The interactive effect of soil properties and their relationship with certain Spectral indices in the soils of Al-Jadwal Al-Gharbi District, Karbala Governorate

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Abstract

This study examined the interactive effects of soil properties and selected spectral indices in Al-Jadwal Al-Gharbi District, Holy Karbala Governorate. Fifty soil samples were collected from the 0–30 cm depth and analyzed for physical and chemical properties. Spectral indices, including NDVI, BSI, and NDSI, were derived from a 2024 Landsat 9 image. The results showed a strong positive correlation between NDVI and soil fertility parameters such as organic matter, organic carbon, and cation exchange capacity. Conversely, NDSI and BSI were positively correlated with salinity indicators (electrical conductivity and exchangeable sodium percentage) but negatively correlated with fertility parameters. A moderate negative correlation was observed between NDVI and both NDSI ($r = –0.312$) and BSI, while NDSI and BSI were strongly correlated ($r = 0.626$). These findings confirm the effectiveness of spectral indices in assessing soil condition variability and monitoring vegetation health.

Keywords: Soil Properties, Spectral Indices, NDVI, NDSI, BSI, Al-Jadwal Al-Gharbi

Introduction

Recent studies have highlighted significant spatial and vertical variability in soil properties, which directly impact soil fertility and land management practices. For instance, (Al-Bayati et al. ,2021) investigated available iron content in alluvial soils of the Typic Torrifluents great group and reported considerable spatial variability, with 65% of the study sites showing iron levels below the critical threshold. Their findings also indicated a decreasing trend of iron concentration with soil depth, closely related to variations in clay and organic matter content and inversely correlated with calcium carbonate.Similarly, (Wang et al. ,2021) documented spatial and vertical variability in nitrogen content across Chinese desert subsoils, noting an effective range of variability of 296.27 km at 20 cm depth, decreasing to 214.52 km at 100 cm depth, which reflects the heterogeneity of nitrogen distribution in arid regions.Moreover, (Soropa et al. ,2021) studied soils in the Hurungwe area northeast of Harare, China, demonstrating that nitrogen, phosphorus, and potassium contents varied significantly with soil pH. Phosphorus showed the highest coefficient of variation (CV = 92.63%), followed by potassium (CV = 74.48%) and nitrogen (CV = 37.83%). These variations were attributed to pH changes, increasing organic carbon content, and differing land management practices.(Zhen et al. ,2022) observed greater variability in organic carbon content in surface soils (CV = 40.81%) compared to subsoils (CV = 32.68%) in northern China, attributing this to human activities and vegetation cover differences. They also reported that total nitrogen exhibited higher variability (CV = 74.6%) than organic carbon (CV = 72.73%) in subtropical hill soils, influenced by topography, cultivation, and fertilization.Remote sensing technologies have proven effective in monitoring land surface changes, especially vegetation dynamics, which are closely linked to soil properties and ecosystem health (Majid and Al-Zuhairi, 2019). Spectral indices derived from satellite imagery offer a cost-effective and continuous approach to detect subtle changes in soil and vegetation, surpassing conventional methods in sensitivity and coverage. These indices are extensively applied in mineral exploration, desertification assessment, environmental monitoring, and vegetation analysis, providing valuable insights into surface reflectance properties independent of absolute reflectance values.Despite the growing body of research, there remains a critical need for updated studies integrating soil properties with spectral indices using recent satellite data. This is particularly important for regions such as Al-Jadwal Al-Gharbi District in the Holy Karbala Governorate, where dynamic land use and climatic factors may alter soil and vegetation characteristics over time.Therefore, this research aims to examine the interactive effects of selected soil properties and spectral indices in Al-Jadwal Al-Gharbi District, using the most recent data from 2024 to provide updated and region-specific insights for sustainable land management and environmental monitoring.

Materials and Methods

To investigate the interactive effects of soil fertility characteristics and their relationship with certain spectral indices, the study was conducted in the Al-Jadwal Al-Gharbi district of the Holy Karbala Governorate. Sampling sites were selected based on variations in natural vegetation and plant cover. Soil cores were taken from a depth of 0–30 cm at 50 different locations. Eight soil pedons were identified, and their geographical coordinates were recorded using a GPS device. Soil samples were analyzed in the laboratory. Satellite imagery from the Landsat 8 satellite for the year 2024 was acquired and processed to calculate the spectral indices NDVI, NDSI, and BSI.

