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**Review Article**

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# Hyperspectral Remote Sensing in Precision Agriculture: Comprehensive Review of Applications and Emerging Technologies

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## ABSTRACT
Hyperspectral remote sensing has emerged as a transformative technology for precision agriculture, enabling detailed characterisation of crop properties, stress conditions, and soil attributes across diverse agricultural landscapes. Unlike conventional multispectral sensors, hyperspectral imaging systems acquire data in hundreds of narrow contiguous spectral bands, facilitating detection of subtle biochemical and biophysical features associated with crop health, nutrient status, and disease. This review systematically synthesises the literature on hyperspectral remote sensing applications in precision agriculture published between 2018 and 2025. The methodology involved comprehensive database searches across Scopus, Web of Science, and Google Scholar, with inclusion criteria focusing on peer-reviewed articles addressing hyperspectral platforms, crop classification, biochemical parameter retrieval, stress detection, yield estimation, soil assessment, and machine learning approaches. Results indicate that satellite missions, including PRISMA, EnMAP, and EMIT, now provide operational spaceborne hyperspectral data for agricultural monitoring at regional scales, complemented by airborne and unmanned aerial vehicle platforms for field-scale applications. Deep learning architectures, including convolutional neural networks and transformer models, have substantially improved classification and retrieval accuracy, with reported accuracies of 90-97% for crop classification tasks. Pre-symptomatic disease detection achieves 85-93% accuracy with detection lead times of 5-10 days. Key challenges include atmospheric correction uncertainties, limited temporal revisit for current satellite missions, and integration with farm management systems. Future missions, including NASA's Surface Biology and Geology and ESA's CHIME will expand global hyperspectral data availability, while advances in artificial intelligence promise automated, scalable analysis workflows for operational precision agriculture.
**Keywords:** hyperspectral remote sensing, precision agriculture, crop monitoring, disease detection, machine learning

## INTRODUCTION
Precision agriculture represents a paradigm shift in agricultural management, moving from uniform field-scale practices toward site-specific management that accounts for spatial and temporal variability in crop conditions, soil properties, and environmental factors (Getahun and Kefale, 2024). This approach enables optimised application of agricultural inputs including fertilisers, pesticides, and irrigation water, thereby reducing environmental impacts while maintaining or improving productivity. Global food demand is projected to increase substantially by 2050, intensifying pressure on agricultural systems to improve efficiency and sustainability (FAO, 2023; Sishodia et al., 2020). Remote sensing technologies provide the observational foundation for precision agriculture by enabling non-destructive, spatially comprehensive assessment of crop and soil conditions across scales ranging from individual plants to entire agricultural regions (Zhang et al., 2024; Karmakar et al., 2024).

Among remote sensing technologies, hyperspectral imaging has emerged as particularly valuable for agricultural applications due to its capacity to detect subtle spectral features associated with crop biochemistry, physiological status, and stress conditions. While multispectral sensors acquire data in relatively few discrete spectral bands typically spanning tens to hundreds of nanometres in bandwidth, hyperspectral systems capture data in hundreds of narrow contiguous bands with typical bandwidths of five to ten nanometres, providing near-continuous spectral coverage across the visible, near-infrared, and shortwave infrared regions (Shuai et al., 2024). This enhanced spectral resolution enables detection of narrow absorption features associated with specific biochemical constituents including chlorophylls, carotenoids, anthocyanins, water, nitrogen compounds, and structural carbohydrates that cannot be resolved by multispectral sensors (Kaushik et al., 2025). Recent assessments confirm hyperspectral data consistently outperform multispectral alternatives for crop biochemical characterisation, particularly at high biomass densities (Tagliabue et al., 2022; Delloye et al., 2023).

The past decade has witnessed substantial expansion in hyperspectral data availability from multiple platforms. Satellite missions including the Italian Space Agency's PRISMA launched in 2019 and the German Aerospace Center's EnMAP operational since 2022 now provide routine spaceborne hyperspectral observations that were previously limited to expensive airborne campaigns (Cogliati et al., 2021; Storch et al., 2023). NASA's EMIT instrument, installed on the International Space Station in 2022, provides additional imaging spectroscopy capability with global coverage (Green et al., 2023). Concurrently, miniaturisation of hyperspectral sensors has enabled their deployment on unmanned aerial vehicles (UAVs), providing ultra-high-resolution observations at field scales with flexible acquisition timing suited to agricultural monitoring requirements (Matese et al., 2024). These technological advances, combined with rapid development of machine learning approaches for high-dimensional data analysis, have substantially expanded the practical applicability of hyperspectral remote sensing for precision agriculture (Adão et al., 2022; Bannari et al., 2024).

Despite these advances, no comprehensive review has synthesised recent developments across the full spectrum of agricultural hyperspectral applications while addressing both technical capabilities and operational implementation challenges. Previous reviews have focused on specific application domains such as disease detection (Rieker et al., 2023), machine learning methods (Shuai et al., 2024), or individual platforms (Matese et al., 2024), but an integrated perspective linking platforms, applications, and emerging technologies remains lacking.

This review provides a comprehensive synthesis of hyperspectral remote sensing applications in precision agriculture, with emphasis on practical implementation and operational considerations. The objectives are fourfold: first, to characterise current hyperspectral platforms and their suitability for agricultural applications; second, to synthesise applications across major agricultural monitoring domains including crop classification, biochemical parameter retrieval, stress detection, yield estimation, and soil assessment; third, to examine data processing approaches with emphasis on machine learning methods; and fourth, to identify challenges limiting operational adoption and future opportunities for advancing precision agriculture applications.

## MATERIALS AND METHODS

### Literature Search Strategy

This systematic review was conducted following established guidelines for agricultural remote sensing literature synthesis. A comprehensive literature search was performed across multiple electronic databases including Scopus, Web of Science, Google Scholar, and IEEE Xplore. The search was conducted between January and March 2025, covering publications from 2018 to 2025 to capture the most recent advances in operational hyperspectral systems while including foundational methodological works from earlier periods where relevant.

### Search Terms and Boolean Operators

The search strategy employed combinations of the following keywords connected with Boolean operators: ("hyperspectral" OR "imaging spectroscopy") AND ("agriculture" OR "crop" OR "precision agriculture" OR "farming") AND ("remote sensing" OR "satellite" OR "UAV" OR "drone" OR "airborne"). Additional targeted searches were conducted for specific application domains using terms including "disease detection," "yield estimation," "soil mapping," "crop classification," "nitrogen," "chlorophyll," "water stress," and "machine learning."

