

Research

Digital soil characteristics mapping for aiding site-specific management practices in the West Nile Delta, Egypt

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Abstract

Soil survey system is the key word for sustainable soil use and management. This study aimed to generate a digital soil mapping (DSM) using various spatial resolutions of freely available digital elevation models (DEMs) i.e., (30 m ALOS “Advanced Land Observing Satellite”, 12.5 m ALOS, 30 m SRTM “Shuttle Radar Topography Mission”, and 90 m SRTM) to assess the spatial variability of soil physio-chemical characteristics in El-Beheira Province, Western Nile Delta. A total of 196 geo-referenced soil profiles were collected from agricultural fields, and the soil’s contents of total nitrogen (TN), potassium (K), available phosphorous (P), calcium (Ca), sulfur (S), magnesium (Mg), zinc (Zn), copper (Cu), manganese (Mn), and boron (B) were analyzed. The study revealed that the soil’s contents of TN, P, S, B, and Cu were low, and Mg was suspected to be higher than K, leading to an Mg-induced K shortage. The study also found wide-ranging spatial variability structures of inverse distance weight (IDW) interpolated maps for several soil physio-chemical characteristics. The DSM further revealed that poor status was present in 85.4% of TN, 91.7% of P, 76.9% of S, and 87% of both B and Cu. The conclusion is that soil variability, as demonstrated in DSM, outweighs uniform treatment, and this discovery will assist extension workers, scientists, and decision-makers in implementing site-specific nutrient management strategies. Validation of the DSM is recommended for crop and variety-specific nutrient treatment rates. Understanding the geographical variance in the soil is critical for long-term nutrient management and higher output.

Keywords Agricultural practices · DEM · DSM · Geomorphology · Landforms · Physiographic · Soil Management · Soil Survey

1 Introduction

Soil science functions a critical role in the development of spatial data by continually creating local, regional, and global land databases [1]. Lithology and geology-hydrology-morphology are in the field of soil science, closely interconnected. while biota and climate are essential to a lesser extent in soil geomorphology in particular [2–5]. Soils intimately linked to the landscape which affirms the paramount function of landform-geomorphology-physiographic in soil pedological processes. Understanding these relationships helps in study of pedologic fundamental level to understand the distribution of contemporary soils geographically. Agriculture soils are Egypt’s most important resource for sustaining the population’s

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livelihood [6, 7]. Due to the country's rapid population expansion, the land is under enormous pressure to produce more to support human well-being [8, 9]. In the Nile Delta, improper land use and management affect agroecosystems and food production due to land degradation [10–13]. Therefore, knowledge-based soil management has become crucial for agricultural productivity and sustainability [14–16]. Managing soil regardless of its spatial heterogeneity has severe environmental consequences, reduces the efficacy of agricultural input applications, increases production costs, and has a negative effect on crop yield and soil health [17–19]. Lack of a well-developed soil information system leads to inadequate soil management strategies [20–22]. Regional heterogeneity in soil attributes has been largely neglected during soil management interventions in Egypt. This indicates that uniform soil management in spatially diverse fields exacerbated macro- and micronutrient deficiencies, resulting in yield variation for the certain field encountering particular management acquaintance inputs [23, 24]. In addition, it would lead to reduced nitrogen use efficiency and inefficient distribution of limited fertilizer resources. For the long-term management of existing soil resources, precise soil information that aids farmers in making farm-level decisions is necessary [25]. In this context, when given spatially explicit soil knowledge, many producers and communities will implement land management techniques that increase crop yields and nutrient content, thereby aiding in the resolution of problems [25, 26].

Knowledge of soil spatial variability and digital mapping is essential for determining the effects of agricultural activities on soil properties, developing appropriate soil management techniques, and promoting site-specific agricultural practices [27–31]. Concerning soil spatial variation, soil information is indispensable for prolonged sustainably managed soil [26]. The existing soil databases are not thorough or precise enough to promote dependable utilization of soil data, within the spatial data infrastructure [32]. Their current capabilities only permit the storage of sparse and intermittently accessible data from conventional soil surveys. The constraint in spatial database development is the expense and time required, particularly for field surveys and soil sampling in remote case studies [33]. To overcome this challenge existing spatial soil information systems should enhance their functionalities beyond storing and utilizing soil maps. They should also be capable of generating more detailed soil maps [34].

Knowledge of landform is crucial in numerous soil-related disciplines, such as environmental vulnerability and impact assessment, regional planning, natural hazard and disaster monitoring, and soil erosion and salinity forecasting [35–37]. In numerous applications, such as global warming planning and soil remediation, landform mapping is essential [38–42]. A quantitative approach to delineate and assess landform is a promising method for understanding and controlling landscape evolution [43–45]. To map landform patterns, conventional field survey, or terrestrial mapping, was a direct method that created maps at various scales using data with varying degrees of precision. Although it was a labor-intensive, costly, and time-consuming technique for extensively mapping swaths, it was effective [46]. Instead, mapping landform using satellite technology was time-, cost-, and space-efficient. Previously, satellite data had a lower spatial resolution than maps created using ground surveys [47].

DSM stands for the development and quantification of soil information systems. It involves using models that utilize soil observations and data from environmental factors to understand the variations, in soil types and properties, over space and time. This approach aims to improve soil management and utilization [48]. DSM generally depicts landscape continuity because models that are quantitatively correlate soil characteristics to the geographic distribution of soil-forming variables capture underlying soil variability [25, 26]. The DSM allows users to locate a domain with similar soil attributes and fertility status. Moreover, it provides access to domain-specific soil property data [49].

Several ancillary data sources, such as DEMs and remote sensing (RS) data, can be used for DSM to measure the spatial variation of landscape and soil properties. These data sources provide information at different spatial and/or temporal levels [50]. The DEM is one of the valuable sources of spatial data that offers valuable insights into the morphometric variations of land surfaces. In addition, DEM enables quantitative measurements of terrain surfaces by assigning terrain attributes such as elevation, slope, plain, and curvature profiles, some of which can be obtained directly from DEMs and others can be derived [51, 52]. Because of their role, in the formation of soil and the increasing availability of DEMs, at different spatial resolutions these characteristics can be employed to describe the spatial diversity of specific landscape processes [53] and are frequently used as supplementary variables in predicting/representing soil classes/properties [54–56]. DEM spatial resolutions can range from less than one meter for light detection and ranging (LiDAR) data to approximately one kilometer for datasets that cover the entire globe [57, 58]. Over time numerous authors have explored the effects of using multiscale resolutions in analysis, for environmental modeling. This exploration has been particularly influenced by the introduction of DEMs, in resolutions [58–61]. The connection, between the environment and the processes that shape soil formation is influenced by factors, at different scales. It highlights the significance of using terrain analysis across scales to accurately predict soil classifications [58, 62–65]. However, the use of this method, which incorporates multiple scales of DEMs for soil class prediction, is still limited in DSM research [61, 66, 67]. Numerous authors have demonstrated that DSM techniques incorporating multi-scale

DEMs improve soil class prediction precision [58, 65, 68]. However, these methodologies have limitations. When it comes to the quantity of scales they can handle or their maximum scale capacity, their computational efficiency, and/or their ability to account for only a subset of terrain characteristics [48, 69].

Geostatistical methods are recognized as a powerful and suitable tool for assessing spatial variability and estimating the inconsistency of landscape and soil properties [70–74]. Geostatistical approaches are based on the concept that nearby objects will be more similar to one another than distant ones. Various geostatistical methods, by modeling the spatial correlation with minimum variance, techniques such as ordinary kriging (OK) and IDW interpolation have been used to forecast the spatial variability of soil parameters [75]. Geostatistical techniques combine nearby observations in a linear fashion to predict the unobserved position [76]. By highlighting the geographic connections between forecasted and sampled places, estimation based on spatial geostatistical approaches makes parameter value prediction for unsampled areas easier and more cost-effective [72, 73, 77].

