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Soil background effects on UAS and proximal remote sensing-derived vegetation indices

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Abstract

Exposed soil, due to low vegetation cover or in open canopy crops, influences scene reflectance derived from remotely sensed data. An experiment was conducted in College Station, TX, to investigate the potential of six unmanned aerial systems (UASs)-derived and proximally sensed vegetation indices (VIs) in suppressing soil background brightness of four treatments in 2020 and 2021. The treatments were dry soil, dry soil with winter wheat (*Triticum aestivum* L.) crop residue, wet soil (WS), and wet soil with winter wheat crop residue (CRWS) in 2020. In 2021, WS and CRWS were replaced with dry sand and dry compost (DC). The VIs were calculated from remotely sensed data of treatment plots. Cotton (*Gossypium hirsutum* L.) canopy cover (%) on different dates of UAS flight was extracted using unsupervised classification. Factors such as shadows, crop residue, soil moisture, and uneven canopy growth influenced the scene reflectance. The shadow on the soil decreased the soil background reflectance to <10%. Soil background variations minimally impacted the UAS-derived VIs. Soil wetness resulted in higher normalized difference vegetation index (NDVI) than dry treatment plots at an estimated mean canopy cover > 30% in 2020. Similarly, higher NDVI was observed for DC treatment plots at an estimated mean canopy cover of <35% in 2021. The perpendicular vegetation index was least influenced by canopy cover or soil background variations. The study suggests that UAS can be used for large-scale research without being affected by soil variability when vegetation cover is above 30%.

Abbreviations: AGL, aboveground level; ANOVA, analysis of variance; CRDS, dry soil with crop residue; CRWS, wet soil with crop residue; DAP, days after planting; DC, dry compost; DS, dry soil; DSA, dry sand; EVI, enhanced vegetation index; FOV, field of view; GCP, ground control point; GPS, global positioning system; LAI, leaf area index; NDVI, normalized difference vegetation index; NIR, near-infrared; PC1 and PC2, principal components 1 and 2; PCA, principal component analysis; PVI, perpendicular vegetation index; SAVI, soil adjusted vegetation index; SAVI_{RE}, soil adjusted vegetation index-red edge; SWIR, short-wave infrared; TSAVI, transformed soil adjusted vegetation index; UAS, unmanned aerial system; VI, vegetation index; WS, wet soil.

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Plain Language Summary

The exposed soil at low vegetation cover or in open canopy crops influences the scene reflectance captured by unmanned aerial systems (UASs, also known as drones). Scene reflectance is total light reflected from soil, crops, and the interaction between soil and crops in a field or plot. An experiment was conducted at College Station, TX, in 2020 and 2021 to evaluate the ability of six vegetation indices (VIs) to suppress soil background brightness variations in a cotton field. The VIs are combinations of different spectral bands (colors). Factors such as shadows, crop residues, soil moisture, and uneven canopy growth influenced the scene reflectance. Among VIs, the perpendicular vegetation index was least affected by variations in soil background brightness or canopy cover. Overall, the general lack of sensitivity of soil backgrounds to the magnitude of UAS-derived VIs encourages the large-scale application of UAS data without concern for soil variations at vegetation cover > 30%.

1 | INTRODUCTION

Unmanned aerial vehicles fitted with sensors, known as unmanned aerial systems (UASs), have recently gained considerable attention from scientists as a reliable and user-friendly remote sensing platform (Shi et al., 2016). Spectral reflectance data acquired using remote sensing platforms play a crucial role in estimating various plant canopy characteristics, such as leaf area index (LAI) (Attia et al., 2015; Maas & Rajan, 2008; Major et al., 2014; North, 2002). Reflectance data in various wavelengths are usually used to calculate vegetation indices (VIs), such as the normalized difference vegetation index (NDVI), for developing mathematical models to determine plant canopy characteristics (Attia et al., 2015; Maas & Rajan, 2008; Major et al., 2014; North, 2002). However, the spectral data captured by UAS are a complex mixture of reflected light from the scene, including light from vegetation, shadows, and soil background (A. R. Huete et al., 1985; Kauth & Thomas, 1976).

To estimate plant canopy characteristics, such as LAI, the reflectance or VIs of image pixels are usually averaged for a specific area of interest or scene within the remotely sensed image. These areas of interest typically consist of plots in agronomic studies with row crops. However, when the canopy cover is less than 100%, variations in soil brightness between the plots can significantly impact the magnitude of reflected radiation. Although soil background effects on VIs are extensively researched in satellite remote sensing studies, such investigations are limited to UAS-based studies involving VIs and empirical models.

Surface conditions during image acquisition strongly affect soil reflectance in agricultural fields. The main factors affecting soil surface reflectance include soil moisture, color, surface roughness, crop residues, and plant shadows. In general, dry bare soil has high reflectance in the visible and

near-infrared (NIR) regions of the spectrum (Maas & Rajan, 2010). However, water forms a thin layer over the soil surface after precipitation or irrigation, resulting in total internal reflection of reflected solar radiation from the soil surface (Philpot, 2010). This reduced reflected solar radiation from wet soil (WS) gives it a signature dark appearance. To address the influence of soil background on scene reflectance, A. R. Huete (1988) introduced a soil adjustment factor ($L = 0.5$) in NDVI and developed a new index called the soil adjusted vegetation index (SAVI). In a recent study conducted by Menefee et al. (2022) using PlanetScope satellite data, a SAVI-based model for predicting carbon uptake from maize (*Zea mays* L.) cropping systems was the least affected to changing soil background conditions.

The presence of crop residues on the soil surface can affect its reflectance (Todd & Hoffer, 1998). As residues decompose into humus, they alter the soil's color, chemical composition, and water-holding capacity over time, affecting its reflectance (Ben-Dor et al., 1997). Fresh residues, however, present a challenge as their spectral reflectance in the visible and NIR spectrum closely resembles those of bare soils, making it challenging to distinguish between the two (C. S. Daughtry, 2001). Similarly, minerals present in the soil impact soil brightness in remotely sensed images. The presence of iron oxides can cause significant variations in spectral reflectance within the 350–2500 nm range due to the different forms of iron in these minerals. For example, soils rich in hematite iron oxides tend to appear red, while those rich in goethite have a yellowish-brown color (Ben-Dor, 2002). Soil surface features, such as clods and cracks, are important factors determining soil roughness and its apparent reflectance. Numerous agricultural soils in the United States are rich in swell-shrink clay minerals that develop cracks during dry periods. These cracks can act as “light traps,” leading to a reduction in soil reflectance. Similarly, tillage practices can decrease the reflectance of soils

by increasing surface roughness (Sinha, 1986). When the soil is tilled, it produces clods of various sizes, which cast shadows on the soil surface and reduce its apparent reflectance (Cierniewski, 1987). These varying soil conditions can impact the estimation of plant canopy characteristics using spectral reflectance.

The soil between plant rows contains illuminated areas and plant shadows in row cropping systems. As a result, remotely sensed images of crop fields typically show a combination of canopy, illuminated soil, and shadowed soil. Although remote sensing data collection is generally performed during solar noon time to minimize the effect of plant shadows, it cannot be completely avoided. The reflectance of WS, being dark in color, can resemble that of shadowed soil. So, the plant shadows on a WS background may not affect the overall scene reflectance. However, if plant shadows fall on bright soil, they can lead to an overall decrease in solar radiation reflectance. Several factors influence the occurrence and size of shadows in a remotely sensed image of a row crop field, including planting density, row spacing, the orientation of leaves, time of remote sensing data acquisition, and time of the year (Kauth & Thomas, 1976). Even when field plots have similar canopy cover and soil background conditions, the shadows can vary depending on these factors (Huemmrich, 1996). A recent study by Lu et al. (2022) found that shadowed soil pixels impacted land cover classification accuracy and evapotranspiration estimation when using UAS remote sensing data in vineyards.

In agronomic or plant breeding studies, field trials are often replicated in multiple locations over several years. When using UAS for data collection in these trials, it becomes important to consider the soil conditions during remote sensing data acquisition, especially when vegetation cover is low. Wiegand et al. (1992) demonstrated that mathematical models developed between VIs and corresponding ground-based observations of LAI were qualitatively similar across five geographical regions. However, the specific values of the coefficients in the empirical relationships differed among locations. Vescovo et al. (2012) investigated new VIs based on ground-based NIR data for grassland phytomass monitoring. They found that the new indices and phytomass relationships were site-specific due to differences in grassland species composition and background reflectance.

The objectives of this study were (1) to examine the effects of soil background variations on reflectance spectra within the 350–2500 nm spectral range and (2) to evaluate the impact of soil background conditions on VIs estimated using both UAS multispectral remote sensing data and handheld spectroradiometer data during the cotton (*Gossypium hirsutum* L.) growing season. The study hypothesized that variations in brightness induced by soil moisture differences would lead to differences in the magnitude of VIs estimated using both proximal and UAS-based remote sensing data at the same level

Core Ideas

- Exposed soil background variations influence the remotely sensed cotton scene reflectance.
- At 30%–35% vegetation cover, soil backgrounds influenced overall reflectance throughout wavelengths 465–860 nm.
- Six vegetation indices (VIs) were evaluated for their ability to suppress soil background brightness.
- The perpendicular vegetation index (PVI) was least influenced by variations in canopy cover or soil background.
- The minimal impact of soil background variations on UAS-derived VIs encourages its use at vegetation cover > 30%.

of vegetation cover. The study also hypothesized that differences in surface roughness and composition of crop residue on the soil surface would result in differences in the magnitude of VIs at the same vegetation cover. Two datasets were used to test these hypotheses: proximal remote sensing data estimated using a handheld spectroradiometer and UAS-based multispectral remote sensing data.

2 | MATERIALS AND METHODS

2.1 | Study site

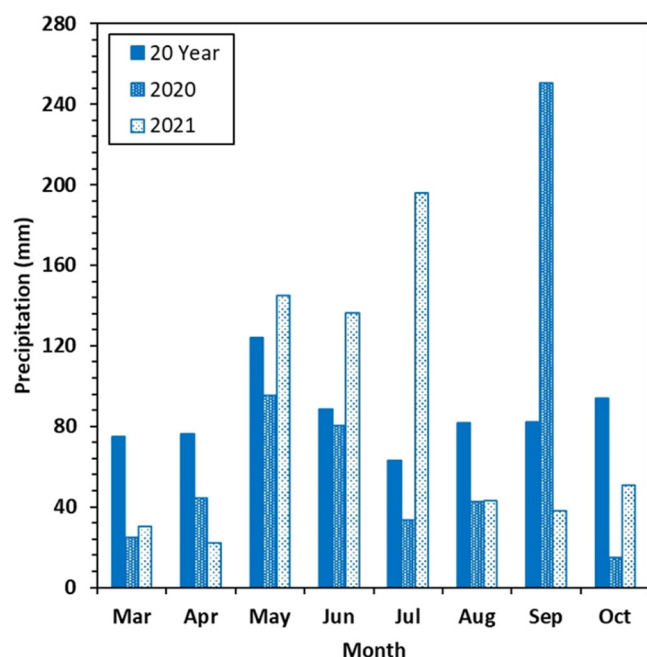
Field experiments with cotton were conducted in 2020 and 2021 at the Texas A&M University Research Farm (30°33' N, 96°26' W) near College Station, TX. The soil type at this location is Belk clay (fine, mixed, active, thermic Entic Hapluderts), and the climate is classified as humid subtropical (Köppen Cfa). The typical cotton growing season (from planting to harvesting) in the study region is from March to October. The long-term (2002–2021) monthly average precipitation for this region is 938 mm (Figure 1). Cumulative growing season precipitation received in 2020 and 2021 was 679 and 749 mm, respectively (Figure 1).

