#7451 ESTIMATING SOIL ORGANIC MATTER FROM CELL PHONE IMAGES

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ABSTRACT

Soil organic matter (SOM) is considered as the backbone of soil health and soil quality. Thus, its' estimation is critical to support the development of management decision including precision agriculture. To overcome challenges of laborious, rather expensive, and time-consuming laboratory measurements, recent advances in image acquisition systems provided a new dimension of image-based SOM prediction. However, challenges remain in using soil images taken directly in the field due to variable soil surface conditions including vegetation cover, illumination, and soil moisture. Soil moisture can significantly influence soil color and thus confounds the relationship between SOM and soil color. This study quantifies the effects of soil moisture on the relationship between SOM and color parameters derived from cell phone images and establishes suitable SOM prediction models under varying conditions of soil moisture contents (SMCs). To simulate the continuous variation of soil moisture in the field, air-dried ground soil samples were saturated and allowed to dry naturally. Images were captured with a cellular phone over time representing various SMCs (set of images). Final set of images were captured on oven-dried samples. Images were preprocessed using illumination normalization to avoid illumination inconsistencies and segmentation technique to remove non-soil parts of the images including black cracks, leaf residues and specular reflection before modelling. Five color space models including RGB, HIS, CIELa*b*, CIELc*h* and CIELu*v* were used to quantify soil color parameters. Univariate linear regression models were developed between SOM and color parameters and an optimal set of color parameters that are capable of resisting variation in SMC was determined. It was observed that SMC exerted a considerable influence on SOM prediction accuracy when its value reached >10%. The threshold of 10% SMC was considered as the critical SMC. Consequently, stepwise multiple linear regression (SMLR) models were developed for soil samples with SMC below and above the critical SMC. For the soil samples at below the critical SMC, the color parameter R based model produced satisfactory prediction accuracy for SOM with R^2_{cv}, $RMSE_{cv}$, and RPD_{cv} values of 0.936, 4.44% and 3.926, respectively. For the soil samples at above the critical SMC, the SOM predictive model including SMC as a predictor variable showed better accuracy (R^2_{cv}=0.819, $RMSE_{cv}$=7.747%, RPD_{cv} =2.328) than that without including SMC (R^2_{cv}=0.741, $RMSE_{cv}$=9.382%, RPD_{cv} =1.922). This study showed potential of cellular phone to be used as a proximal soil sensor fast, accurate and non-destructive estimation of SOM both in the laboratory and field conditions.

Keywords: Proximal soil sensor; Soil moisture content; Cell phone images; Color space models; Stepwise linear regression

INTRODUCTION

Soil organic matter (SOM), the organic matter component of soil, is considered as the backbone of soil health and regulates various physical, chemical, and biological processes and properties. However, like other properties, SOM is highly spatially variable within a field which contributes to the development of variable SOM pool in soil. Therefore, the information on spatial variability of SOM can help decide site-specific management of agricultural resources including application of nitrogen fertilizer and achieve the tradeoff between crop production increase and environment pollution reduction [1], the critical component of precision agriculture.

Traditional procedures for estimating SOM are laborious, costly and require time intensive spatially dense soil sampling (10 m or less) and laboratory analysis [2]. This often restricts the detailed characterization of its spatial variability in field. Furthermore, larger field sizes make detailed characterization unaffordable for many growers. Recently, with the development of technology, various soil sensors have been used to characterize SOM. For example, soil spectroscopy has shown potential to characterize SOM both in-situ and in laboratory conditions [3-11]. Although vis-NIR-MIR spectroscopy has shown great potential in predicting SOM, the related complex processing techniques and expensive equipment restrict their widespread usage in practical agricultural production scenarios. In addition, SOM prediction accuracy is limited using vis-NIR-MIR spectroscopy when uncontrolled soil conditions, like variable soil moisture and surface roughness are confronted [12-14].

Recently, with technological progression and the advancement of image acquisition systems, image-based soil characterization techniques have garnered significant attention from the researchers in soil science. Unlike soil diffuse reflectance spectroscopy, image acquisition devices like digital cameras or even cameras in cellular phone are easily accessible. In the existing image-based SOM or soil organic carbon (SOC) prediction studies [8, 15-17], soil color was used as a proxy to link SOM or SOC with images. Soils with darker color are generally associated with higher OM contents and are regarded fertile and suitable for plant growth [18]. The existence (prevalence) of strong relationship amid soil's color and its organic matter was also confirmed by researchers [19, 20] who came up with a cell-phone application named SOCIT (only pertinent to mineral soils in Scotland) which utilizes this connection. The app provides an approximation of topsoil organic matter content using a photograph of the soil of interest and user's positional information to access location-specific factors [21]. A recent study also reported the development of an algorithm to quantify soil organic matter and soil texture from image parameters using geostatistical and regression-based methods [22]. However, due to the limited scope of the study in terms of soil moisture conditions, the authors pointed out that their algorithm needs further testing.

