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Optical Sensor-Based Soil Color Identification in Tropical and Subtropical Regions

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ABSTRACT

The Soil Color Detector Version 1.0 (SCD V1.0) has been developed to improve both accuracy and efficiency in soil color identification through the integration of optical sensor technology and the utilization of the RGB color index as referenced in the Munsell Soil Color Chart (MSCC). The system underwent extensive testing across various soil types in Indonesia, specifically Ultisols (Baregbeg), Inceptisols (Cilembu), and Andisols (Lembang), as well as subtropical Chernozems (Mollisols) in FH-Erfurt, Germany. The presence of significant differences among the results obtained from the SCD V1.0, the MSCC manual method, and the MetaVue VS3200 spectrophotometric analysis, paired t-tests and analysis of variance (ANOVA) were conducted. The results demonstrated a remarkable accuracy of 100% for soil color name diagram and color index accuracy rates reaching up to 99%. Root Mean Square Error (RMSE) analysis revealed reduced deviations when comparing SCD V1.0 to the MetaVue VS3200 instrument (0.6-0.9), as opposed to comparisons with the MSCC (0.9-1.2), indicating a higher degree of precision in optical-based classifications. Furthermore, reproducibility assessments indicated lower standard deviations for SCD V1.0 (0.10-0.15) in contrast to the MSCC (0.25-0.32), with a strong agreement coefficient of 0.85 across all evaluated soil orders. These results substantiate that SCD V1.0 presents a reliable automated alternative to conventional manual methods of soil color identification, thereby minimizing human error and reducing environmental variability. The implications of this technology are particularly pertinent in soil color identification application for soil classification studies, survey & land evaluation, and digital soil mapping (DSM), especially within tropical and subtropical regions.

Keywords: Soil color identification, optical sensor technology, Munsell Soil Color Chart (MSCC), root mean square error (RMSE), digital soil mapping (DSM)

INTRODUCTION

The chromatic characteristics of soil are influenced primarily by its mineral composition, organic material, and the extent of weathering it has undergone. Various studies underscore the relationship between soil color and its properties. Sainju *et al*. (2022) note that soil color indicates soil composition, with organic matter being a key influence and significantly influenced by iron oxides. Similarly, Kafoor (2017) noted that soil samples with Munsell hues indicating high iron oxide content displayed color values linked to the soil's physical and chemical properties, such as texture and fertility. Iron oxides significantly influence soil color. Darker soils, indicating higher organic matter content, show greater fertility due to reduced nutrient leaching (Ayu *et al*., 2023).

Conventionally, soil scientists have employed the MSCC to facilitate the manual determination of soil color. However, this method is not without its limitations, which include subjectivity, inconsistencies, and time constraints that arise from human visual perception. This challenges are particularly pronounced in tropical and subtropical regions, where soils undergo significant weathering processes, possess diverse mineral compositions, and exhibit high iron oxide content.

As a result, these soils display substantial color variations that necessitate precise classification (Schaetzl & Anderson, 2020). Specific soil orders prevalent in these regions, such as Ultisols, Inceptisols, and Andisols, present distinctive hues that are influenced by oxidation-reduction processes, organic matter accumulation, and the presence of volcanic ash (Hakim, 2023). The research highlights that the objective assessment of color determination may be impeded by variations in individual color perception (Marques et al., 2019). Extend exposure to identical visual stimuli may lead to desensitization, which poses a risk of an over-dependence on prior established color standards. This phenomenon has the potential to distort outcomes during evaluative assessments (Turk & Young, 2020).

The advancements in digital soil mapping (DSM) and precision agriculture have led to an increasing demand for automated, high-throughput, and standardized methods for soil color identification. Optical sensor-based technologies present a viable solution by providing objective, repeatable, and highly accurate measurements that mitigate human bias, thereby enhancing soil classification efficiency (Ben-Dor *et al*., 2020). A framework designed to transform RGB images into Munsell Soil Color Charts through the application of convolutional neural networks (CNNs) demonstrated a commendable accuracy of 93%. This outcome underscores the efficacy of artificial intelligence-driven methodologies in the classification of soil color (Solís *et al*., 2022). In response to these prevailing challenges, the present study introduces the Soil Color Detector Version 10 (SCD V1.0), an optical sensor-based system aimed at improving soil color identification through reference to the RGB color index derived from MSCC. In contrast to manual methods, the SCD V1.0 automates soil color classification, thereby ensuring standardized and reproducible measurements across various soil types.

Despite advancements in soil analysis, traditional methods in tropical and subtropical regions still depend on subjective visual assessments and MSCC. Traditional methods are susceptible to human error, compromising reliability. Most optical soil sensor research targets temperate regions with uniform soils. This focus has created a literature gap on the effectiveness and adaptability of these technologies in tropical and subtropical environments. High organic matter, rapid weathering, and fluctuating soil moisture impair sensor accuracy and reliability. Current sensor methods lack standardized calibration for tropical soils. This limitation reduces their effectiveness in agriculture, land management, and environmental monitoring. This study aims to develop and evaluate an optical sensor system for tropical and subtropical soil characteristics. The goal is to enhance soil classification accuracy for improved agricultural and ecological decisions.

