Remote Sensing of Maize Physiological and Nutrient Dynamics in Response to Fall Armyworm Infestation

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Abstract

Fall Armyworm (FAW) is a major pest, threatening maize production and food security. FAW preferentially attacks nitrogen-rich maize due to its nutritional composition, which accelerates larval development. Understanding the effects of FAW infestation on maize growth and nutrient status is critical for effective crop management. This study (i) examines the impact of FAW infestation on maize using key physiological metrics, including fresh/dry weight, chlorophyll content (as measured by SPAD), leaf area index (LAI), stem length, and leaf dimensions (length, width, and area); (ii) investigates differences in carbon, hydrogen, nitrogen, and sulphur concentrations between healthy and infested maize, and (iii) analyses spectral variability between healthy and infested maize using leaf-level hyperspectral data. Hyperspectral data at the leaf scale were used to identify and distinguish the spectral reflectance between healthy and infested FAW maize crops. Results indicate that infested crops exhibit lower fresh weight, reduced LAI, shorter stems, and smaller leaves compared to healthy crops, highlighting a substantial negative effect on above-ground biomass and overall crop vigour. Infested crops showed higher nitrogen levels than healthy crops. This trend could be attributed to nitrogen redistribution following FAW damage, where nitrogen decreases in attacked leaves and increases in roots, with partial recovery after the pest moves on to another crop. The study establishes a methodological framework for linking laboratory, field, and remote sensing approaches, providing a foundation for future predictive modelling of pest impacts on maize nutrient content and productivity.

1. Introduction

A crop nutrient is defined as "*an essential mineral for the growth and development of the crop*"*;* without which a crop cannot complete the vegetative or reproductive stages of its life cycle (Arnon and Stout, 1939). Crop nutrients are obtained primarily through soils (Silva and Uchida, 2000; FAO, 2022a). The deficiency of essential nutrient elements has been linked reduced growth and yield in crops therefore crop nutrition is a critical factor affecting crop yields. A study by Stewart et al., (2005) reported that the omission of nitrogen in maize decreased yield by 41%. For maize growth, development, and yield maximisation, nitrogen (e.g., protein and amino acids) (Iqbal et al., 2015), carbon, hydrogen, and sulphur are critical constituents of crop biomolecules and contribute to the metabolic and structural functions necessary for crop productivity, defence, and overall physiological functioning.

Nutrient variability in crops can be influenced by several factors, including climate change (Brouder and Volenec, 2008), soil properties, and biotic stressors such as pest infestation (e.g., Fall Armyworm (FAW)). Pest infestation is a severe constraint on maize output, resulting in significant yield losses across many regions worldwide. Several studies (Dzurume et al., 2025a; Dzurume et al., 2025b) have emphasized the growing importance of early detection and monitoring systems to enable timely pest management interventions.

FAW is a phytophagous pest that has been recognised as an invasive species in Africa and Asia since 2016 and 2018, respectively, posing a significant threat to food security (Ali et al., 2023). One of the primary factors influencing host selection by this pest is the nutritional quality of the crop tissue. FAW prefers crops grown in nitrogen-rich environments (Mason et al., 2022). FAW attacks over 350 crops (Ali et al., 2023), but shows a strong preference for maize. Studies have shown that maize provides a more suitable nutritional and energy composition (in terms of carbohydrates) for supporting FAW development from larva to pupa over a shorter period than other crops (e.g., sorghum and sugarcane). This strong host preference further underscores the importance of understanding FAW and maize interactions.

Therefore, understanding the effects of FAW infestation on maize nutrient content, as well as how this influences crop growth and development, is critical. Previous studies have focused on examining nutrient dynamics in crop systems using traditional methods. For example, a study by Wang et al., (2022), investigated the effects of nitrogen supply on maize's defence response against FAW. The comparison of different nitrogen supplies in that study showed that maize supplemented with 52.2 mg/kg of nitrogen exhibited increased susceptibility to FAW, while maize supplemented with 156.6 mg/kg of nitrogen showed improved defence against FAW. However, these methods are time-consuming and labour-intensive. Furthermore, sophisticated laboratory equipment is required for these analyses, which is frequently unavailable, especially in developing countries. In addition, these approaches are limited in scalability and do not capture spatial variability in crop responses.

