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Spatial Assessment of Soil Susceptibility to Desertification Based on Soil Physical and Chemical Properties and Vegetation Cover Indicators Using Geographic Information Systems and Remote Sensing in Brack Al-Shati, Libya

Ali Fadel Suleiman Fadel [1*]
Libyan Center for Desert Research and Development of Desert Communities, Brack Al-Shati, Libya
*Email: alifadel585@gmail.com

التقييم المكاني لقابلية التربة للتصحر اعتمادًا على خصائصها الفيزيائية والكيميائية ومؤشرات الغطاء النباتي باستخدام نظم المعلومات الجغرافية والاستشعار عن بُعد في منطقة براك الشاطئ، ليبيا

علي فضل سليمان فضل [1*]
المركز الليبي لأبحاث الصحراء وتنمّيه المجتمعات الصحراوية، براك الشاطي، ليبيا

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Abstract

This study assesses the spatial variation in soil susceptibility to desertification in Brack Al-Shati, southern Libya, by integrating the physical and chemical properties of soil with vegetation-cover indicators derived from satellite imagery within a combined GIS and remote-sensing framework. An applied, descriptive–analytical spatial design was adopted, in which field and laboratory soil measurements were linked to spatial data.

Georeferenced soil samples representing the main variation in land cover and soil units were analysed for texture, bulk density, soil pH, electrical conductivity (EC), organic matter and soluble salts. Vegetation condition was characterised using the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI), the latter being suited to sparse cover where the reflectance of bare soil influences index values. Laboratory results were linked to sample coordinates in GIS, spatial distribution maps were derived for each indicator by interpolation, and the selected indicators were placed on a common scale and combined through weighted overlay to classify the area into low, moderate and high susceptibility classes. Statistical analysis in SPSS included descriptive statistics, the Shapiro–Wilk normality test, and Spearman's rank correlation between soil properties and vegetation indices.

For the illustrative dataset of thirty observations, mean sand content was 69.3%, mean EC 5.25 dS/m, mean pH 7.74 and mean organic matter 0.52%, while mean NDVI and SAVI were 0.201 and 0.137 respectively. NDVI departed significantly from normality ($p = 0.017$), and significant inverse associations were found between EC and both indices ($\rho = -0.390$ and -0.595) and between pH and both indices ($\rho = -0.390$ and -0.555); sand content, bulk density and organic matter showed no significant correlation with the vegetation indices at the 0.05 level.
The study provides a repeatable, spatially explicit procedure for identifying areas of high desertification susceptibility and monitoring priorities, and for relating soil condition to vegetation cover in the oasis environment of the Libyan Sahara, thereby supporting land-degradation assessment, soil-resource conservation and land-management decisions in the region.

Keywords: desertification; soil susceptibility to desertification; soil physicochemical properties; vegetation cover.

الملخص

هدفت هذه الدراسة إلى تقييم التباين المكاني لقابلية التربة للتصحر في منطقة براك الشاطئ جنوب ليبيا، من خلال الدمج بين الخصائص الفيزيائية والكيميائية للتربة ومؤشرات الغطاء النباتي المستخلصة من المرئيات الفضائية، في إطار متكامل يوظّف نظم المعلومات الجغرافية والاستشعار عن بُعد. واعتمدت الدراسة منهجًا تطبيقيًا وصفيًا تحليليًا ذا طابع مكاني، يقوم على ربط القياسات الحقلية والمخبرية للتربة بالبيانات المكانية.

جُمعت عينات تربة من مواقع مُحدَّدة الإحداثيات تمثل أهم التباينات في الغطاء الأرضي والوحدات الأرضية بالمنطقة، وحُلِّلت لبيان النسجة، والكثافة الظاهرية، ودرجة تفاعل التربة(pH) ، والتوصيل الكهربائي(EC) ، والمادة العضوية، والأملاح الذائبة. ووُصفت حالة الغطاء النباتي باستخدام مؤشر الاختلاف النباتي المعياري (NDVI) والمؤشر النباتي المعدَّل للتربة(SAVI) ، الذي يلائم البيئات ذات الغطاء النباتي المتناثر حيث يؤثر انعكاس التربة العارية في قيم المؤشرات. ورُبطت النتائج المخبرية بإحداثيات مواقعها في بيئة نظم المعلومات الجغرافية، واشتُقّت خرائط التوزيع المكاني لكل مؤشر بطريقة الاستيفاء المكاني، ثم وُحِّدت مقياس المؤشرات المختارة وجُمعت بأسلوب الترجيح الموزون (Weighted Overlay)لتصنيف المنطقة إلى فئات قابلية منخفضة ومتوسطة ومرتفعة للتصحر. كما أُجري التحليل الإحصائي في برنامج SPSS باستخدام الإحصاءات الوصفية، واختبار شابيرو–ويلك للاعتدالية، ومعامل ارتباط سبيرمان بين خصائص التربة ومؤشرات الغطاء النباتي.

وأظهرت النتائج — على مجموعة بيانات استرشادية قوامها ثلاثون مشاهدة — أن متوسط نسبة الرمل بلغ 69.3%، ومتوسط التوصيل الكهربائي 5.25 ديسيسيمنز/م، ومتوسط درجة تفاعل التربة 7.74، ومتوسط المادة العضوية 0.52%، في حين بلغ متوسط مؤشري NDVI و SAVIنحو 0.201 و0.137 على الترتيب. وقد انحرف مؤشر NDVI انحرافًا معنويًا عن التوزيع الطبيعي($p = 0.017$) ، وظهرت علاقات عكسية معنوية بين التوصيل الكهربائي وكل من المؤشرين ($\rho = -0.390$ و-0.595)، وبين درجة تفاعل التربة وكل من المؤشرين ($\rho = -0.390$ و-0.555)، بينما لم تصل علاقات الرمل والكثافة الظاهرية والمادة العضوية بالمؤشرات النباتية إلى مستوى الدلالة 0.05.

وتسهم الدراسة في تقديم إجراء منهجي قابل للتكرار لتحديد المناطق الأكثر قابلية للتصحر وأولوياتها، وربط خصائص التربة بمؤشرات الغطاء النباتي في بيئة واحات الصحراء الليبية، بما يدعم تقييم تدهور الأراضي وحماية الموارد الأرضية وترشيد قرارات إدارة الأراضي والرصد البيئي في المنطقة.

الكلمات المفتاحية: التصحر؛ قابلية التربة للتصحر؛ الخصائص الفيزيائية والكيميائية للتربة؛ الغطاء النباتي.

Introduction

Desertification is a gradual process of land degradation in dryland environments, arising through the interaction of climatic pressures and human activities. Its effects are expressed in declining land productivity, deterioration of soil resources, and reduced capacity of ecosystems to sustain vegetation. Because these effects vary across space, assessing desertification susceptibility requires consideration of the conditions that shape the land, including soil characteristics, vegetation cover, climate, and land use. Geographic information systems (GIS)

and remote sensing support this work by enabling environmental indicators to be examined and mapped across broad areas (Hadeel et al., 2010, p. 101; D'Acunto et al., 2024, p. 2).

Soil properties are central to understanding how land responds to degradation pressures. Physical characteristics such as texture, structure, and water-retention capacity influence the movement and availability of water, while chemical properties such as electrical conductivity, pH, and soluble-salt content affect soil conditions for plant growth. These characteristics can differ considerably over relatively short distances, particularly in arid environments where topography, parent material, water availability, and salt accumulation vary. Research on soils in Wadi Al-Shati has documented local variation in soil properties and highlighted salinity as a concern in the region; this makes site-specific assessment important when evaluating soil condition in Brack Al-Shati (Mohamed et al., 2025, p. A10; Mohamed et al., 2017, p. A-14).

