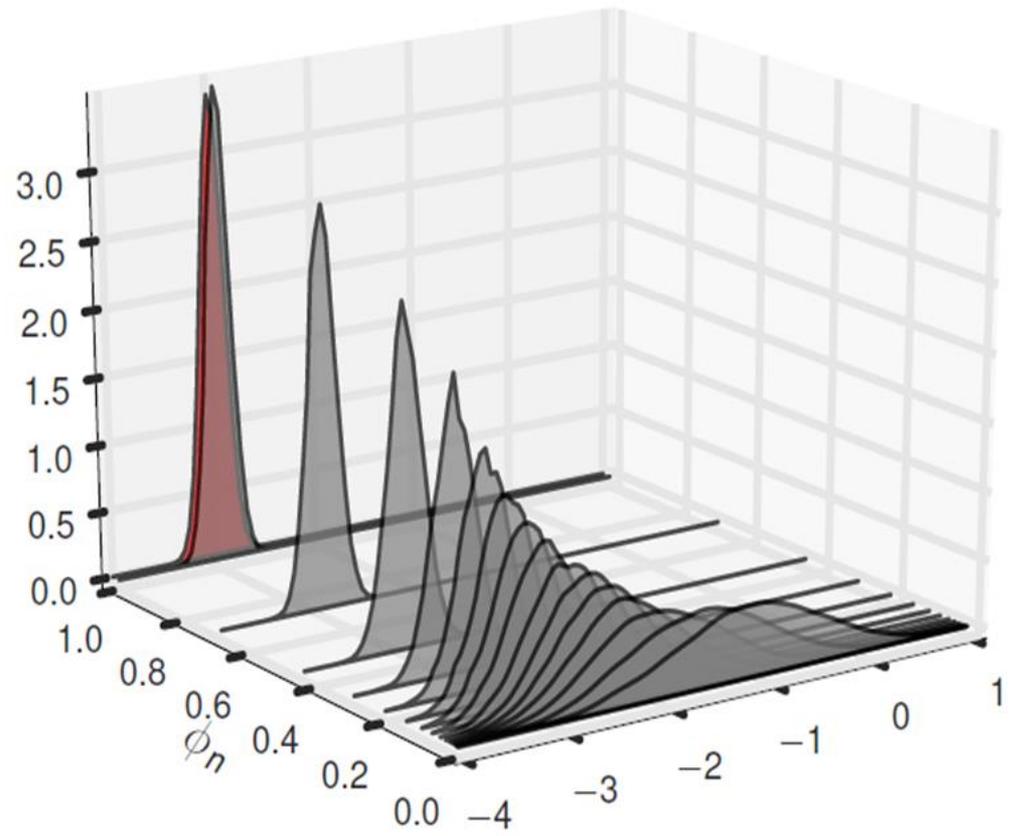
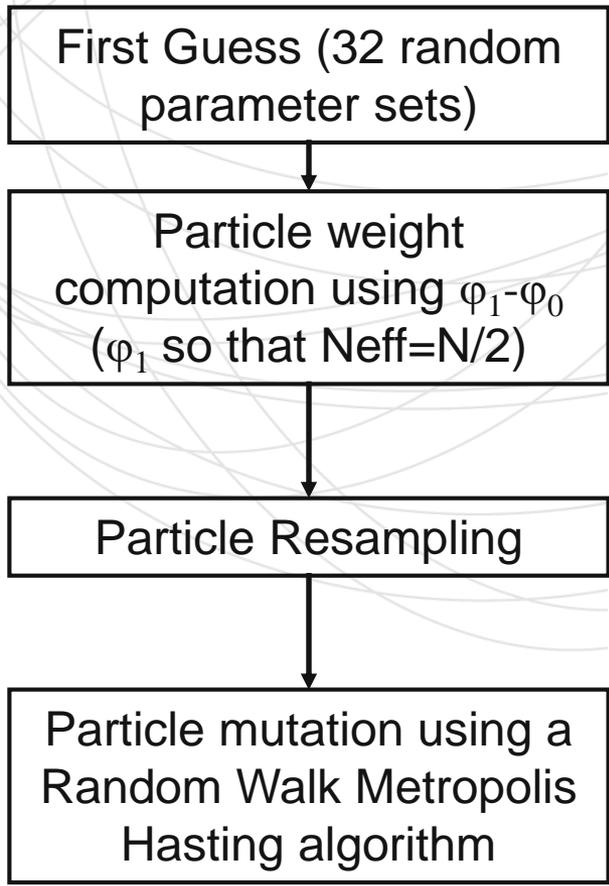
THE ASSIMILATION DESIGN PARAMETER UPDATING STRATEGY



