TEKNOTAN, Vol. 18, No. 1, April 2024
ISSN 1978-1067 (Print), ISSN 2528-6285 (Online)
DOI 10.24198/jt.vol18n1.3

Soil Color Comparison Using Munsell Soil Color Chart and Calibrated Smartphone Camera

Perbandingan Warna Tanah Menggunakan Bagan Warna Tanah Munsell dan Kamera Ponsel yang Telah Dikalibrasi

Valensi Kautsar[1,2]*, Kuni Faizah[3], Arief Ika Uktoro[3]

[1]Agrotechnology Study Program, Faculty of Agriculture, Institut Pertanian Stiper (INSTIPER), Yogyakarta 55281, Indonesia
[2]Plantation Management Master Study Program , Institut Pertanian Stiper (INSTIPER) ,Yogyakarta 55281, Indonesia
[3]Agricultural Engineering Study Program, Faculty of Agricultural Technology, Institut Pertanian Stiper (INSTIPER), Yogyakarta 55281, Indonesia
*E-mail: valkauts@instiperjogja.ac.id

Submitted: 11 January 2024; Accepted: 5 March 2024

ABSTRACT

Soil color is a crucial property in soil fertility assessment and monitoring. However, the subjective nature of the Munsell Soil Color Chart (MSCC) can lead to uncertainty in the analysis. To address this issue, a study was conducted to develop a soil color classification model from smartphone digital imagery based on color analysis and MSCC. The study involved taking 26 soil samples from various soil types and locations in the Special Region of Yogyakarta, Indonesia. Digital images of the soil were taken through a smartphone camera and compared with observations using MSCC to compare color differences (ΔE) based on Lab values. Soil images obtained from indoor studio conditions and calibration using spydercheckr in indoor and outdoor conditions are compared with MSCC and Chromameter values. The L*a*b color space was found to be superior to RGB for predicting and detecting small differences in color. The study also found that the Munsell soil color chart (MSCC) had a lower color difference than the chromameter in all lighting conditions, indicating that the MSCC or visual assessment can better detect the main soil color or soil matrix, while chromameter readings may have errors due to soil impurities.

Keywords: color difference (∆E); L*a*b; RGB; image processing.

ABSTRAK

*Warna tanah merupakan sifat penting dalam penilaian dan pemantauan kesuburan tanah. Namun, subyektifitas pengamat menggunakan Munsell Soil Color Chart (MSCC) dapat menyebabkan ketidakpastian dalam analisis. Untuk mengatasi masalah ini, penelitian dilakukan untuk mengembangkan model klasifikasi warna tanah dari citra digital smartphone berdasarkan analisis warna dan MSCC. Penelitian ini dilakukan dengan mengambil 26 sampel dari berbagai jenis tanah dan lokasi di Daerah Istimewa Yogyakarta, Indonesia. Citra digital tanah diambil melalui kamera smartphone dan dibandingkan dengan hasil pengamatan menggunakan MSCC untuk membandingkan perbedaan warna (ΔE) berdasarkan nilai Lab. Citra tanah yang diperoleh dari kondisi studio dalam ruangan dan kalibrasi menggunakan spydercheckr pada kondisi indoor dan outdoor dibandingkan dengan nilai MSCC dan Chromameter. Nilai L*a*b ditemukan lebih unggul daripada RGB dalam memprediksi dan mendeteksi perbedaan warna. Studi ini juga menemukan bahwa bagan warna tanah Munsell memiliki perbedaan warna yang lebih rendah daripada chromameter pada semua kondisi pencahayaan, yang mengindikasikan bahwa MSCC atau penilaian visual dapat mendeteksi warna tanah utama atau matriks tanah dengan lebih baik, sementara pembacaan chromameter dimungkinkan memiliki kesalahan cukup besar akibat adanya pengotor tanah.*

Kata Kunci: *perbedaan warna (∆E); L*a*b; RGB; pemrosesan gambar*

INTRODUCTION

Pedology is a fundamental aspect of soil science that focuses on examining the chemical and physical characteristics of soils, as well as the processes involved in their formation, distribution, morphology, and categorization. Soil color is one of the characteristics that can provide this information. Precisely assessing soil color is crucial since it yields vital data for soil scientists (Liu et al., 2020; Pegalajar et al., 2018, 2020, 2023). Soil color can provide valuable insights into soil development, composition, age of soil and rock surfaces, and variables that restrict plant growth. Hence, soil color serves as a significant soil indicator and attribute that can be employed to characterize, categorize, and distinguish soils (Fan et al., 2017; Pegalajar et al., 2018, 2023; Priandana et al., 2014). Furthermore, soil color plays a crucial role in determining a range of soil activities and conditions, including oxidation-reduction processes, iron solubility, organic matter content, soil development, and the formation of distinct soil materials like concretions, nodules, plintites, and horizons.

An frequently employed method for analyzing soil color is to utilize the Munsell soil color chart, also known as the Munsell Soil Color Chart (MSCC). The need for soil data in several fields, such as precision agriculture and dynamic environmental monitoring, is driving the advancement of soil sensors that can provide more accurate information, including data on soil color. The utilization of MSCC is prevalent due to its relative simplicity, as it solely involves a qualitative comparison of soil color in the field using MSCC (Fan et al., 2017; Pegalajar et al., 2023; Priandana et al., 2014). The Munsell chart comprises 238 standardized color rectangular pieces (Pegalajar et al., 2018, 2023), organized based on three coordinates: hue (H), Value or brightness level (V), and Chroma or color intensity (C) (Liu et al., 2020; Pegalajar et al., 2023; Sinclair et al., 2024).

The primary issue that has arisen thus far is the ambiguity resulting from the subjectivity of the observer (Bloch et al., 2021; Fan et al., 2017; Milotta et al., 2020; Pegalajar et al., 2023; Priandana et al., 2014). This issue is worsened by the extensive range of hues in MSCC, some of which bear resemblances. For instance, there are similarities between 2.5YR 8/8, 7.5YR 8/8, and 10YR 8/8, all of which have a tendency to appear yellow. Alternatively, in low-light soil circumstances, it becomes challenging to discern the soil color due to the prevalence of dark hues. Sánchez-Marañón et al., (2005) identified a problem related to the high variability observed in MSCC (Munsell Soil Color Chart) measurements based on CIELAB hab, L*, and C*ab analysis. This variability arises from differences in manufacturers, editions, and usage levels, particularly in terms of hue, value, and chroma values. The variations can arise from disparities in printing techniques and/or the gradual loss of color intensity. Sánchez-Marañón et al., (2011) also discuss how sunlight impacts the description of soil color, which is related to brightness. About 79% of the soils had several Munsell notations as a result of variations in sunshine, in addition 45% of soil displayed a stronger reddish or yellowish hue in daylight compared to reference light. Kirillova et al., (2015) further explained that the Munsell System is less accurate in assessing the role of pigments present in soil color.

