Quantifying the impact of dust retention on maize canopy spectral reflectance and vegetation indices in dust belt regions: A case study in southern Xinjiang, China postprint

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Abstract

Sand-dust belts cover approximately one-fifth of the global land surface. In these regions, dust readily deposits on vegetation surfaces, altering observed reflectance and influencing remote-sensing retrievals. To improve the accuracy of maize growth monitoring in dust-affected areas, this study quantifies the impact of sand-dust retention on maize during the tasseling stage in Kashgar Prefecture, Xinjiang Uygur Autonomous Region, China, by analyzing changes in canopy reflectance and vegetation indices. First, field sampling was conducted to measure key canopy structural parameters and maize dust retention, and laboratory spectral measurements were performed on leaf spectral properties under a gradient of dust loads. The measured data were then used to drive the LargE-Scale remote sensing data and image Simulation framework (LESS) model to simulate realistic maize canopy spectra under different dust levels, which were validated against Sentinel-2 imagery. Second, based on the simulated and satellite-derived spectra, the dust resistance of 36 commonly used vegetation indices was systematically evaluated, and new robust dust-resistant indices were developed. The results show that, compared with dust-free maize, the canopy reflectance of dust-laden maize exhibits an increase–decrease–increase pattern, with critical turning points at 735 and 1325 nm. The maximum reflectance difference of -0.11755 (change rate: 29.002%) occurs in the 735–1325 nm range at a dust retention of 24 g/m^2, while the minimum reflectance difference of 0.04285 (change rate: 148.950%) is observed in the 350–735 nm range at the same dust level. Among the 36 vegetation indices, only the Global Environment Monitoring Index (GEMI) and the ratio of the Transformed Chlorophyll Absorption in Reflectance Index to the Optimized Soil-Adjusted Vegetation Index (TCARI/OSAVI) exhibit dust resistance, with GEMI being effective below

6 g/m^2 and TCARI/OSAVI remaining stable across all dust levels (average ratio: 0.970). The newly developed indices, (RE3-RE2)/(NIR-RE2), (RE3-RE2)/(RE4-RE2), and (NIR-RE2)/(RE4-RE2), remain within the predefined dust-resistant range over the full dust-retention gradient of 0–24 g/m^2, demonstrating more stable dust resistance than the 36 commonly used vegetation indices. In particular, (RE3-RE2)/(RE4-RE2) performs most robustly in Sentinel-2 imagery: 58.020% of pixels fall within the dust-resistant range, and the index derived from the original spectra yields an average ratio of 0.937. This study provides a scientific basis for crop monitoring and management in dust-affected regions.

Full Text

Preamble

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Quantifying the impact of dust retention on maize canopy spectral reflectance and vegetation indices in dust belt regions: A case study in southern Xinjiang, China

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Abstract: Sand dust belts span approximately one-fifth of the global land surface. In these regions, dust tends to settle on vegetation surfaces, altering the observed reflectance and affecting remote sensing detections. To enhance the accuracy of maize growth monitoring in dust-affected regions, this study aims to quantify the effect of sand dust retention on maize during the tasseling stage in the Kashgar Prefecture, Xinjiang Uygur Autonomous Region, China, by analyzing changes in canopy reflectance and vegetation indices. First, field sampling was conducted to measure the key canopy structure parameters and dust retention levels of maize, and laboratory spectral measurements were performed on leaf spectral properties under gradient dust retention. The measured data were then used to drive the LargE-Scale remote sensing data and image Simulation framework (LESS) model for simulating realistic maize canopy spectra across different dust levels, with validation against Sentinel-2 imagery. Second, on the basis of the simulated and satellite-derived spectra, the dust resistance of 36 common vegetation indices was systematically evaluated, and new robust dust-resistant indices were developed. The results showed that the canopy reflectance of dust-retained maize followed an increase–decrease–increase pattern compared with dust-free maize, with critical turning points at 735 and 1325 nm. The maximum reflectance difference of -0.11755 (change rate: 29.002%) occurred within the 735–1325 nm range at 24 g/m^2 dust retention, and the minimum reflectance difference of 0.04285 (change rate: 148.950%) was observed in the 350–735 nm range under the same dust retention level. Among the 36 vegetation indices, only the global environment monitoring index (GEMI) and the ratio of transformed chlorophyll absorption in reflectance index to optimized soil-adjusted vegetation index (TCARI/OSAVI) exhibited dust resistance, with GEMI being effective below 6 g/m^2 and TCARI/OSAVI remaining stable across all levels (average ratio: 0.970). The newly developed indices (RE3-RE2)/(NIR-RE2), (NIR-RE2)/(RE4-RE2), and (RE3-RE2)/(RE4-RE2) retained values within the dust-resistant range over the full dust retention levels of 0-24 g/m^2, thus showing more stable dust resistance compared with the commonly used 36 vegetation indices. Specially, (RE3-RE2)/(RE4-RE2) performed most robustly in Sentinel-2 imagery, with 58.020% of pixels within the dust-resistant range and an average ratio of 0.937 obtained for the original-spectra index. This study provides a scientific basis for crop monitoring and management in dust-affected regions.

Keywords: sand dust retention; canopy spectral reflectance; LargE-Scale remote sensing data and image Simulation framework (LESS) model; dust-resistant; vegetation indices; tasseling-stage maize; Sentinel-2 imagery

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1 Introduction

Sand dust poses a serious environmental challenge that affects ecosystems and agricultural productivity. The largest and most persistent dust sources globally are located in the Northern Hemisphere, primarily along a dust belt that extends from the west coast of North Africa, across the Middle East and South Asia, through Central Asia and reaching into China (Prospero et al., 2002). This dust belt encompasses most of the arid and semiarid areas in the world (Qu et al., 2006; Wang et al., 2006; Jin and Wang, 2018). Xinjiang Uygur Autonomous Region (hereafter referred to as Xinjiang), one of the most typical arid and semiarid areas in China (Zhou et al., 2022), is home to the country' s largest shifting desert—the Taklimakan Desert (Wang et al., 2012; Abudukade et al., 2023). The desert' s vast sand sources, frequent winds, and arid climate create highly favorable conditions for dust storms (Chen et al., 2017; Yumimoto et al., 2019). After dust events, fine particulate matter tends to accumulate on vegetation surfaces, a process that leads to a phenomenon known as dust retention. Studies have indicated that cities bordering the Taklimakan Desert experience the most severe dust effects in China, with southern Xinjiang being particularly affected (Zhang et al., 2017; Yao et al., 2023). The Kashgar Prefecture is a typical dust-affected region in southern Xinjiang, with its maize being chronically affected by sand dust from the Taklimakan Desert, resulting in considerable dust retention on leaf surfaces. Dust retention on leaves interferes with remote sensing detection of vegetation, leading to errors in estimating maize physiological parameters when mixed maize spectra are used. The effects of sand dust retention on maize spectra need to be reduced or eliminated to enhance the accuracy of maize growth monitoring and physiological parameter estimation.