THE ASSIMILATION DESIGN: A TEMPERED PARTICLE FILTER

Bayes Theorem:
$$p(\theta|\mathbf{o}) = \frac{p(\mathbf{o}|\theta)}{p(\mathbf{o})} p(\theta) = \prod_{n=1}^K \frac{p(\mathbf{o}|\theta)^{\varphi_n - \varphi_{n-1}}}{p(\mathbf{o})} p(\theta)$$

$$0 = \varphi_0 < \varphi_1 < \varphi_2 < \dots < \varphi_K = 1$$

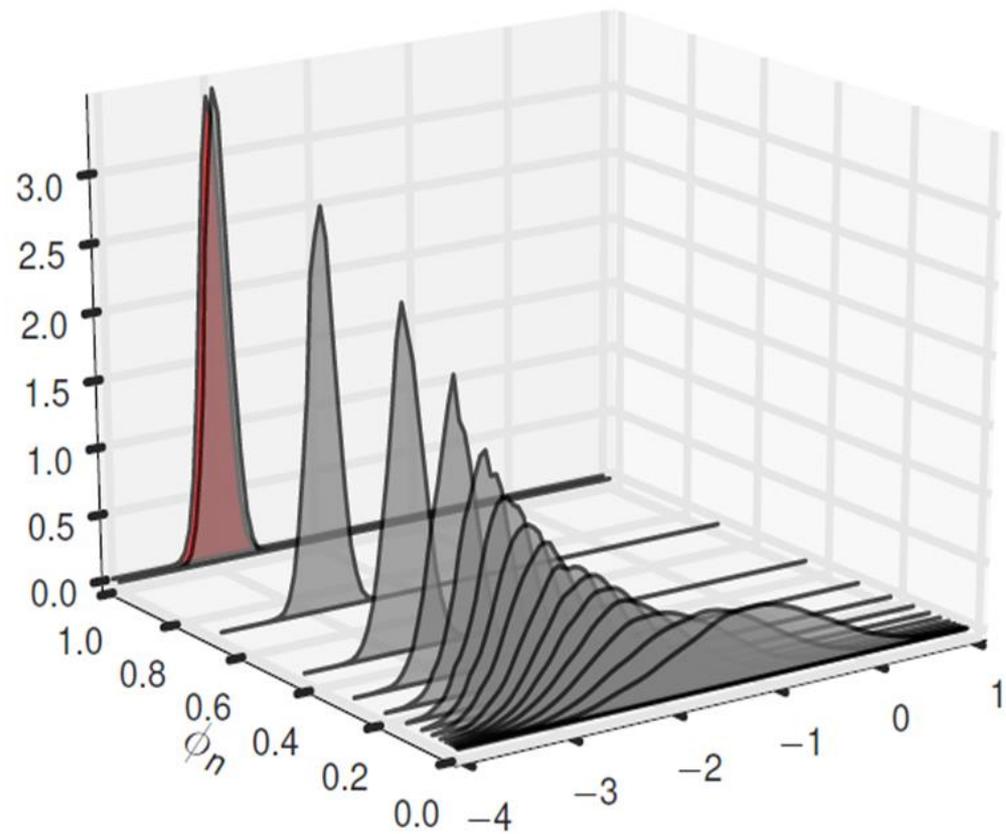
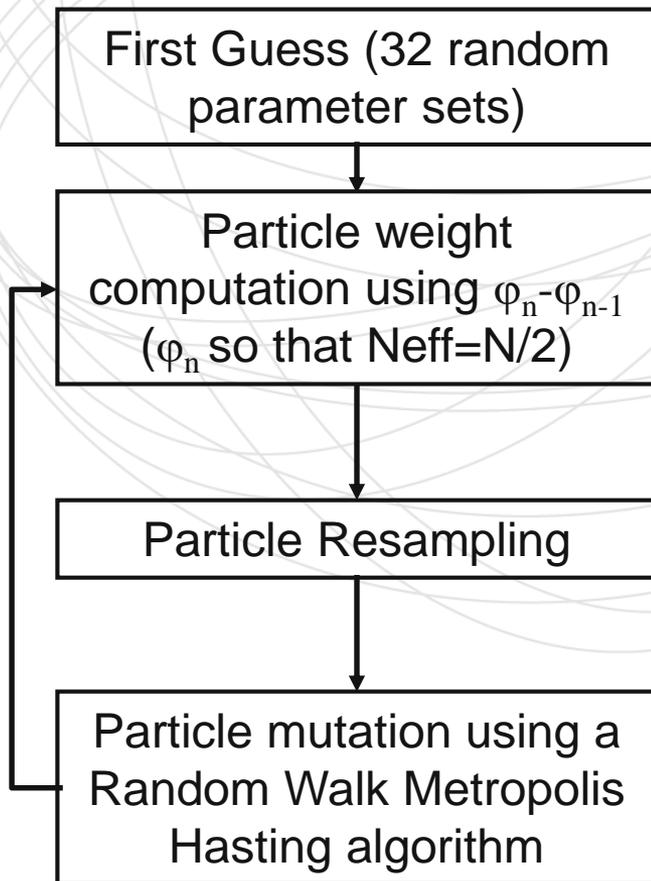


