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THE EFFECTS OF LAND USE TYPES ON SOIL QUALITY INDEX (SQI): THE CASE OF TAY NINH, VIETNAM

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Abstract

Determining the Soil Quality Index (SQI) under the influence of different land-use types is fundamental to sustainable transformation. This study aims to investigate the extent to which different land-use types in Tay Ninh province affect SQI changes. Soil samples were collected from three land-use types, including (i) durian cultivation, (ii) custard apple cultivation, and (iii) cassava cultivation, with 14 soil quotients identified. The SQI determination method was based on PCA analysis, and a Geographic Information System (GIS) using spatial distribution interpolation maps (IDW) was employed. The results showed that SQI values varied significantly depending on land use, with SQI decreasing in the order of custard apple > durian > cassava. Spatially interpolated maps have visually illustrated the changes in SQI at surveyed sites resulting from land-use conversion—specifically, shifting from cassava cultivation to custard apple or durian farming. The study results confirm that monitoring SQI fluctuations is a prerequisite for managing crop restructuring aimed at sustainable development, while also demonstrating that spatially interpolated maps serve as effective support tools for farmers and agricultural officials.

Keywords:

IDW, land use types, Principal Component Analysis (PCA), Soil Quality Index (SQI)

1. INTRODUCTION

Agricultural land is a strategic resource in improving people's quality of life (Morán-Alonso et al. 2025). Land use is changed and adjusted due to socio-economic needs, and this can negatively impact soil quality (Kahsay et al.

2025). Changes in land use, such as focusing on high-cost, high-yield crop varieties along with excessive fertilization and high pesticide dosages, lead to soil degradation (Ahmad et al. 2020; Morán-Alonso et al. 2025). Specifically, this results in the degradation of the soil's physical, chemical, and biological characteristics.(Fu et al. 2021; Kalu et al. 2015).

Soil quality is a crucial component of sustainable land management, directly influenced by land use. Developing effective, sustainable land management strategies requires an accurate assessment of soil quality, especially in areas with diverse land use patterns (Bünemann et al. 2018; Kahsay et al. 2025).

Various soil quality assessment methods have been developed by researchers, related to differences in assessment objectives and the diversity of soil systems. Among them, commonly used soil quality indicators include pH, total organic matter (TOC), available phosphorus, nitrogen, acidity, CEC, and soil texture, primarily used for their flexibility and simplicity, and have been seen as guiding principles for sustainable soil management techniques. (Bünemann et al. 2018; Kahsay et al. 2025)

Total Data Sets (TDS) and Minimum Data Sets (MDS) have been widely applied in soil quality assessment. The MDS index selection method is applied to reduce the time and financial cost of soil quality assessment, eliminate multicollinearity and data duplication, and enhance the clarity of data variability. MDS are generated from TDS using principal component analysis (PCA), a technique widely used in various fields. (Kahsay et al. 2025). Both the Kriging method and the IDW were evaluated to determine the most suitable method for representing the spatial transformation of SQIs. This method allows for a detailed assessment of regional soil quality heterogeneity and enables the implementation of focused land management techniques.(Ibrahim et al. 2025; Zeng et al. 2026)

Tay Ninh province in Vietnam currently has the largest area of custard apple cultivation in Vietnam (with a total cultivated area of nearly 5,600 hectares), and cassava cultivation with a stable area of approximately 60,000-61,900 hectares, ranking second nationwide in area but first in yield. Meanwhile, the area of durian cultivation is increasing sharply due to its high economic efficiency, reaching about 3,000-3,290 hectares (this is a type of land use conversion in recent years). Assessing the soil quality of these three land use types to maintain agricultural efficiency, as well as identifying necessary solutions for soil improvement during the conversion process, is extremely urgent. However, such activities currently lack sufficient information.

Given the reasons mentioned above, this study aims to assess soil quality according to three land-use types in Tay Ninh (custard apple cultivation, cassava cultivation, and durian cultivation) by using the MDS index, linear and non-linear scoring functions to calculate the Soil Quality Index (SQI) based on PCA analysis. The study also used interpolated SQI mapping on a Geographic Information System (GIS) to visually and quantitatively describe soil quality indices for these three types.

