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Soil Organic Carbon Across Forest–Agriculture–Oil Palm Land-Use Trajectories in Ucayali, Peru

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ABSTRACT

Deforestation and agricultural expansion in the Peruvian Amazon are reshaping soil functioning and carbon storage, yet the factors influencing soil organic carbon (SOC) remain poorly understood. This study assessed SOC variability across contrasting land-use systems in Ucayali, Peru, including old-growth forest remnants and secondary forests, cocoa agroforestry, *Brachiaria* pastures, and oil palm plantations of different ages—by integrating 54 composite topsoil sampling units, aggregated into 37 spatially independent analytical locations (0–15 cm, in 2024) with Sentinel-2 spectral variables and land-use history derived from MapBiomass Peru (1985–2024). SOC stocks varied across sites but did not differ significantly among present-day land-use classes, indicating that current land cover alone can be a poor predictor of SOC in this highly heterogeneous Amazonian landscape. In contrast, SOC exhibited negative but nonsignificant associations with land-use history variables: more recent forest conversions retained higher SOC, and lower SOC values tended to occur along land-use intensification pathways. Exploratory analyses of Sentinel-2 variables revealed statistically significant but moderate associations with SOC. However, strong collinearity among predictors and relatively low correlation strength suggest that spectral variables capture broad environmental gradients rather than independent drivers of SOC variability. Although exploratory, these patterns are broadly consistent with the concept of soil carbon debt; however, further studies are needed to understand the underlying mechanisms. Integrating field observations with long-term land-use trajectories provides a more robust methodology for assessing soil degradation in rapidly transforming tropical landscapes.

1 | Introduction

The Peruvian Amazon is undergoing one of the most rapid land-use transformations in South America, driven by deforestation, agricultural expansion, and demographic growth [1–3]. These processes not only threaten biodiversity and regional climate regulation but

also profoundly alter soil functioning and ecosystem stability, undermining food security and rural livelihoods that depend on forest integrity and soil productivity [4, 5]. Within this context, the Ucayali region has emerged as a critical hotspot of land-use change, with extensive forest conversion to agricultural mosaics, pastures, and oil palm plantations over recent decades [6, 7].

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Soil organic carbon (SOC) is a fundamental component of soil quality and a key regulator of ecosystem services, including nutrient cycling, water retention, and climate regulation through carbon storage [8–10]. In humid tropical environments, SOC is highly sensitive to land-use change, as forest conversion reduces organic inputs while enhancing decomposition processes through increased soil temperature, reduced moisture, and physical disturbance [11, 12]. These processes often result in rapid SOC losses that may persist for decades under intensive land uses, contributing to soil degradation and reduced ecosystem resilience [4, 13–17]. Several studies frame SOC losses as a long-term “soil carbon debt” associated with land-use change, emphasizing that present-day carbon stocks reflect cumulative disturbances rather than instantaneous land-cover conditions [18, 19]. This perspective highlights the importance of legacy effects, whereby the timing, frequency, and pathways of land-use transitions exert a persistent influence on soil carbon dynamics. In tropical landscapes, areas with similar current land use may therefore exhibit contrasting SOC levels depending on their disturbance history, recovery time, and management trajectory [20, 21].

Despite this conceptual advance, most SOC assessments in the Peruvian Amazon and other tropical regions remain based on static land-use classifications or point-based measurements [22, 23]. While these approaches provide valuable local insights, they are insufficient to capture landscape-scale heterogeneity and the cumulative effects of land-use history. Global soil databases such as SoilGrids and WoSIS offer large-scale estimates but may underrepresent local gradients related to management intensity, hydroclimatic variability, and historical land-use dynamics in rapidly changing tropical environments [24–26].

Remote sensing provides a promising framework to address these limitations by integrating field observations with spatially explicit environmental covariates. Multispectral sensors such as Sentinel-2 capture information on vegetation structure, surface moisture, and disturbance patterns, which are indirectly linked to SOC dynamics [27–29]. However, spectral predictors alone may be insufficient to explain SOC variability in heterogeneous landscapes where soil carbon is influenced by long-term and cumulative processes.

In addition, SOC variability may be influenced by broader environmental gradients, including moisture availability, vegetation condition, and climatic variability operating across landscapes. Similar interactions among environmental stress, vegetation dynamics, and ecosystem functioning have been reported in other tropical and subtropical forest ecosystems [30–32]. However, soil texture, mineralogical composition, and stabilization mechanisms are likely to exert a more direct influence on SOC storage and persistence in Amazonian soils [11, 33].

Consequently, SOC dynamics emerge from the interaction between historical land-use disturbances and multiple biophysical processes operating across spatial and temporal scales.

Integrating remote sensing data with multidecadal land-use trajectories offers a more comprehensive approach to understanding SOC dynamics. Datasets such as MapBiomass Peru [34] enable the reconstruction of forest conversion pathways and the quantification of disturbance history over time [35, 36]. This

temporal perspective is particularly relevant in the Amazon, where land-use intensification often follows sequential transitions from forest to agricultural systems and plantations, potentially leading to progressive SOC depletion. Yet, empirical evidence explicitly testing the dominance of land-use legacy effects over present-day land cover in Amazonian SOC dynamics remains scarce.

Although these environmental controls are known to influence SOC dynamics, historical land-use information remains largely absent from many regional assessments. Understanding the relative contribution of land-use legacy effects alongside broader ecological controls is therefore essential for improving SOC assessments in rapidly changing tropical landscapes [19].

Therefore, this study aims to: (i) characterize SOC variability across representative land-use systems in Ucayali; (ii) evaluate whether SOC patterns are better explained by current land use or by land-use history and forest conversion timing; and (iii) assess the relationships between SOC and Sentinel-2 spectral variables as exploratory indicators of soil carbon variability. By explicitly testing the role of land-use legacy effects, this study provides new insights into the drivers of soil carbon dynamics in rapidly transforming tropical landscapes and contributes to improving soil degradation assessment in the Amazon.

