



NICOLE LOPES BENTO

**REMOTELY PILOTED AIRCRAFT SYSTEM FOR
MONITORING COFFEE CROPS**

**LAVRAS - MG
2024**

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Tese apresentada à Universidade Federal de Lavras, como parte das exigências do Programa de Pós-Graduação em Engenharia Agrícola, área de concentração em Geoprocessamento e Sensoriamento Remoto, para a obtenção do título de Doutora.

Professor Dr. Gabriel Araújo e Silva Ferraz
Orientador

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2024

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"Pois dele, por ele e para ele são todas as coisas.

A ele seja a glória para sempre! Amém."

Romanos 11:36

RESUMO GERAL

O café é uma commodity de grande importância para a balança econômica brasileira e o estado de Minas Gerais se destaca com maior produção e exportação mundial. Novas técnicas e tecnologias são aplicadas neste setor agrícola, buscando efetivos ganhos de produtividade e rentabilidade das lavouras, aliado a ganhos ambientais. Neste sentido, os Sistemas de Aeronaves Remotamente Pilotadas (*Remotely Piloted Aircraft System* - RPAS) são utilizados como plataformas para o Sensoriamento Remoto (SR) para o monitoramento das lavouras, aliadas a ferramentas de *machine learning* possibilitam a identificação de problemáticas que podem ser solucionadas por meio de manejo adequado e eficiente. Diante deste cenário, esta tese analisou as potencialidades da utilização de RPAS como tecnologia de imageamento aéreo em lavouras cafeeiras por meio de estudos científicos. **(I)** No primeiro estudo foi proposto o levantamento bibliométrico contextualizando o estado da arte sobre a temática de RPAS na cafeicultura, com base nos 20 anos de buscas nas bases de dados mais relevantes, destacando evolução temporal das publicações, análise de desempenho agrupando as principais publicações, principais periódicos, principais pesquisadores, principais instituições, principais países e mapeamento científico de cocitação, palavras-chave, tendências e possibilidades futuras sobre o tema da pesquisa. **(II)** O segundo estudo objetivou classificar e mapear, em áreas cafeeiras, a área ocupada por plantas daninhas, determinar o percentual de área ocupada e indicar estratégias de controle de tratamento a serem adotadas no campo. Para isto, testou-se dois algoritmos de *machine learning* (*Random Forest* - RF e *Support Vector Machine* - SVM) para a classificação das regiões de interesse devido às diferenças espectrais entre os alvos, destacando o RF com melhor desempenho de classificação. Além disso, a economia obtida tratando apenas áreas com presença de ervas daninhas em comparação com o tratamento de toda a área de estudo foi de aproximadamente 92,68%. **(III)** O terceiro estudo relacionou parâmetros derivados de imagens aéreas com base em diferentes índices de vegetação (IVs) e o modelo de altura do dossel (MAD) à compactação do solo em área de lavoura cafeeira. Procedeu a coleta de dados de altura de plantas, caracterização do solo, resistência a penetração do solo e produtividade *in loco* e IVs calculados por imagens aéreas. Os dados multiespectrais apresentaram correlação aos dados de resistência a penetração, sendo possível determinar os IVs NDRE e MTCI com melhor desempenho de estimativa. Deste modo, evidenciou-se a possibilidade de acompanhamento das variações de altura da cultura cafeeira usando RPAS para demarcar zonas compactadas. **(IV)** O quarto estudo objetivou classificar e diferenciar, por meio de algoritmo de *machine learning* (*Random Forest* – RF) plantas cafeeiras submetidas e não submetidas a aplicação foliar do bioestimulante quitosana, indicando uma abordagem válida para modelar a presença do bioestimulante nas plantas cafeeiras, confirmando que o modelo pode auxiliar nas práticas de agricultura de precisão de maneira eficiente. **(V)** O quinto estudo comparou dados de altura de plantas de café obtidos de nuvens de pontos RGB/SfM e LiDAR aerotransportados por RPAS e estimou a compactação do solo através da resistência à penetração em uma lavoura cafeeira, não sendo determinadas diferenças estatísticas significativas entre os sensores utilizados, sendo possível a estimativa precisa de maneira indireta da compactação do solo via sensoriamento remoto.

Palavras-chave: Agricultura Digital; Agricultura de Precisão; Aprendizado de Máquina; Cafeicultura; Índices de Vegetação; Sensoriamento Remoto; Veículo Aéreo Não Tripulado.

GENERAL ABSTRACT

Coffee is a commodity of great importance for the Brazilian economic balance and the state of Minas Gerais stands out with the highest production and exports worldwide. New techniques and technologies are applied in this agricultural sector, seeking practical gains in productivity and profitability of crops, combined with environmental gains. In this sense, Remotely Piloted Aircraft Systems (RPAS) are used as platforms for Remote Sensing (SR) for monitoring crops, combined with machine learning tools, they make it possible to identify problems that can be solved through adequate and efficient management. Given this scenario, this thesis analyzed the potential of using RPAS as aerial imaging technology in coffee plantations through scientific studies. **(I)** In the first study, a bibliometric survey was proposed, contextualizing the state of the art on the topic of RPAS in coffee farming, based on 20 years of searches in the most relevant databases, highlighting the temporal evolution of publications, performance analysis grouping the main publications, main journals, main researchers, main institutions, main countries and scientific co-citation mapping, keywords, trends and future possibilities on the research topic. **(II)** The second study aimed to classify and map the area occupied by weeds in coffee growing areas, determine the percentage of area occupied, and indicate treatment control strategies to be adopted in the field. To this end, two machine learning algorithms (Random Forest - RF and Support Vector Machine - SVM) were tested to classify regions of interest due to spectral differences between targets, highlighting the RF with the best classification performance. Furthermore, the savings obtained by treating only areas with the presence of weeds compared to treating the entire study area was approximately 92.68%. **(III)** The third study related parameters derived from aerial images based on different vegetation indices (VIs) and the canopy height model (CHM) to soil compaction in a coffee plantation area. Data collection was carried out on plant height, soil characterization, resistance to soil penetration, in situ productivity, and VIs calculated by aerial images. The multispectral data correlated with the penetration resistance data, making it possible to determine the NDRE and MTCI VIs with better estimation performance. This way, the possibility of monitoring coffee crop height variations using RPAS to demarcate compacted areas was highlighted. **(IV)** The fourth study aimed to classify and differentiate, using a machine learning algorithm (Random Forest – RF) coffee plants subjected and not subjected to foliar application of the biostimulant chitosan, indicating a valid approach to model the presence of the biostimulant in coffee plants, confirming that the model can assist in precision agriculture practices efficiently. **(V)** The fifth study compared coffee plant height data obtained from RGB/SfM point clouds and LiDAR data collected by RPAS, and estimated soil compaction through penetration resistance in a coffee plantation. No statistically significant differences were identified between the sensors used, and accurate estimation indirectly of soil compaction via remote sensing was demonstrated.

Keywords: Digital Agriculture; Precision Agriculture; Machine Learning; Coffee Farming; Vegetation Indices; Remote Sensing; Unmanned Aerial Vehicle.

INDICADORES DE IMPACTO

A tese, desenvolvida por meio de artigos científicos, aborda a aplicação de Sistemas de Aeronaves Remotamente Pilotadas (RPAS) em diferentes aspectos da cafeicultura, com ênfase na detecção, mapeamento e manejo agrícola. A pesquisa produziu impactos concretos e potenciais, ao demonstrar ganhos de eficiência produtiva, redução de impactos ambientais e promoção da sustentabilidade econômica e social no setor cafeeiro. Dessa forma, o trabalho combina resultados imediatos e mensuráveis com um amplo potencial para expansão de impactos em escala territorial e temporal. No que tange aos impactos tecnológicos e econômicos, destaca-se o uso de RPAS para o mapeamento de compactação do solo, detecção de plantas daninhas e análise de estresse vegetal por meio de classificação espectral. Essa abordagem possibilitou uma redução significativa no uso de insumos químicos, otimizando a alocação de recursos e gerando economia nos custos de manejo agrícola. Além disso, a utilização de sensores RGB, multiespectrais e LiDAR trouxe maior precisão e agilidade no diagnóstico de problemas. O emprego de aprendizado de máquina demonstrou elevado potencial para a automação de processos agrícolas, contribuindo para a modernização do setor. Com relação aos impactos ambientais, o monitoramento por RPAS minimiza a necessidade de intervenções invasivas no solo, promovendo a preservação ambiental e a conservação da biodiversidade. Ademais, a redução do uso de insumos químicos e a otimização do manejo agrícola estão alinhadas aos Objetivos de Desenvolvimento Sustentável (ODS) da Organização das Nações Unidas (ONU), notadamente os ODS 12 (Consumo e Produção Responsáveis), 13 (Ação contra a Mudança Global do Clima) e 15 (Vida Terrestre). A abordagem sustentável reforça a importância do alinhamento com a Agenda 2030, promovendo uma agricultura mais eficiente, inclusiva e ambientalmente responsável. No âmbito dos impactos sociais e culturais, os produtores cafeeiros foram beneficiados, direta e indiretamente, pela introdução de tecnologias e pela adoção de práticas agrícolas modernas. O trabalho também apresenta um caráter extensionista, envolvendo docentes e discentes da Universidade Federal de Lavras (UFLA), com impacto direto na formação de profissionais e na transferência de conhecimento para a comunidade local. A pesquisa se enquadra nas áreas temáticas de tecnologia e produção (área 7) e meio ambiente (área 5), ao promover o aumento da eficiência produtiva e a redução dos impactos ambientais na cafeicultura. A inclusão de parceiros externos e a participação ativa da sociedade no desenvolvimento das soluções reforçam o caráter extensionista das atividades realizadas.

IMPACT INDICATORS

The thesis, developed through scientific papers, addresses the application of Remotely Piloted Aircraft Systems (RPAS) in different aspects of coffee farming, with an emphasis on detection, mapping, and agricultural management. The research has produced both concrete and potential impacts by demonstrating gains in productive efficiency, reducing environmental impacts, and promoting economic and social sustainability in the coffee sector. Thus, the work combines immediate and measurable results with significant potential for expanding its impacts on a territorial and temporal scale. Regarding technological and economic impacts, the use of RPAS for soil compaction mapping, weed detection, and plant stress analysis through spectral classification. This approach enabled a significant reduction in the use of chemical inputs, optimizing resource allocation and generating cost savings in agricultural management. Additionally, the use of RGB, multispectral, and LiDAR sensors enhanced precision and speed in problem diagnosis. The application of machine learning demonstrated high potential for automating agricultural processes, contributing to the modernization of the sector. In terms of environmental impacts, monitoring with RPAS minimizes the need for invasive interventions in the soil, promoting environmental preservation and biodiversity conservation. Furthermore, the reduction in chemical inputs and the optimization of agricultural management align with the United Nations Sustainable Development Goals (SDGs), particularly SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action), and SDG 15 (Life on Land). The sustainable approach underscores the importance of alignment with the 2030 Agenda, fostering a more efficient, inclusive, and environmentally responsible agriculture. Concerning social and cultural impacts, coffee producers were directly and indirectly benefited by the introduction of technologies and the adoption of modern agricultural practices. The work also demonstrates an extensionist nature, involving faculty and students from the Federal University of Lavras (UFLA), with a direct impact on professional training and knowledge transfer to the local community. The research aligns with the thematic areas of the National Extension Policy, of technology and production (area 7) and the environment (area 5), as it promotes increased productive efficiency and reduced environmental impacts in coffee farming. The inclusion of external partners and the active participation of society in the development of solutions reinforce the extensionist nature of the activities carried out.

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FIRST PART

1. GENERAL INTRODUCTION

Coffee growing refers to the prominent agricultural activity in Brazil, with the country being the largest producer and exporter of grains globally and Minas Gerais state is the most significant responsible for this contribution, highlighting this commodity with a considerable share in the Brazilian economy. On the international stage, coffee growth generates great fortune among producing and exporting countries, with important income for farmers and workers in the agricultural sector who work in developing this activity.

Despite the significant participation of coffee farming in the national and international economy, many challenges are encountered in crops that impact the quality, productivity and financial returns of the activity in question. The new era of agriculture is characterized by the rapid collection and interpretation of information and intelligent technologies to manage agricultural activities, promoting management improvements. In this way, the applicability of new techniques and technologies is sought to aid management and intelligent decision-making in the field in the face of problems that interfere with the development and profitability of coffee farming.

Remote sensing, a technique for obtaining information from the Earth's surface without direct contact between the measurement object and the target object of study, through the analysis of spectral behaviour, optimizes studies in different areas of activity, including agriculture. The use of remote sensors coupled to other platforms and with varying amplitudes of acquisition of information from the electromagnetic spectrum allows the investigation of better details of the comportment of coffee crops and makes it possible to verify the action of factors external to the development of agricultural activity.

Remotely Piloted Aircraft (RPA) are among the platform options for acquiring aerial images, making it possible to attach different sensors covering the electromagnetic spectrum, allowing the capture of information about the study target. In addition to the versatility in loading different sensors, benefits of RPA include the better detailing of the study target, allowing configurations to vary the height, speed and overlap of the coverage of the study area, in addition to autonomy in choosing the overflight dates, therefore promoting efficient temporal study.

The advent of high-resolution images, obtained mainly by RPAS, therefore contributes to developing new studies through spectral and spatial information, directing assertiveness in decision-making in the agricultural context. The use of artificial intelligence techniques to the

range of data generated through sub-orbital aerial imaging enables the application, study and use of machine learning techniques through specific algorithms, which allow the identification of patterns in the data for investigation and solving problems observed in the field in a precise and relevant way.

Due to the heterogeneity of coffee plantations, several techniques are still in the implementation phase, revealing gaps in the literature that require further investigation. This thesis seeks to address some of the demands arising from these gaps. The first section presents the theoretical framework, grounded in the applicability of Remotely Piloted Aircraft Systems (RPAS) in coffee farming, as analyzed through a bibliometric study of scientific works from the past 20 years, based on a comprehensive range of search databases (NOTE: The bibliometric analysis considered data up to the year 2022, as the preparation of Paper 1 was completed in that year. Therefore, studies published in 2023 and 2024 were not included in Paper 1. An additional section, titled "ADDITIONAL INFORMATION," was incorporated to expand the study to include the years 2023 and 2024). The second section comprises articles aimed at resolving key issues within agricultural coffee plantations using RPAS technology. Accordingly, the second article focuses on the classification of weeds using machine learning algorithms and the economic assessment of localized versus full-area agrochemical applications. The third article aims to identify compacted areas due to interference with the growth of coffee plants according to the Canopy Height Model and Vegetation Indices. The fourth article addresses the classification and differentiation of coffee cultivars, both treated and untreated with the biostimulant chitosan, through machine learning via the Random Forest algorithm. Finally, the fifth article compares airborne RGB and LiDAR sensors on RPA for the estimation of plant height and soil compaction.

2. LITERATURE REVIEW

2.1 PAPER 1: COFFEE GROWING WITH REMOTELY PILOTED AIRCRAFT SYSTEM: BIBLIOMETRIC REVIEW

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Abstract: Remotely piloted aircraft systems (RPASs) have gained prominence in recent decades primarily due to their versatility of application in various sectors of the economy. In the agricultural sector, they stand out for optimizing processes, contributing to improved sampling, measurements, and operational efficiency, ultimately leading to increased profitability in crop production. This technology is becoming a reality in coffee farming, an essential commodity in the global economic balance, mainly due to academic attention and applicability. This study presents a bibliometric analysis focused on using RPASs in coffee farming to structure the existing academic literature and reveal trends and insights into the research topic. For this purpose, searches were conducted over the last 20 years (2002 to 2022) in the Web of Science and Scopus scientific databases. Subsequently, bibliometric analysis was applied using Biblioshiny for Bibliometrix software in R (version 2022.07.1), with emphasis on the temporal evolution of research on the topic, performance analysis highlighting key publications, journals, researchers, institutions, countries, and the scientific mapping of co-authorship, keywords, and future trends/possibilities. The results revealed 42 publications on the topic, with the pioneering studies being the most cited. Brazilian researchers and institutions (Federal University of Lavras) have a strong presence in publications on the subject and in journals focusing on technological applications. As future trends and possibilities, the employment of technology optimizes the productivity and profitability studies of coffee farming for the timely and efficient application of aerial imaging.

Keywords: digital agriculture; precision agriculture; remote sensing; systematic review; unmanned aerial vehicles (UAVs).

1. Introduction

Considered a commodity of significant relevance worldwide, coffee farming is practiced on a large scale across five continents [1]. Amidst the essential global commodities, coffee farming holds a prominent position, contributing to the global economic balance with an estimated total production of 55 million 60 kg bags for the year 2023 [2]. Coffee is the third most consumed beverage globally, following water and tea. Consequently, the demand for coffee beans is present in every corner of the world, making it a critical global commodity [1]. In addition to its use for consumption, coffee fruits have direct applications in extracting

caffeine used in cola beverages, mixed drinks, biostimulant products, pharmaceuticals, and cosmetics, further enhancing its prominence among global agricultural products [3].

The high demand for agricultural products drives the sector's modernization and encourages the application of tools, techniques, and technologies to optimize field activities, resulting in economic gains [4]. In this context, the adoption of intelligent agriculture is necessary, highlighted by the incorporation of modern agricultural management concepts, including prominent technologies such as wireless sensor networks, the Internet of Things (IoT), big data, artificial intelligence, machine learning, deep learning, and the use of remote sensing through various aerial imaging platforms [5–7]. In addition to the emphasis given to digital agriculture, it is worth highlighting the contribution of coffee farming in a more comprehensive way, based on the participation of small producers who use coffee farming as a form of subsistence, as well as the adoption of sustainable coffee production by agroforestry, with active participation in economic circles [8].

In recent years, remote sensing using remotely piloted aircraft (RPA) has become one of the most widely discussed technologies globally. RPA can be employed in a wide range of professions and applications, including targeted studies in the agricultural sector [9]. RPA, or unmanned aerial vehicles (UAVs), refer to unmanned aircraft remotely operated through interfaces such as computers, simulators, digital devices, or remote controls and programmable for flight plans [10]. When the onboard sensor is integrated into the remotely piloted aircraft, it becomes a remotely piloted aircraft system (RPAS) [11]. Regarding nomenclature, several terms are described in the literature but are considered outdated in the scientific and aviation community, with RPASs or UASs (unmanned aircraft systems) being more appropriate and widely used worldwide, as they encompass the operational complexity of the system [10]. RPAS remote sensing was quickly put into practice as agricultural remote sensing improved, and among the most common types of analyses obtained by RPASs are plant cover monitoring, growth tracking, yield estimates, and crop growth data fields [12].

Research on RPA approaches in coffee farming is becoming increasingly prevalent, relevant, and essential for developing coffee farming, especially regarding timely and efficient agricultural monitoring. Therefore, it is necessary to analyze the existing literature and reveal the intellectual structure of the subject, that is, the organization and arrangement of academic works that deal with this subject of study. As a high-technology and multidisciplinary field, understanding the current scenario and temporal development of scientific studies on this topic is crucial to comprehend the complexity of publications and potential research gaps [13]. In this regard, bibliometric analysis allows the examination of different authors' research trends,

perspectives, and contributions by evaluating the scientific literature on the development of RPA utilization in precision coffee farming. It is worth noting that bibliometric reviews in agriculture are recent but are proving to be effective in synthesizing knowledge and indicating priorities for future research [14].

In summary, the importance of coffee farming on the world stage encouraged the topic of research, mainly supported using digital agriculture. By studying academic works and relations between countries and institutions, it is possible to understand the problems found within the topic that were directed to scientific studies to solve improvements in the field and consequently return economic gains. It also makes it possible to identify gaps in research that require attention to direct potential future scientific research. Therefore, this bibliometric study presents an analysis of the use of RPASs in the agricultural sector of coffee farming and provides the results of searches conducted over the past 20 years in the most relevant databases. Other studies focusing on the use of RPASs in the agricultural sector can be found in the bibliometric analysis of the evolution of precision agriculture research by Pallottino et al. [15], digital agriculture by Sott et al. [16], precision coffee farming by Santana et al. [17], the analysis of drones in agriculture and forestry with academic research published between 1995 and 2017 by Raparelli and Bajocco [18], and an extension of the topic until 2022 by Rejeb et al. [19]. It is worth noting that although other bibliometric reviews have been published, as of the present moment, no study focusing on the use of RPASs in coffee farming has been explored. Thus, this article fills this gap in the literature by identifying this research topic's critical concerns and potential.

2. Methodology

The evolution of scientific research on RPASs in coffee farming was assessed through bibliometric analysis following the procedures described in Figure 1, which includes the search procedures, organization procedures, and bibliometric mapping.

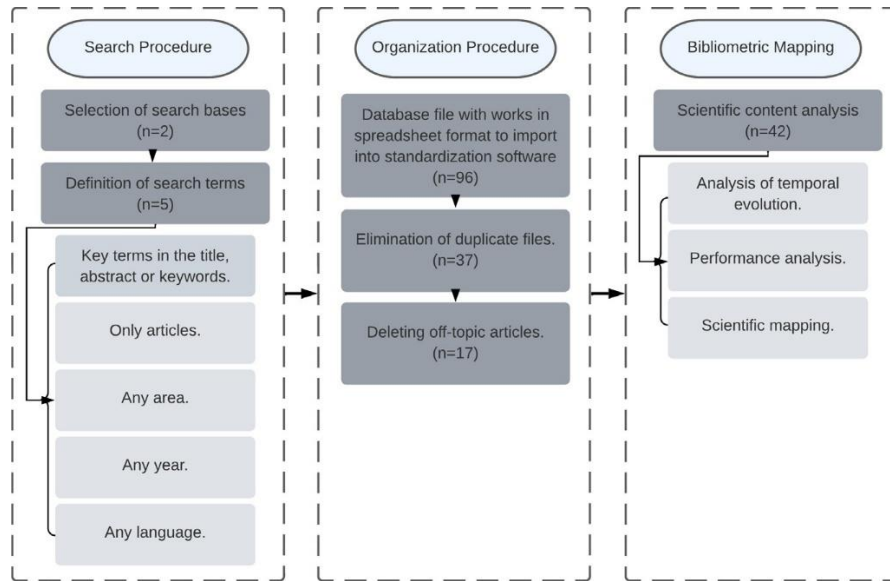


Figure 1. Systematization of processes for bibliometric analysis.

2.1 Search Procedure

In this bibliometric analysis, the databases Web of Science and Scopus were considered, as they provide high-quality and comprehensive data in various categories, and they have quality indicators such as citation count (JCR) and H-index, making them suitable and commonly used for bibliometric studies [20]. The publication is the fundamental element of the dataset derived from the database and includes authors, titles, keywords, cited references, year, affiliations, and other characteristics related to each publication [21].

The choice of search terms is crucial to retrieve publications on the proposed research topic, and it should not be too restrictive to exclude relevant publications or too broad to include unrelated ones. In this study, the search in the Web of Science database was performed using the advanced search option, selecting the “Web of Science Core Collection”. In Scopus, only the “Title, Abstract, Keywords” field was chosen for the search string. In both databases, the following search terms were used: (“remotely piloted aircraft” OR “remotely piloted aircraft system” OR “unmanned aerial system” OR “unmanned aerial vehicle” OR UAV OR UAS OR RPAS OR RPA OR VANT OR DRONE) AND (coffee OR “coffee growing” OR “coffee plants” OR “coffee cultivars” OR “coffee crops” OR “coffee farm” OR “Precision coffee growing”). The searches were not restricted to specific academic fields, languages, or periods, but only publications between 2002 and 2022 were considered.

All relevant publications were gathered and stored by applying the search strings as indicated above. The initial search yielded 42 documents in the Web of Science database and

54 in the Scopus database. The complete bibliographic data were exported in BibTeX (.bib) format for operational purposes.

2.2 Organization Procedure

The next step involved the removal of duplicates and the merging and standardizing of the databases using R software (version 2022.07.1) and the Bibliometrix library. Subsequently, the abstracts of all works were read to assess their relevance to the proposed research topic and proceed with the bibliometric analysis. After these selections, 42 publications were chosen for inclusion in this study and were then subjected to operational analysis using the Biblioshiny package [22] in R software (version 2022.07.1) (R Development Core Team, R project, New Zealand).

2.3 Bibliometric Mapping

Biblioshiny is a package developed for the R language that provides a set of tools for bibliometric research [22]. It stands out as the tool with the most extensive collection of analyses, meeting all the criteria for bibliometric analysis [23]. The rules used for bibliometric mapping consisted of analyzing the temporal evolution of publications, performance analysis by grouping key publications, top journals, top researchers, top institutions, and top countries, and scientific mapping of co-citation, keywords, trends, and future possibilities regarding the research topic.

For the temporal analysis of publications, the general objective and results found in each work were contextualized, finally separating the works by general theme according to thematic coding. The thematic coding identified themes in the literature according to the evaluation of the full text and identification of the central theme and description presented in a table, also identifying the percentage occupied by each theme based on the amount of work developed. The performance analysis in turn included highlighting the main works and journals on the topic based on the number of citations; the main researchers were highlighted based on the H-index, which quantifies the productivity and impact of individual research based on the number of articles and citations; the main institutions were identified based on the amount of work on the topic, making it possible to identify the relationships between institutions; the main countries that produce knowledge on the topic were highlighted based on the number of works published on the topic. Scientific mapping occurred with co-citation mapping based on the identification of researchers who work in the same line of research within the central theme, through works with similar themes as well as highlighting the relationships between the authors;

mapping of keywords was carried out by surveying the occurrence of a keyword at least three times in scientific articles; and the mapping of trends and future possibilities was carried out based on the evolution of the topic and keywords on the study topic.

It is therefore worth highlighting the application of bibliometric studies as a solid quantitative indicator of quality and scientific production in a transparent, fast, cheap, and scalable way, allowing studies to be carried out at an individual, institutional, national, or international level. However, as limitations of bibliometrics, although publication counts provide a measure of research results, they do not provide information about quality, and variations between areas of study must also be considered, as there is a difference in the frequency of publication. Another important fact is that bibliometrics does not consider gray literature, i.e., that produced outside traditional publication, distribution, and language channels; however, it punctuates studies published as articles in scientific journals indexed in databases, enabling understanding of the study topic.

3. Results and Discussion

3.1 Temporal evolution of research and characteristics of the studies

The use of bibliometric analysis enabled the identification of 42 articles on the use of RPASs in the coffee industry between 2002 and 2022. The evolution of these publications is presented in Figure 2, which shows the number of publications per year.

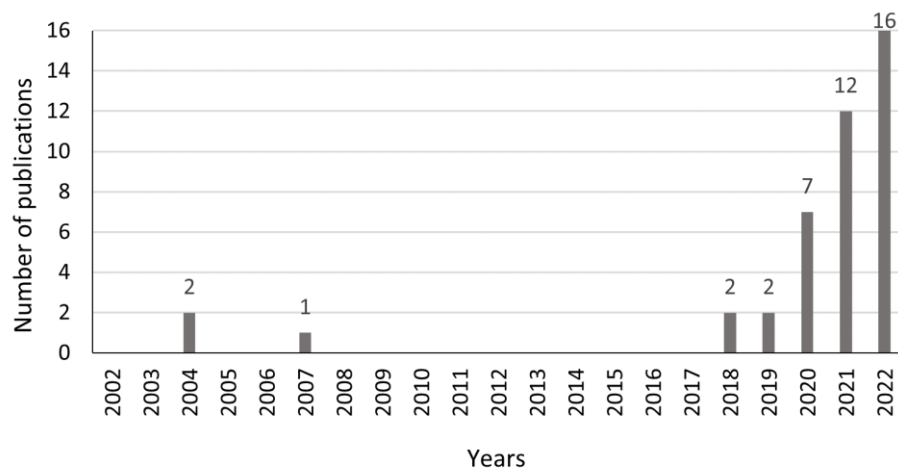


Figure 2. Evolution of research publications on RPAS in coffee growing from 2002 to 2022.

This research topic is recent, evidenced primarily by the popularization and increased access to RPAS technology and the applicability of timely and efficient agricultural imaging. Figure 2 shows that 2004 can be considered the precursor of scientific research on using RPASs in coffee farming, with two studies being presented. The first scientific research was described

in 2004 by Herwitz et al. [24], demonstrating the economic potential of RPASs as platforms equipped with real-time high-resolution imaging systems and attesting to the efficiency of aerial remote sensing for agricultural monitoring with suborbital imaging applications in defining productivity zones. Herwitz et al. [24] performed imaging using a solar-powered aircraft in a coffee plantation in Hawaii, carrying multispectral sensors. The study concluded that the images helped to map invasive weed outbreaks, reveal irrigation and fertilization anomalies, and relate them to harvesting ripe fruits.

Another important study conducted in the same year was by Johnson et al. [25], where multispectral images were collected by a remotely piloted aircraft over a commercial coffee plantation, delineating the reflectance spectrum of four components: green fruit, slightly ripe fruit, ripe fruit, and very ripe fruit. Based on these reflectance spectra, a ripeness index was developed using aerial images to calculate pixel-wise digital count ratios, which proved significant for coffee research.

After 2004, there was a publication gap, with only one new publication observed in 2007. That year, Furfaro et al. [26] published a critical study. In their study, aerial imaging was also performed using an RPAS in a coffee plantation, followed by the application of an intelligent and robust neural network algorithm that operated on the multispectral images to estimate the percentages of fruits classified as green (slightly ripe), yellow (ripe), and brown (very ripe). The algorithm was applied to three study fields representing a wide range of ripe fruits, and a correlation between the predictions and yield data was observed at all maturity levels, indicating the excellent applicability of this technology for this purpose.

Despite these pioneering studies, there is a gap in publications on this topic between 2008 and 2017, mainly due to the high cost of equipment acquisition and the limited resources for image capture and processing, which have improved over the years. Additionally, due to their cost, researchers had access only to conventional cameras in the visible range. In the following years, new studies were implemented with the application of RPAS technology in monitoring and managing coffee plantations, accompanied by advancements in RPAS technology, sensors, software, and the popularization of the technology and its applications. Studies on the application of new techniques in coffee farming have led to changes in the perception of technicians and farmers regarding coffee cultivation and are closely related to technological advances affecting various sectors, including the agricultural sector [27].

