AgriEngineering

Article

Coffee Growing with Remotely Piloted Aircraft System: Bibliometric Review

Nicole Lopes Bento [1], Gabriel Araújo e Silva Ferraz [1,*], Lucas Santos Santana [2] and Mirian de Lourdes Oliveira e Silva [1]

[1] Department of Agricultural Engineering, School of Engineering, Federal University of Lavras—UFLA, Trevo Rotatório Professor Edmir Sá Santos s/n, P.O. Box 3037, Lavras 37200-900, Brazil; nicolelbento@gmail.com (N.L.B.); olivemiri@gmail.com (M.d.L.O.e.S.)

[2] Department of Agricultural and Environmental Engineering (EEA), Institute of Agricultural Sciences (ICA), Federal University of Vales Jequitinhonha and Mucuri—Campus Unaí, Avenida Universitária, nº 1.000, B. Universitários, Unai 38610-000, Brazil; lucas.unemat@hotmail.com

* Correspondence: gabriel.ferraz@ufla.br

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

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

Citation: Bento, N.L.; Ferraz, G.A.e.S.; Santana, L.S.; Silva, M.d.L.O.e. Coffee Growing with Remotely Piloted Aircraft System: Bibliometric Review. *AgriEngineering* **2023**, *5*, 2458–2477. https://doi.org/10.3390/agriengineering5040151

Received: 9 October 2023
Revised: 12 December 2023
Accepted: 12 December 2023
Published: 15 December 2023

1. Introduction

Considered a commodity of significant relevance worldwide, coffee farming is practiced on a large scale across five continents [1]. Amidst the essential global commodities, coffee farming holds a prominent position, contributing to the global economic balance with an estimated total production of 55 million 60 kg bags for the year 2023 [2]. Coffee is the third most consumed beverage globally, following water and tea. Consequently, the demand for coffee beans is present in every corner of the world, making it a critical global commodity [1]. In addition to its use for consumption, coffee fruits have direct applications in extracting caffeine used in cola beverages, mixed drinks, biostimulant products, pharmaceuticals, and cosmetics, further enhancing its prominence among global agricultural products [3].

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

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

Research on RPA approaches in coffee farming is becoming increasingly prevalent, relevant, and essential for developing coffee farming, especially regarding timely and efficient agricultural monitoring. Therefore, it is necessary to analyze the existing literature and reveal the intellectual structure of the subject, that is, the organization and arrangement of academic works that deal with this subject of study. As a high-technology and multidisciplinary field, understanding the current scenario and temporal development of scientific studies on this topic is crucial to comprehend the complexity of publications and potential research gaps [13]. In this regard, bibliometric analysis allows the examination of different authors' research trends, perspectives, and contributions by evaluating the scientific literature on the development of RPA utilization in precision coffee farming. It is worth noting that bibliometric reviews in agriculture are recent but are proving to be effective in synthesizing knowledge and indicating priorities for future research [14].

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

2. Methodology

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

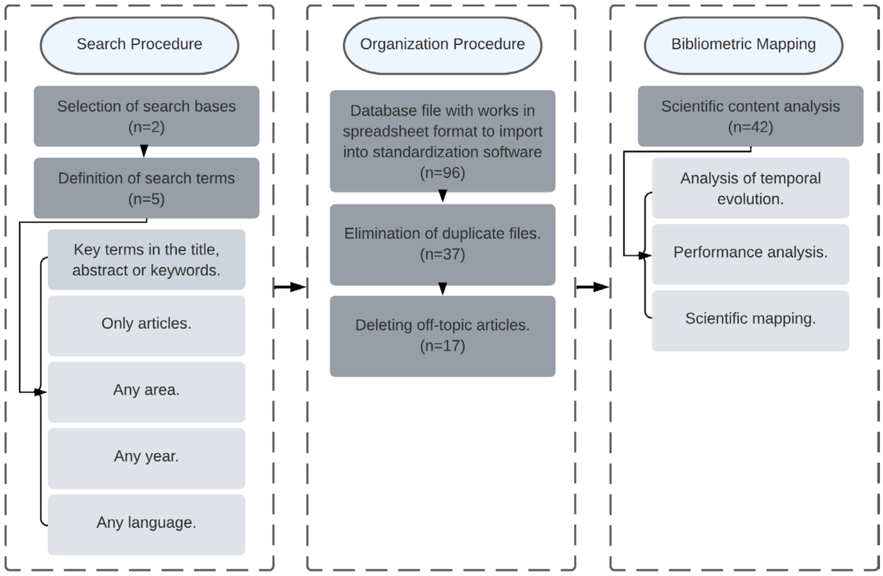

Figure 1. Systematization of processes for bibliometric analysis.

2.1. Search Procedure

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

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

All relevant publications were gathered and stored by applying the search strings as indicated above. The initial search yielded 42 documents in the Web of Science database and 54 in the Scopus database. The complete bibliographic data were exported in BibTeX (.bib) format for operational purposes.

2.2. Organization Procedure

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

2.3. Bibliometric Mapping

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

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

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

3. Results and Discussion

3.1. Temporal Evolution of Research and Characteristics of the Studies

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

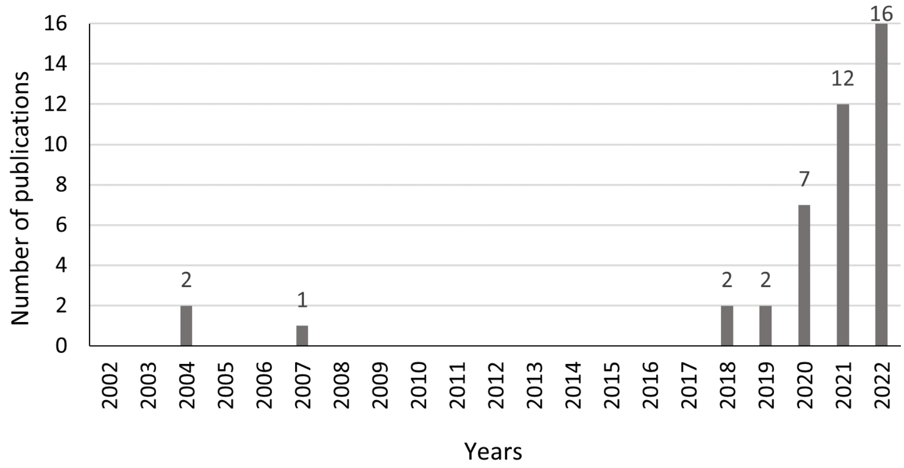

Figure 2. Evolution of research publications on RPASs in coffee growing from 2002 to 2022.

