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Systematic Review

The Role of Remote Sensing for the Assessment and Monitoring of Forest Health: A Systematic Evidence Synthesis

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Abstract: Forests are increasingly subject to a number of disturbances that can adversely influence their health. Remote sensing offers an efficient alternative for assessing and monitoring forest health. A myriad of methods based upon remotely sensed data have been developed, tailored to the different definitions of forest health considered, and covering a broad range of spatial and temporal scales. The purpose of this review paper is to identify and analyse studies that addressed forest health issues applying remote sensing techniques, in addition to studying the methodological wealth present in these papers. For this matter, we applied the PRISMA protocol to seek and select studies of our interest and subsequently analyse the information contained within them. A final set of 107 journal papers published between 2015 and 2020 was selected for evaluation according to our filter criteria and 20 selected variables. Subsequently, we pair-wise exhaustively read the journal articles and extracted and analysed the information on the variables. We found that (1) the number of papers addressing this issue have consistently increased, (2) that most of the studies placed their study area in North America and Europe and (3) that satellite-borne multispectral sensors are the most commonly used technology, especially from Landsat mission. Finally, most of the studies focused on evaluating the impact of a specific stress or disturbance factor, whereas only a small number of studies approached forest health from an early warning perspective.

Keywords: forest health; remote sensing; PRISMA; review

1. Introduction

Forests are complex ecosystems distributed around the globe, covering approximately 31% of Earth's land surface [1]. Such complexity is due to the wide range of climates that forests occupy as well as their typical structural heterogeneity. Forests encompass not just physical and biological components but also the processes and interactions between them. They provide many ecosystem services, such as habitat, raw materials, chemicals, water and scenic beauty, among others [2]. This makes them an invaluable asset for their importance to maintaining biodiversity and mitigating climate change, as well as for their importance to cultural heritage and socio-economic development. Despite these facts, forests are globally affected by different factors, either natural or anthropogenic, that can lead to different grades of forest decline, widely observed around the globe [3–6]. Within the group of natural factors that lead to forest decline, we find a wide variety of elements such as plagues, droughts or nutrient unavailability [7–9]. These factors have always been present, so species and communities have evolved or developed different mechanisms to mitigate them or to recover after these events. There is also a broad range of human-caused stress factors, particularly those derived from global climate change [10]. The importance of human-caused stress factors is due to the speed of the produced changes compared with natural dynamics, their spatial extent and, most of all, the increase in

the magnitude of natural events caused by anthropogenic influence upon climate change. Climate change predictions foresee a global rise in temperatures, changes in precipitation patterns, an increase in extreme weather events and a series of unpredictable changes in climate trends that will put at risk the global health of forests. These climate changes also have the potential of interacting with natural pest dynamics, modifying them in a way that is difficult to predict.

There is not just one definition of forest health because the complexity of the matter, but many authors have addressed this issue from different approaches [10–12]. Amongst them, utilitarian–ecological points of view [13] and the ability of forests to adapt to changes in the environment [14] stand out. This methodological wealth has led to a wide range of monitoring programmes at different levels, from local to international networks. One of the most extensive long-term programmes is the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests), in operation since 1985. Nowadays more than 40 countries are involved. This programme has two main objectives: (1) to provide a periodic general perspective on the variation of forests conditions and (2) to gain knowledge of the cause–effect between forest conditions and stress factors, both natural and anthropogenic, through ongoing monitoring [15]. To achieve its goals, this programme has set a plot network where forest health is analysed on a field-data-gathering basis. Despite the good quality and large amount of data, field-sampling methods have some serious limitations in projects of this scope, such as the great involvement of manpower, monetary and time resources, as well as the difficulty of representing spatial variability and heterogeneity.

The broad range of capabilities of remote sensing technologies and the possibility of assessing health at an early stage [16–18] make remote sensing an excellent choice for assessing forest status both spatially and temporally at low cost [19]. This wide variety of strengths, along with the broadness of the concept of forest health, have led to a wide diversity of studies from a methodological perspective. Some authors have previously reviewed the use of remote sensing in the field of forestry [20,21] or even focused on forest health [12,22–27]. The approaches are varied, most of time focusing on specific attributes related to forest health or, as in the case of Lausch et al. [12,26,27], analysing in a comprehensive way the different aspects of remote sensing applied to forest health. Reviews of previous studies are very useful for the scientific community to support decision-making. Nevertheless, previous approaches to literature review may be subjective and biased towards specific aspects of the analysed topic, such as focusing on some particular species or functional type or reviewing just part of the methodological spectrum. For instance, Pause et al. [25] aimed their review at the integration of in situ and remote sensing data to assess forest health. Likewise, despite the comprehensive review by Lausch et al. [12], lesser attention was paid to the multitemporal component of forest health. The significant increase in papers related to forest health applications of remote sensing since the last published review in 2018 [27], together with the advances in platforms and sensors launched since then, makes it necessary to update the current state of the art. Systematic reviews, which were originally developed in the field of medicine and human health, provide methods and guidelines for a systematic search of literature, with the aim of including all relevant studies on a particular topic and summarizing their information [28]. These methods lead to a decrease in selection bias; as such, Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), an update of the QUORUM Statement, consists of a methodology for developing systematic reviews in the field of human health, composed of a 27-item list divided in four different phases [29]. The objectives of this review are (1) to identify papers published from 2015 to 2020 that studied forest health with remote sensing techniques, (2) to analyse the different methodological approaches to this topic and (3) to quantify the role of different remote sensing technologies addressing forest health issues. To date, no PRISMA methodology has been applied to reviewing the current literature of remote sensing of forest health. Using PRISMA methodology in this

paper affords us a good opportunity to evaluate the state of the art in the last six years (from 2015 to 2020) of the use of remote sensing technologies in the field of forest health.

2. Materials and Methods

This review was conducted following the PRISMA protocol. To perform the review according to PRISMA, we included original journal articles that explored forest health based on remote sensing techniques. These papers had to meet the following eligibility criteria: (1) study forest health from tree to stand scale; (2) only studies of strictly terrestrial forest were selected; (3) among studies of tree–grass biomes, such as savannah, only those studies focusing on tree canopy were included; (4) all studies must focus on actual forest health issues, so those using only simulations were also discarded.

Web of Science was selected as the information source. It was accessed on 15 March 2021 and 30 July 2021 to obtain all the studies included in this review. We used the following keyword chain to carry out the query: "((remote sensing) OR (proximal sensing)) AND (forest OR vegetation OR tree OR woodland) AND (health OR decline OR dieback OR stress OR mortality)". We also applied language and date filters to obtain only articles published in English between 1 January 2015 and 31 December 2020. English language was chosen as it is considered the language of science. Despite some authors recommend not to exclude papers due to language constraints, this criterion could help to include only papers truly accessible to the whole scientific community.

After gathering the journal articles, duplicates were removed, and then titles and abstracts were screened to exclude previous reviews and those articles that did not meet the eligibility criteria defined above. To assure that all papers met the eligibility criteria this phase, each paper was assessed independently by two screeners. They verified point by point the agreement of each record with the criteria and excluded works not in compliance with all of them. As the criteria was clear and concise, just a few disagreements emerged. In those particular cases, both screeners checked together the matching points between the paper and the criteria until agreement.

In this step, we discarded a few articles studying forest health at leaf scale or referring to species community engagement due to disagreement with eligibility criterion (1), several papers studying mangroves (eligibility criterion (2)) and some papers simulating forest health issues (eligibility criterion (3)). The next step was a full reading of the remaining studies to assess them for eligibility and filtering. After that, the remaining papers were finally included in our study.

Once we obtained all the papers to include in the review, we elaborated a list of variables to extract from each study (Table 1). Variables were selected to represent information structured by the location and ecological aspects of the studies (spatial scale, functional type, biome and geographic region), remote sensing technology used (technology, sensor type, platform and/or satellite programme) and applied methodologies (health parameter, early warning, analysis type, analysis unit, classification/regression, statistical method, machine learning and machine learning method, physically based modelling, validation and time series analysis). The spatial scale was defined according to the extent of the study area of each paper. Local scale was set as a small study area with specific characteristics of the location; regional scale comprised broader areas comprising one or several common biomes; continental scale was chosen when the study areas closely matched with some of the geographical regions. These variables tried to represent in a broad manner the possibility of techniques and methods developed to study forest health. Every article was read extensively and information was extracted to a table according to the target variables. Each paper was independently reviewed by two of the authors to avoid inconsistencies between the extracted data. The tables were compared, and disagreements were discussed and resolved by the reviewers involved. Subsequently, the extracted data were analysed using RStudio software with customized scripts in order to obtain the results and to represent them. Data analysis focused on describing the frequency of the different elements

within each variable. No attempt was done to evaluate the quality of the different papers evaluated, i.e., no critical appraisal was done.

Although critical appraisal is strongly recommended for systematic reviews [30], it is not necessary for systematic maps, which is what our systematic evidence synthesis is.

