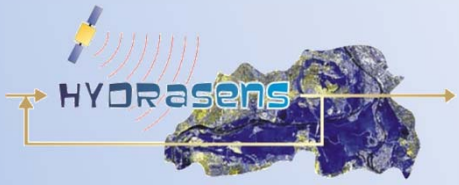

Optimizing a coupled hydrologic-hydraulic model using remotely sensed soil moisture and flood extents

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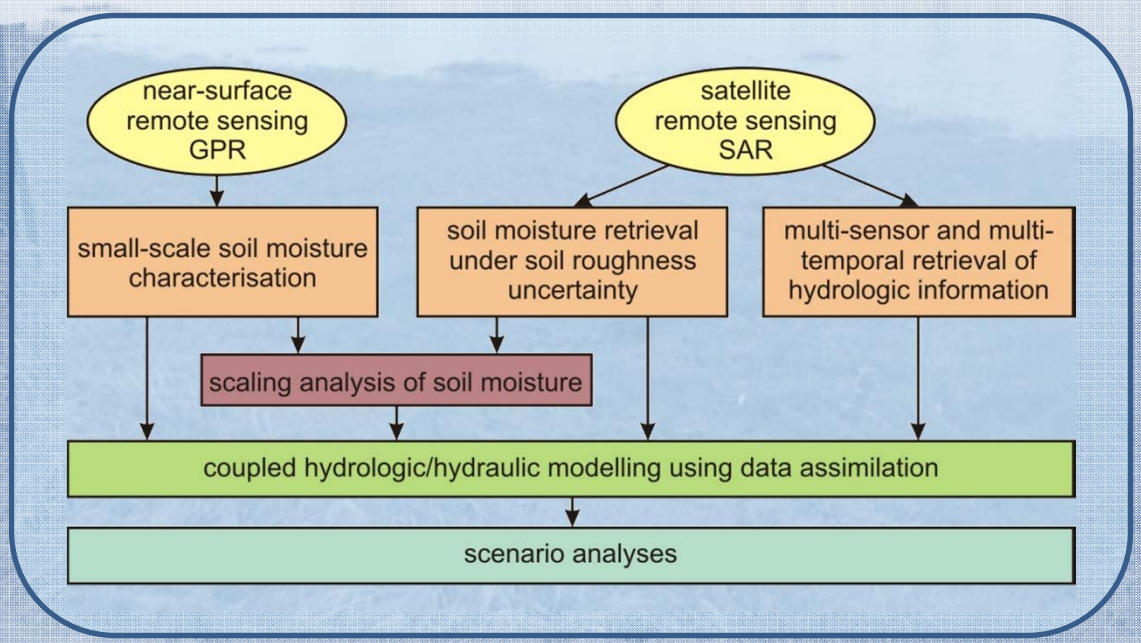
THE HYDRASENS PROJECT

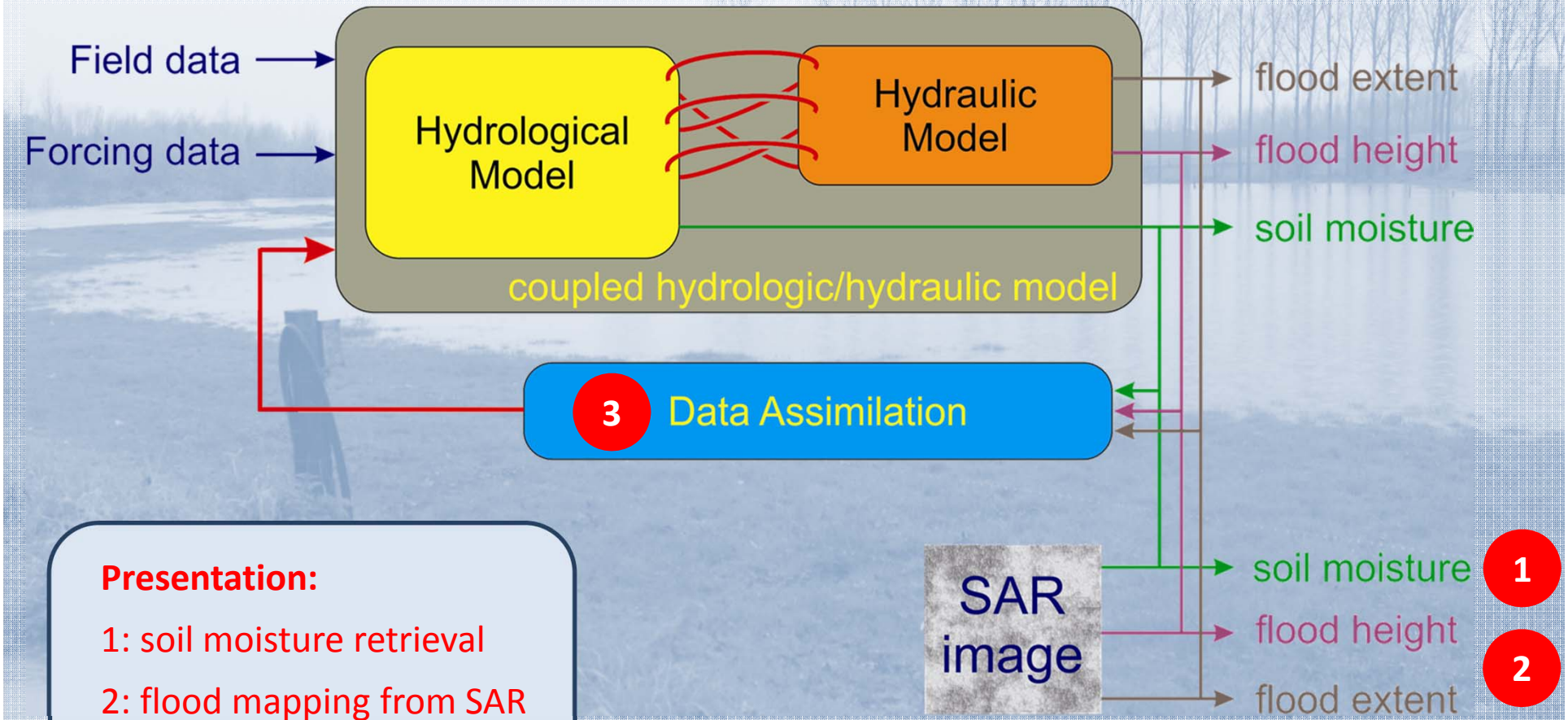
HYDRASENS

- Integrating radar remote sensing, hydrologic and hydraulic modelling for surface water management
- 5-year BELSPO research project (2007-2012)
- 5 Partners: UGent (N. Verhoest, V. Pauwels, B. De Baets), UCL (M. Vanclooster) and CRP-GL (L. Hoffmann)
- Objectives



COMBINING REMOTE SENSING AND MODELLING

How can we combine remote sensing and modelling?



