SOIL ORGANIC CARBON ESTIMATION WITH THE USE OF PROXIMAL VISIBLE NEAR INFRARED SOIL SPECTROSCOPY

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ABSTRACT

Soil is an important natural resource, thus monitoring soils' condition in an efficient and quantifiable way is considered of great importance for site specific management practices. However, soil properties estimation is a laborious procedure that entails great amount of cost and time. To address the need for soil information at large scales, proximal sensing applications are considered as an alternative to analytical wet chemistry. In particular, soil reflectance spectroscopy in the visible and near infrared region (400-2500nm) has been evaluated with promising results. The use of proximal sensing techniques for rapid in situ applications comprise sensors mounted on tractors or at a handheld mode. Soil organic carbon (SOC) is the most widely investigated soil property due to its significance as it affects most of the processes related to soil functions and has presented good correlation with electromagnetic radiation. This work aims to provide a short review of proximal sensing techniques for SOC estimation. It was found that although results have been very promising there are still challenges to be addressed concerning factors that affect measurements i.e. soil moisture and soil roughness.

Keywords*:* proximal sensing, soil organic carbon, soil spectroscopy, VNIR-SWIR**.**

1. INTRODUCTION

Soil can act as a sink of greenhouse gasses (GHGs) through carbon sequestration, or as a source of carbon based GHGs depending on anthropogenic management factors. To that end, soil organic carbon (SOC) is recognized as a significant component affecting climate change adaptation and mitigation (FAO, 2017). Therefore, the need for recording and mapping its spatial distribution has gained great interest. Still, the assessment of SOC changes lacks in commonly accepted estimation methods, relevant data needs, and appropriate modeling approaches that provide consistent, comparable and accurate data to assist in decision making (Jandl *et al.*, 2014). Common analytical methods include dry and wet combustion, while in the past decade remote sensing applications, laboratory and proximal spectroscopic applications are being evaluated as more rapid and non-destructive techniques. Proximal sensing involves in situ measurements with sensors that are in close proximity with soil at approximately two meters (England *et al.*, 2018). These technologies concern either on-the-go sensors mounted on tractors or hand-held instruments that can be used for site specific management and variable rate applications in the field (Christy, 2007). Any on-the-go sensor is desirable to have certain specifications to provide reliable soil measurements that can be summarized as follows: (i) to be free of residues for every new measurement, (ii) allow data acquisition irrespective of the mode, (iii) permit the extraction ofsoil samples efficiently when necessary, (iv) present an adequate volume/mass of soil in a sufficient range of the sensor and (v) perform consistent measurements (Sinfield et al. 2010).

Reflectance spectroscopy is used thoroughly in proximal sensing. An asset of this technique is that several soil properties can be simultaneously measured with a single spectrum acquisition, while common electric or electromagnetic sensors are usually manufactured to measure a specific variable (Wetterlind, Stenberg and Rossel, 2013). However, in situ soil reflectance spectroscopy applications require proper environmental conditions and various pre-treatment methods to mitigate the effect of moisture content, soil roughness and vegetation cover (Nocita *et al.*, 2013).

In this study we discuss indicative studies from the past decade that used proximal sensing techniques for SOC or soil organic matter (SOM) estimation.

2. Soil organic carbon estimation with proximal sensing techniques

Continuous monitoring needs in the agricultural domain have led to the development of in situ soil sensors for rapid, cost-effective and real-time data acquisition that can provide high resolution maps. Kodaira and Shibusawa, (2013) upgraded a prototype real-time soil sensor (RTSS) (SAS 1000, SHIBUYAMACHINERY Co., Ltd.) that was subsequently mounted on a tractor. The RTSS had a sensor unit, a touch panel, a soil penetrator and a set of probes. The unit of the sensor comprised of a computer, a halogen lamp, a micro couple-charged device (CCD) camera, two spectrophotometers with spectral range from 350 to 1100nm and 950 to 1700 nm respectively, and a differential global positioning system. The sensor was designed to acquire spectra at soil depths from 0.05 – 0.35 m and the spectral data were acquired every 4 seconds. The speed of the tractor was 0.56 m s^{-1} similar to the speed needed for some field operations. After each measurement by the RTSS, two soil samples were taken from the same point resulting in 144 samples from an area of 8.94 ha. Results gave an accuracy of R^2 = 0.90 for SOM and the density of spectral acquisitions was adequate for the development of high-resolution maps. There are also commercialised sensors available. Kweon et al., (2013) used the OpticMapper™ from Veris Technologies in a study for SOM estimation that was held in 15 fields of total area 551 ha with wide variation in soil types and SOM concentrations. The specific sensor acquires spectra at two wavelengths (660 and 940 nm) for SOM and six coulter electrodes for cation exchange capacity (CEC) estimations. The measurements were made at a 4-cm depth and with a speed of 2.78–4.17 m s^{-1}, resulting in approximately 150-200 data points per field To that end, a soil moisture sensor was proposed to be added. Results showed that predictions made from individual fields generally gave lower RMSE (0.04-0.91) and higher RPD (1.46-25.03) compared to the universal model (i.e. RMSE ranged from 0.20-1.24 and RPD 0.54-4.39).

