Prediction of soil organic and inorganic carbon concentrations in Tunisian samples by mid-infrared reflectance spectroscopy using a French national library

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Context

The monitoring, reporting and verification of ***soil carbon content*** is a major issue for soil fertility and climate change mitigation policies and managements. Soil carbon is composed of SOC and SIC in some soils.

The **Soil Organic Carbon (SOC)** is the main component of the soil organic matter. It represents about 67% of the total soil carbon on earth (Batjes, 1996).

The **Soil Inorganic Carbon (SIC)** is mainly in the form of calcium carbonate ($CaCO_3$). 30% of the soils are calcareous (Bernoux and Chevallier, 2014), mostly in dry areas. It is considered much less dynamic and dependent of land use and management as SOC.

Mid-infrared reflectance spectroscopy (MIRS) provides accurate estimations of SOC and SIC (e.g., Bellon-Maurel et al. 2011). Following these encouraging soil characterizations by MIRS, some soil spectral libraries covering extensive areas have recently been developed.

Most of the studies dealing with **large soil spectral databases** (national or continental) have calibrated prediction models with samples from a region *A* to predict properties of soil samples from the same region *A* (e.g., McCarty et al. 2002, Clairotte et al., 2016, Barthès et al. 2020).

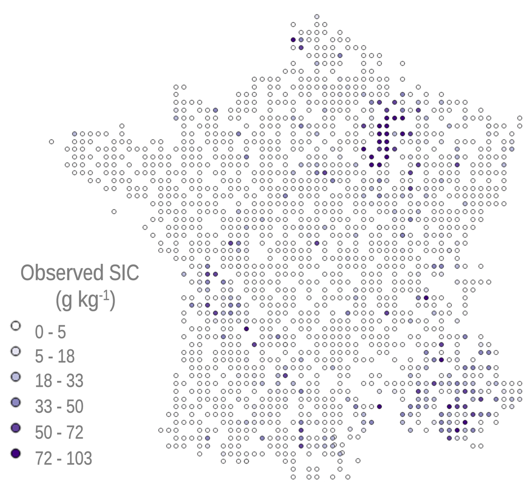
Objective

Analyse how MIRS performs to predict SOC and SIC contents, from a calibration database collected over a region *A*, to predict over a region *B*, where *A* and *B* have no common area and different soil and climate conditions.

Materials

French national library *(Region A)*

- 2178 soil samples (0-30 cm) on a regular grid (16 x 16 km) over 550 000 km²
- Temperate and Mediterranean soils
- Right-skewed distribution of SOC and SIC



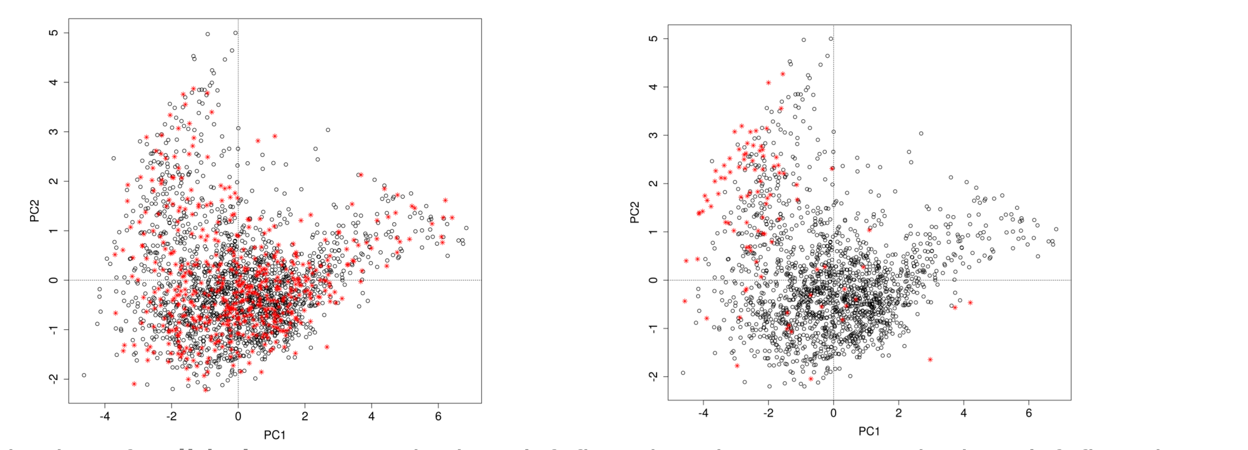
Measured SIC contents for Calibration samples plotted over the French metropolitan territory