Presentation:

1: soil moisture retrieval

2: flood mapping from SAR

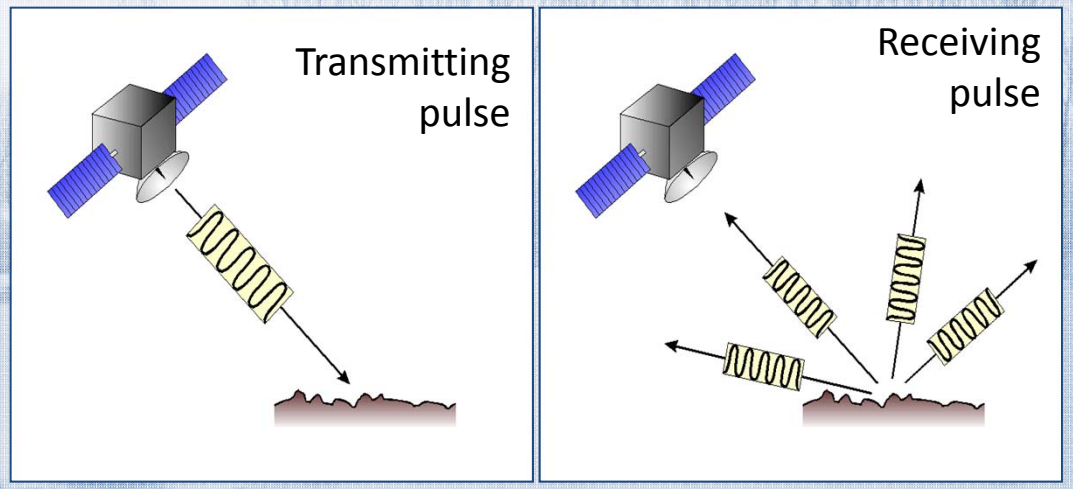
3: assimilation in model

Principle

Radar emits a pulse of microwave energy

Pulse gets scattered at the Earth's surface

Amount of energy scattered back to sensor is measured



Backscattered energy depends on:

- soil moisture content
- soil roughness
- local incidence angle
- vegetation
- electromagnetic properties of the microwave

SOIL MOISTURE RETRIEVAL FROM SAR

Problem: Soil roughness characterization

$$\sigma^0 = f(M_v, s, L, \mathrm{ACF}, \theta, \mathrm{freq}, \mathrm{polarization})$$

$$M_v = f(\sigma^0, s, L, \mathrm{ACF}, \theta, \mathrm{freq}, \mathrm{polarization})$$

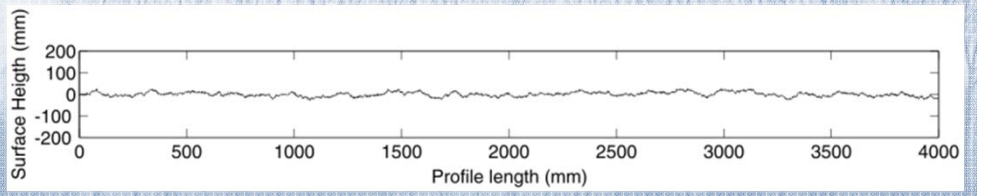
known unknown known

ill-posed problem!

measurements!

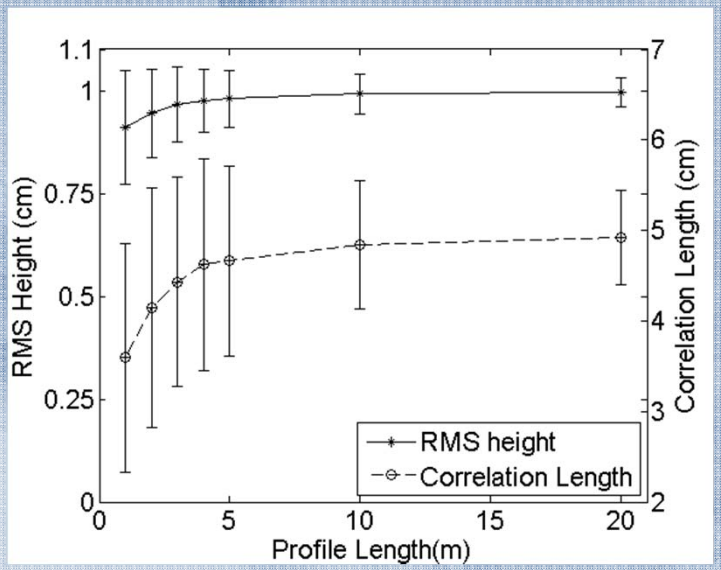
SOIL MOISTURE RETRIEVAL FROM SAR

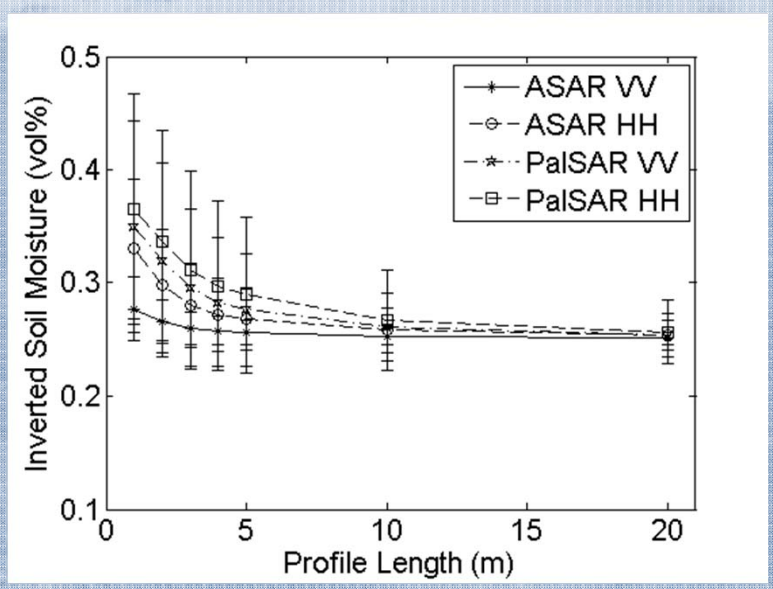
Problem: Soil roughness characterization



Prone to errors!

