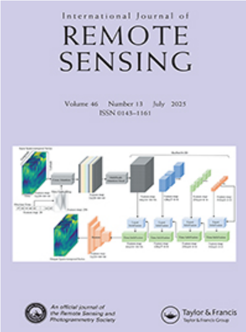

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Optimal flight height and spectral indices for detecting insect injury in peanut crops using UAS

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ABSTRACT

Despite technological advances in agriculture in recent decades, it has been estimated that about 20–30% of peanut production costs are still associated with pest and disease control, due in large part to the unnecessary use of insecticides without proper sampling, a core principle of Integrated Pest Management (IPM). However, technologies like Remote Sensing can be leveraged to provide time savings and speed in detecting injured plants. Therefore, this study aimed to determine the appropriate flight height and geometric resolution to differentiate healthy peanut plants from those injured by *Enneothrips enigmaticus* and *Stegasta bosqueella* using unmanned aircraft systems (UAS). To achieve this, controlled and field studies were conducted using the Parrot Sequoia® multispectral sensor. Five vegetation indices (IRVI, NDVI, NDRE, GRVI, and GCI) were generated and statistically compared between infestation treatments. We observed that remote sensing with UAS can only be used to detect insect-induced injuries in peanut crops at 80 and 120 m flight heights. Additionally, only the IRVI, NDVI, and GRVI indices were effective in characterizing infestations. Our study provides valuable new information that will serve as a foundation for using remote sensing to detect insect infestation injuries in peanut crops.

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Arachis hypogaea; peanut IPM; groundnut pests; peanut pest sampling

1. Introduction

Peanut (*Arachis hypogaea* L.) is grown in many locations, with most production concentrated in Asia, Africa, and North and South America ([USDA] United States Department of Agriculture 2019). However, despite technological advances in agriculture in last decades, it is estimated that about 20–30% of peanut production costs are still associated with pest and disease control (Garcia-Casellas 2004; Michelotto et al. 2017).

Thrips (Thysanoptera: Thripidae) and defoliators (Lepidoptera) are worldwide pests that occur in peanut crop (Abbott et al. 2019; Michelotto et al. 2017; Pinto and Fernandes 2020). These insects damage the peanut leaves and failure to control

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leads to losses in production in addition to retarding plant growth (Jordan, Shew, and Brandenburg 2017; Nogueira et al. 2016). Traditionally, control of these insects has relied on chemical insecticides, often applied without following Integrated Pest Management (IPM) principles or considering the actual pest population size (Pinto et al. 2020; Srinivasan et al. 2018). However, pest sampling is essential in IPM. Failure to conduct sampling can increase production costs and may lead to negative environmental impacts due to unnecessary applications (Pedigo and Rice 2014).

In this context, technologies emphasizing precision agriculture have been developed to improve peanut crop production aspects (El-Sharkawy et al. 2016; Rajan et al. 2014). However, precision agriculture in the context of agricultural entomology has not yet been widely adopted for peanut production and its application for insect pest management remains limited. Remote sensing with unmanned aerial systems (UAS) offers a solution, providing time savings, agility and effectiveness in detecting insect-injured plants (Marston et al. 2020; Yang et al. 2017). Sensors have been used remotely to detect insect-induced changes in plant spectral response using vegetation indices across various crops (Elliott et al. 2015; J. L. Hatfield et al. 2008; Marston et al. 2020).

Crop health detection using sensors often relies on the spatial resolution, which is influenced by the sensor's distance from the target (Campbell and Wynne 2011; Hunt and Rondon 2017). Consequently, determining the optimal flight height for characterizing healthy peanut plants is essential. While studies have explored suitable flight altitudes for insect detection in other crops, such as potatoes (Hunt and Rondon 2017), to our knowledge, no research has specifically investigated the ideal flight height for sampling pests in peanut crops. Given the limited information on precision agriculture for insect pest management in peanut, this study aimed to determine the appropriate flight height and geometric resolution for data collection. Additionally, we sought to differentiate healthy peanut plants from those infested with *Enneothrips enigmaticus* (Thysanoptera: Thripidae) and *Stegasta bosqueella* (Lepidoptera: Gelechiidae), key pests of peanut crops, using vegetation indices. To achieve these objectives, we conducted experiments under controlled conditions and in the field.

2. Material and methods

2.1. Experimental locations

This study consisted of two parts: one conducted under controlled conditions and the other in the field. Both experiments were carried out at the Faculty of Agricultural and Veterinary Sciences – UNESP, Jaboticabal, São Paulo, Brazil (21° 14′ 05″ S, 48° 17′ 09″ W).

