12-2022

Quantifying the Relationship between Soil Organic Carbon and Soil Color in Nebraska

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QUANTIFYING THE RELATIONSHIP BETWEEN SOIL ORGANIC CARBON AND SOIL COLOR IN NEBRASKA

by

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A THESIS

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Master of Science

Major: Natural Resource Sciences

Under the Supervision of Professor Judith K. Turk

Lincoln, Nebraska

December, 2022

QUANTIFYING THE RELATIONSHIP BETWEEN SOIL ORGANIC CARBON AND SOIL COLOR IN NEBRASKA

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University of Nebraska, 2022

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Soil color is easily measured in the field and holds potential to be used as an indirect measurement of soil organic carbon (SOC). Such a method would be a powerful tool, building on decades of Munsell soil color data recorded in soil surveys. The main limitation to this approach is knowledge about the specific color-SOC relationship in a region, which often varies in relation to parent material, soil texture, climate, and land use. A secondary limitation is the subjective nature of the Munsell color data. The objectives of this study are: 1) to develop and evaluate the accuracy of pedotransfer functions (PTFs) for the prediction of SOC based on soil color and texture in the state of Nebraska and 2) to evaluate digital based color measurements methods as field predictors of SOC in Nebraska. To address the first objective, data were obtained from the National Soil Information System (NASIS) database, which included descriptions and characterization data of pedons sampled across Nebraska and bordering portions of surrounding states. The dataset was comprised of 1576 soil pedon descriptions and included samples of various soil textures, Munsell color, and SOC. The second objective was addressed using digital color measurements of 50 soil samples from Kellogg Soil Survey Laboratory archive. Methods used for digital color measurement included a portable color sensor (PCS) and smartphone camera (SPC). Regressions of moist Munsell value versus SOC using the NASIS data had R^2 values ranging from 0.23 to 0.69 for individual MLRAs. In contrast regression developed using the PCS for three selected MLRAs had R^2 values ranging from 0.49 to 0.81. Various PTFs based on the NASIS data resulted in RMSE of prediction ranging from 0.795 to

2.1. Digital color measurements using SPCs were found to be of low accuracy and were weakly related to SOC. The results indicate the potential of using soil color as a predictor for SOC, especially when PCS are used to measure soil color.

ACKNOWLEDGMENTS

First, I would like to thank God for carrying me throughout this journey and helping me to be where I am today. I would not be where I am today without Him.

I would like to thank Dr. Judith Turk who has helped and supported me tremendously in my personal and professional development as a young researcher. I met Dr. Turk when I was an undergraduate at the University of Nebraska through the soil judging team. She is a great professor and mentor, and I am grateful and proud to call her my advisor. She is the best advisor a graduate student could ever ask for. She saw the potential in me when I could not see it myself and helped me to take that leap of faith and do research with her. Which I am glad that she did.

Furthermore, I would like to thank the members of my committee, Dr. Jenny Dauer and Dr. Rebecca Young. As well as Aaron Hird of the Nebraska NRCS. They have made enormous contributions to my project, and therefore to my personal and professional growth

I would also like to thank the whole family at the School of Natural Resources who supported me and gave me a community to belong in. Moreover, I would like to thank the USDA-NRCS who funded this project through my graduate assistantships, and the BPSDM Papua scholarship, without them this project would not be possible.

Finally, I want to thank my family and friends for their love and support. To my late dad, my mom, and my sisters. This thesis is dedicated to all of you.

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CHAPTER 1

INTRODUCTION

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1.1 Soil color and soil organic carbon

Several characteristics influence the color of soil, including organic matter content, moisture state, mineral composition, and land use (Baumann et al., 2016; Evans & Franzmeier, 1988; Franzmeier et al., 1983; Sanchez-Maranon et al., 2015; Schwertmann, 1993; Wills et al., 2007). The relationship between soil color and soil organic carbon (SOC) was established more than a century ago (Brown & O'Neal, 1923, Robinson & McCaughey, 1911). Soil classification systems often recognize soils with thick, dark surface horizons as a distinct class, signifying the importance of soil color for understanding the soil resource and making land use decisions (Schulze et al., 1993). Examples of such classes are the Mollisols order in U.S. Soil Taxonomy and Chernozems in the F.A.O World Reference Base (Veenstra & Burras, 2012). The special status of dark soils stem from the relationship between soil color and SOC, with dark soil colors being indicative of high SOC (Schulze et al., 1993).

The Munsell color system, which describes color by hue (shade), value (lightness), and chroma (saturation), was adopted as the official system used by soil scientists to describe soil color (Pendleton & Nickerson, 1951; Thompson et al., 2013). The Munsell system continue sot be widely used in soil science today. Recently, the study of soil color and SOC has also received much attention as new digital tools are poised to expand quantification of soil color and the demand for SOC data to support climate change and soil heath research has grown (Ferrando Jorge et al., 2021, Schmidt & Ahn, 2021).

However, quantitative relationships between soil color and SOC are difficult to generalize, as most studies focus on a limited number of samples representing a single geographic region (Liles et al., 2013). Generating an adequate dataset to quantitatively measure the correlation between soil color and SOC can be challenging, and requires careful consideration with regards to the size of the sample set, representative landscapes, time required for sampling and analysis, and overall cost.

1.2 Measuring soil organic carbon

Accurate, high-resolution measurement of SOC is critical for quantifying the global carbon pool and mapping its spatial distribution to support climate change mitigation efforts based on soil carbon sequestration (Minasny et al., 2013; Powlson et al., 2011). For example, farmers and landowners who participate in soil carbon credits programs require carbon data to assess the effectiveness of their practices (Mooney, 2004). These data include concentrations of SOC, as well as SOC stocks, which is the mass of carbon per land area, calculated using SOC concentration, bulk density, and horizon thickness.

There are many existing laboratory methods for analysis of SOC, including the Walkley-Black method, dry combustion, loss on ignition, and spectroscopic methods. The Walkley-Black method of chemical oxidation was widely used to measure SOC in soil science laboratories from 1935 until the 1990s (Nelson & Sommers, 1996). However, the use of potassium dichromate ($K_2Cr_2O_7$) for oxidation generates hazardous waste products that are expensive to dispose of safely (Mikhailova et al, 2003). The automated dry combustion method has replaced the Walkley-Black method in modern soil science labs. While dry combustion is an accurate method for determining total soil carbon (*i.e.*, including organic and inorganic), it requires additional measurement and corrections for measurement of SOC in calcareous soils, as well as maintenance of expensive laboratory instrumentation (Mikhailova et al, 2003). Other alternative methods to measure SOC in the laboratory include visible near infrared (Vis-NIR) spectroscopy, and mid-infrared (MIR) spectroscopy, and loss on ignition (LOI) methods. The VisNIR and MIR methods allow for rapid analysis of many samples, but require spectroscopic instrumentation that is not widely available (Viscarra Rossel et al., 2006). The LOI method is relatively simple to perform, uses more widely available equipment (*i.e.*, a muffle furnace), and is routinely performed in soil testing labs. However, LOI is a measure of soil organic matter, not just SOC, therefore the ability to use this method for SOC analysis is dependent on the availability and accuracy of conversion factors used to predict SOC (Baker, 2022). While there are a variety of laboratory methods for analysis of SOC, collection and transport of samples is a fundamentally costly endeavor when a large number of samples is required, thus limiting the frequency of sampling in both time and space (Chatterjee et al., 2009). Field-based methods, therefore, have the potential to better capture the distribution of SOC across landscapes and its dynamic response to changes in management. Soil color is an easy property to measure in the field that is strongly related to SOC, creating potential for application in field-based SOC predictions (Alexander & Knake, 1968; Steinhard & Franzmeier., 1979).

1.3 Pedotransfer functions in soil analysis

Pedotrasfer functions (PTFs) are equations that express the relationship between soil properties. They can be used to estimate missing data (Bouma, 1989; Hamblin, 1991) or to replace direct measurement where cost or labor are prohibitive to obtaining the required data (Liao et al., 2015). The first PTFs were developed to predict soil hydraulic conductivity (Wösten et al., 2001), though previous efforts have also been made to develop PTFs to predict SOC. For example, a semi-quantitative relationship between soil color and organic matter was developed by Steinhardt and Franzmeier (1979) in Indiana which resulted in up to 90% accuracy. Similarly in

1968, a field color chart was developed to predict of soil organic matter for soils of Illinois (Alexander & Knake, 1968). This chart is still widely used today, including in the Soil Health Test Buckets from USDA-NRCS (USDA-NRCS, 2019). Wills and Burras (2007) studied the prediction of SOC using field and laboratory measurements of soil color. They used of the MCCs and chromameter (Minolta CR-310) color measurements, with depth as a secondary prediction factor. However, PTFs cannot be applied outside of the constraints imposed by the range of conditions used to develop the predictive equations. For example, the PTF for SOC developed in Indiana only produces reliable predictions when applied to cultivated soils with silt loam textures (Steinhardt & Franzmeier, 1979). The relationship between SOC and soil color are also different between agricultural field and prairie (Wills & Burras, 2007) This indicates that sample size, geographic range, and land use are all important factors to consider when developing a PTF.

1.4 Digital color sensors

Recent work has explored the application of digital color sensors in soil science (Moritsuka et al., 2019; Stiglitz et al., 2016; Stiglitz et al., 2017). The main limitation to using colorimeters more widely in soil science is their cost. Less expensive options for measuring soil color include smartphone cameras and low-cost portable color sensors (PCSs) (*e.g.*, Nix^{TM}, CS-10, Cube, and Color Muse) (Moritsuka et al., 2019). Low-cost PCSs have the potential for wider application beyond professional soil science community, reaching individuals such as farmers, land-owners, citizen scientists, and K-12 educators. Color measured by PCS compare well with laboratory colorimeter measurements (Stiglitz et al., 2016; Moritsuka et al., 2019). Furthermore, the PCS measurements may be more accurate that visual color assessments using the MCC, although these comparisons may have been biased by the use of aggregated soils with the MCC and disaggregated samples for the colorimeter and PCS measurements (Stiglitz et al., 2016). Other studies have achieved data comparable to a colorimeter using smartphone cameras (SPCs), although care must be taken to carefully control lighting conditions to achieve reliable results (Fan et al., 2017).

1.5 Objective of the study

There is a need for expansion of SOC measurement, to support efforts to improve soil health and mitigate climate change. While many sound laboratory methods exist, these are limited in the frequency with which analysis can be performed in time and space due to the expense and labor involved in collecting, transporting, and analyzing soil samples in the laboratory. Such obstacles are frequently overcome in soil science through the establishment of PTFs, which can be used to predict properties that are difficult to measure directly. Meanwhile, the long-established relationship between SOC and color, along with new technologies for the measurement of color, present expanding opportunities for the development of PTFs for the prediction of SOC. Therefore, the thesis project presented herein was designed with the following primary objectives:

1) To develop a PTF for the prediction of SOC based on soil color and texture in the state of Nebraska.
2) To evaluate the use of PCS and SPC methods of color analysis for the prediction of SOC in Nebraska.

