Integration of TOPSIS and Geostatistical Technique for Soil Quality Assessment under Different Land Uses: A Case Study

Abstract

This study proposes the technique for order preference by similarity to the ideal solution method (TOPSIS) integrated with the geostatistical technique for assessing soil quality in Northern Sohag Governorate, Egypt. Various soil parameters such as sand, silt, clay content, CEC, ESP OC, ECe, pH, and CaCO3 were determined. Afterward, the geostatistics approach using ordinary kriging interpolation and semivariogram was applied to produce a spatialized and detailed map for each soil parameter. Spherical,Exponential,Gaussian,and J-Bessel geostatistical models were used to define the spatial variability of soil properties based on RMS, MSE, and RMSSE. Based on the TOPSIS method, the soil quality index (SQI) and its ranking under land use types in the study area were calculated. The results of SQI ranged from 38.75% to 55.82% and 27.53% to 52.72%, and 5.75% to 26.73% for old cultivated, new cultivated, and desert soil, respectively. The SQI was classified intothree regions. The first hasa fair quality index and covers56.48% (403.91 km^2)of ~~(~~the total geographical area~~) of~~(TGA). The soils of this region are located mainly in old cultivated soils and some new ones. The second regionwas observed in some newly reclaimed soils and desert soils and extended over an area of about 27.75% (198.45 km^2). These soilshave low values of favorable studied indicators, leading to negative effects on the SQI that are defined as poor. The third region is very poor quality, covers about 15.77% (112.78 km^2) of TGA,and is located mainly in desert soilswith low beneficial and high non-beneficial studied indicators.Finally, the results indicate that the integration of TOPSIS and geostatistical techniqueallow for an accurate and practical assessment of the SQI.

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Keywords:soil quality index, ordinarykriging, Semivariogram, TOPSIS.

Introduction

As a natural and one of the basic factors for the survival of nonrenewable resources, the soil has attracted worldwide attention with the increased populations and has become the most fragile ecosystem due to long-term human cultivation. Land use by humans is a vital and direct activity that affects soil quality. Soil quality may be defined as the ability of soil to play a role in natural or managed ecosystems to maintain the productivity of animals and plants while ensuring the healthy life of human beings (Smith et al.,1993 and Lu et al., 2004). It reflects the level of soil management, and it is of great significance to the restoration and mitigation of degraded land, regional land resource management, and sustainable land use, which has become an area of increasing concern (Guo et al., 2017; Li et al., 2013 and Gozukara at al., 2022). Recently, there have been variousapproaches for assessing soil quality (Ditzler and T^ugel, 2002; Xue et al., 2010; Karlen et al., 2008; Yang et al., 2017 and Kim and Jeong, 2020).Due to the different assessment objectives and the complexity of the

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procedure,no standard methodfor soil quality (Huang and Yang, 2009). The technique for order preference by similarity to ideal solution (TOPSIS) modelcan deal with both qualitative and quantitative data during assessment processes and is widely used in many fields, such as water quality assessment, but less used in soil quality assessment (Sun et al.,2018 and Gou et al., 2018). Spatial variability characterization of different soil properties is important in macro and micro scales (Aboelsoud and Abdelrahman, 2017).

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Furthermore, obtaining continuous and accuratespatial data saves cost, time, and effort for the cultivation development process, gives better soil management, and improves land-use sustainability (Abdelrahman et al., 2021). Therefore, geostatistical analyses with the help of GIS tools effectively demonstrate soil data spatially and distribute their variations in a specific area. Geostatistical tools are used in estimating and mapping soil properties by using different semi-variogram models. There are various methods of spatial variability distribution of soil data, such as Kriging, co-Kriging, inverse distance weighting (IDW), and linear regression model (LR) (Lark, 2012). Kriging is the most commonly used technique for geostatistical analysis of soil parameters. Ordinary Kriging as s statistical technique was used frequently to predict soil properties (Tabari et al., 2011). Lopez-Granados et al. (2005) mapped different soil properties using geostatistics and Kriging tools in southern Spain. Behera and Shukla (2015) generated ~~various ~~maps for soil pH, ECe, SOC, and exchangeable bases in acidic Indian soils.Also,Patil et al. (2011) used geostatistics and the spline method of interpolation and mappingsoil organic carbon, available nitrogen, phosphorus, and potassium in Karnataka. Spatial variability maps were also generated for the soil's physical properties in Assam, India (Reza et al. 2015). Behera et al. (2011) assessed the spatial distribution of total and extractable Zinc in India. Vasu et al. (2017) used the Kriging method in West Bengal, India,for characterization and mapping the soil fertility factors. Gülser et al. (2016) used block Kriging to generatethe physical properties map of some Turkish soils. Kriging and co-Kriging interpolation methods were used to generate surface maps of spatial variability of soil Physico-chemical properties in Babylon, Iraq (Saleh, 2018). Shukla et al. (2016) analyzed the spatial variability of soil micronutrients in India's intensively cultivated Trans-Gangetic Plains.

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Thereforein the current study,the soil quality under different land uses was assessed utilizing TOPSIS and Geostatistical Technique in the Northern part of Sohag Governorate, Egypt.This study aimed to (1) evaluate the soil quality under different land uses by applying the TOPSIS model, (2) characterize the spatial variability of soil some soil properties by fitting the best semi-variogrammodel and (3)prepare the spatial variability maps of soil properties and Soil quality index (SQI) using ordinary Kriging technique.

Material and methods

Overview of the Study Area

Northern Sohag (26.51 to 26.9 N, 31.24 to 31.57 E) is a part of Sohag Governorate,Egypt. This area covers approximately 715.14 km^2 and belongs to the arid region of North Africa, generally characterized by hot summers and mild winters with low rainfall. The area under study had three land uses(figure 1) viz. o~~O~~ld cultivated soils, newly reclaimed soils, and Desert soils. Middleton and Thomas (1992) state that a hyperarid climate is common, withan aridity index lower than 0.05.

