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RESEARCH ARTICLE

Utilizing of principal component analysis and geographic information system approach for assessing soil quality index under different land uses: case study

Mustafa, A.A. *

Soil and Water Department, Faculty of Agriculture, Sohag University, 82524 Sohag, Egypt.

Abstract

One of the most popular indicators for delivering accurate information about soil quality is the soil quality index (SQI) that commonly calculated using principal component analysis (PCA). The purpose of this work is to evaluate a SQI using a PCA using additive and weights approaches presuming that different soil uses have varied effects on different soil attributes. Principal component analysis has been used to select a minimal dataset (MDS) from soils with various uses (old cultivated, new cultivated and barren soils) to construct SQI from nine soil indicators. The weights for each indicator were assigned by PCA to the SQI integrated by weights (SQI-W) from the MDS. While, the additive SQI (SQI-A) based on the MDS determined by PCA was finally generated. The results demonstrated that the SQI computed from the PCA using the weights and additive integration PCA could clearly distinguish between the three land uses. As a result, the two techniques were sensitive and capable to distinguish between the soils of the three land uses.

Keywords: Principal component analysis; Soil indicators; Soil quality index.

1. Introduction

One of the biggest problems facing humanity now is global food insecurity. By 2050, there will be a 70% increase in global food demand, and agricultural productivity will be a key factor in ensuring food security worldwide (Baroudy *et al.*, 2020). In addition, it is predicted that there will be more than nine billion people on Earth (Tahmasebinia *et al.*, 2020; Debiagi *et al.*, 2020). As a result, it is projected that both agricultural resources and land may be in limited supply. According to Xiang et al. and Gerten *et al.* (2020), this need calls for long-term evaluation. To enable sustainable soil management, a reliable assessment necessitates an accurate multifaceted quantification of soil quality (Gerten *et al.*, 2020). According to Karlen *et al.* (1997), soil quality is "the ability of a particular kind of soil to function, within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or improve the quality of water and air, and support human health and habitation." However, the calculation of SQI frequently necessitates the use of many variables for more precise decision-making, which increases the complexity and, occasionally, the expense of the task (Almeida *et al.*, 2011). A large number of variables can affect the attributes being evaluated. It is possible to reduce redundant and challenging-to-measure variables, cutting down on both the time and expense of trials (Leite *et al.*, 2009). According to Olive (2017), principal component analysis is employed in conjunction with a few linear combinations of the original variables to describe the dispersion structure. Hotelling first suggested Principal Component Analysis (PCA), a multivariate statistical technique, in 1933 (Huang and Wu, 2007). Principal component analysis (PCA) may analyse multivariate relationships and

.***Corresponding author:** **Abdel-rahman A. Mustafa**
Email: a_mustafa32@agr.sohag.edu.eg
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explain the variation in the data while decreasing the number of variables to various groups of people (Everitt and Dunn, 1992). This analysis is based on the principal component scores. According to Renchern (2002), this method may turn a data set with a large number of variables into a set of comprehensive principal components. It is relatively comparable to the correlation analysis and regression analysis methods. Researchers have used CA in a variety of fields because it permits a significant decrease in the number of variables and the detection of structure in the interactions between various variables (Renchern, 2002). According to Jolliffe & Cadima (2016), huge datasets are becoming more common in a variety of fields, and approaches are needed to significantly reduce their dimensionality in a form that can be understood in to comprehend such datasets. A small number of linear combinations (principal components) of a set of variables are obtained using principal component analysis (PCA) to preserve as much information about the original variables as feasible (Jolliffe, 1972; Jolliffe & Cadima, 2016; Olive, 2017). By choosing the principal components (PCs), eliminating the original variables, and excluding any outliers, according to Morais (2011), PCA helps to reduce the size of a data set. According to Jolliffe & Cadima (2016), PCA is one of the oldest and most popular techniques for performing it. For the research of SQI utilising Geographic Information System (GIS) technique, soil property characterisation, modelling, and mapping at various geographical and temporal scales are necessary (Burrough *et al.,* 2015; Estrada-Herrera *et al.,* 2017). Therefore, it could be advantageous to combine PCA analysis and GIS to map and identify the spatial variation of soil parameters in previously unstudied locations. The primary objective of the current study is to evaluate the SQI using PCA and GIS under various land uses in the southern Sohag Governorate, Egypt.

2. Materials and methods

2.1. Study area and soil samples

The investigated area locates in the southern direction of Sohag Governorate, Egypt. Geologically, the outcrops in the study area range in age from the Eocene to the Quaternary. According to Said (1960) and Conoco (1987), the lithostratigraphic units in the investigated region could be described as follows: The Eocene rocks are represented by Thebes's formation. This formation constitutes the foot of the eastern limestone scarp, extending from Wadi Abu Nafoukh in the south to Awlad El Sheikh in the north. It consists of massive and aminated limestone beds with flint bands and marl. The Late Pliocene or Early Pleistocene is represented by the Issawia formation. It is composed of lacustrine deposits of carbonate and clastic facies (Issawi et al., 1978; Omer, 1996). The Pleistocene and Holocene deposits represent the Quaternary deposits. In addition, this formation is widely distributed on both the surface and subsurface of the Nile Valley (Said, 1981). The area is generally characterized by hot summer and mild winter with low rainfall and high evaporation. There were three land uses investigated viz. old cultivated soils, newly reclaimed soils and barren soils. Based on these land uses and with the help of GPS, forty-eight sampling locations (represent different land uses) were selected (figure 1). Three composite soil samples at a depth of (0-60 cm) were collected in each location in November 2021. The collected soil samples were air-dried, gently ground, sieved through a 2 mm sieve, and stored in plastic containers for further analysis.

