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Influence of Soil Texture and Organic Matter on the Erosion Resistance of Sloped Agricultural Soils of the Peruvian Amazon

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ABSTRACT

Soil erosion is a major driver of soil degradation in the Peruvian Amazon, compromising the productivity and sustainability of agricultural systems established on sloping terrain. This study evaluated the relationship between soil texture, soil organic matter (SOM) and relative erosion susceptibility, expressed through the comprehensive soil erosion resistance (CSER) index, across 48 plots distributed among four sites representing contrasting land-use systems: oil palm in Lamas (LA-OP), primary forest in Picota (PI-FO), coffee in Alto Saposoa (RM-CO) and rice in Yurimaguas (YU-RI). The CSER was calculated using principal component analysis and membership functions based on structural, textural and erodibility indicators. The results revealed positive correlations between CSER and clay content, elevation and SOM, whereas sand content was negatively correlated with the index. Redundancy analysis showed that land use, soil texture and SOM jointly explained 90.34% of the variation in the evaluated indicators, with clay content accounting for the largest independent contribution (32.58%). Generalised linear models indicated that a one-standard-deviation increase in SOM was associated with a 0.04-unit increase in CSER, whereas an equivalent increase in silt content was associated with a 0.04-unit decrease in CSER. In contrast, clay exhibited a positive nonlinear relationship with CSER. These findings suggest that clay and SOM act as protective factors by enhancing soil erosion resistance, whereas higher silt contents are associated with greater soil vulnerability to erosion.

1 | Introduction

The rate of soil erosion in agricultural fields is determined by climatic erosivity and soil erodibility (or resistance). These parameters are influenced by factors that present high variability across time and space, including soil properties, land use and management practices. Soil erosion has been widely recognised as a significant environmental concern stemming

from agricultural practices, with adverse effects on soil health, crop productivity and water quality [1, 2]. In the context of climate change, water erosion is projected to intensify globally due to more frequent and severe extreme weather events. Addressing this challenge requires strategic mitigation approaches, supported by accurate estimates of soil erosion rates, when designing schemes to reduce its impacts [3]. Moreover, soil erosion resistance is a critical property of soils,

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referring to their ability to withstand the erosive force exerted by surface runoff [4].

Soil erosion poses a significant threat to global food security, as it substantially reduces regional food production, degrades landscapes and diminishes soil microbial biodiversity [5], drawing considerable international attention [6]. Soil erosion and soil erosion resistance are closely related and are influenced by multiple factors, including climate, topography, vegetation and soil texture. Beyond its direct physical effects, soil erosion reflects economic, social and particularly environmental issues [7, 8]. It is also a global concern due to the historical prevalence of crop production practices, such as ploughing, harrowing, cropping and repeated tillage, that disturb soil structure [9]. Excessive tillage, in particular, can result in deficient agroenvironmental management, accelerating soil degradation and loss of soil functionality [10].

The Amazon rainforest is essential to our shared future, as it harbours extraordinary biodiversity and encompasses diverse geographical areas with a wide range of soil types, many of which are highly suitable for agricultural production under appropriate environmental conditions. Understanding the structure and function of these soils is therefore crucial [11]. The vast environmental heterogeneity extending from the Andes to the Amazon indicates considerable soil diversity that remains insufficiently studied. In the highest elevations of the Andes, most pedons exhibit substantial accumulation of organic carbon due to cold climatic conditions [12]. In the Peruvian Amazon, approximately 9.6 million hectares of deforested land exist, yet only 1.9 million hectares are currently utilised for agriculture and livestock. The remaining land is underutilised, abandoned or degraded, with depleted soil carbon reserves. Furthermore, even land used for agriculture produces only one-third to one-half of its potential yield under proper management practices [13].

The Amazonian region of San Martín contains approximately 70,000 ha of pastureland, confirming its considerable potential for livestock grazing production. However, this activity has contributed to high rates of deforestation [14]. Many Amazonian regions of Peru have been severely impacted by deforestation in recent decades [15]. Land-use changes and climate variability have significantly affected this region, slowing the decomposition rates of plant organic residues and reducing soil organic matter (SOM) and soil carbon storage. Under appropriate management practices, the integration of trees, shrubs and herbaceous species in agroforestry and silvopastoral systems can enhance biomass production and soil cover, thereby promoting nutrient cycling, biological activity, carbon sequestration and soil carbon storage [16]. These practices also provide critical protection against soil erosion.

In the Peruvian Amazon, information remains limited regarding how the physical, textural, structural and organic properties of soils collectively influence erosion resistance across contrasting agricultural and forest ecosystems. This knowledge gap is particularly relevant in sloping landscapes, where soil texture, bulk density (BD), capillary porosity (CP) and organic matter content can significantly affect soil susceptibility to erosive processes. Particle-size distribution influences soil cohesion, whereas organic matter promotes aggregate formation, enhances structural stability and reduces erodibility. Previous studies in tropical

agroecosystems of the Peruvian Amazon have examined various aspects of soil quality and functionality, including the potential of coffee-based agroforestry systems with shade trees to enhance soil carbon stocks and improve soil conditions [17], as well as rhizosphere-related biological processes in tropical crops [18–20]. However, the integration of physical, textural, structural and organic attributes into composite indicators of soil erosion resistance under contrasting site conditions remains scarce. Therefore, we hypothesised that soil texture and organic matter are key determinants of erosion resistance in sloping agricultural soils of the Peruvian Amazon. In particular, soils with higher clay and organic matter contents were expected to exhibit greater erosion resistance due to improved aggregation and structural stability, whereas soils with higher silt contents were expected to show lower resistance due to their greater susceptibility to erosion.

2 | Materials and Methods

2.1 | Study Area

The study was conducted across five districts: Picota, Pucacaca, Caynarachi, Alto Saposoa and Yurimaguas. The first four districts are located in the San Martín region, whereas Yurimaguas belongs to the Loreto region. Fieldwork took place in eastern Peru between May 2024 and March 2025. The San Martín region spans 51,253.31 km². It is characterised by a subtropical-to-tropical climate, featuring two distinct seasons: a dry season from June to September and a rainy season from October to May. Temperatures range from 23°C to 27°C, and the average annual precipitation is approximately 1500 mm. In contrast, the Loreto Department spans 368,852 km². It has a humid tropical climate, with an average temperature of 27°C (ranging from 20°C to 33°C), an annual rainfall of 2500–3000 mm and consistently high relative humidity of 87%–90% throughout the year [13]. The evaluated ecosystems comprised a primary forest and three agricultural systems (coffee, oil palm and rice). The study sites were located between 5°55'35"S and 7°06'36"S latitude and 77°11'10" W and 76°13'35" W longitude, with elevations ranging from 140 to 1455 m.a.s.l. (Figure 1). Picota lies on low- to medium-alluvial terraces in the Huallaga Valley, featuring flat to gently undulating relief with high agricultural potential. Pucacaca is characterised by low and medium hills with undulating to strongly undulating relief, making it more susceptible to erosion. Caynarachi consists of high hills and sub-Andean foothills with steep slopes, forming a transitional zone between lowland and highland rainforests. Alto Saposoa features sub-Andean mountainous terrain with very steep slopes and numerous ravines, which limit agricultural use and make it more suitable for forest conservation.

2.2 | Sampling Design

Soil sampling was conducted at four sites representing distinct land-use systems, hereafter referred to as site-use categories: oil palm in Lamas (LA-OP), primary forest in Picota (PI-FO), coffee in Alto Saposoa (RM-CO) and rice in Yurimaguas (YU-RI). Twelve sampling units were established within each site-use category. At each sampling unit, a 100-m² plot was delineated, and five soil subsamples were collected and

