Cent. Eur. For. J. 71 (2025) 14–39 sciendo DOI: 10.2478/forj-2024-0022
CENTRAL EUROPEAN Forestry Journal

REVIEW PAPER

Remote sensing forest health assessment – a comprehensive literature review on a European level

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Abstract

Forest health assessments (FHA) have been carried out at European level since the 1980s in order to identify forest damage. The annual surveys are usually conducted without the use of remote sensing tools. However, the increasing availability of remote sensing observations potentially allows conduct FHA more wide-spread, more often, or in more comprehensive and comparable way. This literature review systematically evaluated 110 studies from 2015 to 2022 that use remote sensing for FHA in Europe. The purpose was to determine (1) which tree species were studied; (2) what types of damage were evaluated; (3) whether damage levels are distinguished according to the standard of the *International Co-operative Program on Assessment and Monitoring of Air Pollution Effects on Forests* (ICP-Forest); (4) the level of automation; and (5) whether the findings are applicable for a systematic FHA. The results show that spruce is the most studied tree species. Damage caused by bark beetles and drought were predominantly studied. In most studies only 2 damage levels are classified. Only four studies were able to perform a comprehensive FHA by identifying individual trees, classifying their species and damage levels. None of the studies investigated the suitability of their remote sensing approach for systematic forest health assessments. This result is surprising since programs such as SEMEFOR analyzed the potential of remote sensing for FHA already in the 1990s. We conclude that the availability of new satellite systems and advances in artificial intelligence and machine learning should be translated into FHA practice according to ICP standards.

Key words: forest health assessment; remote sensing; PRISMA; literature review; Europe

Editor: Tomáš Bucha†

1. Introduction

Forest health reflects the condition of the entire forest (eco)system. The condition of a forest can be described in terms of ecosystem diversity (structure, taxonomy and functional diversity), capability of forest species to adapt to changes, the sustainability of drivers and processes of forest dynamics as well as their changes over time within reasonable time frames. According to the Food and Agriculture Organization of the United Nations (FAO), forest health describes the impact of biotic and abiotic environmental factors on the growth, survival, increment and quality of timber and non-timber forest products, habitats, recreation, landscape or cultural values (Trumbore et al. 2015). Lausch et al. (2016) define forest health as the resilience of the forest to external disturbances. To assess forest health, various indicators have been developed such as defoliation and discoloration of leaves. Defoliation is usually used for assessment in temperate and boreal regions such as Europe, Canada and the United States, (FAO 2021). Since many studies are focusing on specific factors like pests that have a negative effect on the health of trees or forest the terms "forest damage", "forest degradation" and "forest damage assessment" are used in the context of assessing forest health. The ICP defines "damage" as an alteration or a disturbance to a part of the tree which may have an adverse effect on the ability to fulfil its functions (Eichhorn et al. 2020). The designation "forest degradation" refers to the reduction of the capacity of a forest to provide goods, socio-cultural and environmental services. It is a process that negatively affects the quality of a forest (FAO 2024). Often the term "forest health" is defined as the absence of damage (Lausch et al. 2016), therefore "forest damage assessment" could be interpreted as kind of "forest health assessment" with specific focus on damages or degradation.

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Since 1985, the health status of forests has been investigated at the European level by the *International Cooperative Program on Assessment and Monitoring of Air Pollution Effects on Forests* (ICP Forests). The ICP has developed its own standards and set of variables such as defoliation, flowering and foliage transparency, which are described in the ICP manual "Visual assessment of crown condition and Damaging Agents" (Eichhorn et al. 2020). While in the 1980s it was mainly air pollution and emissions that led to forest degradation, in recent years it has been predominantly weather extremes such as storms and prolonged drought (Wellbrock & Bolte 2019) in combination with biotic damage factors such as bark beetle infestations.

Most recently, storm Xavier in fall 2017 and hurricane Friederike in February 2018 led to high levels of damaged timber in Germany. The damage was exacerbated by prolonged drought in the growing seasons from 2018 to 2020, which significantly affected the vitality of forest trees. The German Forest Condition Survey 2020 attests a significant deterioration of vitality at the federal level, which is reflected in a mean crown defoliation of 26.5% on average for all tree species. Since the beginning of the forest condition survey, no comparably high values have been detected (BMEL 2022). This trend can also be traced for other European Countries like France, Czech Republic, Slovakia and Hungary, as well as western Bulgaria and coastal Croatia (Michel et al. 2022).

Forest health assessments (FHA) are conducted to quantify the impact and extent of such changes in forest conditions. Surveys are conducted at the state and national level using a standardized methodology. The surveys are carried out terrestrially at permanently defined sampling points by visual assessment of the tree crowns (Wellbrock et al. 2020). The procedure is very time-consuming and spatially sparse. Random sampled trees are assessed in a 16 × 16 km grid or in an 8 × 8 km grid in some federal states of Germany such as like Lower Saxony. In particular, small forest ownerships such as communal forests are not sufficiently represented by the grid (Drechsel 2022). In this context, monitoring forest condition by remote sensing is an interesting alternative to terrestrial methods as it can provide a wide-spread monitoring.

In remote sensing, electromagnetic radiation is used to analyze the environment without contact. Thereby sensors to measure the electromagnetic radiation are mounted either on space-borne systems (satellites), airborne systems (planes, helicopters, drones / uncrewed aerial vehicles UAVs) or on terrestrials systems (e.g., cameras on towers or terrestrial laser scanning). Sensors are commonly distinguished into active and passive sensors. Passive sensors record reflected sunlight or radiation that is naturally emitted by the object. In contrast, active systems emit radiation itself either in the form of laser beams (Light Detection and Ranging LIDAR) or microwaves (Radar) and then record the energy of this radiation that is reflected at the surface (Lillesand et al. 2015). Microwave observations from synthetic aperture radar (SAR) systems have been widely used to create surface and terrain models and are becoming recently more exploited to quantify forest structure at large scales (Pardini et al. 2019; Santoro et al. 2022; Liu et al. 2024) but is not yet fit for purpose for small scale applications in forestry. LIDAR especially airborne laser scanning (ALS) is widely used to map forest height or structure (Pirotti 2011; Wulder et al. 2012).

The spectral, spatial and temporal resolution of the sensors plays a decisive role in the detection and evaluation of environmental influences on ecosystems such as forests. The spectral resolution provides information on which fineness of electromagnetic radiation can be recorded by a sensor. A great number of narrow bands results in a high spectral resolution, while less or wider bands produce the contrary. Sensors with one band are referred as panchromatic, sensors with more than two bands as multispectral (MS) and sensors with multitude of narrow band as hyperspectral (HS). The radiation recorded by the sensor allows to map properties of the surfaces. In this way biochemical and physiological properties of leaves and morphological, structural or phenological properties of entire canopies of trees can be estimated and monitored. Indicators such as leaf area index, leaf water content, or chlorophyll content can be retrieved from multi- and hyperspectral satellite observations and allow conclusions about their vitality (Lillesand et al. 2015; Lausch et al. 2016).

The spatial resolution indicates the size of an object at the Earth surface that can be resolved by a sensor. In many cases spatial resolution equals pixel size (e.g., the Sentinel-2 satellite has up to 10 m spatial resolution and pixel size) but pixel size can be also disaggregated to lower values (e.g., 2 m) but this will not increase the spatial resolution (e.g., objects < 10 m can still not be resolved). Depending on the spatial resolution, information about the distribution, size, shape and extent of objects or features can be derived. While coarse (> 500 m) and medium-resolution (10–500 m) images only allow statements at landscape, ecosystem or stand level, high-resolution (< 10 m) images can be used to differentiate between tree crowns or crown components (Lausch et al. 2016).

The temporal resolution indicates the period between two overflights of the same area (Lillesand et al. 2015). The temporal resolution determines the frequency of successive surveys and controls if information about annual and seasonal changes or at individual disturbance events can be derived. A high temporal resolution contributes to a better differentiation of species, populations, communities or forest types based on their phenological changes or their response to environmental stress (Lausch et al. 2016).

The most widely used platforms for forestry remote sensing include satellites, aircrafts and uncrewed aerial vehicles (UAVs). Satellites have been used for remote sensing for more than 40 years. The Landsat-1 program was launched in 1972, followed by SPOT-1 and Ikonos. Since then, satellite-based systems have been continuously improved in terms of image performance and better spatial and spectral resolution (Wulder et al. 2019). By combining the images from several individual satellites, the temporal resolution can be increased. Compared to airborne platforms, satellites possess a lower spatial resolution, which ranges between 0.3 and 300 m per pixel (Jafarbiglu & Pourreza 2022). However, an advantage of satellite images is the cost factor and the accessibility of the data. Images from medium-resolution satellites (e.g., Landsat, Sentinel-2) can be used free of charge. Although, high-resolution images from commercial satellites such as Rapid Eye, Planet, Ikonos or Geoeye are only limited available free of charge (e.g., for test users or non-commercial application), the costs for those images are relatively cheaper compared to aerial images (Fassnacht et al. 2016; Wu et al. 2020).

As an addition or alternative to satellite sensors, sensors on airplanes offer a higher spatial resolution of 2 to 25 cm per pixel and hence can provide much more detailed information. On the other hand, airborne sensors operate at a regional level and have a smaller ground coverage. Since aerial images are generally very cost-intensive and the quality of satellite images is constantly improving, the use of satellite images is increasing in comparison to aerial images (Jafarbiglu & Pourreza 2022).

In contrast to satellites and airplanes, UAVs have only been used in remote sensing for around 10 years (Minařík & Langhammer 2016). They are significantly cheaper and more flexible to use, which is why their importance in remote sensing is increasing. UAVs offer a considerable increase in spatial resolution (1 to 5 cm / pixel). However, UAVs are used only at a local level and hence have a small ground coverage compared to satellites and airplanes. However, the low flight altitudes close to the tree canopies enable their use for tree species classification and vitality monitoring (Näsi et al. 2018; Kampen et al. 2019; Wu et al. 2020).

Already in the 1990s the European Commission founded projects to complement the forest health assessment at ICP plots by the use of remote sensing. For example, the SEMEFOR (Satellite Based Environmental Monitoring of European Forest) project used medium to coarse resolution satellites such as Landsat TM, IRS-1C and SPOT4 to assess forest health using indicators such as defoliation and discoloration. Defoliation and damage levels could be determined with an error rate of 3–10% in spruce and pine dominated stands (European Commission 2001). However, inadequate results were obtained for plots in steep terrain, with roads running through them or with a proportion of dominant tree species not exceeding 50%. The project illustrated the advantage of satellite images in terms of good spatial and temporal availability for periodic surveys. However, it also showed the disadvantage of the medium to coarse spatial resolution, which does not allow a more precise evaluation of the condition of individual trees or mixed stands (European Commission 2001). Other international efforts such as Global Forest Watch (https://www.globalforestwatch.org/) make use of satellite-based approaches using multispectral observations (Hansen et al. 2013) or Radar observations (Reiche et al. 2018) to provide frequent information about deforestation. The European Earth observation program "Copernicus" offers through its Land Monitoring Service (https://land.copernicus.eu/en) information about land and tree cover, forest type, and biophysical properties of vegetation. However, there is not yet any portal that uses satellite observations to serve the need of forest health assessment according to the ICP standards.

In recent years, there have been several literature studies dedicated to the analysis of forest damage using remote sensing. Lausch et al. (2016, 2017, 2018) present in detail the methods, approaches as well as necessary further developments that should enable remote sensing to survey forest condition. Torres et al. (2021) give a good overview of remote sensing methods used worldwide in the years 2015 to 2020. Other authors, however, focus on country-specific application or specific damage factors.

Holzwart et al. (2020) analyzes the history of remote sensing at the German level during the last 20 years. Other authors focus on remote sensing of forest damage caused by insect feeding (El-Ghany et al. 2020). However, no review studies were found to summarize the practicality of remote sensing for operational forest health assessment. Therefore, the aim of this literature review is to examine studies on forest health assessment conducted in Europe using remote sensing. Of particular interest is the question of the practicality of the approaches for operational monitoring. Specifically, we address the following questions:

1. Which tree species were investigated?
2. What types of damages are evaluated?
3. Are damage levels collected according to ICP standard?
4. What is the level of automation?
5. How relevant are the results for forest health assessment?

2. Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method was used for the systematic evaluation of the studies (Fig. 1). The method provides a systematic evaluation and meta-analysis of literature. Possible sources are first identified and reduced by a pre-selection. Their suitability for the study is then assessed (Moher et al. 2009).

We searched for literature in English language in order to analyze international studies. Selected period

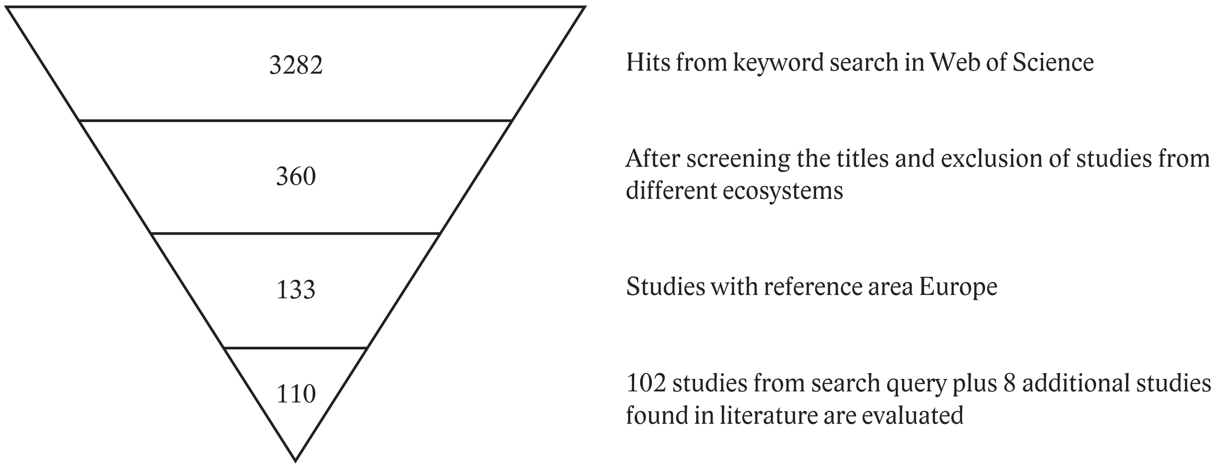

Fig. 1. PRISMA flowchart for selection and inclusion of studies in the analysis.

of consideration was between 1st January 2015 and 31st December 2022, using the search terms "remote sensing AND (tree OR forest) AND (health OR stress OR dieback OR vitality OR mortality)" in the Web of Science online library. Searches were conducted on 12/07/2022 and repeated on 12/07/2023 and returned 3282 articles. First, the titles of the articles were screened. Excluded were all studies that referred to plants other than trees, such as palms, that investigated at other habitats such as aquatic forests (mangroves) or savannas, or that primarily focused at forest fires or wind throws. This selection resulted in 360 articles.

