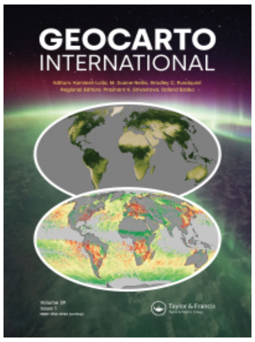

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Multicriteria evaluation and remote sensing approach to identifying degraded soil areas in northwest Peru

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ABSTRACT
Soil is a vital nonrenewable resource characterized by rapid degradation and slow regeneration processes. In this study, soil degradation in Jaén and San Ignacio was assessed *via* a multicriteria evaluation approach combined with remote sensing (RS) data. Nine factors were analyzed classified three categories: environmental, topographic, and edaphological factors. The results revealed that the slope (59.07%) was the main influencing factor, followed by land use and land cover (LULC) (56.36%). The degradation map revealed that 83.48% of the area exhibited moderate degradation, 14.49% low degradation, and 1.56% high degradation. The districts of Pomahuaca and San José de Lourdes demonstrated the largest areas of moderate degradation, accounting for 13.71% and 22.54%, respectively. Bellavista and Huarango exhibited the largest areas of very high degradation, accounting for 0.27% and 0.08%, respectively. The (AHP) method and RS data were employed to assess soil degradation, highlighting the need for sustainable soil restoration and conservation strategies.

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KEYWORDS
Soil degradation; GIS; RS; AHP and evaluation

1. Introduction

Soil is a vital nonrenewable resource that is undergoing rapid degradation and exhibits a slow regeneration process (Nawaz et al. 2013; Siles et al. 2024). Currently, 75% of the world's soils are degraded, with projections suggesting that this figure may exceed 90% by 2050 (Li et al. 2015; Perović et al. 2021). Furthermore, the estimated annual loss is approximately 12 million hectares of land, representing a cost of more than 10% of the global gross domestic product (GDP) (Mzuri et al. 2022). The negative factors contributing to land degradation are considered global issues, with greater prevalence in arid

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regions, where climate change and the unsustainable exploitation of natural resources play significant roles (Adyanova et al. 2023). The loss of natural soil functions; reductions in agricultural productivity, livestock, and biodiversity levels; and impacts on populations and food insecurity can be attributed to anthropogenic activities, natural events, and deforestation (Darvishi Boloorani et al. 2023). A decline in the soil quality is associated with a reduction in its physical, chemical, and biological characteristics (Oraon et al. 2023). In contrast, the principal factors that contribute to soil degradation include topography, climate, land use, and the advancement of human activities (Li et al. 2015; Biswas et al. 2022; Yu and Deng 2022).

To reduce soil degradation and address this issue, it is essential to identify risk areas and implement control measures. This requires the integration of multiple data sources and methodologies to study the implications of degradation, as well as for monitoring and evaluation (Sun et al. 2017; Kawy and Darwish 2019; Yu and Deng 2022). Within this context, in recent years, remote sensing (RS) technology has been reported as an effective, far-reaching, and efficient tool for monitoring and assessing degraded soils (Zhou et al. 2020; Wang et al. 2023). RS technology has been applied in studies related to agricultural management, soil degradation, meteorological risks, desertification, droughts, and erosion (Bishnoi et al. 2021; Kirsten et al. 2023). Furthermore, as early as 2011, RS and geographic information system (GIS) technologies were recognized as valuable tools to better understand changes and identify degraded soils at both the temporal and regional scales (Buenemann et al. 2011; Kawy and Darwish 2019). This was reaffirmed in 2022, when GIS technology was again highlighted as a critical tool for planning, monitoring, and data sharing in the study of degraded soils (Biswas et al. 2022).

Various methodologies have been employed to assess soil degradation, including the Mediterranean Desertification and Land Use Project (MEDALUS) (Meza Mori et al. 2022; Yu and Deng 2022), the revised universal soil loss equation (RUSLE) (Sepuru and Dube 2018), and spectral indices (de Oliveira-Júnior et al. 2022). In addition, other methodologies, such as machine learning (random forest model) (Pásztor 2021), artificial neural networks (ANNs), weights of evidence (WoE) models (Senanayake et al. 2020), and the analytic hierarchy process (AHP) (Mzuri et al. 2022; Darvishi Boloorani et al. 2023), have been adopted. The AHP, which was proposed by Saaty (1977), is a widely utilized method in soil degradation research. This method can be employed to determine the relative importance of various factors contributing to degradation, including land use and land cover (LULC), climate, topography, soil properties, and geology (Wang et al. 2023). In previous research, various methodologies, including GIS, AHP, and RS methodologies, have been employed to analyze soil degradation and implement soil management and conservation measures (El Jazouli et al. 2019; Sandeep et al. 2021; Kucuker and Cedano Giraldo 2022; Mzuri et al. 2022; Panchal and Shrivastava 2022; Das et al. 2023).

In Peru, the area of degraded soil increased by 14.4% between 2015 and 2022 (SINIA 2023) due to intensive agriculture; continuous land use changes, especially in high Andean regions; and overgrazing, logging, and forest burning. These activities have led to the loss of biodiversity and soil-related ecosystem services (de Valença et al. 2017; Castillo et al. 2020; Meza Mori et al. 2022; Gonzáles et al. 2024). This problem is likely to occur in the department of Cajamarca, as 40% of its land area is used for agriculture, with intensive farming particularly prevalent in the provinces of Jaén and San Ignacio, where 45% and 40%, respectively, of the total land is dedicated to agriculture (MIDAGRI 2024). In contrast, the development of intensive agriculture involves the disproportionate use of large amounts of agrochemicals and fertilizers, which leads to soil fertility loss in the long term. In addition, deforestation for the expansion of new agricultural and urban areas resulted in the loss of 7,544 hectares of dry forests and 15,635 hectares of Amazonian forests between 2001 and 2022 in the provinces of Jaén and San Ignacio, respectively (Bedoya Garland et al. 2017; GEO BOSQUES 2023). This phenomenon has contributed to soil degradation. Therefore, in this research, the AHP, GIS, and RS methods were applied to evaluate degraded soils in the provinces of Jaén and San Ignacio from 2023–2024, and environmental, topographic, and soil factors were considered to answer the following questions: (1) What is the primary influencing factor in evaluating degraded soils? (2) What is the level of degradation in the study area? (3) How is degradation spatially distributed in the provinces of Jaén and San Ignacio? By answering these questions, we could identify the degradation level in the study area and thus contribute to land restoration and conservation strategies in northwest Peru.

2. Materials and methods

2.1. Study area

The study area comprises the provinces of Jaén and San Ignacio in the Cajamarca region of northwest Peru (Figure 1). The region is situated at an altitude ranging from 333 to 2,300 m above sea level. Its climatic characteristics are defined by an annual temperature ranging from 25–26 °C and an annual precipitation of 1,200 mm, thus classifying the region as a tropical or humid area. The area is notable for its natural forest cover, which constitutes 23.0% of the total surface area of Jaén and 47.3% of that of San Ignacio. Additionally, the land is characterized by shrublands, sparse vegetation, rocky outcrops, shrub-covered areas, and permanent crops. In Jaén, these categories account for 20.5%, 16.7%, and 13.0%, respectively, of the total land, whereas in San Ignacio, they account for 16.6%, 10.09%, and 10.0%, respectively, of the total land. Furthermore, the region includes land used for agricultural purposes, agricultural land with shrub vegetation, dry forests, and sparse vegetation, which jointly account for 0.0% to 9.4% of the total area of Jaén and 0.0% to 6.8% of that of San Ignacio (SENAMHI 2020).

