Article

Development of a Spatial Model for Soil Quality Assessment under Arid and Semi-Arid Conditions

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Abstract: Food security has become a global concern for humanity with rapid population growth, requiring a sustainable assessment of natural resources. Soil is one of the most important sources that can help to bridge the food demand gap to achieve food security if well assessed and managed. The aim of this study was to determine the soil quality index (SQI) for El Fayoum depression in the Western Egyptian Desert using spatial modeling for soil physical, chemical, and biological properties based on the MEDALUS methodology. For this purpose, a spatial model was developed to evaluate the soil quality of the El Fayoum depression in the Western Egyptian Desert. The integration between Digital Elevation Model (DEM) and Sentinel-2 satellite image was used to produce landforms and digital soil mapping for the study area. Results showed that the study area located under six classes of soil quality, e.g., very high-quality class represents an area of 387.12 km^2 (22.7%), high-quality class occupies 441.72 km^2 (25.87%), the moderate-quality class represents 208.57 km^2 (12.21%), slightly moderate-quality class represents 231.10 km^2 (13.5%), as well as, a low-quality class covering an area of 233 km^2 (13.60%), and very low-quality class occupies about 206 km^2 (12%). The Agricultural Land Evaluation System for arid and semi-arid regions (ALESarid) was used to estimate land capability. Land capability classes were non-agriculture class (C6), poor (C4), fair (C3), and good (C2) with an area 231.87 km^2 (13.50%), 291.94 km^2 (17%), 767.39 km^2 (44.94%), and 416.07 km^2 (24.4%), respectively. Land capability along with the normalized difference vegetation index (NDVI) used for validation of the proposed model of soil quality. The spatially-explicit soil quality index (SQI) shows a strong significant positive correlation with the land capability and a positive correlation with NDVI at R^2 0.86 ($p < 0.001$) and 0.18 ($p < 0.05$), respectively. In arid regions, the strategy outlined here can easily be re-applied in similar environments, allowing decision-makers and regional governments to use the quantitative results achieved to ensure sustainable development.

Keywords: spatial modeling; land capability; ALESarid; GIS; remote sensing; NDVI

1. Introduction

Soil quality (SQ) is one of the most common concepts that has emerged over the last decades and has been used to assess soil under different systems [1–3]. For practical purposes, the judgment of SQ depends on impacts of soil on crop yield, erosion, and quality of surface and ground, food, and air [4]. The meaning of the soil quality index (SQI) is the ability of the soil to function within an ecosystem boundary, whether managed or natural, and to achieve sustainability of crop productivity while maintaining soil from degradation processes [5,6]. In many regions around the world, soil quality is declining rapidly [7], due to many reasons, including, but not limited to, changes in land use types with intensive land use [8,9]. Therefore, the assessment of SQ is considered the basis for monitoring and maintaining the sustainability of agricultural systems [10].

Evaluation of SQ is based on personal knowledge, which leads to a reward for lack of data and a lack of similarity between geographical locations. Thus, SQ evaluation should be carried out in a quantitative, documented, reproducible, and spatially-explicit approach with the lowest level of subjectivity [11]. In addition, indicators that influence soil properties are needed for soil quality assessment [12,13]. Soil fertility, physical, chemical, and biological factors have a crucial role in determining soil suitability for crop production, influencing soil quality and crop yields in turn [14].

The quantification of SQ required a minimum set of data, including a small number of accurately selected soil indicators, such as physical, chemical, and biological properties [15]. Thus, the SQ indicators could be divided into stable and dynamic soil characteristics [16]. The soil texture is considered stable soil properties that have affected the difference in crop productivity, while pH, soil depth, soil water, and nitrate concentrations are dynamic soil characteristics and need to be monitored periodically. This explains the impact of the management process on the difference in plant productivity that affects dynamic soil properties, e.g., the variable rate of application of irrigation or fertilization [1].

Therefore, monitoring of soil quality parameters will help to simplify and increase awareness of the reasons and impacts of climate change and the responses required [17]. This is because soil quality is a measure of soil capacity to function to maintain productivity, to maintain environmental quality, to limit ecosystems and land use, and to promote plant and animal health [18].

Various assessment methods of the spatial variability of soil properties include geostatistics approaches based on measurements at adjacent locations with certain weights assigned to each measurement [19,20]. For instance, classical ordinary Kriging interpolation (OK) can directly illustrate the spatial variation of soil properties [21] as one of the geostatistical methods that have been widely used to evaluate and analyze spatial correlation and spatial variability of soil properties such as physical, chemical, and biological properties [22]. On the other hand, there is a significant positive correlation between soil quality and land capability, which shows that the two approaches are related to the assessment of land for crop production [23]. Recently, several land capability models have been developed to provide a quantified procedure to match land with various actual and proposed uses, particularly for the arid and semi-arid regions, including the study area, for instance, the Agricultural Land Evaluation System for arid and semi-arid regions, (ALESarid) which has been developed by [24]. This model is integrated with GIS software to calculate land capability and could provide a reasonable solution between the accuracy, ease of application, and moderate data demand [25]. Additionally, the normalized difference vegetation index (NDVI) as a biophysical parameter can be calculated from remote sensing data that are sensitive to the dynamic change of vegetation conditions, including several factors, such as soil quality [26,27]. Thus, land capability and NDVI may have better potential to precisely validate the proposed soil quality model.

Consequently, soil quality assessment using GIS and remote sensing (RS) applications is very important for land assessment, facilitating reclamation and cultivation plans, but this

approach needs to be applied in a variety of environments, particularly arid and semi-arid regions. The spatial model developed in this research is expected to be a more accurate methodology for assessing the spatial distribution of soil quality, as it includes soil physical, chemical, and biological indicators.