2. MATERIALS AND METHODS

2.1 Field sampling

Several communes and wards—such as Tan Phu, Tan Chau, and Tan Hoi in Tay Ninh Province, Vietnam—were selected to represent the study area. A total of 21 composite soil samples were collected (comprising 7 samples from durian (D) orchards, 7 from custard apple (Cus) orchards, and 7 from cassava (Cas) fields), with details of their distribution shown in Figure 1. Sampling was conducted during the dry season in November 2025. The top-soil layer, at a depth of 0-30 cm, exhibits dynamic soil quality characteristics compared to other depths. At each location, the sampling area covers approximately 1-2 hectares, with 5 samples taken at the 4 corners along the diagonal centerline, and one composite sample mixed in. The composite soil sample, after collection, should be preserved in plastic bags or polyethylene (PE) containers and transported to the laboratory, air-dried, ground into a fine powder, and sieved through a 2 mm sieve. Analysis will determine bulk density (D), particle density (d), soil texture, total organic matter (TOC), pH, EC, ammonium nitrogen (NH_4^+), Total acidity (Ac_T), Al acidity (Ac_Al), and H+ acidity (Ac_H), Cation exchange capacity (CEC), and available phosphorus (P_av) in the soil.

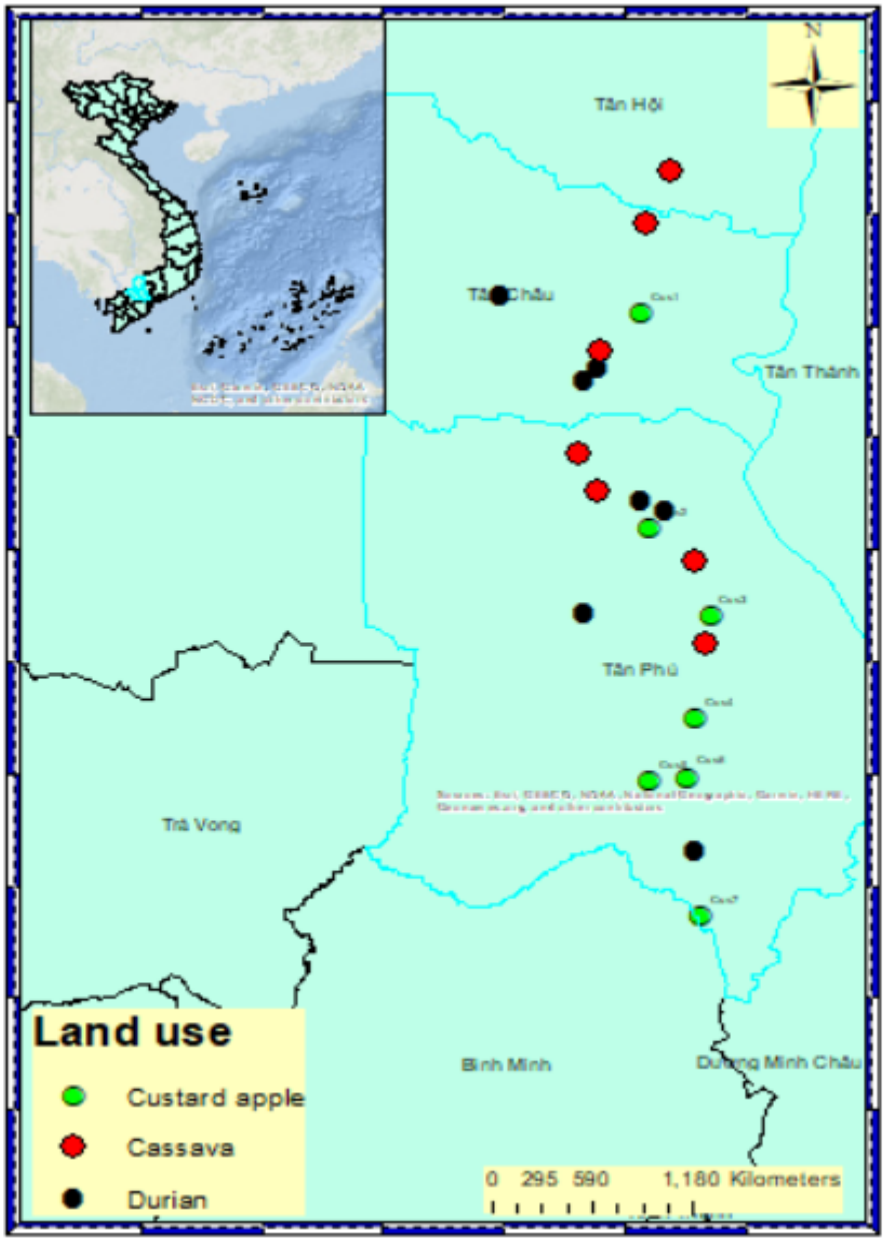


Figure. 1: Map of sampling locations

2.2 Analytical methods

The soil particle density (d) was determined according to TCVN 6863:2001, pH and EC according to ISO 10390:1993, bulk density according to TCVN 8305:2009, total organic carbon (TOC) of the soil by the Walkley-Black method, available P (P_av) according to Olsen, NH_4^+ was determined according to TCVN 6179-1:1996, particle size distribution (particle size grade) was determined by hydrometer method TCVN 6862:2001, and exchangeable acidity (Tan 2005), CEC (Tan 2005)

