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Assessment of Soil Spatial Variability in Agricultural Ecosystems Using Multivariate Analysis, Soil Quality Index (SQI), and Geostatistical Approach: A Case Study of the Mnasra Region, Gharb Plain, Morocco

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Abstract: Accurate assessment of soil quality is crucial for sustainable agriculture and soil conservation. Thus, this study aimed to assess soil quality in the agricultural ecosystem of the Mnasra region within the Gharb Plain of Morocco, employing a comprehensive approach integrating multivariate analysis and geostatistical techniques. Thirty soil samples were collected from the surface layers across thirty selected sites. The results showed significant variations in soil properties across the study area, influenced by factors such as soil texture, parent material, and agricultural practices. Pearson correlation and principal component analysis (PCA) were employed to analyze the relationships among soil properties and compute the Soil Quality Index (SQI). The SQI revealed values ranging from 0.48 to 0.74, with 46.66% of sampled soils classified as "Good" and 53.33% as "Fair". Geostatistical analysis, particularly ordinary kriging (OK) interpolation and semivariogram modeling, highlighted the spatial variability of soil properties, aiding in mapping soil quality across the landscape. The integrated approach demonstrates the importance of combining field assessments, statistical analyses, and geospatial techniques for comprehensive soil quality evaluation and informed land management decisions. These findings offer valuable insights for decision-makers in monitoring and managing agricultural land to promote sustainable development in the Gharb region of Morocco.

Keywords: agriculture; geostatistical analysis; Morocco; principal component analysis; soil quality index; soil spatial variability

1. Introduction

Soil, a fundamental element of terrestrial ecosystems, functions as a complex and vital entity crucial for numerous ecological processes [1]. It serves as the foundational resource for a wide array of land uses and plays a central role in sustainable agriculture [2]. The pursuit of sustainable agricultural development emerges as a universal imperative, transcending geographical disparities [3].

In Morocco, agriculture significantly contributes to the economy, representing 14–20% of the GDP and employing 40% of the total workforce [4]. As a cornerstone of economic development policy, the government has implemented various measures, including the "Green Generation" initiative, aimed at fostering agricultural growth and making it a driving force for economic prosperity [5]. However, agriculture faces the challenge of simultaneously meeting the increasing demand for food and maintaining sustainable practices to preserve soil-mediated ecosystem services, including carbon sequestration, nutrient supply, and water cycle regulation [6].

Agricultural soils play a pivotal role in preserving environmental integrity by contributing to clean air and water, mitigating greenhouse gas emissions, fostering natural biodiversity, ensuring food safety, and striking a balance between soil resources and crop demands while optimizing productivity over the long term [7]. The suitability of soils for agricultural purposes hinges upon the integrity of their physical, chemical, and biological properties [8]. However, the spatial variability of soil characteristics within ecosystems is profoundly influenced by environmental factors such as parent materials, topography, climate, vegetation, and human-induced disturbances [9,10]. Notably, intensive agricultural practices in arid and semi-arid regions have bolstered agricultural output but have concurrently engendered soil degradation, imperiling the sustainability of land use systems [11,12]. The mean yearly rate of soil degradation in Morocco ranges from 23 to 55 t/ha/year, with extreme values spanning from 115 to 524 t/ha/year [13]. This degradation, largely attributed to the confluence of climate change and anthropogenic activities, has resulted in the partial or complete deterioration of fertile land, leading to the loss of soils with the lowest productivity and quality [3].

Soil quality (SQ) encompasses various aspects, reflecting the intricate and multifaceted nature of subterranean systems [14]. Specifically, SQ denotes the soil's ability to adequately serve as a medium for plant growth (productivity), regulate water flow, act as a buffer, and effectively integrate its biological, physical, and chemical components [15]. A primary global objective today is the preservation of overall soil quality [16], which necessitates the identification of soils, determination of optimal management practices, and monitoring changes in soil properties [1]. Consequently, there has been a surge in research efforts aimed at identifying sensitive indicators and methods capable of detecting soil quality changes, thereby facilitating the assessment of soil hazards and management implications [17].

The development of a Soil Quality Index (SQI) holds paramount importance for fostering sustainable agriculture, as SQ is closely linked to soil properties influenced by field management practices. The SQI integrates pertinent soil indicator data into numerical values [18], typically reflecting regional variations in soil's chemical and physical attributes [19]. These attributes, encompassing physical, chemical, and biological characteristics, serve as key indicators of soil health and fertility status [16]. Physical indicators include soil depth, bulk density, porosity, aggregate stability, texture, and compaction, while chemical indicators encompass pH, salinity, organic matter content, nutrient availability, cation exchange capacity, nutrient cycling, and soil contaminant levels [20]. Thus, a comprehensive understanding of soil quality enables the delineation of effective soil management strategies conducive to sustainable agricultural production [21]. Studies on the SQI highlight its utility in evaluating crop productivity and assessing the impact of land use conversion on soil quality and degradation, particularly in native rangelands of upland arid and semi-arid regions [22,23].

The SQI serves as a versatile model for evaluating soil quality and delineating the extent of soil degradation within specific regions [24]. Various techniques are employed to derive the SQI, including the simple additive SQI [20], weighted additive SQI [25], and statistically modeled SQI [26]. Multivariate statistical approaches (MSA), such as cluster analysis and principal component analysis (PCA), are commonly employed to discern the underlying mechanisms influencing soil quality [27,28]. These analytical tools greatly enhance data comprehension and facilitate informed decision-making across diverse fields, including soil science and environmental management [16,29]. Among these methods, PCA stands out as a prominent approach for reducing the dimensionality of data by identifying the most influential variables [30].

Concurrently, Geographic Information Systems (GISs) are recognized for their efficacy in integrating stakeholder preferences and concerns to generate comprehensive evaluations for selecting suitable agricultural activities and sites [31,32]. GISs, alongside geostatistical analyses, constitute contemporary monitoring strategies for assessing soil quality [19]. Integrated GIS and geostatistical analyses prove beneficial in delineating spatial variations in soil properties and predicting them in unsampled locations [33]. Notably, Kriging emerges as a widely utilized interpolation method within geostatistics. It characterizes variable values near original sample locations, exhibiting a statistically higher correlation with observed values in those areas compared to elsewhere [34]. Among Kriging techniques, ordinary Kriging is deemed most suitable for producing accurately predicted distribution maps [35]. Previous research has extensively employed MSA in conjunction with GIS approaches to ascertain SQI [16]. Specifically, in Egypt, a study utilized GIS and MSA to evaluate and map SQI [28], focusing on the El-Fayoum depression in the Western Desert. Additionally, Abdel-Fattah [36] employed PCA to synthesize soil properties and GISs to delineate the spatial distribution of various soil attributes.

The primary aim of our investigative study is to explore and understand soil properties and SQI modeling within the agricultural ecosystem of the Mnasra region, situated within the Gharb Plain of Morocco. The specific objectives of this paper are as follows: firstly, to identify and characterize key soil properties relevant to agricultural productivity in the Mnasra region; secondly, to develop a comprehensive model of the SQI integrating various soil parameters; thirdly, to utilize multivariate analysis techniques, including PCA, to identify underlying patterns and relationships among soil variables; and fourthly, to employ geostatistical analysis techniques for the evaluation of spatial variability and distribution of soil properties across the study area.

2. Materials and Methods

2.1. Description of the Study Area

This research was conducted in the Mnasra region, situated within the Gharb plain, celebrated as the most agriculturally productive area along the Atlantic Ocean, covering an expanse of 488 km^2 (Figure 1). Its boundaries stretch from the city of Kenitra in the south to the Sebou River, marked by a parallel line extending through Sidi Allal Tazi in the east and reaching Merja Zerga near Moulay Bouselham in the north. The Gharb region, located in the northwestern part of Morocco, boasts distinctive geographical and geological attributes. Bordered by the Drader-Souier Plain to the north and the Maamora plateau to the south, the Gharb Plain is flanked by the vast Atlantic Ocean to the west. Embracing a Mediterranean climate with notable oceanic influences, the study area witnesses an average annual precipitation of approximately 551 mm. The rainy season typically spans from October to the end of April, with peak rainfall occurring in November, December, and January. Temperature fluctuations range from 12 °C in winter to 23 °C in summer. Remarkably, potential evaporation exceeds 150 mm during the arid months of June through to September, in contrast to less than 80 mm from December to February.

Geologically, sandy soils extensively cover the coastal zone, comprising approximately 39,000 hectares or 15% of the total area [32]. Notably, the Mnasra region is distinguished by the prevalence of sandy-clay and silty-clay textures. It should also be noted that the soil of the region is occupied by heavy soils (vertisols and fluvisols).

Renowned for sugarcane cultivation, this region contributes significantly to Morocco's sugar production. Agricultural practices encompass intensive vegetable farming, field crop cultivation, and tree crop cultivation systems [37]. These practices involve the application of mineral and organic fertilizers, including Ammonitrate, NPK, urea, as well as livestock manure sourced from cattle and poultry [38].

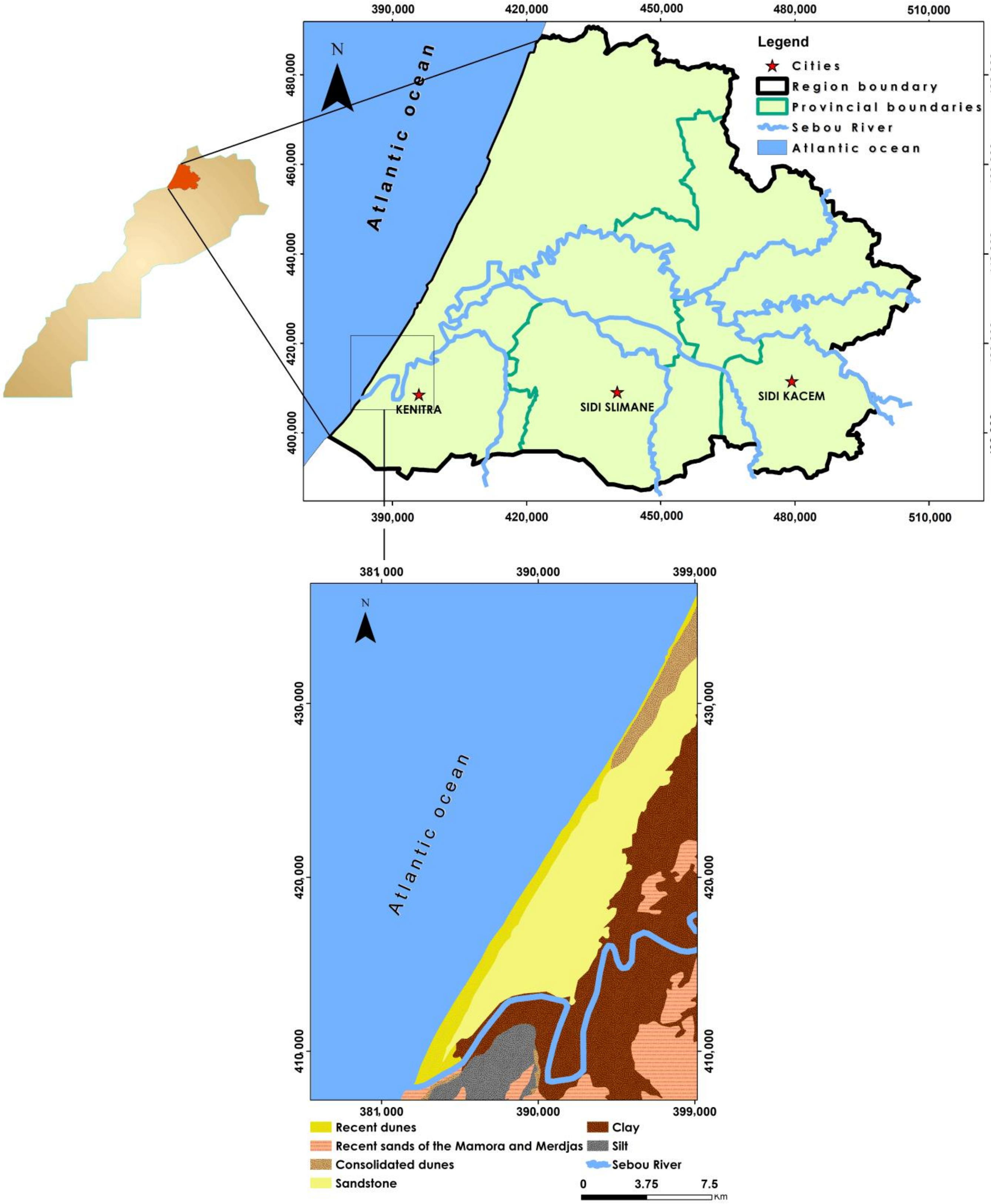


Figure 1. Location of the study area and geological map.

