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RESEARCH ARTICLE

LiDAR imagery-based relief interpretation for soil organic carbon (SOC) estimation in the Quaternary Sumbing and Tertiary Kulon Progo Volcano Transition Zone, Central Java, Indonesia

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Abstract

Typically, the transition zone of quaternary and tertiary volcanoes is a potential area for agricultural development but is prone to landslides. Landslide occurrences and the use of former landslide zones exhibit a distinct soil organic carbon (SOC) distribution, necessitating analysis to sustain agricultural output. Laboratory SOC measurements on landscape size are not expedient, necessitating the development of an estimating method for representation. This study aims to analyze the relationship between relief and SOC using LiDAR (Light Detection and Ranging) data. LiDAR acquisition was carried out to identify relief units as units of analysis. Soil sample measurements were carried out in the laboratory with the parameters analyzed including pH, Bulk Density, Moisture Content, Organic Carbon, Organic Matter, N-total, CN Ratio and Cation Exchange Capacity. The results showed that SOC and relief had R^2 = 0.89 in the upper layer (0 – 20 cm) and 0.86 in the lower layer (20 - 40 cm). Relief has a high correlation with soil characteristics at the top and bottom of soil depths. It is because of relatively stable elevation and relatively dynamic land cover that SOC is spread out in a clustered way. This research can be used as a basis for agricultural land management, especially in areas prone to landslides.

Keywords: Relief; LiDAR; soil organic carbon; volcanic transition zone.

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1. Introduction

Soil organic matter is important in maintaining ecosystem balance, contributing to carbon storage and soil fertility. Carbon stored in soil is the largest carbon reserve in almost all terrestrial biomes (Kutsch et al., 2010). SOC is one of the leading indicators in determining soil quality and productivity, especially in agricultural land. SOC is represented as the most important soil quality indicator that affects soil's physical, chemical, and biological properties (Gerke, 2022; Paz Salazar et al., 2020). SOC significantly affects soil health, food security, greenhouse gas emissions, and climate change. Increasing SOC is considered beneficial for soil function and is associated with increased agricultural productivity (Kim et al., 2021; Liptzin et al., 2022). Therefore, monitoring SOC at the landscape scale is important in sustainable land use planning efforts.

Conventional SOC monitoring using laboratory-based methods has limitations, mainly when applied to large landscape scales. Sampling, analysis, and interpretation of results require a relatively long time and significant resources. This process is a challenge in supporting the need for fast and precise planning. Developing a more practical, fast, and accurate SOC estimation method is necessary to overcome these obstacles. SOC dispersion at the landscape scale should be represented by relief. Relief and other topographic metrics are primary factors affecting SOC distribution. They influence soil movement through water flow and tillage, leading to soil gain in lowland areas and loss in sloping areas (Kołodyńska-Gawrysiak, 2023). The relief approach is anticipated to offer pertinent information to aid in agricultural land management decision-making.

Estimation of SOC distribution can be done quickly by utilizing remote sensing. A remote sensing technique that can be employed is relief interpretation with LiDAR images. LiDAR detects the distance between the sensor and the target by emitting laser pulses and receiving reflections from objects on the ground surface. LiDAR has been widely used in various fields because of its ability to provide detailed and accurate spatial data. LiDAR can collect three-dimensional topographic data quickly and accurately, which is important for various applications such as mapping and modeling (Elaksher et al., 2023). LiDAR can detect the ground surface even under dense vegetation to produce an accurate digital elevation model (DEM). Notably, the data produced in the form of a point cloud allows the creation of a detailed 3D relief model, visualizing topographic features such as slopes, valleys, or ridges (Huang et al., 2023). Topographic data (aspect, slope) from LiDAR proved to be an important variable, suggesting that LiDAR-captured micro-topographic structures help improve the accuracy of SOC estimation with high spatial resolution (He et al., 2025).

Kalijambe Village in Purworejo, Indonesia, has hilly topography dominated by steep slopes. Areas with steep slopes increase the risk of landslides, especially during the rainy season when rainfall intensity is high. Steep slopes not only threaten safety and infrastructure but also impact the environment. Landslides bring environmental consequences such as land degradation, loss of vegetative cover, and disruption of ecosystem equilibrium. Landslides alter the topography of the earth's surface, leading to land degradation. This includes the removal of soil and rock, which can result in the loss of arable land and affect agricultural productivity (Turner, 2018). Landslides cause the loss of soil rich in organic carbon, reducing soil fertility due to the mixing of subsoil with topsoil.