2 | Materials and Methods

2.1 | Study Area

The study was conducted on smallholder farms located along the Federico Basadre Highway (CFB), between the districts of Campo Verde and Neshuya, in the provinces of Coronel Portillo and Padre Abad, within the Ucayali region of the Peruvian Amazon (8.37°–8.85° S, 75.01°–74.82° W; Figure 1). The region has a humid tropical climate (B(r)A) according to the Köppen–Geiger classification, characterized by high temperatures and rainfall throughout most of the year. Mean maximum temperatures range from approximately 30°C in May–June to 33°C in September–October, while minimum temperatures decrease to around 19°C during July–August. Mean annual rainfall is about 2090 mm, with rainfall concentrated between December and April [37].

According to national soil maps, soils across the Campo Verde–Neshuya corridor (lowland Peruvian Amazon, Pucallpa region; 151–275 m a.s.l.) are predominantly Entisols and Inceptisols, characterized by weak to incipient horizon development, with Ultisols occurring locally to a lesser extent [38, 39]. Although these soils belong to similar regional soil groups, they exhibit variation in surface texture, including clay loam, loam, sandy clay loam, and sandy loam.

The landscape is highly fragmented due to ongoing agricultural expansion and forest conversion, forming a mosaic of forests, pastures, agroforestry systems, and perennial crops. Within this heterogeneous landscape, the main land-use systems evaluated in this study included old-growth forest remnants (DPF), secondary forest (DSF), cocoa agroforestry (Tc), oil palm plantations aged 1–9 years (Eg1), 10–18 years (Eg2), and 19–35 years (Eg3), as well as *Brachiaria decumbens* pastures (Pas) (Table 1).

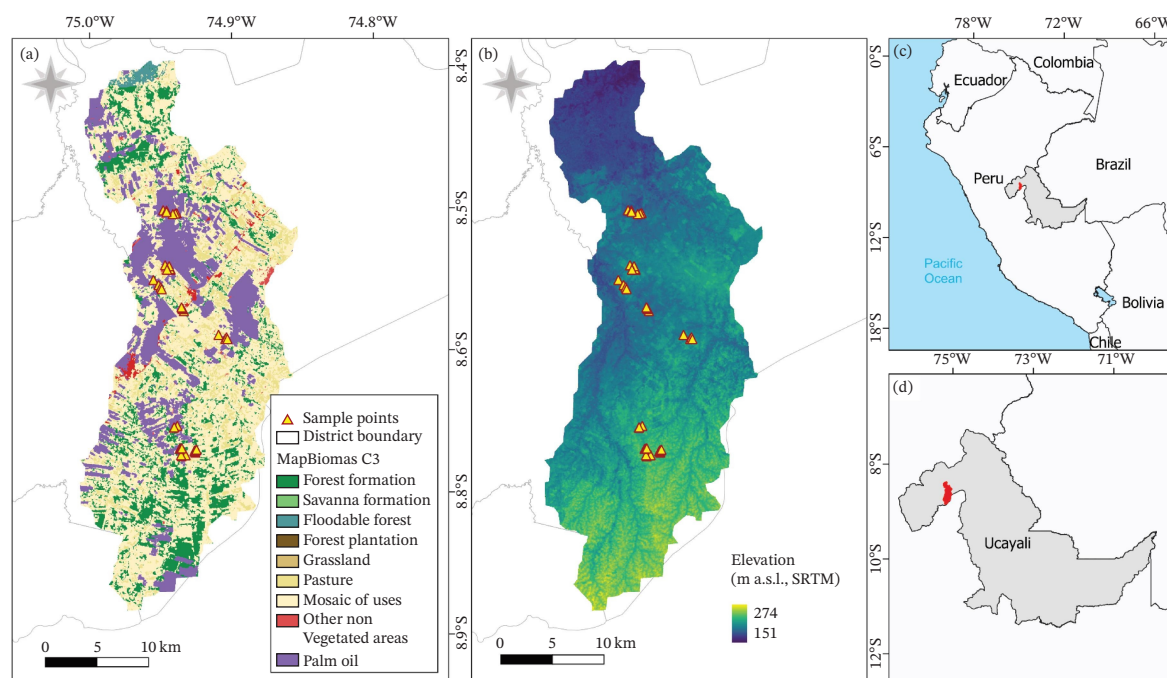


FIGURE 1 | (a) Land-use and forest cover map of the study area in Ucayali, Peru, based on MapBiomass Collection 3 (2024). Classes include forest formations, savanna formations, floodable forest, forest plantations, grasslands, pasture, mosaic of uses, nonvegetated areas, and oil palm plantations. (b) Elevation of the study area derived from the Shuttle Radar Topography Mission (SRTM) dataset. (c) Location of the study area within Peru. (d) Location of the study area within the Ucayali region. In panels (a) and (b), yellow triangles indicate sampling locations, and gray lines represent district boundaries.

2.2 | Sampling Design and Soil Analysis

2.2.1 | Soil Sampling for SOC Analysis

A total of 54 independent topsoil sampling units (0–15 cm) were collected across six localities in the Campo Verde–Neshuya corridor, Ucayali, Peru: Abejaico (Ab), Los Incas (In), Santa Rosa (SR), San Pablo (SP), Bomfin (Bo), and km 51 (K51), between 27 July and 9 August 2024. Each sampling unit corresponded to a homogeneous land-use polygon of approximately 3–5 ha representing a single land-use system within each locality.

The study followed a stratified observational sampling design in which land-use polygons were treated as the primary analytical units. Within each polygon, three to five subsamples were collected depending on polygon size and internal heterogeneity. Subsamples were collected along a zigzag transect established across the polygon, with sampling points spaced at approximately 30-step intervals (~20–25 m) using V-shaped pits with consistent sampling depth (0–15 cm). The subsamples obtained within each polygon were composited into a single sample to represent that sampling unit and to avoid pseudoreplication.

