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Assessing Soil Health Through Multivariate Analysis: A Focus on Durian Cultivation in Cho Lach, Ben Tre Province, Vietnam

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ABSTRACT

Monitoring and evaluating soil quality is a trend in precision farming and sustainable agricultural management. This study used multivariate analysis to evaluate soil quality in durian-growing areas in Ben Tre, Vietnam. Twelve representative composite soil samples were collected, and nine selected soil indices were determined, including pH, EC, TOC, Bulk density, available phosphorus, NH_4^+, CEC, clay content, humus content, and water-holding capacity. The dataset was transformed into new variables using principal component analysis (PCA), deriving relative weights (Wi) and soil normalization scores (Si), which were subsequently used to determine the soil quality index (SQI). The results of the study identified the MDS set consisting of three principal components that explained 84.33% of the variance in the dataset. The three indicators (including % clay, EC, and available phosphorus) represented the principal components. The current SQI of the study area was mostly at the average level (accounting for 83.3% of the area). The results of the SQI calculation based on PCA can help save time, reduce laboratory work costs, and support precise and efficient agricultural management.

INTRODUCTION

Agricultural land is degraded by a combination of internal processes (climate change/weathering, erosion, sedimentation, and geology) and external processes due to human activities (land management strategies, waste management, erosion, deforestation in agriculture, urban planning, and the use of agrochemicals) (Damiba et al. 2024). This land degradation poses major threats to the environment, productivity, and sustainability of agricultural activities (Damiba et al. 2024).

Several methods have been developed to quantify soil quality (SQ) and have been used as decision-support tools. Despite the various methods available, none have gained widespread adoption or recognition because of the intricate and heterogeneous nature of soil systems. This variability often results in inconsistent outcomes when evaluating the same geographical areas (Damiba et al. 2024)

Most methods use physical and chemical indicators and separate or ignore biological indicators. Using this method requires knowledge, and the selection of representative indicators is mostly based on the judgment of "experts." Finally, owing to the intensive field and laboratory work, cost, and time constraints of processing a large set of indicators, it is necessary to reduce a large dataset to a smaller set (Damiba et al. 2024). Currently, the use of multivariate techniques, such as principal component analysis (PCA), for statistical data reduction has become more popular (Abdu et al. 2023). Studies have confirmed that using PCA to reduce the dataset is more sensitive and better for soil quality assessment (Damiba et al. 2024, Rajput et al. 2023).

In the Mekong Delta of Vietnam, agricultural activities such as intensive farming, perennial crop cultivation, and excessive fertilizer use have led to soil degradation. This has resulted in a decline in soil quality and crop productivity. Therefore, urgent management solutions are needed to mitigate the risks to agriculture, one of which is soil quality control based on soil quality index assessments. Durian, currently an emerging agricultural product in Vietnam, holds a very high export value, reaching 3.3 billion USD, accounting for 50% of the total agricultural export value in Vietnam in 2024, according to the Vietnam Customs General Department (VCD).

However, studies using PCA to assess soil quality in Vietnam, especially in durian-growing areas in the Mekong Delta, are still lacking (Table 1). The main parameters affecting soil quality, derived from an extensive dataset (LDS), include nine factors: bulk density, clay content, silt content, water holding capacity, pH, EC, TOC, available phosphorus, and NH_4^+, which were assessed using PCA for durian cultivation in Ben Tre, Vietnam. The findings of this study provide farmers, managers, and policymakers with a straightforward, efficient, and cost-effective method for enhancing agricultural practices.

MATERIALS AND METHODS

Field Sampling Method

Sixty soil samples were collected from 12 locations in durian-growing areas of Cho Lach district, Ben Tre province, Vietnam, in January 2024 (Fig. 1). Two major durian-growing areas were selected, with five samples from area 1 and seven from area 2, representing homogeneous fields based on tree age and growth. Samples were taken at 0-30 cm depth as this surface layer is nutrient-rich, biologically active, and highly sensitive to environmental changes. Each composite sample was collected from a 10 m diameter area by mixing soil from the four corners and the center. The samples were air-dried, crushed, and sieved (2 mm) for analysis. Indicators used to assess soil quality included physical properties (density, clay, silt, and sand) and chemical/nutritional properties (pH, EC, TOC, NH_4^+, and available P). Determination analysis: Bulk density (TCVN 8305:2009), TOC (by Walkley Black method), pH, EC (ISO 10390:1993), available P (ISO 11464, and TCVN 5256:2009), NH_4^+ (Baethgen & Alley 1989), and soil texture (Bouyoucos 1962).