In 2018, studies on this topic regained focus, with Oliveira et al. [28] employing RPASs in precision agriculture as a potential tool for analyzing critical parameters in cultivation, explicitly mentioning the detection of planting failures in coffee plantations. The approach

proposed by these authors involved using mathematical morphology operators to detect failures in planted areas. By doing so, they could observe both the individual positions of the losses and the total length of the failure, facilitating decision making for future actions. The same year, Soares et al. [29] addressed the problem of identifying planting rows in coffee cultivation fields using aerial images obtained by an RPAS. They applied a tiling scheme that allowed for an acceptable approximation of the lines within each tile for straight lines, making it feasible to use the Hough transform. Experimental results compared with ground truth data indicated that the proposed approach successfully approximated the plantation rows. The main contribution of this work was the proposal of a procedure for extracting line segments of plantations from aerial images.

In 2019, the study conducted by Cunha et al. [30] aimed to develop a method for determining the vegetation volume in coffee plantations using digital images obtained by an RPAS and comparing it with the traditional estimation of vegetation volume (tree row volume method), showing no significant differences. The digital image technique was highlighted as being faster and applicable to large areas. Another study by Santos et al. [31] aimed to overcome one of the limitations of photogrammetry by evaluating geometric errors by applying four sets of georeferenced points in a coffee-growing area. They concluded that the lower study overlap ($70\% \times 60\%$) could be recommended for use in the flight plan due to the high resolution of the orthomosaic and the shorter processing time. In 2020, seven studies on the research topic were published. Dos Santos et al. [32] aimed to evaluate the accuracy of photogrammetry using point clouds for estimating the height and crown diameter of coffee trees from aerial images obtained by an RPAS with a visible RGB (red, green, blue) sensor. They also compared the results with in situ measurements taken over 12 months, obtaining a correlation of 87% for height and 95% for diameter values. Oré et al. [33] presented a new methodology for obtaining growth deficit maps with an accuracy of up to 5 cm and a spatial resolution of 1 m, using Differential Synthetic Aperture Radar Interferometry (DInSAR). Wei et al. [34] combined a binarization algorithm with a convolutional neural network (CNN) model to improve the accuracy of coffee flower identification using digital images, highlighting the ability of the proposed method to enhance the precision of coffee flower classification.

In the same year, Parreiras et al. [35] conducted a study to assess the potential of visible vegetation indices obtained from RPAS-collected images for monitoring the spatial variability of leaf nitrogen content in a coffee farm. However, the models could not explain the variability, and no significant correlation was found between the variables, indicating the need to replicate the study during the vegetative phase of coffee plants. Santos et al. [36] aimed to develop a

methodology for determining short-term crop coefficients (K_c) using biophysical parameters from RPAS-detected images of coffee plants. They extracted information from aerial images to calculate biophysical parameters such as leaf area index (LAI), leaf area (LA), and K_c , demonstrating the applicability of the developed methodology for indirect estimation of K_c . Dos Santos et al. [37] monitored the evolution of LAI and land cover percentage in coffee plants using pre-established equations and plant measurements obtained from point clouds combined with applying the structure from motion algorithm to digital images obtained by a sensor attached to an RPAS. This allowed for the temporal and spatial analysis of the variables, leading to the conclusion that the methodology generated consistent results with the literature. Velásquez et al. [38] proposed a diagnostic model for the stage of coffee rust development through the technological integration of remote sensing using multispectral sensors carried by RPAS, wireless sensor networks (multisensor approach), and deep learning (DL) techniques. The results demonstrated that both methods were significantly similar in diagnosing the disease.

In 2021, twelve scientific studies on the research topic were published. Barbosa et al. [39] estimated the variables of coffee tree height, crown diameter, and productivity using an RPAS equipped with a visible sensor and computer vision algorithms. The results demonstrated that a dataset from the most important month (December) could be used for yield prediction models, reducing the need for extensive data collection (e.g., monthly data collection). Marin et al. [40] proposed a framework for detecting the severity of coffee rust using vegetation indices extracted from RPAS images based on a decision tree model, and the study demonstrated a valid approach for modeling this variable.

In the study by Barbosa et al. [41], it was possible to monitor the coffee production cycle, providing producers with more precise, fast, and detailed information based on aerial images obtained by an RPAS and vegetation index calculations. Santana et al. [42] evaluated the quality of semi-mechanized coffee planting on different slopes using statistical process control, thereby identifying possible causes and implications for management and improvements in the crop establishment stage.

The same year, the study proposed by Marin et al. [43] aimed to evaluate the potential of the random forest machine learning method applied to vegetation indices to measure nitrogen content in coffee plants. They identified acceptable results using the Green Normalized Difference Vegetation Index (GNDVI) and the Green Optimized Soil-Adjusted Vegetation Index (GOSAVI), allowing for the spatial distribution evaluation as well as the quantification of deficiency across the entire study area. Bonnaire Rivera et al. [44] and Dos Santos et al. [45] aimed to demonstrate the applicability of precision agriculture and remote sensing for coffee

crop monitoring, identifying areas with higher and lower vegetative vigor based on the Normalized Difference Vegetation Index (NDVI). They showed that this index can be applied to this crop.

The study by Martins et al. [46] aimed to develop a vegetation index for monitoring coffee ripening (CRI), combining the reflectance of the red band and a terrestrial red target placed in the study area. They compared its effectiveness with traditional indices and validated it through different analyses, demonstrating its sensitivity to distinguish between coffee plants ready and not ready for harvest. Felix et al. [47] evaluated the seasonal behavior of five vegetation covers, including coffee, using vegetation indices, meteorological data, and surface soil moisture. They highlighted the potential and low cost of RPASs as a support tool for phenological studies, also assisting in validating satellite-image-derived data. Gomes et al. [48] compared the performance of a modified RGB camera with a multisensor camera for obtaining the NDVI in a coffee cultivation area, identifying that the data obtained by the multisensor camera closely matched the data obtained by the Green-Seeker sensor.

For 2022, sixteen scientific articles were found on the research topic. The study by Santana et al. [17] highlights a bibliometric review of precision agriculture, including precision coffee farming and the use of remotely piloted aircraft in this crop. Rosas et al. [49] focused on applying low-cost materials for radiometric calibration of multispectral images. Santana et al. [50] and Bento et al. [51] evaluated the processing and quality of photogrammetric products based on different flight configurations and image processing obtained in coffee crops, aiming to achieve efficiency in field data collection. These last two studies emphasized that increased image overlap requires longer processing times and does not contribute linearly to the geometric quality of the orthomosaic.

In the same year, Souza et al. [52] characterized the quality of spraying performed by RPASs based on flight height and target position in a mountainous region. They used three flight heights and marks located at the top and base of the plant. The results showed that flight height only influenced the parameters of volumetric diameter, median numerical diameter, and coverage percentage. In the same year, Vitória et al. [53] analyzed the effect of operational flight height and coffee conilon genotypes on canopy destruction deposition and uniformity. The results demonstrated that spraying performance at an average height of 3.0 m was better than at 2.0 m and 4.0 m.

Bento et al. [54] characterized three newly planted coffee cultivars and concluded that the seasons of the year influenced the behavior and development of the cultivars. They detected statistically significant differences for the study variables, except for chlorophyll. In a study

proposed by Rosas et al. [55], vegetation indices could discriminate between coffee fruit ripening classes (unripe and ripe for harvest) in most plantations, with performance directly influenced by crop yield and canopy volume. Bento et al. [56] found that the correlation of yield and productivity prediction estimates by applying vegetation indices optimizes the time spent on field measurements using RPASs. They also highlighted that leaf drop due to harvesting impacts the productivity of the following harvest.

Martello et al. [57] explored visible aerial images to obtain 3D information on coffee crops, including plant height, volume, and productivity data over three harvests in a commercial production area. Bento et al. [58] calculated the height and canopy diameter of newly transplanted coffee plants at three development periods, observed statistical differences between field measurements and aerial images, estimated linear equations between field data and aerial images, and monitored the temporal profile of growth and development of the studied cultivar in the field based on information extracted from aerial images using RPASs, with significant results compared to actual field data. Santos et al. [59] aimed to identify which vegetation indices adequately explained plant chlorophyll and evaluated the relationships between vegetation indices obtained from RPAS images and leaf and canopy chlorophyll in coffee plants during the rainy and dry seasons. Also, focusing on chlorophyll estimation in coffee plants, Arteaga-López et al. [60] identified the support vector machine model with the best performance and the CVI, GNDVI, and GCI vegetation indices with the best results.

The study by Dos Santos et al. [61] aimed to analyze vegetation indices from images of healthy coffee leaves and leaves infested with the coffee leaf miner in two locations (farm and greenhouse). They concluded that healthy leaves exhibited higher index values than infested leaves, with the GRNDVI index standing out as having the best ability to differentiate infected from healthy leaves. Pereira et al. [62] identified the best algorithms for estimating agronomic and physiological parameters in coffee plantations subjected to different treatments for nematode management, while Soares et al. [63] proposed a method for early detection of coffee rust using images obtained from a sensor mounted on an RPA. As can be observed, there has been an evolution in the use of remotely piloted aircraft in coffee farming, ranging from RGB image acquisition and analysis to multispectral images and even the application of RPASs. The imaging conducted by remotely piloted aircraft has been used in planting, detecting pests and diseases, observing plant morphological characteristics, delineating and verifying planting lines, and in coffee productivity studies.

Another notable observation is the increasing use of artificial intelligence in data analysis in recent years, indicating that this may be a trend in future works, as data collection by RPASs

generates an extensive database and opens possibilities for various types of analysis. Brazilian institutions have played a significant role in developing research in this field in recent years, mainly due to the active participation of coffee farming in the Brazilian economy, highlighting the importance of applying new techniques and technologies that optimize agricultural activities. These studies systematically focus on using sub-orbital remote sensing to monitor characteristics that affect coffee production while emphasizing time optimization in the field and intelligent, timely, and effective decision making.

Therefore, based on the temporal analysis of the publications, the general objective and the results found in each work were contextualized, making it possible to separate the works by general theme according to thematic coding as shown in Table 1.

Table 1. Thematic Coding and articles that address them based with research development in RPAS in coffee growing from 2002 to 2022.

Central themes	Papers
Agricultural Monitoring	[24,28–30,42,50–53,57]
Vegetation Indices	[35,41,43–46,48,54,55,59,60]
Biophysical Characteristics	[32,33,36,37,39,58]
Pests and Diseases	[38,40,61–63]
Agricultural Yield	[25,26,34,56]
Perspectives on Technology	[17,31,47,49]

As described in Table 1, it was possible to verify the patterns in the literature based on scientific records. The records separated scientific studies into six major themes: “Agricultural Monitoring”, “Vegetation Indices”, “Biophysical Characteristics”, “Pests and Diseases”, “Agricultural Yield”, and “Perspectives on Technology”. Of the works, the theme of “Agricultural Monitoring” and “Vegetation Indices” had the greatest prominence in the literature, with 26.8% each of the published works. The other themes occurred as 14.6% for “Biophysical Characteristics”, 12.2% for “Pests and Diseases”, and 9.8% for “Agricultural Yield” and “Perspectives on Technology”. It is noteworthy, therefore, that the search for coffee monitoring with RPASs and the application of vegetation indices to understand and monitor the crop in the field highlights the applicability of studies with this predominant theme, both in pioneering and more current works.

3.2 Performance Analysis

3.2.1 Key Publications

Among the analyzed papers, the five publications with the highest number of citations from 2002 to 2022 were selected (Table 2).

Table 2. Top 5 scientific publications with research development in RPAS in coffee growing from 2002 to 2022, ranked by citation number.

R	Title	Authors	PY	Journal	NC
1°	Imaging From An Unmanned Aerial Vehicle Agricultural Surveillance And Decision Support	HERWITZ et al. [24]	2004	Computers and Electronics in Agriculture	316
2°	Feasibility Of Monitoring Coffee Field Ripeness With Airborne Multispectral Imagery	JOHNSON et al. [25]	2004	Applied Engineering in Agriculture	39
3°	A Method For Detecting Coffee Leaf Rust Through Wireless Sensor Networks Remote Sensing And Deep Learning Case Study Of The Caturra Variety In Colombia	VELÁSQUEZ et al. [38]	2020	Applied Sciences	31
4°	Crop Growth Monitoring With Droneborne Dinsar	ORÉ et al. [33]	2020	Remote Sensing	26
5°	Biophysical Parameters Of Coffee Crop Estimated By Uav Rgb Images	DOS SANTOS et al. [32]	2020	Precision Agriculture	18

R: ranking; PY: publication year; NC: number of citations.

The most cited work, with eight times more citations than the second most cited work in this field, is the scientific study conducted by Herwitz et al. [24]. This work was a pioneer in using RPASs for agricultural mapping of coffee crops and was completed in Hawaii. The authors anticipated that the evolution of RPASs would represent a valuable future contribution to regional monitoring of agricultural resources. The work is widely cited and has gained prominence for being published in a highly impactful scientific journal, “Computers and Electronics in Agriculture”.

The second most cited work is that by Johnson et al. [25], which is a pioneering study on coffee fruit ripening conducted through aerial surveys using RPAS technology with an onboard sensor for data collection. The study demonstrated that remote sensing methods could provide an alternative and more comprehensive approach to monitor the ripening status and assess the optimal time for harvest.

The following works in the list of top citations are more recent, from 2020. Velásquez et al. [38] developed a study on coffee leaf rust through the technological integration of remote

sensing, using multispectral cameras in RPASs, wireless sensor networks, and deep learning techniques. This allows coffee farmers to automatically detect the disease, optimizing the production and maintenance of their plantations and replacing the task of manual inspection. Meanwhile, Oré et al. [33] proposed a new method to estimate the growth of first-stage crops based on experimental data and multiple circular flight surveys with RPASs using Differential Synthetic Aperture Radar Interferometry (DInSAR). This method is efficient as the growth rates analyzed are difficult to perceive visually or measure with conventional tools. In the fifth most cited work by Santos et al. [32], the authors used an RPAS for aerial imaging in coffee plantations to extract reliable vegetation indices and biophysical parameters derived from the structure from motion (SfM) algorithm. They estimated the height (h) and crown diameter (d) of coffee trees from RGB (red, green, blue) aerial images, comparing them to field truth collected over 12 months.

All the cited works serve as a basis for research employing aerial imaging to monitor coffee crops for various agricultural applications due to the nature of the techniques used. It is noticeable that studies describing fruit ripening are widely cited in the literature, particularly for understanding yield and the final production of coffee beans, which are strongly related to the profitability and returns of plantations. Grain production measurement in the field is still being studied and is highlighted as a challenge for coffee farming. Studies on weed anomalies, pests, and diseases are also heavily developed due to their influence on the final productivity of the crop and, consequently, on the financial returns associated with agricultural development. In recent years, studies combining RPASs with machine and deep learning techniques have been encouraged and developed, influenced by the refinement of techniques presented in pioneering works.

3.2.2 Main Journals

The journals were ranked in order of importance based on the number of citations from 2002 to 2022 (Table 3). The analysis was based on performance metrics used in the databases and considers the prestige of the journals in which the scientific articles are published. All the journals listed in the ranking predominantly focus on technological approaches from countries such as the United States of America, Estonia, Switzerland, and the United Kingdom, highlighting the extensive application of RPAS studies globally.

Table 3. Top 5 journals with research development in RPAS in coffee growing from 2002 to 2022, ranked by citation number.

R	Journal	SJR	CiteScore	JCR	Hi	ISSN	ND	NC
1°	Computers and Electronics in Agriculture	1.595	11.80	6.757	133	0168-1699	2	330
2°	Applied Engineering In Agriculture	0.284	1.11	0.896	57	0883-8542	2	57
3°	Remote Sensing	1.280	5.45	5.349	144	2072-4292	5	51
4°	Applied Science	0.435	3.70	2.838	52	2076-3417	1	31
5°	Precision Agriculture	1.169	6.54	5.767	70	1573-1618	4	12

R: ranking; SJR (SCImago Journal Rank): Web of Science Index; CiteScore: Scopus Index; JCR (journal impact factor): Scopus Index; Hi: H-index; ND: number of documents; NC: number of citations.

Based on the analysis of the most published journals, the journals “Computers and Electronics in Agriculture” and “Applied Engineering in Agriculture” have significantly contributed to developing the research topic. The journal ranked number 1 in citations features the pioneering work authored by Herwitz et al. [24]. The journal ranked number 2 in citations includes subsequent works by Johnson et al. [25] and Furfaro et al. [26], which also refer to pioneering studies on applying the topic.

These journals notably focus on technological issues in agriculture. “Computers and Electronics in Agriculture” provides international coverage of advances in computer hardware, software, electronic instrumentation, and control systems for solving agricultural problems. “Applied Engineering in Agriculture” publishes research applications in engineering and technology addressing issues in agricultural, food, and biological systems. Similar focuses can be observed in the other journals listed in the ranking described in Table 3.

3.2.3 Main researchers

The leading researchers were ranked in order of importance according to their H-index for the research topic between 2002 and 2022 (Table 4). The H-index was obtained to determine the impact of the author according to the number of publications and citations, considering only works developed by researchers on RPAS in coffee farming in this study.

Table 4. Top 5 relevant publications authors with research development in RPAS in coffee growing from 2002 to 2022, ranked by citation number.

R	Authors	ID	H-i	ND	NC
1°	Gabriel Araújo e Silva Ferraz	Ferraz, G. A. S.	6	18	89
2°	Brenon Diennevam Souza Barbosa	Barbosa, B. D. S.	5	9	79
3°	Lucas Santos Santana	Santana, L. S.	5	11	47
4°	Luana Dos Santos	Dos Santos, L.	5	5	47
5°	Giuseppe Rossi	Rossi, G.	5	7	43

R: ranking; H-i: H-index; ND: number of documents; NC: number of citations.

Ranked first with the highest academic impact on the topic is researcher and professor Gabriel Araújo e Silva Ferraz, with an H-index of 6, 18 published papers, and 89 citations. He is an agricultural engineer from the Federal University of Lavras (UFLA), holds a postdoctoral degree in agricultural engineering from the University of Florence (Italy), a postdoctoral degree in bioclimatology for animals and plants from the National University of Colombia–Medellin campus, a Ph.D. in agricultural engineering (UFLA), a master’s degree in agricultural engineering with a concentration in agricultural machinery and automation (UFLA), and a CAPES/FIPSE scholarship holder in the Brazil–USA sandwich undergraduate program. He is an Associate Professor at the Department of Agricultural Engineering at the Federal University of Lavras, a Postgraduate Program in Agricultural Engineering (UFLA) Professor, and the coordinator of the Agricultural Systems Engineering Center (NESA).

The other researchers have direct collaboration with researcher Gabriel Araújo e Silva Ferraz, being his master’s and doctoral students (Brenon Diennevam Souza Barbosa, Lucas Santos Santana, and Luana dos Santos) as well as his direct partner with the Italian institution, the University of Florence (Giuseppe Rossi).

3.2.4 Main institutions

The central research institutions responsible for developing knowledge on RPASs in coffee farming were identified. The relationships between the scientific organizations that produce knowledge on this topic are presented in Figure 3.

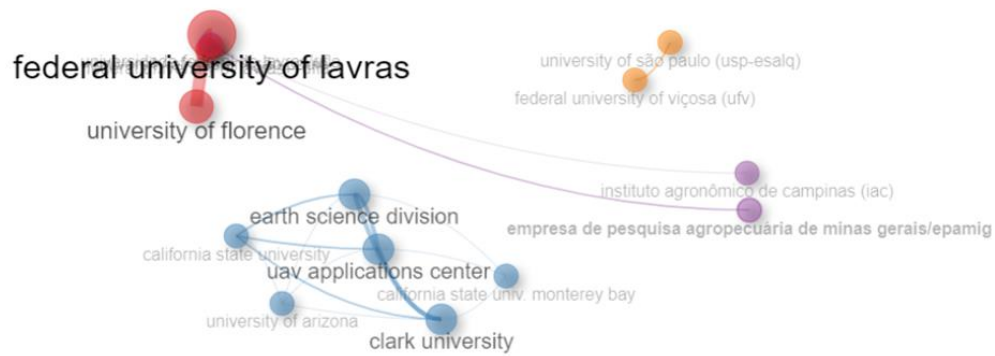


Figure 3. Scientific mapping network of teaching and/or research organizations that produce knowledge on RPAS in coffee growing. Red: the central institution was the Federal University of Lavras (UFLA) and direct partnership with the University of Florence. Blue: proximity between institutions in the United States of America. Orange: proximity between Brazilian institutions, the University of São Paulo and the Federal University of Viçosa; Purple: proximity to the Brazilian research centers IAC and EPAMIG.

The Federal University of Lavras has the highest number of publications on the study topic and is directly related to the University of Florence. Following that, institutions from the United States of America are highlighted, producing content on the subject and having direct partnerships. Subsequently, Brazilian institutions such as the partnership between the University of São Paulo, Federal University of Viçosa, and, finally, the Brazilian Research Centers EPAMIG and IAC stand out, with collaborative work with the Federal University of Lavras.

The analysis shows the relevance of Brazilian institutions in developing scientific research on RPASs in coffee farming, emphasizing the Federal University of Lavras. This is mainly due to the institution's location in the South of Minas Gerais, a region strongly associated with coffee production, traditionally recognized as the largest producer of coffee beans in the country [2]. This encourages the search for the adoption of new techniques and technologies to optimize and improve the development of the crop in the field, leading to the critical role assumed by this institution in coffee research. Bibliometric studies on coffee farming have already demonstrated the strong influence of the Minas Gerais region in this field [16,17,64].

3.2.5 Main countries

The central countries that produce scientific knowledge on RPASs in coffee farming were identified, as shown in Figure 4. Brazil stands out as the country with the most significant

contribution to the development of the topic worldwide, with 31 notable publications on the subject, mainly due to the predominance of Brazilian researchers in the top positions of the publication ranking, solidifying the country's prominence.

Brazil shows significant interest in coffee farming research, as this commodity is essential and active in its economy [1]. Therefore, employing techniques that optimize financial returns in this activity is encouraged, primarily through digital agriculture technologies. In other bibliometric studies on coffee farming, it has also been observed that Brazil has the highest number of related works, mainly due to being the world's largest coffee producer [16]. Thus, many educational and research institutions focusing on coffee farming are further emphasized. Additionally, new technological applications in this field, including the use of RPASs, impact the development of scientific research.

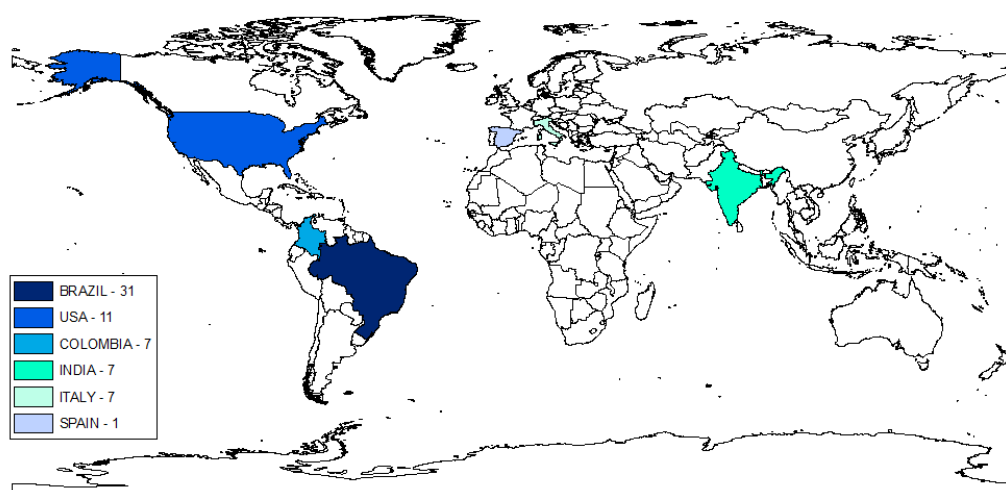


Figure 4. Central countries with research development on RPAS in coffee growing by number of publications from 2002 to 2022.

Italy contributes to the scientific production on the topic, even though it is not a significant player in global coffee production. The collaboration of Italian researchers in this field is driven by their expertise in sub-orbital remote sensing technology and its applications, including coffee farming, through direct collaboration between researchers from Italy and Brazil (University of Florence and Federal University of Lavras, respectively).

The United States, on the other hand, contributes to publications on the topic due to the significant number of agricultural science education and research institutions and its direct partnerships with various institutions. Although the country is not prominent in global coffee production, collaborations between American institutions and other institutions promote studies

related to this topic, a fact that justifies its wide participation in the number of scientific studies developed. One of the few American states with a tropical climate, Hawaii is responsible for almost all the country's coffee production and, notably, the pioneering studies conducted by Herwitz et al. [24] and Johnson et al. [25] were developed in Hawaii.

Colombia, as well as Brazil, a prominent country in world coffee production, presents studies on the focus of this research, seeking effective improvements for the development of the coffee crop, with studies aimed at vegetation indexes, quantification of flowering, productivity, and rust, especially in the Castillo and Caturra varieties, with direct applications of wireless sensor networks, remote sensing, and machine and deep learning.

3.3 Scientific Mapping

3.3.1 Co-citation Mapping

Co-citation mapping allows us to understand the connections between different authors through clustering, as authors within the same cluster regularly share similar ideas, while authors in other clusters have different central ideas. The size represents the author's influence, and the color represents the cluster (knowledge area) in which they were grouped. The results of the co-citation study are presented in Figure 5 for the intellectual base of RPASs in coffee farming.

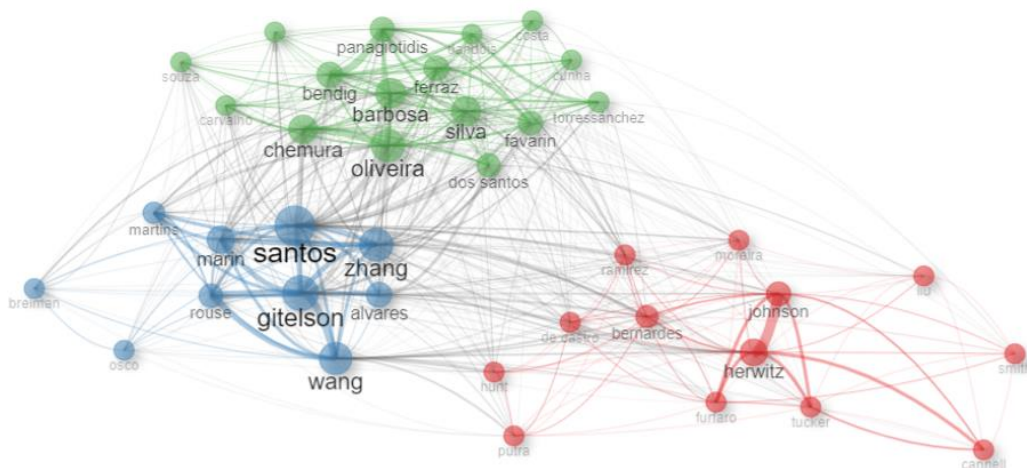


Figure 5. Scientific mapping of the co-citation of the most relevant research authors on RPAS in coffee growing.

As a result, three clusters were generated based on the studies' similarity and intellectual structure. In general, the red cluster houses authors with pioneering studies on the use of RPASs

in coffee farming, including Herwitz, Johnson, and Furfaro. The blue cluster encompasses authors with reflections on vegetation indices, diseases, and crop yield in the field, including Santos, Gitelson, and Zhang. The green cluster includes authors with works focused on using RPASs for agricultural estimation and monitoring, including Oliveira, Barbosa, Chemura, and Ferraz.

Santos stands out prominently in the blue cluster (Figure 4). Her leading publications address the study of biophysical parameters of coffee crops estimated by RGB images obtained by RPASs, aiming to assess the accuracy of photogrammetry techniques using point clouds for estimating canopy height and diameter, and significant estimates of these attributes were obtained using this technique [32]. Another notable study tracked the evolution of leaf area index (LAI) and percentage of land cover (%COV) in coffee crops using pre-established equations and plant measurements obtained from 3D point clouds, combined with the application of the structure from motion (SfM) algorithm to digital images recorded by a camera attached to an RPAS, and the methodology yielded consistent results with the literature [37].

3.3.2 Keyword Mapping

Investigating the most used keywords by authors is another way to analyze the data. Keywords with at least three occurrences in the analyzed documents were selected, and the information is presented in Figure 6 for the research topic of RPASs in coffee farming.

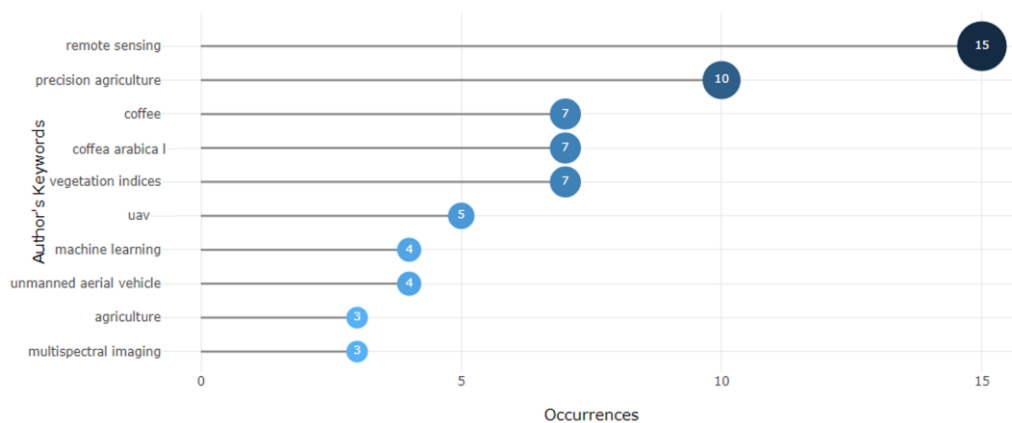


Figure 6. Author's keywords with occurrences above 3 in the analyzed documents for the research topic on RPAS in coffee growing.

