Review

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Effects of Environmental Conditions on Vegetation Indices from Multispectral Images: A Review

Md Asrakul Haque[1], Md Nasim Reza[2,3], Mohammod Ali[2,3], Md Rejaul Karim[1], Shahriar Ahmed[1], Kyung-Do Lee[4], Young Ho Khang[5], Sun-Ok Chung[6,7]*

[1]PhD Student, Department of Agricultural Machinery Engineering, Chungnam National University, Daejeon, Republic of Korea
[2]Postdoctoral Researcher, Department of Agricultural Machinery Engineering, Chungnam National University, Daejeon, Republic of Korea
[3]Postdoctoral Researcher, Department of Smart Agricultural Systems, Chungnam National University, Daejeon, Republic of Korea
[4]Senior Researcher, National Institute of Agricultural Sciences, Rural Development Administration, Wanju, Republic of Korea
[5]Researcher, Jeollabukdo Agriculture Research and Extension Services, Iksan, Republic of Korea
[6]Professor, Department of Agricultural Machinery Engineering, Chungnam National University, Daejeon, Republic of Korea
[7]Professor, Department of Smart Agricultural Systems, Chungnam National University, Daejeon, Republic of Korea

Abstract: The utilization of multispectral imaging systems (MIS) in remote sensing has become crucial for large-scale agricultural operations, particularly for diagnosing plant health, monitoring crop growth, and estimating plant phenotypic traits through vegetation indices (VIs). However, environmental factors can significantly affect the accuracy of multispectral reflectance data, leading to potential errors in VIs and crop status assessments. This paper reviewed the complex interactions between environmental conditions and multispectral sensors emphasizing the importance of accounting for these factors to enhance the reliability of reflectance data in agricultural applications. An overview of the fundamentals of multispectral sensors and the operational principles behind vegetation index (VI) computation was reviewed. The review highlights the impact of environmental conditions, particularly solar zenith angle (SZA), on reflectance data quality. Higher SZA values increase cloud optical thickness and droplet concentration by 40–70%, affecting reflectance in the red (–0.01 to 0.02) and near-infrared (NIR) bands (–0.03 to 0.06), crucial for VI accuracy. An SZA of 45° is optimal for data collection, while atmospheric conditions, such as water vapor and aerosols, greatly influence reflectance data, affecting forest biomass estimates and agricultural assessments. During the COVID-19 lockdown, reduced atmospheric interference improved the accuracy of satellite image reflectance consistency. The NIR/Red edge ratio and water index emerged as the most stable indices, providing consistent measurements across different lighting conditions. Additionally, a simulated environment demonstrated that MIS surface reflectance can vary 10–20% with changes in aerosol optical thickness, 15–30% with water vapor levels, and up to 25% in NIR reflectance due to high wind speeds. Seasonal factors like temperature and humidity can cause up to a 15% change, highlighting the complexity of environmental impacts on remote sensing data. This review indicated the importance of precisely managing environmental factors to maintain the integrity of VIs calculations. Explaining the relationship between environmental variables and multispectral sensors offers valuable insights for optimizing the accuracy and reliability of remote sensing data in various agricultural applications.

Keywords: Remote sensing, Multispectral sensors, Environmental effects, Spectral resolution, Sensor calibration, Vegetation indices

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Corresponding author:
Sun-Ok Chung
E-mail: sochung@cnu.ac.kr

1. Introduction

Remote sensing is the process of acquiring information about an object or phenomenon without making physical contact, typically through the use of satellites, drones, or aircraft equipped with sensors (Janga et al., 2023). Remote sensing in agriculture involves the application of various devices and sensors to gather data over time, then analyze to assess crop and yield conditions, enabling farmers to make informed changes for maximum output (Sishodia et al., 2020). The technology helps detect common threats like pest infestations and weeds early, allowing timely countermeasures, and it is adaptable to different land areas and crop types, ensuring comprehensive agricultural monitoring and management (Karunathilake et al., 2023).

The development of remote sensing technology has significantly enhanced the ability to observe and understand the complex dynamics of the earth's surface. By systematically gathering data from a distance, remote sensing technology has become essential for monitoring environmental changes, assessing land cover variations, and studying diverse agricultural ecosystems (Awokuse and Xie, 2015). Multispectral imagery, a key technique in remote sensing, collects data across various wavelengths of the electromagnetic spectrum. This method captures detailed information from multiple spectral bands, allowing for a comprehensive analysis of the object's surface (Lim et al., 2024).

Investigating the influence of environmental conditions on the precision of multispectral imaging, particularly in the calculation of vegetation indices (VIs), is essential for advancing this application in remote sensing. To enhance the understanding and application of VIs, it is crucial to consider the fusion of spectral band information from unmanned aerial vehicle (UAV), ground, and satellite-based multispectral imaging systems (MIS). Researchers have explored the fusion of multispectral imagery and derived VIs for various applications, such as machine learning algorithms for ground classification and monitoring vegetation across diverse environments (Zhang et al., 2021; Maimaitijiang et al., 2020). Additionally, spectral indices derived from multispectral remote sensing parameters, particularly VIs, are widely used to monitor earth system dynamics, highlighting the importance of multispectral imagery in agricultural and environmental research.

Multispectral imagery, which captures data across multiple spectral bands, offers extensive information beyond what the human eye can perceive. This capability is particularly valuable in vegetation monitoring, where calculating VIs has become fundamental for assessing the health (Kurbanov and Zakharova, 2020), density (Gitelson, 2004), and vigor (Selvaraj et al., 2021) of crops and plants. The prolific use of indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) signifies their importance in applications ranging from ecological research to precision agriculture (PA). In addition to widely used indices like NDVI and EVI, various specialized VIs have been developed for specific purposes and applications. For instance, the Green Normalized Difference Vegetation Index (GNDVI) is effective in correcting soil background influences and is frequently employed in precision farming (Sishodia et al., 2020). Similarly, the Soil Adjusted Vegetation Index (SAVI) is designed to reduce the effects of soil brightness in areas with sparse vegetation, making it particularly valuable for assessing vegetation in semi-arid regions (Almalki et al., 2022). Additionally, wetland mapping and hydrological studies employ the Normalized Difference Water Index (NDWI) to detect the presence of water, utilizing the differences in near-infrared (NIR) and shortwave infrared reflectance of vegetation and water (Ma et al., 2019). These indices are very important in extracting specific information about vegetation properties from remote sensing data, enabling a wide range of applications in environmental monitoring (Arnold et al., 2013), agricultural crop monitoring, and yield predictions (Na et al., 2016), land use planning, and agricultural ecosystem management (Silva et al., 2020).

The role of multispectral imagery in remote sensing is important, as the collected data across distinct spectral bands, allows the calculation of precise VIs. MIS offers higher spectral resolution compared to panchromatic images, which capture only a single band wavelength. This enhanced spectral resolution allows for more detailed observation of precise differences in how objects reflect light, providing a clearer and more detailed understanding of plant health. To maximize the benefits of VIs, it is essential to integrate spectral band data from various sources, including UAVs, terrestrial sensors, and satellite-based multispectral imagery. While hyperspectral imagery provides detailed spectral information on vegetation, multispectral images are still significant for identifying key patterns and trends, offering a comprehensive view of factors affecting the earth's vegetation (Assmann et al., 2018). Besides the agriculture sector, multispectral imagery, through its ability to detect visible and non-visible portions of the electromagnetic spectrum, is useful in multiple applications, such as water quality assessment (Cillero Castro et al., 2020), ocean environment monitoring (Yuan et al.,

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2023) and mining applications (Pour et al., 2021). Furthermore, studies have explored the fusion of spectral band data from multispectral images with derived VIs for ground classification (Zhang et al., 2021), highlighting the importance of combining multispectral imagery and VIs in various remote sensing applications.