Due to the widespread accessibility of GIS tools and DSM methodologies, moving between scales has become easier. For example, geospatial data previously limited by scale may be combined or separated. Currently, it is feasible to create (i) primary surveys with a significantly larger scale range and (ii) derivative or second-generation resource maps from a primary spatial database with a significantly larger scale range than the first survey. The ability to alter scales should be compatible with primary data that permits such scale changes. Obtaining the optimal set of field observations is frequently impossible or prohibitively expensive. Therefore, it is essential to carefully select representative observation sites and extrapolate from them to inaccessible areas. Developing soil-landscape models that integrate recurrent geographic correlations can significantly enhance observational efficacy. Choosing an appropriate scale is part of the process of creating a model. As indicated previously, scale determines what can and cannot be displayed. Robust soil-landscape models are subjected to incremental modifications and refinements in order to represent the growth in knowledge and information during the course of the survey.

A given location may contain a broad area or landscape scale, a deltaic plain (landform) scale, and a tableland position or Pedon (microfeature) scale. The perspectives and objectives of the survey determine the appropriateness of each scale. Each scale is usable, but each expresses information differently and has distinct limitations. As a physiographic unit, for instance, a series of alluvial and aeolian landscape models can be formed and implemented along the wadi plains' border. The landscape contains structurally eroded slopes and alluvial plains. Fluvial processes (and, to a lesser extent, erosional processes) are the most prevalent geomorphic processes with a regional scope. The same region exhibits eroded, structural table land at a finer landform scale than landscape (alluvial plain). Erosion and fluvial processes are the most frequent geomorphic processes, and they are both limited to a localized area. The region contains distinct subsets of landforms at the microfeature scale. Hillslope erosion and deposition (also known as slope wash processes) and fluvial alteration (also known as alluvial deposition processes), which are generally limited, are the most frequent and pervasive geomorphic processes. Different scales produce various results. The first step in creating realistic landscape models is to predict and represent interactions between landscapes, geomorphic processes, and soils using expert knowledge and experience. The original model must be rigorously assessed (ground-truthed) and changed as necessary to appropriately reflect observed soil and landscape linkages, regardless of its format.

This investigation's goal is to use four different freely accessible DEMs with varying spatial resolutions, including ALOS at 30 and 12.5 m and SRTM at 30 and 90 m. The purpose is to generate a comprehensive DSM for El-Beheira Province. The main aim of this study is to estimate and map the spatial variability of digital soil physio-chemical attributes through a comprehensive understanding of landforms. The ultimate goal is to develop and implement highly effective site-specific management plans based on the information obtained from this investigation. By achieving these objectives, this research will make a contribution to the field of soil mapping and management. The outcomes of this study will have the potential to boost crop productivity and nutrient management techniques in the region, benefiting farmers, extension workers, and scientists alike.

2 Materials and methods

2.1 Description of the study area

El-Beheira Province (Fig. 1) has a total area of around 11,529 km² and is situated west of the Nile Delta. It extends from the Mediterranean coast to the northern part of the Western Desert, rising above sea level from north to south. In some northern regions, the ground surface elevation is lower than the sea level. Tablelands and alluvial plains are two significant units that make up the study area's geomorphology [78]. In the south of the area, Tablelands is almost entirely

composed of sandy limestone. It is characterized by landforms: ridges, depressions, and plains. In the north, there are young and old alluvial plains, whose composition alternates with layers of clay and a thin strip of silt [79]. The tablelands are covered with sandy deposits in the north, while gravelly deposits predominate in the south. The plain slope is toward the north and northeast and varies in elevation between 20 and 60 m.

Wadi El-Natroun station's historical climatological data (2004–2021) revealed a mean annual temperature of 21.2 °C and mean monthly temperatures ranging from 13.7 °C in January to 27.8 °C in August, with the highest and lowest temperatures, respectively, for the past ten years being 34.5 °C in July and 7.8 °C in January (Fig. 2). The mean daily maximum temperature shows the highest temperature on an average day for each month. The mean daily minimum also displays the average daily minimum temperature. Hot days and cold nights indicate the average hottest and coldest nights of each month during the past 30 years. In May, the average relative humidity was 52%, but in November and December, it was 70%. The relative humidity drops to its lowest level (about 30%) at around 2 p.m. The wind blows 11 km/h in December and January and 20 km/h in May and June. Winds that come from the north, northwest, and northeast are typically prevalent. Based on the climatic data, the area is distinguished by *Torrif* and *Thermic* for soil moisture and soil temperature regimes respectively.

Four land use land cover types have been distinguished in the study area: agricultural land, urban areas, deserts, and aquatic land. Using the visual interpretation of satellite images over the past twenty years, Desert areas are certainly shrinking. However, there was a huge increase in the agricultural, urban, and aquatic areas.

2.2 Field survey, sampling, and laboratory analyses

The selection of soil profiles has been conducted to accurately represent the units extracted from the DEM. In order to distribute soil sampling locations in a random manner over the study area, a total of 196 soil profiles (yielding a total of 495 soil samples) were excavated across various landform units, with an average distance of separation ranging from 5 to 10 km. During the survey activity, the sample points were traversed, and the latitudes, longitudes, and altitudes of the sampling field were recorded. After navigating and reaching the sampling spot, 1–5 sub-samples of surface soil were collected, taking into consideration the complexity of the topography and the heterogeneity of soil types. The selection of topsoil was based on its susceptibility to the influence of plants and soil management practices [25]. In addition, the

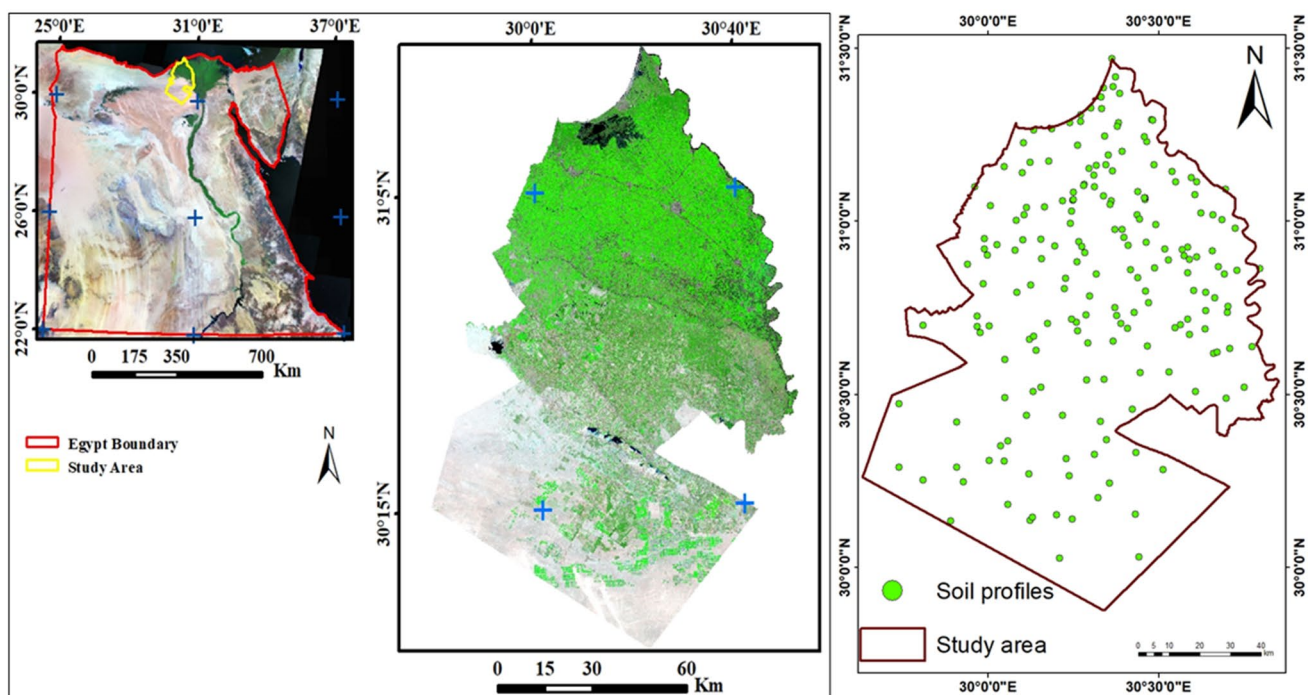


Fig. 1 The research area is in the western Nile Delta in the province of El-Beheira. The Mediterranean Sea, the Nile River (Rashid Branch), the provinces of Alexandria and Matrouh, and the Giza Province form its northern, eastern, western, and southern borders, respectively. The study area is about 11,529 square kilometers. It has several lakes, most notably Lake Idku

