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Application of Low-cost Color Sensor Technology in Soil Data Collection and Soil Science Education

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APPLICATION OF LOW-COST COLOR SENSOR TECHNOLOGY IN SOIL DATA COLLECTION AND SOIL SCIENCE EDUCATION

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ABSTRACT

Sensor technologies provide opportunities to increase the quality and quantity of soils data while introducing new techniques and tools for classrooms. Linear regression models were developed for organic carbon prediction using color data gathered with the Nix Pro™ for dry (R^2 = 0.7978, MSPE = 0.0819), and moist soils (R^2 = 0.7254, MSPE = 0.1536). A mobile application, the Soil Scanner app, was created to allow for a more soil science dedicated interface that would allow users to create their own database consisting of GPS location and soil color data gathered using the Nix Pro™. The final application produced results in multiple color systems, including Munsell, recorded GPS location, sample depth, moisture conditions, "in-field" or "laboratory" settings, and a photograph of the soil sample. All data could then be uploaded to an online database. The GPS location allows for easy integration of data into GIS mapping software for the spatial manipulation of soils data. The application was tested by generating GIS maps showing the gradient of soil color across two field surfaces. The Nix Pro™ color sensor functions as a successful teaching tool and, coupled with the Soil Scanner app, offers a new means of gathering and storing reliable soils data. There is added benefit to having a soil science application that can be updated to include further analysis methods, resulting in an ever growing soils database. A laboratory exercise was developed that introduced students in an entry level soils course to the importance of soil color and the methods used to determine soil color. Students were then asked to determine the color of three soil samples using the Nix Pro™ and the standard Munsell Color Chart before conducting simple statistical analysis and responding to a questionnaire. Responses indicate that the

Nix Pro^{TM} was the preferred method of color analysis and students felt the sensor to be a more reliable method than traditional color books.

DEDICATION

To my husband, Corey Stiglitz, my grandmother, Helen Tennant, my parents, Robin and Rocky Floyd, and to my siblings, Brittney and Brandon Beck. Thank you for your constant love and support throughout this journey.

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CHAPTER ONE

INTRODUCTION

Disruptive technologies have shown to advance and simplify analysis methods allowing more people to become involved in projects in various fields of science and industry. These technologies tend to improve upon existing methods and, sometimes, they can even result in wholly new research techniques. This is often the direct result of the disruptive technology being an inexpensive alternative that also happens to be easier to use than traditional methods which may require complicated steps and practices (Kostoff et al., 2003). Disruptive technologies can even limit human error by eliminating human generated data (e.g. color determined by the human eye) or by limiting the effects of environmental conditions (e.g. outdoor lighting can be countered by controlled lighting conditions) (Shields et al., 1965; Gijsenji et al., 2012). Furthermore, disruptive technologies tend to hasten the process of gathering data making analysis methods much more rapid (Kostoff et al., 2003). As this technology becomes more readily available, more and more scientists turn to mobile sensors, applications, and even cellphones to meet their research needs as inexpensively as possible (Kamholz et al., 1999; Hart and Martinez, 2006).

Disrupting technologies have the potential to improve best management practices (BMPs) using remote sensing and spectral data. Studies have shown that plant chlorophyll concentrations can be determined using the leaf spectral data gathered using a spectrometer. In addition, the reflectance of a leaf can also be used to determine nitrogen concentrations of plants (Yoder and Pettigrew-Crosby, 1995; Gitelson and Merzlyak, 1995; Daughtry et al., 2000). The spectral data of a plant can be used to develop prediction models that can be used on cite to determine the amount of nitrogen that needs to be applied to optimize crop production and minimize leaching and runoff of nitrogen without the need to send samples to a laboratory for results, which can be expensive (Daughtry et al., 2000). Other researchers have developed their own applications that would turn cellphones into soil color sensors by analyzing the pixels of a photograph of a soil sample taken by the cellphone camera. The pixels would be averaged to determine the color values of each soil sample photo (Gomez-Robledo et al., 2013). While the experiment controlled for lighting conditions and eliminated human error due to the human eye's limitations to accurately determine color, the variation in cellphone cameras would introduce unwanted errors.

Stiglitz et al. (2016) tested a new disrupting technology in the form of an inexpensive color sensor, the Nix Pro^{TM}, for its ability to accurately and reliably determine soil color. Results showed that the Nix Pro^{TM} was more accurate to a laboratory standard, the Konica Minolta CR-400 than it was to the Munsell Color Chart. Results also showed that the sensor consistently produced repeatable results making it a reliable alternative to the Munsell Color Chart. The sensor is very portable, rechargeable, controlled via Bluetooth and a mobile device, and has its own light-emitting diode (LED) light source which eliminates much of the human and environmental factor errors. The Nix Pro^{TM} allows for rapid and reliable color analysis and its application offers the opportunity to integrate various other analysis methods to improve upon current methods of soils analysis.

New technologies not only offer a means of improving our BMPs, precision agriculture, and analysis methods in general, but they can also be utilized as convenient and interesting teaching tool in science classrooms. As disruptive technologies are adapted to science fields, it is imperative to introduce students to the new techniques that are developed alongside the new technologies. It is believed that it is becoming necessary for students to learn new technologies as our world becomes more advanced and dependent on technology (Gambrell et al. 2015). Furthermore, new sensor technologies give students the opportunity to learn through hand-on activities and to become familiar with research techniques and practices both in the classroom and in the field. Therefore, effort should be made to include new technologies that are being utilized by researchers in classrooms as well.

This research aims to introduce a new and inexpensive color sensor technology, the Nix Pro^{TM} color sensor, to the field soil science through rapid assessment of soils and as a teaching device in introductory soil science laboratories. There are three main chapters of this research, with chapter two being the first, which determines the potential of a portable color sensor to determine soil organic carbon content. This chapter discusses the development and testing of two carbon prediction models for moist and dry soil conditions using soil color data gathered using the Nix Pro^{TM} color sensor.

Chapter three discusses the development and potential use for the Soil Scanner application that was developed for the purpose of using the Nix Pro^{TM} to gather and store soils data in a cloud databank. This application has the potential for crowd-sourcing and GIS manipulation of soils data which could assist in land management practices and precision agriculture.

Chapter four discusses the potential for the Nix Pro^{TM} to be used as a teaching device in introductory soils laboratories. Student have the opportunity to learn the importance of soil color and the different applications used to determine it in field and laboratory settings through a hands-on learning experience.

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CHAPTER TWO

USING AN INEXPENSIVE COLOR SENSOR FOR RAPID ASSESSMENT OF SOIL ORGANIC CARBON

Abstract

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.

Keywords: Carbon model, CIEL*a*b*, Nix Pro^{TM}, Regression analysis, Soil color coordinates, Ultisols

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 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.

Materials and Methods

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 Fineloamy, 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-mmsieve 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 color systems such as CIEL*a*b*, RGB (red, green, blue), and XYZ (red, green, blue).

Development of SOC prediction models

Regression analysis was conducted using SAS Studio software (SAS Institute Inc., 2014) for the thirty-one soil samples (training set) using measured values from the soil sampling, nutritive analysis and color determination. The dependent variable in all regression models was the soil sample SOC (%), and specific predictor variables considered were depth of the soil sample, and CIEL*a*b* color coordinates to keep the model as simple as possible. Initially, all chosen predictors (depth, L*, a*, and b*) were included in the model to determine which were useful in predicting SOC content of the soil. Using the coefficient of determination (R^2), root mean squared error (RMSE), and residual plots, model fit was assessed. Predictors that were determined insignificant were removed and the model was run again. This process was repeated until only significant predictors remained in the carbon prediction model. A level of significance of 0.05 was used for all regression analyses. Once the models were constructed, the predicted SOC content of the dry and moist soil samples was found using the selected soil sample predictors. The actual SOC content was then plotted against the predicted SOC content for comparison (Fig. 3).

Cross validation of the selected SOC prediction models

Thirty-one additional soil samples (validation set) were gathered from the same soil pits from Simpson Agricultural Station for the purpose of cross validation and were not utilized for model development. Depth and Nix Pro™ CIEL*a*b* color coordinates were recorded for each sample under both dry and moist soil conditions. The data for the samples were used to predict the SOC content using the two prediction models for dry and moist soils. The actual and predicted SOC content of the samples were compared and the mean squared prediction error (MSPE) was calculated for both dry and moist SOC prediction models to determine how well the models would predict SOC content of soils. The smaller the MSPE, the better the model would be at predicting SOC.

Results and Discussion

Development of the SOC prediction model for dry soils

A multiple regression model was conducted using sample depth, L*, a*, and b* as parameters for predicting SOC (%) for dry soil samples Table 2). Table 3 shows that b* is linearly correlated with SOC for moist and dry soils, and is also linearly correlated with sample depth and with a* for dry soils, suggesting that it may not be a desirable predictive parameter to include in the model because of its correlation with the other predictors (i.e., there may be issues with multicollinearity). When all of the predictors were included in the model predicting SOC (%), the residual plots indicated that a quadratic b* effect may be necessary to include in the model. In addition, in the dry soil samples model with all of the predictors, b* was not a significant predictor of SOC (%), adjusting for the other predictors in the model ($p = 0.1107$; Table 4). After considering the quadratic b* effect in the model, the RMSE and R^2 were only marginally improved and were thus left out of the final model. For the dry soil final model, p-values indicate that sample depth (p-value = 0.0011), L* (p-value < 0.0001), and a* (p-value = 0.0002) were useful in predicting SOC (RMSE = 0.42490 and $R^2 = 0.7978$; Table 5). Past studies have shown that there is a correlation between SOC and lightness and darkness of a soil (Sheilds et al., 1968). This could explain why L* had the most significant p-value for dry soils. In addition, it has been reported that a close correlation exists between b* and the iron oxide content of soils (Schwertmann, 1993; Scheinost and Schwertmann, 1995), which at least partially explains the correlation observed here between b* and sample depth. Iron content tends to increase as the degree of weathering increases for a soil horizon, thus, iron content tends to increase with soil depth (Rebertus and Buol, 1985). More importantly, it suggests that including b* in a predictive model for SOC (%) would not be desirable for high iron content soils such as the ones tested in this study. Soil texture was not considered for the models, but soil surface texture and particle size may affect reflectance and result in differing color results which would affect SOC prediction models. Fig. 3a shows a plot of actual SOC (%) versus predicted SOC (%) for the final predictive model for dry soils.

Development of the SOC prediction models for moist soils

Following the general procedures described above for the dry soils, multiple regression analysis was utilized to develop a predictive model for SOC (%) in moist soils considering initially sample depth, L*, a*, and b* as predictive parameters (Table 2). Consistent with the dry soils, once again b* was found to be linearly correlated with SOC but also again with sample depth, L* and a* for the moist soil samples (Table 3). In the model for moist soil samples that included all of the parameters, b* was not a significant predictor of SOC (%) (p-value =0.7353; Table 4). A quadratic b* effect in the model was also considered, but the marginal improvement in predictive capabilities was not statistically significant. For the moist soil final model, the sample depth (p-value = 0.0020), L* (p-value = 0.0043), and a* (p-value = 0.0009) were useful in predicting SOC

(RMSE = 0.49509 and R^2 = 0.7525; Table 5). Typically, SOC content decreases as soil depth increases (Jobbagy and Jackson, 2000). For this reason, depth was considered for both dry and moist soil prediction models. While the samples were moistened, the exact amount of moisture was not measured and, therefore, it is not possible to know exactly how soil moisture would affect the prediction of SOC content in soils. However, the resulting RMSE and R^2 suggests that the chosen parameters were still sufficient at predicting SOC content. Fig. 3b shows a plot of actual SOC (%) versus predicted SOC (%) for the final model for moist soils.