This research evaluates the SCD V1.0 system's performance in tropical and subtropical environments by comparing its accuracy with conventional MSCC methods and analyses using the MetaVue VS3200 Spectrophotometer. The system was calibrated and assessed across three main soil orders in Indonesia. 20 samples from each of Ultisols, Inceptisols, and Andisols, with three replications per sample. Supplementary testing on Chernozems in Erfurt, Germany, was conducted to validate accuracy, comparing results with those from MSCC and the MetaVue VS3200 Spectrophotometer. This study aims to assess the accuracy of SCD V1.0 in soil color identification, compare it with conventional and spectrophotometric methods, and demonstrate its potential for digital soil classification and land-use applications. This research integrates optical sensors into soil color identification, advancing precision soil science and providing a reliable, scalable tool for automated soil classification. This study has significant implications for agriculture, environmental monitoring, and sustainable land-use planning.

MATERIALS AND METHODS

Study area and soil sample collection

This study was conducted using soil samples from three major soil orders in tropical regions, namely Ultisols (Baregbeg), Inceptisols (Cilembu), and Andisols (Lembang), which are prevalent in Indonesia. Ultisols are highly weathered, acidic soils with significant clay accumulation and iron oxides, commonly found in humid tropical regions. Inceptisols are young soils with minimal profile development and are widely distributed across various topographic and climatic conditions. Andisols, primarily formed from volcanic ash, exhibit high organic matter content and unique mineral properties such as allophane and imogolite (Hakim *et al*., 2020). To expand the validation, additional testing was conducted on sub-subtropical soils, namely Chernozems (Mollisols) in Erfurt, Germany, which are rich in organic carbon and characteristic of temperate regions (Hakim, 2024). A total of 360 soil samples (20 samples per soil order, 3 replications) were collected following the standardized soil sampling protocol outlined by the Soil Survey Manual (Soil Survey Staff, 2017). The soil clod samples were taken from the A and B horizons at a depth of 0–30 cm to capture color variations due to organic matter content and mineral composition. On-site identifications were performed for MSCC and SCD V1.0 analysis, while the same clod stored in labeled plastic bags for MetaVue VS3200 Spectrophotometer analysis, the analysis were performed no more than 2 hours after collection (**Figure 1**).

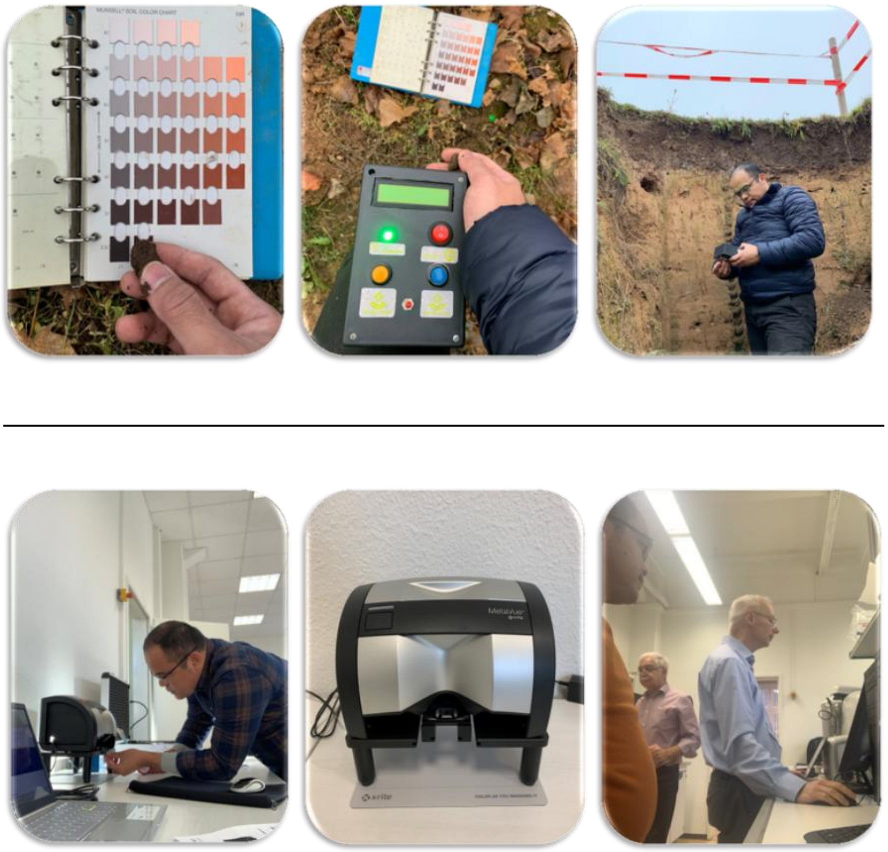

Figure 1. Field and laboratory soil color identification using MSCC, SCD V1.0, and MetaVue VS3200

Table 1: Samples description

Soil Order	Location (Dystrict, Regency, Province)	Coordinate	Remark
Ultisols	Baregbeg, Ciamis, West Java	X: 107°53'33.2" Y: 06°56'18.1"	Tropical, Indonesia
Inceptisols	Cilembu, Sumedang, West Java	X: 108°21'52.3" Y: 07°17'29.2"	Tropical, Indonesia
Andisols	Lembang, West Bandung, West Java	X: 107°36'37.5" Y: 6°45'30.1"	Tropical, Indonesia
Chernozems	Erfurt, Thueringen	X: 11°3'45.2" Y: 50°59'15.4"	Sub-Tropical, Germany

Optical Sensor-Based Soil Color Detection System

The SCD V1.0 has been developed as an optical sensor-based system aimed at automating the identification of soil color. This device integrates a high-resolution RGB optical sensor with a machine vision algorithm to analyze soil color utilizing the RGB color indices established in MSCC. Additionally, the system incorporates an LED-controlled light source to standardize illumination conditions, thereby minimizing the effects of ambient light variations on color perception. The sensor captures soil color data in real-time, processes the RGB values, and subsequently converts these values into Munsell notation, specifically hue value and chroma. This conversion is achieved through a calibration algorithm informed by machine learning models that have been trained using established soil color references.