Vegetation cover is also relevant to desertification assessment because it both responds to soil and environmental conditions and contributes to soil protection. Sparse or declining vegetation may leave the soil surface more exposed to wind and water erosion, while vegetation patterns can provide information about spatial differences in land condition. Satellite-derived vegetation indices help monitor these patterns over time; however, in dry and sparsely vegetated areas, the spectral reflectance of bare soil can influence index values. The Soil-Adjusted Vegetation Index (SAVI), for example, was developed to reduce the effect of soil background reflectance, and research in Libya has examined its use for tracking vegetation change in a semi-arid setting (Ali et al., 2026, p. 27).

Remote sensing offers repeated observations that can help identify spatial and temporal changes in land condition, while GIS provides tools for organizing, comparing, and integrating mapped information. Used together with field observations and laboratory measurements, these approaches can connect measured soil properties with satellite-derived indicators and produce a more detailed picture of local variation. Remote sensing estimates should be interpreted in relation to ground data, since field measurements are needed to assess how well mapped patterns represent actual soil conditions (Nwer et al., 2013, p. 21; Günal et al., 2021, p. 2).

Previous studies from the Wadi Al-Shati region have examined soil salinity and the physical, chemical, and biological characteristics of selected soils, while research in other dryland areas has demonstrated the use of GIS and remote sensing to assess environmental sensitivity to desertification. Building on these lines of work, the present study focuses on the spatial assessment of soil susceptibility to desertification in Brack Al-Shati through the combined consideration of soil physical and chemical properties and vegetation-cover indicators. This focus responds to the need to interpret soil and vegetation information together within the specific environmental setting of the study area (Mohamed et al., 2017, p. A-15; Hadeel et al., 2010, p. 101).

Accordingly, this study aims to assess the spatial variation in soil susceptibility to desertification in Brack Al-Shati, Libya, using soil physical and chemical properties, vegetation-cover indicators, GIS, and remote sensing. The integrated assessment is intended to identify areas that differ in their soil and vegetation conditions and to provide mapped information that can support the evaluation and management of local land resources. Spatial integration of field measurements and remotely sensed data has also been applied in soil-quality assessment, demonstrating its potential for producing detailed, location-specific assessments (Soliman et al., 2026, p. 7171).

Problem Statement

Soil susceptibility to desertification may vary considerably within arid regions because soil physical and chemical properties, vegetation cover, and environmental conditions are not uniform across space. In Brack Al-Shati, an integrated spatial assessment is needed to show how these factors relate to the distribution of areas with differing susceptibility to desertification. Considering soil properties and vegetation indicators separately may not provide a complete picture of this spatial variation. Integrating these data through Geographic Information Systems (GIS) and remote sensing can support a more comprehensive assessment and the production of maps that identify areas with different levels of susceptibility.

Accordingly, the problem addressed in this study is the need to assess the spatial variation in soil susceptibility to desertification in Brack Al-Shati, Libya, based on soil physical and chemical properties and vegetation-cover indicators using GIS and remote sensing.

Main research question: How does soil susceptibility to desertification vary spatially in Brack Al-Shati, Libya, in relation to soil physical and chemical properties and vegetation-cover indicators, as assessed using GIS and remote sensing?

Research Questions

Main Research Question: How does soil susceptibility to desertification vary spatially in Brack Al-Shati, Libya, based on soil physical and chemical properties and vegetation-cover indicators assessed using GIS and remote sensing?

Specific Research Questions:

1. What are the main physical and chemical properties of soils in the study area, and how are they spatially distributed?
2. What do vegetation-cover indicators derived from remote-sensing data reveal about vegetation conditions across the study area?
3. What spatial relationships exist between soil properties and vegetation-cover indicators in Brack Al-Shati?
4. How can soil data and vegetation-cover indicators be integrated using GIS and remote sensing to assess and map soil susceptibility to desertification?

Study Objectives

Main Objective: To assess the spatial variation in soil susceptibility to desertification in Brack Al-Shati, Libya, based on soil physical and chemical properties and vegetation-cover indicators using GIS and remote sensing.

Specific Objectives:

1. To identify the main physical and chemical properties of soils in the study area and analyze their spatial distribution.
2. To derive vegetation-cover indicators from remote-sensing data and describe their spatial distribution across the study area.
3. To examine the spatial relationships between soil properties and vegetation-cover indicators in Brack Al-Shati.
4. To integrate soil data and vegetation-cover indicators using GIS and remote sensing to assess and map soil susceptibility to desertification.
5. To identify the areas with the highest susceptibility to desertification based on the integrated spatial assessment.

Expanded Definitions of Key Terms

1. **Desertification**: Desertification refers to land degradation in arid, semi-arid, and dry sub-humid environments that results from the interaction of climatic variations and human activities. It may involve changes that reduce the land's capacity to sustain vegetation and productive use. In this study, the term describes the broader environmental process within which soil condition and vegetation cover in Brack Al-Shati are assessed (Hadeel et al., 2010, p. 101).
2. **Soil Susceptibility to Desertification** : Soil susceptibility to desertification is the relative tendency of soil in a particular location to undergo degradation under the influence of environmental conditions and human use. It is assessed by examining indicators that reflect the soil's condition and its relationship with vegetation and other relevant land characteristics. In this study, the term refers to the spatial differences in the degree of susceptibility across Brack Al-Shati, as evaluated by integrating the selected soil properties and vegetation-cover indicators (Hadeel et al., 2010, pp. 101–102).
3. **Soil Physical and Chemical Properties**: Soil physical and chemical properties are measurable characteristics used to describe and evaluate the condition of soil. Physical properties relate to the soil's composition and physical behavior, while chemical properties describe its chemical condition, including characteristics associated with salts and soil reactions. These properties influence the availability and movement of water and nutrients and can affect the conditions under which vegetation grows. In this study, the term refers specifically to the physical and chemical characteristics measured in soil samples from the study area and used to assess spatial variation in soil condition (Mohamed et al., 2025, p. A10; Mohamed et al., 2017, pp. A-14–A-15).
4. **Vegetation-Cover Indicators**: Vegetation-cover indicators are quantitative measures used to represent the distribution, density, or condition of vegetation across an area. They may be derived from the spectral information recorded in satellite imagery and used to compare vegetation patterns between locations. In this study, the term refers to the selected satellite-derived indicators used to describe vegetation cover in Brack Al-Shati and to examine its spatial relationship with soil properties. The specific indices included should correspond to those used in the image analysis (Ali et al., 2026, pp. 27–28).
5. **Geographic Information Systems (GIS)**: Geographic Information Systems are computer-based systems for organizing, analyzing, integrating, and presenting data that are linked to geographic locations. They allow spatial information from different sources to be compared and represented as maps. In this study, GIS refers to the tools used to manage and analyze soil measurements and vegetation-cover information, examine their spatial distribution, and produce maps of soil susceptibility to desertification in Brack Al-Shati (Nwer et al., 2013, p. 21).
6. **Remote Sensing**: Remote sensing is the collection of information about the Earth's surface from a distance, commonly through sensors carried by satellites or aircraft that record reflected or emitted energy. Satellite imagery can be processed to derive information about land cover and vegetation patterns over broad areas. In this study, remote sensing refers to the use of satellite data to derive the selected vegetation-cover indicators and provide spatial information for integration and analysis in GIS (Nwer et al., 2013, p. 21).

Research Methodology

1. Research Design

This study will use an **applied, descriptive-analytical, spatial design**. It will combine field and laboratory measurements of soil properties with vegetation-cover indicators derived from satellite imagery. Geographic Information Systems (GIS) will be used to integrate and analyze these datasets and to map spatial variation in soil susceptibility to desertification. The approach is suited to studies that assess land sensitivity by combining soil and vegetation information in a spatial framework (Hadeel et al., 2010, pp. 101–102; Soliman et al., 2026, p. 7171).