2.2. Soil Sampling Collection and Analysis

In this study, soil sampling was conducted in January 2024 at thirty distinct locations (Figure 2). At each location, a composite soil sample representing the root zone (0 to 20 cm depth) was collected using an auger.

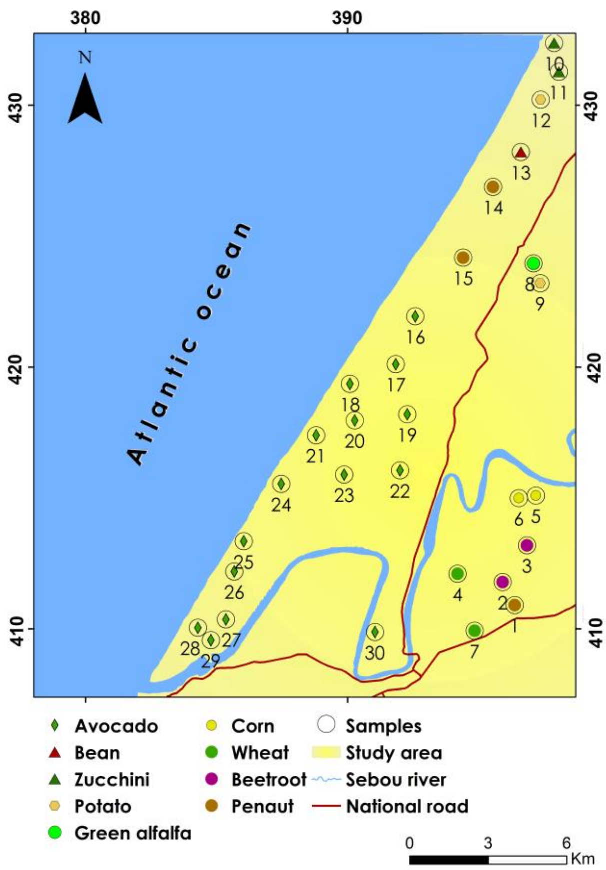


Figure 2. Map of sampling sites and crop types.

The selection of sampling sites was based on considerations of distance between positions and morphological characteristics of the soil to ensure representation of all soil variations. Additionally, latitude, longitude, elevation, and topography data were recorded for each site, accompanied by an investigation into land-use and agricultural activities. The collected soil samples were carefully placed in polyethylene bags and transported to the laboratory. Upon arrival, the samples underwent manual removal of fine roots, stones, and plant organic residues, following which they were air-dried at room temperature. Subsequently, the dried samples were crushed, sieved through a 2 mm mesh sieve, and thoroughly mixed to ensure homogeneity. These prepared samples were then subjected to analysis for twenty physicochemical parameters to assess soil quality.

2.2.1. Soil Physical Properties

The soil particle size distribution was analyzed utilizing the hydrometric method [39]. The soil moisture (%) was assessed by oven-drying 10 g of fresh soil sample at 105 °C for 24 h. The weight of the sample before and after oven drying was recorded, and soil moisture content was computed using Equation (1) [40]:

$$\text{Soil moisture}(\%) = \frac{[\text{Initial wet weight}(\text{g}) - \text{final oven dried weight}(\text{g})]}{\text{Initial wet weight (g)}} \times 100 \quad (1)$$

Soil bulk density was determined based on the volume–mass relationship for each core sample [41]. Total porosity (TP) was subsequently calculated using the values of bulk density (BD) and particle density (PD) [42].

2.2.2. Soil Chemical Properties

Soil pH was determined potentiometrically using a pH meter (Mettler Toledo Seven Easy-728 Metrohm) [43]. Electrical conductivity (EC) was assessed in the saturated soil paste extracted using a conductivity meter (Orion brand, model 162) [44]. Total carbonates were quantified as ($CaCO_3$) using a Collins calcimeter [45]. Soil organic matter (OM) content was determined using the Walkley and Black method [46]. Cation exchange capacity (CEC) was measured utilizing the ammonium acetate extract method (1N NH_4OAc) [47]. Total nitrogen (Av. N) content was calculated using the Kjeldahl method [48]. Available phosphorus (Av. P) was determined through Olsen extraction methods and spectrophotometry analysis (JENWAY 6405 Model) [49]. Exchangeable potassium (Ex. K) and sodium (Na) were quantified using flame photometry (Jenway PFP7 model) [43]. Exchangeable calcium (Ca) and magnesium (Mg) were measured using atomic absorption spectrophotometry (novAA 800 D Analyzer) [43]. Extractable micronutrients iron (Fe), zinc (Zn), copper (Cu), and manganese (Mn) were extracted using the diethylenetriaminepenta-acetic acid (DTPA) method, and their concentrations were determined using a novAA 800 D Analyzer [50].

2.3. Statistical Analysis

To comprehensively understand the soil dynamics within the Mnasra region, multivariate analysis was conducted to identify underlying patterns and relationships among the various soil variables. Descriptive statistics for each soil physicochemical characteristic were computed using IBM SPSS Statistics 25. Measures such as minimum, maximum, mean, variance, standard deviation, coefficient of variation (CV), skewness, and kurtosis were determined to provide a comprehensive overview of the data. Additionally, the correlation between different soil properties was assessed using Pearson correlation coefficient. PCA was employed to reduce the dataset into new variables known as principal components (PCs). This approach aids in mitigating multicollinearity between the original variables and allows for a more concise representation of the data. The principal components elucidate the majority of the variance present in the original variables, facilitating a deeper understanding of the underlying patterns and relationships within the dataset [51,52].

2.4. Soil Quality Index (SQI)

The SQI was computed using Equation (2), as outlined by [53]:

$$\mathrm{SQI} = \sum_{i=1}^{n} \mathrm{Wi} \times \mathrm{Si} \tag{2}$$

where Wi represents the weight of an indicator, Si denotes the score of an indicator, and n signifies the total number of indicators considered.

From the results of PCA, Wi represents the component score coefficient (CSC). Due to variations in scales and units among soil indicators, the scores Si were standardized using Equation (3), following the methodology described by [54]:

$$z = \frac{x - \overline{x}}{\sigma} \tag{3}$$

where, z represents the standardized value, x is the value of a soil indicator, $\overline{x}$ denotes the average value of the indicator, and σ represents the standard deviation of the indicator.

Therefore, the SQI equation based on PCs is formulated as follows (Equation (4)):

$$\mathrm{SQI} - \mathrm{PC} = \sum_{i=1}^{n} \mathrm{CSC} \times z. \tag{4}$$

The comprehensive SQI (CSQI) was then calculated using Equation (5):

$$\mathrm{CSQI} = \sum_{i=1}^{n} \text{Variability of each PC} \times \mathrm{SQI} - \mathrm{PC} = \sum_{i=1}^{n} \text{Variability of each PC} \times \sum_{i=1}^{n} \mathrm{CSC} \times \mathrm{z}. \quad (5)$$

The CSQI, which is determined using z scores, was transformed into a standard normal distribution (with a mean of zero and a standard deviation of one) utilizing Equation (6) [54]:

$$f(\mathrm{x}) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(\mathrm{z})^2}{2}} \quad (6)$$

where e refers to the natural logarithm and z the standardized value.

The soil quality can be classified into the following categories, as shown in (Table 1).

Table 1. SQI classification [28].

SQI Values	SQI Interpretation
From 0.80 to 1	Very good
From 0.60 to 0.79	Good
From 0.35 to 0.59	Fair
From 0.20 to 0.34	Bad
From 0 to 0.19	Very bad

2.5. Geostatistics Analysis

The spatial variability of soil physicochemical properties, including pH, EC, OM, CEC, Av. N, Av. P, Ex. K, Na, Ca, Mg, Fe, Zn, Cu, Mn, sand, silt, clay, and porosity, was assessed using the geostatistical analyst extension module within ArcGIS 10.3. Geostatistical methods, which rely on semivariogram functions and Kriging interpolation as fundamental tools, facilitate the investigation of the spatial distribution of variables exhibiting both randomness and structure [55].

The ordinary kriging (OK) interpolation method was employed to map the spatial distribution of soil characteristics in unsampled locations using Equation (7) [56]:

$$\hat{\mathrm{z}}(\mathrm{x}_0) = \sum_{i=1}^{n} \lambda_i \mathrm{z}(\mathrm{x}_i) \quad (7)$$

where $\hat{\mathrm{z}}(\mathrm{x}_0)$ represents the estimated value at an unsampled location of x_0, $\mathrm{z}(\mathrm{x}_i)$ denotes the measured value at a sampled location x_i, and n is the number of sites surrounded by the search neighborhood used for the estimation.

To represent the average rate of variation of soil properties with distance, semivariogram models are utilized alongside OK for each soil property [7,57]. Eleven semivariogram models were tested, employing cross-validation based on prediction errors for each soil property dataset to identify the most suitable model. The semivariogram was estimated using Equation (8) [58,59]:

$$\gamma(\mathrm{h}) = \frac{1}{2\mathrm{N}(\mathrm{h})} \sum_{i=1}^{\mathrm{N}(\mathrm{h})} [\mathrm{Z}(\mathrm{x}_i) - \mathrm{Z}(\mathrm{x}_i + \mathrm{h})]^2 \quad (8)$$

where $\gamma(\mathrm{h})$ represents the semivariance value for a distance h, $\mathrm{N}(\mathrm{h})$ signifies the number of pairs involved in the semivariance calculation, $\mathrm{Z}(\mathrm{x}_i)$ denotes the value of the attribute Z at position x_i, and $\mathrm{Z}(\mathrm{x}_i + \mathrm{h})$ is the value of the attribute Z separated by a distance h from the position x_i.

The best semivariogram models were selected based on criteria such as 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). The chosen model should ideally exhibit mean error (ME), average standard error (ASE), and mean standardized error (MSE) values close to zero [60]. The flowchart of the procedures used to determine the SQI in this study is shown in (Figure 3).

