Characterization of soil surface properties using radar remote sensing

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Soil parameters and Remote Sensing

- Soil parameters mapping in agricultural areas and especially soil moisture and surface roughness is very usefull for many applications in hydrology, agriculture and risk.

- The free availability of quality remote sensing data encourages the development of operational algorithm for soil parameters mapping at high spatial and temporal resolutions

  - ✓ **Copernicus sensors:** Sentinel-1 radar and Sentinel-2 optical satellites provide data at high spatial resolution (10 m for S1 and 10 to 60 m for S2) and high revisit time (6 days for S1 and 5 days for S2)

  - ✓ Landsat …

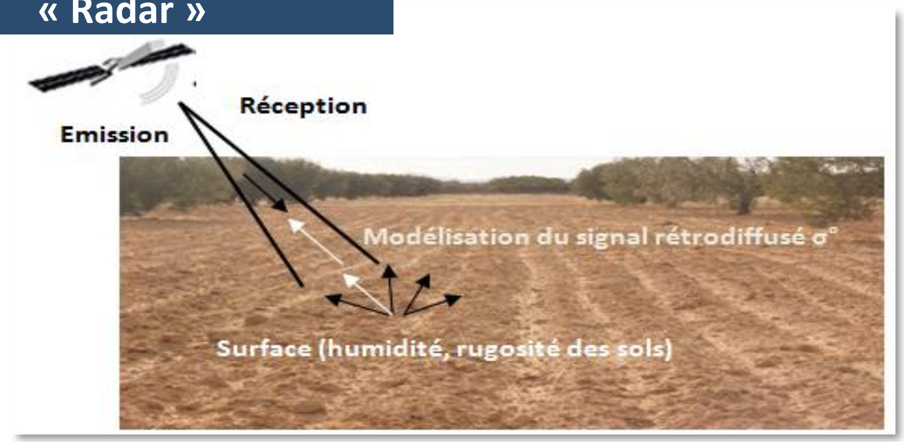
- Radar sensors = Active systems = allow mapping whatever the meteorological conditions (clouds, etc.), both day and night. This is not the case with optical sensors (no data if clouds)

- Radar sensors are sensitive to soil moisture and surface roughness whereas optical sensors are sensitive to vegetation development (chlorophyll, hydric stress, biomass …)

Approach to study soil parameters

✓ Remote Sensing

« Radar »



MODELLING RADAR BACKSCATTERING

- **Radar observation parameters:** (frequency , incidence angle,…)
- **Soil surface parameters:** (**soil moisture,** roughness..)

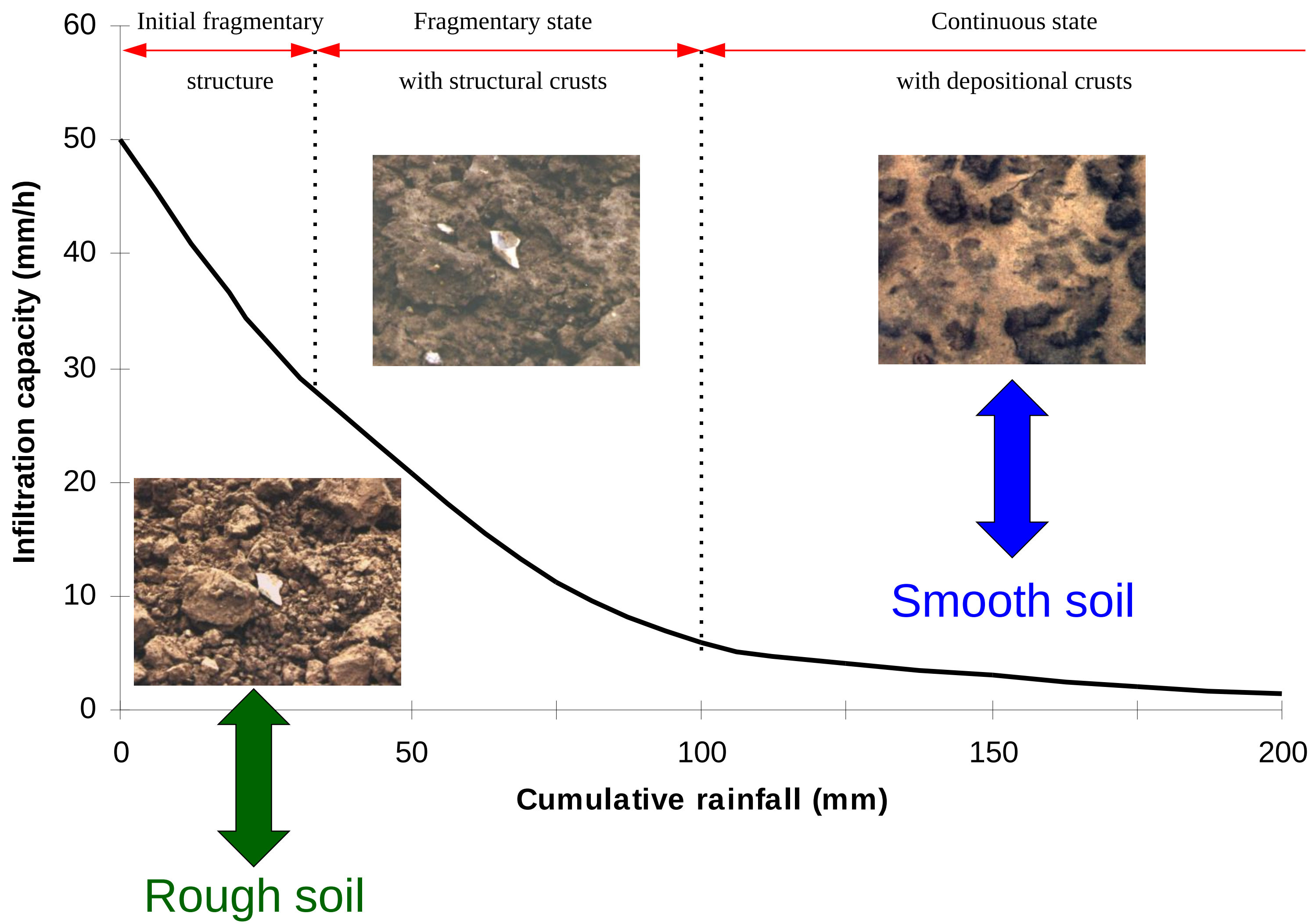
Electromagnetic backscattering Models (Kirchoff, Dubois, Oh, Integral Equation Model …)

