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Soil quality variation associated with land cover in the Peruvian jungle of the Junín region

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ABSTRACT

In the Junín jungle, inappropriate agricultural management practices for a long time can adversely affect soil quality. This has driven the development of multiple soil quality evaluation methods that are highly demanding in terms of economic and human resources. This study aimed to evaluate the effect of land-use change from natural ecosystems to agricultural systems by determining soil quality in the jungle of the Junin Region. Soil samples were collected between December 2021 and July 2022 in the Chanchamayo and Satipo provinces in the Junín region. Seventy-four samples were determined using stratified sampling, along with the support provided by the stacking of five spatial layers. Physical, chemical, and biological indicators, along with land cover type data from the European Space Agency (ESA) WorldCover product, were determined. A minimum data set (MDS) was established through correlation analysis, from which principal component analysis (PCA) was performed. Finally, the weighted soil quality index (SQIw) was calculated by integrating the most essential variables identified through PCA. It was found that forest cover soils had a higher SQIw than soils with crops and grassland cover. According to PCA, the soil quality variables that contributed the most are potassium (K) content and pH. It was concluded that the jungle soil quality in the Junín region is moderate to low, depending on the coverage. In addition, more significant degradation was observed in grassland-covered areas, particularly in the Chanchamayo province than in the Satipo province.

1. Introduction

Soil is a finite natural resource (Mandal et al., 2021) that plays a vital role in sustaining life (Lehmann et al., 2020). Tropical soils are characterized by high diversity (Huntley, 2023) but are under significant pressure due to deforestation, primarily driven by land-use change (Valdez-Nuñez et al., 2019). The endeavor to produce food through agriculture has not only diminished the capacity of ecosystems to provide services but has also significantly impacted climate and the human sphere (Foley et al., 2005). Consequently, this has led to a decline in soil health, productivity, and resilience (Agbeshie et al., 2025).

Soil quality is defined as the ability to sustain plant and animal dry matter production and maintain or improve water and air quality, among other things (Karlen et al., 1997). Different natural origin events and anthropogenic activities change this, with poorly understood long-term effects. Therefore, there are various approaches to address soil quality and options for its evaluation. Generally, it is assessed by measuring a minimum dataset to reduce analysis time and cost

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(Vallejo-Quintero et al., 2020; Yu et al., 2018), which translates into the generation of a soil quality index (SQI).

Soil quality indices (SQI) combine quantitative and qualitative information related to soil (de Paul Obade and Lal, 2016). In certain instances, professionals evaluate the physical properties of the soil. (Reyes, 2019), and in others, its biological ones (Aravindh et al., 2020). Although there is no universally applicable formula to measure soil quality (Andrés-Abellán et al., 2019), its representation in a "numerical" manner allows for easy monitoring and evaluation of soil quality changes and dynamics (Rachman, 2019). Soil quality index evaluations should consider various soil functions. Some functions may be complex, so different soil properties could be significant indicators of soil quality, requiring further research to identify the most important ones (Nortcliff, 2002).

Assessment of agricultural sustainability necessitates an analysis of soil health indicators (Doran and Zeiss, 2000). These indicators, in addition to providing information on different management systems impact on the soil over time, help identify problematic areas and prevent their degradation (Estrada-Herrera et al., 2017; Stefanoski et al., 2016; Velasquez et al., 2007). Likewise, they provide productive and sustainable systems design support (Jamioy-Orozco et al., 2015). Hence, it is crucial to define biological, physical, and chemical indicators and their interconnections (García et al., 2012). This may involve simple additive index values (Nasir et al., 2024) or incorporate various scoring methods (linear and non-linear) to derive an index reflecting soil-related aspects. Furthermore, utilizing statistical techniques such as factor analysis (Raiesi, 2017) and principal component analysis (PCA) to reduce the dimensionality of the dataset, aiding variable selection, alongside data mining methods (Ciarkowska and Gambus, 2020; Sánchez-Navarro et al., 2015), is essential. Even to characterize the soil, they integrate environmental covariates on different scales to estimate its spatial variability (Fathizad et al., 2020; Isong et al., 2022). If we want to emphasize the advantages of working in a spatial context, using soil quality indicators as a primary approach can reveal agroecological functions; however, integrating topography covariates can help better understand their spatial variabilities across contrasting land uses (Kiani et al., 2020).

The SQI provides a more effective means of identifying long-term land-use changes than analyzing individual soil characteristics (Raiesi, 2017). This is evidenced by significant SQI variability observed in specific ecosystems, including forests (Andrés-Abellán et al., 2019), croplands (Sanad et al., 2024), pasture (Samaei et al., 2022), and across diverse land uses, making it a practical tool for monitoring soil quality (Bravo–Medina et al., 2021; Damiba et al., 2024; Uthappa et al., 2024). Beyond land use, SQI can evaluate variations and impacts at various depths under different management conditions (Mukherjee and Lal, 2014; Zhang et al., 2022).

The SQIw method proved the best index for monitoring soil quality changes over time; assigning appropriate weights to its components better reflects how different soil properties impact overall quality (Selmy et al., 2021). Using weighted additive integration of PCA, the calculated SQI successfully differentiated between old cultivated, newly cultivated, and barren land uses (Mustafa, 2023). When SQIw used PCA as a reduction tool to obtain key indicators from a large dataset across land use types, their results indicated that Forest Land had the highest soil quality mean values, followed by Crop Land and Grass Land (Damiba et al., 2024). Similarly, previous research obtains the highest SQI value on the upper slopes, which land use as forests (Meitasari et al., 2024). Compared with the adding soil quality index, SQIw present more sensitive and better performance to predict soil quality due to the application of weights to soil properties (Damiba et al., 2024; Meitasari et al., 2024). SQIw analyzes soil properties normalized according to scoring from contributions of PCA, it allows them to identify MDS for making SQI assessment both practical and cost-effective without compromising the essential information needed to evaluate soil quality (Tesfahunegn, 2014), becoming important when it is used in conditions such as croplands under different anthropogenic interventions (Barrezueta-Unda et al., 2017) or with levels of anthropopressure according of pollutants emission indices assessment (Klimkowicz-Pawlas et al., 2019).

This study, therefore, sets out to generate crucial information on soil quality relevant to tropical soils, with the ultimate aim of supporting more effective and sustainable agricultural management strategies within these ecosystems. Focusing on the Amazonian region of Peru, a key objective is to present a practical and reliable method for the determination of soil quality. This is expected to not only promote the adoption of sound agricultural practices but also to enable the efficient utilization of financial resources.

2. Material and methods

2.1. Study area

The study is located in the jungle zone of the Junín region in Peru, which includes the Satipo (11°15′15″S, 74°38′17″W) and Chanchamayo (11°03′16″S, 75°19′45″W) provinces (Fig. 1). The geography of Chanchamayo province includes the lower eastern slopes of the Andes, encompassing the Bajo Tulumayo, Chanchamayo, and Perené river basins (Tierras Vivas, 2024), with altitudes ranging from 420 to 4700 m.a.s.l., an average annual temperature of 19 °C with a maximum of 33 °C and a minimum of 5 °C, and a maximum yearly rainfall of 3000 mm. Satipo is the largest province in the Junín region, with a remarkable range of elevations, ranging from 200 to 4800 m.a.s.l. The lowest point in the province is along the Tambo River, near the Ucayali Region border. The climate in the province presents an average annual temperature of 20 °C, with a maximum of 35 °C, a minimum of 5 °C, and a maximum yearly rainfall of 4000 mm. Between October and April, the highest rainfall volumes were registered in both places, a large part of the area characterized by a warm, humid, and rainy climate.

According to the World Reference Base classification system (IUSS Working Group, 2007), the dominant soil classes in both regions are Andosols, Cambisols, and Ferralsols. Chanchamayo has a larger area of Cambisols than Satipo. In Satipo, the percentage of Ferralsols is higher, predominantly over plains and undulated land areas. Andosols are present in both regions, but in smaller amounts, and are mainly found in mountainous areas with forests.

Concerning the socio-economic aspect, the study area concentrates on 30 % of the Junín region population, where agriculture is the predominant activity with practices such as slash-and-burn for farm creation as well as forest clearing, concentrating on domestic consumption production of pineapple, orange, tangelo, banana, cassava, and tangerine; and for industry and agro-export, with the supply of coffee, cocoa, complex yellow maize, and ginger (Banco Central de Reserva del Perú, 2023). According to MIDAGRI statistics from public dashboards (https://siea.midagri.gob.pe/siea_bi/), Chanchamayo has 218,950 hectares of agricultural and livestock land, while Satipo has 397,459 hectares, where crops such as orange, pineapple, banana, avocado, coffee, tangerine, cacao, ginger, cassava, and hard yellow corn are spotlighted in order of production. The grassland areas highlight the production of *Pennisetum purpureum* (Elephant grass), and *Brachiaria* spp.

