Unmanned Aerial Vehicles in Forest Health Monitoring

Subjects: Remote Sensing

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Unmanned aerial vehicles (UAVs) are platforms that have been increasingly used over the last decade to collect data for forest insect pest and disease (FIPD) monitoring. These machines provide flexibility, cost efficiency, and a high temporal and spatial resolution of remotely sensed data.

insect pest and disease monitoring | forest | unmanned aerial vehicles | remote sensing

1. Introduction

Forests play a fundamental role in human well-being [1]. They are crucial carbon pools [2], contributing to mitigating the impacts of climate change [3][4] while ensuring important economic and social benefits, providing soil and water protection, and many other relevant environmental services [5].

In recent decades, changes in the frequency and severity of meteorological events seem to be related to a concomitant drop in the vitality of forests, namely with the outbreak of new insect pests and diseases [5][6][7]. These environmental disturbances can facilitate a change in the frequency of the occurrence of forest pests [8], which undoubtedly impacts the development, survival, reproduction, and dissemination of the species [5]. Insects have been recognized as the first indicators of climate change [9]. Reducing forest degradation and increasing its resilience involves managing and preventing these stressors and disturbing agents [10]. In this context, accurate and timely forest health monitoring is needed to mitigate climate change and support sustainable forest management [11].

Field sampling and symptom observation on foliage and trunks are the main methods to identify and register forest pests and diseases [11][12]. When remotely sensed data with high spatial and spectral resolution are collected at ideal times, people can differentiate canopy reflectance signals from noise in forests affected by pests and diseases [13][14]. Traditional field surveys based on forest inventories and observations are restricted by small area coverage and subjectivity [15]. However, when combined with unmanned aerial vehicles (UAVs), spatial coverage can be expanded, response time minimized, and the costs of monitoring forested areas reduced. UAV systems provide images of high spatial resolution and can obtain updated and timely data with different sensors [16][17]. In addition, they can complement the already well-known and explored satellites with airborne remote sensing capabilities [16][18].

UAVs can also be a valuable field data source to calibrate and validate remote sensing monitoring systems [19]. UAVs offer automatic movement and navigation, support different sensors, provide safe access to difficult locations, and enable data collection under cloudy conditions [20]. In addition, these systems can be operated to monitor specific phenological phases of plants or during pest/disease outbreaks [18][21]. In this sense, UAVs are versatile, flexible, and adaptable to different contexts [22]. Despite the relevant advantageous characteristics of UAVs, some limitations can also be identified, such as limited area coverage, battery duration, payload weight, and local regulations [23].

Several literatures have already provided critical aspects related to the application of UAVs to forest insect pest and disease (FIPD) monitoring (**Table 1**).

Table 1. Unmanned aerial vehicle (UAV) remote sensing for forest insect pests and diseases.

No.	Ref.	Year	Title	Journal	Contents
1	[24]	2017	Forestry applications of UAVs in Europe: a review	International Journal of Remote Sensing	A review of UAV-based forestry applications and aspects of regulations in Europe. Three studies about FIPDs were reviewed.
2	[25]	2017	Hyperspectral Imaging: A Review on UAV-Based Sensors, Data Processing and Applications for Agriculture and Forestry	Remote Sensing	A review on UAV-based hyperspectral sensors, data processing, and applications for agriculture and forestry. Three studies about FIPDs were reviewed.
3	[26]	2020	Remotely piloted aircraft systems and forests: a global state of the art and future challenges	Canadian Journal of Forest Research	A review of UAV-based forestry applications. Six studies about FIPDs were reviewed.
4	[16]	2020	Forestry Remote Sensing from Unmanned Aerial Vehicles: A Review Focusing on the Data, Processing and Potentialities	Remote Sensing	A review focusing on data, processing, and potentialities. It covers all types of procedures and provides examples. Nine studies about FIPDs were reviewed.
5	[27]	2021	Recent Advances in Unmanned Aerial Vehicles Forest Remote Sensing—A Systematic Review. Part II: Research Applications	Forests	A systematic review of UAV system solutions, technical advantages, drawbacks of the technology, and considerations on technology transfer. Seventeen studies about FIPDs were reviewed.
6	[28]	2021	The Role of Remote Sensing for the Assessment and Monitoring of Forest Health: A Systematic Evidence Synthesis	Forests	A systematic evidence synthesis about forest health issues with reference to different remote sensing platforms and techniques. Ten studies about UAV–FIPDs were reviewed.

No.	Ref.	Year	Title	Journal	Contents
7	[29]	2021	Remotely Piloted Aircraft Systems to Identify Pests and Diseases in Forest Species: The Global State of the Art and Future Challenges	IEEE Geoscience and remote sensing magazine	A literature review of UAV-based on forest pest and disease monitoring. Thirty-three studies about FIPDs were reviewed.

2. Unmanned Aerial Vehicles in Forest Monitoring

2.1. UAV and Sensor Types

2.1.1. UAV Types

Figure 1 shows the circular packing graph where each circle is a group of UAV types considering the number of propellers and architecture. The bubbles inside the circles represent the sub-groups. Each bubble's size is proportional to the UAV categories used in the studies.

