10 Egypt. J. Soil Sci. **Vol. 64**, No. 1, pp: 153-166 (2024)

# Egyptian Journal of Soil Science

**http://ejss.journals.ekb.eg/**

## Characterization of The Spatial Variability of Some Soil Physicochemical Properties of The El-Gallaba Plain, New Aswan City, Aswan Governorate, Egypt

**Salah H. Abd El-Aziz**[1], **Ahmed Gh. M. Ibrahim**[2], **Esraa G. M. Okashaa**[2] and **Alaa H. Abd El-Azem**[2]

[1] *Soils and Water Department, Faculty of Agriculture, Assiut University*
[2] *Soils and Natural Resources Department, Faculty of Agriculture and Natural Resources, Aswan University*

THE MAJOR aim of the study was to assess and map the spatial variability of some soil properties in El-Gallaba Plain, New Aswan City, using a geostatistical technique. Forty topsoil samples were selected from forty profiles that were dug to represent the study area. The variability of the soil maps was drawn based on the ordinary kriging interpolation method based on the geostatistical analysis. The data indicates that most of the soil samples were rough in texture. The organic matter was extremely low in most soil samples ($\leq$ 4.03 g kg$^{-1}$). The salinity of soil paste extract (ECe) ranges from 0.84 to 28.21 dSm$^{-1}$. The soil reaction (pH) values of the surface soils vary between 7.69 and 8.89. The calcium carbonate values extend between 0.43 and 9.74 %. Gypsum contents in the soil samples range between 0.49 to 4.07%. The CEC of soil samples ranged between 3.73 and 25.35 cmolc ($^{+}$)/kg. The coefficient of variation of soil pH was low (CV<5%), medium for sand fraction (CV<25%), and the rest of the soil properties were high to very high in the coefficient of variation. The normal histogram and QQPlots analysis of the physicochemical properties of the studied soil samples was applied to make the data more normally distributed. Logarithmic transformation of the soil properties data was used to normalize highly skewed and distant datasets because ordinary kriging methods work best if the data are approximately normally distributed. The ordinary Kriging (OK) method was used in the present study as an interpolation method compared to other Kriging methods due to it being simple and having high accuracy for prediction. The data reveal that the Gaussian, J-Bessel, Exponential, Rational Quadratic, and K-Bessel are the best-fitted semivariogram models for all properties selected. Accurate maps efficiently generated using geostatistics were essential to properly understand the spatial variability of the area under study. This study gives useful information about the physical and chemical characteristics and the spatial diversity of this soil.

**Keywords:** New Aswan City; El-Gallaba plain; Spatial Variability; Ordinary Kriging**.**

### 1. Introduction

The simultaneous operation of biological, natural, and chemical processes at different degrees and levels causes soils to be highly variable (Ghartey et al., 2012; Serrano et al., 2014). Describing the spatial variability of soil properties is essential for understanding the complex relationships between soil properties and environmental factors. Knowledge of the spatial variation and relationships between soil properties is important for the evaluation of agriculture. Understanding the distribution of soil characteristics is essential for improving agricultural management practices so that farm inputs can be properly adjusted and applied to the fields and accurate management decisions can be made accordingly (Fathi et al., 2014). In addition, the estimation of the spatial variability of soil properties is important for evaluating the ecology and basic requirements for soil and crop-specific management (Iňigo et al., 2012; Akbas, 2014). Also, Brevik et al. (2016) reported that monitoring and mapping the spatial variability patterns of soil

*Corresponding author e-mail: nour2015karim@gmail.com
Received: 17/09/2023; Accepted: 12/11/2023
DOI: 10.21608/EJSS.2023.237046.1663

characteristics provide valuable information for efficient nutrient management. Furthermore, it is The geostatistical technique can provide more useful, credible, and effective tools for predicting soil properties at non-sampling sites and for explaining the spatial relationship of data using covariate analyses (Webster and Oliver 2007). Using spatial analysis techniques, to assess the land capacity, supports the production of multiple maps, which helps in developing suitable solutions for sustainable agricultural use (Ali et al., 2007). The use of GIS technologies allows the processing of large amounts of spatial data, which gives more accurate information about the soil. In addition, knowledge of the temporal and spatial variations of soil properties is important to evaluate the effects of agricultural works on environmental characteristics (Arnous and Hassan 2006; Goenster-Jordan et al., 2018). The Kriging method is the most powerful and effective interpolation method used in geostatistics applications However, many researchers have used GIS and geostatistics techniques as decision tools in many agricultural applications for the spatial interpolation of soil characteristics, land evaluation, and land suitability assessment (Da Silva et al., 2015; Mevlut 2016; Chang et al., 2014; Swify et al., 2017; Yousif, 2019; Aldabaa and Yousif 2020; Elnaggar 2021; Amer et al., 2021; Selmy et al., 2020 and 2022; Nada et al., 2022; Abdullahi et al. 2023; Okashaa, 2023).

The results indicated that different geostatistical modeling was used to determine the spatial variability of soil characteristics. The normal kriging interpolation performance and the efficiency of the geostatistical model were investigated for each soil characteristic some variables such as average standard error (ASE), mean standard error (MSE), and root mean square error (RMSE). To choose the model that makes accurate predictions, the average standard error (ASE) should be as small as possible, the mean standard error (MSE) should be close to zero, and the root mean square error (RMSE) should be close to one. This indicates that the ordinary kriging technique was applicable and dependable for predicting the spatial distribution of different soil properties (El-Dabaa and Youssef 2020).
The main objectives of this study were to (1) assess the significant soil physicochemical properties of the study area using geostatistical analysis, (2) evaluate and map the spatial variability of soil physicochemical properties using geo-statistics and GIS techniques, and (3) Classify the soils of this area, according to Soil Taxonomy (Soil Survey Staff, 2022). This is to help in creating a decision-making framework and future planning for the studied area.

enabling high productivity and food safety Shalaby et al., 2017 and Lima et al., 2019).

## 2. Materials and Methods

### 2. 1.Study area

The area under study is located in the new Aswan City, about 20 Km west of Aswan governorate. It is a part of the western desert (El-Gallaba plain and a part of wadi El-Kubbaniya) and lies between latitudes 24° 16' 18" and 24° 18' 44" N and longitudes 32° 46' 32" and 32° 45' 38” E. (Figure 1).

### 2.2. Field Description and Soil Sampling

This study aims to realize the spatial variation of certain soil properties. Forty surface soil samples were chosen from forty profiles that were dug to represent the study area according to the geology, topography, and recent aerial photographic maps of the study area. The sites of soil samples were selected using the Global Positioning System "Garmin GPS" and plotted on the map (Figure 2). The samples were stored for various tests after being air-dried, crushed, and passed through a 2 mm screen. Soil physicochemical properties (OM, pH, $CaCO_{3.}$ gypsum content, ECe, CEC, ESP, and texture) were determined.

### 2.3. Laboratory Analyses

According to USDA (2004), the gravel content was calculated based on volume. The particle size distribution was carried out using the standard pipette method described by Gavlak et al., 2003. The electrical conductivity ($EC_e$) was assessed by methods according to Bashour and Sayegh (2007) and soil reaction (pH) of 1:1 soil-to-water suspension was estimated using a glass electrode as reported by Alvarenga et al., (2012). The typical Walkley-Black approach was used to estimate the soil organic matter (OM). The ammonium acetate pH 7.0 technique was used to calculate the cation exchange capacity (CEC) and exchangeable sodium (Jackson, 1973; Bashour and Sayegh, 2007). The gas evolution method of Scheibler's calcimeter was used to estimate total calcium carbonate ($CaCO_3$) gasmetrically (Nelson, 1982; Houba et al., 1995). The acetone precipitation method was used to calculate the gypsum content (Nelson, 1982; Hesse, 1998).

### 2.4. Climatic Conditions

The climatic conditions of the study area are similar to those of other desert areas in Egypt, which show long hot rainless summers and mild winters with scanty rainfall. The minimum temperature is 21.3 $^{O}C$ and the highest is 33.9 $^{O}C$. The average annual temperature is 29.8 $^{O}C$ and the annual precipitation is 0.01 mm. The evapotranspiration has an average yearly rate of 7.2 mm/day. The annual average relative humidity is 36.33%, while the average annual wind speed is 4.3 m/s (Table 1). Accordingly, the temperature regime of the soil is hyperthermic and the moisture regime of the soil is torric.

