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Pedotransfer functions for soil organic carbon stock and soil porosity interpretation in diverse palm oil plantation soils

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ABSTRACT

The accurate estimation of soil organic carbon stocks (SOCs) is crucial in sustainable oil palm plantation management. Pedotransfer functions (PTFs) serve as an essential predictive tool for enhancing the interpretation and estimation of soil organic carbon stocks (SOCs) and soil porosity. This study aims to improve the precision of SOCs and soil porosity predictions across diverse soil types within oil palm plantations through the application of PTFs. The study was conducted using a survey approach and descriptive exploration in an oil palm plantation in Seruyan District, Central Kalimantan. The study area encompassed four distinct soil types (Alfisols, Inceptisols, Ultisols, and Entisols), with six replicates for each soil type. Soil samples were collected from a depth of 0–60 cm. Statistical analyses included ANOVA, Tukey's pairwise comparisons, correlation, and stepwise regression. The results indicated that soil types within oil palm plantations did not significantly affect SOCs but significantly impacted soil porosity. SOCs and porosity estimated using PTFs were lower than those estimated without PTFs. Specifically, SOCs analysis with PTFs ranged from 3.4 to 7.1 kg m^{-2}; without PTFs, the range was higher, between 8.1 and 10.9 kg m^{-2}. Among the soil types, Entisols exhibited higher porosity with PTFs (51.3%), while Ultisols had the lowest porosity (37.9%). The PTFs provide better predictions for SOCs and porosity, and predictor variables that contribute the most are sand, silt, bulk density (BD), and cation exchange capacity (CEC). PTFs provide an advanced, data-driven approach to assessing SOCs and soil porosity in oil palm plantations, supporting the development of smarter, sustainable, and highly efficient management strategies.

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1. INTRODUCTION

Soil plays a pivotal role in capturing and storing carbon, serving as both a crucial reservoir and a dynamic source of energy for diverse ecosystems (Rodrigues et al., 2023). Carbon storage in the soil has a greater impact on climate mitigation and change compared to atmospheric carbon (Dharumarajan et al., 2021). The importance of carbon stock in mitigating climate change is closely linked to biomass fixation, organic matter transformation and decomposition, and soil carbon mineralization, all of which are influenced by soil organic matter (SOM) composition, texture, and structure (Dewi & Nurhutami, 2023; Fekete et al., 2023). SOC Stock (SOCs) is a crucial resource in supporting many ecosystem services (ES) through its role in nutrient cycling, soil stability, soil biodiversity, erosion vulnerability, climate change mitigation, and productivity (Juhos et al., 2024), SOCs can enhance water availability and the water-holding capacity of soil (Abdallah et al., 2021), and water availability is directly related to soil porosity. SOC determines the availability of micropores in the soil, which is a measure of soil productivity (Kibet et al., 2022). Water holding capacity and soil water potential are determined by soil pore size, which is directly related to soil texture (Waite et al., 2019)

The quantity of SOCs found in soil is determined by its inherent properties, environmental aspects like depth, slope,

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and precipitation, as well as land management strategies (Hairiah et al., 2020). To achieve accurate SOC measurements, it is essential to consider these contributing factors (Nguemezi et al., 2021). Most previous research has focused on the impact of land use and environmental variability on SOCs (Jakšić et al., 2021; Tang et al., 2022; Tayebi et al., 2021). Variations in soil texture influence the distribution and retention of SOCs (Nishigaki et al., 2021). Accurate measurement of SOCs and soil porosity is crucial for establishing sustainable land management strategies for oil palm cultivation. Given that oil palm is grown across diverse soil types, these variations in texture must be carefully considered. Specifically, oil palm plantations in Central Kalimantan, Indonesia, encompass a diverse range of soil classifications, including Ultisols, Inceptisols, Entisols, Histosols, and Oxisols, predominantly characterized by loamy sand, sandy loam, and sandy textures (Rini et al., 2023; Sukarman et al., 2022). Failure to account for these textural differences when assessing SOCs and porosity may lead to inaccurate estimations (Wenzel et al., 2022). Consequently, PTFs serve as essential tools to mitigate potential biases in measurement. Pedotransfer Functions (PTFs) were used to develop a model that enhances the prediction of BD and SOCs in topsoil (0–20 cm) across the European Union and the United Kingdom, contributing to more precise large-scale soil modeling (S. Chen et al., 2024).

The oil palm plantation industry in Indonesia has experienced significant expansion, particularly on the islands of Sumatra and Kalimantan (Syahza & Asmit, 2020). According to Kementan (2023) Central Kalimantan has emerged as the leading palm oil producer within Kalimantan, achieving an average yield of approximately 4.52 tons per hectare, amounting to a total production of 8,642,508 tons across 1,912,526 hectares. While the development of oil palm plantations contributes positively to the economic growth of smallholder farmers and national revenue, it also presents several environmental challenges (Apresian et al., 2020). The conversion of forested land into oil palm plantations accelerates the release of CH_4 and CO_2 into the atmosphere, exacerbating greenhouse gas emissions (Cooper et al., 2020; Wan Mohd Jaafar et al., 2020). The increase in CO_2 emissions by oil palm plantations is 0.01577 Gt CO_2 C yr^{-1} (Wan Mohd Jaafar et al., 2020). Moreover, CH_4 absorption rates in mineral soils within oil palm plantations (85 µg m^{-2} h^{-1} CH_4) are substantially lower compared to forest soils (300 µg m^{-2} h^{-1} CH_4) (Drewer et al., 2021). These environmental concerns directly conflict with Sustainable Development Goals (SDGs) 13 and 15, which emphasize climate change mitigation and the preservation of terrestrial ecosystems.

