remote sensing

Review

Earth Observation Based Monitoring of Forests in Germany: A Review

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Abstract: Forests in Germany cover around 11.4 million hectares and, thus, a share of 32% of Germany's surface area. Therefore, forests shape the character of the country's cultural landscape. Germany's forests fulfil a variety of functions for nature and society, and also play an important role in the context of climate levelling. Climate change, manifested via rising temperatures and current weather extremes, has a negative impact on the health and development of forests. Within the last five years, severe storms, extreme drought, and heat waves, and the subsequent mass reproduction of bark beetles have all seriously affected Germany's forests. Facing the current dramatic extent of forest damage and the emerging long-term consequences, the effort to preserve forests in Germany, along with their diversity and productivity, is an indispensable task for the government. Several German ministries have and plan to initiate measures supporting forest health. Quantitative data is one means for sound decision-making to ensure the monitoring of the forest and to improve the monitoring of forest damage. In addition to existing forest monitoring systems, such as the federal forest inventory, the national crown condition survey, and the national forest soil inventory, systematic surveys of forest condition and vulnerability at the national scale can be expanded with the help of a satellite-based earth observation. In this review, we analysed and categorized all research studies published in the last 20 years that focus on the remote sensing of forests in Germany. For this study, 166 citation indexed research publications have been thoroughly analysed with respect to publication frequency, location of studies undertaken, spatial and temporal scale, coverage of the studies, satellite sensors employed, thematic foci of the studies, and overall outcomes, allowing us to identify major research and geoinformation product gaps.

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

1. Introduction

1.1. Forests in Germany: Relevance and Current Challenges

Forests all over the world provide extremely valuable ecosystem services and contribute immensely to human well-being. Services can be grouped into provisioning services, supporting services, regulating services, and cultural services (Figure 1) [1–4]. Forests provide raw materials, such as wood or plant fiber (construction wood, furniture wood, paper, coal, etc.), direct and indirect food products (herbs, fruits, nuts, honey, mushrooms, game, insects etc.), and chemical substances and medicinal products (turpentine, oils, resinate, etc.), as well as oftentimes granting access to pure water sources. Forests support habitats for flora and fauna, are home to a large wealth of biodiversity, and contribute to soil formation and nutrient cycling. Furthermore, forests support the protection of land against erosion, such as coastal erosion along shorelines, or slope erosion in mountainous regions. Self-regulating services include water filtration and air filtration, water retention as well as flood and drought control, climate change levelling via the fixation of carbon in plants and soils from the air and the contribution to pollination and the dispersion of seeds, among others. Cultural services include recreation (e.g., walking, hiking, cycling, riding, cross country skiing, hunting, etc.), aesthetics, environmental education, and spiritual services [5,6].

