



## Review

# Earth-Observation-Based Monitoring of Forests in Germany—Recent Progress and Research Frontiers: A Review

Stefanie Holzwarth <sup>1,\*</sup>, Frank Thonfeld <sup>1</sup>, Patrick Kacic <sup>2</sup>, Sahra Abdullahi <sup>1</sup>, Sarah Asam <sup>1</sup>,  
Kjirsten Coleman <sup>1</sup>, Christina Eisfelder <sup>1</sup>, Ursula Gessner <sup>1</sup>, Juliane Huth <sup>1</sup>, Tanja Kraus <sup>1</sup>,  
Christopher Shatto <sup>3</sup>, Birgit Wessel <sup>1</sup> and Claudia Kuenzer <sup>1,2</sup>

<sup>1</sup> German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Oberpfaffenhofen, 82234 Wessling, Germany; frank.thonfeld@dlr.de (F.T.); sahra.abdullahi@dlr.de (S.A.); sarah.asam@dlr.de (S.A.); kjirsten.coleman@dlr.de (K.C.); christina.eisfelder@dlr.de (C.E.); ursula.gessner@dlr.de (U.G.); juliane.huth@dlr.de (J.H.); tanja.kraus@dlr.de (T.K.); birgit.wessel@dlr.de (B.W.); claudia.kuenzer@dlr.de (C.K.)

<sup>2</sup> Working Group Earth Observation, Institute of Geography and Geology, University of Würzburg, 97074 Würzburg, Germany; patrick.kacic@dlr.de

<sup>3</sup> Department of Biogeography, University of Bayreuth, 95447 Bayreuth, Germany; christopher.shatto@uni-bayreuth.de

\* Correspondence: stefanie.holzwarth@dlr.de

**Abstract:** One-third of Germany's land surface area is covered by forest (around 11.4 million hectares), and thus, it characterizes the landscape. The forest is a habitat for a large number of animal and plant species, a source of raw materials, important for climate protection, and a well-being refuge for people, to name just a few of its many functions. During the annual forest condition surveys, the crown condition of German forests is assessed on the basis of field samples at fixed locations, as the crown condition of forest trees is considered an important indicator of their vitality. Since the start of the surveys in 1984, the mean crown defoliation of all tree species has increased, now averaging about 25% for all tree species. Additionally, it shows a strong rise in the rate of dieback. In 2019, the most significant changes were observed. Due to the drastic changes in recent years, efforts are being made to assess the situation of the forest using different remote sensing methods. There are now a number of freely available products provided to the public, and more will follow as a result of numerous projects in the context of earth-observation (EO)-based monitoring and mapping of the forests in Germany. In 2020, the situation regarding the use of remote sensing for the German forest was already investigated in more detail. However, these results no longer reflect the current situation. The changes of the last 3 years are the content of this publication. For this study, 84 citable research publications were thoroughly analyzed and compared with the situation in 2020. As a major result, we found a shift in the research focus towards disturbance monitoring and a tendency to cover larger areas, including national-scale studies. In addition to the review of the scientific literature, we also reviewed current research projects and related products. In congruence to the recent developments in terms of publications in scientific journals, these projects and products reflect the need for comprehensive, timely, large-area, and complementary EO-based information around forests expressed in multiple political programs. With this review, we provide an update of previous work and link it to current research activities. We conclude that there are still gaps between the information needs of forest managers who usually rely on information from field perspectives and the EO-based information products.

**Keywords:** remote sensing; earth observation; forest; forest monitoring; forest disturbances; forest structure; Germany; review



**Citation:** Holzwarth, S.; Thonfeld, F.; Kacic, P.; Abdullahi, S.; Asam, S.; Coleman, K.; Eisfelder, C.; Gessner, U.; Huth, J.; Kraus, T.; et al. Earth-Observation-Based Monitoring of Forests in Germany—Recent Progress and Research Frontiers: A Review. *Remote Sens.* **2023**, *15*, 4234. <https://doi.org/10.3390/rs15174234>

Academic Editor: Janne Heiskanen

Received: 31 July 2023

Revised: 25 August 2023

Accepted: 25 August 2023

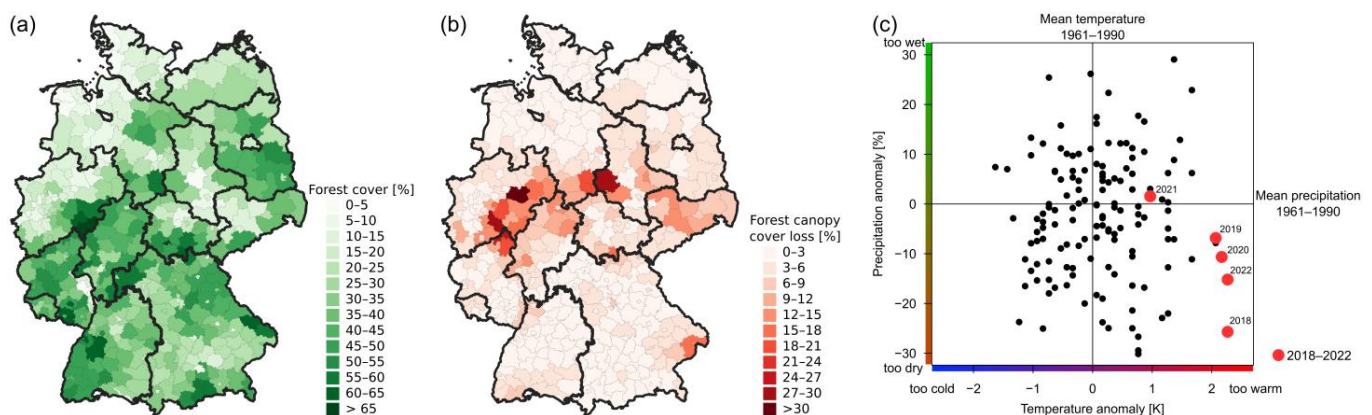
Published: 29 August 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

The topic of earth-observation (EO)-based monitoring of German forests was analyzed in 2020 on the basis of an extensive literature review [1]. However, the authors observed that only three years later, the results do not reflect the current situation and therefore aim to provide an update with this review. The drought years since 2018 have amplified the pressure on Central European forests. The drought mechanisms and impacts were explored exhaustively, leading to various publications (e.g., [2–10]). In Germany, the recent drought years framed severe canopy-cover losses due to forest dieback. These losses were quantified by means of remote sensing data, and for the period of January 2018–April 2021, Thonfeld et al. [11] calculated a canopy-cover loss of 501,000 ha for Germany. After the publication of these figures and further EO-based results concerning the effects of the drought on the German forest (e.g., [4,6,9]), there was a huge media response, and the “concern about the German forests” continues to be a topical and present issue [12]. Policymakers have responded to the recent forest situation (i.e., structure, condition, susceptibility to climate change and other environmental impacts) with various strategy papers and funding for research also in the area of forest monitoring by means of remote sensing [13,14]. Figure 1 compares the forest-cover percentages at the district level in Germany with the distribution of recent forest canopy-cover losses (Figure 1a,b). It can be seen that there is a hotspot region in central Germany reaching from east to west across the country. There is, however, no district without canopy-cover losses. The figure also shows that some of the most heavily affected districts have a considerably large proportion of forest cover, which means that the losses are also rather significant. Figure 1c shows the anomalies of annual mean temperature and annual precipitation with respect to the 1961–1990 average. The past five years (2018–2022) showed large positive anomalies in temperature, which coincided with multiple heatwaves. In addition, four out of the five years showed considerable negative anomalies in precipitation, which coincided with multiple regional droughts. While the droughts and heatwaves did not necessarily ultimately cause forest dieback, these phenomena are known as proximate drivers of forest stress and worsening conditions [15].



**Figure 1.** (a) Forest coverage per district (Landkreis) across all forest types (status of 2020), (b) forest canopy cover loss 2018–April 2021 per district across all forest types [11], (c) annual temperature and precipitation anomalies with respect to the 1961–1990 reference period for Germany (1881–2022) (based on data from the Deutsche Wetterdienst, <https://www.dwd.de/DE/leistungen/zeitreihen/zeitreihen.html#buehneTop>, accessed on 1 July 2023). Four out of the last five years were dryer than the reference average; all five years were considerably warmer than the reference average.

### 1.1. Forests in Germany: Current Challenges

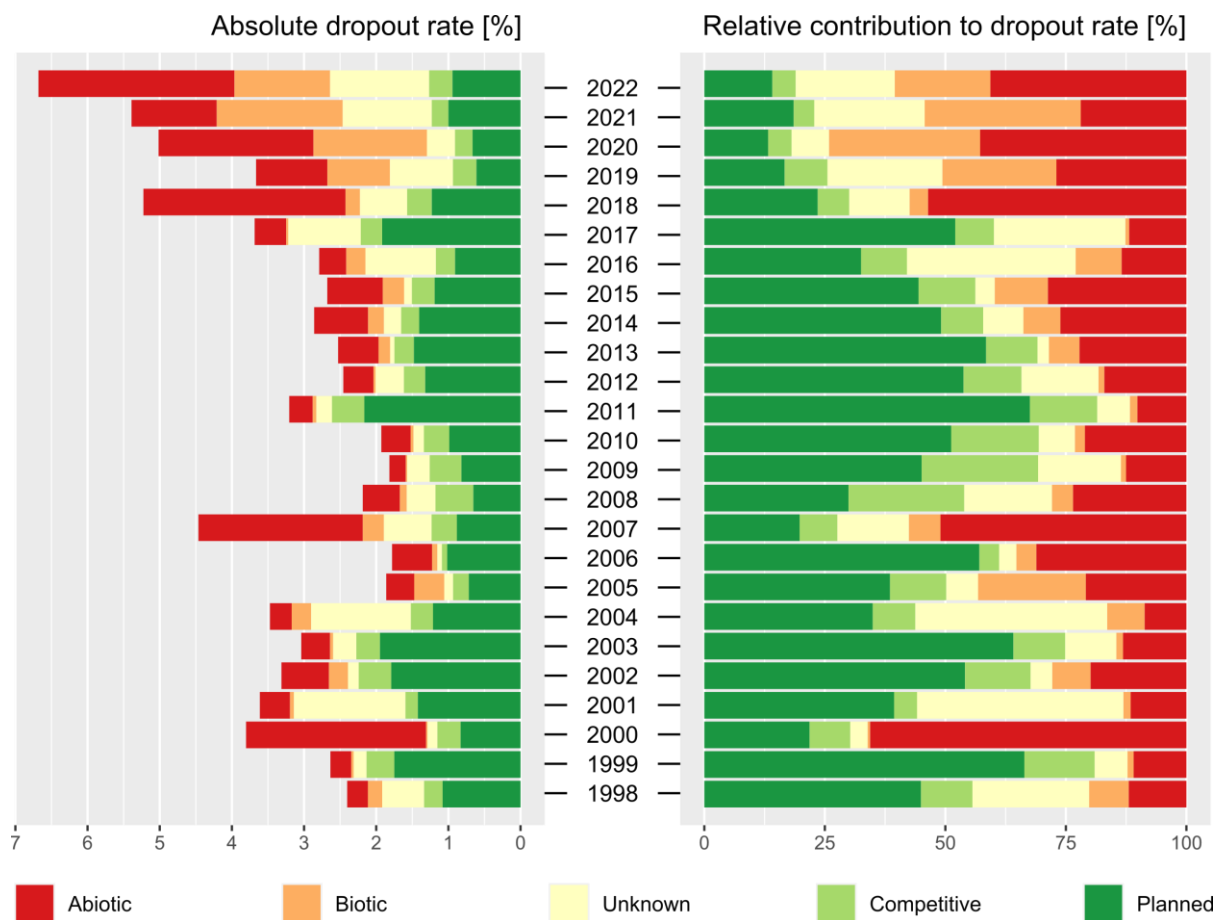
The past five years posed huge challenges to Central European forests. Notable, large storm events hit southeastern, central, and northern Germany (e.g., Friederike in January 2018, Sabine in February 2020, and Zeynep in February 2022). Local storm events and associated windthrow were recorded throughout Germany. Vast areas experienced heat

waves, partly with record-breaking temperatures and associated with remarkable droughts. Rakovec et al. [16] identified the 2018–2020 drought as most severe in Europe over the past 250 years with respect to the areal extent of the affected region, duration, magnitude, and intensity. Most of the ecologically and economically important tree species of Central Europe were affected and showed symptoms of drought stress, such as leaf discoloration and premature leaf shedding, resulting in unprecedented tree mortality [9]. Hot droughts favor the occurrence of insect infestations, particularly through bark beetle (e.g., facilitation of bark beetle survival through the development of additional beetle generations per year, enlargement of potential habitats, and higher susceptibility of trees) [17]. The hot and dry periods starting in 2018 not only resulted in accelerated tree mortality due to unusual strong and wide-spread drought stress but were also often associated with fatal insect outbreaks and the occurrence of an above-average number of fires [11].

German forests are characterized by a few dominant tree species, often occurring in even-aged, homogeneous stands and often at the margins of their ecological niche [1,18]. Most of the forests are managed and play a crucial economic role. While there are only a few options to generate income from forests except their use for timber, the ecosystem services forests are expected to provide are manifold. The need to adapt forests to climate change is well known [5,19–21]. However, the susceptibility of different tree species against particular aspects of climate and climate change (e.g., droughts) often depends on forest management [22]. Therefore, adaptation strategies include the diversification of forests from poorly structured monocultures to mixed stands composed of various tree species and at diverse ages [23], the preference of tree species capable of growing under recent as well as under future climate conditions (e.g., resistance against frost and snow cover, heat and drought tolerance, and storm resistance) [24], and silvicultural strategies aiming at increasing tree resilience against stress [22]. However, these processes and their implementation take time.

The condition of German forests has been monitored at annual intervals since the early 1980s. The assessments are based on ground surveys of crown defoliation satisfying the ICP Forests (International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests) requirements [25]. The latest reports reveal unusually high crown defoliation and hence bad forest conditions among all tree species, with 35% of all sampled trees showing severe signs of crown defoliation, 44% falling within the warning stage, and only 21% without crown defoliation in 2022 [26]. The latter is the lowest value in the timeline.

Figure 2 shows the dropout rate across all tree species in Germany and the relative contribution of the different attributed reasons. The reasons cover biotic and abiotic disturbances as well as competition and planned harvest. Dropout rates and reasons are recorded with the annual crown-condition surveys. The rates are calculated based on the previous year [25]. It can be seen that the rate of planned harvest is reduced after extensive storm events (e.g., cyclone Lothar in late December 1999, cyclone Kyrill in January 2007, cyclone Niklas in March 2015, cyclone Friederike in January 2018, cyclone Sabine in February 2020, or storm Zeynep in February 2022). In years of storm events, the dropout rate caused by abiotic drivers is remarkably high, as is the overall dropout rate. The relative contribution of abiotic drivers can be as high as 65% (e.g., in 2000 after cyclone Lothar). Droughts and heatwaves are other drivers of abiotic dropout. They became increasingly important over the past years [19]. Biotic drivers such as insect infestations often occur in combination with droughts or with heat stress. While the relative contribution of biotic drivers is generally lower than that of planned harvest and abiotic drivers, it became equally important after 2019. The canopy-cover losses since 2018 were unusual [9,11], as confirmed by high dropout rates (Figure 2).



**Figure 2.** Development of the dropout rate since 1998, calculated from the mean values of all tree species native to Germany and broken down by reason for elimination. Although the annual crown-condition assessments started in 1984, data specifying dropout rates are available in sufficient quantity and quality only as of 1998. Data source: Thünen-Institut für Waldökosysteme, 2023, <https://wo-apps.thuenen.de/apps/wze/> (accessed on 19 May 2023).

### 1.2. Earth-Observation-Based Monitoring of Forests in Germany

Operational forest management increasingly demands high-resolution forest information layers derived from earth observation data [27]. Also, the Strategic Research and Innovation Agenda 2030 of the European forest-based sector has asked for remote sensing data to collect detailed and dynamic information, especially in the context of creating climate-change-resilient and stress-tolerant forests [28]. Long-term impacts are monitored using time series such as those from the Landsat and MODIS missions [29,30], whereas short-term impacts require both archived datasets and observations immediately after the event [31]. Long archived time series are used to identify past events and better understand pre-event (e.g., causes) and post-event (e.g., forest recovery) dynamics, and immediate post-event surveys are needed to quantify damage and be responsive in implementing mitigation strategies. Prompt monitoring (e.g., for forest fires or storm events) is becoming more feasible thanks to medium/high spatial resolution and high-repetition frequency imaging systems such as Sentinel 2 [32] and Planet Dove [33]. SAR imagery can also play an important role because of its low sensitivity to atmospheric conditions and is therefore the optimal choice for timely detection [34]. Furthermore, typical aircraft systems such as imaging spectrometers or LiDAR instruments are now increasingly available as spaceborne systems that offer new perspectives to observe forest ecosystems [35–39]. Another driving factor is the availability of open access data and software and the provision of large data archives as so-called analysis ready data (ARD). As the amount of EO data available has

increased dramatically in recent years, new technologies based on cloud computing and distributed systems have made it possible to access, process, and analyze these data [40,41].

In our first review [1], in 2020, we focused on research studies that took place in the context of remote sensing of forests in Germany published up to then (until and including March 2020, 166 publications in total). The analysis allowed us to identify gaps in research and product development. We saw a missing link between the forest-related scientific output in Germany and forest management like the forest inventory programs. There were only few studies on the national level; the majority instead focused on local- to regional-scale areas. Until April 2020, mainly airborne remote sensing sensors were deployed, which also relates to the fact that mono-temporal input data were mostly used. When it comes to research topics, the reviewed studies looked most often into forest structure as an essential parameter to many other forestry-related aspects. We have assumed that, due to the constantly growing number of available EO systems and data as well as the further development of algorithms and computer infrastructure, it will be possible to meet the requirements for EO-based products for the German forest.

Indeed, a lot has been done in this direction in the last years. As we describe below, changes in forests with different focuses can be provided by nationwide maps derived from analyses of remote sensing data. Scientists and developers of the products and users of the information, e.g., public authorities, are networking increasingly. This is promoted above all by networks such as “Copernicus Netzwerkbüro Wald” (Copernicus Networking Office for Forests). Research and development activities in the field of applying different remote sensing methods to forest-related topics are increasingly being supported at the federal and state levels. To some extent, this is also reflected in the strategic documents on a federal level, e.g., the forest strategy of Germany (“Waldstrategie 2050”) [19].

### 1.3. Objectives of this Review

As described above, the forest condition has extremely deteriorated due to the persistent drought in Germany, which has expanded the need for remote-sensing-based monitoring methods. The landscape with respect to the research and use of remote sensing for forestry applications has changed accordingly in Germany. We attempt to illustrate this change with a systematic review of studies, projects, and products from the past 3 years. The goal and the objectives of this second review on EO-based monitoring of forests in Germany are to do the following:

- Give an update (since April 2020) regarding research studies described within scientific publications focusing on forests in Germany, including a categorization on topic, location, extent, spatial resolution, temporal interval, thematic focus, and outcome;
- Present an overview of existing forest-related remote-sensing-based products and projects;
- Consider political and strategic directions in Germany with regard to the use of remote sensing for monitoring the forest;
- Critically discuss limitations and possibilities of EO for different aspects in relation to German forests.

## 2. Methodology of the Review

The focus of this review, as in our previous one, is on the evaluation of scientific publications. However, we expand this focus to projects and products related to EO-based forest monitoring in Germany. The methods of the various reviews and their evaluation are described below. Publications, projects, and developed products were considered for the period from April 2020 up to December 2022. In this short period, over 80 additional scientific papers were published. Therefore, we present an update to our initial review, which contained all studies until April 2020 [1].

### 2.1. Literature Review

The literature review on EO-based forest monitoring in Germany was conducted using *Web of Science* in order to generate a comprehensive database on the relevant literature



spanning the period from April 2020 to December 2022. Therefore, the present review follows up on the initial review on remotely sensed forest monitoring in Germany by Holzwarth et al. 2020, comprising studies until and including March 2020 [1]. A hierarchical search string was created similarly to the one used in Holzwarth et al. 2020 for a representative comparison. The search string is subdivided into three groups, which are concatenated by “AND” operators: forest-context; remote sensing focus; study area within Germany. The keywords within the aforementioned groups are separated by “OR” operators, meaning that at least one keyword of each group needs to be found within the title, abstract, or keywords so that a study is classified as relevant.