2.2 | Experimental design and management

Cotton was planted on May 20, 2020 and April 23, 2021 at a seeding rate of 128,000 seeds ha⁻¹ and 1 m row spacing. Before planting, plots were disked and bedded. Each plot consisted of three rows, and the plot length was 6 m. In 2020, nitrogen was applied as urea ammonium nitrate (32% N) at an

TABLE 1 Soil backgrounds as treatments to study their influence on plot-level reflectance in 2020 and 2021.

Year	No.	Treatment description	Abbreviation
2020	1	Dry soil	DS
	2	Dry soil with winter wheat crop residue	CRDS
	3	Wet soil	WS
	4	Wet soil with winter wheat crop residue	CRWS
2021	1	Dry soil	DS
	2	Dry soil with winter wheat crop residue	CRDS
	3	Dry sand	DSa
	4	Dry compost	DC

**FIGURE 1** Twenty-year long-term (2002–2021) monthly average precipitation and monthly precipitation received in the 2020 and 2021 cotton growing seasons at the study site near College Station, TX.

80 kg ha⁻¹ rate on June 15 (26 days after planting [DAP]). In 2021, nitrogen was applied at a 112 kg ha⁻¹ rate on May 27 (34 DAP). Pre-emergent and post-emergent herbicides were applied as per the recommendation of Texas A&M AgriLife Extension to control weeds.

The experimental design was a randomized complete block design with four treatments and three replications in both years. The treatments consisted of four soil background conditions (Table 1; Figure 2). The soil at the site was dark gray in color on the surface when dry. To achieve different soil background conditions that mimic various conditions, crop residues, play-sand, and water were applied. Two treatments, dry soil (DS) and dry soil with crop residue (CRDS), were the same in both years. However, in 2021, WS and wet soil with crop residue (CRWS) treatments were replaced with dry sand (DSa) and dry compost (DC) soil background treat-

ments. Approximately 1667 kg ha⁻¹ of winter wheat (*Triticum aestivum* L.) residue, oven-dried at 40°C, was hand-applied between cotton rows in plots that required a crop residue background (CRDS and CRWS). Residues were applied at 21 DAP (June 10) in 2020 and 38 DAP (May 31) in 2021. To create WS conditions, 63,333 L ha⁻¹ water per plot was applied approximately 2 h before the UAS flight in WS and CRWS treatment plots. In 2021, to achieve the lighter soil background condition, play-sand was hand-applied in DSa plots at a rate of 33,333 kg ha⁻¹ a week before the first UAS flight. Play-sand was applied again before the third UAS flight acquisition to compensate for the loss of sand due to runoff at a rate of 33,333 kg ha⁻¹. In plots that required compost application, 25,000 kg ha⁻¹ of DC (mushroom) was hand-applied before the first UAS flight. These plots did not lose compost during rainfall events; hence, a second application was not necessary.

2.3 | UAS and image processing

A rotary wing quadcopter (Model M100, DJI) fitted with a multispectral camera (Model RedEdge 3, MicaSense, Inc.) was used for aerial remote sensing data collection (Table 2). The M100 quadcopter was fitted with a global positioning system (GPS) (Model PRO PLUS, DJI) to track the real-time position during the flight. A flight controller (Model N1, DJI) was used to provide commands and control the movement of the UAS. Two lithium-polymer 6S-type batteries (22.8 V, 5700 mAh) were used to power the quadcopter during the flight. All flights were conducted at an altitude of 30 m above-ground level (AGL) with 80% front and side overlaps of images at a flight speed of 4 m s⁻¹. For UAS flights, days with clear sky conditions within ±1 h of local solar noon with wind speeds below 5 m s⁻¹ were selected. The aerial imagery was georeferenced using six ground control points (GCPs) positioned at various locations in the field. The coordinates of these GCPs were collected after each flight using a single-band real-time kinematic global navigation satellite systems receiver (Model REACH RS⁺, EMLID).

TABLE 2 Date of data acquisition using the unmanned aerial system (UAS) in 2020 and 2021.

Number of dates	2020		2021	
	Date (DAP)	Crop growth stage	Date (DAP)	Crop growth stage
1	July 3 (44)	Squaring	June 17 (55)	Squaring
2	July 16 (57)	Squaring	July 2 (70)	Flowering
3	August 4 (76)	Flowering	July 8 (76)	Flowering
4	August 18 (90)	Boll development (closed bolls)	July 27 (95)	Boll development (open bolls)

Abbreviation: DAP, days after planting.

The RedEdge 3 multispectral camera has sensors to capture images in five different spectral bands: blue (465–485 nm), green (550–570 nm), red (663–673 nm), red edge (712–722 nm), and NIR (821–860 nm). The camera had a horizontal field of view (FOV) of 47.2° and was configured for autoexposure. The image acquisition speed of the camera was one image per second for all bands, and the image resolution was 2 cm pixel⁻¹ at 30 m AGL. The GPS attached to the UAS geo-tagged each image. Before the flight, images of a MicaSense calibration panel (MicaSense, Inc.) were collected for radiometric calibration. This calibration panel had 48.9%, 49.0%, 48.9%, 48.8%, and 48.6% reflectance in blue, green, red, red edge, and NIR bands, respectively.

All post-processing operations were conducted using Pix4Dmapper image analysis software (Pix4D SA). Initially, a 3D point cloud was generated from the images and georeferenced using GCP coordinate information collected after each flight. Digital numbers were converted to reflectance using the calibration panel's band reflectance values, and an orthomosaic was generated. The final output was a geometrically and radiometrically calibrated reflectance image of the study area containing all five spectral bands in GeoTIFF format. The reflectance images were used to calculate VIs using the index calculator in Pix4Dmapper. The Composite Bands geoprocessing tool was used in ArcGIS (version 10.7.1, ESRI) to generate true color band composite (RGB) images by layer stacking the five reflectance bands generated in Pix4Dmapper for all the UAS image acquisition dates in 2020 and 2021. The ArcGIS was also used to overlay the plot shapefile on Pix4Dmapper-generated band reflectance and index maps, and the Zonal Statistics toolbox was used to extract mean band reflectance and VIs from each plot. The VI per plot was used to calculate the mean value of each VI per soil background in 2020 and 2021.

2.4 | Vegetation indices

The NDVI is a commonly used ratio-based index using NIR and red reflectance (Equation 1; Rouse et al., 1974) but is strongly influenced by soil background conditions (A. R.

Huete, 1988). The sensitivity of NDVI to increasing LAI becomes weak when biomass is high, resulting in nonlinear relations, often called “NDVI saturation” (Raman et al., 2025; Shi et al., 2016). Compared to NDVI, enhanced vegetation index (EVI; Equation 2) is less sensitive to saturation, and the relationship between EVI and LAI is generally linear for a broader range of LAI (Alexandridis et al., 2020). It is also less sensitive to soil background variations and atmospheric noises due to aerosols (Liu & Huete, 1995).

$$\text{NDVI} = \frac{(\text{NIR} - \text{red})}{(\text{NIR} + \text{red})} \quad (1)$$

$$\text{EVI} = G \times \frac{(\text{NIR} - \text{red})}{(\text{NIR} + C_1 \times \text{red} - C_2 \times \text{blue} + L)} \quad (2)$$

In the equation for EVI, G is a gain factor, C_1 and C_2 are the coefficients of the aerosol resistance term, and L is a soil adjustment factor. The present study used the coefficients adopted in the moderate resolution imaging spectroradiometer-EVI algorithm, which are $L = 1$, $C_1 = 6$, $C_2 = 7.5$, and $G = 2.5$.

Other indices that were developed to minimize the effect of soil background on scene reflectance include the perpendicular vegetation index (PVI) (Richardson & Wiegand, 1977), SAVI (A. R. Huete, 1988), and transformed SAVI (TSAVI) (Baret et al., 1989). PVI was proposed to measure canopy development as the perpendicular distance from the “soil line” to the point of interest in the NIR versus red distribution of pixel values in an image. The soil line is the line connecting image pixels containing only bare soils in the NIR versus red distribution of points, roughly triangular due to the reflectance characteristics of vegetation and soil. PVI is calculated as shown in Equation (3).

$$\text{PVI} = \frac{[\text{NIR} - (a \times \text{red}) - b]}{\sqrt{(1 + a^2)}} \quad (3)$$

In the PVI equation, a and b are the bare soil line's slope and intercept, respectively (Table 3). As the soil dries out, the

TABLE 3 Soil line slopes and intercepts from 2020 and 2021. Slopes and intercepts were obtained from linear regression of bare soil reflectance in near-infrared (NIR) versus red band spectrum at different days after planting (DAP). At 87 and 95 DAP in 2021, the canopy cover of treatment plots was >85%. Bare soil data collected using a spectroradiometer were a complex mixture of soil, shadow, and soil–canopy interactions on these dates. So, no slopes and intercepts were obtained.

Platform	DAP	2020		DAP	2021	
		Slope	Intercept		Slope	Intercept
UAS	44	1.026	0.101	55	1.029	0.097
	57	1.105	0.086	70	1.143	0.097
	76	0.941	0.115	76	1.103	0.146
	90	1.056	0.101	95	1.222	0.146
Spectroradiometer	44	1.639	−0.079	55	1.085	0.083
	57	0.99	0.099	87	N/A	N/A
	76	1.174	0.071	95	N/A	N/A
	90	0.841	0.148			

Abbreviation: UAS, unmanned aerial system; N/A, not applicable.

relative location of image pixels with partial canopy cover changes parallel to the soil line within the NIR versus red distribution (Maas & Rajan, 2008). As a result, PVI is less sensitive to background brightness variations.

SAVI is derived from NDVI and uses a soil adjustment factor, L , to suppress soil brightness influence (Equation 4). Depending on canopy cover, the value of L varies from 1 for low vegetation density to 0 for 100% canopy cover. Generally, an L value of 0.5 is considered optimal for a wide range of vegetation covers to account for soil brightness variations. A new index called the SAVI-red edge (SAVI_{RE}) was tested in the present study (Equation 5). This index was adapted from the classic SAVI index by replacing the red band with a red edge (712–722 nm) to improve the sensitivity of the index to chlorophyll content in plants.

$$\text{SAVI} = \left[\frac{(\text{NIR} - \text{red})}{(\text{NIR} + \text{red} + L)} \right] (1 + L) \quad (4)$$

$$\text{SAVI}_{\text{RE}} = \left[\frac{(\text{NIR} - \text{red edge})}{(\text{NIR} + \text{red edge} + L)} \right] (1 + L) \quad (5)$$

TSAVI was originally proposed by Baret et al. (1989) to reduce errors in SAVI associated with changes in soil line characteristics at low LAI. TSAVI is a measure of the angle between the soil line and the line that joins a vegetation point in the NIR versus red distribution and the intercept of the soil line. Baret and Guyot (1991) modified TSAVI (Equation 6) and included an adjustment factor ($X = 0.08$) to minimize the soil brightness effect.

$$\text{TSAVI} = \frac{a \times (\text{NIR} - a \times \text{red} - b)}{[\text{Red} + a \times \text{NIR} - a \times b + X(1 + a^2)]} \quad (6)$$