Table 1. Summary of the variables extracted from the analysed papers.

Variable	Extracted Data
Year	Year of publication
Spatial scale	Local, Regional or Continental
Functional type	Conifer, Broadleaf or Mixed
Biome	Biomes according to Olson [31]
Geographic region	Name of the geographic region
Technology	Remote sensing technology used
Sensor type	Passive, Active or Both
Platform	Satellite, Airborne, Terrestrial or UAV
Satellite programme	Name of the programme
Health parameter	Parameter used to study health
Early warning	Yes or No
Analysis type	Quantitative or Qualitative
Analysis unit	Object, Pixel or Subpixel
Classification/Regression	Classification or Regression
Statistical method	Parametric, Nonparametric or Both
Machine learning	Yes or No
Machine learning method	Method used
Physically based modelling	Yes or No
Validation	Yes or No
Time series analysis	Yes or No

3. Results

3.1. Selected Papers

From the 3722 papers returned by the query in Web of Science, the subsequent analysis of the title and abstract resulted in the exclusion of 3566 papers, 54 of them due to being previous reviews. Finally, another 47 papers were discarded due to a lack of compliance with the eligibility criteria. Therefore, 107 articles were finally analysed in our study. Figure 1 shows a flowchart of the query process followed.
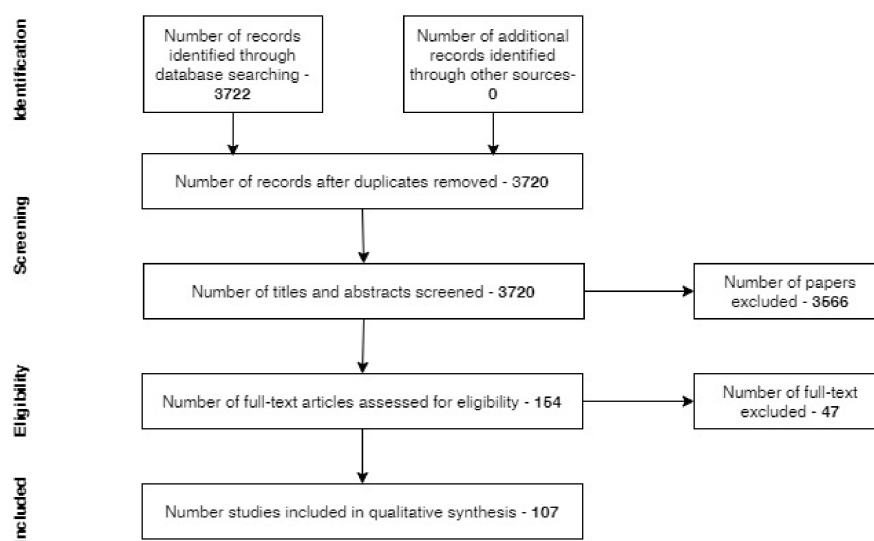

Figure 1. PRISMA flow diagram.

After selecting the articles to analyse, all of them were extensively read. The information from the selected variables was extracted and included in Appendix A, Table A1.

The analysis of the number of papers published by year tended to increase in the 6-year period of study, with a minimum of 11 papers in 2016 and a maximum of 24 in 2019. For 2020, the number of papers was 22, suggesting a sustained rate of papers in the last year (Figure 2).
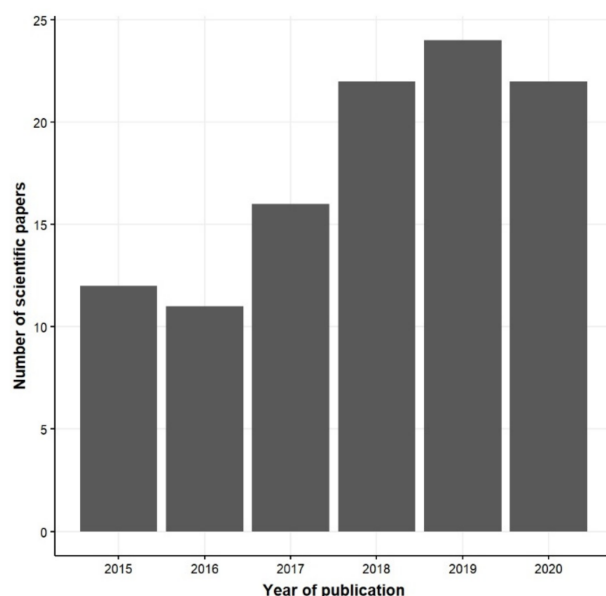

Figure 2. Number of published papers during the period included in the review.

3.2. Location and Ecological Aspects

The studies included in this review, assessed forest health at different spatial scales. The vast majority of the studies (77.6%) were carried out at a local scale, followed by the regional scale (19.6%), whereas 2.8% of the studies considered the continental scale. Regarding the location of the studies, an even distribution is observed between North America (29.9%) and Europe (29%), followed by Asia (22.4%). The remaining studies were carried out in Oceania (10.3%), South America (9.3%) and Africa (1.9%). Moreover, there were two studies encompassing more than one geographic region: North America and South America [32] and Europe, Asia and Africa [33] (Table 2).

The third variable analysed considered the biome evaluated. Temperate broadleaf and mixed forests stood out as the most studied biome, with 35.5% of the studies carried out in this biome, followed by Mediterranean (19.6%), tropical and subtropical moist broadleaf (13.1%) and temperate needle forests (12.1%). The remaining types of biomes were studied to a much lesser extent, none of them reaching more than 10% of the studies. Regarding the functional type studied, broadleaf forests were the most analysed (41.1%), followed by conifer forests (40.2%), with the health of mixed forest being the least evaluated (18.7%) (Table 2). While in North America and Europe conifer was the most studied functional type (75% and 77%, respectively), in Asia, South America and Oceania, broadleaf was the most studied (58.3%, 70% and 72.7%, respectively). Europe, Asia and Oceania also stood out as the geographical regions where local scale studies were developed to a higher degree (90% of the studies in Europe, 87.5% in Asia and 90.9% in Oceania).

Table 2. Results of parameters related to the location and ecological aspects of the papers, including scale, continent, functional type and biome.

Scale	Total	%	Geographic Region	Total	%	Functional Type	Total	%
Local	83	77.6	North America	32	29.9	Broadleaf	44	41.1
Regional	21	19.6	Europe	31	29	Conifer	43	40.2
Continental	3	2.8	Asia	24	22.4	Both	20	18.7
			Oceania	11	10.8			
			South America	10	9.35			
			Africa	2	1.9			

Biome							Total	%
Temperate broadleaf and mixed forests							38	35.5
Mediterranean forests, woodlands and scrub or sclerophyll forests							21	19.6
Tropical and subtropical moist broadleaf forests							14	13.1
Temperate coniferous forests							13	12.1
Several							9	8.4
Temperate grasslands, savannas and shrublands							4	3.7
Tropical and subtropical dry broadleaf forests							3	2.8
Deserts and xeric shrublands							3	2.8
Boreal forests/taiga							2	1.7

3.3. Remote Sensing

Our analysis included the following variables concerning remote sensing science and technology: platform, technology and programme. Results show that 72.9% studies used satellite data, 22.4% used airborne manned platforms, 10.3% used unmanned aerial vehicles (UAV) and 4.7% used terrestrial platforms (Table 3). Furthermore, the vast majority of the studies (91.6%) were based on a single platform, 7.5% included two platforms and only 0.9% used three different platforms.

Table 3. Platforms where the sensors were placed.

Platform	Total	%
Satellite	70	65.4
Airborne	18	16.8
UAV	7	6.5
Airborne and Satellite	4	3.7
Terrestrial	3	2.8
Satellite and UAV	2	1.9
UAV and Airborne	1	0.9
Satellite and Terrestrial	1	0.9
Airborne and UAV and Satellite	1	0.9

With regard to the technology used, passive sensors were indisputably the most widely used technology, with 85% of the studies using them, whereas active sensors were used alone just 4.7% of the time. The remaining 10.3% combined both types of sensors (Figure 3a). More specifically, multispectral data were used in 88 studies, either alone or in combination with other sensors, while LiDAR was used in 15 studies, hyperspectral in 16, thermal in 3 and radar and microwaves in 1 study each (Figure 3a,b).

As previously stated, most sensors used were on board satellite platforms. The most frequently used imagery corresponded to the US programmes Landsat (51.3%) and Terra/Aqua (26.9%), followed by the European Copernicus programme (16.7%) (Figure 3c). Following these programmes appeared commercial satellites (Worldview, Digital Globe) with very high spatial resolution capabilities. Finally, 17.9% of the papers used data from different programmes (Figure 3d).

No apparent differences on the usage of different remote sensing technologies among different functional types were found. On the contrary, multispectral technology was the

most employed among all biomes (82.2% of the studies), but in the cases of temperate coniferous forests and desert and xeric shrublands, it was used in 100% of their studies (13 and 3 papers, respectively).