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Soil Sampling and laboratory analysis

The soil samples were collected from the study area using GPS and a soil cylinder auger at 0–60 cm depths in 34 locations (figure 2). The selected sites represent old cultivated soils, newly reclaimed soils, and desert land. Soil

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samples were prepared for analyzing their physical and chemical properties, whereas they were air-dried, grounded, and sieved. Soil samples were analyzed in the soil testing laboratories using the standard analysis methods given by USDA (2004). The analyzed parameters are clay (%), sand (%), silt (%), exchangeable sodium percentage (ESP %), organic carbon (OC %), electrical conductivity (EC ds/m), soil reaction (pH), cation exchange capacity (CEC cmol(p+)/kg) and calcium carbonate total content (%).

2.3. Soil Quality Evaluation Based on TOPSIS

TOPSIS is a practical method for ranking and selecting several alternatives by measuring Euclidean distances. It evaluates the samples according to the relative distances between positive and negative ideal solutions (Chen et al., 2016). The steps of the TOPSIS method are as follows:

Step 1: Calculation of the normalized decision matrix following the procedure elaborated by (Opricovic and Tzeng, 2004 and Gumus, 2009) as the following equation:

$$nij = \frac{xij}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

Where nij (i=1, 2, ..., m) is the normalized value and xij is the original value

Step 2: Weight Determination of Soil Parameter

It is a paramount step for definingweights for each indicator used in TOPSIS (Lei et al., 2016). The indicators' weights can be calculated objectively by using the entropy theoryas follows:

$$ej = \frac{-1}{In(m)} \sum nijIn(nij)$$

$$dj = 1 - e$$

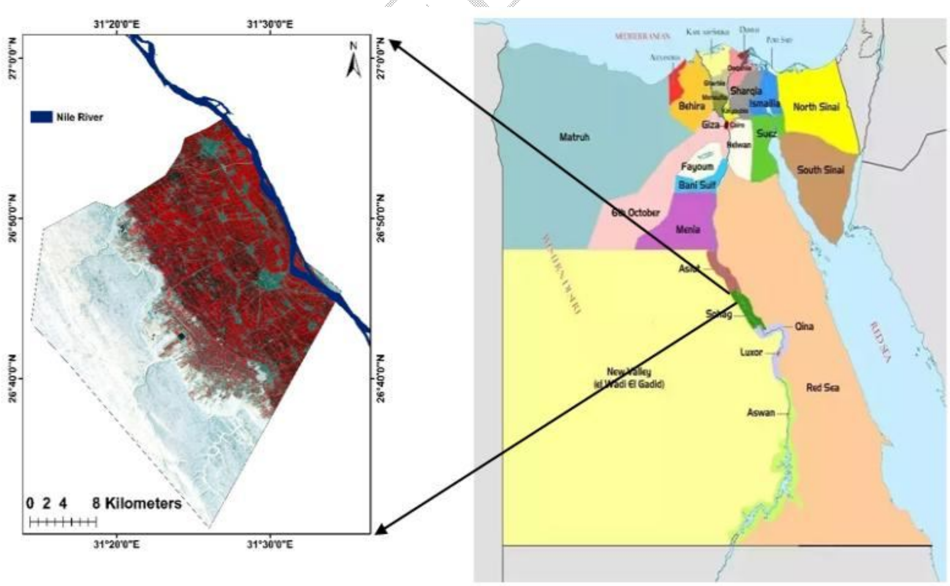

Figure 1. Location of the study area

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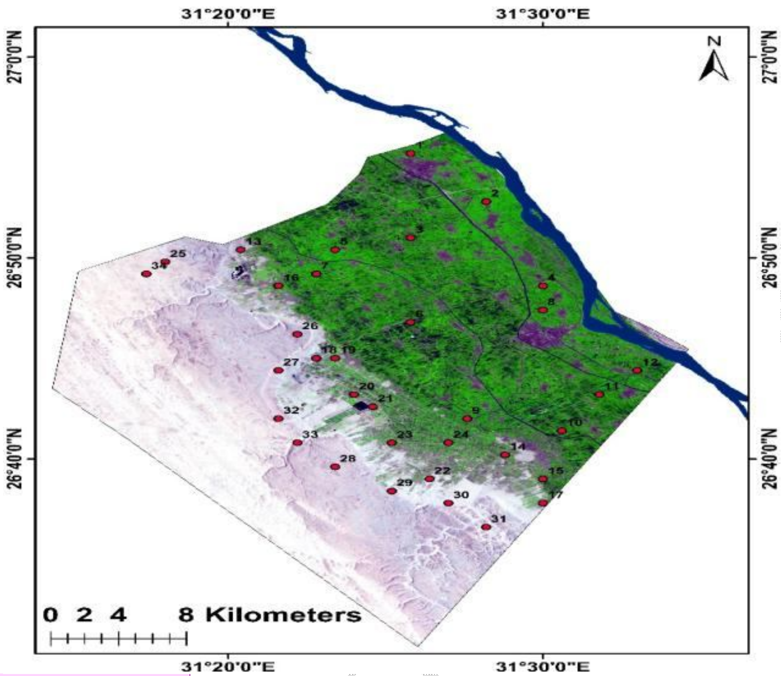

Figure 2. Location of the soil samples.

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$$wj = \frac{dj}{\sum_{i=1}^{m} dj}$$

Where ej is the information entropy of the soil parameter i among the m soil parameters; i = 1, 2, ..,m

dj is the degree of diversity possessed by each criterion

wj is the weight objective for each criterion

Step 3: Calculation of the weighted normalized decision matrix

$$Nij = wj \times nij$$

Step 4: Determination of Positive and Negative Ideal Solutions

TOPSIS is one of the multi-criteria decision analysis methods (Hsu and Hsu, 2008). It ranks objectives based on the distance between the positive and negative ideal solution that should be calculated. In detail, the weighted solutions. Firstly, the standardized matrix must be formulated (Liang and Liu, 2018) then the positive and negative ideal solution can be calculated as follows:

$$v_k^+ = (max\, vlk | k \in k^+ | min\, vlk | k \in k^- |$$

$$v_k^- = (min\, vlk | k \in k^+ | min\, vlk | k \in k^- |$$

Where v_k^+ is the positive ideal solution, and v_k^- is the negative ideal solution.

The distance from the positive/negative ideal solution can be calculated to determine the relative proximity of soil conservation benefit to the ideal solution as the following step.

