LUCAS SANTOS SANTANA

REMOTELY PILOTED AIRCRAFT AND COMPUTER VISION APPLIED TO COFFEE GROWING MANAGEMENT

LAVRAS – MG

2022

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Tese apresentada à Universidade Federal de Lavras, como parte das exigências do Programa de Pós-Graduação em Engenharia Agrícola, para a obtenção do título de Doutor.

Prof. Dr. Gabriel Araújo e Silva Ferraz
Orientador

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Ficha catalográfica elaborada pelo Sistema de Geração de Ficha Catalográfica da Biblioteca Universitária da UFLA, com dados informados pelo(a) próprio(a) autor(a).

Santana, Lucas Santos.

Remotely Piloted Aircraft and Computer Vision Applied to Coffee Growing Management / Lucas Santos Santana. - 2022.

111 p. : il.

Orientador(a): Gabriel Araújo e Silva Ferraz.

Tese (doutorado) - Universidade Federal de Lavras, 2022.

Bibliografia.

1. Precision Coffee-Growing. 2. Digital Agriculture. 3. Computer Vision. I. Ferraz, Gabriel Araújo e Silva. II. Título.

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APROVADA em 25 de novembro de 2022.

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Dedico esta tese em especial a minha MÃE e meu PAI (in memoriam) que me orientaram pelos caminhos da honestidade, da dedicação ao trabalho e a vida.

À minha família pelo amor incondicional depositados ao longo da minha vida. Além dos valores repassados, incentivos, compreensão, respeito e confiança.

À minha namorada por suportar meus devaneios e me apoiar em todos os momentos dessa conquista.

DEDICO

AGRADECIMENTOS

Agradeço principalmente à minha família por todo apoio e carinho, são eles: meu Pai, Osvaldino Borges Santana (*in memoriam*), minha Mãe, Mara Andria dos Santos Santana, meus irmãos Mozarte Santos Santana, Jean Carlos Alvino dos Santos, Linda Mara Alvino dos Santos e minha namorada Josiane Maria da Silva, Obrigado por tudo.

Sou muito grato ao meu orientador, Gabriel Araújo e Silva Ferraz pela confiança e ensinamentos e por me apresentar uma área do conhecimento tão importante dentro da engenharia. Também pela amizade, orientação, confiança e ensinamentos, sempre de forma ética e humilde.

Ao companheirismo dos meus amigos e colegas da engenharia agrícola, que contribuíram com o desenvolvimento do trabalho. Aos meus amigos do NESA que me ajudaram na coleta e processamento dos dados. Aos proprietários e funcionários da Fazenda Bom Jardim pela disponibilidade da área de pesquisa, sempre com alegria em nos receber na propriedade. Aos membros da banca examinadora, por terem aceitado participar da avaliação deste trabalho.

Por fim, agradeço a Universidade Federal de Lavras e ao Departamento de Engenharia pela oportunidade de realizar este doutorado por meio do Programa de pós-graduação em Engenharia Agrícola (PPGEA). Ao apoio concedido pela Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Código de Financiamento 001. Aos incentivos financeiros, as oportunidades de participação em eventos oferecidos pela Embrapa Café - Consórcio Pesquisa Café (projeto 10.18.20.041.00.00). Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) (projeto 305953/2020-6).

*“Tornamos nosso mundo significativo pela coragem de nossas perguntas e pela profundidade de nossas respostas.” (**Carl Sagan**")*

RESUMO GERAL

O uso de tecnologias de agricultura digital e de precisão tem ganhado espaço, se tornando cada vez mais necessárias em diversas etapas da produção cafeeira. Entre as tecnologias emergentes pode-se destacar o uso de Aeronaves Remotamente Pilotadas (ARPs). Pois seus produtos podem ser utilizados como fornecedores de dados para técnicas de aprendizado de máquinas e formas automatizadas de monitoramento. Neste estudo, objetivou-se aplicar produtos cartográficos e fotogramétricos oriundos de ARPs submetidos a técnicas de aprendizado de máquinas e análises de imagens em cafeicultura digital e de precisão. Foram construídos três tipos de pesquisa: Aplicação de produtos cartográficos provenientes de imagens de ARP para projeto de implantação do cafeeiro; Identificação e contagem de plantas em imagens de ARPs; Investigações acerca do desenvolvimento de plantas em áreas de renovação. (I) No primeiro estudo foram avaliados a eficiência de diferentes composições de missão de voo e níveis de nuvem de pontos para geração de Modelos Digitais de Terreno aplicados em cafeicultura. Voos realizados a 120 m de altura e 80 × 80% de sobreposição apresentaram maior assertividade e eficiência. O voo de 90 m de altura apresentou alto detalhamento do terreno, causando diferenças significativas de superfície em relação à topografia obtida pelo Sistema Global de Navegação por Satélite (GNSS). Faixas de inclinação de até 20% são consideradas confiáveis para projetos de cultivo de café de precisão. Mudanças nas configurações de voo e no processamento de imagens são satisfatórias para projetos de café de precisão. A redução de sobreposição de imagem diminuiu significativamente o tempo de processamento sem influenciar a qualidade do Modelo Digital de Terreno (MDT). (II) Na segunda pesquisa, objetivou-se desenvolver um algoritmo para contagem automática de plantas de café e definir a melhor idade da planta para realizar o monitoramento por meio de imagens ARP. Plantas com três meses de desenvolvimento apresentaram 86,5% de assertividade na contagem. Os melhores resultados foram observados em plantios com seis meses de desenvolvimento, apresentando uma média de 96,8% de assertividade na contagem automática de plantas. Essa análise possibilita o desenvolvimento de um algoritmo para contagem automatizada de plantas de café por meio de imagens RGB obtidas por aeronaves pilotadas remotamente e aplicativos de aprendizado de máquina. (III) O objetivo da terceira pesquisa foi monitorar o desenvolvimento das plantas de café plantadas sobre cinzas de restos culturais por meio índices vegetativos em imagens de ARPs, considerando analises de elementos químicos presentes na cinza e analises de solo. Resultados indicam a presença elevada de alumínio e potássio nas cinzas, provocando diferenças significativas no início do desenvolvimento do cafeeiro. Além disso foram observadas variações nos valores de índices vegetativos em regiões com presença de cinzas, destacando os índices NGI e NNIRI. As pesquisas desenvolvidas nesta tese fornecem informações importantes para o avanço de tecnologias de agricultura digital em cafeicultura.

Palavras chave: Sensoriamento remoto. Classificação de imagens. Transplantio. Aprendizado de máquinas. Queima de biomassa.

GENERAL ABSTRACT

Digital and precision agriculture technologies used in coffee farming have gained space and have become necessary in many coffee production stages. Among the emerging technologies, the Remotely Piloted Aircraft (RPA) can be highlighted because their products can be used as data providers for machine learning techniques and automated monitoring forms. This study aimed to apply cartographic and photogrammetric products from RPAs submitted to machine learning techniques and image analysis in digital and precision coffee farming. Three types of research were built: Application of RPA cartographic products for the coffee plant implantation project; Identification and counting of plants in PRA images and Investigations of plants development in renewal areas. (I)The first study evaluated different flight mission composition efficiency and point cloud levels for Digital Terrain Models generation applied in coffee plantations. Flights performed at 120 m Above Ground Land (AGL) and 80 × 80% overlap showed higher assertiveness and efficiency. The 90 m AGL flight showed great terrain detail, causing significant surface differences concerning the topography obtained by Global Navigation Satellite System (GNSS) receivers. Slope ranges up to 20% are considered reliable for precision coffee growing projects. Changes in flight settings and image processing are satisfactory for precision coffee projects. Image overlap reduction significantly lowed the processing time without influencing Digital Terrain Model DTM's quality. (II) The second research aimed to develop an algorithm for automatic counting coffee plants and define the plant's best age to carry the monitoring using RPA images. Plants with four months of development showed 86.5% count assertiveness. The best results were observed in plantations with six months of development, presenting an average of 96.8% of assertiveness in automatically counting plants. This analysis enables an algorithm development for automated counting of coffee plants through RGB images obtained by remotely piloted aircraft and machine learning applications. (III) The objective of the third research was to monitor the coffee plants' development planted on ash from crop residues through vegetative indices in RPA images, analysis of chemical elements presents in the ash and soil analysis. Preliminary results indicate the high presence of aluminum and potassium in the ash, causing significant differences in coffee development beginning. In addition, variations were observed in vegetative indices values in regions with ash presence, highlighting the NGI and NNIRI indices. The research developed by this paper provides essential information for digital agriculture technologies advancement in coffee growing.

Keywords: Remote sensing. Image classification. Planting. Machine learning. biomass burning.

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CHAPTHER I

1. INTRODUCTION

Coffee growing stands out among the world's main crops. This activity represents an essential source of income in several countries. The coffee tree is cultivated in about 60 countries but shows better development in tropical regions due to the excellent soil and climate conditions. Given this, countries such as Brazil, Vietnam and Colombia stand out among the world's primary producers.

The high levels of coffee productivity are driven by technological practices applied during the production stages. Agriculture evolution is characterized by the rapid expansion of information technologies resulting from methods of monitoring, storing, organizing, and controlling digital agricultural activities. Despite excellent productivity rates in coffee farming, there is still a constant need to improve coffee production.

Technologies' insertion in the field has changed coffee production in recent years. New ways of obtaining data for monitoring bring specialized techniques, providing agility in decision-making and contributing to management improvements.

Airborne sensor data are systematically explored by investigations based on high-resolution multispectral images, applications of vegetation indices, spectral responses, and user determined temporal spaces. Increasing reliability over sensing techniques represents a new step for digital agriculture applications. Continuous data collection associated with high precision are attributes sought by digital agriculture applications, involving automatic data formation, processing and analysis.

Remotely Piloted Aircraft Systems (RPAS) is considered emerging technology in arable areas monitoring. This equipment collects photographs from pre-defined missions, speeding up decision-making in the field and providing a new remote monitoring system. Faced with data density resulting from RPAs, digital agriculture technologies can meet the demand for receiving, organizing, and processing the data set, aiming at necessary information for decision making in cultivation. Remote sensing products and computer vision algorithms have contributed positively to coffee growing. The RPAs can obtain data about the coffee tree by providing information on plant anomalies, land for planting, inputs management and post harvest.

Assertiveness in coffee planting plays an essential role in developing this culture. In mechanized crops, plant alignment is considered vital for operation quality. RPA insertion for digital elevation model building can provide detailed information on the terrain quickly and reliably, thus contributing to assertiveness in planting. However, the data collected by RPAs vary according to the flight mission and type of processing, so it is necessary to assess the flight efficiency and the precision of digital terrain models.

In planting coffee operations, errors can occur, causing several failures in the field. Plant losses in the initial stage of development occur due to factors linked to the mechanized transplant system, root breakage, climatic factors, pests, and diseases. The plant's failure count is made from visual samples from walking the field. This process is a slow, expensive, and imprecise method. Therefore, remote sensing and computer vision techniques can offer satisfactory results in identifying and counting plants.

Plants' growth on cultural remains is a practice used in various crops. In coffee growing, to renew of terrain, the remaining plants from the previous planting are cut, organized in lines, and the cultural remains are burned. Therefore, in these areas, patches of ash are visible on the ground. Consequently, it is essential to monitor these regions to know of interference ash in plant development.

Given the evidence, this research aimed to evaluate applications of photogrammetric products obtained by remotely piloted aircraft and computer vision in specific stages of coffee management. To achieve this objective, it was proposed: (I) Monitoring errors in plant alignment caused in steep slope regions, (II) Identification and counting of plants by the machine learning algorithm and (III) Effect and mapping of ashes deposited in the soil after coffee tree burning for crop renewal.

This thesis is presented in four independent chapters, so that the individual reading of each chapter preserves the subject's general problem. Chapter I presents a general introduction followed by a bibliometric review of the literature on precision coffee farming. Chapter II provides a method for efficiently building Digital Elevation Models (DTM) from RPA images. Chapter III proposes a model for identifying and counting coffee plants using computer vision and RPA images. Chapter IV is a temporal assessment application of ash effects on coffee land. Finally, chapter V summarizes the main conclusions of this study and recommendations for future research in the about of coffee plantation management.

2. LITERATURE REVIEW

2.1. ADVANCES IN PRECISION COFFEE GROWING RESEARCH: A BIBLIOMETRIC REVIEW

Article published in *Agronomy* journal (ISSN 2073-4395)
Accepted: 1 August 2021 / Published: 5 August 2021. DOI: https://doi.org/10.3390/agronomy11081557

Abstract: Precision coffee-growing technologies contribute to increased yield, operational efficiency, and final product quality. In addition, they strengthen coffee growing in the global agricultural scenario, which makes this activity increasingly competitive. Scientific research is essential for technological development and offering security regarding its application. For relevant research identification, bibliometric revision methods expose the best studies and their relationships with countries and authors, providing a complete map of research directions. This study identified the main contributions and contributors to academic research generation about precision coffee growing from 2000 to 2021. Bibliometric analysis was performed in VOSViewer software from the referential bases Scopus and Web of Science that identified 150 articles. Based on the number of citations, publications about precision coffee-growing showed Brazilian institutions at the top of the list, and Brazil's close relationships with North American and South African institutions. Geostatistical analysis, remote sensing and spatial variability mapping of cultivation areas were used in most experimental research. A trend in research exploring machine learning technologies and autonomous systems was evident. The identification of the main agents of scientific development in precision coffee growing contributes to objective advances in the development and application of new management systems. Overall, this analysis represents wide precision coffee growing research providing valuable information for farmers, policymakers, and researchers.

Keywords: precision agriculture; analysis; bibliometry; coffee farm; systematic review

1. Introduction

Coffee growing is among the primary agricultural activities in the world [1,2]. It represents an essential source of income for many countries [3,4]. Coffee is produced in about 60 countries, where tropical regions favor its development. Countries like Brazil, Vietnam and Colombia are the main world producers [5].

High rates of coffee yield result from application of technological practices during production and processing stages. Modern agriculture is characterized by the rapid expansion of information technologies arising from monitoring and control of storage, organization and agricultural activities [6]. Using techniques and technologies aimed at high levels of productivity combined with sustainability is known as precision agriculture [7]. Precision agricultural practical can maximize the potential of each region, making the crop more productive and favoring cost reduction [8].

Technological advances in precision agriculture contribute to obtaining accurate and reliable measurements in a crop. This can facilitate monitoring edaphoclimatic variables on a more accurate scale. Thus, designing fertilization plans, seedling selection and agricultural activities make agricultural production more effective [9]. Smart agriculture is crucial to maximizing crop yields and revenues and preserving natural resources [10].

Technologies drive the creation and segmentation of specific classes of precision agriculture. In coffee crops, such technological approaches are known as precision coffee growing. Alves et al. [11] described precision coffee growing as a set of techniques aimed at optimizing agricultural input (fertilizers, correctives, seeds and pesticides) in a function of spatial and temporal variability of factors associated with the ecosystem (water, soil, plant). Recently Kouadio et al. [12] described precision coffee growing as optimization of agricultural inputs (fertilizers, corrective and defensive) related to spatial and temporal variability of factors associated with the water soil plant and atmospheric system.

Crop coffee is cultivated mainly by small farmers, contributing to the low implementation of technology in the field, due to the absence of technical and financial inputs and pilot projects. The practical application in precision agriculture techniques was variable rate distribution, initially used in annual crops and adapted to other crops. Generally, cultures that depend on specific equipment for handling use solutions designed for other cultures, and these adaptations can take years.

The insertion of efficient precision coffee techniques in coffee crops can be found in many studies. When evaluating the transversal application of variable rate fertilizers, Andrade et al. [13] defined optimal lateral fertilizer distribution, and created an efficient and practical method for this type of analysis. Mapping plant attributes in a coffee crop, Ferraz et al. [14], demonstrated the importance of this mapping category for coffee crop management. Using aerial image obtained by remotely piloted aircraft, Santos et al. [15] proposed methods for estimating coffee biophysical parameters. Barros et al. [16] evaluated the operational performance of a fertilizer distribution system. These are some of the practical contributions in the literature.

Evaluating publications about precision coffee growing allows the analysis of studies carried out from planting to a producing the final product. Analyzing trends in research, perspectives and contributions of different actors is essential for assessing scientific literature concerning the development of precision coffee growing. Using techniques applied to literature reviews can create an overview of the subject. Applications of systematic reviews in agriculture are recent but have been shown to be effective in synthesizing knowledge about agricultural literature and indicating priorities for future research [17].

Making systematic reviews allows the selection of studies about a specific topic or interest area, highlighting what is already known and exposing future opportunities [18,19]. These studies establish explicit and rigorously applied criteria, facilitating their later reproduction [20]. Systematic reviews aim to answer a specific research question with a particular search strategy and a literature synthesis presentation [21]. It is essential to emphasize the criteria adopted during a systematic review to minimize bias or personal influences of the researcher in the results [22].

During the research process, scholars are interested in finding publications most relevant in a study area. Thus, researchers use citation tracking to identify the most relevant articles or journals for a particular area [23]. The bibliometric analysis technique contributes to searches by considering the differences between articles by levels of relevance [24,25].

Citation number, publication volume and relevant journals, among other categories, facilitate the scientific diagnosis of a specific area study [26]. Bibliometric analysis makes it possible to identify dynamics and possible trends in scientific production [27]. This method organizes the existing literature, showing its publications trajectory as well as traditional and emerging fields of research [28,29].

There are some bibliometric studies on agriculture in the scientific literature. Among them, Pallottino et al. [30] reported the importance of studies involving precision agriculture over a twenty year period, while Velasco-Muñoz et al. [31] portrayed global research about rainwater use concerning applications in irrigation systems for conservation and sustainability strategies. In another study that used bibliometrics with modeling topic, Kane et al. [32] mapped research about perennial cultures by four scientific research bases. However, no bibliometric studies exist concerning issues related to precision coffee growing.

Mapping research about precision coffee growing has become important, given the significant technological advances reported in several studies carried out at different coffee cultivation stages. Identifying the most important literature about precision coffee growing can facilitate referential search processes and the identification of theoretical premises for future studies.

Given this importance, the objective of this study was to identify the main contributions of studies, researchers, entities and countries, most relevant in academic research about precision coffee growing over the last 20 years by exploring the referential bases Scopus and Web of Science. The results of this study may provide insights into research trends and contribute to research and scientific production practices.

2. Research Methodology

The evolution of precision coffee growing in scientific publications was evaluated by bibliometric analysis according to the procedures described in Figure 1. Bibliometric studies allow identification of possible theoretical trends, intellectual structures of a discipline or study area [33,34]. The work sequence in a bibliometric analysis is divided into data recovery, preprocessing, network extraction, normalization, mapping and visualization analysis [35,36].

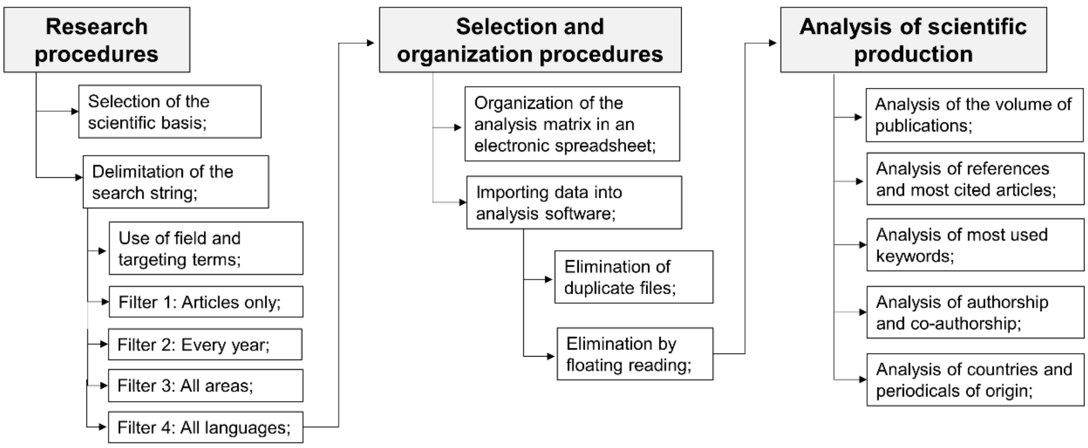

Figure 1. Processes systematization for bibliometric analysis

2.1. Research Procedure

Scopus and Web of Science were selected for conducting the searches, aiming at a representative metadata content. The use of Scopus and Web of Science bases, due to their relevance in bibliometric studies, was a necessary prerequisite [37]. Searches in different scientific bases are essential for correct interpretation and bibliometric indicator use in scientific research evaluation [38,39]. Scientific approaches that adopted bibliometric analysis on other themes used at least one of these bases [40].

When starting a bibliometric analysis, it is necessary to define the search terms to eliminate the generalization of the results. For this, the series of key terms should be not be too restrictive but sufficient to include only the topics of related studies [41]. Precision farming practices aimed at growing coffee are called “precision coffee farming” [11]. This definition contributes to string delimitation, selecting key terms and filtering only those files that depict precision agriculture in coffee culture. The key terms used were “spatial variability”, “precision agriculture”, “remote sensing”, “soil mapping”, “RPA”, “UAV”, “UAS”and “variable rate”. Only publications that contained the key terms in the title, abstract or keywords were used.

In SCOPUS, the string TITLE-ABS-KEY (coffee) AND TITLE-ABS-KEY (“spatial variability” OR “precision agriculture” OR “remote sensing” OR “soil mapping” OR “RPA” OR “UAV” OR “UAS” OR “Variable rate”) was used. In the WEB OF SCIENCE (WOS) database, the string was TS = (Coffee) AND TS = (“precision agriculture” OR “spatial variability” OR “remote sensing” OR “soil mapping” OR “RPA” OR “UAV” OR “UAS” OR “Variable rate”). Searches were not restricted in terms of academic area or languages. However, the selection of the document was restricted to articles published between 2000 and 2021/1st semester.

2.2. Selection and Organization Procedures

Selection and organization process consisted of reviewing the bibliometric data obtained. The searches resulted in 449 documents, 253 papers in Scopus and 196 papers in Web of Science. The next step was to remove duplicate articles because searches with similar parameters can find the same article. Then, documents were submitted to reading the abstracts and verifying similarity with the research theme. After these selections, 299 articles were excluded and 150 articles were chosen for use in this study.

Data were organized in an electronic spreadsheet and imported into VOSviewer bibliographic analysis software for identification and bibliometric networks analysis. VOSviewer is software for constructing and visualizing bibliometric networks. These networks can include journals, researchers and individual publications built on citation, bibliographic coupling, cocitation or coauthorship relationships [42]. In addition, they offer text mining functionality used in the construction and visualization of networks and co-occurrences of terms extracted from scientific literature [43].

2.3. Bibliometric Mapping and Clustering

Based on a multidimensional mapping technique VOSviewer locates the words in a dimensional space, portraying the distance between items according to their similarity. Results are presented in circle form, representing items found in the survey. These items are clustered and represented by color, forming a bibliometric map [44].

Quality criteria for research and journals are citations and scientific impact, as reported by Merton [45]. This rule was used for bibliometric mappings, which took account of annual evolution of publications and citations, leading researchers, most influential countries in publications related to this field, most notable journals, most relevant authors, main keywords used by authors, main keywords found in the most important publications, universities, entities related to these topics, the main areas of knowledge involved, and the trends and terms that indicate future lines of research.

3. Results and Discussion

3.1. Evolution of Publications

Bibliometric analyses found 150 articles about the precision management of coffee growing from 2000 to 2021/1st sem. The evolution of these publications is shown in Figure 2, illustrating the publications for each year.

Precision coffee research is relatively recent, as the first research found in a journal database was from 2004. This initial step in coffee research was performed by Herwitz et al. [46]. Although it was published in 2004, the experiments were carried out in 2002.

Four publications were found in the first years (2000 to 2006). Two articles were published in 2004 by the Herwitz and Johnson research groups, who used the same equipment and experimental field. In an analysis based on unmanned aerial vehicle (UAV) application to monitoring coffee trees, the authors advanced an essential step towards monitoring coffee fields by UAVs. Despite the pioneering nature of this technology in coffee growing, this type of analysis was not adopted by research groups in the coming years. The first hypothesis was related to the impossibility of carrying out similar experiments, because of high costs and few image capture and processing resources.