1. Anderegg, W.R.L.; Trugman, A.T.; Badgley, G.; Anderson, C.M.; Bartuska, A.; Ciais, P.; Cullenward, D.; Field, C.B.; Freeman, J.; Goetz, S.J.; et al. Climate-Driven Risks to the Climate Mitigation Potential of Forests. Science 2020, 368, eaaz7005.
2. FAO. Assessing Forest Degradation: Towards the Development of Globally Applicable Guidlines; Forest Resources Assessment Working Paper 177; Food and Agriculture Organization of the United Nations: Rome, Italy, 2011.
3. Canadell, J.G.; Raupach, M.R. Managing Forests for Climate Change Mitigation. Science 2008, 320, 1456–1457.
4. FAO. Climate Change Guidelines for Forest Managers; FAO Forestry Paper 172; Food and Agriculture Organization of the United Nations: Rome, Italy, 2013; p. 123.
5. FAO. Managing Forests for Climate Change; Food and Agriculture Organization of the United Nations: Rome, Italy, 2010; p. 20.
6. Dale, V.; JOYCE, L.; Mcnulty, S.; Neilson, R.; Ayres, M.; Flannigan, M.; Hanson, P.; Irland, L.; Lugo, A.; PETERSON, C.; et al. Climate Change and Forest Disturbances. BioScience 2001, 51, 723–734.
7. Senf, C.; Buras, A.; Zang, C.S.; Rammig, A.; Seidl, R. Excess Forest Mortality Is Consistently Linked to Drought across Europe. Nat. Commun. 2020, 11, 6200.
8. Seidl, R.; Spies, T.A.; Peterson, D.L.; Stephens, S.L.; Hicke, J.A. Searching for Resilience: Addressing the Impacts of Changing Disturbance Regimes on Forest Ecosystem Services. J. Appl. Ecol. 2016, 53, 120–129.
9. Koricheva, J.; Castagneyrol, B. Science Direct Responses of Forest Insect Pests to Climate Change: Not so Simple. Curr. Opin. Insect Sci. 2019, 35, 103–108.
10. Raffa, K.F.; Aukema, B.H.; Bentz, B.J.; Carroll, A.L.; Hicke, J.A.; Turner, M.G.; Romme, W.H. Cross-Scale Drivers of Natural Disturbances Prone to Anthropogenic Amplification: The Dynamics of Bark Beetle Eruptions. BioScience 2008, 58, 501–517.
11. Lausch, A.; Borg, E.; Bumberger, J.; Dietrich, P.; Heurich, M.; Huth, A.; Jung, A.; Klenke, R.; Knapp, S.; Mollenhauer, H.; et al. Understanding Forest Health with Remote Sensing, Part III: Requirements for a Scalable Multi-Source Forest Health Monitoring Network Based on Data Science Approaches. Remote Sens. 2018, 10, 1120.

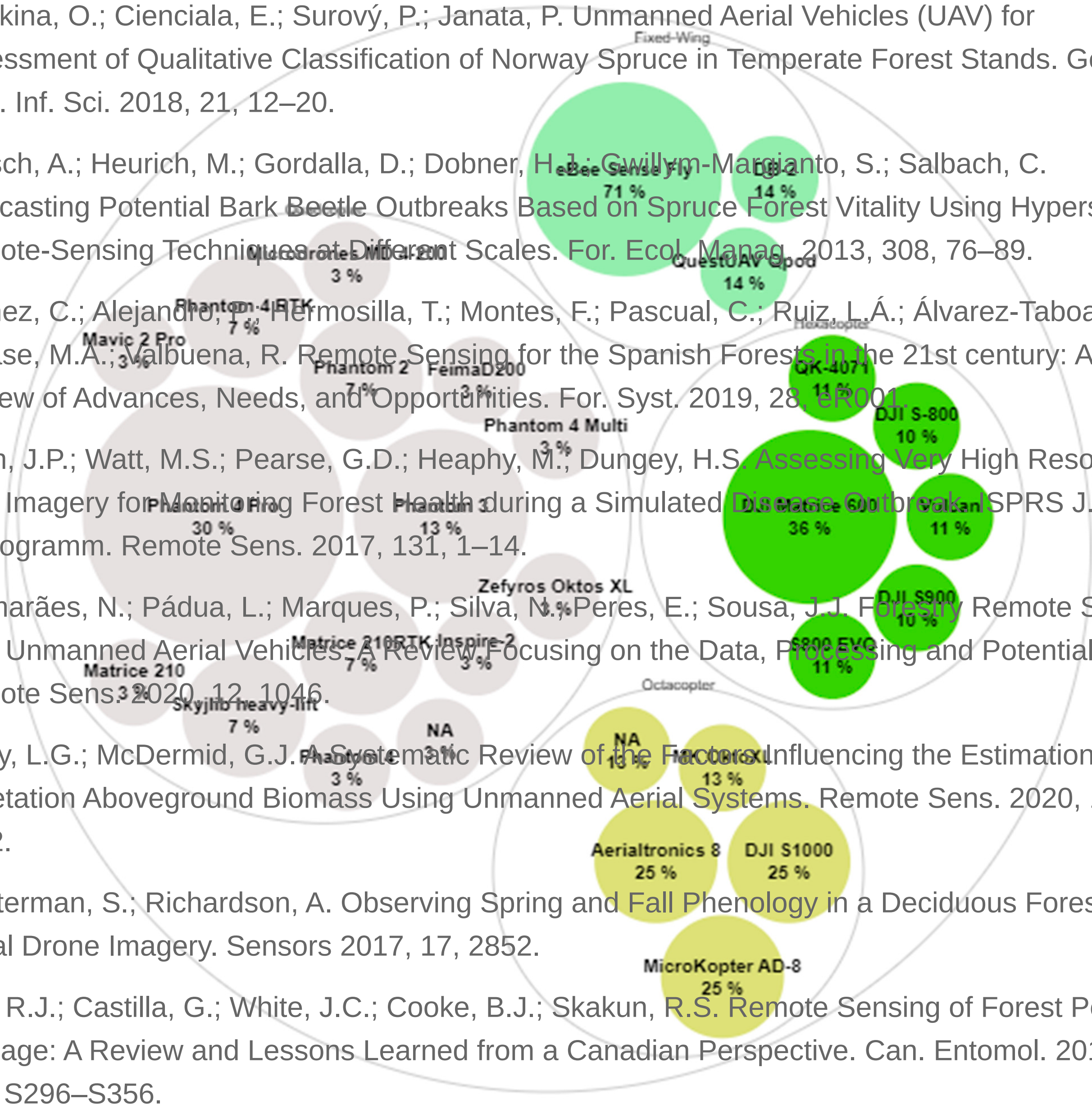

Figure 1. Summary of UAV types and model brands identified in the studies.