However, multispectral images are simultaneously influenced by various environmental factors, including atmospheric conditions (Änäkkälä et al., 2022), sunlight angle (Honkavaara et al., 2012), and surface characteristics such as surface roughness. A study found that with the increase in surface roughness, the resolution of the human visual system (HVS)-based method decreases significantly (Enhui et al., 2019). Although soil cosidered as a disturbing factor in UAV imagery due to its influence, many researchers now prefer using the Modified Soil Adjusted Vegetation Index (MSAVI) or SAVI along with the widely used NDVI or Normalized Differential Red-Edge Vegetation Index (NDRE) for more accurate results (Zhen at al., 2021; Voitik et al., 2023; Fabijańczyk and Zawadzki, 2022). Variations in natural light (Knoop et al., 2020) and atmospheric conditions are also alarming factors that can introduce inconsistencies and reduce image clarity, while dust and pollutants can degrade image quality by settling on optical surfaces (Fan et al., 2022). While each of these factors can individually degrade multispectral data, their combined impact can substantially affect the quality and interpretation of the images, thereby influencing the accuracy of the derived information. Consequently, it is imperative to thoroughly understand and account for these environmental parameters to ensure precise analysis and interpretation of multispectral data in various applications, including remote sensing and vegetation monitoring.

This review aims to provide a comprehensive exploration of the major environmental factors influencing the accuracy of multispectral imagery specifically tailored for VIs data calculation in remote sensing applications. The influence of environmental parameters on the accuracy of multispectral imagery and VIs data calculation has been the subject of various studies. A study on drought pattern estimation using multispectral imagery highlighted the impact of environmental factors on the accuracy of VIs. Atmospheric conditions and soil moisture were identified as key influencers in VI assessment (Buma and Lee, 2019). Multispectral images and VIs for precision farming applications from UAV images and ground applications emphasize the significance of environmental factors in remote sensing for vegetation monitoring (Candiago et al., 2015). The influences of field conditions on raw data quality and VIs highlight the impact of environmental parameters on multispectral images.

These studies emphasized the necessity of considering factors like spatial resolution, field of view, usability, payload mass, and cost when employing remote sensing technologies for vegetation monitoring (Tmušić et al., 2020). Additionally, weather and sun angle are factors that influence aerial-captured multispectral imagery quality (Assmann et al., 2018). Therefore, it is essential to account for these environmental factors to ensure the accuracy and reliability of multispectral imagery and VIs data in agricultural applications. The objective of this review was to provide an overview of the major environmental factors that influence the accuracy of multispectral imagery when calculating VIs in remote sensing applications for monitoring crops vegetation health and related applications in agricultural domains.

2. Multispectral Reflectance Measurement Technologies

Multispectral sensing is a fundamental technique in remote sensing that requires significant data acquisition and processing to accurately analyze and interpret various environmental and surface characteristics. This method allows for a clearer and more comprehensive understanding of the earth's surface characteristics than traditional panchromatic or monochromatic sensing. In multispectral sensing, sensors are equipped with detectors or filters designed to capture radiation within distinct spectral bands (Akkoyun, 2022). These bands are strategically chosen to target features of interest, such as vegetation health (Vlachopoulos et al., 2021). The key advantage of multispectral sensing lies in its ability to discriminate between different surface materials based on their unique spectral signatures.

Multispectral sensing relies on the unique ways in which different materials reflect or emit light across the spectrum. Each material has a distinct spectral signature because of how it interacts with light at various wavelengths (Berger et al., 2022). Through the utilization of multispectral sensors, data can be captured in multiple bands, facilitating the creation of spectral profiles for different surface features (Lu et al., 2020). Subsequent analysis of this data yields valuable insights into the composition, health, and spatial distribution of observed targets (Yang et al., 2020). The selection of spectral bands is of paramount importance and is contingent upon the precise objectives of the remote sensing application. For instance, in the realm of vegetation monitoring, bands sensitive to chlorophyll absorption and near-infrared reflectance are frequently employed (Asadzadeh et al., 2022). Multispectral sensing emerges as a potent and adaptable tool in remote sensing, furnishing a rich repository of data for diverse applications encompassing environmental monitoring, agriculture, urban planning, disaster assessment, and so on. The theoretical principles of multispectral sensing serve as the foundation for extracting meaningful information from the reflectance data.

2.1. Sensor

Technologies for remote sensing (RS) have transformed agricultural research, becoming essential instruments for tracking the dynamics of crop growth and precisely measuring vegetation indicators (Martos et al., 2021). This cutting-edge field includes three major areas (Table 1) such as (i) satellite platforms, which offer global coverage and the ability to monitor over an extended period (Belward and Skøien, 2015); (ii) UAV/airborne systems, which provide unmatched flexibility and high-resolution imagery (Han et al., 2020); and (iii) ground-based platforms, which provide highly accurate, localized data (Gao et al., 2019). Using these platforms, several sensors have been used to obtain the required information (Lan, 2009).

Multispectral sensors, such as those on the Landsat and SPOT satellites, have been instrumental in providing mid-resolution data for analyzing land use, vegetation health, and agricultural trends (Toulios, 2015). The ability of these sensors to capture data in multiple spectral bands allows for the calculation of VIs like the NDVI, which is widely used to assess plant health and monitor crop growth. Integration of KOreaMulti-Purpose Satellite (KOMPSAT)-2 imagery and field measurements were applied in a study to assess the relationship between VIs and crop yield (Lee et al., 2011). The development of high-resolution multispectral imagery from satellites like QuickBird, WorldView, and IKONOS has further enhanced the ability to monitor crop conditions and other vegetation-related metrics at finer spatial resolutions (Khaliq, 2020). A wide range of multispectral sensors, including those on platforms such as Sentinel-2, MODIS, and RapidEye, further support diverse agricultural applications and improve data acquisition and processing techniques (Pejak et al., 2022; Johnson, 2016; Dhau et al., 2019). These developments have enabled more precise agricultural management practices and environmental monitoring.

UAV-based multispectral sensors, such as the MicaSense RedEdge (Di Gennaro et al., 2022), Parrot Sequoia (Deng et al., 2018), and Sentera, have become increasingly popular for their flexibility and high spatial resolution. These UAV-based systems allow for frequent and precise data collection over specific areas, making them invaluable for detailed crop monitoring, precision agriculture, and environmental assessments. The integration of UAV-based multispectral sensors with traditional satellite and ground-based measurements provides a comprehensive approach to vegetation monitoring and enhances the accuracy and utility of remote sensing data. Additionally, UAV-based sensors like the DJI P4 Multispectral and Headwall Nano-Hyperspec deliver high-resolution, localized data for precise agricultural assessments (Choosumrong et al., 2023; Lu et al., 2020).

Ground-based multispectral sensors, such as the Analytical Spectral Devices (ASD) FieldSpec range, complement satellite

Table 1. Comparative analysis of remote sensing methods summarizing the advantages, disadvantages, and applications

Method	Advantage	Disadvantage	Application
Satellite	✓ Global coverage ✓ Long-term monitoring ✓ Consistent data acquisition ✓ Large area coverage (Belward and Skøien, 2015)	✓ Lower spatial resolution ✓ Cloud cover interference ✓ Fixed revisit time ✓ Atmospheric correction needed (Bernstein et al., 2012)	✓ Land use/cover mapping ✓ Crop yield prediction ✓ Vegetation health monitoring ✓ Regional drought assessment.
UAV	✓ Very high spatial resolution ✓ Flexible timing and frequent revisits ✓ Ability to fly under clouds ✓ Cost-effective for small areas (Han et al., 2020)	✓ Limited coverage area ✓ Short flight times ✓ Weather dependency ✓ Regulatory restrictions	✓ Precision agriculture ✓ Crop stress detection ✓ Weed mapping ✓ Irrigation management (Di Gennaro et al., 2022)
Ground-based	✓ Highest accuracy and detail ✓ Direct measurements possible ✓ No atmospheric corrections needed ✓ Ability to collect samples (Gao et al., 2019)	✓ Very limited spatial coverage ✓ Time-consuming and labor-intensive ✓ Point measurements, not continuous	✓ Crop health assessment ✓ Soil moisture measurement ✓ Chlorophyll content estimation ✓ Calibration/validation of satellite and UAV data (Aasen et al., 2018)

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data by providing detailed field measurements that can be used to validate and enhance remote sensing analyses (Aasen et al., 2018). These sensors are particularly useful for collecting ground truth data, which is critical for the accurate interpretation of satellite imagery (Bausch and Khosla, 2010). Ground-based sensors, including the SPAD 502 Plus Chlorophyll Meter and Trimble GreenSeeker, provide critical on-site measurements that enhance the validation and calibration of remote sensing data during crop growth monitoring (Dadhich et al., 2023; Tagarakis et al., 2022).