Soil Quality Index (SQI) Assessment

To determine the influential soil quality indicators in the study area, a statistical analysis was conducted using Excel and SPSS 23. A Pearson correlation matrix was constructed to determine the degree of correlation between the study variables. After identifying the correlated variables, principal component analysis (PCA) was performed (Rangel-Peraza et al. 2017)

By employing PCA, the dimensionality of the dataset is minimized through the extraction of principal components (PCs) and the analysis of orthogonal variable correlations, streamlining the data structure. Furthermore, PCA converts a large dataset with correlated variables into a set of uncorrelated indices. PCA involves the following steps: (i) normalizing the variables, (ii) establishing a correlation matrix, (iii) determining PCs with eigenvalues and percentage of variance, (iv) removing PCs with smaller eigenvalues (eigenvalues <1), and (v) establishing a PC matrix with influencing factor loadings. Communalities were calculated as the percentage of variance accounted for by each variable in the PC. Principal components (PCs) with eigenvalues exceeding 1 and explaining a minimum of 30% of the data variability were chosen for further analysis. The principal components should contribute >70% of the data variation (Salem & Hussein 2019). Removing indicators with loadings below 0.3 in PCA ensures that the model focuses on variables with a strong influence, reduces noise, simplifies results, and increases the explanatory power of the principal components. From these PCs, only variables with significant loadings were included in the minimum dataset (MDS). These "highly loaded" variables were identified as those

Table 1: Some studies assessing soil quality in Vietnam.

No	Location	Evaluation parameters and methods	Reference
1.	Mangrove forests of Thai Binh province	pH, heavy metals and nutrients, and the PCA method	(Nguyen et al. 2024)
2.	Tram Chim National Park, Dong Thap Province, Vietnam	pH, total nitrogen, total phosphorus, total acidity, organic matter, and total exchangeable iron and aluminum. Cluster analysis and PCA analysis	(Giao et al. 2023)
3.	Agricultural region of A Luoi district, Central Vietnam	Differences in soil organic carbon, soil total nitrogen, and soil pH. Using the mean and difference comparison method by ANOVA	(Pham et al. 2018)
4.	Rice and corn farming systems in the mountainous regions of Central Vietnam	Particle size distribution, pH, organic carbon, total nitrogen, total phosphorus, available phosphorus, CEC (phương pháp so sánh)	(Van Binh et al. 2013)

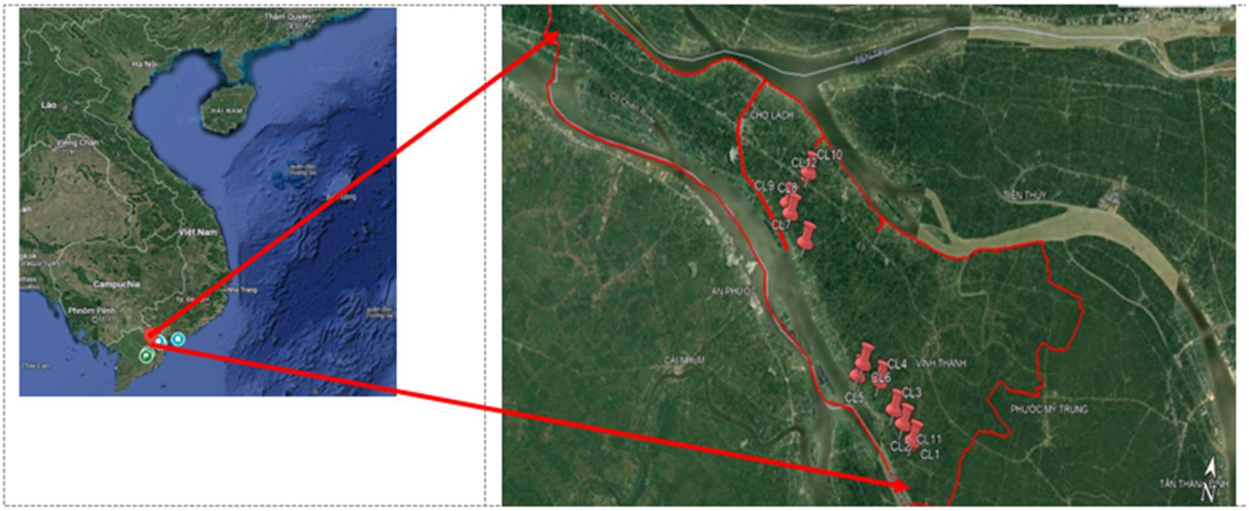

Fig. 1: Location map of Cho Lach district, Ben Tre province, Vietnam (Source: Google Maps).

with the greatest weight on a specific PC, along with others whose absolute loadings were within 30% of the highest recorded values (Abdu et al. 2023). When several indicators were identified within the same principal component (PC), the Pearson correlation matrix was employed to assess their significant relationships ($p < 0.05$) and eliminate redundancy. Indicators with the highest factor loadings were prioritized if they exhibited strong correlations ($r > 0.5$). In cases where correlations are weak ($r < 0.5$), all indicators are retained for further consideration (Damiba et al. 2024).

