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Orbital multispectral imaging: a tool for discriminating management strategies for nematodes in coffee

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Abstract
Background Remote sensing based on multispectral imaging may be useful for detecting vegetation stress responses in agriculture.
Objectives To evaluate the potential of orbital multispectral imaging in discriminating the most effective strategies for reducing plant-parasitic nematode populations, thereby preventing yield losses in coffee production.
Methods Coffee plants were treated with eleven treatments, including Bacillus spp. isolates, commercial biological products, commercial chemical nematicides, and water (control group). Initial and final nematode populations in the soil were quantified, and surface reflectance data were collected using the Planet orbital multispectral sensor. The data were classified using the random tree algorithm.
Results The population of plant-parasitic nematodes was reduced by 35.90% and 55.13% following the application of B. amyloliquefaciens isolate B266 and B. subtilis isolate B33, respectively. Under the conditions of this experiment, multispectral imaging accurately discriminated the most nematicidal treatments, with a global accuracy of 80%.
Conclusions Orbital multispectral imaging can discriminate the most effective treatments used for nematode management in coffee plants, highlighting its potential as a supportive tool in agriculture.

Keywords *Bacillus* spp · Biological control · Machine learning · Pest management · Remote sensing

Introduction

Biophysical analysis of vegetation by remote sensing is a non-destructive and sustainable approach with a wide range of uses in agriculture (Ponzoni et al., 2012; Formaggio & Sanches, 2017; Ali et al., 2019). Attack by pests and pathogens alters the reflectance of the vegetation canopy due to nutritional imbalances in the plant, and changes in the spectral

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response of plants can be detected by remote sensors (Ponzoni et al., 2012; Martins et al., 2017). Plant-parasitic nematodes infect coffee roots and impair plant development (Oliveira & Rosa, 2018). The greater the density of nematodes parasitizing the roots, the greater the damage and the reflex symptoms in the aerial parts of the plants. Thus, remote sensing may be used to monitor different levels of severity of nematodes on coffee plantations (Martins, 2016; Martins et al., 2017).

The management of plant-parasitic nematodes may require the use of various strategies, including preventive practices, crop rotation, the use of antagonistic plants, host resistance, fallow, physical methods, and the application of chemical and/or biological nematicides (Coyne et al., 2018). The cleaning of equipment and the use of planting materials free of nematodes are the main procedures used to hinder the dispersion of these pathogens (Ferraz et al., 2010). Fallow and solarization are useful control methods for nematodes but must be adopted before coffee planting. Crop rotation and the use of antagonistic plants are two of the most important approaches to control plant-parasitic nematodes, although they have limited value for perennial crops such as coffee. The number of high yielding nematode-resistant cultivars for coffee growers in Brazil is limited (Oliveira & Rosa, 2018). When susceptible coffee cultivars are cultivated in nematode-infested soils, the main control methods are the application of chemical and biological nematicides. Due to the health and environmental risks associated with chemical nematicides, biological control agents have been increasingly used for nematode management under tropical conditions (Tolardo et al., 2019).

Bacteria of the genus *Bacillus* are widely used as biological control agents for plant pathogens (Hashem et al., 2019; Mhatre et al., 2019). A wide range of antagonistic compounds produced by *Bacillus* species can suppress different stages of the nematode life cycle, especially survival as eggs or active dispersion and penetration into host roots as juveniles or adults (Liu et al., 2013; Bruzos & Grayston, 2019; Mhatre et al., 2019). *Bacillus*-based formulations have been used for nematode control in soybean (Kang et al., 2020), common bean (Fernandes et al., 2013), tomato (Fernandes et al., 2014), and coffee (Tolardo et al., 2019).

In general, the assessment of the efficacy of bioproducts and chemical nematicides relies on analyses of soil and plants, which may be laborious, time-consuming, and expensive. Since coffee plants infected by nematodes have a spectral variation in their leaves (Martins et al., 2017), remote sensing may be used to detect and map nematode-infected plants in the field under controlled experimental conditions. In this case, orbital multispectral imaging may discriminate plant responses to different management approaches.

This study proposes that multispectral imaging can distinguish the effectiveness of chemical and biological nematicides in coffee plantations under field conditions. To validate this hypothesis, the research aims to assess the capability of orbital multispectral imaging to differentiate between strategies aimed at reducing populations of plant-parasitic nematodes on a commercial scale.

