

Review

Recent Advances in Unmanned Aerial Vehicles Forest Remote Sensing—A Systematic Review. Part II: Research Applications

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Abstract: Forest sustainable management aims to maintain the income of woody goods for companies, together with preserving non-productive functions as a benefit for the community. Due to the progress in platforms and sensors and the opening of the dedicated market, unmanned aerial vehicle–remote sensing (UAV–RS) is improving its key role in the forestry sector as a tool for sustainable management. The use of UAV (Unmanned Aerial Vehicle) in precision forestry has exponentially increased in recent years, as demonstrated by more than 600 references published from 2018 until mid-2020 that were found in the Web of Science database by searching for “UAV” + “forest”. This result is even more surprising when compared with similar research for “UAV” + “agriculture”, from which emerge about 470 references. This shows how UAV–RS research forestry is gaining increasing popularity. In Part II of this review, analyzing the main findings of the reviewed papers (227), numerous strengths emerge concerning research technical issues. UAV–RS is fully applied for obtaining accurate information from practical parameters (height, diameter at breast height (DBH), and biomass). Research effectiveness and soundness demonstrate that UAV–RS is now ready to be applied in a real management context. Some critical issues and barriers in transferring research products are also evident, namely, (1) hyperspectral sensors are poorly used, and their novel applications should be based on the capability of acquiring tree spectral signature especially for pest and diseases detection, (2) automatic processes for image analysis are poorly flexible or based on proprietary software at the expense of flexible and open-source tools that can foster researcher activities and support technology transfer among all forestry stakeholders, and (3) a clear lack exist in sensors and platforms interoperability for large-scale applications and for enabling data interoperability.

Keywords: UAV; drone; precision forestry; forest management; meta-analysis; inventory parameters; biomass; hyperspectral; machine learning; technology transfer



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1. Introduction

It is now undoubted that the scientific production on the use of UAV (Unmanned Aerial Vehicle) for forest remote sensing is growing exponentially, especially in recent years [1]. In this framework, it may prove useful to arrange and analyze the unmanned aerial vehicle–remote sensing (UAV–RS) scientific knowledge and based solutions to make it easily accessible both to researchers and to forestry stakeholders, such as foresters, consulting companies, and public organisms for improving sustainable forest management and conservation [2].

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 remote sensing (RS) applications. The focus is on exploring existing new research papers and dealing with both purely scientific issues and practical applications to the forestry sector. Part I deals with general aspects of applying UAV in natural, semi-natural, and artificial forestry ecosystems, with the aims of (1) creating a selected

bibliographic dataset that other researchers can draw on, (2) analyzing general and recent trends in RS forest monitoring, and (3) reveal gaps in the general research framework. 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 Part I, as underpinning for their activities [3].

In this paper (Part II), the authors intend to give a clear picture of recent advances in forest UAV remote sensing and wish to increase general understanding of the current research topic by synthesizing technical key points from previous scientific papers. In particular, specific goals are threefold: (1) to give an overview of the technical issues addressed by researchers and identify the most popular forestry topics to lay the foundations for the widespread of practical applications through forestry sector stakeholders, (2) to show how different UAV systems (platform + sensor) are used for multipurpose tasks and provide advice on pros and cons of the highlighted solutions, and (3) to reveal critical points (not only at the technological level) where additional effort is needed and suggest future directions to address the research questions that could not be resolved with this synthesis. Part II of the present review is primarily aimed at a skilled audience, such as expert researchers, technicians, and consultants.

After a brief synthesis of the workflow for the dataset creation, the Materials and Methods Section presents the research questions utilized for guiding the systematic analysis along with specific technical issues investigated for each topic. Basing on a rigorous review, results are elaborated to address the pivotal research questions for the set of studies, previously clustered by six forestry topics. Here, the authors present, where applicable, a focus for each topic sub-section on hyperspectral sensors, comparison with other RS platforms, and gathering and use of field data. Then, the discussion section focuses on the comparison of different UAV system solutions, technical advantages and drawbacks of the reviewed UAV technology, and considerations on technology transfer of UAV-RS in a real management context. Finally, the main conclusions stemming from Part II of the present review are drawn, outlining both popular topics and strengths and providing some suggestions for research gap filling and future hot points.

2. Materials and Methods

2.1. Workflow for Dataset Creation

The specific details for searching comprehensive literature and retrieving the final dataset are described in the first paper of this series (Part I) [3]. Briefly, the authors type the Web of Science search engine a combination of semantic keywords for the investigated topic ("UAV", "unmanned aerial vehicle", "UAS" (Unmanned Aerial System), "unmanned aerial system", "drone" + "forest" or "forestry"). Through the exclusion criteria available in the search engine, papers are filtered for time boundaries (from 2018 to 30 June 2020), document type (original articles, conference papers, book chapters), and language (English). The second filtering step consists of applying customized exclusion criteria such as (1) paper adequacy to review aims, (2) relevance of publishing source and paper citations, and (3) online availability within bibliographic resources of our research Institute. Finally, a database of 227 peer-reviewed works was created to analyze and discuss both generic (Part I) [3] and specific issues (Part II) on using UAV-RS in the forestry sector, regarding recent applications (2018–mid-2020).

2.2. Topic Classification and Related Research Questions

Papers have been categorized into six main topics following the main research issues investigated in the selected papers. The addressed topics are listed below while a brief description of each topic is reported in Part I [3]. After categorization, information extraction from each paper is carried out following three degrees of detail. Firstly, general data for paper identification through publication year, author, title, publication name, and publication type are collected. Secondly, technical details common to all research

papers regarding, sensor type, study location (continent and country), forest type, plant group, species are extracted; moreover, a focus on machine learning techniques (crown segmentation algorithms/object detection methods), other RS platform uses or comparison and ground truth data are performed, when relevant. Thirdly, for an in-depth analysis, specific information is gathered considering the particularities of each topic.

This synthesis is then used to address the research questions (RQs), which are reported below together with the topic list and topic-specific information gathered in the third step of paper analysis. The authors compiled the RQs that allowed both a systematic report of the results and a comparison between different papers within the same category.

1. Setting and accuracy of imagery products:

The acquisition, preprocessing and processing of UAV data for forest structure characterization are the key issues within this topic. Photogrammetry software and related versions, where available, are analyzed, which are used for processing UAV data for forest structure characterization.

RQs: What are the flight and imagery processing settings the researchers have focused on? What are the most generated products? How these products and their creation differ between scientific papers?

2. Tree detection and inventory parameters:

This topic encompasses the retrieving of several forest inventory parameters, such as height diameter at breast height (DBH), crown area, etc. Considering that individual tree detection and crown delineation are hot issues within this topic, the focus is on crown segmentation algorithms and object detection methods. Additionally, information on software packages employed to implement machine learning techniques is gathered.

RQs: What are the most investigated forest structural parameters? What purpose their estimation served? What are the main machine learning techniques that have been used for tree detection and delineation?

3. Aboveground biomass/volume estimation:

Biomass estimation is a key issue in UAV-RS forest monitoring. The authors collect the biomass parameter on which the assessment is centered (i.e., aboveground biomass (AGB), overall volume, stock growing volume, carbon content). Then, allometric equations or modeling methods for retrieving and upscaling UAV-monitored biomass are also highlighted.

RQs: What purpose their estimation served? What are the main machine learning techniques that have been used for tree detection and delineation? What kind of allometric equations the do authors use?

4. Pest and disease detection:

Examining papers dealing with forest health monitoring, the review focuses on the host-pathogen system. Therefore, tree species involved in pathogen outbreak are identified and causal agent (disease, insect pest or abiotic stressor) has been classified.

RQs: Which diseases or pests are mainly discussed? In which types of forests is disease incidence most severe? Which sensors are diseases monitored with?

5. Species recognition and invasive plant detection:

In this topic, the recognition goals of the selected studies are underlined. In particular, papers are classified according to their main aim, i.e., assessment of species (dominant or not) in forest stands or spatial analysis of weed/alien plant invasions. A brief description of the general context in which the studies are carried out and target species are also specified. Moreover, as in the case of inventory parameters topic, crown segmentation algorithms and object detection methods are analyzed due to their importance in crown delineation and tree detection.

RQs: What are the main goals for which tree recognition is applied? Which invasive species are mapped the most and in which type of ecosystem/research place? What are the main machine learning techniques that have been used for tree detection and delineation?

6. Conservation, restoration, and fire monitoring:

This section includes a broad range of sub-topics. Hence, there is a need to clarify what is the main objective for each study. The present review categorizes into different groups the selected papers that have the following research purposes: land-use classification, biodiversity conservation, fire monitoring, post-disturbance monitoring, and restoration.

RQs: What are the main sensors employed in the conservation sub-topic? In which cases concerning the restoration is UAV technology used? What are the main research applications, and which are the sensors utilized in fire monitoring?

At the end of each topic section, the authors present, where applicable, a focus on hyperspectral sensors, comparison with other RS platforms, and gathering and use of field data. The RQs that helped us report findings and structure related discussions are the following:

RQs: Which applications are the hyperspectral sensor used for? How are other RS platforms used, and what pros and cons emerge? What are the inventory parameters collected as ground data, and how they are used?

3. Results

3.1. Global Results: A Brief Recap of Part I

A total of 227 papers were selected to form the final dataset of the present systematic review. The global analysis results together with the displaying of the overall dataset are reported in Part I [3]. Below, the authors report a brief synthesis of the general results achieved after applying the second level of the filtering criteria (adequacy, relevance, and paper availability) in Part I. Hence, it emerges that, even in the short timespan analyzed (2018–mid-2020), the trend in the increase of the number of scientific publications in UAV-based forestry research seems to be confirmed, considering also the projection for 2020. Analyzing the geographic distribution of research sites, Asia and Europe are top-ranked for scientific production (33% and 31%, respectively), while Africa presents only five research items. The researchers have focused mainly on natural forests (142 papers) and, among plant groups, on broadleaf woodland (37%). Tree detection and inventory parameters are the most discussed topic (42%), while pest and disease detection are poorly addressed (7%). The settings of image accuracy and AGB estimation are particularly discussed in the natural forest and, as could be expected, species recognition and invasive plant detection are not tackled in the planted/irregular forest. Regarding sensors, it turns out that the RGB (Red Green Blue) camera emerges by far from other technologies, having been used in almost 51% of the selected papers, especially for gathering tree inventory parameters.

From here on, the authors systematically report findings on the selected UAV forestry topics that researchers have dwelt on and on the recent advances gained.

3.2. Setting and Accuracy of Imagery Products

The research papers dealing with setting and accuracy of imagery products are 22 and are reported in Table 1; all of these papers are carried out on natural/irregular forests, except for [4–6].

