Evaluating Bare Soil Properties and Vegetation Indices for Digital Farming Applications from UAV-based Multispectral Images

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***Abstract*— The possibilities of using unmanned aerial vehicles (UAVs)-based on multispectral sensors and data produced from images taken from agricultural areas in digital agriculture applications are being investigated. This research is to determine the effect of bare soil reflection on vegetation indices produced from UAV-based multispectral images in the sustainable management of agricultural lands and to reveal the relationship between soil texture and vegetation indices. In the study, clay, silt, and sand contents were determined by making texture analyses in soil samples obtained by using a random stratified sampling method. A multi-band orthophoto image was created from the UAV-based multispectral data for the study area. Visible Atmospheric Resistant Index (VARI), Normalized difference vegetation index (NDVI), Normalized Difference Red Edge Index (NDRE), Leaf Chlorophyll Index (LCI), Green-Red Vegetation Index (GRVI), which are widely used in digital agriculture, from the multispectral image of the study area. Soil Adjusted Vegetation Index (SAVI), and Green Normalized Difference Vegetation Index (GNDVI) vegetation indices were calculated. The relationships between vegetation indices data set and soil clay, silt, and sand contents were determined statistically ($p < 0.001$). It was determined that the highest correlated vegetation index GNDVI with soil texture. It was determined that there were 0.62, -0.72, and 0.73 correlation coefficients between the GNDVI vegetation index and clay, silt, and sand, respectively. The data produced from UAV-based multispectral images between the bare soil reflection and vegetation indices have been shown to have potential at the farmland scale.**

***Index Terms*— Digital Agriculture, UAV-Based Remote Sensing, Multispectral Image, Plant Vegetation Indices**

I. INTRODUCTION

Unmanned Aerial Vehicle-based remote sensing offers excellent advantages for quickly and easily obtaining agricultural data needed at the farmland scale for smart farming and digital agriculture applications [1]. It is possible to produce a lot of information from vegetation growth to soil conditions with UAV-integrated multispectral images, which have an impact on monitoring environmental sustainability in agriculture [2]. UAV platforms equipped with multispectral sensors, big data obtained with GNSS-GPS and mapping tools, and advanced sensors can collect data that detect the effect of abiotic and biotic stress factors [3],[4]. With the UAV-based multispectral data obtained from farmlands, the distribution of soils, which is an essential source for agricultural production, can be determined according to their type, physical, chemical, and biological properties [5]. In this way, more environmentally friendly practices can be planned to depend on the needs of the cultivar produced for smart farming practices and soil conditions. With these advantages, it has become possible to produce product planning information for the coming years with machine learning algorithms by collecting information about farmland [6].

Orthophoto maps produced from the images taken with UAV-based multispectral sensors enable the determination of the information needed for the soil and plant [7]. UAV-based technologies can be used in agriculture to help make sustainable land management decisions that will save time and long-term efficiency [4]. Determination and monitoring of soil quality under complex effects in agricultural production can be made from UAV-based multispectral images [8]. Vegetation indices produced from images taken with UAV-based multispectral sensors are successfully used for the evaluation of farmlands. Vegetation indices can be obtained at low altitudes more cost-effectively than UAV-based ultra-high spatial resolution images can be taken as often as needed and analysed in semi-real time [9]. Vegetation indices generated from multi-temporal images using UAV provide valuable information on crop yield from very early stages of growth and spatial variability within the crop to be harvested. This information allows it to determine the most appropriate management strategy for the farmland. Unlike satellite images, which have a specific date and day to obtain the image, the UAV can provide ultra-high-resolution images at any time [4]. For this reason, examining the application of vegetation indices produced from ultra-high-resolution images taken with UAVs for digital agriculture is necessary.

