



Article

Spatial Modelling of Soil Quality and Lime Requirement for Precision Management in Humid Tropical Coffee Systems

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Abstract

Soil heterogeneity and acidity are major constraints to *Coffea arabica* production in the Amazonian soils of Peru. This study developed a spatial predictive framework that integrates a weighted Soil Quality Index (SQI_w) and geostatistical modelling (Regression–Kriging and Ordinary Kriging) to estimate lime requirements (LRs) and delineate management zones. A total of 69 coffee-cultivated soil samples were analysed, and spectral information (NDVI) was incorporated to estimate relative yield (RR). Multivariate analysis defined a Minimum Data Set (MDS) composed of exchangeable Na, available P, pH and silt percentage; the highest weights were assigned to P ($W_i = 0.292$) and pH ($W_i = 0.276$). SQI_w exhibited wide variability (0.01–0.87; CV = 51.8%) and was grouped into five classes, with low (43.5%)- and very low (21.7%)-quality classes predominating. SQI_w showed a strong relationship with RR ($r = 0.64$). Geostatistical models performed differently between localities: in Nuevo Huancabamba, Regression–Kriging improved prediction accuracy (SQI_w: $R^2 = 0.58$; LR: $R^2 = 0.396$), whereas in San José de Sisa, Ordinary Kriging provided better fits only for LRs ($R^2 = 0.32$). Nuevo Huancabamba is dominated by moderate-to-high-quality soils (87.29%; SQI_w > 0.6) and low lime requirements (74.94%; <0.84 t ha⁻¹), in contrast with San José de Sisa, where low-quality soils prevail (89.45%; SQI_w < 0.4) alongside high LRs (75.26%; 2.54–7.13 t ha⁻¹). The resulting maps enable targeted interventions—precision liming and focused P fertilisation—to correct acidity and phosphorus deficiency, thereby improving input-use efficiency and enhancing the sustainability of Amazonian coffee systems.



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Keywords: soil quality index; regression kriging; soil acidity; NDVI

1. Introduction

Coffee cultivation is a cornerstone of the global agricultural economy, ranking among the most traded commodities and supporting over 25 million rural households in developing countries [1]. In Peru, coffee is a strategic driver of rural development, generating

more than two million direct and indirect jobs across its value chain and involving over 230,000 farming families in 16 regions, thereby underpinning rural livelihoods and local sustainability [2,3]. National average yield is 0.83 t ha^{-1} ; the San Martín region leads production (20.61% of national output), with an average yield of 1.01 t ha^{-1} and a mean annual growth of 3.3% over the last five years [4]. In El Dorado province, coffee contributes 29.4% of the agricultural gross production value, with mean yields near 1.12 t ha^{-1} [5].

This productive expansion takes place on inherently challenging Amazonian soils. Oxisols and Ultisols in the region exhibit marked natural acidity, where base cations (Ca^{2+} , Mg^{2+} , K^{+}) are replaced by H^{+} and Al^{3+} , leading to low natural fertility and elevated exchangeable aluminium that constrains root growth [6–8]. Acid conditions also limit nutrient availability by promoting P fixation, slowing nitrification and reducing cation-exchange capacity; at $\text{pH} < 5.0$ phosphate is strongly adsorbed by Al oxides, forming insoluble compounds [9,10]. Acidic soils may also exhibit high soluble concentrations of Zn, Cu, Fe and Mn, increasing the risk of micronutrient toxicity [11,12].

Soil acidity is the main edaphic constraint for coffee, causing Al^{3+} and Mn^{2+} toxicities, deficiencies of Ca, Mg, P and N, and reduced fertilizer-use efficiency [13,14]. Liming is the primary corrective measure to raise pH into the optimal 4.9–5.7 range, but uniform lime application is often inefficient under high spatial variability and may lead to over- or under-application when based only on pH and exchangeable Al [15,16]. Overliming can excessively raise pH and diminish cationic micronutrient availability, thereby inducing secondary deficiencies [17,18].

Precision agriculture offers a solution by enabling spatially explicit management. Variable-rate application of fertilizers and amendments improves input-use efficiency and system sustainability by matching inputs to local needs; site-specific recommendations have reduced P and K requirements substantially compared with uniform methods, while liming requirements under variable-rate regimes range widely ($0\text{--}866 \text{ kg ha}^{-1}$) versus conventional single-rate prescriptions [19,20]. Delineation of homogeneous management zones using indicators such as organic matter (OM), pH and electrical conductivity effectively proxies soil fertility potential and informs targeted interventions [21,22].

Remote sensing and GIS-based analyses further strengthen precision soil management by incorporating crop response and environmental variability into spatial decision-making frameworks [23]. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), derived from multispectral satellite imagery, provide a robust proxy for crop vigor and spatial patterns of yield potential, capturing the integrated effects of soil fertility, climate, and management over time. When combined with edaphic, climatic, and topographic covariates within a GIS environment, NDVI enables the delineation of management zones that reflect not only soil chemical constraints but also the spatial variability of crop performance. This multivariate integration improves the reliability of spatial predictions of soil quality indices and lime requirements by accounting for multiple interacting drivers, thereby supporting site-specific lime application strategies consistent with the principles of precision agriculture.

Geostatistical interpolation, particularly kriging, provides robust spatial prediction and uncertainty quantification, with Universal Kriging accommodating deterministic spatial trends [24–26]. Regression–Kriging, which couples a regression model with kriging of residuals, is especially suitable here because it integrates edaphoclimatic covariates, reduces bias from spatially structured residuals, and delivers more accurate, robust estimates in soils with high spatial variability.

This study develops a spatial predictive framework based on Regression–Kriging to estimate liming requirements in coffee plantations by integrating a Soil Quality Index (SQIw) with edaphoclimatic variables. Specific objectives are to: (i) derive the SQIw via

multivariate analysis, (ii) estimate lime requirements across SQIw classes, and (iii) spatially model these requirements to delineate management zones that optimize coffee productivity and sustainability in the Amazon.

2. Methods

2.1. Study Area

This study was conducted in the Peruvian high jungle, within the districts of San José de Sisa and part of Santa Rosa, El Dorado Province, San Martín Region (Figure 1). 69 Soil samples were collected from coffee plantations at a depth of 30 cm: 23 samples from Nuevo Huancabamba (San José de Sisa district) and 46 samples from the San José de Sisa locality (San José de Sisa and Santa Rosa districts).

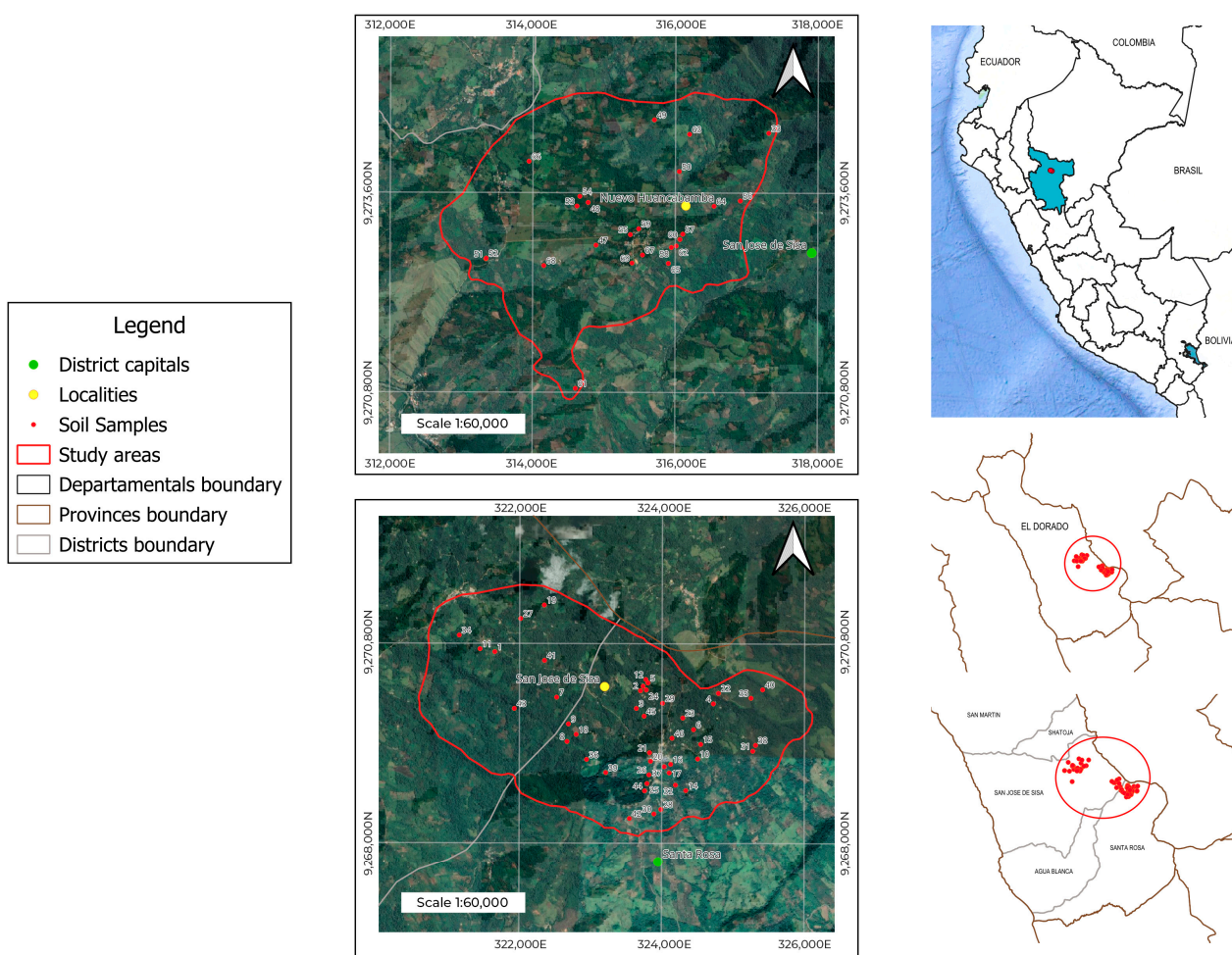


Figure 1. Location map with 69 sampling points in El Dorado province.

San José de Sisa presents a humid climate with a dry-winter regime and temperate conditions and is classified within the Humid Forest life zone. The mean annual temperature ranges from 22 to 24 °C, and the mean annual precipitation is 1359 mm. Elevation varies between 854 and 1392 m above sea level (m a.s.l.). Soils are predominantly Ferralsols (58.7%) and Cambisols (41.3%).

Nuevo Huancabamba exhibits a warm, rainy climate with consistently high humidity throughout the year; however, its life zone is classified as a Dry Forest owing to the characteristic balance between precipitation and evapotranspiration. The mean annual temperature ranges from 24 to 25 °C, while the mean annual precipitation is approximately

1400 mm, and elevation ranges from 469 to 800 m a.s.l. Soils are dominated by Ferralsols (95.7%) with a minor proportion of Acrisols (4.3%).

Climatic normals were obtained from the WorldClim version 2.1 database [27].

2.2. Soil Sampling

Soil sampling was conducted following the procedure described by [28]. Each sample corresponded to a homogeneous management unit (<10 ha), delineated based on slope, soil texture and color. Within each homogeneous zone, ten subsamples were randomly collected from the 0–30 cm soil layer and subsequently composited to obtain a single representative sample. A total of 69 composite soil samples were collected across the main coffee-growing areas of San José de Sisa and Nuevo Huancabamba, El Dorado Province, San Martín Region (Figure 1). Of these, 46 samples were obtained from San José de Sisa, which encompasses approximately 1204.58 ha of agricultural land, and 23 samples from Nuevo Huancabamba, covering about 1219.63 ha. Soil samples were spatially distributed throughout both study areas to capture the variability of coffee production systems, which represent the dominant land use in these localities. The operational steps of the sampling process are illustrated in Figure 2.