The study used peanut plants (*Arachis hypogaea* L.) of the cultivar 'Granoleico', a low-growing variety belonging to the Runner vegetative group ([IAC] Instituto Agronômico de Campinas 2018). The experiment in controlled conditions was carried out in a greenhouse with air conditioning (25 ± 4°C, 70 ± 10% RH and natural light). The field study, on the other hand, was conducted in a 0.5-hectare plot size with a planting density of 18 seeds per meter and a row spacing of 90 cm. While no control was implemented for insect infestations, invasive plants were managed through herbicide applications, and fungicides were used to control plant pathogens following the recommended practices for peanut crop (Costa et al. 2019).

2.2. Greenhouse experiment

Peanut plants were planted in 5-litre pots containing a mixture of soil, sand, and bovine manure in a 2:1:1 ratio. No pest or disease control chemicals were applied during plant growth. Irrigation was provided according to the needs of the plants, with the same watering amount given to each plant.

The insects used in this study were collected from an experimental peanut farm at the Faculty of Agricultural and Veterinary Sciences – UNESP, Jaboticabal, São Paulo, Brazil. The collection process involved manually removing closed leaflets from peanut plants, after confirming the presence of *E. enigmaticus* and *S. bosqueella*. The leaflets were then stored in flat-bottomed glass tubes (8.5 cm × 2 cm) covered with polyvinyl chloride (PVC) film. These tubes were placed in Styrofoam boxes containing ice and transported to the laboratory for insect counting and individualization. After individualization, the insects were placed in Petri dishes (2 cm height × 6.5 cm diameter) containing fresh peanut leaflets under controlled conditions (12 h:12D photoperiod, 25 ± 2°C, and 60 ± 10% RH) and were transferred to the greenhouse on the same day. Double sheets of moistened filter paper, along with hydrophilic cotton, were placed inside the dishes to maintain leaf turgidity.

The youngest leaf on the main stem of peanut plants at 45 days after planting (DAP) was selected for insect infestation. To minimize stress on the insects and reduce the risk of mortality, they were carefully transferred using a thin camel-hair brush, placing them directly between the closed leaflets of the plant. Shortly after transfer, the insects were observed walking, confirming the effectiveness of this method for establishing plant infestation. Four treatments were evaluated: (1) infestation with only *S. bosqueella*; (2) infestation with *E. enigmaticus*; (3) infestation of *S. bosqueella* together with *E. enigmaticus*; and (4) the control treatment (healthy plant). Five replicates were used for each treatment, and the experiment was conducted in a randomized block design.

Data collection occurred 60 DAP to align with the peak period of insect infestation in the field, as this is when the highest levels of infestation typically occur (Pinto & Fernandes unpublished data), using the Parrot Sequoia® multispectral sensor (Sensefly/Parrot Group, Cheseaux-sur-Lausanne, Switzerland). This sensor records the spectral response in the green (550 nm), red (660 nm), red edge (735 nm), and near infrared (790 nm) bands. The sensor was attached to a metal support to standardize image collection at a height of 0.8 to 0.9 meters above the plant canopy during image capture. The images were collected in a predefined time window (early hours of the day, 8:00–10:00 AM). Luminosity correction was performed using a reflectance board following manufacturer's recommendations (SenseFly 2017). After data acquisition, the images were analysed using the Spectronon ProTM software (Resonon, Bozeman, U.S.A.). Here, regions of interest (ROIs, areas on the image corresponding to specific plant samples) were selected manually to ensure greater data homogeneity and extract spectral responses from the different multispectral sensor bands. The vegetation indices were then determined to compare leaf reflectance with the presence or absence of lesions.

2.3. Field-sampling procedures

Field data collection was conducted 60 DAP using an UAV, the eBee SQ (Sensefly/Parrot Group, Cheseaux-sur-Lausanne, Switzerland), equipped with a Parrot Sequoia®

multispectral sensor (Sensefly/Parrot Group, Cheseaux-sur-Lausanne, Switzerland), with green (550 nm ±40 nm), red (660 nm ±40 nm), red-edge (735 nm ±10 nm) and near infrared (790 nm ±40 nm) range bands. In the field, a randomized block design with four treatments and four replications was adopted. Each treatment block consisted in a random selected area of 5×5 m (25 m^2). Within each block, a plant survey was conducted on individual plants, with each sample consisting of a single plant identified and classified according to the symptoms: (1) infestation with only *S. bosqueella*; (2) infestation with *E. enigmaticus*; (3) infestation of *S. bosqueella* together with *E. enigmaticus*; and (4) the control treatment (healthy plant). These infestations mirrored those used in the greenhouse experiment.