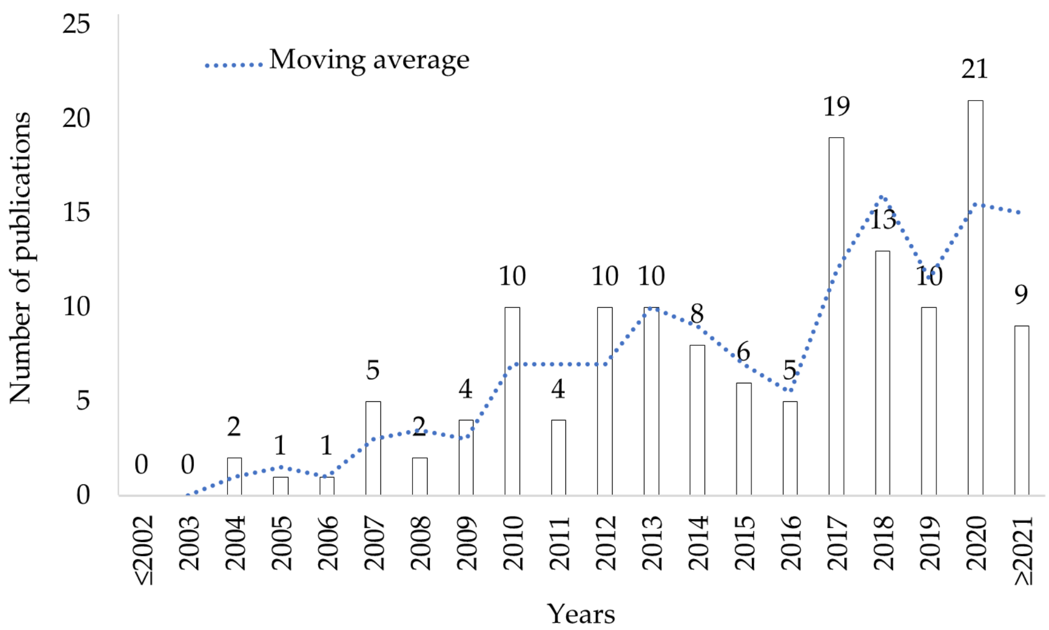

Figure 2. Evolution in precision coffee growing research publications from 2000 to 2021/1st sem.

In the following years, there was a significant increase in publications. From 2007 to 2013, most articles identified referred to spatial variability. During the period, essential discoveries were identified about variability, primary nutrient behavior and new ways of collecting soil for analysis.

A significant increase in research about precision coffee-growing demonstrated the coffee industry’s interest in technological advances. Studies on the application of precise techniques in coffee management over the years have changed the technicians’ and farmers’ perceptions about coffee-growing. The development of such research is closely related to technological advances in agriculture. An important trend of publications on precision agriculture was presented in the research by Pallottino et al., [30], where a linear growth of publications about precision agriculture between 2000 and 2016 was demonstrated. When analyzing the academic progress of the precision coffee growing theme, a reduction in the number of publications between the years 2013 and 2016 stands out. These different publications concern the themes of “precision agriculture” and “precision coffee-growing” and how they may be related to a crop’s characteristics, since in perennial crops, like coffee, vegetative development is reduced, making it time-consuming to obtain data compared to annual crops.

Another important aspect is the amount of research on the same topic. In some cases, the apparent research possibilities are exhausted in a few years. This may have happened in research related to the mapping of soil spatial variability in coffee crops, which led to a volume reduction in publications after 2013 and returning to a high level in 2017.

From 2017 onwards, the publication of articles on precision coffee growing showed a significant increase due to the application of new technologies in agriculture. The main finding after 2017 was the use of remote sensing for monitoring coffee production. In this period, the use of images obtained by Remotely Piloted Aircraft (RPA) was systematically explored.

3.2. Relevant Publications and Characteristics of Papers

Among the 150 files analyzed, ten papers were selected that stood out for having more than 20 citations from 2000 to 2021/1st sem (Table 1). The most cited author in the 20 years of analysis was Herwitz et al. [46]. This is due to the high level of technology used in the experiment available at the time. Furthermore, the authors' findings were applied again with the advent of UAVs in agriculture. The great impact of the research also is related to the journal in which it was published. Computers and Electronics in Agriculture journal is an important journal in agriculture.

Table 1. Top 20 publications scientific on precision coffee growing from 2000 to 2021/1st sem, 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. [46]	2004	Computers and Electronics in Agriculture	277
2°	Separability Of Coffee Leaf Rust Infection Levels With Machine Learning Methods At Sentinel-2 Msi Spectral Resolutions	Chemura, et al. [47]	2017	Precision Agriculture	45
3°	Spatial Variability Of Leaf Wetness Duration In Different Crop Canopies	Sentelhas, et al. [48]	2005	International Journal of Biometeorology	45
4°	Spatial Variability Of Chemical Attributes And Coffee Productivity In Two Harvests	Silva[2], et al. [50]	2008	Ciencia e Agrotecnologia	41
5°	Spatial Variability Of Chemical Attributes And Productivity In The Coffee Cultivation	Silva[2], et al. [49]	2007	Ciencia Rural	40
6°	Spectral Analysis And Classification Accuracy Of Coffee Crops Using Landsat And A Topographic Environmental Model	Cordero-Sancho and Sader [51]	2007	International Journal of Remote Sensing	38
7°	Spatial Variability Of Chemical Attributes Of An Oxisol Under Coffee Cultivation	Silva[1], et al. [52]	2010	Revista Brasileira de Ciencia do Solo	36
8°	Geostatistical Analysis Of Fruit Yield And Detachment Force In Coffee	Ferraz, et al. [53]	2012a	Precision Agriculture	33
9°	Feasibility Of Monitoring Coffee Field Ripeness With Airborne Multispectral Imagery	Johnson, et al. [59]	2004	Applied Engineering in Agriculture	32
10°	Spatial And Temporal Variability Of Phosphorus, Potassium And Of The Yield Of A Coffee Field	Ferraz, et al. [54]	2012b	Engenharia Agricola	31

R: Ranking; Silva 2 : Silva F.M.; Silva 1 : Silva S.D.A; PY: Publication Year and NC: Number of citations.

The most cited study, Herwitz et al. [46], demonstrated the positive aspects of agricultural areas monitored by unmanned aerial vehicles (UAV). The study described field data from combinations of red and infrared image aerial images, resulting in the definition of higher productivity zones, attesting to the efficiency of aerial remote sensing for agricultural monitoring with orbital imaging applications. Despite being published 16 years ago, this research is still used as a basis for various agricultural applications due to the nature of the techniques used.

Advances in remote sensing have been observed in coffee management. Relevant analyses about this technology are described in research by Chemura et al. [47]. The authors evaluated applications of a Sentinel 2 sensor combined with Random Forest (RF) algorithms in the evaluation of coffee leaf rust (CLR) fungus, and demonstrated through vegetation indices the potential of remote sensing applications in identifying and discriminating levels of this fungus.

Among the most cited publications, the research developed by Sentelhas et al. [48] presented reliable methods for monitoring the duration of leaf wetness. Their results were based on installing sensors at different heights and evaluation by geometric mean regression. These results made important contributions to accurate precision irrigation practices and microclimate monitoring and evidenced spatial variability in the duration of wetness by rain, dew, and irrigation.

Pioneering various applications in coffee growing, Silva 2 et al. [49] characterized the spatial variability of chemical attributes of soil by georeferenced sampling and geostatistical techniques. Using the same experimental field, Silva 2 et al. [50] evaluated productivity of the 2002/2003 and 2003/2004 coffee harvests in georeferenced grids of 25 × 25 m2 . The data obtained were sufficient for geostatistical analysis such as semivariogram adjustments and kriging interpolation. In this study, the researchers defined the spatial dependence of chemical attributes and coffee crop yield. Silva's research clarified the wide range of soil chemical attributes justifying the study of variable rate fertilizer application in coffee plantations, which in one the best discoveries about the spatial variability of soil in coffee cultivation.

Among the most cited research, an article by Cordero-Sancho, Sader [51] contributed to precision coffee growing development using remote sensing technologies. Using Landsat satellite images combined with geoprocessing techniques, the authors defined optimal regions for growing coffee, which was the first of several analyzes on remote sensing applications in spatial variability for coffee growing.

Regarding mapping studies of soil variability in coffee culture, Silva 1 et al. [52] evaluated the main chemical attributes including available P, Na, and S, exchangeable Ca, Mg and Al, pH, H + Al, SB, t, T, V, m, MO, ISNa, P-remnant and micronutrients (Zn, Fe, Mn, Cu and B). Multivariate analysis techniques associated with geostatistics facilitated the assessment of soil variability. These authors demonstrated the applicability of mapping the behavior of these nutrients in the soil.

Equipment adjustments for mechanized harvesting operations in coffee farming require extensive information about plant physiology and anatomical factors. The paper of Ferraz et al. [53] used geostatistics to evaluate the detachment strength of coffee fruits in a study carried out on 22 hectares of Arabica coffee. The authors showed the possibility of detachment strength for characterizing spatial patterns of coffee fruits, classified as green or ripe by semivariogram and kriging. They found that exponential functions adjusted in the semivariogram described the structure and magnitude of spatial variation of release strength of green fruits and coffee yield.

Johnson et al. published in 2004 a pioneering article for monitoring coffee maturation by a UAV. It proposed a method to identify the coffee fruit maturation through reflectance in the aerial image. Field collections aggregated the results. The average maturation index per field was significantly correlated with soil based counts recorded by the producer. This work is still the basis for research using aerial scenes to monitor coffee tree.

Using precision agriculture technologies, localized data collection, and geostatistical analysis techniques, Ferraz et al. [54] monitored chemical soil attributes during three consecutive harvests to optimize application of phosphorus and potassium. The study showed that semivariograms allow estimates of the spatial variability of soil chemical attributes, such as amounts of phosphorus and potassium, and their effects on coffee crop yield. This research complemented previous results on the relationship between spatial variability and yield.

The primary research related to precision coffee growing was mainly associated with soil variability (Table 1), but the essential contribution of remote sensing for the mapping of variability in the coffee crop is evident.

3.3. Most Influential Journals

Journals are ranked in order of importance by number of citations (Table 2). When analyzing the journals in Table 2, variations in their specificities were observed, but there was a predominance of journals with technological approaches.

Table 2. Top 6 sources of publications in word on precision coffee growing from 2000 to 2021/1st sem.

R	Journal	SJR[1]	CiteScore[2]	JCR[3]	H-i	ISSN	ND	NC
1°	Computers and Electronics in Agriculture	1.208	8.6	3.858	115	0168-1699	5	409
2°	Precision Agriculture	1.023	8.7	4.454	63	1385-2256	9	398
3°	Revista Brasileira de Ciência do Solo	0.505	2.5	1.2	51	0100-0683	8	291
4°	Engenharia Agrícola	0.289	1.4	0.603	27	0100-6916	11	256
5°	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	1.246	7.2	3.827	88	1939-1404	4	190
6°	Ciência e Agrotecnologia	0.437	2.3	1.144	30	1413-70	4	152

1: Web of Science index, 2: Scopus index, 3: Scopus index, H-i: H index, ND: Number of documents and NC: Number of citations.

The journals “Computers and Electronics in Agriculture” and “Precision Agriculture” significantly contributed to technological development in agriculture. Pallottino et al. [30] carried out bibliometric research to demonstrate advances in precision agriculture and showed that the journals “Computers and Electronics in Agriculture” and “Precision Agriculture” predominate among the most important journals. A journal linked to remote sensing also appeared in this classification, indicating the potential use of this technology in coffee production.

Table 2 shows that the majority of the obtained journals are from Brazil, probably because of intensive coffee production in the country. Even with greater inclusion in the best journals, the country does not occupy first place. This is due to the quality of the journals (H index). The journals “Computers and Electronics in Agriculture” and “Precision Agriculture” are considered emerging in studies for technological application in agriculture as reported by [55]. It was observed that despite having fewer publications, these journals had a larger number of citations. This indicates high interest in searching for publications involving specialized applications in agriculture.

3.4. Publications by Authors

The H-index, which is obtained by the ratio of the number publications and their citations, was used to determine the author's impact on the topic of precision coffee growing. From the H-index values, the Scopus and WoS bases, and the volume of publications, the main authors of publications related to "precision coffee growing" were selected. Among the 186 identified, only 28 authors met the selection criteria established in the bibliometric selection methodology. According to established premises, Professor Fábio Moreira da Silva, from the Agricultural Engineering Department of Federal University of Lavras was the author with the greatest academic impact, with an H-Index of 12 (Scopus and WoS), 20 published documents and 303 citations, followed by Professor Gabriel Araújo e Silva Ferraz also from the Agricultural Engineering Department of Federal University of Lavras, with an H-index of 10 (Scopus) and 5 (WoS), 16 documents published and 203 citations. Details of the other authors can be seen in Table 3.

Table 3. Top six relevant authors of publications on precision coffee growing from 2000 to 2021/1st sem.

R	Authors	Id.	H-i (Scopus)	H-i (WoS)	NC	ND
1°	Fábio Moreira da Silva	Silva, F. M.	12	12	303	20
2°	Gabriel Araújo e Silva Ferraz	Ferraz, G. A. S.	10	5	203	16
3°	Marcelo Silva de Oliveira	Oliveira, M. S.	10	9	192	11
6°	Ivoney Gontijo	Gontijo, I.	6	6	139	8
4°	Julião Soares de Souza Lima	Lima, J. S. S.	11	10	129	9
5°	Samuel de Assis Silva	Silva, S. A.	11	5	117	9

NC: Number of citations, ND: Number of documents, H-i: H index.

By identifying the main authors with documents indexed in the Scopus and WoS databases, the relationships among them were obtained. Only authors who had at least nine citations were selected. This criterion made it possible to classify the 44 authors shown in Figure 3.

The cocitation network is represented by circle charts, in which the size represents the author's influence, and the color of the circle represents the cluster (knowledge area) to which it was grouped. Therefore, it was possible to establish similarities, differences, relations and relevance between members that represent the intellectual base concerning the "precision coffee growing" theme.

By analyzing the cocitation network among the authors, three large clusters were determined. The first cluster, in green, is formed by the presence of three main researchers linked to Federal University of Lavras, with the largest volume of documents. Its main approaches refer to spatial variability of the coffee crop from an agricultural engineering perspective, such as collection network, variable rate application, and yield mapping. Numerical systems and models needed to support decisions about soil fertilization and agricultural management were also observed in this cluster (Figure 3).

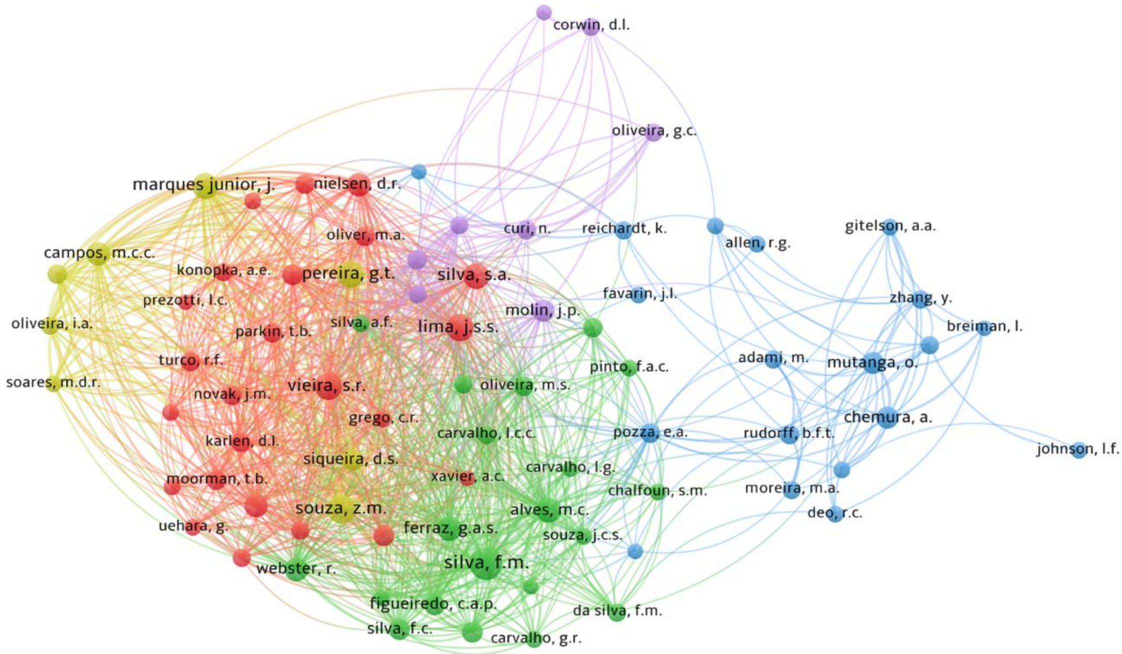

Figure 3. Scientific mapping of the cocitation of authors most relevance in precision coffee growing research. Red and yellow: Solo. Green: variable rate application and productivity mapping. Blue: remote sensing and Purple: plant nutritional status.

In the second cluster, in red, the main focus funded in the research was soil attributes. These authors are linked to North American universities and their research covers topics that aim to understand the location of these nutrients in the soil and their physicochemical characteristics, aimed at better nutrient use and soil conservation. In this cluster, geostatistical techniques for mapping spatial variability stand out. The use of geostatistical techniques in precision coffee growing was also observed in the bibliometric analyzes carried out by [56].

The researchers related to the third cluster, in blue, are characterized by research in coffee-growing by remote sensing analysis. Mapping coffee plantations by remote sensing aims to contribute to the identification of spatial variability using spectral responses [57].

3.5. Most Influential Countries

Evaluation of knowledge producing nations on precision coffee-growing allowed them to be classified according to the number of citations over the years. Publications by country about "precision coffee growing" is shown in Figure 4. The main countries that produce the most scientific knowledge about precision coffee growing were identified. The predominance of Brazilian researchers in the top positions of publications by authors made Brazil the main country contributing to the development of precision coffee farming (Table 3). The 42 most impactful publications about precision coffee growing were carried out by Brazilian researchers.

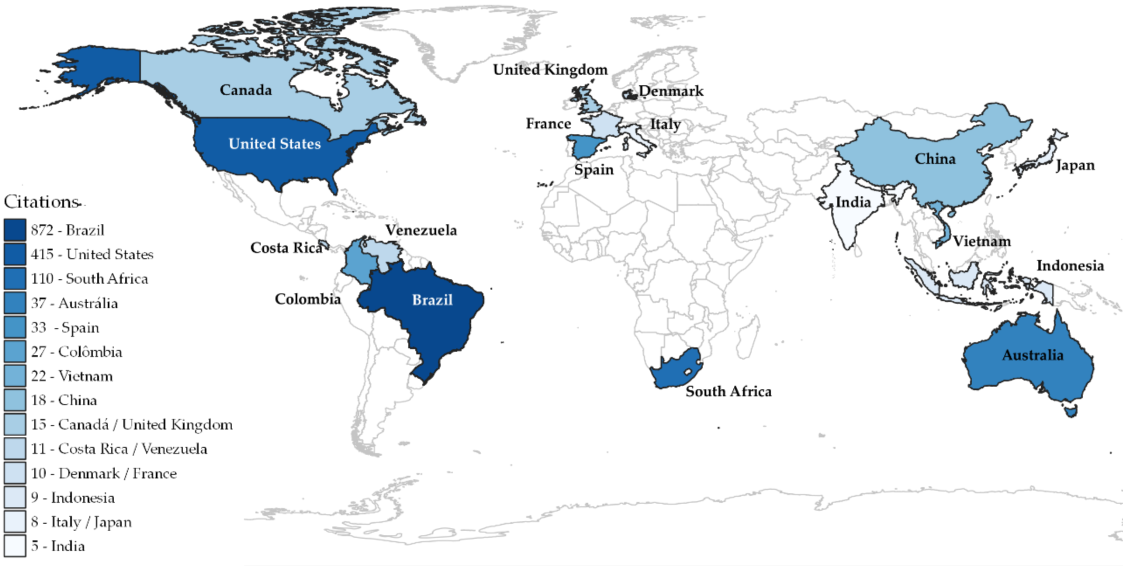

Figure 4. Number of citations by Country.

The economic importance of coffee growing in Brazil, and the large number of research and teaching organizations related to coffee research in the country, impacts directly knowledge development about precision coffee growing. Brazil stands out as one of the countries with the highest investment in research and development in agriculture. These characteristics, associated with great territorial extension, has kept Brazil the leader in agricultural exports [58].

At the date of this study, Brazil is followed by countries such as the United States (four documents) and Colombia (three documents). The extensive presence of Brazilian researchers and journals also made Brazil the top country in producing scientific studies about precision coffee growing.

Although the cultivation of coffee in the United States is not expressive, this country is the second largest producer of knowledge about precision coffee growing. This is due to the coffee area present in the Hawaii region, and the large number of educational and research organizations related to agricultural sciences in USA. It is important to highlight that pioneering work about precision coffee growing was carried out by Herwitz et al. [46] and Johnson, et al. [59], both in the American state of Hawaii (Figure 4).

3.6. Organizations Related to Precision Coffee Growing' Research

Identifying the organizations responsible for developing a knowledge area is of essential importance in biometric analysis, as it allows establishing trends and relationships between these organizations.

Research entities responsible for developing knowledge about precision coffee growing were identified. The relationships among scientific organizations that produce knowledge about this theme is presented in Figure 5. In this study, 31 organizations were highlighted with the highest volume of publications among 155 organizations identified and linked to authors (Figure 5).

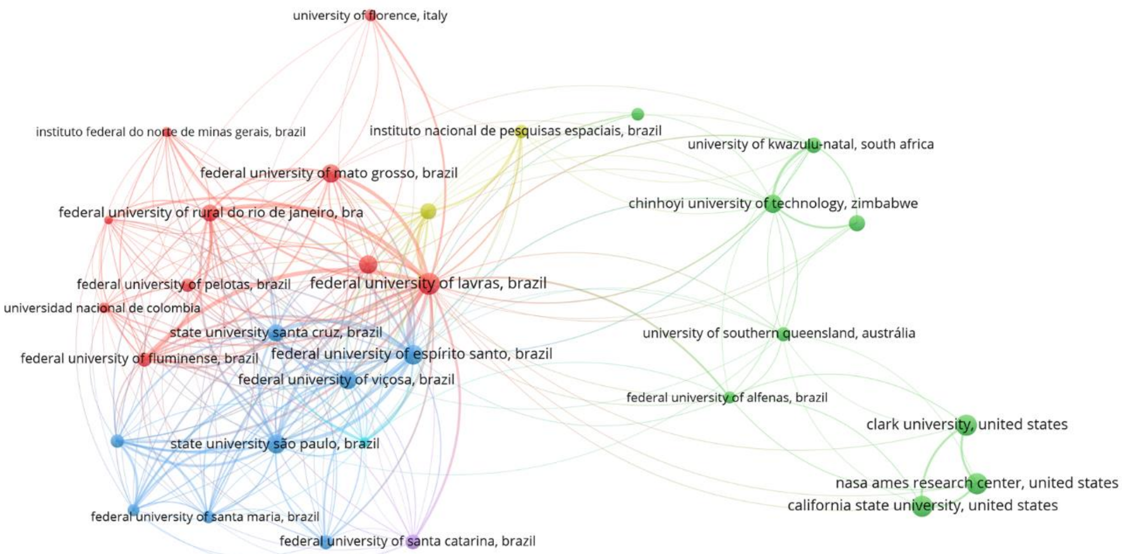

Figure 5. Scientific mapping network of educational and/or research organizations that produce knowledge about precision coffee growing.

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Five groups were defined showing the great contribution of Brazilian universities in research development on precision coffee growing. The main institution was Federal University of Lavras, identified in the center region of the map in red. In the map, this university is linked with almost all other institutions. Directly or indirectly, this university shares research with institutions and internationals research centers, evidencing a strong relationship between Brazil and international institutions. The exchange of research within the country can be seen by the proximity between the red and blue groups, which occurs by the geolocation of these institutions. This geographic proximity facilitates the exchange of congresses and events.

Despite showing low association with each other, the grouping in green demonstrates the proximity between institutions from the United States of America and institutions from South Africa. In this grouping, a Brazilian university is seen as the “Federal University of Alfenas”. This connection occurred due to the proximity of researchers to institutions in the United States of America and South Africa.

The group in yellow is represented by two institutions “Company of technical assistance and rural extension of the state of Minas Gerais” and “National Institute for Space Research - INPE”. Despite connections, this shows that these institutions follow different directions from Brazilian universities.

The analysis shows the relevance of Brazilian organizations in scientific research development about precision coffee growing, with emphasis on the Federal University of Lavras. A systematic bibliometric analysis of literature carried out by Cruz O’Byrne et al. [60], showed the strong relationship of the Federal University of Lavras (UFLA) with coffee research. In searches performed on the Web of Science and Scopus databases, Pabon et al. [61], organized bibliometric data on coffee growing in which they also highlighted UFLA’s contributions to scientific approaches to coffee crops.

The location of the Federal University of Lavras in the south of Minas Gerais state, a region with the largest coffee production in Brazil, contributed to UFLA assuming a very important role in coffee research. In the 2020 harvest, Minas Gerais produced more than 51% of national coffee production (Conab, 2020). The high productivity of this region, favored and driven by edaphoclimatic conditions, attracts researchers and installations concerning the coffee crop. Bibliometric studies about coffee growing presented by Sott et al. [56], highlighted Brazilian research dominance on coffee growing and its important role in agribusiness development.

