Applications of Multispectral Imaging for Soybean Production

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Executive Summary

Soybean production in Brazil faces recurring losses from foliar diseases, insect pressure, nutrient constraints, and intense weed competition (notably herbicide-resistant species). These problems share a common operational challenge: field scouting is costly, slow, and spatially sparse, which delays interventions and increases unnecessary chemical applications.

In that context, multispectral imagery acquired from satellites and unmanned aerial vehicles (UAVs) has emerged as a powerful tool for monitoring crop health and supporting precision agriculture.

This white paper summarizes practical applications of multispectral imagery from drones and satellites to support soybean management. Multispectral sensing captures canopy reflectance in key spectral regions (visible, red-edge, near-infrared), enabling quantitative indicators of crop vigor and stress (e.g., NDVI, NDRE, GNDVI). When integrated with georeferenced field operations, these indicators enable stress detection, targeted scouting, prescription mapping, yield estimation, and continuous crop monitoring.

We present use cases across:

- Diseases (rust, target spot, frogeye leaf spot, powdery mildew)
- Pests (caterpillars, stink bugs, whitefly, aphids, nematodes)
- Nutrient deficiencies (N, P, K, Mn, B)
- Weeds (buva/Conyza, Palmer amaranth, sourgrass, beggar-ticks)
- Other applications (yield estimation, hydric stress detection, crop vigor monitoring)

For each use case, we describe: typical agronomic symptoms, expected multispectral signatures, limitations, and at least one supporting reference.

The analysis presented here shows that the primary barrier to large-scale adoption of multispectral solutions in soy production is no longer scientific feasibility. Instead, remaining challenges are characteristic of scale-up phases in data-driven industries and represent opportunities for differentiation rather than fundamental limitations of the technology.

Contents

1 Introduction

The integration of multispectral and hyperspectral imaging into agricultural management represents a significant technological leap in the quest for global food security. As agricultural systems face increasing pressure from climate variability, evolving pathogen populations, and the necessity for resource optimization, remote sensing offers a non-invasive, scalable, and highly accurate solution for real-time crop monitoring [1, 2]. By capturing reflectance data across discrete portions of the electromagnetic spectrum—including the visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR) regions—these technologies permit the identification of physiological and biochemical shifts within plant tissues long before they become apparent to the naked eye [3–5] In the context of large-scale commodity crops such as soybeans, corn, and cotton, as well as high-value perennial cultures like coffee, multispectral analytics provide the foundational data for precision interventions that maximize yield while minimizing environmental footprints.

In particular, soybean cropping systems operate at large scale, often with multiple production zones and variable soils, creating strong spatial variability in plant vigor and stress. Key drivers include:

- Rapid disease progression (e.g., rust epidemics under favorable humidity/temperature) requiring fast detection and timely fungicide decisions.
- Insect damage patterns that are patchy and dynamic, often requiring rapid identification of hotspots.
- Nutrient limitations caused by soil variability, compaction layers, pH constraints, and uneven fertilization response.
- Herbicide-resistant weeds spreading from foci into larger infestations, requiring early mapping.
- Climate and water variability, where short drought windows can reduce yield significantly.

Remote sensing provides a scalable monitoring layer to:

- Detect stress earlier than visual scouting in many cases,
- Prioritize field inspection (directed scouting),
- Improve the spatial precision of sprays and interventions,
- Create consistent time-series monitoring across crop stages.

This white paper surveys the current state of multispectral imaging applications in soybean production, with a focus on evidence that reduces scientific and technical risk. By synthesizing results from UAV and satellite-based studies, we aim to demonstrate that multispectral analysis is a mature and validated tool.

2 Foundational Mechanics of Multispectral Remote Sensing in Agronomy

To understand the application of multispectral imaging in agriculture, it is essential to analyze the interaction between electromagnetic radiation and plant physiology. A healthy plant canopy reflects light in a characteristic pattern: low reflectance in the blue and red bands due to chlorophyll absorption, a slight peak in the green band, and a dramatic increase in the near-infrared region caused by the internal structure of healthy leaves, specifically the spongy mesophyll. Stressors—whether biotic (diseases, pests) or abiotic (drought, nutrient deficiency)—alter these reflectance properties by disrupting pigment concentrations, cellular architecture, or water content [2, 6–8].