Vegetation Indices (VI) are very effective and appropriate indications to monitor the development and health of crops in qualitative and quantitative vegetation analysis [1]. Plant biophysical properties can be characterized spectrally by vegetation indices, defined as unitless radiometric measurements [10]. Vegetation indices are calculated using the ratios or differences of two or more bands located in the visible (RGB), near-infrared (NIR), and short-wave infrared (SWIR) regions of the electromagnetic spectrum [11]. The significant advantages of vegetation indices are that they are highly correlated with the biophysical parameters of plants and eliminate sensitivity to factors that hinder the interpretation of remote sensing data [12]. The green parts of the plants reflect intensely in the near-infrared (NIR) region due to scattering in the leaf mesophyll. Chlorophyll in green parts strongly absorbs red and blue light [4],

Manuscript received September 21, 2022; accepted November 07, 2023.
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[10],[13].

This study aimed to determine the bare soil effect and its relationship with soil texture on vegetation indices produced from UAV-based multispectral images, which are widely used in digital agriculture applications. The effect of bare alluvial surface soils on vegetation indices was investigated in Isparta ecological conditions. As a result of the study, the impact and critical aspects of bare soil reflection for digital agriculture applications of UAV platforms, multispectral images, and widely used vegetation indices will be reported.

II. Material

This study was conducted on an area of 1080 square meters in a research parcel between Isparta Lakes Region Technopolis and Isparta University of Applied Sciences, Faculty of Agriculture, the Education, Research, and Application Farm. The study area lies between the coordinates of 283116–283157 East and 4190800–4190859 North (UTM WGS 1984 Zone 36N). The study area is located on alluvial soils [14]. Climate Classification is described as sub-humid using Erinç climate classification methods [15]. The average annual precipitation and temperature of the study area, according to long-term meteorological data (1929–2021), are 568.4 mm and 12.3 °C, respectively [16]. The Study area, buffer zone, and soil sample are shown in Figure 1.

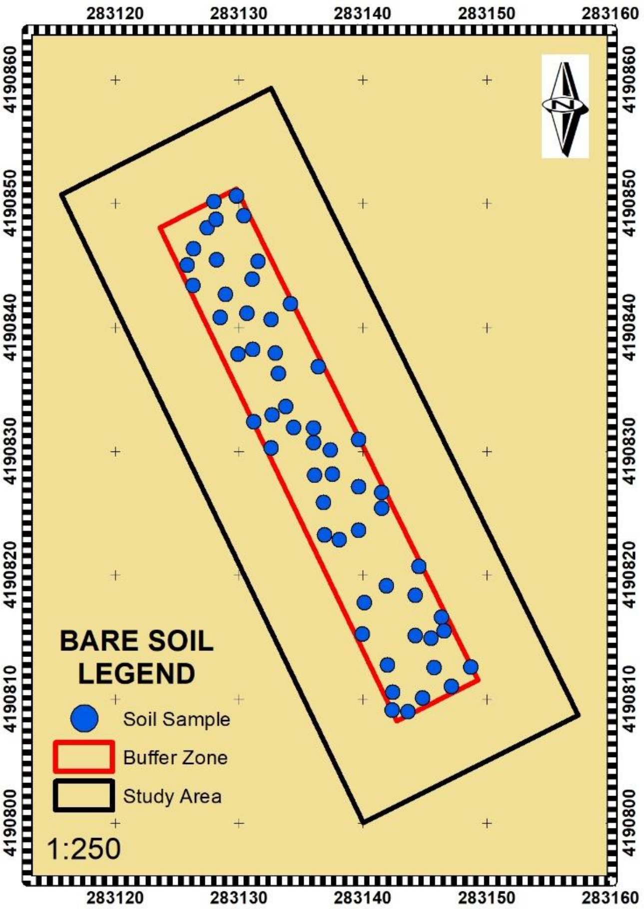

Figure 1. Study area map

The UAV platform used in the study is branded DJI Phantom 4 Pro Quadcopter. Sentera Double 4K Multispectral sensor was used on the UAV platform [4]. The flight weight of the UAV, including the sensor weight developed for digital agriculture applications, is 1500 grams. According to the legislation of the Turkish Civil Aviation General Directorate, it is in the UAV-0 class. The UAV used to acquire multispectral images in the study is shown in Figure 2.