Step 5: Calculate the Distance between the positive and negative ideal solutions

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (Nij - v_k^+)^2}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (Nij - v_k^-)^2}$$

Step 6: Calculation of Soil Quality Index (SQI)

$$SQI = \frac{S_i^-}{S_i^+ + S_i^-} \times 100$$

Where SQIj is the soil quality index of soil sample j, the range of SQIj is [0, 100], and a larger SQI value indicates better soil quality.

2.4. Statistical and Geostatistical Analyses

Classical statistical analysis was implemented using STATISTICA version 7 software (StatSoft, 2004) to investigate the distribution of each soil parameter. This analysis is a prerequisite step before geostatistical analyses. A geostatistical approach was utilized to examine the variability of the soil parameters. The geostatistics approach comprises the calculation of the experimental semivariogram and the prediction at un-sampled locations. Measuring the spatial correlation using a semivariogram is the most advantage of geostatistics (Webster and Oliver, 2007). The semivariogram of each soil parameter was generated using the average squared differences among all pairs of values according to this equation (Webster and Oliver, 2007)

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

Where:

$\gamma(h)$ is the semivariance of the distance interval h,

N(h) is the number of pairs of the lag interval,

Z(xi) is the measured sample value at point i, and

Z(xi + h) is the measured sample value at position (i + h).

The best semivariogram models were selected based on strong spatial dependence (SDC), root mean square error (RMS), mean standardized error (MSE), and root mean square standardized error (RMSSE) (Webster and Oliver, 2007). Gundogdu and Guney (2007) stated that the (SDC) of <0.25, 0.25–0.75, and >0.75 indicate strong, moderate, and weak spatial dependence, respectively. A spatial distribution map of the soil quality index was generated using ordinary kriging interpolation in ArcGIS10.4, applied the kriging method using the equation given byCafarelli et al. (2015):

$$Z^*(Xo) = \sum_{(i=1)}^{N} \lambda i \, Z(xi)$$

where,

Z*(xo) is an estimated variable at location xo,

Z*(Xi) is the value of an inspected variable at location Xi,

λi is the statistical weight attributed to Z*(Xi) for a sample located near xo, and N is the number of observations in the neighborhood of the inspected point.

Results and Discussion

Soil Properties under Different LandUses

The summary of descriptive statistical analysis of the investigated soil parameters is presented in Table 1. These results could be discussed under subtitles as follows:

Old cultivated soils:

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The sand fraction ranged from 26.21% to 75.00%. In contrast, silt and clay fractions varied from 10.60 to 38.73% and 11.51% to 45.93%, respectively. The soils were slight to moderately alkaline, whereas the pH values of these soils varied from 7.44 to 8.21. These soils are non-saline soils, as all values are below 4 dS/m. These soils' cation exchange capacity is low, ranging from 4.03 cmol+/kg to 17.43 cmol+/kg. These soils' low ESP values range from 1.13 to 14.73 %. The soil organic carbon ranged between 0.29% to 1.46%, which indicated low to very high organic carbon content. Calcium carbonate content is low, which ranges from 0.53% to 4.96%.

New cultivated soils:

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

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

Desert soils:

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

Table 1. Descriptive statistical analysis of some soil characteristics

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Land use	property	Mean	Minimum	Maximum	Standard Deviation	Standard Error
[illegible]	sand	54.30	26.21	75.00	16.05	4.63

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

Table 2. Geostatistical analyses and Semivariograms parameters of soil properties

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Soil property	model	RMS	MSE	RMSSE	Range	Nugget	Partial Sill	sill	Nugget /Sill ratios	Spatial dependence
Sand	Spherical	20.520	-0.042	1.005	8688.54	261.39	159.73	421.12	62.07	Moderate
Silt	Exponential	9.111	0.027	1.038	10208.45	18.94	77.61	96.55	19.62	Strong
Clay	Gaussian	13.924	-0.013	0.997	5998.12	121.12	71.16	192.28	62.99	Moderate
CEC	Spherical	4.986	-0.009	1.053	5817.99	7.97	11.43	19.40	41.08	Moderate
ESP	Spherical	4.543	0.032	1.033	5718.99	11.68	3.57	15.25	76.59	Weak
OC	Gaussian	0.344	-0.007	1.006	5998.12	0.07	0.02	0.09	77.78	Weak
ECe	Gaussian	4.819	-0.061	0.920	6200.21	8.14	35.25	43.39	18.76	Strong
pH	J-Bessel	0.277	0.017	1.017	16303.29	0.06	0.01	0.07	85.71	Weak
CaCO3	Exponential	10.882	0.001	0.954	42956.02	85.11	138.83	223.94	38.01	Moderate
SQI	Exponential	10.189	0.039	0.986	15487.61	44.73	101.21	145.94	30.65	Moderate

~~is very low. These soils are calcic, which calcium carbonate content ranging from 17.67% to 38.12%. Cation exchange capacity and exchangeable sodium percentage are low.~~

Soil PropertiesMaps

The tabulated results (table 2) indicated that the spherical model is suitable for predicting the unknown values of sand, CEC, and ESP. At the same time,the exponential model was suitable for silt and CaCO3 content, and the Gaussian model was suitable for Clay and Organic carbon content and ECe—finally, the J-Bessel model for pH.

Geostatistical range values of soil characteristics varied widely from 5718.99 m to 42956.02. Emadi et al. (2010) stated that the values affected by some other values over greater distances have a wide range compared to variableshaving smaller ranges. However, the least value for the range parameter was recorded for ESP and the highest for CaCO3. The nugget effect is related to spatial variability between measurements. Meanwhile, the large nugget effect means that additional sampling of these properties at smaller distances and in larger numbers might be needed to detect spatial dependence, and a greater sampling density will result in a more accurate map (Cambardella et al. 1994).

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The spatial dependence (SD) resultsare moderate for sand, clay, CEC, and CaCO3. In contrast, the SD is weak for ESP, OC, and pH. Finally, it is strong for silt and ECe,meaning that the later factors are inherited. In comparison, a weak spatial dependence SD is due to the orthic factors. Finally, a moderate spatial dependence is controlled by both inherited and orthic factors (Cambardella et al., 1994; Kiliç et al., 2004; Yasrebi et al., 2009 and Kavianpoor et al., 2012). The spatial distribution maps of soil properties affecting SQI in the study area are shown in Figures 4-12.