3.7. Keywords Related to Precision Coffee Growing

Another way of investigating the study field is to analyze authors’ keywords with the highest occurrence rates in all documents. In this phase, words with at least two occurrences are selected. Figure 6 presents analysis of cooccurrence of authors’ keywords in analyzed documents.

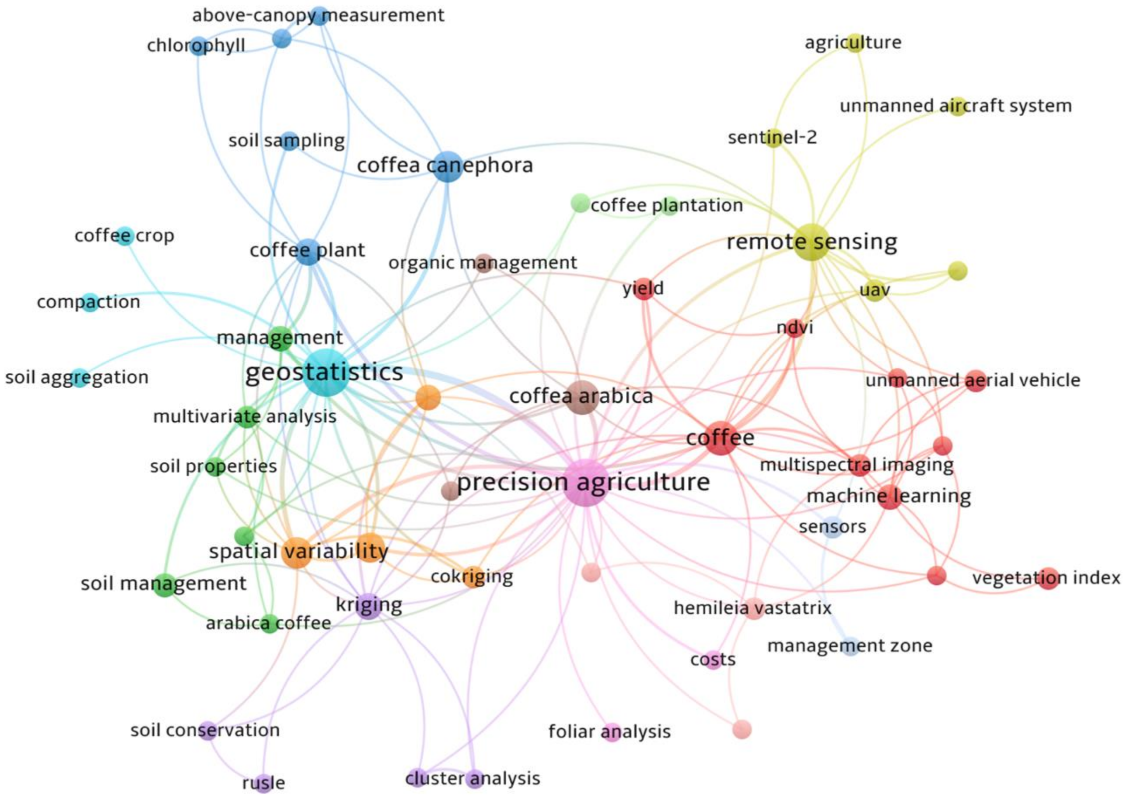

Figure 6. Map of network among author's keywords. Lines indicate co-occurrences between terms. Yellow: remote sensing. Red: remote sensing and machine learning. Green and purple: spatial variability of soil attributes. Azul: technologies applied to the cultivation of coffee canephora. Orange: application of techniques for mapping soil attributes.

Among 369 keywords identified in the studies, only 64 met adopted criteria. As a result, the "precision agriculture" term appeared most frequently, with 42 occurrences, followed by the terms "geostatistics" (40 occurrences), "remote sensing" (17 occurrences), "coffee" (14 occurrences), "Coffea arabica" (13 occurrences) and "spatial variability" (10 occurrences). In this figure it is possible to identify four distinct groups: red, representing technological applications; blue, analyses of canephore coffee; green, research related to monitoring of soil properties, and yellow, remote sensing applications. The groups have a strong connection with the areas of precision agriculture and geostatistics. This indicates that all applications for improvement in management are aimed at precise practices in coffee growing. The presentation of this map also contributes to searches for publications related to specific fields of precision coffee growing and how authors should organize their keywords for easy viewing.

3.8. Trends in Precision Coffee Growing Research

The surveys followed trends according to equipment availability, use of technologies and the value of theme to region. A map was created using a fractional counting method based on bibliographic data in the authors' keyword co-occurrences to understand trends (Figure 7). This map uses different colors to highlight the most commonly used author keywords over the last 20 years.

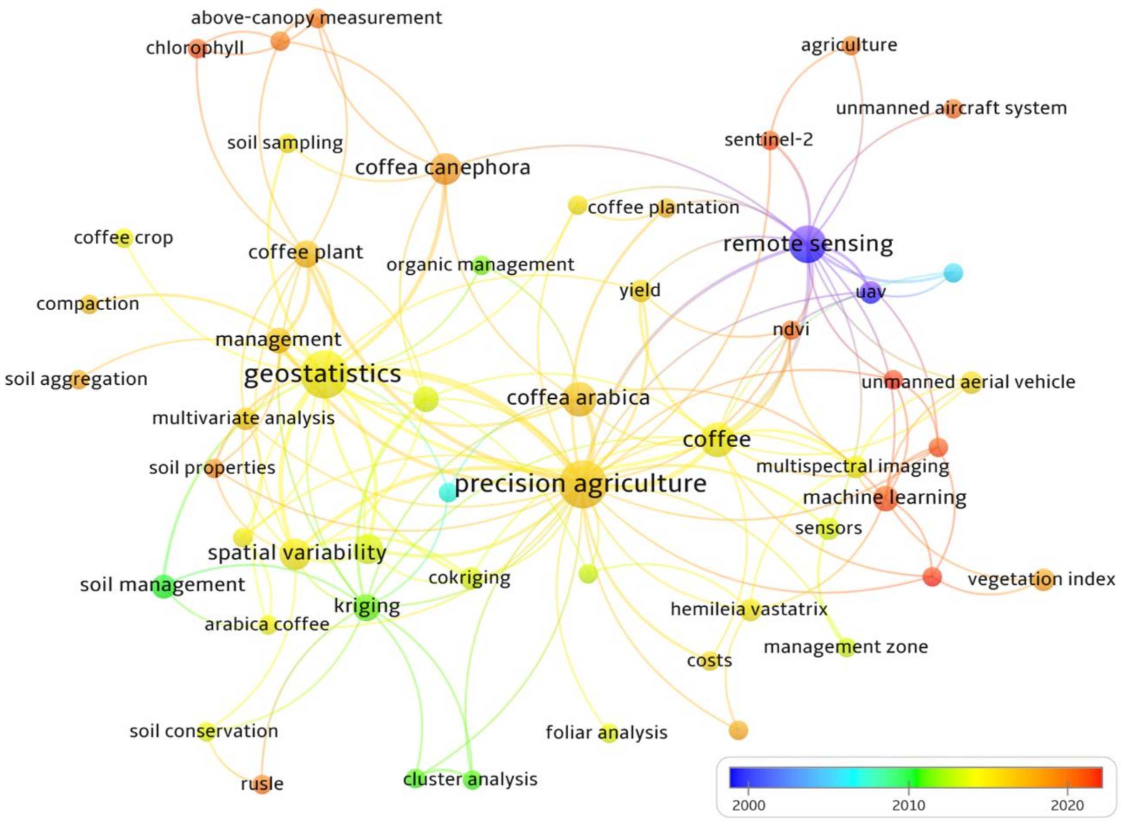

Figure 7. Map based on the co-occurrence of the authors' keywords and evolution from 2000 to 2021/1st sem. The color scale represents the year of keyword predominance.

The information presented in Figure 7 demonstrates the characterization of predominant groups. Three prominent circles stood out: "precision agriculture", "remote sensing" and "geostatistic."

Precision agriculture appears as a trend in precision coffee growing. This occurs because techniques used in precision agriculture are tested in coffee growing, providing a basis for the development of several methods. From 2010 to 2020, there is a grouping in yellow colors and the relationship between "precision agriculture", "geostatistics", and "spatial variability" systematically explored at that time. The saturation of these key-words in searches began in 2018, making this technique well researched. In the following years, remote sensing techniques were again used with the advance of unmanned aerial vehicles.

Research related to remote sensing applications in precision coffee farming is considered pioneering. However, remote sensing technology has been exploited for the last 20 years and continues to be used. Figure 7 shows new trends in this technology, namely the words “multispectral imaging”, “unmanned aerial vehicle”, “ndvi”, “sentinel” and “machine learning”. The emergence of these trends is directly related to applications of remotely piloted aircraft (RPA) in agriculture, bringing to this field technological trends about machine learning.

New research involving precision coffee growing has explored automation profiles, aimed at improvements of crop management, such as mini sensors use to monitor coffee crops in real time [62], capacity evaluation of an Extreme Learning Machine (ELM) model when analyzing soil fertility properties, and the precise estimate of Robusta coffee yield [12]. Spatial determination of nitrogen content in coffee leaves has been made using remotely piloted aircraft, with machine learning techniques to classify aerial images [63]. Orbital sensors are used as a new methodology for obtaining maps about growth deficit (with up to 5 cm precision and 1m spatial resolution), as well as the use of Differential Interferometric Synthetic Aperture Radar—D-InSAR [64].

4. Conclusions

Intellectual base analysis by bibliometric methods allowed evaluation of scientific evolution, research, and authorial references about precision coffee growing. It was possible to infer current conditions and trends regarding the research and scientific publication theme. The main countries, journals, scientific organizations, researchers, and cocitations networks with the greatest relevance about precision coffee growing were highlighted.

There has been a significant increase in scientific publications about precision coffee growing in the last 20 years (2000 to 2021/1st sem). This research solved essential obstacles in the sector and proposed sustainable management methods. The development of precision coffee growing was mainly marked by research to solve spatial variability in soils and plants, contributing to essentials technological advancements such as agricultural input application at a variable rate.

Among the most used technologies in precision coffee growing, remote sensing stands out. This knowledge area has contributed to coffee-growing development since initial research efforts. Furthermore, an emerging area with the advent of remotely piloted aircraft (RPA) has been developed.

The advance of technologies applied in precision coffee growing was demonstrated by keyword mappings in the most important scientific journals. The main keywords used in studies in recent years were “remote sensing,” “machine learning,” “vegetation index,” and “remotely piloted aircraft”, which demonstrates strong trends in automated applications using remote sensing technologies.

The development of this research is mainly linked to coffee producing countries. Brazil’s relevance to scientific knowledge development about precision coffee growing is evident since the country was the leader in terms of publication numbers about precision coffee growing. The Brazilian institution Federal University of Lavras (UFLA) was responsible for the origin of most studies. Most of the studies developed about precision techniques and practices adopted in coffee cultivation have been carried out in the last five years, culminating in the emergence of research produced by countries in the American, European, and African continents.

Author Contributions: Conceptualization, L.S.S. and G.A.e.S.F.; methodology, A.J.d.S.T. and M.S.S.; software, A.J.d.S.T.; validation, L.S.S., G.A.e.S.F. and A.J.d.S.T.; formal analysis, E.P. and G.R.; investigation, M.S.S.; resources, L.S.S. and A.J.d.S.T. ; data curation, M.S.S. and G.A.e.S.F.; writing—original draft preparation, L.S.S. and M.S.S.; writing—review and editing, G.A.e.S.F. and L.S.S.; visualization, G.R. and E.P.; supervision, G.A.e.S.F.; project administration, G.A.e.S.F.; funding acquisition, G.A.e.S.F., G.R. and E.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Embrapa Café—Consórcio Pesquisa Café, project approved n◦ 234/2019, the National Council for Scientific and Technological Development (CNPq), the Research Support Foundation of the State of Minas Gerais (FAPEMIG), the Coordination for the Improvement of Higher Education Personnel (CAPES), the Federal University of Lavras (UFLA) and University of Firenze (UniFI).

Conflicts of Interest: The authors declare no conflict of interest.

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SECOND PART

CHAPTHER II. DIGITAL TERRAIN MODELLING BY REMOTELY PILOTED AIRCRAFT: OPTIMIZATION AND GEOMETRIC UNCERTAINTIES IN PRECISION COFFEE GROWING PROJECTS

Article published in *Remote Sensing* journal (ISSN 2073-4395)
Accepted: 7 February 2022 / Published: 14 February 2022 DOI: https://doi.org/10.3390/rs14040911

CHAPTHER III. IDENTIFICATION AND COUNTING OF COFFEE TREE BASED ON CONVOLUTIONAL NEURAL NETWORK APPLIED TO RGB IMAGES OBTAINED BY RPA

Paper to be submitted in *Sustainability* journal (ISSN 2071-1050)

CHAPTHER IV. RESIDUAL ASH MAPPING AND COFFEE PLANT DEVELOPMENT BASED ON MULTISPECTRAL RPAS IMAGES

Paper to be submitted in *Agronomy* journal (ISSN 2073-4395)

CHAPTER V. FINAL CONSIDERATIONS

CHAPTHER II. DIGITAL TERRAIN MODELLING BY REMOTELY PILOTED AIRCRAFT: OPTIMIZATION AND GEOMETRIC UNCERTAINTIES IN PRECISION COFFEE GROWING PROJECTS

Article published in *Remote Sensing* journal (ISSN 2073-4395)

Accepted: 7 February 2022 / Published: 14 February 2022 DOI: https://doi.org/10.3390/rs14040911

Abstract: The implantation of coffee crop plantations requires cartographic data for dimensioning areas and planning the planting line. Digital terrain model (DTM) obtained from remotely piloted aircraft (RPA) can contribute to efficient data collection for topography making this technique applicable to precision coffee projects. Aiming to achieve efficiency in the collection, processing and photogrammetric products quality, flight configurations and image processing were evaluated. Two hundred sixty five points obtained by GNSS receivers (Global Navigation Satellite System) characterized the topographic surface. Then eighteen flight missions were carried out by RPA in the configurations of altitude Above Ground Level (AGL) and frontal and lateral image overlay. In addition, different point cloud formats evaluated image processing (time) efficiency in DTM. Flights performed at 120m AGL and 80x80% overlap showed higher assertiveness and efficiency in generation DTMs. The 90m AGL flight showed great terrain detail, causing significant surface differences concerning the topography obtained by GNSS. An increase in image overlap requires longer processing times, not contributing linearly to the geometric quality of orthomosaic. Slope ranges up to 20% are considered reliable for precision coffee-growing projects. Above 20% overestimate the slope values of the land. Changes in flight settings and image processing are satisfactory for precision coffee projects. Image overlap reduction was significant in reducing the processing time without influencing the quality of the DTMs models. In addition, image processing performed in shallow point clouds did not interfere with the DTMs quality.

Keywords: Remote sensing; Precision agriculture; Cartography; Digital Elevation Model; SfM.

1. Introduction

Coffee growing represents an important source of income for many countries [1]. Brazil leads global coffee production, with its production accounting for 70% of the global supply [2]. Technological advances relate to growing coffee have contributed to obtaining accurate and reliable measurements of production in the field [3]. Designing and applying techniques that make agricultural production more effective are essential [4]. Thus, smart agriculture practice has become crucial for maximizing yields and preserving natural resources [5].

In coffee regions, planning prior to planting has become indispensable. This crop is mostly grown in mountainous regions, which contributes to increases in errors during the planting stage [6]. Abrupt variations in terrain slope cause a reduction in operational performance and even limitations in machinery use [7]. These limitations can be mitigated by performing efficient topographic planning and addressing costs and mapping accuracy.

Conventional topographic surveys, considered highly accurate, are generally carried out using total stations, Global Navigation Satellite System (GNSS) receivers and optical levels [8]. Theses equipment has a high acquisition cost, requires at least two workers to operate and present the low spatial density of points necessary for digital elevation models (DEMs) generation, which increases survey costs [9]. New technologies, like RPA, offer the option of carrying out topographic surveys and obtaining cartographic data.

Remotely piloted aircraft (RPAs) can generate photogrammetric products based on terrain slope [10]. Photogrammetric processes capture important information about the surface. Among them, DEMs can be obtained by these processes [11,12]. Some research shows applications of DEMs addressing geometric precision characteristics. Uysal et al. [13] evaluated DEMs in images obtained by quadcopters [13]. Whitehead et al. [14] evaluated the DEM quality obtained by RPAs to characterize rivers and watersheds. Sopchaki et al. [15] demonstrated the accuracy of orthomosaics without the use of support points using red, green and blue (RGB) cameras.

Investigations on DEMs used in precision coffee growing are relevant. Selecting the best DEM for planting planning can contribute to cost reductions and increased speed in collecting cartographic data [16]. Growing coffee based on topographic information derived from photogrammetric digital terrain models (DTMs) is a gap to be explored in precision coffee growing, RPAs can provide elevational data through DEMs. The insertion of DTMs from RPAs into topographic projects for coffee growing may provide the precision needed to produce coffee crops in regions with steep slopes. Due to the amount of information involved in agricultural operations, efficient decision making is valuable.

Growing coffee is carried out through planialtimetric projects that help determine planting rows direction. Planning rows contributes to crop uniformity and increases the efficiency of all operations, especially mechanized operations [17]. On plantations on steep slopes, growing coffee involves following the terrain contour lines to reduce limitations to agricultural machinery. In many cases, mechanization on high slopes may be limited or not used; therefore, mapping sloped areas should be performed in the most accurate manner possible. The barriers resulting from conventional topography can be overcome by the use of RPAs as an alternative for obtaining terrain contours and mapping slopes.

The RPAs applications in different segments contributed to the selection of different flight configurations. Therefore, it is important to consider the objective to be achieved and seek strategies to make flights efficient [18]. Capturing aerial images without prior planning can compromise the accuracy of the photogrammetric products. Adequate flight planning can be crucial for generating photogrammetric products efficiently [19].

Reduced flight and image processing times can contribute to increased efficiency in photogrammetric projects [20]. Processing optimization techniques contribute to quick decisions, making the operation agile and reducing implementation costs. Processing images with software based on Structure from Motion (SfM) offers possibilities to configure the workflow, considerably impacting the processing time [21]. The photogrammetric products obtained by SfM are constructed based on the number of dense points filtered in an image [22]. Dense points number varies according to the objective of the study. In digital surface model (DSM) reconstructions, excessive amounts of dense points can reduce cartographic products quality. In addition to the high level terrain detail, high amounts of point clouds make the processing time excessive.

Processing types combination, low and lowest, under different configurations of the flight mission (overlap height), may contribute to improved efficiencies in obtaining photogrammetric products. Different flight mission configurations were explored in this study about increasing efficiency in photogrammetric data collection and precision. Thus, the objective was to verify slope maps uncertainties and their interference in coffee-growing projects by increasing accuracy in measurements of altitude and slope of the terrain combined with flight and processing efficiencies.

2. Materials and Methods

2.1. Study area

The study region encompasses an area of eight hectares for coffee cultivation (Figure 1). It is located in Bom Sucesso, Minas Gerais - Brazil, at 21°00’55”S and 44°54’57”W. The region has a hot and temperate climate, the mean annual temperature is between 20 and 22 °C, the annual rainfall is between 1300 and 1600 mm, and the altitude is between 800 and 1000 m [23].

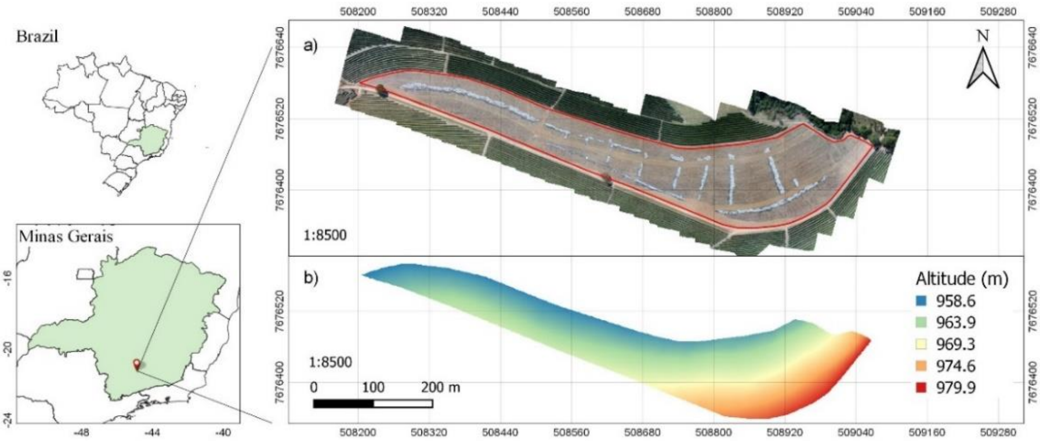

Figure 1. Study area. a) Aerial image and study area delimitation (red) and b) digital terrain model (DTM).

2.2. Data collecting and processing

Photogrammetric and geodesic techniques were performed together, and in some analyses, the methodologies may be confused. Therefore, the steps for conducting the research are presented in a flowchart in Figure 2.

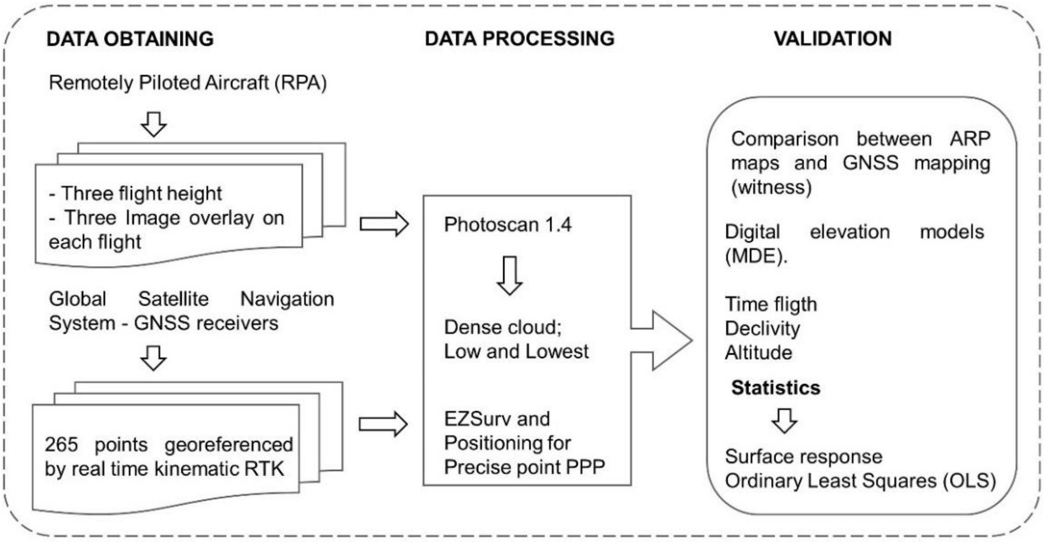

Figure 2. Flowchart for obtaining, processing, and analysing the results.

2.3. Data of GNSS Receivers

A conventional topographic survey method was performed by using GNSS receivers. They were operating in real time kinematic (RTK) mode, consisting of a base and rover with a 0.03 m precision. Spectra Precision equipment model SP60 was used, a receiver of 240 channels at frequencies of C/A, L1, L2 and L3 (Figure 3a). Capturing a total of 265 points (Figure 3b).

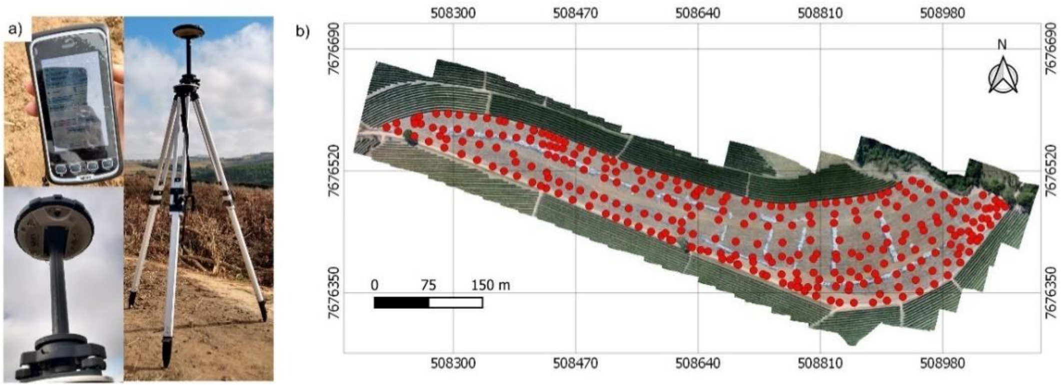

Figure 3. Topographic survey using GNSS receivers. a) GNSS receivers and b) location of points obtained via GNSS.

The data collected by GNSS receivers were processed by using EZSurv software and a digital platform of the Brazilian Institute of Geography and Statistics (IBGE). Geographic coordinates (X, Y and Z) obtained by the equipment installed in the base were adjusted digital platform of the IBGE 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 anywhere in the world [24].