Materials and methods

The steps of this work were carefully defined to evaluate the performance of orbital multispectral image in the discrimination of more nematicidal treatments. The overall framework of the research is shown in Fig. 1.

Experimental conditions

The study was carried out in the municipality of Monte Carmelo, MG, Brazil (18°41′59″S, 47° 33′53″W; 826 m altitude, Tropical climate with dry winters) in an area of 15,113 m^2 with 55 plots cultivated with *Coffea arabica* L. cultivar "Bourbon Amarelo" and drip irrigated (Fig. 2). The plantation was established in 2013, with a spacing of 3.8 m between rows and 0.7 m between plants. The experimental area, plots, and plants were georeferenced using centimeter-accuracy coordinates obtained with Topcon HiPer V dual-frequency GNSS receivers (L1/L2) through real-time kinematic (RTK) positioning. Flags and ribbons were set to identify the plants to be assessed throughout the experiment.

This study consisted of three field stages. In the first stage, held in the week of September 23, 2019, soil samples were collected to determine the initial populations of total plant-parasitic nematodes and the first application of the chemical and biological nematicides was performed. The second stage was carried out in the week of November 25, 2019, with the second application of treatments. In the week of March 12th, 2020, the third stage was carried out, with the acquisition of orbital image and the collection of soil samples to determine the final populations of plant-parasitic nematodes per plot. The method for evaluating nematode populations will be detailed in the nematological analysis section.

The corresponding dates have been chosen due to the ideal conditions observed at this time of year for the life cycle of nematodes: phytonematodes are obligate parasites and need metabolically active roots to fully develop their life cycle. Soil temperatures between 25 °C and 30 °C and soil moisture between 40% and 60% of field capacity (when all soil micropores are filled with water) are ideal for nematode development.

It should be noted that drip irrigation (the irrigation system implemented in the plot of this experiment) only provides enough water to keep the coffee plants turgid and with sufficient metabolism to pass stress phases (between May and September). Only when the rainy