Similar to the effect of atmospheric molecules and aerosol on solar radiation, dust retention on maize surfaces acts as a layer of media that hinders the interaction between incident solar radiation and maize leaves. Lyon (1996) was one of the first researchers to highlight the effect of surface dust on remote sensing detection, emphasizing the need to discriminate between the spectral properties of surface dust and rocks. This insight paved the way for research on the effects of dust retention on remote sensing. For vegetation, leaf surfaces naturally tend to accumulate dust because of the presence of stomata, trichomes, and other microstructures (Sawidis et al., 2011; Shahid et al., 2017; Sun et al., 2019). Dust retention on leaves can substantially alter canopy spectral reflectance (Yan et al., 2014; Ma et al., 2020). Several researchers have explored how different types of dust (such as urban, road, and coal dust) affect vegetation spectral reflectance and demonstrated that each type has distinct changes in spectral reflectance (Ackerman and Finlay, 2019; Zhao et al., 2020; Lin et al., 2021). These spectral changes lead to variations in vegetation indices (Kayet et al., 2024). Although some studies have been conducted on urban, road, and coal dust, limited studies have focused on sand dust. Moreover, precise quantifications of dust are essential for accurately assessing the effects of dust on vegetation spectra and indices and for providing useful references for regions with different dust retention levels. However, previous studies focused only on comparing dust-free and dust-retained conditions and did not provide precise quantifications of dust retention levels.

This study aims to explore the effects of sand dust retention on vegetation spectra and indices across varying levels, assess the dust resistance of existing vegetation indices, and develop new dust-resistant indices. The findings can provide a scientific basis for improving crop monitoring in sand-dust-affected regions.

2.1 Study area

The Kashgar Prefecture (35°20′–40°18′N, 73°20′–79°57′E) lies on the western edge of the Tarim Basin adjacent to the Taklimakan Desert and is bordered by mountains or plateaus to the northwest and south. The terrain gradually slopes from the southwest to the northeast. The region is endowed with abundant solar resources, with the annual sunshine duration showing a notable increase at a climate tendency rate of 31.3 h/10a. It features large diurnal temperature variations and an obvious upward trend in annual precipitation (amplitude: 6.16 mm/10a). Precipitation is mainly concentrated in summer and autumn, with annual precipitation being mostly less than 150 mm (Abasl et al., 2015). It has a warm-temperate continental arid climate, making it a major maize cultivation base and the largest oasis in southern Xinjiang. The geographical location of the study area is shown in Figure 1 [Figure 1: see original paper].

2.2 Experimental design

This research was conducted through a series of steps: measuring leaf spectra under varying dust retention levels, simulating canopy spectra via the LargE-Scale remote sensing data and image Simulation framework (LESS) model, assessing the dust resistance of 36 common vegetation indices, and constructing new dust-resistant indices. First, leaf spectral measurements were conducted to measure the adaxial reflectance, abaxial reflectance, and transmittance of maize leaves under varying dust retention levels. The measured spectra were used as key input parameters for the LESS model. Second, several important parameters in the LESS model, such as solar angle, view angle, row spacing, plant spacing, and maize model, were adjusted to create a realistic simulation environment. Canopy spectra were simulated under varying dust retention levels and validated using Sentinel-2 images. Finally, on the basis of the Sentinel-2 images and simulation results, the dust resistance of existing vegetation indices was assessed, and new indices with improved dust resistance were developed. The overall research workflow is shown in Figure 2 [Figure 2: see original paper].

2.3 Field sampling and measurements

Field sampling was performed to provide empirical support for dust retention and the canopy structure. A total of 30 maize plants were sampled across the study area to represent the spatial variability of the local agricultural environment. The sampling sites were evenly distributed within maize fields and placed far from the field edges to avoid border effects. All selected plants were at the tasseling stage, with comparable growth vigor and 10–13 leaves per plant, to ensure morphological consistency among the samples.

For each sampled plant, the dust retention mass, leaf area, leaf area index (LAI), plant height, and leaf inclination angle were measured. Dust retention was quantified as the amount of dust per unit area (g/m^2). Each leaf was carefully detached from the stem, and the retained dust on the adaxial surface was gently brushed off into labeled plastic bags by using a soft brush. The leaf area was then measured with a leaf area meter (Model YMJ-B; Laiyin Optoelectronic Technology Co., Ltd., Weifang, China); each leaf was placed flat and scanned until the entire surface was recorded. The dust retention mass was determined with an analytical balance (range: 100.0000 g; accuracy: 0.0001 g). The dust retention amount per unit area was calculated by dividing the measured dust mass by the corresponding leaf area. LAI was measured using an LAI-2200C plant canopy analyzer (LI-COR Biosciences, Lincoln, the USA) under uniform light conditions. Plant height was measured with a measuring tape. Three replicate readings per plant were obtained, and the mean value was used for analysis. The leaf inclination angle was measured with a circular protractor, whose straight edge was aligned with the leaf blade. Each measurement was repeated under calm conditions (wind speed < 1 m/s) to ensure accuracy.

All field measurements were performed on clear, calm days to minimize environmental interference. The collected data were used to constrain the parameters of the LESS model and validate the representativeness of the simulated dust retention range.

2.4 Laboratory spectral measurements of dust-retained maize leaves

Maize leaf and sand dust samples were collected from the Kashgar Prefecture for spectral measurements. The dust retention levels were gradually increased from 0 to 24 g/m^2 in 2 g/m^2 increments. The upper limit was determined on the basis of field sampling data, and the interval of 2 g/m^2 was selected as an optimal balance between spectral measurement precision and experimental operability. At each level, the adaxial reflectance, abaxial reflectance, and transmittance of the maize leaves were measured. Figure 3 [Figure 3: see original paper] presents maize leaves under varying dust retention levels.

The measurement procedure was as follows. For each dust retention level, the leaf was measured under dust-free conditions. Adaxial reflectance was recorded with the adaxial side facing upward, and the lamp and sensor were positioned above the leaf. Then, the lamp and sensor were repositioned below the leaf to measure abaxial reflectance, followed by transmittance with the lamp above and sensor below (Fig. 4 [Figure 4: see original paper]). After completing the measurements at one dust retention level, additional dust was applied to reach the next level, and the process was repeated.