### Inclusion and Exclusion Criteria

Articles were included if they: (1) addressed hyperspectral remote sensing applications in agricultural contexts; (2) were published in peer-reviewed journals or conference proceedings; (3) were written in English; and (4) provided empirical results, methodological advances, or comprehensive reviews. Articles were excluded if they: (1) focused exclusively on laboratory spectroscopy without remote sensing components; (2) addressed non-agricultural applications; or (3) were abstracts, editorials, or non-peer-reviewed sources.

### Article Selection and Data Extraction

Initial searches yielded approximately 2,500 articles. Following removal of duplicates and screening of titles and abstracts, 450 articles were assessed for full-text eligibility. Final selection included 95 articles that met all inclusion criteria and provided substantive contributions to the review objectives. Data extraction focused on: platform specifications and performance characteristics; application domains and target parameters; methodological approaches including preprocessing, feature extraction, and machine learning algorithms; reported accuracy metrics; and identified limitations and future directions.

### Synthesis Approach

The extracted information was synthesised thematically according to the major application domains identified in precision agriculture: hyperspectral platforms and sensors, crop type mapping and classification, biochemical and biophysical parameter retrieval, stress and disease detection, yield estimation and prediction, soil property assessment, and data processing and machine learning approaches. Quantitative performance metrics were tabulated where available to enable cross-study comparison of methodological approaches.

## RESULTS AND DISCUSSION

### Hyperspectral Platforms and Sensors for Agriculture

The selection of appropriate hyperspectral platforms depends on application requirements including spatial coverage, spatial resolution, temporal frequency, and operational constraints. Current platforms span satellite, airborne, and unmanned aerial vehicle categories, each offering distinct capabilities suited to different agricultural monitoring scenarios.

#### *Satellite Platforms*

Satellite-based hyperspectral systems provide regional to global coverage essential for large-area agricultural monitoring and crop inventory applications. The period since 2018 has witnessed unprecedented growth in operational spaceborne hyperspectral capability. Table 1 summarises currently operational satellite hyperspectral missions relevant to agriculture. PRISMA (PRecursore IperSpettrale della Missione Applicativa) represents a significant advancement in operational satellite hyperspectral capability, providing 30-metre resolution imagery with 239 spectral bands covering the 400-2500 nm range (Cogliati et al., 2021). EnMAP (Environmental Mapping and Analysis Program) offers similar spectral coverage with improved signal-to-noise ratios and is specifically designed for environmental and agricultural monitoring (Storch et al., 2023; Angelopoulou et al., 2023). Comparative analyses demonstrate that PRISMA and EnMAP data achieve equivalent classification accuracies for major crop types when processed with appropriate machine learning pipelines (Transon et al., 2023; Morcillo-Pallarés et al., 2022). The EO-1 Hyperion sensor, operational from 2000 to 2017, provided the first spaceborne hyperspectral data widely used for agricultural research (Middleton et al., 2013).

**Table 1.** Operational satellite hyperspectral missions for agricultural applications

| Mission | Agency | Launch | Spectral Range (nm) | Bands | Spatial Res (m) | Swath (km) | Revisit (d) |
|---|---|---|---|---|---|---|---|
| Hyperion | NASA | 2000 | 400–2500 | 220 | 30 | 7.5 | 16 |
| CHRIS/PROBA | ESA | 2001 | 400–1050 | 19–63 | 17–34 | 13 | Var. |
| DESIS | DLR | 2018 | 400–1000 | 235 | 30 | 30 | 3–5 |
| PRISMA | ASI | 2019 | 400–2500 | 239 | 30 | 30 | 29 |
| EnMAP | DLR | 2022 | 420–2450 | 228 | 30 | 30 | 27 |
| EMIT | NASA | 2022 | 380–2500 | 285 | 60 | 75 | Var. |

#### Airborne Platforms

Airborne hyperspectral sensors mounted on piloted aircraft provide flexibility in acquisition timing, higher spatial resolution than satellites, and established operational workflows for agricultural surveys. AVIRIS-NG provides improved performance with 5-metre resolution and 425 bands covering 380-2510 nm (Matese et al., 2024). Commercial airborne sensors including HySpex (Norsk Elektro Optikk), CASI (Itres), and AisaFENIX (Specim) support operational agricultural surveys with spatial resolutions from 0.5 to 5 metres depending on flight altitude (Malenovský et al., 2023). Fusion of airborne hyperspectral data with LiDAR point clouds has demonstrated enhanced performance for crop structural parameter retrieval (Dalponte et al., 2022).

#### *Unmanned Aerial Vehicle Platforms*

UAV-based hyperspectral systems have experienced rapid development, enabling ultra-high-resolution imaging at centimetre-scale spatial resolution with flexible deployment for field-scale precision agriculture applications. Table 2 summarises common UAV hyperspectral sensors employed in agricultural research. UAV platforms offer distinct advantages including sub-metre spatial resolution enabling individual plant monitoring, flexible timing to capture optimal phenological stages, and relatively low operational costs compared to piloted aircraft (Matese et al., 2024). Limitations include restricted spatial coverage per flight, sensitivity to atmospheric conditions, battery endurance constraints, and regulatory requirements that may limit operational flexibility. Recent meta-analyses confirm UAV hyperspectral systems achieve significantly higher accuracy than satellite alternatives for within-field crop monitoring (Zheng et al., 2023; Pádua et al., 2022).

**Table 2.** UAV-based hyperspectral sensors for precision agriculture

| Sensor | Manufacturer | Spectral (nm) | Range | Bands | Weight (kg) | Key Applications |
|---|---|---|---|---|---|---|
| Headwall Nano-Hyperspec | Headwall | 400–1000 | | 270 | 0.5 | Disease, stress mapping |
| Specim AFX10 | Specim | 400–1000 | | 224 | 1.4 | Crop monitoring, phenotyping |
| Cubert UHD 185 | Cubert | 450–950 | | 125 | 0.5 | Real-time crop assessment |
| Resonon Pika L | Resonon | 400–1000 | | 281 | 0.6 | Agricultural research |
| AISA KESTREL | Specim | 400–1000 | | 350 | 2.5 | High-performance imaging |

***Platform Selection Considerations***

Platform selection for agricultural applications involves trade-offs among spatial coverage, spatial resolution, temporal flexibility, and cost. Table 3 provides guidance for matching platforms to common agricultural monitoring scenarios. Satellite missions are recommended for regional crop inventories and large-area monitoring, while UAVs are preferred for within-field variability mapping and phenotyping research (Sishodia et al., 2020). Multi-platform fusion strategies that combine satellite revisit frequency with UAV spatial detail are increasingly adopted for operational precision agriculture (Bannari et al., 2024).