Normalization of Indicators

The measured indicators varied in scale and units, necessitating their transformation into standardized scores ranging from 0 to 1. This normalization process enables the integration and averaging of diverse indicators into a unified value, facilitating the assessment of soil function and processes. Additionally, it ensures that critical data points are not overlooked during the evaluation. Both linear and non-linear scoring methods are employed to convert these indicators into dimensionless units within the 0–1 range (Damiba et al. 2024).

Once the soil quality indices were analyzed, the interpretation of the values of the selected influencing parameters was clearly defined. Without an interpretation system, these indices cannot be practically applied. An advanced approach to standardizing soil quality indices is to establish standard non-linear scoring functions, usually of the form i) more is better (Formula 1), ii) optimal range (Formula 3), or iii) less is better (Formula 2), which are the most common in soil science. The shapes of such curves are established based on a combination of reference values and expert judgment. (Bünemann et al. 2018).

In the “more is better” approach, the value of each observation is normalized by dividing it by the maximum observed value, ensuring that the highest value scores 1 and all others are scaled proportionally below 1, as outlined in formula (1) (Bandyopadhyay & Maiti 2021).

$$S_i = LSF = \frac{X}{X_{max}} \qquad \text{...(1)}$$

In scenarios where “less is better,” the minimum observed value is divided by each observation, assigning a score of 1 to the lowest value and scores less than 1 to all other values, as described in Equation (2):

$$S_i = LSF = \frac{X_{min}}{X} \qquad \text{...(2)}$$

Here, Si represents the linear scoring function (LSF), which ranges between 0 and 1, where X is the measured value of a specific soil parameter, and Xmax and Xmin denote the maximum and minimum observed values for that parameter. More is better, including moisture, clay, humus, N, and P; Less is better, including bulk density (Damiba et al. 2024).

For the nonlinear scoring function, the soil indices were transformed according to the sigmoidal curve equation. Formula (3) is as follows:

$$S_i = NLSF = \frac{a}{\left[1 + \left(\frac{X_i}{X_{imean}}\right)^b\right]} \qquad \text{...(3)}$$

The nonlinear scoring function (NLSF) operates on a scale from 0 to 1, with its peak value fixed at 1. In this context, Xi denotes the measured value of soil index i, and Ximean represents the average value of index i. The slope parameter, b, is set to -2.5 for scenarios where higher values are preferable ("more is better") and +2.5 for cases where lower values are desired ("less is better"). pH and EC have optimum thresholds (Damiba et al. 2024).

Calculation of Soil Quality Index (SQI)

SQI is calculated using Formula (4):

$$W - SQI = \sum_{i=1}^{n} W_i . S_i \quad ...(4)$$

Where: Si is the score of index i, n is the total number of relevant indices (Damiba et al. 2024)

Wi is the weight coefficient of index i calculated according to Formula (5)

$$W_i = \frac{PC_i}{\sum PC} \quad ...(5)$$

PCi is the loading of principal component i, and PC is the sum of the loadings of the principal components with eigenvalues >1. Si is calculated based on the formulas for normalizing soil quality indices. Finally, the SQI was calculated. The classification criteria for the main SQI indices include: very low (0-0.19); low (0.20-0.39); medium (0.4-0.59); good (0.6-0.79), and very good (0.8-0.99). (Damiba et al. 2024).

Data Processing

To identify the soil quality indices that have a greater influence in the study area, a statistical analysis was conducted using Excel and SPSS 23. Initially, a descriptive statistical analysis was conducted to examine the variability of the indices and identify any outliers or unusual data points. Subsequently, a Pearson correlation matrix was developed to assess the strength and direction of the relationships among the variables under investigation. PCA reduced the dataset and constructed linear combinations (principal components) of the original variables that explained most of the total original variation. Pearson correlation coefficient was used to determine the correlation between the investigated soil properties, while PCA was used to select the MDS and determine the SQI.