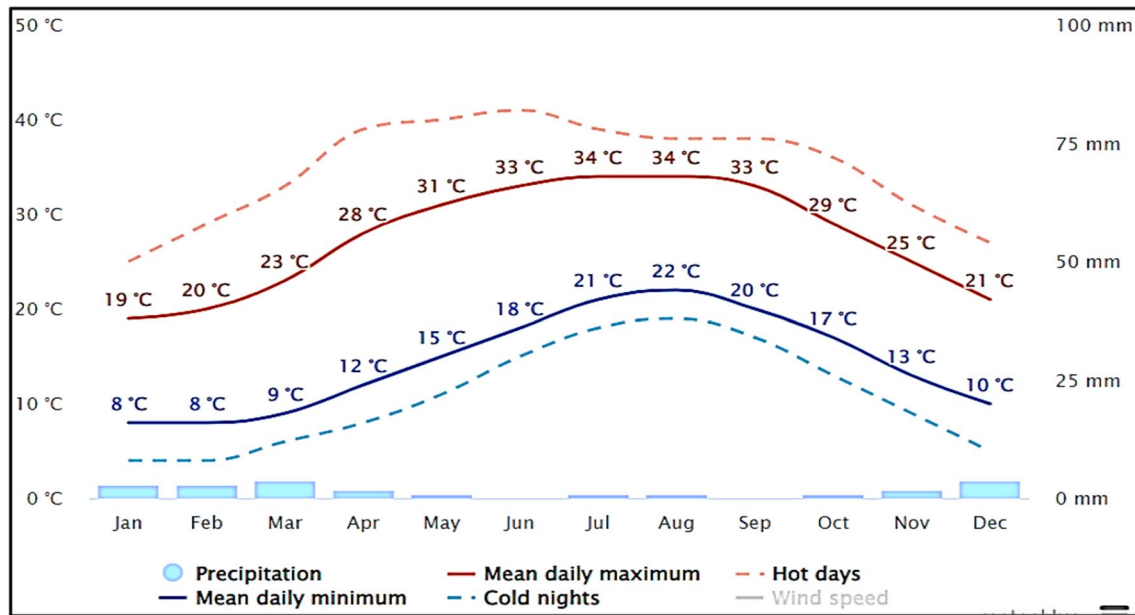


Fig. 2 Average temperatures and precipitation of the study area (1991–2021); In the context of its suitability for agriculture of all kinds, the most important climatic factors in El-Beheira Province are heat, light, sunshine, rain, depressions, and winds. The extent of the severe impact of these elements on agricultural production in the study area is clear. As it comes at the forefront of the factors affecting the quality of production and the quantity of the crop, and this effect is due to the great compatibility between the climatic conditions in the study area and the climatic conditions required for the cultivation and production of different crops

collection of soil samples was facilitated through the utilization of a soil auger, followed by the process of compositing soil samples. Soil samples were collected for annual crops at a depth ranging from 0 to 30 cm, whereas for perennial crops, samples were taken at a depth of 50 cm.

The soil samples were gathered, dried, sieved, and preserved in a polypropylene container in preparation for the determination of soil characteristics, as well as the analysis of physical and chemical attributes. The soil survey laboratory methods handbook [80] was used to conduct laboratory analyses on the saturation soil paste extract. These analyses included determining soil texture, calcium carbonate content CaCO_3 , salinity EC, sodicity pH, soluble cations and anions, organic matter content, and gypsum content. The soil samples were ground up and sieved through a 2 mm mesh and a 0.5 mm mesh sieve before being air dried at ambient temperature and utilized to analyze the mid-infrared diffused reflectance (MIR) spectrum. Using the Mehlich-3 multi-nutrient extraction method [81], soil samples were examined for a number of factors, including TN, P and S, exchangeable cations (Ca, Mg, Na, and K), soil micronutrients (Fe, Cu, Mn, Zn, and B), and cation exchange capacity (CEC). The concentration of the extracted components was determined using an inductively coupled plasma (ICP) spectrometer. The quantities of TN and CEC were also assessed through the application of MIR-diffused reflectance spectral analysis.

The soil's physical and chemical properties are kept in a shape file format. Hence, the conversion of soil properties into raster format is accomplished through the use of IDW interpolation method in the ArcGIS Pro 3.0 software, as suggested by [73].

2.3 Remote sensing data and processing methodology.

This work used four distinct DEMs obtained from two separate sources with different levels of spatial resolution (Fig. 4). The first sources of DEMs are the 30 m SRTM DEM with a spatial resolution of 1 arc-second and the 90 m SRTM DEM with a spatial resolution of 3 arc-seconds. These datasets were obtained from the official website of the United States Geological Survey (USGS), specifically from the following URL: <https://earthexplorer.usgs.gov/>. One other source of DEMs is a 30 m-ALOS and 12.5 m-ALOS DEM obtained from the website <https://search.asf.alaska.edu/>. This particular DEM has a spatial resolution of 30 m for low resolution and 12.5 m for high resolution, which is an upsampled 30 m product.

This research used four tiles of Sentinel-2 satellite imagery (T35RQP, T35RQQ, T36RTU, and T36RTV) to cover the study area. These images were acquired on February 15, 2021, and were obtained from the official website of the European

Space Agency's Copernicus Open Access Hub (<https://scihub.copernicus.eu/dhus/#/home>). The images were already atmospherically and geometrically corrected. The process involved the combination of four images to create a mosaic, which was subsequently adjusted to align with the designated study region (Fig. 1).

2.4 Landform modeling

The main landscape was delineated from the DEM in conjunction with the Sentinel_2 satellite imagery as well as the existing geology and soil maps of the region using the toolbox in ArcGIS Pro Version 3 software. This provides a better visualization of the terrain in the study area. Furthermore, it is necessary to create a three-dimensional representation of the study area's landscape in order to visually depict the interrelationships between the soil and relief elements. This would involve generating maps of topographic variables such as slope and aspect using DEMs. The process of defining landform units for the DSM (Figs. 3 and 4) involved the use of both maps and the overlay function. Initially, a reconnaissance and semi-detailed survey were undertaken across the examined region in order to develop an understanding of the study area's overarching soil patterns and distinctive landscape features. The verification of the primary mapping units was conducted by relying on the pre-field interpretation and the data acquired during the survey. Additionally, taking into account the preliminary analysis and the data collected during the reconnaissance survey, an extensive morphological description of soil profiles was conducted, focusing on variations within landform units.

3 Results

3.1 Landform

The landforms of the investigated areas (Fig. 5) were identified by combining DEM with satellite images and land surveying. The obtained data illustrated that the studied area is divided into seven main landscape units, as shown in Fig. 5, which include several landform units.