**Table 3.** Platform selection guide for agricultural hyperspectral applications

| Application | Spatial Scale | Recommended Platform | Rationale |
|---|---|---|---|
| Regional crop inventory | >10,000 ha | Satellite (PRISMA, EnMAP) | Coverage, repeatability |
| Farm-scale monitoring | 100–10,000 ha | Airborne or satellite | Balance resolution/coverage |
| Field-scale management | 10–100 ha | UAV or airborne | High res, flexible timing |
| Within-field variability | <10 ha | UAV | Centimetre resolution |
| Phenotyping/research | <1 ha | UAV | Ultra-high resolution |

Sensor calibration and radiometric stability are paramount considerations for quantitative remote sensing applications in agriculture. Pre-flight radiometric characterisation, in-flight calibration using reference targets, and post-processing using empirical line calibration methods are standard practices for maintaining data quality across acquisition campaigns (Viaña-Borja et al., 2022). For satellite systems, vicarious calibration using pseudo-invariant calibration sites and inter-calibration against well-characterised reference sensors ensures long-term radiometric consistency essential for multi-temporal vegetation monitoring. The integration of global spectral validation networks, such as AERONET and ACTRIS, provides independent atmospheric characterisation supporting improved atmospheric correction accuracy over agricultural regions (Storch et al., 2023; Cogliati et al., 2021). Understanding and correcting for the adjacency effect where photons scattered from surrounding land cover contaminate pixel radiance measurements is particularly important in heterogeneous agricultural landscapes with small field sizes (Chabrillat et al., 2022).

## Crop Type Mapping and Classification

Accurate discrimination among crop types and cultivars represents a foundational application of hyperspectral remote sensing, supporting agricultural statistics, subsidy administration, crop insurance, and supply chain management. The enhanced spectral resolution of hyperspectral sensors enables differentiation among crops with similar phenological patterns that may be confused in multispectral imagery.

***Spectral Basis for Crop Discrimination***

Different crop species exhibit characteristic spectral signatures determined by canopy architecture, leaf optical properties, pigment composition, and phenological stage. The narrow bands of hyperspectral sensors resolve subtle differences in chlorophyll absorption depths, red-edge position, near-infrared reflectance magnitude, and shortwave infrared water absorption features that enable species-level discrimination (Aneece and Thenkabail, 2022). Hyperspectral data enable discrimination of crops that appear spectrally similar in multispectral imagery, including differentiation among wheat varieties, maize hybrids, and rice cultivars using spectral signatures (Kaushik et al., 2025). Analysis of PRISMA and DESIS satellite data confirms hyperspectral capability for national-scale crop type mapping at 30-metre resolution (Transon et al., 2023). Multi-temporal hyperspectral time series capture phenological trajectories that further improve classification accuracy for spectrally similar crops (Morcillo-Pallarés et al., 2022).

***Classification Approaches and Performance***

Recent advances in machine learning have substantially improved crop classification accuracy from hyperspectral data. Table 4 summarises classification performance across different methods. Support vector machines have been widely applied for hyperspectral crop classification, achieving high accuracy by finding optimal separating hyperplanes in high-dimensional feature space (Aneece and Thenkabail, 2022). Random forests provide robust classification while identifying the most discriminative spectral bands (Aneece and Thenkabail, 2022). Deep learning approaches, particularly convolutional neural networks and transformer architectures adapted for hyperspectral data, have demonstrated superior performance by learning hierarchical spectral-spatial features (Shuai et al., 2024). Three-dimensional CNNs and CNN-Transformer hybrid networks that jointly exploit spectral and spatial information consistently outperform traditional machine learning methods (Yang et al., 2025). Graph neural networks and attention mechanisms further improve performance by modelling spatial dependencies among crop parcels (Hong et al., 2022; Zheng et al., 2023).

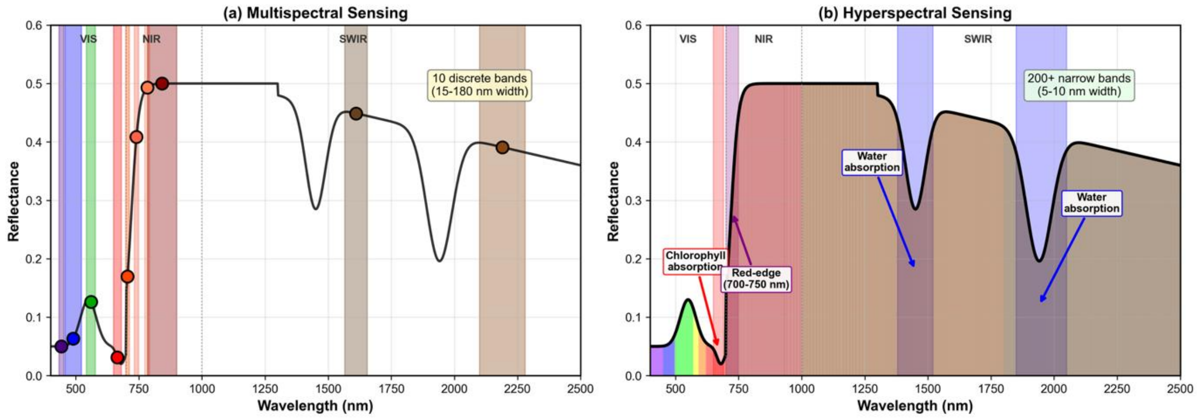


**Fig. 1** illustrates the comparison of multispectral and hyperspectral sensing approaches for vegetation monitoring. Multispectral sensing acquires data in 10 discrete broad bands (15-180 nm width), sampling the vegetation spectrum at selected wavelengths. Hyperspectral sensing provides continuous narrow-band coverage (5-10 nm width) across visible, near-infrared, and shortwave infrared regions, enabling detection of subtle absorption features including chlorophyll absorption near 680 nm, the red-edge transition (700-750 nm), and water absorption bands near 1450 nm and 1940 nm.

