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VISIBLE AND NEAR-INFRARED SPECTROSCOPY AS A TOOL FOR SOIL CLASSIFICATION AND SOIL PROFILE DESCRIPTION

Abstract. This paper presents preliminary results of the use of visible and near-infrared (VIS-NIR) spectroscopy for soil classification and soil profile examination. Three experiments involving (1) three different soil types (Albic Luvisol, Gleyic Phaeozem, Brunic Arenosol), (2) three artificial micro-plots with similar texture (loamy sand, Gleyic Phaeozem) but different soil organic carbon (SOC) content and (3) a soil profile (Fluvisol) have been investigated using VIS-NIR spectroscopy. Results indicated that VIS-NIR is a promising technique for preliminary soil description and can classify soils according to soil properties (especially SOC) and horizons. Instead of complex chemical and physical analyses involved in routine soil profile classification, VIS-NIR spectroscopy is suggested as a useful, rapid, and inexpensive tool for soil profile investigation.

Keywords: VIS-NIR spectroscopy, soil remote sensing, spectral properties

INTRODUCTION

Visible and near-infrared (VIS-NIR) spectroscopy is regarded as an efficient technology to investigate soils for various purposes like soil monitoring, soil mapping, and precision agriculture (Debaene *et al.* 2014b, Stenberg *et al.*

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2010). The method is based on the absorption by the soil constituents of the near-infrared radiation by different chemical bonds such as O-H, C-H, N-H, S-H and C=O. The radiation is absorbed in accordance with the concentration of these constituents. As a result, the NIR spectra contain information about the soil composition but unfortunately NIR spectra consist of overtones and combinations (Roberts *et al*. 2004) from mid-infrared region and are not readily interpretable. Therefore, multivariate statistics are required to build models (e.g. partial least square regression, PLS) and also to interpret spectra. Principal component analysis (PCA) or clustering methods based on spectral data are usually able to classify samples according to different soil properties of interest for a specific study (Debaene *et al*. 2014a, Vasques *et al*. 2014). Most of the soil properties necessary for soil characterization according to the World Reference Base (WRB) for Soil Resources (World Reference Base…, 2014) have been successfully predicted with VIS-NIR models (Ben-Dor *et al.* 2008, Debaene *et al.* 2014b, Paz-Kagan *et al.* 2014, Stenberg *et al*. 2010). The Measures *in situ* have been made possible because of the miniaturization of the technology and the use of fiber optics (Bartmiński *et al*. 2012, Waiser *et al.* 2007). *In situ* measures allow for faster and cheaper analyses and are environmentally friendly. It was proved that *in situ* measurements can result in similar accuracy to laboratory-based measurements (Waiser *et al.* 2007). It is an efficient way of acquiring soil information in a short time and can help when only a small time window is available for analysis. It was proved that *in situ* measurements can be of similar quality to that of laboratory-based measurements (Waiser *et al*. 2007, Wenjun *et al*. 2014). Moreover, soil mapping and soil surveys usually require extensive field observations that could be done by spectroscopy in the field. VIS-NIR spectroscopy is already in use for precision agriculture but is still in research stage (Debaene *et al.* 2013, Kweon and Maxton 2013) since there are yet problems related to field conditions (e.g. soil moisture and surface roughness).

The aim of this study was, therefore, to test for the possibility of using VIS-NIR spectroscopy for rapid soil classification and soil profile examination. We used the method in three different situations by collecting spectra from (1) three different soil types, (2) from artificial micro-plots *in situ* with similar texture but different SOC content and (3) by collecting spectra along a soil profile.

MATERIALS AND METHODS

The method was tested in three situations (schemes 1–3) with wet and dry samples in the laboratory and in the field. Samples were scanned in the VIS-NIR spectral range (350–2,500 nm) and analyzed for chemical and physical properties according to methods described elsewhere (Bartmiński *et al.* 2012, Debaene *et al*. 2010).

1. Three soils from the Lubelskie Voivodeship were selected for their differences in composition and structure. The soils are the followings: Albic Luvisol (AL) from Szerokie, Gleyic Phaeozem (GP) from Zabędzie, Brunic Arenosol (BA) from Zemborzyce. These soils were analyzed for SOC content, N content, soil texture, some macro (Fe, Mn, Ca, Mg) and micro elements (Zn, Pb, Cd). The soil spectra were recorded with a spectroradiometer PRS-3500 (Spectral Evolution, MA, USA) in the 350–2,500 nm rage using a contact probe on samples at field condition (without drying), on dry samples and on wet samples (saturation). Wet and dry samples were scanned 5 times each and samples at "field condition" – several times every three days during two weeks to inspect the effect of natural air drying on spectra.