Pedological resources studies revealed that the parent materials are of various natures, e.g., aeolian, marine, lacustrine, and alluvial deposits and limestone, etc., and located in varied geomorphological positions, e.g., plains, wadis, and tablelands, etc., in the area. From a root concept perspective, identifying soils and recognizing their characteristics must be crucial to ensure the long-term preservation of resources, especially for both field and horticultural crops. By concentrating on two key aspects, pedological and agronomical traits, it was possible to obtain evidence for the main crops' soil qualities and characteristics.

In general, the area occupies a wider variety of soil types, and it is noteworthy that marginal land is already traditionally dedicated to cultivation. While alluvial soils offered deep fertile soils for field crops. In this region, chemical soil qualities and efficient drainage are essential factors in determining soil quality. In the southern part, sand and gravel layers, quartzites, and remnants of petrocalcium horizons are factors in good drainage. The rooting depth and effective soil water storage capacity are both impacted by the amount of gravel present (often above 5–20%). Since this assures crop health and high-quality yields, it is generally known that it is crucial to regulate water supply and drainage appropriately. Numerous soil characteristics, most notably water holding capacity, plant-accessible water, and hydraulic conductivity, have a considerable impact on the control of soil water. However, due to the dearth of organic matter in sandy soils, farmers typically adopt techniques to enhance soil health, such as the utilization of natural organic input resources, occasionally compost.

The outcomes show that the characteristics of the parent material and the current pedogenetic processes have an impact on soil order. According to soil taxonomy, they include Aridisols and Entisols, which correspond to the presence of calcic or gypsum and an excess of salts (saline and sodic). Soil properties in croplands are affected by fertilizer application, nutrient leaching, soil erosion (slight water erosion in the marine and lacustrine deposits and wind erosion in the sandy soils in the south), and Continuation of agriculture. To prevent the deterioration of the farmed soils, these effects should be remedied by sufficient and prospective farming practices techniques. Decisions must take into account all of the chosen research factors.

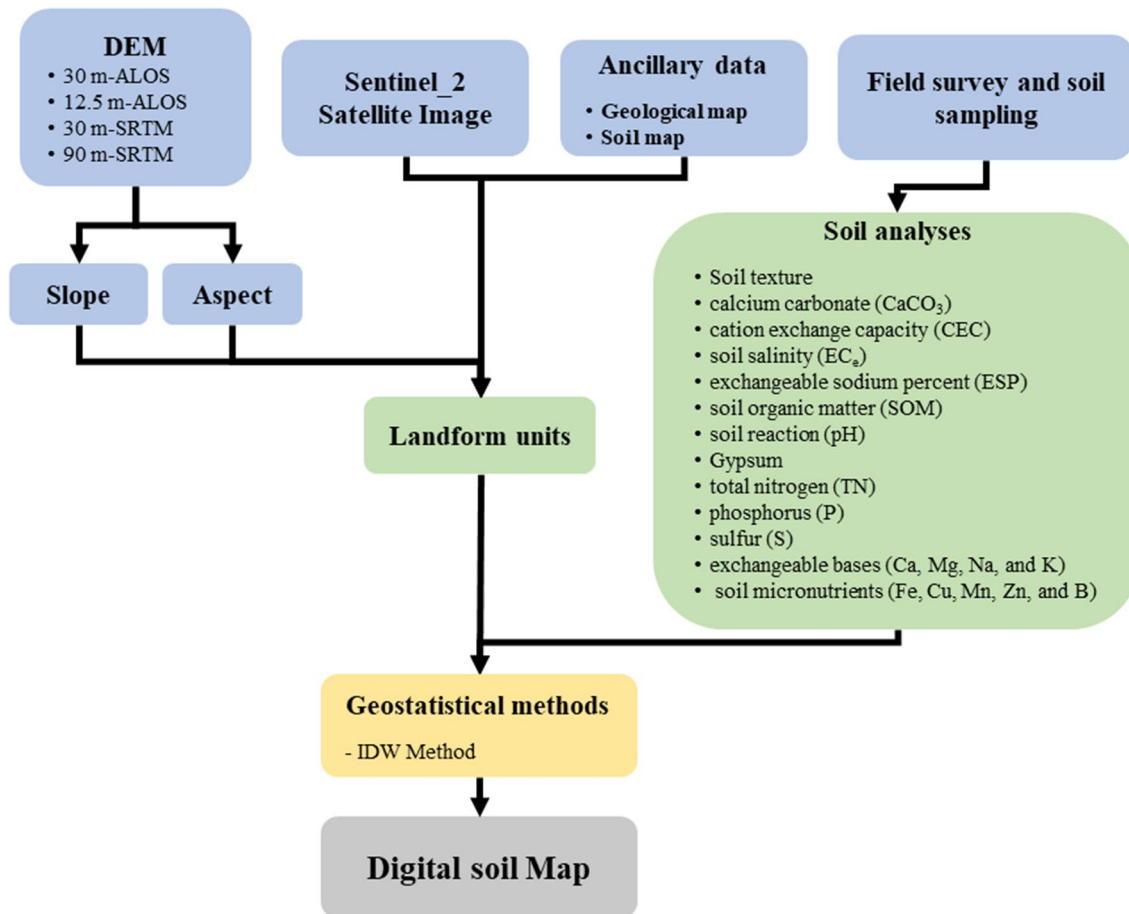


Fig. 3 Flowchart of the methodology for DSM

Landform delineations and mapping were confirmed using studies of soil samples, together with measurements and observations made in the field. This proved the possibility of matching the landform with the potential soil quality. This came out from the clear differences of soil properties among different LF units.

The results obtained from the soil sample analyses, along with field measurements and observations, were used to confirm delineations and mapping. This makes it possible to match a landform with potential soil quality. At the same time, a landform map survey supported by the study of several soil compositional parameters on different lithology formations represents a good cost–benefit approach to investigating the potential of soils.

3.2 Soils

The different landform parameters related to soils in the region are the basis for understanding crop functions. The landform, texture, or CEC of any unit in the investigated area is a key component (Fig. 6) that can provide crops with insights about nutrients and water in the root zone. These features are demonstrated by the results of the examined soil profiles. In addition, the presence of different soil textures serves a crucial function in maintaining soil moisture, which is important during the growing period of crops and is also useful in relation to existing irrigation methods. However, the soils are not uniform in area and vary from the findings from the surface and subsurface layers and/or horizons.

On the horizons at the surface, a small pH fluctuation was seen, with values ranging from 6.4 to 8.4 and an average of 7.2. As a result, it is regarded as neutral to moderately basic on the majority of soils. There were no appreciable variations between horizons. The soil profiles' ECs vary from 0.05 to 42 dS/m. This suggests that classes of "saline soil" exist. The percentage of organic stuff varies from 0.01 to 3.1%. For soil organic carbon, there were considerable variations among soil types. In heavy soils, high values were discovered, while in light soils, low values were discovered. The range of calcium carbonate is 0.04 to 17.21%. The soils growing on alluvial deposits contain very little. Because of leaching in