This research topic is recent, evidenced primarily by the popularization and increased access to RPAS technology and the applicability of timely and efficient agricultural imaging. Figure 2 shows that 2004 can be considered the precursor of scientific research on using RPASs in coffee farming, with two studies being presented. The first scientific research was described in 2004 by Herwitz et al. [24], demonstrating the economic potential of RPASs as platforms equipped with real-time high-resolution imaging systems and attesting to the efficiency of aerial remote sensing for agricultural monitoring with suborbital imaging applications in defining productivity zones. Herwitz et al. [24] performed imaging using a solar-powered aircraft in a coffee plantation in Hawaii, carrying multispectral sensors. The study concluded that the images helped to map invasive weed outbreaks, reveal irrigation and fertilization anomalies, and relate them to harvesting ripe fruits.

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

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

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

In 2018, studies on this topic regained focus, with Oliveira et al. [28] employing RPASs in precision agriculture as a potential tool for analyzing critical parameters in cultivation, explicitly mentioning the detection of planting failures in coffee plantations. The approach proposed by these authors involved using mathematical morphology operators to detect failures in planted areas. By doing so, they could observe both the individual positions of the losses and the total length of the failure, facilitating decision making for future actions. The same year, Soares et al. [29] addressed the problem of identifying planting rows in coffee cultivation fields using aerial images obtained by an RPAS. They applied a tiling scheme that allowed for an acceptable approximation of the lines within each tile for straight lines, making it feasible to use the Hough transform. Experimental results compared with ground truth data indicated that the proposed approach successfully approximated the plantation rows. The main contribution of this work was the proposal of a procedure for extracting line segments of plantations from aerial images.

In 2019, the study conducted by Cunha et al. [30] aimed to develop a method for determining the vegetation volume in coffee plantations using digital images obtained by an RPAS and comparing it with the traditional estimation of vegetation volume (tree row volume method), showing no significant differences. The digital image technique was highlighted as being faster and applicable to large areas. Another study by Santos et al. [31] aimed to overcome one of the limitations of photogrammetry by evaluating geometric errors by applying four sets of georeferenced points in a coffee-growing area. They concluded that the lower study overlap (70% $\times$ 60%) could be recommended for use in the flight plan due to the high resolution of the orthomosaic and the shorter processing time.

In 2020, seven studies on the research topic were published. Dos Santos et al. [32] aimed to evaluate the accuracy of photogrammetry using point clouds for estimating the height and crown diameter of coffee trees from aerial images obtained by an RPAS with a visible RGB (red, green, blue) sensor. They also compared the results with in situ measurements taken over 12 months, obtaining a correlation of 87% for height and 95% for diameter values. Oré et al. [33] presented a new methodology for obtaining growth deficit maps with an accuracy of up to 5 cm and a spatial resolution of 1 m, using Differential Synthetic Aperture Radar Interferometry (DInSAR). Wei et al. [34] combined a binarization algorithm with a convolutional neural network (CNN) model to improve the accuracy of coffee flower identification using digital images, highlighting the ability of the proposed method to enhance the precision of coffee flower classification.

In the same year, Parreiras et al. [35] conducted a study to assess the potential of visible vegetation indices obtained from RPAS-collected images for monitoring the spatial variability of leaf nitrogen content in a coffee farm. However, the models could not explain the variability, and no significant correlation was found between the variables, indicating the need to replicate the study during the vegetative phase of coffee plants. Santos et al. [36] aimed to develop a methodology for determining short-term crop coefficients (Kc) using biophysical parameters from RPAS-detected images of coffee plants. They extracted information from aerial images to calculate biophysical parameters such as leaf area index (LAI), leaf area (LA), and Kc, demonstrating the applicability of the developed methodology for indirect estimation of Kc. Dos Santos et al. [37] monitored the evolution of LAI and land cover percentage in coffee plants using pre-established equations and plant measurements obtained from point clouds combined with applying the structure from motion algorithm to digital images obtained by a sensor attached to an RPAS. This allowed for the temporal and spatial analysis of the variables, leading to the conclusion that the methodology generated consistent results with the literature. Velásquez et al. [38] proposed a diagnostic model for the stage of coffee rust development through the technological integration of remote sensing using multispectral sensors carried by RPAS, wireless sensor networks (multisensor approach), and deep learning (DL) techniques. The results demonstrated that both methods were significantly similar in diagnosing the disease.

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

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

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

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

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

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

Bento et al. [54] characterized three newly planted coffee cultivars and concluded that the seasons of the year influenced the behavior and development of the cultivars. They detected statistically significant differences for the study variables, except for chlorophyll. In a study proposed by Rosas et al. [55], vegetation indices could discriminate between coffee fruit ripening classes (unripe and ripe for harvest) in most plantations, with performance directly influenced by crop yield and canopy volume. Bento et al. [56] found that the correlation of yield and productivity prediction estimates by applying vegetation indices optimizes the time spent on field measurements using RPASs. They also highlighted that leaf drop due to harvesting impacts the productivity of the following harvest.

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

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

Another notable observation is the increasing use of artificial intelligence in data analysis in recent years, indicating that this may be a trend in future works, as data collection by RPASs generates an extensive database and opens possibilities for various types of analysis. Brazilian institutions have played a significant role in developing research in this field in recent years, mainly due to the active participation of coffee farming in the Brazilian economy, highlighting the importance of applying new techniques and technologies that optimize agricultural activities. These studies systematically focus on using sub-orbital remote sensing to monitor characteristics that affect coffee production while emphasizing time optimization in the field and intelligent, timely, and effective decision making.