**Table 4.** Comparison of classification methods for hyperspectral crop mapping

| Method | Typical Accuracy (%) | Strengths | Limitations |
|---|---|---|---|
| Maximum Likelihood | 75–85 | Simple, interpretable | Assumes normal distribution |
| Support Vector Machine | 85–92 | Effective for high dimensions | Parameter sensitivity |
| Random Forest | 83–90 | Robust, feature importance | May overfit |
| 1D/3D-CNN | 88–95 | Joint spectral-spatial features | Requires large training data |
| Transformer/Hybrid | 90–97 | Long-range spectral context | Computationally intensive |

### Operational Considerations

Operational crop mapping using satellite hyperspectral data faces challenges, including limited temporal revisit constraining multi-temporal approaches, cloud contamination reducing usable acquisitions, and processing complexity for large-area applications. Fusion approaches combining hyperspectral observations with multispectral time series offer potential for leveraging complementary data strengths (Camps-Valls et al., 2021). Transfer learning strategies reduce dependence on site-specific training data by adapting models across geographic regions and sensor types (Bannari et al., 2024). National crop inventories utilising PRISMA and EnMAP data have demonstrated wall-to-wall mapping capabilities at a continental scale, with overall accuracies exceeding 88% when combined with field survey data for calibration (Transon et al., 2023; Pascual-Venteo et al., 2022). The development of open-access processing chains and standardised product formats through initiatives such as the EnMAP Box software environment has substantially lowered barriers to operational hyperspectral crop mapping (Pignatti et al., 2022).

### Crop Biochemical and Biophysical Parameter Retrieval

Quantitative retrieval of crop biochemical and biophysical parameters represents a primary strength of hyperspectral remote sensing, exploiting the relationship between narrow-band spectral features and specific plant constituents. These parameters provide direct indicators of crop nutritional status, photosynthetic capacity, and growth conditions.

#### ***Biochemical Parameters***

Hyperspectral sensors enable retrieval of biochemical constituents through detection of characteristic absorption features. Table 5 summarises key biochemical parameters retrievable from hyperspectral data. Chlorophyll content estimation has received extensive attention due to its relationship with nitrogen status and photosynthetic capacity. The red-edge region (700-750 nm) provides optimal sensitivity to chlorophyll variations, with narrow-band indices such as the MERIS Terrestrial Chlorophyll Index outperforming broadband alternatives (Gallo et al., 2023; Zhang et al., 2024). Leaf nitrogen content retrieval has direct implications for fertiliser management, with studies demonstrating operational nitrogen mapping using hyperspectral data (Liu et al., 2021; Berger et al., 2020). Carotenoid and anthocyanin retrieval supports assessment of photosynthetic efficiency and stress tolerance, with recent studies demonstrating improved accuracy using physically-based approaches (Delloye et al., 2023; Féret et al., 2021).

**Table 5.** Biochemical parameters retrievable from hyperspectral remote sensing

| Parameter | Spectral Basis | Key Wavelengths (nm) | Typical $R^2$ |
|---|---|---|---|
| Chlorophyll a+b | Red absorption, red-edge | 550, 670, 705, 750 | 0.80–0.92 |
| Carotenoids | Blue absorption | 450, 470, 510 | 0.70–0.85 |
| Anthocyanins | Green absorption | 550, 700 | 0.65–0.82 |
| Leaf nitrogen | Protein absorption | 1510, 1730, 2180 | 0.75–0.90 |
| Leaf water content | Water absorption | 970, 1200, 1450, 1940 | 0.82–0.94 |
| Cellulose/lignin | Structural absorption | 2100, 2270, 2330 | 0.70–0.85 |

The optical properties of leaves fundamentally determine how foliar biochemistry is expressed in remotely sensed reflectance spectra. Radiative transfer models, including PROSPECT-PRO, explicitly account for the contributions of chlorophyll a and b, carotenoids, anthocyanins, water, dry matter, and protein to leaf optical properties (Ustin and Jacquemoud, 2020; Féret et al., 2021). These models provide a physical framework linking leaf constituents to measurable spectral features, enabling inversion procedures that retrieve constituent concentrations from hyperspectral measurements. The integration of PROSPECT with canopy radiative transfer models such as SAIL, forming the widely used PROSAIL coupled model, extends this capability to canopy-scale reflectance measurements (Jacquemoud et al., 2009). Hybrid methods employing PROSAIL simulations to train machine learning emulators have demonstrated particularly robust generalisation across diverse crops and growth stages, reducing the need for extensive field calibration datasets (Verrelst et al., 2024; Berger et al., 2020).

***Biophysical Parameters***

Biophysical parameters characterising canopy structure complement biochemical retrievals for comprehensive crop monitoring. Leaf area index (LAI) retrieval benefits substantially from hyperspectral data compared to multispectral alternatives, particularly at high LAI values where multispectral indices saturate. Radiative transfer model inversion using PROSAIL and its variants provides physically-based parameter retrieval (Verrelst et al., 2024; Berger et al., 2020). Gaussian process regression and neural network emulators have substantially accelerated radiative transfer model inversion while maintaining physical interpretability (Rivera-Caicedo et al., 2023). Canopy water content estimation using shortwave infrared bands provides early warning of drought stress before visible wilting occurs (Tagliabue et al., 2022).

***Retrieval Methods***

Parameter retrieval methods have evolved substantially with advances in machine learning. Empirical approaches establish statistical relationships between spectral indices and measured parameters. Physical model inversion uses radiative transfer models to simulate canopy reflectance, then inverts these relationships to retrieve parameters. Hybrid methods combining radiative transfer simulations with machine learning achieve optimal performance by providing physical interpretability with computational efficiency (Verrelst et al., 2024; Berger et al., 2020). Systematic benchmarking of retrieval methods confirms hybrid approaches outperform purely empirical or physical methods across diverse crop types and growth stages (Rivera-Caicedo et al., 2023).