2.5 | Field-based hyperspectral data collection

Spectral data ranging from 350 to 2500 nm were collected using a handheld spectroradiometer in 2020 and 2021 (Model FieldSpec 4, Analytical Spectral Devices). Wavelengths from 400 to 750 nm are in the visible, 751 to 1100 nm in the NIR, and 1101 to 2500 nm in the short-wave infrared (SWIR) spectrum. In 2020, hyperspectral data were collected on all four dates immediately after the UAS flights. In 2021, hyperspectral data were collected on two dates immediately after the UAS flights (at 55 and 95 DAP) and at 87 DAP (boll development stage). A fiber optic cable with an FOV of 25° was attached to FieldSpec 4 to facilitate data collection. Before making measurements from plots, radiance data were collected from a white Spectralon reference panel (Model FieldSpec 4, Analytical Spectral Devices) with 99% reflectance in all bands to optimize the instrument and convert radiance data to reflectance. This was repeated twice during plot measurements to account for changing sun angle positions. For estimating canopy reflectance, data were collected by positioning the tip of the fiber optic cable about 20–25 cm above the canopy from five locations within the plot at 44 and 57 DAP in 2020 and 55 DAP in 2021, respectively. The diameter of FOV was ~9–11 cm. However, at higher canopy cover at 76 and 90 DAP in 2020 and 87 and 95 DAP in 2021, fiber optic cable was positioned 15–20 cm above the canopy. The diameter of FOV was ~7–9 cm. Data were collected approximately 20–25 cm above the soil surface to estimate soil reflectance from five locations within the plot. Data for shadowed WS and DS were collected from four sites within the field at about 15 cm above the soil surface at 90 DAP in 2020 and 87 DAP in 2021. All data were post-processed in ViewSpecPro software (Analytical Spectral



FIGURE 2 Unmanned aerial system (UAS)-derived true color composite field images for (A) 2020 and (B) 2021. In 2020, the treatments consisted of four soil backgrounds—dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), and wet soil with crop residue (CRWS). In 2021, WS and CRWS were replaced with dry compost (DC) and dry sand (DSa). Oven-dried winter wheat crop residue was used for soil backgrounds with crop residue and mushroom compost for DC.

Device) to obtain reflectance values. Finally, mean canopy and soil surface reflectance throughout 350–2500 nm were calculated for each plot. However, the mean value of five reflectance from the canopy and five from the soil per plot suggests that both canopy and soil equally contributed to the scene reflectance. In field conditions, the plot area covered by the canopy changed with canopy growth. So, the mean soil

reflectance per plot accounted for its contribution to scene reflectance by multiplying the former by the exposed soil area (%) per plot on each data collection date. The mean value of accounted soil and canopy reflectance per plot throughout 350–2500 nm was calculated to estimate scene reflectance per plot.

Further, the mean value of scene reflectance per treatment plot was calculated for each data collection date in 2020 and 2021. Shadowed soil also contributed to the scene reflectance at high canopy cover in 2020 and 2021. However, for the accountability of shadowed and illuminated soil separately in the scene reflectance, this study did not estimate the percentage of shadowed soil per plot. In addition to scene reflectance, the mean reflectance of bare soil (DS background) in NIR (821–860 nm) and red (712–722 nm) bands corresponding to the multispectral sensor mounted on the UAS was also calculated for soil line slope and intercept at each data collection date in 2020 and 55 DAP in 2021 (Table 3). For proximally sensed data, wavebands and bandwidth corresponding to the multispectral sensor were used to estimate reflectance in blue, green, red, red edge, and NIR spectrum. These wavebands were used to calculate VIs such as NDVI, EVI, PVI, SAVI, SAVI_{RE}, and TSAVI for each plot, as shown in Equations 1–6. Using VI per plot, the mean value of each VI per soil background was calculated in 2020 and 2021.

2.6 | Unsupervised image classification to estimate canopy cover

An unsupervised classification, Otsu thresholding (Otsu, 1979), for each imagery was performed in ArcGIS to estimate the percent canopy cover. The plot shapefile was overlaid on the NDVI map per the UAS data acquisition date. The binary thresholding function was used to classify pixels in the imagery into the foreground (canopy) and background (soil) classes. The tabulate area function in the Spatial Analyst Tools was used to calculate the area covered by canopy and soil pixels. Each plot's canopy cover (%) was determined by dividing the number of canopy pixels by the total pixels in that plot.

2.7 | Data analysis

Data collected in 2020 and 2021 were analyzed in SAS version 9.4 (Statistical Analysis System Institute). Assumptions for normality were tested using PROC UNIVARIATE, based on the descriptive statistics (approximately equal mean, median, and mode) and the Shapiro–Wilk test. A principal component analysis (PCA) was performed in 2025 JMP Student Edition version 18.2.2 (JMP Statistical Discovery LLC) to investigate spectral differences in soil backgrounds and the contribution of reflectance bands in soil background separation. Data

visualization was performed in Microsoft Excel Version 2507 (Microsoft 365 Subscription, Microsoft Corporation), and boxplots were generated to study the distribution of blue, green, red, red edge, and NIR band reflectance and VIs across soil backgrounds (treatments). The change in reflectance and VIs due to surface modification of dry and wet bare soils in 2020 and 2021 was calculated as shown in Equation (7).

% Change in band reflectance or VIs of the modified soil background

$$= \left(\frac{\text{Band reflectance or VI}_{\text{modified soil}} - \text{band reflectance or VI}_{\text{bare soil}}}{\text{Band reflectance or VI}_{\text{bare soil}}} \right) \times 100 \quad (7)$$

where the % change in band reflectance or VIs of the modified soil background represents relative change, band reflectance or $\text{VI}_{\text{modified soil}}$ represents band reflectance or VIs of soil backgrounds, CRDS, CRWS, DSa, and DC, and band reflectance or $\text{VI}_{\text{bare soil}}$ represents band reflectance or VIs of soil backgrounds, DS and WS in 2020 and 2021.

A paired *t*-test was performed in SAS using PROC TTEST to compute variations in soil background reflectance and VIs derived from the spectroradiometer. The NIR versus red reflectance scatterplots for each UAS image acquisition date were generated in ENVI (Version 5.3.1, L3Harris Technologies, Inc.) to extract soil line slope and intercept. Similarly, the soil line slope and intercept for proximal data collected using a spectroradiometer were derived from the linear regression equation of NIR versus red reflectance scatterplots. Analysis of variance (ANOVA) was performed using PROC ANOVA for treatment plot comparisons (canopy cover and VIs) based on Fisher's least significant difference ($p < 0.05$) on UAS image acquisition and proximal data collection dates.

3 | RESULTS

3.1 | Surface conditions affect reflectance spectra and VIs of bare soil

First, we analyzed the spectral data collected using the handheld spectroradiometer from both WSs and DSs, which revealed differences in reflectance attributed to various surface conditions (Figure 3). The dark soil backgrounds, WS in 2020 and DC in 2021, decreased the overall soil reflectance, whereas the reflectance of bright soils, DS and CRDS in 2020 and DS, CRDS, and DSa in 2021, was higher in the 350–2500 nm range. We particularly examined the variations in bare soil reflectance of the five wavebands corresponding to the multispectral sensor on the UAS, and the VIs were esti-

mated using these wavebands. PVI and TSAVI were excluded from this comparison because they are soil line-based indices.

A PCA was performed to investigate the spectral differences in soil backgrounds and the contribution of blue, green, red, red edge, and NIR band reflectance in soil background separation (Figure 4). The principal components 1 (PC1) and 2 (PC2) together explained 99.64% of the total spectral

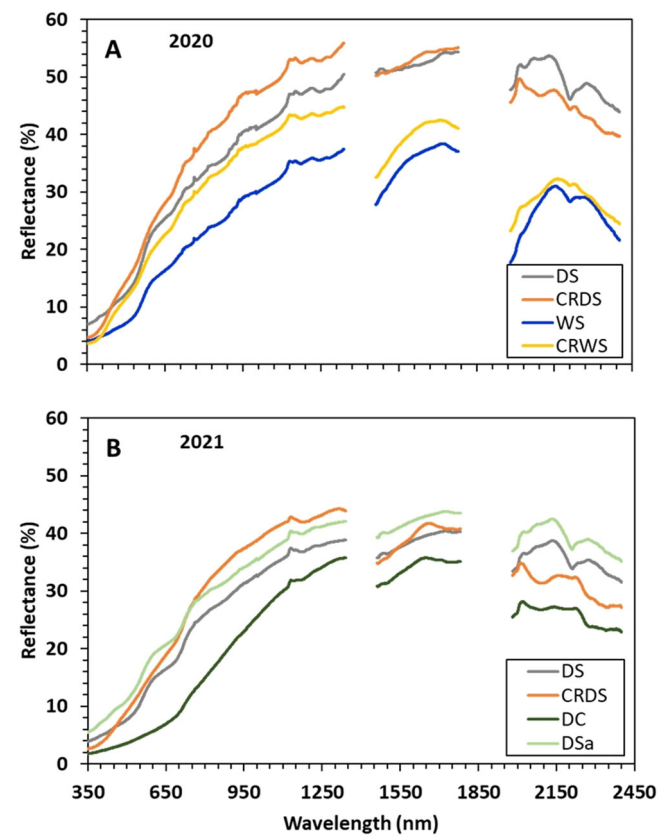


FIGURE 3 Mean reflectance of soil plotted against wavelengths (350–2500 nm). Each spectral curve is the mean value of eight measurements per soil background collected using a spectroradiometer at 44 days after planting (DAP) in 2020 and 55 DAP in 2021. Reflectance at 1341–1460 nm, 1781–1980 nm, and 2401–2500 nm ranges were influenced by atmospheric water vapor absorption and were removed. The soil backgrounds in 2020 were dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), and wet soil with crop residue (CRWS). In 2021, WS and CRWS were replaced with dry soil covered with dry compost (DC) and dry soil covered with dry sand (DSa).

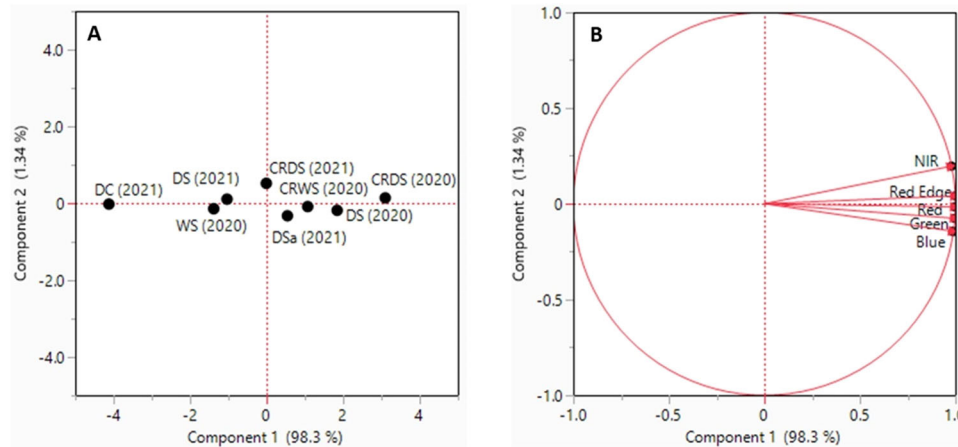


FIGURE 4 Principal component analysis (PCA)-derived (A) scores plot and (B) loadings plot. The scores plot shows spectral differences in soil backgrounds, dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), wet soil with crop residue (CRWS), dry soil covered with dry compost (DC), and dry soil covered with dry sand (DSa), in 2020 and 2021. The loadings plot shows the contribution of five reflectance bands, blue, green, red, red edge, and near-infrared, to soil background separation. Each band reflectance of a soil background is the mean value of eight measurements collected using a spectroradiometer at 44 days after planting (DAP) in 2020 and 55 DAP in 2021. The values, 98.3% for principal component 1 (X-axis) and 1.34% for principal component 2 (Y-axis), represent the percentage of variance explained by each component.