Accurate soil organic carbon stock (SOCs) data is essential in oil palm plantations to guide land management, reduce CO_2 emissions, and ensure sustainable productivity. Pedotransfer functions (PTFs) enhance SOCs estimation by utilizing existing data, such as bulk density and organic carbon, efficiently, minimizing effort, time, and costs (Bagnall et al., 2022; Van Looy et al., 2017). Reliable PTFs with low error rates are critical for policy decision-making (Arbor et al., 2023). Bulk density, expressed in g cm^{-3} or Mg m^{-3}, is calculated as the soil's dry weight divided by its total volume, including particle and pore spaces (Schillaci et al., 2021). It serves as an indicator of porosity (Qin et al., 2022), water availability, and SOCs levels (dos Reis et al., 2024). Extensive research has utilized PTFs to improve the accuracy of SOCs assessment estimates by correcting for organic carbon content and bulk density (S. Chen et al., 2024; Palladino et al., 2022; Ziviani et al., 2024). The application of PTFs has been demonstrated to enhance measurement precision and reduce potential errors in bulk density calculations, a critical determinant of SOCs levels (Do et al., 2024). Previous studies have examined land degradation neutrality through the use of carbon sequestration pedotransfer functions across various land use and land cover classifications in humid tropical regions (Chidozie et al., 2021).

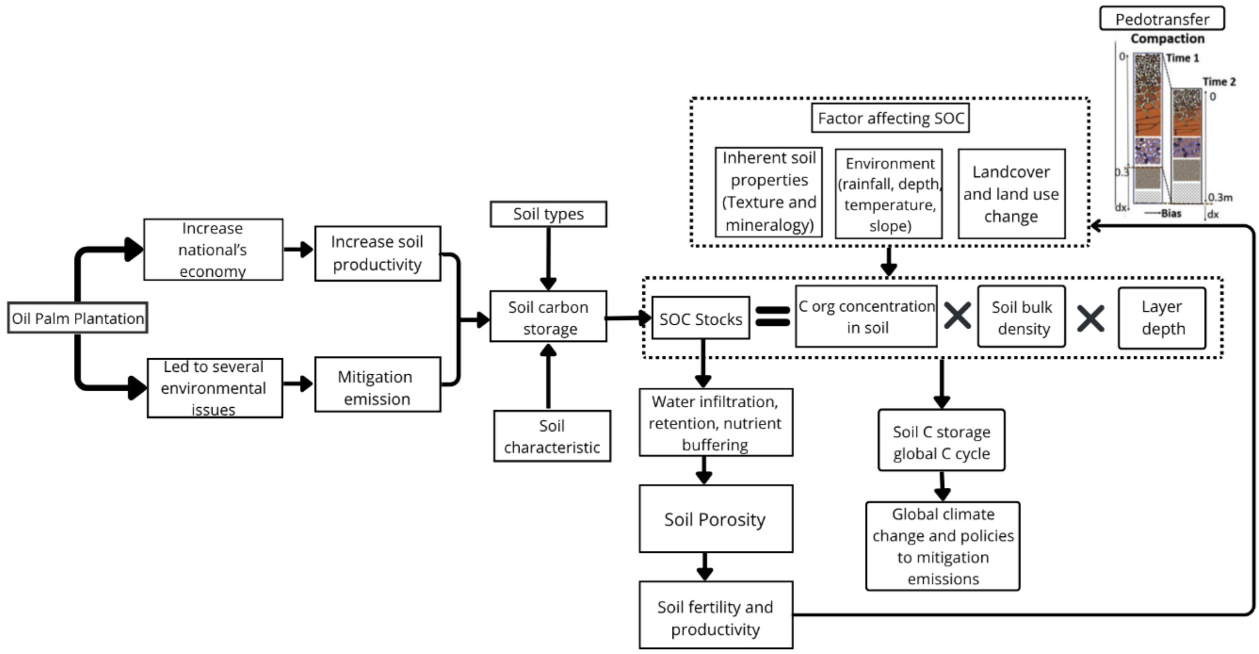

Figure 1. The manuscript layout highlights the significance of evaluating SOCs and porosity using PTFs in oil palm plantations.

As PTFs' estimations are inherently location-specific (Schiedung et al., 2022) and derived from existing analytical datasets, further research is required to refine estimation methodologies across different soil types within Central Kalimantan's oil palm plantations. Therefore, this study aims to: (1) assess SOCs and soil porosity using models that incorporate PTFs and those that do not; and (2) determine the key soil parameters that influence SOCs and soil porosity across varying soil types within oil palm plantations in Central Kalimantan, Indonesia. The manuscript layout, which emphasizes the importance of evaluating SOCs and porosity using PTFs in oil palm plantations, is presented in Figure 1.

2. MATERIAL AND METHODS

2.1. Soil Sampling

The research was conducted in Asam Baru Village, Danau Seluluk District, Seruyan Regency, Central Kalimantan, with coordinates 2°26'26" S – 112°15'43" E, annual rainfall of 2,342 mm, and a flat slope gradient. The survey used a descriptive explorative approach and a purposive sampling method to determine the sampling points (Fig. 2). Purposive sampling is an efficient method for capturing variability sources with a limited sample size, tailored to specific research needs (Ariyanto et al., 2021; Dong et al., 2021). Soil sampling was conducted by describing the soil profile (De Feudis et al., 2022) to a depth of 60 cm, and topsoil and subsoil horizons were taken from oil palm plantation land with four different soil types: Inceptisols, Entisols, Ultisols, and Alfisols (each with 6 replications).