The remote sensing media can be broadly categorized into passive and active techniques, each offering unique advantages for various applications (Fig. 1). Passive optical methods involve the detection of naturally emitted or reflected light, while active techniques rely on the transmission of light and subsequent measurement of the reflected or backscattered signal (Khanal et al., 2017). The integration of both passive and active optical methods has become increasingly prevalent, with the emergence of hybrid multi-sensor systems that combine cameras and laser scanners. This trend towards integration has significantly enhanced the capabilities of optical remote sensing, enabling more comprehensive and accurate data acquisition for a wide range of environmental monitoring and mapping applications.

The use of passive optical methods, such as multispectral and hyperspectral imaging has been instrumental in capturing detailed information about land cover, vegetation health, and other surface characteristics. These methods involve the detection of sunlight reflected from the earth's surface across different spectral bands, allowing for the extraction of valuable information related to VIs, soil composition, and other environmental parameters (Pallazi et al., 2019). Active optical techniques, on the other hand, have proven to be highly effective for mapping topographic features, bathymetry, and subsurface structures (Bebaeian et al., 2019). These methods typically involve the transmission of laser or other light sources, with subsequent measurement of the reflected or backscattered signal. The integration of both passive and active optical methods has significantly enhanced the capabilities of optical remote sensing, enabling more comprehensive and accurate data acquisition for a wide range of agricultural implementations (Sadeghi et al.,

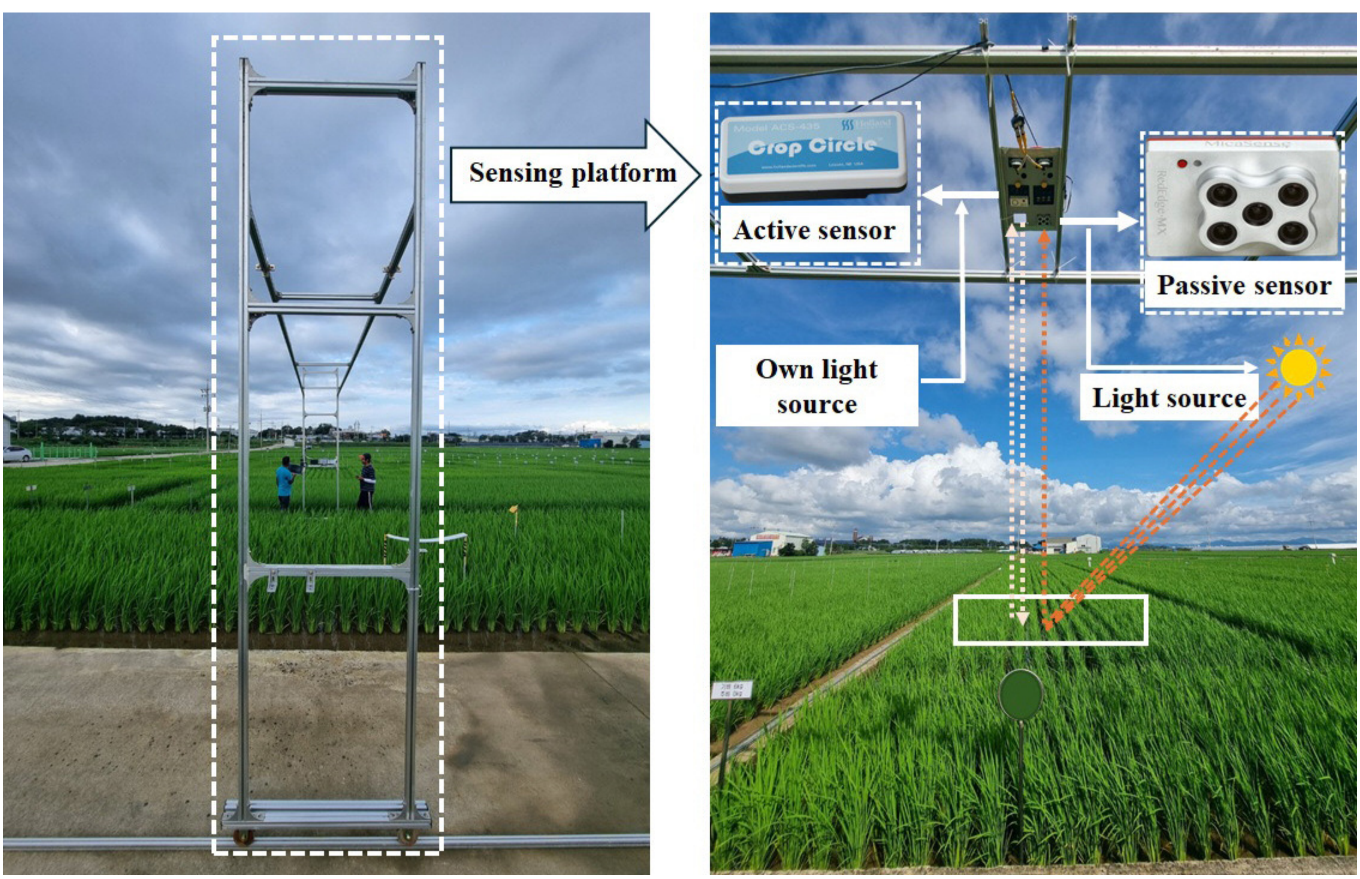

Fig. 1. Active and passive optical sensing methods.

2017; Fang et al., 2018). Table 2 outlines the applications of these sensors along with the data acquisition methods for agricultural research.

2.2. Measurement and Data Processing

The accurate measurement and processing of multispectral data are crucial for the effective monitoring of crop growth and vegetation health. Various types of sensors, including satellite-based, UAV-mounted, and ground-based sensors, are employed to capture this data (Table 2). Satellite-based sensors such as those on the Landsat series, Sentinel-2, MODIS, SPOT series, RapidEye constellation, and Planet constellation provide a range of resolutions and temporal frequencies, capturing multispectral data that are processed using various image analysis techniques, VIs, and machine learning methods (Chaves et al., 2020; Pejak et al., 2022; Johnson, 2016; Navarro et al., 2016; Dhau et al., 2019; Myers, 2021). These sensors enable large-scale monitoring and detailed analysis of VIs, such as the NDVI, which are essential for assessing plant health.