variation across the five bands. The five reflectance bands contributed strongly (98.3%) to PC1 loadings, with minimal contribution (1.34%) to PC2 (Figure 4B). Similarly, the scores plot in Figure 4A shows that all soil backgrounds in 2020 and 2021 were clearly separated in PC1 but clustered near the origin in PC2 ($PC2 \approx 0$). Similar to the five reflectance bands (Figure 4B), three soil backgrounds in 2020 (CRDS, DS, and CRWS) and one in 2021 (DSa) clustered in the positive PC1, suggesting their higher overall reflectance in all five bands. The soil backgrounds, WS in 2020 and DS and DC in 2021, clustered in the negative PC1. The alignment of these soil backgrounds showed an inverse association with the five reflectance bands, reflecting their contrasting spectral characteristics, contributing to their comparatively low overall reflectance. The location of CRDS in 2021, on the origin in PC1 and slightly positive in PC2, suggests that its spectral pattern did not align strongly with the soil backgrounds in the positive and negative PC1. Based on the soil brightness, the 2020 soil backgrounds clustered from positive to negative PC1. Similarly, in 2021, sand being brighter resulted in DSa in the positive PC1, followed by CRDS on the origin and DS in the negative PC1, but close to the origin. The soil background, DC, being dark in appearance because of compost, aligned in the negative PC1, far from the origin. The results confirm the strong influence of soil brightness on the five reflectance bands and reflect that the soil backgrounds in 2020 were spectrally distinct from those in 2021. Soil conditions, especially the higher precipitation observed in the data collection months of June and July in 2021 (Figure 1), may be the reason for the 2020 soil backgrounds being spectrally different from those of 2021. The spectral distinction between the 2020 and 2021 soil backgrounds resulted in comparatively

low overall reflectance in 2021 (Figures 3 and 5). The PCA results in Figure 4 were found to be similar to the spectral curve in Figure 3 and the boxplots in Figure 5, confirming the consistency of the results across the analyses.

The distribution of soil background band reflectance and VIs resulted in overlapping of boxplots in 2020 and 2021 (Figure 5). However, variations in soil background reflectance and VIs were observed for their mean values in both years (Figure 6). As discussed earlier, the higher precipitation during the data collection months of June and July 2021 (Figure 1) may be the reason for the comparatively lower reflectance of soil backgrounds (Figure 5A–E), resulting in higher VIs in 2021 (Figure 5F–I). The reflectance of soil backgrounds with crop residue (CRDS and CRWS) in 2020, across all five bands, was more variable than others in both years.

In 2020, the soil reflectance range of WS was lowest across all five bands—blue (6%–7%), green (10%–12%), red (16%–19%), red edge (18%–22%), and NIR (23%–26%) (Figure 5A–E). Although WS conditions decreased the overall reflectance of the soil in the entire 350–2500 nm range (Figure 3A), compared to dry bare soil, DS, the reduction in soil reflectance of WS ranged from 31% to 42% in the visible, red edge, and NIR bands (Table 4). This reduction in reflectance led to a significant increase in the magnitude of NDVI, EVI, SAVI, and $SAVI_{RE}$ compared to that of DS at $p < 0.01$ (Table 4; Figure 6).

Next, we examined the changes in soil reflectance when fresh crop residue was placed on the surface of dry and wet bare soils. The residue on the DS was also dry, while the residue on the WS was wet. In both cases, the presence of crop residue significantly increased both visible and NIR reflectance ($p < 0.05$; Table 4; Figure 3A,B). Compared to the

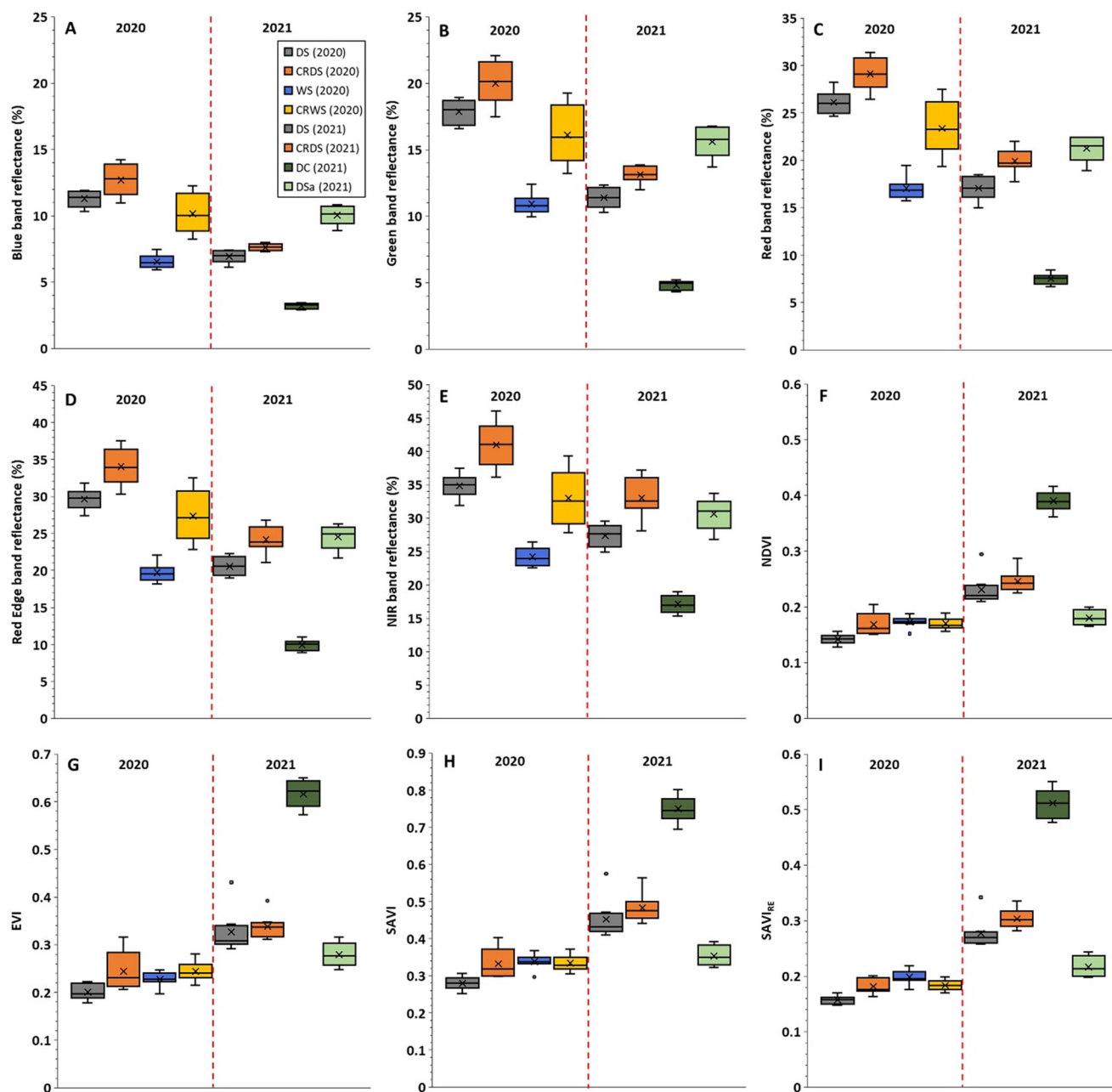


FIGURE 5 Distribution of reflectance values in (A) blue, (B) green, (C) red, (D) red edge, and (E) near-infrared (NIR) bands, as well as vegetation indices (VIs), (F) normalized difference vegetation index (NDVI), (G) enhanced vegetation index (EVI), (H) soil-adjusted vegetation index (SAVI), and (I) SAVI-red edge ($SAVI_{RE}$), across soil backgrounds in 2020 and 2021. Boxplots represent the interquartile range, tails represent minimum and maximum values, the black line and the marker “x” within each box are median and mean, respectively, and the points outside the boxplot range are outliers. A spectroradiometer was used to collect eight reflectance per soil background, dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), wet soil with crop residue (CRWS), dry soil covered with dry compost (DC), and dry soil covered with dry sand (DSa), at 44 days after planting (DAP) in 2020 and 55 DAP in 2021.

other soil backgrounds, the soil reflectance range of CRDS was highest across all five bands—blue (11%–14%), green (18%–22%), red (26%–31%), red edge (30%–38%), and NIR (36%–46%) in 2020 (Figure 5A–E). The soil reflectance of CRWS in 2020 ranged from 8% to 39% and CRDS in 2021 ranged from 7% to 37% across all five bands. Addition of crop residues resulted in an increase in reflectance, ranging

from 36% to 55% for WS and 10% to 21% for DS (Table 4). This increase in reflectance also increased the NDVI, SAVI, and $SAVI_{RE}$ of the DS surface (Table 4; Figure 6). No significant influence of crop residue on the EVI of DS was observed in both years ($p > 0.05$). However, adding residues on the WS surface did not significantly influence the magnitude of NDVI, EVI, and SAVI, but a significant decrease in $SAVI_{RE}$

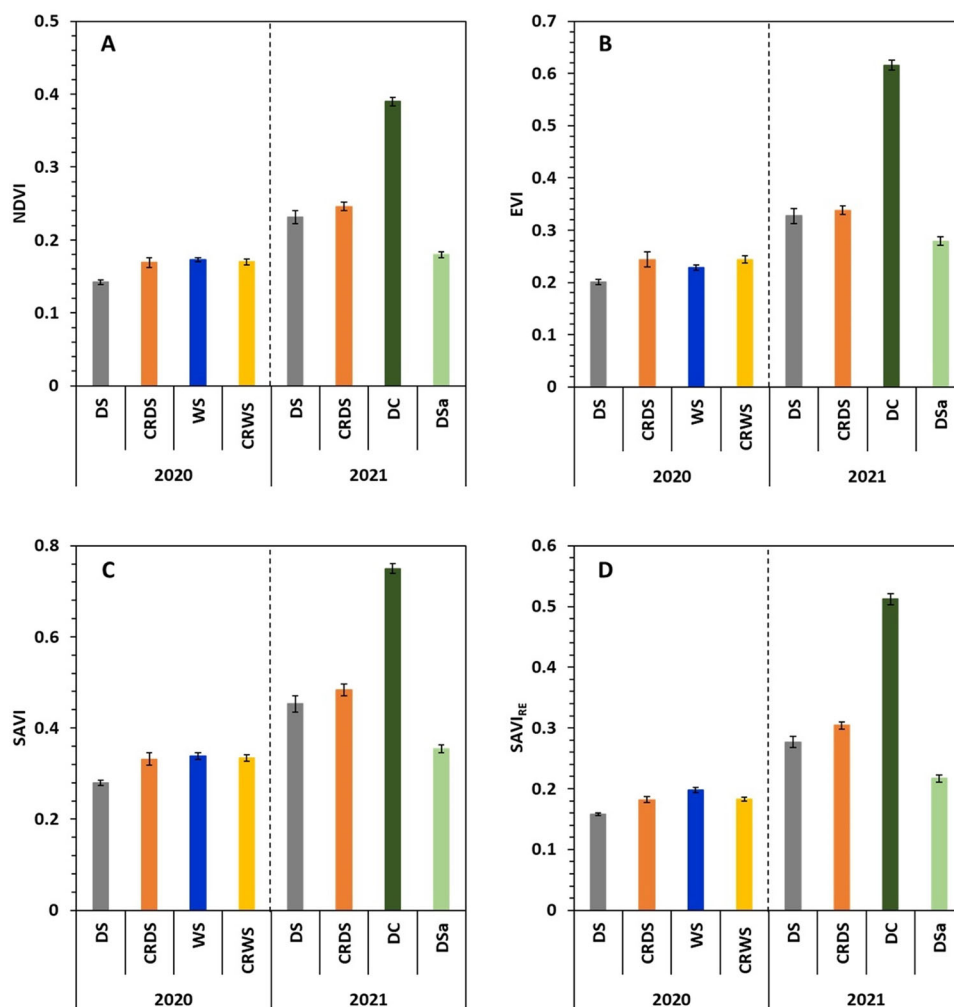


FIGURE 6 Vegetation indices (VIs) of soil backgrounds, dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), wet soil with crop residue (CRWS), dry soil covered with dry compost (DC), and dry soil covered with dry sand (DSa), derived from proximally sensed reflectance collected using a spectroradiometer at 44 days after planting (DAP) in 2020 and 55 DAP in 2021. The VIs, (A) normalized difference vegetation index (NDVI), (B) enhanced vegetation index (EVI), (C) soil adjusted vegetation index (SAVI), and (D) SAVI-Red Edge (SAVI_{RE}), were derived from the mean value of eight measurements. The error bars represent the standard error of the mean.