2.2. Soil sampling and analysis

This study employed a stratified sampling method to generate point locations using five spatial layers (vegetable cover, current land use, permeability, texture, and soil depth) as inputs to divide the area into multiple strata. One criterion for spatial selection established sampling zones below 1500 m.a.s.l. from a digital elevation model (DEM), with the aim of reducing the area to be covered during sampling. In the R software (R Core Team, 2018), the stacking of spatial layers was used as an argument in the 'spsample' function of the 'sp' package (Pebesma and

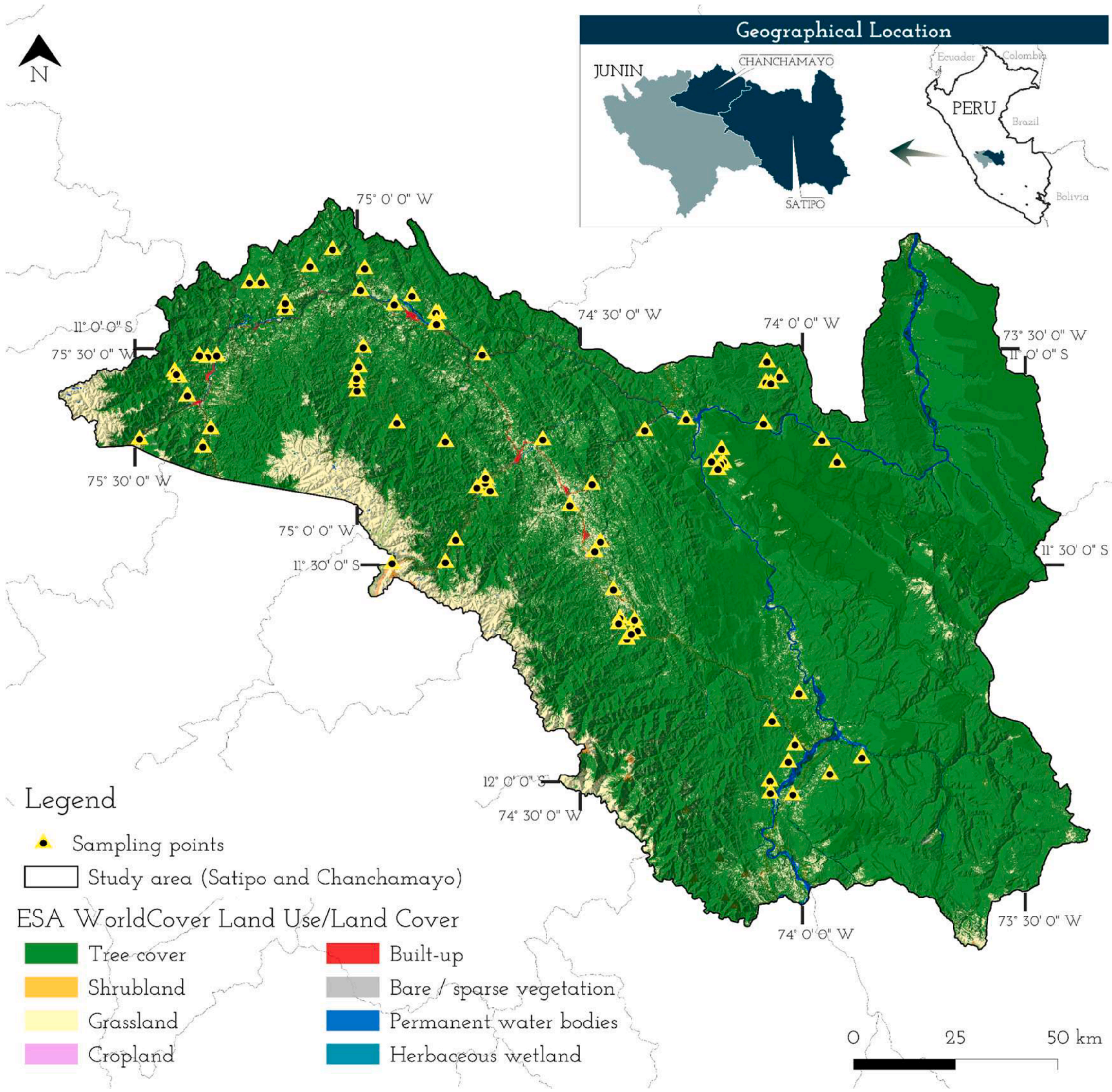

Fig. 1. Study area with marked sampling point locations.

Bivand, 2005) to establish the sampling points. A total of 74 soil samples were collected at a depth of 30 cm between December 2021 and July 2022 (Fig. 1).

Physical, chemical, and biological properties were determined at the Soil, Water, and Foliar Laboratory (LABSAF) of the Pichanaki Agrarian Experimental Station (EEA) at the National Institute for Agrarian Innovation (INIA). The pH in soil-water ratio 1:1 was determined using the EPA 9045D method (EPA, 2004); the electrical conductivity (EC) in soil-water ratio 1:5 according to ISO 11265 (ISO, 1994); the organic matter (OM) by oxidation with potassium dichromate (Walkley and Black, 1934); available phosphorus (P) according to Olsen's method (Olsen et al., 1954); the extractable potassium (K) with 1 N ammonium acetate pH 7 (Bazán-Tapia, 2017); exchangeable acidity (Al+*H*) by extraction with 1 N KCl (Yuan, 1959); texture by the hydrometer method (Bouyoucos, 1936); and soil respiration (Rs) with alkali capture (Anderson, 1983). Rs is an indirect method for assessing microbial activity, which quantifies the CO_2 produced by microorganisms. This chemical method measures respiration by capturing CO_2 in a basic solution (NaOH) and subsequently determining its concentration by titration (FAO, 2023). The Eq. (1) is used to calculate the amount of CO_2 released by respiration during the interval between readings. The workflow is illustrated in Fig. 2.

$$CO_2 = \frac{[(v * Nb) - (g * Na)] * 22}{W \ * \ ddi} \tag{1}$$

Where:

CO_2 = amount of CO_2 absorbed (mg).
v = volume of base used (mL).
Nb = normality of the base used.
g = acid flow recorded (mL).
Na = acid normality.
W = dry weight of soil sample (g).
ddi = days since installation or last reading.

The 'psych' R package (Revelle, 2023) was then utilized to generate descriptive statistics for the identified soil properties.

2.3. Land cover classification

The land cover classification was carried out using data collected in the field by observing current land use. The identified classes were aligned with the ESA WorldCover 2021 v200 product (Zanaga et al., 2022). With its 10 m spatial resolution, this product is based on

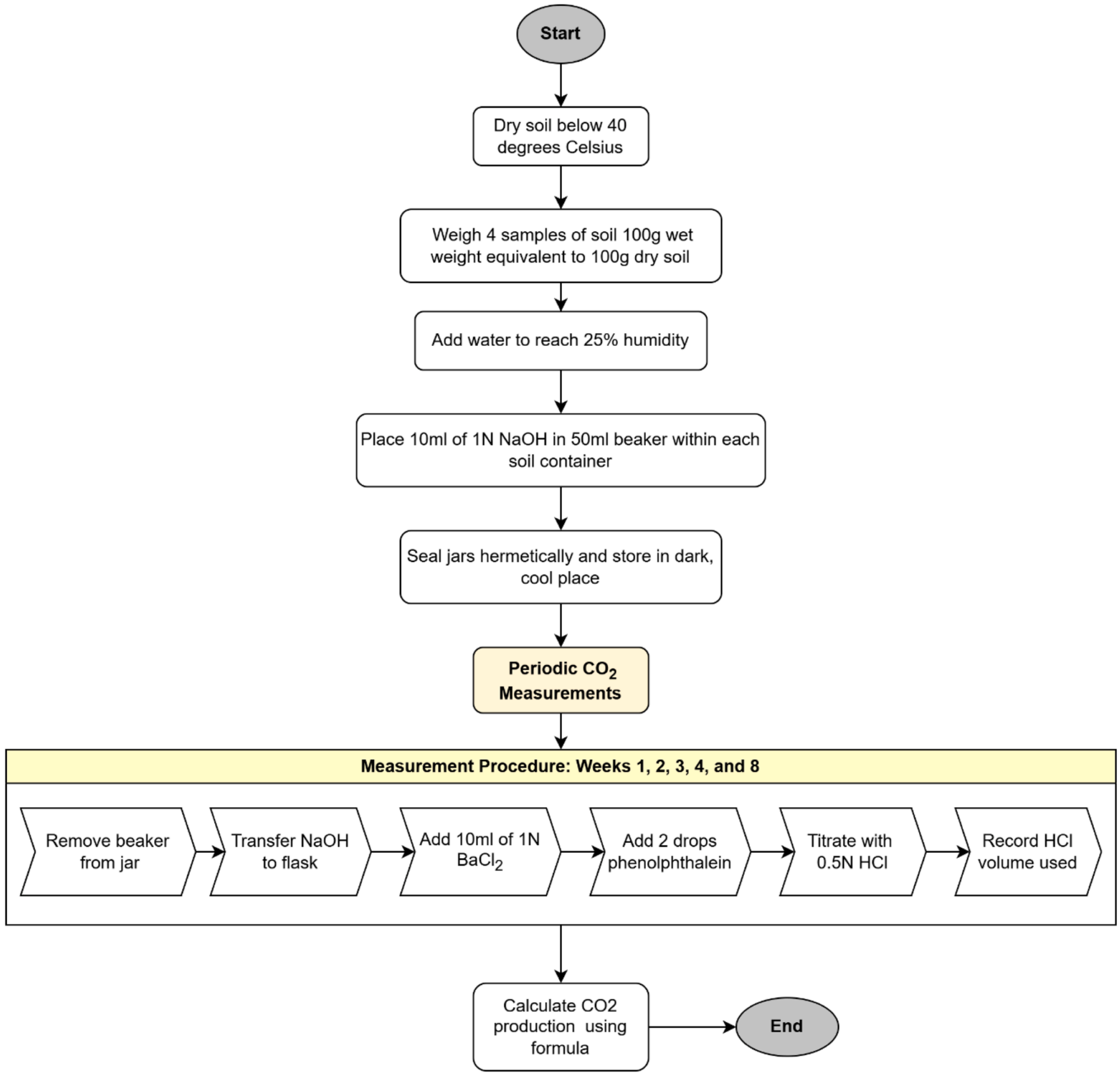

Fig. 2. A laboratory workflow detailing the volumetric method used for measuring soil respiration.