The study area hosts a population of 351.4 thousand inhabitants, with Jaén as the most populous province, at 207.6 thousand people, and San Ignacio as the least populous province, at 143.8 thousand inhabitants (INEI 2022). Both provinces collectively cover a total of 172,856 hectares of agricultural land. The primary agricultural activities are the cultivation of coffee (2,294.48 t), rice (12,442.2 t), and cacao (420.97 t) (MIDAGRI 2024).

A flowchart of the methodology for identifying areas exhibiting signs of degradation in the provinces of Jaén and San Ignacio from 2023 to 2024 is shown in (Figure 2). Environmental, edaphic, and topographic criteria were established, with each criterion comprising subcriteria that influence soil degradation. The AHP method was employed to determine the relative importance of each subcriterion (Mzuri et al. 2022). The obtained degradation map was subsequently validated *via* visual interpretation *via* high-resolution images.

2.2. Determination of criteria and subcriteria

The selection of criteria is essential for the analysis and evaluation of degraded soil areas, and criteria were defined according to the objectives and characteristics of the study area. Therefore, on the basis of a literature review, the primary criteria and subcriteria were determined (El Jazouli et al. 2019; Sandeep et al. 2021; Mzuri et al. 2022). On this basis, a hierarchy was established comprising three primary criteria: environmental, topographical,

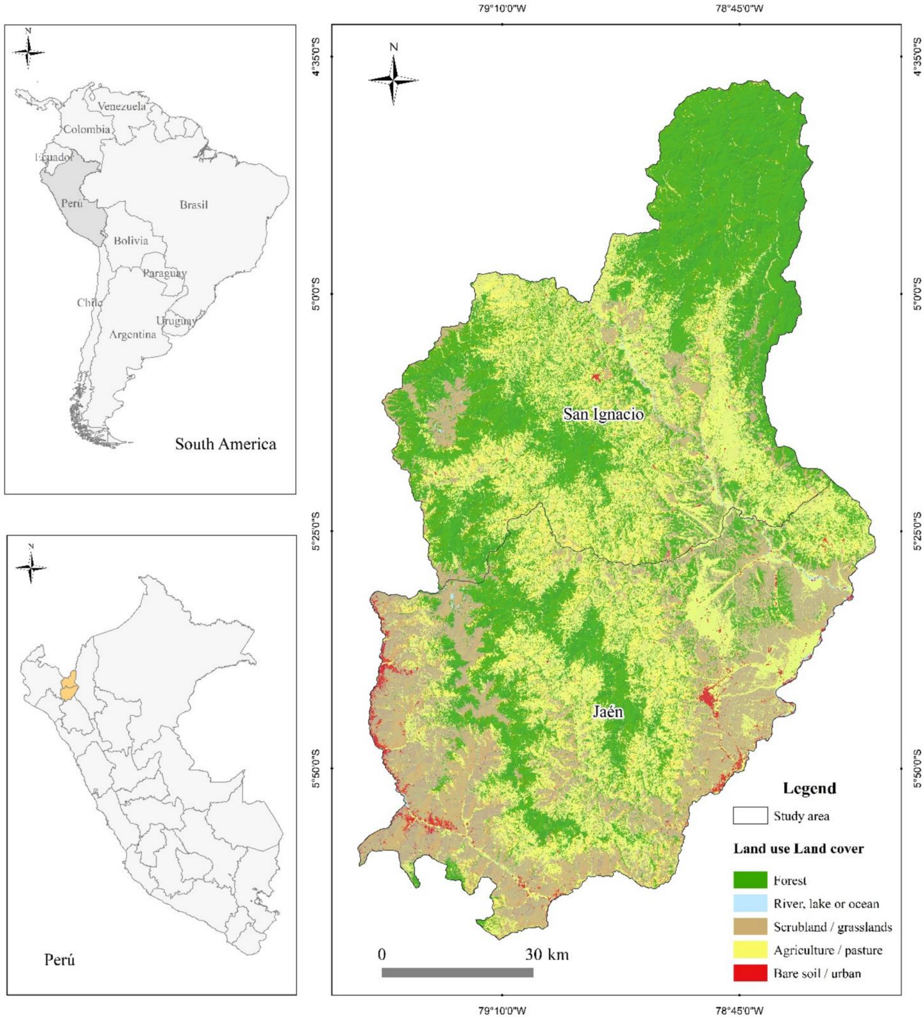

Figure 1. Geographical location of the provinces of Jaén and San Ignacio. The land use and land cover (LULC) classification consists of five categories, with Forest (depicted in green) being the most abundant.

and edaphic criteria. These criteria were further divided into nine subcriteria. The first criterion, namely, environmental factors, comprises three subcriteria: LULC, temperature, and precipitation. The second criterion, topographical factors, includes three subcriteria: altitude, slope, and aspect. The third criterion, namely, edaphic factors, encompasses three subcriteria: pH, texture, and organic matter. These criteria are closely related to soil degradation. Each criterion and subcriterion was classified into five degradation levels, namely, very low (I), low (II), moderate (III), high (IV), and very high (V) (Table 1), on the basis of the methodologies of Mzuri et al. (2022) and Sandeep et al. (2021).

To generate temperature and precipitation maps, the WorldClim 2.1 database was employed, with average monthly data from 1970 to 2000, thus providing average monthly data from 1970 to 2000 at a spatial resolution of 1 km (Fick and Hijmans 2017). To create slope and aspect maps, data were obtained from the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) with a spatial resolution of 30 m *via* the slope and aspect tools in ArcGIS 10.8. Furthermore, the altitude map was reclassified *via* the same

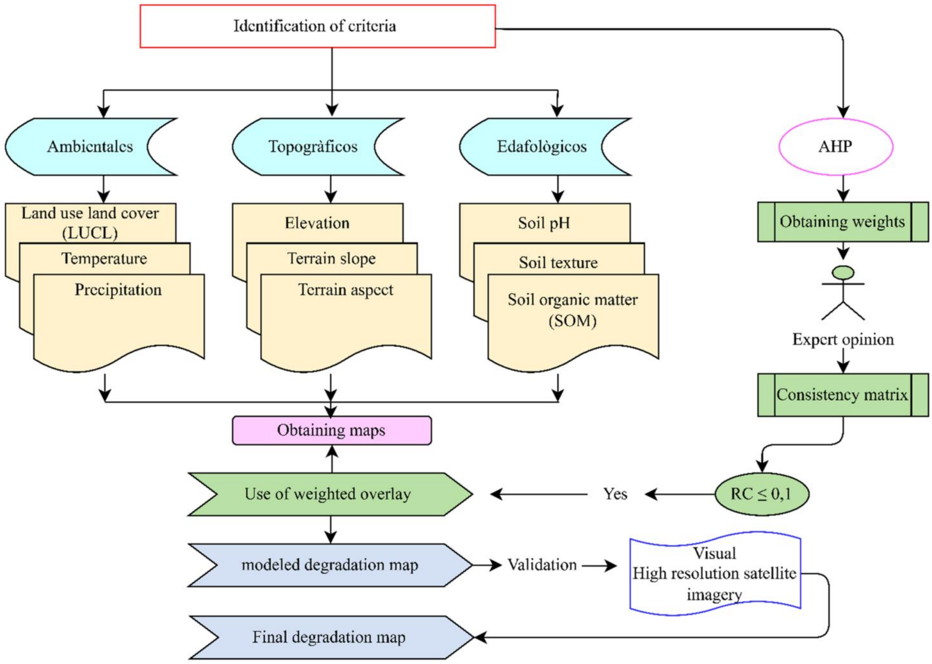

Figure 2. Flowchart of the methodological framework used to identify degraded areas in the provinces of Jaén and San Ignacio.

