

Evaluating the Predictive Potential of NDVI and MSAVI for Soil Properties in the Rangeland of Southern Al-Jabal Al-Akhdar, Libya

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Abstract

This study was conducted in the southern Al-Jabal Al-Akhdar in northeastern Libya to investigate the possibility of predicting certain soil properties using the Normalized Difference Vegetation Index (NDVI) and the Modified Soil Adjusted Vegetation Index (MSAVI). A large number of soil samples were collected from 28 sites in the study area. A linear regression model was used with the spectral indicators as independent variables and soil properties as dependent variables. The results showed a positive relationship between all the studied soil properties and the selected indicators, although the correlation was weakly positive for most properties. It was noted that some properties achieved significance levels up to 100%. The results indicated the superiority of MSAVI over NDVI, as correlation coefficients were higher with all studied soil properties except for pH, where NDVI outperformed MSAVI. Although the average R^2 values were less than 0.52 in all models, the possibility of predicting soil properties using these indicators is feasible since all correlation relationships were positive regardless of their strength. On the other hand, it is clear that the NDVI and MSAVI indices calculated from the Landsat ETM+ sensor of the Landsat satellite is unsuitable for predicting surface soil properties in the study area, as the correlation coefficient did not exceed 0.52. This may be attributed to low accuracy (30m pixel size). It is suitable for assessing and mapping vegetation cover since it covers a vast area, but this feature is considered a disadvantage for predictive models. Therefore, it is recommended to use higher resolution images (5 or 1m pixel size), which may yield positive results, especially for the properties that had a significance level of 100% in all repetitions.

Keywords. NDVI, MSAVI, Soil Properties, Soil Prediction, Landsat 7 ETM+.

Introduction

Soil is considered one of the most valuable natural resources and provides an essential environmental medium for all terrestrial living organisms [1]. Sustainable land management and land-use planning require reliable information on the spatial distribution of soil's physical and chemical properties, which affect all landscape functions. Despite numerous studies conducted to identify spatial patterns of soil property distribution at various scales and in different landscapes, little is known about the underlying relationships behind the spatial distribution of soil properties. The spatial and temporal assessment of soil properties is important for sustainable agricultural, hydrological, and environmental management [2,3]. However, the rapid and reliable assessment of soil properties has become one of the major challenges in environmental monitoring. Traditional field sampling and laboratory analysis to determine and monitor soil properties are accurate but time-consuming and require significant effort to obtain the necessary number of samples.

Few studies have been conducted to investigate the possibility of predicting the chemical and physical properties of soil using remote sensing technology, which is considered a highly efficient and cost-effective means of gathering information about land cover. Remote sensing can provide data on vegetation cover, its health, and monitor its growth stages. Various methods have been explored in many studies, leading to the development of numerous analytical techniques that utilize remote sensing data and take advantage of spectral vegetation indices (SVI) as indicators.

The Normalized Difference Vegetation Index (NDVI) has been employed to predict soil moisture [4] and nutrient cycling in soil [5]. However, no regional or local studies have been conducted on this, except for a single study that explored the possibility of predicting soil surface condition indicators using the vegetation index in the southern Green Mountain area [6]. All the aforementioned studies confirmed a strong positive correlation between NDVI values and certain soil properties. Collecting soil samples for analysis is a difficult process that requires time, effort, and money, especially when the area to be covered is large, as is the case in Libya. Therefore, the use of remote sensing technology will save time, money, and effort, especially if a model is successfully designed to calculate soil properties using spectral vegetation indices. The research aims to explore the possibility of using remote sensing technology to predict certain chemical and physical soil properties at the local level in the Green Mountain area by using NDVI and the Modified Soil-Adjusted Vegetation Index (MSAVI). Additionally, it seeks to determine which of the two indices is more suitable for the local conditions.

Methods

Study area

The study area, as shown in (Figure 1), is located on the southern slope of the Green Mountain region in northeastern Libya. It is situated approximately at 32°N and 21°E, covering an area of about 3000 square kilometers. The climatic factors of the study area can be summarized as follows. The region enjoys a mild to hot climate, with temperatures ranging from 10°C to 30°C. The average minimum temperature is 0.5°C, while the maximum can reach 50°C. The humidity is relatively low, with the average monthly humidity exceeding 50% from February to September, and reaching around 80% from December to January.