Cross validation of the SOC prediction models

The R^2 values for dry and moist soil predictive models were comparable to those found by Wills et al. (2007) as all values were significant and accounted for a large amount of error within the model. A cross validation was conducted using the SOC predictive models for dry and moist soils and thirty-one additional soil samples (validation set) from the thirteen experimental soil pits. The models were used to predict the SOC content of the additional samples using their depth and color data. The actual and predicted SOC content of each additional sample was compared and the MSPE was calculated for the dry soils predictive model (MSPE = 0.0819; Table 5) and moist soils predictive model (MSPE=0.1536; Table 5). The results suggest that the models are sufficient at predicting SOC content. Having models that can predict SOC content of soils, and thereby soil quality, would be a useful addition to the Soil Quality Test Kit Guide (1999) which aims to determine a soil's “ability to perform basic functions” by gathering minimum data in field settings.

The results of the regression analyses suggest that sample depth, L*, and a* are the best variables for predicting SOC in both dry and moist South Carolina Ultisols. There was a notable trend in SOC content compared to depth, specifically that SOC content decreased as depth increased as seen in Table 1 making depth a wise choice to include in a prediction model. The L* value of each sample also seemed to have a notable impact of the SOC content. Given that Ultisols are red in color, it would be expected that the a* value for redness would influence soil characteristics such as SOC content. While b* did not prove to be a strong predictor of SOC content in the soils of the Piedmont region of South Carolina, it may be a sufficient indicator of SOC in soils of another type that contain either yellow or blue pigments. The R^2 values for dry and moist soil predictive models were respectable, suggesting that the models created are sufficient for predicting SOC content of soils of South Carolina. It is important to note that the created models may also be sufficient predictors of SOC for soils of the same type that are typical of the Blue Ridge, Piedmont, and Valley and Ridge regions of the United States. The MSPE values for the two models suggests that while both models are sufficient predictors of SOC content, the model for dry soils is better at predicting SOC.

Conclusions

The models developed in this study likely have limitations. The soil samples used for this experiment were from an agricultural farm in the Piedmont region of South Carolina and were low in SOC content and high in iron content which may negatively impact the ability to predict SOC based on color. Soils that are not used agriculturally may have different characteristics that would impact SOC content and the accuracy of the models may vary. It is likely that different models will need to be developed for soils of different types, regions, and land-uses. This would, however, not require site-specific models, as it should be possible to develop models that are applicable across large areas with similar soil types and land uses. Furthermore, each method of color analysis would potentially produce carbon models unique to the device being used, as different illuminations, fields of view, and scanning angles may produce varying color results.

Regardless of the current limitations, there is promise in the Nix Pro™ technology and its ability to predict SOC content of soils. Carbon prediction models offer a rapid and inexpensive method of soil quality assessment. Rapid SOC analysis could assist in determining best management practices or soil reclamation methods that would help preserve and restore farmland and other habitats. Prediction models would also offer a means of monitoring carbon pools in areas being affected by deforestation, permafrost thawing, and climate change (Potter, 1999; Christensen et al., 2004). There is notable advantage in determining a close estimation of SOC without having to send samples to a nutrient analysis laboratory, which takes time to produce results and can become costly depending on the number of samples being analyzed. Rapid SOC field assessment tools, such as this proposed soil sensor based method, can enable a much higher spatial density of samples which may improve our understanding of the distribution of SOC across the landscape. Many researchers in various fields of science would benefit from the development of regional carbon predictions models that require only a few soil parameters, such as sample depth and soil color, to function properly and provide an estimate of SOC content.

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APPENDIX A

Table 1

Selected soil properties for practice soil pit 2 (Stiglitz et al., 2016).

Horizon	Lower depth	Texture	Sand	Silt	Clay	SOC	pH in water	BS	CEC	P	K	Ca	Mg	Zn	Mn	Cu	B	Na
	(cm)		(%)					(%)	(meq/100g)	(mg/kg)								
Ap	17	SL	68	16	16	1.3	5.1	34	4.4	5.5	17	189	30	1.2	8	0.25	0.15	4.0
Bt1	45	C	43	12	45	0.6	5.9	44	5.0	1.5	20	339	53	0.5	2	0.40	0.20	7.0
Bt2	81	C	38	4	58	0.4	6.2	39	5.2	0.5	11	290	63	0.2	1	0.30	0.20	5.5
Bt3	105+	-	40	4	56	0.3	5.8	30	5.7	0.5	8	247	52	0.3	0	0.35	0.25	5.5

*SL = sandy loam, C = clay.

Table 2. Example of dry and moist soil variables for practice soil pit 4.

Horizon	SOC (%)	Depth (cm)	L*	a*	b*
		Dry Soils			
Ap	1.30	11	52.16	12.41	24.70
Bt1	0.44	28	52.61	19.54	31.53
Bt2	0.36	59	53.16	17.68	30.75
Bt3	0.26	90	49.12	19.89	30.42
		Moist Soils			
Ap	1.30	11	34.24	12.32	20.63
Bt1	0.44	28	38.84	21.06	27.91
Bt2	0.36	59	37.52	19.32	28.17
Bt3	0.26	90	35.41	22.29	28.67

Table 3. Pearson correlation (r) values among soil variables for dry and moist soils (p-values in parentheses).

Parameter	SOC	Depth	L*	a*	b*
			Dry soils		
SOC	---	-0.69681 (<0.0001)	-0.29296 (0.1097)	-0.62770 (0.0002)	-0.84271 (<0.0001)
Depth		---	-0.05174 (0.7822)	0.56299 (0.0010)	0.66960 (<0.0001)
L*			---	-0.35450 (0.0504)	0.21120 (0.2541)
a*				---	0.67985 (<0.0001)
b*					---
			Moist soils		
SOC	---	-0.69681 (<0.0001)	-0.34680 (0.0560)	-0.70689 (<0.0001)	-0.72698 (<0.0001)
Depth		---	0.04513 (0.8095)	0.57325 (0.0007)	0.57238 (0.0008)
L*			---	0.02802 (0.8811)	0.62670 (0.0002)
a*				---	0.59742 (0.0004)
b*					---

Table 4. Parameter estimates and ANOVA results for initial SOC prediction models.

Model	Parameter	Parameter estimate	Parameter p-value	Model p-value	Root MSE	R-squared
Dry soils	SOC	8.51924	<0.0001	<0.0001	0.41189	0.8170
	Depth	-0.00812	0.0172			
	L*	-0.07588	0.0034			
	a*	-0.07699	0.0172			
	b*	-0.06942	0.1107			
Moist soils	SOC	5.63852	<0.0001	<0.0001	0.50339	0.7266
	Depth	-0.01079	0.0109			
	L*	-0.05643	0.1285			
	a*	-0.09163	0.0106			
	b*	-0.01686	0.7353			

Table 5. Parameter estimates and ANOVA results for final SOC prediction models.

Model	Parameter	Parameter estimate	Parameter p-value	Model p-value	Root MSE	R-squared	MSPE
Dry soils	SOC	8.50860	<0.0001	<0.0001	0.42485	0.7978	0.0819
	Depth	-0.01060	0.0011				
	L*	-0.10138	<0.0001				
	a*	-0.11292	0.0002				
Moist soils	SOC	5.70287	<0.0001	<0.0001	0.49509	0.7254	0.1536
	Depth	-0.01146	0.0020				
	L*	-0.06625	0.0043				
	a*	-0.09830	0.0009				

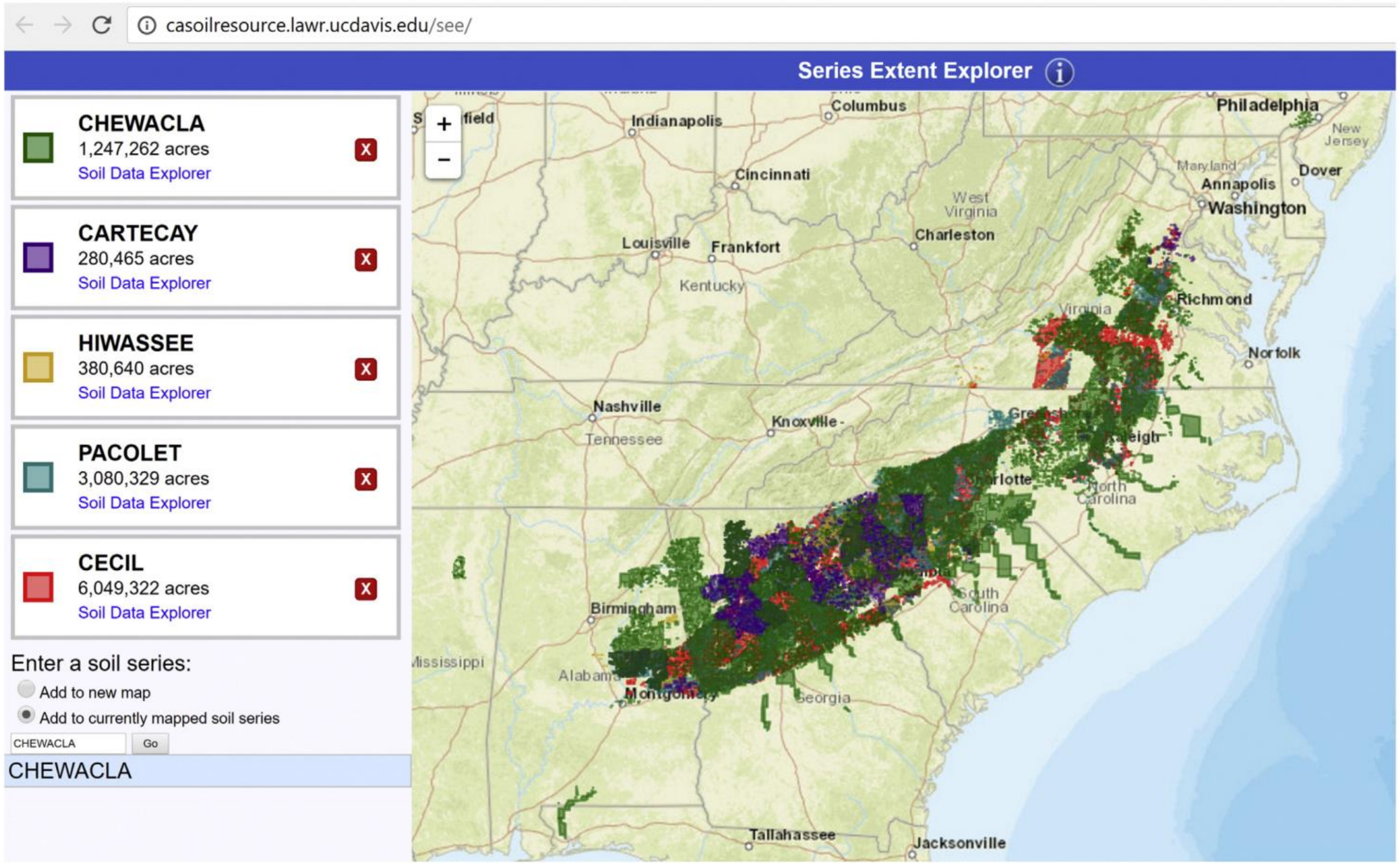
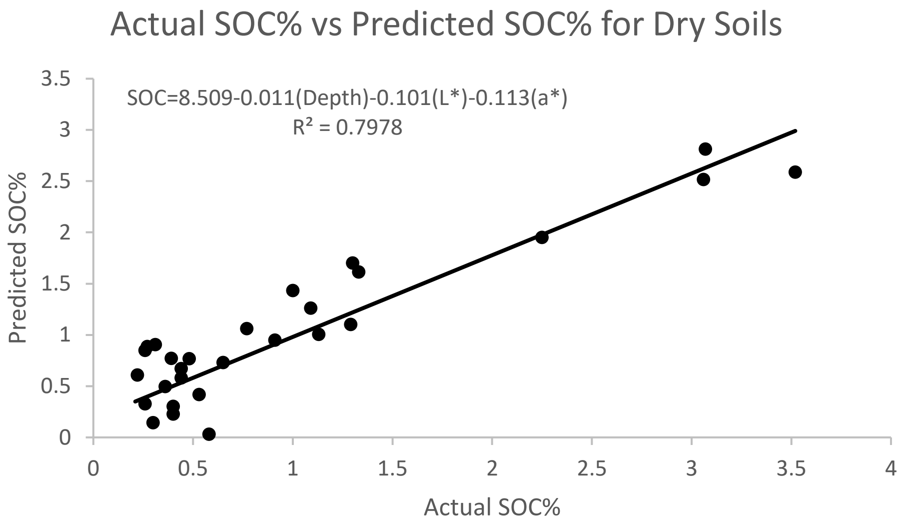


Figure 1. Map showing the extent of the soil series collected for analysis (Series Extent Explorer, 2016).