This study aimed to analyze the distribution of SOC in Kalijambe Village, Purworejo, using a LiDAR-based relief approach. Model development with a LiDAR-based relief approach is expected to assist in rapid SOC monitoring. Finally, the model's construction will mirror the SOC distribution in landscape covering. More detailed SOC distribution information can help in planning sustainable agricultural practices, such as more appropriate fertilizer management and soil conservation techniques. The more detailed SOC distribution information can help in planning sustainable agricultural practices, such as more appropriate fertilizer management and soil conservation techniques.

2. Methodology

The study was conducted in Kalijambe, Purworejo, Central Java, Indonesia (7° 34′ 52″ S, 110° 3′ 56″ E). Kalijambe is located in the transition zone of the Kulon Progo Tertiary volcano and the Sumbing Quaternary volcano (Figure 1).

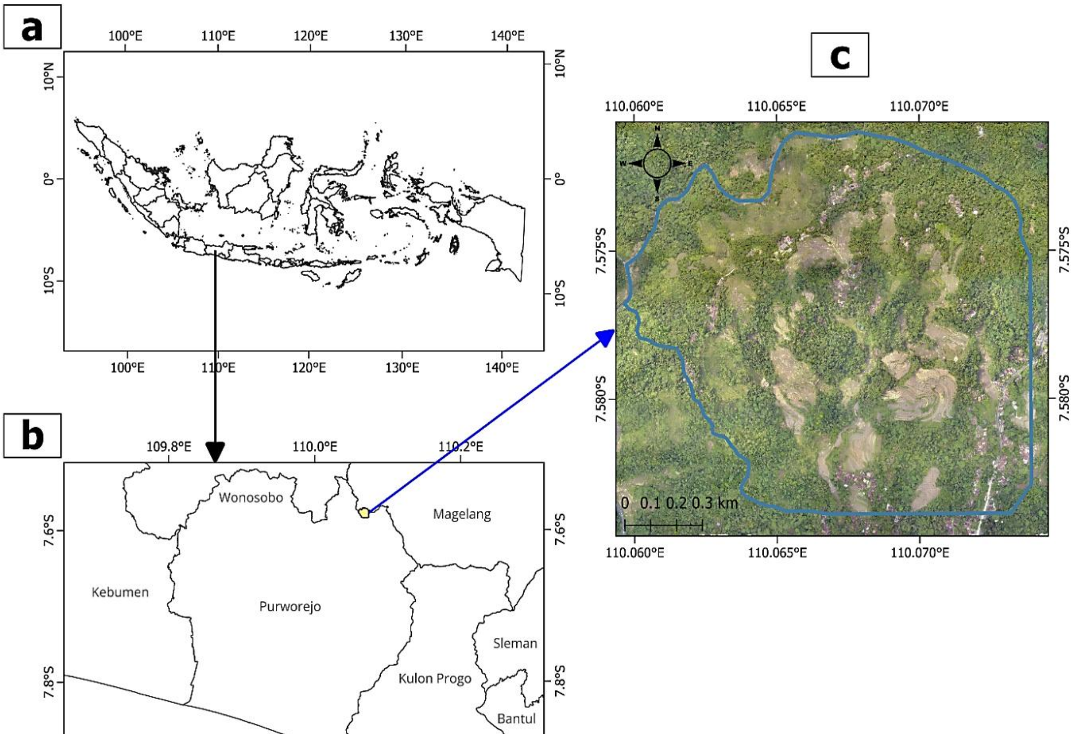

Figure 1. Study site: a.) Indonesia; b.) Purworejo Regency; c.) Kalijambe Village.

