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Quantitative Evaluation of Soil Quality Using Principal Component Analysis: The Case Study of El-Fayoum Depression Egypt

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Abstract: Soil quality assessment is the first step towards precision farming and agricultural management. In the present study, a multivariate analysis and geographical information system (GIS) were used to assess and map a soil quality index (SQI) in El-Fayoum depression in the Western Desert of Egypt. For this purpose, a total of 36 geo-referenced representative soil samples (0–0.6 m) were collected and analyzed according to standardized protocols. Principal component analysis (PCA) was used to reduce the dataset into new variables, to avoid multi-collinearity, and to determine relative weights \( Wi \) and soil indicators \( Si \), which were used to obtain the soil quality index (SQI). The zones of soil quality were determined using principal component scores and cluster analysis of soil properties. A soil quality index map was generated using a geostatistical approach based on ordinary kriging (OK) interpolation. The results show that the soil data can be classified into three clusters: Cluster I represents about 13.89% of soil samples, Cluster II represents about 16.6% of samples, and Cluster III represents the rest of the soil data (69.44% of samples). In addition, the simulation results of cluster analysis using the Monte Carlo method show satisfactory results for all clusters. The SQI results reveal that the study area is classified into three zones: very good, good, and fair soil quality. The areas categorized as very good and good quality occupy about 14.48% and 50.77% of the total surface investigated, and fair soil quality (mainly due to salinity and low soil nutrients) constitutes about 34.75%. As a whole, the results indicate that the joint use of PCA and GIS allows for an accurate and effective assessment of the SQI.

Keywords: soil quality index; soil evaluation; geographic information; cluster analysis

1. Introduction

Precision agriculture is based on the use of a set of techniques and technologies devised to assess the spatial variability of soil and plant properties to facilitate and optimize soil management, which often requires the use of several variables to support decision-making [1,2]. However, in some cases, numerous soil variables are required to assess soil quality. Because some of these variables can be redundant, the ability to identify key parameters/variables can reduce both the time and costs of in situ and laboratory analyses and optimize models and procedures for spatio-temporal soil assessment [3]. In this context, principal component analysis (PCA) is recognized as one of the most widely used methods for reducing the number of variables by identifying those that are most
significant in the data. In addition, PCA is useful for different aspects of farming processes, for example, the assessment of vegetative growth and the discrimination of maturation stages needed for optimizing the modeling of crop yield. The spatial variability of the chemical/physical attributes of soil is generally denoted by the Soil Quality Index (SQI) [4]. Since soil quality is linked to soil productivity, a reliable assessment requires an accurate multi-faceted quantification to support sustainable soil management [5]. The SQI is defined as the ability (within the ecosystem) of the soil to supply plants with the nutrients needed to maintain the crop yield throughout growth stages [6–8]. The SQI includes physical, chemical, and biological characteristics, which can be used to indicate the fertility status and soil health [9] through a quantitative assessment [10]. The physical indicators include soil depth, bulk density, porosity, aggregate stability, texture, and compaction, whereas the chemical indicators include pH, salinity, organic matter content, phosphorus availability, cation exchange capacity, nutrient cycling, and the level of contaminants in the soil [11]. The physical indicators inform us of the root growth, speed of plant emergence, and water infiltration, while the chemical indicators provide information on organisms and nutrient availability, as well as water for plants and the mobility of contaminants [9]. Rangel-Peraza et al. [12] reported a highly significant correlation between chemical soil properties (electric conductivity (EC), pH, cation exchange capacity (CEC), and organic matter (OM)) and the soil quality index. The major factors that influence soil quality are bulk density, soil CEC, root depth, and soil texture [13]. Hence, understanding the soil quality is important for illustrating the potential steps of proper soil management for sustainable agricultural production [14]. Recently, several methods have been developed for estimating soil quality, including quantitative and qualitative methods [11,15]. The quantitative and qualitative evaluations of soil quality are linked to the diagnostic properties of the soil. Mohamed et al. [16] and Martínez-Salgado, Gutiérrez-Romero, Janssens, and Ortega-Blu [9] reported that certain features are closely related to the soil quality (including visual indicators), such as erosion, the presence of weeds, color, and the types of coverage. Quantitative assessments of soil quality depend on data obtained from laboratory analyses of physical and chemical properties, while qualitative assessments depend on direct observation of the soil [8]. Moreover, the spatio-temporal dimensions must be considered in the SQI assessment, because soil properties are not permanent characteristics [17–19]. The use of Geographic Information System (GIS) technology has facilitated the computation of the spatial variability of different phenomena [20], including investigations on soil properties. Therefore, integrated GIS and geostatistical analyses can be useful for assessing the spatial variation of soil properties and predicting them in unsampled locations. For example, the use of variogram analyses can capture and accurately map the complex spatial relationships between soil data layers [21–23]. Kriging is one of the most commonly used interpolation methods [24], and it can suitably support precise farming based on the identification of homogeneous sub-sets of similar yield-limiting factors [25,26]. PCA and cluster analysis are among the most widely used multivariate analysis methods for the recognition, classification, and modeling of data [27], including for soil investigations. PCA is a statistical approach that is useful for reducing the number of features in the dataset through the identification of the most important principal components (PCs), which explain the maximum information content present in the data [28]. PCA has many advantages:

1. Removes correlated features that undermine the statistical significance of an independent variable [29];
2. Improves algorithm performance, which can be significantly degraded if too many features are present in models, and speeds up analyses [30];
3. Reduces overfitting: PCA helps in overcoming the overfitting issue by minimizing the number of variables in the investigated dataset [31];
4. Improves visualization: PCA transforms a high-dimensional dataset into a low-dimensional one while preserving the information content and making data visualization and exploration easier [32,33]
The main aim of the present study is to assess, characterize, and map the SQI using a multivariate analysis based on the joint use of PCA and GIS in El-Fayoum depression in the Western Desert of Egypt.

