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Assimilation of remote sensing-derived water stage data into coupled hydrologic-hydraulic models:

Proof of concept study

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Lisbon, Portugal, 18-22 October 2010

Motivation

The way remote sensing data is traditionally used in flood management:

- Purely reactive service (e.g. Charter activities)
- Extraction of flooded areas
- *A posteriori* calibration of flood inundation models

Objectives of this research activity:

- Introduce the z and t dimensions in flood inundation mapping based on remote sensing data
- Optimize flood predictions through the assimilation of remote sensing data

Hypothesis:

- Remote sensing-derived water levels, through data assimilation, can significantly increase the quality of near real-time flood inundation forecasts

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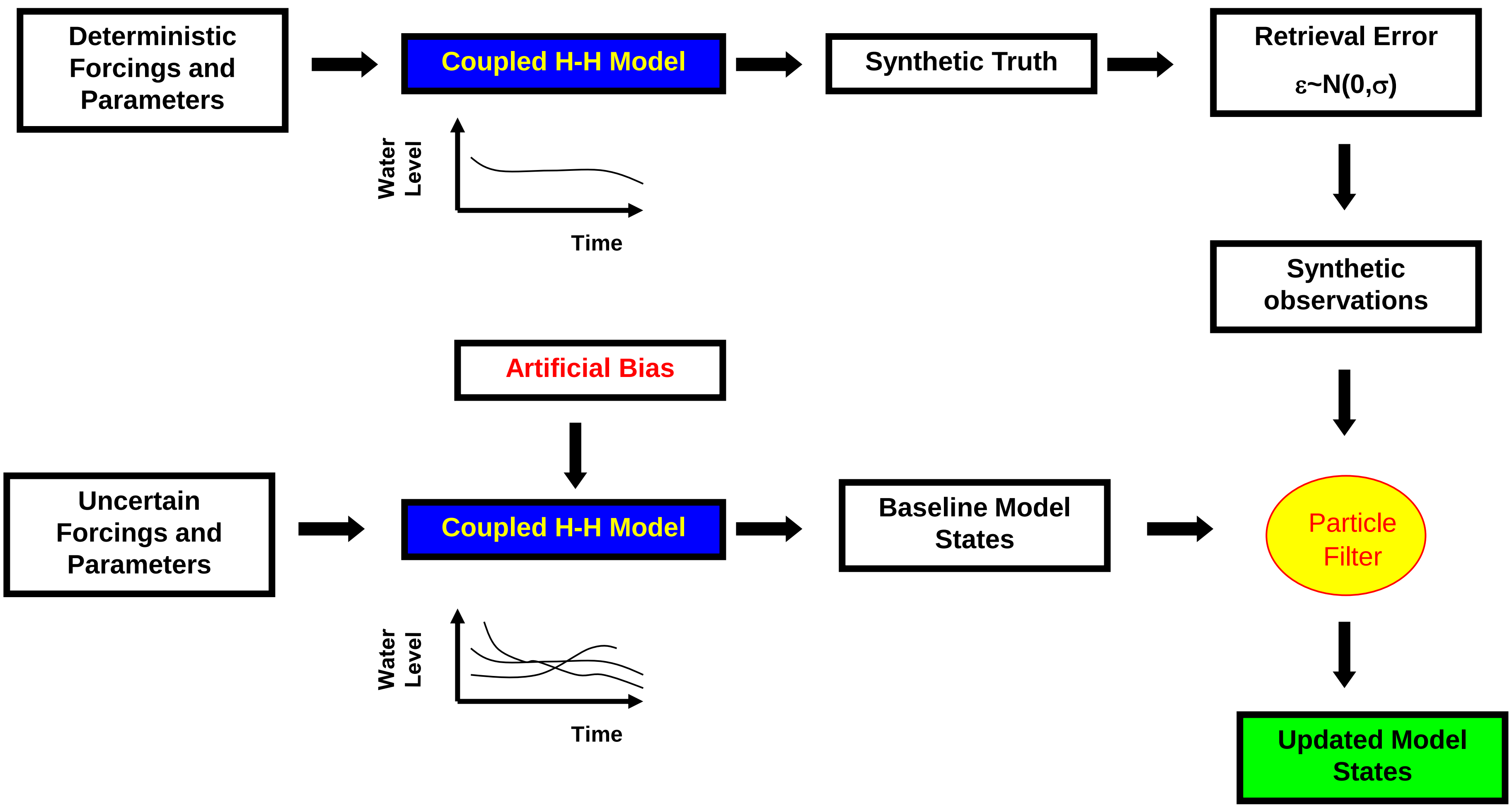
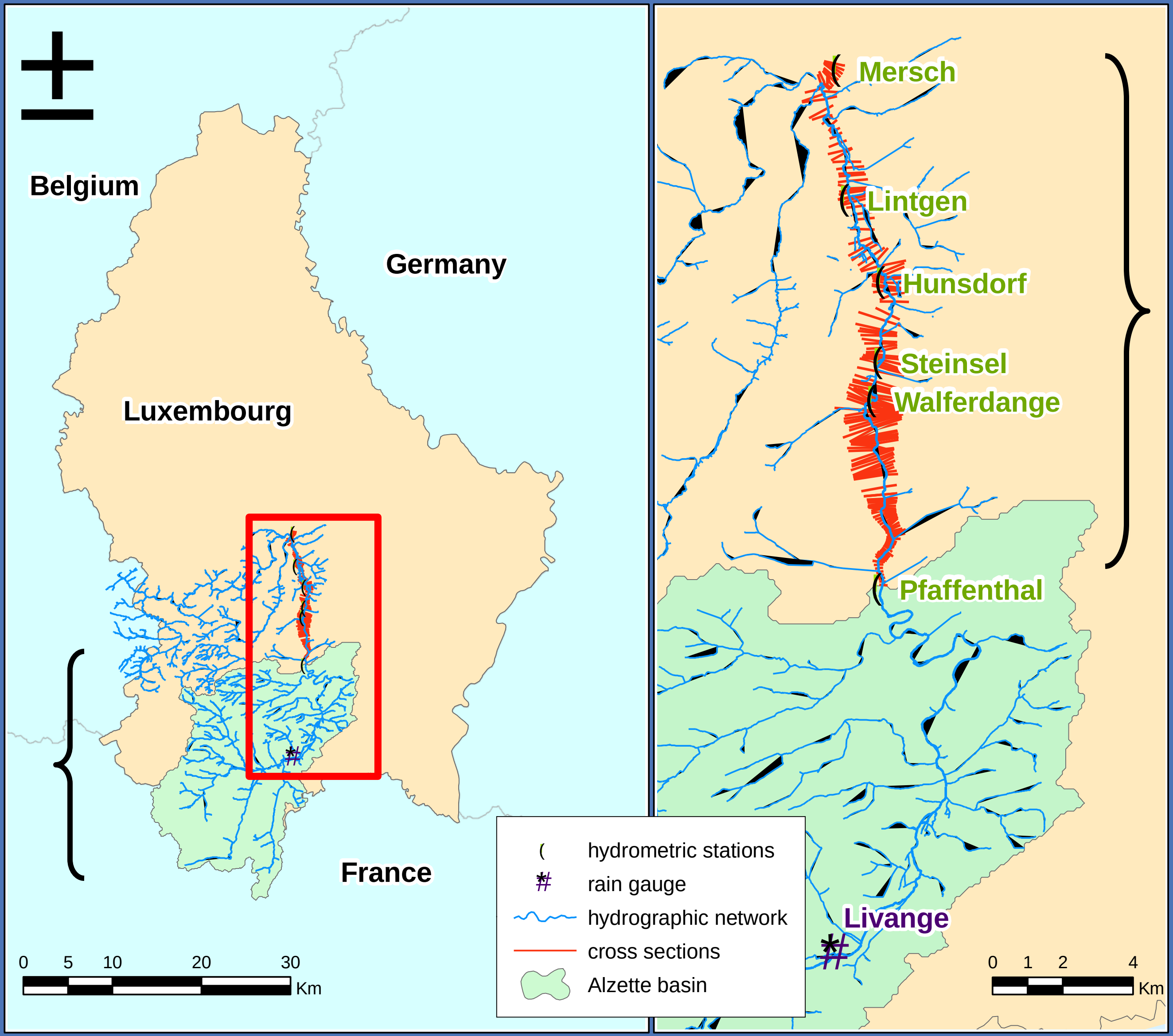
Synthetic experiment