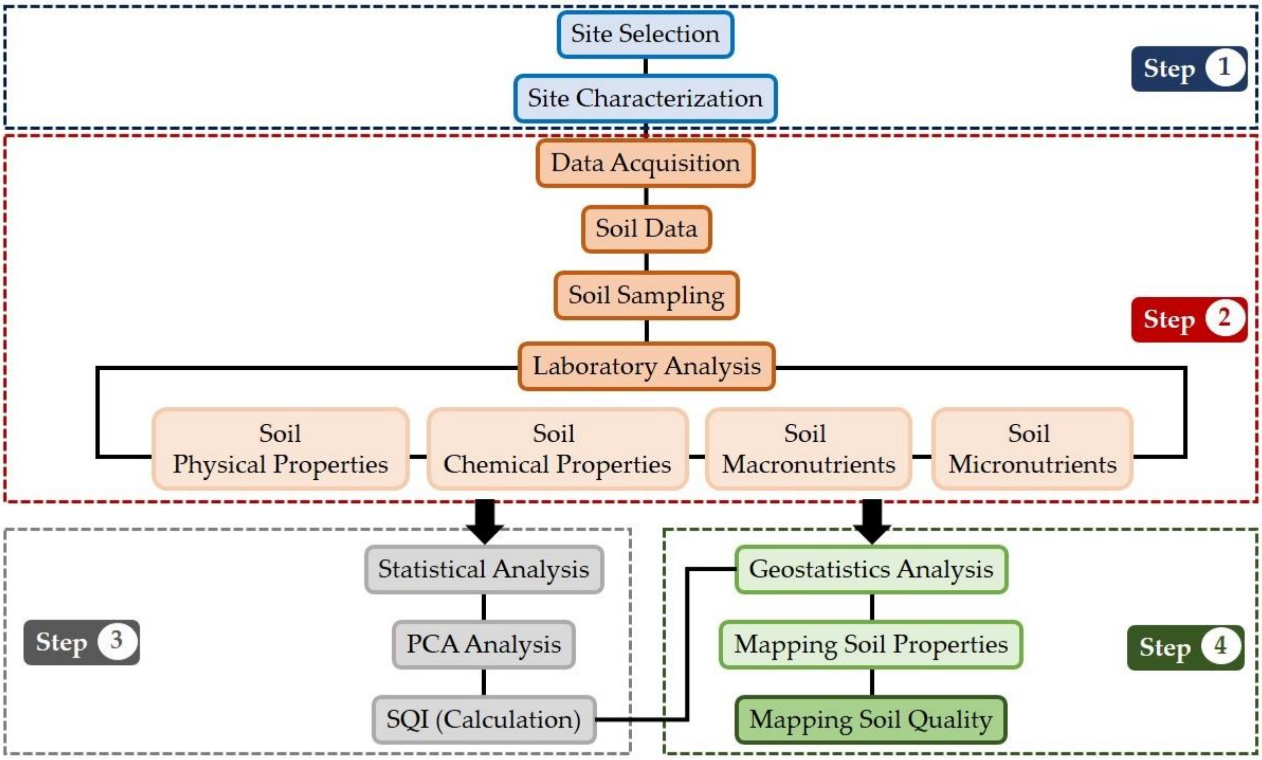


Figure 3. Soil quality assessment workflow depicting the four main steps.

3. Results and Discussion

3.1. Soil Physical Properties

3.1.1. Particle Size Distribution and Soil Texture

The soil physical characteristics of the study area are summarized in (Table 2). The analysis revealed varying proportions of sand, silt, and clay across the surface layer (0–20 cm) representing a range of soil texture categories.

Table 2. Soil physical properties of the sampling sites in the study area.

Samples	Sand (%)	Silt (%)	Clay (%)	Textural Class	Moisture (%)	Bulk Density (g/cm^3)	Particle Density (g/cm^3)	Total Porosity (%)
S1	88.21	6.21	5.57	Sand	0.90	1.58	2.90	45.52
S2	28.21	45.43	26.36	Loam	1.40	1.46	2.30	36.52
S3	24.71	54.57	20.71	Silty loam	6.70	1.41	2.30	38.70
S4	22.86	48.21	28.93	Clay Loam	3.10	1.44	2.30	37.39
S5	19.64	47.86	32.50	Silty clay loam	3.70	1.45	2.20	34.09
S6	12.14	55.79	32.07	Silty clay loam	4.00	1.40	2.20	36.36
S7	20.29	37.71	42.00	Clay	7.50	1.38	2.10	34.29
S8	21.00	57.71	21.29	Silty loam	11.40	1.39	2.30	39.57
S9	90.21	6.86	2.93	Sand	1.80	1.58	2.80	43.57
S10	87.86	7.57	4.57	Sand	2.50	1.55	2.60	40.38
S11	89.79	2.79	7.43	Sand	1.50	1.56	2.60	40.00
S12	88.29	5.14	6.57	Sand	3.30	1.55	2.60	40.38
S13	90.21	2.86	6.93	Sand	1.30	1.57	2.80	43.93
S14	90.07	7.93	2.00	Sand	3.20	1.57	2.80	43.93
S15	88.07	0.43	11.50	Loamy sand	3.70	1.49	2.50	40.40
S16	89.64	5.43	4.93	Sand	0.90	1.52	2.60	41.54
S17	91.36	5.43	3.21	Sand	3.60	1.59	2.80	43.21
S18	92.36	5.14	2.50	Sand	3.89	1.59	2.80	43.21
S19	83.36	11.93	4.71	Loamy sand	5.25	1.54	2.60	40.77
S20	81.00	9.14	9.86	Loamy sand	4.79	1.53	2.60	41.15

Table 2. *Cont.*

Samples	Sand (%)	Silt (%)	Clay (%)	Textural Class	Moisture (%)	Bulk Density (g/cm^3)	Particle Density (g/cm^3)	Total Porosity (%)
S21	79.86	7.79	12.36	Sand loam	4.71	1.49	2.50	40.40
S22	81.79	8.71	9.50	Loamy sand	3.96	1.53	2.60	41.15
S23	90.07	5.86	4.07	Sand	5.26	1.58	2.80	43.57
S24	88.14	7.14	4.71	Sand	2.69	1.55	2.60	40.38
S25	86.00	5.64	8.36	Loamy sand	3.20	1.52	2.60	41.54
S26	86.21	7.50	6.29	Loamy sand	2.28	1.55	2.60	40.38
S27	87.50	10.21	2.29	Sand	8.14	1.56	2.70	42.22
S28	81.14	4.71	14.14	Sand loam	5.21	1.46	2.30	36.52
S29	81.64	5.21	13.14	Sand loam	4.97	1.48	2.45	39.59
S30	83.43	12.43	4.14	Loamy sand	1.29	1.53	2.60	41.15

The data indicate that sand content ranged from 12.14% to 92.36%, with an average of 71.50%. Silt content varied from 0.43% to 57.71%, with an average of 16.65%. Meanwhile, clay content ranged from 2.00% to 42.00%, with an average of 11.85%. Consequently, the soil texture triangle (Figure 4) illustrated that sand predominated in the study area, comprising 43.33% of the sampled zones, with an additional 23.33% classified as loamy sand.

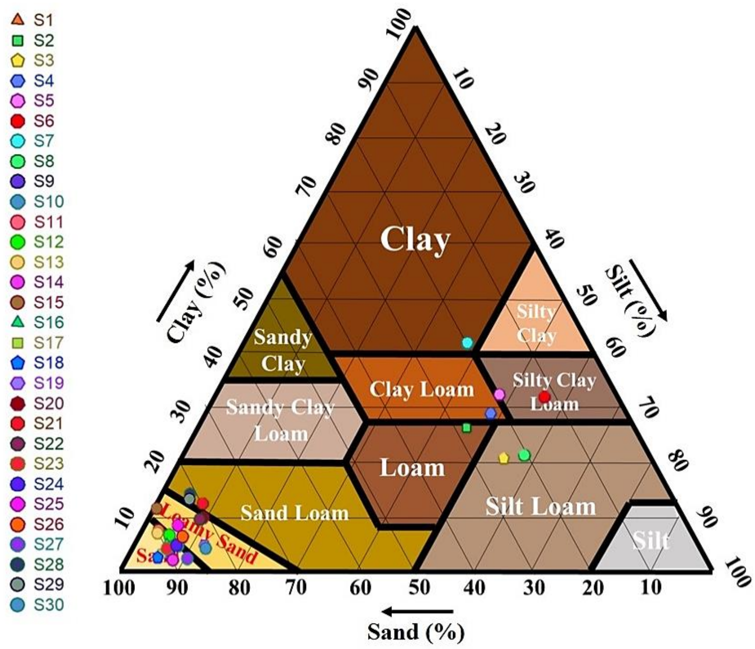


Figure 4. Soil texture triangle.

Samples S21, S28, and S29 (approximately 10%) in the surface layer were categorized as sand loam. A silty loam texture was observed only in samples S3 and S8 within the surface layer, while samples S5 and S6 exhibited silty clay loam texture. Clay, clay loam, and loam textures were solely present in samples S7, S4, and S2, respectively.

3.1.2. Soil Moisture, Bulk Density, Particle Density, and Soil Porosity

The analysis revealed that soil moisture content ranged from 0.90% to 11.40%, with a mean of 3.87%. The highest moisture content was observed in sample S8, whereas the lowest was recorded in sample S1. Soil bulk density serves as a crucial indicator of soil drainage characteristics [61]. Across all selected zones, soil bulk density ranged from 1.38 g/cm^3 to 1.59 g/cm^3, with an average of 1.51 g/cm^3. Total porosity of the soil exhibited a range from 34.09% to 45.52% across all sampled soils, with an average of 40.39%. Sample S1, characterized by sandy texture, demonstrated the highest total porosity, while sample S7, classified as clay soil texture, exhibited the lowest total porosity. This disparity underscores the influence of soil texture on porosity, with sandy soils typically possessing higher porosity than clayey soils due to differences in particle size and arrangement.

3.2. Soil Chemical Properties

3.2.1. Soil pH, Electrical Conductivity, Soil Organic Matter, $CaCO_3$ Content, and Cation Exchange Capacity

Descriptive statistics data for the studied soil properties are summarized in (Table 3).

Table 3. Statistical characterization of soil chemical properties.

Parameters	Minimum	Maximum	Mean	Variance	Std. Dev.	CV	Skewness	Kurtosis
pH	6.61	8.33	7.46	0.14	0.38	0.05	−0.08	0.06
EC (dS/m)	0.15	3.05	0.76	0.52	0.72	0.95	1.98	3.64
OM (%)	1.61	10.08	3.4	2.8	1.67	0.49	2.37	8.03
$CaCO_3$ (%)	0	4.28	0.68	1.14	1.06	1.56	2.01	3.8
CEC (cmol/kg)	1.34	3.11	2.09	0.27	0.52	0.24	0.44	−0.96
Macronutrients of soils								
Av. N (mg/kg)	65.56	193.53	107.72	1452.26	38.1	0.35	0.94	−0.18
Av. P (mg/kg)	0.82	103.47	25.81	653.6	25.56	0.99	1.63	2.41
Ex. K (mg/kg)	65	362.5	177.5	9721.55	98.59	0.55	0.62	−1.01
Na (mg/kg)	2.83	6.54	4.78	0.39	0.62	0.13	−0.38	3.67
Ca (mg/kg)	3	34.5	14.9	104.16	10.2	0.68	0.75	−0.91
Mg (mg/kg)	0	9.5	3.51	7.18	2.67	0.76	0.55	−0.53
Micronutrients of soils								
Fe (mg/kg)	1.77	13.82	5.44	9.35	3.05	0.56	1.23	1
Zn (mg/kg)	2.49	120.8	17.75	487	22.06	1.24	3.88	17.22
Cu (mg/kg)	0	18.85	1.72	16.84	4.1	2.38	3.15	10.87
Mn (mg/kg)	0.28	8.87	3.47	6.94	2.63	0.75	0.56	−0.96

Soil pH, a measure of the soil's acidity or alkalinity, plays a crucial role in determining the availability of essential nutrients for plant growth [62]. In the sampled site, soil pH values ranged from 6.61 to 8.33, with a mean of 7.46. The standard deviation and coefficient of variation (CV%) are reported as 0.38 and 0.05, respectively (Table 3). The lower CV in pH compared to other soil chemical parameters can be attributed to the uniform conditions observed in the study area, as indicated by the minimal skewness (−0.08). The alkaline nature of the soil is attributed to various factors such as alkaline parent material, climate, topography, and precipitation [7]. Similar results have been reported in the Hail region of Saudi Arabia by Alharbi and Aggag [63].