Sentinel-1 and Sentinel-2 image data, ensuring greater accuracy in distinguishing various land cover types within the study area. The discrete classification map offers 11 classes: Tree cover, Shrubland, Grassland, Cropland, Built-up, Bare/sparse vegetation, Snow and Ice, Permanent water bodies, Herbaceous wetland, Mangroves, and Moss and lichen. They are defined using the internationally recognized Land Cover Classification System (LCCS) developed by the United Nations (UN) Food and Agriculture Organization (FAO). The UN-LCCS system, a hierarchical classification, allows for adjusting the thematic detail of the legend to the amount of information available (Van De Kerchove et al., 2022).

2.4. Weighted soil quality index (SQIw) calculation

A correlation matrix was created to identify a minimum data set (MDS) without redundant indicators. The stats package (R Core Team, 2018) was used to calculate Pearson correlation coefficient values, and the 'ggcorrplot' package (Kassambara, 2022) was used to visualize the matrix. Then, a PCA was conducted using all principal components (PC). The 'prcomp' function of the same stats package was utilized to obtain the variables eigenvalues and contributions, and the 'fviz_pca_var' function of the 'factoextra' package (Kassambara and Mundt, 2020) was employed to plot these contributions. The indicators were adjusted using linear methods to assign a score to each indicator, following the "more is better" from Eq. (2) and "less is better" from Eq. (3) methods outlined by Andrews et al. (2002). The indicator values for this study can be found in Table 1. To calculate the specific weightings (*Sw*) for each component, we divided the variance percentage of each principal component (PC) by the accumulated variance percentage of the last PC. Next, from Eq. (4), we obtained the variable weighting (*W*) by multiplying it by the contribution values of each principal component (PC). Finally, the weighted soil quality index (*SQIw*) was computed using Eq. (5) as described in Andrews et al. (2002). These processes were carried out using the code supported by the 'Tidyverse' package functions

Table 1
Maximum (lmax) and minimum (lmin) limit values for soil quality indicators.

Indicators	Unit	Relation	lmax	lmin
OM	%	More is better	6	2
pH		Less is better	7,5	5
P	ppm	More is better	20	8
K	ppm	More is better	390	78
Bd	$g \bullet cm^{-3}$	Less is better	1,5	1,15
Rs	CO_2 $mg \bullet g^{-1}$ of $soil \bullet day^{-1}$	More is better	0924	0,3687

Note: OM = Organic matter; *P* = Phosphorus; *K* = Potassium; Bd = Bulk density; Rs = Soil respiration.

(Wickham et al., 2019). The weighted soil quality index (*SQIw*) was calculated using the following equations:

$$Vn = \left(\frac{lm - lmin}{lmax - lmin}\right) \tag{2}$$

$$Vn = 1 - \left(\frac{lm - lmin}{lmax - lmin}\right) \tag{3}$$

$$W = \sum_{i=1}^{n} \left(\frac{Pe_i}{100}\right) * \left(\frac{C_i}{100}\right) \tag{4}$$

$$SQIw = \sum_{i=1}^{n} (W_i * Vn_i) \tag{5}$$

where *Vn* is the normalized value; *Imin* is the minimum indicator value; *Imax* is the indicator maximum value; *lm* is the indicator mean value; *W* is the weighting of the variable; *Pe* is PC specific weighting; C is the variable contribution in the PC; *n* is the number of selected PCs, and *SQIw* is the weighted soil quality index.

The criteria to define the maximum and minimum values for the pH, OM, P, and K indicators were based on those established by Cantú et al. (2007). For Bd, Estrada-Herrera et al. (2017) were considered, and Rs according to Vargas-Terminel et al. (2022). The procedure is illustrated in Fig. 3.

Then, the data with the obtained values from the *SQIw* generation were subjected to variance analysis, taking coverage as a factor.

3. Results

3.1. Soil quality physical, chemical, and biological indicators

A set of soil indicators was evaluated and is presented in Table 2 for the study. The average values obtained reflect the typical soil characteristics under tropical conditions. Forest coverage soils have a 3.37 % OM percentage, 6.5 pH, sandy clay loam textural class, and a 1.33 *g*•cm-3 Bd. Cropland coverage soils present a 2.66 % OM percentage, 5.49 pH, sandy loam textural class, and 1.31 *g*•cm-3 Bd. Grassland coverage soils show a 2.19 % OM percentage, 5.52 pH, sandy loam textural class, and 1.35 *g*•cm^{-3} Bd.

Soils with the three land cover types have very low EC ranging from 0.01 to 0.07 mS•m-1. similarly, the indicators with the most significant variation were P content (mg•kg-1), K (mg•kg-1), and Al+*H* (meq•100 g-1). Grassland coverage soils had the lowest values of P and K and the highest Al+*H*. Crop coverage soils had the highest available phosphorus values. Forest coverage soils had the highest values of K and the lowest values of Al+*H*. The standard error indicates a greater K (mg•kg^{-1}) and sand percentage variation.

3.2. Land cover class identification

Cropping the land cover classes (LCC) layer from the ESA WorldCover 2021 v200 product (Zanaga et al., 2022), over 85.08 % and 91.85 % are occupied by tree cover in Chanchamayo and Satipo, respectively. Following this, the next largest area is grassland cover (12.92 % in

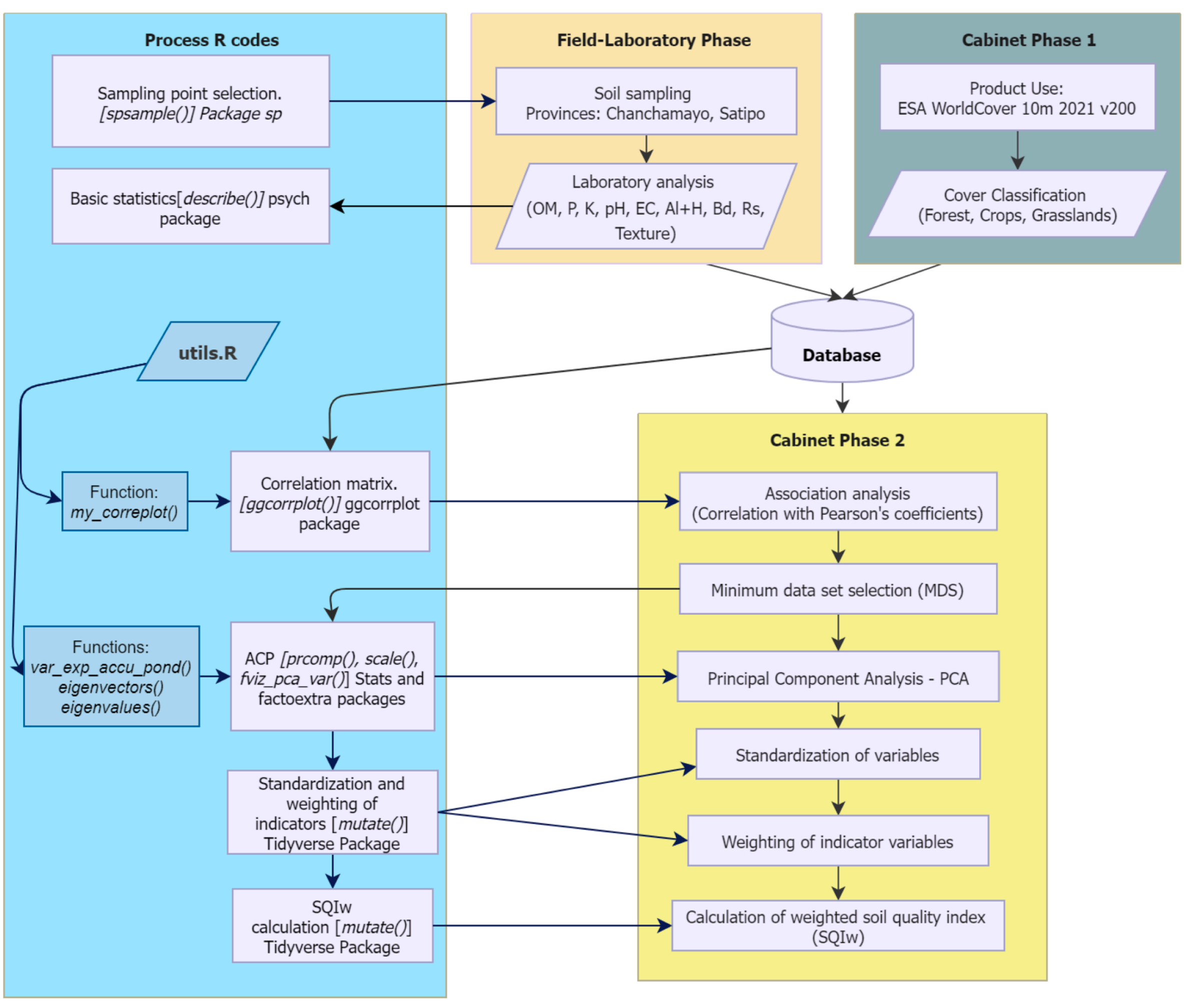

Fig. 3. Methodology flow used for the weighted soil quality index calculation.