Study site

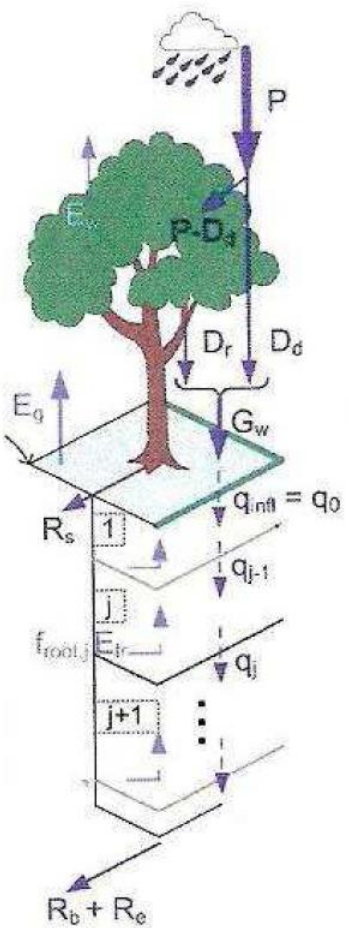


Hydraulic model

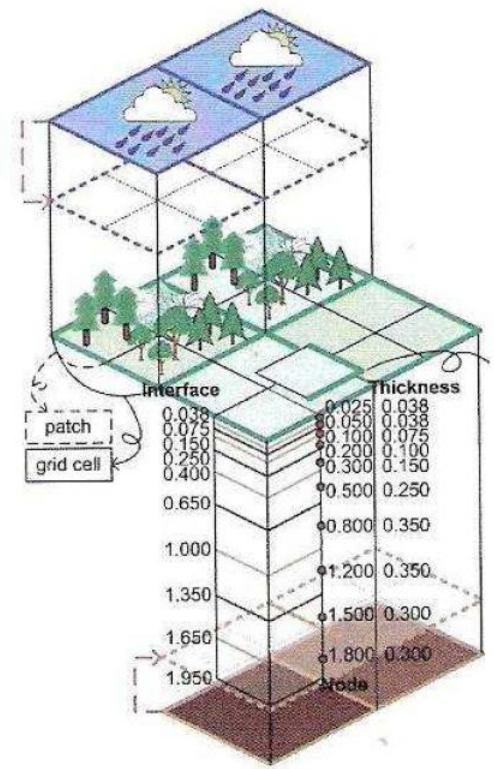
Hydrologic model

Hydrologic model

Community Land Model (CLM)



- Fully process-based water and energy balance model.
- Multiple land cover types can be represented within one grid cell.

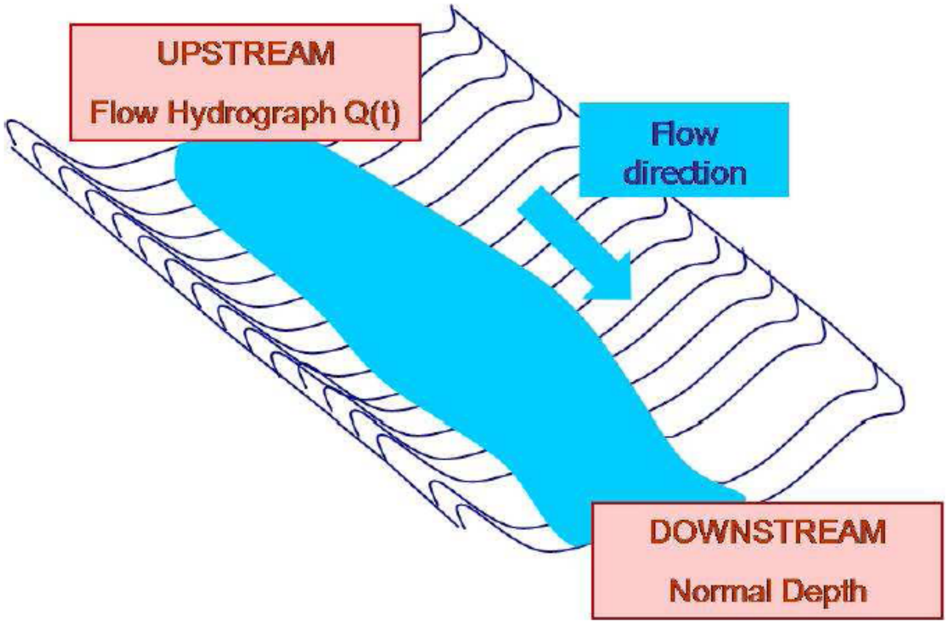


Hydraulic model

Inputs:
- River reach geometry
- Boundary/initial conditions
- Flood event characteristics

⇒ **HEC-RAS** ⇒

Outputs:
- Discharge
- Water level
- Flood extent



HEC-RAS:
- 1-D flood propagation.
- Numerical solution to the de Saint-Venant equations.
- Model parameters: channel and floodplain roughness values.

The Particle Filter: Introduction

- One of the assumptions of the Kalman filter is Gaussianity of the observation and model errors, which is frequently not met in practice

- This can lead to a suboptimal functioning of the algorithm

- In the particle filter, the assumption of Gaussianity is relaxed

- **Fundamental principle:** represent the required posterior density by a set of random samples and weights and to compute estimates based on these samples and weights

- In other words, N_p particles are generated, each with a state vector $x_{i,k}$ and weight $w_{i,k}$

The Particle filter: Procedure

1. **Generate particles** from a known distribution, assign the same weight to each particle, and apply the model

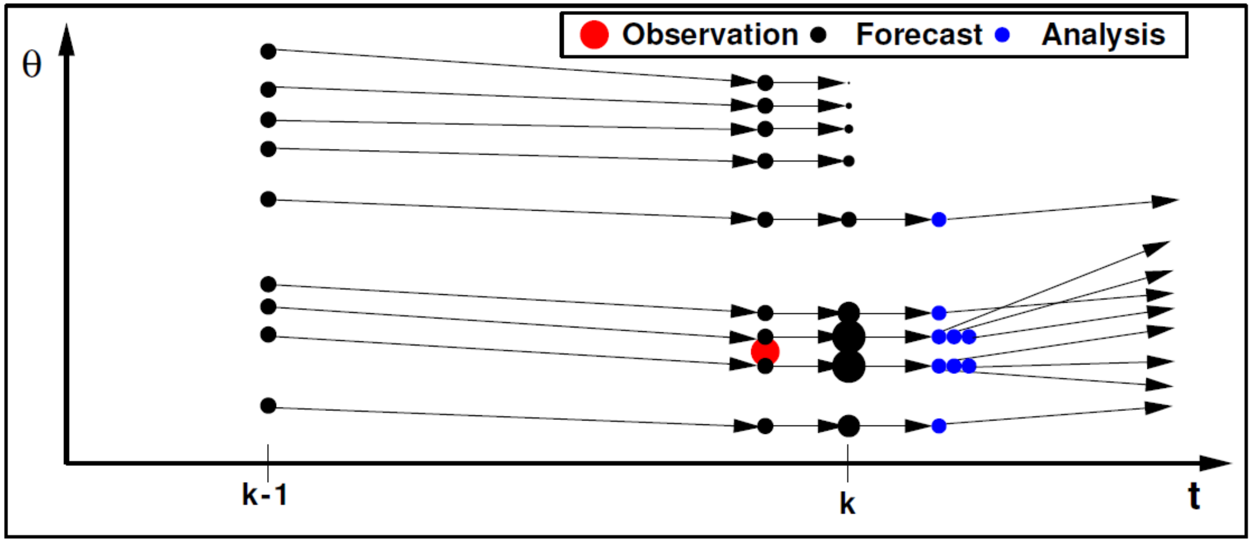
2. If an observation becomes available, calculate the **weight** of each particle. One way to do this, is through the use of a Gaussian likelihood, for each observation j of the N_o observations.The value of the state variables does not change

