A NOVEL PROTOCOL FOR ROBUST IN-FIELD MONITORING OF CARBON CONTENT

STAJNKO, D., KELC, D., LAKOTA, M. & BERK, P.

Abstract: *Visible–near-infrared–shortwave-infrared (VNIR–SWIR) spectroscopy is one of the most promising sensing techniques to meet growing demands for soil information and data. To ensure the successful application of this technique in the field, efficient methods for tackling negative moisture effects on soil spectra are critical. In this chapter paper, the effects of soil moisture content (SMC) from spectra are reviewed. The reviewed techniques encompass the most common spectral pre-processing and algorithms, as well as less frequently reported methods including approaches within the remote sensing domain. Examples of studies describing their effectiveness in the search for calibration model improvement are provided. Moreover, the advantages and disadvantages of the different techniques are summarized. The future researches should be focused on a wider range of soil types, in-field conditions, and systematic experiments considering several SMC levels to enable the definition of threshold values for the effectiveness of the discussed methods is recommended.*

Key words: *VNIR–SWIR spectroscopy, soil, SOC, sampling*

Authors´ data: Full. Prof. Stajnko, D[enis]; Assist. Kelc, D[amjan]; Assoc. Prof. Lakota, M[iran]; Assist. Dr Berk, P[eter]; University of Maribor, Faculty of Agriculture and Life Sciences, Pivola 10, SI-2311, Hoče, Slovenia, denis.stajnko@um.si, damijan.kelc@um.si, miran.lakota@um.si, peter.berk@um.si

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1. Introduction

Quantifying soil organic carbon (C) content in the soil is of great interest because of soil management, soil mapping, and C sequestration. Most recently, there has been strong interest in mapping soil organic C to quantify the amount of C stored in the soil for C sequestration contracts. Quantifying carbon in the soil for C sequestration accounting is difficult because soil carbon is highly variable in space and time, and very management dependent (Morgan et al., 2009).

However, the conventional soil laboratory analysis is time, cost, and labour intensive, thus alternative sensing methods are therefore being developed and tested in both the laboratory and field in proximal and remote sensing setups in order to increase the number of samples analysed and to enable the streaming of sufficient amounts of data (Berk et al., 2014, Berk et al. 2016).

Soil reflectance measurement across the electromagnetic spectrum from 400 to 2500 nm has become routine for the proximal sensing of soil attributes. This practice has gained momentum in recent years, with the proliferation of soil spectral libraries (SSLs) coupled with in-situ metadata such as soil descriptions, climate data, and geographical coordinates (Viscarra Rossel et al., 2010).

Proximal sensing techniques can potentially decrease the costs related to sample collection, registration, packaging, transport, drying, sieving, and chemical use. In the past few decades, the VNIR–SWIR spectroscopy technique has been increasingly used and proved in soil science as most promising for measuring the soil carbon. The visible (400–700 nm), NIR (700–1000 nm), and SWIR (1000–2500 nm) wavelengths of the electromagnetic spectrum contain useful information on the organic and inorganic matter in soil. Absorptions in the NIR and SWIR range originate from not only the overtones of O–H, SO_4 and CO_3 groups but also the combinations of fundamental features of H_2O, CH_4, and CO_2 (Viscarra Rossel et al., 2010). Thus, the in-field prediction of soil properties from VNIR–SWIR spectra is increasingly being seen as a practical means of rapidly and cost-effectively acquiring analytical information (Janik, et al., 2016). In the laboratory the soil mainly tends to be air-dried, which contrary to the use of in-field spectroscopy where the soil spectra are always influenced by external parameters such as variable soil moisture content (SMC)(Roudier et al. 2017).

Three spectrally active forms of water can be observed in soil, namely the water incorporated into the mineral lattice (with an OH absorption of around 2200 nm), the hygroscopic water adsorbed on the surface of clay minerals (with OH absorption features near 1400 and 1900 nm), and the free water occupying soil pores (with OH absorption features near 1400 and 1900 nm)(Ben-Dor, 2016). For these reasons, soil moisture is the most dominant phenomenon that reduces the soil reflectance response and hinders the harmonization and alignment between field and laboratory spectra. Increasing SMC leads to a decrease in the accuracy of soil property estimation using VNIR–SWIR spectra as water absorption bands can overlap with those of organic matter and soil minerals at high moisture contents (Knadel et al., 2023).