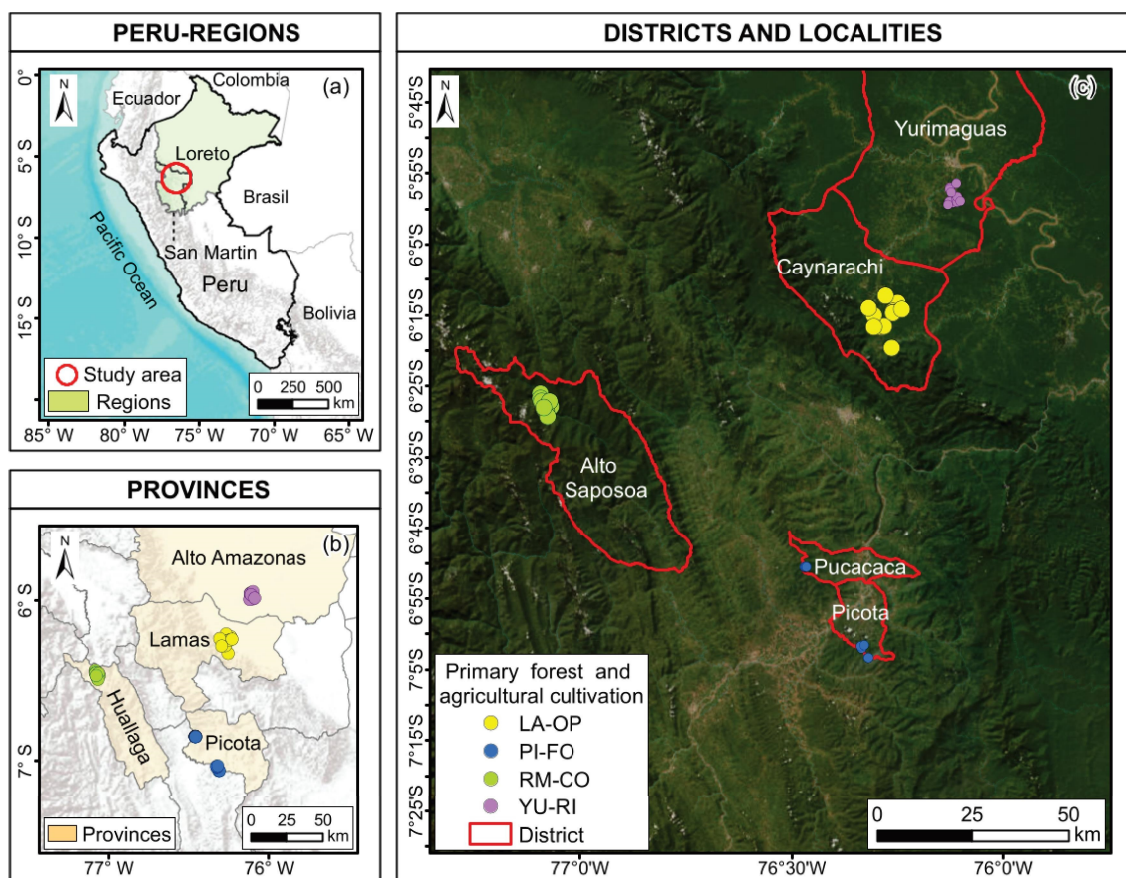


FIGURE 1 | Location of the study area in the Peruvian Amazon: (a) country and region; (b) provincial boundaries; (c) district boundaries with the distribution of sampling points in the systems: oil palm in Lamas (LA-OP), primary forest in Picota (PI-FO), coffee in Alto Saposoa (RM-CO) and rice in Yurimaguas (YU-RI).

homogenised to obtain a composite sample. A total of 48 composite samples were collected for subsequent analyses. Sampling was performed as described by Yu et al. [21]. Soil samples were obtained from excavation pits measuring 1.0×0.8 m. Prior to excavation, the sampling areas were cleared of vegetation and surface debris. Soil was collected from the 0–30-cm layer using a spade and a metal probe, as previous studies [22, 23] have reported significant variations in soil erodibility and organic carbon within this depth interval. The composite samples were subsequently subjected to physico-chemical characterisation.

2.3 | Determination of Soil Edaphic and Nutritional Parameters

Soil samples were collected using a spade from five locations within each plot, namely the four corners and the centre. The samples were homogenised to form a composite sample weighing approximately 1 kg. All collected samples were analysed at the accredited laboratory of the National Institute of Agrarian Innovation (INIA), Peru. Soil texture was determined using the hydrometer method, and pH was measured with a potentiometer in a 1:2.5 soil-to-water suspension [24]. Total nitrogen was determined by the Kjeldahl method (Bremner, 1996), available phosphorus by the Olsen method [25] and available potassium content [24].

2.4 | Determination of Soil Organic Carbon (SOC) and Carbon Density

SOC was determined in the laboratory using the method developed by Walkley and Black [26], applying the following equation:

$$\text{SOC}(\text{tC} \cdot \text{ha}^{-1}) = \text{CO} \times \text{Pf} \times \text{DA}, \quad (1)$$

where CO is the SOC content (%), Pf is the soil sampling depth (cm), and DA is the BD ($\text{g} \cdot \text{cm}^{-3}$).

The SOC density (SOCD) was computed by the following equation described by Orton et al. [27]:

$$\text{SOCD} = \frac{\text{Hh}[\text{DAh} \times \text{SOCh} \times (1 - \text{Ch})]}{100}, \quad (2)$$

where SOCD is the density of SOC ($\text{tC} \cdot \text{ha}^{-1}$), Hh is the thickness of soil (cm), DAh is the BD of soil ($\text{g} \cdot \text{cm}^{-3}$), SOCh is the SOC in hectares ($\text{tC} \cdot \text{ha}^{-1}$), and Ch is the volume percentage of the fraction > 2 mm.

2.5 | Calculation of Soil Erosion Resistance Index

The comprehensive soil erosion resistance (CSER) index was developed as a composite indicator integrating multiple attributes related to soil resistance to erosion. The indicators included in the index were selected based on their proven relevance in

previous studies and comprised the mean weight diameter (MWD) of aggregates [28], the soil structure stability index (SSSI) [29], the clay ratio (CR) [30], the soil organic carbon cementing agent index (SCAI) [31] and the soil erodibility factor (K factor) [32].

To determine the MWD of soil aggregates, the fine-aggregate fraction obtained by sieving was used. Fine aggregates were defined as the material passing through Sieve No. 4 (4.75 mm) and retained on Sieve No. 200 (75 µm), a widely accepted criterion for distinguishing the sandy fraction from finer particles with greater cohesive properties [33]. In the present study, however, a 38-µm sieve was additionally used to further characterise the fine fraction included in the aggregate stability analysis:

$$\text{MWD} = \sum_{i=1}^n x_i w_i, \quad (3)$$

where MWD is the mean weight diameter (mm), x_i is the mean diameter between two adjacent sieves (mm), and w_i is the weight fraction of the aggregates remaining on the i th sieve (%).

The SSSI is typically used to indicate the risk level of soil structure degradation. The SSSI can be calculated according to the following equation [29]:

$$K = \left\{ 0.2 + 0.3 \exp \left[-0.256 \text{SAN} \left(1 - \frac{\text{SIL}}{100} \right) \right] \right\} \times \left[\frac{\text{SIL}}{\text{CLA} + \text{SIL}} \right]^{0.3} \times \left[1.0 - \frac{0.25 \text{SOC}}{\text{SOC} + \exp^{3.72 - 2.95 \text{SOC}}} \right] \times \left[1.0 - \frac{0.7 \text{SN}_1}{\text{SN}_1 + \exp^{-5.51 + 22.9 \text{SN}_1}} \right], \quad (7)$$

where SAN represents the sand presence (%); SIL represents the silt (%); CLA represents the clay (%); SOC represents the SOC (%); and $\text{y SN}_1 = 1 - \text{SAN}/100$.

To integrate the selected indicators into a single measure of soil erosion resistance, principal component analysis (PCA) and membership functions were employed. The indicators were first standardised to eliminate differences in measurement scales and ensure comparability. PCA was subsequently applied to derive the factor loadings (λ) and the variance explained (VE) by each retained principal component. These parameters were then used to calculate the unnormalised (w) and normalised (w^*) weights according to the following expressions:

$$w_i = \sum_{j=1}^m \lambda_{ij}^2 \cdot \text{VE}_j, \quad (8)$$

$$w_i^* = \frac{w_i}{\sum_{i=1}^p w_i}, \quad (9)$$

where w and w^* represent the unnormalised and normalised weights assigned to indicator i , respectively; λ_{ij} is the factor loading of indicator i on principal component j ; VE_j denotes the VE by component j ; m corresponds to the number of retained principal components; and p represents the total number of indicators used to construct the CSER index.

The original values of each indicator were then normalised (S_i) to a common scale between 0 and 1 using membership functions, based on the direction of their relationship with

$$\text{SSSI} = 100 \cdot \frac{\text{SOM}}{\text{Clay} + \text{Silt}}, \quad (4)$$

where SOM represents the SOM content (%). $\text{SSSI} \geq 7\%$ indicates a low risk of soil structure degradation, $5\% < \text{SSSI} < 7\%$ implies a high risk of soil structure degradation, and $\text{SSSI} \leq 5\%$ usually represents severe loss of organic matter leading to soil structure degradation.