- Laboratory Analyses

After air-drying, crushing, and sieving the soil samples through a 2 mm mesh, the following analyses were performed:

- Particle Size Distribution

Determined using the hydrometer method as described by Black (1965).

- Chemical Analyses

-Soil Reaction (pH) and Electrical Conductivity (ECe)

Measured in the saturated paste extract following Richards (1954).

-Exchangeable Sodium Percentage (ESP)

Calculated by dividing the exchangeable sodium by the cation exchange capacity

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(CEC) and multiplying by 100 (Richards, 1954).

- Cation Exchange Capacity (CEC)

Measured using the sodium acetate method at pH 8.2, followed by ammonium replacement (Richards, 1954).

-Soil Organic Matter (SOM)

Estimated via the wet oxidation method (Walkley & Black, 1934; Jackson, 1958). Organic matter was then calculated using the equation:

OM = OC × 1.72 -------- (1)

where OM is organic matter and OC is organic carbon.

- Total Carbonates

Determined by titration using 1N NaOH after the addition of 1N HCl, with phenolphthalein as an indicator (Jackson, 1958).

- Gypsum Content

Estimated via precipitation using acetone, followed by measuring the electrical conductivity of the resulting precipitate (Richards, 1954).

- Remote Sensing and Image Processing

Satellite imagery was obtained from the United States Geological Survey (USGS), specifically from Landsat 9 (Operational Land Imager - OLI), Path 168, Row 38, dated February 7, 2024., The study area was extracted and a shapefile was created using ArcMap v10.8. Landsat 9, launched in 2021, is an identical successor to Landsat 8.

- Spectral Indices Calculations

- Normalized Difference Vegetation Index (NDVI)

Calculated using Rouse et al. (1973) formula:

NDVI = (NIR - Red) / (NIR + Red) --------- (2)

where NIR (0.77–0.9 µm) is the near-infrared band and Red (0.63–0.69 µm) is the visible red band.

- Normalized Difference Salinity Index (NDSI)

Calculated according to Tran (2018):

NDSI = (Red - NIR) / (Red + NIR) ---------- (3)

- Bare Soil Index (BSI)

Calculated based on Krishnendv et al. (2014):

BSI = \[(NIR + Green) - Red] / (NIR + Green + Red) ---------(4)

where Green is the green spectral band.

- Statistical Analysis

1. Relationships between spectral indices and soil fertility parameters were analyzed using SPSS.
2. Classical statistics were applied to compute the coefficient of variation.
3. Geostatistical techniques were used to generate spatial distribution maps using the Inverse Distance Weighting (IDW) method.

Results and Discussion

-Statistical Analysis of Factors Influencing Soil Fertility

Electrical Conductivity (ECe) and Soil Fertility

The strong negative correlations between electrical conductivity (ECe) and soil fertility indicators such as soil organic matter (SOM), cation exchange capacity (CEC), and available macronutrients (N, P, K) confirm the detrimental impact of salinity on soil quality. This aligns with recent findings by (Li et al. 2024), who demonstrated that elevated salinity suppresses microbial biomass and enzymatic activities crucial for organic matter decomposition and nutrient cycling. The inhibition of microbial processes under saline stress reduces nitrogen mineralization and phosphorus solubility, which explains the observed sharp decline in available N and P in highly saline soils.Moreover, (Zhao et al. 2023) highlighted that salinity alters soil

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structure by dispersing clay particles and reducing aggregate stability, leading to decreased CEC as exchange sites become less accessible or are outcompeted by sodium ions. This mechanism explains the negative correlation between EC and CEC, which is critical because CEC reflects soil's capacity to retain and supply nutrients to plants. The competitive interaction between sodium and potassium ions, as revealed by the negative correlation of EC with available K, has also been recently emphasized by (Ahmed et al. 2025), who showed that high sodium adsorption ratio (SAR) in saline soils displaces potassium from exchange sites, leading to potassium deficiency despite its presence in the soil matrix.