The nature of soil organic matter (SOM) is responsible for many soil properties such as compaction, fertility, water retention, soil structure stability, and it constitutes one of the major resources in the global carbon cycle.

Since SOM is mainly concentrated on the top Ao horizon that is exposed to the sun's radiation, it is a perfect property to be assessed by IS technology. This notion is strengthened by the fact that pure SOM material consists of unique spectral fingerprints that can be correlated to content, composition, and maturity (Ben-Dor, 2016).

The main lack of VNIR–SWIR spectroscopy represents its significantly dependence on the soil moisture content as increasing SMC determines a reduction in the reflected energy from topsoil (low reflectance). However, there is considerable difference between the visible and SWIR regions: visible wavelengths saturated to 20% of volumetric water content while the reflectance in the SWIR region continued to respond to soil moisture variation up to 50% (Figure1).

Generally, the strongest effect of water absorptions can be seen in the bands near 1400 and 1900 nm, while on the hand also the high content of clay may be detected near 2150 nm, so it effects the results. Thus the most reliable reflectance bands for detecting SOC lies in 350–700 nm range (Stajnko et al. 2019).

Studies dedicated to the issue of soil moisture removal from spectra and using mathematical techniques are not that common in comparison to other topics investigated within the area of soil spectroscopy. The large majority of them used regional or local datasets, one reported on the application of a national SSL to a field dataset, one considering soils representative for a national scale, and one reported the results for a European scale (Stajnko et al. 2016). The investigated samples originate mostly Europe (few countries only) with only few examples of studies from USA, Brazil, and Australia.

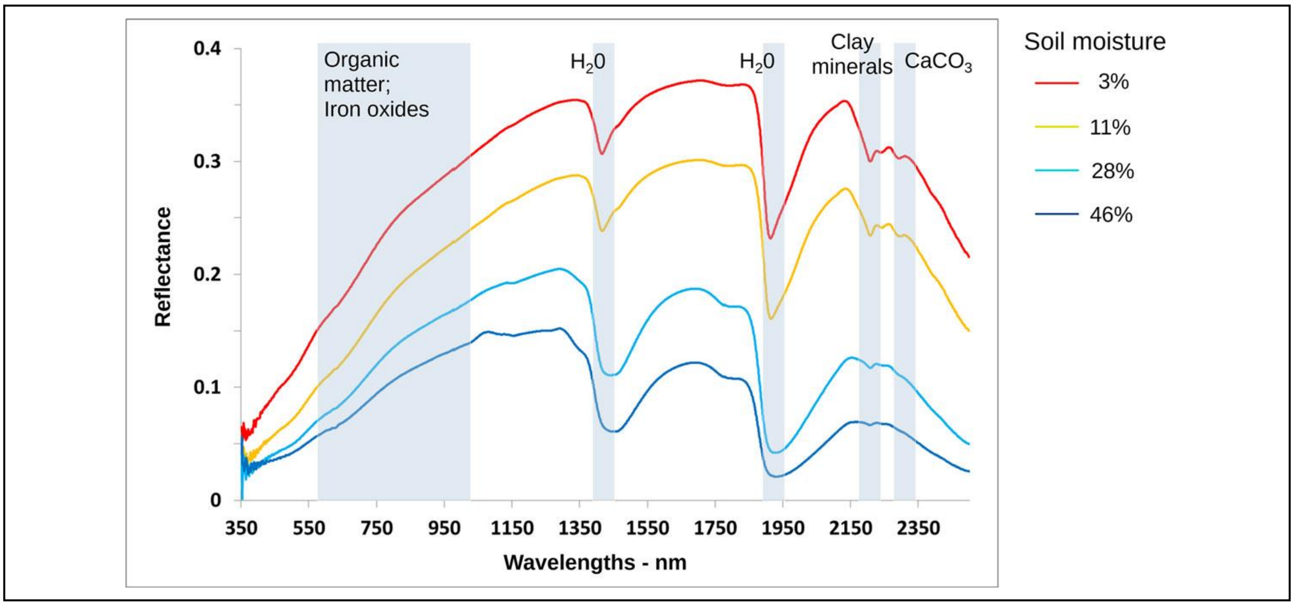

Fig. 1. Location of the reflectance depressions related to soil properties and changes in reflectance according to four levels of soil moisture percentage for the same soil sample.