The thematic search on forest-related literature is based on the following keywords describing forested areas or structural elements of forests: “forest”, “tree”, “timber”, “wood”, “woodland”, and “wood land”.

In the following, a filter on studies integrating remote sensing sensors was specified using the keywords “remote sensing”, “earth observation”, “satellite”, “spaceborne”, “airborne”, “UAV”, “UAS”, “multispectral”, “hyperspectral”, “imaging spectroscopy”, “SAR”, “radar”, “Lidar”, “stereo”, “thermal”, “Sentinel”, “Landsat”, “MODIS”, “AVHRR”, “Envisat”, “SPOT”, “RapidEye”, “WorldView”, “IKONOS”, “Quickbird”, “Pleiades”, “Geoeye”, “Planet”, “Skysat”, “DESI”, “PRISMA”, “EnMAP”, “Hyperion”, “COSMO”, “ALOS”, “TerraSAR”, “TanDEM”, “RADARSAT”, “ASTER”, “SRTM”, “ICESat”, “GEDI”, “ECOSTRESS”, and “Copernicus”.

The third thematic group, “study area in Germany”, is defined by the keywords “German\*”, “Europe”, “Schleswig Holstein”, “Lower Saxony”, “North Rhine-Westphalia”, “Hesse”, “Rhineland-Palatinate”, “Saarland”, “Baden-Wuerttemberg”, “Mecklenburg-Western Pomerania”, “Hamburg”, “Bremen”, “Berlin”, “Brandenburg”, “Saxony-Anhalt”, “Saxony”, “Thuringia”, and “Bavaria”.

The literature search was conducted on 9 February 2023, amounting to a total number of 695 studies (exact search). We excluded all studies with “random forest” approaches without a forest focus and papers that did not cover study sites in Germany. The subject of each of the remaining studies was recorded and verified as to its relevance. The final number of relevant studies amounts to 84, which were carefully read and which build the basis for this review [3,6,10,11,42–121]. Those studies do not cover terrestrial remote sensing analysis since the focus of this review is on airborne and spaceborne sensors. Furthermore, studies on the coverage of Europe are considered as relevant if explicit forest areas in Germany or Germany as a whole were also included within the analysis and presentation of results.

A second pillar of scientific work related to German forests is formed by the research branches of the federal forest authorities. There are nine institutions and centers covering twelve German federal states that are organized in a working group with a focus on remote sensing of forests [122]. These are as follows:

- Northwest German Forest Research Institute (Hesse, Lower Saxony, Saxony-Anhalt, and Schleswig-Holstein);
- Competence Center Forest and Forestry (Landesbetrieb Sachsenforst, Saxony);
- Forestry Research and Competence Centre (ThüringenForst, Thuringia);
- Bavarian State Institute of Forestry (Bavaria);
- Forest Research Institute Baden-Württemberg (Baden-Württemberg);
- Research Institute for Forest Ecology and Forestry Rhineland-Palatinate (Rhineland-Palatinate);
- Research Unit Silviculture and Forest Growth (Landesforst Mecklenburg-Vorpommern and Mecklenburg–Western Pomerania);
- State Competence Center Forestry Eberswalde (Landesbetrieb Forst Brandenburg, Brandenburg);
- Center for Forest and Timber Management (Landesbetrieb Wald und Holz Nordrhein-Westfalen and North Rhine-Westphalia)

To our knowledge, Saarland and the cities of Hamburg, Bremen, and Berlin do not operate dedicated research units with remote sensing expertise.

Experts from these research centers at the federal state level often author and co-author peer-reviewed papers in scientific journals. However, their main target groups are stakeholders and actors of the German forest sector. Therefore, a large part of the scientific output of these research centers is published in dedicated journals not necessarily listed in citation indices and often in the German language, for example, *AFZ—Der Wald* (<https://www.forstpraxis.de/zeitschriften/afz-derwald>, accessed on 8 May 2023) or *Natur und Landschaft* (<https://www.natur-und-landschaft.de/>, accessed on 8 May 2023). The EO-related articles in these journals often acknowledge the specific history and resulting structure of German forests and are hence highly relevant for local and regional stakeholders. However, they do not show up in this review because they are not searchable in *Web of Science*.

## 2.2. Existing Forest-Related Products

In addition to the literature from recent years, we conducted a review of existing remote sensing products that have been increasingly introduced to the different sectors dealing with forestry recently. Only those products documented in at least one scientific publication were considered in order to meet the requirement of a scientific review; i.e., there are more (mainly commercial) products available, but they are not considered in this publication. Searching the internet for EO-based products cannot be as systematic as in the case of a literature review (see Section 2.1). Therefore, we cannot guarantee completeness under any circumstances, but we consider the results to be a good overview. Besides the necessity of an underlying publication, the products had to meet the following criteria:

- Spatial coverage within Germany. Europe-wide products that include Germany were also considered;
- Sufficient information on the spatial and temporal resolution and the temporal coverage of the products as well as the EO data used.

The products were examined in more detail with regard to the underlying method and the research topic as well as the availability of a validation concept and quality assessment. The result of the review includes a list of nine products that were released in the last few years.

## 2.3. Existing Forest-Related Projects

For the review of projects that had their start date within the period from April 2020 to December 2022 (literature review period), we searched different available databases;

- *German Project Information System* (GEPRIS), which includes projects funded by the German Research Foundation (DFG);
- *CORDIS (Community Research and Development Information Service)*, the European Commission's database covering projects funded by the EU's framework programs;
- The grant program of the German Federal Ministry of Food and Agriculture (BMEL) called "*Waldklimafonds*" (Forest Climate Fund);
- Database of projects in the funding programs of the BMEL, supervised by the Project Management Agency (BLE);
- Project database of the German Environment Agency (UBA)
- Project data base of the German Copernicus Network Office Forest ("*Copernicus Netzwerkbüro Wald*").

Only projects using remote sensing data for forest-related objectives were considered. In total, 34 research projects were examined within this review. As with the products, we cannot guarantee completeness. The funding body and the research field of interest were primarily considered but also, of course, the remote sensing data that were used within the projects (Table S1).

### 3. Results

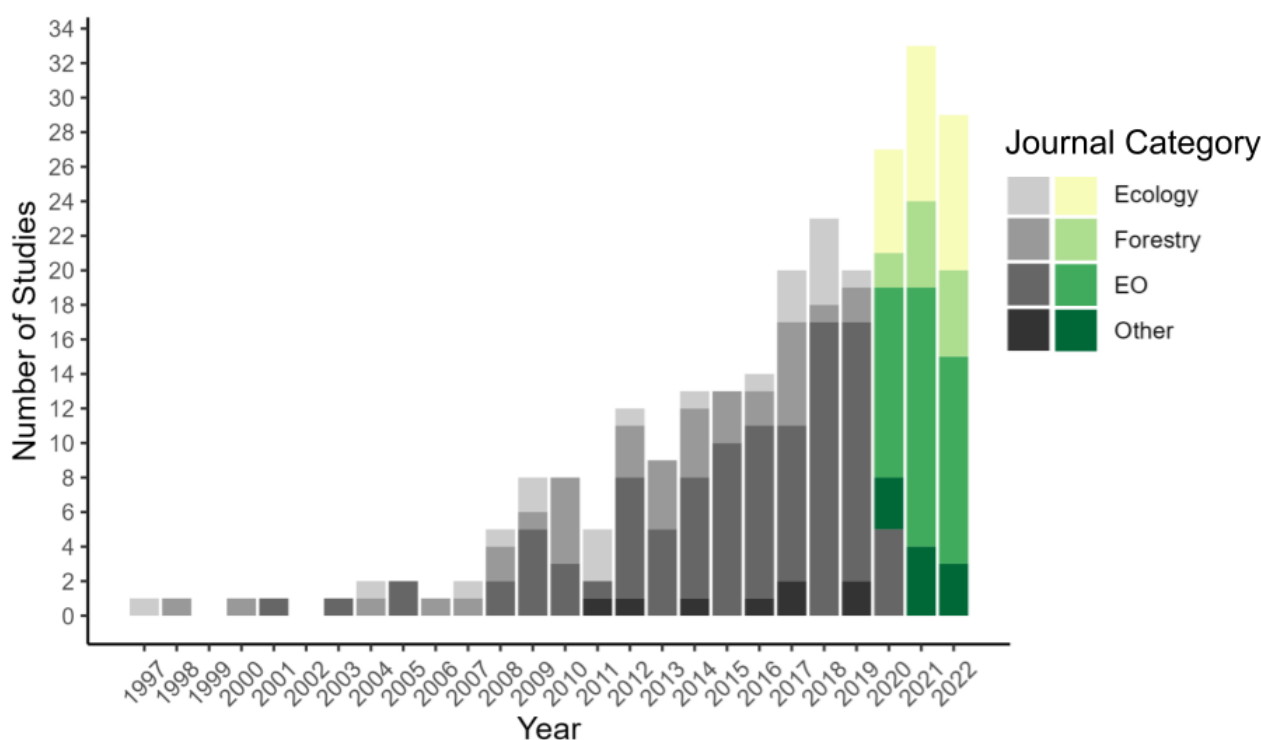
Our focus in this section is on the systematic evaluation of the literature review. Products and projects are evaluated in relation to the results of the literature review; in other words, we try to put the different review results in context with each other.

#### 3.1. Literature Review

A total of 84 research studies are considered within the literature review [3,6,10,11,42–121]. We systematically analyzed the publications according to different criteria, which are reflected in the following sub-chapters.

##### 3.1.1. Review Results: Temporal Development of Publications, Author Affiliation, and Funding of Studies

In the years 2020 to 2022, a total number of 84 relevant research articles were published, which were investigated in this literature review. Figure 3 shows the temporal development of the number of research studies. The greenish bars represent the research articles subject to this review, while grey bars show the research articles covered within the previous review [1]. With 22 studies in 2020, 33 studies in 2021, and 29 studies in 2022, the increase already observed over the previous 23 years continued with an absolute maximum of articles in 2021. With a total of 38 articles, most studies (45% of articles in this review) were published in journals focusing on remote sensing, although their share did not further increase, as observed for the period covered in the previous review [1]. However, a larger number of papers, namely 24 research articles (29%), was published in ecology-related journals within the last three years. The number of papers from this review published in forestry journals was 12 (14%), and papers from other journals were 10 (12%).

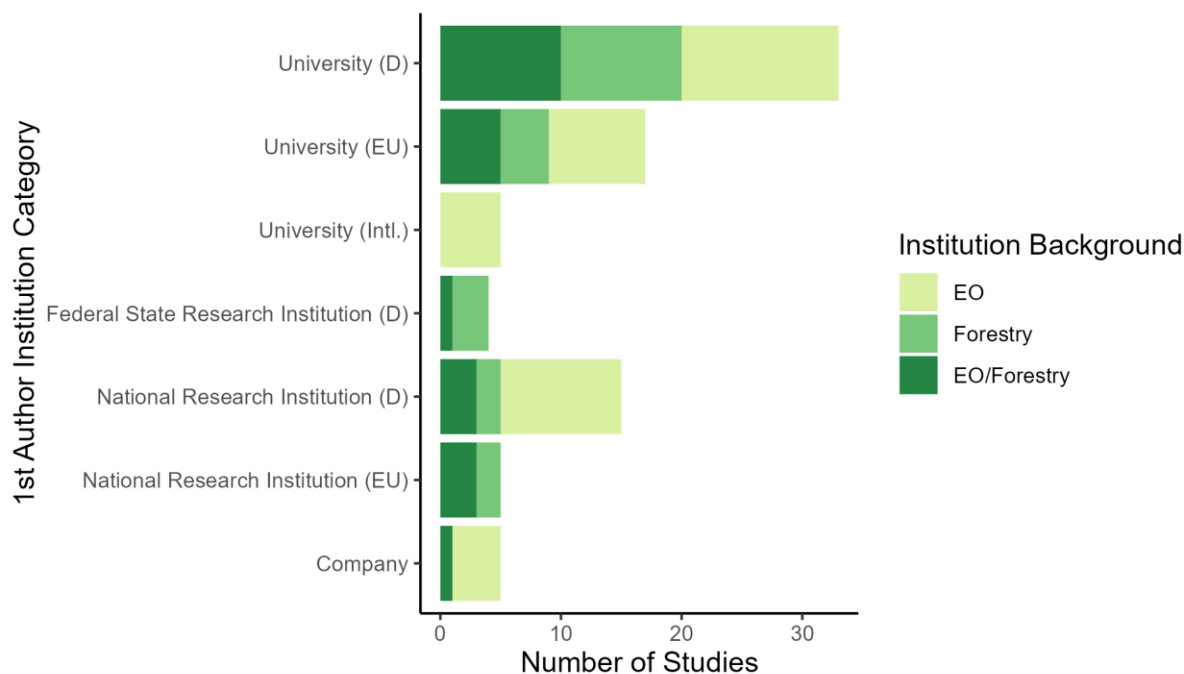


**Figure 3.** Studies ordered by year of publication subdivided into different journal categories. This review covers the studies in greenish colors. The results of the previous review [1] are depicted in greyish colors.

The majority of the first authors of investigated research articles are scientists from German universities (33 articles), followed by European universities (15 articles) (Figure 4). First authors employed at German federal and state research institutes contributed overall



with 18 contributions to the articles investigated in this literature review. Few articles were published from international institutions or universities and companies. In total, 62% of first authors are scientists employed at German universities or German research institutions. The majority of authors have an institutional background in remote sensing (49%) or both EO/forestry (27%), while 24% have a forestry background.



**Figure 4.** Number of studies by research institution.

In comparison to the first author institutions identified in the first review [1], the distribution among institution categories is very similar. The share of studies of first authors from European state research institutions and companies has slightly increased. With respect to the institution background, we found that a larger share of publications for the years 2020–2022 (this review) can be assigned to institutions with a background on both EO and forestry (Figure 4, dark green), while in the previous review, most first author institutions were categorized as having a focus on either EO or forestry only [1].

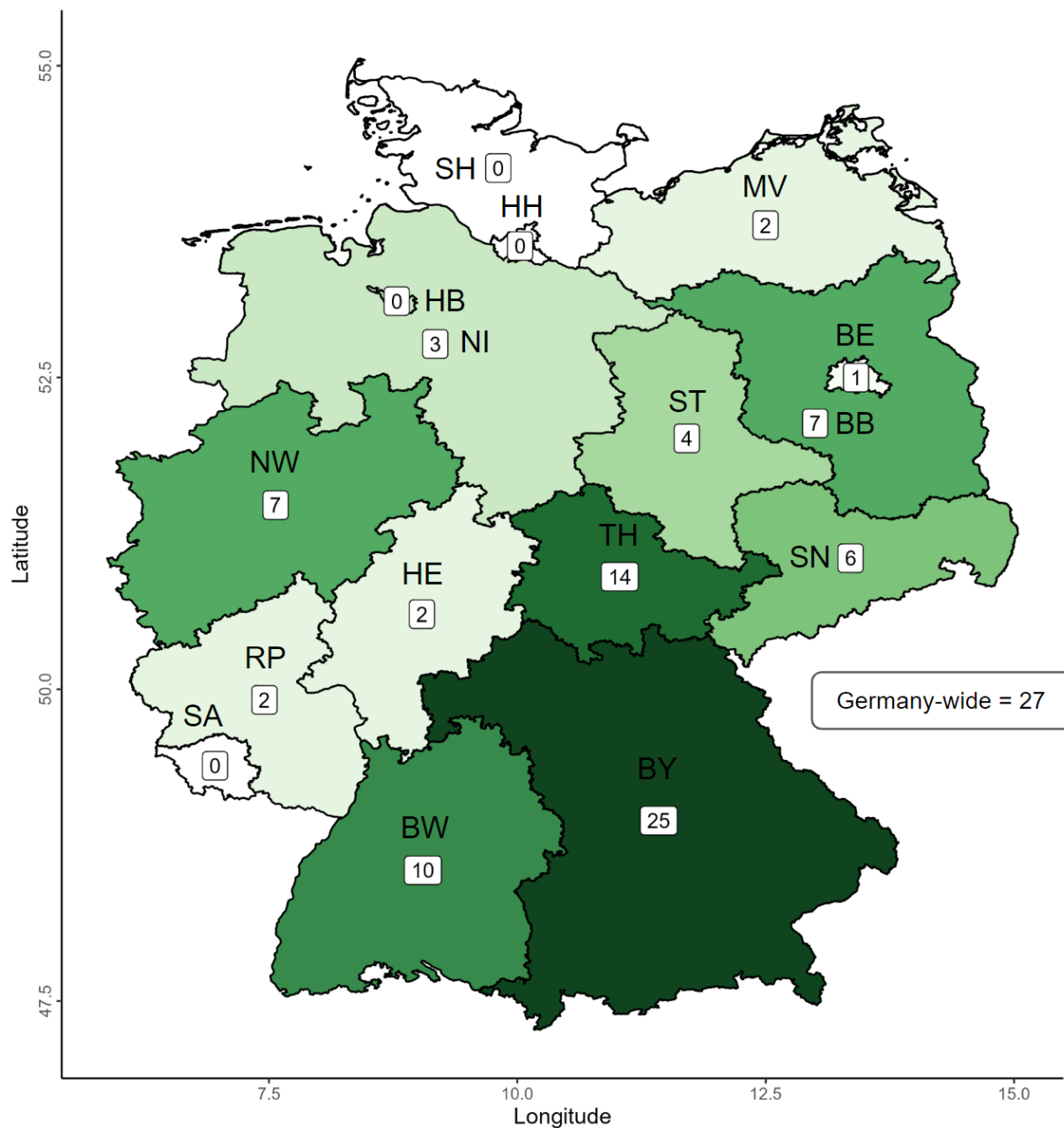
Considering the funding of the 84 research studies, 18% were financed by national ministries. Furthermore, 13% of the studies received funding from federal state ministries (mainly Bavaria). The German Research Foundation (DFG) also funded 13% of the published studies. In total, 50% of the research studies received financial support from various German institutions, while 23% of the studies have received EU funding (e.g., European Research Council, European Union), and 33% were funded or co-funded by foreign funding sources (e.g., national research councils, universities, national ministries and science foundations from European countries, and research grants/R&D program/scholarships from China).

### 3.1.2. Review Results: Spatial Coverage, Spatial Extent, and Investigated Forest Scale

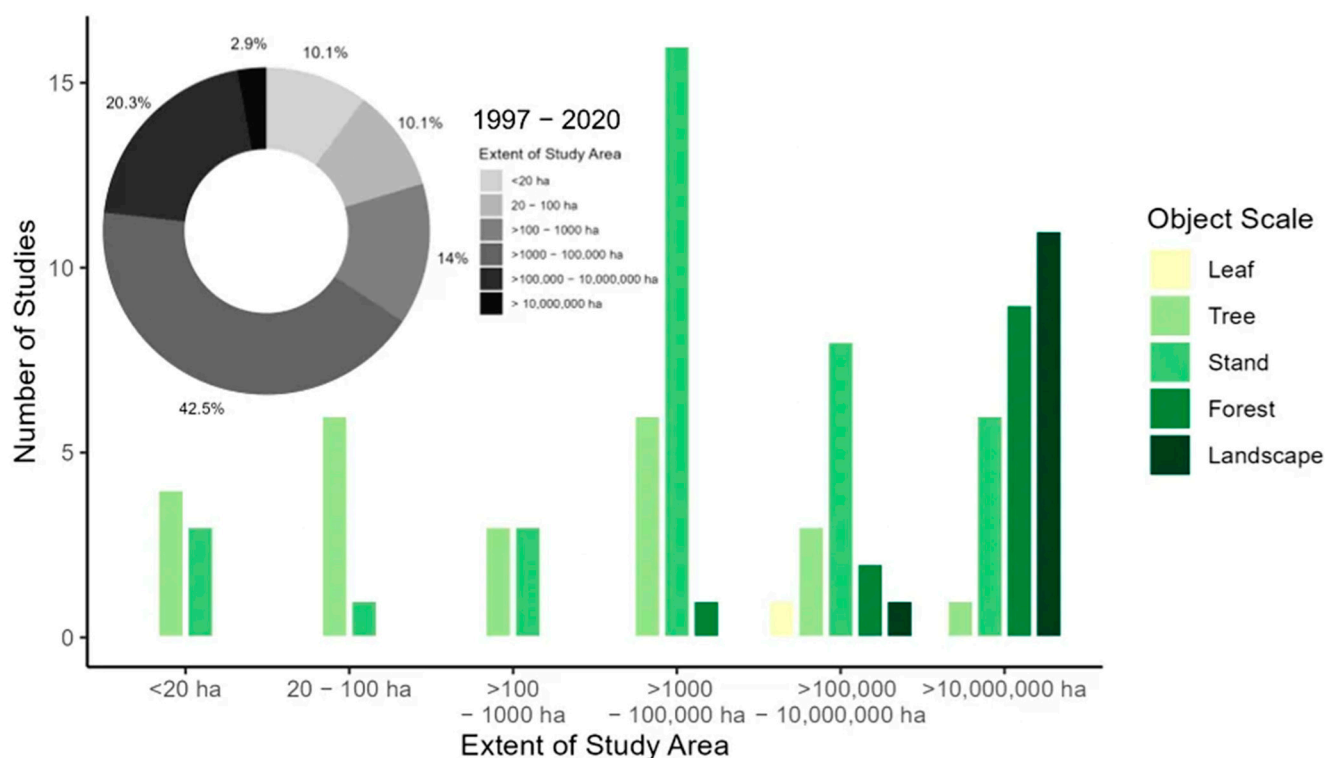
For an in-depth understanding of the spatial distribution of study areas and investigated object scales, a classification by federal state (Figure 5) and a comparison of the study area's extent to the number of studies grouped by object scale (i.e., leaf, tree, stand, forest, or landscape) was conducted (Figure 6).