The following equations present the calculation formulae for CR and SCAI, respectively [30, 31]:

$$\text{CR} = \frac{\text{Sand} + \text{Silt}}{\text{Clay}}, \quad (5)$$

$$\text{SCAI} = \frac{\text{MWD}}{C}, \quad (6)$$

where Sand, Silt and Clay, respectively, represent the content of sand, silt and clay (%) in the soil, MWD is the mean weight diameter, and parameter C indicates the content of SOC (%).

Soil erodibility was calculated using the model proposed by Williams et al. [32] as follows:

the CSER. Direct membership functions were applied to MWD, SSSI and SCAI because higher values indicate improved soil structural conditions and enhanced erosion resistance. In contrast, inverse membership functions were used for K_{ap} and CR, as increasing values of these indicators are associated with greater erodibility and reduced soil resistance to erosion.

Table 1 presents the indicators used to construct the CSER index and their respective contributions to the first two principal components (PC1 and PC2). The indicators included were the MWD of aggregates, SSSI, SCAI, apparent soil erodibility factor (K_{ap}) and CR. The table also reports the factor loadings of each indicator on PC1 and PC2, their unnormalised (w) and normalised (w^*) weights, the VE and the eigenvalues associated with each principal component. Direct or inverse membership functions were assigned based on the expected relationship between each indicator and the CSER.

Finally, the CSER was estimated by calculating the weighted sum of the normalised scores of the five selected indicators, as expressed by the following equation:

$$\text{CSER} = 0.22S_{\text{MWD}} + 0.20S_{\text{SSSI}} + 0.19S_{\text{SCAI}} + 0.17S_{K_{\text{ap}}} + 0.22S_{\text{CR}}. \quad (10)$$

Thus, the CSER synthesised the information from the five indicators into a single composite metric. Accordingly, higher index values were interpreted as reflecting greater integrated soil resistance to erosion.

TABLE 1 | Indicators used to construct the comprehensive soil erosion resistance (CSER) index.

Indicators	λ		Weight		Expected relationship with CSER	Membership function (S_i)
	PC1	PC2	w_i	w_i		
MWD	0.16	-0.66	0.190	0.22	Direct	$(x_i - x_{\min})/(x_{\max} - x_{\min})$
SSSI	-0.61	-0.13	0.176	0.20	Direct	$(x_i - x_{\min})/(x_{\max} - x_{\min})$
SCAI	0.60	-0.05	0.165	0.19	Direct	$(x_i - x_{\min})/(x_{\max} - x_{\min})$
K_{ap}	0.47	0.33	0.142	0.17	Inverse	$(x_{\max} - x_i)/(x_{\max} - x_{\min})$
CR	-0.15	0.66	0.187	0.22	Inverse	$(x_{\max} - x_i)/(x_{\max} - x_{\min})$
Eigenvalues	2.27	2.04				
VE	0.45	0.41				

2.6 | Statistical Analyses

Data analyses were conducted in R version 4.5.0 using the RStudio environment. After estimating the CSER index as described above, the Pearson correlation analysis was performed to evaluate the relationships among all study variables. Subsequently, the numerical variables were standardised, and a redundancy analysis (RDA) was conducted using the *vegan* package to examine the multivariate relationships between the CSER indicators and the explanatory variables, including site-land use, soil texture and SOM. Based on the RDA results, a biplot was constructed to visualise the distribution of observations, CSER indicators and explanatory variables within the ordination space. The significance of the overall model, explanatory terms and canonical axes was assessed using permutation tests. In addition, variance partitioning analysis was performed to quantify the independent and shared contributions of the explanatory variables to the multivariate variation in the CSER indicators.

In addition, generalised linear models (GLMs) were fitted to evaluate the relationships between the CSER, its constituent indicators and the selected explanatory variables. Models were

estimated using the *glmmTMB* package, with probability distributions and link functions selected according to the characteristics of each response variable and the Akaike information criterion (AIC). Candidate models were compared using the *MuMIn* package. Subsequently, the partial effects of soil texture and SOM on the CSER and its individual indicators were estimated. Model performance was assessed using simulated residual diagnostics implemented in the *DHARMA* package, including tests of residual uniformity, outlier detection, overdispersion or underdispersion and homogeneity of variance.

3 | Results and Discussion

3.1 | Description of Variables by Site-Land-Use Category

Table 2 shows marked differences in soil properties among the evaluated site-land-use categories. LA-OP exhibited the highest mean sand content ($\bar{x} = 58.43\%$, $CV = 23.10\%$) and CR ($\bar{x} = 4.89$, $CV = 23.10\%$). PI-FO recorded the highest mean clay ($\bar{x} = 31.35\%$, $CV = 19.60\%$) and silt contents ($\bar{x} = 32.86\%$, $CV = 25.78\%$), as well as higher CP ($\bar{x} = 0.53$, $CV = 7.90\%$) and MWD of aggregates

TABLE 2 | Descriptive statistics of elevation, soil properties and the comprehensive soil erosion resistance (CSER) index across site-land-use categories.

Variable	LA-OP $\bar{x}$ (CV, %)	PI-FO $\bar{x}$ (CV, %)	RM-CO $\bar{x}$ (CV, %)	YU-RI $\bar{x}$ (CV, %)
Elevation (m.a.s.l.)	197.17 (3.72)	409.58 (14.44)	1450 (4.86)	140.08 (4.54)
Clay (%)	19.21 (39.86)	31.35 (19.6)	24.4 (28.89)	27.23 (37.34)
Silt (%)	22.36 (33.6)	32.86 (25.78)	22.78 (13.08)	25.55 (20)
SOM (%)	1.94 (17.08)	5.61 (22.44)	5.97 (31.7)	1.47 (51.32)
COS ($t\text{-ha}^{-1}$)	32.36 (18.56)	80.68 (21.5)	100.02 (30.63)	24.01 (54.55)
SOCD ($t\text{-ha}^{-1}$)	4.68 (22.13)	10.08 (23.34)	14.55 (31.92)	3.41 (59.31)
BD	1.44 (8.27)	1.24 (8.93)	1.45 (8.05)	1.4 (9.78)
CP (%)	0.46 (9.81)	0.53 (7.9)	0.45 (9.73)	0.47 (11.02)
MWD	1.15 (39.36)	1.89 (19.41)	1.49 (28.16)	1.63 (37.19)
SSSI	4.98 (24.12)	8.89 (23.99)	12.82 (31.4)	2.87 (60.89)
SCAI	1.04 (38.17)	0.61 (27.5)	0.48 (50.7)	2.14 (35.54)
K_{ap}	0.07 (8.97)	0.07 (10.22)	0.06 (7.36)	0.08 (7.87)
CR	4.89 (40.22)	2.3 (27.19)	3.47 (42.76)	3.09 (42.64)

Note: The table shows the mean ($\bar{x}$) and coefficient of variation (CV, %) for the variables assessed by site and land use: Lamas with oil palm (LA-OP), Picota with primary forest (PI-FO), Alto Saposa with coffee (RM-CO) and Yurimaguas with rice (YU-RI). The following parameters were considered: elevation, clay, silt, sand, soil organic matter (SOM), soil organic carbon (SOC), soil organic carbon density (SOCD), bulk density (BD), capillary porosity (CP), mean weight diameter (MWD), soil structural stability index (SSSI), soil organic carbon cementing agent index (SCAI), apparent K factor of erodibility (K_{ap}), clay ratio (CR) and comprehensive soil erosion resistance (CSER) index.

($\bar{x}$ = 1.89 mm, CV = 19.41%). In contrast, RM-CO was located at the highest elevation ($\bar{x}$ = 1450 m above sea level, CV = 4.86%) and exhibited the highest values of SOM ($\bar{x}$ = 5.97%, CV = 31.70%), SOC ($\bar{x}$ = 100.02 mg ha⁻¹, CV = 30.63%), soil organic carbon density ($\bar{x}$ = 14.55 kg m⁻³, CV = 31.92%), BD ($\bar{x}$ = 1.45 g cm⁻³, CV = 8.05%) and SSSI ($\bar{x}$ = 12.82, CV = 31.40%). Finally, YU-RI showed the highest values for the SCAI ($\bar{x}$ = 214, CV = 35.54%) and the apparent soil erodibility factor (K_{ap}) ($\bar{x}$ = 0.08, CV = 7.87%).

