PHYSICS-BASED ML AND POLARIMETRIC SAR FOR SOIL MOISTURE RETRIEVAL

Lorenzo Giuliano Papale[a], Fabio Del Frate[a], Leila Guerriero[a], Giovanni Schiavon[a], Jean Bouchat[b]

[a]Department of Civil Engineering and Computer Science Engineering (DICII), “Tor Vergata” University of Rome, 00133 Rome, Italy
[b]Universitè catholique de Louvain, Louvain-la-Nueve, Belgium

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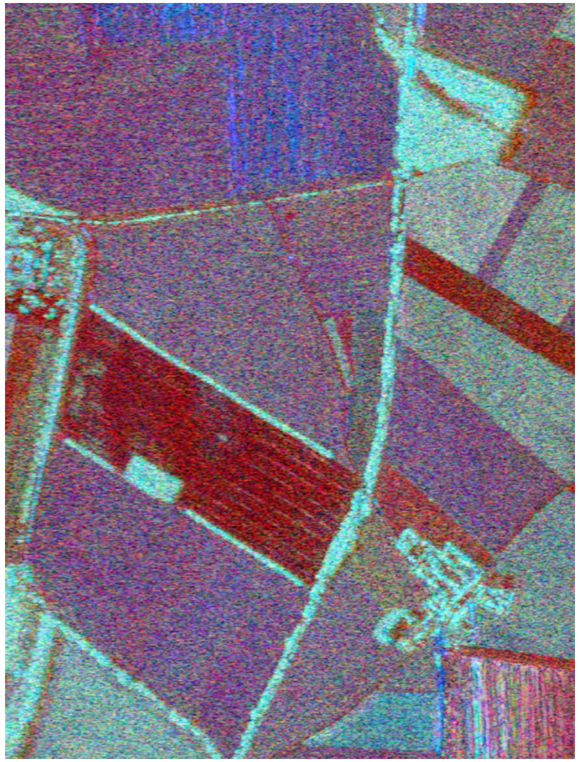

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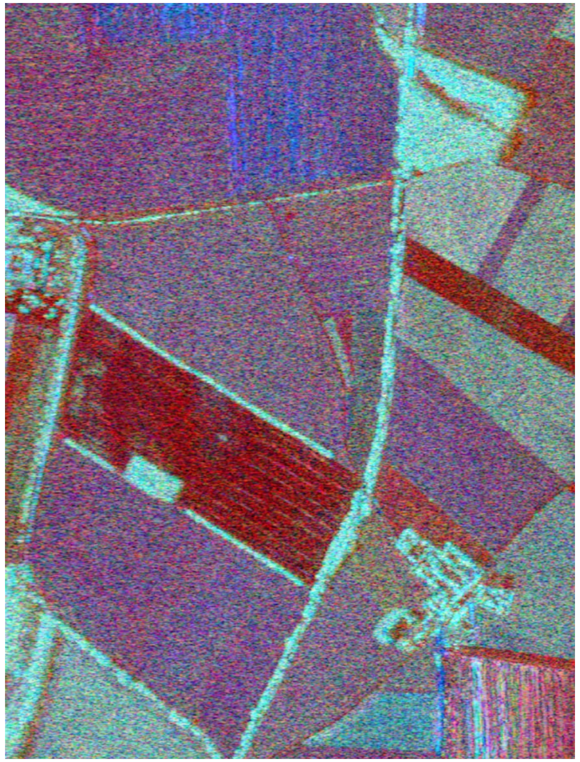
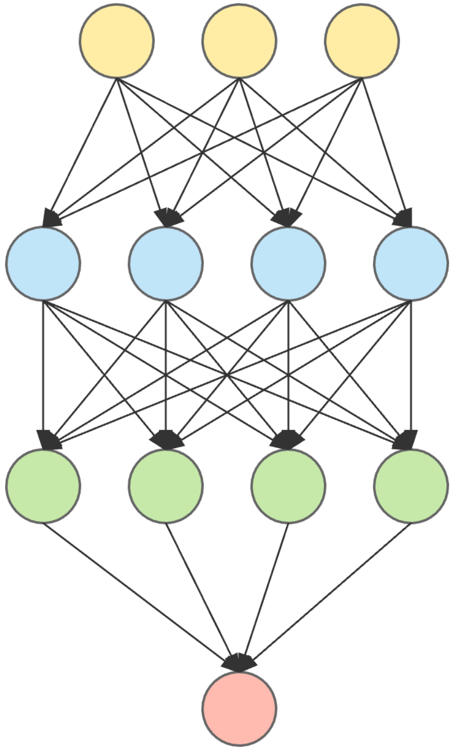




Objectives

- To generate a **simulated dataset** with the **Tor Vergata Electromagnetic Model**;
- to assess the **sensitivity** to **soil moisture** of simulated total backscatter and the soil component;
- to **train** a ML model, particularly an **Artificial Neural Network** (ANN) in order to **separate** the **scattering contributions** from simulated **Mueller Matrix**;
- to **test** the trained **ANN model** on simulated data to evaluate the performances;
- to **apply the ANN model** to **real SAR data** (ESA BelSAR 2018 dataset, courtesy of esa);
- to assess the **sensitivity** to **soil moisture** of measured total backscatter and the estimated **soil-related contributions** (i.e., surface, and double bounce scattering components);

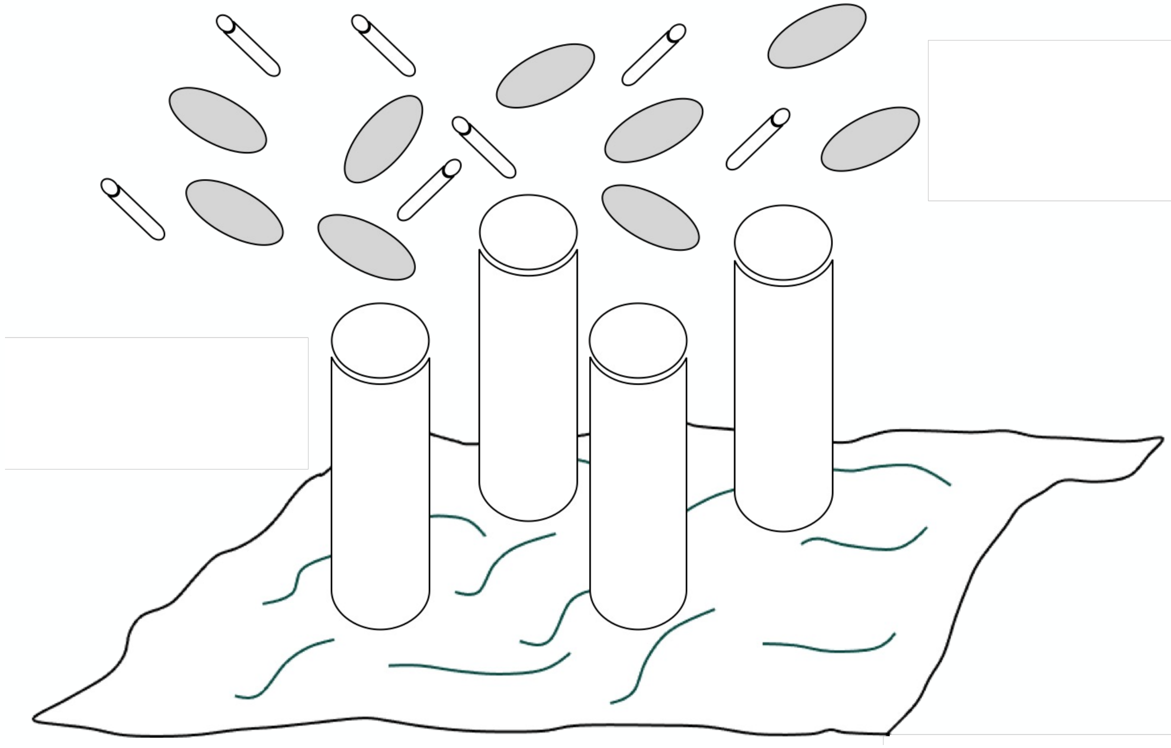
The Tor Vergata Scattering Model

It is based on the radiative transfer theory applied to discrete scatterers with simple shapes [5] and specific absorbing and scattering properties to model the **corn plant** structure elements.

