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Soil Quality Evaluation Using GIS Techniques: A Case Study of North Nile Delta, Egypt.

Hussein I. Hussein [a], Ahmed S. Abuzaid [a], Abdellatif D. Abdellatif [b], and Hassan H. Abbas [a]
[a] Soils and Water Department, Faculty of Agriculture, Benha University, Egypt
[b] Soils, Water, and Environment Research Institute (SWERI), Agricultural Research Center (ARC), Egypt
Corresponding author: Hussein-i-h@hotmail.com

Abstract

The present work aimed at using GIS spatial analysis tools to map soil quality (SQ) of the cultivated lands for sustainable agricultural development. The study covers an area of about 2306.43 km^2 in the north Nile Delta of Egypt (31°08' 38" to 31° 36' 15.53" N and 31°01' 16.67" to 31° 54' 40.37" E). Thirty-two surface soil samples (0 – 30 cm) were collected and analyzed for their chemical and physical properties. Within GIS platform, raster layers for SQ indicators were generated using the inverse distance weight (IDW) technique. They were normalized using fuzzy membership functions, and finally the fuzzified layers were integrated using the geometric mean algorithm to develop the SQ maps. Results revealed that soils of very high and high qualities covered nearly 32% of the total area. Soils of moderate quality occupied 18% of the total area, while soils of very low and low qualities occupied 37% of the total area. To improve soil quality status, it is recommended to cultivate salt-tolerant crops, apply leaching fraction, and construct sufficient drainage systems, adopt organic and gypsum application, and operate tillage using appropriate equipment at proper time. The proposed model would help in decision making for sustainable agronomic practices in the studied area.

Keywords: Soil quality index; GIS spatial analysis; fuzzy logic; North Nile Delta

Introduction

The soil quality (SQ) refers to “the intrinsic capacity of a soil to contribute to ecosystem services, including biomass production” **(Bouma *et al.*, 2017)**. The capacity of soil to function under a specific use is governed chiefly by certain key properties known as SQ indicators. They include a wide range of measurable physical, chemical, and biological attributes, which control soil performance and its ecosystem services **(Nieder *et al.*, 2018)**. Some indicators, including mineral composition, texture, and depth are static since they are inherent soil properties. In contrast, other indicators such as pH, salinity, sodicity, and organic matter content, are highly dynamic since they are manageable soil properties **(Sholeye *et al.*, 2021)**.

The SQ assessment is predicting the capacity of a soil to provide a certain ecosystem function **(de la Rosa and Sobral, 2008)**. Such a process is a key step in decision-making to (1) rank the croplands, (2) design suitable management strategies, (3) conserve the natural resources, and (4) establish an early alarming system for potential deteriorations in the soil multi-functionality **(Abuzaid and Bassouny, 2018)**. Moreover, this process offers an effective way to improve the soil ecological quality to perfect management system as well as keep the productive capacity of soil sustainable **(Shao *et al.*, 2021)**.

The SQ is identified by assessing a variety of indicators using two distinct approaches; qualitative and quantitative. Both the qualitative and quantitative approaches are in vogue **(Vasu *et al.*, 2020)**. The qualitative approach provides a simple and time-saving assessment of the current status of the SQ can also detect any possible changes. However, it entails an appropriate knowledge and experience to calibrate field observations and present an accurate description of SQ **(Thakur *et al.*, 2022)**. The quantitative approach, on the other hand, offers a dynamic assessment in which the SQ is determined using analytical data. It is a sophisticated method, which depends mainly on a variety of chemical, physical, and biological indicators. In this approach, threshold values of indicator are used for depicting the SQ status **(Vasu *et al.*, 2020)**.

In recent years, the concept of soil quality index (SQI) has been initiated to handle these issues and provide a comprehensive assessment of SQ **(de Paul Obade *et al.*, 2022; Nieder *et al.*, 2018; Thakur *et al.*, 2022; Vasu *et al.*, 2020)**. The SQI is a function of indicators and can integrate qualitative and quantitative data into a single value **(de Paul Obade *et al.*, 2022)**. It also provides practical outcomes to draw comparisons and verify whether the SQ is declined or improved in response to agronomic practices **(Vasu *et al.*, 2020)**.

The spatial analysis tools integrated with GIS provide sophisticated techniques to analyze entities in accordance with their dimensions and associated attributes **(Reddy, 2018)**. Interpolation techniques can predict unmeasured values of any geographic point using a limited number of measurements **(Shi and Wang, 2021)**. The inverse distance weight (IDW) is one of the most common interpolation methods used in the agricultural field **(Bartelme, 2022; Piovan, 2020; Reddy, 2018)**. According to **ESRI (2019)**, the IDW predicts cell values through averaging the values of sampled data locations in the vicinity of each processing cell. Therefore, the closer a point is to the center of the cell being estimated, the more influence, or weight; it has in the averaging process.

The north Nile Delta region, the backbone of the agricultural sector in Egypt, undergoes various degradation processes, which negatively affect the soil ecosystem functions **(Abuzaid, 2017; Abuzaid and Bassouny, 2018; Mohamed, 2017a; Negm *et al.*, 2019)**. Hence, precise monitoring and appraisal of SQ status is of a great concern to conserve the cultivated lands in this vital region. In this context, the present work aimed at using GIS tools to model and map SQI in an area located in the northern Nile Delta of Egypt.