Figure 2. Example of soil profile (out of 7 total soil profiles used in the study) for practice soil pit 4 used during 2014 Southeast Regional Collegiate Soils Contest (October 5–9, 2014).

a.



b.

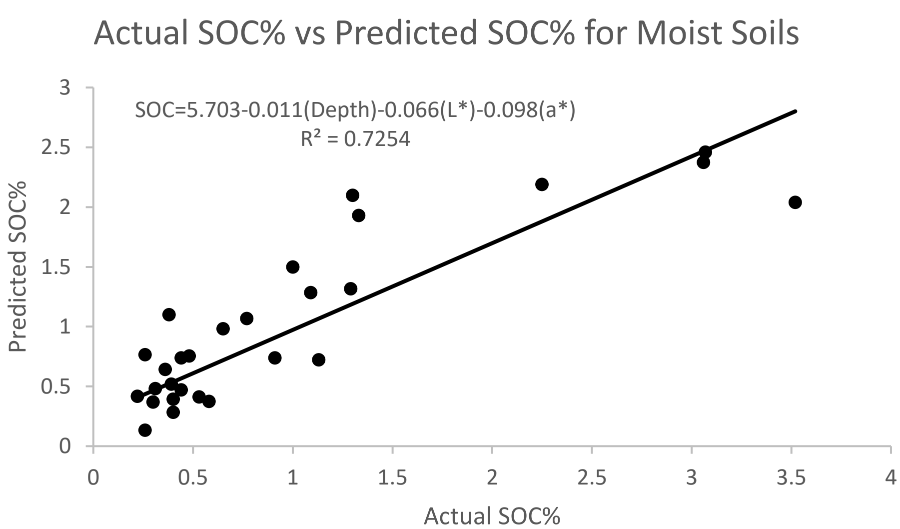


Figure 3. Plots of actual SOC (%) content versus predicted SOC (%) content for a) dry and b) moist soil samples for the training data set.

CHAPTER THREE

SOIL COLOR SENSOR DATA COLLECTION USING A GPS-ENABLED SMARTPHONE APPLICATION

Abstract

Application of accurate and low-cost sensor technology to collect soil color data provides an opportunity to increase the density, quality and quantity of soil data to monitor our changing soil resources. The objective of this study was to develop a mobile application that would enable users to create their own soils database consisting of GPS location and soil color data gathered using the application and a mobile sensor. A mobile application was created utilizing the Nix™ Pro color sensor that produces multiple color results, including Munsell color notation. The application also allows users to toggle between “in-field” sampling as well as dry or moist soil samples. Users can choose to record GPS location and a photo of the soil sample to upload into an online database for storage. The application was tested for functionality in the field and for its ability to match Munsell notation values determined using a Munsell Soil Color Chart (MSCC). Field data were synchronized to a cloud database and subsequently retrieved and used to produce a Geographic Information Systems (GIS) layout showing sample point locations and soil color attributes. The Soil Scanner application allows for rapid analysis and collection of soils data that can be stored for further study and reference using various color systems and location data.

Keywords: Cloud storage, Geographic Information Systems (GIS), Munsell Color Chart, Spatial, Soil classification, Soil survey

Introduction

Soil color is an important property used by the USDA Natural Resources Conservation Service (NRCS) to describe soils and it can be a strong indicator of other soil properties such as iron and organic matter contents (Lynn and Pearson, 2000; Sugita and Marumo, 1996). The Munsell Soil Color Chart (MSCC) notation, which commonly is used to describe soil color, often can be found in soil series descriptions and online databases provided by the NRCS to characterize and describe soil horizons (Soil Survey Staff, 2016). Studies have shown that there are discrepancies in the printing quality of MSCC color chips as well as a strong potential for fading that can make the charts unreliable (Sánchez-Marañón et al., 2005 ; Viscarra Rossel et al., 2006), yet the MSCC has been the standard in-field method of soil color determination for decades (Shields et al., 1965). The color charts also are more qualitative than quantitative, leading many soil scientists to turn to alternative methods of color analysis (Kirillova et al., 2015). Instruments such as spectrophotometers and colorimeters often are used in lieu of a MSCC (Thompson et al., 2013); however, these instruments can be expensive and may require an external power source which makes in-field color determination very difficult. More recently, scientists have been testing and creating new methods of color determination that are more field-friendly as well as less expensive (Levin et al., 2005).

Stiglitz et al. (2016a) tested a new and inexpensive color sensor, the Nix™ Pro, as a mobile method of soil color determination. The Nix™ Pro sensor is controlled via Bluetooth® and a mobile app through a smartphone. Multiple soil samples were analyzed for color in moist and dry soil conditions and indoor and outdoor lighting. The Nix™ Pro color values were compared to MSCC as well as a Konica Minolta CR-400 laboratory colorimeter. The results showed that the Nix™ Pro produced repeatable readings and that the color values of the Nix™ Pro and Konica Minolta CR-400 were very similar. Stiglitz et al., 2016a; Stiglitz et al., 2016b concluded that the Nix™ Pro would be a good alternative to the MSCC as an in-field soil color determination method. However, the application used to control the Nix™ Pro is not directed towards the field of soil science. Ideally, the application would allow for data storage and produce MSCC notation as well because it is the most commonly used color system.

In a study by Gómez-Robledo et al. (2013) a cellphone application was created to determine the color of soil samples from pictures taken with the cell phone camera. Software was developed to scan the pixels in the soil sample pictures taken by the camera and convert the subsequent red, green, and blue (RGB) color values to digital red, green, and blue (XYZ) and to Munsell hue, value, and chroma (HVC). The results were promising and demonstrated that cellphone cameras and a simple color conversion application can be utilized as effective soil color sensors. Han et al. (2016) also used a smartphone camera to process color images of soil samples. After processing the RGB values obtained from the images, it was once again concluded that cellphone cameras are effective at determining soil color. Han et al. (2016) were able to accurately classify soils, however, it was noted that differences in cellphone hardware may result in a change in accuracy of results and software stability. Furthermore, environmental factors such as soil moisture and lighting conditions would still affect the study results.

Regardless of the drawbacks of cellphone cameras, these mobile devices have proven to be a useful tool in soil science and related fields. Beaudette and O'Geen (2010) developed an iPhone application to deliver on-demand access to soil survey information from any location with cellphone coverage. Migliaccio et al. (2015) proposed turf irrigation application that develops recommended irrigation schedules based on inputs of form data and real-time weather data. User input data include soil type (texture) information as well as location and rooting depth. Soil texture information is used to assign estimated field capacity. Other user inputs include information about the field area and sprinkler type (to indicate water rate). Real-time weather data, including temperature, humidity, solar radiation, and wind speed are used to estimate water loss through evapotranspiration (ET). The application was shown to reduce overall water usage when compared to time-based irrigation schedules. Bartlett et al. (2015) created a smartphone application for an irrigation scheduling tool on a cloud-based server.

Mobile technologies are advancing soil science as new applications and analysis methods are created. In addition, new technologies provide opportunities for outreach and raising awareness of many scientific issues faced today as mobile technologies are becoming more widely available and affordable (Ciampitti and McCornack, 2016). With development of new mobile devices and applications, subjects such as soil quality can be readily studied, not only by professionals but also by students in classroom settings (Karlen et al., 2003). To ensure that new applications are efficient learning tools in the classroom, Israelson (2015) proposed “the App Map” which is a basic rubric for judging the effectiveness of an application. In general, if a mobile application would function well in a classroom setting and improve knowledge of an area of science, then it would also function well in field settings.

Mobile devices offer the opportunity to quickly and easily analyze certain soil properties. However, current mobile applications commonly face limitations based on the device and environmental conditions. There should be one set device capable of running analysis on soils through an application that would allow for constantly updating soils data and storage. Finally, the application and device should be user friendly and inexpensive. As such, the objective of this study was to create an Android-based application capable of working with the Nix™ Pro color sensor that would: (i) produce cyan, magenta, yellow, and black (CMYK), XYZ, RGB, CIEL*a*b*, and MSCC color values, (ii) record GPS locations, and (iii) upload collected data to a constantly updating Cloud databank.

Materials and Methods

Developing the color application

Development of the Soil Scanner mobile application was completed using Google's integrated development environment (IDE) software, Android Studio 2.0, to compile and edit the code for the application. Java was chosen as the programming language and the Android software development kit (SDK) was used to develop the application into Android friendly software. Access to the Nix™ Pro application program interface (API) was provided by the Nix™ Pro development team allowing for smoother integration of the already-existing color sensing functions of the sensor into the Soil Scanner application. The original Nix™ Pro application is free to download and the Soil Scanner application will also be available to download upon finalization.

Upon completion, the application was able to connect to a Nix™ Pro color sensor, download a Munsell color reference table, and scan soil samples for color (Fig. 1). Resulting color systems include CMYK, CIEL*a*b*, XYZ, RGB, and Munsell notations. Users have the option to choose whether the samples are analyzed in a field setting and if the soil samples are dry or moist. Choosing the field setting option enables the user to obtain the GPS location of the sample. In addition, the user has the option to take a reference photo of soil samples using the mobile device's camera to be saved with all other collected data, though a photograph is not required (Fig. 2). Recently scanned data will appear within the application and the user has the option of uploading all data to an online database for storage (Fig. 3).

Integration of color systems into the color application

The Nix™ Pro API included code to produce CMYK, CIEL*a*b*, XYZ, and RGB color results as default color systems within the Soil Scanner application. A goal was to include Munsell color notation as well to coincide with current soil science standards for soil descriptions. An external Munsell database that contained the equivalent RGB and CIEL*a*b* color values for each Munsell HVC was developed from preexisting data gathered from WallkillColor (2006). Missing Munsell values were found using BabelColor software (BabelColor, 2015). Only Munsell values found in the

Munsell Soil Color Chart were used. Using this database, an algorithm was used to determine the closest RGB or CIEL*a*b* to Munsell color matches by calculating the Euclidean distance of the color resulting values. This method produced three Munsell notations with the shortest Euclidean distance from the analyzed soil sample color. The resulting three Munsell notations correlate to the closest matching colors. From the interface, the closest Munsell color value can be viewed and chosen from three resulting color swatches that accompany the color systems (Fig. 2).