2. Materials and Methods

2.1. Study Area

The study area is located in El-Fayoum Governorate, Western Desert of Egypt. It is bounded by latitudes 29°15′–29°35′ N and longitudes 30°32′30″–30°52′30.59″ E. The study area is characterized by an elevation that reaches 23 m above sea level. The area is connected to the Nile River by the Hawara canal through the Bahr Yousef canal (Figure 1). The physiographic units of El-Fayoum depression include three main landscapes, i.e., lacustrine plain, fluvio-lacustrine plain, and alluvial plain [34]. The main landforms in the area are recent and old lake terraces, depressions, plains, and basins [35] with varying vegetation cover; therefore, the sensitivity to desertification differs widely in the study area [36]. The climate of the study area is characterized by a hot and dry summer with limited winter rainfall and bright sunshine throughout the year. The area has low annual rainfall of around 7.2 mm/year, and the mean minimum and maximum annual temperatures are 14.5 and 31.0 °C, respectively. The lowest evaporation rate (1.9 mm/day) is recorded in January, while the highest value (7.3 mm/day) is recorded in June [34].

Figure 1. Study area and locations of soil samples.

2.2. Sampling and Soil Analysis

The soil samples were collected using GPS and a soil cylinder auger (Figure 1) at depths of 0–60 cm in 36 different locations. One mixed sample in each location was collected that represents the soil of root zone. The selected sites represent spatial changes in the study area, which is characterized by wide variation of physiographic features, such as lacustrine plain, fluvio-lacustrine plain, and alluvial plain [34]. The area is characterized by slope levels ranging between −15 and 45 m above sea level, and the change in slope has directly affected vegetation density and land suitability [37]. The soil classifications in the study area include Vertic Torrifluvent, Typic Haplocalcids, Typic Torrifluvents, Typic Haplogypsids, Typic Haplosalids, Typic Torripsamments, and Typic Haplargids [34]. The samples were air-dried, ground, and passed through a 2 mm sieve to prepare them for physical and chemical analyses according to standardized protocols described.
in [38–40]. The soil reaction (pH) of a 1:2.5 soil-to-water suspension was measured using a glass electrode [39]. The soil electrical conductivity was assessed in saturated soil paste extract (ECe) [39]. The Walkley and Black method was used to determine the soil organic matter [38,40]. Available nitrogen was determined by distillation using the micro-Kjeldahl method [40]. Available phosphorus was determined calorimetrically using the ascorbic acid method [40]. Available potassium was extracted with 1N NH4OAc at pH 7 and was measured using a flame-photometer device [40]. The exchangeable sodium percentage (ESP) was computed based on the mathematical equation described by van Reeuwijk [38]. The sodium acetate method was used to measure CEC [38]. Soil particle analyses were performed according to an international pipette method and based on the percentage of sand, silt, and clay; the soil texture was determined using the international texture triangle [38].

### 2.3. Statistical Analysis

Descriptive statistics of the studied soil characteristics include the minimum, maximum, arithmetic mean, and standard deviation, which were computed using SPSS version 25. The Shapiro–Wilk test was used to assess the normal distribution of the data. The Pearson correlation coefficient (r) was used to examine the linear relationships between the variables. XLSTAT software 2016 and SPSS version 25 were used to conduct the principal component analysis (PCA). PCA was used to reduce the dataset into new variables, which are called principal components (PCs), as well as to avoid multicollinearity between the original variables. These PCs explain most of the variation present in the original variables.

### 2.4. Soil Quality Index (SQI) Calculation and Mapping

The SQI was calculated using Equation (1) according to Cude [41]:

\[
SQI = \sum_{i=1}^{N} W_i \times S_i
\]

(1)

where \( W_i \) is the relative weight of each indicator and has values ranging between 0 and 1, and \( S_i \) is the value of each soil indicator.

\( W_i \) expresses the component score coefficient (CSC) that is obtained from the PCA results. Because the soil indicators have different scales and units, the \( S_i \) values are standardized using Equation (2) [42]:

\[
z = \frac{x - \bar{x}}{\sigma}
\]

(2)

where \( z \), \( x \), \( \bar{x} \) and \( \sigma \) refer to the standardized value, the value of a soil indicator, the average of a soil indicator, and the standard deviation of a soil indicator, respectively.

Therefore, the SQI equation based on principal components (PCs) becomes the following (Equation (3)):

\[
SQI - PC = \sum_{i=1}^{N} CSC \times z
\]

(3)

Thus, the comprehensive SQI (CSQI) is computed using Equation (4):

\[
CSQI = \sum_{i=1}^{N} \text{Variability of each PC} \times SQI - PC
\]

(4)

The CSQI, which is calculated using \( z \) scores, is transformed into a standard normal distribution (which has a mean of zero and a standard deviation of one) using Equation (5) [42]:

\[
f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x)^2}{2}}
\]

(5)
where $e$ and $z$ refer to the natural logarithm, equal to approximately 2.718, and the CSQI, which is computed using $z$ scores, respectively.

Aprisal, Bambang, and Harianti [13] reported that the soil quality could be classified into the following conditions: very good (0.8–1), good (0.6–0.79), fair (0.35–0.59), bad (0.20–0.34), and very bad (0–0.19).

2.5. Cluster Analysis

From the PC scores of soil samples, a cluster analysis was performed using $k$-means to categorize the observations into groups [43–45]. This analysis was applied to classify the soils into specific zones according to their properties. A one-way ANOVA test and Duncan multiple range (DMR) test were performed for comparisons between the different soil zones that were generated.

The cluster analysis results were also simulated using the Monte Carlo approach, one of the most popular and widely used methods for simulation and probabilistic analyses based on the generation of a large number of random samples. This step was adopted to confirm the clusters obtained from the previous analyses [46,47].

2.6. Geostatistical Analyses

The geostatistical approach was adopted to predict the values of variables in unsampled locations using the ordinary kriging (OK) method. Semivariograms of the soil parameters were generated using the average squared differences among all pairs (Equation (6)) [48]:

$$
\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (Z(x_i) - Z(x_i + h))^2
$$

(6)

where $\gamma(h)$ is the semivariance of the distance interval $h$, $N(h)$ is the number of pairs of the lag interval, $Z(x_i)$ is the measured sample value at point $i$, and $Z(x_i + h)$ is the measured sample value at position $(i + h)$.