Regarding the models used by the number of propellers, the quadcopter model DJI Phantom 4 Pro was used in 30% of the studies and DJI Phantom 3 in 14%. With regard to octocopters, the most used models were the DJI S1000 (25%), Arealtronics (25%), and the MicroKopter Droidwors AD-8 (25%). Thirteen percent made no distinction based on the model used. The hexacopter DJI Matrice 600 model was used in 36% of the works. Finally, in the fixed-wing segment, the most popular was the eBee Sense Fly model with 71% usage, followed by the Quest UAV Qpod (14%) and DB-2 (14%).

Regarding the choice of platform, the most widely adopted was the rotary-wing, which stands out due to its flexibility, versatility, maneuverability, and its ability to hover, offering a much easier automated experience [20][30][31]. Fixed-wing drones are more efficient, stable in crosswind flights, and have short flight times per unit of a mapped area [32]. However, they are less versatile for making small flights when compared with rotary-wing drones. In

12. Brovkina, O.; Cienciala, E.; Surový, P.; Janata, P. Unmanned Aerial Vehicles (UAV) for Assessment of Qualitative Classification of Norway Spruce in Temperate Forest Stands. Geo-Spat. Inf. Sci. 2018, 21, 12–20.

13. Lausch, A.; Heurich, M.; Gordalla, D.; Dobner, H.J.; Gwillym-Margianto, S.; Salbach, C. Forecasting Potential Bark Beetle Outbreaks Based on Spruce Forest Vitality Using Hyperspectral Remote-Sensing Techniques at Different Scales. For. Ecol. Manag. 2013, 308, 76–89.

14. Gómez, C.; Alejandro, P.; Hermosilla, T.; Montes, F.; Pascual, C.; Ruiz, L.Á.; Álvarez-Taboada, F.; Tanase, M.A.; Valbuena, R. Remote Sensing for the Spanish Forests in the 21st century: A Review of Advances, Needs, and Opportunities. For. Syst. 2019, 28, eR001.

15. Dash, J.P.; Watt, M.S.; Pearse, G.D.; Heaphy, M.; Dungey, H.S. Assessing Very High Resolution UAV Imagery for Monitoring Forest Health during a Simulated Disease Outbreak. ISPRS J. Photogramm. Remote Sens. 2017, 131, 1–14.

16. Guimarães, N.; Pádua, L.; Marques, P.; Silva, N.; Peres, E.; Sousa, J.J. Forestry Remote Sensing from Unmanned Aerial Vehicles: A Review Focusing on the Data, Processing and Potentialities. Remote Sens. 2020, 12, 1046.

17. Poley, L.G.; McDermid, G.J. A Systematic Review of the Factors Influencing the Estimation of Vegetation Aboveground Biomass Using Unmanned Aerial Systems. Remote Sens. 2020, 12, 1052.

18. Klosterman, S.; Richardson, A. Observing Spring and Fall Phenology in a Deciduous Forest with Aerial Drone Imagery. Sensors 2017, 17, 2852.

19. Hall, R.J.; Castilla, G.; White, J.C.; Cooke, B.J.; Skakun, R.S. Remote Sensing of Forest Pest Damage: A Review and Lessons Learned from a Canadian Perspective. Can. Entomol. 2016, 148, S296–S356.

20. Pádua, L.; Vanko, J.; Hruška, J.; Adão, T.; Sousa, J.J.; Peres, E.; Morais, R. UAS, Sensors, and Data Processing in Agroforestry: A Review towards Practical Applications. Int. J. Remote Sens. 2017, 38, 2349–2391.

21. Rullan-Silva, C.D.; Olthoff, A.E.; Delgado de la Mata, J.A.; Pajares-Alonso, J.A. Remote Monitoring of Forest Insect Defoliation. A Review. For. Syst. 2013, 22, 377–391.

22. Yao, H.; Qin, R.; Chen, X. Unmanned Aerial Vehicle for Remote Sensing Applications—A Review. Remote Sens. 2019, 11, 1443.

23. Manfreda, S.; McCabe, M.; Miller, P.; Lucas, R.; Pajuelo Madrigal, V.; Mallinis, G.; Ben Dor, E.; Helman, D.; Estes, L.; Ciraolo, G.; et al. On the Use of Unmanned Aerial Systems for Environmental Monitoring. Remote Sens. 2018, 10, 641.

addition, rotary-wing drones are more suitable for mapping small and complex sites, while fixed-wing drones are more appropriate for covering large extension areas [33]. Conversely, a faster vehicle may have issues in mapping small objects and insufficient overlap [31]. In spite of this, both UAV types offer the possibility to collect data from short intervals and at a local scale, which is relevant for multitemporal studies [15][34]. Notably, the preference for quadcopters may be related to the low-cost acquisition, the wide availability on the market, and the assessment of FIPD in small areas [26]. For example, the DJI Phantom series was the most frequently used in this segment. The hexacopters and octocopters from the DJI series choice were due to the payload capabilities in the remaining studies. Finally, eBee Sense Fly stands out for its maturity in the market. The arguments presented indicate that rotary-wing drones are the most suitable for FIPD monitoring. However, more comparative studies are needed to support the appropriate UAV architecture for this forestry application. Despite these facts, platform choice depends on the survey requirements, the budget, and the experience of the researcher or practitioner. An important point to mention is the market offer of hybrid VTOL (vertical take-off and landing), of which the only disadvantage is the complex system mechanism [35][36].