Testing the color application

Once the development of the Soil Scanner application was completed, the functionality and accuracy of the Munsell color results were tested. The default CMYK, CIEL*a*b*, XYZ, and RGB color results of the Nix™ Pro API were not altered; therefore, it was not necessary to test the accuracy of these results because the Nix™ Pro sensor has previously been demonstrated to produce reliable color results (Stiglitz et al., 2016a). The cellphone used for the experiment was a Samsung Galaxy S6 Edge running Android version 5.1.1 with a camera resolution of 16 megapixels. Thirty-one oven-dried, crumbled soil samples that were collected at varying depths from thirteen soil pits, as described in Stiglitz et al. (2016a), were analyzed for Munsell color using the Nix™ Pro color sensor, the Soil Scanner application, and a smartphone used only to control the application through Bluetooth® connection. The resulting Munsell notations were compared to Munsell notations previously determined by NRCS staff for moist samples and one researcher for dry samples using the MSCC for each soil sample (Table 1). The

Euclidean distance for each soil sample was calculated to determine the effectiveness of the application to match human perceived color using a MSCC.

The original soil pits used to gather the thirty-one samples utilized for the color analysis were filled to continue agricultural production on the Simpson Agricultural Experiment Station in Pendleton, South Carolina and could not be used for GIS mapping. Therefore, a GIS map was generated using GPS locations and soil color data for additional surface sample locations located at the Station (Fig. 4) to determine the functionality of the application. Soil scans were located based on the cell phone GPS and attributes from the color sensor were imported into a GIS system (Fig. 5). Point locations were interpolated using Inverse Distance Weighting to create a surface map of the a* (green to red) values for Simpson Agricultural Experiment Station samples from the CIEL*a*b* color data. Soils found at the sample locations are predominantly Ultisols and include Cecil clay loam, Pacolet sandy loam, Cartecay-Chewacla complex, Hiwassee sandy loam, and Cecil sandy loam and have a geographic range from Georgia to Virginia, south to north, and from the eastern coast to Alabama, Tennessee, and Kentucky. These soil series are abundantly found along the Blue Ridge Mountains, Piedmont, and Valley and Ridge regions of the eastern United States.

In addition, 264 dry, crumbled soil samples collected from the Willsboro Farm located in Willsboro, NY were analyzed for color using the Soil Scanner application and the resulting three Munsell notations were compared to the previously determined Munsell notation that was determined by one researcher using a MSCC. The soils located on the Willsboro Farm are of glacial till origin and are located in a lacustrine plain. Soil series include Bombay, Churchville, Covington, Howard, Kingsbury, Claverack, Cosad, Deerfield, Stafford, Amenia, Massena, and Nellis and can be categorized into Alfisols, Entisols, and Inceptisols soil orders (Mikhailova et al., 1996). Again, the Euclidean distance was determined for each of the three sensor determined Munsell notations in comparison to the visually determined Munsell notations. A GIS map was generated of the sample locations to map the variation of L* (darkness to lightness) across the study area.

Results and Discussion

Soil color application measurements

The Euclidean distance between previously determined MSCC color (actual MSCC color) for each soil sample was compared to the three measured MSCC colors for each soil sample using the Soil Scanner application. Results showed that, for Simpson Agricultural Experiment Station samples, the first measured MSCC color for dry soils was, on average, two color chips away from the known MSCC color (standard deviation (SD) = 0.96). The second and third measured MSCC colors for dry soils were, on average, three color chips away (SD = 1.21 and SD = 1.54, respectively). The first measured MSCC color for moist soils was, on average, two color chips away from the known MSCC color (SD = 2.06). The second measured MSCC color for moist soils was, on average, three color chips away from the known MSCC color (SD = 1.97). The third measured MSCC color for moist soils was, on average, four color chips away from the known MSCC color (SD = 3.28; Table 2).

For dry samples taken from the Willsboro Farm, the first measured MSCC color was, on average, three color chips away from the known MSCC color (SD = 1.05). The second and third measured MSCC colors were, on average, four color chips away (SD = 1.99 and SD = 2.31 respectively; Table 3). When considering that the human eye was used to perceive the known soil sample color using a MSCC and that multiple participants determined the MSCC color of each sample, these results were to be expected. Past studies have shown that the human eye perceives color differently from person to person and in various illuminations (Villafuerte and Negro, 1998) and matching MSCC color chips can result in calculated differences of three MSCC units (Sánchez-Marañón et al., 2011). In a recent study by Han et al. (2016) a smartphone based camera were used for soil classification by using machine learning to analyze the soil color, but differences in illumination as well as variation in smartphone camera sensors were highly variable. In contrast, this study uses a Bluetooth® linked color sensor with a standardized light source and sensing hardware which controls for light and sensor differences rather than relying on pixels in a photo taken by the smartphone itself.

Potential uses and future directions

Simplified and accurate soil color determination, using a low-cost color sensor interfaced to a smartphone application, can enhance data quality while also adding sample location information (through GPS). Having location information associated with the color data increases the value of this data and may help update soil spatial databases.

While there are limitations in the accuracy of a smartphone GPS, it is also possible to improve location data by using an external Bluetooth® GPS with the application. The ability to include a geo-referenced photo adds both context and a check on data-quality to a soil color reading. Soil color information is provided in the standard Munsell notation, and also in other color systems that are easier to use in quantitative comparisons. Cloud storage of soil color and sample attribute data provides a way to back up the data, but an internet connection is not required during sampling (which can reduce the cost of data acquisition).

Using an application and sensor also increases the speed of soil color sampling; so a much larger number of samples is possible, which further will enable both statistical comparisons as well as studies that examine the spatial variability of soil color (and the associated soil properties). Past studies have shown that soil color data allow for rapid assessment of soil organic matter (Bartholomeus et al., 2008; Stiglitz et al., 2016b). There is also potential to predict other soil attributes, such as metal oxides and depth to water table, as soil color is heavily influenced by these traits (Franzmeier et al., 1983; Schwertmann, 1993). The soil samples taken from the Simpson Agricultural Station for color analysis were high in iron content, and therefore appeared very red in color. Statistical comparisons between the Soil Scanner color data and laboratory determined iron content data could result in iron prediction models based on soil color.

Fig. 5 shows an interpolation map of the a* (red) value from the CIEL*a*b* color data gathered from the surface scans on the Simpson Agriculture Experiment Station. The map appears to show a gradient of red from the left to the right of the map suggesting that the soils lose red intensity from the left to the right of the map. This gradient suggests that the left side of the map has a higher iron concentration that gradually decreases towards the right side of the map. Fig. 6 shows an interpolation map of the L* (darkness to lightness) value from the CIEL*a*b* color data gathered from the surface scans on the Willsboro Farm. The map shows locations that are much lighter in color which also appear as a lighter color on the map. The lighter color suggests that these areas may be more highly eroded compared to the other darker locations as past studies have shown that soils that appear lighter in color tend to be more eroded (Metternicht and Fermont, 1998). Data uploaded to cloud storage can be subsequently downloaded and plotted in GIS for spatial visualization and analysis. Soil Scanner data can be analyzed in this way for multiple soil components that could assist in generating soil erosion, fertility, and moisture maps using GIS software.

Current efforts in soil science application development include the successful sharing of spatial soil databases (e.g. SSURGO) through smartphone applications based on the location reported by the internal phone GPS (Beaudette and O'Geen, 2010). These efforts have shown the ability of applications to provide detailed soils data while users are in the field. This dramatically improves the potential impact of the soils databases by providing context to field surveys. Future developments of the soil color application may include a similar methodology to not only provide sensor-based color measurements, but also soils information from these internet-enabled databases. Another advantage of smartphone based applications is that it is possible to organize data collection using a series of custom drop-down menus and forms so that detailed information can be collected with as few errors as possible (Hansen et al., 2016). The soil color application may be extended in the future to include data entry options for other soil and land cover attributes to further augment spatial databases.

Conclusions

A mobile application for gathering soil color and GPS data that uses information from a Bluetooth® paired commercial color sensor was developed and tested in field and laboratory settings. Sensor data, photos and location information are stored on the local Android device and subsequently synced to a cloud database where it can be retrieved at a later time. The mobile application reports multiple color results, including Munsell Soil Color Chart (MSCC). The application also allows users to toggle between “in-field” sampling as well as dry or moist soil samples. The application was tested for functionality in the field as well as its ability to match Munsell notation values determined using MSCC. Cloud-stored data can be downloaded and used in GIS analysis of point locations and soil color attributes. The Soil Scanner application provides the opportunity to increase the spatial density of accurate soil color measurements for soil classification and interpretation.

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APPENDIX A

Table 1. Munsell Color Chart and Soil Scanner application color codes for soil horizons of practice soil pit 2 from the Simpson Agricultural Experiment Station in the Munsell Color Chart codes (n = 31 soil samples).

Soil Horizon	Lower depth (cm)	Munsell Color Chart Hue (V), Value (V), Chroma (C)			Soil Scanner first Munsell set Hue (H), Value (V), Chroma (C)			Soil Scanner second Munsell set Hue (H), Value (V), Chroma (C)			Soil Scanner third Munsell set (Hue, Value, Chroma)		
		H	V	C	H	V	C	H	V	C	H	V	C
Dry Soil													
Ap	11	7.5YR	6	4	10YR	5	4	7.5YR	5	4	2.5YR	5	4
Bt1	28	5YR	5	8	5YR	5	6	2.5YR	5	6	7.5YR	5	6
Bt2	59	7.5YR	6	6	2.5YR	5	6	10R	5	6	5YR	5	6
Bt3	90+	5YR	5	6	7.5YR	5	6	10R	4	6	5YR	5	6
Moist Soil													
Ap	11	5YR*	4	4	7.5YR	3	4	5YR	3	4	10YR	3	4
Bt1	28	5 YR	4	6	5YR	4	6	7.5YR	4	4	10YR	4	4
Bt2	59	2.5YR	4	6	5YR	4	6	2.5YR	4	6	7.5YR	4	6
Bt3	90+	10YR	4	6	10R	3	6	5YR	4	6	7.5YR	4	6

Table 2. Average Euclidean distance between the known Munsell Color Chart codes and the Munsell Color Chart codes determined by the Soil Scanner application for samples gathered from the Simpson Agricultural Experiment Station.

Euclidean Distance/Standard Deviation	Munsell vs. Soil Scanner first Munsell set	Munsell vs. Soil Scanner second Munsell set	Munsell vs. Soil Scanner third Munsell set
	Dry soil		
Distance	2.00	3.00	3.00
Std. Dev.	0.96	1.21	1.54
	Moist soil		
Distance	2.00	3.00	4.00
Std. Dev.	2.06	1.97	3.28

Table 3. Average Euclidean distance between the known Munsell Color Chart codes and the Munsell Color Chart codes determined by the Soil Scanner application for samples (n = 264) gathered from the Willsboro Farm.