Table 2
Descriptive statistics of physical, chemical, and biological soil quality indicators.

Indicators	LCC	Mean	SD	MIN	MAX	Range	SE
OM (%)	T	3,37	1,81	0,49	8,7	8,21	0,3
	C	2,66	1,47	0,69	7,02	6,33	0,26
	G	2,19	1,70	0,79	5,14	4,35	0,76
P (mg•kg^{-1})	T	5,61	7,08	0	41,6	41,6	1,16
	C	6,77	11,72	0	57,6	57,6	2,07
	G	1,52	2,05	0	4,4	4,4	0,92
K (mg•kg^{-1})	T	291,3	235,25	13	880	867	38,68
	C	116,7	164,63	8	703	695	29,1
	G	43,7	53,02	0	131	131	23,71
Al+*H* (meq•100 g^{-1})	T	0,5	0,74	0	3,9	3,9	0,12
	C	0,53	0,57	0,05	2,0	1,95	0,1
	G	0,82	0,82	0,08	2,03	1,95	0,37
pH	T	6,5	1,19	3,84	7,9	4,06	0,2
	C	5,49	1,11	3,93	7,98	4,05	0,2
	G	5,52	0,71	5,01	6,61	1,6	0,32
EC (mS•m^{-1})	T	0,07	0,05	0	0,15	0,15	0,01
	C	0,04	0,02	0,01	0,11	0,1	0
	G	0,01	0	0,01	0,02	0,01	0
Sand (%)	T	51,82	12,5	35	79,5	44,5	2,06
	C	53,18	14,03	23,7	79,5	55,8	2,48
	G	56,68	18,25	33,7	77,2	43,5	8,16
Silt (%)	T	26,65	10,44	9,6	47,4	37,8	1,72
	C	27,3	10,63	9,6	43,6	34	1,88
	G	24,24	14,53	10	47,6	37,6	6,5
Clay (%)	T	21,53	9,31	7,1	48,7	41,6	1,53
	C	19,5	11,31	5,1	62,7	57,6	2
	G	19,06	8,42	6,6	28,6	22	3,77
Bd (g•cm^{-3})	T	1,33	0,12	1,17	1,64	0,47	0,02
	C	1,31	0,11	1,1	1,64	0,54	0,02
	G	1,35	0,18	1,16	1,63	0,47	0,08
Rs (CO_2 mg•g^{-1} of soil•day^{-1})	T	0,89	0,14	0,53	1,09	0,56	0,02
	C	0,81	0,22	0,53	1,28	0,75	0,04
	G	0,76	0,17	0,61	1,02	0,41	0,08

* LCC is Land cover class; SD is the standard deviation; MIN is the minimum value; MAX is the maximum value; SE is the standard error; OM is organic matter; P is phosphorus; K is potassium; Al+*H* is exchangeable acidity; EC is electrical conductivity; Bd is bulk density; Rs is soil respiration; T is tree cover; C is cropland, and G is grassland.

Chanchamayo, 6.87 % in Satipo), and finally, in both places, cropland cover represents <0.04 % in proportion. For the purpose of this study, these three LCCs were chosen to assess soil quality, despite the existence of other cover types. By counting the occurrences of each identified LCC in the sample sites, we can calculate the respective proportion in each province (Fig. 4).

3.3. Soil quality indicators selection

Pearson's statistics indicated a high positive correlation between EC, available K, and pH (Table 3). Likewise, there was a high negative correlation between pH and exchangeable acidity. Thus, the available P, available K, pH, OM percentage (chemical indicator), Bd (physical indicator), and Rs (biological indicator) were established as the minimum dataset (MDS) for quality index construction.

3.4. Principal component analysis (PCA)

PCA was performed using six selected indicators. Tables 4 and 5 show the eigenvalues, explained variances, and contributions of each component. The first two components achieved an explained variance of over 55 % in both provinces.

A biplot graph including variables together with observations is shown in Fig. 5. First, concerning the variables, there is a higher correlation between K and pH and between P, OM, and Rs, but a low correlation of these regarding Ad is observed. Similarly, the variables that contributed the most to PCA were K and pH. However, pH was the least important variable for Chanchamayo soils, where Rs was the highest contributory variable. In the case of Satipo province, the most contributing variable was K, while the lowest contribution was OM.

In Fig. 5, it is evident that 78 % of grassland cover and most of the cropland cover soils are situated on the negative side of the first component (PC1). These soils are associated with lower K content and lower Rs, although their behavior does not show clear trends. On the other hand, tree cover soils exhibit no distinct behavior across the biplot quadrants. These soils are predominantly positioned on the negative side of PC2, making up 70 % of them. Additionally, when considering K

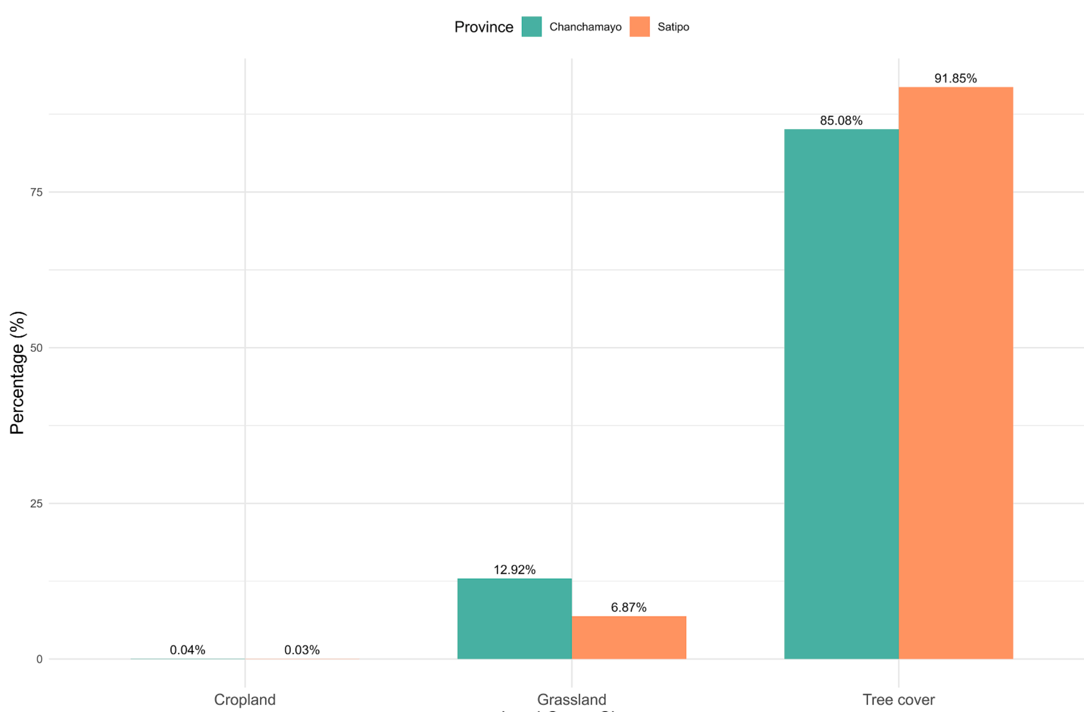

Fig. 4. Land cover class percentage distribution identified for each province.

Table 3
Pearson correlation matrix of the analyzed soil properties.

	OM	P	K	Al+H	PH	EC	Sand	Silt	Clay	Bd	Rs
OM	1										
P	0,31**	1									
K	0,18	0,05	1								
Al+H	0,02	−0,16	−0,12	1							
PH	0,06	0,09	0,56***	−0,6***	1						
EC	0,45***	0,18	0,73***	−0,19	0,69***	1					
Sand	−0,02	−0,03	−0,16	−0,1	0,04	−0,1	1				
Silt	−0,02	−0,17	0,23	0,24*	−0,04	0,17	−0,67***	1			
Clay	0,04	0,21	−0,03	−0,13	−0,01	−0,04	−0,62***	−0,16	1		
Bd	−0,13	−0,03	−0,18	−0,05	−0,07	−0,04	−0,02	−0,08	0,11	1	
Rs	0,25*	0,22	0,38***	0,14	0,1	0,49***	−0,05	0,15	−0,1	0,17	1

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 4
Principal components analysis results for the Chanchamayo province.

Variables	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalues	1878	1369	1043	0658	0587	0464
Explained variance	0313	0228	0174	0110	0098	0077
Accumulated variance	0313	0541	0715	0825	0923	1
Quality indicators - contribution values for each PC						
OM	34,204	1505	0392	0246	29,148	34,504
P	28,126	7037	0288	0003	59,303	5244
K	3872	34,931	14,344	40,789	2203	3861
pH	0068	3004	83,553	12,218	0168	0990
Bd	8542	35,028	1423	45,779	0734	8494
Rs	25,188	18,495	0001	0965	8443	46,907

Table 5
Principal components analysis results for the Satipo province.

Variables	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalues	2125	1326	1115	0746	0554	0135
Explained variance	0354	0221	0186	0124	0092	0022
Accumulated variance	0354	0575	0761	0885	0978	1
Quality indicators - contribution values for each PC						
OM	8291	0332	45,764	29,673	15,853	0087
P	10,174	8317	30,222	29,576	20,700	1011
K	39,921	0336	6631	0001	0466	52,646
pH	29,018	4435	11,153	4663	23,200	27,532
Bd	0277	46,795	6057	27,336	18,086	1449
Rs	12,321	39,785	0173	8751	21,694	17,275

and pH, it is evident that Chanchamayo soils do not align with available K and pH, which is of low importance for the province. Consequently, it is understood that these soils have lower quality.