2. Three artificial micro-plots (IUNG-PIB, Puławy) with a loamy sand texture but different soil organic carbon content (high, medium, low). These artificial plots are coming from a Gleyic Phaeozem soil. The plot with high SOC content is from the top soil. The low SOC content plot from a deeper part of the profile and the medium SOC content is a mixture of both. The three plots spectra were recorded *in situ* by the PRS-3500 (Spectral Evolution, MA, USA) using the contact probe. Each micro-plot was scanned 10 times at different location on the plot to look at the spatial variability at the plot scale.

3. A soil profile from an Albic Luvisol (Podmieście, the Masovian Voivodeship). The profile is 150 cm deep. Samples were taken along the profile every 20 cm starting at 10 cm in the topsoil until 150 cm. Three replicates at each depth were taken every 20 cm to look at the horizontal variability of the horizon. Soil spectra were recorded in the laboratory using the Mobile Sensor Platform (MSP) Veris spectrophotometer in bench top mode.

The use of a contact probe (PSR-3500) and of the sapphire window in contact with the sample (Veris) are a way to avoid contamination with ambient light. Raw spectra were smoothed using a moving average (MA) of width 11 (number of neighboring spectra for the average). Standard normal variate (SNV), first and second Savitzky-Golay derivatives were applied to the spectra as mathematical pretreatment. For each of the three experiments a principal component analysis (PCA) was done to explore and reduce the information contained in the spectra. The PCA is a good way to identify possible grouping of samples and outliers and is a first step for further investigation of the data using other tools. Finally, the spectra of the three schemes were combined and used for classification of the soils using the PLS-DA method.

RESULTS AND DISCUSSION

Scheme 1

Spectra of scheme 1 for the assessment of spectra with different moisture content are presented in Figure 1 and mean spectra for each soil types from that scheme in Figure 2. Chemical and physical composition of samples are presented in Table 1. The initial soil moisture contents for scheme 1 were 17.5%, 22.7% and 8.0% and at saturation –33.6%, 38.5% and 23.7% for AL, GP and BA, respectively.
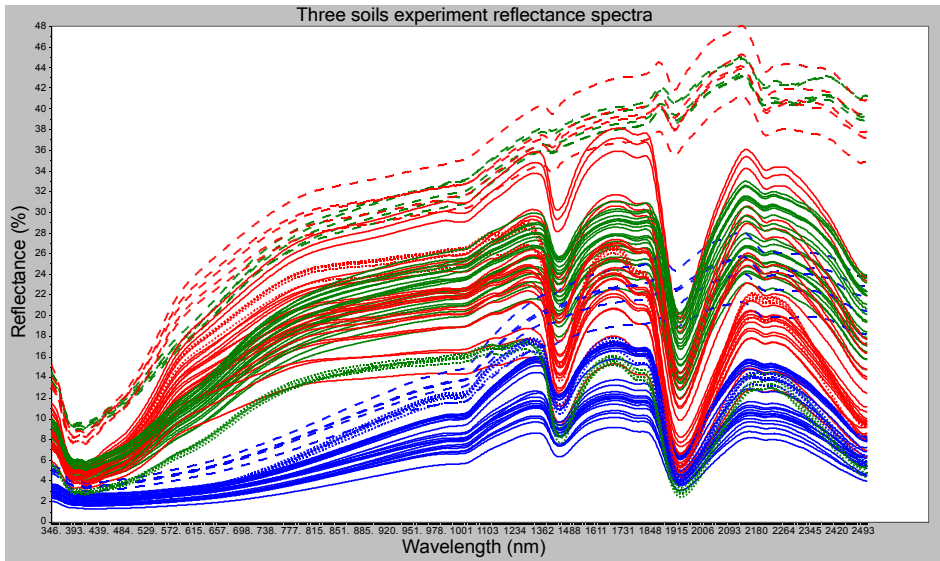

Fig. 1. Reflectance spectra of scheme 1 samples. Red (Albic Luvisol), green (Brunic Arenosol) and blue (Gleyic Phaeozem). Dry samples are presented as dashed lines and the saturated samples as dotted lines. There is a regular reflectance increase with the drying of the samples.

