INTEGRATION OF GIS-PCA-AHP METHODS FOR SOIL QUALITY INDEX ASSESSMENT IN NAGARI NANGGALO, KOTO XI TARUSAN SUBDISTRICT, PESISIR SELATAN REGENCY, INDONESIA

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ABSTRACT

The determination of the Soil Quality Index (SQI) is a valuable activity for land resource planning and management. This study aimed to evaluate the SQI in Nagari Nanggalo, Koto XI Tarusan Subdistrict, Pesisir Selatan Regency, Indonesia, by integrating the Principal Component Analysis (PCA) method with the Analytical Hierarchy Process (AHP) and visualizing the results using Geographic Information Systems (GIS) with spatial interpolation using the Inverse Distance Weighted (IDW) method. Based on the PCA analysis, six principal components were identified and weighted using the AHP, namely pH (17.40%), Organic-C (34.67%), Base Saturation (13.53%), Bulk Density (18.50%), K-exchangeable (5.34%), and Hydraulic Conductivity (10.56%). The SQI analysis results showed that 87.90% (324.48 ha) of the area was classified as poor and 12.10% (44.67 ha) as moderate. This study indicated that the area had generally poor soil quality. However, it should be noted that proper soil management, as well as soil and water conservation measures, need to be considered to improve the current condition and enhance the soil's carrying capacity. The SQI map developed in this study serves as a useful tool for decision-making in land management.

Keywords: AHP; PCA; GIS; Soil Quality Index (SQI)

1. Introduction

Soil is one of the primary components of ecosystems, playing a crucial role in supporting life on Earth (Abdu et al., 2023). High-quality soil enables ecosystems to function optimally, including carbon sequestration, water filtration, and biodiversity

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support (Abuzaid et al., 2022). In agriculture, healthy soil serves as the foundation for crop productivity, as it contains adequate nutrients, has a well-structured composition, and maintains optimal water retention capacity (Alam et al., 2022). However, unsustainable agricultural practices such as excessive use of pesticides and chemical fertilizers, as well as poor soil management can degrade soil quality. This degradation leads to reduced soil fertility, increased erosion, and diminished capacity to support crops and soil ecosystems (Bayrakli et al., 2023). Maintaining soil health is not only essential for agricultural productivity but also for overall environmental sustainability, as observed in the Pesisir Selatan Regency.

Pesisir Selatan Regency, West Sumatra, possesses a substantial area of suboptimal land. Suboptimal land refers to land with physical, chemical, and biological constraints that limit its suitability for seasonal crop cultivation (Sefano et al., 2024). These constraints include steep slopes and low soil fertility. In Pesisir Selatan, suboptimal land is predominantly found in hilly and coastal areas. These lands are generally utilized for perennial crops such as coconut, rubber, and gambier. However, the productivity of these crops remains relatively low due to various limiting factors. According to data from the Central Agency of Statistics of West Sumatra, in 2022 the total area of suboptimal land in Pesisir Selatan reached 124,000 hectares, of which only approximately 40,000 hectares are utilized for agricultural activities, including in Nagari Nanggalo (CAS, 2022).

Nagari Nanggalo is a village located in Koto XI Tarusan District, Pesisir Selatan Regency. It covers an area of 3.69 km², accounting for approximately 0.76% of the total area of Koto XI Tarusan District. Nagari Nanggalo possesses a substantial land area suitable for the agricultural sector. According to land use maps from the Geospatial Information Agency, of the total 369 hectares of land, 146.92 hectares are utilized as rice fields, 11.19 hectares as dryland farming, 163.71 hectares as mixed plantations, 35.71 hectares for settlements, and 11.61 hectares as river areas (GIA, 2023). The village experiences an average annual rainfall of 3,498 mm (WSPWRMA, 2022) and is classified under the Schmidt and Ferguson (1951) climate classification as a very wet climate (Type A). However, the existing land in Nagari Nanggalo is classified as suboptimal, with soil quality that remains inadequate for supporting sustainable agriculture (Sefano et al., 2024).

Efforts to maintain and improve soil quality can involve crop rotation practices, the application of organic fertilizers, and agroforestry systems, which help enhance soil quality and mitigate the negative impacts of human activities (Bel-Lahbib et al., 2023). Additionally, preserving soil quality contributes to climate change mitigation by increasing the soil's capacity to store carbon. SQI assessment plays a vital role in regenerative agricultural practices, which not only boost crop yields but also preserve ecosystems for future generations (Çelik & Sürücü, 2024).

Soil quality assessment is a complex process that involves the interaction of various physical, chemical, and biological factors (Chaudhry et al., 2024). Physically, key indicators of soil quality include soil structure, texture, porosity, and water-holding capacity. Compacted or eroded soils, for instance, exhibit physical degradation that adversely affects productivity. Chemically, the presence of essential nutrients such as

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nitrogen, phosphorus, and potassium, along with soil pH, plays a crucial role in determining soil fertility. An imbalance in chemical properties can disrupt soil ecosystems and hinder plant growth. Additionally, biological components, including microorganisms, soil fauna, and organic matter, contribute significantly to nutrient cycling and soil structure maintenance (Demir, 2024). Soil biodiversity is often a primary indicator of soil ecosystem health, and the loss of soil microorganisms can signal soil degradation. These factors do not operate independently but interact and influence each other (Dengiz & Demirağ Turan, 2023). For example, soil microorganisms require a stable physical environment and balanced chemical composition to sustain their activities, while microbial activity, in turn, can enhance soil structure and nutrient availability. This complexity underscores the need for a holistic approach and continuous monitoring in soil quality assessment, rather than reliance on a single parameter (Faloye et al., 2024). Modern assessment tools based on multi-criteria decision analysis (MCDA), such as Principal Component Analysis (PCA) and the Analytical Hierarchy Process (AHP), can be employed to comprehensively evaluate soil quality indices and better understand their intricate interactions.