Radar Backscatter σ^0

RADAR SIGNAL INVERSION

Relationship between surface roughness and runoff

- Smooth soil has a poor infiltration capacity compared to rough soils

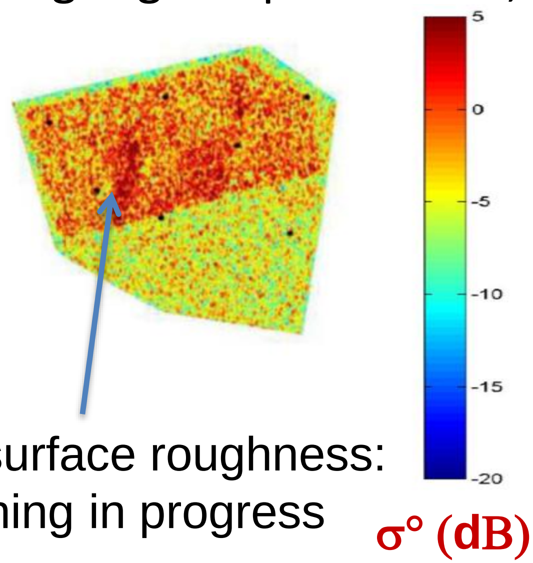


Sensitivity of radar signal to soil roughness

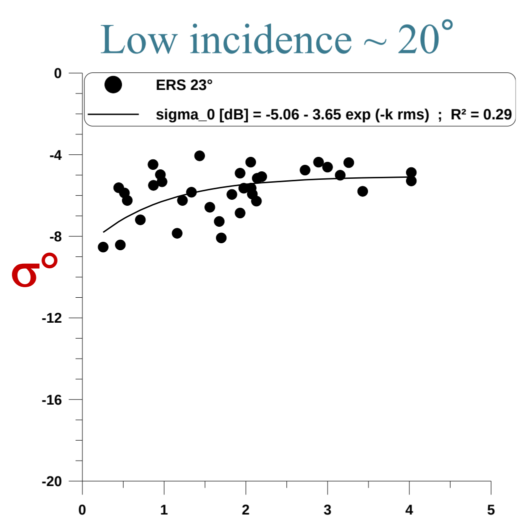
- Radar signal backscattered by a bare soil increases with the surface roughness (*Hrms*) according to a logarithmic or exponential law to then become constant after a certain roughness threshold (depends on the wavelength and the radar's incidence angle).

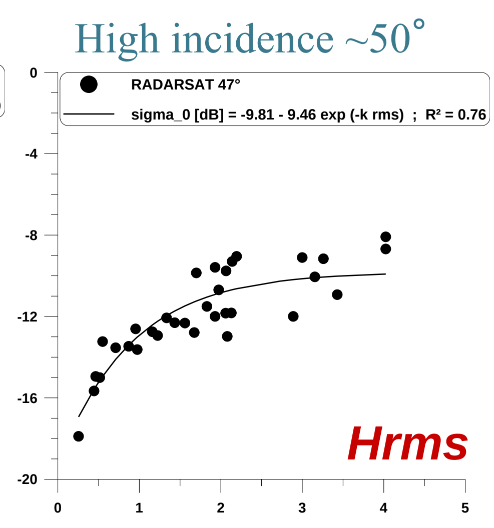
- This threshold corresponds to *Hrms* values of 4 cm in L-band, 1 cm in C-band, and around 0.5 cm in X-band.

- Only large wavelengths (e.g. L-band) and strong incidence angles (e.g. 45º) allow to map three roughness classes (smooth "sowing," rough "great plowed soil," moderately rough "small plowed soil").