(a)

(b)

(c)

(d)
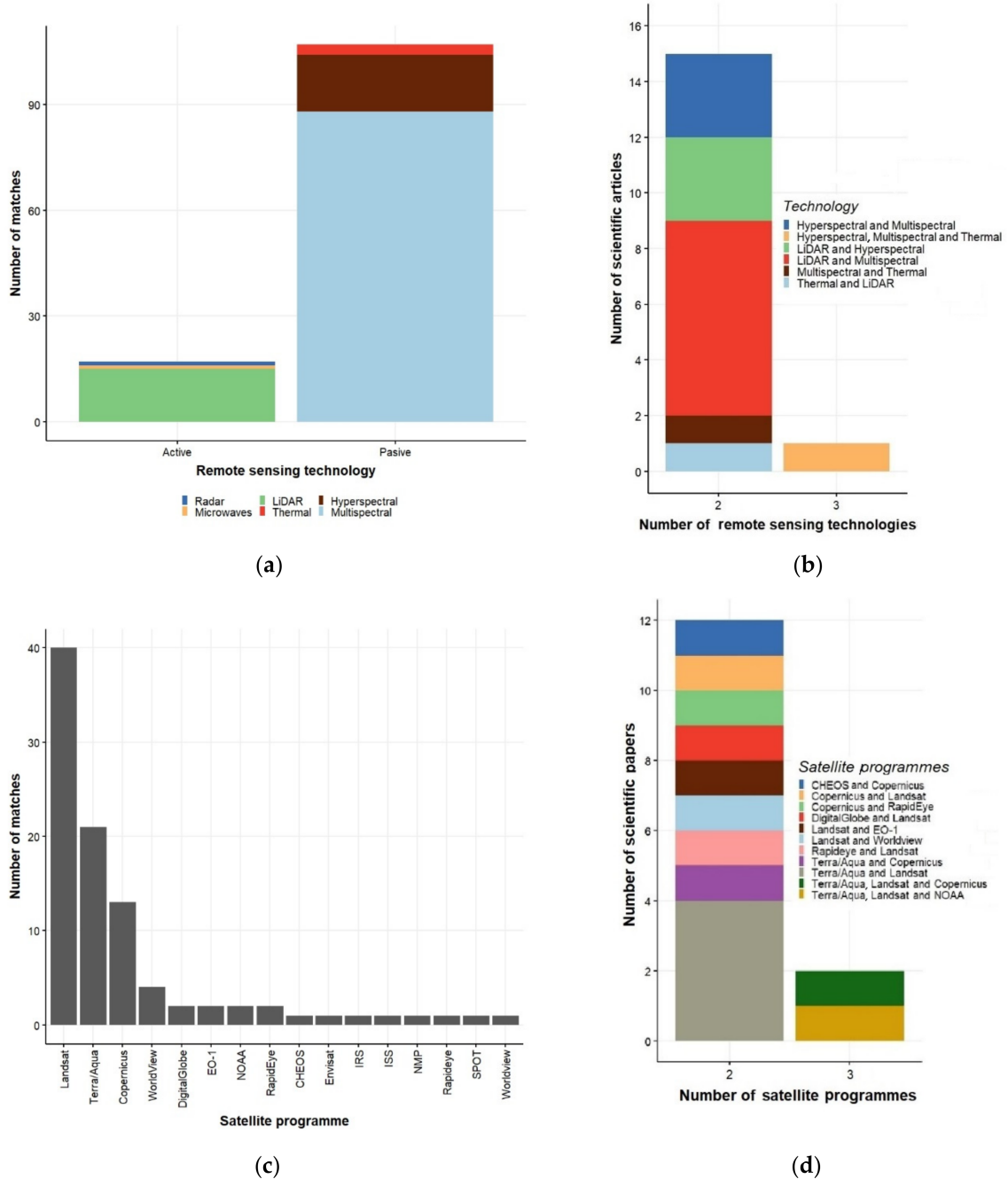
Figure 3. Summary of result related to remote sensing technologies, including: (**a**) type of remote sensing technologies, (**b**) number of different remote sensing technologies included in every study, (**c**) satellite programme and (**d**) number of different satellite programmes included in every study.

3.4. Applied Methodologies

Due to "forest health" being an open concept, we flagged different health parameters analysed in the different studies. Moreover, most of the studies analysed a single health parameter (66.6%), but some analysed forest health based on several parameters, such as the case of Tane [34], who tried to detect conifer mortality under drought and beetle infestation (Figure 4). The use of the different health parameters among the different

biomes appears to be generally well distributed, with the exception of the use of stress and plague in tropical and subtropical moist broadleaf forests, temperate coniferous forests and tropical and subtropical dry broadleaf forests. In these biomes, stress and plague parameters were used in the 71.4%, 84.6% and 100% of the cases, respectively.

Figure 4. Health parameters addressed in each paper and combinations.

Developing early warning systems has been pointed out as paramount to improve forest management and to reduce and mitigate the impact of climate change [35,36]; only 14% of the studies devel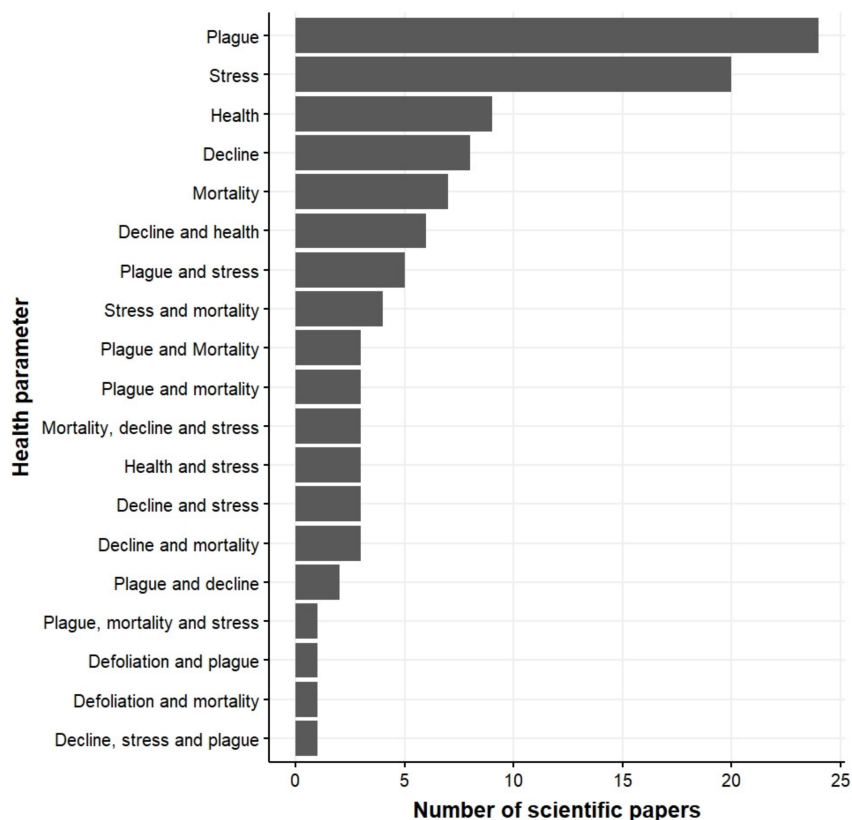oped early warning approaches to forest health, whereas the remaining 86% of the studies focused on assessing the impact of different elements on forest health (Table 4). In 13 out of 15 papers that included early warning approaches, the studied health parameter was stress or plague. In addition, no apparent relationship between early warning approaches and studies developed in different biomes was found, except in the case of temperate broadleaf and mixed forest. In this case, this approach was present in 8 out of 15 studies. Furthermore, articles included in this review usually studied forest health at a specific moment, but 42 (39.2%) of the papers employed multitemporal or time series analysis.

This assessment was mainly carried out qualitatively, with 45.8% of the studies providing continuous data, whereas 37.4% were based on quantitative analyses providing the degree of damage. The remaining 16.8% provided both, quantitative and qualitative assessment (Table 4). Regarding the unit of analysis, most of the studies (72%) used a pixel approach, although in the case of high-resolution imagery, the Geographic Object-Based Image Analysis (GEOBIA) approach was preferred (15.9%). Both approaches were used in nine (8.4%) of the papers analysed, and the remaining papers included a subpixel approach (Table 4). It should be noted that all of the studies but one that applied two or more of these approaches in the same research included OBIA in their methodology, and all of them developed the study at local scale.

Table 4. Results of parameters related to the methodological approach of the papers, including early warning, analysis type, analysis unit, classification/regression and machine learning method.