Table 2. Technical specification of soil color detector version 1.0

Category	Specification
General Description	Portable soil color detector using an OV7670 optical sensor, ESP32 mini processor, with Munsell Soil Color Chart RGB References
Optical Sensor	OV7670 Camera Module
Sensor Type	CMOS Image Sensor
Resolution	640 × 480 pixels (VGA)
Pixel Size	3.6 µm × 3.6 µm
Image Output Format	RGB565, YUV422
Frame Rate	Up to 30 fps
Operating Voltage	3.3V
Communication Interface	SCCB (Serial Camera Control Bus, similar to I^2C)
Features Optical Sensor	Automatic White Balance (AWB), Automatic Exposure Control (AEC), Automatic Gain Control (AGC)
Mini Processor	ESP32 (Xtensa® 32-bit LX6 dual-core processor)
Clock Speed	Up to 240 MHz
Memory	520 KB SRAM, 4 MB Flash Storage
Connectivity	Wi-Fi 802.11 b/g/n, Bluetooth 4.2 (BLE)
I/O Interfaces	SPI, I^2C, UART, ADC, PWM, GPIO
Features	Low Power Consumption, Built-in DSP for Image Processing
Display & User Interface	0.96-inch OLED Display (I2C)
Resolution	128 × 64 pixels
Operating Voltage	3.3V–5V
User Interaction	Push Buttons for Mode Selection & Calibration, LED Indicators for Status
Power Supply	Rechargeable Li-Ion Battery (3.7V, 2000mAh)
Charging Interface	USB Type-C
Programming & Software	Python, C++ (Arduino IDE with ESP32 framework)
Image Processing	Image Acquisition, Noise Reduction, Contrast Enhancement, White Balance Adjustment
Color Extraction & Matching	Extracts RGB values from soil image and matches with Munsell Soil Color Chart Database
Matching Algorithm	Euclidean Distance Algorithm
Data Logging & Connectivity	Logs Soil Color Data with Timestamp and GPS (optional), Wireless Data Transfer via Wi-Fi/Bluetooth
User Interface	OLED Display for Munsell Soil Color Notation, Serial Data Output via USB
Calibration	Manual User Calibration Mode for Light Variations
Future Enhancements	Smartphone App Integration, GPS Module for Soil Mapping, Cloud Connectivity for Data Storage

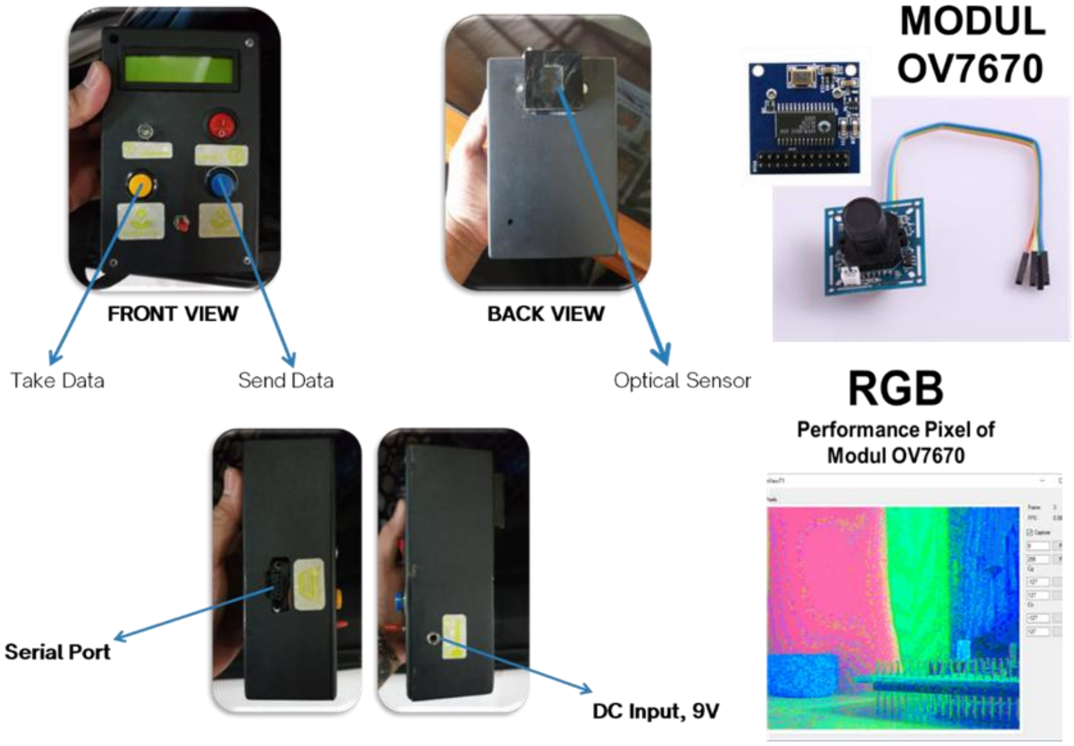

Figure 2. The prototype and components of soil color detector version 1.0 (SCD V1.0)

