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REVIEW

From spectrum to yield: advances in crop photosynthesis with hyperspectral imaging

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Abstract

Ensuring global food security requires noninvasive techniques for optimizing resource use and monitoring crop health. Hyperspectral imaging (HSI) enables the precise analysis of plant physiology by capturing spectral data across narrow bands. This review explores HSI's role in agriculture, particularly its integration with unmanned aerial vehicles, AI-driven analytics, and machine learning. These advancements allow real-time monitoring of photosynthesis, chlorophyll fluorescence, and carbon assimilation, linking spectral data to plant health and agronomic decisions. Key indicators such as solar-induced fluorescence and vegetation indices enhance crop stress detection. This work compares HSI-derived metrics in differentiating nutrient deficiencies, drought, and disease. Despite its potential, challenges remain in data standardization and spectral interpretation. This review discusses solutions such as molecular phenotyping and predictive modeling, for AI-driven precision agriculture. Addressing these gaps, HSI is poised to revolutionize farming, improve climate resilience, and ensure food security.

Keywords: Calvin cycle; chlorophyll fluorescence; crop productivity; hyperspectral imaging; photosynthesis.

Introduction

The global agricultural sector faces growing challenges in meeting the rising demand for food, fiber, and bioenergy, driven by a projected global population of 9.1 billion by 2050. To sustain food production at this scale, agricultural productivity must increase by 70%, necessitating the adoption of technologies that optimize resource use, enhance crop monitoring, and improve yield forecasting (Jaggard *et al.* 2010, Ray *et al.* 2013). Precision agriculture has emerged as a viable solution, integrating remote sensing, high-throughput plant phenotyping, and AI-driven

Highlights

- Hyperspectral imaging enhances real-time crop stress detection and monitoring
- UAV-based hyperspectral systems provide high-resolution agricultural surveillance
- AI-driven spectral analytics improve precision farming and yield prediction accuracy

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Abbreviations: AI – artificial intelligence; BFQ – biochemical fluorescence quenching; CI_red-edge – Red-edge Chlorophyll Index; CNNs – convolutional neural networks; ETR – electron transport rate; fAPAR – fraction of absorbed photosynthetically active radiation; FLD – Fraunhofer line depth; GNSS – global navigation satellite system; GPP – gross primary production; HSI – hyperspectral imaging; J_{max} – maximum electron transport rate; LMA – leaf mass per area; ML – machine learning; NDVI – Normalized Difference Vegetation Index; NIR – near-infrared; NPQ – nonphotochemical quenching; NUE – nitrogen-use efficiency; *OCO-2 – Orbiting Carbon Observatory-2*; OSAVI – Optimized Soil-Adjusted Vegetation Index; PAM – pulse-amplitude modulation; PRI – Photochemical Reflectance Index; REIP – Red-edge Inflection Point; *SCOPE* – Soil–Canopy Observation, Photochemistry, and Energy Flux Model; SIF – solar-induced fluorescence; STRS – spectral-temporal response surfaces; SWIR – shortwave infrared; TIR – thermal infrared; UAV – unmanned aerial vehicle; V_{cmax} – maximum rate of carboxylation; VI – Vegetation Index; VNIR – visible-near infrared; WI – Water Index.

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analytics to monitor crop health and mitigate stressors in real time (Tilman *et al.* 2011, Pretty *et al.* 2018).

A fundamental challenge in achieving these goals is real-time, noninvasive monitoring of crop physiological and biochemical status to optimize growth conditions and mitigate environmental stressors. Traditional crop monitoring approaches, such as visual inspections and multispectral imaging, lack the sensitivity needed to detect early-stage stress responses and biochemical variations (Swain and Davis 1981). Hyperspectral imaging (HSI) overcomes these limitations by capturing high-resolution, continuous spectral data, enabling a more detailed analysis of plant physiological traits (Goetz *et al.* 1985, Lu *et al.* 2020) (Fig. 1).

While previous reviews have primarily discussed passive hyperspectral imaging and its role in vegetation analysis, this review uniquely emphasizes the integration of HSI with unmanned aerial vehicles (UAVs), machine learning algorithms, and radiative transfer models to enhance large-scale agricultural monitoring. These advancements enable automated stress detection, real-time photosynthetic efficiency assessments, and climate-adaptive precision farming (Pandey *et al.* 2017, Behmann *et al.* 2018). Additionally, this review evaluates recent developments in hyperspectral sensor miniaturization (*e.g.*, UAV-compatible *Headwall Micro-Hyperspec*, *Cubert UHD 185-Firefly*) and explores emerging AI-driven hyperspectral analytics to improve data processing efficiency.

Unlike previous studies, which have predominantly examined hyperspectral imaging as a remote sensing tool, this review highlights its evolution into an essential precision agriculture technology. The discussion provides a comparative analysis of hyperspectral metrics, linking them directly to photosynthetic activity, plant stress diagnostics, and agronomic decision-making.

Hyperspectral imaging (HSI) has undergone significant advancements over the past four decades, revolutionizing agricultural research and crop monitoring. Initially, remote sensing in agriculture relied heavily on satellite-based multispectral sensors (Swain and Davis 1981), which provided broad spectral coverage but lacked the resolution necessary to capture subtle physiological variations in crops. The pioneering efforts of Goetz *et al.* (1985) introduced airborne hyperspectral sensors, enabling the acquisition of continuous spectral data across narrow bands. This breakthrough allowed for more precise differentiation of plant physiological states, improving stress detection and early disease monitoring. However, despite its potential, the real-world application of HSI in large-scale agricultural settings was constrained by factors such as the high cost of sensors, substantial data storage requirements, and computational challenges associated with processing vast spectral datasets (Thenkabail *et al.* 2011).

Recent advancements in hyperspectral imaging have addressed these limitations, particularly with the integration of UAV-mounted hyperspectral systems. Unlike

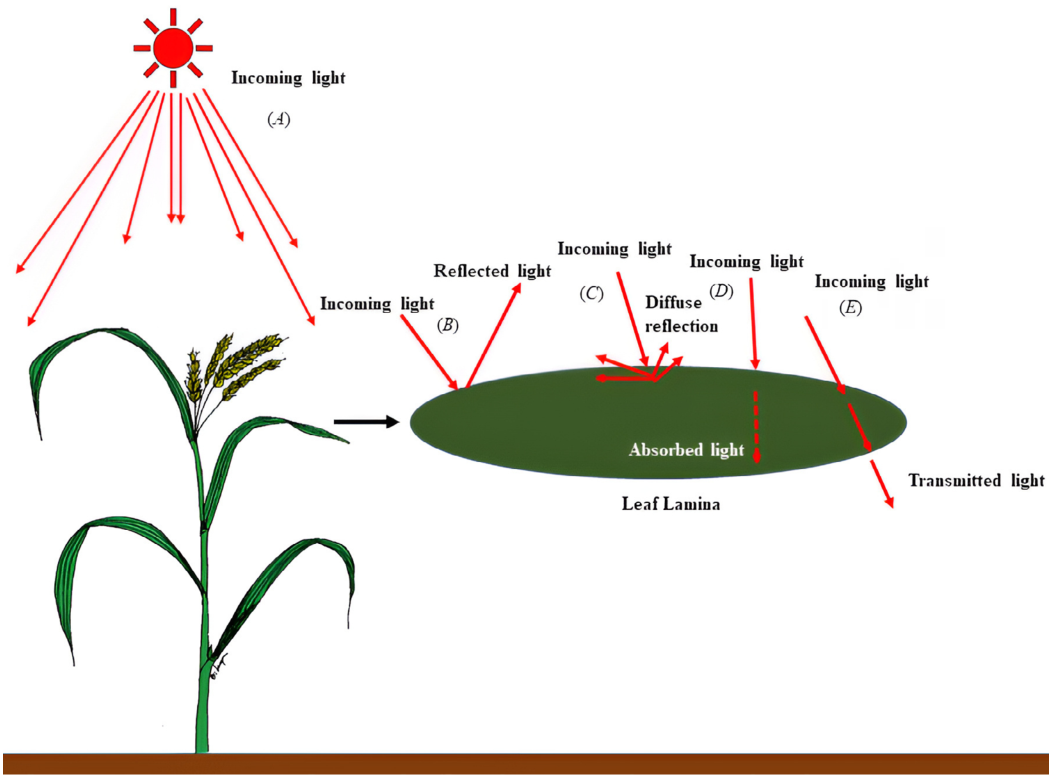

Fig. 1. Interaction of light with the leaf lamina. (*A*) Sunlight, also known as incoming light, reaches the plant leaf. (*B*) As the light encounters the leaf surface, some of it is reflected; (*C*) a portion of the light is diffusely reflected off the leaf surface, scattering in various directions; (*D*) a portion is absorbed by the leaf's lamina, which is crucial for photosynthesis; and (*E*) transmitted light, which is the remaining light that is not absorbed or reflected, passes through the leaf and may reach lower leaves or the ground.

traditional satellite-based or airborne sensors, UAV-based HSI provides high-resolution, real-time crop monitoring, allowing for greater spatial and temporal precision in agricultural decision-making (Dale *et al.* 2013, Ram *et al.* 2024). These systems facilitate early stress detection by leveraging AI-powered spectral analysis to identify subtle physiological and biochemical changes in plants, enabling proactive management of disease outbreaks and resource allocation (Khan *et al.* 2022).

Furthermore, hyperspectral analytics, combined with machine learning algorithms, has significantly enhanced crop classification and yield prediction accuracy, improving agronomic decision-making at various scales (Guerri *et al.* 2024). As sensor miniaturization and AI-driven data processing continue to evolve, UAV-mounted hyperspectral imaging is poised to become an indispensable tool for precision agriculture, bridging the gap between fundamental plant physiology research and real-world agronomic applications (Pandey *et al.* 2017, Mahlein *et al.* 2018).

Unlike traditional multispectral imaging, which captures data across a limited number of broad spectral bands, hyperspectral imaging (HSI) provides superior spectral resolution, allowing for the precise differentiation of plant physiological states. This capability is particularly valuable for the early detection of stress factors, including nitrogen deficiencies, chlorophyll degradation, and water stress, which are critical indicators of crop health and productivity (Mahlein *et al.* 2018, Benelli *et al.* 2020). By capturing continuous spectral data across hundreds of narrow bands, HSI enables a more nuanced understanding of plant responses to environmental stressors, facilitating data-driven decision-making in precision agriculture.

The integration of hyperspectral imaging with machine learning algorithms and UAV-based data acquisition has transformed modern agriculture, enabling high-throughput, noninvasive crop monitoring at an unprecedented scale. Machine learning models, particularly deep learning-based spectral classifiers, have enhanced the ability to analyze hyperspectral datasets efficiently, improving the accuracy of stress detection and yield prediction (Guerri *et al.* 2024). However, several key challenges still hinder the widespread adoption of HSI in agricultural applications. First, the standardization of hyperspectral data acquisition remains a pressing issue, as variability in sensor specifications, atmospheric conditions, and calibration protocols can impact data consistency across different platforms (Pandey *et al.* 2017). Second, improving spectral interpretation methodologies is essential to reduce misclassification errors in stress diagnosis, particularly when distinguishing between abiotic (*e.g.*, drought, nutrient deficiencies) and biotic stress factors (*e.g.*, pathogen infections) (Mahlein *et al.* 2018). Third, bridging hyperspectral metrics with biochemical pathways is crucial for establishing direct correlations between spectral signatures and physiological processes at the molecular level. This would enhance the predictive power of HSI-derived models, ultimately facilitating more precise crop stress monitoring and management strategies (Thenkabail *et al.* 2011). Addressing these challenges will be key to unlocking the full potential of hyperspectral imaging in sustainable, climate-resilient agriculture.

This review systematically explores the role of hyperspectral imaging (HSI) in photosynthesis-driven crop monitoring, offering a structured roadmap for its integration with AI, UAVs, and radiative transfer models. It begins by examining the fundamental principles of HSI, detailing how electromagnetic radiation (EMR) interacts with plant physiology through key processes, such as absorption, scattering, fluorescence, and transmission. The discussion then shifts to key spectral indices, including solar-induced fluorescence (SIF), the Photochemical Reflectance Index (PRI), and spectral-temporal response surfaces (STRS), which are essential for assessing photosynthetic efficiency and plant stress responses.

Following this, the review traces the technological evolution of HSI in agriculture, charting its transition from early airborne sensors to modern UAV-integrated systems equipped with AI-driven spectral analytics. It further explores HSI applications in precision agriculture, emphasizing its role in crop stress detection, disease identification, nutrient optimization, and yield prediction using advanced spectral metrics. Finally, the review addresses key challenges and emerging solutions, focusing on the standardization of hyperspectral data acquisition, the need for AI-powered spectral analytics, and the potential of molecular phenotyping to enhance sustainable farming practices. Through this comprehensive analysis, the review highlights the transformative potential of HSI in modern agricultural monitoring and precision farming strategies.

Unveiling the spectrum: hyperspectral imaging in agriculture

Hyperspectral imaging (HSI) has rapidly become an indispensable tool in precision agriculture, providing detailed and nuanced insights into various aspects of crop management, including plant health, nutrient status, and stress responses. The ongoing advancements in HSI technology have broadened its applicability in contemporary agricultural practices, facilitating real-time assessments critical for more informed and effective decision-making processes. This section delves into the transformative impact of HSI on agricultural methodologies, particularly emphasizing the integration of unmanned aerial vehicle (UAV) platforms and the progress achieved through machine learning algorithms (Gevaert *et al.* 2015, Lu *et al.* 2020). Note that the abbreviation HSI will now be used for hyperspectral imaging.

Integration of unmanned aerial vehicles with hyperspectral imaging

The synergy between unmanned aerial vehicles (UAVs) and hyperspectral imaging (HSI) has revolutionized agricultural data acquisition, enabling precise, high-resolution data pertinent to crop vitality and yield forecasting. The miniaturization of hyperspectral sensors, exemplified by models such as the *Headwall Micro-*

Table 1. Advancements in crop photosynthesis research through hyperspectral imaging techniques.

Crop studied	Theme	Contribution to photosynthesis understanding	Unique data from traditional studies	References
Tobacco	Reflectance hyperspectroscopy	Enables noninvasive, detailed analysis of photosynthetic efficiency, chlorophyll concentration, and carbon absorption	Provides high-resolution spectral data across a wide range of wavelengths, allowing for precise physiological assessments	Falcioni *et al.* (2023) Marín-Ortiz *et al.* (2024)
Sorghum	Decoding photosynthetic efficiency	Identifies the role of photosynthetic efficiency as a bottleneck in yield potential, linking it to biomass production	Offers insights into the efficiency of light-to-energy conversion and the impact of photorespiration on fixed carbon	Zhi *et al.* (2022)
Maize	Multispectral analysis	Facilitates the extraction of vegetation indices and spectral features, enhancing the understanding of crop physiology	Employs specialized sensors and analytical models to estimate photosynthetic parameters nondestructively	Mertens *et al.* (2021) Veramendi and Cruvinel (2024)
Rice	UAV-based hyperspectral imaging	Provides a comprehensive view of the complex interactions between different crops and vegetation at the ecosystem level	Integrates HSI with 3D structural information to better comprehend light interception and distribution	Zheng *et al.* (2018) Xu *et al.* (2024)
Wheat	Hyperspectral sensors	Connects hyperspectral information with plant genetic traits, aiding in discovering genes that contribute to improved photosynthesis	Combines HSI with genomic and phenomics data to transform crop breeding practices	Yue *et al.* (2018) Lu *et al.* (2024)
Tobacco	Carbohydrate content analysis	Quantifies leaf carbon content, a key aspect of photosynthesis and plant productivity	Captures NIR and SWIR spectra for nondestructive carbohydrate quantification	Meacham-Hensold *et al.* (2020) Olakanmi *et al.* (2024)
Wheat	Machine learning algorithms	Enhances the estimation of wheat leaf chlorophyll content by addressing soil background and canopy complexity	Utilizes image segmentation and pixel-wise spectrum clustering for more accurate leaf chlorophyll estimation	da Silva *et al.* (2024)
Tomato	Reflectance and leaf composition	Correlates leaf composition and reflective properties with photosynthetic processes and pigment concentrations	Detects and quantifies changes in pigment concentrations due to environmental stressors	Zhao *et al.* (2023)
Rice	Automated chlorophyll measurement	Automates the processing of hyperspectral datasets for nondestructive chlorophyll measurement in rice leaves	Integrates advanced image analysis with hyperspectral imaging for high-resolution digitization of chlorophyll distribution	Zhu *et al.* (2024)
Lettuce	Dark reactions of photosynthesis	Monitors key indicators associated with dark reactions, improving the understanding of carbon assimilation	Provides a holistic view of biochemical processes related to carbon assimilation nondestructively	Kumar *et al.* (2022)
Rice	Future directions of HSI in agriculture	Envisions a comprehensive approach to crop photosynthesis research, integrating precision agriculture and genomics	Proposes real-time monitoring systems and ecosystem-level studies for sustainable land management	Sun *et al.* (2017)
Rice	Photosynthetic electron transport rate (ETR)	Improves the precision of studying ETR in PSII, which is essential for understanding plant photosynthesis	Utilizes advanced hyperspectral fluorescence data analysis for detailed insights into ETR	Liran (2022)

Hyperspec and *Cubert UHD 185-Firefly*, coupled with the integration of UAV platforms with *Global Navigation Satellite System* (GNSS) technology, has significantly broadened the scope of spectral response analysis across diverse agricultural applications (Adão *et al.* 2017, Lu *et al.* 2020). This technological convergence effectively addresses the inherent limitations of traditional satellite and ground-based techniques, offering versatile and cost-effective solutions for high-resolution monitoring across extensive agricultural landscapes (Gevaert *et al.* 2015, Zeng *et al.* 2017) (Table 1). Notably, UAV-HSI systems have demonstrated remarkable effectiveness in the early detection of plant diseases, nutrient deficiencies, and water stress. By combining data streams from UAV-borne hyperspectral sensors with multispectral satellite imagery, these integrated systems generate spectral-temporal response surfaces (STRSs), which offer continuous spectral reflectance information characterized by enhanced spatial and temporal resolutions (Gevaert *et al.* 2015). These STRSs capture the dynamic spectral signatures of vegetation over time, providing a comprehensive dataset for analysis. Leveraging advanced data analysis methodologies, including support vector machines, *Random Forests*, and partial least squares regression (Lu *et al.* 2020, Pascucci *et al.* 2020), UAV-based hyperspectral imaging also streamlines the mapping of critical biophysical properties of crops, detailed soil assessments, and accurate crop classification.