2.2. butterfly Soil samples analyses

The collected soil samples were analyzed for their properties such as: Particle size distribution (Piper, 1950); using the sodium hexametaphosphate for dispersion in calcareous soils (USSL Staff, 1954), calcium carbonate, cation exchange capacity and exchangeable sodium (Black, 1982); (ECe), soil pH, organic matter content (Jackson, 1973).

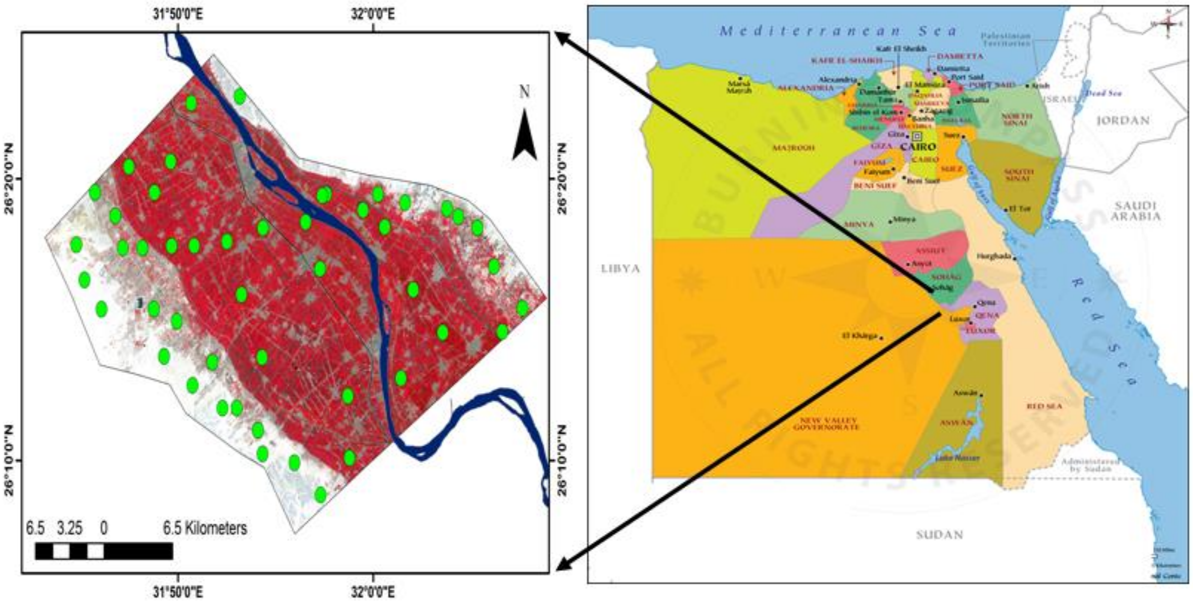


Figure 1. Location Map of study area and locations of soil samples.

2.3. Statistical analysis

The Statistica software version 7 (Stat Soft Inc.,2004) was used for computing minimum, maximum, mean, standard deviation and standard error. Before, PCA, the Pearson correlation coefficient was utilized to verify linear relationships among the soil variables. The Kaiser–Meyer–Olkin (KMO) method was used to assess the adequacy samples for the whole data set, with KMO values larger than 0.5 indicating the suitability of the data for PCA. In addition, data fitness was determined using the Bartlett test, and the results revealed a $p < 0.05$, which further confirmed the data fitness for PCA (Jolliffe and Cadima, 2016).

2.4. Soil quality index (SQI) determination

The first step is the selection of the minimum data sets (MDS) with PCA according to the procedure given by Andrews *et al.* (2002). The considered PCA is the principal component (PC) with an eigenvector $\lambda > 1$ and which were at least 5 % of the total accumulated variance. Secondly, linear transformations were carried out on each indicator to normalize all their values to the range between 0 and 1(Andrews *et al.*, 2002). Finally, the indicators were integrated to form the soil quality index (SQI):

Two approaches were used viz. the weighted (SQI-W) and the additive (SQI-A) by using the following equations (1) and (2), respectively:

$$SQI - W = \sum_{i=1}^{n} WiSi \ldots.. (1)$$

$$SQI - A = \sum_{i=1}^{n} \frac{Si}{n} \ldots\ldots (2)$$

where S_i is the normalized indicator and W_i is the weight of each indicator which calculated according to equation (3).

$$Weight = \frac{\%\, variancePCi}{\%Total\ variance} / \sum_{i=1}^{n} \frac{variancePCi}{\%Total\ variance} \ldots\ldots (3)$$

where % variance PC_i is the percentage of variance explained by the PC for indicator i, %Total variance is the percentage of variance explained by all the PCs in the MDS.