Largely influences accuracy of soil moisture retrieval

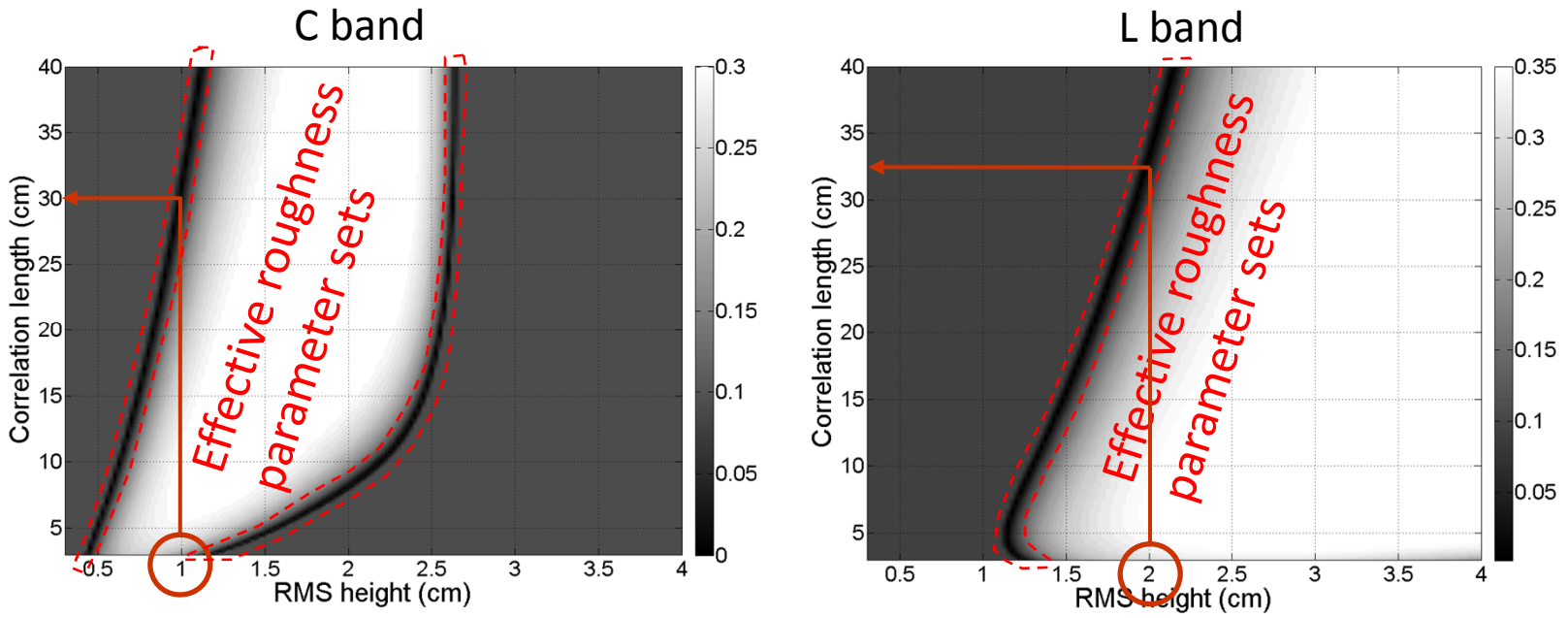




***Solution*: Effective Soil Roughness Parameters**

Determine roughness parameters as 'needed' by the model

⇒ Calibrate roughness!

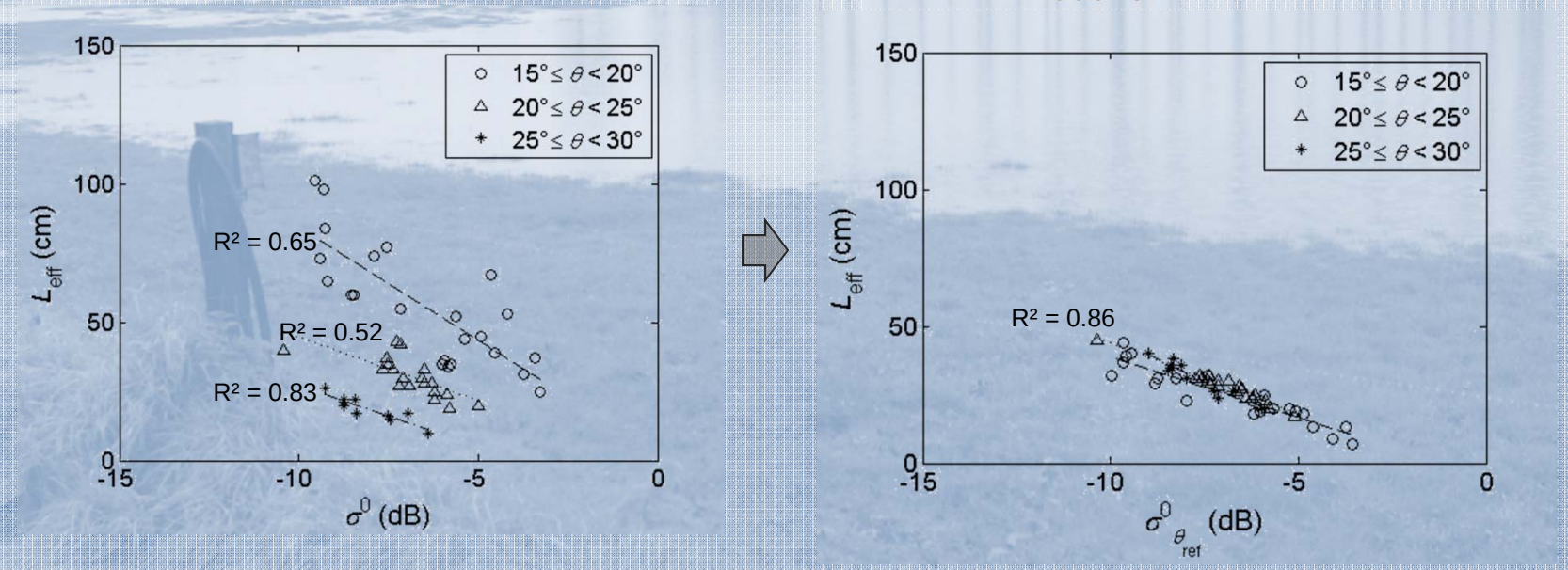


Effective correlation length, corresponding to an RMS height of 1 or 2 cm

***Solution*: Effective Soil Roughness Parameters**

- *effective roughness parameter* depends on:
  - Backscatter (σ^0)
  - Incidence angle (θ)
- Normalization of backscatter to θ_{ref} (= 23):

$$\sigma^0_{\theta_{ref}} = \sigma^0 \frac{\cos^2\theta_{ref}}{\cos^2\theta}$$



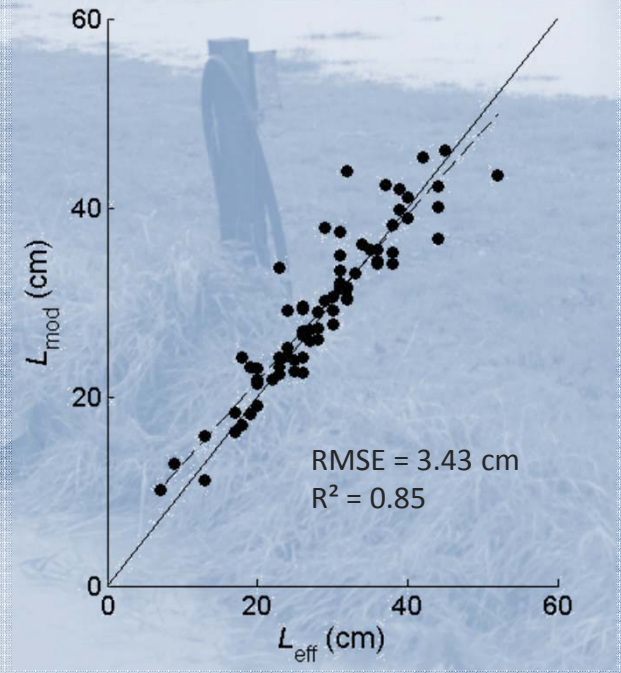
The effective correlation length L_{eff}, which by definition leads to perfect soil moisture retrieval, displays a linear relationship with normalized backscatter $\sigma^0_{\theta_{ref}}$

Solution: Effective Soil Roughness Parameters

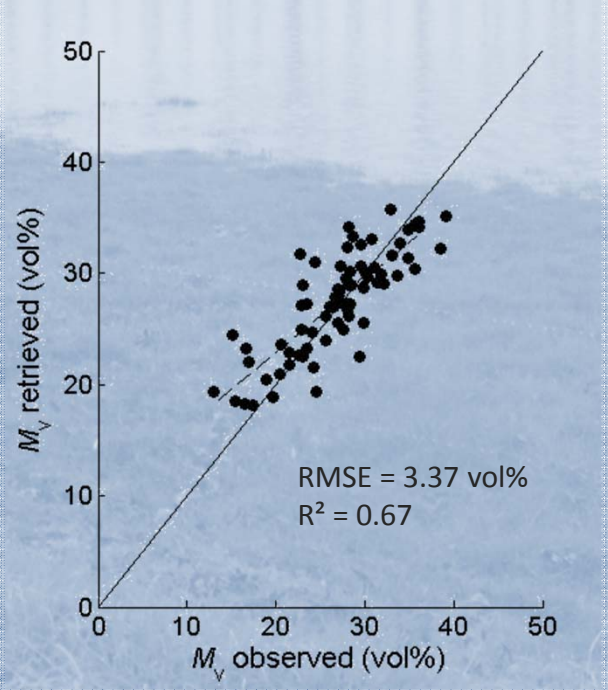
- Relationship between L_{eff} and Radarsat-1 backscatter modeled through linear regression:

$$L_{mod} = a + b\sigma^0_{\theta_{ref}}$$

- Retrieval of field average effective correlation length

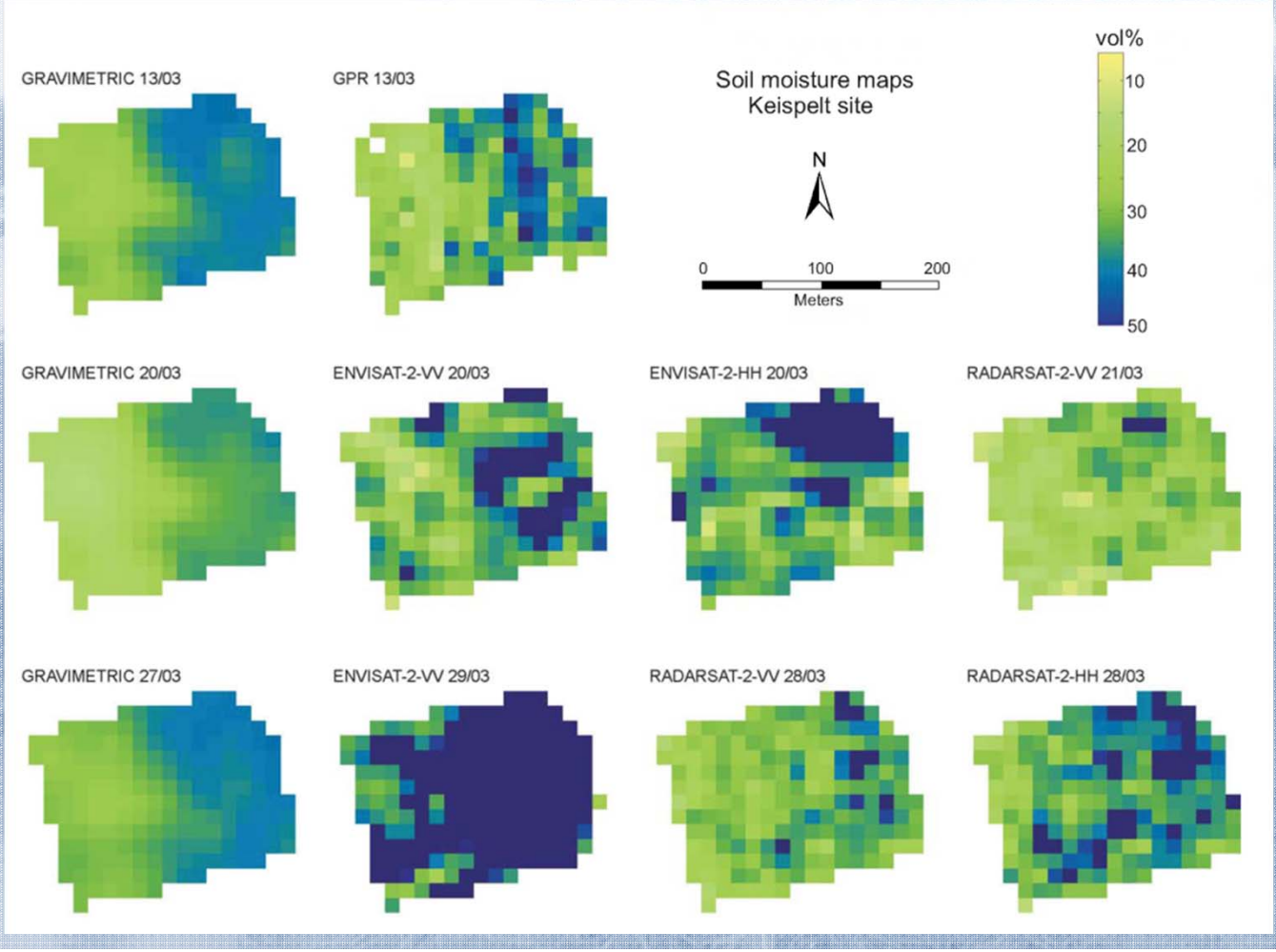


- Soil moisture retrieval based on the IEM, with L_{mod} and s = 1 cm



Solution: Effective Soil Roughness Parameters

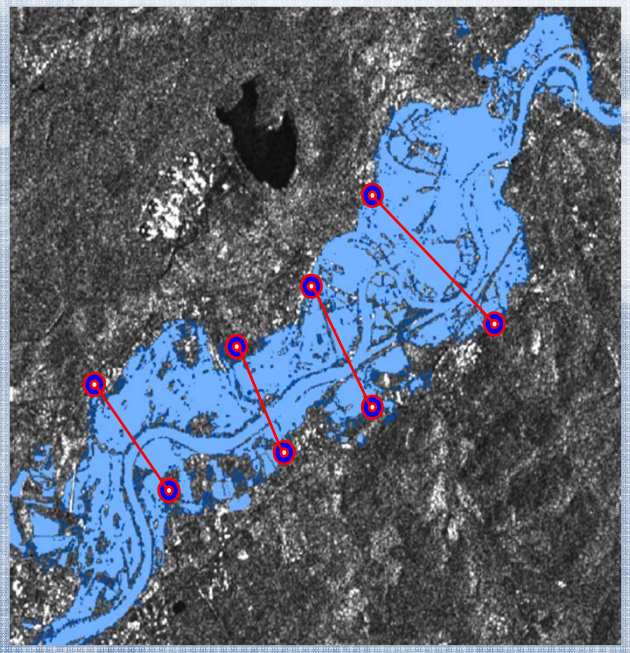
Comparison with field campaigns (gravimetric + GPR)

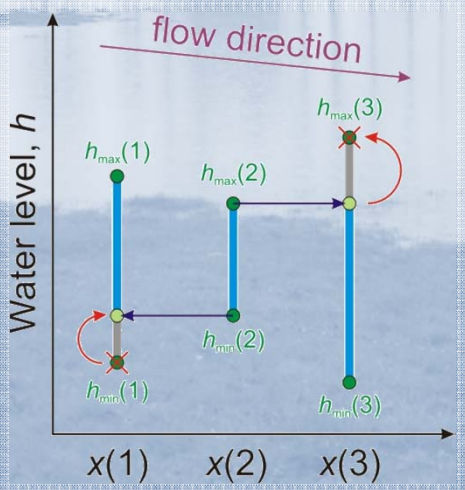


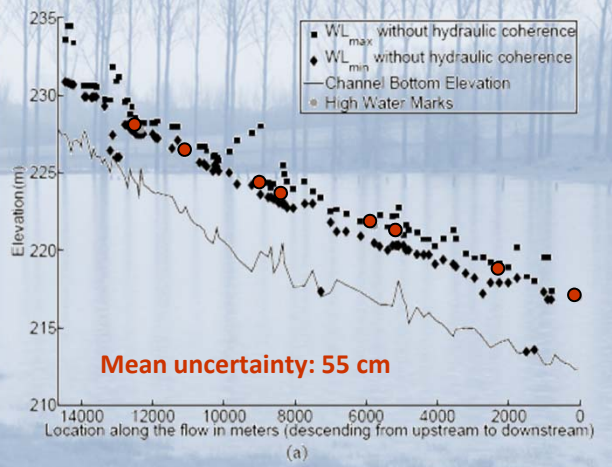
FLOOD MAPPING FROM SAR

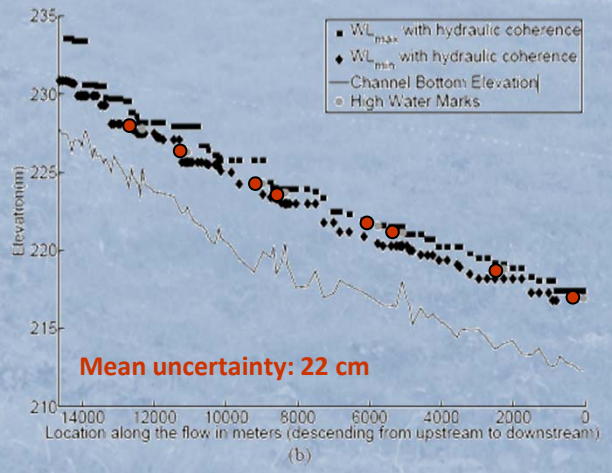
***Problem*: Floodplain delineation prone to errors and uncertainty**