High surface roughness: ploughing in progress

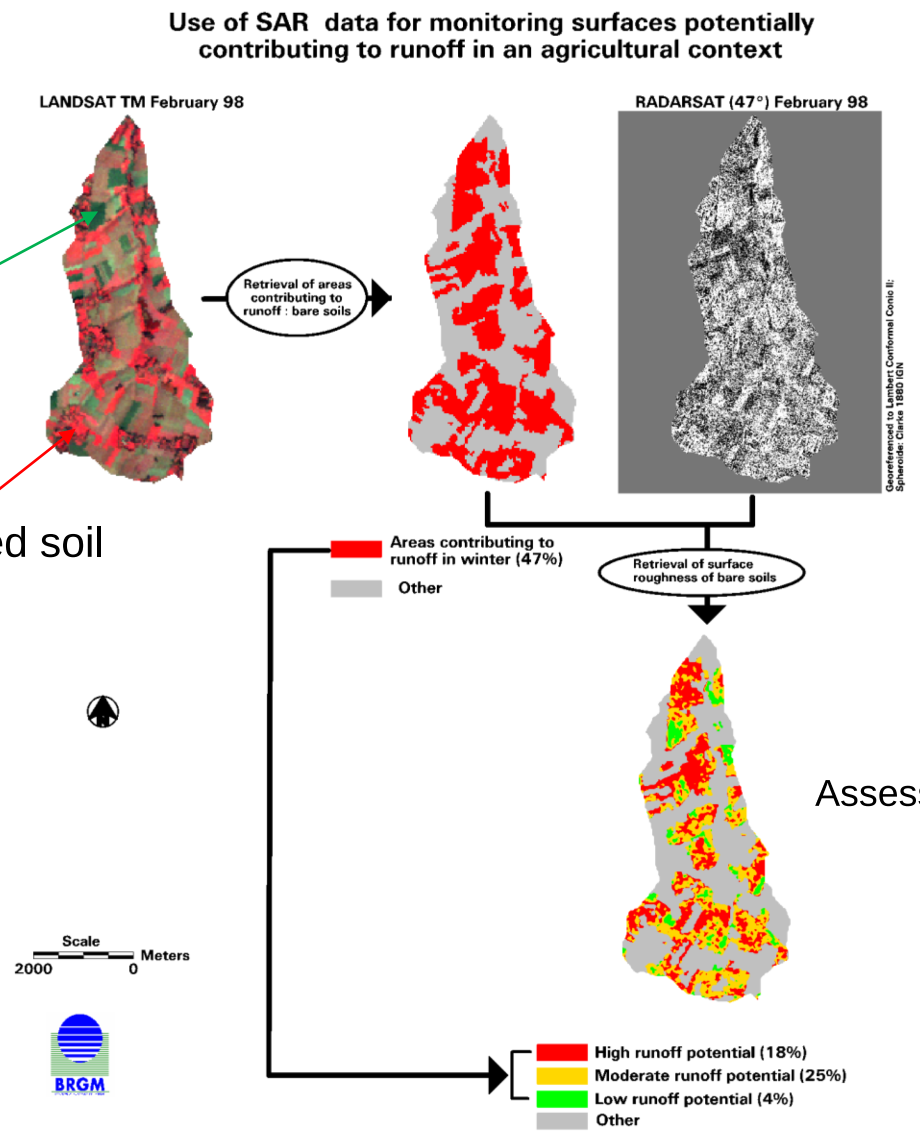




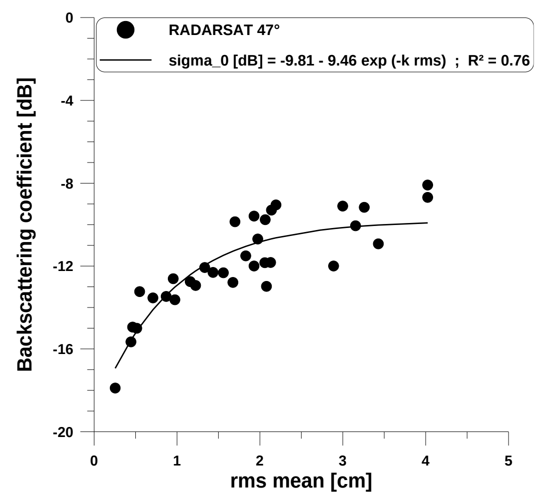
Mapping of areas contributing to runoff

Bare soil

Vegetated soil



σ° RADARSAT 50°



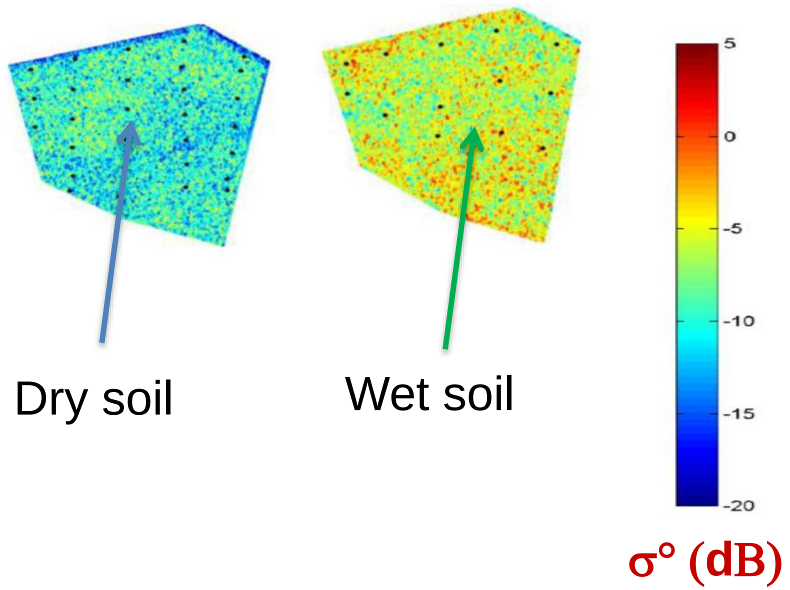
rms

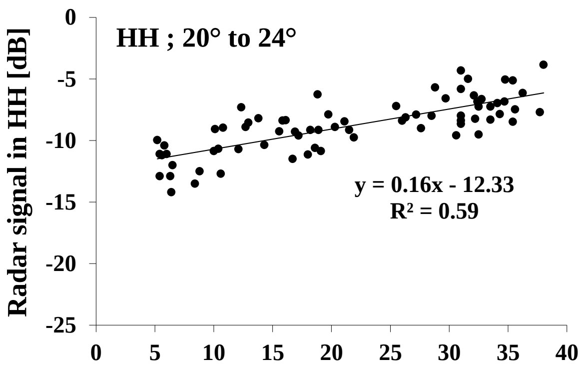
Assess to areas contributing to runoff

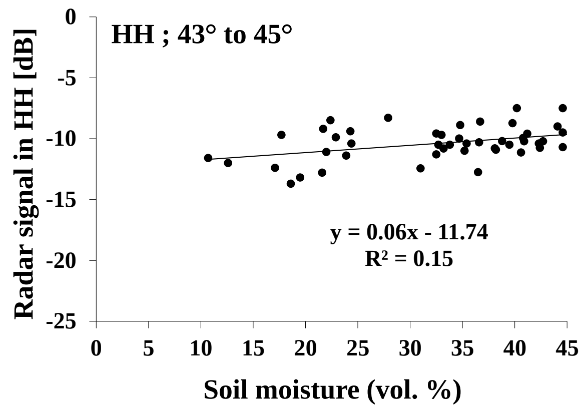
Sensitivity of radar signal to soil moisture

- Radar signal increases with the soil moisture (*SSM*) according to a logarithmic law. After a soil moisture of around 35 vol.%, the radar signal starts to decrease with the increase of *SSM* ➔ Estimation of *SSM* cannot be done after this threshold of around 35 vol.%.

- Optimal configuration for obtaining the best sensitivity of the radar signal to soil moisture (weak influence of the roughness): weak radar incidence angle (15º-35º) and low radar wavelength (X-band).







An operational high resolution Soil moisture retrieval algorithm using Sentinel images

Introduction

- Currently, several satellite missions provide surface soil moisture estimations at different spatial resolutions (low to medium spatial resolutions):

    - ✓ SMAP: 36 km x 36 km, 9 km x 9 km, 1 km x 1 km
    - ✓ ASCAT: 25 km x 25 km, 12.5 km x 12.5 km, 1 km x 1 km
    - ✓ SMOS: 25 km x 25 km
    - ✓ New: Copernicus Land distributes the first soil moisture estimations over the European continent at 1-km using S1 data

- An operational approach for mapping soil moisture at high spatial resolution (plot scale) in agricultural areas was developed by coupling S1 and S2 images:

    - ✓ based on the inversion of the Water Cloud Model (WCM) combined with the modified IEM, and using the neural networks technique
    - ✓ **S^{2}MP: Sentinel-1/Sentinel-2 derived soil Moisture at Plot scale**

Water Cloud Model (WCM)

➢ **Vegetated cover soil:** (Attema and Ulaby 1978)

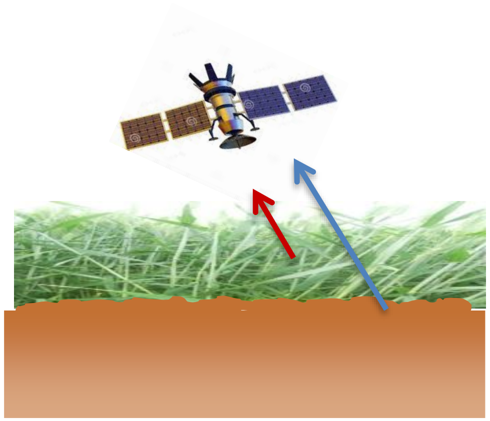
$$\sigma^0_{tot} = \sigma^0_{veg} + T^2\,\sigma^0_{soil}$$

$$\sigma^0_{veg} = A.V_1.\mathrm{Cos}\,\theta\ (1 - T^2)$$

$$T^2 = \mathrm{Exp}\,(-2.B.V_2.\sec\theta)$$

σ^0_{soil} = computed using the IEM calibrated by Baghdadi et al. (correlation length is replaced by a fitting parameter)