The best semivariogram models were selected based on strong spatial dependence (SDC), mean error (ME), root-mean-square error (RMSE), mean standardized error (MSE), root-mean-square standardized error (RMSSE), and average standard error (ASE). If the values of ME, MSE, and ASE are close to zero and the RMSE is close to one, this indicates that the quality and suitability of the predicting model are high [49]. In addition, ratios of nugget to sill (SDC) of <0.25, 0.25–0.75, and >0.75 indicate strong, moderate, and weak spatial dependence, respectively [50].

A spatial distribution map of the soil quality index was generated using ordinary kriging interpolation in ArcGIS software version 10.2, where the kriging method was applied to predict the values of variables in unsampled locations and to interpolate the spatial soil properties using Equation (7) [51]:

$$
Z^*(x_o) = \sum_{i=1}^{N} \lambda_i Z(X_i)
$$

(7)

where $Z^*(x_o)$ is an estimated variable at location $x_o$, $Z^*(X_i)$ is the value of an inspected variable at location $X_i$, $\lambda_i$ is the statistical weight that is attributed to $Z^*(X_i)$ for a sample located near $x_o$, and N is the number of observations in the neighborhood of the inspected point. The flowchart of the procedures used to determine the soil quality index in this study is shown in Figure 2.
3. Results and Discussion

3.1. Soil Characteristics of the Study Area

The soil characteristics of the study area are listed in Table 1. In particular, the pH values range from 7.09 to 8.65, with an average value of 7.86 ± 0.47, which indicates that the conditions of the study area are mildly/strongly alkaline [40]. The results indicate that the study area is characterized by moderate to high salinity soils, with ECe values varying from 0.87 to 20.33 dSm$^{-1}$ with an average value of 5.30 ± 5.05 dSm$^{-1}$ [52]. The CEC of the study area varies within a wide range, between 3.45 and 40.23 cmolckg$^{-1}$ soil, with an average of 20.62 ± 8.79 cmolckg$^{-1}$ soil.

The ESP values range from 1.86 to 17.13, with an average of 9.75 ± 3.67, which indicates that the area is not exposed to sodicity hazards [53]. The OM contents range from low to high in the study area, in agreement with [40], with an average of 0.69 ± 0.46. The available N ranges between 1.33 mg kg$^{-1}$ (2.98 kg N ha$^{-1}$) and 61.6 mg kg$^{-1}$ (138 kg N ha$^{-1}$) with an average of 19.91 ± 17.42 mg kg$^{-1}$ (44.6 ± 39 kg N ha$^{-1}$), indicating that the nitrogen content in the area is low [40]. The available P content ranges from low (2.33 mg kg$^{-1}$; 12.0 kg P ha$^{-1}$) to high (19.84 mg kg$^{-1}$; 101 kg P ha$^{-1}$), with an average of 9.50 ± 4.51 mg kg$^{-1}$ (48.7 kg P ha$^{-1}$), and available K ranges from low (32.76 mg kg$^{-1}$; 88.1 kg K ha$^{-1}$) to high (734 mg kg$^{-1}$; 1972 kg K ha$^{-1}$), with an average of 183.5 ± 193 mg kg$^{-1}$ (493 ± 519 kg K ha$^{-1}$), which is classified as high according to [40]. The soil texture, which refers to the proportions of silt, clay, and sand, varies from 8.19 to 44.76%, 24.98 to 62.09%, and 12.98 to 55.95%, respectively.

Figure 2. The flowchart of the procedures for the soil quality evaluation.

Where Z*(xo) is an estimated variable at location xo, Z*(Xi) is the value of an inspected variable at location Xi, λi is the statistical weight that is attributed to Z*(Xi) for a sample located near xo, and N is the number of observations in the neighborhood of the inspected point.
Table 1. Soil characteristics of the study area.

| Property                  | N | Minimum | Maximum | Mean  | Std. Deviation | Shapiro–Wilk |
|---------------------------|---|---------|---------|-------|----------------|--------------|
| pH                        | 36| 7.09    | 8.65    | 7.86  | 0.47           | 0.06         |
| EC, dS/m                  | 36| 0.87    | 20.33   | 5.3   | 5.05           | <0.0001      |
| CEC, cmol/c/kg soil       | 36| 3.45    | 40.23   | 20.62 | 8.97           | 0.7          |
| ESP                       | 36| 1.86    | 17.13   | 9.75  | 3.67           | 0.23         |
| OM, %                     | 36| 0.07    | 1.77    | 0.69  | 0.46           | 0.04         |
| N, mg kg⁻¹                | 36| 1.33    | 61.55   | 19.91 | 17.42          | 0            |
| P, mg kg⁻¹                | 36| 2.33    | 19.84   | 9.5   | 4.51           | 0.08         |
| K, mg kg⁻¹                | 36| 32.76   | 733.77  | 183.52| 193.09         | <0.0001      |
| Silt, %                   | 36| 8.19    | 44.76   | 26.58 | 8.98           | 0.615        |
| Clay, %                   | 36| 24.98   | 62.09   | 42.54 | 10.055         | 0.193        |
| Sand, %                   | 36| 12.98   | 55.94   | 30.88 | 12.31          | 0.078        |

