

Review

Recent Advances in Unmanned Aerial Vehicle Forest Remote Sensing—A Systematic Review. Part I: A General Framework

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Abstract: Natural, semi-natural, and planted forests are a key asset worldwide, providing a broad range of positive externalities. For sustainable forest planning and management, remote sensing (RS) platforms are rapidly going mainstream. In a framework where scientific production is growing exponentially, a systematic analysis of unmanned aerial vehicle (UAV)-based forestry research papers is of paramount importance to understand trends, overlaps and gaps. The present review is organized into two parts (Part I and Part II). Part II inspects specific technical issues regarding the application of UAV-RS in forestry, together with the pros and cons of different UAV solutions and activities where additional effort is needed, such as the technology transfer. Part I systematically analyzes and discusses general aspects of applying UAV in natural, semi-natural and artificial forestry ecosystems in the recent peer-reviewed literature (2018–mid-2020). The specific goals are threefold: (i) create a carefully selected bibliographic dataset that other researchers can draw on for their scientific works; (ii) analyze general and recent trends in RS forest monitoring (iii) reveal gaps in the general research framework where an additional activity is needed. Through double-step filtering of research items found in the Web of Science search engine, the study gathers and analyzes a comprehensive dataset (226 articles). Papers have been categorized into six main topics, and the relevant information has been subsequently extracted. The strong points emerging from this study concern the wide range of topics in the forestry sector and in particular the retrieval of tree inventory parameters often through Digital Aerial Photogrammetry (DAP), RGB sensors, and machine learning techniques. Nevertheless, challenges still exist regarding the promotion of UAV-RS in specific parts of the world, mostly in the tropical and equatorial forests. Much additional research is required for the full exploitation of hyperspectral sensors and for planning long-term monitoring.

Keywords: UAV; drone; forest; precision forestry; remote sensing; meta-analysis; management; natural woodland; plantation forests



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1. Introduction

1.1. A First Look at the Use of Drones in the Forestry Sector

Natural, semi-natural and planted forests are a key asset worldwide, providing a broad range of positive externalities. These kinds of benefits can be included in three main categories such as goods (timber, food, fuel, and bioproducts), ecosystem services (carbon storage, nutrient cycling, water, air quality, and wildlife habitat), and social and cultural features (recreation, traditional resource uses, and well-being) [1]. In this context, sustainable forest planning and management require understanding both short and long-term woodland dynamics [2]; furthermore, a modernization of forestry inventory frameworks is needed and driven by the ongoing uncertainty on the future condition of forests related to climate [3]. Ordinary inventory operations require the collection of field data with labor-intensive, time-consuming, and, no less important, increasingly expensive acquisition procedures. Besides, field campaigns are restricted to small areas, so that the

number of field inventories that can be reasonably completed is drastically limited [2]. For the adoption of precision forestry practices, promptness is a key requirement and this is especially true when the forest structure is changing in a hardly predictable way due to pressure from biotic or abiotic factors [3].

Remote sensing (RS) platforms, such as unmanned aircraft systems (UAS), satellites, and airplanes fitted with dedicated sensors are rapidly going mainstream. They are still being developed for full optimization, among other sectors, of forest management and their relevance for decision support is growing crucially for forestry managers, entrepreneurs, and researchers [4]. RS provides data at different resolutions in terms of space, spectral band, and time allowing forest modeling under different conditions and for various management purposes (economic, monitoring, conservation, restoration). Unlike traditional field-based inventories, the full-coverage often guaranteed by RS platforms provides data on many primary forestry parameters [1]. Nevertheless, RS applications for forestry often require images with a high temporal resolution [5]. Considering the traditional airborne and spaceborne RS platforms, the spatial and temporal resolutions provided by satellite-based data are usually not suited to achieving regional or local forestry objectives while aircraft, even if their products have a more appropriate spatial scale, are expensive when regular time-series monitoring is desired [6]. Moreover, data from manned aircraft and satellite platforms are vulnerable to cloudy sky conditions, which attenuate electromagnetic waves and cause information loss and data degradation [7]. Drones (hereafter called Unmanned Aerial Vehicle—UAV), equipped with GPS and digital cameras, are suitable for real-time applications, inasmuch as they combine high spatial resolution and quick turnaround times with lower operational costs [8]. Thanks to their flexibility of use, UAVs are becoming one of the emergent technological tools, with a wide perspective, as well as increasing applicability [9] and therefore, for precision forestry application especially at a local scale, they overtake traditional RS platforms. It is also important to note that recent UAV advances, along with computer vision and other related research topics, have created many opportunities for practical forestry by facilitating and improving field data collection in terms of temporal and spatial accuracy, with the possibilities of creating customized datasets according to specific needs [10].

The major drawbacks in using UAVs rather than other RS platforms are represented by generic technical issues that are not related to the inner features of forests. To the best of the authors' knowledge, only Surový and Kuželka [10] report that the effective extent of detailed UAV data is limited to several forest stands because the high resolution and high-frequency data cannot be efficiently acquired for the whole extent of a very large forest. In general, the main disadvantages of UAV flights are imposed by battery duration and therefore by small area coverage, payload weight [11], and sensitivity to some bad weather conditions (i.e., wind, precipitation, and sudden and sharp light conditions variation) [4,12]. In the post-flight workflow, UAV imagery products involve massive data processing capability [1], often with a combination of robust image processing software and sophisticated machine learning systems; all this results in substantial computation requirements and therefore high expense in terms of money and time [13]. Current limitations for UAV activity are also enforced by policy and regulations (restrictions on airspace use). This is one of the major factors that prevent researchers from testing all of the possibilities for UAV civil applications [7]. Despite the critical issues listed, the advantages of using UAV instead of other RS platforms far outweigh the drawbacks. If used appropriately and combined with ground surveys and local knowledge, UAVs can constitute a valuable tool in monitoring and mapping forests, especially over small areas, responding to the growing need for more accurate data [14]. In the last years, UAVs have been recognized as an effective complement to traditional vehicles due to their economy, safety, maneuverability, positioning accuracy, high spatial resolution, and data acquisition on demand [5,7]. UAV imagery, due to its extremely high possible spatial resolution (fixed-wing up to 2 cm/pixel; rotary: sub-millimeter), is a cost-effective data source for providing detailed reference information [15], especially for a research project or service-based business with a tight

budget. UAVs can carry a wide range of task-oriented sensors [16,17] whose operation is not affected by clouds due to the low flight altitude [4]. UAV missions can be planned flexibly, avoiding poor weather conditions, providing data availability on-demand, and enhancing temporal resolution [6]. The availability of UAV imagery in NRT (Near Real-Time) is another feature that can help agroforestry operations, due to the possibility of identifying problems faster and, consequently, reacting quickly, reducing losses, and, in the case of professional foresters, economic outlays [4]. UAVs can thus be used in real-time operations, for example in wildfire detection using thermal sensors [6]. Regarding academia, the use of UAV allows researchers to acquire complex imagery (i.e., hyperspectral) themselves and with higher frequency than in the past when specialized companies provided all the airborne imagery [10]. Furthermore, thanks also to the constant technological development, UAV costs in terms of material and operational charges are diminishing, while processing capabilities and dedicated artificial intelligence (AI) algorithms, i.e., machine learning, improve [13]. Finally, UAVs can save time, manpower, and financial resources for practitioners, public authorities, and researchers [6]. For all the aforementioned pros, interest in UAV has been increasing and this technology has become a focus of research [5].