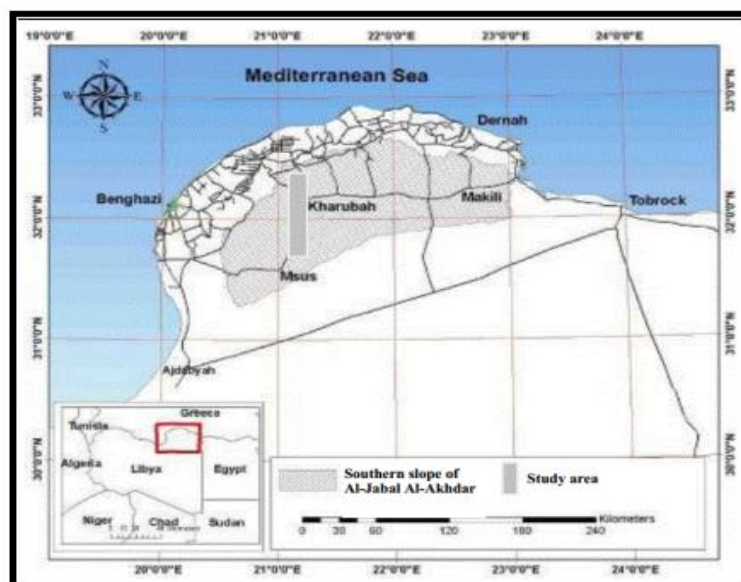


Figure 1. A map of the Green Mountain with the study area highlighted

The winds are predominantly from the northwest in the summer and from the northeast in the winter. The region is also affected by southerly winds (the "Qibli" wind), which are hot and often accompanied by sandstorms. The average wind speed is 10-25 km/h, occasionally reaching up to 60 km/h. The highest sunshine intensity is around 600 calories/cm² during June and July, while the lowest intensity ranges between 178-256 calories/cm² during December and January. Rainfall in the area occurs from September to March and is characterized by variability and irregularity. The highest annual rainfall is around 350 mm/year. The area is covered by woody shrubs with succulent stems and leaves, with *Haloxylon* and *Anabasis articulata* being the most common genera [7].

Site Selection

A total of 28 sites were selected across the study area using Systematic Random Sampling, to ensure comprehensive and balanced coverage of all parts of the region while minimizing bias.

Soil Sampling

From each site, 8 soil samples were collected using a Systematic Sub-sampling approach, where the sampling points were evenly distributed to represent the internal variability of the site. The total number of samples collected was 224 soil samples. Samples were taken from the predetermined depth (0–20 cm) in accordance with the objective of the study. The samples were placed in clean plastic bags, and the information for each site (geographical coordinates, date of sampling, and site notes) was recorded to ensure proper documentation. The chemical and physical soil properties were measured as follows:

Field Capacity (Moisture)

Field moisture was measured by the weight difference of the samples before and after drying in an oven at 105°C for 24 hours

Field Capacity (Water Holding Capacity)

The tension method was used to estimate the soil's field capacity [8].

Soil Texture

The hydrometer method was used, where the soil was treated with hydrogen peroxide to remove organic matter, followed by soil particle dispersion using Calgon solution. The proportions of sand, silt, and clay were then determined.

Organic Matter Content

Organic matter content was estimated using the ignition method. A 10-gram soil sample was dried in an oven at 105°C for 24 hours to determine the dry weight. The sample was then returned to an oven at 450°C for 24 hours, and the weight difference was used to calculate the organic matter content.

PH (Hydrogen Ion Concentration)

The pH was measured using a pH meter after saturating the soil sample with distilled water. After one hour, equilibrium was achieved, and the pH was directly measured by the meter.

Electrical Conductivity

Electrical conductivity of the soil samples was determined in their aqueous extract using a conductivity meter (E.L.E.), and results were expressed in millimhos per centimeter (mmhos/cm).

Calcium Carbonate Content

A specific weight of the soil samples was treated with sulfuric acid, and the calcium carbonate content was calculated based on the volume of carbon dioxide released using a calcimeter.