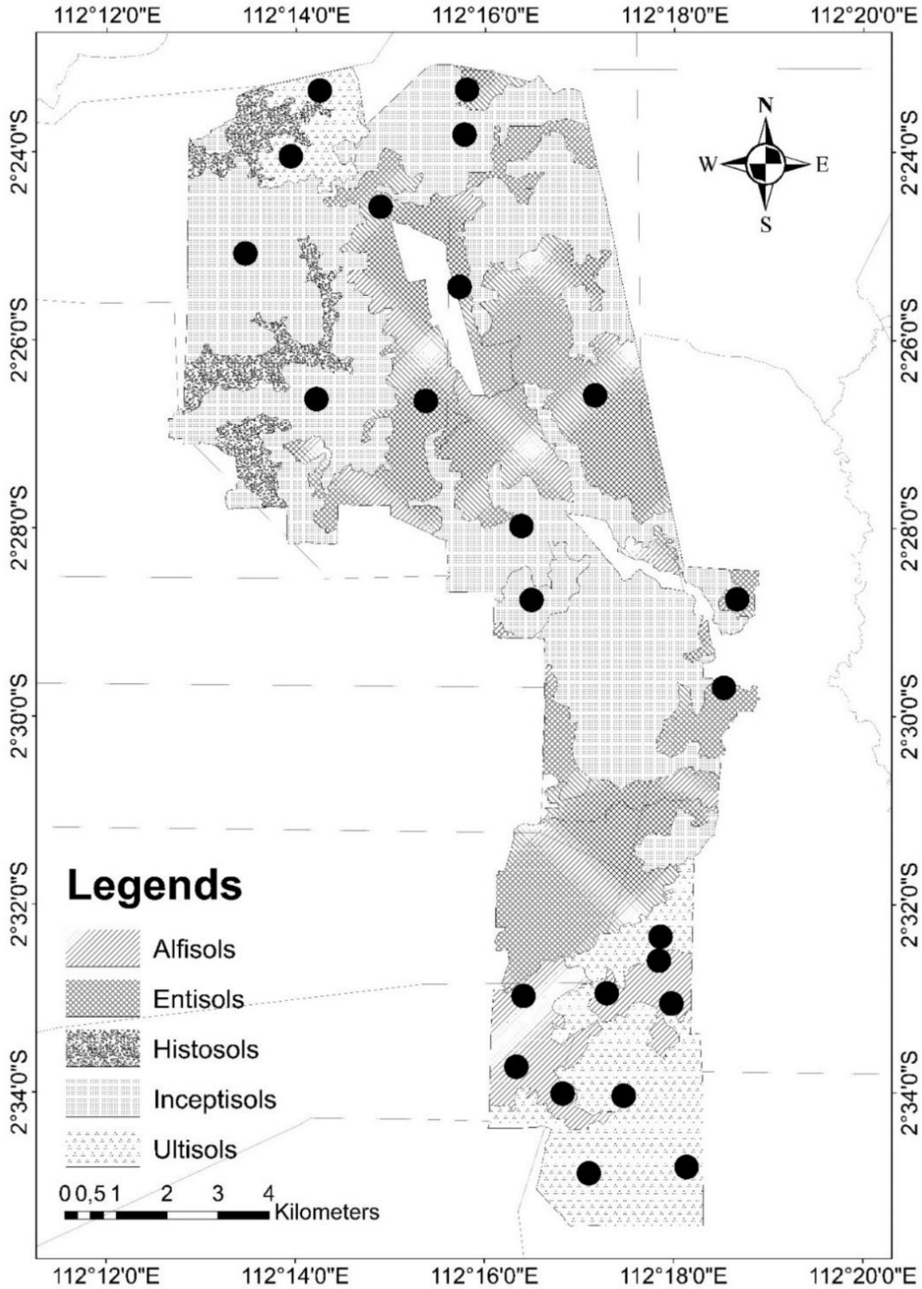

Figure 2. Map of sampling location

2.2. Data Collection and Analysis

The correction factors in PTFs applications encompass a variety of soil parameters such as pH H_2O, pH KCl, organic carbon (C-org), bulk density (BD), particle density (PD), soil texture (silt, sand, clay), elevation, cation exchange capacity (CEC), and microbial carbon (C-mic) (Khan & Chiti, 2022). These parameters were measured using standardized methods: pH with a pH meter (Hale et al., 2020), soil texture through the pipette method (Igaz et al., 2020), bulk density via gravimetry (Hikouei et al., 2021) and particle density using a pycnometer (Santos et al., 2022). CEC was determined by NH_4OC extraction (Nel et al., 2023), organic carbon with the Walkley-Black method (Mustapha et al., 2023), and microbial carbon through fumigation and extraction (Bertozzi et al., 2020). These measurements play a crucial role in refining PTFs equations and improving prediction accuracy.

2.3. Pedotransfer Functions for C-org

The PTFs equation that corrects C-org to produce *Cref* is expected to be used on various types of mineral soils in oil palm plantations to estimate SOC stock. The *Cref* equation is the corrected C-org shown in Equations 1 and 2 by Hairiah et al. (2020).

$$Cref = 0.9 \times ((\text{Dlow } 0.705 - \text{Dup } 0.705)/((0.705 \times (\text{Dlow} - \text{Dup})) \times \text{EXP}(A) \text{ ......} [1]$$

$$A = 1.333 + 0.00994 \times \text{Clay\%} + 0.00699 \times \text{Silt\%} - 0.156 \times \text{pH} + 0.000427 \times \text{Elev} + 0.834 \times \text{Andisol?} + 0.363 \times \text{Wetland?} \text{ ......} [2]$$

With Dlow representing lowermost soil depths and *Dup* representing the uppermost (cm), pH with pH KCl, Elev for elevation (masl), and Andisol? and Wetland? have a value of 1, if Andisol and Wetland are found at the research location. clay% and silt% particles are obtained from soil texture analysis.

2.4. Pedotransfer Functions for Bulk Density

The corrected bulk density (BDref) uses a texture-based PTFs that consists of silt, sand, and clay. The PTFs equation results estimate BD for the available C-org in soil with specific textures. The *BDref* equation by Hairiah et al. (2020) is shown in Equation 3.

