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Using an inexpensive color sensor for rapid assessment of soil organic carbon

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A B S T R A C T

Quantifying soil organic carbon (SOC) is important for soil management, precision agriculture, soil mapping and carbon dynamics research. Inexpensive sensor technologies offer the potential for rapid quantification of SOC in laboratory samples as well as in the field. The objective of this study was to use a commercially-available color sensor to develop SOC prediction models for both dry and moist soils from the Piedmont region of South Carolina. Thirty-one soil samples were analyzed for lightness to darkness, redness to greenness, and yellowness to blueness (CIEL*a*b*) color using a Nix Pro™ color sensor. Soil color was measured under both dry and moist soil conditions and the depth of each soil sample was also recorded. Using L*, a*, b* and soil depth for each sample as initial predictors, regression analyses were conducted to develop SOC prediction models for dry and moist soils. The resulting residual plots, root mean squared errors (RMSE), and coefficients of determination (R^2) were used to assess model fits for predicting the SOC content of soil. Cross validation was conducted to determine the efficiency of the predictive models and the mean squared prediction error (MSPE) was calculated. The final models included soil depth, L*, and a* as independent variables (dry soils $R^2 = 0.7978$ and MSPE = 0.0819, moist soils $R^2 = 0.7254$ and MSPE = 0.1536). The results suggest that soil color sensors have potential for rapid SOC determination, and soil depth and color are useful in predicting SOC content in soils.

1. Introduction

Soil organic carbon (SOC) is one of the key soil properties related to ecosystem services (Adhikari and Hartemink, 2016) and it is measured by the Natural Resource Conservation Services (NRCS) to determine soil quality (Karlen et al., 2003, USDA/NRCS, 1996). Organic carbon in soil serves many purposes in soil fertility and structure by improving water retention and infiltration, promoting soil organism growth, and by holding essential nutrients in the soil for healthy plant growth and production (Oades, 1984, Fontaine et al., 2003). In addition, soils play a major role in the carbon cycle by sequestering carbon dioxide from the atmosphere which would otherwise add to the effects of climate change (Li et al., 2007, Kheir et al., 2010). Disturbances in normal soil environments, such as deforestation and thawing permafrost, can lead to excessive release of stored carbon in the form of greenhouse gasses, such as carbon dioxide and methane, into the atmosphere (Potter, 1999; Christensen et al., 2004). Adhikari and Hartemink (2016) argue that soil is a vast determinant of a nation's economic standing and is linked to ecosystem service. Given the importance of soil and SOC both globally and agriculturally, there is a need for methods of rapid soil analysis and SOC determination that are inexpensive and easy-to-use.

It is well known that SOC content influences the color of a soil (Baumgardner et al., 1969). Studies have shown that because of this, it is possible to use a soil's reflectance to determine SOC content, making it possible to develop prediction models based on soil color (Bartholomeus et al., 2008). For this reason, many have turned to using visible near-infrared spectroscopy to determine SOC content in soils (Morgan et al., 2009, Vasques et al., 2007). However, spectrometers can be expensive and many soil scientists may not be familiar with the resulting spectra data.

In a study by Wills et al. (2007), soil color in Munsell Color Chart notation, along with other soil qualities, were used to create a SOC prediction model for agricultural and prairie soils of the Midwest United States. Soil color value and chroma along with depth of the soil sample produced the most accurate SOC prediction model. However, SOC predictions can be limited based on regional soils. Different soil types will appear different in color based on SOC origin and soil mineralogy making it necessary to gather a large soil sample set that encompasses all soil types and SOC content before a universal SOC prediction model can be developed (Bartholomeus et al., 2008). Studies have shown that there is significant variation among Munsell Color Charts that can

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result in inaccurate color measurements which would lead to inaccurate SOC predictions (Sanchez-Maranon et al., 2005). In addition, Munsell Color Chart notation does not allow for simple statistical analysis which could complicate the process of creating a SOC prediction model for various regional soils (Kirillova et al., 2014).

Fortunately, there are a number of color systems to classify the color of soils that can be used in soil science (Viscarra Rossel et al., 2006). Recently, an inexpensive color sensor (Nix Pro™) was evaluated for its ability to determine soil color (Stiglitz et al., 2016a, b). The Nix Pro™ produces color results in lightness to darkness, redness to greenness, and yellowness to blueness (CIEL*a*b* notation) and other color systems, is rechargeable and portable, and has its own light source making it a great mobile alternative to the Munsell Color Chart. The Nix Pro™ offers a new method of color analysis that is accurate, rapid, and convenient for statistical analysis (Stiglitz et al., 2016a, b). Using the Nix Pro™ as a colorimeter would assist in gathering data necessary for developing SOC prediction models efficiently and reliably. The objectives of this study were (i) to gather soils data from the Piedmont region of South Carolina for analysis, (ii) create a SOC prediction model for dry soils of the Piedmont region of South Carolina, and (iii) create a SOC prediction model for moist soils of the Piedmont region of South Carolina.

2. Materials and methods

2.1. Study area and soil samples

The study area and samples for this experiment are as described previously by Stiglitz et al. (2016a, b) and were collected from the Piedmont region of South Carolina. For development of the predictive models, thirty-one samples (i.e., training set) were gathered from thirteen soil pits at the Simpson Agricultural Experimental Station near Pendleton, South Carolina. The following soils were represented in the collected samples (Fig. 1): Cecil clay loam (Fine, kaolinitic, thermic Typic Kanhapludults), Pacolet sandy loam (Fine, kaolinitic, thermic Typic Kanhapludults), Cartecay-Chewacla complex (Coarse-loamy, mixed, semiactive, nonacid, thermic Aquic Udifluvents and Fine-loamy, mixed, active, thermic Fluvaquentic Dystrudepts), Hiwassee sandy loam (Fine-loamy, mixed, active, thermic Fluvaquentic Dystrudepts), and Cecil sandy loam (Fine, kaolinitic, thermic Typic Kanhapludults) (Soil Survey Staff, 2016). The soil series that were collected are typical of the Blue Ridge Mountains, Piedmont, and Valley and Ridge regions of the eastern United States, spanning from Virginia to Georgia, north to south, and from the coast to Alabama, Tennessee, and Kentucky. In addition, thirty-one separate samples were taken from the soil pits for the purpose of cross validation (i.e., validation set).