~~3.3. **Pearson Correlation Matrix**~~

~~The correlations between soil indicators are listed in Table 3. The sand fraction has a statistically significant negative relationship (p < 0.05) with all other soil indicators except for ECe, pH, and CaCO3 content which exhibits a significant positive relationship. Contrary to that, the case is in finer fractions (silt and clay). CEC is significantly positively correlated (p < 0.05) with silt and clay and significantly negatively correlated with CaCo3. In contrast, it has a non-significant positive correlation with ESP and OC contents. Soil ESP has non-significant positive correlations (p < 0.05) with all indicators except for sand, which was a negative correlation. The results show that ECe has a significant positive relationship with CaCO3 and sand content (p < 0.05). At the same time, the correlations between ECe and silt, clay, CEC, and OC were positive. The soil organic carbon has a significant positive correlation (p < 0.05) with Silt, clay, and CEC, while it has a significant negative correlation with sand, ECe, pH, and CaCO3. The calcium carbonates have a significant negative correlation (p < 0.05) with silt, clay, CEC, and OC. In comparison, it has a significant positive correlation with sand and ECe ESP and a non-significant negative correlation with ESP. Correlation coefficients matrix between each soil parameter.~~

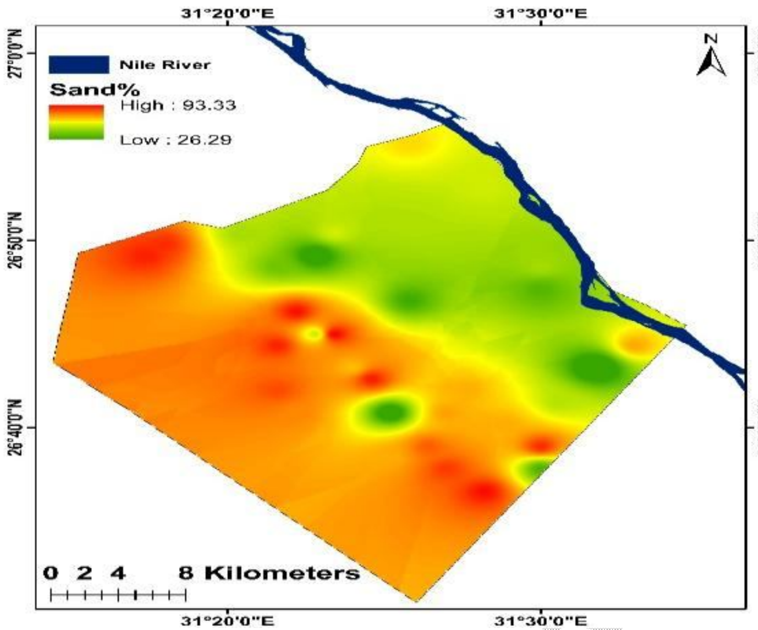
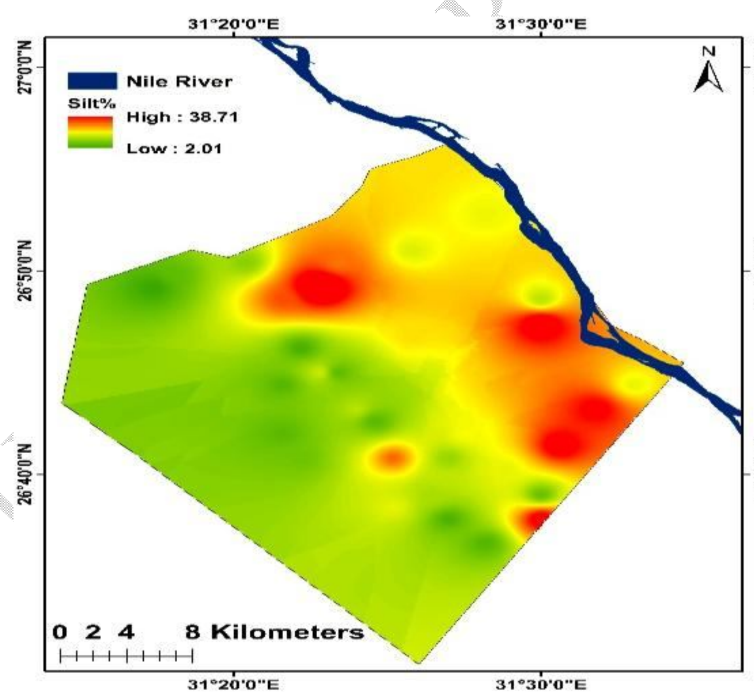