UAV-based sensors, including the MicaSense RedEdge series, Tetracam ADC series, Sentera sensors, SlantRange series, DJI P4 Multispectral, and Headwall Nano-Hyperspec, offer high-resolution and localized data collection capabilities. These sensors are mounted on UAVs and are particularly useful for

Table 2. Multispectral sensors, platforms, and applications

Multispectral sensor		Application	Data acquisition and processing	Reference
Satellite-based sensors	Landsat series (Landsat 8, 9)	Monitoring land use, vegetation health, and agricultural trends	Spaceborne sensor capturing mid-resolution multispectral data; processed using various image analysis techniques	Chaves et al. (2020)
	Sentinel-2	Monitoring crop health, yield prediction, and soil properties	Spaceborne sensor capturing high-resolution multispectral data; processed using various VIs and machine learning techniques	Pejak et al. (2022)
	MODIS	Assessing large-scale vegetation dynamics and crop productivity	Spaceborne sensor providing moderate-resolution data; processed for NDVI and other VIs	Johnson (2016)
	SPOT series (SPOT 5, 6)	Monitoring crop growth and land cover classification	Spaceborne sensor capturing high-resolution multispectral images; processed for detailed analysis of VIs	Navarro et al. (2016)
	RapidEye constellation	Monitoring agricultural practices and crop stress detection	Spaceborne sensor capturing multispectral data with high temporal frequency; processed for VIs and crop condition assessment	Dhau et al. (2019)
	Planet constellation (PlanetScope, SkySat)	High-frequency monitoring of crop growth and health	Spaceborne sensor providing high-resolution, high-frequency multispectral data; processed for detailed crop analysis	Myers (2021)
UAV-based sensors	MicaSense RedEdge series	Monitoring crop health and stress, generating VIs	Mounted on UAVs for high-resolution multispectral data collection; processed for all VIs	Vidican et al. (2023); Kurbanov and Zakharova (2020)
	Tetracam ADC series	Assessing crop health and vigor	UAV-mounted sensors capturing multispectral data; processed for various VIs	Mazzetto et al. (2009)
	Sentera sensors	Monitoring crop conditions and generating VIs	UAV-mounted sensors capturing high-resolution multispectral images; processed for detailed crop analysis	Bhagat et al. (2019)
	SlantRange 3p and 4p series	Precision agriculture and crop monitoring	UAV-mounted multispectral sensors capturing high-resolution data; processed for NDVI, NDRE, and other indices	Pasichnyk et al. (2020)
	DJI P4 multispectral	Monitoring crop health and generating VIs	UAV-mounted multispectral sensor capturing high-resolution data; processed for NDVI, NDRE, and other indices	Choosumrong et al. (2023)
	Headwall nano-hyperspec	Detailed hyperspectral imaging for crop health monitoring	UAV-mounted hyperspectral sensor capturing continuous spectral data; processed for detailed crop condition analysis	Lu et al. (2020)

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Table 2. Continued

Multispectral sensor		Application	Data acquisition and processing	Reference
Ground-based sensors	ASD FieldSpec series	Field measurements for crop monitoring	Handheld or tripod-mounted spectrometer; captures spectral data for ground truth validation	Sparks (2017)
	Spectral Evolution PSR+ series	Spectral measurements for crop health assessment	Handheld spectrometer capturing detailed spectral data; processed for VIs and crop condition analysis	Hruska (2021)
	Crop Circle Phenom series (Active crop canopy sensor)	Measuring crop canopy reflectance and health	Ground-based active sensor capturing spectral data; processed for VIs and crop condition analysis	Cummings et al. (2021)
	SPAD 502 Plus Chlorophyll Meter	Measuring leaf chlorophyll content	Handheld meter capturing chlorophyll data; processed for crop health assessment	Dadhich et al. (2023)
	FieldScout CM 1000 NDVI Meter	Measuring NDVI and crop health	Handheld meter capturing NDVI data; processed for crop health assessment	Sriram et al. (2022)
	Trimble GreenSeeker handheld crop sensor	Measuring NDVI and crop health	Handheld sensor capturing NDVI data; processed for crop health assessment	Tagarakis et al. (2022)
	LI-COR LI-1800 Portable Spectroradiometer	Ground-based spectral measurements for crop health assessment	Handheld spectroradiometer capturing detailed spectral data; processed for VIs and crop condition analysis	Vidican et al. (2023)

ADC: analog-to-digital converter, ASD: analytical spectral devices, PSR: polarimetric scanning radiometer, CM: chlorophyll meter.

precision agriculture and detailed crop monitoring, providing data processed for various VIs, such as NDVI and NDRE, to assess crop health and stress (Vidican et al., 2023; Kurbanov and Zakharova, 2020; Mazzetto et al., 2009; Bhagat et al., 2019; Pasichnyk et al., 2020; Choosumrong et al., 2023; Lu et al., 2020).

Ground-based sensors like the ASD FieldSpec series, Spectral Evolution PSR+ series, Crop Circle Phenom series, SPAD 502 Plus Chlorophyll Meter, FieldScout CM 1000 NDVI Meter, Trimble GreenSeeker, and LI-COR LI-1800 Portable Spectroradiometer provide critical on-site measurements that are vital for validating and calibrating remote sensing data. These handheld or tripod-mounted devices capture detailed spectral data, which are processed to generate VIs and assess crop conditions accurately (Sparks, 2017; Hruska, 2021; Cummings et al., 2021; Dadhich et al., 2023; Sriram et al., 2022; Tagarakis et al., 2022; Vidican et al., 2023). These integrated approaches of using satellite, UAV, and ground-based sensors enhance the precision and reliability of agricultural monitoring and management practices.

3. Crop Growth Status Monitoring Using Multispectral Imagery

In recent years, multispectral is likely to create possibilities in the field of remote sensing, offering valuable insights into agricultural prospects. Multispectral imaging involves capturing image data within specific wavelength ranges across the electromagnetic spectrum, typically using sensors that measure reflected energy in specific portions of the spectrum. These technologies have found extensive use in environmental monitoring, precision agriculture, mineral exploration, and ocean environment assessment. The distinct advantages of multispectral imaging have led to its widespread adoption in diverse fields. Multispectral imaging, with its ability to detect visible and non-visible portions of the electromagnetic spectrum, has proven instrumental in various remote sensing applications.

However, multispectral imaging has become more enticing for the calculation of VIs for crop growth (Lee et al., 2019), offering valuable insights into various environmental and agricultural applications. This technique involves capturing image data within specific wavelength ranges across the electromagnetic spectrum, typically using sensors that measure reflected energy in specific portions of the spectrum. The reflectance data obtained from multispectral imaging is crucial for the calculation of various VIs, such as the NDVI, SAVI, and GNDVI (Pereira et al., 2017). These indices are derived from the reflectance of different light wavelengths and are designed to capture specific characteristics of vegetation. For example, NDVI, one of the most widely used VIs, is calculated from the red and NIR bands of multispectral imagery. It provides a normalized measure of the "greenness" of vegetation and is a key tool in applications ranging from

Table 3. Common VIs using remotely sensed reflectance data

Vegetation indices	Formula	Reference
Normalized differential vegetation index (NDVI)	$NDVI = \frac{NIR - RED}{NIR + RED}$	Rouse et al. (1974)
Normalized differential red-edge vegetation index (NDRE)	$NDRE = \frac{NIR - RE}{NIR + RE}$	Gitelson et al. (1974)
Green-red vegetation index (GRVI)	$GRVI = \frac{NIR}{Green}$	Tucker et al. (1979)
Green normalized differential vegetation index (GNDVI)	$GNDVI = \frac{NIR - GREEN}{NIR + GREEN}$	Gitelson et al. (1996)
Enhanced vegetation index (EVI)	$EVI = \frac{2.5(NIR - RED)}{(NIR = 6 \times RED - 7.5 \times BLUE) + 1}$	Huete et al. (1997)
Soil-adjusted vegetation index (SAVI)	$SAVI = \frac{(NIR - RED)(1 + L)}{NIR + RED + L}$	Huete (1988)
Optimized soil adjusted vegetation index (OSAVI)	$OSAVI = 1.6 [\frac{NIR - RED}{NIR + RED + 0.16}]$	Rondeaux et al. (1996)
Modified soil adjusted vegetation index (MSAVI)	$MSAVI = \frac{2 \times NIR + 1 - \sqrt{(2 \times NIR)^2 - 8(NIR - RED)}}{2}$	Qi et al. (1994)
Renormalized differential vegetation index (RDVI)	$RDVI = \frac{NIR - RED}{\sqrt{NIR + RED}}$	Roujean et al. (1995)
Canopy chlorophyll content index (CCCI)	$CCCI = \frac{(NDRE - NDRE_{min})}{(NDRE_{max} - NDRE_{min})}$	Barnes et al. (2000)
Simple ratio (SR)	$SR = \frac{NIR}{RED}$	Jordan (1969)
Modified simple ratio (MSR)	$MSR = \frac{(NIR/RED) - 1}{\sqrt{(NIR/RED) - 1}}$	Chen (1996)

RE: red-edge, L: soil adjustment factor.

ecological research to precision agriculture. However, a significant limitation of NDVI is its tendency to saturate under conditions of high biomass or dense vegetation. (Huete et al., 2002). This phenomenon occurs when further increases in vegetation density or chlorophyll content no longer result in a proportional increase in NDVI values (Gitelson, 2004).