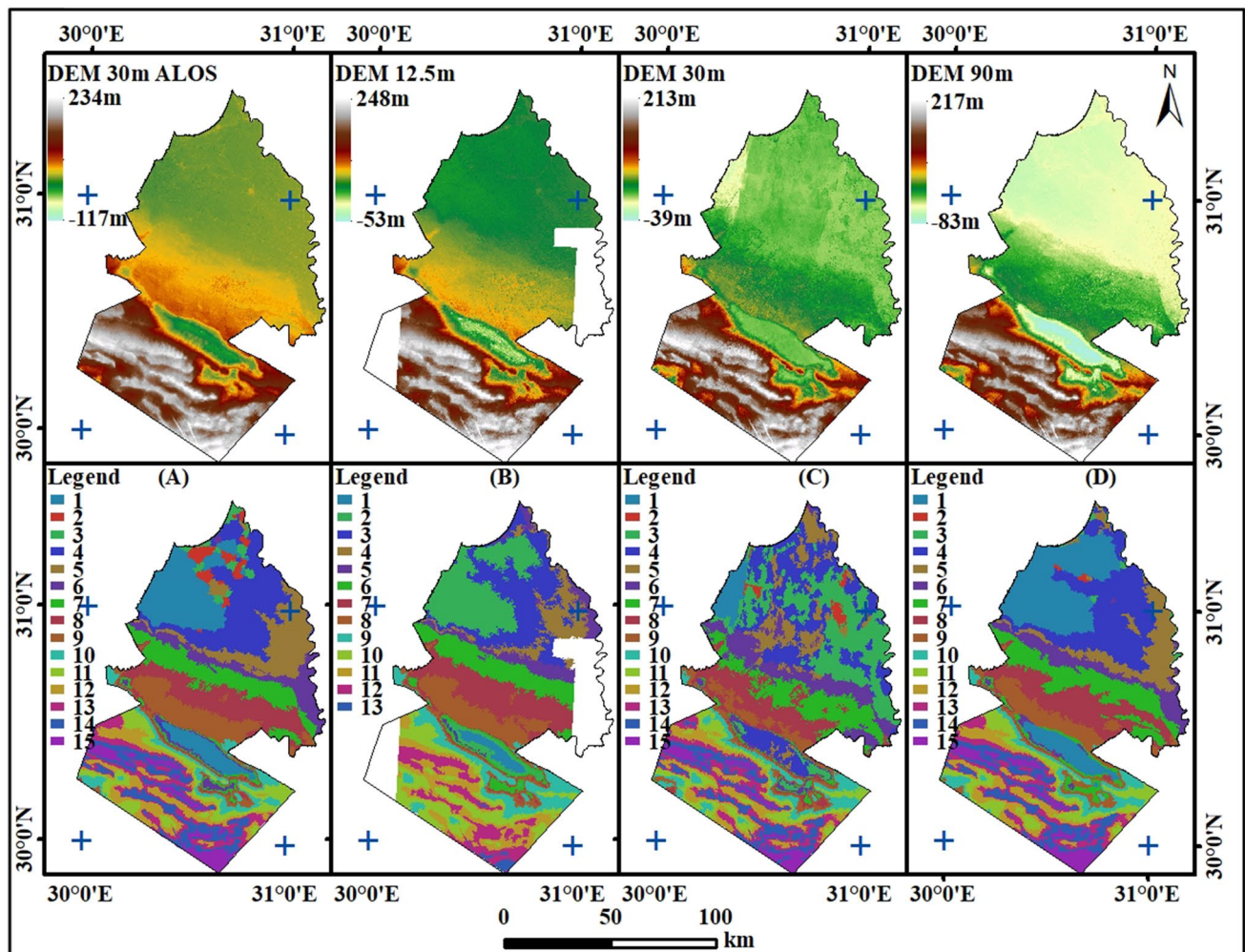


Fig. 4 DEM along with the discrete presentation (A, B, C, and D for 30 m-ALOS DEM, 12.5 m-ALOS DEM, 30 m-SRTM DEM, and 90 m-SRTM DEM, respectively); representation of the bare ground topographic surface of the Earth. DEMs are created from a variety of sources

farmed calcareous soils, the CaCO_3 content often rises in the lower horizon. In a relatively uniform pattern, clay, clay loam, and sandy clay loam were the main soil textural types. While loamy soils, which are thought to be the most favorable for agriculture, predominated in most site soil profiles, clay textural classes dominated the deltaic plain. Sandy and sandy loam soils were present in the region's tableland zones in the south.

Soil characteristics (Fig. 4) are important for land use planning. El-Beheira Province has the highest concentration of crop compositions in Egypt. This study is an evaluation of the agronomic suitability for crop zone management in the continental Mediterranean environment through a mapping effort. Our study incorporates data from 196 soil profiles (495 soil samples), the majority of which were created on calcareous, sodic, and saline soils. AbdelRahman et al. [13] identified the tremendous pedo-diversity in this area, including the Entisols and Aridisols. Pedological analyses show that agricultural and sustainable crop production in this region is ideal. Landform helps plan campaigns to improve the image of the region as well as the most efficient use of land. The multiplicity of variables affecting growth, development, crop quality, and yields makes it important to evaluate the potential of natural land units on the basis of landform. Soils differ in this way in a distinctive way for each landform. Accordingly, the capabilities of supplying crops with water and minerals vary for each landform unit.

It was found that cultivated land in the Nile delta of the investigated area, with deep soils and good drainage, promotes crops with good root development and favorable growth conditions. whereas yield's composition and quality are characterized by the effect of soil's physio-chemical limits. In the north of the investigated units, Compacted or shallow soils in lacustrine and marine deposits may prohibit roots from obtaining oxygen, water, and nutrients, which restricts root growth. Therefore, it is recommended to use delta plain soil, which is characterized by deep soil and good water

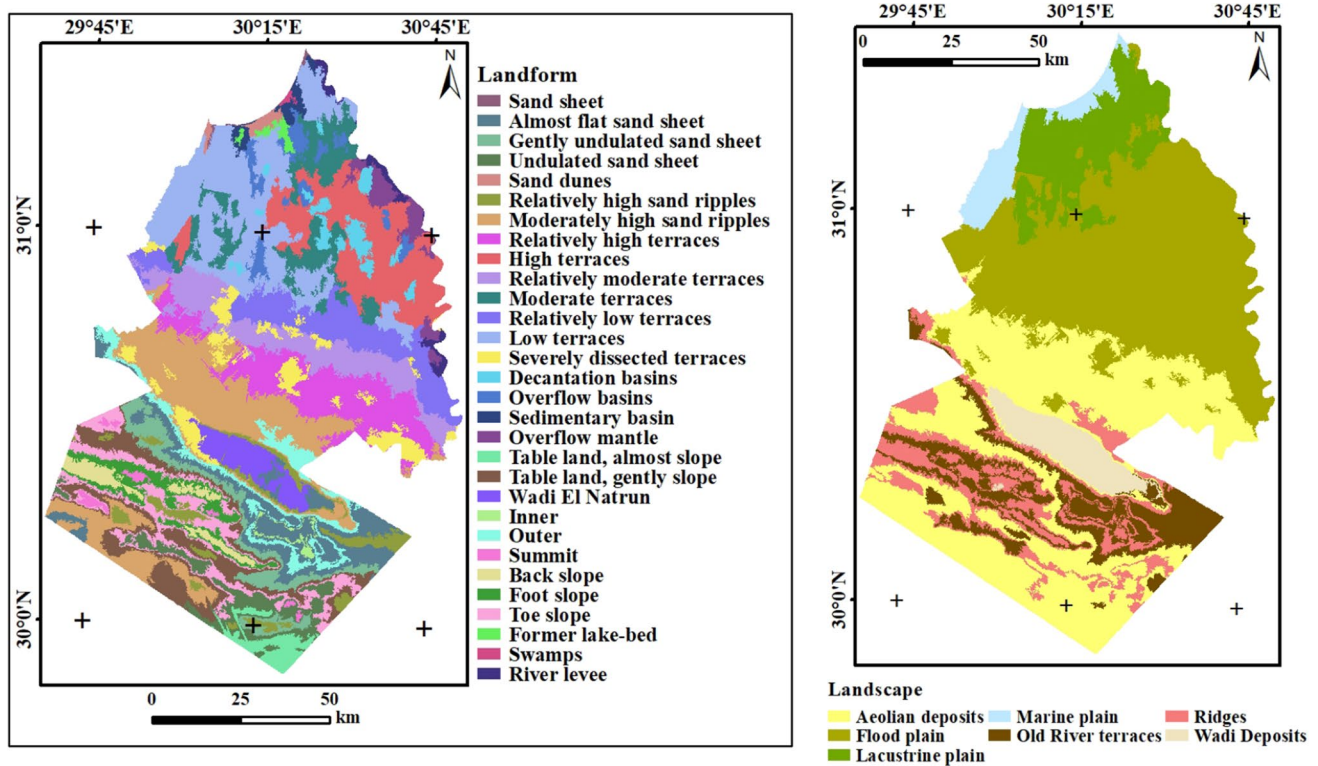


Fig. 5 Landforms are associated with landscape; they are features of the surface terrain that are shaped and created by a natural process, such as tectonic plate movement and erosion. Natural landscapes are made up of a variety of landforms. Often, landforms are not unique to a single landscape