Available Phosphorus

Available phosphorus was measured using a spectrophotometer.

Nitrogen Content

The Kjeldahl method was used to measure nitrogen content. Ammonia gas was trapped in boric acid, then titrated with sodium hydroxide.

Micronutrients

Iron, zinc, manganese, and copper content were measured using Atomic Absorption Spectroscopy (AAS), and the results were expressed in parts per million (ppm).

Remote Sensing Data

Landsat 7 satellite imagery was used to calculate selected spectral vegetation indices. Previous research indicates that the Landsat Enhanced Thematic Mapper Plus (ETM+) system has been useful for calculating vegetation index values to monitor and map land degradation over large areas [9]. Therefore, we attempted to test this system, which covers large areas and saves time and money. The satellite imagery was captured in September 2006, with eight bands as shown in (Table 1). The imagery used was from the same year as the soil samples were collected and analyzed (2006), and it is freely available from the U.S. Geological Survey.

Table 1. Specifications and Data of the Selected satellite imagery.

Landsat	Instrument	Acquisition date	Path /row	Spectral bands		Resolution/ m
				band	Wavelength (µm)	
Landsat 7	ETM+	Sep.2006	183/38	1	0.45 - 0.52	30
				2	0.525 - 0.60	30
				3	0.63 - 0.69	30
				4	0.77 - 0.90	30
				5	1.55 - 1.75	30
				6	10.40 - 12.5	60
				7	2.09 - 2.35	30
				8	0.52 - 0.90	15

ERDAS Imagine V.9 software was used for radiometric and geometric correction of the satellite images and to calculate the values of the NDVI and MSAVI indices. The nearest neighbor method was used to handle gaps in the image resulting from radiometric errors. For atmospheric errors, linear regression was applied using ERDAS Imagine software. Geometric errors were corrected using the Universal Transverse Mercator (UTM) projection system for geometric adjustment. GIS data from the 28 ground points were used to correct the geometric errors and verify their accuracy. The selected indices were calculated using the following equations:

$$\text{NDVI} = (\text{NIR} - \text{R}) / (\text{NIR} + \text{R}) \dots \text{Equation 1}$$

$$\text{MSAVI} = ((2\text{NIR} + 1 - \sqrt{((2\text{NIR} + 1)^2 - 8(\text{NIR} - \text{R})))}) / 2 \dots \text{Equation 2*}$$

Where: NIR = Near-Infrared band, R = Red band

A linear relationship was assumed between the values of the selected spectral indices and certain soil properties. In other words, soil properties could be predicted using the NDVI and MSAVI indices. A linear

regression model was applied between the soil properties and the selected spectral indices to test this hypothesis.

Statistical Analysis

A total of 28 values for each index were calculated from the 28 sites where soil samples were collected in 2006. A linear regression model was applied using SPSS software at a significance level of 5%. 70% of the paired samples were randomly selected for the prediction model, while the remaining 30% were used for evaluation. This process was repeated three times to estimate the average correlation coefficient (R^2) for both the prediction and evaluation models.

Results and Discussion

Soil Chemical and Physical Properties

(Tables 2 and 3) present the results of laboratory analyses for the chemical and physical properties of the soil in the study area. Most sites were characterized by low field moisture and low field capacity.

The pH values across all sites were alkaline, which is expected due to the predominance of calcium carbonate as the parent material. The majority of sites showed a significant decrease in organic matter, which is typical for arid and semi-arid areas.

From the mechanical soil analysis results, we observed a decrease in clay content in the southern sites of the study area. Nitrogen levels were generally low across all sites, ranging from 0.01 to 0.31. There was also a lack of available phosphorus in most of the study sites. As for the micronutrients, all sites suffered from an iron deficiency, with an average of 6 ppm, and zinc, which did not exceed 3.4 ppm. Manganese was abundant in all sites, in contrast to copper, which had very low values.