The coordinates recalculated by PPP were added to the EZSurv software for coordinate adjustment. Then, points reordering in the project was carried out, which consisted of coordinates adjusting according to base, rover and satellite triangulation. This step elimination the defective collection signals and aligns them with the new coordinates provided by PPP available in Universal Transverse Mercator (UTM) coordinates.

2.4. Aircraft and flight characteristics

Aerial images were obtained by a DJI Phanton 4 advance RPA (Figure 4) with a RGB sensor with a 1” focal aperture to capture photos of up to 20 megapixels and a spatial resolution of 12 mm to 120 m from the target.

Figure 4. Equipment used for image collection. Remotely piloted aircraft (RPA), a quadcopter type.

Flight planning began with area delineation and definition of take off points. Before starting the flight, some safety factors were observed, including climatic conditions, wind speed, presence of objects, poles, trees, and electrical transmission towers [25]. Next, nine flight missions were planned in Drone Deploy software under different configurations: AGL at 90, 120 and 150 m and overlapping images: 70%x70%, 80%x80% and 90%x90%, which were performed in two replicates totalling 18 flights.

The images collected were processed in Agisoft PhotoScan software, version 1.4.3., which is based on the SfM algorithm. SfM approaches can be considered superior to other approaches in terms of accuracy when the user intends to generate orthomosaics and DTMs [26,27].

2.5. Photogrammetric processing

The methodology used to process the images involved a four step process, as described by Flynn and Chapra [28] and Rusnák et al. [29]. Step 1: Image aligned, phototriangulation process implemented, and a sparse point cloud was generated. Step 2: A sparse point cloud, densification, and detailed representation of the mapped area were developed. Step 3: The dense point cloud and accurate representation of the three-dimensional mapped terrain - DSM were constructed. Step 4: Texture was applied to the DSM model, and a DTM was created and classified into five categories: very high, high, medium, low, and lowest.

Given the large number of points filtered by the SfM, the DEMs use a reduced point mesh. Photogrammetric products are obtained by various processes, which can involve hours of processing, and processing time can be reduced based on the selection of some parameters. Therefore, to increase flight efficiency and maintain design accuracy, different processing combinations were used (Table 1).

Table 1. Interactions between flight parameters and variations in dense cloud processing.

N° processing	Dense cloud	Overlap (Front x side)	Above Ground Level (AGL)
1	low	70x70%	90 m
2	lowest		
3	low	80x80%	
4	lowest		
5	low	90x90%	
6	lowest		
7	low	70x70%	120 m
8	lowest		
9	low	80x80%	
10	lowest		
11	low	90x90%	
12	lowest		
13	low	70x70%	150 m
14	lowest		
15	low	80x80%	
16	lowest		
17	low	90x90%	
18	lowest		

2.6. Validation

The reports obtained after data processing were compiled and analysed. In this stage, the processing time for each combination and the accuracy errors generated in orthomosaic formation were considered. Each processing time (combination) was analysed statistically in OriginPRO17 software and represented as a response surface: axis (X), flight height; axis (Y), image overlap; and response axis (Z), processing time. This analysis offers the user a mechanism for predicting the processing time through an equation. Response surface methodology (RSM) is one of the most commonly used multivariate techniques for process optimization and is particularly effective for multivariate systems [30]. By fitting a polynomial model to the experimental data, it was possible to predict the response for all possible factor combinations for the chosen experimental group [31] and a regression model was used to optimize the output variable influenced by the independent variables [32].

The DTMs obtained by photogrammetric (RPAs) and geodesic (GNSS) surveys were evaluated using ArcGIS 10.4 software. The data from the properly processed GNSS receivers were considered the control because their data were highly reliable (0.03 m).
The digital models were compared using ordinary least squares (OLS) functions using Spearman's classification. For this comparison, it was necessary to extract points from the photogrammetric models in a 2x2 m mesh. The Spearman classification assesses whether there is a relationship between two variables and whether this can be described through a monotonic function.

From an estimate of the parameters in a linear regression model, the OLS function minimizes the sum of squares and the differences between the observed responses and the responses predicted by a linear function of the explanatory variables. This can be observed as the sum of the squared vertical distances between each data point in the set and the corresponding point in the regression line [33]. In the OLS equation, the mathematical model is applied to the explanatory variables to better predict the dependent variable. In the regression equation, the dependent variable is always Y, and the explanatory variables are always Xs. Each explanatory variable is associated with a regression coefficient that describes the strength and sign of the relationship between this variable and the dependent variable as show in Equation 1 [34]:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... \beta nXn + e \qquad (1)$$

where

Y: dependent variable,

Xn: explanatory variable,

βn: coefficient, and

e: random residual error.

Model confidence can be evaluated based on six rules: (1) the coefficients have the expected signs; (2) there is no redundancy between the explanatory variables; (3) the coefficients are statistically significant; (4) the residuals are normally distributed; (5) there is a strong adjusted R squared value; and (6) the residuals are not spatially correlated [34]. Collinearity among the variables was determined according to the six rules of the OLS model.

DSMs accuracy was evaluated from the mean residual errors at each flight height, across the 36 models obtained by SfM photogrammetric processing and models obtained by GNSS receivers, and the summary of the variables (OLS results).

3. Results and Discussion

3.1. Processing time

In many cases, data processing time is considered a limiting factor to using technologies in the field. Combinations of overlap, flight height, and parameters were analysed in the software to optimize the time required to obtain photogrammetric data (Figure 5).

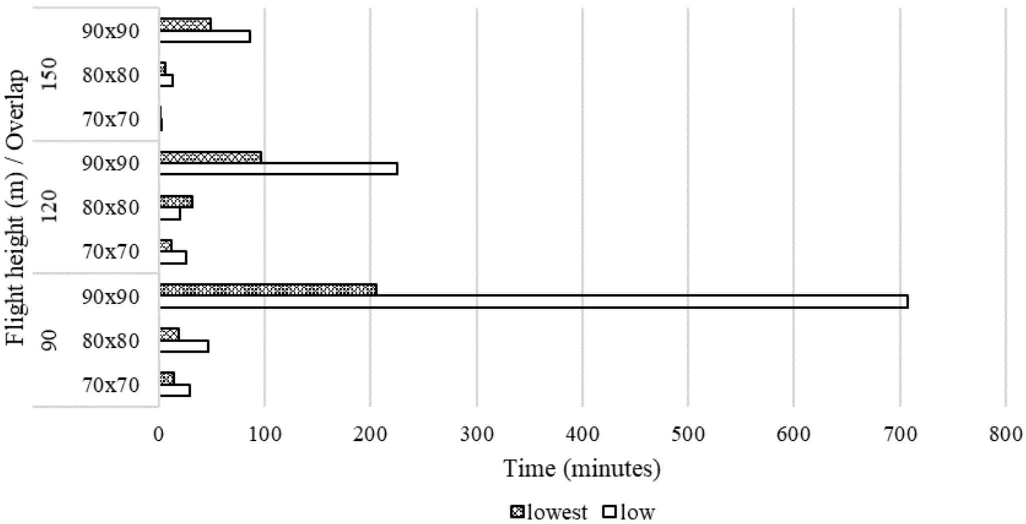

Figure 5. Processing time as a function of combinations between flight altitude, image overlap, and software parameters (point cloud: low and lowest).

In terms of processing time, the 150 m AGL flight missions showed the best results. The three overlap levels evaluated at this flight height showed processing times less than 100 minutes (Figure 5). The 70×70% image overlap for flights at 150 m showed shorter processing times due to the low number of images. These parameters showed the best results without considering image accuracy.

Long image processing times occurred at the 90 m flight height and 90x90% overlap, followed by those at the 120 m flight (AGL) and 90x90% overlap. Excessive processing times results in some applications being unfeasible; in this case, the variations in the available processors should be considered. In addition, errors at the time of image collection and errors related to hardware may occur; this scenario would require new collection efforts, making information collection even more time consuming. By evaluating processing time influence on RPA images, Torres-Sánchez et al. [35] showed that long processing times can be problematic for operations that require rapid results. In their studies, a reduction in overlap and an increase in flight altitude caused drastic reductions in processing time.

Optimization of processing time is an important factor when using digital models on coffee farms. Farms still face several obstacles regarding data processing. The inclusion of technologies related to production in the field is seen as an application that requires a high investment. Using conventional processors for data processing may facilitate access to and the application of these digital models in coffee growing areas. Cost reductions related to using these technologies must be well managed and understood; this set of analyses enables the viability of precision agriculture projects [36].

An important factor for optimizing the processing of aerial images is point clouds. As shown in Figure 5, the processing time was affected by the reduction in the point cloud from low to lowest. The overlap of 90x90% and an AGL of 90 m resulted in a reduction in processing time from 700 to 200 minutes. Similar results were found in studies by Dandois et al. [37] who, by evaluating altitude, overlap, and climate conditions in forest structure estimates by RPAs, showed that a reduction in the number of point clouds can be an approach to optimizing processing without reducing the quality of the photogrammetric products.

Time optimization in capturing images contributes to rapid data collection without interfering with the quality of photogrammetric products. Pre-flight planning can be an important tool for data collection optimization. Figure 6 presents a fitted model to estimate the time spent on data collection by RPAs between 90 and 120 m (AGL) and with an overlap of images between 70 and 90%.

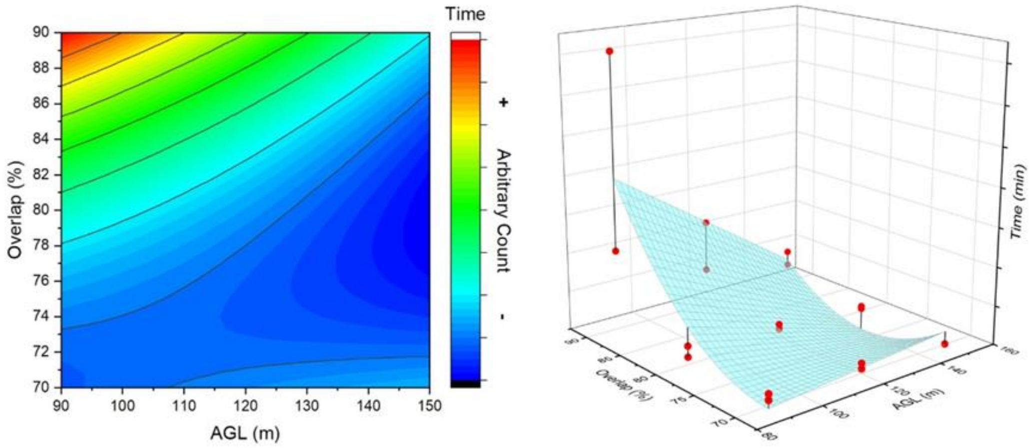

Figure 6. The model for flight time pre-planning function as image overlay and flight height (AGL).

Adequately reducing the number of images and refining the flight parameters significantly decrease the software processing time. Determining guidelines for this optimization, particularly in terms of strategies for more efficient image collection, contributes to being able to conduct studies in large areas [38]. In addition, the collection of aerial images in a reduced amount of time results in less interference regarding the difference in luminosity and provides more accurate DTMs [39].

3.2. SfM processing accuracy

Presenting the errors that occur during image processing makes the discussion about flight efficiency more comprehensive. The errors caused during image processing are shown in Table 2. These errors are linked to the difficulty the software had in processing the images; these errors may be related to noise, poorly sized overlaps, and incorrect image georeferencing.

Table 2. Errors in meters obtained through processing reports of PhotoScan 1.4 software.

AGL	Overlap (%)	Latitude (x)	Longitude (y)	Altitude (Z)	Accuracy (m)
90 m	70x70	3.158	2.641	1.17	1.27
	80x80	3.244	2.98	1.15	0.55
	90x90	1.748	1.44	0.64	0.75
120 m	70x70	2.93	2.04	1.21	1.71
	80x80	4.24	3.66	1.42	1.58
	90x90	2.29	2.04	0.92	0.51
150 m	70x70	4.46	4.09	1.72	0.37
	80x80	5.82	5.34	2.14	0.88
	90x90	2.97	2.69	1.16	0.45

The best results occurred with the overlap of 90x90% (Table 2); however, there is a contradiction because the flights with the 90x90% overlap had high processing times due to the amount of information. The best accuracy occurred with the overlap of 70x70% and the 150 m flight heights, and this value, outside the expected range, is associated with the stable conditions of the RPAs at the time of their flights. Even with a high level of accuracy, the flight at 150 m AGL and a 70x70% overlap had an error in latitude and longitude above 4 m.

Given the errors shown in Table 2, high overlaps and low AGLs contributed to accuracy in the positioning of latitude and longitude. This shows that DEMs from low flight heights can be arbitrarily accurate in their horizontal measurements.

3.3. Precision of digital surface models

The DSMs were evaluated based on the precision level presented at each point compared to the that in the model obtained by GNSS. The assumption of normality was verified by applying the residual histogram obtained by the overall mean accuracy for each AGL (Figure 7). In these analyses, the means of all overlaps during each flight were considered. The histogram lines were evaluated according to the similarity between the sides, and biased models have abnormal curves.

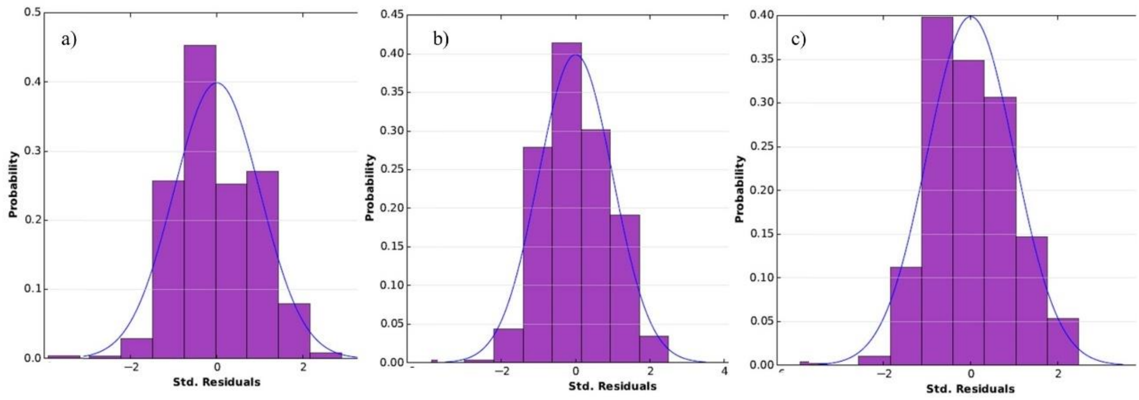

Figure 7. Residual histogram of errors, a) 90 m, b) 120 m and c) 150 m AGL.

It was observed that the data obtained from the 120 m AGL flights corresponded to a data curve closer to a normal distribution, which indicates that it is the best AGL in terms of error distribution. The 90 and 150 m AGL flights showed nonnormally curves in relation to the normal curve. AGLs 90 and 150 m show abnormality about the ideal curve. In AGL 90 m, despite having low residual variation, a group of values reaches residual errors above 0.4 m. This result can be explained by the high level of terrain detail obtained due to the reduced pixel size, leading the algorithm to confuse certain points of the terrain. By evaluating the effects of point density in DTMs, Agüera-Veja et al. [40] reported that high point density implies redundant results and an excessive increase in terrain detail.

The flights at 150 m AGL (Figure 7b) showed variations below 0.4 m, but their data were not consistent. This data composition makes it difficult to understand the errors obtained, thus indicating that flights performed at 150 m AGL had low reliability levels. The uniform distribution of the systematic errors obtained for the 90 m AGL flights did not guarantee that the DTM presented was superior to the others. Stott et al. [41] evaluated the accuracy of DTMs obtained by high precision RPAs and noted that sets of topographic data derived from SfM may have spatially erroneously distributed complexes, conferring distorted interpretations of the terrain.

The SfM algorithm compensates for the errors due to issues with measuring accuracy by defining how close the measurement is to a reference value. Normally, the algorithm displays the true surface by estimating the mean error value, so the positive and negative deviations can be compensated, preventing a systematic error. The numerical and spatial distributions of errors should also be considered when investigating the quality of the measurement [42].

Errors presented in standard deviations form were obtained by comparing digital models of RPA and receivers GNSS. Figure 8 shows the point errors of each flight height considering the mean values of overlap. In addition, the data presented on the slope map were derived from the model obtained by the GNSS. Positive standard deviation values were found in regions with slopes between 20 and 35%. On steep slopes, the 3D reconstruction algorithm overestimated the slope; and on low slopes, the deviation errors were estimated below the actual position. In regions with steep slopes, Westoby et al. [43] explain that an aerial approach would be particularly advantageous for use on topographically simple terrains, such as flood plains at the bottom of a valley. However, as with stereoscopic reconstruction, steep or almost vertical topography is probably problematic for the SfM technique.

These are important findings when working on a project to create planting rows. The overestimation of sloped regions can identify areas as not suitable for mechanized coffee planting, thus reducing the complete optimization of the area for planting. When obtaining orthomosaics from RGB aerial images, producers and technicians should pay attention to these results and perform an inspection in the field to validate the results. Growing coffee inappropriately on steep slopes causes soil erosion and reduced productivity due to the loss of fertility on the soil surface, resulting in areas of that are of minimal use to a producer [44].

Overestimation of slopes in coffee areas can also be a barrier to mechanized harvesting. Self propelled harvesters can be regulated according to terrain variations, and some models can be used when there is a 25% inclination. Prior planning of harvest time can be carried out for coffee on slopes. Mechanized harvesting requires 21.6% more time when performed on slopes above 20% than when performed on lower slopes [45]. This demonstrates that of slopes above the normal inclination interfere with other operations in coffee growing areas.

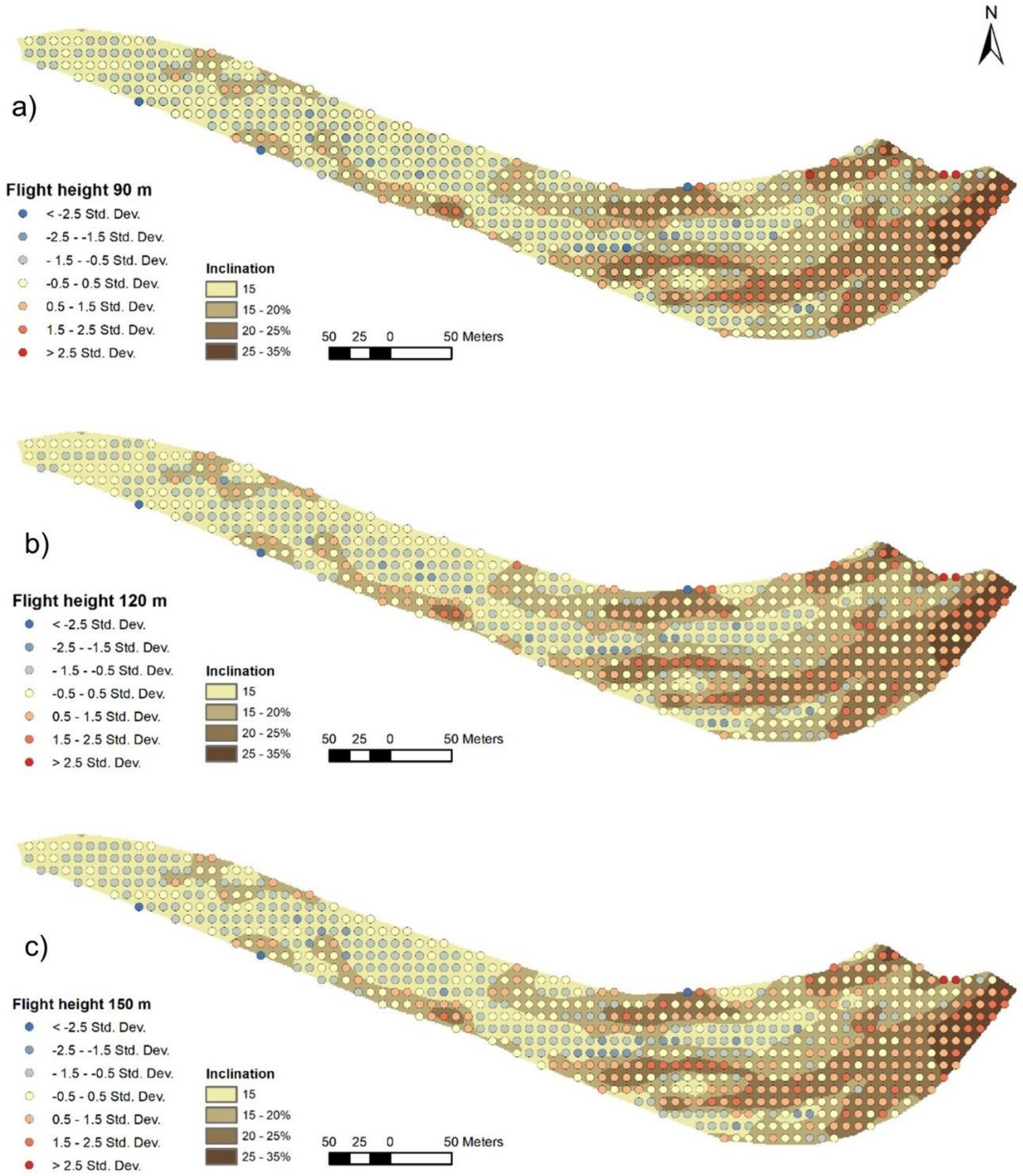

Figure 8. Standard deviation between the DTMs obtained by the GNSS receptors and RPAs, a) 90 m, b) 120 m and c) 150 m.

Higher standard deviations occurrence in areas of steep slopes than in other areas was also observed in studies by [46]. Variations were found in the DEM in areas with a high slope gradient and surface roughness. The authors explain the relevance of this finding for geomorphic studies since the processing time is greater for steep slopes. This generates inaccuracies in the models in these locations, causing erroneous interpretations. This scenario can be considered a significant impediment for regions intended for coffee growing since regions with high slopes require specific management – mainly in terms of applying soil conservation and area optimization techniques.

The analyses shown in Figure 8 show the common error between the models. Regions with slopes as high as 15% occur within the error domain, with a standard deviation below the ideal mean. This type of error was found in studies by Lamsters et al. [47], who worked with orthophotos for image reconstruction of glaciers, and the authors observed a constant domain of errors in the flat regions. This type of error was also discussed in the studies by James and Robson [48]; when capturing images in regions with flat topography, the authors observed that the errors in the DTMs were below average. Therefore, for this type of terrain, flights should be conducted by applying slopes to the image capturing sensor.

Despite this type of error, issues with planning and implementing coffee productions in regions considered to have a flat topography are minimal. Even below the ideal altitude, the contour lines considered in this type of project will follow the same direction.

Statistical details of the different combinations of flight configurations are shown in Figure 9. This figure shows the influence of different flight configurations and image processing on topographic quality compared to the classic topography obtained by GNSS receivers. Given this relationship, it is possible to observe in general that the 150 m AGL flights showed the best correlations; but in reviewing the data, we observed that the 120 AGL flight with an 80% overlap resulted in a low processing time and provided the best result.

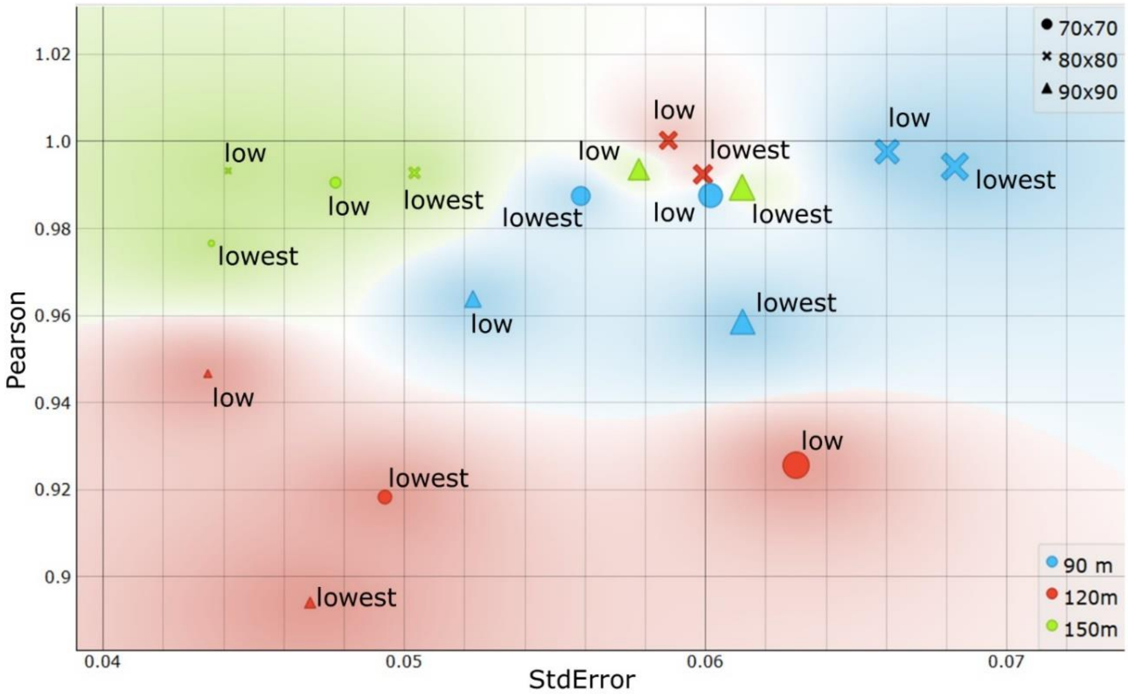

Figure 9. Ordinary least squares (OLS) results for flight heights, overlays and point clouds compared to those obtained through the topographic survey by GNSS receivers. X-axis: Pearson correlation, y-axis: standard deviation in meters. Color: AGL, figure format: image overlap, and figure size: error.

