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The Use Remotely Piloted Aircraft in Counting Agricultural and Forestry Plants: a Systematic Review

O Uso de Aeronaves Remotamente Pilotadas na Contagem de Plantas Agrícolas e Florestais: uma Revisão Sistemática

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Abstract

In recent years, plant counting using data collected by sensors embedded in remotely piloted aircraft systems (RPAS), combined with machine learning algorithms, has become popular in the agroforestry sector, especially in crop planning, crop production estimation, among other applications. This study aimed to perform a systematic review of the literature on plant counting in the agricultural and forestry sector that uses data from sensors embedded in RPAS. We sought to identify the principal bibliometric indicators of scientific production and, through content analysis, the main characteristics and trends of the studies. A total of 33 scientific articles obtained on the Scopus and Web of Science platforms were used. Then, a content qualitative analysis of each article was conducted to identify the main thematic categories: agricultural and forest species, platform and sensors, software, and algorithm. There was an increase in scientific publications as of 2017. The USA presented the higher number of researches performed, with eight publications. There was a significant presence of RGB (Red, Green and Blue) sensors followed by multispectral. The algorithms Convoluctional Neural Network (CNN), Structure from Motion (SfM), and K-means stood out for the recurrence of use, either singularly or associated. Studies with this purpose drive new research development, where this technology utilization is revealed as a potential instrument to understand the usage trends, subsidize and encourage the information acquisition, promoting improvements and progress for research in the agroforestry scope.

Keywords: RPAS; Machine learning; Algorithms

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Resumo

Nos últimos anos, a contagem de plantas por meio da utilização de dados coletados por sensores embarcados em sistemas de aeronaves remotamente pilotadas (ARP), aliados a algoritmos de aprendizado de máquina vem se popularizando no setor agroflorestal, especialmente no planejamento da lavoura, estimativa da produção, entre outras aplicações. O presente estudo teve como objetivo realizar uma revisão sistemática da literatura acerca da contagem de plantas no setor agrícola e florestal que utiliza dados provenientes de sensores acoplados em ARP. Buscou-se identificar os principais indicadores bibliométricos das produções científicas e, por meio da análise de conteúdo, as principais características e tendências dos estudos. Foram utilizados 33 artigos científicos obtidos nas plataformas *Scopus* e *Web of Science*. Em seguida, procederam-se as análises qualitativas do conteúdo de cada artigo com a finalidade de identificar as principais categorias temáticas: espécies agrícola e florestal, plataforma e sensores, *software* e algoritmo. Nos artigos analisados houve aumento nas publicações científicas a partir de 2017. Os EUA apresentaram o maior número de pesquisas realizadas, com oito artigos. Notou-se uma presença significativa de sensores RGB (*Red*, *Green* e *Blue*) seguido dos multiespectrais. Os algoritmos *Convoluctional Neural Network* (CNN), *Structure from Motion (*SfM) e *K-means* destacaram-se pela recorrência de uso, seja de forma singular ou em associação. Estudos com esse propósito vêm impulsionando o desenvolvimento de novas pesquisas, onde a utilização desta tecnologia se revela como um instrumento potencial para compreender as tendências de utilização, subsidiar e fomentar a obtenção de informações, promovendo melhorias e avanços para as pesquisas agroflorestal.

Palavras-chave: RPAS; Aprendizado de máquina; Algoritmos

1 Introduction

Technological advances have resulted in an exponential increase in the development of embedded sensors in remotely piloted aircraft systems (RPAS). With the development of versatile, lightweight, and low-cost portable sensors, RPAS can be transformed into remote sensing platforms that can provide images with high spatial, spectral, and temporal resolution. In addition, they allow greater flexibility in the acquisition time without restrictions on soil conditions since the established altitudes are respected, they have less dependence on weather conditions, and make it possible to acquire data without the interference of cloud (Berni et al. 2009; Barros et al. 2024).

The use of remote images captured by RPAS is becoming a relevant tool since it has a great potential to predict specific details at the beginning of the plants emergence. It was not previously possible with conventional aerial photographs or satellite images due to its low spatial resolution. Remote sensing with RPAS has already become a reality, which has been showing potentialities in the agricultural production process (Ehsani & Maja 2013; Gómez-Candón et al. 2014), weeds plants (Sá et al. 2018; Kattenborn et al. 2019), biophysical parameters estimation (Zou et al. 2019), plant count (Kalanta et al. 2017; Albuquerque et al. 2020), forest inventory and wood volume estimation (Embrapa 2019), among other applications that have been executable in this panorama. Planting density and stand, is one of the most common tools of the agroforestry sector. It provides details about the crop stand, helping to make immediate decisions and improve crop management strategies, for example, replanting, application of inputs, pest control, nutritional deficiencies, among others (Jesus et al. 2023).

According to Gülci (2019), there are several commercial software such as Agisoft PhotoScan and Pix4D, as well as open-source software, such as Visual SfM, that can be used to obtain and/or analyze RPAS images. The Pix4D and Agisoft PhotoScan software directly access the image metadata and, through pre-established routines, or user manipulation, make it possible to generate the images orthomosaic, Digital Elevation Model (DEM), and sparse point cloud (densification triangulation). The Structure from Motion (SfM) technique, according to Baltsavias et al. (2008) and Westoby et al. (2012), can generate 3D point clouds and create 3D models. Canopy height models are produced using 3D point clouds obtained using digital cameras and used to estimate the height of trees (Birdal et al. 2017), canopy width (Panagiotidis et al. 2017), tree diameter (Fritz et al. 2013), location of the tree and count (Mohan et al. 2017), analysis of variables (position, height of the tree and diameter of the canopy) (Guerra-Hernández et al. 2016).

Algorithms such as SfM (Oh et al. 2020), Support Vector Machine (SVM) (Hassan et al. 2016); Artificial Neural Network (ANN) (Liu et al. 2020), Decision Tree (DT) (Varela et al. 2018), K-means (Shirzadifar et al. 2020), among others, presented large contributions in the treatment of spatial data, providing performances with high precision in the count of agricultural and forestry plants. Thus, the use of these technologies (RPAS, collection/processing software and algorithms) can be considered as the response to the needs of agriculture 4.0 and forest 4.0.