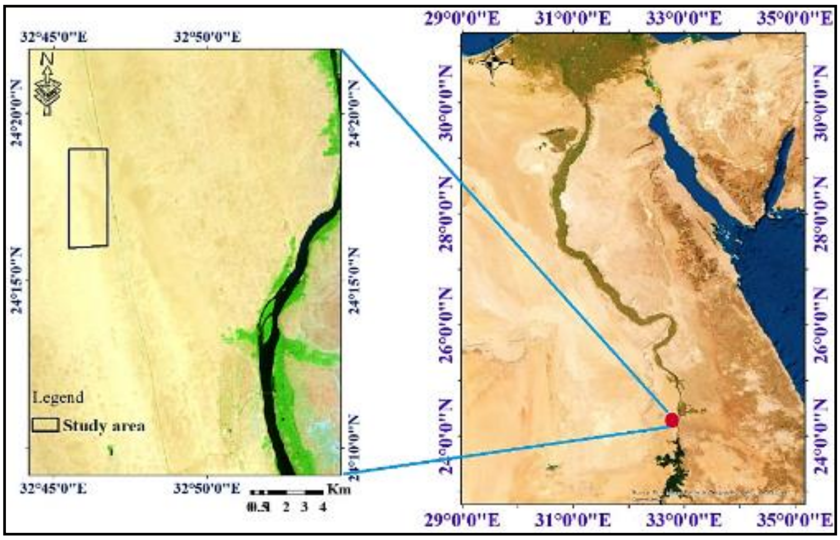


**Fig. 1. Location map of the area under study.**

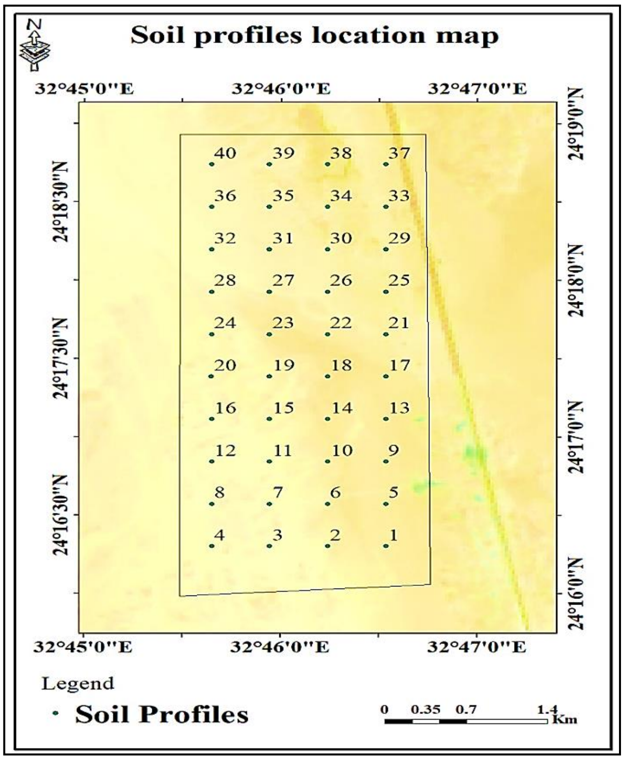


**Fig. 2. The soil profile map of the area under study.**

**Table 1. Meteorological data of the area under study (Station of Aswan).**

| Year | Temperature (°C) | | | Relative | Evaporation | Wind velocity | Rainfall |
|---|---|---|---|---|---|---|---|
| | Man. | Max. | Mean | Humidity (%) | (mm/day) | (m/sec.) | (mm) |
| 10-19 | 16.9 | 35.3 | 26.1 | 25.9 | 8.2 | 3.3 | 0.01 |
| 2020 | 21.3 | 33.9 | 29.8 | 27.3 | 7.2 | 4.3 | 0.01 |

### 2.4. Soil Classification:

According to the recorded meteorological data, soil morphological description, and data on soil properties, the soil profiles were categorized down to the subgroup level according to Soil Classification (Soil Survey Staff. 2022).

### 2.5. Statistical and geostatistical analyses

The Various descriptive statistics (range, mean, minimum, maximum, standard deviation, standard error, kurtosis, skewness, and coefficient of variation) of the soil property data were calculated using SPSS 17 to describe the spatial variability of the physicochemical properties of soils. According to Wilding (1985), the soil coefficient of variation (CV) was classified into three categories: low variance (CV < 15%), moderate variance (15% < CV ≤ 35%), and highly variable (CV > 35).

In ArcGIS 10.2.2., the studied soil data were joined to the sampling location (spatial). Programs and maps displaying the spatial distribution were drawn up to determine the variety of soil properties. Several soil property maps using point data were produced by ArcMap GIS 10.2.2. such as pH, OM, $CaCO_3$, gypsum, ECe, CEC, ESP, and texture using geostatistical analyses in ArcGIS 10.2.2. (ESRI, 2019).

The kriging procedure used the semi-variogram model selected from a collection of mathematical functions that describe spatial relationships fitted with weighted range, nugget, sill, and missing squares (Goovaerts, 1998). The Ordinary Kriging (OK) interpolation technique was employed to estimate soil property values for un-sampled sites. Compared to the other Kriging methods, the Ordinary Kriging (OK) technique is the best procedure due to its simplicity and prediction accuracy (Isaaks and Srivastava 1989; Sarangi et al., 2005). The kriging technique operates best if the data is almost normally distributed (Johnston et al., 2001). Transformations were used to make the data ordinarily distributed and to meet the assumption of equal variance in the data. In ArcGIS statistical analysis, histograms and normal QQPlots were used to find the transformations required to make the data more typically distributed. A trend analysis was made for each soil feature. Logarithmic transformations were used for abnormal and highly skewed data.

The semi-variogram models were estimated using the following equation:

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

where γ ($h$) is the semivariance value for a distance h, $N(h)$ is the number of pairs involved in the semi-variance calculation, Z ($x_i$) is the value of the attribute Z in the position xi, Z ($x_i + h$) is the value of the attribute Z separated by a distance h from the position xi.

For each soil attribute dataset**,** eleven semi-variogram models were tested in this study. Prediction performance was evaluated by cross-validation that checks the accuracy of the generated surfaces. Cross-validation allows us to determine which model provides the best predictions. These models included Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, K-Bessel, J-Bessel, and Stable models. For a model to provide accurate predictions, the average standard error (ASE) should be as small as possible, the mean standard error (MSE) should be close to zero, and the root mean square error (RMSE) should be close to one (Johnston et al., 2001).

$$ME = \frac{1}{N} \sum_{i=1}^{N} [Z^*(x_i) - Z(x_i)] \quad (2)$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{Z^*(x_i) - Z(x_i)}{\delta^2(x_i)}\right] \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [Z^*(x_i) - Z(x_i)]^2} \quad (4)$$

$$ASE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \delta^2(x_i)} \quad (5)$$

$$RMSSE = \sqrt{\frac{\frac{1}{N} \sum_{i=1}^{N} [Z^*(x_i) - Z(x_i)]^2}{\delta^2(x_i)}} \quad (6)$$

## 3. Results

### 3.1 Statistical Analyses

The results revealed that the study soil display high spatial variations in its physicochemical properties. The data on the important properties of the study soil samples are submitted as descriptive statistics in Table (2).

The range values of the soil sample properties range between 1.20 and 63.86 among the soil properties**.** The mean values of the studied properties ranged from 0.29 to 93.83, the standard error (SE) varied from 0.05 to 2.08 and the standard deviation (SD) values varied between 0.29 and 13.17 for the soil samples. The coefficient of variation (CV%) ranges from 3.47% to 179.78% among all soil properties. In addition, soil pH has low values of variables (CV < 5%), but the variance was medium for sand fraction (CV < 25%), and high to very high for the rest of the properties. The positive skewness values range from 0.85 to 2.59 and the negative values ranged between -0.89 and -0.41 for the studied soil properties. Kurtosis ranges from 2.67 to 15.35 among all studied characteristics.

### 3.2. Soil Properties

The obtained results shown in Table (2) revealed that the proportion of sand in these soils ranges from 57.6 to 99.2% with an average value of 93.83%, as the coefficient of variance value was 7.96%. Silt ranges from 0.40 to 19.60% with an average value of 2.11%, while clay differs between 0.40 and 22.8% with an average value of 4.06%, with the variance being 169.78 and 100.36%, respectively. The gravel content (by volume, %) of soil samples ranged from 0.08% to 63.94% with an average of 14.14%, and a CV value of 93.17%. The soil texture is mainly composed of sand, loamy sand, and sandy loam (Table 3).