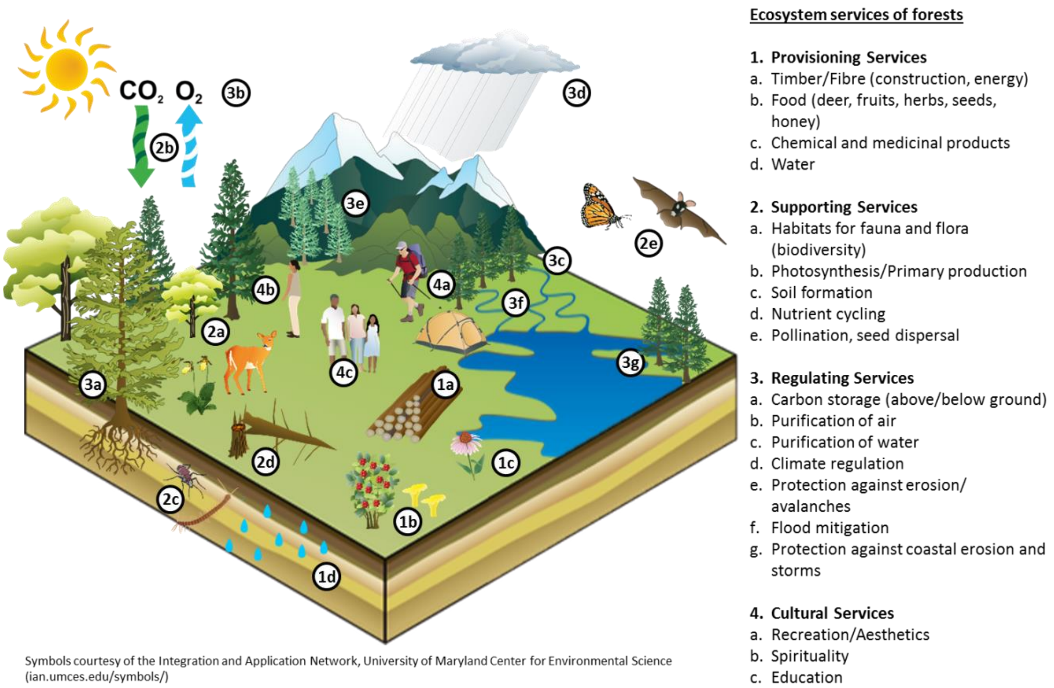

Figure 1. Ecosystem services of forests, subdivided into provisioning services, supporting services, regulating services, and cultural services.

In Germany, around 11.4 million hectares, a share of 32% of the country's surface area, are forest covered. The previously mentioned services demonstrate the enormous indirect value forests play in our daily life. However, forests also represent an important economic factor: forests in Germany provide income for around two million forest owners, and 125,000 companies in the forestry and timber sector employ 1.1 million people—mainly in rural areas. In 2014, the sector generated a turnover of 178 billion euros and 55 billion euros in gross value added [7].

According to the remote sensing-based Global Forest Watch, Germany lost 754,000 hectares of tree cover from 2001 to 2019 equivalent to a 6.0% decrease since 2000 [8]. This loss occurs due to settlement and infrastructure expansion (e.g., urbanization, road construction), resource exploration (e.g., opencast mining), and agricultural expansion as well as natural hazards (storms, droughts, pests, fires, avalanches, etc.) [9]. In recent decades, forests in Germany have been facing a large number of challenges, leading to increased attention in public media.

Severe summer droughts in 2003, 2018, and 2019 have led to stress, a much lower resilience and death of many trees. In stands of lower overall tree health, bark beetle infestations spread to a much larger extent than in past decades. For 2017 and 2018, over 80% of the forested area in Germany showed an increased crown transparency over all species [10]. All these forest disturbances are expected to increase and accelerate in the coming years and decades [11].

Due to the alarming damage to over 32 million m^3 of timber during the 2018 drought, and approximately 105 million m^3 of wood damaged during the 2019 drought, national ministries and agencies in Germany have called for an action plan to develop counter measures and mitigation plans. Measures to be decided upon will be enacted at a federal level by the Federal Ministry of Food and Agriculture (BMEL), the Federal Ministry of the Environment, Nature Conservation and Nuclear Safety (BMU), and at a federal level state run and private organizations and agencies. These are supported by national and federal research institutions, non-governmental organizations (NGOs), as well as forestry-related chairs at universities in the individual federal states (see Section 4).

Common to all players of the institutional landscape in the forest sector is an articulated strong demand for reliable, repeatable, and quantitative information on the dynamics and current status of Germany's forest [12]. Information on national and federal forest cover area, forest loss, species composition, impacts of drought stress, location, and size of disturbance patches can be assessed in situ. However, findings here are usually assessed locally and extrapolated to a federal or national scale. Earth observation (EO)-based analyses—if undertaken in a concerted effort at the federal and national scale—has a lot to offer with respect to its extensive coverage and the offering of timely, quantitative information on the forest resource.

1.2. Earth Observation-Based Analyses Supporting Informed Decision-Making

During the last five years, satellite-based EO has entered a new era. Whereas, for many years, a continuous, daily, or near daily monitoring of a certain area of interest on our Earth could only be undertaken based on low to medium resolution data of satellite sensors such as AVHRR (1 km to 4 km spatial resolution since the early 1980s), MODIS (between 1 km to 250 m resolution since 1999), or MERIS (300 m, only available 2002–2012), higher resolution sensors such as onboard the Landsat satellites (30 m spatial resolution) only granted a bi-weekly observation opportunity due to a repetition rate of 16 days. The launch of the European Sentinel satellite fleet in 2014 by the European Space Agency (ESA) has led to a paradigm shift with respect to EO-based monitoring capacities. Based on a combination of higher resolution multispectral sensors such as TM, ETM+, and OLI on Landsat-5, 7, and 8 (30 m), the upcoming Landsat 9 mission to be launched in late 2021, and especially the European Sentinel satellites, such as Sentinel-2 A and B (10 m to 20 m resolution), Sentinel-3 (300 m resolution), and synthetic aperture (SAR) sensors, such as Sentinel-1 A and B (10 m to 20 m spatial resolution), it is now possible to monitor every place on Earth at high resolution at a near daily interval. Next to these satellites, there are also higher resolution sensors available such as Ikonos, Quickbird, Worldview, or micro-satellites like those controlled by the Planet corporation [13–15]. Whereas SAR (Synthetic Aperture Radar) data is weather independent, cloud cover can be a limiting factor for passive remote sensing systems. However, with such a fleet of sensors, even in partially cloudy mid-latitude regions such as Germany, it is now possible to generate high spatial resolution information products at high temporal resolution and optimally at weekly to monthly intervals.