This result demonstrates that the AGL flight height can be configured to make the flight more efficient. In addition, some values found during processing for lowest flights did not differ visually. Therefore, it is possible to reduce processing times while maintaining acceptable levels of accuracy.

The best results shown in Figure 9 are the coefficients observed for the following configurations: 90 m flight, 90x90% overlap, and low point density; 120 m flight, 80x80% overlap, and low and lowest point densities; and 150 m flight, 80x80% overlap, and low and lowest point densities. The comparison of these results with the information related to processing time shows that the 150 m flight with 80x80% overlap and a low point density is notable. This flight configuration collects less data and shows significant results in relation to the other configurations. However, when comparing these results with the distribution of errors (Figure 7), the 120 m flights with 80x80 overlap and a low point density and those with 80x80 overlap and a lowest point density are preferred due to better data uniformity.

Figure 9 highlights an important issue for flight configurations. All flights performed with 80x80% overlap, regardless of processing time and flight height, showed a correlation above 98. This overlap is the most appropriate for topographic surveys conducted by using images obtained by RPAs.

Flight optimization should be performed by implementing some processing and precision limits. An increase AGL in flights results in fewer passes over an area, and thus, fewer images are superimposed. Thus, when performing flights in small areas, flight optimization can cause a reduction in the quality of photogrammetric products James and Robson [38] highlight the number of images in certain regions and note that the heterogeneity of some areas can decrease and increase errors when fewer images are collected. Thus, the authors recommend capturing at least three images of an area of interest.

This information may be valid for coffee-growing projects in small areas. In many countries, especially in globally relevant coffee producing regions, such as South American countries, farms used for coffee plantations are less than 2 hectares (Jha et al., 2011). In these cases, image capture can be configured by increasing the overlap area, reducing the flight speed, and obtaining at least three images per area.

In a discussion on image number, Piermattein et al. [49] highlighted that high numbers of images provide more detailed DEMs. This assumption can be variable and depends on the type of product obtained. As seen in the results presented in Table 2, the increase in the number of images did not show linear significance. The 90x90 overlaps may have added a high level of detail to the DEMs, and when compared with traditional topographic methods, these overlap levels were considered inferior. High levels of detail combined with an altitude reduction were reported by Avtar et al. [50], who evaluated different flight heights for biophysical analysis of palm trees, and the authors observed a significant contribution of lower altitudes to an increase in errors. This result was attributed to the high level of detail in the image.

The workflow required when processing images involves specific processing steps for objects with high levels of detail. These steps are not necessary for generating DTMs that are applied in agriculture because these steps can significantly increase topographic detail and have relatively high processing times [51]. Photogrammetric products generation requires specific knowledge regarding the type of information that needs to be obtained. Recurring errors occur during data collection, and the increase in the number of images needed to improve the accuracy of a DTM is the main error observed in some cases. According to Micheletti et al. [52], the increase in the number of images collected does not linearly increase DTMs accuracy and may lead to an unnecessary increase in data processing time.

Cartographic data obtained DTMs are necessary for suitable planting arrangements and soil management for conservation for coffee growing projects. However, the high amount of topographic detail in many cases is unnecessary for coffee growing projects since the recommended commercial spacing between rows is above 3.5 m. What is essential for implementing the coffee growing project is a reliable determination of sloped regions, as this directly interferes with mechanized equipment. Tavares et al. [53] found a direct effect of the slope in coffee growing areas on the mechanized operational field capacity. They showed the operational field capacity decreased harvesting activities of sweeping coffee at slopes above 15%.

Planning and optimization of the image acquisition protocols is challenging in complex natural terrain [54]. But, flights optimization in coffee growing projects is valid, and some points should be emphasized. As noted, regions with slopes above 20% are overestimated. In areas with this characteristic, control points on the soil are necessary, which reduces error levels to the geodetic precision level in [55]. It is important to consider the overestimated errors, as this can lead to a reduction in areas suitable for mechanized planting. Höfig and Araújo-Junior [56] showed the ability to mechanize coffee plants in sloping regions. Their research showed that mechanization on slopes of 0-5% is extremely recommended, that on slopes of 5.1-10% is very recommended, that on slopes of 10.1-15% is recommended, that on slopes of 15.1-20% is moderately recommended, and that on slopes above 20% is not recommended. Given this assertion, one can consider digital models derived from photogrammetric processes capable of generating a slope map for use in mechanized coffee growing projects.

Cartographic projects for coffee growing from DTMs derived from photogrammetric techniques can be an important tool and contribute to operational improvements. However, it is notable that areas with a greater than 20% slope can show slope values above the actual measurements.

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

4. Conclusion

The most accurate DTM was derived from the photogrammetric products from the 120 m AGL flight, with frontal and lateral overlap of 80x80%. The reduction in image overlap was significant in reducing in processing time without influencing the quality of the DTMs.

Images processing in lowest point clouds did not affect the quality of the DTMs. In addition, there was a considerable reduction in processing time.

Slope mapping obtained by RPAs was considered efficient up to a 20% slope, above which the models overestimated the elevation. A dominant error effect was observed in regions with low slopes, usually in photogrammetric constructions that did not use of control points in the soil.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “Conceptualization, L.S.S. and G.A.S.F.; methodology, M.S.S. and R.O.F.; software, D.B.M.; validation, L.S.S., G.A.S.F. and R.O.F.; formal analysis, D.B.M. and G.R.; investigation, M.S.S.; resources, E.P.; data curation, L.S.S., R.O.F. and M.S.S.; writing—original draft preparation, L.S.S.; writing—review and editing, G.A.S.F. and L.S.S.; visualization, G.R.; supervision, D.B.M. and E.P.; project administration, G.A.S.F.; funding acquisition, G.R. and E.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Embrapa Café— Coffee Research Consortium, project approved n◦ 234/2019, the National Council for Scientific and Technological Development (CNPq), the Coordination for the Improvement of Higher Education Personnel (CAPES) and the Federal University of Lavras (UFLA) and University of Firenze (UniFI).

Acknowledgments: The authors would like to thank farm Bom Jardim.

Conflicts of Interest: The authors declare no conflict of interest.

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CHAPTHER III. IDENTIFICATION AND COUNTING OF COFFEE TREE BASED ON CONVOLUTIONAL NEURAL NETWORK APPLIED TO RGB IMAGES OBTAINED BY RPA

Paper to be submitted in *Sustainability* (ISSN 2071-1050)

Abstract: Computer vision algorithms used for counting plants can be an indispensable alternative for managing coffee growing. This research aimed to develop an algorithm for automatic counting of coffee plants and define the plant's best age to carry the monitoring using Remotely Piloted Aircraft (RPA) images. Based on a Convolutional Neural Network (CNN) system and Open Source Computer Vision Library (OpenCV). The analyzes were carried out in coffee-growing areas at stage development of three, six and twelve months after planting. After obtaining images, the data set was organized and inserted into a You Only Look Once (YOLOv3) neural network. The training stage was performed using 7458 plants age three, six, and twelve months, reaching stability of iterations between 3000 and 4000it. Plants detection within twelve months is not possible due to crowns unification. Plants with three months of development showed 86.5% counting accuracy. Plants' characteristics at this age may have influenced accuracy reduction, and the low uniformity of the canopy may have made it challenging to define a pattern by the neural network. In plantations with six months of development, were identified 96.8% of accuracy in counting plants automatically. This analysis enables an algorithm development for automated counting of coffee plants through RGB images obtained by remotely piloted aircraft and machine learning applications.

Keywords: Remote Sensing; Deep Learning; Precision Coffee-growing; Digital Agriculture; Plant Count.

1. Introduction

Technological applications in agriculture contribute to significant agribusiness development [1,2]. Technologies emerging applied to monitoring agricultural fields based on remote sensing represent an important advance for agriculture [3,4], contributing to improvements in management and increased productivity [5,6]. These technologies involve image processing, Artificial Intelligence, Geographic Information Systems, Sensor networks and Global Positioning Systems [7]. Providing remote sensing technologies and digital agriculture interaction includes IoT, cloud processing, big data analytics, machine learning, deep learning, and computer vision [8].

High spatial resolution images obtained by RPA enable observations of vegetative vigour and failures in agricultural fields [9]. The analysis of images using computer vision is essential in agricultural research. They are techniques used to identify several characteristics of vegetation in agriculture [10,11].

Computer vision agricultural monitoring has become an essential technology in crop management [12], characterized by algorithms applications for classifying and detecting specific objects of interest in photos and videos [13]. Algorithms learning allows the automatic discovery of representations necessary for detection and classification from raw data input into the system [14,15]. Heterogeneous landscapes, sometimes presented in agriculture, can present difficulties in object detection. Machine learning models show better results in predicting and identifying anomalies. Convolutional Neural Networks (CNN), Long Short Term Memory (LSTM), and Deep Neural Network (DNN) are the most applied algorithms [16,17]. Machine learning used to images obtained by RPA can be seen in research by Osco et al. [18], CNN to geolocation and counting citrus plants. Lewis and Espineli [19] convolutional neural network to detect nutritional deficiencies in coffee plantations. Kerkech et al. [20] deep learning with colourimetric spaces and vegetation indices to detect vine diseases.

Advanced algorithms for object detection use Convolutional Neural Networks (CNNs) [21]. CNN presents a remarkable performance in locating objects in images with complex backgrounds [22]. A CNN has a convolution layer in which the filtering process is related to different input parts [23]. Furthermore, many computer vision problems are mitigated by convolution neural networks [24].

Research on CNN applications in RPA images is usually performed on multispectral and hyperspectral sensors. These sensors have a high acquisition cost, so the insertion of these technologies in agriculture faces resistance. RPAs with RGB sensors exploration can be a low-cost alternative. Images RGB used to identify plants in the agricultural field can be made viable by applying digital processing techniques and computer vision insertion [25].

Digital agriculture technology integration in coffee farming still requires improvements that enable productivity gains and crop profitability [26]. In coffee growing, plant identification through computer vision can contribute to the field management [27]. A suitable coffee field formation is determined by correctly establishing added plants. But in transplanting, errors can occur several cultivation field failures. Plants' losses in the initial development stage occur due to factors linked to the mechanized transplanting system, defects in plants root system, climatic factors, pests, and diseases [28]. Therefore, culture implantation after, it is necessary to replant in plants that did not survive. Thus, the number of plants missing from the cultivation stand is surveyed from visual samples made by walking throughout the field and marking the places where replanting is necessary. This method is a slow, costly and imprecise method. In this way, the application of remote sensing and computer vision techniques can offer satisfactory results in identifying and counting plants [29].

The automatic detection and counting of plants in coffee farming can quickly and safely provide georeferenced information on the points that need replanting. This information contributes to the number of plant management in each stand and the number of workers who carry out the replanting. Given the questions presented, this research aimed to develop a method for detecting and counting coffee plants based on CNN You Only Look Once (YOLOv3) and open CV tools. The study's contributions are as follows: (i) to propose a prototype of a coffee plant counting algorithm based on pattern recognition; (ii) Identification of ideal plant age for identification and counting.

2. Materials and methods

2.1. Image data acquisition

Image capture was performed by a Remotely Piloted Aircraft (RPA) model Phantom 4 Advance (Figure 1). This aircraft has a GPS/GLONASS global positioning system for automated missions and a 1" focal aperture RGB spectral sensor Complementary Metal-Oxide-Semiconductor (CMOS).

Figure 1. Equipment used to images obtain RGB. (a) radio control and device for flight mission, (b) Remotely Piloted Aircraft (RPA).

Flight plan settings were started by area inspection to define the takeoff point ("home"). In addition, climatic conditions were verified: clouds number, insolation levels, wind speed, and presence of birds. Checked these characteristics, the flight mission was defined as a height of 30 m, speed of 3 m/s, and lateral and longitudinal overlap of 80% obtaining a spatial resolution of 1.68 cm in three spectral bands Red, Green, and Blue (RGB).

The coffee plantations is characterized by Coffea arabica L. (Catuaí Vermelho IAC 99 cultivar) were used, planted in the spacing of 3.5 m between rows and 0.5 m between plant. The flights were carried between three, six, and twelve months of implantation. This strategy allows understanding how the plant's coffee age interferes with the algorithm's accuracy in identifying plant numbers. Stages of growth evaluation (Figure 2) form the test image bank.

(a) (b) (c)

Figure 2. Example of plants age evaluated after planting: (a) three months, (b) six months, and (c) twelve months.

Aerial images were processed using Agisoft PhotoScan 1.4 software. Processing parameters used for mosaic formation and RGB bands union were: Align photos (High), build a dense cloud (medium), build mesh (medium) and build orthomosaic surface (mesh).

2.2. Image processing

Large images allow for greater detection accuracy in neural networks, especially for smaller objects over the field of view [30]. But they are rarely used, as they require high computational demand, time, and greater financial resources for processing [31]. In orthomosaics of agricultural fields to represent the entire cultivation area, the scenes have expressive dimensions for computer vision techniques. The windowing technique corrected these limitations, consisting of orthomosaic pieces cut to the same dimensions.

Thus, the images were cut in dimensions of 512x512 pixels and submitted to a neural network.

Images training was performed using deep learning techniques. The learning of accurate models using deep learning can be limited by the need for large amounts of data, mitigated by the need for labeling [32]. Analyzes interferences were improved from samples insertion by data augmentation. This device artificially increases the number of images in a database using geometric transformations (Figure. 3). The process mirrors (horizontally and vertically) and changes the orientation of the images (45º and 90º). Thus, the neural network considers a mirrored image, or rotated, a new image distinct from the original. As rotation increases degree, the data label is no longer preserved transformation [33].

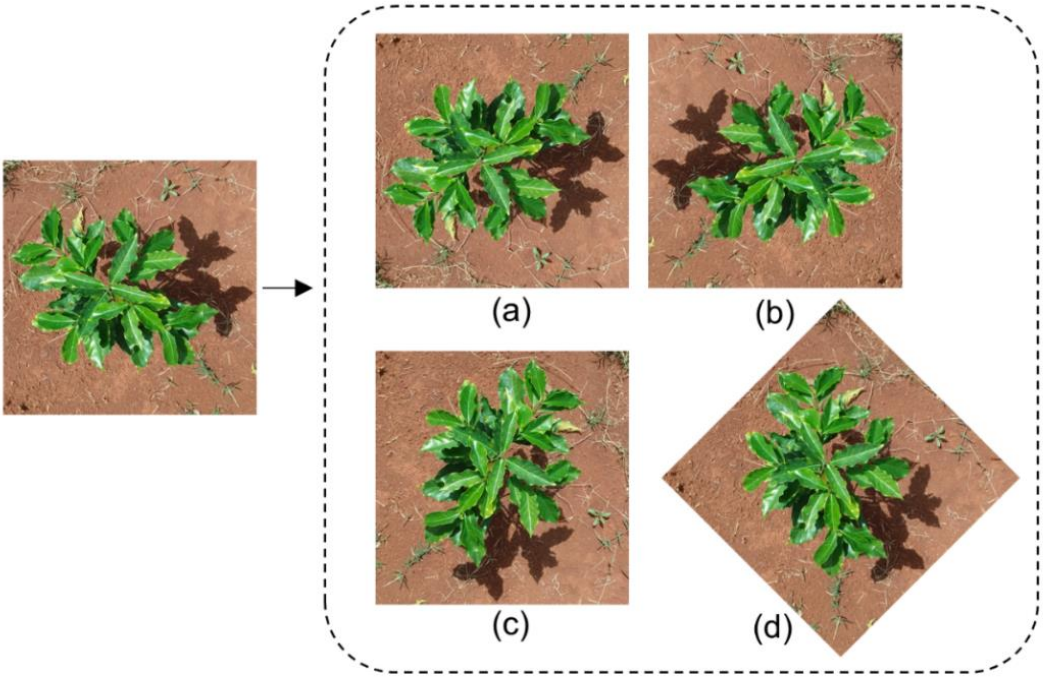

Figure 3. Data augmentation representation. (a): vertical mirroring, (b): horizontal mirroring, (c): 90° rotation, and (d): 45° rotation.

The data augmentation application made it possible to increase the training images to 1302 clippings, totaling 7458 plants (Table 1). The plant's amount in the images differs from the real amount because the same plant is located between two or more clippings. Therefore, plants' virtual amounts are higher.

Enlarging images avoids the overfitting problem, which occurs when a statistical model overfits the dataset training process. This problem causes the model to be accurate only when tested with the training set, not being able to make correct predictions on datasets unusual [34].

Table 1
Final number of cuttings and plants identified in the dataset at coffee development ages.

Development stage (age)	Images (cuts)	Objetos (plants)
Training	1302	7458
Three months[1]	187	931
Three months[2]	161	811
Six months[1]	216	770
Six months[2]	966	6216

[1]area 1, and [2]area 2

Final preparation involved image labeling applied in test training. The procedure consisted of inserting a text file containing the terrain truth parameters in each dataset slice. These parameters are represented by a rectangular bounding box parameterized: center point, position, width, and height [35], parameters extracted from each plant present in the image. For the clippings that contained plants with twelve months of implantation, the labels were not made due to plant individualizing impossibility.

2.3. Deep learning

Algorithm learning was carried from network training contained in the fundamental truth. In this step, the neural network knows the desired output result for the respective clipping. Thus, the errors obtained in the output are backpropagated (gradient descent algorithm) to adjust and reduce future errors. The connection between neurons has a numerical value responsible for weighting the signal transmitted to subsequent neurons, called synaptic weights [36].

The network learning process changes the synaptic weights throughout training until finding the best filter values for the dataset [37]. The synaptic weights are adjusted based on the error signals, bringing the actual response closer to the desired response [38]. This process aims to calculate the local error gradient (the direction in which the calculated average error value tends to increase) to correct the synaptic weights and opposite slope direction in the local minimum error search [39].

2.4. Detection algorithm

Object recognition was performed using a network architecture YOLO third improvement (You Only Look Once) algorithm described by Redmon et al. [40]. The ability to perform class prediction and bounding box simultaneously differs from YOLOv3 from traditional algorithms. Furthermore, it only uses a neural network to predict bounding boxes and class probabilities [41].

Architecture YOLO transforms the detection problem into a regression problem, increasing detection speed compared to Regional based convolutional neural networks R-CNN [42]. Making the architecture completely optimizable, unlike the detectors of R-CNN-based architectures where each stage needs to be trained separately [43]. YOLO is classified as a single stage object detector, dividing the input image into a grid, then adding safety scores in the bounding boxes [44]. YOLO network models of 1000, 2000, 3000, and 4000 iterations were obtained during the training process, making it possible to compare results between the models.

The YOLOv3 based coffee plant detector consists of a few steps. The first step is to process the dataset to remove erroneous and blurred images. The remaining photos are labeled and enlarged, and the training and testing set is allocated. The second step involves inserting the images into the YOLOv3 coffee plant detector for training and model optimization. The third stage is characterized by building the bounding box and the class score simultaneously, making the forecast images available.

Figure 4 shows the coffee plant detector based on YOLOv3 processes: internal structure convolutional, residual, upsampling, and concatenation.

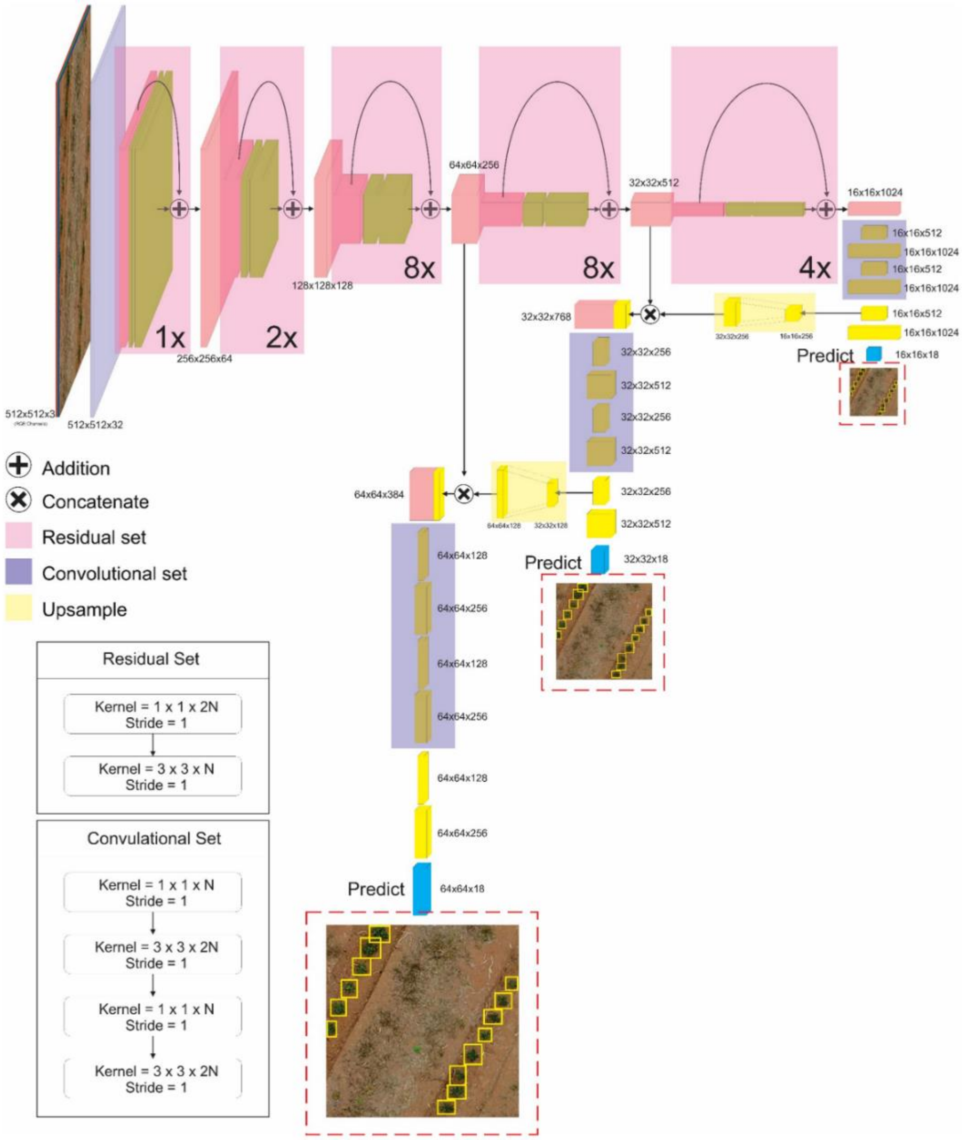

Figure 4. Structure of coffee plants detector based on YOLOv3.

The YOLOv3 architecture training process uses a grid cell where the object center is responsible for making the prediction. Each grid cell has three bounding boxes known as anchor boxes (Figure 5). Anchor boxes have pre selected sizes based on database objects, making the learning process easier. That way, the network doesn't need to learn the geometric aspects from the start. It just adjusts the anchor boxes to the correct location.

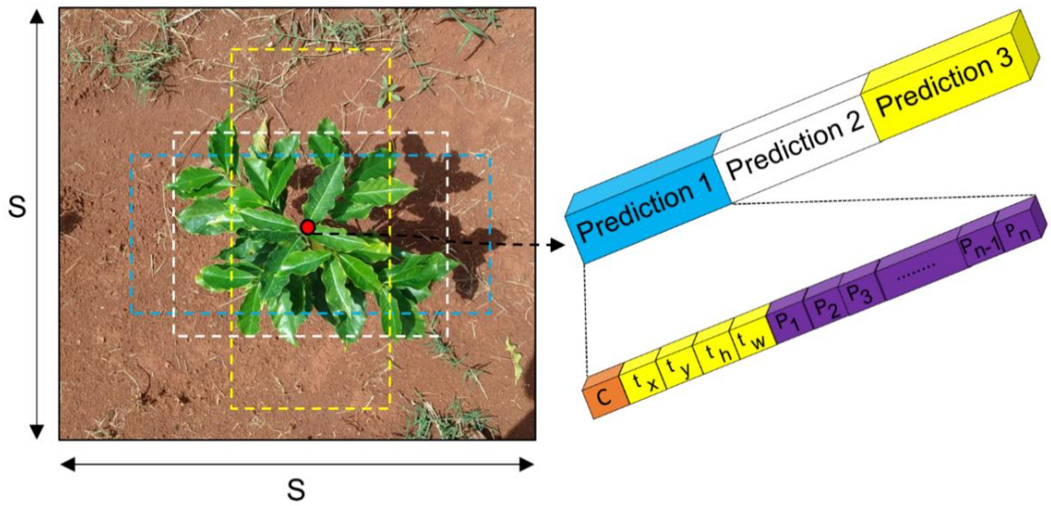

Figure 5. Structure of coffee plants identification by bounding boxes in the YOLOv3 network

The prediction vector is represented by the respective bounding box confidence value having an object (C), four values representing the bounding box (t_x,t_y,t_h, and t_w), and each class probabilities (p1,p2,p3 ,...,pn-1 and pn). Eq. (1) gives the predictions amount generated in YOLOv3 output:

$$S \cdot S \cdot \{3 \cdot (1 + 4 + C)\} \quad (1)$$

Where:

- S: grid dimension;
- C: classes number in the database.

