Improving spectral techniques to determine soil organic carbon by accounting for soil moisture effects

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Abstract

In the past airborne hyperspectral remote sensing did not generate as accurate results as proximal spectroscopy due to some natural surface constraints, as vegetation, moisture, roughness, etc. In particular, the unknown moisture content at the moment of airborne data collection causes a decrease of accuracy of the SOC prediction model. This study aims to quantify the effect of soil moisture on the accuracy of SOC measurements, and to propose a method to determine SOC content for moist samples with unknown moisture content. Soil samples were collected along a transect, located in the Grand-Duchy of Luxembourg. The normalized soil moisture index (NSMI) was used to estimate soil moisture and to spectrally classify soil samples. SOC was predicted combining soil spectra and multiple regression models from dry up to 25% moisture content. The SOC content prediction of NSMI classified datasets did not show a decrease of accuracy compared to the models with a-priori knowledge of soil moisture.

Keywords: soil organic carbon, soil moisture, laboratory spectroscopy, NSMI.

Introduction

Soil organic carbon (SOC) has been accurately measured by means of visible near-infrared spectroscopy (VNIRS) under laboratory controlled conditions (Xie et al., 2011). Field spectroscopy showed as well to be an efficient tool to infer SOC content (Stevens et al., 2008; Morgan et al., 2009). Airborne hyperspectral remote sensing did not generate as accurate results as proximal spectroscopy due to some natural surface constraints, as vegetation, moisture, roughness, etc (Selige et al, 2006). In particular, soil moisture drastically alters the soil albedo and, thus, the mineral and organic matter spectral signatures. Previous studies described two important effects: (i) the interaction between light and soil increases the probability of absorption by soil due to the higher relative index of refraction between air and soil than that between water and soil (Twomey et al, 1986); (ii) the non-linear decrease of spectral reflectance with increasing moisture content, independent of soil types (Whiting et al., 2004). Spectral prediction of moisture content, mostly conducted under laboratory controlled conditions, gave promising results (Weidong et al., 2003). However, a general method for soil moisture assessment under field conditions and for different soil types has not been developed. This study aims to: (i) quantify the effect of soil moisture content on the accuracy of SOC measurements, and (ii) propose a method to determine SOC content for moist samples with unknown moisture content.

Methodology

The study area consisted of a transect (~60 km long and ~7 km wide) crossing north-southward the Grand-Duchy of Luxembourg. In June 2010, 107 topsoil samples (0 - 5 cm) were collected. Soil samples were taken to the laboratory, air-dried, and sieved. Soil sub-samples were oven-dried at 105 ^{0}C during 24 h, to calculate the moisture content. Soil organic carbon was analysed by dry-combustion with a VARIOMAX C/N analyser (Elementar Analysis, Germany). Soil samples were put in Petri dishes, and artificially wetted from 5 to 25% moisture content. Afterwards, soil spectral reflectance was collected in the laboratory with a contact probe device connected to an ASD Fieldspec-Pro radiometer (ASD, Boulder, Co), 1 nm steps in the 350-2500 nm wavelength range. Several pre-processing techniques, commonly used in soil spectroscopy, were applied for the enhancement of spectral features: transformation of reflectance (R) spectra in absorbance (log (1/R)), to reduce possible spectra non-linearity's; random noise reduction and signal to noise ratio (SNR) improvement using the Savitzky-Golay filter (Savitzky and Golay, 1964); spectral resolution enhancement and background effect elimination with first derivative and mean-centre function (Viscarra-Rossel et al., 2006). Based on main soil texture and SOC content, the datasets were divided in calibration (2/3) and validation set (1/3). Soil moisture was estimated developing a linear model between GSM and NSMI (Haubrock et al., 2008). Partial least square regression (PLSR) (Wold et al., 2001) was chosen as multivariate method to develop the SOC prediction models, for all moisture classes.

Results and discussion

The global SOC range was between 9.05 and 50.22 g C kg^{-1}, and presented differences among soil types. As observed by Liu et al. (2002), spectral reflectance decreased with increasing moisture for all soils types (figure 1a). The visual estimation of figure 1a pointed out that, as the overall reflectance declined with increasing moisture, the slope of the curves between 1800 and 2500 nm tended to increase, and the maximum reflectance shifted toward shorter wavelengths, around 1700 nm (Whiting et al., 2004).

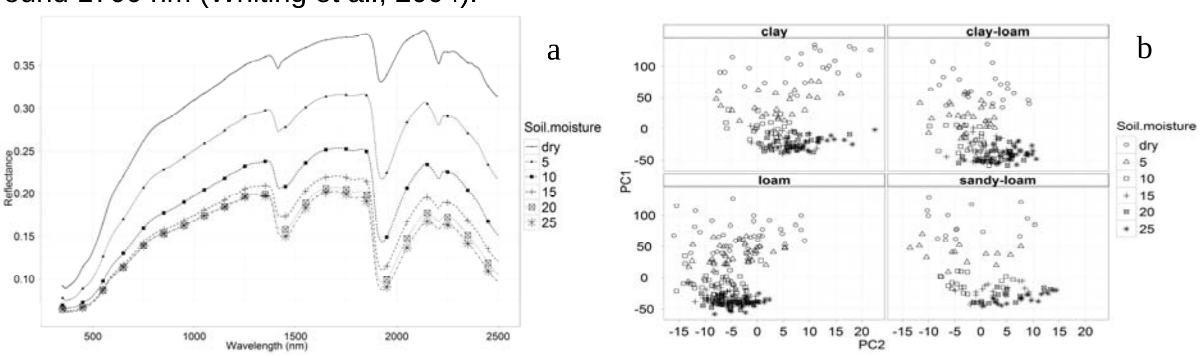

Figure 1: a) mean spectral reflectance by moisture content; b) Principal component analyses of raw spectra by soil type as a function of soil moisture.