To achieve accurate georeferencing of the samples for later identification in aerial images, a mobile GNSS receiver (Global Navigation Satellite System) model R6® (Trimble, Sunnyvale, CA, U.S.A.) was used. This receiver exchanged information with a fixed antenna with a known position and georeference based on the Datum SIRGAS2000 (Geocentric Reference System for the Americas) using the Stop and Go positioning method, post-processed. This equipment and method were also used for georeferencing control points on the ground, later employed in generating the orthomosaic of the study area.

Data collection then proceeded at four flight heights: 80 m, 120 m, 200 m, and 400 m, resulting in geometric resolutions (Ground Sample Distance – GSD) of 7.5 cm, 11.3 cm, 18.8 cm, and 37.7 cm, respectively. There was no influence of clouds observed during image acquisition. Based on the collected images, orthorectified controlled mosaics from the experimental area were generated using Pix4Dmapper software (Pix4D/Parrot Group, Cheseaux-sur-Lausanne, Switzerland). Reflectance values from the different bands were then extracted from the orthomosaic, and the vegetation indices were calculated.

2.4. Data analysis

Five vegetation indices (IRVI, NDVI, NDRE, GRVI, and GCI) identified in the literature (Table 1) were calculated to investigate relationships between their values and the different types of pest damage in peanut plants. These indices were selected based on previous findings by J. Pinto et al. (2020), which highlighted the importance of the NIR portion of the spectrum for injury detection in peanut, as well as their proven effectiveness in detecting vegetation stress, particularly in response to environmental factors and pest damage. The IRVI index was chosen for its sensitivity to plant stress and its ability to differentiate between healthy and stressed vegetation;

Table 1. Spectral vegetation indices used to quantify the different symptoms in peanut growing in greenhouse and field conditions.

Index	Abreviation	Equation	Reference
Inverse Ratio Vegetation Index	IRVI	*rRED/rNIR*	Richardson and Wiegand (1977)
Normalized Difference Vegetation Index	NDVI	*(rNIR – rRED)/(rNIR + rRED)*	Rouse et al. (1974)
Normalized Difference Red Edge Index	NDRE	*(rNIR – rRED-edge)/(rNIR + rRED-edge)*	Gitelson and Merzlyak (1994)
Green-Red Vegetation Index – GRVI	GRVI	*(rGREEN – rRED)/(rGREEN + rRED)*	Tucker (1979)
Green Chlorophyll Index	GCI	*(rNIR/rGREEN) – 1*	Gitelson et al. (2003)

NDVI, a widely used index, was included for its reliability in monitoring vegetation health and distinguishing between healthy and stressed plants; NDRE was selected for its sensitivity to chlorophyll content and its ability to detect subtle changes in plant health, which is crucial for identifying early-stage pest damage; GRVI was chosen for its effectiveness in detecting differences in plant health based on the green and red regions of the spectrum, highlighting pest-induced stress; and GCI was included due to its strong correlation with chlorophyll content, providing insights into photosynthetic activity that can be impacted by pest damage. This analysis was conducted for both the greenhouse images and the field-derived orthomosaics to compare how these indices perform in different environments and under varying pest damage scenarios.

The effects of treatments (pest types and their injuries), flight heights, and their interaction were analysed using mixed linear models (PROC MIXED; SAS Institute, 2015) with a significance level of $\alpha = 0.05$. Additionally, to assess treatment effects at each flight height, ANOVAs were performed, followed by Tukey's HSD (Honestly Significant Difference) test for multiple comparisons of means ($\alpha = 0.05$) using PROC MIXED (SAS Institute, 2015).

3. Results

3.1. Greenhouse experiment

The NDRE, GCI, IRVI, and NDVI indices were not effective in identifying plants infested by either *E. enigmaticus* or *S. bosqueella* (Figure 1). In contrast, the GRVI index successfully distinguished infested plants from non-infested ones. Notably, the spectral response in the combined infestation treatment (*E. enigmaticus* + *S. bosqueella*) closely resembled that of the *E. enigmaticus*-only treatment for all vegetation indices evaluated (Figure 2).

Across treatments, uninfested peanut plants exhibited higher reflectance in the red edge (735 nm) and near-infrared (750–800 nm) regions compared to infested plants, which displayed similar spectral patterns characterized by reduced reflectance in these regions (Figure 2 and 3). In the visible spectrum (500–700 nm), all treatments demonstrated a consistent pattern of relatively low and uniform reflectance across wavelengths.