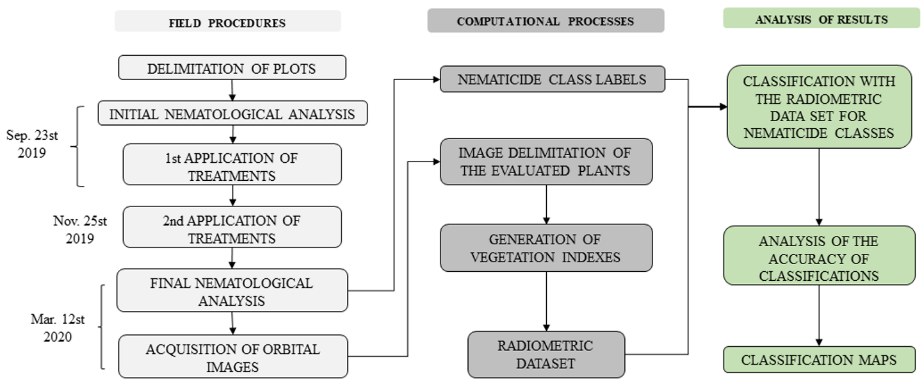

Fig. 1 Overall flowchart of methodology

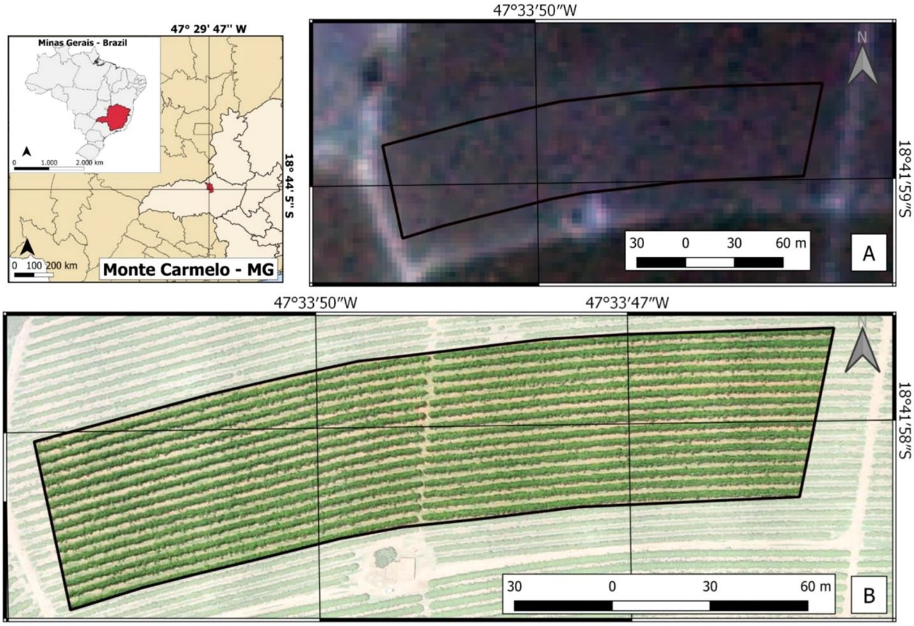

Fig. 2 Location of the experimental field in Monte Carmelo, Minas Gerais, Brazil. In (**A**) the analyzed orbital image of the Planet sensor.In (**B**) the area is represented in an aerial image

season begins (beginning of September for the Cerrado region of Minas Gerais), conditions become favorable for nematodes.

Biological and chemical treatments

The experiment was arranged in a randomized design with 11 treatments and five replicates (Fig. 3), with each experimental plot consisting of 28 plants, with two plants at each end used as buffer zone. All bacterial isolates and commercial products were applied on the soil surface on both sides of each plant using a backpack sprayer. A spray volume of 500 L ha^{-1} was used and covered a 50-cm-wide band under the plant canopy. The organic materials present on the soil surface, such as leaves and small branches, were removed before the application and replaced after the soil treatment.

For the management of plant-parasitic nematodes, coffee plants were treated with seven *Bacillus* isolates separately (*B. subtilis* isolates B18, B202 and B33; *B. thuringiensis* isolate B22; *B. safensis* isolate B53; *B. amyloliquefaciens* isolate B266; *Bacillus methylotrophicus* isolate B05). The isolates belong to the Laboratory of Microbiology and Plant Pathology of the Federal University of Uberlândia – Campus Monte Carmelo and were applied at a dose of 4 L ha^{-1} and with a concentration of 1×10^9 CFU (colony forming unit) mL^{-1}. In addition, in isolated plots the plants were treated with a commercial biological product based on *B. subtilis* + *B. licheniformis* (CB – commercial biological treatment; dose of 300 g of product ha^{-1}); combined application of abamectin (dose of 375 mL ha^{-1}) (first application) + application of commercial biological product based on *B. subtilis* + *B. licheniformis* (dose of 300 g of product ha^{-1}) (second application) (CCB - commercial chemical and biological

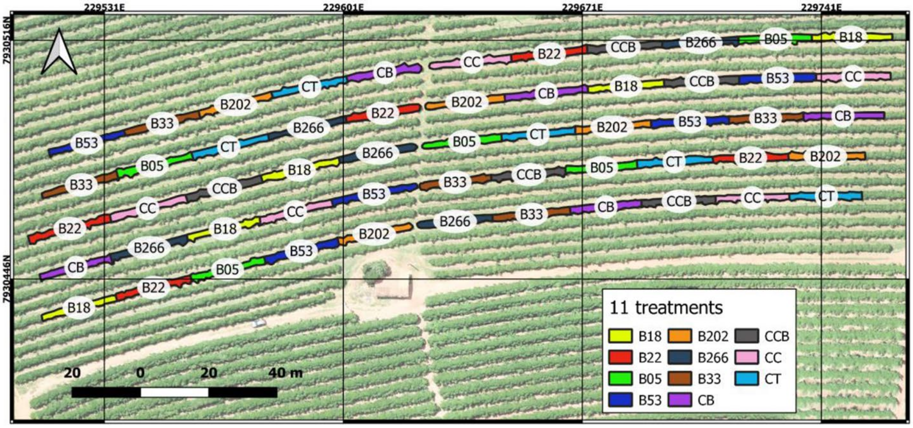

Fig. 3 Distribution of treatments in the experimental field. CB - commercial biological treatment; CCB - commercial chemical and biological treatment; CC - commercial chemical treatment; CT – control treatment

treatment); and a commercial chemical nematicide based on fluensulfone (CC – commercial chemical treatment; dose of 2 L ha^{-1}). Water was applied as a control (CT – Control treatment).