That said, the present study was designed to perform a systematic review (SR) of the literature about the count of agricultural and forestry plants using RPAS images. As a specific objective, it was sought to identify the principal bibliometric indicators of scientific productions and, through content analysis, identify the main characteristics of the studies. After this introductory section, the article is structured as follows: Section 2, SR method performed; section 3 analysis of results and section 4 discussion and final considerations.

2 Methodology and Data

For the elaboration of this research, was performed an SR of scientific publications in the RPAS field and its use in plant count (agricultural and forestry). A priori, the international databases of scientific production were delimited to use in the search of articles, being: Web of Science (WOS), a Thomson Reuters' product, and Scopus, a multidisciplinary database produced by the publishing company Elsevier. The terms descriptors were then defined, as shown in Table 1.

The publication date (January 1, 2010, to December 31, 2022) and the language (English) were used as search filters. Among the returned articles were evaluated its titles, summary, and keywords to include or exclude those not related to the scope. At the end of this process, 33 research fitted SR sampling parameters (Figure 1).

Subsequently, a descriptive analysis was performed using the bibliometric indicators present in the indexing fields provided by the databases, with the discrimination of the following items: authorship and publication year. The content qualitative analyzes of each article were executed to identify the main thematic categories: species studied, platform, sensors, software, and algorithm. After analyzing the categories, we sought to answer the sequential questions (Table 2).

Table 1 Descriptors used in the bibliographic survey on the Web of Science and Scopus platforms.

Themed axes	Descriptive terms
Plataform	"RPAS", "Drone", "Unmanned Aerial Vehicle"
Area	"Agriculture", "Forest"
Application	"Count"

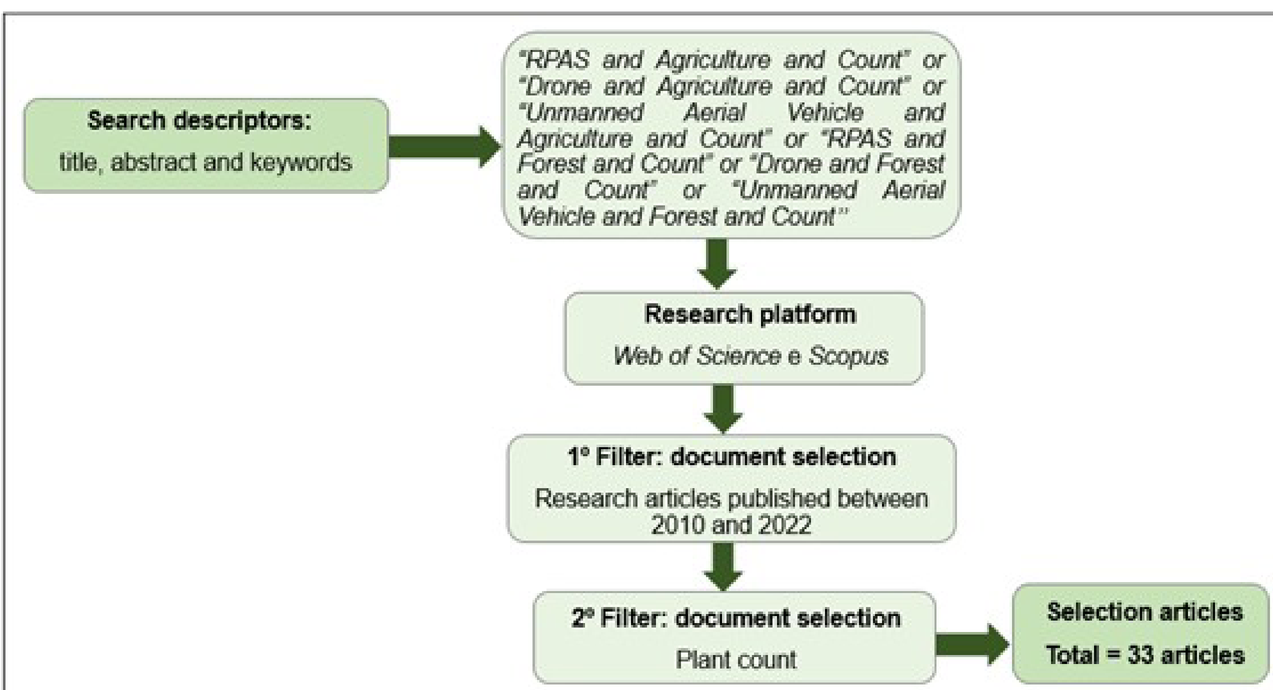

Figure 1 Procedures and criteria that were established to perform the bibliometric analysis on RPAS images use in the plant count.

Table 2 Questions that guided the survey results.

Questions	
Question 1	How did evolve the interest of the studies on the use of data obtained by plant count?
Question 2	What are the countries that are conducting studies on this theme?
Question 3	What are the (agricultural/forestry) species studied?
Question 4	What are the most commonly embedded sensors on RPAS platforms?
Question 5	What were the technical parameters of flight?
Question 6	What are the main software used?
Question 7	What are the main algorithms used?

3 Results and Discussion

This section shows the results obtained from SR, which allowed us to know the overall panorama of the plants count using data from sensors embedded in RPAS. The results are organized by research.

3.1 Question 1: How Did Evolve the Interest of the Studies About Data Obtained by Plant Count?

Initially, the analysis of the 33 articles of SR (Figure 2) was carried out to check the temporal evolution. It was verified that the publications number on the count of agricultural and forest species using RPAS has been continuously increasing, showing exponential growth from 2017, already in 2021 there was a decrease.