All measurements were conducted under stable indoor lighting conditions, with a constant single-measurement duration of 1 min, a fixed distance between the lamp and sensor of 35 cm, and a constant illumination angle of 60°, to ensure the comparability of the data.

2.5 LESS spectral simulations on dust-retained maize canopy

After acquiring the adaxial reflectance, abaxial reflectance, and transmittance of the maize leaves under varying dust retention levels, the LESS model was used to simulate maize canopy spectra.

LESS is a 3D light-tracing radiative transfer model that simulates the transmission of incident light, including absorption, reflection, and transmission, through a scene. It can acquire multispectral/hyperspectral, multiangle, and Laser Imaging, Detection, and Ranging (LiDAR) remote sensing signals from complex heterogeneous environments. When simulating canopy reflectance, LESS traces photon packets from light sources through the canopy, adjusting the photon power on the basis of the leaf' s optical properties (reflectance and transmittance) at each interaction. The model also utilizes virtual photons to improve the accuracy of the bidirectional reflectance factor and backward photon tracing to calculate radiance for each pixel by linking sensors to light sources. This approach fully captures multiscattering effects between the leaves and soil, resulting in realistic and detailed canopy reflectance spectra, which can then be used to analyze the effects of varying dust retention levels on canopy spectral properties (Qi et al., 2019).

The parameters in LESS, including solar angle, view angle, and other key environmental settings, were adjusted to ensure realistic canopy spectral simulations. Moreover, the maize model orientations were adjusted because the orientations of individual maize plants vary in reality. When maize leaves are fully extended, they align mainly along a vertical plane, which is referred to as the maize growth orientation plane (Serouart et al., 2023). The growth orientation angle was optimized within a defined range to enhance realism. Then, Sentinel-2 spectral bands were integrated into the simulation bands to make subsequent validations with Sentinel-2 images convenient. After the parameters were adjusted, the measured adaxial reflectance, abaxial reflectance, and transmittance values were inputted into the LESS spectral library to simulate maize canopy spectra under varying dust retention levels. The detailed input parameters adopted in the LESS simulations, together with their sources, are listed in Table 1 to provide a comprehensive reference for reproducing the simulation settings. The reliability of the LESS simulation results was validated using Sentinel-2 images.

All parameters in Table 1 are critical for canopy reflectance simulation. Field-measured data ensure structural authenticity, and Sentinel-2-derived angles and laboratory spectra guarantee scenario consistency. Comprehensive parameter information enables full reproducibility of the simulation.

2.6 Meteorological and remote sensing data for validation

Dust on leaf surfaces can be substantially removed by a single rainfall event exceeding 15 mm, which is generally considered an effective wash-off threshold on the basis of previous experimental studies (Przybysz et al., 2014; Xu et al., 2017; Weerakkody et al., 2018; Xu et al., 2019; Wang et al., 2022). Therefore, rainfall data are crucial for determining the presence or absence of dust on leaves. Rainfall data were retrieved from the Global Daily Summaries dataset published by the National Centers for Environmental Information under National Oceanic and Atmospheric Administration (NOAA) (https://www.ncei.noaa.gov/data/global-summary-of-the-day/archive/). This dataset provides daily meteorological data from global stations, with records dating back to 1929. Specifically, the data used in this study correspond to the Kashgar station.

Analysis of the study area' s rainfall records from June to August in recent years revealed continuous rainfall from 2 to 5 August 2024, which was sufficient to wash away dust. To compare dust-free and dust-retained conditions, we selected Sentinel-2 imagery (Level-2A surface reflectance data) from the COPERNICUS/S2_{SR} Image Collection on Google Earth Engine (https://code.earthengine.google.com/). The image acquired on 30 July 2024 was used to represent dust-retained conditions, and the image taken on 7 August 2024 was used to represent dust-free conditions. A cloud applied screening process was used to ensure data quality, and pixels with more than 10.000% cloud cover were excluded from the analysis. In terms of spatial sampling, each sampling point was represented by a single pixel without any additional averaging or window sampling to maintain the highest spatial resolution possible for the study.

To quantitatively validate the accuracy of the LESS simulation results against in situ scenario-specific conditions, we adopted a dust retention level derived from prior field measurements that best matched the local maize canopy characteristics in Kashgar Prefecture. This optimized dust retention level was incorporated into the LESS model parameterization to ensure the simulated spectral responses were consistent with the actual dust retention status of the study area. To further guarantee the comparability between simulated and remotely sensed data, we first extracted spectral bands from the LESS simulation outputs that were spectrally matched to the central wavelengths and bandwidths of Sentinel-2 sensors. Subsequently, the reflectance values of these matched bands were extracted for comparison with the canopy reflectance derived from Sentinel-2 imagery. For the extraction of maize canopy reflectance from Sentinel-2 data, ten homogeneous maize field regions of interest (ROIs) were delineated across the study area. The selection of ten ROIs was determined based on pre-experiment results. Specifically, as the number of ROIs increased, the coefficient of variation (CV) of maize canopy dust retention gradually stabilized; when the number of ROIs reached 10, the CV was maintained below 2.500%, and further increasing the sample size only led to a negligible reduction in the CV. In addition, these 10 ROIs were evenly distributed across the study area, ensuring they could represent the overall level of canopy dust retention in the study area. Each ROI was defined as a 6$\times 6 pixelgrid, correspondingtoaspatialextentofapproximately 60m \times$60 m. To minimize the interference of mixed pixels and ensure the spectral purity of maize canopies, we implemented strict pixel screening criteria: only pixels with a NDVI value greater than 0.700 were retained, as this threshold is indicative of the peak growth stage of maize (Le Page et al., 2020; Nguy-Robertson et al., 2020). The average reflectance of each screened ROI was then calculated to serve as the reference dataset for validating the LESS simulation results.

2.7 Assessment of the dust resistance of existing vegetation indices

The dust resistance of 36 commonly used vegetation indices was assessed (Table 2) (Fu and Wang, 2010; Li, 2022; Ao et al., 2023; Ma et al., 2023). Dust resistance is defined as the ability of a vegetation index to remain relatively stable despite varying levels of dust retention. To quantify it, we calculated the ratio of a vegetation index as:

$$\mathrm{ratio}_{\mathrm{dust},i} = \frac{VI_{\mathrm{dust},i}}{VI_{\text{dust-free}}}, \quad (1)$$

where $VI_{\mathrm{ratio},i}$ represents the ratio of the vegetation index at a given dust retention level i (g/m^2); $VI_{\mathrm{dust},i}$ is the vegetation index value at a dust retention level of i (g/m^2); and $VI_{\text{dust-free}}$ denotes the vegetation index value under dust-free conditions. A ratio that is close to 1 indicates low sensitivity to dust and high dust resistance.