1.2. UAV in Forest Remote Sensing: Research Topics, Vehicle Type, and Sensors

The use of smart and low-cost tools such as UAVs in precision forestry has increased exponentially in recent years, as demonstrated by the large number of papers published from 2018 until mid-2020; more than 600 references were found when searching for “UAV” + “forest” and considering articles, systematic reviews, conference proceedings and books [18]. By summarizing the results of some recent review papers [4,5,13,19], it follows that the range of UAV academic topics investigated by researchers is very wide and it also involves the use of UAV together with other RS platforms. Two main clusters among research topics can be outlined: (i) dendrometric parameters estimation (ii) monitoring and conservation activities. Regarding the estimation of basic physiological features, UAVs have been used with varying levels of success in 2D and 3D mapping applications such as individual tree detection or estimation of tree height, leaf area index (LAI), chlorophyll content, tree crown dimension, and location. In this cluster a subgroup of topics, regarding the estimation of derived dendrometric parameters, can be connected directly also with practical forestry activities: monitoring growth status, measuring plant density, merchantable biomass estimation, species identification, inspection of forestry operations, diseases detection and management, and post-harvest data (i.e., forest stockpiles measuring, truckload soil structure degradation). The second cluster includes the use of UAV for monitoring, conservation, and restoration activities required by the impact of climate change on forests and the change in the level of woodland biodiversity. In particular, UAVs are used, from an ecological point of view, for the mapping and control of weed vegetation and invasive alien species; deforestation monitoring and estimation of deforestation rates utilizing the identification of gaps; forest wildfire management and detection, especially for prevention and post-fire monitoring, by identifying and constructing risk maps and supporting shut down operations. UAV and their sensors are also applied to quantify aboveground biomass (AGB) and monitor it over time to assess the impacts of climate and land-use changes on the global carbon cycle of forest ecosystems and to understand their effects on woodland resilience and health. Furthermore, UAVs can track wildlife, detect woodland land-use change, monitor legal restrictions, and, in general, monitor habitats that are difficult to reach (wetlands, rock faces, coastal ecosystems) or where trespassing is undesirable [4,5,13,19].

UAVs employed for forestry applications and reviewed in this study are classified according to their size as small, mini, and micro vehicles and can also be categorized on the basis of wing type. Generally, in regard to civilian usage, UAVs can be rotor-based, fixed-wing, or can adopt hybrid solutions (Figure 1). They are user-friendly platforms with take-off mass ranging from a few tens of grams up to 25 kg and over [5] and with a flight time comprised between a couple of minutes and a few hours of autonomy [4]. Fixed-wing

platforms are adequate for monitoring larger areas with a pre-defined flight plan but need space for landing [1]. On the other hand, multi-rotor UAVs are more maneuverable, having easier take-off and landing and are preferred by researchers because they are usually cheaper and more flexible for demonstrative/scientific studies [4].



Figure 1. Unmanned aerial vehicle (UAV) types for remote sensing civilian usage: rotary-wing (a,b), fixed-wing (c,d), unmanned helicopter (e), and hybrid solution (f).

The progress in sensor implementation particularly concerned their miniaturization to lessen the payload to be transported. This big step forward has allowed us to equip the UAV with a broad range of sensors and tools: high-resolution digital cameras, infrared/thermal cameras, multi-spectral cameras (passive sensors), lidar—Laser Imaging Detection and Ranging (active sensors)—as well as chemical instrumentation for sensing Volatile Organic Compounds (VOCs) [20–22] and also tools for distributing agro-forestry products [23]. The possibility of equipping UAV with a wide choice of sensors in association with georeferencing systems has supported forestry scientific research by monitoring anomalies and trends which, if observed by traditional means from the ground, could have manifested in a less obvious way [24].

RS applications very often separate RGB channels and work with individual red, green, and blue channels to provide valuable visual information for foresters [25]. Instead, for assessing vegetation properties, information obtained in the NIR region (from 750 nm

to approximately 1400 nm), where the high reflectance of vegetation occurs, should be used. Indeed, the NIR band results crucial for most forestry applications precisely because healthy vegetation that is actively growing and producing energy from photosynthesis reflects more in the NIR region [4]. Thermal cameras operate approximately in the spectrum at wavelengths from 8000 to 15,000 nm and detect electromagnetic radiation which can be experienced as heat. Thanks to these sensors, the pixel's digital number can be transformed into a temperature measurement [26]. Multispectral sensors sense broadbands, usually 4–12, and are extensively used for vegetation analysis, given that they often include NIR together with multiple bands (e.g., R, G, B, red edge) [27]. The hyperspectral sensor is gradually becoming more common in UAV forestry applications. It has very high spectral resolutions sensing hundreds of narrow bands up to 2 nm in wavelength. Hyperspectral sensors produce images in which each pixel contains the whole spectrum of the sensed wavelengths. In this way, greater imagery information than all the other passive devices is provided [28] but a few drawbacks, such as high operation costs and complex equipment are inevitable with today's technology [13]. Lidar is an active laser-based remote-sensing technology that uses focused laser light pulses by transmitting them to the surface with a fast repeat rate. It measures the time taken for the reflections to be detected by the sensor (transmitter-target-receptor) to determine the distance to targets (objects, surface). By repeating this process with a fast sequence, lidar generates a 3D point cloud of the surface [4,13].

Regarding the use of UAV sensors in forestry applications, it can be emphasized how the RGB sensors are suitable to estimate Fractional Vegetation Cover (FVC) [29], to find features within a certain area (e.g., tree crown size estimation) [30], and to detect invasive species [31]. Instead, through reflectance analysis with wavebands outside of the visible spectrum, the multispectral, infrared, and hyperspectral sensors are most suitable for LAI [32] and for identifying the presence/absence of certain components or materials (e.g., disease [33,34] and water stress detection [35]). Thermal sensors are used effectively to detect water stress [36] and in forest fire monitoring [37] and wildlife detection [38] while multispectral sensors can be applied for determining burned areas in a post-fire scenario [39]. Lidar sensors can provide accurate measurements targeting land objects for an effective forest inventory, also being capable of gathering data also below the canopy [40]. By penetrating the forest canopy, lidar is a powerful tool for the direct 3D measurement of various tree attributes, even at a fine-grained scale [41]. It can be used for individual tree detection and crown delineation [42–44], for retrieving inventory parameters such as diameter [45], height [46] and biomass [47] and for predicting carbon dynamics [48]. Lidar metrics are both ecologically meaningful and management-relevant, as demonstrated by their applications in overstory characterization [49], forest restoration [50], wildfire prevention [51] and post-fire monitoring [52]. Nevertheless, a careful comparison must always be made with optical sensors considering the relatively high cost of lidar technology [53,54]. For instance, to determine vegetation height, optical sensors are a plausible choice, because they offer the possibility of image 3D reconstruction using Structure from Motion (SfM) algorithms and, at the same time, they have higher cost-effectiveness compared to lidar [4].

1.3. Systematic Review Goals

In a framework where scientific production is exponentially growing, a systematic analysis of UAV-based forestry research papers is of paramount importance to understand trends, overlaps and gaps, since forestry applications include a wide range of scientific topics.