Remote sensing provides a practical means to overcome this limitation, as it enables the assessment of nutrient status in crops before and after pest infestations, for example, by using multispectral and hyperspectral datasets (Lu et al., 2020). For instance, a study conducted by Asner et al., (2015) used imaging spectroscopy to quantify the carbohydrate content of a leaf. Using multispectral data, Dlamini et al., (2021), predicted seasonal variations in the concentrations of nitrogen in the leaves of key floodplain wetland vegetation types. Mahajan et al., (2014) and Dreccer et al., (2014) used hyperspectral data to monitor nitrogen and carbohydrate levels in wheat, respectively. Therefore, the use of hyperspectral remote sensing offers detailed information for estimating crop biochemical properties (e.g., chlorophyll, and water contents) and biophysical properties (e.g., LAI, biomass) thereby enabling improved understanding of vegetation physiological status, evaluation of crop nutrient status, and monitoring of crop disease due to its narrow spectral bands and fine resolution (Lu et al., 2020; Sishodia et al., 2020). This makes hyperspectral remote sensing particularly suitable for detecting subtle biochemical and physiological changes induced by pest stress.

Firstly, understanding the responses of maize nutrient content to FAW infestation is important because it helps clarify the extent to which these nutrients limit maize growth and reproduction. Secondly, maize is a key staple crop, providing a significant share of calories and energy worldwide and contributing approximately 20% of global calorific intake; therefore, it is vital to improve its yield and productivity as well as support human health and well-being. To our knowledge, no study has used integrated laboratory, field, and remote sensing approaches to understand the changes in maize nutrients caused by FAW infestation. As a result, the purpose of this study is to investigate the impacts of FAW infestation on the biophysical and biochemical properties of maize using laboratory, field, and remote sensing approaches. Specifically, the study seeks to determine the extent to which FAW infestation alters key maize characteristics, such as chlorophyll (SPAD) and nitrogen content and, how it alters the spectral response. It is hypothesized that FAW infestation will lead to a reduction in these biophysical and biochemical properties, and a spectral difference between infested and healthy maize, reflecting the detrimental effects of the pest on maize health and productivity.

2. Materials and methods

2.1 Study area

The Jordan Valley (Fig. 1), the lowland segment of the Jordan River Rift between the Sea of Galilee and the Dead Sea, is one of Jordan's main irrigated agricultural zones and supports year-round horticulture and field crops due to its warm climate, long growing season and deep alluvial soils (FAO, 2022b). Maize (Zea mays L.) plays a central role in Jordan Valley farming systems both as a cultivated field crop and as a key source of fodder within mixed crop-livestock enterprises (USDA and FAS, 2025). Maize is also seen as a rotation crop in irrigated systems. Farmers also produce tomatoes, peppers, beans, wheat, soybeans, and potatoes, among other crops. The presence of FAW was first detected in Jordan in September 2020 (NPPO-Jordan, report JOR-01/1 2020).

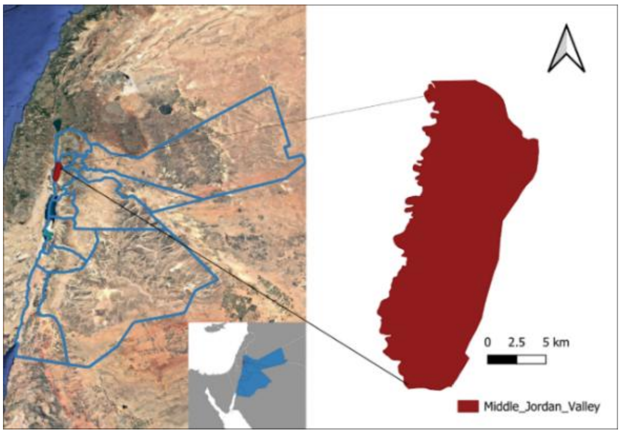

Figure 1: Location of the study area in Jordan.

2.2 Field data collection

During the 2025 maize growing season, crop biophysical and biochemical parameters were collected in 56 fields in the study area, based on a random sampling method. In each field, we collected 10 samples (for each sample, all the below-mentioned parameters were measured) resulting in 560 data samples. The fields were separated into two classes: healthy and infested. Data collected included information on the location of the infestation, time of observation, crop growth stage, crop height, number of leaves, infestation severity (healthy or infested), and leaf samples for nutrient content analysis. Maize leaf samples were collected, stored in brown envelopes, and sent to the University of Jordan to be dried.

