Rapid and inexpensive assessment of soil total iron using Nix Pro color sensor

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Abstract
In this study, an inexpensive Nix Pro (Nix Sensor Ltd.) color sensor was used to develop prediction models for soil iron (Fe) content. Thirty-eight soil samples were collected from five agricultural fields across the Animas watershed to develop and validate soil Fe prediction models. We used color space models to develop three different parameter sets for Fe prediction with Nix Pro. The different color space sets were used to develop three new predictive models for Nix Pro-based Fe content against the lab-based inductively coupled plasma analyzed Fe content. The model performances were assessed using the coefficient of determination, root mean square error, and model p-value. Three models (International Commission on Illumination’s lightness, ±a axis (redness to greenness), and ±b axis (yellowness to blueness) [CIEL*a*b]; red, green, blue [RGB]; and cyan, magenta, yellow, key [black] [CMYK]) were significant in predicting the Fe content using colorimetric variables with $R^2$ ranging from 0.79 to 0.81. The mean square prediction error (MSPE) and Kling–Gupta efficiency (KGE) Index were calculated to validate models and CMYK was predicted to be a better model (MSPE = 0.13; KGE = 0.601) than CIEL*a*b and RGB models. The results suggest Nix Pro is useful in predicting soil Fe content.

1 | INTRODUCTION

Morphological properties like soil color have been widely used to quantify soil chemical properties due to the spectral response of the soil matrix in the visible wavelength range (400–700 nm) of electromagnetic spectrum (Viscarra Rossel et al., 2006). However, the noncontiguous pattern of hue, value, and chroma color in Munsell color charts do not allow the numerical modeling or statistical analysis of soil properties (Munsell Color Company, 1994; Viscarra Rossel et al., 2006).

Measurement of soil colors using the CIE (International Commission on Illumination) $L^*a^*b^*$ (L, perceptual lightness, $a$, greenness to redness, $b$, blueness to yellowness), RGB (red, green, and blue), and CMYK (cyan, magenta, yellow, key plate or black) system or color spaces have allowed soil scientists to develop prediction models to correlate soil color with spectrochemical properties like soil pH, organic matter, heavy metal(loid)s, nitrogen, and potassium (Barman et al., 2018; Kshirsagar et al., 2018; Melville & Atkinson, 1985; Viscarra Rossel et al., 2006).

Abbreviations: CIE, International Commission on Illumination; CMYK, cyan, magenta, yellow, key (black); ICP, inductively coupled plasma; KGE, Kling–Gupta efficiency; $L^*a^*b^*$, Lightness, ±a axis (redness to greenness), and ±b axis (yellowness to blueness); MSPE, mean square prediction error; RGB, red, green, blue; RMSE, root mean square error
Viscarra Rossel et al., 2009). To that end, iron (Fe) mineralogy is strongly related to soil color. The red-to-brown color of soils can be attributed to high Fe oxide concentration (Fontes & Carvalho, 2005). We chose soil Fe, as it serves as a biogeochemical engine that regulates carbon and nutrient (nitrogen and phosphorus) cycling in soils, spanning from tropical to tundra ecosystems (Bhattacharyya et al., 2018; Chen et al., 2020; Hall & Silver, 2013; Herndon et al., 2019; Li et al., 2012).

Conventional laboratory analysis using spectroscopic techniques like atomic absorption spectrometry and inductively coupled plasma (ICP) are accurate in measuring the total soil Fe content (Matthews et al., 2020). However, these methods are time-consuming and expensive (Jha et al., 2021; Mancini et al., 2020; Matthews et al., 2020; Weindorf et al., 2014). The advancement of proximal soil sensing devices overcomes these limitations of laboratory analysis (Horta et al., 2015; Viscarra Rossel & McBratney, 1998; Weindorf et al., 2014).

Recently, a color sensor (Nix Pro, Nix Sensor Ltd.), generally used in paint industry, was used to determine soil color (Stiglitz et al., 2016) and soil organic carbon (Mukhopadhyay et al., 2020; Stiglitz et al., 2017). The Nix Pro color sensor costs US$349 and is operated via Bluetooth with each measurement taking less than 5 s (Mukhopadhyay et al., 2020).

The objectives of this study were (a) to develop three prediction models for total Fe content using Nix Pro determined CIEL*a*b, RGB, and CMYK color spaces from three agricultural fields in Animas Watershed in New Mexico and (b) to validate and compare the developed model equations in soil samples collected from two different fields in Animas watershed.