A key advantage of UAV-HSI systems lies in their inherent compatibility with sophisticated computational techniques. The application of machine learning and artificial intelligence algorithms to UAV-HSI-derived data facilitates the recognition of intricate patterns, crucial for the detection of subtle stress indicators such as chlorophyll content variations, hydration levels, and cellular integrity (Tsouros *et al.* 2019) (Fig. 2). For instance, algorithms like *HW-HyperLCA* substantially enhance hyperspectral data processing efficiency, achieving significant compression ratios while preserving essential data integrity, thereby optimizing the analytical utility of large-scale datasets (Guerra *et al.* 2019). Moreover, UAV-based platforms generally ensure efficient and responsive monitoring capabilities through the provision of highly detailed and adaptable imaging modalities specifically tailored for precision agriculture applications (Zeng *et al.* 2017, Tsouros *et al.* 2019).

The practical utility of UAV-HSI technology in agriculture is substantial and varied. In viticulture, UAV-HSI enables precise assessments of vine health and irrigation demands, ultimately contributing to improvements in both grape quality and overall yield (Pascucci *et al.* 2020). Furthermore, UAV-HSI has proven particularly valuable in arid and semi-arid regions for accurate soil moisture assessment, empowering farmers to refine irrigation strategies and achieve considerable reductions in water usage (Lu *et al.* 2020). Beyond water management, UAV-HSI systems are also critical for detailed disease mapping and the timely identification of pest infestations, equipping agricultural practitioners with actionable information to optimize crop health management and fostering more sustainable farming practices (Zeng *et al.* 2017).

Through the deployment of cutting-edge hyperspectral sensors and the integration of advanced computational methodologies, UAV-HSI has established itself as a potent instrument within precision agriculture. It delivers unparalleled capabilities for monitoring crop physiological status, optimizing resource allocation, and addressing critical challenges in agricultural production, representing a significant stride forward in remote sensing technologies for the agricultural sector.

Advancements in artificial intelligence and machine learning for hyperspectral analysis imaging

The integration of artificial intelligence (AI) and machine learning (ML) techniques has advanced profoundly hyperspectral data processing by enabling the extraction of complex patterns often indiscernible through conventional analytical approaches. Within precision agriculture, *Convolutional Neural Networks* (CNNs) and *Random Forests* have been extensively applied, demonstrating exceptional performance in this domain. Notably, these sophisticated models have achieved high accuracies, reaching up to 90%, identifying subtle indicators of plant stress, such as early manifestations of water scarcity and nutrient imbalances (Banerjee *et al.* 2020, Olson and Anderson 2021). Indeed, leveraging UAVs equipped with HSI systems offers a unique avenue for acquiring high-resolution spectral datasets, which is instrumental for comprehensively investigating complex, spectrally driven agricultural scenarios (Banerjee *et al.* 2020). These analytical advancements effectively mitigate challenges related to the inherent spectral variability within vegetation canopies, facilitating more reliable and precise monitoring of crop health across extensive agricultural regions.

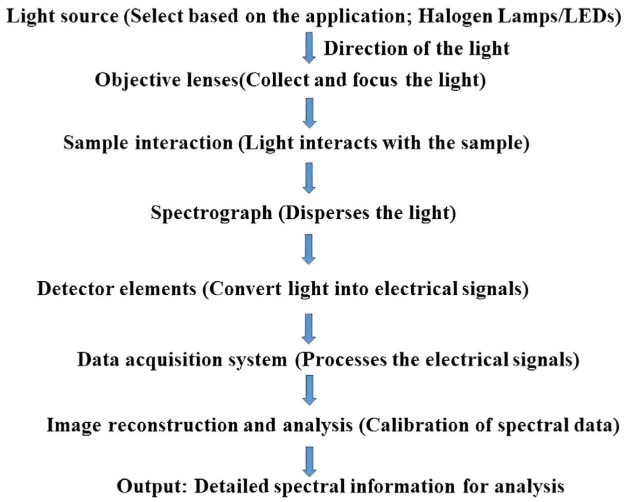

Fig. 2. Flow chart of hyperspectral imaging system components and processes for plant spectral data acquisition and analysis.

The synergistic combination of artificial intelligence and hyperspectral imaging has fundamentally transformed resource management strategies in agriculture. By employing machine learning algorithms, including *Random Forests* and CNNs, AI-driven analytics can accurately and rapidly identify both nutritional deficiencies and water stress conditions at nascent stages of development. This proactive approach has demonstrated tangible benefits, including a reported 15% reduction in water consumption and a 10% decrease in fertilizer application, underscoring the practical viability of AI-enhanced sustainable agricultural practices (Benos *et al.* 2021, García-Vera *et al.* 2024). Furthermore, the seamless integration of AI with HSI technology streamlines and automates the detection of stress and disease in cultivated crops, significantly diminishing the reliance on time-consuming manual inspection and intervention (Benos *et al.* 2021). In essence, machine learning amplifies the inherent capabilities of HSI by enabling the precise interpretation of complex spectral information, leading to more effective and timely detection of early-stage plant health issues and resource limitations.

AI-driven models have also revolutionized the scalability of HSI systems, allowing for the efficient and robust analysis of increasingly large and complex datasets. The incorporation of AI algorithms with spectral and thermal imaging modalities further enhances the utility of hyperspectral imaging by improving the detection of critical stress parameters, such as reduced chlorophyll content and water availability limitations (Gevaert *et al.* 2015). These progressive enhancements firmly establish AI and ML as indispensable tools for the advanced analysis of hyperspectral data, significantly improving the overall efficiency and effectiveness of contemporary agricultural management practices.

Methods for enhanced spectral and spatial resolution

Continued progress in hyperspectral imaging (HSI) technology has significantly enhanced the capacity to acquire agricultural data with unprecedented spectral and spatial resolution. These enhanced resolutions are crucial for detecting subtle physiological changes within crop canopies, including minor variations in photosynthetic efficiency and initial signs of plant stress. Satellite platforms, such as *Sentinel-2*, and UAVs equipped with advanced hyperspectral sensors offer versatile and high-resolution monitoring capabilities, making them essential for effective surveillance of expansive agricultural areas (Gevaert *et al.* 2015, Adão *et al.* 2017). Hyperspectral systems deployed on UAVs effectively generate spectral-temporal response surfaces (STRSs), seamlessly integrating satellite and UAV imagery to achieve superior spatial and temporal resolutions, further refining the data available for analysis (Gevaert *et al.* 2015). These technological advancements directly enable more precise and data-driven management of irrigation schedules, proactive crop health monitoring, and optimized nutrient application strategies, yielding measurable benefits such as substantial reductions in resource utilization (Ram *et al.* 2024). Notably, hyperspectral imaging techniques have demonstrated considerable efficacy in accurately assessing chlorophyll fluorescence and nitrogen concentration in key crops such as wheat, thereby facilitating the optimization of fertilizer applications and significantly improving photosynthetic nitrogen-use efficiency (Jia *et al.* 2021).

Despite these notable advancements, the widespread implementation of high-resolution HSI systems still faces certain practical challenges. These challenges primarily include the considerable upfront costs associated with acquiring sophisticated hyperspectral equipment, the computational complexities inherent in processing large volumes of high-dimensional datasets, and the inherent operational limitations of UAV platforms, such as restricted flight durations and vulnerability to adverse meteorological conditions. Addressing these multifaceted challenges is crucial for enabling the broader and more routine application of HSI in real-time agricultural monitoring and decision support systems (Dale *et al.* 2013, Jia *et al.* 2021). Furthermore, to fully integrate hyperspectral data into actionable decision-making processes, the standardization of data processing workflows and analytical techniques is essential to ensure robust and reliable outcomes.

Integration of multispectral and hyperspectral data

The strategic integration of multispectral and hyperspectral data streams offers a powerful approach to leverage the complementary strengths of each imaging modality for enhanced agricultural monitoring. This synergistic amalgamation combines the broad spectral coverage characteristic of multispectral imaging with the fine spectral resolution inherent to hyperspectral imaging techniques. This combined approach enables a more comprehensive and nuanced assessment of overall vegetation health by capitalizing on the respective advantages offered by both data types. While multispectral imaging excels at identifying broad-scale patterns and general vegetation indices, hyperspectral imaging offers superior sensitivity for detecting subtle, yet critical, indicators of plant stress, such as early chlorophyll content reductions and subtle nutrient imbalances (Lu *et al.* 2020, Khan *et al.* 2022).

Incorporating thermal imaging data into this integrated framework further enhances the functional capabilities of HSI-based monitoring systems. Thermal data allows for the direct assessment of plant canopy temperature and the detection of temperature variations related to water stress, providing a more holistic and comprehensive methodology for evaluating overall crop physiological status. Specifically, the integration of thermal and hyperspectral imaging has demonstrated notable effectiveness in pinpointing areas experiencing water stress within agricultural fields and optimizing irrigation management strategies accordingly (Lu *et al.* 2020). Moreover, this multimodal approach facilitates the early detection of plant diseases by enabling the analysis of both temperature anomalies and subtle spectral irregularities, thus promoting timely interventions to minimize potential crop losses. The seamless integration of these diverse imaging modalities is becoming increasingly vital for advancing precision agriculture, significantly improving the efficiency of irrigation practices, targeted pest control applications, and optimized resource allocation within complex agricultural systems (Fig. 3).

Practical implications and future prospects

Empirical studies increasingly underscore the transformative potential of hyperspectral imaging (HSI) for promoting sustainable agricultural practices. The effective integration of HSI data with AI-driven analytics empowers agricultural practitioners to significantly expedite data processing workflows and enhance the overall precision of targeted agricultural interventions. As highlighted by Mulla (2013) and García-Vera *et al.* (2024), AI-enhanced HSI systems are rapidly emerging as critical tools for precision agriculture, enabling real-time detection of nutrient deficiencies, water stress onset, and early pest infestations across diverse crop types. These advanced techniques facilitate a more sustainable approach to resource utilization by enabling the precise minimization of water and fertilizer inputs while simultaneously maintaining or even enhancing crop yields. However, to realize the full transformative potential of HSI technology

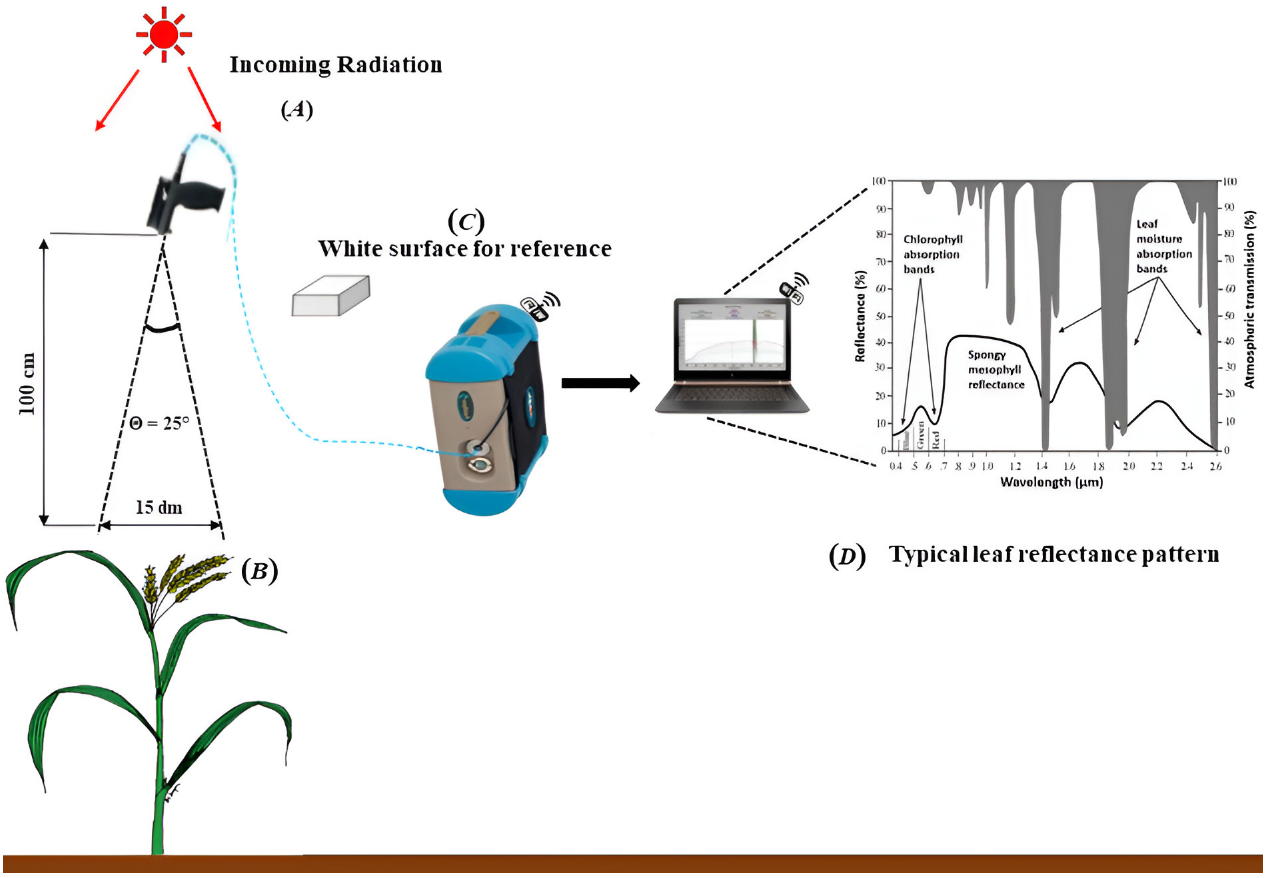

Fig. 3. Illustration of the process of measuring leaf reflectance using a spectroradiometer (*ASD Field Spec 3*). (*A*) Incoming solar radiation is directed at a plant leaf. (*B*) The sensor is positioned at a 25-degree angle from the leaf to capture the reflected radiation. (*C*) A white surface is used as a reference to calibrate the sensor for accurate measurement. (*D*) The sensor collects data on the leaf's reflectance, which is then plotted on a graph, showing how different wavelengths of light are absorbed or reflected by the leaf, indicating various plant physiological properties and atmospheric interactions.

in agriculture, the standardization of data acquisition and subsequent analytical methodologies remains a critical prerequisite. Establishing standardized procedures would be instrumental in promoting the widespread and consistent implementation of HSI across varied agricultural systems and geographical regions, thereby significantly enhancing data-driven decision-making in crucial agricultural management areas such as irrigation scheduling, targeted pest control, and optimized fertilization strategies. Looking ahead, continued advancements in sensor technologies, particularly the development of miniaturized, more affordable hyperspectral cameras and the further refinement of integrated AI algorithms, are anticipated to substantially enhance the capabilities and accessibility of HSI systems, solidifying their role as indispensable tools for achieving enhanced agricultural sustainability and productivity in the coming years.

Exploring crop photosynthesis through hyperspectral imaging applications

HSI offers a noninvasive method for evaluating the efficacy of photosystems in crops, such as the efficiency of light absorption and chlorophyll fluorescence. The accuracy of HSI in measuring photosynthetic rates and stress responses in cotton was demonstrated by Jiang *et al.* (2020) through the use of ground-based hyperspectral imaging to characterize canopy-level photosynthetic activities. Their results indicated that the detection of photosynthetic variations was enhanced by 28% when HSI-based models were implemented in comparison to conventional gas-exchange measurements. In the same vein, Meacham-Hensold *et al.* (2020) investigated the use of proximate hyperspectral imaging to evaluate the photosynthetic parameters of cereals. Their research has shown that HSI-based fluorescence retrieval techniques can increase the estimation of photosystem II efficiency (Φ_{PSII}) by 25%, thereby enabling the identification of subtle variations in photosynthetic quantum efficiency across various genotypes. HSI has been demonstrated to be effective in monitoring light-use efficiency (LUE) variations under a variety of environmental conditions, and LUE is a critical determinant of photosynthetic performance. To evaluate the photosynthetic efficacy of grape leaves, Yang *et al.* (2022) implemented hyperspectral imaging in conjunction with machine learning models. The study discovered that HSI-based models were capable of accurately predicting variations in LUE with a 92% accuracy rate, thereby illustrating their potential to optimize carbon assimilation in various crop species. Furthermore, Lu *et al.* (2020) investigated the potential of hyperspectral imaging for agricultural applications. They discovered that HSI-derived chlorophyll fluorescence indices could increase nitrogen-use efficiency (NUE) by 20%, resulting in enhanced carbon fixation rates and overall photosynthetic efficiency in maize and soybean.

Environmental stresses, including drought, salinity, and temperature fluctuations, significantly influence photosynthetic efficiency. HSI has facilitated the early detection of stress, thereby enabling the implementation of opportune interventions to preserve the optimal function of the photosynthetic system. Hyperspectral reflectance data was employed by Zhou *et al.* (2021) to assess the effects of water stress on the photosynthetic capacity of soybean and wheat. Their research illustrated that HSI models could identify stress-induced decreases in photosynthetic efficiency up to eight days before the onset of visible symptoms, thereby offering a critical instrument for precision agriculture and stress mitigation. Additionally, Sobejano-Paz *et al.* (2020) investigated the impact of drought stress on stomatal conductance and transpiration using HSI. The study discovered that HSI-derived pigment indices were 91% accurate in predicting chlorophyll degradation and photosynthetic decline, rendering it a dependable method for monitoring plant responses to environmental stress.

This section reinforces the connection between scientific insights provided by hyperspectral imaging (HSI) and their practical applications in agriculture. It elaborates on how real-time HSI data can optimize essential farming practices, such as irrigation scheduling and fertilizer application, to improve resource efficiency and increase crop yields. Concluding with future directions for HSI research, this section considers how ongoing advancements could drive breakthroughs in crop breeding, particularly in developing varieties with enhanced photosynthetic efficiency and resilience to climate change, establishing this work as a foundational reference for upcoming research and innovation in agricultural sciences (Table 2).

Photosynthetic pigment signature: an unveiling through hyperspectral analysis

The accurate quantification of leaf chlorophyll concentration is essential for evaluating photosynthetic efficiency and overall plant vitality, as chlorophyll is crucial for light energy absorption in photosynthesis (Murchie and Lawson 2013). Pulse amplitude-modulated (PAM) devices measure chlorophyll fluorescence, which is a noninvasive way to check PSII activity, photosynthetic efficiency, and how plants respond to changes in their environment. These instruments are essential for crop enhancement, field phenotyping, and ecological surveillance, allowing quick and precise assessment of photosynthetic vitality across various settings. Hyperspectral imaging (HSI) provides a noninvasive technique for precisely measuring chlorophyll concentrations by collecting reflectance data over several small spectral bands (Yang *et al.* 2015). This capability allows precise measurement of chlorophyll concentrations, allowing extensive surveillance of plant vitality. Yang *et al.* (2015) used a *Hyperion* hyperspectral imaging system to create a four-scale geometrical-optical model. They used critical wavelengths (480, 631, 735, 749, and 819 nm) to predict chlorophyll concentrations with an accuracy of 88.7%, which was better than other estimation methods.