Second, since the literature review is focused on assessment of forest health in Europe, we further selected only publications relating to countries in geographic Europe. The remaining 133 studies were examined in detail. In a further step, 23 articles were excluded from the evaluation because they were not related to remote sensing or did not make statements about tree vitality or forest health. In addition, eight further studies were included that were found in the literature of the investigated articles journals and fulfilled the criteria of the search query.

3. Results

3.1 Location and time of publications

A total of 110 studies were evaluated for the period from 1st January 2015 to 31st December 2022. Most of the studies were published in the years from 2019 to 2022 (Fig. 2). In this context, remote sensing was used to assess tree and forest vitality in 24 countries in Europe. Most studies were conducted in Spain (24), followed by Poland (12), Czech Republic (10), and Germany (8) (Fig. 3, Table 1). Some studies were conducted in multiple locations, so the total number of studies shown in Table 1 is 117. An overview of all the results is shown in Table S1.

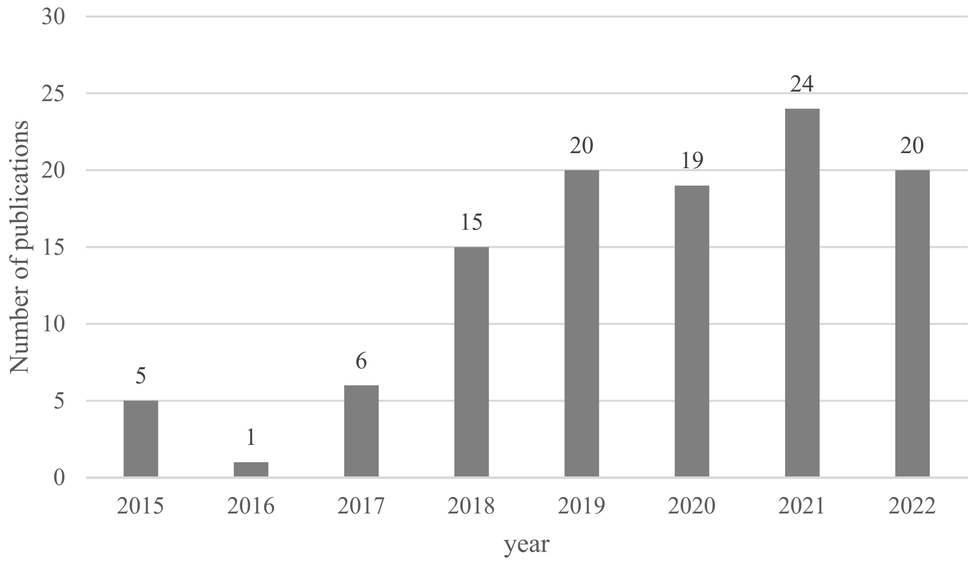

Fig. 2. Number of publications by years.

Fig. 3. Distribution of studies on monitoring of forest damage by remote sensing.

Table 1. Publications per country.

Country	Number of publications	Investigated tree species
Europe	3	No data
Austria	2	*Picea abies*, *Fraxinus excelsior*, *Fagus sylvatica*, *Abies alba*, *Pinus nigra*, *Pinus sylvestris*
Belarus	1	No data
Belgium	3	*Alnus glutinosa*, *Aesculus* spp., *Tilia* spp., *Acer* spp., *Platanus*
Bulgaria	6	*Picea abies*, *Pinus sylvestris*, *Pinus nigra*, *Fagus sylvatica*, *Ailanthus altissima*, *Abies alba*, *Cercis siliquastrum*, *Diospyros lotus*, *Fraxinus ornus*, *Tilia argentea*, *Tilia platyphillos*, *Sambucus nigra*, *Sophora japonica*
Croatia	2	*Quercus*, *Carpinus betulus*, *Robinia pseudoacacia*
Czech Republic	9	*Picea abies*, *Fagus sylvatica*, *Abies alba*
Finland	3	*Picea abies*
France	2	*Abies alba*, *Picea abies*, *Pseudotsuga menziesii*
Germany	9	*Picea abies*, *Pinus sylvestris*, *Fagus sylvatica*, *Quercus robur*, *Tilia cordata*, *Tilia × europaea*, *Acer platanoides*, *Robinia pseudoacacia*
Great Britain	5	*Quercus robur*, *Quercus petraea*, *Betula pubescens*, *Larix kaempferi*, *Larix eurolepis*, *Fraxinus excelsior*, *Pinus sylvestris*, *Pinus contorta*
Greece	4	*Abies cephalonica*, *Olea europaea*
Ireland	1	*Quercus robur*, *Quercus petraea*, *Betula pubescens*
Italy	9	*Pinus pinea*, *Olea europaea*, *Quercus robur*, *Quercus frainetto*, *Quercus pubescens*, *Quercus cerris*, *Fagus sylvatica*, *Quercus ilex*, *Picea abies*, *Abies alba*, *Pinus nigra*, *Pinus sylvestris*
Latvia	1	*Picea abies*
Norway	2	*Picea abies*
Poland	12	*Quercus robur*, *Quercus petraea*, *Carpinus betulus*, *Tilia cordata*, *Picea abies*, *Acer platanoides*, *Betula pendula*, *Betula pubescens*, *Pinus sylvestris*, *Alnus glutinosa*
Portugal	4	*Quercus suber*, *Alnus glutinosa*, *Eucalyptus* spp.
Romania	3	*Fagus sylvatica*, *Picea abies*, *Abies alba*
Slovakia	3	*Picea abies*
Slovenia	1	*Fagus sylvatica*, *Larix decidua*, *Pinus sylvestris*, *Picea abies*, *Abies alba*

Spain	24	*Pinus halapensis*, *Pinus pinaster*, *Pinus nigra*, *Pinus sylvestris*, *Pinus pinea*, *Pinus radiata*, *Quercus ilex*, *Quercus suber*, *Phillyrea latifolia*, *Arbusto unedo*, *Ulmus pumila*, *Fagus sylvatica*, *Prunus dulcis*
Sweden	2	*Picea abies*
Switzerland	5	*Picea abies*, *Fagus sylvatica*, *Abies alba*, *Pinus sylvestris*, *Alnus glutinosa*, *Larix decidua*, *Acer pseudoplatanus*, *Quercus robur*, *Pinus mugo*, *Castanea sativa*, *Quercus petraea*, *Pseudotsuga menziesii*, *Tilia cordata*, *Betula pendula*
Ukraine	1	*Pinus* spp., *Alnus glutinosa*, *Betula* spp.

3.2 Investigated ecosystem and forest types and levels

Most studies investigate trees in forests (101 studies) (Table 2). Five studies examined trees in plantations, four the vitality of trees in parks. Within the forest ecosystem, primarily coniferous forests (37 studies) and mixed forests (35) were investigated. Deciduous forests, on the other hand, were the subject of 29 studies. Nine studies consider all forest types, which is mainly the case when the vitality of forest trees is analyzed on a country level or Europe-wide.

More than half of the studies assess the health of trees or forests at the level of the individual tree. About one third of the studies analyze vitality at the stand level. This means that no distinction is made between individuals but several neighboring trees are considered as one unit. Five studies use both individual tree and stand level. A total of seven studies consider forest vitality at the ecosystem level (Table 2).

Table 2. Sites of the studied trees and considered levels.

Sites	Number
Forest	101
Plantation	5
Park	4
Type of forests	**Number**
Deciduous forest	24
Coniferous forest	37
Mixed forest	35
All types	9
No data	5
Level	**Number**
Single tree	58
Forest stand	36
Single tree and forest stand	5
Forest stand and ecosystem	2
Ecosystem	7
No data	2

3.3 Type and level of damage

Regarding the type of damage, most studies differentiate between biotic and abiotic damages. The majority of publications (48) examined biotic damage. The most important damaging organisms are insects, especially bark beetles. In comparison, abiotic damage was rarely investigated. In 16 available studies, mainly drought-related damage was identified. A total of seven publications consider the interaction of abiotic and biotic damage, such as the influence of drought on fungal infestations, or the effects of storm events on bark beetle calamities. It is noteworthy that 36 studies do not provide information on the type of damage determined (Table 3).

Table 3. Types of damage.

Type of damage	Pests / abiotic impact	Number
Biotic	Bark beetles	21
	Leaf beetles	1
	Moth	4
	Protista	6
	Nematodes	1
	Bacteria	2
	Fungi	13
Abiotic	Drought	16
	Storm	1
	Nutrient deficiency	1
	Stone impact	1
Biotic and abiotic	Storm and bark beetle Drought and fungi or bark beetle or interaction	3
Without data		36

The classification of the damage levels on the reference plots is mainly based on the loss of leaves or the discoloration of the foliage. The majority of the studies do not make any statement on damage levels (Table 4). In most cases, only vegetation indices were collected without a classification. 30 studies distinguish between two damage levels, according to “dead” and “living” or “healthy” and “diseased” trees. When classifying three damage levels, 22 publications differentiate between “healthy”, “diseased” and “dead” or “light damage”, “moderate damage” and “dead trees”. Studies with four or five damage levels show further vitality classes according to the foliage or leaf discoloration of the considered trees. Two studies distinguish six different levels of damage although these classifications differ from conventional vitality classes for trees (Table 4). Recanatesi et al. (2019) investigates six risk classes for tree death based on vegetation indices. Baders et al. (2022) classifies trees according to different crown damage, dead trees and trunk and root damage.

3.4 Investigated tree species

Among the most studied genera is the spruce (*Picea*). It was mentioned in 39 studies. All studies, except one, refer to the species *Picea abies* [L.] Karst.. Pine (*Pinus*) is also frequently addressed in 24 studies. This genus is

Table 4. Examination of damage levels.

Number of damage levels	Number of publications	Damage level designation
No level	34	
2	30	healthy/diseased or alive / dead
3	22	healthy/diseased / dead or slight / moderate / dead
4	16	No damage / slight / moderate and heavy damages or dead trees
5	6	No damages to dead trees
6	2	Different classes according to vegetation indices or crown damages or other types of damages

represented by many more species (*Pinus sylvestris* L., *P. halapensis* Mill., *P. pinaster* Aiton, *P. pinea* L., *P. nigra* J. F. Arnold, *P. radiate* D. Don, and *P. mugo* Turra). Among the deciduous tree genera, oak (*Quercus*) is the most frequently genera studied, which encompass species such as *Quercus ilex* L., *Q. robur* L., *Q. petraea* [Matt.] Liebl., *Q. suber* L., *Q. frainetto* Ten., *Q. pubescens* Willd. and *Q. cerris* L.(Fig. 4).

The studies differ greatly in terms of the number of tree species investigated. The majority (62) of the publications investigates only the vitality of one tree species. 13 studies determine the vitality of two tree species and eleven studies three different tree species. No information about the tree species investigated is provided in 17 studies (Table 5).

Table 5. Number of evaluated tree species.

Number of evaluated tree species in studies	Number of publications
1	62
2	13
3	11
4	2
5	2
9	1
11	1
14	1
No data	17

3.5 Technologies used to evaluate forest damage

Satellites represent the most used platform for forest health assessment with 45%. UAV (19%) and aircraft (17%) are used significantly less. Purely terrestrial methods were used in only one publication and combined with aircraft in another. Combining aircraft and satellite imagery, on the other hand, is a frequently used method (12%). In 89 studies, vitality is surveyed using passive sensors, and another 20 studies combine passive and active sensors. In contrast, the use of exclusively active sensors plays a minor role with only one study. Multispectral remote sensing data are used most frequently (79 studies). Ten studies use hyperspectral data and a total of 20 studies combine different technologies (Table 6).

In the period from January 2015 to December 2022, satellite images from the Copernicus mission Sentinel-2 (33) and Landsat (19) were predominantly used. Products from "World-View" and "Terra and Aqua" (MODIS) were used far less often. Other high-resolution commercial satellite imagery is barely used (< 4 studies) (Fig. 5).

As a method for inferring tree damage, classification approaches (52) was used far more frequently than regression approaches (19). In seven studies, both methods were combined. About one third of the studies, on the other hand, did not provide any information. Machine learning methods were used most frequently. In particular, the random forest algorithm (28), principal component analysis / partial least square discriminate analysis (17), and support vector machine (15) were used most often (Table 7).

The majority of the studies assessed the vitality of trees at the individual tree level or at the individual and stand level (Table 2). We then assessed which steps of the analysis were conducted in an automatic way (Table 8). Most frequently, individual trees are first extracted from the remote sensing data and then assessed in terms of

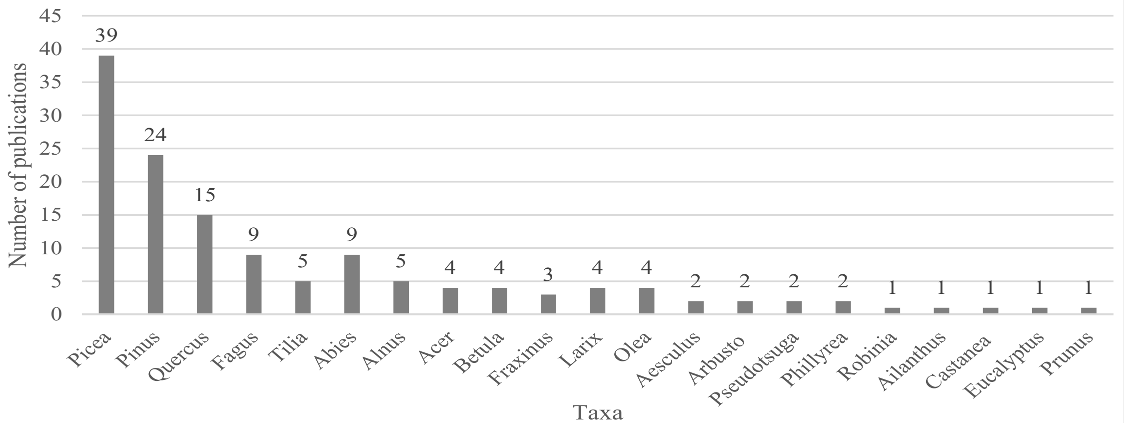

Fig. 4. Studied tree genus (number of publications).

Table 6. Applied remote sensing technologies.