In practice, the network does not predict absolute values of coordinates and dimensions of bounding boxes. This is done for a better network during training stability. Also, the prediction values range from 0 to 1 so that the model is better focused.

The following equations performed the transformation of predicted values into absolute values.

$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w \, e^{t_w}$$
$$b_h = p_h \, e^{t_h}$$

Where (c_x, c_y) are cell displacement in the image and (ph, pw) are anchor boxes dimensions previously selected.

The loss function of YOLOv3 used to quantify network error predictions during training to minimize it through the gradient descent algorithm can be separated into three parts: loss of location ($Loss_{coord}$), loss of confidence ($Loss_{conf}$), and loss of classification ($Loss_{class}$) [30].

$$Loos = Loss_{coord} + Loss_{conf} + Loss_{class}$$

Since it is a numerical regression problem, the location loss function calculates (coordinates and boxes dimensions) are used MSE (Mean Square Error). If the ground truth of some coordinate prediction is $\hat{t}_*$, this subtraction with the predicted coordinate t_* is the error gradient (Eq. 2).

$$Loss_{coord} = \sum_{i=1}^{SxS}\sum_{j=1}^{B} \mathbb{1}_{ij}^{obj}\,(2 - w_i \cdot h_i)\left[\left(\sigma\left(t_{x_{ij}}\right) - \sigma(\hat{t}_{x_i})\right)^2 + \left(\sigma\left(t_{y_{ij}}\right) - \sigma\left(\hat{t}_{y_i}\right)\right)^2\right] + \sum_{i=1}^{SxS}\sum_{j=1}^{B} \mathbb{1}_{ij}^{obj}\,(2 - w_i \cdot h_i)\left[\left(t_{w_{ij}} - \hat{t}_{w_i}\right)^2 + \left(t_{h_{ij}} - \hat{t}_{h_i}\right)^2\right] \quad (2)$$

The MSE was multiplied by $(2 - w_i \cdot h_i)$, where $\mathbf{w_i}$ and $\mathbf{h_i}$ are the width and height of the ground truth about the total image size, used to increase the location error weight for smaller objects.

In calculating confidence loss and the class function (Eq. 3 and 4), the BCE (Binary Cross Entropy) function was used, which is more appropriate for situations in which one wishes to measure the proximity of the predicted probability distribution to reality.

$$Loss_{\ conf} = -\sum_{i=1}^{SxS}\sum_{j=1}^{B} \mathbb{1}_{ij}^{obj}\left[\hat{C}_i \log\left(C_{ij}\right) + \left(1 - \hat{C}_i\right)\log\left(1 - C_{ij}\right)\right] - \sum_{i=1}^{SxS}\sum_{j=1}^{B} \mathbb{1}_{ij}^{noobj}\left[\hat{C}_i \log\left(C_{ij}\right) + \left(1 - \hat{C}_i\right)\log\left(1 - C_{ij}\right)\right] \quad (3)$$

$$Loss_{class} = -\sum_{i=1}^{SxS}\sum_{j=1}^{B} \mathbb{1}_{ij}^{obj} \sum_{c\in classes}\left[\hat{p}_i(c)\log\left(p_{ij}(c)\right) + \left(1 - \hat{p}_i(c)\right)\log\left(1 - p_{ij}(c)\right)\right] \quad (4)$$

During training, the network is forced to have a single bounding box responsible for each object. This is done by selecting among the three boxes the one that has the highest over Union (IoU) metric value with the object's genuine bounding box (ground truth). When this occurs, $\mathbb{1}_{ij}^{obj}$=1, otherwise $\mathbb{1}_{ij}^{obj}$=0. Even with satisfactory results, the bounding box is ignored when having loU with an object greater than 0.7. Boxes with IoU values below 0.7 will only be penalized in the loss of confidence function for non-objects, therefore $\mathbb{1}_{ij}^{noobj}$=1 [30]

2.5. Validation

This step consists of clippings submitted to the neural network for plants detection. Detection tests were performed for coffee plants at different age stages to verify trained model's generalization power and to know the best age for model application. The plantations with plants presenting three and six months were tested in two replications. For 12 month old plants, the tests were not performed since ground truth is needed to measure the quantity and quality of detections. Ground truth values were not obtained because the plant's canopy was mixing, making it impossible to build a bounding box.

Quantity and quality of detection identification were performed by comparing the predicted and desired outputs present in the ground truth of each test clipping. So, it makes it possible to identify:

True Positive (TP) – objects that are coffee plants and were detected;
False Positives (FP) – objects that are not coffee plants and have been detected;
False Negatives (FN) – objects that are coffee plants and were not detected.

TP, FP, and FN detection classification are performed using the Intersection over Union (IoU) metric, defined as the ratio between the intersection and union of the predicted box with the ground truth box (desired output) (Figure 6).

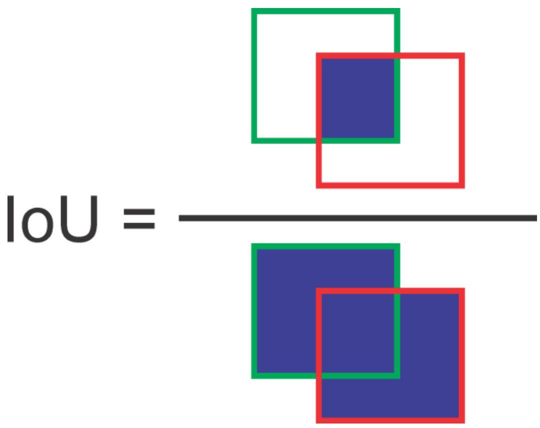

Figure 6. Representation of intersection over union (IoU).

The validation metric was set to an IoU threshold of 0.5. Therefore, for detection with IoU>0.5, the predicted box is considered to be a true positive (TP), otherwise it is a false positive (FP) [45]. In addition, detections made on imaging with non existent objects of interest were false positives. The amounts of TP and FP make it possible to calculate two essential metrics, accuracy and recall.

Precision – Infers detections accuracy produced by the neural network, characterized by correct predictions percentage, calculated as follows Eq. 5.

$$Precisão = \frac{TP}{TP + FP} \therefore Precisão = \frac{(correct\ detections)}{(all\ detections\ performed)} \tag{5}$$

Recall – Infers neural network ability to detect all relevant cases in the test dataset, known as model sensitivity, and can be obtained through the Eq. 6.

$$Recall = \frac{TP}{TP + FN} \therefore Recall = \frac{(correct\ detections)}{(all\ plants\ from\ the\ test\ dataset)} \tag{6}$$

Models generally have proportionally inverse behaviour. This is because models favour a high hit rate and reduce detections performed number. In this way, sensitive models can perform detection that does not correspond to the object of interest, presenting low precision. Satisfactory results are found in models that show equilibrium.

The balance assessment was performed using graphical analysis using the PR curve (Precision-Recall) to determine whether the model has a reasonable hit rate as sensitivity increases. In addition, a comparison was made between the models with different training iterations, using as a criterion the area below the PR curve, characterized as Average Precision (AP).

2.6. Plant count

The coffee plant counting process was carried out on plant detections result, so detection quality contributes to the accuracy in counting. The plants count was performed by tools provided by the OpenCV library, using the Python language. Segmentation techniques were used to highlight only the pixels representing the bounding boxes [46].

The neural network was previously configured to generate bounding boxes in cyan, the target colour in the segmentation. In this analysis, the areas with pixels in this colour are bounding boxes kept in the orthomosaic, while the other pixels assume the black colour. Areas aggregation of interest made it possible to binarize the orthomosaic, which consists of images only the colours white and black, with interest being areas in the white pixels.

After identification and counting training, the algorithm was applied to a commercial coffee crop for six months. Using the same flight parameters applied in the training and testing stages.

3. Results

3.1. Training

The samples taken during model training are shown in Figure 7. The data set inserted in the YOLOv3 network achieves satisfactory results after adjustments. It is possible to observe an expressive evolution in plant detection errors faces of learning iterations. Despite still decaying, the iterations above 3000it were adequate for coffee plant identification.

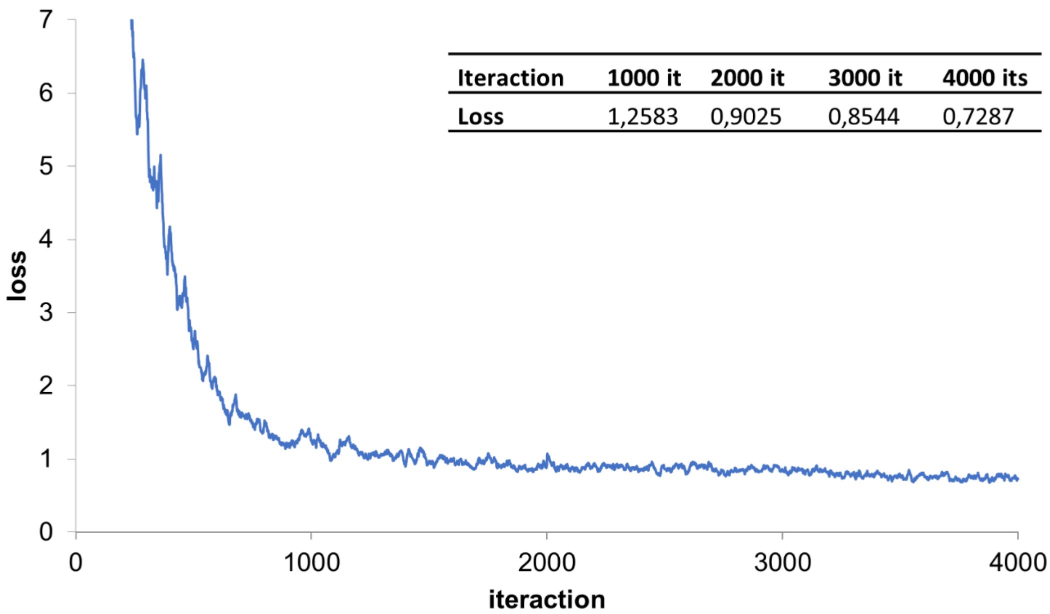

Figure 7. Training results of YOLOv3 network for coffee plants detection.

As shown in Figure 7, the cost function decays during training. It occurs because the backpropagation algorithm changes network weights based on the error surface gradient of descent. It minimizes the difference between obtained and desired output at each training iteration. This network behavior follows the surface slope direction created by the objective function (loss), a process of descent until stability is reached [47].

3.2. Coffee plant detection

Different coffee plant ages directly alter plants' identification. Tests performed at various ages demonstrate the interference of these characteristics in plant detection (Table 2). Table 2 shows multiple iterations used performance and the precision, average precision, and recall values.

Table 2
Performance of different iteration models at different vegetative plant stages.

Vegetative stage	Model	TP	FP	FN	Precision	Recall	AP
Three months[1]	1000 it.	282	220	529	0.562	0.348	0.36
	2000 it.	357	272	454	0.568	0.44	0.375
	3000 it.	438	318	373	0.579	0.54	0.463
	4000 it.	417	353	394	0.542	0.514	0.392
Three months[2]	1000 it.	517	37	414	0.933	0.555	0.777
	2000 it.	707	57	224	0.925	0.759	0.842
	3000 it.	770	96	161	0.889	0.827	0.887
	4000 it.	705	66	226	0.914	0.757	0.872
Six months[1]	1000 it.	507	55	263	0.902	0.658	0.862
	2000 it.	593	94	177	0.863	0.77	0.853
	3000 it.	695	118	75	0.855	0.903	0.873
	4000 it.	705	109	65	0.866	0.916	0.874
Six months[2]	1000 it.	4848	282	1368	0.945	0.78	0.943
	2000 it.	5351	399	865	0.931	0.861	0.951
	3000 it.	5664	544	552	0.912	0.911	0.944
	4000 it.	5899	532	317	0.917	0.949	0.955

TP: True Positive, FP: False Positive, FN: False Negative, AP: Average Precision and Recall: Model Sensitivity, [1]:area 1, and [2]: area 2

Model plant detection conferred the best accuracy in plants within six months of development. As observed in Table 2, relevant detection results were found in plants images six months of age applied between 3000 and 4000 iterations, as they presented precision, recall, and AP values above 0.8. The results were inferior found in plants of three months even applying 4000it. It can be observed the values are close in TP, FP, and AP.

The detection corresponds to an image submitted to a neural network with objects of interest, "coffee plants" delimited by bounding boxes. These detections' segmentation, which determines the plant count, was altered and represented by the contour and filling bounding interior (Figure 8).

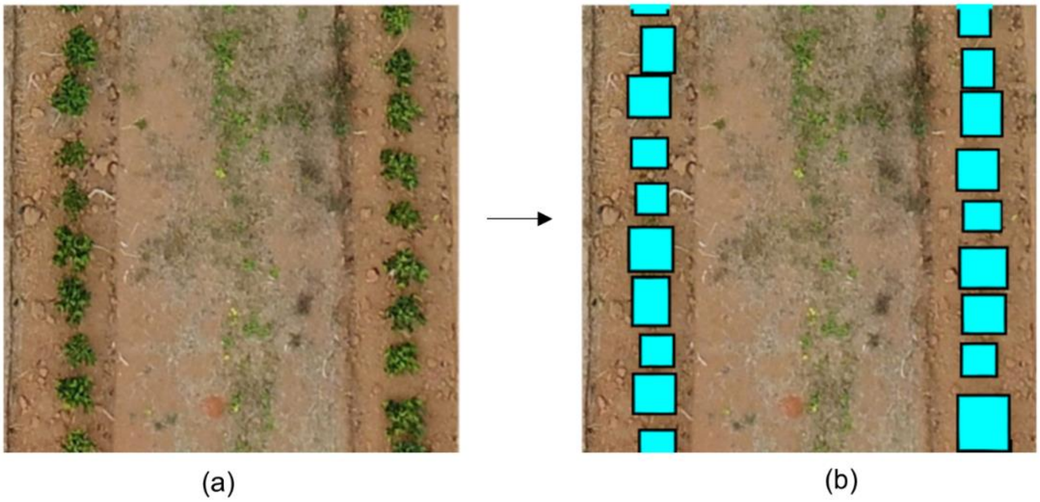

Figure 8. Cutout detections. (a) input image and (b) identification result.

Bounding boxes formation is an important step (Figure 8). This detection process images conditions for the next step, the plant count. Furthermore, the final output object detection model is a list of bounding boxes that would ideally contain all the plants and their relative locations. The main goal is for box numbers to match the plant's number in the image.

3.3. Plant count

Using segmentation techniques from the OpenCV library in Python for counting plants, the sequence is shown in Figure 9. Initially, the input image received the bounding boxes, then the black backgrounds were applied, the noise was removed, and the area center was determined.

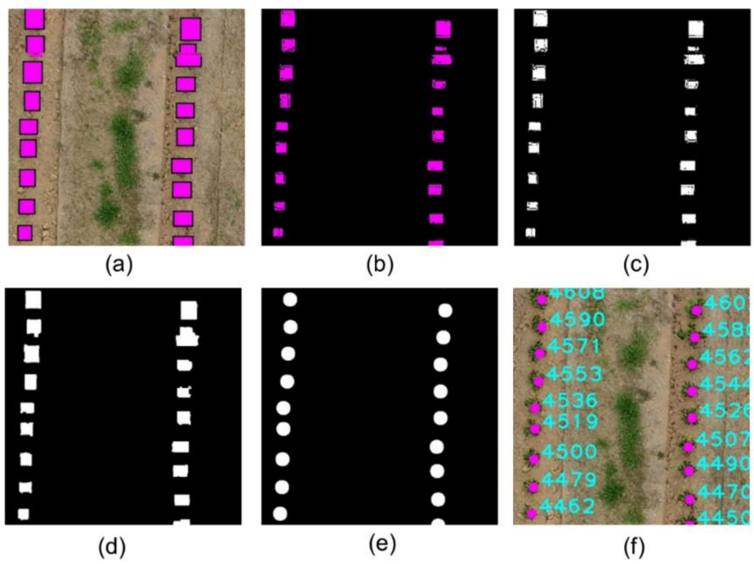

Figure 9. Segmentation process: Detection of filled rectangles (a); Color segmentation cyan (b); Binarization (c); Dilation (d); Determination of the center each area (e) and Circle count (f).

The final segmentation process (Figure 9) marks the plants by circles and their respective number in the orthomosaic. Also, it was possible to identify some counted plants' failures in this step. They are errors caused by false positives presence, compensating in some cases for false negatives occurrence.

The plant counting process depends directly on correct object identifications. As observed, the ability to identify plants within six months of age showed greater accuracy. Table 3 presents plants' manual counts (three and six months of development) and the trained algorithm capacity, applied to the best iteration tests (3000 and 4000it).

Table 3.
Ability to identify and count coffee plants of different ages.

Ages	**Manual count**	**Algorithm (4000 it.)**		**Algorithm (3000 it.)**	
	Count	Absolute count	error (%)	Absolute count	error (%)
Three months[1]	860	735	14.5	771	10.3
Three months[2]	943	716	24.1	769	18.5
Six months[1]	713	690	3.2	674	5.5
Six months[2]	5962	5687	4.6	5523	7.4

[1]area 1 and [2]area 2

The best automatic counting indexes performed by the YOLOv3 algorithm were identified in plants with six months of development, presenting a performance of 96.8% correct. This high assertiveness may be related to plant uniformity in this period, facilitating object characterization.

3.4. Counting prototype performance

The final performance validation was performed by applying the algorithm in a commercial cultivation area. This step demonstrated some characteristics occurrences that make it possible to identify the errors and algorithm successes practically (Figure 10).

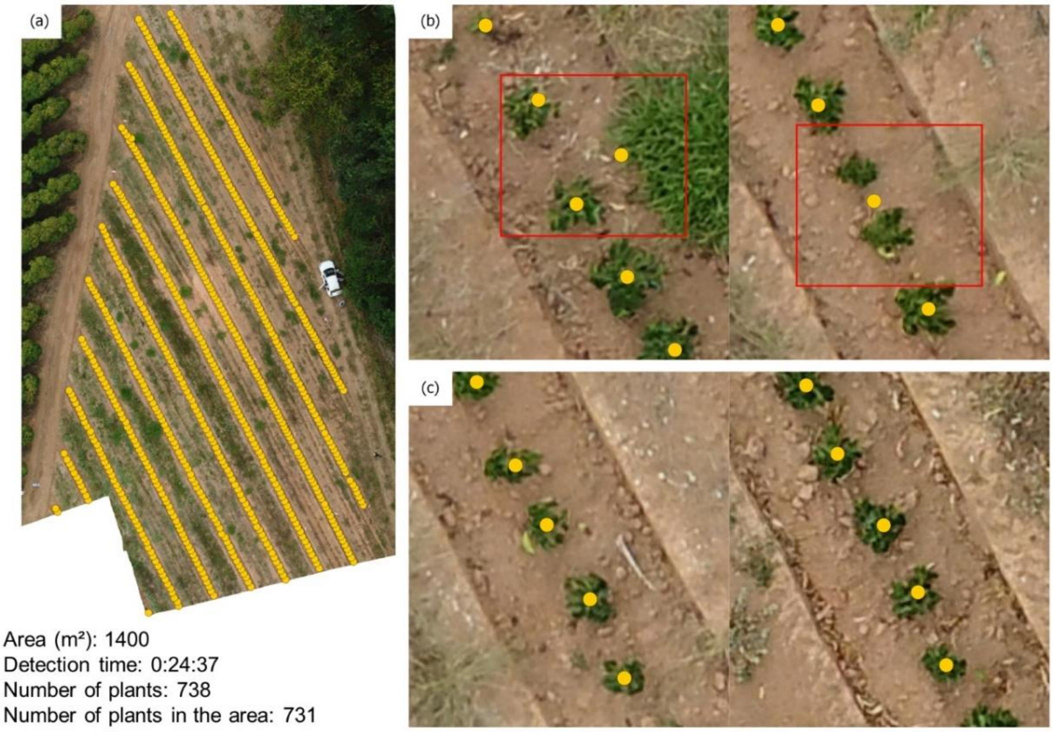

Figure 10. Application of plant counting algorithm in the commercial planting area. (a) cultivation area within six months of implantation, (b) errors occurred during identification and (c) correct identification and counting.

Despite the satisfactory performance in commercial plantations (Figure 10a), it is observed that at some points, the plant counting algorithm can be influenced by errors in coffee plant implantation. Two situations of spacing between plants variations are presented in Figure 10b. As the algorithm works on constant identifications, the abrupt spacing variation can cause detection errors. Therefore, it is essential to carry out the planting by distributing the correct spacing between the plants. In addition, the management of invasive plants contributes to better detection.

4. Discussions

4.1. Training

Errors reduction (losses) affected by the network occurred mainly before 1500 iterations. Above 1500, the results oscillated within a small range. The probable cause for this occurrence is stagnation due to the backpropagation algorithm having a minimum surface error location. At low iterations, the most apparent learning procedure disadvantage is that the error surface may contain local minima, so gradient descent is not guaranteed to find a global minimum [48]. This suggests that training beyond 4000 iterations would not have better results than those already obtained. A local minimum solution is not always wrong. It can be very close to what a global minimum solution would be. The optimization algorithm objective is to guide the search for a viable solution point where some prescribed criterion is satisfied, usually that some error measure is below a given tolerance [49].

In the presented training, model quality measuring only with the loss value was sufficient. The training was considered satisfactory since loss values result in exorbitant values in complex training problems. After completing training through the backpropagation algorithm, the test set presentation allows for evaluating whether the solution found is acceptable or not [50]. Criteria satisfied are defined in the testing stage, in which there are metrics that better characterize network quality.

4.2. Coffee plant detection

The plant identification stage presents different characteristics between coffee plants' ages. According to the training amount, a significant evolution of "Recall" model sensitivity occurs; the pattern was observed in all evaluates. This indicates a higher detection model specificity in the first iterations, increasing the generalization capacity with iterations increase. Generalization ability development contributes to a loss of precision, but the loss of precision shows to be small throughout the training. Reflecting on AP value maintenance at good values suggests that at 4000 iterations end, there is a model with good sensitivity and precision. Detection accuracy is the most critical parameter in evaluating the model's performance [51].

The best results were obtained for more developed plants in the six-month plant tests. Characteristics of plants aged less than six months can be confused with other invasive plants as they have a smaller canopy size. The relationship of plant ages may vary depending on the culture, which indicates that training should be specified according to culture formation [52].

Detecting a plant's difficulty may be due to biological morphology, spectral characteristics, visual textures, and spatial contexts [53]. It is attributed to similarities between crops and weeds, density environments, plant configuration, high definition canopy mapping, and conflicts between shade and lighting [54]. However, the uniform coloration of leaves and some crops' growth patterns improve the recognition accuracy of these objects [55].

In the coffee case, the optimal recognition point is in plants six months after planting. The analysis showed the inability to recognize plants at twelve months and the low accuracy in plants at three months. Plants differ best from soil and weeds within six months of planting. In addition, they still have separate crowns, contributing significantly to the well-developed algorithm performance.

4.3. Counting prototype performance

The tests carried out in commercial cultivation were satisfactory for identification and counting. They demonstrated the high potential of RPAs RGB images in automatic plant counting. The counting prototype's best results were observed in plants six months after planting, mainly influenced by plant uniformity. YOLO-based algorithms behave more assertively when applied to objects with well defined formats. This feature was also found in studies by Sozzi et al. [56], demonstrating that YOLO models effectively counted white grape clusters, highlighting a potential application in robotic platforms used and under development for application in viticulture.

The result presented in Figure 10 shows that some plants were not recognized. Despite the image's high spatial resolution, some errors can still be found. Evaluating weed detection in RGB images, Hasan et al. [51] explained that emerging technologies' use improves the accuracy and speed of automatic detection systems. As an example, spectral indices applications can improve performance.