Soil electrical conductivity serves as a measure of soil salinity and can also indicate nutrient availability in the soil [64]. In the sampled area, the measured salinity values ranged from 0.15 to 3.05 dS/m, with an average of 0.76 dS/m. These values indicate low soil salinity, which is considered suitable for agriculture, as previously noted by Richards [65]. The standard deviation and coefficient of variation (CV%) for soil salinity are reported as 0.72 and 0.95, respectively (Table 3).

Soil OM is widely recognized as a crucial regulator of soil quality, directly impacting the availability of both macronutrients and micronutrients for plant uptake. Across the sampled sites, soil organic matter content ranged from 1.61% to 10.08%, with a mean of 3.4%, a standard deviation of 1.67, and a coefficient of variation (CV%) of 0.49 (Table 3). The variability in soil organic matter content was notably distinct among all selected sites. Sample S28 exhibited the highest OM content, classified as very rich, while sample S24 presented the lowest OM content, categorized as moderately low. The higher percentage of organic matter observed in some samples may be attributed to the application of organic manures and the implementation of soil management practices such as balanced fertilization, known to enhance soil organic matter levels [66]. However, it is important to note that the variability in soil organic matter content may also be influenced by pedogenic processes influenced by micro-topographical variations [67].

The $CaCO_3$ content ranged from 0% to 4.28%, with an average of 0.14% across all sampled soils. The standard deviation and coefficient of variation (CV%) for $CaCO_3$ content are reported as 1.06 and 1.56, respectively (Table 3). The distribution of $CaCO_3$ is influenced by various factors including the soil formation process, mineralogy, and climate of a particular region. Additionally, irrigation water quality, soil texture, and the parent material of an area also play significant roles in determining the distribution of calcium carbonate in soil [68].

Overall, the results presented in (Table 3) indicate that the samples exhibited a very low CEC capacity, falling within the range of 1.34 to 3.11 cmol/kg, according to the classification by Hazelton and Murphy [69]. The mean, standard deviation, and CV% values for CEC were calculated to be 2.09 cmol/kg, 0.52, and 0.24, respectively.

3.2.2. Soil Macronutrients

The results indicate considerable variability in Av. N content within the studied area. The available N levels ranged from 65.56 to 193.53 mg/kg, with a mean value of 107.72 mg/kg (Table 3). This mean falls within the low category of nitrogen content as per the classification proposed by Baruah and Barthakur [47]. The standard deviation of 38.1 indicates the degree of dispersion of Av. N values around the mean, suggesting a moderate level of variability. The coefficient of variation (CV%) of 0.35 further confirms this variability relative to the mean, indicating that the data dispersion is relatively low compared to the mean. The highest Av. N values were observed in samples S5 and S6, while the lowest value was recorded in sample S20. The presence of higher nitrogen levels in samples S5 and S7 may be attributed to factors such as organic matter content, or proximity to nitrogen sources like fertilizers or organic residues. Conversely, the lower nitrogen content in sample S20 may be due to factors such as soil leaching or nitrogen uptake by vegetation.

The results demonstrate a wide range of Av. P concentrations within the studied area (Table 3). The available P levels varied from 0.82 to 103.47 mg/kg, with a mean of 25.81 mg/kg. The standard deviation of 25.56 indicates moderate variability in available *p* values around the mean. The coefficient of variation (CV%) of 0.99 suggests a relatively high degree of variability in Av. P concentrations relative to the mean. Sample S7 exhibited the highest Av. P concentration, while sample S2 displayed the lowest. The factors contributing to these variations may include soil properties, proximity to phosphorus sources such as fertilizers. The classification based on Baruah and Barthakur [47] revealed that 46.66% of the samples were categorized as having low *p* content, indicating a deficiency that could potentially limit plant growth and productivity. Conversely, 20% of the samples were classified as having medium *p* concentrations. Notably, 33% of the samples were classified as having high *p* content, suggesting optimal *p* levels for plant growth and agricultural productivity.

Exchangeable K levels ranged from 65 to 362.5 mg/kg, with a mean of 177.5 mg/kg (Table 3). The standard deviation of 98.59 indicates a moderate level of variability in Ex. K values around the mean. A coefficient of variation (CV%) of 0.55 suggests that the variability in Ex. K concentrations relative to the mean is moderate. Sample S4 exhibited the highest Av. K concentration, while sample S25 displayed the lowest. This variability in Ex. K concentrations may be influenced by factors such as soil texture, mineral composition, land management practices, and proximity to potassium sources such as fertilizers. Classification based on Baruah and Barthakur [47] indicated that 56.66% of the samples were classified as having high K concentrations, suggesting an ample supply of potassium for plant growth and agricultural productivity. Additionally, 43.33% of the samples was classified as having medium K content, indicating satisfactory levels for plant growth. It has been observed that heavy soils containing more clay tend to have large reserves of potassium [66]. Clay-rich soils typically exhibit higher soil K indices on analysis, contributing to the availability of potassium to crops.

The analysis of Na, Ca, and Mg concentrations in the soil revealed distinct patterns of variability across the studied area. The concentrations of Na ranged from 2.83 to 6.54 mg/kg, with a mean of 4.78 mg/kg and a standard deviation of 0.62, resulting in a coefficient of variation (CV%) of 0.13 (Table 3). The concentrations of Ca ranged from 3 to 34.5 mg/kg, with a mean of 14.9 mg/kg and a standard deviation of 10.2, resulting in a CV% of 0.68. The concentrations of Mg ranged from 0 to 9.5 mg/kg, with a mean of 3.51 mg/kg and a standard deviation of 2.67, resulting in a CV% of 0.76. Sample S25 exhibited the highest Na concentration, while sample S5 displayed the highest Ca concentration, and sample S22 showed the highest Mg concentration. Conversely, sample S4 exhibited the lowest Na concentration, sample S30 displayed the lowest Ca concentration, and samples S15, S23, S25, and S26 showed the lowest Mg concentrations. These variations in Na, Ca, and Mg concentrations may be influenced by several factors, including soil mineralogy, weathering processes, and land management practices. The higher variability observed in Ca and Mg concentrations, as indicated by higher CV% values, suggests greater heterogeneity in these elements compared to Na.

3.2.3. Soil Micronutrients

The analysis of Fe, Zn, Cu, and Mn concentrations in the soil revealed significant variability across the studied samples (Table 3). The concentrations of Fe ranged from 1.77 to 13.82 mg/kg, with a mean of 5.44 mg/kg and a standard deviation of 3.05, resulting in a coefficient of variation (CV%) of 0.56. The concentrations of Zn ranged from 2.49 to 120.8 mg/kg, with a mean of 17.75 mg/kg and a standard deviation of 22.06, resulting in a CV% of 1.24. Cu concentrations varied only in some samples, ranged from 0 to 18.85 mg/kg, 1.72 with a mean of 1.72 mg/kg and a standard deviation of 4.1, resulting in a CV% of 2.38. Mn concentrations ranged from 0.28 to 8.87 mg/kg, with a mean of 3.47 mg/kg and a standard deviation of 2.63, resulting in a CV% of 0.75. Sample S28 exhibited the highest Fe and Zn concentrations, while sample S14 showed the highest Mn concentration. Conversely, sample S24 displayed the lowest Fe concentration, sample S25 exhibited the lowest Zn concentration, and sample S1 had the lowest Mn concentration. Additionally, 56.66% of the samples were classified as having high Fe concentrations, and all samples had high Zn concentrations. Moreover, 56% of the samples were classified as having high Mn concentrations, as mentioned by Reddy [70]. Cu concentrations were only detected in samples S1 to S8, with the highest concentration observed in sample S3. The micronutrient distribution can vary due to parent material, climatic conditions, and anthropogenic activities [71].

3.3. Relationships between Soil Properties

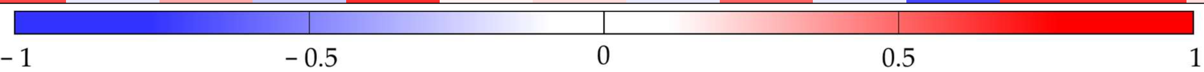
3.3.1. The Correlation Studies between Various Physicochemical Parameters

A Pearson correlation matrix was generated using the actual values of the 21 soil properties selected for statistical analysis, as listed in (Table 4). These properties include pH, EC, OM, CEC, Av. N, Av. P, Ex. K, Na, Ca, Mg, Fe, Zn, Cu, Mn, sand, silt, clay, moisture, BD, porosity, and $CaCO_3$.

In interpreting the correlation matrix, correlation coefficients (r) close to +1 or −1 indicate strong positive or negative correlations, respectively, between two variables. Conversely, an r-value near zero suggests a weak or nonexistent correlation [72]. Generally, correlations with r-values exceeding 0.7 are considered high, while those falling between 0.5 and 0.7 indicate moderate correlations [73].

Table 4. Correlations coefficients among soil physicochemical properties.

Variables	pH	EC	OM	CEC	Av. N	Av. P	Ex. K	Na	Ca	Mg	Fe	Zn	Cu	Mn	Sand	Silt	Clay	Moisture	BD	Porosity	$CaCO_3$
pH	1																				
EC	0.358	1																			
OM	0.248	0.166	1																		
CEC	0.318	0.434	0.421	1																	
Av. N	0.297	0.290	0.670	0.571	1																
Av. P	−0.148	−0.062	0.509	0.187	−0.028	1															
Ex. K	0.267	0.282	0.449	0.528	0.394	0.019	1														
Na	0.017	−0.206	0.070	−0.296	−0.198	0.200	−0.293	1													
Ca	0.487	0.413	0.263	0.585	0.728	−0.142	0.529	−0.303	1												
Mg	0.038	0.174	0.082	0.214	0.149	0.034	0.102	−0.331	0.004	1											
Fe	−0.013	0.131	0.631	0.456	0.364	0.541	0.278	−0.028	0.407	−0.033	1										
Zn	−0.174	0.013	0.664	−0.024	−0.264	0.457	−0.043	0.030	−0.009	−0.122	0.466	1									
Cu	0.303	0.319	0.059	0.441	0.619	−0.222	0.291	−0.003	0.666	0.232	0.223	−0.196	1								
Mn	−0.373	0.147	−0.175	0.118	−0.247	−0.037	−0.001	−0.167	−0.305	0.204	0.024	−0.029	−0.052	1							
Sand	−0.518	−0.278	−0.276	−0.742	−0.819	0.113	−0.476	0.186	−0.802	−0.187	−0.326	0.266	−0.675	0.229	1						
Silt	0.512	0.254	0.213	0.697	0.777	−0.203	0.466	−0.192	0.799	0.191	0.317	−0.310	0.714	−0.200	−0.978	1					
Clay	0.472	0.290	0.357	0.739	0.804	0.059	0.442	−0.155	0.718	0.159	0.306	−0.160	0.531	−0.255	−0.929	0.830	1				
Moisture	0.266	−0.070	0.472	0.307	0.240	0.447	0.153	0.275	0.211	0.069	0.595	0.051	0.294	−0.101	−0.399	0.414	0.328	1			
BD	−0.491	−0.159	−0.436	−0.685	−0.685	−0.005	−0.383	0.059	−0.620	−0.126	−0.359	0.070	−0.560	0.288	0.882	−0.819	−0.896	−0.508	1		
Porosity	−0.457	−0.260	−0.406	−0.622	−0.594	−0.095	−0.355	0.064	−0.558	−0.153	−0.213	−0.065	−0.402	0.223	0.774	−0.672	−0.868	−0.273	0.834	1	
$CaCO_3$	0.466	0.439	0.205	0.665	0.787	−0.051	0.498	−0.229	0.815	0.155	0.299	−0.173	0.608	−0.118	−0.873	0.829	0.855	0.209	−0.668	−0.757	1



The analysis revealed several significant correlations among the soil properties. The pH exhibited significant positive correlations with Ca (r = 0.487), silt (r = 0.512), clay (r = 0.472), and $CaCO_3$ (r = 0.466), while its correlations with EC, OM, CEC, Av. N, Ex. K, Na, Mg, Cu, and moisture were positive but not significant. Soil EC showed significant positive correlations with CEC (r = 0.434), Ca (r = 0.413), and $CaCO_3$ (r = 0.439). Additionally, its correlations with OM, Av. N, Ex. K, Mg, Fe, Zn, Cu, Mn, silt, and clay were positive but not significant. Soil organic matter (OM) exhibited significant positive correlations with CEC, Av. N, Av. P, Ex. K, Fe, Zn, and moisture (r = 0.421, 0.670, 0.509, 0.449, 0.631, 0.664, and 0.472, respectively), but it showed non-significant positive correlations with Na, Ca, Mg, Cu, silt, clay, and $CaCO_3$. Soil OM plays a crucial role in influencing soil chemical, physical, and biological properties, thereby affecting nutrient and water availability to crops [35]. CEC exhibited significant positive correlations with available Av. N, Ex. K, Ca, Fe, Cu, silt, clay, and $CaCO_3$. Av. N showed significant positive correlations with Ex. K, Ca, Mg, Fe, Cu, silt, clay, and $CaCO_3$. In addition, other significant correlations were observed, such as sand being significantly negatively correlated with silt and clay, while sand exhibited significant positive correlations with soil BD and porosity.