To characterise crop responses to pest infestation, several physiological and morphological parameters were measured, including fresh weight, chlorophyll content (as SPAD), leaf area index (LAI), stem length, and leaf dimensions (length, width, and area). Chlorophyll (SPAD) was measured with a SPAD-502, while LAI was measured with a LAI-2200 Plant Canopy Analyser. These parameters are critical for interpreting spectral responses linked to pest stress since they offer complementary indicators of crop vigour, and photosynthetic status, all of which are known to affect leaf spectral reflectance.

2.3 Reflectance measurements

The spectral signature of a crop varies with crop variety, growth stage, crop condition, crop, soil and water management, and environmental factors. Maize leaf reflectance spectra were measured using an ASD FieldSpec 3 equipped with a contact probe and its internal halogen light source. The FieldSpec collects data in the 350 to 2500 nm spectral range. Several measurements were made per observation point to determine a single mean spectral reflectance value. The fields, which included samples from both healthy and infested maize crops, were used to extract the average spectral values from the spectral bands. This enabled comparison of spectral responses between healthy and infested maize.

2.4 Laboratory measurements

The fresh weight of each leaf sample was measured using a high-precision digital scale. To determine dry weight, all leaf samples were oven-dried to eliminate moisture content. Specifically, maize leaf samples were dried at 60°C (140°F) until they reached a constant weight, which typically required

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approximately 48 hours. Following drying, the leaf samples were finely ground into a powder and stored under appropriate conditions for subsequent nutrient analysis. To quantify nutrient composition, CHNS elemental analysis was used to determine the carbon, hydrogen, nitrogen, and sulphur content of all leaf samples. The concentrations were reported as percentages on a dry weight basis.

2.5 Statistical analysis

Differences between healthy and infested crops were assessed for each morphological trait using a Welch's t-test, which does not assume equal variances between groups (Welch, 1947); statistical significance was determined at $p < 0.05$.

3. Results

3.1 Effect of infestation on leaf biomass and chlorophyll (SPAD)

In terms of biomass and chlorophyll content, infested crops had substantially lower fresh weight than healthy crops (Fig. 2). The distribution of fresh weight in healthy crops was broader, whereas the infested crops showed a narrower distribution concentrated at lower values. These patterns are consistent with a significant negative effect of infestation on above-ground biomass. SPAD (leaf chlorophyll) readings were lower in infested crops than healthy crops.

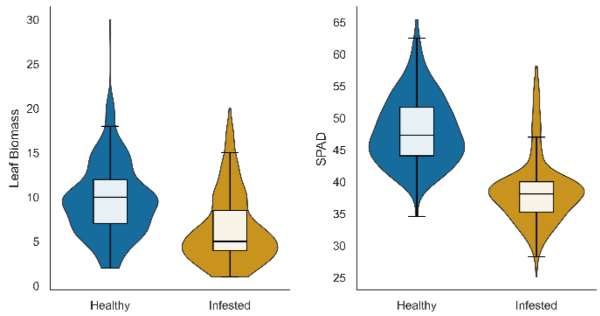

Figure 2: Comparison of leaf biomass and chlorophyll status/SPAD between healthy and infested maize.

3.2 Changes in morphology and leaf traits due to infestation

Regarding structural traits, for LAI, healthy crops exhibited higher mean values than infested crops (Fig.3). The scatter points indicate that although there was overlap, the healthy class clustered at higher LAI compared to the infested class. Stem length, likewise, showed that healthy crops tended to have longer stems than infested crops, with the infested class showing a lower median. The same pattern was observed for the leaf dimensions. Healthy crops exhibited consistently higher values for leaf area, width, and length compared to infested crops. Although some overlap existed between groups, the distributions for healthy crops were shifted toward larger values. In contrast, infested crops were generally associated with lower leaf dimension values.

All measured leaf traits (LAI, stem length, leaf area, leaf width, and leaf length) were significantly lower in infested crops compared to healthy crops, indicating a strong negative effect of infestation on crop morphology (Table 1).