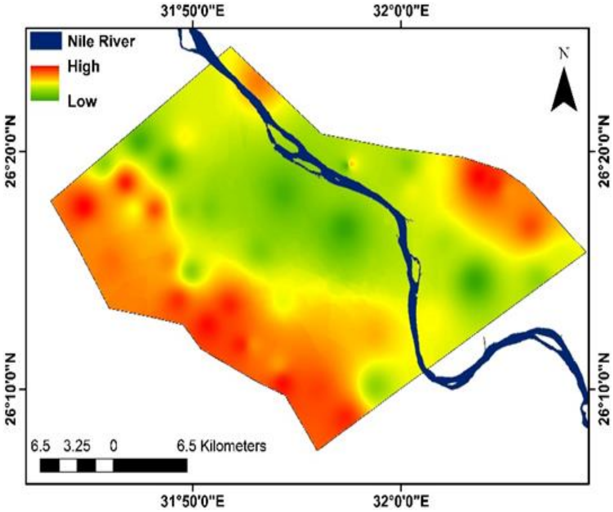
3. Results

3.1. Seasonal population dynamics of pomegranate butter fly, D. livia

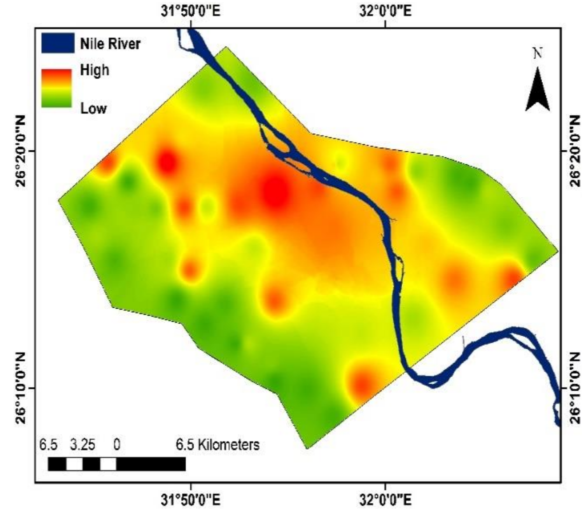
The summary of descriptive statistical analysis of the investigated soil parameters is presented in Table 1. The spatial variations maps of different soil indicators are shown in figure 2.

3.1.1. Old cultivated soils

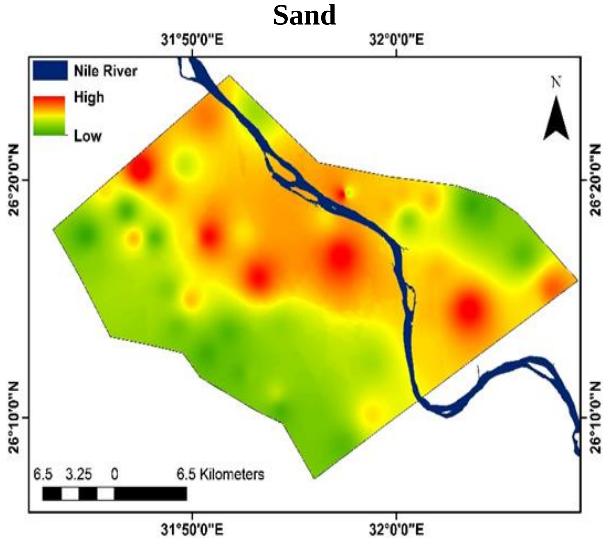
The sand fraction ranged from 26.21 to 75.00 %. In contrast, silt and clay fractions varied from 10.60 to 38.73% and 11.51 to 45.93 %, respectively. The soils were slightly to moderately alkaline, whereas the pH values of these soils varied from 7.44 to 8.21. These soils are non-saline soils, as all values are below 4 dS/m.