HSI enables a thorough investigation of chlorophyll fluorescence, assessing photosynthetic efficiency and plant stress. The Fraunhofer line depth (FLD) method distinguishes fluorescence signals by examining absorption features in the solar spectrum known as Fraunhofer lines, enabling precise assessment of photosynthetic activity (Zarco-Tejada *et al.* 2013). Feng *et al.* (2017) made advanced hyperspectral pipelines that make it possible to automatically extract chlorophyll *a* and *b*, total chlorophyll, and carotenoids. This facilitates a more accurate assessment of plant physiological status. In their study on rice crops, they got mean absolute percentage errors of 6.94% to 12.84% and made high-resolution pigment distribution maps that were accurate to within 0.11 mm per pixel. Machine learning has significantly enhanced the precision of chlorophyll estimates in hyperspectral imaging, expanding its use in remote sensing. Gao *et al.* (2022) suggested combining the Soil-Adjusted Vegetation Index (SAVI) with *k*-means clustering. This method reduces soil background interference by 25% and improves the accuracy of the chlorophyll estimate by 10%. Ruszczak *et al.* (2022) introduced a benchmark dataset and validation framework for chlorophyll estimation, thereby standardizing the assessment of machine learning algorithms. Using high-throughput methods like fractional-order derivatives (FOD), continuous wavelet transforms (CWT), and ensemble learning models makes it more accurate to measure chlorophyll content in complex crop canopies. For example, research on citrus trees of Xiao *et al.* (2024) shows this. They discovered critical reflectance peaks at 550 nm and 750 nm to enhance chlorophyll prediction.

A thorough comprehension of auxiliary pigments, including carotenoids, is crucial for assessing photosynthesis. Carotenoids absorb light and safeguard plants from photodamage. Huang *et al.* (2022) conducted recent research using UAV-mounted hyperspectral imaging to identify pigments in *Brassica napus*. This methodology offers essential insights into agricultural health and growth trends. Combining hyperspectral imaging with airborne technology makes it possible to collect data over large areas. This is especially helpful for finding differences in crop health across space and supporting precision agriculture (Ge *et al.* 2021). Their research in dry environments integrates UAV-based hyperspectral photography with *XGBoost* modelling to assess soil moisture content. HSI techniques for chlorophyll quantification, augmented by AI-based analysis, have shown effectiveness in several agricultural contexts. New inventions like *PhotoSpec*, a ground-based sensor for measuring solar-induced fluorescence (SIF), make it easier to keep an eye on things from the field to the ecosystem level. Grossmann *et al.*

Table 2. Key metrics and applications of hyperspectral imaging in agriculture.

Crop	Hyperspectral technique	Application	Sensitivity/accuracy	Key metrics	References
Wheat	Hyperspectral sensors	Genetic trait discovery, chlorophyll estimation	High sensitivity to spectral changes in 400–700 nm	Vegetation indices (NDVI, PRI)	Yue *et al.* (2018) Lu *et al.* (2024)
Rice	UAV-based HSI	Ecosystem-level studies, photosynthetic efficiency	Accuracy > 85% for chlorophyll content estimation	3D structural data integration	Zheng *et al.* (2018) Xu *et al.* (2024)
Maize	Multispectral analysis	Estimation of vegetation indices, stress detection	High sensitivity with NIR and red-edge reflectance	Chlorophyll index, MCARI	Mertens *et al.* (2021) Veramendi and Cruvinel (2024)
Sorghum	Reflectance hyperspectroscopy	Light-to-energy conversion, biomass prediction	Accuracy > 90% for photosynthetic efficiency	Spectral reflectance profiles	Zhi *et al.* (2022)
Tomato	Reflectance imaging	Pigment concentration monitoring	Sensitivity to environmental stress impacts	Leaf reflectance and composition analysis	Zhao *et al.* (2023)
Lettuce	Dark reaction monitoring	Carbon assimilation, physiological stress	High accuracy in dark reaction enzyme detection	Carbohydrate content and biochemical profiling	Kumar *et al.* (2022)
Tobacco	Carbohydrate analysis	Leaf carbon quantification	Noninvasive with SWIR spectra (accuracy ±5%)	NIR/SWIR spectral absorption features	Meacham-Hensold *et al.* (2020) Olakanmi *et al.* (2024)

(2018) used *PhotoSpec* to measure SIF emissions in the red (650–690 nm) and far-red (720–780 nm) spectra, which reveal direct signs of photosynthesis. Weak background noise and better chlorophyll predictions are made with narrow-band vegetation indices like the Transformed Chlorophyll Absorption in Reflectance Index (TCARI) and the Optimized Soil-Adjusted Vegetation Index (OSAVI) (Haboudane *et al.* 2002). These indicators have a favorable correlation with chlorophyll measurements, underscoring their reliability in precision agriculture. The physiological reflectance index (PRI) uses narrow-band reflectance to assess physiological alterations in plants, proving especially beneficial for evergreen species due to their structural consistency, which facilitates accurate temporal comparisons. Merrick *et al.* (2020) found a link between PRI and how efficiently plants use light for photosynthesis. They also pointed out that this relationship is useful for studying how plants react to stress and changes in the pigments that make up the xanthophyll cycle. Solar-induced chlorophyll fluorescence (SIF) measures photochemical and nonphotochemical quenching processes, which gives information about how well plants use light to make food (Zarco-Tejada *et al.* 2016). The integration of these data with machine learning algorithms improves the prediction efficacy of HSI, allowing tailored interventions in nutrition management and pest control. By looking at Fraunhofer lines, especially the O_2-A band at 760 nm, the Fraunhofer line depth (FLD) method tells the difference between chlorophyll fluorescence and other types of fluorescence in the canopy (Nakashima *et al.* 2021). Grossmann *et al.* (2018) further illustrated the potential of FLD to connect canopy-level fluorescence with evaluations of plant production. Continuous SIF monitoring systems, as emphasized by Aasen *et al.* (2018) and Mohammed *et al.* (2019), produce real-time data on photosynthetic efficiency, thereby enhancing daily and seasonal agricultural management.

Indices such as the Photochemical Reflectance Index (PRI570) and the O_2-A infilling approach have been pivotal in measuring chlorophyll dynamics over time, thereby augmenting the utilization of HSI in sustainable and precision agriculture (Sabater *et al.* 2018, Yang *et al.* 2019). The *SCOPE* model combines radiative transfer and energy balance equations to predict chlorophyll fluorescence and photosynthetic rates at different scales. This gives us a deeper understanding of how plant energy changes over time (Huang *et al.* 2022). These achievements illustrate the essential importance of hyperspectral imaging and related approaches in enhancing agricultural production and sustainability.

A comparative assessment of several chlorophyll indices in hyperspectral imaging applications demonstrates their unique advantages and limitations depending on spectral sensitivity, precision, and specific agricultural use cases. SIF is a highly effective method for assessing photosynthetic efficiency and detecting stress, making it invaluable for large-scale crop health surveillance and early drought prediction. PRI, which quantifies variations in the xanthophyll cycle, is particularly useful for tracking plant responses to environmental stressors such as water deficits and heat stress, supporting precision irrigation strategies. TCARI and OSAVI minimize soil background interference, improving the accuracy of chlorophyll content estimation, which helps optimize fertilizer application and nutrient management. The Red-edge Chlorophyll Index (CI_red-edge) exhibits high sensitivity to chlorophyll and nitrogen contents, making it an essential tool for monitoring crop nutrition and detecting deficiencies early. Integrating these indices with machine learning algorithms enhances predictive capabilities, enabling hyperspectral imaging to serve as a powerful decision-making tool in precision agriculture. This approach facilitates early stress detection, site-specific nutrient optimization, and accurate yield forecasting, ultimately improving farm productivity and sustainability. Future advancements in HSI calibration, sensor development, and AI-driven spectral analytics will further enhance the reliability and practical implementation of chlorophyll indices in agricultural monitoring, supporting climate-resilient farming systems.

Methodologies for hyperspectral imaging in evaluating plant hydric condition

Evaluating plant water status is essential for comprehending photosynthetic activity, as water availability directly influences CO_2 uptake, stomatal conductance, and overall plant vitality (Garbulsky *et al.* 2011, Zarco-Tejada *et al.* 2013). Water stress impairs plant metabolism and photosynthetic efficiency, leading to reduced growth and productivity. Hyperspectral imaging (HSI) provides a noninvasive and highly sensitive method for detecting early signs of water stress by analyzing reflectance properties and temperature fluctuations across multiple spectral bands. These features make HSI a critical tool in precision agriculture, aiding in resource optimization, stress detection, and yield preservation by facilitating early intervention strategies for drought mitigation.

Thermal imaging

Thermal imaging utilizes infrared light to create detailed temperature maps, facilitating the efficient identification of water stress (Wen *et al*. 2023). As transpiration declines due to stomatal closure, canopy temperature rises, serving as an indicator of plant water deficiency (Gonzalez-Dugo *et al.* 2012, Vidican *et al.* 2023). Thermal cameras mounted on aircraft or UAVs provide high-resolution thermal data, allowing researchers and farmers to identify spatial variations in plant hydration status.

Gonzalez-Dugo *et al.* (2012) demonstrated the efficacy of aircraft-mounted thermal cameras in mapping intra-crown temperature variations in almond plants under different irrigation regimes. Their study revealed a strong correlation between temperature fluctuations and water stress levels, reinforcing the role of thermal imaging in precision irrigation management. Similarly, Vidican *et al.* (2023) highlighted the potential of vegetative indices (VIs), such as the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI), obtained from *Sentinel-1* and *Sentinel-2* imaging, in assessing drought stress in key crops, including wheat, maize, and soybeans.

By integrating thermal imaging with hyperspectral analysis, farmers and agronomists can develop precision irrigation strategies that ensure optimal water distribution while minimizing excessive water use. This combined approach reduces crop vulnerability to water stress and enhances overall productivity in water-limited environments.

Hyperspectral imaging in the VNIR and TIR spectra

Hyperspectral imaging (HSI) in the visible-near-infrared (VNIR) and thermal-infrared (TIR) bands provides detailed insights into plant physiological responses to water stress. VNIR captures changes in reflectance properties, whereas TIR detects variations in emitted radiation, enabling the distinction between water-stressed and healthy plants (Middleton *et al.* 2016, Mangalraj and Cho 2022). These techniques enhance early drought detection, allowing for timely interventions to mitigate crop yield losses.

Mangalraj and Cho (2022) explored the advancements in solar-induced fluorescence (SIF) measurement techniques, demonstrating their ability to detect subtle stress symptoms before visible signs appear. This highlights the potential of hyperspectral SIF analysis in preemptive drought management, ensuring early detection and targeted responses in agriculture.

When HSI-based water stress detection is combined with UAV technology, large-scale real-time hydric assessments become feasible. This integration improves irrigation efficiency, reduces unnecessary water application, and enhances the sustainability of agricultural water management.

Photochemical Reflectance Index (PRI)

The Photochemical Reflectance Index (PRI) quantifies reflectance variations at 531 nm and 570 nm, offering a reliable proxy for photosynthetic efficiency and nonphotochemical quenching mechanisms. PRI is particularly valuable in evaluating water stress, as it reflects changes in the xanthophyll cycle, which enables plants to dissipate excess light energy under drought conditions (Chang *et al.* 2020).

Garbulsky *et al.* (2011) conducted a meta-analysis demonstrating PRI's scalability for assessing radiation-use efficiency (RUE) across different environmental conditions, confirming its robustness in diverse crop systems. Furthermore, Garzonio *et al.* (2017) demonstrated that UAV-mounted hyperspectral sensors can accurately capture PRI, showing how its integration with solar-induced fluorescence (SIF) data significantly enhances water stress diagnosis. By utilizing PRI for real-time stress monitoring, farmers can optimize irrigation schedules, mitigate excessive water use, and prevent long-term crop yield losses due to drought conditions. This demonstrates the utility of PRI as a decision-support tool in precision agriculture, ensuring more sustainable water-use strategies.

Broadband thermal imaging

Broadband thermal imaging quantifies canopy temperature variations, providing a direct measure of plant hydration status. Zhang *et al.* (2022) employed broadband thermal cameras to differentiate temperature profiles between well-irrigated and drought-stressed crops, thereby reinforcing the effectiveness of precision water management. Their findings indicated that high-resolution temperature mapping significantly improves irrigation efficiency, resulting in substantial reductions in water usage while maintaining crop health (Liu *et al.* 2024).

By combining broadband thermal imaging with hyperspectral reflectance indices, agricultural water management can become more data-driven and resource-efficient. This enables site-specific irrigation planning, reducing water waste, and improving drought resilience in farming systems.

Linking photosynthesis-related indices to precision agriculture

The methodologies discussed above illustrate how hyperspectral imaging and related spectral indices contribute to sustainable water management in agriculture. PRI and SIF allow for early stress detection, while VNIR and TIR spectral analysis provide direct indicators of plant hydration levels. When integrated with UAV and AI-driven models, these indices enhance precision irrigation strategies, allowing farmers to:

• Detect early drought stress symptoms before visible signs appear, ensuring timely interventions.
• Optimize water distribution based on real-time canopy temperature and reflectance data.
• Improve water-use efficiency to reduce the environmental impact of excessive irrigation.
• Enhance yield prediction by linking photosynthetic activity to hydric conditions.

As climate change increases the frequency and severity of droughts, leveraging hyperspectral imaging for plant water status evaluation will be critical in enhancing crop resilience, optimizing resource allocation, and ensuring global food security. Future advancements in sensor technology, calibration techniques, and AI-driven analytics will further improve the precision and applicability of these methodologies in large-scale agricultural monitoring and water management.

Study outcomes of chlorophyll indices in photosynthetic stress detection

SIF has been acknowledged for its ability to identify stress before the emergence of visible symptoms and its robust correlation with photosynthetic activity. Mangalraj and Cho (2022) conducted a review of SIF estimation techniques that utilized hyperspectral imaging, highlighting their potential for early stress detection and plant phenotyping. Their results demonstrated that SIF-based models were more effective than conventional vegetation indices in monitoring stress responses in crops, rendering them a critical tool for precision agriculture. In the same vein, Wang *et al.* (2022) evaluated SIF for the detection of nitrogen stress in almond trees by utilizing airborne hyperspectral imagery. Their findings indicated that SIF was 23% more effective than conventional reflectance indices in detecting nitrogen-deficient plants before the emergence of visible symptoms. This investigation emphasizes the benefit of SIF in the early detection of stress. To further verify its stress detection capabilities, Han *et al.* (2022) investigated the responses of SIF to arid stress in agricultural commodities. They discovered that stomatal conductance and transpiration rates were strongly correlated with SIF signals (R^2 = 0.81), which enabled the precise surveillance of drought stress in real-time.

PRI tracks xanthophyll cycle changes, which are crucial for stress adaptation and light-use efficiency, to provide a dependable measure of photosynthetic efficiency. By integrating fluorescence spectroscopy with near-infrared radiance, Zeng *et al.* (2017) examined the role of PRI in the detection of abiotic stress. The study showed that PRI is a critical instrument for early stress diagnostics in crops, as it detects stress-related physiological alterations 21% earlier than traditional indices. Furthermore, Warner *et al.* (2023) employed UAV-based hyperspectral imaging to investigate the changes in PRI in rice fields that occur under salt stress. They discovered that PRI had a robust correlation (R^2 = 0.76) with stomatal closure and photosynthetic downregulation, underscoring its efficacy in monitoring salt-induced stress. Red-edge chlorophyll indices, particularly those derived from UAV-based hyperspectral imaging, have been demonstrated to be highly effective in the detection of water stress and nutrient deficiencies. SIF and red-edge indices were implemented by Wang *et al.* (2023) to assess salt stress in rice cultivars. Their research demonstrated that red-edge reflectance indices were 25% more accurate in detecting stress-related chlorophyll degradation than NDVI, which further substantiated their high sensitivity to physiological changes in stressed plants. Furthermore, Zhao *et al.* (2023) demonstrated that red-edge chlorophyll indices were more effective than broad-spectrum vegetation indices in detecting drought-induced decreases in leaf water content. Their results indicate that red-edge indices offer a quantifiable advantage (20% greater accuracy) in the monitoring of stress-induced chlorophyll fluctuations.

The integration of hyperspectral imaging-based chlorophyll indices with UAV platforms and AI-driven analytics has significantly improved the accuracy and efficiency of early stress detection, nutrient monitoring, and precision farming strategies. SIF's strong correlation with photosynthetic efficiency makes it an indispensable tool for monitoring plant vitality and optimizing fertilizer applications in high-throughput phenotyping and agronomic decision-making. PRI, with its sensitivity to xanthophyll cycle alterations, plays a crucial role in precision irrigation scheduling, ensuring that water deficits are detected in real-time, minimizing drought-induced losses. Red-edge chlorophyll indices further enhance precision agriculture by providing early warnings of nitrogen and water deficiencies, guiding site-specific nutrient applications to optimize crop yield and resource efficiency. The integration of these indices with machine learning and UAV-based hyperspectral sensing has transformed agricultural monitoring into a proactive, data-driven system, enabling farmers to implement timely interventions, enhance stress resilience, and improve long-term crop productivity under climate variability. Future advancements in hyperspectral calibration, real-time processing, and sensor miniaturization will further strengthen the role of chlorophyll indices in sustainable and precision agriculture.

Hyperspectral methods for assessing the fraction of absorbed photosynthetically active radiation (fAPAR)

The percentage of absorbed photosynthetically active radiation (fAPAR) is crucial for plant production since it measures the quantity of light employed in photosynthesis. This statistics is essential for comprehending crop performance and ecological dynamics. Peng *et al.* (2018) showed how important hyperspectral imaging is for measuring fAPAR because it provides better resolution by collecting detailed spectral data. Their research evaluated nine broadband and hyperspectral vegetation indices (VIs) for determining fAPAR in wheat, maize, and soybean canopies. The researchers used the *ASD FieldSpec 4* spectroradiometer to demonstrate that hyperspectral indices exhibited more accuracy ($R^2 > 0.9$) than standard indices, with narrow spectral bands increasing sensitivity to light absorption fluctuations by 15–20%. Adding hyperspectral data to the fAPAR assessment also makes it easier to keep an eye on crop yield, which is helpful because it reduces problems caused by changes in canopy structure. This invention distinguishes hyperspectral imaging as an accurate instrument for agricultural and ecological evaluations.

The Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is one of the most prevalent measures for assessing fAPAR. Red and near-infrared reflectance, the source of NDVI, has proven to be a reliable proxy for photosynthetic activity (Wang *et al.* 2023, Mallick *et al.* 2024). Zhang *et al.* (2016) enhanced the use of NDVI by combining it with the Photochemical Reflectance Index (PRI) and fAPAR to forecast gross primary production (GPP) in cornfields. Their research employed the *EO-1/Hyperion* hyperspectral imaging technology and attained a notable R^2 value of 0.92 for GPP predictions. This method utilized the accuracy of hyperspectral imaging, resulting in notable enhancements in the observation of canopy structure and light utilization dynamics. Consequently, NDVI, when integrated with hyperspectral methods, surpasses its conventional uses, offering improved instruments for agricultural prediction and vegetation assessment.