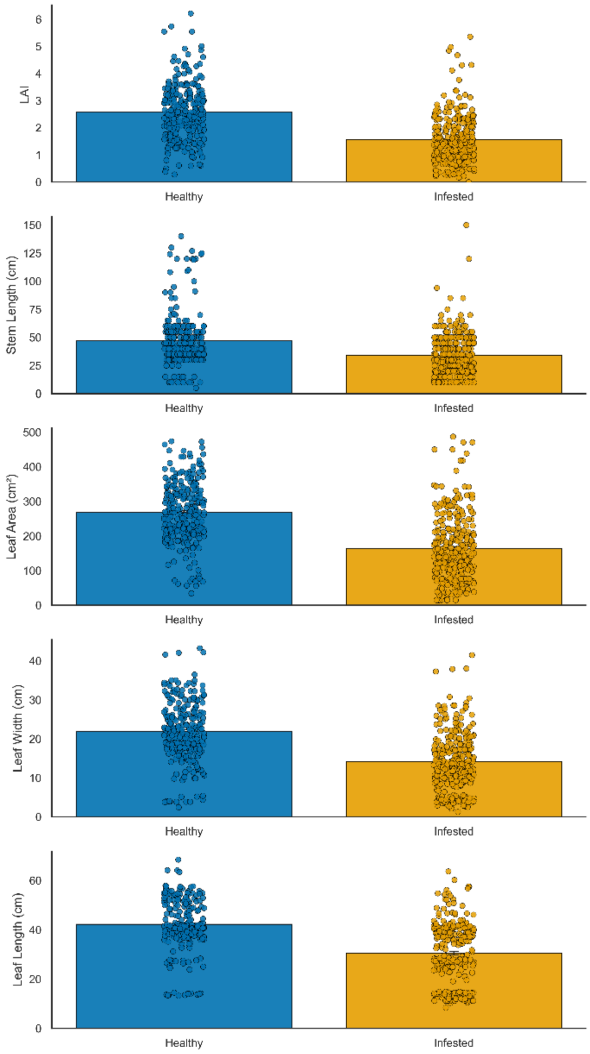

Figure 3: Morphological and leaf trait differences between infested and healthy crops (from top to bottom: LAI, stem length, leaf area, leaf width and leaf length).

Variable	Healthy (mean ± SD)	Infested (mean ± SD)	t-statistic	p-value
LAI	2.58 ± 1.01	1.57 ± 0.87	12.482	1.80×10^{-31}
Stem Length (cm)	46.81 ± 23.59	34.14 ± 18.59	6.967	1.02×10^{-11}
Leaf Area (cm^2)	267.65 ± 87.01	163.79 ± 96.51	13.296	3.58×10^{-35}
Leaf Width (cm)	21.88 ± 7.48	14.24 ± 7.35	12.084	5.93×10^{-30}
Leaf Length (cm)	42.19 ± 10.01	30.52 ± 12.42	12.195	2.19×10^{-30}

Table 1: Statistical comparison of morphological traits between healthy and infested crops using Welch's t-test ($p<0.05$)

3.3 Impact of infestation on elemental (nutrients) composition

In relation to nutrient composition, the boxplots show the concentrations of carbon (C), hydrogen (H), nitrogen (N), and sulphur (S) in healthy and infested samples (Fig.4). Overall, the median values of C, H, and N were slightly higher in infested samples compared to healthy ones, though the variation was considerable within both classes. Specifically, C ranged from approximately 33-45%, H from 4-6.5%, and N from 1.5-4%, with overlapping distributions between the classes. Sulphur (S) concentrations were generally low (<1%) in both healthy and infested samples.

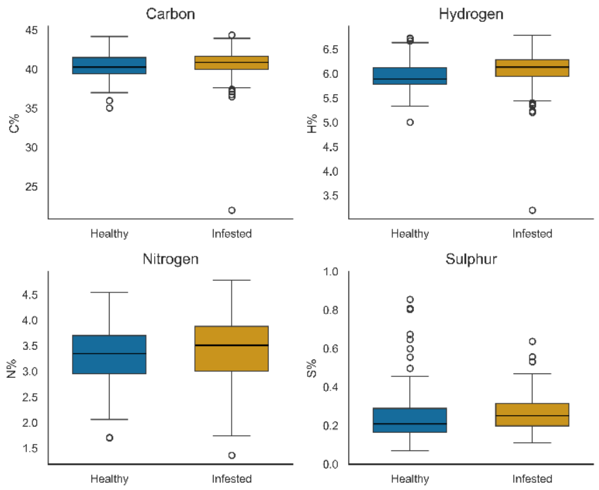

Figure 4: Comparison of C, H, N, and S concentration percentages in healthy and infested maize crops.