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

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

Table 1. Thematic coding and articles that address them based on research development in RPASs in coffee growing from 2002 to 2022.

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

3.2. Performance Analysis

3.2.1. Key Publications

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

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

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

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

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

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

The following works in the list of top citations are more recent, from 2020. Velásquez et al. [38] developed a study on coffee leaf rust through the technological integration of remote sensing, using multispectral cameras in RPASs, wireless sensor networks, and deep learning techniques. This allows coffee farmers to automatically detect the disease, optimizing the production and maintenance of their plantations and replacing the task of manual inspection. Meanwhile, Oré et al. [33] proposed a new method to estimate the growth of first-stage crops based on experimental data and multiple circular flight surveys with RPASs using Differential Synthetic Aperture Radar Interferometry (DInSAR). This method is efficient as the growth rates analyzed are difficult to perceive visually or measure with conventional tools. In the fifth most cited work by Santos et al. [32], the authors used an RPAS for aerial imaging in coffee plantations to extract reliable vegetation indices and biophysical parameters derived from the structure from motion (SfM) algorithm. They estimated the height (h) and crown diameter (d) of coffee trees from RGB (red, green, blue) aerial images, comparing them to field truth collected over 12 months.

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

3.2.2. Main Journals

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

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

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

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

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

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

3.2.3. Main Researchers

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

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

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

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

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

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

3.2.4. Main Institutions

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

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

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

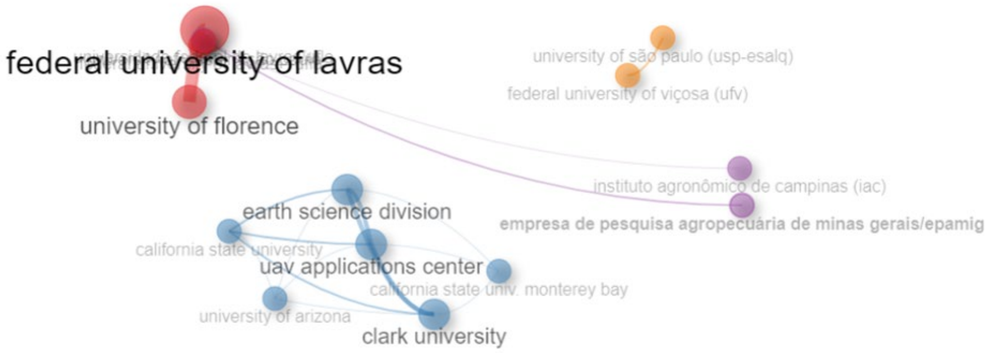

Figure 3. Scientific mapping network of teaching and/or research organizations that produce knowledge on RPASs in coffee growing. Red: The central institution was the Federal University of Lavras (UFLA) and direct partnership with the University of Florence. Blue: Proximity between institutions in the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

3.2.5. Main Countries

The central countries that produce scientific knowledge on RPASs in coffee farming were identified, as shown in Figure 4. Brazil stands out as the country with the most significant contribution to the development of the topic worldwide, with 31 notable publications on the subject, mainly due to the predominance of Brazilian researchers in the top positions of the publication ranking, solidifying the country's prominence.

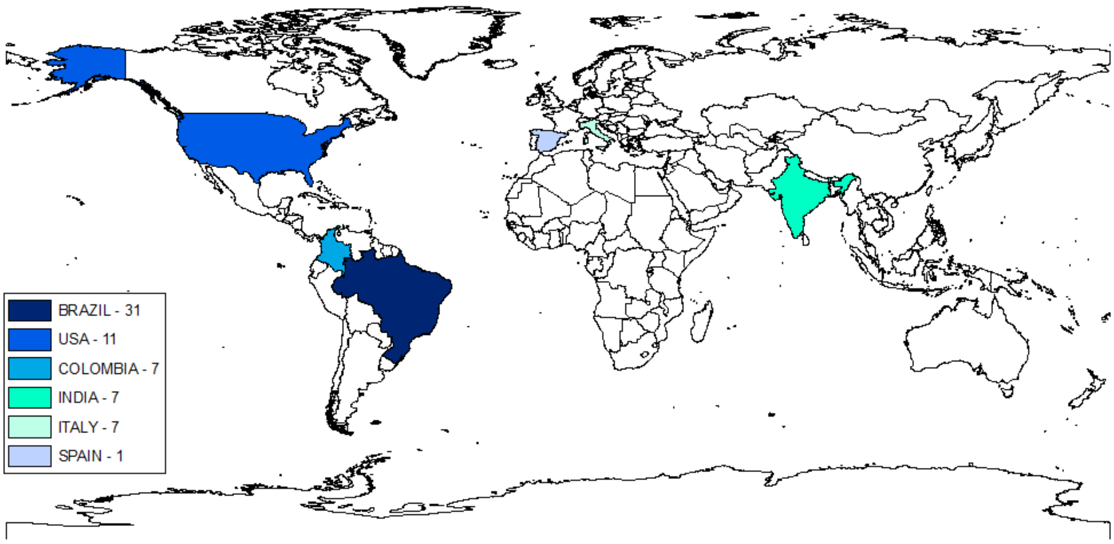

Figure 4. Central countries with research development on RPASs in coffee growing by number of publications from 2002 to 2022.

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

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

The United States, on the other hand, contributes to publications on the topic due to the significant number of agricultural science education and research institutions and its direct partnerships with various institutions. Although the country is not prominent in global coffee production, collaborations between American institutions and other institutions promote studies related to this topic, a fact that justifies its wide participation in the number of scientific studies developed. One of the few American states with a tropical climate, Hawaii is responsible for almost all the country's coffee production and, notably, the pioneering studies conducted by Herwitz et al. [24] and Johnson et al. [25] were developed in Hawaii.