storage capacity, for grains and field crops to avoid exposure to water stress in the summer. In contrast, tableland areas are preferable for horticulture crops. Since the relationship between soil and crop behavior and yield production is so complex, it is typically impossible to compare a soil map with a potential crop quality map. Therefore, there is a need to determine the soil and its properties to ensure their basic properties.

Frequently, traditional agricultural practices in the region were established on inadequate land, conserving more fertile soil for growing grains and other food crops. As a result, the lands of the region occupy a wide range of soil types, so there are various types of crops suitable for the climate of the region. Lands are highly susceptible to soil degradation, which can result in decreased soil fertility and quality, decreased water intrusion and storage, poor ground and surface water quality, and hazards related to reducing and adapting to climate change. Furthermore, 30 landform units with great potential for cultivation were proposed. Therefore, this map can be used as a tool with the different types of units in the near future for selecting optimum situations for growing high-quality crops. Additionally, contribute to better crop area management and thus have significant administrative consequences for decision-makers.

3.3 Primary nutrients (N, P, and K)

TN values vary between 0.01 to 0.53%, with a mean + SD of $0.21 \pm 0.05\%$. It showed moderate variability (Table 1). The spatial analysis revealed that 53, 32.4, 23, and 2.6% of the area exhibited very low (< 0.1%), low (0.1–0.15%), optimum (0.15–0.30%), and high (0.30–0.50%) TN. Data regarding available P revealed low to moderate variability, stretching between 0.27 and 25.17 mgkg^{-1} with a mean + SD value of $3.45 \pm 3.56 \text{ mgkg}^{-1}$. Spatially, 91.7 percent of the total area was very low, and the remaining 8.3 percent was low. The exchangeable K varies from 0.57 to 3.75 $\text{cmol}(+)\text{kg}^{-1}$, with an average value of $0.89 \pm 0.37 \text{ cmol}(+)\text{kg}^{-1}$ (Table 1). The DSM demonstrated that 47, 39, 3, and 11% of the total area had low (0.2–0.5 $\text{cmol}(+)\text{kg}^{-1}$), optimum (0.5–1.5 $\text{cmol}(+)\text{kg}^{-1}$), high (1.5–2.3 $\text{cmol}(+)\text{kg}^{-1}$), and very high (> 2.31 $\text{cmol}(+)\text{kg}^{-1}$) levels of soil K (Table 1).

Soils are almost neutral, with pH values varying between 6.40 and 8.43. According to measurements of soil salinity, EC ranges from 0.05 to 42 dS/m, which is low to moderate in some subsurface layers and high in others. Organic matter is

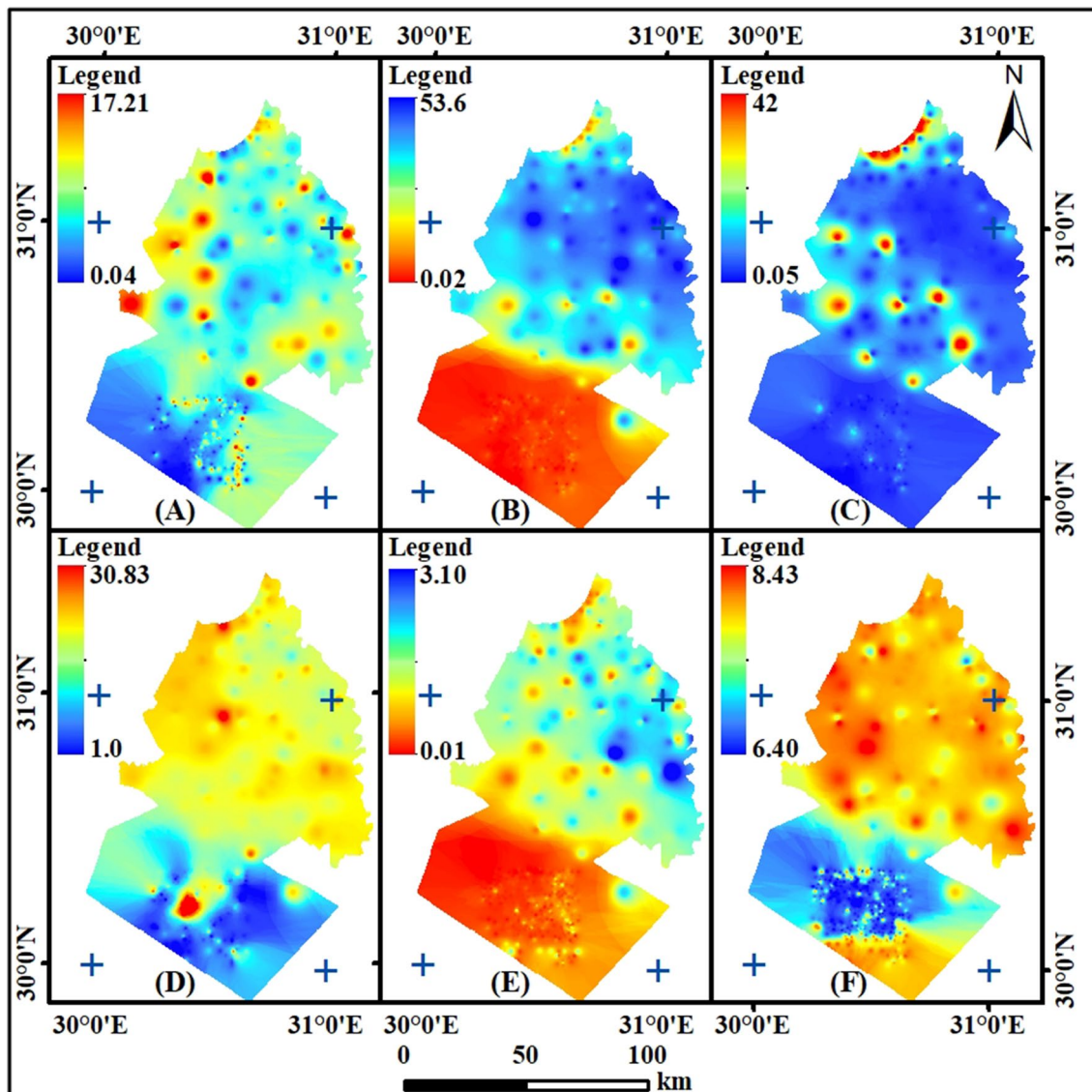


Fig. 6 Some soil characteristics—the most important properties of soils—are presented in the map. It means the composition of soils and their effects on cultivation: **A** calcium carbonate (CaCO_3); **B** cation exchange capacity (CEC); **C** soil salinity (EC_e); **D** exchangeable sodium percent (ESP); **E** soil organic matter (SOM); and **F** soil reaction (pH)

present in concentrations between 0.01 and 3.1%, while the CaCO_3 level ranges from 0.04 to 17.22% (Table 2). The soils are varied, from calcareous to saline to alkaline, with ESP ranging from 1.00 to 30.3%. The soils also vary from poor fertile to very high fertile soils, with CEC values of 0.02 to $53.6 \text{ cmol}(+)\text{kg}^{-1}$.