As we can infer from Table 1, the most used photogrammetry software is AgiSoft Photoscan (AgiSoft LLC, St. Petersburg, Russia), from version 1.2.2 to 1.4.6 [4,7–17]. Some of the reviewed studies perform a comparison among leading structure from motion (SfM) packages for UAV image processing [5,18,19]. In particular, Brach et al. [19] examine six of the most frequently used photogrammetric software in forestry applications: AgiSoft Photoscan, DroneDeploy (San Francisco, CA, USA), Pix4Dmapper (Pix4D S.A., Lausanne, Switzerland), APS (Menci Software S.r.l., Arezzo, Italy), PrecisionMapper (PrecisionHawk, Raleigh, NC, USA), and Maps Made Easy (Drones Made Easy, San Diego, CA, USA). In addition to photogrammetric software performances, researchers have focused on image acquisition setting in terms of flying height [16,18], overlap [7,13,16], timing [10,20,21] and resolution [16].

The comparison of UAV digital aerial photogrammetry (DAP) imagery products with other imagery sources represents an interesting issue in analyzing this topic. A terrestrial laser scanning (TLS) derived ground point cloud is employed as the ground reference for UAV digital terrain model (DTM) in teak plantations [4], while Graham et al. [22] compare error values of the UAV digital elevation model (DEM) with airborne laser scanning (ALS) point clouds generated in stratified classes of canopy cover.

Only a few studies utilize the hyperspectral sensor. Hakala et al. [11] and Oliveira et al. [15] use a 2D Fabry–Pérot interferometer-based (FPI) camera (prototype 2012b) (VTT Photonic Devices and Measurement Solutions, Espoo; Finland), while Yu et al. [23] present a pipeline to correct spatial coordinates of images acquired by a Gaia sky-mini pushbroom hyperspectral imaging system.

UAVs are compared with other RS platforms using airborne lidar [12] or spaceborne optical sensors, such as in [14], in which mangroves are mapped also with Pleiades multi-spectral images. Moreover, aircraft imagery products are used as a reference for accuracy assessment [13,24].

Through the present topic, only four studies carried out intensive field campaigns. Diaz et al. [5] and Aguilar et al. [4] acquire data from a TLS. Jayathunga et al. [12] collect, in two consecutive years, DBH, species, and height of eight canopy trees in each of the 105 plots, while Ruwaimana et al. [14] obtain measurements from mangroves plots and recorded the existing land-use/cover of the study area. This scarceness in terms of field data gathering demonstrates how research efforts are aimed to image acquisition setting and processing workflow.

Among the most representative papers, Seifert et al. [16] aim to increase knowledge on the influence of altitude, image overlap, and image resolution on a multi-view geometry (MVG) reconstruction of a forest from RGB video-based UAV imagery. Low flight altitudes (15–30 m) yield the highest reconstruction details, particularly in combination with high image overlaps (95% for forward and 70% for side overlap). Conversely, lower altitudes required a reduced UAV speed to avoid motion blur and hence reduced UAV endurance and area covered with one battery load. Diaz et al. [5] propose a multi-camera array for acquiring nadir-oblique images and conclude that, in open canopy deciduous forest patches, the system increases the estimation of maximum canopy height by 50% in comparison to a single camera system. Discussing multiplatform data fusion for lidar, Guan et al. [6] show a lidar data registration framework to avoid manual efforts and overcome errors due to forest complexity and irregularity. Unlike [25], they merge three different datasets (namely, backpack and UAV lidar with multi-scan terrestrial lidar), reaching a satisfying data registration accuracy (horizontal root-mean-square error (RMSE) < 30 cm and vertical RMSE < 20 cm).

Table 1. Reviewed studies for setting and accuracy of imagery products topic: sensor, research place, tree species, and photogrammetry software.

Research Paper	Sensor	Research Place	Species	Photogrammetry Software
Fraser and Congalton [18]	RGB	USA	Various	AgiSoft PhotoScan, Pix4Dmapper Pro 3.2
Frey et al. [7]	RGB	Germany	Norway Spruce	AgiSoft PhotoScan
Goodbody et al. [10]	Multispectral	Canada	Maple, birch	AgiSoft Photoscan
Hakala et al. [11]	Hyperspectral	England	Unspecified	AgiSoft Photoscan
Jayathunga et al. [12]	RGB	Japan	Sakhalin fir (dominant), Various	AgiSoft Photoscan 1.3.2
Ni et al. [13]	RGB	China	Larch	AgiSoft Photoscan 1.2.2
Ruwaimana et al. [14]	Multispectral	Malaysia	Mangroves	AgiSoft Photoscan
Aguilar et al. [4]	RGB	Ecuador	Teak	AgiSoft Photoscan 1.4.4
Brach et al. [19]	RGB	Poland	Unspecified	Various (6)
Graham et al. [22]	RGB	Canada	Douglas fir, hybrid spruce, western redcedar	Pix4Dmapper Pro 4.1
Kellner et al. [20]	Lidar	Czech Republic	European beech, Norway spruce	-
Oliveira et al. [15]	Hyperspectral	Brazil/Finland	Tropical forest, birch	AgiSoft Photoscan 1.2.6
Polewski et al. [25]	Lidar	China	Metasequoia, poplar	LiForest ¹
Seifert et al. [16]	RGB (Video)	Germany	Norway spruce, sycamore maple, silver birch	AgiSoft Photoscan 1.4.0
Tomastik et al. [17]	RGB	Slovakia	Beech, larch, Norway spruce	AgiSoft Photoscan 1.4.6
Wallace et al. [8]	RGB	Chile	Various	AgiSoft Photoscan 1.4.1
Diaz et al. [5]	RGB	Argentina	Ponderosa pine	MicMac ² , Pix4Dmapper Pro 3.0.17 and 4.1.24, VisualSFM ³
Fletcher and Mather [21]	RGB, Multispectral	Australia	Eucalyptus	Pix4Dmapper 4.2.6-4.3.33
Graham et al. [24]	RGB	Canada	Douglas fir, hybrid spruce, western redcedar	Pix4Dmapper Pro 4.1
Guan et al. [6]	Lidar	China	Scots pine, Manchurian red pine	LIDAR360 ¹
Jurjevic et al. [9]	RGB	Croatia	Various	Agisoft PhotoScan 1.4.3
Yu et al. [23]	Hyperspectral	China	Various	DPW Photomod ⁴

¹ GreenValley International, Berkeley, CA, USA ² Free and open source software (Rupnik et al. 2017) <https://github.com/micmacIGN/micmac> (accessed on 16 February 2021) ³ Free for personal, non-profit or academic use (Wu, 2013) <http://ccwu.me/vsfm/> (accessed on 16 February 2021) ⁴ Racurs, Moscow, Russia. Abbreviations: RGB = Red Blue Green.

3.3. Tree Detection and Inventory Parameters

Most of the papers analyzed in the present review are classified within the tree detection and inventory parameters topic, consisting of 95 research works (Table 2). The topic encompasses a wide range of research issues. Detection techniques and inventory parameter extraction are often joint together in the workflow of the reviewed studies. Detection mainly concerns the localization of a single whole tree through the forest structure both in planted [26–28] and in natural/irregular forests [29–31]. In some case, even newly grown leaves [32,33], seedling [34], stump [35], fallen log [36], and forest gaps [37] are the detected target. Moreover, detection (especially for crown) may be followed by object classification [38–41]. The more frequent inventory parameters extracted in the reviewed

studies, alone or as a combination, are height [42–47], DBH [48–53], crown diameter [54–57], Leaf Area Index (LAI) [58–60], and thermal data [61–63]. In addition to the common tree features, tasks regarding phenology [64,65], phenotyping [66–68], light behavior [69,70], photosynthetically active radiation [71], and solar radiation to infer on seedling growth [72] are also accomplished. Furthermore, the first group of dendrometric characteristics is often related to works that have practical or technology transfer purposes.

More than half of the papers (49) use specific algorithms or machine learning techniques to automatically detect, segment, and classify trees. Many studies segment tree crown through the watershed algorithm [39,73–78] and similar ones, such as the inverse watershed [79,80] and the marker-controlled watershed [54,81–83]. Others use convolutional neural networks (CNN) based on existing architectures [38,41,84,85] or novel ones [86]. Comparison among segmentation techniques is also carried out [87–90]. As shown in Table 2, the mainstream software tools are eCognition (Trimble Geospatial, Westminster, CO, USA), Matlab (MathWorks, Natick, MA, USA) and R (with LidR and rLidar packages) (free software <https://www.r-project.org/> (accessed on 16 February 2021)).

Forest hyperspectral applications are quite limited in this topic (only four papers). Image recording is carried out with customized solutions [78,91,92] or with an off-the-shelf sensor, i.e., FirefLYE 185 (Cubert GmbH, Germany) [93].

Regarding other RS platform comparison/use (13 papers), authors focus mainly on the use of aircraft ALS as opposed to UAV–DAP for estimating tree height [94,95] and canopy features [96,97]. Satellite images are used as ancillary data for observing plant phenology [98] and calculating new spectral indexes [93]; on the contrary, St-Onge and Grandin [99] utilize a spaceborne sensor as the main data source for measuring individual tree height.

About 70% of the research works gather field data. For the sake of brevity, only a few papers that stress this issue (citing the word “field” in the title) are briefly reported—Hentz et al. [74] and Ganz et al. [77] measure height on standing trees, while Jin et al. [100] also record age and DBH, together with height.

By highlighting the most interesting works, Gu et al. [83] focus on segmentation routine. In particular, they compare the accuracy of segmentation using structural versus spectral information, concluding that single tree crowns segmented using the spectral lightness are more accurate compared to a canopy height model (CHM) approach. Abdollahnejad et al. [79] consider successfully the extrapolation of the UAV data to a larger area, using a correlation with Pleiades satellite ($R^2 = 0.94$). Finally, recent research [101] analyzes three data sources (field survey, UAV–DAP, and UAV–ALS) to measure height and DBH in a high-value timber forest; about tree height, the authors conclude that UAV–DAP could underestimate this inventory parameter, while traditional field height measurement is likely to be influenced by individual species.

Table 2. Reviewed studies for tree detection and inventory parameters topic: sensor, tree species, segmentation algorithm/object detection method, software for object detection, other remote sensing (RS) platforms use/comparison, and field data gathering.

Research Paper	Sensor	Species	Segmentation/Object Detection Algorithm	Software	Field Data
Abdollahnejad et al. [72]	RGB	Scots pine			•
Abdollahnejad et al. [79]	RGB	Scots pine	Inverse watershed	ArcGIS ¹	•
Alexander et al. [29]	RGB	Tropical forest			
Bagaram et al. [37]	RGB	Beech, Turkey oak	Contrast split segmentation	eCognition Developer	•

Table 2. Cont.