3.2. Pearson Correlation Matrix, Bartlett’s, and Kaiser Meyer Olkin (KMO) Tests

The correlations between soil indicators are listed in Table 2. The soil pH has a statistically significant negative relationship \((p < 0.05)\) with all other soil indicators except for silt content (which exhibits a significant positive relationship). Soil EC has significant positive correlations \((p < 0.05)\) with N \((r = 0.59)\), P \((r = 0.43)\), ESP \((r = 0.55)\), and clay \((0.35)\), while its correlations with K \((r = 0.30)\), CEC \((r = 0.23)\), and organic matter \((r = 0.26)\) are positive but not significant. The results show that EC has a significant negative relationship with pH and silt \((p < 0.05)\). The soil organic matter has a significant positive correlation \((p < 0.05)\) with CEC, available N, available P, available K, and clay, while it has a non-significant positive correlation \((r = 0.24)\) with ESP and a non-significant negative correlation \((r = −0.06)\) with silt. CEC is significantly positively correlated \((p < 0.05)\) with available N, P, K, ESP, and clay, while it has a non-significant positive correlation with silt. Available N is significantly positively correlated \((p < 0.05)\) with available P, available K, ESP, and clay, and it has a significant positive correlation with silt. Available P is significantly positively correlated \((p < 0.05)\) with available K, ESP, and clay and negatively correlated with silt. Available K has a significant positive correlation \((p < 0.05)\) with clay, while it has a non-significant positive correlation with ESP and non-significant negative correlation with silt.

Table 2. Correlation coefficients among soil properties.

| Variables | pH | EC  | OM  | CEC | N   | P   | K   | ESP | Silt |
|-----------|----|-----|-----|-----|-----|-----|-----|-----|------|
| EC, dS/m  | −0.72 |     |     |     |     |     |     |     |      |
| OM, %     | −0.36 | 0.26|     |     |     |     |     |     |      |
| CEC, cmol/c/kg soil | −0.33 | 0.23| 0.66|     |     |     |     |     |      |
| N, mg kg⁻¹ | −0.71 | 0.59| 0.77| 0.70|     |     |     |     |      |
| P, mg kg⁻¹ | −0.64 | 0.43| 0.78| 0.63| 0.84|     |     |     |      |
| K, mg kg⁻¹ | −0.61 | 0.30| 0.69| 0.67| 0.89| 0.82|     |     |      |
| ESP       | −0.58 | 0.55| 0.24| 0.34| 0.39| 0.40| 0.32|     |      |
| Silt, %   | 0.52 | −0.47| −0.06| 0.15| −0.34| −0.41| −0.33| −0.24|      |
| Clay, %   | −0.48 | 0.35| 0.41| 0.76| 0.65| 0.52| 0.64| 0.60| −0.16|

Note: Values in bold are different from 0 with a significance level alpha = 0.05.

Soil pH affects other soil variables and controls the soil physical, chemical, and biological properties [54,55]; thus, pH demonstrates significant correlations with other properties. The negative correlation between EC and pH is largely dependent on the leaching process of major cations (Ca, Mg, Na, and K), as the reduction of these cations increases the pH and decreases EC and ESP. This process is also accompanied by increased mineralization and dissociation processes of organic matter, which explains the negative relation [56]. The increased decomposition of OM at low pH values leads to increases in H⁺ ion content, soil CEC, and the availability of macronutrients (N, P, and K) [54,57]. Additionally, higher soil pH leads to increases in the mineralizable fractions of N and
C ratios, where the bonds between clays and organic constituents are broken [58]. Clay content is associated with an increase in CEC and basic alkali cation adsorption, which is negatively correlated with pH [57]. There are positive correlations between soil EC, macronutrients (N, P and K), base cations, and clay content; these results agree with those in [59]. Increased OM has a positive correlation with clay content, which leads to increases in CEC and N, P and K contents; in addition, OM improves soil physical and chemical properties [60,61]. Negative correlations were identified between clay and silt. The reverse effects exerted by clay and silt on other soil properties mainly depend on the ratio in which they contribute to soil particle size distribution because the surface area and CEC of clay are greater than those of silt [57].

Table 3 shows the results of Bartlett’s test of sphericity and the KMO test of sampling adequacy. The significance level of Bartlett’s test of sphericity was <0.0001, and the observed chi-square value was 334.63, which is larger than the critical chi-square value of 61.66; therefore, the variables are not completely uncorrelated, and PCA is appropriate for the dataset [62]. The results show that the KMO value is greater than 0.6, which indicates that the sample size is suitable for assessing the factor structure, in agreement with Barrett and Morgan [63]. According to results of these tests, the variables are not completely uncorrelated; the variables included in the model can explain the phenomenon, and a Principal Component Analysis is suitable [64–66].

3.3. Soil Quality Index Using Principal Component Analysis
3.3.1. Principal Component Analysis

The results of PCA are summarized in Table 4. The first three Principal Components (PCs) have eigenvalues greater than 1; therefore, these PCs were used according to the method described by Kaiser [67], while the other PCs were excluded (Table 4 and Figure 3). The results show that the first three PCs explain 83.63% of the total variance. According to the factor loadings, the first PC, which explains 56.45% of the total variance, has higher positive correlations with EC, OM, CEC, available NPK, ESP, and clay, while the second PC, which explains 16.76% of the total variance, is strongly correlated with silt. The third PC explains 10.41% of the total variance and is correlated with ESP. The PCA biplot in Figure 4 shows both the PC scores of samples and the loadings of variables.

The soil quality index was generated using the results of PCA using Equation (3) as follows:

\[
\begin{align*}
\text{SQI-PC1} &= -0.14 \times z_\text{pH} + 0.11 \times z_\text{EC} + 0.13 \times z_\text{OM} + 0.13 \times z_\text{CEC} + 0.17 \times z_\text{N} + 0.16 \times z_\text{P} + 0.15 \times z_\text{K} + 0.11 \times z_\text{ESP} - 0.07 \times z_\text{SILT} + 0.13 \times z_\text{CLAY} \\
\text{SQI-PC2} &= 0.27 \times z_\text{pH} - 0.34 \times z_\text{EC} + 0.25 \times z_\text{OM} + 0.33 \times z_\text{CEC} + 0.05 \times z_\text{N} + 0.05 \times z_\text{P} + 0.12 \times z_\text{K} - 0.19 \times z_\text{ESP} - 0.42 \times z_\text{SILT} + 0.09 \times z_\text{CLAY} \\
\text{SQI-PC3} &= -0.01 \times z_\text{pH} + 0.14 \times z_\text{EC} - 0.26 \times z_\text{OM} + 0.23 \times z_\text{CEC} - 0.16 \times z_\text{N} - 0.28 \times z_\text{P} - 0.23 \times z_\text{K} + 0.58 \times z_\text{ESP} + 0.38 \times z_\text{SILT} + 0.43 \times z_\text{CLAY}
\end{align*}
\]
Using Equation (4), the CSQI was computed as follows:

\[
CSQI = 0.5645 \times PC1 + 0.1676 \times PC2 + 0.1041 \times PC3
\]

The CSQI, which was computed using z scores, was transformed into a standard normal distribution using Equation (5). The results of CSQI are presented in Table 5 and Figure 5. The results reveal highly significant correlations between the different soil indicators and SQI.