After Herbst et al., 2019

THE ASSIMILATION DESIGN: A TEMPERED PARTICLE FILTER

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After Herbst et al., 2019

SYNTHETIC TWIN EXPERIMENTS

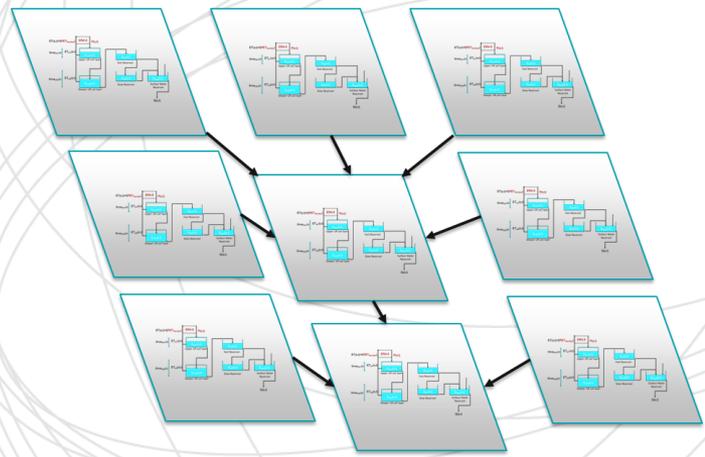


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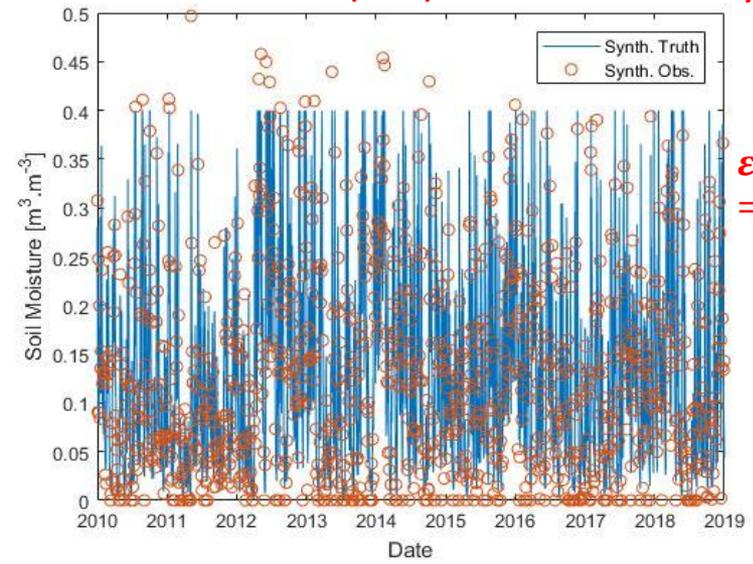


SYNTHETIC TWIN EXPERIMENTS: SYNTHETIC TRUTH AND OBSERVATION

Model forward run (9 years, hourly)