In complex data analysis involving multiple variables, the combination of PCA and the AHP serves as an effective approach for data-driven decision-making (Jalhoum et al., 2024). PCA is employed to reduce data dimensionality by identifying principal components that capture the majority of variance within a dataset (Kahsay et al., 2023). This process filters out redundant or uncorrelated information, resulting in a more streamlined yet representative dataset. For instance, in environmental analysis, PCA can be utilized to categorize variables such as water quality, temperature, and humidity into a few principal components, making the data more manageable (Kaya et al., 2022). The outputs from PCA then serve as refined inputs for further analysis using methods such as the AHP, enhancing the decision-making process by prioritizing key factors based on structured criteria.

After PCA reduces data dimensionality, the AHP is employed to determine the weight of each criterion based on a structured subjective assessment. The AHP enables users to perform pairwise comparisons of various criteria and establish priorities according to their relative importance. This process generates criterion weights that can be utilized for decision-making, such as selecting optimal locations or prioritizing interventions. The combination of PCA and the AHP is particularly valuable in scenarios where large and complex datasets must be processed into measurable and weighted recommendations (Kaya et al., 2022). In the context of natural resource management, this approach facilitates analyses that integrate both objective data (through PCA) and expert-driven subjective evaluations (via AHP). Furthermore, Multi-Criteria Decision Analysis (MCDA) can be integrated with geospatial technologies such as Geographic Information Systems (GIS), enhancing spatial decision-making and enabling a more comprehensive evaluation of environmental and resource-related challenges.

Geospatial technology, particularly GIS, plays a crucial role in visualizing spatial data in an intuitive and effective manner for decision-making processes (Lenka et al., 2022). GIS enables the integration of location-based data, such as topographic maps,

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demographic information, and environmental parameters, into interactive visual representations. This visualization not only facilitates the analysis of spatial patterns but also provides a comprehensive understanding of the geographic relationships between various parameters (Marion et al., 2022). For instance, GIS can be utilized to map agricultural land distribution by integrating data on elevation, rainfall, and soil quality. Through GIS-based Multi-Criteria Decision Analysis (MCDA), decision-making can be conducted using a more systematic and data-driven approach. This capability establishes GIS as an essential tool across various fields, including natural resource management, environmental conservation, and urban development, with significant potential to support sustainable development initiatives (Sefano et al., 2024).

To understand and address challenges related to soil quality in Nagari Nanggalo, an integrated scientific approach is required. This study aims to identify the most significant soil quality indicators based on the region's agrarian conditions. Subsequently, a combined methodology of PCA and the AHP was applied to assess soil quality levels by reducing data complexity and systematically determining the weight of each indicator. As a final step, the analysis results were utilized to map the SQI using GIS, generating spatial representations that support agrarian planning and sustainable land management. This study is expected to provide strategic guidance for decision-making related to agricultural sustainability and environmental conservation in Nagari Nanggalo.

2. Methods

2.1 Study area

Nagari Nanggalo is located in Koto XI Tarusan subdistrict, Pesisir Selatan Regency (Figure 1), at coordinates 100° 28' – 100° 29' E and 1° 13' – 1° 15' S, covering an area of 369.15 hectares (0.76% of the total area of the subdistrict) and an elevation range of 0-170 meters above sea level (MASL) with 80% of the area at an elevation of 0-10 MASL. The region has an average annual rainfall of 3,498 mm and an average temperature of 29.1°C; therefore, the area belongs to the A-type climate category (very wet) according to Schmidt and Ferguson (1951), with no dry months throughout the year. Agricultural land in Nagari Nanggalo relies solely on rainfall, without any technical irrigation systems. The area contains two soil orders: 1) Inceptisols, with a great group of Dystrudepts covering 323.3 hectares (87.57%), and 2) Entisols, with a great group of Tropofluvents covering 46.45 hectares (12.5%). Soil samples were taken from the Dystrudepts great group, which is characterized by flat topography. Land use in Nagari Nanggalo includes forests (23.35%), rice fields (27.39%), community gardens (5.24%), shrubs (6.72%), fields (21.77%), settlements (12.39%), and rivers (3.15%). The region physiography consists of an alluvial plain, formed by sedimentation from the Batang Tarusan River and erosion from the surrounding hills, leading to deposits of clay and silt (Sefano et al., 2024).

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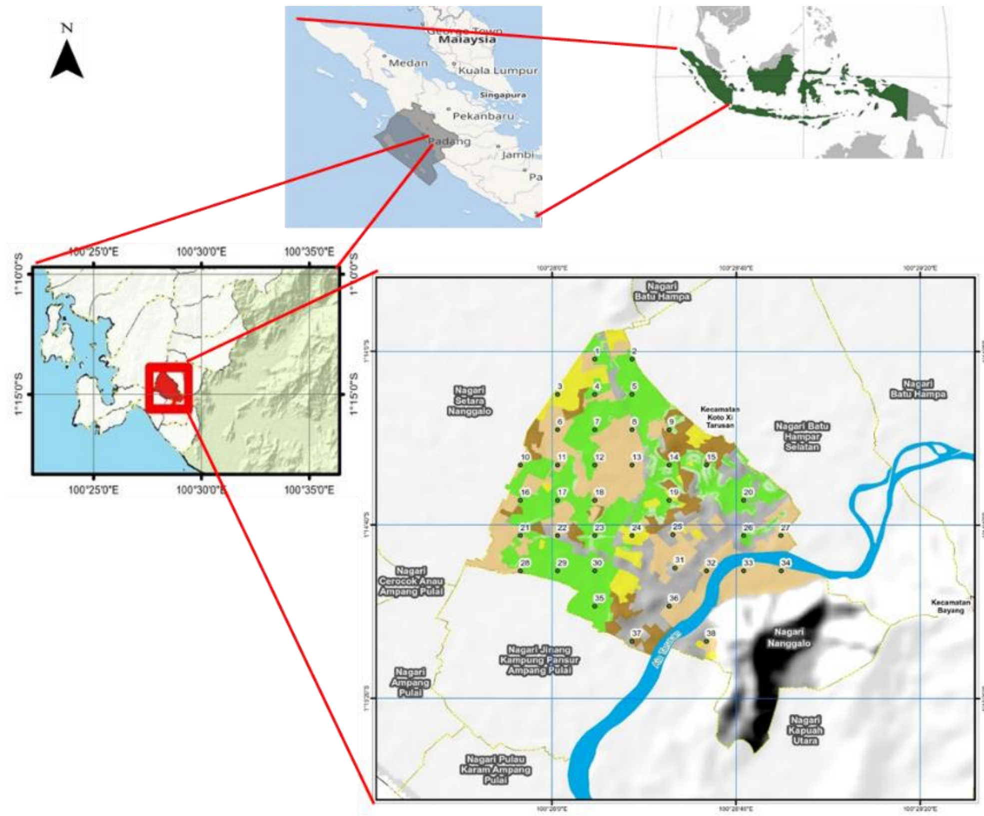