Consequently, NDVI becomes less responsive to variations in vegetation beyond a certain threshold of greenness or canopy density, thereby reducing its effectiveness in capturing subtle differences in highly vegetated areas (Mutanga and Skidmore, 2004; Gu et al., 2013). The precision of vegetation calculations is directly influenced by the accuracy of reflectance data obtained from sensors (Matternicht et al., 2018). This accuracy is crucial for various agricultural operations, as it enables precise assessments of crop and plant nutrient status, facilitating targeted fertilizer applications. Additionally, accurate reflectance measurements allow for thorough checks on growth status, ensuring timely interventions when necessary. Ultimately, reliable reflectance data serves as a cornerstone for optimizing agricultural practices, enhancing productivity, and promoting sustainability in the food production system. Based on the basic characteristics of the sensors, a number of environmental parameters affect the accuracy of the reflectance data.

However, the reflectance from different parts of a plant varies due to variations in their anatomical and biochemical characteristics (Ge et al., 2011). Plant tissues have unique spectral signatures influenced by factors such as chlorophyll content, water content, and structural properties (Courault et al., 2005). In remote sensing applications, understanding the reflectance from different plant components is crucial for extracting meaningful information related to plant health and physiological conditions. Leaves, as fundamental components of plant anatomy, exhibit distinctive reflectance patterns influenced by the presence of chlorophyll (Maes et al., 2012). Chlorophyll, a vital pigment in

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photosynthesis, absorbs light in specific spectral regions, creating discernible reflectance features. In the NIR region, healthy leaves display elevated reflectance due to minimal chlorophyll absorption (Zhang et al., 2019). This heightened NIR reflectance, coupled with lower reflectance in the visible spectrum, especially in the red region, forms a characteristic spectral response. The contrasting reflectance between these spectral regions serves as a key indicator of leaf health and photosynthetic activity. In remote sensing, this spectral behavior is effectively leveraged in indices such as the NDVI (Zhang et al., 2019), and many more VIs (Table 3), where higher NDVI values signify healthier vegetation, and other VIs carry variable insights for individual crops. Other VIs are visualised differently for each crop.

On the other hand, non-vegetated surfaces, such as bare soil, manifest different reflectance characteristics distinct from those of vegetation. Bare soil typically exhibits higher reflectance in the visible spectrum, primarily influenced by soil composition and moisture content (Mohammed et al., 2019). In the NIR region, however, soil reflectance tends to be lower. This stark contrast in reflectance between the visible and NIR regions becomes instrumental in discriminating between vegetated and non-vegetated areas in remote sensing applications. Remote sensors, capturing these reflectance differences, enable the development of classification algorithms that effectively distinguish between land cover types. Understanding the reflectance from variable portions of a plant, such as leaves, stems, and flowers allows for more detailed insights into plant conditions (Fernandez et al., 2018). Researchers often use hyperspectral sensors, which capture a large number of narrow spectral bands, to analyse detailed reflectance patterns from different plant components (Castaldi et al., 2017). This detailed spectral information aids in the development of more sophisticated models and indices for precise vegetation analysis.

4. Factors Affecting Multispectral Reflectance Data

The fundamental characteristics of multispectral sensors, as discussed above, are subject to the influence of various environmental parameters. The accuracy and applicability of multispectral imagery in agricultural contexts are profoundly influenced by several environmental parameters, whose intricate interplay can significantly shape the reliability and effectiveness of data interpretation and subsequent decision-making processes. Atmospheric corrections represent one of the most prominent factors impacting multispectral data quality (Pan et al., 2022). Aerosols, water vapor, and various gases present in the atmosphere can exert considerable influence by altering the path of incoming radiation and causing distortions in observed reflectance (Sabater et al., 2020). These disturbances, which manifest as scattering or absorption of light, introduce complexities in accurately quantifying surface properties and vegetation characteristics (Qamar et al., 2023). Consequently, the precision of vegetation calculations, such as indices for crop health or nutrient status, may be compromised, leading to less reliable outcomes in multispectral remote sensing applications.

The dynamic nature of sunlight angle throughout the day poses another layer of complexity. Variations in solar geometry influence the illumination conditions across agricultural landscapes, resulting in temporal fluctuations in spectral signatures (Willockx et al., 2022). This phenomenon underscores the importance of considering diurnal changes in lighting when acquiring and analyzing multispectral data to mitigate potential inaccuracies arising from differing illumination angles. Furthermore, surface properties, including vegetation density, canopy structure, and soil moisture content, contribute additional layers of complexity to multispectral data interpretation. Heterogeneities in these surface characteristics can lead to spatial variations in reflectance patterns, further complicating the extraction of meaningful information from multispectral imagery. In practical agricultural applications, the impact of environmental parameters on multispectral imagery extends to various critical tasks, including early detection of plant health issues, disease identification, and precise water management. Inaccuracies stemming from atmospheric distortions, varying sunlight angles, and surface property heterogeneity can impede the ability to detect subtle changes in vegetation conditions or accurately assess crop stress levels. Consequently, the reliability of multispectral data in informing agronomic decisions, such as targeted interventions for pest management or irrigation optimization, may be compromised.

To address these challenges and enhance the utility of multispectral remote sensing in agriculture, it is imperative to develop robust strategies for environmental parameter correction and data normalization. Advanced atmospheric correction algorithms can mitigate the effects of atmospheric interference, enabling more accurate estimation of surface reflectance. Additionally, techniques for geometric and radiometric calibration can help standardize multispectral data across different illumination conditions and surface types. Moreover, integrating additional information, such as meteorological data and ground-based measurements, can further refine multispectral analyses and improve the accuracy of derived agronomic insights (Jang et al., 2024). This review provides a detailed examination of these major environmental factors, delving into their intricate interactions and discussing their implications for accurate reflectance data interpretation in remote sensing applications. Understanding and mitigating the effects of these factors are essential for enhancing the reliability and precision of remote sensing analyses across diverse landscapes and applications.