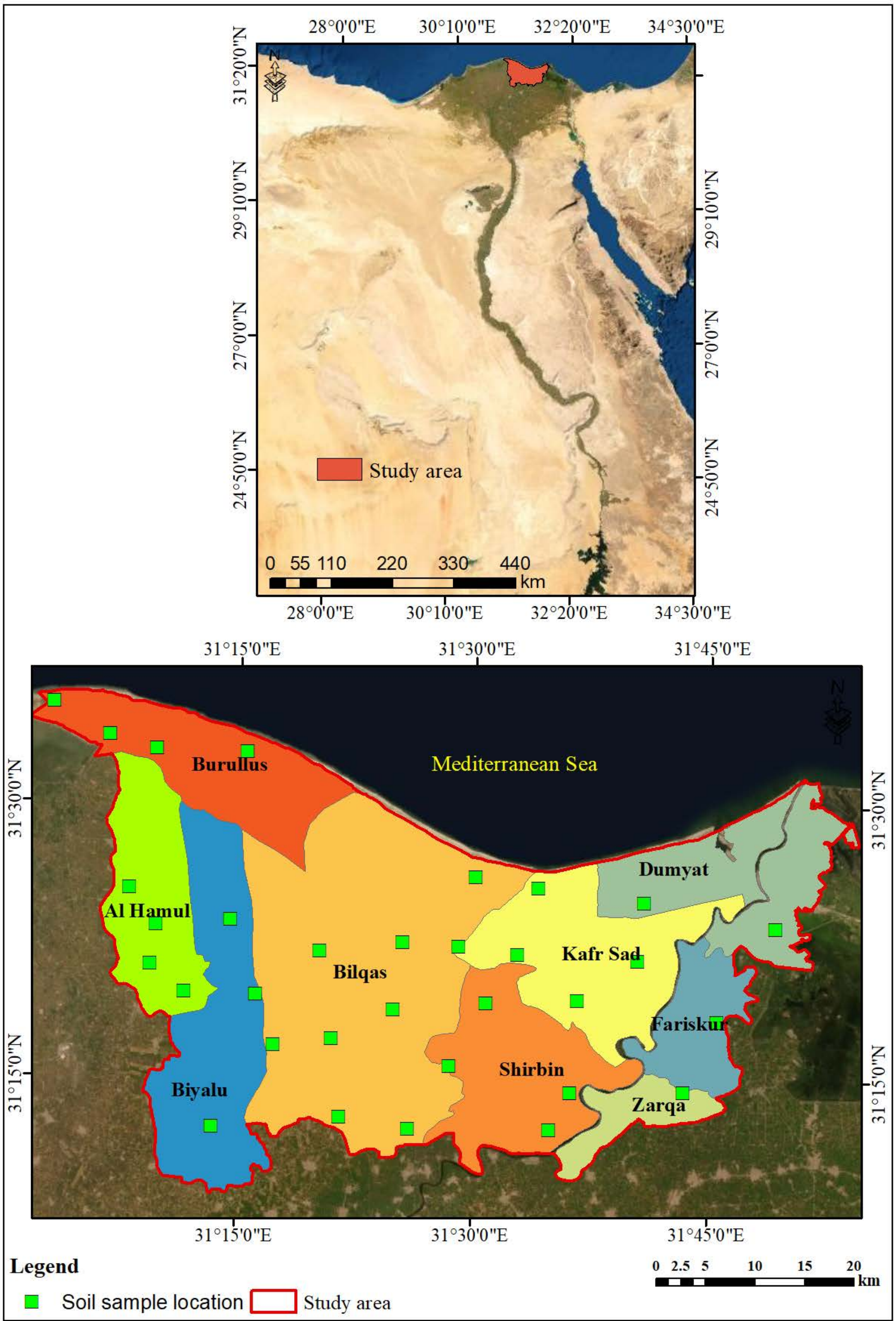

Figure 1. Location map of the studied area

2. Materials and methods

2.1. Study area

The studied area includes Damietta Governorate, two districts in Dakahlia Governorate (Bilqas and Shirbin), and three districts in Kafr El-Sheikh Governorate (Burullus, Al-Hamul, and Biyala). The geographic location lines in the UTM (Universal Transverse Mercator) zone 36 between latitudes 31°08' 38" to 31° 36' 15.53" N and longitudes 31°01' 16.67" to 31° 54' 40.37" E (Fig. 1) and covers a total area of 2306.43 km^2 (230643 ha). The area is dominated by a Mediterranean climate with hot arid summer and mild rainy winter. The minimum temperature is 6.4 ºC (in February), while the maximum one is 36.7 ºC (in July). The total annual rainfall varies from 30 to 194 mm year^{-1}. The mean annual relative humidity differs between 50.1 and 75.5%, while the mean annual wind speed varies from 2.15 to 17.32 km h^{-1}.

2.2. Field work and laboratory analyses

Thirty-two georeferenced disturbed and undisturbed surface soil samples (0 – 30 cm) were collected from the studied area as shown in Fig. 1. The disturbed samples were air-dried, crushed, and passed through a 2-mm sieve. The undisturbed samples were used for determining soil bulk density (BD). The laboratory analyses were accomplished using standard methods set by **Soil Survey Staff (2014)**.

The soil chemical analyses included pH (in 1:2.5 soil-water suspensions), electrical conductivity (EC) in soil paste extracts, cation exchange capacity (CEC), exchangeable sodium percentage (ESP), and organic matter (OM) content. The physical analyses included particle size distribution (using standard pipette method); field capacity (FC) and permanent witling point (PWP) using gravimetric methods; available water (AW) calculated as the difference between FC and PWP; BD using the soil core method; total porosity (TP) considering the particle density as 2.65 Mg m^{-3}; and hydraulic conductivity (HC).

2.3. Modeling soil quality

2.3.1. Indicator selection

The indicators used for determining SQI included five chemical indicators (pH, EC, OM, CEC, and ESP), and seven physical indicators (sand, silt, clay, AW, BD, TP, and HC). Selection of these indicators depended mainly upon available literature **(Abdellatif and Abuzaid, 2021; Abuzaid *et al.*, 2022; Fadl and Abuzaid, 2017; Hazelton and Murphy, 2016; Saleh *et al.*, 2021)**.