2.1.2. Sensor Types

Figure 2a illustrates the number of remote sensing sensors, and **Figure 2**b shows the top 10 model camera brands coupled with UAVs. The passive remote sensor quantities were grouped into four categories: (i) RGB, i.e., the simplification of multispectral red–green–blue (RGB); (ii) multispectral, including RGB, near-infrared, and red-edge bands; (iii) hyperspectral; and finally, (iv) thermal sensors. Light detection and ranging (LiDAR) was the only active sensor found in the studies.

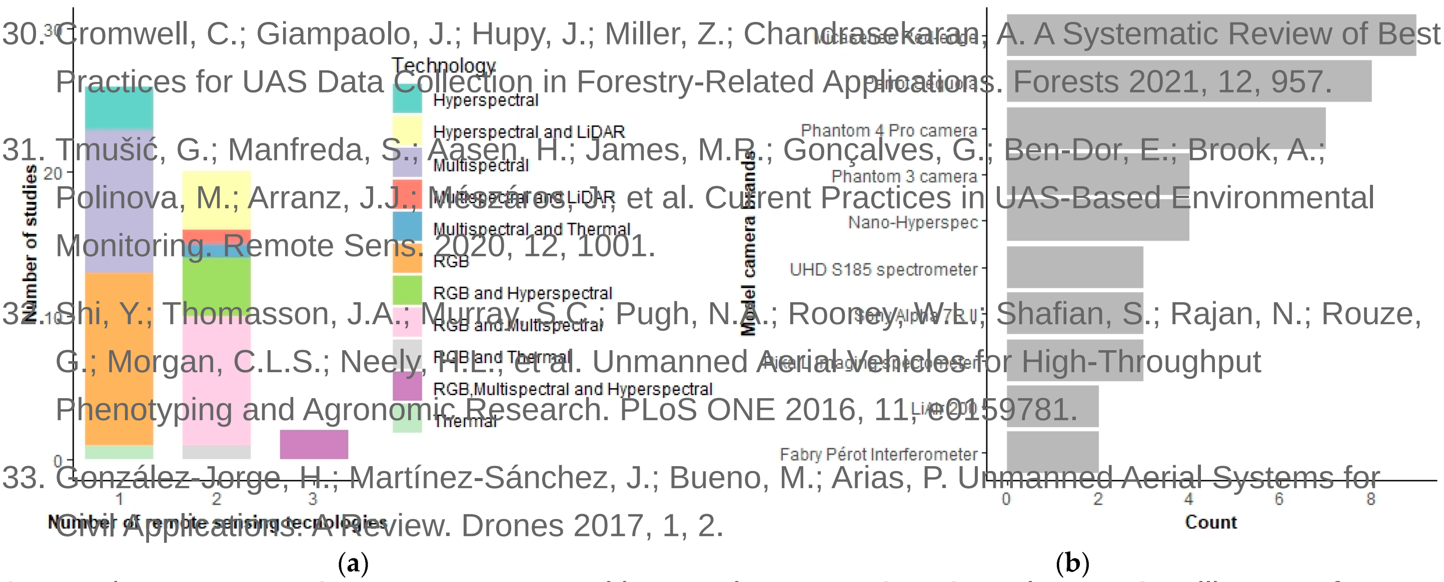

Figure 2. Summary of sensor types, including: (**a**) types of remote sensing technology identified in each study; (**b**) top 10 model camera brands.

Concerning the sensor model brands coupled with different UAV architectures, the multispectral cameras Micasense Red-edge and Parrot Sequoia were the most widely used (**Figure 2**b).

24. Torresan, C.; Berton, A.; Carotenuto, F.; Di Gennaro, S.F.; Gioli, B.; Matese, A.; Miglietta, F.; Vagnoli, C.; Zaldei, A.; Wallace, L. Forestry Applications of UAVs in Europe: A Review. Int. J. Remote Sens. 2017, 38, 2427–2447.

25. Adão, T.; Hruška, J.; Pádua, L.; Bessa, J.; Peres, E.; Morais, R.; Sousa, J. Hyperspectral Imaging: A Review on UAV-Based Sensors, Data Processing and Applications for Agriculture and Forestry. Remote Sens. 2017, 9, 1110.

26. Eugenio, F.C.; Schons, C.T.; Mallmann, C.L.; Schuh, M.S.; Fernandes, P.; Badin, T.L. Remotely Piloted Aircraft Systems and Forests: A Global State of the Art and Future Challenges. Can. J. For. Res. 2020, 50, 705–716.

27. Dainelli, R.; Toscano, P.; Di Gennaro, S.F.; Matese, A. Recent Advances in Unmanned Aerial Vehicles Forest Remote Sensing—A Systematic Review. Part II: Research Applications. Forests 2021, 12, 397.

28. Torres, P.; Rodes-Blanco, M.; Viana-Soto, A.; Nieto, H.; García, M. The Role of Remote Sensing for the Assessment and Monitoring of Forest Health: A Systematic Evidence Synthesis. Forests 2021, 12, 1134.

29. Eugenio, F.C.; PereiradaSilva, S.D.; Fantinel, R.A.; de Souza, P.D.; Felippe, B.M.; Romua, C.L.; Elsenbach, E.M. Remotely Piloted Aircraft Systems to Identify Pests and Diseases in Forest Species: The Global State of the Art and Future Challenges. IEEE Geosci. Remote Sens. Mag. 2021, 10, 2–15.

30. Cromwell, C.; Giampaolo, J.; Hupy, J.; Miller, Z.; Chandrasekaran, A. A Systematic Review of Best Practices for UAS Data Collection in Forestry-Related Applications. Forests 2021, 12, 957.

31. Tmušić, G.; Manfreda, S.; Aasen, H.; James, M.R.; Gonçalves, G.; Ben-Dor, E.; Brook, A.; Polinova, M.; Arranz, J.J.; Mészáros, J.; et al. Current Practices in UAS-Based Environmental Monitoring. Remote Sens. 2020, 12, 1001.