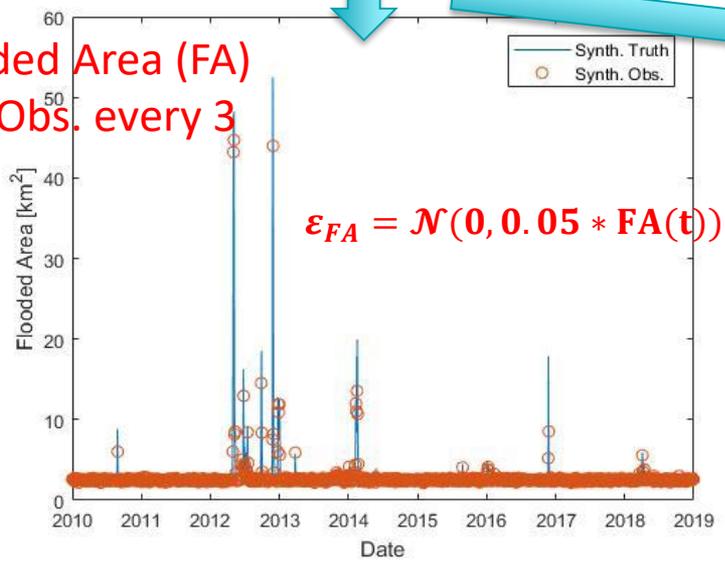


Soil moisture (SM): One Obs. every 3 days

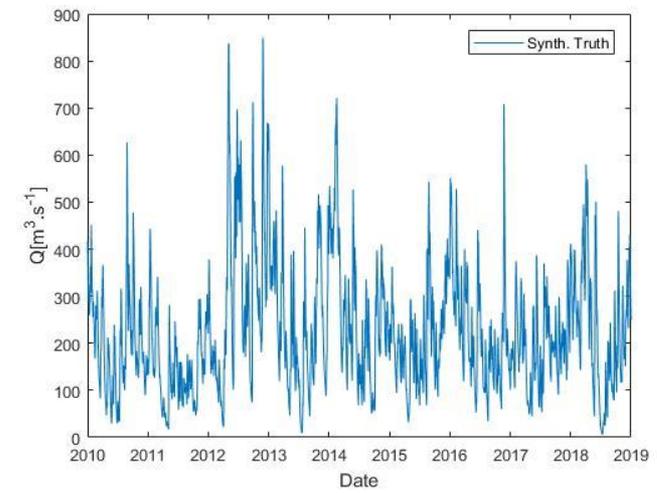


$\epsilon_{SM} = \mathcal{N}(0, 0.04)$