3.4 Secondary nutrients (Ca, Mg and S)

Exchangeable Ca ranged from 2.87 to $16.30 \text{ cmol}(+)\text{kg}^{-1}$ with a mean value of $6.35 \pm 1.21 \text{ cmol}(+)\text{kg}^{-1}$. DSM based on the rating of [83] indicated that 21, 73, and 6% of the total area had low ($2\text{--}5 \text{ cmol}(+)\text{kg}^{-1}$), medium ($5\text{--}10 \text{ cmol}(+)\text{kg}^{-1}$), and high ($10\text{--}20 \text{ cmol}(+)\text{kg}^{-1}$) exchangeable Ca, respectively. Meanwhile, soil exchangeable Mg varied between low ($0.9 \text{ cmol}(+)\text{kg}^{-1}$) and high ($11 \text{ cmol}(+)\text{kg}^{-1}$) with a mean value of $2.44 \pm 0.57 \text{ cmol}(+)\text{kg}^{-1}$. In terms of area coverage, about 19, 77, and 4% of the area were low ($0.5\text{--}1.5 \text{ cmol}(+)\text{kg}^{-1}$), medium ($1.5\text{--}3.3 \text{ cmol}(+)\text{kg}^{-1}$), and high ($3.3\text{--}8.3 \text{ cmol}(+)\text{kg}^{-1}$) in Mg contents, as rated by [84]. Furthermore, the mean S content (mgkg^{-1}) was 7.38 ± 1.25 , where it ranges from very low (3.67 mgkg^{-1}) to low (18.20 mgkg^{-1}). It was also found to be moderately variable (Table 1) as a result of external and inherent factors. The CEC of

Table 1 Descriptive statistics of soil nutrients

Soil properties	Unit	Min	Max	Mean	SD	CV ¹
Ca	cmol(+)kg ⁻¹	2.87	16.30	6.35	1.21	19.06
Mg	cmol(+)kg ⁻¹	0.90	11.00	2.44	0.57	23.36
K	cmol(+)kg ⁻¹	0.57	3.75	0.98	0.37	37.76
TN	%	0.01	0.53	0.21	0.05	23.81
P	mgkg ⁻¹	0.27	25.17	3.45	3.56	103.19
S	mgkg ⁻¹	3.67	18.20	7.38	1.25	16.94
Cu	mgkg ⁻¹	0.09	4.37	0.47	0.21	44.68
Fe	mgkg ⁻¹	16.23	99.11	54.74	23.73	43.35
Mn	mgkg ⁻¹	27.19	134.94	78.87	25.43	32.24
Zn	mgkg ⁻¹	1.23	23.69	7.27	5.43	74.69
B	mgkg ⁻¹	0.03	1.79	0.49	0.23	46.94
CEC	cmol(+)kg ⁻¹	11.18	45.13	20.97	2.44	11.64
OM	%	0.01	3.1	1.4	0.05	3.57

¹Coefficient of variation. < 15 = low variation, 15–35 = moderate variation, > 35 = high variation [82]

Table 2 Descriptive statistics of Soil characteristics of the Study area

Statistics	Soil characteristics					
	pH	EC (dSm ⁻¹)	OM (%)	ESP	CEC (cmol(+)kg ⁻¹)	CaCO ₃ (%)
Count	495	495	495	495	495	495
Min	6.4	0.05	0.01	1.0	0.02	0.04
Max	8.4	42	3.1	30.8	53.6	17.2
Mean	7.2	4.4	0.5	8.9	9.2	3.5
Stdev	0.6	6.9	0.5	4.8	14.2	2.9
CV	8.8	155.6	110.2	53.5	154.1	81.7
Skewness	0.5	4.5	1.9	1.0	1.8	1.6
Kurtosis	-1.5	20.0	3.2	1.9	1.6	3.1

¹Coefficient of variation. < 15 = low variation, 15–35 = moderate variation, > 35 = high variation

²Skewness: <|±0.5|= normal distribution (symmetrical), ±0.5–1.0 = moderately (positively or negatively) skewed of character, and >|±1| highly (positively or negatively) skewed of character [82]

the soils investigated was between 2.36 cmol(+)kg⁻¹ (low) and 53.67 cmol(+)kg⁻¹ (high), with a mean value of 19.20 ± 3.66 cmol(+)kg⁻¹ (Table 1). Based on [84], about 47% of the total area was found to have medium (15–25 cmol(+)kg⁻¹) CEC.

3.5 Soil micronutrients

The concentrations of soil micronutrients were spatially variable (Table 1). Mn had a low variability (CV of 24%), whereas B, Cu, Fe, and Zn had a high variability (CV of 19% to 37%) (Table 1). B (0.03–1.79, 0.49); Cu (0.09–4.37, 0.47); Fe (16.23–99.11, 54.74); Mn (27.19–134.94, 78.87); and Zn (1.23–23.69, 7.27) were the range and mean concentrations (mgkg⁻¹). The results of the geographical analysis revealed that 47, 49, and 4% of the study area had very low (0.5 mgkg⁻¹), low (0.5–0.8 mgkg⁻¹), and optimum (0.8–2.0 mgkg⁻¹) B levels, respectively. Cu content was less than 0.9 mgkg⁻¹ on 93 percent of the overall area, which is the Egyptian soil limit. Fe, Mn, and Zn contents in the entire area were over the essential levels of 80, 25, and 1.5 mgkg⁻¹, respectively. As a result of the computerized soil map, it was discovered that Fe, Mn, and Zn were not limiting elements.

4 Discussion

4.1 The study and mapping of soil characteristics based on landforms in the fields

It is clear from Fig. 6 that all types of DEMs are scalable in all kinds of land inventory methods. Figures 3 and 5 indicated the importance of DEM with a spatial resolution of 30m in the intensive and detailed survey. Therefore, we recommend using DEM types as in the flowchart of Fig. 6. DEM 30 showed its ability to distribute in the field on the map and predicted the performance of different landform units under various management techniques, i.e., crop yield under other management practices. DEM 30 outperformed all DEMs in terms of defining and describing the various soil types, as well as describing the thickness and features of the surface and subsurface layers within each class and the outcomes of laboratory analyses (Fig. 7).

Total N in soil is made up of inorganic and organic nitrogen, with the latter having a higher share. Plants, on the other hand, utilize the inorganic portion of N. This means that the optimal TN cannot be considered a guarantee regarding plant productivity. The low level of TN could be attributed to reduced soil OC content, insufficient and unbalanced fertilizer use, intensive cropping systems, and N losses through leaching [85, 86]. Similarly, nutrient mining and low OM application, which were frequent in the research area, could have contributed to the decreased TN level. High fluctuations in P concentration may have caused differences in soil management. Limited levels of P application, uptake through plentiful crop harvest, low return of crop residues, and soil erosion could all contribute to P deficiency in soils [24, 85]. Furthermore, fixation may harm P availability in soils [24]. Therefore, in order to restore insufficient levels of phosphorus in the soil and ensure excellent crop productivity, the application of phosphorus in the form of inorganic fertilizers, manure, crop residues, and lime must be taken into account.