Sand Size is the average particle size of sand (default 290), the value of organic matter in the soil (1.7 × C-org), and Topsoil with a value of 0 or 1. The results of the soil characteristic analysis used as correction factors are shown in Table 2.

$$BDref = \text{IF}((\text{Clay\%} + \text{Silt\%}) < 50; 1/((-1.984 + 001841 \times 1.7 \times \text{C} - \text{org} + 0.032 \times \text{Topsoil?} + 0.00003576 \times (\text{Clay\%} + \text{Silt\%})) + 67.5/(\text{SandSize} + 0.424 \times \text{LN}(\text{SandSize}))); 1/((0.603 + 0.003975 \times \text{Clay\%} + 0.00207 \times (1.7 \times \text{C} - \text{org})2 + 0.01781 \times \text{LN}(1.7 \times \text{C} - \text{org}))) \text{ ......} [3]$$

2.5. Determination of SOC Stocks (SOCs)

Each sampling point's SOCs (kg m^{-2}) are calculated using Equation 4. The research location has minimal rock presence, so it can be ignored in this equation. The SOCs equation is shown in Equation 4 (Suleymanov et al., 2023).

$$\text{SOCs} = (\text{SOC} \times \text{BD} \times \text{D})/10 \text{ ......} [4]$$

where SOCs is SOC stock; SOC is the organic carbon content in %; BD is bulk density, g cm^{-3}; D is the layer thickness; and 10 is the conversion factor from ton ha^1 to kg m^{-2}. In the PTFs equation, SOC will be replaced with *Cref* and BD with *BDref* as shown in Equation 5. This substitution aims to determine the extent to which SOCs values are corrected using the PTFs equation. Then, the SOCs assessment results will be classified based on the classification by Burghardt et al. (2018), as presented in Table 1.

$$\text{SOCs\_ref} = (\text{SOC} \times \text{BDref} \times \text{D})/10 \text{ ......} [5]$$

2.6. Determination of Soil Porosity

Soil porosity is assessed twice using different models (Eq. 6 & 7). The first model uses the parameters BD and PD without any corrected factors, and the second model replaces BD with *BDref* as the corrected factor from PTFs. The equation used to assess porosity is based on the research by Rahayu et al. (2020).

Table 1. Classification of SOC stock (SOCs)

No.	SOCs (kg m^{-2})	Class
1	<2	Very low
2	2-4	Low
3	4-8	Moderate
4	8-16	High
5	16-24	Very High
6	>24	Extremely

Table 2. Soil properties in different soil types

Soil Type	pH H_2O	pH KCl	Clay %	Silt %	Sand %	Elevation (masl)	CEC (cmol(+) kg^{-1})	C-mic (μ g^{-1})
				Mean ± Standard Deviation				
Inceptisol	5.92a±0.30	4.80a±0.01	26.00ab±16.54	20.93ab±13.62	53.07ab±24.07	95.38b±42.3	16.91b±4.46	0.24ab±0.13
Entisol	6.30a±0.61	4.66a±0.65	16.97a±8.83	13.77a±13.77	69.27b±16.33	70.85ab±22.43	11.19a±4.77	0.19a±0.05
Ultisol	6.20a±0.05	4.28a±0.01	18.21ab±0.10	27.52ab±2.52	54.28ab±2.73	49.55a±2.68	15.56ab±2.01	0.28ab±0.07
Alfisol	6.23a±0.20	4.66a±0.15	34.74b±34.74	30.27b±5.28	34.98a±16.20	61.50ab±3.83	13.07ab±1.70	0.37b±0.06
p-value	0.305	0.083	0.045*	0.028*	0.018*	0.024*	0.048*	0.012*

Remarks: * = significant; ** = very significant; numbers followed by the same letter in the same row show no significant difference with the level of 5%

$$Porosity\ (\%) = (1 - \left(\frac{BD}{PD}\right) \times 100\% \quad [6]$$

$$Porosity\_ref\ (\%) = (1 - \left(\frac{BDref}{PD}\right) \times 100\% \quad [7]$$

2.7. Statistical Analysis

Statistical analysis was performed using Minitab Statistical software 22 and RStudio 4.2.2, including One-Way ANOVA (Analysis of Variance) with independent factors being soil type and the dependent factor being soil characteristic traits. If significant, it is followed by Tukey's pairwise comparisons test ($p < 0.05$). The relationships between soil properties are determined using Pearson's correlation. Stepwise regression determines the most accurate model for estimating SOCs and porosity.

3. RESULTS

3.1. Soil and Environmental Characteristics

The soil type in oil palm plantations significantly ($p < 0.05$) affects soil properties, including clay, silt, sand, elevation, CEC, and C-mic. However, it does not significantly ($p > 0.05$) influence pH H_2O and pH KCl (Table 2). The pH H_2O ranges from 5.92 to 6.3, while the pH KCl ranges from 4.28 to 4.80. Clay content in the soil is significantly influenced by soil type, with the highest values observed in Alfisols (34.7%), which differ significantly from Entisols (16.9%) but not from Inceptisols (26%) and Ultisols (18.2%). This pattern is consistent with the silt content, where Alfisols have the highest values. These are not significantly different from Ultisols and Inceptisols, but they do differ significantly from Entisols. In contrast, Entisols exhibit the highest sand content, which is significantly different from Alfisols. Soil type also significantly ($p<0.05$) affects CEC and C-mic. The highest CEC is observed in Inceptisols (16.9 cmol kg^{-1}), showing no significant difference from Ultisols and Alfisols, whereas the lowest CEC is found in Entisols. Similarly, the highest C-mic is seen in Alfisols (0.37 µg g^{-1}), and the lowest is in Entisols (0.19 µg g^{-1}), with no significant difference from Ultisols and Inceptisols.

3.2. Pedotransfer for C-organic

Soil type does not significantly affect ($p > 0.05$) C-org and *Cref* (Table 3). Uncorrected C-org has a higher concentration, ranging from 1.47% to 1.86%, compared to *Cref*, which ranges from 0.77% to 1.09%. C-org values for Inceptisols (1.86%) are not significantly different from Alfisols (1.63%), Ultisols (1.56%), and Entisols (1.63%), with the order being Inceptisol > Alfisol > Ultisol > Entisol. After correction, resulting in *Cref*, while differences are not significant, there is a change in the order of carbon concentration for each soil type to Inceptisol > Entisol > Ultisol > Alfisol, with *Cref* values of 1.09%, 0.98%, 0.93%, and 0.77%, respectively (Table 3). The *Cref* value for Entisols is 53% lower than the C-org value, and other soil types also show reductions ranging from 33% to 41%.