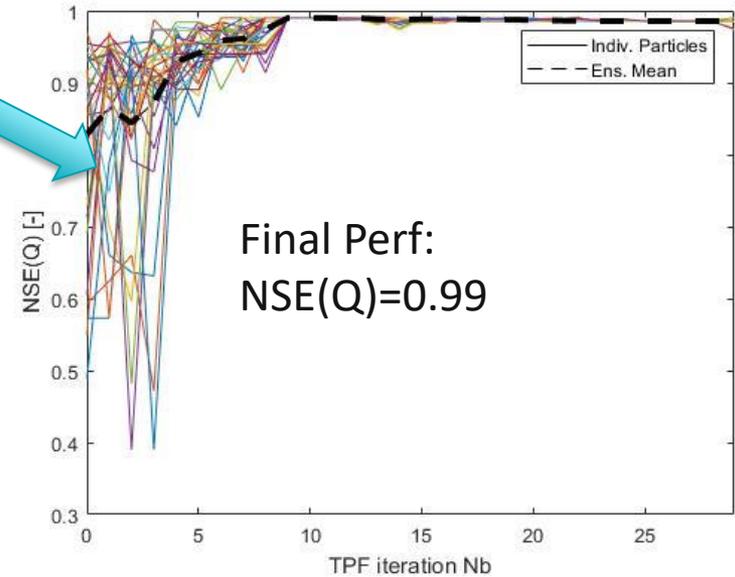
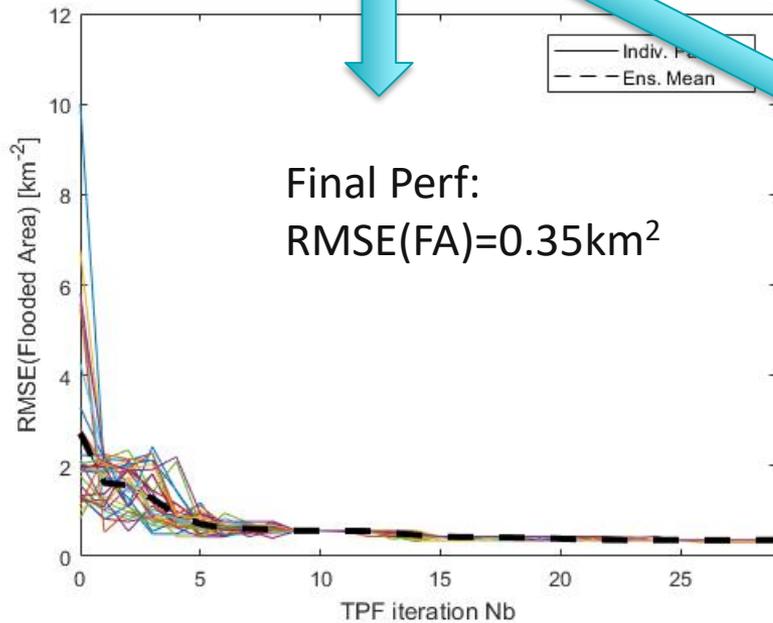
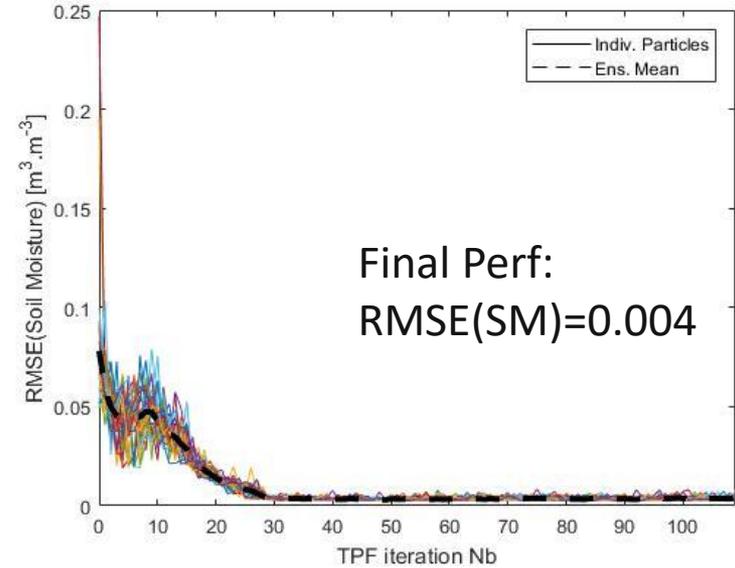
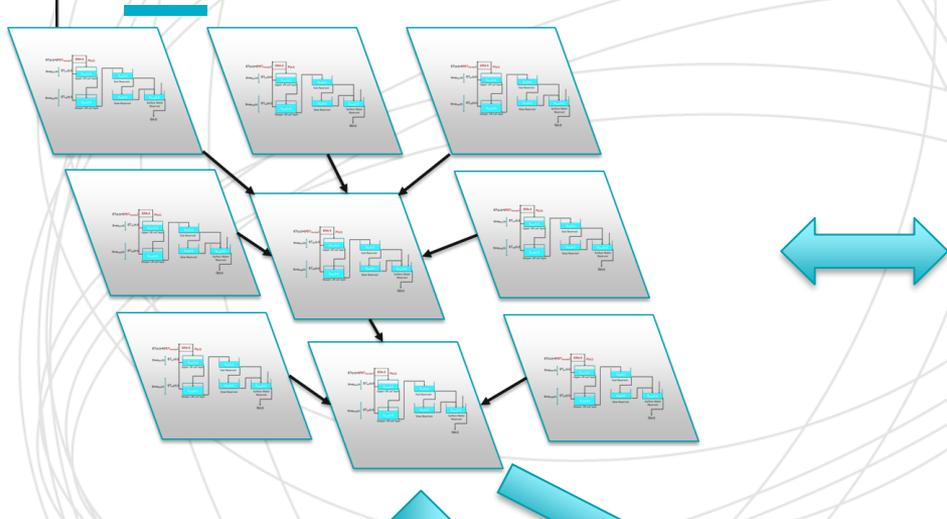
Flooded Area (FA)
One Obs. every 3
days