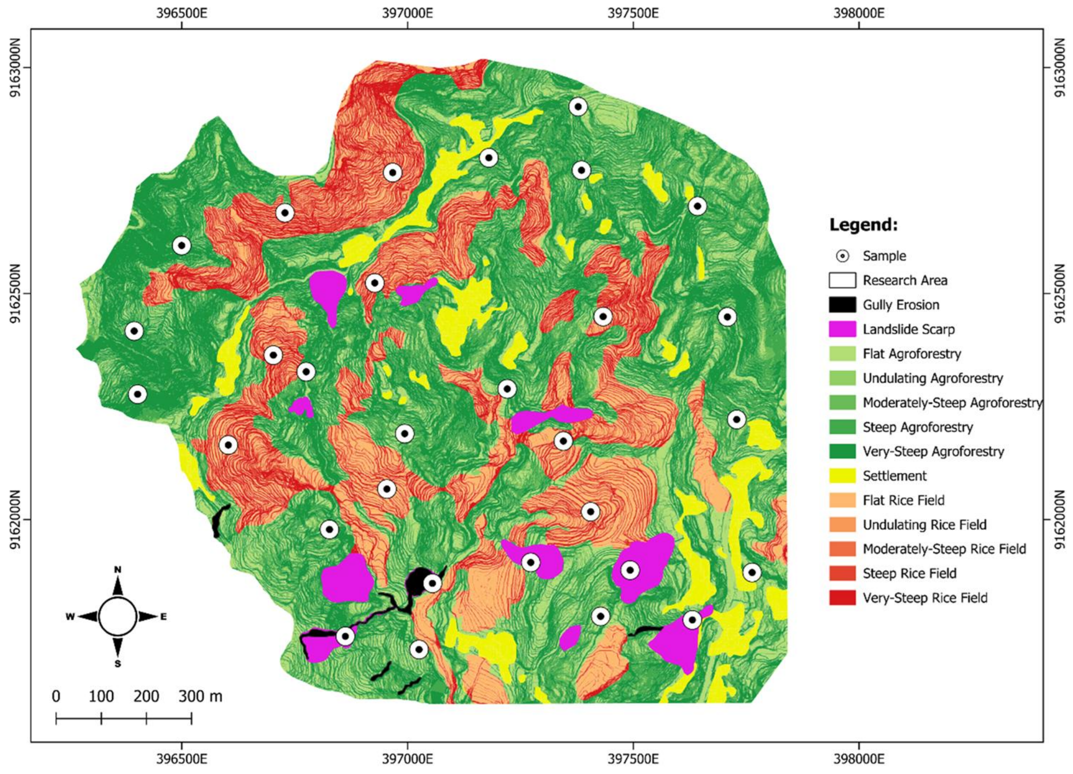

Figure 2. Sampling Points.

Material from the Menoreh volcano is found in the Kulon Progo Tertiary volcanic deposition zone. Menorah volcanic material is tuffaceous with auto classic, fluviatile, tuff, and tuff sandstone parent rocks (Priyono & Sartohadi, 2011). The volcanic parent material, mainly volcanic ash from Mount Sumbing, forms andisol soil. Andisol soil has andic properties caused by the weathering of tephra or other parent materials containing large amounts of volcanic glass. Amorphous minerals such as ferrihydrite, imogolite, allophane, and Al/Fe-humus complexes are the primary constituents of andisol soil. Mount Sumbing exhibits elevated levels of allophane and imogolite, with allophane diameters between 2.24 and 5.93 nm and imogolite lengths ranging from 24 to 187 nm (Fauziah et al., 2022).

Soil Sampling

This study used a quantitative approach and qualitative description to determine the effect of relief on SOC. Remarkably, the parameters measured included organic carbon, organic matter, N-total, CEC (Cation Exchange Capacity), pH, Bulk Density (BD), and moisture content. The soil samples analyzed were 30 points at two different soil depths (0-20 cm and 20-40 cm). Sampling was carried out by considering five topography variations and land use variations (Figure 2). Stratified random sampling was used to ensure the representation of sample distribution. Data was analyzed using multiple linear regression to determine the effect of relief on SOC. Soil sample analysis was carried out in the laboratory to produce precise quantitative values. The spatial distribution of SOC was analyzed using the Fractal Analysis method to identify the spatial distribution pattern of SOC.

Extract LiDAR to interpret the relief information

The initial stage is converting LiDAR data into digital elevation model (DEM) data. LAS format raw data is transformed into raster data. For the conversion, the geographic information system (GIS) programming tool "LAS Dataset to multi-point, followed by Point to Raster" is utilized. Following processing, the data from the DEM are utilized as the foundation for relief interpretation. Relief interpretation is conducted through visual analysis and manual identification. Field assessments are conducted to validate the interpretation outcomes. The land units resulting from the interpretation are 12 units. Soil sampling was carried out on 12 selected land units with repetition in several units so that 30 soil samples were obtained. The carbon value of each soil sample was analyzed in the laboratory using the Walkey-Black approach. Organic matter content can be measured quantitatively volumetrically by titration of bichromate acid (H2K2Cr2O7) (Sartohadi et al., 2012).

SOC Calculation

SOC calculation is carried out using the formula published by the SNI 7724 (2011):

$$Ct = Kd \times \rho \times \%C$$

Where *Ct* (soil carbon content (grams/cm^2)); *Kd* (depth of soil sample, expressed in centimeters, cm); *ρ* (bulk density, grams/cm^3); *%C* organic (carbon content measured in the laboratory). Preparing the SOC estimation model is the initial step in displaying the SOC estimation value. The first stage is calculating the semivariance and fractal dimension (Milos & Bensa, 2016) and continuing with interpolation.

Fractal Analysis

Spatial distribution of SOC was analyzed using the Fractal Analysis method to identify the spatial distribution pattern of SOC. In fractal analysis, semivariance calculations can be used to measure the level of similarity between pairs of soil property points at a certain distance, with detailed formulas presented in the following equation.

$$\gamma(h) = \frac{1}{2\,N(h)} \sum_{i=1}^{N(h)} (Z_{x+h} - Z_x)^2$$

Where γ(h) represents semivariance, h represents distance, N(h) represents the number of points used, Z(x) represents the SOC value at location x, and Z(x+h) represents the SOC value at location x summed at a certain distance (h). Semivariograms derived from semivariance data are needed for the data interpolation procedure. Interpolation is performed with a statistical-spatial methodology. Following data extraction, a quantitative method and qualitative description are used to read the data. Determining the value derived from laboratory measurement of soil characteristics and integrating relief to SOC is the quantitative approach.