Technology	Number	Platform	Number	Sensor	Number
Active	1	Satellite	50	ALS	1
Passive	89	Aircraft	19	ALS / Thermal	1
Active / passive	20	UAV	21	Hyperspectral / Thermal	1
		Earth born	1	Hyperspectral	10
		Satellite / aircraft / UAV	1	Hyperspectral / ALS	4
		Satellite / aircraft	12	Hyperspectral / Multispectral	2
		Satellite / UAV	1	Hyperspectral / Thermal	1
		Aircraft / UAV	5	Multispectral	79
				Multispectral / ALS	7
				Multispectral / Radar	3
				Multispectral / Thermal / ALS	1

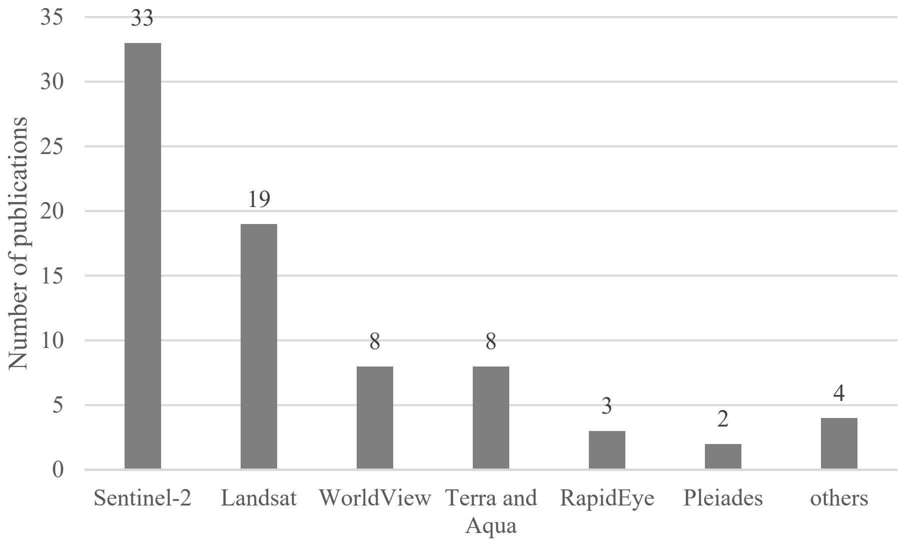

Fig. 5. Satellite programs (number of publications).

Table 7. Data analysis techniques for determining the damage level or vitality.

Classification / Regression	Number	Method of evaluation	Number
Classification	52	Random Forest (RF)	28
Regression	19	Support Vector Machine (SVM)	15
Classification / Regression	7	Principal component analysis (PCA), partial least square discriminate analysis (PLS-DA)	17
No information	32	Neutral Networks (NN)	7
		Maximum Likelihood (MLE)	6
		Convolutional Neural Network (CNN)	4
		Geographic Object-based Image Analysis (GEOBIA)	2
		Boosted regression trees	1
		k-Mean-Clustering	1
		k-nearest neighbors (kNN)	3
		Principal component gradient analyses (PCGA)	1
		Classification and Regression Trees algorithm (CART)	1
		Bayesian estimator	1
		Cumulative distribution function (CDF)	1
		Multi-Pyramid Features Extraction	1
		Machine learning (without further designation)	1
		No data	35

their vitality (32 studies). In eight studies, only the vitality is assessed without having previously performed a single tree detection or tree species classification. Three studies classify tree species and vitality without a previous single tree extraction. Only four publications both detect individual trees, classify them by tree species, and then assess the vitality.

The classification of damage levels is mainly based on needle and leaf loss (defoliation) or yellowing of foliage on the reference plots. These characteristics are mostly derived using vegetation indices, texture, and or individual spectral bands (e.g., near infrared (NIR), Red edge, and visual bands). 77 studies use vegetation indices to determine damage levels. The Normalized Difference

Table 8. Performed data analysis steps in assessing the vitality of trees at the individual tree level.

Working steps	Number
No statement about work steps	11
Classification of damage level	8
Tree detection + classification of damage level	32
Tree species classification + classification of damage level	3
Tree detection + tree species classification + damage level	4

Vegetation Index is mostly applied and used in 70 studies. Texture features are used to evaluate damage levels in only seven studies (Table S2).

3.6. Accuracies of the forest damage level classification

In the following, the achieved overall accuracies of the damage level classification are considered in order to show which factors influence the accuracy of the classification. Looking at the overall accuracy of the classifications in damage levels, it can be seen that the accuracy varied between 80% and 88% for 2 to 5 damage levels. A clear relation between the accuracy and the number of damage levels is not recognizable. With a number of six damage levels, the accuracy achieved is significantly lower at 56%, but there is only one reference study for this value (Fig. 6). The algorithms used for classification seem to have a stronger effect on accuracy. While methods such as Object-Based Image Analysis (GEOBIA) and k-nearest neighbors achieve an overall accuracy of 80% and 78%, respectively, artificial neural networks, maximum likelihood and multi-pyramid feature extraction achieve significantly higher values with accuracies of over 90%. Table 9 shows the average values of the achieved overall accuracies. In contrast, the use of multispectral (82%) and hyperspectral (83%) sensors hardly differs in terms of accuracy. The accuracy of both multispectral and hyperspectral sensors can be substantially increased by combining them with thermal sensors or radar (Table 9).

Regressions were used in 19 studies. In seven further studies, both regression and classification were used. However, only eight studies made a statement about the performance of the regression analysis (based on the coefficient of determination). The coefficient lies between $R^2 = 0.52$ and $R^2 = 0.93$ in the studies considered. Due to the small number of studies, it is difficult to identify a relationship between the coefficient of determination and the number of damage levels or sensors used. However, the study by Smigaj et al. (2015) achieves a significantly worse result ($R^2 = 0.52$) than the other studies, which have a coefficient of determination between $R^2 = 0.79$ and $R^2 = 0.93$. This could be related to the use of a thermal sensor instead of multispectral or hyperspectral sensors. The studies by Barka et al. (2018) with $R^2 = 0.86$ and Rodes et al. (2021) with $R^2 = 0.93$ achieved the highest coefficient of determination for the derivation of damage based on defoliation.

Table 9. Overall accuracies of the algorithms and applied technologies.

Algorithm	Overall accuracy [%]
k-nearest Neighbors	78
Ordinary least squares Regression	80
CNN	80
Support Vector Machine (SVM)	83.5
Random Forest (RF)	85.9
GEOBIA	80
Artificial neural networks	90
Maximum-Likelihood	90.5
Multi-Pyramid Features Extraction	93.8
Technology	**Overall accuracy [%]**
Multispectral	82
Hyperspectral	83
Multispectral / radar	91
Hyperspectral / thermal	90

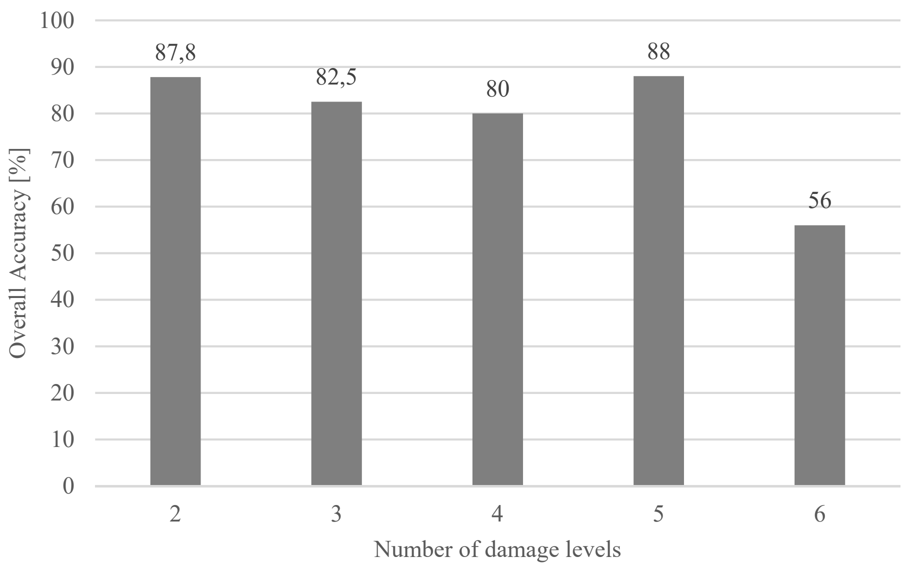

Fig. 6. Average overall accuracy achieved in relation to the number of damage levels.

4. Discussion

4.1. Investigated tree species and type of damage

The results of the literature search show that the genus *Picea* was the most frequently studied (39 studies). According to the FAO (2020), spruce is one of the most important main tree species of 14 of the 23 countries examined in this study. Both the distribution and the economic interests associated with spruce seem to put the tree species in the focus of studies. Directly related to the frequent mention of spruce is the high number of studies (19) on bark beetle damage. In particular, the species *Ips typographus* L. represents the most important pest of the tree species (Bayerische Landesanstalt für Wald und Forstwirtschaft 2020).

The pine genus has also been considered in numerous studies. Similar to spruce, it is widespread in Europe and is one of the main tree species in 12 of the 23 countries listed (FAO 2020). Most studies on damage to pines were published in Spain (11 of 24 publications). The species considered were *Pinus halepensis* Mill., *P. pinea* L., *P. pinaster* Aiton, *P. nigra* J. F. Arnold, and *P. sylvestris* L. The tree damage described therein was attributed to numerous pest groups, including nematodes, moths, bark beetles, bacteria, fungi, and drought, in contrast to spruce.

Among the deciduous tree species, the genus *Quercus* was the most frequently studied (15 publications). Most publications on damage to oaks were also from Spain (6 publications) and considered the species *Quercus ilex* L. as well as *Q. suber* L. Biotic damage by protists (*Phytophthora cinnamomi* Rands) was evaluated. In Central Europe, the genus was studied in only four publications and was represented by the species *Quercus robur* L. and *Q. petraea* [Matt.] Liebl.

The genus *Fagus* was investigated nine times. In all studies, the species *Fagus sylvatica* L. was considered. It is noteworthy that four out of eight studies do not mention the type of damage. In three publications, damage caused by drought is examined and related to the extreme weather events, as confirmed by studies of Thonfeld et al. (2022) and Lukeš (2021). With regard to research questions 1 and 2, it can be summarized that mainly biotic damage, in particular bark beetles, were investigated. Although the ratio of coniferous to deciduous tree species investigated is balanced, the genera *Picea* and *Pinus* were investigated much more frequently.

4.2. Remote sensing technologies used to evaluate forest damage

Satellites are the most widely used platform - especially the Copernicus Sentinel-2 and the US Landsat satellite programs. This widespread used is likely because of the free access to these data and the relatively easy use and interpretation for forest applications of those optical multispectral imagery.

The use of drones for damage assessment plays an increasingly important role. 21 of the 101 studies used UAV, and seven other studies combined UAV with other platforms. According to Torres et al. (2021), in the period from 2015 to 2020, only seven studies worldwide used UAV and four others combined UAV with other systems. The increasing use of UAVs in environmental monitoring is related, among other things, to decreasing cost of acquisition and operation, flexible deployment and independence from cloud cover, and very high resolution of the imagery (Hu et al. 2021). Nevertheless, the use of crewed airborne vehicles is still a proven tool. In 19 publications, remote sensing data were collected using aircraft, and in 18 other studies, images from aircraft were combined with those from satellites or UAVs.

Multispectral sensors have been predominantly used for the detection of tree damage (79). Multispectral sensors can measure electromagnetic radiation in the range from 400 to 2,500 nm. They are therefore suitable for analyzing vegetation. The reflection and absorption behavior of plants in the wave range between 430 and 660 nm allows conclusions to be drawn about their vitality (Curran 1980). However, the high number of studies using multispectral sensors seems to be related to the Sentinel-2 and Landsat satellite programs, which exclusively use multispectral sensors. Although hyperspectral sensors are particularly well suited to quantify a high number of different biochemical and biophysical spectral features in forest ecosystems and are also capable of distinguishing more than 20–30 different tree species (Lausch et al. 2016), they have only been used 15 times. The high spectral resolution of hyperspectral instruments is more crucial than spatial resolution for assessing spruce health (Abdollahnejad et al. 2021). The limited use of hyperspectral imagery is likely caused by the availability of hyperspectral data which was not freely available from a satellite platform. The German hyperspectral Environmental Mapping and Analysis Program (EnMap) satellite, launched in 2022, might enable the development of further methods for forest health assessment (Dotzler et al. 2015; Guanter et al. 2015) but data availability is yet limited. This situation will improve with the advent of Copernicus Hyperspectral Imaging Mission (CHIME), a pair of satellites to be launched in 2028 and 2030, respectively (Rast et al. 2021).

Most studies (77) use vegetation indices for damage detection. The most commonly applied was NDVI, which is one of the most used vegetation indices according to Hawryło et al. (2018). The accuracy of damage level classification seems to depend more on the algorithm used than on the number of damage levels differentiated between or the type of data used. Multispectral and hyperspectral data hardly differed from each other on average, while methods such as Artificial Neural Networks, Maximum-Likelihood and Multi-Pyramid Feature Extraction with accuracies above 90% showed large differences to other algorithms such as k-Nearest Neighbors (78%). The highest overall accuracies were obtained by Duarte et al. (2020) with 98.5% and Poblete et al. (2021) with 98%, which relied on Random Forest and Support Vector Machines for classification. However, recent approaches using Deep Learning methods also achieve very good results. The convolutional neural networks (CNNs) Silvi-Net of Briechle et al. (2021) achieves an overall accuracy of 95%.

The assessment of tree vitality was carried out at different levels. In the evaluation of the studies, a differentiation was made between individual tree, stand and ecosystem levels.

While some studies focused on stand or ecosystem level, 54 studies investigated vitality at the single tree level. This level is important because it allows to differentiate forest vitality in terms of (i) diversity at taxonomic, structural, and functional levels, (ii) genetic diversity affecting adaptive capacity, and the (iii) factors, processes, and their traits affecting vitality (Lausch et al. 2016).

33 of the 58 studies exclusively examine vitality of monocultures of tree species or pure stands, which simplifies the analysis because a prior identification of tree species is not required. Consequently, these studies do not provide information about the usefulness of methods for determining tree damage in mixed stands, as indicators for damages such as vegetation indices are tree species-specific (Barka et al. 2018).

In contrast, the annual forest health assessment according to ICP standard distinguishes between tree species and vitality at individual tree level. For this purpose, indicators such as foliage (needle or leaf) loss, leaf discoloration, crown transparency, flowering and fruit formation are assessed. In addition, biotic and abiotic damage factors such as drought and insect feeding are documented. From the information of needle and leaf loss, damage levels from 0 (no crown defoliation) to 4 (dead tree) are evaluated (BMEL 2021).