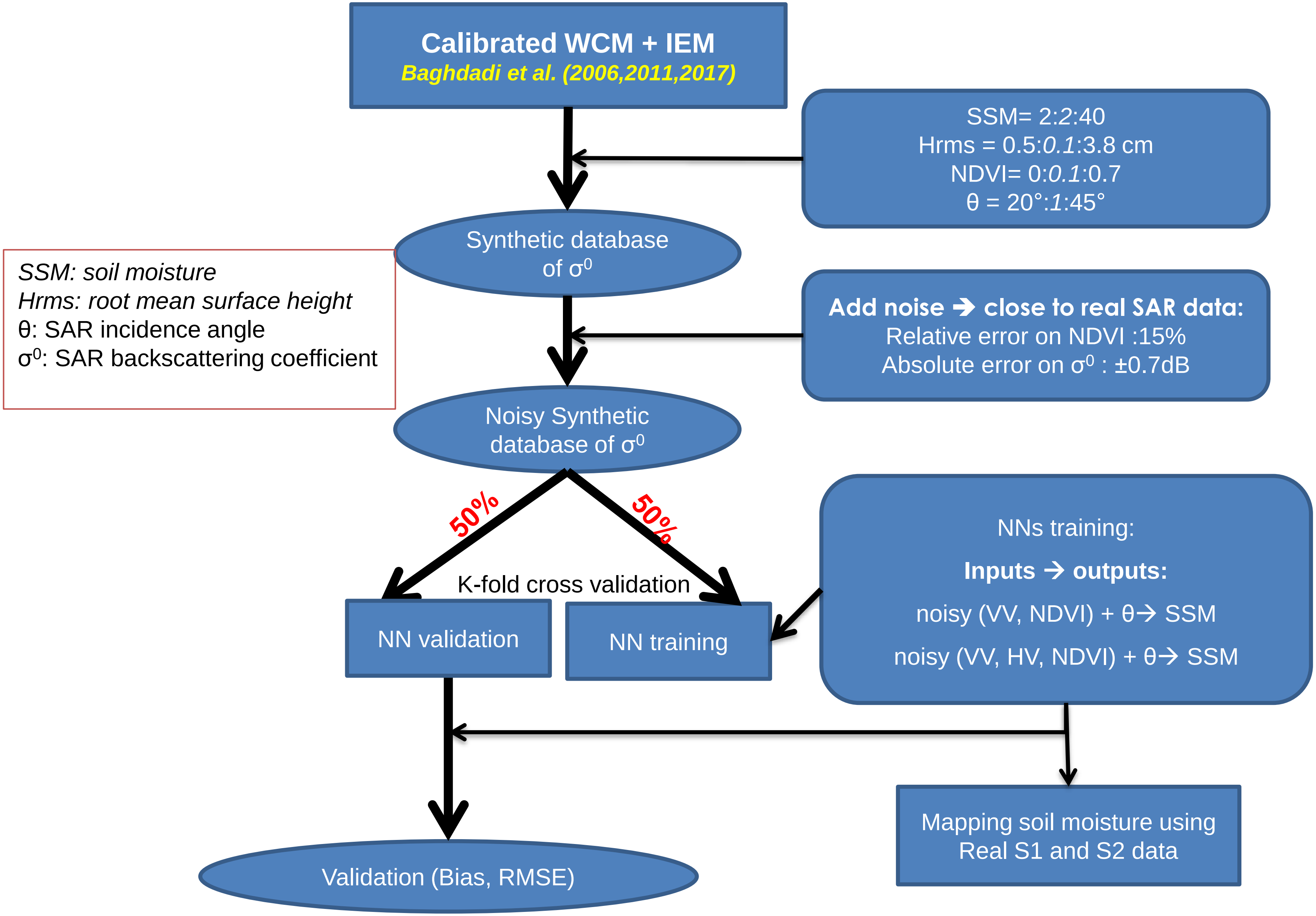
- σ^0_{tot} : backscattered radar signal (linear unit)
- $\boldsymbol{\sigma^0_{veg}}$ **:** Vegetation contribution (linear unit)
- $\mathbf{T^2}$ **:** Attenuation
- $\boldsymbol{\sigma^0_{soil}}$ **:** Soil contribution (linear unit)
- $\mathbf{V_1 = V_2}$ **:** vegetation descriptors (BIO (kg/m2), VWC (kg/m2), HVE (m), LAI (m2/m2), FAPAR, FCOVER, and **NDVI**)
- **θ :** Incidence angle
- **A et B:** fitting parameters depend on vegetation descriptors and radar configuration



➢ **Estimation of *SSM only for crops and grassland***

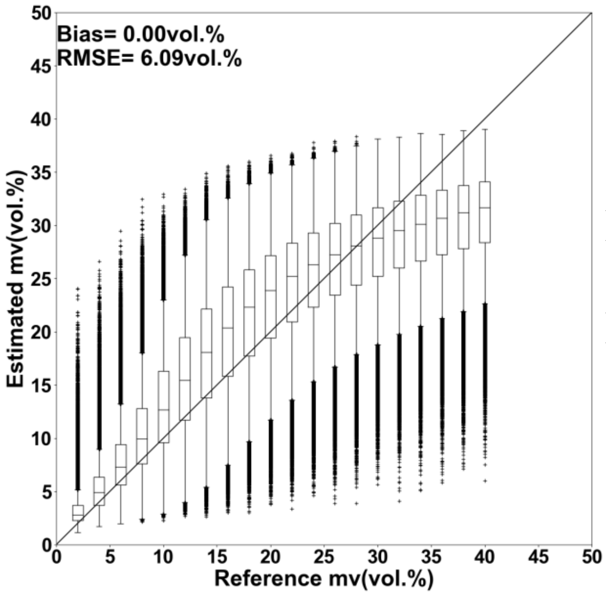
➢ **Main limitation: NDVI > 0,7 (low penetration of the radar signal in C-band)**