Among the 122 keywords identified in the studies, only 11 met the adopted criteria. The most frequently occurring term was “remote sensing”, with 15 occurrences, followed by “precision agriculture”, with 10 occurrences, which, respectively, refer to the applied technique and the study theme when employing RPASs in coffee farming. The subsequent terms relate to

coffee itself, with “coffee” and “*Coffea arabica* L.” occurring seven times each. Following in occurrence are the actual data acquisition equipment, with the terms “UAV” and “unmanned aerial vehicle” occurring five and four times, respectively, and words referring to the applications for obtaining the proposed results, such as “vegetation indices”, “machine learning”, “agriculture”, and “multispectral images”, with seven, four, three, and three occurrences, respectively.

3.3.3 Trend Mapping/Future Possibilities

Overall, research on RPASs in coffee farming predominantly discusses the application of remote sensing techniques, indicating the potential of the technology in agricultural monitoring and timely and efficient decision making. Trends in studies on the proposed topic emerged with the direct application of RPASs for real-time mapping of coffee crops in the field, along with central ideas and concepts of RPASs, as well as the discussion of parameters and recommendations for the correct use and implementation of RPASs in agricultural activities. Subsequently, the focus of research expanded to synthesizing the services of RPASs, which were already employed in other agrarian crops and applicable to coffee farming. This includes several studies discussing RPAS applications in precision agriculture tasks, such as predicting plant growth and development and coffee crop yield. It was noted that the field of study progressed as RPASs were incorporated into artificial intelligence techniques, such as machine learning and deep learning, emphasizing new technological trends. Artificial intelligence techniques also allow the ability to deal with large amounts of nonlinear data, by analyzing data captured by RPASs and other ground- based and remote sensing systems for prediction and intelligent and effective decision making [64]. The advent of deep learning techniques offers robust and intelligent methods to improve the mapping of the Earth’s surface and agricultural sectors [65].

The literature on RPASs in coffee farming has increased in the past decade, as indicated by the number of publications in recent years. However, it is worth noting that the field of knowledge on the subject has not reached its maturity, as there are still many unanswered questions. In this sense, some gaps allow for research with this thematic focus. In this way, systematic reviews are effective in synthesizing knowledge about agricultural research and indicating research priorities [66].

Furthermore, it is known that acquiring and analyzing spectral data requires human and operational costs. Therefore, there is a need for rapid and efficient evolution of prediction methodologies based on data collected by RPASs, along with machine learning techniques, to

avoid routine human involvement. Understanding the processes that result in the final productivity of the crop and applying such analyses using techniques and technologies allows the anticipation and correction of issues that could lead to low profitability of the plantations; therefore, this should be the focus of research on RPASs in coffee farming.

Figure 7 shows the trends in the proposed topic from the beginning of the studies in 2002 to the present day, based on the fractional counting method using bibliographic data on the co-occurrence of author keywords. The map uses different colors of nodes to highlight the most frequently used author keywords over the past 20 years of study.

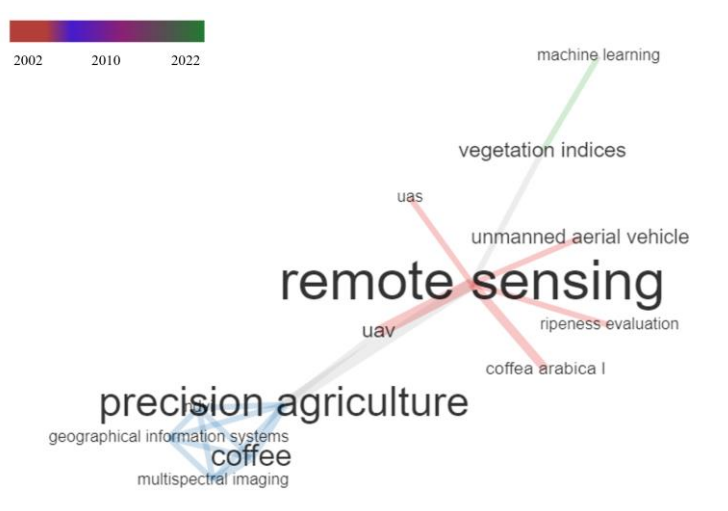


Figure 7. Co-occurrence map of authors' keywords from 2002 to 2022. The color scale in the nodes represents the year of the predominance of the keyword.

From 2002 to 2010, there is a cluster highlighted in red, indicating the initial terms of the technique “remote sensing”, the instrument used “unmanned aerial vehicle” (UAV), “UAS”, the coffee species under study “*Coffea arabica* L.”, and the theme of “ripeness evaluation” systematically explored during that time. In the following years until 2010, highlighted by the blue node, remote sensing techniques began to be used with the direct application of terms such as “precision agriculture”, “Geographical Information Systems”, and “multispectral imaging”. From 2016 onwards, identified by the purple node following the green one, the recent application of products obtained through aerial imaging using RPAS is evident, with the application of keywords related to “vegetation indices” and, more recently, highlighted by the application of “machine learning”, which promises to be the trend in studies on the analyzed theme in this study.

These techniques and technologies can be used to increase knowledge about field variables, significantly influencing the quality of coffee production since the quality of the beans/beverage reflects characteristics such as climate, soil, altitude, cultivation, and management. Machine learning stands out due to its high computational performance, which allows the understanding of different field processes [67]. However, in future years, significant transformations in the coffee industry can be expected, taking into consideration environmental and sustainability aspects. Despite the challenge of improving productivity, sustainable management will be increasingly necessary due to the importance of employing intelligent forms of control regarding climate change.

It is noteworthy that the demands of coffee growing have not yet been fully met; thus, studies with an emphasis on the stress issues to which plants may be subjected (pests, diseases, nutritional levels, and impacts of climate and soil), as well as their returns of productivity, can be obtained using data collected by RPASs in coffee plantations with the most different characteristics, above all, using digital agriculture and machine and deep learning techniques. Thus, future researchers are recommended to explore the potential gaps and insights for conducting investigations and future possibilities on how RPAS technology can help farmers determine the condition of their crops by evaluating issues that affect plant development and growth, with direct applications of themes such as machine learning, deep learning, big data, and the Internet of Things (IoT). Active involvement of farmers in academic research is particularly recommended, emphasizing the field factors and contributing to the theoretical and practical advancement of research in this proposed thematic study. This way, the correct application of smart agriculture is essential to maximize crop yield and profitability and preserve natural resources [68].

Therefore, bibliometric studies are strongly encouraged due to the growing interest in the study of knowledge networks manifested in recorded scientific knowledge [69]. In this way, researchers can identify the most relevant academic records and analyze the interrelationships of different areas of knowledge, especially due to the exponential increase in the production of academic records, making gains in all areas [70,71]. Furthermore, as fields of inquiry mature and become complex, scholars must seek to make sense of the knowledge generated to reveal new contributions, capture research trends, identify which topics are studied, and delve deeper into the structure of knowledge and possible directions of research [72].

4. Conclusions

This study concludes that the temporal evolution of research on the subject has allowed us to identify a significant increase in scientific publications; the performance analysis highlighted the critical publications on the subject, which refer to pioneering publications on the application of RPASs in coffee farming; “Agricultural Monitoring” and “Vegetation Indices” were the two main research themes highlighted according to thematic coding; the prominent journals notably address agricultural technology issues, demonstrating the applicability of RPASs for data collection and efficient implementation in the agricultural sector; the principal researchers, countries, and institutions are associated with the work of Professor Gabriel Araújo e Silva Ferraz from the Brazilian institution Federal University of Lavras; the scientific co-authorship mapping allowed us to observe the presence of authors with initial applications of RPASs in agriculture and direct applications of RPASs in coffee farming for estimating plant biophysical parameters and supporting management and decision making; the keywords identified the techniques behind the use of RPASs, words related to the agricultural crop itself, different nomenclatures for aerial image acquisition tools, and studies that can be directed based on the collected images; and the scientific applications related to crops’ final production and financial yield are encouraged, focusing on technological advancements, including machine learning and deep learning.

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Conflicts of Interest: Data are contained within the article.

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2.2 ADDITIONAL INFORMATION

As a way to complement the study presented in Paper 1 of this thesis, the bibliometric analysis was expanded using the same search databases (Scopus and Web of Science) and the same search terms (“remotely piloted aircraft” OR “remotely piloted aircraft system” OR “unmanned aerial system” OR “unmanned aerial vehicle” OR UAV OR UAS OR RPAS OR RPA OR VANT OR DRONE) AND (coffee OR “coffee growing” OR “coffee plants” OR “coffee cultivars” OR “coffee crops” OR “coffee farm” OR “Precision coffee growing”) for the years 2023 and 2024.

For these two additional years of study, 65 works on the subject were identified, with 37 published in 2023 and 28 in 2024 (Figure 1). This highlights a significant increase in scientific production, with a greater number of works produced in the last two years (2023 and 2024) compared to the previous 10 years of study (2002–2022), as presented in Paper 1 of this thesis. And the five most relevant works from the past two years are presented in Table 1.

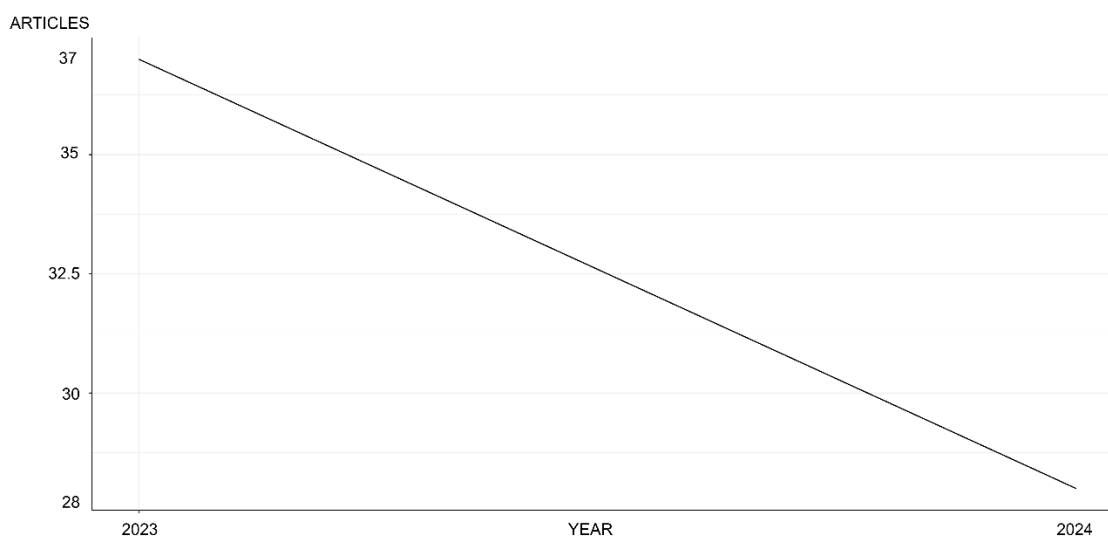


Figure 1. Evolution of research publications on RPAS in coffee growing from 2023 and 2024.

Table 1. Top 5 scientific publications with research development in RPAS in coffee growing from 2023 and 2024, ranked by citation number.

R	Title	Authors	PY	Journal	NC
1°	Efficiency of Fungicide Application an Using an Unmanned Aerial Vehicle and Pneumatic Sprayer for Control of <i>Hemileia vastatrix</i> and <i>Cercospora coffeicola</i> in Mountain Coffee Crops	VITÓRIA et al.	2023	Agronomy	12

2°	A novel deep learning architecture for disease classification in Arabica coffee plants	RAMAMURTHY et al.	2024	Concurrency and Computation: Practice and Experience	11
3°	A Method For Detecting Coffee Leaf Rust Through Wireless Sensor Networks Weed Detection and Mapping of a Coffee Farm by a Remotely Piloted Aircraft System	BENTO et al.	2023	Agronomy	7
4°	Evaluation of the Water Conditions in Coffee Plantations Using RPA	SANTOS et al.	2023	AgriEngineering	5
5°	Efficiency of Fungicide Application an Using an Unmanned Aerial Vehicle and Pneumatic Sprayer for Digital mapping of coffee ripeness using UAV-based multispectral imagery	MARTINS et al.	2023	Computers and Eletronics in Agriculture	5

R: ranking; PY: publication year; NC: number of citations.

The most cited work produced in the last two years focuses on evaluating the efficiency of spray droplet deposition in coffee plantations located in mountainous regions, combined with the efficacy of fungal disease control. This study tested both the application efficiency using an unmanned aerial vehicle and the effectiveness of the applied products (VITÓRIA et al., 2023). The second most cited work proposes an effective method for detecting diseases in Arabica coffee plants using the EfficientNetB0 architecture (deep learning), achieving an accuracy of 84% (RAMAMURTHY et al., 2024). The third most cited work aimed to classify and map areas occupied by weeds, determine the percentage of occupied area, and propose control strategies for field treatments in coffee plantations. The study concluded that differentiation between target classes was feasible due to spectral differences among the targets, with the Random Forest algorithm showing the best classification performance. Moreover, the cost savings achieved by treating only areas with weed presence, compared to treating the entire study area, was approximately 92.68% (BENTO et al., 2023). Following this, the fourth most cited work focused on evaluating water conditions in a coffee plantation using precision agriculture techniques combined with geostatistics and high-resolution imagery. The study concluded that geostatistical analysis was a valuable tool for spatializing the water potential variable. Conversely, vegetation indices derived from images captured by a Remotely Piloted Aircraft were less effective in assessing the water conditions of coffee plants (SANTOS et al., 2023). Finally, the fifth most cited work from the last two years addressed predicting coffee fruit maturation using spectral and textural variables and identifying the best variables for developing spatiotemporal variability maps of coffee fruit maturation. The study demonstrated

the feasibility of using spectral and textural variables derived from aerial images to map and monitor fine-scale spatiotemporal changes in fruit maturation (MARTINS et al., 2023).

Regarding the themes of other studies published in 2023 and 2024, notable topics include the use of vegetation indices, studies on diseases, pests, and weeds affecting coffee crops, plantation and harvest planning, plant counting, flowering quantification, the impact of frost and drought, soil compaction, chemical application rates, the use of thermal sensors, machine learning algorithms (including neural networks and convolutional neural networks), predictions of maturation and production yield, as well as studies focused on the use of aircraft for spraying, emphasizing application rates, hydraulic nozzles, and droplet and spray deposition.

The journals with the highest number of publications over the past two years are presented in Figure 2. They primarily include interdisciplinary academic journals focused on production and horticultural engineering science, agronomy, and agroecology, as well as those addressing aspects of remote sensing science, from sensor design and validation/calibration to its applications in geosciences, environmental sciences, ecology, and civil engineering. Additionally, these journals encompass topics related to real-world challenges in modern biosystems engineering. All journals encourage scientists to publish their experimental and theoretical results with the highest level of detail, ensuring that the methods and approaches are presented comprehensively to enable the reproducibility of results.

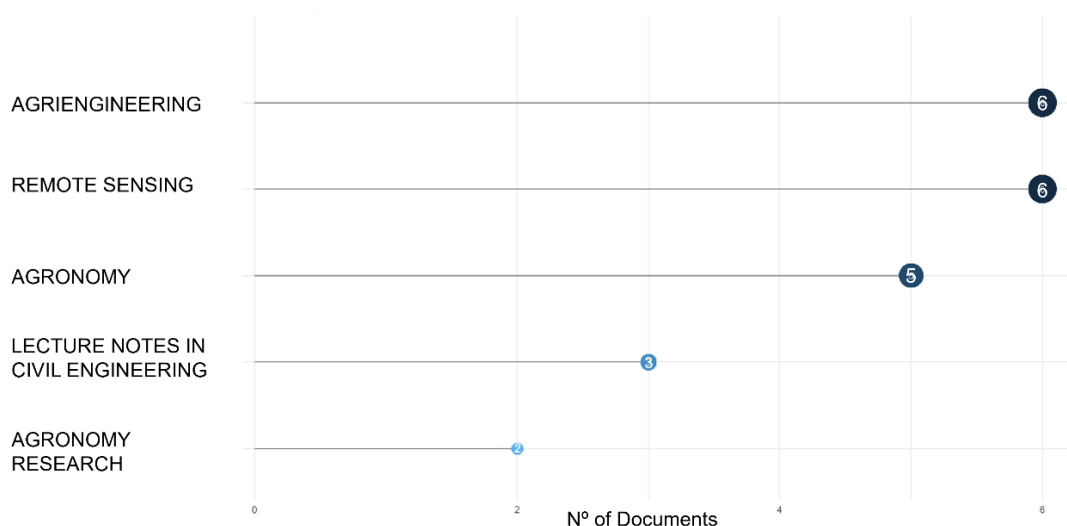


Figure 2. Top 5 journals with research development in RPAS in coffee growing from 2023 and 2024, ranked by documents number.

The most relevant authors from the past two years are presented in Figure 3, based on the number of documents published on the research topic in 2023 and 2024. Professor Gabriel Araújo e Silva Ferraz (FERRAZ G.) remains the most prominent author in this field, with other

authors from his direct partnership, including graduate students (BENTO N. and MARIN D.) and professors from Italy (CONTI L. and ROSSI G.).

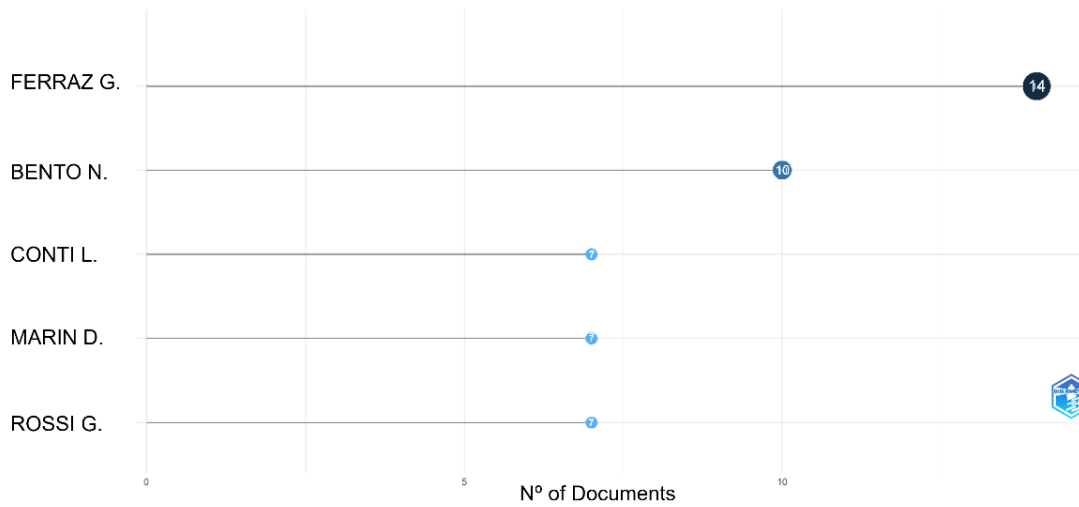


Figure 3. Top 5 relevant publications authors with research development in RPAS in coffee growing from 2023 and 2024, ranked by documents number.

The institutions with the highest number of publications in the past two years are presented in Figure 4, highlighting the Federal University of Lavras (Brazil) and its direct partnership with the University of Florence (Italy) and the Agricultural Research Company of Minas Gerais (EPAMIG). Additionally, other prominent Brazilian institutions include the Federal University of Viçosa and the Federal University of Uberlândia. The countries with the highest number of publications in the past two years are presented in Figure 5, highlighting the countries of the previously mentioned universities, as well as other nations that have also published scientific works on the topic central to this bibliometric study.



Figure 4. Top 5 relevant affiliations with research development in RPAS in coffee growing from 2023 and 2024, ranked by documents number.

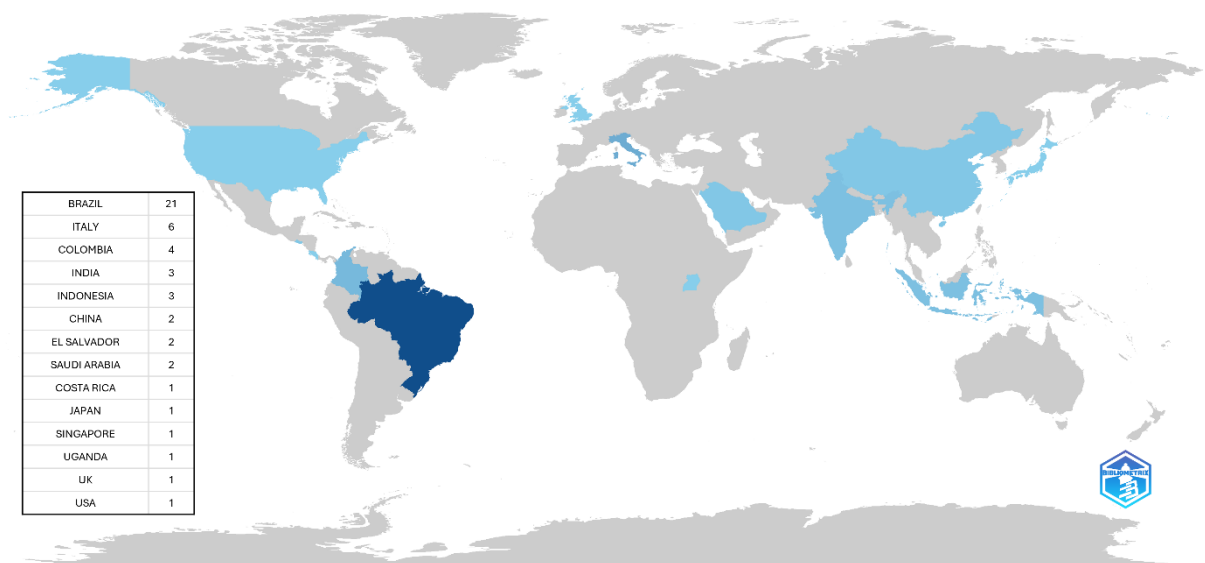


Figure 5. Central countries with research development on RPAS in coffee growing by number of publications from 2023 and 2024.

The significant increase in the number of publications related to the central theme of this thesis in the past two years (2023 and 2024) highlights the growing interest in the development of relevant scientific research on the application of RPAS (Remotely Piloted Aircraft Systems) in coffee farming, as emphasized in section 2.2. This trend underscores the importance of advancing agricultural studies by addressing existing knowledge gaps and exploring new perspectives through the application of innovative techniques and technologies. The continuation and expansion of these investigations are crucial for promoting scientific and technological advancements, contributing to the strengthening of more efficient, sustainable, and competitive practices in coffee farming, while also consolidating the strategic relevance of this topic for both the agricultural sector and science in general.

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SECOND PART

3. PAPERS:

3.1 WEED DETECTION AND MAPPING OF A COFFEE FARM BY A REMOTELY PILOTED AIRCRAFT SYSTEM

Article published in *Agronomy* (ISSN 2073-4395)

Accepted: 10 March 2023 / Published: 12 March 2023

DOI: <https://doi.org/10.3390/agronomy13030830>

3.2 SOIL COMPACTION MAPPING BY PLANT HEIGHT AND SPECTRAL RESPONSES OF COFFEE IN MULTISPECTRAL IMAGES OBTAINED BY REMOTELY PILOTED AIRCRAFT SYSTEM

Article published in *Precision Agriculture* (ISSN 1573-1618)

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DOI: <https://doi.org/10.1007/s11119-023-10090-0>

3.3 REMOTELY PILOTED AIRCRAFT SYSTEM AND MACHINE LEARNING FOR DETECTION OF COFFEE PLANTS SUBJECTED TO FOLIAR APPLICATION OF CHITOSAN

Article submitted to *European Journal of Remote Sensing* (ISSN 2279-7254)

3.4 PLANT HEIGHT AND SOIL COMPACTION IN COFFEE CROPS BASED ON LIDAR AND RGB SENSORS CARRIED BY REMOTELY PILOTED AIRCRAFT

Article to be submitted to *Agronomy* (ISSN 2073-4395)

3.1 WEED DETECTION AND MAPPING OF A COFFEE FARM BY A REMOTELY PILOTED AIRCRAFT SYSTEM

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Abstract: The differentiation between the main crop and weeds is an important step for selective spraying systems to avoid agrochemical waste and reduce economic and environmental impacts. In this sense, this study aims to classify and map the area occupied by weeds, determine the percentage of area occupied, and indicate treatment control strategies to be adopted in the field. This study was conducted by using a yellow Bourbon cultivar (IAC J10) with 1 year of implementation on a commercial coffee plantation located at Minas Gerais, Brazil. The aerial images were obtained by a remotely piloted aircraft (RPA) with an embedded multispectral sensor. Image processing was performed using PIX4D, and data analysis was performed using R and QGIS. The random forest (RF) and support vector machine (SVM) algorithms were used for the classification of the regions of interest: coffee, weed, brachiaria, and exposed soil. The differentiation between the study classes was possible due to the spectral differences between the targets, with better classification performance using the RF algorithm. The savings gained by only treating areas with the presence of weeds compared with treating the total study area are approximately 92.68%.

Keywords: digital agriculture; multispectral images; precision coffee farming; remote sensing.

1. Introduction

Brazil is currently the largest producer, exporter, and consumer of coffee in the world and the country is responsible for approximately 47% of the world's coffee production, and based on forecasts for the 2023 harvest, a good productivity margin, totaling 54.94 million bags of 60 kg, is expected for exports [1]. Among the cultivated species, *Coffea arabica* L. is the coffee most appreciated by consumers and therefore has great economic value. Due to the importance of this commodity in the Brazilian trade balance, scientific studies are encouraged to solve the problems encountered in the field. Thus, improvements are suggested, aiming at the optimization and profitability of coffee plantations.

To enhance the yield and decrease the cost of coffee crops, the correction and adaptation of problems encountered in the field are sought, and the efficient and timely control of weeds is a critical task in agricultural production, since the inadequate management of plant weeds reduces the yield of the main crop and increases the negative impacts on the environment [2]. Agrochemicals represent a considerable part of the cost of a crop, and the traditional methods of blanket spraying promote great waste because there is no selectivity at the time of application

[3]. In this sense, the mapping and detection of weeds through precision agriculture technologies allows greater economic and environmental sustainability. This technique can contribute to reducing environmental impacts by identifying specific areas for spraying agrochemicals [4]. In addition, the use of computer techniques and technologies combined with the agricultural problem allow the reduction in human work in the field, mainly when identifying weed spots in the crop lines and between the plants in the crop line [5].

In coffee crops, weeds, when poorly controlled, are in direct competition with coffee plants for water, light, and nutrients. Among the invasive species, the species morning glory (*Ipomea* sp.) belongs to the Convolvulaceae family, which includes more than 350 species distributed in 18 genera [6]. Morning glory are fast-growing climbing plants that inhabit the most varied environments, with heights ranging from 1 to 3 m [7]. This species can also cause damage to harvests since its branches are intertwined with the plants of interest, affecting the performance of agricultural harvesting machines as well as manual harvesting, which compromises the yield and efficiency of these processes [8]. It is therefore necessary to identify the different types of weeds that are harmful to the crop and the control mechanism for weeds [9].

Technological advancements have introduced a promising data acquisition approach in the field using proximal aerial platforms such as remotely piloted aircraft (RPA). The advantages of RPA in relation to satellite platforms have been described by several authors who highlighted the possibilities of coupling different sensors using lightweight batteries with a long life and optimizing the coverage of a large area with higher spatial resolution in a short time. This is presented as an important requirement for the mapping of weeds by the detection of small objects, consolidating itself as a new means of obtaining spatial, spectral, and temporal quality parameters [10,11].

Remote sensing technologies combined with machine learning methods can contribute to the identification of weeds in coffee plantations. In the literature, the main methods applied for weed identification using RPA images are based on algorithms combined with classification tools and spectral characterization. In this process, the pixels are segmented and classified according to their reflectance values [12,13]. Machine learning algorithms allow land cover mapping, which has become frequently used due to the applicability of different sensors, yielding better results than other commonly used classifiers [14]. Among these algorithms, random forest (RF) [15] and support vector machine (SVM) [16] have great flexibility and are widely applied for spectral classifications. Therefore, they allow the generation of land cover maps affected by spectral patterns, which enable the identification and study of the spatial distribution of weed infestation, making it possible to develop treatment maps with different

application demands according to the distribution of the plants in the crop, which has economic and ecological implications. It is also noteworthy that machine and deep learning-based crop and weed identification systems have the potential to save money and, at the same time, reduce environmental stress [17].

The mapping of weeds based on aerial images obtained by RPA is incipient, since there are few studies with this theme, especially for coffee crops. Weed mapping studies have been performed in cereals [18], corn fields [19], sunflower fields [20], and wheat and barley [21]. Furthermore, regarding the use of RPA to carry out aerial imaging for management recommendations in agricultural areas, its use for the localized spraying of agrochemicals stands out [22]. The advantages include a lower payload capacity, performing spraying on time [23], reducing health-related problems by reducing the number of workers and workload [24], and also promoting lower environmental impacts due to the application occurring in a localized and specific way [25].

In this context, the objective of this study is to use RPA for the diagnosis of an area and to map coffee plantations containing weeds (morning glory, *Ipomea* sp.) through classification algorithms, demonstrating the applicability of the procedure as well as the implementation of strategic control through selective spraying in coffee plantations.