RESULTS AND DISCUSSION

Determination of Soil Quality Physicochemical Parameters

The results of the nine selected physical and chemical soil indicators of the 12 combined soil samples from the orange-growing area of Ben Tre, Vietnam, are presented in detail in Table 2. The results showed that the bulk density of 12 soil samples in the growing area has an average value of 0.98 g cm^{-3}, ranging from 0.90-1.06), with CL6 having the highest at 1.06 $g.cm^{-3,}$ and the lowest at CL1 is 0.90 $g.cm^{-3}$, Table 2. According to field observations, sample CL1 is the soil for growing trees in the commercial stage, using more foliar fertilizers; therefore, the air permeability is still maintained at a high level and is more porous. The overall bulk density of the study area was only different for sample CL 1 (lowest) and CL 6 (highest); the remaining samples were not significantly different (according to One-way ANOVA). The results show that the partition was not large. This can be explained by the fact that the value of durian is currently very high; therefore, gardeners always try to use a lot of organic amendments to maintain the physical properties of the soil. The results are similar to those of previous studies, where the bulk density of the Mekong Delta orange growing area fluctuated from 0.71 to 1.09 $g.cm^{-3}$ (Phuong 2024).

The average pH was 4.67, with the lowest and highest pH values being 3.99 and 5.42 for samples CL4 and CL1, respectively. The pH values of these two samples were significantly different from the remaining 10 samples (according to One-way ANOVA), with pH ranging from 4.2 to 5.0. The overall pH of the study area formed six statistically significant areas in increasing order: CL 4; (CL7, CL2, CL5); (CL9, CL10); (CL8, CL11, CL6); (CL12, CL3); and CL1. This shows that the pH fluctuation is very large, which may be due to the nature of the soil properties of the growing area (the location of the soil samples was collected with its characteristics according to field observations) and may also be due to the cultivation process, such as tillage, fertilization, and the use of pH-improving substances. According to the assessment by Amacher et al. (2007), the soil pH in the study area was moderately acidic. Acid-intolerant crops are affected depending on the levels of Al and Fe leaching. Because durian trees only grow well in soil with a pH of 5.5 to 6.5 (Amran et al. 2023), durian gardeners in the Mekong Delta always monitor pH throughout the cultivation process. The results of the pH analysis of the soil samples were similar to those of previous studies in the orange-growing area of the Mekong Delta, with a pH ranging from 3.65 to 6.8. (Phuong 2024). This may be because the durian growing area in the study also originated from acidic soil, a typical soil type in the Mekong Delta (Husson et al. 2000).

The EC of the soil samples had an average value of 0.08, with the lowest and highest values being 0.05 and 0.11 $mS.cm^{-1,}$ corresponding to samples (CL1, CL11) and (CL4, CL7), respectively (Table 2). The overall EC of the study area formed five statistically significant areas from low to high: (CL1, CL11), (CL3, CL12), (CL6, CL2, CL5), (CL8, CL9, CL10), and (CL4, CL7). This shows that, similar to pH, the EC values fluctuated greatly. Excluding the salinity process, EC is mainly due to the use of inorganic fertilizers, organic matter, and pH-improving agents (e.g., lime and dolomite). This could be one of the causes of fluctuations in EC. When the EC is <0.2 mS.cm^{-1}, it indicates low salt levels in the soil, which is not good for plants, whereas the recommended EC range is 0.2-0.5 mS.cm^{-1} (Mukherjee & Lal 2014). The results were similar to those of previous studies. When determining the EC of the orange growing area in the Mekong Delta, the EC fluctuated from 0.08 to 0.58 mS.cm^{-1} (Phuong 2024). This may indicate that the main cause of soil EC change is the use of soil pH improvers, a regular (weekly) activity by farmers to control the pH.

CEC in soil samples averaged 28.8 and ranged from 19.0 to 28.8 cmol.kg^{-1}. The results obtained were similar to those of a previous study in Vinh Long, Vietnam, which ranged from 22.6 to 29.5 cmol.kg^{-1} (Phuong 2024).

The average TOC of the soil samples was 2.50%, ranging from 1.29 to 3.34%, with CL8 having the highest TOC value of 3.34% and the lowest in the CL4 soil sampling area was 1.29% (Table 2). The overall TOC of the study area formed three statistically significant, distinct areas: (CL4, CL3), (CL1, CL10, CL11, CL6, CL9, CL2, CL5, CL12, CL7), and CL8. The results showed that the TOC value of the study area did not fluctuate significantly. This may be because gardeners paid great attention to using organic matter for soil improvement and organic fertilizers for nutrient supplementation. In general, most soil samples had TOC >1.0%. According to Mukherjee & Lal (2014), the TOC was within the average limit. This can be explained by the high cost of organic matter and the humid tropical climate with alternating sunshine and rain, which accelerates organic matter decomposition in the soil. Furthermore, the process of cutting water to stimulate off-season flowering also increases the aeration process, which increases the decomposition of organic matter. The research results are lower than those of a previous study in the Mekong Delta orange growing area, with an average TOC of 4.2% (Phuong 2024). This difference may be due to the type of crop and the organic matter addition process during cultivation.

