

# Contribution of Sentinel-2 seedbed spectra to the digital mapping of soil organic carbon concentration

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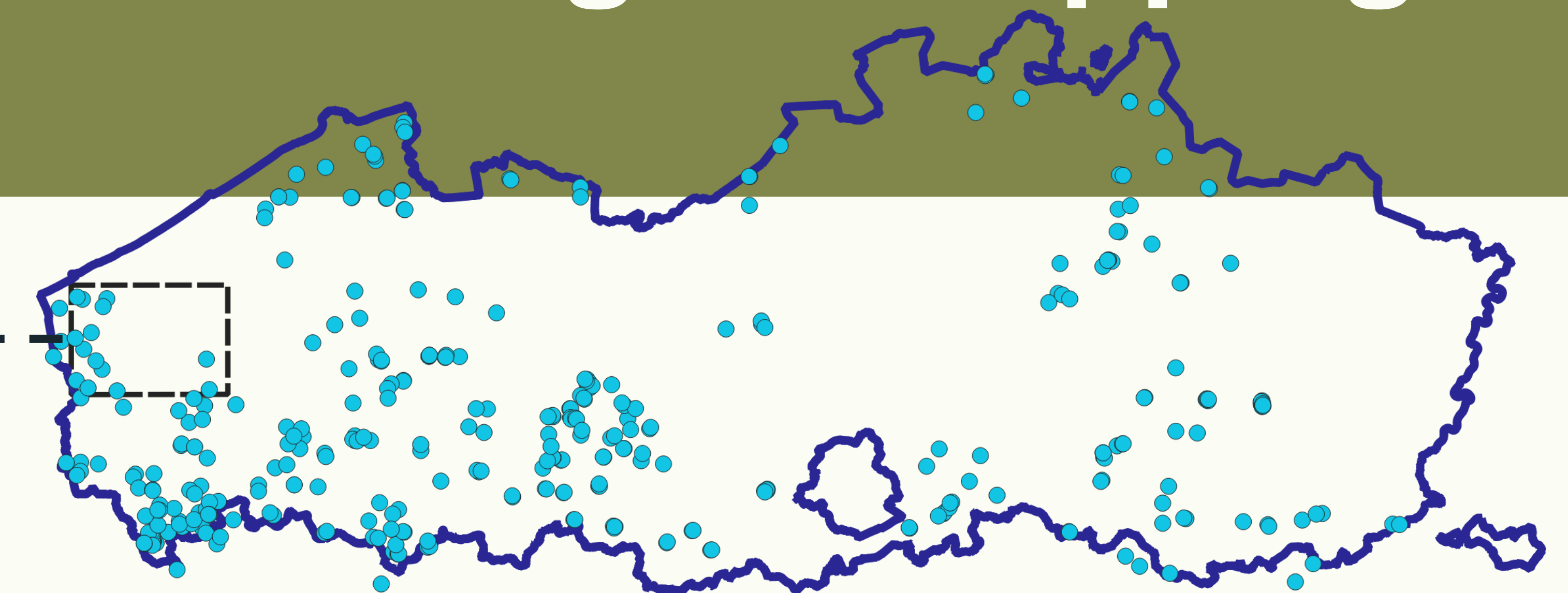
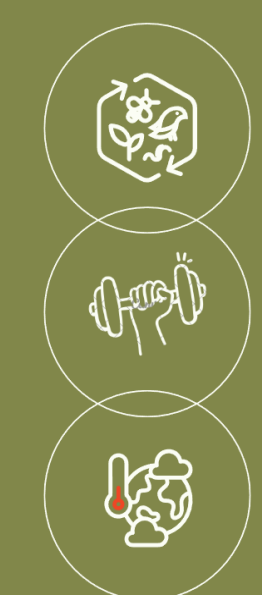