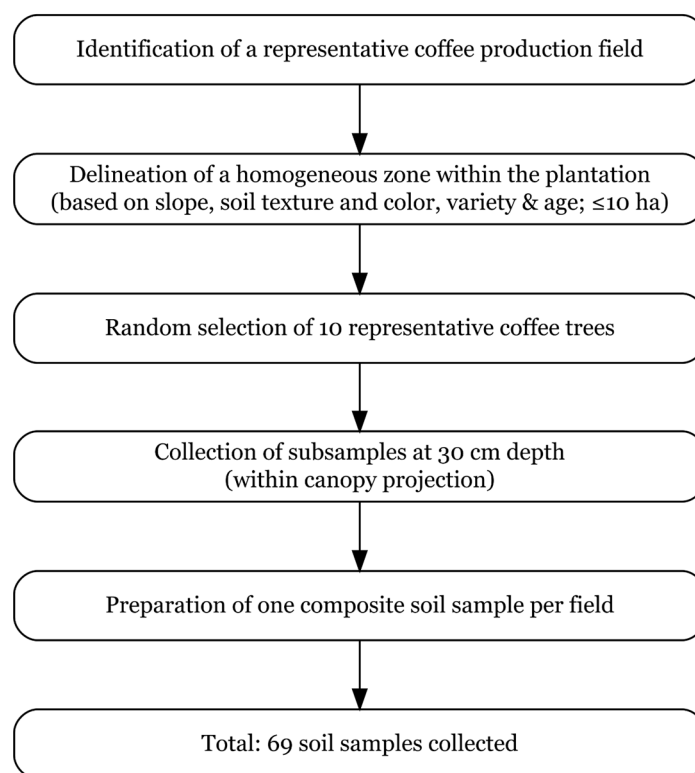


Figure 2. Operational flowchart of the soil sampling design applied in coffee plantations.

2.3. Soil Analysis

Soil samples were analyzed at the Network of Soil, Water and Foliar Laboratories of the National Institute of Agrarian Innovation (LABSAF-INIA). Samples were pre-treated, air-dried at $40\text{ }^{\circ}\text{C}$ and sieved to 2 mm [29]. Soil texture was determined by the Bouyoucos hydrometer method [30]. Soil pH was measured following the standardized EPA 9045D method [31]. Electrical conductivity (EC) was measured according to [32] ISO 11265:1994/Cor.1:1996. Calcium carbonate (CaCO_3) content was determined by acid neutralization (calcimeter) following [30]. To convert EC measured in diluted soil–water

extracts to the electrical conductivity of the saturated paste extract (EC_e), we followed the procedure proposed by [33]:

$$EC_e = \left(1.054 + \frac{283.4}{49.699 + 0.524 \times Clay\% - 0.339 \times Sand\%} \right) \times EC_{1:5}$$

Soil organic matter was estimated by the Walkley–Black method [34], and available phosphorus was determined by the Bray–Kurtz method [35]. Exchangeable bases (Ca^{2+} , Mg^{2+} , K^+ and Na^+) were extracted with ammonium acetate and quantified following [36]. Effective cation exchange capacity (ECEC) was calculated as the sum of exchangeable cations. Bulk density ($g\ cm^{-3}$) was estimated using pedotransfer functions reported by [37,38]. In general form the pedotransfer relationship used can be expressed as:

$$BD = 1.66 - (0.004 \times Clay) - (0.002 \times Silt) - (0.005 \times OM)$$

2.4. Determination of Relative Coffee Yield (RR)

2.4.1. Extraction of the Normalized Difference Vegetation Index (NDVI)

NDVI was computed in Google Earth Engine using Sentinel-2 Surface Reflectance Harmonized imagery (Level-2A) for the period June 2021–June 2024. This temporal window was selected to derive a multi-year average NDVI, thereby reducing interannual variability related to climatic fluctuations, crop phenology, and atmospheric noise, and providing a more stable and representative indicator of coffee canopy vigour.

The four-year period was defined based on the fact that, at the time of soil sampling in 2024, the youngest coffee plantation in the study area was four years old. This criterion ensured that all images used in the analysis corresponded to areas consistently occupied by coffee throughout the selected interval, avoiding the inclusion of spectral signals associated with previous land uses or other crops.

NDVI was calculated as $(NIR - Red)/(NIR + Red)$ using Sentinel-2 bands B8 and B4. To minimize cloud-related effects, a cloud-masking procedure based on the QA60 quality band was applied, and only cloud-free pixels were retained. Subsequently, multi-year mean NDVI values were extracted at each soil sampling location and linked to their geographic coordinates, ensuring that NDVI predominantly reflected persistent spatial differences in canopy vigour associated with underlying soil conditions.

2.4.2. Calculation of Relative Yield (RR)

Relative yield (RR) was estimated using NDVI as a proxy for crop vigor and productive performance. NDVI has been shown to provide an early, rapid and low-cost estimate of crop yield and thus serves as a useful complement to conventional assessments [39]. For each sampling point, the temporal mean NDVI was computed from the cloud-filtered observations; RR was then calculated as the ratio between each point's mean NDVI and the maximum mean NDVI observed across all sampling points:

$$RR = \frac{meanNDVI}{maxNDVI}$$

2.5. Development of the Weighted Soil Quality Index (SQI_w)

2.5.1. Selection of the Minimum Data Set (MDS)

The relationship between RR and soil properties was evaluated using Spearman's rank correlation coefficient (ρ), appropriate for non-linear relationships and non-normally distributed data. Variables showing moderate to strong associations with RR ($|\rho| \geq 0.40$) were retained for further analysis. Variables with skewness > 1.0 were log-transformed,

and those with skewness between 0.5 and 1.0 were square-root transformed to improve distributional symmetry.

Pairwise Pearson correlations were then computed among the retained variables to detect collinearity. Variable pairs with $|r| > 0.70$ were considered collinear; within each collinear pair, one variable was excluded, preferentially retaining the variable exhibiting the stronger correlation with RR or greater analytical reliability. The remaining variables were standardized (z-score) and subjected to principal component analysis (PCA). Components with eigenvalues greater than 1 were retained, and for each retained component the two variables with the largest absolute loadings were selected to compose the MDS. The resulting MDS variables were used to construct the weighted SQIw.

2.5.2. Assignment of Weights to the MDS Variables

Principal component analysis (PCA) was applied to the MDS to calculate the relative weights (W_i) of each variable based on their contributions to the principal components that together accounted for at least 70% of the cumulative variance. The weight assigned to each variable was obtained as a weighted sum of its individual contributions (C_{ij}), adjusted by the proportion of variance explained by each component (V_j), following the expression:

$$W_i = \frac{\sum_{j=1}^p (C_{ij} \times V_j)}{\sum_{j=1}^p V_j}$$

2.5.3. Normalization of Variables

The MDS variables were normalized to a dimensionless scale ranging from 0 to 1, where values approaching 1 indicate favorable soil-quality conditions and values near 0 reflect limiting conditions. Normalization was performed using threshold ranges defined in Table 1. Three scoring functions were applied “more is better”, “less is better” and “optimal range” depending on the expected relationship between each variable and soil quality. This procedure standardized measurement units and facilitated direct comparison among the different soil-quality indicators.

Table 1. Theoretical thresholds and response types of the soil variables used for normalizing the weighted soil quality index (SQIw) in coffee cultivation.

Variable	Lmin	Lopt_Low	Lopt_High	Lmax
Silt (%)	10	—	—	50
Na (cmol kg ⁻¹)	0.0	—	—	0.6
P (mg kg ⁻¹)	0.4	4.0	11	20
pH	4.9	—	—	5.2

2.5.4. Calculation of the Weighted Soil Quality Index (SQIw)

The SQIw was calculated by linearly combining the normalized values (N_i) of the selected indicators, weighted according to their relative contributions (W_i) derived from the PCA. The index was computed following the expression:

$$SQI_W = \sum_{i=1}^n (W_i \times N_i)$$

Classified as very low (<0.3), low (0.3–0.5), moderate (0.5–0.6), high (0.6–0.7), and very high (>0.7).

2.6. Calculation of Agricultural Lime Requirement (LR) for Coffee Cultivation

The LR was determined based on soil pH and organic matter (g kg^{-1}) using the method proposed by [40], which expresses LR in t ha^{-1} .

$$LR = 0.1059 \times [(6.0 - pH) \times OM]^{0.8729}$$

2.7. Comparative Analysis of LR Across SQIw Classes and SQIw Across Study Zones

Differences in LR and SQIw among soil-quality classes and between study zones were evaluated using non-parametric tests. A Kruskal–Wallis test was applied to assess overall effects ($p < 0.05$), followed by pairwise Dunn's tests with Bonferroni adjustment for multiple comparisons.

2.8. Regression Kriging

Regression kriging was applied for the spatial prediction of SQIw. This technique combines multiple linear regression with kriging of the residuals, using a set of predictor variables (Table 2). The spatial estimation was expressed according to the following equation.

$$\hat{Z}(S_0) = \sum_{i=0}^N Z(S_i)$$

where $Z(S_i)$ approaches the measured value at location i ; S_i is the unknown estimated value at point i ; N represents the number of measured values; and i denotes the prediction location (an unsampled point) [41].

Table 2. Environmental predictors.

Variable	Description
Topographic variables	Digital Elevation Model (DEM); slope; aspect; hillshade
Topographic indices	Topographic Position Index (TPI); Terrain Ruggedness Index (TRI); Topographic Wetness Index (TWI)
Landform classification	Geomorphons (categorical variable with 10 landform classes: flat, summit, ridge, shoulder, spur, slope, hollow, footslope, valley, depression)
Vegetation indices	Normalised Difference Vegetation Index (NDVI); Soil-Adjusted Vegetation Index (SAVI); Normalised Difference Water Index (NDWI)
Climatic variables	Annual total precipitation; annual mean temperature

Model Validation

The semivariogram model was selected based on the fit metrics RMSE, MAE and R^2 , considering as optimal the model with the lowest RMSE and MAE values and an R^2 close to 1 [42,43]. The RMSE and MAE values quantify the average deviation between observed and predicted soil properties and therefore represent the level of uncertainty associated with the spatial predictions. From a soil management perspective, these error levels are sufficiently low to support the delineation of management zones and the identification of areas with comparable soil conditions, which is more relevant for site-specific interventions than exact point-scale accuracy. The R^2 values indicate that the kriging models adequately capture the dominant spatial patterns of soil variability, which are critical for precision soil management decisions.

The predictive performance and robustness of the kriging interpolations were assessed using leave-one-out cross-validation (LOOCV). Although alternative validation approaches such as k-fold or split-sample validation exist, LOOCV was selected due to the relatively limited number of soil samples and the need to maximize the use of available observations

for model calibration. This method provides an unbiased and reliable estimate of prediction error and is widely recommended for local-scale geostatistical applications where sample density is constrained [44].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [Z_1(x_i) - Z_2(x_i)]^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Z_1(x_i) - Z_2(x_i)|$$

$$R^2 = 1 - \frac{\sum_{i=1}^n [Z_1(x_i) - Z_2(x_i)]^2}{\sum_{i=1}^n [Z_1(x_i) - Z_1]^2}$$

where n represents the number of samples, and $Z_1(x_i)$ and $Z_2(x_i)$ denote the predicted and observed values at site i , respectively.

3. Results

3.1. Statistical Distribution of Soil Properties

Descriptive statistics revealed high variability in most soil chemical properties, as indicated by coefficients of variation exceeding 50% for key variables such as available phosphorus, exchangeable bases, active acidity (H^+ and Al^{3+}), and effective cation exchange capacity (Table 3). Soils were predominantly acidic, with low to moderate organic matter contents and widespread phosphorus deficiency. In contrast, physical properties, including texture and bulk density, exhibited comparatively lower variability and generally favorable conditions for root development. This pronounced chemical heterogeneity across the study area indicates that uniform soil management practices are unlikely to be effective and supports the need for site-specific soil management strategies.

Table 3. Descriptive statistics of 17 physicochemical parameters related to the potential and current quality of coffee-growing soils.