The average available phosphorus of the soil samples was 68.42 mg kg^{-1}, ranging from 25.4 to 117.1), in which CL5 had the highest available phosphorus content of 117.1 mg kg$^{-1,}$ and the lowest of CL3 was 25.4 mg kg^{-1}, Table 2. Most of the soil samples had an available phosphorus content >30 mg kg^{-1}. Kalu et al. (2015) reported that in soils with high phosphorus reserves, slightly acidic conditions can increase the risk of environmental impacts in aquatic systems through soil erosion. The overall available phosphorus in the study area formed three statistically significant, distinct zones: (CL8, CL9, CL10), (CL1, CL2, CL3, CL4, CL5, CL6, CL7), and (CL11, CL12). The level of regional division based on available phosphorus is not significant. This shows that most gardeners use a lot of phosphorus fertilizer in cultivation to stimulate flowering and branching in the context of acidic soil with low pH and high Al and Fe contents.

NH_4^+ content of the 12 soil samples had an average content of 39.1 kg^{-1}, ranging from 15.4 to 74.2, of which CL12 had the highest NH_4^+ content of 74.2 kg^{-1} and CL10 had the lowest of 15.4 kg^{-1} (Table 2). NH_4^+ in the entire study area formed three statistically significant, distinct areas: (CL8, CL9, CL10), (CL1, CL2, CL3, CL4, CL5, CL6, CL7), and (CL11, CL12). The distribution results of NH_4^+ were similar to those of readily available phosphorus, showing that gardeners regularly focused on fertilizer use, so it did not create many zones.

The average clay content of the 12 soil samples was 28.8%, ranging from 19.5-36.6, of which CL 1, CL 4, and CL 9 had the highest clay content of 36.6%, and the lowest was in the soil sampling area, CL 3 and CL 11 had 19.5% (Table 2). The average sand content in the soil in the study area was 23.3%, with the lowest being 12.8 (CL 11) and the highest being 30.8 (CL 1). The soil in the study area is a type of soil with high clay and silt content (loam), which is suitable for agriculture.

WHC of the soil samples was 71.2%, ranging from 59.5-78.0%, with CL10 having the highest water holding capacity of 78.0% and the lowest in the CL3 soil sampling area at 59.5%. All samples had a water holding capacity of>50%. According to Mukherjee and Lal (2014), all soil samples provided adequate water for crops.

The characteristics of each physicochemical index were determined and analyzed. However, the correlations of the indices also need to be considered as a basis for principal component analysis (PCA) and calculation of the SQI value of the soil in the study area.

Correlation Analysis Results

Table 3 presents the relationships among soil properties, revealing a strong inverse correlation ($p < 0.01$) between soil pH and EC (-0.787), whereas pH exhibited a perfect positive association with water holding capacity (WHC) at 1.00. Soil EC had a statistically significant negative relationship with WHC ($p < 0.01$) relationship with WHC ($r = -0.787$). This may explain why, at low pH, some minerals in the soil may be more soluble, releasing ions such as Al^{3+}, Fe^{3+}, and Mn^{2+}.

Soil pH negatively correlated with EC, as a decrease in pH raises H^+ ion content and enhances cation leaching (Ca, Mg, Fe, Al, Na, and K). Additionally, mineral fertilizer use further lowers pH and increases EC in acid sulfate soils (Abdel-Fattah et al. 2021). The use of pH modifiers such

Table 2: Statistics of the results for determining the selected soil indices.