As an answer to research question 3, it can be noted that none of the evaluated studies could accomplish this set of indicators and damage levels according to ICP standard. However, six out of 110 studies (Dimitrov et al. 2018; Kampen et al. 2019; Algeet Abarquero et al. 2020; Hornero et al. 2020; Rodes et al. 2021; Ho et al. 2022) were able to distinguish five damage levels equal to ICP standard.

In order to generate statements regarding vitality or damage at the level of individual trees, various data analysis steps are necessary. The results show that only a small part of the studies was able to automatically detect single trees or delimit their canopy, classify the tree species and determine the vitality or damage of the tree. Only four studies performed all three mentioned steps of tree identification, tree species classification, and damage assessment (Stereńczak et al. 2020; Briechle et al. 2021; Chan et al. 2021; Safonova et al. 2021), which answers research question 4.

The targeted application of remote sensing for forest health assessment was only subject of research in Barka et al. (2018). Nevertheless, most studies focus on the detection of specific damages or damage events of one or a few tree species in limited study areas. It can therefore be concluded that remote sensing was not used for the forest condition survey regarding the study period from 2015 to 2022 (research question 5).

5. Conclusions

The studies published in the period from 1st January 2015 to 31st December 2022 mainly consider the vitality or damage of forest trees of the genera *Picea*, *Pinus* and *Quercus* (Research question 1). Primarily biotic damage factors were determined of which *Ips typographus* L. was the most abundant pest mentioned (Research question 2). Satellite images from Landsat and from Copernicus Sentinel-2 were mostly used as a basis, although UAV are becoming increasingly important for forest health assessment. Although about half of the studies consider forest condition at the single-tree level, the majority of publications do not differentiate between damage levels or only between "dead and living" trees. Only 6 studies classify 5 damage levels according to ICP standard. An approach that is able to assess more indicators for tree crown assessment such as needle or leaf loss, leaf discoloration, crown transparency, flowering and fruit formation was not found (research question 3). An automated derivation of tree crown, tree species and damage levels was implemented in only four studies, and this only applies to a maximum number of three undifferentiated tree species (research question 4). Remote sensing was specifically applied for forest health assessment in only a few studies like Barka et al. (2018) and the SEMEFOR project in the 1990s (research question 5). Nevertheless, most studies focus on the detection of specific damages or damage events of one or a few tree species in limited study areas. Those results demonstrate the need for a more targeted research and exploitation of remote sensing to quantify and describe forest health. Thereby, methodologies should be developed and tested that serve the need for forest health assessment according to ICP Forest standards. Such a targeted approach would not only facilitate an easier and more widespread standardized forest monitoring but could also help the remote sensing community to satisfy the call for more ground observations, which are available from ICP. This requires building bridges between remote sensing science and forestry through improved cooperation, communication and the willingness to share data, algorithms and finally services.

References

Abdollahnejad, A., Panagiotidis, D., 2020: Tree Species Classification and Health Status Assessment for a Mixed Broadleaf-Conifer Forest with UAS Multispectral Imaging. Remote Sensing, 12:3722.

Abdollahnejad, A., Panagiotidis, D., Surovy, P., Modlinger, R., 2021: Investigating the Correlation between Multisource Remote Sensing Data for Predicting Potential Spread of *Ips typographus* L. Spots in Healthy Trees. Remote Sensing, 13:4953.

Abdullah, H., Darvishzadeh, R., Skidmore, A., Groen, T., Heurich, M., 2018: European spruce bark beetle (*Ips typographus* L.) green attack affects foliar reflectance and biochemical properties. International Journal of Applied Earth Observation and Geoinformation, 64:199–209.

Adrien, M., Piégay, H., Lisein, J., Claessens, H., Lejeune, P., 2016: Classification of riparian forest species and health condition using multi-temporal and hyperspatial imagery from Unmanned Aerial System. Environmental Monitoring and Assessment, 188:146.

Ahmed, S., Nicholson, C. E., Muto, P., Perry, J., Dean, J., 2021: Applied aerial spectroscopy: A case study on remote sensing of an ancient and semi-natural woodland. PLoS ONE, 16:e0260056.

Algeet Abarquero, N., Guillen-Climent, M., Mas, H., Tomé, J., Fernández-Landa, A., 2020: Using hipersepctral images for decay detection in *Pinus halepensis* (Mill.) in the Mediterranean forest. Revista de Teledetección, 55:59–69.

Ali, A. M., Abdullah, H., Darvishzadeh, R., Skidmore, A. K., Heurich, M., Roeoesli, C. et al., 2021: Canopy chlorophyll content retrieved from time series remote sensing data as a proxy for detecting bark beetle infestation. Remote Sensing Applications: Society and Environment, 22:100524.

Allen, B., Dalponte, M., Ørka, H., Næsset, E., Puliti, S., Astrup, R. et al., 2022: UAV-Based Hyperspectral Imagery for Detection of Root, Butt, and Stem Rot in Norway Spruce. Remote Sensing, 14:3830.

Andrija, K., Linardić, D., Pernar, R., 2021: Framework for Spatial and Temporal Monitoring of Urban Forest and Vegetation Conditions: Case Study Zagreb, Croatia. Sustainability, 13:6055.

Ariza Salamanca, A., Navarro-Cerrillo, Bonet-García, Palazón, Polo, M. J., 2019: Integration of a Landsat Time-Series of NBR and Hydrological Modeling to Assess *Pinus pinaster* Aiton. Forest Defoliation in South-Eastern Spain. Remote Sensing, 11:2291.

Avetisyan, D., Borisova, D., Velizarova, E., 2021. Integrated Evaluation of Vegetation Drought Stress through Satellite Remote Sensing. Forests, 12:974.

Baders, E., Romāns, E., Desaine, I., Krisans, O., Seipulis, A., Donis, J. et al., 2022, An Integration of Linear Model and 'Random Forest' Techniques for Prediction of Norway Spruce Vitality: A Case Study of the Hemiboreal Forest, Latvia. Remote Sensing, 14:2122.

Balazy, R., Ciesielski, M., Waraksa, P., Zasada, M., Zawiła-Niedźwiecki, T., 2019a: Deforestation Processes in the Polish Mountains in the Context of Terrain Topography. Forests, 10:1027.

Balazy, R., Hycza, T., Kamińska, A., Osińska-Skotak, K., 2019b: Factors Affecting the Health Condition of Spruce Forests in Central European Mountains-Study Based on Multitemporal RapidEye Satellite Images. Forests, 10:943.

Barka, I., Lukeš, P., Bucha, T., Hlásny, T., Strejček, R., Mlčoušek, M. et al., 2018: Remote sensing-based forest health monitoring systems-case studies from Czechia and Slovakia. Central European Forestry Journal, 64:259–275.

Barmpoutis, P., Stathaki, T., Kamperidou, V., 2019: Monitoring of Trees' Health Condition Using a UAV Equipped with Low-cost Digital Camera. ICASSP 2019-2019 IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP). Brighton, UK, p. 8291–8295.

Barnes, C., Balzter, H., Barrett, K., Eddy, J., Milner, S., Suarez Minguez, J., 2017: Individual Tree Crown Delineation from Airborne Laser Scanning for Diseased Larch Forest Stands. Remote Sensing, 9:231.

Bárta, V., Lukeš, P., Homolova, L., 2021: Early detection of bark beetle infestation in Norway spruce forests of Central Europe using Sentinel-2. International Journal of Applied Earth Observation and Geoinformation, 100:102335.

Blaga, L., Josan, I., Herman, G., Grama, V., Nistor, S., Suba, N.-S., 2019: Assessment of the Forest Health Through Remote Sensing Techniques in Valea Roşie Natura 2000 Site, Bihor County, Romania. Journal of Applied Engineering Sciences, 9:207–215.

Briechle, S., Krzystek, P., Vosselman, G., 2021: Silvi-Net – A dual-CNN approach for combined classification of tree species and standing dead trees from remote sensing data. International Journal of Applied Earth Observation and Geoinformation, 98:102292.

Brovkina, O., Cienciala, E., Zemek, F., Lukeš, P., Fabiánek, T., Russ, R., 2017: Composite indicator for monitoring of Norway spruce stand decline. European Journal of Remote Sensing, 50:550–563.

Brovkina, O., Cienciala, E., Surovy, P., Janata, P., 2018: Unmanned aerial vehicles (UAV) for assessment of qualitative classification of Norway spruce in temperate forest stands. Geo-Spatial Information Science, 21:12–20.

Bryk, M., Kołodziej, B., Pliszka, R., 2021: Changes of Norway Spruce Health in the Białowieża Forest (CE Europe) in 2013–2019 during a Bark Beetle Infestation, Studied with Landsat Imagery. Forests, 12:34.

Buras, A., Rammig, A., Zang, C., 2020: Quantifying impacts of the 2018 drought on European ecosystems in comparison to 2003. Biogeosciences, 17:1655–1672.

Camino, C., Araño, K., Berni, J. A., Dierkes, H., Trapero-Casas, J. L., León-Ropero, G. et al., 2022: Detecting *Xylella fastidiosa* in a machine learning framework using Vcmax and leaf biochemistry quantified with airborne hyperspectral imagery. Remote Sensing of Environment, 282:113281.

Candotti, A., De Giglio, M., Dubbini, M., Tomelleri, E., 2022: A Sentinel-2 Based Multi-Temporal Monitoring Framework for Wind and Bark Beetle Detection and Damage Mapping. Remote Sensing, 14:6105.

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

Cârlan, I., Mihai, B.-A., Nistor, C., Große-Stoltenberg, A., 2020: Identifying urban vegetation stress factors based on open access remote sensing imagery and field observations. Ecological Informatics, 55:101032.

Chan, A., Barnes, C., Swinfield, T., Coomes, D., 2020: Monitoring ash dieback (*Hymenoscyphus fraxineus*) in British forests using hyperspectral remote sensing. Remote Sensing in Ecology and Conservation, 7:306–320.

Chaparro, D., Piles, M., Martinez Vilalta, J., Vall-llossera, M., Vayreda, J., Banqué-Casanovas, M. et al., 2018: Modelling Forest Decline Using Smos Soil Moisture and Vegetation Optical Depth. IGARSS 2018 – 2018 IEEE International Geoscience and Remote Sensing Symposium, Valencia, Spain, p. 1459–1462.

Chi, D., Degerickx, J., Yu, K., Somers, B., 2020: Urban Tree Health Classification Across Tree Species by Combining Airborne Laser Scanning and Imaging Spectroscopy. Remote Sensing, 12:2435.

Cucca, B., Recanatesi, F., Ripa, M., 2020: Evaluating the Potential of Vegetation Indices in Detecting Drought Impact Using Remote Sensing Data in a Mediterranean Pinewood. In: Gervasi, O. et al. (eds.): Computational Science and Its Applications – ICCSA 2020. ICCSA 2020. Lecture Notes in Computer Science, vol. 12253. Cham, Springer, p. 50–62.

Curran, P., 1980: Multispectral remote sensing of vegetation amount. Progress in Physical Geography: Earth and Environment, 4:315–341.

Dalponte, M., Kallio, A., Ørka, H., Næsset, E., Gobakken, T., 2022: Wood Decay Detection in Norway Spruce Forests Based on Airborne Hyperspectral and ALS Data. Remote Sensing, 14:1892.

Degerickx, J., Roberts, D., Mcfadden, J., Hermy, M., Somers, B., 2018: Urban tree health assessment using airborne hyperspectral and LiDAR imagery. International Journal of Applied Earth Observation and Geoinformation, 73:26–38.

Descals, A., Verger, A., Yin, G., Filella, I., Penuelas, J., 2022: Widespread drought-induced leaf shedding and legacy effects on productivity in European deciduous forests. Remote Sensing in Ecology and Conservation, 9:76–89.

Dimitrov, S., Georgiev, G., Georgieva, M., Gluschkova, M., Chepisheva, V., Mirchev, P. et al., 2018: Integrated assessment of urban green infrastructure condition in Karlovo urban area by in-situ observations and remote sensing. One Ecosystem, 3:e21610.

D'Odorico, P., Schönbeck, L., Vitali, V., Meusburger, K., Schaub, M., Ginzler, C. et al., 2021: Drone-based physiological index reveals long-term acclimation and drought stress responses in trees. Plant, Cell & Environment, 44:3552–3570.

Dotzler, S., Hill, J., Buddenbaum, H., Stoffels, J., 2015: The Potential of EnMAP and Sentinel-2 Data for Detecting Drought Stress Phenomena in Deciduous Forest Communities. Remote Sensing, 7:14227–14258.

Duarte, A., Acevedo Muñoz, L., Gonçalves, C., Mota, L., Sarmento, A., Silva, M. et al., 2020: Detection of Longhorned Borer Attack and Assessment in Eucalyptus Plantations Using UAV Imagery. Remote Sensing, 12:3153.

Einzmann, K., Atzberger, C., Pinnel, N., Glas, C., Böck, S., Seitz, R. et al., 2021: Early detection of spruce vitality loss with hyperspectral data: Results of an experimental study in Bavaria, Germany. Remote Sensing of Environment, 266:112676.

El-Ghany, N., Abd El-Aziz, S., Marei, S., 2020: A review: application of remote sensing as a promising strategy for insect pests and diseases management. Environmental Science and Pollution Research, 27:33503–33515.

Fassnacht, F. E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L. T. et al., 2016: Review of studies on tree species classification from remotely sensed data. Remote Sensing of Environment. 186: 64–87.

Fernandez-Carrillo, A., Patočka, Z., Dobrovolný, L., Franco-Nieto, A., Revilla-Romero, B., 2020: Monitoring Bark Beetle Forest Damage in Central Europe. A Remote Sensing Approach Validated with Field Data. Remote Sensing, 12:3634.

García-Montero, L., Pascual, C., Martin-Fernández, S., Sanchez-Paus Diaz, A., Patriarca, C., Martín-Ortega, P. et al., 2021: Medium- (MR) and Very-High-Resolution (VHR) Image Integration through Collect Earth for Monitoring Forests and Land-Use Changes: Global Forest Survey (GFS) in the Temperate FAO Ecozone in Europe (2000–2015). Remote Sensing, 13:4344.

Georgiev, G., Georgieva, M., Dimitrov, S., Iliev, M., Trenkin, V., Mirchev, P. et al., 2022: Remote Sensing Assessment of the Expansion of *Ips typographus* Attacks in the Chuprene Reserve,Western Balkan Range. Forests, 13:39.