Various studies on soil color analysis employ different techniques, including decision tree (Gozukara et al., 2021; X. Zhang et al., 2018), random forest (Liu et al., 2020; Mancini et al., 2020), K-nearest neighbor (Marqués-Mateu et al., 2018; Priandana et al., 2014; Y. Zhang & Hartemink, 2019), fuzzy systems (Pegalajar et al., 2018, 2020; Zhu et al., 2010), artificial neural networks (Pegalajar et al., 2018, 2020), and machine learning (Mancini et al., 2020). Nevertheless, the majority of investigations are carried out within controlled environmental settings and employ advanced equipment. Various techniques utilizing smartphone cameras have been suggested to address this issue. For instance, Gómez-Robledo et al. (2013) employed a mobile phone camera to quantify soil color. The findings demonstrated that the utilized model exhibited comparable precision to some prior investigations that utilized specialist instruments in controlled environmental settings. Utilizing suitable techniques in smartphone digital image processing may produce a high level of precision. These techniques involve the conversion of RGB values into XYZ space and HVC (Han et al., 2016) or L*a*b color space (Kirillova et al., 2015). Another instance can be observed in the study conducted by Han et al., (2016) and Pegalajar et al., (2023), where the researchers categorize soil using color sensors in smartphone photographs. Issues undeniably accompany the utilization of photos produced by mobile phones. The primary issue lies in the fact that the straight conversion of RGB values typically disregards camera sensitivity and image quality. Consequently, the resulting estimated value will exhibit a significant range within the same sample. Hence, it is necessary to use referencing, including self-referencing and non-self-referencing methods (such as using a referencing board), to prepare the image for subsequent processing (Souza et al., 2018).

Due to the diverse range of mineralogical composition and physical and chemical properties of soil, it is necessary for research to utilize spectral samples that accurately reflect the variety of soil (Costa et al., 2020). A study conducted by Marqués-Mateu et al., (2018) examined color consistency and measured soil color in a controlled laboratory setting. However, the study demonstrated that the use of Munsell charts tended to provide reasonably correct Hue, although Values and Chroma produced greater values than the real soil color. Moreover, a study conducted by (Fan et al., 2017) demonstrated the feasibility of analyzing smartphone photographs captured in the field using grey cards. The study also demonstrated the potential of employing smartphone photos for soil color assessment using the color difference (ΔE) method. Therefore, the objective of this study was to introduce a more objective approach to soil color identification through the calculation of color differences. These differences are intended to compare smartphone image data obtained under different conditions (indoor studio, indoor with SpyderCheckr, and outdoor with SpyderCheckr) with the ground truth provided by the MSCC or NH310 Chromameter.

METHODOLOGY

Soil sampling and preparation

A total of 26 soil samples were taken randomly by considering soil classification. Soil classification was based on geospatial information data from Regional Development Planning Agency of Yogyakarta Special Region (http://geoportal.jogjaprov.go.id). The locations of all soil collections are shown in Figure 1. In this study, we employed an approach where each soil sample represented by a single point was considered a distinct entity. This decision was made considering that variations in soil color at different points may yield different outcomes.

Alluvial soil is formed from young sediment deposits. Cambisol soil is also newly developed soil without significant clay content increase in the subsoil layer. Grumusol soil, rich in aggregates, features a brittle structure formed from organic and mineral materials. It typically exhibits excellent drainage properties and is conducive to healthy plant growth. Found in widespread areas with tropical and subtropical climates, often witness soil shrinkage and cracking during the dry season, followed by swelling and high plasticity during the rainy season. Latosol soil evolves from volcanic material with clay content exceeding 40% and base saturation less than 50%. Mediterranean soil exhibits brown to reddish soil color with base saturation exceeding 50%. Meanwhile, regosol soil has relatively coarse texture with sand content exceeding 60% (Gunawan et al., 2020; Hall et al., 1983).

In order to ensure precise soil analysis, soil samples were taken from the top layer, known as the topsoil, at a depth of 0-20 or 30 cm. The identification of the topsoil layer was based on the visual characteristics of the soil and its morphology. Subsequently, the soil was carefully cleared of any twigs, stones, and other debris. The sample was collected in the morning to afternoon under sunny conditions, without any recent rainfall. This would facilitate the soil preparation process and result in the homogen natural color of the soil matrix. The soil was subjected to air-drying for a period of 10-21 days, which varied based on the soil's condition, subsequent to the sample process. After being air-dried, the soil was sifted through a 2 mm and 0.5 mm sieve to separate it into three sizes: 0.5 mm, 2 mm, and larger aggregates. The soil with a particle size of 2 mm was utilized for obtaining digital images and for soil texture analysis. The soil with a particle size of 0.5 mm was employed for analyzing organic matter content. The soil in disturbed aggregate form was utilized to obtain soil color data using MSCC values.

Digital image acquisition, processing, and analysis

To obtain smartphone digital image data, the soil is placed in a petri dish and a digital image is taken with a smartphone Vivo V23e. To ensure the validity of soil color, we sampled by identifying the dominant color within diverse areas on the petri dish. The sampling area varied depending

TEKNOTAN, Vol. 18, No. 1, April 2024
ISSN 1978-1067 (Print), ISSN 2528-6285 (Online)
DOI 10.24198/jt.vol18n1.3

on the level of color homogeneity within the area. This approach aimed to minimize bias and ensure consistency in soil color sampling. Aggregate soil is used for color classification assessment on MSCC, which is then converted into RGB form. The smartphone camera specifications used are using 64 MP, aperture value f/1.8, focal length 26mm. The image from the smartphone camera is then extracted using ImageJ software, an open-source image processing software to obtain RGB values (Schneider et al., 2012). Then after that the RGB value is converted to the L*a*b color space value. Research by Kirillova et al., (2015) showed that conversion from the Munsell system to the CIE-L*a*b* system significantly improved the color character due to Fe pigments. Since Munsell is a subjective assessment that heavily relies on the observer, utilizing an objective tool like a chromameter for comparing data obtained with images generated by smartphones would result in a much more accurate assessment. Thus, we also collected soil color data using the NH310 chromameter (3NH, Shenzhen Threenh Technology Co., Ltd, China). Color extraction using the Nh310 chromameter was carried out by placing soil samples that had been covered with thin plastic on the chromameter sensor. The use of thin plastic is intended so that the color obtained can be accurate without disturbing the chromameter sensor. The workflow of this research is illustrated in Figure 2.