Figure 1 Location map of the study area

2.2 Soil sampling and analysis

Field data collection and soil sampling were carried out with attention to variations in land use. Samples were taken from four types of land use including paddy fields, dryland agriculture, mixed plantations, and shrubs. Soil profiles were opened to measure soil depth conditions. Representative soil samples from a depth of 0 to 30 cm were collected to examine the soil's physical, chemical, and biological properties. At each sampling site, coordinates were recorded using a Garmin Montana 750i Navigator GPS model. The soil sampling method used in this study was the Systematic Grid Sampling method (Wollenhaupt & Wolkowski, 1994; Watson et al., 2022), where coordinates were selected according to predetermined distances between points. This method is often used in spatial pattern studies as it facilitates the creation of map patterns derived from grids. Therefore, a distance of 250m x 250m was chosen between each sampling point. A total of 38 soil samples were collected for this study. The collected soil samples were air-dried, gently crushed with mortar and pestle, well-mixed, and passed through a 2-mm sieve. A 0.5-mm sieve was used to determine total nitrogen (TN) and organic carbon (OC). The processed soil samples were then analyzed at the Chemistry and Fertility Laboratory of Andalas University, Padang, following standard analysis procedures (Table 1).

Soil quality assessment was conducted using a modified method based on Mausbach and Seybold (1998), incorporating specific criteria for each parameter (Table 2). The scores for each parameter were assigned on a relative scale ranging from 0 to 100, where 0–20 indicates very poor, 20–40 poor, 40–60 moderate, 60–80 good, and 80–

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100 very good soil quality with the criteria for physical, chemical and biological properties of soil from the Republic of Indonesia Soil Research Center in 2023.

Table 1
Standard laboratory methods for soil sample analysis

Parameters	Applied standards for measurement
1. Physical properties	
Bulk Density, BD ($g.cm^{-3}$)	Gravimetry (Soil Research Institute of Indonesia (SRII), 2023)
Porosity, PR (%)	Gravimetry (Soil Research Institute of Indonesia (SRII), 2023)
Hydraulic Conductivity, HC ($cm.h^{-1}$)	Constant Head Permeameter (Soil Research Institute of Indonesia (SRII), 2023)
2. Chemical properties	
pH H_2O (1:5)	Electrometry (Soil Research Institute of Indonesia (SRII), 2023)
Electrical Conductivity, EC ($dS.m^{-1}$)	Electrometry (Soil Research Institute of Indonesia (SRII), 2023)
Organic-C, OC (%)	Walkley dan Black (Soil Research Institute of Indonesia (SRII), 2023)
Total Nitrogen, TN (%)	Kjeldahl (Soil Research Institute of Indonesia (SRII), 2023)
Available Phosphorous, Av.P ($mg.kg^{-1}$)	Bray 1 (Soil Research Institute of Indonesia (SRII), 2023)
Cation Exchange Capacity, CEC ($cmol.kg^{-1}$)	Leaching NH_4OAc 1 M (Soil Research Institute of Indonesia (SRII), 2023)
Ca, Mg, K, Na – Exchangeable ($cmol.kg^{-1}$)	AAS (Soil Research Institute of Indonesia (SRII), 2023)
Base Saturation, BS (%)	AAS (Soil Research Institute of Indonesia (SRII), 2023)
3. Biological properties	
Soil Respiration, SR (mg $CO_2.m^{-2}.day^{-1}$)	Titration (Sefano et al., 2023)
Biomass-C, BC (mg $C.100g^{-1}$)	Fumigation-incubation Technique (Schinner et al., 1996)

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Table 2
Rating of land use requirements for SQI

Parameter	Factor rating				
	Very Good (100)	**Good (80)**	**Moderate (60)**	**Poor (40)**	**Very Poor (20)**
1. Physical properties					
BD ($g.cm^{-3}$)	0.66	-	0.67-1.14	-	>1.14
PR (%)	>75	-	58-75	-	<57
HC ($cm.h^{-1}$)	>12.7	6.35-12.6	0.52-6.34	0.15-0.51	<0.15
2. Chemical properties					
pH H_2O (1:5)	7.0-7.5	6.51-7.1	5.51-6.50	4.6-5.50	<4.5
EC ($dS.m^{-1}$)	<1.0	2.0	3.0	4.0	>4.1
OC (%)	>5.1	3.1-5.0	2.1-3.0	1.1-2.0	<1.0
TN (%)	>0.75	0.51-0.75	0.21-0.50	0.1-0.2	<0.1
Av.P ($mg.kg^{-1}$)	>15.1	11.0-15.0	8-10	5.0-7.9	<4.9
CEC ($cmol.kg^{-1}$)	>40.1	25.0-40.0	17.0-24.9	5.1-16.9	<5.0
Ca-Exch ($cmol.kg^{-1}$)	>20.1	11.0-20.0	6.0-10.9	2.1-5.9	<2.0
Mg-Exch ($cmol.kg^{-1}$)	>8.1	2.1-8.0	1.1-2.0	0.4-1.0	<0.3
K-Exch ($cmol.kg^{-1}$)	>1.0	0.8-1.0	0.4-0.7	0.1-0.3	<0.1
Na-Exch ($cmol.kg^{-1}$)	>1.0	0.8-1.0	0.4-0.7	0.1-0.3	<0.1
BS (%)	>80	61-80	41-60	20-40	<20
3. Biological properties					
SR (mg $CO_2.m^{-2}.day^{-1}$)	>32	17-31	11-16	5-10	<5
BC (mg $C.100g^{-1}$)	>60	41-60	21-40	10-20	<10