From the obtained data (Tables 2 and 3), the pH values of the surface soils varied between 7.69 and 8.89 with an average value of 8.26 and a CV value of 3.47%. The organic matter values ranged from 0.07 to 4.03 g/kg, with an average value of 0.43 g/kg, with the coefficient of variation being 142.91%. The values of calcium carbonate for the soil samples vary between 0.43 and 9.74% with an average value of 5.37%**.** The coefficient of variation for the calcium carbonate content was 43.27%. The content of gypsum in the studied soils ranged from 0.49 to 4.07%, with an average value of 1.24%. The coefficient of variation (CV%) for gypsum was 72.13%.

The data showed that the salinity of soil samples (ECe) values ranged between 0.84 and 28.21 $dsm^{-1}$, with an average value of 2.56 $dsm^{-1}$, and the coefficient of variation was 179.78%. The exchangeable sodium percentage (ESP) in soil samples varied between 1.01% and 17.45%, with an average of 5.57%. The ESP values' coefficient of variation (CV%) was 51.45%. Cation exchangeability (CEC) values vary between 3.73 and 25.35 cmol $(^{+})$/kg, with an average value of 8.81 cmol $(^{+})$/kg. The coefficient of variation values was 51.24%**.**

**Table 2. Statistical analysis of soil properties in the area under study.**

| Property | Range | Min. | Max. | Mean | SD | SE | CV% | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| OM (g/kg) | 3.96 | 0.07 | 4.03 | 0.43 | 0.62 | 0.09 | 142.91 | 0.22 | 4.65 |
| $CaCO_3$ (%) | 9.31 | 0.43 | 9.74 | 5.37 | 2.32 | 0.36 | 43.27 | -0.66 | 2.69 |
| Gypsum (%) | 3.58 | 0.49 | 4.07 | 1.24 | 0.89 | 0.14 | 72.13 | 1.02 | 3.91 |
| pH (1:1) | 1.20 | 7.69 | 8.89 | 8.26 | 0.29 | 0.05 | 3.47 | 0.43 | 2.67 |
| ECe (dS/m) | 27.37 | 0.84 | 28.21 | 2.56 | 4.61 | 0.72 | 179.78 | 2.59 | 10.15 |
| ESP (%) | 16.44 | 1.01 | 17.45 | 5.57 | 2.86 | 0.45 | 51.45 | -0.89 | 5.87 |
| CEC $cmol^{(+)}$/Kg | 21.62 | 3.73 | 25.35 | 8.81 | 4.51 | 0.71 | 51.24 | 0.85 | 3.90 |
| Gravel% | 63.86 | 0.08 | 63.94 | 14.14 | 13.17 | 2.08 | 93.17 | -1.36 | 4.96 |
| Sand % | 41.6 | 57.60 | 99.2 | 93.83 | 7.47 | 1.18 | 7.96 | -3.30 | 15.35 |
| Silt % | 19.2 | 0.40 | 19.6 | 2.11 | 3.58 | 0.56 | 169.78 | 1.09 | 3.48 |
| Clay% | 22.4 | 0.40 | 22.8 | 4.06 | 4.08 | 0.64 | 100.36 | -0.41 | 3.22 |

SD: standard deviation, SE: standard error, and CV%: coefficient of variation.

## 4. Discussion

Soil variability is a result of the different formation factors of soils and their intensity, and the influence of pedogeomorphic processes, which have an impact on the soil ecosystem. The results revealed that the studied soil displayed high spatial variations in its physicochemical properties (Table 2).

### 4.1. Descriptive statistics

From previous results, descriptive statistics showed a large variance in the soil characteristics of the examined surface soil samples. The data show that the soil properties differ in most of the descriptive statistics values among the studied soil samples. The data reveal that the range values of the soil properties differ among these properties, which indicates that some soil properties have a very large difference between their lowest and highest values such as ECe, ESP, gravel content, sand, and clay. On the opposite, the OM and pH range values indicated that their smallest and highest values are close to each other (Okashaa, 2023).

The sand fraction has high mean values while low values were recorded for the other studied properties. A high standard deviation (SD) indicates that the data numbers are diffusion over a wide range of values or the mean, while a low standard deviation points out that the property values are close to the mean. The coefficient of variation (CV) is a helpful statistic for comparison of the degree of variance from one data property to another, even if the means are very different from one to another. According to (Wilding, 1985), a coefficient of variation (CV) of lower than 15% indicates low variability, 15%-35% indicates modest variance, and a CV over 36% shows strong variance. High to very high variance in soil properties may be owing to the nature of the soil and the climatic conditions. The highest variation was registered in soil salinity (ECe) due to its arid nature and absence of leaching caused by lack of precipitation and climatic conditions, although the least variation was found in soil pH which is hard to be afflicted by such conditions due to the buffering capacity of soil to change pH.

Skewed data were observed for all soil properties except for calcium carbonate, pH, and sand data in the studied soil properties. The skewness is positive for soil characteristics. These results indicate that these soil property data did not show an ordinary distribution, therefore, log transformation was applied. The skewness, whether positive or negative, can be owing to outliers in some of the soil properties. Kurtosis is a description of the form of a likelihood distribution in a similar way to the concept of skew. After evaluating the skewness and kurtosis values, it was observed that the data on all soil properties except calcium carbonate, pH, and sand needed to be transformed to produce them typically distributed using the geostatistical analysis.

### 4.2. Soil Physiochemical Properties

#### 4.2.1. Particle-size distribution

The obtained results indicated that the proportion of sand dominates the soil particles in most of the soil samples (El-Desoky and Sayed, 2019).

The low variance was observed in the sand fraction due to the nature of the sandy soil. In addition, the poor values of the fine particle ratios reflect the sand textures of the original sediments in the western desert. The soil texture is mainly composed of sand, loamy sand, and sandy loam (El-Kady, and Sayed, 2021).

#### 4.2.2. Soil reaction (pH)

From the obtained data, most of the studied soils were slightly to moderately alkaline, with a coefficient of variation (CV%) being very low variability (Okashaa, 2023).

#### 4.2.3. Soil organic matter content

Organic matter (OM) is an important component of soil, especially when it is found in abundance. The organic matter values are highly variable because the soil is poor in OM content due to the sterile nature of the soil, scant native greenery cover, and highly arid climatic conditions according to (Fadl et al., 2022).

#### 4.2.4. Calcium carbonate (CaCO3) content

The soil samples were slight to moderately calcareous. The coefficient of variance for the calcium is very high, indicating a very high variability (Abd El-Aziz, 2018).

#### 4.2.5. Gypsum content

Most of the soil samples had low gypsum content indicating that these soils were developed from parent sediments that were poor in gypsum. There was a significant variation in the gypsum content with the coefficient of variation being very high according to (Azzam, 2016).

#### 4.2.6. Soil salinity ($EC_e$)

The result of the data showed that the salinity of the soil was very slightly saline. The coefficient of variation of soil salinity was very high. On the other hand, the variance of $EC_e$ is considered one of the highest variations between soil properties (Elbeih, 2021).

#### 4.2.7. Exchangeable sodium percentage (ESP)

The data showed that most of the soil samples (97.50%) within the study area had ESP values of less than 15%. The coefficient of variation (CV%) of the ESP values was strong variation, indicating significant variance (Abd El-Aziz, 2018).

#### 4.2.8. Cation exchange capacity (CEC)

Cation exchangeability (CEC) is used as a measure of soil fertility. The investigated soil samples have very low cation exchange capacity (CEC) due to their coarse texture and very low organic matter content. The variation in cation exchange capacity was high in the soil samples (El-Kady, and Sayed, 2021).

## 5. Soil classification

Soils were classified according to field observation and description of morphological features, laboratory physical and chemical data criteria, as well as climatic data from the region of the area under study (Table 1). Based on Soil Survey Staff (2022), the studied soils were categorized to the subgroup level. In general, the soils in the study area are classified as Entisols soils. Two sub-orders are recognized, under this order, as Psamments and Orthents. The recognized subgroups are Typic Torripsamments, Typic Quartzipsamments, and Typic Torriorthents (Table 3).