Tunisian set *(Region B)*

- 96 soil samples (0-10 cm) over 80 000 km² (northern half of Tunisia)
- Mainly Mediterranean and arid soils.
- Right-skewed distribution of SOC and SIC

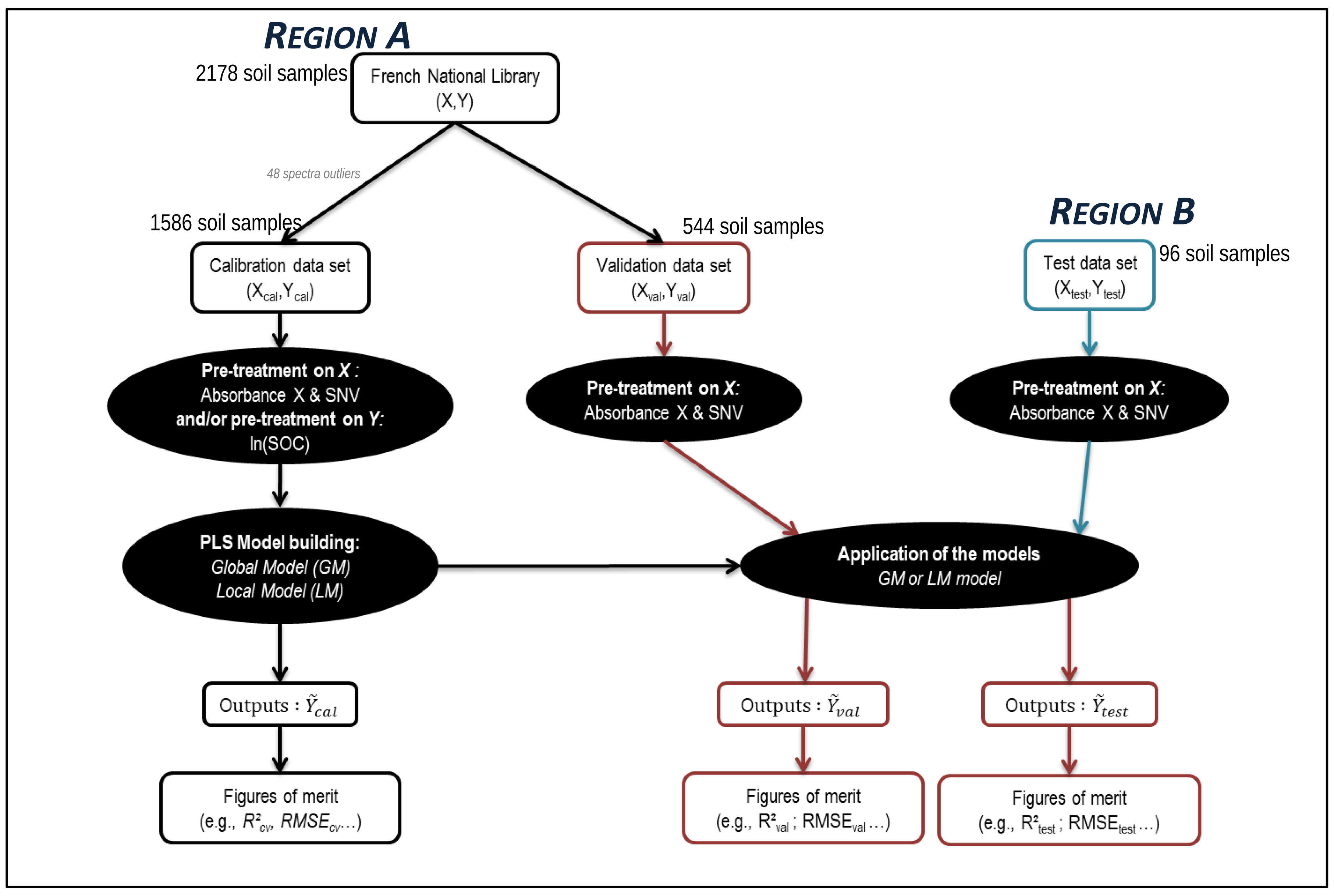
Analysis on both datasets

- Organic carbon content (CHN analyser)
- Inorganic carbon content (Calcimeter)
- Mid-infrared reflectance spectroscopy