3.4 Relationships and distributions of key variables in healthy and infested crops

The density plots (diagonal plots in Fig. 5) reveal partially distinct distribution patterns for some variables. For example, LAI shows a noticeable shift between healthy and infested classes, with the healthy class exhibiting a higher mean value. The paired variable scatterplots in Fig. 5 indicate positive relationships between certain variables, such as LAI and SPAD, with slightly different clustering patterns for each class. Some scatterplots, such as those comparing leaf biomass and nitrogen, show more dispersed patterns with limited class separation. While some variables demonstrate partial separation between healthy and infested crops, there is considerable overlap, indicating that no single variable perfectly discriminates between the classes.

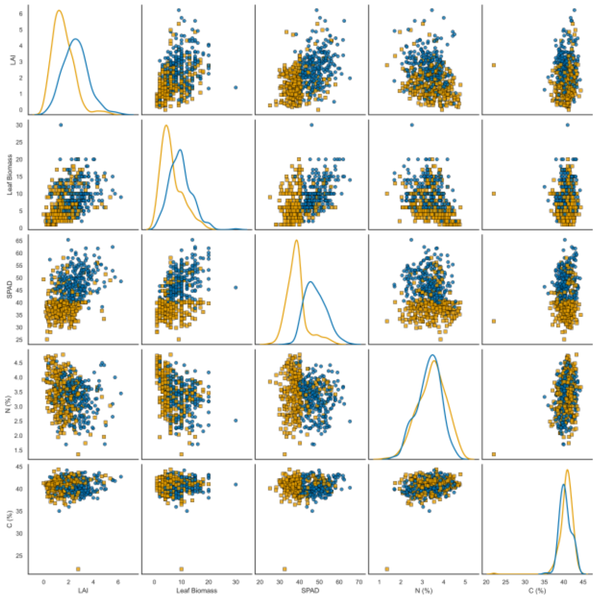

Figure 5: Pairwise relationships and distributions of selected variables across healthy (blue) and infested (orange).

3.5 Leaf spectral reflectance

Spectral analysis revealed distinct differences between healthy and infested maize. Fig. 6 shows the differences in mean spectral reflectance between healthy and infested maize. In the visible region (about 450-700 nm), infested maize has a higher reflectance than healthy maize indicating potential reductions in chlorophyll absorption due to stress or damage. Healthy maize exhibits higher reflectance in the near-infrared region, indicating a more intact leaf cellular structure compared to infested maize.

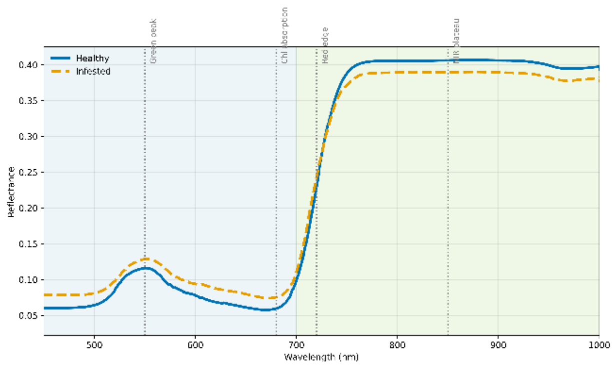

Figure 6: The mean reflectance spectra of healthy and infested maize crops with highlighted important wavelength windows.

4. Discussion

This study aimed to explain the biophysical and biochemical responses of maize crops due to FAW infestation. The findings highlight the effects of infestation on leaf biomass, leaf morphology, and the concentrations of key nutrient elements (C, H, N, and S), providing insights into how biotic stress influences crop performance and nutrient composition. Notable differences in fresh/dry weight, chlorophyll content (as measured by SPAD) and LAI between healthy and infested crops can be attributed to alterations in resource allocation and metabolic activity induced by pest damage. Leaf spectra offer the potential to provide spatial perspective on infestation dynamics and crop health across the study area.

The inclusion of physiological and morphological crop features provides further context for understanding the spectral responses. Chlorophyll content (SPAD), fresh weight, and LAI are indicators of crop physiological status and canopy structure, both of which influence leaf optical characteristics. The observed spectral variability can therefore be attributed to changes in these features linked to FAW infestation, which helps to explain how FAW-induced stress is demonstrated in maize reflectance.

The reduction in leaf biomass relative to SPAD supports evidence that FAW infestation suppresses crop growth by decreasing photosynthetic capacity. High-density herbivore feeding reduces photosynthetic area and removes resources, resulting in cumulative biomass loss over time (Zvereva and Kozlov, 2012), and that was the case in this study. Our results are consistent with prior experimental and meta-analytic studies reporting that herbivory typically reduces growth substantially and that the magnitude of photosynthetic or chlorophyll declines can be variable (Zvereva and Kozlov, 2012). In crop, aphid and other sap-feeder infestations have been shown to reduce chlorophyll (SPAD values) and growth, but the timing and magnitude vary with infestation intensity and duration (Goławska et al., 2010).