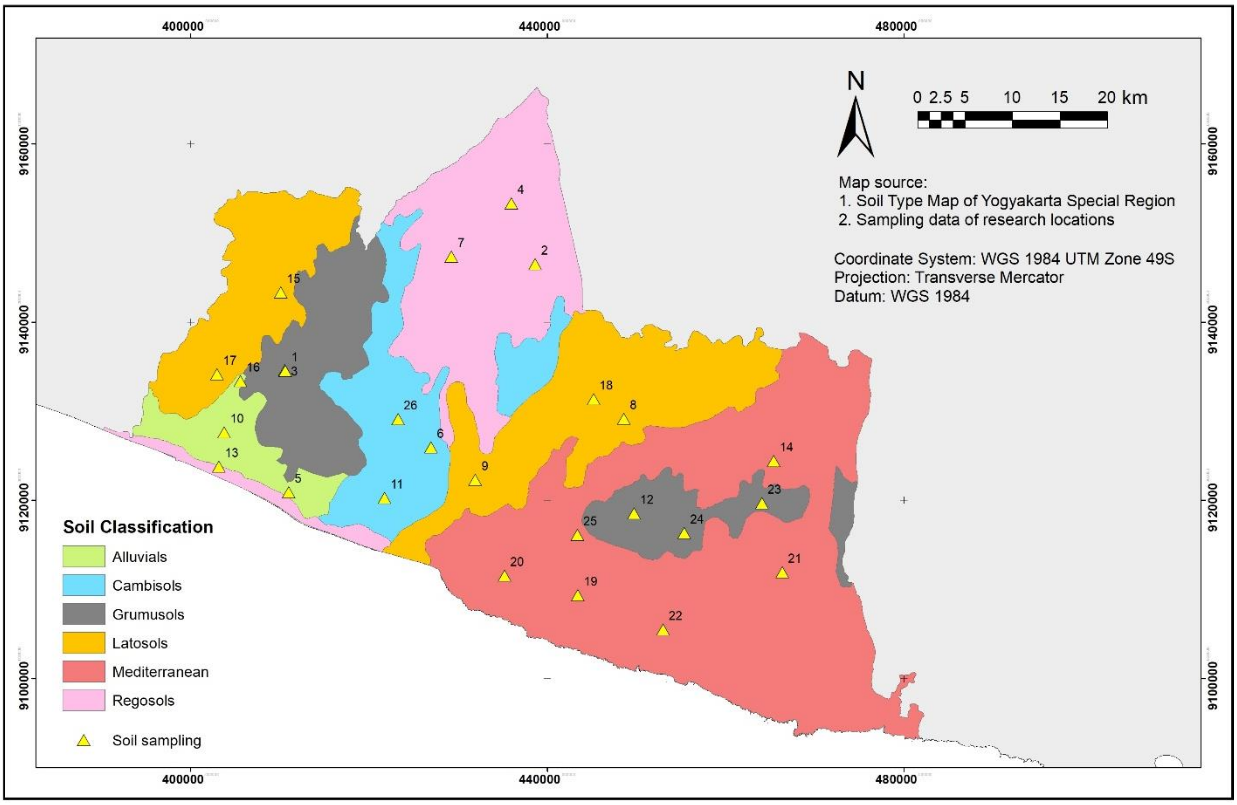

Figure 1. Soil sampling location in Yogyakarta Special Region

Table 1. The arrangement of image acquisition

Settings	Outdoor with Spydercheckr calibration (OC)	Indoor with spydercheckr calibration (IC)	Indoor studio (IS)
Camera height	50 cm	72 cm	40 cm
White balance	Sunshine	Sunshine	Auto
ISO	320	100	Auto
Shutter speed	1/4000	1/10	Auto
Zoom	1 x	2 x	2 x