Considering soil moisture content and soil texture as the most significant factors affecting the accuracy of a prediction model, Kuang and Mouazen (2013) aimed to estimate their effect on SOC estimations. They used an on-line sensor developed by Mouazen and Ramon, (2006) mounted on a tractor. The sensor had a spectral range of 305-2200 nm and penetrated soil at a 15cm depth. Model calibration and validation was made for processed soils, fresh soils and on-line measurements. It was observed that removing the moisture content (MC) resulted in better calibration models, while MC together with increased clay content resulted in deterioration of the models' accuracy. However, this was not the case for dry calibration models as clay content increased accuracy. Furthermore, they proposed that the most suitable field conditions for on-line measurements are when the soil is dry and the clay content is relatively high.

Knadel et al. (2015) evaluated a sensor data fusion using the multi-sensor platform (MSP) from Veris Technologies in two different fields to provide supplementary information about soils' condition (i.e. soil temperature and electrical conductivity). During field measurements it was shown that 15 calibration samples were adequate for a 14.6 ha field. For better model calibration along with the spectral data, electrical conductivity and soil texture were also used as predictors. Spectra at the range of 500 to 1073 nm had lower quality than the range of 1073 to 2130 nm. However, excluding them from model calibration did not improve the models' performance. Overall, the results for SOC estimation were improved by the use of sensor fusion.

Considering ambient conditions, Rodionov et al. (2015) enclosed a spectrometer in a dark chamber mounted on a tractor to achieve illumination independent measurements. The system was designed for bare soil measurements and was tested in two modes; continuous and stop-and-go. For model calibration they first estimated soil moisture according to Rodionov et al., (2014) and after selecting the appropriate model they proceeded to SOC estimations. It was observed that apart from MC, another factor that provided errors in SOC predictions were gravels due to their brightness. The continuous mode presented spectral discontinuities due to different integration times, though this effect could be eliminated by reducing the number of spectra per scan. The stop-and-go mode gave R^2 = 0.65, while the same samples with conventional laboratory spectral measurements gave R^2= 0.94.

Even though bare soil conditions are ideal for in situ measurements, during such measurements there is a high possibility that there will be either green vegetation or straw covers that may lead to overestimation of SOC (Bartholomeus *et al.*, 2011). Rodionov et al. (2016) in a combined field and laboratory study used the same spectra to distinguish SOC from photosynthetic and non-photosynthetic vegetation. To estimate the effect of vegetation fractional cover, the experiment was conducted under laboratory conditions where soil samples were placed in petri dishes and the degree of plants and straws was gradually increased (24 soil samples with 13 covering degrees). Straw cover was characterized by the Cellulose Absorbance Index (CAI) and green vegetation was measured by different known indices, such as the Normalized Difference Vegetation Index (NDVI) etc. The aforementioned indices were estimated and then subtracted from field measurements to prevent SOC overestimation. While the spectral response of straw was not very distinctive both the use of CAI and NDVI were recommended to be utilized. Measurements were performed with a tractor driven closed chamber developed by Rodionov et al., (2015). For model calibration, MC and roughness were also accounted prior the evaluation of the straw and green vegetation influence. Although this study confirmed the overestimation of SOC content with the presence of green vegetation and straw coverage, the proposed method gave moderate predictions with R^2= 0.58-0.66.