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

3.3. Scientific Mapping

3.3.1. Co-Citation Mapping

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

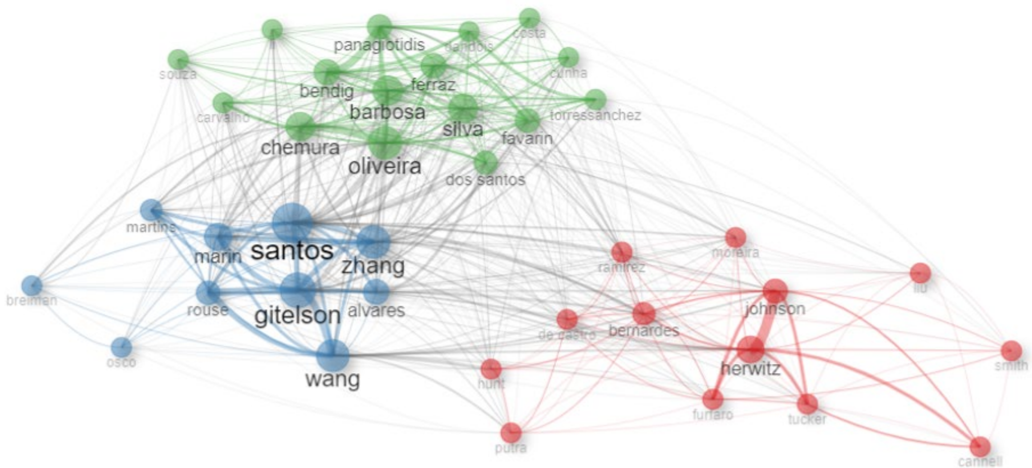

Figure 5. Scientific mapping of the co-citation of the most relevant research authors on RPASs in coffee growing.

As a result, three clusters were generated based on the studies' similarity and intellectual structure. In general, the red cluster houses authors with pioneering studies on the use of RPASs in coffee farming, including Herwitz, Johnson, and Furfaro. The blue cluster encompasses authors with reflections on vegetation indices, diseases, and crop yield in the field, including Santos, Gitelson, and Zhang. The green cluster includes authors with works focused on using RPASs for agricultural estimation and monitoring, including Oliveira, Barbosa, Chemura, and Ferraz.

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

3.3.2. Keyword Mapping

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

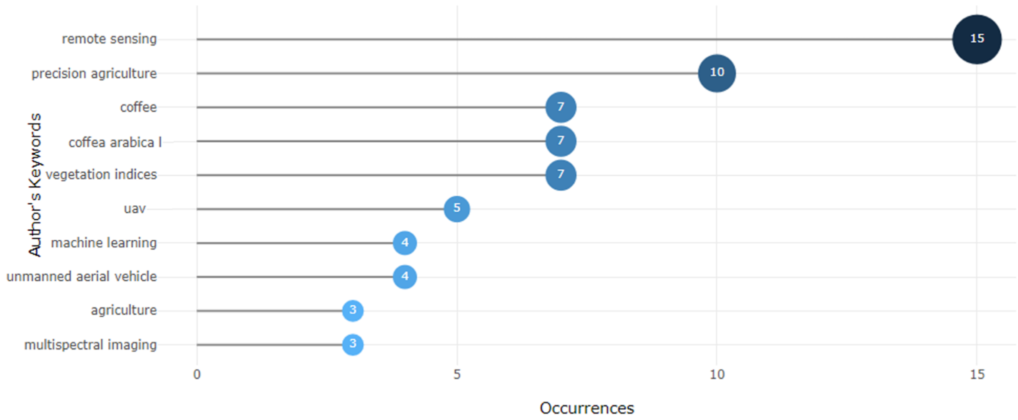

Figure 6. Authors' keywords with occurrences above 3 in the analyzed documents for the research topic on RPASs in coffee growing.

Among the 122 keywords identified in the studies, only 11 met the adopted criteria. The most frequently occurring term was "remote sensing", with 15 occurrences, followed by "precision agriculture", with 10 occurrences, which, respectively, refer to the applied technique and the study theme when employing RPASs in coffee farming. The subsequent terms relate to coffee itself, with "coffee" and "Coffea arabica L." occurring seven times each. Following in occurrence are the actual data acquisition equipment, with the terms "UAV" and "unmanned aerial vehicle" occurring five and four times, respectively, and words referring to the applications for obtaining the proposed results, such as "vegetation indices", "machine learning", "agriculture", and "multispectral images", with seven, four, three, and three occurrences, respectively.

3.3.3. Trend Mapping/Future Possibilities

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

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

Furthermore, it is known that acquiring and analyzing spectral data requires human and operational costs. Therefore, there is a need for rapid and efficient evolution of prediction methodologies based on data collected by RPASs, along with machine learning techniques, to avoid routine human involvement. Understanding the processes that result in the final productivity of the crop and applying such analyses using techniques and technologies allows the anticipation and correction of issues that could lead to low profitability of the plantations; therefore, this should be the focus of research on RPASs in coffee farming.

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

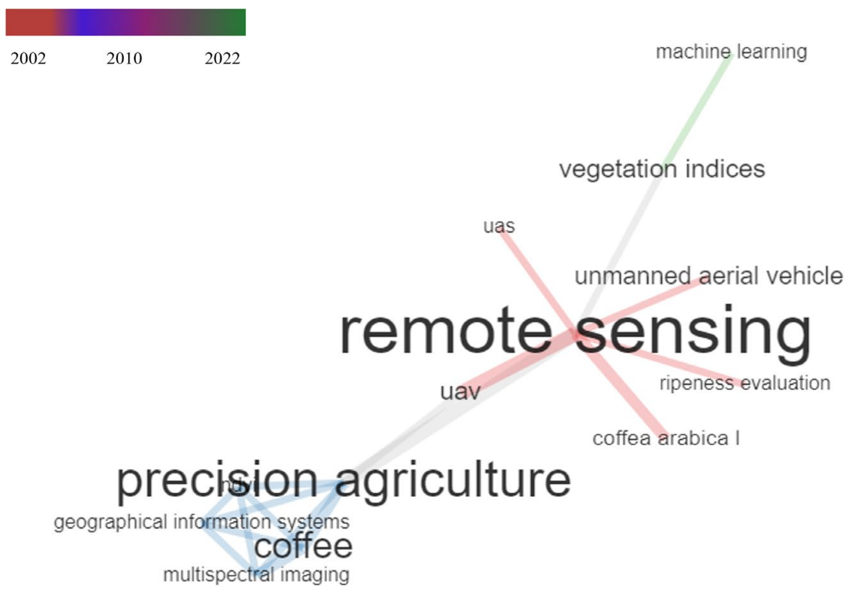

Figure 7. Co-occurrence map of authors' keywords from 2002 to 2022. The color scale in the nodes represents the year of the predominance of the keyword.