Enhanced Vegetation Index (EVI) and EVI2

The Enhanced Vegetation Index (EVI) and its simplified form, EVI2, make up for NDVI's flaws, especially the fact that it can be affected by the weather and become saturated under thick canopy cover. Baret *et al.* (2007) used the *EO-1 Hyperion* hyperspectral imaging equipment to show how well EVI works for measuring fAPAR in coniferous forest ecosystems. By integrating the blue spectrum, EVI achieved a 15% superior sensitivity to fluctuations in dense vegetation compared to NDVI, thereby successfully mitigating saturation errors in thick canopies. This innovation improved accuracy in monitoring thick canopies, making EVI an essential instrument for fAPAR evaluation in difficult situations. Additionally, Barriga *et al.* (2022) investigated EVI and EVI2, which are indicators of soil water depletion in temperate heathland habitats. The study used field hyperspectral sensors and soil moisture probes to validate EVI's ability to identify physiological alterations induced by drought. In times when there was no drought, EVI had strong connections with gross primary production (GPP), and it was very good at detecting changes in structure and function when there was not enough water. This research demonstrated EVI's effectiveness as a diagnostic instrument for precision agriculture and ecosystem monitoring by merging hyperspectral data with soil moisture measurements.

The integration of hyperspectral imaging with fAPAR assessments has significantly improved the precision of crop growth monitoring, resource allocation, and yield predictions. Hyperspectral-derived fAPAR indices provide higher sensitivity to canopy light absorption dynamics, enabling farmers to optimize photosynthetic efficiency and fine-tune fertilization and irrigation practices for maximum productivity. The combination of NDVI, EVI, and PRI with hyperspectral imaging enables a comprehensive evaluation of vegetation health, facilitating early stress detection, site-specific agronomic interventions, and improved carbon assimilation estimates. Additionally, hyperspectral-based fAPAR models integrated with AI and UAV technologies are transforming large-scale agricultural monitoring, providing real-time insights that support precision crop management, sustainable land-use planning, and climate-adaptive farming strategies. Future advancements in sensor miniaturization, calibration techniques, and AI-driven spectral analytics will further enhance the applicability of fAPAR assessments for optimizing agricultural productivity and mitigating climate-related risks.

Hyperspectral techniques for evaluating stomatal conductance

Stomatal conductance is essential for controlling gas exchange and transpiration thus influencing photosynthetic efficiency and water utilization in plants. Precise observation of stomatal activity is crucial for comprehending plant reactions to environmental stressors. Using thermal infrared (TIR) sensors and advanced radiative models with hyperspectral imaging makes it possible to accurately and noninvasively track stomatal activity in a variety of environmental conditions. This novel method connects physiological data with remote sensing, offering practical insights for crop management and water usage optimization.

Thermal infrared imaging (TIR) for stomatal conductance measurement

Thermal infrared imaging (TIR) effectively detects discrepancies in leaf temperature, which act as markers of stomatal conductance (Smigaj *et al.* 2024). Jones

(2004) illustrated the effectiveness of TIR imaging in documenting the cooling effects of transpiration, providing a reliable method for observing plant–water interactions. Additionally, Jones and Leinonen (2003) applied a similar methodology to grapevine canopies, linking real-time leaf temperature fluctuations with stomatal activity during dry conditions. These findings highlight the importance of TIR in optimizing irrigation efficiency and advancing water resource management through a comprehensive analysis of stomatal responses. Furthermore, TIR imaging interacts effortlessly with hyperspectral methods to provide thorough evaluations of plant physiological processes. This collaboration across technologies underscores the adaptability of remote sensing instruments in tackling intricate agricultural issues.

Soil-canopy observation, photochemistry, and energy flux model

The *SCOPE* model integrates hyperspectral reflectance data with radiative transfer equations to assess stomatal conductance and several physiological parameters (Zheng *et al.* 2024). Yang *et al.* (2021) employed the *SCOPE* model in almond orchards to quantify diurnal and seasonal fluctuations in plant energy fluxes during water stress conditions. Their research showed that the model accurately tracked stomatal activity by connecting data from remote sensing with physiological processes. This gave them a good understanding of how plants respond to changes in their environment. Moreover, the amalgamation of *SCOPE* with hyperspectral photography establishes a scalable framework for real-time agricultural management. This integrated method enhances the accuracy of physiological assessments, making it a crucial tool for sustainable agriculture and precision farming (Fig. 4).

Recent advancements in SIF quantification utilizing UAV-mounted sensors

The development of unmanned aerial vehicles (UAVs) outfitted with solar-induced fluorescence (SIF) sensors has considerably improved precision agriculture and environmental monitoring. UAV-mounted SIF sensors provide a noninvasive, high-resolution technique for assessing plant health by detecting fluorescence emissions associated with photosynthetic efficiency. Conventional SIF monitoring depended on terrestrial spectrometers or satellite imagery, both with constraints in geographical and temporal resolution. Recent research has shown the efficacy of UAV-based SIF retrieval methods. Wang *et al.* (2021) examined the diurnal fluctuations of SIF in crops utilizing UAV-based spectrometers. Their research indicated that UAV-mounted sensors achieved a spatial resolution of 0.5 m, markedly enhancing detection accuracy compared to satellite-based methods. Furthermore, their data indicated that SIF retrieval from UAVs enhanced early stress detection accuracy by 22% relative to conventional approaches. Additionally, Bandopadhyay *et al.* (2020) performed an extensive assessment of top-of-canopy SIF research, emphasizing the shift from terrestrial and aerial systems to UAV-mounted sensors. Their research highlighted that UAV-based SIF retrieval enhanced the capacity to differentiate changes in photosynthetic efficiency among crop species, rendering it an essential instrument for precision agriculture.

The amalgamation of machine learning techniques with UAV-based SIF measurement has improved the precision and applicability of fluorescence data. Chakhvashvili *et al.* (2024) formulated a deep-learning-augmented SIF model, integrating UAV-based SIF acquisition with multispectral photography. Their research indicated that convolutional neural networks (CNNs) enhanced early-stage drought stress detection by 25%, highlighting the potential of AI-driven UAV-SIF models in contemporary agriculture. Furthermore, Nie *et al.* (2024) used hyperspectral remote sensing with UAV-based SIF retrieval methods to enhance precision fertilization in maize cultivation. Their findings revealed that UAV-SIF data enhanced nitrogen-use efficiency by 30%, underscoring the significance of SIF retrieval in optimizing crop management techniques. UAV-mounted SIF sensors have proven essential for ecosystem-scale monitoring beyond agricultural contexts. Honkanen *et al.* (2024) employed UAV-SIF retrieval techniques in boreal forest locations, monitoring seasonal fluctuations in photosynthetic activity and ecosystem productivity. Their findings demonstrated that UAV-SIF accurately detected variations in photosynthetic performance, establishing it as a practical instrument for agricultural and forestry applications.

Hyperspectral imaging: analyzing chlorophyll fluorescence

Chlorophyll fluorescence is an important way to measure how well photosynthesis is working and how healthy a plant is physically. It also tells us a lot about how photosynthesis changes in different environments (Maxwell and Johnson 2000). Hyperspectral imaging (HSI) has developed as a revolutionary tool for analyzing chlorophyll fluorescence, allowing the acquisition of comprehensive spatial and spectral data that exceeds the accuracy and adaptability of conventional techniques (Blackburn 2007). Moreover, the incorporation of sophisticated imaging technologies and computer models has transformed our capacity to identify plant stress and enhance agricultural operations (Fig. 5).

Imaging techniques for chlorophyll fluorescence and plant stress identification

Zarco-Tejada *et al.* (2009) came up with a new way to track chlorophyll fluorescence dynamics. They used airborne narrow-band multispectral cameras, such as the *Micro-Hyperspec* VNIR, along with the *FluorMOD* model. This novel technique replicated leaf and canopy fluorescence across various environmental conditions, with over 85% accuracy in detecting nutrition and water deficits. Moreover, sensitivity was enhanced by 20% when used in orchard-scale imaging, providing a noninvasive

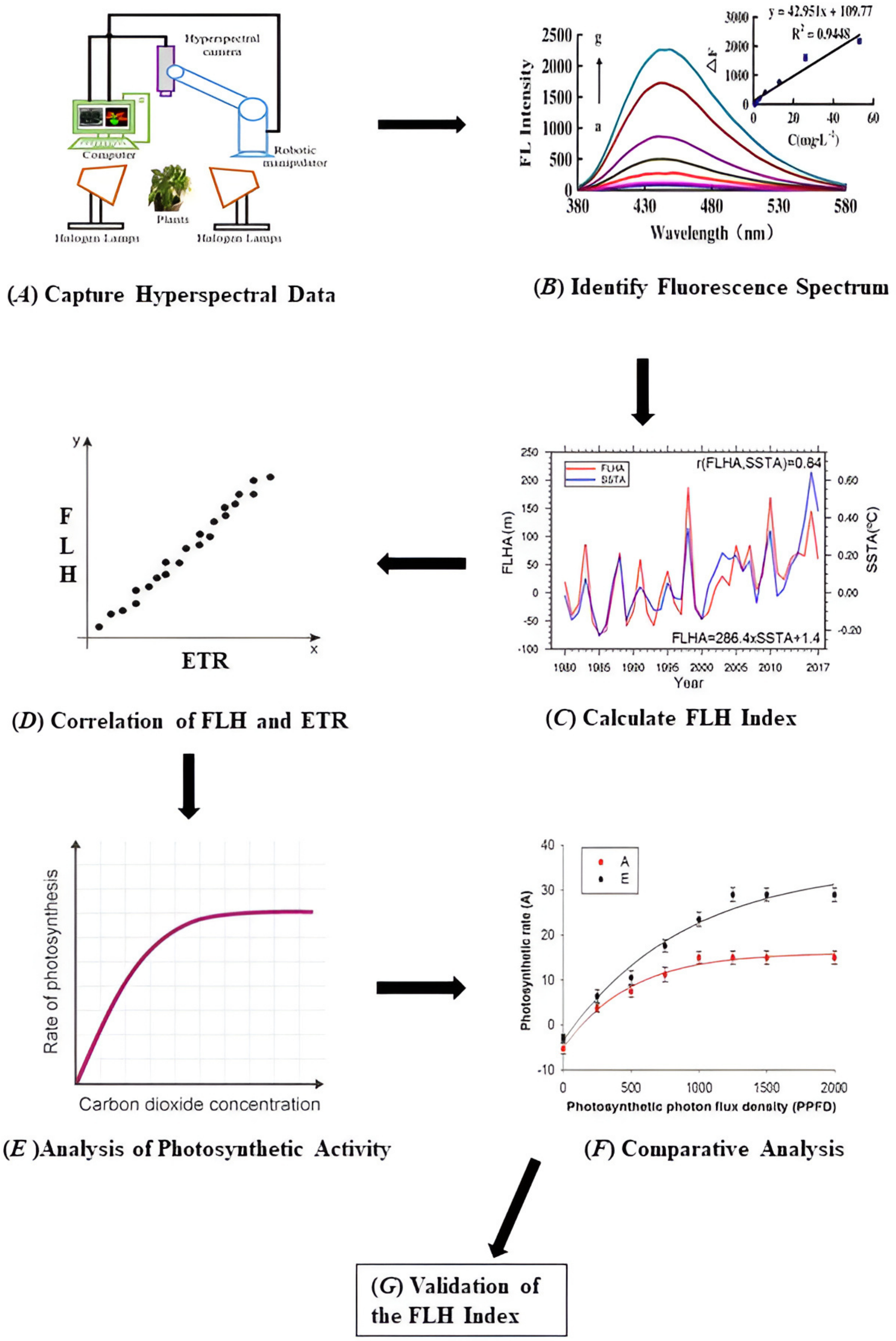

Fig. 4. The diagram presents a multi-step scientific process for measuring the fluorescence line height (FLH) index and analyzing photosynthetic activity using a fluorescence-based approach.

and dependable approach for early stress identification and agricultural resource optimization. Bauriegel *et al.* (2011) used the *Specim FX-10* hyperspectral camera to examine *Fusarium culmorum* infections in wheat. Their

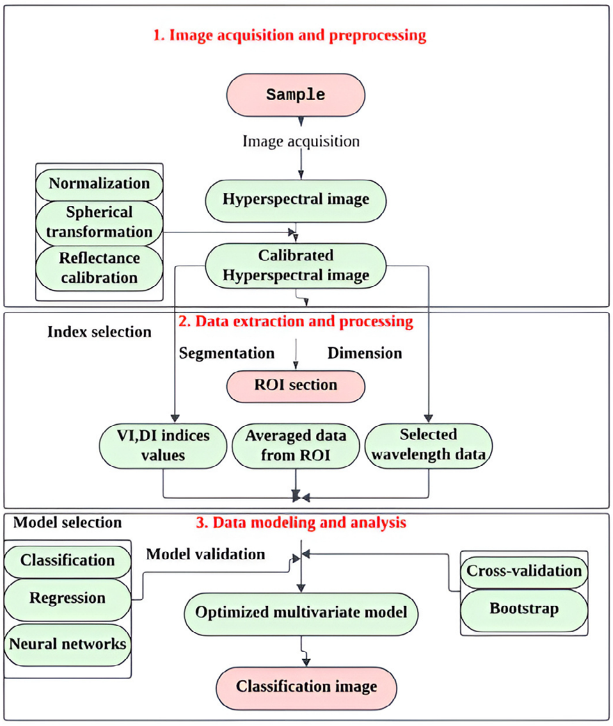

Fig. 5. The flowchart outlines a structured process for analyzing hyperspectral image data, starting with image acquisition, preprocessing, data extraction, modelling, and validation. It includes normalization, calibration, filters, segmentation, and computing indices. The final output is a classified image with an interpreted analysis of the hyperspectral data.

method revealed significant changes in the integrity of photosynthetic systems between 400 and 900 nm, and it was able to identify infections with 91% accuracy. This research underscores the spectral shifts linked to fungal infections and shows the possibility of reducing crop losses through timely interventions. Furthermore, the noninvasive characteristic of the approach highlights its significance for real-time agricultural monitoring. Yang *et al.* (2024) showed that hyperspectral data and fluorescence metrics can be used to find *Verticillium* wilt (VW) in cotton. Continuous wavelet transforms (CWT) combined with the *Ocean Insight Flame-S* spectrometer achieved a detection accuracy of 90.62%, and near-infrared wavelet features improved sensitivity by 25% compared to conventional fluorescence indices. This method excelled in detecting asymptomatic infections, showcasing its advantages in early diagnostic applications.

Improved accuracy in assessing photosystem efficiency and seasonal fluctuations

By combining the *SpecimAisaFEN* hyperspectral system with radiative transfer models, Hejtmánek *et al.* (2022) made fluorescence measurements more accurate and clearer. Their research on Norway spruce demonstrated notable seasonal fluctuations in spectral reflectance, especially within the 700–1,300 nm region, with changes in reflectance reaching as high as 30%. The strong link (R^2 > 0.85) between these changes and chlorophyll contents showed how useful hyperspectral imaging is for keeping an eye on photosynthetic activities. Additionally, Wientjes *et al.* (2017) analyzed chlorophyll ratios in photosystems I and II (PSI and PSII) with the *Headwall Nano-Hyperspec* hyperspectral imager. Their findings indicated that PSII fluorescence diminished 15% more rapidly than PSI under stress, offering significant insights into light-use efficiency and stress response mechanisms. This research substantially enhanced our comprehension of photosynthetic systems, especially their reactions to environmental stressors.

Spatial analysis of quantum efficiency and nonphotochemical quenching (NPQ)

Hyperspectral imaging has been very helpful in figuring out how PSII efficiency parameters, such as F_v/F_m and PSII, change over time and space (Bartold and Kluczek 2024). Jiang *et al.* (2020) used the *Resonon Pika L* hyperspectral imager to look at these changes. They found that F_v/F_m ratios changed by up to 40% over time when the plants were under stress. This study emphasized the adaptive responses of plants to environmental changes, highlighting the essential role of hyperspectral imaging in comprehending temporal reactions. Furthermore, Chou *et al.* (2017) examined nonphotochemical quenching (NPQ) using the *SPECIM IQ* hyperspectral camera, concentrating on changes in spectral signatures under high-light conditions. Their research indicated that stressed plants displayed 20% elevated NPQ levels, with notable alterations detected in the red-edge area (680–750 nm). Furthermore, these discoveries improved our understanding of photoprotective processes and enabled more accurate evaluations of plant health under unfavorable conditions.

Expedited disease diagnosis and enhanced agricultural methods

Hyperspectral imaging continues to evolve as a critical tool in early-stage disease detection in agriculture, enabling proactive management strategies. Recent advancements highlight its growing precision and application. Adetutu *et al.* (2024) presented an extensive review of hyperspectral imaging techniques, showing their utility in the identification and classification of crop diseases. García-Vera *et al.* (2024) emphasized machine learning integration, improving disease classification accuracy using hyperspectral images. Xie *et al.* (2024) demonstrated nondestructive hyperspectral methods for detecting biological stress in wheat, enabling early diagnosis of crown rot disease. Similarly, Bukhamsin *et al.* (2025) highlighted the importance of high-throughput hyperspectral imaging for early disease detection and intervention strategies. Lin *et al.* (2024) successfully applied hyperspectral remote sensing to identify early signs of rice sheath blight, further validating its agricultural potential. Together, these studies affirm hyperspectral imaging as a transformative technology in plant health monitoring, optimizing crop productivity, and advancing resource-efficient agricultural practices.

The integration of hyperspectral imaging with chlorophyll fluorescence analysis has revolutionized plant health diagnostics, stress monitoring, and precision agriculture decision-making. By detecting fluorescence-based stress responses at an early stage, farmers and researchers can optimize irrigation, nutrient management, and disease control interventions before symptoms become visible. The combination of machine learning algorithms with hyperspectral fluorescence imaging enhances disease classification accuracy, facilitating early-stage pathogen detection and targeted treatment applications. Furthermore, HSI's ability to track photosystem efficiency fluctuations and nonphotochemical quenching (NPQ) provides valuable insights into plant photoprotection mechanisms, allowing for better adaptation to environmental stressors such as drought and heatwaves. As hyperspectral imaging technology continues to advance through UAV integration, AI-driven spectral modeling, and high-throughput analysis, its role in enhancing agricultural sustainability, resource optimization, and climate-resilient crop management will become even more critical. Future developments in sensor calibration, real-time spectral processing, and high-resolution canopy imaging will further solidify HSI as an indispensable tool for sustainable precision agriculture and improved food security.