Most studies on forest monitoring integrating remote sensing imagery analyzed forests in Bavaria (Figure 5). Moreover, the Bavarian Forest National Park in the Southeast is a known hotspot of forest-related research [1,123], comprising eleven studies of the present review. The federal states with at least ten studies are Thuringia (13 studies) and Baden-

Württemberg (ten studies). Hainich National Park, located in Thuringia, serves as another well-established research area, with a total of seven studies. North Rhine-Westphalia (seven studies) and Brandenburg (six studies) hold similar total numbers of studies investigated. The fewest studies were conducted in the federal states of Mecklenburg-Western Pomerania (one study), Saarland (one study), Rhineland-Palatinate (two studies), Hesse (two studies), Lower Saxony (three studies), Saxony-Anhalt (three studies), and Saxony (four studies). No studies were carried out in Schleswig-Holstein, Berlin, Bremen, and Hamburg. Overall, there is a latitudinal gradient presenting a higher number of studies in southern Germany. In addition to the studies at sub-national level, there are 27 studies assessing forest conditions with national coverage.



**Figure 5.** Number of studies per federal state. Germany-wide studies are indicated separately. (SH, Schleswig-Holstein; NI, Lower Saxony; NW, North Rhine-Westphalia; HE, Hesse; RP, Rhineland-Palatinate; SA, Saarland; BW, Baden-Wuerttemberg; MV, Mecklenburg-Western Pomerania; HH, Hamburg; HB, Bremen; BE, Berlin; BB, Brandenburg; ST, Saxony-Anhalt; SN, Saxony; TH, Thuringia; BY, Bavaria).



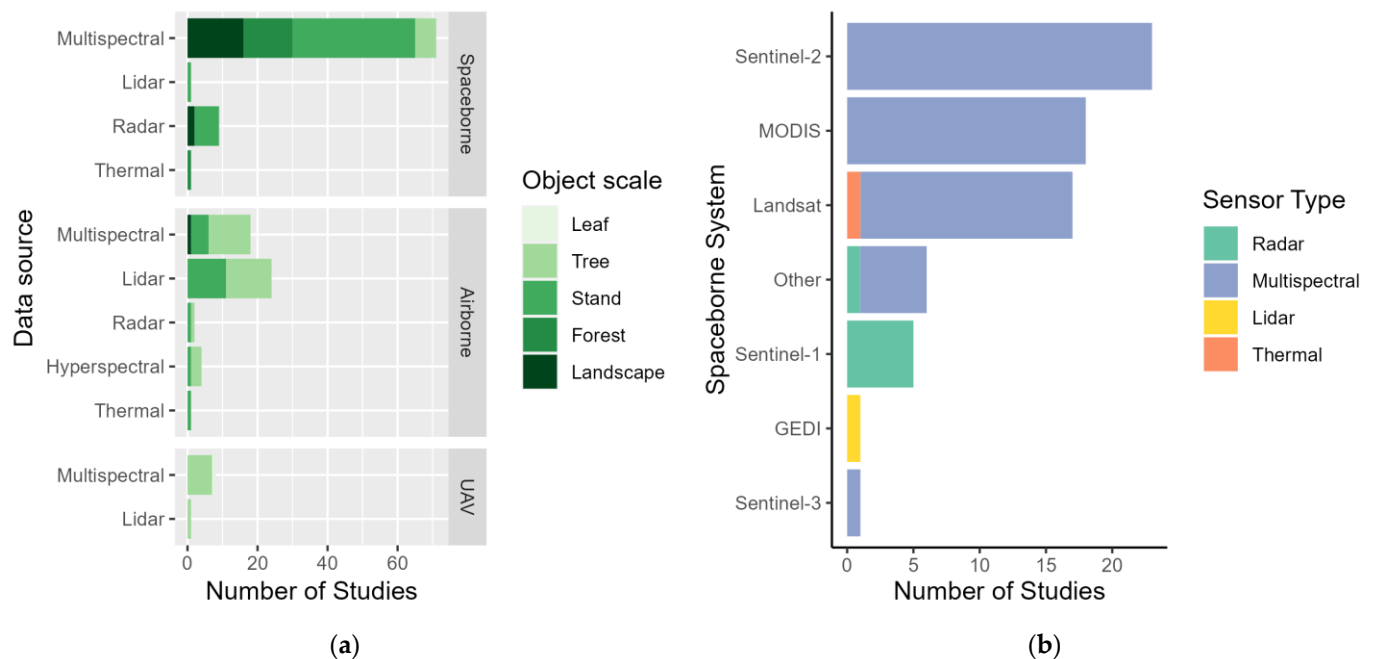
**Figure 6.** Size of study areas in relation to the observed object scale. The subplot depicts the results from Holzwarth et al. 2020 [1] for comparison.

Figure 6 depicts a relationship between the extent of the study area and the object scale. There are 27 studies that were conducted in study areas with an extent greater than 10,000,000 ha (studies at German-wide coverage), mostly assessing larger-scale objects, i.e., landscape (eleven studies), forest (nine studies), and stand (six studies). In contrast, small-scale studies (lower than 100 ha) assessed forests at the leaf (one study), tree (nine studies), and stand level (two studies). The analysis of forests at the stand level (34 studies in total) was the most-often-applied scale of all groups of study area extent. To summarize, there is a general positive correlation between the extent of the study area and object scale, i.e., forests or landscapes assessed based on large-scale study areas. Furthermore, the strongest difference from the initial review of Holzwarth et al. 2020 calling for more national remote sensing products [1] is that the share of German-wide studies increased from 2.9% to 28%.

### 3.1.3. Review Results: Employed Earth-Observation Sensors

Looking at the remote sensing sensors employed, it is noticeable that, compared to our first literature review, the number of studies based on satellite data now outnumber those using aircraft data by a considerable margin (Figure 7a). A total of 58 studies made use of spaceborne systems, and 32 publications dealt with airborne data, whereas only 7 exploited UAV (unmanned aerial vehicle) data for their purposes. Twenty-two studies used spaceborne and airborne data, and one study made use of all three platforms [106]. Data acquired by UAV are mainly used to retrieve information at tree level, and only one study observed the leaf level using data at the highest spatial resolution of 1 cm recorded within our literature review [92]. The publications that used airborne data only considered mostly objects at stand (seven studies) and tree (five studies) level. Twenty studies combined airborne and spaceborne data, and one observed forest on the landscape level, six on the stand level, and thirteen went down to tree level. Forty-six publications described the use of spaceborne data only to monitor forests in Germany. Almost 50% of these studies used the data to observe the forest on stand level, which reflects the typical spatial resolution of many of the spaceborne sensors of 10–30 m. Moreover, 25% did

consider the broader scale of looking at the forest and landscape level. Only one study dealt with satellite-derived information on the tree level [108].

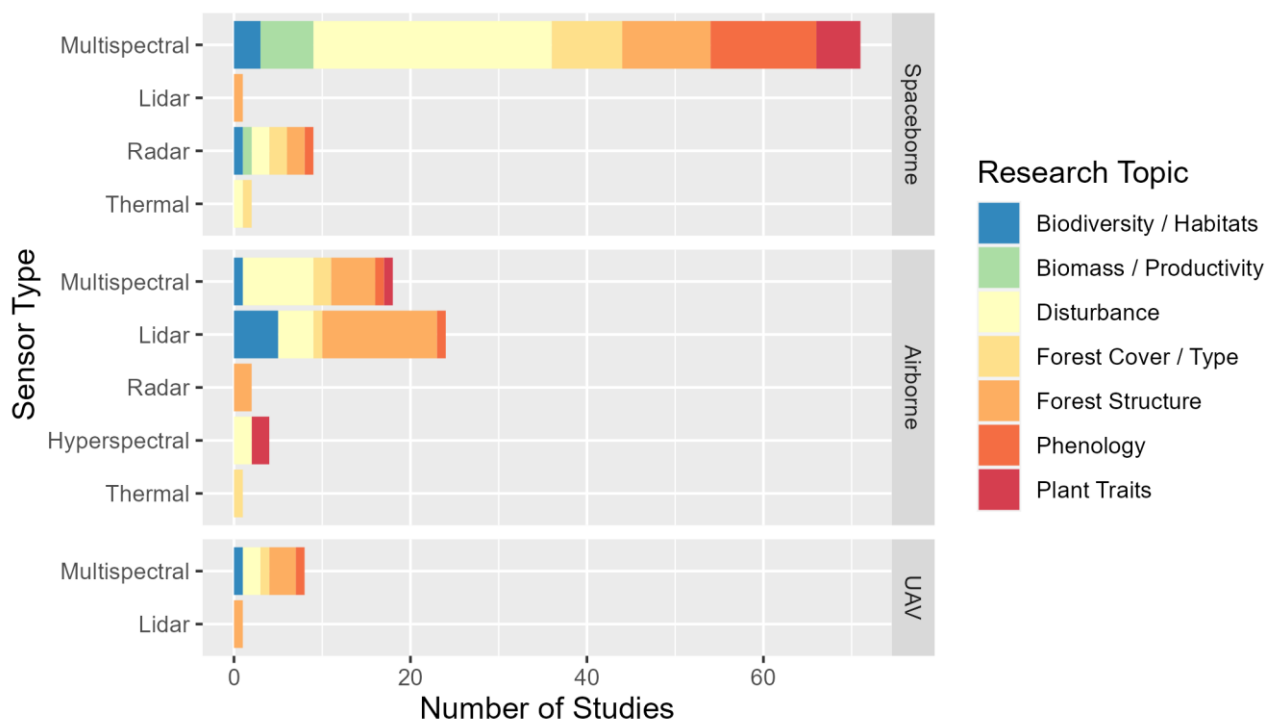


**Figure 7.** (a) Number of studies in relation to the platform and sensor type by the object scale investigated. (b) Number of studies in relation to the different spaceborne systems used.

When analyzing the type of the employed remote sensing spaceborne systems (Figure 7a,b), more than 90% are multispectral sensors (Sentinel-2; Landsat; MODIS; MERIS; Sentinel-3; Planet; WorldView-3; OCO-2). Overall, 50 of the overall 59 studies made use of Sentinel-2, Landsat, and MODIS data. Two studies also used the thermal data of Landsat [46,89]. Four publications described the use of radar data, where three employed C-band data (Sentinel-1) and one L-band data (SMAP) [82]. Only one study considered spaceborne LiDAR data (GEDI) within the timeframe of our review [42]. Considering the airborne sensors (Figure 7a), 13 of the 33 studies used multispectral systems (including RGB-CIR camera systems), and four made use of imaging hyperspectral systems. In half of the studies (16 times), lidar systems were mounted on the aircraft and employed within the studies. Of the 12 studies that used airborne together with spaceborne data, 50% made use of airborne LiDAR data. Only two studies dealt with L-band radar data [50,86] and one with thermal data (VarioCAMhr) [89]. Drones (UAV) were mainly equipped with multispectral sensor systems (6 including RGB-CIR) and once with a lidar system [107] (Figure 7a).

We also analyzed the different sensor systems used for the topics identified within this review (Figure 8). Looking at the spaceborne systems, multispectral data were used for all kinds of research topics. Microwave remote sensing data were considered for all kinds of research topics except plant traits. Three studies on biodiversity/habitats [64,71,90] analyzed multispectral and radar data, two of them also linked to forest structure [71,90]. Out of the 28 studies on disturbance, only one study made use of thermal data (Landsat) [46], and two studies used radar in combination with multispectral [67,118], whereas 25 employed multispectral data only (10 Sentinel-2; 11 Landsat; 7 MODIS—note that there are also combinations of the three sensors used, and therefore, the sum does not equal 25). There are nine studies on forest cover/type, where eight used multispectral sensor systems (also in combination with thermal and radar), and one used Sentinel-1 solely to classify forests [56]. The only publication with GEDI data [42] as an input source is assigned to forest structure. Of the other 11 studies dealing with this research topic, one study used Sentinel-1 and Sentinel-2 data [71] as input sources, while the rest made use of multispectral sensors only. Of the 12 studies on

phenology, all used multispectral data, and only one study considered Sentinel-2 together with Sentinel 1 [118]. Out of the five studies on plant traits, all used multispectral data only. When considering the use of aircraft data, there are five studies on biodiversity/habitats that used airborne LiDAR data for their research. ALS data are also often employed for applications in the context of forest structure (13 studies). Furthermore, these data are used for studies on forest disturbance (four studies). Another research paper utilized LiDAR data in the context of forest cover/type [105]. Moreover, one study [94] used airborne LiDAR data together with UAV and spaceborne data to study the vertical forest phenology of *Fagus sylvatica*. Multispectral sensor systems mounted on aircraft were integrated across all research topics: seven times for forest disturbance, twice for forest cover/type, five times for forest structure, and once each for biodiversity/habitats [45], phenology [3], and plant traits [74]. Hyperspectral data (HySpex and AisaFenix) were evaluated in the areas of forest disturbance [58,68] and plant traits [70,112]. The two publications that made use of airborne radar L-band data (F-SAR and TomoSAR) were assigned to the research topic forest structure [50,86]. There is one study that used VarioCAMhr thermal data in the context of detecting tree species effects on forest canopy temperatures [89]. None of the studies on biomass/productivity used airborne data, which is reasonably understandable, as these are usually large-scale investigations. The seven research publications that included UAV data in their investigations included almost all research topics with the exception of biomass/productivity and plant traits. There is one study on biodiversity [102] that used a multispectral UAV system. The same kind of data was employed twice for research work on forest disturbance and four times for forest structure. This very high resolution multispectral data were also used for forest cover/type (tree species identification) [92] and phenology (together with the airborne thermal data) [106]. The RIEGL miniVUX-1UAV LiDAR system was used to study forest structure (individual tree point clouds and tree measurements) [107].



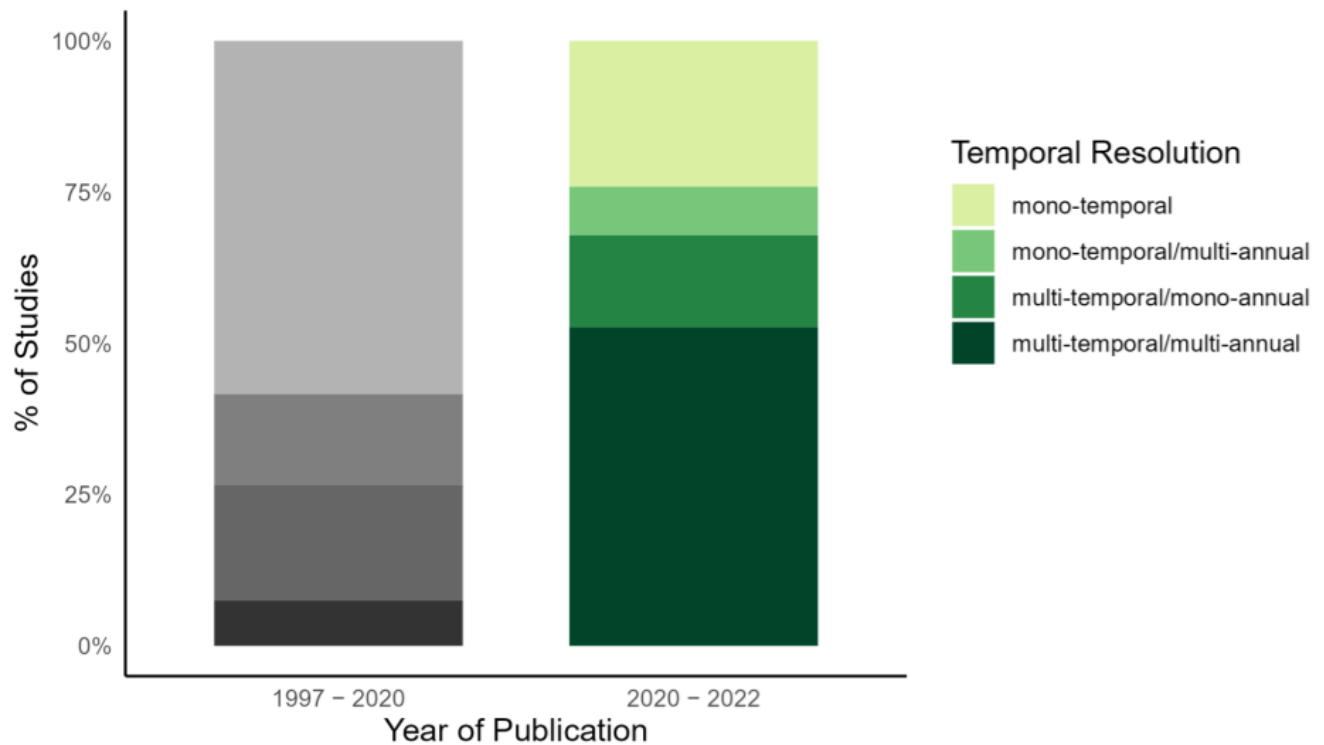
**Figure 8.** Number of times a given sensor type was used in relation to platform type and research topic by sensor type employed. Note that studies could be counted multiple times if they investigated multiple research topics or utilized multiple platforms or sensor types.

### 3.1.4. Review Results: Temporal Resolution

As expected, for the new evaluation period of 2020–2022, there was a trend shift towards multi-temporal/multi-annual studies, which account now for half of the studies



(50%) in contrast to the earlier period with 18.5% (Figure 9). While the highest proportion of studies published in the 1997–2020 period were mono-temporal (58%), this portion decreased to 26%. The proportion of mono-temporal studies with repeated observations in different years (mono-temporal/multi-annual) remains the lowest and relatively stable at 7% (8% in 1997–2020). The same applies to short intra-annual time-series, i.e., multi-temporal/mono-annual, at 17% (15% in 1997–2020).