3.5. *Soil quality index under different land cover classes*

The evaluated soils in the Junín region were of low to moderate quality (Cantú et al., 2007), as shown in Fig. 6. However, the data analysis revealed no significant differences in the soil quality index in relation to coverage (p-value > 0.05). The soil quality values of tree cover were double those of grassland coverage. In the present study, tree cover soils presented the highest available K values (average = 291 mg•kg^{-1}), while grasslands coverage soils had the lowest values (average = 43.7 mg kg^{-1}), being lower than the proposed minimum value for the Bray method (78 mg kg^{-1}). Likewise, forest coverage soil pH presented higher levels with a 6.5 average and lower exchangeable acidity values (0.5 mEq•100 g^{-1}). This is not the case with cropland or grassland covers with moderately acidic soils and higher exchangeable acidity values. Since K and pH were the variables that contributed the most to the PCA and, therefore, to the SQIw, it is understood that tree cover had the highest soil quality compared to other cropland and grassland areas.

On the other hand, Chanchamayo has lower soil quality values than Satipo for all land cover classes. It is important to note that there is a smaller amount of tree-cover soil in that province.

4. Discussions

We used six physical, chemical, and biological soil indicators to develop a comprehensive soil quality index (SQI) providing a more complete assessment of present soil conditions. The averages of the indicators show an interesting fact: OM, K, P, and Rs were higher in the tree cover and cropland classes (Table 2). In specific, available potassium high value and higher soil pH qualified forest coverage soils as having the highest SQI. Regarding this, Bravo–Medina et al. (2021) evaluated the effect of land use change on soil quality under similar conditions in the Ecuadorian Amazon and found that land use type had significant effects on soil properties and, thus, on soil quality. Furthermore, higher quality values have been found in soils with natural vegetation (de Paul Obade and Lal, 2016), primary forest (Raiesi and Beheshti, 2022; Zhang et al., 2019), and in agroforestry systems cultivated soils compared to rainfed and gravity irrigated production systems (Gelaw et al., 2015). On the other hand, Vallejo-Quintero et al. (2020) determined lower SQI values for conventional grassland concerning coffee cultivation. These indicators were chosen based on their significant impact on soil fertility, taking into account the predominant land cover types, which are mainly citrus and coffee plantations.

PCA in this study used soil available P and K, pH, OM percentage, Rs, and Bd as soil quality indicators (Tables 4 and 5). Adequate Bd, well distributed around its pores, allows for good infiltration, gas exchange, and root development of plants. Meanwhile, Rs is a reference for root abundance and the richness of macro, *meso*, and microfauna in the soil, ensuring efficient nutrient recycling through its role in decomposing organic components such as plant material and dead organisms. OM broadly influences the physical, chemical, and biological properties of soil, particularly in aggregate stability, nutrient cycling, water retention, disease suppression, pH buffering, cation exchange capacity, and root development of the plants (Celestina et al., 2019). Previous experiences in constructing an SQI have considered pH, OM, N, P, K, cation exchange capacity (CEC), calcium (Ca), and magnesium (Mg) as chemical indicators (Estrada-Herrera et al., 2017; Martínez-Rodríguez et al., 2021), in addition to soil organic carbon (SOC), iron (Fe) and exchangeable acidity (Jamioy-Orozco et al., 2015). In terms of physical indicators, several studies have included soil porosity (Bravo–Medina et al., 2021; Gelaw et al., 2015), in addition to Bd (Bünemann et al., 2018; Vallejo-Quintero et al., 2020), as characteristics that determine soil compaction. Finally, microbial biomass carbon (Brandão-Rocha et al., 2022; Gelaw et al., 2015), microbiota population, enzyme activity (Brandão-Rocha et al., 2022), phosphate solubilizing bacteria, dehydrogenase activity, and heterotroph density (Castillo-Valdez et al., 2021;

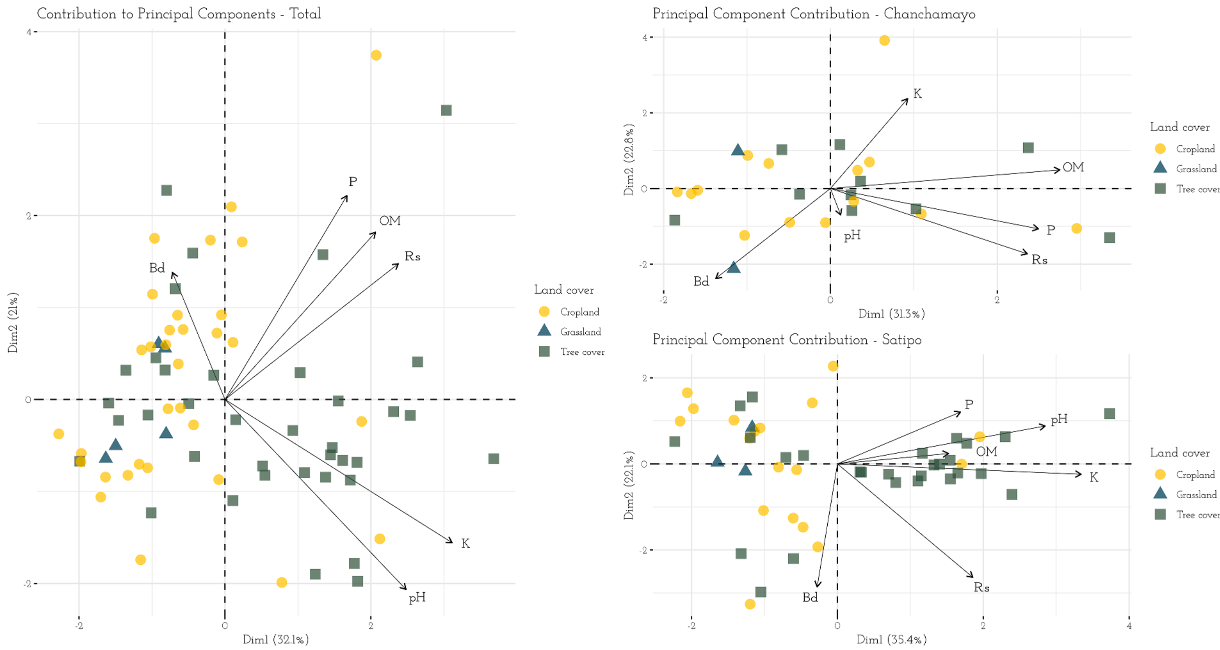

Fig. 5. PCA Biplot graph (variables and observations) considering all data and province-level results.

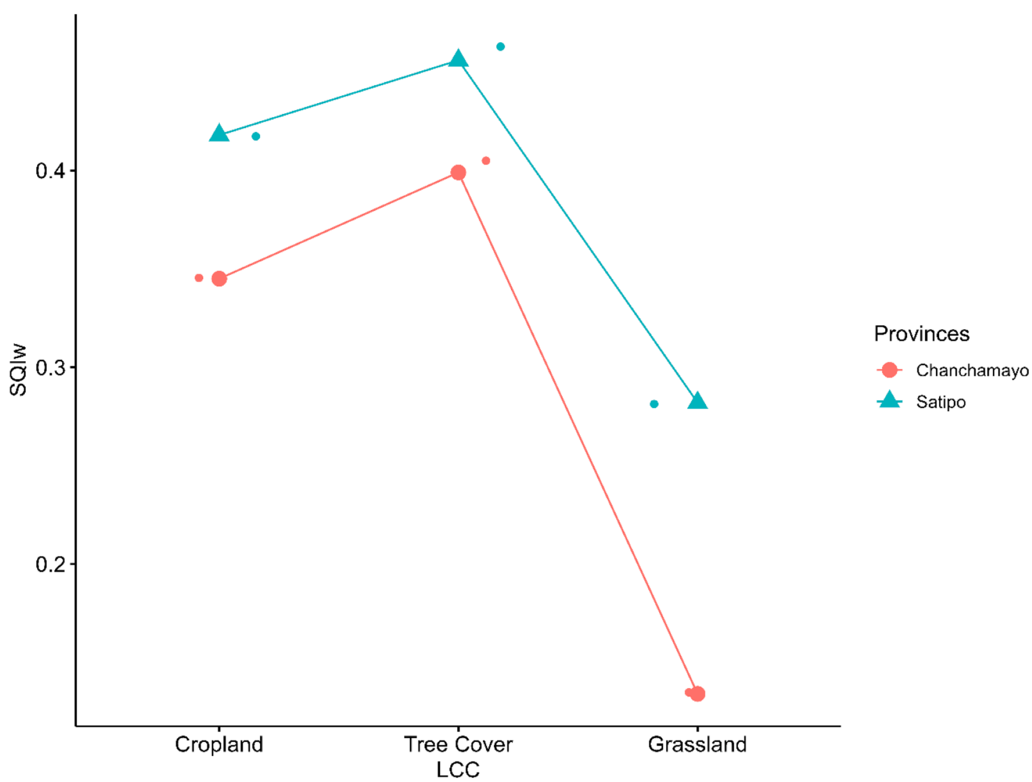

Fig. 6. Weighted soil quality index (SQIw) by land cover class (LCC) in the provinces of Junín Region.