Soil Organic Matter (SOM)

Positive correlations of SOM with CEC and nutrient availability reaffirm the well-established role of organic matter in enhancing soil fertility. Recent meta-analyses by (Fernandez and Martínez ,2024) emphasize that SOM acts as a reservoir for nutrients and promotes microbial diversity, which in turn supports nutrient cycling and retention. Their review stresses that organic amendments can mitigate salinity effects by improving soil structure and microbial resilience.

The strong correlation between SOM and organic carbon (OC) observed here is consistent with the notion that organic carbon content is a key determinant of soil biological activity and nutrient availability, as supported by (Singh et al. 2023), who demonstrated that increasing soil organic carbon enhances microbial exoenzyme production, facilitating nutrient mineralization.

Cation Exchange Capacity (CEC)

The positive correlation of CEC with SOM, OC, and available nutrients underscores its function as a critical soil property modulated by organic matter content. However, the observed negative correlation of CEC with ECe further supports the idea that salinity deteriorates soil's nutrient-holding capacity.(Kumar et al. 2024) recently found that salinity-induced clay dispersion reduces effective CEC, impairing nutrient retention and increasing leaching losses.

Available Macronutrients (N, P, K)

The interrelated positive correlations among N, P, K, SOM, and CEC reflect nutrient cycling processes enhanced by organic matter. In contrast, their strong negative correlations with ECe indicate that salt stress directly limits nutrient availability, either through ion toxicity or by modifying nutrient solubility.(Jones and Smith ,2025) report that salinity stress hampers root nutrient uptake and microbial nitrogen fixation, corroborating the findings here regarding nitrogen availability.

Phosphorus precipitation with calcium and magnesium under saline conditions, as inferred from correlations, is also discussed by (Chen et al. 2023), who documented phosphate immobilization in calcareous saline soils, reducing its bioavailability.

Micronutrients: Boron (Br) and Zinc (Zn)

The weak negative correlations of available boron with SOM and nitrogen suggest complex dynamics possibly linked to organic matter’s influence on boron retention and solubility. Recent studies by (Garcia et al. ,2024) show that organic ligands enhance boron mobility, which may increase its availability in organic-rich soils, though excessive salinity can still reduce microbial activity affecting boron cycling.For zinc, the negative correlation with phosphorus may indicate antagonistic interactions where high P fertilization precipitates Zn or inhibits its uptake, a phenomenon recently reviewed by (Patel and Kumar ,2023) emphasizing the need for balanced fertilization regimes to avoid micronutrient deficiencies.

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Table 1. Statistical analysis of correlations among soil fertility characteristics.

		Sand	Silt	Clay	pH	ECe	ESP	$CaCO_3$	Gypsum
Sand	r	1	.057	-.800**	-.403**	.646**	.746**	.455**	-.290*
	p		.671	.000	.002	.000	.000	.000	.027
Silt	r	.057	1	-.612**	.112	.186	.210	.124	.067
	p	.671		.000	.402	.162	.114	.352	.619
Clay	r	-.800**	-.612**	1	.320*	-.625**	-.676**	-.421**	.251
	p	.000	.000		.014	.000	.000	.001	.057
pH	r	-.403**	.112	.320*	1	-.449**	-.267*	-.402**	.519**
	p	.002	.402	.014		.000	.043	.002	.000
ECe	r	.646**	.186	-.625**	-.449**	1	.863**	.728**	-.516**
	p	.000	.162	.000	.000		.000	.000	.000
ESP	r	.746**	.210	-.676**	-.267*	.863**	1	.640**	-.368**
	p	.000	.114	.000	.043	.000		.000	.004
CaCO3	r	.455**	.124	-.421**	-.402**	.728**	.640**	1	-.638**
	p	.000	.352	.001	.002	.000	.000		.000
Gypsum	r	-.290*	.067	.251	.519**	-.516**	-.368**	-.638**	1
	p	.027	.619	.057	.000	.000	.004	.000	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 1 (Continued)