BD differed among the site-land-use categories evaluated. The highest mean values were observed in RM-CO and LA-OP, at 1.45 and 1.44 g · cm⁻³, respectively, followed by YU-RI (1.40 g · cm⁻³), whereas PI-FO exhibited the lowest mean BD (1.24 g · cm⁻³). Although higher BD is generally associated with soil compaction, reduced pore space and greater susceptibility to erosion [34–36], its effect should not be interpreted in isolation. For instance, RM-CO simultaneously exhibited a high BD (1.45 g · cm⁻³), low CP (0.45) and one of the lowest MWDs of aggregates (1.49 mm). In contrast, PI-FO was characterised by a lower BD and among the highest levels of SOM, SOC and structural stability. These findings suggest that BD alone is insufficient to explain soil resistance to erosion, as the CSER reflects the combined influence of compaction, porosity, aggregate stability, texture and SOC.

The SCAI reflects the contribution of SOC to aggregate cementation and stability. Zhang et al. [37] reported higher SCAI values in croplands than in grasslands and forest ecosystems. Similarly, in the present study, SCAI values were highest in YU-RI, followed by LA-OP, PI-FO and RM-CO, with mean values of 2.14, 1.04, 0.61 and 0.48, respectively. Comparable values were reported by Li et al. [22], who observed SCAI values of approximately 2.3 in abandoned land, 2.0 in fruit orchard soils and 1.9 in forest soils. The SSSI, in contrast, was highest in RM-CO, indicating greater structural stability and a positive association with the CSER index. Aggregate stability is a key indicator of soil resistance to erosion and an important determinant of the productive potential of sloping agricultural lands [38]. Li et al. [22] reported higher SSSI values in forest soils and lower values in cultivated lands. However, the pattern observed in the present study differed: The highest SSSI values were recorded in RM-CO and the lowest in YU-RI.

3.2 | Correlation Analysis of the Study Variables

Figure 2 illustrates the significant correlations between the CSER index and the evaluated soil physical, textural, structural and organic properties. CSER exhibited strong positive correlations with the MWD of aggregates (r = 0.87, p < 0.001) and clay content (r = 0.86, p < 0.001), as well as moderate positive correlations with elevation (r = 0.34, p < 0.05) and the SSSI (r = 0.29, p < 0.05). These relationships indicate that higher values of these attributes are associated with greater soil resistance to erosive processes. Similarly, CSER was positively correlated with CP (r = 0.42, p < 0.01), SOM (r = 0.47, p < 0.001), SOC (r = 0.43, p < 0.01) and SOCD (r = 0.37, p < 0.01). These findings further suggest that higher organic matter content and improved pore characteristics enhance soil resistance to erosion, highlighting the important roles of soil texture and organic matter in maintaining soil structural integrity and reducing susceptibility to erosion.

In contrast, CSER was negatively correlated with the CR (r = -0.87, p < 0.001), sand content (r = -0.59, p < 0.001),

apparent soil erodibility factor (K_{ap}) (r = -0.56, p < 0.001) and BD (r = -0.42, p < 0.01). These relationships indicate that higher values of these variables are associated with lower soil resistance to erosive processes. The strong negative correlation between CSER and CR is particularly noteworthy. As CR is calculated as the ratio of the sand and silt fractions to the clay fraction [(sand + silt)/clay], higher values reflect a greater proportion of relatively noncohesive particles compared with clay. Consequently, elevated CR values indicate poorer soil structural conditions and greater susceptibility to erosion, consistent with the observed negative association with CSER.

Although the correlation matrix includes all pairwise relationships among the evaluated variables, particular attention was given to correlations involving CSER, as it constitutes the principal response variable and integrative indicator of soil erosion resistance in this study. The remaining associations provide complementary information on the interactions among the soil's physical, textural, structural and organic attributes.

SOC stocks were highest in RM-CO (100.02 t · ha⁻¹), followed by PI-FO (80.68 t · ha⁻¹), LA-OP (32.36 t · ha⁻¹) and YU-RI (24.01 t · ha⁻¹). This pattern suggests that greater carbon accumulation may be associated with higher vegetation cover, increased organic matter inputs and lower levels of soil disturbance. However, the contribution of SOC to soil erosion resistance should not be interpreted in isolation, as CSER integrates multiple physical, textural, structural and organic attributes that collectively determine the soil's resistance to erosion. Similarly, Othmani et al. [39] reported positive correlations between erodibility and silt (0.63%) and negative correlations with organic matter (-0.32%) and the soil stability index (-0.26%). In this study, SCAI showed a moderate positive correlation with erodibility, consistent with Li et al. [22], whereas SSSI exhibited a strong negative correlation with erodibility. This pattern suggests that soil erodibility increases as aggregate content and stability decline [40]. Aggregate stability is a critical structural attribute of soils because it controls surface erosion, water infiltration, plant growth and carbon stabilisation. It not only reflects the fragility of soil aggregates under detrimental external forces but also provides an estimate of soil sensitivity to erosion [41]. Consequently, improving aggregate stability is an effective way to enhance erosion resistance [42]. Given its strong ecological and functional relevance, aggregate stability could serve as a valuable descriptor of soil health in long-term monitoring programmes at national-to-continental scales, although it is still rarely applied [43].

CSER exhibited strong positive correlations with MWD, clay content and CP and significant negative correlations with sand content and K_{ap} [22]. These relationships suggest that higher sand content and greater erodibility are associated with lower CSER values, indicating soils that are more susceptible to erosion [22]. In contrast, although the correlation between CSER and SSSI was relatively weak, it was statistically significant, indicating a consistent association between the two variables. This finding supports the role of structural stability in enhancing soil resistance to erosion, as greater aggregate stability is generally associated with reduced vulnerability to erosive processes.