Projection of Validation spectra (red, on left figure) and Test spectra (red, on left figure) onto the first two principal components built with Calibration spectra (circle points, on both figures)

Methods



- **Global prediction model**

Global regressions (*GM*) were built from all the calibration samples of Region *A* and applied to validation of Region *A* and test samples of Region *B*.

- **Local prediction models** (Nocita et al. 2014)

Local regressions (*LM*) were built from spectral neighbors of each predicted samples among the calibration samples of Region *A* and applied to validation of Region *A* or test samples of Region *B*.

- The PLS regression method was used to built regression models.

Results

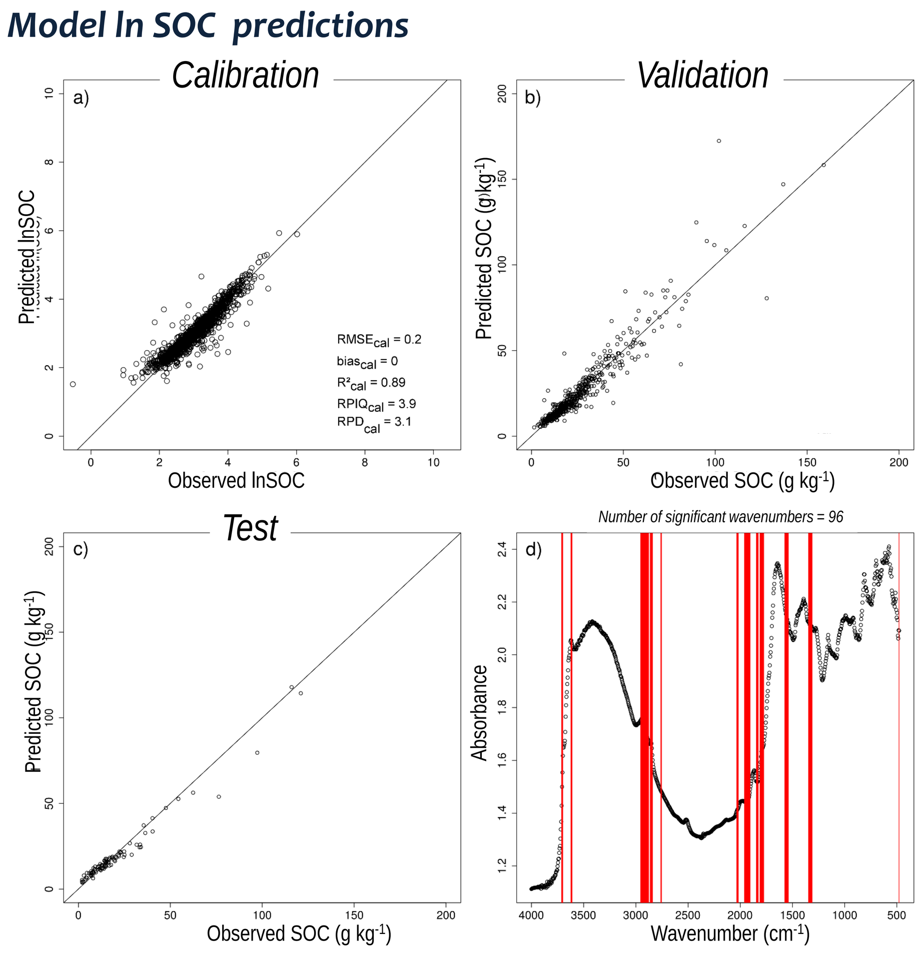
Figures of merit of all the prediction models calculated