DEM (Farr et al. 2007; López et al. 2020). With respect to the edaphic subcriteria, data were sourced from the global soil mapping project SoilGrids, which provides data at a spatial resolution of 250 m and at a depth of 20 cm (Hengl et al. 2017). The organic matter layer (soil organic matter, SOM) was derived from the percentage of soil organic carbon (SOC), thereby utilizing the conversion factor (1.72) proposed by van Bermelan (Ingram and Fernandes 2001).

To generate a land cover and land use (LULC) map, data on the following classes were collected: (i) forest, (ii) water, (iii) shrub- and grasslands, (iv) agricultural land and pastures, and (v) bare soil and urban areas. Of these, 70% of the data were employed for training purposes, whereas 30% of the data were utilized for validation. An annual mosaic of Sentinel-2 images (ID: COPERNICUS/S2_SR) for 2023 was constructed *via* the Google Earth Engine (GEE) platform (Gorelick et al. 2017; Nazarova et al. 2020). The processing steps involved the removal of clouds and cloud shadows in the images, in accordance with the methodology proposed by Castillo et al. (2020). A series of spectral indices were calculated, including the normalized difference vegetation index (NDVI) (Tucker 1979), the soil-adjusted vegetation index (SAVI) (Huete 1988), the enhanced vegetation index (EVI) (Huete et al. 2002), the normalized difference water index (NDWI) (McFeeters 1996), and the atmospherically resistant vegetation index (ARVI) (Tanre et al. 1992). Furthermore, topographic variables, including elevation, slope, and aspect (ID: 'USGS/SRTMGL1_003'), were identified to augment the number of predictor variables for classification. The spectral bands, spectral indices, and topographic variables were subsequently integrated into a multiband mosaic, which was classified *via* the random forest (RF) classification model (Breiman 2001). This process resulted in the generation of an LULC map for the study area, achieving a kappa index of 0.96.

Table 1. Criteria and subcriteria for the identification of degraded soil areas in the Jaén and San Ignacio provinces.

Subcriteria	Unit	Very low 1	Low 2	Moderate 3	High 4	Very high 5	References
				Environmental			
Land use land cover (LULC)	Category	Forest	Water	Scrub- and grasslands	Agriculture and pastures	Bare soil and urban areas	(El Jazouli et al. 2019; Mzuri et al. 2022; Das et al. 2023)
Average annual temperature	°C	<30	30-33	33-36	36-39	>39	(Sandeep et al. 2021)
Annual precipitation	mm	<550	550-600	600-650	650-700	>700	(Mzuri et al. 2022)
				Topographic			
Elevation	m.s.n.m	<550	550-1,000	1,000-2,000	2,000-2,300	>2,300	(El Jazouli et al. 2019; Mzuri et al. 2022)
Terrain slope	%	<2	2-10	10-20	20-35	>35	(Perović et al. 2021; Mzuri et al. 2022; Yu and Deng 2022; Das et al. 2023)
Terrain aspect		Northwest, west	Southwest, south	Southeast	Easth, northeast	North	(El Jazouli et al. 2019)
				Edaphological			
Soil pH		> 4.5	4,5–5,5	5,5–6,5	6,5–7,2	>7.2	(Perović et al. 2023)
Soil texture		SCL, L	LS, CL	SC, SiL, SiCL	Si, C, SiC	S	(Perović et al. 2021; Das et al. 2023)
Soil organic matter (SOM)	%	<10	5-10	3-5	3-1	<1	(Perović et al. 2023, 2021)

Where texture is: S: Sandy; C: clay; L: loam; Si: silt.

2.3. Analytic hierarchy process (AHP) method

The AHP method, was employed to facilitate a comparison and weighting of the criteria and subcriteria, with the objective of assessing their relative importance. This was achieved *via* the completion of a pairwise comparison matrix (Shekhar and Pandey 2015; Achu et al. 2020), by a group of soil health experts, in accordance with the Saaty nine-point scale (Saaty 1977) (Table 2). The group of experts involved in soil health comprised researchers from various institutions, including the National Institute of Agricultural Innovation (INIA), UNTRM, and UNALM.

To determine the reliability of the data, the consistency ratio (CR) was used, which can be calculated *via* Equation 1:

$$CR = \frac{CI}{RI} \qquad \text{Equation 1}$$

where:

CR: consistency ratio;

CI: consistency index; and

RI: random index, which determines the reliability of the pairwise comparison. The values of the RI range from 0 to 1.

The consistency index (CI) was calculated by dividing the difference between the largest value of the matrix λ_max and the number of matrix variables (n) by the difference between the number of matrix variables (n) and 1, according to Equation 2. Additionally, three variables were considered in the matrix. Thus, the RI value was 0.58 (Table 3).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \qquad \text{Equation 2}$$

The working matrix was accepted if the CR value was equal to or less than 0.1. If the CR value exceeded 0.1, the pairwise comparison matrix was recalculated (Saaty and Vargas 2012).

2.4. Generation of the modeled soil degradation map

To generate a map of the modeled soil degradation, weighted values were calculated *via* the AHP method and employed in conjunction with the reclassified maps *via* the ArcMap 10.8.1 weighted overlay tool (López et al. 2020). The environmental, topographic, and edaphic maps were integrated and generated *via* WorldClim, SoilGrids, Sentinel-2, and SRTM-NASA data. A soil degradation map was subsequently produced. Furthermore, the LULC map was employed to categorize the extent of degradation in accordance with the parameters delineated in Table 1. Notably, LULC map generation involved the utilization of spectral indices (NDVI, SAVI, EVI, NDWI, and ARVI) and the processing of images to remove clouds and shadows, as well as the creation of annual mosaics. To validate the degradation map, specific sites were identified on the basis of degradation levels *via* high-resolution satellite images from Google Earth and visual validation (Mzuri et al. 2022; Das et al. 2023). Furthermore, the degradation map was complemented with the incorporation

Table 2. Saatýs pairwise comparison matrix scale (Saaty 1977).

Value	Definition
1	Equally, important
3	Moderate important
5	Significantly more important
7	Much more important
9	Extremely more important
2,4, 6, 8	Values of intermediate importance

Table 3. Random index values conditional on the n value of the matrix (Saaty 1977).