3.2 Question 2: What Are the Countries that Are Conducting Studies on This Theme?

The most prominent countries in the production of scientific articles were the United States (9), followed by China (4) and Spain (3) (Figure 3). It is noted that throughout the African continent there is no scientific publication on this topic. The fact that the USA has more publications may be related to the agricultural activity concentration in its

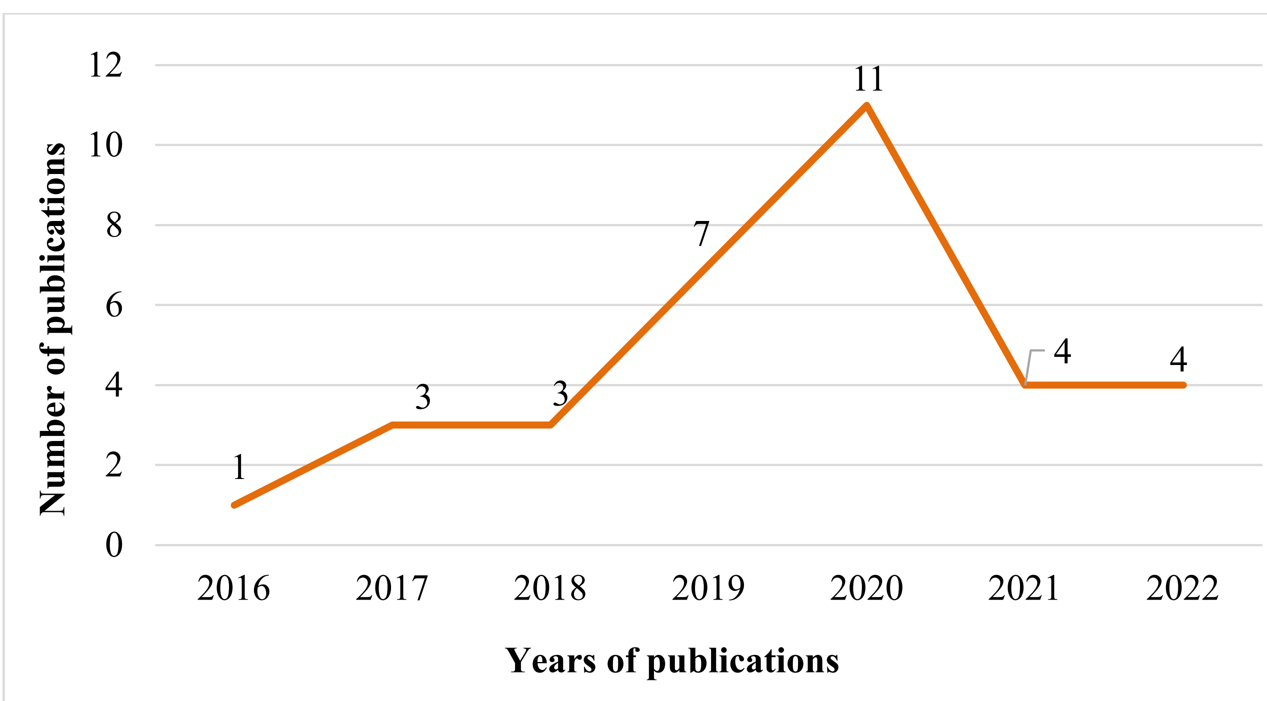

Figure 2 Temporal evolution of articles on the use of RPAS in the count of agricultural and forestry species.

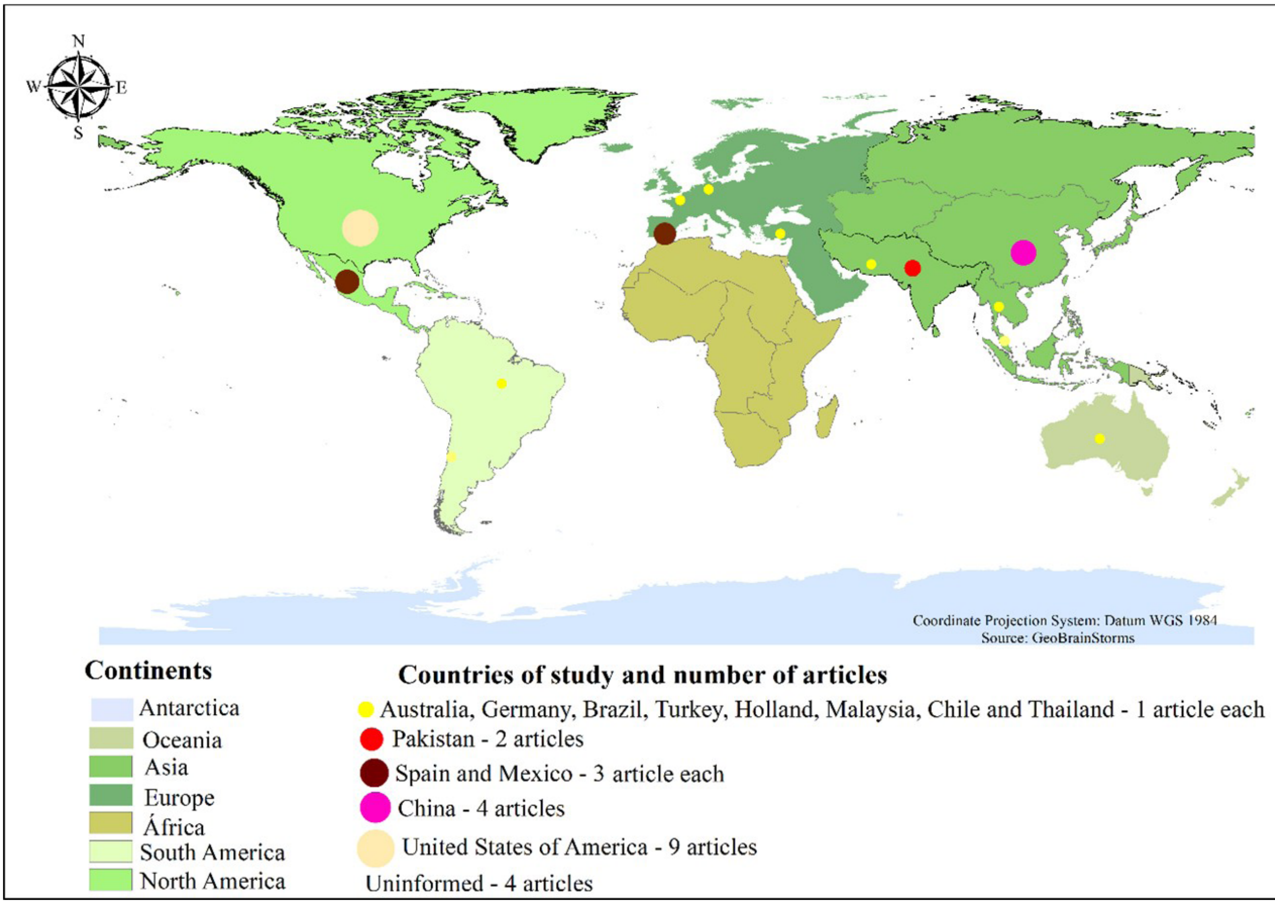

Figure 3 Global distribution of articles published in 2016 - 2022 on the use of RPAS images in plant count.

territory, mainly in the Great Plains, where, according to Souza et al. (2010), are established agricultural belts, such as the wheat belt, corn belt, and cotton belt.