Euclidean Distance/Standard Deviation	Munsell vs. Soil Scanner first Munsell set	Munsell vs. Soil Scanner second Munsell set	Munsell vs. Soil Scanner third Munsell set
	Dry soil		
Distance	3.00	4.00	4.00
Std. Dev.	1.05	1.99	2.31

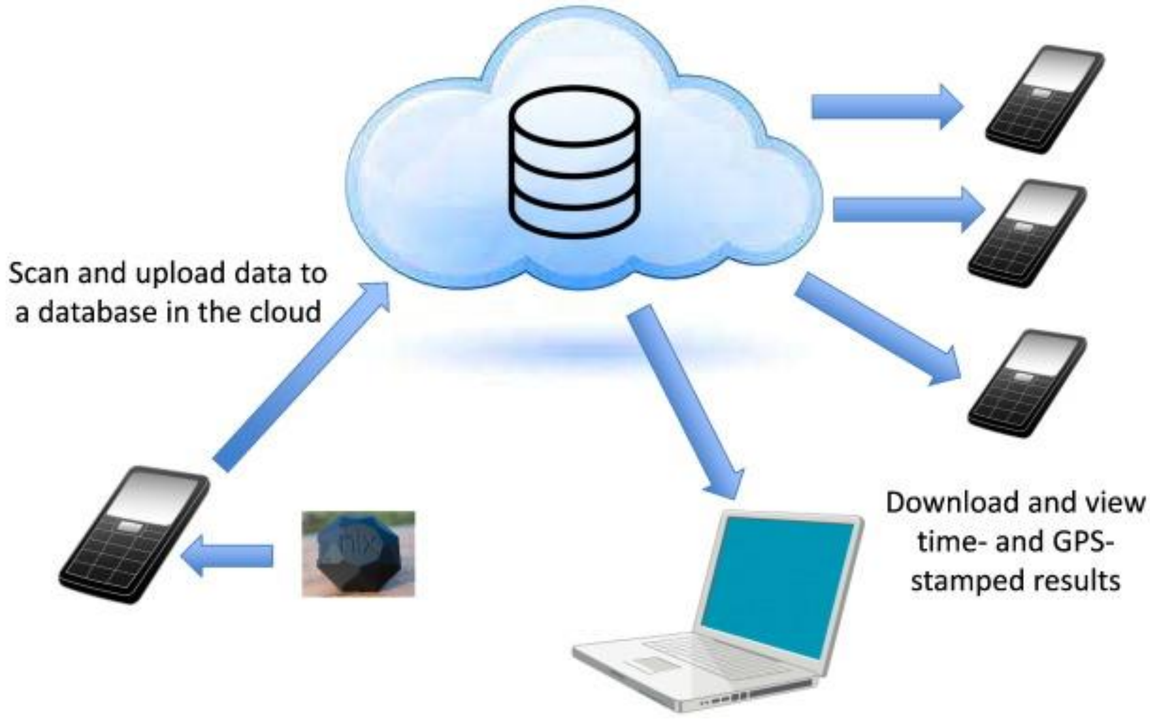

Figure 1. Functional diagram of the Color Scanner application.

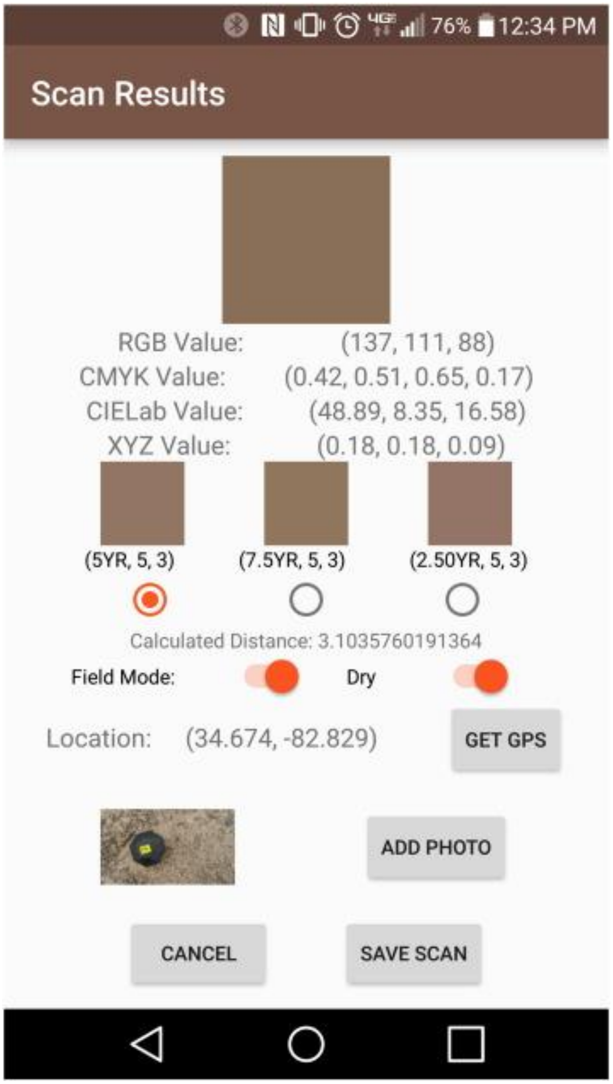

Figure 2. Example of the Soil Scanner interface that shows all possible color system values for a soil sample and options for "Field Mode", "Dry" soil, GPS location, and attaching a photo of the soil sample.

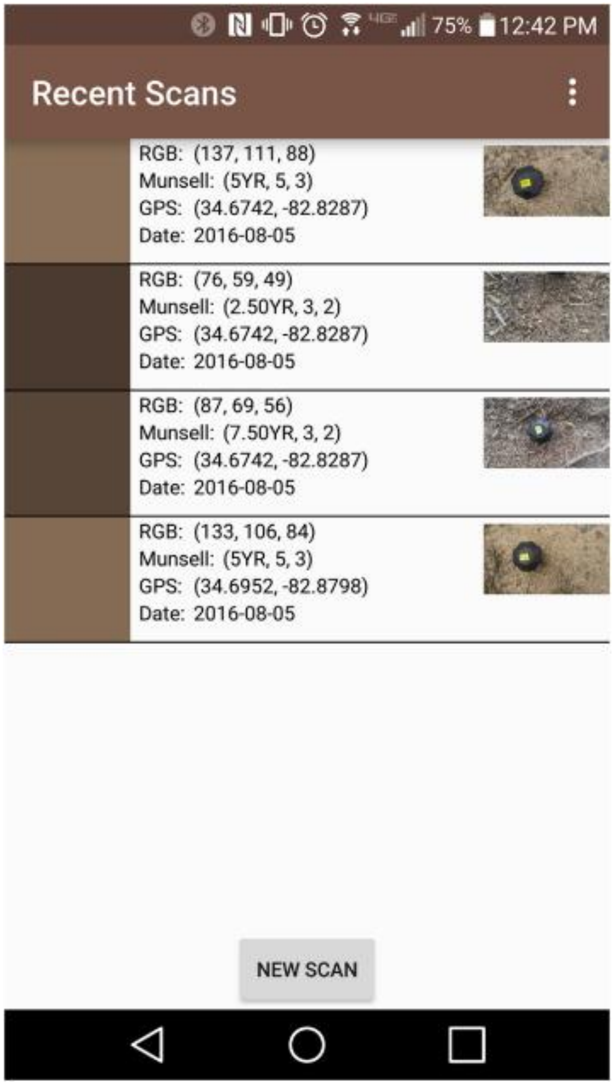

Figure 3. Example of stored soil scan data using the Soil Scanner application.

Figure 4. Example of a soil surface being scanned using the Nix™ Pro color sensor.

Figure 5. GIS layouts showing: scan locations (top), soil color attributes (middle), and interpolated a* (red) color values using Inverse Distance Weighting (bottom) for the Simpson Agricultural Experiment Station.

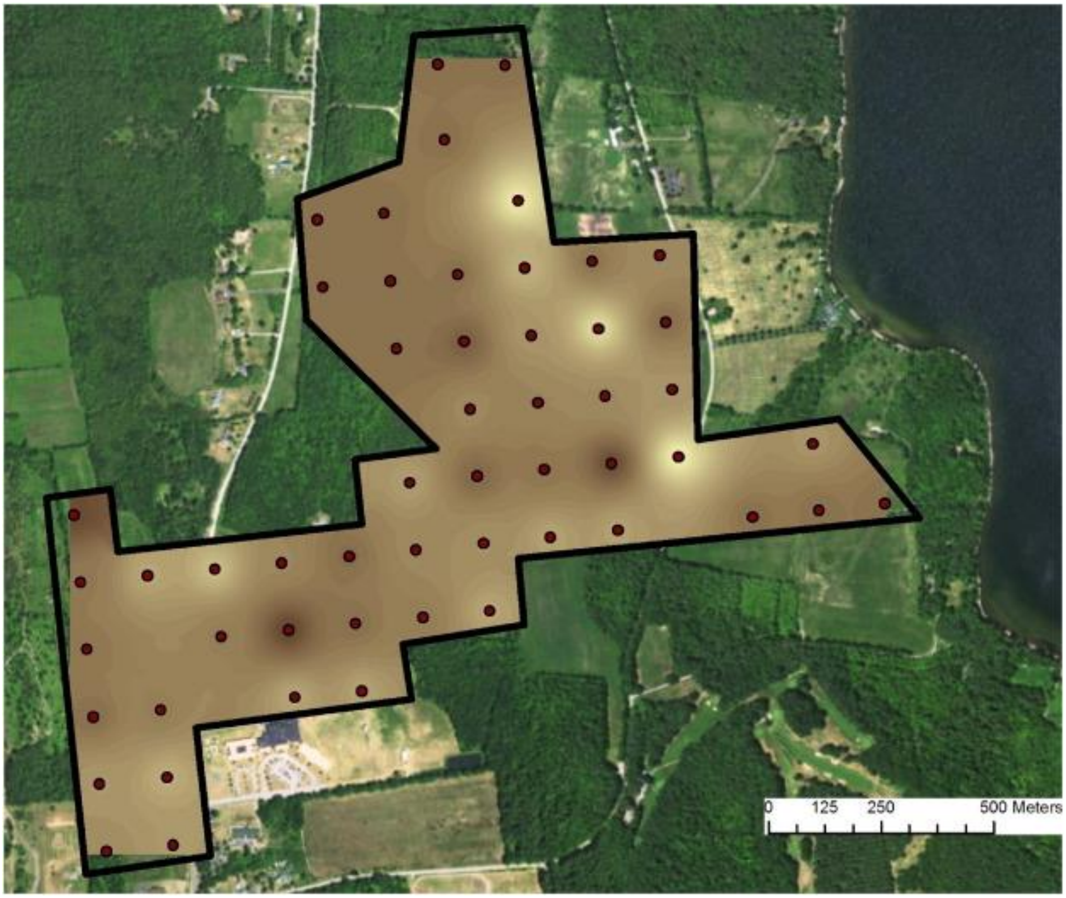

Figure 6. GIS layout showing scan locations and interpolated L* (darkness to lightness) color values using Inverse Distance Weighting for the Willsboro Farm.

CHAPTER FOUR

TEACHING SOIL COLOR DETERMINATION USING AN INEXPENSIVE COLOR SENSOR

Abstract

As new technologies are introduced to soil science it is important to determine the potential and preference for such innovations among users. The Nix Pro™ color sensor, an inexpensive mobile color sensor, was tested by college students for its ability to determine soil color in comparison with the use of a traditional Munsell color chart. Sixty-four Clemson University students from various fields of study (forestry, wildlife biology, and environmental and natural resources) had a hands-on experience with the Nix Pro™ color sensor and the Munsell color chart during FNR 2040: Soil Information Systems course taught in the fall of 2015. Students completed a laboratory exercise to determine soil color using the two methods of color determination (Munsell color chart and Nix Pro™). Students then filled out a survey providing answers to 15 questions related to their previous experience with soil color analysis, the ease of use of the two color analysis methods, and which method of color analysis they preferred. Eighty-three percent of the students preferred to use the Nix Pro™ color sensor over the Munsell color chart, 76% judged the Nix Pro™ to be less subjective to environmental conditions, and 91% believed the Nix Pro™ to be less subjective to user sensitivities. Student responses to survey questions regarding use of the Nix Pro™ color sensor were positive overall,

indicating that there is great potential in using the new color sensor in teaching soil science.