32. Shi, Y.; Thomasson, J.A.; Murray, S.C.; Pugh, N.A.; Rooney, W.L.; Shafian, S.; Rajan, N.; Rouze, G.; Morgan, C.L.S.; Neely, H.L.; et al. Unmanned Aerial Vehicles for High-Throughput Phenotyping and Agronomic Research. PLoS ONE 2016, 11, e0159781.

33. González-Jorge, H.; Martínez-Sánchez, J.; Bueno, M.; Arias, P. Unmanned Aerial Systems for Civil Applications: A Review. Drones 2017, 1, 2.

34. Dash, J.; Pearse, G.; Watt, M. UAV Multispectral Imagery Can Complement Satellite Data for Monitoring Forest Health. Remote Sens. 2018, 10, 1216.

35. Watts, A.C.; Ambrosia, V.G.; Hinkley, E.A. Unmanned Aircraft Systems in Remote Sensing and Scientific Research: Classification and Considerations of Use. Remote Sens. 2012, 4, 1671–1692.

The preferred models of the cameras—related to the type and payload of the drones used in the studies—were the DJI Phantom camera, the Tetracam, and the Sony camera, which is known for its quality and specification [12][37][38][39][40][41]. The Micasense series was the leader of the multispectral cameras, containing five bands that capture data in the RGB, near-infrared, and red-edge regions (400–900 nm). The compact size and weight allow it to be used in a large variety of UAV types. Another preferred multispectral sensor is the Parrot Sequoia, which has a low price when compared with the Micasense series. This camera collects four discrete bands: green, red, red-edge, and NIR (530–810 nm). The interest in this type of camera is due to its ability to obtain information on the state of vegetation, thereby offering the chance calculate vegetation indices, since vegetation is more reflective in the infrared region [42] for disease detection [21].

As for the hyperspectral sensors—Nano-Hyperspect, the Pika L. imaging spectrometer, and the UHD S185 spectrometer—these were the most used because they are adopted on a considerable variety of professional drone types. These sensors have a much broader spectrum than multispectral sensors, which allows the discrimination of small changes in pigmentation and minor anomalies [43], such as water content, and the structure of the tree crown [38]. For these reasons, their use is growing. Despite this, the authors of [44] stress that operational efforts, storage needed due to the high dimensional data and noise, and weight [45] are the main constraints of this type of sensor.

2.2. UAV Data Collection

2.2.1. Area Coverage

The largest mapped area was 16,043 ha, distributed over four sections of 3397 ha, 3825 ha, 5283 ha, and 3537 ha. The smallest area size mapped was 0.12 ha. Eighty seven percent of the studies carried out mappings up to 200 ha, and the remaining were exclusively above 200 ha. The median amount of covered area was 12.25 ha.

2.2.2. Technical Flight Parameters

Table 2 shows the flight height and GSD descriptive statistics by sensor type used in the studies. GSD results from the combination of flight height, focal length, and sensor resolution [31]. It is crucial to define the camera settings to determine GSD, which corresponds to the distance between pixel centers. The highest flight altitude was 700 m, and the lowest was 20 m performed with a hyperspectral sensor. The median of flight height for thermal sensor was 75 m, and the highest was 100 m using multispectral sensors.

Table 2. Flight height and GSD descriptive statistics by sensor type.

		Flight Height (m)			GSD (m)		
Sensor Type	No.	Max	Min	Median	Max	Min	Median
RGB	29	700	30	90	0.080	0.015	0.028
Multispectral	27	200	50	100	0.170	0.020	0.070

36. Zong, J.; Zhu, B.; Hou, Z.; Yang, X.; Zhai, J. Evaluation and Comparison of Hybrid Wing VTOL UAV with Four Different Electric Propulsion Systems. Aerospace 2021, 8, 256.

37. Klouček, T.; Komárek, J.; Surový, P.; Hrach, K.; Janata, P.; Vašíček, B. The Use of UAV Mounted Sensors for Precise Detection of Bark Beetle Infestation. Remote Sens. 2019, 11, 1561.

38. Zhang, N.; Wang, Y.; Zhang, X. Extraction of Tree Crowns Damaged by Dendrolimus Tabulaeformis Tsai et Liu via Spectral-Spatial Classification Using UAV-Based Hyperspectral Images. Plant Methods 2020, 16, 1–9.

39. Zhang, N.; Zhang, X.; Yang, G.; Zhu, C.; Huo, L.; Feng, H. Assessment of Defoliation during the Dendrolimus Tabulaeformis Tsai et Liu Disaster Outbreak Using UAV-Based Hyperspectral Images. Remote Sens. Environ. 2018, 217, 323–339.

40. Syifa, M.; Park, S.-J.; Lee, C.-W. Detection of the Pine Wilt Disease Tree Candidates for Drone Remote Sensing Using Artificial Intelligence Techniques. Engineering 2020, 6, 919–926.

41. Park, H.G.; Yun, J.P.; Kim, M.Y.; Jeong, S.H. Multichannel Object Detection for Detecting Suspected Trees with Pine Wilt Disease Using Multispectral Drone Imagery. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2021, 14, 8350–8358.

42. Müllerová, J.; Bartaloš, T.; Brůna, J.; Dvořák, P.; Vítková, M. Unmanned Aircraft in Nature Conservation: An Example from Plant Invasions. Int. J. Remote Sens. 2017, 38, 2177–2198.

43. Näsi, R.; Honkavaara, E.; Lyytikäinen-Saarenmaa, P.; Blomqvist, M.; Litkey, P.; Hakala, T.; Viljanen, N.; Kantola, T.; Tanhuanpää, T.; Holopainen, M. Using UAV-Based Photogrammetry and Hyperspectral Imaging for Mapping Bark Beetle Damage at Tree-Level. Remote Sens. 2015, 7, 15467–15493.