The depth for each soil sample collected was recorded. Subsamples of each soil were sent to the Clemson University Agricultural Service Lab for nutrient analysis and to the University of Georgia Soil, Plant and Water Analysis Lab to be analyzed for texture and total carbon content (Fig. 2 and Table 1). Samples were analyzed for texture using the standard NRCS soil textural triangle and soil carbon percent was determined by lost on ignition. Soil samples were oven dried, crumbled, and passed through a 2-mm sieve before being analyzed for color. Soil samples, about 1 in. in diameter, were placed on a plate and the surfaces of each sample were leveled to allow for the sensor to rest on a flat sample surface which prevented any outside light from entering the viewing area of the sensor. Dried soil samples were moistened using a water dropper to dampen the soil surface. The soil samples were then analyzed for color using a Nix Pro™ color sensor for both moist and dry soil conditions with results recorded in CIEL*a*b* following the methods described previously by Stiglitz et al. (2016a, b). The Nix Pro™ color sensor cost $349 and is controlled via Bluetooth using a free to download mobile application. The sensor has its own LED (light emitting diode) light source, rechargeable battery, and produces color results in various

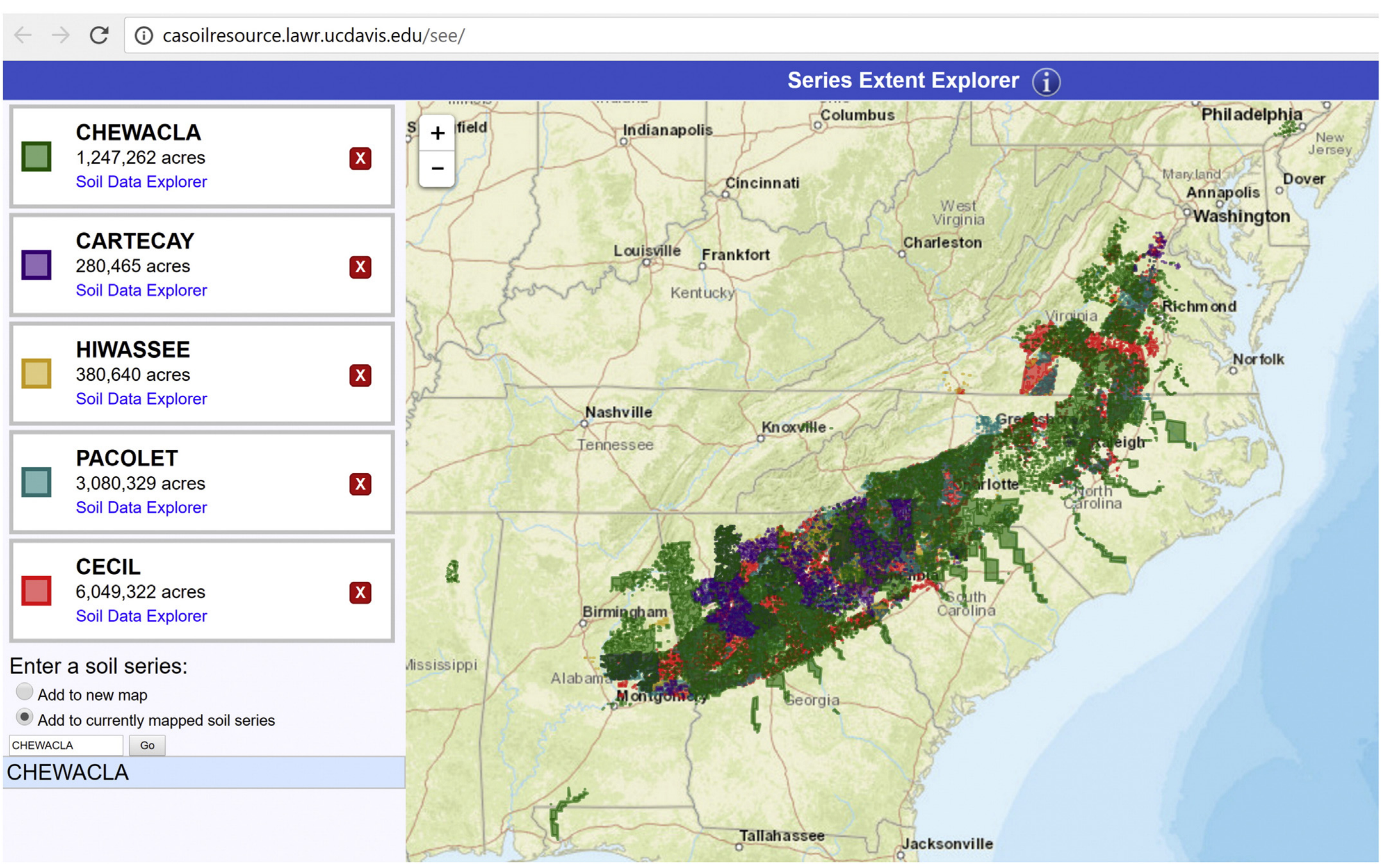

Fig. 1. Map showing the extend of the soil series collected for analysis (Series Extent Explorer, 2016).