Variable	Unidad	Mean	SD	CV	Min	Median	Max
pH	ratio	4.87	1.14	23.46	3.40	4.60	7.50
EC	dS m ⁻¹	1.06	0.54	50.60	0.23	1.02	2.59
OM	%	4.30	2.76	64.18	0.70	3.50	13.90
CaCO ₃	%	0.30	1.00	338.07	0.00	0.00	4.70
P	mg kg ⁻¹	10.27	12.40	120.78	0.40	6.60	84.60
K	mg kg ⁻¹	112.56	63.49	56.40	20.00	103.97	292.26
Sand	%	54.64	13.37	24.48	33.31	51.38	79.53
Silt	%	19.25	5.85	30.36	5.93	19.34	32.07
Clay	%	26.11	9.41	36.05	10.74	27.84	43.59
BD	g cm ⁻³	1.50	0.05	3.24	1.42	1.48	1.58
Ca	cmol kg ⁻¹	10.54	12.82	121.53	0.31	4.10	50.29
Mg	cmol kg ⁻¹	1.46	1.38	95.08	0.11	0.97	7.85
Kexc	cmol kg ⁻¹	0.31	0.21	69.76	0.00	0.27	1.01
Na	cmol kg ⁻¹	0.13	0.18	137.09	0.00	0.00	0.60
H	cmol kg ⁻¹	1.61	1.67	103.80	0.00	0.70	5.40
Al	cmol kg ⁻¹	1.22	2.17	177.61	0.00	0.00	9.10
ECEC	cmol kg ⁻¹	15.21	12.47	82.04	0.14	11.77	55.49

3.2. Multivariate Statistical Analysis for Selecting the MDS

Spearman's rank correlation analysis was first applied to identify soil variables associated with the relative yield of Coffee fields (RR) and to reduce the dimensionality of the

dataset (Figure 3). Sodium (Na) showed the strongest positive association with RR, followed by pH, whereas phosphorus (P), organic matter (OM), aluminum (Al), and exchangeable acidity (H) were negatively correlated. Based on the adopted threshold ($|r| \geq 0.40$), these variables were selected as candidates for the minimum data set (MDS).

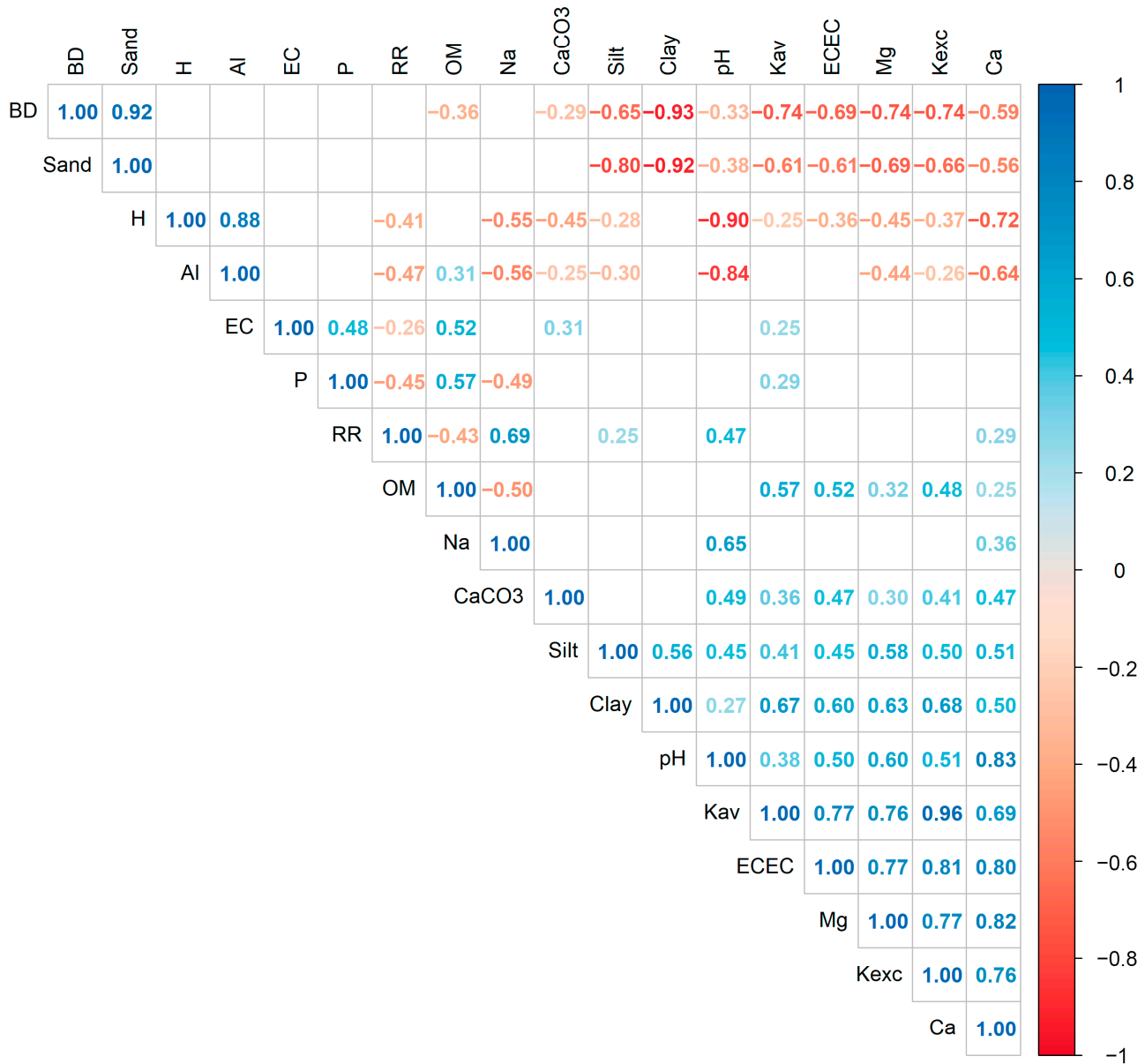


Figure 3. Non-parametric Spearman bivariate correlation matrix between 17 soil physicochemical variables and Relative Yield (RR). Only statistically significant correlations are shown ($p < 0.001$).

In addition, Ca, EC, and silt were retained despite their lower correlation coefficients because of their well-established pedological relevance for characterizing soil acidity status, exchangeable base balance, and water-related processes. This step ensured that key functional soil attributes were not excluded solely on statistical grounds.

Subsequent Pearson correlation analysis was used to assess multicollinearity among the selected variables (Figure 4). Strong correlations were observed between pH and Ca, and inverse relationships were observed between pH and both Al and H, reflecting the chemical behavior of acidic soils. To avoid redundancy, pH was retained as an integrative indicator of soil acidity, while Ca, Al, and H were excluded from the final MDS.

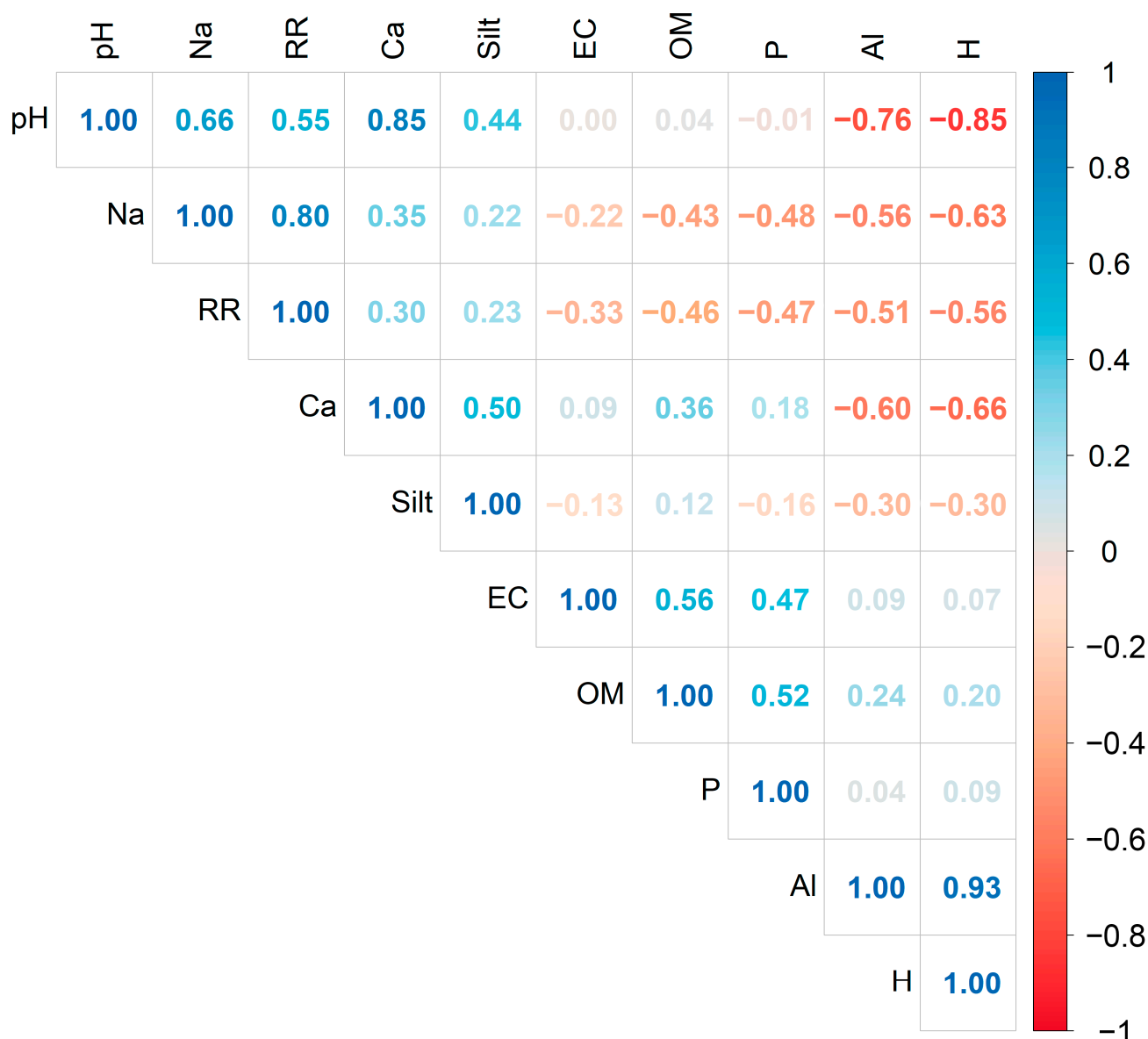


Figure 4. Pearson bivariate correlation matrix among nine soil physicochemical variables and Relative Yield (RR). Only statistically significant correlations are shown ($p < 0.001$).

Similarly, negative associations between P and acidity-related variables highlighted the role of Al and H in limiting phosphorus availability. Exchangeable bases (Na and Ca) showed inverse relationships with potential acidity, supporting their relevance for soil fertility diagnosis. Based on this combined statistical and pedological evaluation, the final MDS retained variables that were both minimally redundant and functionally representative of soil quality constraints affecting coffee production.

Principal component analysis (PCA) reduced the dimensionality of the soil dataset and identified two components with eigenvalues greater than 1, explaining 68.71% of the total variance (Table 4). PC1, which accounted for 41.33% of the variance, was mainly associated with exchangeable Na, available P, organic matter, and EC, representing a gradient related to nutrient availability and salinity effects. PC2 explained 27.39% of the variance and was dominated by pH and silt content, reflecting soil acidity and textural control over nutrient retention and leaching processes.

Table 4. Principal Component Analysis (PCA) of soil variables.

PCs ^a	PC1	PC2	PC3	PC4
Eigenvalue	2.48	1.64	0.85	0.56
Variance (%)	41.33	27.39	14.18	9.29
Cumulative Variance (%)	41.33	68.71	82.89	92.19
Factor loadings/eigen vector for each variable ^{b,c}				
P	0.76	0.28	0.13	0.53
OM	0.71	0.51	−0.20	−0.15
pH	−0.44	0.80	0.23	0.22
Silt	−0.33	0.62	−0.66	−0.07
Na	−0.81	0.35	0.40	−0.08
EC	0.66	0.40	0.37	−0.44

^a Only components with eigenvalues > 1 are highlighted (Kaiser criterion). ^b Variables in bold denote absolute loadings ≥ 0.50 . ^c Variables with underlined factor loadings are considered highly weighted and compose the MDS.