44. Iordache, M.-D.; Mantas, V.; Baltazar, E.; Pauly, K.; Lewyckyj, N. A Machine Learning Approach to Detecting Pine Wilt Disease Using Airborne Spectral Imagery. Remote Sens. 2020, 12, 2280.

45. Stuart, M.B.; McGonigle, A.J. Hyperspectral Imaging in Environmental Monitoring: A Review of Recent Developments and Technological Advances in Compact Field Deployable Systems. Sensors 2019, 19, 3071.

46. Cardil, A.; Vepakomma, U.; Brotons, L. Assessing Pine Processionary Moth Defoliation Using Unmanned Aerial Systems. Forests 2017, 8, 402.

47. Minařík, R.; Langhammer, J.; Lendzioch, T. Automatic Tree Crown Extraction from Uas Multispectral Imagery for the Detection of Bark Beetle Disturbance in Mixed Forests. Remote [illegible]

4[illegible] Health [illegible] 2021, 12, 1145.

		Flight Height (m)			GSD (m)		
Sensor Type	No.	Max	Min	Median	Max	Min	Median
Hyperspectral	12	140	20	95	0.560	0.047	0.200
Thermal	4	122	60	75	0.980	0.150	0.211

In terms of GSD, the maximum value was 0.98 m with the thermal sensor, and the minimum was 0.015 m, acquired by an RGB sensor. The median flight height for thermal sensors' was 75 m, and the highest was 100 m for the multispectral sensors. The RGB sensors' median GSD was 0.028 m, and the highest was 0.211 m with the thermal sensors.

2.3. Data Processing and Analytical Methods

2.3.1. Spatial Unit Analysis

Object-based approach and pixel-based approach are commonly used methods. As a minimal unit in a digital image, pixels may be used for every scale study. However, only spectral properties are considered in analytical methods, while object-based approaches are performed using segmentation approaches that group objects based on statistical or feature similarities. This approach is mainly performed before feature extraction and applying classifiers, since these methods cannot add contextual information [28].

2.3.2. Segmentation of Single Tree Objects

Table 3 summarizes the segmentation single tree methods.

Table 3. Summary of segmentation single tree methods in the studies.

Segmentation Single Tree	Method	Synopsis	Studies
Manually	Manually segmented trees	Digitalization of each tree crown above imagery using GIS software.	[15][34][39][46][47][48][49][50][51][52][53]
	Local maxima filter and Buffer	Local maxima filter within a rasterized CHM to detect the treetops, then a buffer applied on the treetop using GIS software.	[37][46][54][55][56]
Raster-based	Mean shift algorithm	GEOBIA method. Multispectral image segmentation using ArcGIS segment mean shift tool.	[57]
	Multiresolution segmentation	GEOBIA method. Multispectral image segmentation using eCognition software multiresolution segmentation tool.	[12][58][59]

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5... age Degree Caused by Pine Shoot Beetle to Yunnan Pine Using UAV-Based Hyperspectral Images. Forests 2020, 11, 1258.
51. Guerra-Hernández, J.; Díaz-Varela, R.A.; Ávarez-González, J.G.; Rodríguez-González, P.M. Assessing a Novel Modelling Approach with High Resolution UAV Imagery for Monitoring Health Status in Priority Riparian Forests. For. Ecosyst. 2021, 8, 61.
52. Yu, R.; Luo, Y.; Zhou, Q.; Zhang, X.; Wu, D.; Ren, L. A Machine Learning Algorithm to Detect Pine Wilt Disease Using UAV-Based Hyperspectral Imagery and LiDAR Data at the Tree Level. Int. J. Appl. Earth Obs. Geoinf. 2021, 101, 102363.
53. Yu, R.; Ren, L.; Luo, Y. Early Detection of Pine Wilt Disease in Pinus Tabuliformis in North China Using a Field Portable Spectrometer and UAV-Based Hyperspectral Imagery. For. Ecosyst. 2021, 8, 44.
54. Abdollahnejad, A.; Panagiotidis, D. Tree Species Classification and Health Status Assessment for a Mixed Broadleaf-Conifer Forest with Uas Multispectral Imaging. Remote Sens. 2020, 12, 3722.
55. Smigaj, M.; Gaulton, R.; Barr, S.L.; Suárez, J.C. UAV-Borne Thermal Imaging for Forest Health Monitoring: Detection Of Disease-Induced Canopy Temperature Increase. In International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences—ISPRS Archives; Paparoditis, N., Raimond, A.-M., Sithole, G., Rabatel, G., Coltekin, A., Rottensteiner, F., Briottet, X., Christophe, S., Dowman, I., Elberink, S.O., et al., Eds.; International Society for ... 349–
5... Aerial ... or. Ecol.
5... on Tree ... 3, 80.
5... -Based ... 015, 6,
5... on in ... ion UAV Images Using Object-Oriented Classification. J. For. Res. 2021, 577.