Vallejo-Quintero et al., 2020) have been used as biological properties.

When choosing soil quality indicators, I found that potassium levels in tropical soils are dynamic and complex (Paramisparam et al., 2021). The high aluminum and iron content, coupled with intense weathering and leaching (Paramisparam et al., 2021; von Uexkuell, 1968), results in lower potassium availability in humid tropical soils compared with semi-arid or arid zones (Pagel, 1972). Potassium values between 200 and 300 ppm for heavy soil (soils with Bd close to 1.0 g. cm^{-3}) are considered adequate (Yost and Uchida, 2000). For this reason, the maximum value assigned to K in the standardization does not underestimate the SQI calculation. The high values found for the Satipo soils represent an opportunity to conduct a more detailed study of potassium dynamics.

The results showed that Satipo soils were of the highest quality (Fig. 6), mainly because they had less anthropic intervention and a higher percentage of forest area. This was evidenced by Encarnación and

Zárate (2010), who showed that more than 60 % of the vegetation types in this province are represented by varied forest formation at different altitudes. The forest land use type causes a higher soil available potassium level, as well as a higher pH, which are major important characteristics in the soil quality qualification of Junín, Peru. In contrast, Chanchamayo Province has a higher percentage of land covered by crops and grasslands, indicating greater human activity.

A low SQI, such as that for grassland and cropland, has a negative impact on soil quality. This implies improving agricultural and livestock practices to conserve and promote the increase in SQI to achieve sustainable use of soil resources. Ma et al. (2024) have provided evidence of the high soil quality found in a natural forest compared to a paddy for planting rice and an orchard for planting grapefruit. In the same way, Nabiollahi et al. (2018) found that the mean values for all SQIs were significantly higher in forestland than in cropland.

Organic matter becomes more crucial with increasing consistent biomass contributions, thereby promoting nutrient recycling. This is especially true in ecosystems with minimal management that support accumulation, conservation, and mature age. Ma et al. (2024) noted that forests, compared to other land uses, significantly bolster soil organic carbon levels through substantial plant biomass deposition. Concerning tree cover, a higher SQI is associated with a continuous and diverse influx of organic matter that serves as food for active soil fauna. Minimal human intervention was used to accomplish this, along with achieving a longer lifespan compared with cropland and grassland. Although biomass also contributes to cropland, greater anthropogenic intervention results in a lower SQI. Although Grassland has a greater underground biomass thanks to its root abundance, livestock activity limits the soil indicators that can contribute to a greater SQI.

This study has several implications, such as the asses of multiple soil indicators with PCA and the additive weights equation get to generate a reliable soil quality index (SQI) with minimal indicators. However, a more detailed evaluation that allows assessing the sensitivity to different agricultural management systems can facilitate its interpretation and implementation for specific regions and soils under similar conditions worldwide (Bedolla-Rivera et al., 2020). Lately, the crucial role of soil resources in environmental and societal well-being has spurred an increased focus on comprehensive and ongoing soil health monitoring, using the SQI as a primary indicator (Granatstein and Bezdicek, 1992). We can use SQI to assess the effects of converting tropical forests into agricultural land. The effects of converting forests to different land uses, including silvopastoral systems, show considerable variation in soil quality, with trends toward decreasing (Bravo–Medina et al., 2021; Uthappa et al., 2024). One aim of the study is to protect and enhance the long-term sustainability of agricultural productivity rather than focusing on obtaining high values for specific soil characteristics using SQI.

During the study, we saw that SQI primarily focused on bio, chemical, and physical soil conditions aspects. However, it is also important to recognize that a comprehensive evaluation of soil security causes considers the soil health concept as a potential connector between soil security and one health, joining their five dimensions, including the capability and condition of the soil (Swan et al., 2024). Monitoring the SQI overtime can provide invaluable insights into the sustainability of agricultural land management practices and their long-term impact on the overall soil security of a given region.

5. Conclusions

The process of constructing the weighted soil quality index (SQIw) allowed soil properties integration with the greatest influence over its quality, revealing its potential as an effective tool for soil quality determination and monitoring. The present study constructed the SQIw from six physical, chemical, and biological indicators. Of these, available potassium ($mg\bullet kg^{-1}$) and pH were found to be the most important determinants of soil quality. In addition, it was found that soils with tree cover, which have a higher potassium content and neutral pH values, presented higher SQIw values than cropland and grassland coverage soils, presenting these latter deficient potassium values and higher acidity. Finally, it was concluded that jungle soils in the Junín region are of moderate to low quality depending on the coverage, with greater degradation in the Chanchamayo province compared to the Satipo province, where, in addition to having more soils under tree cover, there are also soils with a higher K content. For our study area, the SQI proved crucial in quantifying soil health and evaluating land management practices, especially in relation to changes in agricultural land use. This orientation highlights the inherent potential of soil to support agricultural productivity, while also protecting it from degradation and maintaining its functional integrity. In the future, this can be applied to monitoring the impacts of agriculture management decisions.

During the development of the study, we noted the lack of recent research on soil quality indicators and their optimal values for tropical ecosystems was a significant methodological challenge in selecting, combining, and scoring indicators. Sometimes, this condition prevents comparison with similar agroecological conditions. Therefore, future research should focus on improving the effectiveness and robustness of SQI in diverse agricultural settings to promote sustainable agriculture and ecosystem health. Therefore, the integration of technologies such as Geographic Information System (GIS), remote sensing (Ormanci and Dengiz, 2024), and machine learning (Diaz-Gonzalez et al., 2022) holds immense promise for enhancing the efficiency, accuracy, and scalability of SQI assessments. If the SQI is dynamic temporally because of changes to management practices, research must look at the development of region-specific benchmarks that will broaden our understanding of the factors influencing soil quality in different contexts.

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CRediT authorship contribution statement

Carlos Carbajal: Writing – original draft, Visualization, Formal analysis. **Fernanda Moya-Ambrosio:** Writing – original draft, Validation, Methodology. **Antony Barja:** Software. **Elvis Ottos-Diaz:** Formal analysis, Data curation. **Cinthya Aguilar-Tito:** Investigation. **Orlando Advíncula-Zeballos:** Formal analysis. **Juancarlos Cruz-Luis:** Project administration. **Richard Solórzano-Acosta:** Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Agbeshie, A.A., Awuah, R., Amoako, V., Akurugu, R.A., Ofori-Adjei, N.B., Abugre, S., Sarfo, D.A., 2025. Soil quality response to land use change in a tropical semi-deciduous forest zone of Ghana. Sustain. Environ. 11, 2464389. https://doi.org/10.1080/27658511.2025.2464389.

Anderson, J.P.E., 1983. Soil respiration. In: Page, A.L. (Ed.), Methods of Soil Analysis, Agronomy Monographs. American Society of Agronomy, Soil Science Society of America, Madison, WI, USA, pp. 831–871.

Andrés-Abellán, M., Wic-Baena, C., López-Serrano, F.R., García-Morote, F.A., Martínez-García, E., Picazo, M.I., Rubio, E., Moreno-Ortego, J.L., Bastida-López, F., García-Izquierdo, C., 2019. A soil-quality index for soil from Mediterranean forests. Eur. J. Soil Sci. 70, 1001–1011. https://doi.org/10.1111/ejss.12798.

Andrews, S.S., Karlen, D.L., Mitchell, J.P., 2002. A comparison of soil quality indexing methods for vegetable production systems in Northern California. Agric. Ecosyst. Environ. 90, 25–45. https://doi.org/10.1016/s0167-8809(01)00174-8.

Aravindh, S., Chinnadurai, C., Balachandar, D., 2020. Development of a soil biological quality index for soils of semi-arid tropics. Soil 6, 483–497. https://doi.org/10.5194/soil-6-483-2020.

Banco Central de Reserva del Perú, 2023. Caracterización del departamento de Junín. BCRP - Sucursal Huancayo, Perú.

Barrezueta-Unda, S., Paz-González, A., Chabla-Carrillo, J., 2017. Determinación de indicadores para calidad de suelos cultivados con cacao en provincia de El Oro-Ecuador determination of indicators for quality of soils cultivated with cocoa in the province El Oro-Ecuador. Rev. Cumbres 3, 17–24. https://doi.org/10.48190/cumbres.v3n1a2.

Bazán-Tapia, R., 2017. Manual de procedimientos de los análisis de suelos y agua con fines de riego. Instituto Nacional de Innovación Agraria - INIA.

Bedolla-Rivera, H.I., Xochilt Negrete-Rodríguez, M.D.L.L., Medina-Herrera, M.D.R., Gámez-Vázquez, F.P., Álvarez-Bernal, D., Samaniego-Hernández, M., Gámez-Vázquez, A.J., Conde-Barajas, E., 2020. Development of a Soil Quality Index for Soils under Different Agricultural Management Conditions in the Central Lowlands of Mexico: Physicochemical, Biological and Ecophysiological Indicators. Sustainability 12, 9754. https://doi.org/10.3390/su12229754.

Bouyoucos, G.J., 1936. Directions for making mechanical analyses of soils by the hydrometer method. Soil Sci. 42, 225–230. https://doi.org/10.1097/00010694-193609000-00007.