	pH		EC mS cm^{-1}		TOC %		Pav mg kg^{-1}		NH_4^+ mg kg^{-1}		BD g cm^{-3}		CEC cmol kg^{-1}		Clay %		Silk %		WHC %	
	Value	SD	Value	SD	Value	SD	Value	SD	Value	SD	Value	SD	Value	SD	Value	SD	Value	SD	Value	SD
CL 1	5.42	0.14	0.05	0.02	2.06	0.02	55.9	12.0	29.4	7.0	0.90	0.02	32.4	0.9	36.6	0.9	30.8	0.8	72.0	1.0
CL 2	4.28	0.07	0.08	0.01	2.64	0.3	85.2	6.3	43.7	3.2	0.92	0.03	30.5	0.8	34.1	0.9	20.5	0.5	67.5	1.5
CL 3	5.14	0.05	0.06	0.02	1.50	0.10	25.4	9.1	35.1	0.8	1.00	0.05	17.7	0.5	19.5	0.5	15.4	0.4	59.5	0.5
CL 4	3.99	0.03	0.11	0.01	1.29	0.01	80.4	2.0	39.4	8.9	0.98	0.00	32.5	0.9	36.6	0.9	28.2	0.7	75.0	1.0
CL 5	4.30	0.01	0.08	0.02	2.98	0.14	117.1	6.3	43.7	0.3	0.99	0.03	30.4	0.8	34.1	0.9	25.6	0.6	69.0	1.0
CL 6	4.92	0.04	0.07	0.01	2.60	0.01	54.2	6.6	33.7	1.9	1.06	0.04	21.6	0.6	24.4	0.6	28.2	0.7	73.0	1.0
CL 7	4.18	0.01	0.11	0.01	3.24	0.04	68.6	1.6	44.8	0.5	0.98	0.02	19.7	0.5	21.9	0.6	20.5	0.5	73.5	0.5
CL 8	4.79	0.01	0.09	0.01	3.34	0.18	85.1	11.2	22.2	1.9	1.04	0.02	21.9	0.6	24.4	0.6	17.9	0.4	71.5	0.5
CL 9	4.65	0.05	0.09	0.01	2.67	0.01	57.3	0.3	23.5	1.3	0.93	0.01	32.6	0.9	36.6	0.9	23.1	0.6	75.5	0.5
CL 10	4.55	0.04	0.10	0.01	2.22	0.02	54.5	0.6	15.4	3.8	0.95	0.02	26.0	0.7	29.3	0.8	28.2	0.7	78.0	1.0
CL 11	4.85	0.02	0.05	0.02	2.38	0.10	74.2	4.1	64.2	2.2	1.05	0.02	17.8	0.5	19.5	0.5	12.8	0.3	65.5	0.5
CL 12	5.02	0.03	0.06	0.01	3.02	0.06	63.0	2.8	74.2	1.3	0.94	0.02	26.0	0.7	29.3	0.8	28.2	0.7	74.5	0.5
Min	3.99		0.05		1.29		25.4		15.4		0.90		19.00		19.5		12.8		59.5	
Max	5.42		0.11		3.34		117.1		74.2		1.06		37.50		36.6		30.8		78.0	
Mean	4.67		0.08		2.50		68.4		39.1		0.98		28.84		28.8		23.3		71.2	

BD: Bulk density, g cm^3; Pav: available phosphorus, mg kg^{-1}; WHC: average water holding capacity.

Table 3: Results of correlation analysis of soil indices.

	pH	EC	TOC	Pav	NH_4^+	D	CEC	Clay	Silk	WHC
pH	1									
EC	-0.787**	1								
TOC	-0.088	0.142	1							
Pav	-0.043	-0.392*	0.122	1						
NH_4^+	0.010	-0.398*	0.156	0.984**	1					
BD	-0.024	-0.021	0.126	0.160	0.094	1				
CEC	-0.252	0.177	-0.140	-0.245	-0.215	-0.659**	1			
Clay	-0.241	0.178	-0.138	-0.247	-0.218	-0.664**	**0.995****	1		
Silk	-0.006	0.128	-0.100	-0.255	-0.173	-0.427**	0.651**	0.655**	1	
WHC	-0.119	0.186	-0.111	-0.256	-0.171	-0.575**	0.773**	**0.779****	0.711**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed)

as lime and dolomite reduces the mobility of surface ions such as Al and Fe, thereby decreasing EC. Additionally, higher pH enhances organic matter decomposition and soil aeration, resulting in a strong positive correlation between pH and the WHC.

Available P showed a significant positive correlation with NH_4^+ ($r = 0.984$, $p < 0.01$), likely due to the combined application of NPK fertilizers. However, the correlation between NH_4^+, available P, and other soil properties was weak and unclear, possibly because of factors such as soil texture, TOC, and microbial activity, which can alter these relationships.

Bulk density showed a moderately significant negative correlation with WHC ($r = -0.575$, $p < 0.01$), whereas clay content had a significant positive correlation with WHC ($r = 0.779$, $p < 0.01$). These changes in soil texture likely result from erosion processes (surface runoff, underground flow, flooding) or the dissolution and accumulation of Al and Fe. This aligns with the findings of Husson et al. (2000), who highlighted the high spatial physical variability of acid sulfate soils.