The number of used soil samples varied from as few as 18 to as many as 3993, with a half of the papers based on less than 150 samples. In most cases (34 studies), laboratory measurements were considered, with 9 of them in situ measurements were additionally conducted.

The remaining studies were dedicated to satellite and airborne data. In most studies dealing with effects of moisture on spectra and the estimation of soil properties by means of techniques to reduce or remove it, data pre-processing has been used. It is already known that different pre-processing techniques can improve the use of spectral data for soil property prediction. Nevertheless, few researchers have compared the effects of common pre-processing in relation to the effects of moisture on soil reflectance (Knadel et al., 2023).

The effect of soil moisture and SOC content on the depression of reflectance may be clearly seen in Figure 2a and Figure2b, respectively, whereby the general curve of NIR reflection remains the same in soil samples regardless different percentages of soil moisture (Vindiš et al., 2016, Stajnko et al. 2022).

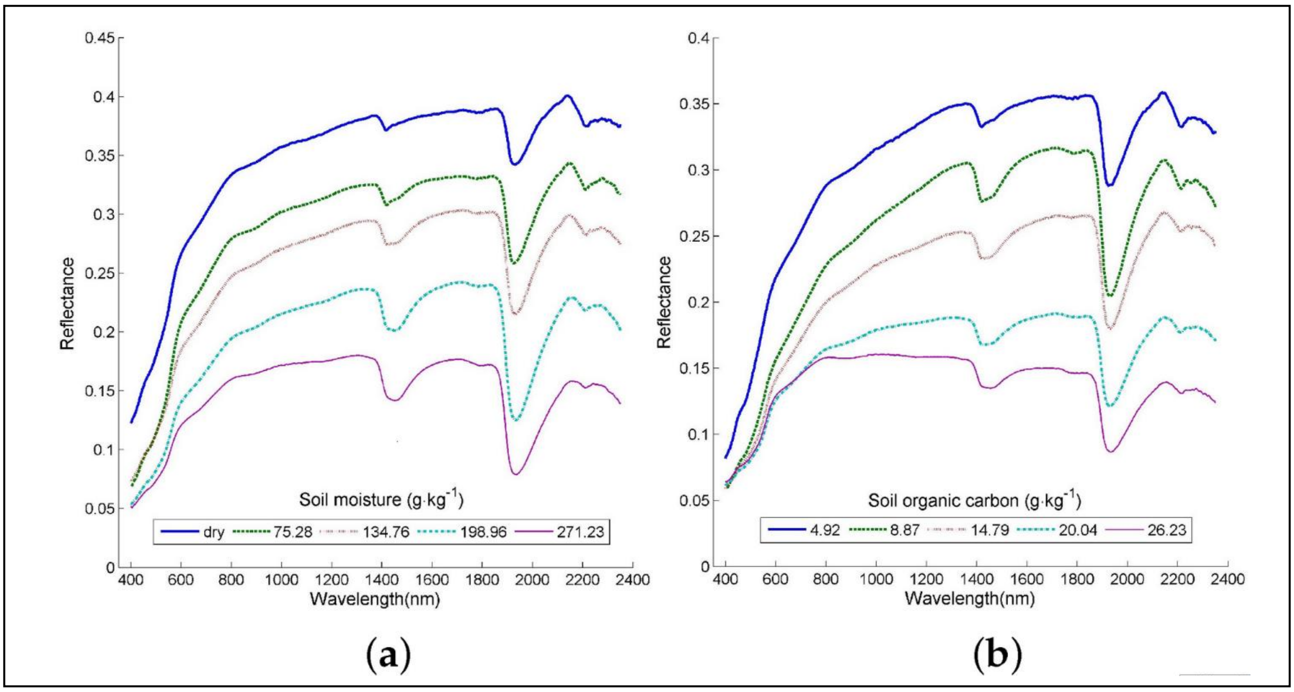

Fig. 2. The effects of moisture (a) and SOC (b) on the specific depression of the same soil sample.