3. Results and discussion

LiDAR extraction

LiDAR data has an accuracy of ±3cm, while aerial photographs have a 5cm spatial resolution. Four Ground Control Points (GCPs) and Benchmarks (BMs) were used in the LiDAR acquisition process. Figure 3 shows the final results of the LiDAR data extraction process into DEM. To obtain information on land use in the Kalijambe area (Figure 4), orthophotos from LiDAR photography were manually digitized (Figure 4). Manual digitizing enables more detailed land use classification and mapping, including agroforestry, rice fields, and settlements.

The findings show that the slope class at the study site is dominated by very steep (35%) and steep (26%) classes (Table 1). Interestingly, even with extreme slope conditions, the community still uses the land for agroforestry (Table 2). Using slopes as cultivation areas can increase land vulnerability to geomorphic processes such as erosion, subsidence, and landslides (Abebe et al., 2025). Nevertheless, it was discovered that numerous lands with steep gradients were utilized for agricultural purposes during this investigation. Steep land is often managed by people with low access to resources, resulting in low-moderate productivity. Agricultural expansion onto steep slopes in response to poverty and limited flat land (Zhang et al., 2023). Proper land management and flow regulation are needed to minimize the threat of erosion and landslides.

Table 1
Slope Gradient Variation

Slope Class	Area (ha)	Percentage (%)
Flat	28.05	16
Undulating	16.93	10
Moderately-Steep	22.60	13
Steep	45.90	26
Very-Steep	61.92	35
Total	147.35	100

Table 2
Land use of Kalijambe

Land Use	Area (ha)	Percentage (%)
Settlement	10.69	6%
Agroforestry	116.86	67%
PaddyField	47.86	27%
Total	147.35	100

Spatial distribution of SOC

The analysis of 30 samples showed that the interaction between soil depth, topography, and land use influenced the average SOC value. Furthermore, the SOC value was also influenced by the land management practices applied. Rice fields at 0–20 cm and 20–40 cm depths displayed variable SOC patterns (Table 3). Specifically, variations in SOC values in rice fields were influenced by complex interactions between topography, erosion rates, land management practices, and organic matter accumulation. Organic matter accumulation tends to increase on sloping land because of less erosion. Steep slopes have organic matter that can be transported by erosion, although at some point, re-accumulation occurs at the foot of the slope. Accumulation is often influenced by sediment deposition carrying organic matter, which can be increased by the presence of vegetation (Satriawan et al., 2017; Wu et al., 2023).