3.2. Field

Our results show that the vegetation indices were only effective in differentiating peanut plants with symptoms caused by *E. enigmaticus* and these identifications varied depending on the flight height (Table 2). Also, there was no significant interaction between symptom type and flight heights, indicating that the spectral response is influenced by these factors independently (Table 2).

The IRVI and NDVI indices allowed identification of *E. enigmaticus* infestation, but only in peanut plants at flight heights of 80 and 120 meters (resolutions of 7.5 and 11.3 cm). The GCI index also allowed identification of *E. enigmaticus* infestation only at flight heights of 80 and 120 meters (7.5 and 11.3 cm GSD). The NDRE index could

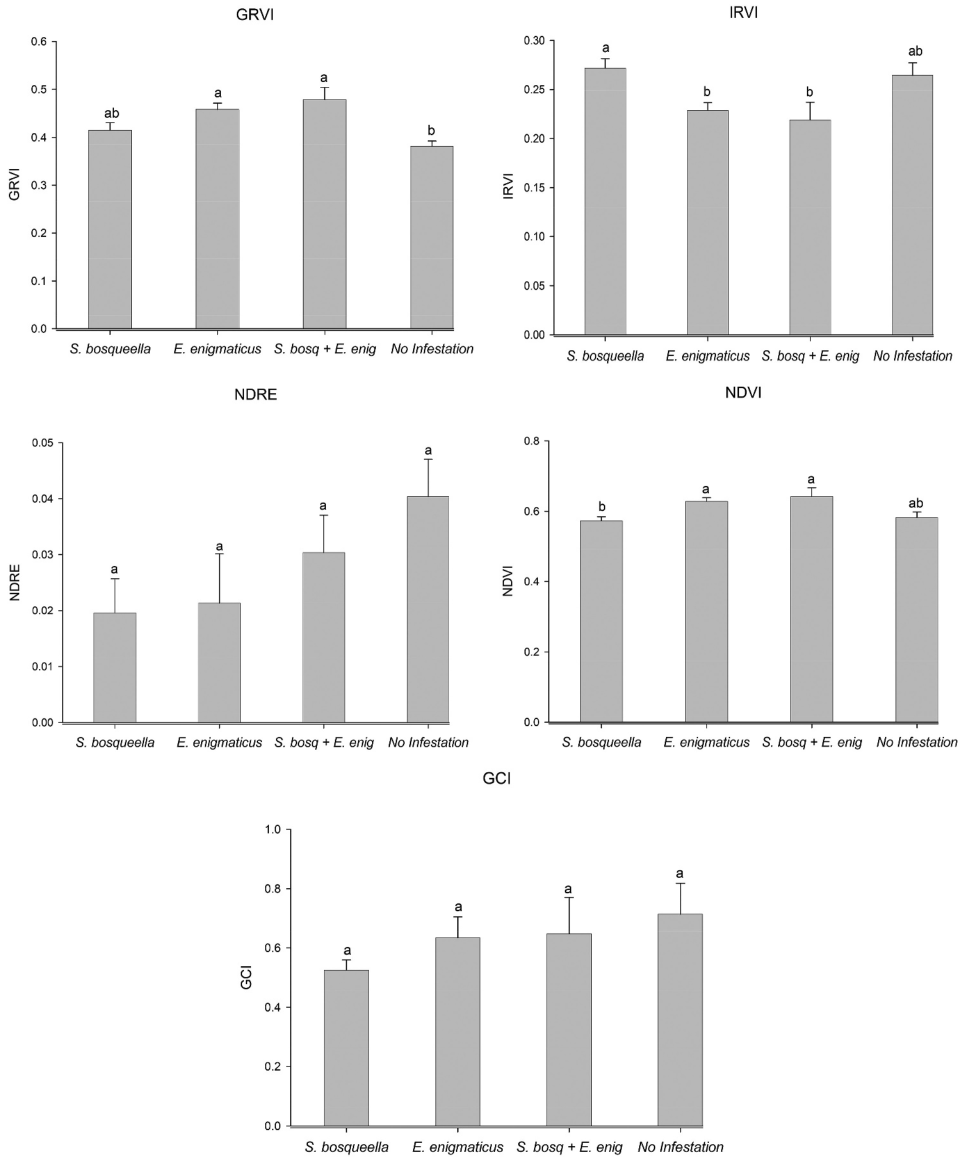

Figure 1. Vegetation indices adopted to classify the different types of infestation in peanut plants grown in a greenhouse condition.

only identify plants infested by *E. enigmaticus* at the 80-meter height (7.5 cm GSD). For the GRVI index, identification of *E. enigmaticus* infestation was possible at flight heights of 80, 120, and 200 m (7.5, 11.3, and 18.8 cm GSD). We observed that the vegetation indices IRVI, NDVI, NDRE, GRVI, and GCI were relatively consistent across different flight heights (Table 3). Statistical analysis confirmed that there were no significant differences ($p < 0.05$) in vegetation index values within each treatment across different flight heights, except for the GRVI index in uninfested plants (lowercase in the row, Table 3).