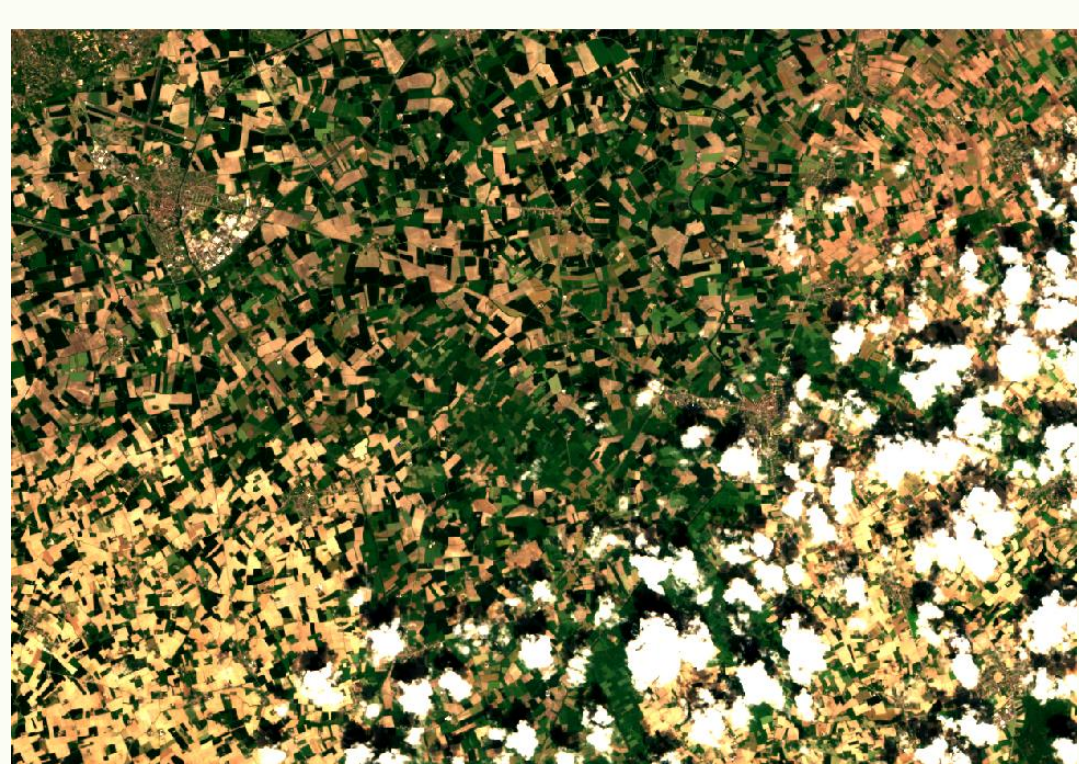
Fig. 1. Study area of Flanders, northern Belgium, with location of the calibration dataset measured on cropland in 2021 as part of the citizen science project Curieuze Neuzen (n=360).



Soil organic carbon (SOC) is a fundamental component of terrestrial ecosystems, providing several benefits for soil health and having great potential for climate change mitigation and adaptation. Understanding the spatial distribution of SOC can help formulate sustainable soil management practices.

This study aims to:

- assess the potential of Sentinel-2 derived bare soil spectra for estimating SOC% and granulometric fractions in the plough layer (0-30cm) of agricultural parcels in northern Belgium,
- evaluate the contribution of bare soil spectra and environmental variables to the digital mapping of SOC% in the region.