2 | MATERIALS AND METHODS

2.1 | General study area and soil sampling

The soil samples for this study were collected from agricultural fields across the Animas watershed, New Mexico. Soil properties of the sampling locations are presented in Supplement 1a. For developing the prediction model for total soil Fe content, 24 soil samples were collected using a stainless-steel auger from three agricultural fields from surface depth of 0–7.5 cm during the 2019 postgrowing season (November–December). The exact locations of the fields are not presented in this manuscript to maintain landowner anonymity. Further, for cross validation of the model, 14 additional soil samples were collected from two separate agricultural fields. The soil samples were analyzed in the laboratory using Optima 4300 Dual View Inductively Coupled Plasma–Atomic Emission Spectrometry (ICP–AES; Perkins-Elmer) (method described in Supplement 1b) and scanned with Nix Pro color sensor.

2.2 | Scanning of soil using Nix Pro color sensor

The mobile application “Nix” was downloaded on an iPhone 11 mobile device and connected to the device before every scan. The Bluetooth is automatically disconnected when not in use and the sensor turns off to save energy. Approximately 25,000 scans can be completed using a fully charged Nix Pro sensor. The sensor has its own light emitting diode (LED) as the light source for reflection (Stiglitz et al., 2017). Before scanning the soil samples, a thin (2-to-3-cm) layer of stacked white pages was scanned to confirm the calibration of Nix Pro. The soil layer of 2–3 cm was spread and leveled over a clean white paper surface to ensure that the sensor lies flat and does not have any interfering reflections in the viewing cone/area of the sensor due to the nonsoil matrix. The soil samples were then scanned using the sensor and results were recorded in CIEL*a*b, RGB, and CMYK color notations. These three-color models were compared and prediction equations were developed for determining total soil Fe content. Three notations, CIEL*a*b, RGB, and CMYK, were used to develop the prediction models for this study. The Nix Pro scanning data acquired using the sensor on the mobile application was exported as a csv file for further analysis in R Studio (version 3.4.1) statistical software.

2.3 | Development of prediction models

Prediction models were developed using multiple regression analysis for 24 soil samples (collected from three fields) comparing the ICP analyzed Fe content with Nix Pro measured color parameters. The dependent variable in all three regression models (CIEL*a*b, RGB, and CMYK) was soil Fe content (percentage) and specific predictors or independent variables were the color space parameters in three different types of color spaces. The model performances were assessed using the coefficient of determination ($R^2$), root mean square error (RMSE), and model $p$-value. A level of significance of .05 was used for regression analysis and assessing the best-fit model. After developing the model
| Model | Parameter | Parameter estimate | Standard error | Model p value | Root mean square error | KGE value | KGE parameters |
|-------|-----------|--------------------|----------------|--------------|------------------------|-----------|---------------|
| CIEL*a*b | Soil Fe | -0.545 | 0.441 | <.001 | 0.216 | 0.416 | 0.71 | 0.99 | 0.49 |
| | L | 0.177 | 0.021 | | | | | | |
| | a | 0.074 | 0.056 | | | | | | |
| | b | 0.427 | 0.059 | | | | | | |
| RGB | Soil Fe | -1.104 | 0.451 | <.001 | 0.223 | 0.421 | 0.66 | 1.00 | 0.53 |
| | R | -0.028 | 0.024 | | | | | | |
| | G | -0.139 | 0.039 | | | | | | |
| | B | 0.249 | 0.038 | | | | | | |
| CMYK | Soil Fe | 10.153 | 4.191 | <.001 | 0.213 | 0.600 | 0.77 | 0.99 | 0.67 |
| | C | 12.603 | 3.829 | | | | | | |
| | M | 8.468 | 5.878 | | | | | | |
| | Y | -26.224 | 4.159 | | | | | | |
| | K | -6.130 | 3.593 | | | | | | |

Note. CIEL*a*b, International Commission on Illumination’s lightness, +a axis (redness to greenness), and ±b axis (yellowness to blueness); RGB, red, green, blue; CMYK, cyan, magenta, yellow, key (black).

*r represents Pearson product-moment correlation coefficient.

*β represents the ratio between the mean of the simulated values and the observed value for Fe content.

*α is the standard deviation of simulated and observed values.