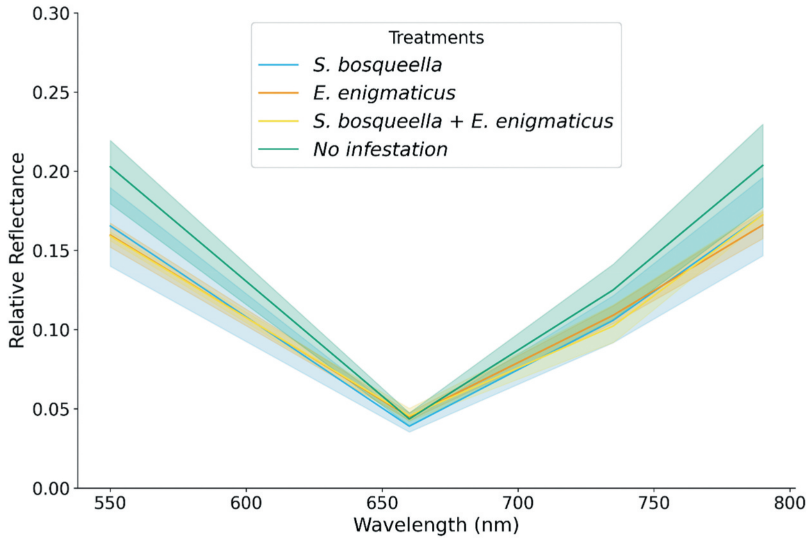

Figure 2. Spectral reflectance signature for infested and uninfested peanut plants in greenhouse conditions.

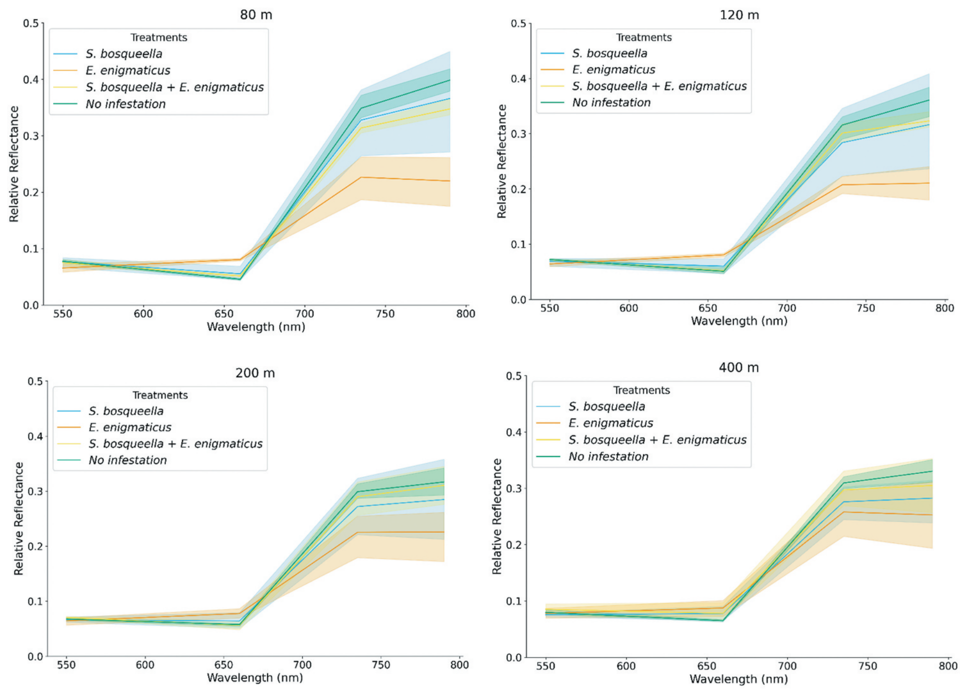

Figure 3. Spectral reflectance signature of infested and uninfested peanut plants in 80, 120, 200 and 400 metres flight heights in peanut fields.

Table 2. Factorial analyses between the vegetation indices evaluated vs. symptoms and unmanned aircraft systems flight height.