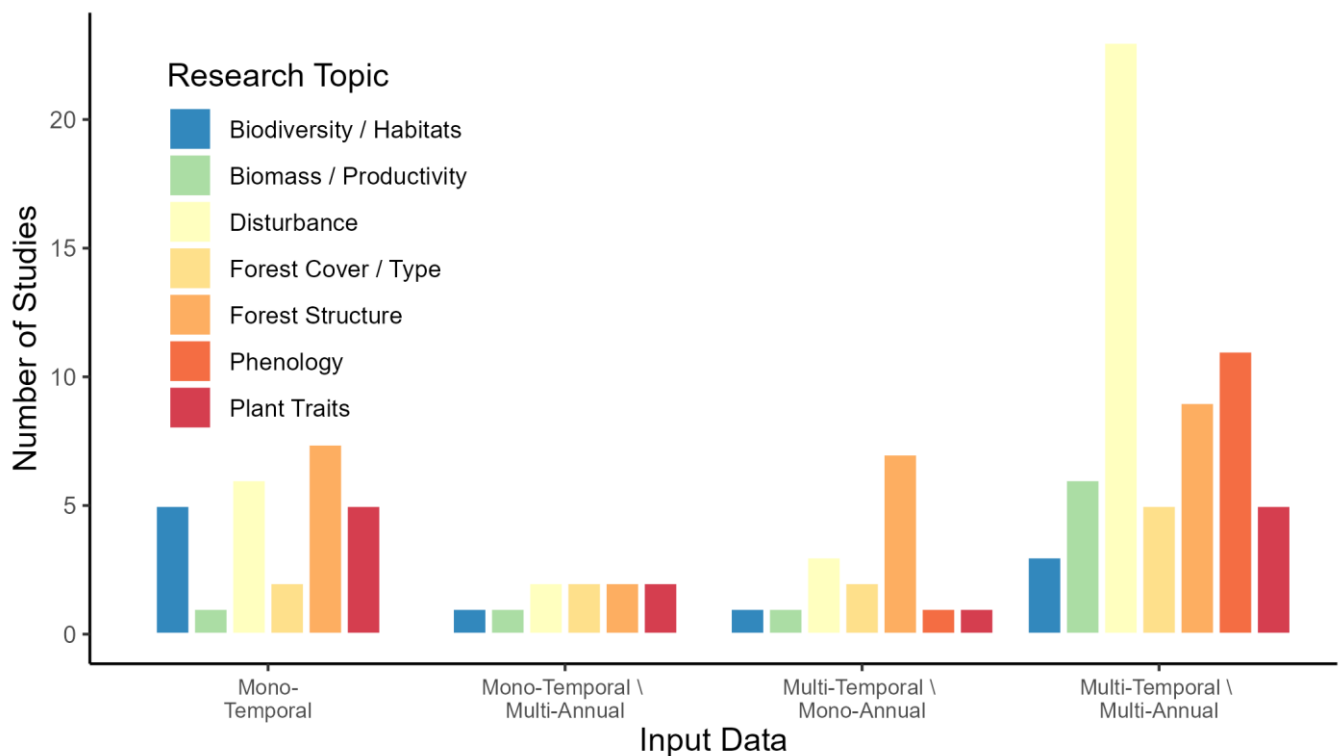


**Figure 9.** Comparison of the temporal resolution of input data sources of the two different review periods.

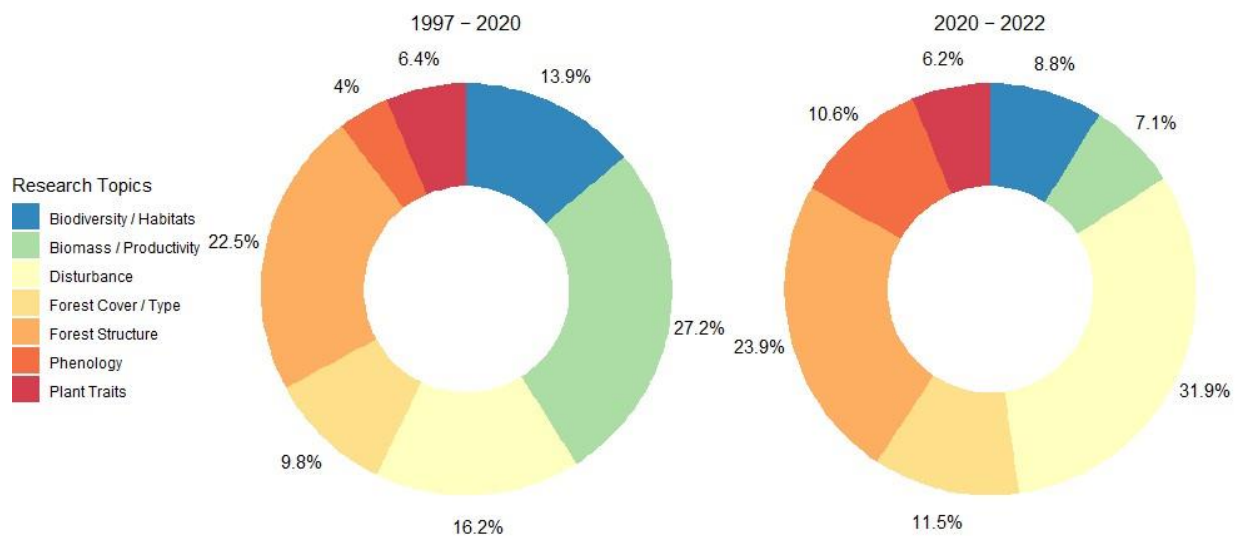
Looking at the application domains (Figure 10), especially for disturbance and phenology, multi-temporal/multi-annual approaches were used. This might be attributed to the availability of Sentinel-2 datasets and issues related to climate change that require such evaluation of data. Surprisingly, the highest number of studies for disturbance, apart from multi-temporal/multi-annual, was found in mono-temporal studies; these are mainly case studies using deep learning approaches [53,91] or images from airborne campaigns [68,72,88]. For forest structure, convolutional neural networks (CNNs) were often utilized, so some studies in this diverse group used multi-temporal intra-annual and multi-annual studies, too [43,54,71]. For biodiversity/habitats, the number of studies with more than one time point as input data is quite small; here, studies still rely on mono-temporal input data (e.g., [103,105]).

### 3.1.5. Review Results: Research Topics

Disturbance is the most dominating research topic addressed in the research papers of this review (Figure 11). Its percentage almost doubled from 16.2% to 32.1% since our first review [1]. Publications related to forest structure rank second with 24.1% (compared to 22.5% in [1]). The remaining categories were more or less equally addressed with biodiversity/habitats at 8.9%, biomass/productivity with only 7.1% (compared to 27.2% in [1]), forest cover/type with 10.7%, and phenology with 10.7%. Plant traits were in the focus of research in only 6.2% of the studies.



**Figure 10.** Temporal resolution of input data sources for seven application domains.



**Figure 11.** Examined research topic categories. Comparison of the previous and the current review. Note that some studies cover several topics, which may result in multiple entries.

These results reflect the relatively new availability of data suitable for the mapping of disturbances (e.g., dense time series, adequate spectral bands, and high spatial resolution through Sentinel-2) and forest structure (e.g., LiDAR data and high spatial resolution multispectral or SAR sensors) and increasing computational capacities capable of processing dense time series.

#### Disturbance

The category of forest disturbance comprised 36 of 84 (43%) papers in this review [3,6,10,11,46,48,49,52,53,58,59,62,63,67,68,72,79,84,88,91,94–99,103,110,111,115–118,120] compared to 28 of 166 papers (17%) in our initial review [1]. Disturbances to forest systems include causes and effect; therefore, within this category of studies, broad themes emerged.

Four papers each investigated disturbances related to drought [6,48,63,79] and issues related specifically to the Norway spruce, notably bark beetle infestations [58,68,72,120]. Two studies each focused on windthrow [53,88], wildfire [67,98], and storms [98,116]. Only four papers were related solely to disturbance, mainly mapping [88,91,97,99], with one investigation related to demographic structural changes in response to disturbances [96].

Overall, we found that disturbance related to drought was the most commonly investigated theme with 36 papers [6,10,11,48,49,63,79,94,110,118]. In our previous review, the most common theme was bark beetle infestations with respect to forest disturbances, while drought was only explicitly covered in two studies [1]. The authors' conclusions are varied: Beloiu et al. [48] found that saplings have a higher capacity to recover and survive subsequent drought events, while early leaf shedding was detected in response to droughts in a paper by Brun et al. [3]. Haberstroh et al. [63] reported a legacy effect of drought in the following summer and the replacement of *P. sylvestris* by understory trees as a result of the 2018 drought. West et al. [110] noted that using a combination of sensors at multi-temporal time steps in a beech forest can result in better representation of drought-affected canopy health. Shekhar et al. [10] demonstrated that there was a 31% decrease in solar-induced fluorescence (SIF) following the 2018 drought in central Europe; meanwhile, a study by Buras et al. [49] suggested drought-induced forest decline in the last two decades. Meyer et al. [79] highlighted the relationship between the normalized difference vegetation index (NDVI) and ring-width indices (RWI), which can capture growth and depression in beech and oak trees in response to drought. The combination of MODIS imagery and NDVI generated the best results for measuring spectral response to drought conditions in an investigation by Philip et al. [6]. Finally, we noted the calculation of a novel radar drought index for estimating drought stress due to aspect and temperature in a paper by Kaiser et al. [118].

A few papers investigated uncommon themes with respect to forest disturbances. Among them, Szymczak et al. [101] used airborne RGB and LiDAR data to create a GIS (geographic information system) tool for detecting fallen trees along railway lines as well as calculating risk of treefall for individual trees. The European Forest Condition Monitor is a web-based tool created by Buras et al. [49] for monitoring forests across Europe, characterizing forest condition and highlighting an increase in forest decline. Gnilke et al. [62] presented a method for distinguishing abrupt and gradual forest disturbances using MODIS multi-temporal and multi-annual EVI data. A method utilizing Landsat thermal data was demonstrated by Barta et al. [46] to identify increased and decreased surface temperature during the onset and recovery of disturbance events in a mixed forest over Bavarian Forest National Park.

Although windthrow was a productive topic in our last review, since 2020, only five papers dealt directly with this theme [53,91,98,100,116]. Among them, Steffen et al. [100] aimed to produce a method to monitor infrastructure at risk of damage by windthrown trees, while two studies investigated the potential for deep learning image analysis to detect windthrow [53,91]. Regarding analysis, statistical methods were quite broad. Here, we noted an equal number of papers utilizing deep learning methods [53,88,91,111,115] and random forest [59,97–99,116].

### Forest Structure

With a total of 21 studies, “forest structure” is the second most represented research topic (Figure 11) in accordance with the reference period (1997–2020) of the pervious review [1]. As in the reference period of the first review, the studies published between 2020 and 2022 considered either the structure at the individual tree level regarding tree metrics such as position, height, trunk diameter, or crown structure [42,43,50,56,57,64,65,71,86,93,105,114,121] or analyzed tree species composition, horizontal and vertical stand structure, or deadwood abundance at the stand level [42,43,50,56,57,64,65,71,86,93,105,114,121]. The vast majority of the studies were conducted in mixed managed forests stands.

While the studies considered in the previous review primarily used airborne LiDAR data to assess structure at the individual tree and stand level, the more recent studies relied on more diverse data sources. At the individual tree level, airborne and UAV-based multispectral and LiDAR data with sub-meter spatial resolution were mainly used (e.g., [54,107,115]), while spaceborne and airborne multispectral, LiDAR, and SAR data with spatial resolutions up to 30 m were employed at the stand level (e.g., [42,43,65]).

In line with the previous reference period, the focus of the most recent studies was on mapping horizontal, vertical, and species composition with regard to inventory, biodiversity monitoring, and sustainable forest and natural hazard management, among others.

Most of the studies on the individual tree level aimed at characterizing individual trees and deadwood in terms of their exact location and dimensions (tree height, diameter at breast height, and crown diameter and volume) to enable an improved area-wide inventory to support sustainable forest management [54,73,115] or strategic management regarding urban climate, human well-being, and climate change adaptation in urban areas [83]. Additionally, the detection and parameterization of individual trees was also used in a targeted natural hazard management for damage prevention, as shown by Steffen et al. [100] and Szymczak et al. [101]. Both studies proposed an approach to identify trees with the potential to damage infrastructural elements (e.g., roads and railroads) in the case of a hazard event such as windthrow.

By comparison, the studies at the stand or higher object scale (i.e., forest or landscape) generally addressed either large-scale area-wide inventories (e.g., [42,43,56]) or the relationship between structural complexity and biodiversity, micro climate, and productivity, among others (e.g., [71,93,105]). In the context of sustainable forest management and monitoring as well as conservation of biodiversity, parameters of horizontal and vertical stand structure (i.e., stand density, height distribution, canopy closure, and layering) as well as species composition were related to forest development stages (e.g., [86]), diversity indices (e.g., [105]), and ecomorphological trait variations (e.g., [57]). Beyond that, Zong et al. [114,121] investigated visibility within forest stands using LiDAR-based metrics in the context of animal behavior.

Like the studies of the first review, most studies derived mono-temporal datasets, providing an indication of the instantaneous structural complexity only, while two recent studies considered multiple time steps within one year, allowing the assessment of its seasonal evolution [65,86].

#### Forest Cover/Type

Since our initial review [1], twelve new studies on forest cover/type were published, eight of which focused primarily on the core topic [51,61,69,82,85,89,92,108], while two had an additional focus on biodiversity and habitats [45,105], and one study each also focused on structure [56] and disturbance [52] related to forest cover.

With regards to object scale, one study focused on the leaf [92], three looked at individual trees [45,105,108], stands were investigated in three studies [69,82,89], with one study focused on the object scale of a forest [85], and four studies investigated landscape-scale forest cover [51,52,56,61] in an effort to map forest cover across Europe. The type of forests investigated were mostly mixed coniferous and deciduous [51,52,56,61,69,85,92,105,108], with just two papers focused exclusively on deciduous tree species [45,89], while one paper investigated exclusively coniferous trees [82] for detecting bark-beetle-infested spruce stands. The type of sensors used to investigate forest cover was varied: spaceborne multispectral data was used either alone [51,52,69,85,108] or in combination with other sensor or platform types [61,82,89]. Sources of spaceborne multispectral data were Sentinel-2, MODIS, or Landsat. All of the spaceborne multi-spectral studies utilized multi-temporal data. Moreover, one paper utilized dense, two-year multi-temporal data, which only slightly outperformed other studies that relied on fewer data [69]. Airborne and UAV data were used exclusively in three papers [45,92,105]. One paper each used Sentinel-1

radar [56] and airborne LiDAR [105] only, with one study also integrating thermal data [89] acquired from Landsat.

While the main topic of the majority of papers [51,52,56,61,69,85,108] was broad-scale coverage and species mapping, fewer studies [45,82,89,92,105] looked into small-scale experimental methods testing. Of the five experimental studies, the topics were wide-ranging. Richter et al. [89] aimed to detect the role of species' influence on canopy temperature regulation via linkages with in situ and thermal remote sensing data. Torresani et al. [105] proposed a new methodology for estimating species diversity using LiDAR data via the so-called height variation hypothesis. An ecology-focused paper by Axer et al. [45] used remote sensing to build a spatial model of seed dispersion and subsequent regeneration of oak species. Detection of spruce crown transparency following bark beetle infestation was modeled by Montzka et al. [82], with a method that can be coupled with ground-based national inventory monitoring schemes. Furthermore, we noted the emergence of one study [92] that utilized convolutional neural networks (CNNs) to detect tree species in high-resolution UAV imagery. It was the only such paper within the topic of forest cover and type to conduct an analysis using deep learning.

Finally, we report one study [51] that received critical response on the methods, results, and the implications of its work, which can be found in [124–126].

### Phenology

Twelve papers on forest phenology were published during the focus period of this review. Half of the papers concentrated solely on the topic of phenology [55,75,77,80,104,106], while one of them had a secondary focus on disturbance [118]. The remaining five papers dealt with phenology as a secondary research topic and had their main focus on disturbance [3,49,62,117] and biomass/productivity [47].

The phenological analyses were mainly broad-scaled and conducted at the European or national level. The exceptions are the studies of Uphus et al. [106], who focused on smaller sites in Bavaria for detailed analyses of climate effects on phenology of beech at tree level; Misra et al. [80], who investigated start of season/end of season in complex alpine areas; Kaiser et al. [118], who combined optical and SAR data for analyzing disturbance and phenology in the Donnersbergkreis in Rheinland-Pfalz; and Beloiu et al. [48], who analyzed drought impacts by combining Sentinel-2 data with in situ plots in central Germany.

All of the studies used optical time series data, while one of them [118] combined optical with SAR (Sentinel-1) data. The pure optical analyses focused on MODIS [47,49,62,77,80], on Landsat [117], on Sentinel-2 [104,106], and on Sentinel-2 in combination with Landsat [75], MODIS [55], and Planet [3].

The majority of the papers investigated start and/or end of season phenological responses within the broader context of climate-induced anomalies [3,55,75,77,80,104,106]. Kowalski et al. [75] combined Landsat and Sentinel-2 data to estimate the start of season phenological period in deciduous forests. In a paper by Misra et al. [80], it was found that both spring and preceding winter temperatures could influence spring phenology along an Alpine elevational gradient, while Uphus et al. [106] investigated the phenological mismatch along a vertical gradient within a forest based on the discrepancy in temperatures between the over and understory of the canopy. Papers by Liu et al. [77], Descal et al. [55], and Brun et al. [3] focused on the end of season and drought-induced senescence. Brun et al. [3] found that early wilting was related to increased temperatures and low precipitation, which could have an impact via a reduction in greenness the following spring. Descals et al. [55] also uncovered legacy effects suggesting a decline in productivity over time following early leaf shedding.

In an investigation of the effects of the 2018 drought, Bastos et al. [47] focused on vulnerability and response to the event by modelling a predicted forest condition based on the conditions of the preceding 16 years. Two papers studied catastrophic disturbances to forest phenology: Grunig et al. [117] focused on fire events and drivers, while Gnilke et al. [62] were able to distinguish disturbance responses using MODIS-enhanced vegetation index



(EVI). Finally, an interactive web information tool was introduced by Buras et al. [49], known as the European Forest Condition Monitor, which has revealed broad-scale greenness over Europe using 5.3-hectare resolution MODIS NDVI data since 2001.

### Biodiversity

Ten studies were classified as research on biodiversity [45,57,64,66,71,90,102,105,114,121]. The analysis of biodiversity was conducted on different object scales: There are four studies each on the tree [45,66,102,105] and stand scale [57,71,114,121] and one study each on the forest [64] and landscape scale [90]. All studies focused on mixed forests except Thiel et al. 2020 [102] (deciduous forest). Furthermore, three studies conducted biodiversity analysis through spaceborne remote sensing [64,71,90]. The research by Hoffmann et al. 2022 [71] is the only study on biodiversity analysis that combined different sensor types (Sentinel-1 and Sentinel-2). Further spaceborne imagery was derived from the optical sensors Landsat [64] and MODIS [90]. There are six studies that integrated airborne sensors [45,57,66,105,114,121] in contrast to a single study based on UAV data [102]. Airborne laser scanning data from Riegl sensors was obtained in the studies of Drag et al. 2021 [57], Heidrich et al. 2020 [66], Zong et al. 2021 [114], and Zong et al. 2022 [121].

In comparison to the initial review [1], which held a share of about 14% of biodiversity studies, in the present review, about 8% of the studies investigated biodiversity. Further dissimilarities are that the initial review had a stronger focus on animal species (almost half of the studies) [1], whereas only about one-third of the studies of the present review integrated data on animal diversity (saproxylic beetles [57]; multi-taxa [66]) and spatial behavior (red deer [121]). Recent reviews on remotely sensed biodiversity analysis assessed the opportunities of biodiversity monitoring through concepts based on spectral diversity [37,127–129]. The concept behind spectral diversity is based on the spectral variation hypothesis stating that diversity (heterogeneity) in the spectral properties from remote sensing sensors is linked to species diversity. Therefore, elevated values in spectral diversity can represent a greater variety of ecological niches and habitats, thus favoring the increase of taxonomic diversity and ecosystem functions [130]. In the present review, the studies of Heidrich et al. 2020 [66], Rocchini et al. 2021 [90], and Torresani et al. 2020 [105] integrated spectral diversity concepts based on optical diversity at the ecosystem scale [90] and diversity in metrics of airborne laser scanning at the tree scale [66,105].

### Biomass/Productivity

From the publications included in this review, eight studies were classified as having a focus on or contributing to research on biomass/productivity [10,47,59,76,81,87,113,119]. Three of these studies are on the European scale [10,59,81]. Others cover central Europe [47] and Bavaria [76]. Three studies include individual sites: European-wide sites including four Integrated Carbon Observing System (ICOS)-affiliated forest ecosystem sites in Germany [87], eddy covariance data of temperate forest ecosystems located between 35°N and 65°N including five sites in Germany [113], and local study sites in Thuringia [119]. Most studies made use of spaceborne multispectral data, including MODIS, Landsat, OCO-2, and TROPospheric Monitoring Instrument (TROPOMI). One study used radar C-band data from Sentinel-1 [119].