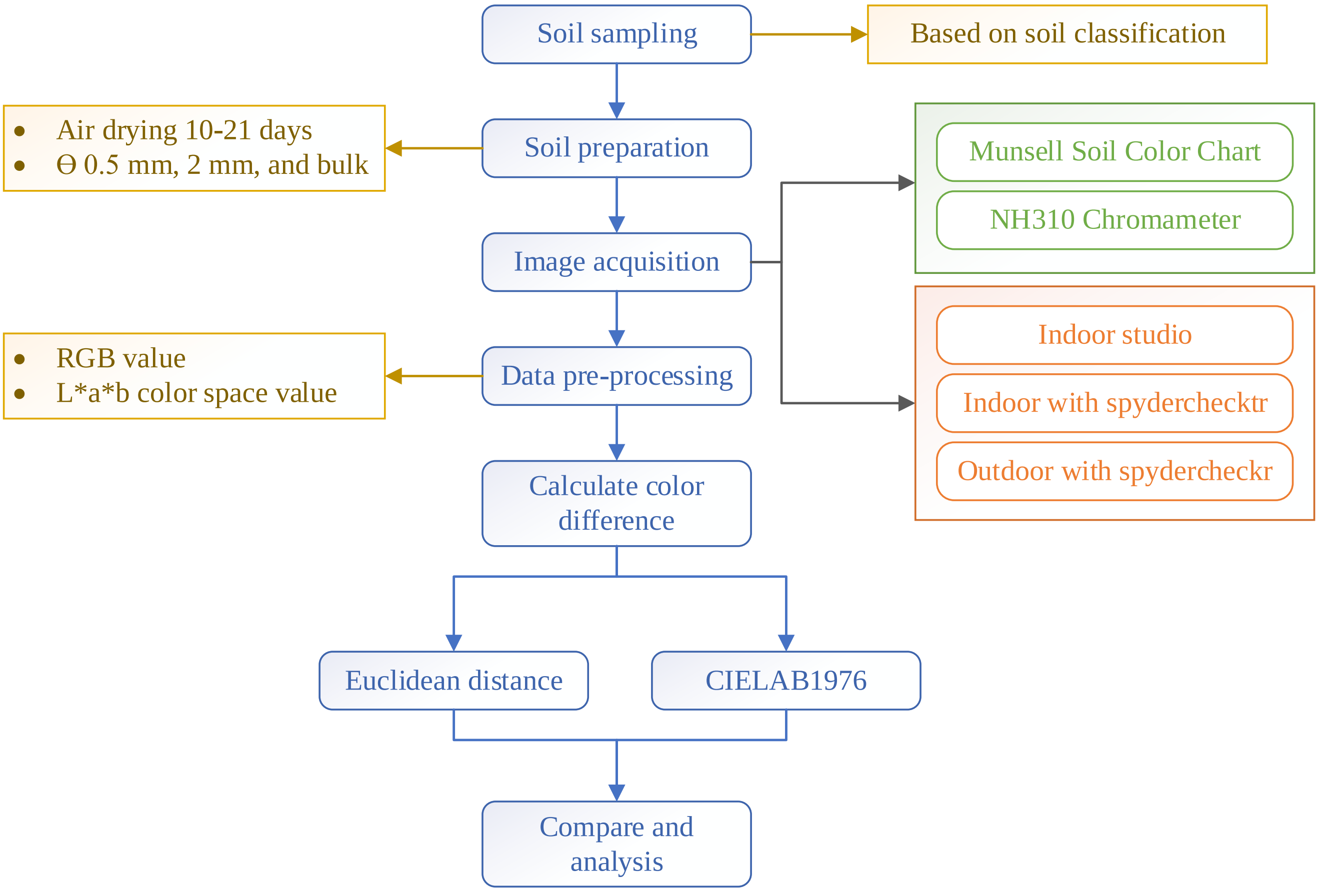

Figure 2. Research flow

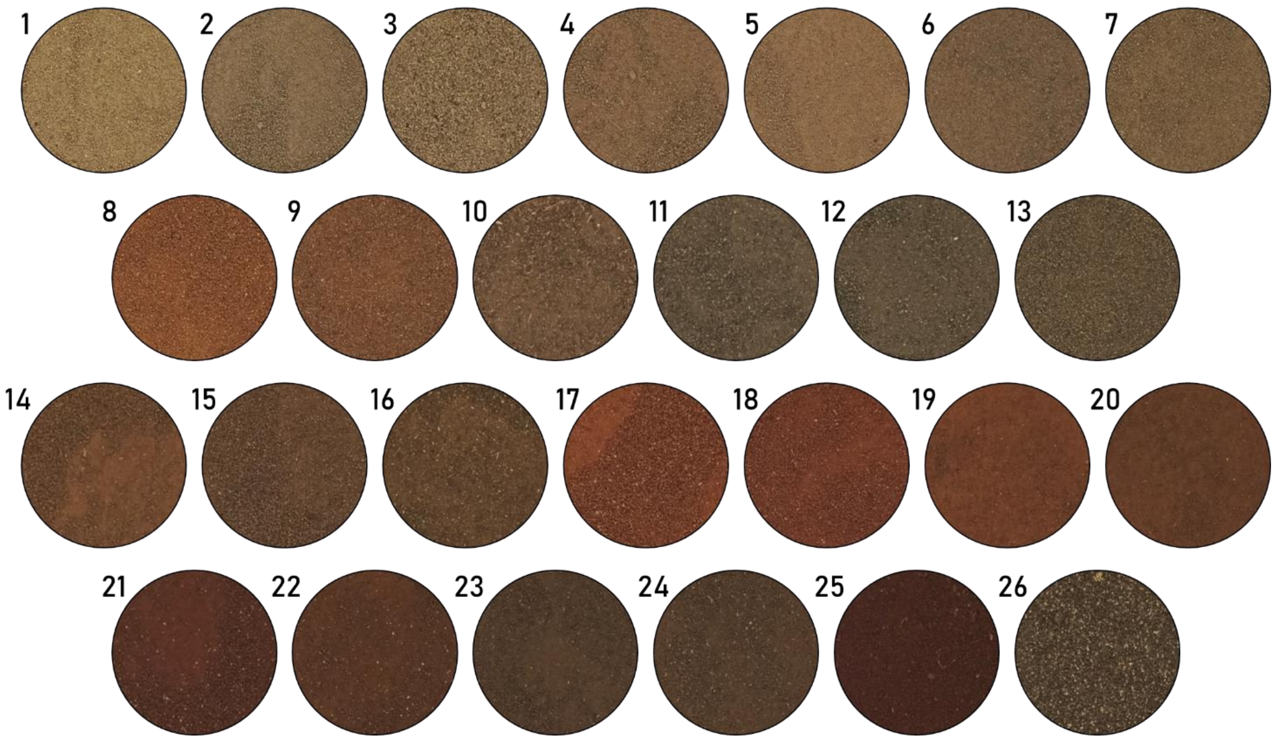

Figure 3. Photograph of the 26 soil samples utilized in the research

TEKNOTAN, Vol. 18, No. 1, April 2024
ISSN 1978-1067 (Print), ISSN 2528-6285 (Online)
DOI 10.24198/jt.vol18n1.3

The board referencing method utilizes the SpyderCheckr 48 (Datacolor, USA), a standardized tool widely employed in color management within digital imaging. The SpyderCheckr 48 comprises 48 color patches with known spectral reflectance values, facilitating the calibration and profiling of digital imaging devices to ensure accurate and consistent color reproduction. This tool is commonly employed in various fields, including photography, graphic design, and scientific imaging, to maintain fidelity in color representation across different devices and environments (Belosokhov et al., 2022; Ebner et al., 2021; Moore et al., 2021). Color calibration is done by applying the color calibration matrix obtained from Spydercheckr color parameters. Spydercheckr used to calibrate the color parameters of images generated from smartphones, which are taken with indoor and outdoor scenarios at the same time (morning at 08.00-10.00, sunny condition). While the indoor studio employs a mini studio with controlled luminescence, the studio lighting is regulated to ensure consistent measurement standards across all soil types. The color differences are aimed at comparing the data generated from smartphone images under various conditions (indoor studio, indoor with SpyderCheckr, and outdoor with SpyderCheckr) with the ground truth (MSCC or NH310 Chromameter). Several studies employ color difference (ΔE) in determining the variance between two sets of image data (Mancini et al., 2020; Nodi et al., 2023). Color difference (ΔE) was measured using the Euclidean Distance (Equation 1) and CIE-LAB1976 (Equation 2) calculations.

$$\Delta E = \sqrt{\Delta R^2 + \Delta G^2 + \Delta RB^2} \quad (1)$$

$$\Delta E_{L^*a^*b^*} = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2} \quad (2)$$

L*a*b color space is considered superior to RGB, hence, while Euclidean Distance based on RGB values is simpler, conversion is necessary to ensure better accuracy of the obtained values.