The two first components of the principal component analysis (PCA) of raw spectra explained more than 90% of the variability. As observed by Mouazen et al. (2006), the spectral properties of samples with a moisture content between dry and 10% MC could be clearly grouped, while from 15% to 25% moisture content the PC1 and PC2 scores were mixed and not differentiable (figure 1b). Prior to starting calibration and validation procedures to infer SOC content, samples from 15% to 25% moisture content were grouped together (>=15 in table 1), as the effect of water on spectral reflectance was considered negligible beyond 15% moisture content. PLSR models for the prediction of SOC content were developed for all levels of moisture content. Moreover, calibration models developed with dry samples were tested on validation sets of wet soil spectra (table 1), in order to estimate the effects of soil moisture when "dry" calibration was applied to wet spectra (problem of the unknown moisture content of the soil surface during airborne remote sensing campaigns). All the calibrations models developed for different level of soil moisture content **(dry, 5, 10, >=15)** gave a RMSE not larger than 5 g C kg^{-1} and an RPD not lower than 2 (table 1), comparable with those obtained under laboratory conditions by Kooistra et al. (2003) and Viscarra-Rossel et al. (2006).

Table 1: PLSR model results after validation for different MC% levels (dry, 5, 10,>=15) for dry calibration applied to wet soils (dry-5, dry-10, dry->=15) and predicted MC by NMSI (dry- NSMI, 5-NSMI, 10-NSMI, >=15-NSMI)

Moisture content (%)	RMSEP (g C kg^{-1})	R^2	RPD
Measured moisture class			
dry	4.72	0.78	2.06
5	4.48	0.79	2.07
10	3.45	0.87	2.6
>=15	4.21	0.8	2.00
Measured dry calibration applied to wet samples			
dry-5	12.17	0.63	0.68
dry-10	20.27	0.56	0.4
dry->=15	30.21	0.25	0.26
Moisture content predicted by NSMI			
dry.NSMI	4.40	0.80	2.16
5.NSMI	4.45	0.81	2.25
10.NSMI	4.27	0.83	2.37
>=15.NSMI	3.58	0.86	2.42

Low quality predictions were obtained when dry calibrations were tested on wet validation sets (**dry-5, dry-10, dry->=15**). The three validation models gave an increasing error when applied to validation sets with higher moisture contents. The NSMI predicted soil moisture with a R^2 after validation of 0.74, at 95% of significance (figure 2).

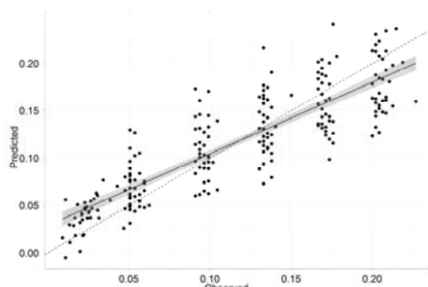

Figure 2: Predicted vs. observed values of gravimetric moisture content based on NSMI method (dashed line= 1:1 identity line; bold line = line of best fit; shaded areas: confidence intervals at the 95% confidence level)

The results were comparable with the soil moisture predictions present in literature. Mouazen et al. (2005) had a R^2 of 0.75 from predicting soil surface water ranging from 0.5 to 26% moisture content. The NSMI showed good prediction ability especially considering the variety of soil types in Luxembourg. The linear model based on NSMI generated the predictions which were used to build a new moisture content classification, whose results were tested to predict SOC. The comparison between the models based on the NSMI classification (dry- NSMI, 5-NSMI, >=15-NSMI) and the correspondent model develop with known moisture content (dry, 5, 10,>=15) (table 1) pointed out that the soil moisture classification based on NSMI was reliable and the SOC content models produced after applying the classification gave a mean lower error than the models developed with a-priori knowledge of soil moisture. In literature there are many examples of accurate methods developed to predict soil moisture from VNIR spectroscopy (Lobell et Asner, 2002; Whiting et al., 2004; Mouazen et al., 2006). The advantages of the NSMI to classify soil samples based on soil moisture comes directly from the possibility to predict moisture content from spectral data, without calculating water content in the laboratory.

Conclusions

Soil moisture dramatically alters the soil spectral reflectance detect by remote sensor. The effect has been widely described in literature and the findings of this study confirmed the trend. The analyses of spectral data indicated that i) soil moisture drastically alters spectral reflectance until 15% of humidity, and ii) the reflectance decreases faster with increasing wavelength. The PLSR built using dry soils could not be used to predict SOC of moist soils. The NSMI showed to be an accurate and spectroscopy based tool to develop a soil moisture classification of the soil samples. SOC content prediction realized after NSMI classification generated accurate predictions for all soil moisture levels. The methodology proposed in this research might find application for the prediction of SOC content based on airborne remote sensing data. Although moisture content would be unknown at the moment of data collection, the NSMI might be helpful due to (i) the small number of field samples necessary to validate the prediction models (compared to the amount of data collected during a flight campaign), and (ii) the simple application of a band ratio, sensitive to soil types variation (see table 1), and spectrally independent from SOC absorption bands.

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