Based on the highest absolute loadings and to avoid redundancy among correlated variables, Na, P, pH, and silt were selected as the minimum data set (MDS). These variables capture the dominant chemical and physical constraints affecting soil quality in coffee-growing systems and were subsequently used to compute the soil quality index (SQIw).

3.3. Edaphic Influence of the MDS Variables on the Weighted SQIw

The weighting values (W_i) obtained for the MDS variables (Figure 5) reveal the relative importance of each soil property in shaping the Weighted SQIw. Available P exhibited the highest weight ($W_i = 0.292$), followed closely by pH ($W_i = 0.276$), indicating their dominant role in determining soil quality. In contrast, Na ($W_i = 0.263$) and silt content ($W_i = 0.169$) showed comparatively lower influence. Overall, these results underscore that P availability and soil acidity are the primary drivers of soil quality in coffee-growing systems.

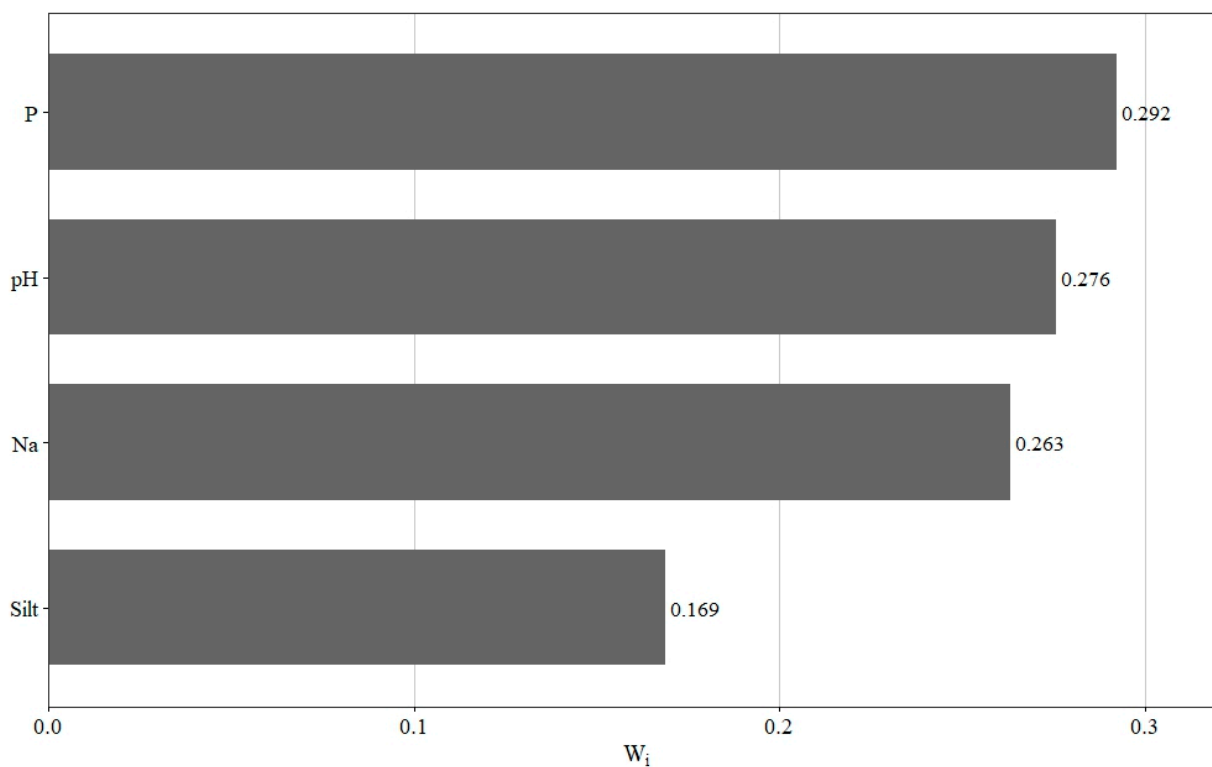


Figure 5. Relative weights (W_i) of the minimum data set (MDS) indicators used in the estimation of the weighted Soil Quality Index (SQIw).

The frequency histogram of the SQI_w (Figure 6) exhibited a positively skewed distribution with high variability (CV = 51.75%), with values ranging from 0.01 to 0.87. Based on the defined classification thresholds, SQI_w was grouped into five categories: very low (<0.30), low (0.30–0.50), moderate (0.50–0.60), high (0.60–0.70), and very high (>0.70). The class distribution indicated that low-quality soils represented the largest proportion (43.50%), followed by very low-quality soils (21.70%) and high-quality soils (15.90%). This pattern reflects a predominance of soils with limiting quality levels primarily associated with strong acidity.

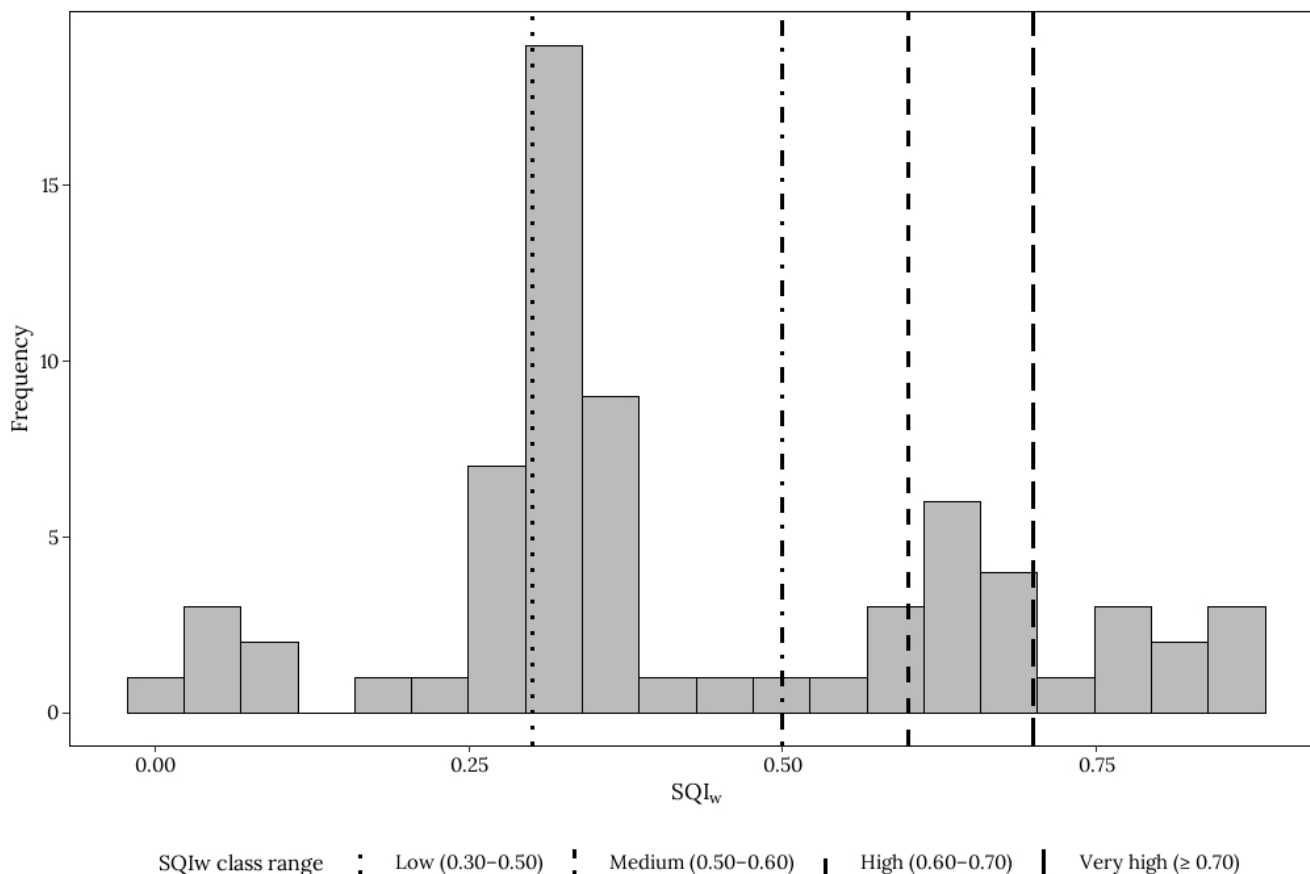


Figure 6. Distribution of the weighted Soil Quality Index (SQI_w) in coffee-growing soils from the localities of San José de Sisa and Nueva Huancabamba.

Among the variables analyzed, soil pH exhibited the strongest positive correlation with the SQI_w ($r = 0.71$; Table 5), indicating that higher-quality soils were characterized by values closer to neutrality (6.29 ± 0.74), whereas soils classified as very low quality showed pronounced acidification (4.09 ± 0.43). These patterns were consistent with the negative correlations observed for exchangeable H ($r = -0.58$) and exchangeable Al ($r = -0.45$), both of which increased markedly in the lower SQI_w classes (2.38 ± 1.54 and $1.89 \pm 2.48 \text{ cmol kg}^{-1}$, respectively).

Regarding soil texture, silt content showed a moderate positive correlation with the SQI_w ($r = 0.47$), indicating that soils with intermediate proportions of fine particles tended to exhibit higher relative quality. Exchangeable Na also presented a strong positive correlation ($r = 0.74$). Both variables are related to water infiltration through the soil profile and, consequently, to the leaching of exchangeable bases. Available P exhibited a moderate negative correlation with the SQI_w ($r = -0.37$), with the highest concentrations occurring in the very low- and low-quality classes. This pattern does not reflect an improvement in soil quality; rather, P accumulation in these soils may be

associated with concurrent increases in organic matter (OM) and electrical conductivity (EC), suggesting enhanced mineralization. In contrast, the increase in OM coincided with marked rises in Al and H, which supports the negative correlation between P and the SQIw.

Table 5. Mean values of the soil variables across different SQIw classes.