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0,58	0,9	1,12	1,24	1,32	1,41	1,45	1,49

Table 4. Weighting of the criteria and subcriteria.

Criterion	Weigth (%)	Rank	Sub criterion	Rank	Weight (%)
Environmental factors	50.23	1	Land use land cover (LULC)	1	56.36
			Average annual temperature	3	14.43
			Annual precipitation	2	29.20
Topographic factors	34.73	2	Elevation	2	28.85
			Terrain slope	1	59.07
			Terrain aspect	3	12.08
Edaphological factors	15.34	3	Soil pH	3	12.76
			Soil texture	1	45.02
			Soil organic matter (SOM)	2	42.23

of protected natural areas (PNAs), which were included to evaluate the level of degradation. This entailed superimposing the PNA maps from SERNANP (2024), accounting for regional conservation areas (RCAs), private conservation areas (PCAs), and PNAs.

3. Results

3.1. Determined criteria and subcriteria

After surveys were conducted among soil health experts and the criteria evaluated (Table 1), environmental factors were identified as the most important, accounting for 50.23%, followed by topographic factors at 34.73% and pedological factors at 15.34%. Among the sub-criteria, slope (59.07%), land use and land cover (LULC, 56.36%), and soil texture (45.02%) were considered the most significant. Conversely, aspect (12.08%), pH (12.76%), and mean annual temperature (14.43%) were ranked as the least prominent factors (Table 4).

3.2. Generation of subcriteria maps

The reclassified maps based on the nine evaluated subcriteria (Figure 3), represented by a color gradient from light green to deep red, illustrate the variability in the degradation level for the environmental, topographic, and edaphological criteria, as classified in Table 1.

The percentage (%) and area (km^2), based on the reclassification of the evaluated subcriteria, indicated that land use and land cover (LULC) exhibited the largest area of very low degradation (40.08%). In contrast, precipitation showed a very high degradation level (88.87%) among environmental criteria. Topographic criteria, on the other hand, revealed degraded areas across all levels for each sub-criterion: elevation, aspect, and slope displayed low (25.83%), moderate (51.26%), and very high (66.04%) degradation levels, respectively. Meanwhile, sub-criteria such as texture, organic matter, and pH within topographic criteria showed very low (80.70%), low (51.02%), and moderate (46.97%) degradation levels, respectively (Table 5).

3.3. Determination of criteria

After generating reclassified the maps for each criterion, it was observed that environmental factors exhibited low to moderate degradation levels (Figure 4(a)). Additionally,

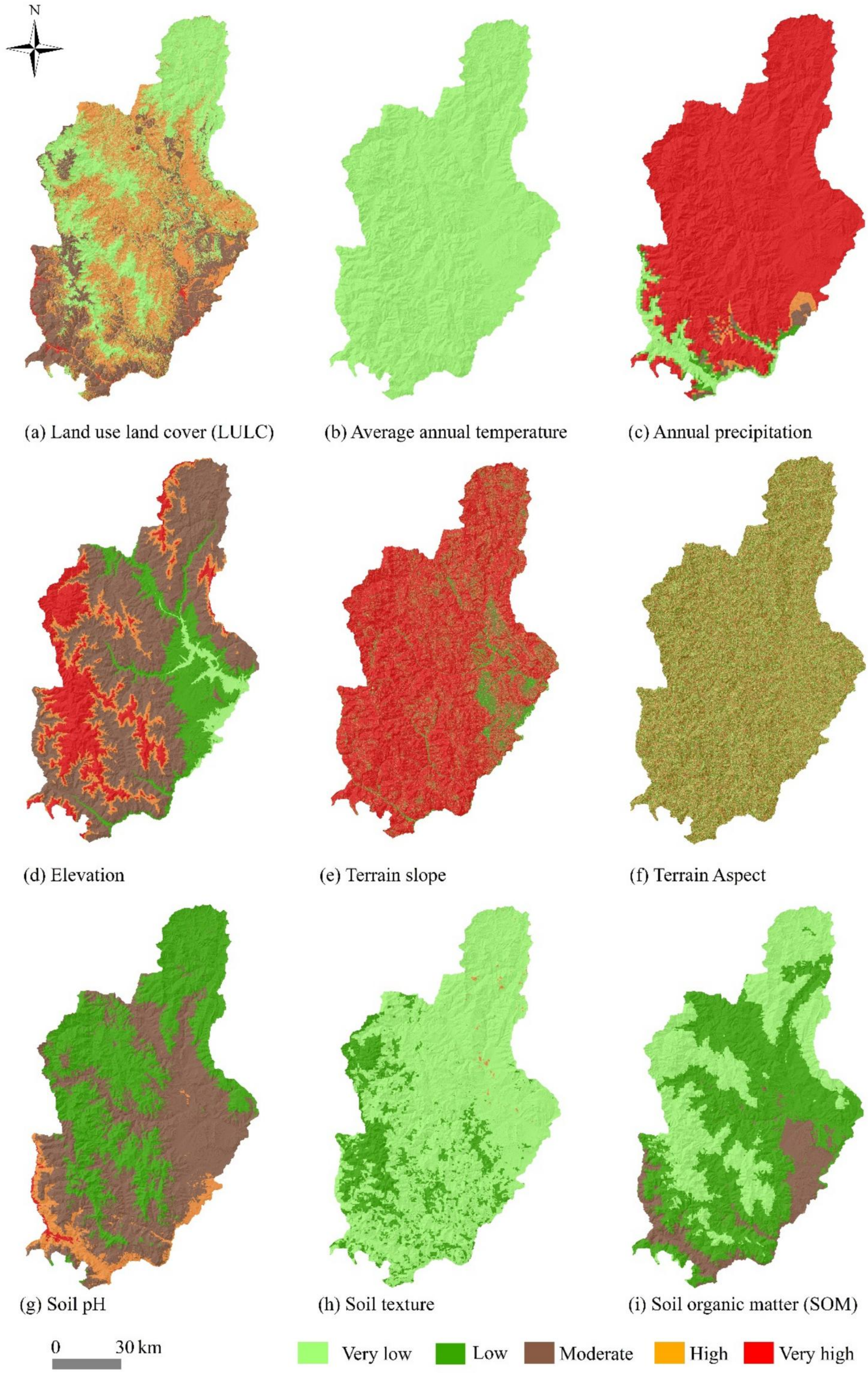

Figure 3. Maps of the subcriteria (a-i), environmental criteria (a-c), topographic criteria (d-f), and pedological criteria (g-i). The map shows color gradients ranging from green (very low degradation) to deep red (very high degradation).

Table 5. Surface area in km^2 according to the soil degradation level for each subcriterion.