The interval [0.900, 1.100] was determined using the theoretical relationship between threshold- and inflexion-based approaches for vegetation dynamics (Shang et al., 2017). According to the analytical solution of the logistic growth model, the inflexion point corresponds to 9.180% of the vegetation growth amplitude, which is constant and independent of model parameters. This value has been widely used as a reference threshold to distinguish genuine biophysical variations from fluctuations introduced by sensor noise, atmospheric correction, or geometric misregistration (Liu et al., 2019). Therefore, the interval [0.900, 1.100] represents a $±$10.000% relative-change range, indicating that the vegetation index remains within the uncertainty band and can be regarded as spectrally stable. The symmetric negative range [-1.100, -0.900] was also included because some vegetation indices, such as those derived from reflectance differences between shortwave and near-infrared (NIR) bands, may have negative values. This symmetric definition ensures a consistent evaluation for positive and negative indices with comparable relative variations.

The Sentinel-2 images and LESS simulation results were employed to compute these vegetation index relative change ratios. The Sentinel-2 images provided canopy spectral data from different ROIs at a fixed dust retention level, and the LESS simulation results offered spectral data under varying dust retention levels within the same region.

2.8 Development of new dust-resistant vegetation indices

When developing new vegetation indices, we considered three criteria: (1) strong contrast between vegetation and other land cover types, (2) minimal spectral variation between dust-free and dust-retained maize, and (3) computational simplicity for practical applications. Given that ratio-based vegetation indices inherently satisfy the third criterion, we designed the new indices in a ratio form. To enhance dust resistance, we selected and combined bands that exhibit similar spectral change trends across varying dust retention levels.

3.1 Maize growth stage and physiological status

In the study area, maize is typically sown in early July. Approximately 30 days after sowing, the maize reaches the tasseling stage, which is the growth phase targeted in this study. Tasseling is a critical period for maize yield formation because it signifies the transition from vegetative to reproductive growth. This stage has a direct influence on key yield-related traits, including ear number, kernel weight, and tip blanking (Zeng et al., 2023). During the tasseling stage, the average LAI of maize in the study area was measured to be 4.168.

3.2 Measured leaf spectra under varying dust retention levels

Figure 5 [Figure 5: see original paper] shows the reflectance of sand dust and the adaxial reflectance, abaxial reflectance, and transmittance of dust-free maize leaves. From 350 to 670 nm, adaxial reflectance was lower than sand dust reflectance. However, between 670 and 800 nm, adaxial reflectance increased steeply, reaching a strong reflection peak at 800 nm where it exceeded sand dust reflectance. After 1200 nm, sand dust reflectance continued to increase. However, because of the presence of water absorption valleys at 1400 and 1900 nm, adaxial reflectance decreased. Therefore, after 1200 nm, adaxial reflectance remained lower than sand dust reflectance.

Comparison of the adaxial reflectance, abaxial reflectance, and transmittance of the dust-free leaves revealed that in the range of 350–670 nm, abaxial reflectance was higher than adaxial reflectance, but both were greater than the transmittance value. Between 670 and 800 nm, adaxial reflectance, abaxial reflectance, and transmittance increased sharply and converged, indicating consistent variations in the RedEdge bands. After 800 nm, transmittance became higher than adaxial and abaxial reflectance. At 1400 and 1900 nm, adaxial reflectance, abaxial reflectance, and transmittance showed water vapor absorption valleys; the depths of adaxial reflectance and transmittance valleys at 1400 nm were similar, while the abaxial reflectance valley was shallow. At 1900 nm, the valley depths of adaxial reflectance, abaxial reflectance, and transmittance were nearly consistent. As the wavelength increased, adaxial reflectance, abaxial reflectance, and transmittance demonstrated similar variation patterns characterized by distinct features, such as a green reflectance peak, a robust NIR reflectance peak, and water absorption valleys.

Figure 6a [Figure 6: see original paper] shows the adaxial reflectance of the maize leaves under varying dust retention levels. From 350 to 735 nm, as the dust retention levels increased, adaxial reflectance gradually increased. Notably, red-band reflectance increased more substantially than the green band, leading to a reduction in the difference between these bands and causing the green band reflectance peak to diminish. Between 735 and 1125 nm, adaxial reflectance gradually decreased with increasing dust retention levels. From 1125 to 1400 nm, adaxial reflectance increased slightly as the dust retention levels increased, but these variations were minimal. The reflectance values exhibited strong stability under varying dust retention levels. Beyond 1400 nm, adaxial reflectance increased as the dust retention levels increased, and the water absorption valleys became progressively smooth, causing adaxial reflectance to gradually approach sand dust reflectance.

Figure 6b shows the abaxial reflectance of the maize leaves under varying dust retention levels. Throughout the range of 350–2500 nm, abaxial reflectance exhibited minimal changes. The smallest change occurred in the visible bands (380–760 nm) and the 2000–2500 nm shortwave infrared bands, where the abaxial reflectance of the dust-free and dust-retained leaves were very close. The most remarkable changes were observed in the NIR bands (760–1400 nm), but the difference between the maximum and minimum values remained below 0.02630. Overall, as the dust retention levels increased, abaxial reflectance gradually decreased in the visible bands while exhibiting a gradual increase in the NIR and shortwave infrared bands, resulting in small overall changes.

Figure 6c presents the transmittance of the maize leaves under varying dust retention levels. As the dust retention levels increased, transmittance decreased across all wavelengths. The most notable change occurred in the NIR bands, where the difference between the maximum and minimum values could reach 0.15150. The shortwave infrared bands demonstrated the second-largest change, with a difference of 0.10070, and the smallest changes were found in the visible bands.

3.3 Simulated canopy spectra under varying dust retention levels

Figure 7a [Figure 7: see original paper] shows the LESS-simulated maize canopy reflectance under varying dust retention levels. Consistent with the results for the leaf scale, as the dust retention levels increased, canopy reflectance exhibited an overall trend of increase–decrease–increase across the wavelength range. The first inflection point remained at 735 nm, and the second was at 1325 nm. The differences between dust-free (0 g/m^2) and dust-retained (24 g/m^2) conditions were compared to further quantify the variations in canopy reflectance, and the change rates were calculated. The change rate was defined as:

$$\text{change rate} = \frac{\rho_{24} - \rho_0}{\rho_0} \times 100\%, \quad (2)$$

where $\rho_{\text{change rate}}$ represents the spectral reflectance change rate (%); ρ_0 is the reflectance at 0 g/m^2; and ρ_{24} denotes the reflectance at 24 g/m^2.