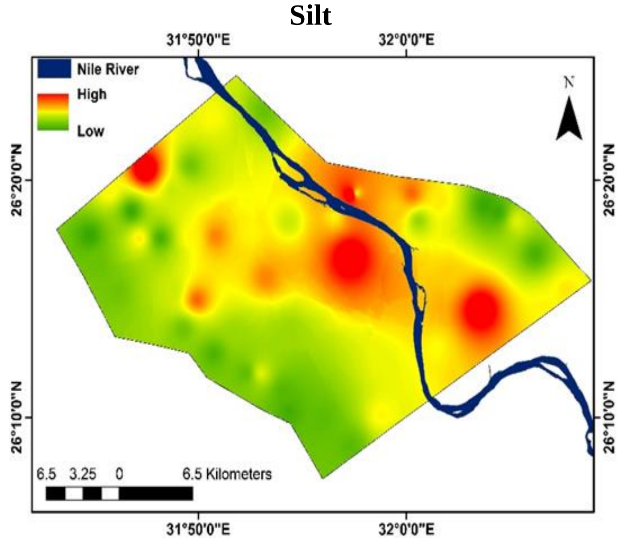
Sand



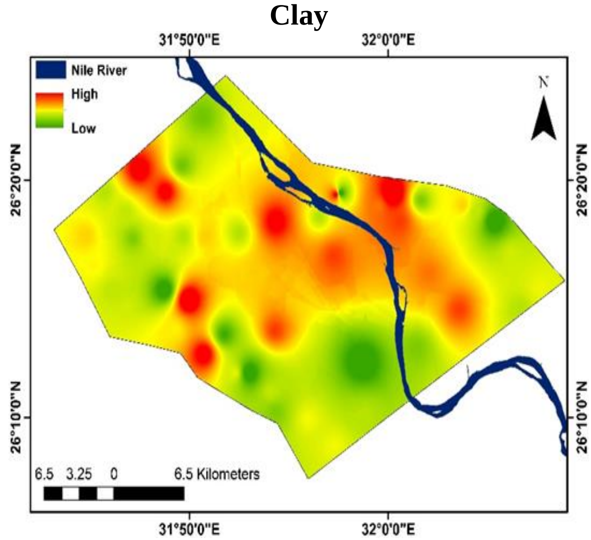
Silt



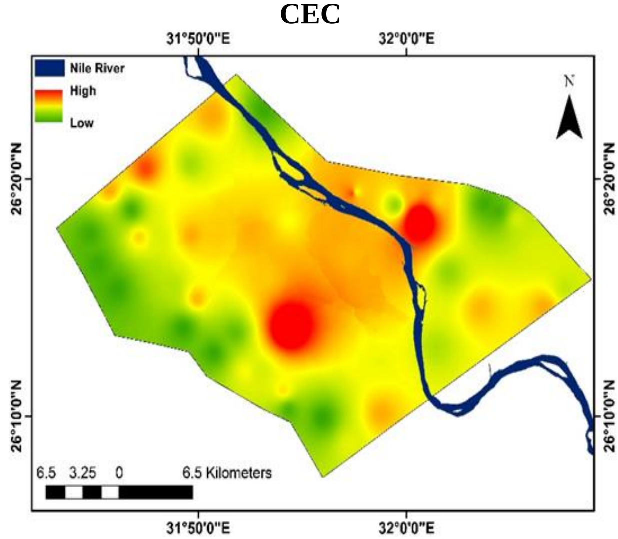
Clay



CEC



ESP



OC

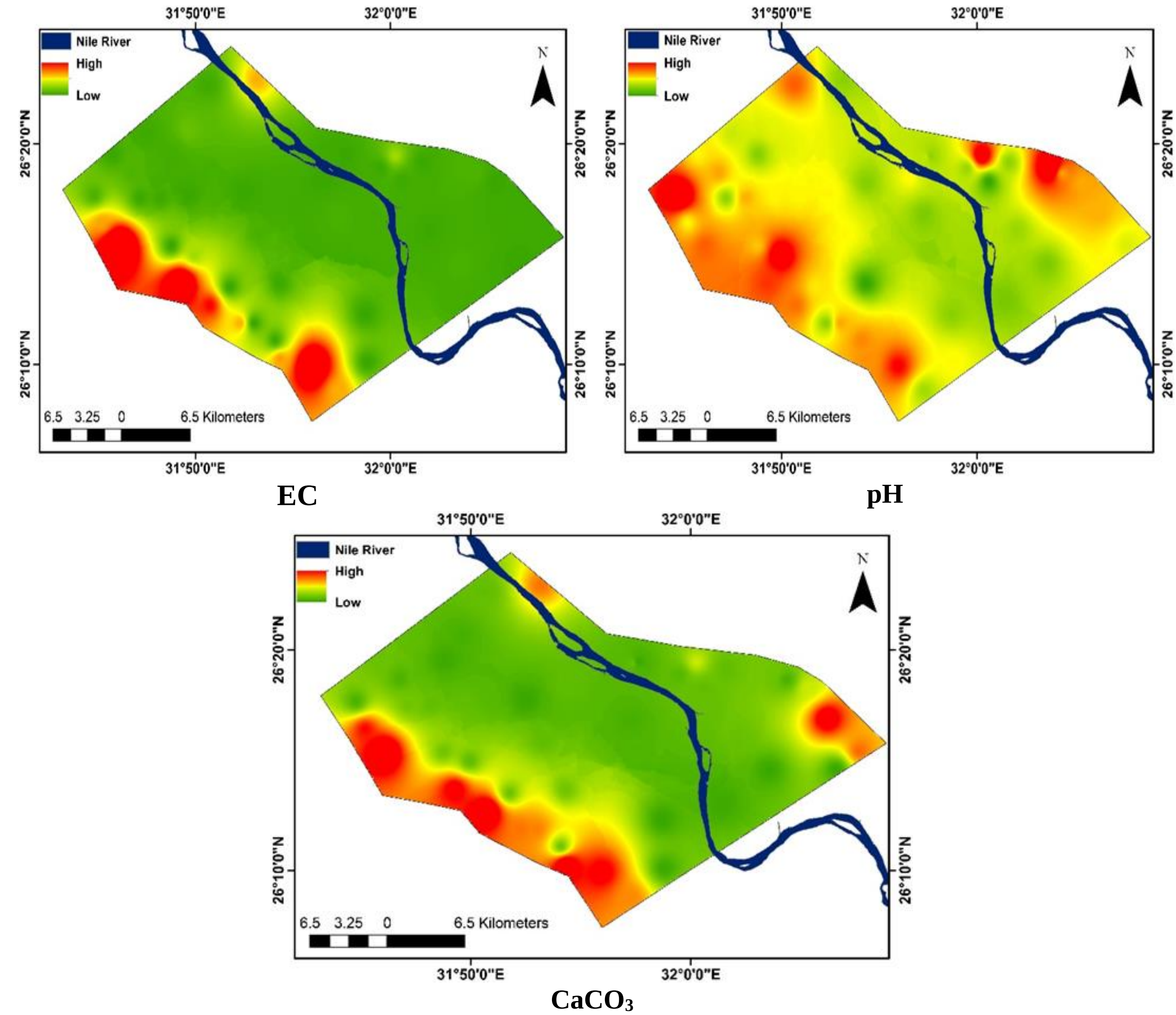


Figure 2. The spatial variations maps of different soil indicators

The cation exchange capacity ranges from 4.03 cmol+/kg to 17.43 cmol+/kg. The ESP values are low and range from 1.13 to 14.73 %. The soil organic carbon ranged between 0.29 to 1.46%, which indicated low to very high organic carbon content. Calcium carbonate content is low, which ranges from 0.53% to 4.96%.

3.1.2. Newly cultivated soils

These soils have a slightly higher coarse fraction and a lesser finer fraction than the previous soils. The average sand, silt, and clay values were 67.92, 12.55 and 19.56 %, respectively.