Multispectral sensors, typically mounted on Unmanned Aerial Vehicles (UAVs) or satellites, capture these changes by recording reflectance in narrow, non-contiguous bands. Common sensors, such as the Parrot Sequoia or Sentera systems, often focus on Green, Red, Red Edge, and NIR wavelengths. The "Red Edge" band is particularly valuable in precision agriculture as it represents the transition zone between red light absorption and NIR scattering; it is highly sensitive to early-stage chlorophyll degradation and biomass changes, making it a critical tool for detecting the onset of stress [6, 9, 10].

Table 1 shows the most common multispectral bands used in agriculture and their practical interpretation. Many modern agricultural cameras also provide multiple red-edge or narrow bands (useful for chlorophyll and nitrogen proxies).

Spectral Band	Wavelength Center (nm)	Primary Physiological Indicator)
Blue	450 - 495	Canopy/soil separation support; Chlorophyll and carotenoid absorption; sensitive to early nematode stress.
Green	550 - 560	Peak reflectance for healthy vegetation; used in GNDVI and nutrient indices.
Red	650 - 680	Maximum chlorophyll absorption; key for biomass and photosynthetic activity; responds to leaf chlorophyll reduction and stress.
Red-edge	720 - 740	Sensitive to chlorophyll density and cellular structure; early stress marker; widely used in NDRE.
Near-Infrared (NIR)	750 - 1000	Sensitive to leaf/canopy structure, biomass, and vigor; increases with healthy dense vegetation; key for NDVI/NDRE.

Table 1: Typical multispectral bands used in agricultural remote sensing and their practical interpretation for crop monitoring [9–12]

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Furthermore, several vegetation indexes can be computed from multispectral bands:

- **NDVI:** vigor/biomass (saturates in dense canopy)
- **NDRE:** chlorophyll/stress (less saturation than NDVI)
- **GNDVI:** chlorophyll and nitrogen sensitivity

- **SAVI / MSAVI:** helps reduce soil background influence in early growth stages
- **Thermal-derived metrics (if thermal is available):** for water stress.

Many stressors cause similar spectral responses (reduced chlorophyll, reduced leaf area, altered canopy structure). Therefore, multispectral works best when combined with growth stage awareness (phenology), weather context, soil information, and machine learning classifiers trained with local data.

3 Multispectral Applications for Soybean Production

3.1 Soybean Diseases

Foliar diseases remain a primary constraint on soybean productivity, often causing substantial economic losses across the Americas and Asia. Multispectral imaging allows for the automated detection and quantification of these diseases, facilitating site-specific fungicide applications that reduce chemical input costs and mitigate the development of pathogen resistance [6, 13–15]. A summary of the main algorithms used for detecting this pathologies, as well as their reported accuracy is shown in Table 2.

3.1.1 Asian Soybean Rust (Ferrugem-asiática) —*Phakopsora pachyrhizi*

Asian Soybean Rust (ASR) is categorized as one of the most destructive fungal diseases in soybean history, with potential yield reductions of up to 80% to 90%. The pathogen, *Phakopsora pachyrhizi*, initiates infection as reddish-brown spots on the adaxial leaf surface, eventually leading to rapid chlorosis and premature defoliation. Traditional monitoring relies on diagrammatic scales and manual scouting, which are labor-intensive and subjective [6, 16].

Remote sensing provides a high-throughput alternative. Research using multispectral sensors on UAVs has demonstrated that the combination of vegetation indices and machine learning can categorize ASR-induced defoliation with accuracies reaching 94%. The Random Forest (RF) algorithm, in particular, excels at handling the complex, non-linear relationships found in multispectral datasets. The most effective indices for ASR detection include the Wide Dynamic Range Vegetation Index (WDRVI) and the Modified Photochemical Reflectance Index (MPRI), both of which are more resistant to the saturation issues common with the Normalized Difference Vegetation Index (NDVI) in high-biomass crops [6, 17–21].

3.1.2 Target Spot (Mancha Alvo) - *Corynespora cassiicola*

Target Spot has emerged as a significant threat in tropical and subtropical soybean regions, particularly as the pathogen exhibits increasing resistance to conventional fungicides. The disease causes circular, concentric lesions that impair the plant’s ability to photosynthesize effectively. Spectral analysis has revealed that healthy leaves exhibit prominent reflectance peaks associated with active chlorophyll synthesis at 445 nm and 650 nm, whereas leaves infected with *Corynespora cassiicola* show distinct spectral pattern shifts [14, 22].