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

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

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

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

4. Conclusions

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

Author Contributions: Conceptualization, N.L.B. and G.A.e.S.F.; methodology, N.L.B., L.S.S., and M.d.L.O.e.S.; software, N.L.B. and L.S.S.; validation, N.L.B., G.A.e.S.F., L.S.S., and M.d.L.O.e.S.; formal analysis, N.L.B.; investigation, N.L.B.; resources, G.A.e.S.F.; data curation, N.L.B.; writing—original draft preparation, N.L.B. and M.d.L.O.e.S.; writing—review and editing, N.L.B., G.A.e.S.F., L.S.S., and M.d.L.O.e.S.; visualization, N.L.B.; supervision, N.L.B.; project administration, N.L.B. and M.d.L.O.e.S.; funding acquisition, G.A.e.S.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 10.18.20.041.00.00, the National Council for Scientific and Technological Development (CNPq) project 305953/2020-6, the Minas Gerais Research Funding Foundation (Fapemig) projects PPE-00118-22 and BPD-00040-22, the Coordination for the Improvement of Higher Education Personnel (CAPES), and the Federal University of Lavras (UFLA).

Data Availability Statement: Data are contained within the article.

Acknowledgments: We would like to thank the Embrapa Brazilian Coffee Research Consortium, 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).

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

References

1. ICO. *Coffee Market Report*; ICO: London, UK, 2023; pp. 1–13.
2. Companhia Nacional de Abastecimento—(CONAB). "Acompanhamento da Safra Brasileira—CAFÉ". *Obs. Agrícola* **2023**, *1*, 1–60.
3. Mesquita, C.; de Melo, E.M.; de Rezende, J.E.; Carvalho, J.S.; Júnior, M.A.F.; Moraes, N.C.; Dias, P.T.; Dias, P.T.; de Carvalho, R.M.; de Araújo, W.G. *MANUAL DO CAFÉ: Implantação de Cafezais*; EMATER-MG: Belo Horizonte, Brazil, 2016; Available online: http://www.sapc.embrapa.br/arquivos/consorcio/publicacoes_tecnicas/livro_implantacao_cafezais.pdf (accessed on 25 July 2023).
4. Tang, Y.; Dananjayan, S.; Hou, C.; Guo, Q.; Luo, S.; He, Y. A survey on the 5G network and its impact on agriculture: Challenges and opportunities. *Comput. Electron. Agric.* **2021**, *180*, 105895. [CrossRef]
5. Parsaeian, M.; Shahabi, M.; Hassanpour, H. Estimating Oil and Protein Content of Sesame Seeds Using Image Processing and Artificial Neural Network. *J. Am. Oil Chem. Soc.* **2020**, *97*, 691–702. [CrossRef]
6. Tantalaki, N.; Souravlas, S.; Roumeliotis, M. Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems. *J. Agric. Food Inf.* **2019**, *20*, 344–380. [CrossRef]
7. Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* **2018**, *18*, 2674. [CrossRef] [PubMed]
8. Wienhold, K.; Goulao, L.F. The Embedded Agroecology of Coffee Agroforestry: A Contextualized Review of Smallholder Farmers' Adoption and Resistance. *Sustainability* **2023**, *15*, 6827. [CrossRef]
9. FAO; ITU. *E-Agriculture in Action: Drones for Agriculture*; ITU: Bangkok, Thailand, 2018.
10. Radoglou-Grammatikis, P.; Sarigiannidis, P.; Lagkas, T.; Moscholios, I. A compilation of UAV applications for precision agriculture. *Comput. Netw.* **2018**, *172*, 107148. [CrossRef]
11. Tsouros, D.C.; Bibi, S.; Sarigiannidis, P.G. A review on UAV-based applications for precision agriculture. *Information* **2019**, *10*, 349. [CrossRef]
12. Limin, B.W.; Jia, L.; Lingbo, Y.; Zhongxin, C.; Xiaolong, W.; Ouyang, B. Applications of unmanned aerial vehicle images on agricultural remote sensing monitoring. *Trans. Chin. Soc. Agric. Eng.* **2013**, *29*, 136–145.
13. Khan, S.; Tufail, M.; Khan, M.T.; Khan, Z.A.; Iqbal, J.; Wasim, A. Real-time recognition of spraying area for UAV sprayers using a deep learning approach. *PLoS ONE* **2021**, *16*, e0249436. [CrossRef]
14. Singh, A.P.; Yerudkar, A.; Mariani, V.; Iannelli, L.; Glielmo, L. A Bibliometric Review of the Use of Unmanned Aerial Vehicles in Precision Agriculture and Precision Viticulture for Sensing Applications. *Remote Sens.* **2022**, *14*, 1604. [CrossRef]
15. Pallottino, F.; Biocca, M.; Nardi, P.; Figorilli, S.; Menesatti, P.; Costa, C. Science mapping approach to analyze the research evolution on precision agriculture: World, EU and Italian situation. *Precis. Agric.* **2018**, *19*, 1011–1026. [CrossRef]
16. Sott, M.K.; Furstenau, L.B.; Kipper, L.M.; Giraldo, F.D.; Lopez-Robles, J.R.; Cobo, M.J.; Zahid, A.; Abbasi, Q.H.; Imran, M.A. Precision Techniques and Agriculture 4.0 Technologies to Promote Sustainability in the Coffee Sector: State of the Art, Challenges and Future Trends. *IEEE Access* **2020**, *8*, 149854–149867. [CrossRef]
17. Santana, L.S.; Ferraz, G.A.e.S.; Teodoro, A.J.d.S.; Santana, M.S.; Rossi, G.; Palchetti, E. Advances in Precision Coffee Growing Research: A Bibliometric Review. *Agronomy* **2021**, *11*, 1557. [CrossRef]
18. Raparelli, E.; Bajocco, S. A bibliometric analysis on the use of unmanned aerial vehicles in agricultural and forestry studies. *Int. J. Remote Sens.* **2019**, *40*, 9070–9083. [CrossRef]
19. Rejeb, A.; Rejeb, K.; Abdollahi, A.; Zailani, S.; Iranmanesh, M.; Ghobakhloo, M. Digitalization in Food Supply Chains: A Bibliometric Review and Key-Route Main Path Analysis. *Sustainability* **2022**, *14*, 83. [CrossRef]