3.3. Pedotransfer for Bulk Density

Soil type does not significantly affect ($p > 0.05$) BD but significantly affects ($p < 0.05$) Bdref (Table 4). Uncorrected BD values are lower, ranging from 1.18 to 1.27 g cm^{-3}, compared to BDref values, which range from 1.26 to 1.32 g cm^{-3}.

Table 3. Means of C-org and Cref for different soil types

Soil Type	C-org, %	Cref, %
	Mean ± Standard Deviation	
Inceptisol	1.86a±0.55	1.09a±0.48
Entisol	1.47a±0.91	0.98a±0.70
Ultisol	1.56a±0.49	0.93a±0.31
Alfisol	1.63a±0.17	0.77a±0.11
p-value	0.71	0.70

Remarks: numbers followed by the same letter in the same row show no significant difference at the level of 5%

Table 4. Means of BD and BDref for different soil types

Soil Type	BD, g cm^{-3}	*BDref*, g cm^{-3}
	Mean ± Standard Deviation	
Inceptisol	1.19a±0.09	1.26ab±0.17
Entisol	1.18a±0.09	1.27ab±0.12
Ultisol	1.27a±0.05	1.32a±0.22
Alfisol	1.18a±0.07	0.99b±0.20
p-value	0.16	0.02*

Remarks: numbers followed by the same letter in the same row show no significant difference at the level of 5%

Table 5. Means of SOCs and SOCs_ref for different soil types

Soil Type	SOCs, kg m^{-2}	SOCs_ref, kg m^{-2}
	Mean ± Standard Deviation	
Inceptisol	10.32a±4.71	6.66a±4.20
Entisol	8.98a±8.06	6.87a±4.29
Ultisol	10.92a±3.83	7.09a±3.21
Alfisol	8.15a±8.15	3.43a±1.61
p-value	0.78	0.48

Remarks: numbers followed by the same letter in the same row show no significant difference at the level of 5%

However, for Alfisols, the BD (1.18 g cm^{-3}) is higher compared to *BDref* (0.99 g cm^{-3}). The BD values for Entisols (1.27 g cm^{-3}) are not significantly different from Inceptisols (1.19 g cm^{-3}), Alfisols (1.18 g cm^{-3}), and Ultisols (1.19 g cm^{-3}), with the order being Entisol > Inceptisol > Alfisol > Ultisol. The lowest *BDref* is found in Alfisols (0.99 g cm^{-3}), which is significantly different from Ultisols (1.32 g cm^{-3}), but not from Entisols (1.27 g cm^{-3}) and Inceptisols (1.26 g cm^{-3}). Corrected BD for Alfisols shows a decrease of 16.1% compared to uncorrected BD, while other soil types experience an increase ranging from 3.78% to 7.09%.

3.4. Pedotransfer for Soil Organic Carbon Stock (SOCs)

Soil type does not significantly affect SOCs ($p > 0.05$) and SOCs_ref (Table 5). The SOCs calculated using uncorrected C-org have higher concentrations, ranging from 8.15 to 10.92 kg m^{-2}, compared to those calculated with Cref, which range from 3.43 to 7.09 kg m^{-2}. The SOCs values for all soil types fall into the high category, with the order being Ultisols (10.92 kg m^{-2}) > Inceptisols (10.32 kg m^{-2}) > Entisols (8.98 kg m^{-2}) >

Alfisols (8.15 kg m^{-2}). After correction, the SOCs_ref values fall into the low and medium categories. Alfisols (3.43 kg m^{-2}) are in the low category, while Ultisols (7.09 kg m^{-2}), Entisols (6.87 kg m^{-2}), and Inceptisols (6.66 kg m^{-2}) are in the medium category. The decrease in SOCs for Alfisols is 57.9% compared to uncorrected SOCs, while other soil types experience a decrease ranging from 23.4% to 35.4%.

3.5. Pedotransfer for Soil Porosity

Soil type significantly influences ($p < 0.05$) uncorrected porosity (Porosity) and corrected porosity (Porosity_ref) (Table 6). Uncorrected porosity values range from 37.98% to 51.2%, which are higher than corrected porosity values, ranging from 36.21% to 49.79%, except for Alfisol. Alfisol shows a higher corrected porosity (53.2%) compared to its uncorrected value (45.37%). The highest Porosity_ref is found in Alfisols (53.2%), which significantly differs from Ultisol (36.21%) but not significantly from Entisol (49.79%) and Inceptisol (45.67%). Uncorrected porosity is highest in Entisol (51.24%), significantly different from Ultisol (37.98%) but not from Inceptisol (47.28%) and Alfisol (45.37%) (Table 6). After correction, Alfisol's porosity increased by 14.8%, while other soil types experienced a decrease ranging from 2.8% to 4.6%. This adjustment reveals that Alfisol has the highest porosity post-correction, whereas Entisol had the highest porosity before correction.

3.6. Correlations Between Soil Properties

Significant correlations were found between soil properties, especially among correction factors (Fig. 3). Porosity had a significant negative correlation with silt (r = -0.46), CEC (r = -0.43), and a very significant negative correlation with BD. Porosity_ref had a significant negative correlation with CEC (r = -0.41), SOCs (r = -0.43), SOCs_ref (r = -0.46), and a very significant negative correlation with BD (r = -0.69) and BDref (r = -0.86). BDref had a significant positive correlation with *Cref* (r = 0.42), SOCs (r = 0.43), and a very significant positive correlation with SOCs_ref (r = 0.56), while BD did not significantly correlate with these parameters. Silt had a significant positive correlation with C-mic (r = 0.50) and Clay (r = 0.42). The silt and clay fractions not only maintain C-org stability but also influence the presence of C-mic (Mao et al., 2024). Sand had a significant positive correlation with BDref (r = 0.45). SOCs had a very significant positive correlation with Cref (r = 0.85), C-org (r = 0.83), and SOCs_ref (r = 0.93).