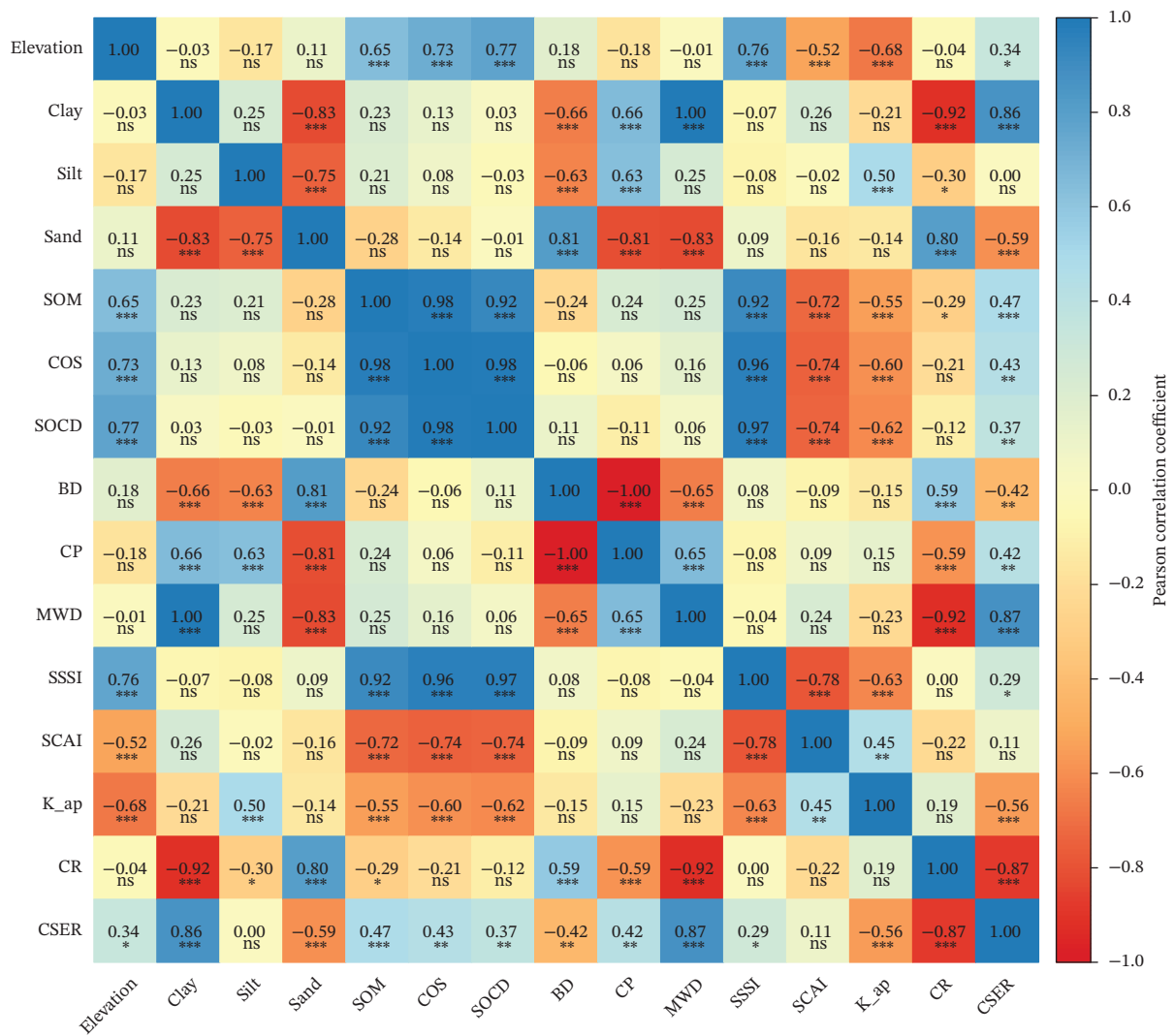


FIGURE 2 | Pearson correlations among the studied variables. The correlation matrix summarises the Pearson correlation coefficients among elevation, clay, silt, sand, soil organic matter (SOM), soil organic carbon (SOC), soil organic carbon density (SOCD), bulk density (BD), capillary porosity (CP), mean weight diameter (MWD) of aggregates, soil structure stability index (SSSI), soil organic carbon cementing agent index (SCAI), apparent soil erodibility factor (K_{ap}), clay ratio (CR) and the comprehensive soil erosion resistance (CSER) index. The colour scale represents both the direction and strength of the correlations: Blue shades indicate positive correlations, whereas red shades indicate negative correlations. Greater colour intensity reflects stronger associations between variables. Statistical significance is indicated as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ and ns, $p > 0.05$.

3.3 | Multivariate Relationships Among CSER Indicators as Influenced by Site–Land-Use Category and Soil Properties: An RDA

When evaluating indicators of overall soil resistance to erosion, it is important to recognise that these attributes do not operate independently but rather interact as a complex set of interrelated properties influenced by site–land-use conditions, SOM and textural characteristics. Therefore, an RDA was performed to summarise the joint variation of the CSER indicators and to examine their relationships with the associated explanatory variables. The RDA model explained 90.34% of the total variation in the response matrix. The first two canonical axes adequately captured the multivariate structure represented in the ordination, jointly accounting for 82.41% of the explained variation, with RDA1 and RDA2 contributing 43.08% and 39.33%, respectively (Figure 3).

Subsequently, the goodness of fit of both the response and explanatory variables to the RDA1–RDA2 ordination space was evaluated. For the CSER indicators, the first two canonical axes explained between 62.11% and 98.97% of their total variation. MWD and CR were more strongly associated with the second canonical axis, whereas SSSI, SCAI and K_{ap} were more strongly associated with the first canonical axis. Among the explanatory variables, clay exhibited the highest goodness of fit ($r^2 = 95.45\%$), followed by SOM ($r^2 = 80.47\%$) and site–land-use category ($r^2 = 52.16\%$). In contrast, silt showed a relatively poor fit ($r^2 = 7.24\%$), indicating that its variation was only weakly represented within the first two canonical axes.

The RDA biplot revealed distinct patterns of association between the CSER indicators and the explanatory variables. Along the first canonical axis (RDA1), SOM and samples from coffee cultivation areas (CO) were positively associated with SSSI, as

indicated by their orientation towards the positive side of the axis. In contrast, samples from rice cultivation areas (RI) were associated with SCAI and K_{ap} and were positioned towards the negative side of RDA1. Along the second canonical axis (RDA2), samples from oil palm areas (OP) were positively associated with the CR, whereas clay content and samples from primary forest areas (FO) were associated with MWD, as evidenced by their projection towards the negative side of the axis. In contrast, silt was located close to the origin of the ordination space, indicating a weak association with the CSER indicators represented by the first two canonical axes.

Although the RDA biplot identified distinct patterns of multivariate association among the CSER indicators and explanatory variables, these relationships should be interpreted as exploratory ordination patterns. Accordingly, their statistical significance was formally assessed using permutation tests applied to the overall model, the explanatory terms and the canonical axes.

Permutation tests confirmed the presence of a significant multivariate structure in the overall RDA model ($F = 63.91$, $p_{perm} < 0.01$). At the level of explanatory variables, site-land-use category, clay content, silt content and SOM each made significant contributions to the joint variation in the CSER indicators

($p_{perm} < 0.01$). Furthermore, the first four canonical axes were statistically significant ($p_{perm} < 0.01$), whereas the fifth axis (RDA5) was not ($p_{perm} = 0.80$). Consequently, subsequent interpretation focused on RDA1 and RDA2, as these axes explained the largest proportion of the multivariate structure represented in the ordination biplot (Table 3).

Given the significance of both the overall RDA model and the explanatory variables, a conditional RDA was performed to quantify the independent contribution of each predictor to the multivariate variation in the CSER indicators. The results showed that clay made the largest adjusted independent contribution (adjusted $R^2 = 32.58\%$), followed by silt (6.44%), SOM (6.34%) and site-land-use category (4.32%). These findings indicate that, after accounting for variation shared among predictors, clay explained the largest proportion of unique variation in the CSER indicators, highlighting its dominant role in shaping the multivariate structure of soil erosion resistance (Table 4).

The highest values of SOC, SOCD and SOM were recorded in RM-CO and PI-FO, reinforcing the central role of carbon in improving soil structure and, consequently, enhancing erosion resistance. In reduced-tillage lands, organic carbon tends to accumulate in more stable forms, enhancing soil structure, water

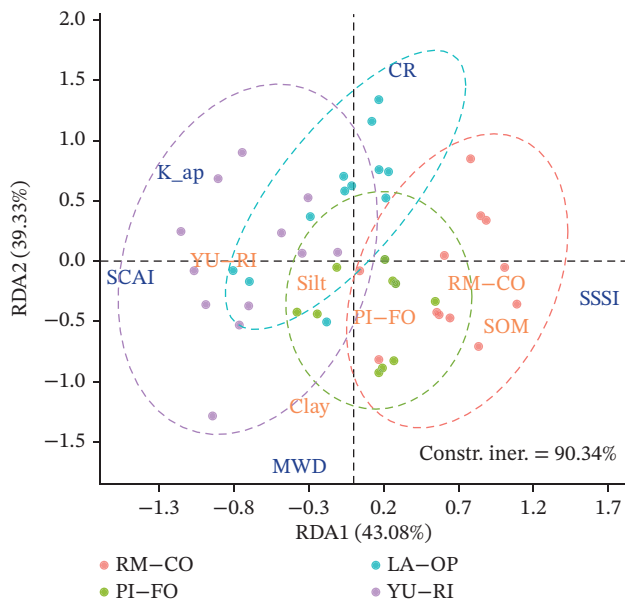


FIGURE 3 | Redundancy analysis (RDA) of CSER indicators in relation to soil texture, organic matter and site-land-use category. The RDA biplot illustrates the multivariate relationships between the indicators of the comprehensive soil erosion resistance (CSER) index and the explanatory variables evaluated in this study. The CSER indicators included the mean weight diameter (MWD) of aggregates, soil structure stability index (SSSI), clay ratio (CR), soil organic carbon cementing agent index (SCAI) and apparent soil erodibility factor (K_{ap}). The explanatory variables comprised soil organic matter (SOM), clay content, silt content and site-land-use category: oil palm in Lamas (LA-OP), primary forest in Picota (PI-FO), coffee in Alto Saposoa (RM-CO) and rice in Yurimaguas (YU-RI). The model explained 90.34% of the total variation in the response matrix, and the first two canonical axes jointly accounted for 82.41% of the explained variation. Points represent individual soil samples, whereas the dashed ellipses denote the 95% confidence regions associated with each site-land-use category.

TABLE 3 | Permutation tests for the RDA model, explanatory variables and canonical axes.

Evaluated component	Df	Variance	F	p_{perm}
Overall model	6	4.52	63.91	< 0.01
Explanatory variables				
Site-land-use category	3	2.47	69.96	< 0.01
Clay	1	1.46	123.99	< 0.01
Silt	1	0.29	24.56	< 0.01
Soil organic matter (SOM)	1	0.29	25.03	< 0.01
Canonical axes				
RDA1	1	2.15	182.86	< 0.01
RDA2	1	1.97	175.11	< 0.01
RDA3	1	0.30	27.52	< 0.01
RDA4	1	0.09	8.42	< 0.01
RDA5	1	0.00	0.37	0.80

Note: The table presents the significance of the redundancy analysis (RDA) model, the explanatory variables and the canonical axes based on 5000 permutations. Reported statistics include degrees of freedom (Df), the variance explained by each evaluated component, the F statistic and the permutation-based probability value (p_{perm}). Components with $p_{perm} < 0.01$ were considered statistically significant. The residual variance of the model was 0.48295, with 41 residual degrees of freedom. Elevation was initially evaluated as an explanatory variable; however, because it did not make a significant contribution to the joint variation of the CSER indicators, it was excluded from the final model.