Overall, the reflectance is lower when the SOC content is higher. The effect of SOC on spectra is well-known and was demonstrated by e.g. Demattê *et al.* (2004). This is especially true in the 350–1,350 nm range for saturated samples. The lowering of reflectance with the increase in the SOC content is partially due to the greater light absorption due to darker color in the visible range in addition to the adsorption of infrared energy by the C bonds. On dry samples, there is a significant spectral variability with AL and GP in contrary to the BA spectra that do not present much variations. It is probably due to the fact that these two soils are forming aggregates that have an influence on the scattering of light while sandy soil tends to produce less aggregates because of the very low content of fine particles. That could explain the variation in the soil spectra
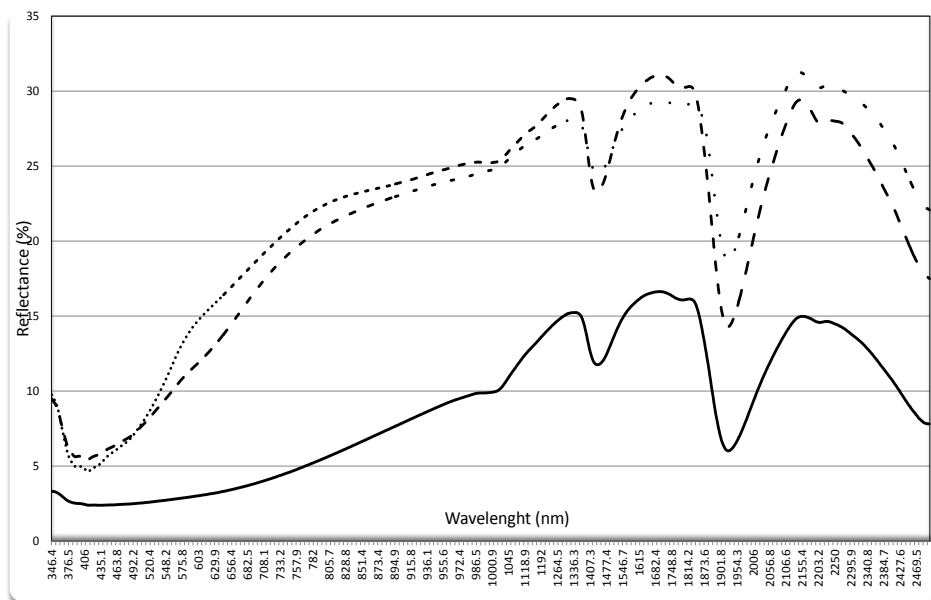
Fig. 2. Mean spectra for Albic Luvisol (dotted line), Brunic Arenosol (dashed line) and Gleyic Phaeozem (solid line)

TABLE 1. CHEMICAL AND PHYSICAL SOIL PROPERTIES OF SAMPLES USED IN THIS STUDY

Sample	Fe	Mn	Cu	Zn	Pb	Ca	Mg	K	Cd	SOC	N
					Scheme 1						
GP	1.18	37.26	22.30	112.00	20.30	2.18	2,298	2921.00	<DL	2.78	0.27
BA	0.15	38.60	3.26	19.70	<DL	794.00	195	290.70	<DL	1.62	0.12
AL	1.11	34.08	10.80	44.40	<DL	1.41	6,044	3738.00	<DL	0.46	0.07
(mm)	d (0.1)	d (0.5)	d (0.9)	<0.002	0.002–0.02	0.02–0.05	0.05–0.1	0.1–0.25	0.25–0.5	0.5–1.0	1.0–2.0
GP	7.17	40.92	536.70	3.36	23.46	28.93	9.98	5.43	17.04	11.19	0.62
BA	22.70	322.26	665.51	1.23	7.61	12.26	7.37	10.10	37.40	23.42	0.62
AL	4.44	29.71	68.51	5.21	28.23	43.54	21.29	1.72	–	–	–
					Scheme 2						
Low	–	–	–	–	–	–	–	–	–	0.63	–
Medium	–	–	–	–	–	–	–	–	–	2.82	–
High	–	–	–	–	–	–	–	–	–	6.16	–
(mm)	1–0.5	0.5–0.25	0.25–0.10	0.10–0.05	0.05–0.02	0.02–0.006	0.006–0.002	<0.002			
Low	13	35	32	5	5	4	2	4	–	–	–
Medium	12	37	30	5	5	2	3	6	–	–	–
High	10	32	33	4	8	3	3	7	–	–	–

Fe, SOC, N and granulometry in %; other properties in mg kg^{-1}; DL – detection limit

(Barthès *et al*. 2008, Madari *et al.* 2006). The reflectance is higher with dry samples as expected (Wenjun *et al.* 2014). The features of wet and saturated samples are more discernable, especially at 1,400 and 1,900 nm (water absorption) and 2,200 nm water and clay minerals absorption. The wet (at saturation) samples presentlow spectral variation. This is probably due to the levelling of the soil surface roughness (Cierniewski *et al.* 2015) by water. The changes in spectra reflectance with sample drying is caused by the change in moisture content (Fabre *et al.* 2015) and, to some extent, to the related changes in surface roughness (Croft *et al*. 2009) and the formation of aggregates and crust as the samples are drying. The crusting effect on VIS-NIR spectra was investigated by Eshel *et al.* (2004). Authors observed similar lowering of the reflectance with crusting.