2.3 Laboratory equipment and chemicals

The chemicals used in the experiment were analytical grade chemicals from Merck $(NH_4)6Mo_7O_{24}$, $SnCl_2.2H_2O$, $K_2Cr_2O_7$, and from China including H_2SO_4, CH_3COONH_4, KCl, HCl, KH_2PO_4, NaOH, HNO_3, NaOH, H_2O_2, Na_3PO_3, H_3PO_4.

2.4 Determining the Soil Quality Index (SQI)

The PCA-based evaluation method includes identifying the TDS dataset, scoring (Si), selecting MSDs, determining the weight of each principal component i (W_PCi), and calculating the SQI. This results in specific evaluations. Soil quality index assessment method was carried out through the following main steps:

2.4.1 Scoring of soil indicators

Scoring functions come in three main forms: as much as possible (equation 1), as little as possible (equation 2), and optimal range (equation 3) (Bandyopadhyay & Maiti 2021; Damiba et al. 2024; Van Phuong 2025). The goal of this is to standardize each soil index.

$$S_i = \frac{X}{X_{max}} \quad (1)$$

$$S_i = \frac{X_{min}}{X} \quad (2)$$

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

X_{max} and X_{min} = The highest and lowest observed values for each soil indicator.

In equation 3, NLSF = a nonlinear scoring function that varies from 0 to 1, a = the maximum value of 1, Xi = the value of soil index i, Ximean = the average value of soil index i, b = the slope of the equation, and is set to -2.5 for the “more is better” curve and +2.5 for the “less is better” curve.

2.4.2 TDS Selection

TDS is determined based on the Bartlett test for sphericity and the KMO test for sample completeness. The Bartlett test for sphericity requires a value of <0.0001, and on the Kaiser-Meyer-Olkin (KMO) scale, values range from 0.5 to 0.7 (average), 0.7 to 0.8 (good), 0.8 to 0.9 (excellent), and >0.9 (perfect) (Van Phuong 2025)

2.4.3 Setting up MSD

PCA identifies key PCs (eigenvalue ≥1, variance ≥5%) that cumulatively explain ≥70% of total variance, forming the MDS to highlight area-specific soil characteristics (Ibrahim et al. 2025)

For each PC, only those indicators with load values reaching 90% of the load of the highest indicator are retained. If a PC has more than one retained indicator, it is considered in conjunction with the Pearson correlation coefficient. If those soil indicators have a correlation coefficient < 0.6, they will be retained in the MDS. Conversely, if they correlate well (correlation coefficient r > 0.6), these variables are considered redundant. In that case, only the variable with the highest load in the group is selected for inclusion in the MDS. (Ibrahim et al. 2025; Van Phuong 2025).

2.4.4 Calculating SQI

Determine the weights (W) after identifying the representative principal components. Specifically, the weight (Wi) for each PC is calculated based on the variability that the PC containing that parameter explained, divided by the total cumulative variability of all selected PCs (Equation 4).

$$W_i = \frac{PC_i}{\sum PC} \quad (4)$$

Where Wi is the weighting coefficient calculated according to Equation 5, and Si is the average index score of the i-th factor. PCi is the load of principal component i, and PC is the total load of principal components with eigenvalues >1. Si is calculated based on equations 1, 2, and 3. These weights then serve as key factors in constructing the Soil Quality Index (SQI) through a weighted supplementary function (equation 4). The SQI values are calculated using equation 5.

$$SQI = \sum_{i=1}^{n} W_i . S_i \quad (5)$$

The classification criteria for SQI describe soil quality levels as very low (<0.4), medium (0.4-0.6), good (0.6-0.8), and very good (>0.8), and are presented in the ArcGIS application (Damiba et al. 2024; Ibrahim et al. 2025).