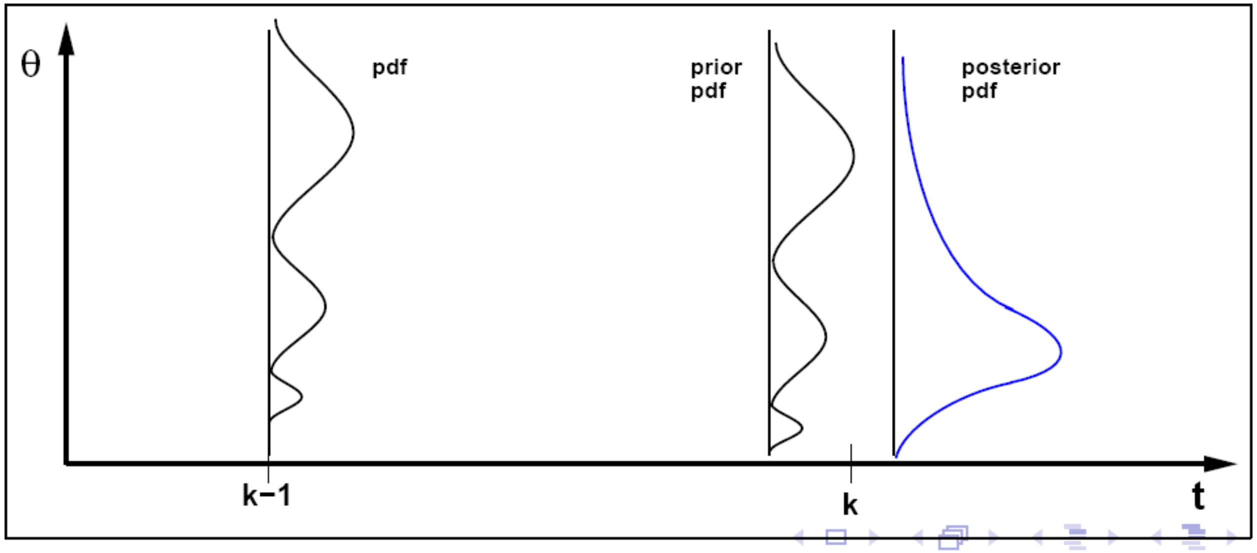
3. The weighted mean corresponds to the **state estimate** at time step k

4. Finally, the particles are **re-sampled** in proportion to their weight. A number of particles will have equal state variables. However, they are forced with disturbed forcings and have different parameters, so after one time step their values will be different

5. **Re-initialize** and **apply** model

The Particle filter: Procedure





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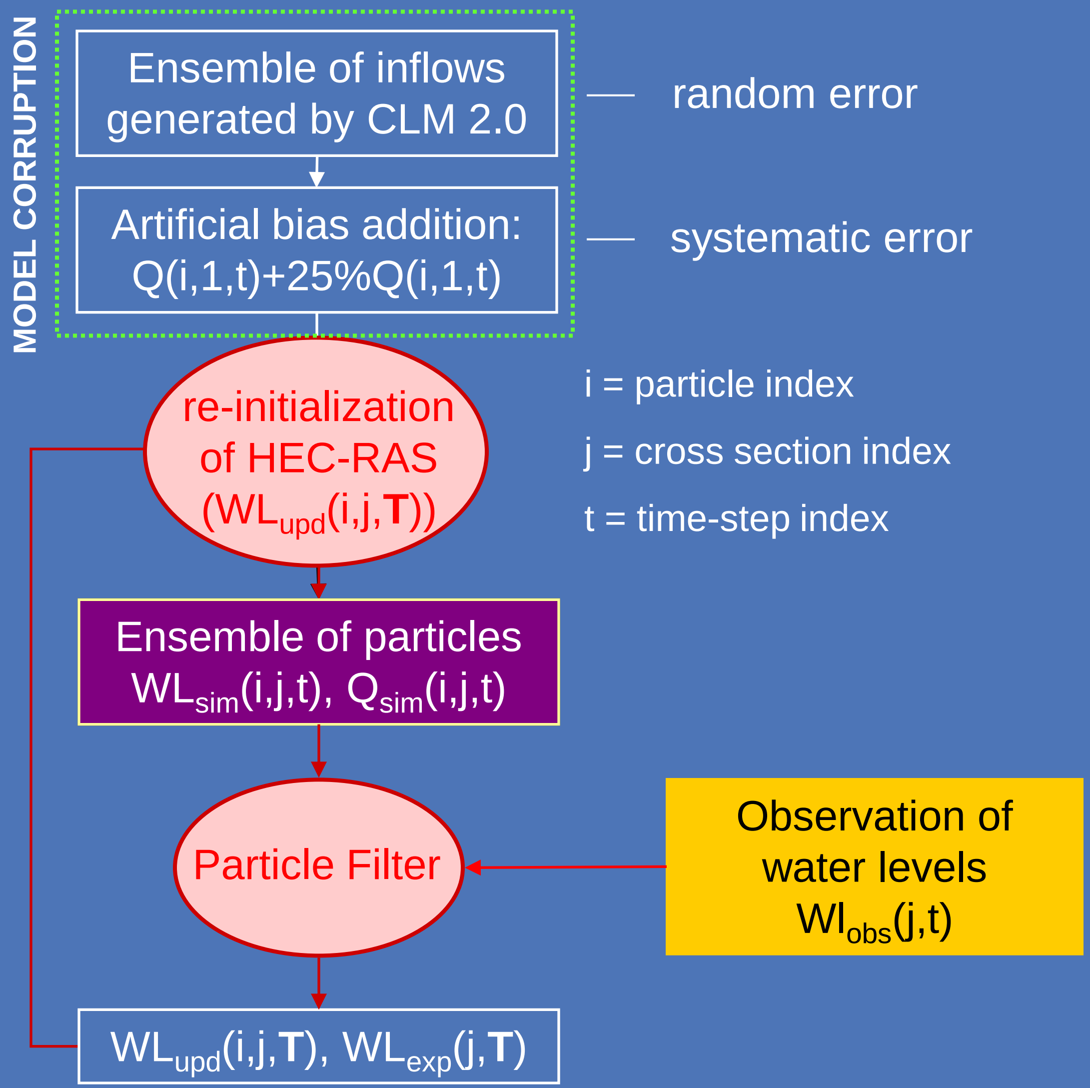
Assimilation scheme