2. Materials and Methods

2.1. Study Area

The study area is the Samambaia Farm, which is located in the municipality of Santo Antônio do Amparo, Zona Campos das Vertentes, Minas Gerais (MG) state, between the meridians 507,000 and 507,100 m W and parallels 7,691,400 and 7,691,500 m S in the UTM projection zone 23S and Sirgas 2000 geodesic reference (Figure 1). The municipality is located in the Atlantic Forest Biome with Dystrophic Red–Yellow Latosol [26] and a subtropical rainy climate with a temperate, dry winter, and warm summer (Cwb) according to the Köppen classification [27].

The experiment is characterized by an area of the coffee plantation (*Coffea arabica* L.) planted in November 2018, one year prior to data collection. The planted cultivar is Yellow Bourbon (IAC J10) as registered in the National Cultivar Registry (NCR) of the Ministry of Agriculture, Livestock, and Supply [28]. The area has a spacing of 3.8 m between rows, 0.5 m in the planting row, an average altitude of 1022.00 m above sea level, and the presence of brachiaria (*Brachiaria decumbens*) between the rows.

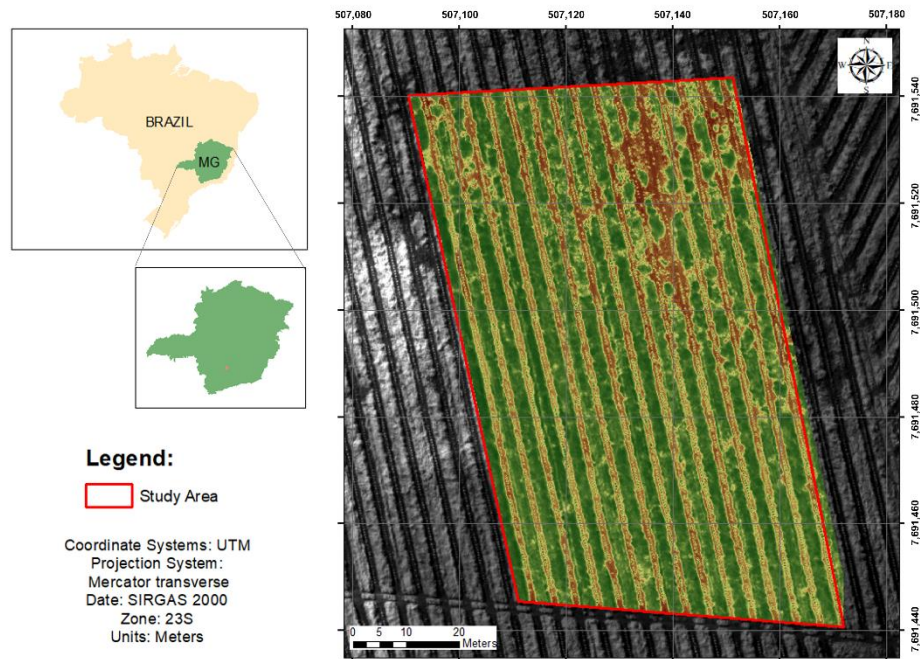


Figure 1. Location of the study area.

2.2. Collection of Aerial Data

Aerial imaging was collected based on two flights on 13 December 2019 by a remotely piloted aircraft, Matrice 100 (DJI, ShenZhen, China), equipped with a multispectral camera (Parrot Sequoia, MicaSense, Seattle, WA, USA) and an irradiance sensor (S sunshine sensor) with reflectance values described in the green (GRE 530–570 nm), red (RED 640–680 nm), borderline red (REG 730–740 nm), near infrared (NIR 770–810 nm), and visible (RGB 380–720 nm) spectral bands (Figure 2). The orthomosaics generated in the first flight were used for training and validation of the model and the orthomosaics generated in the second flight were used to predict the distributions of the study classes and thus proceed with subsequent studies and recommendations.

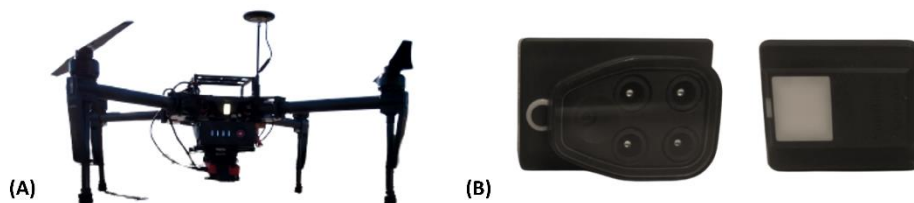


Figure 2. (A) RPA Matrice 100; (B) Parrot Sequoia and sunshine sensor.

The flight plan was generated using Precision Flight software (Precision Hawk, Raleigh, NC, USA) with parameters defined as follows: above ground level (AGL) distance of 50 m,

flight speed of 8 m/s, with forward and side overlap of 80% and 80%, respectively, and a flight direction transverse to the planting row. The flight had a standardized schedule between 11:00 am and 1:00 pm, so there was no shading influence. The radiometric calibration of the images was performed using a calibration plate from the manufacturer of the sensor used to capture the images.

2.3. Image Processing

Aerial image processing was performed using Pix4D Mapper version 4.4.12 (Pix4D, Lausanna, Switzerland), and the orthomosaic product generated for each spectral band is related to the sensor used. The processing workflow consists of three different steps: initial processing, mesh/point cloud generation, and orthorectification as described in Figure 3.

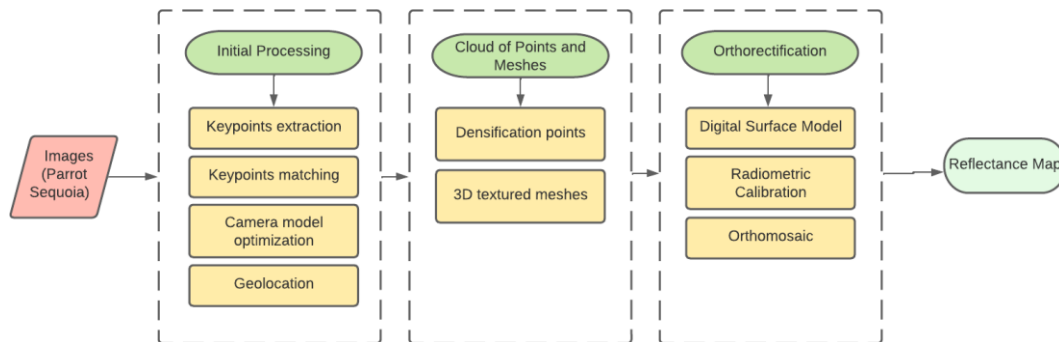


Figure 3. Image processing flow in Pix4D Mapper software.

The image processing software used is based on the detection of keypoints, which refer to the computer vision technique to locate key parts of objects in an image, that is, the keypoints refer to each characteristic point found in an image. Thus, in the first stage, specific image features (keypoints) were identified, these keypoints were found and combined, the internal and external parameters of the sensor were calibrated, and finally, the geolocation information of the collected images was determined. The tie points are automatically created during this stage. In the second stage, densified points were created; that is, more tie points are created on top of the existing ones to create a densified point cloud, and the 3D textured mesh was also created based on the densified point cloud. In summary, keypoints refer to the characteristic points of the image, tie points are points generated after connecting points with similar characteristics (keypoints), and densified points are the creation of a greater number of points to represent the terrain.

The orthomosaic consists of joining several images to form a single image based on the process of orthorectification, a method in which the perspective distortions of the images are removed. This way, in the third stage, the orthomosaics of each spectral band of the sensor (in this case, the RGB bands and individual GRE, RED, REG, and NIR bands) are created, in which the value of each pixel indicates the reflectance of the imaged object.

2.4. Classification Method (Training and Validation)

The training and validation steps are shown in Figure 4 and consist of (a) preprocessing and exploratory data analysis; (b) sampling of the classes of interest using orthomosaic images; (c) classification procedure using support vector machine (SVM) and random forest (RF) algorithms; (d) validation and verifying the performance of the SVM and RF classifiers; and (e) applying the best classifier in the prediction of the total area and the identification of the percentage of occupation of each class of study, with procedures performed in the QGIS 3.22.8 (QGIS Development Team, Open-Source Geospatial Foundation) and R Studio (R Development Core Team, R project, Austria, Vienna) software.

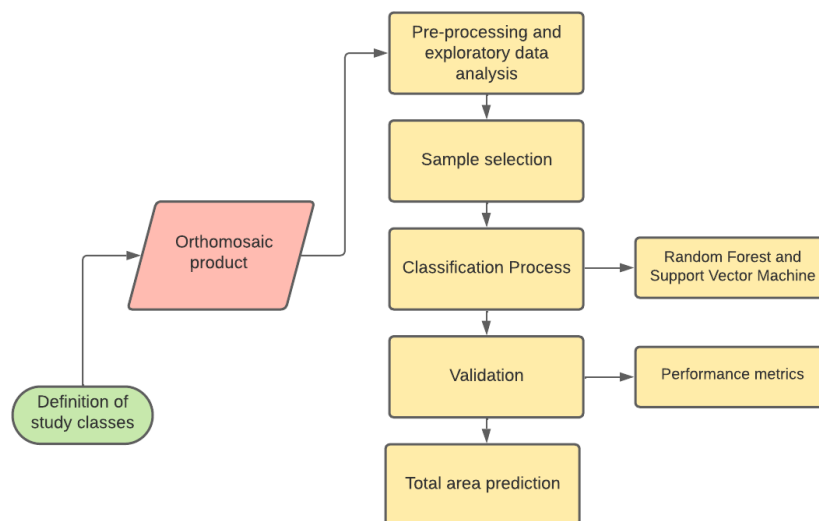


Figure 4. Flowchart of the classification process with the methodological steps used.

In the classification process, four classes of interest were established: coffee, weed (morning glory), brachiaria, and exposed soil. The training samples of the classes of interest were selected based on the interpretation of the high-resolution orthomosaic image produced by the images collected by the RPA. For each class, a training shapefile with regions of interest (ROIs) was obtained, and a total of 650 samples were generated and distributed as follows: coffee ($n = 150$); weed ($n = 150$); soil ($n = 200$); and brachiaria ($n = 150$). Sample collection

was performed using QGIS 3.22.8 with the Semi-Automatic Classification Plugin (SCP). Due to the spatial quality of the generated orthomosaic image, it cannot be assumed that a set of pixels that includes the sampled shapefile represents each class of interest. Thus, the points corresponding to all pixels belonging to ROIs for each study class were used as samples, increasing the number of samples (total of 8284 samples) with a procedure performed in R Studio. In summary, the samples were initially collected in shapefile format (650 samples), and then the rasters referring to each spectral band were extracted pixel-by-pixel from the contours of the shapefile, thus increasing the number of training samples (8284 samples) and improving the classification quality by increasing the number of samples for evaluation. The spectral signatures of each class of interest were generated by the ROIs using QGIS 3.22.8 to characterize the behavior of the reflectance of the pixels in each spectral range of the study.

Subsequently, using R, these samples were randomly divided into training and validation samples in proportions of 70% and 30%, respectively, with 5799 training samples and 2485 validation samples. Classification using the training samples was based on separation information from the reflectance spectrum using the SVM [29] and RF [15] classifiers in R. For SVM classification, the polynomial kernel function was applied, and for RF classification, the number of decision trees (Ntree) equal to 100 and the number of variables to be tested (Mtry), corresponding to the square root of the number of input variables, were defined [30]. For RF classification, the analysis of the Gini index was also applied, allowing the importance of each input variable of the algorithm for the classification process to be described. According to the application of the analysis via Mean Decrease in Gini, variables that present nodes with greater classification purity will have higher values and, therefore, have greater importance in the classification algorithm widely used in analyses of this type [31,32].

The data were validated based on the validation sample percentage with direct comparison to the reference data (training samples). The performance evaluation and classification quality of each algorithm were obtained through information derived from the confusion matrix using the overall accuracy, producer accuracy, user accuracy, and external metrics F1 score metrics [33], as well as the area under the ROC curve and kappa index [34].

The classifier algorithm with the best performance metrics was used to predict the total area and to identify the percentage of occupied area for each study class. Based on the information from the classifier, the prediction map of the classes of study was generated (location and percentages of area occupied by each class of study) using the QGIS 3.22.8 software. This map makes it possible to identify the presence of weed occupation in the field

and thus proceed with management based on the localized application of agrochemicals only in the compromised areas by weeds.

The analysis of the costs involved in the process of weed control was also performed, considering for this the current price quote of the weed control product in question, in this study the product HEAT (Saflufenacil), and considering the spray volume to be used only in areas with weeds versus the spray volume to be used in the total area (conventional application). Thus, the effect of savings was highlighted by showing the financial costs that would be spent for the application of agrochemicals in the total area versus the financial costs spent for the application of agrochemicals, considering only the application in areas occupied by weeds.

3. Results

3.1. Overall Classifier Accuracy

The results of the overall accuracy, kappa index, F1 score, and area under the ROC curve of the classifications using the RF and SVM algorithms are presented in Table 1 (results considering all classes of study). In general, satisfactory values of the analyzed metrics, which indicate good classifier performance for the differentiation of the study classes, were achieved using both algorithms. However, it should be emphasized that the values obtained using the RF algorithm were higher than those using the SVM algorithm.

Table 1. Performance metrics for the RF and SVM classification algorithms.

Algorithm	Global Accuracy	Kappa Index	F1	AUC
RF	99.24	98.86	98.91	99.91
SVM	98.71	98.08	96.52	99.83

The results for the classification algorithms were validated by means of confusion matrices, as shown in Table 2 for the RF algorithm and Table 3 for the SVM algorithm (results considering the study classes individually). As previously demonstrated by the satisfactory values of the performance metrics, few errors between the classified thematic classes were observed through the confusion matrices of both classification algorithms (Table 2 and Table 3). For both classifiers, the class with the greatest confusion, according to analysis via confusion matrix, was the exposed soil; this class has higher values of sampled pixels, which also result in an increase in errors. However, the errors were minimal and did not compromise the statistical results of the classification performance.

Table 2. Confusion matrix for the RF machine learning algorithm.

Classes		Reference				Total	ET1 (%)
		Brachiaria	Coffee	Weed	Soil		
Prediction	Brachiaria	481	0	0	0	481	0
	Coffee	0	400	2	11	413	3.15
	Weed	0	0	372	0	372	0
	Soil	0	5	1	1213	1219	0.50
	Total	481	405	375	1224	2485	-
ET2 (%)		0	1.23	0.80	0.89	-	-

Legend: Error type 1 (ET1); error type 2 (ET2).

Table 3. Confusion matrix for the SVM machine learning algorithm.

Classes		Reference				Total	ET1 (%)
		Brachiaria	Coffee	Weed	Soil		
Prediction	Brachiaria	481	0	0	0	481	0
	Coffee	0	392	2	15	409	4.15
	Weed	0	1	371	0	372	0.26
	Soil	0	12	2	1209	1223	1.15
	Total	481	405	375	1224	2485	-
ET2 (%)		0	3.21	1.07	1.22	-	-

Legend: Error type 1 (ET1); error type 2 (ET2).

User accuracy are the estimates of fractions of mapping pixels, for each class, correctly classified, whereas producer accuracy are the sample fractions of pixels of each class correctly assigned to their classes by the classifiers [35]. In this regard, analyzing the discrimination between the thematic classes through the producer and user accuracies (Figure 5), similar behaviors for the algorithms, with good discrimination of the study classes, are evident. Based on Figure 5A, satisfactory results are observed for the average producer accuracy, with higher hits for the brachiaria class and a slight superiority of the RF algorithm when compared with the SVM algorithm. In turn, based on Figure 5B, satisfactory results are also observed for the average user accuracy, with high hits for the brachiaria and weed classes, and again a slight superiority of the RF algorithm when compared with the SVM algorithm. For the producer and user accuracies of both algorithms, the class with the lowest hit rate was that of coffee plants. However, with values greater than 95%, which indicate satisfactory values for this metric, the applicability of the algorithms for all classes of study is demonstrated.

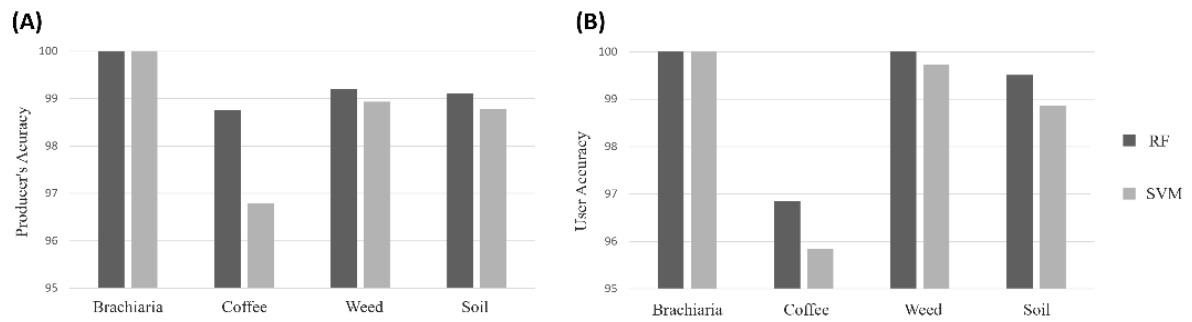


Figure 5. Average producer and user accuracy for each thematic class for (A) RF and (B) SVM.

3.2. Mapping and Quantification of the Study Classes

From the RF classifier, which yielded superior performance metrics, it was possible to describe the importance of each variable for the classification process through the Mean Decrease in Gini (Figure 6). Thus, it was noted that the variable of the NIR spectral band had the greatest importance for the classification, followed by the REG and RED spectral bands, and the least importance for the classification was the GRE spectral band, which is also highlighted in the spectral signatures of the study classes, according to Figure 7.

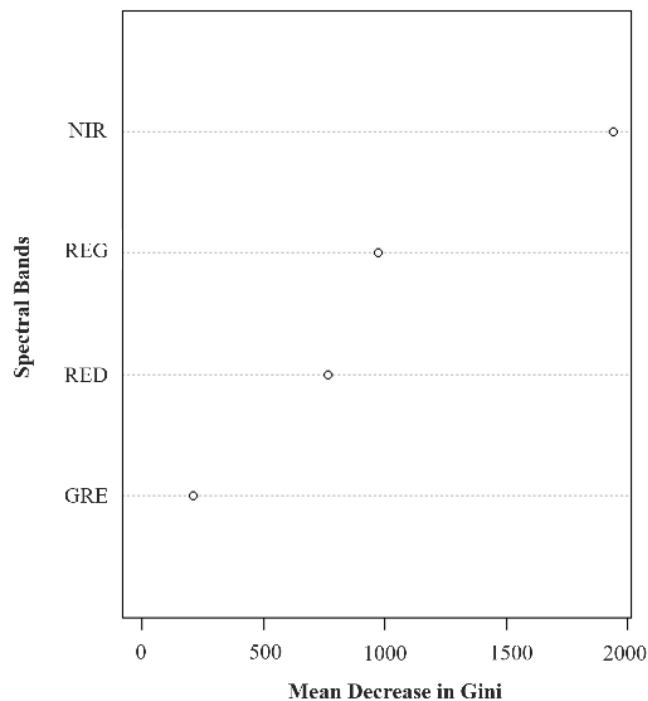


Figure 6. Importance variables by Mean Decrease in Gini in spectral bands.

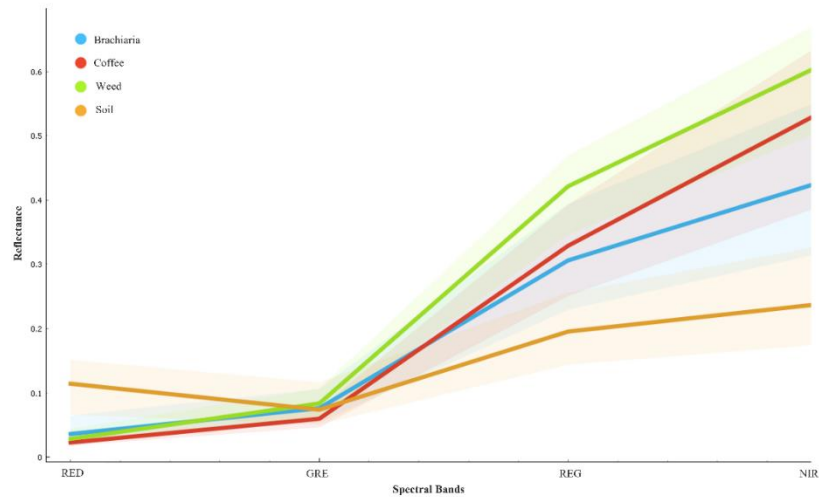


Figure 7. Spectral signature of each study class.

The map of the distribution of classes with the RF classifier (the prediction of classes by the classifier algorithm) is shown in Figure 8. In this figure, the spatialization for the study area and the percentage of occupation of the thematic classes in the study area are shown. There is a large discrimination between the analyzed classes, highlighting the quality of the classifier in determining the percentage of weed occupation (7.07%) in the crop and differentiating it from the coffee plant (16.42%), brachiaria (11.96%), and soil (64.54%).

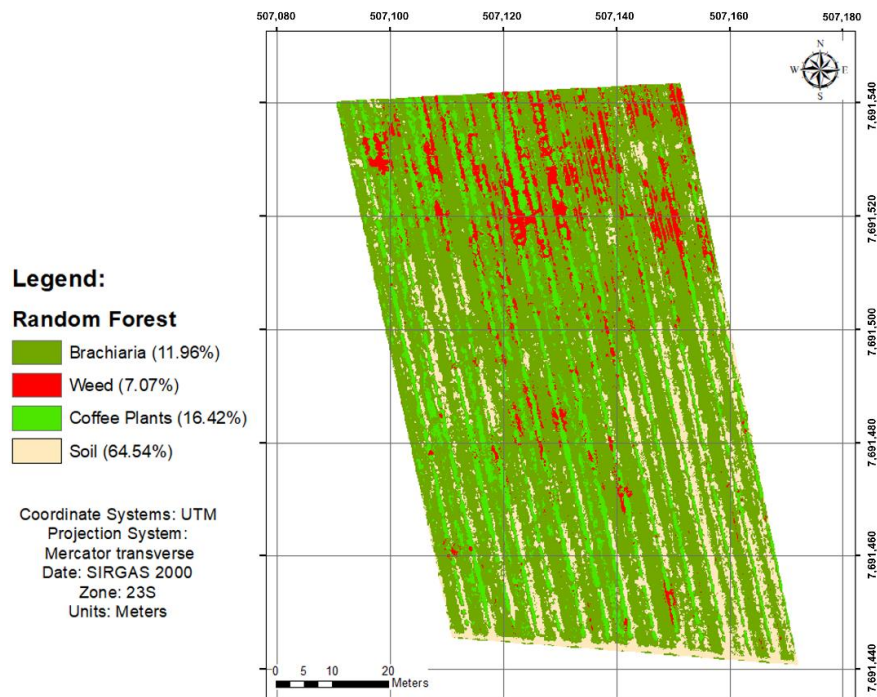


Figure 8. Land cover map with the RF classifier and the corresponding percentages for each class.

Figure 8 also allows the diagnosis of the areas occupied by weeds with respect to their location and percentage of occupation. It was possible to identify strategic points for the local application of the agrochemical control of morning glory in the coffee plantation, allowing the recommendation of the spray volume and the comparison of the volume of spray that would be applied in the total area (180.3 L) versus the volume of spray applied in only areas with the presence of weeds (13.2 L) and enabling the analysis of financial costs involved in this process.

4. Discussion

4.1. General Precision of the Classifiers

As shown in Table 1, the overall accuracy, kappa index, F1 score, and area under the ROC curve values allowed the reliable discrimination of the study classes. The accuracy values indicate how often the classifier correctly estimates the proposed classes, with values closer to 100% indicating the excellent fit of the model to the proposed classes [36]. Considering the levels of evaluation of the kappa index, values above 0.81 indicate excellent performance [37]. Conversely, the area under the ROC curve (AUC) quantifies the discriminatory power of a model with values above 90% considered excellent for this variable [38]. For the producer and user accuracy values (Figure 5), a very high hit rate was obtained for all study classes using both algorithms, which can also be highlighted in the individual analysis by classes in the respective confusion matrices (Table 2 and Table 3). It should be noted that the classes with the highest confounding error were soil and coffee plants; however, low error percentages of approximately 4% for both inclusion and omission errors were obtained.

It is shown that the creation of a batch of decision trees as well as class division hyperplanes for the RF and SVM algorithms, respectively, was possible with the use of the multispectral bands of the sensor onboard the RPA used in this study. It is evident that the classifiers showed great similarity in class discrimination in the study area, which may be related to the low number of classes analyzed, the size of the study area, and the large spread of the weeds in the field; however, there were still pixels classified with erroneous classes, which may be directly related to the pixel-by-pixel classification method. Thus, for both tested algorithms, all performance metrics are within the limits of excellence in terms of classification acceptance; however, a better performance was observed using the RF. It is noteworthy that pixels classified as erroneous classes are checked whenever the classification does not reach 100% quality; however, the high classification performance evidenced by the satisfactory values of the analyzed performance metrics stands out, both in general analysis and in analysis by class via a confusion matrix.

The RF algorithm has characteristics that make it beneficial for classification. This algorithm is less affected by outliers and data with noise, is nonparametric, supports data with various statistical distributions, has a high capacity for processing large-scale data and data from various sources, and has greater accuracy in terms of classification when compared with other classifiers such as SVM and maximum likelihood [39,40]. Another benefit of this algorithm is the possibility of using the analysis of the variables of importance through the Mean Decrease in Gini, which allows an overview of the behavior of the variables during the classification process and the identification of those variables with greater and lesser importance weights (Figure 6).

By comparing the classification algorithms used in this study, it was observed that the SVM algorithm required a longer processing time than the RF algorithm. In addition, the difference in the accuracy of the classification algorithms usually occurs due to a subsampling of the separation hyperplanes of the SVM, which leads to an increase in processing time when compared with the RF algorithm [14].

The difficulty in detecting plants occurs due to the presence of dense environments, the plant configuration, high-definition canopy mapping, and conflicts between shade and lighting [41]. In addition to crop and weed segmentation methods, procedures that consider the spectral characteristics of plants are interesting to help classify different plants in the field [42]. The sensor wavelength directly affects the interaction response of electromagnetic energy with the targets present on the Earth's surface [43]. It was observed in this study that the NIR spectral range was more important in the classification obtained using the RF model. This is justified by the fact that there is a greater difference in the spectral response between the study classes in this spectral range. The spectral signature of the soil is considerably less variable, and due to its composition, it has a high absorption capacity and therefore low reflectance in the NIR spectral range, especially under water deficit conditions. The vegetation, in turn, has a spectral signature with greater variation along the electromagnetic spectrum. An emphasis is placed on the high reflectance in the NIR spectral range due to the interaction of the incident energy with the structure of the spongy mesophyll of the leaves present within this structure. Thus, the greater the internal scattering is, the greater the reflectance in this spectral range.

Thus, class differentiation was facilitated by employing the NIR spectral range to separate the soil and vegetation classes. However, when only vegetation is analyzed, the coffee plant, weed, and brachiaria classes are included. Despite having close reflectance characteristics (due to vegetative spectral behavior), the NIR range was also the maximum and minimum amplitude

values that occurred between these classes, allowing the differentiation of the vegetation into the subclasses used in this study (Figure 7).

Such variation in the vegetation cover reflectance in the NIR spectral range mainly depends on the internal structure of the leaves due to their organization and structural spacing but is also influenced by the number of leaves and the canopy architecture, which are variable in the coffee plant, weed, and brachiaria classes. This effect occurs because the energy transmitted through the upper layer of the leaves is partially reflected to the lower layer, and part of this energy is transmitted by the upper layer of the leaves and thus the reflected energy increases, which also explains the reasons for such variation in the NIR range [44–46]. In our study of the spectral behavior of the NIR band, also influenced by the behavior of the canopy, in addition to the internal structure of the plants, the highest reflectances were observed for plants with the highest density of leaves and weeds, followed by coffee plants, and finally by brachiaria. The reflectance variations are observed when analyzing the spectral signatures in which the most appropriate NIR spectral range are selected, as it has more defined limits of adequacy for each thematic class, as highlighted in Figure 8, with higher reflectance values in the NIR range for weeds, followed by coffee plants, and finally by brachiaria. However, although the NIR band is the most important band in the classification, its use alone was not enough to proceed with the differentiation between the study classes. For this reason, the other spectral bands were used to achieve better results in the proposed classification.

In accordance with the evidence presented in this study, several studies also demonstrated the applicability of using classification algorithms to individualize weeds in a field [13,47–49]. Multiple related works highlighted the use of the NIR spectral range when discriminating classes of land use and occupation in agricultural crops [19,50,51].

4.2. Diagnosis and Recommendation

In general, satisfactory and accurate weed classification results were obtained due to the use of high-spatial-resolution images. It is also noteworthy that the abundance of weeds and, consequently, the training dataset were key factors in the accuracy of the classification.

The classifier adjustment errors are mainly due to the irregular shape of the weeds, which prevented a good manual design and resulted in the overestimation of the actual weed infestation, ranking slightly higher than the actual information between the reference and the intended data. It should be noted, however, that from an agronomic point of view, overestimation is not a problem because it reduces the chance of a lack of control in the field by excluding untreated weeds [52].

In this study, the application of treatment agrochemicals to weeds occurred in a conservative manner, adopting the presence of weeds as the limit indicative of treatment. Thus, it provides minimal product savings but encourages controlled and environmentally correct applications when compared with the application in which the total area is treated and promotes cost reduction and greater economic returns of the coffee activity. Understanding the distribution of weeds in the crop through the evaluation of infestation promotes the adequate application of herbicides, allowing the adoption of more effective control measures and reducing the risk of unnecessary applications of agrochemicals [53].