Source : Soil Research Institute of Indonesia (SRII), 2023

2.3 Principal Component Analysis (PCA)

The analysis of soil physical, chemical, and biological properties was followed by correlation testing and PCA using XL-STAT software. PCA is a method used to identify a Minimum Data Set (MDS) that accurately represents soil quality information (Alam et al., 2022). Statistical approaches were used on 38 samples in the calibration set to select the variables that form the MDS. The selection of the MDS with PCA was done according to Andrews et al. (2002) considering the principal components (PC) with an eigenvalue $\lambda > 1$ and which explain at least 5% of the total accumulated variance. The matrix of components was obtained via Varimax rotation, which minimizes the number of variables with higher loading values in each PC and makes it easier to interpret the results (Peris et al., 2008). The variable was selected with the highest rotated loading in absolute value in each PC identified, together with the variables that differed from that value by 10% (Andrews et al., 2002). In order to reduce the redundancy of the variables in the MDS, when several variables in a PC fulfilled the previous conditions, the Pearson's correlations ($P < 0.05$) between them were taken into account. In the case of correlations, the variables with the highest loading values were selected as indicators, and in the absence of correlations between the variables in the same PC, all the variables were selected as indicators.

2.4 Criteria weight estimation with AHP

The AHP method was used to determine the influence of each research parameter as well as to assign weights to these parameters through a pairwise comparison matrix based on expert opinions (Saaty, 2008). The experts were selected from agricultural academics at Andalas University and Padang State University and local government officials. A total of 10 experts were chosen. Among the pairwise matrices constructed, the one with the most consistent Consistency Ratio (CR) (CR <10%) was selected. This selection was carried out to ensure that the expert assessments were truly consistent and could accurately represent the actual conditions.

The first step involved hierarchy construction, in which the decision problem was decomposed into three levels: (i) the overall goal at the top level, (ii) the criteria and sub-criteria at the intermediate levels, and (iii) the decision alternatives at the bottom level. This hierarchical structure allows for systematic analysis of complex problems by breaking them down into smaller, more manageable components.

The second step was the pairwise comparison process, where each element at a given level was compared with every other element in terms of its relative importance toward the parent element in the level above. The comparisons were conducted using Saaty's 1–9 fundamental scale, where a score of 1 indicates equal importance and 9 represents extreme importance of one element over another. The judgments were organized into a pairwise comparison matrix, from which the priority vector (eigenvector) was derived to represent the relative weights of the elements.

The third step involved the consistency check to ensure the logical soundness of the judgments. The Consistency Index (CI) was calculated as Equation 1:

$$\boldsymbol{CI} = \frac{\boldsymbol{\lambda}\,\mathbf{max} - \boldsymbol{n}}{\boldsymbol{n}-\mathbf{1}} \tag{1}$$

where λmax is the maximum eigenvalue of the matrix, and n is the number of elements compared. The Consistency Ratio (CR) was then obtained by dividing CI by the Random Index (RI) for the corresponding matrix size. A CR value of 0.10 or less was considered acceptable, indicating that the pairwise comparisons were reasonably consistent. If the CR exceeded 0.10, the comparisons were revised. This systematic approach ensured that the derived priorities were both mathematically consistent and logically coherent, enabling reliable aggregation of the results for final decision-making. The AHP calculations in this study were conducted using *Super Decisions* software version 3.2, an application for data analysis using the AHP method, ensuring that the consistency ratio calculation results are automatically generated by the application.

2.5 Method of analysis using GIS

After assigning weights to each parameter using the AHP, spatial interpolation using the Inverse Distance Weighted (IDW) method was performed with ArcGIS 10.4 software to generate raster layers for each criterion. The IDW method assumes that interpolated values will be more similar to sample data points that are closer rather than those that are farther away (Ozsahin & Ozdes, 2022). This method determines the value of an unknown point using a linear weighted combination of a set of sample points, making it suitable when combined with the AHP (Chu & Le, 2022). The values in the raster layers were then reclassified into common SQI. Finally, the weighted overlay method was used to generate the overall SQI raster layer (Everest & Gür, 2022). The reclassified raster layers were overlaid by multiplying the SQI value of each raster cell by the weight of the layer and summing the values to produce the overall SQI map (Equation 2).

$$S = \sum_{i=0}^{n}(WiXi) \quad (2)$$

Where, S is the suitability, Wi is the weight of factor i, and Xi is the criterion score of factor i.

3. Results and discussion

3.1 Principal Component Analysis (PCA)

The results of the PCA analysis are presented in Figure 2.