The model takes as input:

- **sensor** configuration (signal frequency, incidence angle, polarization);
- **soil** properties (soil moisture and roughness);
- **vegetation** parameters (plant height and scatterers properties → **Growth model**).

Corn plant modelling

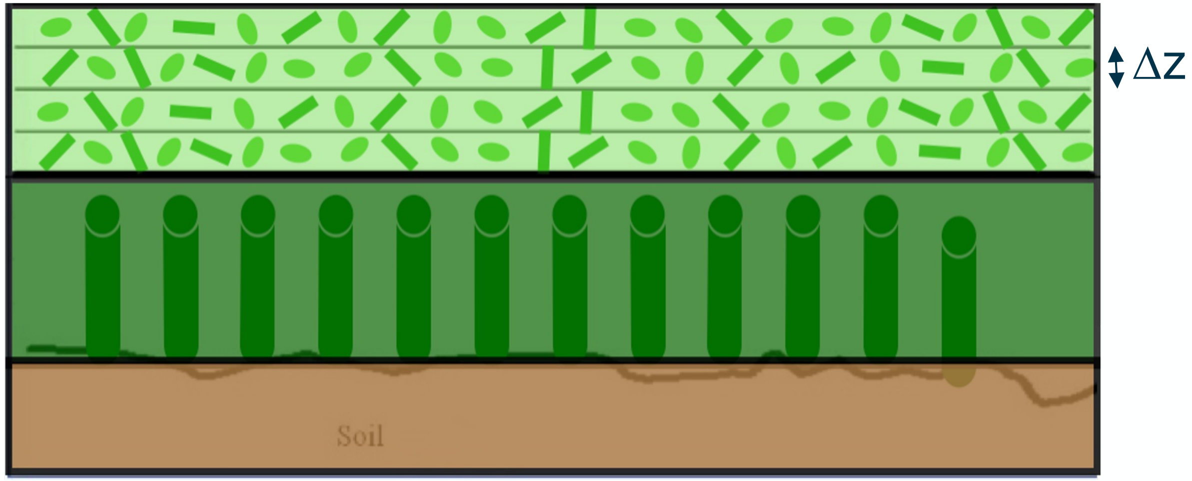


[1] L. G. Papale, F. Del Frate, L. Guerriero and G. Schiavon, "A Physics-Based ML Approach for Corn Plant Height Estimation with Simulated Sar Data," *IGARSS 2022 - 2022 IEEE IGARSS Symposium*.

The Tor Vergata Scattering Model

- The vegetation layer is subdivided into N infinitesimal sublayers where single scattering occurs;

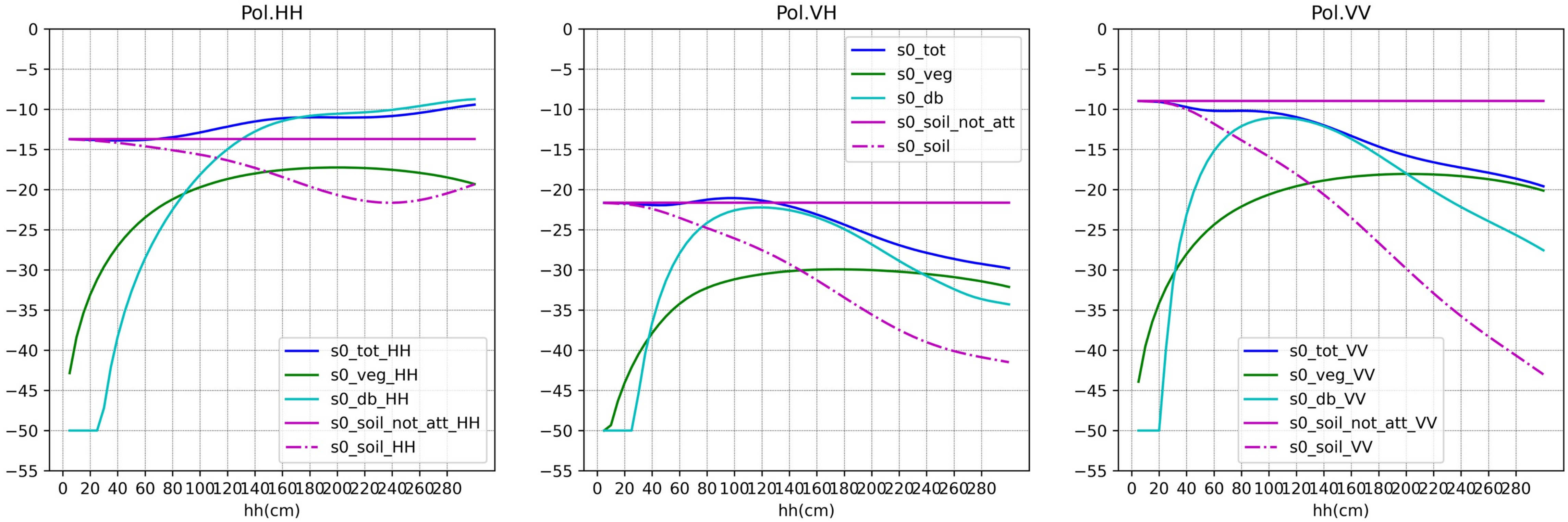
- then, the "Matrix doubling" algorithm [2] models the scattering interactions of any order (e.g., attenuation and scattering effects) between each layer and sublayer.



[2] M. Bracaglia, P. Ferrazzoli, and L. Guerriero, "A fully polarimetric multiple scattering model for crops," Remote Sens. Env., pp. 170-179, 1995.

The Tor Vergata Scattering Model - Simulations

- The model provides as output the total backscatter and its contributions (i.e., surface, volume and double bounce scattering) associated to the soil and the vegetation layer.