### Table 4. Summarization of Principal Component Analysis.

| Component | Score Coefficient Matrix (CSC) | Factor loadings |
|-----------|--------------------------------|-----------------|
| pH        | −0.14                          | 0.27            |
| EC, dS/m  | 0.11                           | −0.34           |
| OM, %     | 0.13                           | 0.25            |
| CEC, cmolc/l | 0.13                        | 0.33            |
| N, mg kg\(^{-1}\) | 0.17                       | 0.05            |
| P, mg kg\(^{-1}\) | 0.16                       | 0.05            |
| K, mg kg\(^{-1}\) | 0.15                       | 0.12            |
| ESP       | 0.11                           | −0.19           |
| Silt, %   | −0.07                          | 0.42            |
| Clay, %   | 0.13                           | 0.09            |

### Table 5. Comprehensive soil quality index (CSQI) calculation based on studied soil indicators using PCA.

| Sample No | pH  | EC  | OM  | CEC | N   | P   | K   | ESP | Silt | Clay | CSQI-PC1 | CSQI-PC2 | CSQI-PC3 | CSQI\(^1\) | CSQI\(^2\) |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|------|------|----------|----------|----------|-----------|-----------|
| 1         | 1.55| 1.08| 2.32| 0.58| 2.39| 2.29| 2.16| 2.01| 0.64 | 0.70 | 1.64     | 0.73     | −0.15    | 1.03       | 0.85       |
| 2         | 1.64| 0.64| 1.18| 0.93| 1.89| 1.86| 1.79| 0.25| 0.92 | 1.33 | 1.14     | 0.91     | −0.19    | 0.78       | 0.78       |
| 3         | 1.66| 0.60| 0.74| 0.03| 0.70| 0.38| 1.06| 0.38| 0.73 | 1.03 | 0.40     | 0.31     | 0.36     | 0.32       | 0.62       |
| 4         | 1.30| 0.49| 2.06| 1.81| 2.21| 1.80| 2.85| 0.15| 0.81 | 1.23 | 1.59     | 1.58     | −0.66    | 1.09       | 0.86       |
| 5         | 1.17| 0.40| 0.90| 1.28| 2.05| 1.53| 2.79| 0.01| 1.18 | 0.84 | 1.20     | 0.92     | −0.48    | 0.78       | 0.78       |
| 6         | 1.25| 0.29| 0.87| 0.49| 0.38| 0.28| 0.09| 0.34| 0.50 | 0.74 | 0.25     | 0.45     | 0.46     | 0.27       | 0.61       |
| 7         | 1.10| 0.56| 1.76| 2.19| 1.52| 2.01| 1.63| 0.86| 0.03 | 1.94 | 1.59     | 1.64     | 0.28     | 1.20       | 0.89       |
| 8         | 0.63| 0.77| 0.62| 1.93| 0.91| 0.23| 0.29| 0.53| 0.11 | 1.81 | 0.85     | 0.81     | 1.24     | 0.74       | 0.77       |
| 9         | 0.03| 0.62| 0.24| 1.28| 0.53| 0.01| 0.17| 0.47| 0.25 | 1.52 | 0.61     | 0.27     | 1.23     | 0.52       | 0.70       |
| 10        | 1.27| 2.97| 0.14| 0.34| 0.69| 0.48| 0.33| 1.21| 1.16 | 0.07 | 0.52     | −1.13    | 1.30     | 0.24       | 0.59       |
| 11        | 1.08| 2.77| 0.40| 0.25| 0.75| 0.03| 0.42| 1.29| 0.90 | 0.34 | 0.56     | −0.97    | 1.34     | 0.29       | 0.61       |
| 12        | 1.13| 2.42| 1.13| 0.21| 0.14| 0.17| 0.58| 1.48| 0.24 | 0.03 | 0.57     | −0.46    | 0.84     | 0.33       | 0.63       |
| 13        | 0.31| 0.19| 0.25| 0.98| 0.63| 0.74| 0.45| 0.58| 0.96 | 1.18 | 0.58     | 0.12     | 0.98     | 0.45       | 0.67       |
| 14        | 0.20| 0.44| 0.96| 1.38| 0.73| 0.03| 0.56| 0.53| 2.05 | 0.66 | 0.54     | −0.19    | 1.24     | 0.40       | 0.66       |
| 15        | 0.42| 0.37| 1.34| 1.87| 0.95| 0.83| 0.72| 0.05| 1.58 | 0.95     | 0.82     | 0.53     | 0.61       | 0.62       | 0.73       |
| 16        | 0.42| 0.39| 0.38| 0.76| 0.61| 0.45| 0.42| 0.31| 0.40 | 1.75 | 0.60     | 0.36     | 0.89     | 0.49       | 0.69       |
| 17        | 0.61| 0.24| 0.51| 0.53| 0.54| 0.24| 0.56| 0.37| 0.36 | 0.37 | 0.35     | 0.31     | 0.24     | 0.28       | 0.61       |
| 18        | 0.31| 0.35| 1.30| 1.73| 0.93| 1.20| 0.78| 0.05| 0.86 | 1.19 | 0.95     | 0.80     | 0.31     | 0.71       | 0.76       |
| 19        | 1.25| 0.47| 0.92| 0.12| 0.04| 0.31| 0.31| 1.96| 0.80 | 1.36     | 0.45    | −0.08    | 1.70       | 0.42       | 0.66       |
| 20        | 1.51| 0.50| 0.57| 0.32| 0.02| 0.71| 0.53| 2.15| 0.31 | 1.46 | 0.56     | 0.18     | 1.65     | 0.52       | 0.70       |
Table 5. Cont.