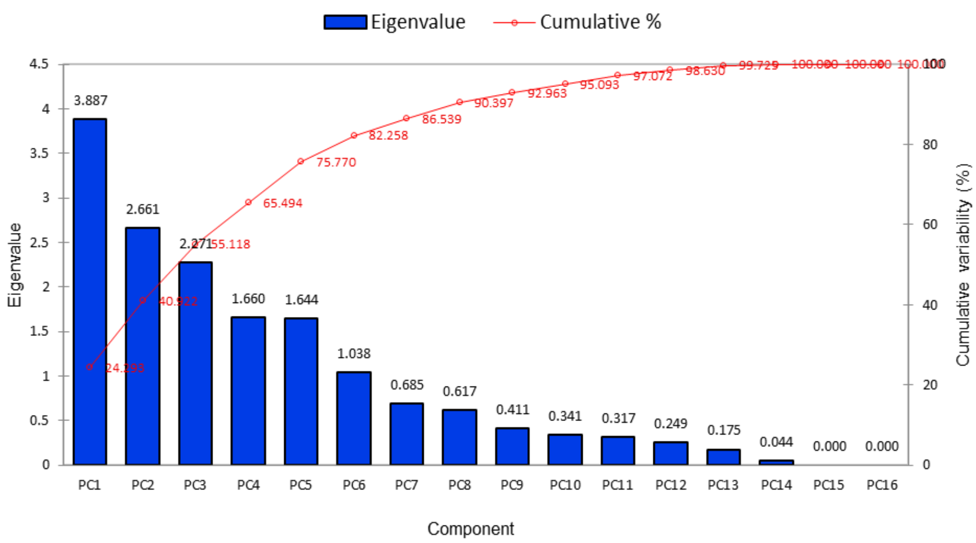

Figure 2 Total variance explained

Figure 2 illustrates the eigenvalues and the cumulative percentage of the total variance explained by each principal component, indicating the number of principal components that should be retained in the analysis to adequately represent the original data structure while reducing its complexity. As shown in Figure 2, six significant components (PC1–PC6) were identified. These six principal components meet the criteria and are considered important as each explains more variance than an individual original variable. The total variance explained by these six components amounts to 81.981%, indicating that approximately 82% of the total data variability can be accounted for by the first six principal components alone. Biplot and observations of PC1 and PC2 are shown in Figure 3. The parameters contributing to these principal components are presented in Table 3.

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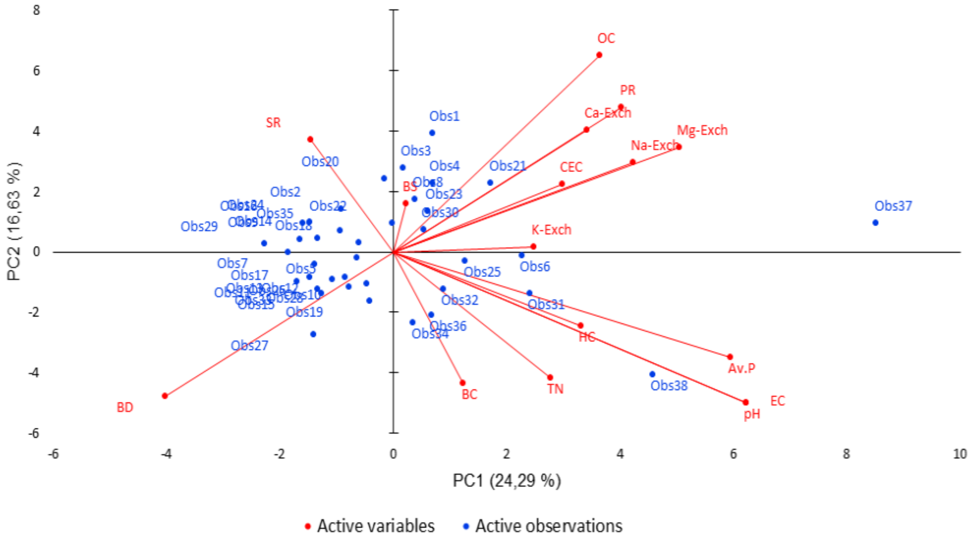

Figure 3 Biplot PC1 and PC2 and data observation

Table 3
Loading plot and communality component

Variable	PC1	PC2	PC3	PC4	PC5	PC6	Communality
BD	-0.501	-0.494	0.223	**0.642**	0.132	0.020	0.975
PR	0.501	0.494	-0.223	-0.642	-0.132	-0.020	0.975
HC	0.412	-0.253	0.133	0.075	-0.591	**-0.429**	0.791
pH	**0.774**	-0.515	-0.089	0.109	-0.153	0.145	0.929
EC	0.773	-0.515	-0.089	0.109	-0.153	0.145	0.929
OC	0.453	**0.668**	0.006	0.130	0.076	0.302	0.765
TN	0.344	-0.431	-0.142	-0.157	0.481	0.294	0.668
Av.P	0.740	-0.358	0.079	0.119	-0.283	0.131	0.793
CEC	0.372	0.231	-0.746	0.206	0.043	-0.342	0.909
Ca-Exch	0.425	0.414	0.654	0.118	-0.134	-0.238	0.868
Mg-Exch	0.629	0.358	0.133	0.247	0.397	-0.169	0.788
K-Exch	0.309	0.018	-0.031	0.314	**0.658**	-0.380	0.772
Na-Exch	0.526	0.303	0.181	0.247	0.193	0.306	0.594
BS	0.027	0.164	**0.939**	-0.064	-0.027	0.136	0.932
SR	-0.182	0.381	-0.413	0.365	-0.220	0.397	0.687
BC	0.154	-0.448	0.157	-0.580	0.447	-0.025	0.785
Expl. Variance	3.887	2.661	2.271	1.660	1.644	1.038	13.161
% Cumulative Variance	0.243	0.409	0.551	0.655	0.758	0.823	

Based on Table 3, the PCA analysis results in six principal components (PC1 to PC6), which cumulatively explain 82.3% of the total data variability. Each principal component is characterized by variables with high loading values (either positive or negative), indicating their dominant contribution to the respective component. The

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key variables defining each principal component are as follows: PC1 = pH, PC2 = organic carbon (OC), PC3 = base saturation (BS), PC4 = bulk density (BD), PC5 = exchangeable potassium (K-exch), and PC6 = hydraulic conductivity (HC). The results of the PCA analysis were then assessed based on the AHP analysis.