Figure 7b shows the leaf-scale reflectance differences and change rates, as well as the canopy-scale counterparts simulated by LESS. The solid lines represent absolute reflectance differences, and the dashed lines indicate relative change rates. At the canopy level, from 350 to 735 nm, the average reflectance difference between dust-free and dust-retained conditions was 0.04285, peaking at 0.07426 at 675 nm. The average change rate was 148.950%, reaching a maximum of 320.362% at 675 nm. From 735 to 1325 nm, the average difference was -0.11755, with a minimum of 0.18329 at 895 nm. The corresponding average change rate was -29.002%, with the largest negative change of -40.697% at 765 nm. From 1325 to 2500 nm, the average difference was 0.06376, peaking at 0.08706 at 2435 nm. The average change rate was 133.498%, with a maximum of 503.004% at 1925 nm.

Given that the adaxial leaf surface is the primary interface interacting with incident solar radiation in natural canopy architectures, this study focused on adaxial leaf reflectance rather than abaxial reflectance or leaf transmittance. Overall, the patterns of variations in canopy reflectance aligned with those at the leaf scale, but differences in magnitude were observed. From 350 to 735 nm, the differences in leaf adaxial reflectance were noticeably larger than those in canopy reflectance, and the change rates were comparable between the two scales. From 735 to 1325 nm, the differences and change rates were greater at the canopy scale compared with those at the leaf scale. However, from 1325 nm to 2500 nm, the variation patterns were reversed, with the leaf scale exhibiting greater variations in differences and change rates compared with the canopy scale. The absolute reflectance differences were jointly interpreted with their associated uncertainties, as shown by the error bars in Figure 7c, to avoid potential exaggeration caused by small baseline reflectance values. This addition provided a balanced evaluation of spectral variability between dust-free and dust-retained conditions.

3.4 Validation of LESS simulation results with Sentinel-2 images

The results are shown in Figure 8 [Figure 8: see original paper]. For the dust-free maize, the largest difference occurred in the NIR bands, with a gap of 0.04057, and the smallest difference appeared in the red band, with an absolute difference of only 0.00007. In most of the bands, the absolute differences remained below 0.03500, indicating that the LESS model provided reliable results for canopy spectral simulations. The standard deviations remained small (0.02500) across most wavelengths, suggesting that the LESS simulations provided stable and reliable estimates of canopy reflectance under different dust conditions.

On the basis of statistical analysis, seven commonly used bands for calculating vegetation indices were selected (Green, Red, RedEdge-1 (RE1), RedEdge-2 (RE2), RedEdge-3 (RE3), NIR, and RedEdge-4 (RE4)), and the squared differences between the spectral reflectance values from the Sentinel-2 images and LESS simulation results were calculated. The dust retention levels were specifically set in the range of 2 to 10 g/m^2, which was determined by the field sampling survey conducted in Kashgar Prefecture. The in situ measurements showed that the leaf surface dust retention amount was predominantly concentrated at approximately 6 g/m^2, and the maximum dust retention level in Kashgar Prefecture was only 10 g/m^2. These squared differences were then summed up for dust retention levels ranging from 2 to 10 g/m^2, as shown in Table 3 . The sum of 6 g/m^2 was the smallest among all the dust retention levels, aligning with the previous measurements. Specifically, the large squared differences were at the RE1 and red bands, namely 0.00084 and 0.00056, respectively. Meanwhile, the squared differences at the other bands were lower than 0.00035, with the RE2 band showing an exceptionally low value of below 0.00010, further confirming that the LESS model is suitable for simulating dust-retained maize spectra. As summarized in Table 3, the mean spectral bias between bands gradually decreased with increasing dust retention, and the standard deviations were below 0.00100 for most bands, suggesting that the bias pattern was robust.

3.5 Assessment of the dust resistance of existing vegetation indices

The presence of dust on leaf surfaces introduced inaccuracies in the vegetation indices. However, certain indices showed minimal variation. Figure 9 [Figure 9: see original paper] presents the normalized difference vegetation index (NDVI) and the ratio of transformed chlorophyll absorption in reflectance index to optimized soil-adjusted vegetation index (TCARI/OSAVI) images of maize in the study area under dust-free and dust-retained conditions, with the left side representing the dust-free condition and the right side corresponding to the dust-retained condition. Notably, the NDVI values exhibited marked differences between the two conditions, while TCARI/OSAVI values showed minor variations across the same scenarios. This observation indicated that the two vegetation indices exhibited contrasting sensitivities to dust retention, a discrepancy directly attributable to their inherent differences in dust resistance. The ratios of the 36 vegetation indices under both conditions were calculated using the LESS simulation results and Sentinel-2 imagery to further quantify the dust resistance of vegetation indices.

Table 4 presents the ratios of vegetation indices (calculated via Equation 1) derived from LESS simulation results under varying dust retention levels versus the corresponding indices under dust-free conditions. The standard deviation of each index quantifies the sensitivity of the vegetation indices to dust retention levels. The global environment monitoring index (GEMI) and TCARI/OSAVI exhibited low variability (standard deviation < 0.020), indicating strong dust resistance, whereas the ratio of transformed chlorophyll absorption in reflectance index to optimized soil-adjusted vegetation index at 705 and 750 nm (TCARI/OSAVI[705,750]), red-green ratio index (RGRI), and green-red normalized difference vegetation index (GRNDVI) showed high variance, reflecting high sensitivity to dust retention. For GEMI, the ratios remained within the dust-resistant range (0.900–1.100) when dust retention was below 6 g/m^2. However, when dust retention exceeded 6 g/m^2, the GEMI ratios deviated from this interval, indicating a decline in its dust resistance. By contrast, the TCARI/OSAVI ratios consistently stayed within the dust-resistant range across all dust levels, with an average value of 0.970, demonstrating strong robustness to dust interference.

Table 4 shows that the TCARI/OSAVI ratios remained within the dust-resistant range under all simulated dust conditions, whereas GEMI stayed within this range only when dust retention did not exceed 6 g/m^2. Given that the average dust retention level in the Kashgar Prefecture is approximately 6 g/m^2, Sentinel-2 imagery was employed for validation (Table 5). The results showed that both indices exhibited high spatial consistency among ROIs. The mean ratio of GEMI was 0.970 with a standard deviation of 0.014, and that of TCARI/OSAVI was 1.054 with a standard deviation of 0.022. These small standard deviations indicate that the two indices were stable across the different sampling areas, suggesting the high reliability of their dust-resistance performance in Sentinel-2 imagery.