Prediction model	on validation samples of Region A				on test samples of Region B			
	R^2_{val}	$RMSE_{val}$ g kg-1	$Bias_{val}$ g kg-1	RPD_{val}	R^2_{test}	$RMSE_{test}$ g kg-1	$Bias_{test}$ g kg-1	RPD_{test}
GM for SIC predictions	0.98	2.1	0.0	7.6	0.96	5.2	0.2	4.9
LM for SIC predictions	0.99	1.8	0.0	8.8	0.96	5.6	1.7	4.6
GM for SOC predictions	0.88	7.2	-0.4	2.7	0.64	16.0	-5.2	1.3
LM for SOC predictions	0.93	5.4	-0.7	3.6	0.89	6.9	0.5	3.0
GM for ln(SOC) predictions*	0.90	6.6	-0.1	2.9	0.97	4.2	0.7	4.9
LM for ln(SOC) predictions*	0.92	5.7	-0.1	3.4	0.93	5.8	-0.6	3.6

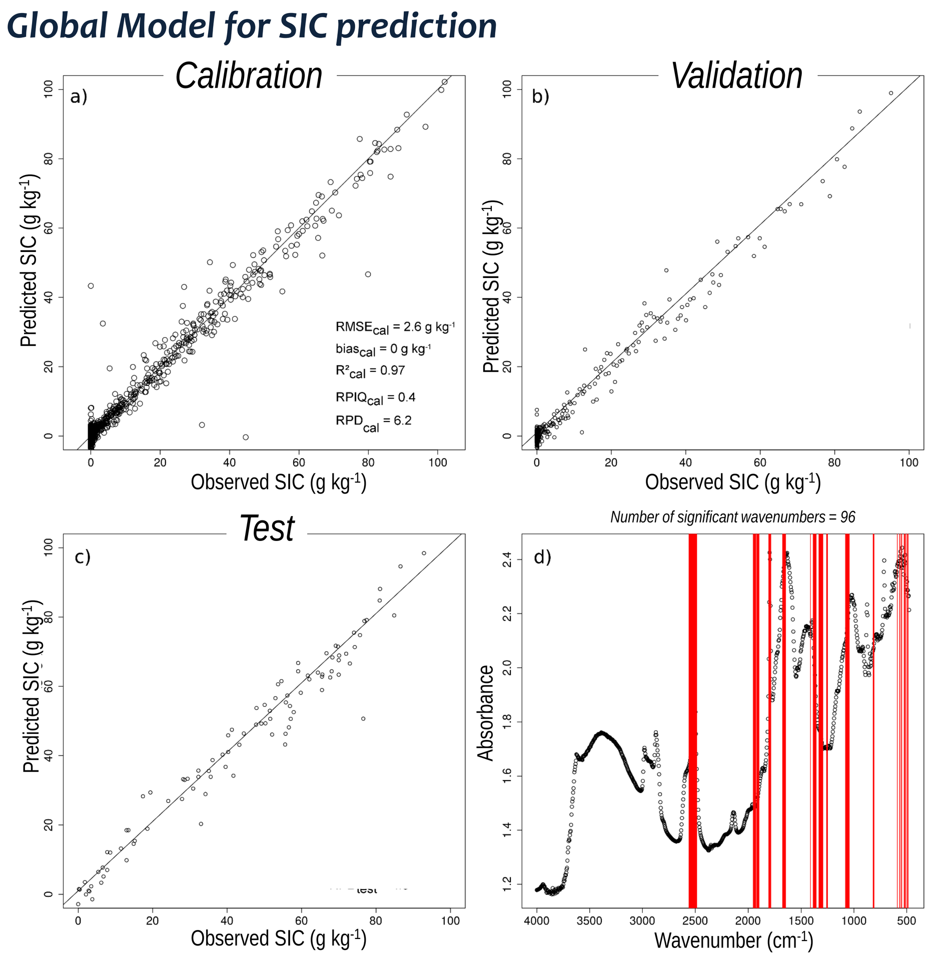
*ln(SOC) predictions were backtransformed in g kg-1

The best models for SOC and SIC predictions

Global Model ln SOC predictions



Global Model for SIC prediction



Highlights

- When both calibration and validation samples originate from the same pedo-climatic context, SIC and SOC predictions are accurate.
- When calibration and test samples originate from different pedo-climatic contexts, the SOC prediction performance decreases, whereas the SIC prediction performance remains accurate.
- MIRS is a promising tool for SIC determination, even when the calibration and test samples originate from different contexts.
- In-transformation of SOC data improved prediction accuracy, for global prediction especially

Reference

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