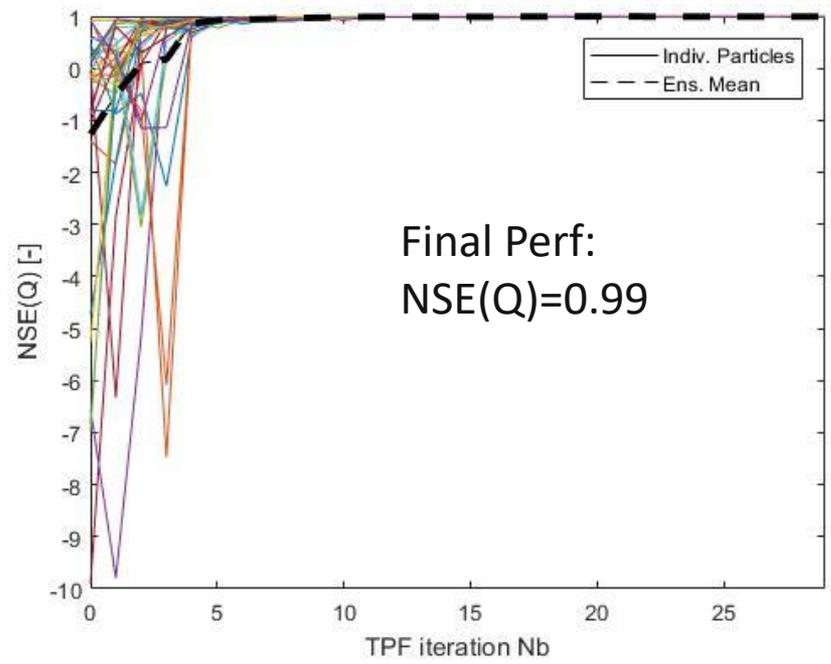
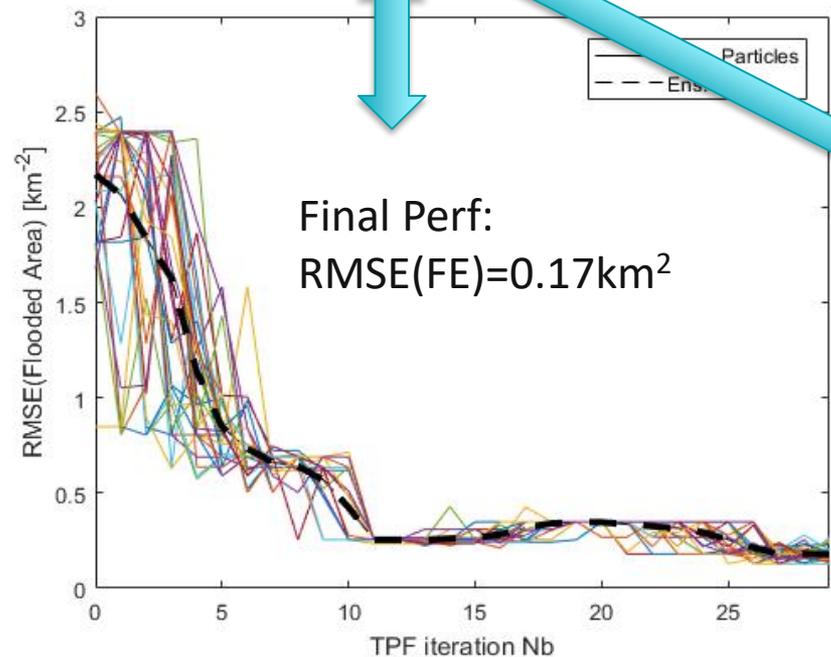
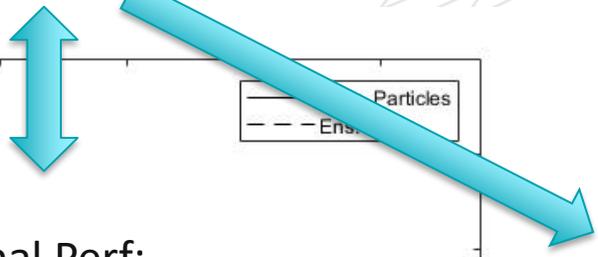
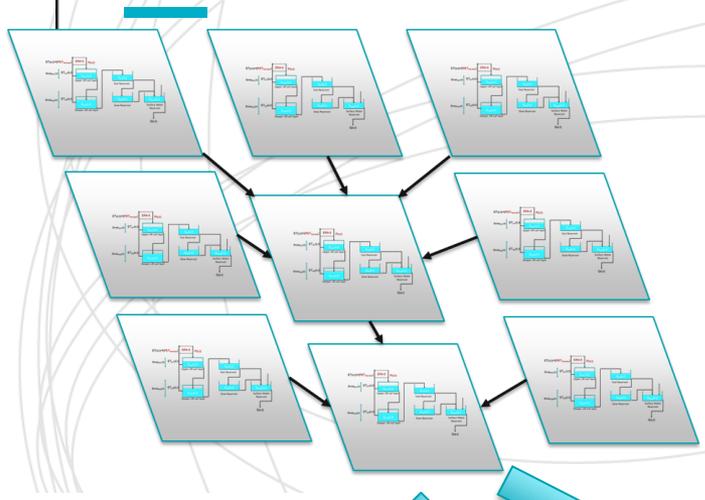
$\epsilon_{FA} = \mathcal{N}(0, 0.05 * FA(t))$