Early Warning	Total	%	Analysis Type	Total	%
No	92	86	Qualitative	49	45.8
Yes	15	14	Quantitative	40	37.4
			Both	18	16.8
Analysis Unit			**Classification/Regression**		
Pixel	77	72	Classification	40	37.4
OBIA	17	15.9	Regression	39	36.4
Subpixel	2	21.9	Both	18	16.9
Pixel and OBIA	9	8.4			
Pixel and Subpixel	1	0.9			
Subpixel-OBIA	1	0.9			
Machine Learning Method				**Total**	**%**
Random Forest				20	18.7
SVM				3	2.8
Boosted Regression Trees				2	1.9
kNN				2	1.9
CART and Random Forest and SVM				1	0.9
Cubist and Random Forest and SVM and Extreme Gradient Boosting Trees				1	0.9
Feature Analyst				1	0.9
kNN and SVM and Random Forest				1	0.9
Maximum Entropy Algorithm				1	0.9
SVM and SAM				1	0.9
SVM and Gradient Boosting Machine				1	0.9
SVM and kNN and Boosted Regression Trees				1	0.9
TreeNet				1	0.9
Random Forest and kNN				1	0.9
Neural Networks				1	0.9
NA				68	63.5

Concerning the statistical analysis techniques, classification was used more often (37.4%) than regression(36.4%) since most of the papers aimed at providing a qualitative analysis of forest health status, focusing on different health parameters such as stress or plagues among others rather than a quantitative representation of the damage. A total of 16.8% of the papers provided both a quantitative and qualitative analysis. Remarkably, 9.3% of the studies did not used either regression or classification approaches, but used correlation analysis [37–39], inversion of radiative transfer models [40] or time series analysis [41] (Table 4). Interestingly, despite the recent popularity of machine learning algorithms, a bit more than a third of the studies (36.4%) used this modelling framework, and almost two-thirds used other statistical approaches. Within the machine learning approach, Random Forest was the most preferred algorithm (Table 4). Furthermore, most of the articles made use of empirically based modelling, but only two of them (1.9%) used physically based models.

Finally, with regard to the validation of the studies, 67.3% of them performed some kind of validation to assess the quality and the potential of the study.

4. Discussion

Forest health has been studied for decades from different perspectives. The literature on this topic is very large and varied. In the last 6 years, an increase in the number of papers related to forest health and remote sensing has been observed, especially since 2018. It should be noted that as of this year, Copernicus data have been used in some of the papers and UAVs have begun to be used to gather data. In addition, the rise in the number of papers fitting this scope might reflect the interest in studying the increase of observed forest decay and mortality worldwide [42,43], in addition to an increase of interest

in public opinion on topics related to the effects of global climate change. Most papers included in this review focused on studying forest health at the local scale. Gathering field data, especially in broad areas, is time and budget consuming, so developing remote sensing-based methodologies allowing researchers to scale up local estimates of forest health to broader areas is an interesting topic that requires further attention.

Despite the fact that forest decay has been reported across the globe, most of the studies were carried out in North America and Europe. We found that diverse biomes were represented through the different articles in our study from temperate to Mediterranean or tropical. Tropical forests, in spite of occupying a high percentage of forested lands on the planet and harbouring a great biodiversity, were not as highly represented in the papers included in this review. The high cloud coverage present in most of the year in this biome constrains the possibility of developing studies applying optical methods. Nevertheless, radar technology can perform better in this kind of condition, but it was applied only once [41] in tropical biomes in the papers included in the review. Furthermore, remote sensing has been traditionally aimed at studying carbon content and fixation [44] due to its important role in the global carbon cycle. Nevertheless, in addition to deforestation and forest degradation, these forests also face health issues affecting their functioning.

It should be noticed that a high number of studies focused on Mediterranean forests, even though their presence on the planet is limited, based on their total area. The importance of these forests lies in their function as biodiversity hotspots, along with tropical forests [45]. Mediterranean forests, especially those placed in the Mediterranean Basin, host a great variety of vegetation species and many of them are endemic [46]. In addition to being historically affected by human activity, this type of forest is prone to be affected in the future by extreme droughts, and some of the diseases present in forests that are now considered minor may become more severe. Furthermore, invasion of exotic species and punctual disturbances such as fires or storms are expected to increase [47].

Southern Hemisphere woodlands (some of them in Mediterranean areas) share some of the risks mentioned above, such as changes in precipitation and fire regimes [48]. Studies focusing in this area during the length of our review tended to use multispectral sensors carried on aircrafts as the main technology. Future studies could benefit from methodologies developed in other Mediterranean areas that make use of the different sensors placed in satellites, in addition to exploiting the time series generated by programmes such as Landsat or Copernicus.

We should underline the low number of studies in taiga, even though it represents a high percentage of forested land on the planet. It also contrasts with the tradition of Nordic countries in forest management and the important role that this biome plays as a carbon pool [49].

Regarding the functional types studied in the different papers, our results indicate that broadleaved forests were studied at an extent that was similar to conifer forests, both ahead of studies that comprised mixed or both functional types together. This fact concurs with data extracted from FAO [50] that claims that the production of coniferous industrial roundwood in 2018 was 30% of the global production, while non-coniferous reached 22% of the total. This can be explained by the interest in conducting research based on the economic return of the forest (for timber production), the chances of obtaining some kind of ecosystem service [51] or the changes in forest value due to climate change [52]. Furthermore, the interest in studying conifer forests might be related to the special sensitivity to climate change of these forests, especially to droughts, and the changes in growth rates and increased mortality rates [53].

Satellite platforms stand out as the most used in the articles analysed due to their global systematic observation of the Earth's surface, the catalogue of historic data and the high temporal and spatial resolution of some of them. Moreover, the free access to Landsat, MODIS and Sentinel data, and their suitable spectral characteristics to evaluate different forest health parameters, makes them the most commonly used. Despite the recent release of Sentinel-2 imagery with better temporal and spatial resolutions and with the inclusion of

a red-edge band, Landsat is still the satellite mission most employed in this kind of study. Some of the potential studies of this kind usually take a long time to gather the necessary data, sometimes years. Thus, it is possible that this trend will change in the near future.

Sensors on board manned or unmanned aircrafts and terrestrial platforms offer higher spatial resolution information, which can provide more spatial detailed information. Moreover, structural information derived from photogrammetric point clouds using structure from motion (SfM) techniques can complement the spectral information of these sensors. Nevertheless, airborne UAV and terrestrial platforms are more limited in terms of spatial and temporal coverage. Despite UAV being far less scalable and with higher unitary cost than using satellite data, hence limiting the possibility of gathering data over time, the use of UAVs to collect remote sensing data has been increasing over the years. In fact, the first article found in our review that included this kind of platform dated from 2017 [54], and in 2018 we found three articles using UAV data [55–57], four in 2019 [58–61] and three in 2020 [62–64]. UAVs are very versatile platforms that can host many different sensors, can obtain very high spatial resolutions, fly over difficult-to-reach areas and are a relatively cheap tool but are limited by weather conditions, flight regulations, payload and autonomy range, which limits the area of study [65,66]. Terrestrial platforms, however, have some accessibility limitations and low potential to cover large areas.

Different remote sensing techniques can help to assess forest health in different ways. Methods based in shortwave spectral information of vegetation canopies provide us with information on the biophysical condition of the vegetation [67] as well as on its moisture content [68,69] and structural information [70], but their penetration capability through the canopy is very limited, and it is also greatly influenced by weather conditions, mainly cloudiness.

According to the results of this review, multispectral sensors are the main choice for forest health assessment. They normally take information in three zones of the electromagnetic spectrum where vegetation has different behaviours. The visible region (0.4–0.7 μm), where pigment concentration has a relevant importance due to a high absorption of solar irradiance, yields low reflectance values. In the near-infrared region (NIR 0.7–1.2 μm), higher reflectance values in vegetation are caused by cellular structure, which produces a larger leaf transmittance and reflectance, increased by the multiple scattering between the canopy leaves. In the boundary between the visible and NIR zones, the red-edge is located. Bands in this zone have a high potential to estimate chlorophyll and nitrogen content [71], as it is a transition zone between the high leaf chlorophyll absorption in the red and very little absorption in the NIR. Lastly, mid-infrared is divided into short-wave infrared or SWIR (1.2–2.5 μm) and mid-infrared (2.5–8 μm), with the former one having potential uses in measuring moisture content [72]. Among the sensors and platforms capable of obtaining information at these wavelengths are Landsat, MODIS, MSI from Sentinel-2, Worldview and RapidEye, as well as hyperspectral sensors such as AVIRIS. Multispectral sensors covering some specific wavelengths placed in the red-edge, NIR and SWIR regions have proved their potential to assess forest health indicators such as water content [73], leaf discoloration [74], leaf area index [75] and pigment content [76]. Furthermore, most effects due to the presence of plagues are shown by any of the above indicators, making multispectral sensors suitable to also assess and detect forest pest damage. As an example, Abdullah [77] found significant differences in NIR and SWIR regions between healthy and infested trees with bark beetles, as expected from the changes produced by this plague in the physiological and biochemical status of the trees. In addition, it is important to consider that both plagues and abiotic stresses such as droughts can show similar symptoms.