Topics covered by the investigated publications included gross primary productivity (GPP), evapotranspiration, carbon mitigation potential, and forest background reflectivity. Krause et al. [76] assessed carbon mitigation potentials for Bavaria by applying a process-based ecosystem model. Remote sensing data were not applied in this study, but satellite data-based land-cover information was used. The authors found that mitigation potential in existing forests is limited or even negative. Monthly trends in GPP and evapotranspiration across undisturbed core forest areas in Europe were assessed by Montibeller et al. [81] based on MODIS data between 2000 and 2020. Productivity increased during spring and autumn in nearly half of the investigated forest area but did not compensate for summer decrease in 25% of core forest areas. Mueller et al. [119] characterized evapotranspiration

dynamics over temperate coniferous forest sites in Thuringia based on Sentinel-1 backscatter time series. They found that SAR backscatter signal of coniferous forests is sensitive to evapotranspiration under some scenarios.

Two studies focused on vulnerability but are relevant in the context of biomass as well. Bastos et al. [47] investigated the vulnerability of European ecosystems to hot summers in 2018 and 2019. A set of statistical models was trained for the period 2001–2017 and then used to predict the impacts of dry and hot summers in 2018 and 2019 on MODIS EVI. Forzieri et al. [59] quantified the vulnerability of European forests to fires, windthrows, and insect outbreaks during 1979–2018 using random forest regression. The best model explained 34–49% of variance in relative biomass loss ( $R^2$ ). The authors found that about 33.4 billion tons of forest biomass could be seriously affected by the investigated disturbances.

Pisek et al. [87] retrieved and validated forest background reflectivity from the MODIS Bidirectional Reflectance Distribution Function (BRDF, for measuring albedo) data across European forests using an approach for estimating understory NDVI from daily MODIS BRDF, at a 500 m gridded spatial resolution, over the extended network of the ICOS forest ecosystem sites. The performance of the method was found to be limited over forests with closed canopies, where the signal from the understory was much attenuated.

Solar-induced fluorescence (SIF) data were used within two studies to predict GPP. Shekhar et al. [10] used high-resolution SIF data from the Orbiting Carbon Observatory-2 (OCO-2) satellite, which are proposed to be a proxy for GPP to capture the impact of the 2018 European drought and heat across different vegetation types. They analyzed SIF time-series variation and anomalies. Comparison between MODIS and OCO-2 indicated that for coniferous and mixed forests, SIF has a quicker response and a possible higher sensitivity to drought compared to MODIS FPAR and NDVI. The authors suggested that SIF can serve as a complementary dataset to MODIS's vegetation indices [10]. Yazbeck et al. [113] also investigated SIF data and tested how well solar-induced chlorophyll fluorescence can predict the inter-daily variation of GPP during the growing season and under stress conditions. They used observation from forested eddy covariance flux sites in North America and Europe and SIF data from the TROPOMI satellite. SIF was found to be a good predictor of GPP when accounting for inter-site variation.

#### Plant Traits

Seven of the publications included in this review dealt with plant characteristics, so-called plant traits. As in the previous review, leaf area index, LAI, [44,65,112,113], and leaf or canopy chlorophyll or nitrogen content [44,70,78] were most frequently considered, while SIF [113], leaf angle [65], and tree size/crown height [74] were less of a focus. Again, most studies were conducted in mixed forests, with the exception of Hase et al. [65] and Korolyova et al. [74], whose study sites were in deciduous and coniferous forests, respectively. In all but one publication [65], the study areas were relatively large, with spatial coverages of 7000 ha or more up to the size of all of Europe. As a result, plant traits were mainly considered at the stand or forest level. Again, a regional focus included the German–Czech transborder region of Bavarian Forest and Šumava National Parks: four out of seven studies were performed in this area.

As in the previous review paper, the preferred data basis for the analysis of plant traits was spaceborne multispectral data, i.e., Sentinel-2 [44,65], Landsat 5 [74], MODIS/MERIS [78], and TROPOMI [113]. Airborne hyperspectral (e.g., the AisaFENIX sensor, used by Hoeppepner et al. [70] and Xie et al. [112]) or airborne multispectral data [74] had a smaller share.

The employed methodologies include the use of radiative transfer models [44,65], machine learning methods as the random forest technique [70,78], artificial neural networks [44], or Gaussian processes regression [112] as well as partial least-squares regression [70]. As expected, this continues the shift towards machine learning methods noted in the last review.

Four of the seven publications were related to the estimation of plant traits themselves based on remote sensing data: Hoeppepner et al. [70], e.g., tried to estimate canopy chloro-

phyll content in the Bavarian Forest National Park using hyperspectral data. The study yielded best results with partial least-squares regression ( $RMSE = 0.25 \text{ g/m}^2$ ,  $R^2 = 0.66$ ) and indicated specific spectral regions that were important for estimate canopy chlorophyll content retrieval.

Loozen et al. [78] studied spatial patterns of canopy nitrogen content of different European forests (including over 100 study sites in Germany) and investigated the extent to which including environmental variables as predictors would improve models compared to using remote sensing data alone. They found that environmental variables improved all predictions but were particularly important for plots in deciduous broadleaf forests. Considering all 818 European plots, Loozen et al. [78] were able to map canopy nitrogen content using the random forest technique with an accuracy of  $R^2 = 0.62$  and relative  $RMSE = 0.18$ . Among the remote sensing products tested, the MODIS EVI was the most significant predictor of canopy nitrogen content.

With respect to LAI, Xie et al. [112] showed that Gaussian processes regression yielded the best results using the full spectrum of hyperspectral sensor data (compared to narrow-band vegetation indices), retrieving accuracies of  $R^2 = 0.67$  and  $RMSE = 0.53 \text{ m}^2/\text{m}^2$  for the heterogeneous mixed mountain forest of the Bavarian Forest National Park.

Ali et al. [44] predicted leaf chlorophyll content (LCC), canopy chlorophyll content (CCC), and LAI with Sentinel-2 data using a radiative transfer model inversion by merit function and compared it to five machine learning algorithms. Although the look-up table inversion by merit function yielded the best results for all three plant traits compared to in situ measurements (LCC:  $R^2 = 0.27$  and  $RMSE = 3.9 \mu\text{g}/\text{cm}^2$ ; CCC:  $R^2 = 0.65$  and  $RMSE = 0.33 \text{ g}/\text{m}^2$ ; LAI:  $R^2 = 0.47$  and  $RMSE = 0.73 \text{ m}^2/\text{m}^2$ ), random forest regression was comparably accurate (LCC:  $R^2 = 0.34$  and  $RMSE = 4.1 \mu\text{g}/\text{cm}^2$ ; CCC:  $R^2 = 0.65$  and  $RMSE = 0.34 \text{ g}/\text{m}^2$ ; LAI:  $R^2 = 0.47$  and  $RMSE = 0.75 \text{ m}^2/\text{m}^2$ ) while requiring far less CPU time (121.5 s versus 36 h for the LUT inversion).

The other three of the seven publications did not focus on the estimation of plant traits themselves but on the influence of climate factors on plant traits and subsequent survival dynamics of Norway spruce during a prolonged multi-year bark beetle outbreak [74] on the impact of forest vegetation structure and physiology on the relationship between solar-induced fluorescence and forest GPP [113] and on understanding the relationship between simulated near-infrared canopy reflectance and LAI and leaf angles, respectively [65].

### 3.2. Forest-Related Products

Overall nine products were identified (Table 1), which are described in scientific publications or/and scientific reports (e.g., EU high-resolution layer forest) [11,30,49,61,108,131–136]. The publishers of these products are three companies, one federal state research institute, two German national research institutes, two European national research institutes, and one German university. These products cover most of the above-mentioned research topics. Only plant traits are so far not covered by any of the products. Many products concern forest disturbance and forest structure also beyond the nine products that are examined in more detail herein (i.e., products with no underlying scientific publication), which is consistent with the findings from the literature review. As far as validation and quality assessment are concerned, information on this subject is not published for all products. In the following section, the spatial and temporal resolution and coverage of the products and the remote sensing sensors used are examined in more detail.

#### 3.2.1. Content of Available Products

The nine products cover different information about Germany's forests: biodiversity-relevant structures displayed in forest structure maps, which include, e.g., tree and forest cover information, deciduous/coniferous forest maps, stand height, and gap information [61]; active forest fires and fire risk information to evaluate forest fire danger and to map burnt areas [135]; tree cover density and dominant leaf type, which in turn indicates the forest type [131,132]; forest condition based on NDVI time series data (i.e., EO-based greenness to

map forest decline) [49]; vitality changes of trees [134]; tree canopy-cover loss information [11]; tree species mapping [108,133]; and designation of clearcut areas [30].

**Table 1.** Forest-related products relevant to this review.

Name	Producer/ Publisher	Spatial Coverage	Spatial Resolution	Temporal Coverage	Update Interval	EO Data Used	Publication/Data Access
Monitoring Biodiversity with Remote Sensing Tools (MoBiTools)	Forest Research Institute Baden-Württemberg (FVA)	Baden-Württemberg	5 m	2013 2016 2019	3 years	Aerial imagery Sentinel-2	[61,137]
European Forest Fire Information System (EFFIS)	EC (JRC)	Europe	375 m 250 m	since 2000	2–3 h	VIIRS MODIS	[135,138]
Copernicus Land Monitoring Service High-resolution layer forest	EEA	Europe	10 m 20 m	2012 2015 2018	3 years	Sentinel-2	[131,132,139]
European Forest Condition Monitor (EFCM)	Technical University Munich	Europe	231 m	since 2000	8 days	MODIS	[49,140]
Tree Canopy Cover Loss	DLR	Germany	10 m	2018–2021	monthly	Sentinel-2 Landsat-8	[11,141]
Dominant Tree Species	Thünen Institute	Germany	10 m	2017/2018	one time	Sentinel-1 Sentinel-2	[133,142]
Forest Monitor “Waldmonitor”	Naturwaldakademie, Remote Sensing Solutions (RSS)	Germany	10 m	2017	one time	Sentinel-2	[108,143]
Global Forest Change/Watch	University of Maryland, Google	Global	30 m	2000–2022	yearly	Landsat	[30,144]
ForestWatch	LUP Luftbild Umwelt Planung	Germany	10 m	2018–2022	yearly	Sentinel-2	[134,136]

### 3.2.2. Spatial Coverage and Spatial Resolution

The Global Forest Watch (GFW) provides data and tools to monitor the forest worldwide with a 30 m spatial resolution [30]. Three of the observed products covering Europe are at different spatial resolutions: The European Forest Fire Information System (EFFIS) [135] and the European Forest Condition Monitor (EFCM) [49] offer a spatial resolution between 200 m and 400 m, while the Copernicus forest layer is at 10 m and 20 m resolution [132]. There are four Germany-wide products with a 10 m spatial resolution [11,108,133,134] and one product covering the federal state of Baden-Württemberg at a 5 m spatial resolution [61].

### 3.2.3. Temporal Coverage and Update Interval

When looking more closely at the temporal coverage of the nine products, none go back further than the year 2000. Three products rely on time series from MODIS and/or Landsat after the year 2000. Five products cover the Sentinel-2 data from 2015 or later. They either use 2016 or 2017 as the reference year to monitor forest changes since there was relatively little drought damage visible in the German forest in these two years.

The highest temporal update of 2–3 h exists for forest fire monitoring (EFFIS) [135]. The second highest temporal resolution of eight days exists for the European Forest Condition Monitor [49], which is also used to observe changes in phenology. The product of canopy-cover loss offers information on a monthly basis [11]. Yearly products are provided with GFW [30] and ForestWatch [134]. Two products correspond to one time cut (i.e., mapping of tree species [108,133]). The remaining two products have an update interval of three years [61,131].

### 3.2.4. Earth Observation Sensors Employed

Six of the analyzed products rely on Sentinel-2 data, mostly in combination with other sensors (e.g., Landsat-8, Sentinel-1, or MODIS). The two Europe-wide products with the lower geometric resolution use MODIS time series. Only one product uses aerial imagery

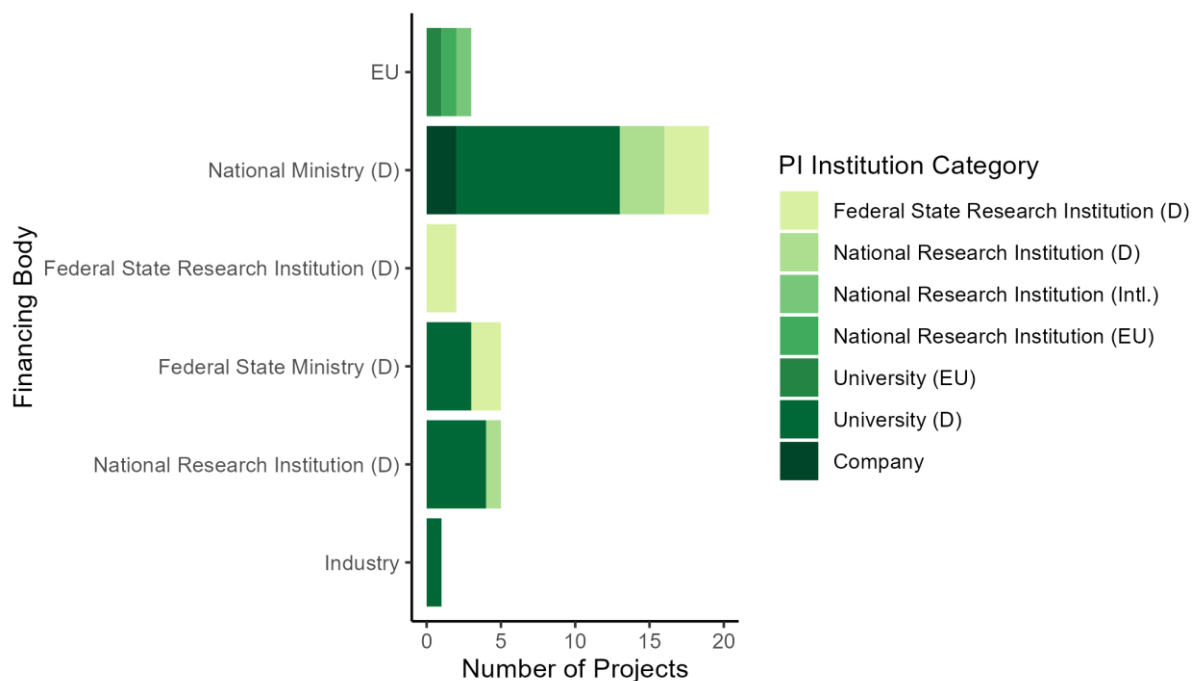
(which is also the product with the highest spatial resolution), whereby these data are used in combination with Sentinel-2 [61].

### 3.3. Forest-Related Projects

The 34 projects identified for this review are examined in more detail below with regard to the funding bodies and the research topics addressed.

#### 3.3.1. Funding

Various funding bodies finance research projects on forests in Germany. One of the main funding bodies is the BMEL. Together with the BMUV (Federal Ministry for the Environment, Nature Conservation, Nuclear Safety, and Consumer Protection), they jointly launched the program “Forest Climate Fund/Waldklimafonds” that has been continuously running since 2013. Eight of thirty-four ongoing projects examined in this study, which were started after April 2020 and before January 2023, are funded by the Forest Climate Fund. Other funding sources are the European Commission (EU) with its Horizon Europe program, the Federal Ministry of Education and Research (BMBF), the Federal Ministry of Economic Affairs and Climate Action (BMWK), the Federal Ministry of Digital and Transport (BMDV) (such as mFUND), the federal research institutions DFG and the Helmholtz Association (HGF), the Volkswagen Foundation, as well as several grants from the ministries of the German federal states Bavaria and Lower Saxony. The institutions that usually lead project consortia funded by federal government are universities, while universities do not lead any of the EU-funded projects that fulfil our criteria (Figure 12).



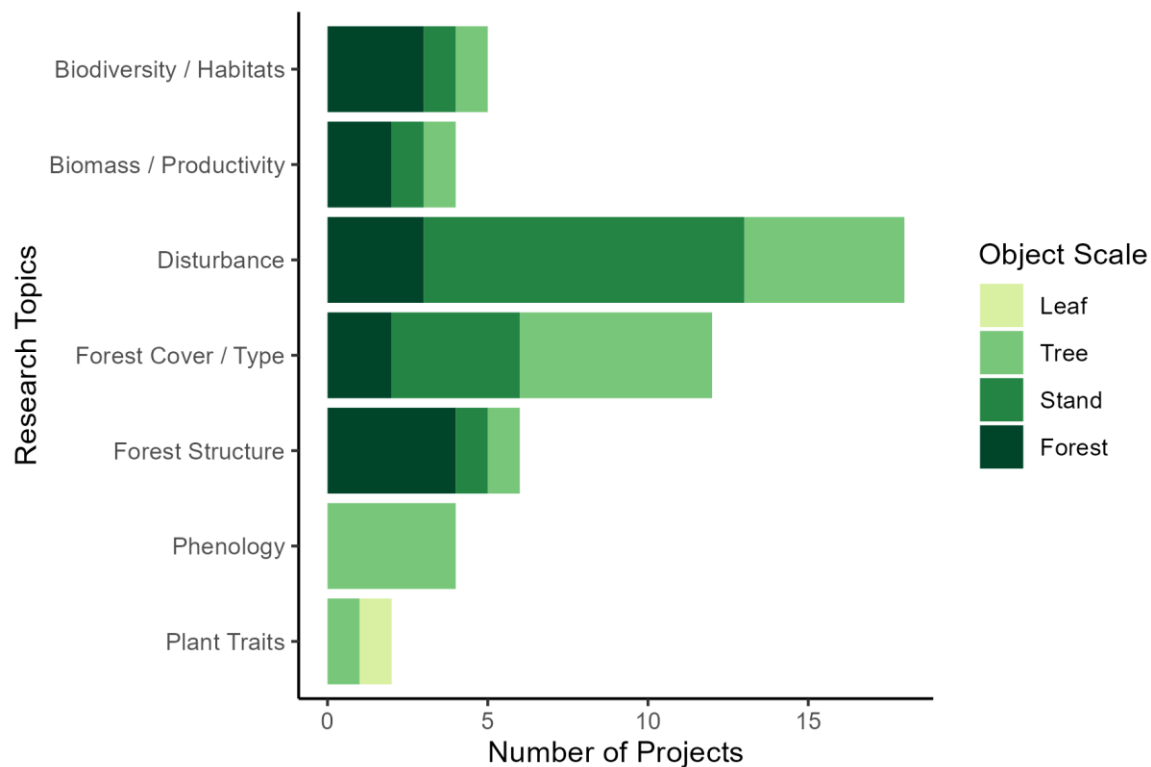
**Figure 12.** Financing bodies of research projects and the associated institution category of the principal investigator (PI).

#### 3.3.2. Topics and Used Sensors

Thematically, the projects studied are diverse. With 14 projects, the largest part deals with the topic of forest disturbance. Six projects assess forest types and the forest cover of Germany with the help of EO data. On the other hand, phenology is investigated in four projects, forest structure in two projects, and biodiversity and plant traits in one project each. Six projects assigned themselves several of the above topics and more, such as habitats and productivity.



More than half of the reviewed projects deal with forest disturbance as one of their topics, followed by forest cover/type, which is a subject of almost 30% of the projects. While disturbance and forest cover/type are mainly analyzed at the tree and stand scale, projects dealing with biodiversity/habitats, biomass/productivity, and forest structure work are 50% or more on the forest scale. Phenology is analyzed exclusively in projects that work on the tree scale and plant traits on leaf and tree scale (Figure 13).



**Figure 13.** Research topic categories of the projects and the corresponding observed object scale.

Within the projects, various Earth-observation sensors are used. Overall, 55% of the projects focus on one sensor only, while the rest follow multi-sensor approaches. The most prominent sensor used in the projects is Sentinel-2 (60% of the projects). In comparison, Sentinel-1 is considered in only one-third of the projects. A similar importance can be observed for UAV data, which are used in 35% of the projects, and six projects (17.5%) even use UAVs exclusively. In each case, four projects use LiDAR data, hyperspectral data, or aerial photography data or use a combination of these.

#### 4. Discussion

The extensive and systematic review of the literature and of existing forest-related products and projects clearly shows the changes in recent years in the use of EO for different forest-related purposes. Especially in the field of forest damage, the scientific community is working intensively on solutions to support foresters, forest owners, forest managers, or ecologists in their work by means of products derived from remote sensing. In the following, we will take a closer look at the forest strategy developed for Germany, discuss the necessity of forest disturbance monitoring, consider user requirements and the possibilities offered by remote sensing, and give an overview of future developments.