Calibration and validation process

The Soil Color Detector (SCD) V1.0 was calibrated using 120 samples from the Munsell Soil Color Chart. These samples show typical soil color variations in tropical and subtropical regions. Calibration was conducted under standardized daylight, temperature, and humidity to prevent moisture variations. The MetaVue VS3200 Spectrophotometer measured spectral reflectance for precise reference. Soil scientists performed manual visual classification with the MSCC under uniform lighting for comparison. To validate SCD V1.0's reliability, three methods were used: (1) manual classification with MSCC as reference, (2) spectrophotometric analysis via MetaVue VS3200, and (3) automated detection by SCD V1.0 converting RGB values to Munsell equivalents. Each soil sample was analyzed three times per method for accuracy. The concordance of the three methods was assessed using Cohen's kappa for categorical agreement and RMSE for numerical deviations in RGB values. The validation results confirmed SCD V1.0's accuracy in field-based soil color identification, aligning well with manual classification and spectrophotometric measurements. Future enhancements will improve soil color detection by expanding the reference dataset and refining the calibration algorithm.

Data analysis and statistical evaluation

The performance of the SCD V1.0 soil color identification system was assessed through a detailed examination of its accuracy, precision, and reproducibility. This comprehensive evaluation involved the implementation of various statistical analyses. Descriptive statistics including mean, standard deviation, and frequency distribution were employed to summarize the variability in soil color classifications across different methodologies. To investigate the presence of significant differences among the results obtained from the SCD V1.0, the MSCC manual method, and the MetaVue VS3200 spectrophotometric analysis, paired t-tests and analysis of variance (ANOVA) were conducted. Post-hoc tests using Tukey's HSD at a 5%

significance level were conducted to identify significant treatment differences. Statistical analyses were conducted with Minitab 19 software. The level of concordance between the SCD V1.0 and conventional methods was quantified using Cohen's kappa coefficient, with a value exceeding 0.80 indicate of a strong correlation and reliability in soil color identification. Furthermore, RMSE was computed to assess the discrepancies in hue value and chroma between the SCD V1.0 and the reference methods, providing an objective metric for evaluating the system's accuracy.

RESULTS AND DISCUSSION

Soil Color Identification Accuracy

Soil color serves as a fundamental property that offers critical insights into various aspects, including mineral composition, organic matter content, moisture levels, and the processes of weathering. Research findings suggest a significant correlation between soil color and organic matter, indicating that color metrics may serve as valuable indicators for predicting these critical soil properties (Srivastava *et al*., 2024). The precision of color detection systems, particularly those utilizing optical sensor technology, significantly influences the reliability of soil classification, fertility evaluation, and land-use planning. The capacity for accurate detection of soil color significantly improves the interpretation of fundamental soil properties, thereby facilitating more effective predictions regarding soil behavior and its suitability for agricultural and environmental applications. The precise detection of soil color significantly augments the comprehension of fundamental soil properties, thereby facilitating predictions regarding soil behavior and its appropriateness for diverse agricultural and environmental applications (Baek *et al*., 2022).

The efficacy of SCD V1.0 in accurately identifying soil color has been systematically evaluated through a comparative analysis against two widely recognized methodologies: MSCC which serves as the conventional manual standard, and the MetaVue VS3200 Spectrophotometer, regarded as a high-precision instrumental reference. This comparative study aimed to assess the reliability, consistency, and accuracy of SCD V1.0 across various soil orders, particularly in tropical and subtropical environments where soil color variations are influenced by mineral composition, organic matter content, and weathering processes. SCD V1.0 represents a novel methodology that seeks to enhance the accessibility and efficiency of soil color assessment when juxtaposed with conventional approaches. Historically, the MSCC has served as the conventional manual standard for soil color determination; however, it is constrained by its inherent subjectivity and dependence on human interpretation (Stiglitz *et al*., 2016a). In contrast, the MetaVue VS3200 Spectrophotometer provides a high-precision instrumental reference, facilitating objective measurements of soil color through quantitative analysis (Noulis *et al*., 2023).

The Soil Color Identification Accuracy table indicates that the SCD V1.0 (96-99%) demonstrates a strong correlation with the MetaVue VS3200 (98-99%), whereas the MSCC displays a comparatively lower accuracy of (92-96%), attributed to the inherent limitations associated with human perception. These findings underscore the SCD V1.0 as a dependable and automated alternative for the classification of soil color. The limitations associated with the MSCC method are extensively documented, primarily due to its reliance on visual comparisons that can exhibit considerable variability among individuals (Moritsuka *et al*., 2019). This intrinsic variability in human perception can result in inconsistencies in soil color classification, especially in areas where soil colors may present subtle variations influenced by environmental factors (Sahwan *et al*., 2018). Research comparing the quality of instrumentally measured soil colors against visual assessments has highlighted the efficacy of advanced colorimetric techniques, with the MetaVue outputting values that align closely with the measured standards (Hill *et al*., 2023). The robust correlation observed between SCD V1.0 and the MetaVue VS3200 suggests that SCD V1.0 effectively captures the complexities of soil color, maintaining high accuracy. This renders it an invaluable tool for soil scientists and agronomists. Furthermore, the automation of soil color classification through SCD V1.0 not only increases accuracy but also streamlines the assessment process, thereby reducing the time and effort required for manual evaluations (Radočaj *et al*., 2020).