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CHAPTER 2

QUANTIFYING THE RELATIONSHIP BETWEEN SOIL ORGANIC CARBON AND SOIL COLOR IN NEBRASKA

2.1 Abstract

Soil color is easily measured in the field and holds potential to be used as an indirect measurement of soil organic carbon (SOC). The main limitation to this approach is knowledge about the specific color-SOC relationship in a region, which often varies in relation to parent material, soil texture, climate, and land use. The primary objective of this study is to develop and evaluate the accuracy of pedotransfer functions (PTFs) for the prediction of SOC based on soil color and texture in the state of Nebraska. Data were obtained from the National Soil Information System (NASIS) database, including all pedons sampled across Nebraska and adjoining areas of surrounding states. The dataset was comprised of 1576 soil pedon descriptions and included samples with various soil textures, Munsell colors, and SOC. The relationship between Munsell value and SOC fit best to a logarithmic regression ($R^2 = 0.547$), which shows a rapid decline in Munsell value with increasing SOC for samples with less than 1% SOC and a gradual decline in Munsell value with increasing SOC for samples with 1 to 6% SOC. Certain MLRAs and texture classes were noted to exhibit stronger relationships between color and texture than others. The most accurate predictions, with root mean square error (RMSE) of 0.795, includes use of texture-specific regression equations for selected textures (silt loam, silty clay loam, loamy sand, and loamy very fine sand) and a generalized equation for all other textures. This PTF shows potential for SOC prediction based on soil color, but also reveals challenges inherent to the development of a generalized method for prediction of SOC based on color.

2.2 Introduction

Healthy soils are the foundation of sustainable agriculture and land management. There are many parameters that are used to assess soil health, including water holding capacity, aeration, bulk density, and soil organic carbon (SOC) (Allen et al, 2011). Of these, SOC is of particular interest because it is correlated with many attributes of healthy soils, including soil structure, aggregate stability, porosity, and microbial activity (Billings et al, 2021). Furthermore, the soil is an immense pool of carbon. There is more carbon in the soil than in the atmosphere and all plant life combined (Powlson et al., 2011; Scharlemann et al., 2014). Consequently, managing soils to store more carbon in the form of SOC is a widely pursued strategy for climate change mitigation (Sommer & Bossio, 2014). Mollisols are the dominant soil type in Nebraska, and are considered to be some of the most fertile and high-yielding soils in the world. However, due to management practices that fail to return carbon to the soil, it is estimated that 50% of SOC stored in Mollisols has been lost gloabally (Xu et al., 2020).

There is potential for mitigating climate change and improving soil health through land management practices that increase SOC. Agricultural management practices, such as cover crops, compost, rotational livestock grazing and no-till could improve overall soil health and remove carbon from the atmosphere (Blanco-Canqui et al, 2015; Byrnes et al, 2018; Blanco-Canqui, 2021). The soil health gap concept was developed to address the topic of land management effects on soil health by comparing SOC between native and managed lands (Maharjan et al., 2020). For example, in Scotts Bluff County, NE, SOC levels of surface soils vary greatly between lands under various management practices, such as grassland (4.4% SOC), no-till cropland (2.2% SOC), conventionally tilled cropland (1.8% SOC), and exposed subsoil (0.7% SOC) (Maharjan et al., 2020). However, there are limitations. In some cases, no-till practices increase SOC at the surface (0-20 cm) while decreasing SOC in the subsurface (20-

35cm) (Olson & Al-Kaisi, 2015). Thus, there is a need for continued SOC monitoring to evaluate soil's response to management practices intended to increase SOC..

There are many laboratory methods for determining SOC. The automated dry combustion method is commonly used to measure total soil carbon because of its accuracy and precision (Mikhailova et al, 2003). In soils without carbonates, total soil carbon can be assumed equivalent to SOC, but in calcareous soils, inorganic carbon must be accounted for, either by treating the sample to remove carbonates before dry combustion (Nelson & Sommers, 1996), or by analyzing inorganic carbon separately and calculating SOC as the difference (Sherrod et al., 2002). The Walkley-Black method of wet chemical oxidation using potassium dichromate ($K_2Cr_2O_7$) was widely used between 1935 and the 1990s (Nelson & Sommers, 1996), but is rarely used in modern laboratories due to the production of hazardous dichromate waste (Mikhailova et al., 2003). Other methods for SOC analysis include loss on ignition (LOI), visible-near infrared (Vis-NIR), and mid-infrared (MIR) methods. The LOI method is relatively simple to perform and is routinely used in soil testing laboratories as a measure of soil organic matter. However, converting soil organic matter to SOC requires knowledge about the chemical composition of the organic matter, which often varies between regions and with depth in the soil (Baker, 2022). The Vis-NIR and MIR methods are spectroscopic methods that can detect absorption properties associated with organic matter and can be used to calculate SOC, but require specialized instrumentation (Liu et al., 2019; Seybold et al., 2019). Overall, there are a variety of laboratory methods for analysis of SOC which are suitable for various research purposes. However, the main drawback to all these methods is their expense and the amount of time required to collect samples, transport them to the laboratory, and run the analysis (Chatterjee et al., 2009). Because of these constraints, the majority of the SOC analyses are limited to specific experimental sites with un-replicated samples (Liles et al., 2013). With the urgent need for SOC data to support programs aimed at improving soil health and mitigating climate change, there is a demand for diverse methods of SOC analysis, which can be selected by the user based on the relative importance of cost-effectiveness, speed, and accuracy for a particular application. Farmers and landowners who participate in soil carbon credits program could benefit from a simple, field-based method of quantifying SOC (Mooney, 2004). Thus, there is a growing need for an effective, practical, and quick method of measuring SOC in the field.

One of the possible methods to quantify SOC in the field is by utilizing pedotransfer functions (PTFs). The purpose of a PTF is to identify a statistical relationship that relates a soil property that is difficult to measure, to another property that is quick, easy, and inexpensive to measure. This relationship can then be used to estimate the property of interest. Early work on PTFs mainly focused on predicting soil hydraulic properties, such as saturated hydraulic conductivity (Wösten et al., 2001). Over the years, PTFs have been developed to predict other soil properties such as water retention and bulk density (Pachepsky & Rawls, 2003). Prediction of soil properties from PTFs is less costly and labor intensive than direct measurement of soil properties (Schillaci et al., 2021). While it is not advisable for PTFs to fully replace more traditional methods of analysis (Nasta et al., 2020; Yi et al., 2016), they can be a valuable tool when the data needed is not readily available or easy to obtain (Bouma, 1989; Hamblin, 1991).

Previous work has been conducted on the development of PTFs for estimation of SOC, most using soil color as the main predictor variable (Liles et al., 2013; Wills et al., 2007). The Munsell color charts (MCCs) are the standard field-based method of measuring soil color. The MCCs describe color in terms of hue (shade), value (lightness), and chroma (saturation) (Pendleton & Nickerson, 1951; Thompson et al., 2013). Existing field descriptions collected using the MCCs, such as those contained in the USDA National Soils Information System (NASIS), provide a ready-to-use dataset for PTF development. Furthermore, the MCCs are easy to use, making it possible to engage a large user base, including citizen scientists, in the monitoring of SOC (Ferrando Jorge et al., 2021). However, the accuracy of color measurement using the MCCs is limited by the subjectivity inherent to the method, which depends on correct color interpretation by the human eye, and may be challenging to use accurately under less than ideal lighting conditions (Stiglitz et al., 2016; Turk & Young, 2020). Digital tools, such as Bluetooth-connected color sensors and smartphone applications that uses the phone's camera to measure color, have been used in recent studies as an alternative method to measure soil color in the field, which produced comparable results with the MCCs (Stiglitz et al., 2017; Fan et al., 2017; Moritsuka et al., 2019). These methods overcome some of the limitations of MCC, as they do not rely on the interpretation by the human eye, and some digital tools have a built-in light source, thus avoiding errors related to poor lighting conditions.

Nevertheless, color charts as a tool for SOC estimation are appealing due to their simplicity and ease of use. A prominent example of this is the color chart for estimating soil organic matter content in mineral soils in Illinois (Alexander & Knake, 1968). This chart is still widely used today, including in the Soil Health Test Buckets from USDA-NRCS (USDA-NRCS, 2019). Although such color charts are widely used, regionally-specific versions of the charts have yet to be developed, even though it has long been recognized that the relationship between color and SOC varies among soil landscapes (Schulze et al., 1993). Differences in parent material, soil texture, climate, and land use may all contributed to the variety of relationships between SOC and soil color. In the case of soil texture, the same amount of organic matter typically produces a darker color in a coarse-textured soils compared to a fine-textured soil (Steinhardt & Franzmeier, 1979). Steinhardt and Franzmeier (1979) developed a semi-quantitative relationship between soil color and organic matter in Indiana with up to 90% accuracy, but this level of accuracy can only be achieved when applied to cultivated silt loam soils under conventional tillage conditions. The diversity of soil texture and climate across Nebraska suggest that a large amount of data will be required to develop PTFs that can accurately predict SOC throughout the state (Elder, 1969).

To quantify the relationship between SOC and color in Nebraska, a localized approach is needed. The primary objective of this study is to develop and compare the accuracy of different PTF equations to predict SOC based on soil color and texture in the state of Nebraska.

2.3 Materials and methods

Analysis of soil databases

The study area encompasses 13 Major Land Resource Areas (MLRAs) (Fig. 2.1), which vary in climate from subhumid to semi-arid and include a wide variety of soil parent material (*e.g.*, residuum, loess, eolian sand, pre-Illinoian till, and alluvium) (Elder, 1969). All available pedon description and laboratory characterization data for soils within the state of Nebraska, as well as areas of surrounding states that share MLRA within Nebraska, were accessed through the National Soil Information System (NASIS). A dataset was extracted, which included moist Munsell color, SOC, and particle size distribution for 1576 pedons. For 121 pedons, only dry color was reported and moist color was assumed to be one value chip lower than dry color. Moist color was selected for use in the analysis as it is easier to measure in the field in most situations. Organic carbon data in NASIS was determined by either the Walkley-Black method of chemical oxidation or calculated as the difference between total carbon (measured by dry combustion) and inorganic carbon (measured by calcimeter) (Burt, 2014). Only those horizons with SOC between 0 and 5.8% were included in the dataset, which mean 107 horizons were removed from the dataset prior to analysis. Zero is a logical lower threshold and the upper threshold of 5.8% corresponds with the cutoff between mineral soil materials and mucky-modified materials (Schoeneberger et al., 2012). Particle size distribution was obtained by pipette method (Burt, 2014). The dataset included all 12 soil texture classes recognized in the USDA system (Schoeneberger et al., 2012).

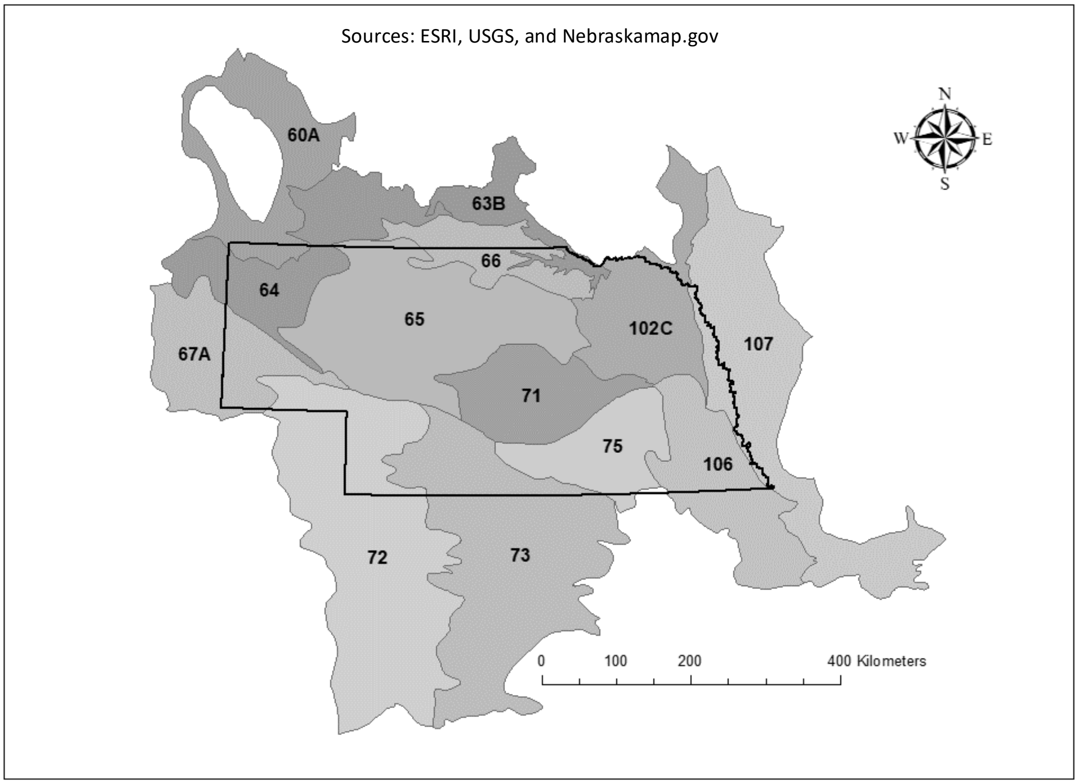

Figure 2.1. Study area included 13 Major Land Resource Areas (MLRAs) in the state of Nebraska and portions of surrounding states: Pierre Shale Plains and Badlands (60A), Southern Rolling Pierre Shale Plains (63B), Mixed Sandy and Silty Tableland (64), Nebraska Sandhills (65), Dakota-Nebraska Eroded Tableland (66), Central High Plains (67), Central Nebraska Loess Hills (71), Central High Tableland (72), Rolling Plains and Breaks (73), Central Loess Plains (75), Loess Uplands (102C), Nebraska and Kansas Loess Drift Hills (106), Iowa and Missouri Deep Loess Hills (107).