***Solution*: Make use of DEM + hydraulic principles**





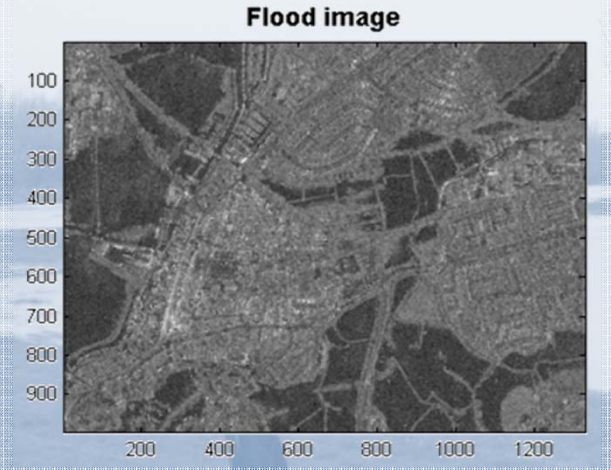


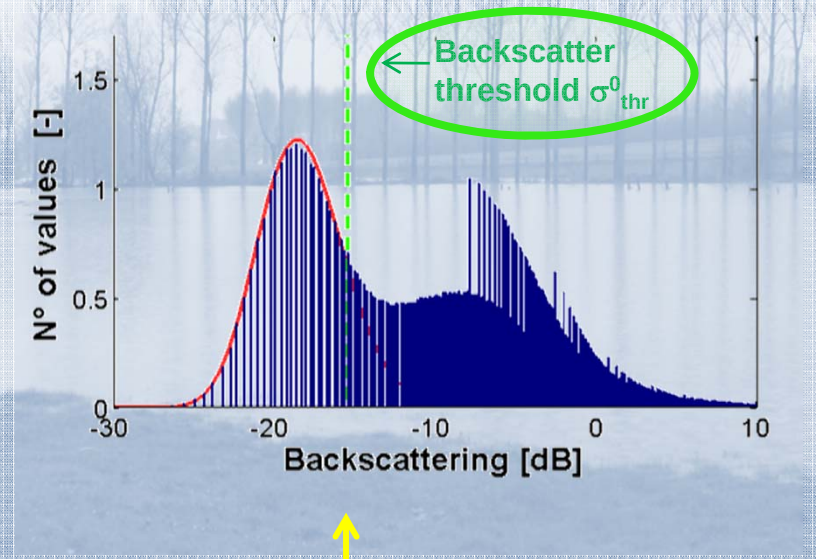


FLOOD MAPPING FROM SAR

***Problem*: Floodplain delineation prone to errors and uncertainty**

***Solution*: Optimize threshold for flooded pixel**





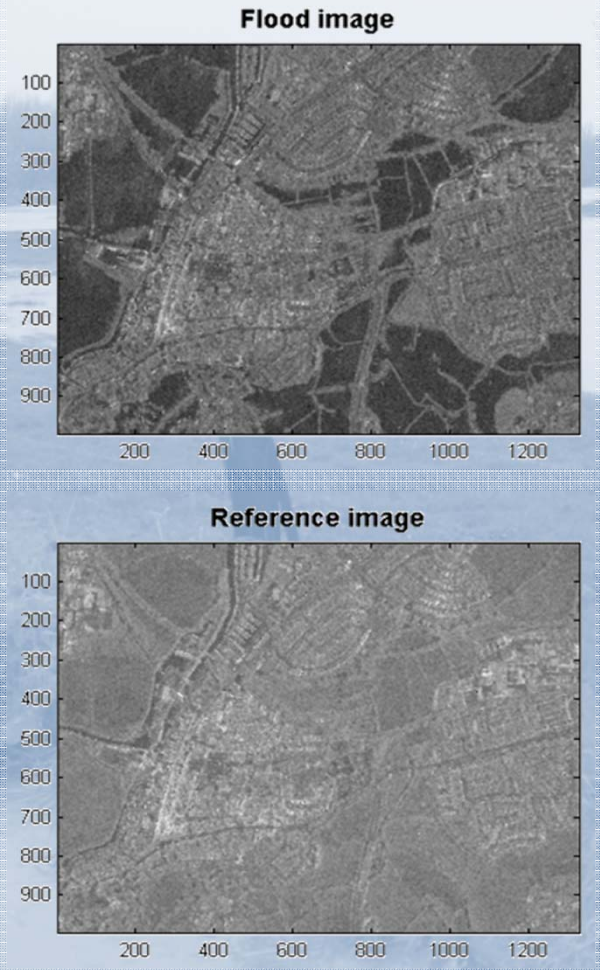
minimal threshold that ensures good fit of gamma distribution for open water bodies

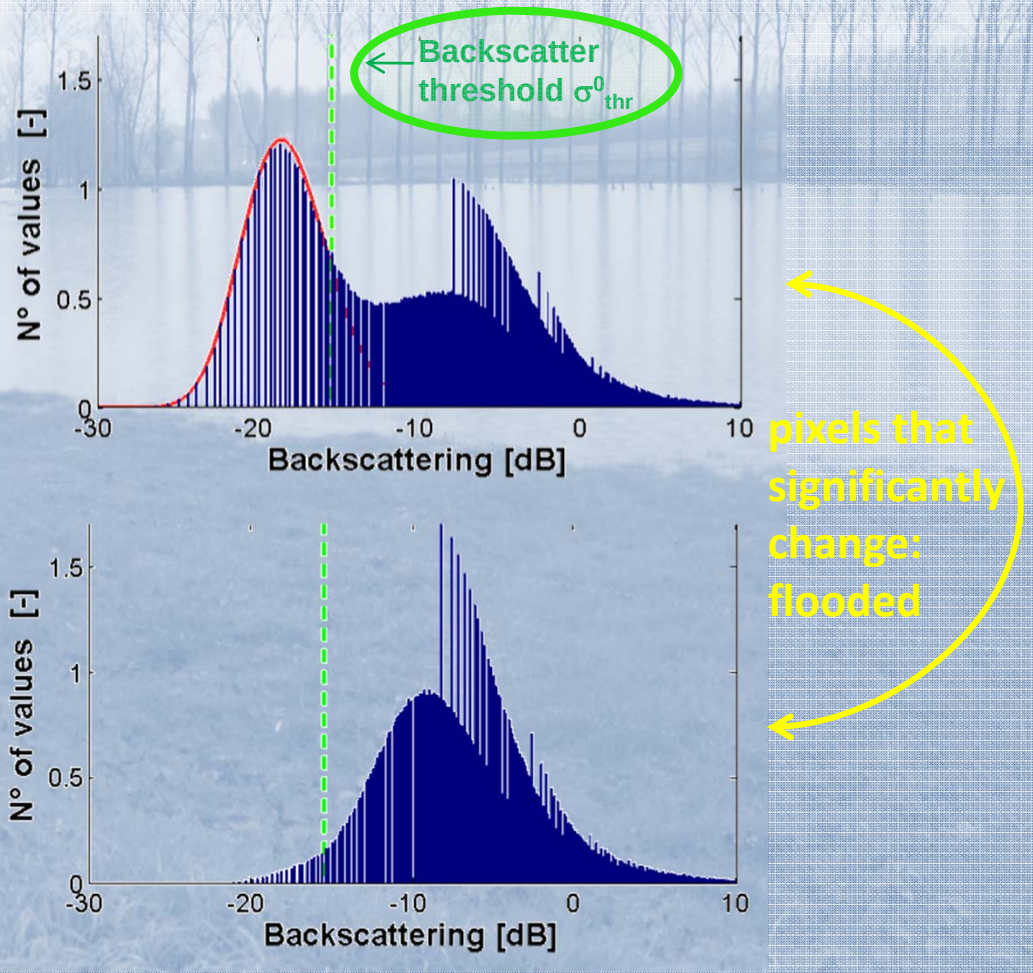
region growing + change detection with non-flooded image