Because some sampling units were located very close to each other, the dataset was aggregated prior to remote sensing and land-use analyses to ensure spatial independence between sampling units. When multiple samples corresponded to the same spatial location or pixel neighborhood, SOC values were averaged. As a result, the modeling dataset comprised 37 spatially independent sampling locations used for analyses with Sentinel-2 spectral predictors, TerraClimate variables, and land-use history covariates (Table 1).

Sampling was conducted under standardized field conditions, avoiding disturbed or recently managed areas. All samples and associated metadata are publicly available in Zenodo [40].

2.2.2 | Management Practices

Overall management intensity across the study area is low. Oil palm plantations are characterized by limited soil disturbance after establishment and sporadic, nonstandardized fertilization. Cocoa agroforestry systems are managed with minimal soil disturbance, with shade trees maintained and organic residues retained on the soil surface. Pastures are managed under continuous grazing with low stocking density and no fertilization or mechanical soil preparation after establishment. A summary of land-use history and management characteristics is provided in Table 1.

First non-forest year corresponds to the first year in which a non-forest class was detected in the MapBiomass time series. This transition may represent temporary disturbance, small-scale agricultural use, or classification uncertainty and does not necessarily indicate complete forest removal. These remnants retained mature forest structure and canopy cover throughout most of the MapBiomass record, despite evidence of localized historical disturbance.

2.2.3 | SOC Measurement

SOC analysis was conducted at the Soil Analysis Laboratory (LASPAF–UNALM) following standardized laboratory protocols. Soil organic matter (OM, %) was determined using the Walkley–Black wet oxidation method [41], which estimates oxidizable organic carbon through dichromate oxidation.

TABLE 1 | Land-use history characteristics for each system based on farmer interviews.

System	Locality	n	Dominant prior land cover	First non-forest year (median)	Age range (years)	Dominant trajectory
DPF (old-growth forest remnants)	Ab, SR, K51	6	Forest	1995	20–30	Forest → Mosaic → Forest
DSF (secondary forest)	Ab, SP, Bo	10	Forest	1990	20–35	Mosaic → Forest
Tc (cocoa agroforestry)	Ab	6	Forest	2005	10–20	Forest → Mosaic
Pas (<i>Bracharia</i> pasture)	Ab, SR, In	5	Forest	2000	15–25	Forest → Mosaic/Pasture
Eg1 (oil palm 1–9 years)	SP, In	5	Forest	2016	1–9	Forest → Mosaic → Oil palm
Eg2 (oil palm 10–18 years)	Ab, SR, Bo	19	Forest	2004	10–18	Forest → Mosaic → Oil palm
Eg3 (oil palm 19–35 years)	SP, Bo	3	Forest	1992	19–35	Forest → Mosaic → Oil palm

Organic carbon concentration (%C) was calculated by converting OM to carbon content using the conventional Van Bemmelen factor, assuming that soil organic matter contains 58% carbon:

$$C(\%) = \frac{OM(\%)}{1.724}. \quad (1)$$

Bulk density (BD) was determined using undisturbed soil samples collected with cylindrical cores of known volume (100 cm^3). Three undisturbed soil cores were collected per sampling unit from the same sampling locations. The volume of the soil core (V_s) was calculated as $V_s = \pi r^2 h$, where V_s is the cylinder volume (cm^3), r is the radius of the cylinder (cm), and h is the cylinder height (cm).

After collection, soil samples were oven-dried to constant mass, and BD was calculated as follows:

$$BD = \frac{Pms}{V_s}, \quad (2)$$

where BD is bulk density (g cm^{-3}), Pms is the oven-dry mass of the soil sample (g), and V_s is the cylinder volume (cm^3).

SOC stocks for the 0–15 cm layer were calculated using carbon concentration, BD, and sampling depth according to

$$\text{SOC}(\text{Mg C ha}^{-1}) = C(\%) \times BD(\text{g cm}^{-3}) \times \text{depth}(\text{cm}) \times 0.1, \quad (3)$$

where 0.1 is the conversion factor used to express results in Mg C ha^{-1} . The same procedure was applied consistently across all sampling locations.

2.3 | Remote Sensing Spectral Data and Vegetation Indices

Sentinel-2 MSI Level 2A surface reflectance products were processed in Google Earth Engine (GEE) [42] to derive spectral predictors describing vegetation condition and surface moisture. Cloud and cirrus contamination were masked using the QA60 band and the maskS2clouds function. All spectral bands were harmonized to a common spatial resolution of 20 m (see Supporting Information 1). Vegetation indices, including the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red-Edge Index (NDREI), and the Normalized Difference Water Index (NDWI), were calculated to capture vegetation condition and surface moisture dynamics relevant to SOC variability [43–45] (Table 2).

For each sampling location ($n = 37$), mean spectral values were extracted within a buffer of up to two pixels ($\sim 40 \text{ m}$) around each georeferenced point to reduce geolocation mismatch and pixel-level noise.

2.4 | Historical Land-Use Reconstruction

Historical land-use and land-cover (LULC) data were obtained from MapBiomas Peru (Collection 3.0, 1985–2024) [35], providing annual time series at 30-m spatial resolution. From these data, land-use history indicators describing the timing, frequency, and pathways of landscape transformation were derived (Table 3).

For forest sites, the first non-forest year represents the earliest detection of a non-forest class in the annual MapBiomas time

series. In some cases, these transitions were temporary and were followed by forest recovery, resulting in trajectories such as Forest $\rightarrow$ Mosaic $\rightarrow$ Forest. Therefore, these indicators were interpreted as evidence of historical disturbance rather than permanent forest conversion.

These variables were spatially linked to soil sampling locations in GEE and used as explanatory covariates to assess legacy effects of land-use change on SOC. In addition, annual LULC sequences were used to reconstruct simplified land-use trajectories.

2.5 | Statistical Analyses

Due to the relatively small and unbalanced sample sizes among land-use systems, as well as departures from normality detected during exploratory analyses, nonparametric statistical approaches were adopted. Therefore, differences in SOC among land-use systems were evaluated using the Kruskal–Wallis test, which does not require normally distributed residuals and is robust to unequal sample sizes. When significant, pairwise differences were assessed using Dunn’s post hoc test with Benjamini–Hochberg (BH) correction for multiple comparisons.