Criterion	Sub criterion	Very low (1) km^2	%	Low (2) km^2	%	Moderate (3) km^2	%	High (4) Km^2	%	Very high (5) Km^2	%
Environmental	Land use land cover (LULC)	3,949.81	40.08	30.10	0.31	2,255.65	22.89	3,499.52	35.51	118.73	1.20
	Average annual temperature	9,853.81	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Annual Precipitation	498.51	5.06	177.95	1.81	198.57	2.02	222.15	2.25	8,756.63	88.87
Topographic	Elevation	350.15	3.55	1,527.39	15.50	5,051.00	51.26	1,236.62	12.55	1,688.65	17.14
	Terrain slope	36.59	0.37	598.62	6.08	1,259.66	12.78	1,451.17	14.73	6,507.76	66.04
	Terrain aspect	2,419.60	24.5	2,545.45	25.83	1,097.13	11.13	2,467.98	25.05	1,323.65	13.43
Edaphological	Soil pH	0.00	0.00	4515.83	45.83	4,628.63	46.97	651.47	6.61	57.88	0.59
	Soil texture	7,951.76	80.70	1,874.88	19.03	0.19	0.00	26.99	0.27	0.00	0.00
	Soil organic matter (SOM)	3,671.76	37.26	5,027.56	51.02	1,154.27	11.71	0.23	0.00	0.00	0.00

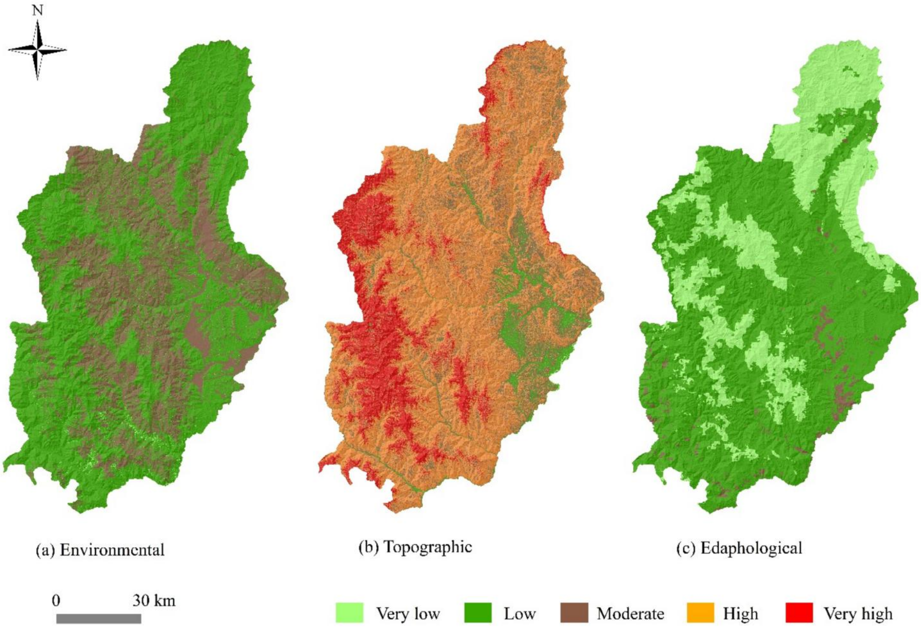

Figure 4. Maps of the criteria: (a) environmental, (b) topographic, and (c) edaphological factors. According to the map, (b) shows the only criterion exhibiting areas of very high degradation, marked in deep red.

Table 6. Area in (%) of the various degradation levels for each criterion.

Criterion	Very low (1) Km^2	%	Low (2) Km^2	%	Moderate (3) Km^2	%	High (4) Km^2	%	Very high (5) Km^2	%
Environmental	34.23	0.35	6,442.55	65.38	3,377.03	34.27	0.00	0.00	0.00	0.00
Topographic	20.64	0.21	611.96	6.21	1,865.69	18.93	5,671.53	57.56	1,683.98	17.09
Edaphological	2,874.64	29.17	6,742.74	68.43	236.43	2.40	0.00	0.00	0.00	0.00

topographic factors showed the highest levels of degradation (Figure 4(b)), primarily located in the western areas of the Jaén and San Ignacio provinces. Pedological factors, meanwhile, indicated degradation levels ranging from very low to moderate (Figure 4(c)).

The topographic criterion encompassed all levels of soil degradation within the study area, with the largest area classified as level (IV), i.e. high degradation (57.56%). In contrast, the environmental and edaphological criteria were reclassified into three degradation levels, with the most significant degraded area found at the low (II) level accounting for 65.38% and 68.43%, respectively, of the total study area (Table 6).

3.4. Soil degradation zones

A modelled soil degradation map was generated for the provinces of Jaén and San Ignacio (Figure 5), classifying degradation into five levels, from (I) very low to (V) very high. Moderate degradation (III) was the most prevalent level, covering an area of 8,222.07 km^2, which represents 83.48% of the total study area, followed by low degradation (II), with 1,428.97 km^2 (14.49%) of the total area. In contrast, high degradation (IV) and very high degradation (V) accounted for only 1.56% and 0.46%, respectively, of the total territory. Furthermore, very low degradation (I) was observed in both provinces,