Vegetation index	Factor	F-value	p-value
IRVI	Infestation type	24.02	<.0001
	height	2.67	0.0589
	Infestation x height	0.50	0.8678
NDVI	Infestation type	26.34	<.0001
	height	3.65	0.0194
	Infestation x height	0.74	0.6699
NDRE	Infestation type	11.14	<.0001
	height	3.74	0.0175
	Infestation x height	0.74	0.6670
GRVI	Infestation type	21.70	<.0001
	height	4.27	0.0099
	Infestation x height	1.19	0.3247
GCI	Infestation type	19.62	<.0001
	height	4.18	0.0108
	Infestation x height	1.31	0.2590

Similar to the greenhouse study results, uninfested plants showed higher reflectance in the red edge and NIR portion of the electromagnetic spectrum (Figure 3) at all flight heights (80, 120, 200, and 400 m). In contrast, plants infested with *E. enigmaticus* reduced the plant's ability to reflect NIR light. The extent of this impact is evident as it consistently shows lower reflectance at different flight altitudes.

4. Discussion

This study demonstrates that UAS equipped with multispectral sensors can effectively detect insect damage in peanut crops when operated at flight heights of 80 and 120 meters, corresponding to GSD of 7.5 and 11.3 centimetres, respectively. The GRVI index successfully distinguished plants infested by *E. enigmaticus* from non-infested plants. This finding was consistent across controlled greenhouse and field conditions. Remote sensing techniques have proven valuable for insect detection in various crops (Backoulou et al. 2011; Marston et al. 2020; Sudbrink et al. 2003), in plant-disease detection (Chen et al. 2019) and other stresses related to peanut crop (Carley et al. 2018). However, information on UAS-based insect detection specifically in peanuts remained scarce. This pioneering study establishes a benchmark for UAS flight heights for insect damage detection in peanuts using multispectral sensors. This information can be used to guide further research and applications of this technology.

Our findings indicate that effective insect damage detection in peanut crops using UAS equipped with multispectral sensors requires flight heights of 80 or 120 metres (7.5 and 11.3 cm GSD, respectively). While these specific heights may be impractical in situations with obstacles, they fall within the regulatory flight limits established by agencies like Brazil's National Civil Aviation Agency (ANAC 2020) and the Federal Aviation Administration (FAA) in the United States (Dorr and Duquette 2016). Detection performance decreased significantly at higher flight heights (200 and 400 metres, corresponding to resolutions of 18.8 and 37.7 cm), likely because pixel size is a critical factor in pest infestation detection, as previously observed in other studies (Hunt and Rondon 2017). This decrease in performance may also be attributed to the relatively small canopy size of peanut plants. A higher GSD reduces the ability to capture fine-scale spectral variations

Table 3. Interaction deployment between different types of symptoms versus flight height of an unmanned aerial systems-based remote sensing in peanut crop.