Spring seedbed Sentinel-2 spectra (April-May 2021)\*

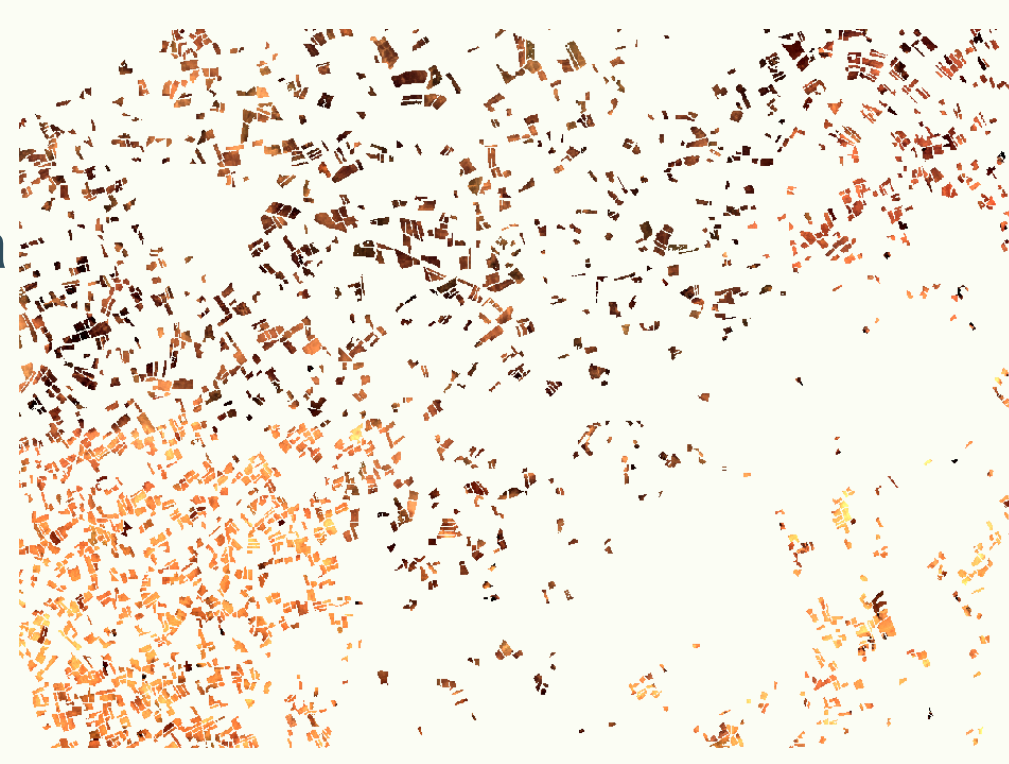


Fig. 2. Sentinel-2 image 30 May 2021.

Fig. 3. Sentinel-2 image 30 May 2021: parcels in seedbed state.