In the current research, a spatial model for soil quality assessment was developed to evaluate soil quality based on physical, chemical, and biological soil properties, RS and GIS data. The results of the proposed model were correlated with both land capability and the NDVI of the study area. This study could be used as an assessment tool to help decision-makers and land managers to map and assess soil quality under arid and semi-arid conditions. The concept of the current study can be utilized to other sites of a similar subject.

2. Materials and Methods

Various phases were carried out to achieve the research objective, including the definition of the physiographic units using the DEM and Sentinel-2 image, fieldwork to collect samples and check the boundaries of the physiographic units, laboratory analysis for physical, chemical, and biological soil properties, and the development of a spatial model for soil quality assessment along with its validation with the land capability and NDVI of the study area (Figure 1).
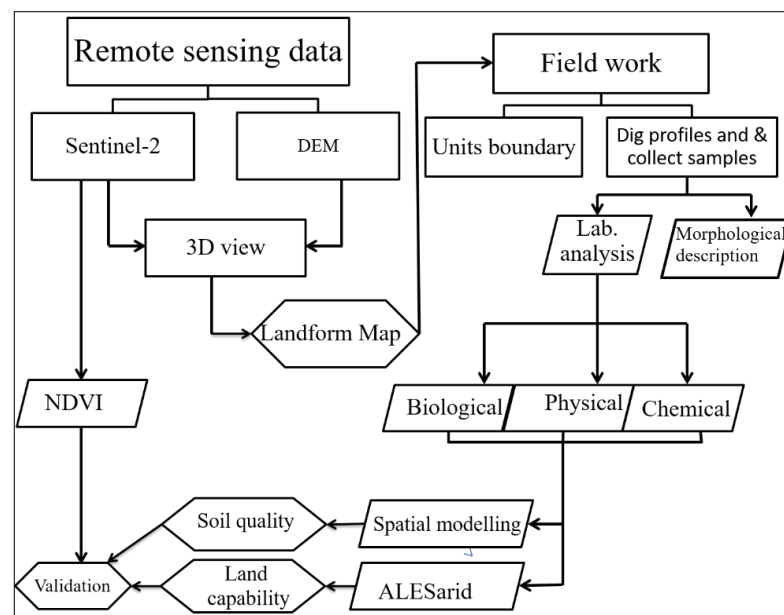
Figure 1. Summary of the methodology used in this research, including satellite image analysis, fieldwork, laboratory analysis, spatial model, and validation.

2.1. Location of the Study Area

El Fayoum depression in the Western Desert of Egypt covers an area of approximately 1707 km^2. It is bounded by 30°15′ and 31°06′ N latitudes and 29°10′ and 29°34′ E longitudes (Figure S1). The climate data of the study area showed that the mean annual precipitation is 7.2 mm/year and the mean minimum and maximum annual temperatures are 14.5 and 31.0 °C, respectively. The lowest evapotranspiration value was 1.9 mm/day recorded in January, while the highest value was 7.3 mm/day. The soil moisture and temperature regimes are Torric and thermal, respectively [28].

2.2. Digital Image Processing

Sentinel-2 image acquired on 14 August 2019 under clear sky conditions was used to produce landforms and digital soil mapping with the aid of the DEM of the study area. The multi-spectral bands of Sentinel-2 image have a ten-meter spatial resolution for bands

2, 3, 4, and 8, respectively. The DEM provided at 30-m spatial resolution and produced by the NASA Shuttle Radar Topographic Mission (SRTM) (Figure 2). SNAP and ENVI 5.4 were utilized for image processing, including spectral subset, radiometric calibration, atmospheric, and geometric corrections. UTM Zone 36N coordinate system using WGS 84 datum was assigned as a projection system.
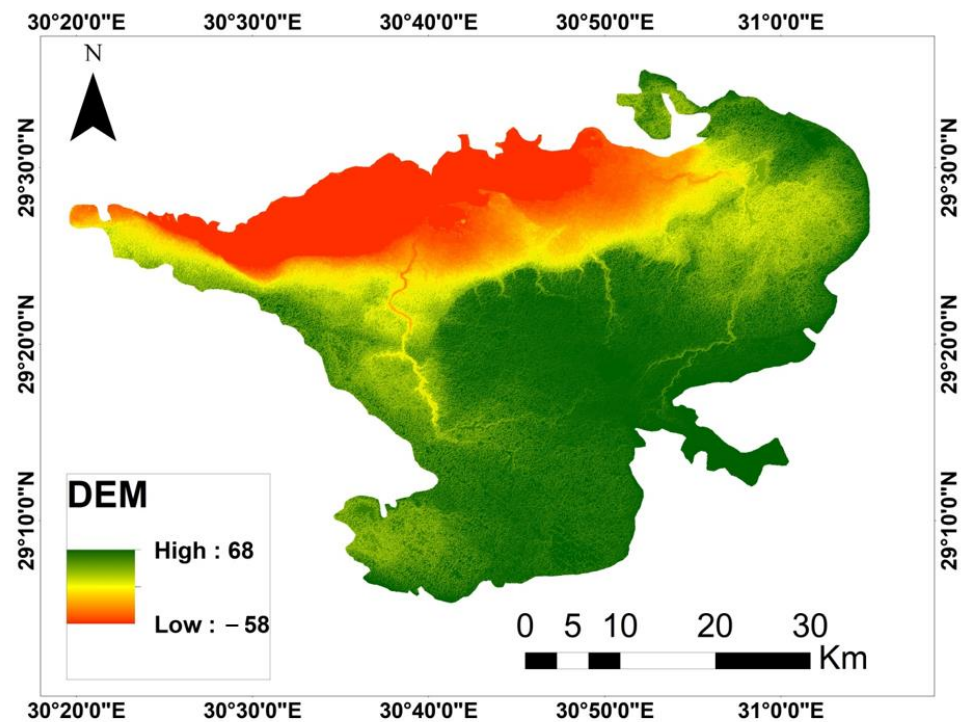

Figure 2. Digital elevation map for the study area.