Abbreviations: app, application; CIEL*a*b*, lightness, redness, and yellowness; CMYK, cyan, magenta, yellow, and black; FNR, Forestry and Natural Resources; FNR 2040: Soil Information Systems course; HVC, hue, value, and chroma; SAMR, substitution, augmentation, modification, and redefinition; XYZ, red, green, and blue.

Introduction

Soil science research can be enhanced by technological advances. More specifically, researchers are trying to identify newer and superior methods of determining soil quality to develop better sustainable practices. As technologies advance, so does the need for soil quality education and assessment, because many people do not understand the importance of soil in land management or the methods to identify a healthy soil (Karlen et al., 2003; Krzic et al., 2014). One such indicator of soil quality that can be enhanced by sensor technology in the classroom and in field applications is soil color (Soil Survey Staff, 1999). Soil color is a key factor in soil classification and can be an indicator of many chemical and physical properties of soil such as organic matter and iron oxide content (Santana et al., 2013).

Munsell soil color charts (Fig. 1a) have been used to determine soil color since 1949 (Thompson et al., 2013). The various color chips representing hue, value, and chroma (HVC) and viewing windows on each page make identifying the color of a soil relatively easy. For this reason, many still turn to this method when identifying soil color in the field (Sánchez Marañón et al., 2005). However, previous research (Rabenhorst et al., 2015) has shown that some Munsell soil color charts are produced with matte finish color chips whereas others have gloss finishes, which can create discrepancies in color interpretation results among the charts being used. The quality of color chips may also vary with age of the book (e.g., pigment fading) or from printing errors at the time of manufacturing (Sánchez Marañón et al., 2005). Other researchers (Viscarra Rossel et al., 2006; Kirillova et al., 2015) have noted the difficulties in conducting statistical analyses using Munsell color notation. Taken together, the issues above have led researchers and practitioners to search for alternate methods to determine soil color more consistently and accurately.

Gómez-Robledo et al. (2013) proposed the idea of using a smartphone camera and mobile app to determine soil color. The mobile app was capable of determining red–green–blue color values of pixels in photos of soil samples taken by the smartphone camera. The researchers were successful at accurately determining soil color; however, it was noted that camera and camera settings would vary between different phone models, which would result in discrepancies in color results among users. Regardless, there is potential for using mobile technology in classrooms as mobile devices have become ubiquitous. Ideally, new color analysis methods should be consistent between sensing devices.

Recent research conducted by Stiglitz et al. (2016) evaluated the Nix Pro™ color sensor (Fig. 1b) as a new method for soil color determination. The sensor is portable and utilizes its own light source, making it ideal for in-field use. Color results can be recorded in various color systems such as CMYK (cyan, magenta, yellow and black), XYZ (red, green, and blue), and CIEL*a*b* (lightness, redness, and yellowness), thereby making statistical analysis of the results easier to conduct than when using the Munsell color notation. Stiglitz et al. (2016) showed that the Nix Pro™ color sensor was able to produce consistent color results very similar to that of a standard laboratory colorimeter (Konica Minolta CR-400) under both moist and dry soil conditions, making it a promising method of soil color identification. Although the Nix Pro^{TM} sensor showed promising results for the researchers, it is important to determine how receptive others are to this new technology as a method of color identification. Harrington et al. (2013) states that incorporating current research in the classroom excites and interests students making the Nix Pro^{TM} a more desirable tool for soil science education.

Both the Munsell soil color chart and the Nix Pro^{TM} color sensor provide an important learning opportunity for students to learn how to identify soil color and the importance of this process in soil science through hands-on science. Flick (1993) denotes hands-on science as “an instructional strategy where students are actively engaged in manipulating materials,” and states that there are usually three conditions that must be met to say that students actively engaged in an activity:

- Students individually or in groups manipulate objects or events in the natural environment.
- Students apply various facets of intelligence for the purpose of understanding a part of their natural environment.
- Students are held accountable for their observations, inferences, and conclusions.

Soil color identification is often conducted on-site in outdoor conditions, which allows students to be very interactive with each other and their environment. Studies have shown that learning outdoors helps “develop their knowledge and skills in ways that add value to their everyday experiences in the classroom” (Dillon et al., 2006).

Gambrell et al. (2015) state that “students are entering an age when knowledge of technology is a necessity and not a luxury.” It is important to give students the foundation they need to use new technologies in soil science by teaching these new methods in the classroom so they will not be left behind. Given that the Nix Pro™ color sensor is a new technology to soil science and is controlled by a mobile app, there is great teaching potential for the sensor in classrooms. However, it has yet to be determined if the app used to control the sensor would, in fact, be instrumental in increasing students' knowledge and understanding of soil color.

Puentedura (2010) proposed basic frameworks for evaluating educational applications for their effectiveness at assisting students in understanding course materials. The SAMR model (substitution, augmentation, modification, and redefinition) was introduced to assist teachers in transforming learning through use of technology by considering how an application changed their current method. Substitution is when a technology acts as a direct tool substitute but makes no change to functionality. Augmentation is when a technology acts as a direct tool substitute and improves functionality. Substitution and augmentation are considered enhancements to learning techniques. Modification allows for significant redesign of tasks using the new technology. Redefinition allows for the creation of new tasks that were previously inconceivable using the new technology. Modification and redefinition are considered transformations to learning techniques (Puentedura, 2010).

Israelson (2015) proposed a rubric (the App Evaluation Rubric) for evaluating the effectiveness of an application as a teaching method based on four categories: multimodal features, literacy content, intuitiveness of app navigation, and user interactivity. Although Isrealson's rubric was proposed for literacy courses, it also can be applied to soil science because the framework evaluates the effectiveness of applications as educational tools. Multimodal features can be explained simply as how engaging the application is. Literacy content refers to the accuracy of literacy content and can be changed to the accuracy of color content to meet the evaluation needs of the Nix Pro^{TM} app. Intuitiveness of app navigation refers to how easy the application is to navigate. User interactivity represents how well an app engages the user and how easily the content may be manipulated by the user.

Together the SAMR model (Puentedura, 2010) and the App Evaluation Rubric (Israelson, 2015) provide a framework for evaluating the Nix Pro^{TM} color sensor application. Allowing students to address the categories of the rubric provides excellent feedback on the functionality of the Nix Pro^{TM} and gives a unique understanding of what users look for in a new technology in soil science. Previous studies have shown that feedback from students reveals how effective an involved exercise can be at helping them understand the importance of land management practices (Krzic et al., 2015). Rewording the categories of the rubric in the form of a questionnaire enables a comparison between the Munsell color chart and the Nix Pro^{TM} color sensor to determine which method is preferred by students and why the choice was made. With these goals in mind, the objectives of this study were to (1) develop a laboratory exercise to teach students how to identify soil color and its importance to soil science, (2) give students the opportunity to use new methods of color analysis, and (3) evaluate the efficacy of the Nix Pro^{TM}.

Materials and Methods

Course background

Soil Information Systems (FNR 2040) is a 4-credit course in the Department of Forestry and Environmental Conservation at Clemson University, Clemson, SC (Clemson University, 2015–2016). The course consists of three 1-hour lectures followed by a 2-hour laboratory each week. Maximum capacity is 60 to 75 students for the course and 15 students for each laboratory section. FNR 2040 is an introductory soil course that focuses on the input, analysis, and output of soil information utilizing graphical information technologies (global positioning systems, geographic information systems, direct/remote sensing) and soil data systems (soil surveys, laboratory data, and soil data storage) (http://www.gis.clemson.edu/elena/EnvInfoSysHome.htm). The course satisfies curriculum requirements for degree majors in forestry, wildlife, and environmental and natural resources.

"Hands-on" learning

The hands-on learning model by Flick (1993) was used to establish a laboratory exercise for 65 Clemson University students. The SAMR model by Puentedura (2010) and App Evaluation Rubric by Israelson (2015) were used to determine the efficiency of the Nix Pro™ color sensor app, and student responses to the questionnaire were evaluated in terms of four categories (multimodal features, color content, intuitiveness of app navigation, and user interactivity).

Students worked both individually and in groups of three to complete the color analysis laboratory exercise. Students were required to determine soil color for themselves and then work in their groups to answer questions regarding the exercise. Three different soil samples (Fig. 2) were analyzed both indoors and outdoors to provide students with the opportunity to work in a natural setting. The laboratory exercise required students to consider factors that affect soil color and why these factors would be important to a soil scientist (Fig. 3). Statistical analyses were also conducted by the students to give them an understanding of the sort of data that can be gathered and processes to assist in soil characterization. Finally, students were held accountable for their analysis by comparing their results to that of their lab partners and answering laboratory questions and a questionnaire in reference to their observations (Fig. 4).

Laboratory assignments and exercises

Students were required to bring an Android or Apple device with them to lab that was capable of downloading and installing the Nix Pro^{TM} color sensor app. During the lab, students were given background information on soil color (Fig. 3) and its importance in soil science and a brief background on the Munsell color chart and the Nix Pro^{TM} color sensor. Students were guided through the process of downloading and using the Nix Pro^{TM} color sensor app to use the sensor to scan soil samples for soil color analysis under indoor lighting conditions. The students were then taken outside and taught how to use the Munsell color chart under standard outdoor lighting conditions. There were three different soil samples used for the exercise that were prepared before the lab to make sample conditions as consistent as possible. Students worked in groups of three, with each student individually determining soil color with both the Munsell color chart and the Nix Pro^{TM} color sensor. After each student recorded his/her own results in a table provided to them (Fig. 4), they reunited with their group members and recorded their partners' results in the same table creating three color results for each soil sample that would allow for statistical analysis. Students were asked to calculate the mean and standard deviation for each soil sample using the three results gathered by each group member for each method of color analysis (Munsell color chart and Nix Pro^{TM} color sensor). Students were then asked to complete a questionnaire about their prior knowledge of soil color analysis and the different methods of color analysis.

Results and Discussion

The goal of this laboratory exercise was to give students a better understanding of soil color and its importance and to evaluate the effectiveness of the Nix Pro^{TM} color sensor based on student responses. Some questionnaire responses were recorded as a rating on the scale of 1 to 5, with 1 being a poor rating and 5 being a very good rating (Table 1). Other responses were recorded as the proportion of the class that chose "yes" or "no" as an answer, or "Nix Pro^{TM}" or "Munsell color chart" as an answer (Table 2). Finally, students were asked to provide any additional written feedback regarding the laboratory exercise (Table 3).

SAMR model: Substitution, augmentation, modification, and redefinition (Puentedura, 2010).

Substitution is when a technology acts as a direct tool substitute but makes no change to functionality. The Nix Pro^{TM} app and sensor perform the same task as the Munsell color chart to determine soil color. However, the Nix Pro^{TM} produces color results differently than the Munsell color chart and therefore cannot be considered a merely a substitution for the Munsell color chart. Augmentation is when a technology acts as a direct tool substitute and improves functionality. As previously mentioned, the two methods of color analysis in question perform the same function. Because the Nix Pro^{TM} produces color results that allow for easier statistical analysis, it can be argued that the Nix Pro^{TM} does improve functionality (Viscarra Rossel et al., 2006). Likewise, the functionality of color determination is improved with the Nix Pro^{TM} because the user subjectivity is greatly minimized. Therefore, it can be concluded that the Nix Pro^{TM} app is an augmentation of the standard color determination method.

Modification allows for significant redesign of tasks using the new technology. Redefinition allows for the creation of new tasks with the new technology that were not possible previously. The Nix Pro^{TM} app does create new possibilities in soil science; however, new tasks are not created within the app itself. Therefore, the Nix Pro^{TM} app cannot be considered a modification or redefinition of the Munsell color chart. Taken together, the Nix Pro^{TM} app is an augmentation that enhances traditional color analysis using the Munsell color chart.