The PCA (Fig. 3) is already able to separate/cluster these different soils without any further chemometrics. There is a clear clustering according to soil type and moisture content. It is possible to observe the effect of drying on the spectra. The samples are moving along the first principal component (PC) from right to left while drying and from top to bottom. The spectra of saturated samples are focused in a small area in contrary to spectra from wet (field) and especially dry samples. The results demonstrate the importance of analyzing samples with similar moisture content.
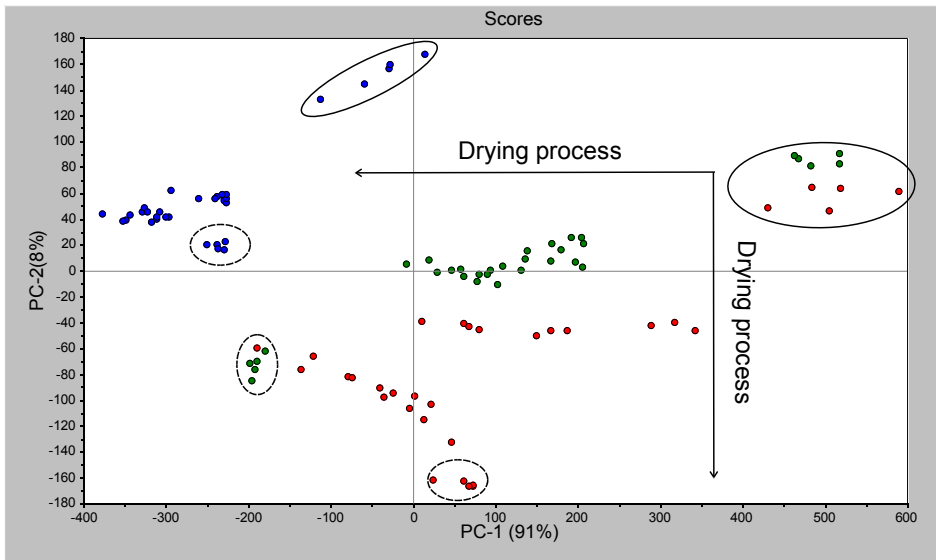

Fig. 3. PCA scores of samples scanned in scheme 1. Red (Albic Luvisol),
green (Brunic Arenosol) and blue (Gleyic Phaeozem)

Scheme 2

The spectra from scheme 2 are presented in Figure 4. There is a clear decrease of the reflectance with the increase in the SOC content as observed in scheme 1. The overall shape is similar to all samples as expected since samples are of similar texture (loamy sand). There is more variability in medium SOC content spectra probably due to the mixing of the top soil with deeper layers. The spectra are clearly related to the SOC content in that example since the soil textures are similar (Table 1) and, therefore, have no effect on the spectral characteristics (Debaene *et al.* 2014b). The reflectance for the low SOC content samples in the 400–1,000 nm range has a different shape since that region of the spectra is influenced by the SOC content. That region was proved elsewhere to be of interest for SOC prediction using spectral reflectance measurements (Aïchi *et al.* 2009, Kweon and Maxton 2013).