FLOOD MAPPING FROM SAR

***Problem*: Floodplain delineation prone to errors and uncertainty**

***Solution*: Optimize threshold for flooded pixel**

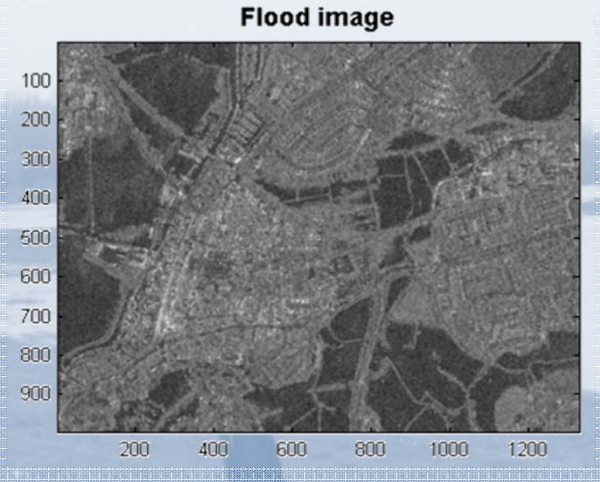


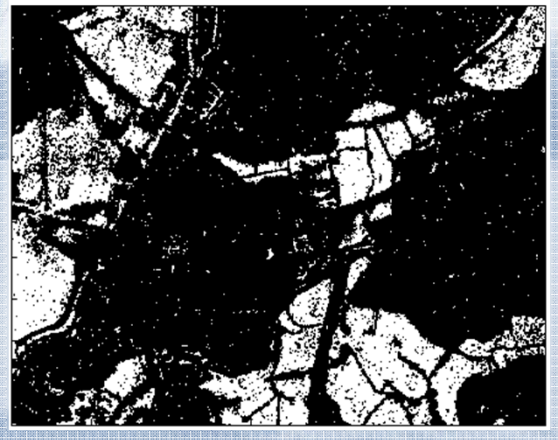


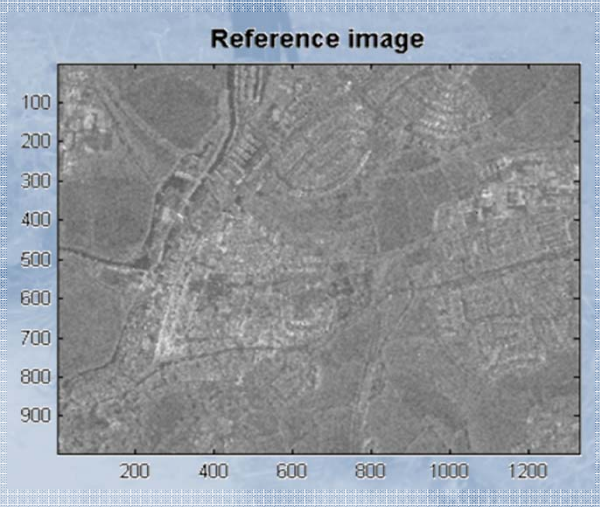
FLOOD MAPPING FROM SAR

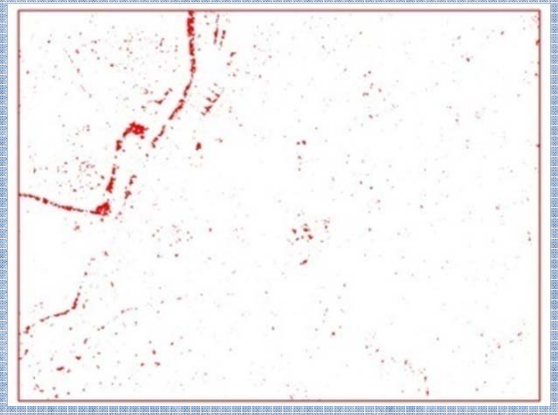
***Problem*: Floodplain delineation prone to errors and uncertainty**