3.3 Question 3: What Are the (Agricultural/Forestry) Species Studied?

In Figure 4, it is possible to observe the classification of publications concerning agricultural species addressed in scientific articles. *Zea mays* L. (corn) had the highest representation (29.2%) among papers, followed by *Gossypium hirsutum* L. (cotton), Musa sp. (banana), *Brassica napus* (colza), and *Oryza sativa* (rice) in which they totaled 8.3% each.

Analyzing the forest species (Figure 5), 50% are represented by coniferous forests (*Pinus brutia* (Ten.), *Pinus contorta* (Douglas ex Loudon), *Pseudotsuga menziesii* (Mirb.), *Picea engelmannii* (Parry ex Engelme) and *Abies lasiocarpa* (Hook), another species with great representation in the forestry sector is Eucalyptus sp. However, in the SR was found only one article related to the LiDAR sensor (Light Detection and Ranging), which may be related to the high cost of LiDAR sensors integrated into RPAs.

3.4 Question 4: What Are the Most Commonly Embedded Sensors on RPAS Platforms?

As for the pattern of types of sensors embedded in the RPAS platforms (Figure 6), 81.82% of the articles analyzed were with passive sensors, most of them in conjunction with multi-engine platforms. Passive RGB and multispectral sensors represented 72.73% and 9.09% of publications, respectively. This increase in the use of RGB sensors may be linked to the high cost of multispectral sensors, the ease of use, the high availability of RGB cameras, and their applicability, which is higher in the face of digital image processing. Eugenio & Zago (2019) point out that one of the facilities to acquire RPAS “read to fly” is the integrated

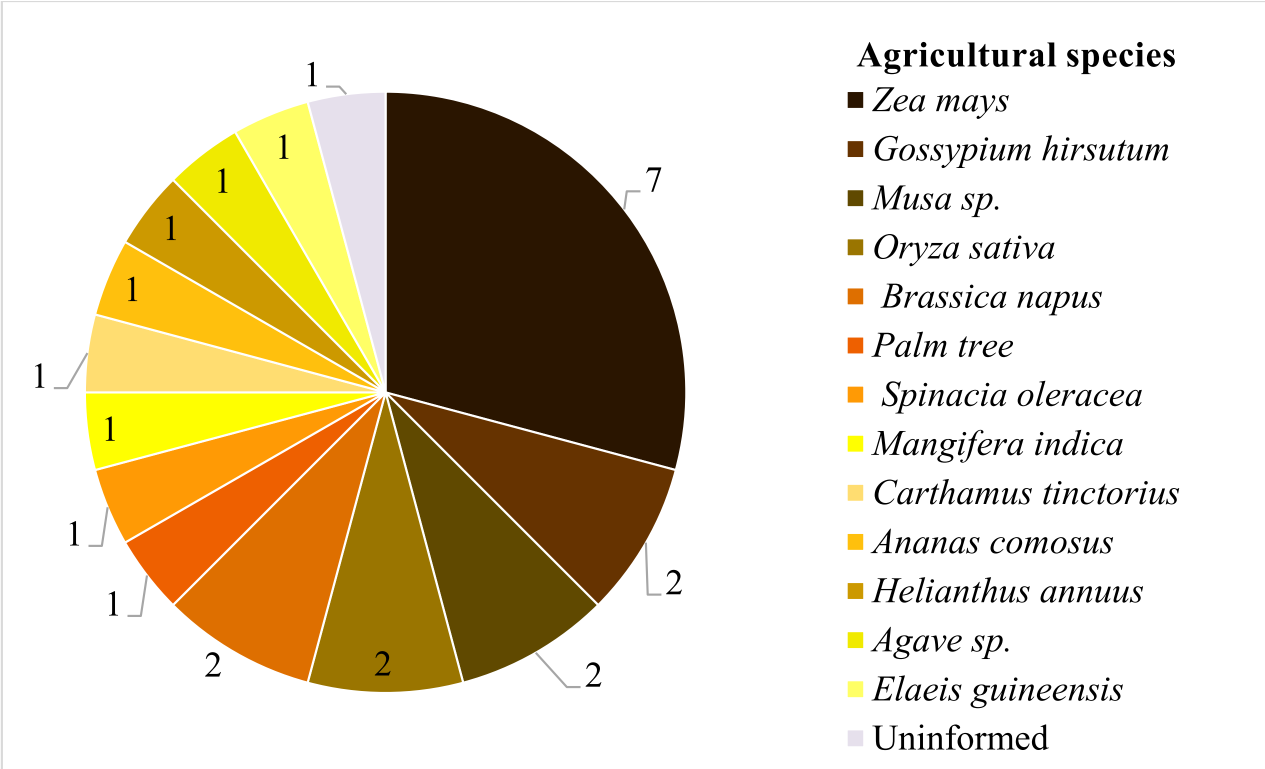

Figure 4 Classification of publications regarding agricultural species.