Non-commercial bacterial isolates were streaked onto Petri dishes containing solid medium 523 (Kado & Heskett, 1970) and incubated at 25 °C for 48 h. After that, 1 cm³ of the colonized medium was transferred to 250 mL conical flasks containing liquid medium 523. The flasks were shaken at 25 ± 2 °C and 150 rpm for 5 days in the dark. The bacterial suspensions adjusted to OD 600 = 1.8 corresponding to approximately 1×10^9 CFU mL^{-1}. The choice of this concentration was based on liquid formulations of commercial products based on *Bacillus* spp.

Nematological analysis

Soil samples were collected on September 23, 2019 (initial population) and March 12th, 2020 (final population). Approximately 150 cm^3 of soil was collected from the rhizosphere (up to 20 cm deep) of the central plant of each experimental plot. In the laboratory, nematodes were extracted by the centrifugal flotation method (Jenkins, 1964). The experimental area was initially infested on average with 247 J_2/150 cm^3 of soil of total nematodes (including genera *Pratylenchus*, *Meloidogyne*, *Rotylenchulus*), considering that the J_2 (second juvenile stage) is the infective stage of the nematode. Furthermore, in the area there is an annual calendar of insecticide and fungicide applications to control pests and diseases, however nematicides have not been applied for control.

The difference between the values of the final (March 12th, 2020) and initial (September 23, 2019) populations of plant-parasitic nematodes in each plot was used to evaluate the effectiveness of the treatments. The effects were classified into three categories based on the magnitude of the nematode population reduction. These categories are: high reduction of individuals (High effect) for reductions above 15%, moderate reduction or a slight increase of individuals (No effect) for reductions between 15% and increase up to 25%, and increase of individuals (Negative effect) for cases where the nematode population increased above 25%. These classifications were determined by comparing nematode reproduction factors based on the control treatment (CT), with specific limits defined to categorize the degree of reduction or increase in individuals.

Data processing

Acquisition of multispectral image

Orbital image was obtained from the Planet sensor on March 12th, 2020. The PS2 (telescope name) instrument was used from the PlanetScope constellation with a bayer-mask CCD sensor and a spatial resolution of 3 m. The spectral bands of this instrument are Blue (455–515 nm), Green (500–590 nm), Red (590–670 nm) and NIR (780–860 nm). This image has a surface reflectance product suitable for analytical and visual applications with a 3b processing level. The frame size was approximately 24 km x 8 km. The image was deposited in a repository (www.planet.com), after atmospheric and geometric corrections; that is, the pixels were orthorectified and presented in surface reflectance.

According to Planet imagery product specifications (2022), for atmospheric correction, atmospheric models are used using MODIS water vapour, ozone and aerosol data, providing reliable data and consistent surface reflectance scenes. Still according to Planet imagery specifications, the geometric corrections applied to this product correct optical distortions caused by optical sensors and band co-registration.

Vegetation indices

In order to better characterize each treatment, consolidated spectral indices of vegetation were calculated (Table 1). Vegetation indices are mathematical formulations used as an image processing technique to analyze the spectral behavior of vegetation reflectance, potentiating the discrimination of agricultural targets. In this study, vegetation indices designed to estimate vegetation biomass, plant vigor, and leaf pigments were used: NDVI – Normalized Difference Vegetation, VARI – Visible Atmospherically Resistant Index, ARVI – Atmospherically Resistant Vegetation Index, SR – Simple Ratio, CVI – Chlorophyll Vegetation Index, GNDVI – Green Normalized Difference Vegetation Index, MPRI – Modified Photochemical Reflectance Index, TGI – Green Triangular Index, and SIPI – Structure Insensitive Pigment Index.

Supervised classification using the random tree algorithm

To evaluate the potential of using images to discriminate between the most effective nematicidal treatments, a decision tree-based algorithm was applied, following the methodology outlined in remote sensing studies of coffee trees by Marin et al. (2021). Specifically, the study opted for the random tree algorithm over random forest, as indicated by Mishra and Ratha (2016), who found random tree classification to be marginally superior in certain contexts. The decision tree structured algorithm, such as random tree, was chosen for its ability to analyze multispectral or hyperspectral imagery data and classify different treatments based on their spectral signatures.