2.3.2. Raster layer generations

The IDW interpolation technique was applied to generate raster layers for the twelve SQ indicators. The IDW estimates unknown values (v) for any geographic location (x) depending on the number (n) and weight (w) of measured neighboring sample points (m) as follows (ArcGIS 10.8 help; **ESRI, 2019**):

$$v(x) = \sum_{i=1}^{n} w_i m_i / \sum_{i=1}^{n} w_i \quad (1)$$

The weight is computed using the distance (d) between the point x and the surround point (m) and the power constant (p), which determines the significance of the sample points upon the interpolated value as follows:

$$w_i = \frac{1}{{d_i}^p} \quad (2)$$

2.3.3. Raster layer normalization

The fuzzy membership functions (FMFs) were applied to convert each pixel (cell) in the raster layers to a membership value μ(x) ranging from 0 to 1. Three FMFs were applied, i.e. linear-positive (Eq. 3), linear-negative (Eq. 4), and near (Eq. 5). The linear FMFs build linear relationships between minimum and maximum value of a variable (*x*) that are fed by the user. The Eq. 3 was applied to indicators being preferred in higher values (e.g. CEC, OM, and AW). The Eq. 4 was applied to indicators being preferred in low values (e.g. EC, ESP, and BD). The near function calculates memberships around an intermediate value, where a value of 1 is assigned at the critical limit and decreases to 0 for values that deviate from this limit. The user inputs two values, i.e. spread (f_1) and midpoint (f_2) to calculate the membership. The expressions of the applied FMFs are as follows (ArcGIS 10.8 help; **ESRI, 2019**):

$$\mu(x) = \begin{cases} 1 \; if \; x \geq max \\ \frac{x - min}{max - min} \; if \; min < x < max \\ 0 \; if \; x \leq min \end{cases} \quad (3)$$

$$\mu(x) = \begin{cases} 1 \; if \; x \leq min \\ \frac{max - x}{max - min} \; if \; min < x < max \\ 0 \; if \; x \geq max \end{cases} \quad (4)$$

$$\mu(x) = \frac{1}{1 + f_1 \times (x - f_2)^2} \quad (5)$$

2.3.4. Developing the SQIs

In this step, three indices were developed, i.e. chemical soil quality index (CSQI), physical soil quality index (PSQI), and the overall soil quality index (OSQI). The CSQI and PSQI were calculated based on the geometric mean algorithm of indicator scores (S) as follows **(Kosmas *et al.*, 1999)**:

$$\mathrm{CSQI} = \left[S_{pH} \times S_{EC} \times S_{OM} \times S_{CEC} \times S_{ESP}\right]^{1/5} \quad (6)$$

$$\mathrm{PSQI} = \left[S_{Sand} \times S_{Silt} \times S_{Clay} \times S_{AW} \times S_{BD} \times S_{TP} \times S_{HC}\right]$$

The OSQI was calculated as follows:

$$\mathrm{OSQI} = [\mathrm{CSQI} \times \mathrm{PSQI}]^{1/2} \quad (8)$$

Each of the three layers of the developed indices were reclassified into five classes; very low, low, moderate, high, and very high using the using the Jenks's natural breaks classifier **(Jenks, 1976)**.

3. Results and discussion

3.1. Soil chemical properties

Descriptive statistics of soil properties are presents in Table 1, and the interpolated maps of chemical properties are shown in Fig. 2. Results illustrate that the soil pH ranged from 7.01 to 8.43 with an average of 7.76. The EC varied from 0.40 to 20.46 dS m^{-1} with an average of 6.42 dS m^{-1}. According to **Soil Science Division Staff (2017)**, the ranges of pH and EC demonstrate that the soils were neutral to strongly alkaline and non-saline to strongly saline. The OM content varied from 1.50 to 28.40 g kg^{-1} with an average of 14.69 g kg^{-1}. The CEC ranged from 1.90 to 50.41 cmolc kg^{-1} with an average of 25.83 cmolc kg^{-1}. According to **Hazelton and Murphy (2016)**, the soils had extremely low to moderate OM content and a very low to very high CEC. The ESP differs from 1.44 to 50.85 and averages 13.90. Hence, the soils were affected by non to very high sodicity hazards as set by FAO 39 guidelines **(Abrol *et al.*, 1988)**.

Table 1. Descriptive statistics of soil properties in the studied area

Property	Unit	Min	Max	Mean	SD	CV, %
pH	---	7.01	8.43	7.76	0.36	4.62
EC	dS m^{-1}	0.40	20.46	6.42	5.49	85.65
OM	g kg^{-1}	1.50	28.40	14.69	6.77	46.06
CEC	cmolc kg^{-1}	1.90	50.41	25.83	14.60	56.52
ESP	---	1.44	50.85	13.90	10.58	76.14
Sand	%	12.90	98.10	46.19	26.56	57.52
Silt	%	0.95	39.50	23.17	12.64	54.55
Clay	%	0.95	52.55	30.64	16.39	53.48
FC	%	8.70	43.10	29.76	10.75	36.12
PWP	%	2.90	29.40	17.94	8.13	45.32
AW	%	5.80	15.70	11.82	2.98	25.20
BD	Mg m^{-3}	1.23	1.97	1.41	0.21	14.83
TP	%	21.36	50.96	43.67	8.35	19.12
HC	cm h^{-1}	0.13	21.41	2.81	5.42	192.73

EC, electrical conductivity; OM, organic matter; CEC, cation exchange capacity; ESP, exchangeable sodium percentage; FC, filed capacity; PWP, permanent wilting point; AW, available water; BD, bulk density; TP, total porosity; HC, hydraulic conductivity; SD, standard deviation; CV, coefficient of variation

The soils showed properties (pH, EC, ESP, and OM) typical for dryland agroecosystems **(Chhabra, 2021; Jafari *et al.*, 2018; Osman, 2018)**. The predominance of basic cations, including alkali metals (Na and K) and alkaline earth metals (Ca and Mg) render the dryland soils neutral to alkaline **(Sholeye *et al.*, 2021)**. The increased soil salinity could attributed mainly to climate factors (low rainfall and high evaporation) besides agronomic practices such as irrigation with marginal-quality waters, excessive use of agrochemicals **(Negm *et al.*, 2019)**. The development of sodicity problems is due to the excessive use of brackish waters with high sodium contents **(Negm *et al.*, 2017)**. The Na^{+}, in turn, can replace Ca^{2+} and Mg^{2+} on soil colloids, being the predominant exchangeable cation **(Chhabra, 2021)**. The arid conditions (high temperature and low moisture availability) prevailing the studied area favor the oxidation process and prevent accumulations of organic substances in soils **(Jafari *et al.*, 2018)**.