Hyperspectral technology uses the same kind of information as multispectral, but it is gathered from a greater number of bands with narrower bandwidth that provide us with very specific information. Ahmad [78] used hyperspectral bands to calculate different indices related to the biochemical content of the vegetation, such as carotenoid reflectance index 1 (CRI1) or photochemical reflectance index (PRI), as well as information related to canopy water content, such as the water band index (WBI). It should be noted that

computing vegetation indices with hyperspectral data might be considered a sub-optimal usage of this type of information, as the relevant information is extracted from only a few bands. However, no study in this review was found that optimally used the hyperspectral data cube by applying dedicated techniques such as inversion of radiative transfer models, feature extraction or spectral mixture analysis. Despite hyperspectral imaging being able to offer good capabilities to detect impacts of stressors on vegetation, the low number of operational satellite missions during the period analysed limited their application. Recently launched and future satellite missions such as CHIME, PRISMA, EnMAP or HyspIRI may help address this lack.

Active sensors emit microwave beams in the case of radar, or laser beams in the case of LiDAR, and measure the time and/or intensity of the beams to travel back to the sensor after the surface of study reflected them. These kinds of sensors are very useful for studying vegetation structure due to their capacity to penetrate through the canopies. In addition, synthetic aperture radar (SAR) has the possibility of operating under cloudy weather conditions, unlike optical sensors or LiDAR. Despite this fact, the information that it provides is limited to moisture and structural information [79,80], yet the potential of SAR sensors remains largely unexplored [81].

LiDAR is also a good choice when the objective is to study vegetation structure, allowing accurate assessment of defoliation associated with forest decline and insect attacks [61,82,83]. Among the studies included in the review, Balzotti [84] used LiDAR data to study temporal variation of forest structure parameters, such as canopy height and gap distribution, and Huo [85] used it to explore different grades of defoliation. Radar data are commonly used to study parameters or events related to moisture content as in Van Emmerik [86], where passive radar was applied to detect water stress in the Amazon.

Including data obtained from different kinds of sensors in the methodology has been tested not just in forest health studies but also in other fields [81,87–90]. Studies that combine sensors try to take advantage of the strengths and to avoid weak points of the different technologies. Approaches are varied; we found in this review that studies that fulfil this characteristic tend to integrate the data in different phases of the methodology, exploiting the potential of each technology. For example, Abdullah [77] used two different types of sensors—multispectral (OLI) and thermal (TIRS), both carried by Landsat 8 satellite—to generate vegetation indices and canopy surface temperature and to subsequently integrate them in the analysis of bark beetle infestation through the use of leaf traits, such as stomatal conductance, chlorophyll fluorescence and water content. Similarly, Campbell [62] integrated information from three different platforms, including UAV, airborne and satellite, and three different kinds of sensors, RGB, LiDAR and multispectral. Thus, they combined the spectral and the structural information that passive and active sensors are able to provide, such as tree crown delineation (LiDAR), individual tree mortality interpretation (RGB) and tree mortality at regional scale (multispectral). In spite of their more complex procedures and sometimes the need for higher processing capacity, combining different remote sensing technologies could lead to a better understanding of forest health.

Just as in the case of multisensor approaches, studies that incorporate data from different platforms try to bring specific strengths together. Navarro-Cerrillo [91], for example, used airborne data (LiDAR) to segment images at the individual tree level, while using satellite imagery to generate vegetation indices to classify tree-damage levels. In the case of Campbell [62], UAV, airborne and satellite data were integrated to develop a multiscale approach to mapping tree mortality.

The variety of technologies and methodologies applied to the study of forest health aligns with the variety of forest health definitions. It is an open concept that—depending on the scale, among other factors—can be studied from different perspectives. Concerning forest health, according to Trumbore [10], at the scale of an individual, health can be defined as the absence of disease. If our interest shifts to larger areas, this concept gets more diffuse, and indicators of forest health turn out to be more difficult to define. In this review, we included different keywords or concepts that could be grouped in two different

classes—namely, causes and consequences of a decrease in forest health. Most of the articles focused on one of them, but as a result of including the two classes of concepts and the co-occurrence of these kind factors, it was easy to find papers that targeted more than one of these concepts. Different causes of disease and observed symptoms used to appear together, many times one as a direct consequence of the other, such as in Pérez-Romero [92], where the presence of a plague, in this case *Thaumetopoea pityocampa*, caused different levels of defoliation. Similarly, in Marusig [39], the stress produced by droughts led to forest decline. Regarding forest health terms, most of the studies focused on plagues, followed by decay. The results from studies dealing with changes in the relationship between forests and pests or pathogens due to climate change were varied. Nevertheless, expected rising temperatures, extreme and more frequent droughts and climate extremes will increase forest vulnerability [93]. Moreover, native plague and pathogen species that in the past were not a significant problem in forests could become one in the future [94].

Most of the studies attempted to quantify the damage caused by different biotic or abiotic factors on forest health, yet development of early warning systems based on remote sensing could allow making decisions about corrective measures to avoid or reduce the impact of such factors on forest health. The meaning of early warning varies among different fields, but some studies try to answer key questions about this concept, such as "How early is early?" or "Why is this a threat?" among others [95]. An early knowledge of forest health decline could help us to prevent not just ecologic but also economic losses. According to Trumbore [10], it is very important to define thresholds for rapid forest decline since it could take decades to restore the capacity of forests to provide services. In other areas such as security, research has shown that the economic benefits of developing and implementing early warning systems sometimes exceed the costs by more than 10 times [96]. We found that methodologies applied to assess forest health in a direct early warning approach were varied, but almost every study focused on plagues or stress. Abdullah [77] tried to identify an early stage of bark beetle infestation on the differences in some leaf traits between infested and healthy leaves. Likewise, Zhan [63] studied three stages of a pest infestation, one of them the early stage, when the attack has been detected but the leaves are still green. The three stages were identified based on visual assessment of canopy colour, defoliation damage and the presence of beetle holes in the trunk. On the contrary, Rogers [97] studied early signals of mortality based on the temporal series of a vegetation index. We should underline the lack of studies addressing early symptoms or setting early warning thresholds despite the importance of the matter. Moreover, the existence of satellite programmes, such as Landsat, with a large temporal database, in addition to relatively new missions with more suitable technical specifications, such as Sentinel, along with better and powerful processing machines, makes it easier nowadays to develop and implement forest health early warning systems.

Despite having found just fifteen papers addressing this matter, many of the methodologies developed in the rest of the articles could be adapted and applied in an early warning perspective, especially those including time series analysis and spectral trajectories, such as Bode [98], Cohen [99] or Assal [100]. Methodologies based on structural changes, therefore those using active sensor as LiDAR or SAR, are less susceptible to be applied to address early symptoms due to structural changes taking longer to manifest than biochemical or water content changes. Moreover, structural changes are a manifestation of a more severe impact than changes in water or pigment content, as in the case of bark beetle infestation. Changes between its first infestation stage and its second stage are characterised by changes in spectral information, in particular leaf colour, while changes between the second and third stages are based in structural changes that concretely involve defoliation [77]. Finally, it is noteworthy to admit that the capability of remote sensing data for detecting a symptom of a disease at an early stage is limited to the type of affliction. For example, early warning of defoliating insects is limited to cases in which the attack has already succeeded (i.e., observed by a decrease in leaf biomass/pigment concentration), and hence the damage has likely been already significant. On the other hand, droughts

and/or trunk/root diseases that cause a hydric stress are detected earlier with thermal infrared data than with data in the solar spectrum, as stomata closure induces an increase of canopy temperature.

In addition to the wide variety in the remote sensing technologies that the studies chose, their statistical methods were also diverse. In terms of statistical methods that help to develop different kinds of monitoring systems, time series analysis and multitemporal analysis stand out. We found diverse approaches to this matter, but most of them were based in the study of the trend or the temporal variation of a parameter during a temporal series, such as in Anderson [68], Assal [100] or Pasquarella [86]. They are very useful tools that help to understand forest health dynamics [101] and are a good complement to early warning systems. In this review, we found that a bit more than a third of the articles made use of time series data. On the contrary, the combination of early warning and time series was found in only seven of the articles, most of them including Landsat data as part of their dataset. This fact is possibly due to Landsat collections offering free of charge satellite imagery from 1972 to the present time, and hence, the importance of long-term data collection programmes, such as some of the earth observation satellite programmes.