by 8% was observed ($p < 0.05$). The percentage increase in NIR reflectance was higher than the changes in red reflectance in the case of DS covered with residues. However, in the case of WS covered with residues, the percentage increase in red and NIR reflectance was similar. This similarity in red and NIR reflectance changes led to the observed lack of variations in VIs between wet bare soil and soil with wet crop residues on the surface (Table 4; Figure 6). In the SWIR region from 1460 to 1780 nm, no significant difference ($p > 0.05$) was observed in the reflectance of DS and DS covered with crop residues (Figure 3A,B). However, crop residue increased the soil reflectance from the 1460 to 1780 nm range in the case of WS (Figure 3A). In the SWIR region (between 1980 and 2400 nm), crop residue decreased the overall dry bare soil reflectance in both years. There was no significant difference ($p > 0.05$) in reflectance for WS due to the presence of residue.

In 2021, two new treatments, compost and DSa, were included in the study. The presence of DC and DSa gave a dark appearance to DC and bright appearance to DSa soil backgrounds, respectively. The addition of DC significantly decreased ($p < 0.001$) the proximally sensed reflectance of DS throughout the 350–2500 nm wavelength range (Figure 3B). Among all four soil backgrounds, the soil reflectance range of DC was lowest in blue (3.0%–3.4%), green (4%–5%), red (7%–8%), red edge (9%–11%), and NIR (15%–19%) bands (Figure 5A–E), resulting in a significant increase ($p < 0.0001$) in the NDVI, EVI, SAVI, and SAVI_{RE} (Table 4; Figures 5F–I and 6). Unlike DC, the addition of light-colored DSa significantly increased ($p < 0.001$) the proximally sensed reflectance (Figures 3B and 5A–E), contributing to a significant decline ($p < 0.01$) in NDVI, SAVI, and SAVI_{RE} of DS (Table 4; Figures 5F–I and 6). Similar to crop residue, the addition of DSa showed no significant influence on the EVI of DS.

TABLE 4 Change in reflectance and vegetation indices (VIs) due to surface modification of dry and wet bare soils in 2020 and 2021.

Wavebands/VI	% Change in reflectance and VIs					
	Wet bare soil compared to dry bare soil	Wet soil with crop residue compared to wet bare soil	Dry soil with crop residue compared to dry bare soil	Dry soil with crop residue compared to dry bare soil	Compost on dry soil compared to dry bare soil	Sand on dry soil compared to dry bare soil
	2020	2020	2020	2021	2021	2021
Blue	−42***	55***	12*	10**	−54***	45***
Green	−39***	48***	12*	15**	−58***	37***
Red	−35***	37***	11**	17**	−56***	24***
Red edge	−34***	39***	15**	18**	−52***	19***
NIR	−31***	36***	18**	21**	−37***	12***
NDVI	22***	−2NS	19*	6*	69***	−22**
EVI	13**	7NS	21NS	3NS	88***	−15NS
SAVI	21***	−1NS	19*	7*	66***	−22**
SAVI _{RE}	25***	−8*	15**	10**	85***	−22**

Abbreviations: EVI, enhanced vegetation index; NDVI, normalized difference vegetation index; NIR, near-infrared; SAVI, soil adjusted vegetation index; SAVI_{RE}, soil adjusted vegetation index-red edge.

NS, *, **, and *** indicate $p > 0.05$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively, in paired t -test.

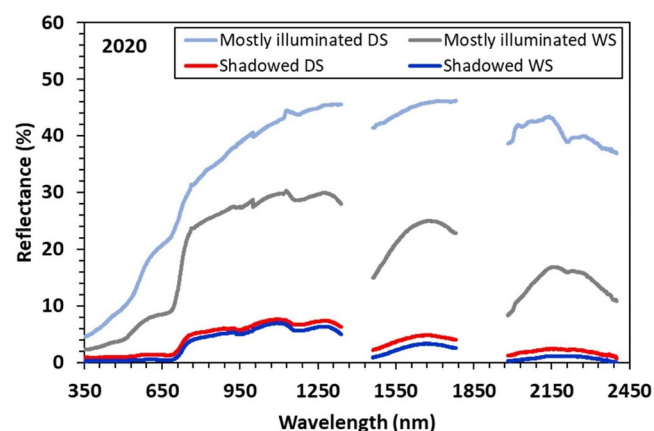


FIGURE 7 Hyperspectral reflectance of mostly illuminated and shadowed wet soil (WS) and dry soil (DS) collected using a spectroradiometer at high vegetation cover, 90 days after planting (DAP), in 2020. Each spectral curve is the mean value of four measurements collected at ± 1 h of solar noon. Reflectance in 1341–1460 nm, 1781–1980 nm, and 2401–2500 nm was influenced by atmospheric water absorption and was removed. Canopy cover almost covered the ground at high vegetation cover, 87 DAP, in 2021. So, bare soil reflectance data were not collected in 2021.

3.2 | Effect of shadows on reflectance spectra and VIs of DSs and WSs

Spectral data for mostly illuminated and shadowed soils were collected using the handheld spectroradiometer from the cotton field in 2020. The presence of shadows on WS and DS reduced their apparent reflectance to $<10\%$ at the 350–2500 nm wavelength range (Figure 7).

Compared to the mostly illuminated DS, a significant decline ($p < 0.01$) in mean soil reflectance (%) of shadowed DS by 89%, 91%, 94%, 90%, and 84% in blue, green, red, red edge, and NIR bands, respectively, was observed (Table 5; Figure 7). Also, the mean soil reflectance (%) of shadowed WS was significantly lower ($p < 0.01$) than mostly illuminated WS by 92%, 93%, 94%, 90%, and 82% in blue, green, red, red edge, and NIR bands, respectively. So, the apparent reflectance of shadowed WS was significantly lower ($p < 0.001$) than shadowed DS by 70%, 61%, 63%, and 44% in blue, green, red, and red edge bands, respectively, in 2020 (data not available for 2021). The decrease in apparent reflectance of illuminated dry bare and WS surfaces also influenced their VIs (Table 5). No significant influence of shadow on the wet bare soil's EVI and SAVI was observed.

3.3 | UAS-derived VIs were unaffected by soil variations when mean canopy cover $> 30\%$

During the early squaring stage (44 DAP) in the 2020 growing season, the estimated mean canopy cover of treatment plots ranged between 30% and 32% and was not significantly different ($p > 0.05$; Figure 8; Figure S1). UAS-derived VIs during that growth stage showed no significant difference among the treatment plots (Figure 9).

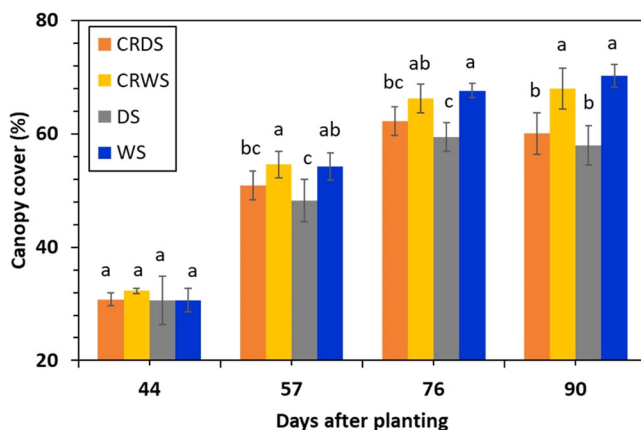
During the squaring stage in 2020 (57 DAP), changes in mean canopy cover were observed between treatment plots (Figure 8; Figure S1). DS treatment plots (DS; mean canopy cover of 48%) had significantly lower ($p < 0.05$) canopy cover compared to WS and WS with crop residue treatment plots (WS and CRWS; mean canopy cover of 54% and 55%,

TABLE 5 Change in reflectance and vegetation indices (VIs) of dry and wet bare soils due to the presence of shadows at 90 days after planting (DAP) in 2020.

Wavebands/VI	% Change in reflectance and VIs		
	Shadowed compared to the mostly illuminated dry bare soil	Shadowed compared to the mostly illuminated wet bare soil	Shadowed wet bare soil compared to shadowed dry bare soil
Blue	−89**	−92***	−70***
Green	−91**	−93***	−61***
Red	−94**	−94**	−63***
Red edge	−90***	−90**	−44***
NIR	−84***	−82*	−16NS
NDVI	166**	80*	29**
EVI	340***	96NS	10NS
SAVI	137**	55NS	24**
SAVI _{RE}	137**	89*	38**

Abbreviations: EVI, enhanced vegetation index; NDVI, normalized difference vegetation index; NIR, near-infrared; SAVI, soil adjusted vegetation index; SAVI_{RE}, soil adjusted vegetation index-red edge.

NS, *, **, and *** indicate $p > 0.05$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively, in paired t -test.

**FIGURE 8** Canopy cover of treatment plots—dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), and wet soil with crop residue (CRWS) at 44, 57, 76, and 90 days after planting (DAP) in 2020. The error bars represent the standard error of the mean. The letters on the bars represent significant differences ($p < 0.05$) in canopy cover among treatment plots at each DAP.

respectively). Similarly, the mean canopy cover of DS with crop residue (CRDS) treatment plots, 51%, was significantly lower than that of CRWS by 7%. Among the six VIs investigated in this study, NDVI, EVI, SAVI, TSAVI, and PVI were responsive to this difference ($p < 0.05$) in canopy cover among treatment plots (Figure 9). Dry treatments, DS and CRDS, showed significantly lower NDVI, SAVI, and TSAVI compared to wet treatments, WS and CRWS. Similarly, the EVI and PVI of DS were significantly lower ($p < 0.05$) than those of WS and CRWS. The SAVI_{RE} showed no significant difference between the treatments, although canopy cover differed between treatment plots, as described previously.