Research Paper	Sensor	Species	Segmentation/Object Detection Algorithm	Software	Field Data
Balsi et al. [73]	Lidar	Hazel	Watershed	-	
Carr and Slyder [102]	RGB	Various	Iteratively growing from seed points)	Customized tool	•
Chen et al. [33]	RGB	Tropical savanna	Constrained energy minimization/Otsu method	-	
Demir [28]	RGB	Stone pine			•
Fankhauser et al. [45]	RGB	Ponderosa pine, lodgepole pine			•
Feduck et al. [34]	RGB	White spruce, lodgepole pine	CART algorithm/Multiresolution	Salford Predictive Modeler v. 70 ² /eCognition 9.1	•
Goodbody et al. [39]	RGB	Various	Watershed by immersion segmentation/Random forest (OBIA)	-	•
Guerra-Hernandez et al. [94]	RGB	Eucaliptus			•
Guo et al. [60]	Multispectral	Mangrove			•
Hentz et al. [74]	RGB	Eucalyptus, Loblolly pine	Watershed	ArcGIS 10.4	•
Huang et al. [81]	RGB	Fragrant olive, Buddhist pine	Marker-controlled watershed	Matlab	
Iizuka et al. [61]	Thermal, RGB	<i>Acacia crassicaarpa</i> Northern wattle			
Iizuka et al. [75]	RGB	Japanese cypress	Watershed	SAGA-GIS ³ 5.0.0	•
Kattenborn et al. [52]	RGB	Southern beech			•
Klosterman et al. [98]	RGB	Oak, maple			•
Kuzelka and Surovy [51]	RGB	Norway spruce, European beech			•
Lin et al. [32]	RGB	Big leaved mahogany			
Mayr et al. [76]	RGB	Savannah	Watershed	SAGA-GIS	•
Medauar et al. [103]	Multispectral	Eucaliptus			
Mokros et al. [49]	RGB	Beech			•
Morales et al. [85]	RGB	Moriche palm	CNN semantic level segmentation	-	
Puliti et al. [35]	RGB	Unspecified	Iterative region growing	R software	•
Qiu et al. [104]	RGB	Pear	Seed region growing	-	
Rosca et al. [92]	Hyperspectral	Tropical forest			•
Shin et al. [105]	Multispectral	Ponderosa pine	Top-to-bottom region growing	R software	•
Thomson et al. [91]	Hyperspectral	Tropical forest			•

Table 2. Cont.

Research Paper	Sensor	Species	Segmentation/Object Detection Algorithm	Software	Field Data
Webster et al. [62]	Thermal, RGB	Norway spruce			
Yan et al. [106]	Lidar	Metasequoia, poplar	Improved NCut segmentation/Marker controlled watershed	Microsoft Visual Studio 2013 ⁴ (programed using C++) and MATLAB 2016a/ ArcGIS 10.2	
Blonder et al. [68]	Multispectral	Quaking aspen			•
Brieger et al. [54]	RGB	Larch, Siberian pine, Siberian spruce	Marker-controlled inverse watershed	R software	
Carl et al. [40]	RGB, Multi-spectral	Black locust	OBIA with multiresolution segmentation/CNN developed by the authors	eCognition Developer/Python ⁵	•
Chakraborty et al. [107]	RGB	Unspecified	Multi-resolution	eCognition Developer	•
Chung et al. [95]	RGB	Various			•
dos Santos et al. [38]	RGB	<i>Dipteryx alata</i>	Faster R-CNN, YOLOv3, RetinaNet	Base codes freely available	
Durfee et al. [108]	Multispectral	Juniper			•
Fawcett et al. [109]	RGB	Oil palm	Centroidal Voronoi tessellation	R software	•
Ganz et al. [77]	Lidar, RGB	Douglas fir	Watershed	-	•
Gulci [55]	RGB	Calabrian pine	ForestCAS	R software	•
He et al. [43]	RGB	Cunninghamia, pine			•
Huang et al. [46]	RGB	Various			•
Imangholiloo et al. [78]	Hyperspectral, RGB	Scots pine, Norway spruce	Watershed	SAGA-GIS 2.3.2	•
Jayathunga et al. [96]	RGB	Various			•
Krause et al. [44]	RGB	Scots pine			•
Lendzioch et al. [59]	RGB	Norway spruce	Manual	-	•
Li et al. [57]	Lidar	Metasequoia, poplar	Top-to-bottom region growing	-	
Liang et al. [50]	Lidar	Scots pine, Norway spruce, birch			•
Maturbongs et al. [89]	RGB	Douglas fir	Variable window filter, Graph-theoretical, Watershed	R software, Tree Extraction software, ArcGIS 10.5.1	
Nuijten et al. [82]	Multispectral	Various	Marker-controlled watershed	R software	•
Panagiotidis et al. [36]	RGB	Norway spruce, Scots pine	Canny approach edge detection/Hough transformation	Matlab 2017b	

Table 2. Cont.

Research Paper	Sensor	Species	Segmentation/Object Detection Algorithm	Software	Field Data
Park et al. [65]	RGB	Tropical forest	Stochastic gradient tree Boosting	R software	•
Puliti et al. [97]	RGB	Norway spruce, Scots pine			•
Rissanen et al. [69]	RGB	Various			•
Santini et al. [66]	Thermal, Multispectral, RGB	Aleppo pine			
Santini et al. [67]	Multispectral	Black pine			•
Schneider et al. [110]	Lidar	Beech, tropical forest			•
Shashkov et al. [111]	RGB	Pine, birch, spruce, fir			•
St-Onge and Grandin [99]	RGB	Black spruce			•
Tian et al. [42]	RGB	Metasequoia			•
Wang et al. [26]	RGB	Oil palm	HOG features and SVM classifier	-	
Wu et al. [87]	Lidar	Kew tree	Watershed, Polynomial fitting, Individual tree crown segmentation, Point cloud Segmentation	-	•
Xu et al. [31]	RGB	Saxaul			•
Xu et al. [93]	Hyperspectral	Manchurian red pine, larch			
Yancho et al. [112]	Lidar	Western hemlock, Western red-cedar, Douglas fir	Modified top-to-bottom region growing	R software	•
Yilmaz and Gungor [90]	RGB	Various	Polynomial fitting based methodology	Matlab	
Yin and Wang et al. [56]	Lidar	Mangrove	Seeded region growing, Marker controlled watershed	Matlab 2017a	•
Yurtseven et al. [41]	RGB	Various	OBIA (unspecified)	eCognition	•
Zhang et al. [58]	RGB	Dahurian larch, white birch, aspen	Algorithm by Liu, 2017	-	•
Zeng et al. [71]	Lidar	<i>Cyclocarya paliurus</i>			•
Apostol et al. [113]	RGB	Norway spruce, beech	Multiresolution segmentation/OBIA	eCognition ver. 7	•
Balkova et al. [80]	Multispectral	Beech, spruce, fir	Inverse watershed	-	
Brullhardt et al. [70]	RGB	Various			
Chen et al. [84]	Lidar	Unspecified	Fully CNN	-	
Dalla Corte et al. [48]	Lidar	Camden white gum			•

Table 2. Cont.

Research Paper	Sensor	Species	Segmentation/Object Detection Algorithm	Software	Field Data
D’Odorico et al. [64]	Multispectral	White spruce			•
Dong et al. [114]	Lidar	Various	Graph-based segmentation	-	
du Toit et al. [115]	Lidar	Douglas fir	Top-to-bottom region growing	R software	
Gil-Docampo et al. [30]	Multispectral	Scots pine, birch, rowan			•
Gu et al. [83]	RGB	Various	Marker-controlled watershed	-	
Hastings et al. [88]	Lidar	Various	5 algorithms available in lidR package	R software	
Hu et al. [86]	RGB	Larch	Neural network developed by the authors	-	
Isibue and Pingel [116]	RGB	Various			•
Jin et al. [100]	RGB	Pines, Japanese larch, Manchurian fir			•
Jurado et al. [117]	RGB, Multi-spectral	Oak, pine, eucalyptus	K-means clustering algorithm	-	•
Krisanski et al. [53]	RGB	White peppermint			•
Kuzelka et al. [118]	Lidar	Norway spruce, Scots pine	Voronoi diagram	-	•
Li et al. [119]	RGB	Mongolian pine, larch	Supersixel segmentation, half-Gaussian fitting method	Matlab 2018a	•
Marzahn et al. [63]	Thermal, Multispectral	Various			
Moe et al. [101]	RGB	Monarch birch, castor aralia, Japanese oak			•
Picos et al. [27]	Lidar	Eucalyptus			
Vanderwel et al. [47]	RGB	Lodgepole pine, white spruce, trembling aspen			•
Yan et al. [120]	Lidar	Metasequoia, poplar	Self-adaptive bandwidth mean shift	Matlab 2016a	•

¹ ESRI, Redlands, CA, USA ² Minitab LLC, State College, PA, USA ³ System for Automated Geoscientific Analyses, free software (Böhner et al. 2006) <https://sourceforge.net/projects/saga-gis/> (accessed on 16 February 2021) ⁴ Microsoft, Redmond, WA, USA ⁵ Free software <https://www.python.org/> (accessed on 16 February 2021). Abbreviations: CART = Classification and Regression Trees; OBIA = Object-Based Image Analysis; CNN = Convolutional Neural Network; NCut = Normalized Cut; R-CNN = Region Based Convolutional Neural Network; YOLO = You Only Look Once; HOG = Histogram of Oriented Gradients; SVM = Support Vector Machine; The symbol • indicates field data gathering in the research.

3.4. Aboveground Biomass/Volume Estimation

Biomass estimation is certainly encompassed in the topic of inventory parameters, but considering its importance in research and professional forestry from an economic and ecological point of view, we choose to report the related results in a dedicated section. Moreover, this choice is corroborated by the high number of selected papers (45) (Table 3). All reviewed studies start from one or more remote-sensed basic inventory parameters (i.e., height, DBH, crown diameter) and then estimate the biomass. When it comes to biomass, most papers refer to AGB (43%) and volume (31%), in particular, to stem volume [121–125].

Other authors refer to biomass as carbon stock [126–129], pruning wood biomass [130], or woody debris volume [131].

Once biophysical parameters such as DBH, height, or canopy diameter have been estimated by UAV, biomass can be calculated mainly in two ways—through allometric equations or targeted models. Allometric equations provide an efficient way to estimate biomass but require genus- or species-specific equations. Nevertheless, numerous studies use allometric equations from the literature [128,132–139]. The other way through which biomass can be estimated is represented by general (multi-species) and often newly developed models. The most popular models among the reviewed studies are represented by simple or multiple linear regression models [124,127,130,140–146]. It is worth noting that machine learning regression techniques are also exploited, in particular, random forest regression [122,126,147,148], support vector regression [122,126,149], and k-nearest neighbors [150], and artificial neural network model [126].