Georgieva, M., Belilov, S., Dimitrov, S., Iliev, M., Trenkin, V., Mirchev, P. et al., 2022: Application of Remote Sensing Data for Assessment of Bark Beetle Attacks in Pine Plantations in Kirkovo Region, the Eastern Rhodopes. Forests, 13:620.

Guanter, L., Kaufmann, H., Segl, K., Foerster, S., Rogaß, C., Chabrillat, S. et al., 2015: The EnMAP Spaceborne Imaging Spectroscopy Mission for Earth Observation. Remote Sensing, 7:8830.

Guillen-Climent, M. L., Mas, H., Fernández-Landa, A., Algeet-Abarquero, N., Tomé J. L., 2020: Using hipersepctral images for decay detection in *Pinus halepensis* (Mill.) in the Mediterranean forest. Revista de Teledetección, 55:59–69.

Guerra, J., Díaz Varela, R., Ávarez-González, J., Rodríguez-González, P., 2021: Assessing a novel modelling approach with high resolution UAV imagery for monitoring health status in priority riparian forests. Forest Ecosystems, 8:61.

Hansen, M. C., Potapov, P., Moore, R., Hancher, M., Turubanova, S., Tyukavina, A. et al., 2013: High-Resolution Global Maps of 21st-Century Forest Cover Change. Science, 342:850–853.

Hawryło, P., Bednarz, B., Wezyk, P., Szostak, M., 2018: Estimating defoliation of Scots pine stands using machine learning methods and vegetation indices of Sentinel-2. European Journal of Remote Sensing, 51:194–204.

Hernandez Clemente, R., North, P. R. J., Hornero, A., Zarco-Tejada, P., 2018: Monitoring Forest Health with Sun-Induced Chlorophyll Fluorescence Observations and 3-D Radiative Transfer Modeling. IGARSS 2018–2018 IEEE International Geoscience and Remote Sensing Symposium, Valencia, Spain, p. 5999–6002.

Ho, B., Kocer, B. B., Kovac, M., 2022: Vision based crown loss estimation for individual trees with remote aerial robots. ISPRS J. Photogramm. Remote Sensing, 188:75–88.

Holzwarth, S., Thonfeld, F., Abdullahi, S., Asam, S., Canova, E., Gessner, U. et al., 2020: Earth Observation Based Monitoring of Forests in Germany: A Review. Remote Sensing, 12:3570.

Hornero, A., Hernández-Clemente, R., North, P., Beck, P., Boscia, D., Navas-Cortés, J. A. et al., 2020: Monitoring the incidence of *Xylella fastidiosa* infection in olive orchards using ground-based evaluations, airborne imaging spectroscopy and Sentinel-2 time series through 3-D radiative transfer modelling. Remote Sensing of Environment, 236:111480.

Hornero, A., Zarco-Tejada, P., Quero, J., North, P. R. J., Francisco José, R.-G., Sánchez-Cuesta, R. et al., 2021: Modelling hyperspectral- and thermal-based plant traits for the early detection of *Phytophthora*-induced symptoms in oak decline. Remote Sensing of Environment, 263:112570.

Hu, Y., Yang, C., Yang, J., Li, Y., Jing, W., Shu, S., 2021: Review on unmanned aerial vehicle remote sensing and its application in coastal ecological environment monitoring. IOP Conference Series: Earth and Environmental Science, 821:012018.

Huo, L., Lindberg, E., Persson, H., 2020: Normalized Projected Red & SWIR (NPRS): A New Vegetation Index for Forest Health Estimation and Its Application on Spruce Bark Beetle Attack Detection. IGARSS 2020–2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, p. 4618–4621.

Huo, L., Persson, H., Lindberg, E., 2021. Early detection of forest stress from European spruce bark beetle attack, and a new vegetation index: Normalized distance red & SWIR (NDRS). Remote Sensing of Environment, 255:112240.

Jafarbiglu, H., Pourreza, A., 2022: A comprehensive review of remote sensing platforms, sensors, and applications in nut crops. Computers and Electronics in Agriculture, 197:106844.

Junttila, S., Näsi, R., Koivumäki, N., Imangholiloo, M., Saarinen, N., Raisio, J. et al., 2022: Multispectral Imagery Provides Benefits for Mapping Spruce Tree Decline Due to Bark Beetle Infestation When Acquired Late in the Season. Remote Sensing, 14:909.

Kälin, U., Lang, N., Hug, C., Gessler, A., Wegner, J., 2019: Defoliation estimation of forest trees from ground-level images. Remote Sensing of Environment, 223:143–153.

Kamińska, A., Lisiewicz, M., Stereńczak, K., Kraszewski, B., Sadkowski, R., 2018: Species-related single dead tree detection using multi-temporal ALS data and CIR imagery. Remote Sensing of Environment, 219:31–43.

Kamińska, A., 2023: Spatial autocorrelation based on remote sensing data in monitoring of Norway spruce dieback caused by the European spruce bark beetle *Ips typographus* L. in the Białowieża Forest. Sylwan, 166:719–732.

Kampen, M., Lederbauer, S., Mund, J.-P., Immitzer, M., 2019: UAV-Based Multispectral Data for Tree Species Classification and Tree Vitality Analysis. Conference: Dreiländertagung der DGPF, der OVG und der SGPF in Wien, Österreich – Publikation der DGPF, Band 28, 2019, p. 623–639.

Kanerva, H., Honkavaara, E., Näsi, R., Hakala, T., Junttila, S., Karila, K. et al., 2022: Estimating Tree Health Decline Caused by *Ips typographus* L. from UAS RGB Images Using a Deep One-Stage Object Detection Neural Network. Remote Sensing, 14:6257.

Katkovsky, L., Beliaev, B., Siliuk, V., Beliaev, M., Sarmin, E., Davidovich, Y., 2020: Remote spectral methods for detecting stress coniferous. E3S Web of Conferences, 223:02004.

Khoury, S., Coomes, D. A., 2020: Resilience of Spanish forests to recent droughts and climate change. Global Change Biology, 26:7079–7098.

Klouček, T., Komarek, J., Surovy, P., Hrach, K., Janata, P., Vašíček, B., 2019: The Use of UAV Mounted Sensors for Precise Detection of Bark Beetle Infestation. Remote Sensing, 11:1561.

Kotlarz, J., Kubiak, K., Spiralski, M., 2022: Monitoring Effects of Drought on Nitrogen and Phosphorus in Temperate Oak Forests Using Machine Learning Techniques. Polish Journal of Environmental Studies, 31:1137–1151.

Lambert, J., Denux, J.-P., Verbesselt, J., Balent, G., Cheret, V., 2015: Detecting clear-cuts and decreases in forest vitality using MODIS NDVI time series. Remote Sensing, 7:3588–3612.

Laštovička, J., Švec, P., Paluba, D., Kobliuk, N., Svoboda, J. et al., 2020: Sentinel-2 Data in an Evaluation of the Impact of the Disturbances on Forest Vegetation. Remote Sensing, 12:1914.

Lausch, A., Erasmi, S., King, D. J., Magdon, P., Heurich, M., 2016: Understanding Forest Health with Remote Sensing -Part I – A Review of Spectral Traits, Processes and Remote-Sensing Characteristics. Remote Sensing, 8:1029.

Lausch, A., Erasmi, S., King, D. J., Magdon, P., Heurich, M., 2017: Understanding Forest Health with Remote Sensing-Part II – A Review of Approaches and Data Models. Remote Sensing, 9:129.

Lausch, A., Borg, E., Bumberger, J., Dietrich, P., Heurich, M., Huth, A. et al., 2018: Understanding Forest Health with Remote Sensing, Part III: Requirements for a Scalable Multi-Source Forest Health Monitoring Network Based on Data Science Approaches. Remote Sensing, 10:1120.

Lillesand, T., Kiefer, R. W., Chipman, J., 2015: Remote Sensing and Image Interpretation, 7th Edition. Hoboken, John Wiley & Sons, 736 p.

Liu, X., Frey, J., Denter, M., Zielewska-Büttner, K., Still, N., Koch, B., 2021: Mapping standing dead trees in temperate montane forests using a pixel- and object-based image fusion method and stereo WorldView-3 imagery. Ecological Indicators, 133:108438.

Liu, X., Neigh, C. S. R., Pardini, M., Forkel, M., 2024: Estimating forest height and above-ground biomass in tropical forests using P-band TomoSAR and GEDI observations. International Journal of Remote Sensing, 45:3129–3148.

Lukeš, P., 2021: Monitoring of Bark Beetle Forest Damages. In: Södergård, C., Mildorf, T., Habyarimana, E., Berre, A. J., Fernandes, J. A., Zinke-Wehlmann, C. (eds): Big Data in Bioeconomy. Cham, Springer, pp. 351–361.

Maltezos, E., Grammalidis, N., Katagis, T., Gitas, I. Z., Charalampopoulou, V. (Betty), 2019: Development of automated workflows (spatial models) for forest monitoring with the use of time-series of multispectral optical and SAR data. In: Papadavid, G., Themistocleous, K., Michaelides, S., Ambrosia, V., Hadjimitsis, D. G. (eds.): Seventh International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2019). Presented at the Seventh International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2019), SPIE, Paphos, Cyprus, p. 60.

Marx, A., Tetteh, G. O., 2017: A Forest Vitality and Change Monitoring Tool Based on RapidEye Imagery. IEEE Geoscience and Remote Sensing Letters, 14:801–805.

Meyer, B. F., Buras, A., Rammig, A., Zang, C. S., 2020: Higher susceptibility of beech to drought in comparison to oak. Dendrochronologia, 64:125780.

Migas-Mazur, R., Kycko, M., Zwijacz-Kozica, T., Zagajewski, B., 2021: Assessment of Sentinel-2 Images, Support Vector Machines and Change Detection Algorithms for Bark Beetle Outbreaks Mapping in the Tatra Mountains. Remote Sensing, 13:3314.

Minařík, R., Langhammer, J., 2016: Use of a Multispectral UAV Photogrammetry for Detection and Tracking of Forest Disturbance Dynamics. ISPRS – Int. Arch. Photogramm. Remote Sensing and Spatial Information Sciences, XLI-B8:711–718

Moher, D., Liberati, A., Tetzlaff, J., Altman, D., The PRISMA Group, 2009: Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. Journal of Clinical Epidemiology, 62:1006–1012.

Moreno-Fernández, D., Viana-Soto, A., Camarero, J., Zavala, M., Tijerin-Triviño, J., García, M., 2021: Using spectral indices as early warning signals of forest dieback: The case of drought-prone *Pinus pinaster* forests. Science of The Total Environment, 793:148578.

Moreno-Fernández, D., Camarero, J., García, M., Lines, E., Sánchez-Dávila, J., Tijerin-Triviño, J. et al., 2022: The Interplay of the Tree and Stand-Level Processes Mediate Drought-Induced Forest Dieback: Evidence from Complementary Remote Sensing and Tree-Ring Approaches. Ecosystems, 25:1738–1753.

Näsi, R., Honkavaara, E., Blomqvist, M., Paivi, L.-S., Hakala, T., Viljanen, N. et al., 2018: Remote sensing of bark beetle damage in urban forests at individual tree level using a novel hyperspectral camera from UAV and aircraft. Urban Forestry & Urban Greening, 30:72–83.

Navarro Cerrillo, R., Varo, M., Acosta, C., Palacios, G., Sánchez-Cuesta, R., Francisco José, R.-G., 2019: Integration of WorldView-2 and airborne laser scanning data to classify defoliation levels in *Quercus ilex* L. Dehesas affected by root rot mortality: Management implications. Forest Ecology and Management, 451:117564.

Navrozidis, I., Alexandridis, T., Moshou, D., Haugommard, A., Lagopodi, A., 2022: Implementing Sentinel-2 Data and Machine Learning to Detect Plant Stress in Olive Groves. Remote Sensing, 14:5947.

Navrozidis, I., Mourelatos, S., Nieto, F., Alexandridis, T., Moshou, D., Pantazi, X. et al., 2019: Olive Trees Stress Detection Using Sentinel-2 Images. IGARSS 2019 – 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, pp. 7220–7223.

Nowakowska, J., Hsiang, T., Patynek, P., Stereńczak, K., Olejarski, I., Oszako, T., 2020: Health Assessment and Genetic Structure of Monumental Norway Spruce Trees during A Bark Beetle (*Ips typographus* L.) Outbreak in the Białowieża Forest District, Poland. Forests, 11:647.

Ogaya, R., Barbeta, A., Başnou, C., Penuelas, J., 2015: Satellite data as indicators of tree biomass growth and forest dieback in a Mediterranean holm oak forest. Annals of Forest Science, 72:135–144.

Ogaya, R., Daijun, L., Barbeta, A., Penuelas, J., 2020: Stem Mortality and Forest Dieback in a 20-Years Experimental Drought in a Mediterranean Holm Oak Forest. Frontiers in Forests and Global Change, 2:89.

Pardini, M., Armston, J., Qi, W., Lee, S. K., Tello, M., Cazcarra Bes, V. et al., 2019: Early Lessons on Combining Lidar and Multi-baseline SAR Measurements for Forest Structure Characterization. Surveys in Geophysics, 40:803–837.

Pérez-Romero, J., Navarro-Cerrillo, R. M., Palacios-Rodriguez, G., Acosta, C., Mesas-Carrascosa, F. J., 2019: Improvement of Remote Sensing-Based Assessment of Defoliation of *Pinus* spp. Caused by Thaumetopoea pityocampa Denis and Schiffermüller and Related Environmental Drivers in Southeastern Spain. Remote Sensing, 11:1736.

Peters, R., Miranda, J. C., Schönbeck, L., Nievergelt, D., Fonti, M., Saurer, M. et al., 2020: Tree physiological monitoring of the 2018 larch budmoth outbreak: preference for leaf recovery and carbon storage over stem wood formation in *Larix decidua*. Tree Physiology, 40:1697–1711.

Piedallu, C., Dallery, D., Bresson, C., Legay, M., Gégout, J.-C., Pierrat, R., 2022: Spatial vulnerability assessment of silver fir and Norway spruce dieback driven by climate warming. Landscape Ecology, 38:341–361.

Piragnolo, M., Pirotti, F., Zanrosso, C., Lingua, E., Grigolato, S., 2021: Responding to Large-Scale Forest Damage in an Alpine Environment with Remote Sensing, Machine Learning, and Web-GIS. Remote Sensing, 13:1541.

Pirotti, F. 2011: Analysis of full-waveform LiDAR data for forestry applications: a review of investigations and methods. iForest – Biogeosciences and Forestry, 4:100–106.