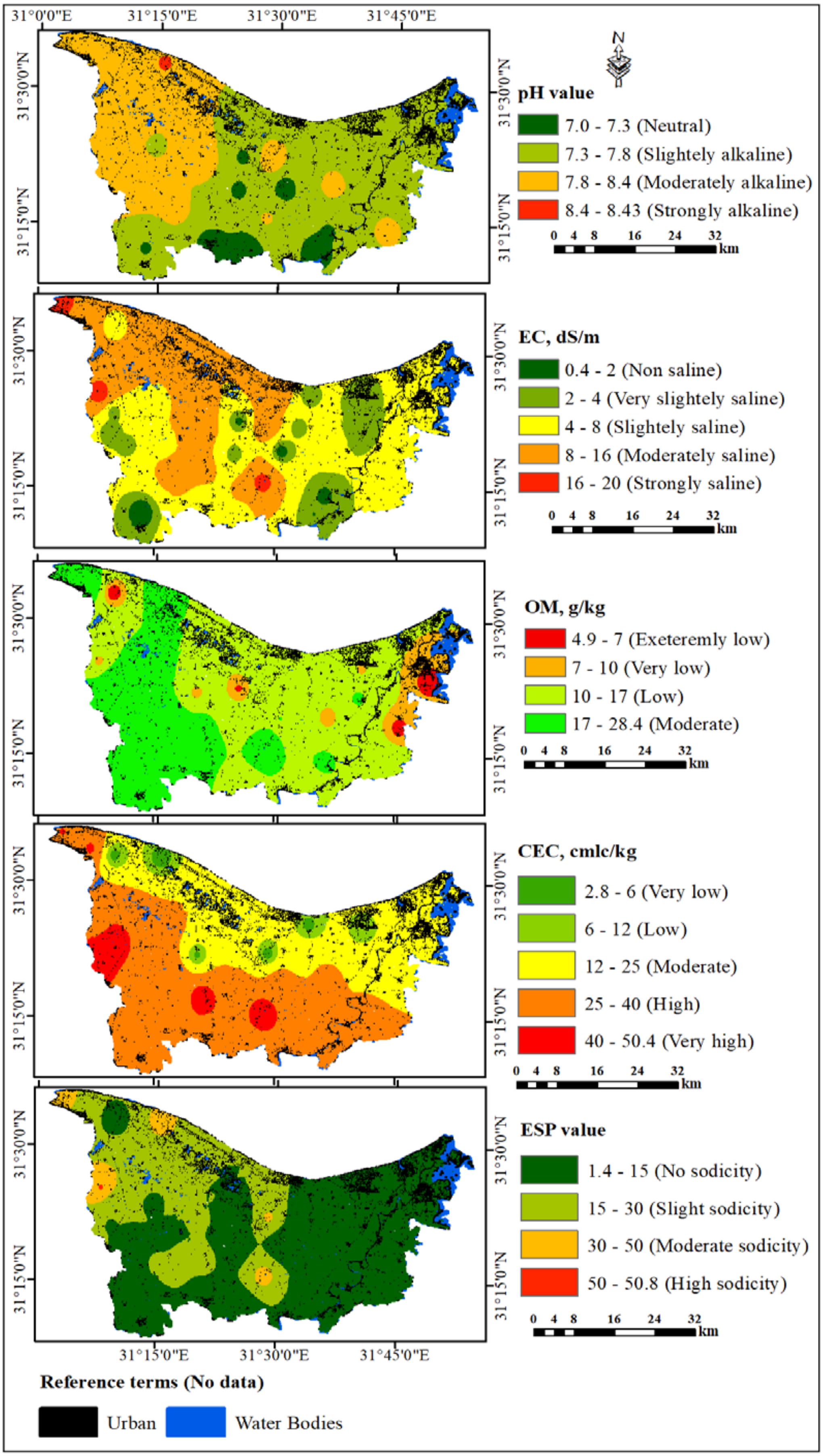

Figure 2. Maps of soil chemical properties

3.2. Soil physical properties

Results of soil physical properties (Table 1), and their illustrations in Fig. 3 show that the ranges of sand, silt, clay were 12.90 to 98.10, 0.95 to 39.50, and 0.95 to 52.55%, respectively. The soils had varied textural classes ranging from sand to clay with clay being the most dominant class. The ranges of FC, PWP, and AW were 8.70 to 43.10, 2.90 to 29.40, and 5.80 to 15.70%, respectively with average values of 29.76, 17.94, and 11.82%, respectively. According **Hazelton and Murphy (2016)**, the soils had a very low to very high water holding capacity and a very low to medium available soil-water content. The soil BD varied from 1.23 to 1.97 Mg m^{-3} with an average of 1.41 Mg m^{-3}, while TP ranged 21.36 to 50.96% with a mean value of 43.67%. The ranges of BD illustrate that the soils were affected by a slight to extreme compaction hazards **(FAO/UNEP, 1979)**. The soil HC ranged from 0.13 to 21.41 cm h^{-1} with a mean value of 2.81 cm h^{-1}. According to **Hazelton and Murphy (2016)** the soils had a very low to very high water infiltration rate.

The soils showed wide ranges of sand, silt, and clay contents across the studied area. This is because the studies soils are relatively young soils evolved on stratified materials from different alluvial, lacustrine, and marine sediments **(Mohamed, 2017a)**. However, most of these soils are composed of the Nile silt deposits owing to the frequent flooding during different geological eras **(Elbasiouny and Elbehiry, 2019)**. This could explain the predominance of the clayey soils in the studies area. In response to variations in soil textures, the dependent properties, i.e. FC, PWP, and HC showed also wide ranges. The soil texture has been identified as the most crucial soil property affecting soil physical conditions **(Bassouny and Abuzaid 2017; Hazelton and Murphy, 2016; Mukherjee, 2022)**. The BD and TP displayed narrow ranges, probably due to similar agronomic practices and land use type in the studied area **(Abuzaid and El-Husseiny, 2022)**.