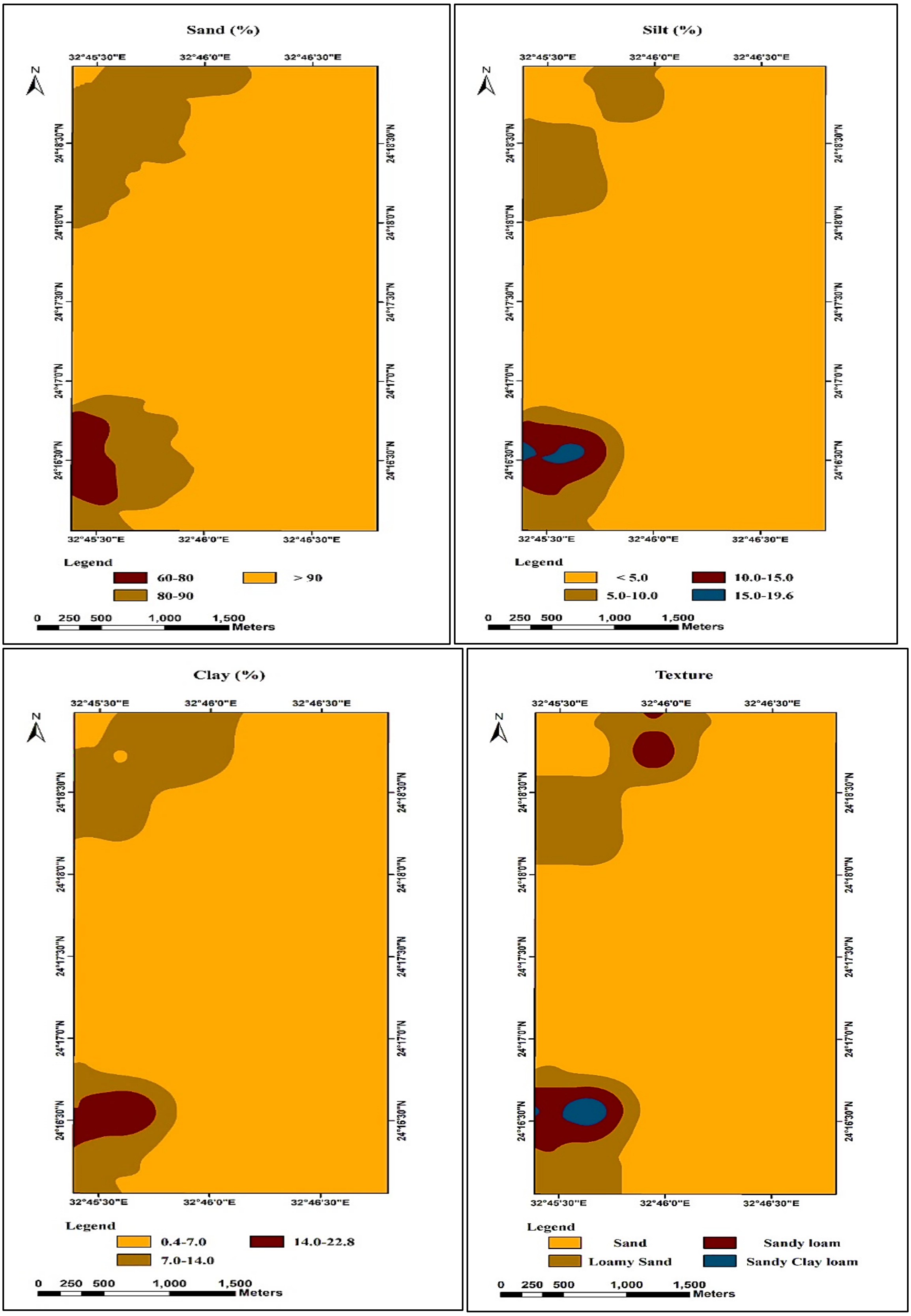


**Fig. 3. Maps of spatial distribution for sand, silt, clay, and texture grade of the soil surface layers.**

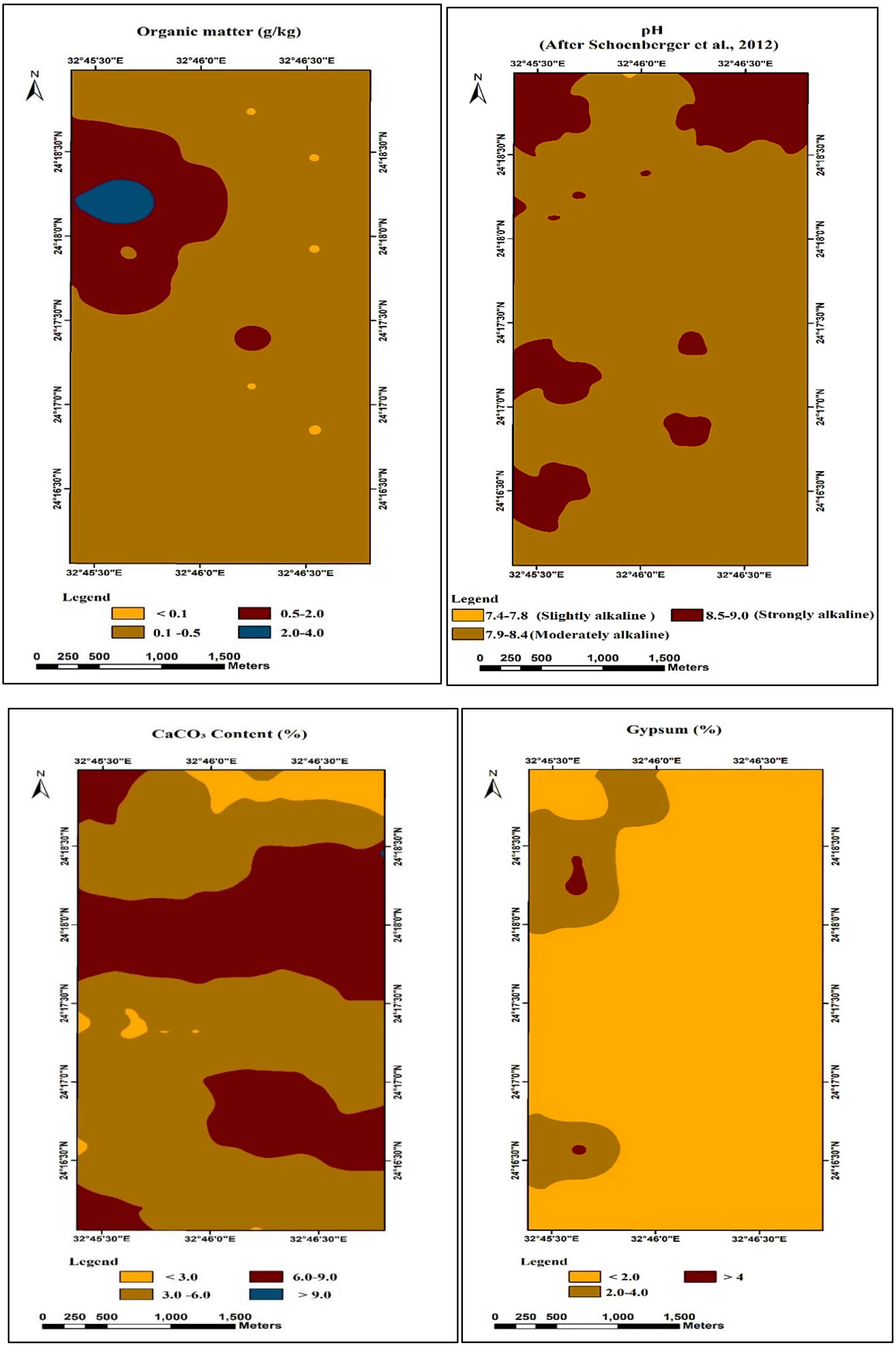


**Fig. 4. Maps of spatial distribution for OM, pH, $CaCO_3$, and gypsum of the soil surface layers.**

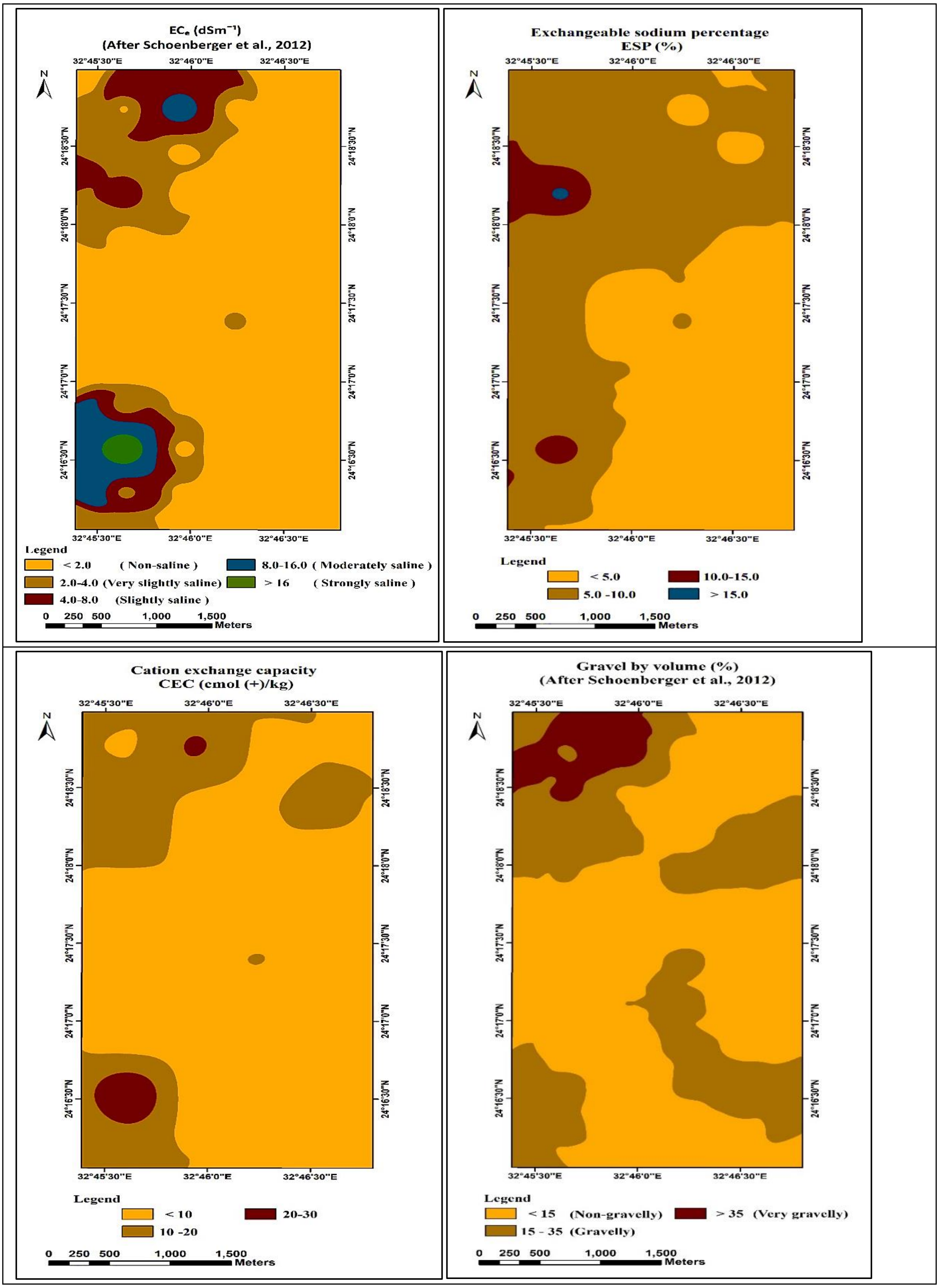


**Fig. 5. Maps of spatial distribution for ECe, ESP, CEC and gravel content of the soil surface layers.**

**Table 3. Some soil properties of the surface layers of the studied area.**

| Sample No. | OM (g/kg) | pH (1:1) | $EC_e$ (dS/m) | Gypsum (%) | $CaCO_3$ (%) | ESP (%) | CEC $cmol^{(+)}$/Kg | Gravel (%) | Particle size distribution | | | | Classification |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | Sand (%) | Silt (%) | Clay (%) | Texture | |
| 1 | 0.20 | 8.32 | 2.94 | 1.27 | 8.00 | 6.92 | 17.63 | 20.90 | 84.0 | 7.6 | 8.4 | G LS | Typic Torripsamments |
| 2 | 0.47 | 8.13 | 1.11 | 0.76 | 3.30 | 1.51 | 5.95 | 2.62 | 99.2 | 0.4 | 0.4 | S | Typic Quartzipsamments |
| 3 | 0.34 | 8.40 | 1.28 | 0.77 | 2.87 | 4.56 | 8.17 | 5.77 | 98.4 | 0.4 | 1.2 | S | Typic Quartzipsamments |
| 4 | 0.34 | 7.92 | 1.69 | 1.25 | 5.74 | 3.21 | 7.40 | 14.07 | 98.8 | 0.8 | 0.4 | S | Typic Quartzipsamments |
| 5 | 0.47 | 8.80 | 28.21 | 4.07 | 1.48 | 13.96 | 25.35 | 23.57 | 57.6 | 19.6 | 22.8 | G SCL | Typic Torriorthents |
| 6 | 0.20 | 8.02 | 1.23 | 0.76 | 6.09 | 4.13 | 3.73 | 3.53 | 99.2 | 0.4 | 0.4 | S | Typic Quartzipsamments |
| 7 | 0.34 | 7.93 | 1.48 | 1.97 | 7.39 | 4.86 | 7.69 | 18.97 | 98.0 | 1.2 | 0.8 | G S | Typic Quartzipsamments |
| 8 | 0.40 | 8.10 | 1.27 | 0.75 | 6.26 | 4.70 | 7.11 | 22.19 | 96.8 | 1.2 | 2.0 | G S | Typic Quartzipsamments |
| 9 | 0.20 | 7.85 | 2.09 | 1.02 | 5.22 | 5.45 | 6.72 | 9.48 | 96.4 | 2.0 | 1.6 | S | Typic Torriorthents |
| 10 | 0.20 | 8.10 | 1.22 | 1.27 | 4.96 | 4.69 | 5.76 | 4.39 | 99.2 | 0.4 | 0.4 | S | Typic Torriorthents |
| 11 | 0.47 | 8.85 | 1.32 | 0.77 | 7.39 | 4.57 | 5.47 | 22.82 | 97.2 | 1.2 | 1.6 | G S | Typic Quartzipsamments |
| 12 | 0.07 | 7.85 | 1.05 | 0.76 | 6.09 | 3.97 | 7.01 | 8.42 | 94.0 | 0.4 | 5.6 | S | Typic Quartzipsamments |
| 13 | 0.34 | 8.75 | 1.66 | 1.03 | 6.09 | 6.00 | 6.82 | 15.64 | 94.8 | 0.4 | 4.8 | G S | Typic Quartzipsamments |
| 14 | 0.34 | 8.30 | 0.98 | 0.51 | 6.09 | 5.11 | 5.28 | 15.43 | 96.8 | 0.4 | 2.8 | G S | Typic Quartzipsamments |
| 15 | 0.07 | 8.12 | 1.20 | 1.27 | 6.52 | 5.07 | 5.57 | 19.54 | 96.8 | 0.8 | 2.4 | G S | Typic Quartzipsamments |
| 16 | 0.13 | 8.31 | 1.38 | 0.51 | 4.78 | 1.34 | 3.73 | 0.08 | 98.4 | 0.4 | 1.2 | S | Typic Quartzipsamments |