Brandão-Rocha, A.F., Silva-Siquieroli, A.C., de Andrade Silva, A., De Lima Carneiro, A. M., Fernandes-Vasconcelos, B.N., Rodrigues-Gondim, D.D., 2022. Indicadores de qualidade do solo em sistemas agroecológicos no cerrado mineiro. Soc. Nat. 34. https://doi.org/10.14393/sn-v34-2022-62940.

Bravo–Medina, C., Goyes–Vera, F., Arteaga–Crespo, Y., García–Quintana, Y., Changoluisa, D., 2021. A soil quality index for seven productive landscapes in the Andean–Amazonian foothills of Ecuador. Land Degrad. Dev. 32, 2226–2241. https://doi.org/10.1002/ldr.3897.

Bünemann, E.K., Bongiorno, G., Bai, Z., Creamer, R.E., de Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T.W., Mäder, P., Pulleman, M., Sukkel, W., van Groenigen, J.W., Brussaard, L., 2018. Soil quality – a critical review. Soil Biol. Biochem. 120, 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030.

Cantú, M.P., Becker, A., Bedano, J.C., Schiavo, H.F., 2007. Evaluación de la calidad de suelos mediante el uso de indicadores e índices. Cienc. Suelo 25, 173–178.

Castillo-Valdez, X., Etchevers-Barra, J.D., Hidalgo-Moreno, C.M.I., Aguirre-Gómez, A., 2021. Evaluación de la calidad de suelo: generación e interpretación de indicadores. Rev. TERRA Latinoam. 39. https://doi.org/10.28940/terra.v39i0.698.

Celestina, C., Hunt, J.R., Sale, P.W.G., Franks, A.E., 2019. Attribution of crop yield responses to application of organic amendments: a critical review. Soil Tillage Res. 186, 135–145. https://doi.org/10.1016/j.still.2018.10.002.

Ciarkowska, K., Gambus, F., 2020. Building a quality index for soils impacted by proximity to an industrial complex using statistical and data-mining methods. Sci. Total Environ. 740, 140161. https://doi.org/10.1016/j.scitotenv.2020.140161.

Damiba, W.A.F., Gathenya, J.M., Raude, J.M., Home, P.G., 2024. Soil quality index (SQI) for evaluating the sustainability status of Kakia-Esamburmbur catchment under three different land use types in Narok County, Kenya. Heliyon 10, e25611. https://doi.org/10.1016/j.heliyon.2024.e25611.

de Paul Obade, V., Lal, R., 2016. Towards a standard technique for soil quality assessment. Geoderma 265, 96–102. https://doi.org/10.1016/j.geoderma.2015.11.023.

Diaz-Gonzalez, F.A., Vuelvas, J., Correa, C.A., Vallejo, V.E., Patino, D., 2022. Machine learning and remote sensing techniques applied to estimate soil indicators – review. Ecol. Indic. 135, 108517. https://doi.org/10.1016/j.ecolind.2021.108517.

Doran, J.W., Zeiss, M.R., 2000. Soil health and sustainability: managing the biotic component of soil quality. Appl. Soil Ecol. 15, 3–11. https://doi.org/10.1016/S0929-1393(00)00067-6.

Encarnación, F., Zárate, R., 2010. Vegetación, informe temático. Proyecto mesozonificación ecológica y económica para el desarrollo sostenible de la provincia de satipo. Convenio IIAP, DEVIDA y la Municipalidad Provincial de Satipo, Iquitos - Perú.

EPA, U., 2004. Method 9045D: soil and waste pH. Soil Waste PH 1–5.

Estrada-Herrera, I.R., Hidalgo-Moreno, C., Guzmán-Plazola, R., Almaraz Suárez, J.J., Navarro-Garza, H., Etchevers-Barra, J.D., 2017. Indicadores de calidad de suelo para evaluar su fertilidad. Agrociencia 51, 813–831.

FAO, 2023. Standard operating procedure for soil respiration rate. Rome.

Fathizad, H., Ardakani, M.A.H., Heung, B., Sodaiezadeh, H., Rahmani, A., Fathabadi, A., Scholten, T., Taghizadeh-Mehrjardi, R., 2020. Spatio-temporal dynamic of soil quality in the central Iranian desert modeled with machine learning and digital soil assessment techniques. Ecol. Indic. 118, 106736. https://doi.org/10.1016/j.ecolind.2020.106736.

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science 309, 570–574. https://doi.org/10.1126/science.1111772.

García, Y., Ramírez, W., Sánchez, S., 2012. Indicadores de la calidad de los suelos: una nueva manera de evaluar este recurso. Pastos Forrajes 35, 125–138.

Gelaw, A., Singh, B., Lal, R., 2015. Soil quality indices for evaluating smallholder agricultural land uses in northern Ethiopia. Sustainability 7, 2322–2337. https://doi.org/10.3390/su7032322.

Granatstein, D., Bezdicek, D.F., 1992. The need for a soil quality index: local and regional perspectives. Am. J. Altern. Agric. 7, 12–16. https://doi.org/10.1017/S0889189300004380.

Huntley, B.J., 2023. Ecology of Angola: Terrestrial Biomes and Ecoregions. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-031-18923-4.

ISO, D., 1994. Soil quality. Determination of the Specific Electrical Conductivity. International Organization for Standardization Geneva.

Isong, A.I., Kingsley, J., Okon, P.B., Ogban, P.I., Afu, S.M., 2022. Soil quality estimation using environmental covariates and predictive models: an example from tropical soils of Nigeria. Ecol. Process. 11, 66. https://doi.org/10.1186/s13717-022-00411-y.

IUSS Working Group, 2007. World reference base for soil resources 2006, first update 2007, world soil resources reports No.103. FAO, Rome.

Jamioy-Orozco, D.D., Menjivar-Flores, J.C., Rubiano-Sanabria, Y., 2015. Indicadores químicos de calidad de suelos en sistemas productivos del Piedemonte de los Llanos Orientales de Colombia. Acta Agronóm. 64. https://doi.org/10.15446/acag.v64n4.38731.

Karlen, D.L., Mausbach, M.J., Doran, J.W., Cline, R.G., Harris, R.F., Schuman, G.E., 1997. Soil quality: a concept, definition, and framework for evaluation (A Guest Editorial). Soil Sci. Soc. Am. J. 61, 4–10. https://doi.org/10.2136/sssaj1997.03615995006100010001x.

Kassambara, A., 2022. Ggcorrplot: visualization of a correlation matrix using "ggplot2.".

Kassambara, A., Mundt, F., 2020. factoextra: extract and visualize the results of multivariate data analyses.

Kiani, M., Hernandez-Ramirez, G., Quideau, S.A.M., 2020. Spatial variation of soil quality indicators as a function of land use and topography. Can. J. Soil Sci. 100, 463–478. https://doi.org/10.1139/cjss-2019-0163.

Klimkowicz-Pawlas, A., Ukalska-Jaruga, A., Smreczak, B., 2019. Soil quality index for agricultural areas under different levels of anthropopressure. Int. Agrophys. 33, 455–462. https://doi.org/10.31545/intagr/113349.

Lehmann, J., Bossio, D.A., Kögel-Knabner, I., Rillig, M.C., 2020. The concept and future prospects of soil health. Nat. Rev. Earth Environ. 1, 544–553. https://doi.org/10.1038/s43017-020-0080-8.

Ma, L., Si, H., Li, M., Li, C., Zhu, D., Mao, Z., Yan, Y., Jiang, K., Yu, P., 2024. Influence of land use types on soil properties and soil quality in Karst regions of Southwest China. Agronomy 14, 882. https://doi.org/10.3390/agronomy14050882.

Mandal, D., Chandrakala, M., Alam, N.M., Roy, T., Mandal, U., 2021. Assessment of soil quality and productivity in different phases of soil erosion with the focus on land degradation neutrality in tropical humid region of India. CATENA 204, 105440. https://doi.org/10.1016/j.catena.2021.105440.

Martínez-Rodríguez, Ó.G., Can-Chulim, Á., Ortega-Escobar, H.M., Bojórquez-Serrano, J. I., Cruz-Crespo, E., García-Paredes, J.D., Madueño-Molina, A., 2021. Fertilidad e índice de calidad del suelo de la cuenca del Río San Pedro en Nayarit. Rev. TERRA Latinoam. 39. https://doi.org/10.28940/terra.v39i0.766.

Meitasari, R., Hanudin, E., Purwanto, B.H., 2024. Comparison of two soil quality assessment models under different land uses and topographical units on the southwest slope of Mount Merapi. Soil Water Res. 19, 77–89. https://doi.org/10.17221/76/2023-SWR.

Mukherjee, A., Lal, R., 2014. Comparison of soil quality index using three methods. PLoS One 9, e105981. https://doi.org/10.1371/journal.pone.0105981.

Mustafa, A.A., 2023. Utilizing of principal component analysis and geographic information system approach for assessing soil quality index under different land uses: case study. SVU Int. J. Agric. Sci. 5, 45–63. https://doi.org/10.21608/svuijas.2023.210997.1285.

Nabiollahi, K., Taghizadeh-Mehrjardi, R., Eskandari, S., 2018. Assessing and monitoring the soil quality of forested and agricultural areas using soil-quality indices and digital soil-mapping in a semi-arid environment. Arch. Agron. Soil Sci. 64, 696–707. https://doi.org/10.1080/03650340.2017.1373188.

Nasir, M.J., Haider, M.F., Ali, Z., Akhtar, W., Alam, S., 2024. Evaluation of soil quality through simple additive soil quality index (SQI) of Tehsil Charsadda, Khyber Pakhtunkhwa, Pakistan. J. Saudi Soc. Agric. Sci. 23, 42–54. https://doi.org/10.1016/j.jssas.2023.09.001.