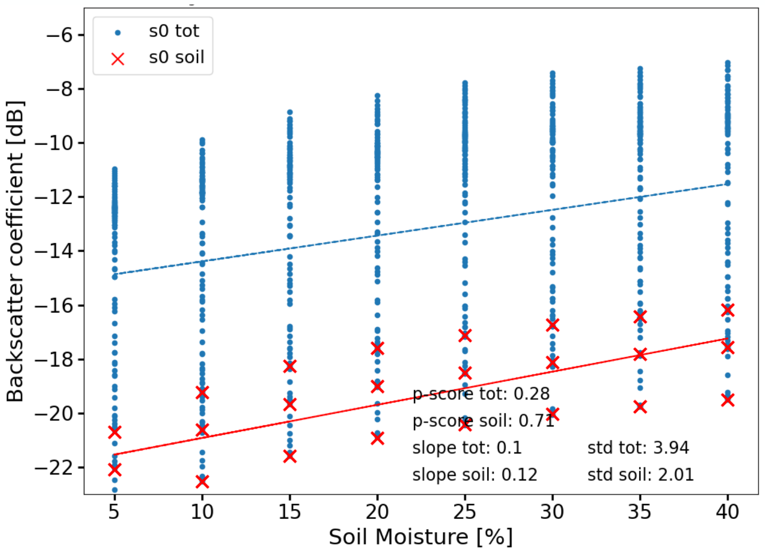


Simulated backscatter at L-band (1.2 GHz), θ = 32,5°, SM = 10%, SR = 1.0 cm

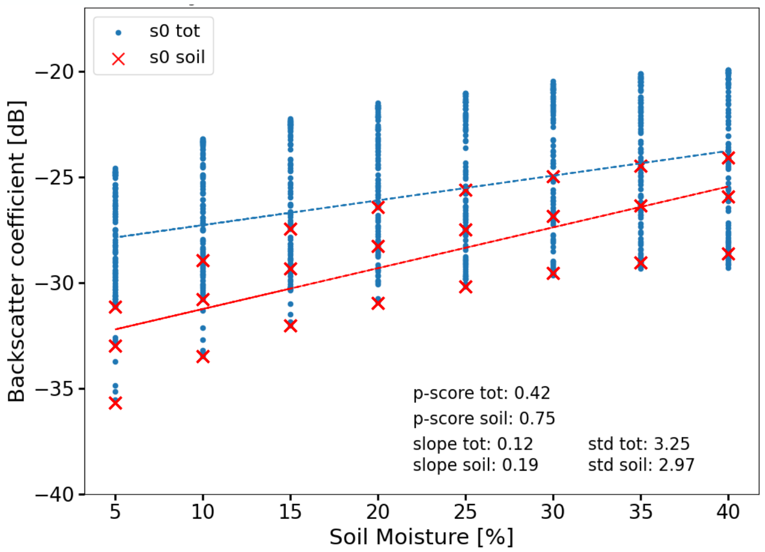
Simulated dataset: soil moisture sensitivity analysis

The correlation to soil moisture of the simulated total backscatter and the soil component was computed. As a result, for the three polarizations HH, VH and VV polarizations, a greater Pearson correlation coefficient was obtained for the soil component if compared to the total backscatter.

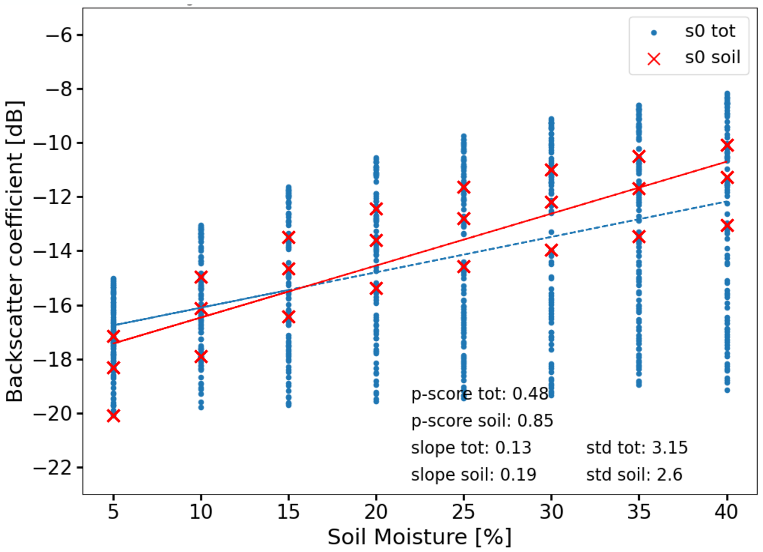
HH



VH



VV

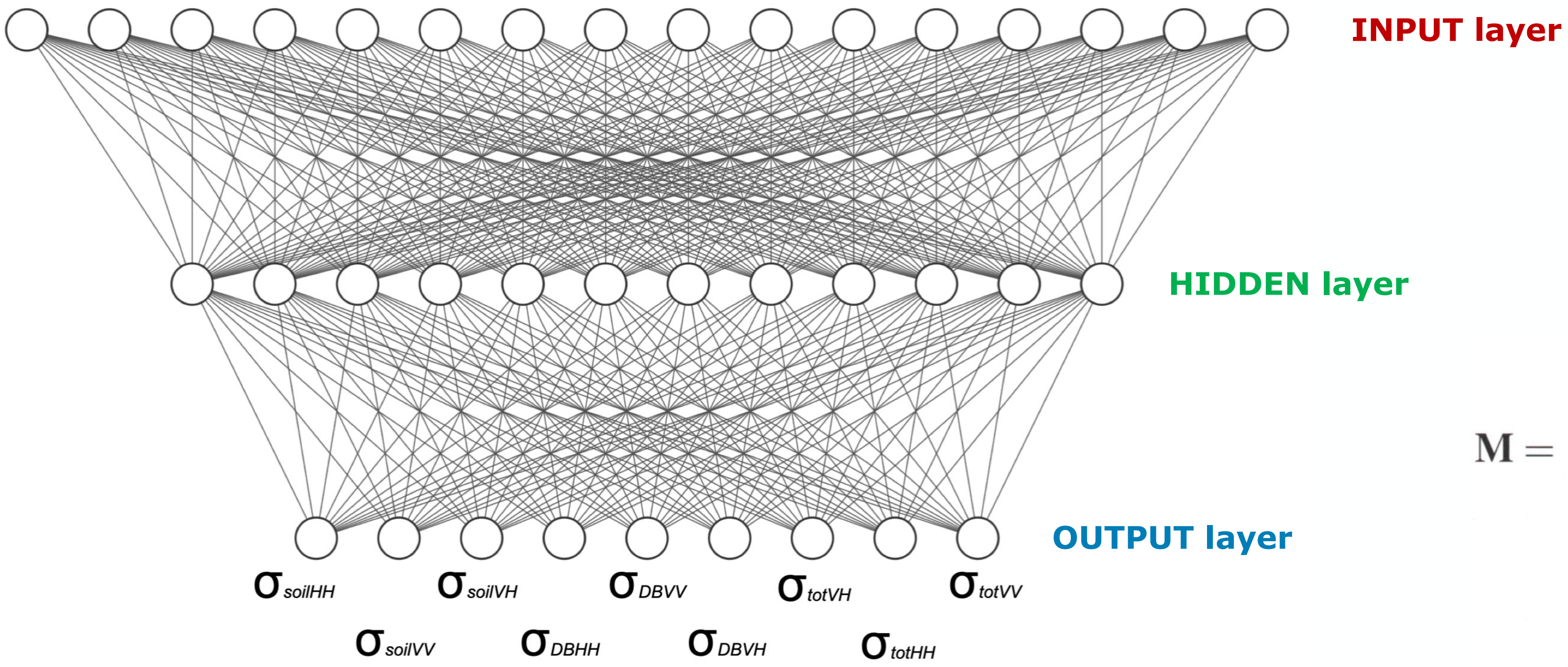


Plant height = [0-300 cm], θ = 42.5°, SM = [5 - 40 %] SR = [0.75-1.25 cm]