Vegetation index	Treatments	Flight Heights 80 m	120 m	200 m	400 m	F(D)	P(D)
IRVI	*S. bosqueella*	0.17 ± 0.06 Ba	0.22 ± 0.067 Ba	0.26 ± 0.067 ABa	0.29 ± 0.05 ABa	1.44	0.2450
	E. enigmaticus	0.39 ± 0.05 Aa	0.39 ± 0.04 Aa	0.38 ± 0.09 Aa	0.38 ± 0.1 Aa	0.04	0.9893
	S. bosqueella + *E. enigmaticus*	0.15 ± 0.002 Ba	0.16 ± 0.01 Ba	0.19 ± 0.03 Ba	0.27 ± 0.06 ABa	1.80	0.1603
	No infestation	0.11 ± 0.0004 Ba	0.14 ± 0.02 Ba	0.18 ± 0.01 Ba	0.20 ± 0.01 Ba	0.89	0.4558
	F	9.12	7.99	4.96	3.43	–	–
	P	<.0001*	0.0002*	0.0046*	0.0247*	–	–
NDVI	*S. bosqueella*	0.71 ± 0.08 Aa	0.65 ± 0.08 Aa	0.60 ± 0.09 ABa	0.56 ± 0.06 ABa	2.00	0.1280
	E. enigmaticus	0.45 ± 0.05 Ba	0.44 ± 0.04 Ba	0.47 ± 0.08 Ba	0.47 ± 0.09 Ba	0.10	0.9595
	S. bosqueella + *E. enigmaticus*	0.74 ± 0.004 Aa	0.72 ± 0.02 Aa	0.69 ± 0.04 Aa	0.59 ± 0.07 ABa	2.27	0.0935
	No infestation	0.79 ± 0.001 Aa	0.75 ± 0.03 Aa	0.69 ± 0.019 Aa	0.67 ± 0.01 Aa	1.51	0.2258
	F	10.96	9.29	5.02	3.29	-	-
	P	<.0001*	<.0001*	0.0044*	0.0290*	–	–
NDRE	*S. bosqueella*	0.06 ± 0.02 Aa	0.05 ± 0.02 ABa	0.014 ± 0.02 Aa	0.009 ± 0.01 Aa	1.94	0.1360
	E. enigmaticus	−0.02 ± 0.03 Ba	0.002 ± 0.02 Ba	−0.003 ± 0.01Aa	−0.02 ± 0.02 Aa	0.54	0.6584
	S. bosqueella + *E. enigmaticus*	0.05 ± 0.01 Aa	0.03 ± 0.01 ABa	0.03 ± 0.01 Aa	0.01 ± 0.02 Aa	1.32	0.2788
	No infestation	0.07 ± 0.005 Aa	0.07 ± 0.004 Aa	0.03 ± 0.01 Aa	0.03 ± 0.008 Aa	2.17	0.1050
	F	6.90	3.43	1.22	1.82	–	–
	P	0.0006*	0.0247*	0.3129	0.1575	–	–
GRVI	*S. bosqueella*	0.17 ± 0.09 Aa	0.07 ± 0.09 ABab	0.03 ± 0.08 ABab	−0.008 ± 0.05 Ab	2.78	0.0524
	E. enigmaticus	−0.10 ± 0.03 Ba	−0.12 ± 0.03 Ba	−0.09 ± 0.06 Ba	−0.05 ± 0.07 Aa	0.30	0.8273
	S. bosqueella + *E. enigmaticus*	0.19 ± 0.01 Aa	0.16 ± 0.02 Aa	0.12 ± 0.04 Aa	0.05 ± 0.05 Aa	1.66	0.1884
	No infestation	0.26 ± 0.005 Aa	0.18 ± 0.04 Aab	0.08 ± 0.02 Ab	0.10 ± 0.02 Aab	3.13	0.0349*
	F	12.20	6.74	3.94	2.18	–	–
	P	<.0001*	0.0008*	0.0142*	0.1044	–	–
GCI	*S. bosqueella*	3.69 ± 0.44 Aa	3.51 ± 0.50 Aa	3.21 ± 0.49 ABa	2.73 ± 0.25 Aa	1.78	0.1636
	E. enigmaticus	2.32 ± 0.24 Ba	1.42 ± 0.70 Ba	2.46 ± 0.27 Ba	2.22 ± 0.34 Aa	2.20	0.1014
	S. bosqueella + *E. enigmaticus*	3.64 ± 0.11 Aa	3.49 ± 0.17 Aa	3.40 ± 0.27 ABa	2.61 ± 0.34 Aa	2.15	0.1068
	No infestation	4.1 ± 0.078 Aa	3.99 ± 0.15 Aa	3.67 ± 0.17 Aa	3.14 ± 0.10 Aa	1.97	0.1324
	F	6.19	13.19	2.71	1.45	–	–
	P	0.0013*	<.0001*	0.0559	0.2414	–	–

Means followed by different letters, uppercase in the column and lowercase in the row, differ significantly from each other by Tukey's test ($p < 0.05$) * significant data.

associated with individual plant responses to pest damage, potentially hindering the accurate identification of infested plants and compromising detection effectiveness. By contrast, crops with larger canopies or leaves may yield better results, as their size provides more distinct spectral information, facilitating differentiation between infested and non-infested plants. Additionally, the practical implications of these findings for large-scale agricultural monitoring include a trade-off between detection accuracy and coverage area. Lower flight heights improve detection accuracy but require more time to capture and analyse imagery due to the smaller coverage area per flight. This could be a logistical and operational challenge for monitoring large fields. To balance this trade-off, we suggest careful planning of flight schedules and leveraging efficient processing workflows to ensure timely and accurate assessments while managing operational costs.

The configuration of the spectral reflectance curve revealed the spectral characteristics of the different treatments and indicated the wavelengths for recording data to detect symptoms caused by *E. enigmaticus* and *S. bosqueella* in peanut plants. The analysis of both spectral curves (field and greenhouse) allowed for clear differentiation between healthy and *E. enigmaticus*-infested plants only. This is likely related to the nature of the injury caused by this insect. *Enneothrips enigmaticus* feeds on developing plant tissues (young, closed leaflets), interfering with cell growth and altering leaf morphology. The affected tissue becomes filled with air, giving it a silvery appearance (Jager et al. 1993), which is visible mainly when leaflets are open. Thus, as biotic stress implies changes in leaf reflectance (Prabhakar, Prasad, and Rao 2012) and these changes result in distinct spectral signatures (Liu, Lee, and Singh Chahl 2017), the reduced reflectance in the red edge (735 nm) and near-infrared (790 nm) wavelengths could be identified.