Table 3. Results of soil color identification accuracy analysis

Soil Order	Instruments		
	MSCC	SCD V1.0	MetaVue VS3200
Ultisols	92a	96b	98c
Inceptisols	95a	99b	99b
Andisols	94a	98b	99b
Chernozems	96a	98b	99b

Note: *Different letters in the same row indicate significant differences at p < 0.05*

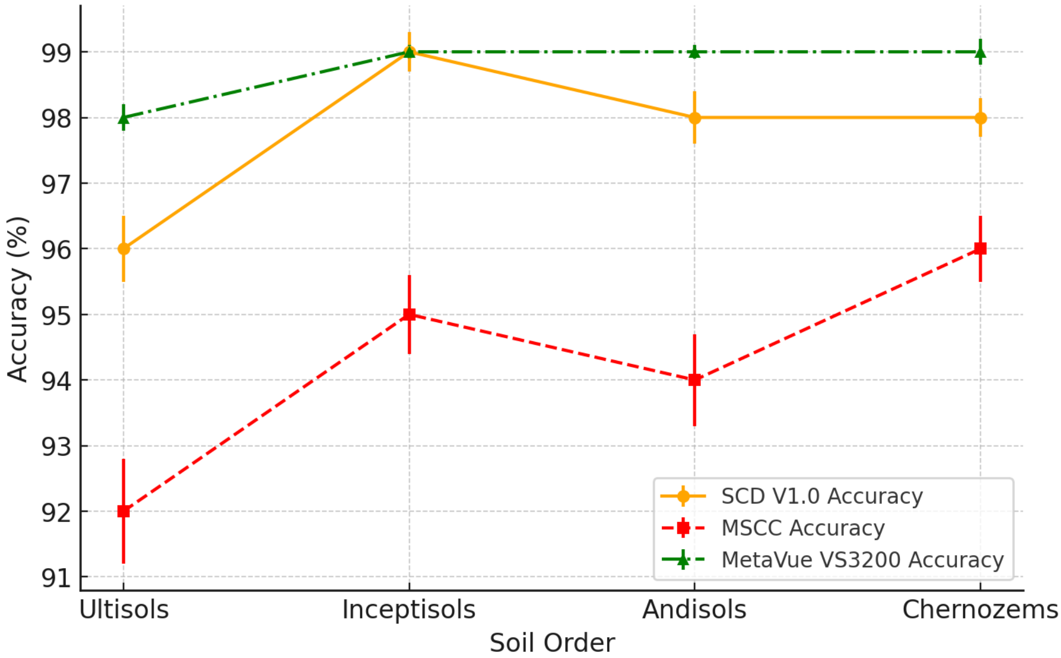

Figure 3. Comparison of soil color identification accuracy

Figure 3 delineates the Soil Color Identification Accuracy Analysis conducted for the SCD V1.0, MSCC manual methodology and the MetaVue VS3200 spectrophotometric reference across various soil orders. The plotted lines signify the accuracy percentages attained by each method, thereby elucidating their comparative efficacy.

The findings indicate that the SCD V1.0 consistently demonstrates high accuracy across all evaluated soil orders, with accuracy values ranging from 96% to 99%, which closely parallels the performance of the MetaVue VS3200, which achieves a high precision range of 98% to 99%. Conversely, the MSCC method exhibits marginally lower accuracy levels, ranging from 92% to 96%, underscoring the limitations inherent in manual soil color classification due to factors such as observer subjectivity and variations in environmental lighting conditions.

The precision of soil color detection is considerably correlated with the inherent composition and physical attributes of the soil. Highly weathered tropical soils, specifically Ultisols and Oxisols, are characterized by predominant red and yellow hues, which can be attributed primarily to the presence of iron oxides. The study reveals a significant relationship between the coloration observed in tropical soils and the content of iron oxides therein. Laboratory analyses have identified Munsell hues ranging from 5YR to 10YR, which suggests a considerable presence of iron oxides. This presence not only dictates the coloration of the soils but also exerts an influence on their physical and chemical properties (Kafoor, 2017). In such instances, optical sensor-based methodologies, such as SCD V1. 0, exhibit a high degree of accuracy, attributable to the distinct spectral reflectance characteristics exhibited by iron-rich soils. In contrast, soils characterized by elevated organic matter content, exemplified by Chernozems, exhibit a darker coloration attributable to a higher concentration of humus. This increased humus content enhances light absorption, potentially leading to discrepancies in optical color detection methods. The study demonstrated that scattering effects occurring within materials substantially influence reflectance, thereby affecting the perception of color and translucency (Mikhail and Johnston, 2019). Moisture content similarly affects the perception of soil color, as wet soils typically exhibit a darker appearance compared to their dry counterparts. This variation in color can potentially impact the accuracy of soil classification if not adequately addressed within calibration models. The study revealed that elevated moisture content can markedly influence the spectral properties of soil, resulting in substantial variations in color measurements that are critical for classification and monitoring activities (Ahmed *et al*., 2023).