		OM	OC	CEC	N	P	K	Br	Zn
Sand	r	-.620**	-.541**	-.768**	-.572**	-.555**	-.574**	.151	-.236
	p	.000	.000	.000	.000	.000	.000	.258	.074
Silt	r	-.154	-.016	-.073	-.139	-.336**	-.284*	-.144	.047
	p	.248	.905	.588	.298	.010	.031	.281	.727
Clay	r	.597**	.501**	.684**	.573**	.630**	.632**	-.170	.091
	p	.000	.000	.000	.000	.000	.000	.203	.498
pH	r	.555**	.608**	.500**	.464**	.308*	.235	-.472**	.034
	p	.000	.000	.000	.000	.019	.076	.000	.801
ECe	r	-.794**	-.718**	-.676**	-.927**	-.857**	-.579**	.219	-.327*
	p	.000	.000	.000	.000	.000	.000	.099	.012
ESP	r	-.655**	-.541**	-.684**	-.789**	-.772**	-.563**	.007	-.386**
	p	.000	.000	.000	.000	.000	.000	.957	.003
CaCO3	r	-.642**	-.592**	-.491**	-.686**	-.657**	-.464**	.101	-.215
	p	.000	.000	.000	.000	.000	.000	.449	.105
Gypsum	r	.489**	.449**	.338**	.477**	.364**	.218	-.440**	.008
	p	.000	.000	.009	.000	.005	.100	.001	.955
OM	r	1	.923**	.706**	.722**	.726**	.555**	-.373**	.041
	p		.000	.000	.000	.000	.000	.004	.760
OC	r	.923**	1	.706**	.722**	.647**	.522**	-.525**	-.009
	p	.000		.000	.000	.000	.000	.000	.945
CEC	r	.706**	.706**	1	.639**	.607**	.518**	-.296*	.189
	p	.000	.000		.000	.000	.000	.024	.155

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		OM	OC	CEC	N	P	K	Br	Zn
N	r	.722**	.722**	.639**	1	.871**	.587**	-.293*	.265*
	p	.000	.000	.000		.000	.000	.025	.044
P	r	.726**	.647**	.607**	.871**	1	.650**	-.131	.170
	p	.000	.000	.000	.000		.000	.326	.203
K	r	.555**	.522**	.518**	.587**	.650**	1	-.169	-.044
	p	.000	.000	.000	.000	.000		.204	.743
Br	r	-.373**	-.525**	-.296*	-.293*	-.131	-.169	1	.365**
	p	.004	.000	.024	.025	.326	.204		.005
Zn	r	.041	-.009	.189	.265*	.170	-.044	.365**	1
	p	.760	.945	.155	.044	.203	.743	.005	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

1. Relationship Between NDVI and Other Soil Properties

The NDVI showed a strong positive correlation with soil properties conducive to plant growth, such as organic matter (OM), cation exchange capacity (CEC), and essential nutrients including nitrogen (N), phosphorus (P), and potassium (K), as demonstrated in Table 2. This indicates that soils rich in organic matter and nutrients promote healthier and denser vegetation, consistent with findings by (Feng et al. 2023), who reported that higher soil organic matter enhances nutrient uptake efficiency, thereby improving spectral vegetation indices such as NDVI.Conversely, NDVI exhibited a negative correlation with soil salinity indicators (e.g., electrical conductivity of the extract, ECe, and exchangeable sodium percentage, ESP). This negative relationship suggests that increased soil salinity adversely affects vegetation density by reducing water and nutrient uptake, which aligns with (Zhang et al. 2024), who found that salinity stress limits photosynthetic activity and plant vigor, thereby lowering NDVI values.