2.3. Delineation of the Landform Map

The visual interpretation for the multi-spectral Sentinal-2 image dropped over the DEM in ArcScene to provide a 3D vision for the landform units' extraction. This method revealed the clear difference in elevations found in every delineated landscape. By this method, we were able to separate the different landform units based on the visual interpretation of the satellite image and DEM in a 3D visualization mode, field check with the aid of previous studies that were carried out on this area trying to give the most appropriate nomenclature to landforms [29].

2.4. Field Survey and Laboratory Analysis

Field surveys were conducted to dig 40 soil profiles, one hundred and twenty representative soil samples were taken from all soil profile. The depth of soil profiles ranges from 40 to 110 cm. To be well represented, one composite sample was collected from each layer in the soil profiles (Figure S2a). Land use and geology maps of the study area are shown in Figure S2b,c. Each landform was represented by several soil profiles according to their characteristics. Detailed morphological descriptions of soil profiles were elaborated on the basis outlined by [30]. Soil samples were air-dried, and the fine earth (<2 mm) particles were used for chemical analysis, based on the manual of soil survey laboratory methods [31]. Based on the morphological characteristics, physical and chemical properties of the soil, we assessed soil quality and capability in the study area. Additionally, these soils are classified as sub-large groups based on the 2014 Soil Survey Staff, the World Reference Base for Soil Resources (WRB; IUSS Working Group, 2015) [28].

2.5. Evaluation of Soil Quality Index (SQI)

SQI were calculated according to MEDALUS methodology [32], as shown in Equation (1).

$$SQI = (It * Is * Id * Idr * ICaCO_3 * IOM * Iec)^{1/7} \tag{1}$$

where It is soil texture index, Is is slope gradient index, Id is soil depth index, Idr is drainage condition index, $ICaCO_3$ is the content of calcium carbonate index, IOM is soil organic matter index, and Iec is soil salinity index.

2.6. Development of a Spatial Model for Evaluating Soil Quality Index

The development of a spatial model was based on the Model Builder tool in ArcGIS. Model Builder was used to automate, document selected spatial analysis and data management processes as a diagram of gathered chains, which are a sequence of geo-processing tools that use the output of one process as the input to another process. The following procedures implemented in this study to assign the weighting factor of each soil indicator for getting the final SQI map (Figure 3): Step 1 different soil properties interpolated from point-based to a raster layer, step 2 different soil properties raster layers from step 1 reclassified into six classes (e.g., very low, low, slightly moderate, moderate, high, and very high), the reclassified values assigned to an evaluation scale from 1 (high quality) to 6 (low quality), step 3 different class of soil properties raster layers from step 3 assigned to an index (Table S1), step 4 feeding Equation (2) the different outputs from step 3 to map SQI, and step 5 reclassify the output raster layer from step 4 based on Table S2, the final resulting raster assessed and displayed as soil quality map.

Figure 3. Spatial model structure for assessing soil quality.

2.7. Validation of SQI Model Based on Land Capability

The land capability of the study area was evaluated by ALESarid. The outputs of this model can be shown in simple and handy maps showing the spatial distribution of land capability. The extracted land capability value was compared with the soil quality index for each mapping unit in the study area using SPSS software to obtain a correlation coefficient between them at a 0.05 significance level (*p*-value).

2.8. Calculation of Normalized Difference Vegetation Index (NDVI)

The NDVI was calculated on 10 August for four years (2017, 2018, 2019, and 2020). This index is a dimensionless index that reflects the presence and density of vegetation based on the simulated red and NIR reflectance, as shown in Equation (2).

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

where *NIR* is the near-infrared reflectance and *R* is the red reflectance.

3. Results

3.1. Physiographic of the Investigated Area

The physiographic units of the studied area are represented in Figure 4 and Table S3. The alluvial plain included recent terraces and basins covering an area of 843.43 and 218.54 km^2, respectively. On the other hand, recent terraces were classified into moderately high and basins were classified into overflow and decantation, meanwhile lacustrine plain included terraces (relatively low, relatively high, and moderately high) covering an area of 194.66 km^2. The fluvial-lacustrine plain included old terraces (relatively low and relatively high), covering an area of 264.94 km^2.
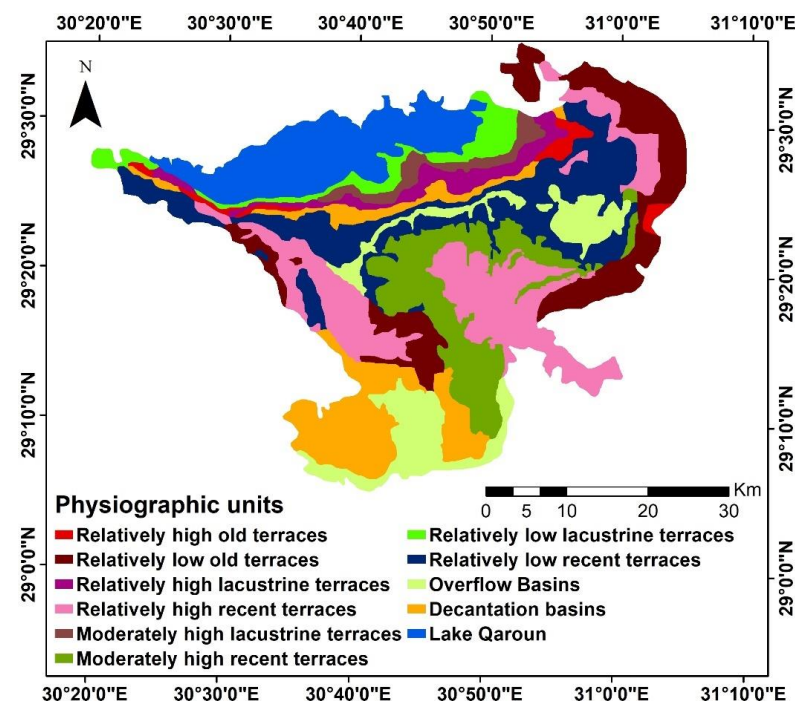

Figure 4. Spatial distribution of the physiographic units.