2.5 Data processing

A one-way ANOVA was used to determine differences in treatment means; the Tukey test was selected if variances were homogeneous (Levene's test Sig. ≥ 0.05), whereas Tamhane's T2 was chosen otherwise. Descriptive statistics and Pearson correlation first assessed soil variation and inter-variable relationships. PCA then extracted principal components to reduce data and select the MDS for SQI calculation. To eliminate variables with little or no correlation with others, the study relies on the MSA (Measure of Sampling Adequacy) values located on the diagonal of the

Anti-image Correlation matrix. Variables with an MSA < 0.5 are considered for removal through an iterative process: the variable with the lowest MSA is removed in each step, and the analysis is re-run until the KMO (> 0.5) and Bartlett (Sig < 0.05) criteria are met, indicating suitability for PCA. Finally, SQI was spatially mapped via IDW interpolation (Ibrahim et al. 2025; Kahsay et al. 2025). SPSS 23 software was employed for the data processiing.

3. RESULTS AND DISCUSSION

3.1 Influence of land use types on the physical properties of soil

Table 1 presents the results of pH determination from 21 soil samples of three crops, showing average values of 6.30 for durian (ranging from 6.10 to 6.65), 5.92 for custard apple soil (ranging from 5.53 to 6.27), and 6.46 for cassava soil (ranging from 6.27 to 6.61). One-way ANOVA analysis showed that cassava soil pH was significantly higher than durian and custard apple soil pH, while the two types of soil did not differ significantly. The required pH range is a minimum of 5.04 and a maximum of 9.62.(Kahsay et al. 2025)

Table 1: Average values of soil indicators by land use type

		Durian	Custard apple	Cassava			Durian	Custard apple	Cassava
pH		6.30a	5.94a	6.47b	CEC		7.39a	7.12a	6.10a
	SD	0.15	0.22	0.09		SD	2.20	1.67	1.14
EC		0.12b	0.12b	0.07a	Clay		7.66a	7.31a	6.21a
	SD	0.03	0.04	0.05		SD	2.48	1.89	1.24
TOC		1.89a	1.34a	1.21a	Silt		6.96a	5.49a	6.67a
	SD	0.46	0.21	0.26		SD	2.32	2.19	1.93
P_av		61.86b	66.78b	21.14a	Sand		85.38a	87.20a	87.13a
	SD	25.96	20.12	9.58		SD	3.46	3.20	1.71
NH_4^+		3.71a	16.26b	7.37b	Ac_T		0.21a	0.16a	0.34b
	SD	3.03	10.57	2.73		SD	0.09	0.03	0.14
d		2.40a	2.60a	2.57a	Ac_Al		0.12a	0.09a	0.23b
	SD	0.25	0.30	0.31		SD	0.06	0.04	0.13
D		0.97a	0.96a	0.93a	Ac_H		0.09a	0.08a	0.11a
SD		0.06	0.05	0.01			0.03	0.03	0.03

Ac_T: total acidity, Ac_Al: aluminum acidity, d: particle density

Different 'a' and 'b' letters in the same row indicate statistically significant differences according to One-way ANOVA ($p<0.05$).

The average EC values of the three land use types (Table 1) show insignificant differences. The average EC values are 0.12 mS/cm (durian), 0.12 mS/cm (custard apple), and 0.07 mS/cm (cassava), respectively. The EC of cassava-

growing soil is significantly lower than the other two types of soil. Specifically, the EC values are higher in durian and custard apple orchards, indicating that the nutrient ion content in the soil is better maintained than in cassava-growing soil (according to discussions with farmers during sampling and the results of NH_4^+ and readily available phosphorus analysis), but still below the 0.5 mS/cm threshold, proving that the soils are suitable for cultivation .

The TOC content (Table 1) showed insignificant variation among different cultivation types, reflecting the low TOC retention capacity of the soil in the area. The average TOC value was highest in durian-growing soil (1.89%), followed by custard apples (1.34%), and lowest in cassava (1.22%). However, the differences were not statistically significant according to One-way ANOVA analysis. According to Mukherjee and Lal's classification, all these values fall within the medium to low group (<3%) (Mukherjee & Lal 2014).

The TOC content (Table 1) shows insignificant variation between different cultivation types, reflecting the low TOC retention capacity of the soil in the area. The average TOC value was highest in durian-growing soil (1.89%), followed by custard apple (1.34%), and lowest in cassava (1.21%). However, the difference was not statistically significant according to One-way ANOVA analysis. According to Mukherjee and Lal's classification, all these values fall within the medium to low group (<3%). This may be due to the frequent mineralization of organic matter in arid soils, which rapidly degrades TOC content in the soil; for example, cassava receives less irrigation than durian or custard apple. A similar explanation was found in the study by Larionova et al (Larionova et al. 2017). Furthermore, since cassava is an annual crop, plowing activities also increase the decomposition of organic matter. (Ma et al. 2024).