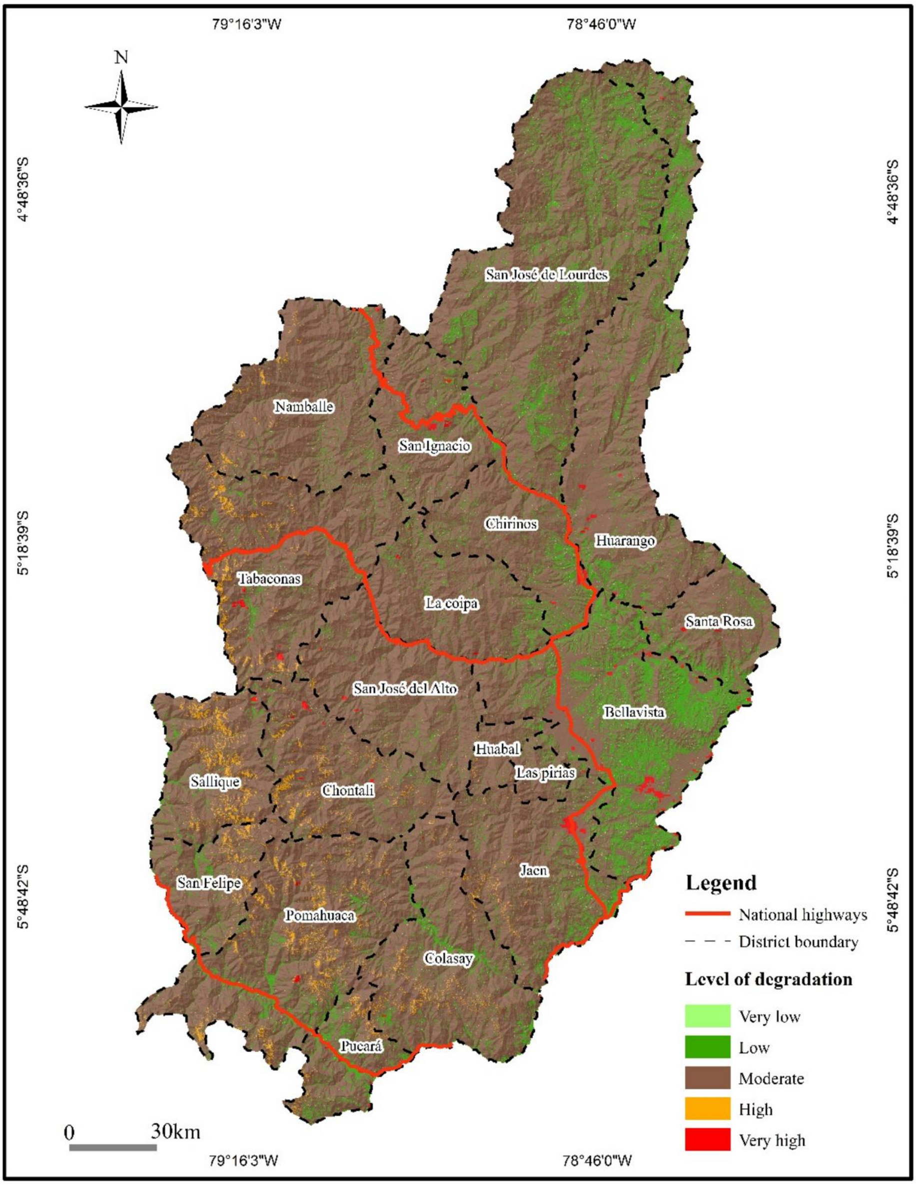

Figure 5. Soil degradation map for the provinces of Jaén and San Ignacio. The brown shading, which is the most prevalent color, indicates a moderate degradation level and is located in the Southern and Western portions of the map.

measuring 0.01 km^2, corresponding to 0.0002% of the total area (Figure 6). Therefore, the provinces of Jaén and San Ignacio exhibited a larger area of moderate degradation and a smaller area of very low degradation (I).

The province of Jaén covers an area of 5,066.62 km^2, of which 82.07% was classified as exhibiting moderate degradation (III), followed by 14.85% with low degradation (II). Moreover, 2.45% and 0.62% of the area exhibited high (IV) and very high (V) degradation levels, respectively. At the district level, the district of Pomahuaca reported showed moderate degradation (III), accounting for 13.71% of its total area. However, certain districts

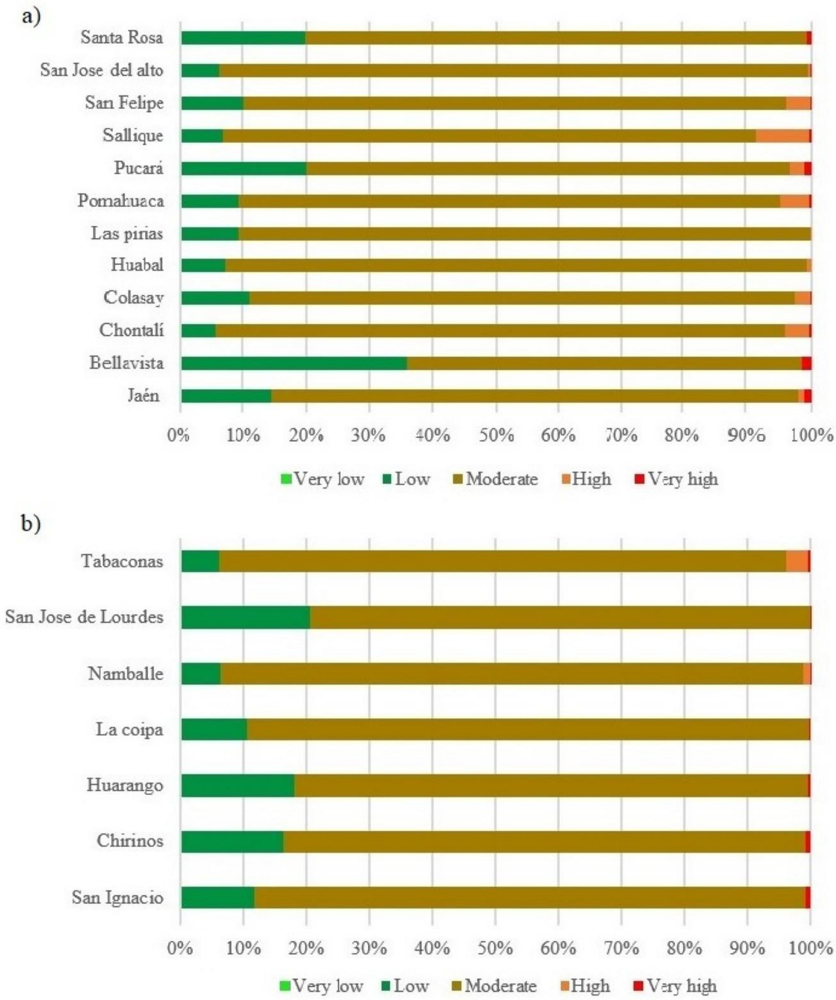

Figure 6. Proportions (%) of soil degradation in the districts of Jaén and San Ignacio provinces. a) Districts of the province of Jaén; b) districts of the province of San Ignacio. The moderate degradation level (III), indicated by brown coloration, accounts for the largest area in each district of its respective province.

exhibited a larger extent of degradation than others did. For example, Bellavista demonstrated the largest area of very high degradation (V), at 0.27%, followed by the district of Jaén (0.14%) and Pucará (0.04%) (Figure 6(a)). In contrast, the province of San Ignacio exhibited an area of 4,787.18 km^2, encompassing moderate degradation (III) at 84.89%, low degradation (II) at 14.13%, high degradation (IV) at 0.68%, and very high degradation (V) at 0.30%. At the district level, San José de Lourdes indicated the largest area of moderate degradation (III), at 22.54%. However, the districts with areas exhibiting very high degradation (V) include Huarango (0.08%), Tabaconas (0.07%), and Chirinos (0.05%) (Figure 6(b)).

The validation of the soil degradation map was conducted at five representative sites, each corresponding to a different level of degradation (Figure 7). Site 1 exhibited very low degradation, site 2 showed low degradation, site 3 displayed moderate degradation, site 4