3.2. Spatial Distribution of Soil Indicators

3.2.1. Chemical Soil Quality Indicators (CSQI)

The chemical soil quality indicators (CSQI) are dynamic indicators and change by the land management process. CSQI were selected based on the sensitivity to disturbance and soil ecosystem function performance. CSQI included (EC, pH, CEC, ESP, SAR, and CaCO$_3$),

as represented in Figure 5. The average pH ranges from 7.62 to 8.57. The spatial distribution of ECe shows that the study area has a wide range of ECe values, as it ranges from 1.33 to 36.22 dS/m. The results of Cation Exchange Capacity (CEC) indicate that the lowest value of CEC 18 cmole/kg, while the highest one 53.69 cmole/kg. Exchangeable sodium percentage (ESP) and Sodium Adsorption Ratio (SAR) values range from 9.93% to 26.96% and from 7.74% to 24.28%, respectively. The CaCO$_3$ content ranges from 3.39% to 29.73%.
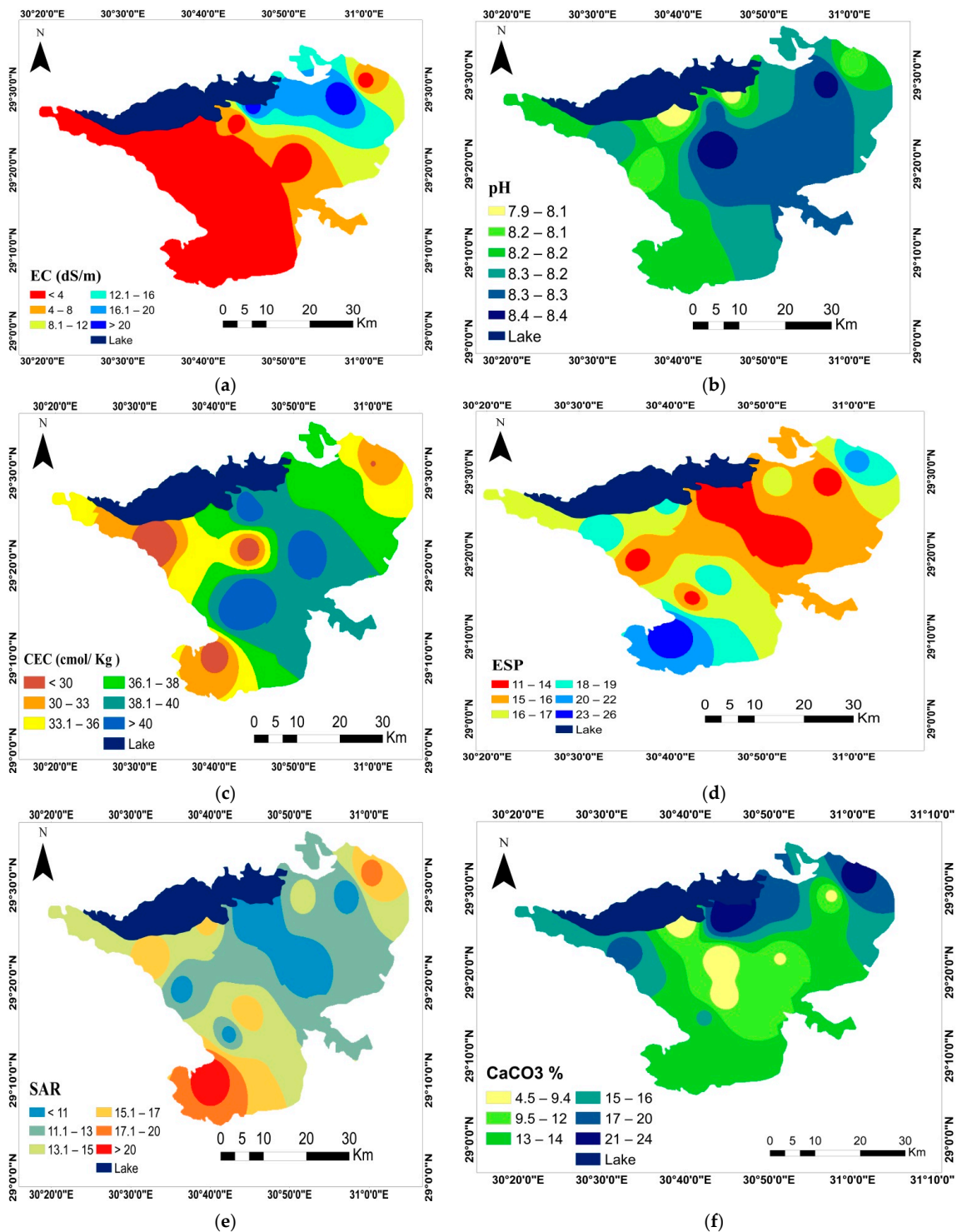
Figure 5. Spatial distribution of chemical soil properties (**a**) electric conductivity (EC: dS/m), (**b**) soil reaction (pH), (**c**) cation exchange capacity (CEC: cmole/kg), (**d**) exchangeable sodium percent (ESP), (**e**) sodium absorption ratio (SAR), and (**f**) calcium carbonate percentage (CaCO$_3$: %).