Considering the total study area of 6010.24 m², the plot occupied by weeds is equivalent to 7.07%, i.e., 439.06 m² of the study area, as shown in Figure 8. To control morning glory weeds, 300 L of spray solution per hectare (HEAT–saflufenacil) was applied via a directed spray at a ratio of 100 g of HEAT to 100 L of water (see HEAT/BASF package insert). Considering the application in the total area, the spray volume would be 180.3 L, and considering the application only in areas occupied by weeds, the spray volume would be reduced to 13.2 L. Thus, the economic saving of herbicide, calculated in terms of the area not required for application, is 92.68% in relation to a conventional application of uniform total area. In conclusion, considering the current price of this herbicide, which would cost USD 42.00 for the producer to treat the total area, would be reduced to only USD 3.00 to treat only the areas affected by weeds. These values were applied to this study area; however, they show the importance and application of such methodology when performing the adequate monitoring of coffee crops affected by weeds, which is relevant in reducing producer costs and minimizing the use of agrochemicals as well as their impacts. Therefore, precision agriculture not only reduces costs and waste, but also improves yield and environmental quality [54].

However, it is essential to maintain a crop environment with weed control and management, and rapid detection is a crucial step to avoid yield loss and improve the profitability of agricultural activities. The young coffee plants, after planting and until the first year of fixation in the field, are very sensitive to the interference of weeds, and their growth and reproductive life are strongly affected if weed control is not addressed in a timely manner [55].

Traditional methods of identification and treatment with herbicide applications to weeds require a large amount of time and have a high treatment cost, which in many cases prevents application efficiency [50]. The use of a sensor coupled to an RPA enables the rapid collection of information. Effective results in the study area are obtained for the diagnosis and controlled application of agrochemicals in the area. Identifying weed species as a morning glory in coffee

cultivation promotes improvements in the management and economy of products for their control in addition to providing the producer with a current mapping of the development and history of invasion of these plants.

5. Conclusions

The use of high-resolution images obtained by RPA for the classification of vegetation allowed the differentiation of coffee plants from weeds, and promising results were obtained. The use of high-performance and cost-free classification algorithms yielded satisfactory values for the performance metrics analyzed, with a slight superiority of the RF algorithm. The application of agrochemicals only in the area covered by weeds allows a savings of 92.68% when compared with the condition of application in the total area, showing economic gains and environmental protection.

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3.2 SOIL COMPACTION MAPPING BY PLANT HEIGHT AND SPECTRAL RESPONSES OF COFFEE IN MULTISPECTRAL IMAGES OBTAINED BY REMOTELY PILOTED AIRCRAFT SYSTEM

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Abstract

Soil compaction is considered one of the main threats to structural soil degradation, and it promotes increased densification of soil particles, impairs ecosystem services, the plant development, and therefore affects agricultural profitability. In this sense, this study aimed to analyze the feasibility of using a Remotely Piloted Aircraft System (RPAS) by relating parameters derived from aerial images based on Vegetation Indices (VIs) and the Canopy Height Model (CHM) with soil compaction in a coffee plantation area. The study was conducted in a commercial coffee plantation with the cultivar Mundo Novo with 14 years of implantation. Two aerial surveys were carried out, the first to determine the CHM and define the sampling points and the second for radiometric calculations of VIs. In the sampling point were collected data plant height, soil characterization, soil penetration resistance and productivity. Images were processed by Pix4D software, and the data analysis at QGIS and RStudio. As at results, no statistically significant differences were detected between the different plant height zones in the soil chemical analysis; significant statistical differences between plant height zones were detected for penetration resistance, which is correlated to productivity data; and the radiometric data presented a correlation with the penetration resistance data, making it possible to determine VIs (NDRE and MTCI) with correlation to the compaction data allowing the estimation of such variable. In this way, the possibility of monitoring the height variations of the coffee crop using RPAS to demarcate compacted zones was evidenced.

Keywords: Digital Agriculture. Precision Coffee Farming. Unmanned Aerial Vehicle. Vegetation Index. Remote Sensing.

Introduction

Brazilian coffee production is important internationally (Belan et al., 2020). This country is considered the largest producer and exporter and second largest consumer of coffee in the world (IOC, 2022). According to data from the National Supply Company (Companhia Nacional de Abastecimento - CONAB), 2023 production of the Brazilian crop is estimated at 62.3 million processed bags of coffee, including Arabica and Conilon (CONAB, 2023). Brazil is also notable for its application of plant breeding technologies, biotechnology for crop adaptation to climatic conditions, use of planting technology, crop management techniques, plant mineral nutrition, harvest and postharvest techniques, and use of sustainable management

(Marin et al., 2021a).

Coffee production in Brazil stands out worldwide, but in the field, management problems still directly influence this crop productivity (Khemira et al., 2023). Mechanized systems insertion in coffee cultivation contributes to increased productivity but entails physical problems in the soil structure (Andrade et al., 2018). Soil compaction occurs mainly in mechanized agricultural areas. In coffee growing, this factor limits plant development (Martins et al., 2012). Soil compaction refers to increased soil density, resulting in soil porosity loss and volume due to air expulsion caused by particle rearrangement (Keller et al., 2019; Leyva, 2021), mainly harming ecosystem services related to plant development (Zhang et al., 2006).

The compaction scenario in agricultural soils limits plants' access to the essential elements necessary for their development (Toigo et al., 2010) making root development difficult in different soil depth profiles (Alaoui & Diserens, 2018). Compaction measurement can be performed by directly measuring soil parameters, including bulk density, water capacity, total porosity, texture and apparent electrical conductivity (Lipiec et al., 2003; Lidong, 2020).

Traditionally soil resistance to penetration has been determined using penetrometers to assess crop growth, seedling emergence, root elongation and crop yield (Vaz et al., 2011). Traditional methods require extensive field collection and subsequent laboratory analysis. Technologies insertion in agriculture contributes to indirect measurement development of plant and soil parameters.

Showing high potential for monitoring anomalies in agriculture, Remotely Piloted Aircraft Systems (RPAS) are potentially applicable in several monitoring methods (Bento et al., 2022a). The sensors built into the RPAS capture data in high spatial resolution, allowing possible interference observation in individual plant development (Ponti et al., 2016). Thus, data extracted from different mathematical combinations in the electromagnetic spectrum can be used by Vegetation Indexes (VIs) serving multiple purposes in precision agriculture, mainly plant development.

Coffee growing monitoring using RPAS is systematically explored pests and disease detection (Santos et al., 2022; Marin et al., 2021a), nitrogen variability (Marin et al., 2021b), soil mapping based on altimetric studies for planting suitability (Santana et al., 2021), identification of zones vulnerable to frost (Marin et al., 2021c), physically measure vegetation height and diameter (Bento et al., 2022b) and provision of data for building VIs (Barbosa et al., 2021). Several approaches show the application of RPAS in coffee growing. However, studies on remote sensing techniques application in compaction resistance detection heterogeneity in coffee crops still need to be completed.

Remote sensing technologies have shown a potential to determine and understand soil compaction in time and space scales (Shaheb et al., 2021). RPAS are emerging technologies capable of providing information on spatially distributed anomalies, contrasting crop growth patterns, dry zones, and changes in root distribution. Proving to be variation indicative in soil compaction degree (Batey & Mckenzie, 2006; Batey, 2009; Santos et al., 2019). Investigations on soil compaction effects by remote sensing were evidenced in the research of Kulkarni et al. (2010) using plant spectral response by vegetation index applications Green Normalized Difference Vegetation Index (GNDVI) in compacted soils. The studies by Klopfenstein (2016) determined the soil compaction caused by agricultural wheelsets by sensing images and recommended a model for remote control of wheelsets. By studying machine traffic in maize crops, Khanal et al. (2021) demonstrated the potential of remote sensing technologies combined with machine learning techniques for compaction mapping.

Soil compaction mapping in annual crops can be explored annually due to the homogeneity and temporality of crops. The coffee growing is considered a perennial crop, which prevents annual soil mapping, making it difficult to map compaction by verifying variation in the soil surface. In this way, verifying plant development, mainly height, can indirectly map the soil in coffee growing. Thus, determining compacted areas through vegetation indices, considering that plants vary in height and change in spectral responses according to the compaction zone, can be a way of monitoring soil compaction in coffee cultivation. Thus, this study aimed to analyze the feasibility of using RPAS by relating parameters derived from aerial images based on VIs and the CHM with soil compaction in a coffee plantation area.

Material and methods

Study area

The study area contains commercial coffee plantations located in the municipality of Santo Antônio do Amparo, Minas Gerais, Brazil (meridians 508,2200 and 508,400 m West and parallels 7,676,380 and 7,676,560 m South, in the Universal Transverse Mercator (UTM) projection system, zone 23 S, SIRGAS 2000). It has 2.10 hectares of coffee plantations (*Coffea arabica* L.) that are 14 years old, with a spacing of 3.5 m between the planting rows and 0.5 m between the plants with cultivar Mundo Novo (IAC 379/19) registered in the National Cultivar Registry - RNC of the Ministry of Agriculture, Livestock and Supply- Map (Fig. 1).

According to the Köppen classification, the climate in this area is humid and temperate, with dry winters and rainy summers (Cwa), with average annual rainfall and temperature of

1,530 mm and 19.4 °C, respectively (Martins et al., 2018). The area has an average altitude of 1,022.00 m and is in the Atlantic Forest Biome. The soil classification refers to a typical dystrophic Red-Yellow Latosol, A moderate, clayey to very clayey texture and with flat relief and occurs in well-drained environments, being very deep and uniform in color, texture and structure characteristics in depth (EMBRAPA, 1999).



Fig. 1 Study area and location of collection points.

The experimental design involved 18 points distributed among plants with variations in their heights. The sampling points were predefined by aerial imaging and the creation of the CHM that defines zones based on differences in plant height, with 9 tall-plant zones and 9 low-plant zones in which field data collection was directed (Fig. 2), being the form of capturing images and creating the CHM detailed in the following topics.

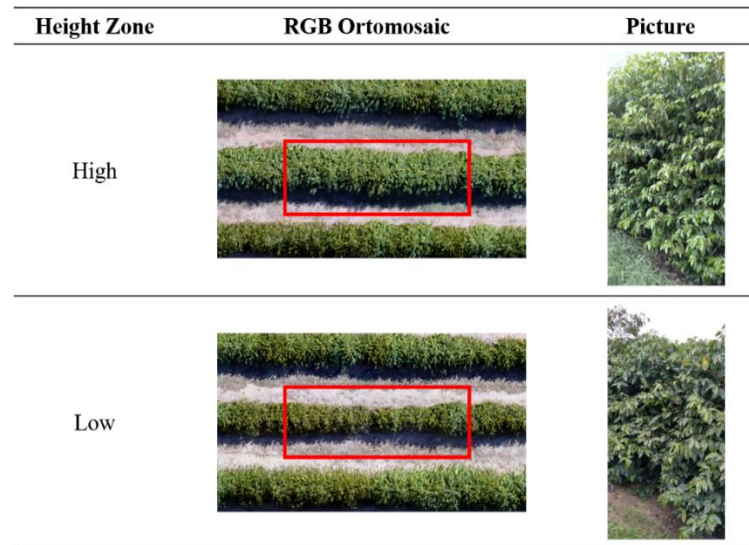


Fig. 2 Description of the height zones of coffee plants identified using the canopy height model to select sampling points in each zone.

Collection of aerial data

In this study, two aerial surveys were performed. The first on August 27, 2021 was used to obtain the CHM and determine the sample points. On October 29, 2021, the second was used to obtain orthomosaics for radiometric studies. The aerial images were surveyed using a 3DR Solo (3D Robotics, Berkeley, CA, USA) (Fig. 3A). According to the manufacturer's specifications, the 3DR Solo is a quad-rotor aerial vehicle powered by the 3DR Pixhawk 2 autopilot system, with flight control and guidance LEDs that enable the navigation, the altitude, and communications to be controlled during the flight through telemetry and in real time with control inputs over the Wi-Fi network. This system also has a flight autonomy of approximately 20 min depending on the weight loaded in the equipment, a maximum load capacity of 0.42 kg, a maximum altitude of 122 m, a range of 800 m, and a maximum speed of 24.58 ms⁻¹.

In the 3DR Solo, was embedded sensor Parrot Sequoia (RGB and multispectral) (MicaSense, Seattle, WA, USA) and an irradiance sensor (Sunshine Sensor- MicaSense, Seattle, WA, USA) with GPS included (Fig. 3B). The Parrot Sequoia camera has an RGB reading range (visible) (380 to 720 nm) and 4 spectral sensors with spectral bands Green (550 to 590 nm), Red (60 to 700 nm), Red-edge (735 to 745 nm), and Near Infrared (NIR) (760 to 820 nm). And sensor dimensions of 47 mm x 39.6 mm x 18.5 mm and focal aperture of 61.9 High-Frequency Oscillatory Ventilation (HFOV)(4 mm) (Franzini et al., 2019). The flight plan was carried out in the Mission Planner software (Osborne, 2018) based on the basic input parameters of the system, automatically defining the flight with waypoints. The flight

parameters adopted related to the launch and landing location of the aircraft (definition of the home point), wind direction, topographic conditions of the area, flight height in meters, flight speed in m s⁻¹, overlap level, and direction of flight of the longitudinal or transverse type. The information on overlap, speed, direction, and flight height above ground level (AGL) was standardized at 80 × 80%, 5 m s⁻¹, direction transverse to the planting row, and 40 m, respectively. Location control plates were also positioned on the ground during the second flight.

Before and after the flights, images were captured from the radiometric calibration plate (MicaSense, Seattle, WA, USA) to standardize the reflectance values of the flights since the panel has a known reflectance relationship and allows precise compensation of the incident light conditions (Fig. 3C) and a standardized time between 11:00 and 13:00.

The captured RGB images were 16 MP, with a definition of 4608 × 3456 pixels, a focal length of 4.88 mm, and a spatial resolution of 0.011 m. The individual bands captured were 1.2 MP, with a definition of 1280 × 960 pixels, a focal length of 3.98 mm, and a spatial resolution Ground Sample Distance (GSD) of 0.047 m. The time-lapse capture parameters had a fixed interval according to the overlap calculation and a height of 1.45 s.

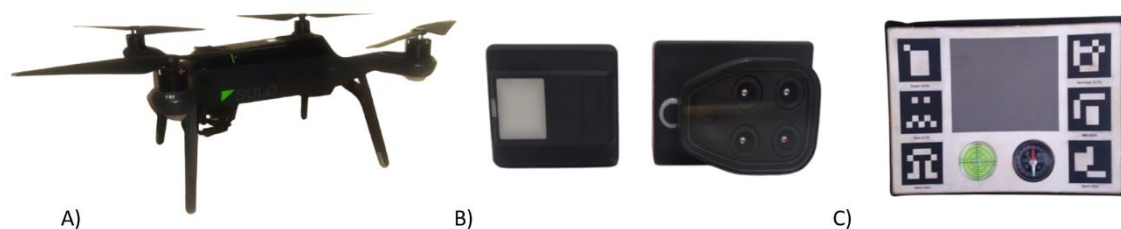


Fig. 3 A) RPA 3DR SOLO; B) Irradiance sensor (sunshine) and Parrot Sequoia multispectral camera; and C) Radiometric calibration panel.

Image processing

The images collected in the study area were processed using the software Pix4D Mapper version 4.4.12 (Pix4D, Lausanna, Switzerland) according to the methodology described in Fig. 4.

Initially, the images were aligned by triangulation and the creation of automatic correction link points, subsequently generating a dense point cloud, surface texture, a digital surface model (DSM), a digital terrain model (DTM), and finally, an orthorectification of the

images; then, the final mosaic of each spectral band and RGB composition were obtained, considering the radiometric correction through photo plate insertion that resulted in the orthomosaic with reflectance values.

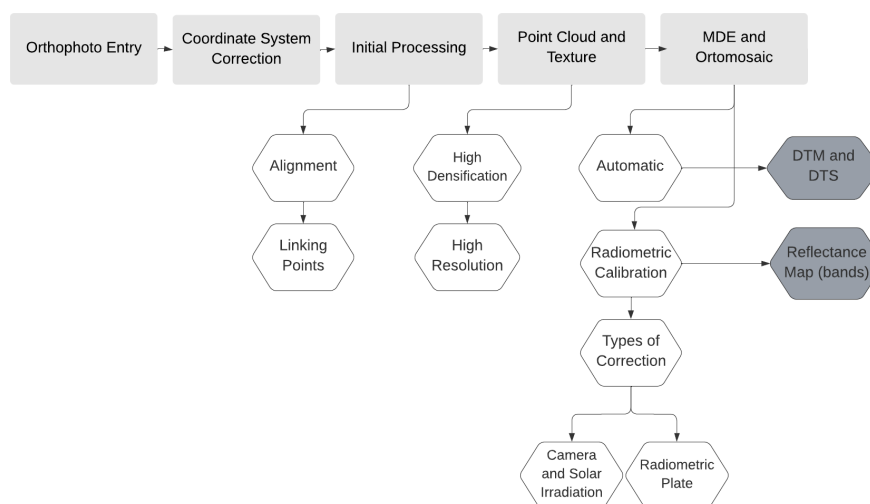


Fig. 4 Processing flowchart in Pix4D software.

Field data collection

Concomitant with the date of aerial data collection, topographic data were collected, and measurements and sampling were performed at the sampling points. The topographic survey was conducted using the Global Navigation Satellite System - Real Time Kinematic (GNSS RTK) instrument (Trimble Navigation Limited, Sunnyvale, California, USA) based on 6 predefined points in the border areas of the study area, and information was collected at each study sample point, totalling 24 points screened. The points were tracked and fixed in the field in kinematic mode (margin of error less than 0.03 m) using a pair of Spectra precision GNSS antennas operating in RTK mode with a base and rover.

The data collected by the GNSS receivers were processed using the EZSurv software and a digital platform of the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística - IBGE). The geographic coordinates (X, Y, and Z) obtained by the equipment installed in the base were adjusted in the IBGE digital platform by Precise Point Positioning (PPP). This positioning method applies an orbit and clock correction in GNSS and a position within a global frame of reference worldwide (Grinter & Roberts, 2011).

The coordinates recalculated by PPP were added to EZSurv software for coordinate adjustment. Subsequently, the points were reordered in the project, which consisted of adjusting the coordinates according to the base, rover, and satellite triangulation. This step eliminated the

defective collection signals and aligned them with the new coordinates provided by the PPP available in UTM coordinates.

In addition to the topographic data at each sampling point, measurements of coffee plant height (Fig. 5A), soil penetration resistance (Fig. 5B), and soil moisture (Fig. 5C), were taken, and samples were collected and sent to the laboratory for a complete soil chemical analysis (Fig. 5D).

The height measurements were performed with a conventional measuring tape, measuring the distance between the ground to the top of the plant (vertical measurement). The analysis of soil penetration resistance was performed with digital penetrometer equipment from Falker 'PenetroLOG', which provides an instantaneous measurement with geographic coordinate information and identifies the compacted layer by determining the intensity of the soil compaction. The principle of use of the equipment is based on the vertical displacement of the rod as it is inserted into the ground, the insertion speed must be kept as constant as possible (international standards recommend drilling at 3 cm s⁻¹) and the measurement data are directly displayed on the screen of the sensor and stored digitally in the device. The measurement distance occurs in the range of 0 to 50 cm from the main stem of the plant, ensuring the collection of information regarding the development of the roots and the collection intervals were performed at depths from 0 to 60 cm, for each centimeter of the measurement, considering the mean value in this study. Soil moisture was calculated to verify possible interference with the obtained values of soil penetration resistance.

The soil moisture analysis was performed based on the traditional method, with greater precision and simple determination in the laboratory. The procedure consists of soil dried in an oven to determine mass of soil moisture lost on drying and then converted to volumetric water contents using Bulk Density measurements (ABNT, 1986). The complete soil analysis (pH, macronutrients, micronutrients, organic matter, and texture) was performed in an associated laboratory, and the samples were collected at the 18 sampling points with the aid of a dutch auger at a depth of 0 to 20 cm, stored in appropriate material, and sent to the laboratory for analysis.

To estimate the coffee yield of the 18 sampling points, the fruits were manually harvested in cloths and measured in a container graduated in liters. Three plants were collected from each sampling point, and the average value for the sampling point in liters/ plant was obtained from these plants.

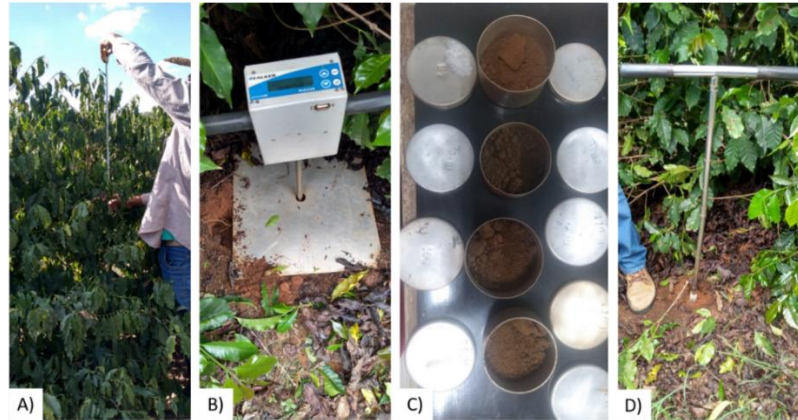


Fig. 5 Data collection of A) plant height B) resistance to soil penetration; C) soil moisture; and D) collection of soil data.

Data analysis and results

Initially, the CHM was run in QGIS software version 3.6.2 (QGIS Development Team, Open Source Geospatial Foundation) using the ‘Map Algebra’ tool by subtracting the DSM from the DTM according to Eq. 1. Based on the height zones, the locations of tall and short plants were detected, and 18 sampling points were determined.

$$\text{CHM} = \text{DSM} - \text{DTM} \quad (1)$$

where CHM is the canopy height model (cm), DSM is the digital surface model (cm) and DTM is the digital terrain model (cm).

Soil and moisture analysis data were used to identify any variable responsible for interfering with compaction. Initially, the normality of the data was verified using the Anderson-Darling test (Anderson & Darling, 1952) and then the significant differences between low and high-height zones were verified using the multiple comparison T Test at 5% ($p < 0.05$) probability. Subsequently, the significant differences between the data for the sampling points between the high and low plant zones were tested for plant height, penetration resistance, and productivity using the multiple comparisons T Test at 5% ($p < 0, 05$) probability.

Subsequently, the soil penetration resistance values were analyzed with plant height data to observe whether the penetration resistance values were below or above the critical limits expressed in the literature and their interference in the development of coffee plants. The normality of the data was initially verified using the Anderson-Darling test (Anderson & Darling, 1952), followed by a correlation analysis of plant height and penetration resistance data based on the Pearson correlation coefficient (R) and coefficient of determination (R²)

(according to data normality).

All the procedures were performed using RStudio software (R Development Core Team, R project, New Zealand).

The multispectral data obtained from the aerial images of the study area were subjected to VIs calculations to identify indirect relationships between the results from the remote sensing images and field data. A total of 13 VIs was used, as described in Table 1, calculated using QGIS software version 3.6.2, highlighting that the use of individual wavelength response data yield useful information, and the fundamentals of radiometry can provide the basis for using measurements made by sensors in more complex mathematical functions (Holland et al., 2012). The study plants were individualized through manual segmentation to extract the pixel values and calculate between spectral bands to obtain the VIs values, considering the GSD of 0.047 m in this study.

The correlation between the penetration resistance data obtained in the field and the radiometric data of the VIs was determined to analyze the fit and estimate of the correlation equations. For this purpose, the normality of the data was also verified using the Anderson-Darling test (Anderson & Darling, 1952). Regression analysis was used to obtain the R2 and Root Mean Square Error (RMSE) to validate the analyses using RStudio software.

Table 1 Vegetation indices used.

Vegetation indices	Acronyms	Equations ^[1]	References
Normalized Difference Vegetation Index	NDVI	$(R_{NIR} - R_R) / (R_{NIR} + R_R)$	Rouse et al. (1974)
Green Normalized Difference Vegetation Index	GNDVI	$(R_{NIR} - R_G) / (R_{NIR} + R_G)$	Shanahan et al. (2001)
Normalized Difference Red-Edge Index	NDRE	$(R_{NIR} - R_{REG}) / (R_{NIR} + R_{REG})$	Buschmann & Nagel (1993)
Green Optimal Soil Adjusted Vegetation Index	GOSAVI	$(1+0.16) (R_{NIR} - R_G) / (R_{NIR} + R_G + 0.16)$	Rondeaux et al. (1996)
Meris Terrestrial Chlorophyll Index	MTCI	$(R_{NIR} - R_{REG}) / (R_{REG} + R_R)$	Dash & Curran (2004)
Modified Photochemical Reflectance Index	MPRI	$(R_G - R_R) / (R_G + R_R)$	Yang et al. (2008)
Green-Red Ratio Index	GRRI	$(R_G) / (R_R)$	Gamon & Surfus (1999)
Normalized Different Index	NDI	$(R_G - R_R) / (R_G + R_R + 0.01)$	Mao et al. (2003)

Green Red NDVI	GRNDVI	$(R_{NIR} - (R_G + R_R)) / (R_{NIR} + (R_G + R_R))$	Wang et al. (2007)
First Modified Chlorophyll Absorption Ratio Index	MCARI1	$1.2 (2.5((R_{NIR} - R_G) - 1.3(R_{NIR} - R_G)))$	Haboudane et al. (2004)
Excess Red Vegetation Index	EXR	$1.44 (R_R - R_G)$	Meyer et al. (1998)
Modified Simple Ratio	MSR	$(R_{NIR} / R_R) - 1 / \sqrt{(R_{NIR} / R_R) + 1}$	Chen (1996)

Caption: ^[1] R_{NIR} , reflectance values obtained by the sensor in the near infrared range. R_{REG} , reflectance in the range between red and infrared. R_R , reflectance in the red range. R_G , reflectance in the green range.

Results

RPAS experimental design

The RPAS design was used to confirm a previous survey of the study area as well as to prepare the CHM and define the sampling points is shown in Fig. 6. The map shows the different plant height zones, highlighting the zones of high plants with values varying in height from 2.00 to 3.00 m and zones of low plants with values ranging from 1.00 to 2.00 m in height.

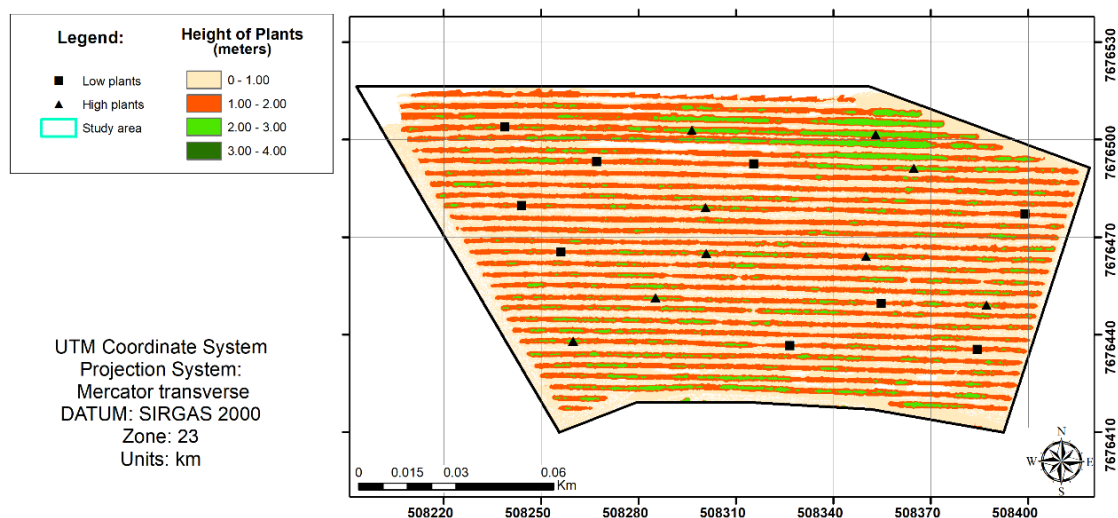


Fig. 6 Canopy Height Model (CHM) and definition of height zones for tall plants and low plants.

Soil analysis

The soil characterization data for the high and low plant zones are presented by boxplot analysis and statistical differentiation by means test (Fig. 7). The values for the soil fertility variables showed a correlation between the two different height zones analyzed, both for the maximum and minimum values, with no significant differences between the zones. Notably,

soil fertility variables did not limit plant development in any of the height difference zones.