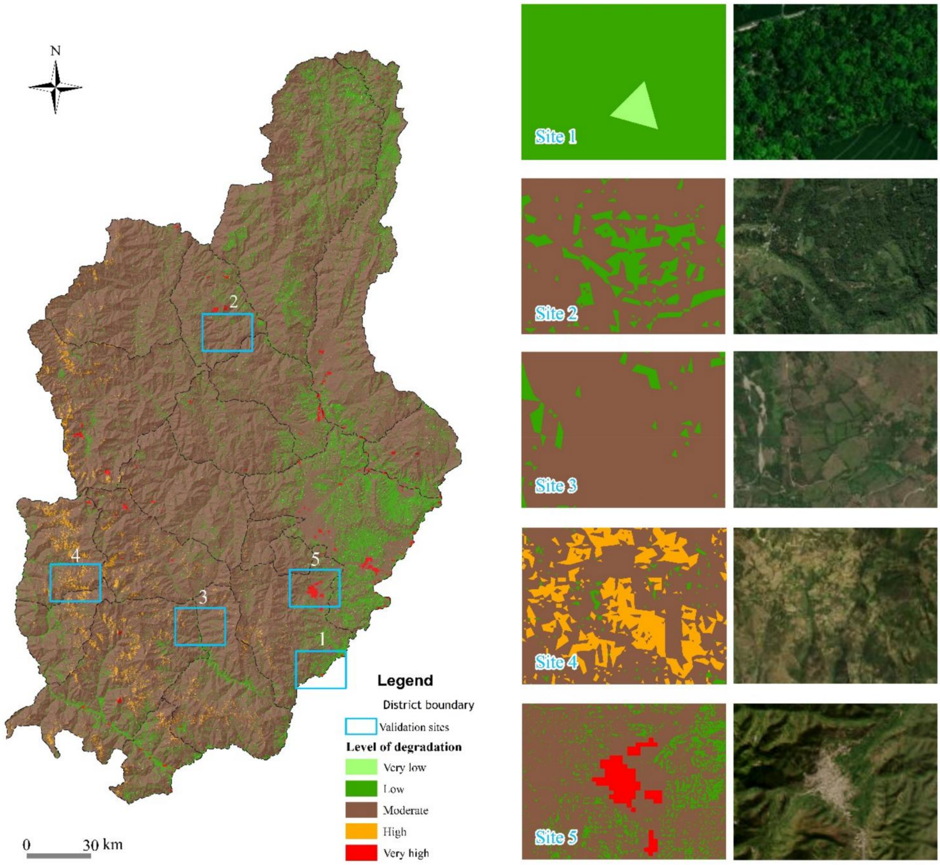

Figure 7. Validation of degradation zones in the study area. At each site, the degradation level is illustrated according to the modeled map, facilitating the analysis and validation of the soil degradation data across the study area.

demonstrated high degradation, and site 5 revealed very high degradation. Visual comparison, performed using high-resolution images from Google Earth within the GEE platform, confirmed consistency between the degradation levels identified at the selected sites, the Google Earth imagery, and field-based visual observations.

3.5. Soil degradation in protected natural areas (PNAs)

The overlay of the soil degradation map with the map of Protected Natural Areas (PNAs) in the provinces of Jaén and San Ignacio revealed that these zones are highly associated with a moderate level of degradation (III), represented by the brown coloration (Figure 8). This degradation is primarily concentrated in the western regions of both provinces.

The protected areas (Figure 9) were categorized within the moderate degradation class, with the greatest proportion found in the Paraíso PCA of the San Felipe peasant community (94.44%), followed by the PCA San Juan of the Sallique peasant community (92.28%), which also shows a significant proportion of high degradation (5.27%). However, very high degradation levels were generally uncommon in the evaluated areas.

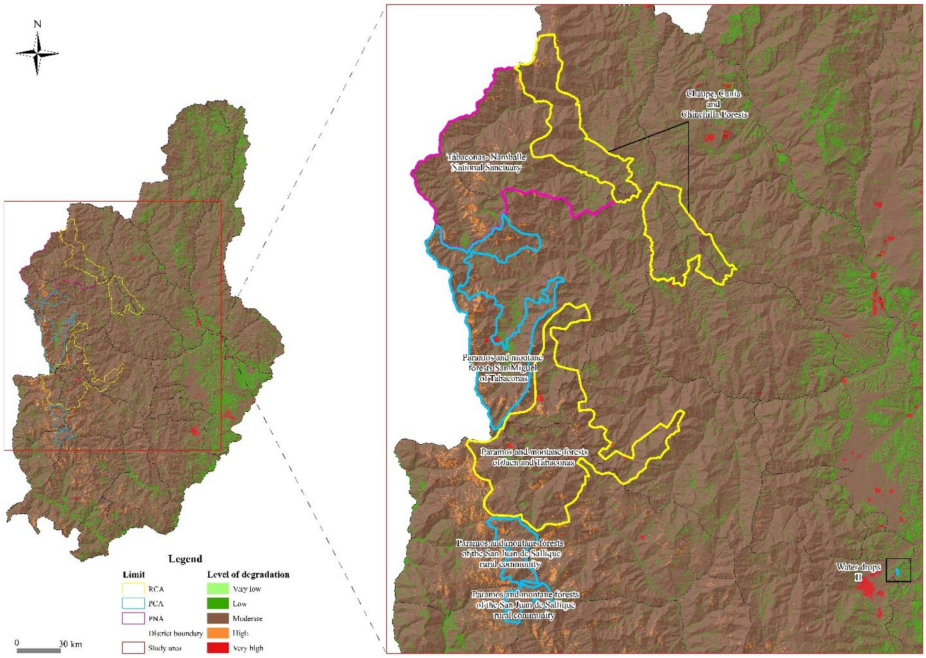

Figure 8. Degraded conserved areas. The yellow areas indicate regional conservation areas (RCAs), the light blue areas indicate private conservation areas (PCAs), and the magenta areas denote protected natural areas (PNAs). All these areas exhibited a relatively high proportion of moderate degradation.

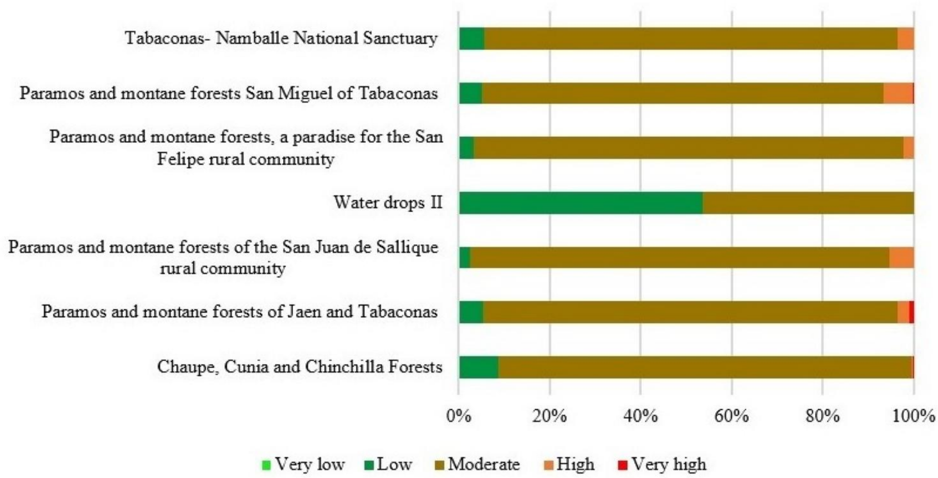

Figure 9. Proportion (%) of the degraded protected areas.

4. Discussion

The results of this study demonstrated the reliability of using the AHP method alongside RS data and GIS technology to assess soil degradation in the provinces of Jaén and San Ignacio. The AHP method facilitated the identification and integration of environmental, topographic, and pedological criteria within the study area. For each criterion, three sub-criteria were determined, resulting in a total of nine factors evaluated by soil health experts. Each variable impacted the assessment of soil degradation to varying degrees. During the weighting of the criteria, the CR values occurred within acceptable limits (less than 0.1), as indicated by Saaty and Vargas (2012). This suggests that the weights assigned to each subcriterion and criterion are reliable. The use of the AHP technique is an excellent method for decision-making and evaluating various alternatives with minimal error (Feddema and Freire 2001; López et al. 2020; Lebuy et al. 2022).