In terms of the minimum analysis unit, the pixel has been the most typically used, followed by object-based and sub-pixel analysis, respectively. The pixel has been broadly used as the unit of analysis because it is the minimal unit in a digital image and its use is therefore capable of being extended to studies at every scale and from a wide variety of methodological perspectives. On the contrary, OBIA has been applied in fewer studies and mostly in those where the need of identifying objects or individual trees is crucial. This methodological approach is very useful in studies with very high spatial resolution data availability. Spectral unmixed techniques have been commonly used in agricultural studies and have been applied together with hyperspectral data. In our study, we found that in the last 6 years, spectral unmixing methods have been used in the field of forest health with spectral satellite data. He [102] used spectral unmixing techniques to extract spectra from green vegetation, non-photosynthetic vegetation and bare soil and later used OBIA techniques to generate high resolution disease maps.

Depending on the perspective and the approach of the study, quantitative or qualitative methods were used according to the need to estimate or measure (quantitative) or according to the need to differentiate between different health statuses (qualitative). It must also be noted that some qualitative studies were based in a previous quantitative analysis. According to the chosen statistical approach, modelling techniques were chosen. Parametric and nonparametric techniques were found among the papers. One of the facts to be emphasized is the increase during last five years of studies that included machine learning (ML) within their statistical methods. Recent progress in processing capacity and the development of new methods and algorithms will drive new uses in the near future. These techniques have the potential to deal with highly dimensional data in addition to being able to classify into categories the complex features that have been widely used in the field of forestry. Typical applications of these particular statistical methods are the estimation of structural parameters [103–105], modelling and prediction of disturbances [106,107], species classification [108,109], tree biochemical traits retrieval [110,111] and biomass dynamics [112,113]. We found that Random Forest (RF) is the ML algorithm that was most applied. It could be used both as classifier and as a regression algorithm, and according to Cutler [114], RF has some advantages compared with other ML methods. Apart from performing with high accuracy, RF allows the researcher to determine the importance of the predictor variables, hence allowing for a more transparent interpretation of the model structure and variable sensitivity than other ML methods, such as artificial neural networks, which could act more like a black box.

Additionally, RF has the capability of modelling complex relationships between different variables and the flexibility to develop several statistical analyses. Apart from RF, other ML methods were used by Hawrylo [115], who compared the performance of some ML algorithms for estimating pine defoliation. Regarding statistical methods, the low appear-

ance of physically based methods among the studies included in this review should also be noted. Only two articles [40,116] included this technique in their methodologies. Physically based methods, such as radiative transfer models (RTM), describe the absorption, transmission and multiple scattering processes that occur when electromagnetic radiation passes through a medium, in this case a tree canopy. The inversion of RTMs offer researchers a great opportunity to retrieve different vegetation variables (e.g., canopy structure, pigment and water concentration, leaf temperature) with remote sensing data when access to in situ data for developing a statistical model is limited. Despite their potential to achieve this goal, research including this approach has to deal with problems such as the need for high processing capacity, which can be solved nowadays with the current computing capabilities of a personal computer, but also particularly with parallel cloud computing and the use of graphical processing units (GPUs).

5. Conclusions

This paper reviewed the use of remote sensing for the assessment of forest health in a systematic way. The number of different sensors and platforms is limited, but nonetheless, the flexible combinations of them make remote sensing a good perspective from which study forest health. Despite this review being conducted to cover just the last six years, it is possible to observe how the remote sensing field and specifically its forest health branch is incorporating new methods and technologies as they evolve.

The US Landsat mission was the most used source of data among the studies included in this review. In spite of new satellite missions with a priori better specifications to our goal, such as Sentinel, the long data history and the open data politics (as with Copernicus programme) still makes Landsat the most chosen. Despite the development and emergence of new technologies and methods, multispectral data are still the most used remote sensing technology in the field of forest health.

In spite of the knowledge of forest health early warning systems, as well as the knowledge of current approaches to forest health and all the available methodological strategies, the development of early warning systems is still required to mitigate the impacts of climate change. Moreover, the combination of time series analysis and multitemporal studies with early warning approaches could boost the performance of these studies.

Methodological approaches to forest health monitoring and assessment from a remote sensing perspective are varied and their use depends on the goals that are sought to achieve in each study. Among the different statistical methods found in the analysed papers ML algorithms stood out, and their use has been increasing over the years both for regression and classification purposes.

Appendix A

Table A1. Extracted data from the articles included in the review.

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[117]	2019	Regional	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	Landsat	Plague
[77]	2019	Local	Both	Temperate broadleaf and mixed forests	Europe	Multispectral and Thermal	Passive	Satellite	Landsat	Plague
[78]	2020	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	Asia	Hyperspectral	Passive	Airborne		Health and Stress
[32]	2019	Regional	Broadleaf	Several	North America and South America	Multispectral	Passive	Satellite	Landsat	Stress and Mortality
[118]	2015	Regional		Several	South America	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[68]	2018	Regional	Broadleaf	Tropical and subtropical moist broadleaf forests	South America	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[119]	2015	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	South America	Hyperspectral	Passive	Satellite	NMP	Stress
[120]	2018	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	Oceania	Multispectral	Passive	Terrestrial		Plague

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	TimeSeries Analysis
[117]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	TreeNet	No	Yes	Yes
[77]	Yes	Quantitative	Pixel	Regression	Both	No		No	Yes	No
[78]	No	Quantitative	Pixel	Classification		No		No	Yes	No
[32]	Yes	Quantitative	Subpixel	Regression	Parametric	No		No	Yes	No
[118]	No	Qualitative	Pixel	Classification		No		No	No	Yes
[68]	No	Quantitative	Pixel	Classification		No		No	No	Yes
[119]	No	Quantitative	Pixel	Classification		No		No	No	N
[120]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	No

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[100]	2016	Regional	Both	Temperate grasslands, savannas and shrublands	North America	Multispectral	Passive	Satellite	Landsat	Mortality, Decline and Stress
[121]	2020	Local	Broadleaf	Temperate broadleaf and mixed forests	North America	LiDAR	Active	Terrestrial		Plague and Decline

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[122]	2017	Local	Conifer	Temperate grasslands, savannas and shrublands	North America	Multispectral	Passive	Satellite	Terra/Aqua and Landsat and Copernicus	Plague and Mortalityt
[123]	2019	Local	Conifer	Several	Europe	Multispectral	Passive	Satellite	RapidEye	Decline and Health
[84]	2017	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	Oceania	LiDAR	Active	Airborne		Decline
[70]	2017	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	Asia	Hyperspectral and Multispectral	Passive	Satellite	EO-1	Stress and Decline
[67]	2017	Local	Broadleaf	Temperate broadleaf and mixed forests	Oceania	Hyperspectral	Passive	Airborne		Health and Stress
[124]	2015	Local	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Terra/Aqua	Stress

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[100]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	Yes
[121]	No	Qualitative	Pixel	Classification	Nonparametric	Yes	Random Forest	No	No	No
[122]	No	Quantitative	Subpixel	Both	Parametric	No		No	Yes	Yes
[123]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	No
[84]	No	Quantitative	Pixel	Classification		No		No	No	No
[70]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	No
[67]	No	Qualitative	Pixel	Classification	Parametric	No		No	No	No
[124]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	No

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[125]	2018	Regional	Both	Temperate broadleaf and mixed forests	Europe	Multispectral	Passive	Satellite	Copernicus and Landsat	Health
[126]	2018	Regional	Conifer	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	Landsat	Decline and Stress
[127]	2020	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Oceania	Multispectral	Passive	Airborne		Decline and Mortality
[128]	2016	Regional	Both	Tropical and subtropical moist broadleaf forests	South America	Multispectral	Passive	Satellite	Terra/Aqua	Stress

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[98]	2018	Local	Conifer	Temperate grasslands, savannas and shrublands	North America	Multispectral	Passive	Satellite	Landsat	Plague
[129]	2019	Local	Broadleaf	Boreal forests/taiga	North America	Multispectral	Passive	Satellite	Terra/Aqua and Landsat and NOAA	Plague and Stress
[130]	2019	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	South America	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[131]	2020	Local	Conifer	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	Landsat	Plague

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[125]	No	Both	Pixel	Regression	Parametric	No		No	Yes	Yes
[126]	No	Quantitative	Pixel	Regression	Nonparametric	No		No	Yes	Yes
[127]	No	Both	OBIA	Classification		No		No	Yes	No
[128]	No	Quantitative	Pixel	Classification		No		No	No	Yes
[98]	No	Quantitative	Pixel	Regression	Both	Yes	Cubist and Random Forest and SVM and Extreme Gradient Boosting Trees	No	Yes	Yes
[129]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	Yes
[130]	No	Quantitative	Pixel	Classification	Nonparametric	No		No	No	Yes
[131]	No	Both	Pixel	Both	Nonparametric	Yes	Random Forest	No	Yes	Yes

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[132]	2017	Local	Conifer	Temperate broadleaf and mixed forests	Europe	Hyperspectral and Multispectral and Thermal	Passive	Airborne and Satellite	Terra/Aqua and Landsat	Decline and Health
[55]	2018	Local	Conifer	Temperate broadleaf and mixed forests	Europe	Multispectral	Passive	UAV		Decline and Health
[133]	2019	Local	Broadleaf	Boreal forests/taiga	North America	Multispectral	Passive	Satellite	Terra/Aqua and Landsat	Health
[56]	2018	Local	Conifer	Temperate broadleaf and mixed forests	Europe	Multispectral	Passive	UAV		Mortality, Decline and Stress