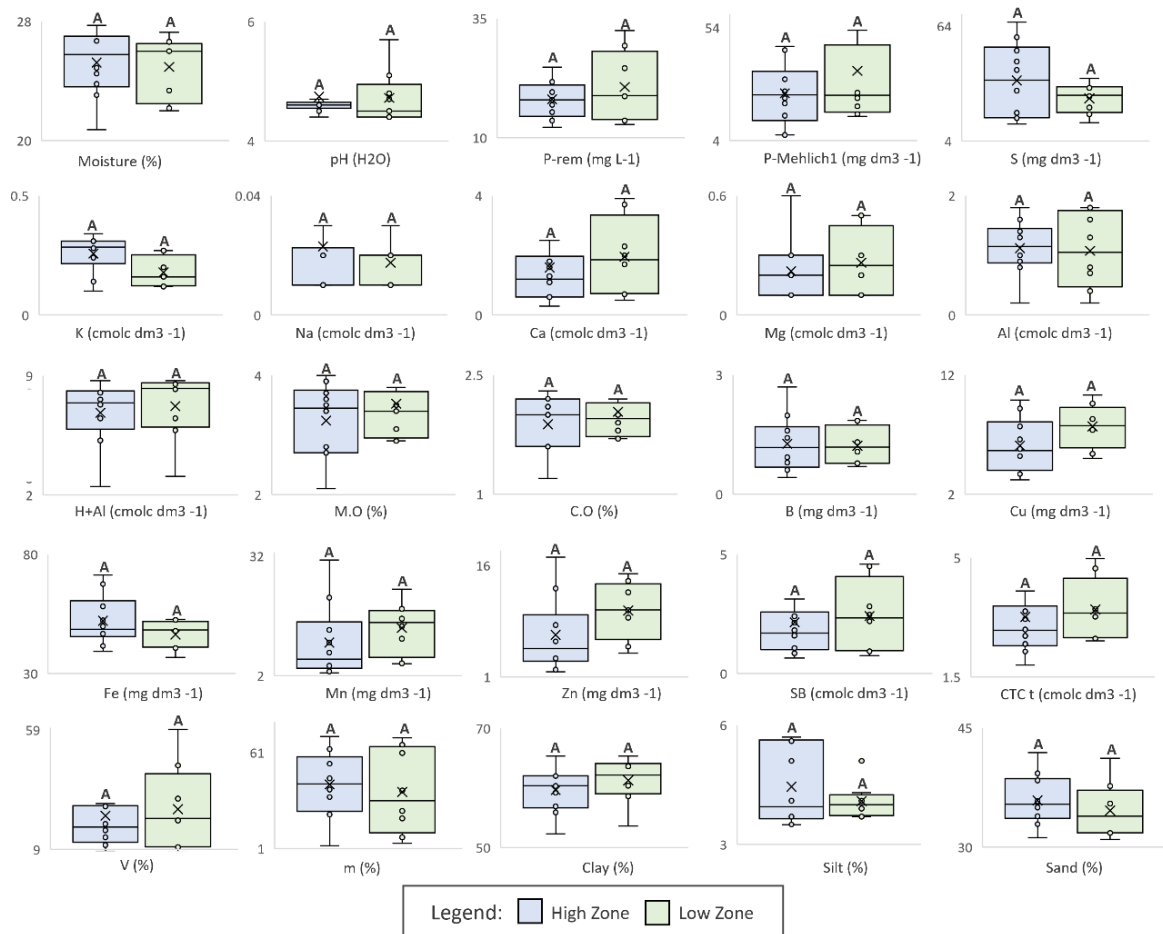


Fig. 7 Results of soil chemical analysis and statistical differences between tall and short plant zones.

¹Boxplots accompanied by the same letters indicate that data do not show statistical differences by the t test at 5% probability.

Soil compaction, resistance to soil penetration, and coffee yield

The difference between the plant height zones was determined in this study. Thus, it is possible to observe in Fig. 8 the data regarding penetration resistance (Fig. 8A), plant height (Fig. 8B), and productivity (Fig. 8C), considering the different study zones (high and low plants), via boxplots and statistical differentiation by means test.

As shown in Fig. 8, the plant height, soil penetration resistance, and coffee yield data, in turn, showed statistically significant differences according to the two plant height zones defined in this study. Plants with shorter heights showed greater resistance to penetration and consequently, lower productivity at the sampling points analyzed. The opposite was also

observed, i.e., plants of higher height, showed lower resistance to penetration and higher productivity at the sampling points analyzed.

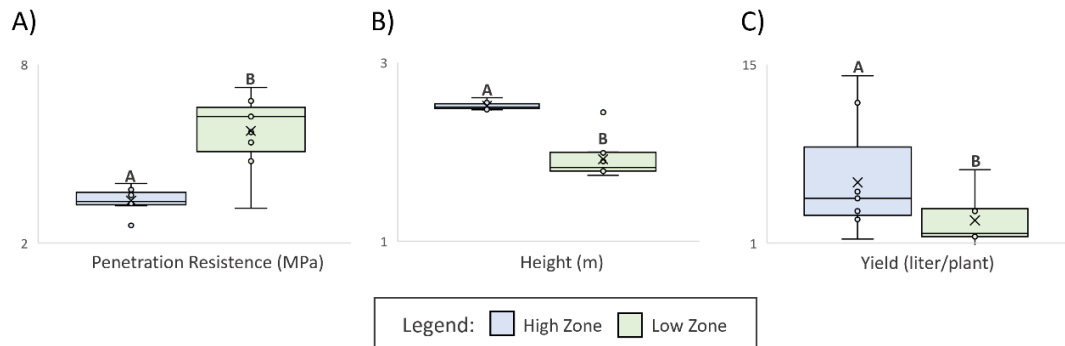


Fig. 8 Statistical differences between the zones of tall and short plants¹ for the variables of resistance to penetration (A), plant height (B) and productivity (C).

¹Boxplots accompanied by the same letters indicate that data do not show statistical differences by the t test at 5% probability.

Considering the statistical differentiation described between the penetration resistance and plant height data for the two study zones, the linear correlation between these variables was verified. Figure 9 shows the analyses in the form of a scatter plot, including the R and R² values and regression equation.

Considering the CHM for the height zones analyzed, the penetration resistance data were correlated with the height data, thus allowing the determination of a linear regression equation that describes the relationship between the study variables. A negative correlation was found based on the R of -0.881; i.e., the shorter the height, the greater the penetration resistance data were and vice versa. Conversely, R² expresses the proportion of the variation in the response variable explained by the variation in the explanatory variable, and the calculated value of 0.776 was adequate to describe the representativeness of this relationship between the study variables. Therefore, it is noteworthy that the independent variables present in the models present high accuracy in responding to the variation in the predicted results.

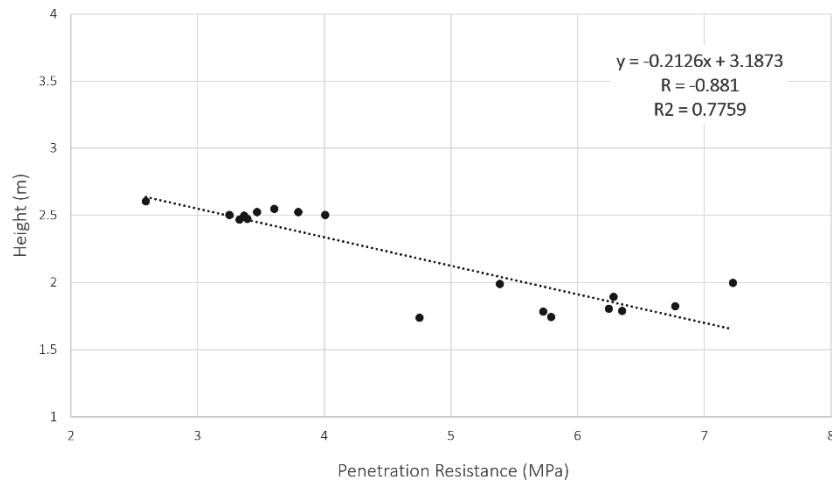


Fig. 9 Scatter plot, correlation coefficient (R), coefficient of determination (R2) and regression equation between Height (y) and Penetration Resistance (x).

Vegetation indices

Given the monitoring capacity through the application of Vis (GSD 0.047 m), the correlation between penetration resistance and the VIs was determined (Table 2) as described by R, R2, RMSE, and Mean Absolute Error (MAE) for the penetration resistance data and the VIs. It is noteworthy that the magnitude of the reflectance values of the spectral bands in this study were 0.0231–0.0344 Red, 0.0523–0.0780 Green, 0.1667–0.4554 Red-edge and 0.2433–0.6828 Near Infrared.

Table 2 Statistical coefficients between penetration resistance and vegetation indices.

Vegetation Index	R	R2	RMSE	MAE
NDVI	-0.485	0.236	0.020	0.016
GNDVI	-0.422	0.178	0.012	0.009
NDRE	-0.850	0.723	0.014	0.012
GOSAVI	-0.593	0.352	0.013	0.011
MTCI	-0.875	0.765	0.022	0.018
MPRI	-0.655	0.429	0.029	0.023
GRI	-0.387	0.150	0.274	0.210
NDI	-0.480	0.231	0.035	0.029
GRNDVI	-0.629	0.396	0.020	0.016
MCARI1	-0.554	0.307	0.018	0.014
EXR	0.594	0.354	0.003	0.002
MSR	-0.475	0.255	0.333	0.259

Caption: Statistical indices: R (correlation coefficient), R2 (determination coefficient), RMSE (mean squared error) and MAE (mean absolute error).

By analyzing the statistical coefficients (R, R2, RMSE, and MAE) described in Table

2, the best VIs was selected to describe the relationships between the penetration resistance variables and radiometric data. Thus, Fig. 10 shows the distribution of the Normalized Difference Red-Edge Index (NDRE) and the MERIS Terrestrial Chlorophyll Index (MTCI) for the study area, as well as the regression equations for estimating the values of resistance to penetration indirectly using the VIs. The average values of the NDRE index and MTCI explained 72% and 76% of the variation in soil compaction in the study area, respectively.

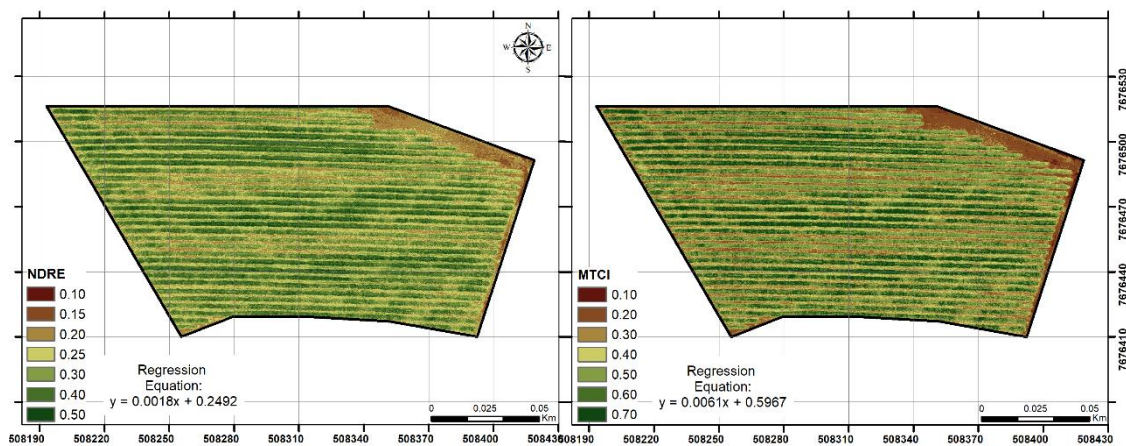


Fig. 10 Spatial distribution of vegetation indices in the study area and regression equation to estimate penetration resistance.

Discussion

RPAS experimental design

Previous aerial images of coffee-growing areas provide several opportunities for management improvements. The initial data collected provided information for developing the field experiment and studying compaction based on the hypothesis that the difference in plant height occurred due to the action of soil compaction. Notably, the easiest approach for determining compaction was creating the CHM, highlighting specific points of the experimental design using RPAS.

The use of the RPAS enabled the acquisition of data representative of soil compaction (terrain sampling) and the development of the surface model and the mathematical model. Based on this approach, systematic sampling was performed, demonstrating the reliability of the data and the generated model to replace the actual surface. Finally, the procedures were used to identify the zones with plant height differences, and then, the sampling points were chosen and distributed (Fig. 6).

The mapping of the point that indicate areas of possible compaction that interfere with

plant development can be used in coffee cultivation techniques as a management alternative in compacted zones and as a decision tool (Andrade et al., 2018). Thus, the proposed methodology based on the creation of the CHM was efficient at identifying coffee plant heights with a RPAS and guiding studies of precision coffee cultivation.

The flight parameters were sufficient for describing the characteristics of the terrain and the elements present on its surface, making it possible to highlight the zones with plant height differences through the CHM. Thus, notably, studies that use RPAS are relevant because they generate photogrammetric products based on terrain modelling, capturing important information about the ground's surface. In addition, it should be noted that proper flight planning and data processing are essential for efficiently developing good quality products (Bento et al., 2022a).

Soil analysis

The soil variables analyzed (Figure 7) showed no statistically significant differences between the different plant height zones. It is well known that soil provides the necessary elements to promote plant development and growth (Dias et al. 2021). In addition, soils have natural variability due to natural and anthropogenic factors that act at various spatial and temporal scales. However, this natural variation was insufficient to promote significant differences between the study zones, thus, this natural variation was removed as a factor that could have caused the differences in plant heights.

Among the analyzed parameters, soil moisture can influence the collection of penetration resistance data and interfere with results (Campos et al., 2013). In this study, the soil moisture values also did not show significant differences in the different plant height zones analyzed. Thus, even with adequate nutrition, as presented in the complete soil analysis, plant growth perhaps this is because was negatively affected by the reduction in root growth due to soil compaction. Therefore, it should be noted that the change in compaction in this terrain can be caused by several external factors, such as the traffic of agricultural machinery and/or equipment for implementing coffee activities. However, the cause of compaction was not the focus of this study's investigation.

Soil compaction, resistance to soil penetration, and coffee yield

Significant differences were detected between the plant height, soil penetration resistance, and coffee yield data according to the two different plant height zones because soil compaction is characterized by increased density and decreased soil porosity, resulting in

resistance to full plant root system development (Taylor & Brar, 1991). In addition, the presence of a compacted layer in soil decreases its useful depth, hindering the development of coffee plants due to decreased water infiltration into the soil that prevents plant root growth, resulting in low production yields (Fernandes et al., 2012). Studies on this topic for other agricultural crops, such as corn, wheat and soybean, have also been conducted. Olubanjo & Yessufou (2019) detected that increased soil compaction also reduced corn grain yield by 18.8%; Igoni and Ayotamuno (2016) investigated the level of compaction with an adequate limit so as not to affect corn grain yield; Berisso et al. (2012) examined whether subsurface compaction induced by repeated traffic with wheel loads of approximately 10 Mg persisted 14 years after the compaction event; and Secco et al. (2009) evaluated the impact of three compaction states on the physical attributes and grain yield of corn, wheat and soybean.

The penetration resistance values ranged from 2.590 to 4.006 MPa for the tall plant zone and from 3.167 to 7.223 MPa for the low plant zone. The penetration resistance values (MPa) were classified and studied based on the interpretations recommended by Falker (2010) for clayey soils with a scale of tolerance levels to penetration without loss of productivity and restriction: with a low level 2.5 MPa, the intermediate level 2.5–4.0 MPa, and the high soil compaction level above 4.0 MPa. In addition, the Soil Survey Staff (1993) classified penetration resistance below 0.01 MPa as extremely low, from 0.01 to 0.1 MPa as very low, 0.1 to 1.0 MPa as low, 1.0 to 2.0 MPa as moderate, 2.0 to 4.0 MPa as high, 4.0 to 8.0 MPa as very high, and above 8.0 MPa as extremely high. The comparison of the results measured in the field with the reference data is based on the correct and adequate use of the penetrometer, according to the recommendations for service provided by the manufacturer, and on the standardization of soil moisture values.

Soil penetration resistance is indicative of compaction and directly related to the development of agricultural crops in the field. It also is reflected in root growth based on the pressure between particles or aggregates, favoring or limiting root growth in length and diameter, making it impossible for aerial plant parts to grow, and thus, soil penetration resistance is important in the evaluation of soil management (Tormena et al., 2002). For a coffee crop, because it is a perennial crop in which the soils are not turned annually, penetration resistance values of up to 4 MPa are tolerated due to the permanence and continuity of the pores and greater aggregate stability and biological activity (Carvalho, 2013).

Soil compaction directly influences plant height, which in turn strongly affects coffee crop productivity, as highlighted in studies of other agricultural crops (Santos et al., 2022; Silva et al., 2018; Girardello et al., 2014). In this study, the mean penetration resistance values

explained 77% of the variation in plant canopy height and productivity. As shown in Fig. 9, for the tall plants in the low penetration resistance zones, the productivity values ranged from 1.3 to 14.1 L/plant, and for the short plants in the high penetration resistance zones, the productivity values ranged from 0 to 6.75 L/plant. This result perhaps this is because plants generally don't have access to nutrients and water when root development is reduced, and free spaces in the soil decrease, which in turn decreases the amount of oxygen, resulting in decreased plant development and consequent crop production (Toigo et al., 2010).

Some techniques have been implemented to reduce the negative impacts caused by soil compaction. The use of agricultural mechanization, which includes the use of subsoiling and scarification has become essential to mitigating the influence of compaction. The use of decompaction machines is considered essential for optimizing production and reducing costs on coffee plantations, and these actions contribute to adequate soil management that has less of an impact on the amount of soil deformation (Andrade et al., 2018).

In addition to each soil type's intrinsic characteristics, compaction increases may be related to inadequate management of agricultural operations. The inappropriate weight of machinery has been highlighted as the main cause of agricultural soil compaction (Mileusnić et al., 2022). The increased intensity of agricultural machinery, the action of the wheels, setting in one place over some time or due to the various passes in soil, cause physical and mechanical changes, as observed directly in the soil as well as in the plants (Fernandes et al., 2012). Thus, it is necessary to understand the pressure levels that soil withstands and/or the soil moisture during mechanized agricultural operations so that the additional compaction caused by agricultural machinery is prevented (Silva et al., 2006).

Notably, the capacity of soil water retention by the action of the compaction process influences and limits plant development in periods of low rainfall (lower water absorption by the plants) or high rainfall (causing surface runoff problems and low water infiltration) (Silva et al., 2005) and therefore soil density defines the amount of water that can potentially be stored in the soil. Thus, in summary, compacted soils usually have low productivity, reduced water infiltration, lower aeration capacity, resistance to root penetration, susceptibility to the development of root diseases, and lower survival capacity since, under stressful conditions, a plant suffers and even interrupts its process development (Souza et al., 2019). All this information highlighted by the previously mentioned authors can justify and support the results detected in this study.

Thus, there was a negative correlation between the plant height data and the penetration resistance data with correlation coefficients (R of -0.881) and determination (R² of 0.766) using

a linear regression equation. The mechanical impedance and/or poor aeration created after soil compaction may explain this negative correlation, however, this study did not seek to identify the causes of compaction in the study area but to verify whether the compacted areas presented limitations in the development of plants and vice versa. Thus, using the height variable, obtained by the RPAS, can in turn estimate the penetration resistance variable, considered an “inverse estimation”, as normally soil compaction data is used to infer plant growth, and in this study the use of RPAS was used for aerial imaging and plant height surveys to correlate soil compaction, taking into account in this study not to interference of other external factors (availability of water and nutrients in the soil).

Vegetation indices

The results of the VIs in estimating soil compaction, as described in Table 2, demonstrated the potential of the NDRE index and MTCI to estimate the response variable based on the statistical coefficients used in this study. Notably, the error values described indicate the good accuracy of the model for the variables analyzed according to these performance metrics (Jamieson et al., 1991).

In general, the NDRE and MTCI indices use the combination of the refraction of the red-edge band, as this band best estimates soil compaction because this edge has a strong sensitivity of the change in the energy reflectance of the wavelength since it refers to the point of sudden change in reflectance when located in the transition layer between the spectral band of red (low reflectance by plants) and near-infrared spectral bands (high reflectance by plants) (Cao et al., 2019), with both spectral bands present in the sensor used in this study. Thus, the red-edge band is known to be sensitive to differences in plant chlorophyll content and water stress and is positively correlated with photosynthetic response (Barnes et al., 2017) and justifies its use due to the high-density canopy cover of adult coffee plants.

Thus, when a plant is affected by some stress factor, the leaf pigments undergo changes and/or the leaf structure wilts due to cell impacts from water deficit action, altering the spectral response of the plants (Ponzoni & Shimabukuru, 2010; Jensen, 2009). This scenario was observed in the field because the plants located in the areas of greatest resistance to penetration (areas of greater compaction) had, in addition to lower heights, smaller leaves and wilting. Soil compaction, resulting in high resistance to root penetration, promotes low oxygen concentrations due to hypoxic conditions, resulting in less vigorous and unsustainable plants (Sjulgard et al., 2021) in annual and perennial crops such as coffee.

Since root growth can be impaired due to the increase in impedance through a

compacted layer, a reduction in the height and leaf area index of the crop can be expected, as well as a significant effect on the plant leaves (Pacheco et al., 2015). This effect is due to factors such as reduced water content, poor aeration effects, reduced stomatal conductance, reduced chlorophyll concentration, and reduced photosynthetic rate, as highlighted in studies on diverse agricultural crops (Li et al., 2010; Manik et al., 2019). In addition, the photosynthetically active radiation intercepted by a plant depends on several parameters in which the leaf structure of a plant is influenced by the plant height and canopy structure. Thus, a larger plant can intercept more radiation and, therefore, is better represented by spectral studies derived from reflectance data (Serrano et al., 2000).

However, the links among compaction, root growth, and leaf development may be the basis for the relationship between VIs and the effects of compaction, when considering the non-limiting effects of water and nutrients on plant development, as in this study. Thus, using VIs to detect and describe such action through the spectral response of leaves optimizes field work by reducing the time needed for the work and consequently costs since VIs can show that compaction affects the access, availability, and absorption of elements by plants.

Scientific studies on precision coffee farming that use RPAS to detect areas where reduced plant biomass might be an indication of compaction or other growth-limiting factors are still scarce, highlighting the applicability of this study. Notably, for other agricultural crops, studies have been developed and concluded that soil compaction patterns can be determined using such technology and that these patterns influence crop development. Lindenstruth (2020) used multispectral image analysis based on RPAS to detect the soil compaction patterns in two sugar beet fields using the NDVI. Lidong (2020) tested the ability of RPAS to detect compaction with good correlations between soil compaction and corn canopy height. Leite et al. (2012) used data from a RPAS and VIs derived from digital numbers and estimated reflectance to distinguish the treatments and evaluate soil compaction in bean crops.

The approach presented in this study to detect compaction with crop growth indicators, such as the CHM and VIs derived from aerial imaging obtained from RPAS, appears promising. As shown by the relationships found in the correlations and regression estimates, the plant growth responses can be partially explained by a compacted layer. This fact supports the idea of how remote sensing can detect compaction and its variation among agricultural crops and how a RPAS can be useful for monitoring and adopting strategies to control and mitigate soil compaction.

Conclusions

This study concludes that: it was possible to detect zones of plant height differences based on an aerial survey using the Remotely Piloted Aircraft System; the soil chemical variable data showed no statistically significant differences between the zones of high and low resistance to penetration and therefore did not influence nor limit the growth and development of the plants in the field; the penetration resistance data showed a negative correlation with the plant height data, making it possible to estimate the linear regression equation between these variables; with increasing soil compaction, the development and productivity of coffee plants decreased; the vegetation indices (NDRE and MTCI) described the soil compaction in this study and can be used to estimate this effect in coffee plantations; and it is emphasized that the adoption of techniques and technologies that optimize the identification of problems in the field are encouraged, therefore, the application of the proposed methodology has a high probability of being used in crops.

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3.3 REMOTELY PILOTED AIRCRAFT SYSTEM AND MACHINE LEARNING FOR DETECTION OF COFFEE PLANTS SUBJECTED TO FOLIAR APPLICATION OF CHITOSAN

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Abstract

Considered a biostimulant, chitosan can affect the physiological responses of plants to water deficit, acting as an antitranspirant under agricultural stress. Currently, images obtained by Remotely Piloted Aircraft Systems (RPAS), together with machine learning techniques, aid in resolving agricultural problems, including water issues. Therefore, the objective of this study was to differentiate between coffee plants subjected to the foliar application of chitosan and those not subjected to it, based on spectral data extracted from RPAS-acquired images and classification via machine learning. For this purpose, the random forest (RF) classifier was applied to two coffee cultivars (Catuaí Amarelo 2SL and Catuaí Vermelho IAC 99) over two years of study (2021 and 2022). The images were obtained by a 3DR SOLO aircraft with a Parrot Sequoia sensor, processed in PIX4D Mapper software and analysed in QGIS and RStudio software. The results showed good performance metrics for differentiating between coffee plants subjected and not subjected to the foliar application of chitosan, indicating that this method is a valid approach for modelling the presence of the biostimulant in coffee plants, thus confirming that the model can efficiently support the practices of precision agriculture.

Keywords: Digital Agriculture; Multispectral Images; Precision Coffee Growing; Remote Sensing.

Introduction

Chitosan is a substance with high biotechnological potential derived from the process of partial deacetylation of chitin (considered the second most abundant polymer in nature, after cellulose) present in large amounts in the exoskeletons of crustaceans, insects, and fungal cell walls (Huq et al., 2022). In turn, several properties inherent to materials of renewable origin, such as nontoxicity, nonallergy, biocompatibility, biodegradability, analgesic and coagulant properties, and antimicrobial action against fungi and bacteria, enable its application in biological systems (Pella et al., 2018).

Chitosan has several characteristics that make it suitable for use in different applications, especially agricultural and environmental applications. Some of the applications include pesticides, herbicides, insecticides, fertilizers, soil conditioning agents, plant disease control agents, antitranspirants, biostimulants and seed and nutrient coatings (Kumaraswamy et al., 2018; Chen et al., 2017). It also promotes numerous defense responses related to biotic and abiotic stresses, especially in the protection of plants against environmental stress. In plants,

chitosan improves drought tolerance in plants by stimulating their physiological responses to water deficit, suggesting the potential of this biopolymer to act as an antitranspirant in agricultural situations of water deficit. Drought tolerance is induced via increased water use efficiency and greater defense against oxidative stress (Hidangmayum et al., 2019). Thus, when applied topically, chitosan improves stomatal conductance, increases the abscisic acid content and reduces transpiration in plants without changing their height, leaf area, root or biomass (Román-Doval et al., 2023).

Agricultural studies on the use of chitosan have already demonstrated its ability to delay or prevent the spread of diseases, fungi, bacteria and viruses and to increase and stimulate the defense mechanisms of plants, such as beans (Abd El-Aziz & Khalil, 2020), cucumber (Gangireddygar et al., 2021), rice (Liu et al., 2012), sweet potato (Xing et al., 2018), pear (Meng et al., 2020), strawberry (Feliziani et al., 2015), grapevine (Reglinski et al., 2010), dragon fruit (Zahid et al., 2015), wheat (Masjedi et al., 2017), barley (Behboudi et al., 2015). , 2018), sugarcane (Silveira et al., 2019), and others. However, in the context of coffee cultivation, there are few studies with the direct application of chitosan. The significance of this crop is the enormous contribution to the world economy since Brazil is the largest producer and exporter of coffee in the world (CONAB, 2023). As such, given the needs described for coffee crops, the applicability of chitosan as a form of agricultural management is addressed, allowing us to circumvent the physiological and morphological disturbances that affect the development and yield of coffee crops.

Thus, the use of techniques and technologies that demonstrate the responses of plants in the field allows for the accurate study of agricultural crops, intelligent decision making and increased profitability (Bento et al., 2022). The use of suborbital remote sensing with Remotely Piloted Aircraft Systems (RPAS) is recommended because they allow aerial imaging closer to the surface, ensuring greater spectral resolution, as well as the use of multispectral sensors, which ensure greater resolution of radiometric measurement and may also target smaller study areas, ensuring lower costs (Santos et al., 2019). RPAs are defined in summary as remotely piloted aircraft operated through interfaces such as computers, simulators, digital devices, or remote controls, with the pilot not being on board (Santos et al., 2019).

In recent years, the use of products obtained by RPAS combined with machine learning techniques has introduced a new way of examining various sets of data serving different areas, such as precision agriculture (Calou et al., 2020). Machine learning allows solving nonlinear issues by employing datasets from various sources and exposing hidden information in the data initially provided (Liakos et al., 2018; Qiu et al., 2016). The use of different computational

algorithms allows the generalization of patterns, allowing robust and flexible prediction models to be developed for increasingly diverse study objectives (Priya & Ramesh, 2020).

In the context of precision coffee farming, machine learning techniques have been used to study plant diseases (Marin et al., 2021a), productivity (Barbosa et al., 2021; Kouadio et al., 2018), leaf nitrogen (Marin et al., 2021b), identification and counting of plants (Santana et al., 2023) and weeds (Bento et al., 2023). However, the use of chitosan in the study of coffee plants subjected to foliar management has not yet been discussed in the literature, which is a gap that demands attention and directs new promising results of applicability. Therefore, this study aimed to evaluate the potential use of multispectral images obtained by RPAS together with the use of machine learning techniques to differentiate coffee plants subjected and not subjected to the foliar application of chitosan.

Identifying plants that respond positively to the application of chitosan can lead to more precise adjustments in agricultural management. Plants treated with biostimulants such as chitosan tend to exhibit improvements in growth, root development, and photosynthesis, resulting in increased productivity. For coffee growers, this practice can translate into higher crop yields and better grain quality, directly impacting profits. Moreover, this approach simplifies the monitoring of established trials, enabling more consistent assessments of plant responses and facilitating long-term agricultural planning. The application of chitosan as it is a less invasive method, compared to the use of synthetic fertilizers or pesticides, generates a positive impact on the plants, which in turn benefits the soil, biodiversity, and agricultural ecosystems, while also meeting the growing demand for more sustainable agricultural practices.

Methodology

Study Area

The study area refers to a commercial coffee crop (*Coffea arabica* L.) located in the municipality of Ijaci, Minas Gerais, Brazil (501,780 and 502,320 m E and 7,659,700 and 7,659,140 m N), in the projection system Universal Transverse Mercator (UTM), 23S zone, SIRGAS 2000 (Figure 1). The crop was planted in 2008 and has a spacing of 3.6 metres between rows and 0.5 metres between plants, with two different cultivars, Catucaí Amarelo (2SL) (subarea A) and Catucaí Vermelho (IAC 99) (subarea B), registered in the National Register of Cultivars - RNC, of the Ministry of Agriculture, Livestock and Food Supply - Mapa.

The experimental design consisted of randomized blocks, with different foliar application treatments (with/without chitosan) (Figure 1). The division consists of two study lines per coffee cultivar, with 8 blocks per study line, 4 blocks subjected to chitosan application

and 4 blocks without chitosan application, with 6 replicates per block. Each replicate refers to a study plant; thus, each experimental unit is composed of 8 total plants, with 6 plants being the focus of investigation. The lateral lines of each experimental line were also considered as borders.