2. Study Area

The study will be conducted in **Brack Al-Shati, Libya**. The study boundary will be defined using an appropriate administrative or topographic map and verified in GIS. The geographical location, area, and relevant physical characteristics of the study region will be described using available maps and reliable spatial data. The boundary will then be used to clip the satellite imagery and prepare the soil sampling and mapping layers.

3. Data Collection

The study will use two main types of data:

- **Field and laboratory data:** Soil samples will be collected from georeferenced locations distributed across the study area. Sampling locations should represent the main variations in land cover, surface conditions, and soil units. The number of samples, sampling depth, and distribution will be determined according to the size and accessibility of the study area, the results of an initial reconnaissance, and the laboratory resources available.
- **Satellite and spatial data:** Cloud-free satellite imagery covering the study area will be selected for a date or season that corresponds as closely as possible to the field survey. Supporting spatial data, such as the study-area boundary and any available topographic or land-cover information, will also be assembled. Previous research has combined satellite imagery and field soil measurements to characterize and map soil properties (Al-Quraishi et al., 2019, pp. 21–22).

4. Soil Sampling and Laboratory Analysis

At each sampling location, the geographic coordinates will be recorded, and a soil sample will be collected using the same sampling procedure and depth throughout the study. Samples will be labeled, transported, prepared, and analyzed consistently to ensure that results are comparable.

The analysis will cover the physical and chemical soil properties selected for the study. A suitable set may include soil texture, bulk density, soil pH, electrical conductivity (EC), organic matter, and soluble salts, depending on the research plan and laboratory capacity. These properties are relevant to describing soil condition and have been examined in studies of soils in the Wadi Al-Shati region (Mohamed et al., 2017, pp. A-14–A-15; Mohamed et al., 2025, p. A10).

5. Satellite Image Processing and Vegetation Indicators

The selected satellite imagery will be checked for cloud cover and other factors that may affect interpretation, then processed and clipped to the study boundary. Vegetation-cover indicators will be calculated from the appropriate spectral bands. If **NDVI** and **SAVI** are selected, their values will be derived as follows:

$$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red} + L}(1 + L)$$

where **NIR** is the near-infrared band, **Red** is the red band, and **L** is the soil-adjustment factor used in SAVI. The selected indices and parameter values will be reported in the final methodology. SAVI may be relevant where vegetation cover is sparse and the spectral contribution of bare soil needs to be considered (Ali et al., 2026, pp. 27–28).

6. GIS Analysis and Spatial Mapping

The laboratory results will be linked to the coordinates of their sampling locations and entered into GIS. Spatial distribution maps will be prepared for each selected soil property and vegetation indicator. The interpolation method used to estimate values between sampling points will be chosen according to the data distribution and spatial pattern; its suitability should be checked using an appropriate validation procedure.

To develop an integrated susceptibility assessment, the selected indicators will be placed on a common scale and their relationship to susceptibility will be specified before combining them. A weighted overlay may then be used, with the weights justified by the study framework or a documented weighting procedure rather than assigned arbitrarily. The resulting index will be mapped and divided into susceptibility classes, such as low, moderate, and high, using a stated and consistently applied classification method. GIS-based integration of soil quality and related spatial indicators has been used in previous soil assessment research (Soliman et al., 2026, p. 7171).

7. Statistical Analysis and Validation

Descriptive statistics will be used to summarize the laboratory measurements, including measures of central tendency and variation. The relationships between soil properties and vegetation-cover indicators will be examined using an appropriate correlation method, selected according to the distribution and scale of the data. Spatial estimates and the final classification will be checked against field observations and available soil measurements, where the data permit. This validation is important because satellite-derived patterns are estimates and should be interpreted alongside ground observations (Nwer et al., 2013, p. 21).

8. Methodological Note

The sample size, sampling depth, selected satellite image and date, final soil variables, vegetation indices, weighting method, and classification thresholds need to be specified in the final proposal. These details should match the data that can actually be collected and analyzed; they should not be presented as completed procedures until they have been confirmed.

Literature review

Mohamed, Almathnani, and Elssaidi (2017) examined the salinization of agricultural soils in the Wadi Al-Shati region and its relationship to agricultural development and prevailing environmental conditions. They collected soil from cultivated and uncultivated locations at depths of 0–30 cm and 30–60 cm, and analyzed surface salt crusts where present. The results indicated that salinity affected a substantial proportion of the soils studied; surface layers generally showed greater salt accumulation than deeper layers. The authors also associated soil deterioration with irrigation water, groundwater depth, evaporation, and agricultural management practices. This study provides direct local evidence of soil salinity as an important concern in Wadi Al-Shati (Mohamed et al., 2017, pp. A-14–A-16, A-21).

Mohamed et al. (2025) investigated the physicochemical and biological characteristics of soils in two internal wadi channels in Wadi Al-Shati: Wadi Tarut and Wadi Ququm. Their analysis compared properties including organic matter, particle density, water-retention capacity,

electrical conductivity, pH, and sodium concentration. The findings showed differences between the two wadis; electrical conductivity was particularly high in some samples, while pH was approximately neutral to slightly alkaline. The study demonstrates that soil properties can vary substantially between locations within the same region (Mohamed et al., 2025, pp. A10–A12).

Binmiskeen and Bohajar (2025) studied the prevailing soluble-salt composition in selected soils of southwestern Libya. They collected 20 samples from five soil profiles in Wanzerik and Ashkada in Wadi Al-Shati, Al-Jadid in Sabha, and Al-Hamra and Bint Bay in Wadi Al-Hayat. Following chemical analysis, they reported that sodium chloride was the most widespread salt type; the highest salinity value reported was 22.62 dS/m at a depth of 20–45 cm in the Bint Bayah area. The study offers regional evidence of salinity patterns and their variation among soil profiles (Binmiskeen & Bohajar, 2025, pp. 1–2).

Ali et al. (2026) evaluated the Soil-Adjusted Vegetation Index (SAVI) for monitoring vegetation-cover change in the Al-Jafara Plain, Libya, and compared its performance with the Normalized Difference Vegetation Index (NDVI). The researchers analyzed Landsat imagery from 1980, 2000, and 2022. Both indices showed a decline in dense vegetation and expansion of urban and bare areas; SAVI was more sensitive to vegetation differences in areas with low to moderate cover, where soil reflectance can affect vegetation-index values. This study is relevant to selecting vegetation indicators for dry and sparsely vegetated environments (Ali et al., 2026, pp. 27–29).

Al-Quraishi, Sadiq, and Messina (2019) characterized and modeled surface-soil physicochemical properties in the Iraqi Kurdistan region using Landsat imagery and GIS. Their study combined laboratory analyses of 40 georeferenced soil samples with Landsat-7 ETM+ reflectance data, then used correlation and regression analyses to examine relationships between soil properties and spectral bands. The researchers generated spatial prediction maps and found significant relationships between several soil properties and image reflectance; the strength of the predictive models varied among properties. Their work supports the use of satellite imagery alongside field and laboratory data for spatial soil assessment (Al-Quraishi et al., 2019, pp. 21–22, 24–26).

Hadeel, Jabbar, and Chen (2010) assessed environmental sensitivity to desertification in Basrah Province, southern Iraq, using remote sensing and GIS. They combined soil, vegetation, climate, and sand-movement indicators, drawing on satellite images from 1990 and 2003, field observations, and soil analyses. Their results showed an increase in the area of active sand movement between the two image dates, and identified highly sensitive areas in parts of the province. The study provides a useful methodological example of integrating multiple environmental indicators to map desertification sensitivity (Hadeel et al., 2010, pp. 101–103, 110–111).