i = particle index

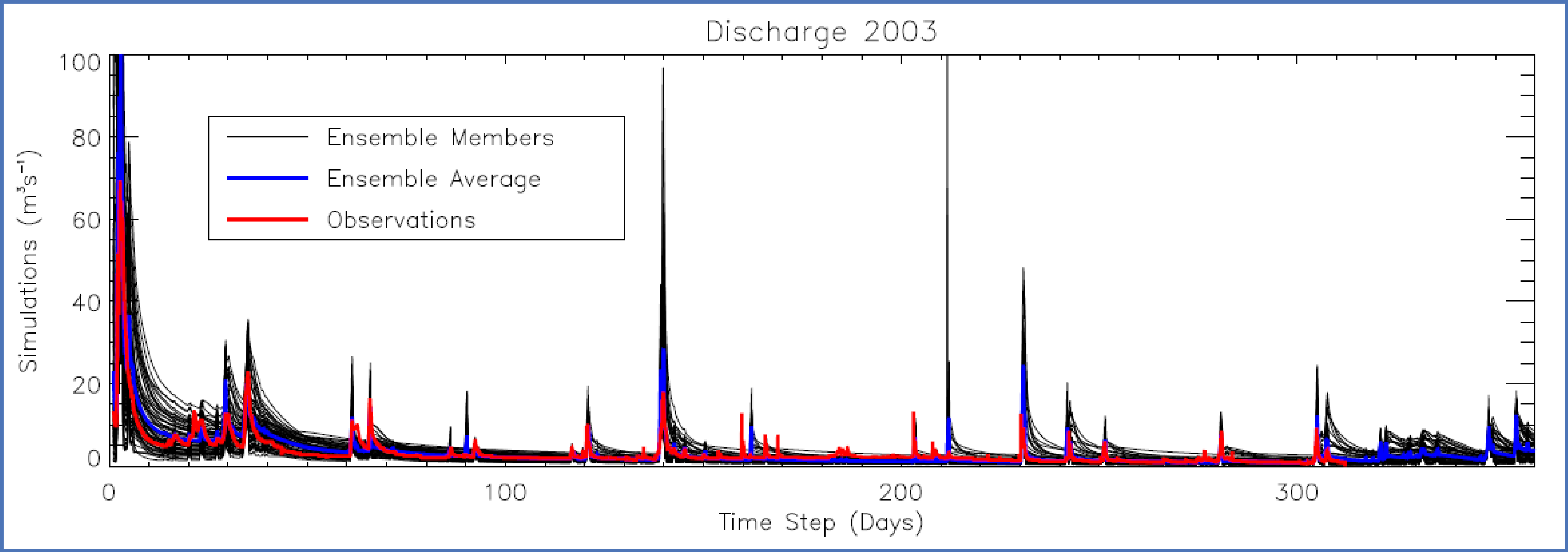
j = cross section index

t = time-step index

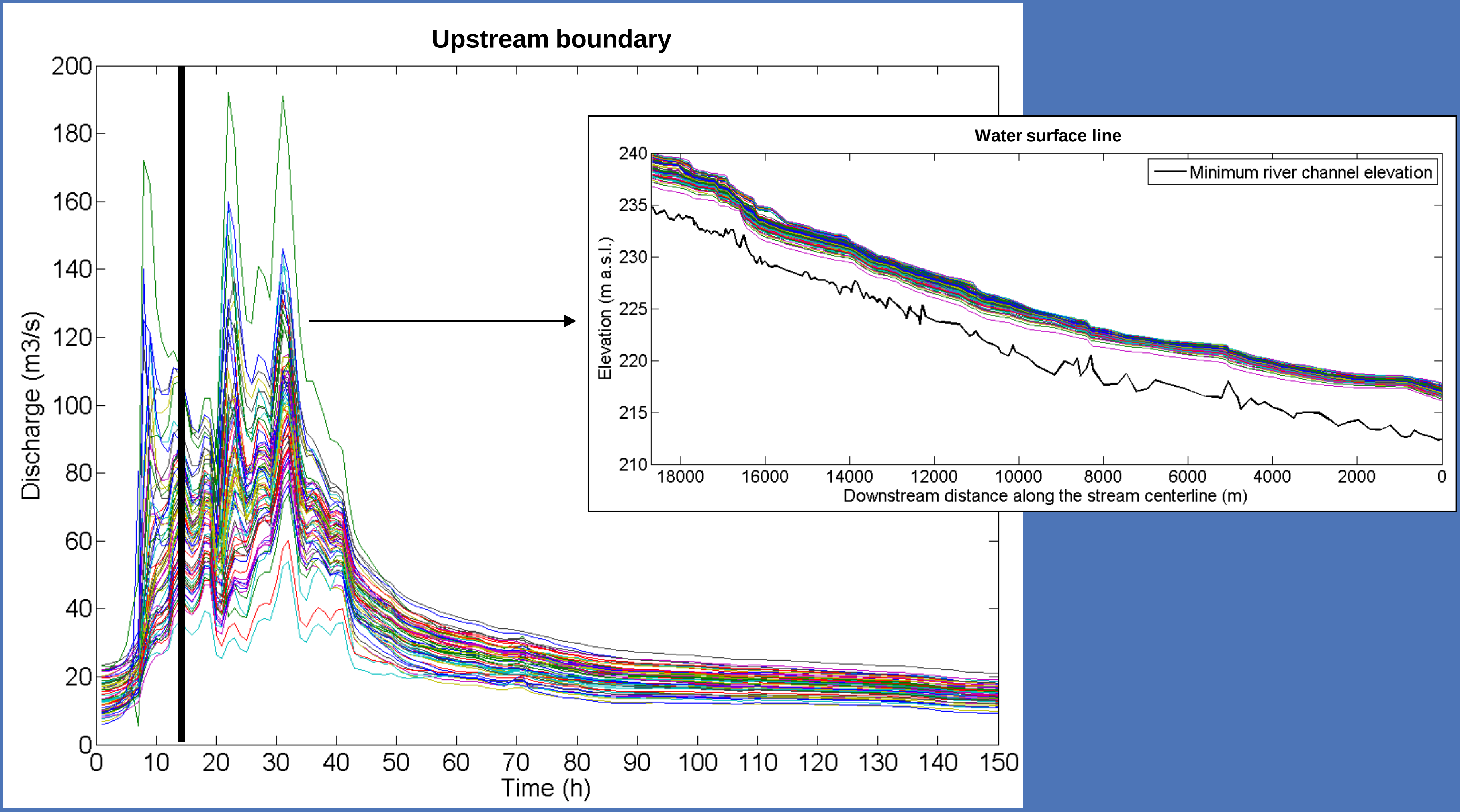
Results: Generation of ensembles

• Parameter sets and forcing data of each particle are obtained by adding a random error (with known distribution) to the parameter set and meteorological forcings.

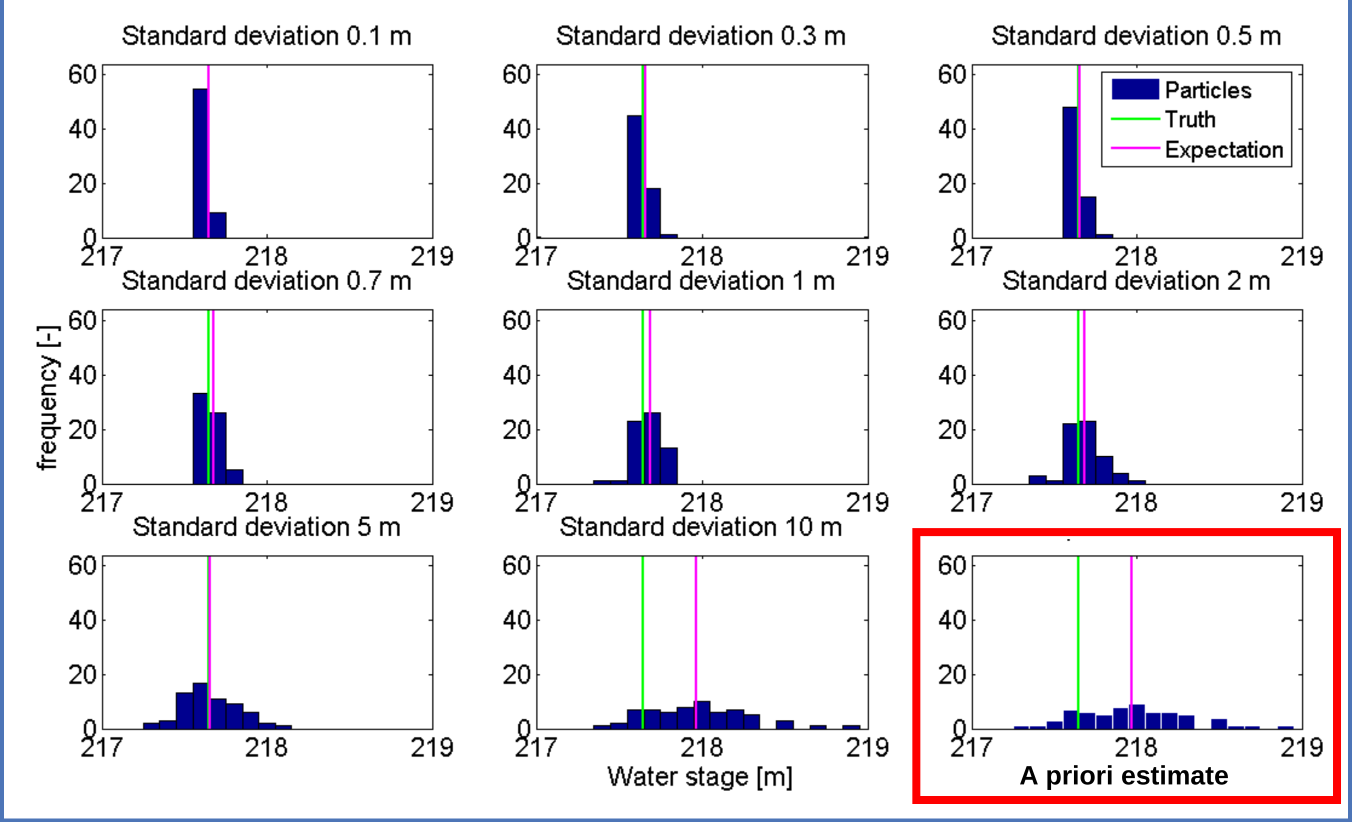
• It is expected that on average the ensemble mean differs from the observation by a value that is equal to the time average of the ensemble spread.