Poblete, T., Navas Cortés, J., Camino, C., Calderón Madrid, R., Hornero, A., Gonzalez-dugo, V. et al., 2021: Discriminating *Xylella fastidiosa* from *Verticillium dahliae* infections in olive trees using thermal- and hyperspectral-based plant traits. ISPRS Journal of Photogrammetry and Remote Sensing, 179:133–144.

Prăvălie, R., Sirodoev, I., Nita, I.-A., Patriche, C., Dumitraşcu, M., Roşca, B. et al., 2022: NDVI-based ecological dynamics of forest vegetation and its relationship to climate change in Romania during 1987–2018. Ecological Indicators, 136:108629.

Puletti, N., Mattioli, W., Bussotti, F., Pollastrini, M., 2019: Monitoring the effects of extreme drought events on forest health by Sentinel-2 imagery. Journal of Applied Remote Sensing, 13:1.

Rast, M., Nieke, J., Adams, J., Isola, C., Gascon, F., 2021: Copernicus Hyperspectral Imaging Mission for the Environment (Chime). EEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, pp. 108–111.

Recanatesi, F., Giuliani, C., Ripa, M., 2018: Monitoring Mediterranean Oak Decline in a Peri-Urban Protected Area Using the NDVI and Sentinel-2 Images: The Case Study of Castelporziano State Natural Reserve. Sustainability, 10:3308.

Recanatesi, F., Giuliani, C., Rossi, C., Ripa, M., 2019: A Remote Sensing-Assisted Risk Rating Study to Monitor Pinewood Forest Decline: The Study Case of the Castelporziano State Nature Reserve (Rome). In: Calabrò, F., Della Spina, L., Bevilacqua, C. (eds): New Metropolitan Perspectives. ISHT 2018. Smart Innovation, Systems and Technologies, vol 100. Cham, Springer, pp. 68–75.

Reiche, J., Hamunyela, E., Verbesselt, J., Hoekman, D. H., Herold, M., 2018: Improving near-real time deforestation monitoring in tropical dry forests by combining dense Sentinel-1 time series with Landsat and ALOS-2 PALSAR-2. Remote Sensing of Environment, 204:147–161.

Rodes, M., Torres, P., García, M., 2021: Assessing tree decay in an urban park using PlanetScope images: the case of Cerro Almodovar Park. Proc. SPIE 11864, Remote Sensing Technologies and Applications in Urban Environments VI:118640L.

Romero-Ramirez, F., Navarro-Cerrillo, R., Varo, M., Quero, J., Doerr, S., Hernandez Clemente, R., 2018: Determination of forest fuels characteristics in mortality-affected *Pinus* forests using integrated hyperspectral and ALS data. International Journal of Applied Earth Observation and Geoinformation, 68:157–167.

Rullán, C., Olthoff, A., Pando, V., Pajares, J., Delgado, J., 2015: Remote monitoring of defoliation by the beech leaf-mining weevil *Rhynchaenus fagi* in northern Spain. Forest Ecology and Management, 347:200–208.

Safonova, A., Hamad, Y., Dmitriev, E., Georgiev, G., Trenkin, V., Georgieva, M. et al., 2021: Individual

Tree Crown Delineation for the Species Classification and Assessment of Vital Status of Forest Stands from UAV Images. Drones, 5:77.

Santoro, M., Cartus, O., Wegmüller, U., Besnard, S., Carvalhais, N., Araza, A. et al., 2022: Global estimation of above-ground biomass from spaceborne C-band scatterometer observations aided by LiDAR metrics of vegetation structure. Remote Sensing of Environment, 279:113114.

Schratz, P., Muenchow, J., Iturritxa, E., Cortés, J., Bischl, B., Brenning, A., 2021: Monitoring Forest Health Using Hyperspectral Imagery: Does Feature Selection Improve the Performance of Machine-Learning Techniques? Remote Sensing, 13:4832.

Senf, C., Seidl, R., Poulter, B., 2021: Post-disturbance canopy recovery and the resilience of Europe's forests. Global Ecology and Biogeography, 31:822–825.

Smigaj, M., Gaulton, R., Barr, S., Suarez Minguez, J., 2015: UAV-Borne Thermal Imaging for Forest Health Monitoring: Detection of Disease-Induced Canopy Temperature Increase. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-3/W3:349–354.

Smigaj, M., Gaulton, R., Suárez, J. C., Barr, S. L., 2019: Canopy temperature from an Unmanned Aerial Vehicle as an indicator of tree stress associated with red band needle blight severity. Forest Ecology and Management, 433:699–708.

Solano, F., Di Fazio, S., Modica, G., 2019: A methodology based on GEOBIA and WorldView-3 imagery to derive vegetation indices at tree crown detail in olive orchards. International Journal of Applied Earth Observation and Geoinformation, 83:101912.

Stereńczak, K., Bartłomiej, K., Miłosz, M., Żaneta, P., 2017: Inventory of standing dead trees in the surroundings of communication routes – The contribution of remote sensing to potential risk assessment. Forest Ecology and Management, 402, 76–91.

Stereńczak, K., Mielcarek, M., Modzelewska, A., Kraszewski, B., Fassnacht, F., Hilszczański, J., 2019: Intra-annual *Ips typographus* outbreak monitoring using a multi-temporal GIS analysis based on hyperspectral and ALS data in the Białowieża Forests. Forest Ecology and Management, 442:105–116.

Stereńczak, K., Mielcarek, M., Kamińska, A., Kraszewski, B., Piasecka, Ż., Miścicki, S. et al., 2020: Influence of selected habitat and stand factors on bark beetle *Ips typographus* (L.) outbreak in the Białowieża Forest. Forest Ecology and Management, 459:117826.

Sturm, J., Santos, M., Schmid, B., Damm, A., 2022: Satellite data reveal differential responses of Swiss forests to unprecedented 2018 drought. Global Change Biology, 28:2956–2978.

Tilly, N., Reddig, F., Lussem, U., Bareth, G., 2020: First investigation of mediterranean oak tree vitality with high-resolution WorldView-3 data: Comparing ten vegetation indices and three machine learning classifiers. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B3-2020:1069–1076.

Thonfeld, F., Gessner, U., Holzwarth, S., Kriese, J., da Ponte, E., Huth, J. et al., 2022: A First Assessment of Canopy Cover Loss in Germany's Forests after the 2018–2020 Drought Years. Remote Sensing, 14:562.

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

Trumbore, S., Brando, P., Hartmann, H., 2015: Forest health and global change. Science, 349:814–818.

Trujillo-Toro, J., Navarro Cerrillo, R., 2019: Analysis of Site-dependent *Pinus halepensis* Mill. Defoliation Caused by 'Candidatus *Phytoplasma pini*' through Shape Selection in Landsat Time Series. Remote Sensing, 11:1868.

Varo, M., Navarro Cerrillo, R., 2021: Stand Delineation of *Pinus sylvestris* L. Plantations Suffering Decline Processes Based on Biophysical Tree Crown Variables: A Necessary Tool for Adaptive Silviculture. Remote Sensing, 13:436.

Walshe, D., McInerney, D., Van De Kerchove, R., Goyens, C., Balaji, P., Byrne, K., 2019: Detecting nutrient deficiency in spruce forests using multispectral satellite imagery. International Journal of Applied Earth Observation and Geoinformation, 86:101975.

Wellbrock, N., Bolte, A., 2019: Status and Dynamics of Forests in Germany: Results of the National Forest Monitoring. Cham, Springer, 384 p.

Wu, D., Johansen, K., Phinn, S., Robson, A., Tu, Y.-H., 2020: Inter-comparison of remote sensing platforms for height estimation of mango and avocado tree crowns. International Journal of Applied Earth Observation and Geoinformation, 89:102091.

Wulder, M., White, J., Nelson, R., Næsset, E., Ørka, H., Coops, N. et al., 2012: LiDAR sampling for large-area forest characterization: a review. Remote Sensing of Environment, 121:196–209.

Wulder, M. A., Loveland, T. R., Roy, D. P., Crawford, C. J., Masek, J. G., Woodcock, C. E. et al., 2019: Current status of Landsat program, science, and applications. Remote Sensing of Environment, 225:127–147.

Žabota, B., Kobal, M., 2022: The Use of UAV-Acquired Multiband Images for Detecting Rockfall-Induced Injuries at Tree Crown Level. Forests, 13:1039.

Zagoranski, F., Pernar, R., Seletković, A., Ančić, M., Kolić, J., 2018: Monitoring the Health Status of Trees in Maksimir Forest Park Using Remote Sensing Methods. South-east European forestry, 9:81–87.

Zarco-Tejada, P., Hornero, A., Beck, P., Kattenborn, T., Kempeneers, P., Hernandez Clemente, R., 2019: Chlorophyll content estimation in an open-canopy conifer forest with Sentinel-2A and hyperspectral imagery in the context of forest decline. Remote Sensing of Environment, 223:320–335.

Other sources

Bayerische Landesanstalt für Wald und Forstwirtschaft, 2020. Buchdrucker und Kupferstecher an Fichte. LWF Merkbl. (In German).

BMEL – Bundesministerium für Ernährung und Landwirtschaft, 2022. Ergebnisse der Waldzustandserhebung 2021 [WWW Document]. BMEL. Available at https://www.bmel.de/DE/themen/wald/wald-in-deutschland/waldzustandserhebung.html (accessed 2.16.23). (In German).

Drechsel, J., 2022. Waldzustandsbericht der Landeshauptstadt Hannover. (In German).

Eichhorn, J., Roskams, P., Potočić, N., Timmermann, V., Ferretti, M., Mues, V. et al., 2020: Part IV: Visual Assessment of Crown Condition and Damaging Agents. In: UNECE ICP Forests Programme Coordinating Centre (ed.): Manual on methods and criteria for harmonized sampling, assessment, monitoring and analysis of the effects of air pollution on forests. Eberswalde, Germany, Thünen Institute of Forest Ecosystems, 49 p. + Annex

European Commission, 2001: Directorate-General for Research and Innovation, EUR 19435 Satellite Based Environmental Monitoring of European Forests, Publications Office.

Food and Agriculture Organization (FAO) of United Nations, 2020. Country Reports | Global Forest Resources Assessments | Food and Agriculture Organization of the United Nations [WWW Document]. Available at https://www.fao.org/forest-resources-assessment/fra-2020/country-reports/en/ (accessed 2.18.23).

Food and Agriculture Organization (FAO) of United Nations, 2021. Available at https://www.fao.org/forestry-fao/pests/99464/en/ last updated: Friday, November 19, 2021.

Food and Agriculture Organization (FAO) of United Nations, 2024. Available at https://www.fao.org/forestry-fao/pests/99464/en/ last updated: Sunday, June 30, 2024.

Henkel, A., Hese, S., Thiel, C., 2022: Erhöhte Buchenmortalität im Nationalpark Hainich? AFZ – derWald. (In German).

Michel, A., Kirchner, T., Prescher, A.-K., Schwärzel, K., 2022: Forest Condition in Europe: The 2022 Assessment. ICP Forests Technical Report under the UNECE Convention on Long-range Transboundary Air Pollution (Air Convention). Braunschweig, Thünen-Institut, Bundesforschungsinstitut für Ländliche Räume, Wald und Fischerei.

Wellbrock, N., Eickenscheidt, N., Hilbrig, L., Dühnelt, P., Holzhausen, M., Bauer, A. et al., 2020: Thünen Working Paper 84: Leitfaden und Dokumentation zur Waldzustandserhebung in Deutschland. Braunschweig, Thünen-Institut für Waldökosysteme, 97 p. (In German).

Supplementary material

Table S1. Results of the PRISMA-Study (Part 1).

Source	Country	Site	Type of forest	Platform	Technology	Studied tree species	Type of damage [abiotic/ biotic]	Specific damage	Number of damage levels
Abdollahnejad & Panagiotidis 2020	Czech Republic	Forest	Mixed forest	UAV	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Abdollahnejad et al. 2021	Czech Republic	Forest	Coniferous forest	Satellite	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	4
Abdullah et al. 2018	Germany	Forest	Mixed forest	Satellite	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	2
Adrien et al. 2016	Belgium	Forest	Mixed forest	UAV	Multispectral	*Alnus glutinosa*	Biotic	Protista – *Phytophthora alni*	2
Ahmed et al. 2021	Great Britain	Forest	Deciduous forest	UAV	Multispectral	*Quercus robur / petraea*, *Betula pubescens*	No data	No data	2
Algeet Abarquero et al. 2020	Spain	Forest	Mixed forest	Aircraft	Hyperspectral	*Pinus halapensis*	Biotic	Nematode – *Bursaphelenchus xylophilus*	5
Andrija et al. 2021	Croatia	Forest	Mixed forest	Satellite	Multispectral	No data	No data	No data	No level
Ariza Salamanca et al. 2019	Spain	Forest	Coniferous forest	Satellite	Multispectral	*Pinus pinaster*	No data	No data	3
Avetisyan et al. 2021	Bulgaria	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	No data	Abiotic	Drought	No level
Baders et al. 2022	Latvia	Forest	Coniferous forest	UAV	Multispectral	*Picea abies*	Abiotic / biotic	No data	6
Balazy et al. 2019a	Poland	Forest	Coniferous forest	Satellite / Aircraft	Multispectral	*Picea abies*	No data	No data	2
Balazy et al. 2019b	Poland	Forest	Coniferous forest	Satellite	Multispectral	*Picea abies*	Abiotic / biotic	No data	No level
Barka et al. 2018	Czech Republic (CZ) / Slovakia (SK)	Forest	Mixed forest	Satellite	Multispectral	No data	No data	No data	4 CZ / 10 SK
Barmpoutis et al. 2019	Greece	Forest	Mixed forest	UAV	Multispectral	fir	No data	No data	3
Barnes et al. 2017	Great Britain	Forest	Coniferous forest	Aircraft	ALS	*Larix kaempferi*, *Larix × eurolepis*	Biotic	Protista – *Phytophthora ramorum*	4
Bárta et al. 2021	Czech Republic	Forest	Coniferous forest	Satellite	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	4
Blaga et al. 2019	Romania	Forest	Deciduous forest	Satellite	Multispectral	No data	No data	No data	No level
Briechle et al. 2021	Germany / Ukraine	Forest	Mixed forest	Aircraft / UAV	Multispectral / ALS	*Pinus sylvestris*, *Betula*, *Alnus glutinosa*	No data	No data	3
Brovkina et al. 2018	Czech Republic	Forest	Mixed forest	UAV	Multispectral	*Fagus sylvatica*, *Abies alba*, *Picea abies*	No data	No data	2
Brovkina et al. 2017	Czech Republic	Forest	Coniferous forest	Satellite / Aircraft	Multispectral	*Picea abies*	No data	No data	3
Bryk et al. 2021	Poland	Forest	Mixed forest	Satellite	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	No level
Buras et al. 2020	Europe	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	No data	Abiotic	Drought, heat	No level
Cardil et al. 2017	Spain	Forest	Coniferous forest	UAV	Multispectral	*Pinus*	Biotic	Moth – *Thaumetopoea pityocampa*	3
Chan et al. 2020	Great Britain	Forest	Deciduous forest	Aircraft	Hyperspectral	*Fraxinus excelsior*	Biotic	Fungi – *Hymenoscyphus fraxineus*	3
Chaparro et al. 2018	Spain	Forest	No data	Satellite	Multispectral / Radar	No data	Abiotic	Drought	no level
Chi et al. 2020	Belgium	Forest	Deciduous forest	Aircraft	Hyperspectral / ALS	*Acer* spp., *Aesculus*, *Tilia*	No data	No data	3
Cucca et al. 2020	Italy	Forest	Mixed forest	Satellite	Multispectral	*Pinus pinea*	Abiotic / biotic	Drought / *Tomicus destruens*	No level