| 17 | 0.20 | 8.30 | 1.67 | 1.02 | 0.78 | 7.23 | 7.01 | 1.45 | 94.8 | 1.2 | 4.0 | S | Typic Quartzipsamments |
| 18 | 0.20 | 8.18 | 1.25 | 0.76 | 0.78 | 1.01 | 6.92 | 4.19 | 95.2 | 0.4 | 4.4 | S | Typic Quartzipsamments |
| 19 | 0.67 | 8.60 | 2.27 | 1.26 | 3.48 | 5.48 | 10.10 | 24.67 | 95.2 | 0.4 | 4.4 | G S | Typic Quartzipsamments |
| 20 | 0.40 | 8.28 | 0.87 | 1.02 | 5.65 | 4.00 | 6.53 | 0.25 | 97.2 | 0.4 | 2.4 | S | Typic Torripsamments |
| 21 | 0.81 | 8.36 | 1.04 | 1.01 | 6.61 | 5.67 | 7.59 | 7.98 | 97.2 | 0.8 | 2.0 | S | Typic Quartzipsamments |
| 22 | 0.47 | 8.05 | 1.42 | 1.02 | 8.00 | 4.83 | 6.63 | 7.58 | 96.0 | 0.8 | 3.2 | S | Typic Quartzipsamments |
| 23 | 0.27 | 8.15 | 1.30 | 0.51 | 5.65 | 5.12 | 7.11 | 5.35 | 96.4 | 1.2 | 2.4 | S | Typic Torripsamments |
| 24 | 0.27 | 8.12 | 1.47 | 1.02 | 6.35 | 3.12 | 7.40 | 3.37 | 95.6 | 0.4 | 4.0 | S | Typic Torriorthents |
| 25 | 0.34 | 8.10 | 1.33 | 1.52 | 6.61 | 5.32 | 8.17 | 16.09 | 94.4 | 2.0 | 3.6 | G S | Typic Quartzipsamments |
| 26 | 0.40 | 8.18 | 1.99 | 1.01 | 7.48 | 5.43 | 9.14 | 8.37 | 96.0 | 2.0 | 2.0 | S | Typic Quartzipsamments |
| 27 | 0.40 | 8.10 | 1.81 | 0.99 | 6.35 | 5.78 | 7.88 | 27.34 | 92.0 | 1.6 | 6.4 | G S | Typic Quartzipsamments |
| 28 | 0.07 | 7.97 | 1.39 | 1.26 | 6.09 | 4.54 | 4.99 | 15.43 | 95.2 | 1.2 | 3.6 | G S | Typic Torripsamments |
| 29 | 4.03 | 8.60 | 5.82 | 3.99 | 6.96 | 17.45 | 17.25 | 20.52 | 84 | 8.8 | 7.2 | G LS | Typic Quartzipsamments |
| 30 | 0.67 | 8.18 | 1.54 | 0.74 | 5.13 | 5.81 | 5.08 | 19.80 | 96.4 | 1.2 | 2.4 | G S | Typic Quartzipsamments |
| 31 | 0.40 | 8.38 | 1.60 | 1.00 | 8.70 | 5.69 | 8.37 | 2.38 | 95.6 | 0.8 | 3.6 | S | Typic Torripsamments |
| 32 | 0.27 | 8.35 | 1.98 | 1.34 | 6.17 | 6.50 | 9.33 | 33.83 | 92.4 | 2.0 | 5.6 | G S | Typic Quartzipsamments |
| 33 | 1.01 | 7.99 | 3.67 | 3.81 | 3.13 | 7.86 | 15.51 | 42.75 | 84.4 | 6.8 | 8.8 | V G LS | Typic Torriorthents |
| 34 | 0.40 | 8.60 | 1.01 | 0.51 | 3.13 | 6.19 | 9.33 | 7.77 | 96.0 | 0.4 | 3.6 | S | Typic Torripsamments |
| 35 | 0.40 | 8.27 | 1.19 | 0.75 | 5.48 | 5.93 | 8.27 | 2.44 | 97.2 | 0.8 | 2.0 | S | Typic Torripsamments |
| 36 | 0.07 | 8.36 | 0.98 | 0.75 | 9.74 | 4.22 | 11.84 | 7.23 | 95.2 | 0.8 | 4.0 | S | Typic Quartzipsamments |
| 37 | 0.13 | 8.89 | 1.80 | 1.53 | 8.52 | 7.34 | 10.20 | 31.38 | 90.0 | 3.6 | 6.4 | G S | Typic Torripsamments |
| 38 | 0.34 | 7.69 | 12.90 | 2.84 | 0.43 | 8.56 | 20.53 | 63.94 | 78.0 | 8.0 | 14 | E G SL | Typic Torriorthents |
| 39 | 0.07 | 8.64 | 0.84 | 0.49 | 4.96 | 3.88 | 8.46 | 3.63 | 98.0 | 0.4 | 1.6 | S | Typic Torripsamments |
| 40 | 0.40 | 8.45 | 1.28 | 0.74 | 0.43 | 5.76 | 9.04 | 0.33 | 95.2 | 0.8 | 4.0 | S | Typic Torripsamments |