4.1. Solar Zenith Angle

SZA in multispectral imaging systems is one of the major factors to keep in observation as it affects the reflectance data. This angle significantly influences the amount of sunlight reaching the sensor, impacting the quality and accuracy of the captured data. Proper consideration of the SZA is crucial for optimizing the performance and reliability of multispectral imagery. During the data collection from any remote sensing platform, SZA has always had a significant impact in diverse sectors. Some novel observational approaches were employed to examine MODIS satellite retrieval biases in cloud optical thickness (τ) and effective radius (re) at high SZA (θ_0), using three different MODIS bands (1.6, 2.1, and 3.7 μm). Significant variations were observed, with results indicating a rapid increase in τ and a decrease in $re_{2.1}$ and $re_{3.7}$ at high θ_0 (Grosvenor and Wood, 2014). These changes collectively contributed to an overall increase in cloud droplet number concentration (Nd) of 40–70%. MODIS swath data was potentially implicated at high θ_0, underscoring the importance of considering SZA effects in the interpretation of cloud properties from satellite observations (Gao et al., 2014). Additionally, some other findings notified that a major Bidirectional Reflectance Distribution Function (BRDF) effect arises from the day-of-year effect and can cause variations of 0.04–0.06 reflectance compared to mid-summer observations. However, when less variability in SZA was found, the view angle effect became a major effect for agricultural applications and can cause variations of about (–0.01, 0.02) for a red band and about (–0.03, 0.06) for an NIR band (Gao et al., 2014).

In terms of UAV observation, the impact of SZA was found on UAV-based multispectral images in diverse crop breeding trials at different latitudes. Several VIs were influenced by SZA, while the simple ratio (SR) index exhibited less variability across SZA in both high and low-latitude zones, suggesting its suitability for reliable field-based phenotyping applications (Valencia-Ortiz et al., 2021).

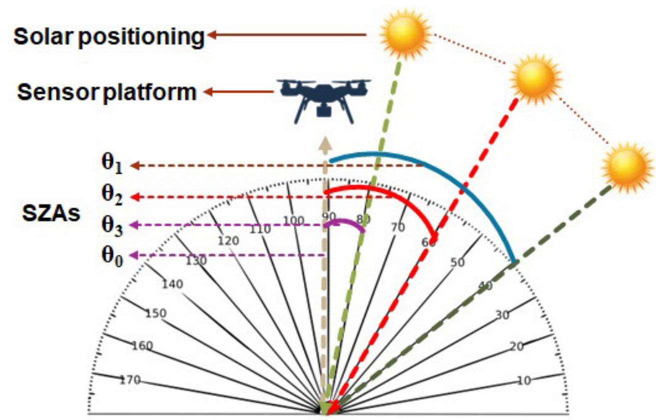

Fig. 2. Variations of SZAs in remote sensing; θ_1 with the high SZA where after a while SZA reduces to θ_0.

Variations in SZA (Fig. 2) wield a notable influence on the extraction of vegetation phenology from multispectral satellite imagery, with discernible impacts on the sensitivity of key indices such as NDVI and EVI. Notably, NDVI demonstrated heightened sensitivity compared to EVI, as elucidated in prior studies (Ma et al., 2020). Among some environmental factors examined, it was found that SZA had a more pronounced effect on UAV-derived NDVI values than factors such as flight altitude (FA) and growth stages (Jiang et al., 2020). Due to less sun angle (near to nadir, θ_0) isotropic scattering occurs in the atmosphere, reducing the amount of shadows during that period that enhanced the consistency of multispectral data. (Camacho-de Coca et al., 2001).

Similarly, from a ground-based perspective, investigations revealed that smaller SZAs like θ_3 shown in Fig. 2 exhibited diminished effects on VI calculations as well as displayed less greenness variability (Pinter et al., 1987). The impact of SZA on multispectral reflectance data and VI calculation is a critical consideration in remote sensing. Another research demonstrated the sensitivity of VIs to solar geometry, with the continuous change in narrow red and near-infrared bands and their VIs as a function of SZA being examined throughout the growing season. The study found 45° as a recommended SZA for data collection over the traditional "high sun" practice (Middleton et al., 1991). Further investigation was carried out to examine the impact of sunlight conditions on the consistency of VIs in croplands, emphasizing the significant influence of solar geometry on VI values. The study found that in general, the VIs decreased with decreasing SZA in a clear sky condition, with this response being significantly affected by the growth stage and diffuse radiation conditions (Salem et al., 2023). Similarly, a ground-based approach

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was carried out to investigate the effect of SZAs on the consistency of VIs (NDVI and GRVI) derived from spectral measurements. The study found that NDVI (0.4–0.8) and GRVI (< 0) decrease with solar zenith angle, especially under clear skies during the middle growth stage, emphasizing the need to account for these factors in accurate vegetation monitoring (Ishihara et al., 2015).

These findings collectively underscore the substantial influence of SZA on multispectral reflectance data and VIs, emphasizing the need to account for solar geometry variations to ensure the accuracy and reliability of VIs across diverse landscapes and growth stages. Significant studies were carried out regarding the viewing geometry. The influence of angular view, SZA, and viewing geometry on VIs obtained from multispectral imagery is profound and multifaceted. These factors critically affect how light interacts with vegetation and is captured by the sensor, thereby influencing the accuracy and sensitivity of the derived VIs. Variations in viewing angles, such as oblique views at –40° and –60° VZA, can substantially improve the capture of canopy structure and reduce the impact of shadows, leading to more accurate estimations of vegetation parameters like nitrogen concentration. Specifically, oblique angles often enhance the precision of measurements by mitigating shadow effects and improving the uniformity of light capture across the canopy (Lu et al., 2019).

Moreover, the anisotropic behavior of VIs, where the indices' responses vary with different view angles, underscores the significant role of viewing geometry. This variability is particularly evident in indices related to light use efficiency and leaf pigments, which demonstrate pronounced angular responses influenced by the proportion of non-photosynthetic material and the type of vegetation. The reflectance anisotropy of the Hemispherical Directional Reflectance Factor (HDRF) further modulates these angular responses, highlighting the need for careful consideration of viewing geometry in remote sensing applications. Overall, these findings emphasize that the choice of viewing geometry is crucial for accurate vegetation assessment and underscores the importance of accounting for these effects in the interpretation and application of multispectral imagery (Verrelst et al., 2008). Proper consideration and mitigation of the effects of SZA are essential for optimizing the performance and reliability of multispectral imagery for various environmental monitoring and agricultural applications.

4.2. Atmospheric Conditions

The influence of atmospheric conditions on reflectance data in remote sensing is a critical consideration, as it can significantly impact the accuracy and reliability of multispectral imagery. Atmospheric effects, such as the scattering and absorption of sunlight by atmospheric molecules and aerosols, can lead to variations in reflectance data, affecting the quality of satellite images (McNaim et al., 2002; Enclona et al., 2004). "Reduction of Atmospheric Effects in Satellite Images during the COVID-19 Induced Lockdown" by the Journal of the Indian Society of Remote Sensing discusses the impact of atmospheric effects, such as the scattering and absorption of sunlight by atmospheric molecules and aerosols, on satellite images (Joshi et al., 2020).

It provides insights into the reduction of atmospheric effects in satellite images during the COVID-19-induced lockdown, highlighting the significance of atmospheric conditions on reflectance data. Many researchers emphasized the significant influence of atmospheric conditions such as atmospheric haze (Nguyen et al., 2015; He et al., 2023), scattering (Mazur et al., 2018), water vapour absorption (Li et al., 2023) and aerosol content (Somvanshi et al., 2020) on multispectral sensor data. The impact of atmospheric light scattering on pixel intensities varies significantly across different altitudes and wavelengths. Notably, higher altitudes tend to show both positive and negative changes in pixel intensity (Fig. 3), with shorter wavelengths (460 nm) generally experiencing more substantial negative effects, while longer wavelengths (850 nm) display both large decreases and some increases at specific altitudes (Mazur et al., 2018).