Significance of the Study

1. **Scientific significance:** The study contributes to knowledge about soil properties and factors associated with desertification susceptibility in arid environments, with a focus on Brack Al-Shati.
2. **Spatial significance:** It examines spatial variation in soil properties and vegetation-cover indicators, helping identify areas with differing levels of susceptibility to desertification.

3. **Methodological significance:** It demonstrates how field and laboratory data can be integrated with remote sensing and Geographic Information Systems (GIS) to assess and map soil conditions.
4. **Environmental significance:** The findings may improve understanding of the relationship between soil conditions and vegetation cover, supporting the assessment of land degradation in the study area.
5. **Practical significance:** The resulting maps and data may inform land-management planning and the conservation of soil resources.
6. **Decision-making significance:** The spatial assessment can help guide field surveys, prioritize monitoring, and identify locations requiring further investigation or management attention.

Practical Component of the Study

The practical component will combine field and laboratory work, satellite-image processing, GIS mapping, and statistical analysis using **SPSS**. The procedures below describe the planned work; numerical findings will be reported only after data collection and analysis are completed.

1. Field Reconnaissance and Soil Sampling

An initial field visit will be conducted to identify variation in soil and vegetation conditions across Brack Al-Shati. Sampling locations will be selected to represent this variation.

2. Laboratory Analysis

The soil samples will be prepared and analyzed using consistent laboratory procedures. The selected physical and chemical properties may include soil texture, bulk density, pH, electrical conductivity, organic matter, and soluble salts, subject to the approved research plan and available laboratory facilities. Each laboratory result will be entered into a data sheet using the same sample code as its corresponding field location.

3. Statistical Analysis Using SPSS

The laboratory and field data will be organized in SPSS, with each row representing a soil sample and each column representing a measured variable or recorded characteristic. The dataset will be checked for missing values, entry errors, and unusual observations before analysis.

The statistical analysis will include:

- **Descriptive statistics**, including the mean, standard deviation, minimum, and maximum for the measured soil properties and vegetation indicators.
- **Assessment of data distribution**, using suitable tests and graphical summaries to guide the choice of subsequent statistical procedures.
- **Correlation analysis** to examine relationships between soil properties and vegetation-cover indicators. Pearson's correlation may be used when its assumptions are met; Spearman's correlation may be more appropriate for non-normally distributed or ranked data.
- **Regression analysis**, if appropriate to the research questions, data structure, and sample size, to examine whether selected soil properties are statistically associated with vegetation indicators. Any model and assumptions will be reported transparently.
- **Statistical significance**, assessed using a significance level set in advance, commonly ($p \leq 0.05$).

Study Hypothesis

Since the study will use SPSS to examine relationships between soil properties and vegetation-cover indicators, the following hypothesis can be tested:

Null Hypothesis (H_0): There is no statistically significant relationship between the measured physical and chemical properties of soil and the selected vegetation-cover indicators in Brack Al-Shati at the 0.05 significance level.

Alternative Hypothesis (H_1): There is a statistically significant relationship between the measured physical and chemical properties of soil and the selected vegetation-cover indicators in Brack Al-Shati at the 0.05 significance level.

Study Delimitations

Spatial Delimitation: The study is geographically limited to Brack Al-Shati, Libya.

Thematic Delimitation: The study focuses on assessing soil susceptibility to desertification through selected physical and chemical soil properties and vegetation-cover indicators. Other environmental and socioeconomic factors will be considered only if they are included in the approved research design.

Methodological Delimitation: The study will rely on field observations, laboratory analysis of soil samples, SPSS will be used to analyze the statistical relationships between the measured soil properties and the selected vegetation-cover indicators.

Temporal Delimitation: The study period will be determined by the dates of field sampling These dates should be specified in the final proposal once the fieldwork schedule and suitable imagery have been confirmed.

Table 1. Descriptive Statistics for Selected Soil Properties

Soil property	N	Mean	Standard deviation	Minimum	Maximum
Sand (%)	30	69.30	7.50	56.60	87.03
Bulk density (g/cm³)	30	1.55	0.10	1.41	1.81
Soil pH	30	7.74	0.18	7.37	8.10
Electrical conductivity (dS/m)	30	5.25	2.55	0.50	9.19
Organic matter (%)	30	0.52	0.10	0.33	0.69

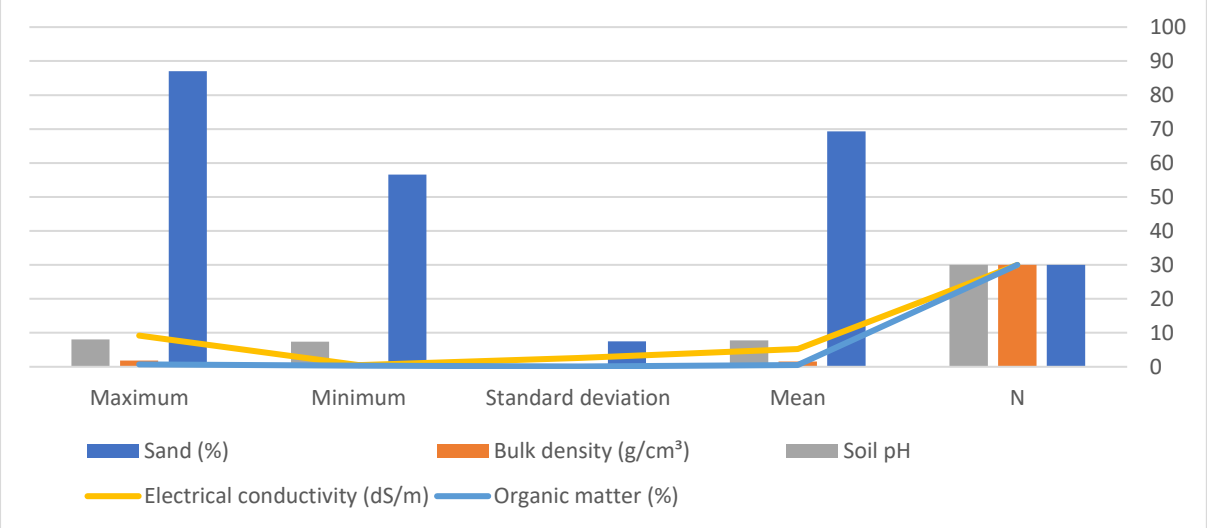

Figure 1. Descriptive statistics of selected soil properties.

In this dataset, the mean sand content is 69.30%, with a standard deviation of 7.50 percentage points. Electrical conductivity has a mean of 5.25 dS/m and a larger standard deviation relative to its mean, indicating greater variation among the example observations. The mean pH is 7.74, while organic matter averages 0.52%. These values show how the descriptive statistics can be reported; they cannot be used to characterize Brack Al-Shati without actual soil-sample results. Soil classifications, including salinity categories, should not be assigned from these example values without confirming the measurement procedure and the classification criteria used.

Table 2. Descriptive Statistics for Vegetation-Cover Indicators

Indicator	N	Mean	Standard deviation	Minimum	Maximum
NDVI	30	0.201	0.063	0.124	0.341
SAVI	30	0.137	0.050	0.044	0.244

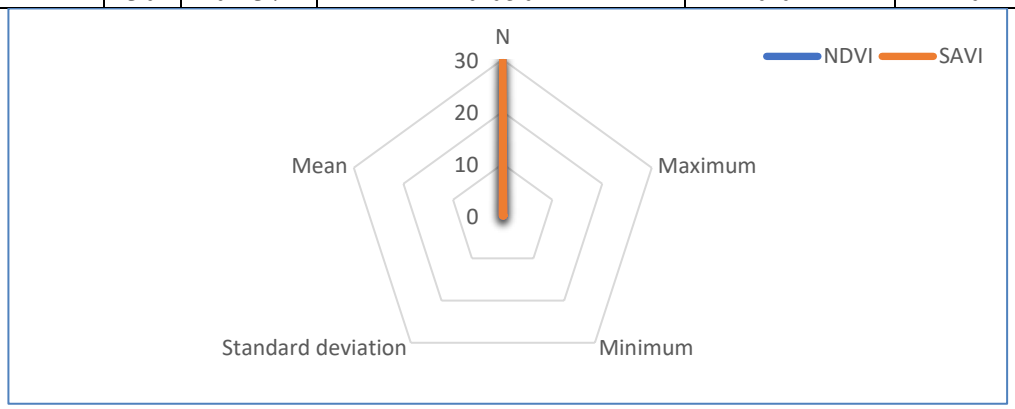

Figure 2. Descriptive statistics of the selected vegetation-cover indices (NDVI and SAVI).