3.7. Regression Analysis of SOCs and Soil Porosity

The regression models generated for SOCs and Porosity and their comparisons between models with uncorrected and corrected (PTFs) indicators to select the most accurate regression model for each SOCs and Porosity indicator (Table 7). The correlation analysis identifies key indicators that contribute to the SOCs and porosity equation model. The SOCs and soil porosity equations consist of two models each. Model 1a represents the SOCs equation with BD (r=0,32), C-org (r=0.83), sand (r=0,16), silt (r=-0,19), clay (r=-0,08), and CEC (r=-0,40) as contributing indicators, while Model 1b corresponds to the SOCs_ref equation with Bdref (r=0.56), Cref (r=0.93), sand (r=0.38), silt (r=-0.37), clay (r=-0.28), and CEC (r=-0.26). Model 2a defines the soil porosity equation with BD (r=-0.79), SOCs (r=-0.29), silt (r=-0,46), clay (r=-0,08), sand(r=0,3), and C-mic (r=-0,21), whereas Model 2b represents the soil porosity_ref equation with BDref (r=-0.86), SOCs_ref (r=-0.46), silt (r=-0.04), clay (r=0.26) , sand (r=0.14), and C-mic (r=0.03). All generated models exhibit R^2 values ranging from 0.65 to 0.91, with the lowest value observed in the porosity model without corrected BD and SOCs (Model 2.a). Determining equations through regression analysis, incorporating BD and SOCs corrected via PTFs has resulted in predictive models for Porosity_ref and SOCs_ref that demonstrate higher accuracy than models without correction of BD and SOCs. Model 1.b (R^2 = 0.91), which represents SOCs with corrected BD and C-org (BDref and Cref), produces a more accurate equation than Model 1.a (uncorrected equation; R^2 = 0.75). Model 2.a has a lower R^2 value (0.65) compared to Model 2.b (0.81). This indicates that Models 1.b and 2.b are better able to explain variations in soil porosity and SOCs and exhibit higher accuracy than Models 1.a and 2.a.

Table 6. Means of porosity and porosity_ref for different soil types

Soil Type	Porosity, %	Porosity_ref, %
	Mean ± Standard Deviation	
Inceptisol	47.28b±6.54	45.67ab±10.05
Entisol	51.24b±4.14	49.79ab±6.09
Ultisol	37.98a±5.87	36.21a±11.58
Alfisol	45.37ab±4.61	53.26b±9.10
p-value	0.003**	0.030*

Remarks: *= significant; **= very significant; numbers followed by the same letter in the same row show no significant difference with the level of 5%

Table 7. Model of pedotransfer functions

	Independent variable	Dependent variable	R-sq (adj)	*p-value*	Regression Equation
Model 1.a	SOCs	BD, C-org, Sand, Silt, Clay, CEC	0.75	0.000**	SOCs = -24.32 + 6.861 C-org + 17.03 BD + 0.0414 Sand
Model 1.b	SOCs_ref	BDref, Cref, Sand, Silt, Clay, CEC	0.91	0.000**	SOCs_ref = -4.79 + 10.826 Cref + 0.0872 Silt + 0.1521 CEC
Model 2.a	Porosity	BD,SOCs, Silt, Clay, Sand, C-mic	0.65	0.000**	Porosity = 123.0 - 68.1 BD + 0.0855 Sand
Model 2.b	Porosity_ref	BDref, SOCs_ref, Silt, Clay, Sand, C-mic	0.81	0.000**	Porosity_ref = 112.53 - 0.3259 % Silt - 48.59 BDref

Remarks: * = significant; ** = very significant

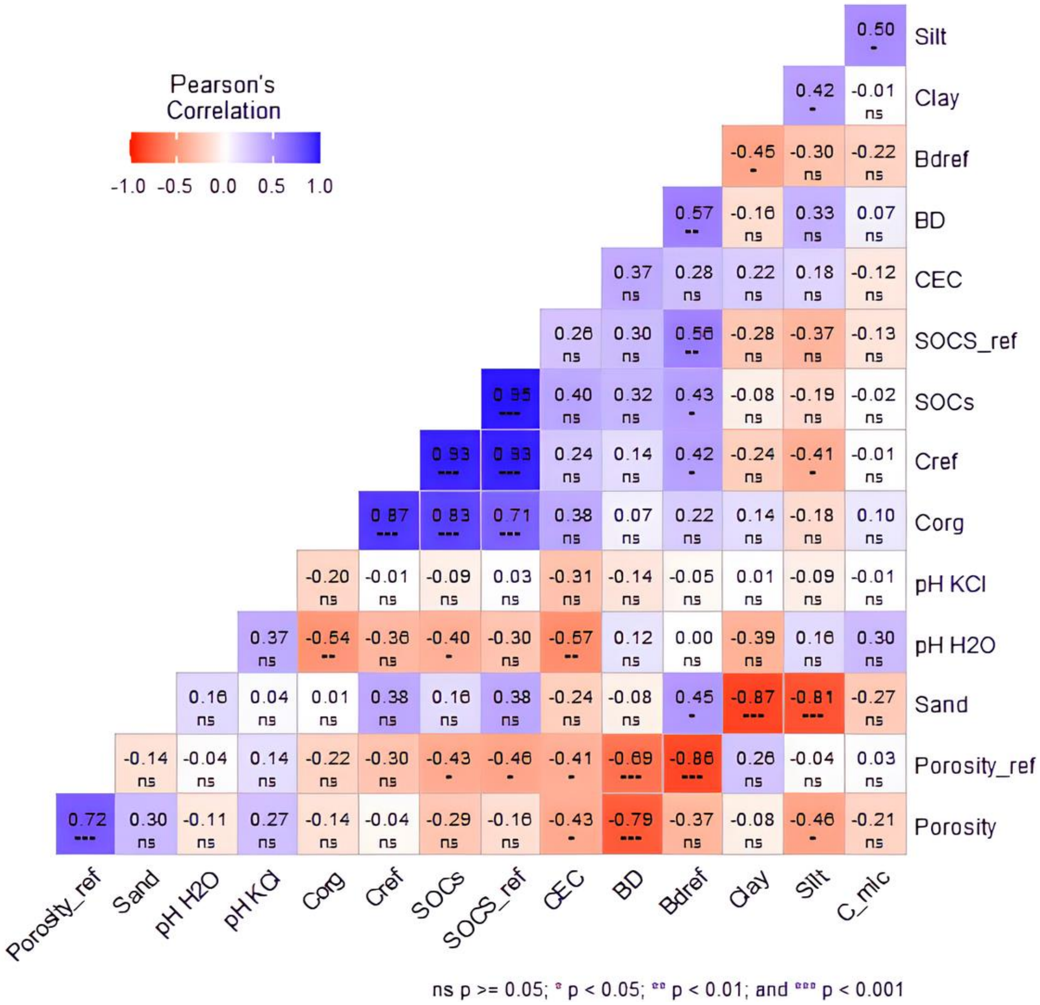

Figure 3. Correlation plot among SOCs, Porosity and predictor variables.

