# Mapping soil organic carbon content by combining time series of Sentinel-2 and Sentinel-1 with vis-NIR laboratory spectra – Application to study site in Brittany (France)

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**Résumé**

Mapping Soil organic carbon (SOC) is essential for continuous monitoring of its spatial and temporal dynamics. In this study, we developed a method using time series of Sentinel-2 (S2) data combined with Sentinel-1 (S1) and vis-NIR laboratory spectra to map SOC content of agricultural soils. The study site, located in Brittany (northwest France), is an agricultural area of 1.5 km$^2$. Soil samples were collected from agricultural fields within this site, their SOC content measured and their spectra recorded under laboratory conditions. The SOC content ranged from 15.2 to 49.4 g.kg-1. Deep neural network algorithms were implemented after dividing the data set built up from the time series of S2 and S1 images into calibration (70%) and validation (30%) sets. Three random draws of the validation sets were performed to assess model robustness. Four approaches were tested: (1) models developed using S2 bands as a single input, (2) applying multiple factor analysis (MFA) to select 12 of 40 indices calculated from S2 data and adding them to the S2 bands, (3) adding soil moisture derived from the time series of S1 (SM1), and (4) gradually adding five indices calculated from laboratory spectra, in descending order of their correlation with SOC. Model performance was compared based on validation results, and semi-variograms for observed and predicted SOC were then used to analyze the maps generated. Results showed that only models using approach 4 were validated (RPIQ = 1.78±0.19 - 3.07±0.6). The addition of SM1 improved model robustness since predictive performance remained stable over the 3 random draws of the validation sets. In approach 4, laboratory indices showed

*Intervenant

significant correlations with SOC content. Thus, we were able to validate our models once we added the two indices with the highest correlation. Semivariograms of the predicted values showed lower sill-to-nugget ratios but similar shapes to the observed values. Finally, the developed method allowed us to map 70% of the area of the study site.