Figure 4. The spatial distribution maps of sand



~~Figure 5. The spatial distribution maps of silt~~

Figure 5. The spatial distribution maps of silt

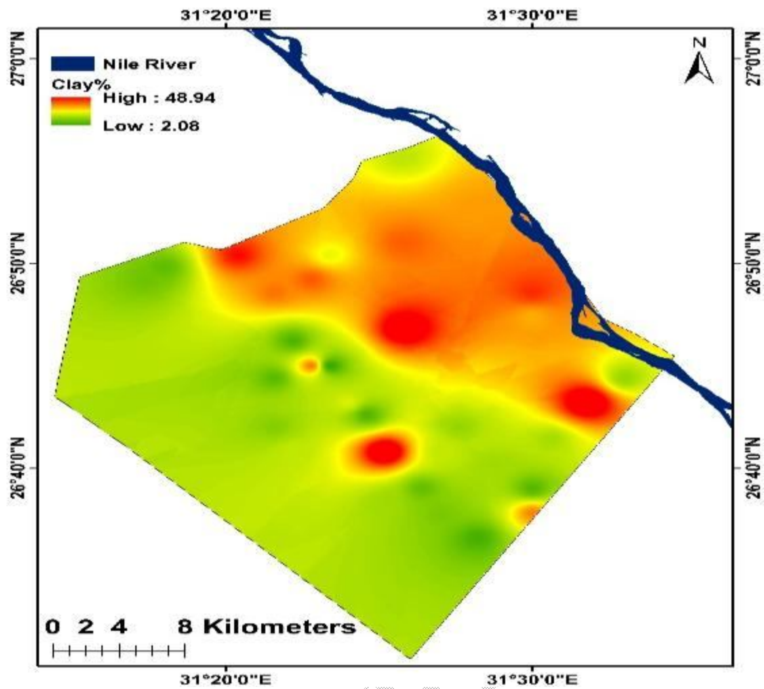


Figure 6. The spatial distribution maps of clay

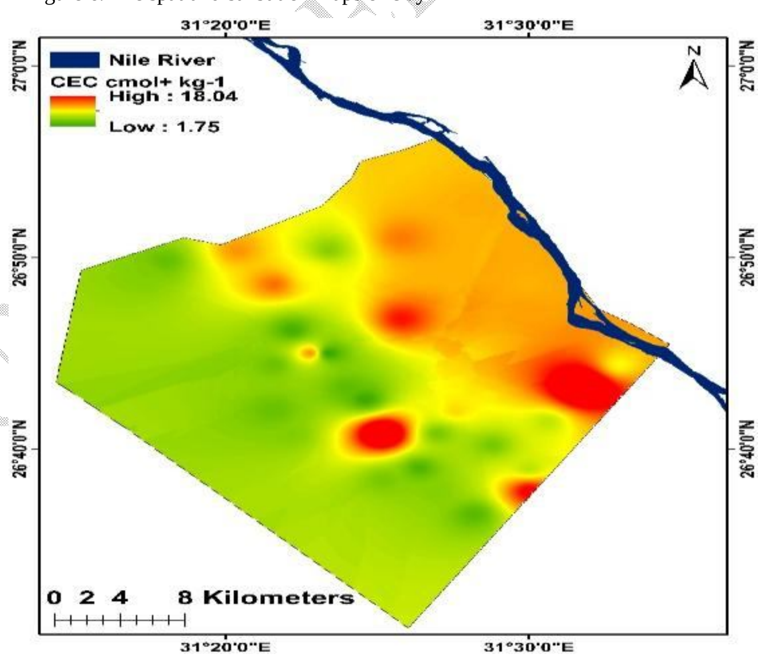


Figure 7. The spatial distribution maps of CEC

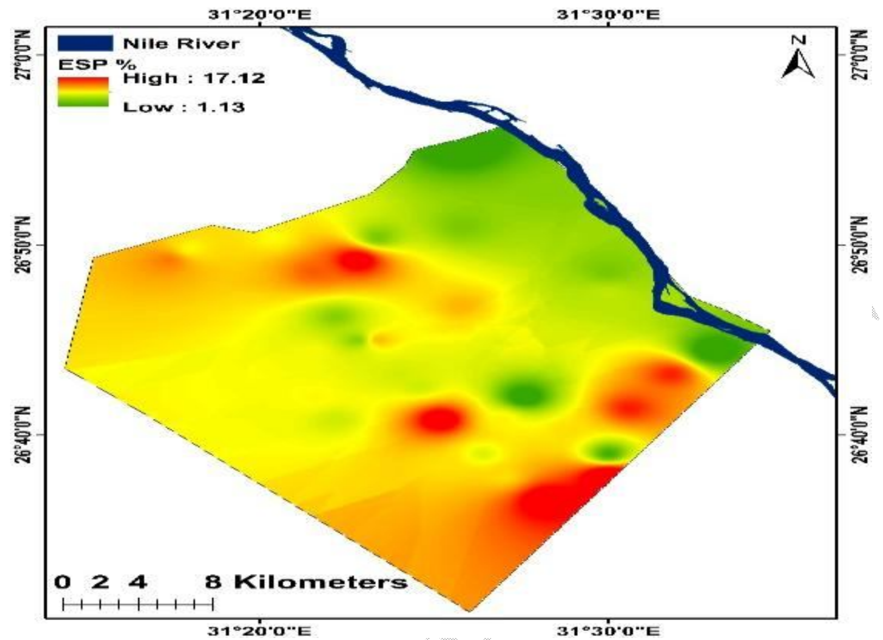


Figure 8. The spatial distribution maps of ESP

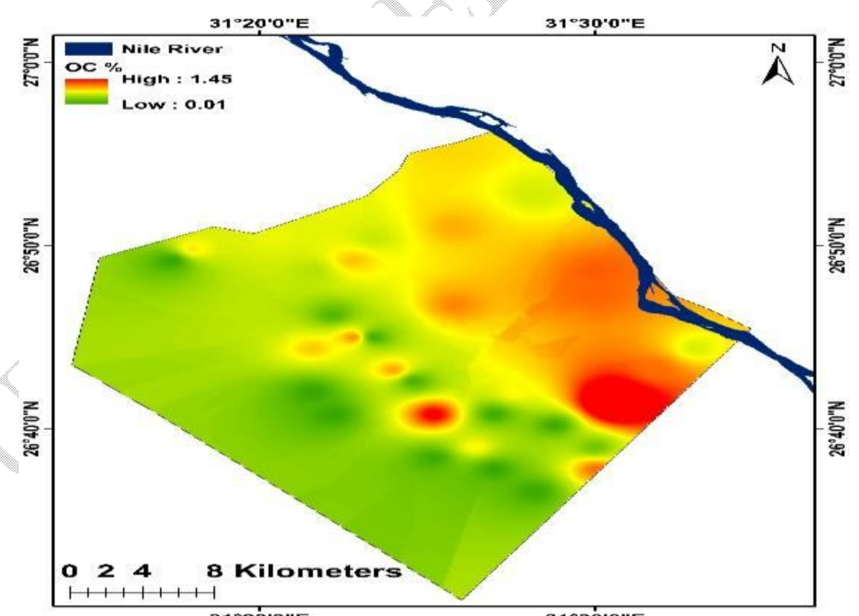


Figure 9. The spatial distribution maps of OC

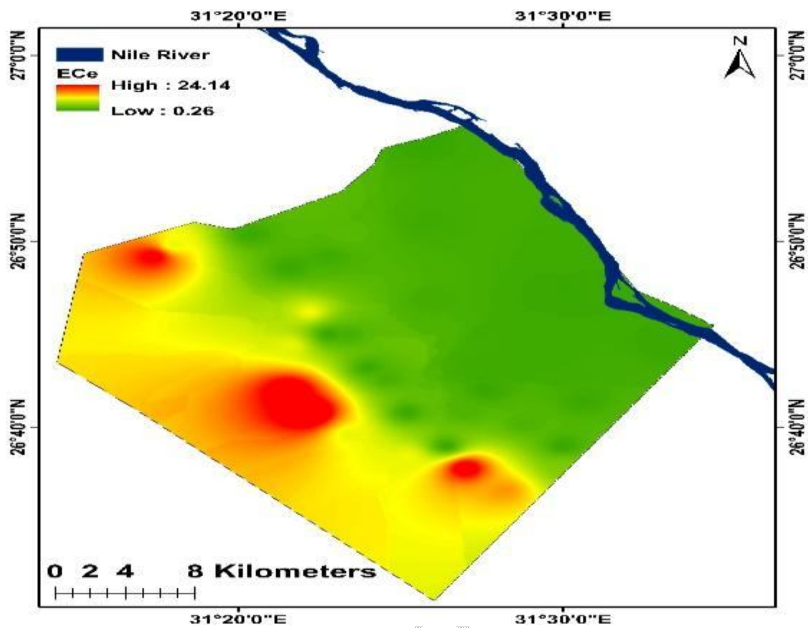


Figure 10. The spatial distribution mapsof ECe

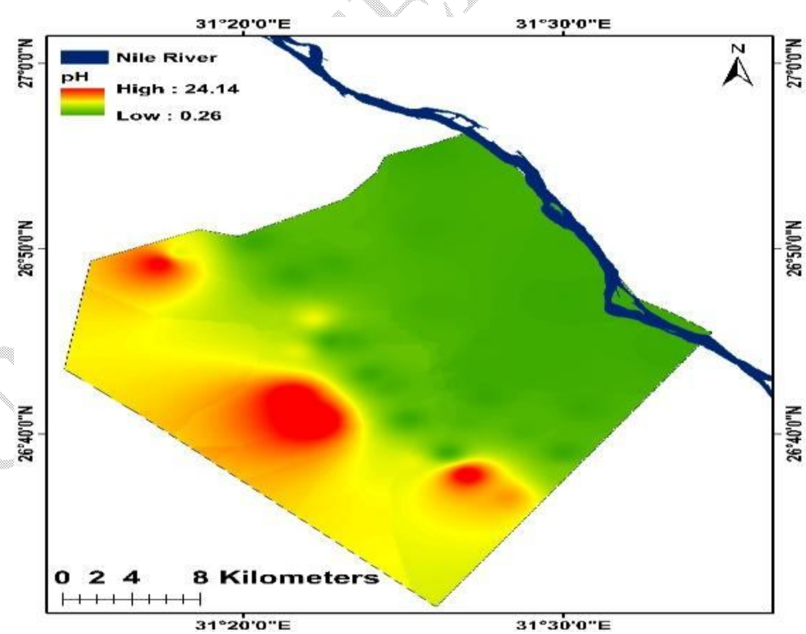


Figure 11. The spatial distribution maps of pH

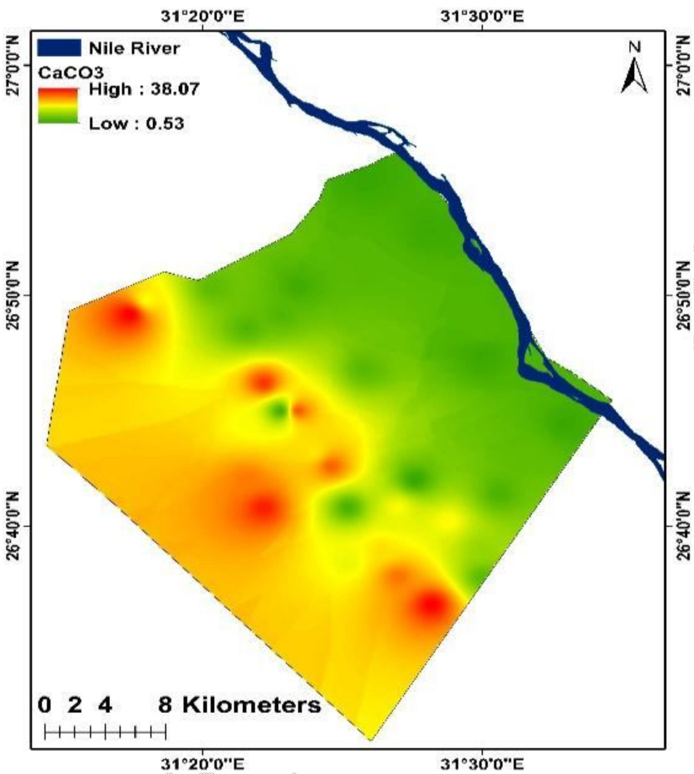


Figure 12. The spatial distribution maps $CaCO_3$

3.3. Pearson Correlation Matrix

The correlations between soil indicators are listed in Table 3. The sand fraction has a statistically significant negative relationship ($p < 0.05$) with all other soil indicators except for ECe, pH, and CaCO3 content which exhibits a significant positive relationship. Contrary to that, the case is in finer fractions (silt and clay). CEC is significantly positively correlated ($p < 0.05$) with silt and clay and significantly negatively correlated with CaCo3. In contrast, it has a non-significant positive correlation with ESP and OC contents. Soil ESP has non-significant positive correlations ($p < 0.05$) with all indicators except for sand, which was a negative correlation. The results show that ECe has a significant positive relationship with CaCO3 and sand content ($p < 0.05$). At the same time, the correlations between ECe and silt, clay, CEC, and OC were positive. The soil organic carbon has a significant positive correlation ($p < 0.05$) with Silt, clay, and CEC, while it has a significant negative correlation with sand, ECe, pH, and CaCO3. The calcium carbonates have a significant negative correlation ($p < 0.05$) with silt, clay, CEC, and OC. In comparison, it has a significant positive correlation with sand and ECe ESP and a non-significant negative correlation with ESP. Correlation coefficients matrix between each soil parameter.

Table 3. Correlation coefficients among soil properties.