**Crop Stress and Disease Detection**

Early detection of crop stress and disease represents a high-value application of hyperspectral remote sensing, enabling timely intervention to prevent yield losses. Hyperspectral sensors detect subtle physiological changes associated with stress conditions before visible symptoms appear.

***Water Stress Detection***

Water stress induces physiological changes affecting spectral reflectance at multiple wavelengths. Initial stomatal closure reduces transpiration, while prolonged stress causes chlorophyll degradation, reduced leaf water content, and altered cell structure. These changes produce detectable spectral signatures, including reduced chlorophyll absorption, blue-shifted red-edge position, and decreased water absorption depth (Matese et al., 2024). The Photochemical Reflectance Index (PRI), calculated from narrow bands near 531 and 570 nm, provides a sensitive indicator of photosynthetic light-use efficiency and early water stress (Gamon et al., 1992; Zarco-Tejada et al., 2013). Studies demonstrate pre-visual detection of water stress several days before visible wilting symptoms appear. Recent UAV-based assessments confirm PRI and derivative indices detect irrigation deficit effects within 48-72 hours under field conditions (Suárez et al., 2022).

Canopy temperature obtained from thermal infrared sensors provides a complementary indicator of water stress through evapotranspiration effects; however, hyperspectral biochemical indicators can detect stress responses at earlier stages than thermal signatures because biochemical changes precede evaporative responses. The combination of PRI-derived light use efficiency metrics with hyperspectral water content indices provides a multi-indicator framework for comprehensive water status assessment (Suárez et al., 2022; Zarco-Tejada et al., 2013). Operational early warning systems for drought stress management integrating hyperspectral UAV surveys with automated irrigation scheduling have been demonstrated in Mediterranean vineyards and citrus orchards, reducing irrigation water use by 15-25% without significant yield penalty (Matese et al., 2024).

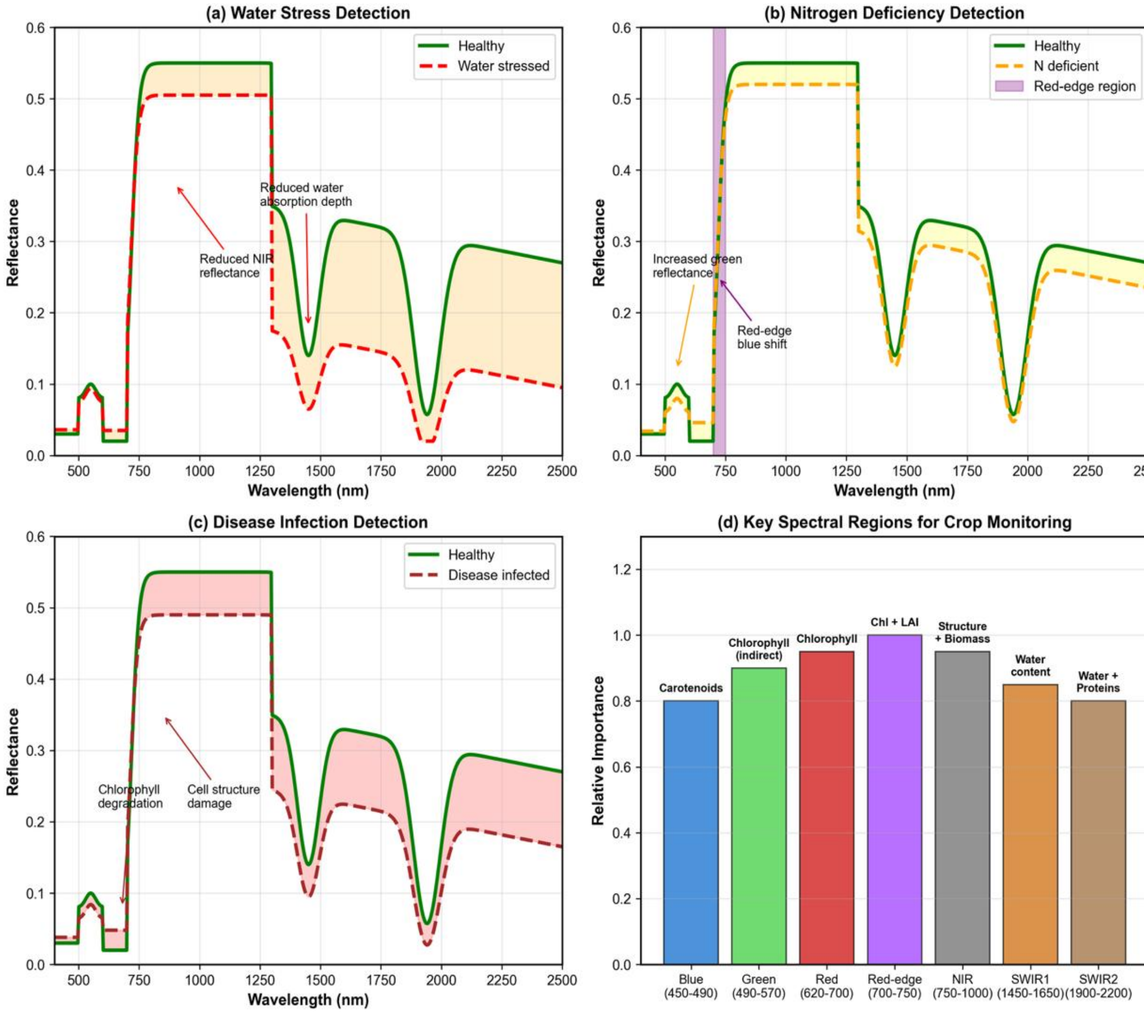


**Fig. 2** presents spectral signatures of healthy and stressed crops showing diagnostic features detectable by hyperspectral sensors. Water stress causes reduced NIR reflectance and decreased water absorption depth. Nitrogen deficiency produces blue-shifted red-edge and increased green reflectance. Disease infection causes chlorophyll degradation and cell structure damage.

***Nutrient Deficiency Detection***

Nutrient deficiencies produce characteristic spectral changes related to their physiological effects. Nitrogen deficiency reduces chlorophyll synthesis, causing decreased absorption in the red region and blue-shifted red-edge position. Hyperspectral remote sensing enables not only detection of nutrient stress but also discrimination among different deficiency types (Liu et al., 2021). Iron, magnesium, and potassium deficiencies each produce distinct spectral signatures enabling targeted remediation through precision variable-rate fertiliser application (Féret et al., 2021). Recent studies using UAV hyperspectral imagery demonstrate within-field nitrogen variability mapping with root mean square errors below 5 kg N $ha^{-1}$ (Liu et al., 2021; Delloye et al., 2023).