The Machine Learning Model

The ANN architecture

4 x 4 Mueller matrix elements —> 16 elements



Data preparation:

- Noise addition
- Input data normalization
- Train/Test splitting

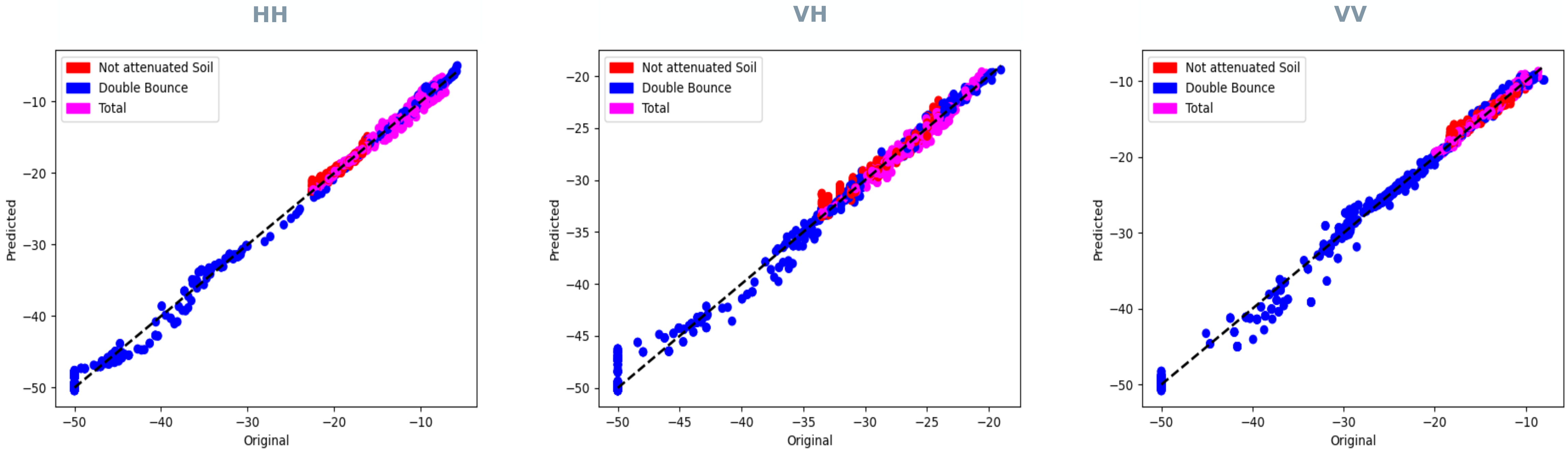
The Mueller Matrix [3]

$$\mathbf{M} = \begin{bmatrix} |S_{vv}|^2 & |S_{vh}|^2 & \mathfrak{Re}(S_{vv}S_{vh}^*) & -\mathfrak{Im}(S_{vv}S_{vh}^*) \\ |S_{hv}|^2 & |S_{hh}|^2 & \mathfrak{Re}(S_{hv}S_{hh}^*) & -\mathfrak{Im}(S_{hv}S_{hh}^*) \\ 2\mathfrak{Re}(S_{vv}S_{hv}^*) & 2\mathfrak{Re}(S_{vh}S_{hh}^*) & \mathfrak{Re}(S_{vv}S_{hh}^* + S_{vh}S_{hv}^*) & -\mathfrak{Im}(S_{vv}S_{hh}^* - S_{vh}S_{hv}^*) \\ 2\mathfrak{Im}(S_{vv}S_{hv}^*) & 2\mathfrak{Im}(S_{vh}S_{hh}^*) & \mathfrak{Im}(S_{vv}S_{hh}^* + S_{vh}S_{hv}^*) & \mathfrak{Re}(S_{vv}S_{hh}^* - S_{vh}S_{hv}^*) \end{bmatrix}$$

[3] Long, D., & Ulaby, F. (2015). Microwave radar and radiometric remote sensing. Artech.

The Machine Learning Model: ANN performances

The following scatterplots represent the **comparison** between the **simulated backscatter coefficients** and the ones **estimated** by the ANN. The **total backscatter** and the one associated to the **attenuated soil** are in very good agreement. For the **double bounce** contribution, the points show **more dispersion**.

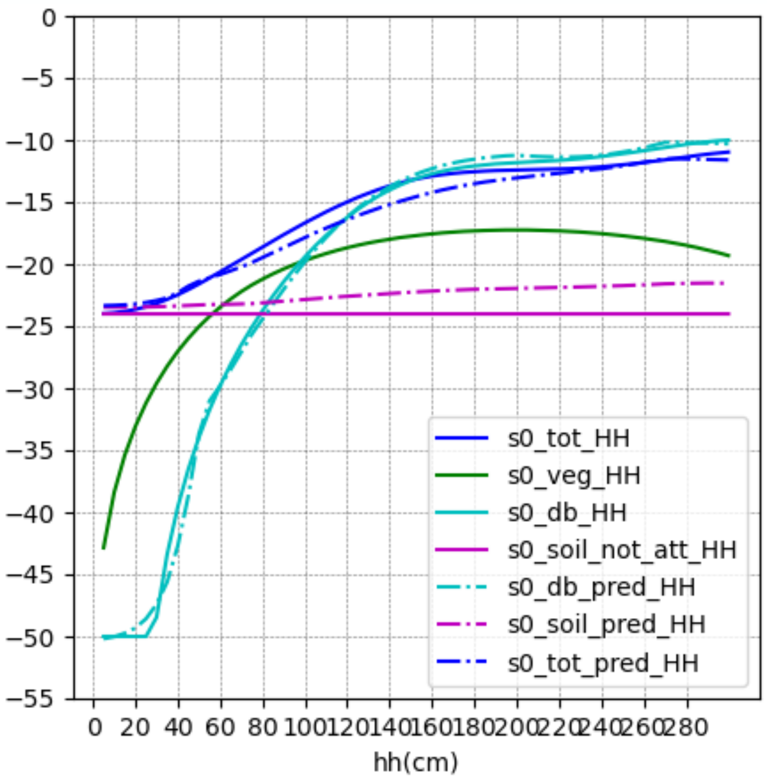


RMSE < 1 dB

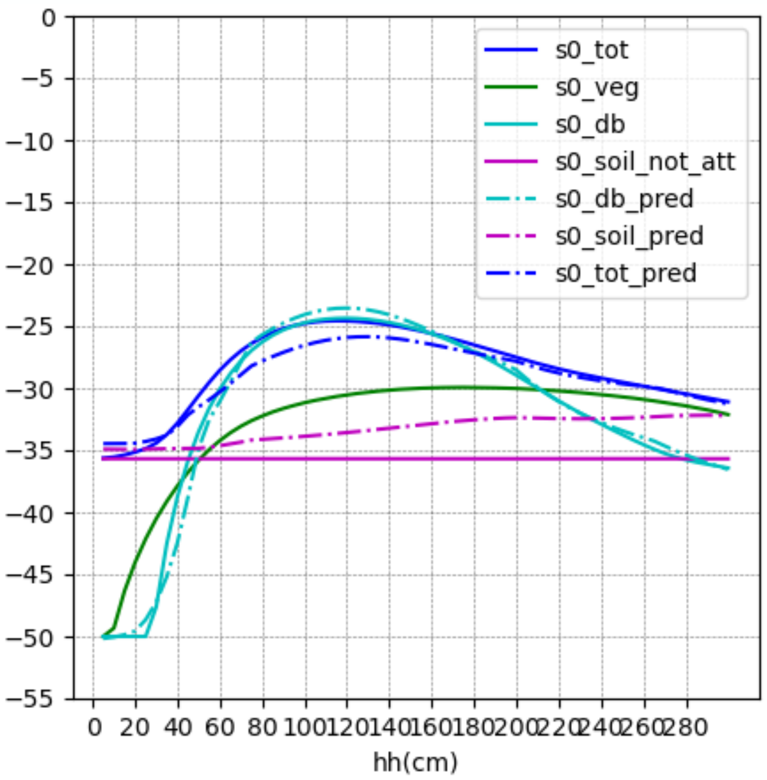
The Machine Learning Model: ANN performances

The ANN was applied to a **simulated case study** to compare the original soil-related contributions and the estimated ones. In this particular case it seems that the ANN **overestimates the soil contribution** while **underestimates the total backscatter**.