The present review is organized into two parts (Part I and Part II) and tries to accomplish a systematic analysis of the recent peer-reviewed literature (2018–mid-2020) on using UAV in forestry RS applications. Scientific papers regarding environmental chemical sensing (i.e., VOCs, particulate matter) and canopy sampling have been excluded. It is important to mention that the main object of this study is small, mini, and micro UAVs

with the related imaging sensors since these types of vehicles are simple to use, affordable, and easy to carry.

This paper (Part I) reviews the state-of-the-art research studies capable of remote sensing forest ecosystems. In a broad context, the authors wish to increase the understanding of the current research topic framework. In particular, specific goals are threefold: (1) create a carefully selected bibliographic dataset that other researchers can draw on for their scientific works; (2) analyze general and recent trends in RS forest monitoring (publishing source, keywords, research place, forest type, sensors) (3) reveal gaps of the general research framework where an additional activity is needed and suggest possible solutions. To provide a general framework of current research, the targeted audience is mainly represented by forest stakeholders (entrepreneurs, technicians, public authorities) and young researchers who want to approach UAV-RS in forestry. Furthermore, even skilled researchers could benefit from this Part I, which can provide a large bibliographic database as underpinning for their activities.

Section 2 presents the workflow for the dataset creation and forestry research topics categorization. In Section 3 results are elaborated for the global analysis concerning cross aspects to the totality of the works selected in the first and second filtering step. Then in Section 4, general discussions are reported; they encompass overall issues including the geographic distribution of researches, the use of sensors, and the presence of multi-temporal analysis. Finally, in Section 5 the main conclusions derived from Part I of the present review are drawn, outlining both strengths and challenges from a global point of view and providing some suggestions for filling the identified research gaps.

To give a clear picture of the entire review, the aims and the audience of Part II [55] are briefly described below. This part identifies the most popular technical issues and shows the pros and cons of different UAV solutions. The six research topics are fully analyzed and discussed with a particular focus on: hyperspectral sensors, comparison with other RS platforms, machine learning techniques, and use of field data. The authors seek to reveal critical points (not only at the technical level) where additional effort is needed, such as the technology transfer of UAV-RS in a real management context. Bearing this in mind, Part II of the present review is primarily aimed at expert researchers, technicians and consultants.

2. Materials and Method

2.1. Dataset Creation: Scientific Paper Search, Filtering, and Selection

The authors performed a comprehensive literature search using the Web of Science (WoS—Clarivate Analytics) search engine to extract peer-reviewed studies related to the use of UAV platforms for forestry remote sensing applications and published between 2018 and mid-2020. The search descriptors were a combination of keywords related to UAV platforms, namely “UAV”, “unmanned aerial vehicle”, “UAS”, “unmanned aerial system”, “drone” and terms related to forest science and management, namely “forest” and “forestry”. At this point in the database creation workflow, double-step filtering was conducted. The first step consisted of exploiting the exclusion criteria directly available in the WoS search engine, that is publication year, document type, and language (Figure 2). In particular, for each keyword combination entered in the research field “Topic”, the investigation was limited to 2018, 2019, and mid-2020 (30 June) to encompass only the most recent applications of UAV in forest remote sensing. In this way, the present systematic review differs from other bibliographic analyses by making readers aware of the latest research findings in this sector. Only original articles, conference papers, and book chapters published in the English language were screened.

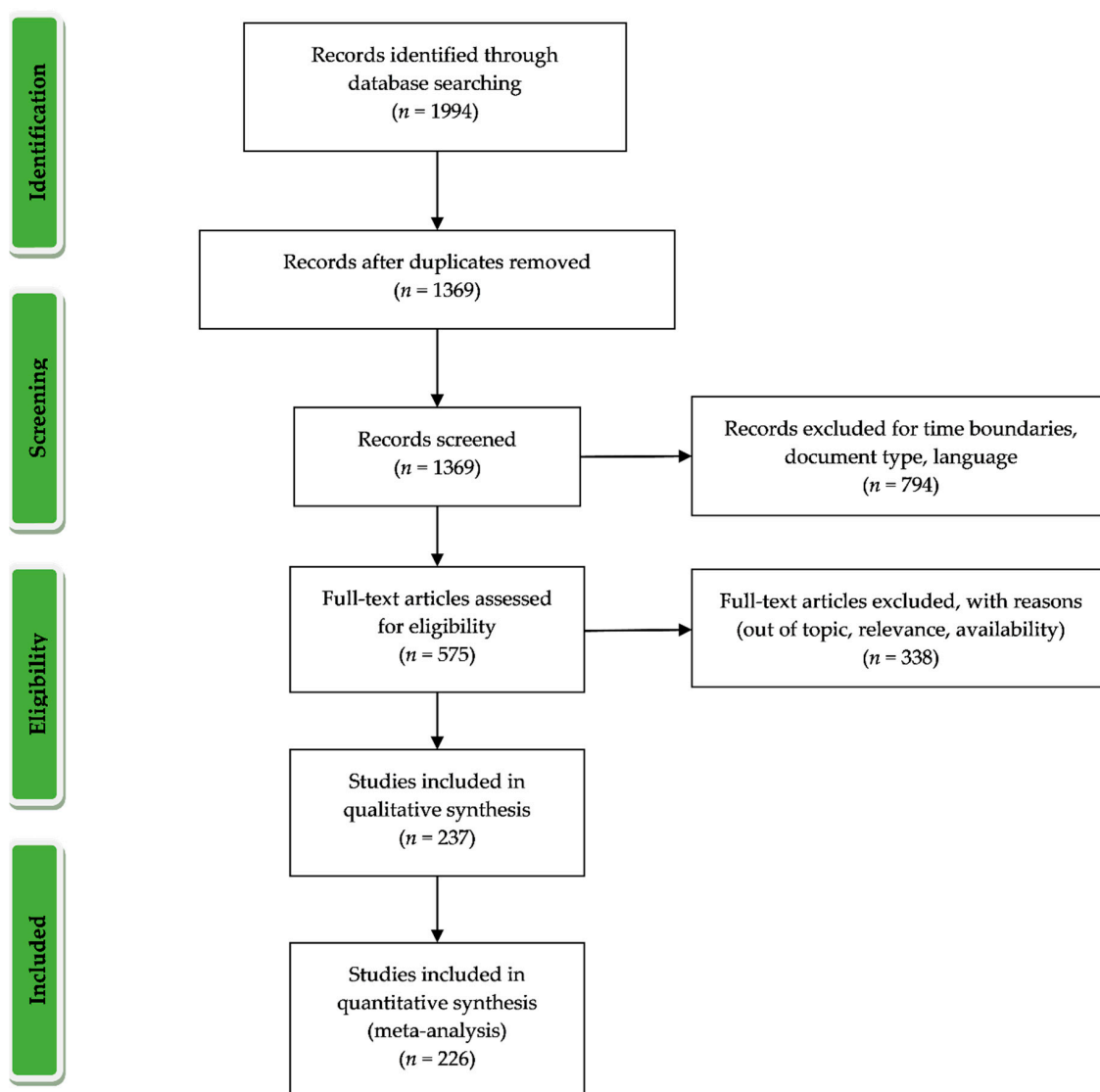


Figure 2. Workflow (PRISMA diagram) showing the phases of the database creation (n = number).