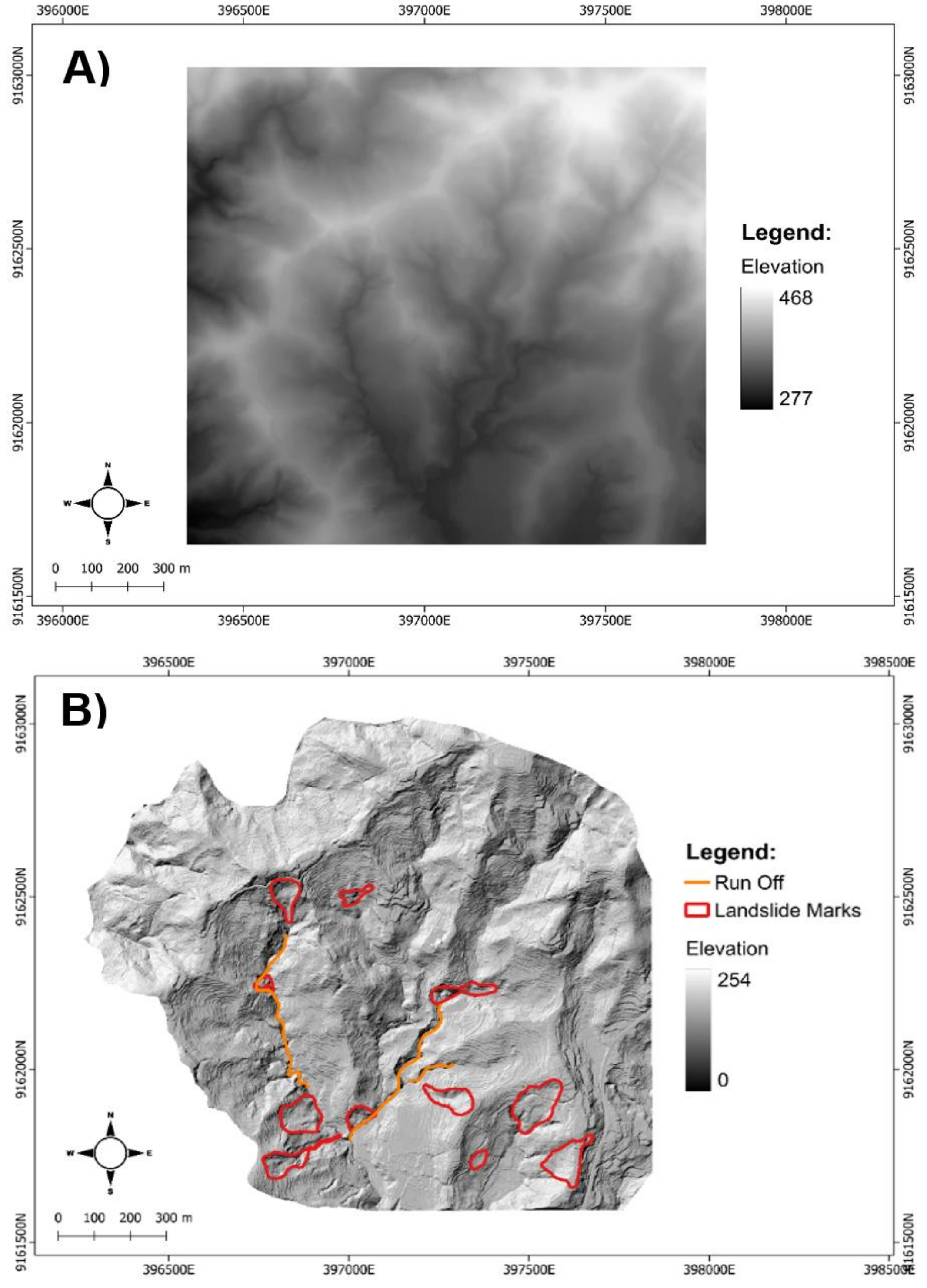

Figure 3. LiDAR extraction: DEM (A) and Hillshade (B).

SOC values tend to fluctuate in agroforestry. However, SOC in agroforestry tends to be higher than in rice fields. This difference indicates that agroforestry has a better capacity to maintain and increase soil organic matter content. Agroforestry has higher SOC than rice fields due to its higher vegetation diversity. Trees in agroforestry also protect the soil from erosion, especially on steep slopes, so that organic matter can accumulate better. Intensive soil cultivation practices in rice fields can cause loss of organic carbon, especially in the top layer, through accelerated decomposition and release of carbon into the atmosphere.

Spatial modeling reveals a correlation between SOC values, land use, and environmental factors (Figure 5). The red areas, reflecting low SOC values, are identified as rice fields and landslide areas. Low SOC in rice field areas and landslide areas can be caused by intensive land management activities in rice fields and minimal return of organic matter to the soil. Landslides can accelerate the loss of topsoil rich in organic matter, resulting in low SOC (Błońska et al., 2018).