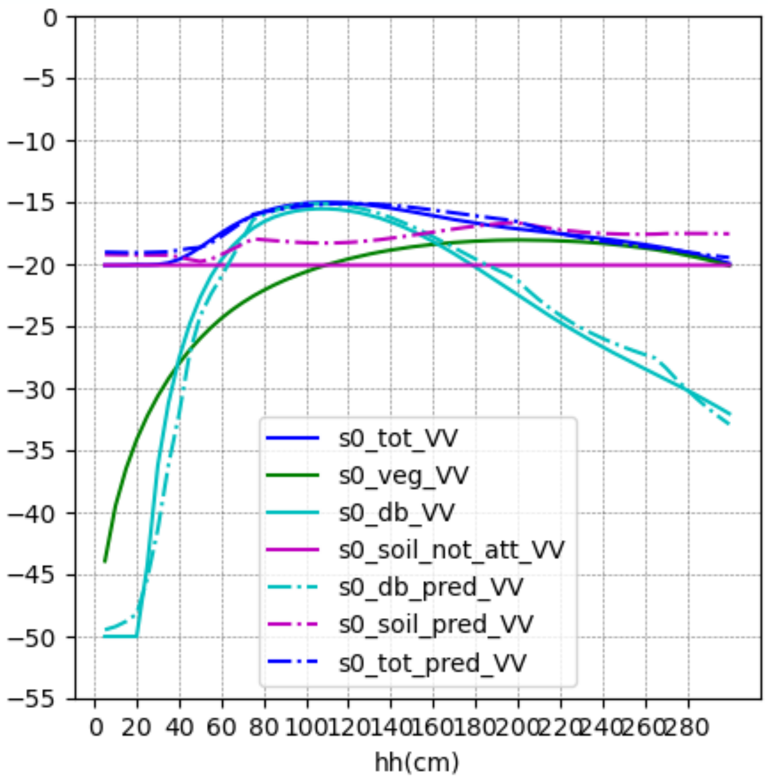
HH



VH



VV



Simulated backscatter at L-band (1.2 GHz), θ = 32,5°, SM = 10%, SR = 1.0 cm

Real SAR data: The ESA BelSAR 2018 dataset

esa

The Airborne mission

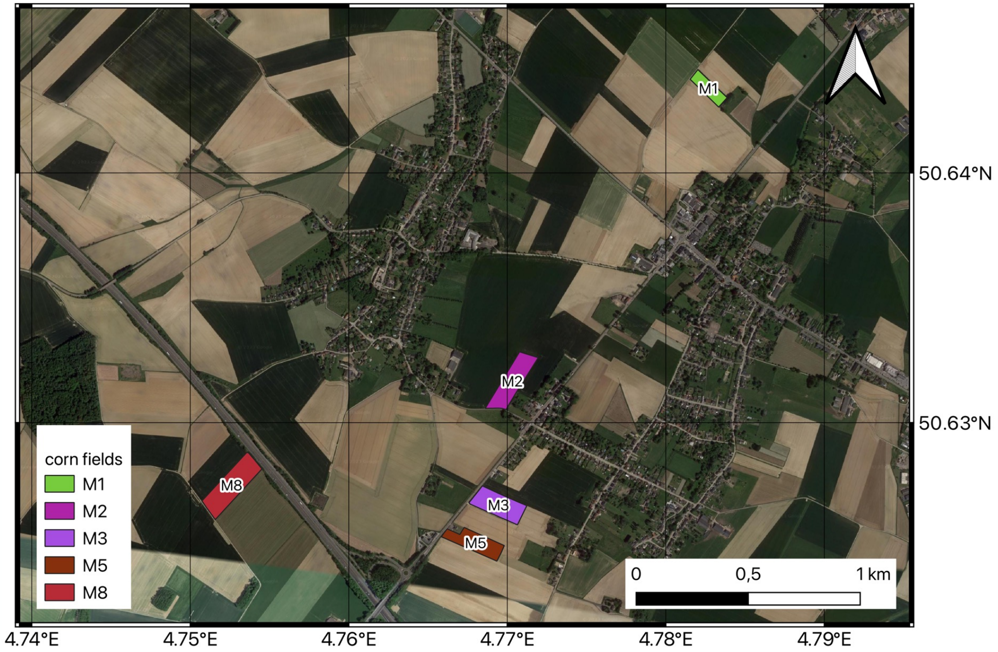
- The airborne campaign took place during the 2018 growing season, between the end of May and mid-September over a test site located in Belgium.

- The L-band full-polarimetric radar acquisitions were collected during a series of five flight missions.

The Field campaign

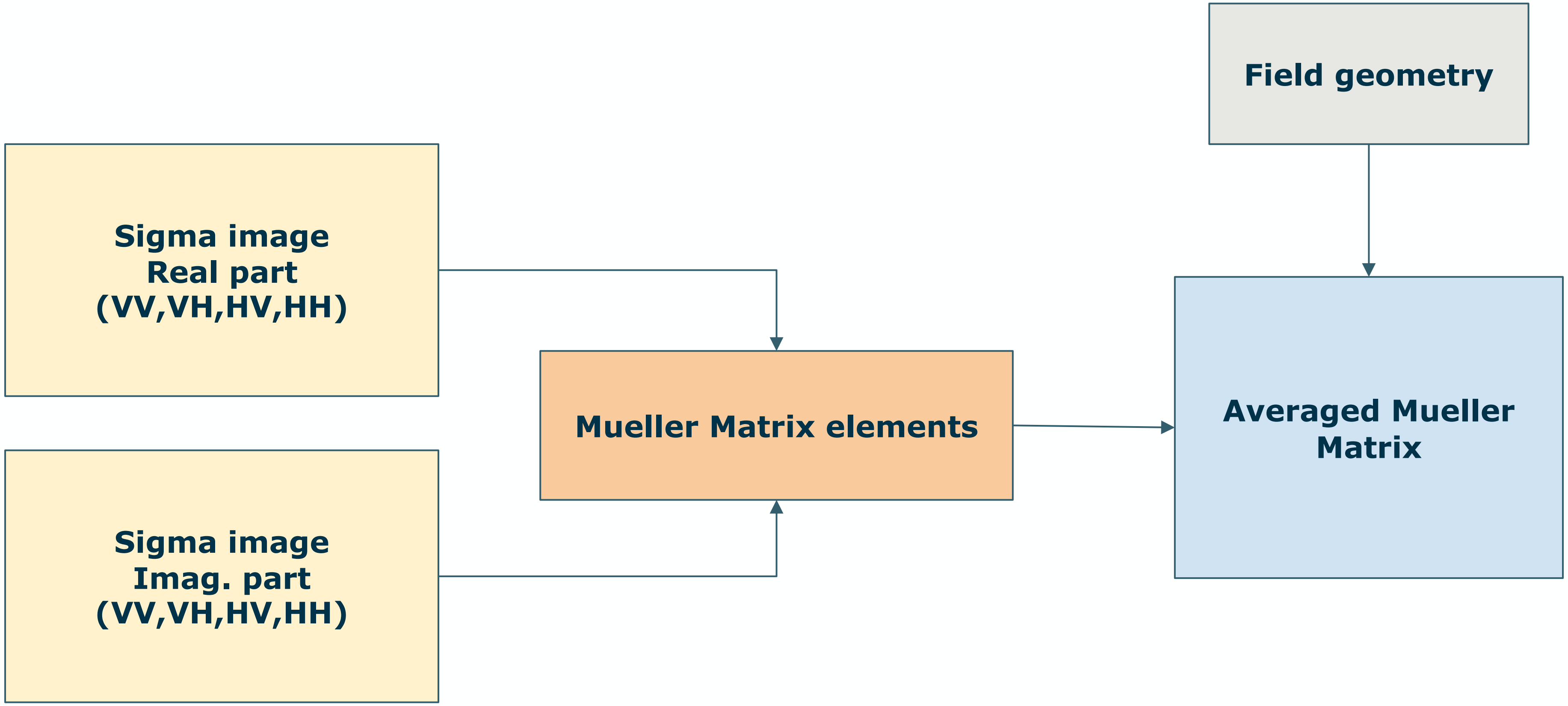
- Along with each flight mission, vegetation and soil- related variables were collected over corn and wheat fields in the area of interest.