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[134]	2017	Local	Both	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	Terra/Aqua	Stress and Mortality
[37]	2015	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Landsat	Stress
[62]	2020	Local	Conifer	Deserts and xeric shrublands	North America	LiDAR and Multispectral	Both	Airborne and UAV and Satellite	Landsat	Mortality
[54]	2017	Local	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	UAV		Plague

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[132]	No	Qualitative	Pixel	Regression	Parametric	No		No	Yes	No
[55]	No	Qualitative	Pixel and OBIA	Classification		No		No	Yes	No
[133]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	Yes
[56]	No	Quantitative	Pixel	Regression	Nonparametric	No		No	Yes	Yes
[134]	No	Both	Pixel	Both	Both	Yes	Random Forest	No	Yes	Yes
[37]	No	Quantitative	Pixel			No		No	Yes	No
[62]	No	Qualitative	Pixel and OBIA	Regression	Parametric	No		No	Yes	No
[54]	No	Both	OBIA	Both	Parametric	No		No	Yes	No

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[135]	2020	Local	Broadleaf	Temperate broadleaf and mixed forests	Europe	Hyperspectral	Passive	Airborne		Plague and Mortality
[136]	2016	Local	Broadleaf	Deserts and xeric shrublands	South America	Multispectral	Passive	Satellite	Landsat	Stress
[99]	2016	Continental	Both	Several	North America	Multispectral	Passive	Satellite	Landsat	Decline
[137]	2018	Regional	Broadleaf	Several	Oceania	Multispectral	Passive	Satellite and Terrestrial	RapidEye and Landsat	Health
[40]	2019	Local	Conifer	Temperate broadleaf and mixed forests	Europe	Multispectral	Passive	Satellite	Copernicus and RapidEye	Health
[58]	2019	Local	Conifer	Temperate coniferous forests	Europe	Multispectral	Passive	UAV		Decline, Stress and Plague
[138]	2015	Local	Conifer	Deserts and xeric shrublands	Asia	Multispectral	Passive	Satellite	Landsat	Mortality
[139]	2020	Local	Both	Temperate broadleaf and mixed forests	Europe	Multispectral	Passive	Satellite	Copernicus	Plague

Table A1. *Cont.*

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[135]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	LDA and PCA-LDA and PLS-DA and RF	No	Yes	No
[136]	Yes	Both	Pixel and OBIA	Both	Parametric	No		No	No	Yes
[99]	No	Quantitative	Pixel	Regression	Nonparametric	Yes	Random Forest Neural Network and Regression Trees	No	Yes	Yes
[137]	No	Both	Pixel	Both	Nonparametric	Yes		No	Yes	Yes
[40]	No	Quantitative	Pixel			No		Yes	Yes	No
[58]	No	Quantitative	Pixel			No		No	No	No
[138]	No	Qualitative	Pixel	Regression	Parametric	No		No	No	Yes
[139]	Yes	Both	Pixel	Both	Parametric	No		No	Yes	Yes

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[140]	2017	Local	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	North America	Multispectral	Passive	Airborne		Mortality
[141]	2015	Local	Conifer	Temperate coniferous forests	North America	Multispectral	Passive	Airborne		Plague and Mortality
[142]	2020	Local	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	IRS	Mortality, Decline and Stress
[143]	2020	Regional	Conifer	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	Terra/Aqua and Copernicus	Plague
[144]	2016	Local	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	Landsat	Plague
[145]	2019	Local	Both	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	Landsat	Mortality
[33]	2017	Regional	Both	Several	Africa and Asia and Europe	Hyperspectral	Passive	Satellite	Envisat	Stress
[146]	2020	Local	Conifer	Temperate broadleaf and mixed forests	Europe	Multispectral	Passive	Satellite	Copernicus	Health

Table A1. *Cont.*

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[140]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	Feature Analyst	No	Yes	No
[141]	No	Qualitative	Pixel	Classification	Parametric	No		No	Yes	No
[142]	Yes	Qualitative	Pixel			No		No	No	Yes
[143]	Yes	Qualitative	Pixel	Classification		No		No	No	Yes
[144]	No	Qualitative	Pixel	Regression	Parametric	No		No	No	No
[145]	No	Qualitative	Pixel	Regression		No		No	No	No
[33]	Yes	Quantitative	Pixel	Regression	Parametric	No		No	No	No
[146]	No	Qualitative	Pixel	Classification	Nonparametric	Yes	Random Forest	No	Yes	Yes

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[38]	2020	Local	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	Copernicus	Plague
[147]	2015	Local	Both	Temperate coniferous forests	Europe	Multispectral	Passive	Satellite	Landsat	Plague
[115]	2018	Local	Conifer	Temperate broadleaf and mixed forests	Europe	Multispectral	Passive	Satellite	Copernicus	Plague
[115]	2019	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	North America	Multispectral	Passive	Satellite	Landsat	Mortality
[148]	2015	Local	Conifer	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	NOAA	Stress
[82]	2019	Continental	Conifer	Several	North America	Multispectral	Passive	Satellite	Landsat	Plague
[85]	2019	Local	Conifer	Temperate broadleaf and mixed forests	Asia	LiDAR	Active	Terrestrial		Stress
[149]	2019	Local	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	Landsat	Decline

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[38]	No	Qualitative	Pixel			No		No	Yes	No
[147]	No	Qualitative	Pixel	Classification	Parametric	No		No	Yes	No
[115]	No	Quantitative	Pixel	Both	Nonparametric	Yes	kNN and SVM and Random Forest	No	Yes	No
[102]	No	Quantitative	Subpixel and OBIA	Both	Parametric	No		No	Yes	No
[148]	No	Qualitative	Pixel	Regression	Parametric	No		No	No	Yes

Table A1. *Cont.*

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[82]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	Random Forest	No	Yes	Yes
[85]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	Random Forest	No	Yes	No
[149]	Yes	Both	Pixel	Both	Both	Yes	SVM	No	No	Yes

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[150]	2018	Local	Both	Temperate broadleaf and mixed forests	Europe	LiDAR and Multispectral	Both	Airborne		Mortality
[151]	2016	Local	Both	Temperate broadleaf and mixed forests	North America	LiDAR and Multispectral	Both	Airborne		Plague and Mortality
[152]	2019	Local	Broadleaf	Tropical and subtropical dry broadleaf forests	Asia	Hyperspectral and Multispectral	Passive	Satellite	Landsat and EO-1	Health and Stress
[153]	2016	Local	Conifer	Temperate coniferous forests	Asia	Multispectral	Passive	Satellite	Landsat	Decline
[154]	2020	Regional	Both	Several	Europe	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[155]	2019	Regional	Broadleaf	Tropical and subtropical moist broadleaf forests	Africa	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[9]	2016	Regional	Both	Tropical and subtropical moist broadleaf forests	Asia	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[156]	2018	Local	Conifer	Temperate coniferous forests	North America	LiDAR and Multispectral	Both	Airborne		Stress

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[150]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	Random Forest	No	Yes	No
[151]	No	Qualitative	Pixel	Classification	Nonparametric	Yes	SVM	No	Yes	No
[152]	No	Qualitative	Pixel	Classification	Nonparametric	Yes	SVM and SAM	No	Yes	No
[153]	No	Qualitative	Pixel	Classification	Parametric	No		No	No	No
[154]	No	Quantitative	Pixel	Regression	Parametric	No		No	No	Yes
[155]	No	Both	Pixel	Both		No		No	Yes	Yes
[69]	No	Quantitative	Pixel	Regression	Parametric	No		No	No	Yes
[156]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	No

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[39]	2020	Local	Both	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Copernicus	Decline and Stress
[157]	2020	Local	Conifer	Temperate broadleaf and mixed forests	Oceania	Hyperspectral	Passive	Airborne		Plague and Stress
[158]	2020	Local	Conifer	Temperate broadleaf and mixed forests	Oceania	LiDAR and Multispectral	Both	Airborne and Satellite	WorldView	Plague and Stress
[159]	2016	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	Asia	Multispectral	Passive	Satellite	SPOT	Health
[160]	2018	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Oceania	LiDAR	Active	Airborne		Mortality
[161]	2020	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	South America	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[162]	2017	Local	Broadleaf	Tropical and subtropical moist broadleaf forests	Asia	Multispectral	Passive	Satellite	Terra/Aqua	Stress
[163]	2016	Local	Broadleaf	Temperate broadleaf and mixed forests	North America	Multispectral	Passive	Satellite	WorldView	Plague and Decline