Our results demonstrate that FAW infestation significantly suppressed vegetative growth (e.g., stem length) and leaf morphological traits (leaf area, width and length) in maize crops, as evidenced by lower mean values of these parameters in infested compared to healthy maize as shown in Table 1. This structural injury is consistent with the mechanistic understanding that herbivory by FAW damages foliage and reduces the crop’s capacity to expand its leaf area, thereby limiting light capture and biomass accumulation. While much of the literature on FAW focuses on yield losses, monitoring leaf and stem traits offers early indicators of infestation severity. For instance, Sugeetha et al. (2024) found morphological traits (crop height, leaf length and width) correlate with FAW damage in maize inbreds at 30 and 60 days after sowing, which aligns with genotype-based resistance variation reported in maize for FAW (Kamweru et al., 2023). These findings highlight the potential of morphological traits as early indicators of FAW infestation.

Crop performance and growth are driven by nutrient availability. Infested crops showed higher nitrogen levels than healthy crops. This trend could be explained by the fact that when FAW damages crops, nitrogen levels decrease in the affected leaves while increasing in the roots. After the pest has moved on to another crop, nitrogen levels in the damaged leaves partially recover. As measurements for infested maize were only taken after crop damage had occurred, this dynamic response could have influenced the outcomes. Liu et al. (2024) reported a similar pattern. Damaged crops may redirect carbon and nutrients toward defence chemicals (e.g., secondary metabolites, structural barriers) rather than growth, thereby limiting stem elongation and leaf expansion. This dynamic nutrient redistribution highlights the complexity of crop responses to herbivore stress.

The spectral and SPAD readings gathered in the field clearly show that feeding damage caused by FAW damage led to chlorophyll deterioration. Reduced photosynthetic activity might result from this damage, and these physiological changes have a direct impact on reflectance in the visible, red-edge, and near-infrared regions. Compared to healthy crops, infested crops exhibit higher reflectance in the red region and lower reflectance in the near-infrared region, indicating structural changes and chlorophyll degradation. The spectrum differences between the infested and healthy crops indicate that pest-induced stresses can be identified using spectral indices such as the Normalised Difference Vegetation Index (NDVI) and the Normalized Difference Red Edge (NDRE), which are sensitive to early damage-induced changes in crop biophysical and biochemical properties. This reinforces the importance of spectral indices for early detection of pest-induced stress.

5. Conclusions

In summary, the results indicate that FAW infestation led to significant reductions in maize biophysical and biochemical properties, along with detectable changes in spectral reflectance, indicating clear differences in growth and crop physiology between healthy and infested crops. Future studies should (i) incorporate longer temporal monitoring and more maize genotypes encompassing both resistant and susceptible lines, and (ii) focus on integrating spectral measurements with environmental variables to develop predictive models capable of forecasting pest outbreaks at broader spatial scales. In areas like Asia and Africa where agricultural production is extremely susceptible to pest pressures, such methods could aid in the creation of early warning systems for pest control. Similar spectral mechanisms may affect canopy reflectance that can be detected by current and upcoming hyperspectral satellite missions, including EnMAP (Environmental Mapping and Analysis Program) , HysIS (Hyper Spectral Imaging Satellite), CHIME (Copernicus Hyperspectral Imaging Mission for the Environment), and emerging commercial constellations such as Pixxel, while their integration with established multispectral platforms such as Sentinel-2, Landsat, PlanetScope, and WorldView offers complementary advantages in terms of temporal frequency and spatial coverage, even though this study focuses on leaf-level spectral responses. In addition, combining multiple variables is likely to improve classification performance; therefore, future analyses should explore multivariate approaches (e.g., feature stacking or machine learning models) to better capture interactions among variables. By combining spectral indications with environmental factors and remote sensing datasets, machine learning techniques could enhance pest identification even more.

From a management standpoint, understanding the biochemical and biophysical alterations induced by FAW before the onset of visible pigment degradation could provide early indicators of infestation severity, supporting more timely and targeted intervention strategies. Overall, this study demonstrates the potential of integrating physiological, biochemical, and spectral data to improve pest monitoring and support more effective maize crop management.

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