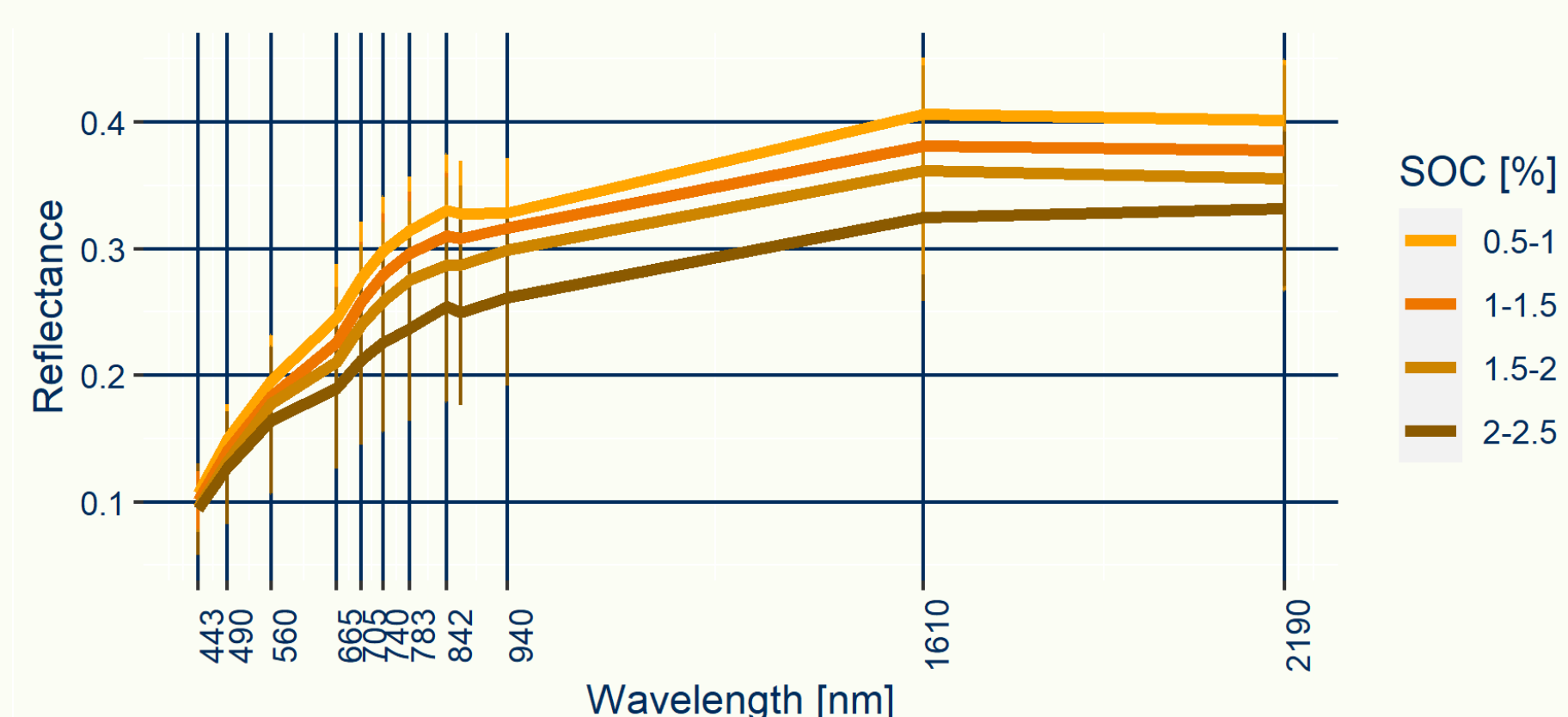


Fig. 4. Median spectral reflectance per spectral band measured by Sentinel-2 (spring seedbed) for the calibration dataset.

\*Ibrahim & Gobin (2021). Sentinel-2 Recognition of Uncovered and Plastic Covered Agricultural Soil. *Remote Sens.* 2021, 13(21), 4195; <https://doi.org/10.3390/rs13214195>

**Abbreviations:** soil organic carbon concentration (SOC%), machine learning (ML), generalised linear model (GLM), partial least squares regression (PLSR), random forest (RF), curvilinear regression (CR), generalised boosted regression model (GBM), coefficient of determination ( $R^2$ ), ratio of performance to deviation (RPD), ratio of performance to interquartile range (RPIQ), relative root mean square error (rRMSE), B2-B12 (Sentinel-2 spectral bands 2 to 12), mean annual temperature (T), mean annual precipitation (P), mean annual evapotranspiration (ET), elevation (DEM), compound topographic index (CTI), vegetation cover (VC), dry matter productivity (DMP), visible (VIS), near infrared (NIR), shortwavelength infrared (SWIR).