The average exchangeable acidity (Total, Al^{3+}) (Table 1) showed negligible differences between durian and custard apple cultivation, while acidity was significantly higher compared to cassava cultivation. Specifically, the total acidity values were 0.21 cmol/kg, 0.20 cmol/kg (custard apple), 0.16 cmol/kg (cassava), and 0.34 cmol/kg (cassava), with exchangeable acidity (Al^{3+}) values of 0.12 cmol/kg (cassava), 0.09 cmol/kg (durian), and 0.23 cmol/kg (custard apple), respectively. Cassava soil tended to be more acidic, possibly due to less use of soil conditioners in acidity control, especially aluminum-induced acidity. Furthermore, cassava plants have a high adaptability to acidity, so less control is required (Muiruri et al. 2021). Meanwhile, the average H^+ acidity values showed no significant difference, at 0.09 cmol/kg (cassava), 0.08 cmol/kg (durian), and 0.11 cmol/kg (custard apple), respectively, with a narrow range of variation from 0.05 to 0.15 cmol/kg. This indicates that the soil surface contains similar levels of H^+ ions.

The average CEC of all three types of produce was moderate, with no significant differences, at 7.39 cmol/kg (durian), 7.12 cmol/kg (custard apple), and 6.10 cmol/kg (cassava), respectively.

The content of available phosphorus (P_2O_5) showed significant differences between different land use types. The average values in durian and custard apple orchards did not differ significantly, at 61.86 mg/kg and 66.78 mg/kg, respectively, both exceeding the 30 mg/kg threshold, which is considered to indicate good phosphorus reserves.(Amacher Michael C et al. 2007). Conversely, cassava-growing soils have a significantly lower average

phosphorus content, reaching only 21.14 mg/kg. This difference stems directly from nutrient management practices: fruit orchards such as durian and custard apple are typically fertilized adequately, while cassava-growing soils – often cultivated on light, gray, infertile soils – receive less fertilizer and are prone to leaching. A similar explanation is found in the study by De et al., suggesting human impact on soil nutrition (De et al. 2022). The ammonium (NH_4^+) content in the soil (Table 1) showed significant variation among different land use types, clearly reflecting differences in land use regimes. The highest average value was found in custard apple soil (16.26 mg/kg), followed by durian (3.71 mg/kg), and the lowest in cassava (7.37mg/kg). This can be explained by the fact that durian and cassava are approaching harvest, whereas custard apple trees are currently developing fruit and require higher levels of nitrogen.

The particle density of the soil from the three land use types (Table 1) showed average values that did not differ significantly, at 2.40 g/cm³ (durian), 2.60 g/cm³ (custard apple), and 2.57 g/cm³ (cassava), reflecting the uniform particle characteristics in the surveyed area. Like particle density, the bulk density of the three land use types did not differ significantly. The bulk density of durian-growing soil ranged from 0.88 to 1.06 g/cm³, with an average value of 0.97 g/cm³; custard apple-growing soil was stable, ranging from 0.93 to 1.05 g/cm³ with an average of 0.97 g/cm³; and cassava-growing soil ranged within the narrowest range of 0.92 to 0.94 g/cm³ with an average of 0.93 g/cm³. Overall, most soil samples had a bulk density of < 1.50 g/cm³ or were within the ideal range, favorable for root development and biological activities in the soil.(Amacher Michael C et al. 2007).

The results of the mechanical composition analysis of the soil samples from the three types of land use showed that they all belonged to the sandy loam soil group, with a clear predominance of sand (ranging from 82% to 93%). Specifically, the average sand content was 87.2% (custard apple), 87.1% (cassava), and 85.4% (durian), respectively. Meanwhile, the clay content (4.9% - 12.2%) and silt content (2.6% - 10.3%) were at medium to low levels. The average values for clay, silt, and sand content of the three types did not differ significantly.

3.2 Soil quality assessment

According to preliminary surveys based on Pearson analysis, Bartlett's test, and KMO index, soil indices such as EC, D, d, and Ac_H have poor correlations with most other indices and may contribute little to the overall structure, so they were excluded. The total TDS dataset is now reduced to only 10 indices, including pH, TOC, P_av, NH_4^+, clay, silt, sand, CEC, Ac_T, and Ac_Al.