For retrieving single tree basic features, many studies (46%) utilize segmentation algorithms. As in Section 3.3, the watershed algorithm and its variants are the most used [122,125,130,135,137,145,151–154].

The hyperspectral sensor is used only by Zou et al. [155]. They collect hyperspectral images to predict the growth rate of a Chinese fir (*Cunninghamia lanceolata*) plantation through a 176-band off-the-shelf camera (Gaiasky-mini2-VN, Zuolihanguang, Beijing, China).

Overall, 38% of the reviewed studies handle images gathered from other RS platforms. Manned aircraft are always equipped with a lidar sensor for establishing a reference dataset [156], for comparing results in respect to UAV [124,127,135,140,142,152], or for constructing reliable DTMs [140,148,157]. Instead, satellite platforms are exploited to upscale biomass estimation generated by UAV to broader areas. Both optical and radar sensors carried by different platforms are used, such as Sentinel-2, WorldView-2, and Gao fen-2 (optical) and ALOS-2, PALSAR-2, Sentinel-1, and Gaofen-3 SAR (radar) [122,147,149].

All the selected studies, except for a few (seven papers), present field data. Following the selection criterion reported in Section 3.3, five articles are highlighted. Together with the measurement of common tree inventory parameter (DBH, height, crown diameter) [123,129,132,138,158,159], a tough task consisting of mangrove species recognition is accomplished by Otero et al. [132] and Wang et al. [158]. Moreover, Fernandes et al. [129] take several soil samples for carbon content analysis and measure directly in the field the aboveground fresh weight of the endemic grey willow (*Salix atrocinerea*), in which no allometric equation was found.

Regarding the handful of newsworthy papers, Hyypä et al. [121] compute stem volume using lidar in a regular conifer stand with a relative RMSE of 10.1%, compared to TLS. The peculiarity is that data are obtained with an under-canopy flying UAV that was manually piloted with the help of video goggles receiving a live video feed from the onboard camera. Puliti et al. [138] assess the growing stock volume through UAV-ALS by wondering if it can be carried out without field data. Using field data only for independent validation, they conclude that the need for fieldwork can be reduced only to the acquisition of some data for quality control. Regarding carbon dynamics simulation, Fujimoto et al. [160] develop an end-to-end process based on UAV-SfM and the individual model FORMIND 3.2 (free software, <http://formind.org/model/> (accessed on 16 February 2021)). They visualize carbon dynamics with a time horizon up to 2100, inferring that the investigated forest will bear a reasonable demand for timber.

Table 3. Reviewed studies for aboveground biomass (AGB)/volume estimation topic: sensor, tree species, biomass parameter, allometric equation/modeling method, segmentation algorithm, other RS platforms use/comparison, and field data gathering.

Research Paper	Sensor	Species	Biomass Parameter	Allometric Equation/Modeling Method	Crown Segmentation Algorithm	Other RS Platform Use/Comparison	Field Data
Alonzo et al. [151]	RGB	Black spruce, white spruce, birch, aspen	AGB	Sum of individual crown volumes	Watershed, Mean-shift		•
Giannetti et al. [140]	Lidar, Multispectral	Beech, silver fir, Norway spruce, Scots pine, birch	Growing stock volume	Multivariate linear regression models (3)		Aircraft	•
Jayathunga et al. [141]	RGB	Various	Merchantable volume, carbon stock	Generalized linear mixed model		Helicopter	•
Lin et al. [161]	RGB	Minjiang fir	AGB	New allometric equation (predictor variable: H)	Multi-resolution segmentation		
Liu et al. [150]	Lidar	Kew tree	AGB	Partial least squares, K-nearest neighbors models	Point cloud segmentation		•
Otero et al. [132]	RGB	Mangroves	AGB	Allometric equation by Ong et al. (2004)			•
Pena et al. [133]	RGB, Multispectral	Poplar	Dry biomass	$Biomass = a (DBH)^2 \times H$			•
Puliti et al. [157]	RGB	Norway spruce, Scots pine, birch	Growing stock volume	Hierarchical model-based inference		Satellite (main)	•
Brede et al. [153]	Lidar	Beech, oak, Norway spruce, fir	Volume	TreeQSM method	Marker-controlled inverse watershed		
Cao et al. [162]	Lidar, RGB	Dawn redwood, poplar	AGB	Exponential predictive models (3)			•
Domingo et al. [142]	Multispectral	Tropical forest	Biomass (generic)	Multiple linear regression models (5)			•
Fujimoto et al. [160]	RGB	Cypress, cedar	AGB	FORMIND model	ForestCAS		•
Gonzalez-Jaramillo et al. [134]	RGB, Multispectral	Tropical forest	AGB	Allometric equation by Chave et al. (2005), NDVI-based equation by Das and Singh (2014)			

Table 3. Cont.

Research Paper	Sensor	Species	Biomass Parameter	Allometric Equation/Modeling Method	Crown Segmentation Algorithm	Other RS Platform Use/Comparison	Field Data
Guerra-Hernandez et al. [152]	RGB	Eucalyptus	Growing stock volume	Power function models (2)	Watershed	Aircraft	•
Jayathunga et al. [148]	RGB	Erman's birch (dominant), Sakhalin fir	Living biomass	Simple/multiple linear regression model, Random Forest		Aircraft	•
Li et al. [126]	RGB	Mangroves	Above ground carbon stock	Random Forest, Support Vector Regression, Artificial Neural Network (Regression models)	Multi-resolution segmentation		•
McClelland et al. [127]	Lidar, RGB	Various	Carbon content	Functional and linear model by Zhao et al. 2009		Aircraft	
Navarro et al. [149]	RGB	Red mangrove	AGB	Support vector regression models (2)	ForestCAS	Satellite	•
Ni et al. [156]	RGB	Larch (dominant), birch, aspen	AGB	Power function models (3)		Aircraft	•
Ota et al. [163]	RGB	Teak	AGB	Type 1 Tobit model			•
Qiu et al. [154]	Lidar	Mangroves	AGB	Individual tree-based inference method	Marker-controlled watershed	Satellite	•
Shen et al. [164]	RGB, Multispectral	Kew tree	Volume	Partial least squares regression models (2)			
Swinfield et al. [128]	Lidar, RGB, Multispectral	Tropical forest	Aboveground carbon density	Allometric equation by Jucker et al. (2017)			
Tian et al. [159]	Lidar	Euphrates poplar	Biomass (generic)	Customized allometric model for GLAS lidar			•
Vaglio Laurin et al. [135]	RGB	Tropical forest	AGB	Allometric equation by Chave et al. (2014)	Watershed	Aircraft	•
Wang et al. [139]	Lidar	Various	AGB	Finnish species-specific allometric equations	Algorithm by Wang et al. (2016)		•

Table 3. Cont.

Research Paper	Sensor	Species	Biomass Parameter	Allometric Equation/Modeling Method	Crown Segmentation Algorithm	Other RS Platform Use/Comparison	Field Data
Wang et al. [165]	Lidar	Mangroves	AGB	G~LiDAR model			•
Windrim et al. [131]	RGB	Radiata pine	Woody debris volume	$V = \pi (d^2/4) L$ (cylinder volume)	Convolutional Neural Network		•
Xu et al. [146]	Lidar, RGB	Japanese zelkova, Paper mulberry, Blue sandalwood	Volume, AGB	Multivariate linear regression			•
Zou et al. [155]	Hyperspectral	Chinese fir	Biomass (generic)	-			
Di Gennaro et al. [130]	Multispectral	Sweet chestnut	Pruning wood biomass	Linear model	Watershed		•
d'Oliveira et al. [143]	Lidar	Rubber tree, Brazil nut	AGB	Multiple linear regression models (2)		Aircraft	•
Fernandes et al. [129]	RGB, Multispectral	Various	Carbon stock	Non-linear regression model			•
Hyypä et al. [121]	Lidar	Scots pine	Stem volume	Method by Hyypä et al. (2020)			•
Iizuka et al. [122]	RGB	Japanese cypress	Stem volume	Random forest regression, Support vector regression	Watershed	Satellite	
Jones et al. [144]	RGB	Gray mangrove	Biomass (generic)	Linear regression models			•
Kotivuori et al. [123]	RGB	Unspecified	Stem volume	Non-linear regression model		Aircraft	•
Lu et al. [136]	Lidar	Black locust	AGB	Allometric equation by the Chinese state forestry administration	Point cloud segmentation		•
Navarro et al. [137]	RGB	Gray mangrove	AGB	Allometric equations by Owers et al. (2018) and Fu and Wu (2011)	Marker-controlled watershed		•
Puliti et al. [138]	Lidar	Scots pine, Norway spruce, birch	Growing stock volume	Species-specific allometric models	Algorithm by Dalponte and Coomes (2016)		•

Table 3. Cont.

Research Paper	Sensor	Species	Biomass Parameter	Allometric Equation/Modeling Method	Crown Segmentation Algorithm	Other RS Platform Use/Comparison	Field Data
Puliti et al. [122]	Lidar, RGB	Radiata pine	Stem volume	Multiple linear regression models		Aircraft	•
Wang et al. [158]	Lidar	Mangroves	AGB	G~LiDAR~S2 model		Satellite	•
Yrttimaa et al. [125]	RGB	Scots Pine	Stem volume	Stem taper curve	Marker-controlled watershed		•
Zhou et al. [145]	Lidar, RGB	Larch, Chinese pine	Biomass (generic)	Linear models (stepwise regression method)	Watershed		•
Zhu et al. [147]	RGB	<i>Sonneratia apetala</i>	AGB	Random forest regression		Satellite	•

Abbreviations: AGB = Aboveground Biomass; DBH = Diameter at Breast Height; H = Height; NDVI = Normalized Difference Vegetation Index; GLAS = Geoscience Laser Altimeter System. The symbol • indicates field data gathering in the research.

3.5. Pest and Disease Detection

Pest and disease detection is the least represented topic in this review (17 papers) (Table 4). The researchers dealing with this issue mainly focus on coniferous forests (59%) and in particular on various species of pine [166–172] and Norway spruce (*Picea abies*) [173–175]. A broad range of pathogenic organisms are investigated, including insects [167–169,175–177], fungi [172–174,178], bacteria [179], and nematodes [170,171]. Other target stressors for plants are represented by the hemiparasitic plant (*Amyema miquelii*) [180] and herbicide-induced stress [166], while Padua et al. [181] discuss a case study regarding three key plagues affecting sweet chestnut (*Castanea sativa*).