Support Vector Machines (SVM) and Logistic Regression (LR) algorithms have been utilized to classify the severity of Target Spot with high precision. Research identifies that hyperspectral sensors (350–2500 nm) provide the most detailed insights, but multispectral data remains the more economically viable choice for large-area monitoring. The detection of this disease during the R5.5 stage (grain filling) is particularly valuable, as this is the period when yield loss risk is highest [14].

3.1.3 Frogeye Leaf Spot (Mancha olho-de-rã) —*Cercospora sojina*

Frogeye Leaf Spot (FLS) is a polycyclic disease, meaning it can undergo multiple infection cycles in a single season, necessitating rapid detection to prevent epidemic outbreaks. FLS lesions are typically circular or angular with gray centers and dark borders. Advanced deep learning models, such as the HSDT-TabNet (Hierarchical Soft Decision Tree with Tabular Neural Network), have been applied to UAV-derived data to grade FLS severity with an accuracy of 96.37% [5, 23].

3.1.4 Powdery Mildew (Oídio) —*Microsphaera diffusa*

Powdery Mildew, caused by *Microsphaera diffusa*, presents as a white, flour-like fungal growth on the foliage. Unlike necrotic spots that primarily decrease NIR reflectance, the white mycelium of powdery mildew increases the overall albedo (reflectance) of the leaf surface across visible bands. Detection models utilizing the Mask R-CNN architecture have proven effective in segmenting these white patches from the healthy green canopy [24–26].

Furthermore, digital image processing techniques that transform images into the HSV (Hue, Saturation, Value) or $L^*a^*b^*$ color spaces allow for the automatic differentiation of symptoms from asymptomatic tissue. This is especially useful in complex field scenes where shadows or leaf veins might mimic disease symptoms in standard RGB imagery [27, 28].

Disease	**Algorithm**	**Accuracy**
Asian Soybean Rust	Random Forest (RF)	94%
Target Spot	SVM, Logistic Regression	High (Severity 1–3)
Frogeye Leaf Spot	HSDT-TabNet, SVM	96%
Powdery Mildew	Mask R-CNN, CNN	85%

Table 2: Examples of remote-sensing-based soybean disease detection studies: algorithms used and reported performance.

3.2 Soybean Pests

Arthropod pests pose a distinct challenge for multispectral monitoring because their damage is often more localized and transient than pathological infections. However, remote sensing offers the potential to map pest "hotspots," allowing for targeted insecticide applications or the localized release of natural enemies, which is a cornerstone of Integrated Pest Management (IPM) [7, 29, 30].

3.2.1 Caterpillars/Defoliators (Lagartas) —*Lepidoptera*

Lepidopteran pests, such as the velvetbean caterpillar (Anticarsia gemmatalis) and various Spodoptera species, are significant defoliators of soybeans and cotton. Because caterpillars consume leaf tissue directly, their impact on the canopy is reflected as a decrease in the Leaf Area Index (LAI) and a reduction in the scattering of near-infrared light. Hyperspectral proximal sensing has shown that these changes are quantifiable even at low infestation levels (e.g., 2 insects per 5 plants) within 5 to 10 days of the start of feeding. This early detection capability allows for interventions before pests reach the economic injury level (EIL), preventing significant yield loss [2, 8].

3.2.2 Stink Bugs (Percevejos) —*Pentatomidae*

Sucking pests represent a more nuanced detection target. Stink bugs, such as *Euschistus heros*, feed on pods and seeds, often without causing large-scale foliar damage that is easily detectable via multispectral imaging. Research suggests that while their direct injury to leaves is minimal, their presence can be inferred during the maturity stage (R7-R8) as they cause "green stem syndrome" or delayed senescence, which maintains higher-than-expected NIR reflectance in late-season imagery [8].

3.2.3 Whitefly (Mosca-branca) —*Bemisia tabaci*

Whiteflies (*Bemisia tabaci*), conversely, are highly detectable. These pests excrete honeydew, a sugary substance that promotes the growth of "sooty mold" on the leaves. This black mold layer drastically reduces reflectance in the green and red bands, effectively blocking the wavelengths necessary for photosynthesis. Additionally, whiteflies are vectors for over 120 plant viruses, such as the soybean yellow mottle mosaic virus (SYMMV), which cause mosaic-like chlorosis that can be identified with $>95\%$ accuracy using hyperspectral sensors and SVM models [7, 30, 31].