Source	Country	Site	Type of forest	Platform	Technology	Studied tree species	Type of damage [abiotic/ biotic]	Specific damage	Number of damage levels
D'Odorico et al. 2021	Switzerland	Forest	Coniferous forest	UAV	Multispectral	*Pinus sylvestris*	Abiotic	Drought	No level
Dalponte et al. 2022	Norway	Forest	Mixed forest	Aircraft	Hyperspectral	*Picea abies*	Biotic	Fungi	2
Degerickx et al. 2018	Belgium	Forest	Deciduous forest	Aircraft	Hyperspectral / ALS	*Acer* spp., *Aesculus*, *Platanus*, *Tilia*	No data	No data	4
Duarte et al. 2020	Portugal	Forest	Deciduous forest	UAV	Multispectral	*Eucalyptus* spp.	Biotic	Bark beetle – Eucalyptus longhorned borer *Phoracantha* spp.	2
Einzmann et al. 2021	Germany	Forest	Coniferous forest	Aircraft	Hyperspectral	*Picea abies*	No data	No data	2
Fernandez–Carrillo et al. 2020	Czech Republic	Forest	Mixed forest	Satellite	Multispectral	*Picea abies*	Biotic	Bark beetle	4
García–Montero et al. 2021	Europe	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	No data	No data	No data	No level
Georgiev et al. 2022	Bulgaria	Forest	Mixed forest	Satellite / Aircraft / UAV	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	2
Georgieva et al. 2022	Bulgaria	Forest	Coniferous forest	UAV	Multispectral	*Pinus sylvestris*, *Pinus nigra*	Abiotic / biotic	Storm, Bark beetle, moth	2
Guerra et al. 2021	Portugal	Forest	Deciduous forest	UAV	Multispectral	*Alnus glutinosa*	biotic	Protista – *Phytophthora alni*	3
Hawryło et al. 2018	Poland	Forest	Coniferous forest	Satellite	Multispectral	*Pinus sylvestris*	No data	No data	No level
Hernandez Clemente et al. 2018	Spain	Forest	Deciduous forest	Aircraft	Hyperspectral	*Quercus ilex*	Biotic	Protista – *Phytophthora*	No level
Ho et al. 2022	Switzerland	Forest	Mixed forest	UAV	Multispectral	No data	No data	No data	5
Hornero et al. 2020	Italy	Forest	Deciduous forest	Satellite / Aircraft	Multispectral	*Olea europaea*	Biotic	Bacteria – *Xylella fastidiosa*	5
Hornero et al. 2021	Spain	Forest	Deciduous forest	Aircraft	Hyperspectral / Thermal	*Quercus ilex* subsp. *ballota*	Biotic	Protista – *Phytophthora cinnamomi*	4
Huo et al. 2020	Sweden	Forest	Coniferous forest	Satellite	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Huo et al. 2021	Sweden	Forest	Coniferous forest	Satellite	Multispectral / Radar	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Junttila et al. 2022	Finland	Forest	Mixed forest	Aircraft / UAV	Multispectral / ALS	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Kälin et al. 2018	Switzerland	Forest	Mixed forest	Ground–based platform	Multispectral	*Picea abies*, *Fagus sylvatica*, *Abies alba*, *Pinus sylvestris*, *Alnus glutinosa*, *Larix decidua*, *Acer pseudoplatanus*, *Quercus robur*, *Pinus mugo*, *Castanea sativa*, *Quercus petraea*, *Pseudotsuga menziesii*, *Tilia cordata*, *Betula pendula*, other bushes	No data	No data	No level
Kamińska et al. 2018	Poland	Forest	Mixed forest	Aircraft	Multispectral / ALS	*Quercus robur*, *Q. petraea*, *Carpinus betulus*, *Tilia cordata*, *Picea abies*, *Acer platanoides*, *Betula pendula*, *B. pubescens*, *Pinus sylvestris*, *Alnus glutinosa*	No data	No data	2
Katkovsky et al. 2020	Belarus	Forest	Mixed forest	Satellite	Multispectral	No data	No data	No data	2
Khoury & Coomes 2020	Spain	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	No data	Abiotic	Drought	No level
Klouček et al. 2019	Czech Republic	Forest	Mixed forest	UAV	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Kotlarz et al. 2022	Poland	Forest	Mixed forest	Aircraft / UAV	Multispectral	*Quercus robur*	Abiotic	Drought	No level

Source	Country	Site	Type of forest	Platform	Technology	Studied tree species	Type of damage [abiotic/ biotic]	Specific damage	Number of damage levels
Lambert et al. 2015	France	Forest	Coniferous forest	Satellite	Multispectral	*Abies alba*, *Picea abies*, *Pseudotsuga menziesii*	Abiotic	Drought	4
Laštovička et al. 2020	Czech Republic / Slovakia	Forest	Coniferous forest	Satellite	Multispectral	*Picea abies*	Biotic	Bark beetle	No level
Liu et al. 2021	Germany	Forest	Mixed forest	Satellite	Multispectral	No data	No data	No data	2
Maltezos et al. 2019	Greece	Forest	Deciduous forest	Satellite	Multispectral / Radar	No data	No data	No data	No level
Marx & Tetteh 2017	Germany	Forest	Mixed forest	Satellite	Multispectral	*Pinus*	No data	No data	4
Meyer et al. 2020	Germany	Forest	Deciduous forest	Satellite	Multispectral	*Fagus sylvatica*, *Quercus robur*	abiotic	Drought	No level
Migas-Mazur et al. 2021	Poland / Slovakia	Forest	Coniferous forest / Deciduous forest	Satellite	Multispectral	*Picea abies*	Abiotic / biotic	Storm, Bark beetle	3
Moreno-Fernández et al. 2021	Spain	Forest	Mixed forest	Satellite	Multispectral	*Pinus pinaster*	Abiotic	Drought	No level
Näsi et al. 2018	Finland	Forest	Coniferous forest	Aircraft / UAV	Hyperspectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Navarro Cerrillo et al. 2019	Spain	Forest	Deciduous forest	Satellite	Multispectral / ALS	*Quercus ilex*	Biotic	Protista – *Phytophthora*	2
Navarro Cerrillo et al. 2019	Portugal	Forest	Deciduous forest	Satellite / UAV	Multispectral	*Quercus suber*	Biotic	No data	2
Navrozidis et al. 2019	Greece	Plantation	No data	Satellite	Multispectral	*Olea europaea*	Biotic	Fungi – *Verticillium dahliae*	2
Nowakowska et al. 2020	Poland	Forest	Coniferous forest	Aircraft	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	4
Ogaya et al. 2015	Spain	Forest	Deciduous forest	Satellite	Multispectral	*Quercus ilex*, *Phillyrea latifolia*, *Arbusto unedo*	Biotic	Moth – *Catocala nymphagoga*	No level
Ogaya et al. 2020	Spain	Forest	Deciduous forest	Satellite	Multispectral	*Quercus ilex*, *Phillyrea latifolia*, *Arbusto unedo*	Abiotic	Drought	No level
Peters et al. 2020	Switzerland	Forest	Coniferous forest	Satellite	Multispectral	*Larix decidua*	Biotic	Moth – *Zeiraphera griseana*	No level
Pérez-Romero et al. 2019	Spain	Forest	Coniferous forest	Satellite	Multispectral	*Pinus halepensis*, *P. pinea*, *P. pinaster*, *P. nigra*, *P. sylvestris*	Biotic	Moth – *Thaumetopoea pityocampa*	4
Piragnolo et al. 2021	Italy	Forest	No data	Satellite	Multispectral	No data	Abiotic	Storm	No level
Poblete et al. 2021	Italy / Spain	Plantation	No data	Aircraft	Hyperspectral / Thermal	*Olea europaea*	Biotic	Fungi – *Verticillium dahliae* / bacteria – *Xylella fastidiosa*	2
Prăvălie et al. 2022	Romania	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	*Fagus sylvatica*, *Picea abies*, *Abies alba*	No data	No data	4
Recanatesi et al. 2018	Italy	Forest	Deciduous forest	Satellite / Aircraft	Multispectral	*Quercus robur*, *Q. frainetto*, *Q. pubescens*, *Q. cerris*	No data	No data	No level
Recanatesi et al. 2019	Italy	Forest	Coniferous forest	Satellite / Aircraft	Multispectral	*Pinus*	Biotic	Bark beetle – *Tomicus destruens*	6
Rodes et al. 2021	Spain	Park	Mixed forest	Satellite / Aircraft	Multispectral	*Pinus pinea*, *Ulmus pumila*	No data	No data	5
Romero-Ramirez et al. 2018	Spain	Forest	Coniferous forest	Aircraft	Hyperspectral / ALS	*Pinus sylvestris*, *P. nigra*	No data	No data	2
Safonova et al. 2021	Bulgaria	Forest	Mixed forest	UAV	Multispectral	*Picea abies*, *Fagus sylvatica*	No data	No data	4

Source	Country	Site	Type of forest	Platform	Technology	Studied tree species	Type of damage [abiotic/ biotic]	Specific damage	Number of damage levels
Schratz et al. 2021	Spain	Forest	Coniferous forest	Aircraft	Hyperspectral	*Pinus radiata*	Biotic	Fungi – *Diplodia sapinea*, *Fusarium circinatum*, *Armillaria mellea*, *Heterobasidion annosum*, *Lecanosticta acicola*, *Dothistroma septosporum*	No level
Senf et al. 2021	Europe	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	No data	No data	No data	No level
Smigaj et al. 2015	Great Britain	Forest	Coniferous forest	Aircraft / UAV	Multispectral / Thermal / ALS	*Pinus sylvestris*, *P. contorta*	Biotic	Fungi – *Dothistroma septosporum*	No level
Solano et al. 2019	Italy	Plantation	Deciduous forest	Satellite / Aircraft	Multispectral / ALS	*Olea europaea*	No data	No data	No level
Stereńczak et al. 2017	Poland	Forest	Mixed forest	Aircraft	Multispectral / ALS	No data	No data	No data	2
Stereńczak et al. 2020	Poland	Forest	Mixed forest	Aircraft	Hyperspectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	2
Stereńczak et al. 2019	Poland	Forest	Mixed forest	Aircraft	Hyperspectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	2
Sturm et al. 2022	Switzerland	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	No data	Abiotic	Drought	2
Trujillo-Toro & Navarro Cerrillo 2019	Spain	Forest	Coniferous forest	Satellite	Multispectral	*Pinus halepensis*	Biotic	Bacteria – *Candidatus Phytoplasma pini*	3
Varo & Navarro Cerrillo 2021	Spain	Forest	Coniferous forest	Satellite / Aircraft	Multispectral	*Pinus sylvestris*	No data	No data	3
Walshe et al. 2019	Ireland	Forest	Coniferous forest	Satellite	Multispectral	*Picea sitchensis*, *Picea abies*	Abiotic	Nutrient deficiencies	2
Zagoranski et al. 2018	Croatia	Park	Mixed forest	Satellite	Multispectral	*Quercus*; *Carpinus betulus*, *Robinia pseudoacacia*	No data	No data	No level
Zarco-Tejada et al. 2019	Spain	Forest	Coniferous forest	Satellite / Aircraft	Multispectral	*Pinus pinaster*, *Pinus nigra*	Abiotic / biotic	Drought, fungi	No level
Ali et al. 2021	Germany	Forest	Mixed forest	Satellite / Aircraft	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Rullán et al. 2015	Spain	Forest	Deciduous forest	Satellite	Multispectral	*Fagus sylvatica*	Biotic	Leaf feedling beetle – *Rhynchaenus fagi*	No level
Minařík & Langhammer 2016	Czech Republic	Forest	Coniferous forest	UAV	Multispectral	*Picea abies*	Abiotic / biotic	Storm, Bark beetle	3
Kampen et al. 2019	Austria	Forest	Mixed forest	UAV	Multispectral	*Picea abies*, *Fraxinus excelsior*	Biotic	Fungi – *Hymenoscyphus pseudoalbidus*	5
Dimitrov et al. 2018	Bulgaria	Park	No data	UAV	Multispectral	*Ailanthus altissima*, *Abies alba*, *Cercis siliquastrum*, *Diospyros lotus*, *Fraxinus ornus*, *Tilia argentea*, *T. platyphillos*, *Sambucus nigra*, *Sophora japonica*	Biotic	Fungi – *Allantophomopsis pseudotsugae*, *Botryosphaeria dothidea*, *Cryptostroma corticale*, *Diplodia sapinea*, *Dothistroma pini*, *Ophiostoma novo-ulmi*	5
Tilly et al. 2020	Spain	Forest	Deciduous forest	Satellite / Aircraft	Multispectral	*Quercus ilex*, *Q. suber*	No data	No data	3
Cârlan et al. 2020	Romania	Park	Mixed forest	Satellite	Multispectral	No data	No data	No data	No level