The dissimilarities that exist between the spectra of Gleyic Phaeozem from scheme 1 and those from scheme 2 are due to the differences in the SOC content and soil texture (more fine particles in samples from the micro-plots) but also to the difference in moisture content (Table 1, Fig. 1 and 4). These factors and especially the soil moisture are still a challenge when it came to classify soil samples with VIS-NIR spectroscopy. It appears here that the SOC content is the main property affecting the sample spectra. On a PCA score plot (not presented here), there is a clear clustering of samples according to the SOC content
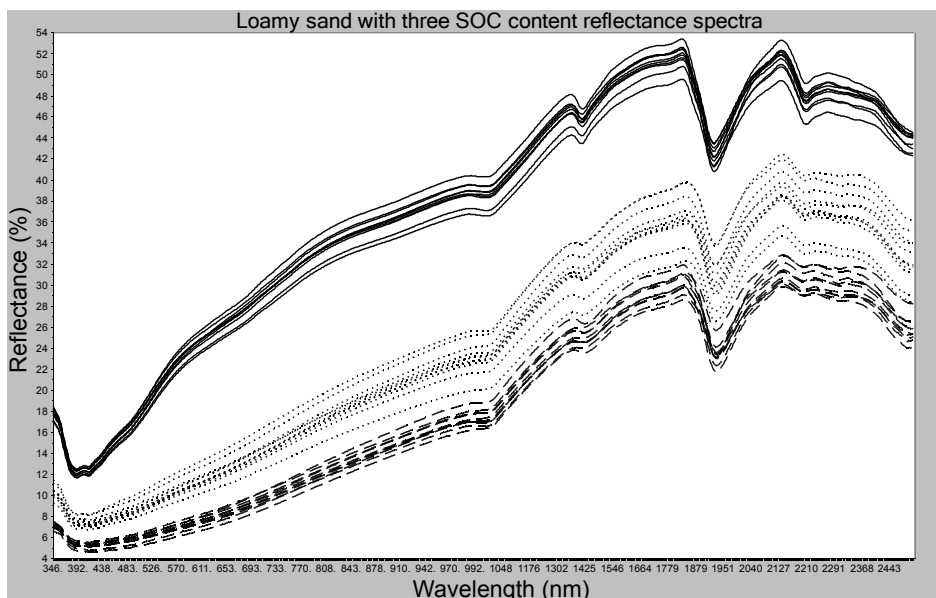

Fig. 4. Spectra of three loamy sands with different soil organic (SOC) content. Dashed lines – high SOC content, dotted lines – medium SOC content, low SOC content – solid lines

(7 samples from each micro-plots were analyzed for SOC) with samples moving along the PC1 according to their SOC content (negative PC1 values for high SOC to positive for low SOC content).

Profile

The spectra from soil profile samples were reduced to 400–2,200 nm range due to low signal-to-noise ratio. The spectra from scheme 3 samples were all very similar. The only visible difference to the naked eyes was the baseline shifts (not presented here). The PCA plot shows the high horizontal variability along the soil profile. That result emphasizes the need for further investigations about possibility of using VIS-NIR spectroscopy for analyzing soil profiles. Even if spatial variability is evident (the three samples from a similar depth are not correctly grouped). It appears obvious that there is a clustering of samples according to the depth (Fig. 5). This could be due to e.g. changes in sample color with depth due to a lower SOC content.
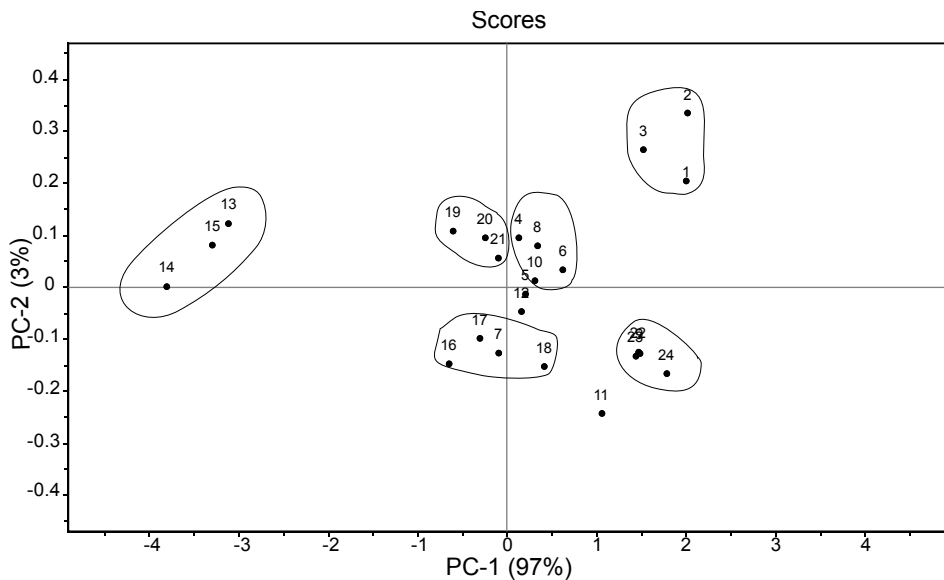

Fig. 5. PCA scores of samples scanned in scheme 3 (soil profile)

CONCLUSIONS

This study presents visible and near-infrared spectroscopy as a promising technology for rapid *in situ* soil classification and to profile description. The main advantages of the method are the speed, low cost and possibility of acquiring spectra *in situ*. These are promising results about the possibility of

using VIS-NIR spectroscopy for investigating soil classification and soil profile description using that technology. However, more in-depth investigation with several soil profiles and more soil types are needed to completely remove the need of classical methods of soil investigation.

ACKNOWLEDGEMENTS

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