Higher spatial resolution-covering and area-covering datasets enable the derivation of information products on nation-wide forest cover dynamics and distribution, but also the derivation of detailed information products on forest loss, species composition, and changes thereof, forest disturbances due to droughts, fires, storms, and plagues, as well as forest recovery and regrowth.

At the European level, the use of satellite-based forest information has been promoted in various ways during the last decade. The Forestry Thematic Exploitation Platform (Forestry TEP) was developed in a project contracted by the European Space Agency (ESA) to enable a more effective use of Copernicus and other EO data in support of forest ecosystem monitoring and sustainable forest management. Within the Forestry TEP, commercial, research, and public sector users in the forestry sector worldwide have efficient access to satellite data-based processing services and tools for the production of value-added forest information products [16].

The Copernicus Land Monitoring System also contains a high resolution forestry layer with three types of products available for the years 2012 and 2015: tree cover density, dominant leaf type (deciduous, coniferous etc.), and a forest type product following the forest definition of the Food and Agriculture Organization (FAO) [17]. Sentinel-2 data as well as Landsat 8 data was mainly used as a primary input data source for the 2015 products [18].

However, an examination of EO-based studies and geo-information products available in Germany reveals that local and regional studies and EO-based information products prevail, and that quantitative information at a federal and even national scale is rarely generated. Federal authorities and forest research institutions still use—if at all—remotely sensed forest information rather experimentally and do not facilitate operational monitoring. Here, however, lies an exceptional potential for timely, repeatable, large scale assessments supporting the traditionally ongoing in-situ assessments on the ground.

The objectives of this review on EO-based monitoring of forests in Germany are to:

- present a well-rounded, up to date, fact-based introduction to forests in Germany, including spatial distribution, composition, management, the institutional landscape, and current pressing challenges of societal relevance
- present the results of an in-depth review and analyses of all EO-based research studies focusing on forests in Germany including a categorization on topic, location, extent, spatial resolution, temporal interval, thematic focus, and outcome
- critically discuss what spaceborne EO can contribute to informed decision-making by agencies and stakeholders from the forest sector, and what information cannot be provided by EO-based analyses
- identify national-scale research gaps and geo-information-product gaps
- discuss how a concerted effort of EO-based, national-scale mapping can contribute to forest characterization, forest monitoring, and, finally, forest protection and ecosystem preservation in Germany.

2. Forests in Germany

2.1. Historic Development and Current Status of German Forests

Today's forest distribution in Germany is the result of a long anthropogenic land use history. At the end of the last glacial maximum, most tree species had retreated to Southern Europe, south of the Alps. In the early Holocene, only a few tree species spread northwards with many of them at high rates as a response to climate warming [6]. Consequently, the number of tree species in Central Europe is rather low [19]. Potential natural vegetation in Germany, however, would be a landscape of forests, mainly beech and mixed beech forests, oak forests, and oak-hornbeam-mixed forests with coniferous forests in high-altitude environments [5,11]. Due to anthropogenic activity, the vast majority of forests were cleared and converted to other land uses with the smallest forest extent occurring during the Middle Ages, when the demand for forest products was the highest. At that time, land was urgently needed to extend settlements and to grow crops, hence accelerating deforestation. After the Little Ice Age with its side-effects such as extreme weather events, diseases, and over-exploitation of forest and land resources, people started reforestation. The share of forests increased again and reached approximately the extent of today in the 15th century. In 1975, the law for the preservation of the German forest came into force (*Bundeswaldgesetz*) [20].

However, forests in Germany are often in unfavourable locations where agriculture is unproductive or even impossible: locations with poor soils, stagnant water, or in low mountain ranges and alpine terrain, where it is usually difficult to access with rougher climate and often more pronounced topography. Figure 2b shows that the share of forests in low mountain ranges and alpine terrain is higher than average whereas the forest proportion in lowlands with often favourable soil conditions is below average. About 55.5% of German forests are located in areas with slopes larger than 5%, and 15.2% are located in areas with slopes larger than 30%. Hence, there is little forest cover in Northern, North-western, and Central-east Germany, whereas Central and Southern Germany have a higher forest coverage (Figure 2a).