3.3.2. Principal Component Analysis

The PCA of various soil variables described the overall sensitivity pattern of the soil parameters and revealed the correlation between the soil variables based on the factor loadings from each principal component (PC). High eigenvalue PCs were considered to represent the maximum variations among different soil properties. The PCA loading for 21 variables allows the extraction of five principal components, explaining 76.21% of the overall variance of the data (Table 5).

Table 5. Principal component analysis results of selected soil variables.

Variables		Components				
		PC1	PC2	PC3	PC4	PC5
pH	Factor loadings	0.554	−0.124	−0.315	−0.312	0.375
EC		0.402	−0.116	0.441	−0.344	0.148
OM		0.403	0.779	0.051	−0.198	0.222
CEC		0.795	0.123	0.342	0.070	0.031
Av. N		0.830	−0.143	−0.032	0.083	−0.196
Av. P		0.014	0.818	0.087	0.150	0.077
Ex. K		0.555	−0.037	0.303	−0.133	−0.227
Na		−0.203	0.288	−0.651	0.212	0.013
Ca		0.848	−0.100	0.026	−0.278	−0.288
Mg		0.199	−0.121	0.458	0.385	0.594
Fe		0.441	0.705	0.199	0.111	−0.376
Zn		−0.111	0.763	0.206	−0.424	−0.008
Cu		0.684	−0.220	−0.031	0.231	−0.172
Mn		−0.224	−0.065	0.680	0.409	−0.055
Sand		−0.968	0.136	0.095	−0.098	0.011
Silt		0.927	−0.193	−0.094	0.144	−0.074
Clay		0.932	−0.020	−0.086	0.006	0.101
Moisture		0.431	0.535	−0.263	0.488	−0.004
BD		−0.884	−0.091	0.214	−0.094	−0.126
Porosity		−0.807	−0.085	0.100	0.105	−0.289
$CaCO_3$		0.894	−0.159	0.076	−0.073	−0.059
Eigenvalue		8.869	2.965	1.849	1.284	1.038
Variability (%)		42.235	14.117	8.805	6.115	4.940
Cumulative (%)		42.235	56.352	65.157	71.272	76.213

The axes PC1, PC2, and PC3 represents more than 65.15% of the data (Figure 5). Based on these percentages, the processes governing the physicochemical properties of the selected soils are essentially contained in these five components.

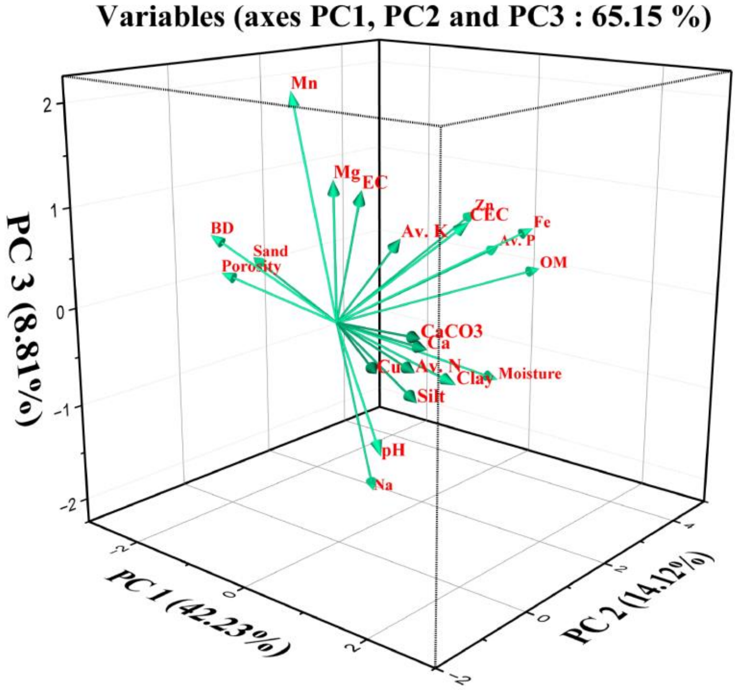


Figure 5. Principal component analysis for soil physicochemical properties.

The PC1 accounts for 42.23% of the total variation, with large positive loadings of pH, CEC, Av. N, Ex. K, Ca, Cu, silt, clay, and $CaCO_3$. Additionally, PC1 is negatively correlated with sand, indicating an inverse relationship between sand content and the variables loading positively on PC1. In other words, as sand content decreases, the levels of pH, CEC, Av. N, Ex. K, Ca, Cu, silt, clay, and $CaCO_3$ tend to increase, contributing to higher values of PC1. This component captures the combined variation of several important soil properties related to fertility, nutrient availability, and soil texture. Higher values of PC1 may correspond to soils with higher fertility, greater nutrient availability, and finer texture characterized by higher silt and clay content.

With high positive loadings of OM, Av. P, Fe, Zn and moisture, the PC2 explains 14.11% of the overall variance. Soils with higher values of PC2 may have higher organic matter content, improved phosphorus availability, and better micronutrient status, along with increased moisture levels.

The PC3 accounts for 8.80% of the total variability in the dataset. It is characterized by significant positive loadings of EC and Mn. Soils with higher values of PC3 may have higher levels of EC, reflecting greater soil salinity or ion concentration, and higher Mn content, which can influence various biochemical processes in soil and affect plant growth. In addition, PC3 is negatively correlated with sodium Na.

The PC5 explained approximately 4.94% of the total variance in the dataset. It is primarily characterized by a significant positive loading value for Mg of 0.59. It underscores the significance of Mg in soil composition and its potential implications for soil fertility, plant nutrition, and overall soil health.

3.4. Assessment of SQI According to PCA

The SQI was derived from the results of PCA using Equation (4) with the CSC obtained from (Table 6).

Subsequently, the CSQI was calculated using z-scores and transformed into a standard normal distribution utilizing Equation (6). The outcomes of CSQI are depicted in (Figure 6) and (Table 7).

In this study, the SQI ranged from 0.48 to 0.74 across the sampled soils, with a mean value of 0.60. The classification of the SQI into two categories, Good (Green) and Fair (Yellow), provides insights into the overall soil quality of the studied area (Figure 6).

Approximately 46.66% of the sampled soils were classified as "Good", with SQI values ranging from 0.8 to 1. This category includes samples S2, S3, S4, S5, S6, S7, S8, S12, S24, S25, S26, S27, S28, and S30. On the other hand, the remaining 53.33% of sampled soils were classified as "Fair", indicating slightly lower soil quality. These samples, including S1, S9, S1, S11, S13, S14, S15, S16, S17, S18, S19, S20, S21, S22, S23, and S29, fell within a lower SQI range. The identification of specific samples with the highest and lowest SQI values further emphasizes the spatial variability in soil quality within the study area. Sample S5 and S7 exhibited the highest SQI values, indicating relatively superior soil health and fertility characteristics. Conversely, sample S18 recorded the lowest SQI value, suggesting potential soil degradation or lower fertility levels in that particular area.

Table 6. Supplementary data indicating the component score coefficient matrix values and contribution of variables in the principal component analysis.

Variables		Component				
		PC1	PC2	PC3	PC4	PC5
pH	Component Score Coefficient Matrix (CSC)	0.186	−0.072	−0.232	−0.275	0.368
EC		0.135	−0.067	0.324	−0.304	0.145
OM		0.135	0.452	0.037	−0.174	0.218
CEC		0.267	0.072	0.251	0.062	0.030
Av. N		0.279	−0.083	−0.023	0.073	−0.192
Av. P		0.005	0.475	0.064	0.133	0.076
Ex. K		0.186	−0.021	0.223	−0.118	−0.222
Na		−0.068	0.167	−0.479	0.188	0.013
Ca		0.285	−0.058	0.019	−0.245	−0.283
Mg		0.067	−0.070	0.337	0.340	0.584
Fe		0.148	0.409	0.147	0.098	−0.370
Zn		−0.037	0.443	0.151	−0.374	−0.008
Cu		0.230	−0.128	−0.023	0.204	−0.169
Mn		−0.075	−0.038	0.500	0.361	−0.054
Sand		−0.325	0.079	0.070	−0.086	0.011
Silt		0.311	−0.112	−0.069	0.127	−0.072
Clay		0.313	−0.012	−0.063	0.005	0.099
Moisture		0.145	0.311	−0.194	0.430	−0.004
BD		−0.297	−0.053	0.157	−0.083	−0.124
Porosity		−0.271	−0.050	0.074	0.092	−0.283
$CaCO_3$		0.300	−0.092	0.056	−0.064	−0.058
Eigenvalue		8.869	2.965	1.849	1.284	1.038
Variability (%)		42.235	14.117	8.805	6.115	4.940
Cumulative (%)		42.235	56.352	65.157	71.272	76.213

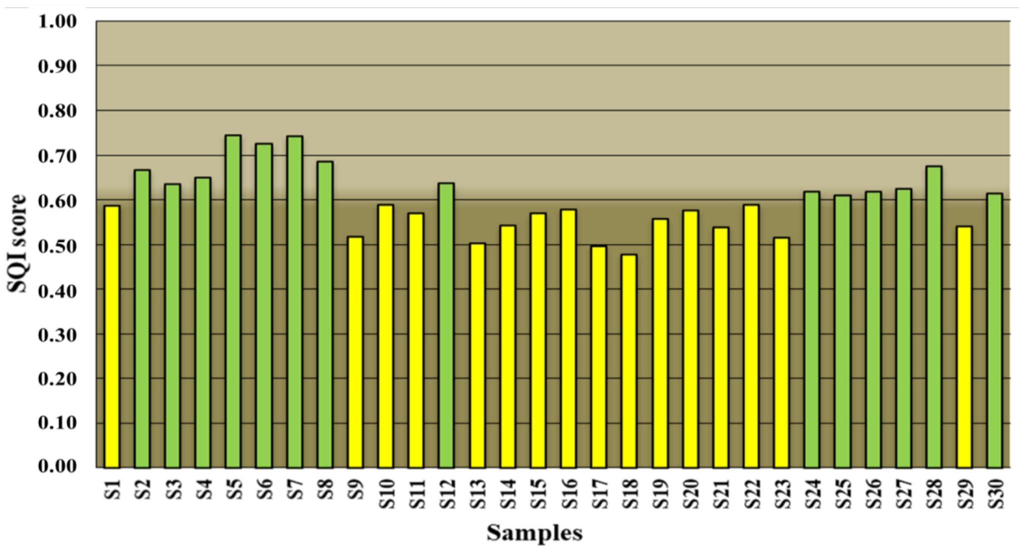


Figure 6. SQI results in the selected sites.