2.5.1 | SOC Differences Among Current Land-Use Systems

Differences in SOC among land-use systems were evaluated using the Kruskal–Wallis test, followed by Dunn’s post hoc comparisons with BH correction when significant. Effect size was quantified using epsilon-squared (ϵ^2). Descriptive statistics (mean, standard deviation, median, interquartile range, minimum, and maximum) were calculated for each land-use system.

2.5.2 | SOC in Relation to Forest Conversion Timing

Relationships between SOC and forest conversion timing were assessed using linear, robust (Huber M-estimator), and median quantile regression models ($\tau = 0.5$). To account for heteroscedasticity and potential outliers, heteroscedasticity-consistent standard errors (HC3) were used. Uncertainty in SOC change rates was quantified using 95% confidence intervals derived from bootstrap resampling (2000 iterations).

2.5.3 | SOC Differences Among Land-Use Trajectories

Sampling points were grouped according to dominant land-use trajectories derived from MapBiomas time series (1985–2024). Only trajectory groups with at least three sampling points were retained for statistical comparison. Differences in SOC among trajectory groups were evaluated using the Kruskal–Wallis test followed by Dunn’s post hoc comparisons with BH correction. Effect size was quantified using epsilon-squared (ϵ^2).

2.5.4 | SOC Relationships With Sentinel-2 Spectral Variables

SOC observations were integrated with Sentinel-2 spectral bands and vegetation indices to explore their relationships with spectral reflectance. Field data were matched with cloud-free dry-season Sentinel-2 composites for 2024 (± 30 –60 days around sampling). Predictor values were extracted in GEE at sampling locations,

averaging values within a buffer of up to two pixels (~ 40 m) to reduce geolocation mismatch and pixel-level noise.

Bivariate relationships between SOC and spectral variables were assessed using Spearman rank correlation coefficients. To control for multiple testing, p values were adjusted using the BH procedure. Correlation strength and direction were interpreted based on coefficient magnitude and statistical significance.

To evaluate redundancy among predictors, pairwise correlations between spectral variables were examined, and multicollinearity was further assessed using variance inflation factors (VIF). Variables exhibiting strong collinearity ($|\rho| > 0.80$ or $VIF > 5$) were carefully evaluated and excluded when necessary to avoid redundancy and overinterpretation. Given the exploratory nature of this analysis and the limited sample size, results were interpreted as patterns of association rather than evidence of predictive relationships.

3 | Results

3.1 | SOC Across Current Land-Use Systems

SOC stocks showed moderate variability across land-use systems, ranging from 10.7 to 18.1 Mg C ha $^{-1}$ (Figure 2; Table 4). The highest mean values were observed in old-growth forest remnants (18.1 ± 5.3 Mg C ha $^{-1}$) and cocoa agroforestry systems (15.2 ± 2.8 Mg C ha $^{-1}$), whereas oil palm plantations exhibited a declining trend with age, from 17.5 ± 11.5 Mg C ha $^{-1}$ in young stands (Eg1) to 10.7 ± 3.2 Mg C ha $^{-1}$ in the oldest plantations (Eg3). Secondary forest and pasture systems showed intermediate SOC values (13.8 ± 3.1 and 12.6 ± 3.5 Mg C ha $^{-1}$, respectively).

Despite these differences in central tendency, SOC stocks did not differ significantly among land-use systems (Kruskal–Wallis $\chi^2 = 3.62$, $p = 0.605$), and the estimated effect size was negligible ($\epsilon^2 < 0.01$), indicating that current land use explains only a small fraction of SOC variability. However, SOC exhibited moderate and significant spatial heterogeneity across localities (see Supporting Information 2–3).

3.2 | SOC and Forest Conversion Timing

SOC exhibited negative slope estimates across all models; however, confidence intervals overlapped zero and no statistically significant relationship was detected. Slopes ranged from -0.063 to -0.153 Mg C ha $^{-1}$ year $^{-1}$ across OLS (HC3), robust (Huber M-estimator), and median quantile regression. However, confidence intervals overlapped zero in all cases (OLS: -0.268 to 0.142 ; Huber: -0.315 to 0.091 ; quantile: -0.383 to 0.078), and these relationships were not statistically significant and remained uncertain due to high variability across sites (Figure 3a).

To further explore land-use dynamics, separate linear models were fitted for dominant transition pathways (Figure 3b–c). For forest-to-agriculture conversions, SOC showed a positive but nonsignificant association with time since conversion (SOC = $8.92 + 0.383$ years; $R^2 = 0.22$, $p = 0.069$). In contrast, a significant negative relationship was observed for the transition from agricultural land to oil palm plantations (SOC = $14.82 - 0.489$ years; $R^2 = 0.22$, $p = 0.015$).

TABLE 2 | Vegetation indices derived from the Sentinel-2 MSI sensor used in this study.

Index	Name	Equation	Reference
NDVI	Normalized Difference Vegetation Index	$(B8 - B4)/(B8 + B4)$	[46]
NDREI	Normalized Difference Red-Edge Index	$(B5 - B4)/(B5 + B4)$	[47]
NDWI	Normalized Difference Water Index	$(B3 - B8)/(B3 + B8)$	[48]

3.3 | SOC Across Land-Use Transition Pathways

Land-use trajectories derived from the MapBiomass Peru time series (1985–2024) showed that most sites originated from forest and transitioned toward agricultural uses. The most frequent pathway was Forest → Oil palm ($n = 26$), followed by Forest → Mosaic of agriculture and pasture ($n = 13$), whereas Mosaic → Oil palm ($n = 4$) and Forest → Forest ($n = 5$) were less common. Lower SOC values were observed in more intensive land-use pathways (Figure 4). Higher values were observed in Forest → Forest (median = 17.2 Mg C ha⁻¹) and Forest → Mosaic of agriculture and pasture (median = 15.3 Mg C ha⁻¹), whereas lower values occurred in Mosaic of agriculture and pasture → Oil palm (median = 11.5 Mg C ha⁻¹) and Forest → Oil palm (median = 11.85 Mg C ha⁻¹). Differences among pathways were marginally nonsignificant (Kruskal–Wallis $\chi^2 = 7.41$, $df = 3$, $p = 0.06$; Figure 4), although the effect size was moderate ($\epsilon^2 = 0.10$).