In this chapter we aimed to familiarize readers with a range of available techniques and their effectiveness for: (i) tackle moisture effects on predicting soil organic carbon (SOC), (ii) to present the possibility of in-situ sampling instead of the air-dried laboratory analysis. A thorough explanation of soil moisture and VNIR–SWIR spectra interactions is presented below to provide background information for the complexity of this phenomenon.

2. Measurements and instruments

Detecting and calculating the SOC-content directly in the field should include also measurement of several physical parameters of the soil such as moisture, texture, pH, clay content and EC values. Some of them might be proceed with the TDR sensor and others with measurements of soil reflection of VNIR–SWIR, which is done with ASD spectroradiometer.

2.1 TDR sensor

TDR sensor enables continuous measurement of soil moisture without destroying the soil profile. A conductor that is inserted into the ground sends electrical reflections along the conductors around the ground. TDR sensors use parallel rods, acting as transmission lines. A voltage is applied to the rods and reflected back to the sensor for analysis. The speed or velocity of the voltage pulse along the rod is related to the apparent permittivity of the substrate. In relatively wet soil the velocity of the pulse is slower than in drier soil. To measure these reflections, the TDR is sending an incident signal to the conductor and listen for its reflections. Similar to capacitance and frequency domain sensors, TDR sensors must have good contact with the soil, because any air gaps will lead to erroneous measurements. The measurement volume of TDR sensors depends on the length of the rods. The probability of air gaps forming during installation increases with longer rods. Additionally, longer rods will measure a greater length of the soil profile and moisture content can vary significantly from shallow to deeper depths making interpretation of data difficult. TDR sensors should not be used in high saline soils or soils with high bulk electrical conductivity or high attenuation. In soils with high EC values, the voltage pulse is not reflected back along the rod and, therefore, is not measured. The pulse is attenuated beyond the length of the rod. TDR probes have been found to have errors in soils with EC values of 1.32 dS/m.

For accurate calculations of the C-content the following parameters are necessary: volume content of water, gravimetric water content, total dissolved solids, total suspended solids (filter), soil temperature and EC.

Fig. 3. Fieldscout TDR 350.

2.2 ASD FieldSpec

The ASD spectroradiometer covers a spectral range of 350–2500 nm and was equipped with the ASD high-intensity contact probe with a 6.5 W quartz halogen lamp and a spot size of reflectance measurement of about 10 mm. The contact probe has a fixed spatial relationship between the detector fibre optic cable and the light source, allowing the measurement of a directional radiance value. The soil spectral radiances were acquired between 350 nm and 2500 nm with the contact probe using an integration time of 50 ms and a spectral resolution of 1 nm and then converted into absolute reflectance by using a NIST calibrated panel (Spectralon—reference standard, S/N 5221—Sphere Optics Inc., Durham, NH, USA) to derive absolute reflectance spectra.

The spectra were acquired by maintaining the same viewing geometry (nadir view) to minimize directional effects resulting from properties of the target with a directional set-up. Data at wavelengths less than 400 were discarded since they were too noisy.

Fig. 4. ASD FieldSpec 4 full-range spectroradiometer.

The soil samples had been air-dried and passed through a 2 mm sieve. They were then put individually into Petri dishes (little cylinders 8.7 cm in diameter, 1.6 cm in height) forming a layer considered as optically infinitely thick.