RESULTS AND DISCUSSION

Several efforts have been made to quantitatively improve the accuracy and precision of soil color. These efforts can be classified into three. First, use of a special device to detect soil color. This method has constraints on the availability and cost of tools or devices that are relatively expensive compared to the use of the commonly used MSCC. Second, the use of digital images taken using smartphones or other devices (such as spectrophotometers, colorimeters, digital cameras with color analysis software, and hyperspectral imaging devices) to classify colors. This method, especially the use of smartphones, is considered a straightforward approach for analyzing soil color, suitable for general use with accessible devices such as smartphones, enabling broader application. Currently, researchers are more inclined to develop this method as it is more feasible for implementation. This method can be done using direct or indirect methods. The direct method means taking images that are processed with an application on a smartphone, while the indirect method is through image processing that is separate from the smartphone. However, this approach has limitations due to variations in screen conditions, brightness settings, and color gamut production. Therefore, steps are necessary to mitigate the impact of variability in color analysis, which includes device calibration, standardizing environmental conditions, integrating internal controls, and utilizing statistical analysis to enhance result consistency and accuracy (Gómez-Robledo et al., 2013; Han et al., 2016; Nodi et al., 2023; Pegalajar et al., 2020, 2023; Priandana et al., 2014; Sinclair et al., 2024; Souza et al., 2018; X. Zhang et al., 2018).

Sampling results showed that the 26 soils taken had a fairly diverse color range from gray-brown to blackish (Figure 3). There are six types of soils found in the research area, namely alluvials, grumusols, cambisols, latosols, Mediterranean, and regosols. Analysis of soil color using the munsell soil color chart (MSCC) showed that observations were not made easily due to the very specific color and abundant color variety of the MSCC. Therefore, a better method of measuring soil color is needed.

The color difference (ΔE) value indicates how much the colors of the two data differ. The lower the value, the smaller the difference. The Euclidean Distance method compares the RGB color space from the camera image with benchmark data, which includes the Munsell Soil Color Chart (MSCC) or Chromameter. Calculation of color difference (ΔE) using the Euclidean Distance method between indoor studio (IS) images and MSCC showed similar than other comparisons, MSCC with indoor or outdoor using spydercheckr calibration (Figure 4). Based on soil type, Mediterranean shows lower values, ranging from 24.89 to 37.90 depending on the image source used as a comparison to MSCC, compared to other soil types.

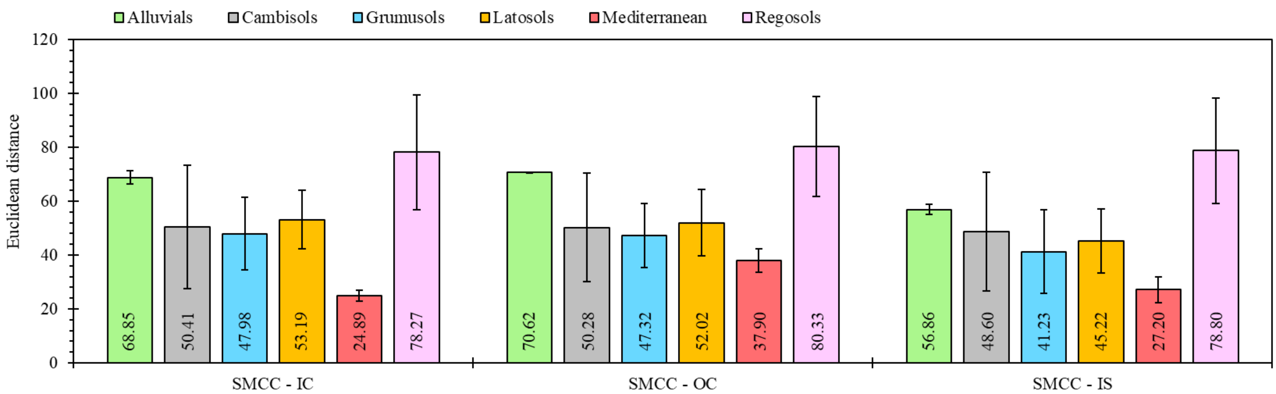

Figure 4. Color difference RGB-Euclidean Distance based on soil classification using MSCC as ground truth. Bars indicate standard error. Remarks: IC: indoor with spydercheckr calibration, OC: outdoor with spydercheckr calibration, IS: indoor with studio luminescence

The use of chromameter as ground truth shows a value that is much different from the results obtained using a smartphone camera. In the calculation of the color difference between the chromameter and the indoor image through calibration, values of 69.33 and 74.37 were obtained for regosol and grumusol soils, respectively, while other soils had color difference values of more than 85 (Figure 5). In outdoor natural lighting, after calibration, the color difference values were still high, ranging from 71.30 to 105.4. While in isolated light conditions through the indoor studio showed values ranging from 71.37-95.45. This indicated that the use of Euclidean distance using the RGB color space is not able to accurately assess the difference in color produced from the camera and the ground truth used. Nodi et al., (2023) elucidated that employing the RGB color model and Euclidean distance yielded an average prediction rank of 82-101 for the Samsung S10 and 40-80 for the Google Pixel 5.