3.2.2. Physical and Biological Soil Quality Indicators

There are five soil texture classes in the study area (i.e., sandy clay loam, clay, sandy loam, clay loam, and loam). From Figure 6, the spatial variation range of sand, clay, and silt percentages are 19.7%–70.3%, 12.2%–40.1%, and 14.5%–58.5%, respectively. The effective soil depth ranges from 50 to 120 cm, while organic matter (OM) content ranges from 0.23% to 1.98%.
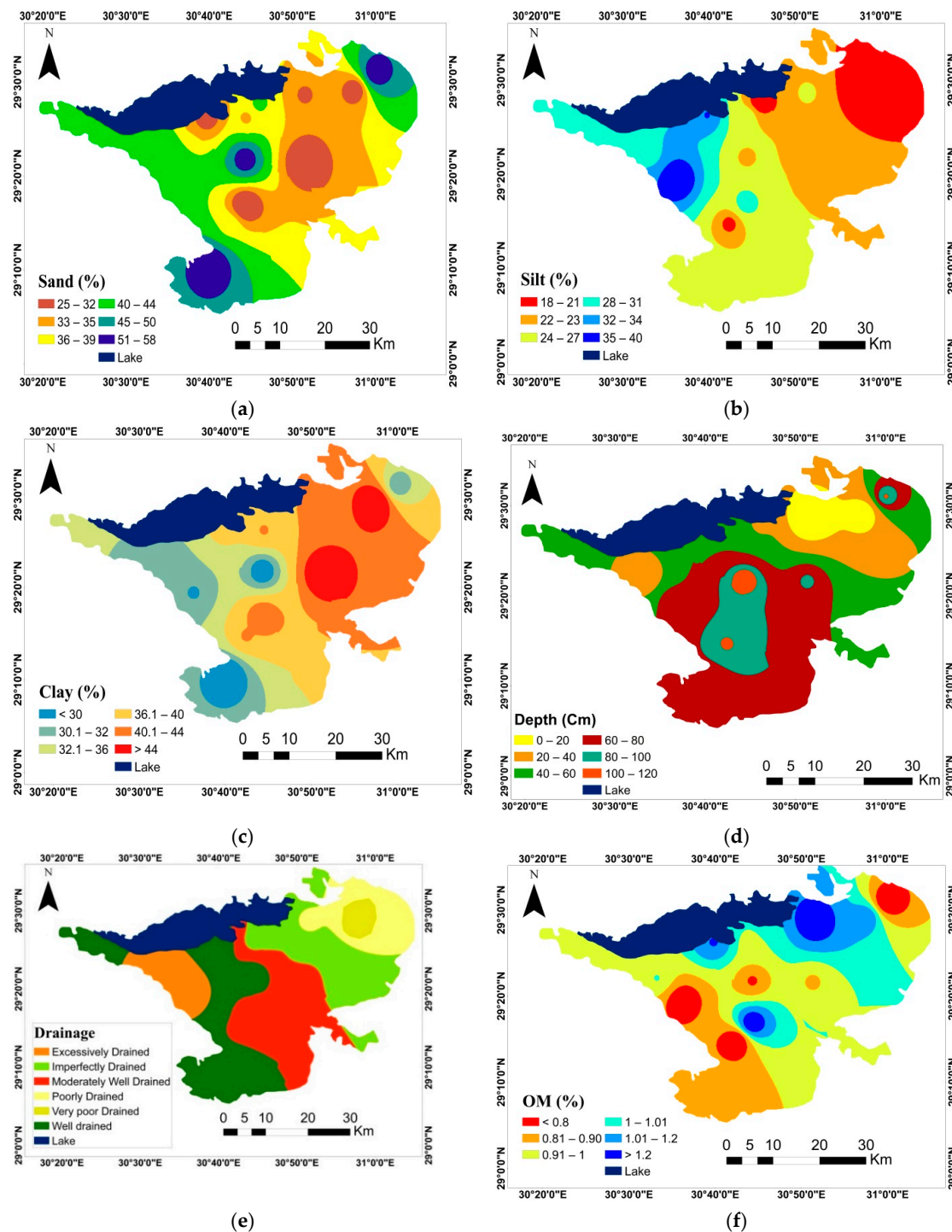
Figure 6. Spatial distribution of some physical and biological soil properties (**a**) sand (%), (**b**) silt (%), (**c**) clay (%), (**d**) depth (cm), (**e**) drainage condition, and (**f**) soil organic matter (OM%).

3.3. Digital Soil Map of the Study Area

Digital soils map of the study area are classified according to morphological, physical, and chemical properties to five sub great groups namely Typic haplargids, Typic haplocalcids, Typic haplosalids, Typic torrifluvents, and Vertic torrifluvents with an area of 109.32 km², 185.59 km², 360.24 km², 43 km², 767.51 km², and 136.20 km², respectively (Figure 7). In addition, soil classification based on the World Reference Base (WRB) system included Endo calcaric luvisols, Luvic calcisols, Hypersalic haplic solonchaks, Fluvisols, and Vertisols, it is provided in Figure S3.
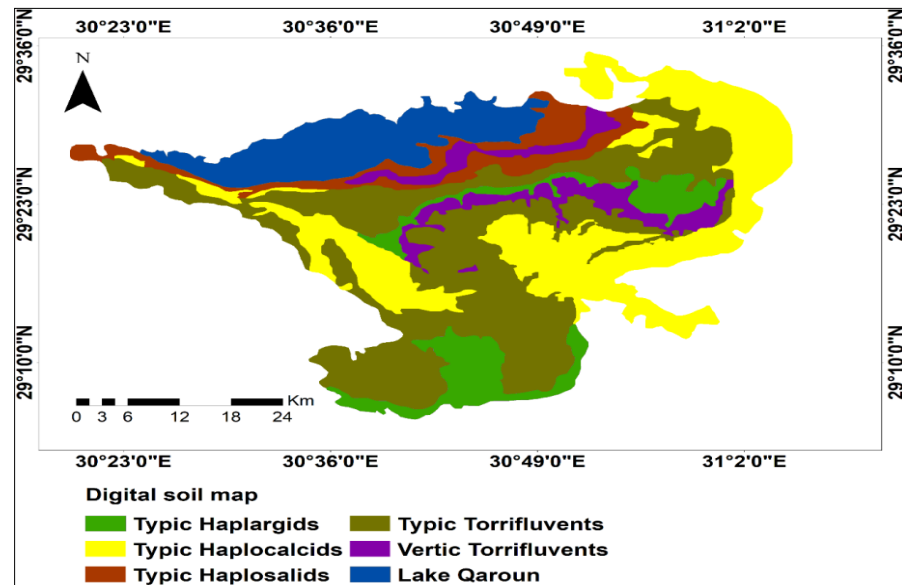

Figure 7. Digital soil map of sub great groups.