Results: Generation of ensembles



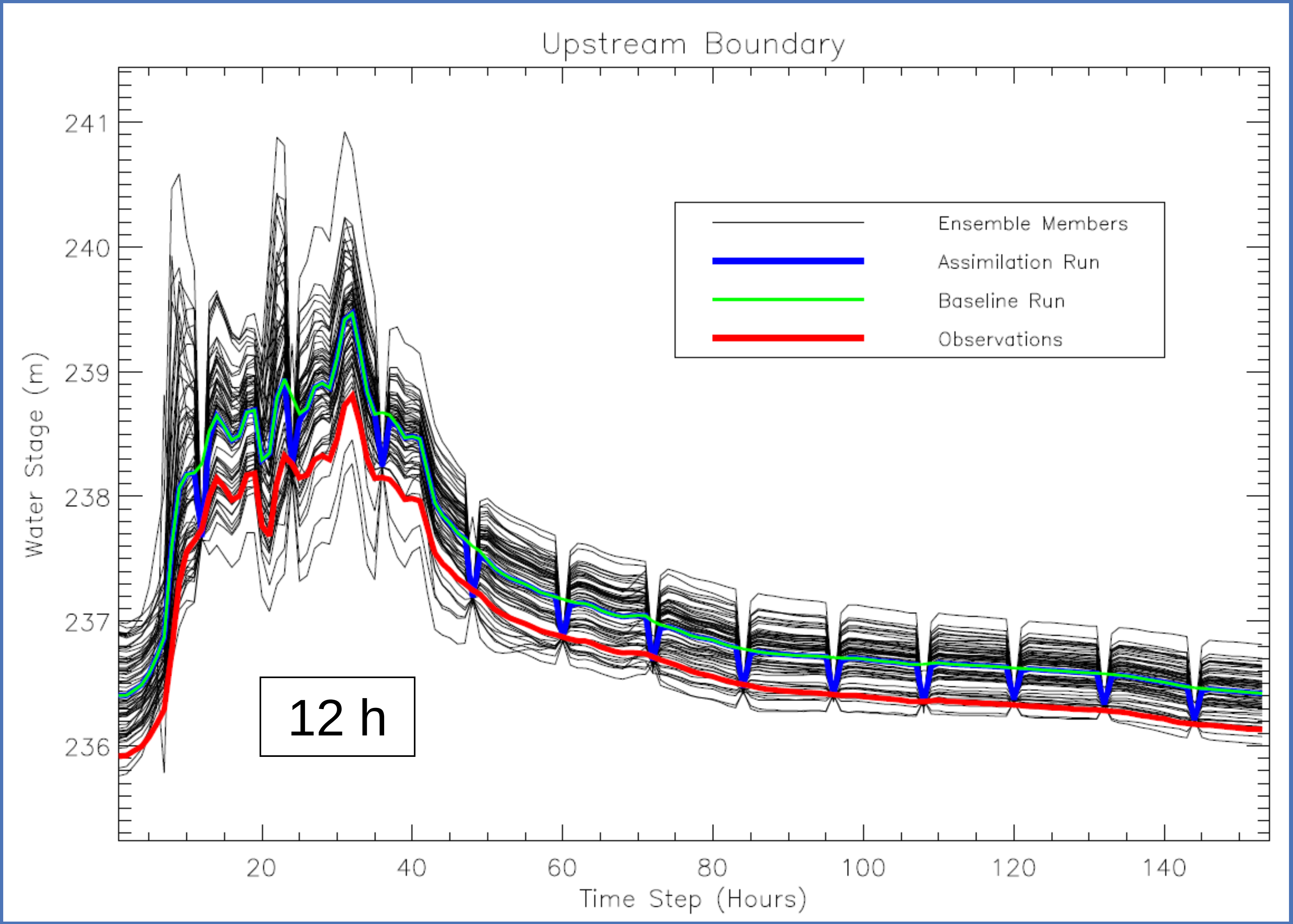
Results: Water stage assimilation



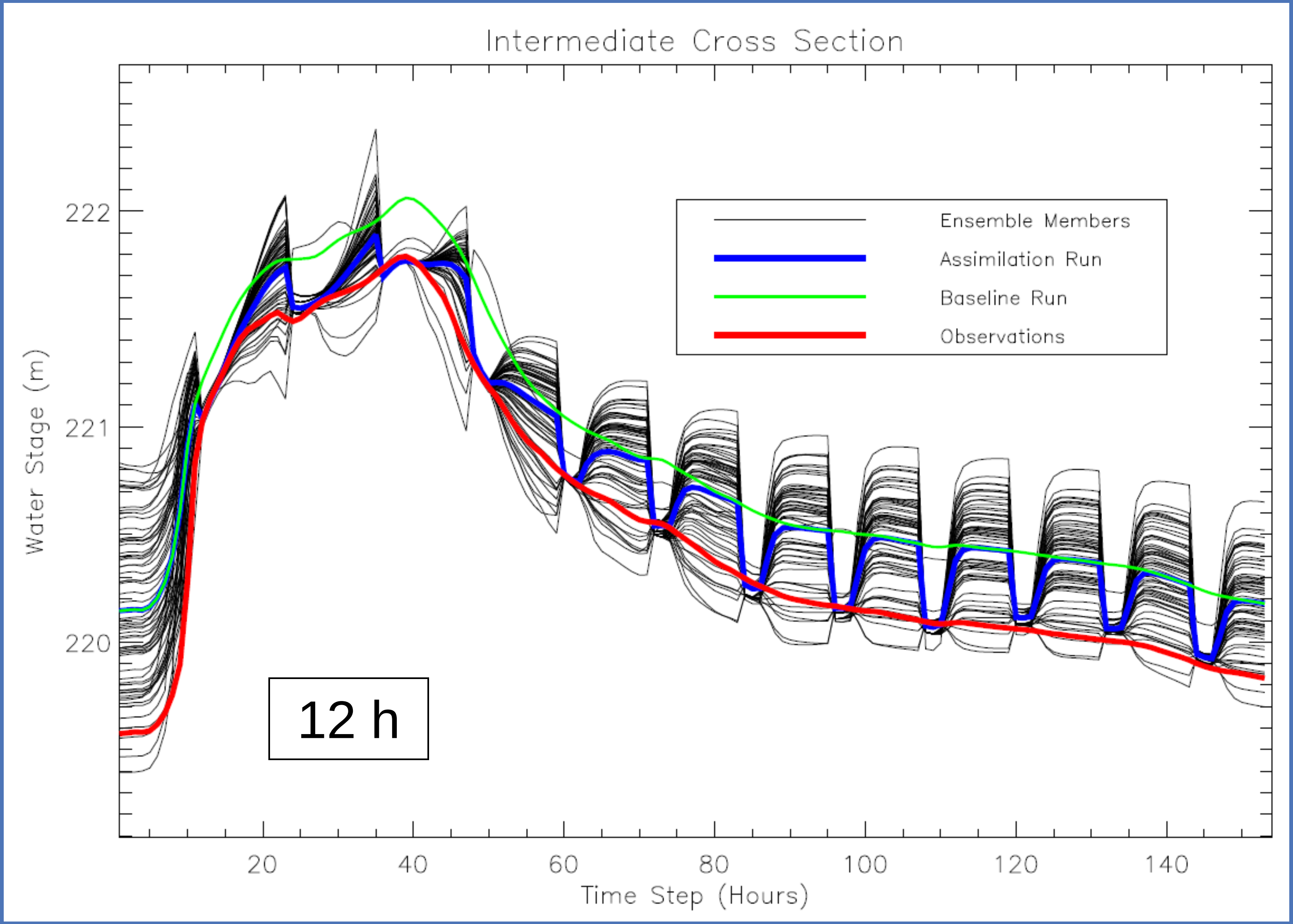
• For lower observation errors, fewer particles are retained, and many replicas of the particle closest to the synthetic truth are created.

• 30 cm observation error is considered as a realistic value

Results: Water stage assimilation



Results: Water stage assimilation



Results: Water stage assimilation

- At the time step of the update, the model error is strongly reduced, but the improvement disappears immediately at the upstream boundary.

- Further downstream the improvement disappears after a couple of time steps.

- Data would thus have to be assimilated at each time step, which is not realistic!

- The real problem is bias in the model results. The Particle filter (and also the Kalman filter) is a method designed to filter noise, not systematic errors.

Inflow correction scheme

- At the assimilation step k, the estimate of the water stage $E(x_k)$ is used to retrieve the corresponding estimate of the discharge $E(Q_k)$, using the internal rating curve.