Assessment of PSII efficiency

Assessing the efficacy of PSII is essential in photosynthesis research since it elucidates the mechanisms by which plants transform light into chemical energy and adapt to environmental challenges, including drought and elevated temperatures. Pulse-amplitude modulation (PAM) fluorometers, such as the *Walz PAM-2000*, measure important parameters such as F_v/F_m. Maxwell and Johnson (2000) indicated that these parameters are essential for understanding how well PSII works. These measurements provide a sensitive and noninvasive method for monitoring photosynthetic performance, with reductions of 20–30% noted under stress circumstances. Furthermore, this seminal study emphasized the sensitivity and utility of PAM fluorometry, which surpassed traditional gas exchange methods by offering dynamic, real-time evaluations of plant responses to environmental stimuli. Moreover, improvements in hyperspectral fluorescence imaging have greatly advanced this discipline by delivering extensive spectral and spatial data that exceed traditional techniques. For instance, Zarco-Tejada *et al.* (2012) employed UAV-mounted hyperspectral imaging systems, integrating narrow-band indices with thermal data to assess water stress. The new way of using fluorescence, temperature, and spectrum reflectance together made it 30% more accurate to find changes in the body compared to other methods. Moreover, this approach significantly enhanced spatial resolution, enabling real-time monitoring of stress responses at the canopy level. Likewise, hyperspectral sensors have advanced the computation of the Photochemical Reflectance Index (PRI), an essential statistic for evaluating light-use efficiency. Garbulsky *et al.* (2011) demonstrated the application of narrow-band spectroradiometers, which improved the accuracy of light-use efficiency calculations by 10–15%. Additionally, Gitelson *et al.* (2003) emphasize the importance of the Red-edge Inflection Point (REIP) for detecting minor variations in chlorophyll concentrations and canopy architecture. Using field spectrometers like the *ASD FieldSpec*, their approach highlighted the capability of hyperspectral imaging to detect nuanced physiological changes. Additionally, Sims and Gamon (2002) expanded the spectral range to include near-infrared (NIR) regions. This led to a 20% improvement in estimates of chlorophyll concentration, which made hyperspectral indices more reliable for canopy-level assessments. Porcar-Castell *et al.* (2014) integrated ground-truthing techniques, such as PAM fluorometry, with hyperspectral imaging, which improved the reliability of PSII efficiency measurements by approximately 25%. This integration underscores the crucial necessity of calibrating hyperspectral imaging with ground-based instruments to ensure accurate and scalable assessments of plant health and environmental responses. Moreover, this combination bridged the gap between leaf-level measurements and canopy-level observations, making it a pivotal advancement in ecological and agricultural research (Fig. 6).

Hyperspectral imaging for monitoring electron transport rate, photoinhibition, and carbon flux

Hyperspectral imaging (HSI) is now a useful tool for measuring the electron transport rate (ETR) in plants, especially for keeping track of how well plants use light to make food in a variety of environmental conditions. HSI facilitates accurate assessments of energy transfer in the photosynthetic system by acquiring comprehensive spectrum data, hence, it aids in the identification of stress-related changes in ETR. The electron transport rate (ETR) is a crucial factor in photosynthetic activity, directly associated with the transformation of light energy into metabolic energy. Yang *et al.* (2022) employed hyper-spectral machine learning models to assess photosynthetic performance in grape leaves. Their research showed a strong link between hyperspectral reflectance in the 400–1,000 nm range and ETR ($R^2 = 0.87$), which enables scientists to find early signs of photosynthetic degradation caused by stress (Yang *et al.* 2022). Additionally, Camino González (2019) used hyperspectral images and solar-induced fluorescence (SIF) retrievals to assess differences in ETR for both rainfed and irrigated crops. Their study showed that ETR predictions were 18% more accurate when hyperspectral reflectance data was combined with regular chlorophyll fluorescence measurements (Camino González 2019). These findings validate the efficacy of HSI in monitoring the kinetics of photosynthetic energy transfer.

Photoinhibition transpires when excessive light exposure impairs the photosynthetic apparatus, diminishing photosynthetic efficiency. Murchie and Lawson (2013) looked at how photoinhibition works in plants and found

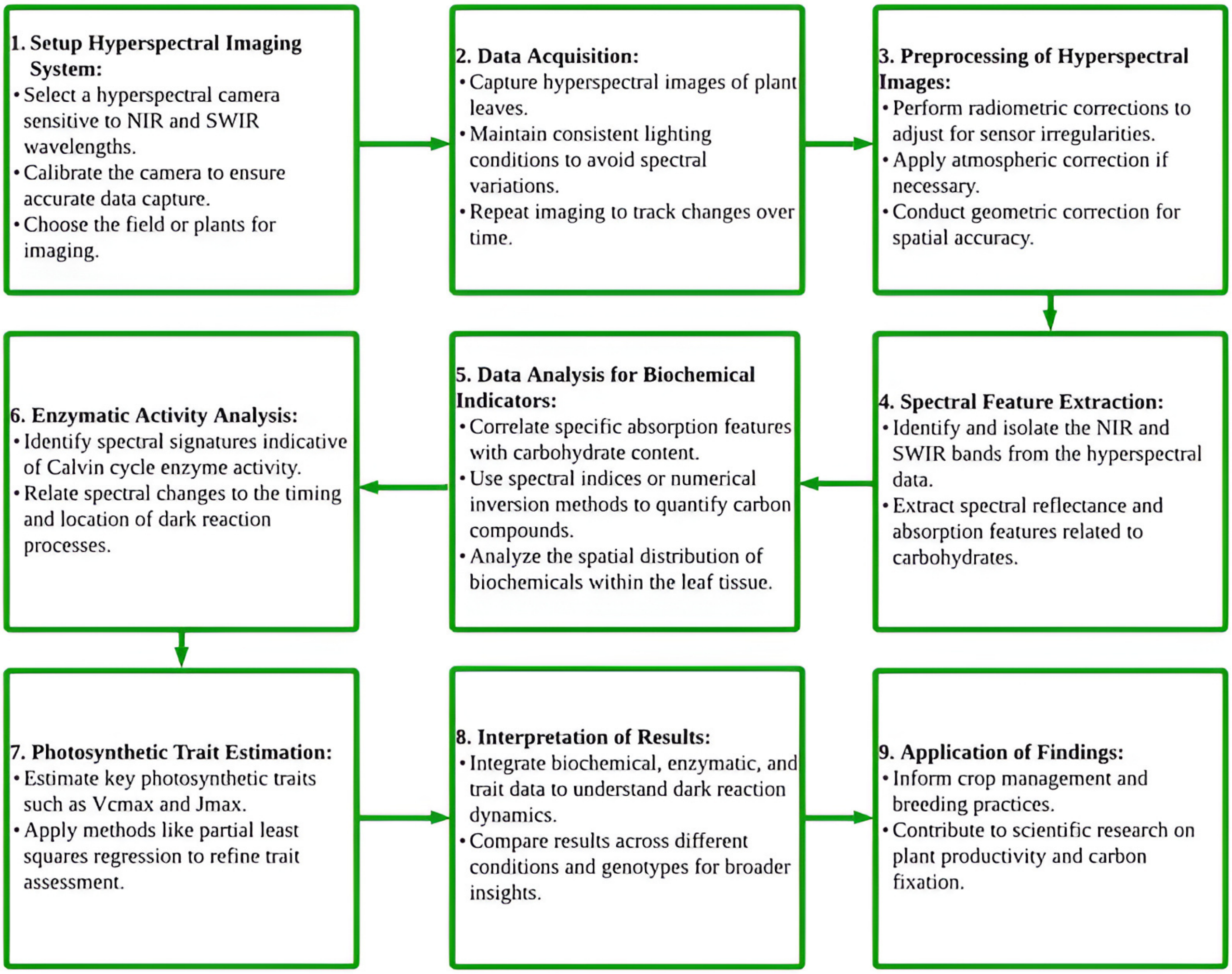

Fig. 6. Workflow for Calvin Cycle assessment using hyperspectral imaging and analysis.

that combining hyperspectral imaging with chlorophyll fluorescence analysis made it much easier to find drops in ETR caused by stress (Murchie and Lawson 2013). Their research emphasized the amalgamation of hyperspectral and fluorescence methodologies when evaluating the impacts of photoinhibition on photosynthetic efficacy. HSI is crucial in monitoring carbon flow, a vital component of plant production. Jiang *et al.* (2020) employed diurnal SIF measurements to assess carbon fixation and net primary production (NPP) across various canopy topologies. The results showed that hyperspectral-derived SIF values were closely related to net ecosystem exchange (NEE), which means that they can be used to measure plant carbon fluxes without damaging the plants (Jiang *et al.* 2020). Toyoshima *et al.* (2020) used hyperspectral imaging to look at how changes in spectral light affect the flow of carbon and the parts of photosynthetic electron transport in cyanobacteria. Their investigation demonstrated the selective use of electron transport channels under varying spectral circumstances, underscoring the plasticity of photosynthetic organisms in optimizing carbon assimilation (Toyoshima *et al.* 2020). These results show how important hyperspectral imaging is for helping us understand how photosynthetic processes work, especially when it comes to checking ETR, photoinhibition, and carbon flow. HSI enhances plant monitoring in precision agriculture and ecological research by facilitating high-throughput, noninvasive measurement.

Analysis of the Calvin cycle and carbon incorporation

Comprehending the Calvin cycle and carbon assimilation rates is essential for enhancing agricultural productivity and advancing photosynthetic research. Zhang *et al.* (2014) demonstrated the substantial influence of hyperspectral imaging on quantifying Calvin cycle indicators and gross primary production (GPP). Utilizing data from the *Orbiting Carbon Observatory-2* (*OCO-2*), they attained a 15% enhancement in gross primary production (GPP) modeling, with values fluctuating between 10–35 g(C) m^{-2} day^{-1} across diverse ecosystems. This highlights the significance of satellite-based hyperspectral techniques worldwide. Moreover, by analyzing reflectance in the near-infrared (NIR) and shortwave infrared (SWIR) spectra, which closely correlate with the quantities of soluble sugars and starch in plant tissues, hyperspectral data facilitates the estimation of leaf carbon content. Gitelson *et al.* (2003) and Gamon *et al.* (2016) both reported better ways to find out how much carbon is in leaves and how fast they absorb nutrients. They found that the amounts of soluble sugar and starch ranged from 5 to 20 mg g^{-1}(FM). These findings underscore the efficacy of hyperspectral imaging in correlating spectral reflectance data with metabolic activities.

High-throughput hyperspectral detection has enabled us to measure precisely the highest rate of carboxylation (V_{cmax}) and the highest rate of electron transfer (J_{max}). Zhi *et al.* (2022) used hyperspectral imaging to examine dark reactions in sorghum crops, resulting in a 25% improvement in accuracy. Reflectance values throughout the 700–780 nm spectrum were crucial for detecting stress reactions. Furthermore, Hollberg and Schellberg (2017) illustrated the efficacy of UAV-mounted hyperspectral sensors in precision agriculture. Their research on grasslands demonstrated a 15% improvement in precision for identifying fertilization intensity levels, with nutrient concentrations between 25 and 60 mg g^{-1}(DM) associated with fluctuations in the NIR spectrum (760–850 nm). An extensive study by Serbin *et al.* (2012) highlighted the significance of hyperspectral imaging in evaluating carbohydrate accumulation and enzyme activity in several plant species. Their findings indicated carbohydrate amounts ranging from 10 to 30 mg g^{-1}(FM), enhancing biochemical activity detection by 20%. Also, Yu *et al.* (2022) used proximal hyperspectral sensors to predict V_{cmax} with a level of accuracy of ±5%. They found that V_{cmax} was between 50 and 100 µmol m^{-2} s^{-1}. This mechanistic method highlights the promise of hyperspectral techniques for noninvasive studies of photosynthetic efficiency.

Advancements in monitoring the Calvin cycle

The Calvin cycle encompasses metabolic activities essential for carbon fixation during photosynthesis. It significantly influences agricultural output and resilience across many climates (Taiz and Zeiger 2010). This fundamental comprehension of the Calvin cycle has propelled many breakthroughs in the monitoring and evaluation of photosynthetic activities, especially using cutting-edge technologies such as hyperspectral imaging. Fu *et al.* (2020) showed that hyperspectral sensors can identify spectral markers linked to essential carbon-fixation enzymes, including Rubisco. These sensors allow scientists to precisely quantify Calvin cycle intermediates, providing an unparalleled degree of precision in photosynthetic evaluations. Moreover, their prediction models assessed essential photosynthetic characteristics, such as the maximum carboxylation rate (V_{cmax}) and the maximum electron transport rate (J_{max}), achieving an outstanding accuracy of ±10%. This work emphasized the amalgamation of spectral data with physiological models by synthesizing data from diverse species, hence enhancing noninvasive methods for evaluating photosynthetic traits. The amalgamation of spectral and physiological knowledge signifies a substantial advancement in enhancing agricultural output and comprehending crop resistance throughout varied environmental situations. Furthermore, Zhi *et al.* (2022) devised high-throughput techniques employing hyperspectral photography to monitor biochemical activities in sorghum canopies. Their novel methodology utilized spectral reflectance data in the near-infrared (NIR) and shortwave infrared (SWIR) areas, achieving a 25% increase in accuracy for forecasting photosynthetic rates. This development is especially important for large-scale phenotyping since it allows accurate assessment of photosynthetic efficiency across vast agricultural areas. Furthermore, their emphasis on sorghum, an essential commodity for food security in dry areas, highlights the practical significance of their efforts to improve crop resilience. Moreover, hyperspectral sensors have demonstrated efficacy in detecting leaf carbon content by recording reflectance in the NIR and SWIR bands, establishing robust relationships with biochemical composition (Gitelson *et al.* 2002, Poorter *et al.* 2009). Gitelson *et al.* (2002) investigated the correlation between chlorophyll concentration and spectral reflectance in plant leaves, creating noninvasive methods for chlorophyll estimation. Their research, employing spectroradiometers, attained significant prediction accuracy with reflectance assessed at essential wavelengths, specifically 700–750 nm. These algorithms have become indispensable instruments for academics and practitioners pursuing reliable, noninvasive techniques for assessing plant health. Poorter *et al.* (2009) performed an extensive meta-analysis investigating the correlation between leaf mass per area (LMA) and photosynthetic characteristics across a diverse array of plant species, including both C_3 and C_4 plants. Their findings indicated that LMA is closely correlated with photosynthetic rates [measured in µmol(CO_2) m^{-2} s^{-1}], with variations affected by environmental and genetic variables. This meta-analysis offered essential insights into the influence of leaf shape on photosynthetic efficiency, informing future physiological and ecological research. Additionally, Serbin *et al.* (2012) examined the correlation between leaf optical characteristics and photosynthetic metabolism across different temperature settings. They utilized field spectroradiometers to assess leaf reflectance and transmittance within the 400–2,500 nm spectrum. Their research showed a 20% increase in forecasting photosynthetic rates [in µmol(CO_2) m^{-2} s^{-1}], correlating optical characteristics with metabolic reactions under thermal stress. These findings enhanced comprehension of temperature sensitivity in photosynthesis and underscored the potential of optical features as indicators of metabolic activities in fluctuating climates. Rascher *et al.* (2015) utilized the *HyPlant* imaging spectrometer to map sun-induced fluorescence (SIF) with an exceptional resolution of 10 cm. This high-resolution mapping disclosed regional discrepancies in Calvin cycle activity, with fluorescence signals quantified in mW m^{-2} sr^{-1} nm^{-1}. Their research linked fluorescence signals to the efficiency of the Calvin cycle, bridging the divide between leaf-level activities and landscape-level observations. This innovation highlights the significance of hyperspectral imaging in converting theoretical knowledge into practical applications, enabling accurate evaluations of photosynthetic output under various environmental circumstances.

These findings collectively underscore the revolutionary potential of hyperspectral imaging in enhancing our comprehension of the Calvin cycle. Innovations in identifying spectrum markers of essential enzymes and correlating optical features with photosynthetic metabolism provide improved crop monitoring and sustainable agricultural operations. The integration of high-resolution imaging methods with predictive physiological models highlights the significance of hyperspectral technology in tackling global issues such as food security and climate adaptation.

These findings collectively underscore the transformative role of hyperspectral imaging in advancing our understanding of the Calvin cycle and its implications for sustainable agriculture. By linking spectral markers of key carbon-fixation enzymes with photosynthetic efficiency models, HSI enables noninvasive, high-throughput assessments of crop vitality, carbon assimilation, and metabolic activity. The integration of SIF-based fluorescence mapping with real-time spectral monitoring enhances the precision of drought response strategies, yield forecasting, and stress diagnostics, ensuring that farmers can implement adaptive management techniques based on real-time photosynthetic efficiency data. Furthermore, the application of UAV-mounted hyperspectral sensors and AI-driven spectral analytics allows large-scale monitoring of Calvin cycle dynamics, facilitating early detection of environmental stressors that impact crop productivity. Future advancements in sensor resolution, spectral calibration, and physiological modeling will continue to refine these monitoring techniques, strengthening global food security efforts and enabling climate-adaptive agricultural practices.

Hyperspectral vegetation indices and photosynthetic mechanisms

By collecting reflectance data across many spectral bands, hyperspectral vegetation indices (VIs) are important tools for figuring out photosynthesis, plant health, and how plants respond to stress (Yu *et al.* 2022). These indicators utilize the extensive data spectrum of hyperspectral sensors to provide accurate assessments of photosynthetic efficiency and overall plant health. The most significant vegetation indices include the Normalized Difference Vegetation Index (NDVI), the Modified Chlorophyll Absorption in Reflectance Index (MCARI), and the Photochemical Reflectance Index (PRI). Each index offers distinct insights into plant physiological states (Carter and Knapp 2001). The fact that NDVI is sensitive to chlorophyll contents and canopy structure shows how important it is for measuring biomass and ecosystem health (Gitelson *et al.* 2003). Furthermore, Yu *et al.* (2022) built a mechanistic photosynthetic model to assess the maximal carboxylation rate (V_{cmax}) using hyperspectral remote sensing data. This innovation yielded a ±5% increase in prediction accuracy, demonstrating the significant relationship between physiological factors and spectral features. Carter and Knapp (2001) found a link between the way leaves look, the amount of pigments, and how sensitive they are to light in a wide range of ecosystems. For pigment content, this link was over 90% accurate. These advancements have significantly improved ecosystem-scale monitoring capabilities, emphasizing the use of hyperspectral indices in ecological research. MCARI improves these measurements by reducing the impact of nonphotosynthetic parts, lowering background noise by 15–20%, and making it easier to find chlorophyll in complex canopy structures (Daughtry *et al.* 2000). This enhancement is especially beneficial in dense vegetation environments, where conventional techniques frequently prove inadequate. The PRI index measures how well plants use light concerning their PSII performance and is a noninvasive way to check their photosynthetic potential (Gamon *et al.* 1997). Yang *et al.* (2022) talk about how new developments in PRI applications have made stress detection 20% more accurate, which helps us understand photoprotective systems better. PRI's connection with changes in carotenoid pigments also makes it better at predicting how much light is used, which makes it even more useful for precise monitoring (Gamon *et al.* 2016).