Table 1 Vegetation indices used in this study

Vegetation indices	Formula	Reference
NDVI	$\frac{(NIR-R)}{(NIR+R)}$	Rouse et al. (1974)
CVI	$NIR * \frac{R}{G^2}$	Vincini et al. (2008)
GNDVI	$\frac{(NIR-G)}{(NIR+G)}$	Gitelson et al. (1996)
MPRI	$\frac{(G-R)}{(G+R)}$	Yang et al. (2008)
VARI	$\frac{(G-R)}{(G+R-B)}$	Gitelson et al. (2002)
SR	$\frac{(R)}{(NIR)}$	Jordan (1969)
TGI	$G - (0{,}39 * R) - (0{,}61 * B)$	Hunt et al. (2011)
ARVI	$\frac{(NIR-(2*R)+B)}{(NIR+(2*R)+B)}$	Kaufman and Tanre (1992)
SIPI	$\frac{(NIR-B)}{(NIR-R)}$	Zarco-Tejada (2000)

NDVI (Normalized Difference Vegetation); CVI (Chlorophyll Vegetation Index); GNDVI (Green Normalized Difference Vegetation Index); MPRI (Modified Photochemical Reflectance Index); VARI (Visible Atmospherically Resistant Index); SR (Simple Ratio); TGI (Green Triangular Index); ARVI (Atmospherically Resistant Vegetation Index); SIPI (Structure Insensitive Pigment Index). R=red wavelength (590–670 nm); G=green wavelength (500–590 nm); B=blue wavelength (455–515 nm); NIR=near infrared wavelength (780–860 nm)

Machine learning techniques allow systematic processing and classification of remote sensing data. In this process, the operator identifies some of the pixels belonging to the desired classes, allowing the algorithm to locate the other pixels belonging to those classes. The overall processing is based on pre-established statistical rules, including the random tree algorithm, which is used when the dependent variable is qualitative (Kalmegh, 2015; Zanotta et al., 2019).

The data were subjected to cross-validation, with random division into 10 data sets (Dash, 2013; Kuhn & Johnson, 2013). After tests with empirical values, zero was assigned to the maximum depth of the random tree making it unlimited. Then, a model was adjusted using all samples, except for the first subset, so that at the end, all data were trained and tested by the random tree algorithm using the Weka 3.9.4 software (Witten & Frank, 2002).

The extraction of surface reflectance from the bands and spectral indices was performed for the three central plants of each plot, which were georeferenced and positioned on the Planet image, resulting in a data set of 165 sample elements (3 plants for each of the 55 plots). Segmentation and labeling of each sample element was performed using the ROI (Region of Interest) tool of the software Envi 5.0 (Exelis Visual Information Solutions, Boulder, Colorado).

Data mining was previously performed to select the best data sets for each classification. These sets are detailed below.

Classification of the most nematicidal treatments

The classification was performed with the objective of verifying the discrimination potential of the radiometric dataset of the orbital image. The radiometric dataset was composed of B, G, R, NIR bands and the vegetation indices NDVI, CVI, GNDVI, MPRI, VARI, SR, TGI, ARVI, and SIPI. The classes for nematode control were: High effect; No effect and Negative effect.

Classification accuracy analys

A confusion matrix was created to assess the accuracy of the classifications (Sartori et al., 2009; Martins et al., 2017). Errors of commission and omission of the confusion matrices were analyzed using the software Weka. The error of commission is the error of assigning a pixel to one class when it belongs to some other reference class (Eq. 1). The error of omission, as seen in Eq. 2, occurs when the pixels belonging to the reference class was not recognized by the classifier. Both equations are derived from the confusion matrix.

$$E_{co} = \frac{X_{+i} - X_{ii}}{X_{+i}} \tag{1}$$

Where E_{co} is the error of commission; X_{+i} is the sum of the column i of the confusion matrix; X_{ii} is the diagonal value of column i.

$$E_{o} = \frac{X_{i+} - X_{ii}}{X_{i+}} \tag{2}$$

Where $E_{o\ i}$ is the error of omission; X_{i+} is the sum of line i of the confusion matrix; X_{ii} = diagonal value of line i.