Nortcliff, S., 2002. Standardisation of soil quality attributes. Agric. Ecosyst. Environ. 88, 161–168. https://doi.org/10.1016/S0167-8809(01)00253-5.

Olsen, S.R., Cole, C.V., Watanabe, F.S., Dean, L.A., 1954. Estimation of available phosphorus in soils by extraction with sodium bicarbonate. US Department of Agriculture, Washington DC.

Ormanci, I.F., Dengiz, O., 2024. Establishing and verifying soil quality index model based on GIS and remote sensing for cultivated lands under semi-humid terrestrial ecosystem. Int. Soil Water Conserv. Res. https://doi.org/10.1016/j.iswcr.2024.10.004.

Pagel, H., 1972. Comparative studies on the content of exchangeable and resupply able potassium in important soils of the arid and humid tropics. J. Trop. Subtrop. Agric. Trop. Vet. Sci. 10, 35–51. KMU Leipz.

Paramisparam, P., Ahmed, O.H., Omar, L., Ch'ng, H.Y., Johan, P.D., Hamidi, N.H., 2021. Co-application of charcoal and wood ash to improve potassium availability in tropical mineral acid soils. Agronomy 11, 2081. https://doi.org/10.3390/agronomy11102081.

Pebesma, E.J., Bivand, R.S., 2005. Classes and methods for spatial data in R. R News 5, 9–13.

R Core Team, 2018. R: a language and environment for statistical computing (manual). R Foundation for Statistical Computing, Vienna, Austria.

Rachman, L.M., 2019. Development of technique to determine soil quality index for assessing soil condition. J. Phys. Conf. Ser. 1375, 012046. https://doi.org/10.1088/1742-6596/1375/1/012046.

Raiesi, F., 2017. A minimum data set and soil quality index to quantify the effect of land use conversion on soil quality and degradation in native rangelands of upland arid and semiarid regions. Ecol. Indic. 75, 307–320. https://doi.org/10.1016/j.ecolind.2016.12.049.

Raiesi, F., Beheshti, A., 2022. Evaluating forest soil quality after deforestation and loss of ecosystem services using network analysis and factor analysis techniques. CATENA 208, 105778. https://doi.org/10.1016/j.catena.2021.105778.

Revelle, W., 2023. psych: procedures for psychological, psychometric, and personality research: r package version 2.3.6.

Reyes, W., 2019. Comparación de tres métodos de evaluación de la calidad física en un suelo vertisol de la llanura de coro, Falcón-Venezuela. CIENCIAMATRIA 5, 144–173. https://doi.org/10.35381/cm.v5i8.91.

Samaei, F., Emami, H., Lakzian, A., 2022. Assessing soil quality of pasture and agriculture land uses in Shandiz county, northwestern Iran. Ecol. Indic. 139, 108974. https://doi.org/10.1016/j.ecolind.2022.108974.

Sanad, H., Moussadek, R., Mouhir, L., Oueld Lhaj, M., Dakak, H., El Azhari, H., Yachou, H., Ghanimi, A., Zouahri, A., 2024. Assessment of soil spatial variability in agricultural ecosystems using multivariate analysis, soil quality index (SQI), and geostatistical approach: a case study of the Mnasra Region, Gharb Plain, Morocco. Agronomy 14, 1112. https://doi.org/10.3390/agronomy14061112.

Sánchez-Navarro, A., Gil-Vázquez, J.M., Delgado-Iniesta, M.J., Marín-Sanleandro, P., Blanco-Bernardeau, A., Ortiz-Silla, R., 2015. Establishing an index and identification of limiting parameters for characterizing soil quality in Mediterranean ecosystems. CATENA 131, 35–45. https://doi.org/10.1016/j.catena.2015.02.023.

Selmy, S.A.H., Abd Al-Aziz, S.H.A., Jiménez-Ballesta, R., Jesús García-Navarro, F., Fadl, M.E., 2021. Soil quality assessment using multivariate approaches: a case study of the Dakhla Oasis Arid Lands. Land 10, 1074. https://doi.org/10.3390/land10101074.

Stefanoski, D.C., de Figueiredo, C.C., Santos, G.G., Marchão, R.L., 2016. Selecting soil quality indicators for different soil management systems in the Brazilian Cerrado. Pesqui. Agropecu. Bras. 51, 1643–1651. https://doi.org/10.1590/S0100-204X2016000900064.

Swan, T., McBratney, A., Field, D., 2024. Linkages between soil security and one health: implications for the 2030 sustainable development goals. Front. Public Health 12. https://doi.org/10.3389/fpubh.2024.1447663.

Tesfahunegn, G.B., 2014. Soil quality assessment strategies for evaluating Soil degradation in Northern Ethiopia. 10.1155/2014/646502.

Tierras Vivas, 2024. Chanchamayo: coffee capital of Peru [WWW Document]. URL https://www.tierrasvivas.com/en/travel-blog/chanchamayo-peru (accessed 3.21.25).

Uthappa, A.R., Devakumar, A.S., Das, B., Mahajan, G.R., Chavan, S.B., Jinger, D., Jha, P. K., Kumar, P., Kokila, A., Krishnamurthy, R., Mounesh, N.V., Dhanush, C., Ali, I., Eldin, S.M., Al-Ashkar, I., Elshikh, M.S., Fahad, S., 2024. Comparative analysis of soil quality indexing techniques for various tree based land use systems in semi-arid India. Front. For. Glob. Change 6. https://doi.org/10.3389/ffgc.2023.1322660.

Valdez-Nuñez, R.A., Rojas-García, J.C., Ríos Ruiz, W.F., 2019. Microbiological indicators of tropical soils quality in ecosystems of the north-east area of Peru. Sci. Agropecu. 10, 217–227. https://doi.org/10.17268/sci.agropecu.2019.02.07.

Vallejo-Quintero, V.E., Afanador-Barajas, L.N., Coca-Peña, D.A., Vargas-Giraldo, A.F., Bautista-Murcia, M.F., Mendoza-Hernández, A., 2020. Evaluación de la calidad de suelos en agroecosistemas de Colombia a través de la selección de un conjunto mínimo de datos. Colomb. For. 23. https://doi.org/10.14483/2256201x.14856.

Van De Kerchove, R., Zanaga, D., Xu, P., Tsendbazar, N., Lesiv, M., 2022. Product user manual V 2.0.

Vargas-Terminel, M.L., Flores-Rentería, D., Sánchez-Mejía, Z.M., Rojas-Robles, N.E., Sandoval-Aguilar, M., Chávez-Vergara, B., Robles-Morua, A., Garatuza-Payan, J., Yépez, E.A., 2022. Soil respiration is influenced by seasonality, forest succession and contrasting biophysical controls in a tropical dry forest in northwestern Mexico. Soil Syst. 6, 75. https://doi.org/10.3390/soilsystems6040075.

Velasquez, E., Lavelle, P., Andrade, M., 2007. GISQ, a multifunctional indicator of soil quality. Soil Biol. Biochem. 39, 3066–3080. https://doi.org/10.1016/j.soilbio.2007.06.013.

von Uexkuell, H.R., 1968. Potassium nutrition of tropical crops. The Role of Potassium in Agriculture. John Wiley & Sons, Ltd, pp. 385–421. https://doi.org/10.2134/1968.roleofpotassium.c18.

Walkley, A., Black, I.A., 1934. An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. Soil Sci. 37, 29–38. https://doi.org/10.1097/00010694-193401000-00003.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the tidyverse. J. Open Source Softw. 4, 1686. https://doi.org/10.21105/joss.01686.

Yost, R.S., Uchida, R., 2000. Interpreting soil nutrient analysis data, in: Plant Nutrient Management in Hawaii's Soils, Approaches for Tropical and Subtropical Agriculture. Hawaii.

Yu, P., Liu, S., Zhang, L., Li, Q., Zhou, D., 2018. Selecting the minimum data set and quantitative soil quality indexing of alkaline soils under different land uses in northeastern China. Sci. Total Environ. 616–617, 564–571. https://doi.org/10.1016/j.scitotenv.2017.10.301.

Yuan, T.L., 1959. Determination of exchangeable hydrogen in soils by a titration method. Soil Sci. 88, 164–167. https://doi.org/10.1097/00010694-195988030-00008.

Zanaga, D., van de Kerchove, R., Daems, D., de Keersmaecker, W., Brockmann, C., Kirches, G., Wevers, J., Cartus, O., Santoro, M., Fritz, S., Lesiv, M., Herold, M., Tsendbazar, N.-E., Xu, P., Ramoino, F., Arino, O., 2022. ESA WorldCover 10 m 2021 v200.https://doi.org/10.5281/ZENODO.7254221.

Zhang, Y., Wang, L., Jiang, J., Zhang, J., Zhang, Z., Zhang, M., 2022. Application of soil quality index to determine the effects of different vegetation types on soil quality in the Yellow River Delta wetland. Ecol. Indic. 141, 109116. https://doi.org/10.1016/j.ecolind.2022.109116.

Zhang, Y., Xu, X., Li, Z., Liu, M., Xu, C., Zhang, R., Luo, W., 2019. Effects of vegetation restoration on soil quality in degraded karst landscapes of southwest China. Sci. Total Environ. 650, 2657–2665. https://doi.org/10.1016/j.scitotenv.2018.09.372.