Figure 2. UAV with multispectral sensor

The specifications of the Sentera Double 4K multispectral sensor used in the study are given in Table 1.

TABLE 1. THE SPECIFICATIONS OF THE SENSOR.

Sensors	12.3MP BSI CMOS
Spectral Bands	Blue: 446nm x 60nm width Green: 548nm x 45nm width Red: 650nm x 70nm width Red Edge: 720 nm x 40nm width Near-Infrared (NIR): 840nm x 20nm width
Size	59 mm x 41 mm x 44.5 mm
Weight	80 grams
Power	8W typical / 12W maximum
Image Format	JPEG
Field of View	1080p ranges 30° - 60° HFOV
Data Capture	12.3 MP Stills 4K Ultra HD video @ 30fps 1080p/720p Video H.264 encoding

Vegetation indices are calculated from multispectral image data commonly collected in digital agriculture [12]. The vegetation indices are used in the production of many agricultural data such as leaf area, chlorophyll content, land survey, mapping, monitoring, plant health monitoring, effects of disease and pest, weed density, and irrigation stress [4]. These vegetation indices are given in Table 2.

TABLE 2. VEGETATION INDICES USED IN THE STUDY

Vegetation Index	**Equations**
Normalized Difference Vegetation Index [17]	$\mathrm{NDVI} = \left(\frac{(Near\ Infrared - Red)}{Near\ Inrared + Red}\right)$
Normalized Difference Red Edge Index [18]	$NDRE = \left(\frac{(NIR - Red\ edge)}{NIR + Red\ edge}\right)$
Leaf Chlorophyll Index [19]	$LCI = \left[\left(\frac{NIR}{Green}\right) - 1\right]$
Visible Atmospheric Resistant Index [20]	$VARI = \left(\frac{(R_{GREEN} - R_{RED})}{R_{GREEN} + R_{RED} - R_{BLUE}}\right)$
Green Normalized Difference Vegetation Index [21]	$GNDVI = \left(\frac{(NIR - Green)}{(NIR + Green)}\right)$
Green-Red Vegetation Index [22]	$GRVI = \left(\frac{(Green - Red)}{(Green + Red)}\right)$
Soil Adjusted Vegetation Index [23]	$SAVI = \left(\frac{(NIR - Red)}{(NIR + Red + L)}\right)(1 + L)$

III. METHOD

The method used in the study is shown in Figure 3. The study area is given a 5-meter buffer-zone in ArcGIS software. The fifty-six sampling points were determined by using the random sample algorithm in the buffer-zone area in ArcGIS software. Degraded soil samples were taken from these points at 0-20 cm depth for texture analysis. Soil samples were sieved after drying via a 2 mm sieve in the laboratory. The texture was determined on the soil samples prepared for analysis using the hydrometer method [24]. The percentage of sand, silt, and clay contents was determined in the soil samples taken from the study area.

The coordinates of 15 ground control points were taken with GNSS-GPS in order to obtain high spatial accuracy in the images taken by unmanned aerial vehicles from the study area. In Sentera FieldAgentTM software, flight plan features were created as a flight altitude of 200 feet (60.96 meters), 60% horizontal and vertical overlap, spatial resolution of 3.3 cm/pixel, and flight speed (10 mph (16.09 km/h). UAV-based multispectral images were taken from the study area by autonomous flight. UAV-based imaging from the study area was carried out on August 10, 2019, between 12:00 and 14:00, according to the flight plan. 368 multispectral images of the reflection of the bare surface soil were taken in jpeg format.

Image processing studies were carried out using Pix4D (demo) and ArcGIS software to generate information from the reflection of the bare surface soil. The radiometric correction was performed on 368 images using Pix4D software. The multispectral orthophoto was produced with high geospatial accuracy using the flight plan and ground control points [4]. The vegetation indices given in Table 2 were calculated using the reflectance map of the multispectral image produced in Pix4D software. The calculated vegetation index value of each soil sampling point was obtained using ArcGIS software. The results of the texture analysis and vegetation indices were created as a database of 56- sample point data. Statistical analyses were made using the database of the results of the study. Statistical analyses were made in the R Studio program [25].