- For the present study, a group of five corn plots close to each other were selected.



ESA BelSAR 2018 SAR data processing

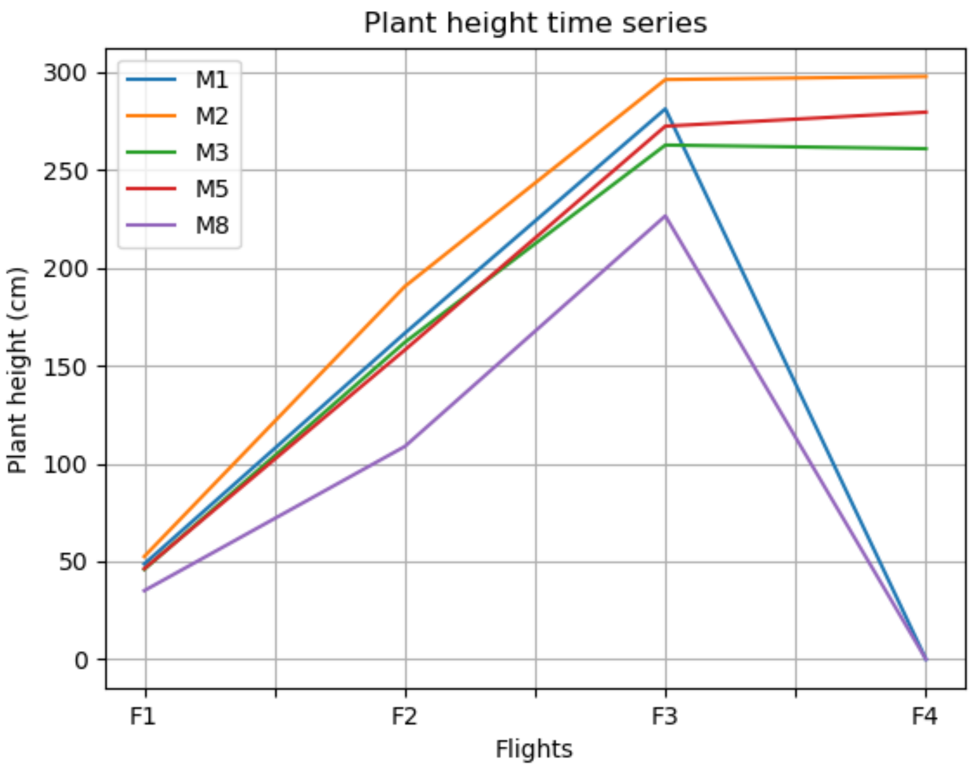
Radar data were **already processed** by *MetaSensing BV* and delivered as **σ-calibrated** SLC focused SAR data. Data were released in ground range geometry with a **ground sampling distance of 1 m**.

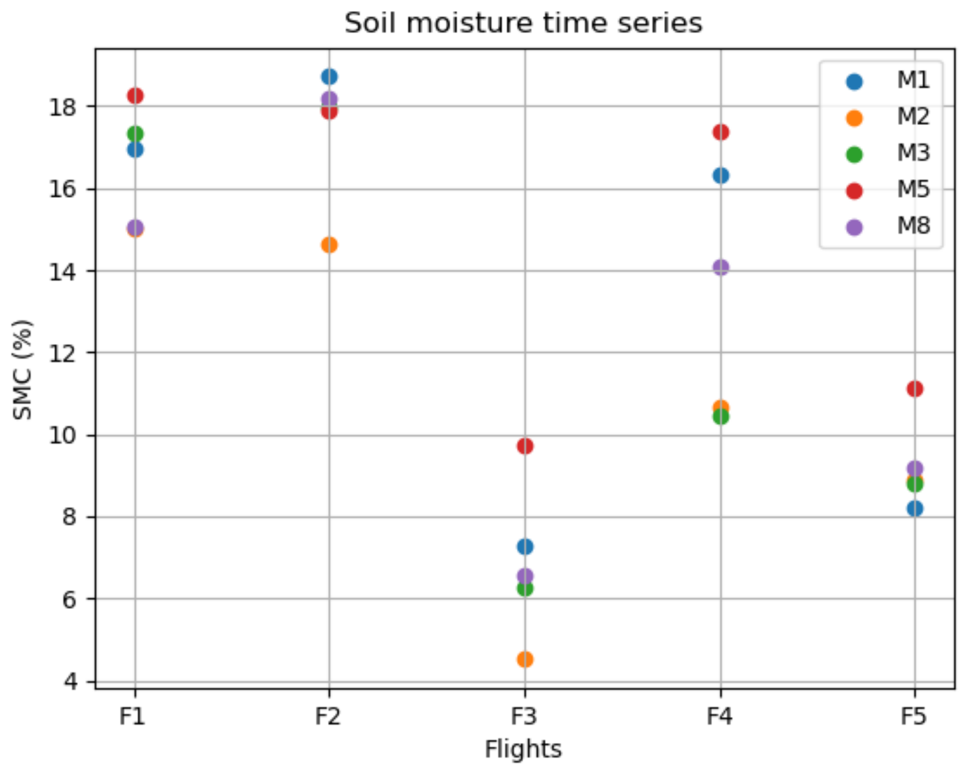


Real SAR data: The ESA BelSAR 2018 in-situ data

The in-situ measurements were derived for each corn field:

- The **plant height** values cover a range between **~50 cm** and **~300 cm**. At Flight 5, all the fields have been harvested;
- The **soil moisture** values come from ~4% to ~18%.