TABLE 4 | Variance partitioning analysis showing the independent contribution of explanatory variables to the multivariate variation in CSER indicators.

	Site-land-use category	Soil organic matter	Silt	Clay
R^2	4.75%	5.90%	5.99%	29.35%

retention and resistance to erosion [42]. This is further supported by Pan et al. [44], who reported that active SOC stocks positively affect the soil erodibility factor.

Similarly, in site-land-use categories with higher SOC content, SCAI values were lower, whereas SSSI values were higher. This pattern suggests that greater carbon accumulation does not necessarily translate into higher SCAI values; however, it is associated with enhanced soil structural stability, as reflected in higher SSSI values. These findings indicate that increased carbon storage contributes to improved aggregate stability and, consequently, lower susceptibility to erosive processes. According to Li et al. [22], coffee and primary forest soils present a low risk of structural degradation, as indicated by SSSI values exceeding 7%. In contrast, soils under oil palm (LA-OP) and rice cultivation (YU-RI), where SSSI values were below 5%, may be more susceptible to structural degradation and associated erosion risks.

3.4 | Univariate Relationships Between CSER, Land Use and Soil Properties

Following the evaluation of the multivariate structure of the CSER indicators through RDA, a complementary univariate analysis was adopted to quantify the individual relationships suggested by the ordination model. Accordingly, separate GLMs were fitted, incorporating site-land-use category as a control variable. This factor was modelled as a fixed effect rather than a random effect, as this specification yielded superior model performance in terms of goodness of fit and diagnostic assumption checks.

Table 5 presents the results of the GLMs, which showed that clay content was significantly associated with CSER and all of its constituent indicators. SOM and silt content were significantly associated with CSER, as well as with MWD, SSSI, SCAI and K_{ap} . In addition, the site-land-use category was significantly associated with CSER and with the SSSI, SCAI and K_{ap} indicators.

Although the ANOVA results indicate which explanatory variables were significantly associated with each response variable, they do not describe the direction or shape of these relationships. Accordingly, the partial response curves derived from the selected GLMs were analysed to evaluate the functional form and magnitude of the effects of the significant predictors on CSER and its associated indicators.

Initially, the CSER composite index was evaluated, as it integrates the overall response of soil to erosion processes (Figure 4). In this context, SOM exhibited a positive linear relationship with CSER (Figure 4A), whereas silt showed a negative linear relationship (Figure 4B). In contrast, clay exhibited a nonlinear increase in the index, characterised by significant linear, quadratic and cubic components (Figure 4C).

The partial relationships between SOM, silt and clay and the individual CSER indicators were subsequently analysed to describe both the direction and functional form of their trends.

SOM exhibited a nonlinear positive relationship with MWD, showing an overall increasing trend characterised by significant linear and cubic components (Figure 5A). Similarly, silt displayed a nonlinear association with MWD, with noticeable fluctuations along the trend and significant linear and cubic effects (Figure 5B). In contrast, clay showed a positive linear relationship with MWD (Figure 5C).

SOM and SSSI exhibited a nonlinear relationship, characterised by an overall increasing trend and significant polynomial effects ranging from the linear term up to the sixth-order term (Figure 6A). In contrast, both silt and SSSI, and clay and SSSI, showed nonlinear relationships, with decreasing trends described by significant linear and quadratic components (Figure 6B,C).

SOM and SCAI exhibited a nonlinear, decreasing relationship, characterised by significant linear and quadratic components (Figure 7A). In contrast, silt showed a linear association with SCAI, with a slight decreasing trend (Figure 7B). Conversely, clay and SCAI displayed a nonlinear, increasing relationship, also characterised by significant linear and quadratic components (Figure 7C).

SOM and K_{ap} exhibited a nonlinear relationship, characterised by an initial decrease followed by an increase, with significant linear and quadratic components (Figure 8A). In contrast, silt showed a positive linear association with K_{ap} (Figure 8B), whereas clay exhibited a negative linear relationship with K_{ap} (Figure 8C).

Finally, for CR, only the partial fit for clay was reported, as it was the only predictor found to be significant in the ANOVA. Clay and CR exhibited a nonlinear decreasing relationship, characterised by significant linear, quadratic and cubic components

TABLE 5 | Generalised linear models relating CSER and its indicators to site-land-use category, soil texture and soil organic matter.

	CSER	MWD	SSSI	SCAI	K_{ap}	CR
<i>ANOVA (p value)</i>						
Site-land-use category	< 0.001	0.33	< 0.001	< 0.001	< 0.001	0.90
SOM	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.63
Clay	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Silt	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.77
<i>Model selection</i>						
Distribution	Gaussian	Gaussian	Gamma	Gamma	T	Gamma
AIC	−205	−389	−102	−206	−417	−248

Note: The table presents the ANOVA *p* values derived from the generalised linear models (GLMs) fitted for the comprehensive soil erosion resistance (CSER) index, mean weight diameter (MWD) of aggregates, clay ratio (CR), soil organic carbon cementing agent index (SCAI), soil structure stability index (SSSI) and apparent soil erodibility factor (K_{ap}), as a function of soil texture (clay and silt content), soil organic matter (SOM) and site-land-use category. In addition, the probability distribution, link function and Akaike information criterion (AIC) selected for the final model are reported for each response variable.

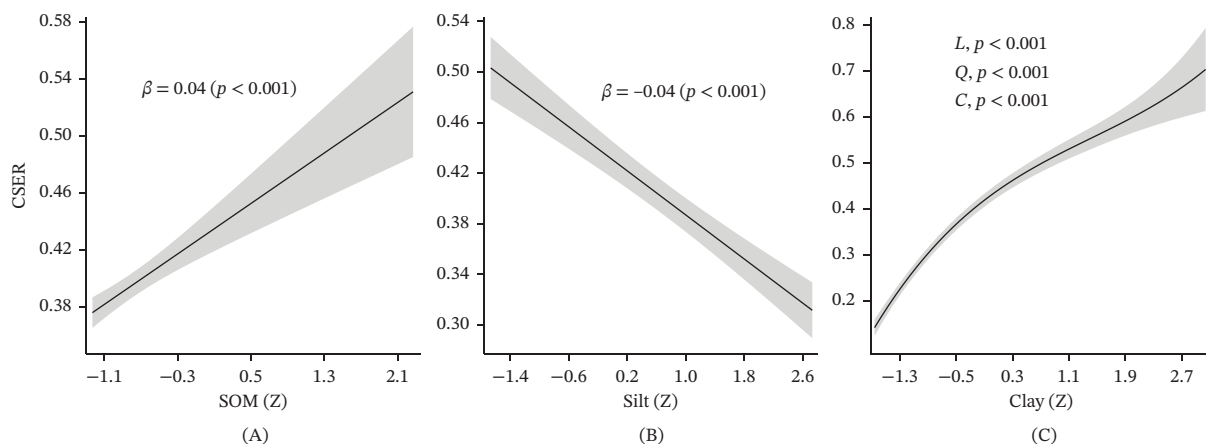


FIGURE 4 | Univariate relationships between soil texture, soil organic matter and the CSER index. Panels (A, B, C) present the partial fits of the GLMs for soil organic matter (SOM), silt and clay, respectively, against CSER. Predictor variables were standardised (Z scores). The solid line indicates the fitted trend, whereas the shaded area represents the 95% confidence interval. In panels (A, B), the β coefficient is interpreted as the additive change in the expected mean of CSER. In panel (C), the nonlinear relationship was modelled using orthogonal polynomials to minimise multicollinearity. Reported p values denote the statistical significance of model terms.