UAV imagery products are mostly generated by using RGB sensors, also in combination with hyperspectral, multispectral, and thermal ones (53%). Hyperspectral sensors are used mainly in the wavelength range from visible to near-infrared (450–950 nm) but with a different number of spectral channels and hyperspectral imaging systems. Thus, a prototype FPI hyperspectral camera with 24 bands is used in [175], an off-the-shelf Headwall Nano-Hyperspec (Headwall Photonics Inc., Bolton, MA, USA) in [178], while Zhang et al. [168] compose their hyperspectral system with a UHD 185 imaging spectrometer (Cubert GmbH, Ulm, Baden-Württemberg, Germany).

Other RS platform products are exploited for several purposes within this topic. Regarding aircraft, Smigaj et al. [172] acquire a lidar dataset to calculate CHM and then multiple structural metrics, while Nasi et al. [175] use the same hyperspectral sensor mounted both on a UAV and on a Cessna aircraft to compare images with a different spatial extent. Multispectral imagery from spaceborne sensors is used in combination with UAV products to increase the monitored area for detection of physiological stress by using RapidEye [166] and Landsat 8 [167].

The fieldworks and surveys are mainly aimed at recognizing the presence/severity of the stress-induced damages. Moreover, fundamental dendrometric variables, such as DBH and tree height [173,175,180], and weather parameters [172], are surveyed.

Regarding the most interesting researches, the authors have selected the papers by Kloucek et al. [176], Cardil et al. [169], and Smigaj et al. [172]. Kloucek et al. [176] evaluate the possibilities of UAV-mounted RGB and modified near-infrared sensors to detect bark beetle infestation (*Ips typographus*) at different stages for individual trees. They assess the severity of infestation damages through various vegetation indexes and perform recognition of still green but already infested trees (so-called green attack), using a retrospective time series. Instead, for quantifying pine processionary moth (*Thaumetopoea pityocampa*) defoliation, the results by Cardil et al. [169] show the effectiveness of using NDVI (Normalized Difference Vegetation Index) in mixed forests; moreover, they gain a high accuracy (81.8%) in classifying automatically pines among non-defoliated, partially defoliated, and completely defoliated trees. Using a thermal sensor in a Scots pine (*Pinus sylvestris*) monoculture plantation, Smigaj et al. [172] monitor changes in the forest physiological status due to the red band needle blight (*Dothistroma septosporum*). They find a fairly good correlation between canopy temperature depression and disease levels (R^2 up to 0.41), which may be related to loss of cellular integrity, necrosis, and desiccation.

Table 4. Reviewed studies for pest and disease detection topic: sensor, research place, tree species, type of pest/disease/stress, and field data gathering.

Research Paper	Sensor	Research Place	Species	Type of Stressor	Field Data
Brovkina et al. [173]	Multispectral	Czech Republic	Norway spruce	Honey fungus (<i>Armillaria ostoyae</i>)	•
Dash et al. [166]	Multispectral	New Zealand	Radiata pine	Herbicide-induced stress	•
Ganthaler et al. [174]	RGB	Austria	Norway spruce	Needle bladder rust (<i>Chrysomyxa rhododendri</i>)	•
Maes et al. [180]	RGB, Thermal	Australia	Grey box, red ironbark	Box mistletoe (<i>Amyema miquelii</i>)	•
Nasi et al. [175]	Hyperspectral	Finland	Norway spruce	European spruce bark beetle (<i>Ips typographus</i>)	•
Otsu et al. [167]	RGB	Spain	Black pine, Scots pine	Pine processionary moth (<i>Thaumetopoea pityocampa</i>)	•
Padua et al. [181]	Multispectral	Portugal	Sweet chestnut	Chestnut ink disease (<i>Phytophthora cinnamomi</i>), chestnut blight (<i>Cryphonectria parasitica</i>), oriental chestnut gall wasp (<i>Dryocosmus kuriphilus</i>)	•
Sandino et al. [178]	RGB, Hyperspectral	Australia	Paperbark tea trees	Myrtle rust (<i>Austropuccinia psidii</i>)	•
Zhang et al. [168]	Hyperspectral	China	Manchurian red pine	Chinese pine caterpillar (<i>Dendrolimus tabulaeformis</i>)	•
Barmpoutis et al. [182]	RGB	Greece	Fir	Stress (general)	
Cardil et al. [164]	Multispectral	Spain	Scots pine, holm oak	Pine processionary moth (<i>Thaumetopoea pityocampa</i>)	•
Dell et al. [179]	RGB	Malaysia	Red mahogany	Bacterial wilt (<i>Ralstonia</i> spp.)	
Jung and Park [170]	Multispectral	Korea	Pine	Pine wilt disease (<i>Bursaphelenchus xylophilus</i>)	
Kloucek et al. [176]	RGB, Multi-spectral	Czech Republic	Norway spruce, mountain-ash, beech, silver fir	European spruce bark beetle (<i>Ips typographus</i>)	
Lee and Park [171]	RGB	Korea	Pine	Pine wilt disease (<i>Bursaphelenchus xylophilus</i>)	
Safonova et al. [177]	RGB	Russia	Siberian fir (dominant)	Four-eyed fir bark beetle (<i>Polygraphus proximus</i>)	
Smigaj et al. [172]	Thermal	Scotland	Scots pine	Red band needle blight (<i>Dothistroma septosporum</i>)	•

The symbol • indicates field data gathering in the research.

3.6. Species Recognition and Invasive Plant Detection

The selected papers (24) and their recognition goals are listed in Table 5. Within this topic, all the UAV applications are carried out in natural/irregular forests and distributed among all the continents, except for Africa. There are also two types of “special” study sites, such as arboretum [183,184] and plant nursery [185]. Moreover, it should also be noted that the complete range of UAV-mountable optical sensors, both passive and active, are successfully utilized for species detection goals throughout the selected papers.

A total of nine research works aim to identify invasive plants, especially in places where the biodiversity rate is high, such as in subtropical and tropical forests (Ecuador, Chile, Costa Rica, Malaysia), in mountain zones (China), or isolated ecosystems (New Zealand). The invasive plants that were chosen as targets belong to perennial creepers, i.e., lianas and bitter vine (*Mikania micrantha*) [186–188], conifers, i.e., *Pinus* spp. [189,190], and broad-leaved trees, i.e., *Acacia* spp. [190,191] and black locust (*Robinia pseudoacacia*) [192].

Crown segmentation algorithms and object detection methods are widely tested and discussed for species detection. The most used automatic segmentation method is the multiresolution segmentation algorithm [193–196]. Machine learning techniques are especially exploited to recognize and classify plant species. Among the most frequent, there are support vector machine [183,188,197–200], random forest [184,189,191,193,194,201], convolutional neural networks [192,202–204] and k-nearest neighbor [184,188,199,205]. Performing machine learning algorithms, authors are supported by different software packages, such as eCognition [188,194,198], ENVI (Harris Geospatial Solutions, Boulder, CO, USA) [183,185], and R [191,206].

Applications of the hyperspectral sensor are numerous within this topic (eight papers). Hyperspectral cameras, which are exploited for detecting spectral features of different tree species, can be classified into two major groups. Many authors use commercial solutions, such as Cubert UHD 185 [199], Senop Rikola (Rikola Ltd., Oulu, Finland) [201,204], and two FPI-based models by Senop [196,205]. Conversely, the UAVs that were flown by Tuominen et al. [184] and Nezami et al. [202] mount FPI-based prototype cameras. All the cited hyperspectral cameras acquire images from the visible to the near-infrared spectral range, except Tuominen et al. [184], who use also a short-wave infrared hyperspectral sensor.

In this section, the comparison/use of other RS platforms refers to few cases mainly because of the hitch to accomplish tree species identification task by airborne or spaceborne sensors, often associated with a low spatial resolution. Nevertheless, Rivas-Torres et al. [195] use Landsat 8 fusion imagery to obtain the vegetation map of the Galapagos archipelago, while Kattenborn et al. [190] test the upscaling of the UAV-estimated species cover to the spatial scale of Sentinel-1 and Sentinel-2. Aircraft are used to obtain ALS-derived CHM [201] and both lidar and multispectral datasets to compare them with the same acquired by UAV [189].

All the studies carrying field campaigns (13) survey features of the target plant, such as species [183,196,199,200], flower counting [191], crown shape [193], liana load [186] and spectral signals [198]. Additionally, other tree-related parameters are gathered, i.e., height, DBH, health status, and age [189,197,201,205,206].

Among the noteworthy papers, mangrove species discrimination through NDVI is performed by Yaney-Keller et al. [197]. At 100 cm/pixel resolution, UAV-derived tree metrics result not statistically different from ground measurements, unlike at 10 cm/pixel, indicating lower accuracy as the resolution becomes extremely fine. In freshly new research work, Casapia et al. [206] quantify the abundance of non-timber palm species, i.e., they delineate palm crowns using color and textural information and then test four different machine learning techniques, yielding the best results with the random forest classifier (85% overall accuracy). Moving to European forests, de Sa et al. [191] seek to map the invasion of Portuguese coastal areas by an alien species (Sydney golden wattle, *Acacia longifolia*) through its flowering. The authors generate flower presence/absence maps using supervised random forest but the correlation between the number of in-field counted flowers and the area covered by flowering result weak.

Table 5. Reviewed studies for species recognition and invasive plant detection topic: sensor, research place, recognition goal, target species, crown segmentation algorithm/object detection method, and field data gathering.

Research Paper	Sensor	Research Place	Recognition Goal	Target Species	Crown Segmentation/Object Detection	Field Data
Cao et al. [199]	Hyperspectral	China	Classification of seven mangrove species	Mangroves	Bottom-up region-merging/K-nearest neighbor, support vector machine	•
de Saet al. [191]	Multispectral	Portugal	Mapping an invasive plant through its flowering	Sydney golden wattle	Random forest	•
Franklin and Ahmed [193]	Multispectral	Canada	Classification of 4 hardwood species	Aspen, white birch, sugar maple, red maple	Multi-resolution/Random forest	•
Gini et al. [185]	Multispectral	Italy	Classification of 11 species in a plant nursery	Various	Maximum likelihood classifier	
Komarek et al. [183]	RGB, Multispectral, Thermal	Czech Republic	Classification of tree, shrub, and herbaceous species in an arboretum	Various (arboretum)	Edge method/Support vector machine	•
Liu et al. [198]	Multispectral	China	Detection of an endangered tree species	<i>Firmiana danxiaensis</i>	SVM/Bottom-up region-merging	•
Mishra et al. [194]	Multispectral	Nepal	Mapping tree and shrub species along the Himalayan ecotone	Himalayan fir, bell rhododendron	Multi-resolution, spectral difference segmentation/Random forest	
Rivas-Torres et al. [195]	RGB	Ecuador	Mapping native and invasive vegetation in the Galapagos Islands	Various	Multi-resolution/Fuzzy membership function	
Saarinén et al. [205]	Hyperspectral, RGB	Finland	Quantifying deciduous species richness as a biodiversity indicator	Scots pine, Norway spruce, birch, alder	Watershed/K-nearest neighbor	•
Tuominen et al. [184]	Hyperspectral	Finland	Recognition of 26 tree species in an arboretum	Various (arboretum)	K-nearest neighbor, random forest	
Dash et al. [189]	Lidar, Multispectral	New Zealand	Detection of invasive exotic conifers in New Zealand	Scots pine, ponderosa pine	Random forests, logistic regression.	•
Kattenborn et al. [190]	RGB	Chile	Mapping woody invasive species in Chile	<i>Radiata pine</i> , <i>gorse</i> , Silver wattle	Maximum entropy	
Sothe et al. [200]	Hyperspectral, RGB	Brazil	Classification of 12 tree species in a subtropical forest	Subtropical forest	Support vector machine	•
Waite et al. [186]	RGB	Malaysia	Assessing liana infestation in a tropical forest	Liana (tropical forest)		•
Wu et al. [188]	RGB	China	Mapping an invasive plant in a mountain area	Bitter vine	Support vector machine, classification and regression tree, K-nearest neighbor	

Table 5. Cont.