Water was slowly poured down from the side of the box to reach full saturation. When free water disappeared from the soil surface (i.e., 24 hours after wetting), the reflectance was measured. Measurements were performed four times during the drying process. In order to reduce the differences between the surface and the rest of the sample, Petri dishes were covered for two hours before the acquisition of spectra. The soil moisture content was then measured by weighing the samples after each ASD spectral acquisition and soil moisture was expressed as:

$$SM = \frac{\mathrm{Ww} - \mathrm{Wd}}{\mathrm{Wd}} \tag{1}$$

where Ww and Wd are, respectively, the weight of soil samples at wet and oven dry conditions. The main characteristics of the spectral datasets we used are reported in Table 1.

2.3 Dateset

Visible–near-infrared–shortwave-infrared (VNIR–SWIR) spectroscopy is one of the most promising sensing techniques to meet growing demands for soil information and data, because the scanning is rapid, instruments can be field portable, and costs are fixed.

The protocol for soil samples collection enables to elaborate the effects of different scanning options and soil surface pre-treatments on the spectra (compared to predictions from dried and sieved (<2mm) laboratory spectra. For testing the effects of soil surface pre-treatments and scanning position the following treatments were investigated in five replicate scans:

a) Surface rough– least possible treatment
b) Surface flat – flattened/compacted
c) Cut probe – along core/spade surface
d) Air dried - unsieved
e) Air dried - sieved <2 mm

Once the samples were taken from the fields, a laboratory protocol with two independent datasets was used for calibration of VNIR spectrum of samples, which consists of (1) standard - calibration dataset, which contains of Lucky Bay sand, (2) the validation dataset containing of soil samples processed under condition (air-dried-unsieved and air-dried-sieved). (Figure 5).

Fig. 5. The air dry – unsieved soil samples (left) and air dry - sieved <2 mm samples (right) with the standard Lucky Bay sand in the middle of each image.

The dataset for testing the VIS-NIR is composed of 24 soil samples collected at a depth of 10 cm, coming from four sites in Slovenia; Ljubljana (Lat. 46.048.168, Lang. 14.471.084), Maribor1 (Lat. 46.408.573, Lang. 16.002.008), Maribor2 (Lat. 46.408.657, Lang. 16.001.654) and Pivola (Lat. 46.500.248, Lang. 15.629.452). Spectral radiance was acquired on each sample using an Analytical Spectral Device (ASD Inc., Boulder, CO, USA) Field Spec Fr Pro spectroradiometer.

3. Accuracy of VNIR–SWIR

3.1 The accuracy of the TDR measurements

Table 1 represents four different TDR measurements: volumetric water content (VWC), electroconductivity (EC), total dissolved solids (Tds) and total suspended solids (Tss). The amount of VWC range from 19.12 g to 47.74 and is strongly connected with soil type. In contrast, Tds and Tss differ from the VWC pattern, because they depend particularly on the amount of available nutrients in the soil, which are the biggest in the Pivola P1 amounting 34.36 mg/L.

Site and trial id	VWC [g]	EC [mS/cm]	Tds [mg/L]	Tss [mg/L]	GWC [g]
Ljubljana SOIL 1	47.74	0.23	25.22	22.18	32.3
Ljubljana N8_K2	42.16	0.134	27.76	26.12	28.4
Ljubljana T1_NPK	34.28	0.14	27.68	22.78	29.5
Ljubljana T8_K2	39.22	0.142	26.64	23.26	31.2
LjubljanaT12_K2	37.58	0.128	24.92	23.96	28
Ljubljana N12_K2	46.42	0.21	24.68	22.74	30.6
Maribor1 SOIL 2	12.68	0.038	22.76	20.86	15.4
Maribor1 T2	24.84	0.044	22.12	19.82	20.6
Maribor1 SOIL 3	31.02	0.054	23.28	21.68	17.9
Maribor1 NTO_2	21.34	0.02	24.74	20.92	19.1
Maribor1 NTE_1	19.12	0.014	26.2	22.28	17.9
Maribor1 NTE_2	21.26	0.022	27.7	24.66	17.71
Maribor1 Evers_1	26.14	0.05	27.06	22.5	18.2
Maribor1 SOIL 4	19.12	0.01	27.46	27.52	17.4
Maribor2 RNT	26.54	0.028	30.5	21.76	19.5
Maribor2 RMT	30.36	0.064	28.24	20.52	20.2
Maribor2 RCT	25.82	0.038	26.44	21.48	19.7
Pivola SOIL 5	31.48	0.086	26.4	21.82	23
Pivola P5	33.50	0.07	24.16	19.8	24.6
Pivola P6	27.02	0.072	26.08	22.2	19.3
Pivola P2	32.28	0.066	29.76	23.74	19.2
Pivola P1	37.34	0.12	34.36	24.82	18.8
Pivola P4	38.36	0.096	33.24	22.74	23.9