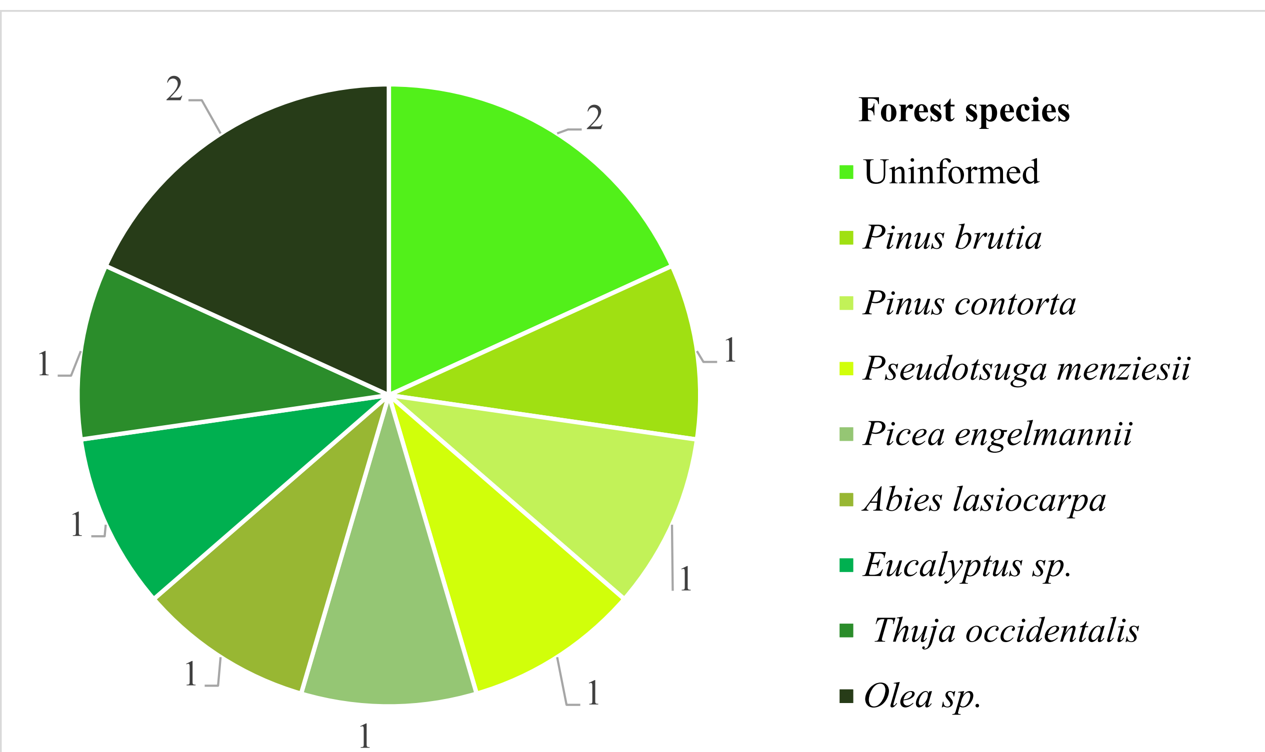

Figure 5 Classification of publications regarding forest species.

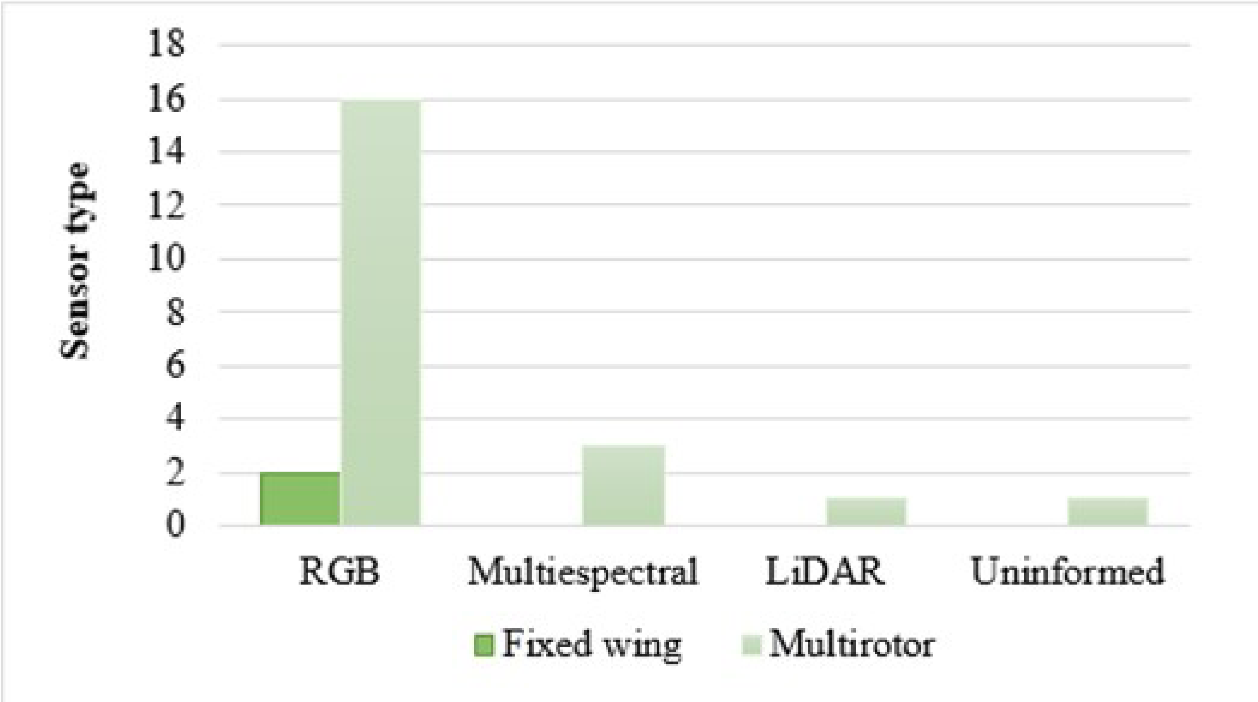

Figure 6 Main sensors embedded in RPA platforms for agricultural and forestry applications.

camera direct from the factory, commonly an RGB. On the other hand, only 6.06% used active sensors (LiDAR).

This result may be related to the still limited use of these sensors in RPAS, as they have a high cost when compared to passive sensors. Favorskaya & Jain (2017) highlighted that the use of LiDAR in RPAS presents challenges concerning system calibration. As for sensors not reported in the articles, these totaled 12.12%. For all sensors, the preference was multirotor platforms. Studies reported by Eugenio et al. (2020) revealed a tendency to use multirotor RPAS platforms when compared to fixed-wing platforms. It should be mentioned that studies based on RGB images and multispectral mainly used Sony and MicaSense cameras, respectively.

3.5 Question 5: What Were the Technical Parameters of Flight?

Concerning photogrammetric parameters, it is common for the articles to describe simplified data regarding the Ground Sample Distance (GSD), flight altitudes, and overlapping rates. The pixel in the image acquired with RPAS represents a specific land area, and this ratio occurs through the flight height, which has a direct relationship with the GSD size. The GSD represents the pixel of the image in terrain units (usually in centimeters). Among all the articles analyzed, the GSD ranged from 0.19 cm to 0.88 cm.