Quality increase in the plant identification in RGB images without applying spectral treatments can be obtained by rigorous standardization in attributes such as luminosity, capture height, camera tilt angle, and crop type. Ahmad et al. [57] showed that before improving the image processing algorithm alone, one should alleviate the lighting effect and enhance image quality at acquisition time. According to Gu et al. [58], distance and the proper shooting angle are essential. This can affect the recognition effect to a certain extent, evidencing correct distances importance from the target. In commercial plantations, the identification failure is caused by unequal plant characteristics, such as tipping over at planting time, retarded growth, and attack by pests.

Even with the characteristics faced in a survey carried out in commercial cultivation, obtaining RGB images is considered a low cost. So, these images use, without complex treatment procedures, provide technicians and producers with the option of a new way of coffee tree monitoring.

5. Conclusion

An algorithm based on machine learning was developed for coffee plant automatic counting in remotely piloted aircraft RGB images. It presents 96.8% of accuracy in images without spectral treatment.

The analysis showed the best stage of development to carry out the detection was in plants six months after transplanting. They were attributed to leaf mass amount and the well defined shape of the plants at this stage. In this age, the plant crowns have not yet been mixed with other plants, contributing to the algorithm's good performance. Also, there is less confusion between coffee plants and weeds at this age. Plants of 12 month is not indicated for coffee plant detection automatic, as mixing between the coffee plants canopies influences the individual identification of plants in RGB images.

The results presented can contribute to software development for automatic plant counting and automatic location of coordinates in fault regions in coffee plantations.

Author Contributions: Conceptualization, L.S.S. and G.A e S.F.; methodology, G.H.R. dos S. and N.L.B.; software, G.H.R. dos S.; validation, G.H.R. dos S., L.S.S. and G.A e S.F. formal analysis, N.L.B., R de O.F.; investigation, L.S.S; resources, R de O.F.; data curation, L.S.S. and N.L.B.; writing—original draft preparation, L.S.S. G.H.R dos S.; writing—review and editing, L.S.S. and G.A e S.F.; visualization, R de O.F.; supervision, G.A e S.F.; project administration, G.A e S.F..; funding acquisition, G.A e S.F. and R de O.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Embrapa Café- Consórcio Pesquisa Café, project approved n◦ 234/2019, the National Council for Scientific and Technological Development (CNPq), the Coordination for the Improvement of Higher Education Personnel (CAPES).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors acknowledge the Embrapa Café Consórcio Pesquisa Café, the National Council for Scientific and Technological Development (CNPq), the Coordination for the Improvement of Higher Education Personnel (CAPES), the Federal University of Lavras (UFLA) and Bom Jardim Farm.

Conflicts of Interest: The authors declare no conflict of interest.

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CHAPTHER IV. RESIDUAL ASH MAPPING AND COFFEE PLANT DEVELOPMENT BASED ON MULTISPECTRAL RPA IMAGES

Paper to be submitted in Agronomy (ISSN 2073-4395)

Abstract: Coffee growing area renovation is carried out after cutting and burning previous plant materials; this practice deposits residual ash on the soil. The mapping of these residues can provide essential information on soil chemical element behaviour and their interference with coffee development. Thus, the research objective was to monitor the effects of burning plant residue by analysing the chemical elements present in ash, soil analysis and the application of vegetative indices obtained by RPA images. The samples were submitted to conventional soil analysis and atomic emission spectrometry (pure ash). The RPA multispectral images were used to form 31 vegetative indices. Thus, at the soil and ash collection points, the index performance was evaluated for six months and divided into three collection times. Then, the data were statistically analysed to evaluate which index best separated the plants in regions with and without ash in the soil. The pure ash deposits revealed an expressive presence of K, Ca, Mg and Al in addition to pH elevation. However, when analyzing soil elements, aluminum contents were high in the region without ash. In areas with ash, the high temperature at the burning time may have caused elemental chemical transformations in the Al composition, making this element unavailable in soil analysis. The vegetative indices showed a significant difference only in coffee four months after planting. Among the 31 evaluated indices, only 20 are satisfactory for ash analysis. The burning of plant residues promotes the neutralization of Al. In addition, ash deposits in the soil added some essential elements for plant development. Negatively, they raise the PH and make micronutrients unavailable. The best vegetative indices for ash monitoring were Normalized Near Infrared Index (NNIRI) and Normalized Green Index (NGI). In this way, previous ash mapping can contribute to variable application in elements such as K and limestone.

Keywords: precision agriculture, remote sensing, soil chemistry

1. Introduction

Coffee growing represents an essential source of income for many countries [1,2]. Applying techniques that make agricultural production more efficient is essential [3,4]. Technological advances in coffee cultivation have contributed to obtaining accurate and reliable measurements for crop monitoring [5]. This makes intelligent agricultural practices crucial for maximizing yields and conserving natural resources [6,7].

Emerging technologies such as Remotely Piloted Aircraft Systems (RPAs) substantially contribute to the significant development of agriculture [8–11]. The mapping of coffee growing areas by RPAs was applied to identify frost damage [12], determine biophysical parameters of coffee [7,13], and develop a method to detect coffee rust [14]. All of these papers proved the applicability of RPA technology in coffee growing areas, but none addressed ash in the soil and its effects on coffee plant development.

Precision coffee growing presents technological developments offering several monitoring possibilities. Applications of RPAs in coffee growing areas provide opportunities for mapping components present on the soil surface. The possibility of soil mapping by RPAs is evidenced in research on sustainable agriculture [15], soil monitoring for irrigation management [16], soil salinity [17], soil plant dynamics and the environment [18]. The advantage of remote sensing technologies is that they offer highly assertive monitoring possibilities [19].

In some cases, cutting, molding, and burning plant biomass are used to renovate coffee-growing areas. Biomasses are combustible organic materials containing carbon, hydrogen, oxygen, minerals and moisture [20]. Typically, woody materials, nonwoody agricultural waste, aquatic biomass, process waste, municipal solid waste, and animal and industrial waste are included [21]. Biomass combustion produces ash composed of elemental oxides, SiO2, CaO, and K2O, usually forming >60% ash from virgin biomass. Ashes from biomass-containing residues typically contain more Al2O3 and Fe2O3 than ash from virgin biomass [22]. The ashes can be used for soil fertilization in agriculture [23].

In coffee growing, one of the forms of management promotes ash deposits, which are formed by agricultural residues with a significant volume of biomass. Traditional techniques incorporate all these residues into the soil to contribute to plantation subsequent fertilization. Plant growth on agricultural waste is used in various crops [24]. In this management, crop residues are burned to renew the stand, forming visible areas of ash in the soil. Knowledge of techniques for efficiently using chemical elements deposited by burning biomass is essential to maximize environmentally safe alternatives and achieve sustainability. In addition, ash mapping can contribute to fertilizers' variable rate applications, aiming to take advantage of the chemical elements already deposited by the ash [25]. In the literature, few studies explore ash mapping in agriculture. In addition, the existing articles explore ash application from other sources. In coffee management, previous crop biomass is burned on the ground, which makes the study even more specific. Ash management is still little explored in coffee farming, as we did not find articles related to this study.

Given this premise, monitoring regions with ash deposits is essential to know which elements are present on the ground after biomass burning. Additionally, it is important to know which elements are identified in conventional soil analysis and their possible interference with plant development. Therefore, this study aimed to evaluate (I) the chemical elements present in ash and their correlation with vegetative development after planting; (II) the performance of vegetative indices applied to areas mapping with ash deposits; and (III) the temporal mapping of ash deposited after the renovation burning of coffee plantations by vegetative indices.

2. Material and methods

2.1. Study area

The study region comprises an area of 8 hectares intended for coffee cultivation (Figure 1). It is located in Santo Antônio do Amparo, Minas Gerais, Brazil, at the coordinates 21°00’55.55” S e 44°54’57.75” W. The regional climate is characterized as hot and temperate. The regional climate is warm and temperate, with annual average temperatures between 20 and 22 °C, yearly rainfall between 1300 and 1600 mm and altitudes between 800 and 1000 metres [26].

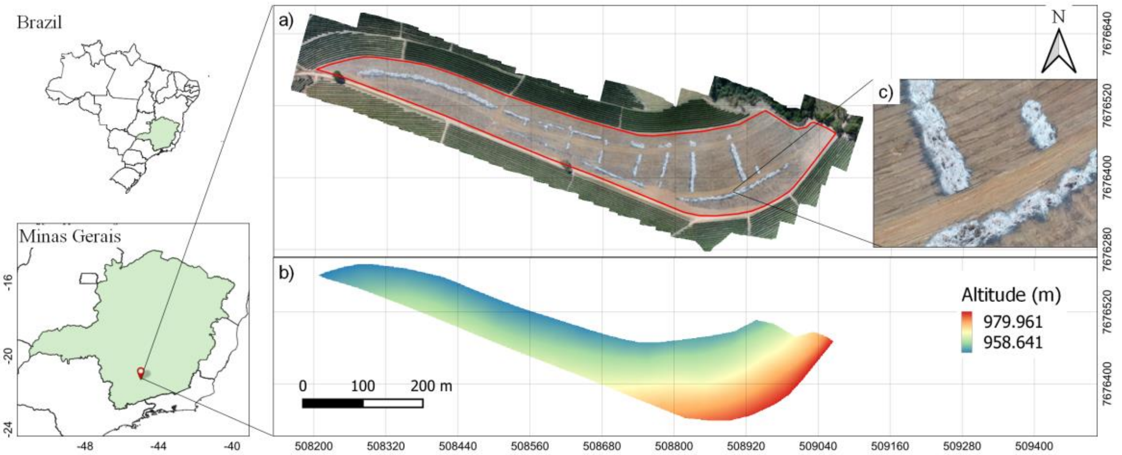

Figure 1. Study area. a) Study area boundary (red), b) Digital Terrain Model (DTM) and c) regions with ash deposits.

2.2. Field data collection

2.2.1. Soil chemical properties

Samples were taken in two distinct regions (natural soil and soil with ash present) at 0-0.20 m depth. The area was divided into three sampling blocks. Each block comprised six ash samples and six natural soil samples, totalling 36 samples (Figure 2).

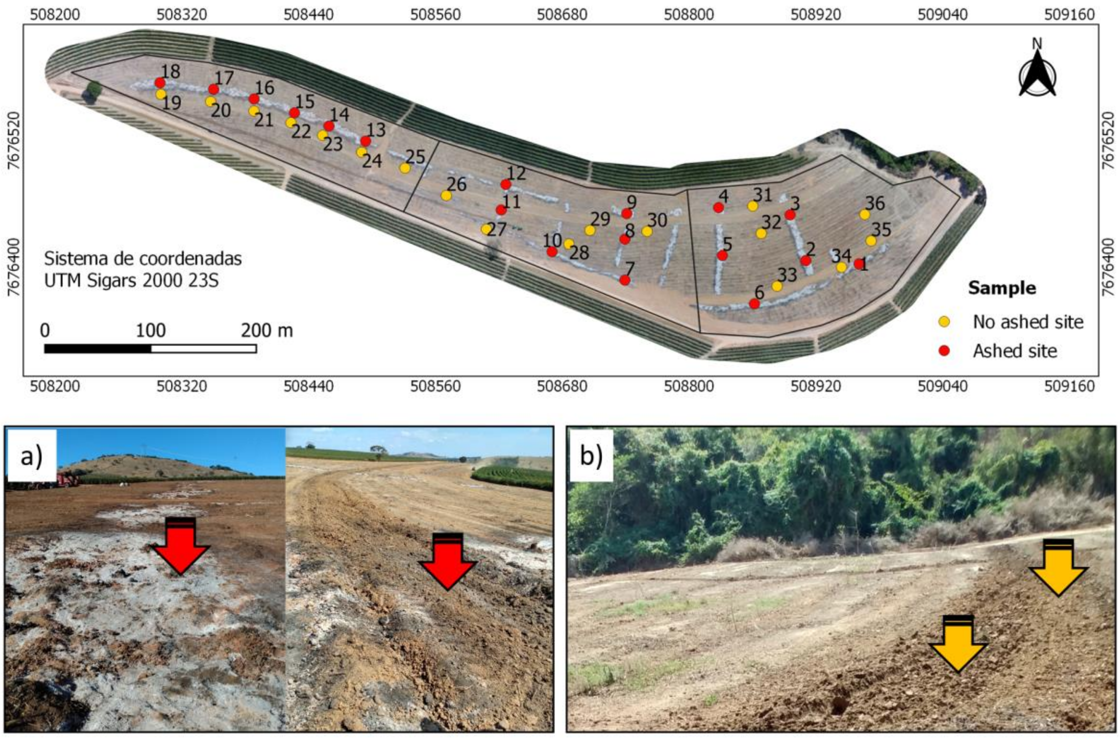

Figure 2. Sampling points map, a) collection of samples in regions with ash deposits and b) collection of samples in regions without ash.

The collected samples were sent to a soil analysis laboratory to determine P, K, Ca, Mg, Al, Ca, Mg, K, B, Zn, S and P, cation exchange capacity (CTC), soil pH, organic matter and base saturation. These results were subjected to statistical analysis to verify the degree of interference of ash deposits on soil nutrient availability.

2.2.2. Chemical analysis of ash

The ash was collected in the previously mapped locations. Two samples were collected, composed of six subsamples of pure ash, and then taken to the laboratory, where they were subjected to chemical analysis. After a multi-acid digestion process (hydrofluoric acid, perchloric acid, hydrochloric acid and nitric acid), the materials were analysed by inductively coupled plasma atomic emission spectrometry (ICP–OES). This analysis can quantify the presence of the following elements: Ag, Al, As, Ba, Be, Bi, Ca, Cd, Co, Cr, Cu, Fe, Ga, Gd, K, La, Li, Mg, Mn, Mo, Na, Ni, P, Pb, S, Sb, Sc, Se, Sn, Sr, Th, Tl, Ti, U, V, W, Y, and Zn.

2.3. Photogrammetric Data Collection

Photogrammetric data were collected at one, four and six months after planting coffee. The images were collected by a Matrice 100 Remotely Piloted Aircraft RPA (DJI, Shenzhen, China) (Figure 3a). A quadcopter weighing 2431 g and 600 mm in horizontal length, with a flight capacity of 20 minutes with 500 g payload and 2 km distance from the radio control was used. This RPA was equipped with a sequoia camera (Figure 3b). The collected images were used to determine the vegetative indices (VIs)

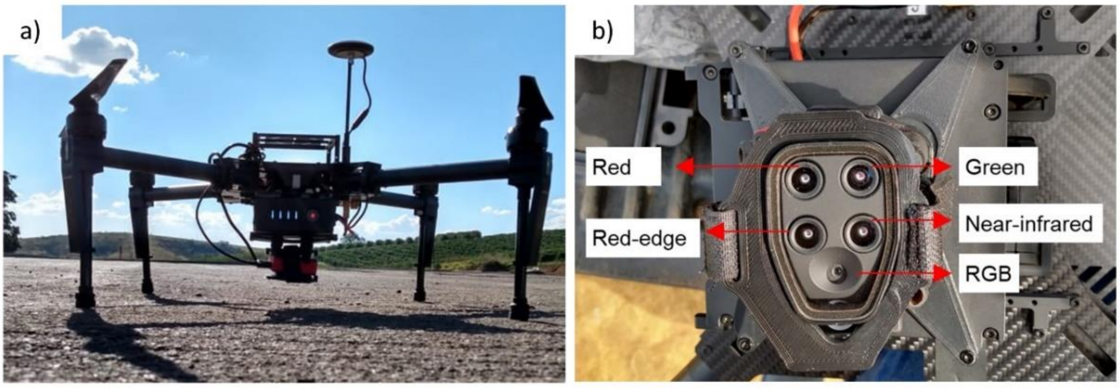

Figure 3. a) Remotely Piloted Aircraft DJI Matrice 100, b) Parrot Sequoia multispectral camera.

The Sequoia sensor (Figure 3b) had a high-resolution RGB camera with a 4608 × 3456-pixel sensor, 1.34 μm pixel size and 4.88 mm focal length; the ground sampling distance (GSD) was from 1.9 cm to 70 m above ground level (AGL). In addition, four monochromatic cameras were sensitive to the following spectral bands: green (G, 530–570 nm), red (R, 640–680 nm), red edge (RE, 730–740 nm), and near-infrared (NIR, 77-810 nm). These sensors featured a resolution of 1280 × 960 pixels, a pixel size of 3.75 μm and a focal length of 3.98 mm; the GSD was 6.8 cm at a 70 m flight height (AGL) [27].

Before starting the flights, safety factors were observed, highlighting weather conditions, wind speed, presence of objects, poles, trees and electrical transmission towers [10]. Flight planning was performed using Precision Flight software (Version 1.3.2, Precision Hawk, Raleigh, NC, USA). The input parameters were added considering better flight efficiency, reduced number of turns made by aircraft and adequate place for landing and take-off. Thus, the flight characteristics were 90 m (AGL), frontal and lateral overlap of the images 80x80% and flight speed of 6 m/s.

All flights were carried out between 10:00 am and 1:00 pm to reduce shading interference. In addition, the image capture was complemented by radiometric sensor calibration, achieved by accurately compensating for incident light conditions and generating quantitative data on a calibration (reference) plate to capture images according to variations in sunlight during flight.

2.4. Image processing

The collected images were processed in the software PIX4Dmapper version 4.4.12 (Pix4D, Lausanne, Switzerland). This software has an algorithm based on Structure-from-Motion (SfM). SfM approaches can be considered superior in accuracy when the user intends to generate orthomosaic and DTM [28,29]; in addition, they contain computer vision techniques that enable photogrammetry algorithms that achieve high-precision processing on aerial images [30].

The standard Pix4Dmapper "Ag Multispectral" model was used to generate the orthomosaics of individual spectral bands (green, red, red edge and near-infrared). The images were georeferenced using control points previously collected in the field area by a differential GNSS (Trimble Navigation Limited, Sunnyvale, California, USA) model SP 60 of spectrum precision with a vertical precision of 0.07 m to improve orthomosaic precision. After generating the orthomosaics, the vegetation indices were calculated in Pix4D and exported with the TIFF extension for further analysis.

2.5. Vegetation índices

Vegetation indices (VIs) are fundamental measurements in coffee plant vegetative development analysis [31,32]. Thirty-one vegetation indices (Table 1) were selected based on the database Index [33] to find the best index for mapping the ash. The vegetation indices associated with Parrot Sequoia camera spectral bands were considered. Then, the indices were calculated in images of coffee trees four, six and ten months after implantation.

Table 1. Vegetation indices of multispectral images obtained using RPA. A: Red Band; G: Green Band; NIR: Infrared band; RED: Red band

Index	Equation
Normalized Green Index (NGI)	$\mathrm{G}/(\mathrm{NIR}+\mathrm{RE}+\mathrm{G})$
Normalized Red Edge Index (NREI)	$\mathrm{RE}/(\mathrm{NIR}+\mathrm{RE}+\mathrm{G})$
Normalized Red Index (NRI)	$\mathrm{R}/(\mathrm{NIR}+\mathrm{RE}+\mathrm{R})$
Normalized NIR Index (NNIR)	$\mathrm{NIR}/(\mathrm{NIR}+\mathrm{RE}+\mathrm{G})$
Modified Double Difference Index (MDD)	$(\mathrm{NIR}-\mathrm{RE})-(\mathrm{RE}-\mathrm{G})$
Modified Normalized Difference Index (MNDI)	$\frac{(\mathrm{NIR}-\mathrm{RE})}{(\mathrm{NIR}-\mathrm{G})}$
Modified Enhanced Vegetation Index (MEVI)	$\frac{2.5*(\mathrm{NIR}-\mathrm{RE})}{(\mathrm{NIR}+6*\mathrm{RE}-7.5*\mathrm{G}+1)}$
Modified Normalized Difference Red Edge (MNDRE)	$\frac{[\mathrm{NIR}-(\mathrm{RE}-2*\mathrm{G})]}{[\mathrm{NIR}+(\mathrm{RE}-2*\mathrm{G})]}$
Normalized Difference Vegetation Index (NDVI)	$\frac{(\mathrm{NIR}-\mathrm{R})}{(\mathrm{NIR}+\mathrm{R})}$
Modified Red Edge Transformed Vegetation Index (MRETVI)	$1.44*((\mathrm{NIR}-\mathrm{R})-2.5*(\mathrm{RE}-\mathrm{R}))$

Index	Equation
Red Edge Ratio Vegetation Index (RERVI)	$\frac{\text{NIR}}{\text{RE}}$
Red Edge Difference Vegetation Index (REDVI)	$\text{NIR} - \text{RE}$
Red Edge Renormalized Different Vegetation Index (RERDVI)	$\frac{(\text{NIR} - \text{RE})}{\sqrt{\text{NIR} + \text{RE}}}$
Red Edge Wide Dynamic Range Vegetation Index (REWDRVI)	$\frac{(\text{a} * \text{NIR} - \text{RE})}{(\text{a} * \text{NIR} + \text{RE})}\ (\text{a} = 0.12)$
Red Edge Soil Adjusted Vegetation Index (RESAVI)	$1.5 * \left[\frac{(\text{NIR} - \text{RE})}{(\text{NIR} + \text{RE} + 0.5)}\right]$
Red Edge Optimal Soil Adjusted Vegetation Index (REOSAVI)	$(1 + 0.16)(\text{NIR} - \text{RE})/(\text{NIR} + \text{RE} + 0.16)$
Modified Red Edge Soil Adjusted Vegetation Index (MRESAVI)	$0.5 * [2 * \text{NIR} + 1 - \sqrt{(2 * \text{NIR} + 1)2 - 8 * (\text{NIR} - \text{RE})}\,]$
Optimized Red Edge Vegetation Index (REVIopt)	$100 * (\text{lnNIR} - \text{lnRE})$
Red Edge Chlorophyll Index (CIre)	$\text{NIR}/\text{RE} - 1$
Modified Red Edge Simple Ratio (MSR_RE)	$\frac{(\text{NIR}/\text{RE} - 1)}{\sqrt{(\text{NIR}/\text{RE} + 1)}}$
Red Edge Normalized Difference Vegetation Index (RENDVI)	$\frac{(\text{RE} - \text{R})}{(\text{RE} + \text{R})}$
Red Edge Simple Ratio (RESR)	RE/R
Modified Red Edge Difference Vegetation Index (MREDVI)	$\text{RE} - \text{R}$
DATT Index (DATT)	$(\text{NIR} - \text{RE})/(\text{NIR} - \text{R})$
Normalized Near Infrared Index (NNIRI)	$\text{NIR}/(\text{NIR} + \text{RE} + \text{R})$
Modified Transformed Chlorophyll Absorption In Reflectance Index (MTCARI)	$3 * [(\text{NIR} - \text{RE}) - 0.2 * (\text{NIR} - \text{R})\left(\frac{\text{NIR}}{\text{RE}}\right)$
Modified Red Edge Simple Ratio (MRESR)	$(\text{NIR} - \text{R})/(\text{RE} - \text{R})$
Modified Normalized Difference Red Edge (MNDRE2)	$\frac{(\text{NIR} - \text{RE} + 2 * \text{R})}{(\text{NIR} + \text{RE} - 2 * \text{R})}$
Red Edge Transformed Vegetation Index (RETVI)	$0.5 * [120 * (\text{NIR} - \text{R}) - 200 * (\text{RE} - \text{R})]$
NDVI (normalized difference vegetation index)	$\frac{(\text{NIR} - \text{R})}{(\text{NIR} + \text{R})}$
MTCI (terrestrial chlorophyll index)	$\frac{\text{NIR} - \text{RE}}{\text{RE} + \text{R}}$
Nnormalized difference red edge (NDRE)	$\frac{\text{NIR} - \text{RE}}{\text{NIR} + \text{RE}}$

Vegetation indices were processed in Rstudio and QGIS software to understand plant development in regions with ash deposits and in naturally cultivated soils. The index images were cut and separated into areas with ash (Ash–on) and areas without ash (Ash-off) to understand ash's direct effect on plants. Then, seven samples were collected in the vegetative indices at the same soil collection points by a 0.25 m buffer in each plant, totalling 126 samples for each variable. Thus, 31 index values evaluated for each identified region were obtained.

2.6. Statistical analysis

Soil analysis data were statistically analysed and expressed as an average in each treatment to indicate ash effects on the soil. In this analysis, SISVAR 5.6 software was used. Then, data normality was verified before starting the exploratory analysis (descriptive statistics). A "one-way" analysis of variance (ANOVA) was performed after normality verification. The F test was used, followed by the mean test (Tukey with 5% error probability). This proportional analysis statistically verifies the interference of ash on soil nutrients by conventional samples.

. The vegetative indices were evaluated by applying means tests to verify significant differences between plants located inside (Ash-on) and outside (Ash-off) the ash areas. For this, the Anderson–Darling test initially verified data normality [34]. Thus, for data with normal distribution, multiple comparisons T-test was applied at 5% ($p < 0.05$) of probability and for data without normal distribution, multiple comparisons Wilcoxon test at 5% ($p < 0.05$) was applied probability. All procedures were performed using RStudio software (R Development Core Team, R project, New Zealand).