Variable	Pearson Correlation	SQIw				
		Very High	High	Medium	Low	Very Low
Sand (%)	−0.29	46.06 ± 11.44	51.46 ± 12.89	57.07 ± 19.76	57.68 ± 12.27	56.12 ± 14.64
Silt (%)	0.47	24.56 ± 5.67	21.87 ± 6.56	19.59 ± 10.73	17.81 ± 3.84	16.61 ± 5.50
Clay (%)	0.13	29.41 ± 8.58	26.67 ± 8.07	23.35 ± 10.00	24.50 ± 9.84	27.25 ± 10.26
pH	0.71	6.29 ± 0.74	5.76 ± 0.54	5.60 ± 0.62	4.38 ± 1.03	4.09 ± 0.43
OM (%)	−0.17	2.85 ± 0.81	4.09 ± 2.49	2.23 ± 0.38	5.15 ± 3.36	4.15 ± 2.18
EC (ds m ^{−1})	−0.19	0.86 ± 0.52	1.03 ± 0.46	0.71 ± 0.23	1.13 ± 0.55	1.14 ± 0.60
CaCO ₃ (%)	0.26	0.96 ± 1.63	0.25 ± 0.81	0.00 ± 0.00	0.27 ± 1.05	0.00 ± 0.00
P (mg kg ^{−1})	−0.37	5.91 ± 1.62	4.51 ± 3.45	1.67 ± 1.32	12.23 ± 15.57	15.17 ± 12.02
K (mg kg ^{−1})	0.12	132.25 ± 77.05	125.97 ± 68.34	69.04 ± 36.16	104.11 ± 67.15	115.23 ± 43.72
Ca (cmol kg ^{−1})	0.52	19.95 ± 12.73	17.48 ± 12.69	5.99 ± 3.95	8.54 ± 14.06	4.12 ± 2.91
Mg (cmol kg ^{−1})	0.29	1.81 ± 0.87	1.75 ± 0.79	0.98 ± 0.63	1.27 ± 1.63	1.47 ± 1.59
Na (cmol kg ^{−1})	0.74	0.37 ± 0.13	0.28 ± 0.19	0.34 ± 0.18	0.02 ± 0.06	0.04 ± 0.09
H (cmol kg ^{−1})	−0.58	0.08 ± 0.06	0.07 ± 0.06	0.10 ± 0.00	2.38 ± 1.54	2.49 ± 1.56
Al (cmol kg ^{−1})	−0.45	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	1.89 ± 2.48	1.83 ± 2.47
ECEC (cmol kg ^{−1})	0.34	22.69 ± 12.92	19.97 ± 13.36	7.63 ± 4.60	14.43 ± 13.51	9.80 ± 6.10
BD (g cm ^{−3})	−0.17	1.48 ± 0.04	1.49 ± 0.05	1.52 ± 0.06	1.50 ± 0.05	1.50 ± 0.05
RR	0.64	0.48 ± 0.04	0.44 ± 0.05	0.47 ± 0.03	0.38 ± 0.03	0.39 ± 0.05

Finally, the RR derived from coffee plantations showed a strong positive correlation with the SQIw ($r = 0.64$). This pattern confirms the ability of the index to capture the functional response of the crop: areas with higher SQIw values exhibited greater vegetative vigor, whereas lower index values corresponded to plantations with reduced canopy density and lower photosynthetic activity. Integrating RR into the analysis strengthens the link between soil quality and the physiological expression of coffee in the field, supporting the agronomic relevance of the SQIw as a composite indicator of soil conditions and crop performance.

3.4. Non-Parametric Comparison of Agricultural Lime Requirement Across SQIw Classes and Study Zones

Agricultural LRs differed significantly among SQIw classes (Figure 7a). The highest median LR values were observed in the Low (4.36 t ha^{−1}, $p_{\text{adj}} < 0.01$) and Very Low classes (4.24 t ha^{−1}, $p_{\text{adj}} < 0.001$), in contrast to the High (0.76 t ha^{−1}) and Very High classes (0.00 t ha^{−1}), which required minimal or no liming.

Significant differences were also detected in SQIw values between the two study localities (Figure 7b; $p_{\text{adj}} < 0.0001$). Nueva Huancabamba exhibited more than 50% of its coffee-growing soils within the high-quality category (median = 0.67), whereas San José de Sisa was predominantly characterized by soils within the very low-quality class (median = 0.32).

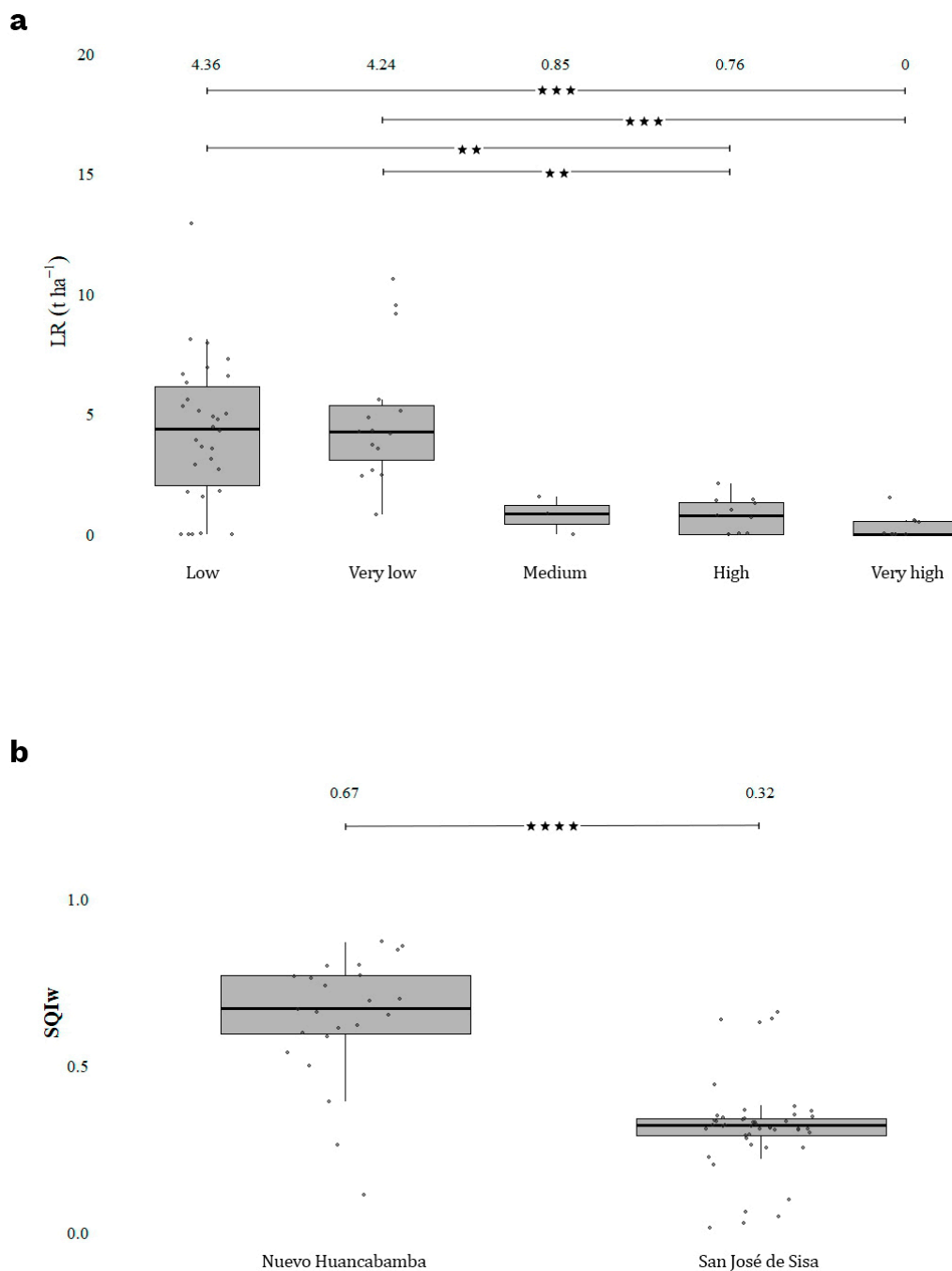


Figure 7. (a) Comparison of agricultural lime requirement (LR) across SQIw classes, and comparison of (b) SQIw between coffee-producing localities. Results correspond to Dunn’s post hoc test following the Kruskal–Wallis analysis, with Bonferroni correction for multiple comparisons. Statistical significance levels “****”, “***”, and “**” indicate $p\text{-adj} < 0.0001$, $p\text{-adj} < 0.001$, and $p\text{-adj} < 0.01$, respectively.

3.5. Modelling and Spatial Zoning of the Soil Quality Index (SQIw) and Lime Requirement (LR)

Semivariogram analysis revealed strong spatial dependence for the LR in both localities (PSV = 0.95), indicating that the lime requirement is primarily governed by intrinsic soil properties with limited random variability (Table 6). This strong spatial structure supports high reliability of kriging-based predictions and allows detailed spatial delineation of liming management zones.

Table 6. Statistical indicators from cross-validation for the prediction models of lime requirement and the Soil Quality Index (SQIw).

Locality	Variable	Model	Nugget (C ₀)	Sill (C ₀ + C)	Range (m)	PSV (C/C ₀ + C)	Cross-Validation		
							RMSE	MAE	R ²
Nuevo Huancabamba	LR	OK	0.029	0.58	1497.54	0.95	0.847	0.661	0.021
		RK	0.004	0.09	1497.54	0.95	0.527	0.438	0.396
	SQIw	OK	1.527	3.21	1497.62	0.52	0.219	0.179	0.278
		RK	0.252	0.53	1497.62	0.52	0.122	0.098	0.580
San Jose de Sisa	LR	OK	0.432	8.63	1479.11	0.95	2.483	1.920	0.320
		RK	0.074	1.55	1479.11	0.95	2.390	1.745	0.314
	SQIw	OK	3.835	8.05	1479.00	0.52	0.144	0.103	0.154
		RK	0.742	1.56	1479.00	0.52	0.077	0.054	0.087

In contrast, SQIw exhibited moderate spatial dependence (PSV = 0.52), reflecting its integrative nature as a composite index that combines soil chemical properties with vegetation response derived from NDVI. The higher nugget effect observed for SQIw suggests greater influence of local-scale variability related to management practices and biological factors, which is expected for composite indicators. Consequently, SQIw maps are robust for identifying relative soil quality patterns and management priorities, although they should be interpreted at a slightly coarser decision-making scale than LR maps.

The combined use of Regression–Kriging and Ordinary Kriging allowed the selection of the most appropriate modelling approach according to the dominant sources of variability at each site. Regression–Kriging outperformed OK in Nuevo Huancabamba, where auxiliary environmental variables explained a significant portion of the spatial trend, whereas in San José de Sisa, the spatial structure captured by OK alone was sufficient, indicating limited added value of regression covariates at that site.

Table 7 summarizes the areal distribution by classes of LR and the SQIw. The total agricultural area of the study sites Nueva Huancabamba and San José de Sisa was 1204.57 ha and 1219.63 ha, respectively.

Table 7. Distribution of lime requirement (LR) and SQIw in the San José de Sisa (a,b) and Nuevo Huancabamba (c,d) localities.

(a)	LR (t ha ⁻¹)	Total (ha)	(b)	SQIw	Total (ha)
	<0.33	363.03		<0.40	10.23
	0.33–0.84	550.87		0.40–0.50	39.28
	0.84–1.36	242.07		0.50–0.60	103.57
	1.36–1.87	45.70		0.60–0.70	491.37
	≥1.87	2.91		≥0.70	560.13
	Área Total (ha)	1204.58		Área Total (ha)	1204.58
(c)	LR (t ha ⁻¹)	Total (ha)	(d)	SQIw	Total (ha)
	<2.54	161.14		<0.20	33.88
	2.54–4.84	504.59		0.20–0.30	447.59
	4.84–7.13	413.33		0.30–0.40	643.40
	7.13–9.43	110.22		0.40–0.50	67.92
	≥9.43	30.35		≥0.50	26.84
	Área Total (ha)	1219.63		Área Total (ha)	1219.63

In Nueva Huancabamba, the LR is concentrated mainly in the <0.33 t ha⁻¹ (29.77%) and 0.33–0.84 t ha⁻¹ (45.17%) classes, which together account for approximately 74.93%

of the total area; classes $> 1.36 \text{ t ha}^{-1}$ represent only 3.99% (Table 7a). Regarding the Soil Quality Index (SQIw), values > 0.70 (46.50%) and $0.60\text{--}0.70$ (40.79%) predominate, indicating that more than 87% of the area exhibits moderate to high soil quality (Table 7b).

By contrast, in San José de Sisa, the LR is mainly distributed in the $2.54\text{--}4.84 \text{ t ha}^{-1}$ range, which comprises 41.37% of the area, followed by $4.84\text{--}7.13 \text{ t ha}^{-1}$ (33.89%), reflecting a substantially greater liming demand than in Nuevo Huancabamba (Table 7c). With respect to SQIw, the $0.30\text{--}0.40$ (52.75%) and $0.20\text{--}0.30$ (36.70%) classes predominate, indicating that roughly 90% of the area has low to moderate soil quality (Table 7d).

The spatial distribution of the Soil Quality Index (SQIw) and the liming requirement (LR) is shown in Figures 7 and 8. In Nuevo Huancabamba, extensive zones of medium to high SQIw are observed, which are associated with low to moderate LR and denote generally favourable edaphic conditions (Figure 8). In contrast, San José de Sisa is characterised by a greater proportion of areas with low to medium SQIw accompanied by elevated LR, indicating stronger soil chemical constraints (Figure 9). These spatial patterns confirm marked contrasts in soil quality and liming requirements between the two study sites.