3.4 | Relationships Between Remote Sensing and SOC

Exploratory correlation analysis revealed moderate relationships between SOC and selected Sentinel-2 spectral variables (Figure 5). SOC showed positive correlations with visible bands, particularly B2 ($r = 0.37$) and B3 ($r = 0.36$), as well as with the moisture-related index (NDWI) ($r = 0.35$). In contrast, the red-edge vegetation index (NDREI) exhibited negative relationships with SOC ($r = -0.34$). After adjusting for multiple comparisons, all correlations remained statistically significant ($p_{\text{adj}} < 0.05$). However, given the relatively low correlation coefficients and the presence of strong collinearity among these variables, these relationships should be interpreted with caution.

4 | Discussion

4.1 | Present-Day Land Use is a Weak Predictor of SOC Variability

SOC stocks did not differ significantly among current land-use systems, and the associated effect size was negligible, suggesting that present-day land cover alone may be insufficient to explain SOC variability in the study area. This finding contributes to the growing body of evidence that SOC responses to land use are highly context-dependent in heterogeneous tropical landscapes, where spatial variability and management history often override the effects of current land cover [49].

Although differences among land-use systems were not statistically significant, higher SOC values tended to occur in forest and agroforestry systems, whereas lower values were observed in pastures and older oil palm plantations. These patterns are broadly consistent with ecological mechanisms whereby systems characterized by continuous litter inputs, low disturbance, and

structurally complex vegetation promote SOC accumulation, whereas long-converted and simplified systems tend to reduce carbon inputs and enhance decomposition [4, 50].

However, the absence of differences among land-use classes may reflect both the limitations of static land-cover classifications and the inherently slow response of SOC to land-use change [51, 52]. A substantial fraction of SOC is physically protected within aggregates or chemically stabilized through mineral associations, resulting in turnover times ranging from decades to centuries [53]. Consequently, land-use changes may not necessarily produce rapid or detectable changes in SOC stocks, particularly in highly heterogeneous tropical soils. In addition, the relatively small and unbalanced sample size, together with the omission of potentially important environmental controls, may have reduced the capacity to detect differences among land-use classes [52, 54, 55].

In addition, SOC variability in tropical landscapes is influenced by multiple interacting environmental factors, including soil texture, mineralogical composition, drainage conditions, and local management practices. These factors may contribute substantially to the spatial heterogeneity observed across the study area and could partially obscure land-use effects on SOC [30, 32]. These factors regulate carbon stabilization, decomposition rates, and organic matter accumulation, contributing substantially to the spatial heterogeneity observed across tropical soils and potentially obscuring land-use effects on SOC [30, 32, 33, 56, 57].

4.2 | Land-Use Legacy Effects: Forest Conversion Timing and Transition Pathways

Although statistical support was limited, both conversion timing and trajectory analyses pointed in the same direction, suggesting that SOC may be influenced by cumulative disturbance history over longer timescales. No statistically significant relationship was detected between SOC and forest conversion timing; all regression approaches yielded negative slope estimates, suggesting a tendency for lower SOC values in sites associated with older conversion histories. Likewise, trajectory-based analyses indicated lower SOC values along more intensive land-use pathways, particularly where forest was converted to agricultural mosaics and subsequently to oil palm plantations. Because confidence intervals overlapped zero, these patterns should be interpreted cautiously and viewed as exploratory rather than conclusive evidence of land-use legacy effects, warranting further investigation using larger datasets and broader temporal gradients.

Nevertheless, the observed tendencies are consistent with the concept of soil carbon debt, whereby SOC responses to land-use change may unfold over decades and reflect the cumulative effects of historical disturbances rather than present-day land-cover conditions alone [18, 19]. Under this hypothesis, recently converted areas may retain residual carbon inherited from

TABLE 3 | Land-use history indicators derived from MapBiomass Peru (1985–2024) and used as explanatory variables in SOC modeling.

Indicator	Description	Unit	Derivation	Ecological relevance
Years since last change	Number of years since the most recent LULC transition	Years	2024—last year of detected change	Proxy for recovery time and SOC depletion/recovery dynamics
Year of first forest conversion	First year when forest was converted to nonforest	Year	First transition from forest class in time series	Captures timing of disturbance onset
Change frequency	Total number of LULC transitions per pixel (1985–2024)	Count	Sum of class changes in annual time series	Indicator of disturbance intensity and landscape instability
Transition type	Dominant LULC transition (e.g., Forest → Pasture, Forest → Oil palm)	Categorical	Based on class change sequence	Reflects type of land-use pressure
Dominant trajectory	Simplified pathway of land-use change (e.g., Forest → Mosaic → Oil palm)	Categorical	Aggregated sequence of transitions	Captures cumulative land-use legacy
Time under current land use	Number of consecutive years in current class	Years	Continuous period without change	Indicates system stability and management duration
Forest persistence	Proportion of years classified as forest (1985–2024)	%	Forest years/total years	Proxy for long-term ecosystem integrity

previous forest states, whereas long-established agricultural systems may gradually lose SOC through reduced organic matter inputs and continued decomposition. Similar legacy effects have been reported across tropical and subtropical landscapes, where contemporary SOC stocks frequently reflect past land-use transitions and disturbance histories rather than current vegetation cover alone [11, 20, 21].

The trajectory analysis further supports this interpretation. The trajectory-based analysis suggested a tendency toward lower SOC values along land-use intensification pathways, from forest-dominated systems to agricultural mosaics and oil palm plantations. Higher SOC values were generally associated with less disturbed trajectories (e.g., Forest → Forest), whereas lower values were observed in pathways involving multiple transitions and increasing management intensity. Although these differences were not statistically significant, they are ecologically consistent with previous studies showing that perennial monocultures and repeated land-use transitions may contribute to long-term SOC declines through simplified vegetation structure, reduced litter inputs, and altered nutrient cycling [49]. Additional data are needed to evaluate whether similar processes are occurring in the study area.