Atmospheric Resistant Vegetation Index (ARVI) provides enhanced vegetation information, particularly useful for quantifying

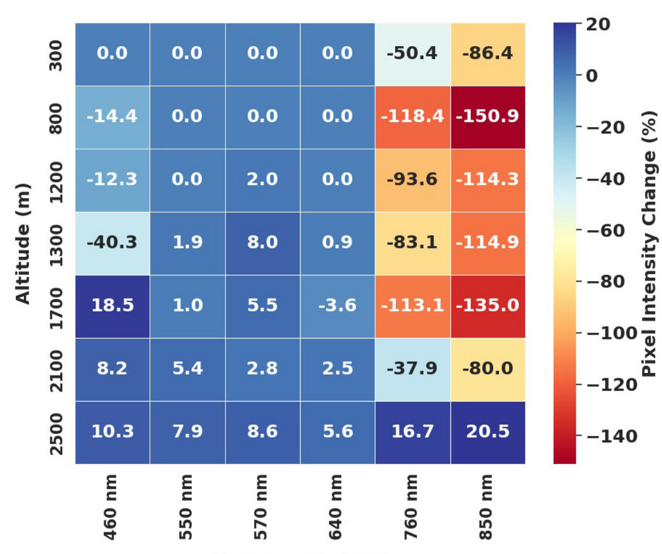

Fig. 3. The impact of atmospheric scattering on pixel intensity (%).

seasonal variations in vegetation, especially in regions with high atmospheric particulate pollution (Somvanshi et al., 2020). A researcher identified atmospheric conditions as major contributors to errors in spectral reflectance and fractional cover estimates derived from multispectral imagery. These factors significantly influenced the accuracy of the top-of-atmosphere (TOA) radiance simulations, which in turn affected the estimation of ground components such as green vegetation (GV), nonphotosynthetic vegetation (NPV), and soil. The findings emphasize the critical role of atmospheric variables in remote sensing analyses, highlighting the need for careful consideration of atmospheric conditions when interpreting multispectral data to minimize errors in fractional cover estimates (Okin et al., 2015). Atmospheric conditions, particularly seasonal weather variations, significantly affect the radiometric quality of UAV imagery, impacting its interpretative potential. A methodology was developed that considered the characteristics of weather conditions to objectively assess image quality under different meteorological conditions, enhancing the accuracy of vegetation indices and remote sensing analyses (Kedzierski et al., 2019).

Some atmospheric factors such as variations in ice crystal habits and aerosol properties create uncertainties and are identified as the primary source of errors, leading to effective radius retrieval biases of several micrometers and optical thickness uncertainties ranging from 1 to 2.5. Instrument noise and calibration uncertainties further contribute to the overall error but to a lesser extent compared to atmospheric variability (Zinner et al., 2016). Another investigation of the effect of atmospheric conditions on remote sensing of vegetation parameters found a notable correlation between atmospheric aerosol content, SZA, observer position, and observation direction with the slope and intercept of the ratio-leaf water content relationship. This research highlights the significance of accounting for atmospheric conditions in remote sensing analyses to improve the accuracy of vegetation parameter assessments (Omran, 2018). Not only highlighting the significant impact of atmospheric conditions on reflectance data, but this study also underscores the necessity for precise atmospheric correction methods to ensure the quality and consistency of reflectance data for environmental monitoring and agricultural applications. A QUick Atmosphere Correction (QUAC) model was introduced to reduce the atmospheric effects on LANDSAT-8 imagery (Bernstein et al., 2012). Recently many researchers have focused on an algorithm for additional correction of Level 2 remote sensing reflectance data, emphasizing the importance of refining correction methods to enhance accuracy in reflectance data analysis. (Korchemkina et al., 2022). Future research should prioritize the development and validation of more sophisticated atmospheric correction algorithms. These improvements will be crucial in enhancing the reliability of remote sensing data for precise environmental monitoring and agricultural management.

4.3. Illumination Conditions and Light Intensity During Data Acquisition Period

The accuracy of multispectral data can be affected by various parameters when images are taken at different times of the day. These parameters include illumination conditions, solar irradiance conditions, and the reflectance of the objects being imaged (Wang et al., 2019). Additionally, the use of multi-date imagery and spectral indices has been found to improve classification accuracy, highlighting the potential of using multispectral data for various applications, such as vegetation mapping and land cover classification (Shamaoma et al., 2023). In terms of predicting the daily variations in rice canopy photosynthesis, a leaf layer light response curve (LRC) model combined with UAV-based multispectral data was employed. The study demonstrates that light intensity, as measured by PAR, plays a crucial role in accurately estimating photosynthetic parameters and their relationship with multispectral vegetation indices, thereby affecting the overall quality and reliability of the multispectral imagery used for monitoring crop growth (Zhang et al., 2020). Another study evaluated the impact of variable illumination on VIs and the estimation of chlorophyll content using UAV imagery captured under different lighting conditions, including sunny,

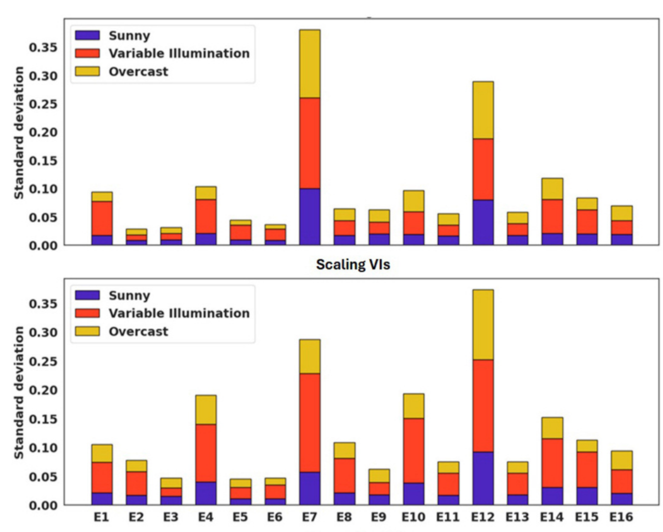

Fig. 4. The standard deviation of all the VIs for soybeans under three different illumination conditions.

overcast, and partially cloudy days (Fig. 4) (Wang et al., 2023).

Additionally, the impact of time of day and sky conditions on various VIs calculated from active and passive sensors and UAV images in a wheat crop with different nitrogen treatments were evaluated. Significant differences were observed in most VIs between different time measurements, regardless of the sensor and day of measurement. The NIR/Red edge ratio, water index, and Red-Edge Inflection Point (REIP) index were identified as the most stable indices over measurement times, indicating that passive and active sensors can be used to measure on-farm at any time of day from 9:00 to 16:00 (Fig. 5) by selecting optimized indices (de Souza et al., 2021).

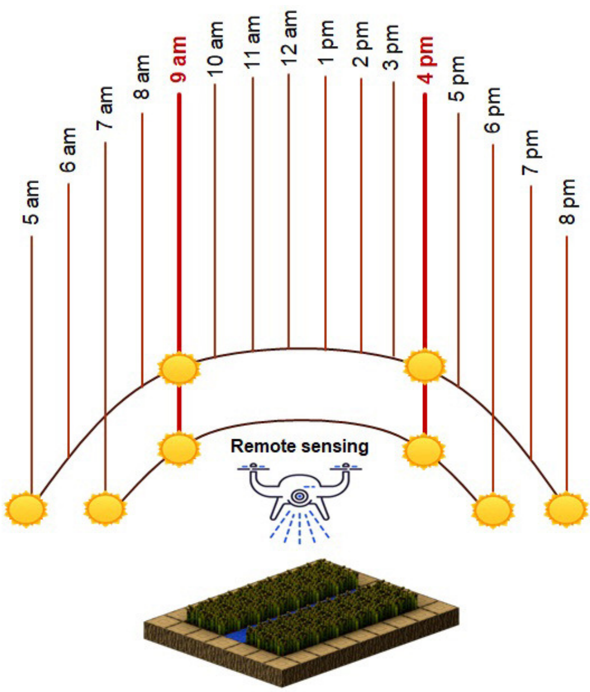

Fig. 5. Ideal data acquisition timing for active and passive sensors.