Research Paper	Sensor	Research Place	Recognition Goal	Target Species	Crown Segmentation/Object Detection	Field Data
Yaney-Keller et al. [197]	Multispectral	Costa Rica	NDVI discrimination between the 7 most abundant mangrove species	Mangroves	Support vector machine	•
Yuan et al. [187]	Thermal, Multispectral	Costa Rica	Detection of liana-infested areas in a tropical forest	Liana (tropical forest)		
Casapia et al. [206]	RGB	Peru	Identifying and quantifying economically important palm tree species	Palms	Region growing and merging/Variation (4)	•
Kattenborn et al. [203]	RGB	New Zealand	Mapping (i) tree species in primary forests, (ii) woody plant invasion, and (iii) vegetation succession	Various	CNN semantic segmentation	
Kentsch et al. [192]	RGB	Japan	Detection of an invasive broadleaf tree in a coniferous coastal forest	Black locust		
Miyoshi et al. [204]	Hyperspectral	Brazil	Identifying single-tree species in a highly vegetated area	Queen palm	CNN	
Miyoshi et al. [201]	Hyperspectral	Brazil	Identifying 8 tree species in a highly diverse forest	Various	Random forest	•
Nezami et al. [202]	Hyperspectral, RGB	Finland	Classifying 3 major tree species in a boreal forest	Scots pine, Norway spruce, silver birch.	3D convolutional neural networks	
Sothe et al. [196]	Hyperspectral	Brazil	Classifying 16 tree species in subtropical forest fragments	Various	Multiresolution region growing/Variation (4)	•

The symbol • indicates field data gathering in the research.

3.7. Conservation, Restoration, and Fire Monitoring

Conservation, restoration, and fire monitoring is a composite topic, and it presents multiple research issues, consisting of 24 papers in total (Table 6). Generally, firefighting has the highest number of scientific works and in particular the post-fire monitoring. This activity is conducted mainly for damage assessment with a multispectral sensor [207–210] and with RGB for planning rehabilitation measures [211]. In only one case [212], fire prevention activity is carried out with the help of a lidar sensor in the characterization of the forest fuels. For conservation targets, UAVs mount an RGB camera for predicting tree-related microhabitats [213], while a multispectral sensor is used in different case studies of plant conservation [214].

Restoration monitoring is a challenging task that can be tackled effectively through UAV. The core issue is the monitoring of restoration in planted [215–217] or natural [218] forests. Thus, in planted forests, mine site revegetation is remotely sensed [219] and detection of conifer seedlings in seismic lines in natural woodland [220].

In this section, drones are never equipped with a hyperspectral sensor.

Satellite platforms are utilized both for comparing multispectral datasets in respect to UAV in the burned landscape [207] and for testing different land-use classifiers with SPOT6 [221] and Pleiades [208] imagery. On the contrary, UAV-acquired images are used as validation dataset to assess the effectiveness of satellite in post-fire monitoring [210] and

in tracking the spring phenology in trees [222]. Moreover, UAV products are examined for compensating for the fraction of vegetation cover computed with Sentinel-2 images [223]. The use of aircraft is present only in a few studies and it is aimed at gaining ALS–DTM and tree metrics [217] and at generating a hyperspectral dataset with the NASA Glenn HSI2 sensor [221].

Field measurements are widely used within this topic (14 papers). Together with common tree characteristics, such as species [208] and health status [218,224,225], pruning height [212], and tree-related microhabitats [213] are also recorded. In land-use case studies, ground truth points for the generation of thematic maps [226,227] and the field reflectance of different land cover types [221] are surveyed.

Regarding the most valuable contributions, Khokthong et al. [224] monitor a biodiversity enrichment assessing the mortality of interplanted trees in an oil palm (*Elaeis guineensis*) monoculture. Although further long-term analysis on other control factors is required, the probability of mortality depends on the amount of oil palm canopy cover, which is related, in turn, to the light requirements of the interplanted species. In a Canadian research study, both aspen (*Populus tremuloides*) sucker density and height decrease significantly as the level of skidder traffic intensity increases. Therefore, the authors propose and successfully verify the suitability of using winter harvesting to mitigate severe soil compaction. In the scope of fire prevention, Fernandez-Alvarez et al. [212] identify priority areas in the wildland-urban interface by using a UAV-mounted lidar; this way, parameters of pruning height and tree spacing are automatically and objectively obtained.

Table 6. Reviewed studies for conservation, restoration, and fire monitoring topic: sensor, main objective, species, and field data gathering.

Research Paper	Sensor	Main Objective	Species	Field Data
Baena et al. [214]	Multispectral	Plant conservation: issues on UAVs use and case studies	Various	
Fernandez-Guisuraga et al. [207]	Multispectral	Post-fire monitoring: vegetation survey on burned areas	Maritime pine	
Nagai et al. [225]	RGB	Forest disturbance: evaluation of heavy snow damage	Japanese cedar	•
Roder et al. [218]	RGB	Post-disturbance monitoring: an inventory of natural regeneration and deadwood	Norway spruce	•
Rossi et al. [208]	Multispectral	Post-fire monitoring: delineation of forest cover after mixed-severity fires	Various	•
Rupasinghe et al. [221]	RGB	Land use: mapping vegetation of coastal areas	Riparian vegetation	•
Whiteside et al. [219]	Multispectral	Restoration: monitoring mine site revegetation at scale	Unspecified	
Almeida et al. [215]	Lidar	Restoration: quantifying forest changes from a mechanical thinning treatment	Various	•
Belmonte et al. [216]	RGB	Restoration: assessing the structure of a mixed-species plantation	Ponderosa pine	•
Berra et al. [222]	Multispectral	Ecosystem monitoring: tracking the temporal dynamics of spring phenology	Various	•
De Luca et al. [226]	Multispectral	Land use: vegetation layer classification in a structurally complex forest ecosystem	Cork oak	•
Fernandez-Alvarez et al. [212]	Lidar	Fire prevention: characterizing the forest fuels in a wildland-urban interface	Eucalyptus	•

Table 6. Cont.

Research Paper	Sensor	Main Objective	Species	Field Data
Fraser and Congalton [227]	RGB	Land use: assessment of thematic map accuracy	Various	•
Iizuka et al. [223]	RGB, Multispectral	Land use: vegetation cover changing in a plantation forest	Northern wattle	
Khokthong et al. [224]	RGB	Biodiversity enrichment: assessing the mortality of interplanted trees in an oil palm monoculture	Various	•
Paolinelli Reis et al. [217]	Multispectral	Restoration: assessing land cover as an indicator of management interventions	Eucalyptus	
Rossi and Becke [211]	RGB	Post-fire monitoring: planning of adaptive rehabilitation measures	Tropical forest	
Sealey and Van Rees [228]	Multispectral	Disturbance mitigation: evaluating suitable practices to lessen soil compaction	Aspen	•
Shin et al. [209]	Multispectral	Post-fire monitoring: classification of forest burn severity	Korean red pine	
Yeom et al. [229]	RGB	Post-fire monitoring: forest fire damage assessment	Unspecified	
Frey et al. [213]	RGB	Biodiversity conservation: predicting tree-related microhabitats for the selection of retention elements	European beech, Norway spruce, silver fir	•
Fromm et al. [220]	RGB	Restoration: detection of conifer seedlings in seismic lines	Various	
Padua et al. [210]	RGB, Multispectral	Post-fire monitoring: assessment of the fire severity and multi-temporal analysis	Various	
Sealey and Van Rees [230]	RGB	Post-disturbance monitoring: effect of residual slash coverage on forest regeneration	Trembling aspen	•

The symbol • indicates field data gathering in the research.

4. Discussion

This section reports the discussions for each topic following the RQs formulated in Section 2.2 as a general guide. Cross issues regarding hyperspectral sensors, comparison with other RS platforms, and gathering and use of field data are argued. Moreover, a comprehensive discussion is dedicated to the application of machine learning techniques. Constraints and opportunities for technology transfer of UAV-RS to a real management context are also debated. Finally, brief considerations are drawn on the costs of different UAV solutions.

In setting and accuracy of imagery products, researchers focus mainly on forward and lateral overlap, acquisition timing through daytime and seasons, view angle, and ground resolution as an outcome of flight altitudes $\times$ sensor resolution. It worth noting that although intensifying forward overlap can be performed without any additional cost in UAV campaigns [231], enhancing lateral overlap would bring up the operational cost due to the requirement of more flight lines [232]. In some research works [5,145,161], an oblique angle (off-nadir) is set for image acquisition in association with low flying altitude; this view from the side rather than from the top (nadir) can be challenging in the analysis when using traditional RS algorithms [233]. Nevertheless, off-nadir acquisition can contribute to the completeness of the image reconstruction as evidenced by Nesbit [234]. The most representative imagery products are point cloud, DTM, DEM, and CHM. Moreover, 3D point clouds contain primary structural information to calculate forest attributes. In particular, point clouds by acquiring both ground surface and tree vegetation allow deriving

CHM, which represents tree height and one of the main sources for estimation of other forest attributes. When acquiring point cloud for deriving CHM, UAV images are recommended to be acquired during the leaf-on season [235] to avoid negative results, such as image aberration. For UAV data acquisition, there are two major structural sources within the reviewed studies—DAP and ALS. The imagery acquired with DAP is then processed using the SfM technique to obtain a 3D point cloud. Sometimes, forest uniform texture, repeating patterns, and potential movement due to wind can be challenging for SfM matching algorithms, potentially leading to incomplete reconstruction or noisy point clouds [236]. Despite this fact, SfM is widely and successfully applied in forest monitoring. Point clouds derived from UAV–DAP and UAV–ALS are substantially denser than those acquired by aircraft-mounted ALS; the latter results in a more continuous canopy representation and improved detection of canopy tops [45], even if the 3D quality is strongly related to flight parameters and camera settings [237]. DAP has recently become a very popular technique because it can require only a consumer-grade solution, which often includes an off-the-shelf RGB sensor as resulted by the current review [7,12,19]. As a major drawback in comparison to UAV–ALS, DAP is limited to the characterization of the outer canopy envelope [238], while lidar can acquire the vertical profile of vegetation also operating under-canopy conditions [121]. Finally, photogrammetry software products are quite numerous on the market and new ones are constantly appearing. Surely, they play a fundamental role in UAV product reconstruction, but they present several critical points, such as high demand for computation time/resource, poor availability of open-source solutions, and, sometimes, limited impact on processing workflow by the user.