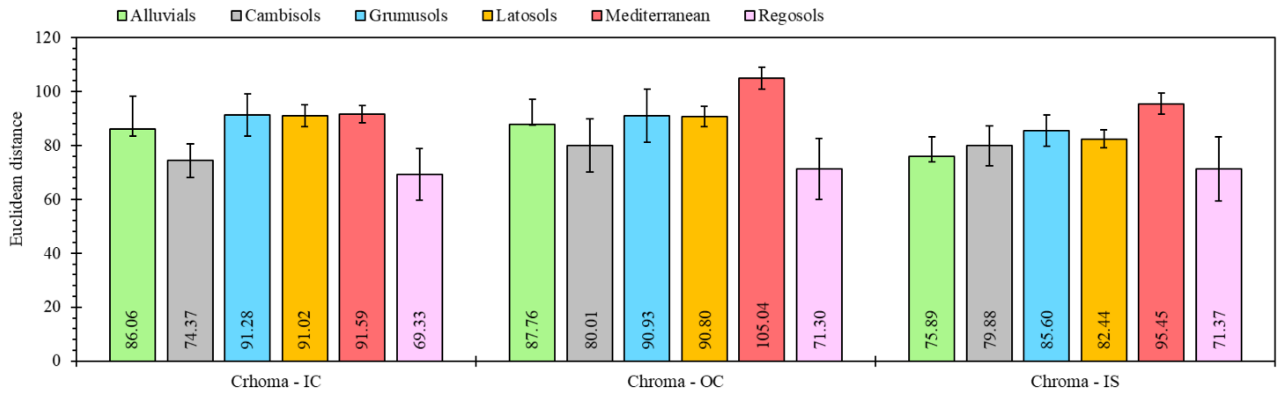

Figure 5. Color difference RGB-Euclidean Distance based on soil classification using Nh3 Chromameter as ground truth. Bars indicate standard error. Remarks: IC: indoor with spydercheckr calibration, OC: outdoor with spydercheckr calibration, IS: indoor with studio luminescence

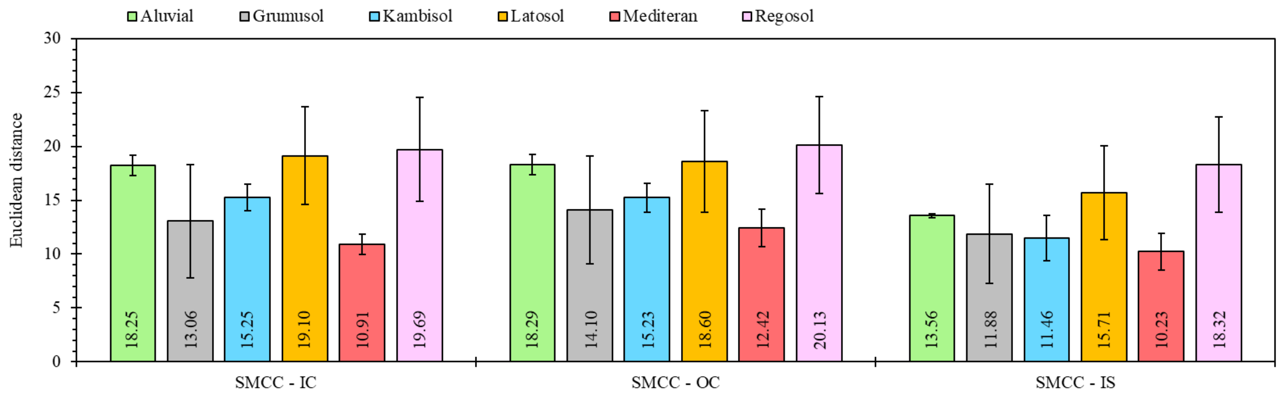

Figure 6. Color difference CIELAB1976 based on soil classification using MSCC as ground truth. Bars indicate standard error. Remarks: IC: indoor with spydercheckr calibration, OC: outdoor with spydercheckr calibration, IS: indoor with studio luminescence

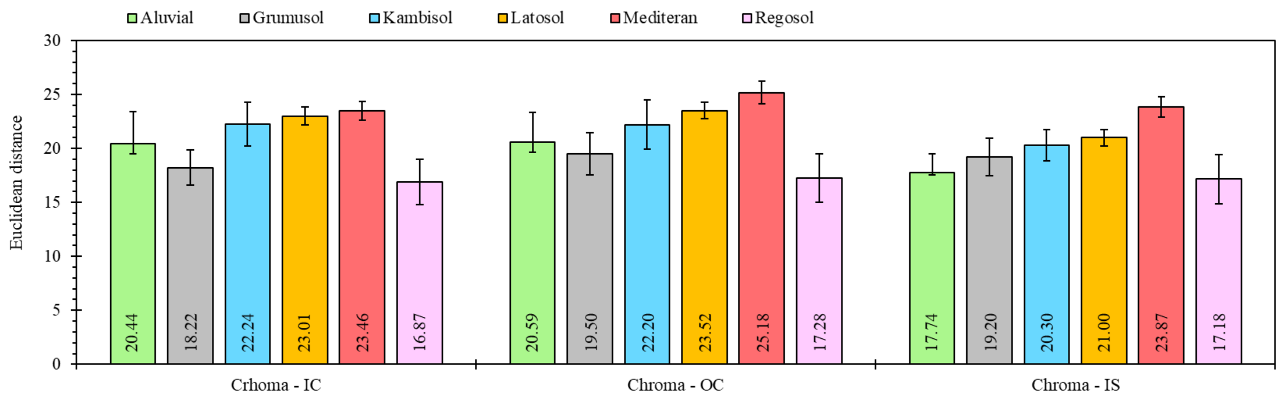

Figure 7. Color difference CIELAB1976 based on soil classification using Nh3 Chromameter as ground truth. Bars indicate standard error. Remarks: IC: indoor with spydercheckr calibration, OC: outdoor with spydercheckr calibration, IS: indoor with studio luminescence

The CIELAB 1976 using L*a*b color space is preferred over the RGB value for several reasons. Unlike the RGB color model, which is based on the capabilities of electronic visual displays, CIELAB is designed to approximate human vision. The L* component in CIELAB closely matches human perception of lightness, making it more suitable for representing how humans perceive color (Azetsu & Suetake, 2021; Connolly & Fleiss, 1997; M. R. Luo, 2014). Additionally, CIELAB is intended to be a perceptually uniform space, where a given numerical change corresponds to a similar perceived change in color. This makes it more effective for predicting and detecting small differences in color, which is particularly useful in industries where color accuracy is critical, such as in printing and manufacturing (Connolly & Fleiss, 1997; M. R. Luo, 2014).

The change from RGB to L*a*b color space showed a very significant change, that is, the color difference value becomes much lower. This demonstrates that the L*a*b color space is much better at color assessment than using RGB values. Mediterranean soils showed ΔE between MSCC and indoor images after calibration of 10.91, lower than grumusols (13.06), cambisols (15.25), or other soil types that have ΔE of more than 18 (Figure 6). In the comparison between MSCC and calibrated outdoor some soil types show higher values than indoor. Meanwhile, the comparison between MSCC and studio images showed lower values than others, ranging from 10.23-15.71 for all soils, except regosols which showed a value of 18.32.