Tab. 1. The list of field trials included in the evaluation of TDR accuracy.

It is clearly seen from Figure 6 that TDR measurements enables a close correlation between VWC and GWC (r^2=0.7179), which serve as excellent general information about the water content in the soil and is perfect information about the water status for predicting irrigation needs.

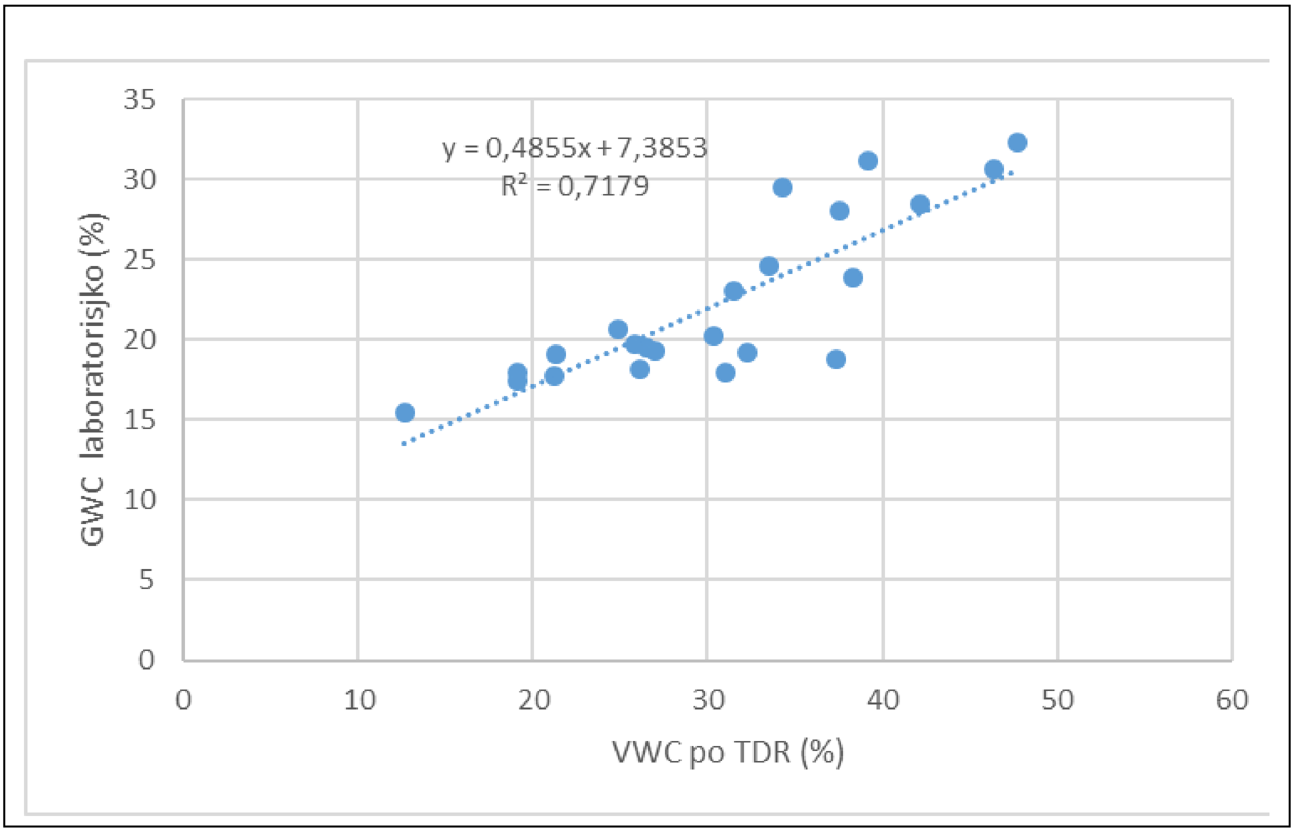

Fig. 6. Correlation between soil water content measured by TDR (GWC) and laboratory (VWC).