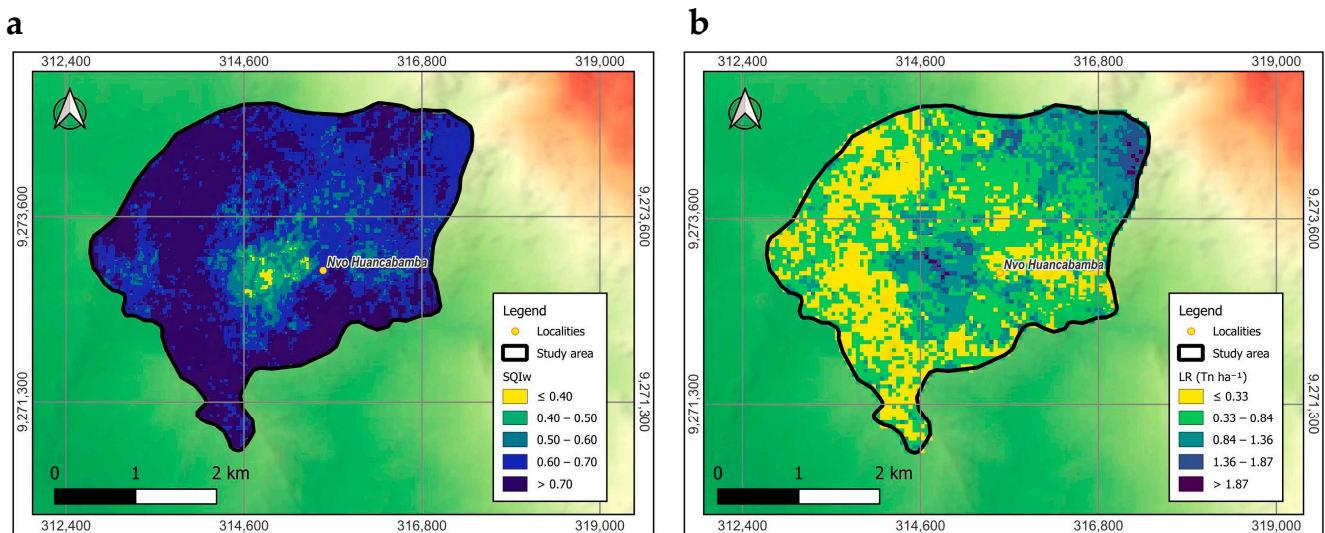


Figure 8. Maps of the spatial distribution of (a) the Soil Quality Index (SQIw) and (b) lime requirement in the Nuevo Huancabamba.

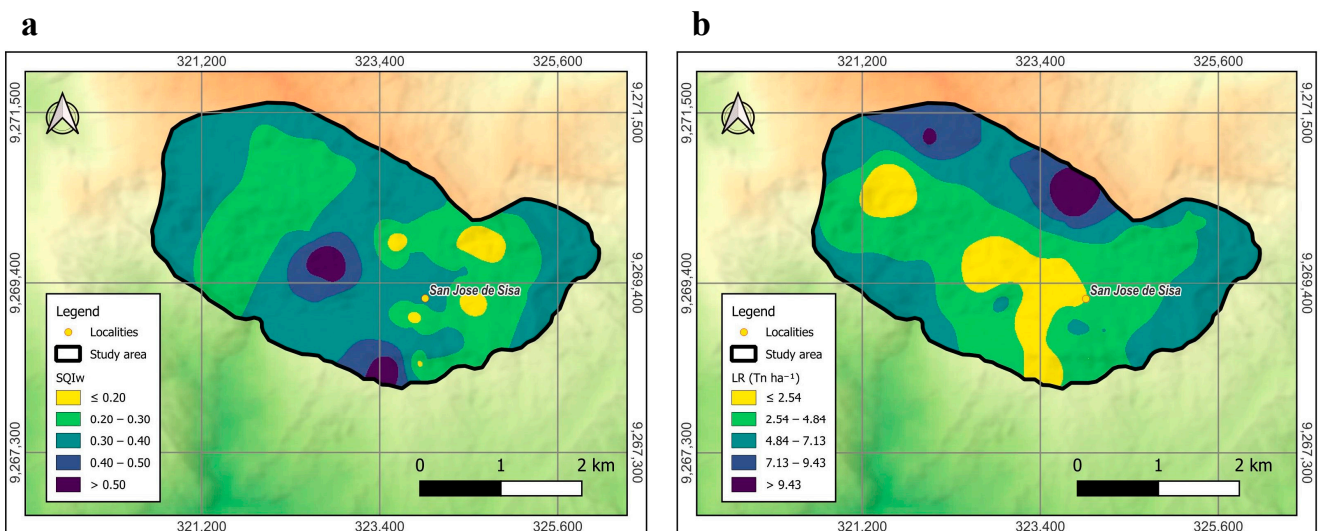


Figure 9. Maps of the spatial distribution of (a) the Soil Quality Index (SQIw) and (b) lime requirement in the San Jose de Sisa.

4. Discussions

4.1. Importance and Application of the Soil Quality Index (SQI_w) in Relation to Relative Yield (RR) of Coffee in the Peruvian Amazon

The NDVI-derived weighted soil quality index (SQI_w) represents a significant advance for the management of coffee production systems characterized by strong edaphic heterogeneity. The positive association observed between the SQI_w and relative yield (RR) confirms the value of the SQI_w as an integrative indicator of soil conditions that regulate crop vegetative vigour and photosynthetic performance, thereby linking below-ground constraints with canopy-level responses captured by spectral information [45]. This integration of soil properties and remote sensing metrics strengthens the delineation of agronomically coherent management zones, a central objective of precision agriculture in perennial tropical crops.

Multivariate analysis identified available phosphorus, soil pH, exchangeable Na and silt content as the variables contributing most to the total variance of the assessed soil systems, thereby justifying their inclusion in the construction of the SQI_w and the delineation of management zones. It is important to emphasize that their selection does not imply direct causal relationships with relative yield (RR); rather, these variables function as integrative proxies of the soil system and its dominant processes.

For instance, available P exhibited a negative correlation with RR; however, this relationship should not be interpreted as a direct yield-limiting effect. In our dataset, both available P and soil organic matter were positively associated with exchangeable Al, a key driver of potential acidity and root toxicity in coffee systems [46], which helps to explain their inverse relationships with RR. Thus, P availability in these contexts appears to co-occur with acidity-related constraints (Al mobilization and P fixation) and functions as an indicator of broader edaphic processes rather than as an isolated fertility benefit.

Similarly, soil pH represents a central regulatory variable that integrates multiple chemical processes, including Al solubility, base saturation and phosphorus availability, all of which indirectly condition root development and nutrient uptake [46]. Silt content emerged as a key textural modulator influencing water infiltration and leaching intensity in these humid environments, thereby indirectly affecting the retention of exchangeable bases and soil chemical stability [47]. Exchangeable Na, although present at low absolute concentrations, acted as a sensitive indicator of base status in highly weathered soils, showing consistent associations with Ca and inverse relationships with potential acidity [48]. Together, these variables capture interacting chemical and physical controls that govern soil functioning and its expression in coffee canopy vigour, as reflected by NDVI.

It is important to acknowledge the limitations of NDVI as an indirect indicator of actual coffee yield. NDVI primarily reflects canopy structure, leaf area, and photosynthetic activity [49], rather than direct fruit production. Its sensitivity can be influenced by canopy density, leaf overlap, phenological stage, and shading [50]. A well-documented limitation is its tendency to saturate at high canopy densities, where further increases in leaf area or biomass do not result in higher NDVI values [51,52]. Nevertheless, the positive correlation between NDVI-derived metrics and the weighted SQI_w in this study indicates that canopy density in the assessed coffee plantations remained within NDVI's sensitive range, avoiding significant saturation. As a result, NDVI provided a reliable basis for relative comparisons of canopy vigour and potential productivity across management zones, supporting its use in deriving the relative yield metric and informing the SQI_w. While NDVI does not replace direct yield measurements, it is widely used to characterize spatial variability in crop vegetative condition and growth, provided its limitations and capabilities are carefully considered [49,53].

Recent GIS- and remote-sensing-based studies have demonstrated that combining soil quality indices with spectral metrics such as NDVI improves the identification of man-

agement zones with differential agronomic responses and input requirements [52]. Areas characterized by higher index values generally exhibit greater productivity and reduced need for corrective amendments, enabling more efficient allocation of resources [54]. The spatial zoning developed in this study, together with the demonstrated predictive capacity of the SQIw, confirms its operational utility for prioritizing agronomic interventions and implementing site-specific fertilization strategies in humid tropical coffee systems.

4.2. Interpretation of the Weighted Soil Quality Index (SQIw) Under Acidic Soil Conditions in Amazonian Coffee Systems

Soil acidity represents the principal edaphic constraint for coffee production because it reduces phosphorus availability and restricts nitrification processes, thereby directly limiting yield potential [55,56]. In the present study, the SQIw exhibited a strong positive correlation with soil pH ($r = 0.71$), which enabled the precise identification of areas with pH values below the optimal range for coffee (5.0–5.5) [57]. Accordingly, zones classified as having low and very low soil quality showed mean pH values of 4.38 ± 1.03 and 4.09 ± 0.43 , respectively. Moreover, more than 50% of the soils within these categories require liming rates exceeding 4.36 and 4.24 t ha⁻¹, respectively, which are significantly different from the requirements of high- ($p\text{-adj} < 0.01$) and very high-quality zones ($p\text{-adj} < 0.001$).

These findings indicate that the SQIw is a robust indicator for identifying areas with differing degrees of acidity-induced degradation and, consequently, differing liming requirements. The comparative median analysis revealed highly significant differences ($p\text{-adj} < 0.0001$) in SQIw values between localities. Notably, 97.79% of the agricultural area of San José de Sisa and 4.11% of that of Nuevo Huancabamba are classified as having low or very low soil quality.

Furthermore, the results show that soil acidity in the studied sites is strongly influenced by the leaching of exchangeable bases, a process that depends on the spatial variation in soil texture. In this study, silt percentage was the only textural fraction significantly correlated with relative yield ($r = 0.25$) and showed the highest correlation with SQIw ($r = 0.47$); it also made a substantial contribution to the variance explained by principal component 2 (factor loading = 0.62). These features position silt content as a modulator of excessive base leaching, as it restricts infiltration in humid, high-precipitation environments [58]. In our dataset, silt contents of $21.87 \pm 6.56\%$ and $24.56 \pm 5.67\%$ observed in high- and very high-quality zones contributed to buffering intensified leaching processes, a condition present in 86.21% of the agricultural soils of Nuevo Huancabamba but only in 2.23% of those in San José de Sisa.

Finally, it is important to highlight the relevance of exchangeable Na as a reliable indicator of edaphic variability in acidic soils. Although Na ranged from 0.00 to 0.60 cmol kg⁻¹—below the 1.0 cmol kg⁻¹ threshold above which sodicity risk is considered high [59]—increases in Na were positively correlated with SQIw ($r = 0.74$) and with relative yield ($r = 0.80$), exerting a marked influence on the variability captured by principal component 1 (factor loading = -0.81). Similarly, to available P, Na functions as an integrative indicator of edaphic variability in acidic soils with very low levels of exchangeable bases, rather than as a direct causal agent of fertility. This behaviour is explained by Na's positive correlation with exchangeable Ca ($r = 0.36$) and its negative correlations with exchangeable H and Al ($r = -0.28$ and $r = -0.30$, respectively).

Taken together, the observed patterns demonstrate that high- and very high-quality soils for coffee in the Peruvian Amazon share clearly differentiated edaphic attributes that underpin their superior agronomic performance. These soils are characterised by elevated exchangeable Ca (17.48–19.95 cmolc kg⁻¹), high ECEC (19.97–22.69 cmolc kg⁻¹), pH values within or above the optimal range (5.76–6.29) and relatively low sand contents (46.06–51.46%), conditions that mitigate base leaching and maintain a chemically stable soil

system. These contrasts with low- and very low-quality soils underscore the importance of indicator variables such as Na, available P, silt percentage and pH; their statistical associations and high factor loadings in the principal components enabled capture of the soil system's functional logic and the construction of an SQIw that is both highly interpretable and spatially coherent.