***Solution*: Optimize threshold for flooded pixel**



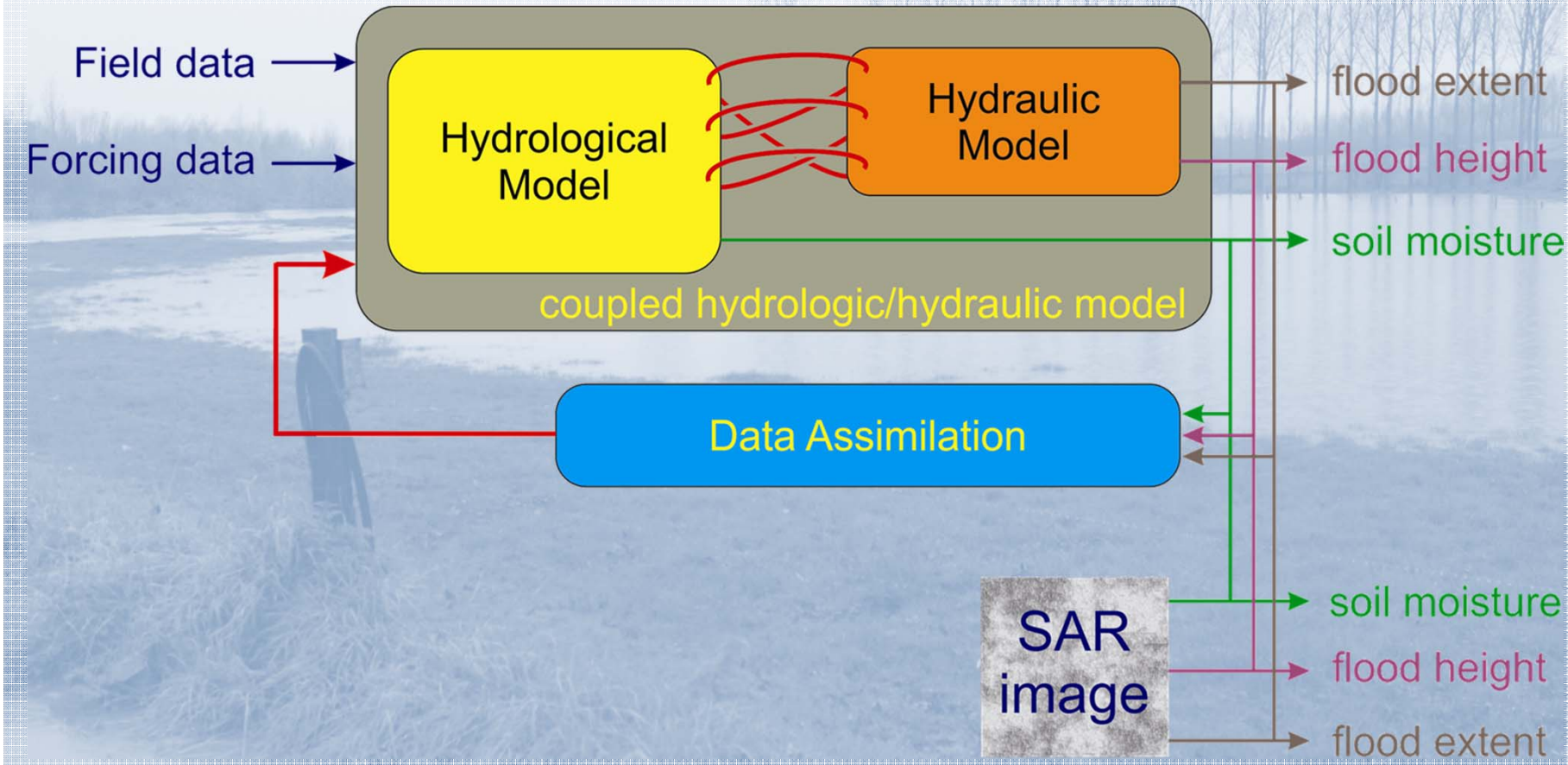






DATA ASSIMILATION

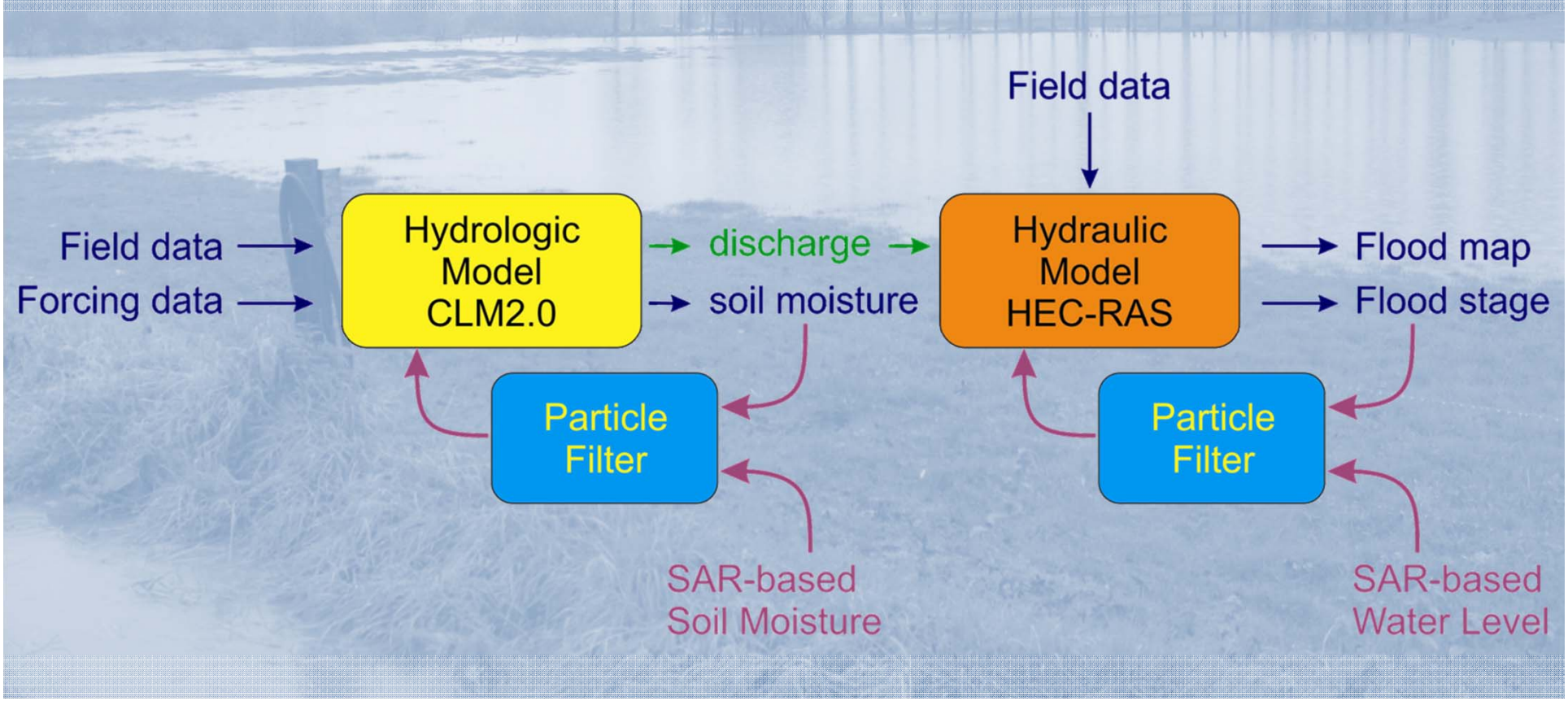
Objective 3: Assimilation of the remote sensing products



Objective 3: Assimilation of the remote sensing products

Solution:

1. Loose coupling hydrologic and hydraulic model
2. Data assimilation framework



Objective 3: Assimilation of the remote sensing products

Case study: Alzette (Luxembourg)

- 356 km^2 drainage area: CLM2.0
- 19 km reach (Pfaffenthal ⟶ Mersch): HEC-RAS

Objective 3: Assimilation of the remote sensing products

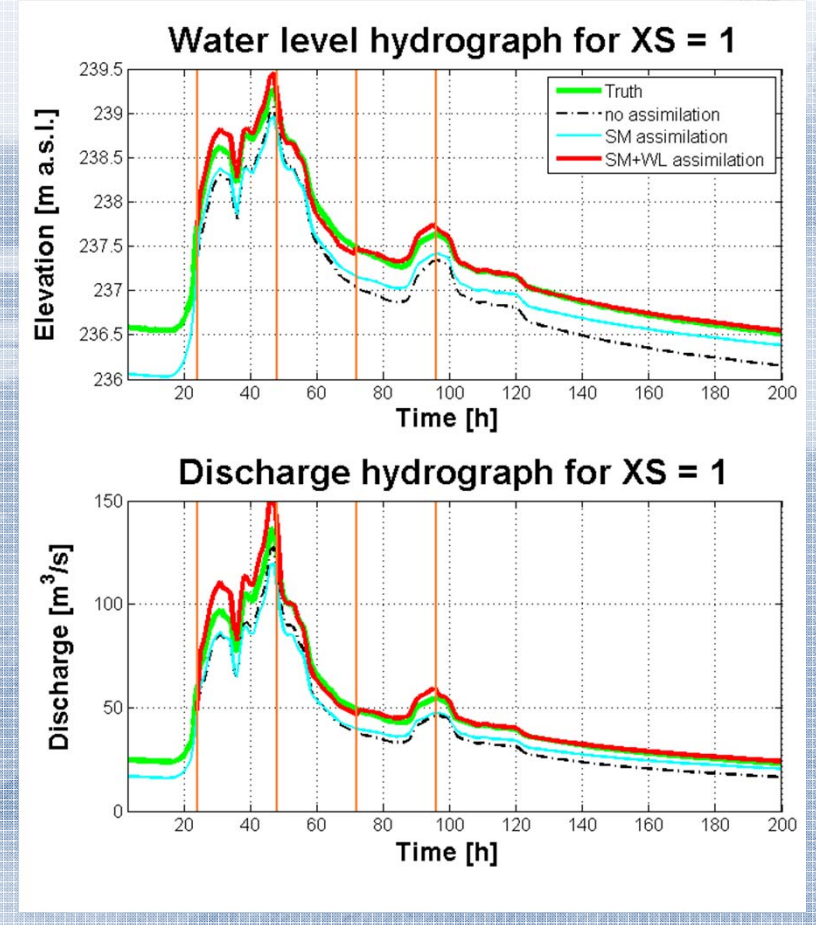
Case study: Alzette (Luxembourg)