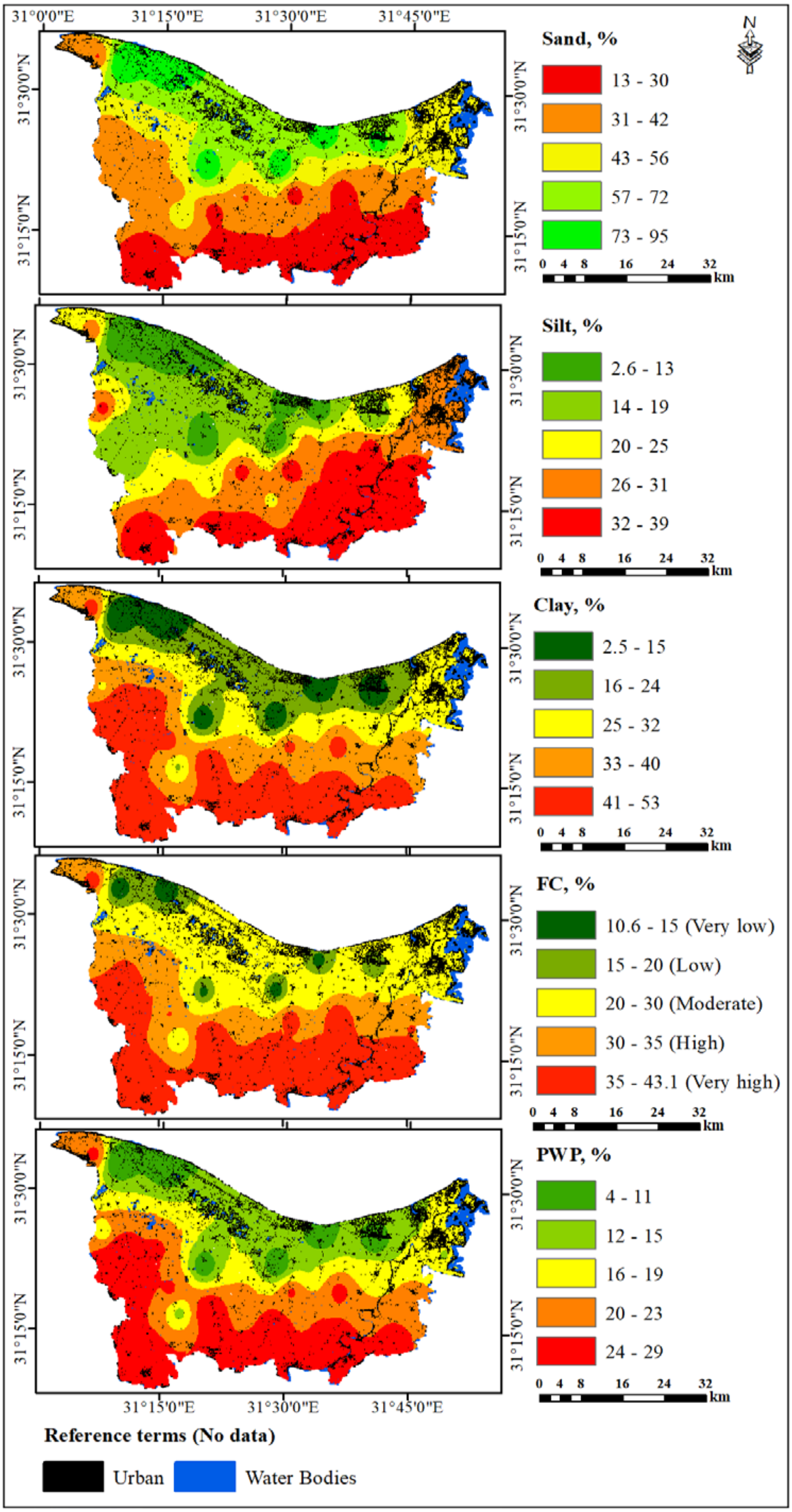

Figure 3. Maps of soil physical properties

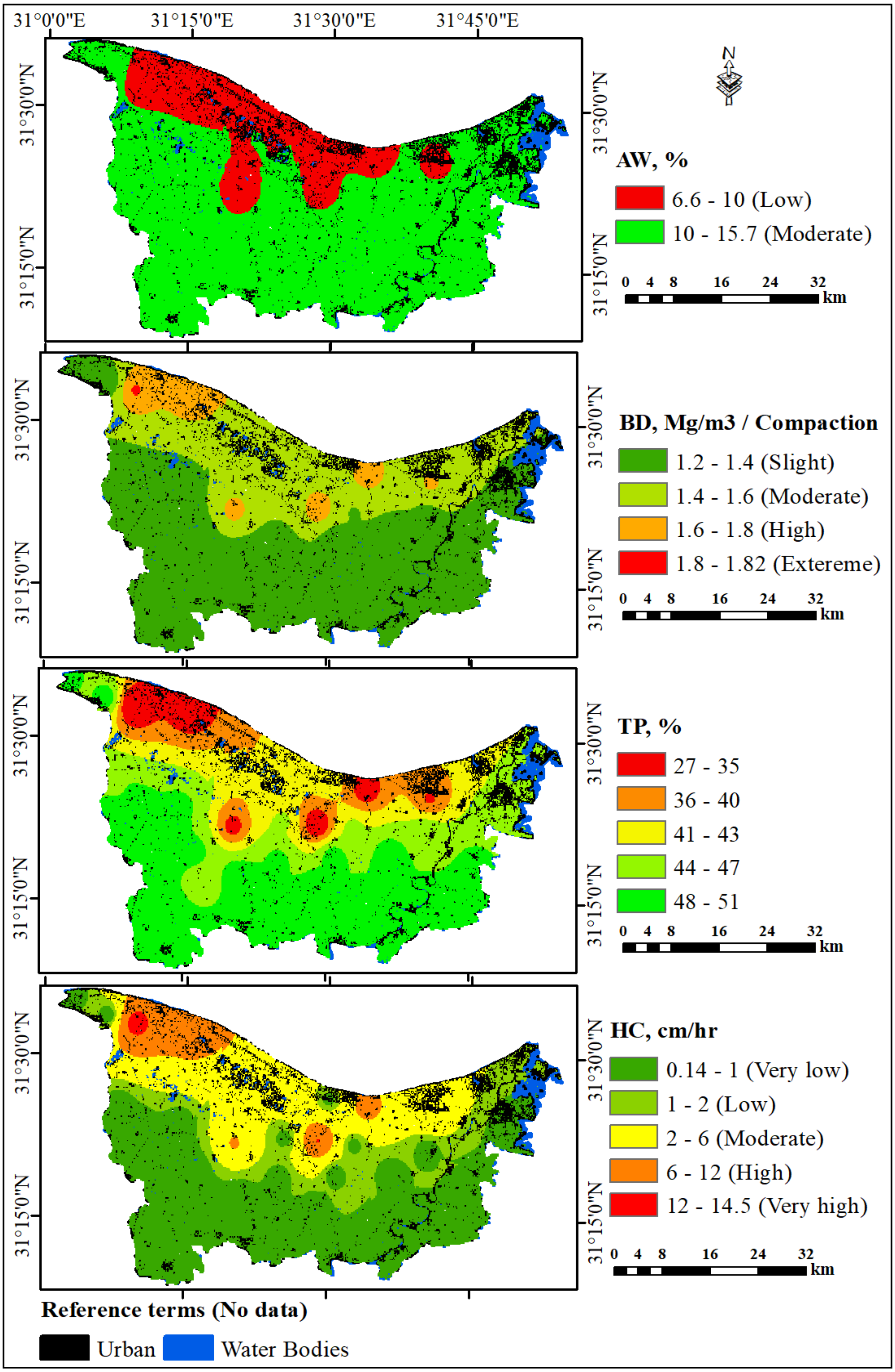

Figure 3. Continues

3.3. Chemical soil quality index (CSQI)

Integrating the fuzzified layers of CSQI indicators, result in Fig. 4 show that the soils had a very low to very high quality. As shown in Table 2, soils of preferred qualities (high and very high) represented nearly 51% of the total area in the southern parts. The moderate quality soils covered about 28% of the total area, occurring in the northern parts besides scattered patches in the middle and southern parts. The poor-quality soils (low and very low) occupied nearly 8% of the studied area in scattered patches across the coastal parts. The main limiting factors are alkaline pH, salinity, sodicity, poor OM content, and low exchange ability. Hence, selecting salt-tolerant crops, applying leaching fraction, and addition of organic and mineral amendments (gypsum) are the most recommended practices **(Abdelaal *et al.*, 2021; Mohamed, 2017b)**.

3.4. Physical soil quality index (PSQI)

Result in Fig. 5 show that the soils had a very low to very high physical quality. Soils of high and very high covered together nearly 32% of the total area and occurred mainly in the southern parts (Table 2). The moderate quality soils covered about 18% of the total area in the middle parts. The poor quality soils (low and very low) covered nearly 37% of the studied area in the coastal areas. The main limitations are structure instability, low water retention, compaction, and extremely low or very rapid water flow. Therefore, improving soil structure via proper use of tillage operations besides additions of organic and/or mineral amendments are essential to enhance the soil physical quality **(Abdelaal *et al.*, 2021; Abuzaid, 2018)**.

3.5. The overall soil quality index (OSQI)

As shown in Fig. 6, the overall soil quality ranged from very low to very high. Results in Table 2 show that soils of very high and high qualities covered together nearly 32% of the total area, and were found mainly in the southern parts. These soils had none to slight physicochemical limitations, which in turn increased the overall soil quality. The moderate quality soils occupied 18% of the total area, and occurred mainly in middle parts besides a scattered patch in the northwestern part. Soils of very low and low qualities covered about 37% of the total area, and occurred mainly in the northern parts besides a scattered patch in the northwestern parts.