Development of carbon and color models

The dataset was subdivided such that 70% of data was used for PTF development and 30% was set aside for validation procedures. Data were assigned for PTF development and validation randomly, at the pedon level, resulting in 1103 pedons selected for PTF development and 473 set aside for validation. The PTF development dataset was used to fit regression equations relating moist Munsell value and SOC. Munsell value was selected for analysis as it is a measure of lightness or darkness, and therefore has the strongest relationship to SOC among the three components of Munsell color. Preliminary analysis included a modification of the profile darkness index, which includes value and chroma, in the analysis (Thompson & Bell, 1996). However, incorporating chroma was found to weaken, rather than improve, the relationship to SOC. Regressions were developed for the full dataset, for individual MLRAs, and for individual texture classes. In the texture-specific family of regressions, some texture classes with limited data were combined: sandy clays were combined with sandy clay loams, silts were combined with silt loams, and very fine sands were combined with fine sands. Each regression, or family of regressions, was used to predict SOC in the validation dataset and evaluated by calculating the root mean square error (RMSE) of the prediction.

2.4 Results

Development of Pedotransfer Functions

The relationship between Munsell value and SOC fit best to a logarithmic regression ($R^2 = 0.547$), which shows a rapid decline in Munsell value with increasing SOC for samples with less than 1% SOC and a gradual decline in Munsell value with increasing SOC for samples with 1 to 5.8% SOC (Fig. 2.2). Certain MLRAs and texture classes were noted to exhibit stronger relationships between color and SOC than others (Table 2.1 and 2.2). Within the MLRA-specific analyses, the best relationships between Munsell value and SOC were found in MLRAs 65 (Nebraska Sandhills), 75 (Central Loess Plains), 106 (Nebraska and Kansas Loess Drift Hills), and 107 (Iowa and Missouri Deep Loess Hills) (Fig. 2.3). While the best relationship for texture specific analysis were found in silty clay loam, silt loam, loamy very fine sand, and loamy sand (Fig. 2.4). The weakest relationships between Munsell value and SOC were found in MLRA 63B (Southern Rolling Pierre Shale Plains), 67 (Central High Plains), 60A (Pierre Shale Plains and Badlands), and 66 (Dakota-Nebraska Eroded Tableland) ($R^2 = 0.23$ to 0.42) and the weakest correlation were found in coarse sandy loam, coarse sand, silty clay, and silt loam (R^2 =0.17 to 0.32).

Validation of the Predictions

Predictions of SOC made using the PTFs described above had varying levels of error, with RMSE ranging from 0.795 to 2.1% (Table 2.3). The general regression equation, developed using all data in the training dataset, produced a prediction with a RMSE of 1.6%. Predictions made using sets of equations sub-divided by MLRA and texture alone did not improve the predictions (Table 2.1 and 2.2); the PTF using MLRA-specific equations yielded predictions with the same RMSE as the general equation (RMSE = 1.6%), whereas the use of texture-specific equations led to an increase in error (RMSE = 2.1%). When the PTFs were modified to use the selected equations, for a subset of MLRAs and textures with the strongest relationships between SOC and color, some improvement was found. When only MLRAs 75, 106, 65, and 107 were included in the analysis, error was reduced, but only slightly (RMSE=1.547%) (Table 2.3). However, when only selected textures were included (silty clay loam, silt loam, loamy fine sand, and loamy sand), a much greater reduction in error was found, with RMSE reduced to 0.795% (Table 2.3).

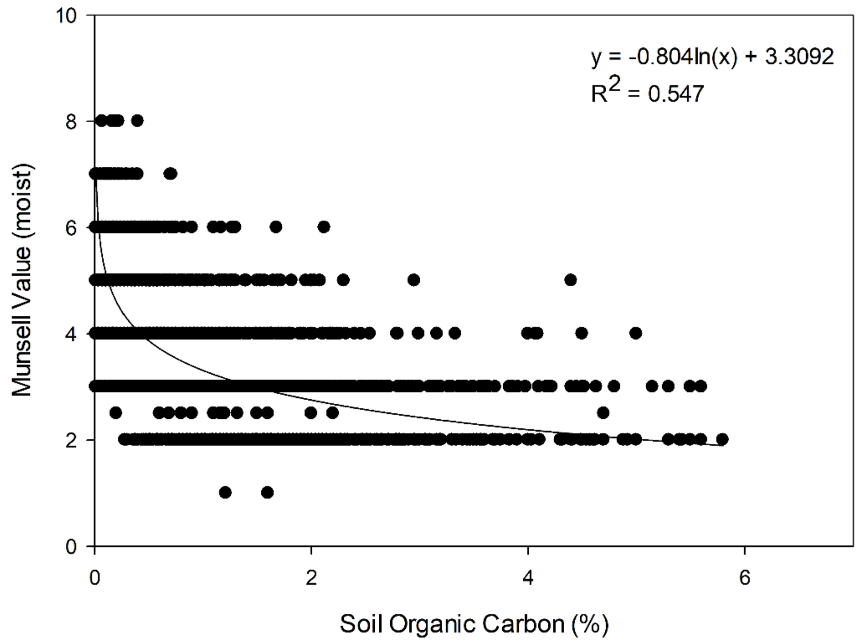

Figure 2.2. Plot of Munsell value (moist) versus soil organic carbon (%), including all data in the training dataset.

Table 2.1 Prediction equations subsetted by Major Land Resource Area (MLRA) derived from simple logarithmic regression. R^2: coefficient of determination.

MLRA	**Equation**	**R^2**
(64) Mixed Sandy and Silty Tableland	y = -0.769ln(x) + 3.67	0.48
(65) Nebraska Sandhills	y = -0.753ln(x) + 3.25	0.58
(66) Dakota-Nebraska Eroded Tableland	y = -0.657ln(x) + 3.37	0.42
(67) Central High Plains	y = -0.681ln(x) + 3.37	0.36
(71) Central Nebraska Loess Hills	y = -0.832ln(x) + 3.31	0.56
(72) Central High Tableland	y = -0779ln(x) + 3.34	0.48
(73) Rolling Plains and Breaks	y = -0.92ln(x) + 3.29	0.51
(75) Central Loess Plains	y = -0.966ln(x) + 3.11	0.69
(102) Loess Uplands	y = -0.687ln(x) + 3.22	0.5
(106) Nebraska and Kansas Loess Drift Hills	y = -0.824ln(x) + 3.16	0.59
(107) Iowa and Missouri Deep Loess Hills	y = -0.824ln(x) + 3.38	0.59
(60A) Pierre Shale Plains and Badlands	y = -0.79ln(x) + 3.91	0.38
(63B) Southern Rolling Pierre Shale Plains	y = -0.512ln(x) + 3.7	0.23

Table 2.2 Description of prediction equations subsetted by textures derived from simple logarithmic regression. R^2: coefficient of determination.

Texture	Equation	R^2
Clay	y = -0.881ln(x) + 3.58	0.37
Clay Loam	y = -0.638ln(x) + 3.49	0.39
Coarse Sand	y = -0.491ln(x) + 3.69	0.25
Coarse Sandy loam	y = -0.454ln(x) + 3.96	0.17
Fine Sand	y = -0.761ln(x) + 3.06	0.49
Fine Sandy loam	y = -0.719ln(x) + 3.26	0.52
Loam	y = -0.904ln(x) + 3.35	0.51
Loamy Coarse Sand	y = -0.599ln(x) + 2.69	0.34
Loamy Fine Sand	y = -0.765ln(x) + 2.92	0.46
Loamy Sand	y = -0.8ln(x) + 3.01	0.54
Loamy Very Fine Sand	y = -0.551ln(x) + 3.8	0.55
Sand	y = -0.681ln(x) + 3.15	0.52
Sandy Clay Loam	y = -0.59ln(x) + 3.49	0.46
Silt Loam	y = -0.958ln(x) + 3.3	0.63
Silty Clay	y = -0.714ln(x) + 3.20	0.31
Silty Clay Loam	y = -0.979ln(x) + 3.17	0.64
Sandy Loam	y = -0.671ln(x) + 3.52	0.32
Very Fine Sandy Loam	y = -0.88ln(x) + 3.36	0.47