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	Sand	Silt	Clay	CEC	ESP	OC	ECe	pH	CaCO3
Sand	1.00								
Silt	-0.85	1.00							
Clay	-0.92	0.58	1.00						
CEC	-0.85	0.59	0.89	1.00					
ESP	-0.37	0.39	0.29	0.29	1.00				
OC	-0.62	0.64	0.49	0.53	0.19	1.00			
ECe	0.47	-0.47	-0.38	-0.37	0.14	-0.50	1.00		
pH	0.34	-0.35	-0.27	-0.24	0.06	-0.39	0.34	1.00	
CaCO3	0.75	-0.69	-0.65	-0.66	0.16	-0.66	0.71	0.48	1.00

Evaluation of SQI under Different Land Use:

Based on the TOPSIS method, the soil quality index (SQI) and its ranking under land use types in the study area were calculated (tables 4, 5, and 6).~~The SQI ranged from 38.75 to 55.82%, 27.53 to 52.72%, and 5.75 to 26.73% for old cultivated, new cultivated, and desert soil, respectively.According toAprisal et al. (2019),the SQI is classified into three quality regions. The first hasa fair quality index and covers56.48% (403.91 km2) of (the total geographical area)ofTGA. The soils of this region are located mainly in old cultivated soils and some newly cultivated soils. This may be due to adding alluvium soils at different amounts on the surface of newly reclaimed soils. The second regionwas observed in some newly reclaimed soils and desert soils and extended over an area of about 27.75% (198.45 km2). These soilshave low values of favorable studied indicators, leading to negative effects on the SQI that are defined as poor(Martinez-Salgado et al., 2010). The third region is very poor quality, covers about 15.77% (112.78 km2) of TGA,and is located mainly in desert soilswith low beneficial and high non-beneficial studied indicators. A box-whisker graph shows the minimum, maximum, median, lower quartile (25%), and upper quartile (75%) of SQI in the studied soils (Figure 5). In addition, the correlation coefficients between the differentsoil indicators and SQI is depicted in Figure (6). The spatial variability of SQI is shown in Figure 7.~~

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Table 4. SQI results based on TOPSIS (Old cultivated soil)

Sample No.	Si+	Si-	SQI	Class	Soil quality
1	0.178	0.125	41.37	3	fair
2	0.167	0.123	42.39	3	fair
3	0.162	0.123	43.25	3	fair
4	0.160	0.124	43.61	3	fair
5	0.173	0.121	41.21	3	fair
6	0.138	0.127	47.88	3	fair
7	0.130	0.128	49.48	3	fair
8	0.144	0.128	47.08	3	fair

Table 5. SQI results based on TOPSIS (New reclaimed soil)

Sample No.	Si+	Si-	SQI	Class	Soil quality
13	0.163	0.120	42.43	3	fair
14	0.196	0.105	34.82	4	poor
15	0.212	0.108	33.70	4	poor
16	0.156	0.121	43.58	3	fair
17	0.149	0.123	45.26	3	fair
18	0.170	0.120	41.43	3	fair
19	0.229	0.087	27.53	4	poor
20	0.199	0.102	33.78	4	poor
21	0.229	0.090	28.13	4	poor
22	0.220	0.093	29.62	4	poor
23	0.130	0.145	52.72	3	fair
24	0.213	0.093	30.40	4	poor

Table 6. SQI results based on TOPSIS (Desert soil)

Sample No.	Si+	Si-	SQI	Class	Soil quality
25	0.233	0.085	26.73	4	poor
26	0.245	0.080	24.69	4	poor
27	0.245	0.080	24.60	4	poor
28	0.233	0.082	26.12	4	poor
29	0.235	0.080	25.40	4	poor
30	0.262	0.062	19.13	5	Very poor
31	0.286	0.042	12.68	5	Very poor
32	0.283	0.047	14.32	5	Very poor
33	0.287	0.049	14.51	5	Very poor
34	0.330	0.020	5.75	5	Very poor

The SQI ranged from 38.75% to 55.82%, 27.53% to 52.72%, and 5.75% to 26.73% for old cultivated, new cultivated, and desert soil, respectively.According toAprisal et al. (2019),the SQI is classified into three quality regions. The first hasa fair quality index and covers 56.48% (403.91 km^2) of the total geographical area (TGA). The soils of this region are located mainly in old cultivated soils and some newly cultivated soils. This may be due to adding alluvium soils at different amounts on the surface of newly reclaimed soils. The second regionwas observed in some newly reclaimed soils and desert soils and extended over an area of about 27.75% (198.45 km2). These soilshave low values of favorable studied indicators, leading to negative effects on the SQI that are defined as poor(Martinez-Salgado et al., 2010). The third region is very poor quality, covers about 15.77% (112.78 km2) of TGA, and is located mainly in desert soilswith low beneficial and high non-beneficial studied indicators. A box-whisker graph shows the minimum, maximum, median, lower quartile (25%), and upper quartile (75%) of SQI in the studied soils (Figure 5). In addition, the correlation coefficients between the differentsoil indicators and SQI is depicted in Figure (6). The spatial variability of SQI is shown in Figure 7.

Comment [I16]: Figure 5 is about spatial distribution maps of silt not about SQI. Didn't you mean figure 13?

Comment [I17]: This figure too, is not about SQI. Didn't you mean figure 14?

Comment [I18]: Here too.. figure 15.