Some of these soils received different amounts of alluvium to enhance their properties. These soils are non-to slightly saline and range from slightly to moderately alkaline. The cation exchange capacity of these soils is low. The ESP values varied from low to high, ranging from 3.39 to 17.13%. The organic carbon content of these soils ranges between very low to moderately high in some soils that received different amounts of alluvium soils. These soils are calcic, and calcium carbonate content ranges from low to extremely high, which ranges from 2.21% to 31.35%.

3.1.3. Barren soils

These soils are uncultivated yet but maybe a prospective area for agricultural activities. These soils have the coarsest fractions (sandy texture class is dominant) compared to the previously discussed soils. These soils are very high saline and range from 7.65 to 24.15 dS/m. In addition, the organic carbon content is very low. These soils are calcic, which calcium carbonate content ranging from 17.67% to 38.12%. Cation exchange capacity and exchangeable sodium percentage are low.

Table 1. Descriptive statistical analysis of some soil characteristics

Land use	property	Mean	Minimum	Maximum	Standard Deviation	Standard Error
Old cultivated lands	sand	54.30	26.21	75.00	16.05	4.63
	Silt	20.25	10.60	38.73	9.24	2.67
	Clay	25.45	11.51	45.93	12.03	3.47
	CEC (Cmol+ kg^{-1})	8.19	4.03	17.43	3.40	0.98
	ESP	6.70	1.13	14.73	4.64	1.34
	OC (%)	0.54	0.29	1.46	0.31	0.09
	ECe (dSm^{-1})	0.68	0.26	1.98	0.48	0.14
	pHe	7.82	7.44	8.21	0.23	0.07
	CaCO3 (%)	2.49	0.53	4.96	1.70	0.49
Newly reclaimed soils	sand	67.92	29.46	93.45	20.61	5.95
	Silt	12.55	4.61	29.33	7.88	2.27
	Clay	19.56	2.00	48.95	14.60	4.21
	CEC (Cmol+ kg^{-1})	6.44	1.73	18.05	4.92	1.42
	ESP	9.04	3.39	17.13	3.91	1.13
	OC (%)	0.31	0.03	0.79	0.26	0.07
	ECe (dSm^{-1})	0.96	0.31	3.65	0.94	0.27
	pHe	7.98	7.66	8.72	0.33	0.10
	CaCO3 (%)	14.28	2.21	31.35	10.74	3.10
Desert soils	sand	85.48	74.73	92.00	6.37	2.01
	Silt	5.50	2.00	13.00	3.17	1.00
	Clay	9.02	3.80	15.08	3.92	1.24
	CEC (Cmol+ kg^{-1})	3.35	2.25	3.92	0.55	0.17
	ESP	8.77	5.36	15.33	2.66	0.84
	OC (%)	0.11	0.01	0.45	0.17	0.05
	ECe (dSm^{-1})	13.19	7.65	24.15	6.47	2.04
	pHe	7.99	7.65	8.32	0.25	0.08
	CaCO3 (%)	27.94	17.67	38.12	8.32	2.63

3.2. Bartlett's test of sphericity and the KMO test of sampling adequacy

Table 2 displays the outcomes of the KMO test of sample adequacy and Bartlett's test of sphericity. The variables are not completely uncorrelated, and PCA is appropriate for the dataset because the observed chi-square value was 141.2, which is larger than the critical chi-square value of 52.4 and the significance level of Bartlett's test of sphericity was 0.0001 (Hutcheson and Sofroniou, 1999). Following Barrett and Morgan (Barrett and Morgan, 2005), the results demonstrate that the KMO value is more than 0.6, indicating that the sample size is adequate for evaluating the factor structure. The variables are not entirely uncorrelated, according to the findings of these tests; the variables in the model can describe the occurrence, and therefore a principal component analysis is appropriate (Huck *et al.,* 2012; Tabachnick and Fidell, 2007).

3.3. Selection of the minimum data set (MDS) and calculation of the weights (Wi)

3.3.1. MDS generated from a principal component analysis

Table 3 provides a summary of the PCA outcomes. Since the eigenvalues of the first two Principal Components (PCs) are greater than one, these PCs were used while the remaining PCs were excluded (Figure 3). According to the findings, the first two PCs account for 73.75% of the overall variance. The first PC, which explains 58.92% of the total variation, has larger positive correlations with silt, clay, CEC, and OC, according to the factor loadings. While the negative relationships between sand, EC, pH, and CaCO3 are stronger. The second PC, which accounts for 14.83% of the overall variance, has a very poor correlation with ESP. The PC1 was chosen as an indication for PC1 in the MDS because it had the highest loading of all variables. The ESP, which has the highest loading in PC2, was chosen as an indicator for PC2 in the MDS due to its higher loading.

Table 2. The Kaiser- Meyer-Olkin (KMO) and Barlett Sphericity tests

KMO Measure of samples Adequacy	KMO	0.78
Barlett test of Sphericity	Chi-Square (observed)	141.2
	Chi-Square (Critical)	52.4
	P- value	<0.0001
	Alpha	0.05

Table 3. Summarization of Principal Component Analysis

		PC1	PC2
Eigenvalue		5.30	1.33
Total variance (%)		58.92	14.83
Cumulative %		58.92	73.75
Sand	Factor loadings	-0.95	0.18
Silt		0.83	0.04
Clay		0.86	-0.31
CEC		0.87	-0.35
ESP		0.55	-0.65
OC		0.74	0.30
EC		-0.63	-0.53
pH		-0.48	-0.39
CaCO3		-0.85	-0.38
Sand	Factor Score Coefficient (FSC)	-0.18	0.13
Silt		0.16	0.03
Clay		0.16	-0.23
CEC		0.16	-0.27
ESP		0.10	-0.49
OC		0.14	0.22
EC		-0.12	-0.39
pH		-0.09	-0.29
CaCO3		-0.16	-0.28