Table 2. Some chemical and physical properties of the soil at the study sites under investigation

Site Number	Percentage of Organic Matter (%)	Electrical Conductivity (mmhos)	pH Value	Mechanical Analysis(%)			Soil moisture content (%)	
				Clay	Silt	Sand	"Field Capacity"	Field Moisture
1	5.17	13.23	7.48	40.60	41.06	15.29	37.12	2.63
2	0.99	13.99	7.58	43.34	40.90	14.22	39.37	7.12
3	2.11	12.45	7.32	44.88	39.20	14.99	36.87	5.39
4	2.58	13.13	7.40	46.00	38.90	15.10	39.12	4.62
5	2.34	16.51	7.32	47.23	37.88	14.89	39.50	4.44
6	2.24	26.12	7.44	44.20	40.40	15.40	38.87	4.85
7	2.43	21.14	7.31	44.60	40.20	15.20	38.75	5.62
8	3.10	2.82	7.81	43.10	41.30	15.60	44.12	3.66
9	2.90	19.36	7.54	44.50	40.55	14.95	37.75	3.90
10	2.05	7.79	7.69	43.50	41.20	15.30	37.50	5.36
11	1.72	6.80	7.65	45.20	39.10	15.70	36.12	3.40
12	2.06	22.63	7.54	44.60	39.90	15.50	38.87	5.93
13	3.25	35.50	7.22	35.40	32.80	29.26	35.37	4.00
14	2.23	35.50	7.25	37.50	33.50	28.58	34.37	3.18
15	1.40	41.00	7.55	34.40	36.30	29.30	32.25	3.61
16	2.78	14.55	7.92	39.71	31.30	28.99	32.50	2.81
17	4.00	19.00	7.70	31.50	39.50	29.00	35.37	1.56
18	4.80	03.50	7.55	40.25	33.20	26.55	34.50	2.38
19	3.70	28.39	7.52	36.60	33.20	30.20	34.50	1.97
20	2.83	32.83	7.42	36.30	33.60	30.10	34.37	2.07
21	2.61	03.67	7.87	32.60	37.40	30.00	37.62	3.41
22	2.93	12.38	7.37	38.48	32.30	29.22	35.12	1.20
23	2.68	47.98	7.43	34.32	36.40	27.61	33.00	2.69
24	1.67	12.81	8.02	33.20	36.00	27.40	35.00	2.80
25	4.08	41.06	7.50	33.00	38.20	28.80	31.62	1.95
26	1.65	41.55	7.40	32.50	36.20	27.85	32.50	1.00
27	2.09	40.48	7.52	27.61	29.60	41.16	33.75	2.30
28	3.36	25.33	7.97	27.75	29.40	41.14	33.37	2.05

Table 3. Some chemical and physical properties of the soil at the study sites under investigation

Site Number	Micronutrients ppm						Calcium Carbonate %	Phosphorus ppm	Nitrogen %
	K	Na	Fe	Zn	Mn	Cu			
1	827.5	866.62	13.61	3.4	78.68	3.60	2.07	12.26	0.31
2	757.1	931.25	6.66	2.9	20.25	2.18	2.08	3.75	0.22
3	761.3	931.50	5.86	.22	27.38	2.37	3.66	3.86	0.02
4	983.7	869.62	8.49	2.3	45.90	2.38	2.99	6.61	0.24
5	1597	1113	6.13	1.8	39.00	2.07	4.08	5.45	0.09
6	720	1251	9.00	1.9	26.7	1.96	13.90	3.65	0.20
7	618.7	1270	5.15	1.3	18.09	1.87	4.74	3.38	0.06
8	1207.9	556.5	11.87	2.7	36.75	2.18	5.76	14.02	0.10
9	1044.7	1182.1	10.82	1.9	43.32	2.57	7.71	8.75	0.07
10	825.1	950.1	11.54	1.2	69.79	2.36	3.77	2.92	0.06
11	978	740	7.32	1.9	36.80	1.76	2.26	8.54	0.08
12	1107	1185	7.41	1.4	45.10	1.63	8.03	9.91	0.08
13	1060	2900	9.90	1.4	14.70	1.00	33.00	11.00	0.04
14	1072	2950	4.80	1.5	6.70	0.90	28.00	07.70	0.04
15	901	3123	2.80	1.0	3.20	0.70	31.00	5.60	0.04
16	1268	790	2.50	1.2	6.30	0.70	31.00	3.30	0.02
17	984.6	1090	4.78	0.8	5.75	0.73	34.21	9.11	0.03
18	1095	500.1	4.93	0.9	11.15	0.61	27.64	9.53	0.04
19	1201	1797.7	4.72	1.0	10.85	0.77	29.94	10.94	0.04
20	810.3	2158.6	5.04	0.7	6.28	1.29	28.71	7.23	0.04
21	1341.7	573.5	3.45	1.0	9.03	0.73	22.09	6.72	0.04
22	858.7	972.7	3.26	1.2	4.68	0.73	26.19	17.32	0.02
23	1234.3	1737.7	2.32	0.9	3.23	0.75	37.00	6.56	0.04
24	1445.4	1021.3	3.34	1.0	4.08	0.85	30.81	6.72	0.01
25	986.9	1482.3	2.17	0.8	3.68	0.65	39.74	7.11	0.03
26	981.3	1581.3	2.02	1.0	3.72	0.64	38.40	6.97	0.02
27	997	1660.4	3.65	0.7	2.94	0.74	32.91	6.56	0.01
28	1075	893.1	3.57	0.8	3.01	0.64	35.12	3.30	0.01