## 1. DSM of SOC%, sand%, silt% and clay% using Sentinel-2 seedbed spectra

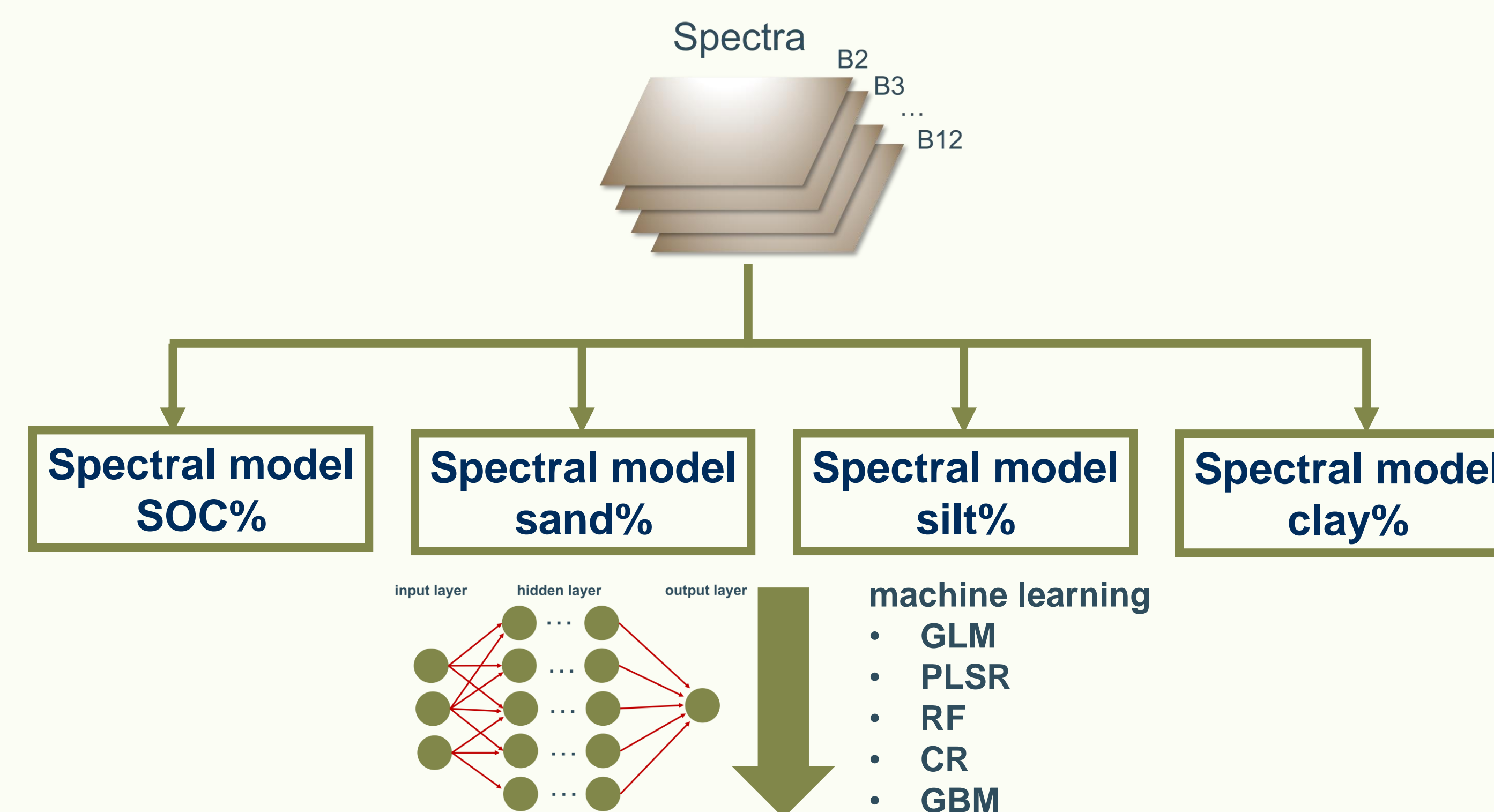


Table 1. Model performance of SOC%, sand%, silt% and clay% for the best performing machine learning algorithm (n=177).

Variable	ML	$R^2$	RPD	RPIQ	rRMSE
SOC%	RF	0.31	1.21	1.30	0.87
sand%	CR	0.75	2.04	2.54	0.51
silt%	CR	0.79	2.19	2.56	0.47
clay%	CR	0.52	1.66	1.44	0.67

## Highlights

- Higher model performance for granulometry than SOC%, especially sand% and silt%, using Sentinel-2 spring seedbed spectra.
- RF outperformed other algorithms for SOC% estimation, while CR performed best for estimation of granulometric fractions.
- Environmental covariates are better predictors for SOC% than S-2 spectra.
- Lower performance for SOC% could be attributed to (i) the low variability of the SOC data used for model calibration, (ii) the type and spatial resolution of the covariates, (iii) the presence of influencing factors related to heterogeneity of study area, and/or (v) the local decoupling of SOC and more 'traditional' covariates such as clay. → future work