SYNTHETIC TWIN EXPERIMENTS: MODEL CALIBRATION USING SM+FA

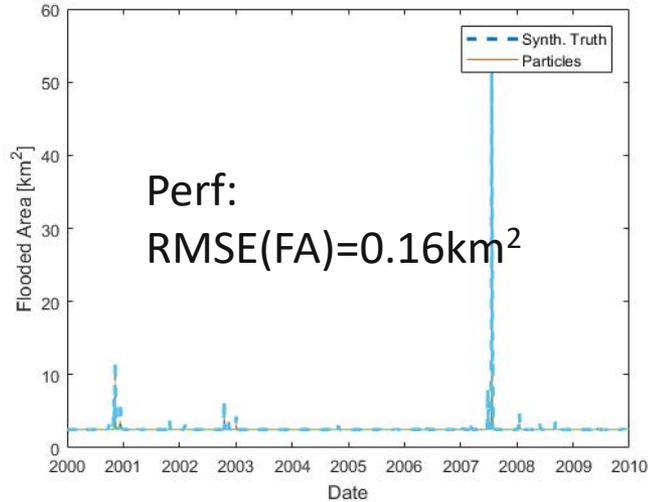


SYNTHETIC TWIN EXPERIMENTS: MODEL CALIBRATION USING FA ONLY

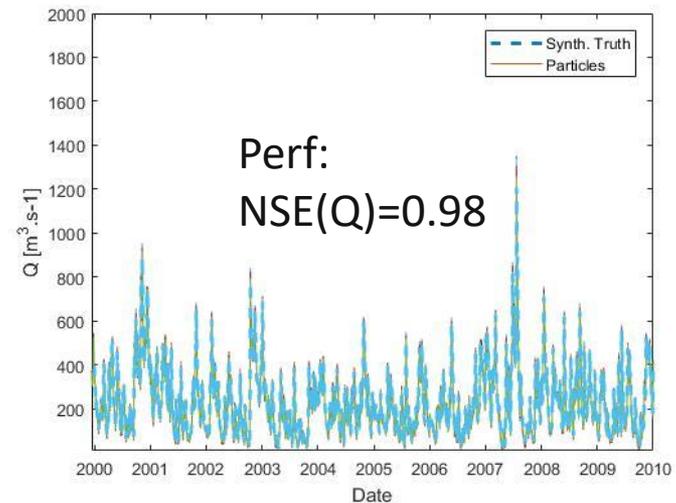
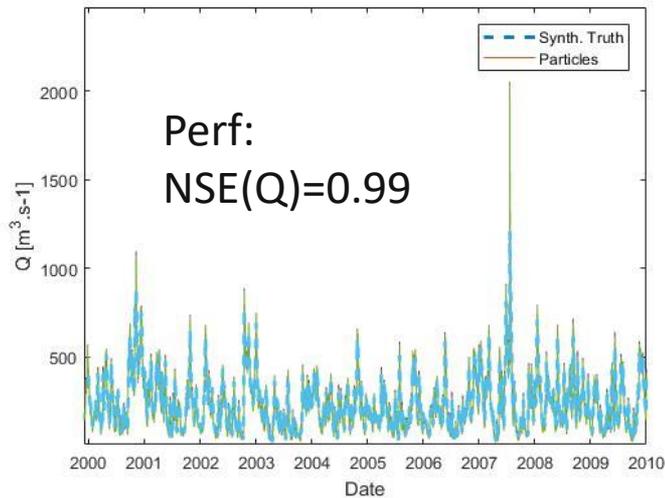
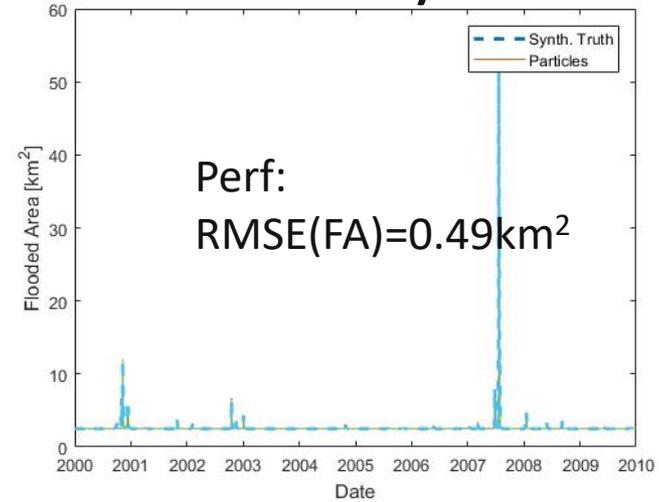