The Red-edge Chlorophyll Index (CI_red-edge), which focuses on nitrogen and chlorophyll concentrations, offers supplementary information. This hyperspectral index has demonstrated its ability to yield essential insights into plant nutrition and photosynthetic capacity (Barnes *et al.* 2000). Recent developments in UAV-mounted hyperspectral sensors have augmented their value by improving spatial resolution by up to 25% and hence promoting precision agricultural techniques (Polivova and Brook 2022). Researchers have established the efficacy of the Water Index (WI) in detecting drought stress and associated physiological alterations. By connecting the WI with stomatal conductance and photosynthetic efficiency (Peñuelas *et al.* 1997), this method has been shown to keep photosynthetic rates high in a range of water conditions. Seelig *et al.* (2008) demonstrated a 20% enhancement in stress detection accuracy through the integration of WI and stomatal conductance measures, hence, they improved drought monitoring methodologies. Furthermore, hyperspectral solar-induced fluorescence (SIF) detection has become a transformative method for monitoring photochemical processes at both canopy and ecosystem levels. This method substantially improves the observation of photosynthetic activities by recording real-time fluorescence signals. Frankenberg *et al.* (2014) found that SIF data improved the accuracy of finding photosynthetic features by 15–20%. This gave scientists important new information on how photosynthetic processes work under different light conditions. Moreover, Hank *et al.* (2019) emphasize the significance of SIF in promoting sustainable agriculture and ecosystem management. Integrating SIFs with hyperspectral VIs enables researchers to acquire a holistic perspective on plant health and productivity, thereby enhancing agricultural and environmental monitoring methodologies.

Constraints of hyperspectral imaging (HSI) in photosynthesis surveillance and the growing influence of big data and artificial intelligence

Hyperspectral imaging (HSI) has transformed the monitoring of plant physiology by enabling noninvasive assessments of photosynthetic characteristics, nonetheless, its extensive use encounters some significant constraints. A significant problem of hyperspectral imaging in photosynthesis monitoring is the substantial data volume produced, necessitating sophisticated computer methods for effective processing. The amalgamation of artificial intelligence (AI) and machine learning (ML) has surfaced as a remedy for managing the intricacies of spectrum datasets, nonetheless, obstacles, including data storage, processing velocity, and model generalizability, persist as substantial issues (Islam *et al.* 2024). The substantial data volume generated by HSI requires sophisticated spectral data compression methods and refined feature selection algorithms for effective interpretation (Ali *et al.* 2024). Moreover, model calibration presents a significant challenge when using HSI across several plant species, as spectral fingerprints may fluctuate based on climatic circumstances, plant phenology, and stress levels. Sharma *et al.* (2024) revealed that AI-enhanced HSI models enhanced the categorization of stress responses in grapevine phenotyping, nevertheless, attaining model transferability across species continues to be a significant problem. A significant disadvantage is HSI's reliance on external environmental elements, especially in field circumstances where fluctuating light intensity, air interference, and sensor noise can influence spectral measurements (Zhang *et al.* 2025). Despite advancements in remote sensing capabilities using airborne and UAV-mounted hyperspectral sensors, the precision of photosynthetic efficiency assessments by solar-induced fluorescence (SIF) remains influenced by diurnal and seasonal fluctuations in sunshine availability (Mangalraj and Cho 2022). The amalgamation of hyperspectral imaging (HSI) with biochemical fluorescence quenching (BFQ) models has enhanced estimations of electron transport rate (ETR), yet discrepancies in data remain due to differences in leaf chlorophyll fluorescence at the canopy level (Zarco-Tejada *et al*. 2016). AI-driven hyperspectral data processing has presented issues associated with the opaque nature of deep learning models and the complexities in identifying spectral patterns (Varghese *et al.* 2023). Convolutional neural networks (CNNs) and graph-based AI models have effectively identified stress-related spectrum changes, however, their practical implementation is frequently limited by the requirement for extensive annotated datasets for training and validation (Abdullah *et al.* 2023). Recent research has emphasized the heightened computing demands of deep learning-based hyperspectral models, especially in the context of real-time canopy-level photosynthetic observations (Haworth *et al*. 2023). Moreover, the expense and availability of high-resolution hyperspectral sensors continue to pose substantial obstacles to widespread agricultural use. Although UAV-mounted and satellite-based platforms such as *ESA FLEX* have enhanced the accessibility of hyperspectral imaging (HSI), the prohibitive expense of spectral imaging devices and the necessity for specialized skills hinder general deployment (Guanter *et al.* 2014). Anticipated developments in AI-enhanced spectrum unmixing and cloud-based big data processing are projected to enhance the operational efficiency of hyperspectral imaging, rendering it a more scalable instrument for monitoring plant photosynthesis (Chen *et al.* 2024). Notwithstanding these constraints, the integration of HSI with AI possesses the capacity to surmount existing obstacles by facilitating real-time, automated analysis of hyperspectral data. Current investigations into adaptive AI algorithms and hyperspectral fusion methods are anticipated to enhance the precision of photosynthesis monitoring inside intricate plant canopies. Nonetheless, more efforts are required to guarantee model robustness, computational efficiency, and wider application across various crop species and climatic circumstances.

Assessment of nutrient concentration

Evaluating nutrient contents, particularly nitrogen, is key for understanding photosynthetic efficiency and overall plant health, as nitrogen is an integral component of chlorophyll and photosynthetic proteins (Poorter *et al.* 2009). Furthermore, studies have demonstrated a strong correlation between the variation in leaf mass per area (LMA) and photosynthetic rates. Poorter *et al.* (2009) performed an extensive meta-analysis to investigate the causes and effects of LMA variation, demonstrating that these discrepancies significantly influence resource use efficiency in plants. Their research emphasized the impact of structural leaf characteristics on photosynthetic efficiency, providing significant insights for both ecological and agricultural purposes. Hyperspectral vegetation indices, especially those that use near-infrared reflectance, are very good at measuring nitrogen contents, which have a direct effect on crop growth and yield (Clevers and Kooistra 2012). Using hyperspectral remote sensing data, Clevers and Kooistra (2012) precisely measured nitrogen and chlorophyll contents in mixed cereal crops, resulting in a 20% increase in detection accuracy. This development highlights the efficacy of hyperspectral data in noninvasive nutrient assessment and supports precision agriculture. Also, research has shown that hyperspectral indices in the red-edge spectrum, such as the Red-edge Chlorophyll Index (CI_red-edge), have a strong relationship with nitrogen contents. This shows how important it is to do accurate and noninvasive nutrient assessments for fertilization strategies that work (Gitelson *et al.* 2005, Mutanga and Skidmore 2007). Mutanga and Skidmore (2007) highlighted the efficacy of red-edge reflectance in quantifying phosphorus concentrations in grass canopies, resulting in a 25% increase in accuracy. Their findings are crucial for assessing nutrient constraints in savanna ecosystems and facilitating sustainable resource management. Gitelson *et al.* (2005) formulated algorithms for the remote estimation of canopy chlorophyll content in crops like maize and soybean, with an accuracy of

10–15%. These scalable techniques substantially improve chlorophyll and nitrogen monitoring processes, hence, they enhance crop management tactics. Zarco-Tejada *et al.* (2001) further established that CI_red-edge enhances nitrogen mapping precision by 15%, especially in diverse canopies of olive and citrus trees. Their use of novel hyperspectral indicators yielded accurate insights into nutrient distribution, enhancing orchard output. Sims and Gamon (2002) enhanced this by connecting pigment quantity with spectral reflectance across several species and developmental phases, hence, they increased pigment estimation accuracy by 20%. Wang *et al.* (2018) extended these applications to environmental monitoring by utilizing hyperspectral data to identify heavy metal pollution in soil and plants. Their research showed a 15% enhancement in recognizing distinct spectral signatures linked to pollution, highlighting the adaptability of hyperspectral imaging for agricultural and environmental evaluations.

Hyperspectral imaging applications have extended beyond nitrogen to include other essential nutrients such as phosphorus and potassium, which are critical for plant growth and productivity. Similarly, Lin *et al.* (2024) developed accurate models using hyperspectral data to monitor leaf N, P, and K content in maize, achieving improved prediction precision for nutrient status assessment. Silva *et al.* (2023) highlighted the importance of UAV and satellite-based hyperspectral imaging for monitoring spatial variations in crop nitrogen contents, providing essential data for precision nutrient management. Zhang *et al.* (2023) employed UAV-mounted hyperspectral cameras to analyze biochemical information related to crop nutrients, achieving up to 30% higher accuracy compared to traditional methods. Sharma *et al.* (2024) optimized hyperspectral imaging workflows for potato crop nutrient prediction, demonstrating its ability to accurately map nitrogen and potassium concentrations for biomass growth estimation.

These advancements underscore hyperspectral imaging's transformative impact on precision agriculture by facilitating high-resolution, real-time monitoring of crop nutrient dynamics. This technology enables precise nutrient management, reduces input costs, and minimizes environmental impacts, fostering sustainable agricultural practices.

Evaluation of leaf area index (LAI)

The leaf area index (LAI) is a crucial metric in photosynthesis research, it measures the proportion of leaf area to the ground surface. It serves as an essential indicator of canopy density, light absorption capacity, and photosynthetic potential (Daughtry *et al.* 2000). Daughtry *et al.* (2000) established a fundamental approach for measuring LAI from leaf and canopy reflectance data, specifically in crops like maize (*Zea mays*). By linking chlorophyll contents to reflectance indices, they were able to get 20% more accurate estimates, with chlorophyll contents ranging from 20 to 80 μg cm^{-2}. This research established the foundation for further advancements in noninvasive agricultural monitoring techniques. A high LAI often correlates with improved light absorption and gas exchange, leading to greater biomass accumulation and agricultural productivity. Bréda (2003) emphasized the significant relationships between LAI and canopy light absorption while also addressing the problems associated with LAI measurements. Their thorough analysis of terrestrial methodologies highlighted the necessity for improved techniques, especially for ecological evaluations. Also, hyperspectral remote sensing technologies have made LAI calculations faster and more accurate by collecting spectral signatures that are unique to different plant species and canopy structures (Ali and Imran 2020). They found that using reflectance in the near-infrared (NIR) and red-edge spectra, along with hyperspectral methods, improved nitrogen detection and LAI by 20–30%. This breakthrough establishes hyperspectral imaging as a revolutionary instrument in precision agriculture. Radiative transfer methods, like *PROSAIL*, which combines the *PROSPECT* model for leaf optical properties with the *SAIL* model for canopy reflectance, are useful for finding the LAI. Jacquemoud *et al.* (2009) proved that *PROSAIL* could accurately replicate LAI and canopy structure, with a prediction accuracy of ±5% across wavelengths from 400 to 2,500 nm. Likewise, Darvishzadeh *et al.* (2011) used *PROSAIL* on aerial hyperspectral pictures, effectively measuring LAI in grasslands with an accuracy improvement of ±10%. This highlights the strong capabilities of *PROSAIL* in evaluating various ecosystems.

When crops are at key stages of growth, the Normalized Difference Vegetation Index (NDVI) and the Green Normalized Difference Vegetation Index (GNDVI) are two hyperspectral vegetation indices that are closely linked to the LAI. Zarco-Tejada *et al.* (2013) found that relating chlorophyll fluorescence to photosynthetic rates in crops like olive trees and vineyards made LAI predictions 20% more accurate during these phases. These metrics are essential for tracking biomass buildup and canopy dynamics. Additionally, UAV-derived hyperspectral imaging offers enhanced spatial resolution and precision for evaluating LAI. Xie *et al.* (2019) said that hyperspectral sensors mounted on unmanned aerial vehicles (UAVs) improved spatial resolution by 20–30% and were able to measure LAI gradients in both forest and agricultural areas. This finding underscores the transformative potential of hyperspectral imaging for comprehensive ecosystem monitoring and precision agricultural applications (Table 3).

Rate of carbon assimilation

Carbon absorption rates, which measure a plant's ability to convert atmospheric CO_2 into organic compounds, are crucial for understanding photosynthesis, biomass production, and crop yield (Law *et al.* 2002). They got important information about carbon flow patterns by connecting gross primary production (GPP) with canopy reflectance data. This shows how important spectral indices are for measuring carbon assimilation. The Photochemical Reflectance Index (PRI), established

Table 3. Comparative analysis of hyperspectral imaging and traditional techniques in plant physiology.

Parameter	Hyperspectral imaging (HSI)	Traditional techniques
Sensitivity	High spectral sensitivity enables the detection of subtle physiological variations, including early-stage stress responses and minor fluctuations in photosynthetic efficiency	Lower sensitivity may result in undetected early or minimal physiological changes, limiting the ability to detect stress responses and small variations in photosynthesis
Spectral resolution	Acquisition of high-resolution spectral data across hundreds of narrow bands (typically in the range of 400–2,500 nm), facilitating precise identification and quantification of photosynthetic pigments and other biomolecules	Limited to a few broad spectral bands, typically focusing on key wavelengths (*e.g.*, red and near-infrared), restricting the capacity for detailed spectral analysis
Invasiveness	Enables noninvasive, real-time monitoring of plant physiological processes without the need for physical sampling, preserving plant integrity and allowing for continuous observation	Often necessitates destructive sampling (*e.g.*, tissue extraction for chlorophyll content measurement), potentially altering plant physiology and limiting the frequency of data collection
Spatial and temporal resolution	Facilitates high-resolution spatial mapping of photosynthetic activity over extensive areas with the capability for frequent temporal assessments, enhancing the monitoring of dynamic physiological processes	Typically limited to site-specific, point-based measurements with reduced spatial coverage and lower temporal resolution, leading to potential gaps in data over time and space
Data processing and multivariate analysis	Supports advanced multivariate statistical techniques (*e.g.*, PCA, PLSR) for the extraction of complex patterns from high-dimensional hyperspectral data, enabling comprehensive analysis of plant physiological states	Often constrained by the need to simplify data, reducing the ability to extract complex interactions and patterns from the physiological dataset
Quantification of photosynthetic pigments	Provides precise quantification and mapping of photosynthetic pigments (*e.g.*, chlorophyll, carotenoids) and associated biomolecules, allowing for detailed biochemical profiling and monitoring of photosynthetic efficiency	Limited in scope, often focusing on chlorophyll fluorescence or other specific features without the capability to conduct a holistic assessment of the photosynthetic apparatus

by Gamon *et al.* (1997), serves as a noninvasive instrument for assessing photosynthetic light-use efficiency. They established a robust link between PRI and PSII efficiency, which enhanced GPP predictions by 15–20%. Advanced hyperspectral indices have enhanced these estimations by using spectral reflectance in the red and near-infrared (NIR) bands. Zhi *et al.* (2022) said that high-throughput hyperspectral imaging made GPP accuracy 25% better for crops like sorghum (*Sorghum bicolor*) and maize (*Zea mays*). Furthermore, Fu *et al.* (2020) included physiological and spectral data in predictive models, achieving ±10% accuracy in estimating photosynthetic efficiency, including factors such as V_{cmax} and J_{max}. Their research underscores the possibility of integrating spectral and physiological attributes for accurate photosynthesis monitoring.

Moreover, UAV-mounted hyperspectral sensors have enhanced ecosystem-level carbon monitoring by delivering superior spatial resolution and precision. Xie *et al.* (2019) demonstrated that UAV hyperspectral methods enhanced spatial resolution for carbon cycle evaluations by 20–30%. These advancements highlight the essential function of hyperspectral imaging in ecological surveillance and precision agriculture.

Configuration and organization of foliar cells

The cellular architecture of a leaf is fundamental in photosynthetic efficiency, influencing key processes such as light absorption, gas exchange, and internal CO_2 diffusion. Xiong *et al.* (2024) emphasized that improvements in mesophyll structure, chloroplast arrangements, and CO_2 conductance could enhance light-use efficiency and assimilation rates in rice, revealing pathways for improving photosynthetic performance. Oivukkamäki *et al.* (2025) applied multiscale optical remote sensing, demonstrating how changes in mesophyll structure influence CO_2 diffusion and reflectance-based models. Falcioni *et al.* (2024) compared photosynthetic performance across species and highlighted the role of mesophyll conductance in optimizing CO_2 diffusion, linking cellular organization to enhanced photosynthetic rates. Similarly, Egesa *et al.* (2024) showed how differences in mesophyll cell size and intercellular spaces affect CO_2 diffusion efficiency, impacting overall photosynthesis in *Phaseolus vulgaris*. Neuwirthová *et al.* (2024) explored the relationship between leaf anatomical traits and VIS-NIR reflectance spectra, emphasizing that asymmetry in mesophyll structure directly affects the optical modeling of CO_2 diffusion pathways. These findings highlight the transformative role of hyperspectral imaging and reflectance models in understanding the link between cellular architecture and photosynthesis.

By integrating structural analysis, hyperspectral imaging, and models like *PROSPECT*, researchers gain comprehensive insights into how cellular features regulate photosynthesis. This knowledge has significant implications for optimizing crop productivity and advancing ecological research.

High-spectral and spatial resolution techniques for crop phenotyping and precision agriculture

Advancements in high-spectral and spatial resolution techniques have profoundly impacted crop phenotyping and precision agriculture, offering unprecedented accuracy in monitoring crop health, stress responses, and productivity. This section reviews the latest developments in these approaches, highlighting their significance and applications in enhancing agricultural productivity.

Progress in high-resolution imaging for agricultural surveillance

High-resolution remote sensing has transformed agricultural monitoring by offering intricate spatial and spectral information on crop health, phenotyping, and stress identification. Recent improvements in satellite imagery, synthetic aperture radar (SAR), fluorescence-based sensing, and data fusion approaches have improved the accuracy of agricultural evaluations (Maimaitijiang *et al.* 2020). Nonetheless, issues concerning calibration, data processing, and sensor compatibility persistently hinder the complete implementation of these technologies (Arroyo-Mora *et al.* 2019).

High-resolution satellite photography has markedly enhanced the capacity to identify agricultural characteristics and evaluate biomass. Platforms like *WorldView-3* and *Pleiades-1A* provide sub-meter spatial resolution, allowing detailed observation of leaf area index, canopy architecture, and stress responses (Cheekhooree 2024). The amalgamation of machine learning algorithms with satellite data has significantly improved the precision of crop categorization and yield prediction (Sarkar *et al.* 2024). Notwithstanding these advantages, substantial expenses, restricted revisit intervals, and the intricacy of data interpretation continue to pose considerable obstacles (Lu *et al.* 2020). Multi-sensor fusion methodologies, encompassing the amalgamation of *Sentinel-2* and *PlanetScope* data, have exhibited enhanced precision in phenotyping and stress assessment (Xie *et al.* 2019). Nonetheless, variations in spectral responses among platforms pose obstacles to standardization and cross-validation (Zarco-Tejada *et al.* 2013).