3.4. Soil Capability Index (CI)

The obtained results of land capability from ALESarid are illustrated in Figure 8a and Table S4. These results indicate that the estimated capability index for the study area was non-agriculture class (C6), poor (C4), fair (C3), and good (C2) with an area of 231.87 km² (13.50%), 291.94 km² (17%), 767.39 km² (44.94%), and 416.07 km² (24.4%), respectively.
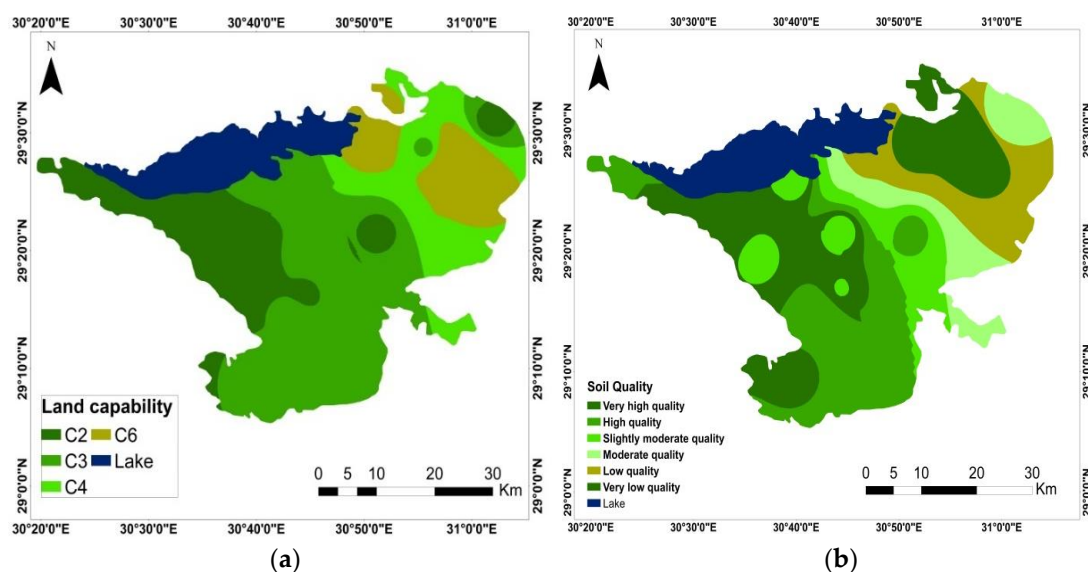

Figure 8. Spatial distribution of CI (**a**) and SQI (**b**).

3.5. Soil Quality Index (SQI)

The results of the proposed model reveal that the study area located under six classes, e.g., very high-quality class occupies 387.12 km^2 (22.7%), high-quality class occupies 441.72 km^2 (25.87%), the moderate quality class represents 208.57 km^2 (12.21%), the slightly moderate-quality class represents 231.10 km^2 (13.5%), in addition, a low-quality class covers an area of about 233 km^2 (13.60%), and finally the very low class occupies about 206 km^2 (12%) (Figure 8b and Table S5).

3.6. The Relationship between SQI, CI, and NDVI

The developed spatially explicit model of soil quality was validated by the land capability index (CI) from ALESarid and NDVI from remote sensing data over the study area. The statistical results show that there is a strong significant association between SQI and CI as $R^2 = 0.86$ at $p < 0.001$ (Figure 9a). There is also a significant relationship between NDVI and SQI as $R^2 = 0.18$ at $p < 0.05$ (Figures 9b and 10).
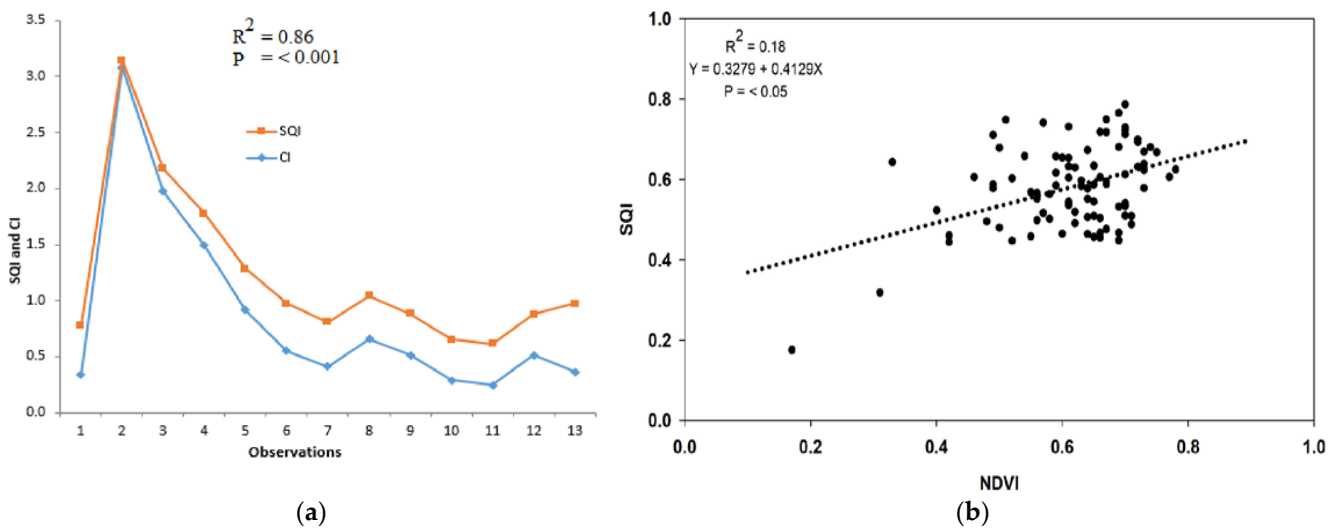