3.2 Analytical Hierarchy Process (AHP)

The pairwise comparison matrix for SQI resulting from PCA analysis consists of six criteria factors: pH, OC, BS, BD, K-exch, and HC. Then, an assessment was carried out by the experts. The pairwise comparison matrices are presented in Tables 4 and 5.

Table 4
Pairwise comparison matrix of SQI factor (CR = 0.094)

Criteria	pH	OC	BS	BD	K-exch	HC
pH	1					
OC	5	1				
BS	1/4	1	1			
BD	3	1/3	2	1		
K-exch	1/9	1/5	1/5	1/2	1	
HC	2	1/5	2	1/3	1	1

Table 5
Relative importance scores for SQI

Criteria	Criteria weight	Percentage	Ranking
pH	0.174	17.40	3
OC	0.347	34.67	1
BS	0.135	13.53	4
BD	0.185	18.50	2
K-exch	0.053	5.34	6
HC	0.106	10.56	5
Total	1	100	

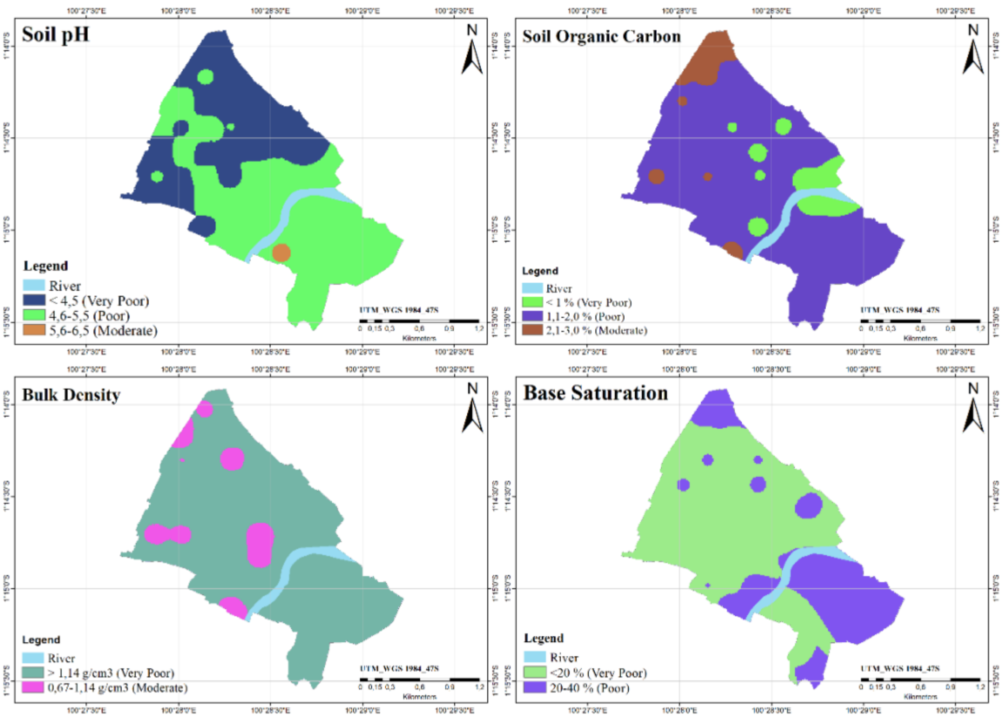
Based on Table 5, the results of the AHP analysis revealed the relative importance of six key parameters in assessing the SQI. Each parameter was assigned a criteria weight and a contribution percentage that reflected its influence on soil quality. Organic carbon (OC) ranked highest with a weight of 0.347 or 34.67%, highlighting its critical role in improving soil structure, enhancing microbial activity, and strengthening cation exchange capacity (CEC). This parameter serves as the dominant component in determining overall soil productivity. The second-highest weight was attributed to bulk density (BD) at 0.185 (18.50%), which plays a major role in determining aeration and root penetration. Soil pH ranked third (17.40%), indicating its importance in maintaining soil reaction stability to support nutrient availability. Base saturation (BS) was placed fourth (13.53%), reflecting its contribution to soil fertility status. Hydraulic conductivity (HC), which contributes to water and nutrient retention, received a weight of 0.106 (10.56%). Meanwhile, exchangeable potassium (K-exch) had the lowest weight (0.053 or 5.34%), suggesting it had the least influence among the parameters. Overall, the AHP provided a systematic approach for identifying the priority parameters that most significantly determined soil quality (Sefano et al., 2024).

3.3 Soil characteristics

Soil is the primary medium and the growing environment for plants. The most important soil characteristics in SQI evaluation based on PCA include soil reaction (pH), organic carbon (OC), base saturation (BS), bulk density (BD), K-exchangeble (K-exch), and hydraulic conductivity (HC). The statistics of the analysis of soil characteristics at 38 sample points in Nagari Nanggalo are shown in Tables 6.