The existing image-based SOM or SOC prediction studies [8, 10, 15, 17, 22] directly used soil color parameters to develop prediction models without considering the contribution of other factors like soil moisture, surface residue, surface roughness and light [23]. These factors are known to influence spectral response in the visible range of the electromagnetic spectrum (400 to 700 nm). Among these factors, soil moisture is the most important one that restricts practical in-situ measurement of SOM. Usually, dry soils are lighter in color than wet soils [24, 25]. As soil moisture content (SMC) increases, soil micro and macro pores are gradually filled with water and alter the physical structure of soil. Consequently, the relative refractivity at the soil particle surface also changes causing the change in soil color [12]. The soil moisture, thus, makes the relationship between SOM and soil color complicated and becomes a key determinant factor for the practical use of image-based SOM prediction. SMC was implicitly involved in the models developed in the above-mentioned studies since the SMCs of soil samples were variable in these studies, but it's influence on SOM prediction was not considered and hence, the given study was planned in which SMC was explicitly considered for SOM prediction.

Following up on the missing links, the research questions addressed in this study were to (1) evaluate the ability of cell phone images to predict SOM using color parameters; (2) quantify the effect of soil moisture on the accuracy of SOM prediction models based on color parameters; and (3) determine the critical moisture content at which it begins to influence SOM prediction accuracy based on color parameters and establish suitable SOM prediction models accordingly.

MATERIALS AND METHODS

Twenty-five soil samples with a wide variation in SOM (3.3-62.7%) were selected for this study, for whom SOM was measured using loss on ignition (LOI) method (Schulte and Hopkins, 1996). Digital images (2322 ×4128 pixels) were captured with a cellular phone 10-megapixel camera set to a holder 32 cm above the sample and the images were saved as Joint Photographic Experts Group (JPEG) standard compression. A total of six sets of images were collected corresponding to six different levels of SMC ("group 1", "group 2", "group 3", "group 4", "group 5" and "group 6" with increasing SMC). The images of oven-dried soil samples formed the components/constituents/parts of "group 1", images of air-dried soil samples of "group 2", three sets of images collected during the natural drying process of "group 3", "group 4" and "group 5" and those of saturated soil samples of "group 6". There were 146 images in all, with 25 images for each group except 24 images for "group 2"and "group 6", and 23 images for "group 1". Before the images were analyzed, preprocessing was carried out with four components: 1) region of interest (ROIs) selection, 2) illumination normalization, 3) image segmentation and 4) color space conversions.

RESULTS AND DISCUSSION

The scatter plot between SOM and color parameter R for all the groups is shown in Fig. 1. It can be witnessed that there exists a negative correlation between the color parameter R and SOM for the first three groups. However, for the latter three groups, the scatter plot demonstrates that an increase in SOM content occurred, without a considerable decrease in the R values. Similar trends were observed in the scatter plots between SOM and other color parameters G and B. The change in the behavior observed (the pattern of distribution of scatter plots) supported that the negative correlation between SOM and color parameters cannot be held with increasing variation in SMC, and that SMC influences color parameter-based SOM prediction in a different manner below and above a specific level and hence, it was crucial to identify that level of SMC after which it exerted significant influence.

Since the decrease in SOM prediction accuracy was not obvious for the first three groups, the SMC frequency distribution for soil samples belonging to these groups was analyzed and the results showed that 95% soil samples had a SMC of less than 10%. Similar patterns were also observed in other studies; for instance, Nocita et al. (2013) grouped together soil samples with a gravimetric SMC >=15% and developed a single SOC model with good prediction accuracy using a PLSR of soil diffuse reflectance in the vis-NIR region. Rienzi et al. (2014) demonstrated that predicting SOC over a range of 10% soil moisture variability did not substantially change prediction quality. Because of the behavior exhibited by our data as well as resemblance to similar studies, a SMC value of 10% was, therefore, determined to be as regarded as the critical SMC in this study (for further exploration).

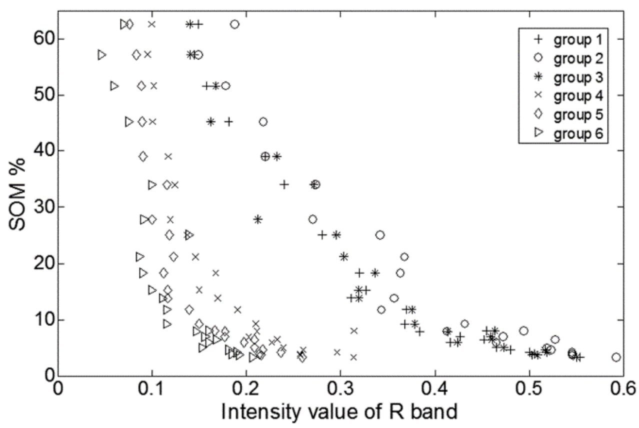

Figure 1. Scatter plots between SOM and color parameter R under varying soil moisture.

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