From the confusion matrix and using the software Weka, the global accuracy (%), which uses only the elements that express the real agreement (main diagonal of the matrix), and the Kappa coefficient (Cohen, 1960) (Eq. 3) was calculated. This later considers all elements of the confusion matrix in its calculation. The kappa index varies from 0 to 1. The higher its value, the better the classification.

$$Kappa = \frac{P_o - P_e}{1 - P_e} \tag{3}$$

Where Po is the relative observed agreement among raters, and Pe is the hypothetical probability of chance agreement.

The visual representations of the discrimination potential of the proposed methods, including image analysis, manual segmentation, and classification methods, were created using QGIS 3.12.2 software (QGIS Development Team, 2009). An aerial survey image from a conventional aerial sensor, chosen for its higher spatial resolution, was used as a reference for the maps to ensure accurate cartographic representation. The blue color was used to represent the correct classifications, while the wrong classifications were represented by the red color.

Results

Table 2 shows that treatments B33, B266, B202, CB and CCB had a reduction in plant parasitic nematode populations. Thus, treatments that resulted in reductions above 15% were classified as a high reduction of individuals and a high nematicidal effect. The highest reduction of nematodes was observed after soil treatment with *Bacillus subtilis* isolate B33 (−55.13), followed by *B. amyloliquefaciens* B266, *Bacillus subtilis* isolate 202, CB and CCB (Table 2). Treatments B18 and B53, which resulted in reductions of less than 15% and an increase in nematodes of less than 25%, were classified as having no effect. In the plots used as control (CT), a reduction of approximately 20% in the total number of nematodes was observed. This variation occurs naturally in field situations due to climatic changes affecting soil conditions, such as temperature and moisture fluctuations (Rani & Resha, 2018). The application of *B. subtilis* isolate B18 and *B. safensis* isolate B53 resulted in an ineffective treatment, similarly to the application of water (Table 2). Soil treatment with *B. thuringiensis* isolate B22, *B. methylotrophicus* isolate B05, and the chemical nematicide fluensulfone increased nematode populations by up to 56.41% (Table 2).

Using the random tree algorithm to classify the multispectral image from the Planet sensor, it was observed that the global accuracy and Kappa coefficient values were 80% and 0.68, respectively. The confusion matrix of the data from the orbital multispectral sensor revealed that the highest errors of omission (26.6%) and commission (23.2%) were observed for the negative effect class (Table 3). The best classification result was observed for the class with a high effect class (Table 3), with the lowest omission error (14.6%) and commission error (17.9%), indicating that the highest accuracy was achieved for the most nematicidal class.

Figure 4 depicts the classification results generated by the random tree algorithm. In the map, numerical values denote identified classes, where red signifies incorrect classifications and blue denotes correct classifications. The figure highlights areas where treatments were less effective or where there was an increase in nematode populations, which may be influenced by the natural spatial variability of the experimental field. In zones where treatments

Table 2 Effect of chemical and biological treatments on the population of plant-parasitic nematodes (PPN) in coffee plants under field conditions

Treatment	Reproduction factor (RF)[1]	% reduction (-) or increase (+) of RF[2]	Class
Bacillus subtilis isolate B33	0.35	−55.13	High effect
B. amyloliquefaciens isolate B266	0.50	−35.90	
B. subtilis isolate B202	0.51	−34.61	
B. subtilis + *B. licheniformis* (CB)	0.64	−17.95	
Abamectin + *B. subtilis* + *B. licheniformis* (CCB)	0.66	−15.38	
Water (CT)	0.78		No effect
B. subtilis isolate B18	0.79	+1.28	
B. safensis isolate B53	0.94	+20.51	
B. thuringiensis isolate B22	1.22	+56.41	Negative effect
B. methylotrophicus isolate B05	1.28	+64.10	
Fluensulfone (CC)	1.31	+67.95	

[1]Reproduction factor (RF = final population/initial population) for each treatment [2]Expressed as the percent difference between the reproduction factor in each treatment and the control (water)

Table 3 Confusion matrix of the nematode classes obtained from an orbital multispectral sensor

Class	High effect	No effect	Negative effect	$\sum$	E_o (%)
High effect	64	5	6	75	14.6
No effect	6	35	4	45	22.2
Negative effect	8	4	33	45	26.6
$\sum$	78	44	43	165	
E_{co} (%)	17.9	20.4	23.2		