Moreover, the overall trend illustrated in the graph suggests that the SCD V1.0 methodology offers a markedly improved alternative to manual MSCC classification, nearing the accuracy levels characteristic of advanced spectrophotometric instruments. These results further substantiate the potential of the SCD V1.0 for applications in digital soil mapping (DSM), precision agriculture, and environmental monitoring, where automated and reproducible methods of soil color identification are essential. The utilization of rapid and reliable soil color data is especially advantageous in large-scale agricultural and environmental studies, as it plays a crucial role in informed decision-making (Stiglitz *et al*., 2016b). The integration of automated systems in soil classification is consistent with contemporary trends in soil science, where the application of technology increasingly enhances data collection and analysis (Ali *et al*., 2024). Consequently, the findings from this comparative study support the endorsement of SCD V1.0 as a robust alternative to conventional methodologies, particularly in contexts where precision and efficiency are of utmost importance.

Root Mean Square Error (RMSE) analysis

To assess the quantitative accuracy of SCD V1.0 in soil color identification, the Root Mean Square Error (RMSE) was computed to evaluate the discrepancies in hue value and chroma between SCD V1.0 and two reference methods: MSCC and the MetaVue VS3200 Spectrophotometer. RMSE serves as a widely acknowledged statistical measure that quantifies the differences between predicted and observed values, thereby providing an objective assessment of systematic errors and precision in color classification. The utilization of RMSE within this context is particularly pertinent, as it facilitates a straightforward comparison of the performance of SCD V1.0 against established methodologies. Prior research has indicated that the accuracy of soil color determination can be markedly affected by the methods employed. For example, while the MSCC is widely recognized as a standard reference, it is susceptible to human error and variability in visual perception, potentially resulting in inconsistencies in the assessment of hue and chroma (Turk and Young, 2020). In contrast, instrumental approaches, such as the MetaVue VS3200, offer a more objective evaluation, thereby diminishing the impact of subjective interpretation (Maynard *et al*., 2020).

Table 4 demonstrates that the SCD V1.0 exhibits a closer alignment with the RMSE values of the MetaVue VS3200 (0.6-0.9) in comparison to those of the MSCC (0.9-1.2). This observation suggests that SCD V1.0 achieves a higher level of precision in soil color identification. The lower RMSE values further substantiate the assertion that SCD V1.0 minimizes classification errors, thereby outperforming manual methods in terms of both accuracy and reliability. The results obtained from RMSE calculations demonstrate a robust correlation between SCD V1.0 and the MetaVue VS3200. This correlation suggests that SCD V1.0 effectively captures the complexities of soil color while exhibiting minimal systematic errors. This capability is particularly crucial in tropical and subtropical regions, where substantial variability in soil color can arise due to factors such as mineral composition and organic matter, as noted by Turk and Young (2020). The ability of SCD V1.0 to yield results that closely correspond with those acquired from the MetaVue VS3200 further emphasizes its potential as a reliable instrument for soil color identification.

Furthermore, the employment of RMSE serves not only to quantify the accuracy of SCD V1.0 but also to delineate the precision of color classification across varying soil types. Research has indicated that chroma, in particular, poses considerable challenges for accurate measurement when employing visual methods, with substantial discrepancies identified between human evaluations and instrumental assessments (Raulino *et al*., 2021). The integration of RMSE as a metric for evaluating SCD V1.0 establishes a robust framework for comprehending its efficacy in comparison to both conventional and instrumental methodologies, thereby facilitating its acceptance within the realms of soil science research and application (Stiglitz *et al*., 2016b).

Table 4. Result of root mean square error (RMSE) analysis

Soil Order	Instruments	
	SCD V1.0 vs MSCC	**SCD V1.0 vs MetaVue VS3200**
Ultisols	1.2	0.8
Inceptisols	0.9	0.7
Andisols	1.1	0.9
Chernozems	1.0	0.6