Principal Component Analysis (PCA)

The analysis of the adequacy and completeness of the dataset was based on the Kaiser-Meyer-Olkin (KMO) measure. The KMO value ranges from 0 to 1, with higher values indicating better sample adequacy. Specifically, the KMO value is "0.6 to 0.7 is average, 0.7 to 0.8 is good, 0.8 to 0.9 is excellent, and >0.9 is perfect" (Plonsky. 2015). We processed and selected the indicators in the dataset to have KMO >0.6. The retained quality indicators showed that the KMO was 0.63, which is acceptable for PCA analysis, including eight indicators: pH, EC, Pav, DB, CEC, clay, silk, and WHC. The indicators were removed because of their low correlation with many other indicators. Bartlett's test is significant ($p < 0.001$). Table 4 shows that the Sig correlation is close to 0.000 (George & Mallery 2019, Plonsky 2015). The KMO and Bartlett test results showed that the dataset was suitable for PCA analysis.

The relationship between the eigenvalues and PCs is shown in Fig. 2. Three principal factors (PCs) were selected with eigenvalues >1 (George & Mallery 2019). These principal factors cumulatively explained 84.33% of the variance (Table 5). The results show that the contribution of the principal components is sufficient to explain the dataset in this study (Salem & Hussein 2019). The eigenvalues decrease from PC 1 to PC 3 to 3.98, 1.76, and 1.01, respectively.

The variables with higher loadings contribute the most to explaining the meaning of each principal component. The three principal components with the largest percentages of total method variance were 49.78%, 21.95%, and 12.59% of the total method variance, respectively, as shown in Table 5.

With such results, the contribution weight of each PC is calculated according to Formula 6 and presented in Table 6: 0.59, 0.26, and 0.15.

The principal component analysis results showed that PC1 contributed to seven indices, except for pH (Table 7). Of these, the highest contributing indices were clay content, CEC, and WHC, at 0.946, 0.943 and 0.88, respectively (Table 7). The clay content was strongly correlated with CEC and WHC (0.995 and 0.779, respectively; Table 3). Therefore,

Table 4: KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.630
Bartlett's Test of Sphericity	Approx. Chi-Square	289.12
	df	28.000
	Sig.	0.000

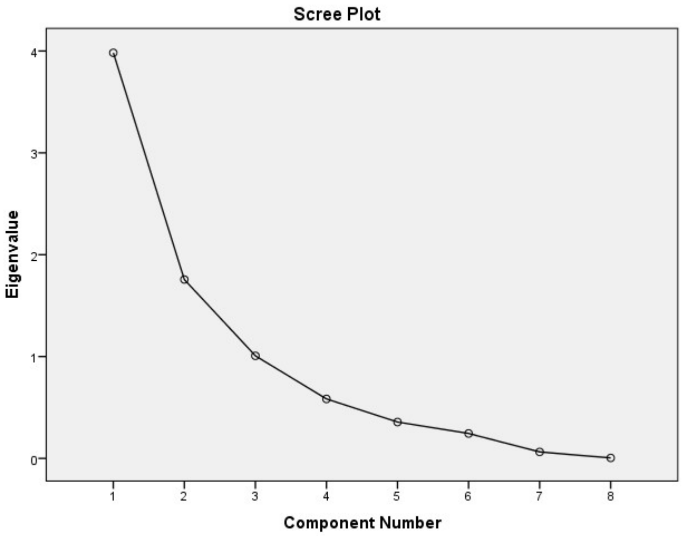

Fig. 2: Relationship between eigenvalues and principal components.

Table 5: Total Variance Explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.982	49.780	49.780	3.982	49.780	49.780
2	1.756	21.954	71.734	1.756	21.954	71.734
3	1.007	12.592	84.326	1.007	12.592	**84.326**
4	0.584	7.301	91.627			
5	0.357	4.463	96.090			
6	0.245	3.058	99.148			
7	0.064	0.796	99.944			
8	0.005	0.056	100.000			

Extraction Method: Principal Component Analysis.

the clay content index was retained as a representative of PC1 in this study. PC1 can be considered representative of the physical properties of the soil in the study area. The results showed that clay content in soil significantly affects other parameters such as soil texture, bulk density, water holding capacity, ion exchange capacity, and nutrient retention. A similar explanation is also found in Kome's report (Kome et al. 2019)

PC2 contributed to two indices (EC and pH) with loading >0.3 (Table 7). Of these, EC had the largest loading (0.90). Because EC and pH have a high negative correlation (r =-0.778), only EC was retained. Therefore, EC was retained as a representative of PC2. The results showed that EC reflected the differences in some soil properties, dissolved

Table 6: Weights of principal components.

PC	% of Variance	Weight
1	49.780	0.59
2	21.954	0.26
3	12.592	0.15
	84.326	

Table 7: Component Matrix.