In relation to flight heights, there was manifold variation, between 10 to 150 meters. However, this was already expected because it covers agricultural and forestry species. The highest height found (150 m) was described by Hassaan et al. (2020), in which they addressed the count of trees in a planted forest, located approximately 80 km from Lahore, capital of Punjab Province in Pakistan. Oh et al. (2020), when counting the cotton plants from RPAS images, they flew to a height of 10 m. The images performed during the airlift are sequential, and thus, it is possible to adjust the overlap index, indicating how much of an image will affect (overlapping) the other. Referring to overlapping rates, used to collect images, on average, 80% front and 70% side were used.

3.6 Question 6: What Are the Main Software Used?

The software used for algorithm applications and image processing was also listed, as shown in Figure 7. The most used for image processing were Pix4D totaling 16.66%, Matlab and ArcGIS with 10.41% each. Pix4D software has as primary function to create models

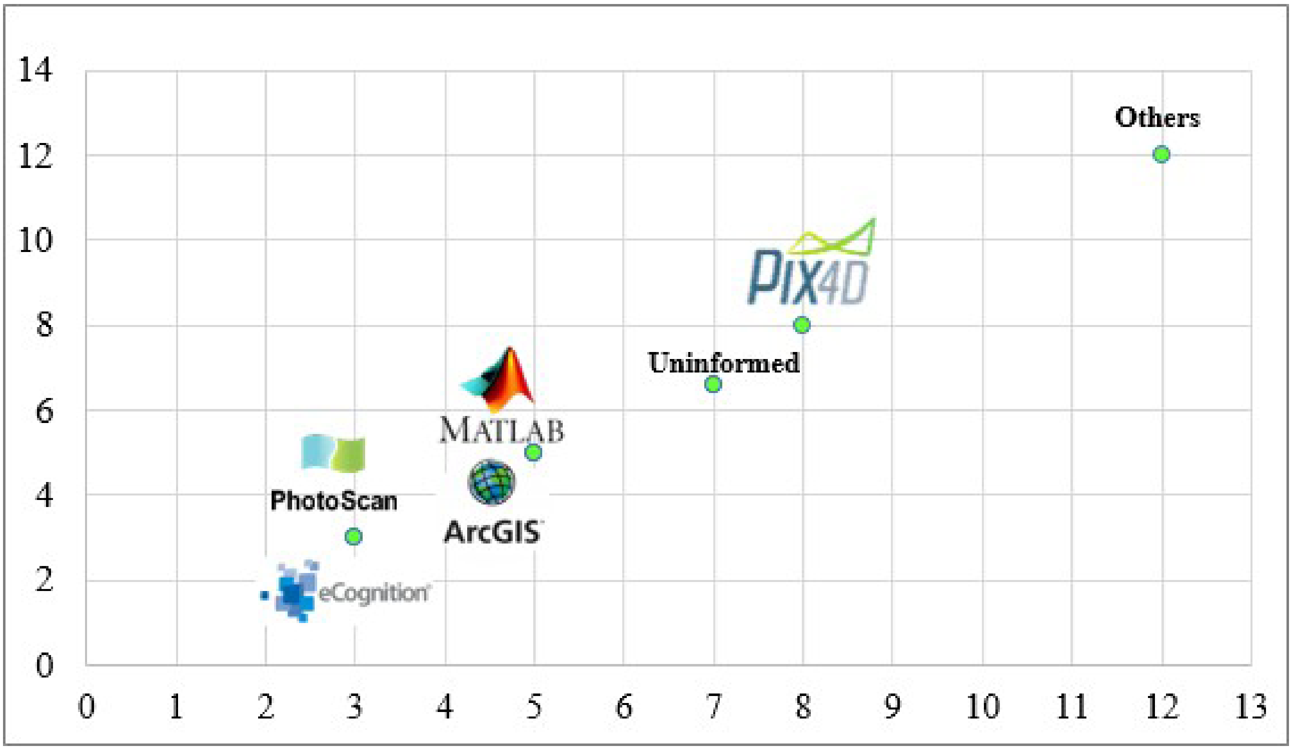

Figure 7 The main software used.

and digital models in 2D and georeferenced 3D and search for high precision of RPAS images.

Regarding Matlab software, this has flexibility when dealing with extensive ML structures, such as pre-processing image, selection and extraction resources, resampling methods, parameter adjustment, training data balancing, and classification precision comparisons (Sheykhmousa et al. 2020) Software and programming language with only one occurrence were counted and presented in the class others, as is the case of the statistical package R, Python, SAS, among others.

3.7 Question 7: What Are the Main Algorithms Used?

Some Machine Learning (ML) algorithms identified in the articles stood out for the recurrence of use, representing an important contribution to improving the results, where they have been obtained when associated with data acquisition via RPAS. The publications analyzed defined the main algorithms based on: Convoclutional Neural Network (CNN) (28.95%), Structure from Motion (SfM) (12%), and K-means (7.89%) in a singular or in association (Figure 8).

A systematic review is a significant tool for knowing the scientific production of a particular research area. In the articles analyzed, it was possible to realize that, since 2016, the count of agricultural and forestry species become gradually performed automated, evidencing the use of methods based mainly on the application of image processing obtained by embedded sensors in RPAS and algorithms adapted to different scenarios and possibilities for settings. The RPAS use, according to the Chabot survey (2018), had a linear increase from 2013 to 2015 and, in 2016 and 2017, had exponential growth. Studies in this scope have been driving the development of new research since they demonstrate that this technology can subsidize and foster information, promoting improvements and advances for research in agroforestry research.