At the end of this phase, bibliometric metadata of the screened research papers are exported from the WoS search engine. Metadata text files are elaborated through a scientific mapping software, VOSviewer [56]. The results of bibliometric networks among the title and abstract keywords most used in the UAV-based forestry research (2018–mid-2020) are presented later, at the beginning of Section 3.

For the eligibility of the screened research papers, the second level of filtering was performed based on the following exclusion criteria: (i) adequacy of the paper topic to the aims of the present review, (ii) mixed criterion accounting for the relevance of publishing source and paper citations, and (iii) scientific paper availability in the research institution's database. For doubtful cases, the authors re-read the full text of the article and excluded those that did not satisfy the aforementioned criteria. Finally, a total of 226 papers were found to be relevant to the study and therefore are included in the systematic analysis. The overall workflow with single steps and with the related number of selected or excluded papers is reported in Figure 2.

2.2. Topic Categorization and Other Classification Criteria

Once all the papers had been read, they were categorized into six main topics, and subsequently, the information needed to address the research questions (reported in Part II) was collected. The selected topics with a brief description are listed below.

2.2.1. Setting and Accuracy of Imagery Products

In this topic, the acquisition, pre-processing, and processing of UAV data for forest structure characterization is discussed. In particular, it encompasses UAV and sensor settings (e.g., UAV altitude, overlap, sensor resolution) and the accuracy features of generated imagery products as, for instance, digital terrain model (DTM), digital elevation model (DEM), canopy height model (CHM), point cloud.

2.2.2. Tree Detection and Inventory Parameters

The topic includes tree detection and the estimation of dendrometric parameters for forest inventory purposes and, in general, the measure of metrics and spatial properties at stand/tree-level. The focus is on assessing the height of the forest population and other inventory parameters like diameter at breast height (DBH), crown area, etc. Individual tree detection with crown delineation is also a hot issue. Tree biomass and volume are excluded from this section.

2.2.3. Aboveground Biomass/Volume Estimation

Considering the scientific relevance and number of articles gathered, the authors decided to devote a separate section to biomass estimation. This topic includes the estimation of aboveground biomass, overall volume, stock growing volume, basal area, and carbon content at stand/tree-level as well as woody debris and fallen logs. As can be well-understood, many of the selected papers start from estimating tree-dendrometric parameters as basic key features to then assess the biomass.

2.2.4. Pest and Disease Detection

Forest health monitoring is covered in this section; in particular, research papers assessing forest status and mortality induced by biotic factors (diseases and insect pests) are collected.

2.2.5. Species Recognition and Invasive Plant Detection

This topic deals with the assessment of dominant species in forest stands and the spatial analysis of weed/alien plant invasions, regarding species classification and invasive plant detection, respectively.

2.2.6. Conservation, Restoration, and Fire Monitoring

A broad range of sub-topics is included in this section. Regarding natural (and semi-natural) forest ecosystems conservation, the main issue is forest biodiversity monitoring at spatial and temporal scale, also through the quantification of canopy spatial structures and gap patterns. In this framework, even research papers dealing with land use are included in the conservation sub-topic. Restoration encompasses the study and implementation of all those interventions that intend to restore a forest ecosystem destroyed by various natural and human factors (i.e., wildfires/arsons, post-mine sites). The forest fire monitoring sub-topic, investigated in this review, can be divided into two main issues: monitoring (before fires), i.e., prevention, e.g., by creating fire risk maps of vegetation; and post-fire monitoring (after fires), i.e., mapping burned areas and assessing fire effects.

In addition to topic categorization, each selected study is assembled in a tabular format according to the following criteria: publication year, author, title, publication name, publication type, DOI, total times cited count, sensor type, study location (continent and country), forest type, plant group, species, machine learning techniques (object detection methods/crown segmentation algorithms), other RS platform use or comparison, ground truth data type. This synthesis is then used to answer the research questions (Part II).

3. Results

Global Analysis Results

This section reports the results elaborated for the global analysis without going into the specifics of each topic cluster (see Part II). In particular, the authors analyzed scientific production of the period 2018–mid-2020 on the use of UAVs in forestry research in terms of papers' number, journals, researcher countries, and keywords used. Figure 3 shows the top 20 sources title (journals and proceedings) of research papers filtered only through the exclusion criteria directly available in the WoS search engine (first-step filtering), namely publication year, document type, and language. The Remote Sensing journal (MDPI publisher) turns out to be by far the most popular source title accounting for 23.4% of the publications filtered; then, there are Forests (4.8%—MDPI), the International Journal of Remote Sensing (3.2%—Taylor and Francis), and the International Geoscience and Remote Sensing Symposium Proceedings (2.7%—IEEE Xplore) together with Remote Sensing of Environment (2.7%—Elsevier).



Figure 3. Treemap of the top 20 source titles for the first-step filtering records.

Regarding the top 20 authors' countries, the bar graph (Figure 4) displays how China and, a step back, the United States of America are the countries that a large share of the researchers who have published on UAVs and forests come from, with 26.5% and 18.4%, respectively. Following these are scientists from Canada (8.8%), Germany (6.7%), and England (5.4%).

Besides, using the abovementioned first-step filtered database, a scientific mapping of title and abstract keyword occurrences was realized through VOSviewer software [56]. The setting options were tuned as follows: title and abstract field, occurrence full counting method, minimum occurrence threshold equal to 10, and default relevance score (60%). Moreover, to ensure that specific terms strictly related to the use of UAVs for forestry applications were highlighted, some generic words (i.e., work, range, task, etc.) were manually excluded. The network mapping (Figure 5) shows the keyword clustered in four groups with colored lines (max numbers set equal to 200) indicating co-occurrence links between terms. The four groups can be labeled as "classification" (red), "biomass estimation" (yellow), "inventory" (blue), and "UAV imagery" (green) clusters. In the red cluster, the main keywords are all related to image classification both in terms of parameters ("vegetation index", "texture", "spatial resolution") and techniques ("random forest", "SVM"—support vector machine, "CNN"—Convolutional Neural Network); there is also a sub-group linked to forest fire monitoring where "UAVs" is the most influential term. The biomass estimation cluster is characterized by the keyword "AGB" together with "Sentinel" and "mangrove forest"; this analysis confirmed the high number of papers dealing with biomass assessment

in mangrove ecosystems also with the use of other RS platforms, like satellites. “Height”, “structure”, “individual tree” and “plot” are the most frequent occurrences in the inventory cluster, which is strictly related to the remote sensed dendrometric parameters as is also confirmed by other terms like “DBH”—Diameter at Breast Height—“basal area”, “field measurement”, and “forest inventory”. In the green cluster, the fulcrum research keyword of “point cloud” around which there are other UAV imagery products such as “DTM”—Digital Terrain Model—and “DEM”—Digital Elevation Model—or terms related to image processing like “photogrammetry” and “DAP”—Digital Aerial Photogrammetry.