The weights obtained *via* the AHP method revealed that the slope (59.07%) and LULC (56.36%) were the most significant factors for assessing soil degradation, followed by texture (45.02%) and SOM (42.23%). The importance of the slope as a factor conforms with previous studies (Torabi Haghighi et al. 2021; Mzuri et al. 2022; Das et al. 2023). However, in regard to the other factors, such as texture and organic carbon, Sandeep et al. (2021) reported values below 0.1. LULC plays a crucial role in maintaining the ecological balance of soils, whether they are forested areas, sparsely populated regions, or bare soil areas, all of which can significantly impact soil erosion (Panahi et al. 2024). Similarly, steeper slopes pose a greater degradation risk, contributing to soil erosion *via* detachment and runoff (Mzuri et al. 2022; Das et al. 2023). In addition to these natural processes, anthropogenic factors and the excessive use of agrochemicals are the primary causes of soil degradation involving physical, chemical, and biological processes (Osman 2014). Notably, Peru ranks among the 30 countries with the highest degradation risk due to fertilizer use (Tang et al. 2021).

The assessment of soil degradation was also influenced by texture and organic matter (Table 4), with results that were higher than those reported by Sandeep et al. (2021). Organic matter is a principal component of SOC and is crucial for identifying healthy and fertile soils (Gutierrez et al. 2022). Moreover, these factors, in conjunction with land use and vegetation cover, are crucial for evaluating the extent of soil degradation (Cerdan et al. 2002; Ruiz-Colmenero et al. 2013). Forests and soils that have been less disturbed by human activities exhibit greater microbial diversity, which is an important factor influencing the presence of organic matter in soils (de Valença et al. 2017). In the study area, the presence of organic matter was reported to be moderate, thereby classifying the soils as suitable for cultivation. The organic matter content ranged from 3% to less than 10%, which is acceptable for agricultural purposes. Furthermore, organic matter affects the abundance of microorganisms and the chemical composition of the soil, both of which are crucial for mitigating soil degradation (Fan et al. 2024). The modeled map demonstrated five distinct degradation levels, ranging from very low (I) to very high (V) (Figure 5). This differs from the findings of Meza Mori et al. (2022) in the identification of areas susceptible to degradation in the Amazon region, which classified the levels as low, moderate and high. The distribution of degraded areas was concentrated in the provinces of Jaén and San Ignacio, with the largest area classified as showing moderate degradation (III). At the district level, Pomahuaca (Jaén) and San José de Lourdes (San Ignacio) contained the largest areas of moderate degradation (III). Pomahuaca is located in the northwest of the province of Jaén and is characterized by large dry forests and an annual rainfall ranging from 620 to 1,350 mm. In contrast, San José de Lourdes is located in the eastern part of the province of San Ignacio, with tropical humid forests and an annual rainfall varying between 1,500 and 2,500 mm. Moreover, the district of Bellavista, located in the northeast of the province of Jaén, is characterized by rice cultivation in its lowlands and cattle and coffee farming in its highlands, with high rainfall from January to March. Similarly, Huarango, located in the west of the province of San Ignacio, is characterized by a transition from tropical dry forests to humid forests, with clay to sandy loam soils and agricultural activities centered on crops such as cocoa, coffee, and rice (SENAMHI 2023; MIDAGRI 2024). These areas exhibited the highest degradation level and were classified into the very high (V) category.

Previous studies have indicated that the districts of Bellavista and Huarango, as well as San José de Lourdes in San Ignacio, feature soils classified as regosols and vertisols. These soils are characterized by moderate natural fertility and intermediate levels of organic matter, largely due to the presence of diverse ecosystems ranging from dry to humid forests (Poma and Alcántara 2011). Furthermore, the northern part of Peru exhibits a tropical environment with extensive vegetation cover, which serves as a reservoir of organic carbon (Gutierrez et al. 2022). On the basis of the obtained results, it could be concluded that the largest areas exhibited moderate degradation (III) due to the aforementioned characteristics. However, some districts within the study area also indicated high proportions of high (IV) to very high (V) degradation. This is due to the intensification of agriculture, poor agricultural practices, indiscriminate use of fertilizers, and loss of pristine forests (Nascimento et al. 2021), all of which negatively affect vegetation and contribute to soil degradation and desertification (Carpio and Taype-Huamán 2021). To maintain soil conservation, the role of protected areas, whether private or regional (PNAs), is fundamental to preserving the existing flora and fauna as part of the regional biodiversity (SERNANP 2024). According to the study results, the highest percentage of degradation was classified as moderate in the provincial PNAs, which must be maintained and improved to avoid the loss of these vital resources. In addition, these areas are sources of income for tourism-related activities in provinces.

The validation process for the degradation map, which entailed the use of high-resolution Google Earth images and field observations, was similar to methodologies applied in the assessment of soil degradation in the Kurdistan region (Mzuri et al. 2022), as well as in studies on vulnerability to degradation in a semiarid system in southern India (Sandeep et al. 2021) and mapping land degradation vulnerability in a river basin in western India *via* the AHP method (Das et al. 2023). However, the visual approach may exhibit inherent limitations with respect to the accuracy of the results, as it does not allow for direct identification of soil physicochemical changes. Therefore, it would be ideal to incorporate soil sampling to conduct a more robust and reliable comparison on the basis of the various degradation levels.

Furthermore, the AHP method depends on the input of experts, which can be inherently subjective. This may be the principal limitation of this research, with the potential to introduce bias into the results. Furthermore, future studies could incorporate a greater number of factors that contribute to soil degradation, thereby providing a more comprehensive perspective. Future research efforts should account for the impacts of critical factors such as climate change, agricultural techniques, and water management on soil degradation dynamics. Therefore, the integration of the AHP method and GIS and RS technologies provided essential information for this study on the level of soil degradation, revealing that moderate degradation was most prevalent in the districts, which could pose significant challenges for those provinces. Consequently, this research is both relevant and important, as the obtained results could inform the implementation of sustainable strategies focused on soil conservation. These strategies may include the use of microorganisms with biotechnological potential to improve the soil structure, the use of vegetative cover, and the application of biochar to improve fertility, among others. Such implementations could facilitate the restoration of soil fertility and improve the quality of life of farmers implementing environmentally friendly practices.

5. Conclusion

In this study, a multimethod approach was employed in which nine factors were integrated to assess soil degradation. The methodology included the use of the AHP, GIS, and RS methods to identify degraded areas in the provinces of Jaén and San Ignacio. The determined weights revealed that the slope (59.07%) and LULC (56.36%) were the main factors influencing soil degradation. Furthermore, five levels of soil degradation were identified, with moderate degradation (83.48%) prevailing across the study area. At the district level, Pomahuaca (13.71%) and San José de Lourdes (22.54%) exhibited the most extensive areas of moderate soil degradation, whereas the districts with very high soil degradation included Bellavista (0.275%) and Huarango (0.08%). It was demonstrated that the integration of the AHP, GIS, and RS methodologies enables effective assessment of degraded soils. The obtained results could be utilized for decision-making purposes regarding the implementation of efficient and environmentally friendly measures for soil quality conservation in the provinces of Jaén and San Ignacio.

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Disclosure statement

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Data availability statement

The data used for the preparation of this manuscript are available upon reasonable request from the corresponding author.

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