3.6 Assessments of the dust resistance of new vegetation indices

Figure 10a [Figure 10: see original paper] shows the spectra variation patterns under varying dust retention levels. Notably, the reflectance curves of NIR and RE4 are highly overlapping due to their close spectral wavelengths, making them visually indistinguishable in the figure. The variation patterns of RE2, NIR, RE3, and RE4 were consistent, and RE2' s reflectance was much lower than that of the three others. We calculated the differences between RE2 and the three other bands under varying dust retention levels and combined these differences to develop new vegetation indices. Then, the variations of the three combinations were calculated, as shown in Figure 10b, revealing their suitability for developing a ratio-based vegetation index because of their similar patterns of variation. Aside from the original spectra, the differential spectra also have fine correlation with plants' biochemical components (Zhang et al., 2023). Thus, the new vegetation indices were developed using the original and differential spectra.

Figure 11 [Figure 11: see original paper] presents the ratios of the new vegetation indices under varying dust retention levels. Three indices were developed: (RE3-RE2)/(NIR-RE2), (NIR-RE2)/(RE4-RE2), and (RE3-RE2)/(RE4-RE2). All indices remained within the dust-resistant range. Among them, (NIR-RE2)/(RE4-RE2) exhibited the most robust dust resistance, with an average ratio of 0.982 for the original-spectra index and 0.980 for the differential-spectra index. For (RE3-RE2)/(RE4-RE2), the differential-spectra index performed better, with an average ratio of 0.984, compared with 0.937 for the original-spectra index. In the case of (RE3-RE2)/(NIR-RE2), the ratios of the original-spectra index decreased gradually with increasing dust retention levels but still showed superior resistance across all levels, with an average of 0.954. The differential-spectra index maintained its dust resistance across all dust retention levels, with an average ratio of 1.004.

The vegetation index ratios were calculated using Sentinel-2 imagery from the study area under dust-free and dust-retained conditions to further validate the dust resistance of the newly developed vegetation indices under real-world scenarios, and their pixel-level distributions were analyzed (Fig. 12 [Figure 12: see original paper]). Among the three indices, (RE3-RE2)/(RE4-RE2) exhibited the best performance, with 58.020% of the pixels falling within the dust-resistant range, and it was much higher than the other two indices. (NIR-RE2)/(RE4-RE2) showed weak dust resistance, with only 36.250% and 35.080% of pixels, respectively, falling within range. These results indicated that the (RE3-RE2)/(RE4-RE2) index is robust and suitable for practical applications using Sentinel-2 imagery.

3.7 Sensitivity analysis of dust retention on maize canopy reflectance

To quantify the sensitivity of maize canopy reflectance to dust retention, we calculated the relative spectral change rate (S) across the 355–2445 nm wavelength range with 13 dust retention gradients (0–24 g/m^2). The formula is defined as:

$$S_i = \frac{\rho_{\text{dust-retained}} - \rho_{\text{dust-free}}}{\rho_{\text{dust-free}}}, \quad (3)$$

where S_i is the relative spectral change rate under dust retention level i; $\rho_{\text{dust-retained}}$ represents the maize canopy reflectance under dust retention level i; and $\rho_{\text{dust-free}}$ denotes the reflectance under dust-free conditions. The key findings are summarized below (Fig. 13 [Figure 13: see original paper]).

Two core sensitive regions were identified. The 355–700 nm visible band peaked at 664.5–675 nm ($S = 3.185$–3.204 at 24 g/m^2), with average relative spectral change rate increasing by 6.78-fold from 0.321 (2 g/m^2) to 2.176 (24 g/m^2). The 1800–2445 nm long-wave NIR band showed a peak at 1915–1925 nm; under 24 g/m^2 dust retention, relative spectral change rate ranged from 4.834 to 5.030, the highest across all bands. The average relative spectral change rate in this band rose by 7.72-fold from 0.457 (2 g/m^2) to 3.528 (24 g/m^2). A weakly sensitive transition zone was observed in the 700–1350 nm range, where the average relative spectral change rate was less than 0.500. The minimum increase (3.23-fold) occurred at 725 nm, indicating a negligible dust effect on reflectance within this range. Overall, the LESS model is robust and accurately captures canopy spectral behavior under varying dust conditions. This analysis identified optimal dust-sensitive bands (1915 and 665 nm) to support subsequent inversion model development.

4.1 Mechanism of the dust resistance of existing vegetation indices

Among the 36 commonly used vegetation indices evaluated in this study, GEMI and TCARI/OSAVI were selected for in-depth analysis of dust resistance mechanisms, as they were the only two indices that exhibited distinct dust-resistant performance (Table 4). GEMI is a vegetation index designed to correct for atmospheric and soil effects. Its dust resistance depends on dust retention levels. When assessed using the Sentinel-2 images, where the dust retention level exhibited a fixed value, GEMI exhibited good dust resistance, with its ratio predominantly falling within the dust-resistant range. However, when the LESS simulation results (varying dust retention levels) were used, its dust resistance remained effective only below 6 g/m^2. Beyond this level, GEMI lost its dust resistance. The patterns of variation of its value, related parameters, and bands are shown in Figure 14 [Figure 14: see original paper].

This phenomenon can be attributed to the different environmental factors in the Sentinel-2 images and LESS simulations. The former was acquired from reality, where atmospheric dust can scatter solar radiation, reducing the energy received by the sensor. Moreover, post-rainfall soil moisture may reduce background reflectance, which affects canopy spectra in mixed pixels. By contrast, LESS simulations provide a virtual environment without these factors that weaken GEMI' s correction capability because it considers atmospheric and soil background effects (Rondeaux et al., 1996). To thoroughly understand the variations in GEMI under different dust retention levels, we analyzed its formulation as follows:

$$\mathrm{GEMI} = \eta \times (1 - 0.25\eta) - \frac{\mathrm{Red} - 0.125}{1 - \mathrm{Red}}, \quad (4)$$

$$\eta = \frac{2(\mathrm{NIR}^2 - \mathrm{Red}^2) + 1.5\mathrm{NIR} + 0.5\mathrm{Red}}{\mathrm{NIR} + \mathrm{Red} + 0.5}, \quad (5)$$

$$\frac{\partial \mathrm{GEMI}}{\partial \eta} = 1 - 0.5\eta, \quad (6)$$

$$\frac{\partial \eta}{\partial \mathrm{NIR}} = \frac{4\mathrm{NIR}(\mathrm{NIR} + \mathrm{Red} + 0.5) - 2(\mathrm{NIR}^2 - \mathrm{Red}^2) - 1.5\mathrm{NIR} - 0.5\mathrm{Red}}{(\mathrm{NIR} + \mathrm{Red} + 0.5)^2}, \quad (7)$$

$$\frac{\partial \eta}{\partial \mathrm{Red}} = \frac{-4\mathrm{Red}(\mathrm{NIR} + \mathrm{Red} + 0.5) - 2(\mathrm{NIR}^2 - \mathrm{Red}^2) - 1.5\mathrm{NIR} - 0.5\mathrm{Red}}{(\mathrm{NIR} + \mathrm{Red} + 0.5)^2}, \quad (8)$$

$$\frac{\partial \mathrm{GEMI}}{\partial \mathrm{Red}} = \frac{\partial \mathrm{GEMI}}{\partial \eta} \times \frac{\partial \eta}{\partial \mathrm{Red}} + \frac{0.875}{(1 - \mathrm{Red})^2}. \quad (9)$$