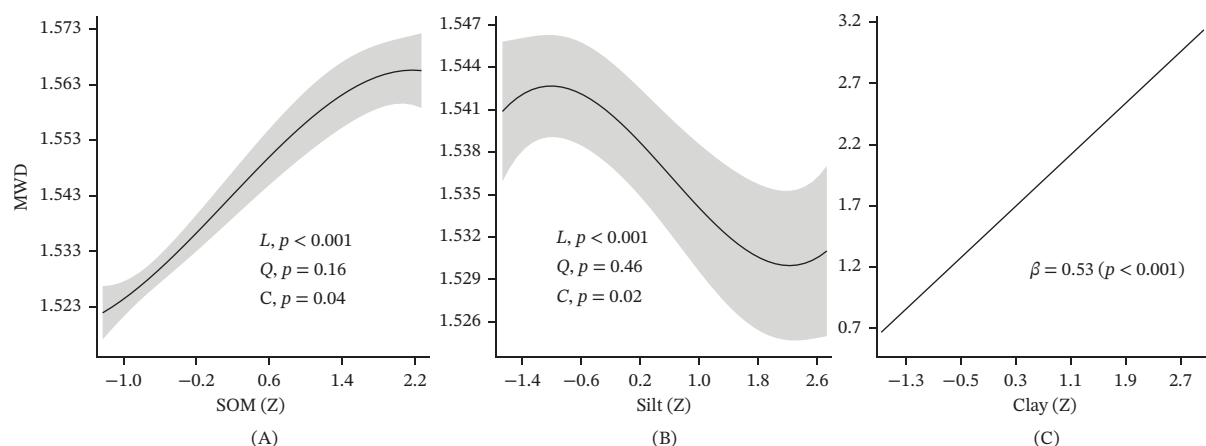


FIGURE 5 | Univariate relationships between soil texture, soil organic matter and mean weight diameter (MWD) of aggregates. Panels (A, B, C) present the partial fits of generalised linear models (GLMs) describing the relationships between soil organic matter (SOM), silt and clay, respectively, and the MWD index. Predictor variables were standardised (Z scores). The solid line represents the fitted trend, and the shaded area denotes the 95% confidence interval. In panel (C), the β coefficient is interpreted as the additive change in the expected mean of MWD. In panels (A, B), nonlinear relationships were modelled using orthogonal polynomials to minimise multicollinearity. Reported p values indicate the statistical significance of model terms.

(Figure 9). The steepest decline in CR occurred between low and intermediate clay contents, followed by a more gradual decrease at higher clay contents.

The highest SOC content was recorded in RM-CO, with an average of $100.02 \text{ t} \cdot \text{ha}^{-1}$, whereas the highest SOM content reached 5.97%. These values are consistent with Vallejos-Torres et al. [17], who reported SOC averages of $118.2 \text{ t} \cdot \text{ha}^{-1}$, and with Grandez-Alberca et al. [45], who found a strong association between coffee and shade trees, with improvements in SOM ranging from 2.8% to 5.7%. Consequently, coffee agroforestry systems have been identified as having a high potential for SOC storage [4], compared with coffee grown without shade trees. In fact, shade-grown coffee systems act as primary reservoirs of SOC and SOM [46] due to continuous organic matter inputs from trees via litterfall, branches, roots, root exudates and stimulation of arbuscular

mycorrhizal fungi; moreover, coffee is a highly mycotrophic plant [18, 47]. The highest SOCD values observed in RM-CO, with an average of $14.55 \text{ t} \cdot \text{ha}^{-1}$, are consistent with the findings of Solórzano et al. [48], who reported values ranging from 8.8 to $16.06 \text{ t} \cdot \text{ha}^{-1}$ in agricultural and forest soils. The elevated SOCD levels in RM-CO observed in this study are partly explained by the higher altitude (1500 m a.s.l.), where lower temperatures slow down SOM decomposition rates. This reduced decomposition favours SOC accumulation, thereby increasing SOCD [49]. Furthermore, soils in RM-CO exhibited lower erodibility (average 0.06), in line with Li et al. [50], who reported values around 0.045 in agricultural soils. Maintaining vegetation cover in these systems could therefore reduce soil erosion by up to 10% [51]. Indeed, vegetation cover management is one of the five key factors included in the universal soil loss equation, reflecting the role of cropping and management practices in modulating soil erosion rates [52].

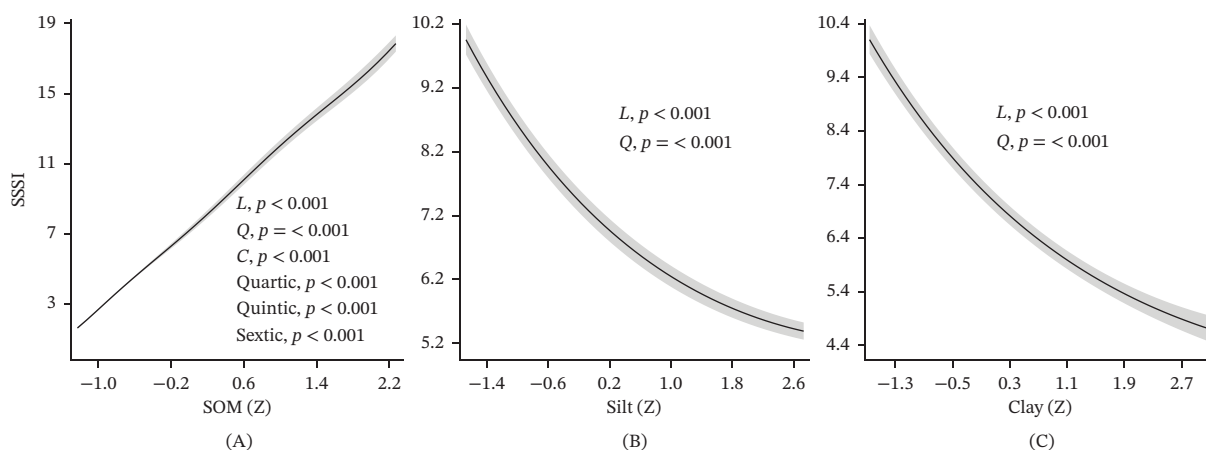


FIGURE 6 | Univariate relationship between soil texture, soil organic matter and the soil structure stability index (SSSI). Panels (A, B, C) present the partial fits from the GLM analyses describing the relationships between soil organic matter (SOM), silt and clay, respectively, and the SSSI. Predictor variables were standardised (Z scores). The solid line represents the fitted trend, whereas the shaded area denotes the 95% confidence interval. In all panels, nonlinear effects were modelled using orthogonal polynomials to minimise multicollinearity. Reported *p* values indicate the statistical significance of the model terms.

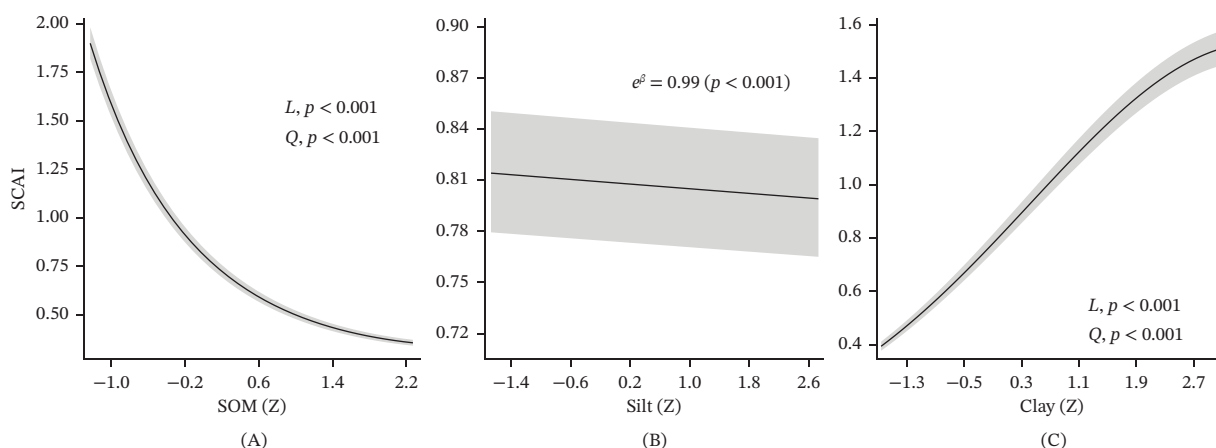


FIGURE 7 | Univariate relationships between soil texture, soil organic matter and the soil organic cementing agent index (SCAI). Panels (A, B, C) present the partial fits of the GLMs describing the relationships between soil organic matter (SOM), silt and clay, respectively, and the SCAI. Predictor variables were standardised using Z scores. The solid line represents the fitted trend, whereas the shaded area denotes the 95% confidence interval. In panel (B), the coefficient e^{β} is interpreted as the multiplicative change in the expected mean SCAI value associated with a one-unit increase in the standardised predictor. In panels (A, C) nonlinear relationships were modelled using orthogonal polynomial terms to minimise multicollinearity. Reported *p* values indicate the statistical significance of the model terms.