##### 4.1. Current Strategic Planning in the German Forest Sector

Parallel to the increase of forest research based on EO data during the past years (see Section 3.1.1), the strategic documents on the federal level also acknowledge the growing importance of remote sensing in the forest sector. Whereas BMEL's "Waldstrategie 2020"

(Forest Strategy 2020) [145] published in 2011 did not mention the topic of “digitization in forestry” explicitly, the “Waldstrategie 2050” (Forest Strategy 2050) [19], as of 2021, clearly refers to remote sensing in two chapters: in chapter 8, “Forestry, Digitization and Technology”, and in chapter 9, “Research and Development”. Specifically, chapter 8 emphasizes that digital data have become increasingly important in all areas of forest management, especially for monitoring purposes. Yet, there still is a demand for the development of user-friendly applications, standardized interfaces, and new business models. In the area of forest research (see chapter 9), further development of forest monitoring through the use of remote sensing and drone technology, among other things, is listed as one of the most important topics.

Furthermore, in order to strengthen national and international forest and wood research, it is expected that networking with other disciplines (including biology, ecology, nature conservation, geography, economics, social sciences, etc.) will be improved [19]. The Forest Strategy 2050 also mentions the creation of national and international platforms for data exchange and the formation of joint alliances as a means to improve collaboration. To achieve this goal, partners in research projects should be included. Equally important is an open-access strategy to make research data freely available. The promotion of relatively short-term research programs is described as inappropriate, and the implementation of inter- and transdisciplinary, longer-term collaborations and research projects is suggested.

The Forest Strategy 2050 takes up central aspects of the Scientific Advisory Board Forest Policy (“Wissenschaftlicher Beirat Waldpolitik”) [13], e.g., regarding the recognition that satellite data as well as the development of user-friendly applications is increasingly demanded in the field of action of digitization.

In a similar direction, the Forest Report of the Federal Government 2021 [146] acknowledges the use of digital forest information for communication and documentation purposes. The document mentions that satellite and drone technologies offer the possibility to capture geospatial data with high accuracy and are already used for networking, rationalization, and the qualitative improvement of forestry, planning, nature conservation, and serving forestry research [146].

In summary, it can be said that some of the points mentioned above are reflected in the objectives of the projects considered within this review (see Section 3.3), and thus, the use of remote sensing for forestry is also being increasingly encouraged by policymakers.

#### 4.2. Forest Disturbance Monitoring: The Most Urgent Task?

A number of papers addressed disturbances, some of them with clear focus on specific drivers (e.g., windthrow [53,88] or fire [98]). However, most of the identified papers did not address specific drivers as the attribution of disturbance events. This is a challenging task, mainly because of limited availability of adequate training data [147] but also because some hazards often emerge as compound or cascading processes (e.g., heatwaves, droughts, insect outbreaks, fire [15,17]). The differentiation of disturbance drivers is very important for appropriate forest management. Therefore, future work will likely and should focus on the attribution of disturbance events in order to support targeted policies, e.g., to reduce salvage logging [148].

Closely related to forest disturbance, however, is reforestation and development of the regenerating forest [99]. This kind of monitoring will probably become more important in the next decades in order to support forest management measures.

#### 4.3. User Needs and Possibilities of EO Based Forest Monitoring

Forest managers working on the ground generally require timely information about forest condition for proper planning of interventions or the identification of risk zones [62,149]. Timely information is of particular interest in the early detection of insect outbreaks. In this review, we found two papers addressing early detection of spruce bark beetle green attack [58,68]. Both studies relied on hyperspectral data and achieved accurate results for the early identification of infested areas. Other studies reported successful use of Sentinel-2 data

for the identification of bark beetle infestations with the limitation that only larger continuous stands of affected trees with severe signs of damage can be recorded [82,120,150]. These findings are in line with previous work that early detection of bark beetle infestations (i.e., green attack stage) by means of spaceborne remote sensing remains a challenge. This does not yet fully meet the requirements of foresters who are looking for early signs of bark beetle infestations at the individual tree level. However, a recent study demonstrated the ability to distinguish affected spruce trees at various attack stages, including the green attack stage, and at tree level based on daily planet data in a study site in Italy [151]. The upscaling of promising approaches to larger areas is still pending [152].

The increasing availability of very-high spatial resolution airborne and UAS (unmanned aircraft system) systems carrying LiDAR and/or multispectral sensors and the advance in deep learning methods have opened new opportunities in the identification of forest properties at the tree or even sub-tree level. This allows for identifying individual tree crowns and their status (e.g., standing deadwood detection [136]). Because of the great importance of deadwood for biodiversity, its discernment from live trees and clear-cuts is important. Further characterization, such as deadwood on the ground versus standing deadwood or vegetation coverage and composition in clear-cut areas, has not yet been adequately addressed.

Generally, the harmonization and integration of proven concepts into monitoring systems along with a clear description of which product is doing what remains vague. The state forests of Rhineland-Palatinate are playing a leading role in the area of translating EO-based products into useful forestry products. They are starting to integrate remote sensing data into strategic and operational forest management [153] with annually updated data products (e.g., forest mask, deciduous/coniferous differentiation) for the entire federal state of Rhineland-Palatinate using the Sentinel-2 data capacity. The products all provide with quality indicators, which is essential for the interpretation of the map products. However, spatial and temporal resolution are still mentioned as limiting factors when it comes to specific problems in the context of forestry.

The challenge of user uptake of remote sensing into operational forest management and monitoring was also reported in the recently published review of Fassnacht et al. [154].

#### 4.4. Future Developments

The Global Ecosystem Dynamics Investigation (GEDI) is the first spaceborne LiDAR instrument (operational since April 2019) that is specifically designed to characterize the three-dimensional vegetation structure of temperate and tropical forests. Despite its great potentials for the analysis of vertical and horizontal vegetation structure properties, only one study [42] integrating GEDI data for Germany was published within the temporal period assessed in the present review. Plausible reasons are the novel data characteristics of GEDI (sampling mission, variety of datasets available) and the maximum latitudinal coverage of 52 ° N, thus challenging Germany-wide studies. Since March 2023, several studies using GEDI data covering Germany have been published [36,155–157]. A further increase in studies making use of GEDI data might be promoted through the confirmed mission extension from end of 2024 to 2031 [158] and upcoming spaceborne long-wavelength SAR (Synthetic Aperture Radar) missions (BIOMASS, NISAR). This might also raise the number of studies on biomass/productivity again.

Despite large spatial coverage, high temporal resolution, and free and open access, Sentinel-1 data have only been used in five studies since 2020 [56,67,71,118,119]. The limited sensitivity of C-band SAR signals to biomass and forest structure may contribute to the infrequent use of Sentinel-1 in forest monitoring. However, an even more crucial factor may be the limitations due to temporal decorrelations inherent in repeat-pass SAR systems such as Sentinel-1. Nevertheless, the continuity of the Sentinel-1 series with the launch of Sentinel-1C and D and the associated high frequency of radar observations enabling near real-time monitoring could render the use of C-band SAR data for forest monitoring attractive in the future.

Even though the number of scientific publications using UAV data is relatively low, more than one-third of the projects considered within our review exploit the use of this very-high-resolution data. Drones are used mainly because they offer flexibility in mapping the forest at small scale down to the leaf level. In a recent review, Ecker et al. [159] investigated the use of UAV-based data in the context of forest health and found an increasing number of publications worldwide, especially since 2018. However, there are still some gaps to be filled in order to efficiently exploit drones within forestry: In the future, sensor technology will be further developed and, consequently, also processing and analysis procedures. The combination of UAV data with other EO data will also be of high interest in the future and is reflected in some of the projects considered in the present review.

The analysis of forest biodiversity through remote sensing holds both challenges and potentials for the future. On one hand, scale differences from field sampling or laboratory experiments to remotely sensed measures ranging from terrestrial to spaceborne observations still need to be bridged for a comprehensive understanding of taxa and ecosystem functions at various spatio-temporal dimensions [160,161]. On the other hand, increased efforts for trans-disciplinary research calling for the integration of remotely sensed data in ecological research are a promising development [162]. The expected future increase of forest disturbances requires the characterization of different post-disturbance structures (e.g., standing deadwood [92]) from airborne to spaceborne perspectives in order to model changes in biodiversity and ecosystem functions [66,163].

In addition to the further development of instruments, the use of artificial intelligence (e.g., convolutional neural networks) is becoming increasingly common, e.g., for the segmentation of deadwood objects from UAV data [115] or the detection of forest damage from satellite data [91,111]. For the training of a deep learning model, extensive, high-quality reference data are indispensable. The creation of such a reference dataset (e.g., tree species) and its provision is partly the content of individual projects.

## 5. Conclusions

In 2020, the paper “Earth Observation Based Monitoring of Forests in Germany: A Review” was published, which included a literature review of the forest landscape in Germany based on 166 papers from 1997–2020. In the last few years, there has been a massive degradation of the forest condition due to far drier- and hotter-than-average weather conditions. According to the past forest condition report of the Federal Ministry of Food and Agriculture from 2022, high crown defoliation has been recorded for all tree species. This alarming development has led to an increase in using remote sensing for monitoring the situation of the German forests, which is also being promoted by policymakers. The overview and in-depth analysis of the developments of the last three years in the context of EO-based monitoring of forests in Germany are presented in this paper and thus complements the review published in 2020. In the course of this review, an additional 84 papers were analyzed, which were published between April 2020 and December 2022. In addition, the review was supplemented by the consideration of existing EO-based products and projects all dealing with forestry-relevant topics.

Comparing the use of remote sensing for German forests before and after 2020 (publication year of our initial review), the following is particularly notable:

- The increasing number of publications that was already observed over the previous 23 years continued, with a growing number of publications in ecology-related journals (29% in the last three years compared to 12.5% in the years before);
- A total of 27% of publications for the years 2020–2022 can be assigned to institutions with an institution background on both EO and forestry in comparison to only 3.5% beforehand;
- The extent of the study areas did increase with many more nationwide studies (from 2.9% to 28%);
- The growing deployment of Copernicus data or satellite data in general: 70% of the studies are based on spaceborne sensor systems, which is an increase of 20%. As

before, mainly multispectral sensors (i.e., Sentinel-2, Landsat, and MODIS) were used, namely 85%;

- A shift towards the usage of multi-temporal/multi-annual EO data, which account now for 50% of the studies in contrast to the earlier period with 18.5%;
- The percentage of studies dealing with the derivation of forest disturbance information doubled from 16.2% to 32.1%.

All these findings are related on the one hand to the current devastating situation of the German forest and, on the other hand, of course, to the increasing amount of freely available high-quality EO data with adequate spectral, spatial, and temporal resolution (e.g., Sentinel-2). Furthermore, the existing computational capacities to process large datasets enable national-scale multi-temporal products. But, the growing acceptance of the use of EO-based techniques for forest monitoring is also reflected in our results. A considerable increase of funding for this very purpose has been made available in recent years, allowing a wide range of projects to be carried out. The integration of remote sensing into operational forest management and monitoring in Germany is facilitated by the growing number of projects connecting a variety of research areas and exploiting a diversity of sensor systems. And this, in turn, leads to a steadily growing number of freely available products that can be utilized by different user communities. In addition, we also expect a further push in developments when more EO satellites are launched (e.g., Biomass, Flex, and further Sentinels). However, there are still gaps when it comes to developing products that can provide information on individual trees. And these are indeed the information that would be most interesting for the foresters facilitating their ground work (e.g., where is the bark-beetle-infested spruce tree?). For these developments, it would be helpful if high-resolution data from sources such as Planet or aerial imagery data were freely available. Other applications might benefit from synchronous LiDAR and multispectral imagery. Whether for reporting or management purposes, EO-based products on the condition of the forest in Germany, particularly with regard to forest disturbance, regeneration, and biodiversity, will be absolutely indispensable.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs15174234/s1>, Table S1: Forest-related projects relevant to this review; Table S2: Acronyms used within the paper.

**Author Contributions:** Conceptualization, C.K.; methodology, S.H., F.T., P.K., S.A. (Sarah Asam), C.E. and B.W.; writing—original draft preparation, S.H., F.T., P.K., S.A. (Sahra Abdullahi), K.C., C.E., U.G., J.H., T.K., C.S. and B.W.; writing—review and editing, S.H., F.T., P.K., S.A. (Sarah Asam), K.C. and C.K.; visualization, C.S., F.T. and S.A. (Sarah Asam). All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** No new data were created or analyzed in this study. Data sharing is not applicable to this article.

**Acknowledgments:** We would like to thank Francesco Niklas Kerpen and Louis Nick Tenbergen for supporting analysis in the review process.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Holzwarth, S.; Thonfeld, F.; Abdullahi, S.; Asam, S.; Da Ponte Canova, E.; Gessner, U.; Huth, J.; Kraus, T.; Leutner, B.; Kuenzer, C. Earth Observation Based Monitoring of Forests in Germany: A Review. *Remote Sens.* **2020**, *12*, 3570. [\[CrossRef\]](#)
2. Ahmed, K.R.; Paul-Limoges, E.; Rascher, U.; Damm, A. A First Assessment of the 2018 European Drought Impact on Ecosystem Evapotranspiration. *Remote Sens.* **2020**, *13*, 16. [\[CrossRef\]](#)
3. Brun, P.; Psomas, A.; Ginzler, C.; Thuiller, W.; Zappa, M.; Zimmermann, N.E. Large-scale early-wilting response of Central European forests to the 2018 extreme drought. *Glob. Chang. Biol.* **2020**, *26*, 7021–7035. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Buras, A.; Rammig, A.; Zang, C.S. Quantifying impacts of the 2018 drought on European ecosystems in comparison to 2003. *Biogeosciences* **2020**, *17*, 1655–1672. [\[CrossRef\]](#)



5. Obladen, N.; Dechering, P.; Skiadaresis, G.; Tegel, W.; Keßler, J.; Höllerl, S.; Kaps, S.; Hertel, M.; Dulamsuren, C.; Seifert, T.; et al. Tree mortality of European beech and Norway spruce induced by 2018–2019 hot droughts in central Germany. *Agric. For. Meteorol.* **2021**, *307*, 108482. [CrossRef]
6. Philipp, M.; Wegmann, M.; Kübert-Flock, C. Quantifying the Response of German Forests to Drought Events via Satellite Imagery. *Remote Sens.* **2021**, *13*, 1845. [CrossRef]
7. Puletti, N.; Mattioli, W.; Bussotti, F.; Pollastrini, M. Monitoring the effects of extreme drought events on forest health by Sentinel-2 imagery. *J. Appl. Remote Sens.* **2019**, *13*, 020501. [CrossRef]
8. Rohner, B.; Kumar, S.; Liechti, K.; Gessler, A.; Ferretti, M. Tree vitality indicators revealed a rapid response of beech forests to the 2018 drought. *Ecol. Indic.* **2021**, *120*, 106903. [CrossRef]
9. Schuldt, B.; Buras, A.; Arend, M.; Vitasse, Y.; Beierkuhnlein, C.; Damm, A.; Gharun, M.; Grams, T.E.E.; Hauck, M.; Hajek, P.; et al. A first assessment of the impact of the extreme 2018 summer drought on Central European forests. *Basic Appl. Ecol.* **2020**, *45*, 86–103. [CrossRef]
10. Shekhar, A.; Chen, J.; Bhattacharjee, S.; Buras, A.; Castro, A.O.; Zang, C.S.; Rammig, A. Capturing the Impact of the 2018 European Drought and Heat across Different Vegetation Types Using OCO-2 Solar-Induced Fluorescence. *Remote Sens.* **2020**, *12*, 3249. [CrossRef]
11. Thonfeld, F.; Gessner, U.; Holzwarth, S.; Kriese, J.; da Ponte, E.; Huth, J.; Kuenzer, C. A First Assessment of Canopy Cover Loss in Germany's Forests after the 2018–2020 Drought Years. *Remote Sens.* **2022**, *14*, 562. [CrossRef]
12. Concern about German Forests. Available online: [https://www.dlr.de/en/latest/news/2022/01/20220221\\_concern-about-german-forests](https://www.dlr.de/en/latest/news/2022/01/20220221_concern-about-german-forests) (accessed on 1 July 2023).
13. *Eckpunkte der Waldstrategie 2050—Stellungnahme des Wissenschaftlichen Beirates Waldpolitik*; Wissenschaftlicher Beirat Waldpolitik beim BMEL: Berlin, Germany, 2020.
14. AG Wald- und Holzforschung. *Stärkung der Wald- und Holzforschung in Deutschland*; AG Wald- und Holzforschung: Berlin, Germany, 2021.
15. de Brito, M.M. Compound and cascading drought impacts do not happen by chance: A proposal to quantify their relationships. *Sci. Total Environ.* **2021**, *778*, 146236. [CrossRef] [PubMed]
16. Rakovec, O.; Samaniego, L.; Hari, V.; Markonis, Y.; Moravec, V.; Thober, S.; Hanel, M.; Kumar, R. The 2018–2020 Multi-Year Drought Sets a New Benchmark in Europe. *Earth's Future* **2022**, *10*, e2021EF002394. [CrossRef]
17. Hlásny, T.; Krokene, P.; Liebhold, A.; Montagné-Huck, C.; Müller, J.; Qin, H.; Raffa, K.; Schelhaas, M.-J.; Seidl, R.; Svoboda, M.; et al. *Living with Bark Beetles: Impacts, Outlook and Management Options*; European Forest Institute: Joensuu, Finland, 2019. [CrossRef]
18. Third National Forest Inventory. Available online: <https://bwi.info/> (accessed on 1 March 2023).
19. *Waldstrategie 2050*; BMEL, Referat 513; Nationale Waldpolitik, Jagd, Kompetenzzentrum Wald und Holz: Berlin, Germany, 2021.
20. Allen, C.D.; Macalady, A.K.; Chenchouni, H.; Bachelet, D.; McDowell, N.; Vennetier, M.; Kitzberger, T.; Rigling, A.; Breshears, D.D.; Hogg, E.H.; et al. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *For. Ecol. Manag.* **2010**, *259*, 660–684. [CrossRef]
21. Bolte, A.; Ammer, C.; Löf, M.; Madsen, P.; Nabuurs, G.-J.; Schall, P.; Spathelf, P.; Rock, J. Adaptive forest management in central Europe: Climate change impacts, strategies and integrative concept. *Scand. J. For. Res.* **2009**, *24*, 473–482. [CrossRef]
22. Schmied, G.; Hilmers, T.; Uhl, E.; Pretzsch, H. The Past Matters: Previous Management Strategies Modulate Current Growth and Drought Responses of Norway Spruce (*Picea abies* H. Karst.). *Forests* **2022**, *13*, 243. [CrossRef]
23. Brang, P.; Spathelf, P.; Larsen, J.B.; Bauhus, J.; Boncina, A.; Chauvin, C.; Drossler, L.; Garcia-Guemes, C.; Heiri, C.; Kerr, G.; et al. Suitability of close-to-nature silviculture for adapting temperate European forests to climate change. *Forestry* **2014**, *87*, 492–503. [CrossRef]
24. Vitasse, Y.; Bottero, A.; Cailleret, M.; Bigler, C.; Fonti, P.; Gessler, A.; Levesque, M.; Rohner, B.; Weber, P.; Rigling, A.; et al. Contrasting resistance and resilience to extreme drought and late spring frost in five major European tree species. *Glob. Chang. Biol.* **2019**, *25*, 3781–3792. [CrossRef]
25. Wellbrock, N.; Eickenscheidt, N.; Hilbrig, L.; Dühnelt, P.-E.; Holzhausen, M.; Bauer, A.; Dammann, I.; Strich, S.; Engels, F.; Wauer, A. *Leitfaden und Dokumentation zur Waldzustandserhebung in Deutschland*; Johann Heinrich von Thünen-Institut: Braunschweig, Germany, 2018.
26. *Ergebnisse der Waldzustandserhebung 2022*; BMEL, Referat 515; Nachhaltige Waldbewirtschaftung, Holzmarkt: Bonn, Germany, 2023.
27. Gschwantner, T.; Alberdi, I.; Bauwens, S.; Bender, S.; Borota, D.; Bosela, M.; Bouriaud, O.; Breidenbach, J.; Donis, J.; Fischer, C.; et al. Growing stock monitoring by European National Forest Inventories: Historical origins, current methods and harmonisation. *For. Ecol. Manag.* **2022**, *505*, 119868. [CrossRef]
28. The Forest-based Sector Technology Platform (FTP). *Strategic Research and Innovation Agenda 2030 of the European Forest-Based Sector*; The European Forestry House: Brussels, Belgium, 2020.
29. Banskota, A.; Kayastha, N.; Falkowski, M.J.; Wulder, M.A.; Froese, R.E.; White, J.C. Forest monitoring using Landsat time series data: A review. *Can. J. Remote Sens.* **2014**, *40*, 362–384. [CrossRef]
30. Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland, T.R.; et al. High-resolution global maps of 21st-century forest cover change. *Science* **2013**, *342*, 850–853. [CrossRef] [PubMed]