- At any time step k during the flood event, the discharge input is corrected as follows:

$$\triangle Q_k = \frac{\overline{Q_k} - E(Q_k)}{\overline{Q_k}}$$

where $\overline{Q_k}$ is the average of the hydrologically modeled discharge.

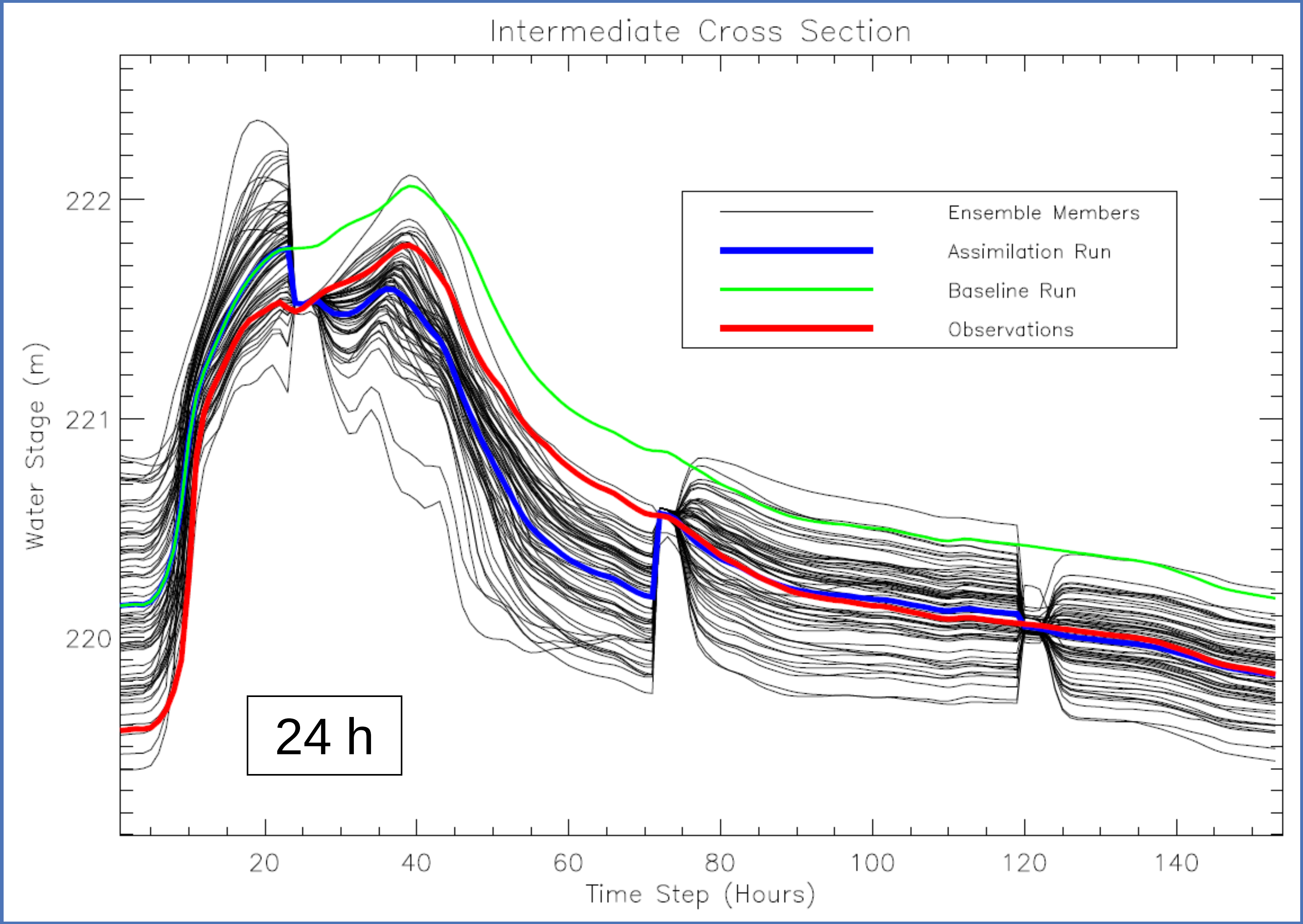
- The assumption is then made that relative errors remain constant throughout the flood event. In other words, the absolute error increases as the discharge increases and vice versa, but with the same relative difference.

- At any time step i the inflow corrected is corrected as follows:

$$Q_i^+ = Q_i - Q_i \triangle Q_k$$

and used as input for the hydrodynamic model.

Results: Water stage assimilation



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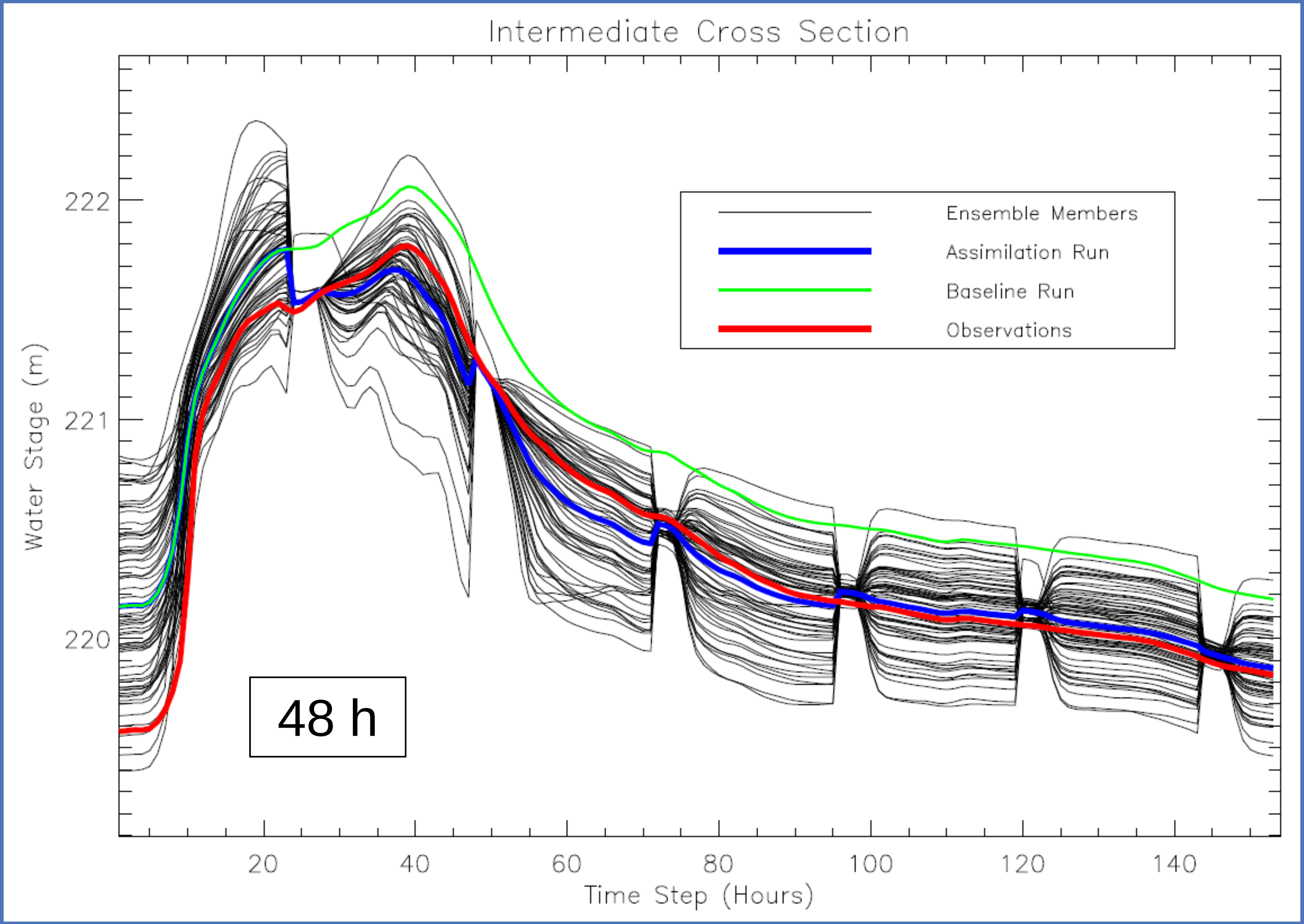
Results: Water stage assimilation



Conclusions

1. Because of the non-Gaussianity of the modelled ensembles and the observations the Particle Filter has been used as assimilation algorithm.