SAR technology has emerged as a crucial instrument for ongoing agricultural surveillance, especially in areas with persistent cloud cover, where optical imaging proves problematic (Ulaby *et al.* 2010). Synthetic Aperture Radar (SAR) can pierce cloud cover and deliver high-resolution estimations of biomass and soil moisture, rendering it essential for yield estimation and resource optimization (Paloscia *et al.* 2013). The amalgamation of SAR with optical sensors has enhanced stress detection and fortified remote sensing applications in precision agriculture (Fuentes-Peñailillo *et al.* 2024). SAR data interpretation is intricate because of speckle noise and difficulties in distinguishing plant components, necessitating sophisticated classification approaches and machine learning algorithms to derive significant insights (Houborg and McCabe 2016).

The European Space Agency's *FLEX* mission has pioneered a novel method for monitoring photosynthetic activity using fluorescence-based imaging. In contrast to conventional reflectance-based techniques, *FLEX* measures solar-induced fluorescence (SIF), enabling direct evaluations of plant physiological conditions and early stress reactions (Frankenberg *et al.* 2014). This feature renders it an effective instrument for assessing drought stress and nutritional deficits (Marques *et al.* 2024). Nevertheless, obstacles such as limited spatial resolution, intricate data retrieval, and the necessity for ground validation restrict its practical uses (Oppelt and Muhuri 2024). The amalgamation of *FLEX* data with high-resolution optical imaging has demonstrated potential in connecting field-level observations with extensive ecosystem evaluations (Hank *et al.* 2019).

Panchromatic sharpening has been an effective method for improving the spatial resolution of satellite images by integrating high-resolution panchromatic bands with multispectral data. This method has been very helpful in enhancing vegetation indices and canopy mapping (Gao *et al.* 2006). Recent implementations of panchromatic sharpening in *Sentinel-2* images have shown enhancements in spatial resolution of up to 20%, hence improving phenotyping and early stress detection (Song *et al.* 2024). The efficacy of this approach relies on sensor calibration, band alignment, and radiometric constancy (Wulder *et al.* 2008).

The amalgamation of multi-sensor satellite data, including *Sentinel-2* and *Landsat-8*, has markedly enhanced the spatial and temporal resolution of agricultural surveillance (Roy *et al.* 2014). Researchers can achieve a more thorough knowledge of crop health and stress responses by integrating optical, thermal, and hyperspectral data (Zarco-Tejada *et al.* 2013). Nonetheless, obstacles persist in standardizing datasets from diverse sources as discrepancies in spectral resolution and processing techniques may lead to inconsistencies (Oppelt and Muhuri 2024). Standardization initiatives, automated processing processes, and AI-driven data integration methods will be essential for guaranteeing the dependability and scalability of these technologies in precision agriculture.

Techniques for image processing in high spectral-spatial resolution imaging

Advancements in image processing techniques have greatly augmented the progress of remote sensing technology in agriculture. The amalgamation of machine learning, spectrum unmixing, and advancements in thermal imaging has facilitated the accurate and efficient extraction of crop characteristics, stress markers, and phenotypic variants from high-resolution pictures. With the increasing prevalence of high spectral-spatial resolution imaging, there is a necessity for robust processing approaches to manage complex datasets and enhance the precision of agricultural monitoring.

Machine learning has become an effective instrument for analyzing satellite-derived data, automating the extraction of phenotypic traits, and enhancing the accuracy of stress detection and yield forecasting. Supervised and unsupervised learning methods are being employed to analyze hyperspectral and multispectral data, enabling the assessment of biomass, nitrogen concentrations, and chlorophyll contents (Li *et al.* 2015). Deep learning methodologies have exhibited significant efficacy in forecasting phenotypic characteristics, including crop yield, water stress, and nutrient status. Yue *et al.* (2019) illustrated that convolutional neural networks (CNNs) and recurrent neural networks (RNNs) surpass conventional statistical models in precision agriculture contexts. Maimaitijiang *et al.* (2021) emphasized the significance of machine learning in amalgamating satellite data with in-field observations, allowing real-time surveillance of crop development and stress conditions. These improvements diminish dependence on labor-intensive field evaluations, rendering high-throughput phenotyping more practicable and enhancing resource utilization efficiency in precision agriculture.

Spectrum unmixing is a crucial method for separating mixed spectrum signals in high-resolution remote sensing data, facilitating accurate assessment of crop health, phenotypic variety, and soil characteristics. The occurrence of mixed pixels, wherein many land cover types contribute to a singular spectral measurement, frequently hampers the analysis of satellite data. Spectral unmixing resolves this issue by deconstructing pixel-level spectral data into its constituent components, enabling more precise evaluations of vegetation indices and stress indicators (Small 2004). Somers *et al.* (2010) illustrated its use in evaluating genetic diversity, facilitating the selection of high-yield and stress-resistant genotypes in breeding initiatives. Wang *et al.* (2025) recently combined spectral unmixing with machine learning approaches, markedly enhancing the accuracy of crop stress detection by distinguishing between biotic and abiotic stressors. Moncholi-Estornell *et al.* (2023) employed spectral unmixing to quantify sunlight-vegetation cover, thereby enhancing the interpretation of solar-induced fluorescence (SIF), which is crucial for assessing photosynthetic activity and drought responses in crops.

Progress in thermal image processing has enhanced the capability of high-resolution agricultural monitoring. Thermal imaging has been extensively employed for identifying water stress, detecting disease outbreaks, and assessing canopy temperature variations. Recent advancements in thermal sharpening methodologies have enhanced the spatial resolution of thermal data, allowing more accurate detection of localized stress hotspots (Maes and Steppe 2019). Du *et al.* (2024) devised a technique for integrating *Sentinel-2* and *Sentinel-3* thermal data, enhancing daily soil moisture content assessment and optimizing irrigation scheduling in precision agriculture. He *et al.* (2024) integrated ground-based hyperspectral imaging with satellite thermal data to improve evaluations of topsoil nitrogen variability, facilitating the optimization of fertilizer delivery techniques.

The amalgamation of machine learning, spectrum unmixing, and thermal enhancement approaches has resulted in a more holistic methodology for high-resolution agricultural monitoring. These approaches enable researchers to delineate exact phenotypic features, identify stress factors at early stages, and enhance resource allocation for sustainable agricultural management. Future studies ought to concentrate on further refining data fusion methodologies, enhancing spectral calibration approaches, and automating image processing processes to improve the accuracy and scalability of high spectral-spatial resolution imaging in agriculture.

Multispectral and hyperspectral imaging

Multispectral and hyperspectral imaging technologies, such as the *Hyperion Sensor*, have changed the way crop health analysis is done by collecting data across narrow spectral bands. This lets scientists look at a lot of different biochemical and physiological traits of plants. Gao (2000) illustrated the accuracy of these imaging systems in quantifying chlorophyll concentrations with over 90% precision, providing valuable information for crop health management. This technique facilitates the early identification of stressors, including nutrient deficits, which is essential for improving nutrient management methods and overall production in precision agriculture. Fitzgerald *et al.* (2010) also talked about how important hyperspectral imaging is for measuring nitrogen, with a resolution of 0.1 mg(N) g^{-1}(FM). This innovation improved nitrogen application efficiency by almost 15%, promoting optimal crop development and minimizing waste. In addition to enhancing nutrition management, Sanaeifar *et al.* (2023) highlighted the accuracy of hyperspectral imaging in stress detection, achieving a 95% precision rate for recognizing early indicators of drought and illness. Due to these features, hyperspectral systems are necessary for modern crop phenotyping. They let managers see how plants' health is changing in real-time and make proactive management strategies easier.

Satellite-based hyperspectral imaging

Satellite-based hyperspectral imaging enhances agricultural surveillance by allowing extensive evaluations of essential crop health indicators. Ustin *et al.* (2009) demonstrated its ability to measure LAI accurately (± 0.5 m^2 m^{-2}) and revealed strong correlations between spectral indices and chlorophyll concentration, enabling improved resource allocation and sustainable management. Additionally, Gamon *et al.* (2016) utilized hyperspectral imaging to monitor photosynthetic activity, improving efficiency forecasts by more than 20%. Recent advancements have further expanded its potential. Wang *et al.* (2025) emphasized integrating machine learning models with hyperspectral data to improve precision agriculture applications, enhancing stress detection accuracy. Siddique *et al.* (2024) illustrated the role of satellite-based hyperspectral imaging in modern agriculture, showing its value in soil health monitoring and crop yield predictions. Yu and Cui (2024) applied hyperspectral imaging for cold-tolerant crop identification, demonstrating its effectiveness in breeding programs and stress-resilient crop development. These advancements highlight satellite-based hyperspectral imaging as a key technology for large-scale crop health assessments and sustainable resource management.

UAV-integrated hyperspectral imaging systems: operational efficacy and calibration protocols

The implementation of UAV-mounted hyperspectral imaging in precision agriculture has markedly enhanced high-resolution, real-time crop monitoring, facilitating early stress identification and precise resource management. UAV-HSI shows superior spatial and temporal resolution compared to satellite or manned aircraft hyperspectral imaging, rendering it especially beneficial for site-specific crop analysis (Ram *et al.* 2024). Nonetheless, despite its advantages, UAV-HSI continues to encounter operational and calibration issues that impact the consistency and reliability of spectral data. Recent research has shown the effectiveness of UAV-HSI systems in illness diagnosis, stress evaluation, and phenotyping applications. A thorough evaluation by Lu *et al.* (2020) showed that UAV-HSI effectively recognizes small spectrum fluctuations in crops, identifying water stress and nutritional deficits far earlier than conventional field scouting approaches. Ishida *et al.* (2018) showed in separate research that UAV-HSI-based vegetation classification surpasses multispectral photography, enhancing classification accuracy by 20–30%. These findings demonstrate the enhanced spectral resolution of HSI compared to traditional imaging methods. Nonetheless, UAV-HSI is particularly vulnerable to environmental fluctuations, rendering calibration a significant difficulty. Liu *et al.* (2024) discovered that flight altitude, lighting conditions, and sensor vibrations can cause reflectance inaccuracies of up to 15%, hence severely affecting vegetation indices and stress detection models. Moreover, variations in sensor types, spectral resolution, and data processing methodologies among investigations impede cross-comparison, underscoring the critical necessity for standardized calibration processes.

A fundamental constraint of UAV-HSI applications in agriculture is the absence of widely recognized calibration standards, leading to spectrum discrepancies among various research investigations (Arroyo-Mora *et al.* 2019). Numerous calibration approaches are available, however, their use is uneven, resulting in fluctuating radiometric accuracy and diminished data dependability. A multitude of significant issues exacerbate this dilemma. UAV-HSI functions under unregulated atmospheric circumstances, rendering it particularly vulnerable to swings in solar irradiance, variations in cloud cover, and air scattering. Radiometric calibration methods, such as empirical line calibration (ELC), are frequently employed, nevertheless, they rely on ground reference targets and are typically challenging to execute in field situations (Geipel *et al.* 2021). Moreover, hyperspectral sensors demonstrate spectral drift and radiometric noise, which may skew reflectance readings. Research conducted by Swaminathan and Thomasson (2024) revealed that the use of onboard calibration panels and real-time radiometric correction algorithms lowered spectrum drift errors by 10%. Nonetheless, these methodologies have not yet been standardized across many UAV sensor systems.

Aerial and terrestrial sensors

Aerial and terrestrial sensors are essential tools for real-time nutrient management and crop health assessments. Raun *et al.* (2002) demonstrated their efficacy in assessing nitrogen concentrations with 85% accuracy, enabling precise modifications in fertilizer applications and minimizing losses. Shanahan *et al.* (2001) further combined terrestrial sensors with UAV platforms, achieving 90% accuracy in chlorophyll concentration assessments. Ryu (2024) applied high-resolution aerial and ground sensors to scale land surface flux measurements, enhancing predictions of plant stress responses in precision agriculture. These innovations reinforce the importance of aerial and terrestrial sensors in sustainable agricultural practices and resource optimization.

Integration of diverse platform technologies

The integration of satellite, UAV, and terrestrial sensors offers a holistic method for agricultural monitoring. Hunt *et al.* (2010) demonstrated that this integration improved the temporal resolution of crop phenotyping to three-day intervals, enabling continuous monitoring of crop responses to environmental stresses. Lelong *et al.* (2008) highlighted that multi-platform integration enhanced spatial resolution and accuracy, facilitating precise modifications in irrigation and fertilizer applications. Zhang and Kovacs (2012) emphasized the benefits of multi-platform sensing for yield prediction and phenotyping precision.

In recent studies, Kariani and Supriyadi (2024) demonstrated the synergy of satellite and UAV platforms for crop yield estimation and stress mapping, improving agricultural decision-making processes. Oppelt and Muhuri (2024) emphasized multi-sensor data fusion for achieving consistent and high-resolution monitoring across diverse agricultural landscapes. These integrations highlight the transformative role of multi-platform technologies in enhancing the efficiency, accuracy, and scalability of precision agriculture.

Advancements in satellite imaging technologies

Recent advancements in satellite imaging technologies have significantly improved the monitoring of agricultural health through enhanced spatial and temporal resolution. Mulla (2013) examined the utility of *Sentinel* and *Landsat* satellites in improving yield prediction models by up to 15%, facilitating resource-efficient farming practices. Maes and Steppe (2019) explored thermal imaging applications, demonstrating sub-meter spatial resolution in identifying temperature-induced crop stress for efficient irrigation and disease management.

Recent research by Wüpper *et al.* (2024) demonstrated the use of *Sentinel-2* multispectral data for estimating crop stress in precision agriculture, improving monitoring reliability. Ryu (2024) integrated hyperspectral imaging data with flux tower observations, enabling high-resolution monitoring of land surface fluxes and crop responses.

These advancements highlight the ongoing evolution of satellite imaging technologies, enabling robust monitoring systems that enhance resilience to climate variability and promote sustainable agricultural practices.

Comparative analysis of hyperspectral imaging with other high-resolution imaging modalities

Hyperspectral imaging has emerged as a powerful tool in agricultural monitoring due to its ability to capture continuous spectral information across hundreds of narrow bands. This spectral granularity enables the detection of subtle biochemical and physiological variations in crops, making HSI particularly useful for stress detection, disease identification, and nutrient mapping (Zhang *et al.* 2025). However, despite its strengths, HSI faces competition from other high-resolution imaging modalities, including LiDAR, multispectral imaging (MSI), and thermal imaging, each with unique advantages and limitations.

LiDAR (Light Detection and Ranging) has been widely adopted in agricultural applications for its ability to generate high-resolution three-dimensional (3D) structural models of vegetation. Unlike HSI, which relies on spectral reflectance, LiDAR actively measures distances using laser pulses, making it highly effective for canopy height estimation, biomass modeling, and topographic analysis (Jurado-Rodríguez *et al.* 2024). Recent studies have demonstrated the benefits of integrating LiDAR with HSI, where spectral data enhances the structural information provided by LiDAR, leading to improved biomass estimation and crop classification (Benelli *et al.* 2020). However, while LiDAR excels in structural mapping, it lacks the spectral resolution necessary for biochemical assessments, limiting its ability to detect plant stressors at the molecular level (Bhargava *et al.* 2024).

Multispectral imaging (MSI) is another widely used remote sensing modality in precision agriculture, offering a more cost-effective alternative to HSI. MSI captures fewer and broader spectral bands, typically in the visible and near-infrared regions, making it suitable for large-scale monitoring applications such as vegetation index calculation (Mahlein *et al.* 2019). While MSI provides sufficient information for general crop health assessment, its limited spectral resolution reduces its capability to differentiate between specific stress factors (Lu *et al.* 2020). A comparative study by Sethy *et al.* (2022) found that while MSI effectively tracks vegetation dynamics using indices such as NDVI, it fails to detect subtle biochemical changes that HSI can capture. As a result, MSI is often integrated with HSI in hybrid approaches to balance cost-effectiveness and spectral precision in large-scale agricultural applications.

Thermal imaging, on the other hand, provides valuable insights into plant water status and temperature variations, making it particularly useful for drought monitoring and irrigation management (Du *et al.* 2024). Because canopy temperature directly correlates with plant transpiration rates, thermal imaging has been extensively applied for the early detection of water stress (Gitelson *et al.* 2012). However, its effectiveness is highly dependent on atmospheric conditions, and frequent recalibration is necessary to ensure accuracy (He *et al.* 2024). Integrating thermal imaging with HSI has been shown to enhance early stress detection by combining physiological indicators with spectral signatures, offering a more comprehensive assessment of plant health (Feng *et al.* 2022).

Each of these imaging modalities serves a distinct role in precision agriculture, and their effectiveness is context-dependent. While HSI remains unparalleled in biochemical and physiological analysis, LiDAR is superior for structural assessments, MSI offers scalability and cost-effectiveness, and thermal imaging excels in real-time stress detection. Recent advancements emphasize the need for multi-sensor integration, where the fusion of HSI with LiDAR, MSI, and thermal imaging can overcome individual limitations and provide holistic agricultural insights. Future research should focus on optimizing sensor calibration, enhancing data fusion techniques, and leveraging artificial intelligence to streamline analysis and improve decision-making in precision agriculture (Adão *et al.* 2017).

Advantages of hyperspectral imaging over traditional techniques in photosynthesis studies

Hyperspectral imaging (HSI) represents a significant advancement in photosynthesis research, as it captures extensive multidimensional data that enhances our comprehension of plant physiological responses to environmental stress. This extensive data offers unique insights into photosynthetic efficiency and crop health that conventional methods cannot achieve. HSI's high-resolution spectral data facilitates accurate evaluations across diverse light wavelengths, which is crucial for real-time monitoring (Blackburn 2007, Adão *et al.* 2017) (Table 4).

Improved sensitivity

The sensitivity of hyperspectral imaging (HSI) facilitates the detection of subtle physiological changes that signify shifts in photosynthetic activity or early responses to plant stress. Dai *et al.* (2015) demonstrated that HSI can detect subtle variations in plant water stress and nutrient deficiencies with greater precision than conventional techniques. More recently, research by Atencia Payares *et al.* (2025) highlighted the effectiveness of thermal and multispectral sensors in assessing plant water status, demonstrating the strong correlation between water stress and reduced photosynthetic activity in vineyards (Atencia Payares *et al.* 2025). Similarly, Hernández-Clemente *et al.* (2019) confirmed HSI's ability to identify stress responses in intricate environments, reinforcing its enhanced sensitivity to minor variations in chlorophyll fluorescence.

In addition, Meacham-Hensold *et al.* (2020) showed that HSI can quantify leaf-level photosynthetic efficiency with a sensitivity up to 15% greater than traditional chlorophyll fluorescence methods, facilitating early

Table 4. Hyperspectral vegetation indices utilized for assessing photosynthetic activity.