Segmentation Single Tree	Method	Synopsis	Studies
	Local maxima filter and mean shift algorithm	Local maxima of a sliding window using the brightness of the multispectral image. Then, the select by location tool is used between treetops and for large-scale mean shift algorithm segments (GEOBIA).	[60]
	Safonova et al. Wavelet-based local thresholding	Tree crown delineation using RGB images. The steps are contrast enhancement, crown segmentation based on wavelet transformation and morphological operations, and boundary detection.	[61]
	Safonova et al. Treetop detection	RGB images are transformed into one grey-scale band image; next, the grey-scale band image is converted into a blurred image; finally, the blurred image is converted into a binary image.	[62]
	Voronoi Tesselations	Local maxima filter within a rasterized CHM calculates the treetops and then uses a Voronoi tessellation algorithm [63].	[64]
	Dalponte individual tree segmentation	Local maxima within a rasterized CHM calculates the treetops and then uses a region-growing algorithm for individual segmentation [65][66].	[47][67]
	Watershed segmentation	Vicent and Soille original algorithm [68]. When the CHM is inverted, tree tops or vegetation clusters look like “basins”.	[69]
		Marker-controlled watershed [70]. Marker and segmentation functions are used for multi-tree identification and segmentation using rasterized CHM [71].	[47][72]
		Binary watershed analysis and the Euclidean distance using rasterized CHM or NIR band.	[52][73]
		Hyyppä et al. [74] methodology.	[43]
	Nyguen Treetops in nDSM data	Based on pixel intensity, an iterative sliding window is passed over the nDSM. Finally, the refinement is applied to eliminate treetops that are too close to each other.	[75]
Vector-based	3D region-growing algorithm	3D region-growing algorithm applied in a point cloud (LiDAR or photogrammetric) using a built-in function for treetop detection [76].	[47][52][77]
	3D segmentation of single trees	Point cloud-based method with tree segmentation using a normalized cut algorithm [78].	[79]

Table 4 summarizes the feature extraction techniques for UAV imagery applied in the studies.

70. Zhen, Z.; Quackenbush, L.; Zhang, L. Trends in Automatic Individual Tree Crown Detection and Delineation—Evolution of LiDAR Data. Remote Sens. 2016, 8, 333.

Table 4. Summary of feature extraction techniques of UAV imagery applied in the studies.

Feature Type	Description	Studies
Spectral features	Statistics of original bands, ratios between bands, vegetation indices	[12][15][34][37][38][39][41][43][44][46][47][48][49][50][51][52][53][54][55][56][57][58][59][60][67][69][72][73][77][79][80][81][82][83][84][85][86][87][88][89]
Textural features	Gray level co-occurrence matrix (GLCM), grey level difference vector (GLDV)	[51][54][72]
Linear transformations	Hue, saturated and intensity (HSI), principal component analysis (PCA)	[38][52][58]
Geo-auxiliary	Original and normalized digital surface models (DSM) such as digital elevation models (DEM), canopy height models (CHM), slope, aspect, height percentiles	[12][46][47][48][51][54][56][64][72][75][77][79][84][86][88]
Multisensor	Inclusion of data obtained from different sensors in analytical methods	[52][55][79][80][84]
Multitemporal	Inclusion of multitemporal data classification in analytical methods	[15][34][54][67][73]

2.3.4. Analysis Type, Algorithms, and Overall Accuracy (OA)

Figure 3 summarizes the algorithms used by the analysis method.

the Lidar Point Cloud. Photogramm. Eng. Remote Sens. 2012, 78, 75–84.

77. Lin, Q.; Huang, H.; Wang, J.; Huang, K.; Liu, Y. Detection of Pine Shoot Beetle (PSB) Stress on Pine Forests at Individual Tree Level Using UAV-Based Hyperspectral Imagery and Lidar. Remote Sens. 2019, 11, 2540.

78. Reitberger, J.; Schnörr, C.; Krzystek, P.; Stilla, U. 3D Segmentation of Single Trees Exploiting Full Waveform LIDAR Data. ISPRS J. Photogramm. Remote Sens. 2009, 64, 561–574.

79. Briechle, S.; Krzystek, P.; Vosselman, G. Classification of Tree Species and Standing Dead Trees by Fusing Uav-Based Lidar Data and Multispectral Imagery in the 3D Deep Neural Network Pointnet++. In ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences; Paparoditis, N., Mallet, C., Lafarge, F., Remondino, F., Toschi, I., Fuse, T., Eds.; Copernicus GmbH: Göttingen, Germany, 2020; Volume 5, pp. 203–210.

80. Näsi, R.; Honkavaara, E.; Blomqvist, M.; Lyytikäinen-Saarenmaa, P.; Hakala, T.; Viljanen, N.; Kantola, T.; Holopainen, M. Remote Sensing of Bark Beetle Damage in Urban Forests at Individual Tree Level Using a Novel Hyperspectral Camera from UAV and Aircraft. Urban For. Urban Green. 2018, 30, 72–83.

81. Minařík, R.; Langhammer, J. Use of a Multispectral UAV Photogrammetry for Detection and Tracking of Forest Disturbance Dynamics. In The International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences—ISPRS Archives; Zdimal, V., Ramasamy, S.M., Skidmore, A., Altan, O., Comiso, J., Thenkabail, P.S., Halounova, L., Safar, V., Planka, L., Raju, P.L.N., et al., Eds.; International Society for Photogrammetry and Remote Sensing: Christian Heipke, Germany, 2016; Volume 41, pp. 711–718.

82. Minařík, R.; Langhammer, J.; Lendzioch, T. Detection of Bark Beetle Disturbance at Tree Level Using UAS Multispectral Imagery and Deep Learning. Remote Sens. 2021, 13, 4768.

83. Megat Mohamed Nazir, M.N.; Terhem, R.; Norhisham, A.R.; Mohd Razali, S.; Meder, R. Early Monitoring of Health Status of Plantation-Grown Eucalyptus Pellita at Large Spatial Scale via Visible Spectrum Imaging of Canopy Foliage Using Unmanned Aerial Vehicles. Forests 2021, 12, 1393.

84. Lin, Q.; Huang, H.; Chen, L.; Wang, J.; Huang, K.; Liu, Y. Using the 3D Model RAPID to Invert the Shoot Dieback Ratio of Vertically Heterogeneous Yunnan Pine Forests to Detect Beetle Damage. Remote Sens. Environ. 2021, 260, 112475.

85. Sandino, J.; Pegg, G.; Gonzalez, F.; Smith, G. Aerial Mapping of Forests Affected by Pathogens Using UAVs, Hyperspectral Sensors, and Artificial Intelligence. Sensors 2018, 18, 944.