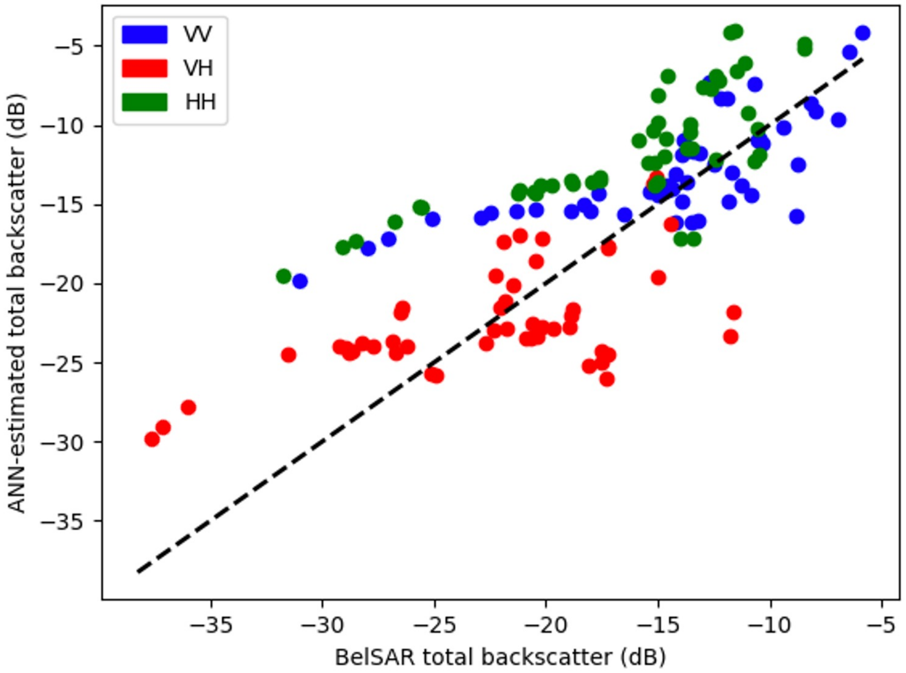


Results: Comparison of total backscatter values

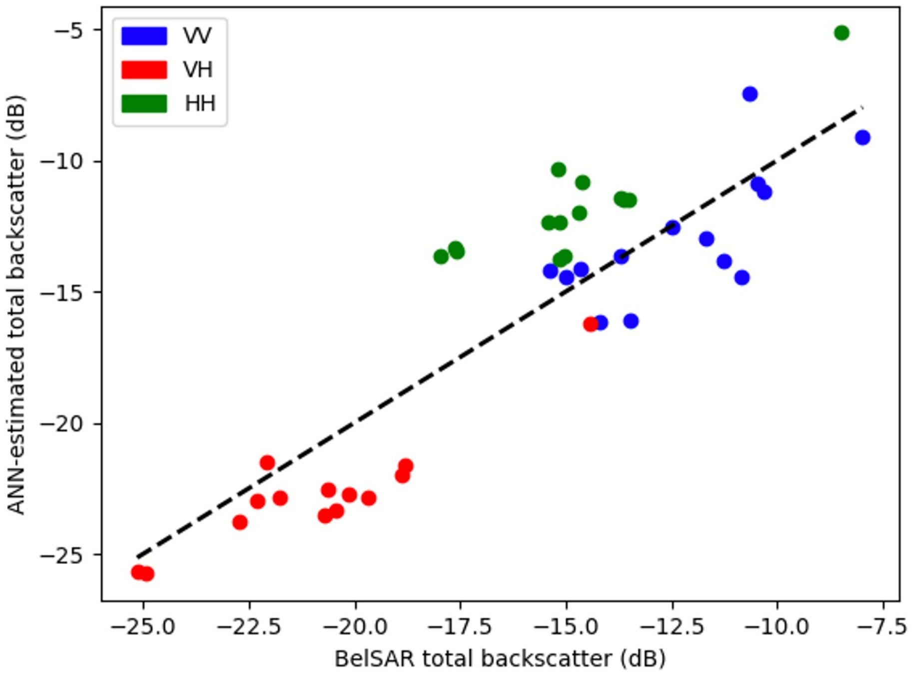
The points included in the following comparison were selected according to a **RMSE < 3 dB**.

The backscatter contributions are **considered** for the sensitivity analysis only when the total backscatter is properly simulated by the model and well estimated by the ANN.

Comparison between observed and estimated total backscatter values

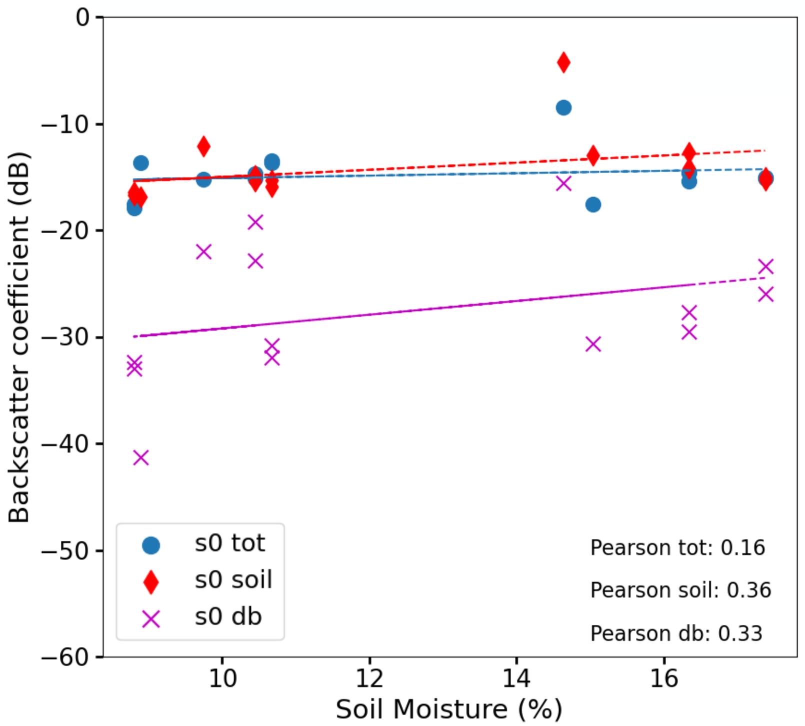


Comparison of selected data (observed VS estimated total backscatter values)



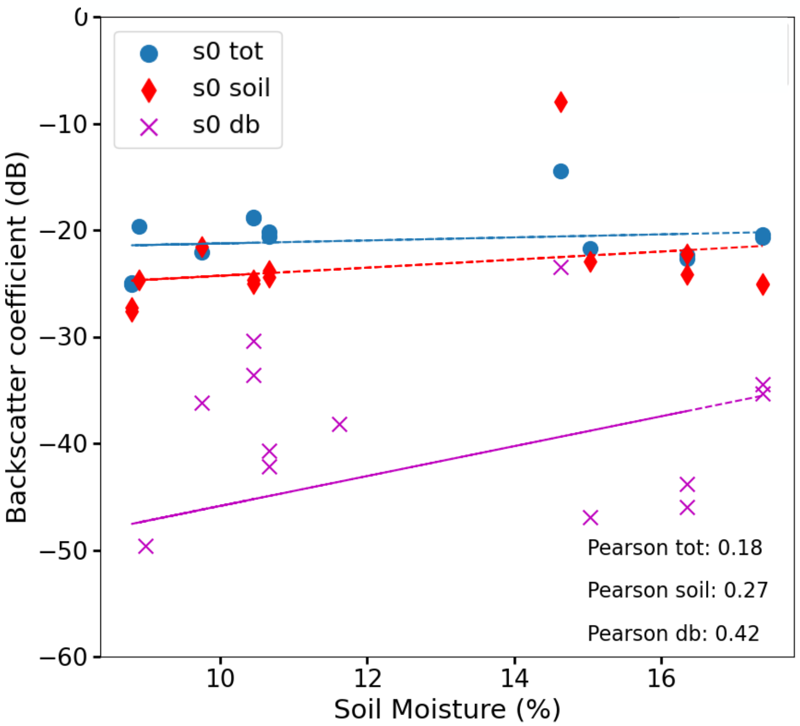
Results: Sensitivity to soil moisture analysis