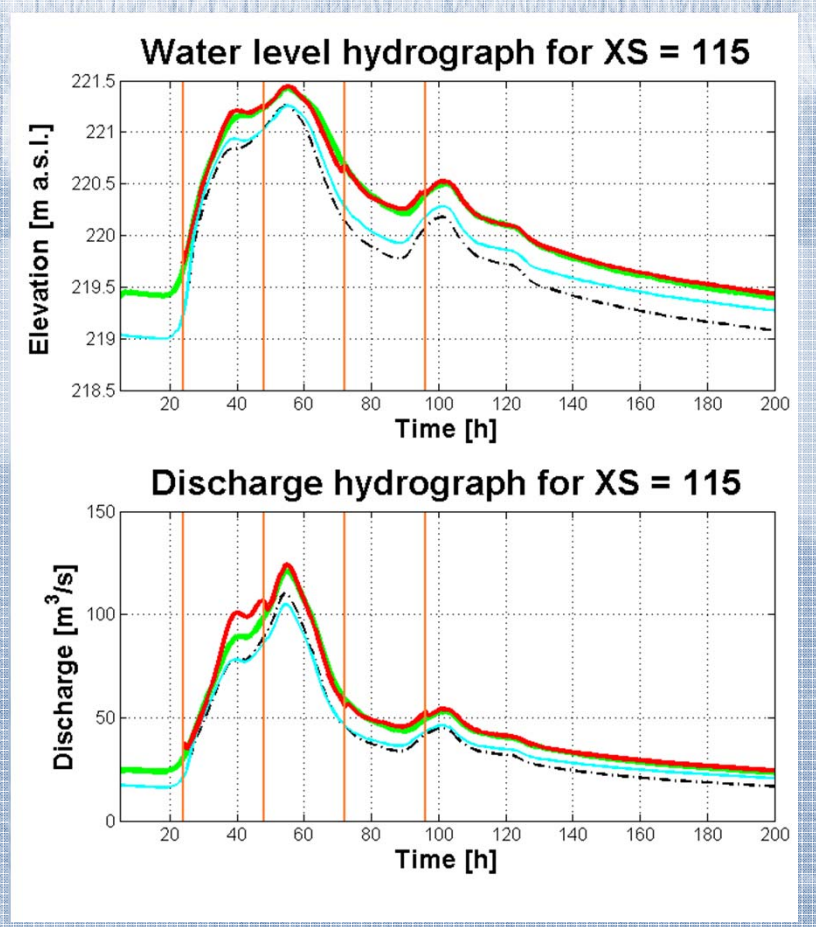
- 356 km^2 drainage area: CLM2.0
- 19 km reach (Pfaffenthal ⟶ Mersch): HEC-RAS

Different scenario's

- No assimilation ('open loop')
- Assimilation of soil moisture data (one observation every 24 hours)
- Assimilation of water level data (one observation every 24 hours)
- Joint assimilation of soil moisture and water level data (one synchronous observation of soil moisture and water level every 24 hours)

Objective 3: Assimilation of the remote sensing products





Objective 3: Assimilation of the remote sensing products

joint assimilation: advantage?

flooding conditions:

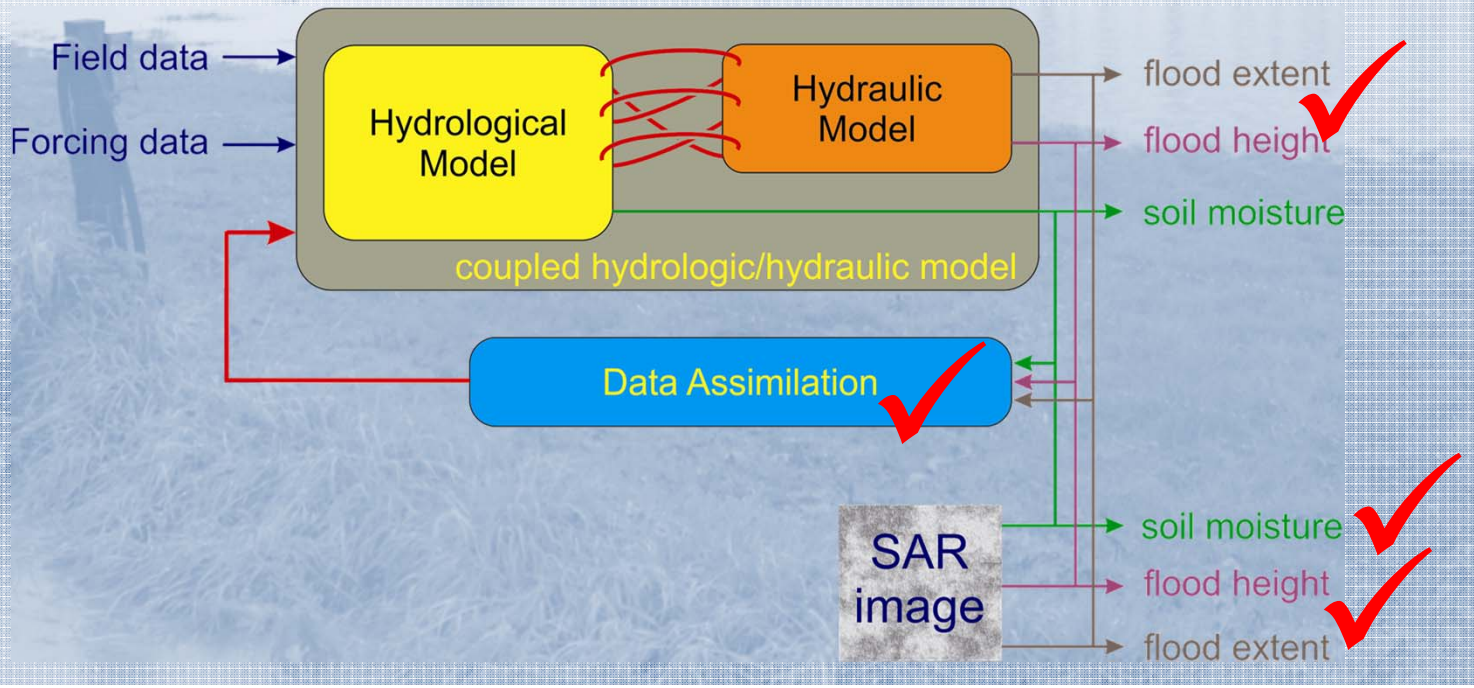
- soil moisture: accurate (very moist to saturated) ⇐ **Steers the model**
- discharge: less accurate

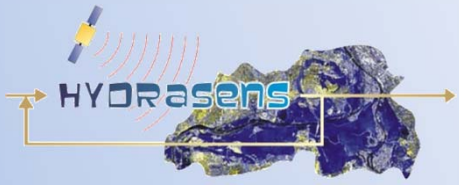
dry conditions:

- soil moisture: less accurate (high variability)
- discharge: high accuracy ⇐ **Steers the model**

CONCLUSIONS

1. Soil moisture retrieval from SAR: soil roughness problem is circumvented
2. Spatial patterns of soil moisture correspond to GPR-based data
3. Flood mapping improved based on hydraulic principles and change detection
4. Data assimilation: Particle Filter is superior to Kalman Filter
5. Joint assimilation of soil moisture and water stage merits model prediction





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thank you for your attention

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