During the flowering stage (76 DAP in 2020), canopy cover differences observed between treatments were similar to the squaring stage (Figure 8; Figure S1). The canopy cover between treatments was significantly different ($p < 0.05$). The estimated mean canopy cover of DS and CRDS was 59% and 62%, respectively, and that of WS and CRWS was 68% and 66%, respectively. Except for NDVI, other UAS-derived VIs showed no significant difference ($p < 0.05$) between WS and CRWS or between DS and CRDS treatment plots (Figure 9). The NDVI of DS was significantly lower than CRDS by 3% (Figure 9).

At the boll development stage (90 DAP), the estimated mean canopy cover of DS and CRDS treatment plots (58% and 60%, respectively) was significantly lower ($p < 0.05$) than WS and CRWS treatment plots (70% and 68%, respectively; Figure 8; Figure S1). Similarly, all six VIs of dry treatment plots, DS and CRDS, were significantly lower ($p < 0.05$) than wet treatment plots, WS and CRWS (Figure 9). Significant difference ($p < 0.01$) among the treatments were observed for all six UAS-derived VIs investigated. No significant difference was observed between dry treatment plots, DS and CRDS, or wet treatment plots, WS and CRWS, for the six VIs.

In 2021, canopy cover did not deviate significantly ($p > 0.05$) between treatment plots during any image acquisition date (Figure 10; Figure S2). Except for NDVI, SAVI, and SAVI_{RE}, the treatment plots were not significantly different for other VIs due to soil background variations at the squaring stage, 55 DAP (Figure 11). The notable difference was the significantly higher ($p < 0.05$) NDVI of plots with DC background compared to bright soil backgrounds, CRDS, and DSa at 55 DAP. Other indices slightly higher ($p < 0.05$) in the DC background at 55 DAP were SAVI and SAVI_{RE}. At 55 DAP, no significant differences between DC, CRDS, and

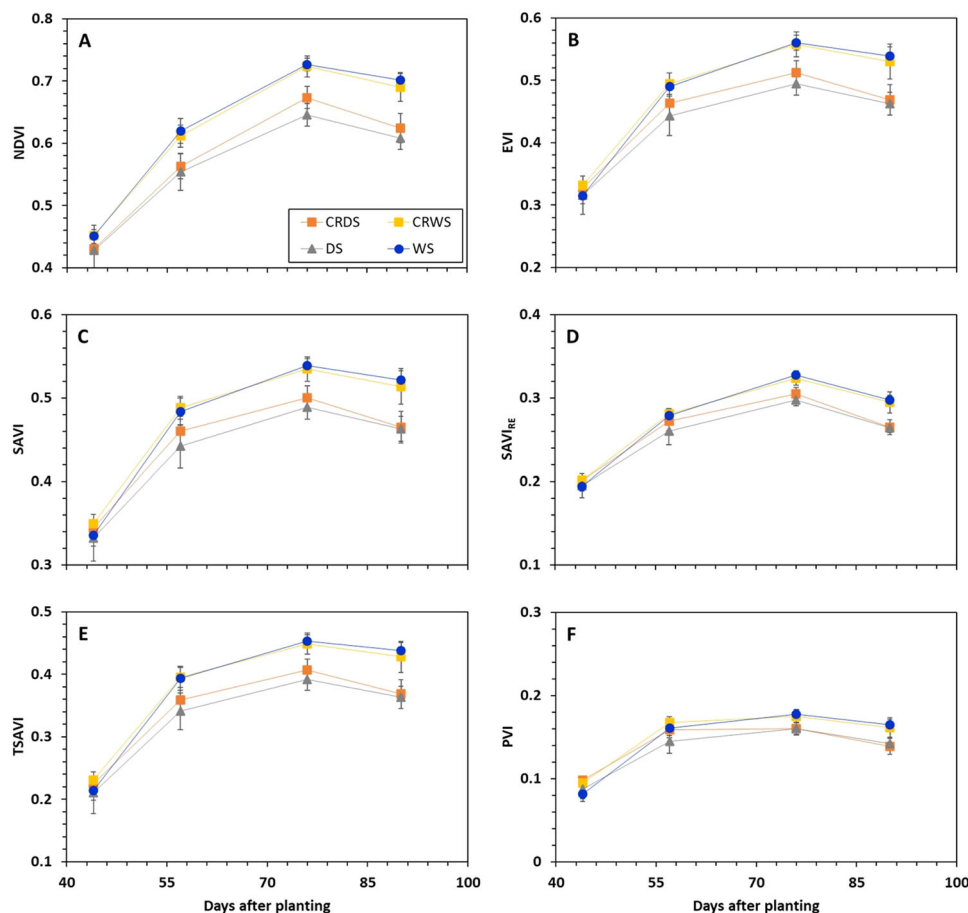


FIGURE 9 Influence of soil background variations on unmanned aerial system (UAS)-derived vegetation indices estimated from the scene (treatment plots) reflectance at different days after planting in 2020. The four treatments were dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), and wet soil with crop residue (CRWS). Vegetation indices estimated in 2020 were (A) normalized difference vegetation index (NDVI), (B) enhanced vegetation index (EVI), (C) soil adjusted vegetation index (SAVI), (D) SAVI-red edge (SAVI_{RE}), (E) transformed soil adjusted vegetation index (TSAVI), and (F) perpendicular vegetation index (PVI). The error bars represent the standard error of the mean.

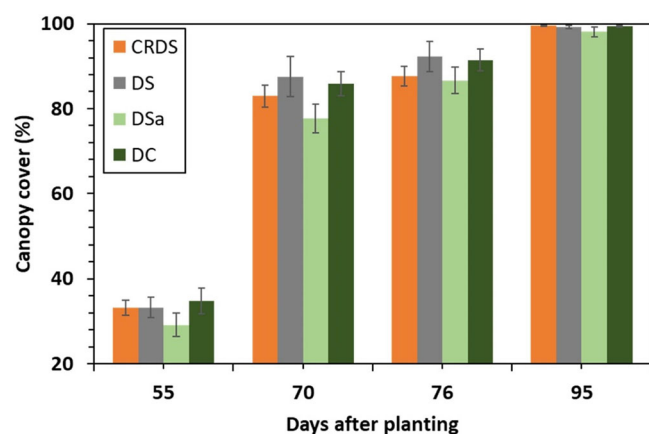


FIGURE 10 Canopy cover of treatment plots—dry soil (DS), dry soil with crop residue (CRDS), dry compost (DC), and dry sand (DSa) at 55, 70, 76, and 95 days after planting (DAP) in 2021. The error bars represent the standard error of the mean. No significant differences ($p < 0.05$) among the canopy cover of treatment plots per DAP were observed.

DS, or between DSa, CRDS, and DS, for the indices influenced by soil brightness, such as NDVI, SAVI, and SAVI_{RE}, were observed. However, at 95 DAP, the SAVI_{RE} of the DC treatment plot was significantly lower ($p < 0.05$) than the DS treatment plot.

3.4 | Proximally sensed VIs of treatment plots were minimally impacted by soil background variations at estimated mean canopy cover higher than 30%

During the early squaring stage in 2020 (44 DAP), a similar estimated mean canopy cover was observed in all four treatments (Figure 8). So, no significant difference ($p > 0.05$) between the treatment plots for proximally sensed VIs was observed (Figure 12). The NDVI for WS was considerably higher ($p < 0.05$) than DS and CRDS by 18% and 21%, respectively. However, NDVI was not much different among DS,

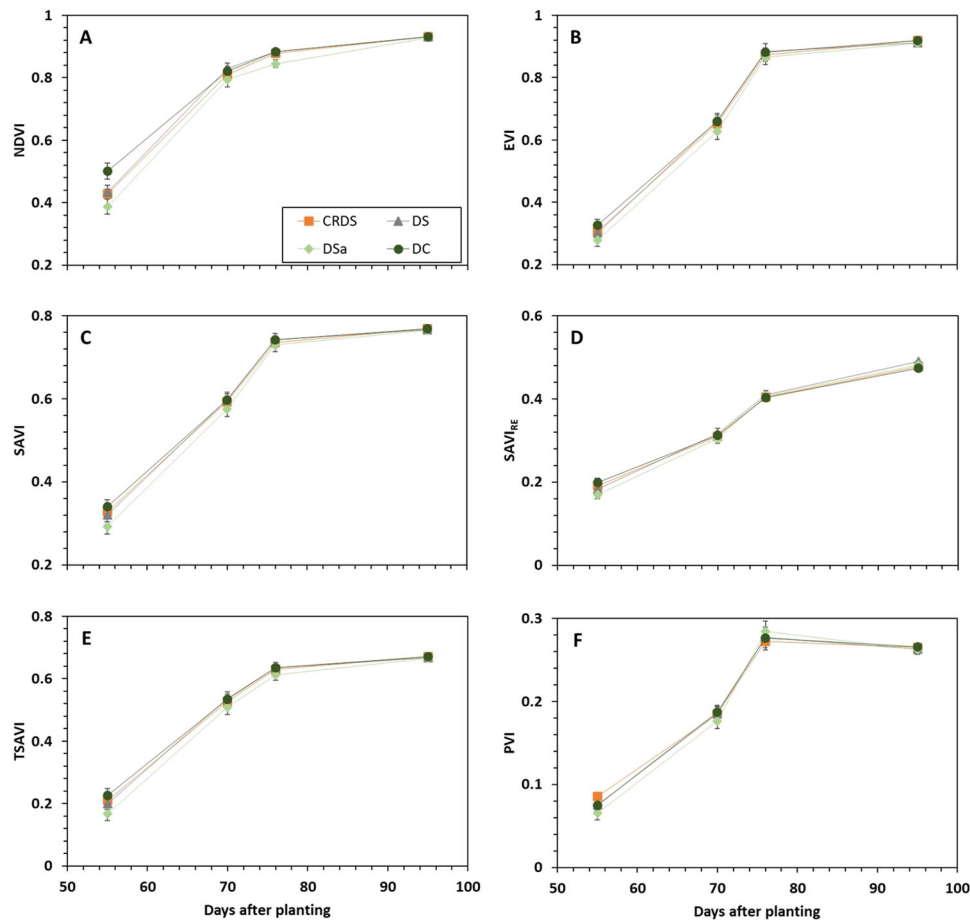


FIGURE 11 Influence of soil background variations on unmanned aerial system (UAS)-derived vegetation indices estimated from the scene (treatment plots) reflectance on different days after planting in 2021. The four treatments were dry soil (DS), dry soil with crop residue (CRDS), dry compost (DC), and dry sand (DSa). Vegetation indices estimated in 2021 were (A) normalized difference vegetation index (NDVI), (B) enhanced vegetation index (EVI), (C) soil adjusted vegetation index (SAVI), (D) SAVI-red edge ($SAVI_{RE}$), (E) transformed soil adjusted vegetation index (TSAVI), and (F) perpendicular vegetation index (PVI). The error bars represent the standard error of the mean.

CRDS, and CRWS or WS and CRWS treatments. TSAVI for WS was significantly higher ($p < 0.05$) than CRDS by 33% (Figure 12). However, TSAVI was not very different among DS, CRDS, and CRWS, or DS, WS, and CRWS. No influence of soil background brightness on SAVI was observed at 44 DAP. A significant difference between the treatment plots was also not observed for EVI, PVI, and $SAVI_{RE}$.

Similarly, at the squaring stage (57 DAP), no proximally sensed VIs except NDVI were influenced by the variations in canopy cover and soil backgrounds (Figure 12). During this growth stage, the canopy cover of DS was significantly lower ($p < 0.05$) than WS and CRWS by 11% and 12%, respectively. Although the canopy cover was not significantly different between WS and CRDS, the NDVI of WS was considerably higher ($p < 0.05$) than that of CRDS by 16%. All the proximally sensed VIs except PVI of WS and CRWS were significantly higher than DS and CRDS at the flowering stage (76 DAP) in 2020 when the estimated mean canopy cover of treatment plots ranged between ~60% and 68%.