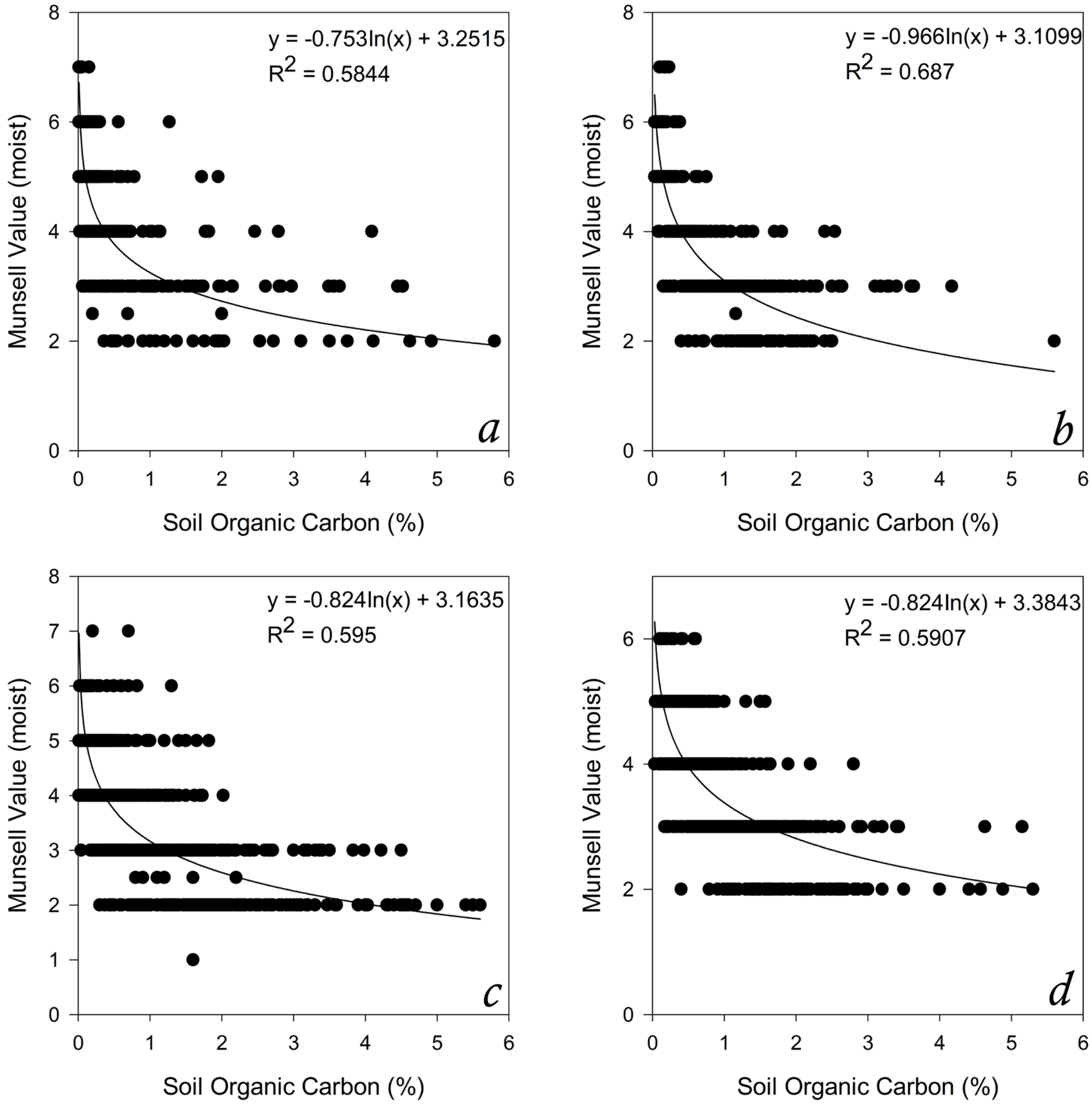

Figure 2.3. Plots of Munsell value (moist) versus soil organic carbon (%) for the specific Major Land Resource Areas (MLRAs) based on the training dataset, including: a) MLRA 65 (Nebraska Sandhills), b) MLRA 75 (Central Loess Plains), c) MLRA 106 (Nebraska and Kansas Loess-Drift Hills), and d) MLRA 107 (Iowa and Missouri Deep Loess Hills).

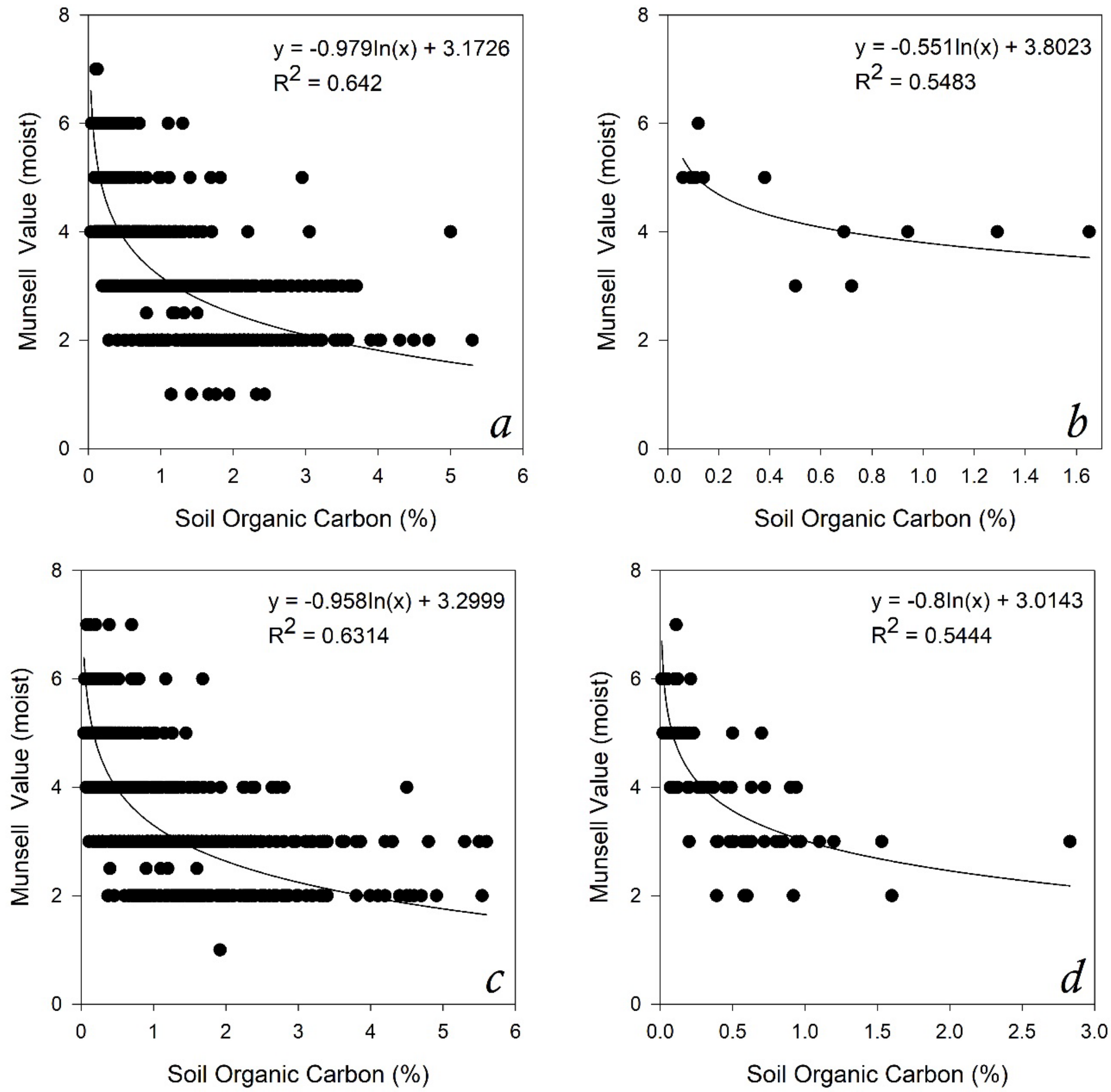

Figure 2.4. Plots of Munsell value (moist) versus soil organic carbon (%) for the specific textures based on the trianing dataset, including: a) silty clay loam, b) loamy very fine sand, c) silt loam,and d) loamy sand.

Table 2.3 Root mean square error (RMSE) analysis of pedotransfer functions applied to the validation dataset. Predictions presented are based on regression derived from the full traning dataset (1), regressions subsetted by Major Land Resource Area (MLRA) (2), regressions for selected MLRAs (75, 106, 65, and 107) (2a), regressions subsetted by soil texture (3), and regression for selected soil textures (silty clay loam, silt loam, loamy very fine sand, and loamy sand) (3a).

Pedotransfer function	RMSE
1. General equation (Fig. 2.2)	1.6
2. MLRA-specific equations (Table 2.1)	1.6
2a. Selected MLRA-specific equations (Figure 2.3)	1.5
3. Texture-specific equations (Table 2.2)	2.1
3a. Selected texture-specific equations (Figure 2.4)	0.8

2.5 Discussion

Current laboratory methods of measuring SOC are time consuming and costly. A PTF that uses color to predict SOC offers a simple, field-based alternative. The results of this study show potential for using PTFs to predict SOC from soil color, especially for soils with textures of silty clay loam, loamy very fine sand, silt loam, and loamy sand. For other soil textures it is recommended to use the generalized equation (Fig. 2.3) as the PTF to estimate SOC. The generalized equation has a coefficient of determination (R^2) of 0.547 which is within the range of R^2 values of other SOC-prediction functions presented in the recent scientific literature, including those that use Bluetooth color sensors instead of the MCCs (Table 2.4). One notable difference between the studies is the choice to utilized only darkness attributes of color (*e.g.,* value, L*), or to incorporate additional attributes of color (*e.g.*, chroma, a*). While some studies found significant improvements with the inclusion of additional attributes of color (Rubinic et al., 2021; Stiglitz et al., 2017), preliminary analysis conducted using the Nebraska dataset found no improvement when chroma was incorporated into the analysis. This may be related to differences in mineralogy between the regions of study. For example, the negative correlation of SOC with a* (redness) on the South Carolina Piedmont may be explained because the presence of organic matter masks iron oxides that give the soils their red color. However, this relationship is less pronounced or absent in soils with less hematite.

Table 2.4 Comparison of studies utilizing soil color to predict soil organic carbon (SOC).

Equation	**Variables**	R^2	**Methods**	**Location**	**Authors**
Piedmont: Y=-0.219(x)+1.273 Coastal plain: Y=-0.05(X)+2.061	L* (Upper 30 cm sampled by horizon in wetlands.)	0.05 (Piedmont) 0.62 (Coastal plain)	Bluetooth color sensor (Nix Pro)	Northern Virginia, USA	Schmidt and Ahn (2021)
y=-0.44(x)+40.08	L* (Upper 10 cm.)	0.58	MCCs Spectrophotometer	London, UK and Chantilly, France	Ferrando Jorge et al. (2021)
Value/chroma: y=-1.586+3.138(x) Chroma: y=-12.884-2.66(x)	Value and Chroma for dry soil (0-30 cm Ap horizon.)	0.76 (value/chroma) 0.88 (chroma)	MCCs.	Zagreb, Croatia	Rubinic et al. (2021)
Dry soil: soc=8.509-0.011(depth)-0.101(l*)-0.113(a*) Moist soil: soc=5.703-0.011(depth)-0.055(l*)-0.083(a*)	Depth, L*, a*; (Whole pedon.)	0.80 (dry) 0.72 (moist)	Bluetooth color sensor (Nix Pro)	Piedmont region of South Carolina, USA.	Stiglitz et al., (2017)

The relationship between SOC and color is strong for some soil textures and weak for others. The weakest correlations between SOC and color were among the textures containing coarse sand (coarse sand, loamy coarse sand, and coarse sandy loam), which yielded R^2 values ranging from 0.17 to 0.34. Perhaps in these soils, color is primarily controlled by the color of the sand grains themself, rather than the coating around them. Interestingly, the correlations are also weak on the other extreme, with the next weakest correlations occurring among soils that are high in clay (clays, clay loams, and silty clays), which had R^2 values ranging from 0.31 to 0.39. Among these soils, the extremely high surface area may be leading to mineral-bound organic forms that are not as strongly reflected in the soil color. The best correlations between SOC and color seems to occur among the loamy and silty textures. This is similar to the findings of past studies, which also found strong relationships between SOC and color specifically among soils with silt loam texture (Steinhardt and Franzmeier, 1979).

Among the MLRAs, the weakest correlations between SOC and color were found in regions dominated by residual parent material. This includes MLRA 63B (Southern Rolling Pierre Shale Plains) ($R^2 = 0.23$) and MLRA 67 (Central High Plains) ($R^2 = 0.36$). This may be related to soil texture, as the relationship between SOC and color was found to be weakest among textures with high percentages of clay and coarse sand. Soils derived from shales in MLRA 63B are rich in clay, while sandstone-derived soils in MLRA 67 may weather to form soils with coarse sandy textures. Interestingly, research in Virginia also found that soils on the residuum-dominated Piedmont showed no correlation between color (L*) and SOC ($R^2 = 0.05$), while soils on the Coastal Plain had significant correlation between these variables ($R^2 = 0.62$) (Schmidt and Ahn, 2021). The authors attribute this to the clay and iron-oxide rich nature of these soils. Other studies of piedmont soils achieved better predictions of SOC when additional variables, such as depth and redness (a*) are incorporated into the model (Stiglitz et al., 2017).