(**a**) (**b**)

Figure 9. Correlation between SQI and CI (**a**) and between NDVI and SQI (**b**).
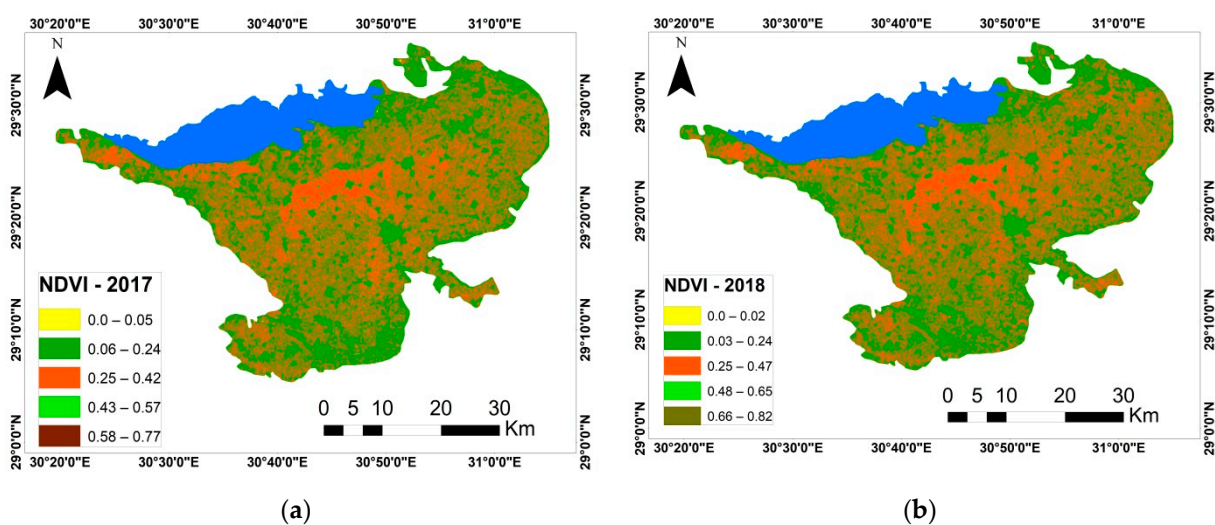

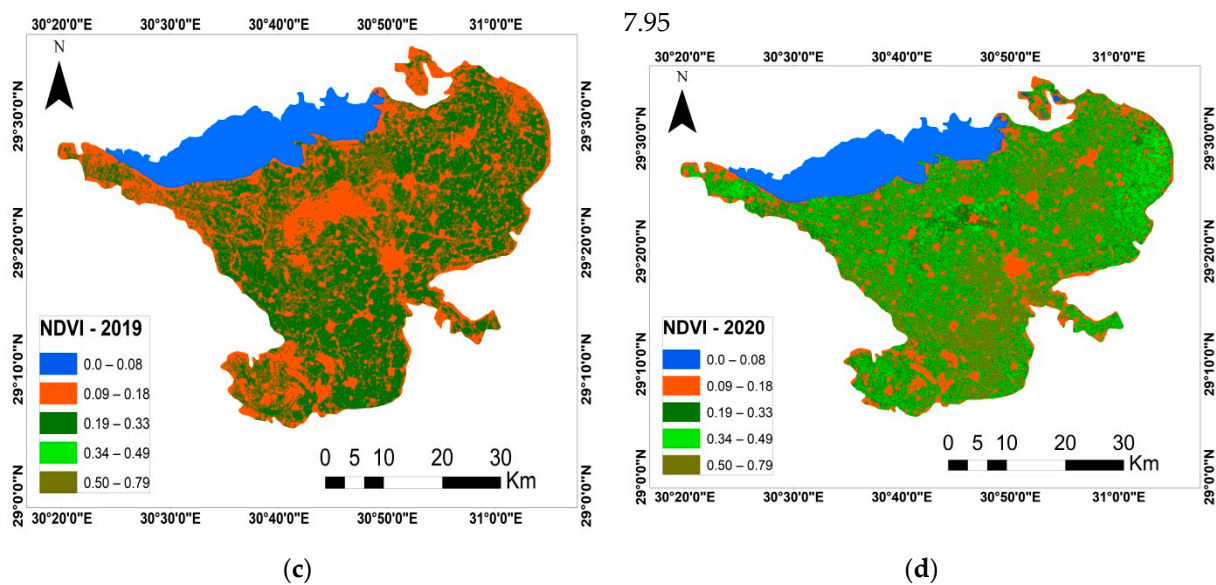(**a**) (**b**)

Figure 10. *Cont.*

Figure 10. NDVI maps from 2017 to 2020.

4. Discussion

To identify areas with better soil quality and those needing more attention because of their vulnerability to degradation, the assessment and application of the method mentioned in this study were used. Those areas with soil that provide optimum plant growth conditions and lower sensitivity to erosive processes have been rated as having higher quality.