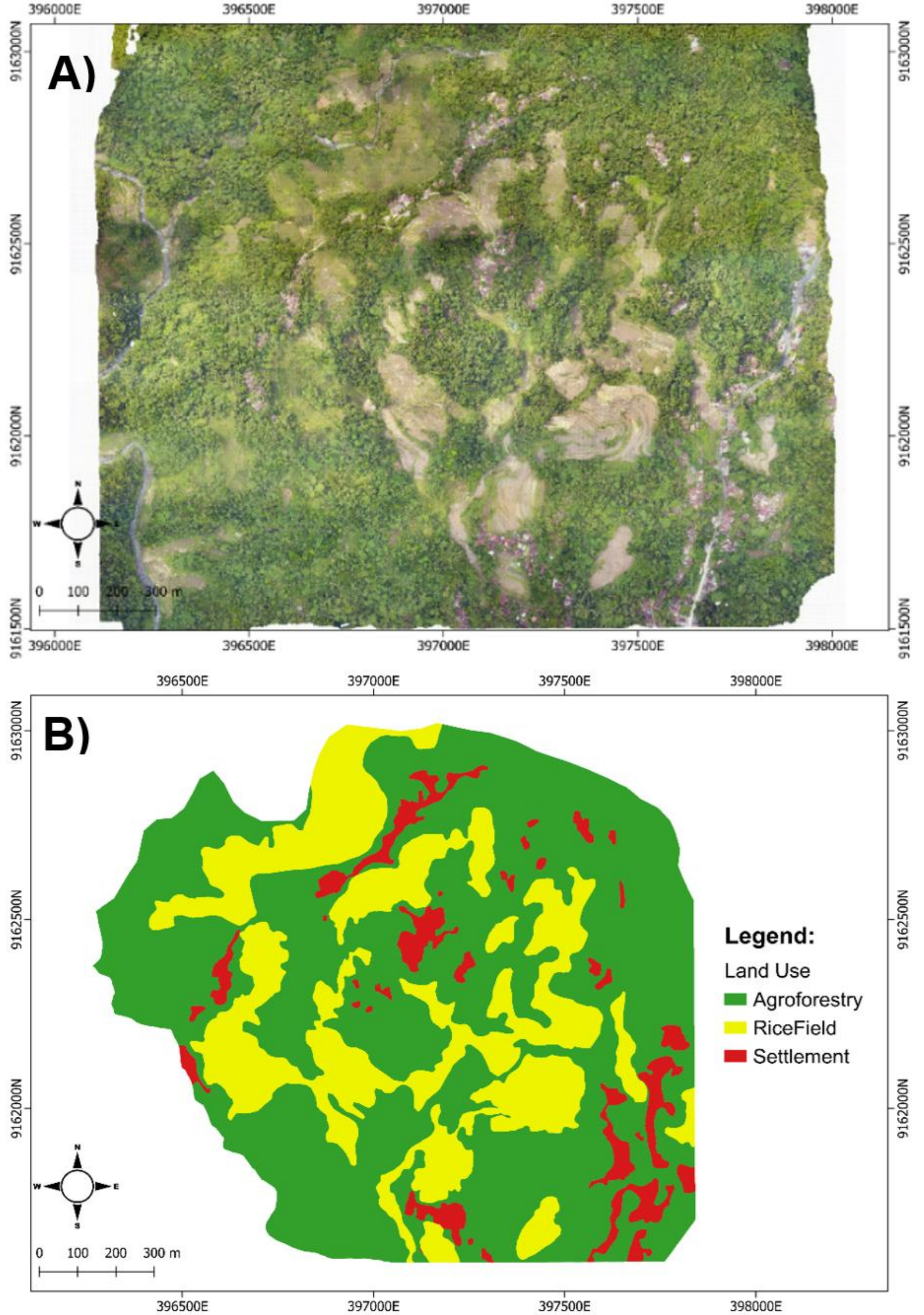

Figure 4. Orthophoto (A) and Land Use of Kalijambe (B).