Spectral Vegetation Indices

The average values for the soil indices were negative, ranging from -0.08 to -0.14 for the NDVI, and from 0.72 to -0.66 for the Modified Soil-Adjusted Vegetation Index (MSAVI), as shown in (Table 4). These results indicate significant variation in the vegetation indices across the sites.

Table 4. Values of Selected Spectral Vegetation Indices

Site Number	MSAVI	NDVI
1	-0.664	0.121
2	-0.663	0.122
3	-0.661	0.128
4	-0.662	0.127
5	-0.681	0.113
6	-0.683	0.110
7	-0.676	0.114
8	-0.675	0.117
9	-0.657	0.135
10	-0.657	0.136
11	-0.670	0.118
12	-0.669	0.118
13	-0.708	0.095
14	-0.696	0.121
15	-0.689	0.118
16	-0.726	0.085
17	-0.726	0.084
18	-0.725	0.085

19	-0.667	0.121
20	-0.667	0.120
21	-0.695	0.109
22	-0.680	0.113
23	-0.728	0.083
24	-0.728	0.083
25	-0.696	0.102
26	-0.689	0.109
27	-0.718	0.095
28	-0.727	0.094

Linear Regression Model between Spectral Indices and Soil Properties

1. Normalized Difference Vegetation Index (NDVI)

The results revealed a positive relationship between all the soil properties studied and the NDVI, although the correlation was weak. Some properties showed a high level of significance, reaching 100% with a positive correlation of 0.4 for copper (Tables 5 and 6). A good positive correlation was found between NDVI and sand fraction, pH, and manganese, with significance levels of 100% (Figure 5). In terms of prediction and validation, no correlation was found between NDVI and organic matter content in the surface soil, where the correlation coefficient was nearly zero in both models (0.03, 0.05), which aligns with some previous studies [10] but contrasts with others [11]. This discrepancy could be due to differences in soil types.

Table 5. Results of Three Prediction Models (NDVI)

Model	Variables	Mean R ²	% of Significant Models (p < 0.05)
Prediction	NDVI - FM	0.20	66
	NDVI - FC	0.17	66
	NDVI - Sand	0.31	100
	NDVI - Silt	0.23	100
	NDVI - Clay	0.28	100
	NDVI - PH	0.33	0
	NDVI - EC	0.01	0
	NDVI - OM	0.03	0
	NDVI - N	0.16	33
	NDVI - P	0.13	0
	NDVI - CaCO ₃	0.00	100
	NDVI - Cu	0.42	100
	NDVI - Mn	0.35	100
	NDVI - Zn	0.20	33
	NDVI - Fe	0.23	66
	NDVI - K	0.22	66

NDVI showed a weak positive correlation with nitrogen, with correlation coefficients of 0.17 and 0.24 in the prediction and evaluation models, respectively. These results are in line with previous studies, where the correlation between NDVI and total nitrogen content was 0.13[12]. A comparison with another study of Da Silva (2016) showed a similar trend in terms of the correlation between NDVI and soil texture, suggesting that NDVI could be used to infer and map soil types based on their mechanical composition [13].