4. DISCUSSION

Entisols, Inceptisols, Ultisols, and Alfisols are all classified as mineral soils with similar physical and chemical characteristics (Owonubi & Mustapha, 2024). However, specific differences become apparent upon closer examination of their physical, chemical, and biological properties (Table 2). Soil type significantly affects several soil characteristics including percentage of sand, silt, and clay, CEC, and C-mic. This study differentiates soils with similar slope gradients, rainfall, and land use to ensure that the results are specifically influenced by inherent factors (soil type). C-org, SOCs, and BD are not directly affected by soil type (Tables 4, 5, & 6), but they are influenced indirectly through ecosystem services, which result from physicochemical properties (Dengiz et al., 2015). Therefore, all ecosystem services need to contribute to the correction of C-org and BD and to the estimation of SOCs and porosity.

Entisols are newly developed soils without horizon development, predominantly consisting of sand fractions due to minimal soil weathering (Warzukni & Jauharlina, 2023). The dominance of sand fractions in soil can lead to several issues, such as low CEC and soil fertility (C-org and C-mic) (da Costa et al., 2020), largely due to the inherent properties of the soil and its parent material (Huang & Hartemink, 2020). C-mic tends to be greater in soils exhibiting a balanced textural composition such as silt loam, sandy loam, and clay loam, in contrast to soils predominantly composed of sandy textures (Li et al., 2020). Among the four soil types, Alfisols are noted for their comparatively more balanced soil textural composition. The lowest C-mic values in Entisols are attributed to the difficulty of microbes attaching to sand fractions, in contrast to Alfisols, which have the highest clay content and consequently the highest C-mic values. This is consistent with the findings of Kusumawati et al. (2020), which indicate that C-mic is significantly affected by soil type differences and depends on the clay content within the soil. The limited biological activity in Entisols is due to physical soil issues, such as poor soil aggregation, and climatic factors, particularly a microclimate that hinders the growth of soil microbes (Herawati et al., 2024).

Soils with larger particle sizes (>2 µm) have lower CEC compared to finer particles (<2 µm) (Bi et al., 2023). This is because larger particles provide a smaller surface area with negative charges for cation retention (Liu et al., 2020). This observation aligns with the study findings, where Entisols, with the highest sand fraction (69.27%), exhibit the lowest CEC compared to other soil types. However, the dominance of sand fractions is not the sole determinant of low CEC. For instance, Alfisols, which have the highest fine texture fractions (clay and silt), do not have the highest CEC; instead, Inceptisols exhibit the highest CEC. This is because Inceptisols have the highest C-org content, although the difference is insignificant (Table 4). Organic matter in soil has numerous negative ion charges and can neutralize pH, thereby increasing the negative charge on colloids and enhancing cation retention in the soil (Purnamasari et al., 2021). Low levels of C-org reduce the soil's negative charge, inhibiting cation exchange. Additionally, soil respiration and microbial-C biomass underscore the critical influence of C-org content on both biological and chemical soil properties (Romadhon et al., 2024). C-org is a crucial indicator in assessing soil quality, fertility, and health due to its diverse roles in supporting ecosystem services within the soil. Thus, obtaining accurate and current C-org values is essential.

C-org is a complex of carbon compounds that includes plant and animal residue, live microbial biomass, and carbon associated with mineral components as organo-mineral complexes, both protected and unprotected (Lal, 2018). Mineral soils, particularly those dominated by sand fractions, generally have low C-org content (Yost & Hartemink, 2019). Soil type does not significantly affect the availability of C-org and Cref (Table 3). However, corrected C-org using pedotransfer functions (PTF) results in lower Cref values. This is consistent with Hairiah et al. (2020), who found that uncorrected C-org ranges from 1.26% to 3.25%, while corrected Cref ranges from 0.577% to 1%. This demonstrates that PTF can provide a more detailed interpretation of data that cannot be fully explained by actual data using the Walkley-Black method alone. The formation of organo-mineral complexes through SOC adsorption by Clay aggregates and chemical reactions (hydrogen bonding) between Clay surfaces and SOC can enhance SOC stabilization (Xue et al., 2022). Therefore, SOC assessments using the Walkley-Black method may be biased by the presence of Clay that dissolves and gets included in the measurement. PTF is needed to correct C-org values using silt and clay, providing actual C-org values without bias from the presence of clay and silt.

Bulk density (BD) represents the dry weight of solid components per unit volume (Sinclair et al., 2020). Although soil type does not significantly affect BD, it significantly affects BDref. BD is generally lower than BDref, except for Alfisols. The observed changes are due to the BDref with soil texture (sand, silt, clay), resulting in more accurate data and a regression model (Arbor et al., 2024). Soil texture plays a critical role in determining soil compactness and the distribution of macro and micro pores, both of which directly affect bulk density conditions (de Lima et al., 2022). Alfisols, with the lowest BDref, also have the smallest sand fraction. According to Alaboz et al. (2021), sand has a significantly positive correlation, and clay has a significantly negative correlation with BD. This is aligned with the study results, showing that BDref has a significant negative correlation with clay and a significant positive correlation with sand, whereas BD does not show a strong correlation with these soil fractions (Fig. 3). Soils dominated by sand fractions are prone to compaction due to weak cohesion between particles, leading to easy compression through sand and silt reorganization and biological disturbances (Huang & Hartemink, 2020). Soil compaction can increase bulk density (Shaheb et al., 2021).