When applied to the validation dataset, the lowest error (RMSE = 0.8%) was found when the analysis was narrowed to focus on four specific texture classes: silt loams, silty clay loams, loamy sands, and loamy very find sands. For other texture, the generalized model works best, and the RMSE is 1.6%. Considering that the overall range of SOC considered in this study is 0 to 5.8%, errors ranging from 0.8 to 1.6% will present a significant degree of uncertainty. Therefore, some caution is warranted in application of the PTF. While it may be able to discern soils with low (0-1.9%), moderate (2-3.9%), or high SOC (4-5.8%), small differences hold little meaning considering the degree of error inherent in the color-based estimates. Much lower error rates can be achieved through technologies such as mid- (MIR) spectroscopy, which is a lower cost alternative to traditional lab methods such as dry combustion. Using MIR, it is possible to achieved predictions with RMSE below 0.1% SOC (Dorantes et al., 2022). While higher error rates may be acceptable for some applications, a RMSE of 0.4% SOC or lower is desirable for applications within the context of climate change mitigation, based on initiatives such as 4 per 1000, which advocates for regenerative agriculture with the aim of increasing SOC by 0.4% per year (Soussana et al., 2019).

2.6 Conclusion

The results of this study that a predictive equation for SOC from soil color can be used mainly on specific soil textures in Nebraska: silty clay loam, loamy very fine sand, silt loam, and loamy sand. Meanwhile, the generalized equation should be used for other soil textures in the database. Textures with coarse sands and high clay percentages are particularly problematic for develop color-based SOC prediction functions. This finding highlights the importance of soil texture in developing color based PTFs for SOC.

Similar to other studies, these results also indicate a correlation between SOC and the attribute of color that measures darkness/lightness (*i.e.*, Munsell value, CIELab L*). There is a rapid decline in Munsell value with increasing SOC in the low range (<1% SOC), and a gradual decline in Munsell value with increasing SOC up to 5.8%. Overall, there is a potential to use soil color as a predictor of SOC, however, users of such PTFs are cautioned to be aware of the limitations and errors. Certain soils, including those with coarse sands, high clay, and residual soils, are poorly fit in the PTFs presented here. Furthermore, even the textures identified as best suited for PTF still yield predictions with significant error rates (RMSE = 0.8), such that minor changes in SOC are unlikely to be detected.

There are many variables to take into account when developing a color-based PTF for prediction of SOC, including regional-specificity, color space (*e.g.,* CIE Lab or Munsell), method of color measurement (*e.g.*, MCC or digital tools), color attributes to include (*e.g.,* value, chroma, or both), moist vs. dry color, and inclusions of other variables (*e.g.*, texture, depth, land use). This study presents PTFs for the state of Nebraska, using the Munsell color system, measured by visual matching with the MCC in the moist state, with texture as the main extraneous variable. These are predictors that are easily measured in the field, which is the main advantage of this approach. However, the study also highlights that immense range of analyses possible given the large amount of Munsell color data available in soil databases such as NASIS. Continued use of legacy data, as well as new datasets exploring the use of digital tools, will surely continue to improve and expand upon the PTFs presented here.

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CHAPTER 3
USE OF SMARTPHONE CAMERAS AND PORTABLE COLOR SENSORS TO PREDICT ORGANIC CARBON IN NEBRASKA SOILS

3.1 Abstract

The Munsell color charts (MCCs) are the predominant method for field description of soil color in most soil survey applications. The main limitation to this method is the subjective nature of the data and the environmental condition which affects illumination during measurement. Recently, the availability of low-cost, digital portable color sensors (PCS) and smartphone cameras (SPCs) has been a promising alternative, albeit their effectiveness is still poorly understood. The primary objective of this study was to evaluate PCS and SPC-based color measurements as field predictors of soil organic carbon (SOC) in Nebraska. This study makes use of pedon description data from the National Soil Information System (NASIS) database, as well as 50 samples requested from the archive of the Kellogg National Soil Survey Laboratory. The R^2 for moist Munsell value and SOC for both PCS and MCC were0.52 and 0.54, respectively. The SPCs however, shows a weak correlation with R^2 value of 0.36 (SPC1-iPhone) and 0.32 (SPC2-Google Pixel). These results indicates that there is a potential of using alternative digital methods of measuring soil color and SOC compared to the MCCs. The use of a Nix Mini 2 portable color sensor, in particular, produced a comparable result with the MCCs.

3.2 Introduction

Soil color is determined by various soil properties and conditions, including soil texture, soil organic matter, soil moisture, soil mineral composition, and land use (Baumann et al., 2016; Evans & Franzmeier, 1988; Franzmeier et al., 1983; Sanchez-Maranon et al., 2015; Schwertmann, 1993; Wills et al., 2007). Measurable quantitative relationships have been identified between soil color and soil organic carbon (SOC) (Steinhardt & Franzmeier, 1979; Liles et al., 2013). As an important indicator of soil health and fertility, the measurement of SOC is of interest to farmers, researchers, and government officials. However, the current methods of measuring SOC can be costly and time-consuming (Schillaci et al., 2021). Furthermore, not everyone seeking SOC data has access to laboratory equipment (Ferrando Jorge et al., 2021). Due to its dynamic nature, SOC is best captured through frequent measurements across time and space, creating a need for simple, low-cost methods of analysis. Indirect measurement of SOC, using soil color as a predictor, presents an alternative solution to this challenge.

The Munsell color charts (MCCs) have been utilized to measure soil color in the field for more than half a century (Pendleton & Nickerson, 1951; Thompson et al., 2013). The MCCs describes soil color by hue, value, and chroma. Hue describes shade, value indicates lightness, and chroma is a measure of saturation (Pendleton & Nickerson, 1951). However, the MCCs are subjective to the individual performing the analysis and results may vary depending on the environment and lighting conditions, which makes this method inconsistent and prone to human error (Turk & Young. 2020; Stiglitz et al., 2016). Lastly, the three color dimensions (hue, value, and chroma) used in MCCs are challenging to enter into statistical analyses (Ibanez-Asensio et al., 2013; Kirillova et al., 2015; Fan et al., 2017).

There are current alternatives offered to measure soil color in the field by utilizing inexpensive portable color sensors (PCS) or smartphone cameras (SPCs) (Stiglitz et al., 2016; Fan et al., 2017; Moritsuka et al., 2019). Both technologies are able to produce results that compare well against a standard, such as MCCs or laboratory colorimeter measurements (Stiglitz et al., 2016; Fan et al., 2017). Thus, PCS and SPC-based measurements of color are useful alternative for measuring soil color in the field that are accessible, accurate, and have the potential for prediction of SOC (Schimit & Ahn, 2021; Stiglitz et al., 2017). Such predictions could help determine best management practices or soil reclamation methods and help to preserve and restore farmland or native habitats. (Stiglitz et al., 2017). The objectives of this study are to: 1) compare PCS and SPC-based color measurements as field predictors of SOC in Nebraska 2) analyze the difference between color space models used in measuring soil color, and 3) analyze the effect of soil moisture state on color prediction.

3.3 Materials and methods

Samples used in the study

The soil samples used in this study were obtained from the Kellogg Soil Survey Laboratory (KSSL) sample archive. The soil samples were selected from pedon description accessed through the National Soil Information System (NASIS) database, which represent the complete range of textures and SOC within three selected Major Land Resource Areas (MLRAs) across Nebraska. Nebraska MLRAs included in this study were MLRA 67 (Central High Plains), MLRA 75 (Central Loess Plains), and MLRA 106 (Nebraska and Kansas Loess Drift Hills). Samples in the archive are stored in an air-dried and disaggregated state. A total of 50 10-g subsamples were obtained for the project, which is the maximum number of subsamples and subsample size allowed for a single project by the KSSL. The soil textures collected include loam, clay, silty clay loam, silt loam, clay loam, and silty clay. The SOC range from 0.08 – 3.91% from the available subsamples.

Color analysis using PCS

The color of each sample was evaluated using a low-cost ($99) PCS (Mini 2, Nix Sensor Ltd), which can be operated using a free application for Android or Apple smartphones. The Nix sensor is pocket-sized, rechargeable, and has a built-in light emitting diode (LED), which allows consistent illumination of the samples regardless of lighting conditions. The Nix sensor records the output of scan results in various color space including XYZ (y = luminance, x and z = virtual primary spectra), RGB (red, green, and blue), CMYK (cyan, magenta, yellow, and black), and CIEL*a*b* (Lightness (L*), redness (a*), and yellowness (b*)). However, the sensor does not give Munsell color space.

A small amount of each sample was spread (diameter ± 2.5 cm) and flattened on an aluminum dish. The samples were moistened using a spray bottle until the color no longer changed as more water was added. The base of the sensor (diameter 1.5 cm) was placed directly on the flat surface of the moist sample, such that no external light entered the scanning area. The Nix Toolkit smartphone application was used to collected data from the sensor. The procedure was also repeated with dry samples to obtain the dry color of the soils.

Color analysis using SPC

The SPCs used in this study are the Apple iPhone XS Max with Dual 12 Megapixel wide-angle and telephoto camera (SPC1), and Google Pixel 4A with 12.2 Megapixel tele-lens camera (SPC2). The Land Potential Knowledge System (LandPKS) application was used to capture the soil color (Herrick et al., 2016). The LandPKS application allows users to learn about the land and produce site-specific data on any specific location in the world (Herrick et al., 2013). One of the features in the application is the soil color measurement tool which allows users to measure soil color using the smartphone camera and a reference card.

LandPKS color measurements were collected for each of the 50 sub-samples from the KSSL archive. Measurements using PCS and SPCs were collected on the same prepared and moistened samples. The smartphone was held 30 cm above the soil surface, which as placed next to the reference card (G7 White Balance Pocket Card, WhiBal). Two desk lamps using 5000K “natural daylight” bulbs were positioned side by side on a 45-degree angle facing the samples to minimize shadows. Overhead fluorescent lighting was turned off so that all light reaching the samples was from the lamps. Within the LandPKS application, the soil color option was selected, which prompts the user to the camera. Both the soil sample and the reference card need to be in the photograph. The user selects areas within the photograph that are to be used for analysis, including the soil sample and the reference card. The LandPKS application reports the color in the Munsell color space, rounded to the nearest chip within the MCC, as well as the CIEL*a*b* and RGB colors. Dry colors were also obtained by repeating the procedure with dry samples.

Munsell chips analysis

The procedure was initially tested on MCCs chips using both PCS and SPCs to evaluate overall accuracy of the color measurements. The MCCs chips were measured to evaluate the error associated with each of the measurement method. Nineteen unique samples from the subset of 50 was chosen to represent the widest range of color from the subsamples. The hue, value, and chroma were recorded for each of the method and subtracted by the original values from field description. The hue was converted into an absolute value by assigning number to each of the page from MCCs: 10R = 1, 2.5YR = 2, 5YR = 3, 7.5YR = 4, 10YR = 5, 2.5Y = 6, and 5Y = 7 (Post et al., 1993).

Data analysis

Analyses were performed for both moist and dry samples using two color space systems: Munsell and CIEL*a*b. Because the PCS used in the study does not report Munsell color, a color analysis software (CT&A Version 6.0.7, BabelColor) was used to transform the colors from CIEL*a*b* to Munsell. The color analysis software was also used to transform NASIS pedon descriptions using MCCs to CIEL*a*b*. Regression analysis was performed between metrics of soil lightness-darkness (Munsell value, CIEL*a*b* L*) and SOC for each set of measurements (PCS, SPC1, and SPC2). Regressions were performed using the full dataset of 50 samples, as well a subset of samples within an individual MLRA.