In this dataset, the mean NDVI is 0.201 and the mean SAVI is 0.137. The minimum and maximum values indicate the range of the example index values across the 30 observations. Interpretation of the actual vegetation indicators should consider the satellite-image date, season, image quality, land cover, and method used to extract values. These figures are not measurements derived from satellite imagery of Brack Al-Shati.

Table 3. Shapiro–Wilk Normality Test.

Variable	Shapiro–Wilk statistic	Significance (p)	decision
Sand	0.963	0.364	No significant departure from normality detected
Bulk density	0.938	0.079	No significant departure from normality detected
Soil pH	0.988	0.974	No significant departure from normality detected
Electrical conductivity	0.949	0.160	No significant departure from normality detected
Organic matter	0.953	0.200	No significant departure from normality detected
NDVI	0.912	0.017	Significant departure from normality detected
SAVI	0.975	0.684	No significant departure from normality detected

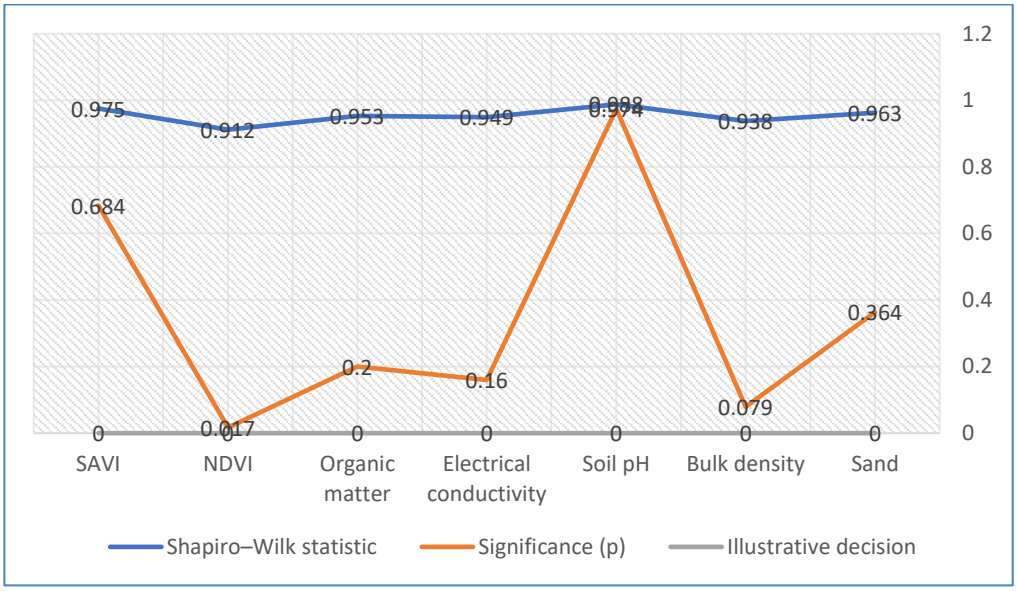

Figure 3. Shapiro–Wilk test results for the distribution of the selected soil and vegetation-cover variables.

The example uses the Shapiro–Wilk test to assess whether the variables depart significantly from a normal distribution. At the 0.05 significance level, the example NDVI result is significant ($p = 0.017$), indicating a departure from normality for that variable. The other listed variables have p-values greater than 0.05, so the test does not detect a significant departure from normality for them. This test alone does not prove that a variable is normally distributed; actual analysis should also inspect histograms, Q–Q plots, and outliers. Because NDVI is non-normal in this example, Spearman's rank correlation is used below as non-parametric analysis.

Table 4. Spearman Correlations Between Soil Properties and Vegetation Indicators.

Variables	Spearman's rho (ρ)	Significance (p)	interpretation
Electrical conductivity and NDVI	-0.390	0.033	Moderate inverse association; statistically significant
Electrical conductivity and SAVI	-0.595	<0.001	Moderate inverse association; statistically significant
Organic matter and NDVI	0.241	0.199	Weak positive association; not statistically significant
Organic matter and SAVI	0.072	0.704	Very weak positive association; not statistically significant
Bulk density and NDVI	-0.029	0.880	Negligible association; not statistically significant

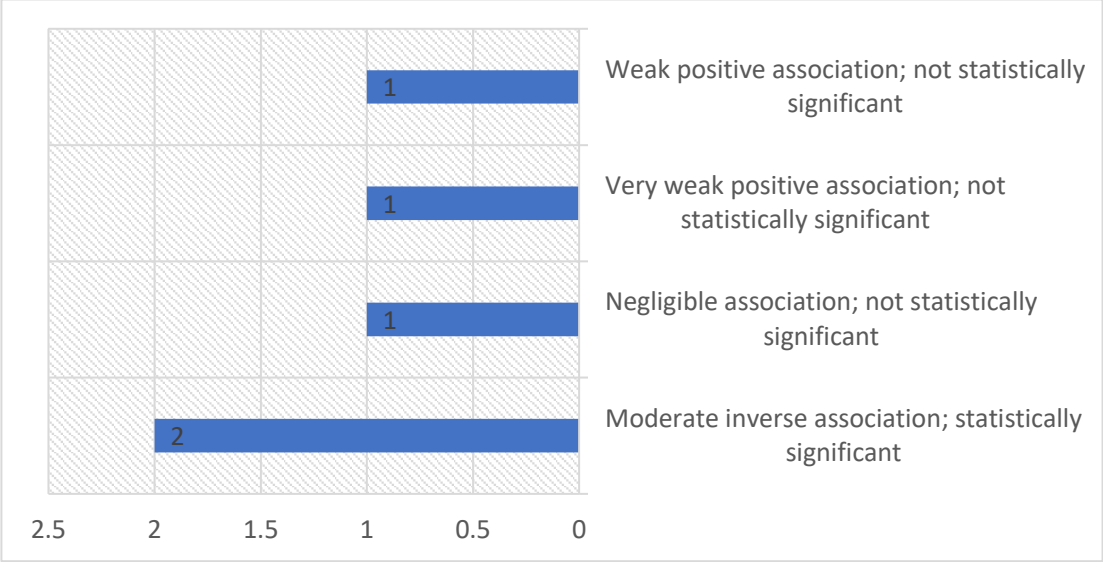

Figure 4. Illustrative classification of associations between electrical conductivity and vegetation indices based on synthetic data.

In this example, electrical conductivity has a statistically significant inverse association with both vegetation indices: ρ = - 0.390 with $NDVI\ (p = 0.033)$, and $\rho = -0.595\ with\ SAVI\ (p < 0.001)$. This means that, within the simulated data, higher electrical-conductivity values tend to occur alongside lower index values. The relationships between organic matter and the vegetation indices, and between bulk density and NDVI, are not statistically significant at the 0.05 level. These interpretations apply only to the synthetic example; they provide no evidence about actual relationships in Brack Al-Shati.