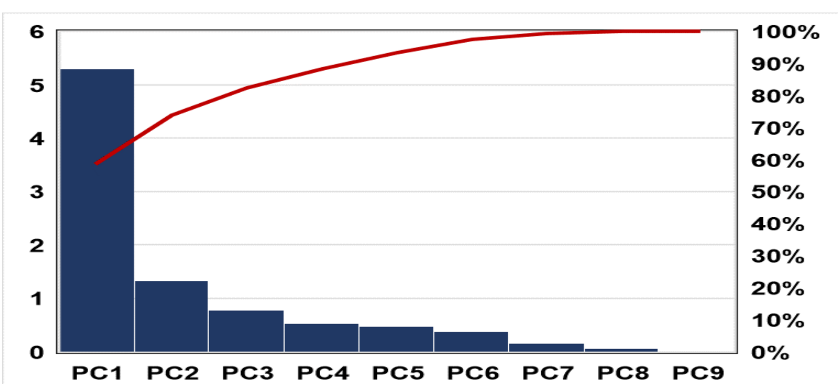


Figure 3. plot for the different components considered for the principal component analysis with eigenvalues.

3.3.2. Calculation of the SQI

Due to their beneficial role in the proper functioning of the soils, the indicators silt, clay, CEC, and OC were regarded as the "more is better" type for the soils in this study while calculating the scores (Si) of the MDS indicators chosen by PCA (Brady and Weil, 2014). While the availability of the major micronutrients in the pH values is negatively impacted by pH (Kabata-Pendias and Pendias, 2001), and coarse particle size negatively impacts soil nutrient retention capacity (Brady and Weil, 2014), the indicator sand, ESP, EC, and pH were considered to be "less is better" in contrast. The weights assigned to each indicator in equation (1) were used to calculate the SQI integrated by weights (SQI-W) from the MDS. While, the final expression of the additive SQI (SQI-A) based on the MDS identified by PCA was described by equation (2). Table (4) displays the results of the descriptive statistical analysis of the SQI-W and SQI-A.

Table 4. The descriptive statistical analysis of SQI-W and SQI-A

SQI	Land Use	Valid N	Mean	Minimum	Maximum	SD	SE
PCA-W	Old cultivated soils	23	2.83	1.73	4.12	0.71	0.15
	Newly cultivated soils	16	1.53	0.80	2.19	0.50	0.13
	Barren soils	9	0.69	0.21	1.14	0.38	0.13
PCA-A	Old cultivated soils	23	0.56	0.45	0.67	0.06	0.01
	Newly cultivated soils	16	0.37	0.17	0.52	0.11	0.03
	Barren soils	9	0.24	0.14	0.33	0.07	0.02

3.4. Comparison of the SQI calculated by PCA-W and PCA- A

SQI applied on the calibration set's soils. The SQI, which was derived using the PCA, weights, and additive integration PCA, distinguished the three land uses clearly ($P < 0.05$). Due to their sensitivity and ability to distinguish between the three soil uses investigated, both were found to be effective (figures 4 and 5). Figure 6 illustrates the regional variations of SQI obtained using the PCA and applying the weights and additive integration PCA.

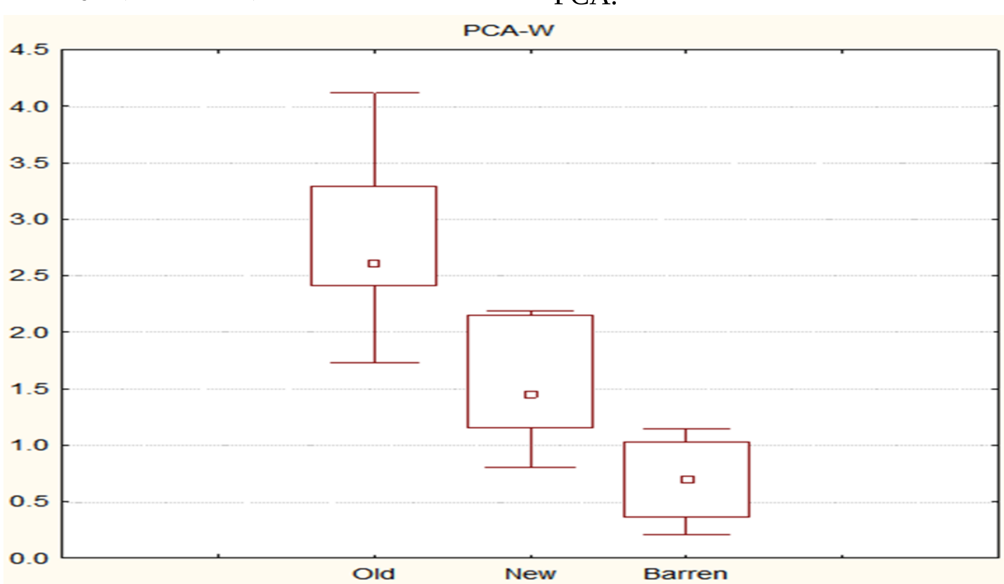


Figure 4. A box-whisker graph showing the minimum, maximum, median, lower quartile (25%), and upper quartile (75%) of SQI using PCA-W.