| Sample No | pH   | EC   | OM   | CEC  | N    | P    | K    | ESP  | Silt | Clay | SQI-PC1 | SQI-PC2 | SQI-PC3 | CSQI 1 | CSQI 2 |
|-----------|------|------|------|------|------|------|------|------|------|------|---------|---------|---------|--------|--------|
| 21        | 1.70 | 0.62 | 1.24 | 1.91 | 0.98 | 1.25 | 0.71 | 2.14 | 0.75 | 0.86 | 1.01    | 0.74    | 1.41    | 0.84   | 0.80   |
| 22        | 0.27 | 0.19 | 0.96 | 0.02 | 0.29 | 0.23 | 0.36 | 0.51 | 1.37 | 0.75 | 0.31    | 0.28    | 0.72    | 0.20   | 0.58   |
| 23        | 0.57 | 0.32 | 0.32 | 0.37 | 0.10 | 0.46 | 0.43 | 0.43 | 0.59 | 0.37 | 0.25    | 0.03    | 0.43    | 0.19   | 0.58   |
| 24        | 0.50 | 0.41 | 0.91 | 0.99 | 0.69 | 1.27 | 0.66 | 0.73 | 1.03 | 0.45 | 0.71    | 0.19    | 0.44    | 0.48   | 0.68   |
| 25        | 0.61 | 0.80 | 0.17 | 0.47 | 0.48 | 0.25 | 0.47 | 0.21 | 2.02 | 0.03 | 0.16    | 0.71    | 0.82    | 0.06   | 0.52   |
| 26        | 0.54 | 0.76 | 0.35 | 0.13 | 0.61 | 1.12 | 0.51 | 0.37 | 1.55 | 0.19 | 0.39    | 0.54    | 0.40    | 0.17   | 0.57   |
| 27        | 0.50 | 0.86 | 1.15 | 0.99 | 1.07 | 1.56 | 0.76 | 0.96 | 1.48 | 0.46 | 0.91    | 0.08    | 0.57    | 0.56   | 0.71   |
| 28        | 1.27 | 0.88 | 0.14 | 0.86 | 0.54 | 0.39 | 0.35 | 1.68 | 1.21 | 0.39 | 0.41    | 0.34    | 1.59    | 0.34   | 0.63   |
| 29        | 1.10 | 0.70 | 0.11 | 0.49 | 0.73 | 0.90 | 0.56 | 0.45 | 1.83 | 0.54 | 0.34    | 0.41    | 0.86    | 0.22   | 0.59   |
| 30        | 0.18 | 0.82 | 1.04 | 0.57 | 0.98 | 1.59 | 0.70 | 0.58 | 0.96 | 0.72 | 0.89    | 0.02    | 0.22    | 0.52   | 0.70   |
| 31        | 0.44 | 0.70 | 0.17 | 0.15 | 0.66 | 0.52 | 0.22 | 0.53 | 0.41 | 0.37 | 0.36    | 0.19    | 0.40    | 0.22   | 0.59   |
| 32        | 0.80 | 0.72 | 1.13 | 0.21 | 0.91 | 0.03 | 0.30 | 0.46 | 0.64 | 0.78 | 0.45    | 0.12    | 0.47    | 0.32   | 0.63   |
| 33        | 1.51 | 0.87 | 1.32 | 0.01 | 1.03 | 0.56 | 0.61 | 0.54 | 0.23 | 0.46 | 0.52    | 0.44    | 0.10    | 0.35   | 0.64   |
| 34        | 0.82 | 0.63 | 0.81 | 0.56 | 0.12 | 0.25 | 0.24 | 1.30 | 0.08 | 1.75 | 0.60    | 0.32    | 1.39    | 0.53   | 0.70   |
| 35        | 0.80 | 0.66 | 0.27 | 0.30 | 0.31 | 0.44 | 0.17 | 1.48 | 0.37 | 1.06 | 0.46    | 0.12    | 1.32    | 0.38   | 0.65   |
| 36        | 0.72 | 0.72 | 1.02 | 0.42 | 0.83 | 1.02 | 0.59 | 0.24 | 0.45 | 0.36 | 0.60    | 0.30    | 0.17    | 0.37   | 0.64   |

1 Calculated according to standardized z scores; 2 the CSQI, which was computed using standardized z scores, was transformed into a standard normal distribution (which has a mean of zero and a standard deviation of one) using Equation (5).

Figure 3. Scree plot for the different components considered for the principal component analysis with eigenvalues greater Table 4. PCA biplot (biplot shows both PC scores of samples and loadings of variables).
3.3.2. Cluster Analysis (k-Means Clustering)

Clustering is an effective statistical approach to data analysis that can be used to classify a large number of variables into specific groups. Each group represents a specific class of soil quality. According to the PC scores of samples, the data were divided into three clusters (Table 6). Cluster I occupies about 13.89% of the total data, Cluster II occupies about 16.67%, and Cluster III occupies the rest of the data, which represents about 69.44%. The results of ANOVA show that a statistically significant difference exists between different clusters, mainly in the SQI.

Figure 4. PCA biplot (biplot shows both PC scores of samples and loadings of variables).