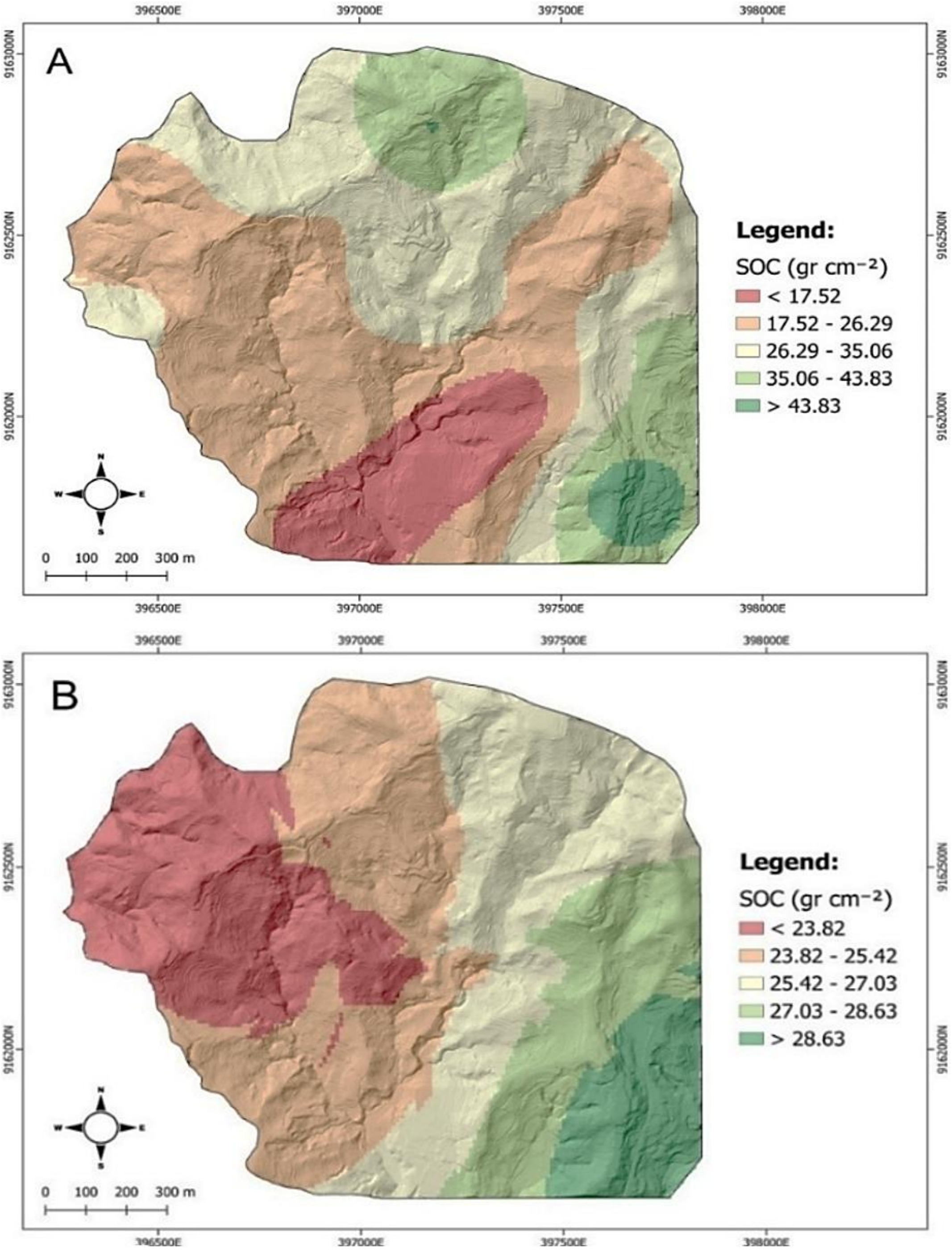

Figure 5. Spatial Distribution Map of SOC at Depth 0 – 20 cm (A), Depth 20 – 40 cm (B).

Notably, the relief approach provides important information regarding topographic factors as the central controller in the spatial distribution of SOC (Table 4). Steep areas tend to have a high potential for SOC loss compared to gentle areas. This finding can be utilized in land management, especially for implementing soil conservation practices and restoring organic carbon content. Topography plays a fundamental role in shaping soil properties and processes. Slope steepness is a key factor influencing the rate of soil erosion, where steeper slopes generally experience higher erosion, resulting in lower SOC levels (Jendoubi et al., 2019). Topography can determine the movement of water and sediment, thus influencing the accumulation or loss of SOC in different landscape positions (Hu et al., 2023).

Table 3
SOC data

Slope (%)	LU	Sample		Average	
		Depth 1	Depth 2	Depth 1	Depth 2
0 - 8	R	32.03; 20.12	20.75; 17.21	26.08	18.98
	A	15.80; 60.18	12.10; 45.09	37.99	28.60
8 – 15	R	23.43; 21.72	23.00; 21.60	22.58	22.30
	A	20.87; 30.71	17.79; 26.32	25.79	22.06
15 – 25	R	-	-	-	-
	A	48.77; 25.65; 6.32	43.58; 25.52; 26.18	33.58	31.76
25 - 45	R	32.79; 21.27; 1.72	14.23; 20.08;1.71	18.59	18.67
	A	37.62; 21.13; 23.37;40.81; 27.58; 9.60	35.97; 20.14; 23.00; 40.15; 25.23; 31.28	26.69	29.30
>45	R	23.90; 21.77	23.86; 19.36	22.84	21.61
	A	35.88; 23.15; 20.57; 37.42; 34.81; 7.68; 40.64; 14.12	20.77; 18.25; 18.31; 37.22; 33.61; 28.46; 28.13; 26.69	26.78	26.43

Remark: LU=Land Use; R=Rice Field; A=Agroforestry; Depth 1=Soil Depth 0 – 20 cm; Depth 2= Soil Depth 20 – 40 cm.

Remarkably, the integration of relief as the central controller of SOC spatial distribution produced a coefficient determination (R^2) of 0.89 at a depth of 0-20 cm. The coefficient value of 0.89 indicates that relief has an effect of 89% on the SOC of the topsoil, and other factors influence the rest. Furthermore, the R^2 value at a 20-40 cm depth is 0.86. The coefficient value of 0.86 or 86% indicates that relief affects 86% of the SOC of the subsoil, and other factors influence the rest. The estimation model produced from the regression is y = 30.99-1.2 * Slope for the topsoil and y = 23.82 + 0.47 * Slope for the subsoil.

Table 4
Integration of relief with soil parameters

Coefficient determination	Value	Model	Soil Layer (cm)
R square	0.89	y = 30.99-1.2*Slope	Above (0 – 20)
Adjusted R2	0.85		
R square	0.86	y = 23.82+0.47*Slope	Below (20 – 40)
Adjusted R2	0.82		

Relationship between relief and soil characteristics

Multiple linear regression revealed a range of 0.11-0.28 for integrating relief with soil properties at 0-20 cm depth. The highest value is found in the parameters of organic carbon (0.28) and pH (0.24), while the lowest is in the parameters of CN Ratio (0.13) and CEC (0.11). This figure shows that relief is closely related to organic carbon and pH, while relief has a low influence on CN Ratio and CEC. Furthermore, at a depth of 20-40 cm, relief has a strong influence on BD (0.27) and organic carbon (0.27) and has a weak influence on CN Ratio (0.13). Specifically, the results of multiple linear regression are presented in Table 5.