UAV technologies proved to be a very effective and powerful tool in the modern management of forest inventories. Their applications in this area are based on detecting the entire tree or some specific features, such as newly grown leaves, seedling, stump, fallen log, and forest gaps. Nevertheless, it is worth noting that the number of works dedicated to the evaluation of forest regeneration (seedling) is surprisingly low. This could be considered a shortcoming for forest practitioners who utilize regeneration status as essential information for management decisions, i.e., for replacing damaged seedlings [239]. In parallel, UAV–RS is fully applied for obtaining accurate information from practical parameters (height, DBH, and crown diameter). The best-described parameter in vegetation assessment is height. Both individual tree delineation or area-based (stand-level) approaches are successfully used for a direct measure of vegetation height. High accuracy in data assessment is obtained also by the two main types of sensors—optical and lidar. In some cases, the reviewed papers investigate research-oriented tasks, such as phenology assessment, phenotyping, and canopy light behavior. The number of scientific papers encompasses within this topic is considerable and their results show a high degree of effectiveness and soundness. This demonstrates how UAV–RS is now a ready-to-use tool applicable in a real management context. Regarding the assessment of forest basic structural parameters, UAV–RS is a quick and reliable technology and research achievements can be made available to forest practitioners. The goal, however, is not entirely accomplished—there is a need for more efforts by academia in technology transfer and training of technicians.

UAV–RS provides an alternative for estimating tree biomass on various forest extents in comparison to field surveys. Despite this being an accurate method, collecting and weighing samples of vegetation is time-consuming, labor-intensive, and destructive [240]. In this framework, UAVs can bridge the gap between ground observations and traditional manned aircraft or spaceborne platforms [148]. Tree biomass estimation is performed aiming at two major research goals—environmental assessment and potential profitability of timber. The environmental research goal is pursued in the natural forest where biomass is often estimated as carbon stock [127–129]. More practical issues are conversely addressed and declined in various aspects for estimation of timber biomass, namely, in estimating the merchantable volume of mixed forests [140], assessing AGB of high-value timber and its sustainability over time for logging operations [160], or quantifying pruning biomass

as a coproduct for sale in a sweet chestnut orchard [130]. No remote sensing method directly measures biomass. Therefore, researchers use basic variables (height, DBH, crown diameter) to indirectly predict biomass through scaling equations/models, which are themselves developed from a relatively small number of trees that have been measured, harvested, and weighed [20]. Several studies use allometric equations from literature; these equations relate biomass to measurable biophysical parameters (DBH, height, or canopy area) and represent an effective method for biomass estimation. Nevertheless, their use is strictly associated with tree genus or species and their development needs calibration with direct biomass information [241]. The other approach for gathering UAV-derived biomass is represented by general or often customized (newly developed) models. They require a formal analysis being implemented through a fitting method, mainly simple and multiple linear regression or machine learning regression. Moreover, most or all these models lean on field data for their construction or validation [129,132,138,158], as demonstrated also by the intensive campaigns performed by 82% of the reviewed studies. Despite these critical issues, custom models have the undoubted advantage of being specific to the forested area under investigation. Finally, a possible way to overcome allometry uncertainty could encompass the estimation of wood volume using very high-density laser scans [242].

Considering that threats to forests are globally increasing, monitoring of forest health is of pivotal importance as part of sustainable forest management [243]. When compared with field assessments, UAV-RS may represent a very suitable solution by providing an objective and modifiable approach, high spatiotemporal resolution, and quick results [166,237]. Hence, the identification of causal agents inducing the declining forest health becomes imperative. The present review collects papers that mostly deal with biotic stressors, such as insects, fungi, bacteria, and nematodes. In particular, the decay of forest health is mainly due to insects belonging to different orders, such as *Coleoptera* (European spruce bark beetle and four-eyed fir bark beetle), *Lepidoptera* (pine processionary moth and Chinese pine caterpillar), and *Hymenoptera* (oriental chestnut gall wasp). A relevant share of the forested area under investigation is composed of conifer trees, such as Norway spruce and various species of pine. These species are located in different countries (Czech Republic, Austria, Finland, Korea), where forests represent a key environmental and economic asset and where UAV-RS technology can be considered quite widespread for few years. UAV imagery products are mostly generated by using RGB sensors, which can detect reflectance increases in the red and green band of discolored vegetation stressed by a pest or disease [244]. Being sensitive to a decrease in the NIR (Near Infrared) reflectance, multispectral cameras are also used to identify and quantify forest defoliation [245]. Although progress needs to be made in research, UAVs can allow managers to effectively operate to maintain healthy and productive forests, as demonstrated by the reviewed papers.

In species recognition and invasive plant detection topic, all the research applications are carried out in natural/irregular forests, especially in places where the biodiversity rate is high, such as in subtropical and tropical forests, and boreal and cold-temperate woodlands. Species detection involves the classification of few dominant hardwood trees, the recognition of mangrove species and economically important palms, and the discrimination of vegetation types (herbaceous, shrub, and tree). In some cases, researchers perform a proof of concept by detecting more than 10 tree species in a plant nursery [185] and arboretum [184]. Invasive plant identification is also a research issue of great interest—isolated and high-biodiverse ecosystems are threatened by perennial creepers, conifers, and broad-leaved trees. Regarding future research, species recognition and invasive plant detection will benefit from the analysis of streamed imagery. Real-time processing will enable timely detection and, in a not very far future, eradication of invasive plant could be performed at the same time together with the identification step [246] (i.e., through spraying drones). In the end, acquiring specific richness and presence of invasive species over time can give information about forest resilience, also after disturbance events, for predicting forest status and its capacity to recover [247].

Conservation, restoration, and fire monitoring is a composite topic comprehending a constellation of scientific issues. Restoration monitoring is performed for mine site revegetation and the evaluation of mechanical thinning. For detection of seedling, drone imagery represents an unrivaled tool by providing ground sampling distance often reaching sub-centimeter level [239]. Land use is declined as thematic map creation or as an indicator of conservation interventions, while studies on biodiversity are addressed to plant conservation, species enrichment, and prediction of tree-related microhabitat. The impacts of logging activities are evaluated in postharvest areas by analyzing the effect of residual slash coverage on forest regeneration and the suitable practices to lessen soil compaction. Wildfires are an increasing global concern especially because of global warming and changes in land use [248]. UAV technologies are employed only in one of the reviewed studies for a crucial activity as fire prevention. On the contrary, post-fire monitoring is debated by various studies, especially for planning adaptive rehabilitation measures and for classifying forest burn severity. Since the reflectance of a burned area has higher visible and SWIR (Short-Wave Infrared) values and lower NIR values in comparison to an untouched forest [249], burned vegetation can be determined by classification through a single-time post-fire image. On the contrary, for large and heterogeneous areas, an approach based on temporal comparison of thermal anomalies is considered more reliable [250]. Moreover, post-fire monitoring is essential for preventing the danger of landslides or other secondary disasters [209]. To a broader extent, understanding forest dynamics and drivers of change are pivotal for preservation in a context of rapid change [250]—UAV–RS can regularly acquire up-to-date and affordable data for all the above-mentioned forest conservation purposes. This confirms the findings of Eugenio et al. [251], who state that the use of UAV for ecosystem conservation has gained notoriety in different directions.

The specific combinations of wavelengths identified through hyperspectral sensors could be used to improve forest inventory and health information and increase information about biodiversity and natural disturbances. The present studies review 19 research papers, in total, acquiring UAV imagery utilizing a hyperspectral sensor. Camera technologies vary from off-the-shelf shelf packages to newly developed commercial products not yet on the market (used for test) and customized/prototype solutions. The most used imaging approach is the line scan (i.e., the so-called pushbroom). Species detection (woodland tree/invasive plant) makes the widest use of hyperspectral sensors (42% of the reviewed studies within this topic). A performance assessment of vegetation indexes retrieved through the hyperspectral sensor and a correct waveband region selection are key factors to identify different species [252]. Moreover, the wavebands selected for classification are influenced by taxonomic and structural features of the plant and the methods and scale at which hyperspectral imagery is acquired [253]. Nowadays, there is a fast-growing trend observed recently in hyperspectral research in terms of technological developments (data collection, data resolution, spatial coverage, and processing) and in the application domain, where multidisciplinary approaches emerged, including forestry applications [254]. Nevertheless, hyperspectral sensors are not yet available, especially in many developing countries, because of the high market prices of commercial packages. This deprives forest managers of a potential monitoring tool whose characteristics could be used to promptly block disease outbreaks or the diffusion of invasive species in tropical and subtropical woodland.

The comparison between UAV and other RS platforms is crucial for understanding how different technologies are used and for selecting the most suitable solution for research and management purposes. Spaceborne platforms are mainly employed for upscaling results derived from UAV to broader areas and as a source of complementary data or in multi-temporal forest monitoring. In a few cases, satellite images are used as the main data source. Manned aircraft, often equipped with lidar, are used for providing reference datasets or for comparing images with a different spatial extent. It is worth mentioning that a new generation of high spatial resolution satellites with a revisit time of less than a week is coming to the fore [255], together with new sources of open satellite imagery,

such as Landsat and Sentinel-2 [256]. Despite all of these developments, compared to satellites, UAV flexibility makes them more suited to acquire local imagery promptly at a very high spatial resolution [257]. Compared to manned aircraft, instead, UAVs represent a growing alternative to commercial airplanes, which are more expensive also than crew-based field campaigns for a typical forest extent [127]. In 2015, Tang and Shao [1] have already reasonably anticipated that the role of drone remote sensing would have overtaken manned aircraft in the near future. Moreover, small unmanned aerial platforms have the advantage of being able to be flown in response to specific events (post-fire monitoring, disease outbreak) and can also fly under a cloudy sky [258]. However, above all it is to be highlighted that, especially in professional forestry, the RS platform choice must be guided by the specific purposes of the activity, considering also the technical skills and resources required for data management and processing.