20. Mueller, S. Estudos métricos da informação em ciência e tecnologia no Brasil realizados sobre a unidade de análise artigos de periódicos? Metrical studies on science and technology information in Brazil having the scientific article as unit of analysis. *Liinc em Rev.* **2013**, *9*. [CrossRef]
21. Sales, F.O.; Marante, Y.; Vieira, A.B.; Silva, E.F. Energy Consumption Evaluation of a Routing Protocol for Low-Power and Lossy Networks in Mesh Scenarios for Precision Agriculture. *Sensors* **2020**, *20*, 3814. [CrossRef]
22. Aria, M.; Cuccurullo, C. bibliometrix: An R-tool for comprehensive science mapping analysis. *J. Informetr.* **2017**, *11*, 959–975. [CrossRef]
23. Moreira, P.S.d.C.; Guimarães, A.J.R.; Tsunoda, D.F. QUAL FERRAMENTA BIBLIOMÉTRICA ESCOLHER? *Um estudo comparativo entre softwares.* **2020**, *6*, 140–158. [CrossRef]
24. Herwitz, S.; Johnson, L.; Dunagan, S.; Higgins, R.; Sullivan, D.; Zheng, J.; Lobitz, B.; Leung, J.; Gallmeyer, B.; Aoyagi, M.; et al. Imaging from an unmanned aerial vehicle: Agricultural surveillance and decision support. *Comput. Electron. Agric.* **2004**, *44*, 49–61. [CrossRef]
25. Johnson, L.F.; Herwitz, S.R.; Lobitz, B.M.; Dunagan, S.E. Feasibility of monitoring coffee field ripeness with airborne multispectral imagery. *Appl. Eng. Agric.* **2004**, *20*, 845–849.
26. Furfaro, R.; Ganapol, B.D.; Johnson, L.F.; Herwitz, S.R. Neural Network Algorithm for Coffee Ripeness Evaluation Using Airborne Images. *Appl. Eng. Agric.* **2007**, *23*, 379–387. [CrossRef]
27. Garcia-Cedeno, A.; Guillermo, J.C.; Barzallo, B.; Punin, C.; Soto, A.; Rivas, D.; Clotet, R.; Huerta, M. PLATANO: Intelligent Technological Support Platform for Azuay province Farmers in Ecuador. In Proceedings of the 2019 IEEE International Conference on Engineering Veracruz (ICEV), Boca del Rio, Mexico, 14–17 October 2019; pp. 1–7.
28. Oliveira, H.C.; Guizilini, V.C.; Nunes, I.P.; Souza, J.R. Failure Detection in Row Crops from UAV Images Using Morphological Operators. *IEEE Geosci. Remote Sens. Lett.* **2018**, *15*, 991–995. [CrossRef]
29. Soares, G.A.; Abdala, D.; Escarpinati, M. Plantation Rows Identification by Means of Image Tiling and Hough Transform Grouping. In Proceedings of the 13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications—VISIGRAPP 2018, Madeira, Portugal, 27–29 January 2018; pp. 453–459.
30. Da Cunha, J.P.A.R.; Neto, M.A.S.; Hurtado, S.M.C. Estimating vegetation volume of coffee crops using images from unmanned aerial vehicles. *Eng. Agríc.* **2019**, *39*, 41–47. [CrossRef]
31. Dos Santos, L.M.; e Silva Ferraz, G.A.; Andrade, M.T.; Santana, L.S.; de Barbosa, B.D.S.; Maciel, D.A.; Rossi, G. Analysis of flight parameters and georeferencing of images with different control points obtained by RPA. *Agron. Res.* **2019**, *17*, 2054–2063. [CrossRef]
32. dos Santos, L.M.; Ferraz, G.A.e.S.; Barbosa, B.D.d.S.; Diotto, A.V.; Maciel, D.T.; Xavier, L.A.G. Biophysical parameters of coffee crop estimated by UAV RGB images. *Precis. Agric.* **2020**, *21*, 1227–1241. [CrossRef]
33. Oré, G.; Alcântara, M.S.; Góes, J.A.; Oliveira, L.P.; Yepes, J.; Teruel, B.; Castro, V.; Bins, L.S.; Castro, F.; Luebeck, D.; et al. Crop Growth Monitoring with Drone-Borne DInSAR. *Remote Sens.* **2020**, *12*, 615. [CrossRef]
34. Wei, P.; Jiang, T.; Peng, H.; Jin, H.; Sun, H.; Chai, D.; Huang, J. Coffee Flower Identification Using Binarization Algorithm Based on Convolutional Neural Network for Digital Images. *Plant Phenom.* **2020**, *2020*, 6323965. [CrossRef]
35. Parreiras, T.C.; Lense, G.H.E.; Moreira, R.S.; Santana, D.B.; Mincato, R.L. Using unmanned aerial vehicle and machine learning algorithm to monitor leaf nitrogen in coffee. *Coffee Sci.* **2020**, *15*, 1–9. [CrossRef]
36. Santos, L.M.; Parreiras, T.C.; Lense, G.H.E.; Santana, D.B.; Moreira, R.S. Coffee crop coefficient prediction as a function of biophysical variables identified from RGB UAS images. *Agron. Res.* **2020**, *18*, 1463–1471. [CrossRef]
37. dos Santos, L.M.; Ferraz, G.A.e.S.; Barbosa, B.D.d.S.; Diotto, A.V.; Andrade, M.T.; Conti, L.; Rossi, G. Determining the Leaf Area Index and Percentage of Area Covered by Coffee Crops Using UAV RGB Images. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 6401–6409. [CrossRef]
38. Velásquez, D.; Sánchez, A.; Sarmiento, S.; Toro, M.; Maiza, M.; Sierra, B. A Method for Detecting Coffee Leaf Rust through Wireless Sensor Networks, Remote Sensing, and Deep Learning: Case Study of the Caturra Variety in Colombia. *Appl. Sci.* **2020**, *10*, 697. [CrossRef]
39. Barbosa, B.D.S.; Ferraz, G.A.E.S.; Santos, L.M.; Santana, L.S.; Marin, D.B.; Rossi, G.; Conti, L. Application of RGB Images Obtained by UAV in Coffee Farming. *Remote Sens.* **2021**, *13*, 2397. [CrossRef]
40. Marin, D.B.; Ferraz, G.A.e.S.; Santana, L.S.; Barbosa, B.D.S.; Barata, R.A.P.; Osco, L.P.; Ramos, A.P.M.; Guimarães, P.H.S. Detecting coffee leaf rust with UAV-based vegetation indices and decision tree machine learning models. *Comput. Electron. Agric.* **2021**, *190*, 106476. [CrossRef]
41. Barbosa, B.D.S.; Ferraz, G.A.e.S.; Costa, L.; Ampatzidis, Y.; Vijayakumar, V.; dos Santos, L.M. UAV-based coffee yield prediction utilizing feature selection and deep learning. *Smart Agric. Technol.* **2021**, *1*, 100010. [CrossRef]
42. Santana, L.S.; e Silva Ferraz, G.A.; Cunha, J.P.B.; Santana, M.S.; de Faria, R.O.; Marin, D.B.; Rossi, G.; Conti, L.; Vieri, M.; Sarri, D. Monitoring Errors of Semi-Mechanized Coffee Planting by Remotely Piloted Aircraft. *Agronomy* **2021**, *11*, 1224. [CrossRef]
43. Marin, D.B.; Ferraz, G.A.e.S.; Guimarães, P.H.S.; Schwerz, F.; Santana, L.S.; Barbosa, B.D.S.; Barata, R.A.P.; Faria, R.d.O.; Dias, J.E.L.; Conti, L.; et al. Remotely Piloted Aircraft and Random Forest in the Evaluation of the Spatial Variability of Foliar Nitrogen in Coffee Crop. *Remote Sens.* **2021**, *13*, 1471. [CrossRef]