The highest SOC and SOM values found in coffee cultivation lands in the Huallaga Province were positively associated with increased soil resistance to erosion, due to the greater contribution of organic matter to soil aggregation and structural stability. Land-use type and conversion time strongly influence SOC stocks, and soil erodibility decreases with increasing organic carbon [53]. Conversely, soil erosion depletes SOC reserves, particularly in agroecosystems and degraded forests, thereby disrupting the global carbon cycle and contributing to climate change [54]. Organic matter is a key factor in reducing soil erodibility; Rugendo et al. [55] recommend incorporating organic matter at adequate levels to mitigate soil erosion. Similarly, organic amendments not only reduce soil erosion but also improve soil conditions, optimise the composition and functioning of soil microbial communities and ultimately enhance soil multifunctionality. Thus, organic matter is

fundamental for safeguarding the ecological integrity of sloped farmlands and promoting sustainable agricultural development [56].

It is essential to acknowledge that variations in soil texture, reflecting the inherent heterogeneity of soils, cannot be completely eliminated. Such variability arises from multiple factors, including parent material, climate, biological processes, topography and time [22], all of which contribute to the inherent complexity of soil characteristics.

Such variability arises from multiple factors, including parent material, climate, biological processes, topography and time [22], all of which contribute to the inherent complexity of soil characteristics. Conversely, favourable outcomes have traditionally been linked to the adoption of best management practices, which encompass a wide range of agronomic, structural and landscape

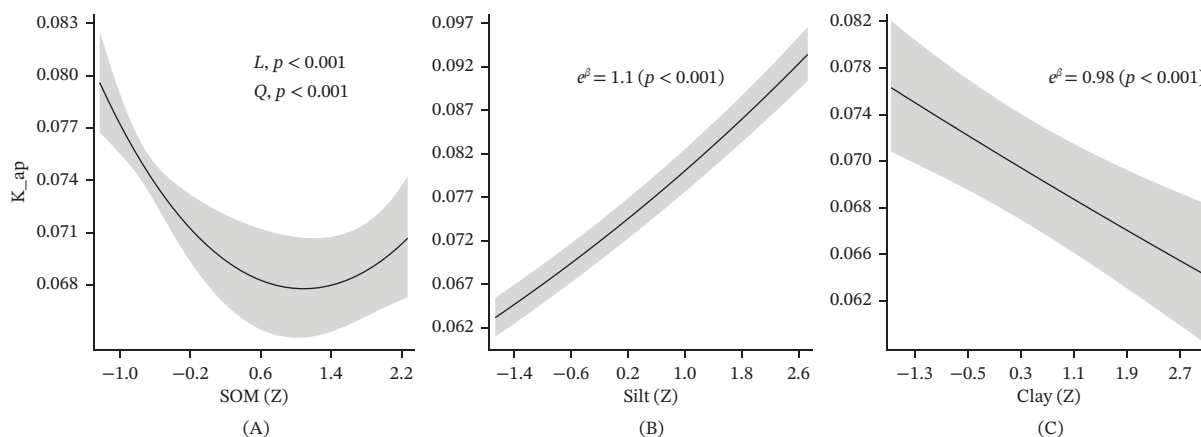


FIGURE 8 | Univariate relationships between soil texture, soil organic matter and the apparent soil erodibility factor (K_{ap}). Panels (A, B, C) present the partial fits of the GLMs describing the relationships between soil organic matter (SOM), silt and clay, respectively, and the K_{ap} . Predictor variables were standardised using Z scores. The solid line represents the fitted trend, whereas the shaded area denotes the 95% confidence interval. In panel (B), the coefficient e^b is interpreted as the multiplicative change in the expected mean K_{ap} value associated with a one-unit increase in the standardised predictor. In panel (A), the nonlinear relationship was modelled using orthogonal polynomial terms to minimise multicollinearity. Reported p values indicate the statistical significance of the model terms.

interventions to mitigate erosion, minimise nutrient losses and sustain soil productivity [57].

Accordingly, soil texture should be regarded as a soil attribute associated with erosion resistance rather than as an independent determinant. In contrast to SOM, textural fractions are governed by relatively stable soil characteristics. Therefore, their relationship with CSER helps elucidate how the physical composition of soil influences structural stability and apparent erodibility.

In this context, CSER exhibited a negative relationship with silt content ($p < 0.001$), indicating that in the evaluated Peruvian Amazon systems, higher proportions of this fraction were associated with lower integrated soil resistance to erosion. This pattern is consistent with previous studies reporting negative

associations between silt content and CSER [22]. This result was also consistent with the behaviour of the structural indicators that comprise the CSER index. MWD, SSSI and SCAI showed negative relationships with silt content ($p < 0.001$), suggesting reduced aggregate stability and less favourable structural conditions for soil erosion resistance. In contrast, K_{ap} was the only indicator positively associated with silt content ($p < 0.001$), indicating that higher proportions of this fraction were linked to increased apparent erodibility factor values, a condition considered less favourable for the overall resistance of soil to erosion.

Complementarily, CSER exhibited a positive relationship with clay content ($p < 0.001$), indicating that, in the evaluated Peruvian Amazon systems, higher proportions of this fraction were associated with greater integrated soil resistance to erosion. This behaviour is consistent with the well-established role of clay in promoting particle cohesion and maintaining soil structure. In this regard, previous studies have reported that overall soil structural stability was positively associated with SOC content and negatively associated with clay content [58]. The observed response was also reflected in the indicators comprising the CSER index. Both MWD and SCAI showed positive associations with clay content ($p < 0.001$), indicating greater aggregate stability and higher levels of SOC-related cementing agents. In contrast, SSSI, CR and K_{ap} exhibited decreasing trends ($p < 0.001$), such that increases in clay content were associated with lower values of these indices.

4 | Conclusion

The evaluated soils exhibited distinct edaphic profiles according to site–land-use conditions, with variations associated with texture, organic matter, structural stability and erodibility indicators. The PI-FO was characterised by higher clay and silt contents, greater CP and a larger MWD of aggregates. The coffee agroforestry system in Alto Saposoa recorded the highest values of SOM, organic carbon, organic carbon density, structural stability and CSER. In contrast, the oil palm system in Lamas was associated with a coarser-textured soil, characterised by a greater

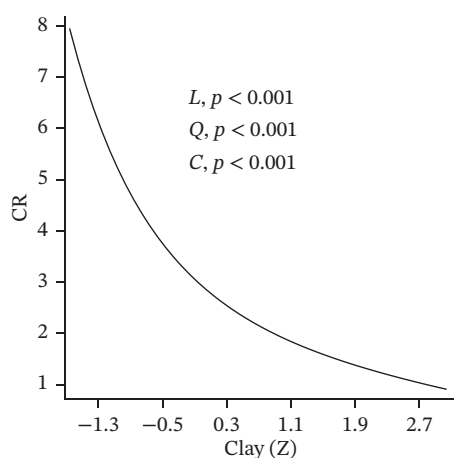


FIGURE 9 | Univariate relationship between clay content and clay ratio (CR). The figure presents the partial fit of the GLM describing the relationship between standardised clay content (Z score) and CR. The solid line represents the fitted trend, whereas the shaded area denotes the 95% confidence interval. The nonlinear relationship was modelled using orthogonal polynomial terms to minimise multicollinearity. Reported p values indicate the statistical significance of the model terms.

predominance of sand content and a higher CR, whereas the rice system in Yurimaguas exhibited higher SCAI and K_{ap} values, indicating greater relative erodibility. These results suggest that soil resistance to erosion is associated with integrated patterns of texture, organic matter and land use rather than with any single soil property. In this context, high CSER values can be interpreted as reflecting greater overall soil resistance to erosive processes.

Correlation analysis revealed that higher clay, SOM, SOC, CP and MWD values were associated with greater resistance to erosion, whereas sand content, BD and K_{ap} were associated with increased susceptibility to erosion. Multivariate analysis showed that variation in the CSER indicators was associated with site–land-use condition, clay, silt and SOM, collectively explaining 90.34% of the constrained variation, with clay making the largest independent contribution (32.58%). Furthermore, GLMs confirmed that clay, SOM, silt and site–land-use conditions were significantly associated with CSER and its constituent indicators. These findings demonstrate that the response of sloping agricultural soils to erosion is mainly related to integrated patterns of soil texture, organic matter and site–land-use conditions rather than to any single soil property.

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Disclosure

All authors have read and approved the final manuscript. Geomar Vallejos-Torres had full access to all study data and takes full responsibility for the integrity of the data and the accuracy of the analyses performed.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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