The chitosan product that was powdered to prepare the solution (liquid) that was applied, using the commercial active from Sigma Aldrich Chemicals (low molecular weight chitosan 448869-250G). Chitosan foliar applications were carried out with an electric knapsack sprayer, totaling three applications in the months of February (23-02-2021), March (30-03-2021) and May (04-05-2021). Chitosan was applied at a concentration of 300 mg.L.-1, solubilized in 0.1% acetic acid, and the dilution of chitosan in acid was carried out on the same day of applications. The volume of mixture used during applications was 400 L.ha.-1, with suitable climatic conditions for the application.

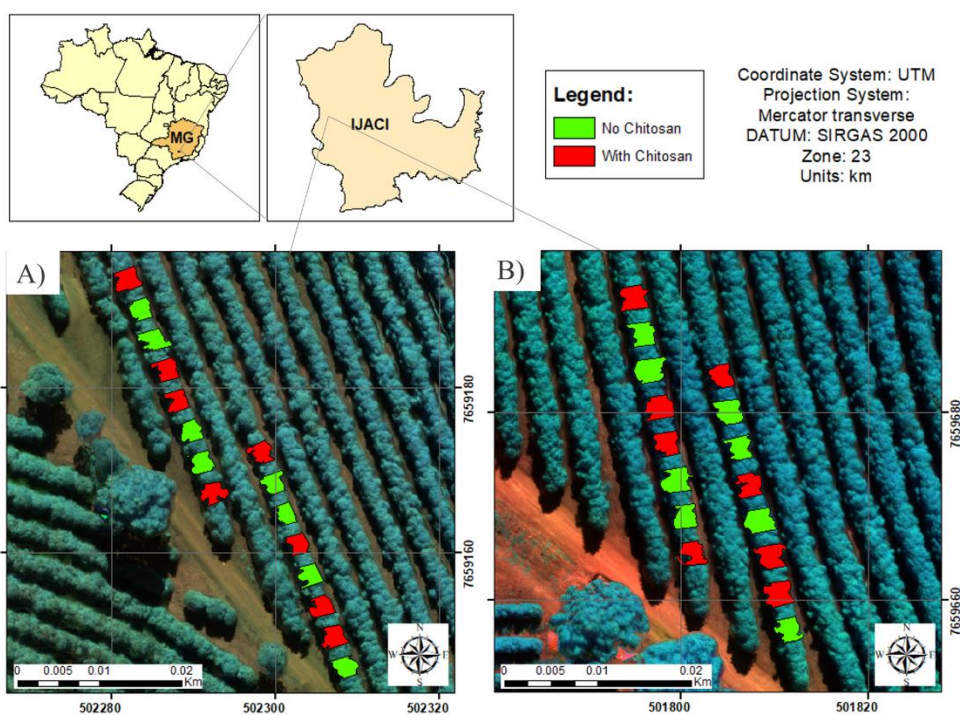


Fig. 1 Study area with separation of the subareas for the coffee cultivars A) Catucaí Amarelo (2SL) and B) Catucaí Vermelho (IAC 99).

Collection and Processing of Air Data

Aerial imaging was performed in June 2020 and 2021 using a 3DR SOLO Remotely Piloted Aircraft (3D Robotics, Berkeley, California) (Figure 2A), which, according to the manufacturer's considerations, has a flight autonomy of approximately 20 minutes (considering

the weight loaded on the vessel), maximum load capacity of 0.42 kg, maximum altitude of 122 m, range of 800 m and maximum speed of 24.58 m/s with navigation, altitude and other communications control by means of telemetry and in real time with control inputs via the Wi-Fi network.

The Parrot Sequoia multispectral sensor (MicaSense, Seattle, WA, USA) and the irradiance sensor (Sunshine Sensor) were embedded in the RPA for aerial imaging (Figure 2B). This sensor has an RGB reading range and 4 spectral sensors with spectral ranges of green (GRE - 550 to 590 nm), red (RED - 660 to 700 nm), red edge (REG - 735 nm to 745 nm), infrared (NIR - 760 to 820 nm) and RGB (380 to 720 nm), and its dimensions are 47 mm x 39.6 mm x 18.5 mm and the focal aperture is 61.9° HFOV (high-frequency oscillatory ventilation) (4 mm).

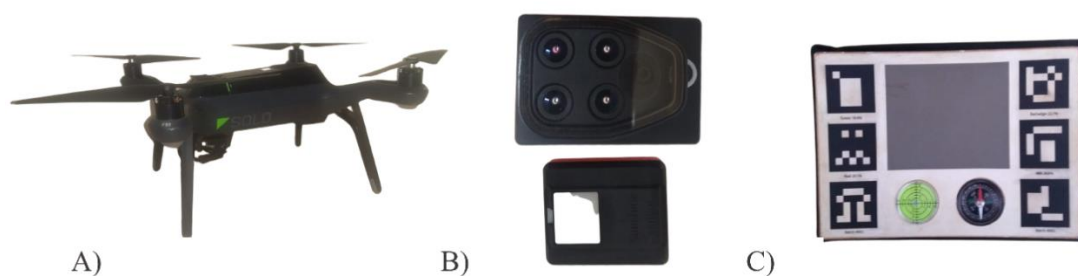


Fig. 2 A) 3DR SOLO RPA; B) Parrot Sequoia and Sunshine sensor; and C) Radiometric calibration plate.

The flight plan was developed semiautomatically using Mission Planner software (Team ArduPilot, Geelong, Australia). Regarding the flight parameters, the aircraft launch and landing location (home point definition), wind direction, topographic conditions of the area, flight direction, flight height in metres and flight speed in m/s were considered. The overlap information (overlap X sidelap), speed and flight height above ground level (AGL) were standardized at 80% X 80%, 5 m/s and 40 m, respectively.

Before and after the flights, images were captured from the radiometric calibration plate (MicaSense, Seattle, WA, USA) for later standardization of the reflectance values of the flights since the panel has a known reflectance curve and allows for accurate compensation of the incident light (Figure 2C). The flights took place at standardized times between 11:00 am and 1:00 pm, a time that avoids shading of the plants due to the position of the sun at the zenith.

The aerial images were processed using Pix4D Mapper software (Pix4D, Lausanna,

Switzerland). The workflow steps refer to the initial alignment of the images through triangulation and creation of link points, subsequently generating the dense point clouds and texture of the scenes, and finally orthorectifying the images to obtain the orthomosaic from the end of each spectral band for each study area and date. The generated orthomosaics had a ground sampling distance (GSD) of 0.052 m.

With the orthomosaic products in hand, the study blocks were individualized using QGIS 3.6.2 software (QGIS Development Team, Open Source Geospatial Foundation), with each experimental unit composed of 6 useful plants, enabling the extraction of the orthomosaic pixel values for each block of plants for the subsequent spectral analyses.

Vegetation Indices

The vegetation indices (VIs) were calculated based on the combination of spectral bands according to the mathematical equations described in Table 1. For this study, 26 different VIs were considered for identifying the indirect relationships of spectral response in coffee plants subjected to the different treatments and to serve as input data for the classification model. The VIs was calculated with the software QGIS 3.6.2 (QGIS Development Team, Open Source Geospatial Foundation) in a GIS environment through the set of functions in ArcToolbox in the Map Algebra tool.

Table 1 Vegetation indices used, followed by their abbreviations, equations and references.

Vegetation Indices	Abbreviations	Equations ^[1]	References
Chlorophyll Index Green	CIg	$(R_{NIR}/R_G - 1)$	Gitelson et al. (2003)
Difference Vegetation Index	DVI	$(R_{NIR} + R_R)$	Perry & Lautenschlager (1984)
Excess Red Vegetation Index	EXR	$1.44(R_R - R_G)$	Meyer et al. (1998)
Green Difference Vegetation Index	GDVI	$(R_{NIR} + R_G)$	Wu (2014)
Green Normalized Difference Vegetation Index	GNDVI	$(R_{NIR} - R_G)/(R_{NIR} + R_G)$	Shanahan et al. (2001)
Green Optimal Soil Adjusted Vegetation Index	GOSAVI	$(1 + 0.16)(R_{NIR} - R_G)/(R_{NIR} + R_G + 0.16)$	Rondeaux et al. (1996)
Green Re-normalized Different Vegetation Index	GRDVI	$(R_{NIR} - R_G)/\sqrt{(R_{NIR} + R_G)}$	Cao et al. (2013)
Green Red NDVI	GRNDVI	$(R_{NIR}) - (R_G + R_R)/(R_{NIR}) + (R_G + R_R)$	Wang et al. (2007)
Green-Red Ratio Index	GRI	$(R_G)/(R_R)$	Gamon & Surfus (1999)
Green Ratio Vegetation Index	GRVI	(R_{NIR}/R_G)	Tucker (1979)

First Modified Chlorophyll Absorption Ratio Index	MCARI1	$1.2(2.5((R_{NIR}-R_G)-1.3(R_{NIR}-R_G)))$	Haboudane et al. (2004)
Modified Double Difference Index	MDD	$(R_{NIR}-R_{REG})-(R_{REG}-R_G)$	Lu et al. (2014)
Modified Normalized Difference Index	MNDI	$(R_{NIR}-R_{REG})/(R_{NIR}-R_G)$	Cao et al. (2013)
Modified Photochemical Reflectance Index	MPRI	$(R_G-R_R)/(R_G+R_R)$	Yang et al. (2008)
Modified Simple Ratio	MSR	$(R_{NIR}/R_R)-1/\sqrt{(R_{NIR}/R_R)+1}$	Chen (1996)
Modified Simple Ratio Green	MSR_G	$(R_{NIR}/R_G)-1/\sqrt{(R_{NIR}/R_G)+1}$	Cao et al. (2013)
Meris Terrestrial Chlorophyll Index	MTCI	$(R_{NIR}-R_{REG})/(R_{REG}+R_R)$	Dash & Curran (2004)
Normalized Different Index	NDI	$(R_G-R_R)/(R_G+R_R+0.01)$	Mao et al. (2003)
Normalized Difference Red Edge Index	NDRE	$(R_{NIR}-R_{REG})/(R_{NIR}+R_{REG})$	Buschmann & Nagel (1993)
Normalized Difference Vegetation Index	NDVI	$(R_{NIR}-R_R)/(R_{NIR}+R_R)$	Rouse et al. (1974)
Normalized Green Index	NGI	$R_G/(R_{NIR}+R_{REG}+R_G)$	Sripada et al. (2016)
Normalized NIR Index	NNIR	$R_{NIR}/(R_{NIR}+R_{REG}+R_G)$	Sripada et al. (2016)
Normalized Red Edge Index	NREI	$R_{REG}/(R_{NIR}+R_{REG}+R_G)$	Cao et al. (2013)
Normalized Red Index	NRI	$R_R/(R_{NIR}+R_{REG}+R_{RED})$	Bausch & Duke (1996)
Renormalized Difference Vegetation Index	RDVI	$(R_{NIR}-R_R)/\sqrt{(R_{NIR}+R_R)}$	Roujean and Breon (1995)
Ratio Vegetation Index	RVI	R_{NIR}/R_R	Richardson & Wiegand (1977)

Legend: ^[1] R_{NIR} , reflectance values obtained by the sensor in the near infrared range. R_{REG} , reflectance in the red edge range. R_R , reflectance in the red band. R_G , reflectance in the green band.

Classification and Validation

The training and validation stages of the classification model consisted of a) preprocessing and exploratory analysis of the data; b) sampling of classes of interest; c) classification procedure by the random forest (RF) algorithm; d) validation and verification of the performance of the classifier; and e) forecasting in the total area, with steps shown in Figure 3 and procedures performed in QGIS 3.22.8 (QGIS Development Team, Open-Source Geospatial Foundation) and R Studio software (R Development Core Team, R project, Austria, Vienna). In this study, the data referring to the 26 VIs and 4 individual spectral bands of the sensor used to capture the images were considered as input data to the classification process.

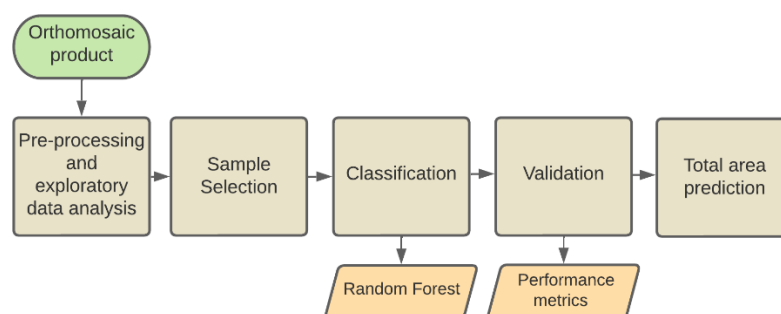


Fig. 3 Flowchart of the classification process with the methodological steps used.

Two classes of interest were considered for the classification process: coffee plants subjected to chitosan application (CQ) and coffee plants not subjected to chitosan application (SQ). The training samples were selected based on the sketch of the study area, based on the correct positioning of the plants subjected to the different treatments, using the software QGIS 3.22.8 (QGIS Development Team, Open Source Geospatial Foundation). The samples were initially collected in shapefile format based on regions of interest (ROIs). The pixels belonging to the ROIs were added as samples, increasing the number of samples, totaling 51409 samples for the cultivar Catucaí Amarelo (2SL) and 54942 samples for the cultivar Catucaí Vermelho (IAC 99), using R Studio software (R Development Core Team, R project, New Zealand).

Subsequently, using R Studio software, the samples were randomly divided into training and validation samples at proportions of 70% and 30%, respectively. The training samples were used in the classification for separating information from the reflectance spectrum using the random forest (RF) machine learning algorithm (Breiman, 2001) in R Studio software. For this analysis, the hyperparameters were defined as follows: the number of decision trees (ntree) was set to 100, and the number of variables tested at each split (mtry) was defined as the square root of the total number of input variables (Gislason et al., 2006). Additionally, an analysis based on the Gini index was performed to describe the importance of each input variable for the classification process. The remaining hyperparameters were set to their default values.

The results were validated using the study's percentage of the validation sample in direct comparison to the reference data. For this, we used information obtained through the confusion matrix according to metrics of global accuracy, sensitivity, specificity and area under the ROC curve. Finally, the classifier algorithm was used to predict the total area of the study classes; therefore, it was possible to identify the blocks of coffee plants subjected and not subjected to the foliar application of chitosan.

Results

The performance metrics are described in Table 2 and refer to the overall accuracy, sensitivity, specificity and area under the ROC curve according to the classification proposed by the algorithm for the two coffee cultivars studied, Catucaí Amarelo (2SL) and Catuaí Vermelho (IAC 99), and the results of this analysis consider the study classes in general, considering the two study classes, coffee plants subjected to chitosan application (CQ) and coffee plants not subjected to chitosan application (SQ). In general, satisfactory values of the performance metrics analyzed were found, which indicate good performance of the classifier for differentiating the study classes.

Table 2 Performance metrics for the RF classification algorithms for the coffee cultivars A) Catucaí Amarelo (2SL) and B) Catuaí Vermelho (IAC 99).

	Overall Accuracy	Sensitivity	Specificity	AUC
A)	0.8025	0.8230	0.7822	0.8087
B)	0.8169	0.8516	0.7812	0.8237

The results of the validation of the classification algorithm for the two coffee classes and cultivars studied were verified using confusion matrices, as described in Table 3. The results of this analysis consider the study classes individually. Based on the values previously presented via performance metrics, the confusion matrix showed low errors between the classified thematic classes, with approximately 18% for SQ and 22% for CQ for the cultivar Catucaí Amarelo (2SL) and 15% for SQ and 22% for cultivar Catuaí Vermelho (IAC 99).

Table 3 Confusion matrices for the RF machine learning algorithm for the coffee cultivars A) Catucaí Amarelo (2SL) and B) Catuaí Vermelho (IAC 99).

		Reference			
		SQ	QC	Total	
A)	Classes				
	Prediction	SQ	6307	1690	7997
		QC	1356	6069	7425
	Total	7663	7759	15422	
		Reference			
B)	Classes				
	Prediction	SQ	5422	1351	6773
QC		945	4825	5770	
	Total	6367	6176	12543	

Legend: SQ - without chitosan; CQ - with chitosan.

Using the RF classifier, it was possible to describe the importance of each variable for the classification process by means of the mean decrease in the Gini, as shown in Figure 4. For

the cultivar Catucaí Amarelo (2SL), the 3 most important variables in the classification were the REG spectral band VIs MNDI and NNIR, and for the cultivar Catuaí Vermelho (IAC 99), the 3 most important variables in the classification were VIs MDD, NDRE and the NIR spectral band.

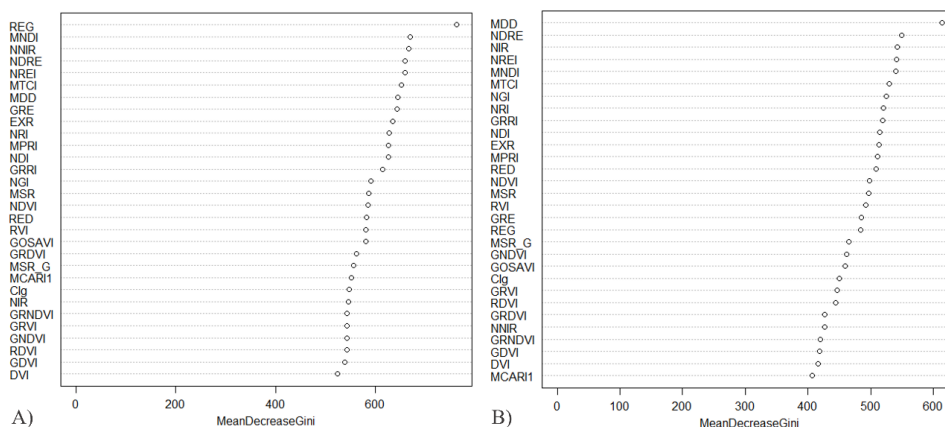


Fig. 4 Importance variables by mean decrease in Gini in the spectral bands for the coffee cultivars A) Catucaí Amarelo (2SL) and B) Catuaí Vermelho (IAC 99).

The map of the distribution of classes with the classifier RF, which describes the prediction of classes by the classifier algorithm for the plant blocks of the two coffee cultivars, is presented in Figure 5, where A) Catucaí Amarelo (2SL) and B) Catuaí Vermelho (IAC 99).

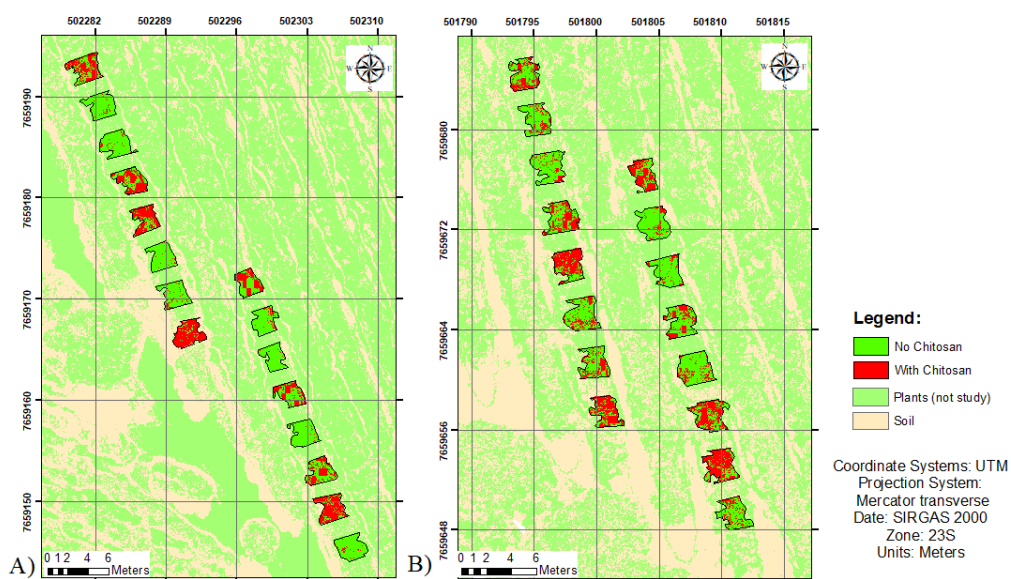


Fig. 5. Prediction map with the RF classifier for the blocks of plants subjected and not subjected to foliar application of chitosan for the coffee cultivars A) Catucaí Amarelo (2SL) and B) Catuaí Vermelho (IAC 99).

Discussion

As shown in Table 2, the performance metrics of overall accuracy, sensitivity, specificity and area under the ROC curve allowed reliable discrimination of the study classes. The global accuracy metric allowed us to verify the estimate of the global correctness ratio of the classifier algorithm, while the sensitivity metric refers to the proportion of true positives among the instances classified as positive, and the specificity metric refers to the proportion of false negatives among the instances classified as negative. Finally, the metric referring to the area under the ROC curve refers to the fit between sensitivity and specificity (De Castro & Ferrari, 2017; Mariano & Paz, 2020).

Notably, values of performance metrics between 70 and 100% represent satisfactory results from moderate to high for classification (Kuhn & Johnson, 2013), as observed in this study, with values always above 78%. For the area under the ROC curve, the performance is represented in the range of normalized limits between 0 and 1 (James et al., 2013, Kuhn & Johnson, 2013). Values closer to 1 highlight better performance (Gonzaga, 2011), as observed in this study with values above 0.80. Thus, it can be said that all performance metrics are within the quality limits as defined by the classification criteria. It should be noted that pixels classified as erroneous classes are checked whenever the classification does not reach 100% accuracy in the individual analysis of the classes.

The RF algorithm has some specificities that optimize the classification procedures since it calculates the average of the decision trees that compose it, which minimizes the variation component of the model, bringing it closer to an ideal model. When developing trees, independent decisions and obtaining a majority vote reduces the fit errors and increases the correctness of the proposed classes (Metha et al., 2019), a fact evidenced in this study. In addition, this algorithm can list the attributes that contribute to decision making and is often used as a feature selection technique, a fact considered essential for data analysis because it allows reducing the complexity/dimensionality of the classification system (Dash & Liu, 1997). Other characteristics that make RF beneficial to classification applications stand out, such as the lower interference of outliers and data with noise, allowing data with different statistical distributions, large-scale data and data from various sources, along with having higher precision when compared to other classification algorithms such as support vector machine and maximum likelihood (Mahdianpari et al., 2017; De Almeida Furtado et al., 2016).

The RF classification errors observed in this study may be associated with the characteristics of the plants when subjected to foliar application of chitosan and consequently with the reflectances presented in their spectral responses. When chitosan is applied foliar to

plants, it promotes changes in the plant's internal structure, producing defense and protection reactions by activating mechanisms of production and/or inhibition of elements and compounds present (Berger et al., 2011). Plants under stress conditions, especially water stress, inhibit the growth of roots and stems and reduce photosynthesis, which may directly affect the leaf size and proportion and consequently changes in the leaf area index (LAI), thus decreasing the uptake and activity in the photosynthetically active area (Xing & Wu, 2012) and altering the spectral responses of plants. Therefore, the adoption of antitranspirant methods, especially the foliar application of chitosan, promotes changes in the plant structure, which was captured via spectral analysis and direct application of image classification.

It was observed in this study that in addition to the use of the individual spectral bands of the sensor, the use of VIs demonstrated improvements in the classification procedure, resulting in spectral differences that were captured by the RF algorithm for the analysed study classes. This occurs mainly because the VIs emphasizes characteristics related to biological variables, such as chlorophyll content and biomass, which are important for differentiating the classes of the study. According to Figure 4, for the cultivar Catucaí Amarelo (2SL) in addition to the REG band, the VIs MNDI and NNIR had greater weight in the classification process, and for the cultivar Catucaí Vermelho (IAC 99) in addition to the NIR spectral band, the VIs MDD and NDRE had greater weight in the classification process.

The active presence of the NIR and REG spectral bands are strongly weighted in the proposed classification, whether used individually or in combination according to VIs. The NIR spectral region is influenced mainly by the internal structure of the leaves due to the interaction of incident energy with the structure of the spongy mesophyll of the leaves (Knipling, 1970). The same occurs in the REG spectral region, located in the sensitive interval between the RED and NIR spectral bands (spectral band of low and high reflectance in plants, respectively), allowing the identification of changes in the levels of chlorophyll in the vegetation affected by stress factors imposed by agricultural practices (Cao et al., 2019; Barnes et al., 2017). Thus, it is noteworthy that the water content of vegetation, according to water stress, alters the reflectance in various regions of the electromagnetic spectrum. In this study it was observed especially in the REG and NIR spectral bands, since it promotes significant changes and adaptations of plants, thus affecting its entire functioning, development, and spectral responses, as demonstrated in studies by Le et al. (2023), Ahmad et al. (2022) and Fiorio et al. (2018).

The prediction map presented in Figure 5 describes the distribution of study classes according to the RF classifier, highlighting the fact that the algorithm obtained high accuracy for the proposed classification by correctly identifying the distribution for the blocks of plants

subjected and not subjected to foliar application of chitosan. In general, satisfactory and accurate results of the proposed classification are due to the use of high spatial resolution images obtained by RPAS, as well as the use of a considerable amount of input variables to the classifier algorithm, which covers spectral bands important for the study of crops, suggesting that methods which incorporate the spectral characteristics of plants are valuable for classifying different characteristics of plants in the field (Chicchón Apaza et al., 2019).

Notably, the application of classification procedures by machine learning is of fundamental importance in the agricultural sector, as it allows the analysis of increasingly complex and numerous data from different origins and sources, producing accurate and reliable results, with smaller risks of errors when properly applied and when performance analyses are performed (Osco et al., 2020). Thus, the results described in this study confirm the possibility of identifying areas subjected to different foliar chitosan applications by means of images obtained from RPAS and machine learning via random forest. Knowing the spatial distribution of areas with different management practices is essential for a proper understanding of the development of agricultural in the field, as well as for anticipating returns in productivity and profitability of crops. The advantage of identifying plants under leaf chitosan management with images based on RPAS is the fast, economical, and non-destructive way of monitoring agricultural crops. However, traditional agronomic methods should not be completely replaced but rather combined with new technologies and computational remote sensing techniques. Studies on the classification of plants with different management practices of foliar application of chitosan using the techniques presented in this study are not reported in the literature, indicating a need to model the presence of the biostimulant in coffee plants.

Conclusions

The results presented in this study showed that the random forest machine learning method, applied to individualized spectral bands and vegetation indices from multispectral images obtained by RPAS, offers an adequate approach to classify coffee cultivars subjected and not subjected to foliar application of chitosan. The model indicated that the spectral bands of the red edge and near infrared, both individually and in combination with vegetation indices, were quite efficient for the proposed classification.

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Disclosure Statement

No potential conflict of interest was reported by the authors.

Data availability statement

All research data supporting this publication are directly available within the publication.

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3.4 PLANT HEIGHT AND SOIL COMPACTION IN COFFEE CROPS BASED ON LIDAR AND RGB SENSORS CARRIED BY REMOTELY PILOTED AIRCRAFT

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Abstract: Remotely Piloted Aircraft (RPA) as sensor-carrying airborne platforms for indirect measurement of plant physical parameters has been discussed in the scientific community. The utilization of RGB sensors with photogrammetric data processing based on Structure-from-Motion (SfM) and Light Detection and Ranging (LiDAR) sensors for point cloud construction is applicable in this context and can yield high-quality results. In this sense, this study aimed to compare coffee plant height data obtained from RGB/SfM and LiDAR point clouds and to estimate soil compaction through penetration resistance in a coffee plantation located in Minas Gerais, Brazil. A Matrice 300 RTK RPA equipped with a Zenmuse L1 sensor was used, with RGB data processed in PIX4D software and LiDAR data in DJI Terra software. Canopy Height Model (CHM) analysis and cross-sectional profile, as well as correlation and statistical difference studies between the height data from the two sensors, were conducted to evaluate the RGB sensor's capability to estimate coffee plant height compared to LiDAR data considered as reference. Based on the height data obtained by the two sensors, soil compaction in the coffee plantation was estimated through soil penetration resistance. The results demonstrated that both sensors provided dense point clouds from which plant height ($R^2=0.7224$, $R=0.8499$, and $RMSE=0.4433$) and soil penetration resistance ($R^2=0.8737$, $R=0.8346$, and $RMSE=0.1360$ m) were accurately estimated, with no statistically significant differences determined between the analyzed sensor data. It is concluded, therefore, that the use of remote sensing technologies can be employed for accurate estimation of coffee plantation heights and soil compaction, emphasizing a potential pathway for reducing laborious manual field measurements.

Keywords: Precision and Digital Agriculture; Remote Sensing; Light Detection and Ranging; Unmanned Aerial Vehicle.

1. Introduction

Driven by a complex genetic mechanism, plant height is an important agronomic and phenotypic characteristic that varies according to the agricultural crop [1]. Measurement is typically conducted manually using a ruler, with a limited sample size in the field, making this approach labor-intensive, low-yield, and prone to increased human measurement errors [2]. Therefore, the employment of techniques and technologies aimed at measuring indirectly variables in the field, including plant height, is encouraged whenever they can capture the true characteristics of the plants. Additionally, plant height allows for important estimations such as leaf area index [3], biomass [4], and productivity [5], highlighting the need for this variable to be quantified with caution and adequately representative of what is observed in the field.

Alternative methods have been developed employing techniques derived from remote sensing, which stands out for generating highly reliable products that assist in the study and

monitoring of agricultural crops. Remote sensing techniques allow for the capture of information from the earth's surface without direct contact between the sensor and the imaged object [6], enabling the study of important characteristics of agricultural crops. Therefore, they can estimate the same variable using various sensor systems, allowing for the observation of which best approximates the real condition of the plant in the field.