Eco (%) = Error of commission. Eo = Error of omission

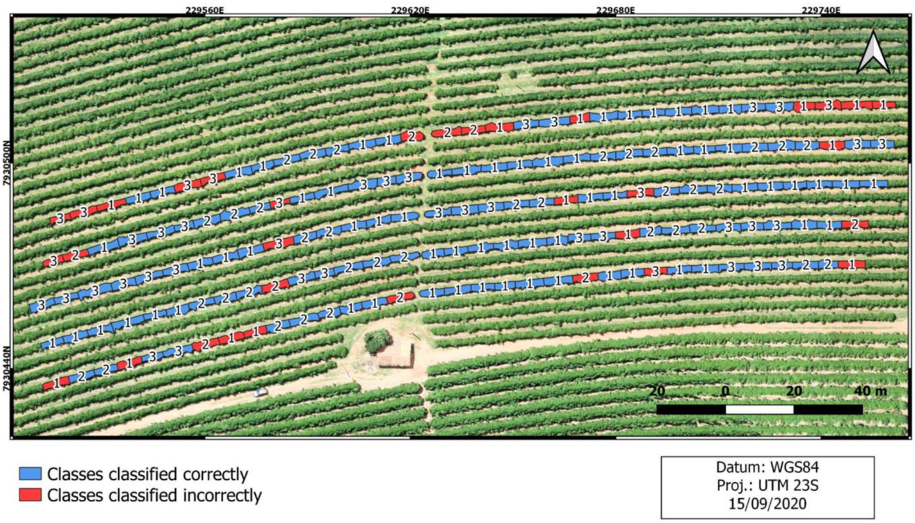

Fig. 4 Pictorial representation of the discrimination of nematicidal treatments by the random tree algorithm. Class 1 = high reduction of individuals (High effect); Class 2 = moderate reduction of individuals (No effect); Class 3 = increase of individuals (Negative effect)

were effective, these are concentrated in specific locations, showing that treatments with *B. subtilis* and other biological products had a significant impact on reducing nematodes.

Discussion

The study utilized orbital multispectral images to discriminate nematode management strategies in coffee plants. This non-destructive method provided a comprehensive view of plant responses to nematode stress compared to traditional soil sampling and laboratory analysis, which are laborious and costly. Planet orbital images have the potential to allow for continuous and large-scale monitoring, offering valuable data for agricultural management.

Studies such as Rodriguez-Gallo et al. (2023) show that drones offer higher spatial resolution and operational flexibility, allowing images to be captured at critical moments in the coffee growing cycle. However, limited space coverage and the need for frequent flights for continuous monitoring can be disadvantages. Proximal sensing, while providing extremely detailed data, is limited in terms of area covered and requires significant data collection effort in the field.

Specifically, the Planet sensor used in this study, with a spatial resolution of 3 m and specific spectral bands (Blue, Green, Red, and NIR), enabled the acquisition of surface reflectance data from coffee plants, essential for classifying the different treatments, as shown in Pereira et al. (2022). The choice of the Planet sensor was based on its ability to provide atmospherically and geometrically corrected images, ensuring the accuracy of spectral data.

Image classification was performed using the random tree algorithm, which proved to be effective in discriminating the most nematicidal treatments with an overall accuracy of 80% and a Kappa coefficient of 0.78, which indicates a substantial degree of accuracy (Landis & Koch, 1977). This machine learning method allowed a detailed analysis of the spectral variations of plants, being a significant advance over conventional biological analysis methods. The study by Martins et al. (2017) used hyperspectral data and RapidEye images to discriminate between healthy and nematode-infected coffee plants, achieving an overall accuracy of 78% and a Kappa coefficient of 0.71. In comparison, our study used multispectral data and achieved slightly higher accuracy, highlighting the effectiveness of vegetation indices and the random tree algorithm in discriminating plant responses to nematicide treatments.

The high classification accuracy in areas with a significant treatment effect suggests that effective nematicide treatments result in detectable spectral changes in the plants. The use of the random tree algorithm proved to be effective in discriminating treatment classes based on spectral data. Although random forest may offer slight improvements in accuracy, the simplicity and computational efficiency of random tree justify its choice in this study. Furthermore, the use of cross-validation and random division of the data into 10 sets ensured the robustness of the model.