## 6. Geo-statistics and spatial analyses

A better understanding of the micro diversity of soil characteristics and soil quality parameters is essential for developing and improving agricultural management practices and maintaining soil fertility. Therefore, geostatistical methods are successfully used to determine spatial dependence and to predict locations where samples are not taken. Also, understanding the temporal and spatial variations of soil properties is important for measuring the effects of agricultural activities on environmental characteristics (Goenster-Jordan et al., 2018).

The studied topsoil properties data (Table 4) was examined by the histogram tool and ordinary QQPlots to see if they showed a regular distribution pattern or not. Histograms are one of the best purposes to swiftly learn a lot about data, including central tendency, spread, modality, shape, and outliers. Normal QQPlots indicate no normality and diagnose skewness and kurtosis. Therefore, if the data is skewed (i.e. far from normal), the points will pervert from the line. Whereas, if all points lie on or near the diagonal line (in a random pattern), this report is that the graph of the variable will display a bell form (normal distribution). According to ArcGIS geostatistical analysis, histograms, and ordinary QQPlots tools are used to perform the required transformations to make the data more typically distributed. Logarithmic transformation was applied to standardize highly skewed and differing data sets.

Exploratory data analysis of soil properties using QQPlots and histogram analyses showed that the calcium carbonate, pH, and sand fraction had a normal distribution while the remainder did not show such a normal distribution. For properties that do not show a normal distribution, a log transformation was applied to bring the distribution closer to a normal distribution. Figure (6) shows that calcium carbonate (CaCO3) is an example of soil properties that have normal distribution data. It has a small positive value of deviations (-0.66) close to zero, and the value of kurtosis is (2.87) which is close to 3.0 indicating that the CaCO3 data do not deviate from a normal distribution (ESRI, 2019). On the contrary, in the case of CEC as an example of skewed data, the analysis indicates that the data deviates from a normal distribution.

This study used the ordinary kriging (OK) approach to produce the patterns distribution of some soil properties. Eleven semivariogram models (circular, spherical, quaternary, pentagonal, exponential, Gaussian, rational quadratic, hole effect, K-Bessel, J-Bessel, and Stable) were chosen for each soil properties dataset. Prediction performance is evaluated by the cross-validation method, which checks the precision of the generated surfaces. After the applicability of different modeling for each soil characteristic examined in this study, the error was calculated using this technique to determine the most accurate predictions of soil properties with the lowest mean standardized error (MSE) values (close to zero) and root mean square error and root mean square standardized error (RMSSE) values close to one. The smallest MSE values suggest that kriging predictors of soil characteristics are closer to the calculated values.

Table (4) shows the selected modeling for the surface mapping of the spatial distribution of soil characteristics and the predictive mistake values for each studied soil characteristic, it also exhibits that various modeling may give better results for different soil properties. The RMSSE values range from 0.99 to 1.22 (close to one), while the MSE.

**Table 4. Fitted semivariogram models for the soil properties of the studied soils.**

| Properties | Model | Prediction Errors | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | RMS | ASE | SE | MS | RMSS | Skewness | Kurtosis |
| OM (g/kg) | Exponential | -0.01 | 0.62 | 0.61 | 0.09 | -0.01 | 1.01 | 0.22 | 4.65 |
| $CaCO_3$ (%) | Gaussian | -0.02 | 2.83 | 2.54 | 0.05 | -0.01 | 1.09 | -0.66 | 2.69 |
| Gypsum (%) | Gaussian | 0.00 | 0.95 | 0.90 | 0.72 | 0.00 | 1.05 | 1.02 | 3.91 |
| pH | J-Bessel | 0.00 | 0.43 | 0.35 | 0.14 | -0.01 | 1.22 | 0.43 | 2.67 |
| $EC_e$ ($dSm^{-1}$) | Rational Quadratic | 0.00 | 5.17 | 4.83 | 0.36 | 0.00 | 1.06 | 2.59 | 10.15 |
| ESP (%) | Exponential | -0.06 | 2.88 | 2.87 | 0.45 | -0.02 | 1.00 | -0.89 | 5.87 |
| CEC $cmol^{(+)}$/Kg | J-Bessel | -0.16 | 4.33 | 4.25 | 0.71 | -0.03 | 1.01 | 0.85 | 3.90 |
| Gravel (%) | Rational Quadratic | -0.04 | 13.45 | 13.33 | 2.08 | 0.00 | 1.01 | -1.36 | 4.96 |
| Sand % | K-Bessel | 0.12 | 7.44 | 7.46 | 1.18 | 0.02 | 0.99 | -3.30 | 15.35 |
| Silt % | Gaussian | -0.03 | 3.36 | 3.35 | 0.56 | -0.01 | 1.00 | 1.09 | 3.48 |
| Clay (%) | Gaussian | -0.07 | 4.24 | 3.95 | 0.64 | -0.02 | 1.07 | -0.41 | 3.22 |
| Texture | Gaussian | 0.27 | 65.83 | 61.32 | - | 0.00 | 1.06 | 2.75 | 9.52 |
| Minimum | | -0.16 | 0.43 | 0.35 | - | -0.03 | 0.99 | -3.30 | 2.67 |
| Maximum | | 0.27 | 65.83 | 61.32 | - | 0.02 | 1.22 | 2.75 | 15.35 |

Abbreviation: RMS = Root Mean Square ASE= Average Standard Error
MS = Mean Standardized RMSS= Root Mean Square Standardized
SE= Standard Error.