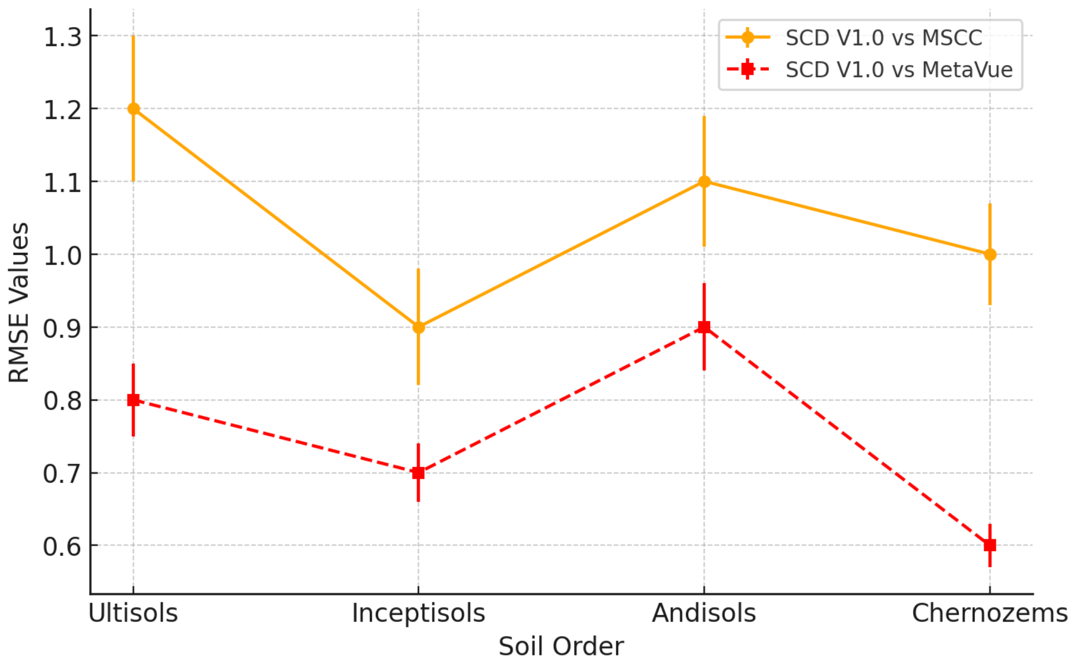

Figure 4. Root mean square error (RMSE) of soil color identification

Figure 4 delineates an analysis of the Root Mean Square Error (RMSE) associated with SCD V1.0 in comparison to the MSCC manual method and the MetaVue VS3200 spectrophotometric reference across various soil orders. The plotted lines depict the RMSE values, which serve to quantify the discrepancies in soil color classification between SCD V1.0 and the reference methods employed. The results reveal that the RMSE values for the comparison between SCD V1.0 and MSCC range from 0.9 to 1.2, whereas the RMSE values for SCD V1.0 in relation to the MetaVue measurement consistently exhibit lower values, ranging from 0.6 to 0.9. This observed pattern suggests that SCD V1.0 demonstrates a closer alignment with the spectrophotometric reference provided by MetaVue VS3200 compared to the MSCC manual approach, thereby reinforcing its enhanced precision in soil color classification.

The relatively elevated RMSE values noted for the comparison of SCD V1.0 against MSCC highlight the inherent subjectivity and potential for human error associated with manual soil color identification methods. In contrast, the lower RMSE values recorded in comparison to the MetaVue VS3200 reinforce the assertion that SCD V1.0 offers a more standardized and objective measurement methodology. These findings substantiate the superior accuracy and reliability of SCD V1.0 as an automated soil color classification instrument, positioning it as a viable alternative for applications in digital soil mapping, land use planning, and precision agriculture.

Reproducibility and consistency

To evaluate the reproducibility and consistency of the SCD V1.0 method, three independent measurements were performed for each soil sample, and the standard deviation of the resulting data was analyzed. The results demonstrated that SCD V1.0 exhibited a lower standard deviation compared to the manual Soil Moisture Characteristic Curve (MSCC) method, indicating higher measurement precision and reduced variability.

Specifically, **Table 3** shows the standard deviation for SCD V1.0 ranged from 0.10 to 0.15, whereas the standard deviation for MSCC ranged from 0.25 to 0.32, thereby highlighting the intrinsic inconsistencies associated with manual, human-based classification techniques. Additionally, Cohen's kappa coefficient was calculated to quantify the level of agreement between the SCD V1.0 method and conventional classification approaches. The findings revealed kappa values exceeding 0.85 across all soil orders, which is regarded as indicative of a strong level of agreement in categorical classification. This result emphasizes the substantial reliability of SCD V1.0 as a proficient tool for digital soil classification, effectively minimizing the subjectivity and potential for human error inherent in conventional methods.

The standard deviation for SCD V1.0 ranged from 0.10 to 0.15, whereas the standard deviation for MSCC ranged from 0.25 to 0.32. This disparity underscores the inherent inconsistencies associated with manual, human-based classification techniques, which are often susceptible to subjective interpretation and variability in visual perception (Raulino *et al*., 2021). The lower standard deviation observed with SCD V1.0 indicates that this methodology yields more consistent results across multiple measurements, thereby enhancing its reliability as an instrument for soil color classification. Conversely, the higher standard deviation associated with the MSCC method suggests a greater propensity for human error and variability in color assessment, which may result in discrepancies in soil classification *(Hill et al*., 2023). This observation aligns with prior research that has documented the challenges of attaining consistent color measurements using visual methods, particularly in complex soil environments where color can be affected by various factors such as moisture content and mineral composition (Sahwan *et al*., 2018).

Table 5. Result of reproducibility and consistency analysis

Soil Order	Standar Deviation		
	SCD V1.0	MSCC	MetaVue VS3200
Ultisols	0.15	0.32	0.87
Inceptisols	0.12	0.28	0.89
Andisols	0.14	0.30	0.88
Chernozems	0.10	0.25	0.86