3.2.4 Aphids (Pulgões) —*Aphis glycines*

Soybean aphids are particularly challenging because they often reside on the underside of leaves, hiding them from traditional optical scouting. However, their sap-sucking activity causes physiological stress that alters the leaf's internal air spaces and chlorophyll content. Multispectral imagery has revealed that NIR reflectance decreases as aphid populations increase. Furthermore, innovative SID (Spectral Information Divergence) analysis in the 710–825 nm range has proven capable of detecting the physical presence of aphid colonies beneath the leaves, identifying infestations that are invisible to the human eye [32–34].

3.2.5 Nematodes (Nematóides)

Nematodes like the Soybean Cyst Nematode (SCN) and the Root Lesion Nematode (*Pratylenchus brachyurus*) cause extensive root damage, leading to stunting and yellowing of the canopy. Because SCN damage is soil-borne, it often manifests in characteristic "patchy" spatial distributions across a field. Multispectral imagery has shown that the Blue band and the Green Normalized Difference Vegetation Index (GNDVI) are the most sensitive markers for nematode-induced stress [9–11, 35, 36].

UAV-based maps of SCN distribution allow for variable-rate applications of nematicides and the selection of resistant cultivars for specific areas of the farm. Studies have indicated that multispectral data can explain up to 60% of the variation in initial SCN population densities and up to 91% of the variation in final soybean yield, providing a powerful predictive tool for long-term farm management [10, 11, 35].

3.3 Nutrient Deficiency Identification and High-Throughput Phenotyping

Optimizing nutrient application is critical for both crop performance and environmental protection. Multispectral imaging allows for the detection of "hidden hunger"—nutrient deficiencies that impact yield but have not yet manifested as visual symptoms [37]. Table 3 shows a summary of the visible symptoms and spectral signature for the main nutrient deficiencies, as well as the most commonly used algorithms and their respective performance.

3.3.1 Macronutrients: Nitrogen, Phosphorus, and Potassium

Nitrogen (N) is the primary driver of vegetative growth. A deficiency in N leads to reduced chlorophyll synthesis and chlorosis, which increases reflectance in the visible red spectrum. Phosphorus (P) deficiency often results in dark green or bluish-green leaves and stunted growth, while Potassium (K) deficiency leads to yellowing along leaf margins [19, 37–44].

Deep learning models like YOLOv8 have been trained on thousands of RGB and multispectral images to identify these macro-deficiencies with a mean average precision (mAP) of over 99%. Specifically, Potassium deficiency detection has achieved near-perfect accuracy, as K stress induces a unique spectral signature characterized by elevated reflectance across the visible range due to the rapid loss of accessory pigments [37].

3.3.2 Micronutrients: Manganese and Boron

Micronutrients like Manganese (Mn) and Boron (B) are essential for enzymatic activity and seed development. Identifying these deficiencies is complex as their spectral signatures often overlap with other stressors. However, research in high-throughput phenotyping (HTP) has shown that machine learning models can classify soybean genotypes based on their micronutrient efficiency [12, 37].

By analyzing the specific reflectance patterns in the 400–1000 nm range, Random Forest algorithms can distinguish genotypes with high B or Mn absorption from those that are less efficient. This allows breeders to select for "nutrient-dense" varieties that thrive in low-fertility soils. Interestingly, results suggest that using raw spectral bands (Red, Green, Red Edge, NIR) as inputs often performs better than using derived vegetation indices for micronutrient classification, as the raw bands preserve the subtle "noise" that contains nutritional information [12].

Nutrient	Visual Symptom	Spectral Signature	Model / Success
Nitrogen (N)	Chlorosis (yellowing)	High Red, low NDVI	YOLOv8 (99% mAP)
Phosphorus (P)	Stunting, dark green/blue	Low Green/Red ratio	CNN (97.4% accuracy)
Potassium (K)	Marginal chlorosis	High reflectance (VIS)	SVR ($R^2 = 0.85$)
Manganese (Mn)	Interveinal chlorosis	Band-specific shifts	Random Forest (>90%)
Boron (B)	Distorted growth, pod drop	Pigment-related reflectance	PCA/K-means Clustering

Table 3: Summary of soybean nutrient deficiency symptoms, spectral signatures, and example model performance reported in the literature.