There are cases that the use of a single sensor is not adequate for estimating soil properties (Ge, Thomasson and Sui, 2011). To that end, Viscarra Rossel et al. (2017) developed a sensor fusion the integrated Soil Condition Analysis System (SCANS). The experimental site was a cattle grazing farm from were 150 soil cores were extracted. For spectroscopic modelling, the Cubist algorithm combined with the RS-LOCAL algorithm was applied to better utilize local soil spectral libraries (SSLs). The external parameter orthogonalization (EPO) algorithm was used to eliminate the effect of water. Results were promising with SOC showing better accuracy (R^2 = 0.83).

Most studies mainly tried to mitigate the effects of MC, whereas Franceschini et al. (2018) used the VNIR-SWIR Veris Spectrometer to correct the effects of external factors and particularly those related to sensor movement during spectral acquisition. In addition to EPO and direct standardization (DS), orthogonal signal correction (OSC) was also implemented for the purposes of the study. Field measurements were compared to laboratory measurements of un-processed soil samples, assuming that MC was approximately the same, hence any differences in the accuracy of predictions could be attributed to factors other than soil moisture. Nevertheless, results were substantially inferior indicating that factors like soil-to-sensor distance and angle, gravels or straws and changes in the illumination conditions, should also be considered.

To overcome the lack of field data and the laborious procedure of creating new SSLs for un-processed field samples, Kühnel and Bogner (2017) evaluated the use of the synthetic minority oversampling technique (SMOTE) to directly use in situ soil spectra. The technique gives extra weight to existing soil samples and generates new synthetic spectra and by that mean it increases the number of existing datasets. Overall the synthetic spectra provided more similar spectral response with in situ spectra rather than those from dry, sieved samples.

There are also portable instruments able to be used for in field applications using a contact probe. Gras et al. (2014) tested seven different practices in the field using the ASDLabSpec 5000 spectrometer (Analytical Spectral Devices, Boulder, CO, USA) to conclude which approach provides the most accurate SOM predictions. These procedures were applied either directly to the soil surface (in cores extracted with an auger) or to clods crumbled from the cores and no external validation was performed as the aim was to select the most efficient approach for spectral acquisition. The most efficient approach for spectral acquisition was in raw core measurements with an RPD = 2.8. Cambou et al. (2016) collected soil samples with a manual auger and the spectral measurements were made to the outer core. PLSR model calibration resulted in R^2 =0.75 and R^2 =0.70 for SOC and SOC stock estimations respectively. It was noted that the accuracy of the results could be related to no compatibility between samples the spectral measurements were made and the samples sent for laboratory estimations.

3. Considerations about proximal sensors

In the previous section many considerations regarding the configuration and operation of proximal soil sensors with emphasis in mobile proximal sensors were presented. To address the effects of ambient conditions, the enclosure of the sensor in a dark chamber is suggested to minimize external light interferences. The sensor’s distance from the ground and the configuration of the artificial illumination angle could affect the intensity and quality of the signal. Another aspect for consideration is the depth of the measurements as there are sensors that acquire the spectral signature from the top layer of the soil and configurations equipped with a soil penetrator that can achieve measurements at various depths. Most studies were conducted in bare soil conditions which are not always representative of large-scale real field conditions; to that end it is imperative to address vegetation cover effect which can lead to SOC overestimation. It was also highlighted that the mode of spectral acquisition i.e. stop-and-go or continuous also affects the quality of the measurements, as a continuous mode could lower the predictions adding excessive noise due to spectral discontinuities of different integration times and vibrations due to the vehicle’s speed.

4. Conclusions

This paper has reviewed spectroscopic proximal sensing techniques for SOC and SOM estimation. It was observed that the sensors configuration and the mode of spectral acquisition plays a significant role to the accuracy of the generated models. Soil moisture levels should be taken into consideration especially when different field data are combined or when a universal calibration model is created, as it significantly affects the soils spectral response. An integrated soil sensing approach with complimentary set of sensors for quantifying different soil properties could provide additional information to improve the model’s accuracy. The selection of the modelling approach varies among different studies and mainly depends on data availability and entails the use of simple linear regression to machine learning techniques. Still there is not a commonly agreed protocol for in situ spectral measurements that could provide reliable and comparable with other studies results.

Acknowledgement

The work was supported by the project “Research Synergy to address major challenges in the nexus: energy-environment-agricultural production (Food, Water, Materials)”—NEXUS, funded by the Greek Secretariat for Research and Technology (GSRT)—Pr. No. MIS 5002496.

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