App evaluation rubric: Multimodal features, color content, intuitiveness of app navigation, and user interactivity.

The Nix Pro^{TM} color sensor and mobile application have many multimodal, or engaging, features. The application requires a mobile device to function, giving students the opportunity to work with a familiar technology. The app offers a color comparison feature and displays a color swatch identical in color to the surface being scanned by the sensor, enabling students to visually verify that the sensor is working properly. This feature takes out the guess work of whether the surface is being scanned properly and gives students confidence that they are properly determining soil color. The Munsell color chart allows students to match soil color based on their own visual inspection of a soil compared to a color chip in the chart. Table 2 shows that when students were asked which method of color analysis they preferred, 83.1% preferred the Nix Pro^{TM} color sensor over the Munsell color chart. When students were asked to provide additional feedback in their own words, many noted that they enjoyed using the Nix Pro^{TM} and that they thought the laboratory was fun, as shown in Table 3, suggesting that the students found the Nix Pro^{TM} color sensor and mobile application engaging.

Color content accuracy is perhaps the most important category from a scientific perspective. The 65 students were asked various questions about the accuracy of the sensor. Table 2 shows that when asked which method was less subjective to user sensitivities, 90.8% of the students reported that the Nix Pro^{TM} was less subjective than the Munsell color chart. When asked which method was less subjective to environmental conditions, 78.5% reported that the Nix Pro^{TM} was less subjective than the Munsell color chart. Past studies have shown that the Munsell color chart is subjective to user sensitivities such as color blindness (Lusby et al., 2013) and potentially even environmental conditions such as lighting and moisture content in the soil (Sánchez Marañón et al., 2011; Mouazen et al., 2007). Out of the 65 students, 96.8% felt that the human eye does not see color the same from person to person. Overall, 89.2% of students felt that the Nix Pro^{TM} color sensor was the more accurate method of color analysis. These results reflect the students' confidence in the Nix Pro^{TM}'s results, suggesting that students may feel more comfortable learning soil color analysis using a color sensor.

Intuitiveness of app navigation is important for the functionality of the Nix Pro^{TM} application in a classroom setting. For students with little prior knowledge of color analysis, having an educational tool that is easy to use could make the process of learning soil color analysis methods relatively simple. Table 1 shows the average and standard deviations of ratings reported by students when asked about their prior knowledge of color analysis and the ease of use of the Munsell color chart and Nix Pro^{TM} color sensor. Students were asked to rate their knowledge of color analysis before the laboratory exercise and an average of 2.0 with a standard deviation of 1.1 was reported. This indicated that the students did not have much experience with color analysis methods prior to the laboratory exercise. When asked to rate the Nix Pro^{TM}'s ease of use, students reported an average rating of 4.2 with a standard deviation of 1.2. Similarly, students gave the Munsell color chart an average ease of use rating of 3.5 with a standard deviation of 1.1. Both the Munsell color chart and the Nix Pro^{TM} were given a rating of fairly easy to very easy to use and students noted on a few occasions that the Nix Pro^{TM} was easy to use as shown in Table 3. These results suggest that the app is fairly easy to navigate if students with little prior knowledge of color analysis found the Nix Pro^{TM} mobile application easier to use than the standard Munsell color chart, which is known for its user-friendly pages (www.munsell.com).

Finally, user interactivity is a key part of any application because if there is no interactive aspect of an app, then the app has no real functionality. The Nix Pro^{TM} color sensor and mobile application offer many features that require user interactivity. The user must locate and sample a soil for color analysis, encouraging hands-on learning in outdoor settings. Users may then compare the color analysis results of their soil sample to that of another sample. A user may even choose to use the color converter feature of the app to change their color analysis results to that of another color notation. Another feature that the Nix Pro^{TM} offers is results in numerous color systems that allow for statistical analysis, which increases interactivity because the results allow for further uses of the app. The Munsell color chart does not allow for simple statistical analysis (Viscarra Rossel et al., 2006; Kirillova et al., 2015), giving the Nix Pro^{TM} an advantage over the standard method of color analysis, which may encourage users to choose the Nix Pro^{TM} as an alternative to the standard method of color analysis.

Students were asked to conduct simple statistical analysis using the two methods' color results and rate the easiness of their analysis on a scale of 1 to 5, with 1 being a very poor rating and 5 being a very good rating. Table 1 shows that students reported an average easiness rating of 3.0 with a standard deviation of 1.2 for statistical analysis using the Munsell color chart notation. This rating is not consistent with reports that the Munsell color chart does not allow for easy statistical analysis. However, a closer examination of the students' work revealed that they attempted statistical analysis only on the value and chroma of the Munsell notation, excluding the hue altogether. In addition, no students recognized the inherent quantitative limitations posed by the Munsell color charts (e.g., the combination of numbers and letters defining hue, uneven step sizes for value and chroma, predominant use of integers). Given that the Munsell color chart represents color three-dimensionally and with coded color chips, statistical analysis cannot be completed easily using unaltered Munsell color chart data. To conduct statistical analysis using Munsell color notation, Euclidean distance is often used to determine how closely color chips match, or Munsell notation must first be converted to other color systems such as XYZ before any statistical analysis can occur (Romney and Indow, 2003; Ruck and Brown, 2015). These methods may not be appropriate for an introductory soil science course in which students are only beginning to learn soil color analysis methods. Students found the Nix Pro™ results easier to use for conducting statistical analysis, with an average rating of 4.2 and a standard deviation of 1.1. Table 2 shows that 87.7% of the students felt that the Nix Pro™ produced more quantitative results, and that 78.5% felt that the Munsell color chart produced more qualitative results. These results are supportive of the studies that have reported the difficulties in statistical analysis when using Munsell color charts. In addition, the results reveal that the Nix Pro™ promotes user interactivity within the app and that additional types of laboratory-or field-based exercises would promote further use of the Nix Pro^{TM} color sensor and its mobile application.

Conclusions

We taught students in an introductory-level soil science course different methods of color analysis. A questionnaire provided after the lab exercise showed that 83.1% of the students preferred the Nix Pro^{TM} color sensor over the Munsell color chart. The average student found the Nix Pro^{TM} color sensor very easy to use, and many students reported that they enjoyed the laboratory experience. The overall results of the questionnaire indicate that the Nix Pro^{TM} is a valuable teaching device and that students are receptive to learning the importance of soil color analysis and its methods.

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APPENDIX A

Table 1. Students' average ratings of their knowledge and ease of use of the Munsell soil color chart and Nix Pro^{TM} color sensor (Fall 2015; n = 65).

Survey Question	Mean ± SD
1. How would you rate your knowledge of soil color analysis prior to this lab? (Circle one: 1=poor, 3=average, 5=excellent)	2.0 ± 1.1
2. How easy was the Munsell Color Chart to use? (1=not easy, 3=average, 5=very easy)	3.5 ± 1.1
3. How easy was the Nix Pro^{TM} color sensor to use? (1= not easy, 3=average, 5=very easy)	4.2 ± 1.2
4. How easy was statistical analysis using Munsell color notation? (1= not easy, 3=average, 5=very easy)	3.0 ± 1.2
5. How would you rate the easiness of statistical analysis using Nix Pro^{TM} color coordinates? (1= not easy, 3=average, 5=very easy)	4.2 ± 1.1

Note: SD = standard deviation

Table 2. Student responses (n = 65) to questions concerning preference and usability of the Munsell soil color chart and Nix Pro™ color sensor.

Questions	Munsell Soil Color Chart (%)	Nix Pro™ color sensor (%)	N/A (%)
1. Which method did you prefer to use for color analysis?			
	15.4	83.1	1.5
2. Which method of color analysis is more quantitative?			
	9.2	87.7	3.1
3. Which method of color analysis is more qualitative?			
	78.5	18.5	3.1
4. Which method of color analysis would be less subjective to user sensitivities?			
	6.2	90.8	3.1
5. Which method of color analysis would be less subjective to environmental conditions?			
	16.9	78.5	4.6
6. Which method of color analysis is more accurate?			
	7.7	89.2	3.1
Question	**Yes (%)**	**No (%)**	**N/A (%)**
7. Do you feel that everyone sees color the same way?			
	0	96.8	3.1

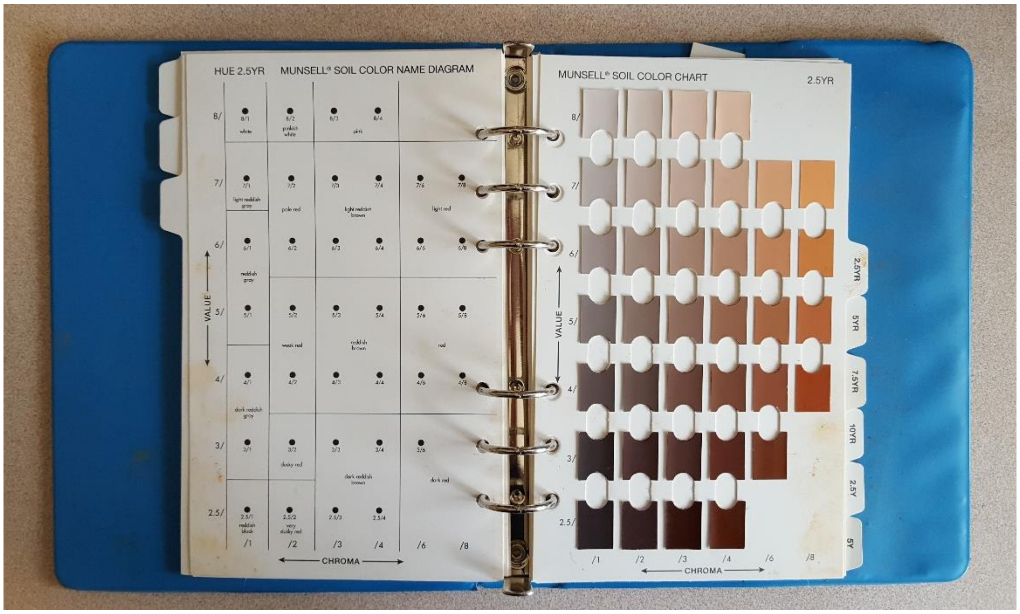
Note: N/A = not answered.

Table 3. Sample of students' responses to the question of advantages and disadvantages of the Munsell soil color chart and Nix Pro^{TM} color sensor and additional comments concerning the exercise.

Munsell Color Chart	Nix Pro^{TM} color sensor
Advantages	
1. You get to make the color determination.	1. Much more precise.
2. No problems with WiFi or connection.	2. Fast, easy, accurate, specific.
3. You get a clear look at the color.	3. Quick, accurate, easy to use.
4. No power involved.	4. Less room for human error.
5. Simple categories.	5. Easy to use with fast results.
Disadvantages	
1. Not as precise, can vary from person to person.	1. Expensive. (Risky to take in the field)
2. Outdated. Not as precise. Tough to use.	2. Electronics are needed.
3. Different results based on lighting.	3. Multiple people can't connect to the same Nix. Unable to do task if phone is not updated.
4. Subjective.	4. Costly.
5. May be colorblind or odd lighting.	5. Lens may be held at different angle making different results.

Additional Comments
1. This was a fun lab.
2. Love the Nix!
3. Nix Pro^{TM} color sensor is the most practical tool compared to Munsell Soil Color Chart.
4. Fun lab. Enjoyed finally using the color chart.
5. Nix Pro^{TM} is better in my opinion.

a.



b.

Figure 1. Methods of color determination: (a) Munsell color chart, (b) Nix Pro^{TM} color sensor.