3.4 Results

Accuracy of color measurement obtained by PCS and SPCs

Through direct measurement of color chips on the MCC, different levels of accuracy were found to be associated with the PCS and both SPCs (Table. 3.1). The PCS was found to be accurate when evaluating hues of low chroma color but reported hues that were slightly too red in the mid-chromas, and nearly a page too red for high chroma colors. The PCS error was low for Munsell value and chroma. The SPC1 showed a high level of error for all components of Munsell color. Hues averaged 4.5 pages too yellow for low-chroma color, 1.5 pages too yellow for mid-chroma colors, and 1.3 pages too red for high-chroma colors. Values averaged nearly one unit higher than the chip measured and chromas averaged nearly one unit too low. Compared to SPC1, SPC2 was more accurate for hue, but less accurate for value and chroma. The average hue was close to the actual page for low and mid chroma colors, but was an average of 1.3 pages too red for high-chroma colors. Values were on average 1.1 units higher than the chip measured and chroma averaged 2 units lower than that of the chip measured.

Table 3.1. Average difference between the measured color and corresponding chip color for three methods: portable color sensor (PCS), smart phone camera (SPC) using iPhone (SPC1), and Google Pixel (SPC2). Hue was transformed to a linear scale by assigning a number value to each page of the Munsell color charts: 10R = 1, 2.5YR = 2, 5YR = 3, 7.5YR = 4, 10YR = 5, 2.5Y = 6, and 5Y = 7 (Post et al., 1993). Standard deviation (±). Positive value indicates lower estimation, negative value indicates higher estimation.

Method	Hue	Value	Chroma
PCS	low = 0 (±0) mid = -0.3 (±0.4) high = -0.9 (±0.5)	0.2 (±0.14)	0.1 (±0.3)
SPC1	low = 4.5 (±0.5) mid = 1.5 (±1.8) high = -1.9 (±1.3)	0.9 (±0)	-0.6 (±1.1)
SPC2	low = N/A mid = -0.2 (±0.4) high = -1.3 (1.5)	1.1 (±0.64)	-2 (±1.15)

Relationship of Munsell Value and SOC

Using Munsell value of moist samples, the PCS used in this study produced data that shows a similar relationship to SOC compared to data collected in the field using the MCCs (Fig. 3.1a,b). The PCS (R^2 = 0.52) and MCCs (R^2=0.54) both show that slightly more than 50% of variance in Munsell value was explained by SOC. One difference between the methods is that the PCS can interpolate between chips on the MCC page (Fig. 3.1a). In contrast, the discrete nature of data collected using the MCCs is a major source of residuals in the Munsell dataset, as the position of data points are restricted to whole numbers on the Munsell-value axis (Fig. 3.1b). Much less of the variation in Munsell value measured with the SPCs could be explained by SOC (Fig. 3.1c,d). The SPCs produced regressions with low R^2 values for both SPC1 (R^2 = 0.36) and SPC2 (R^2 = 0.32). The Munsell Value comparison between the two significant methods of MCCs and PCS shows a comparable variance that can be explained by SOC. Linear regression model using MCCs in the Munsell Value system reveal the R^2 = 0.42, meanwhile the PCS has a similar R^2 = 0.46 (Fig 3.2) For all methods, the relationship between dry Munsell value and SOC was weaker than that of the moist color (R^2 = 0.14-0.4) (Appendix).

Relationship of L and SOC*

Using the CIEL*a*b* color space produced similar results to those obtained using the Munsell color space (Fig. 3.2). While Munsell value and L* are numerically different, both show a similar relationship to SOC in terms of the amount of variance that could be explained by SOC. Using moist L*, the PCS used in this study produced data that shows a similar relationship to SOC compared to data collected in the field using the MCC and converted into the CIEL*a*b* color space (Fig. 3.3a,b). The PCS (R^2 = 0.52) and MCC (R^2=0.54) both show that slightly more than 50% of variance in L* was explained by SOC. The discrete nature of data from collected using the MCC is still an apparent source of residuals, even when the data is converted into the CIEL*a*b* color space (Fig. 3.3a). Much less of the variation in L* measured with the SPCs could be explained by SOC (Fig. 3.3c,d). The SPCs produced regressions with low R^2 values for both SPC1 (R^2 = 0.4) and SPC2 (R^2 = 0.29). Dry color L*, similar to dry Munsell value, showed a weak relationship to SOC regardless of the method of analysis (R^2 = 0.19 – 0.42) (Appendix).

Influence of MLRA and textures on variance of SOC

Further analyses of the data by examining the MLRAs and texture produces relationships in which more variances can be explained by SOC. Regressions using PCS measurement in the CIEL*a*b color space reveal different relationships between L* and SOC for each MLRA, such that the residuals are lower when the regions are analyzed separately (R^2 = 0.47 to 0.81) (Fig .3.4). This is also true for the subset of texture data, although the residuals have a wider range (R^2 = 0.22 to 0.79) (Fig. 3.5). Overall, more variance in color can be explained by SOC when MLRAs and textures are considered separately.

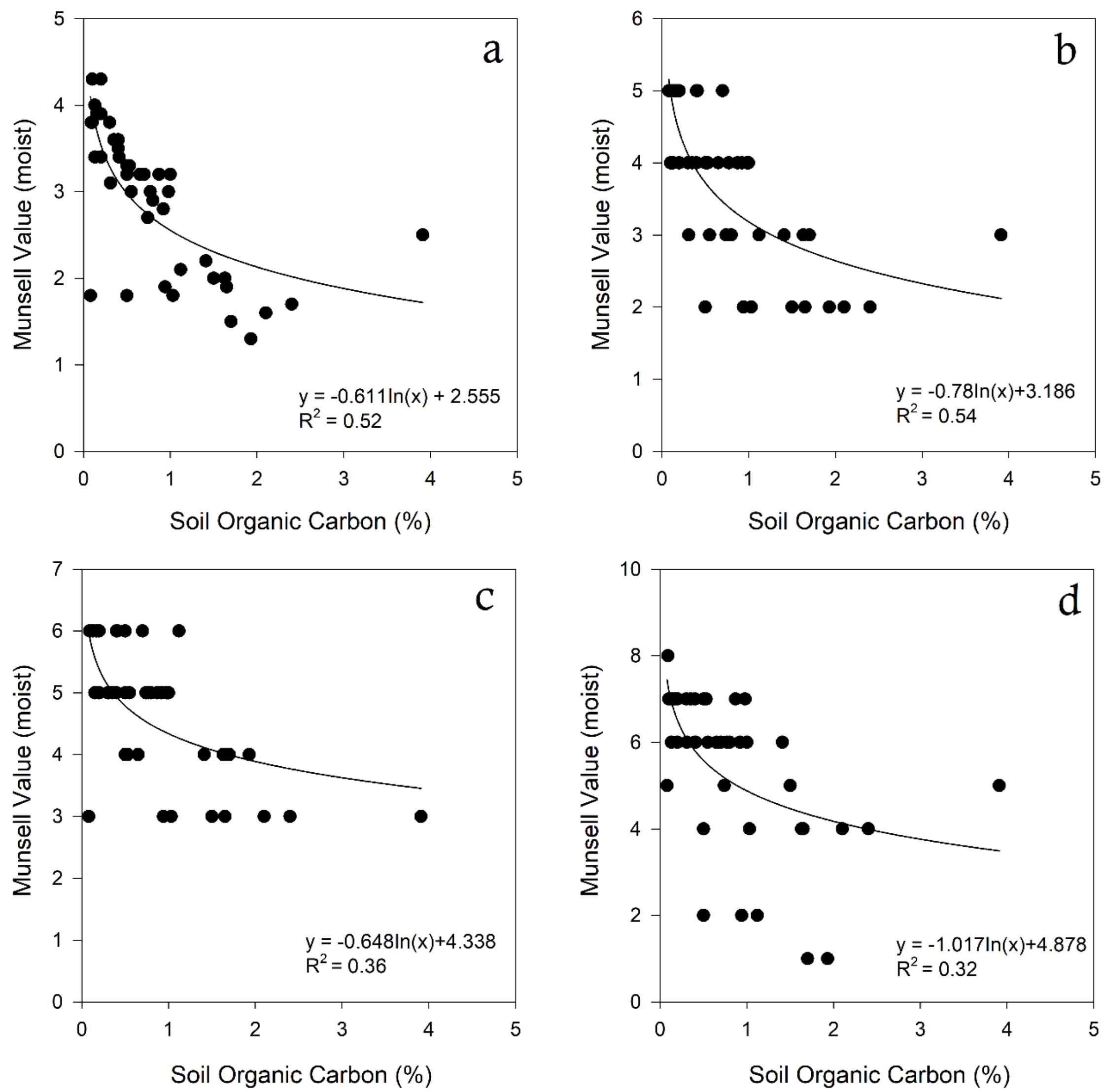

Figure 3.1. *Plots of Munsell value (moist) versus soil organic carbon (%) for a) portable color sensor (PCS) of Nix Mini 2, b) Munsell color charts (MCCs), c) Smartphone Camera 1: iPhone XS Max (SPC1), and d) Smartphone Camera 2: Google Pixel 4A (SPC2).*

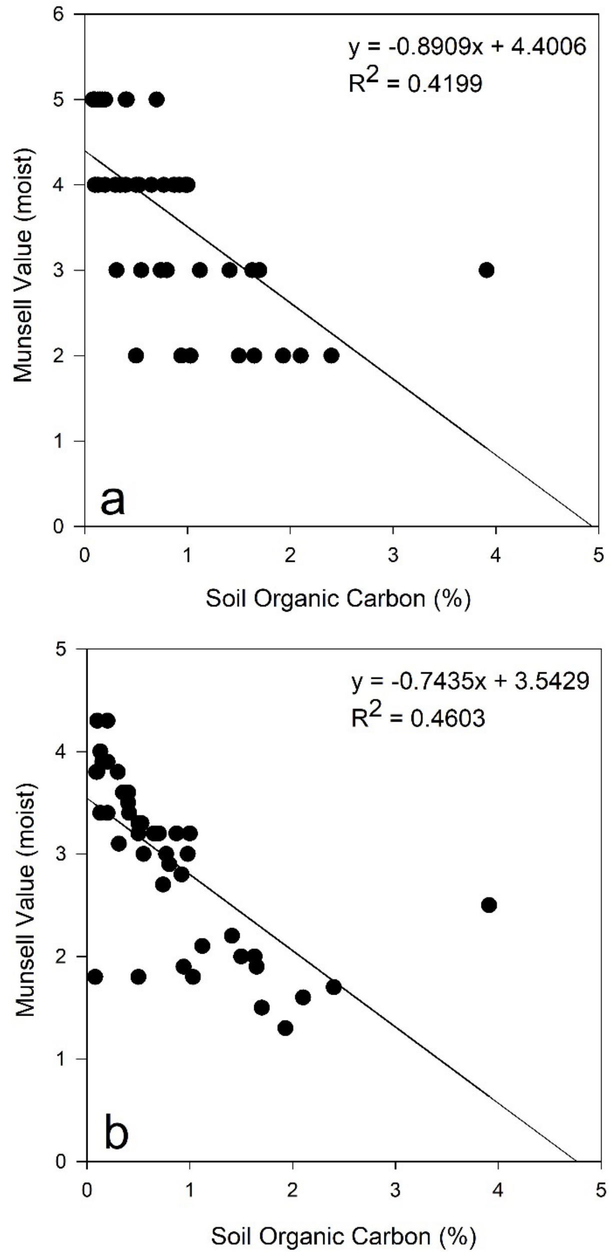

Figure 3.2. *Plots of Munsell value (moist) versus soil organic carbon (%) showing comparison betweenr a) Munsell color charts (MCCs), b) portable color sensor (PCS) of Nix Mini 2.*