Source	Country	Site	Type of forest	Platform	Technology	Studied tree species	Type of damage [abiotic/ biotic]	Specific damage	Number of damage levels
Puletti et al. 2019	Italy	Forest	Deciduous forest	Satellite	Multispectral	*Fagus sylvatica*, Quercus pubescens, *Quercus ilex*	Abiotic	Drought	2
Smigaj et al. 2019	Great Britain	Forest	Coniferous forest	UAV	ALS / Thermal	*Pinus sylvestris*	Biotic	Fungi – *Dothistroma septosporum*	No level
Henkel et al. 2022	Germany	Forest	Deciduous forest	Satellite / Aircraft	Multispectral	*Fagus sylvatica*	Abiotic	Drought, heat	4
Kamińska, 2023	Poland	Forest	Coniferous forest	Aircraft	Multispectral / ALS	*Picea abies*, *Pinus sylvestris*	Biotic	Bark beetle – *Ips typographus*	2
Moreno-Fernández et al. 2022	Spain	Forest	Coniferous forest	Satellite	Multispectral	*Pinus pinea*	Abiotic	Drought	3
Camino et al. 2022	Spain	Forest	Coniferous forest	Satellite	Multispectral	*Abies pinsapo*	Abiotic	Drought	No level
Piedallu et al. 2022	France	Forest	Coniferous forest	Satellite	Multispectral	*Abies alba*, *Picea abies*	Abiotic / biotic	Drought, Competition	2
Kanerva et al. 2022	Finland	Forest	Coniferous forest	UAV	Multispectral	*Picea abies*	Biotic	Bark beetle – *Ips typographus*	3
Navrozidis et al. 2022	Greece	Plantation	Deciduous forest	Satellite	Multispectral	*Olea europaea*	Biotic	Fungi – *Verticillium dahliae*, *Spilocaea oleaginea*	4
Žabota & Kobal 2022	Slovenia	Forest	Mixed forest	UAV	Multispectral	*Fagus sylvatica*, *Larix decidua*, *Pinus sylvestris*, *Picea abies*, *Abies alba*	Abiotic	Stone impact	2
Candotti et al. 2022	Italy / Austria	Forest	Mixed forest	Satellite	Multispectral	*Picea abies*	Abiotic / biotic	Storm, Bark beetle	4
Descals et al. 2022	Europe	Forest	Coniferous forest / Deciduous forest / Mix forest	Satellite	Multispectral	No data	Abiotic	Drought	2
Allen et al. 2022	Norway	Forest	Coniferous forest	UAV	Hyperspectral / ALS	*Picea abies*	Biotic	Fungi – *Heterobasidion*, *Armillaria*	2
Camino et al. 2022	Spain	Plantation	Deciduous forest	Aircraft	Hyperspectral	*Prunus dulcis*	Biotic	Fungi – *Xylella fastidiosa*	2

Table S2. Results of the PRISMA-Study (Part 2).

Source	Vegetation indices	NDVI	Texture	Level	Automated tree detection	Automated tree species classification	Classification of damage level	Classification / regression	Method	Overall accuracy (OA) / Coefficient of determination (R^2)
Abdollahnejad & Panagiotidis 2020	True	True	True	Single tree	True	False	True	Classification	SVM	OA = 84.7%
Abdollahnejad et al. 2021	True	True	False	Single tree	False	False	False	Regression	PCA	No data
Abdullah et al. 2018	True	True	False	Forest stand	No data	No data	No data	Regression	PCA / PLS-DA	No data
Adrien et al. 2016	True	True	True	Single tree	False	True	True	Classification	RF	OA = 90.6%
Ahmed et al. 2021	True	True	False	Single tree	False	True	True	Regression	PCA	No data
Algeet Abarquero et al. 2020	True	False	False	Single tree	False	False	True	Classification	RF / SVM	OA = 90%
Andrija et al. 2021	True	True	False	Forest stand	No data	No data	No data	Regression	PCA	No data
Ariza Salamanca et al. 2019	True	True	False	Forest stand	No data	No data	No data	Regression	RF / SVM / NN	R^2 = 0.79 / RMSE = 0.059
Avetisyan et al. 2021	True	False	False	Ecosystem	No data	No data	No data	No data	No data	No data
Baders et al. 2022	True	True	False	Single tree	True	False	True	Classification	RF	OA = 56%
Balazy et al. 2019a	False	False	No data	Single tree / forest stand	False	False	True	No data	No data	OA = 97%
Balazy et al. 2019b	True	True	False	Forest stand	No data	No data	No data	Classification	Boosted regression tree	No data
Barka et al. 2018	True	True	False	Forest stand	No data	No data	No data	Classification	NN	No data for OA / R^2 = 0.86

Source	Vegetation indices	NDVI	Texture	Level	Automated tree detection	Automated tree species classification	Classification of damage level	Classification / regression	Method	Overall accuracy (OA) / Coefficient of determination (R^2)
Barmpoutis et al. 2019	False	False	True	Single tree	True	False	True	Classification	Multi-Pyramid Features Extraction	OA = 93.8%
Barnes et al. 2017	False	False	No data	Single tree	True	False	True	No data	No data	No data
Bárta et al. 2021	True	True	False	Forest stand	No data	No data	No data	Classification	RF	OA = 78%
Blaga et al. 2019	True	True	False	Forest stand / ecosystem	No data	No data	No data	No data	No data	No data
Briechle et al. 2021	False	False	No data	Single tree	True	True	True	Classification	CNN	OA = 95%
Brovkina et al. 2018	True	True	False	Single tree	False	True	True	Classification	GEOBIA	OA = 74%
Brovkina et al. 2017	False	False	No data	Forest stand	No data	No data	No data	Regression	k-Mean-Clustering	No data
Bryk et al. 2021	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Buras et al. 2020	True	True	False	Ecosystem	No data	No data	No data	Regression	Regression	No data
Cardil et al. 2017	False	False	No data	Single tree	True	False	True	Classification	MLH	OA = 79%
Chan et al. 2020	True	No data	False	Single tree	True	True	True	Classification	RF	OA = 77%
Chaparro et al. 2018	False	False	False	Ecosystem	No data	No data	No data	No data	No data	No data
Chi et al. 2020	True	True	False	Single tree	True	False	True	Classification	RF	OA = 86%
Cucca et al. 2020	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
D'Odorico et al. 2021	False	False	False	Single tree	True	False	True	Regression	Regression	No data
Dalponte et al. 2022	False	False	False	Single tree	True	False	True	Classification / Regression	CNN	OA = 65%
Degerickx et al. 2018	False	False	False	Single tree	True	False	True	Regression	PLSR	R^2 = 0.82, RMSE = 4.4
Duarte et al. 2020	True	True	False	Single tree	True	False	True	Classification	RF	OA = 98.5%
Einzmann et al. 2021	True	True	False	Single tree	True	False	True	Classification	RF	OA = 92%
Fernandez-Carrillo et al. 2020	True	True	False	Forest stand	No data	No data	No data	Classification / Regression	Regression	OA = 80%
García-Montero et al. 2021	False	No data	False	Ecosystem	No data	No data	No data	No data	No data	No data
Georgiev et al. 2022	True	True	False	Single tree / forest stand	False	False	False	No data	No data	No data
Georgieva et al. 2022	True	True	False	Single tree / forest stand	False	False	False	No data	No data	No data
Guerra et al. 2021	True	True	True	Single tree	True	False	True	Classification / Regression	RF / Regression	OA = 67%
Hawryło et al. 2018	True	True	False	Forest stand	No data	No data	No data	Classification / Regression	(kNN) / RF / SVM	OA = 78%
Hernandez Clemente et al. 2018	True	True	False	Single tree	False	False	False	Regression	Regression	No data
Ho et al. 2022	False	No data	False	Single tree	True	False	True	Classification	NN	No data
Hornero et al. 2020	True	True	False	Single tree	False	False	False	Regression	Regression	No data
Hornero et al. 2021	True	True	True	Single tree	True	False	True	Classification	RF / SVM	OA = 82%
Huo et al. 2020	False	No data	False	Forest stand	No data	No data	No data	Classification	No data	No data
Huo et al. 2021	True	True	False	Forest stand	No data	No data	No data	Classification	RF	OA = 91%
Junttila et al. 2022	True	True	False	Single tree	True	False	True	Classification	RF	OA = 89%
Kälin et al. 2018	False	No data	False	Single tree	False	False	True	Classification	CNN	OA = 80%
Kamińska et al. 2018	False	No data	False	Single tree	True	False	True	Classification	RF	OA = 90%

Source	Vegetation indices	NDVI	Texture	Level	Automated tree detection	Automated tree species classification	Classification of damage level	Classification / regression	Method	Overall accuracy (OA) / Coefficient of determination (R^2)
Katkovsky et al. 2020	False	No data	False	Forest stand	No data	No data	No data	Classification	No data	OA = 57%
Khoury and Coomes 2020	True	True	False	Ecosystem	No data	No data	No data	No data	No data	No data
Klouček et al. 2019	True	True	False	Single tree	True	False	True	Classification	MLH	OA = 96%
Kotlarz et al. 2022	False	No data	False	Single tree	True	False	True	Classification / Regression	regression + machin learning	No data
Lambert et al. 2015	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Laštovička et al. 2020	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Liu et al. 2021	True	False	True	Single tree	False	False	True	Classification	RF / SVM / NN	OA = 94%
Maltezos et al. 2019	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Marx and Tetteh, 2017	True	False	False	Forest stand	No data	No data	No data	Classification / Regression	Classification and Regression Trees (CART) algorithm	No data
Meyer et al. 2020	True	True	False	No data	No data	No data	No data	Regression	PCGA	No data
Migas-Mazur et al. 2021	True	True	False	Forest stand	No data	No data	No data	Classification	SVM	OA = 94%
Moreno-Fernández et al. 2021	True	True	False	Forest stand	No data	No data	No data	Classification	Bayesian estimator	No data
Näsi et al. 2018	True	False	False	Single tree	True	False	True	Classification	SVM	OA = 73%
Navarro Cerrillo et al. 2019	True	True	False	Single tree	True	False	True	Classification	RF	OA = 85%
Navarro Cerrillo et al. 2019	True	True	False	Single tree	True	False	True	No data	cumulative distribution function (CDF)	No data
Navrozidis et al. 2019	True	False	False	Forest stand	No data	No data	No data	No data	No data	No data
Nowakowska et al. 2020	False	No data	False	Single tree	False	False	False	No data	No data	No data
Ogaya et al. 2015	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Ogaya et al. 2020	True	True	False	No data	No data	No data	No data	Regression	Regression	No data
Peters et al. 2020	True	True	False	Single tree	False	False	False	No data	No data	No data
Pérez-Romero et al. 2019	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Piragnolo et al. 2021	True	True	False	Forest stand	No data	No data	No data	Regression	RF / KNN	R^2 = 0.84 / RMSE = 10.56
Poblete et al. 2021	False	No data	False	Single tree	False	False	False	Classification	RF / SVM	98%
Prăvălie et al., 2022	True	True	False	Ecosystem	No data	No data	No data	No data	No data	No data
Recanatesi et al. 2018	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Recanatesi et al. 2019	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Rodes et al. 2021	False	No data	False	Single tree	True	False	True	Regression	SVM	R^2 = 0.93, RMSE = 10.87
Romero-Ramirez et al. 2018	True	True	False	Single tree	False	False	False	Regression	Regression	R^2 = 0.91 / RMSE = 0.827
Safonova et al. 2021	False	No data	False	Single tree	True	True	True	Classification	No data	No data
Schratz et al. 2021	True	True	False	Single tree	False	False	True	Classification	RF / SVM	No data
Senf et al. 2021	True	True	False	Forest stand / ecosystem	No data	No data	No data	Classification	RF	No data
Smigaj et al. 2015	False	No data	False	Single tree	False	False	False	No data	No data	No data
Solano et al. 2019	True	True	False	Single tree	True	False	True	Classification	GEOBIA	No data
Stereńczak et al. 2017	True	True	False	Single tree	True	False	True	Classification	MLH	OA = 95%
Stereńczak et al. 2020	True	True	False	Single tree	True	True	True	No data	No data	No data

Source	Vegetation indices	NDVI	Texture	Level	Automated tree detection	Automated tree species classification	Classification of damage level	Classification / regression	Method	Overall accuracy (OA) / Coefficient of determination (R^2)
(Stereńczak et al. 2019	True	True	False	Single tree	True	False	True	Classification	RF	OA = 97%
Sturm et al. 2022	True	True	False	Single tree / forest stand	False	False	False	No data	No data	No data
Varo and Navarro Cerrillo, 2021	True	True	False	Single tree	True	False	True	Classification	RF	OA = 84%
Walshe et al. 2019	False	No data	False	Forest stand	No data	No data	No data	Classification	RF	OA = 89%
Zagoranski et al. 2018	False	No data	False	Single tree	False	False	False	No data	No data	No data
Zarco-Tejada et al. 2019	False	No data	False	Single tree	True	False	True	Classification	MLH	No data
Ali et al. 2021	False	No data	False	Forest stand	No data	No data	No data	Classification	No data	OA = 78%
Rullán et al. 2015	False	No data	False	Forest stand	No data	No data	No data	No data	No data	No data
Minařík and Langhammer, 2016	True	True	False	Single tree	False	False	False	No data	No data	No data
Kampen et al. 2019	False	No data	True	Single tree	True	False	True	Classification	GEOBIA	OA = 86%
Dimitrov et al. 2018	True	True	False	Single tree	False	False	False	No data	No data	No data
Tilly et al. 2020	True	True	False	Single tree	False	False	True	Classification	MLH / RF / SVM	OA = 58%
Cârlan et al. 2020	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Puletti et al. 2019	True	True	False	Forest stand	No data	No data	No data	No data	No data	No data
Smigaj et al. 2019	False	No data	False	Single tree	True	False	True	Regression	Regression	$R^2 = 0.527$
Henkel et al. 2022	True	True	False	Single tree / forest stand	True	False	True	Classification	CNN	No data
Kamińska, 2023	False	No data	False	Single tree	False	False	True	Classification	No data	No data
Moreno-Fernández et al. 2022	True	True	False	Forest stand	False	False	True	Classification	No data	No data
Camino et al. 2022	True	True	False	Forest stand	False	True	False	Classification	RF	No data
Piedallu et al. 2022	False	No data	False	Forest stand	False	False	True	Classification	MLH	OA = 92%
Kanerva et al. 2022	False	No data	False	Single tree	True	False	True	Classification	NN	OA = 90%
Navrozidis et al. 2022	True	True	False	Single tree	False	False	True	Regression	Quadratic discriminant analysis	No data
Žabota & Kobal 2022	True	True	False	Single tree	False	False	True	Regression	Regression	$R^2 = 0.82$
Candotti et al. 2022	True	True	False	Forest stand	False	False	True	Classification	ANN, KNN, RF, SVM	OA = 89%
Descals et al. 2022	True	True	False	Ecosystem	False	False	True	Classification	No data	No data
Allen et al. 2022	True	True	False	Single tree	True	False	True	Classification	SVM	OA = 76%
Camino et al. 2022	True	True	False	Single tree	True	False	True	Classification	SVM	OA = 90%