The reduced reflectance in the red edge region (680–760 nm) is typically associated with two factors: chlorophyll absorption and strong light scattering by the internal cell structure of leaves (Gausman 1985). In the case of *E. enigmaticus* infestation, the observed changes in the near-infrared region are likely linked to cellular alterations within the damaged tissues (Ray et al. 1993). This phenomenon of altered reflectance in the infrared region due to thrip infestation has also been documented in various plant species, including sugarcane (Abdel-Rahman et al. 2010) and cotton (Ranjitha and Srinivasan 2014).

Symptoms caused by *S. bosqueella* feeding are typically localized, affecting specific areas of the plant canopy rather than the entire plant. However, it is important to note that damage caused by this insect can lead to apical meristem injury, which impacts vine growth and, consequently, yield. Longer vines produce more flowers and, therefore, more pods. Canopy reflectance spectra, on the other hand, represent an integrated measure of the optical properties of the entire canopy, combining biophysical and biochemical attributes along with sensor geometry, lighting conditions, and background effects (Asner 1998; Barrett and Curtis 1976; Goel 1988; Myneni, Ross, and Asrar 1989). In this case, the presence of healthy leaf biomass in the *S. bosqueella*-infested plants likely masked the damaged areas, which remained undetected by the sensor due to their limited distribution in the plant. As a result, the vegetation indices obtained were statistically similar to those of the control (uninfested) treatment. This is consistent with the findings of Pinto et al. (2020), who observed that *S. bosqueella* herbivory had a minimal impact on peanut gas exchange and leaf reflectance, with photosynthetic rates comparable to those of the control.

Interestingly, plants suffering from combined infestation by both *S. bosqueella* and *E. enigmaticus* exhibited an increased reflectance in the visible spectrum range. This could be linked to a decrease in chlorophyll content. Conversely, a decrease in near-infrared reflectance was observed, potentially associated with alterations in the internal leaf structure. This spectral response is characteristic of biotic stress in plants (P. L. Hatfield and Pinter 1993). Notably, this pattern was consistent across both controlled and field conditions, highlighting the robustness of the data obtained. In practical agricultural systems, it is common for multiple insect species to infest the same plant simultaneously. This understanding guided our decision to test the combined infestation of *S. bosqueella* and *E. enigmaticus*, the most abundant pest species affecting peanut crops in Brazil. By addressing their combined effects, these results gain relevance under field conditions, where interactions between multiple pest species and their impact on host plants reflect real-world scenarios. However, further studies, particularly in other locations, are needed to evaluate how different pest species, both individually and in combination, influence peanut reflectance. Such investigations will deepen our understanding of pest-specific and combined stress signatures and support the development of more robust and practical monitoring tools for agricultural systems.

The GRVI vegetation index effectively identified peanut plants infested by *E. enigmaticus* in both under controlled (greenhouse) and field conditions. The effectiveness of vegetation indices in various agronomic applications is well documented, with studies reporting satisfactory results in field settings (Lima-Cueto et al. 2019; Wu 2014; Zerbato et al. 2016). We hypothesize that GRVI performed better than other indices because of its sensitivity to changes in the green and red spectral regions, which are directly influenced by pest-induced stress. This combination may provide a more precise signal for detecting biotic stress in smaller plants like peanuts, compared to indices that rely more heavily on NIR or red-edge reflectance, which could be less responsive to the specific stress caused by *E. enigmaticus*.

This study demonstrates the potential of UAS equipped with multispectral sensors for detecting insect damage in peanut crops. We successfully identified infestations caused by *E. enigmaticus* at specific flight heights. However, as a pioneering study, further research is warranted to establish broader applicability. Future investigations should encompass: (1) validation across diverse locations and growth stages: Natural plant growth processes (biomass accumulation, development, senescence, architecture, pigment concentrations) influence reflectance properties (Carter 1993; Lillesand and Kiefer 1994) and could change between the regions; (2) characterization of the responses of peanut plants to *E. enigmaticus* infestation through gas exchange parameters and multi-/hyperspectral remote sensing imagery. This can potentially enable the development of early detection methods, prior to the onset of visible symptoms. Early detection is crucial for effectively integrating remote sensing into IPM programmes for peanuts. By addressing these knowledge gaps, we can facilitate the routine application of UAS in peanut pest management, promoting a more sustainable and precise approach.

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Data availability statement

Data can be obtained by contacting the corresponding authors.

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