The lower SOCs_ref values compared to uncorrected SOCs indicate that SOCs_ref may underestimate SOCs by ignoring the influence of C-org within soil particles. Ignoring C-org contained within coarse soil fractions in coarse-textured soils can also lead to an underestimation of SOCs (Gross & Harrison, 2018). The urgency of correcting SOCs with PTFs is also evident from the stronger correlation between SOCs_ref and BDref compared to the relationship between SOCs and BD, proving that BDref has a higher potential to contribute as a predictive variable. The findings indicate the necessity of applying pedotransfer functions (PTFs) to achieve more accurate estimates of SOC and BD in different soil types. PTF development primarily focuses on refining regression methods to improve estimates by accounting for soil physical and chemical interactions, while many critical factors remain underexplored (Weber et al., 2024). For instance, the correction in C-org values using PTF demonstrates the capability to remove biases associated with traditional measurement methods like Walkey and Black. Similarly, the correction in BD values shows a significant improvement in the estimation of soil bulk density by incorporating soil texture components such as sand, silt, and clay.

Determining porosity_ref uses BDref (corrected BD), while porosity uses BD (BD without correction), so that it produces a different value from porosity without correction. The distribution of porosity_ref data becomes wider because it is influenced by Bdref*,* which has been corrected with soil texture (Table 4). The *p-value* on porosity is lower than porosity_ref, but this does not mean that PTFs is not needed. Uncorrected porosity is significantly influenced by soil type, as the physical properties, structure, and natural particle distribution determine pore space availability. The application of the PTF correction may result in slightly higher *p-values*, but it provides more accurate predictions by including additional variables, such as fine and coarse soil texture. As the PTFs correction usually includes more factors to improve the accuracy of the estimation, it may result in higher *p-values* as it accounts for a wider variability (Bzdok et al., 2020). This may reduce the statistical significance of certain elements, but increase the overall reliability and validity of the results. Corrected porosity (Porosity_ref), as adjusted using Pedotransfer Functions (PTFs), enhances the accuracy of the significant negative relationship between porosity and both SOCs and SOCs_ref. In contrast, uncorrected porosity does not show a significant correlation with SOCs and SOCs_ref (Fig. 3). The relationship between porosity and SOCs is not straightforward but is mediated by correction indicators such as C-org, soil texture particles, and elevation. The study area soils, dominated by sand fractions, exhibit high porosity with a substantial proportion of macropores. High macropore content can reduce SOC content in the soil (Guo et al., 2020), because organic matter inputs are easily transformed into CO_2. Organic matter inputs to the top layer decompose quickly by microbial activity, resulting in slower accumulation and rapid degradation of atmospheric CO_2 (Arunrat et al., 2020). Although adding more organic matter can enhance nutrient release to plants, it does not translate to higher soil absorption due to the rapid turnover.

The limited correlation between SOCs and SOCs_ref with soil fractions (sand, silt, and clay) is not attributable to inaccuracies in measurement but rather to biases caused by the high proportion of sand in the soil. This high sand content disrupts the relationship between fine-textured components (clay and silt) and SOCs, resulting in a non-linear association (Gonçalves et al., 2017). Correlation analysis was performed to identify relationships among soil properties, serving as a reference for distinguishing between independent and dependent variables within the PTFs equation (Alaboz et al., 2021). The chosen predictor variables included clay, silt, sand, C-org, and pH (Z. Chen et al., 2024), C-mic, and CEC. However, one indicator, pH KCl, showed no significant correlation with other indicators and was consequently excluded as a predictor variable. Selecting predictor variables (dependent variables) based on correlation tests with independent variables helps reduce potential errors in the estimation model (Zhang et al., 2020). The accuracy of PTF models is determined based on their coefficients of determination (R^2) values (Sun et al., 2019), with R^2 values closer to 1 indicating a more precise model. The coefficient of determination (R^2) represents the proportion of the dependent variable that can be predicted by the independent variables (Chicco et al., 2021). Soil texture (sand, silt, and clay) contributes to all four estimation models for SOCs and Porosity, highlighting soil texture particles as the most prominent predictors for SOCs, particularly the sand and silt fractions (Hounkpatin et al., 2018). The research findings indicate that after applying corrections using PTFs, the correlation values between SOCs and Porosity with the response variable have improved and become more accurate. A strong correlation between the predictor and response variables indicates that selecting these predictors significantly enhances the performance of PTFs (Perreault et al., 2022). The enhanced accuracy of Models 1.b and 2.b (corrected models) can be attributed to the stronger relationship observed between the predictor variables and the response variables after corrections were applied using PTFs, compared to models without such corrections (Fig. 3). Models 1.b and 2.b provide a more comprehensive explanation of variations in SOCs and porosity, making them more valuable for practical applications in soil research and management, as well as serving as a reference for sustainable oil palm plantation strategies compared to Models 1.a and 2.a. Information on SOCs and Porosity plays a crucial role in guiding land management practices for oil palm plantations (Rahman et al., 2021). Oil palm plantations are often cultivated on marginal lands with diverse soil types, such as Entisols, Ultisols, and Inceptisols (Segara et al., 2019), and other varieties, making it challenging to define a comprehensive land management strategy for oil palm plantations. Therefore, to predict and establish SOCs and porosity values that are both accurate and applicable across varying conditions, it is essential to consider additional soil factors (texture, BD, C-org) through the application of PTFs.

5. CONCLUSION

Our study developed pedotransfer function (PTF) models to predict soil organic carbon (SOC) and porosity in oil palm plantations. Equations using PTFs showed higher predictive accuracy. Accurate SOCs and porosity estimates are essential for policymaking and sustainable land management. Pedotransfer-based approaches enable universal strategies and promote best agricultural practices. Since this study tested PTF models on four mineral soil types, further validation is needed. Future research should examine peat soils and other mineral soil types.

Declaration of Competing Interest

The authors declare that no competing financial or personal interests may appear to influence the work reported in this paper.

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