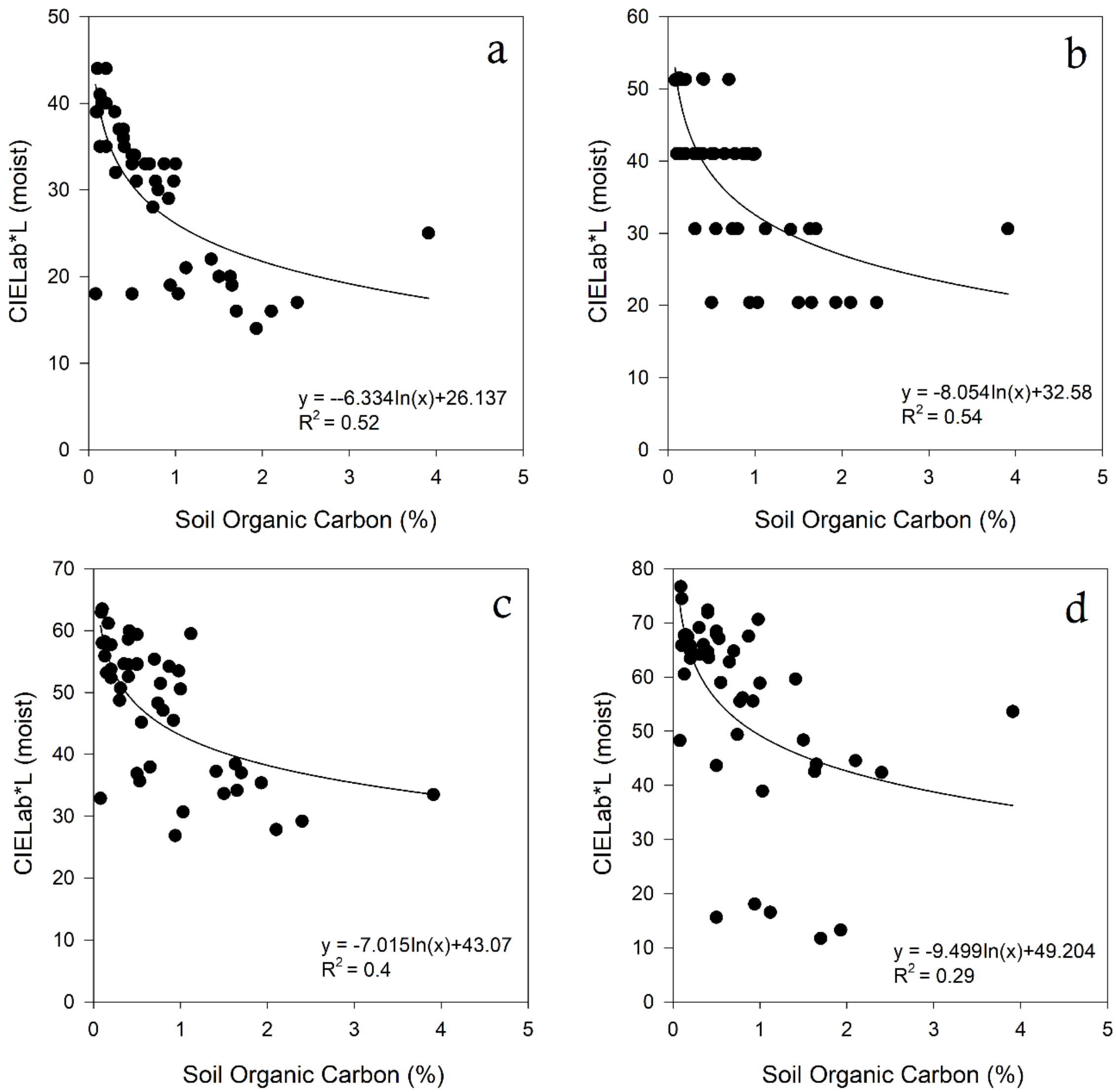

Figure 3.3. *Plots of CIELab*L (moist) versus soil organic carbon (%) for a) portable color sensor (PCS) of Nix Mini 2, b) Munsell color charts (MCCs), c) Smartphone Camera 1: iPhone XS Max (SPC1), and d) Smartphone Camera 2: Google Pixel 4A (SPC2).*

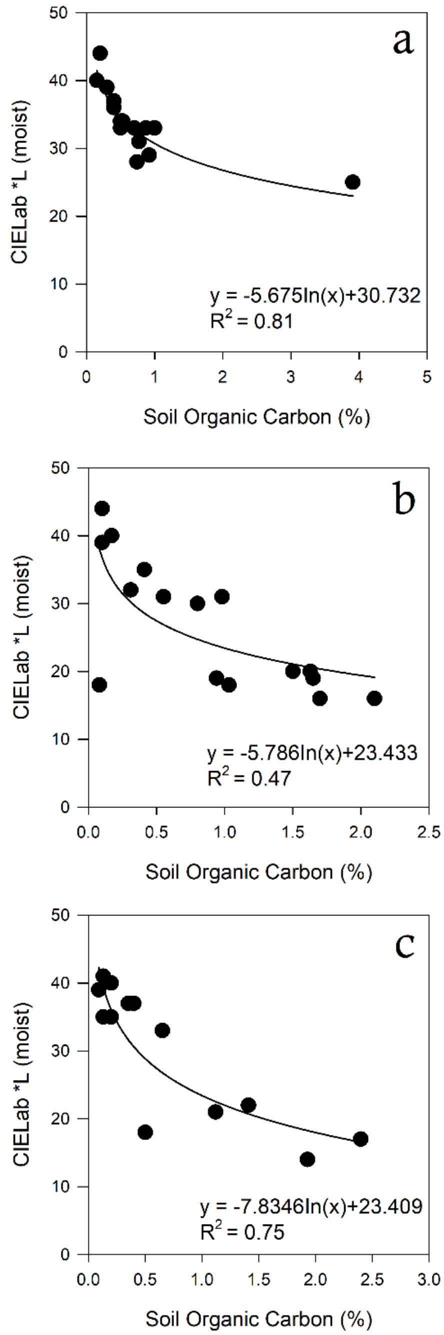

Figure 3.4. *CELab*L of moist samples measured using a PCS plotted versus SOC (%) for each MLRA included in the study: a) Central High Plains (MLRA 67), b) Central Loess Plains (MLRA 75), and c) Nebraska and Kansas Loess-Drift Hills (MLRA 106).*

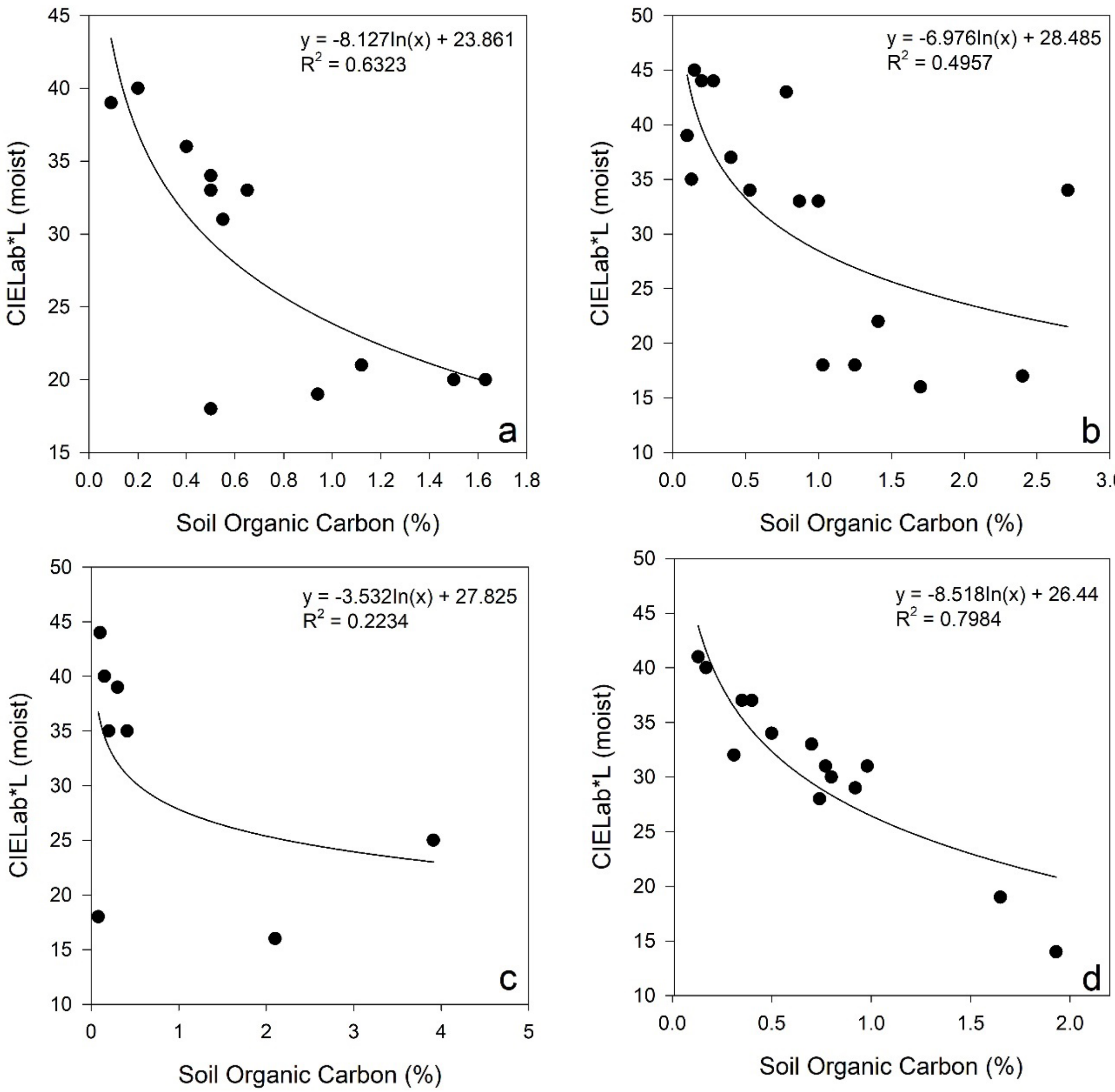

Figure 3.5. *CELab*L of moist samples measured using a PCS plotted versus SOC (%) for each soil textures included in the study: a) silty clay, b) loam, c) silt loam, d) silty clay loam.*

3.5 Discussion

Digital devices for measuring soil color, including PCSs and SPCs, are compelling alternatives to the MCC. The PCS used in this study was the most accurate for measuring Munsell value, and was the best predictor of SOC. When data from all MLRAs was combined, regressions of measurements collected by PCS and MCCs showed similar levels of residuals, however, PCS measurements showed greater reduction in residuals when MLRAs were considered separately. This suggests that there are differences in the SOC-color relationship between the regions, which become more apparent with the higher resolution measurement collected with the PCS compared to the MCCs. The PCS used in this study is approximately half the cost of a new MCC and can interpolate between the chips. One disadvantage is that the application for the PCS does not directly report data in the Munsell color space, so if data needs to be expressed in this form, additional steps are required to convert the data.

Compared to the PCS, the inaccuracy of SPCs at measuring value limits their potential application for predicting SOC. While past studies found that colors determined using SPCs compare well with MCCs (Fan et al., 2017), our SPC results show a high level of inaccuracy (Table 3.1). This may be because the previous study used dry soil color (Fan et al., 2017), while our work focused on moist colors and instead found that moist colors are better for predicting SOC. The darker colors of soils in their moist state may be less accurately measured by the SPC.

Munsell value and CIEL*a*b* both work well for measuring the relationship between the lightness value and SOC. This gives the option for the user to choose the method that works best for them based on the available instrument and their budget. Other studies have suggested that dry color work best, if not better, in measuring soil color and SOC (Rubinic et al., 2021; Stiglitz et al, 2017). However, there seems to be no advantage of incorporating dry color in this study. This could be caused by the different sampling depth and whether subsoil samples are included in the analysis.