Methodology



Results (1/2) : synthetic database

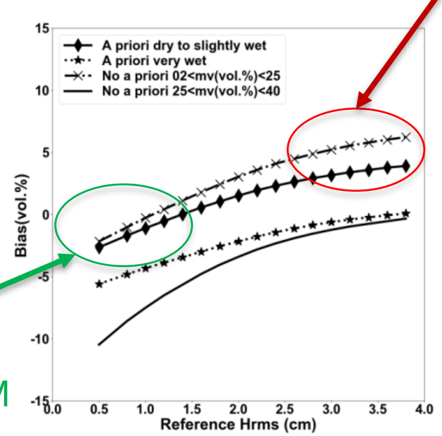
NN: VV + NDVI+ θ ➔ mv

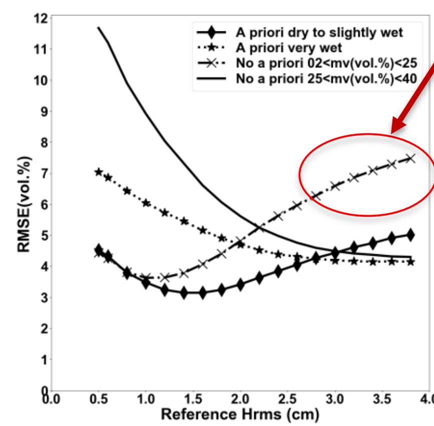


- For *SSM* < 25 vol.% : bias = 2.7 vol.% & RMSE = 5.5 vol.%
- For *SSM* > 25 vol.% : bias = −4.1 vol.% & RMSE = 6.9 vol.%

Over-estimation of *SSM* for high roughness

High RMSE for high roughness



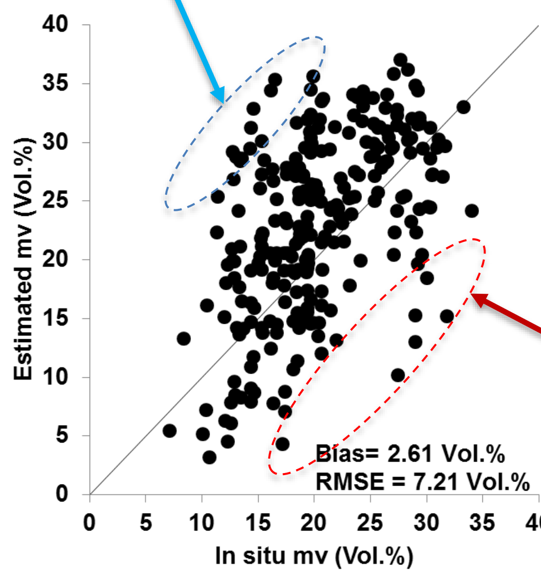


Under-estimation of SSM for low roughness

Results (2/2) : Real database

NN: VV + NDVI+ θ➔ SSM

Over-estimation of *SSM*
for high roughness

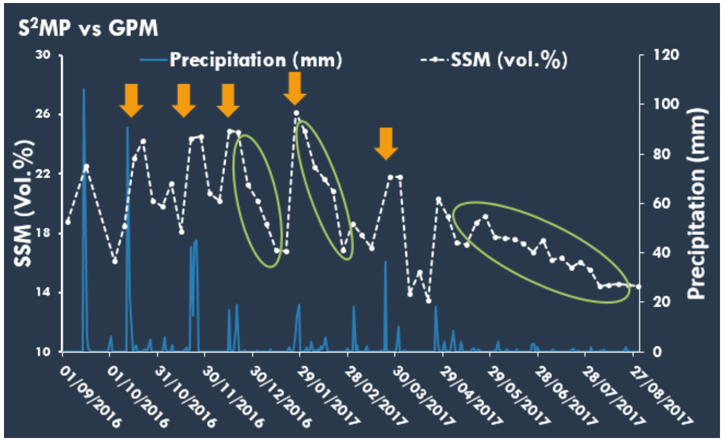


Under-estimation of *SSM*
for low roughness

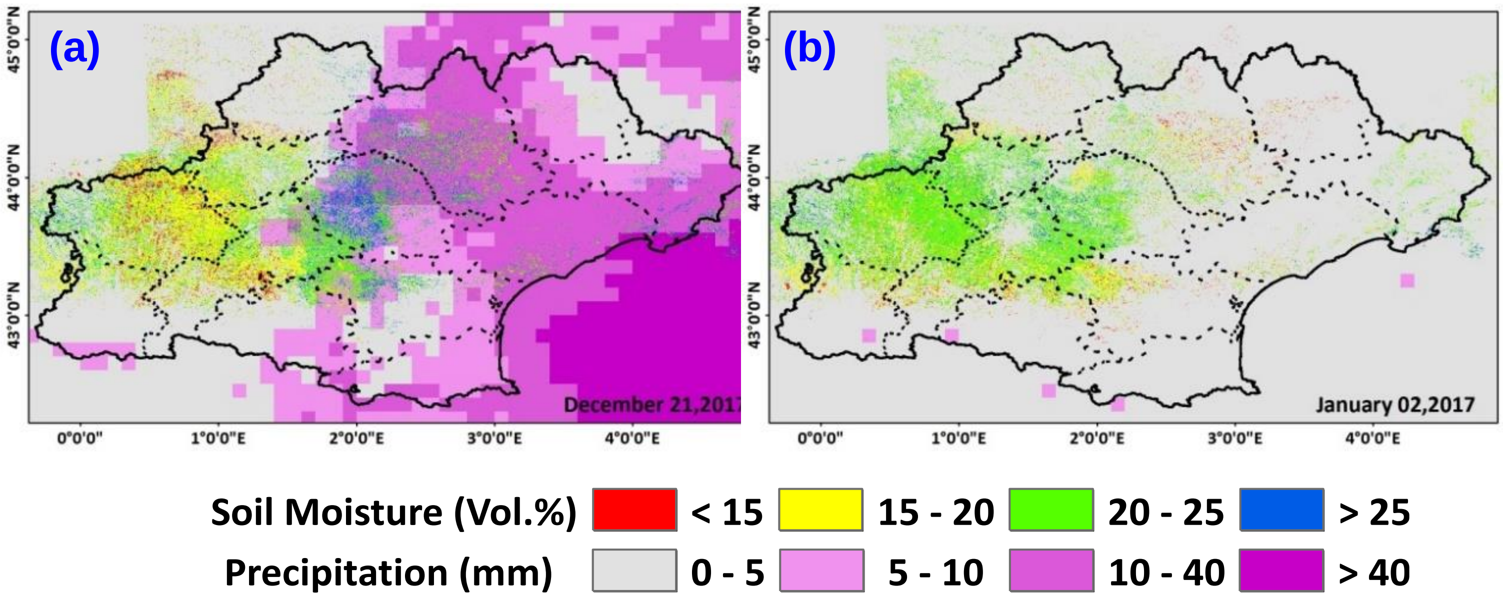
➢ Inversion was performed using real S1 data and NDVI derived from optical images