Three-dimensional point cloud detection techniques of a digitized field can be obtained by airborne sensors on Remotely Piloted Aircrafts (RPAs). RPAs refer to unmanned aircraft remotely controlled through interfaces such as computers, simulators, digital devices, or remote controls, and can be programmed to execute semi-automated flight plans, allowing operator intervention at any time [7]. The airborne sensors can be conventional high-resolution RGB (Red, Green, Blue) type, with images collected as sequences of overlapping images that, when processed using Structure-from-Motion (SfM) algorithms, produce geometrically precise sampled point cloud structures [8]. The LiDAR (Light Detection and Range) sensor, on the other hand, actively scans the terrain by emitting high-frequency laser pulses towards the object, recording the reflected responses and transmission time, and producing a dense point cloud of the sampled terrain [9]. These sensors can, therefore, produce structural parameters of crops, such as height, for example. It is noteworthy that the SfM algorithm allows high-resolution RGB images to be used to produce point clouds with quality similar to those obtained by LiDAR, which is important for the precise study of crop structure [10].

Studies employing point clouds obtained by RGB and LiDAR sensors are already described in the literature, aiming to compare the effectiveness of these two methods in measuring plant characteristics. [11] used RGB sensors on RPA and terrestrial LiDAR for multitemporal crop modeling and developed and evaluated a methodology to estimate plant height data from generated point clouds, obtaining root mean square errors (RMSE) of 0.01 and 0.12 m respectively compared to ground truth data. [12] developed and evaluated a method to rapidly derive crop height and growth rate from multitemporal digital surface models obtained by RGB and LiDAR sensors, with an RMSE of 0.03 m when compared to ground truth. [13] aimed to evaluate the capability of point clouds derived from RGB and LiDAR sensors to capture soil surface variability and spatially variable crop height, observing a strong correlation between the heights derived from the employed sensors. [14] estimated height and biomass using an RPA equipped with LiDAR and multispectral sensors, demonstrating similarity between the prediction results. Thus, all these results show a potential path to reduce the time spent on manual field measurement and expand the use of indirect measurements, as also evidenced in other studies described by [15], [16], [17] and [18]. However, for coffee crops, no

studies were found that compared point clouds obtained using RGB and LiDAR sensors.

However, the integration of technologies for measuring variables in the field should be applied especially to agricultural crops of importance in the global economic balance, especially to indirectly estimate, via correlation, economically less costly variables (RGB sensor) in relation to more costly variables (LiDAR sensor), enabling more accurate targeting of products, highlighting productivity gains, and greater profitability for agricultural areas. In this scenario, coffee cultivation holds a relevant position, contributing to the global economic balance with total production estimates for the 2023/2024 coffee year of 178 million 60-kg bags, with Brazil being the world's leader in coffee production and export [19]. Internationally, coffee cultivation generates significant revenue among producing and exporting countries, with important earnings for farmers and agricultural workers involved in the activity. In this context, this study aims to estimate plant height and soil penetration resistance in coffee plantations through a dense point cloud-based three-dimensional digital model using two sensors, RGB and LiDAR, airborne by RPA, as well as to verify the quality of the proposed estimates.

2. Materials and Methods

2.1 Study Area

Located in the municipality of Santo Antônio do Amparo, Minas Gerais, Brazil, the study area comprises a coffee plantation (*Coffea arabica* L.) established in December 2016, covering 2.10 hectares. The planting was done with a spacing of 3.5 meters between rows and 0.5 meters between plants, using the Mundo Novo Vermelho (IAC 379/19) cultivar, according to the National Cultivar Registry (Registro Nacional de Cultivares - RNC) of the Ministry of Agriculture, Livestock, and Supply (Ministério da Agricultura, Pecuária e Abastecimento - Mapa) (Figure 1).

The area has an average altitude of 1022 meters and is part of the Atlantic Forest Biome, with soil classified as dystrophic Red-Yellow Latosol [20]. The climate characterization of the study area is humid and temperate according to Köppen's classification, with dry winters and rainy summers (Cwa), with average annual precipitation and temperature of 1.530 mm and 19.4 °C, respectively [21].

The experimental design in this study area involves 18 systematically distributed points with variations in plant height (9 points for tall plants and 9 points for short plants), pre-defined based on aerial survey by RPA as described in the study by [22].

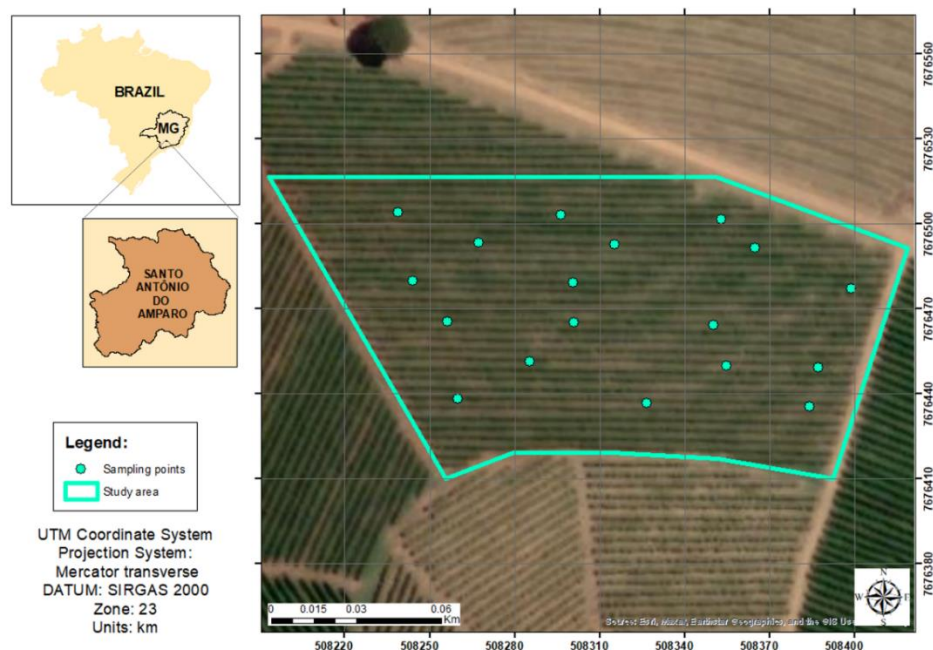


Figure 1. Study area and location of collection points.

2.2 Data Acquisition

The imaging was conducted using the RPA Matrice 300 RTK. According to the manufacturer's specifications, this equipment has a flight time of up to 55 minutes, advanced artificial intelligence capabilities, and a six-directional detection and positioning system. It also features an optimized transmission system with real-time automatic frequency switching between the 2.4 and 5.8 GHz bands, resulting in greater flight stability in high-interference environments, such as transmission lines.

The Matrice 300 RTK was equipped with the Zenmuse L1 sensor for capturing RGB and LiDAR data. This sensor integrates a Livox LiDAR module with a 903 nm wavelength, a high-precision inertial navigation system (IMU), and a 20 MP RGB camera with a 1-inch CMOS sensor, an 8.8 mm focal length, and a mechanical shutter, mounted on a 3-axis stabilized gimbal (Figure 2A). Data collection was performed using the integrated GNSS RTK L1 L2 system on the RPA and corrected using the DJI DRTK-2 base station (Figure 2B), with the base station position adjusted using the IBGE's PPP system. The altimetry's were referenced to the hgeoHNOR2020 model from IBGE, with the average sea level measured at the tide gauge in Imbituba-SC.



Figure 2. A) Matrix 300 RTK with Zenmuse L1 coupled; B) DRTK-2 base fixed to the ground.

The aerial survey was conducted using the DJI Pilot 2 application to define the semi-automated flight plan. The flight parameters include the takeoff and landing location of the aircraft (home point definition), wind direction, topographic conditions of the area, and other information described in Table 1.

Table 1. Settings adopted for flight parameters.

Parameters	Information
Point Cloud Density	164 points/m ²
GSD	2.05 cm/pixel
Terrain Follow	75 meters
Speed	8 m/s
Side Overlap (LiDAR)	50%
Forward Overlap (Visible)	70%
Side Overlap (Visible)	61%
Margem	5 meters
Return Mode	Triple
Sampling Rate	160 KHz
Scanning Mode	Repetitive

2.3 Data Processing

The RGB sensor data was processed using Pix4D Mapper software to create sparse and dense point clouds based on the SfM technique. Initially, image alignment was performed, an automated phototriangulation process where internal camera orientation parameters and external orientation parameters of the aerial photographs are determined, generating a sparse cloud through identified homologous points. Subsequently, the point cloud obtained in the

previous processing stage was densified, increasing the number of points in the cloud and reducing empty spaces. Finally, the final RGB orthomosaic was generated, a process in which orthorectification of the images was performed through orthogonal reprojection and with a constant scale, eliminating or minimizing distortions caused by the sensor system and the surface. Additionally, the Digital Surface Model (DSM) and Digital Terrain Model (DTM) were obtained.

The LiDAR sensor data was processed using DJI Terra software. The point clouds were directly georeferenced using the RTK sensor of the Matrice 300, followed by automatic and then manual classification to define terrain representative points. From these, the DSM and DTM were generated.

2.4 Canopy Height Model

The Canopy Height Model (CHM) was determined based on the two analyzed products (RGB and LiDAR), allowing for the acquisition of coffee plant height information in the field. The CHM expresses the height of a surface object and describes the continuous distribution of the object's surface in the horizontal direction, according to the three-dimensional structure and the height variation in the vertical direction. For the calculation, Equation 1 was used, with the DTM and the DSM as input data. The DTM refers to the solid terrain model representing the elevation of the terrain, containing only the terrain elevation information, while the DSM is based on the DTM and includes the elevation information of other surfaces beyond the soil, such as the height of plants, trees, and constructions.

This analysis was performed using QGIS version 3.6.2 software (QGIS Development Team, Open Source Geospatial Foundation) utilizing the Map Algebra tool. Additionally, to demonstrate the differences between the CHMs obtained from the two study sensors, a cross-sectional profile was drawn in the sample area, and plant height information was extracted using the 3D Analyst toolbar in QGIS version 3.6.2.

$$\text{CHM} = \text{DSM} - \text{DTM} \quad (1)$$

where CHM is the Canopy Height Model (m), DMS is the Digital Surface Model (m) and DTM is the Digital Terrain Model (m).

2.5 Soil Penetration Resistance

To estimate the soil penetration resistance in the coffee plantation based on the plant height data obtained from the RGB/SfM and LiDAR point clouds of the two study sensors, the

method described by [22] was employed, using Equation 2 in QGIS version 3.6.2 software.

$$Y = -0.2126 X + 3.1873 \quad (2)$$

where Y is the Soil Penetration Resistance (MPa), and X is the Canopy Height (m).

2.6 Accuracy Assessment

In this study, plant height definition is initially provided from the dense point cloud obtained by LiDAR, which serves as the reference. The plant height derived from the RGB sensor using the SfM algorithm was then compared to the reference LiDAR plant height. The correlation between the plant height values estimated by LiDAR and the RGB sensor was examined, and a linear model describing the correlation was established. Statistical measures including the Coefficient of Determination (R^2), Correlation Coefficient (R), and Root Mean Square Error (RMSE) were employed to assess the accuracy of the study products for plant height estimation.

The R^2 value was used to evaluate the agreement between the estimated values, the R value to measure the intensity and direction of linear relationships, and the RMSE to measure the deviation between the estimated values. A higher R^2 and R value indicate a better fit of the data, while a lower RMSE indicates higher estimation accuracy.

Subsequently, statistical differences between the estimated plant heights from the RGB sensor and LiDAR were examined. Initially, data normality was verified using the Anderson-Darling statistical test. After confirming data normality, the test T multiple comparison test at a 5% probability level was applied.

Finally, the quality of the soil compaction estimate via penetration resistance was verified for sample points in high plant zones and low plant zones, observing the proximity or non-proximity between the values estimated by the two study sensors based on the statistical analyses of R^2 , R, RMSE, and the T Test multiple comparison at a 5% probability level, with prior normality analysis using the Anderson-Darling statistical test.

All statistical analyses were conducted using R software (R Development Core Team, R project, New Zealand), with processes described in the flowchart in Figure 3.

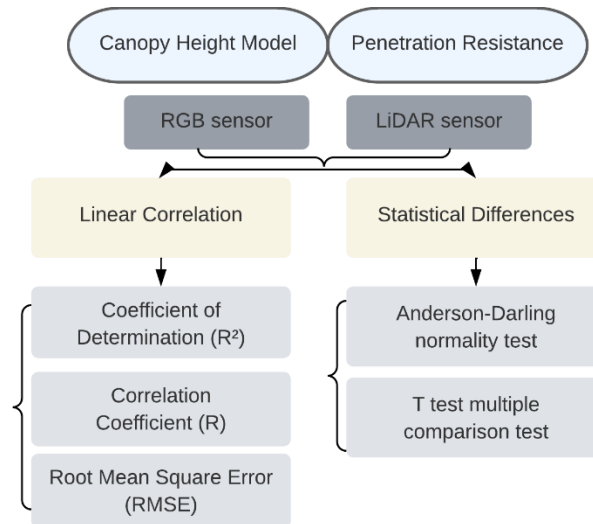


Figure 2. Process flowchart.

3. Results

The descriptive statistics of the coffee plant height variable obtained by the two study sensors (RGB and LiDAR) are described in Table 2, with proximity observed between the obtained values.

Table 2. Descriptive statistics of the height variable, in meters (m), for the 18 study points, estimated by RGB and LiDAR sensors.

Reference	Maximum	Minimum	Average	Standard Deviation
RGB	2.9438	1.0113	2.0563	0.5748
LiDAR	3.0961	1.0407	2.3700	0.5993

The CHMs for the two study sensors are presented in Figure 4. The sampling points were based on the definition presented by [22], considering different height zones of the plants, a fact also observed in the CHMs generated in this study. High plant zones are highlighted with height values ranging from 2.50 to 3.50 meters, and low plant zones with values ranging from 1.50 to 2.50 meters in height. The cross-sectional profile with plant height information obtained by the comparative CHM for the two study sensors is presented in Figure 5, also showing a close resemblance between the obtained results.

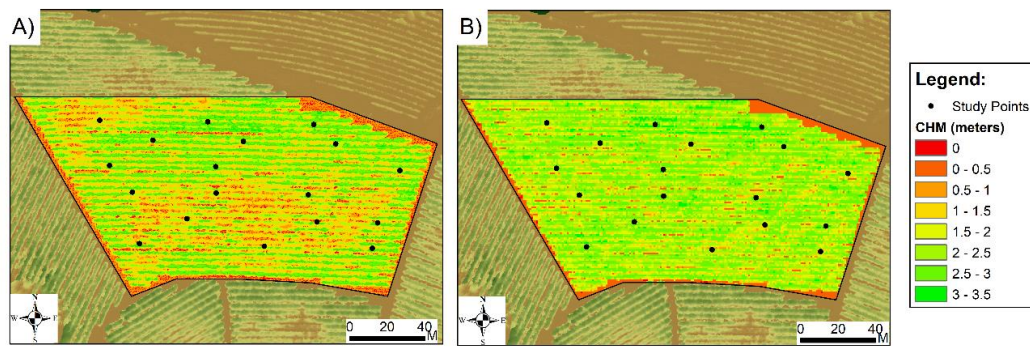


Figure 4. Canopy Height Model (CHM) obtained by the A) RGB; and B) LiDAR.

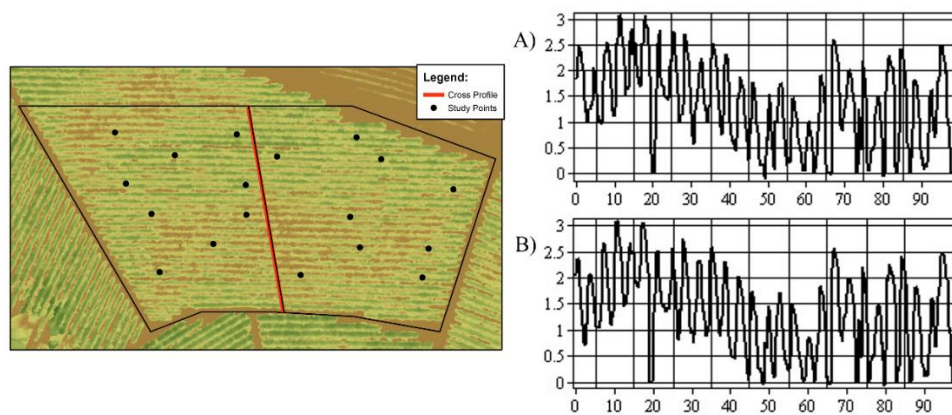


Figure 5. Transverse profile delimited in the study area and height information in meters extracted for the two study sensors A) RGB; and B) LiDAR.

Figure 6, in turn, presents the scatter plot of the height data for the study sensors, which also includes the regression equation, the Coefficient of Determination (R^2) of 0.7224, Correlation Coefficient (R) of 0.8499, and the Root Mean Square Error (RMSE) of 0.4433. Overall, it was observed that the model provided satisfactory estimates for the analyzed metrics, indicating good correspondence between the study variables as the proportion of the variable estimated by one sensor explained by the other sensor.

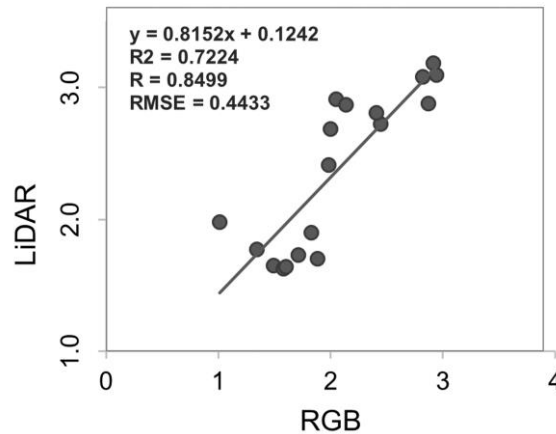


Figure 6. Linear regression graph for RGB and LiDAR sensor with plant height data in meters. It also contains the Linear Regression Equation, the values of the Coefficient of Determination (R^2), Correlation Coefficient (R) and Root Mean Square Error (RMSE).

Based on the exploratory data analysis (Table 2), proximity was observed between the coffee plant height data obtained by the two study sensors. However, the statistical differences by mean test via boxplot analysis for the plant height variable are presented in Figure 6, highlighting that no significant statistical differences were determined by the T Test at a 5% probability level (Figure 7).

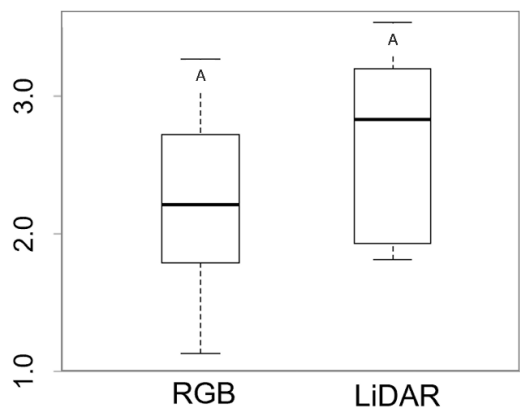


Figure 7. Statistical differences between height (m), between RGB sensor and LiDAR sensor. *Legend: Boxplots accompanied by the same letters indicate that the data do not present statistical differences according to the T Test at 5% probability.

The estimates of the spatial distribution indirectly between plant height and soil penetration resistance (MPa) are presented in Figure 8 for the two study sensors (8A) RGB; and 8B) LiDAR). The values of the statistical metrics for accuracy assessment between the two study sensors were 0.8737 for R^2 , 0.8346 for R , and 0.1360 m for RMSE (Figure 8), with no

significant statistical differences determined by the T Test at a 5% probability level (Figure 9).

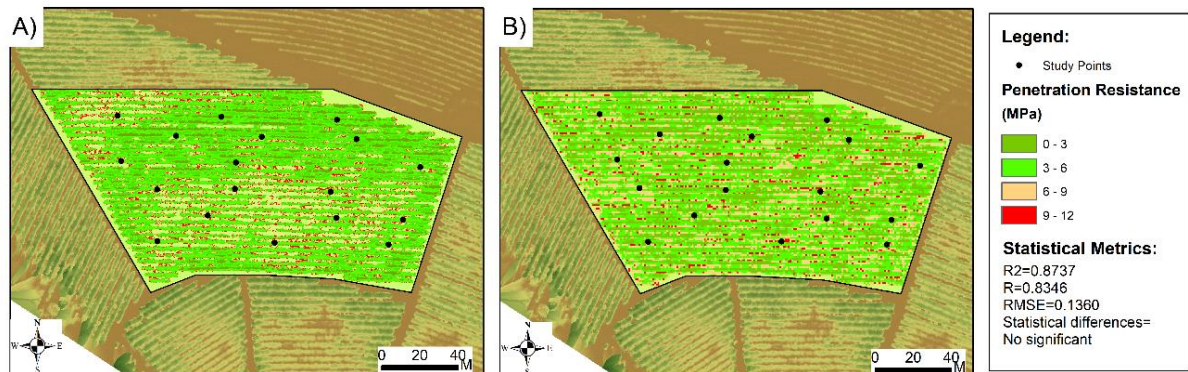


Figure 8. Estimation of the spatial distribution of soil penetration resistance (MPa) according to the regression equation obtained by the A) RGB; and B) LiDAR.

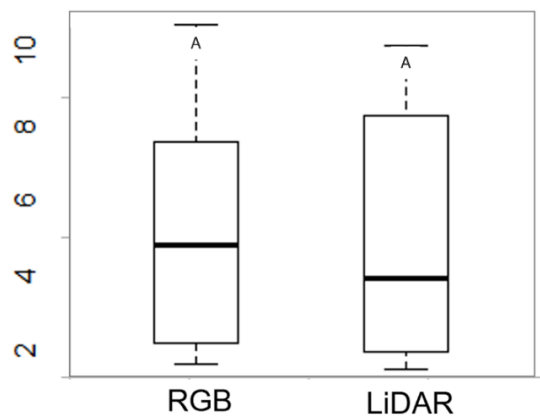


Figure 9. Statistical differences between soil penetration resistance (MPa), between RGB and LiDAR sensor. *Legend: Boxplots accompanied by the same letters indicate that the data do not present statistical differences according to the T Test at 5% probability.

4. Discussion

This study provided an assessment of measuring the plant height variable obtained by RGB sensor with processing via SfM compared to measurement by LiDAR sensor. The CHMs of coffee plants presented in Figure 4, as well as the cross-sectional profile described in Figure 5, depict similar distribution patterns and indicate good representativeness of the sampled coffee plantation with consistent levels of accuracy for both study sensors.

The results demonstrated that the information collected by RGB and LiDAR sensors are fully capable of recreating accurate 3D models and subsequent coffee plant heights. Mapping

the plant height in this study allowed for observing the spatial variability of the study area, detecting points in low plant zones subjected to soil compaction and points in high plant zones not subjected to soil compaction as described by [22].

In terms of evaluation, the results of precision metrics for the study sensors show good agreement ($R^2=0.7224$, $R=0.8499$, and $RMSE=0.4433$ m). It is worth noting that LiDAR scanning and RGB photogrammetry can be collected simultaneously via RPAs, allowing for the integration of both approaches in capturing and generating datasets with information for reconstructing structural information of agricultural areas. However, the method of estimating plant height by RGB sensor is also capable of achieving a high level of precision and has time and cost efficiency compared to the method of estimating plant height by LiDAR sensor.

It is evident, however, that the principles of estimating plant height by RGB sensor via SfM and LiDAR sensor are distinct. Since the SfM algorithm uses two different directions for reconstructing the dense point cloud, while the LiDAR sensor uses only one direction for constructing the dense point cloud, it exhibits greater canopy penetration [23]. In this study, however, despite the different reconstruction methods, the point cloud generated by the SfM algorithm compared to the point cloud generated by the LiDAR sensor was adequate for recreating the agricultural surface.

It is worth noting that a lower fidelity of SfM point clouds from RGB sensors is typically observed because this sensor does not provide complete 3D datasets like the LiDAR sensor, which can store more information per geographic location [24]. Therefore, the accuracy of the RGB product is strongly related to the density of the point cloud generated by point matching using the SfM algorithm, sometimes requiring a greater number of images to improve the quality of the point cloud and achieve high-quality data processing [25].

Upon analysis of the generated results, a slight underestimation of the plant height values estimated by the RGB sensor compared to those estimated by the LiDAR sensor was observed (Table 2), resulting in an increase in RMSE but not affecting the values of R and R^2 (Figure 6). This is likely due to poor image geometry, which leads to terrain occlusion by the plant canopy in most viewing angles. However, this underestimation was not sufficient to determine significant statistical differences for estimating coffee plant height between the two sensors used (Figure 7). Similar conclusions have been reported in studies by [26], [11], [13], [15], and [12].

Based on the penetration resistance estimate described in Figure 8, the values ranged from 1.2829 to 10.2352 MPa for the RGB sensor and from 1.2840 to 10.0968 MPa for the LiDAR sensor, with noticeable proximity between the values estimated by the two study

sensors. The lower penetration resistance values estimated correspond to the high plant zone, i.e., plants less subject to soil compaction, while the higher values correspond to the low plant zone, i.e., plants more subject to soil compaction. As evidenced in the literature, for coffee cultivation, a perennial crop not subjected to annual soil tillage, the tolerated values of penetration resistance are up to 4 MPa, mainly due to pore continuity and aggregate stability [27]. Additionally, sufficient performance metric values with good agreement between them are highlighted to demonstrate the relationships of the soil penetration resistance variable for the two study sensors ($R^2=0.8737$, $R=0.8346$, and $RMSE=0.1360$ m) and non-significant statistical differences at a 5% probability level (Figure 9).

Indirectly estimating soil penetration resistance based on plant height data is crucial for understanding how such effects can influence plant development in the field. Compacted soils typically exhibit low productivity, reduced water infiltration, decreased soil aeration, higher root penetration resistance, lower plant survival capacity, and consequently economic losses in agricultural crop profitability [28].

As observed in this study, the efficiency of remote sensing technologies as a means of obtaining detailed three-dimensional measurements of plant canopy structure allows for the indirect measurement of coffee crop characteristics, such as height and soil penetration resistance. However, the adoption of LiDAR sensor technology is still limited and costly, especially for surveys conducted over medium and large areas. In contrast, the use of RGB sensors is a low-cost alternative configured to provide similar information for capturing three-dimensional structure and describing plant morphological parameters, especially in small areas [29], highlighting the advantage of using RGB sensors for measurement purposes.

Therefore, the results demonstrate that the methodology for indirectly measuring coffee plant characteristics can serve as a monitoring tool for the development of precision agriculture management strategies. It is noteworthy that the prediction of plant height can be employed to provide additional information that complements other study variables, aiming to increase productivity and profitability in agricultural areas.

5. Conclusions

The estimation of coffee plant height and soil compaction through penetration resistance using high-resolution RGB aerial images transported via RPAs showed adequate precision metrics compared to plant height estimation done by LiDAR sensors, being possible to estimate linear regression equation. This highlights the accurate prediction of coffee crop characteristics digitally, with relatively lower costs and less labor-intensive methods than traditional

approaches.

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FINAL CONSIDERATIONS

In recent years, the use of RPAS has emerged as a prominent technology in the agricultural sector. The bibliometric review presented in this thesis highlighted its application within the context of coffee cultivation, a commodity of significant relevance both for the national and global economy. The analysis underscored the research conducted in Brazil, many of which are in collaboration with international institutions, aimed at exploring solutions to the demands of the agricultural field. Moreover, it was possible to identify substantial gaps in the existing literature, which provided the foundation for the subsequent studies carried out in this thesis.

Traditionally, the detection of weeds in coffee plantations is performed manually through in-situ inspections, which demands significant time and labor. To address this limitation, this thesis proposed a study focused on the identification and classification of invasive plants within coffee crops using multispectral images and machine learning algorithms. The proposed classification proved essential in understanding the percentage of weed infestation, thereby optimizing selective spraying systems, which contribute to the reduction of agrochemical waste and minimizing both economic and environmental impacts.

Another point addressed was the indirect estimation of soil compaction in coffee plantations based on canopy height models (CHM) and vegetation indices (VIs), both generated from data collected by RPAS. These results demonstrated the feasibility of monitoring variations in plant height to identify areas of soil compaction, providing an efficient mapping method.

A significant focus was also placed on multispectral analysis combined with machine learning classification enabled the differentiation between coffee plants submitted and not submitted with the foliar application of the biostimulant chitosan. This approach proved to be an efficient method for detecting the presence of the biostimulant in coffee plants, thus offering the potential for more precise adjustments in agricultural management, simplifying direct field analysis, and facilitating long-term agricultural planning.

Finally, the estimation of coffee plant height and soil compaction, evaluated through penetration resistance using high-resolution RGB aerial imagery from RPAS, achieved high accuracy when compared with LiDAR sensor measurements. These findings underscore the precision of digital modeling for coffee crop characteristics, providing a more cost-effective and less labor-intensive alternative to conventional methods, without compromising data quality.

This thesis, therefore, makes a significant contribution to the advancement of RPAS application in coffee cultivation, demonstrating its potential to transform traditional practices, enhance operational efficiency, and reduce environmental impacts. Continuous investigations in this area are of paramount importance, as technological advancements, combined with tools such as machine learning and multispectral analysis, hold the power to further revolutionize agricultural management. Additionally, it is crucial to encourage complementary studies aimed at improving the use of RPAS in other aspects of coffee cultivation. Such research can further expand scientific knowledge and provide innovations that positively impact the productivity, profitability, and sustainability of coffee farming.

As a suggestion for future research, it is emphasized the potential to explore novel vegetation indices that have not yet been addressed in the scientific articles of this thesis, as well as the application of thermal and hyperspectral sensors. Additionally, further exploration of other machine learning techniques, such as neural networks, is recommended, along with the investigation of RPAS as spraying vehicles. The latter, in particular, represents a significant gap in literature, encompassing studies on spray configurations and assessments of the effectiveness of this technology for such purposes.

However, it is important to highlight that the adoption of these technologies in the agricultural sector still faces numerous challenges. These include the high cost of acquiring the tools, limited accessibility, the necessity for specialized training for producers, and the complexity associated with analyzing the vast amount of data generated. These gaps need to be overcome to make the full potential of technology viable, promoting positive returns and economic gains for agricultural crops.