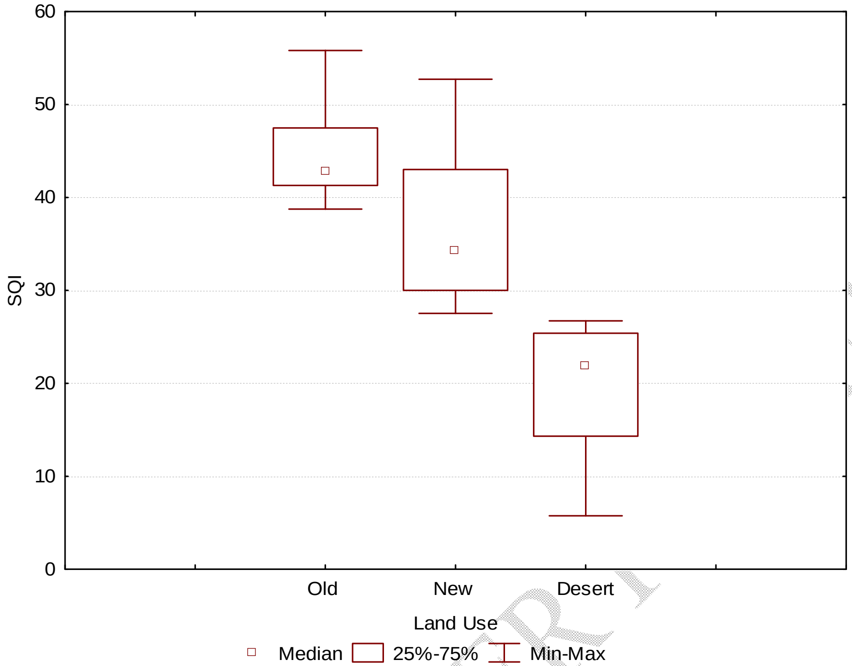

Figure.13. A box-whisker graph showing the minimum, maximum, median, lower quartile (25%), and upper quartile (75%) of SQI.

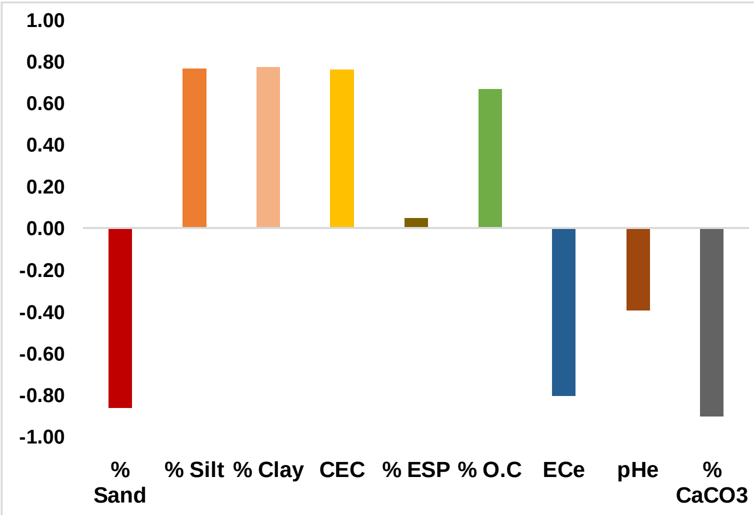

Figure 14. Correlation coefficients between the different soil indicators and SQI

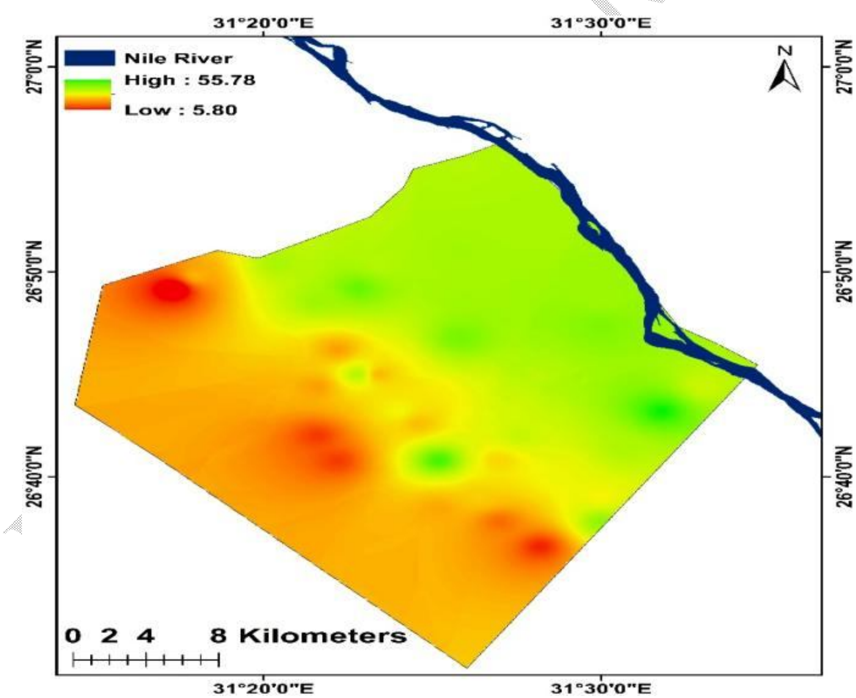

Figure 15. The pattern of the spatial distribution of the SQI

Conclusion

This study has developed integrated TOPSIS and Geostatistical Techniques in the Northern part of Sohag Governorate, Egypt, for soil quality assessment under different land uses. The area under study had three land uses: old cultivated, newly reclaimed, and desert soils. Soil quality is affected by agricultural practices andclimatic conditions, which, in turn, affect the soil's physical, chemical, and fertility properties. This study used the soil's physical and chemical properties to assess the SQI in the study area.The ordinary kriging interpolation method was used to estimate and mapping the unknown values of soil properties. The model's accuracy was confirmed for each soil property based on RMS, MSE, and RMSSE. The results show that the spherical model is suitable for predicting the unknown values of Sand, CEC, and ESP.

In contrast,the exponential model was suitable for silt and $CaCO_3$ content, and the Gaussian model was suitable for Clay and Organic carbon content and ECe—finally, the J-Bessel model for pH.Based on the TOPSIS method, the soil quality index (SQI) and its ranking under land use types in the study area were calculated. The results of SQI ranged from 38.75% to 55.82% and from, 27.53% to 52.72%, and from 5.75% to 26.73% for old cultivated, new cultivated, and desert soil, respectively. The SQI is classified into three quality zones. The first is characterized by a fair quality index representing about 56.48% (403.91 km^2) of the total area. The soils of this zone are located mainly in old cultivated soils and some newly cultivated soils. The second zone is characterized by poor soil quality and covers about 27.75% of the area (198.45 km^2). This class is observed in some newly reclaimed soils and desert soils. These soils have low values of favorable studied indicators, negatively affecting the SQI. The third zone is very poor quality and covers about15.77% (112.78 km^2)and is located mainly in desert soilswitha low content of beneficial and high content of non-beneficial studied indicators.Finally, the present work confirmed that the geostatistical technique and TOPSISare accurate and effective assessments of the SQI.

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