Table 7. CSQI calculation based on studied soil properties using PCA.

Samples	z-pH	z-EC	z-OM	z-CEC	z-Av. N	z-Av. P	z-Ex. K	z-Na	z-Ca	z-Mg	z-Fe	z-Zn	z-Cu	z-Mn	z-Sand	z-Silt	z-Clay	z-Moisture	z-BD	z-Porosity	z-$CaCO_3$	SQI-PC1	SQI-PC2	SQI-PC3	SQI-PC4	SQI-PC5	CSQI-1	CSQI-2
S1	1.12	0.95	0.38	1.06	1.35	0.42	0.33	0.60	1.38	0.94	1.23	0.16	0.71	1.21	0.59	0.55	0.59	1.27	1.17	1.81	0.38	1.40	0.76	1.31	0.87	−0.77	0.83	0.59
S2	0.86	0.11	0.41	1.75	0.70	0.98	1.88	0.51	1.63	0.57	0.69	0.54	0.28	0.92	1.52	1.52	1.35	1.06	0.83	1.37	0.89	1.99	1.08	1.36	0.40	−0.99	1.09	0.67
S3	0.96	0.04	0.07	1.08	0.90	0.86	0.63	0.37	1.48	1.30	0.16	0.49	4.18	0.27	1.64	2.00	0.83	1.21	1.67	0.60	0.64	2.34	0.08	0.70	1.33	−0.74	1.11	0.63
S4	1.06	0.16	0.13	0.89	1.43	0.94	1.88	3.10	1.67	0.74	0.01	0.59	0.25	0.85	1.71	1.67	1.59	0.33	1.17	1.06	2.10	2.02	0.62	0.00	0.34	−0.76	0.92	0.65
S5	0.16	1.99	0.44	1.22	2.25	0.70	1.12	049	1.92	0.55	0.54	0.56	2.34	1.30	1.82	1.65	1.92	0.07	1.00	2.23	3.37	3.22	−0.20	2.31	0.08	−1.89	1.45	0.74
S6	2.26	2.62	0.13	1.89	1.52	0.47	0.96	0.15	1.72	0.94	0.54	0.52	0.97	0.74	2.08	2.07	1.88	0.06	1.83	1.42	1.84	2.86	−0.32	2.17	−1.04	−0.19	1.28	0.73
S7	0.10	0.50	1.33	0.96	2.25	3.04	0.33	0.20	0.55	1.30	1.32	0.47	0.32	0.90	1.80	1.11	2.81	1.55	2.17	2.16	1.49	1.99	2.64	2.11	1.52	−0.56	1.46	0.74
S8	1.04	0.53	1.50	0.66	1.06	0.77	0.18	0.39	1.28	0.18	2.28	0.41	0.76	0.08	1.77	2.17	0.88	3.22	2.00	0.29	0.55	2.15	2.60	0.19	0.90	−1.04	1.30	0.69
S9	1.09	0.65	0.90	0.24	0.41	0.34	0.74	0.67	0.92	0.01	0.37	0.47	0.42	1.92	0.66	0.52	0.83	0.88	1.17	1.12	0.64	0.81	0.79	1.10	0.25	−0.53	0.54	0.52
S10	0.05	0.83	0.90	0.98	0.12	0.52	0.43	0.34	0.87	1.49	0.59	0.46	0.42	0.64	0.57	0.48	0.68	0.59	0.67	0.00	0.64	1.32	0.98	1.47	0.40	050	0.87	0.59
S11	0.03	0.62	0.02	1.46	0.49	0.59	0.58	1.06	0.45	0.18	0.85	1.69	0.42	005	0.64	0.73	0.41	1.01	0.83	0.14	0.22	1.03	1.68	0.60	0.05	−0.61	0.70	0.57
S12	1.12	3.15	0.93	0.66	0.86	0.08	0.89	1.06	0.87	1.86	0.85	0.30	0.42	1.23	0.59	0.61	0.49	0.24	0.67	0.00	0.35	1.85	0.48	2.10	−0.24	1.04	1.07	0.64
S13	0.99	0.21	0.16	0.43	0.86	0.30	0.48	0.58	0.58	0.37	0.67	0.35	0.42	1.22	0.66	0.73	0.46	1.10	1.00	1.25	0.64	0.79	0.58	0.70	0.76	−0.66	0.49	0.50
S14	1.84	0.11	0.33	0.24	0.94	0.20	0.79	0.13	0.92	1.30	0.49	0.09	0.42	2.04	0.65	0.46	0.92	0.29	1.00	1.25	0.64	1.04	−0.08	1.52	0.62	0.12	0.61	0.54
S15	0.03	0.38	0.78	0.43	0.57	0.15	1.80	0.51	0.14	1.31	0.31	0.24	0.42	0.96	0.58	0.86	0.03	0.07	033	0.00	0.64	1.11	0.37	1.46	0.52	0.11	0.69	0.57
S16	1.06	0.65	0.90	0.22	0.66	0.96	0.99	1.48	0.58	0.18	0.66	0.41	0.42	0.10	0.64	0.59	0.65	1.27	0.17	0.41	0.64	1.48	1.56	−0.31	0.21	−0.10	0.82	0.58
S17	0.26	0.04	0.13	0.52	1.02	1.03	1.50	0.36	0.48	0.37	0.47	0.10	0.42	0.09	0.70	0.59	0.80	0.12	1.33	1.00	0.13	0.67	0.51	0.77	0.20	−0.88	0.39	0.50
S18	0.03	0.62	0.02	0.52	0.37	0.91	0.66	0.03	0.48	0.75	0.46	0.25	0.42	1.02	0.73	0.61	0.87	0.01	1.33	1.00	0.38	0.40	0.35	1.64	0.43	−0.44	0.36	0.48
S19	0.73	0.76	0.55	0.56	0.74	0.45	1.06	0.75	0.68	0.94	0.02	0.25	0.42	1.34	0.42	0.25	0.67	0.59	0.50	0.13	0.38	1.23	0.46	1.12	0.47	0.31	0.73	0.56
S20	2.21	0.74	0.67	0.60	1.11	0.37	0.81	0.42	0.87	0.57	0.08	0.02	0.42	0.73	0.33	0.40	0.19	0.39	0.33	0.27	0.64	1.68	0.16	0.48	−0.32	0.51	0.78	0.58
S21	0.23	0.64	0.70	0.81	0.08	0.50	0.79	2.78	0.92	0.75	0.72	0.25	0.42	0.92	0.29	0.47	0.05	0.36	0.33	0.00	0.64	1.07	1.21	0.13	0.72	−0.08	0.67	0.54
S22	0.60	0.37	0.33	0.94	0.66	0.20	0.76	0.44	0.48	2.23	0.83	0.15	0.42	0.95	0.36	0.42	0.22	0.04	0.33	0.27	0.64	1.29	0.28	1.64	0.88	0.68	0.81	0.59
S23	0.65	0.53	0.36	0.94	0.74	0.55	0.53	1.20	0.14	1.31	0.82	0.09	0.42	1.02	0.65	0.57	0.72	0.59	1.17	1.12	0.13	0.65	0.75	1.03	1.13	0.08	0.54	0.51
S24	0.57	0.69	1.07	1.23	1.02	0.65	0.99	0.36	0.30	0.57	1.20	0.38	0.42	1.20	0.58	0.50	0.67	0.50	0.67	0.00	0.12	1.50	1.34	1.51	0.42	−0.18	0.97	0.62
S25	1.61	0.64	0.92	0,75	0.94	0.84	1.14	1.08	0.72	1.31	0.47	0.69	0.42	0.09	0.51	0.58	0.33	0.28	0.17	0.41	0.64	1.73	1.07	0.50	−0.19	0.68	0.95	0.61
S26	0.81	0.73	0.78	1.02	0.57	0.66	1.09	0.27	0.97	1.31	0.83	0.27	0.42	1.06	0.52	0.48	0.52	0.68	0.67	0.00	0.64	1.70	0.93	1.60	0.41	0.26	1.03	0.62
S27	0.34	0.45	0.04	0.57	0.04	2.08	0.99	0.32	0.06	0.19	1.60	0.57	0.42	0.62	0.56	0.34	0.89	1.83	0.83	0.65	0.38	0.92	2.29	0.91	1.08	−0.70	0.82	0.62
S28	0.16	0.01	4.00	0.93	0.66	2.23	0.10	0.51	0.30	0.57	2.74	4.67	0.42	0.27	0.34	0.63	0.21	0.57	0.83	1.37	0.13	1.09	6.03	1.78	−1.09	−0.42	1.38	0.67
S29	0.18	0.35	0.13	0.92	0.25	0.17	0.91	0.41	0.97	0.19	0.79	0.09	0.42	0.60	0.36	0.60	0.12	0.47	0.50	0.28	0.64	1.15	0.42	0.84	0.25	−0.82	0.60	0.54
S30	0.88	0.73	0.67	1.08	0.16	0.42	0.99	0.56	1.17	0.18	0.98	0.56	0.42	0.97	0.42	0.22	0.72	1.10	0.33	0.27	0.64	1.66	1.26	0.95	0.07	−0.42	0.95	0.61

Previous investigations utilizing the Soil Quality Index (SQI) to assess soil quality yielded comparable findings. Aggag and Alharbi [7] indicated that the SQI outcomes delineate the study area into three distinct zones: very good, good, and fair soil quality. Specifically, regions classified as very good and good quality collectively encompass approximately 14.48% and 50.77% of the total surveyed area, while fair soil quality, primarily attributed to salinity and low soil nutrients, accounts for about 34.75%.

3.5. Geostatistical Analysis and Spatial Distribution of Soil Properties

3.5.1. Spatial Variability of Soil Properties

In the pursuit of maintaining soil and plant sustainability, precision agriculture relies heavily on insights garnered from assessing and mapping the spatial variability of soil characteristics [74]. To this end, OK was employed to evaluate the spatial variability of 18 soil variables, encompassing pH, EC, OM, CEC, Av. N, Av. P, Ex. K, Na, Ca, Mg, Fe, Zn, Cu, Mn, sand, silt, clay, and porosity, in order to estimate and map the unknown values of these soil properties. Various semivariogram models were tested for each soil attribute dataset, and the best-fitted models, along with their prediction errors, were identified, as detailed in (Table 8).

The accuracy of the models was assessed based on metrics such as ME, RMSE, MSE, and RMSSE. After cross-validating the performance of eleven semivariogram models, nine models emerged as the most suitable for mapping the spatial variability of the selected properties.

The analysis identified the best-fit model for various soil properties, with Pentaspherical emerging as the optimal model for soil pH, EC, and silt. Exponential best-fit models were found to be suitable for OM and CEC, while a rational quadratic model best fit Av. N, Av. P, sand, and clay. Spherical models were determined as the most appropriate for soil Ex. K and Na, while K-Bessel fit Ca and Cu data well, and the circular model was suitable for Mg. Porosity and Fe exhibited a J-Bessel best-fit model, whereas Gaussian proved optimal for Zn and stable for Mn. These findings align with prior research that observed the prevalence of exponential, stable, K-Bessel, and spherical models for soil chemical properties [75]. Notably, the results indicate RMSSE proximity to one and MSE proximity to zero across the selected soil properties, suggesting that the chosen models effectively fit the data and are well-suited for predicting unsampled soil properties.