SYNTHETIC TWIN EXPERIMENTS: CALIBRATED MODEL EVALUATION

SM+FA



FA only

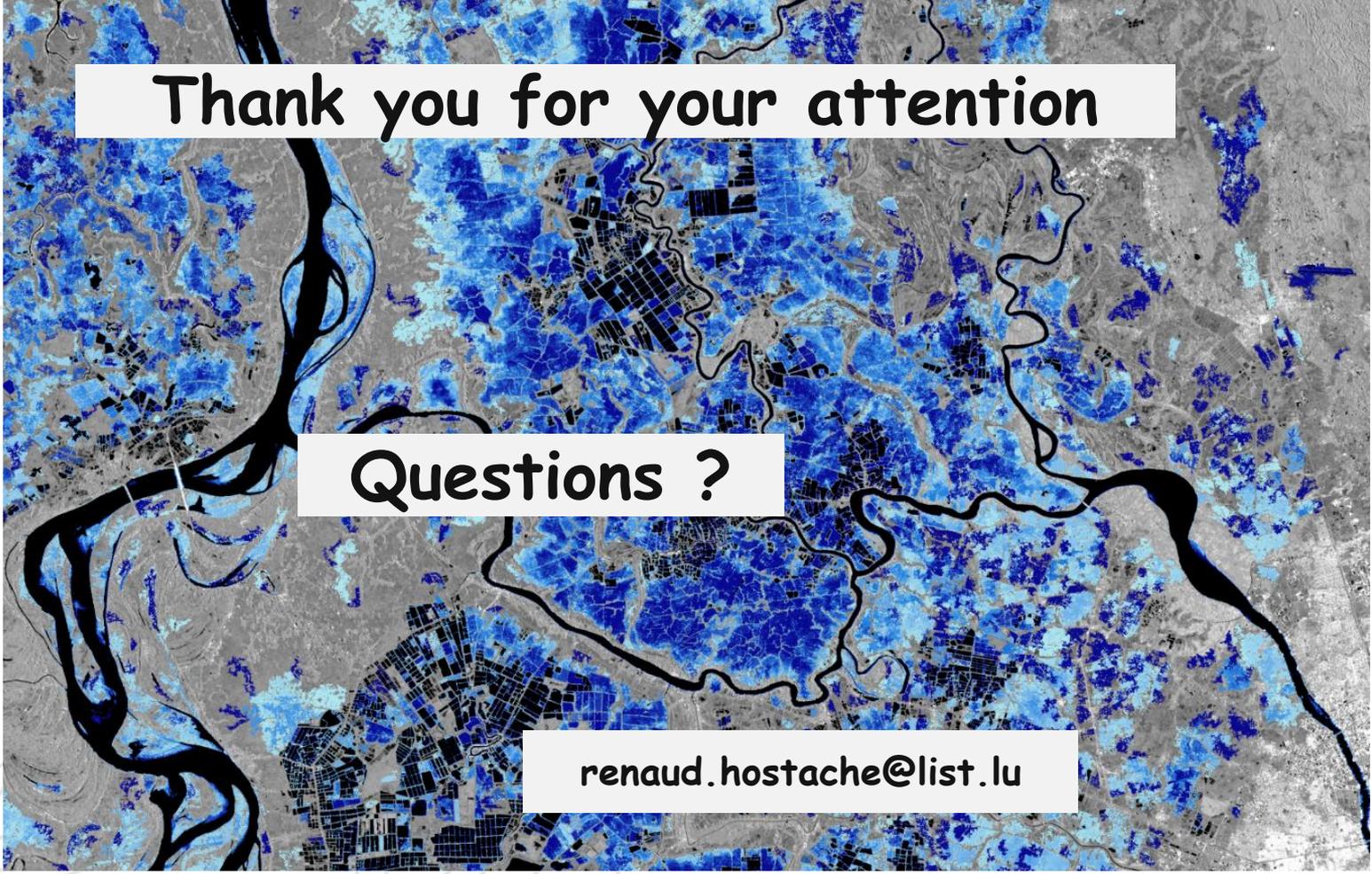


CONCLUSION & NEXT STEPS

- We carried out a synthetic experiment using a TPF of the joint assimilation of satellite flooded area and soil moisture observation
- The results are really promising as the calibrated model is predicting surface runoff accurately both during the calibration and the validation periods
- This opens the floor for applications at large scale over poorly gauged areas

Next steps:

- To further investigate the added value of soil moisture data
- To carry out real test case experiments

An aerial photograph of a landscape with a river system. The river channels are highlighted in black, and the surrounding areas are overlaid with various shades of blue, likely representing water flow or inundation. The background is a grayscale aerial view showing buildings, roads, and vegetation.

Thank you for your attention

Questions ?

renaud.hostache@list.lu

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