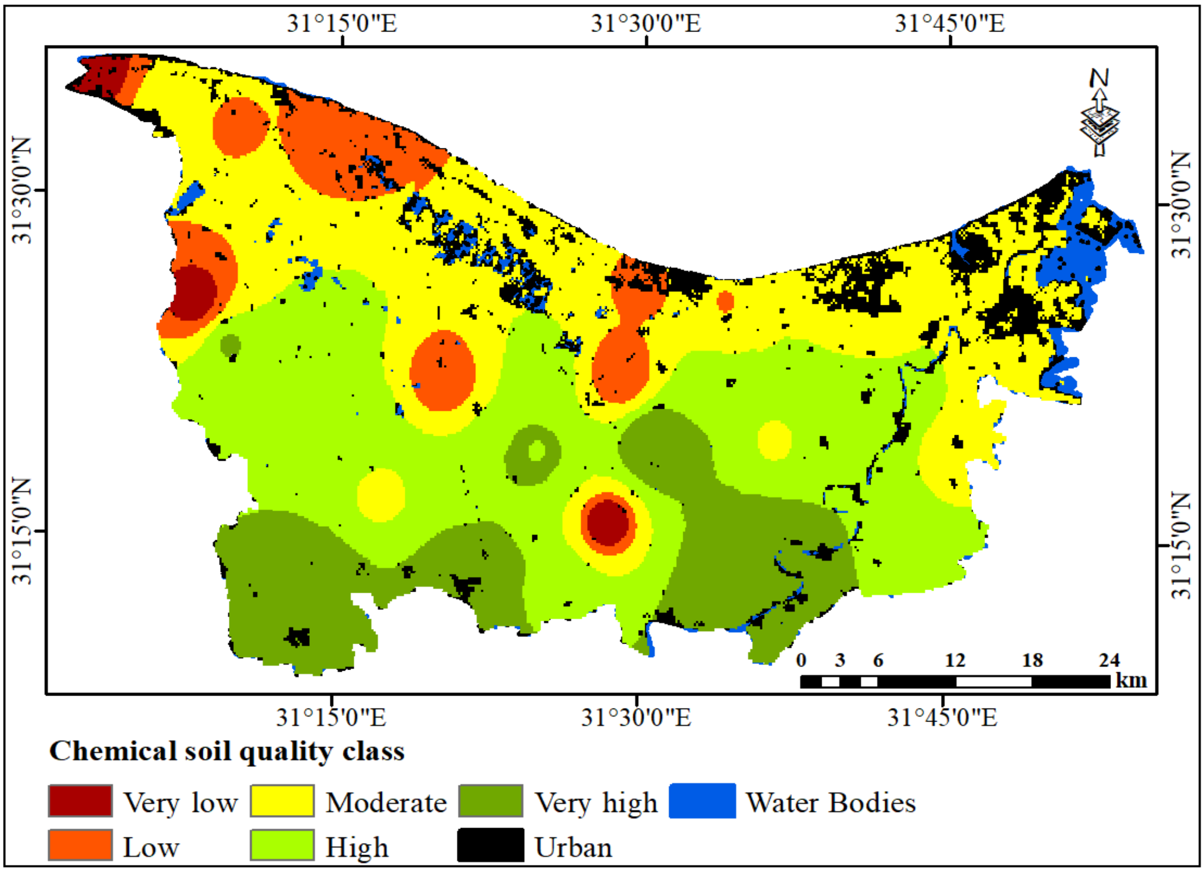

Figure 4. Map of chemical soil quality

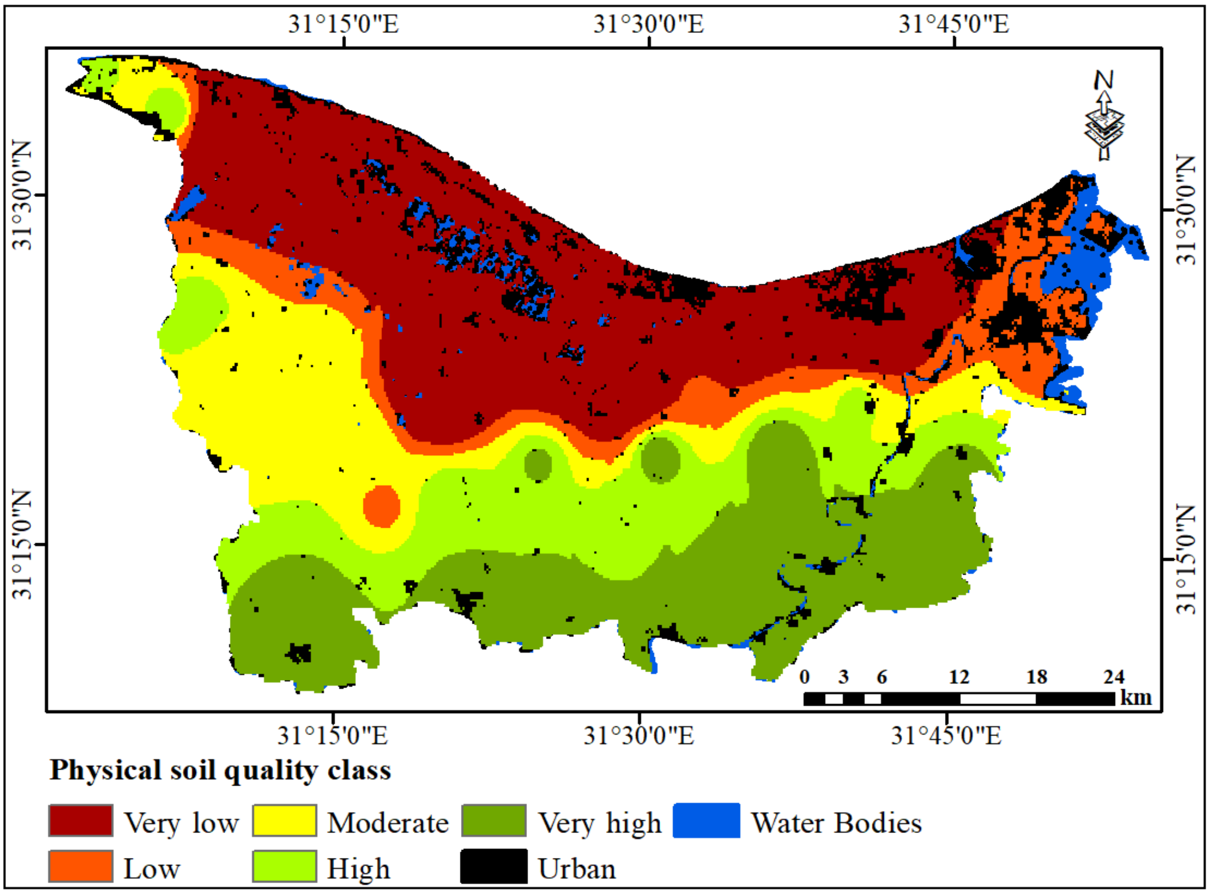

Figure 5. Map of physical soil quality

Table 2. Areas of soil quality classes

Class	Status	Chemical quality		Physical quality		Overall quality	
		Area		Area		Area	
		km^2	%	km^2	%	km^2	%
1	Very low	21.77	0.94	677.84	29.39	671.34	29.11
2	Low	167.53	7.26	172.09	7.46	181.48	7.87
3	Moderate	636.47	27.60	416.43	18.06	424.90	18.42
4	High	793.31	34.40	315.32	13.67	368.34	15.97
5	Very high	389.55	16.89	426.95	18.51	362.57	15.72
Water bodies		134.47	5.83	134.47	5.83	134.47	5.83
Urban areas		163.33	7.08	163.33	7.08	163.33	7.08
Total		2306.43	100%	2306.43	100%	2306.43	100%