***Disease and Pest Detection***

Early detection of crop diseases represents perhaps the highest-value application of hyperspectral remote sensing. Disease infection triggers host plant responses, including changes in pigment content, cell structure, and water relations that produce detectable spectral changes before visible lesion development. Table 6 summarises disease detection capabilities. Hyperspectral sensors can detect Fusarium head blight and other wheat diseases before visible symptoms appear, achieving 94% classification accuracy using Random Forest (Rieker et al., 2023). The spectral signatures of disease relate to changes in pigment composition, cell structure damage, and altered water relations induced by pathogen infection. Machine learning approaches, particularly random forests and deep convolutional neural networks, have proven highly effective for automated disease classification from hyperspectral imagery (Shuai et al., 2024). Attention-based deep learning architectures further improve detection sensitivity, enabling identification of multiple concurrent stress factors from single hyperspectral acquisitions (Hong et al., 2022).

**Table 6.** Pre-symptomatic disease detection using hyperspectral remote sensing

| Disease | Crop | Detection Lead Time | Typical Accuracy | Key Reference |
|---|---|---|---|---|
| Yellow rust | Wheat | 5–10 days | 85–92% | Rieker et al. (2023) |
| Fusarium head blight | Wheat | 3–7 days | 82–89% | Rieker et al. (2023) |
| Late blight | Potato | 2–5 days | 88–93% | Gold et al. (2020) |
| Powdery mildew | Grapevine | 3–6 days | 85–91% | Rieker et al. (2023) |
| Citrus greening | Citrus | 7–14 days | 80–87% | Shuai et al. (2024) |

The practical deployment of hyperspectral disease monitoring requires integration with agronomic decision support systems that translate spectral detections into actionable management recommendations. Geostatistical mapping of disease probability surfaces from hyperspectral UAV surveys provides input for variable-rate fungicide application systems, with potential to reduce fungicide use by 30-50% while maintaining equivalent disease control compared to uniform blanket applications (Rieker et al., 2023; Shuai et al., 2024). Temporal monitoring combining multiple hyperspectral acquisitions tracks disease progression dynamics and validates the efficacy of interventions, supporting adaptive management strategies. Cross-disease spectral signatures and generalised detection models that perform effectively across multiple pathogen types without disease-specific recalibration represent an important research frontier (Hong et al., 2022).

***Yield Estimation and Prediction***

Accurate yield estimation and prediction before harvest supports farm management decisions, market planning, crop insurance assessment, and food security monitoring. Hyperspectral remote sensing provides indicators of crop productivity potential through quantification of biochemical and biophysical parameters directly related to photosynthetic capacity.

**Approaches to Yield Estimation**

Three main approaches link hyperspectral observations with crop yield estimation. Empirical approaches establish statistical relationships between spectral indices and final yield, offering conceptual simplicity but requiring site-specific calibration (Karmakar et al., 2024). Process-based approaches integrate remotely sensed data into crop growth models such as DSSAT, APSIM, or WOFOST, with hyperspectral retrievals of leaf area index, chlorophyll content, and plant water status serving as important constraints (Karmakar et al., 2024). Machine learning approaches capture complex nonlinear relationships between hyperspectral features and yield, with methods such as random forests and neural networks demonstrating strong predictive performance (Karmakar et al., 2024). Deep learning models trained on multi-year hyperspectral time series have demonstrated robust cross-year transfer with $R^2$ values exceeding 0.85 for wheat and maize (Zheng et al., 2023; Camps-Valls et al., 2021).

The integration of hyperspectral retrievals with process-based crop models represents a particularly promising avenue for robust yield forecasting. Assimilating hyperspectral-derived leaf area index, chlorophyll content, and absorbed photosynthetically active radiation into models such as DSSAT and WOFOST constrains model uncertainty and corrects for parameterisation errors that otherwise accumulate through the growing season (Karmakar et al., 2024). Ensemble Kalman filter and particle filter approaches for data assimilation have demonstrated particular effectiveness for dynamic state variable updating (Camps-Valls et al., 2021). The complementarity of hyperspectral observations at multiple scales—satellite data for regional trends, airborne surveys for farm-scale patterns, and UAV imagery for within-field spatial variability—provides a hierarchical monitoring framework suited to precision yield management (Zheng et al., 2023; Sishodia et al., 2020).

**Performance Comparison**

Studies consistently demonstrate hyperspectral advantages of 8-15% improvement in $R^2$ values over multispectral approaches for yield prediction, particularly during early to mid-season (Karmakar et al., 2024). Combining hyperspectral features with meteorological data and soil information in multi-modal deep learning frameworks further improves prediction accuracy by capturing environmental context (Sishodia et al., 2020; Zheng et al., 2023).

***Soil Property Assessment***

Soil properties fundamentally determine agricultural productivity and respond to management practices over time. Hyperspectral remote sensing enables rapid, non-destructive assessment of soil properties across agricultural fields.

***Spectral Basis of Soil Property Retrieval***

Soil reflectance is determined by mineral composition, organic matter content, iron oxide content, moisture status, and particle size distribution. Table 7 summarises key soil properties and their spectral indicators. Soil organic carbon retrieval has received substantial attention due to its importance for soil health, fertility, and climate change mitigation. Hyperspectral sensors detect the broad absorption features of organic matter across visible and shortwave infrared wavelengths (Wang et al., 2022; Li et al., 2024). Large-scale soil spectral libraries combined with machine learning enable operational SOC mapping from airborne and spaceborne hyperspectral data with $R^2$ values of 0.75-0.88 (Castaldi et al., 2022). Clay mineral identification using shortwave infrared hydroxyl absorption features enables soil texture mapping with high spatial detail (Chabrillat et al., 2022).