31. Coops, N.C.; Tompalski, P.; Goodbody, T.R.H.; Achim, A.; Mulverhill, C.; Fassnacht, F. Framework for near real-time forest inventory using multi source remote sensing data. *For. Int. J. For. Res.* **2023**, *96*, 1–19. [\[CrossRef\]](#)
32. Pulvirenti, L.; Squicciarino, G.; Fiori, E.; Fiorucci, P.; Ferraris, L.; Negro, D.; Gollini, A.; Severino, M.; Puca, S. An automatic processing chain for near real-time mapping of burned forest areas using sentinel-2 data. *Remote Sens.* **2020**, *12*, 674. [\[CrossRef\]](#)
33. Francini, S.; McRoberts, R.E.; Giannetti, F.; Mencucci, M.; Marchetti, M.; Scarascia Mugnozza, G.; Chirici, G. Near-real time forest change detection using PlanetScope imagery. *Eur. J. Remote Sens.* **2020**, *53*, 233–244. [\[CrossRef\]](#)
34. Flores-Anderson, A.I.; Herndon, K.E.; Thapa, R.B.; Cherrington, E. *The SAR Handbook: Comprehensive Methodologies for Forest Monitoring and Biomass Estimation*; SERVIR Global Science Coordination Office, National Space Science and Technology Center: Huntsville, AL, USA, 2019.
35. Hill, J.; Buddenbaum, H.; Townsend, P.A. Imaging spectroscopy of forest ecosystems: Perspectives for the use of space-borne hyperspectral earth observation systems. *Surv. Geophys.* **2019**, *40*, 553–588. [\[CrossRef\]](#)
36. Kacic, P.; Thonfeld, F.; Gessner, U.; Kuenzer, C. Forest Structure Characterization in Germany: Novel Products and Analysis Based on GEDI, Sentinel-1 and Sentinel-2 Data. *Remote Sens.* **2023**, *15*, 1969. [\[CrossRef\]](#)
37. Kacic, P.; Kuenzer, C. Forest Biodiversity Monitoring Based on Remotely Sensed Spectral Diversity—A Review. *Remote Sens.* **2022**, *14*, 5363. [\[CrossRef\]](#)
38. Potapov, P.; Li, X.; Hernandez-Serna, A.; Tyukavina, A.; Hansen, M.C.; Kommareddy, A.; Pickens, A.; Turubanova, S.; Tang, H.; Silva, C.E. Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sens. Environ.* **2021**, *253*, 112165. [\[CrossRef\]](#)
39. Vangi, E.; D’Amico, G.; Francini, S.; Giannetti, F.; Lasserre, B.; Marchetti, M.; Chirici, G. The new hyperspectral satellite PRISMA: Imagery for forest types discrimination. *Sensors* **2021**, *21*, 1182. [\[CrossRef\]](#)
40. Di Leo, M.; Minghini, M.; Kona, A.; Spadaro, N.; Kotsev, A.; Dusart, J.; Lumnitz, S.; Ilie, C.M.; Kilsedar, C.E.; Tzotsos, A. Digital earth observation infrastructures and initiatives: A review framework based on open principles. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2023**, *XLVIII-4/W7-2023*, 33–40. [\[CrossRef\]](#)
41. Gomes, V.C.F.; Queiroz, G.R.; Ferreira, K.R. An Overview of Platforms for Big Earth Observation Data Management and Analysis. *Remote Sens.* **2020**, *12*, 1253. [\[CrossRef\]](#)
42. Adam, M.; Urbazaev, M.; Dubois, C.; Schmulius, C. Accuracy Assessment of GEDI Terrain Elevation and Canopy Height Estimates in European Temperate Forests: Influence of Environmental and Acquisition Parameters. *Remote Sens.* **2020**, *12*, 3948. [\[CrossRef\]](#)
43. Alagialoglou, L.; Manakos, I.; Heurich, M.; Cervenka, J.; Delopoulos, A. A Learnable Model with Calibrated Uncertainty Quantification for Estimating Canopy Height From Spaceborne Sequential Imagery. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 4410913. [\[CrossRef\]](#)
44. Ali, A.M.; Darvishzadeh, R.; Skidmore, A.; Gara, T.W.; Heurich, M. Machine learning methods’ performance in radiative transfer model inversion to retrieve plant traits from Sentinel-2 data of a mixed mountain forest. *Int. J. Digit. Earth* **2020**, *14*, 106–120. [\[CrossRef\]](#)
45. Axer, M.; Schlicht, R.; Wagner, S. Modelling potential density of natural regeneration of European oak species (*Quercus robur* L., *Quercus petraea* (Matt.) Liebl.) depending on the distance to the potential seed source: Methodological approach for modelling dispersal from inventory data at forest enterprise level. *For. Ecol. Manag.* **2021**, *482*, 118802. [\[CrossRef\]](#)
46. Barta, K.A.; Hais, M.; Heurich, M. Characterizing forest disturbance and recovery with thermal trajectories derived from Landsat time series data. *Remote Sens. Environ.* **2022**, *282*, 113274. [\[CrossRef\]](#)
47. Bastos, A.; Orth, R.; Reichstein, M.; Ciais, P.; Viovy, N.; Zaehle, S.; Anthoni, P.; Arneth, A.; Gentile, P.; Joetzjer, E.; et al. Vulnerability of European ecosystems to two compound dry and hot summers in 2018 and 2019. *Earth Syst. Dyn.* **2021**, *12*, 1015–1035. [\[CrossRef\]](#)
48. Beloiu, M.; Stahlmann, R.; Beierkuhnlein, C. Drought impacts in forest canopy and deciduous tree saplings in Central European forests. *For. Ecol. Manag.* **2022**, *509*, 120075. [\[CrossRef\]](#)
49. Buras, A.; Rammig, A.; Zang, C.S. The European Forest Condition Monitor: Using Remotely Sensed Forest Greenness to Identify Hot Spots of Forest Decline. *Front. Plant Sci.* **2021**, *12*, 689220. [\[CrossRef\]](#)
50. Cazcarra-Bes, V.; Pardini, M.; Papathanassiou, K. Definition of Tomographic SAR Configurations for Forest Structure Applications at L-Band. *IEEE Geosci. Remote Sens. Lett.* **2022**, *19*, 4002605. [\[CrossRef\]](#)
51. Ceccherini, G.; Duveiller, G.; Grassi, G.; Lemoine, G.; Avitabile, V.; Pilli, R.; Cescatti, A. Abrupt increase in harvested forest area over Europe after 2015. *Nature* **2020**, *583*, 72–77. [\[CrossRef\]](#) [\[PubMed\]](#)
52. Chetan, M.A.; Dornik, A. 20 years of landscape dynamics within the world’s largest multinational network of protected areas. *J. Environ. Manag.* **2021**, *280*, 111712. [\[CrossRef\]](#)
53. Deigele, W.; Brandmeier, M.; Straub, C. A Hierarchical Deep-Learning Approach for Rapid Windthrow Detection on PlanetScope and High-Resolution Aerial Image Data. *Remote Sens.* **2020**, *12*, 2121. [\[CrossRef\]](#)
54. Dersch, S.; Schöttl, A.; Krzystek, P.; Heurich, M. Novel Single Tree Detection by Transformers Using Uav-Based Multispectral Imagery. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2022**, *XLIII-B2-2022*, 981–988. [\[CrossRef\]](#)
55. Descals, A.; Verger, A.; Yin, G.; Filella, I.; Peñuelas, J. Widespread drought-induced leaf shedding and legacy effects on productivity in European deciduous forests. *Remote Sens. Ecol. Conserv.* **2022**, *9*, 76–89. [\[CrossRef\]](#)

56. Dostálová, A.; Lang, M.; Ivanovs, J.; Waser, L.T.; Wagner, W. European Wide Forest Classification Based on Sentinel-1 Data. *Remote Sens.* **2021**, *13*, 337. [\[CrossRef\]](#)
57. Drag, L.; Burner, R.C.; Stephan, J.G.; Birkemoe, T.; Doerfler, I.; Gossner, M.M.; Magdon, P.; Ovaskainen, O.; Potterf, M.; Schall, P.; et al. High-resolution 3D forest structure explains ecomorphological trait variation in assemblages of saproxylic beetles. *Funct. Ecol.* **2022**, *37*, 150–161. [\[CrossRef\]](#)
58. Einzmann, K.; Atzberger, C.; Pinnel, N.; Glas, C.; Böck, S.; Seitz, R.; Immitzer, M. Early detection of spruce vitality loss with hyperspectral data: Results of an experimental study in Bavaria, Germany. *Remote Sens. Environ.* **2021**, *266*, 112676. [\[CrossRef\]](#)
59. Forzieri, G.; Girardello, M.; Ceccherini, G.; Spinoni, J.; Feyen, L.; Hartmann, H.; Beck, P.S.A.; Camps-Valls, G.; Chirici, G.; Mauri, A.; et al. Emergent vulnerability to climate-driven disturbances in European forests. *Nat. Commun.* **2021**, *12*, 1081. [\[CrossRef\]](#)
60. Freudenberg, M.; Magdon, P.; Nölke, N. Individual tree crown delineation in high-resolution remote sensing images based on U-Net. *Neural Comput. Appl.* **2022**, *34*, 22197–22207. [\[CrossRef\]](#)
61. Ganz, S.; Adler, P.; Kändler, G. Forest Cover Mapping Based on a Combination of Aerial Images and Sentinel-2 Satellite Data Compared to National Forest Inventory Data. *Forests* **2020**, *11*, 1322. [\[CrossRef\]](#)
62. Gnilek, A.; Sanders, T.G.M. Distinguishing Abrupt and Gradual Forest Disturbances With MODIS-Based Phenological Anomaly Series. *Front. Plant Sci.* **2022**, *13*, 863116. [\[CrossRef\]](#)
63. Haberstroh, S.; Werner, C.; Grun, M.; Kreuzwieser, J.; Seifert, T.; Schindler, D.; Christen, A. Central European 2018 hot drought shifts scots pine forest to its tipping point. *Plant Biol.* **2022**, *24*, 1186–1197. [\[CrossRef\]](#)
64. Haesen, S.; Lembrechts, J.J.; De Frenne, P.; Lenoir, J.; Aalto, J.; Ashcroft, M.B.; Kopecky, M.; Luoto, M.; Maclean, I.; Nijs, I.; et al. ForestTemp—Sub-canopy microclimate temperatures of European forests. *Glob. Chang. Biol.* **2021**, *27*, 6307–6319. [\[CrossRef\]](#)
65. Hase, N.; Doktor, D.; Rebmann, C.; Dechant, B.; Mollenhauer, H.; Cuntz, M. Identifying the main drivers of the seasonal decline of near-infrared reflectance of a temperate deciduous forest. *Agric. For. Meteorol.* **2022**, *313*, 108746. [\[CrossRef\]](#)
66. Heidrich, L.; Bae, S.; Levick, S.; Seibold, S.; Weisser, W.; Krzystek, P.; Magdon, P.; Naus, T.; Schall, P.; Serebryanyk, A.; et al. Heterogeneity-diversity relationships differ between and within trophic levels in temperate forests. *Nat. Ecol. Evol.* **2020**, *4*, 1204–1212. [\[CrossRef\]](#)
67. Heisig, J.; Olson, E.; Pebesma, E. Predicting Wildfire Fuels and Hazard in a Central European Temperate Forest Using Active and Passive Remote Sensing. *Fire* **2022**, *5*, 29. [\[CrossRef\]](#)
68. Hellwig, F.M.; Stelmaszczyk-Górska, M.A.; Dubois, C.; Wolsza, M.; Truckenbrodt, S.C.; Sagichewski, H.; Chmara, S.; Bannehr, L.; Lausch, A.; Schmultius, C. Mapping European Spruce Bark Beetle Infestation at Its Early Phase Using Gyrocopter-Mounted Hyperspectral Data and Field Measurements. *Remote Sens.* **2021**, *13*, 4659. [\[CrossRef\]](#)
69. Hemmerling, J.; Pflugmacher, D.; Hostert, P. Mapping temperate forest tree species using dense Sentinel-2 time series. *Remote Sens. Environ.* **2021**, *267*, 112743. [\[CrossRef\]](#)
70. Hoepfner, J.M.; Skidmore, A.K.; Darvishzadeh, R.; Heurich, M.; Chang, H.-C.; Gara, T.W. Mapping Canopy Chlorophyll Content in a Temperate Forest Using Airborne Hyperspectral Data. *Remote Sens.* **2020**, *12*, 3573. [\[CrossRef\]](#)
71. Hoffmann, J.; Muro, J.; Dubovyk, O. Predicting Species and Structural Diversity of Temperate Forests with Satellite Remote Sensing and Deep Learning. *Remote Sens.* **2022**, *14*, 1631. [\[CrossRef\]](#)
72. Kemper, L.; Kemper, H.; Kemper, G. Multispectral Aerial Images to Support Biotope Information Systems for Midge Infestation and Bark Beetle Monitoring. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2022**, XLIII-B3-2022, 893–898. [\[CrossRef\]](#)
73. Kempf, C.; Tian, J.; Kurz, F.; D’Angelo, P.; Schneider, T.; Reinartz, P. Oblique view individual tree crown delineation. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *99*, 102314. [\[CrossRef\]](#)
74. Korolyova, N.; Buechling, A.; Ďuračiová, R.; Zabihi, K.; Turčáni, M.; Svoboda, M.; Bláha, J.; Swarts, K.; Poláček, M.; Hradecký, J.; et al. The Last Trees Standing: Climate modulates tree survival factors during a prolonged bark beetle outbreak in Europe. *Agric. For. Meteorol.* **2022**, *322*, 109025. [\[CrossRef\]](#)
75. Kowalski, K.; Senf, C.; Hostert, P.; Pflugmacher, D. Characterizing spring phenology of temperate broadleaf forests using Landsat and Sentinel-2 time series. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *92*, 102172. [\[CrossRef\]](#)
76. Krause, A.; Knoke, T.; Rammig, A. A regional assessment of land-based carbon mitigation potentials: Bioenergy, BECCS, reforestation, and forest management. *GCB Bioenergy* **2020**, *12*, 346–360. [\[CrossRef\]](#)
77. Liu, Q.; Piao, S.; Campioli, M.; Gao, M.; Fu, Y.H.; Wang, K.; He, Y.; Li, X.; Janssens, I.A. Modeling leaf senescence of deciduous tree species in Europe. *Glob. Chang. Biol.* **2020**, *26*, 4104–4118. [\[CrossRef\]](#)
78. Loozen, Y.; Rebel, K.T.; de Jong, S.M.; Lu, M.; Ollinger, S.V.; Wassen, M.J.; Karssenbergh, D. Mapping canopy nitrogen in European forests using remote sensing and environmental variables with the random forests method. *Remote Sens. Environ.* **2020**, *247*, 111933. [\[CrossRef\]](#)
79. Meyer, B.F.; Buras, A.; Rammig, A.; Zang, C.S. Higher susceptibility of beech to drought in comparison to oak. *Dendrochronologia* **2020**, *64*, 125780. [\[CrossRef\]](#)
80. Misra, G.; Asam, S.; Menzel, A. Ground and satellite phenology in alpine forests are becoming more heterogeneous across higher elevations with warming. *Agric. For. Meteorol.* **2021**, *303*, 108383. [\[CrossRef\]](#)
81. Montibeller, B.; Marshall, M.; Mander, Ü.; Uuemaa, E. Increased carbon assimilation and efficient water usage may not compensate for carbon loss in European forests. *Commun. Earth Environ.* **2022**, *3*, 194. [\[CrossRef\]](#)



82. Montzka, C.; Bayat, B.; Tewes, A.; Mengen, D.; Vereecken, H. Sentinel-2 Analysis of Spruce Crown Transparency Levels and Their Environmental Drivers After Summer Drought in the Northern Eifel (Germany). *Front. For. Glob. Chang.* **2021**, *4*, 667151. [\[CrossRef\]](#)
83. Münzinger, M.; Prectel, N.; Behnisch, M. Mapping the urban forest in detail: From LiDAR point clouds to 3D tree models. *Urban For. Urban Green.* **2022**, *74*, 127637. [\[CrossRef\]](#)
84. Musshoff, O.; Buchholz, M.; Kölle, W. Can Satellite-Based Weather Index Insurance Hedge the Mortality Risk of Pine Stands? *J. For. Econ.* **2021**, *36*, 315–350. [\[CrossRef\]](#)
85. Palmero-Iniesta, M.; Pino, J.; Pesquer, L.; Espelta, J.M. Recent forest area increase in Europe: Expanding and regenerating forests differ in their regional patterns, drivers and productivity trends. *Eur. J. For. Res.* **2021**, *140*, 793–805. [\[CrossRef\]](#)
86. Pardini, M.; Cazcarra-Bes, V.; Papathanassiou, K.P. TomoSAR Mapping of 3D Forest Structure: Contributions of L-Band Configurations. *Remote Sens.* **2021**, *13*, 2255. [\[CrossRef\]](#)
87. Pisek, J.; Erb, A.; Korhonen, L.; Biermann, T.; Carrara, A.; Cremonese, E.; Cuntz, M.; Fares, S.; Gerosa, G.; Grünwald, T.; et al. Retrieval and validation of forest background reflectivity from daily Moderate Resolution Imaging Spectroradiometer (MODIS) bidirectional reflectance distribution function (BRDF) data across European forests. *Biogeosciences* **2021**, *18*, 621–635. [\[CrossRef\]](#)
88. Polewski, P.; Shelton, J.; Yao, W.; Heurich, M. Instance segmentation of fallen trees in aerial color infrared imagery using active multi-contour evolution with fully convolutional network-based intensity priors. *ISPRS J. Photogramm. Remote Sens.* **2021**, *178*, 297–313. [\[CrossRef\]](#)
89. Richter, R.; Hutengs, C.; Wirth, C.; Bannehr, L.; Vohland, M. Detecting Tree Species Effects on Forest Canopy Temperatures with Thermal Remote Sensing: The Role of Spatial Resolution. *Remote Sens.* **2021**, *13*, 135. [\[CrossRef\]](#)
90. Rocchini, D.; Salvatori, N.; Beierkuhnlein, C.; Chiarucci, A.; de Boissieu, F.; Förster, M.; Garzon-Lopez, C.X.; Gillespie, T.W.; Haufler, H.C.; He, K.S.; et al. From local spectral species to global spectral communities: A benchmark for ecosystem diversity estimate by remote sensing. *Ecol. Inform.* **2021**, *61*, 101195. [\[CrossRef\]](#)
91. Scharvogel, D.; Brandmeier, M.; Weis, M. A Deep Learning Approach for Calamity Assessment Using Sentinel-2 Data. *Forests* **2020**, *11*, 1239. [\[CrossRef\]](#)
92. Schiefer, F.; Kattenborn, T.; Frick, A.; Frey, J.; Schall, P.; Koch, B.; Schmidlein, S. Mapping forest tree species in high resolution UAV-based RGB-imagery by means of convolutional neural networks. *ISPRS J. Photogramm. Remote Sens.* **2020**, *170*, 205–215. [\[CrossRef\]](#)
93. Seidel, D.; Annighöfer, P.; Ehbrecht, M.; Magdon, P.; Wöllauer, S.; Ammer, C. Deriving Stand Structural Complexity from Airborne Laser Scanning Data—What Does It Tell Us about a Forest? *Remote Sens.* **2020**, *12*, 1854. [\[CrossRef\]](#)
94. Senf, C.; Buras, A.; Zang, C.S.; Rammig, A.; Seidl, R. Excess forest mortality is consistently linked to drought across Europe. *Nat. Commun.* **2020**, *11*, 6200. [\[CrossRef\]](#)
95. Senf, C.; Mori, A.S.; Müller, J.; Seidl, R. The response of canopy height diversity to natural disturbances in two temperate forest landscapes. *Landsc. Ecol.* **2020**, *35*, 2101–2112. [\[CrossRef\]](#)
96. Senf, C.; Seibald, J.; Seidl, R. Increasing canopy mortality affects the future demographic structure of Europe's forests. *One Earth* **2021**, *4*, 749–755. [\[CrossRef\]](#)
97. Senf, C.; Seidl, R. Mapping the forest disturbance regimes of Europe. *Nat. Sustain.* **2020**, *4*, 63–70. [\[CrossRef\]](#)
98. Senf, C.; Seidl, R. Storm and fire disturbances in Europe: Distribution and trends. *Glob. Chang. Biol.* **2021**, *27*, 3605–3619. [\[CrossRef\]](#) [\[PubMed\]](#)
99. Senf, C.; Seidl, R.; Poulter, B. Post-disturbance canopy recovery and the resilience of Europe's forests. *Glob. Ecol. Biogeogr.* **2021**, *31*, 25–36. [\[CrossRef\]](#)
100. Steffen, M.; Schipek, M.; Lohrengel, A.-F.; Meine, L. Identification of windthrow-endangered infrastructure combining LiDAR-based tree extraction methods using GIS. *J. Appl. Remote Sens.* **2021**, *15*, 014522. [\[CrossRef\]](#)
101. Szymczak, S.; Bott, F.; Babeck, P.; Frick, A.; Stöckigt, B.; Wagner, K. Estimating the hazard of tree fall along railway lines: A new GIS tool. *Nat. Hazards* **2022**, *112*, 2237–2258. [\[CrossRef\]](#)
102. Thiel, C.; Mueller, M.M.; Eppe, L.; Thau, C.; Hese, S.; Voltersen, M.; Henkel, A. UAS Imagery-Based Mapping of Coarse Wood Debris in a Natural Deciduous Forest in Central Germany (Hainich National Park). *Remote Sens.* **2020**, *12*, 3293. [\[CrossRef\]](#)
103. Thiel, C.; Müller, M.M.; Berger, C.; Cremer, F.; Dubois, C.; Hese, S.; Baade, J.; Klan, F.; Pathe, C. Monitoring Selective Logging in a Pine-Dominated Forest in Central Germany with Repeated Drone Flights Utilizing a Low Cost RTK Quadcopter. *Drones* **2020**, *4*, 11. [\[CrossRef\]](#)
104. Tian, F.; Cai, Z.; Jin, H.; Hufkens, K.; Scheifinger, H.; Tagesson, T.; Smets, B.; Van Hoolst, R.; Bonte, K.; Ivits, E.; et al. Calibrating vegetation phenology from Sentinel-2 using eddy covariance, PhenoCam, and PEP725 networks across Europe. *Remote Sens. Environ.* **2021**, *260*, 112456. [\[CrossRef\]](#)
105. Torresani, M.; Rocchini, D.; Sonnenschein, R.; Zebisch, M.; Haufler, H.C.; Heym, M.; Pretzsch, H.; Tonon, G. Height variation hypothesis: A new approach for estimating forest species diversity with CHM LiDAR data. *Ecol. Indic.* **2020**, *117*, 106520. [\[CrossRef\]](#)
106. Uphus, L.; Lüpke, M.; Yuan, Y.; Benjamin, C.; Englmeier, J.; Fricke, U.; Ganuza, C.; Schwindl, M.; Uhler, J.; Menzel, A. Climate Effects on Vertical Forest Phenology of *Fagus sylvatica* L., Sensed by Sentinel-2, Time Lapse Camera, and Visual Ground Observations. *Remote Sens.* **2021**, *13*, 3982. [\[CrossRef\]](#)