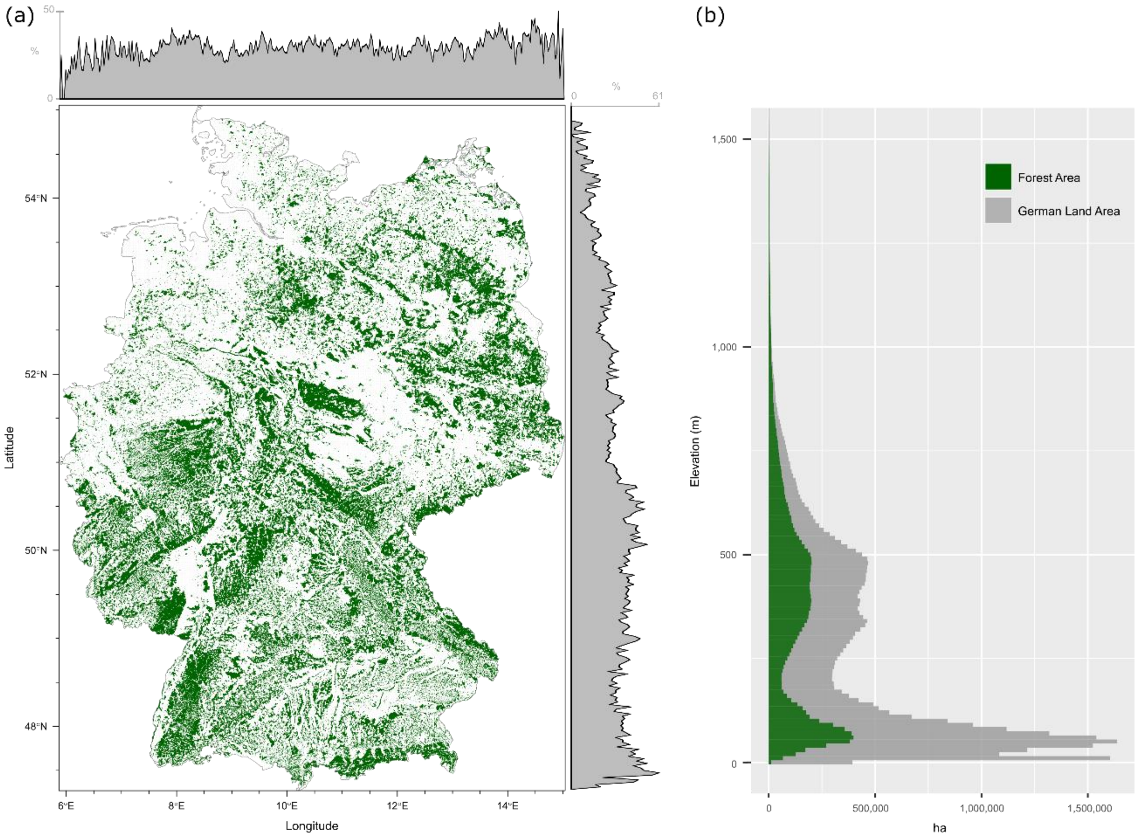

Figure 2. Forest cover in Germany (**a**) and elevation distribution of forest compared to Germany (**b**). Data source: Forest cover is taken from the DLM250 (*Digitales Landschaftsmodell* digital landscape model 1:250,000). The elevation histograms are based on TanDEM-X data with 90-m spatial resolution.

With respect to the distribution within the 16 federal states of Germany, forested areas cover between 11% and 42.3% of the respective federal area. The federal states of Rhineland-Palatinate and Hesse are both characterized by more than 40% of forest cover, whereas states such as Lower Saxony, Mecklenburg Western Pomerania, Schleswig Holstein, and the city states of Bremen and Hamburg all have less than 25% of forested area, namely between 11% and 25%. In terms of the total forest area, Bavaria has the largest forest area with 2.6 million hectares [21] (Figure 3).