**Table 7.** Soil properties retrievable from hyperspectral remote sensing

| Property | Spectral Basis | Key Wavelengths (nm) | Typical $R^2$ |
|---|---|---|---|
| Organic carbon | Broad absorption | 450–700, 1700–2200 | 0.75–0.88 |
| Clay content | OH absorption | 1400, 1900, 2200 | 0.72–0.86 |
| Iron oxides | Electronic transitions | 480, 550, 670, 870 | 0.78–0.90 |
| Moisture content | Water absorption | 1450, 1940, 2200 | 0.82–0.92 |
| $CaCO_3$ | Carbonate absorption | 2340 | 0.75–0.88 |

The development of hyperspectral soil spectral libraries containing thousands of georeferenced samples has enabled machine learning approaches that generalise across pedological and climatic gradients. Transfer learning from large continental libraries to site-specific calibration datasets substantially reduces ground sampling requirements for operational soil mapping programmes (Castaldi et al., 2022; Chabrillat et al., 2022). Recent applications of deep learning, including 1D convolutional neural networks and long short-term memory networks trained on spectral time series, have further improved SOC prediction accuracy compared to traditional partial least squares regression, particularly across diverse soil types (Li et al., 2024; Wang et al., 2022). The availability of operational spaceborne hyperspectral data from PRISMA and EnMAP has enabled national-scale soil organic carbon mapping at unprecedented spatial resolution, opening new possibilities for soil carbon accounting in climate mitigation strategies (Castaldi et al., 2022).

**Challenges and Solutions**

A fundamental constraint for optical soil property retrieval is the requirement for bare soil exposure. Strategies include temporal compositing to identify bare soil windows, spectral unmixing to estimate soil contribution in partially vegetated areas, and multi-sensor fusion combining hyperspectral observations with other data sources (Angelopoulou et al., 2023; Casa et al., 2024). The adoption of Soil Composite Mapping Processors that aggregate multi-date observations into optimal bare soil composites has substantially extended the spatial coverage of operational soil mapping (Castaldi et al., 2022). Integration of hyperspectral data with soil spectral libraries and digital elevation models further improves prediction accuracy across diverse pedological contexts (Chabrillat et al., 2022).

***Data Processing and Machine Learning Approaches***

The high dimensionality of hyperspectral data necessitates specialised processing workflows to extract meaningful agricultural information.

***Preprocessing Requirements***

Hyperspectral data require systematic preprocessing before agricultural analysis. Atmospheric correction converts at-sensor radiance to surface reflectance using radiative transfer codes such as MODTRAN, ATCOR, or FLAASH (Storch et al., 2023). Noise reduction through filtering or dimensionality reduction addresses the relatively low signal-to-noise ratio of individual narrow bands (Shuai et al., 2024). Cross-sensor radiometric harmonisation remains critical for multi-temporal and multi-sensor analyses, with recent studies developing calibration workflows for PRISMA and EnMAP data (Cogliati et al., 2021; Storch et al., 2023).

**Machine Learning Frameworks**

Table 8 summarises current machine learning approaches for hyperspectral agricultural applications. Deep learning approaches have transformed hyperspectral analysis. Convolutional neural networks adapted for hyperspectral data achieve superior performance by learning hierarchical features (Shuai et al., 2024). Transformer architectures and Mamba-based models show strong promise for temporal analysis of hyperspectral time series, capturing long-range spectral dependencies with improved efficiency (Yang et al., 2025). Graph neural networks leverage spatial relationships among crop parcels, while attention mechanisms enable explicit modelling of spectral band importance (Hong et al., 2022). Foundation models and self-supervised pre-training on large hyperspectral datasets are emerging as a paradigm for reducing dependence on labelled training data (Camps-Valls et al., 2021; Bannari et al., 2024).

**Table 8.** Machine learning approaches for hyperspectral precision agriculture

| Approach | Strengths | Best Applications | Training Needs |
|---|---|---|---|
| Random Forest | Robust, interpretable | Classification, feature selection | Moderate |
| SVM | Effective for small samples | Classification, regression | Low–Moderate |
| Partial Least Squares | Handles collinearity | Parameter retrieval | Moderate |
| 1D-CNN | Learns spectral features | Classification, retrieval | High |
| 3D-CNN/Transformer | Spectral-spatial learning | Image classification | Very high |
| Graph Neural Network | Spatial context modelling | Crop mapping, segmentation | High |

The rapid evolution of deep learning architectures has fundamentally changed the hyperspectral analysis landscape. Spectral transformers such as SpectralFormer employ self-attention mechanisms to learn cross-spectral band dependencies that conventional CNNs may overlook (Hong et al., 2022). Mamba-based architectures offer linear computational complexity with respect to sequence length, addressing the quadratic scaling limitation of standard transformers and making temporal analysis of long hyperspectral time series computationally tractable (Yang et al., 2025). Self-supervised pre-training on large unlabelled hyperspectral archives reduces dependence on expensive labelled training data, with contrastive learning approaches demonstrating strong downstream performance for crop classification and parameter retrieval tasks (Gallo et al., 2023). Super-resolution and data fusion methods that combine hyperspectral with multispectral imagery further expand the utility of existing datasets (Zhang et al., 2022; Yokoya et al., 2022).

**Dimensionality Reduction and Feature Selection**

The high dimensionality of hyperspectral data creates both an analytical opportunity and a computational challenge. Hundreds of correlated spectral bands contain redundant information that can degrade machine learning model performance through the 'curse of dimensionality', necessitating dimensionality reduction prior to analysis. Principal component analysis and its variants remain widely applied for unsupervised dimensionality reduction, compressing hundreds of bands into a small number of uncorrelated components that retain most spectral variance (Paoletti et al., 2022). Supervised feature selection approaches, including band importance rankings from random forests and recursive feature elimination, identified the most agriculturally informative spectral bands, enabling efficient models with reduced computational requirements (Aneece and Thenkabail, 2022). Autoencoder architectures provide non-linear dimensionality reduction that preserves complex spectral manifold structure, with spectral encodings demonstrating superior downstream classification and retrieval performance compared to linear methods (Hong et al., 2022; Shuai et al., 2024). Continuum removal and derivative spectroscopy are standard pre-processing steps that enhance absorption features by normalising baseline reflectance variability, improving the sensitivity of spectral indices to target biochemical constituents (Ustin and Jacquemoud, 2020).