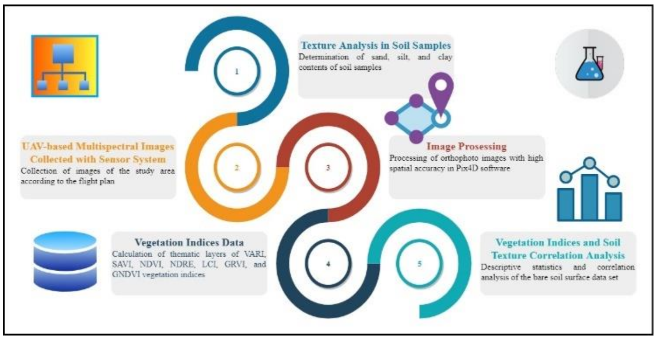

Figure 3. The method used in this study

IV. RESULTS AND DISCUSSIONS

In the study, the effect of bare soil surface reflection on vegetation indices, which are widely used in digital agriculture applications, was determined. Soil texture, which has an effect on bare soil surface reflection and is important for soil quality and management, has been determined. Images taken from the working area with unmanned aerial vehicles were processed using Pix4D (Demo) software. The image of the study area with high geolocational accuracy (RMSE (cm) [4]) was obtained with a spatial accuracy of 2 centimeters. Spatial data were obtained with 4333 multispectral pixels for 1080 square meters of the study area. Vegetation indices were calculated using a study area reflectance map in the index calculation algorithm in Pix4D (Demo) software. The vegetation index values produced for each pixel were included in the data set using ArcGIS software from the pixels corresponding to the soil sampling points from the bare soil surface in farmland. Using the multispectral sensor data of the study area, an orthophoto with a spatial resolution of 25 cm was produced. A database of soil sand, silt, and clay content and vegetation indices was created. The descriptive statistics results of the features in the database are given in Table 3.

Since the reflection values obtained from the soil surface show low reflection in the vegetation index values developed for plant vegetation, negative values were calculated. The low standard deviation and coefficient of variability of the data set, which are measures of variability, are summarized in Table 3. The average values of the soil texture in the data set were determined as the soil texture class "LOAM" using the soil texture calculater developed by the US Department of Agriculture [26].

It was determined that the features in the data set showed normal distribution using the Kolmogorov-Smirnov test of normality [27]. Using the KS test function in the R studio program, it was calculated that the data set showed a normal distribution ($p>0.05$). Then, Pearson correlation analysis was performed in the R Studio program. Confidence intervals of the analysis results were calculated for the data set at the 0.05, 0.01, and 0.001 significance levels.

The relationships between the vegetation index values produced from the bare soil surface reflection in the soil properties used in the data set and the soil texture are shown in Figure 4 according to the significant levels ($p<0.05$*, 0.01**, and 0.001***). The vegetation index values produced from the bare soil surface reflection data in the Data Set were highly correlated with the vegetation indices based on the calculation of similar multispectral bands. It has been determined that the vegetation indices, which are widely used in digital agriculture applications, are low due to the low reflection of bare soil. Unlike the NDVI vegetation index, the GNDVI vegetation index uses the green band instead of the red band (Table 2). The highest correlations were calculated between the GNDVI vegetation index and soil texture properties ($p<0.001$). A positive high correlation of 0.73 was obtained between the GNDVI index and the soil sand content. A negative high correlation of 0.72 was obtained between the GNDVI index and the soil silt content. A positive high correlation of 0.62 was obtained between the GNDVI index and the soil clay content. Positive and negative high correlations were calculated between soil texture to the VARI, SAVI, NDVI, and GRVI indices produced using bare soil surface reflection (Figure 3). In the correlation analysis between the soil properties on the data set with loamy soil texture, a negative correlation was calculated between Sand and Silt, and between Clay and Silt.