Specifically, the results obtained show that R^2 for pH characteristics against relief has a value of 0.24 and 0.16. Variations in relief can affect the accumulation of rainwater, where the interaction between water, CO_2, and soil minerals can affect soil pH, especially in areas with varying relief. Rainwater flowing on the soil surface can carry organic matter and minerals that regulate soil pH (Belandina et al., 2025). Water can flow faster in areas with steeper slopes, reducing contact time with the soil and reducing the accumulation of organic matter that can lower pH (Setiawan et al., 2019).

Table 5
Relationship between relief and soil characteristics

Coefficient Determination	Soil Characteristics	Value	Soil Layer (cm)
R^2	pH	0.24	Above (0 – 20)
	BD (Bulk Density)	0.20	
	Moisture Content	0.16	
	Organic Carbon	0.28	
	Organic Matter	0.19	
	N-total	0.14	
	CN Ratio	0.13	
	CEC	0.11	
R^2	pH	0.16	Below (20 – 40)
	BD (Bulk Density)	0.27	
	Moisture Content	0.16	
	Organic Carbon	0.27	
	Organic Matter	0.24	
	N-total	0.21	
	CN Ratio	0.13	
	CEC	0.16	

Overall, the effect of relief on BD shows R^2 of 0.20 (0-20 cm) and 0.27 (20-40 cm). BD is influenced by soil composition and structure, which can vary depending on relief. Relief also plays a role in regulating drainage and water accumulation, affecting BD. Higher relief tends to have better drainage, which can reduce BD because it reduces the water content in the soil (Mulyani et al., 2023). In addition, the R^2 results for moisture content characteristics against relief are 0.16 in both soil layers. Areas with steeper slopes tend to have lower moisture content than flat areas because water flows faster from steep land surfaces. Increased surface water flow velocity minimizes soil moisture buildup and infiltration by lowering water contact time (Anggraeni et al., 2022).

In the top layer, the relationship between relief toward c-organic and organic matter results are 0.28 and 0.19, whereas in the lower layer are 0.27 and 0.24. Relief significantly influences soil organic matter by determining various environmental factors, such as temperature, humidity, and water flow patterns. Areas with higher elevations tend to have lower temperatures, so the activity of microorganisms in decomposing organic matter is slower. As a result, the accumulation of organic matter and organic C in soil at high elevations is usually greater than in lowland areas (Li et al., 2020). Relief influences the total N and CN ratio by 0.14 and 0.13 in the upper layer and 0.21 and 0.13 in the lower layer. On steep slopes, erosion often causes the loss of topsoil rich in organic matter and nutrients, including nitrogen, so the soil's total N content tends to be lower. Conversely, nitrogen can accumulate in the foothills or plains due to deposits of erosion material. In areas with high elevations or areas with low temperatures, the decomposition of organic matter is slower. CN tends to be higher because carbon accumulates more than nitrogen. Conversely, in lowland areas or with high humidity, the decomposition process is faster, causing the C/N ratio to be lower (Qiao et al., 2020; Dong et al., 2021).

For the upper layer, the R^2 value for the link between relief and soil CEC is 0.11, while for the lower layer, it is 0.16. Elevation variations in relief affect the weathering of soil minerals, which can determine the type and amount of clay minerals that play a significant role in CEC. Relief, directly and indirectly, affects the distribution and variation of soil CEC through its role in erosion, deposition, and accumulation of organic and mineral materials (Slessarev et al., 2021; Zhao et al., 2021).

This research is in line with Rasel et al. (2017) who developed SOC prediction by utilizing remote sensing, especially LiDAR. In this research, a relief approach is used in the hope of producing a model to predict SOC in a fast time. SOC mapping and analysis can be done more systematically, which can help with more sustainable land use planning. However, the drawback in this research is the need for more sampling so that the resulting predictions are more accurate.

4. Conclusions

SOC plays an important role in influencing soil fertility through its influence on nutrient availability. LiDAR is closely associated with relief because it produces high-resolution spatial data. LiDAR can accurately provide detailed information related to the relief of an area. Furthermore, relief consistently affects the distribution of SOC. Specifically, relief strongly influences organic carbon, pH, and BD values. An interesting topic to be studied in the future is the development of relief-based SOC prediction models that can utilize machine learning by integrating additional data. Additional data such as rainfall, soil type, and microbial activity can be added to improve prediction accuracy.

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