Figure 5. Correlation coefficients among the different soil indicators with SQI.
Table 6. Results of clustering analysis (k-means clustering).

| Observation | Class | Distance to Centroid | Observation | Class | Distance to Centroid |
|-------------|-------|----------------------|-------------|-------|----------------------|
| Sample 1    | 1     | 20,405               | Sample 19   | 3     | 42,857               |
| Sample 2    | 1     | 88,513               | Sample 20   | 3     | 14,292               |
| Sample 3    | 2     | 150,358              | Sample 21   | 3     | 42,775               |
| Sample 4    | 1     | 117,091              | Sample 22   | 3     | 34,889               |
| Sample 5    | 1     | 106,341              | Sample 23   | 3     | 21,216               |
| Sample 6    | 2     | 37,283               | Sample 24   | 3     | 29,534               |
| Sample 7    | 1     | 119,473              | Sample 25   | 3     | 21,470               |
| Sample 8    | 2     | 15,665               | Sample 26   | 3     | 14,196               |
| Sample 9    | 2     | 87,178               | Sample 27   | 3     | 50,381               |
| Sample 10   | 3     | 47,456               | Sample 28   | 3     | 35,095               |
| Sample 11   | 3     | 35,431               | Sample 29   | 3     | 19,728               |
| Sample 12   | 3     | 21,836               | Sample 30   | 3     | 37,255               |
| Sample 13   | 3     | 19,036               | Sample 31   | 3     | 58,097               |
| Sample 14   | 3     | 23,596               | Sample 32   | 3     | 42,278               |
| Sample 15   | 3     | 44,994               | Sample 33   | 3     | 20,554               |
| Sample 16   | 3     | 22,714               | Sample 34   | 2     | 12,668               |
| Sample 17   | 3     | 10,775               | Sample 35   | 2     | 26,036               |
| Sample 18   | 3     | 54,312               | Sample 36   | 3     | 19,239               |

3.3.3. Simulation of Cluster Analysis

The cluster analysis results were confirmed using Monte Carlo simulations based on 200 random values of the SQI for the three clusters (first, second, and third). Figure 6 shows the normal probability distribution, where the p value of the Anderson–Darling normality test is >0.05. The SQI simulation results are acceptable, with standard deviations of 0.03, 0.07, and 0.10 and mean values of 0.88, 0.67, and 0.37 for the first, second, and third cluster, respectively. The coefficient of variance (CV) was used to assure the quality of the cluster analysis [47]; the resulting CVs are 3.18%, 9.55%, and 26.25% from the average values of the first, second, and third cluster, respectively. Additionally, the mean values are close to the median values of 0.88, 0.68, and 0.38 for the first, second, and third cluster, respectively. Therefore, the mean values of the obtained SQIs are representative of the most probable SQI values of this study area.

Figure 6. Soil Quality Index simulation for the first (a), second (b), and third cluster (c).
3.4. Mapping Soil Properties and Soil Quality Index

3.4.1. Mapping Soil Properties

The ordinary kriging interpolation method was used to estimate and map the unknown values of soil properties. The model’s accuracy was confirmed for each soil property based on ME, RMSE, MSE, and RMSSE, as shown in Table 7. The results show that the exponential model is the most suitable for predicting the unknown values of most of soil properties (CEC, ESP, Av.N, Av.P, clay, and silt), followed by the K-Bessel model for pH and OM. Tetraspherical is the most suitable for ECe and Av.K. Finally, the spherical model is suitable for sand content. In addition, the results indicate that RMSSE is close to one and the MSE is close to zero for the selected soil properties; therefore, the selected models fit the data and are suitable for predicting the unsampled soil properties [68,69].

The results show that the spatial dependence (SD) is strong for all soil properties except for ESP and OM, for which SD is moderate and weak, respectively. A strong dependence may be attributable to natural factors, such as soil texture and terrain factors, while moderate and weak dependence may be due to other factors, such as inappropriate agricultural practices and agricultural management [70,71]. Figure 7 shows the spatial distribution maps of soil properties; pH varies from 7.06 to 9.28, and soil ECe ranges from low to high soil salinity (0.88–21 dS/m). This difference in soil salinity is a result of the activity of land degradation processes in the Fayoum depression, where inadequate drainage conditions reduce salinity, which is also a common feature in the soils of the North Delta [72,73]. The results show that the study area has low soil OM contents, ranging between 0.4% and 1%. The results indicate that the area is poor in nutrient content, except for some spots in the north of the area that contain reasonable values of soil nutrients; the maximum values are 66, 18, and 860 for Av. N, P, and K, respectively (Figure 7).

Spatial distribution maps of soil properties affecting the SQI in the study area shown in Figure 7.

Table 7. Geostatistical analyses and semivariogram parameters of soil properties.

| Soil Attribute | Model   | Nugget | Partial Sill | Sill   | Nugget/Sill | Major Range | SDC    | ME       | RMSE     | MSE       | RMSSE     | ASE   |
|----------------|---------|--------|--------------|--------|-------------|-------------|--------|----------|----------|-----------|-----------|-------|
| pH             | K-Bessel| 0.00   | 0.25         | 0.25   | 0.00        | 6834.73     | Strong | −0.025   | 0.26     | −0.07     | 1.97      | 0.16  |
| ECe            | Tetraspherical | 0.00  | 28.43        | 28.43  | 0.00        | 4097.26     | Strong | 0.149    | 3.75     | 0.03      | 0.81      | 4.92  |
| CEC            | Exponential | 0.00  | 109.91       | 109.91 | 0.00        | 13,286.94   | Strong | 0.205    | 7.48     | 0.02      | 1.13      | 6.59  |
| ESP            | Exponential | 0.00  | 7.84         | 13.93  | 0.44        | 6767.76     | Moderate| 0.261    | 3.31     | 0.07      | 0.94      | 3.53  |
| OM             | K-Bessel | 0.02   | 0.24         | 0.90   | 0.00        | 8069.50     | Weak   | 0.004    | 0.49     | 0.01      | 0.99      | 0.50  |
| Av. N          | Exponential | 0.00  | 436.44       | 436.44 | 0.00        | 8997.19     | Strong | 0.418    | 13.39    | 0.02      | 0.86      | 15.45 |
| Av. P          | Exponential | 2.16  | 21.11        | 23.27  | 0.09        | 4117.22     | Strong | 0.123    | 4.70     | 0.02      | 1.02      | 4.66  |
| Av. K          | Tetraspherical | 0.00  | 64,817.40    | 64,817.40 | 0.00        | 10,056.06   | Strong | 0.814    | 181.6    | 0.01      | 1.24      | 146.1 |
| Clay           | Exponential | 0.00  | 113.55       | 113.55 | 0.00        | 7915.15     | Strong | 0.284    | 7.32     | 0.03      | 0.90      | 8.28  |
| Silt           | Exponential | 0.00  | 98.41        | 98.41  | 0.00        | 7638.38     | Strong | −0.103   | 6.91     | −0.02     | 0.89      | 7.81  |
| Sand           | Spherical  | 0.00   | 171.92       | 171.92 | 0.00        | 7698.37     | Strong | −0.323   | 7.85     | −0.02     | 0.99      | 8.09  |