Regarding the publications' origin, the US-led in quantitative terms. Raparelli & Bajocco (2019), in accomplishing the bibliometric analysis on the RPAS use in agricultural and forestry studies, also have elapsed that the US is the country with the highest publications number. Agricultural and forestry species were quite diversified in the studies, highlighting the species *Zea mays* and coniferous forests. Shirzadifar et al. (2020) used high-resolution images of RPAS to count and detect the number of corn plants as well as to verify the uniformity of the settlement shortly after germination. Using RGB

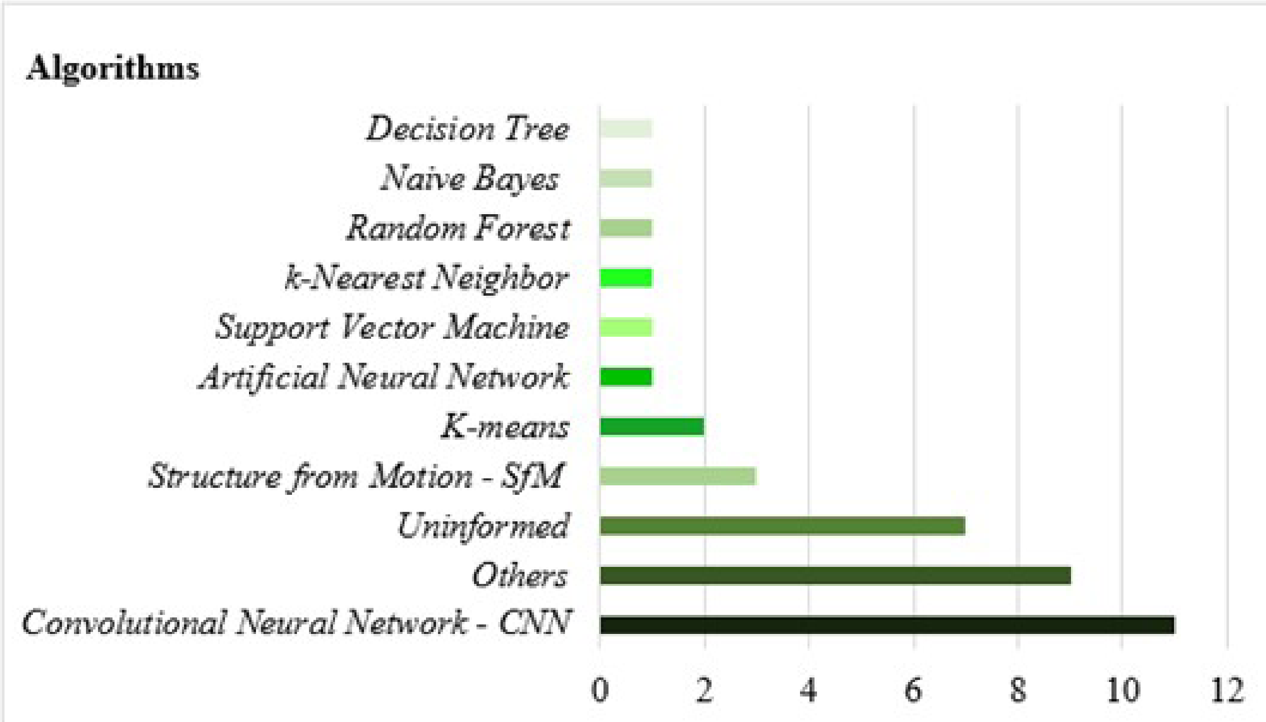

Figure 8 Main algorithms used for plant count.

images purchased by RPAS, García-Martínez et al. (2020) analyzed the automatic counting of corn plants by comparing models with normalized cross-correlation. Bai et al. (2022) developed a method to count corn and sunflower numbers quickly and non-destructively using high-resolution UAV imagery.

Feng et al. (2020) tested high-resolution image performance in the evaluation of cotton seedlings, focusing on counting and uniformity of stands. Liu et al. (2021) used Deep learning (DL) for detection and counting of oil palm and Neupane et al. (2019) automated bananas tree count during the initial growth phase. Sarabia et al. (2020) proposed a methodology for automatic detection, geolocation, and olive counting from high-resolution multispectral images. Ampatzidis & Partel (2019) stress that information related to the number of plants in a field of cultivation is essential for farmers since it helps them to estimate productivity, assess density and errors that occurred during the seedling's deployment process.

The interest in analyzing coniferous forests may be related to the growing timber industry, which according to Farjon (2018), almost all the timber of conifers go to the paper industry, although about two-thirds of the world's coniferous plantations are intended for production wooden. It should also emphasize that coniferous species are easier to interpret with remote sensing methods, especially at the individual tree level. Favarin et al. (2013) conducted the count and measurement of the height of a *Pinus taeda* settlement with great detail due to the high spatial resolution provided by the RGB sensor coupled to the RPA. Goldbergs et al. (2018) emphasize that different techniques in images of RPAS sensors have been implemented to identify and count trees. Picos et al. (2020) used sensors of detection and light range (LiDAR) to detect and estimate the height of eucalyptus trees.

As for the standard of the sensors types on the RPAS platforms, it is clear the preference, so far, by using images in the RGB standard. It was observed that there was a preference for using the multirotor platform. One of the functionalities of this platform is that they have simplified pilotage, capacity for landing and takeoffs in vertical, and adequacy to the small areas evaluation when compared to fixed-wing models (Moutinho 2015; Eugenio et al. 2020). In this way, the RPAS equipped with RGB and multispectral, sensors are excellent technological options for development in plant count (Wu et al. 2029; Fantinel 2024).

Before obtaining images via the RPAS platform, some parameters need to be determined and defined as, for example, GSD, flight height, and overlay rates. These parameters influence the images purchased. Albuquerque et al. (2020), when using RPAS images for automatic counting of trees in forest restoration areas, used

120 m flight altitude and 70% images overlapping, reaching GSD less than 10 cm/pixel. Fuentes-Peñailillo et al. (2019), when operating the RPAS for emergence sunflower count, used a height of 30 m, overlapping 90% and 70% lateral overlap, and a GSD near 0.86 cm/pixel.

The association of AM algorithms and data obtained by embedded sensors in RPAS also presented promising results in the count of agricultural and forestry species. Due to their hierarchy and design flexibility, CNN models have provided significant progress in that scope. Recent research has investigated the potential of the CNN approach applied to images obtained from sensors carried by RPAS (Djerriri et al. 2018; Salamí et al. 2019). Osco et al. (2020) presented a CNN approach to estimate the number and location of citrus trees from multi-spectral RPAS images.

Convoluctional Neural Networks (CNN) are a Deep Learning (DL) technique that, according to Lecun et al. (1989), was initially developed to implement the automated recognition of postal code data in the US. According to Zhang et al. (2016), CNN was recently introduced into the community of geosciences and remote sensing for Big Data analyzes, especially in image recognition. CNN, for Lecun (2015), are multilayer networks designed for the standards recognition directly from pixels, without the need for complex pre-processing.