44. Rivera, L.B.; Bonilla, B.M.; Obando-Vidal, F. Procesamiento de imágenes multiespectrales captadas con drones para evaluar el índice de vegetación de diferencia normalizada en plantaciones de café variedad Castillo. *Cienc. Y Tecnol. Agropecu.* **2021**, *22*, 1578. [CrossRef]
45. dos Santos, S.A.; Ferraz, G.A.e.S.; Figueiredo, V.C.; Santana, L.S.; Campos, B.F.D. Supervised classification and NDVI calculation from remote piloted aircraft images for coffee plantations applications. *Coffee Sci.* **2021**, *16*, 1–9. [CrossRef]
46. Martins, R.N.; Pinto, F.d.A.d.C.; de Queiroz, D.M.; Valente, D.S.M.; Rosas, J.T.F. A Novel Vegetation Index for Coffee Ripeness Monitoring Using Aerial Imagery. *Remote Sens.* **2021**, *13*, 263. [CrossRef]
47. Felix, F.C.; Avalos, F.A.; DE Lima, W.; Cândido, B.M.; Silva, M.L.; Mincato, R.L. Seasonal behavior of vegetation determined by sensor on an unmanned aerial vehicle. *An. Da Acad. Bras. De Ciências* **2021**, *93*, e20200712. [CrossRef] [PubMed]
48. Gomes, A.P.A.; de Queiroz, D.M.; Valente, D.S.M.; Pinto, F.d.A.d.C.; Rosas, J.T.F. Comparing a Single-Sensor Camera with a Multisensor Camera for Monitoring Coffee Crop using Unmanned Aerial Vehicles. *Eng. Agrícola* **2021**, *41*, 87–97. [CrossRef]
49. Rosas, J.T.F.; Pinto, F.d.A.d.C.; de Queiroz, D.M.; Villar, F.M.d.M.; Martins, R.N.; Silva, S.d.A. Low-cost system for radiometric calibration of UAV-based multispectral imagery. *J. Spat. Sci.* **2020**, *67*, 395–409. [CrossRef]
50. Santana, L.S.; Ferraz, G.A.e.S.; Marin, D.B.; Faria, R.d.O.; Santana, M.S.; Rossi, G.; Palchetti, E. Digital Terrain Modelling by Remotely Piloted Aircraft: Optimization and Geometric Uncertainties in Precision Coffee Growing Projects. *Remote Sens.* **2022**, *14*, 911. [CrossRef]
51. Bento, N.L.; Ferraz, G.A.E.S.; Barata, R.A.P.; Santana, L.S.; Barbosa, B.D.S.; Conti, L.; Becciolini, V.; Rossi, G. Overlap influence in images obtained by an unmanned aerial vehicle on a digital terrain model of altimetric precision. *Eur. J. Remote Sens.* **2022**, *55*, 263–276. [CrossRef]
52. Souza, F.G.; Souza, F.G.; Portes, M.F.; Portes, M.F.; Silva, M.V.; Silva, M.V.; Teixeira, M.M.; Teixeira, M.M.; Júnior, M.R.F.; Júnior, M.R.F. Impact of sprayer drone flight height on droplet spectrum in mountainous coffee plantation. *Rev. Bras. De Eng. Agrícola E Ambient.* **2022**, *26*, 901–906. [CrossRef]
53. da Vitória, E.L.; de Oliveira, R.F.; Crause, D.H.; Ribeiro, L.F.O. Effect of flight operative height and genotypes on conilon coffee spraying using an unmanned aerial vehicle. *Coffee Sci.* **2022**, *17*, 1–9. [CrossRef]
54. Bento, N.L.; Ferraz, G.A.e.S.; Barata, R.A.P.; Soares, D.V.; dos Santos, L.M.; Santana, L.S.; Ferraz, P.F.P.; Conti, L.; Palchetti, E. Characterization of Recently Planted Coffee Cultivars from Vegetation Indices Obtained by a Remotely Piloted Aircraft System. *Sustainability* **2022**, *14*, 1446. [CrossRef]
55. Rosas, J.T.F.; Pinto, F.d.A.d.C.; de Queiroz, D.M.; Villar, F.M.d.M.; Valente, D.S.M.; Martins, R.N. Coffee ripeness monitoring using a UAV-mounted low-cost multispectral camera. *Precis. Agric.* **2022**, *23*, 300–318. [CrossRef]
56. Bento, N.L.; Ferraz, G.A.S.; Barata, R.A.P.; Santana, L.S.; Faria, R.O.; Soares, D.V. Evaluation of coffee plant attributes by field collection and remotely piloted aircraft system images. *Span. J. Agric. Res.* **2022**, *20*, e0205. [CrossRef]