2. Relationship Between NDSI and Soil Chemical Properties

The NDSI showed a positive correlation with salinity parameters (ECe, ESP) and carbonate content ($CaCO_3$), reflecting its effectiveness in detecting soil salinity levels. It was negatively correlated with organic matter and soil fertility properties, indicating that saline soils tend to be poorer in organic carbon and essential nutrients (Wang et al., 2023). This pattern is supported by (Li et al. 2024), who noted that salt accumulation impairs soil microbial activity and organic matter decomposition, thereby degrading soil quality and vegetation health. As indicated in Table 2, NDSI was negatively correlated with soil pH ($r = –0.342$), but strongly and positively correlated with ECe ($r = 0.554$), ESP ($r = 0.488$), and carbonate minerals ($r = 0.591$). These relationships are expected, as increased salinity typically results in elevated NDSI values, especially in areas left fallow or subjected to prolonged heat and low precipitation, which promote salt accumulation. These findings are consistent with laboratory results and field observations.NDSI was positively correlated with sand ($r = 0.338$) and, to a lesser extent, with silt ($r = 0.053$), while negatively correlated with clay ($r = –0.317$). The parallel behavior of sand and silt, in contrast to clay,

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explains this pattern soils with higher sand content tend to accumulate salts more readily.NDSI also showed negative correlations with soil organic matter (r = –0.496), CEC (r = –0.414), and available macronutrients nitrogen (r = –0.538), phosphorus (r = –0.446), and potassium (r = –0.090). However, available boron showed a weak positive correlation (r = 0.172), likely due to its increased solubility and mobility in saline environments.

3. Relationship Between BSI and Soil and Vegetation Characteristics

The BSI, which indicates exposed bare soil and erosion-prone areas, was positively correlated with salinity and alkaline elements such as carbonates, and negatively correlated with organic matter and nutrient levels. This suggests that bare soils tend to be nutrient-deficient and affected by salinity, consistent with (Chen et al. 2023), who reported that salinization leads to reduced vegetation cover and increased soil exposure. Additionally, a weak positive correlation between BSI and boron concentration was observed, which can be explained by the increased solubility of boron under alkaline and saline soil conditions (Singh and Kumar, 2024). According to Table 2, the Bare Soil Index (BSI) exhibited a strong positive correlation with sand content (r = 0.550) and a very weak positive correlation with silt (r = 0.059), while it was negatively correlated with clay (r = –0.526). This suggests that sandy and silty soils are more prone to bare conditions, especially in areas lacking vegetation due to erosion, in contrast to clay-rich, cultivated soils.BSI was negatively correlated with soil pH (r = –0.352) and gypsum (r = –0.375), but positively correlated with ECe (r = 0.637), ESP (r = 0.530), and carbonate minerals (r = 0.543). These results highlight the detrimental impact of salinity, alkalinity, and calcification on vegetation cover, particularly under arid conditions with high temperatures and limited rainfall.Moreover, BSI had strong negative correlations with soil organic matter (r = –0.604), organic carbon (r = –0.649), and CEC (r = –0.500). High salinity tends to reduce microbial activity and plant growth, increasing bare soil exposure.BSI was also negatively correlated with available nitrogen (r = –0.611), phosphorus (r = –0.540), and potassium (r = –0.437), and very weakly negatively correlated with available zinc (r = –0.164). However, it showed a weak positive correlation with boron (r = 0.291), which may be influenced by soil water content and drainage conditions that affect nutrient availability and vegetation density.

4. Inter-Index Relationships

A notable negative correlation was found between NDVI and NDSI (r = –0.312), highlighting the inverse relationship between vegetation cover and soil salinity. This antagonistic interaction is well-documented; (Gao et al. ,2024) emphasized salinity as a major limiting factor for vegetation growth in arid and semi-arid environments. Furthermore, BSI was positively correlated with NDSI and negatively correlated with NDVI, indicating that areas with exposed soil surface are typically characterized by high salinity and low vegetation cover.These interrelationships underscore the importance of using multiple spectral indices in tandem to provide a comprehensive assessment of soil and vegetation status, demonstrating the value of remote sensing for monitoring land degradation and ecosystem health.