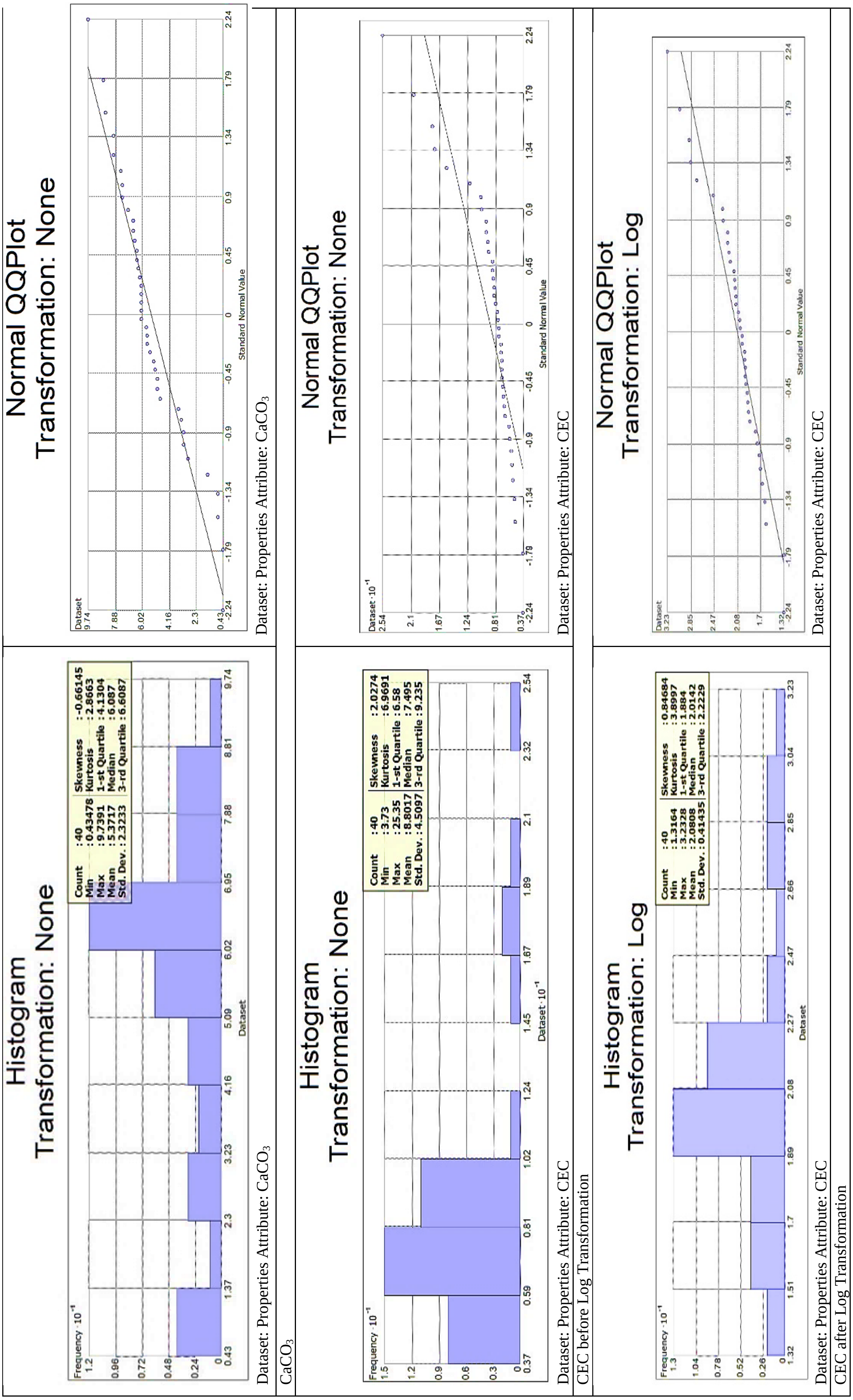


**Fig. 6. Histograms and QQPlot for $CaCO_3$ (normally distributed) and CEC (before and after Log Transformation).**

values are close to zero and vary between -0.03 to 0.02. These results indicate that previous models correctly define the surfaces of the spatial distribution of these properties. It is found that Gaussian, J-Bessel, Exponential, Rational Quadratic and K-Bessel models are the best-fitted semi-variogram models. The spatial distributions of these properties for the surface layers of the studied soils are shown in Figures (3, 4, 5). The generated spatial distribution maps revealed that the clay fraction and CEC were nearly congruent in their spatial distribution across the study area. the spatial distributions of these soil properties (clay, and CEC) were similar to those of soil texture grades. Consequently, fine-textured soils were found to have the highest values of these soil properties, while coarse-textured soils had the lowest. In addition, the spatial distributions of CEC, clay, and soil texture are nearly identical because CEC and soil texture are all related to the clay fraction content of the soil. The created spatial distribution maps illustrated that ECe, and ESP had congruent spatial distribution patterns throughout the area under study. Also, ECe and ESP are similar in their distributions because they are related to each other.

The figures show that there is no specific pattern for the spatial distribution of organic matter, $CaCO_3$, and pH. With some exceptions for soil calcium carbonates, the study area's center parts had the highest values.

## 7. Conclusion

From the previous discussion and the results obtained, it is clear that the spatial variance technique can provide more useful, reliable, and effective tools for predicting soil properties at non-sampling sites. In addition, geo-statistics approaches afford an alternative to conventional statistics for delineating the spatial relationships and variation of soil attributes. This study investigated the spatial variability of soil properties in El-Gallaba Plain, New Aswan City, using geostatistical techniques. The ordinary Kriging (OK) method was used as an interpolation method compared to other Kriging methods because it is simple and has high prediction accuracy. The data showed that the soils of the study area were slightly to moderately alkaline, and slightly saline, with non-sodicity. The particle size distribution exhibited soil textures that ranged from sandy to loamy sand soils. Moreover, soils in the study area exhibited low gypsum content and low organic matter (OM). Furthermore, cation exchange capacity is low. The data reveal that the Gaussian, J-Bessel, Exponential, Rational Quadratic and K-Bessel models are the best-fitted semi-variogram patterns for all given properties. In general, efficiently making accurate maps using geostatistical analysis techniques is essential to properly understand the present spatial variation in the studied area. This study gives useful information and fresh sentience about the physical and chemical properties and spatial variability of these soils.

## References


Abdullahi M. B. A. A. Elnaggar. M. M. Omar, A. Murtala , M. Lawal and A. A. Mosa. (2023). Land Degradation, Causes, Implications and Sustainable Management in Arid and Semi-Arid Regions: A Case Study of Egypt. Egypt. J. Soil Sci., 63 (4). 10.21608/EJSS.2023.230986.1647

Akbas, F., (2014). Spatial Variability of soil color parameters and soil properties in an alluvial soil. African J. of Agric. Res., 9 (12):1025-1035. DOI:10.5897/AJAR2013.8316

Aldabaa, A.A. and I.A.H. Yousif (2020). Geostatistical approach for land suitability assessment of some desert soils. Egypt. J. Soil Sci., 60 (3): 195-209. https://10.21608/ejss.2020.26767.1350

Ali, R.R., G.W., Ageeb, and M.A. Wahab (2007). Assessment of soil capability for agricultural use in some areas west of the Nile Delta, Egypt: an application study using spatial analyses. J. Appl. Sci. Res. 3 (11): 1622-1629.

Alvarenga P., P. Palma, A. de Varennes, and A.C., Cunha-Queda (2012). A contribution towards the risk assessment of soils from the São Domingos Mine (Portugal): Chemical, microbial and ecotoxicological indicators, Environ. Pollut., 161: 50-56. DOI: 10.1016/j.envpol.2011.09.044

Amer B. S., K.F. Moussa, A.A. Sheha and M.K. Abdel-Fattah (2021). Spatial Variability of Some Soil Properties in Sahl Al-Hussainiyah, Sharkia Governorate, Egypt. Zagazig J. Agric. Res. 48 (1): 123-135. http:/www.journals.zu.edu.eg/journalDisplay.aspx

Arnous, M.O., and M.A.A. Hassan (2006). Image processing and land information system for soil assessment of El-Maghara Area, North Sinai, Egypt. The 2nd International Conf. on Water Resources and Arid Environment.