57. Martello, M.; Molin, J.P.; Angnes, G.; Acorsi, M.G. Assessing the Temporal and Spatial Variability of Coffee Plantation Using RPA-Based RGB Imaging. *Drones* **2022**, *6*, 267. [CrossRef]
58. Bento, N.L.; Ferraz, G.A.e.S.; Barata, R.A.P.; Soares, D.V.; Santana, L.S.; Barbosa, B.D.S. Estimate and Temporal Monitoring of Height and Diameter of the Canopy of Recently Transplanted Coffee by a Remotely Piloted Aircraft System. *Agriengineering* **2022**, *4*, 207–215. [CrossRef]
59. dos Santos, L.M.; Ferraz, G.A.e.S.; Carvalho, M.A.d.F.; Teodoro, S.A.; Campos, A.A.V.; Neto, P.M. Use of RPA Images in the Mapping of the Chlorophyll Index of Coffee Plants. *Sustainability* **2022**, *14*, 13118. [CrossRef]
60. Arteaga-López, N.; Delgado-Calvache, C.; Casanova, J.-F.; Figeroa, C. Coffee Crops Analysis Using UAVs Equipped with Multispectral Cameras. *Rev. Fac. Ing.* **2022**, *31*, e14870. [CrossRef]
61. dos Santos, L.M.; Ferraz, G.A.e.S.; Marin, D.B.; Carvalho, M.A.d.F.; Dias, J.E.L.; Alecrim, A.d.O.; Silva, M.d.L.O.e. Vegetation Indices Applied to Suborbital Multispectral Images of Healthy Coffee and Coffee Infested with Coffee Leaf Miner. *Agriengineering* **2022**, *4*, 311–319. [CrossRef]
62. Pereira, F.V.; Martins, G.D.; Vieira, B.S.; de Assis, G.A.; Orlando, V.S.W. Multispectral images for monitoring the physiological parameters of coffee plants under different treatments against nematodes. *Precis. Agric.* **2022**, *23*, 2312–2344. [CrossRef]
63. Soares, A.d.S.; Vieira, B.S.; Bezerra, T.A.; Martins, G.D.; Siquieroli, A.C.S. Early Detection of Coffee Leaf Rust Caused by *Hemileia vastatrix* Using Multispectral Images. *Agronomy* **2022**, *12*, 2911. [CrossRef]
64. Inoue, Y. Satellite- and drone-based remote sensing of crops and soils for smart farming—A review. *Soil Sci. Plant Nutr.* **2020**, *66*, 798–810. [CrossRef]
65. Osco, L.P.; Marcato Junior, J.; Marques Ramos, A.P.; de Castro Jorge, L.A.; Fatholahi, S.N.; de Andrade Silva, J.; Matsubara, E.T.; Pistori, H.; Gonçalves, W.N.; Li, J. A Review on Deep Learning in UAV Remote Sensing. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102456. [CrossRef]
66. Koutsos, T.M.; Menexes, G.C.; Dordas, C.A. An efficient framework for conducting systematic literature reviews in agricultural sciences. *Sci. Total. Environ.* **2019**, *682*, 106–117. [CrossRef] [PubMed]
67. Ren, J.; Jing, X.; Wang, J.; Ren, X.; Xu, Y.; Yang, Q.; Ma, L.; Sun, Y.; Xu, W.; Yang, N.; et al. Automatic Recognition of Laryngoscopic Images Using a Deep-Learning Technique. *Laryngoscope* **2020**, *130*, E686–E693. [CrossRef] [PubMed]
68. Yost, M.A.; Kitchen, N.R.; Sudduth, K.A.; Massey, R.E.; Sadler, E.J.; Drummond, S.T.; Volkmann, M.R. A long-term precision agriculture system sustains grain profitability. *Precis. Agric.* **2019**, *20*, 1177–1198. [CrossRef]

69. Gusenbauer, M. The age of abundant scholarly information and its synthesis– A time when 'just google it' is no longer enough. *Res. Synth. Methods* **2021**, *12*, 684–691. [CrossRef] [PubMed]
70. Gusenbauer, M. Search where you will find Amost: Comparing the disciplinary coverage of 56 bibliographic databases. *Scientometrics* **2022**, *127*, 2683–2745. [CrossRef]
71. Merigó, J.M.; Yang, J.-B. A bibliometric analysis of operations research and management science. *Omega* **2017**, *73*, 37–48. [CrossRef]
72. Ferreira, M.P.; Pinto, C.F.; Serra, F.R. The transaction costs theory in international business research: A bibliometric study over three decades. *Scientometrics* **2013**, *98*, 1899–1922. [CrossRef]