Reference	Early Warning	ANALYSIS TYPE	Analysis Unit	Classification/Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[39]	No	Qualitative	Pixel		Parametric	No		No	No	No
[157]	No	Quantitative	Pixel and OBIA	Regression	Both	Yes	Random Forest	No	Yes	No
[158]	Yes	Quantitative	Pixel and OBIA	Regression	Both	Yes	Random Forest	No	Yes	No
[159]	No	Quantitative	Pixel			No		No	Yes	No
[160]	No	Both	Pixel	Both	Nonparametric	Yes	Random Forest and kNN	No	Yes	No
[161]	No	Both	Pixel	Regression	Parametric	No		No	Yes	Yes
[162]	No	Both	Pixel			No		No	No	Yes
[163]	Yes	Qualitative	OBIA	Both	Both	Yes	Random Forest	No	Yes	No

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[164]	2017	Regional	Broadleaf	Tropical and subtropical moist broadleaf forests	South America	Multispectral	Passive	Satellite	Terra/Aqua and Landsat	Decline
[59]	2019	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite and UAV	Copernicus	Decline
[91]	2019	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	LiDAR and Multispectral	Both	Airborne and Satellite	WorldView	Decline
[165]	2015	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Terra/Aqua	Defoliation and Mortality
[86]	2018	Local	Broadleaf	Temperate broadleaf and mixed forests	North America	Multispectral	Passive	Satellite	Landsat	Plague
[166]	2017	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	North America	LiDAR and Hyperspectral	Both	Airborne		Stress
[92]	2019	Local	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Landsat	Defoliation and Plague
[57]	2018	Local	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	North America	Hyperspectral	Passive	UAV		Stress and Mortality

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[164]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	Yes
[59]	No	Qualitative	OBIA	Classification		No		No	Yes	Yes
[91]	No	Quantitative	OBIA	Classification	Nonparametric	Yes	Random Forest	No	Yes	No
[165]	No	Quantitative	Pixel	Regression	Parametric	No		No	No	Yes
[86]	No	Both	Pixel	Regression	Parametric	No		No	No	Yes
[166]	Yes	Both	OBIA	Classification	Nonparametric	Yes	SVM and Gradient boosting machine	No	Yes	No
[92]	No	Quantitative	Pixel	Regression	Nonparametric	Yes	kNN	No	No	Yes
[57]	No	Quantitative	OBIA	Regression	Nonparametric	No		No	Yes	No

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[167]	2017	Regional	Both	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	Landsat	Stress
[168]	2019	Regional	Both	Mediterranean forests, woodlands and scrub or sclerophyll forests	North America	Microwaves	Passive	Satellite	Terra/Aqua	Stress and Mortality
[169]	2018	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Copernicus	Decline and Health
[97]	2018	Continental	Both	Several	North America	Multispectral	Passive	Satellite	Terra/Aqua and Landsat	Decline and Mortality
[170]	2015	Local	Broadleaf	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Landsat	Plague
[60]	2019	Local	Conifer	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	UAV		Plague
[171]	2018	Local	Broadleaf	Temperate broadleaf and mixed forests	Oceania	Multispectral	Passive	Satellite	Landsat and Worldview	Health
[172]	2016	Local	Broadleaf	Temperate grasslands, savannas and shrublands	Oceania	LiDAR and Hyperspectral	Both	Airborne		Health

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[167]	No	Quantitative	Pixel	Both	Parametric	No		No	No	No
[168]	No	Quantitative	Pixel	Regression	Nonparametric	Yes	Random Forest	No	No	No
[169]	No	Quantitative	Pixel	Classification		No		No	No	No
[97]	Yes	Quantitative	Pixel	Regression	Parametric	No		No	No	Yes
[170]	No	Quantitative	Pixel	Regression	Parametric	No		No	Yes	No
[60]	Yes	Qualitative	Pixel and OBIA	Classification	Nonparametric	No		No	Yes	No
[171]	No	Quantitative	Pixel		Both	Yes	Random Forest	No	Yes	No
[172]	No	Both	OBIA	Classification	Nonparametric	Yes	Random Forest	No	Yes	No

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[173]	2020	Local	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	Terra/Aqua	Decline and Mortalityt
[61]	2019	Local	Conifer	Temperate broadleaf and mixed forests	Europe	Thermal and LiDAR	Both	UAV and Airborne		Plague and Stress
[167]	2019	Local	Both	Temperate broadleaf and mixed forests	Europe	LiDAR and Hyperspectral	Both	Airborne		Plague and Mortality
[174]	2020	Local	Conifer	Temperate broadleaf and mixed forests	Europe	LiDAR and Multispectral	Both	Airborne		Plague
[34]	2018	Regional	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	North America	Hyperspectral	Passive	Airborne		Plague, Mortality and Stress
[175]	2019	Local	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Multispectral	Passive	Satellite	Landsat	Plague and Stress
[41]	2017	Regional	Broadleaf	Tropical and subtropical moist broadleaf forests	South America	Radar	Active	Satellite	ISS	Stress
[176]	2017	Local	Conifer	Temperate broadleaf and mixed forests	North America	Multispectral	Passive	Satellite	Landsat	Plague

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[173]	No	Qualitative	Pixel	Regression	Parametric	No		No	No	Yes
[61]	No	Quantitative	Pixel and OBIA	Regression	Parametric	No		No	Yes	No
[83]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	Random Forest	No	No	No
[174]	No	Both	Pixel	Both	Nonparametric	Yes	Boosted Regression Trees	No	Yes	No
[34]	No	Qualitative	Pixel and Subpixel	Classification	Nonparametric	Yes	Random Forest	No	Yes	No
[175]	No	Quantitative	Pixel	Both	Nonparametric	Yes	kNN	No	Yes	Yes
[41]	No	Qualitative	Pixel			No		No	No	Yes
[176]	No	Quantitative	Pixel	Both	Both	Yes	Boosted Regression Trees	No	Yes	No

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[177]	2015	Local	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	DigitalGlobe	Decline and Health
[178]	2015	Local	Broadleaf	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	DigitalGlobe and Landsat	Decline and Health
[179]	2017	Regional	Both	Temperate broadleaf and mixed forests	North America	Multispectral	Passive	Satellite	Landsat	Plague
[180]	2020	Local	Conifer	Temperate broadleaf and mixed forests	Oceania	Multispectral	Passive	Airborne		Health
[181]	2018	Regional	Conifer	Temperate coniferous forests	North America	Multispectral	Passive	Satellite	Landsat	Plague
[182]	2018	Local	Conifer	Tropical and subtropical dry broadleaf forests	Asia	Multispectral	Passive	Satellite	Landsat	Plague
[183]	2020	Local	Conifer	Tropical and subtropical dry broadleaf forests	Asia	Multispectral	Passive	Satellite	WorldView	Plague
[116]	2018	Local	Conifer	Mediterranean forests, woodlands and scrub or sclerophyll forests	Europe	Hyperspectral and Multispectral	Passive	Airborne and Satellite	Copernicus	Decline

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[177]	No	Qualitative	Pixel	Classification	Parametric	No		No	Yes	No
[178]	No	Qualitative	Pixel	Classification	Nonparametric	Yes	Random Forest	No	Yes	No
[179]	No	Qualitative	Pixel	Classification	Nonparametric	Yes	Maximum Entropy Algorithm	No	Yes	No
[180]	No	Qualitative	OBIA	Classification	Nonparametric	Yes	SVM and kNN and Boosted regression trees	No	Yes	No
[181]	No	Quantitative	Pixel	Both	Nonparametric	Yes	Random Forest	No	No	No
[182]	Yes	Both	Pixel	Classification		No		No	Yes	Yes
[183]	No	Qualitative	OBIA	Regression	Both	Yes	Random Forest	No	Yes	No
[116]	No	Quantitative	Pixel and OBIA	Regression		No		Yes	Yes	No

Table A1. *Cont.*

Reference	Year	Spatial Scale	Functional Type	Biome	Geographic Region	Technology	Sensor Type	Platform	Satellite Programme	Health Parameter
[63]	2020	Local	Conifer	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite and UAV	CHEOS and Copernicus	Plague and Mortality
[64]	2020	Local	Conifer	Temperate broadleaf and mixed forests	Asia	Hyperspectral	Passive	UAV		Plague
[184]	2018	Local	Conifer	Temperate broadleaf and mixed forests	Asia	Multispectral	Passive	Satellite	Landsat	Plague

Reference	Early Warning	Analysis Type	Analysis Unit	Classification/ Regression	Statistical Method	Machine Learning	ML Method	Physically Based Modelling	Validation	Time Series Analysis
[63]	Yes	Qualitative	Pixel and OBIA	Classification	Nonparametric	Yes	CART and Random Forest and SVM	No	Yes	No
[64]	No	Qualitative	Pixel	Classification	Nonparametric	Yes	SVM	No	Yes	No
[184]	No	Quantitative	Pixel	Regression	Parametric	No		No	No	Yes

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