HH



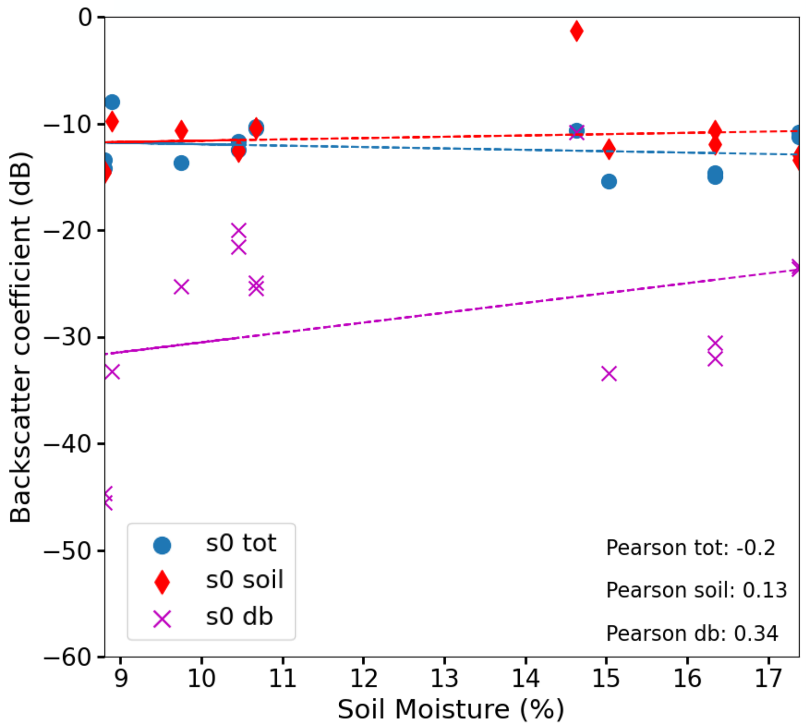
For **HH**, the **soil** and the **double bounce** contributions seem to be **more correlated** to the soil moisture if compared to the **total backscatter**.

VH



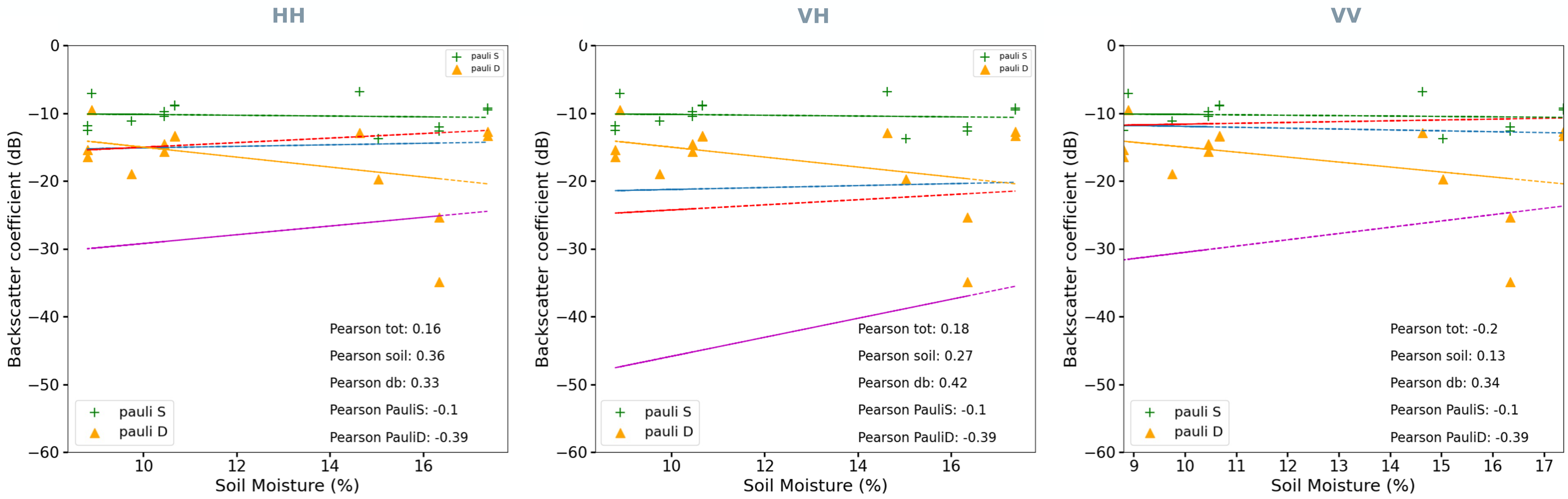
For **VH**, the **double bounce** contribution seems to be **significantly correlated** to the soil moisture. The soil contribution is more correlated than the **total backscatter**.

VV



For **VV**, the **double bounce** contribution is again **significantly correlated** to the soil moisture. The soil contribution is less correlated but more than the total backscatter.

Results: Sensitivity to soil moisture analysis – Pauli decomposition



The Pauli decomposition has been applied to BelSAR selected data.

$$\alpha = \frac{S_{HH} + S_{VV}}{\sqrt{2}}, \beta = \frac{S_{HH} - S_{VV}}{\sqrt{2}}$$

As a result, the **surface component** shows to be not sensitive to soil moisture variations. On the other hand, the **dihedral scattering component** shows a negative correlation.

Conclusions and future works

Conclusions:

- This study aims at highlighting the **potentiality of the synergic use of ML and electromagnetic modelling** for SAR polarimetry applications;
- the preliminary results suggest that the **estimated soil-related scattering contributions** can be useful for **soil moisture retrieval** applications;
- the **total backscatter** is **not properly estimated** by the ANN (when compared to real data) due to the fact that to apply a ML model trained with simulated data could be challenging;
- The **Pauli decomposition** showed to be **less sensitive** to soil moisture if compared the estimated soil-related scattering contributions.

Future works:

- to adopt the same procedure on **spaceborne full-polarimetric SAR data** at L-band;
- to include the **soil roughness** parameter as an **input** of the **ANN**;
- to add **physical constraints** to the **ANN** to separate the contributions in a more **reliable** way;
- to train an **ANN for soil moisture retrieval** to validate the proposed approach;
- to **compare** the **estimated contributions** with the results of other **polarimetric decompositions**.

We would like to thank the **ESA BelSAR2018-Campaign** (https://doi.org/10.5270/ESA-bccf2d9) **team** for the collection of the SAR and on-field datasets used in this work.

Thank you for your attention!

UCLouvain

We would like to thank Jean Bouchat and the University of Louvain for the support provided for the ESA BelSAR data processing procedure.