At the boll development stage (90 DAP), the canopy cover of DS and CRDS was significantly lower ($p < 0.05$) than WS and CRWS. The SAVI and TSAVI of the dry treatment, CRDS, were lower than the wet treatment, WS, by 13% and 23%, respectively. Other proximally sensed VIs were not influenced by the variations in canopy cover at the estimated mean canopy cover of treatment plots 58%–70%.

Figure 13 shows that at similar canopy cover at 55 DAP in 2021, the treatment plots were significantly different ($p < 0.05$) for NDVI, $SAVI_{RE}$, and TSAVI. Dark background, DC, showed significantly higher ($p < 0.05$) NDVI compared to the bright backgrounds, CRDS, DS, and DSa, at an estimated mean canopy cover of 29%–35% during the squaring stage (55 DAP) in 2021. Similarly, TSAVI and $SAVI_{RE}$ of DC were significantly higher ($p < 0.05$) than DS and DSa. Compared to the plots with dark backgrounds, DC, EVI, and SAVI of the plots with bright backgrounds, DSa, were lower by 28% and 28%, respectively. Since the estimated mean canopy cover of treatments was not different ($p < 0.05$) at this stage. The

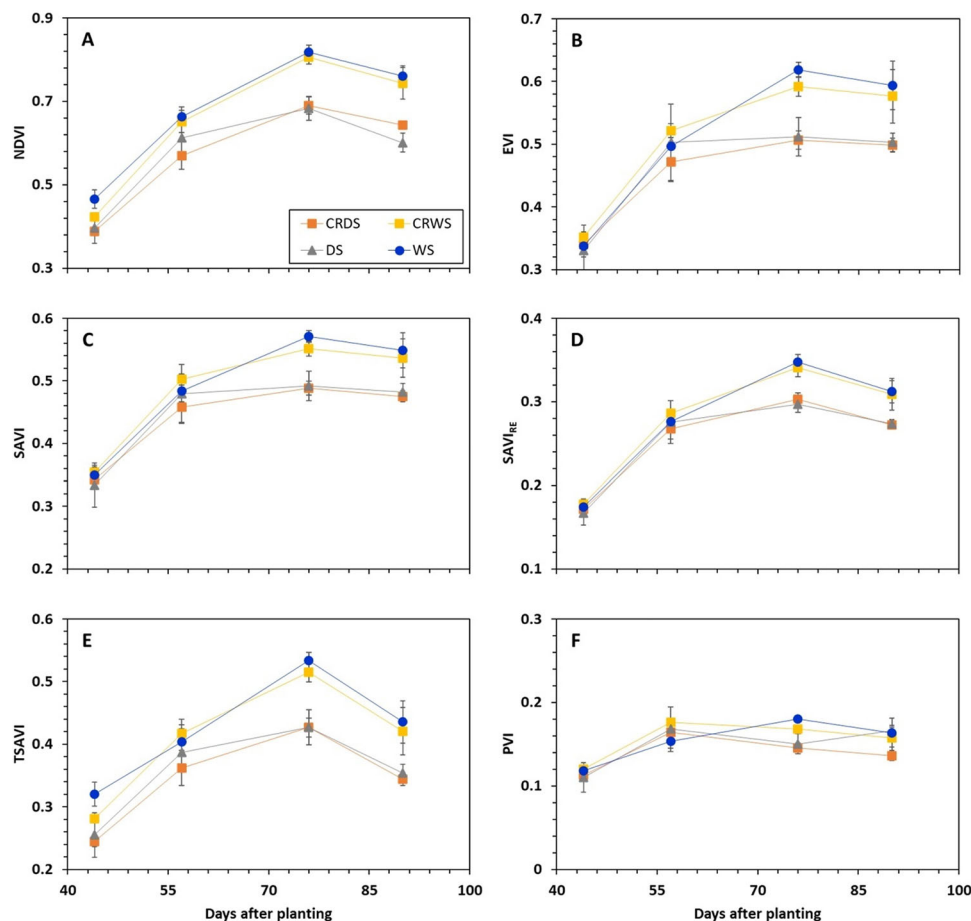


FIGURE 12 Influence of soil background variations on proximally sensed vegetation indices estimated from the scene (treatment plots) reflectance at different days after planting in 2020. The four treatments were dry soil (DS), dry soil with crop residue (CRDS), wet soil (WS), and wet soil with crop residue (CRWS). Vegetation indices estimated in 2020 were (A) normalized difference vegetation index (NDVI), (B) enhanced vegetation index (EVI), (C) soil adjusted vegetation index (SAVI), (D) SAVI-red edge (SAVI_{RE}), (E) transformed soil adjusted vegetation index (TSAVI), and (F) perpendicular vegetation index (PVI). The error bars represent the standard error of the mean.

PVI of treatment plots was not influenced by the variations in soil backgrounds in 2021.

At 87 and 95 DAP, the canopy cover of treatment plots was >85%. Bare soil reflectance data collected using a spectroradiometer were a complex mixture of illuminated soil, shadowed soil, and soil–canopy interaction. As evidenced in Figure 7, the shadow can significantly influence the bare soil reflectance throughout 350–2500 nm. So, the soil line-based VIs were not estimated at these two dates, and no comparisons between proximally sensed VIs were made.

4 | DISCUSSION

The UAS has become a popular remote sensing tool in climate-smart farming, precision agriculture, variety testing, and so forth. However, several studies show that the presence of crop residues, soil wetness, compost, shadows, and so forth, on the soil surface alters the spectral properties of

bare soil (Jones et al., 2015; Ladoni et al., 2010; Lu et al., 2022; Todd & Hoffer, 1998), thereby influencing the remotely sensed data and affecting decision-making. This study investigated the influence of soil background variations on VIs of scene reflectance, that is, treatment plots, derived from remotely sensed data collected using the UAS and proximal spectroradiometer.

WS, being darker, showed lower proximally sensed reflectance than DS throughout the 350–2500 nm wavelength range, resulting in significantly higher ($p < 0.01$) NDVI, EVI, SAVI, and SAVI_{RE} of the former (Figures 3A and 6A). Our findings are consistent with results reported in previous studies (Díaz & Blackburn, 2003; A. R. Huete et al., 1985; Jones et al., 2015). For example, the increase in NDVI observed in our study falls within the reported range of a 15%–35% increase in bare soil NDVI in maize fields under wetter conditions (Jones et al., 2015). C. S. Daughtry (2001) found that the reflectance of bare soil and crop residues in visible and NIR spectra are similar if the residues are fresh. However, the

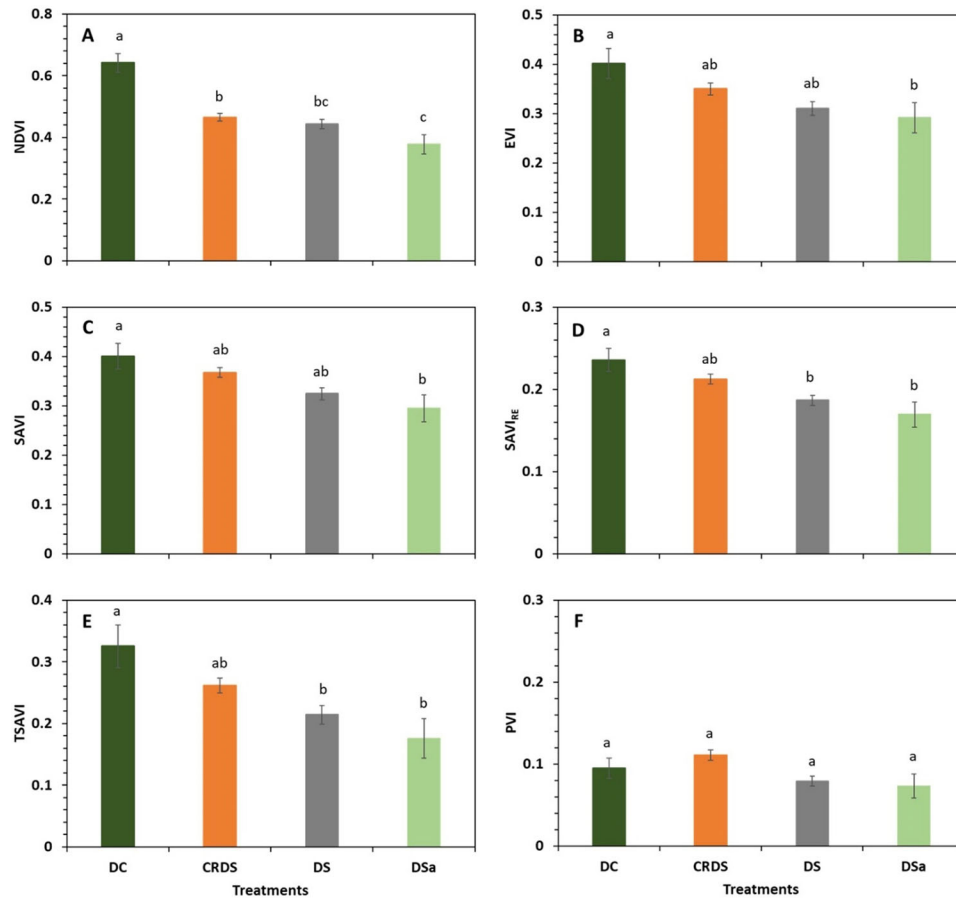


FIGURE 13 Influence of soil background variations on proximally sensed vegetation indices estimated from the scene (treatment plots) reflectance at 55 days after planting (DAP) in 2021 when canopy cover was low. The four treatments were dry soil (DS), dry soil with crop residue (CRDS), dry compost (DC), and dry sand (DSa). Vegetation indices estimated in 2021 were (A) normalized difference vegetation index (NDVI), (B) enhanced vegetation index (EVI), (C) soil adjusted vegetation index (SAVI), (D) SAVI-red edge (SAVI_{RE}), (E) transformed soil adjusted vegetation index (TSAVI), and (F) perpendicular vegetation index (PVI). The error bars represent the standard error of the mean. The letters on the bars represent significant differences ($p < 0.05$) among the vegetation index (VI) of treatment plots.

addition of dry crop residue resulted in a significant increase ($p < 0.05$) in proximally sensed visible and NIR reflectance as well as NDVI, SAVI, and SAVI_{RE} of DS (Table 4; Figures 3 and 6).

The lignin and cellulose content, moisture content, and degree of decomposition influence the spectral reflectance of crop residues (C. S. T. Daughtry et al., 1996; Quemada & Daughtry, 2016). Compost contains humic substances that are dark in color and have strong absorbance in the 400–2500 nm range (Ladoni et al., 2010). So, the addition of DC significantly decreased ($p < 0.001$) the proximally sensed reflectance of DS throughout the 350–2500 nm wavelength range, resulting in a significant increase ($p < 0.001$) in the NDVI, EVI, SAVI, and SAVI_{RE} (Table 4; Figures 3B and 6). Unlike DC, the addition of light-colored DSa significantly increased ($p < 0.001$) the proximally sensed reflectance (350–2500 nm wavelength range), contributing to a significant decline ($p < 0.01$) in NDVI, SAVI, and SAVI_{RE} of DS (Table 4; Figures 3B and 6). Our results demonstrated

the significance of the impact that management practices and soil changes can have on soil reflectance and VIs. Under bare soil conditions, changes in reflectance resulting from variations in moisture, crop residue, or the addition of compost could markedly influence the magnitude of VIs. In specific applications, these changes could be a valuable tool for detecting management practices using remote sensing technologies, such as the application timings of organic amendments (Martí-Jerez et al., 2023) and the amount of crop residues on the soil surface (Quemada & Daughtry, 2016). Our findings also indicated that the three-band EVI with the soil adjustment factor exhibited the least susceptibility to changes in reflectance caused by the presence of crop residue under both dry and wet conditions, making it a potentially less effective VI if the goal is to detect crop residue and moisture changes on the surface. No significant influence of dry crop residue, wet crop residue, or DSa on the EVI of dry bare soil is consistent with the previous study by A. Huete et al. (1999) that the soil adjustment factor and blue band reflectance in

EVI help suppress soil background brightness variations and atmospheric influences.