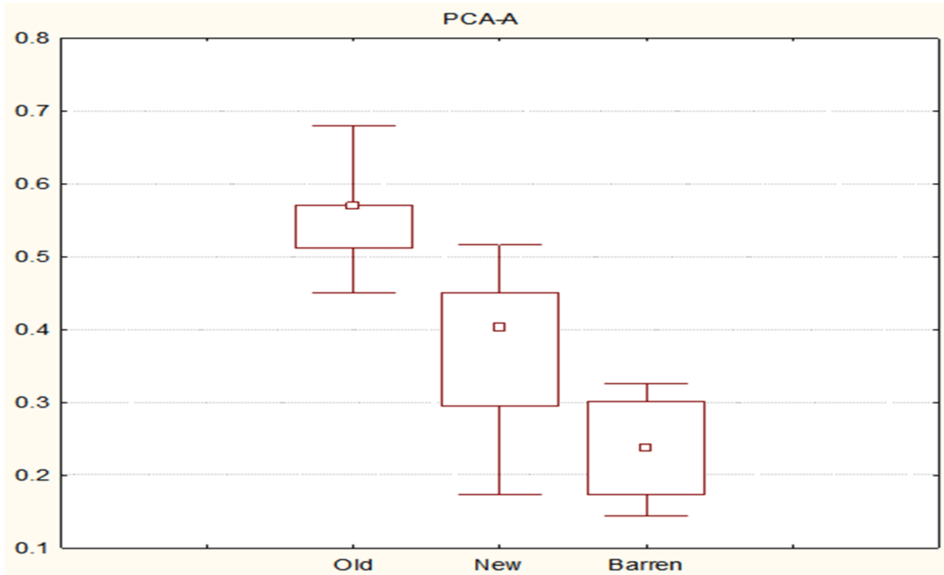


Figure 5. A box-whisker graph showing the minimum, maximum, median, lower quartile (25%), and upper quartile (75%) of SQI using PCA-A.

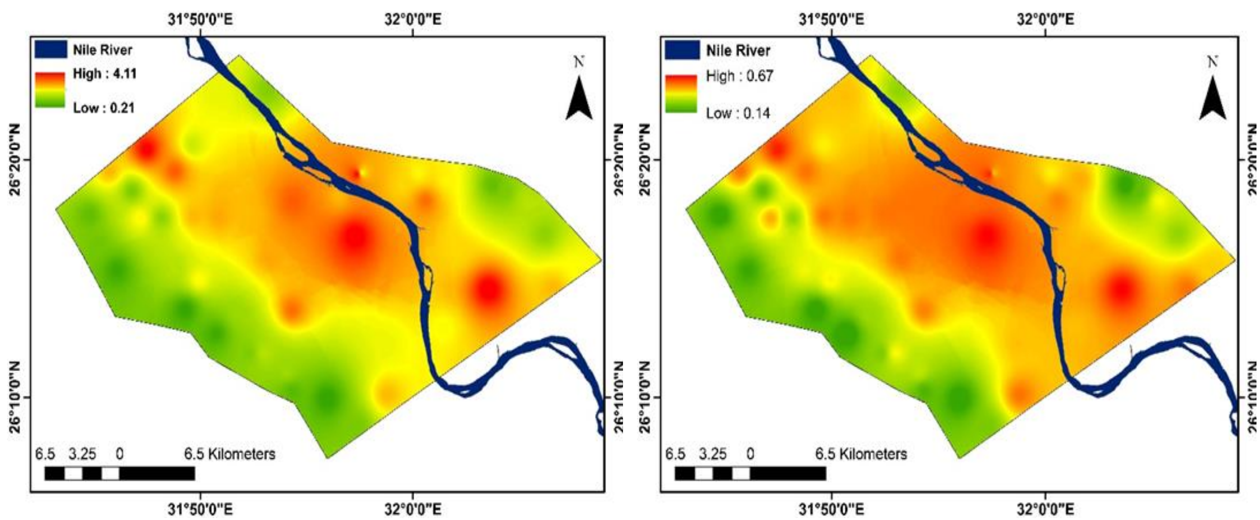


Figure 6. The spatial variations of SQI calculated from the PCA.

3.5. Pearson Correlation Matrix between soil indicators and SQI –W and SQI-A

Table 5 provides a list of the correlations between soil indicators. All other soil indicators, except for ECe, pH, and $CaCO_3$ content, show a statistically significant positive connection ($p < 0.05$) with the sand fraction. Silt and clay have significant positive correlations with CEC with correlation coefficients 0.59 and 0.89, respectively. While $CaCO_3$ has significant negative correlation (r= -0.69 and -0.65, respectively). However, there is no statistically significant positive link between CEC and ESP and OC contents. Except for sand, where there was a negative association, all indices and soil ESP have non-significant positive correlations ($p < 0.05$). The findings demonstrate that ECe and $CaCO_3$ and sand content have a significant positive connection ($p < 0.05$). Simultaneously, there were positive associations between ECe and silt, clay, CEC, and OC. In contrast to its substantial negative association with sand, ECe, pH, and $CaCO_3$, the soil organic carbon exhibits a significant positive correlation (p 0.05) with silt, clay, and CEC. Silt, clay, CEC, and OC all have a significant negative connection with calcium carbonates (p 0.05). In contrast, it shows a non-significant negative association with ESP and a strong positive correlation with both sand and ECe. Regarding the relationship between SQI and soil indicators, sand, EC, pH, and $CaCO_3$ all exhibit significant negative correlations with SQI calculated either using weights or additive techniques. SQI, on the other hand, significantly positively correlated with silt, clay, CEC, and OC. Additionally, SQI-W and SQI-A showed negligible differences, with excellent positive correlation coefficients (r) of 0.952 (figure 7).