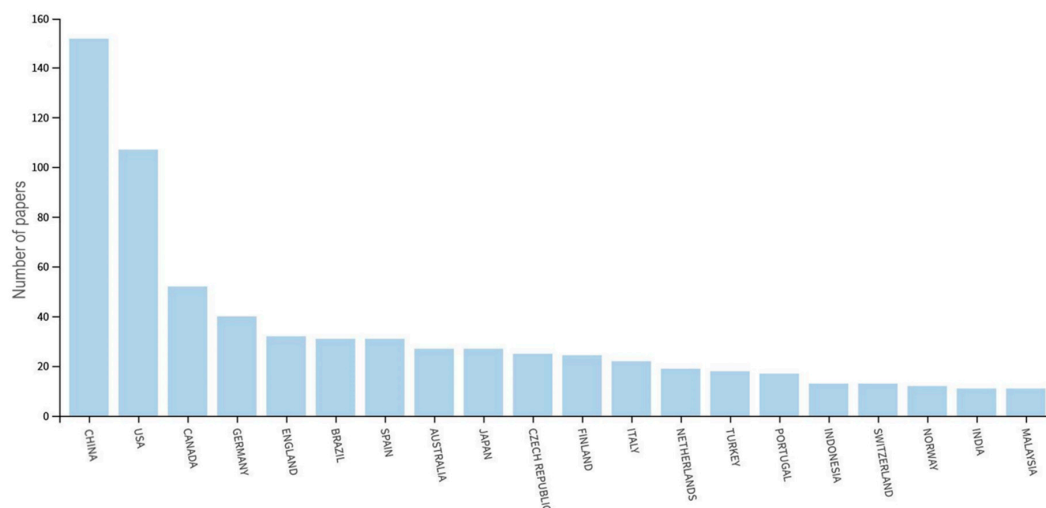


Figure 4. Bar graph of the top 20 authors’ countries for the first-step filtering records.

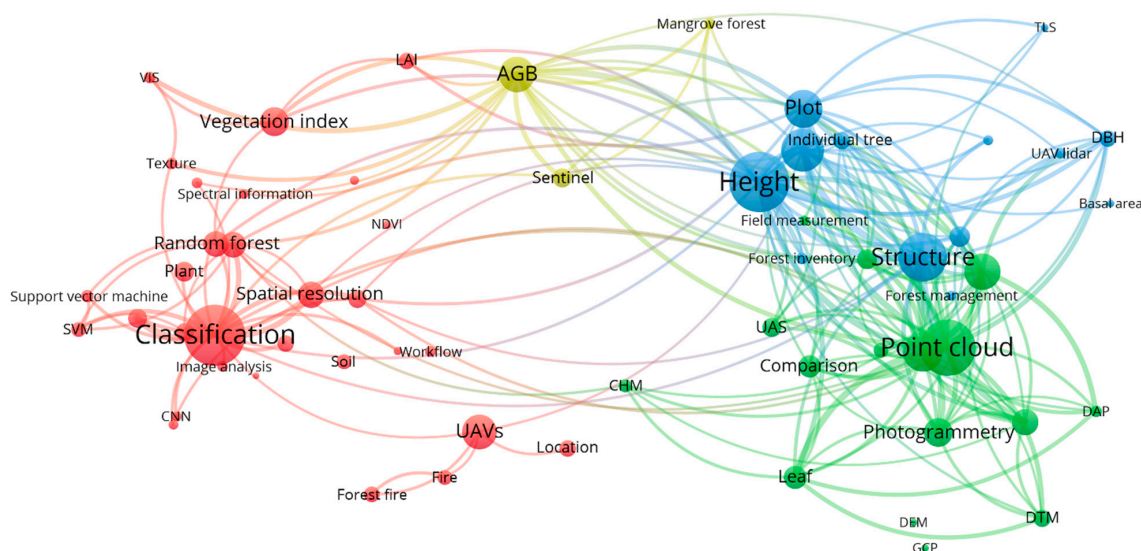


Figure 5. Scientific mapping of keyword networks for UAV in forestry applications based on the cluster method (2018–mid-2020). Abbreviations: GCP = Ground Control Point; NDVI = Normalized Difference Vegetation Index, OBIA = Object-Based Image Analysis, TLS = Terrestrial Laser Scanning, VIS = Visible Spectrum; other abbreviations are reported in the text.

Regarding the co-occurrence between keywords of different clusters, an in-depth analysis reveals that “point cloud” could be reasonably considered as the key element of UAV-RS in forestry being strongly tied (thick lines) with all the main keywords of other clusters such as “structure”, “AGB”, and “classification”. It is worth noting that interconnections between different clusters occur also in the case of “AGB” and “vegetation index”, “AGB” and “plot”, “height” and “random forest”. No words regarding the hyperspectral

sensor, flight regulation, and multi-temporal analysis stand out according to the minimum occurrence threshold. This scientific mapping could reveal research gaps to further explore.

Applying the second level of filtering following adequacy, relevance, and availability exclusion criteria (Section 2), a total of 226 papers were selected to form the final dataset of the present systematic review (Table 1). The eligible research studies are tabulated according to forest type, plant group, and topics to highlight the high amount of data from which this analysis started and to outline some statements based on the abovementioned clustering criteria. Forest type includes planted woodland, which may have one or more characteristics such as species purity, even-age and regularly spaced, and natural/not regular woodland, mixed, uneven-aged, and irregular-spaced forests, where the spatial variability of vegetation is very high and where the use of UAV is more challenging. The nomenclature of plant groups reflects the plant types found in the articles together with a practical classification among conifer (a group of gymnosperms), broadleaved trees (angiosperms, both deciduous and evergreen), mixed plants (conifer + broadleaf), and other (*Ginkgo biloba* L. and trees for which no taxonomic hint is specified in the reviewed articles). Overall, the researchers focused mainly on natural forests (63%) and, among plant groups, on broadleaf woodland (84 research papers). Focusing on plant groups, the majority of tree species are classified as conifer (50%) in planted forests whereas they are mixed in natural ones (42%). Tree detection and inventory parameters are the most discussed topic (95 articles in total) also confirming that it is a key issue in the forestry sector for all the stakeholders (researchers, practitioners, and public authorities). On the contrary, pest and disease detection is addressed only in 17 papers, meaning that the topic has not yet fully entered UAV forestry applications. The setting of image accuracy and AGB estimation are particularly discussed in the natural forest while UAVs are utilized in a few tasks of conservation, restoration, and fire monitoring throughout forest types and plant groups. Finally, as could be expected, species recognition and invasive plant detections are not tackled in the planted forest.

Table 1. Overall research paper dataset tabulated according to forest type, plant group, and topic.