The absence of statistically significant relationships between SOC and land-use history does not necessarily imply the absence of legacy effects [55]. Several factors may have limited the ability to detect existing relationships, including the relatively small and unbalanced sample size, the high spatial heterogeneity characteristic of Amazonian soils, and the inherently slow response of SOC to land-use change [11]. In addition, the time elapsed since conversion may have been insufficient for measurable differences in SOC to emerge in some land-use systems [52]. Consequently, further studies based on larger datasets and broader temporal gradients are needed to evaluate the influence of land-use history on SOC dynamics more robustly.

4.3 | Sentinel-2 Spectral Variables Capture Broad but Nonindependent SOC Signals

The correlation analysis revealed only moderate associations between SOC and selected Sentinel-2 variables, indicating that spectral information explains only a limited fraction of SOC variability. Such results are consistent with the complex and multifactorial nature of soil carbon dynamics. Sentinel-2 does not measure SOC directly, but rather captures surface reflectance signals associated with vegetation cover, moisture conditions, litter accumulation, and soil exposure [28, 29]. Furthermore, dense tropical canopies may partially obscure soil-related spectral signals, limiting the ability of optical sensors to detect SOC variation directly. Consequently, relatively weak spectral relationships should not necessarily be interpreted as poor performance of Sentinel-2, but rather as evidence that SOC is influenced by multiple interacting ecological and environmental processes operating across spatial and temporal scales. Similar limitations have been reported in remote sensing studies showing that optical sensors are generally more effective at identifying broad environmental gradients than at directly retrieving soil properties in heterogeneous landscapes [28, 43, 45, 58, 59]. Among the evaluated predictors, NDWI showed the strongest positive association with SOC, suggesting that moisture-related conditions may contribute to SOC variability in the study area. This interpretation is consistent with recent

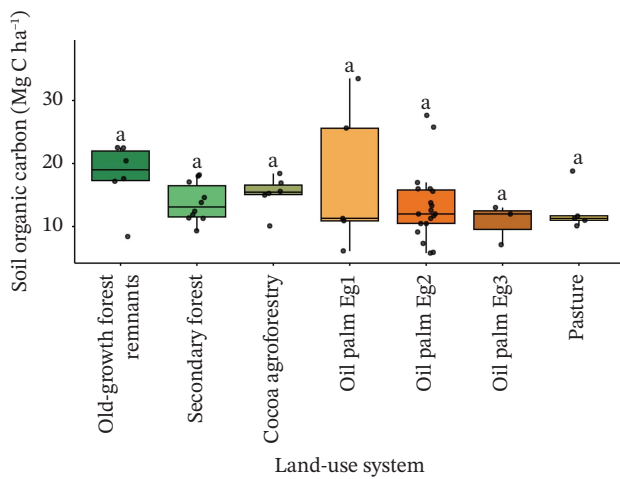


FIGURE 2 | Soil organic carbon (SOC) stocks (Mg C ha^{-1}) across land-use systems in Ucayali, Peru. Boxplots show the median, interquartile range, and variability among independent sampling points; dots represent individual observations.

studies demonstrating that soil moisture and texture can exert a stronger influence on spectral reflectance and SOC prediction than SOC itself, highlighting the indirect nature of optical remote sensing signals [59]. Soil moisture regulates key processes controlling carbon accumulation and turnover, including microbial activity, litter decomposition, nutrient cycling, and organic matter stabilization. In contrast, NDREI exhibited a negative relationship with SOC, suggesting that canopy greenness is not necessarily coupled with soil carbon storage in disturbed tropical landscapes. Areas with high vegetation vigor may still contain relatively low SOC stocks if they have experienced past disturbance, agricultural intensification, or soil degradation [45]. This apparent decoupling reinforces the idea that vegetation indices primarily reflect current ecosystem functioning, whereas SOC represents the cumulative outcome of long-term processes such as disturbance history, vegetation turnover, microbial processing, and soil stabilization mechanisms [51, 60]. Similar evidence from tropical forests indicates that increased organic matter inputs do not necessarily translate into greater SOC storage because carbon stabilization is strongly regulated by organo-mineral interactions and soil geochemical processes [50].

The strong collinearity among spectral predictors further indicates that Sentinel-2 variables do not provide independent mechanistic information about SOC. Instead, they capture

overlapping signals related to vegetation cover, moisture availability, litter accumulation, and soil exposure. Previous studies have similarly shown that Sentinel-2 can contribute to soil carbon mapping, but its predictive capacity is often constrained by vegetation masking, environmental heterogeneity, and the indirect nature of the spectral signal [58, 61]. Therefore, remote sensing variables should be interpreted as indirect proxies of environmental conditions rather than direct predictors of SOC. The integration of Sentinel-2 information with field measurements, land-use history, terrain attributes, and other environmental covariates is likely to provide a more robust methodology for assessing SOC dynamics and soil degradation in rapidly changing Amazonian landscapes.

4.4 | Implications, Limitations, and Future Research

The combined results suggest that land-use legacy effects may contribute to SOC variability and deserve greater consideration than assessments based solely on present-day land cover. Although the evidence remains exploratory, the observed patterns indicate that incorporating land-use history may improve the identification of areas potentially vulnerable to long-term carbon loss, consistent with the soil carbon debt concept and previous evidence of SOC losses following tropical land-use change [18, 19, 52]. From a management perspective, recently converted systems may still retain residual SOC from previous forest states, whereas older agricultural systems and long-established oil palm plantations may be more susceptible to carbon depletion. This interpretation is consistent with studies from the Brazilian Amazon showing that site history and management can be as important as, or even more important than, soil type in determining soil carbon dynamics following land-use change [62]. Integrating field observations, remote sensing information, and multidecadal land-use histories derived from annual land-cover time series provides a promising framework for supporting soil conservation, restoration, and sustainable land-use planning in rapidly transforming Amazonian landscapes [34, 35].