2. Remote sensing derived water stages allow sequentially updating flood forecasting models

3. The performance of the filtering depends on the quality of data, significant model improvements are achieved with sigma < 0.7 m

4. For water stage assimilation, the impact of assimilation deteriorates almost immediately. This is due to to the impact of errors in the upstream boundary. An correction scheme has been developed to solve this problem.

5. The required imaging frequency depends of the time correlation of model errors, in our case study the sampling frequency had to be < 24 hours during the rising limb of a flood

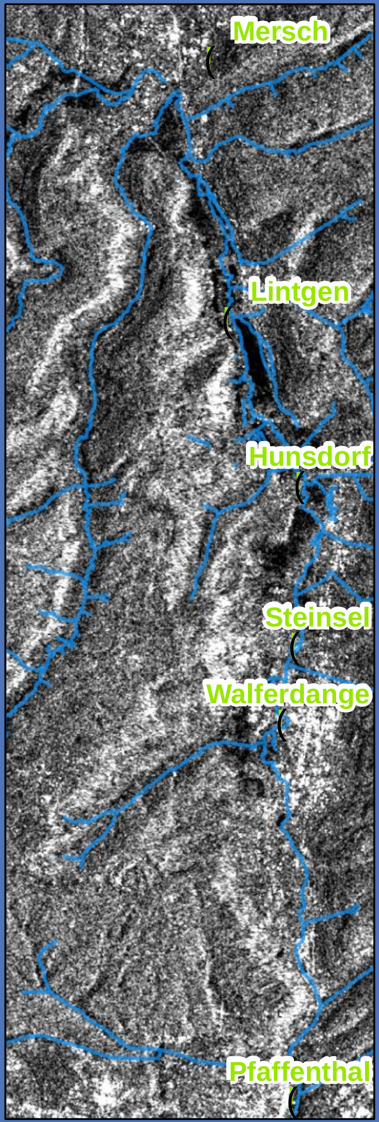
Open questions

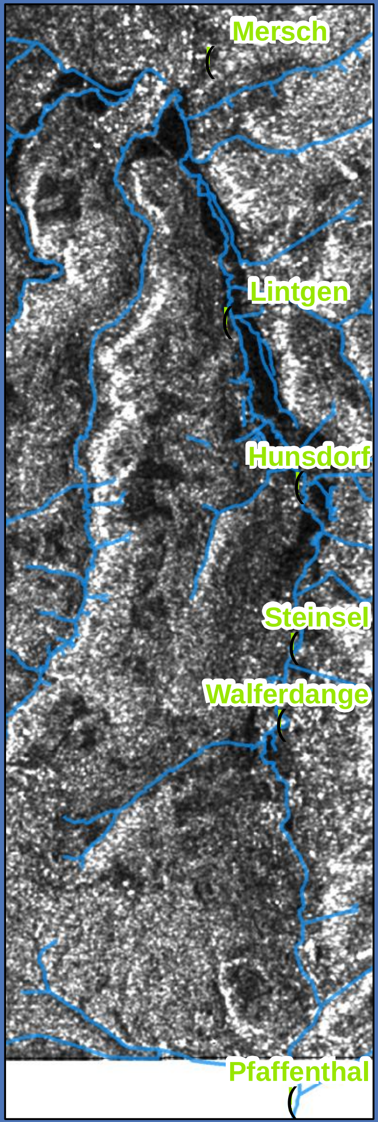
1. Does the filter work with real event data ?

2. Can the filter easily adapt to spatially variable non gaussian distributions of water stage observations ?

3. What to do if other sources of error come into effect (e.g. lateral inflows, hydraulic model parameters, geometry errors etc.) ?

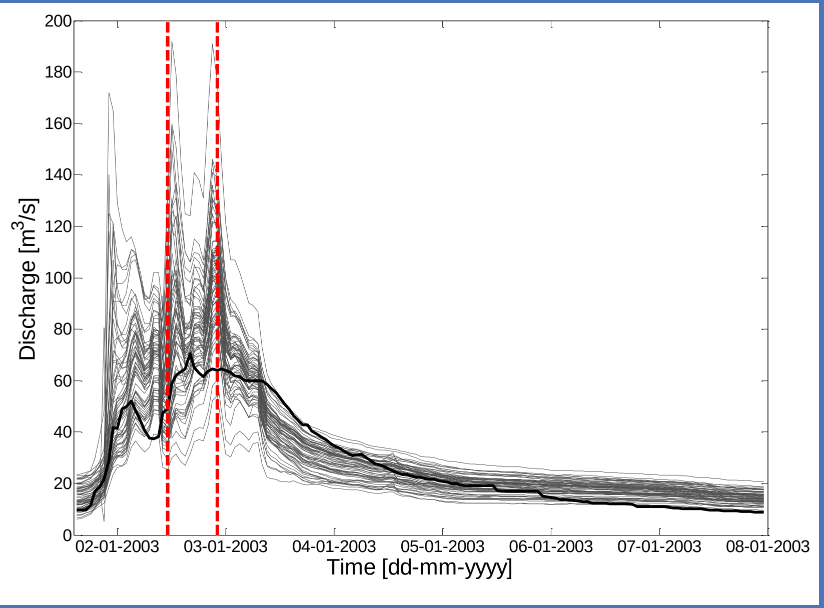
Case study: Remote sensing data



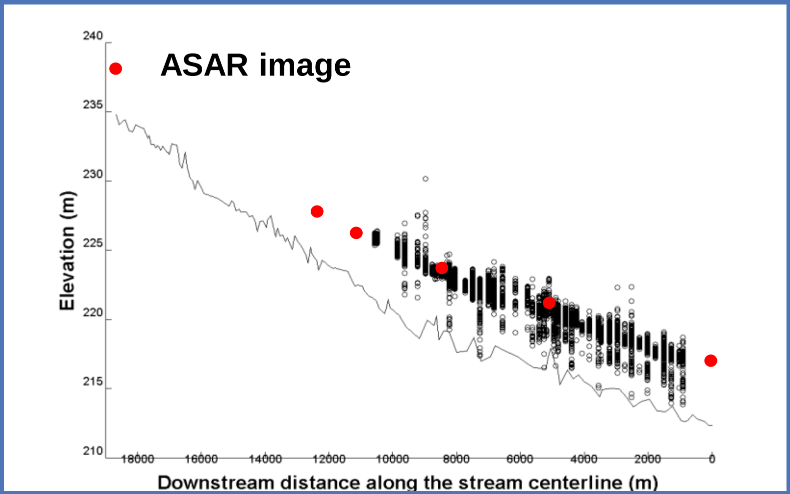


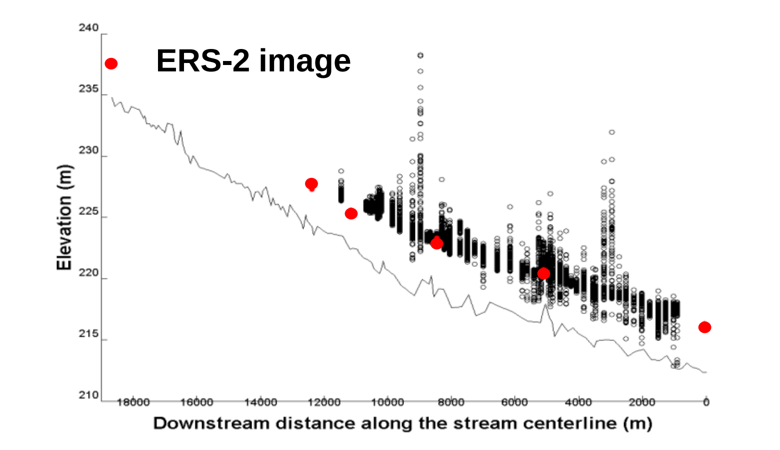
Data ascquisition:

- ERS-2 SAR
- ENVISAT ASAR



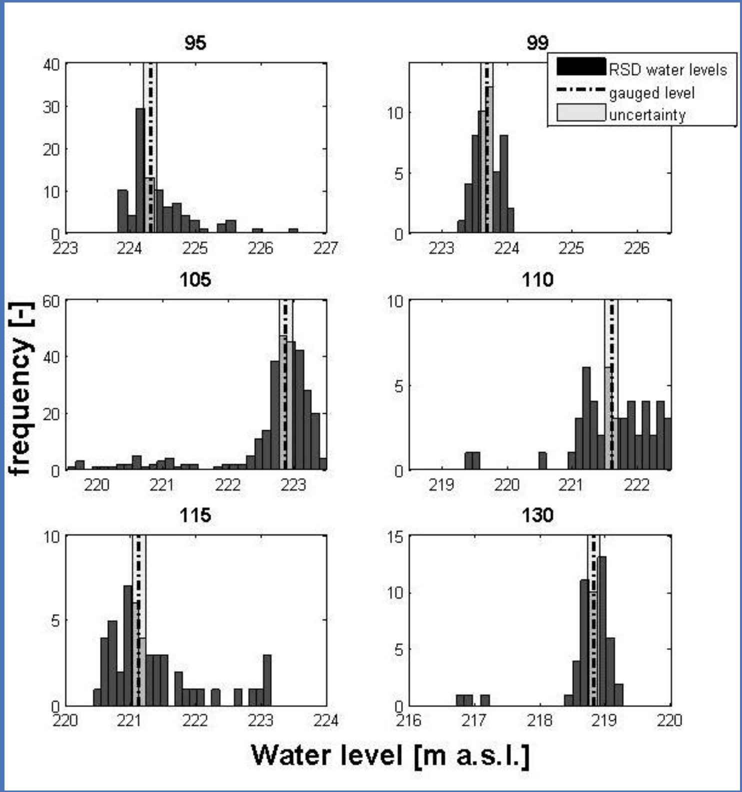
Case study: Water stage retrieval





Sources of uncertainty:

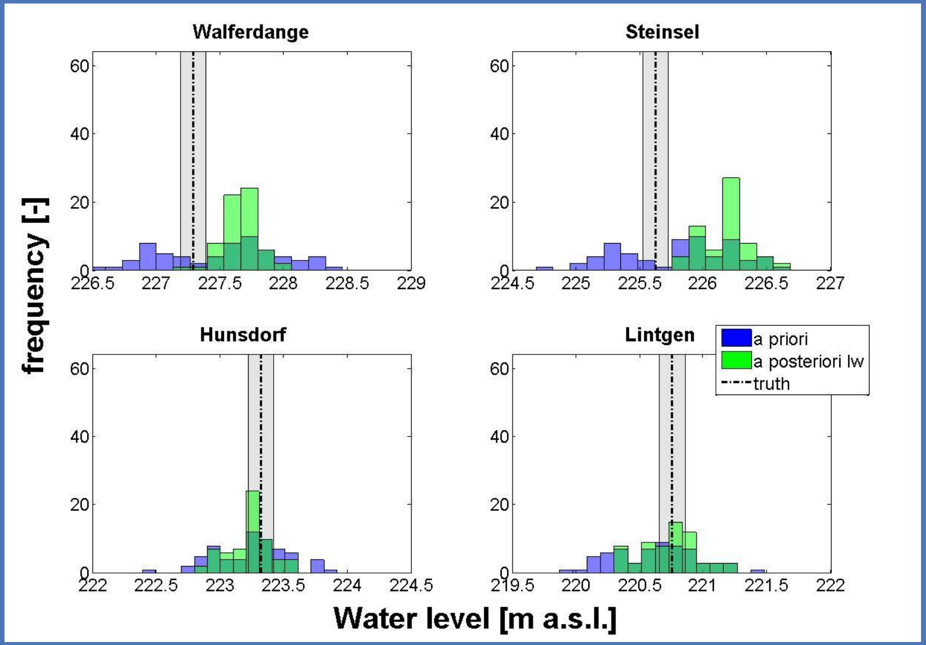
1. Parameters of flood delineation algorithm
2. Uncertainty of DEM



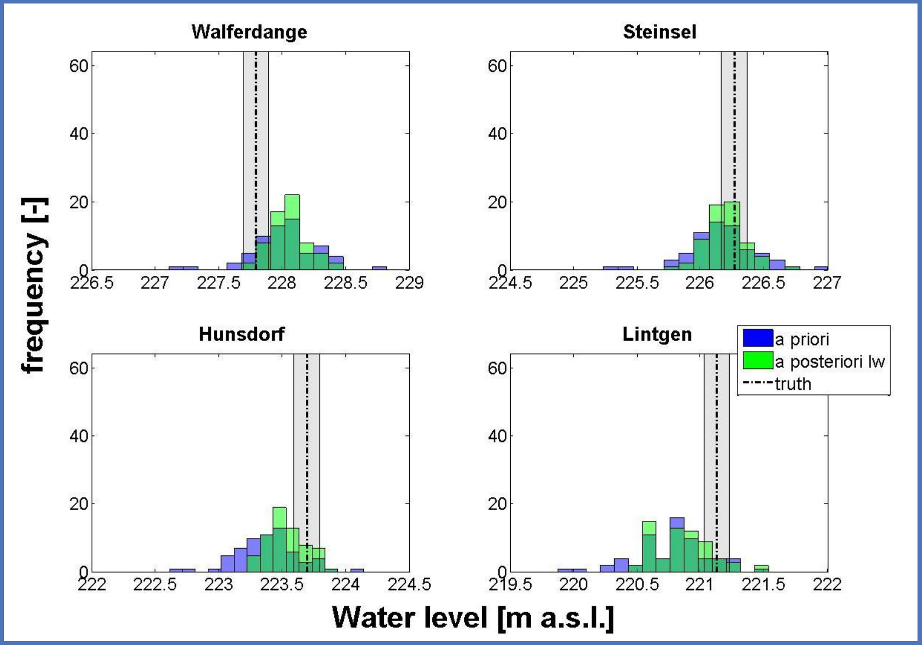
Result:
cross section-specific water level pdf

Results: Water stage assimilation

ERS-2 SAR



ENVISAT ASAR



Result:
- **Reduction of spread**
- **Effectiveness highly variable in space**
- **Bias in observations needs to be removed prior to assimilation**
- **Model performance not uniform**

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Towards operational use

Challenges ahead and possible solutions:

1. Time for acquisition, data delivery and image processing needs to be reduced

   Possible solution: multi-mission data, grid technologies

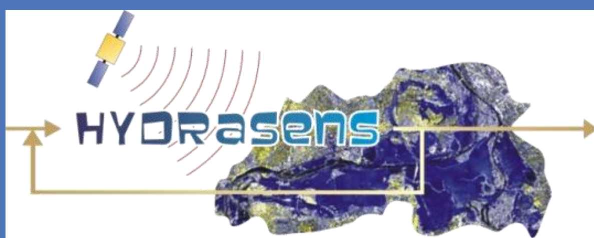
2. Problem related to skewness in observation data needs to be addressed

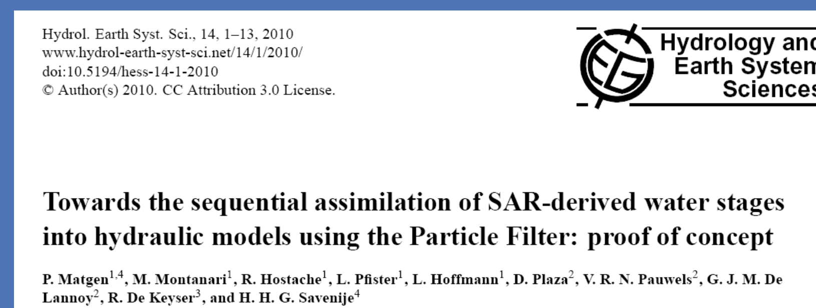
   Possible solution: upcoming SWOT mission, high resolution SAR imagery

3. Lack of sufficient topographic data

   Possible solution: global DEM data for estimating channel bathymetry

Questions ?




Hydrol. Earth Syst. Sci., 14, 1–13, 2010
www.hydrol-earth-syst-sci.net/14/1/2010/
doi:10.5194/hess-14-1-2010

Hydrology and Earth System Sciences

Towards the sequential assimilation of SAR-derived water stages into hydraulic models using the Particle Filter: proof of concept

P. Matgen[1,4], M. Montanari[1], R. Hostache[1], L. Pfister[1], L. Hoffmann[1], D. Plaza[2], V. R. N. Pauwels[2], G. J. M. De Lannoy[2], R. De Keyser[3], and H. H. G. Savenije[4]

Project website:
http://lhwm.ugent.be/hydrasens/

Recent paper:
Matgen et al., HESS, 14(1), 2010

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