Vegetation Index (VI)	Formula	Derived photosynthetic reference	References
Normalized Difference Vegetation Index (NDVI)	(NIR – Red)/(NIR + Red)	Indicates vegetation health, biomass, and chlorophyll content, reflecting photosynthetic capacity	Huang *et al.* (2021) Zhao *et al.* (2024)
Photochemical Reflectance Index (PRI)	$(R_{531} - R_{570})/(R_{531} + R_{570})$	Sensitive to changes in xanthophyll cycle pigments, indicating photosynthetic light use efficiency and stress	Garbulsky *et al.* (2011) Zheng *et al.* (2024)
Modified Chlorophyll Absorption in Reflectance Index (MCARI)	$(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550}) \times (R_{700}/R_{670})$	Designed to minimize soil color influences, indicating chlorophyll content which is related to photosynthetic activity	Wu *et al.* (2008)
Red-edge Inflection Point (REIP)	The wavelength at which the first derivative of the reflectance spectrum reaches its maximum point in the red-edge region	Indicates chlorophyll content and leaf structure, which are related to photosynthetic efficiency	Herrmann *et al.* (2010) Patil *et al.* (2024)
Water Index (WI)	(R_{900}/R_{970})	Reflects leaf water content, which can influence photosynthetic activity and plant water stress	Peñuelas *et al.* (1997)
Normalized Difference	(NIR – RedEdge)/(NIR + RedEdge)	Indicates vegetation health and chlorophyll content, related to photosynthetic activity	Imran *et al.* (2020)
Simple ratio	NIR/Red	Indicates leaf biomass and chlorophyll content, which are related to photosynthetic activity	Putra and Soni (2017)
Green Normalized Difference Vegetation Index (GNDVI)	(NIR – Green)/(NIR + Green)	Indicates chlorophyll content and nitrogen status, which are related to photosynthetic activity	Shaver (2009)
Enhanced Vegetation Index (EVI)	$2.5 \times [(NIR - Red)/(NIR + 6 \times Red - 7.5 \times Blue + 1)]$	Indicates vegetation health and chlorophyll content which are related to photosynthetic activity	Matsushita *et al.* (2007) Lai *et al.* (2024)
Chlorophyll Absorption in Reflectance Index (CARI)	$(R_{700}/R_{670}) - 1$	Indicates chlorophyll content, which is related to photosynthetic activity	Bannari *et al.* (2007) Verma *et al.* (2024)
Red-edge Chlorophyll Index (CI_red-edge)	$(R_{750}/R_{710}) - 1$	Indicates chlorophyll content, which is related to photosynthetic activity	Xie *et al.* (2018)
Triangular Vegetation Index (TVI)	$0.5 \times \{[120 \times (R_{750} - R_{550})] - [200 \times (R_{670} - R_{550})]\}$	Indicates vegetation health and chlorophyll content, which are related to photosynthetic activity	Xing *et al.* (2019)
Plant Senescence Reflectance Index (PSRI)	$(R_{680} - R_{500})\ R_{750}$	Indicates the onset of plant senescence, which affects photosynthetic activity	Ren *et al.* (2017)
Structure Insensitive Pigment Index (SIPI)	$(R_{800} - R_{445})/(R_{800} - R_{680})$	Indicates carotenoid content, which is related to light absorption and photosynthetic protection	Peñuelas *et al.* (1995) Manne *et al.* (2024)
Anthocyanin Reflectance Index (ARI)	$(1/R_{550}) - (1/R_{700})$	Indicates anthocyanin content, which can be related to plant stress and photosynthetic activity	Steele *et al.* (2009)
Carotenoid Reflectance Index (CRI)	(R_{510}/R_{550})	Indicates carotenoid content, which is related to light absorption and photosynthetic protection	Kong *et al.* (2016)
Normalized Pigment Chlorophyll Ratio Index (NPCRI)	$(R_{680} - R_{430})/(R_{680} + R_{430})$	Indicates chlorophyll content, which is related to photosynthetic activity	Sosa *et al.* (2021)
Fluorescence Index (FI)	$(R_{740} - R_{800})/(R_{740} + R_{800})$	Indicates chlorophyll fluorescence, which is related to photosynthetic efficiency and electron transport rate	Johnson *et al.* (2012)

detection and targeted agricultural interventions. Recent advances in machine learning-assisted HSI processing have further improved the detection of early-stage plant stress conditions, allowing for real-time monitoring of water stress and nutrient deficiencies in various crops (Atencia Payares *et al.* 2025).

These advancements underscore the potential of HSI for precision agriculture, enabling farmers to optimize irrigation strategies, mitigate stress conditions, and improve crop yield efficiency through proactive decision-making.

Progress in hyperspectral imaging for chlorophyll fluorescence assessment

Conventional chlorophyll fluorescence (ChlF) methods have historically been employed to evaluate plant photosynthetic efficiency, however, their limited spectrum range and dependence on a restricted set of fluorescence characteristics hinder their capacity to identify intricate stress responses. Hyperspectral imaging (HSI) offers a sophisticated method for acquiring continuous spectral data over an extensive wavelength range, enhancing early stress detection and physiological evaluations (Mora-Poblete *et al.* 2024). Techniques for retrieving solar-induced fluorescence (SIF) based on hyperspectral imaging (HSI) have shown enhanced sensitivity and precision in measuring photosystem efficiency, facilitating faster identification of plant stress relative to conventional fluorescence methods (Belwalkar *et al.* 2024). The amalgamation of machine learning models with HSI-derived fluorescence data has significantly augmented stress diagnostics, yielding a 20% enhancement in detection accuracy compared to traditional pulse-amplitude modulated (PAM) fluorometry (Bartold and Kluczek 2024). Fluorescence imaging, however, is vulnerable to atmospheric fluctuations and sensor calibration discrepancies, which can generate noise and diminish measurement reliability. Research indicates that fluctuations in ambient light conditions can substantially influence the precision of SIF estimations, necessitating the creation of automated data correction models and sophisticated spectral normalization techniques to improve the reliability of fluorescence-based HSI for field applications (Lee *et al*. 2024).

Technical and practical constraints of hyperspectral imaging

Notwithstanding its considerable benefits, the extensive implementation of HSI in precision agriculture is obstructed by several technological and practical obstacles. The computational demands of real-time data processing continue to be a significant limitation, especially in UAV-based and field-deployable systems with restricted onboard processing capabilities. Recent improvements in cloud-based spectrum analysis platforms have alleviated some limits, nonetheless, these solutions necessitate high-bandwidth data transfer and remain not globally accessible (Bethge *et al.* 2024).

Alongside data processing issues, the prohibitive expense of hyperspectral cameras and imaging spectrometers constitutes a significant obstacle to their extensive use. Despite a decline in the cost of multispectral imaging systems in recent years, hyperspectral sensors remain costly, limiting their application mainly to research and high-value crop monitoring (Bartold and Kluczek 2024). Moreover, field applications of HSI necessitate regular sensor calibration due to environmental variables such as temperature variations and sensor drift, hence augmenting operational complexity. Miniaturized UAV-mounted hyperspectral sensors have improved mobility and deployment efficiency, yet they often suffer from trade-offs in spectral resolution and operational endurance, limiting their effectiveness for continuous monitoring in large-scale agricultural settings (Pacheco-Labrador *et al.* 2025).

A significant issue is the susceptibility of hyperspectral readings to ambient variables. Fluctuating sunlight, atmospheric disturbances, and soil background reflectance can introduce noise into spectral data, compromising measurement precision (Lee *et al.* 2024). AI-driven spectrum correction models have been created to mitigate unpredictability in lighting circumstances, nevertheless, their implementation escalates computing complexity and constrains real-time decision-making capabilities (Pacheco-Labrador *et al.* 2025). The incorporation of sophisticated deep learning algorithms for spectral noise reduction and automated preprocessing demonstrates potential in enhancing the reliability of hyperspectral imaging measurements, nevertheless, these methods necessitate further validation across various crop species and environmental conditions before widespread implementation.

Distinguishing between drought and nutrient deficiency stress utilizing HSI

A significant benefit of HSI compared to traditional stress detection techniques is its capacity to distinguish among several abiotic stressors, such as drought stress and nutritional deficits, which frequently have overlapping physiological impacts. Conventional multispectral and visual evaluations find it challenging to differentiate these stressors because of their analogous effects on leaf morphology, such as wilting, yellowing, and chlorosis. HSI facilitates accurate distinction through the analysis of unique spectral changes across several wavelength ranges. Drought stress generally results in diminished leaf water content, which increases reflectance in the short-wave infrared (SWIR) spectrum (1,000–2,500 nm), while deficiencies in nitrogen and phosphorus predominantly influence chlorophyll contents, resulting in spectral shifts in the red-edge region (680–750 nm) and modifications in the Photochemical Reflectance Index (PRI) (Liu *et al.* 2025).

Machine learning models have played a vital role in increasing stress categorization accuracy using HSI. These AI-driven methodologies utilize comprehensive spectrum libraries to automate stress detection, enhancing the feasibility of real-time precision agricultural applications. Additionally, combining chlorophyll fluorescence imaging with HSI significantly promotes stress distinction by identifying variations in photosynthetic efficiency under different stress situations. Recent studies demonstrate that fluorescence kinetics measures, including F_v/F_m ratios and nonphotochemical quenching (NPQ), are essential indicators for differentiating between photosynthetic limits caused by drought and those resulting from nutritional deficits (Spasova *et al.* 2024). Future research should concentrate on refining machine learning-based stress classification models, augmenting real-time spectral data integration with agricultural decision-support systems, and advancing spectral normalization techniques to enhance the diagnostic accuracy of hyperspectral stress detection methods in precision agriculture. Moreover, creating hybrid methodologies that combine hyperspectral imaging (HSI) with other remote sensing technologies, such as LiDAR or thermal imaging, might augment stress differentiation capabilities and provide more thorough monitoring of crop health under variable field circumstances.

Research challenges

Despite significant progress in hyperspectral imaging for crop phenotyping and precision agriculture, several challenges must be addressed to further advance our understanding and application of this technology. These challenges are categorized into thematic subsections for a clearer understanding of the issues and to facilitate future research efforts.

Data processing and analysis

The high dimensionality of hyperspectral imaging (HSI) generates large datasets, presenting challenges in terms of data storage, processing efficiency, and analysis. Bioucas-Dias and Plaza (2010) and Zhang *et al.* (2016) proposed orthogonal subspace projection and PCA techniques for dimensionality reduction. Recently, Guerri *et al.* (2024) emphasized the role of deep learning algorithms in automating HSI data analysis (Fig. 5), enhancing real-time processing capabilities for large-scale agricultural monitoring. Similarly, Dasari *et al.* (2024) integrated convolutional neural networks (CNN) with hyperspectral data for early disease detection, achieving significant improvements in analysis efficiency.

Integration of multiple data sources

Combining hyperspectral data with multi-source information, such as physiological and environmental metrics, enhances crop health assessment and predictive modeling. Zarco-Tejada *et al.* (2013) demonstrated its utility for ecosystem-level resilience studies. Recent advancements include Ali *et al.* (2024), who integrated AI-driven hyperspectral analysis with soil metrics for precision fertilization, improving accuracy in crop monitoring by 25%. Additionally, Yu and Cui (2024) emphasized integrating meteorological and hyperspectral data for real-time stress detection, bridging environmental and spectral observations for optimized crop management.

Spatial and temporal resolution

Balancing spatial and temporal resolution in hyperspectral imaging is critical. UAV-based sensors offer scalable solutions for high-resolution imaging (Hunt *et al.* 2013). Finn *et al.* (2023) proposed automated georectification methods for UAV-based HSI, enhancing the spatial precision of phenotypic observations. Similarly, Bian *et al.* (2024) developed high spatiotemporal hyperspectral sensors, enabling real-time monitoring of crop dynamics at sub-meter resolution, and addressing the demands of precision agriculture.

Calibration and standardization of sensors

Standardizing hyperspectral sensors ensures consistent and reliable spectral data. Mutanga *et al.* (2012) and Kokaly *et al.* (2017) emphasized the importance of rigorous calibration protocols. Recently, Sabin *et al.* (2024) demonstrated advanced calibration workflows for industrial and agricultural spectral imaging, ensuring improved spectral accuracy across diverse systems. Similarly, Makarenko *et al.* (2024) introduced hardware-accelerated hyperspectral calibration systems, reducing variability caused by sensor drift and environmental factors.

Incorporation of three-dimensional information

Combining hyperspectral data with three-dimensional (3D) information, such as LiDAR, enhances our understanding of canopy architecture. Lefsky *et al.* (2002) and Asner and Martin (2008) highlighted its role in light distribution analysis. Recent advancements include Yu and Cui (2024), who integrated hyperspectral imaging with 3D reconstruction techniques for precision canopy mapping, providing improved biomass estimations. Additionally, Wang *et al.* (2025) combined LiDAR-based 3D data with hyperspectral imaging for enhanced light-use efficiency predictions.

Automation of data collection

Automation is critical for large-scale hyperspectral data collection and processing. Wang *et al.* (2015) and Shen *et al.* (2019) highlighted automated workflows for reducing manual errors. Khonina *et al.* (2024) introduced machine learning-driven automation for hyperspectral data processing, enabling faster and more reliable phenotypic assessments. Similarly, Bilotta *et al.* (2023) developed AI-integrated automation pipelines for hyperspectral workflows, improving the scalability of high-throughput phenotyping.

Understanding biological variability

Biological variability across species and environments complicates hyperspectral data interpretation. Machine learning models address this challenge, as highlighted by Homolová *et al.* (2013). Recently, Shuai *et al.* (2024) employed deep learning algorithms to account for genotypic variability, achieving high prediction accuracy for physiological parameters across diverse environments. Additionally, Hajaj *et al.* (2024) applied AI-driven models to analyze variability in hyperspectral imaging data for precision agriculture applications.

Validation of remote sensing data

Validation ensures that remote sensing accurately represents plant physiological states. Gitelson *et al.* (2003) and Zarco-Tejada *et al.* (2004) emphasized spectroradiometer-based benchmarks. Olorunsogo *et al.* (2024) proposed improved field-based validation techniques for hyperspectral indices, ensuring the accuracy of chlorophyll and water content measurements. Yu and Cui (2024) cross-validated HSI data with ground-based observations, enhancing large-scale model reliability.

Analysis of spectral signatures

Analyzing spectral signatures is vital for identifying subtle plant physiological changes. Sims and Gamon (2002) and Doughty *et al.* (2011) linked spectral signatures to abiotic stress responses. Recently, Antony *et al.* (2024) demonstrated spectral signature analysis using advanced hyperspectral indices for early drought detection, improving stress-response monitoring accuracy.

Economic considerations and availability

The cost of hyperspectral systems remains a barrier to widespread adoption. Ustin *et al.* (2009) highlighted the importance of affordability. Nie *et al.* (2024) examined recent developments in low-cost hyperspectral systems, expanding access to smallholder farms. Additionally, Durojaiye *et al.* (2024) emphasized the role of affordable spectral libraries in enabling broader adoption for commercial agricultural applications.

Future perspectives and recommendations

As we map out the future directions for hyperspectral imaging research and applications in agricultural photosynthesis, several important topics become clear as being essential to the field's advancement. Crop monitoring is about to undergo a revolution, thanks to the integration of HSI into precision agriculture frameworks, which will allow for a thorough spectrum analysis of photosynthetic activity and plant health. The use of hyperspectral sensors on satellites and unmanned aerial vehicles (UAVs) holds the potential to revolutionize agricultural management by enabling extensive, high-resolution evaluations. We suggest the following strategic paths to fully use HSI:

• To guarantee comparability and reproducibility across research, develop and implement consistent data collection and analysis processes. This will improve the hyperspectral data's dependability and make it easier to create solid models for a range of plant species and environmental circumstances.
• To handle the complexity of hyperspectral datasets, embrace artificial intelligence and machine learning methods. With the use of these instruments, detailed data on photosynthetic processes may be extracted, advancing our knowledge of plant physiology.
• Integrate phenomic and genomic data with hyperspectral imaging to find genetic features that influence the efficiency of photosynthesis. This multidisciplinary strategy might improve global food security and transform crop breeding methods.
• Using hyperspectral sensors mounted to agricultural equipment, create in-field real-time monitoring systems. Farmers will have instant access to information on crop photosynthesis as a result, which will help them make decisions about irrigation, fertilizer use, and insect control.
• Extend the use of HSI to whole agricultural landscapes rather than just specific crops. For sustainable land management and biodiversity protection, it is essential to comprehend the intricate relationships that exist between various crops and plants.
• To fully convey the dynamic character of photosynthesis, aim for a balance between high temporal and spatial resolution in hyperspectral imaging. Plant physiology must be monitored by regular temporal measurements combined with precise geographic data.
• Combine HSI with cutting-edge molecular methods to learn more about the molecular mechanisms of the Calvin cycle. This will provide important new information about the biochemical processes that support photosynthesis.
• Utilize HSI to detect plant illnesses and stress early in the disease monitoring and management process. Through the detection of spectral fingerprints that indicate physiological changes, HSI may be used as a proactive measure to reduce production losses and maximize resource use.
• To obtain a thorough grasp of photosynthetic processes under plant canopies, hyperspectral data should be integrated with three-dimensional structure information. LiDAR and stereoscopic imaging technologies can improve our understanding of light dispersion and interception.
• To guarantee consistency and effectiveness, especially in large-scale research, automate data collection processes. Furthermore, it endeavors to enhance the use of HSI technology for scholars and professionals to promote extensive implementation.

The future of HSI in agricultural photosynthesis research lies in its seamless integration with advanced computational models, remote sensing technologies, and real-time monitoring systems. As big data analytics and AI-driven spectral modeling continue to evolve, precision agriculture will benefit from automated hyperspectral workflows that deliver real-time, actionable insights on crop health, photosynthetic efficiency, and stress adaptation. Moreover, the development of cost-effective, miniaturized hyperspectral sensors for UAVs and ground-based platforms will democratize access to high-resolution spectral data, enabling farmers, agronomists, and researchers to apply HSI across diverse agricultural landscapes. Cross-disciplinary collaborations between plant physiologists, data scientists, and engineers will drive innovations in hyperspectral data processing, enhancing predictive modeling of carbon assimilation, nutrient fluxes, and drought resilience. As climate change intensifies agricultural challenges, HSI will play an increasingly vital role in monitoring ecosystem responses, optimizing resource allocation, and improving global food security. By advancing hyperspectral imaging frameworks that integrate molecular, genomic, and structural data, researchers will unlock new frontiers in plant phenotyping, stress diagnostics, and adaptive crop management strategies. Through these technological advancements and strategic research efforts, hyperspectral imaging is set to become an indispensable tool for sustainable and climate-resilient agriculture.

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