Similar to WS and DC, shadows also result in the dark color of bare soil. Zarco-Tejada et al. (2004) found that shadows decline the apparent reflectance of illuminated soil up to <20% at 500–800 nm wavelengths. Similarly, Suarez et al. (2010) found that the soil background brightness and presence of shadows in fruit orchards resulted in a decline in R^2 for the relationship between epoxidation state and photochemical reflectance index, used for fruit quality assessment by 23%. As observed in Figure 7, the proximally sensed apparent reflectance of shadowed DSs and WSs < 10% at 350–2500 nm wavelengths is consistent with the previous research by Zarco-Tejada et al. (2004) and Suarez et al. (2010). Although the presence of shadows decreased overall reflectance of DSs and WSs, in the multispectral band (465–860 nm), the effect was more pronounced in red spectrum (663–673 nm) (Table 5; Figure 7). The spectral reflectance of shadowed WS is influenced by the dark soil surface as well as soil moisture. A film of moisture coating the soil particles results in total internal reflection of the incident radiation (Ångström, 1925; Philpot, 2010). The repeated reflection within the film may have increased the absorption probability, thus decreasing the reflected radiation captured by the remotely sensed tool (Ångström, 1925). So, shadows had a significantly stronger influence on WS than DS reflectance in the visible spectrum (Figure 7). In addition, the presence of soil moisture also results in the absorption of spectral bands, especially SWIR, by water (Bach & Mauser, 1994; Lekner & Dorf, 1988). The findings suggest that UAS-based or proximally sensed data should be collected at solar noon with minimal shadow in the field. In addition, the VIs that can suppress the effects of all dark-colored soils, such as WS, soil rich in compost, shadowed soil, etc., should be used for climate-smart farming, precision agriculture, or variety testing.

The band reflectance and VIs of soil backgrounds derived from proximally sensed data were influenced by variations in soil background (Figures 3–7). However, for scene reflectance, both canopy cover and soil background are important factors in determining the magnitude of its VIs (Croft et al., 2014). At low to intermediate canopy cover, variations in exposed soil background influence the spectral reflectance of the scene (A. R. Huete, 1988; A. R. Huete et al., 1985). The scene reflectance in our study was the reflectance of treatment plots at different growth stages of cotton. Unlike proximally sensed soil background NDVI, SAVI, or SAVI_{RE} (Figure 6), the addition of crop residue showed no significant influence ($p < 0.05$) on the UAS-derived and proximally sensed VIs of DS and WS treatment plots at estimated mean canopy cover $\geq 30\%$ in 2020 and 2021 (Figures 9, 11, 12, and 13). The lack of sensitivity of soil backgrounds on magnitude VIs could be attributed to similar relative variation in red, red edge, and NIR reflectance of soil backgrounds (Figure 3) and similar estimated mean canopy cover of treat-

ment plots (Figures 8 and 10). In 2020, the estimated mean canopy cover of dry treatment plots (DS and CRDS) at the flowering stage (76 DAP) was similar (59%–62%). However, a significant increase ($p < 0.001$) in UAS-derived NDVI of DS treatment plots on the addition of dry crop residue suggests that the NDVI was influenced by variations in soil background brightness, as evidenced by the spectroradiometer data in Figures 3–6. No influence of dry and wet crop residue on the VIs of DS and WS treatment plots, respectively, suggests that variations in soil background due to the presence of crop residue minimally impacted the VIs of the treatment plots.

The UAS-derived VIs of dry treatment plots, DS and CRDS, were lower than wet treatment plots, WS and CRWS, at the squaring (57 DAP), flowering (76 DAP), and boll development (90 DAP) stages in 2020 (Figure 9; wet treatments data not available for 2021). Similar observations were made for all six proximally sensed VIs during the flowering (76 DAP) and boll development (90 DAP) stages in 2020 (Figure 12). The proximally sensed VIs, NDVI, EVI, SAVI, TSAVI, and PVI of treatment plots were influenced by soil wetness even at the squaring stage (57 DAP) when the estimated mean canopy cover was 48%–55%. This could be attributed to the significantly higher ($p < 0.05$) estimated mean canopy cover and dark color of WS treatment plots (Figure 8). Based on a comparison of indices in suppressing soil background brightness, Baret and Guyot (1991) concluded that the soil line-based index, TSAVI, works best in estimating LAI at lower canopy cover. However, Bausch (1993) found that TSAVI was more influenced by soil background variations than SAVI. The findings from our study show that UAS-derived and proximally sensed SAVI_{RE} of treatment plots were less affected by variations in soil backgrounds compared to SAVI and TSAVI (Figures 9 and 12). The influence of soil wetness on the VIs suggests that remotely sensed data collected immediately after irrigation or rainfall may affect the decision-making process. High precipitation in June and July 2021 (Figure 1), when remote sensing data were collected, resulted in a weaker association between soil backgrounds and band reflectance compared to 2020, which received less precipitation in the data collection months (Figure 4). Compared to 2020, high precipitation in 2021 may have decreased the brightness of soil backgrounds. However, the association of band reflectance with 2021 soil backgrounds was similar to that of 2020—bright soil backgrounds were strongly associated, whereas dark soil backgrounds showed weak association. Although an increase in soil moisture results in a decrease in soil background reflectance, the reduction in relative reflectance becomes moderate with the rise in moisture level, when the soil has already gained a dark color (Kaleita et al., 2005). Such changes in soil background reflectance impact UAS-derived VIs, contributing to uncertainty in estimating grain yield and quality (Almeida-Ñauñay et al., 2023).

As evidenced by the spectroradiometer data, DC was the least reflective compared to other soil backgrounds in 2021 (Figures 3–5). Darker soil substrates generally have higher ratio-based indices (Elvidge & Lyon, 1985; A. R. Huete et al., 1985). So, the UAS-derived and proximally sensed NDVI of the DS treatment plots covered with DC was significantly higher ($p < 0.05$) than the DS treatment plots with DSa and dry crop residue (Figures 11 and 13). The significant increase ($p < 0.05$) in the proximally sensed NDVI, SAVI_{RE}, and TSAVI of DS treatment plots on the addition of DC at an estimated mean canopy cover of 30%–35% in 2021 is consistent with the findings by Elvidge and Lyon (1985) and A. R. Huete et al. (1985) (Figure 13). However, no influence of DC on UAS-derived VIs of DS treatment plots was observed (Figure 11). This could be attributed to the similar canopy cover of treatment plots (Figure 10), suggesting that soil background variations minimally impacted the UAS-derived VIs. The higher spatial resolution data collected by the spectroradiometer, resulting in detailed information on soil backgrounds, could be a reason for the difference in DC influence on proximally sensed and UAS-derived DS treatment plots VIs. Compared to the red band, the deeper penetration of the red edge in the canopy makes it more sensitive to soil background, resulting in a significant decline ($p < 0.05$) in UAS-derived SAVI_{RE} of DS treatment plots on the addition of DC during the boll development stage (95 DAP). The treatment plots' VIs, not influenced by crop residue and DC on DS, encourage the use of UAS in large-scale climate-smart farming practices such as conventional tillage and organic farming.

Several studies have reported the influence of soil background variations on VIs, especially the darker soil backgrounds showing higher ratio-based indices such as NDVI in row crops like cotton (A. R. Huete et al., 1985; Jones et al., 2015). With crop growth, the canopy covers the inter-row spaces, thus diminishing the soil background effects on plot-based VIs. In our study, differences in treatment plots' VIs (UAS and proximal sensing) were mainly because of the differences in canopy reflectance due to varying canopy cover. A potential concern was the higher NDVI of plots that had DC backgrounds when vegetation cover was <35%. However, if used as a nutrient source, compost is typically applied before planting and incorporated into the soil via tillage, thus reducing its impact on the VIs. Nevertheless, caution should be used when estimating early growing season NDVI in row crops with compost application. The UAS and proximal data were collected at ± 1 h from solar noon when crop shadows were minimal. As demonstrated with the spectroradiometer data in Figure 7, a substantial amount of plant shadows could reduce the overall reflectance and impact plot-based VIs (Tunca et al., 2018). Hence, we recommend collecting UAS and proximal data when shadows are minimal. The effect of soil wetness on proximally sensed plot-based NDVI was observed at an

estimated mean canopy cover of >30%. In contrast, other plot-based VIs were influenced at an estimated mean canopy cover > 60% (Figure 12). Compared to other UAS-derived and proximally sensed plot-based VIs, the PVI was least affected by the variations in soil backgrounds or canopy cover. It suggests that PVI could be used to investigate crop traits to support large-scale variety improvement, precision agriculture, or climate-smart farming. Overall, the general lack of sensitivity of soil backgrounds on the magnitude of VIs is encouraging. It would facilitate the large-scale application of UAS remote sensing data without being concerned about soil variations across locations when vegetation cover is above 30%.

5 | CONCLUSIONS

This study examined how soil background brightness and canopy cover influence band reflectance and VIs from UAS and proximal sensing platforms. At low canopy cover (30%–35%), bright backgrounds strongly affected reflectance, while dark or wet backgrounds had weaker effects. At early growth stages, agricultural researchers and farmers should take caution when using the UAS and proximal remote sensing tools to monitor crop health and growth. As canopy cover increased, soil background influence declined, although shadows, crop residue, and soil moisture still introduced variability. VIs with soil adjustments (e.g., SAVI, TSAVI, and PVI) were designed to reduce background effects, but all showed sensitivity at low canopy cover. At canopy cover > 35%, UAS-derived VIs were minimally affected, with PVI being the least sensitive overall. The low sensitivity of PVI against variations in soil background and canopy cover promotes its use for multi-location research. The minimal impact of soil background variations on the UAS-derived VIs encourages its use in large-scale climate-smart farming, precision agriculture, and variety testing. However, the findings also suggest caution when interpreting VIs at early growth stages, especially after rainfall or in fields with variable residue or moisture. A limitation of this research was the lack of soil and crop residue characterization data. Future studies could focus on the impact of residues with different spectral signatures as well as test these results on various soil types.

AUTHOR CONTRIBUTIONS

Rahul Raman: Conceptualization; data curation; formal analysis; investigation; methodology; software; writing—original draft. **Haly L. Neely:** Conceptualization; funding acquisition; methodology; project administration; resources; supervision; writing—review and editing. **Nithya Rajan:** Conceptualization; funding acquisition; methodology; project administration; resources; supervision; writing—review and editing. **Jeffrey Siegfried:** Data curation; software. **Amir**

M. H. Ibrahim: Writing—review and editing. **Curtis B. Adams:** Writing—review and editing. **Robert G. Hardin:** Writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data analyzed for this study are presented in this article, and a Supplemental Material is included. Additional data will be made available from the corresponding author upon reasonable request.

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