Table 6. Results of Three Validation Models (NDVI)

Model	Variables	Mean R ²	% of Significant Models (p < 0.05)
	NDVI - FM	0.21	33
	NDVI - FC	0.13	33
	NDVI - Sand	0.20	33
	NDVI - Silt	0.13	0
	NDVI - Clay	0.19	0
	NDVI - PH	0.07	0
	NDVI - EC	0.09	0
	NDVI - OM	0.05	0
	NDVI - N	0.24	33

Validation	NDVI - P	0.09	0
	NDVI - CaCO ₃	0.38	33
	NDVI - Cu	0.30	33
	NDVI - Mn	0.33	66
	NDVI - Zn	0.19	0
	NDVI - Fe	0.19	0
	NDVI - K	0.11	0

2. Modified Soil-Adjusted Vegetation Index (MSAVI)

The MSAVI showed more promising results, with a positive correlation to most of the studied soil properties, though at varying degrees. The correlation coefficients ranged from 0.01 with phosphorus to 0.52 with calcium carbonate and copper (Table 7). The most evident positive correlations were found between MSAVI and the three fractions of the soil texture, calcium carbonate, copper, and manganese in validation models; however, the results were opposite to those of the prediction models for MSAVI, where the correlation coefficients decreased with most soil properties, and the significance levels decreased to below 66% (Table 8). This decrease in correlation and significance in evaluation models for both indices can be attributed to the small sample size used in the evaluation (30% of the total samples).

Table 7. Results of Three Prediction Models (MSAVI)

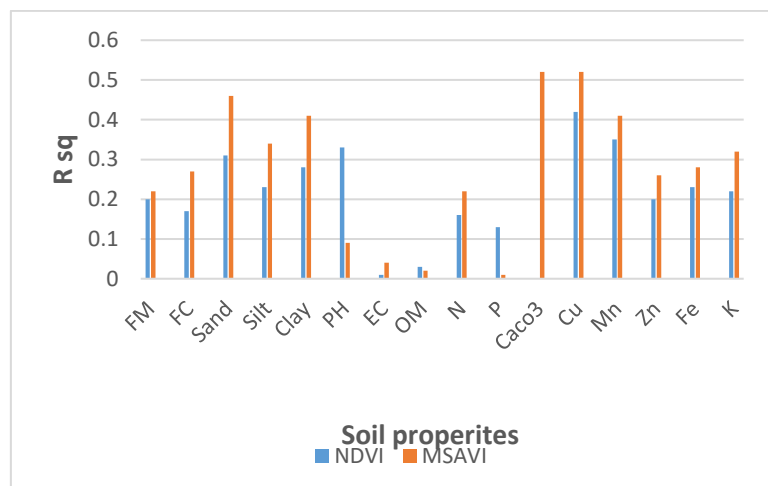
Model	Variables	Mean R ²	of significant (p<0.05) %
Prediction	MSAVI - FM	0.22	66
	MSAVI - FC	0.27	100
	MSAVI - Sand	0.46	100
	MSAVI - Silt	0.34	100
	MSAVI - Clay	0.41	100
	MSAVI - PH	0.09	0
	MSAVI - EC	0.04	0
	MSAVI - OM	0.02	0
	MSAVI - N	0.22	66
	MSAVI - P	0.01	0
	MSAVI - CaCO ₃	0.52	100
	MSAVI - Cu	0.52	100
	MSAVI - Mn	0.41	100
	MSAVI - Zn	0.26	100
	MSAVI - Fe	0.28	100
	MSAVI - K	0.32	100

Table 8. Results of Three Validation Models (NDVI)

Model	Variables	Mean R ²	of significant (p<0.05)%
Validation	MSAVI - FM	0.26	33
	MSAVI - FC	0.21	33
	MSAVI - Sand	0.34	33
	MSAVI - Silt	0.18	33
	MSAVI - Clay	0.34	66
	MSAVI - PH	0.18	33
	MSAVI - EC	0.10	0
	MSAVI - OM	0.03	0
	MSAVI - N	0.37	33
	MSAVI - P	0.11	0
	MSAVI - CaCO ₃	0.47	66
	MSAVI - Cu	0.41	33
	MSAVI - Mn	0.40	66
	MSAVI - Zn	0.27	33
	MSAVI - Fe	0.21	33
	MSAVI - K	0.15	0