107. Weiser, H.; Schäfer, J.; Winiwarter, L.; Krašovec, N.; Fassnacht, F.E.; Höfle, B. Individual tree point clouds and tree measurements from multi-platform laser scanning in German forests. *Earth Syst. Sci. Data* **2022**, *14*, 2989–3012. [\[CrossRef\]](#)
108. Welle, T.; Aschenbrenner, L.; Kuonath, K.; Kirmaier, S.; Franke, J. Mapping Dominant Tree Species of German Forests. *Remote Sens.* **2022**, *14*, 3330. [\[CrossRef\]](#)
109. Wernicke, J.; Seltsmann, C.T.; Wenzel, R.; Becker, C.; Körner, M. Forest canopy stratification based on fused, imbalanced and collinear LiDAR and Sentinel-2 metrics. *Remote Sens. Environ.* **2022**, *279*, 113134. [\[CrossRef\]](#)
110. West, E.; Morley, P.J.; Jump, A.S.; Donoghue, D.N.M. Satellite data track spatial and temporal declines in European beech forest canopy characteristics associated with intense drought events in the Rhon Biosphere Reserve, central Germany. *Plant Biol.* **2022**, *24*, 1120–1131. [\[CrossRef\]](#) [\[PubMed\]](#)
111. Wittich, D.; Rottensteiner, F.; Voelsen, M.; Heipke, C.; Müller, S. Deep Learning for the Detection of Early Signs for Forest Damage Based on Satellite Imagery. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2022**, *V-2-2022*, 307–315. [\[CrossRef\]](#)
112. Xie, R.; Darvishzadeh, R.; Skidmore, A.K.; Heurich, M.; Holzwarth, S.; Gara, T.W.; Reusen, I. Mapping leaf area index in a mixed temperate forest using Fenix airborne hyperspectral data and Gaussian processes regression. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *95*, 102242. [\[CrossRef\]](#)
113. Yazbeck, T.; Bohrer, G.; Gentine, P.; Ye, L.; Arriga, N.; Bernhofer, C.; Blanken, P.D.; Desai, A.R.; Durden, D.; Knohl, A.; et al. Site Characteristics Mediate the Relationship between Forest Productivity and Satellite Measured Solar Induced Fluorescence. *Front. For. Glob. Chang.* **2021**, *4*, 695269. [\[CrossRef\]](#)
114. Zong, X.; Wang, T.; Skidmore, A.K.; Heurich, M. Estimating fine-scale visibility in a temperate forest landscape using airborne laser scanning. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *103*, 102478. [\[CrossRef\]](#)
115. Bulatov, D.L. Instance segmentation of deadwood objects in combined optical and elevation data using convolutional neural networks. In Proceedings of the SPIE Remote Sensing, Earth Resources and Environmental Remote Sensing/GIS Applications XII, Virtual Conference, 13–17 September 2021.
116. Garamszegi, B.; Jung, C.; Schindler, D. Multispectral Spaceborne Proxies of Predisposing Forest Structure Attributes to Storm Disturbance—A Case Study from Germany. *Forests* **2022**, *13*, 2114. [\[CrossRef\]](#)
117. Grunig, M.; Seidl, R.; Senf, C. Increasing aridity causes larger and more severe forest fires across Europe. *Glob. Chang. Biol.* **2023**, *29*, 1648–1659. [\[CrossRef\]](#) [\[PubMed\]](#)
118. Kaiser, P.; Buddenbaum, H.; Nink, S.; Hill, J. Potential of Sentinel-1 Data for Spatially and Temporally High-Resolution Detection of Drought Affected Forest Stands. *Forests* **2022**, *13*, 2148. [\[CrossRef\]](#)
119. Mueller, M.M.; Dubois, C.; Jagdhuber, T.; Hellwig, F.M.; Pathe, C.; Schmulius, C.; Steele-Dunne, S. Sentinel-1 Backscatter Time Series for Characterization of Evapotranspiration Dynamics over Temperate Coniferous Forests. *Remote Sens.* **2022**, *14*, 6384. [\[CrossRef\]](#)
120. Zimmermann, S.; Hoffmann, K. Evaluating the capabilities of Sentinel-2 data for large-area detection of bark beetle infestation in the Central German Uplands. *J. Appl. Remote Sens.* **2020**, *14*, 024515. [\[CrossRef\]](#)
121. Zong, X.; Wang, T.; Skidmore, A.K.; Heurich, M. LiDAR reveals a preference for intermediate visibility by a forest-dwelling ungulate species. *J. Anim. Ecol.* **2022**, *92*, 1306–1319. [\[CrossRef\]](#)
122. Ackermann, J.; Adler, P.; Engels, F.; Franz, S.; Hoffmann, K.; Jütte, K.; Rüffer, O.; Sagischewski, H.; Seitz, R. Die Arbeitsgruppe Forstliche Fernerkundung der Länder. *AFZ-Der Wald* **2019**, *22*, 16–17.
123. Latifi, H.; Holzwarth, S.; Skidmore, A.; Bruna, J.; Červenka, J.; Darvishzadeh, R.; Hais, M.; Heiden, U.; Homolová, L.; Krzystek, P.; et al. A laboratory for conceiving Essential Biodiversity Variables (EBVs)—The ‘Data pool initiative for the Bohemian Forest Ecosystem’. *Methods Ecol. Evol.* **2021**, *12*, 2073–2083. [\[CrossRef\]](#)
124. Wernick, I.K.; Ciais, P.; Fridman, J.; Hogberg, P.; Korhonen, K.T.; Nordin, A.; Kauppi, P.E. Quantifying forest change in the European Union. *Nature* **2021**, *592*, E13–E14. [\[CrossRef\]](#)
125. Palahi, M.; Valbuena, R.; Senf, C.; Acil, N.; Pugh, T.A.M.; Sadler, J.; Seidl, R.; Potapov, P.; Gardiner, B.; Hetemaki, L.; et al. Concerns about reported harvests in European forests. *Nature* **2021**, *592*, E15–E17. [\[CrossRef\]](#)
126. Breidenbach, J.; Ellison, D.; Petersson, H.; Korhonen, K.T.; Henttonen, H.M.; Wallerman, J.; Fridman, J.; Gobakken, T.; Astrup, R.; Næsset, E. Harvested area did not increase abruptly—How advancements in satellite-based mapping led to erroneous conclusions. *Ann. For. Sci.* **2022**, *79*, 2. [\[CrossRef\]](#)
127. Wang, R.; Gamon, J.A. Remote sensing of terrestrial plant biodiversity. *Remote Sens. Environ.* **2019**, *231*, 111218. [\[CrossRef\]](#)
128. Rocchini, D.; Santos, M.J.; Ustin, S.L.; Feret, J.B.; Asner, G.P.; Beierkuhnlein, C.; Dalponte, M.; Feilhauer, H.; Foody, G.M.; Geller, G.N.; et al. The Spectral Species Concept in Living Color. *J. Geophys. Res. Biogeosci.* **2022**, *127*, e2022JG007026. [\[CrossRef\]](#)
129. Rocchini, D.; Torresani, M.; Beierkuhnlein, C.; Feoli, E.; Foody, G.M.; Lenoir, J.; Malavasi, M.; Moudry, V.; Šimová, P.; Ricotta, C. Double down on remote sensing for biodiversity estimation: A biological mindset. *Community Ecol.* **2022**, *23*, 267–276. [\[CrossRef\]](#)
130. Palmer, M.W.; Earls, P.G.; Hoagland, B.W.; White, P.S.; Wohlgemuth, T. Quantitative tools for perfecting species lists. *Environmetrics* **2002**, *13*, 121–137. [\[CrossRef\]](#)
131. *High Resolution Land Cover Characteristics. Tree-Cover/Forest and Change 2015–2018*; European Environment Agency (EEA); Copernicus Land Monitoring Service (CLMS); Copenhagen, Denmark, 2021.
132. *Copernicus Land Monitoring Service—High Resolution Layer Forest: Product Specifications Document*; European Environment Agency; Copenhagen, Denmark, 2017.



133. Blickensdörfer, L.; Oehmichen, K.; Pflugmacher, D.; Kleinschmit, B.; Hostert, P. *Dominant Tree Species for Germany (2017/2018)*; Thünen-Institut, Institut für Waldökosysteme: Eberswalde, Germany, 2022. [\[CrossRef\]](#)
134. Frick, A.R.K. Beispiele für die Anwendung Künstlicher Intelligenz mit Erdbeobachtungs- und Multi-Source Geodaten für das Naturschutz- und Waldmonitoring. In *BfN-Schriften 640*; Bundesamt für Naturschutz: Bonn, Germany, 2022.
135. San-Miguel-Ayanz, J.; Schulte, E.; Schmuck, G.; Camia, A.; Strobl, P.; Libertá, G.; Giovando, C.; Boca, R.; Sedano, F.; Kempeneers, P.; et al. Comprehensive Monitoring of Wildfires in Europe: The European Forest Fire Information System (EFFIS). In *Approaches to Managing Disaster—Assessing Hazards, Emergencies and Disaster Impacts*; IntechOpen: London, UK, 2012.
136. Schiefer, F.; Schmidlein, S.; Frick, A.; Frey, J.; Klinke, R.; Zielewska-Büttner, K.; Junttila, S.; Uhl, A.; Kattenborn, T. UAV-based reference data for the prediction of fractional cover of standing deadwood from Sentinel time series. *ISPRS Open J. Photogramm. Remote Sens.* **2023**, *8*, 100034. [\[CrossRef\]](#)
137. FVA. MoBiTools. Available online: <https://www.fva-bw.de/top-meta-navigation/fachabteilungen/biometrie-informatik/mobitools> (accessed on 1 June 2023).
138. EC. European Forest Fire Information System EFFIS. Available online: <https://effis.jrc.ec.europa.eu/> (accessed on 1 June 2023).
139. Copernicus. HRL Forests. Available online: <https://land.copernicus.eu/pan-european/high-resolution-layers/forests> (accessed on 1 June 2023).
140. Buras, A. Forest Condition Monitor. Available online: <http://interaktiv.waldzustandsmonitor.de/> (accessed on 1 June 2023).
141. DLR. Tree Canopy Cover Loss. Available online: <https://geoservice.dlr.de/web/maps/eoc:tcclde> (accessed on 1 June 2023).
142. Blickensdörfer, L. Dominant Tree Species for Germany (2017/2018). Available online: [https://atlas.thuenen.de/layers/Dominant\\_Species\\_Class:geonode:Dominant\\_Species\\_Class](https://atlas.thuenen.de/layers/Dominant_Species_Class:geonode:Dominant_Species_Class) (accessed on 1 June 2023).
143. Remote Sensing Solutions GmbH. Waldmonitor. Available online: <https://www.remote-sensing-solutions.com/waldmonitor-deutschland/> (accessed on 1 June 2023).
144. Watch, G.F. Global Forest Watch. Available online: <https://map3d.remote-sensing-solutions.de/waldmonitor-deutschland/#> (accessed on 1 June 2023).
145. *Waldstrategie 2020*; Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz (BMELV): Berlin, Germany, 2011.
146. *Waldbericht der Bundesregierung 2021*; BMEL, Referat 513; Nationale Waldpolitik, Jagd, Kompetenzzentrum Wald und Holz: Berlin, Germany, 2021.
147. Masek, J.G.; Hayes, D.J.; Joseph Hughes, M.; Healey, S.P.; Turner, D.P. The role of remote sensing in process-scaling studies of managed forest ecosystems. *For. Ecol. Manag.* **2015**, *355*, 109–123. [\[CrossRef\]](#)
148. Müller, J.; Noss, R.F.; Thorn, S.; Bäessler, C.; Leverkus, A.B.; Lindenmayer, D. Increasing disturbance demands new policies to conserve intact forest. *Conserv. Lett.* **2019**, *12*, e12449. [\[CrossRef\]](#)
149. Torresan, C.; Benito Garzón, M.; O’Grady, M.; Robson, T.M.; Picchi, G.; Panzacchi, P.; Tomelleri, E.; Smith, M.; Marshall, J.; Wingate, L.; et al. A new generation of sensors and monitoring tools to support climate-smart forestry practices. *Can. J. For. Res.* **2021**, *51*, 1751–1765. [\[CrossRef\]](#)
150. König, S.; Thonfeld, F.; Förster, M.; Dubovyk, O.; Heurich, M. Assessing Combinations of Landsat, Sentinel-2 and Sentinel-1 Time series for Detecting Bark Beetle Infestations. *GIScience Remote Sens.* **2023**, *60*, 2226515. [\[CrossRef\]](#)
151. Dalponte, M.; Cetto, R.; Marinelli, D.; Andreatta, D.; Salvadori, C.; Pirotti, F.; Frizzera, L.; Gianelle, D. Spectral separability of bark beetle infestation stages: A single-tree time-series analysis using Planet imagery. *Ecol. Indic.* **2023**, *153*, 110349. [\[CrossRef\]](#)
152. Abdullah, H.; Skidmore, A.K.; Darvishzadeh, R.; Heurich, M.; Pettorelli, N.; Disney, M. Sentinel-2 accurately maps green-attack stage of European spruce bark beetle (*Ips typographus*, L.) compared with Landsat-8. *Remote Sens. Ecol. Conserv.* **2018**, *5*, 87–106. [\[CrossRef\]](#)
153. Hill, J.; Buddenbaum, H.; Langshausen, J.; Hill, A.; Rock, G.; Schneider, T. Die Entwicklung einer operativen Sentinel-2-basierten Prozesskette zur landesweiten Bewertung von Vitalitätsverlusten sowie biotischer und abiotischer Waldschäden in Rheinland-Pfalz und Luxembourg. In *Proceedings of the Forstwissenschaftliche Tagung*, Freising, Germany, 13–16 September 2021.
154. Fassnacht, F.E.; White, J.C.; Wulder, M.A.; Næsset, E. Remote sensing in forestry: Current challenges, considerations and directions. *For. Int. J. For. Res.* **2023**, cpad024. [\[CrossRef\]](#)
155. Ceccherini, G.; Girardello, M.; Beck, P.S.A.; Migliavacca, M.; Duveiller, G.; Dubois, G.; Avitabile, V.; Battistella, L.; Barredo, J.I.; Cescatti, A. Spaceborne LiDAR reveals the effectiveness of European Protected Areas in conserving forest height and vertical structure. *Commun. Earth Environ.* **2023**, *4*, 97. [\[CrossRef\]](#)
156. Mandl, L.; Stritih, A.; Seidl, R.; Ginzler, C.; Senf, C.; Disney, M.; Vaglio Laurin, G. Spaceborne LiDAR for characterizing forest structure across scales in the European Alps. *Remote Sens. Ecol. Conserv.* **2023**. [\[CrossRef\]](#)
157. Rajab Pourrahmati, M.; Baghdadi, N.; Fayad, I. Comparison of GEDI LiDAR Data Capability for Forest Canopy Height Estimation over Broadleaf and Needleleaf Forests. *Remote Sens.* **2023**, *15*, 1522. [\[CrossRef\]](#)
158. Return of the Gedi: Space-Based, Forest Carbon-Mapping Laser Array Saved. Available online: <https://gedi.umd.edu/return-of-the-gedi-space-based-forest-carbon-mapping-laser-array-saved/> (accessed on 12 June 2023).
159. Ecke, S.; Dempewolf, J.; Frey, J.; Schwaller, A.; Endres, E.; Klemmt, H.-J.; Tiede, D.; Seifert, T. UAV-Based Forest Health Monitoring: A Systematic Review. *Remote Sens.* **2022**, *14*, 3205. [\[CrossRef\]](#)
160. Jetz, W.; Cavender-Bares, J.; Pavlick, R.; Schimel, D.; Davis, F.W.; Asner, G.P.; Guralnick, R.; Kattge, J.; Latimer, A.M.; Moorcroft, P.; et al. Monitoring plant functional diversity from space. *Nat. Plants* **2016**, *2*, 16024. [\[CrossRef\]](#)

161. Randin, C.F.; Ashcroft, M.B.; Bolliger, J.; Cavender-Bares, J.; Coops, N.C.; Dullinger, S.; Dirnböck, T.; Eckert, S.; Ellis, E.; Fernández, N.; et al. Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models. *Remote Sens. Environ.* **2020**, *239*, 111626. [[CrossRef](#)]
162. Cavender-Bares, J.; Schneider, F.D.; Santos, M.J.; Armstrong, A.; Carnaval, A.; Dahlin, K.M.; Fatoyinbo, L.; Hurtt, G.C.; Schimel, D.; Townsend, P.A.; et al. Integrating remote sensing with ecology and evolution to advance biodiversity conservation. *Nat. Ecol. Evol.* **2022**, *6*, 506–519. [[CrossRef](#)] [[PubMed](#)]
163. Bae, S.; Levick, S.R.; Heidrich, L.; Magdon, P.; Leutner, B.F.; Wollauer, S.; Serebryanyk, A.; Nauss, T.; Krzystek, P.; Gossner, M.M.; et al. Radar vision in the mapping of forest biodiversity from space. *Nat. Commun.* **2019**, *10*, 4757. [[CrossRef](#)] [[PubMed](#)]

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.