TABLE 3. DATABASE DESCRIPTIVE STATISTICS

Bare Soil Database	Sample (N)	Minimum	Mean	Maximum	Standard Deviation	Coefficient of Variation	Skewness	Kurtosis
VARI	56	-0.11	-0.10	-0.08	0.00	-5.19	-0.18	0.01
SAVI	56	-0.55	-0.48	-0.40	0.04	-7.66	-0.28	-0.33
NDVI	56	-0.37	-0.32	-0.27	0.02	-7.66	-0.28	-0.33
NDRE	56	-0.19	-0.17	-0.13	0.01	-5.76	0.64	2.28
LCI	56	-0.16	-0.14	-0.11	0.01	-7.87	0.10	0.30
GRVI	56	-0.08	-0.07	-0.06	0.00	-5.50	-0.27	-0.10
GNDVI	56	-0.31	-0.26	-0.20	0.03	-10.41	-0.37	-0.46
Sand	56	42.72	43.10	43.63	0.26	0.60	0.39	-0.92
Silt	56	33.52	34.20	34.81	0.41	1.20	-0.21	-1.29
Clay	56	22.38	22.71	23.04	0.18	0.77	0.11	-0.99

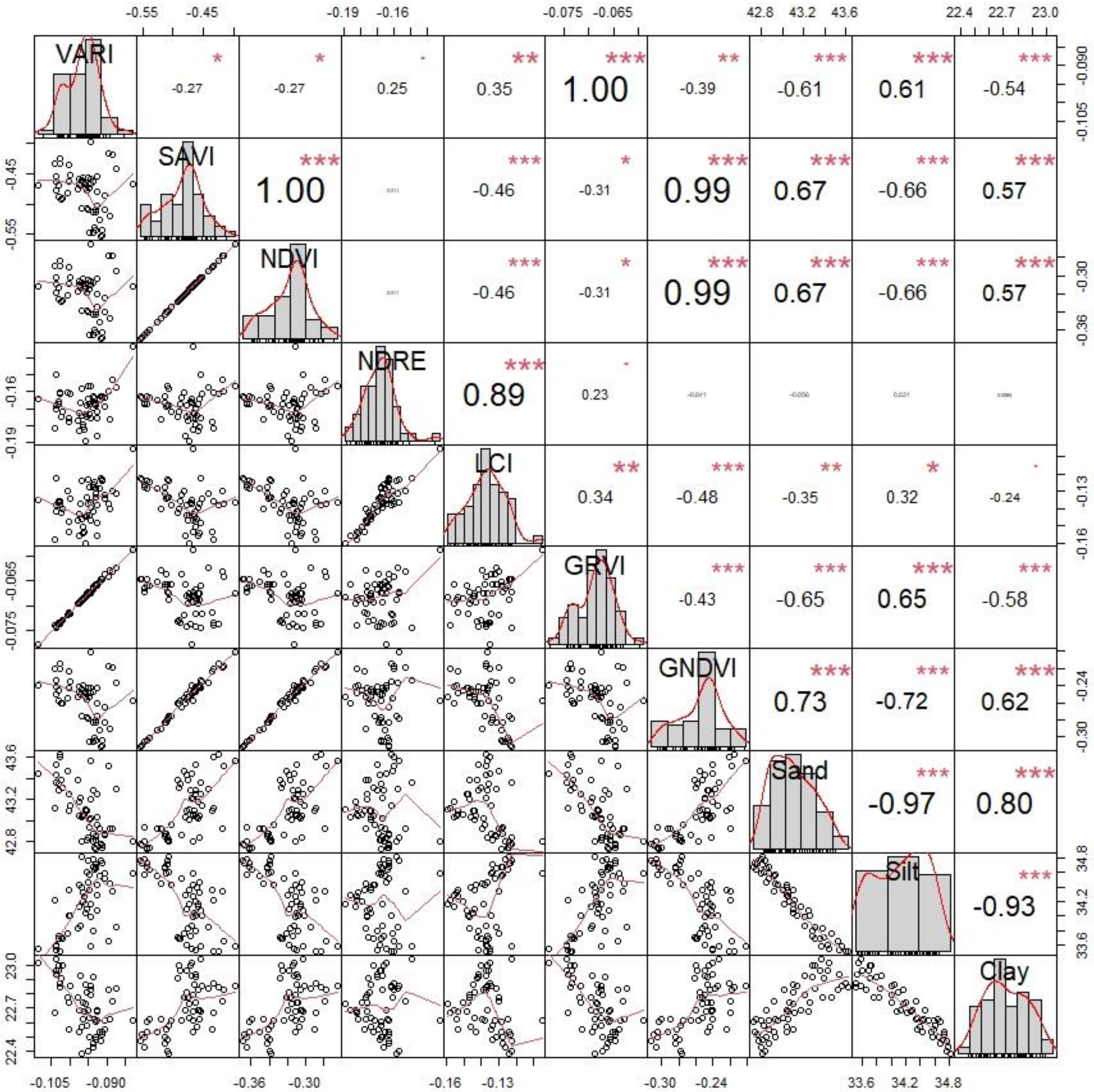

Figure 4. Database correlation matrix

In digital agriculture applications, vegetation indices produced from UAV-based multispectral images are widely used in the determination of abiotic and biotic stress factors in farmlands [12], [28]. Advances in technology and data processing algorithms provide an incredible convenience in the agricultural industry [4].

As a result, it becomes evident that the interaction between bare soil surface reflection and vegetation indices holds substantial implications for digital agriculture applications. The comprehensive analysis conducted here elucidates the intricate relationship between soil texture, a critical factor in soil quality and management, and the performance of widely utilized vegetation indices in assessing agricultural lands [32].

Several contemporary studies within the field of digital agriculture corroborate and extend the significance of these findings. For instance, Reference [29] emphasized the critical role of vegetation indices derived from UAV-based multispectral images in monitoring abiotic stress factors, such as nutrient deficiencies and water stress, in farmlands. Our findings align with this research, highlighting the practical utility of these indices in detecting stressors affecting crop health.

Furthermore, Reference [30] explored the influence of soil texture on the performance of vegetation indices, drawing parallels with our analysis. They emphasized the potential for utilizing these indices in precision agriculture practices to optimize fertilizer and irrigation management. This synergy between our study and existing literature underscores the relevance of our research in informing sustainable farming practices.