Comparison between Indices

(Figure 6) shows that the MSAVI outperformed the NDVI, with higher correlation coefficients for all soil properties under study, except for pH, where NDVI outperformed MSAVI. Of particular interest is the strong contrast between the indices in their correlation with calcium carbonate, where NDVI showed no correlation ($R^2 = 0$), while MSAVI demonstrated a strong positive correlation ($R^2 = 0.52$). These results suggest that MSAVI is more reliable than NDVI when vegetation cover is low, as MSAVI was more strongly correlated with all the studied soil properties (Tables 47–50). The higher correlation values for MSAVI suggest it is better suited for areas with low vegetation cover, reducing the effect of soil brightness on NDVI values [14].



Discussion

This study provides an attempt to rapidly predict certain chemical and physical properties of soil in the southern slopes of the Green Mountain in northeastern Libya. The results may help assess soil quality and guide local land use policies and legislation. The findings confirm that both the NDVI and MSAVI are positively correlated with all soil properties, showing no negative correlations in all results. We expect that both indices can be used to predict surface soil properties locally, provided that more accurate satellite imagery is used. These results align with both empirical and theoretical studies that have confirmed the importance of the NDVI and MSAVI in predicting soil properties in arid and semi-arid regions [14, 15, and 6]. From the current results, it is clear that the NDVI and MSAVI derived from Landsat ETM+ satellite imagery is not suitable for predicting surface soil properties in the study area, as the correlation coefficients did not exceed 0.52. This could be due to the low resolution (30m pixel size) of the images, which are useful for vegetation mapping but less suitable for prediction models. Although the average R^2 values were below 0.52 across all models, predicting soil properties using these indices is still possible since all correlations were positive, albeit weak.

The MSAVI index performed significantly better than NDVI in this study, aligning with previous studies that suggest MSAVI offers several advantages over NDVI for certain soil types [5]. This finding aligns with the theoretical framework and numerous previous studies that have affirmed the importance of spectral vegetation indices, particularly in arid and semi-arid regions. For instance, a study in a roughly similar area indicated strong positive relationships between the NDVI and some soil surface condition indicators [6]. Furthermore, studies in semi-arid Spanish steppes supported the notion that spectral indices can be predictive of soil functions and properties [17, 18].

On the other hand, our results partially contradict some studies that reported stronger relationships. For example, a study found a strong correlation between NDVI and soil organic carbon ($R^2 = 0.72$) [10], whereas in our current study, the correlation was very weak ($R^2 = 0.03$ for prediction, 0.05 for validation). This discrepancy can be explained by differences in soil type, vegetation cover, and the resolution of the satellite data used. Their study utilized more advanced Landsat 8 data, while our study relied on older, less spatially resolved Landsat 7 ETM+ data (30 meters). However, the generally low R^2 values (< 0.52) across all models point to a major limitation, which can be primarily attributed to the low spatial resolution (30 meters) of the Landsat satellite imagery used. While these images are excellent for large-scale vegetation assessment, they are insufficient for predictive modeling of soil properties that change sharply over shorter distances. This limitation is consistent with cautions raised by [2], which recommended using imagery with higher spectral and spatial resolution for accurate soil property modeling. These findings are consistent with most previous studies and guide on how spectral indices can be used for soil assessment over large spatial scales [15, 17, 6]. The results also open the door for using remote sensing data for surface soil property prediction, mapping, and monitoring, which can help conserve this valuable natural resource and save time, effort, and money.

Conclusion

Although the current models using Landsat data do not provide high predictive accuracy, the consistently positive trend of all relationships, coupled with the clear superiority of MSAVI, reveals promising potential. These results confirm the validity of the methodology of using spectral indices to predict soil properties, as documented in previous literature, but they simultaneously emphasize the critical need to use higher spatial resolution remote sensing data (e.g., 5m or 1m), and potentially higher spectral resolution data (e.g., Hyperion), to achieve results with practical credibility in fragile environments like the study area.

Conflict of interest. Nil

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