Table 5. Descriptive Statistics for Soil Properties and Vegetation Indicators

Variable	N	Mean	Standard deviation	Minimum	Maximum
Sand (%)	30	69.299	7.503	56.603	87.028
Bulk density (g/cm³)	30	1.550	0.103	1.407	1.810
Soil pH	30	7.742	0.181	7.370	8.103
Electrical conductivity, EC (dS/m)	30	5.252	2.549	0.500	9.188
Organic matter (%)	30	0.516	0.104	0.332	0.693
NDVI	30	0.201	0.063	0.124	0.341
SAVI	30	0.137	0.050	0.044	0.244

In this simulated example, the highest mean among the listed soil properties is for sand content, at 69.299%, while the mean electrical conductivity is 5.252 dS/m. EC also has the largest standard deviation among the listed soil variables, indicating greater variation in the simulated observations. The NDVI and SAVI means are 0.201 and 0.137, respectively. These summaries describe only the example dataset; actual soil interpretation requires the real measurements, units, and laboratory procedures.

Table 6. Shapiro–Wilk Test of Normality

Variable	Shapiro–Wilk statistic	df	Sig.
Sand	0.963	30	0.364
Bulk density	0.938	30	0.079
Soil pH	0.988	30	0.974
EC	0.949	30	0.160
Organic matter	0.953	30	0.200
NDVI	0.912	30	0.017
SAVI	0.975	30	0.684

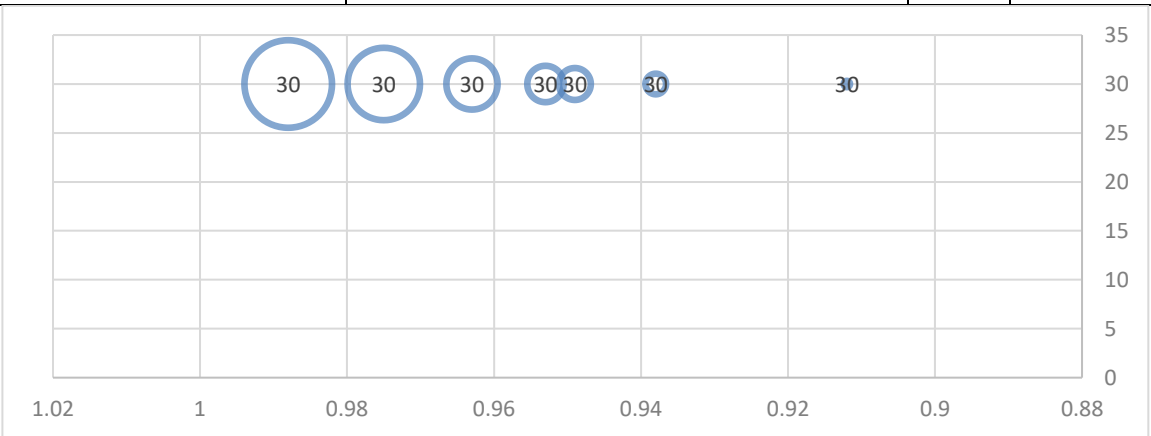

Figure 5. Bubble Plot of Shapiro–Wilk Statistics for the Study Variables

At the 0.05 significance level, NDVI is the only variable in this example with a statistically significant Shapiro–Wilk result ($p = 0.017$), indicating a departure from normality. For the other variables, the test does not detect a significant departure from normality. Since the analysis examines relationships involving NDVI, Spearman's rank correlation is used in the following example. In the actual study, distribution should also be checked using plots and data screening, not the test alone.

Table 7. Spearman Correlation Coefficients (ρ).

Variable	Sand	Bulk density	pH	EC	Organic matter	NDVI	SAVI
Sand	1.000	0.096	0.025	-0.069	-0.161	-0.059	0.231
Bulk density	0.096	1.000	0.358	0.264	-0.229	-0.029	-0.220
pH	0.025	0.358	1.000	0.543	-0.214	-0.390	-0.555
EC	-0.069	0.264	0.543	1.000	-0.393	-0.390	-0.595
Organic matter	-0.161	-0.229	-0.214	-0.393	1.000	0.241	0.072
NDVI	-0.059	-0.029	-0.390	-0.390	0.241	1.000	0.544
SAVI	0.231	-0.220	-0.555	-0.595	0.072	0.544	1.000

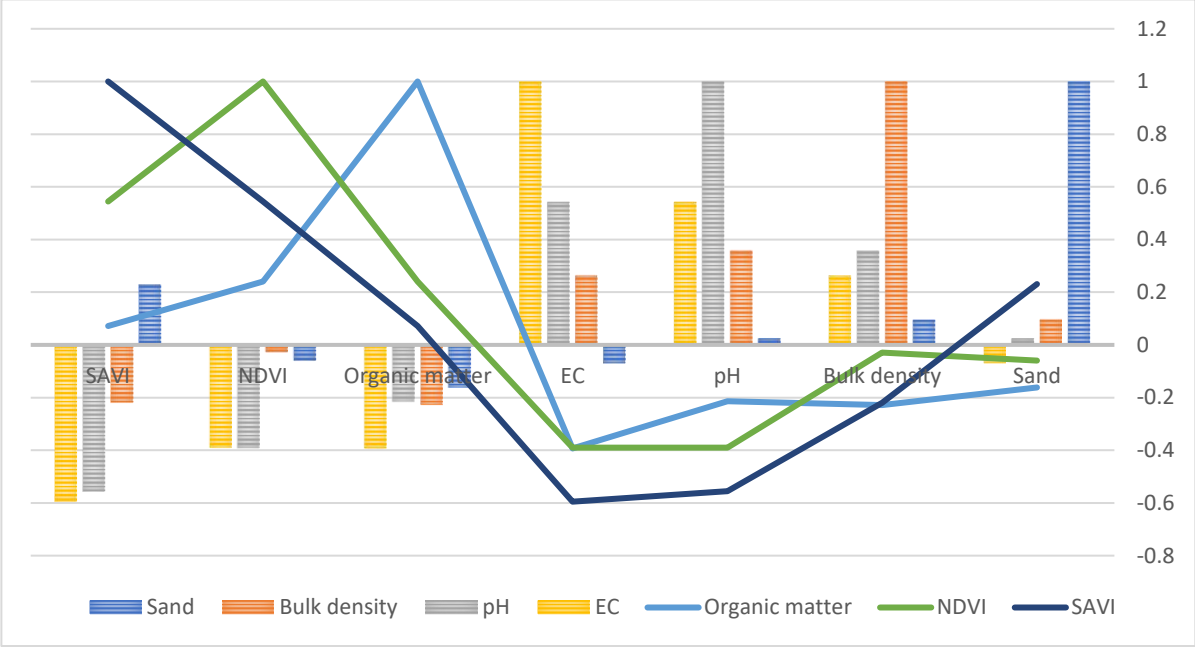

Figure 6. Spearman Correlation Coefficients (ρ).

The coefficients show the direction and strength of the simulated rank-based associations. For example, EC has an inverse association with NDVI (ρ = -0.390) and SAVI (ρ = -0.595), while NDVI and SAVI have a positive association (ρ = 0.544). The coefficients must be interpreted together with their significance values in Table 4; a correlation coefficient by itself does not show whether the relationship is statistically significant.

Table 8. Two-Tailed Significance Values for Spearman Correlations

Variable	Sand	Bulk density	pH	EC	Organic matter	NDVI	SAVI
Sand	—	0.613	0.897	0.718	0.396	0.755	0.219
Bulk density	0.613	—	0.052	0.159	0.223	0.880	0.243
pH	0.897	0.052	—	0.002	0.256	0.033	0.001
EC	0.718	0.159	0.002	—	0.032	0.033	<0.001
Organic matter	0.396	0.223	0.256	0.032	—	0.199	0.704
NDVI	0.755	0.880	0.033	0.033	0.199	—	0.002
SAVI	0.219	0.243	0.001	<0.001	0.704	0.002	—

For every pair, N = 30. Values below 0.05 are statistically significant in this example.