Indices	Component		
	1	2	3
pH		0.868	-0.384
EC	0.325	**-0.904**	
Pav	-0.374		0.882
DB	-0.719		
CEC	0.943		
Clay	0.946		
Silk	0.772		
WHC	0.877		

Extraction Method: Principal Component Analysis.

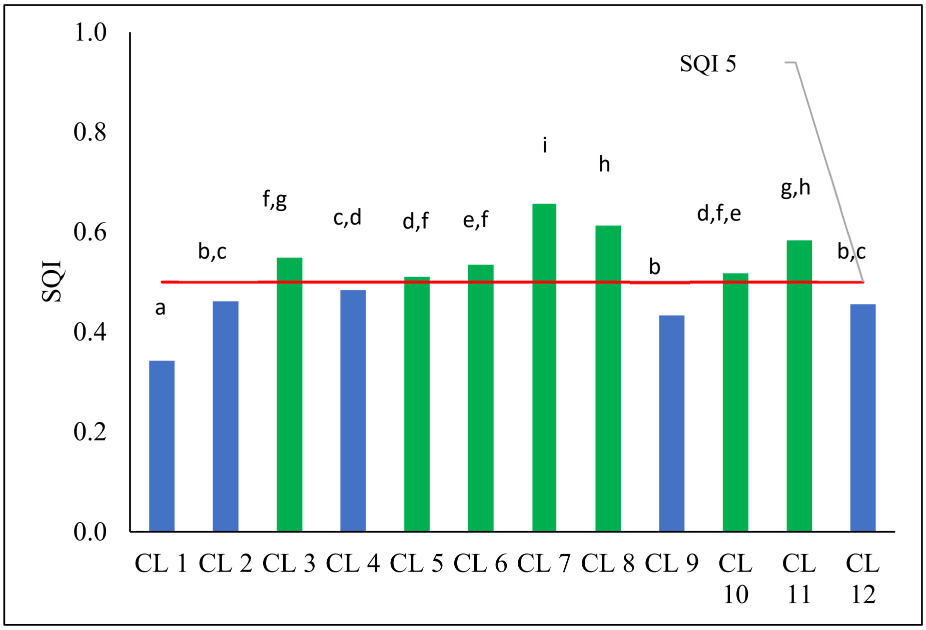

Fig. 3: Soil quality index (SQI) of the soil samples. The letters a$^{,b,c,d,e,f,g,h,\text{ and } i}$ indicate statistically significant differences in the SQI values.

ion content between soil samples, and the nutrient absorption capacity of durian trees.

PC3 had a high contribution from the indices with load >0.3, including available phosphorus and pH (Table 7). Of these, Pav had the largest load of 0.88 (Table 7), which is representative of PC3. Based on the contributing indices, this main component can be considered a factor affecting soil quality. The results showed that the role of valuable P in the development of durian trees is one of the main indicators determining agricultural activities, especially in acidic soil.

The expression to calculate the SQI of the soil in the study area is presented in Equation (7).

$$SQI = w_{PC1}S_{Clay} + w_{PC2}S_{EC} + w_{PC3}S_{Pav} \quad ...(6)$$

The SQI calculation yielded an average value of 0.51, with the highest value (0.66) in sample CL7 and the lowest value (0.34) in sample CL1. One-way ANOVA revealed significant SQI differences across the study area, dividing it into eight distinct sub-locations (Fig. 3). According to Damiba et al.'s classification, 83.3% of the 12 locations had moderate SQI (0.4-0.59), 8.3% had good (0.6-0.79), and 8.3% had low SQI (Damiba et al. 2024). The study revealed that soil quality in the area, based on PCA, varied significantly, mostly at a moderate level. Regular monitoring and the use of soil improvers and nutrient supplements are essential for maintaining soil health and preventing degradation, which impacts durian productivity. With 83.3% of SQI at moderate levels, government and agricultural organizations should urgently advise farmers on solutions to enhance soil quality and mitigate the risks of declining productivity.

CONCLUSION

Soil quality was determined by considering nine indices derived from 12 soil samples collected from the durian growing area of Ben Tre, Vietnam. The selected indices included pH, EC, TOC, Bulk density, CEC, available phosphorus, NH4+, clay content, and water holding capacity by creating a minimum data set, and SQI calculation based on PCA was performed. This study showed that most soil samples in the study area had a medium soil quality index (SQI). The review of the study data determined that the selected parameters as representatives, such as clay content, EC, and Pav, can be used to determine and monitor soil quality. PCA is a useful tool for assessing soil quality. Furthermore, the research results also confirmed that regular monitoring of soil quality and the use of interventions in soil quality management to maintain soil quality stability, in particular, and sustainability in agricultural activities in general are very urgent.

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