Table 3 presents the results of the Bartlett test and the KMO index, showing that the observed Chi-square value is 912.271 with a significance level of p = 0.000 (< 0.05), indicating that the variables are correlated and are perfectly suitable for conducting PCA analysis. In addition, the KMO value is 0.519 (> 0.5), indicating that the sample size is large enough to ensure reliability for principal component analysis. Thus, the TDS dataset fully meets the necessary conditions for performing PCA (Abdel-Fattah et al. 2021)

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.519
Bartlett's Test of Sphericity	Approx. Chi-Square	912.271
	df	45
	Sig.	.000

The relationship between eigenvalues and PCs is shown in Figure 2. Four principal factors (PCs) were selected with eigenvalues >1, namely 3.096, 2.806, 1.419, and 1.115, and accounted for over 84.373% of the variance of the original data (Table 4). The contribution levels of the PCs were 30.96, 28.07, 14.19, and 11.15%, respectively, for PC1, PC2, PC3, and PC4 (Table 3).

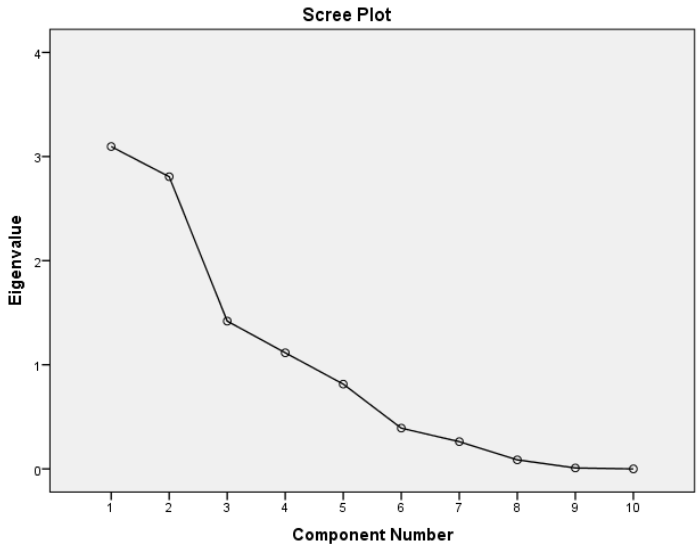


Figure. 2: Scree plot

Table 3: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.096	30.962	30.962	3.096	30.962	30.962
2	2.806	28.065	59.027	2.806	28.065	59.027
3	1.419	14.191	73.218	1.419	14.191	73.218
4	1.115	11.154	84.373	1.115	11.154	84.373
5	0.814	8.142	92.514			

6	0.391	3.914	96.428	**W_PC1**	**0.37**
7	0.262	2.617	99.045	**W_PC2**	**0.33**
8	0.087	0.867	99.912	**W_PC3**	**0.17**
9	0.009	0.087	99.998	**W_PC4**	**0.13**
10	0.000	0.002	100.000		

Extraction Method: Principal Component Analysis.

The weights W_PC1, W_PC2, W_PC3 and W_PC4 calculated based on (equation 4) have results of 0.37, 0.33, 0.17 and 0.13 respectively (Table 3).

Table 4: Component Matrix

	Component			
	PC1	PC2	PC3	PC4
pH	0.663	-0.294	-.078	-.405
TOC	0.042	-0.419	**0.724**	0.283
P_av	0.726	-0.231	0.013	0.270
NH_4^+	0.443	-0.347	-0.541	-0.484
Silt	0.305	-0.560	-0.461	**0.574**
Sand	0.194	**0.887**	0.285	-0.267
Ac_T	**0.828**	-0.096	0.305	-0.045
Ac_ Al	0.690	-0.349	0.392	-0.155
Clay	0.561	0.764	-0.157	0.249
CEC	0.569	0.746	-0.173	0.274

Extraction Method: Principal Component Analysis.

In PC1, the indices with high absolute loads include Ac_T, P_av, Ac_Al, and pH, with high loads of 0.828, 0.726, 0.690, and 0.663, respectively, indicating that these parameters contribute significantly to PC1 (Table 4). The indices in PC1 may originate from the potential acidity in the soil structure and from the high use of phosphate fertilizers in cultivation (according to field surveys). No index has a load value within 10% of the Ac_T load value (Abdu et al. 2023; Damiba et al. 2024); therefore, only Ac_T is retained as representative of PC1.

PC2 contains high load indices including Sand, Clay, and CEC, which are 0.887, 0.764, and 0.746, respectively. These soil indices represent the contribution of the soil structure. No load values fall within the 10% variation range compared to Sand. Therefore, Sand is retained as the representative of PC2.