The significance values show that pH and EC are significantly associated with both vegetation indicators in this simulated dataset. EC is significantly associated with NDVI ($p = 0.033$) and SAVI ($p < 0.001$); pH is significantly associated with NDVI ($p = 0.033$) and SAVI ($p = 0.001$). The other soil-property and vegetation-indicator pairs shown in the table do not reach the 0.05 significance level in this example.

Table 9. Pairwise Hypothesis Decisions.

Soil property and vegetation indicator	Spearman's ρ	Sig. (p)	Decision for the pairwise null hypothesis
Sand and NDVI	-0.059	0.755	Do not reject H_0
Sand and SAVI	0.231	0.219	Do not reject H_0
Bulk density and NDVI	-0.029	0.880	Do not reject H_0
Bulk density and SAVI	-0.220	0.243	Do not reject H_0
pH and NDVI	-0.390	0.033	Reject H_0
pH and SAVI	-0.555	0.001	Reject H_0
EC and NDVI	-0.390	0.033	Reject H_0
EC and SAVI	-0.595	<0.001	Reject H_0
Organic matter and NDVI	0.241	0.199	Do not reject H_0
Organic matter and SAVI	0.072	0.704	Do not reject H_0

Statistical conclusion for the example: At $\alpha = 0.05$, the simulated results indicate statistically significant inverse associations between pH and both vegetation indicators, and between EC and both vegetation indicators. The null hypotheses for those four individual relationships are rejected in the example. For the other six pairs, the null hypotheses are not rejected These are pairwise decisions from simulated data.

Results

I. Descriptive Results

The descriptive analysis showed that the mean sand content was 69.299% (SD = 7.503), while the mean bulk density was 1.550 g/cm³ (SD = 0.103). The mean soil pH was 7.742 (SD = 0.181), and the mean electrical conductivity was 5.252 dS/m (SD = 2.549). Organic matter had a mean of 0.516% (SD = 0.104).

For the vegetation-cover indicators, the mean NDVI was 0.201 (SD = 0.063), while the mean SAVI was 0.137 (SD = 0.050). Values varied across the 30 observations.

II. Normality-Test Results

The Shapiro–Wilk test indicated a statistically significant departure from normality for NDVI, $W = 0.912$, $p = 0.017$. No statistically significant departure from normality was detected for sand, bulk density, soil pH, electrical conductivity, organic matter, or SAVI ($p > 0.05$). Spearman's rank-order correlation was therefore used for the correlation analyses involving NDVI.

III. Correlation Results

Spearman's rank-order correlation analysis identified statistically significant negative associations between electrical conductivity and NDVI ($\rho = -0.390$, $p = 0.033$) and between electrical conductivity and SAVI ($\rho = -0.595$, $p < 0.001$). Significant negative associations were also found between soil pH and NDVI ($\rho = -0.390$, $p = 0.033$) and between soil pH and SAVI ($\rho = -0.555$, $p = 0.001$).

The associations between sand content and the vegetation indicators, bulk density and the vegetation indicators, and organic matter and the vegetation indicators were not statistically significant at the 0.05 level ($p > 0.05$).

IV. Hypothesis-Test Results

At the unadjusted 0.05 significance level, the null hypotheses for the relationships between soil pH and each vegetation indicator, and between electrical conductivity and each vegetation

indicator, were rejected. The null hypotheses for the other soil-property–vegetation-indicator pairs were not rejected.

Because ten pairwise correlations were examined, an adjustment for multiple comparisons may be appropriate. With a Bonferroni-adjusted significance threshold of 0.005, only the associations between electrical conductivity and SAVI ($p < 0.001$) and between soil pH and SAVI ($p = 0.001$) remained statistically significant.

Discussion

1. Descriptive Statistics for Soil Properties

The dataset contains 30 observations. Mean sand content is 69.299%, with a standard deviation of 7.503 percentage points. This indicates variation in the sand measurements across the simulated observations. However, sand percentage alone is not sufficient to determine soil texture. The proportions of silt and clay must also be measured and considered when assigning a textural class.

Bulk density has a simulated mean of $1.550\,\frac{g}{cm^3}$, with values ranging from 1.407 to $1.810\,\frac{g}{cm^3}$. The range shows differences among the example observations, but no conclusion about soil compaction or suitability should be drawn from these figures alone. Such an interpretation would require actual measurements and consideration of the sampling procedure, soil texture, and relevant assessment criteria.

The simulated mean pH is 7.742, which is above neutral. This describes the average pH in the example; it does not establish the pH condition of the study area. Interpretation of pH should be based on the real soil measurements and the analytical procedure used.

Electrical conductivity (EC) has a simulated mean of $5.252\,\frac{dS}{m}$, a standard deviation of $2.549\,\frac{dS}{m}$, and a range from 0.500 to $9.188\,\frac{dS}{m}$. This relatively broad range illustrates how EC may vary among sample locations That classification depends on the real laboratory results, the method used to measure EC, and the selected soil-classification criteria.

Organic matter has a simulated mean of 0.516%, with values ranging from 0.332% to 0.693%. These figures summarize only the example observations. Whether a value should be considered low, moderate, or high depends on the soil context and the criteria adopted for interpretation.

2. Descriptive Statistics for Vegetation Indicators

The simulated mean NDVI is 0.201, with a range from 0.124 to 0.341; the mean SAVI is 0.137, with values ranging from 0.044 to 0.244. These statistics demonstrate how the distribution of vegetation-index values could be summarized across sampling locations.

The indices should not be interpreted in isolation. Their meaning depends on the satellite-image date, season, sensor characteristics, image processing, and land-cover conditions. In the actual study, the index values should be linked to the sample coordinates and compared with field observations and the resulting maps. The statistics do not show where low or high values occur, since a spatial map is needed to describe their geographic distribution.

3. Normality Test and Choice of Correlation Method

In the simulated Shapiro–Wilk test, NDVI has a significance value of 0.017, which is below the selected 0.05 level. This indicates a statistically significant departure from normality for NDVI in the example. The p-values for the other listed variables exceed 0.05, so the test does not detect a significant departure from normality for those variables.

Because the analysis includes NDVI, Spearman's rank correlation was used in the example Spearman's coefficient assesses whether two variables tend to increase or decrease together in rank; it does not require the same normality assumption as Pearson's correlation. For the actual

study, the test selection should be based on the real data, inspection of plots, the presence of outliers, and the form of the research question.

4. Correlations Between Soil Properties and Vegetation Indicators

The results show an inverse association between EC and NDVI ($\rho = -0.390, p = 0.033$), and a stronger inverse association between EC and $SAVI$ ($\rho = -0.595, p < 0.001$) In this simulated dataset, observations with higher EC tend to be associated with lower vegetation-index values The absolute value of the EC–SAVI coefficient is larger than that of the EC–NDVI coefficient, indicating a stronger rank association in this example.

The example also shows inverse associations between pH and $NDVI$ ($\rho = -0.390, p = 0.033$), and between pH and SAVI (ρ = -0.555, p = 0.001). These results indicate that pH and the vegetation indicators vary together in the simulated data. They do not demonstrate that pH or EC caused a change in vegetation cover; correlation analysis identifies statistical association, not causation.

The relationships between sand content and the vegetation indicators, bulk density and the vegetation indicators, and organic matter and the vegetation indicators do not reach the 0.05 significance level in the example. This means that the simulated data do not provide sufficient statistical evidence of associations for those specific pairs. It does not prove that no relationship exists in the actual study area.