Table 5. Correlation coefficients among soil properties

	Sand	Silt	Clay	CEC	ESP	OC	EC	pH	$CaCO_3$	SQI-W	SQI-A
Sand	1.00										
Silt	-0.85	1.00									
Clay	-0.92	0.58	1.00								
CEC	-0.85	0.59	0.89	1.00							
ESP	-0.37	0.39	0.29	0.29	1.00						
OC	-0.62	0.64	0.49	0.53	0.19	1.00					
EC	0.47	-0.47	-0.38	-0.37	0.14	-0.50	1.00				
pH	0.34	-0.35	-0.27	-0.24	0.06	-0.39	0.34	1.00			
$CaCO_3$	0.75	-0.69	-0.65	-0.66	0.16	-0.66	0.71	0.48	1.00		
SQI-W	-0.92	0.82	0.82	0.83	0.30	0.75	-0.66	-0.52	-0.79	1.00	
SQI-A	-0.91	0.79	0.83	0.81	0.08	0.74	-0.70	-0.55	-0.91	0.96	1.00

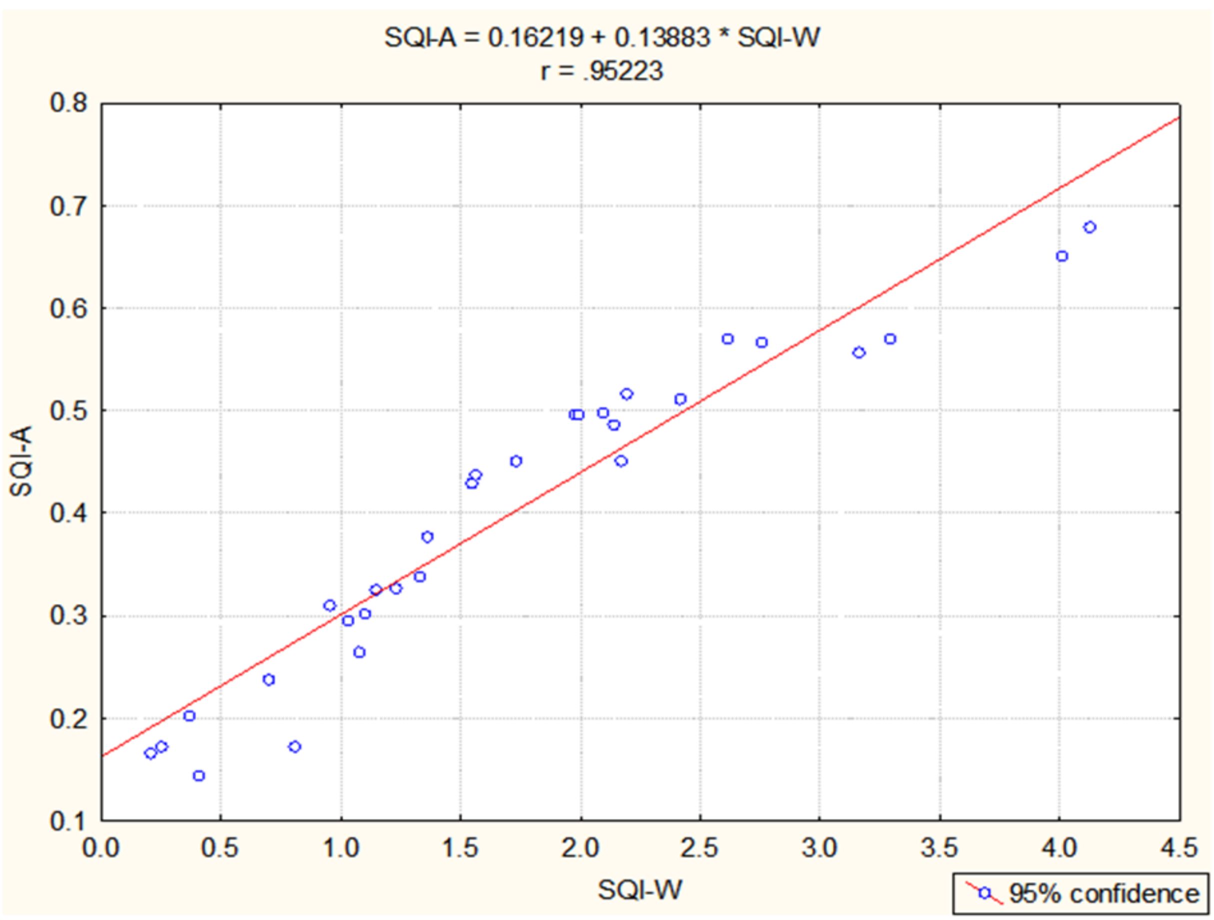


Figure 7. The correlation between SQI calculated from the PCA

4. Conclusion

The capacity to choose soil quality indicators by PCA that create a minimal data set (MDS) with which to calculate soil quality indices (SQI) capable of discriminating soil quality has been investigated in this study, presuming that diverse land uses yield soils with varying qualities. To do this, principal component analysis (PCA), the method often used to calculate the SQI, was utilised to analyse soil samples from three different land uses (old cultivated, newly cultivated, and barren). The analysis revealed variations in the soil quality. We think that future studies on soil quality and other edaphological studies may benefit from the PCA.

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Institutional Review Board Statement
All Institutional Review Board Statements are confirmed and approved.
Data Availability Statement
Data presented in this study are available on fair request from the respective author.
Ethics Approval and Consent to Participate
Not applicable
Consent for Publication
Not applicable.
Conflicts of Interest
The author disclosed no conflict of interest starting from the conduct of the study, data analysis, and writing until the publication of this research work

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