The analysis revealed that all soil properties exhibited varying degrees of spatial dependence (SD), ranging from moderate to weak and strong (Table 8). Notably, Av. N, Na, and clay demonstrated strong spatial dependence, attributed primarily to geomorphological and soil structural factors, including parent material, depth to bedrock, topography, and soil texture [76]. Conversely, EC, OM, CEC, Av. P, Ex. K, Ca, Mg, Zn, Cu, Mn, sand, silt, and porosity exhibited moderate spatial dependence, likely influenced by a combination of soil structural and extrinsic factors, including leaching processes [35]. Additionally, pH and Fe showed weak spatial dependence, suggesting lesser influence from extrinsic random factors such as climatic conditions, land use changes, and soil management practices like fertilization and irrigation system uniformity [27].

The spatial distribution maps generated through OK interpolation showed that the soil pH ranges from 6.61 to 8.33, with higher values observed in the southeast portion (Figure 7a).

Similarly, EC ranges from 0.16 to 3.05 dS/m, with higher values concentrated in the eastern part (Figure 7b). Soil OM values range from 2.84 to 4.5%, with higher concentrations in the southern region (Figure 7c). Elevated levels of Av. N, Av. P, and Ex. K are primarily found in the southeast, northeast, east, and northwest fields, with values ranging from 158.36 to 193.54 mg/kg for Av. N, 47.14 to 69.95 mg/kg for Av. P, and 306.23 to 362.5 mg/kg for Ex. K, respectively (Figure 8).

Soil CEC, Na, Ca, Mg, Fe, Zn, Cu, Mn and porosity also exhibit varying distribution patterns across the area, with higher values generally observed in the east, southeast, and northeast fields compared to the west and southwest fields (Figures 8–10).

Table 8. Semivariogram parameters of the selected soil properties.

Soil Properties	Best-Fitted Model	Nugget	Partial Sill	Sill	Nugget/Sill	SDC	Prediction Errors				
							ME	RMSE	MSE	RMSSE	ASE
pH	Pentaspherical	14.00	0.01	14.01	1.00	Weak	0.0002	0.4121	0.0001	1.0040	0.4124
EC	Pentaspherical	0.21	0.31	0.52	0.40	Moderate	0.0001	0.6436	−0.0121	1.0279	0.6294
OM	Exponential	2.23	0.86	3.09	072	Moderate	−0.0491	1.8557	−0.0308	1.1149	1.6535
CEC	Exponential	0.20	0.20	0.40	0.50	Moderate	0.0064	0.4698	0.0061	0.9902	0.4774
Av. N	Rational Quadratic	134.36	1569.66	1704.02	0.08	Strong	0.0227	20.4236	−0.0074	0.8568	25.7317
Av. P	Rational Quadratic	482.63	198.86	681.49	0.71	Moderate	−0.3996	25.6871	−0.0168	1.0083	25.4855
Ex. K	Spherical	3848.17	8340.20	12,188.37	0.32	Moderate	0.0218	96.2504	−0.0131	1.0418	91.4128
Na	Spherical	0.00	0.45	0.45	0.00	Strong	0.0001	0.5846	−0.0105	1.0390	0.5285
Ca	K-Bessel	52.22	85.12	137.34	0.38	Moderate	0.1509	7.6766	0.0114	0.9176	8.1934
Mg	Circular	2.63	5.11	7.74	0.34	Moderate	−0.0325	2.8651	0.0044	1.0653	2.6544
Fe	J-Bessel	7.46	2.15	9.61	0.78	Weak	−0.0835	3.2337	−0.0272	1.0882	2.9493
Zn	Gaussian	293.68	498.12	791.80	0.37	Moderate	−0.2277	23.5815	−0.0053	1.2340	18.4944
Cu	K-Bessel	9.53	13.19	22.72	0.42	Moderate	0.0000	3.1222	−0.0008	0.9045	3.5267
Mn	Stable	3.41	3.41	6.82	0.50	Moderate	−0.0051	2.0940	−0.0030	0.9645	2.1785
Sand	Rational Quadratic	313.16	580.08	893.24	0.35	Moderate	−0.5418	21.7406	−0.0104	0.8659	25.7928
Silt	Pentaspherical	141.53	294.18	435.71	0.32	Moderate	0.4637	14.6749	0.0210	0.9392	15.7000
Clay	Rational Quadratic	8.72	100.29	109.01	0.08	Strong	0.2189	9.4223	0.0117	1.0640	8.7242
Porosity	J-Bessel	5.47	2.81	8.28	0.66	Moderate	0.0182	2.7933	0.0037	1.0681	2.6031

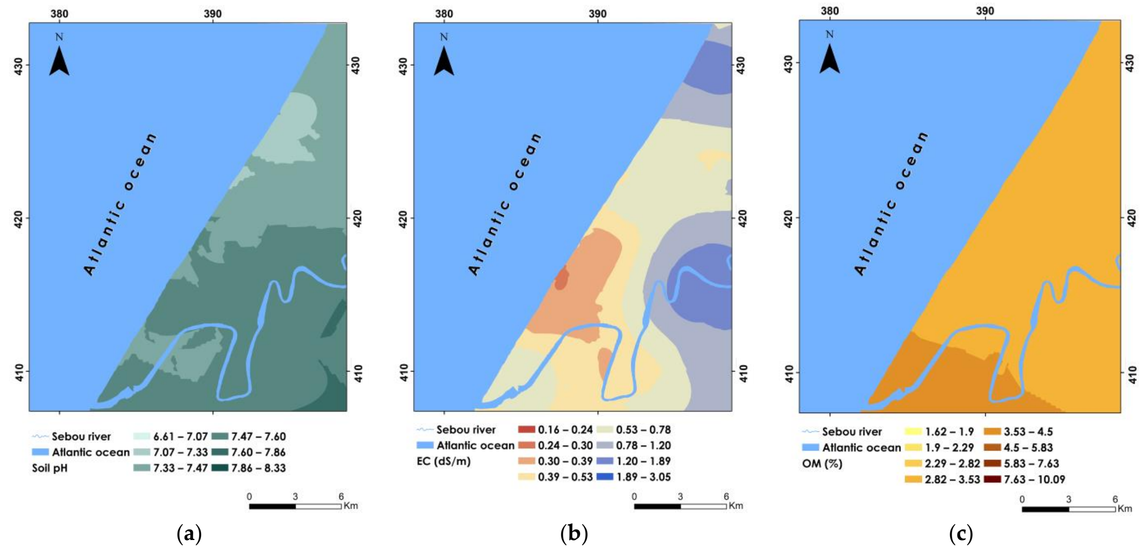


Figure 7. Spatial distribution (kriged) maps of (**a**) soil pH, (**b**) EC, and (**c**) OM.

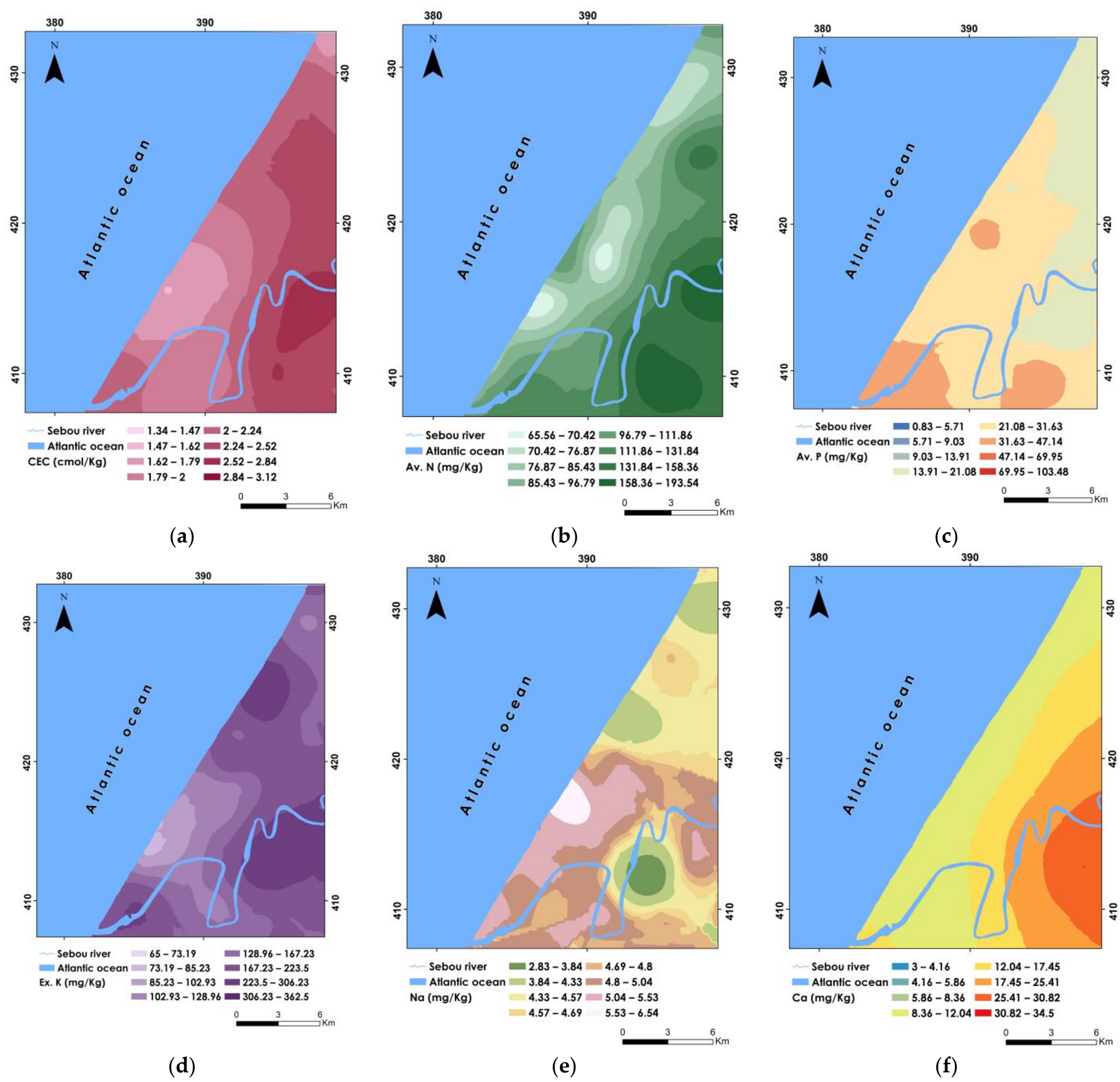


Figure 8. Spatial distribution (kriged) maps of (**a**) CEC, (**b**) Av. N, (**c**) Av. P, (**d**) Ex. K, (**e**) Na, and (**f**) Ca.