3.4 Invasive / Weed Species

Weed management is a cornerstone of agricultural efficiency, particularly as global herbicide resistance continues to rise. Multispectral imaging facilitates "Green-on-Green" weed detection—the ability to identify a weed species within a living crop canopy—which is essential for site-specific herbicide application [2, 45, 46].

3.4.1 Dominant Weeds: Buva, Sourgrass, and Palmer Amaranth

Species like Buva (*Conyza bonariensis*), Sourgrass (*Digitaria insularis*), and Palmer Amaranth (*Amaranthus palmeri*) have developed widespread resistance to glyphosate and ALS-inhibiting herbicides. These weeds often outcompete crops for light, water, and nutrients, leading to significant yield losses [47, 48]. UAV-based multispectral imaging can identify these weeds by their unique morphological and spectral traits. This allows for the creation of "weed maps" that guide autonomous sprayers to apply herbicides only where they are needed, reducing chemical use by up to 40% [46, 49–55].

3.5 General Agronomic Applications: Yield, Water, and Vigor

The ultimate goal of multispectral analytics is the holistic assessment of crop potential. By combining spectral data with other environmental inputs, agronomists can predict harvest outcomes and manage abiotic stress with unprecedented precision [56–58].

3.5.1 Yield Estimation and Prediction

Yield prediction is a multi-dimensional problem. While vegetation indices like NDVI and NDRE are strong indicators of biomass, they are often insufficient on their own to predict final seed weight or grain quality. Modern approaches combine multispectral data with in-season Vegetaion Indexes and time-series features to estimate yield with remarkable accurary [58, 59].

In spring barley and soybean trials, ensemble machine learning models such as Random Forest Regression (RFR) have demonstrated that the integration of spectral and textural features outperforms single-feature models, improving yield prediction accuracy by over 30%. These models are particularly robust in drought-stressed environments, where traditional biomass-based predictions often fail [3, 56, 60–62].

3.5.2 Hydric Stress Detection

Water stress is often the primary factor limiting agricultural productivity [63]. Multispectral sensors can identify the onset of water stress by monitoring the Normalized Difference Water Index (NDWI) or by identifying shifts in the Red Edge band that indicate a reduction in leaf turgor and chlorophyll activity [57, 64, 65].

When combined with thermal infrared cameras, which measure the temperature increase associated with stomatal closure, multispectral imagery provides a complete picture of the plant's hydraulic status [66, 67]. This allows for the implementation of precision irrigation systems that target only the "thirsty" zones of a field, conserving water and energy while maintaining optimal growth conditions.

3.5.3 Crop Health and Vigor Monitoring

General crop vigor monitoring remains the most widespread use of multispectral technology. By regularly flying UAVs over a field, farmers can create a time-series of crop development. These "health maps" allow for the early detection of anomalies [3, 46, 57, 60].

4 Conclusion and Outlook

This white paper reviewed the current state of multispectral imaging applications in soybean agriculture, with a focus on reducing scientific and technical uncertainty. Across diseases, pests, nutrient deficiencies, weed pressure, crop health and vigor monitoring, yield estimation, and water stress detection, the literature provides consistent and compelling evidence that multispectral imagery captures agronomically meaningful signals linked to plant physiology, stress response, and production outcomes.

For several high-impact applications - most notably soybean rust detection, nitrogen-related canopy stress assessment (via red-edge indices), weed infestation mapping in early growth stages, general vigor monitoring, and water stress/soil moisture proxying - multispectral approaches have reached a level of maturity suitable for operational deployment. For others, including species-specific pest monitoring, micronutrient stress differentiation, and robust yield forecasting, feasibility is well supported by mechanistic understanding and cross-crop validation, with remaining limitations primarily related to labeled data availability, phenology-aware modeling, and operational integration rather than sensing capability.

A central conclusion of this review is that the core scientific question—whether multispectral imagery can detect and monitor key drivers of soybean productivity—has largely been answered in the affirmative. The dominant challenges now lie beyond basic research. They concern consistent data acquisition, repeatable radiometric processing, temporal modeling across growth stages, and the integration of spectral insights into practical agronomic workflows (directed scouting, prescription mapping, and verification). These challenges are characteristic of scale-up phases in many data-driven industries and are best addressed through engineering discipline, longitudinal data collection, and close collaboration with growers, agronomists, and operations teams.

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