3.2 Detection of SOC with the VNIR–SWIR spectroscopy

Figure 7 depicted four samples of VNIR–SWIR spectroscopy's readings, whereby SOIL 1 and SOIL 2 are characterized by silty clay loam texture as Eutric Cambisols, located in the Subalpine region with an average annual temperature of 9.8 °C and mean annual precipitation 1400 mm, while SOIL 3 and SOIL 4 are classified as Distric Hypogley, with a loamy texture (light soil) located in the Sub-panonic geo-region with continental climate with an average annual temperature of 10.9 °C and precipitation of 926 mm, respectively.

Soil depth (cm)	SOC (%)			
	SOIL 1 (No-till)	SOIL 2 (Conventional)	SOIL 3 (No-till)	SOIL 4 (Conventional)
0-10	2.88±0.05^{a}	2.39±0.03^{a}	1.60±0-01^{a}	1.45 ±0.01^{a}
10-20	1.98±0.03^{b}	2.23±0.05^{b}	1.33±0.01^{b}	1.40±0.01^{b}
20-30	1.22±0.06^{c}	1.88±0.08^{c}	1.03±0.01^{c}	1.33±0.01^{c}
30-60	0.56±0.04^{d}	0.67±0.04^{d}	0.63±0.05^{d}	0.68±0.05^{d}
Total	6.64	7.71	4.29	4.86

Tab. 2. Soil organic carbon (SOC) content in four samples. Different letters indicate significant differences across treatments and soil layers according to Duncan's test ($p<0.05$).

Each pair of samples includes two different soil tillage technologies; SOIL 2 and SOIL 4 were conventionally tilled with mouldboard plough and rotary harrow, while on SOIL 1 and SOIL 3 no-till technology was applied for 12 years.