An important limitation of this study is the relatively small and unbalanced analytical dataset, which comprised 37 spatially independent locations distributed across multiple land-use systems and trajectory classes. This imbalance reduced statistical power and may have limited the ability to detect existing differences among groups. Consequently, nonsignificant results should not necessarily be interpreted as evidence of the absence of land-use effects on SOC [55, 63]. Future studies incorporating

TABLE 4 | Soil organic carbon (SOC) across land-use systems.

Land-use system	<i>n</i>	Mean $\pm$ SD ($\text{Mg C} \cdot \text{ha}^{-1}$)	Median (IQR) ($\text{Mg C} \cdot \text{ha}^{-1}$)
Old-growth forest remnants	6	18.1 $\pm$ 5.28	19.0 (4.68)
Secondary forest	10	13.8 $\pm$ 3.10	13.1 (4.95)
Cocoa agroforestry	6	15.2 $\pm$ 2.81	15.5 (1.50)
Oil palm Eg1	5	17.5 $\pm$ 11.55	11.3 (14.70)
Oil palm Eg2	19	13.4 $\pm$ 5.70	12.0 (5.30)
Oil palm Eg3	3	10.7 $\pm$ 3.16	12.0 (2.95)
Pasture	5	12.6 $\pm$ 3.53	11.3 (0.70)

Note: Values are presented as median (IQR) and mean $\pm$ SD.

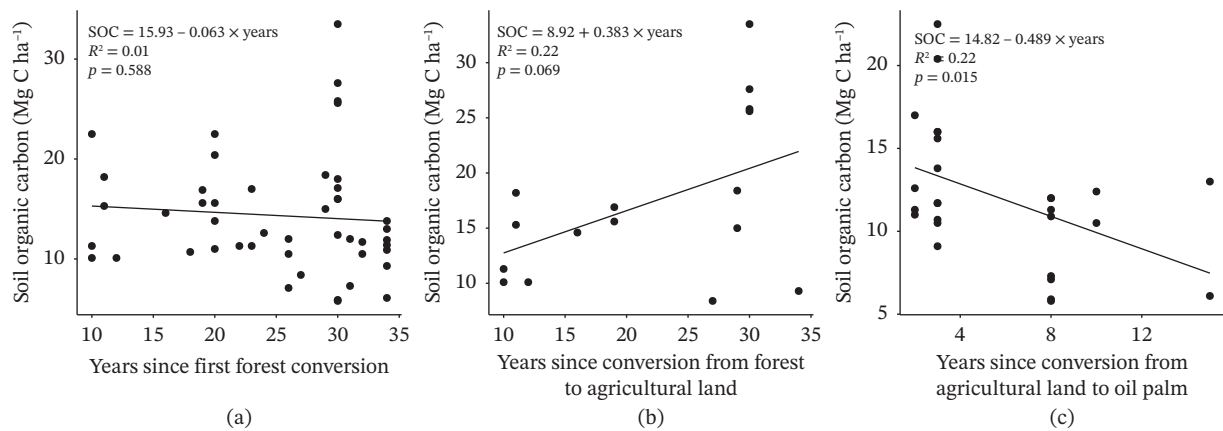


FIGURE 3 | Soil organic carbon (SOC, 0–15 cm) in relation to time since land-use conversion in Ucayali, Peruvian Amazon. (a) Years since first forest conversion. (b) Years since conversion from forest to agricultural land. (c) Years since conversion from agricultural land to oil palm plantations. Points represent sampling locations, and lines indicate linear regression fits. Equations, R^2 , and p values are shown in each panel.

larger and more balanced sampling designs would allow a more robust evaluation of land-use legacy effects and SOC dynamics across Amazonian landscapes.

Another limitation is that SOC measurements were restricted to the 0–15 cm soil layer. Although surface horizons are generally the most responsive to land-use change and are commonly used for monitoring soil degradation, deeper soil layers may store substantial carbon stocks and exhibit different responses to disturbance and land-use transitions [64, 65]. Therefore, the patterns reported here should be interpreted as representative of surface SOC dynamics rather than total ecosystem soil carbon storage. Future studies incorporating deeper soil profiles would provide a more comprehensive assessment of land-use legacy effects on carbon storage in Amazonian soils.

Several environmental covariates known to influence SOC dynamics, including soil texture, mineralogical composition, drainage conditions, topographic position, and historical management practices, were not incorporated into the present analyses because comparable information was not available for all

sampling locations. These factors are known to regulate carbon stabilization, decomposition rates, and organic matter accumulation through organo-mineral interactions, aggregate protection, hydrological controls, and vegetation–soil feedbacks [11, 33, 50, 53, 56]. Consequently, part of the observed SOC variability may reflect the influence of these environmental controls rather than land-use history alone. Similar relationships among SOC, clay content, BD, and porosity have been reported in the Cerrado–Amazon transition, highlighting the importance of soil physical properties as regulators of carbon storage [66]. Future studies integrating environmental covariates, deeper soil profiles, land-use trajectories, and additional remote sensing information (e.g., Sentinel-1, terrain attributes, and multi-temporal datasets) would provide a more comprehensive understanding of the mechanisms governing SOC dynamics in Amazonian soils [26, 45, 65–67].