The use of chromameter as ground truth shows fairly uniform values (Figure 7). Comparison with the calibrated indoor shows color differences ranging from 16.87-23.46. While comparison with calibrated outdoor shows values less than 20 in grumusols and regosols soils, while other soil types are more than 20. In comparison of chromameter with indoor studio lighting shows regosols, alluvials, and grumusols soils, respectively 17.18, 17.74, and 19.20.

This research showed that there was a superior use of the L*a*b color space compared to RGB based on the color difference value. In addition, this study also highlighted that the use of MSCC had a lower color difference than the chromameter in all lighting environment conditions despite being calibrated. This better used of munsell was unexpected, as munsell relies solely on visuals in color assessment, while chromameter read color directly quantitatively. This finding indicates that the use of MSCC or visually was able to detect better the main soil color or soil matrix. While chromameter readings may had errors due to the color of soil impurities. In general, the color of the soil matrix is often not uniform due to the presence of impurities, for example from the soil parent material. Some dark soils such as black, brown or reddish have bright or white impurities, whereas regosols that are quite light in color have darker impurities. Manual reading of the MSCC by an observer can easily distinguish between the soil matrix and the impurities.

Furthermore, the considerable color difference between the MSCC or chromameter and the soil image indicates the presence of impurities mixed with the soil due to the crushing of the soil to a smaller size. Soil crushing has the advantage of increasing the color homogeneity of the soil matrix, although this study shows a disadvantage, that is the soils taken have quite a lot of impurities, so that the crushing impurities will interfere with the reading of the digital image from the smartphone. The presence of soil impurities is a immense challenge, thus it is necessary to utilize artificial intelligence to distinguish between the soil matrix and soil impurities.

CONCLUSION

The study's sampling results revealed a diverse color range in the 26 soils taken, highlighting the need for a better method of measuring soil color. The research demonstrated the superiority of the Lab color space over the RGB value, as it is more effective for predicting and detecting small differences in color. Additionally, the study found that the use of the Munsell soil color chart (MSCC) had a lower color difference than the chromameter in all lighting environment conditions, despite being calibrated. This unexpected finding indicates that the MSCC or visual assessment can better detect the main soil color or soil matrix, while chromameter readings may have errors due to soil impurities. The presence of soil impurities was identified as a significant challenge, necessitating the use of artificial intelligence to distinguish between the soil matrix and soil impurities. Overall, the study's findings emphasize the importance of accurate and precise soil color analysis, particularly in the presence of soil impurities.

REFERENCES

Azetsu, T., & Suetake, N. (2021). Chroma Enhancement in CIELAB Color Space Using a Lookup Table. *Designs*, *5*(2), Article 2. https://doi.org/10.3390/designs5020032

Belosokhov, A., Yarmeeva, M., Kokaeva, L., Chudinova, E., Mislavskiy, S., & Elansky, S. (2022). Trichocladium solani sp. Nov.—A New Pathogen on Potato Tubers Causing Yellow Rot. *Journal of Fungi*, *8*(11), Article 11. https://doi.org/10.3390/jof8111160

Bloch, L. C., Hosen, J. D., Kracht, E. C., LeFebvre, M. J., Lopez, C. J., Woodcock, R., & Keegan, W. F. (2021). *Is It Better to Be Objectively Wrong or Subjectively Right? 9*(2), 132–144. https://doi.org/10.1017/aap.2020.53

Connolly, C., & Fleiss, T. (1997). *A study of efficiency and accuracy in the transformation from RGB to CIELAB color space | IEEE Journals & Magazine | IEEE Xplore*. *6*(7), 1046–1048. https://doi.org/10.1109/83.597279

Costa, J. J. F., Giasson, É., da Silva, E. B., Coblinski, J. A., & Tiecher, T. (2020). Use of color parameters in the grouping of soil samples produces more accurate predictions of soil texture and soil organic carbon. *Computers and Electronics in Agriculture*, *177*, 105710. https://doi.org/10.1016/j.compag.2020.105710

Ebner, M., Nabavi, E., Shapey, J., Xie, Y., Liebmann, F., Spirig, J. M., Hoch, A., Farshad, M., Saeed, S. R., Bradford, R., Yardley, I., Ourselin, S., Edwards, A. D., Führnstahl, P., & Vercauteren, T. (2021). Intraoperative hyperspectral label-free imaging: From system design to first-in-patient translation. *Journal of Physics D: Applied Physics*, *54*(29), 294003. https://doi.org/10.1088/1361-6463/abfbf6

Fan, Z., Herrick, J. E., Saltzman, R., Matteis, C., Yudina, A., Nocella, N., Crawford, E., Parker, R., & Van Zee, J. (2017). Measurement of Soil Color: A Comparison Between Smartphone Camera and the Munsell Color Charts. *Soil Science Society of America Journal*, *81*(5), 1139–1146. https://doi.org/10.2136/sssaj2017.01.0009

Gómez-Robledo, L., López-Ruiz, N., Melgosa, M., Palma, A. J., Capitán-Vallvey, L. F., & Sánchez-Marañón, M. (2013). Using the mobile phone as Munsell soil-colour sensor: An experiment under controlled illumination conditions. *Computers and Electronics in Agriculture*, *99*, 200–208. https://doi.org/10.1016/j.compag.2013.10.002

Gozukara, G., Zhang, Y., & Hartemink, A. E. (2021). Using vis-NIR and pXRF data to distinguish soil parent materials – An example using 136 pedons from Wisconsin, USA. *Geoderma*, *396*, 115091. https://doi.org/10.1016/j.geoderma.2021.115091

Gunawan, J., Hazriani, R., & Mahardika, R. Y. (2020). *Buku Ajar Morfologi dan Klasifikasi Tanah*. Fakultas Pertanian Universitas Tanjungpura.

Hall, G. F., Smeck, N. E., & Wilding, L. P. (1983). *Pedogenesis and soil taxonomy: Vol. II. The Soil Orders*. Elsevier Distributors for the U.S. and Canada, Elsevier Science Pub. Co.