Except in south areas that indicated a K deficit, the soil exchangeable K content alone seemed to satisfy the K need. On the other hand, gaining knowledge of the soil's basic cation saturation values is critical for better agronomic interpretation and preventing nutrient imbalances. As the amount of Ca and Mg in soils increases, exchangeable K absorption decreases, and a K deficiency develops. The potential of Mg-induced K deficit on a substantial section of the territory was reported in light of this hypothesis. This could be influenced by soil characteristics. Different sources have briefly described similar situations in Egypt [87]. Wheat has shown a positive response to K fertilizer treatment on soils suspected of having Mg-induced K deficiency [88, 89]. As a result, a K fertilizer application is required. The basic cations in the exchange site were in the following order: Ca > Mg > K. The high percentage of soil clay particles (inorganic colloids) can be linked to the medium-to-high amount of exchangeable Ca. According to [90], between 11 and 64% of the total soil samples (n = 789) had high (40–50%) and extremely high (> 50%) clay content, respectively. As a result, the ability of soils to hold exchangeable Ca increases as the fraction of soil colloids increases [91]. A greater level of leaching and a lower soil pH could be linked to the low exchangeable Ca content. As a result, in insufficient areas, the use of calcium fertilizers should

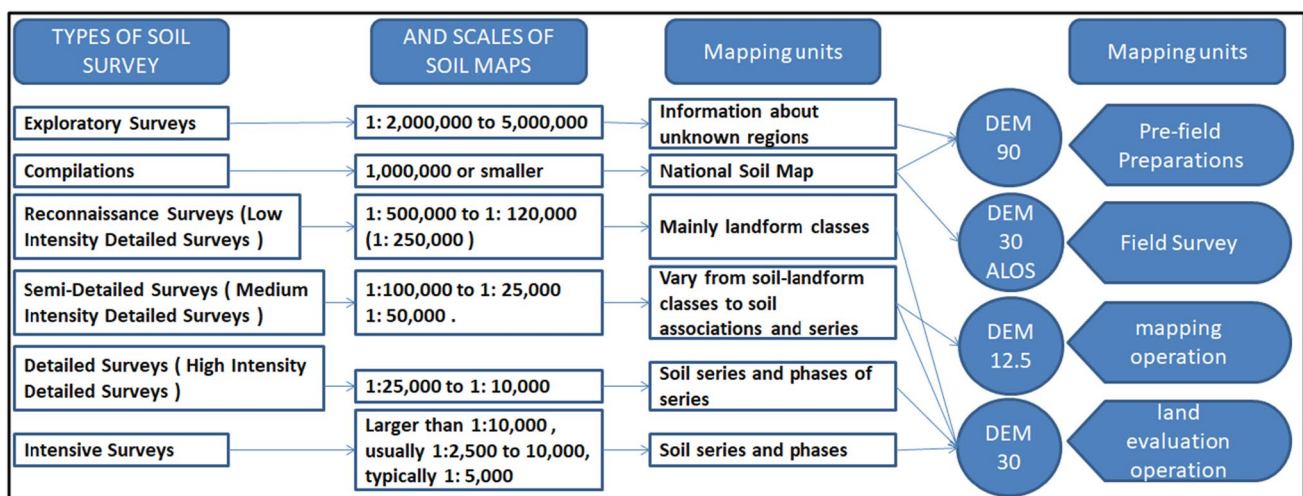


Fig. 7 Mapping of soil characteristics in the fields; the process of defining natural soil bodies, classifying and grouping the delineated soils into map units, and obtaining information on soil characteristics in order to understand and show soil spatial distribution on a map

be explored. Although exchangeable Mg hasn't been a nutrient that has restricted crop production, its average status demonstrates that Mg can be a recurring issue. Meanwhile, poor soil OM, lack of application of S-containing fertilizer, and crop loss of S may all contribute to the low S concentration [85, 92, 93]. Furthermore, using N and P-containing fertilizers may result in a scarcity of nutrients such as S [94]. The use of S-containing fertilizers is suggested as a solution to these shortages. Furthermore, OM application and crop residue management should be coordinated.

CEC ranged from low to high, with the majority falling into the moderate category (Table 1). It was discovered under a moderate variable, which might be attributable to external and internal influences. In areas with low soil OM concentration, both the type and amount of clay minerals may control the CEC [24]. A medium level of CEC could have resulted from the moderate to high percentage of clay particles.

Nutrient mining by crops, non-use of B and Cu-containing fertilizers, decreased soil OC, and low organic fertilizer application could all contribute to the low levels of B and Cu in the soil [85, 92]. [95] claims that soils with low OM concentrations are more likely to be deficient in B than soils with high OM content. Fe-rich parent materials and significant Fe dissociation in soils may be responsible for the optimal soil Fe content of the research area. Similarly, [96] discovered that increased Fe content could be related to parent materials. Furthermore, Fe deficiency in low pH soils is extremely rare [97], since it is known to dissolve in reducing and low pH environments. Because Mn bioavailability is regulated by pH and redox conditions, the soil's low pH character is the most likely cause of the high Mn content.

4.2 Site-specific soil management practices

There are widespread shortages in N, P, K, S, B, and Cu. Soil management measures such as conservation tillage, crop residue management and incorporation, and soil conservation practices are recommended to maintain and enhance soil carbon. Nutrient deficits would be corrected as well. Chemical fertilizer comprising N, P, S, B, and Cu is also advised. K fertilizer is recommended in locations where Mg-induced K shortages exist. Lime can also be used to address calcium and magnesium deficits. Meanwhile, crop and variety-specific nutrient delivery rates will be investigated further. Under current agricultural practices, landform is considered the main aspect of unit management [98–101].

5 Conclusion

Landform analysis helped us figure out how morphological, physical, and chemical soil properties in different units are related. Where the location of the landforms had an impact on some of these soil properties. Also, the differences in properties reflect the conditions of the terrain. The pedogenic features are tied to the relevance between the soil composition and landform units. The majority of the examined soil profiles come from clayey and sandy components with various compositions and soil depths. Some profiles' high CaCO_3 content was linked to their calcareous parent materials.

The presence of soil spatial variability was demonstrated using descriptive and geospatial variability analysis. The influence of intrinsic qualities and insufficient soil management measures could explain the variation. The DSM divided the land into multiple management zones, removing the need for blanket soil nutrient interventions. The soil-limiting nutrients were identified as N, P, K, S, B, and Cu, albeit with varying degrees of regional variability. Based on the DSM provided, farmers can be instructed to cultivate crops using site-specific nutrient applications. Nonetheless, we advocated for nutrition rate calibration.

The study's findings give an overall summary of soil properties and types in the Nile Delta and the adjacent sandy soil cultivation area. Cropping systems are generally established where soil features, such as drainage, texture, soil depth, etc., are optimum for yield production. In general, the soils in this area are neutral to slightly alkaline, with moderate carbonate contents, while EC is low to high; most of these soils have a sandy, sandy loam, sandy clay loam, or loamy clay texture, with medium to high clay contents, but the OM contents are low. Based on the findings, soil conditions seem to be optimal and sustainable for agricultural production when managed and cropped appropriately. The evaluations offered here might be very helpful in determining the sustainability of the land and could be crucial in determining how irrigation systems should be included in future plans for agricultural management.

Sustainable crop production in underdeveloped nations faces a significant challenge in making the best use of limited resources. Accurate land assessment systems that apply the principle of differentiated management of soil fertility and agricultural production based on landform units have great potential for active use. However, for various reasons, it is not always possible to achieve a sustainable effect from them. The degree of limitation of soil attributes varies, and in order to mitigate their negative effects on crop productivity, ad hoc management measures will be necessary. It is

evident that farm management decisions for sustainable crop production benefit more from the kind and degree of reduction of climatic, soil, and landscape attributes in the various map units since they are readily updated and applied.

The study of soils and their interactions with other components of the ecosystem provides the prerequisite knowledge to minimize degradation types and hazards. This contributes to the selection of appropriate soil conservation operations in accordance with the environmental systems of the region.

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Declarations

Ethics approval and consent to participate Not applicable.

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