Figure 7. The spatial distribution maps of the soil parameters in the study area.
3.4.2. Mapping the Soil Quality Index

OK interpolation was used to interpolate the spatial variability of soil quality in the study area based on the results of CSQI, which was calculated using Equation (4). The results are shown in Table 5.

The results of the SQI range from 0.88 to 0.37. The SQI is classified into three quality zones according to Aprisal, Bambang, and Harianti [13], as shown in Figure 8 and Table 8. The soil is affected by its composition as well as the surrounding environmental and climatic conditions [74–76]; the first zone is characterized by a very good quality index that represents about 14.48% (70.52 $\times$ 10^6 ha) of the total area. The soils of this zone are characterized by adequate values of all soil characteristics. The second zone is characterized by good soil quality: this class covers about 50.77% of the area (247.19 $\times$ 10^6 ha). The third zone is fair (low quality) and covers about 34.7% (169.17 $\times$ 10^6 ha). The soil pH is mild in the first zone and strong in the second and third zones. The status of available N and available P in the second and third zones is low and medium, respectively. Available K is classified as high in the second zone and medium in the third zone.

The organic matter, clay, EC, available N, available P, available K, and CEC are the most effective factors contributing to the SQI in the Fayoum depression [12,13]. The low values of these parameters lead to negative effects on the SQI [9]. The physical indicators (depth, bulk density, porosity, aggregate stability, texture, and compaction) affect the
organization of the particles and pores, explaining their impacts on root growth, speed of plant emergence, and water infiltration [9].

Table 8. Statistical analysis of the zonation of soil parameters and quality index in the study area.

| Indicators | First Zone | Second Zone | Third Zone | Pr > F | Sig. |
|------------|------------|-------------|------------|--------|------|
| pH         | 7.22 b     | 7.71a       | 8.02 a     | 0.001 | Yes  |
| EC, dS/m   | 4.46 c     | 6.14 b      | 8.50 a     | 0.244 | Yes  |
| OM, %      | 1.46 a     | 0.68 b      | 0.54 b     | 0.000 | Yes  |
| CEC, cmolc/kg | 32.8 a | 27.49 b | 16.54 b | 0.000 | Yes  |
| N, mg kg⁻¹⁻¹ | 54.96 a | 25.99 b | 11.45 c | 0.000 | Yes  |
| P, mg kg⁻¹⁻¹ | 18.08 a | 10.03 b | 7.67 b | 0.000 | Yes  |
| K, mg kg⁻¹⁻¹ | 616.84 a | 237.47 b | 83.9 c | 0.000 | Yes  |
| ESP        | 11.93 ab   | 12.5 a      | 8.65 b     | 0.020 | Yes  |
| Silt, %    | 20.28 a    | 24.62 a     | 28.31 a    | 0.161 | No   |
| Clay, %    | 54.67 a    | 55.9 a      | 36.93 b    | 0.000 | Yes  |
| SQI        | 0.88 a     | 0.67 b      | 0.37 c     | 0.000 | Yes  |
| Area, ha (%) | 7052     | 24,719      | 16,919     | 0.000 | Yes  |

Note: The letters are symbols of Duncan test that the means followed by the same letter in each row are not significantly different from one another at a 5% probability level (Duncan Multiple Range Test).

Figure 8. The spatial distribution patterns of the SQI.
4. Conclusions

The precise evaluation of soil quality is a very important issue for precise farming (in particular) and for the proper management of sustainable agricultural practices (in general). This evaluation facilitates the identification of the most suitable crops and the potential agricultural uses of the area. Soil quality is affected by agricultural practices and climatic conditions, which, in turn, affect the physical, chemical, and fertility properties of the soil. In this study, the nutrients and physical and chemical properties of the soil were used to assess the SQI in the El-Fayum depression, in the Western Desert of Egypt. For the purpose of these investigations, PCA analysis was jointly used with GIS to capture, quantify, and map the soil quality index of the study area. The results showed that the PCs of PCA explained 83.6% of the total variance of soil data. In addition, the soil data were classified into three clusters: Cluster I represented about 13.89% of soil samples, Cluster II represented about 16.67%, and Cluster III represented the rest of the soil data, i.e., 69.44% of samples. The use of GIS to map soil properties immediately highlighted the changes and spatial variation in SQI from one place to another. The exponential model was the most suitable for predicting the unknown values of the majority of the soil properties (CEC, ESP, Av.N, Av.P, clay, and silt), followed by the K-Bessel model for pH and OM. The study area was classified into three zones based on the variation in CSQI values. These zones differed in both the number and type of the limiting factors that reduced the soil quality. In particular, zone 1 was characterized by significant improvement in the soil nutrients and chemical properties, whereas zones 2 and 3 were affected by a decrease in the soil’s nutrient contents, in addition to an increase in soil salinity in zone 3. The areas categorized as very good and good quality occupied about 14.48% and 50.77%, respectively, of the total surface investigated, and fair soil quality (mainly due to salinity and low soil nutrients) constituted about 34.75%. As a whole, the results reflect that the joint use of PCA and GIS allows for an accurate and effective assessment of the SQI.

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