Han, P., Dong, D., Zhao, X., Jiao, L., & Lang, Y. (2016). A smartphone-based soil color sensor: For soil type classification. *Computers and Electronics in Agriculture*, *123*, 232–241. https://doi.org/10.1016/j.compag.2016.02.024

Kirillova, N. P., Vodyanitskii, Yu. N., & Sileva, T. M. (2015). Conversion of soil color parameters from the Munsell system to the CIE-L*a*b* system. *Eurasian Soil Science*, *48*(5), 468–475. https://doi.org/10.1134/S1064229315050026

Liu, F., Rossiter, D. G., Zhang, G.-L., & Li, D.-C. (2020). A soil colour map of China. *Geoderma*, *379*, 114556. https://doi.org/10.1016/j.geoderma.2020.114556

Luo, M. R. (2014). CIELAB. In R. Luo (Ed.), *Encyclopedia of Color Science and Technology* (pp. 1–7). Springer. https://doi.org/10.1007/978-3-642-27851-8_11-1

Mancini, M., Weindorf, D. C., Monteiro, M. E. C., de Faria, Á. J. G., dos Santos Teixeira, A. F., de Lima, W., de Lima, F. R. D., Dijair, T. S. B., Marques, F. D., Ribeiro, D., Silva, S. H. G., Chakraborty, S., & Curi, N. (2020). From sensor data to Munsell color system: Machine learning algorithm applied to tropical soil color classification via Nix™ Pro sensor. *Geoderma*, *375*, 114471. https://doi.org/10.1016/j.geoderma.2020.114471

Marqués-Mateu, Á., Moreno-Ramón, H., Balasch, S., & Ibáñez-Asensio, S. (2018). Quantifying the uncertainty of soil colour measurements with Munsell charts using a modified attribute agreement analysis. *CATENA*, *171*, 44–53. https://doi.org/10.1016/j.catena.2018.06.027

Milotta, F. L. M., Furnari, G., Quattrocchi, C., Pasquale, S., Allegra, D., Gueli, A. M., Stanco, F., & Tanasi, D. (2020). Challenges in automatic Munsell color profiling for cultural heritage. *Pattern Recognition Letters*, *131*, 135–141. https://doi.org/10.1016/j.patrec.2019.12.008

Moore, C. A., Brown, A. E., Sias, C. A., Robinson, T. R., & Allik, T. H. (2021). Performance characterization of low light level color imaging sensors. *Infrared Imaging Systems: Design, Analysis, Modeling, and Testing XXXII*, *11740*, 34–49. https://doi.org/10.1117/12.2585777

Nodi, S. S., Paul, M., Robinson, N., Wang, L., & Rehman, S. U. (2023). Determination of Munsell Soil Colour Using Smartphones. *Sensors*, *23*(6), 3181. https://doi.org/10.3390/s23063181

Pegalajar, M. C., Ruiz, L. G. B., & Criado-Ramón, D. (2023). *Munsell Soil Colour Classification Using Smartphones through a Neuro-Based Multiclass Solution*.

Pegalajar, M. C., Ruiz, L. G. B., Sánchez-Marañón, M., & Mansilla, L. (2020). A Munsell colour-based approach for soil classification using Fuzzy Logic and Artificial Neural Networks. *Fuzzy Sets and Systems*, *401*, 38–54. https://doi.org/10.1016/j.fss.2019.11.002

Pegalajar, M. C., Sánchez-Marañón, M., Baca Ruíz, L. G., Mansilla, L., & Delgado, M. (2018). Artificial Neural Networks and Fuzzy Logic for Specifying the Color of an Image Using Munsell Soil-Color Charts. In J. Medina, M. Ojeda-Aciego, J. L. Verdegay, D. A. Pelta, I. P. Cabrera, B. Bouchon-Meunier, & R. R. Yager (Eds.), *Information Processing and Management of Uncertainty in Knowledge-Based Systems. Theory and Foundations* (pp. 699–709). Springer International Publishing. https://doi.org/10.1007/978-3-319-91473-2_59

Priandana, K., S, A. Z., & Sukarman. (2014). Mobile Munsell Soil Color Chart Berbasis Android Menggunakan Histogram Ruang Citra HVC dengan Klasifikasi KNN. *Jurnal Ilmu Komputer Dan Agri-Informatika*, *3*(2), 93–101. https://doi.org/10.29244/jika.3.2.93-101

Sánchez-Marañón, M., García, P. A., Huertas, R., Hernández-Andrés, J., & Melgosa, M. (2011). Influence of Natural Daylight on Soil Color Description: Assessment Using a Color-Appearance Model. *Soil Science Society of America Journal*, *75*(3), 984–993. https://doi.org/10.2136/sssaj2010.0336

Sánchez-Marañón, M., Huertas, R., & Melgosa, M. (2005). Colour variation in standard soil-colour charts. *Soil Research*, *43*(7), 827–837. https://doi.org/10.1071/SR04169

Schneider, C. A., Rasband, W. S., & Eliceiri, K. W. (2012). NIH Image to ImageJ: 25 years of image analysis. *Nature Methods*, *9*(7), Article 7. https://doi.org/10.1038/nmeth.2089

Sinclair, R., Nodi, S., & Kabir, M. A. (2024). Evaluating mobile applications for estimating soil properties: Quality of current apps, limitations and future directions. *Computers and Electronics in Agriculture*, *216*, 108527. https://doi.org/10.1016/j.compag.2023.108527

Souza, W. S., Oliveira, M. A. S. de, Oliveira, G. M. F. de, Santana, D. P. de, & Araujo, R. E. de. (2018). Self-Referencing Method for Relative Color Intensity Analysis Using Mobile-Phone. *Optics and Photonics Journal*, *8*(7), Article 7. https://doi.org/10.4236/opj.2018.87022

Zhang, X., Liu, H., Zhang, X., Yu, S., Dou, X., Xie, Y., & Wang, N. (2018). Allocate soil individuals to soil classes with topsoil spectral characteristics and decision trees. *Geoderma*, *320*, 12–22. https://doi.org/10.1016/j.geoderma.2018.01.023

Zhang, Y., & Hartemink, A. E. (2019). *Digital mapping of a soil profile*. *70*(1), 27–41. https://doi.org/10.1111/EJSS.12699

Zhu, A.-X., Qi, F., Moore, A., & Burt, J. E. (2010). Prediction of soil properties using fuzzy membership values. *Geoderma*, *158*(3), 199–206. https://doi.org/10.1016/j.geoderma.2010.05.001