The widely employed VIs, namely the NDVI and the EVI, exhibited notable sensitivity to variations in illumination conditions (IC). Specifically, a more pronounced correlation was observed between EVI and IC compared to NDVI and IC. Leveraging the capabilities of Google Earth Engine and Landsat data, the study conducted an extensive assessment of the temporal dynamics of IC and VIs in a mountainous tropical forest spanning from 1984 to 2017. The findings underscored the significance of accounting for IC when interpreting VIs over prolonged periods, especially in regions characterized by irregular topography, thereby augmenting the precision of VI monitoring (Martin-Ortega et al., 2020). Another spectral sensor GreenSeeker included the validation of sensor responses under various environmental conditions, such as canopy coverage, standoff distance, and tilting angle. The research identified a valid range of conditions for accurate measurements and observed that the NDVI response was influenced by factors such as solar radiation, SZAs, temperature, and relative humidity. Additionally, the study highlighted the impact of surface wetness on the NDVI response, emphasizing the need to consider and compensate for these variables when using active spectral sensors for vegetation monitoring (Kim et al., 2012). Overall, the ideal conditions for capturing multispectral data are a clear sunny day (Fig. 4) or an overcast day with uniform cloud coverage. Adverse lighting conditions can impact the accuracy and consistency of data collection, making it important to consider the time of day and sky conditions when acquiring multispectral images. An increasing number of researchers have dedicated their efforts to exploring the impact of environmental

Table 4. Environmental factors affecting the multispectral sensors

Environmental factors	Key findings	Sensor type	Reference
Atmospheric conditions	Visibility and SZA made contributions to spectral and fractional cover errors.	Multispectral satellite camera	Okin and Gu (2015)
SZA	NDVI values increased with an increase in SZA, exposed soil, and vegetative surface components under soil background influence.	Airborne hyperspectral mapper (HyMap)	Welch et al. (1973)
Time of data acquisition and light intensity	The measured value was difficult to fully express the group characteristics of the object for the passive sensors.	Multispectral sensors	Kirchhof et al. (1980)
Soil moisture content	Spectral bands near 1,400 nm and 1,900 nm are typically avoided due to strong interference by atmospheric moisture.	Multispectral visible and NIR sensors	Blair and Baumgardner (1977)
Vegetation density	An overall accuracy (OA) of 75% was obtained for the dense (tree cover area) vegetation, while cropland and grassland areas had 59.4% and 65% OA respectively.	Multifrequency SAR and multispectral sensor	Bauer et al. (1979)

SAR: synthetic aperture radar.

factors on multispectral sensors, building upon existing findings in this rapidly evolving field (Table 4).

4.4. Other Environmental Factors

In multispectral remote sensing, the calculation of VIs is influenced by a range of environmental factors beyond the commonly recognized parameters such as SZA, radiometric calibration, atmospheric conditions, illumination conditions, and light intensity. A literature study introduced the factors as follows:

- Cloud cover plays a crucial role in determining the quality of multispectral imagery and, consequently, impacts the accuracy of VIs (Ajayi and Ojima, 2022).
- Rainfall events caused fluctuations in soil and vegetation water content, leading to variability in the reflectance values recorded by sensors (Bhaga et al., 2020).
- Humidity levels significantly affect atmospheric scattering and absorption, which can distort the spectral signatures captured by sensors (Zieger et al., 2010).
- Temperature fluctuations played an important role in influencing plant physiological processes (Ahmed et al., 2011; Charrier et al., 2015; Yang et al., 2023).
- Spatial and temporal variations due to topographical features, land cover changes, and seasonal dynamics add to the complex interplay of factors influencing multispectral imagery for VIs calculation (Huang et al., 2023).
- Altitude direction, time and cloud generated 8% to 11% variations in multispectral reflectance while the VI variability was 1% to 5% (Ahn et al., 2020).
- Bad weather conditions and night period can cause less accuracy in multispectral data. A study found that in these conditions Radar Vegetation Index (RVI) is considered an alternative to the VIs derived from multispectral imagery (Kim et al., 2014).

By combining insights from various studies, this overview emphasizes the necessity of comprehensively understanding these environmental factors to improve the reliability and accuracy of VIs derived from multispectral remote sensing data.

5. Discussion and Future Directions

This review highlights the intricate relationship between environmental variables and the accuracy of multispectral reflectance data used in VIs for remote sensing applications. Our analysis reveals that atmospheric conditions, solar geometry, radiometric calibration, illumination conditions, and environmental parameters significantly influence the quality and reliability of multispectral reflectance data, with direct implications for agricultural operations and ecosystem monitoring. High SZA have been shown to increase cloud optical thickness by 40–70% and alter cloud droplet characteristics, leading to substantial reflectance fluctuations in the red (−0.01 to 0.02) and NIR (−0.03 to 0.06) bands. These fluctuations critically impact VI accuracy, suggesting that optimal data collection should occur at an SZA of 45° to minimize these effects. Variations in atmospheric aerosols and water vapor content can lead to surface reflectance fluctuations of up to 10–20% and 15–30%, respectively. The observed improvement in satellite image accuracy during the COVID-19 lockdown, due to reduced atmospheric effects, underscores the importance of robust atmospheric correction techniques. Seasonal changes in temperature and humidity can alter reflectance values by up to 15%, while high wind speeds (15–20 m/s) can reduce NIR reflectance by up to 25% due to leaf orientation changes. These findings emphasize the need for continuous monitoring and adjustment of VI calculations to account for temporal environmental variations.

Moving forward, future research directions should focus on the development of advanced correction algorithms and calibration techniques to mitigate the effects of these environmental variables and enhance the precision of VIs derived from multispectral imagery.

- Effective data filtering requires the establishment of novel calibration techniques for multispectral sensors (Mamaghani and Salvaggio, 2019; Minařík et al., 2019; Jain and Pandey, 2021; Simoneau and Aubé, 2023; Shin et al., 2023). Traditional methods frequently fall short when addressing the unique problems presented by different datasets, but the precision and reliability of data interpretation can be improved by using novel calibration methods.
- Future research should prioritize the development and validation of correction algorithms that can account for the dynamic effects of SZA, aerosol optical thickness, water vapor, and other atmospheric factors on reflectance data.
- The integration of meteorological data with multispectral imaging, coupled with machine learning models for complex data analysis, offers promising avenues for enhancing VI calculations and overall data reliability.
- Continued exploration of novel sensor technologies and data fusion techniques is essential for expanding the capabilities of multispectral remote sensing, particularly for environmental monitoring and agricultural applications.

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– Interdisciplinary collaborations among researchers, practitioners, and policymakers are crucial for leveraging multispectral imagery in informed decision-making and sustainable resource management, especially in the context of global environmental changes.

By pursuing these future directions, the field of remote sensing can be advanced and contribute to more effective strategies for monitoring and managing earth ecosystems and natural resources.

6. Conclusions

In conclusion, this review highlights the substantial influence of environmental variables on multispectral sensors and VI calculations in remote sensing applications. The overview reveals that atmospheric conditions, solar geometry, radiometric calibration, and illumination conditions play crucial roles in shaping the quality and reliability of the data collected from multiple multispectral sensors. Cloud cover, rainfall events, humidity levels, temperature fluctuations, and spatial-temporal variations in topography and land cover further contribute to the complexity of VI calculation. Addressing these environmental factors through advanced correction algorithms, calibration techniques, and integration of ancillary data is imperative to ensure the accuracy and consistency of VIs derived from multispectral sensor data. By developing a deeper understanding of these environmental influences, researchers and practitioners can optimize the utility of multispectral imagery in various fields. This includes environmental monitoring, agriculture, land use planning, and ecosystem management. Such optimization fosters informed decision-making and supports sustainable resource management practices. Moving forward, continued research and innovation in correction methods and calibration techniques will further enhance the reliability and applicability of multispectral remote sensing, facilitating advancements in environmental science and resource management on a global scale.

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Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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