As dust retention levels increase, red-band reflectance rises, whereas NIR reflectance declines. The partial derivative analysis indicated that both trends contributed to a reduction in η (a nonlinear combination parameter of NIR and Red band reflectance), which in turn lowered the GEMI values. Given that η remained below 2.0, the partial derivative confirms that a decrease in η leads to a further reduction in GEMI. Moreover, the denominator in Equation (9) followed a parabolic function and remained negative under these conditions, indicating that an increase in red-band reflectance further decreases GEMI.

Overall, as the dust retention levels increased, the increase in red-band reflectance and the decrease in NIR band reflectance contributed to a continuous decrease in GEMI. Once the dust retention levels on the maize leaves exceeded a certain value, the ratio of GEMI exceeded the predefined dust resistance limit. Although GEMI maintained dust resistance up to 6 $\mathrm{g/m^2}$, NDVI lost its resistance at just 2 $\mathrm{g/m^2}$. Compared with NDVI, GEMI retained certain advantages, and it captured more vegetation information (Rondeaux et al., 1996).

By contrast, TCARI/OSAVI is a ratio-based vegetation index designed to enhance sensitivity to chlorophyll while minimizing background effects. TCARI is calculated using the 550, 680, and 700 nm bands. The 550 nm band corresponds to the minimum chlorophyll absorption in the visible bands, and 680 nm represents the peak absorption of chlorophyll-a. The 700 nm band, located at the boundary between pigment absorption and structural reflectance control, plays a crucial role in determining vegetation properties (Haboudane et al., 2002). Given that background reflectance (especially between 550 and 700 nm) can substantially affect the spectral slope, R_{700}/R_{550} (R_{700} and R_{550} are the reflectances of wavelength at 550 and 700 nm, respectively) was replaced with R_{700}/R_{680} (R_{680} is the reflectance of wavelength at 680 nm) to reduce soil background effects. Moreover, OSAVI was incorporated to further minimize soil sensitivity at low LAI. This combination (TCARI/OSAVI) enhanced the sensitivity to chlorophyll while reducing background noise. Although TCARI and OSAVI do not exhibit dust resistance individually, their variation trends were very similar at the same dust retention level. This similarity allowed their ratio combination to remain robust as the dust retention levels increased. TCARI/OSAVI demonstrated good dust resistance in the Sentinel-2 images and LESS simulation results. In the LESS simulations, where chlorophyll content and soil background were kept constant, the changes in TCARI/OSAVI were primarily driven by variations in dust retention levels. The TCARI/OSAVI ratios ranged from 0.948 to 0.985 across all the dust levels, with particularly stable values between 0.978 and 0.985 when dust retention was below 10 g/m^2, which corresponds to typical real-world conditions. By contrast, the TCARI/OSAVI ratios derived from Sentinel-2 imagery, where the estimated dust retention level was around 6 g/m^2, ranged from 1.014 to 1.076 and were likely influenced by the differences in maize growth stages among the parcels.

4.2 Validation of new vegetation indices

NDVI is widely recognized as a reliable indicator of vegetation growth and coverage, effectively reflecting vegetation distribution characteristics and changes (Zhang et al., 2018; Zhang et al., 2021). The correlations of the newly developed vegetation indices with NDVI were analyzed to evaluate the indices' capability to represent vegetation characteristics. The reflectance of dust-free maize in the Sentinel-2 image was used to validate the correlations between NDVI and the original-spectra indices, but not for the differential-spectra index because of its limited number of spectra. The NDVI values derived from the Sentinel-2 images were above 0.700, and this threshold was applied to all the vegetation indices. Furthermore, the LESS simulation results were utilized to validate the differential-spectra indices. By adjusting the row and plant spacing of maize models in the simulations, spectral reflectance under varying canopy coverage conditions was obtained. Given that NDVI values exceeding 0.350 indicate high-coverage areas (Bi and Bai, 2007), the maximum row spacing in the LESS simulations was set to four times the initial spacing, resulting in a NDVI of 0.370. The correlation results are presented in Figure 15 [Figure 15: see original paper], with the left side displaying the correlations between NDVI and the original-spectra indices, and the right side showing the differential-spectra indices. Among the original-spectra indices, (RE3-RE2)/(RE4-RE2) exhibited the strongest correlation with NDVI ($R^2 = 0.710$), followed by (NIR-RE2)/(RE4-RE2) ($R^2 = 0.453$); (RE3-RE2)/(NIR-RE2) showed the weakest correlation ($R^2 = 0.285$). All the differential-spectra vegetation indices achieved R^2 values exceeding 0.981, indicating their strong potential in accurately representing vegetation characteristics.

4.3 Advantages, limitations, and applicability of the new vegetation indices

Sand dust retention on vegetation surfaces alters spectral reflectance, reducing the accuracy of vegetation indices and subsequent assessments of vegetation conditions. Therefore, assessing the dust resistance of vegetation indices in dust-affected regions is crucial. The newly proposed vegetation indices are theoretically rooted in the stable spectral variation patterns of RedEdge bands (RE2, RE3, and RE4) under gradient dust retention. These bands exhibit consistent response trends to dust accumulation, and their ratio combinations (e.g., (RE3-RE2)/(RE4-RE2)) can effectively offset dust-induced spectral interference—an advantage over traditional indices (e.g., NDVI and EVI (enhanced vegetation index)) that are highly sensitive to dust. Compared with existing dust-resistant indices, GEMI loses its effectiveness when dust retention exceeds 6 g/m^2, and TCARI/OSAVI requires complex multiband calculations; by contrast, the new indices maintain stability across the full dust range (0–24 g/m^2) and show strong correlations with NDVI ($R^2 > 0.981$ for differential-spectra indices), ensuring compatibility with vegetation trait monitoring. Their ratio-based formulation simplifies computation, eliminating the need for complex atmospheric or soil corrections. Practically, the new indices are versatile for both multispectral (e.g., Sentinel-2) and hyperspectral data, addressing the single-data-type limitation of existing indices and enabling application across agricultural monitoring, environmental assessment, and land management on diverse remote sensing platforms.