Table 6
Statistical analysis of laboratory data

Statistic	Mean	Std dev	Median	Min	Max	RMSE
pH H_2O	4.56	0.317	4.51	4.16	5.66	0.05
OC (%)	1.45	0.503	1.45	0.70	2.44	0.34
BD ($g.cm^{-3}$)	1.22	0.129	1.21	0.93	1.56	0.67
BS (%)	17.52	7.853	15.05	8.31	48.39	0.43
HC ($cm.h^{-1}$)	1.97	1.385	2.00	0.32	4.13	0.28
K-exch (cmol/kg)	0.36	0.088	0.34	0.23	0.57	0.60



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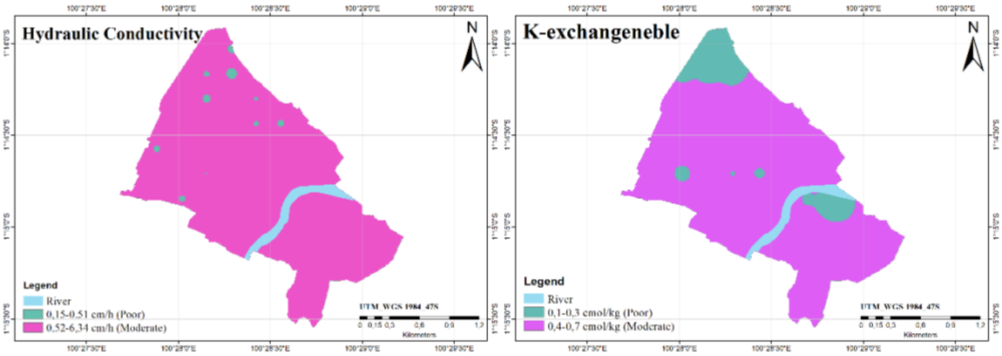

Figure 4 Map of characteristic soil quality distribution

Based on Table 6 the chemical and physical soil properties after the flash flood in Nagari Nanggalo showed relatively degraded conditions. The soil pH ranged from 4.16 to 5.66, with an average of 4.56, indicating that the soil was highly acidic, typical of Ultisols and Inceptisols that have undergone intensive leaching of base cations due to heavy rainfall and floodwater flow (Marion et al., 2022). As shown in Figure 4, the soil pH analysis indicated that 0.75% (2.73 ha) of the area was moderate, 60.04% (221.64 ha) was poor, and 39.21% (144.78 ha) was very poor quality. This acidity condition affected the low base saturation (BS), with an average of only 17.52%, indicating the dominance of H^+ and Al^{3+} ions in the cation exchange complex, thereby reducing soil fertility chemically (Martín-Sanz et al., 2022). As shown in Figure 4, the soil BS analysis indicated that 67.31% (248.47 ha) of the area was poor, and 32.69% (120.68 ha) was very poor quality. The OC content averaged 1.45%, with a minimum value of 0.70%, indicating a decline in soil organic matter, most likely due to the erosion of the topsoil layer and decomposition of organic residues during inundation (Missaoui et al., 2023). As shown in Figure 4, the soil OC analysis indicated that 6.47% (23.88 ha) of the area was moderately, 84.13% (310.57 ha) was poor, and 8.96% (34.70 ha) was very poor quality.

Based on Table 6, the bulk density (BD) had an average value of 1.22 g.cm^{-3}, which was still in the moderate category; however, the maximum value reached 1.56 g.cm^{-3}, indicating compaction in several locations, which could hinder root growth and water infiltration (Ozsahin & Ozdes, 2022). As shown in Figure 4, the soil BD analysis indicated that 8.78% (32.42 ha) of the area was moderate, and 91.22% (336.73 ha) was poor quality. The HC varied considerably (0.32–4.13 cm/hour), but the average of 1.97 cm/hour reflected low to moderate infiltration, suggesting a decline in soil structure due to surface runoff and sediment deposition (Pacci et al., 2022). As shown in Figure 4, the soil HC analysis indicated that 99.03% (365.57 ha) of the area was moderate, and 0.97% (3.58 ha) was poor quality. The K-exch was relatively low (average 0.36 cmol/kg), indicating substantial nutrient leaching caused by the flood (Sefano et al., 2024). As shown in Figure 4, the soil K-exch analysis indicated that 88.95% (328.36 ha) of the area was moderate, and 11.05% (40.79 ha) was poor quality. Overall, these parameters reflected the direct impact of the flood on soil degradation both chemically and physically, reinforcing the findings of low SQI values across most parts of the study area.

3.4 Soil quality index (SQI)

The SQI is influenced by land characteristics, including the physical, chemical, and biological environmental conditions of the soil, which are the primary media that can influence plant growth and development (Ritung et al., 2007). Land characteristics are crucial in SQI evaluation, particularly in analyzing potential problems that may arise from interactions between these environmental characteristics.