Despite these limitations, the study integrates field-based SOC measurements, multidecadal land-use histories, and Sentinel-2 spectral information within a rapidly changing Amazonian landscape, providing one of the first exploratory assessments of

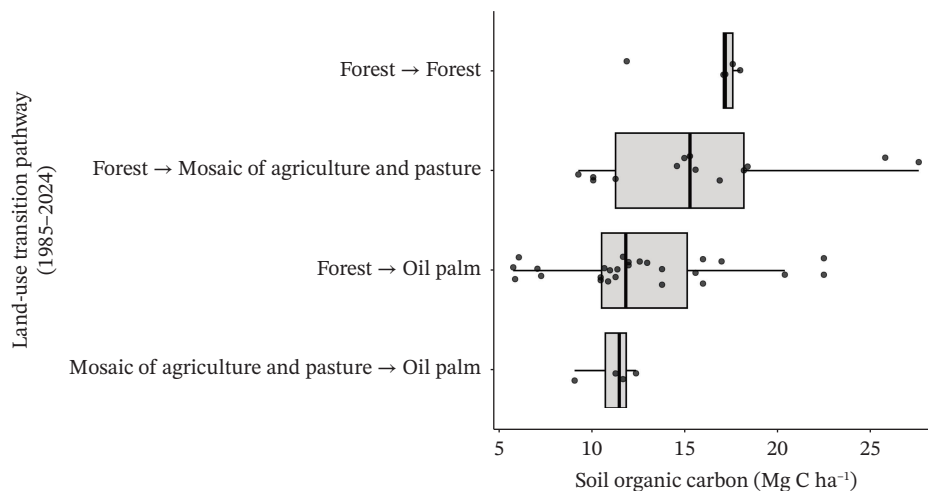


FIGURE 4 | Soil organic carbon (SOC, 0–15 cm) across major land-use transition pathways in Ucayali, Peru. Boxplots represent the median, interquartile range, and variability among sampling locations, with points indicating individual observations.

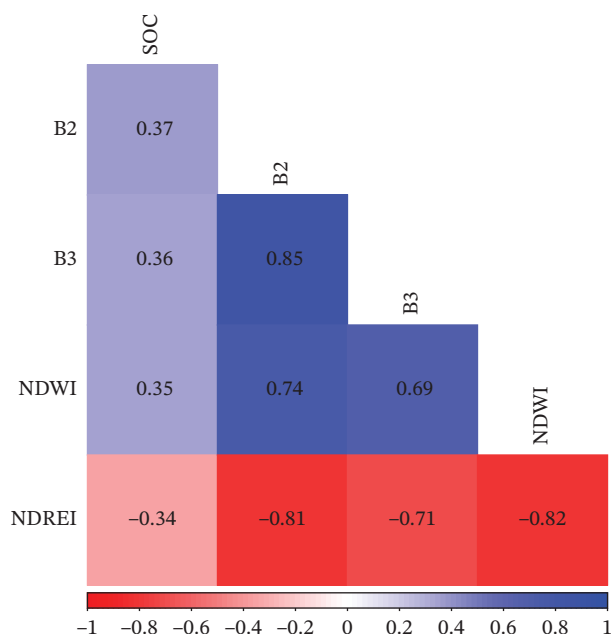


FIGURE 5 | Correlation matrix between soil organic carbon (SOC) and Sentinel-2 spectral predictors. The matrix shows Spearman correlation coefficients among SOC, selected Sentinel-2 MSI spectral bands (B2, B3), and vegetation indices (NDWI and NDREI). Only the lower triangle is displayed. Color gradients indicate the strength and direction of correlations (blue = positive, red = negative). Coefficients are shown within each cell.

land-use legacy effects on SOC dynamics in the Peruvian Amazon.

5 | Conclusions

- This study contributes to understanding SOC variability in Ucayali and highlights that present-day land-use classes alone do not adequately explain observed SOC patterns. Despite observable differences in central tendency, current land use showed no significant effect on SOC, highlighting the limitations of static land-cover classifications in heterogeneous tropical landscapes. The findings primarily reflect SOC dynamics in the upper 15 cm of the soil profile.
- Although statistically significant effects of land-use history on SOC were not detected, several observed patterns were consistent with the hypothesis that historical land-use dynamics may contribute to SOC variability. Negative regression slopes and lower SOC values in more intensive land-use trajectories suggest potential legacy effects associated with past disturbances. However, these relationships remain uncertain due to limited statistical support, relatively small and unbalanced sample sizes, and the high spatial heterogeneity characteristic of Amazonian soils. Consequently, further studies are needed to determine the extent to which land-use history influences SOC dynamics in the region.
- Exploratory analysis of Sentinel-2 spectral variables revealed statistically significant but moderate associations with SOC. However, strong collinearity among predictors and

relatively low correlation strength indicate that spectral variables capture broad environmental gradients rather than independent drivers of SOC variability.

- Overall, the findings suggest that land-use history and local environmental heterogeneity may contribute to SOC variability in the Peruvian Amazon. Integrating long-term land-use trajectories with field observations may provide valuable insights into soil degradation processes and complement approaches based solely on current land cover or spectral proxies.

Author Contributions

Carlos Abanto-Rodríguez conceived the study, coordinated the research, conducted data analysis, interpreted the results, and led the writing of the manuscript. Juan Carlos Guerra Blas contributed to data analysis, interpretation of results, and manuscript drafting and revision. Dennis del Castillo Torres, Noe Ramírez-Flores, Diego Gonzalo García Soria, John Alison Bravo Nieto, and Hipolito Murga-Orrillo contributed to field data collection, methodological discussions, and manuscript review. Nadia Masaya Panduro-Tenazoa supported field activities and data organization. João Luiz Lopes Monteiro Neto contributed to the interpretation of results and manuscript revision. Deyvis Cano contributed to the interpretation of results and revision. Deysi Paola Guerra-Blas contributed to the management of Sentinel-2 data and visualization.

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Disclosure

All authors read and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets generated and analyzed during this study are publicly available in the Zenodo repository at <https://doi.org/10.5281/zenodo.17549901>.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Supporting Information.** Supporting information 1: Characteristics of the MSI Sentinel-2 sensor spectral bands used in this study, including spectral and spatial resolution. Supporting information 2: Soil organic carbon (SOC) stocks across sampling localities in Ucayali, Peru, presented as boxplots showing median, interquartile range, and variability among sites, with statistical groupings based on Dunn's test with Benjamini–Hochberg correction. Supporting information 3: Pair-wise comparisons of soil organic carbon among sampling localities using Dunn's test with Benjamini–Hochberg correction, including Z statistics, *p* values, and adjusted *p* values.