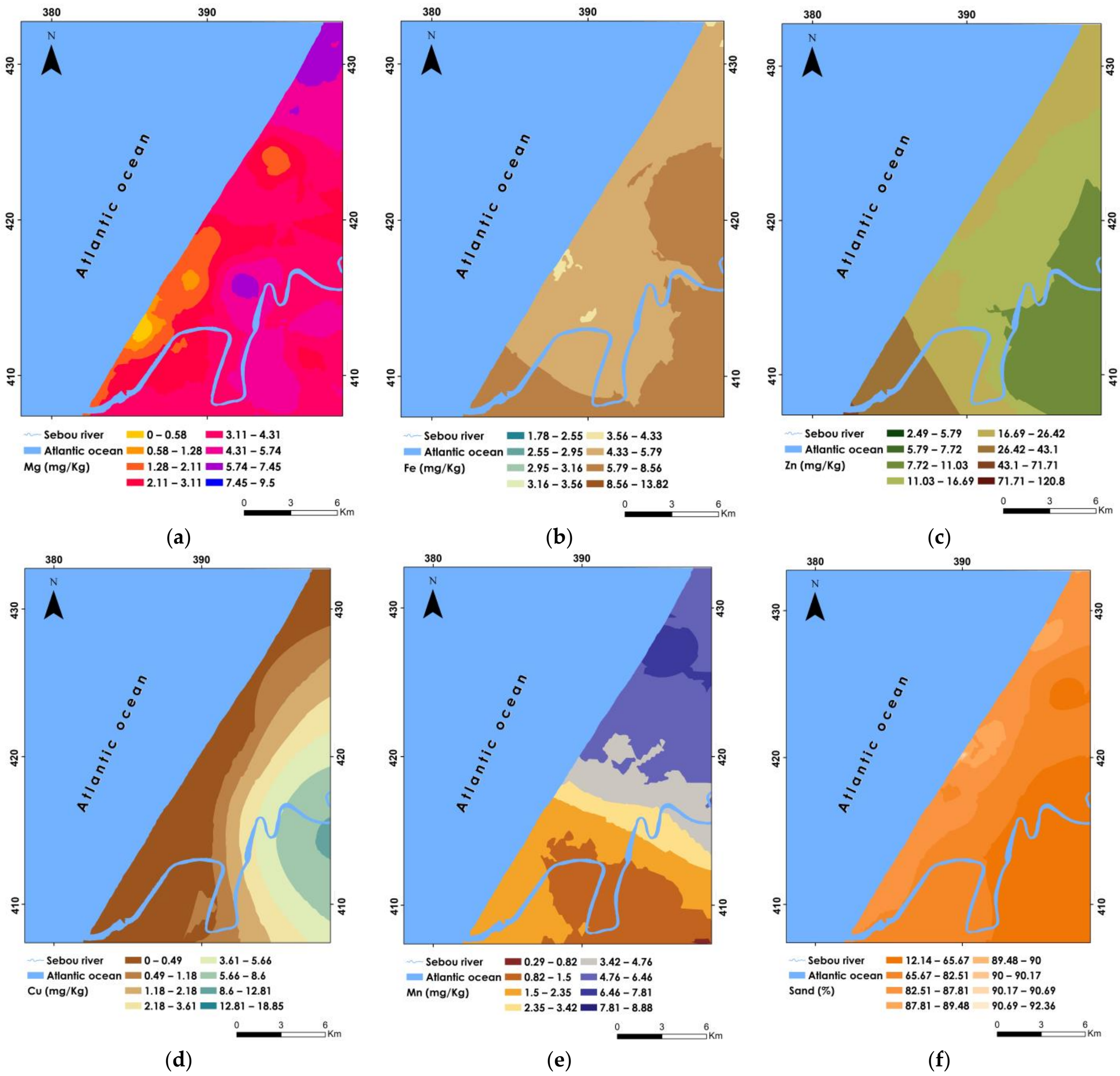


Figure 9. Spatial distribution (kriged) maps of (**a**) Mg, (**b**) Fe, (**c**) Zn, (**d**) Cu, (**e**) Mn, and (**f**) Sand.

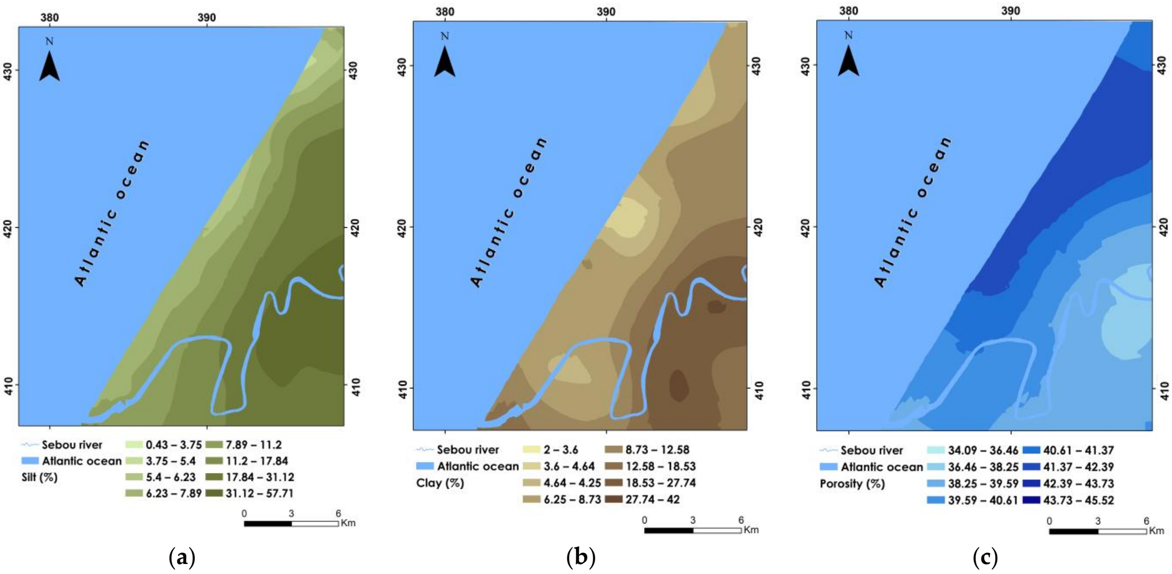


Figure 10. Spatial distribution (kriged) maps of (**a**) silt, (**b**) clay, and (**c**) porosity.

3.5.2. Spatial Analysis of SQI

The spatial variability of soil quality in the study area, interpolated using OK (Figure 11), reveals a range of SQI values from 0.48 to 0.73.

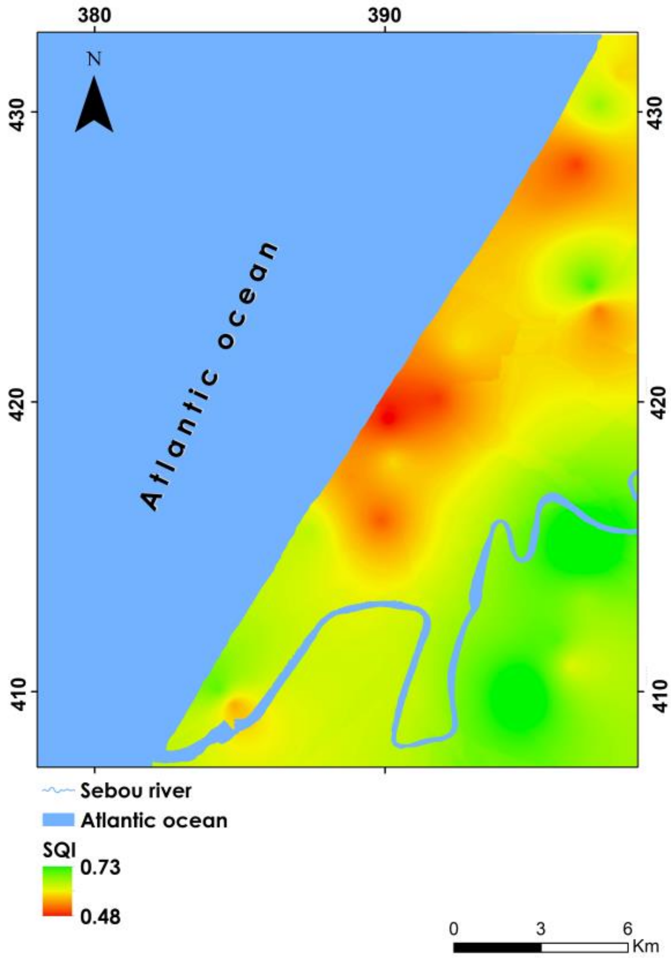


Figure 11. The spatial distribution of the SQI in the study area.

Areas with higher soil quality values are predominantly located in the south, southeast, and southwest sections of the field, characterized by a very good quality index and adequate values across all soil characteristics. Conversely, the middle and northwest portions exhibit lower SQI values, indicating poorer soil quality. Factors such as clay composition, organic matter content, EC, Av. N, Av. P, Ex. K, and CEC are identified as the most influential contributors to SQI [77]. Low values of these parameters negatively impact SQI, while physical indicators like depth, bulk density, porosity, aggregate stability, and compaction affect soil structure and root growth, influencing water infiltration and plant emergence speed [78]. Soil texture plays a pivotal role in water-holding capacity, soil structure, and nutrient availability, with particle size surface area identified as a critical determinant [79,80]. Additionally, soil texture has a significant influence on the distribution and retention of soil OM. Soils with finer textures, such as clay, tend to have higher surface areas and greater capacity to retain organic matter compared to sandy soils [32,42]. To improve soil quality and productivity and prevent land degradation in the northwest and central fields, enhancing soil organic matter through organic manure application and conservation agriculture practices is recommended. Soil organic matter significantly influences soil function and is pivotal in enhancing various soil properties, as indicated by numerous previous studies [81–84].

4. Conclusions

This research aimed to characterize the physical and chemical attributes of soil in order to evaluate the SQI within the agricultural landscape of the Mnasra region, nestled within Morocco's Gharb Plain, employing an integrated methodology that incorporates multivariate and geostatistical analyses. To achieve this objective, thirty soil samples were collected from the surface layers (0–20 cm) across thirty designated sites.

The study unveiled considerable disparities in soil attributes including pH, EC, OM, CEC, and nutrient content (Av. N, Av. P, and Av. K), each displaying distinct spatial distributions influenced by factors like soil texture, parent material, and agricultural practices. Statistical analyses, encompassing Pearson correlation and PCA, unveiled inter-relationships among these soil properties, facilitating the computation of the SQI. PCA revealed five PCs, collectively explaining 76.21% of the overall variance in soil properties. Additionally, SQI calculations offered a comprehensive evaluation of soil health, indicating variations in soil quality across distinct zones within the study area. SQI values ranged from 0.48 to 0.74 among sampled soils, with a mean value of 0.60. Approximately 46.66% of sampled soils were classified as "Good", while 53.33% were categorized as "Fair", suggesting a slightly lower overall soil quality. The geostatistical analysis uncovered distinct spatial patterns for various soil properties, with different semivariogram models proving optimal based on the specific property. For instance, the Pentaspherical model was ideal for pH, EC, and silt, while exponential models suited OM and CEC. Rational quadratic models provided the best fit for Av. N, Av. P, sand, and clay. Spherical models were appropriate for Av. K and Na, with K-Bessel fitting well for Ca and Cu, and the circular model for Mg. Porosity and Fe displayed a J-Bessel best-fit model, while Gaussian and stable models were optimal for Zn and Mn, respectively. Moreover, the analysis highlighted varying degrees of spatial dependence across soil properties, influenced by both intrinsic soil factors and extrinsic environmental factors.

The study identifies varying soil quality across the landscape, influenced by factors such as organic matter, clay content, and nutrient availability. It emphasizes the im-portance of integrated methodologies involving field assessments, statistical analyses, and geospatial techniques for comprehensive soil quality evaluation. These findings offer valuable insights for decision-makers in agricultural land management, facilitating sustainable development in Morocco's Gharb region. Proposed actions include enhancing organic matter, optimizing nutrient levels, improving soil structure, implementing erosion control measures, and promoting sustainable land use practices like agroforestry and crop rotation. These strategies aim to address soil degradation, enhance agricultural productivity, and contribute to global efforts in environmental conservation and sustainable land management. It is essential to incorporate additional analyses such as heavy metals and pesticides assessments to develop comprehensive control strategies aimed at mitigating the adverse impacts of agricultural practices and safeguarding soil quality for future generations.

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