4.1. Physiographic and Soil Chemical, Physical and Biological Properties

Physiographic mapping units could be delineated by interpreting satellite images that are considered to be one of the most common and economically advanced mechanisms [33]. Physiographic units have been identified and delineated by landscape interpretation from the integration between satellite image and DEM with the assistance of various maps and field studies. The results show that the main landscapes in the area studied were alluvial, lacustrine, and river-lacustrine plains. The highest EC value is found in relatively low lacustrine terraces, which are situated in the Qaroun Lake area. Arid climate and intrusion of lake water are the main reasons for rising salinity in low lacustrine terraces. [34] stated that in arid and semi-arid conditions where precipitation is low and sporadic and evaporation is high, most salinized soils are present. A suggested management plan is, therefore, required for high-salt soil by leaching salts from soil using high-quality irrigation water [35]. However, more than 30% of the studied area is non-saline (EC < 4 dS/m), confirming the importance of SQI in identifying agricultural areas. The results of CEC have a wide range, based on the percentage of clay and organic matter in the soil, as there are significant positive correlations between CEC, clay, and organic matter [36]. The high sodium percentage can negatively affect soil properties, such as soil structure and soil hydrology, reducing crop productivity. Soil more than 15 ESP has become alkali soil and can be reclaimed by adding gypsum to the soil [37]. Areas close to Qaroun Lake had the highest value of $CaCO_3$ that could be due to shell fragments. The highest $CaCO_3$ value in some soils can lead to very hard layers impermeable to water and crop roots and the fixation of P fertilizer when added to calcareous soils. [38] found a strong P retention in calcareous soils, although the application of OM contributed to its mobility. The soil of the study area has a wide range of texture, physical, chemical, hydrological, and biological properties. Consequently, soil fertility may be affected by such changes in soil properties that affect the availability and storage of nutrients. The physical soil quality indicator (PSQI) is mainly affected by soil texture as a variation affecting the physical properties of soils, such as water retention and stability of soil aggregates. The drainage conditions

of the study area range from poor to good drainage, which may have an impact on soil properties. The proposed management plan for improving poor drainage in the area under study can be carried out using two methods of tile drainage and surface ditching. The main objective of the tile drainage and ditch systems is to lower the water table in the soil below the root zone of the plant [39]. The soil organic matter (OM) content is a very important indicator for the biological soil quality indicator (BSQI). Furthermore, OM could be considered as a sole indicator of soil degradation [40], confirming its importance in soil quality assessment. OM percentage is important for maintaining a perfect soil structure, increasing the availability of nutrients that increase soil fertility and maintain the balance of the agro-ecosystem. The OM content is relatively low in the study area as the arid and semi-arid climatic conditions have a negative effect on the OM content due to the high-temperature increase in the rate of decomposition of organic material in the soil [41,42].

4.2. CI Status of the Study Area

Using soil properties, the land capability index for the area under investigation has been estimated using ALESarid. The results showed that most of the study area located under fair class representing 44.9% of the total area, which means that these soils are suitable for cultivation over a long period, but they have some hazards and limitations (i.e., high salinity, high ESP, and high $CaCO_3$) of some units, which cause an increase in soil reaction in addition to the sandy texture of some mapping units. All these hazards reduce plant choice or require moderate, easy-to-use conservation practices. Similar studies have determined SQI using soil properties in semi-arid ecosystems but used different approaches with GIS and RS such as Multi-Criteria Decision Analysis (MCDA) [43,44], PCA, geostatistic, AHP-Fuzzy [45], and integration of type-2 fuzzy sets with AHP [46].

4.3. SQI Using Geospatial Techniques

The spatial trend of soil quality increases from north to east and this trend is consistent with current conditions, as low soil quality in the north may be due to a high percentage of calcium carbonate, a high percentage of sodium exchangeable, high salinity, and low concentration of organic matter and intensive mismanagement practices in agriculture [47] have shown that organic matter, clay, EC, and CEC are the most influential factors in the determination of SQI, confirming the importance of using these parameters in the current study. Developing soil quality classes can minimize agricultural management costs, such as improving soil quality for a slightly moderate class, which may need improvement compared to low-quality soils, and two types of soils need improvement.

4.4. Validation of Soil Quality Index Model

There is a significantly high correlation between the SQI and CI correlations ($R^2 = 0.86$, $p < 0.001$), which means that this study produces an accurate soil quality assessment model for the study area. SQI and CI are two methods for assessing the potential of land for a specific type of use. It is a newly developed method, while land evaluation has been in use since 1961 [48]. They found a highly significant correlation between the SQI rating and CI classes. NDVI is helping in mapping and predicting the extent of land degradation [49] and also allowing farmers, traders, and insurers to make well-informed agricultural decisions on time for achieving precision agriculture. There is a positive correlation ($R^2 = 0.18$, $p < 0.05$) between NDVI and SQI, therefore, it is suggested that the sample sizes should be increased to ensure the correlation between them in future studies.

5. Conclusions

GIS is a useful tool for storing, retrieving, and manipulating a large amount of data needed to calculate and map different soil parameters. The production map of spatial distributions for soil properties is the most important step in the assessment of SQI. The results show that the study area located under six soil quality classes (e.g., very high-quality class: 387.12 km^2 (22.7%), high-quality class: 441.72 km^2 (25.87%), moderate quality class:

208.57 km^2 (12.21%), slightly moderate-quality class: 231.10 km2 (13.5%), low-quality class: 233 km^2 (13.60%), and very low class: 206 km^2 (12%)). The results of the SQI spatial model developed were accepted with the current situation in the study area and were highly correlated with the results of the land capability. It is very important to assess soil quality periodically to identify agricultural practices that cause soil growth and crop productivity. In conclusion, the spatial model proposed in this study could be a more accurate methodology for assessing the spatial distribution of soil quality by including soil physical, chemical, and biological indicators.

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