## 2. DSM of SOC% using Sentinel-2 seedbed spectra and environmental covariates

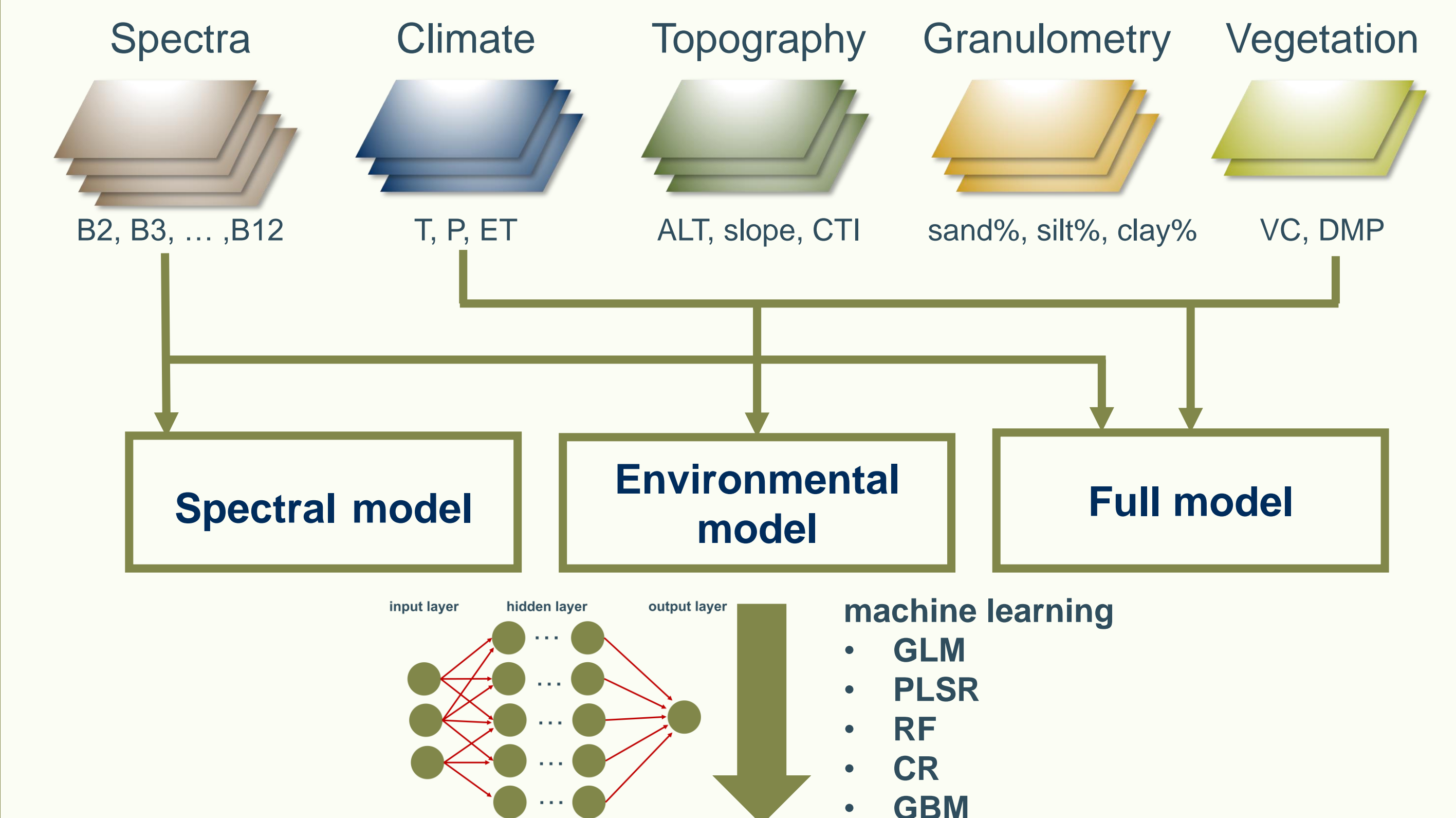


Table 2. Model performance of SOC% for the spectral, environmental and full model using random forest (n=177).