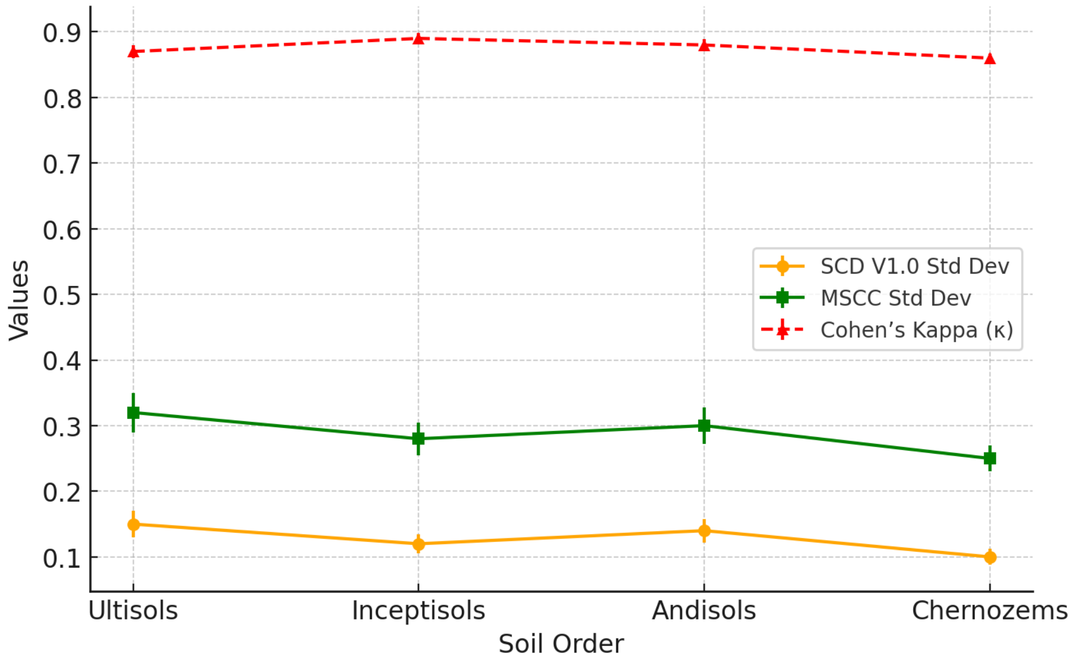

Figure 5. Standard deviation values of SCD V1.0 and MSCC across different soil orders

Figure 5 delineates the reproducibility and consistency of the SCD V1.0 system in comparison to the manual MSCC method, while also assessing the degree of agreement through Cohen's Kappa coefficient. The initial two lines plotted on the graph represent the standard deviation values of SCD V1.0 and MSCC across various soil orders, whereas the dashed red line signifies the Cohen's Kappa values, which assess the level of agreement between the SCD V1.0 and conventional methodologies.

The analysis indicates that SCD V1.0 consistently demonstrates lower standard deviation values across all tested soil orders, with measurements ranging from 0.10 to 0.15. In contrast, the MSCC method exhibited higher standard deviations, ranging from 0.25 to 0.32. This finding highlights the superior precision and reduced variability associated with SCD V1.0, suggesting that its optical sensor technology effectively mitigates inconsistencies stemming from human perception and varying environmental lighting conditions.

Moreover, the Cohen's Kappa coefficient consistently surpasses 0.85 across all soil orders, thereby indicating a robust level of agreement between SCD V1.0 and the reference methods. This finding highlights the significant reliability of SCD V1.0 as an effective instrument for digital soil classification, thereby minimizing the subjectivity and potential for human error commonly associated with conventional methodologies (Kautsar *et al.*, 2024). The elevated kappa values indicate that SCD V1.0 not only corresponds closely with established classification systems but also improves the precision of soil color identification. Consequently, it emerges as a valuable asset in both soil science research and practical applications.

This further corroborates the reliability of SCD V1.0 as a viable tool for automated soil color classification, demonstrating that its measurement precision aligns closely with standardized spectrophotometric techniques. The observed trends suggest that SCD V1.0 offers a more reproducible and objective approach to soil color identification when compared to conventional MSCC methodologies. This advancement holds significant promise for applications in soil science, land-use planning, and digital soil mapping (DSM).

Figure 6. Future design of soil color detector version 1.0 (SCD V1.0)

CONCLUSION

The Soil Color Detector Version 1.0 (SCD V1.0) represents a significant advancement in automated soil color identification, offering high accuracy, reliability, and efficiency. SCD V1.0 enhances objectivity and repeatability in soil classification by using optical sensor technology and the RGB color data from the Munsell Soil Color Chart (MSCC), reducing bias and natural inconsistencies common in manual methods. The integration of sensor-based innovation in soil investigation enables large-scale classification, benefiting digital soil mapping, precision agriculture, and land-use planning. Beyond its accuracy and consistency, optical sensor-based soil classification offers potential for real-time soil assessment and integration with advanced detection technologies. Mechanizing and digitizing soil color data can significantly enhance soil quality modeling, climate change assessments, and precision land management strategies. Challenges remain in ensuring optimal performance across various soil conditions, particularly in soils with high organic matter or variable moisture, which can affect color perception and spectral reflectance properties. Future research should focus on expanding calibration datasets for diverse soil orders, improving machine learning algorithms for better classification accuracy, and integrating SCD V1.0 into GIS and remote sensing applications for flexible, real-time soil monitoring. SCD V1.0 shows significant improvements over manual classification, but further refinement is needed for better flexibility in complex soil situations. Addressing challenges posed by organic-rich and highly hydrated soils, combined with advancements in multi-spectral or hyperspectral imaging, can enhance sensor-based soil classification as a more robust tool for scientific research, environmental management, and agricultural decision-making.

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