More than 60% of studies through the entire dataset collect ground data. Field campaigns are carried out to gather mainly basic inventory parameters (DBH, height, crown diameter), tree species, or health status. In several studies, also ground control points are acquired through GPS (Global Positioning System) for the geometric calibration of UAV-derived imagery products. Ground measurements of woodland features consume substantial resources in terms of both time and cost at any spatial scale. Moreover, in-field surveys are de facto impossible over large spatial and temporal scales [259]. Nevertheless, field data gathering still plays a crucial role in forest monitoring and management. They are often labeled as “ancillary data,” but this definition seems a bit reductive, considering their importance. Among the reviewed studies, they are indeed collected and used for dataset validation, accuracy assessment, result comparison, and regression analysis in biomass estimation. Few studies [123,138] try not to use field data but, necessarily, they are obligated to rely on previous surveys or collect new measurements for comparing results or validating their workflow.

The implementation of automatic processes is crucial to extract information and provide forest inventories from remote sensing data [260]. Object-based image analysis (OBIA) is usually composed of two main phases, namely, (1) image segmentation and (2) feature extraction and classification. [261]. Crown segmentation algorithms and object detection methods are intensively exploited through inventory parameters, biomass estimation, and species recognition to automatically detect, segment, and classify trees. Image segmentation is a critical and important step in the OBIA process. Most of the approaches for individual tree crown delineation utilize interpretation of CHM derived from photogrammetric or lidar 3D point cloud by applying different algorithms, such as the watershed algorithm and its variants, the multiresolution segmentation algorithm, and existing or new developed convolutional neural networks architectures. Machine learning offers great potential for the efficient processing of remote sensing data, and it is often used for final object classification in OBIA. These techniques are especially exploited to recognize and classify plant species. Among the most frequent, there are support vector machines, random forest, and convolutional neural networks. Automatic tree detection is a complex process in imagery processing. Different types and numerous objects could be identified through UAV images; therefore, robust algorithms are required to correctly detect the targeted objects [262]. Performing crown segmentation and machine learning algorithms, authors are supported by different software packages both proprietary applications, i.e., eCognition, Matlab, and ENVI, and open-source applications, i.e., R (especially with LidR and rLidar packages). Through built-in algorithms, they can identify objects from UAV imagery exploiting spatial, spectral, and texture forest characteristics and thus extract specific tree features [263]. Machine learning algorithms are efficient tools and ensure standardization of the process. Their results are not necessarily more correct than those achieved through visual interpretation. However, they can handle automatically massive workloads, thus allowing to extend monitoring over large forested areas—this is one of the undoubted advantages that has boosted their use in UAV forest monitoring. Nevertheless, the implementation and use of automatic processes for image analysis have some weak

points. One of the major obstacles is the perceived lack of interpretability of these methods, which are often considered to be black-box models [264]. The full replicability of the results using such techniques is made difficult by complex workflows (sometimes also for researchers!) and by proprietary software that limits the ability to understand some processing outcomes [21]. This weak point strongly hinders the technology transfer of image automatic analysis and limits the fruition for professional users to the mere acceptance of the results rather than to the understanding of the entire processing workflow.

Hereafter, this discussion section brainstorms two general aspects of UAV–RS forestry research—technology transfer and operational costs.

Research in forestry remote sensing often has an applied perspective, as demonstrated by numerous reviewed papers (39%) containing in the abstract words related to management. Tackling the challenges of knowledge transfer from scientists to managers is a key issue for the development of sustainable forestry. Hence, it is of pivotal importance to focus on how remote sensing advances can be converted into valuable and available tools to forest managers. They are doubtful about the operational potential of RS techniques [265]. The objectives of technology transfer are often quite tough to define by mutual consent of researchers and managers. To obtain the best achievements, there is a need for explicit space for collaboration and sometimes it is required to challenge the work routine of managers for seeking adapted solutions [266]. This process could be assisted by a technology transfer professional and a pool of scientists with different expertise to avoid narrow solutions. In the case of UAV platforms, researchers can be considered both RS data producers and RS tool developers. As data producers, they can provide affordable and easy-to-use datasets; as developers, they can implement tailored tools using raw data and interacting closely with forest managers [267]. Therefore, after the identification of the objectives, researchers bear most of the burden of developing new solutions to make RS more accessible to professionals. The final step in conveying RS techniques is the evaluation by final users. Tailored tools must be easy to use and integrated into existing workflows [265]. Moreover, feedback from practitioners on real use and gained results is fundamental also for continuously improving the proposed solutions. Having said that, what are the concrete actions to improve the technology transfer process? For sure, one of the pillars on which technology transfer must be based is training. It can also be carried out through remote classes including at the same time in-person visits by specialists to forestry companies. Secondly, the tailored processing routines developed by researchers should be embedded into flexible and interoperable open-source toolboxes. These tools could be a foundation that forest stakeholders could adapt to specific projects [267]. Thirdly, it is necessary to facilitate access to RS data to broaden the user base, also by implementing open and user-friendly environments to handle data [268]. This issue concerns particularly forest management in developing countries considering that expertise in RS data acquisition and analysis is mainly held by stakeholders of wealthier countries [269]. Part I of the present review [3] reported on how UAV–RS research studies are poor in places where the forest heritage is enormous (especially in Africa and South America)—technology transfer is essential, but, in these cases, its success does not depend only on researchers' efforts but involves all forestry stakeholders, especially public organisms.

UAV platform and sensor technologies are constantly evolving; moreover, forest monitoring can be considered a niche sector compared to other UAV civilian applications. Therefore, a thorough cost analysis of UAV for forest application is not easy to complete nor is it one of the main objectives of this study. However, it can be stated that simple remote sensing approaches can be sometimes deployed with only minor investment [267]. Nevertheless, the fixed costs are often relatively high, and implementing a remote sensing approach can be prohibitive for forest stakeholders. Global costs include designing the operational plan, deploying the platform, and acquiring processing software. Not least, performing certain analyses requires technical skills, and therefore, external trained staff or training course for in-house personnel are required. Below, some examples of budget assessment for UAV in forestry applications are reported. Padua et al. [270] estimate costs

of UAV systems in small areas (up to 50 ha) as follows: EUR 10,000 for disease detection and identification (multispectral), EUR 3000 for vegetation height maps (optical), and EUR 2000 for biomass estimation (optical). For broader areas (up to 5 km²), the estimated costs are EUR 30,000 and EUR 25,000 for forest inventory (lidar) and post-fire burn area estimation (multispectral), respectively. In the Canadian boreal forest, Chen et al. [271] measure vegetation height for 30 sites on seismic lines (overall extension of ca. 3 ha). They estimate a total cost, including field crew, of about EUR 9300 for UAV-ALS and EUR 6800 for UAV-DAP. A possible solution for reducing costs of UAV-RS could be represented by high-performing and fully free software for image processing, which is increasingly appearing on the market or customized full packages, directly usable by final users. This last hypothesis, even if more suitable, seems to be more difficult to pursue due to the different missions of stakeholders involved in forest management. Moreover, UAV-forestry narrow market provides relatively limited opportunities for companies to develop tools adapted to any specific goals of woodland monitoring. This is why the authors hope for greater collaboration among companies, researchers, and forestry stakeholders to implement new solutions that are increasingly suited to the needs of forest management.

5. Conclusions

The present study analyzes a substantial body of literature by gathering a comprehensive dataset (227 articles) dealing with UAV forest remote sensing over a recent timespan (2018–mid-2020). This Part II of the review discusses specific technical issues of applying UAV-RS research in different forest ecosystems. As reported also in Part I [3], the final assessment presents many positives, but few weak points also emerge.

UAV-RS contributes to understanding forest ecosystems better by allowing insights into forest status and dynamics. Regarding strong points, UAV data acquisition is based mainly on two consolidated structural sources, i.e., DAP and ALS. SfM processing technique is particularly exploited and investigated with positive results by the reviewed papers. UAV-RS is fully applied for obtaining accurate information from practical parameters (height, DBH, and crown diameter) with a considerable number of researches dealing with this topic. Their effectiveness and soundness demonstrate that UAV-RS is now ready to be applied in a real management context. Researchers have made a lot of effort to estimate tree biomass, especially through allometric custom models, which have the undoubted advantage of being specific to the forested area under investigation.

Nevertheless, challenges still exist regarding both purely technical (real-time image processing, hyperspectral sensor spreading, RS platform interoperability) and general issues (i.e., flight regulatory regime, technology transfer), and they can hinder UAV-RS progress. Therefore, improvable and unclear issues require additional research. To help managers maintaining healthy and productive forests, the number of articles tackling pest and disease detection should be greatly increased. Real-time species recognition should be desirable for an on-the-flight detection and timely eradication of invasive plants, by merging the steps of image acquisition and processing. Even though huge efforts are being made in this direction, great potentials remain to be explored for the hyperspectral sensor. Hyperspectral imagery is too little used. Novel applications for species recognition or pest and disease detection should be based on the capability of acquiring spectral signature, which is linked with tree characteristics and status. Greater interoperability would be desirable between UAV and freely available satellite data, even if they are not always easy to access for professionals. Spaceborne imagery could be used as a screening tool to pinpoint forest anomalies and then, where problems or peculiarities arise, UAVs could be deployed to perform in-depth monitoring. Although field data are widely gathered throughout the reviewed papers, they should be leveraged more for model validation, especially when using UAV to predict vegetation biomass as this guarantees robust and transferable results. The use of automatic processes for image analysis is certainly destined to grow and represents a leap forward for UAV-RS forest monitoring—sometimes they seem to be black boxes due to the poor flexibility of proprietary software and the complexity

of workflow. These aspects can be very challenging and can hinder the technology transfer and thus the full understanding (conscious fruition) of non-specialist users, such as forest managers and professionals.

While the technical skills of researchers are appropriate for addressing the complexity of forest UAV–RS, there is still a lot that can be accomplished to bridge the gap between academia and forest stakeholders. For improving technology transfer, researchers should develop approaches that are robust to slightly different contexts and that take advantage of easy-to-collect data. Additionally, processing routines tailored to stakeholder needs should be embedded into flexible and interoperable open-source tools. To boost the technology transfer, there is also a need for funding through public and dedicated resources. Moreover, cooperation projects could help the spread of RS monitoring in some areas where it is lacking and where its use could be strongly recommended to help manage and protect the huge forest heritage. Of course, the burden of technology transfer cannot be entirely borne by researchers, and for this reason, the authors hope for an effective collaboration among all forestry stakeholders to develop new solutions increasingly tailored to forest management.

In completing this review, the authors came across only a few studies (here not encompassed) dealing with the use of UAV as a tool of forestry operations. These are limited to aerial seeding [272,273] and to pesticide spraying [274], which, for the sake of completeness, is not yet allowed in large areas within the European Union. Nevertheless, the rapid advancement of UAV–RS seems to be unstoppable, and developing unmanned operating platforms could be one of the new frontiers of UAV research in forestry applications.

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