86. Dell, M.; Stone, C.; Osborn, J.; Glen, M.; McCoull, C.; Rimbawanto, A.; Tjahyono, B.; Mohammed, C. Detection of Necrotic Foliage in a Young Eucalyptus Pellita Plantation Using Unmanned Aerial Vehicle RGB Photography—A Demonstration of Concept. Aust. For. 2019, 82, 79–88.

87. Qin, J.; Wang, B.; Wu, Y.; Lu, Q.; Zhu, H. Identifying Pine Wood Nematode Disease Using Uav Images and Deep Learning Algorithms. Remote Sens. 2021, 13, 162.

88. Yu, R.; Luo, Y.; Li, H.; Yang, L.; Huang, H.; Yu, L.; Ren, L. Three-Dimensional Convolutional Neural Network Model for Early Detection of Pine Wilt Disease Using Uav-Based Hyperspectral Images. Remote Sens. 2021, 13, 4065.

89. Yu, R.; Luo, Y.; Zhou, Q.; Zhang, X.; Wu, D.; Ren, L. Early Detection of Pine Wilt Disease Using Deep Learning Algorithms and UAV-Based Multispectral Imagery. For. Ecol. Manag. 2021, 497, 119493.

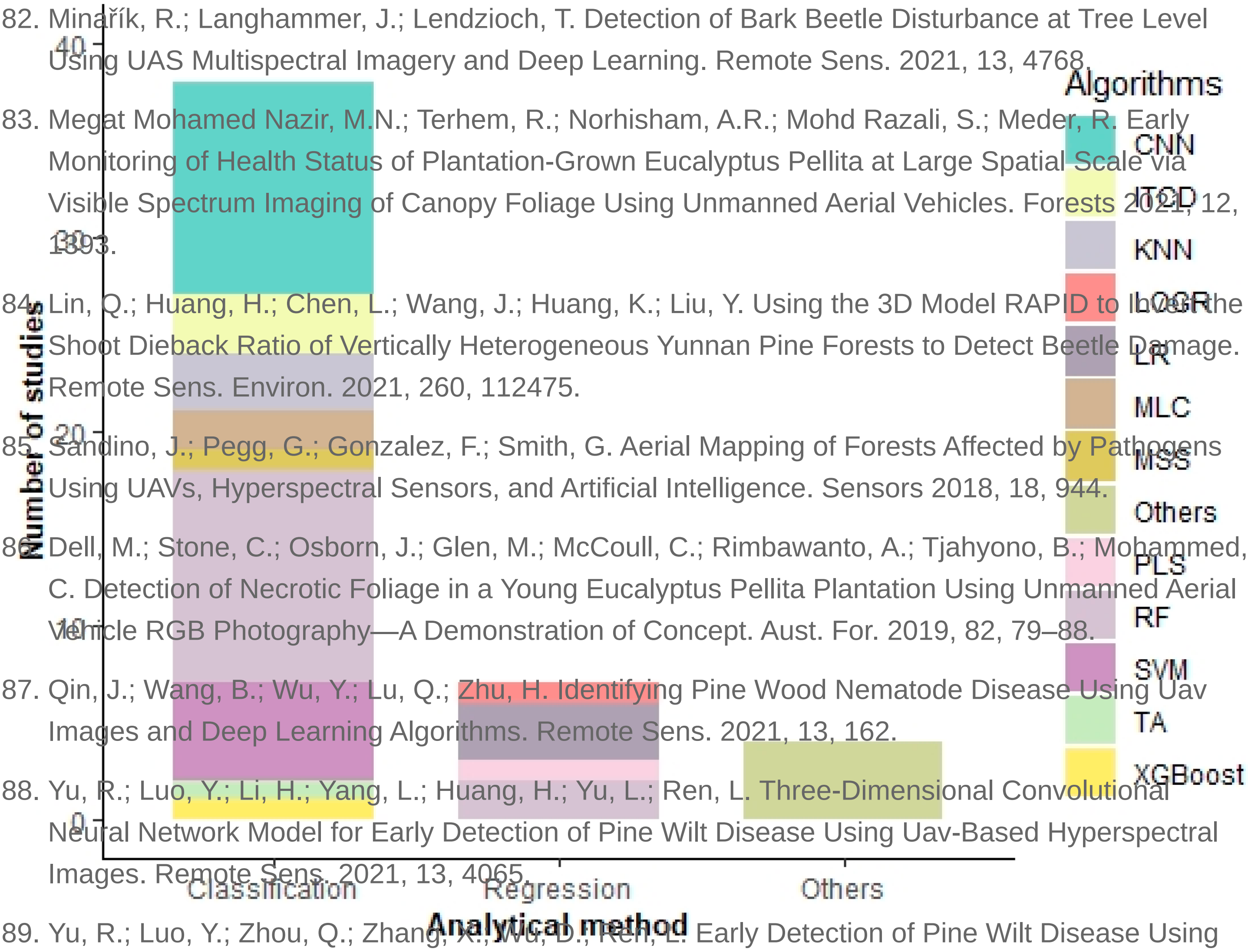

Figure 3. Summary of the algorithms used in the studies: CNN: convolutional neural network; ITCD: individual tree crown delineation; KNN: K-nearest neighbor; LOGR: logistic regression; LR: linear regression; MLC: maximum likelihood; MSS: multiscale segmentation; PLS: partial least squares; RF: random forest; SVM: support vector machine; TA: thresholding analysis; XGBoost: eXtreme gradient boosting.

The classification approach is broadly used for quantifying trees. Regarding the analysis methods, most of the studies used a classification approach. Regression studies focus on a different level of damage and provide statistical significance for regression coefficients and the relation between classes. Statistical methods, physically based models such as radiosity applicable to porous individual objects to calculate different vegetation variables, and specific frameworks were also used to estimate the level of damage.