German forests are dominated by coniferous species with about 54% of the forested area, whereas broad leaved and mixed forests contribute to 31% and 13%, respectively [22]. Mixed forests are defined as forests in which at least two tree species occupy at least 10% of the area. The most dominant tree species is spruce, covering 2.8 million hectares (25% of German forest area), mainly dominating in the southern part of Germany, followed by pine, covering 2.4 million hectares (23%) with predominant occurrences in the central and north-eastern part of the country. Dominating broad leaved species are beech, covering 1.7 million hectares (16%), especially in the western and southwestern parts of Germany, followed by oak, covering 1.1 million hectares (11%) distributed all over the country's territory. These four dominant species comprise 75% of Germany's woodland [10]. A total of 51 species or groups of species were recorded during the last national inventory campaign in 2012. Out of them, 11 species make up 90% of Germans forests (common spruce, common pine, copper beech, sessile oak and English oak, common birch, common ash, black alder, European larch, Douglas fir, and sycamore maple) [21]. Figure 4 shows the distribution of the most frequent tree species among the federal states. There is a large heterogeneity. For example, Brandenburg and Berlin (BB) are dominated by pine (about 70%) whereas Baden-Württemberg (BW) has seven tree species or groups of tree species with a share of more than 5%, and Hamburg and Bremen (HB) are dominated by deciduous tree species (about 75%). In Figure 4, Oak includes all oak species including northern red oak; deciduous long life includes maple species, maple-leaved plane tree, sweet chestnut, ash, hornbeam, lime species, walnut species, false acacia, horse chestnut, sorb tree, holly, elm, and white ash; deciduous short life includes birch species, wild service tree, alder species, poplar species, bird cherry, wild cherry, wild fruit, and all other deciduous tree species are not mentioned separately. Spruce includes all species of spruce and other conifers except Douglas fir, pine, larch, and fir. Fir includes silver fir, coastal fir, and other firs. Pine includes all species of pine; larch includes all larch species (https://www.bundeswaldinventur.de/service/fachbegriffe-und-abkuerzungen/).

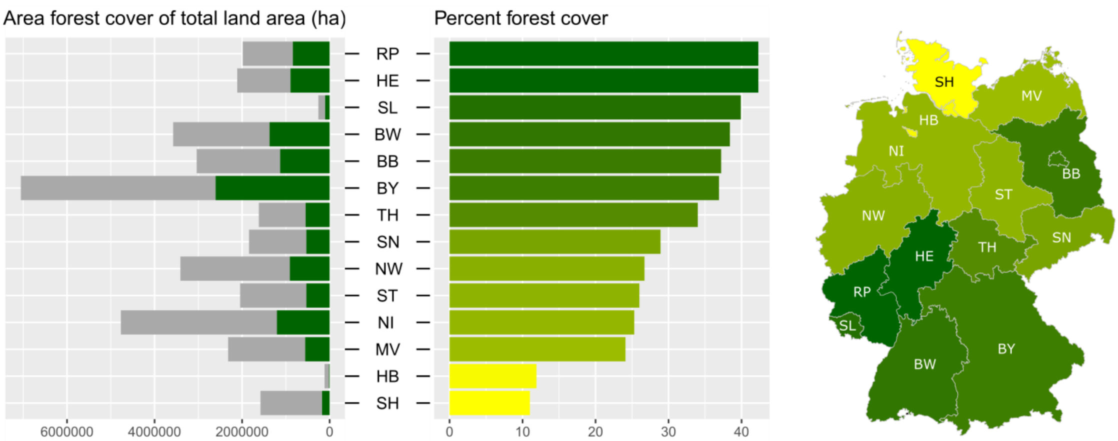

Figure 3. Forest cover in Germany per federal state in decreasing order of percentage. The left-hand part of the figure shows the forest area and total area of each federal state in hectares (SH = Schleswig-Holstein, NI = Lower Saxony, NW = North Rhine-Westphalia, HE = Hesse, RP = Rhineland-Palatinate, SL = Saarland, BW = Baden-Wuerttemberg, MV = Mecklenburg-Western Pomerania, HB = Hamburg and Bremen, BB = Berlin and Brandenburg, ST = Saxony-Anhalt, SN = Saxony, TH = Thuringia, BY = Bavaria).