Forest Type	Plant Group	Topic				
		Setting and accuracy of imagery products	Tree detection and inventory parameters	AGB/volume estimation	Pest and disease detection	Species recognition and invasive plant detection
Planted	Broadleaf	Aguilar et al. [57]	Balsi et al. [58] Guerra-Hernandez et al. [59] Iizuka et al. [60] Medauar et al. [61] Mokros et al. [62] Qiu et al. [63] Blonder et al. [64] Carl et al. [65] Fawcett et al. [66] Wang et al. [67] Zeng [68] Dalla Corte et al. [69] Picos et al. [70]	Pena et al. [71] Guerra-Hernandez et al. [72] Navarro et al. [73] Lu et al. [74]	Maes et al. [75] Padua et al. [76] Sandino et al. [77] Dell et al. [78]	Almeida et al. [50] Iizuka et al. [79] Paolinelli Reis et al. [80] Sealey and Van Rees [81] Sealey and Van Rees [82]
	Conifer	Diaz et al. [83] Guan et al. [84]	Abdollahnejad et al. [85] Demir [86] Feduck et al. [87] Goodbody et al. [88] Iizuka et al. [89] Shin et al. [90] Webster et al. [91] Durfee et al. [92] Ganz et al. [54] Gulci [93] He et al. [94] Imangholiloo et al. [95] Krause et al. [96] Lendzioch et al. [97] Maturbongs et al. [98] Puliti et al. [99] Santini et al. [100] Santini et al. [101] Tian et al. [102] D'Odorico et al. [103] du Toit et al. [104] Hu et al. [105] Kuzelka et al. [45] Li et al. [106]	Lin et al. [107] Windrim et al. [108] Zou et al. [109] Hyypa et al. [40] Iizuka et al. [110] Puliti et al. [111] Yrttimaa et al. [112]	Brovkina et al. [113] Dash et al. [114] Nasi et al. [115] Jung and Park [116] Smigaj et al. [117]	Fernandez-Guisuraga et al. [118] Nagai et al. [119] Belmonte et al. [120] Shin et al. [39]
	Mixed	Polewski et al. [121]	Hentz et al. [122] Huang et al. [123] Kuzelka and Surovy [124] Yan et al. [125] Cao et al. [53] Li et al. [126] Yan et al. [127]			Khokhthong et al. [128]
	Other		Puliti et al. [129] Wu et al. [130] Chen et al. [131]	Liu et al. [132] Shen et al. [133]		Whiteside et al. [134]

Table 1. Cont.

Forest Type	Plant Group	Topic					
Natural/not regular	Broadleaf	Goodbody et al. [135] Ruwaimana et al. [136] Oliveira et al. [137] Fletcher and Mather [138] Jurjevic et al. [139]	Alexander et al. [140] Bagaram et al. [141] Chen et al. [142] Guo et al. [32] Kattenborn et al. [143] Klosterman et al. [144] Lin et al. [145] Mayr et al. [146] Morales et al. [147] Rosca et al. [148] Thomson et al. [149] dos Santos et al. [150] Park et al. [151] Schneider et al. [152] Xu et al. [153] Yin and Wang et al. [46] Dong et al. [154] Krisanski et al. [155] Moe et al. [156]	Otero et al. [157] Domingo et al. [158] Gonzalez-Jaramillo et al. [159] Li et al. [160] Ota et al. [161] Qiu et al. [162] Tian [163] Swinfield et al. [164] Vaglio Laurin et al. [165] Xu [166] Wang et al. [167] Di Gennaro et al. [168] d'Oliveira et al. [47] Jones et al. [169] Navarro et al. [170] Wang et al. [171] Zhu et al. [172]	Cao et al. [173] de Sa et al. [174] Franklin and Ahmed [175] Liu et al. [176] Sothe et al. [177] Waite et al. [178] Wu et al. [179] Yaney-Keller et al. [180] Yuan et al. [181] Casapia et al. [31] Kentsch et al. [182] Miyoshi et al. [183]	Rupasinghe et al. [184] De Luca et al. [185] Fernandez-Alvarez et al. [51] Rossi and Becke [186]	
	Conifer	Frey et al. [187] Jayathunga et al. [188] Ni et al. [189] Graham et al. [190] Graham et al. [191]	Fankhauser et al. [192] Brieger et al. [193] Panagiotidis et al. [194] St-Onge and Grandin [195] Xu et al. [196] Yancho et al. [197] Yilmaz and Gungor [198] Jin et al. [199]	Fujimoto et al. [200] Zhou et al. [201]	Ganthaler et al. [202] Otsu et al. [203] Zhang et al. [33] Barmpoutis et al. [204] Lee and Park [205]	Roder et al. [206] Fromm et al. [207]	
	Mixed	Fraser and Congalton [208] Kellner et al. [209] Seifert et al. [210] Tomastik et al. [211] Wallace et al. [212] Yu et al. [213]	Carr and Snyder [214] Chung et al. [215] Huang et al. [216] Jayathunga et al. [217] Liang et al. [218] Nuijten et al. [219] Rissanen et al. [220] Shashkov et al. [30] Yurtseven et al. [221] Zhang et al. [222] Apostol et al. [223] Balkova et al. [224] Brullhardt et al. [225] Gil-Docampo et al. [226] Gu et al. [227] Hastings et al. [228] Isibue and Pingel [229] Jurado et al. [230] Marzahn et al. [231] Vanderwel et al. [232]	Alonzo et al. [233] Giannetti et al. [234] Jayathunga et al. [235] Puliti et al. [236] Brede et al. [237] Jayathunga et al. [238] McClelland et al. [239] Ni et al. [240] Wang [241] Fernandes et al. [242] Kotivuori et al. [243] Puliti et al. [244]	Cardil et al. [34] Kloucek et al. [245] Safonova et al. [246]	Gini et al. [247] Komarek et al. [248] Mishra et al. [249] Rivas-Torres et al. [250] Saarinen et al. [251] Tuominen et al. [252] Dash et al. [253] Kattenborn et al. [254] Kattenborn et al. [255] Miyoshi et al. [256] Nezami et al. [257] Sothe et al. [258]	Baena et al. [259] Rossi et al. [260] Berra et al. [261] Fraser and Congalton [262] Frey et al. [263] Padua et al. [264]
	Other	Hakala et al. [265] Brach et al. [266]	Chakraborty et al. [267]			Yeom et al. [268]	

Regarding publication years, the selected research papers were 72 in 2018, 99 in 2019, and 55 in the first half of 2020. Hence, it turns out that the number of scientific publications in UAV-based forestry research is continuously increasing during the reference period also considering the projection for 2020 (six more research items in comparison to mid-2019). This trend is in line with the exponential growth of the discipline since 2012 [5] but also with the fast growth of general UAV research [269].

Figure 6 shows a geographic analysis of the dataset. The pie chart size represents the number of research works conducted on the five continents, with the six topics being highlighted in different colors. Each pie chart is centered on the capital city of the country which is at the top rank of the continent. Asia and Europe (including also Russia) are the most prolific continents with 76 and 70 paper, respectively, but, while for Asian research place the applications are more focused on tree detection and inventory parameters, in Europe the scientific works cover a wider range of topics and are split among several countries. In South America, the species recognition topic is well represented (7) thanks to invasive plant detection in the Amazon rainforest. Among continents, North America (which includes also Central America) has the highest incidence (59%) of the tree detection and inventory parameters topic while the 23% of papers from Oceania deal with pest and disease detection. Finally, in Oceania and Africa, UAVs are only used 13 and 5 times, respectively. Regarding nation ranking within each continent, the countries that have hosted the highest number of researches are China (40—Asia), USA (14—North America),

Brazil (11—South America), Finland, Spain and Czech Republic (10—Europe), Australia (8—Oceania), and Ghana (2—Africa).