3.6 Conclusion

Soil color, measured with a PCS, can be used to predict SOC. Overall, the relationship between color and SOC is similar, regardless of whether measurements are taken with the PCS or manually with the MCCs. However, SPC measurements were found to be less accurate, which limits their potential application for prediction SOC. Munsell value and CIEL*a*b* both show strong relationships to SOC and are suitable for development of predictive functions. Functions are provided here in both color spaces. Each of the three Nebraska MLRAs show a unique function, therefore the equations presented here are best suited to use on soils from these MLRAs. Moist color was found to be a better predictor of SOC compared to dry color. However, the result is limited to some factors including the range of soil textures, lighting conditions for the SPCs (which only used one type of artificial lightning), and the total number of samples (n=50) used in the study. Larger sample set will allow the validation of the dataset using subset of the samples. Another limitation is the aggregation state of the soil samples that varied between lab samples (disaggregated) and the field sample data (aggregated) which can affect the color measured in the analysis. Therefore, further studies are needed to investigate the relationship between SOC and soil color with broader range of samples under different soil type and textures, aggregation state, moisture state, and different natural lighting conditions.

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3.8 Appendix

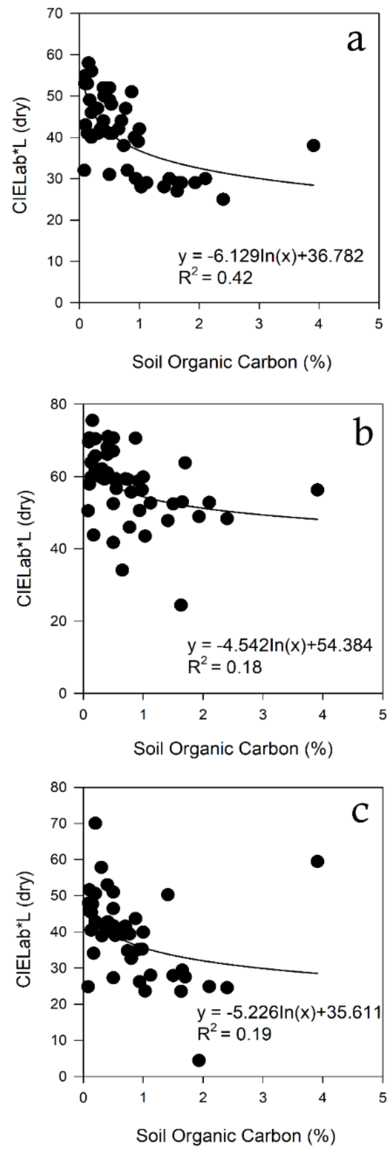

Figure 3.6. *CELab*L of dry samples plotted versus SOC (%) measured using different methods included in the study: a) Portable Color Sensor (PCS,) b) Smartphone Camera 1: iPhone XS Max (SPC1), and c) Smartphone Camera 2: Google Pixel 4A (SPC2).*

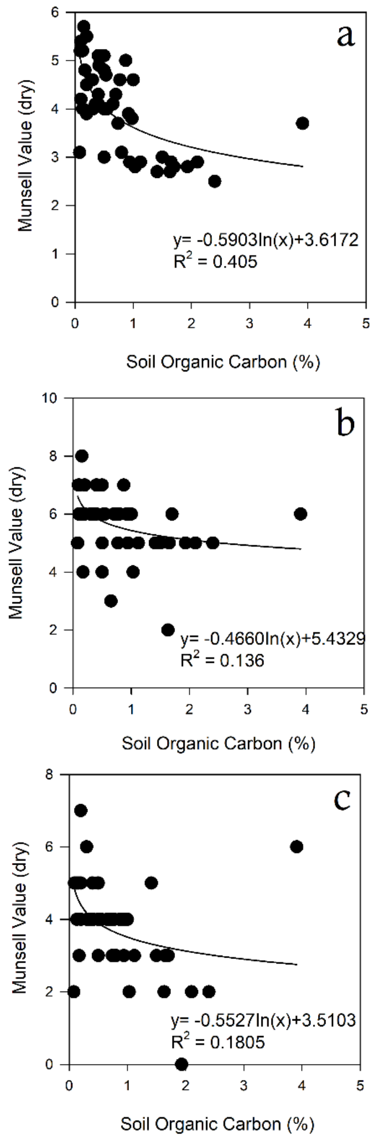

Figure 3.7. *Munsell Value of dry samples plotted versus SOC (%) measured using different methods included in the study: a) Portable Color Sensor (PCS,) b) Smartphone Camera 1: iPhone XS Max (SPC1), c) Smartphone Camera 2: Google Pixel 4A (SPC2).*

CHAPTER 4

SUMMARY AND RECOMMENDATIONS

4.1 Key Findings

- Predictive equation for SOC from soil color can be used mainly on specific soil textures: silty clay loam, loamy very fine sand, silt loam, and loamy sand. Meanwhile, the generalized equation should be used for other soil textures in the database. Textures with coarse sands and high clay percentages are particularly problematic for development of color-based SOC prediction functions. This finding highlights the importance of soil texture in developing color based PTFs for SOC.
- Digital devices for measuring soil color, including PCSs and SPCs, are compelling alternatives to the MCC. The PCS used in this study was the most accurate for measuring moist Munsell value, and was the best predictor of SOC.
- The color space system of Munsell and CIELa*b* work similarly on measuring the relationship between the moist lightness value and SOC. This gives the option for the user to choose the method that works best for them based on the available instrument and their budget
- There is no significant advantage of incorporating dry color in this study. The dry color shows a weak relationship to SOC for both color space systems (Munsell and CIELa*b) regardless of the method of analysis.

4.2 Summary

This project aimed to evaluate and quantify the relationship between SOC and soil color in the state of Nebraska, while testing alternative digital methods in measuring soil color and their relationships with SOC.

The primary objectives of this work were to:

3) Develop a PTF for the prediction of SOC based on soil color and texture in the state of Nebraska, and
4) Evaluate the use of a low-cost color sensor and a mobile application using that uses the smartphone camera for color analysis for the prediction of SOC in Nebraska.

Chapter 2 of this thesis addressed objective number one. The pedon data was collected from the National Soil Information System (NASIS) database, which included soil characterization data within the state of Nebraska, as well as portions of surrounding states that share Major Land Resource Areas (MLRAs) with Nebraska. The study area encompassed 13 MLRAs with only those horizons with SOC between 0 and 5.8% included in the dataset. The dataset was subdivided, such that 70% of data was used for PTF development and 30% was set aside for validation procedures. The PTF development dataset was used to fit regression equations relating moist Munsell value and SOC. Regressions were developed for the full dataset, for individual MLRAs, and for individual texture classes. The results showed the relationship between Munsell value and SOC fit best to a logarithmic regression (R2 = 0.547), which had a rapid decline in Munsell value with increasing SOC for samples with less than 1% SOC, and a gradual decline in Munsell value with increasing SOC for samples with 1 to 5.8% SOC. Among the MLRAs, the best relationships between Munsell value and SOC were found in MLRAs 65 (Nebraska Sandhills), 75 (Central Loess Plains), 106 (Nebraska and Kansas Loess Drift Hills), and 107 (Iowa and Missouri Deep Loess Hills). Meanwhile the weakest correlations between SOC and color were found in regions dominated by residual parent materials. This includes MLRA 63B (Southern Rolling Pierre Shale Plains) and MLRA 67 (Central High Plains). Some of the textures in the study yielded a good relationship between SOC and soil color, while others resulted in poor relationships. The best relationship for texture-specific analysis were found in silty clay loams, silt loams, loamy very fine sands, and loamy sands while the weakest correlations between SOC and color were amount the textures containing coarse sand (coarse sands, loamy coarse sands, and coarse sandy loams). These result indicates that a predictive equation for SOC from soil color can be utilized for specific soil textures. Meanwhile, the generalized equation shoul be used for other soil textures in the database. Textures with coarse sands and high clay percentages are particularly problematic for develop color-based SOC prediction functions. This finding highlights the importance of soil texture in the development of PTFs relating to soil color and SOC.

Chapter 3 of this thesis addressed objective number two. The soil samples used in this study were obtained from the Kellogg Soil Survey Laboratory (KSSL) sample archive. The soil samples were selected from pedon descriptions accessed through the National Soil Information System (NASIS) database, which represent the complete range of textures and SOC within three selected Major Land Resource Areas (MLRAs) across Nebraska. MLRA 67 (Central High Plains), MLRA 75 (Central Loess Plains), and MLRA 106 (Nebraska and Kansas Loess Drift Hills). Two main methods of using PCS and SPCs to determine soil color were compared against the MCCs. The color of each sample was evaluated using a PCS (Mini 2, Nix Sensor Ltd), with is low-cost ($99) and can be operated using a free application for Android or Apple smartphones. Soil color was also determined with SPCs of Apple iPhone XS Max (SPC1) and Google Pixel 4A (SPC2), which utilized the LandPKS mobile application available within both operating systems. Both moist and dry color of the samples was measured. The study also compared the Munsell value against the CIELa*b* color space system. The results showed that the PCS used in this study produced SOC data that shows a similar relationship to the data collected in the field using the MCCs. The PCS ($R^2 = 0.52$) and MCCs (R^2=0.54) both show that slightly more than 50% of variance in Munsell value was explained by SOC. Meanwhile the SPCs produced regressions with low R^2 values for both SPC1 ($R^2 = 0.36$) and SPC2 ($R^2 = 0.32$). In all analyses, dry samples produced a weaker correlation between soil color and SOC regardless of the methods used. Overall, these results indicate that there is a potential of using alternative digital methods of measuring soil color and SOC compared to the MCCs. The use of PCS of Nix Mini 2 sensor especially produced a comparable similar result with MCCs. Meanwhile, the SPCs yielded a weaker result and had different variances depending on the specific phone and camera type. The comparison between color space systems of Munsell and CIELa*b* showed a similar result which offers a flexibility and choice in selecting the methods used in predicting SOC from soil color. Furthermore, moisture conditions affected the measurement of the relationship between soil color and SOC which favor moist soil conditions over dry soil in this study.

4.3 Limitations and recommendation for future research

There are many variables to take into account when developing a color-based PTF for prediction of SOC, including regional-specificity, color space (*e.g.,* CIELa*b* or Munsell), method of color measurement (*e.g.*, MCC or digital tools), color attributes to include (*e.g.,* value, chroma, or both), moist vs. dry color, and inclusions of other soil variables (*e.g.*, texture, depth, land use). This study presents PTFs for the state of Nebraska, using the Munsell color system, measured by visual matching with the MCC in the moist state, with texture as the main extraneous variable. These are predictors that are easily measured in the field, which is the main advantage of this approach. However, this study also highlights the immense range of analyses possible given the large amount of Munsell color data available in soil databases, such as NASIS. For future research direction, the continued use of legacy data, as well as new datasets exploring the use of newer digital tools, will surely continue to improve and expand upon the PTFs presented in here. Furthermore, the results presented from comparison of PCS and SPCs to MCCs was limited by a variety of factors including the range of soil textures included, lighting conditions for some analyses, and the limited amounts of samples (n=50) used in the study.

Larger sample set will allow the validation of the dataset using subset of the samples. Another limitation is the aggregation state of the soil samples that varied between lab samples (disaggregated) and the field sample data (aggregated) which can affect the color measured in the analysis. Therefore, further studies are needed to investigate the relationship between SOC and soil color with broader range of samples under different soil type and textures, aggregation state, moisture state, and different natural lighting conditions.