Dataset	$R^2$	RPD	RPIQ	rRMSE
Spectral model	0.31	1.21	1.30	0.87
Environmental model	0.42	1.31	1.65	0.76
Full model	0.45	1.43	1.53	0.74

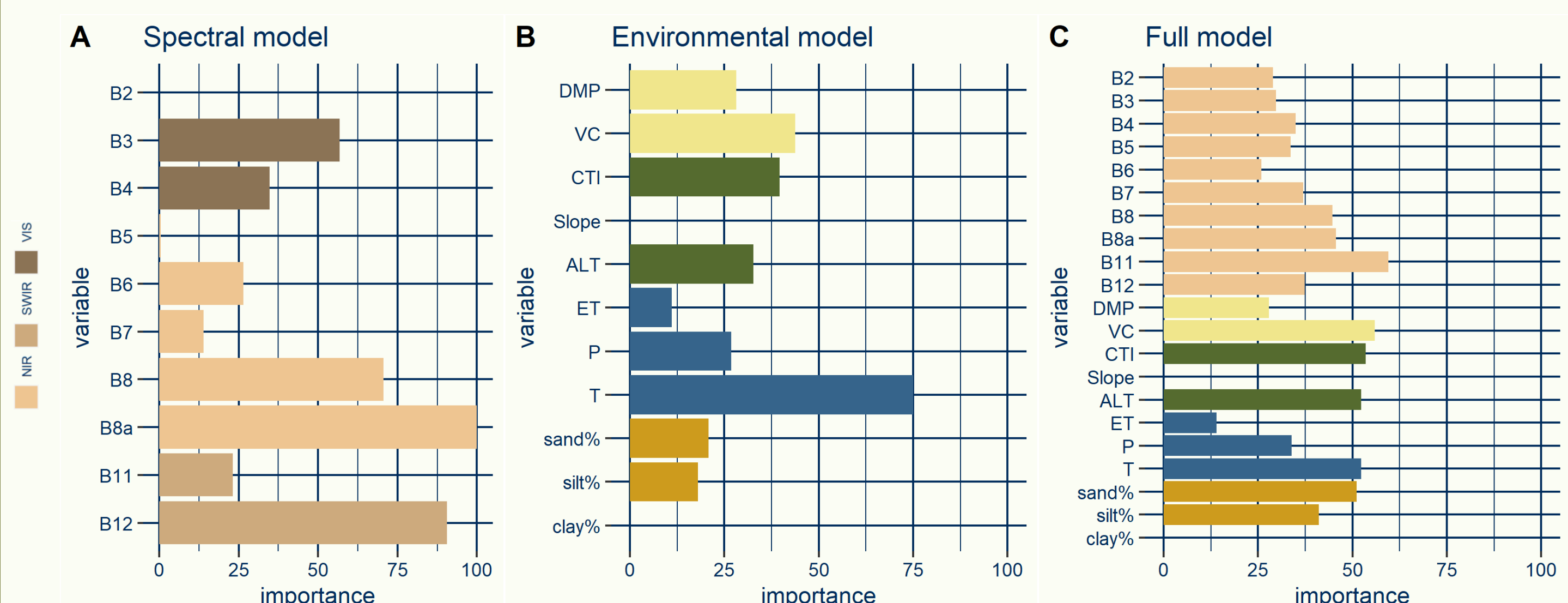


Fig. 5. Relative variable importance for estimating SOC% using random forest and A) spring seedbed spectra, B) environmental covariates and C) all covariates.