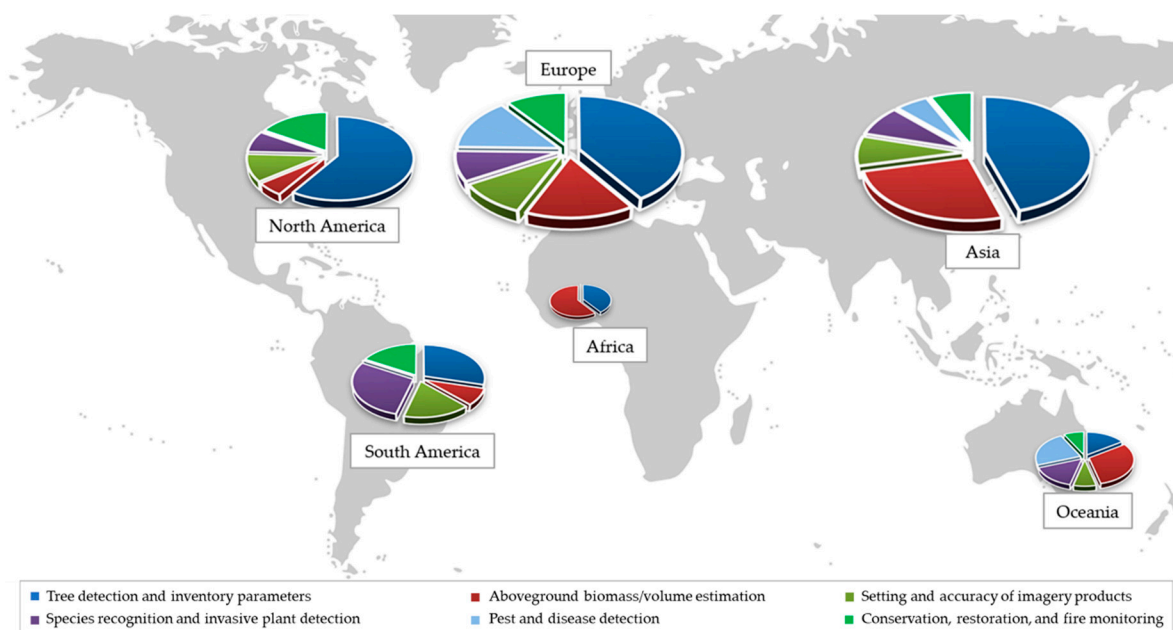


Figure 6. Geographic distribution of research works according to the research place. The pie chart size represents the number of papers while topics are highlighted in different colors.

An analysis of the trend in the use of the main UAV-mounted sensors in the reviewed papers is presented in Figure 7. In the process of label creation, for simplicity, cameras sensing separately in the RGB and NIR spectral range are classified as a single multispectral sensor. When thermal and hyperspectral sensors are used in the same study in combination with others, the authors prioritize the abovementioned sensors. Finally, sensor combination expresses the use of both active and passive sensors. RGB, multispectral, and lidar sensors result as the most utilized technologies (Figure 7a): they account for about 80% of the entire dataset, with RGB emerging far from the other types with 114 uses, followed by multispectral and lidar. Deepening the analysis through the forestry topics (Figure 7b), it results that species recognition and invasive plant detection is mainly based on the hyperspectral sensor, while lidar is UAV-mounted in studies exploring tree detection and inventory parameter issues, even if this topic seems to cross all categories of sensors. AGB estimation is tackled especially with RGB, lidar and sensor combination (where lidar is also present). For conservation, restoration, and fire monitoring purposes, multispectral and RGB sensors (and their combination) are the most used, representing 92% of the studies on this topic.

The authors also conducted a brief analysis of the use of multi-temporal images for assessing forest characteristics and woodland ecosystem state over time. Hence it follows that less than ten studies base their results on a different time-series imagery product. Some of them take advantage of satellite images [114,254,264], while others [135,144,261] perform more than fifteen UAV flights for monitoring tree phenology but within one growing season. It is important to note that only two reviewed papers [76,256] collect UAV-acquired images over a timespan longer than one year.

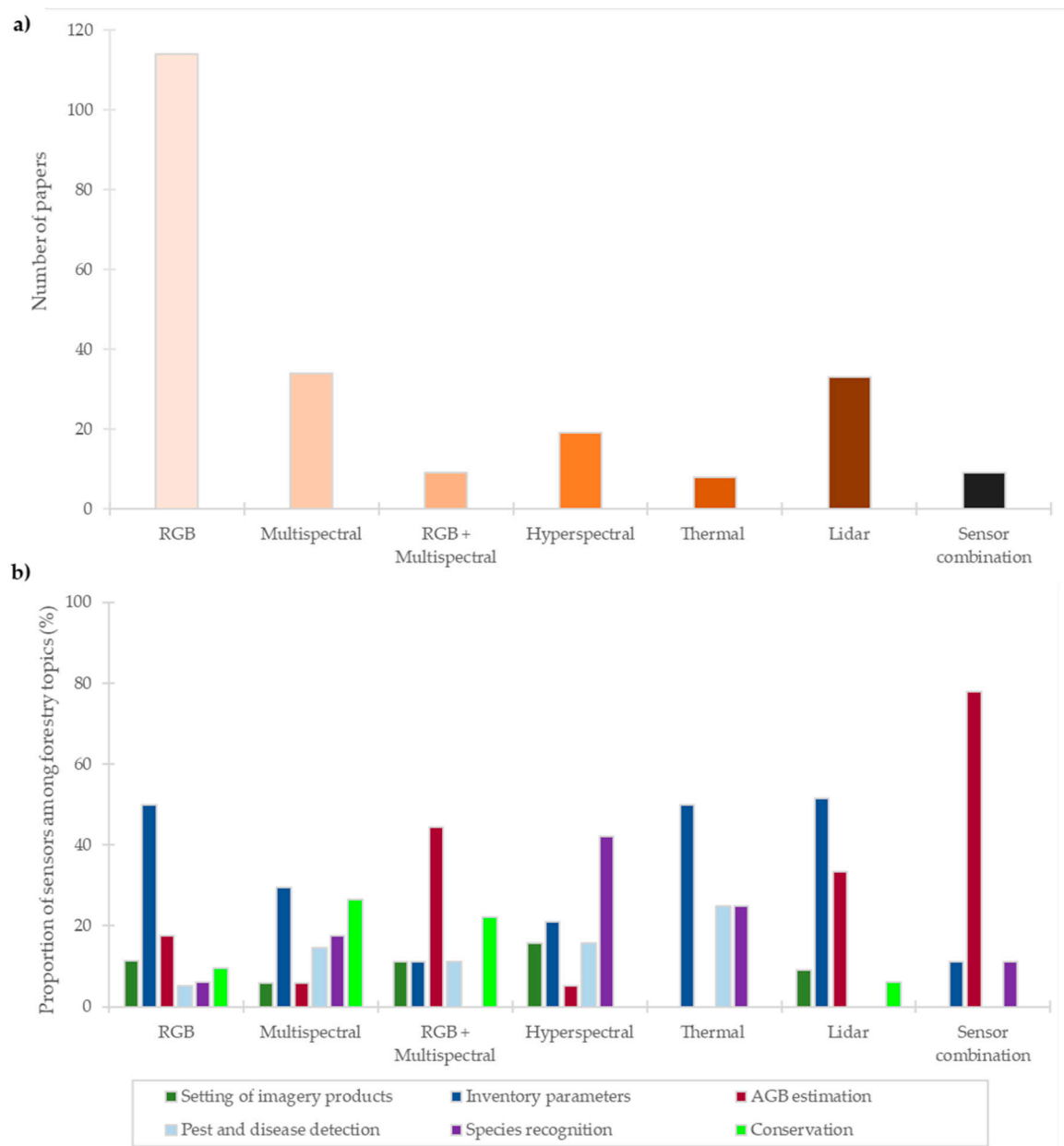


Figure 7. (a) Distribution of different types of sensors in the reviewed dataset; (b): percentage of studies that used a given sensor, by forestry topics.