CNN's main task is to extract significant resources from the input image. Convolution neural networks consist of three main types of layers: Convolution layers (operation), subsampling layers (pooling - this layer generates a smaller resolution version than convolutional), and layers fully connected (combines all actions to hold the classification of the objects present in the image) (Aparna et al. 2018; O'shea & Nash 2015).

Plant count is a laborious and time-consuming task. To resolve this issue, recent surveys have demonstrated the potential of CNN algorithms applied to images obtained from embedded sensors. CNN's have proven to be a highly efficient approach to agriculture as Wu et al. (2019), when processing high-resolution images captured in situ by RPAS, based on CNN to estimate the count and density of rice seedlings. Madec et al. (2019), evaluated the efficacy of CNN in wheat cob density using high-resolution images. Kitano et al. (2019) aimed to develop a tool for counting corn crop plants as well as propose an approach to this count using CNN and RGB images obtained by RPAS.

Chen et al. (2017), Neupane et al. (2019), and Ubbens et al. (2018) used CNN for fruit and leaf count. Olsen et al. (2018) and Liu et al. (2021) used for detection and counting of sorghum panicles and palm counts via RPAS images, respectively. Valente et al. (2020) employed an excess Green Index combination (EXG), OTSU, and CNN method to identify and count spinach plants.

In addition to CNN's, the Structure FROM Motion Algorithm (SFM) was also used in plants count. SFM was initially proposed by Ullman (1979) to carry out the three-dimensional interpretation and the movement of an object from two-dimensional transformations of their perspective projections, that is, photographs of these objects, without being Initial of any three-dimensional information. In this way, the SFM, according to Westoby et al. (2012), simultaneously determines the location in the space in which the images were captured and the geometry of the elements present in these projections, and it is not necessary to know in advance the control points with three-dimensional coordinates to discover the positions of the cameras at the time of exposure and vice-versa. Simply Jurado et al. (2020) highlight that the SFM can detect the same regions of overlapping images, determine their geometric relationships and infer the rigid structure of the scene (set of points) with the pose (position and orientation) of all cameras.

Mohan et al. (2017), evaluated the SFM algorithm for automatic detection and individual tree count. Gülci (2019) estimated the count of trees, height, and the area of the crops in a young set of pine-da calabria employing SFM. It was also possible to find out in some studies the use of K-Means. This is a clustering algorithm used to determine the natural spectral clusters present in a data set, where the number of the clusters to be located is provided in advance (Lin et al. 2015). Kestur et al. (2018) proposed the Extreme Learning Machine (ELM) method for detection, design, and count of treetops and, finally, compared with K-Means. To perform the fast and accurate count of wheat, Xu et al. (2020) used K-Means grouping for automatic segmentation of images.

4 Conclusion

The primary motivation for this work stemmed from recognizing the importance and necessity of exploring the use of RPAS in plant counting. In today's context, technologies play a critical role in enhancing planning strategies to achieve optimal performance.

RPAS contribute to time optimization, facilitate the identification of timely improvements and corrections, aid in cost management, and boost production in both the agricultural and forestry sectors.In addition, with plant count it is possible to analyze planting efficiency and measure the final harvest, thus having a more assertive profit margin forecast compared to expected results. In this way, developing new remote sensing methods that explore solutions via machine learning, associated with images purchased by plant count, is essential to monitoring and maintenance of healthy and resilient ecosystems.

Finally, it is valid to reaffirm the importance of consolidating and disseminating scientific production as sources of studies to subsidize the construction of new knowledge concerning this theme, so relevant and current.

5 Challenges and Future Perspectives

Data acquisition through RPAS platforms combined with the processing of ML and DL techniques in plant counting is still challenging, since the acquisition of these data requires technical knowledge and experience to process them. In addition, counting plants at an early stage of development requires data with high and very high spectral resolution, which means collecting data at lower altitudes, which can make surveying large areas unfeasible. In this context, the size of learning networks and the large volume of data make it possible to automatically extract precise resources and adequate representations for high precision classification tasks, however there is the cost of longer processing time and the use of computers and servers with potential to store this data (Sedona 2019; Bourscheidt 2019).

As an alternative in this sense to Vali et al. (2020), data providers, which have recently introduced the cloud platform, are used to store, access and analyze data directly, which offers the possibility of integrating data from different sources in the near future. According to Bourscheidt (2019), another relevant aspect is the use of supercomputers, normally used for complex and large-scale modeling and/or simulations. However, this solution may be less interesting for non-academic users, since the internet speed in certain places can be low (longer upload time) and with that, this high volume of data can be impractical to work in the cloud.

Another important point to be highlighted is that most image processing has costs, whether in the acquisition of software or even to perform the processing in the cloud. Free alternatives have been developed, but they still do not have a friendly user interface, as they require specific knowledge in programming (Bourscheidt, 2019), thus limiting their use by a certain part of the agricultural and forestry sector.

In relation to RPAS, there are limitations with regard to battery autonomy and, consequently, the restriction in the duration of the flight time, with an average of 30 minutes for multirotors and 60 minutes for fixed wing. In this way, improving sensor technologies and improving the battery's payload capacity will enable efficient data collection strategies in large agricultural and forest areas.

With the increase in the use of RPAS, Eugenio et al. (2020) highlights that there was also an increase in the number of platforms (fixed-wing and multirotor) and software that deliver, for example, production estimate maps for the rural producer, through the collection of data from multispectral cameras and even with RGB cameras.

Also according to Eugenio et al. (2020), there is the challenge of skilled labor, since the use of RPAS by people who are not able to understand all the factors that affect the quality of the final product. Thus, developing studies on monitoring agricultural and forestry crops, along with integrating other tools, such as vegetation indices and RPAS equipped with spraying devices, is essential to enhance the precision agriculture and forestry system.

The development of tools and the improvement of remote sensing techniques based on RPAS when combined with ML can bring more and more benefits, in terms of economic development in the agricultural and forestry scope, as well as to support the adoption of public policies that reach different sectors of society.

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Conflict of interest

The authors point out that there is no conflict of interest by submitting the manuscript.

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All data included in this study are publicly available in the literature.

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