PC3 contains high absolute load indices of TOC and NH_4^+, at 0.72 and 0.541, respectively. No load values fall within 10% of the highest load value, so only TOC is retained to represent PC3.

PC4 contains silt and NH_4^+ with high loading values of 0.574 and 0.484, respectively. The results show that the fine particle size in the soil interacts with NH4+. Silt was the only parameter selected to represent PC4 because no loading value fell within 10% of the absolute loading value of silt. (Damiba et al. 2024).

PC1, PC2, PC3, and PC4, with their indices including Ac_T, Sand, TOC, and Silt, were selected as representative components of the MDS explaining 84.373% of the total dataset.

The general formula for calculating the SQI (Equation 4) for sampling locations in the cultivated area is presented in Equation 7.

$$SQI = S_{Ac_T} * 0.37 + S_{Sand} * 0.33 + S_{TOC} * 0.17 + S_{Silt} * 0.13 \quad \text{(Eq. 1)}$$

Fig. 3, presents the SQI results for three land use types, specifically SQI values of 0.70, 0.71, and 0.59 for durian, custard apple, and cassava cultivation, respectively. The average SQI of cassava-growing land was significantly lower than that of custard apple and durian-growing land according to the One-way ANOVA analysis. This may be due to the higher economic efficiency of custard apple and durian cultivation, meaning more frequent use of fertilizers, organic matter, and acidity control agents compared to cassava cultivation. This is considered a major challenge for farmers when converting land use types, such as from cassava to durian or custard apple, which are more valuable and economically efficient, as they require capital and agronomic knowledge.