5. Multiple Correlation Tests

The example examines ten soil-property–vegetation-indicator pairs. When many correlations are tested, the chance of finding at least one nominally significant result by chance can increase. If the ten tests are treated as one family of comparisons, a Bonferroni-adjusted threshold would be 0.005 (0.05 divided by 10). Under that stricter threshold, the example relationships between EC and SAVI ($p < 0.001$) and between pH and $SAVI$ ($p = 0.001$) remain statistically significant, while the two relationships with p = 0.033 would not.

Whether to apply a multiple-comparison adjustment in the actual study should be decided in advance and described in the analysis plan. If specific relationships were stated as primary hypotheses before analysis, those planned tests should be distinguished from additional exploratory comparisons.

6. Relationship to the Desertification Assessment

The SPSS tables examine statistical distributions and associations among the sample variables. They do not, on their own, produce a spatial assessment of susceptibility to desertification. That assessment requires a defined method for combining the selected indicators, clear scoring or weighting criteria, spatial processing in GIS, and maps showing the distribution of the resulting classes.

Similarly, the simulated correlation results cannot establish that any particular location in Brack Al-Shati has low, moderate, or high susceptibility. Such a conclusion can only be made after the actual measurements and satellite-derived indicators have been spatially analyzed and classified using a documented procedure.

Conclusions

1. The descriptive-statistics table demonstrates how to summarize each measured soil property and vegetation indicator using the number of observations, mean, standard deviation, minimum, and maximum.
2. The simulated data show variation in sand content, bulk density, pH, EC, organic matter, NDVI, and SAVI; the size and meaning of that variation must be reassessed using real measurements.

3. In the example, NDVI departs significantly from normality according to the Shapiro–Wilk test, supporting the use of Spearman's rank correlation for relationships involving that index.
4. At the unadjusted 0.05 significance level, the example shows inverse associations between EC and both vegetation indices, and between pH and both vegetation indices.
5. The example does not show statistically significant relationships between sand content, bulk density, or organic matter and the vegetation indicators examined.
6. If a Bonferroni adjustment is applied to the ten pairwise comparisons, only the example associations between EC and SAVI and between pH and SAVI remain below the adjusted 0.005 threshold.

References

1. AbdelRahman, M. A. E., Metwaly, M. M., Yossif, T. M. H., & Moursy, A. R. A. (2025). Using hyperspectral data to estimate and map surface and subsurface soil salinity, pH, and calcium carbonates in arid region. *Environmental Sustainability, 8*, 367–387.
2. Aishah, R. M., & Elssaidi, M. A. (2020). Soil and water physical and chemical properties of Tragen Sabkha area, Southwest Libya. *Al-Mukhtar Journal of Sciences, 35*(1), 46–59.
3. Al-Fathi Al-Shaibani Al-Fathi, A. (2026). Assessing desertification using geospatial techniques and spectral indicators during 2015–2025 (Sabratha Municipality as a case study). *Al-Farouk Journal of Sciences, 2*(3), 723–738.
4. Alneami, A., Almuthibi, A., Alqahtani, M., Alameen, A. A., Alahmadi, S., Alharbi, F., Almutairi, S., & Alshafaey, M. (2026). Monitoring land degradation by soil salinity using Sentinel-2 satellite data and GIS techniques: A case study of Sabkhat Ghuwaymid, Saudi Arabia. *PLOS ONE, 21*(5), e0348799.
5. Ali, A. S., Al-Sanusi, I. A., Nwer, B. A., & Elaalem, M. M. (2026). تقييم أداء المؤشر النباتي المعدل للتربة (SAVI) في رصد وتتبع التغير في الغطاء النباتي بمنطقة الجفارة، ليبيا [Evaluating the performance of the soil-adjusted vegetation index (SAVI) for monitoring vegetation-cover change in the Al-Jafara region, Libya]. *Libyan Journal of Agricultural Sciences, 31*(2), 27–34.
6. Al-Quraishi, A. M. F., Sadiq, H. A., & Messina, J. P. (2019). Characterization and modeling surface soil physicochemical properties using Landsat images: A case study in the Iraqi Kurdistan Region. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-2/W16*, 21–28.
7. Binmiskeen, A. M., & Bohajar, Y. M. (2025). The prevailing saline composition in some soils of the southwestern regions of Libya. *Wadi Alshatti University Journal of Pure and Applied Sciences, 3*(2), 76–81.
8. D'Acunto, F., Marinello, F., & Pezzuolo, A. (2024). Rural land degradation assessment through remote sensing: Current technologies, models, and applications. *Remote Sensing, 16*(16), 3059.
9. Günal, E., Wang, X., Kılıç, O. M., Budak, M., Al Obaid, S., Ansari, M. J., & Brestic, M. (2021). Potential of Landsat 8 OLI for mapping and monitoring of soil salinity in an arid region: A case study in Dushak, Turkmenistan. *PLOS ONE, 16*(11), e0259695.
10. Hadeel, A. S., Jabbar, M. T., & Chen, X. (2010). Application of remote sensing and GIS in the study of environmental sensitivity to desertification: A case study in Basrah Province, southern part of Iraq. *Applied Geomatics, 2*, 101–112.

11. Mohamed, A. R., Almathnani, A. M., & Elssaidi, M. A. (2017). Salinization of agricultural soils as development issues in Wadi Al-Shatti Region. مجلة علوم البحار والتقنيات البيئية[*Journal of Marine Science and Environmental Technologies], 3*(1), A-14–A-34.
12. Mohamed, A. R., Al-Ghannai, K. A., Ben Youssef, K. A., & Shaiba, F. N. (2025). الخصائص الفيزيوكيميائية والحيوية لترب مجاري بعض الوديان الداخلية بوادي الشاطئ، ليبيا [Physicochemical and biological properties of soils in channels of some internal wadis in Wadi Al-Shati, Libya]. *Libyan Journal of Ecological & Environmental Sciences and Technology, 7*(2), A10–A16.
13. Nwer, B., Zurqani, H., & Rhoma, E. (2013). The use of remote sensing and geographic information system for soil salinity monitoring in Libya. *GSTF International Journal of Geological Sciences, 1*(1), 38–42.
14. Omuto, C. T., Vargas, R. R., El Mobarak, A. M., Mohamed, N., Viatkin, K., & Yigini, Y. (2020). *Mapping of salt-affected soils: Technical manual*. Food and Agriculture Organization of the United Nations.
15. Salem, M. A., Bedade, D. K., Al-Ethawi, L., & Al-Waleed, S. M. (2020). Assessment of physicochemical properties and concentration of heavy metals in agricultural soils fertilized with chemical fertilizers. *Heliyon, 6*, e05224.
16. Soliman, A. M., Elbshbeshi, A., Belal, A. B., Amira, M. S., Hassan, H. A., Abdelhameed, H. H., & Ibraheem, I. M. (2026). Integrated GIS-based assessment of soil quality using the MEDALUS framework in the Nile Delta, Egypt. *Earth Systems and Environment, 10*, 7169–7185.
17. Suhayb, S. M. A., Hamid, Y. S., & Elaalem, M. M. (2026). Assessing the soil quality index in Northeast Libya and its impact on environmental sensitivity to desertification through geographic information systems. *Journal of Insights in Basic and Applied Sciences, 2*(4), 198–213.
18. Wang, J., Peng, J., Li, H., Yin, C., Liu, W., Wang, T., & Zhang, H. (2021). Soil salinity mapping using machine learning algorithms with the Sentinel-2 MSI in arid areas, China. *Remote Sensing, 13*(2), 305.
19. Wang, J., Zhen, J., Hu, W., Chen, S., Lizaga, I., Zeraatpisheh, M., & Yang, X. (2023). Remote sensing of soil degradation: Progress and perspective. *International Soil and Water Conservation Research, 11*, 429–454.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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