**Technical and Operational Challenges**

Despite substantial advances, several challenges limit broader operational adoption of hyperspectral remote sensing in precision agriculture. Atmospheric correction remains a significant source of uncertainty, with residual errors particularly affecting water vapour absorption bands and aerosol correction in complex environments (Storch et al., 2023). The limited temporal coverage of current satellite hyperspectral missions constrains effective phenological monitoring, as revisit periods of 27-29 days for PRISMA and EnMAP are substantially longer than the 5-day revisit of Sentinel-2 (Transon et al., 2023). Furthermore, the large data volumes and high processing complexity associated with hyperspectral imagery pose practical barriers, necessitating specialised software and advanced computational resources (Shuai et al., 2024; Adão et al., 2022).

Operational barriers continue to limit the adoption of hyperspectral technologies. Limited availability of validation data reduces confidence in retrieved products, as ground truth collection is costly and existing validation networks are geographically biased (Karmakar et al., 2024). Uncertainty surrounding cost-benefit trade-offs further constrains adoption, particularly for UAV-based systems requiring substantial capital investment. Moreover, integration with farm management platforms remains immature, with a lack of standardised protocols for hyperspectral data interoperability (Getahun and Kefale, 2024). Addressing these barriers requires coordinated efforts from sensor manufacturers, data service providers, and agricultural extension services (Bannari et al., 2024).

Radiometric calibration consistency across sensors and acquisition dates represents a persistent challenge for multi-temporal and multi-sensor hyperspectral applications. Cross-calibration workflows developed for PRISMA and EnMAP data streams provide radiometric harmonisation at sub-per cent accuracy, a prerequisite for detecting subtle agricultural changes across seasons and years (Viaña-Borja et al., 2022; Storch et al., 2023). Sun-sensor-target geometry effects, including bidirectional reflectance distribution function (BRDF) anisotropy, introduce systematic errors in multi-angular acquisitions that must be corrected for accurate parameter retrieval, particularly in row crops with pronounced canopy structure (Morcillo-Pallarés et al., 2022). Advances in physics-aware machine learning approaches that embed radiometric correction directly into neural network architectures offer a promising pathway toward end-to-end calibration-to-application workflows (Camps-Valls et al., 2021; Paoletti et al., 2022).

Interoperability between hyperspectral data products and commercial farm management software platforms represents a largely unresolved challenge that limits the uptake of precision hyperspectral services among farming enterprises. The diversity of sensor configurations, spectral resolutions, and reflectance calibration approaches across platforms results in heterogeneous data products that are difficult to integrate within unified analytical workflows. International standardisation efforts coordinated through organisations such as the Committee on Earth Observation Satellites (CEOS) and OGC are developing common data formats and application programming interfaces that will facilitate seamless integration of hyperspectral products within broader precision agriculture data ecosystems (Malenovský et al., 2023; Adão et al., 2022). Farmer-facing visualisation tools that communicate hyperspectral-derived insights in agronomically interpretable formats such as variable-rate prescription maps and field-specific treatment recommendations will be essential for bridging the gap between technical data products and practical farm management decisions (Getahun and Kefale, 2024; Bannari et al., 2024).

## FUTURE PERSPECTIVES

Several developments will shape the future of hyperspectral remote sensing in precision agriculture. NASA's Surface Biology and Geology (SBG) mission, planned for late 2020s launch, will provide global hyperspectral coverage with improved revisit capability. ESA's CHIME (Copernicus Hyperspectral Imaging Mission) will focus on European agricultural monitoring with enhanced spectral and spatial resolution (Rast et al., 2019; Malenovský et al., 2023). Continued sensor miniaturisation is reducing the cost and weight of hyperspectral systems, enabling integration on smaller platforms, while snapshot hyperspectral cameras that eliminate motion artefacts are approaching research-grade spectral performance (Pádua et al., 2022). Advances in artificial intelligence are increasingly automating hyperspectral analysis workflows, with transfer learning and foundation models enabling robust performance even under limited training data conditions (Camps-Valls et al., 2021; Hong et al., 2022). Deeper integration with digital agriculture frameworks, including IoT sensor networks and farm management platforms, is expected to embed hyperspectral capabilities within comprehensive decision support systems (Sishodia et al., 2020; Zheng et al., 2023).

Spectranomics—the integration of spectral diversity metrics from imaging spectroscopy with biodiversity and ecosystem function assessment represents an emerging frontier with direct relevance to agricultural agroecosystem monitoring (Asner and Martin, 2023). By characterising the functional diversity of crop communities, spectranomics approaches provide new indicators of ecosystem resilience and productivity potential. The ongoing development of hyperspectral benchmark datasets, including openly accessible repositories of co-registered field measurements and hyperspectral imagery, will accelerate model development and cross-site comparisons (Thenkabail and Lyon, 2021). Standardisation of validation protocols, including consistent definitions of accuracy metrics and sampling designs, is essential for meaningful cross-study comparisons and operational product quality assessment, and will be critical for demonstrating the commercial value of precision hyperspectral services to end users (Transon et al., 2023; Rivera-Caicedo et al., 2023).

## CONCLUSIONS AND RECOMMENDATIONS

Hyperspectral remote sensing has matured into a powerful tool for precision agriculture, offering capabilities for crop monitoring, stress detection, and soil assessment that substantially exceed multispectral alternatives. This review has synthesised advances across the full spectrum of agricultural applications.

Key findings include: (1) satellite hyperspectral data are now operationally available from PRISMA, EnMAP, and EMIT; (2) biochemical parameter retrieval represents the strongest advantage of hyperspectral sensing, with $R^2$ improvements of 0.15-0.20 compared to multispectral approaches; (3) pre-symptomatic disease detection achieves 85-93% accuracy with 5-10-day lead time; (4) deep learning approaches, including graph neural networks and transformer architectures, have substantially improved analysis accuracy; and (5) challenges remain in atmospheric correction, temporal coverage, and operational integration. For practitioners, hyperspectral remote sensing is recommended for applications requiring biochemical characterisation, early stress detection, or discrimination among spectrally similar targets. Future research priorities include the development of robust transfer learning approaches, foundation models for hyperspectral data, and standardised integration with digital agriculture platforms.

## DECLARATIONS

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The author declares that there is no conflict of interest regarding the publication of this manuscript.

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### Author Contributions

The author solely conceived the study, conducted the literature review, analyzed and synthesized the information, and prepared the manuscript.

### Data Availability

No new data were generated or analyzed in this study. All information presented is based on previously published literature, which has been properly cited.

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