### 3. RESULTS AND DISCUSSION

#### 3.1 Development of prediction models for total soil Fe content

The percentage of total Fe content was considered as the dependent variable in each model. Colorimetric variables used in each model were L, a, and b in Model 1; R, G, and B in Model 2; and C, M, Y, and K in Model 3 (Table 1). The model parameter estimates, standard error, model p-values (α = .05), and RMSE were calculated to assess the significance of the model to determine the total Fe content. All three models were significant (α = .05) in predicting the soil Fe content. The RMSE was lowest for CMYK model (RMSE = 0.213), followed by CIEL*a*b model (RMSE = 0.216), and least for RGB model (RMSE = 0.223). The coefficient of determination ($R^2 = 0.81$) was also highest for CMYK model (Figure 1a-c). Therefore, CMYK model was comparatively a better model in estimating the soil total Fe content than CIEL*a*b ($R^2 = 0.80$) and RGB ($R^2 = 0.79$) models. The bimodal distribution of data in Figure 1 is attributed to different soil series and soil properties of the two fields as described in Supplement 1a. The texture for soils from Field 1 was coarse loamy to fine loamy in range, whereas that in Field 2 was fine loamy over sandy skeletal.

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**TABLE 1** Estimation of model parameters, Kling–Gupta efficiency (KGE) estimates and ANOVA results for initial prediction model for soil total Fe content ($n = 24$)

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3.2 Cross validation of soil total Fe prediction models

Validating a prediction model is a major aspect of assessing the use and robustness of the developed equation (Bellocchi et al., 2010; Wallach & Goffinet, 1989). The ICP-determined and Nix Pro-predicted soil total Fe content were compared (Figure 1d–f) for all three models and mean square prediction error (MSPE) was calculated for each model. Low values of MSPE indicate strong model performance (Dhanoa et al., 1999; Stiglitz et al., 2017). On comparing the three models, the CMYK model had the lowest (0.13) MSPE value. The MSPE values of CIEL*a*b and RGB models were similar (0.18). Therefore, based on cross validation of three models, CMYK was the better model to predict the total soil Fe content using Nix Pro. The CMYK model for the validation samples had the highest coefficient of determination (0.92). The CIEL*a*b and RGB models had similar coefficients of determination for 14 model validation soil samples as obtained previously for 24 model development soil samples. Therefore, the highest coefficient of determination of CMYK model denotes that the proportion of the variance in the ICP analyzed soil total Fe content (dependent variable) predictable from the C, M, Y, and K color space parameters (independent variables) is better than CIEL*a*b and RGB models. This was also confirmed by evaluating the KGE value and parameters ($r$, $\beta$, $\alpha$) presented and described in Table 1. The CMYK model (KGE value = 0.601) was considered the best fitted model because the KGE value, $\beta$, and $\alpha$ was closest to 1, and $r$ value was higher than CIEL*a*b (KGE value = 0.416) and RGB models (KGE value = 0.421).

3.3 Implication and future directions

The models developed in this study were limited to agricultural fields in Animas watershed, New Mexico. The total soil Fe content in agricultural fields have been reported in the range of 11,058 to 27,721 mg kg$^{-1}$ (Jha, 2020). Therefore, this research forms the basis of expanding the study for other areas to develop region-specific models in both agricultural and nonagricultural lands. It is also important to evaluate the performance of this sensor over a range of soil samples with low to high soil Fe content. The application of this new color sensor is dependent on soil types; therefore, there is a need to apply this instrument in wide spectrum and range of soils in different agroecological regions.
4 | CONCLUSIONS

We developed a technique to determine soil Fe content that can be widely used by farmers and extension scientists in acidic soils to estimate soil Fe content and recommend management practices based on this information. This sensor method can help understand the spatial distribution of soil Fe with significant spatial autocorrelation between sampling locations in a field.

The soil samples collected in this area had low organic carbon content. Therefore, the impact of spectral interferences due to absorbance or reflectance of organic matter content in this study was not considered. However, this study can be expanded and evaluated in areas with high organic contents. It is also important to evaluate the soil Fe content under different redoximorphic conditions as Fe oxides changes its oxidation state changes from Fe$^{2+}$ to Fe$^{3+}$. Regardless of its limitations, Nix Pro is promising for determining soil Fe content using the currently available color spaces by developing and validating site/region specific prediction models.

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AUTHOR CONTRIBUTIONS

Gaurav Jha: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Resources; Software; Validation; Visualization; Writing-original draft; Writing-review & editing. Debjani Sihii: Conceptualization; Funding acquisition; Investigation; Methodology; Project administration; Resources; Supervision; Validation; Visualization; Writing-original draft; Writing-review & editing. Biswanath Dari: Conceptualization; Methodology; Project administration; Resources; Supervision; Validation; Visualization; Writing-original draft; Writing-review & editing. Harpreet Kaur: Formal analysis; Software; Validation; Visualization. Mallika Arudi Nocco: Conceptualization; Project administration; Resources; Supervision; Writing-review & editing. April Ulery: Project administration; Resources; Supervision; Writing-review & editing. Kevin Lombard: Project administration; Resources; Supervision; Writing-review & editing.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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