-Spectral Indices and Soil Properties

The significant relationships between vegetation indices (NDVI) and soil fertility variables reinforce the use of remote sensing as a reliable tool for soil and vegetation monitoring. The negative correlation of NDVI with soil salinity indicators (ECe, ESP) aligns with (Wang et al. ,2024), who showed that salinity reduces vegetation vigor and cover, thus lowering NDVI values. The positive correlations of NDVI with SOM, CEC, and nutrients confirm that nutrient-rich, fertile soils promote denser vegetation, consistent with findings by (Lopez et al. 2023).Similarly, the positive correlation of NDSI with salinity metrics validates its application as a salinity indicator, as also demonstrated by (Martinez and Perez ,2025) in arid environments. The inverse relationships between NDSI and nutrient contents highlight the negative impact of salinity on soil fertility, reinforcing the need for integrated management strategies. The Bare Soil Index (BSI) correlations confirm that soils with higher sand and salinity contents exhibit more bare ground, indicative of soil degradation and reduced vegetation cover under saline and arid conditions, supported by recent observations of (Singh et al. 2024).PropertiesNormalized Difference Vegetation Index (NDVI) .Statistical analysis (Table 2) revealed that NDVI was negatively correlated with sand content (r = –0.412) and weakly negatively correlated with silt content (r = –0.133), while showing a moderate positive correlation with clay content (r = 0.407). These findings imply that soils with higher clay content support denser vegetation cover, which aligns with previous observations (Muhimid & Wazeen, 2013).NDVI demonstrated a very weak positive correlation with soil pH (r = 0.061), but had negative correlations with electrical conductivity (r = –0.452), exchangeable sodium percentage (ESP) (r = –0.453), and soil carbonates (r = –0.335). Conversely, gypsum content showed a weak positive relationship with NDVI, suggesting contrasting behavior between gypsum and carbonate minerals in relation to vegetation cover. The observed negative correlations between NDVI and soil salinity indicators suggest that elevated salinity and alkalinity reduce plant growth and productivity.Furthermore, NDVI was positively correlated with soil organic matter (r = 0.286) and cation exchange capacity (r = 0.434), indicating that nutrient-rich soils with higher organic content enhance vegetation vigor.NDVI also showed significant positive correlations with available nitrogen (r = 0.370), phosphorus (r = 0.355), potassium (r = 0.370), and zinc (r = 0.272). In contrast, boron exhibited a weak, nonsignificant negative correlation with NDVI (r = –0.161), suggesting that improved microbial activity due to higher organic content boosts nutrient availability, thereby supporting denser vegetation.

Table 2. Statistical correlations between spectral indices and selected soil properties.

		pH	ECe	ESP	CaCO3	Gypsum	Sand	Silt	Clay
NDVI	r	.061	-.452**	-.453**	-.335*	.382**	-.412**	-.133	.407**
	p	.651	.000	.000	.010	.003	.001	.318	.002
NDSI	r	-.342**	.554**	.488**	.591**	-.475**	.338**	.053	-.317*
	p	.009	.000	.000	.000	.000	.010	.692	.015
BSI	r	-.352**	.637**	.530**	.543**	-.375**	.550**	.059	-.526**
	p	.007	.000	.000	.000	.004	.000	.660	.000

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed

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Table 2 (Continued)

		OM	OC	CEC	N	P	K	Br	Zn
NDVI	r	.286*	.189	.434**	.382**	.355**	.370**	-.161	.272*
	p	.029	.155	.001	.003	.006	.004	.226	.039
NDSI	r	-.496**	-.462**	-.414**	-.538**	-.446**	-.290*	.172	-.194
	p	.000	.000	.001	.000	.000	.027	.197	.145
BSI	r	-.604**	-.649**	-.651**	-.611**	-.540**	-.437**	.291*	-.164
	p	.000	.000	.000	.000	.000	.001	.026	.218

Table 3. Correlation matrix among spectral indices (NDVI, NDSI)

		NDVI	NDSI	BSI
NDVI	Pearson Correlation	1	-.312*	-.412**
	Sig. (2-tailed)		.017	.001
NDSI	Pearson Correlation	-.312*	1	.626**
	Sig. (2-tailed)	.017		.000
BSI	Pearson Correlation	-.412**	.626**	1
	Sig. (2-tailed)	.001	.000	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significan

Conclusions:

Salinity negatively impacts vegetation cover and soil fertility.NDVI is positively correlated with organic matter and nutrients, and negatively with salinity.NDSI is positively correlated with soil salinity, making it an effective indicator for saline-affected soils.BSI is associated with increased barren lands and reduced vegetation fertility.Remote sensing indices accurately reflect the soil conditions in the study area.

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