Crossing information from soil samples and mapping by RPAs can generate confusion in reproducing methods; therefore, the methodological steps are presented in Figure 4.

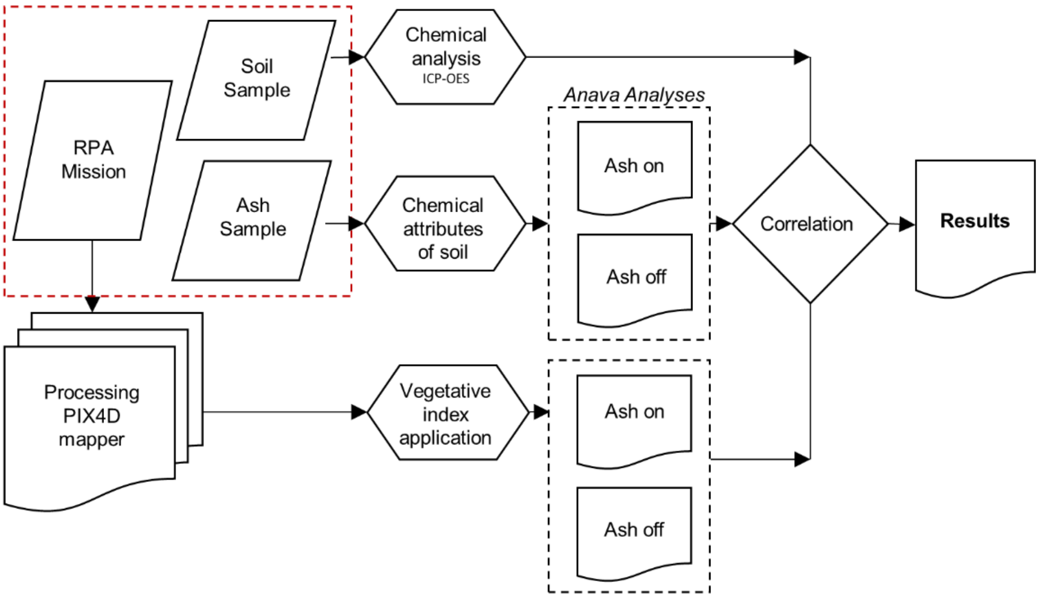

Figure 4. Flowchart for carrying out ash influences analysis on coffee trees

The best indices were selected after statistical analysis. The criterion adopted was the index that presented significant differences in the mean tests. Then, a Pearson correction was applied to the data with and without ash, so the lowest correlations corresponded to the best vegetative indices.

3. Results and discussions

3.1. Ash analysis

Pure ash analyses were essential to determine which nutrients were deposited on the soil after the plant remains burning from the previous crop. Table 2 presents the inductively coupled plasma atomic emission spectrometry (ICP–OES) analysis results. Although the analysis results provide 41 chemical elements, the table shows quantitative results above the lower detection limit.

Table 2. Chemical elements present in pure ash by elemental analysis (ICP-OES)

Analyte	**Al**	**Ca**	**Cr**	**Cu**	**Fe**	**K**	**Mg**	**Mn**	**Na**	**Ni**	**S**	**Ti**	**Zn**
Unity	%	%	ppm	%	%	%	%	%	%	ppm	%	%	%
Amount	2.48	13.71	28	0.037	0.99	11.32	2.85	0.08	0.01	13	0,09	0,08	0.011

The elements found in ash agree with research already in the literature, evidencing the notable presence of K, Mg, Ca and Al. Pandey and Singh [35] demonstrated the potential of nutrient incorporation in arable soils by showing a high presence of K and Mg.

Ash deposits on the ground can also provide an unwanted element for cultivation, aluminium (Al) addition. As shown in Table 2, ash was composed of 2.48% Al. Aluminium is known to restrict root growth, making plants inefficient at absorbing nutrients and water. In addition, it can inhibit the microbial processes involved in the soil–plant relationship [36]. The aluminium toxicity level interferes with the availability, absorption, transport, and utilization of essential nutrients such as phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), Fe, molybdenum (Mo) and boron (B) [37].

Soil chemical changes caused by ash on the surface can be confirmed in conventional soil chemical analyses. This is a point of fundamental importance, as this analysis generates essential information for recommendations on fertilization, liming and other forms of soil management. In this research, it is possible to observe that pure ash's chemical elements can change the soil chemical composition.

3.2. Soil analysis

Ash's effect on changes in the percentage of soil nutrients is presented in average values, according to Tukey's tests (Figure 5).

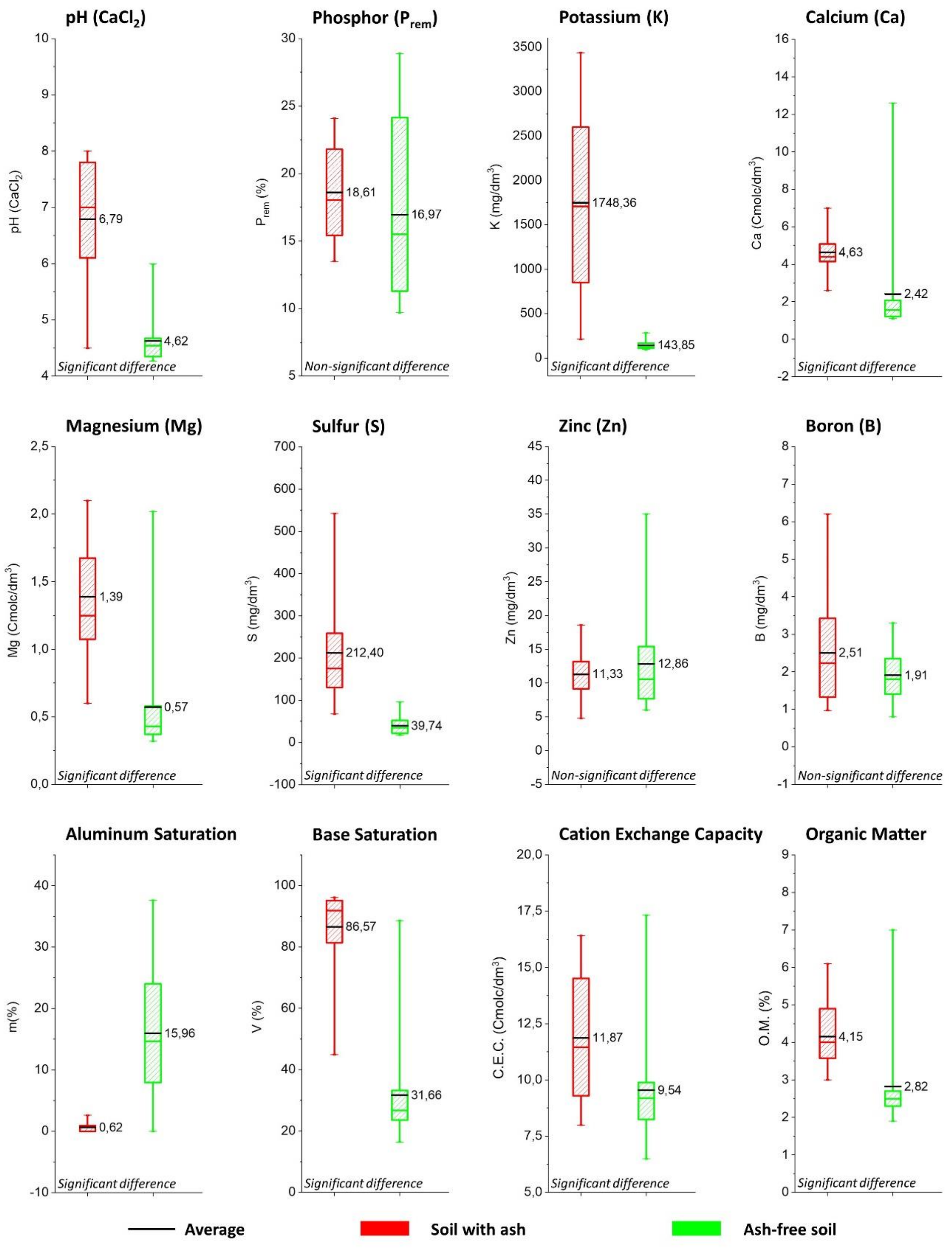

Figure 5. Results analysis of average tests of soil chemical attributes, obtained by Tukey test at 5% error.

The information presented in Figure 5 shows significant differences between some important elements for plant development. In addition, the parameters obtained can be used for fertilization recommendations in coffee-growing management. A fact to be highlighted in the soil analysis is Al value inversion. In this analysis, the most significant presence of aluminium is in areas without ash. One hypothesis for this occurrence is high-temperature action in soil, modifying aluminium $Al2(OH)3$ to $Al2O3$. According to Certini [38], fire causes changes in soil properties along a thermal gradient. Temperatures above 400 °C cause mineral transformation compounds such as Al and Fe oxyhydroxides, and approximately 600 °C thermal fusion of clay minerals can occur. Thus, the aluminium found in pure ash (Table 2) is probably in the $Al2O3$ form since the burning process causes the aluminium to reach its maximum oxidation form. $Al2O3$ is a form of aluminium that does not harm plant development.

Some authors, such as [39–41], show the application of ash as promising for improvements in crop conditions. These studies mention the use of ash in agricultural areas, but they have applied industrial ash from different burning processes. Biomass burning in the field can promote unexpected results for variations in chemical and physical parameters in the soil [42]. This occurrence may have affected the soil in the regions where the coffee biomass was burned.

The soil pH presented a significant difference (Figure 5); pH is a primary soil variable since it influences biological, chemical and physical processes, affecting plant growth and biomass production [43]. Ash application is described in the literature as a way to increase the pH and deposition of macronutrients, such as K, Mg and Ca [44]. Similar results are shown in Figure 5, highlighting greater variations for the K element; this occurrence is due to the organic matter of coffee residues containing N and K in their natural composition [45]. According to Nolasco et al. [46], ash has a beneficial effect as a base fertilization and, mainly, as a cover. As a result of its chemical composition of slow solubilization of macro- and micronutrients, it can be compared to an NPK formula with a ratio of 1:3:7 plus Ca, Mg and micronutrients.

Some coffee farms, burning plant biomass is used for renewal of cultivation. This practice provides essential nutrients for plant development, but how ash is distributed in the field can cause excess or deficiency of some nutrients. Figure 6 shows the coffee plant's characteristics in regions with ash deposits. This imbalance may have occurred because the heaped for burning accumulated at specific points in the field, depositing a significant amount of nutrients such as K, Ca and Mg (Figure 5).

Figure 6. Coffee plants four months after planting in regions with ash deposits.

As shown in Figure 6, coffee plants are affected by nutrient imbalances. Moyin-Jesu et al. [47] explained that high K/Ca and K/Mg ratios present in the soil before fertilization influence treatment with NPK fertilization. This leads to an imbalance in the nutrient supply of K, Ca, and Mg to the coffee crop. For better use of these nutrients by plants, precision coffee growing techniques are necessary. The postburn areas have been treated as homogeneous in conventional coffee growing area management. Figure 5 shows the differences between the Ash-on and Ash-off areas, especially with pH, K, Ca, Mg, and Al. Therefore, knowledge about the presence of nutrients in Ash deposits after burning and inferences about significant differences in coffee plantations can be explored in precision coffee growing techniques.

3.3. Vegetative indices analysis

Vegetative index application demonstrates class variations over time. Vegetative indices were applied at three development dates, but significant differences were observed only four months after coffee planting. The means tests applied for the first and sixth months after planting did not present significant results. In these stages of plant development, the indices do not differentiate plants in regions inside and outside the ash deposits. Therefore, vegetation index studies for plants inside and outside the ash area are presented only for plants four months after planting. The results are via boxplots with statistically significant differentiation by mean tests (Figure 7). Among the 31 indices tested for ash monitoring, only 20 showed significant differences according to the means test.

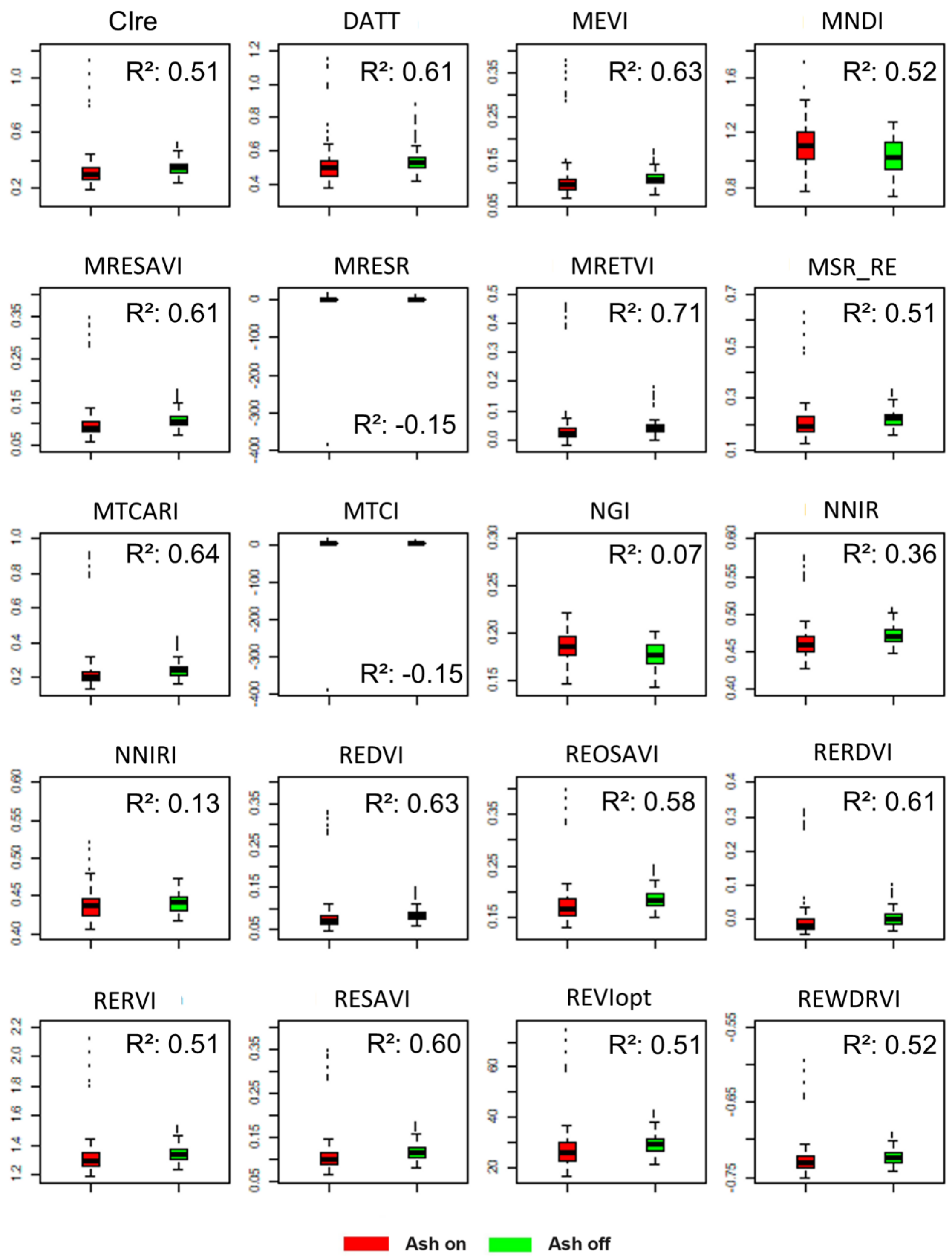

Figure 7. Vegetation indices with significant differences and Pearson R^2 correlation between areas with and without ash in coffee plants within four months of planting.

In coffee plantations, high plant similarity in the initial development makes it impossible to identify some anomalies. In this way, the evaluation of the first month can be understood, as the index finds it challenging to differentiate plants in ash regions. In the initial stage of development, the plant is in a transition phase; in some cases, it still uses nutrients present in the substrate [48]. Difficulties in evaluating the early stages of coffee plants were also evidenced in studies by Bento who [26] applied vegetative indices to differentiate the development of cultivars after planting. The authors demonstrated low-density interference leaves for vegetative index performance in the first months after planting.

The analysis presented in Figure 7 demonstrates that vegetative indices with low correlations between Ash-on and Ash-off areas can be considered the best ones to differentiate these areas. As shown in Figure 7, the normalized near infrared index (NNIRI) and normalized green index (NGI) present the best R^2 results: 0.13 and 0.07, respectively. NGI index application was demonstrated in the research by Garba et al. [49], evidencing the ability to differentiate pasture growth at different stages. Green band presence in the NGI and NNIRI indices points to changes in chlorophyll; according to Gitelson et al. [50], bands selected in GREEN, RED and RE, presented chlorophyll absorption features that can be used to determine the content of leaf chlorophyll with the modified chlorophyll absorption reflectance index. Analysing Figure 6, it is possible to observe that changes in leaf colour in regions with ash deposits correlate with better vegetative index performance using the green band.

The performance of the 20 vegetative indices presented fair values for monitoring plants in ash areas. However, the limitation of some VIs is related to the proximity between the average values obtained at the sampling points, which makes it challenging to map the effect of ash on plant development. Despite providing nutrients to the plants, the ash deposits present an uneven distribution, even within the contoured area. In addition, at some sampling points, nutrients may have been lost through leaching and surface transport. The best way to take advantage of these nutrients is to incorporate them into the soil after burning.

The uneven distribution of ash in the field interferes with the performance of vegetative indices. Additionally, it interferes with the spectral response, reducing the efficiency of vegetative indices created by multispectral images. Plant development characteristics may also have contributed to the low performance of some indices. Notably, the analysed plants' ages may have influenced the correct performance of the vegetative indices. Sivanpillai and Booth [51] showed that a low amount of biomass drives similar spectral responses, impairing, in some cases, the analysis by vegetative indices.

The best vegetative index identification for ash monitoring offers the opportunity to carry out mapping throughout the study area. In Figure 8, the vegetative indices NGI and NNIRI were applied for monitoring four months after the coffee plantation. Figure 8a shows the mapping using RGB images before culture installation. The RGB mapping highlights the importance of mapping soon after the biomass is burned because, over time, the ash disappears from the surface, making it difficult to locate regions with ash.

Figures 8 b) and c) show the best indices for ash monitoring among the 31 initially selected. In applying the indices to the total area, it is observed that some points were harmed, explained mainly by the surface runoff, causing ash accumulation and an increase in index values.

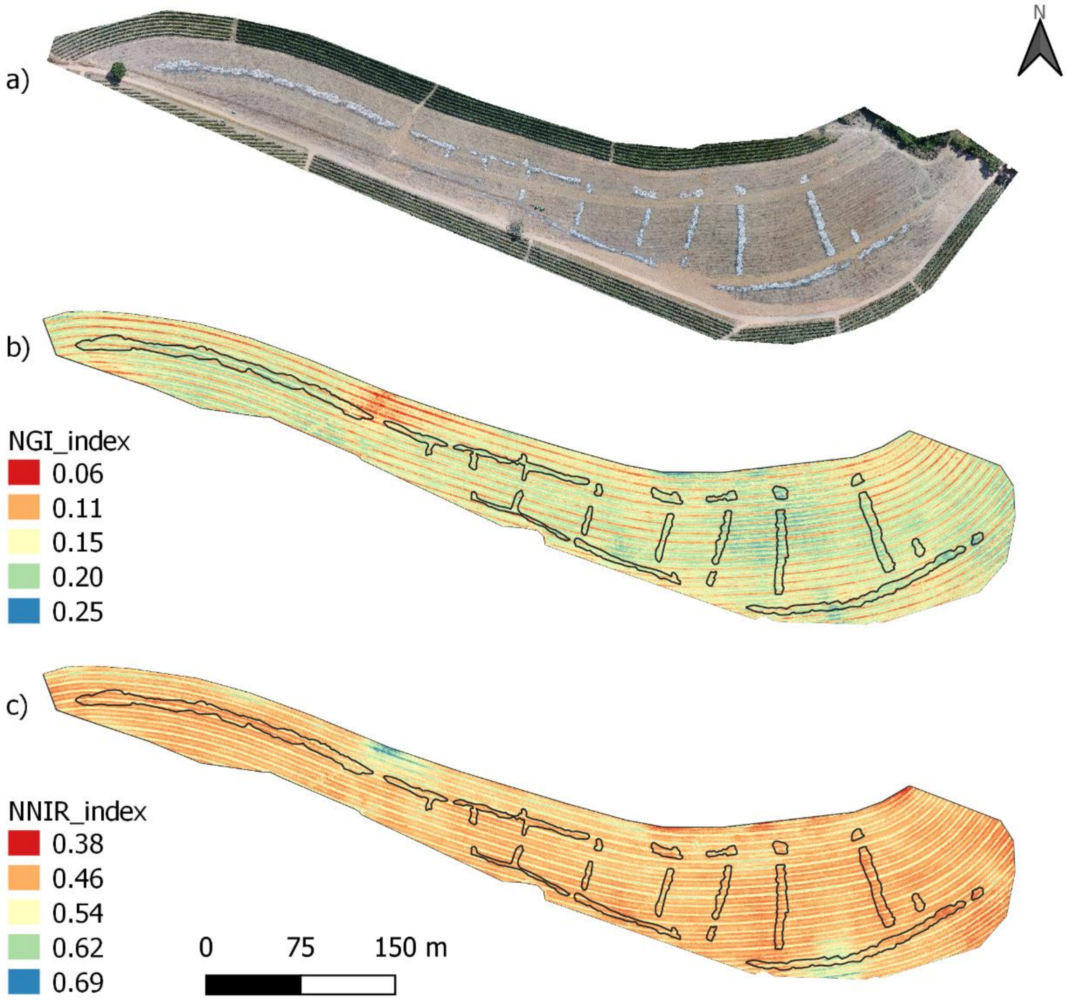

Figure 8. Monitoring by NGI and NNIRI index in coffee plants with four months of planting: a) Ash location (RGB), b) NGI index and c) NNIRI index.

Evaluation assertiveness by indices was positive only in the third month after planting. This was probably due to nutrient vulnerability losses soon after burning since they were not incorporated into the soil. Nutrient-deposited vulnerability by ash on the surface is intensified by natural variables such as precipitation, wind and soil. Over time, the disappearance of points affected by ash can be influenced by rainfall, causing a leaching effect, carrying some nutrients and mixing with the soil. Thomaz et al. [52] reported ash's temporal effect on the soil and indicated that K is rapidly transferred from the ash to the soil after repeated rainfall. In contrast, ash with Mg content is gradually leached into the soil, while Ca and P are leached even more slowly.

4. Conclusions

Plant residue burning in the field promoted the modification of Al present in the soil; then, the ash deposits on the soil raised the pH and added essential elements for plant development, such as K, Mg and Ca.

The best indices for mapping plants in Ash regions were the Normalized NIR Index (NNIRI) and Normalized Green Index (NGI) for plants four months after planting. The performance of these indices indicates that the monitoring of areas with ash should be guided in monitoring variations in chlorophyll.

Previous ash mapping can contribute to the realization of variable application in elements such as K and limestone. Vegetative indices can only be applied after four months of coffee development.

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CHAPTER V. FINAL CONSIDERATIONS

In the last decade, precision coffee growing has expanded significantly. The review article evidenced several techniques involving the application of remotely piloted aircraft and machine learning in coffee growing. In this technological progress, the research carried out in Brazil stands out, producing fundamental articles for future precision coffee farming applications.

A fundamental application for opening new uses of RPAs in coffee farming was evidenced in tests for planting alignment projects application. It was demonstrated in this research ways to efficiently obtain the contours through Digital Terrain Models (DTM) formed by RPAs. Thus, technicians and producers could insert the best settings and processing for DTM generation into the topographic survey with RPAs. This data contributes to quick data acquisition with efficient information for the planting alignment project.

In coffee growing, producers face difficulty knowing the real plants' number in a field. Traditionally, plants are identified manually, requiring the worker's time. For this problem, an algorithm for coffee tree automatic counting in images obtained by RPA was developed in this thesis. This is an unprecedented paper for the coffee growing, whose results were promising for software assembly or applications aimed at producers and technicians.

In coffee growing renewal, some producers use cutting and burning biomass, which deposits ashes on the surface, harming the plantation's subsequent development. The ash was mapped using vegetation indices and soil samples; this analysis demonstrated vegetation indices' potential for monitoring the ash on the soil in coffee cultivation. In addition, some indications about nutrients deposited by ash.

Precision coffee growing expansion has become a target of several studies, which are applied at all management stages. The research presented was carried out from observations in the field and the need for technological applications at specific points. Therefore, research complementation is important, considering other variables not addressed in the studies presented.

Finally, this research demonstrated different applications of images obtained by RPAs and their practical applications in coffee plantations. Therefore, it is expected that the union between science and practice, which this work has brought, can generate benefits for coffee growers, the environment and society.