Soil moisture maps

- A good coherence was observed between the temporal evolution of the soil moisture and the precipitation records derived from the GPM data (Global Precipitation Measurement)

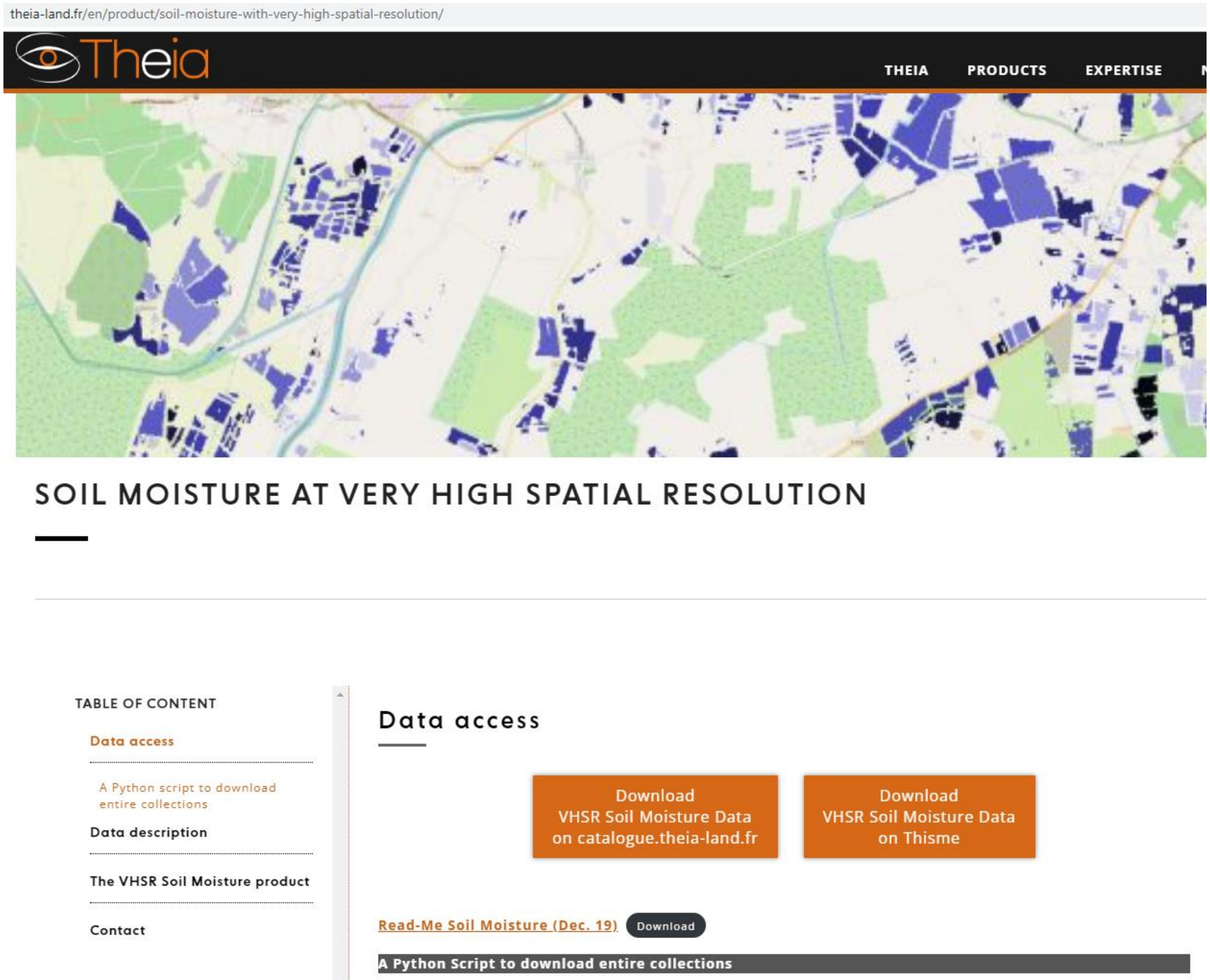


- **High SSM-Rainfall correlation**
- **High SSM estimations following rainfall events**
- **Decreases in estimated SSM due to absence of rainfall**



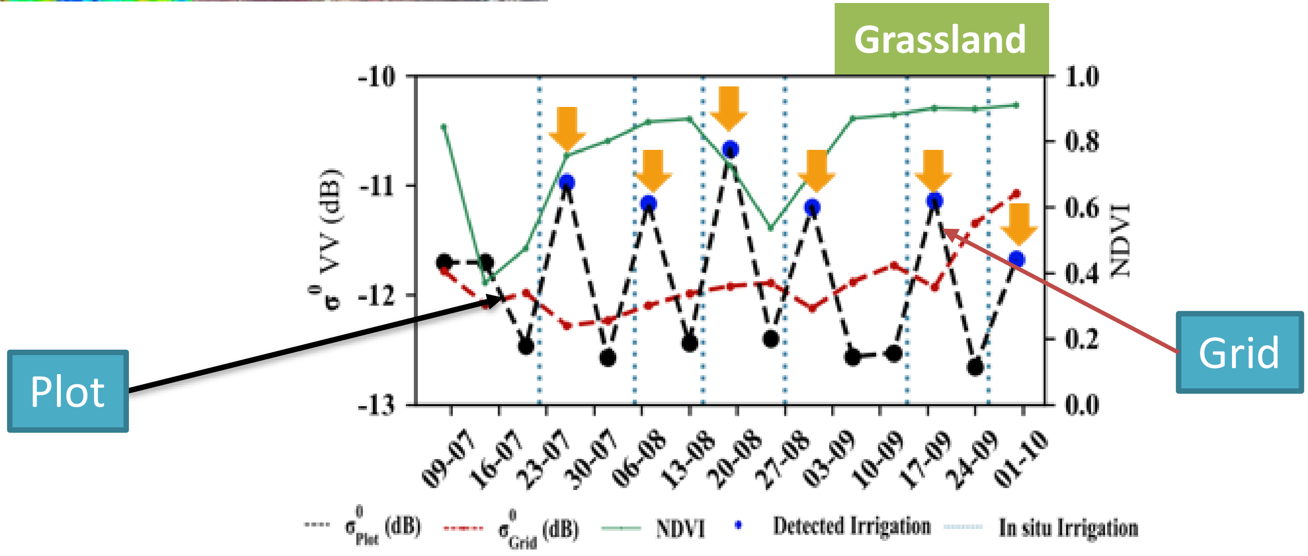
Soil moisture maps on the Theia website

French Land Data Center Theia : https://www.theia-land.fr/en/product/soil-moisture-with-very-high-spatial-resolution/