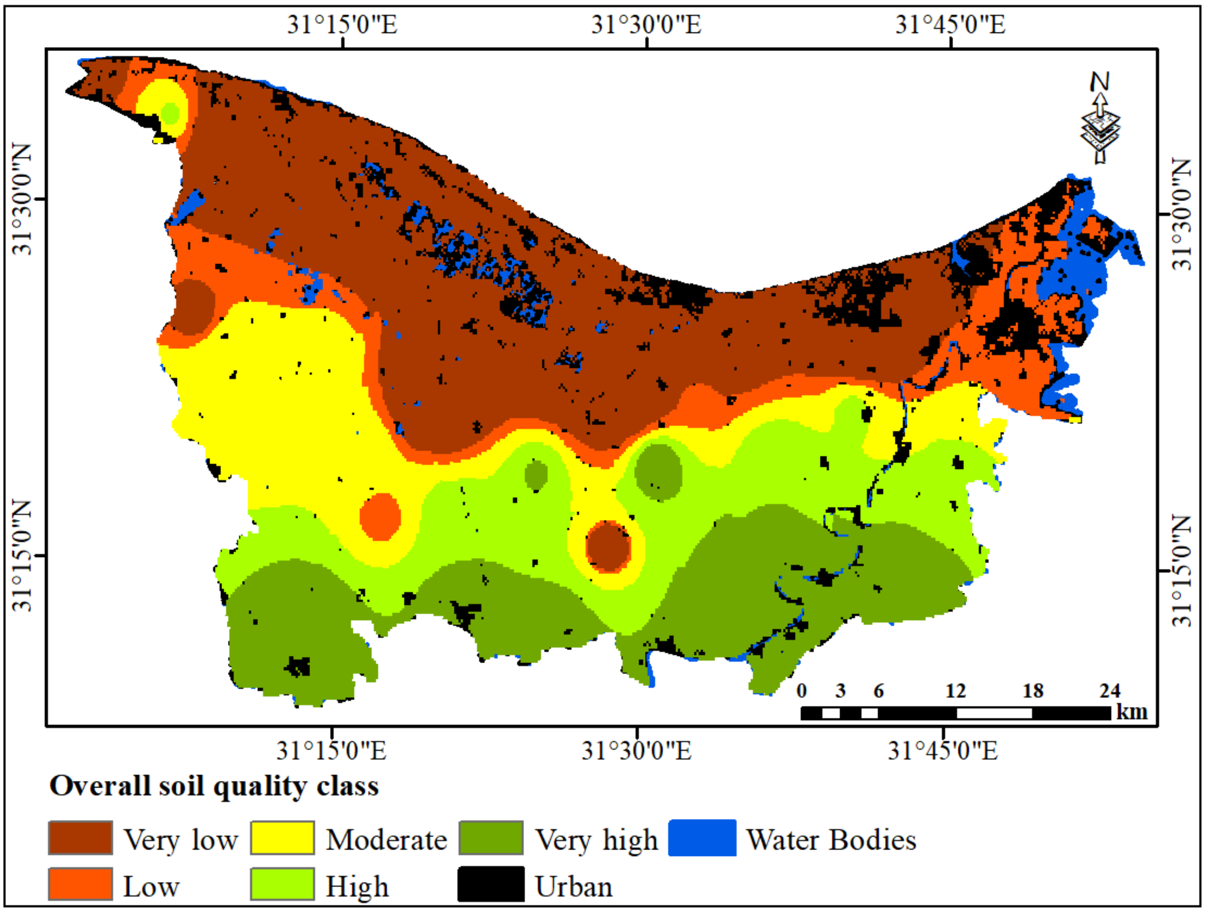

Figure 6. Map of the overall soil quality

Conclusion

The IDW interpolation technique could adequately produce thematic layers for these indicators, which were normalized using linear and near FMFs. The geometric mean algorithm was applied to the raster layers to generate three indices, i.e. CSQI, PSCQI, and the overall SQI. The studied soils had varied overall quality classes ranging from the very low to very high. Soils of favorable quality (very high and high) covered nearly 32% of the total area, and occurred mainly in the southern parts. The intermediate quality status was found mainly across the middle section and occupied nearly 18% of the total area. The worst quality conditions were found mainly in the northern parts, where soils of very low and low qualities occupied together 37% of the total area. To improve the overall soil quality status, it is advocated to (1) cultivate salt-tolerant crop species; (2) apply leaching fraction and construct sufficient drainage systems to mitigate salinity; (3) adopt organic and gypsum application to enhance soil structural stability; and (4) operate tillage using appropriate equipment in proper time to reduce soil compaction.

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تقييم جودة التربة باستخدام تقنيات نظم المعلومات الجغرافية: دراسة حالة لشمال دلتا النيل - مصر

حسين إبراهيم حسين *، أحمد سعيد أبوزيد*، عبداللطيف دياب عبداللطيف**، حسن حمزة عباس*

* قسم الأراضي والمياه – كلية الزراعة – جامعة بنها – مصر

** معهد بحوث الأراضي والمياه والبيئة – مركز البحوث الزراعية – مصر

يهدف هذا البحث إلى استخدام أدوات التحليل المكاني لنظم المعلومات الجغرافية لرسم خرائط جودة التربة للأراضي الزراعية لتحقيق التنمية الزراعية المستدامة. أجريت الدراسة على مساحة 2306.43 كيلومتر مربع في شمال دلتا النيل بمصر. تم جمع 32 عينة تربة سطحية (0 - 30 سم) وتحليل الخواص الكيميائية والفيزيائية. تم إستخدام تقنية مقلوب المسافة الموزونة (IDW) الملحقة بنظم المعلومات الجغرافية لإنشاء الطبقات الشبكية (Raster) لمؤشرات جودة التربة. وتم إستخدام الدوال الضبابية لتحويل قيم التحليلات المعملية إلى مقياس يتراوح من صفر إلى 1، وتم دمج الطبقات الضبابية بإستخدام خوارزمية المتوسط الهندسي لإنتاج خرائط جودة التربة. أظهرت النتائج أن التربة ذات الجودة العالية جداً والعالية شغلت ما يقرب من 32 ٪ من المساحة الإجمالية. وشغلت التربة ذات الجودة المتوسطة 18٪ من المساحة الكلية ، بينما شغلت التربة ذات الجودة المنخفضة والمنخفضة جدًا حوالي 37٪ من المساحة الإجمالية. لتحسين حالة جودة التربة ، يوصى بزراعة المحاصيل متحملة الملوحة، وإضافة الكسر الغسيلي أثناء الري، وإنشاء أنظمة صرف كافية ، وإضافة المحسنات العضوية والغير عضوية، وإجراء عمليات الحراثة باستخدام المعدات المناسبة في الوقت المناسب. من الممكن الإعتماد على نتائج هذه الدراسة في اتخاذ القرار المناسب بشأن الممارسات الزراعية المستدامة في منطقة الدراسة.