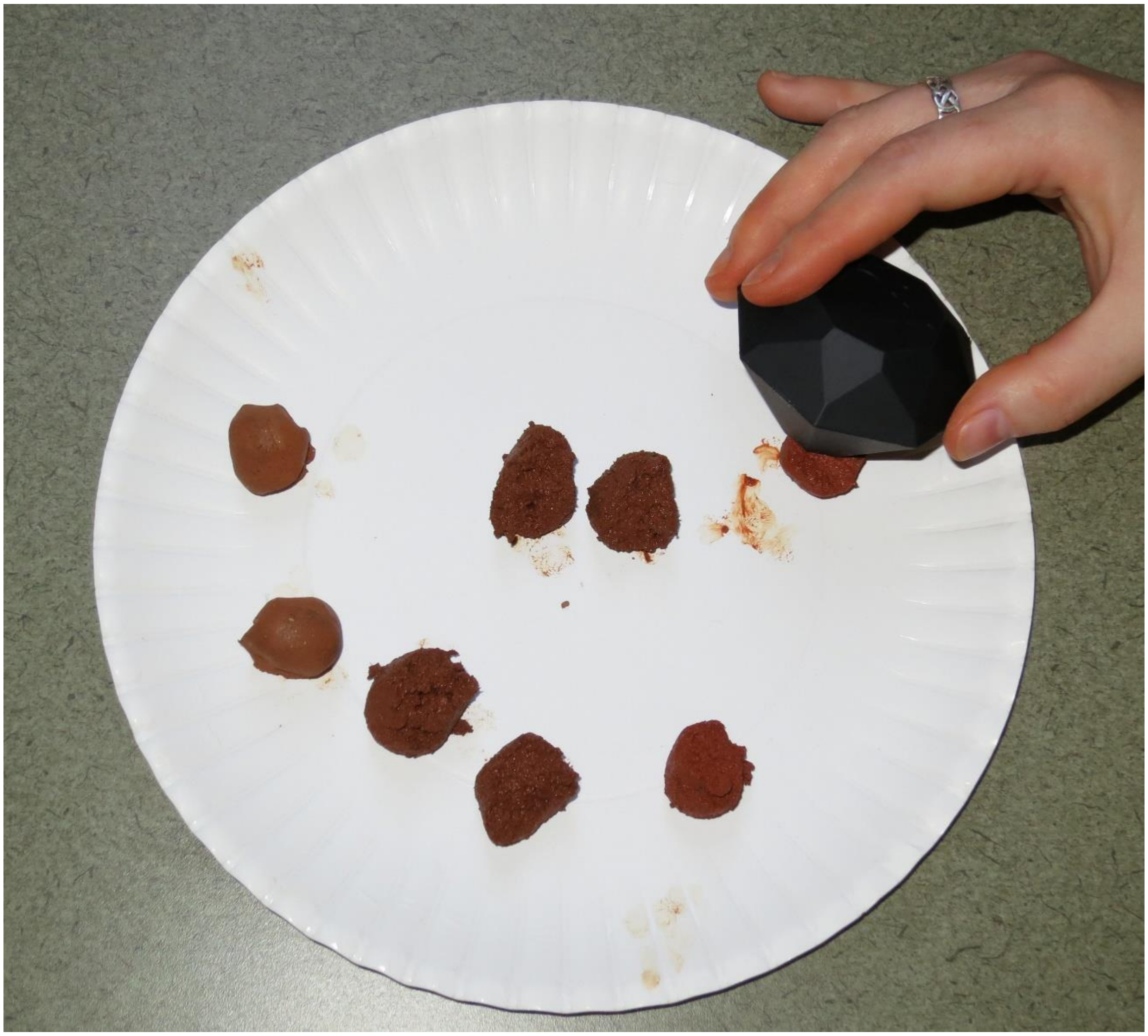


Figure 2. Example of soil samples being analyzed for color using the Nix Pro™ color sensor.

Lab 11: Soil Color Determination (Comparison of Munsell Color Chart to Nix Pro™)
Student Name: ______________________________

Today we will be looking at two different methods of color analysis: the Munsell Color Chart and the Nix Pro™ color sensor. You will be working in groups of three, but you will determine soil sample colors individually using the two methods.

Overall Objectives:

- **Learn about the importance of soil color.**
- **Learn how to analyze color using the Munsell Color Chart.**
- **Learn how to analyze color using the Nix Pro™ color sensor.**
- **Compare the Munsell Color Chart to the Nix Pro™ color sensor for color analysis.**
- **Complete a questionnaire on the two methods of color analysis.**

Rationale

Color is an essential soil trait to consider when classifying soils. Color can be an indication of many soil properties, such as organic matter content, metal concentrations, and redox features. Generally, the darker the soil, the greater the amount of organic matter making soil color significant for agriculture. Redox features are also of particular importance because it is an indication of water levels in a soil which may create construction limitations. For these reasons, soil color is often a topic of study in soil science.

How do we determine soil color?

The Munsell Color Chart

The Munsell Color Chart measures color by hue, value, and chroma as is reported as a fractional notation, such as 2.5YR ¾, where 2.5YR is hue, 3 is value, and 4 is chroma.
Hue represents color and each page in a Munsell Soil Color Chart is a different hue, represented in the upper right corner of each page.
Value is the lightness or darkness of a color and is represented as a decreasing number scale on the left vertical axis of each page. The smaller the number, the darker the color.
Chroma is the degree of saturation of a color and is represented as an increasing number scale across the bottom of each page. The larger the number, the more vibrant the color.

Figure 3. Instructions for the laboratory exercise.

Sample Number	Student Initials	Munsell Color Chart Notation			Nix Pro™ CIEL*a*b* Color Coordinates		
		Hue	Value	Chroma	L*	a*	b*
1							
Average							
Standard Deviation							
2							
Average							
Standard Deviation							
3							
Average							
Standard Deviation							
4							
Average							
Standard Deviation							
5							
Average							
Standard Deviation							
6							
Average							
Standard Deviation							

Questions:

1. Did you get the same Munsell Color Chart results as your lab partners?

2. By how much did your Munsell results vary? (Standard Deviation)

Figure 4. One of the assignments given to the students during the soil color analysis laboratory exercise.

CHAPTER FIVE

CONCLUSION

This research introduces the Nix Pro^{TM} color sensor as a means to rapidly assess soil organic carbon, crowd-source and store soils data, and as a teaching device in introductory soils laboratories.

Chapter two discusses the methods used to develop SOC% prediction models using soil color data gathered using the Nix Pro^{TM} and sample horizon depth for both moist and dry soil samples in Ultisols of South Carolina. Regression analysis was found to be an effective method to develop the prediction models. Final models include sample horizon depth, sample lightness to darkness values (L*), and sample green to red values (a*) as significant predictors of soil organic carbon for both moist and dry soils. Small prediction error values suggests that the models are effective at predicting SOC%. The Nix Pro^{TM} proves to be an effective method for gathering soil color data for predicting SOC%.

Chapter three introduces the Soil Scanner application that was developed to better utilize the Nix Pro^{TM} color sensor for soil science analysis. The application produces color results in CIEL*a*b*, RGB, CMYK, XYZ, and Munsell Color Chart HVC. The application is also capable of recording the GPS location of soil samples, field or lab settings, moist or dry soil conditions, and photographs of the samples. Soils data can be uploaded into a Cloud databank and shared with other researchers offering the potential for crowd-sourcing of soils data. In addition, the GPS location and soils data can be uploaded into software for GIS manipulation allowing for the spatial analysis of soil color which could help to determine the concentration of metals or even organic matter in soil.

Chapter four discusses the potential of the Nix Pro^{TM} as a means of teaching students in an introductory soils laboratory soil color analysis methods as well as the students' receptiveness to the new sensor technology. Results suggest that the majority of students did not have much prior knowledge of soil color analysis methods. Regardless, the majority of students found the sensor easy to use, accurate, and preferable to the Munsell Color Chart. Students seem to be receptive to new sensor technologies in classrooms and appear to prefer newer methods to traditional analysis methods.

There is increasing demand for more advanced and inexpensive technologies in the field and in classroom settings. As scientific analysis methods move forward, more technologies are being developed and introduced to meet the needs of researchers and educators alike (Shannon et al., 2008; Arsenault et al., 2005). Many turn to cellphones and mobile applications as an inexpensive alternative to laboratory spectrometers for color analysis, but as previously mentioned, cellphone cameras and settings can vary from one phone to another creating unwanted error within the analysis (Venkataramani et al., 2005). Spectrometers are a standard method used for determining soil color, however, they are often limited by a power source, expensive, and many scientists may not be familiar with spectral data that the device produces leading many to turn to less expensive, user-friendly methods (Levin et al., 2005). For a technology to be “disruptive,” it has to have the capabilities to disrupt the normal methods that have been used thus far, which is usually done when the technology simplifies known techniques, is inexpensive, easy to use, and is easily accessible to people of all backgrounds and experience for use in a research or industry field (Kostoff, 2004).

The Nix Pro™ was not originally created for soil science, but rather for interior design for the purpose of identifying and matching colors. The device itself is very simple to use making it ideal for many people of varying backgrounds to become accustomed to. This research has geared the sensor towards the soil science field to fill the need for a tool that can rapidly assess and monitor soil properties. In doing so, there is now a mobile application that can be further updated as new analysis methods are developed based on soil color to continuously expand the data gathered using the Nix Pro™ and Soil Scanner application. In the future, the SOC prediction models may be included within the application as well to further field analysis methods and reduce the cost of SOC analysis.

This research has several application within the scientific and agricultural communities. For example, many farmers send hundreds of soil samples to laboratories each year for nutrient analysis. This helps them to better determine how much fertilizer should be applied to fields each year and which management practices would better suite each field. Soil organic carbon is often included within the result of this analysis and is an indication of soil fertility (West and Post, 2002). Farmers would directly benefit from the ability to determine SOC% for themselves each year through a simple analysis using an inexpensive color sensor. Having a device on hand that would allow for an unlimited number of SOC analysis would also assist farmers to better determine areas of concern for management practices as areas low in SOC may require less tilling to prevent further loss of organic matter through oxidation (Shepherd et al., 2002). This could also be visually determined through spatial distribution maps generated through GIS applications.

Another application of the Soil Scanner and Nix Pro™ is a means to monitor changing soil conditions through changing SOC and soil color over time. This is important as researchers continue to observe and predict the effects of climate change on the environment. Studies have already shown that permafrost in the subarctic regions are thawing and releasing increasing amounts of carbon into oceans (Osterkamp and Romanovsky, 1999; Akerman and Johansson, 2008; Rowland et al., 2010). In addition, previously frozen peat soils are becoming waterlogged creating anaerobic conditions where microbial activity metabolizes SOC into the greenhouse gas, methane (Dunfield et al., 1993). The cloud-based databank that is a part of the Soil Scanner application offers a means to gather and store long-term soils data that would allow climate scientists to monitor the potential of a soil to contribute to climate change over time by way of SOC as an energy source for microbial activity and potential pollutant.

The Nix Pro™ color sensor has shown to be easy to use, its color results allow for easier, more rapid statistical analysis, and it produces color results with more accuracy than the human eye (Stiglitz et al., 2016). This disruptive technology has the potential to improve upon our analysis methods by way of SOC prediction models, crowd-sourcing, and GIS manipulation of soils data. In addition, the Nix Pro™ can be used to teach students the importance of soil color and the many different applications it has in the field of soil science through a hands-on learning experience. The techniques discussed in this research can be utilized to improve upon BMPs at the farm-scale, crowd-source vast amounts of data for a more largescale soils analysis, or monitor changing soil conditions over time as the effects of climate change shape the world.

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