4. Discussion

Forests, but also other natural resources, need monitoring, management, and preservation, which increasingly profit from UAV remote sensing. As a rule, the capabilities of UAS are evaluated in terms of spectral, spatial and temporal resolution, as well as processing time, area coverage and cost-efficiency. When the monitored woodland has a quite small area, the use of drones is surely advantageous for the amplitude and precision in the acquisition of the spectral range, the centimetric resolution, and daily monitoring frequency. Conversely, among the main drawbacks of UAV compared to other RS platforms may be cited processing time (i.e., about ten times greater than that of a satellite) [136], inability to survey large areas due to the battery and regulatory limitations, and the lack of consistent data collection and processing workflows for multitemporal analysis [270].

The results presented in this Part I show how forestry RS is expanding exponentially. The growth is witnessed by the increased number of scientific papers (also in the short

timespan analyzed) and by several journals belonging to different scientific publishers. From scientific mapping, it emerges that the research issues are mainly heading towards the estimation of inventory parameters among which AGB stands out for importance; at a methodological level, researchers look expectantly at the use of UAV-DAP and machine learning techniques for tree identification and classification purposes. The screened papers cover both natural and planted forests composed of coniferous, broadleaved, or mixed species. Researchers make use of a wide range of UAV-mounted sensors (passive and active); in this context, the RGB camera with centimetric resolution now seems a consolidated and mature technology.

Despite all this, there are several critical issues that the academic world must address to further improve the general quality of research in UAV forest remote sensing as also revealed by the scientific mapping of the most frequent keywords. This review highlights that the number of papers in some continents is often inversely proportional to their huge forest heritage: the case of Africa is striking (only five studies published), but also South America has a quite small number of researches. In parallel, tropical and equatorial forests (representing about 30% of emerged land areas) are under-represented biomes, with only <14% of studies. Remote sensing methods represent a powerful tool for investigating spatial and temporal patterns of vegetation in these challenging environments; this is especially true for low-flying UAV imagery which is not affected by atmospheric artifacts from highly seasonal cloud cover and aerosol loads [271]. The resulting lack of knowledge about tropical and equatorial woodland could perhaps be ascribed to the geographic distribution of research centers, which are often located in developed countries, but also to UAV's limited flight range associated with the inaccessibility of tropical forests that make these ecosystems technically hard to monitor, as long as BVLOS (Beyond Visual Line of Sight) flight strategy will be authorized. Besides, in this context, the availability of ready-to-fly UAV platforms at affordable prices seems to be too recent and it might not allow end-users from developing countries to perform image acquisition with a simpler tool in comparison to customized ones. In the case of UAV, it is difficult to suggest a possible solution through open data accessibility to potential end-users, as in the case of some satellite platforms. As stated by Huylenbroeck et al. [272], using the RS tools to monitor natural resources is not neutral: these methods could exclude stakeholders who do not have access to the technology.

Hyperspectral sensors certainly represent a promising tool for future RS progress but, in this review, less than 10% of papers were found to utilize the technology. This could be due to the difficulties in calibration and setting of prototype/customized solutions, in addition to the high market prices of commercially available packages. In this sense, the ongoing cost reduction of off-the-shelf hyperspectral cameras could certainly boost the use of the sensor. By exploiting the ability to choose numerous bands in a precise spectral range, UAV-mounted hyperspectral cameras can provide the tree spectral signature that, in turn, could be used for species recognition or disease detection.

The capability of acquiring UAV images with high frequency provides new opportunities to study forest evolution. Although UAVs can easily acquire a dense time series, only a few research papers deal with the central issue of multi-temporality to describe vegetation dynamics. Multi-temporal analysis can sometimes replace the spectral range, as in some studies where UAV time series are mainly exploited for intra-annual application such as phenology monitoring. Other papers compare single-season UAV imagery products with relatively coarse resolution satellite images. Less than 1% of research works gather multi-seasonal UAV data; in particular, a three-year UAV image time series is used both for species identification in a Brazilian Atlantic forest [256] and chestnut health monitoring [76]. The poor use of UAV-acquired image time series is an issue that must certainly be addressed by future research. Doing this, it is of pivotal importance to find a balance among the size of the remote-sensed area, spatial and temporal resolution without running into the drawbacks of field surveys again (i.e., high cost and labor).

Finally, although the legal situation of UAV flying is analyzed quite recently [273], none of the selected papers tackle this issue. Many countries still lack legislation that regulates the use of UAV both for research and commercial purposes. Some authors [4,274] highlight the importance of integrating as soon as possible UAV in the airspace through a specific regulatory regime. The legislative framework should be concerted by all the stakeholders to realize UAS's full potential and increase its usage while ensuring individual citizens' safety and privacy rights. A debate on conditions under which drones can be operated is required where this is lacking (i.e., within the European Union) or in specific situations where human artifacts could raise some concerns (i.e., agroforestry, the riparian ecosystem in developed countries). In the end, UAV regulations should be improved addressing not only forestry monitoring but also innovative uses such as management operations including, for instance, chemical distribution.

5. Conclusions

An accurate review of recent papers is essential for further progress in UAV forest remote sensing, particularly both for researchers getting ready to enter the research topic or for those wishing to deepen a single scientific issue.

To the best of the authors' knowledge, this study gathers and analyzes one of the most comprehensive datasets (226 articles) among recent systematic reviews dealing with UAV forest remote sensing. To date, this set of technologies can doubtless be considered popular and well-established, especially within academia, as is shown by the increasing number of papers published in the 2018–mid-2020 timespan.

This Part I of the review analyzed and discussed general aspects of applying UAS (aerial vehicle + sensors) in natural, semi-natural and artificial forestry ecosystems. Certainly, the final assessment presents more positives than negatives as evidenced by the strong points emerging from this study. Among these, there is a broad range of topics discussed in the reviewed studies from which the importance emerges of retrieving tree inventory parameters often with DAP and machine learning techniques. RGB is the most used sensor technology for different forestry research purposes. Not least, the scientific dynamism and growing interest in forestry-UAV-RS is proved by the plentiful research groups, journals, and publishers involved.

Nevertheless, challenges still exist and therefore much additional research is required. UAV-RS should be tested and promoted both in natural and semi-natural forests such as tropical, equatorial and riparian ones. Some parts of the world, in particular Africa and South America, may benefit from greater investment in UAV-RS research so as to have an additional tool to better manage their forest ecosystems. Regarding technical issues, the hyperspectral sensor has many potentialities that are not yet fully exploited and long-term monitoring over a multiple-year timespan should be increased throughout, along with forestry topics where relevant. Finally, considering the general framework of aviation, a proper UAV flight regulation for research purposes should be harmonized among different countries, also for the forestry sector. Future research directions should consider the outlined weak points.

Specific technical issues regarding the application of UAV in forest remote sensing are analyzed and further discussed in Part II [55] of this systematic review. The pros and cons of different UAV solutions throughout the six research topics are showed together with some activities where additional effort is needed, such as the technology transfer. Unlike Part I, Part II of the present review is addressed to a more skilled audience.

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