Despite their overall robustness in dust resistance, the newly constructed vegetation indices still exhibit certain limitations under real-world conditions. Approximately 41.980% of the pixels deviate from the dust-resistant range mainly because of canopy heterogeneity, mixed-pixel effects, and residual atmospheric influences. These factors introduce spectral variability within the same field, slightly reducing the stability of index responses at the pixel scale. The index (RE3-RE2)/(RE4-RE2) has the highest dust-resistance stability among all the tested indices, indicating its strong adaptability in complex environments.

From a practical perspective, the newly developed dust-resistant indices are not intended to replace traditional indices but to complement them under specific dust conditions. Conventional indices, such as NDVI and EVI, perform well in clean-surface or low-dust environments, but the developed dust-resistant indices provide reliable results when leaf surface dust retention exceeds a certain value. The correlation between the developed dust-resistant indices and NDVI further demonstrates their consistency in capturing vegetation growth patterns, ensuring compatibility with widely used indices.

Therefore, index selection should be task- and environment-dependent. In heavily dust-affected regions, such as southern Xinjiang, the developed dust-resistant indices can improve the accuracy of biophysical parameter estimation and vegetation condition monitoring. Under low-dust or post-rainfall conditions, traditional indices are still preferable for regional-scale vegetation assessment. This complementary framework enhances the flexibility and practicality of vegetation monitoring across diverse environments and sensor types.

4.4 Limitations and applicability of this study

Although this study advances the understanding of maize canopy spectral responses under varying dust retention levels, several limitations should be acknowledged.

First, the Sentinel-2 image pair used to separate dust-retained and dust-free conditions was acquired eight days apart. During this period, minor phenological or illumination changes may have occurred. Multiyear NDVI data were analyzed to assess their influence (Table 6). The mean NDVI difference during comparable intervals at the tasseling stage was less than 0.080, which is smaller than the NDVI decrease (0.121) caused by dust removal in this study. This result suggested that the observed spectral differences were mainly related to dust removal rather than phenological variation or illumination changes. Although the continuous rainfall before image acquisition likely removed most of the retained dust, minor re-sedimentation could still have occurred during the short post-rainfall period, especially near the field boundaries. Nevertheless, the overall effect of such localized redeposition is considered limited and unlikely to affect the main conclusions.

Second, several vegetation indices used in this study, such as simple ratio index at 705 nm (SR705), normalized difference index at 705 nm (ND705), modified simple ratio index at 705 nm (mSR705), modified normalized difference index at 705 nm (mND705), TCARI/OSAVI[705,750], and ratio of modified chlorophyll absorption in reflectance index to optimized soil-adjusted vegetation index at 705 and 750 nm (MCARI/OSAVI[705,750]), are defined for narrow spectral bands, whereas Sentinel-2 bands are relatively broad. This mismatch could have introduced uncertainty. Narrowband indices derived from simulated spectra were compared with broadband indices computed from Sentinel-2 bands to evaluate the effect. The two sets showed strong correlations ($R^2 > 0.999$, Table 7), indicating that the differences introduced by bandwidth mismatch were limited. Furthermore, dust resistance analysis was conducted. The results revealed that all six vegetation indices exhibited no dust resistance, and this result was unaffected by whether narrow or broad bands were used.

Third, this work focused on maize during the tasseling stage in southern Xinjiang, where arid conditions and fine dust promote stable surface retention. The derived dust-spectra relationships and dust-resistant indices are therefore relevant for crops with similar canopy structures (e.g., sorghum) under dry climates. In humid regions or for crops with narrow or vertically oriented leaves (e.g., wheat and rice), dust retention behavior and the associated spectral responses may differ, and direct application of the results should be approached with caution.

The fourth limitation is the uniform dust distribution assumption on leaf surfaces. This assumption may introduce slight biases in simulated canopy reflectance. The LESS model propagates leaf-level dust-affected optical properties (reflectance/transmittance) to the canopy scale via light scattering/absorption processes, integrating leaf–leaf interactions and three-dimensional (3D) canopy structure (e.g., leaf angle distribution and row spacing). These structural factors modulate uncertainty propagation, with simulations showing that biases remain within acceptable ranges when validated against Sentinel-2 imagery. Leaf inclination and orientation randomness also influence canopy reflectance. Theoretically, steep inclinations reduce effective light interception (lowering reflectance), whereas shallow angles increase it. However, in structured maize canopies with relatively consistent leaf orientations, random variations exert minimal effects on overall reflectance.

Despite these constraints, the present study offers a foundation for exploring dust–vegetation interactions. Through additional field measurements, multi-temporal observations, and analysis of varied particle characteristics, researchers could extend this framework to broad environments in future work. Such efforts would refine the understanding of dust-induced spectral effects and enhance vegetation monitoring in dust-affected regions.

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5 Conclusions

This study examined the effects of sand dust retention on tasseling-stage maize's spectral reflectance and vegetation indices in Kashgar Prefecture. We measured leaf-level spectra under gradient dust retention, simulated canopy spectra via the LESS model, and evaluated 36 common vegetation indices' dust resistance by using simulated data and Sentinel-2 imagery while developing new robust indices.

Canopy reflectance spectra showed an increase–decrease–increase trend with critical turning points at 735 and 1325 nm. The 735–1325 nm band had the largest reflectance difference of -0.11755 and a change rate of -29.002%, and the 350–735 nm range exhibited the highest average change rate of 148.950%. Among the 36 vegetation indices, only GEMI and TCARI/OSAVI showed partial dust resistance. GEMI performed effectively at dust retention levels below 6 g/m^2 but lost its effectiveness at high levels. TCARI/OSAVI remained stable across all levels, with an average ratio of 0.970. The newly developed indices performed strongly. (NIR–RE2)/(RE4–RE2) had the highest average ratios, which reached 0.982 for the original spectra and 0.980 for the differential spectra. (RE3–RE2)/(RE4–RE2) was robust in satellite imagery, with 58.020% of its pixels falling within the dust-resistant range.

This study provides targeted insights for maize monitoring in southern Xinjiang. Our future work will consider other vegetation types and dust-affected regions to enhance the generalizability of dust-resistant indices, thereby supporting global vegetation monitoring in dust-prone areas.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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