One notable highlight from our study is the strong positive correlation observed between the Green Normalized Difference Vegetation Index (GNDVI) and soil sand content, as well as the negative correlations with soil silt and clay content. This finding opens avenues for targeted interventions in farmland management. Building on this, Reference [31] recently demonstrated how GNDVI can be leveraged to tailor irrigation strategies in loamy soils, resulting in improved crop yields and crop efficiency. These studies collectively emphasize the practical implications of our research in guiding precision agriculture techniques for enhanced productivity and sustainability.

In conclusion, our study adds a valuable layer of understanding to the intricate relationship between bare soil surface reflection, soil texture, and vegetation indices in digital agriculture. By aligning with contemporary research and highlighting the practical implications of our findings, we underscore the importance of leveraging this knowledge to drive sustainable and efficient agricultural practices in an increasingly technology-driven world.

V. CONCLUSION

In this study, the effect of the reflection of the bare surface soil on the reflection characteristics of the commonly used vegetation indices was determined. In the study and future studies, it is stated that the reflections obtained from the soils in the similar texture group and the problems arising from the reflection of the bare soil in the areas where agricultural products are grown should be considered. A high correlation was determined between soil texture and GNDVI, one of the vegetation indices commonly used in digital agriculture applications. It is suggested that it can be used to evaluate bare surface soil and lands after tillage works are carried out by plowing or after the product has been removed in future studies. With the developments in data processing algorithms, it is important for the management of data obtained by digital agricultural applications, therefore it is recommended to use high-resolution UAV-based multispectral data by using other soil properties for further studies.

ACKNOWLEDGMENT

We would like to thank IUAS, the Faculty of Agriculture, the Education, Research, and Training Farm team, and the coordinator for their support in acquiring data. Part of this work was presented orally at the V. International Conference on Data Science and Applications 2022(ICONDATA'22).

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