Bashour, I.I., and A.H. Sayegh (2007). Methods of Analysis for Soils of Arid and Semi-Arid Region, American University of Beirut, Lebanon. FAO, Rome.

Brevik, E.C., Calzolari, C., Miller, B.A., Pereira, P., Kabala, C., Baumgarten, A., Jordán, A (2016). Soil mapping, classification, and pedologic modeling: history and future directions. Geoderma 264, 256–274. https://doi.org/10.1016/j.geoderma.2015.05.017.

Chang, D., J. Zhang, L. Zhu, S.H. Ge, P.Y. Li, and G.S. Liu (2014). Delineation of management zones using an active canopy sensor for a tobacco field. Compute. Electr. Agric., 109: 172-178.

Da Silva, A.F., A.P. Barbosa, C.R. Lopes Zimback, P.M.B. Landim and A. Soares (2015). Estimation of croplands using indicator kriging and fuzzy classification. Compute. Electr. Agric., 111: 1-11. DOI:10.1016/j.compag.2014.11.020

Elnaggar, A. A., Kh. H. El-Hamdi, A. E. Gohar and M. Omar (2021). Spatial Variability of some Soil Physical, Chemical and Fertility Properties in Northern Nile-Delta of Egypt. J. of Soil Sci. and Agric. Eng. 12 (11):749-756. http://www.jssae.journals.ekb.eg/

ESRI (2019). Are Map version 10.2.2. User Manual. ESRI, 380 New York Street Redlands, California, 92373-8100, USA.

Fathi H., H. Fathi and H. Moradi (2014). Spatial variability of soil characteristics for evaluation of agricultural potential in Iran Merit Research. J. of Agric. Sci. and Soil Sci., 2(2):024-031. DOI:10.3923/jest.2015.13.24

Gavlak R., D. Horneck and R.O. Miller (2003). Soil, Plant, and, Water Reference Methods for the Western Region. Oregon State University Corvallis, OR.

Ghartey, E.O.; G. N. N. Dowuona; E. K. Nartey; T. A. Adjadeh; Y.D.I. Lawson (2012). Assessment of Variability in the Quality of an Acrisol under Different Land Use Systems. Open J. of Soil Sci., 2: 33-43. doi:10.4236/ojss.2012.21006

Goenster-Jordan, S., R. Jannoura, G. Jordan, A. Buerkert and R.G. Joergensen (2018). Spatial variability of soil properties in the floodplain of a river oasis in the Mongolian Altay Mountains. Geoderma, 330: 99-106.https://doi.org/10.1016/j.geoderma.2018.05.028

Hesse, P.R (1998). A Textbook of soil chemical analysis CBS Publishers and Distributors, Delhi, India. https://doi.org/10.1017/S0014479700005202

Houba, V. J. Huijbregts, A. W. Wilting, P.I. Novozamsky, and G. Gort (1995). Sugar yield, nitrogen uptake by sugar beet, and optimal nitrogen fertilization in relation to nitrogen soil analyses and several additional.
https://doi.org/10.1016/j.compag.2014.09.019

Iňigo, Andrades; J.I.1 Alonso- Martirena; A.Marín and R. Jiménez-Ballesta (2012). Soil Property variability in a humid natural Mediterranean environment: La Rioja, Spain. Spanish J. Soil Sci. 2 (1):38-54. DOI:10.3232/SJSS.2012.V2.N1.03

Isaaks, E.H., and R.M. Srivastava (1989). An introduction to applied geostatistics. Oxford, New York: Oxford University Press.

Jackson, M.L. (1973). Soil chemical analysis. Prentice-Hall of India Private Limited, New Delhi, India

Johnston, K., J. M. Ver Hoef, K. Krivoruchko, and N. Lucas (2001). Using ArcGIS geostatistical analyst (Vol. 380): ESRI Press, Redlands, AC.

Lima, T.M., Weindorf, D.C., Curi, N., Guilherme, L.R., Lana, R.M., Ribeiro, B.T (2019). Elemental analysis of Cerrado agricultural soils via portable X-ray fluorescence spectrometry: inferences for soil fertility assessment. Geoderma 353, 264–272. https://doi.org/10.1016/j.geode rma.2019.06.045.

Mevlut, U. (2016). Determination of agricultural soil index using geostatistical analysis and GIS on land consolidation projects: A case study in Konya/Turkey. Comput. Electr. Agric., 123:402-409. https://doi.org/10.1016/j.compag.2016.03.019

Nada W. M, M. H. Bahnassy, and D. M. Ahmed (2022). Soil Maps based on GIS and ALES-Arid Model as Tools for Assessing Land Capability and Suitability in El-Sadat Region of Egypt. Egypt. J. Soil Sci.62 (4): 311 -324. 10.21608/EJSS.2022.164837.1542

Nelson, R.E. (1982). Carbonate and gypsum. P181-198. In: A.L. Page, R.H. Miller and D.R. Keeney (eds.) Methods of soil analysis. Part 2-Chemical and microbiological properties (2nd edition). Agronomy 9 Am. Soil Soc., Madison, WI., USA.

Okashaa, E. G. M. (2023). Land Capability and Suitability Assessment of New Aswan Area, Aswan Governorate, Egypt. M.Sc. Thesis, Fac. of Agric. and Nat. Res. Aswan Univ., Aswan, Egypt

Sarangi, A., C.A. Madramootoo, P. Enright, and H. Chandrasekharan (2005). Prediction of spatial variability of phosphorous over the St-Esprit watershed. Water, air, and soil poll., 168 (1): 267-288. DOI:10.1007/s11270-005-1777-5

Selmy S., S.H. Abd El-Aziz, A. El-Desoky, and M. El-Sayed (2022). Characterizing, predicting, and mapping of soil spatial variability in Gharb El-Mawhoub area of Dakhla Oasis using geostatistics and GIS approaches. J. of the Saudi Soc. of Agric. Sci. 21 (6): 383–396.

Selmy, S.A.H., S.H. Abd El-Aziz, M.A. Gameh, and A. Abdelsalam (2020). Characterization and mapping spatial variability of Entisols derived from shale in Dakhla Oasis, Egypt. Arab. J. of Geosc., 13: 592. DOI:10.1007/s12517-020-05540-2

Serrano. S. Shahidian and J. Marques da Silva (2014). Spatial and Temporal Patterns of Apparent Electrical Conductivity: DUALEM *vs.* Veris Sensors for Monitoring Soil Properties Sensors, 14, 10024-10041. https://doi.org/10.3390/s140610024

Shalaby, A., M.E. AbdelRahman and A.A. Belal (2017). A GIS Based Model for Land Evaluation Mapping: A Case Study North Delta Egypt. Egypt. J. Soil Sci. 57 (3):339 – 351.

Soil Survey Staff (2022). Keys to soil taxonomy.13th ed. United States Department of Agriculture, Natural Resources Conservation Service, Washington, DC.USA.

Swify, Samar S.F, S.H. Abd El-Aziz, S.A.H. Selmy, A. Elgharably, and H.M.A. Ragheb (2017). Assessment and Spatial Variability Mapping of Soil Available Phosphorus and Potassium of Coarse-textured Soils in New Valley, Egypt Using Geostatistical Technique. Assiut J. Agric. Sci., 48 (5): 255-274. DOI: 10.21608/ajas.1999.5557

USDA (2004). Soil survey laboratory methods manual. Soil Survey Investigation Report No. 42 Version 4.0. https://doi.org/10.1016/j.catena.2011.05.023

Webster, R. and M.A. Oliver (2007). Geostatistics for environmental scientists, Second Edition. John Wiley and Sons. West Sussex, England.

Wilding, L.P. (1985). Spatial variability: its documentation, accommodation, and implication to soil surveys. P.166-194, in D.R. Nielsen and J. Bouma (ed.). Soil Spatial Variability, Pudoe, Wageningen, Netherlands. http://pascalfrancis.inist.fr/vibad/index.php?action=getRecordDetail&idt=8485840

Yousif, I.A.H. and A.S. Ahmed (2019). Integration of land cover changes and land capability of wadi El-Natrun depression using vegetation indices. Egypt. J. Soil Sci., 59 (4): 385- 402.

Yousif, I.A.H. (2019). Soil Suitability Assessment Using MicroLEIS Model: A Case Study in Wadi ElHeriga, North Western Coast Zone, Egypt. Egypt. J. Soil. Sci. 59 (3): 209-221. DOI: 10.21608/ejss.2019.12598.1272