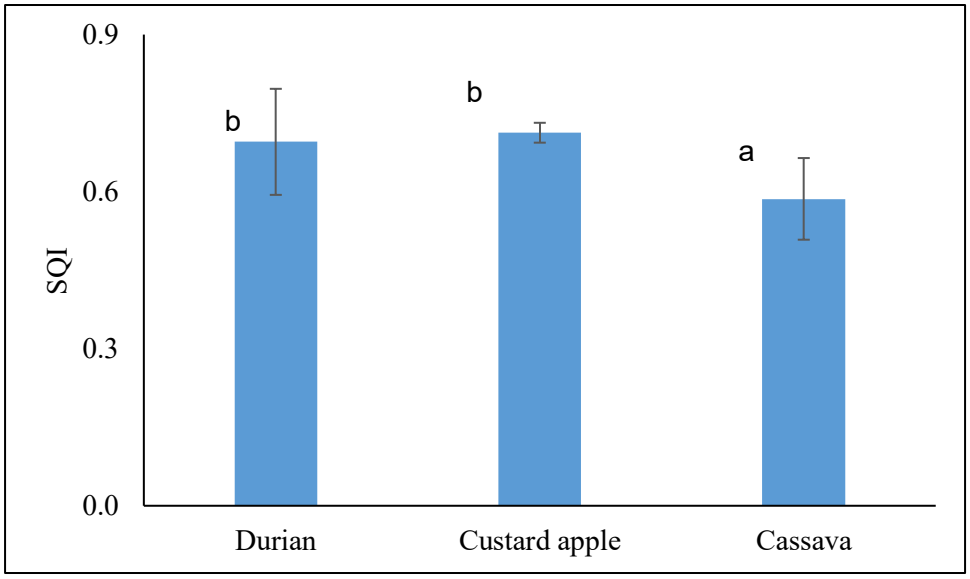


Figure. 3: Representing the Soil Quality Index (SQI) for 3 land use types

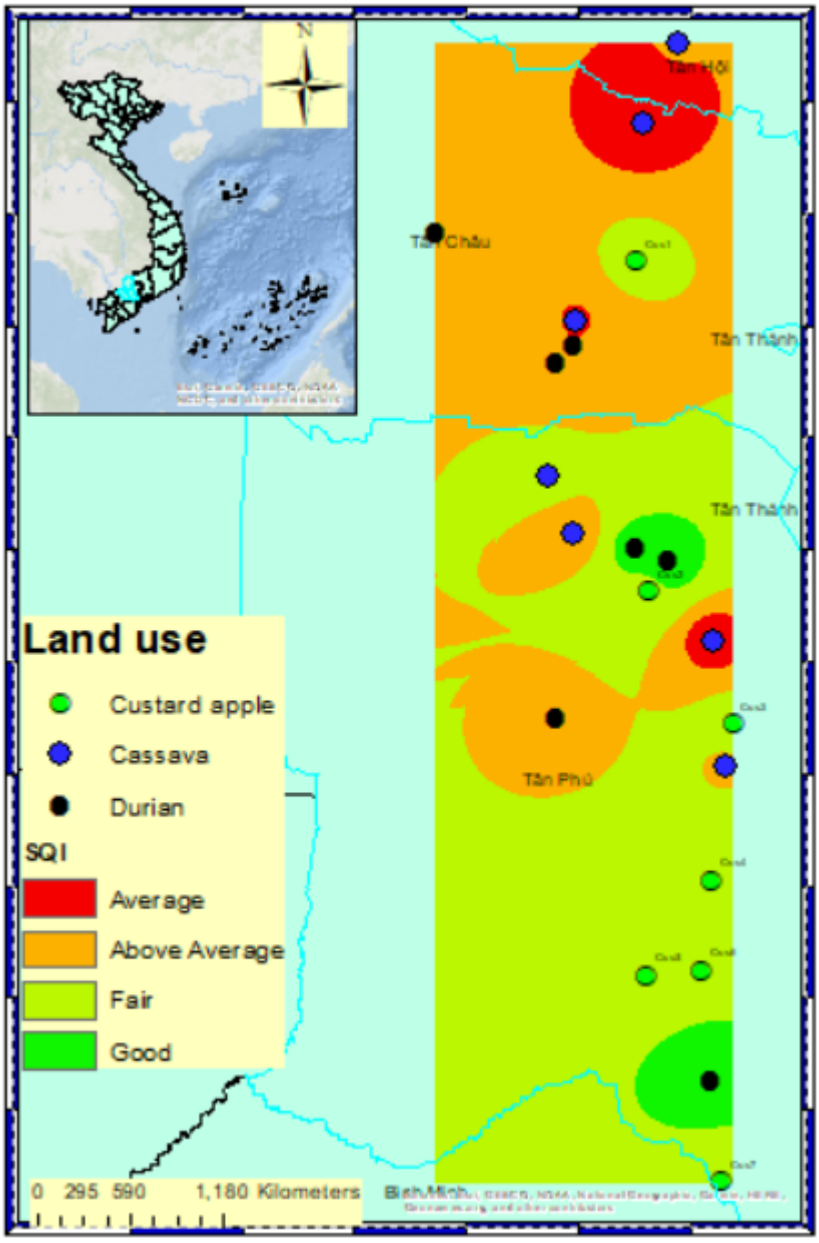


Fig. 2: Representing the Soil Quality Index (SQI) for 3 land use types

3.3 Distribution of SQI by land use type.

Fig. 4 shows that the three types of crops grown in Tay Ninh do not form distinct specialized farming zones but are intercropped. This development reflects the economic development needs of farmers who desire higher profits. Figure 4 shows the SQI values categorized into four groups, each represented by a different color. The SQI distribution of cassava farms is generally at an average level (red and orange), while durian farms are at a better level (orange and green). The results show that there is a shift in land use from cassava cultivation to durian cultivation, but investment is limited, so the quality is not yet satisfactory. Custard apple cultivation, being a

traditional crop with many benefits, maintains relatively good soil quality. In areas where the conversion from custard apple to durian has occurred, the soil quality is good. Overall, research results show a trend of shifting from cassava and custard apple cultivation to durian. The spontaneous conversion of land use for high-value crops, combined with the indiscriminate use of fertilizers and pesticides, can alter soil quality indices (SQI), potentially leading to soil degradation and rendering the land unsuitable for these new crops. Although specific agronomic practices were not examined in this study, the findings regarding soil quality reflect the current conditions in the surveyed areas and serve as a basis for future crop conversion strategies.

4. CONCLUSION

This study assesses the soil quality of three land-use management practices in several communes in Tay Ninh, Vietnam, using Principal Component Analysis (PCA) with the support of scoring techniques (linear and nonlinear) to determine the SQI for each land-use type. The SQI values varied significantly ($p < 0.05$) depending on land use type. The SQI decreased in the following order: Custard apple > Durian > Cassava. The study also indicates that developing an SQI can be a key solution for monitoring the impacts of land-use changes, thereby contributing to the proposal of measures to manage soil quality. The findings confirm that regular soil quality assessment serves as a useful metric during the process of land-use conversion. Meanwhile, the SQI spatial distribution map provides a visual aid for farmers and agricultural officials when considering land-use planning and soil quality control measures for land-use conversion, aiming for sustainable agriculture. However, due to the limited number of samples and the lack of specific data on cultivated areas, the application of the interpolated spatial distribution map remains restricted; it serves primarily as a visual representation rather than a source of precise information.

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