4.3. Spatial Modelling of the Weighted Soil Quality Index (SQIw) and Liming Requirement (LR)

Spatial modelling of the weighted soil quality index (SQIw) and the liming requirement (LR) enabled the delineation of differentiated management zones in both localities, revealing marked contrasts in edaphic conditions. In Nuevo Huancabamba, the predominance of moderate-to-high SQIw values and low liming requirements suggests soils with greater chemical stability, improved base retention and higher productive potential, favouring low-intensity management strategies. By contrast, San José de Sisa exhibits extensive areas with low-to-medium SQIw and high liming requirements, indicating the need for more intensive interventions aimed at acidity correction and fertility restoration. These findings are consistent with previous reports indicating that targeted correction of soil acidity is essential to optimize nutrient availability and productivity in tropical systems [28,60].

From a precision-agriculture perspective, spatial maps derived from Ordinary Kriging and Regression-Kriging constitute key tools for delineating site-specific management units, thereby avoiding blanket applications of amendments and fertilizers. Such zoning enhances input-use efficiency, reduces production costs and mitigates environmental impacts—critical outcomes for agricultural systems operating in fragile ecosystems such as the Peruvian Amazon. Prior studies have demonstrated that management practices informed by spatial variability can substantially increase productive efficiency and soil sustainability [61–63]. In this context, the integrated use of SQIw and LR as zoning criteria directly contributes to strengthening the resilience of Amazonian coffee agroecosystems against ongoing chemical degradation of soils.

Although the predictive performance of the spatial models showed moderate R^2 values in some cases, these levels are consistent with previous studies in heterogeneous tropical environments, where soil chemical properties are influenced by complex, non-linear interactions and limited sampling density [61,63]. From a practical perspective, such predictive accuracy is sufficient to delineate management zones and discriminate liming requirement classes, which is more relevant for variable-rate applications than point-scale precision. Nevertheless, the inherent spatial uncertainty associated with kriging predictions implies that liming recommendations should be interpreted as decision-support guidance rather than exact application rates, particularly near class boundaries. Incorporating this uncertainty into site-specific management strategies—through conservative lime rates, field verification or phased corrections—can reduce the risk of over-liming and enhance nutrient-use efficiency, thereby supporting sustainable soil management in Amazonian agroecosystems [28,60].

5. Conclusions

The results of this study demonstrate that construction and spatial modelling of a weighted Soil Quality Index (SQIw) provide robust tools for diagnosing soil functional status and guiding site-specific management in coffee systems of northeastern Peru. Pronounced acidity, high spatial variability in chemical properties and textural heterogeneity indicate that base leaching and related chemical degradation are the principal constraints on productivity, thereby justifying differentiated liming and fertilisation strategies. The Minimum Data Set (MDS)—comprising pH, available P, exchangeable Na and silt percentage—captured the principal functional gradients governing soil quality in these environments, and the

weighted combination of these indicators produced an index highly sensitive to acidification processes, aluminium saturation, base cation depletion and infiltration dynamics.

The positive correlation observed between SQI_w and relative yield (RR) confirms the index's capacity to reflect crop performance, while the strong associations of SQI_w with pH, Na and silt underscore the controlling role of active acidity and texture in regulating fertility. Pronounced contrasts between sites were evident: Nuevo Huancabamba exhibited a greater proportion of soils with moderate–high SQI_w and correspondingly low lime requirements, which are indicative of greater chemical stability and lower degradation; conversely, San José de Sisa was dominated by low-quality soils characterised by strong acidification, elevated exchangeable Al³⁺ and intensive losses of Ca²⁺ and Mg²⁺, which translate into substantially higher liming demands.

Spatial modelling using Regression–Kriging and Ordinary Kriging revealed differential model performance conditioned by the spatial structure and heterogeneity of each locality. In Nuevo Huancabamba, the inclusion of edaphoclimatic covariates improved predictive capacity and enabled the production of higher-resolution maps, whereas in San José de Sisa, the spatial dependence was more effectively captured by Ordinary Kriging. The complementary application of these geostatistical approaches permitted the delineation of management zones with agronomic coherence, making them suitable for prioritising liming and targeted nutritional interventions.

Overall, these findings demonstrate that integrating multivariate analysis, soil quality indexing and advanced geostatistics provides a rigorous scientific basis for precision agriculture in Amazonian coffee landscapes. The SQI_w and the derived lime-requirement maps support a move away from uniform amendment practices towards spatially differentiated management that improves input-use efficiency, reduces chemical degradation and enhances the long-term sustainability and resilience of Peruvian coffee agroecosystems.

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References

1. Food and Agriculture Organization of the United Nations (FAO). *Final Evaluation of the Project “Sustainable Management of Agrobiodiversity and Recovery of Vulnerable Ecosystems in the Andean Region of Peru through the Globally Important Agricultural Heritage Systems Approach”*, 4th ed.; Food and Agriculture Organization of the United Nations: Rome, Italy, 2025. [CrossRef]
2. Ministry of Agricultural Development and Irrigation (MIDAGRI) Agricultural Statistics Information System—SIEA-BI. Available online: <https://app.powerbi.com/view?r=eyJrIjoiN2U3NTdkYTktOTk5Ny00NjQ5LTg0ZjEtMmIzYzlmZWlwMDhlIiwidCI6IjdmMDg0NjI3LTdmNDAtNDg3OS04OTE3LTk0Yjg2ZmQzNWYzZiJ9> (accessed on 1 February 2026).

3. PRODUCEmpresarial. *Sectoral Research Study on Coffee*, 1st ed.; Ministerio de la Producción: Lima, Peru, 2025. Available online: https://www.produceempresarial.pe/wp-content/uploads/2025/02/Estudio-de-Investigacion-Sectorial-del-Cafe_VF.pdf (accessed on 1 February 2026).
4. INCORE INCORE PERÚ | Regional Competitiveness Index. Available online: <https://incoreperu.pe/> (accessed on 1 February 2026).
5. Sistema Integrado de Estadística Agraria Agricultural Area of Peru. Available online: <https://web.archive.org/web/20250718192451/https://siesa.midagri.gob.pe/portal/informativos/superficie-agricola-peruana> (accessed on 1 September 2025).
6. Rosas Patiño, G.; Ávila Pedraza, E.Á.; Sánchez Castillo, V. Soil acidity limits agricultural production: A review focused on the Colombian Amazon. *RIAA* **2025**, *16*, 13.
7. Agegnehu, G.; Amede, T.; Erkossa, T.; Yirga, C.; Henry, C.; Tyler, R.; Nosworthy, M.G.; Beyene, S.; Sileshi, G.W. Extent and Management of Acid Soils for Sustainable Crop Production System in the Tropical Agroecosystems: A Review. *Acta Agric. Scand. Sect. B—Soil Plant Sci.* **2021**, *71*, 852–869. [[CrossRef](#)]
8. Chiapini, M.; Schellekens, J.; Oliveira Junior, J.C.; Calegari, M.R.; Vidal-Torrado, P. Pedogenesis in Very Deep Autochthonous Ferralsols of the Paraná Igneous Province (Brazil). *CATENA* **2023**, *224*, 106981. [[CrossRef](#)]
9. Barrow, N.J.; Hartemink, A.E. The Effects of pH on Nutrient Availability Depend on Both Soils and Plants. *Plant Soil* **2023**, *487*, 21–37. [[CrossRef](#)]
10. Nie, Z.; Li, J.; Liu, H.; Liu, S.; Wang, D.; Zhao, P.; Liu, H. Adsorption Kinetic Characteristics of Molybdenum in Yellow-Brown Soil in Response to pH and Phosphate. *Open Chem.* **2020**, *18*, 663–668. [[CrossRef](#)]
11. Armatmontree, C.; Leksungnoen, P.; Nansahwang, A.; Aramrak, S.; Kongsil, P.; Wisawapipat, W. Iron Toxicity Downregulates Root-Proton Efflux and Decreases Zinc Accumulation in Cassava. *Ann. Agric. Sci.* **2023**, *68*, 97–104. [[CrossRef](#)]
12. Gonçalves, D.A.M.; Pereira, W.V.D.S.; Johannesson, K.H.; Pérez, D.V.; Guilherme, L.R.G.; Fernandes, A.R. Geochemical Background for Potentially Toxic Elements in Forested Soils of the State of Pará, Brazilian Amazon. *Minerals* **2022**, *12*, 674. [[CrossRef](#)]
13. Márquez, F.R.; Quispe, P.; Molleapaza, N.; Cabrera, S.; Peña, J. Relationship between soil characteristics and altitude with the sensory quality of coffee grown under agroforestry systems in Cusco, Peru. *Sci. Agropecu.* **2020**, *11*, 529–536. [[CrossRef](#)]
14. Cerda, M.; Salgado, M.; Esquinca, H.; Gomez, A. Agronomic management of acidity and aluminum in coffee plantation soils, *Coffea arabica* in Berriozabal, Motozintla. *Cienc. Lat.* **2022**, *6*, 147–164. [[CrossRef](#)]
15. Alvarez, V.H.; Ribeiro, A.C. *Recommendations for the Use of Corrective Agents and Fertilizers in Minas Gerais*, 5th ed.; Soil Fertility Commission of the State of Minas Gerais: Mina Gerais, Brazil, 1999; pp. 43–56.
16. Aramburu Merlos, F.; Silva, J.V.; Baudron, F.; Hijmans, R.J. Estimating Lime Requirements for Tropical Soils: Model Comparison and Development. *Geoderma* **2023**, *432*, 116421. [[CrossRef](#)] [[PubMed](#)]
17. Ejigu, W.; Selassie, Y.G.; Elias, E.; Molla, E. Effect of Lime Rates and Method of Application on Soil Properties of Acidic Luvisols and Wheat (*Triticum Aestivum*, L.) Yields in Northwest Ethiopia. *Heliyon* **2023**, *9*. [[CrossRef](#)]
18. Sanders, J.R. The Effect of pH on the Total and Free Ionic Concentrations of Manganese, Zinc and Cobalt in Soil Solutions. *J. Soil Sci.* **1983**, *34*, 315–323. [[CrossRef](#)]
19. Da Silva, H.G.; Marques, M.L.; Ciacci, L.F.; Oliveira, A.S.D.; Marques, R.F.D.P.V.; Rocha, M.H.F.D.F.; Rodrigues, L.S.; Freitas, A.S.D. Spatial analysis of soil chemical attributes and generation of fertilizer and soil amendment application maps for coffee cultivation. *RSD* **2022**, *11*, e524111234997. [[CrossRef](#)]
20. Ferraz, G.A.e.S.; Da Silva, F.M.; Oliveira, M.S.; Avelar, R.C.; Sales, R.S. Spatial variability of the dosage of P₂O₅ and K₂O to fertilize in variable rate and in a conventional way in a coffee field. *Coffee Sci.* **2015**, *10*, 346–356.
21. Galindo Pacheco, J.; Vargas Díaz, R.; Martínez Niño, C.; Franco Florez, C. Analysis of Spatial Variation in Soil Fertility for the Delimitation of Homogeneous Management Zones in Precision Agriculture. *Dekamuaagropec* **2024**, *5*, 74–86. [[CrossRef](#)]
22. Cunha, T.J.F.; Mendes, A.M.S.; Giongo, V. Soil organic matter. In *Recurso Solo: Propriedades e Usos*; Nunes, R.R., Rezende, M.O.O., Eds.; Cubo: São Carlos, Brazil, 2015; Volume 9, pp. 273–293.
23. Poma-Chamana, R.; Vilca-Gamarra, C.; Hermoza, N.; Mercado, R.; Mejía, S.; Rengifo, R.; Quispe, K. Estimation and Mapping of Soil Fertility Index in Arid Agricultural Environments of the Tambo Valley Using Regression Kriging. *Front. Soil Sci.* **2025**, *5*, 1706974. [[CrossRef](#)]
24. Burgess, T.M.; Webster, R. Optimal Interpolation and Isarithmic Mapping of Soil Properties. II Block Kriging. *Eur. J. Soil Sci.* **1980**, *31*, 333–341. [[CrossRef](#)]
25. Schabenberger, O.; Gotway, C.A. *Statistical Methods for Spatial Data Analysis: Texts in Statistical Science*, 1st ed.; Chapman and Hall/CRC: New York, NY, USA, 2017; ISBN 978-1-315-27508-6.
26. DeMers, M.N. *Fundamentals of Geographic Information Systems*, 2nd ed.; J. Wiley: New York, NY, USA, 2000; ISBN 0-471-31423-4.
27. Fick, S.E.; Hijmans, R.J. WorldClim 2: New 1-km Spatial Resolution Climate Surfaces for Global Land Areas. *Int. J. Climatol.* **2017**, *37*, 4302–4315. [[CrossRef](#)]
28. Havlin, J.L.; Tisdale, S.L.; Nelson, W.L.; Beaton, J.D. *Soil Fertility and Fertilizers: An Introduction to Nutrient Management*, 8th ed.; Pearson Education India: Uttar Pradesh, India, 2016; ISBN 978-93-325-7034-4.