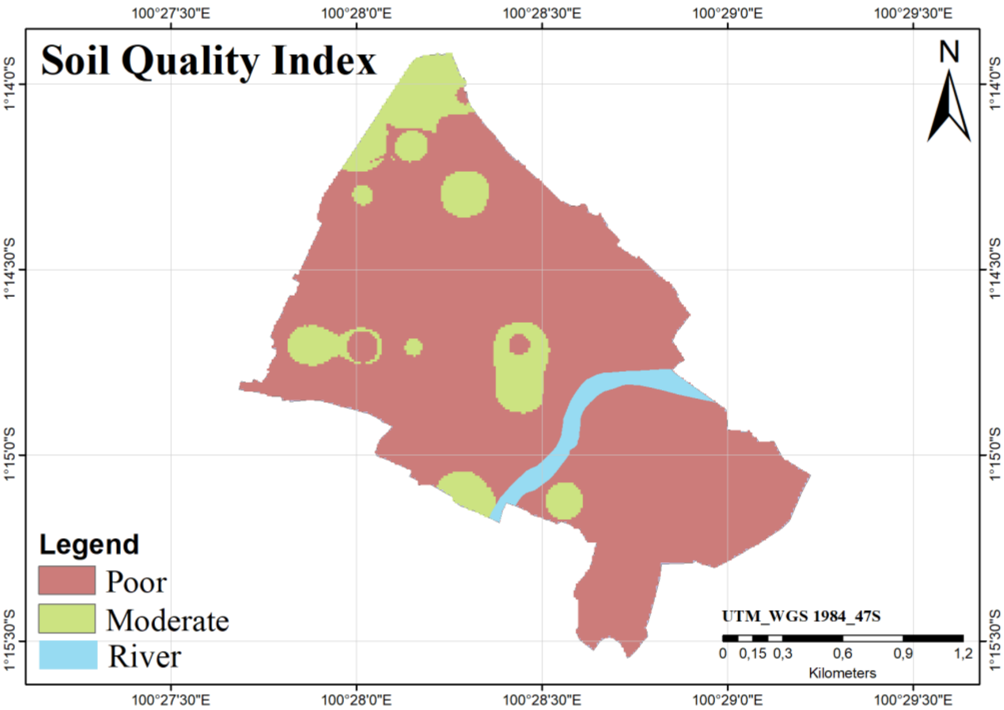

Figure 5 Overall SQI class-map

The weighted overlay results are shown in Figure 5. The value of the SQI indicates that 87.90% (324.48 ha) of the area is poor and 12.10% (44.67 ha) of the area is moderate quality. The dominance of areas with low SQI values indicated significant degradation of the physical, chemical, and biological properties of the soil as a direct consequence of the previous flash flood disaster (Sefano, 2025).

The dominant soil types in the area, Entisols and Inceptisols, played a major role in determining the soil's ability to retain its quality following extreme environmental disturbances (Fiantis, 2017). Entisols, being young soils with minimally developed horizons, generally had relatively low organic matter content and moderate to low cation exchange capacity (CEC), making them vulnerable to nutrient leaching during heavy surface runoff (Wakatsuki & Rasyidin, 1992). Inceptisols, on the other hand, despite having more developed profiles, typically exhibited acidic reactions, low CEC, and low base saturation (Fiantis, 2017). These characteristics further reduced the soil's capacity to support plant growth in the absence of external inputs such as lime or organic fertilizers. The combination of these properties rendered most of the study area incapable of naturally restoring soil quality after the flash flood, which brought extensive erosion, nutrient leaching, sediment deposition, and biomass decay. The spatial distribution illustrated in Figure 5 also showed that areas classified as moderate SQI were mostly located in zones relatively protected from the main flood flow or in slightly elevated terrain, and therefore less exposed to direct inundation and sediment deposition. This pattern could be explained through local geomorphological and hydrological perspectives, where low-lying areas or depressions commonly served as the primary runoff channels transporting sediments, rocks, and organic and inorganic materials from upstream regions (Singh et al., 2023). This depositional process likely formed new surface soil layers that were nutrient-poor and poorly porous, resulting in a sharp decline in SQI. In contrast, areas that escaped direct flood flow maintained relatively intact soil profiles, with microbial activity undisturbed and soil structure still supporting water infiltration and root development (Vasu et al., 2024). The remaining zones with moderate SQI were most likely those that benefited from vegetative cover or topographic features that buffered water flow. These findings underscored the importance of landscape management and vegetative buffer conservation in mitigating post-disaster soil degradation (Watson et al., 2022). Therefore, in post-flood recovery and rehabilitation strategies, it is necessary to adopt an agroecological approach that takes local soil characteristics into account, such as the application of organic matter to enhance soil organic carbon, liming to increase pH, and vegetative conservation to stabilize soil structure and enhance the ecological function of the land.

To ensure the reliability of the SQI model used in this study, a validation process was conducted by comparing model outputs with independent soil sampling data. Model validation of the SQI was performed using independent field measurement data of selected soil quality parameters, including pH, OC, BD, BS, HC, and K-exch. These measured values were compared against the predicted SQI values using statistical indices such as the Root Mean Square Error (RMSE) and Pearson correlation coefficient (r). The results indicated an RMSE value of 0.084, reflecting a relatively low average prediction error, and a strong positive correlation ($r = 0.81$, $p < 0.01$) between modeled SQI and observed field data. This statistical agreement suggests that the SQI model effectively captured the spatial variability of soil quality across the study area. However, minor discrepancies were noted in flood-deposited zones where rapid post-disaster surface changes could not be fully represented in the model due to temporal gaps between flooding and sampling. These validation outcomes reinforce the reliability of the SQI model for guiding soil management and rehabilitation interventions, while also highlighting the need for continuous model refinement through temporal monitoring and incorporation of dynamic soil processes. SQI class in the study area shown in Table 7.

Table 7
SQI class in the study area

Criteria	Level of SQI	Area (ha)	Percentage (%)
pH H_2O	Moderately	2.73	0.75
	Poor	221.64	60.04
	Very Poor	144.78	39.21
	Total	369.15	100
OC (%)	Moderately	23.88	6.47
	Poor	310.57	84.57
	Very Poor	34.70	8.96
	Total	369.15	100
BD ($g.cm^{-3}$)	Moderately	32.42	8.78
	Poor	336.73	91.22
	Total	369.15	100
BS (%)	Poor	248.47	67.31
	Very Poor	120.68	32.69
	Total	369.15	100
HC ($cm.h^{-1}$)	Moderately	365.57	99.03
	Poor	3.58	0.97
	Total	369.15	100
K-exch ($cmol.kg^{-1}$)	Moderately	328.36	88.95
	Poor	40.79	11.05
	Total	369.15	100

4. Conclusion and recommendations

Based on our research, it can be concluded that in the SQI based on the PCA analysis, six principal components were identified and weighted using the AHP, namely pH (17.40%), OC (34.67%), BS (13.53%), BD (18.50%), K-exch (5.34%), and HC (10.56%). The SQI analysis results showed that 87.90% (324.48 ha) of the area was classified as poor and 12.10% (44.67 ha) as moderate. This study indicated that the area had generally poor soil quality. However, it should be noted that proper soil management, as well as soil and water conservation measures, need to be considered to improve the current condition and enhance the soil's carrying capacity. The SQI map developed in this study serves as a useful tool for decision-making in land management.

Data availability statement: The data from this study are available upon request; please contact the corresponding author for replicability and transparency reasons.

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