The highest omission and commission errors occurred in the class indicating an increase in nematode population, highlighting the difficulty the algorithm faced in distinguishing areas where ineffective treatments or nematode populations increased. The errors were greater in the first and last row, potentially due to variations in the efficiency of the drip irrigation, creating microenvironments with different soil moisture levels and impacting the spectral response of plants.

Although low, the altimetric variation in the experimental area can influence the distribution and drainage of irrigation water, affecting plant health and nematode infestation. This introduces noise into the spectral data, making precise classification more difficult by the algorithm. A similar condition occurred in Giridhar et al. (2016), who investigated the spectral response of different soils under varying moisture conditions. The results showed that soil moisture variability affected spectral reflectance, introducing noise into the data and making accurate classification difficult. This variability may occur due to the uneven distribution of irrigation water, influenced by elevation variations, affecting plant health and nematode infestation. Furthermore, the initial condition of the plants significantly impacts the results. Healthier plants or those with better vigor may respond differently to treatments, and physiological variation among plants within the same treatment can result in varied responses captured in the spatial analysis.

Regarding the treatments used, the results support the use of biological control agents, particularly Bacillus isolates, as a viable alternative to chemical nematicides, since this application resulted in nematode population reductions of 50.45% (*B. amyloliquefaciens*) and 65.12% (*B. subtilis*), respectively. These findings align with previous research indicating the efficacy of Bacillus species in suppressing nematode populations (Liu et al., 2013; Bruzos & Grayston, 2019; Mhatre et al., 2019). The ability of these isolates to produce a wide range of antagonistic compounds that target various stages of the nematode life cycle could explain their high nematicidal activity.

Limitations and future challenges

The methodology applied in this study is potentially applicable to other crops and agricultural conditions, standing out for its ability to provide continuous and large-scale monitoring. The accurate classification of the most nematicidal treatments using orbital multispectral imaging and machine learning can be generalized to different regions and soil types, provided it is adequately calibrated.

Although the results are promising, it is necessary to consider the limitations imposed by environmental variations, such as topography and soil moisture, which can introduce noise into the spectral data. Additionally, the physiological variability of plants within the same treatment can affect the classification accuracy.

Future investigations should focus on integrating different data sources, such as hyperspectral, proximal sensors, and drone data, to increase the spatial and temporal resolution of the analyses. The application of the Random Tree algorithm showed good classification capabilities but may be limited by the complexity of the interaction between nematicide treatments and the natural characteristics of the experimental field. Exploring deep learning techniques, such as convolutional neural networks (CNNs), could offer significant improvements in classification ability, especially when dealing with complex and heterogeneous data. Cross-validation and calibration of the models with larger datasets can also enhance the accuracy and robustness of the classifications.

Additionally, it is important to conduct validation studies in different field conditions and with different coffee varieties to confirm the robustness and general applicability of the proposed methodology. The development of integrated management strategies that consider the spatial and temporal variability of nematode infestations can contribute to more sustainable and efficient agricultural practices.

Conclusions

This study aimed to evaluate the potential of orbital multispectral imaging to discriminate the effectiveness of different nematicide treatments in coffee plantations. The results confirm that orbital remote sensing can effectively identify spectral changes in coffee trees associated with infection with plant-parasitic nematodes, as well as treatments used to reduce populations of these pathogens.

The results showed that treatments with *B. subtilis* (B33) and *B. amyloliquefaciens* (B266) were particularly effective, significantly reducing nematode populations. The random tree algorithm yielded a global accuracy of 80%, underscoring its reliability in classifying treated areas based on their spectral responses.

However, differences in topography, irrigation, soil type, and climate conditions can affect the spectral signatures of plants and lead to errors in the classification process. Thus, the complexity of the interactions between nematicide treatments and environmental factors suggests that future management strategies should account for these natural variations to improve accuracy.

For practical applications, this approach could complement traditional nematode control and provide an integrated strategy for sustainable agriculture. This study highlights the need to refine remote sensing techniques and algorithms to improve nematode control strategies. Future research should integrate other methods, such as hyperspectral imaging and drone-based platforms, to improve detection. In conclusion, the ability to non-destructively and accurately monitor nematode populations using orbital multispectral imaging represents a significant advancement, offering a promising tool for enhancing crop health and yields.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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