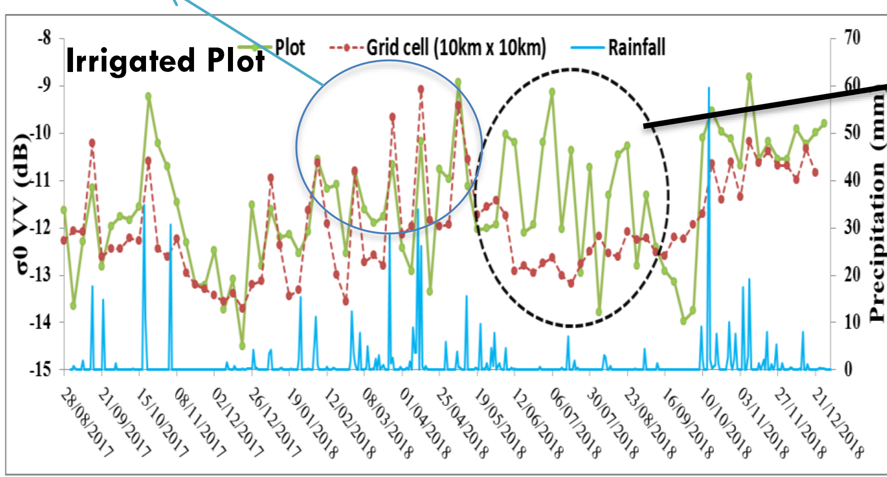
Mapping irrigated areas using radar and optical remote sensing data

Irrigation mapping at plot scale



➢ The radar signal averaged over large grids (10 km x 10 km) helps to discriminate between rain and irrigation

With rainfall events: Coherence between Plot S1 and grid S1 signals

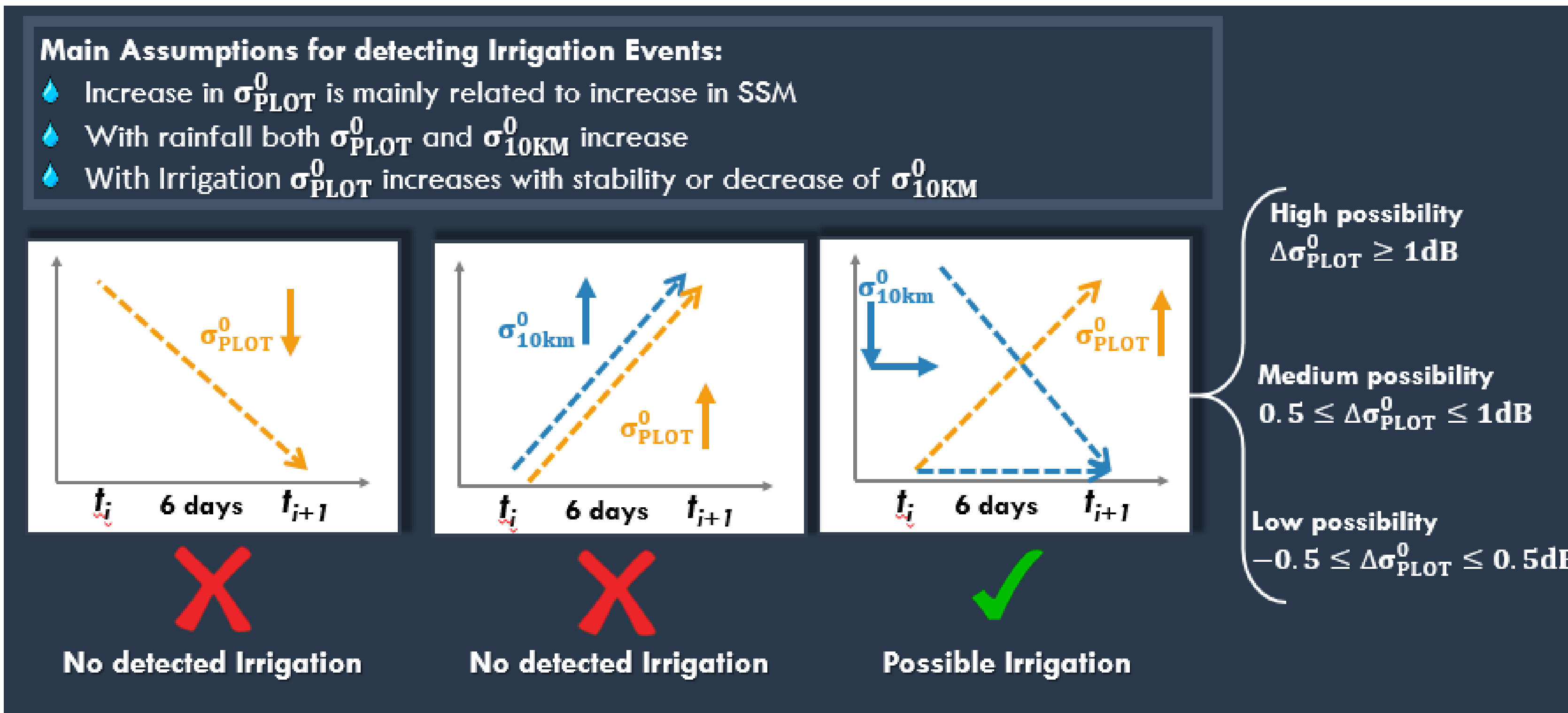


Without rainfall events: Frequent change of Plot S1 signal with stability of grid S1 signal

Detection of irrigation events

- **Detecting Irrigation Events:** We develop a decision tree algorithm (IEDM: Irrigation event detection model) to detect irrigation events using S1 and S2 time series data

  - ✓ S1 and S2 satellites provides images with a revisit time better than one week, which could be adequate for irrigation detection at plot scale.