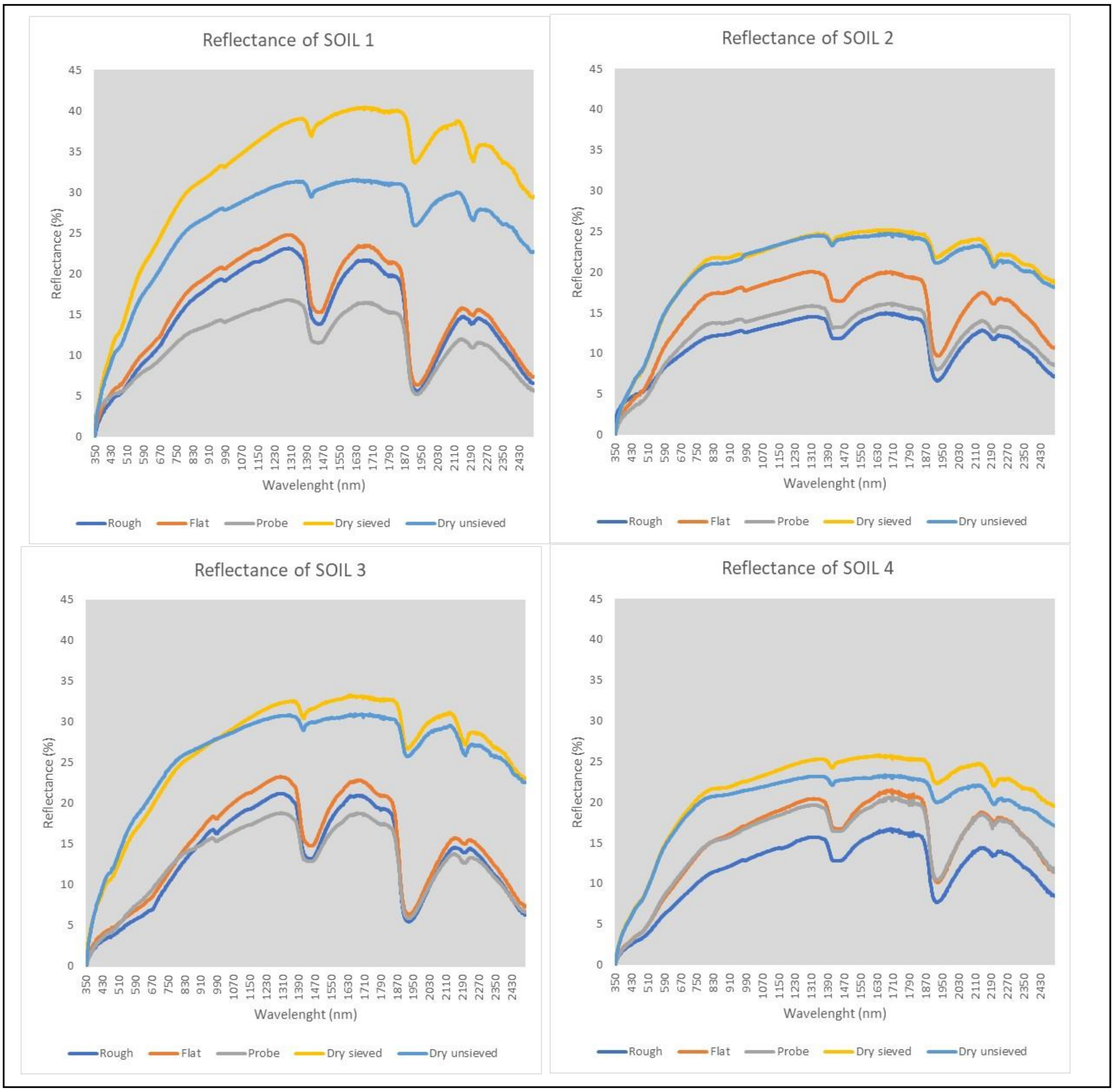

Fig. 7. The effects of moisture and SOC on the specific depression of four soil samples (0-10 cm depth).

Eutric Cambisols has on average 1,5 times higher SOC then Distric Hypogley, however the soil tillage has significant effect on the SOC and its distribution over the soil horizons on both soils, whereby in no-till the biggest SOC was found in 0-10 cm depth i.e. 2.88 % on SOIL 1 and 1.60 % in SOIL 3, respectively. In deeper layers the amount of SOC was smaller in comparison to conventional tillage, due to mixing upper in down layers.

When comparing the reflectance on particular soil type the same patters might be clearly seen, meaning that lower content of SOC effects on approximately 10 % lower reflectance of all bands, whereby special focus needs to be paid on 350–700 nm band, which is in close correlation with SOC (Figure 7). However, still the quantification of the SOC values form spectra needs to be proceed.

Those examples showed that effectiveness of VNIR–SWIR spectroscopy is possible whenever additional calibration models are applied. Moreover, advantages and disadvantages of the different techniques needs to be considered, when a wider range of soil types, in-field conditions, and systematic experiments is recommended for threshold specific values.

4. Conclusion

A fast and simple analysis of soil characteristics by using VNIR–SWIR measurements directly in the field was tested on several soil samples. The measurements with TDR spectrometer, which is necessary for predicting soil moisture showed high accuracy level and ASD spectroradiometer for receiving spectra in 400–2500 nm bands, respectively. The results of spectra showed significant differences between different soils and tillage.

However, in contrast to laboratory spectroscopy soil moisture significantly limits the accuracy of VNIR–SWIR for direct quantification of soil organic carbon content preventing a direct instant in-field data collection. For this reason, future work should involve testing of different mathematical and statistical models for efficiently removing the effect of moisture on the spectra. Thus a procedure would enable quick and accurate collecting of huge amount of SOC data needed to monitoring global carbon sequestrations into the soil.

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