29. ISO 11464; Soil Quality—Pretreatment of Samples for Physico-Chemical Analysis. ISO: Geneva, Switzerland, 2006. Available online: <https://www.iso.org/standard/37718.html> (accessed on 17 June 2025).
30. Ministry of the Environment and Natural Resources (SEMARNAT). *NORMA Oficial Mexicana NOM-021-RECNAT-2000: Establishing Specifications for Soil Fertility, Salinity, and Classification; Studies, Sampling, and Analysis*; Diario Oficial de la Federación: Mexico City, Mexico, 2002; 73p.
31. United States Environmental Protection Agency (EPA). *EPA Method 9045D: Soil and Waste pH*; U.S. Environmental Protection Agency: Washington, DC, USA, 2004; pp. 1–5.
32. ISO 11265; Soil Quality—Determination of the Specific Electrical Conductivity. ISO: Geneva, Switzerland, 2025. Available online: <https://standards.iteh.ai/catalog/standards/iso/7303276e-d089-486b-afe5-a90b75fe8831/iso-11265-1994> (accessed on 1 February 2026).
33. Kargas, G.; Londra, P.; Sotirakoglou, K. The Effect of Soil Texture on the Conversion Factor of 1:5 Soil/Water Extract Electrical Conductivity (EC1:5) to Soil Saturated Paste Extract Electrical Conductivity (ECe). *Water* **2022**, *14*, 642. [\[CrossRef\]](#)
34. Walkley, A.; Black, I.A. AN EXAMINATION OF THE DEGTJAREFF METHOD FOR DETERMINING SOIL ORGANIC MATTER, AND A PROPOSED MODIFICATION OF THE CHROMIC ACID TITRATION. *METHOD Soil Sci.* **1934**, *37*, 29–38. [\[CrossRef\]](#)
35. Bray, R.H.; Kurtz, L.T. DETERMINATION OF TOTAL, ORGANIC, AND AVAILABLE FORMS OF PHOSPHORUS IN SOILS. *Soil Sci.* **1945**, *59*, 39. [\[CrossRef\]](#)
36. Thomas, G.W. Exchangeable Cations. In *Methods of Soil Analysis. Part 2. Chemical and Microbiological Properties*, 2nd ed.; Page, A.L., Miller, R.H., Keeney, D.R., Eds.; Agronomy Monographs; Wiley: Madison, WI, USA, 1982; Volume 9, pp. 159–165, ISBN 978-0-89118-072-2.
37. Manrique, L.A.; Jones, C.A. Bulk Density of Soils in Relation to Soil Physical and Chemical Properties. *Soil Sci. Soc. Am. J.* **1991**, *55*, 476–481. [\[CrossRef\]](#)
38. Rawls, W.J. ESTIMATING SOIL BULK DENSITY FROM PARTICLE SIZE ANALYSIS AND ORGANIC MATTER CONTENT1. *Soil Sci.* **1983**, *135*, 123–125. [\[CrossRef\]](#)
39. Lopresti, M.F.; Di Bella, C.M.; Degioanni, A.J. Relationship between MODIS-NDVI Data and Wheat Yield: A Case Study in Northern Buenos Aires Province, Argentina. *Inf. Process. Agric.* **2015**, *2*, 73–84. [\[CrossRef\]](#)
40. Teixeira, W.G.; Víctor Hugo Alvarez, V.; Neves, J.C.L.; Paulucio, R.B. Evaluation of Traditional Methods for Estimating Lime Requirement in Brazilian Soils. *Rev. Bras. De Ciência Do Solo* **2020**, *44*, e0200078. [\[CrossRef\]](#)
41. Esri Cómo Funciona Kriging—ArcGIS Pro | Documentación. Available online: <https://pro.arcgis.com/es/pro-app/latest/tool-reference/3d-analyst/how-kriging-works.htm> (accessed on 2 April 2025).
42. Bromberg, F.; Pérez, D.S. Spatial Interpolation Using Machine Learning in Vineyards in the Province of Mendoza, Argentina. In *Proceedings of the XLI JAIIO—Jornada Argentina de Informática e Investigación Operativa*; Sociedad Argentina de Informática e Investigación Operativa: La Plata, Argentina, 2012; pp. 71–82.
43. Fu, Y.; Song, J.; Guo, J.; Fu, Y.; Cai, Y. Prediction and Analysis of Sea Surface Temperature Based on LSTM-Transformer Model. *Reg. Stud. Mar. Sci.* **2024**, *78*, 103726. [\[CrossRef\]](#)
44. Fernández Villafañez, S. Tree-Based Regression and Classification Methods. Bachelor’s Thesis, Universidad de Valladolid, Escuela de Ingenierías Industriales, Departamento de Estadística e Investigación Operativa, Valladolid, Spain, 2022.
45. Valbuena-Calderón, O.E.; Rodríguez-Pérez, W.; Suárez-Salazar, J.C. Soil Quality under Two Management Schemes in Coffee-Growing Areas in Southern Colombia. *Agron. Mesoam.* **2016**, *28*, 131. [\[CrossRef\]](#)
46. Quispe, K.; Mejía, S.; Carbajal, C.; Alejandro, L.; Verástegui, P.; Solórzano, R. Spatial Variability of Soil Acidity and Lime Requirements for Potato Cultivation in the Huánuco Highlands. *Agriculture* **2024**, *14*, 2286. [\[CrossRef\]](#)
47. Maita, S.M.; Quispe, K.; Díaz-Chuquizuta, H.; Rengifo Sánchez, R.; Mercado Chinchay, R.; Cuevas Gimenez, J.P.; Solórzano, R. Soil Spatial Variability in High-Yield Peruvian Amazon Coffee: A Geostatistical Approach for Precision Fertilization. *Front. Soil Sci.* **2025**, *5*, 1701602. [\[CrossRef\]](#)
48. Solórzano, R.; Llerena, R.; Mejía, S.; Cruz, J.; Quispe, K. Spatial Distribution of Cadmium in Avocado-Cultivated Soils of Peru: Influence of Parent Material, Exchangeable Cations, and Trace Elements. *Agriculture* **2025**, *15*, 1413. [\[CrossRef\]](#)
49. Huang, S.; Tang, L.; Hupy, J.P.; Wang, Y.; Shao, G. A Commentary Review on the Use of Normalized Difference Vegetation Index (NDVI) in the Era of Popular Remote Sensing. *J. For. Res.* **2021**, *32*, 1–6. [\[CrossRef\]](#)
50. Jiang, Z.; Huete, A.R.; Chen, J.; Chen, Y.; Li, J.; Yan, G.; Zhang, X. Analysis of NDVI and Scaled Difference Vegetation Index Retrievals of Vegetation Fraction. *Remote Sens. Environ.* **2006**, *101*, 366–378. [\[CrossRef\]](#)
51. Gao, S.; Zhong, R.; Yan, K.; Ma, X.; Chen, X.; Pu, J.; Gao, S.; Qi, J.; Yin, G.; Myneni, R.B. Evaluating the Saturation Effect of Vegetation Indices in Forests Using 3D Radiative Transfer Simulations and Satellite Observations. *Remote Sens. Environ.* **2023**, *295*, 113665. [\[CrossRef\]](#)
52. Revelo Luna, D.A.; Mejía Manzano, J.; Montoya Bonilla, B.; Hoyos García, J. Analysis of the Vegetation Indices NDVI, GNDVI, and NDRE for the Characterization of Coffee Crops (*Coffea Arabica*). *Ing. Desarro.* **2021**, *38*, 298–312. [\[CrossRef\]](#)

53. Zhao, Q.; Qu, Y. The Retrieval of Ground NDVI (Normalized Difference Vegetation Index) Data Consistent with Remote-Sensing Observations. *Remote Sens.* **2024**, *16*, 1212. [[CrossRef](#)]
54. Ochoa, P.A.; Chamba, Y.M.; Arteaga, J.G.; Capa, E.D. Estimation of Suitable Areas for Coffee Growth Using a GIS Approach and Multicriteria Evaluation in Regions with Scarce Data. *Appl. Eng. Agric.* **2017**, *33*, 841–848. [[CrossRef](#)]
55. Zhang, S.; Zhu, Q.; De Vries, W.; Ros, G.H.; Chen, X.; Muneer, M.A.; Zhang, F.; Wu, L. Effects of Soil Amendments on Soil Acidity and Crop Yields in Acidic Soils: A World-Wide Meta-Analysis. *J. Environ. Manag.* **2023**, *345*, 118531. [[CrossRef](#)]
56. Li, X.; Zhang, X.; Zhao, Q.; Liao, H. Genetic Improvement of Legume Roots for Adaptation to Acid Soils. *Crop J.* **2023**, *11*, 1022–1033. [[CrossRef](#)]
57. Quispe, K.; Hermoza, N.; Mejia, S.; Romero-Chavez, L.E.; Ottos, E.; Arce, A.; Solórzano Acosta, R. Spatial Analysis of Soil Acidity and Available Phosphorus in Coffee-Growing Areas of Pichanaqui: Implications for Liming and Site-Specific Fertilization. *Agriculture* **2025**, *15*, 1632. [[CrossRef](#)]
58. Hadas, A. Germination and Seedling Establishment. In *Encyclopedia of Soils in the Environment*; Hillel, D., Hatfield, J.L., Eds.; Elsevier: Oxford, UK, 2005; Volume 4, pp. 130–137, ISBN 978-0-12-348530-4.
59. Daba, A.W. Rehabilitation of Soil Salinity and Sodicity Using Diverse Amendments and Plants: A Critical Review. *Discov Environ.* **2025**, *3*, 53. [[CrossRef](#)]
60. Fageria, N.K.; Baligar, V.C. Chapter 7 Ameliorating Soil Acidity of Tropical Oxisols by Liming For Sustainable Crop Production. In *Advances in Agronomy*; Elsevier: Oxford, UK, 2008; Volume 99, pp. 345–399, ISBN 978-0-12-374360-2.
61. McBratney, A.; Whelan, B.; Ancev, T.; Bouma, J. Future Directions of Precision Agriculture. *Precis. Agric.* **2005**, *6*, 7–23. [[CrossRef](#)]
62. Moral, F.J.; Terrón, J.M.; Marques da Silva, J.R. Delineation of Management Zones Using Mobile Measurements of Soil Apparent Electrical Conductivity and Multivariate Geostatistical Techniques. *Soil Tillage Res.* **2010**, *106*, 335–343. [[CrossRef](#)]
63. Mulla, D.J. Twenty Five Years of Remote Sensing in Precision Agriculture: Key Advances and Remaining Knowledge Gaps. *Biosyst. Eng.* **2013**, *114*, 358–371. [[CrossRef](#)]

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