Detection of irrigation events

Plot	Irrigation Events	Detected Irrigations	False Detections	Sensitivity	Precision	F-score
P1	15	12	2	80.0%	85.7%	82.4%
P2	13	11	1	84.6%	91.6%	87.3%
P3	5	5	2	100%	71.4%	83.3%
Total	**33**	**28**	**5**	**84.4%**	**87.5%**	**85.9%**

Operational mapping of irrigated plots

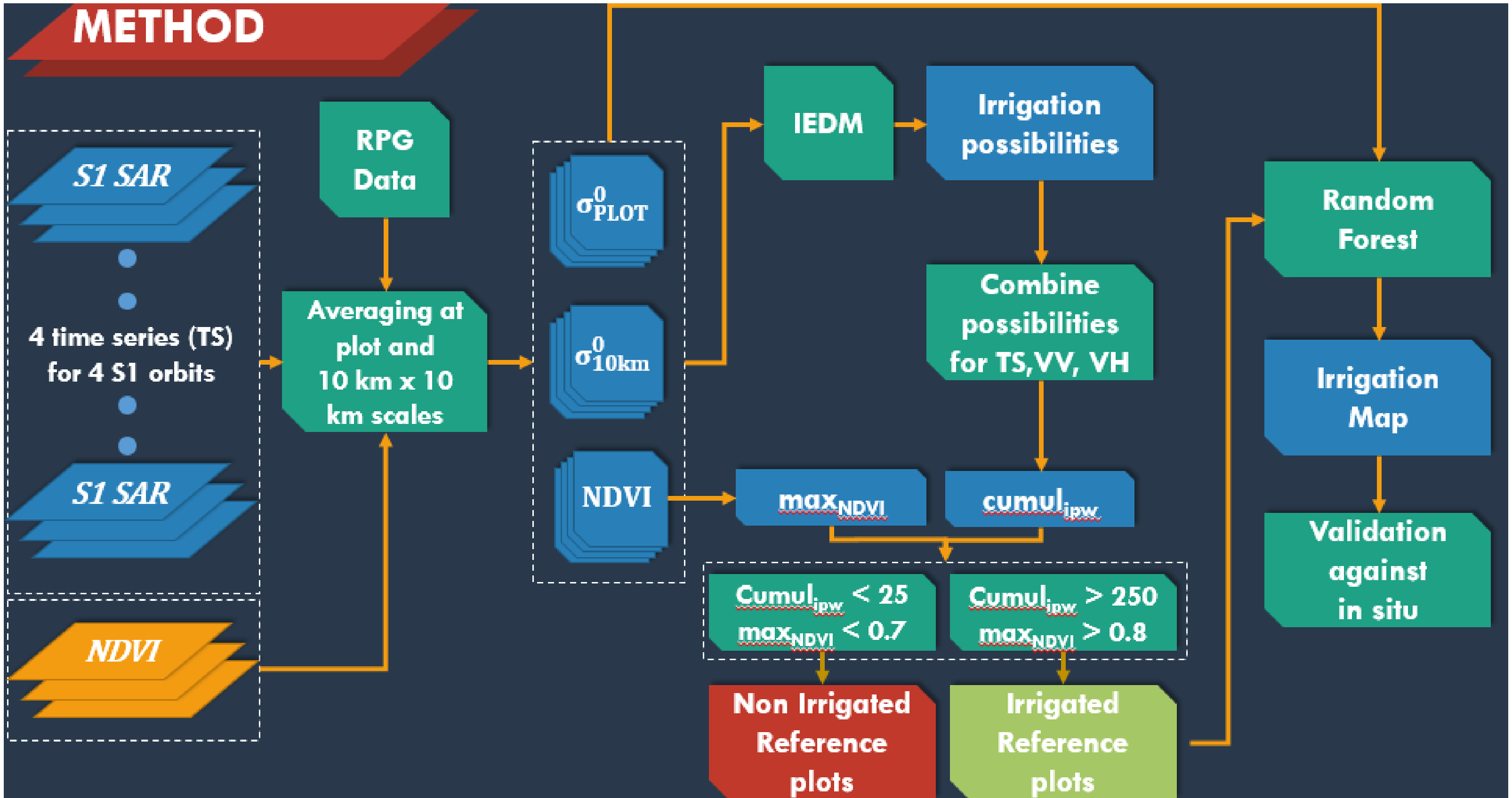
➢ Supervised classifiers

- Use terrain data
- With supervised classifiers, it is difficult to generalize the same classifier on other years and other regions
- No in situ data ➔ No Irrigation map

➔ We propose an operational mapping of irrigated plots using S1 and S2 time series: without depending on in situ data

- Generate a reference dataset (irrigated / no-irrigated plots) before using supervised classification models
  - ✓ Irrigated plots must have several irrigation events
  - ✓ Irrigated plots must have high maximum NDVI value during the crop growth cycle
- Use this reference dataset in the construction of the supervised classification model

Operational mapping of irrigated plots



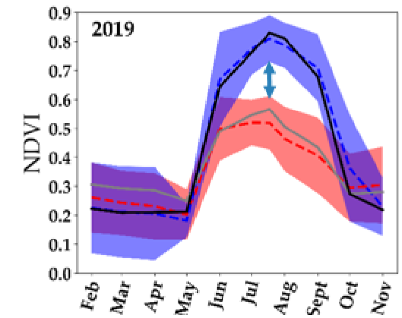
Accuracy metrics for the proposed S²IM vs RF built using in situ data

Year	Method	Overall Accuracy	F score	F score irrigated	F score non-irrigated
2020	**RF S²IM**	**84.3%**	**84.1%**	**86.4%**	**81.3%**
	RF in situ	89.0%	87.5%	90.2%	88.1%
2019	**RF S²IM**	**93.0%**	**92.8%**	**93.0%**	**92.5%**
	RF in situ	91.3%	91.3%	91.2%	91.3%
2018	**RF S²IM**	**81.8%**	**82.2%**	**86.8%**	**70.0%**
	RF in situ	88.0%	86.9%	92.0%	73.6%
2017	**RF S²IM**	**72.8%**	**74.0%**	**78.1%**	**62.0%**
	RF in situ	78.3%	76.5%	85.7%	53.7%

Operational mapping of irrigated plots

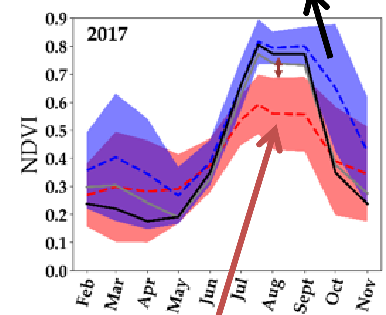
Climatic conditions of the studied region

- Over humid areas, mapping irrigated areas faces more challenges and can have lower accuracies than that obtained over arid and semi-arid areas



Irrigated

- If the studied area is humid:
- ✓ Frequent rainfall events ➔ lesser difference in the vegetation index between the irrigated and rain-fed plots.
- ✓ Less chance to detect irrigation using radar data because the soil is humid for irrigated and no-irrigated plots,



Non irrigated