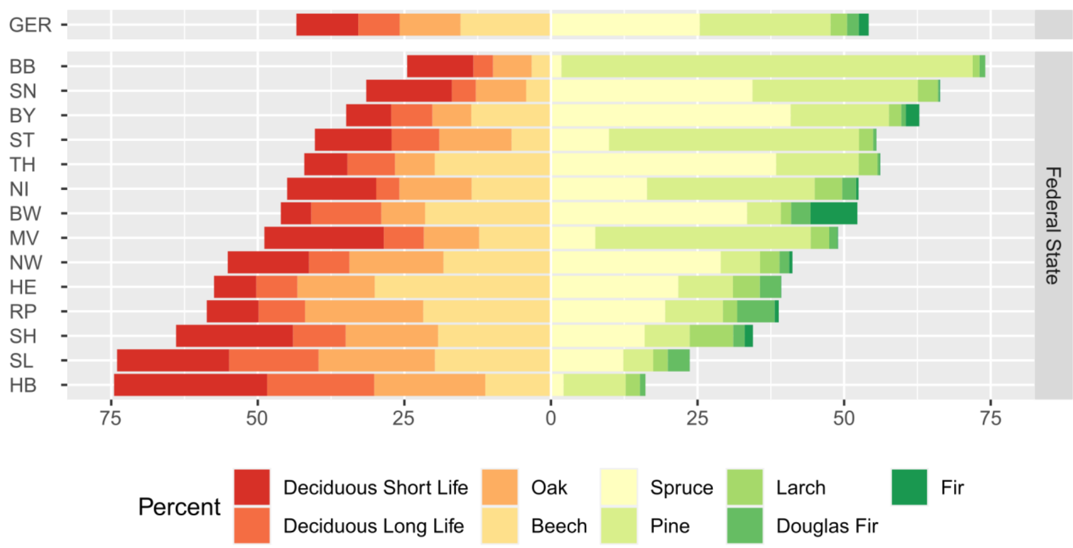

Figure 4. Tree species distribution in Germany per federal state. Orange to reddish colours show deciduous tree species while yellow to greenish colours show coniferous tree species (data source: BWI 2012, https://bwi.info).

With respect to species' diversity and composition, over 25% of Germany's forested area are non-natural pure stands (monocultures), about 10% are semi-natural pure stands, about 10% are mixed forests with two tree species, 22% are mixed forests with mainly three tree species, and only 26% are forests with four or more tree species [23,24]. Pine and spruce are often planted in pure stands. The degree of cultivation or "naturalness" is classified into five classes: 1—almost natural, 2—semi-natural, 3—partly semi-natural, 4—accentuated by silviculture, and 5—conditioned by silviculture. The criteria of this classification are (i)—the proportion of tree species of the natural forest community, (ii) the proportion of the main tree species of the natural forest community, (iii) the completeness of the main tree species of the natural forest community, (iv) the share of non-European tree species (https://www.bundeswaldinventur.de/service/fachbegriffe-und-abkuerzungen/). Only 15% of German forest can be considered almost natural and another 21% can be considered a semi-natural forest, 41% are only considered partly semi-natural, 7% are accentuated by silviculture, and 16% are conditioned by silviculture. In young stands, the share of almost natural, semi-natural, and partly semi-natural is 25%, 26%, and 31%, respectively, with 5% accentuated by culture and 13% conditioned by culture [21]. Nearly the entire forest in Germany is anthropogenically impacted. Over recent years, the share of spruce has constantly reduced, mainly due to storm damage, to be replaced by mixed stands that are more natural to most locations and that are more resistant against disturbances [24]. In addition, large areas of forest, in particular spruce forest, were severely affected by the 2018/2019 droughts, resulting in the unplanned harvest of trees after die-off as a response to water stress and insect infestation [25]. The effects of recent droughts as well as storm events will be reflected in the next inventory, which is going to take place in 2021/2022.

The average age of German forests is 77 years. Less than a quarter are older than 100 years with oak, beech, and fir having the highest average age (about 100 years) and Douglas fir having an average age of only 45 years [21]. The age distribution of deciduous and coniferous trees is shown in Figure 5. It can be seen that there is a tendency of increasing the share of deciduous trees.

Figure 5. Age structure of German forests as recorded in the last two inventories (2002 and 2012). Age is given in years. Error bars (1 standard error) are depicted in black.

There are 39 protected forest areas distributed all over Germany—some of them being designated as national parks, which is the highest protection level. Among them are the German Black Forest, the Bavarian Forest National Park, and the forested areas of the Bavarian Alps. Three quarters of these protected forest areas are located in the southern half of Germany. Whereas these protected forest areas as well as many other forest areas are state forests or federal state forests (owned by the country or the federal state, summing up to 52%), a substantial proportion of forest in Germany—namely 48% or about 5.48 million hectares—is privately owned, and half of it has a size less than 20 hectares.

Figure 6 provides an overview of forest ownership in Germany [22]. It can be seen that there are huge differences between federal states.

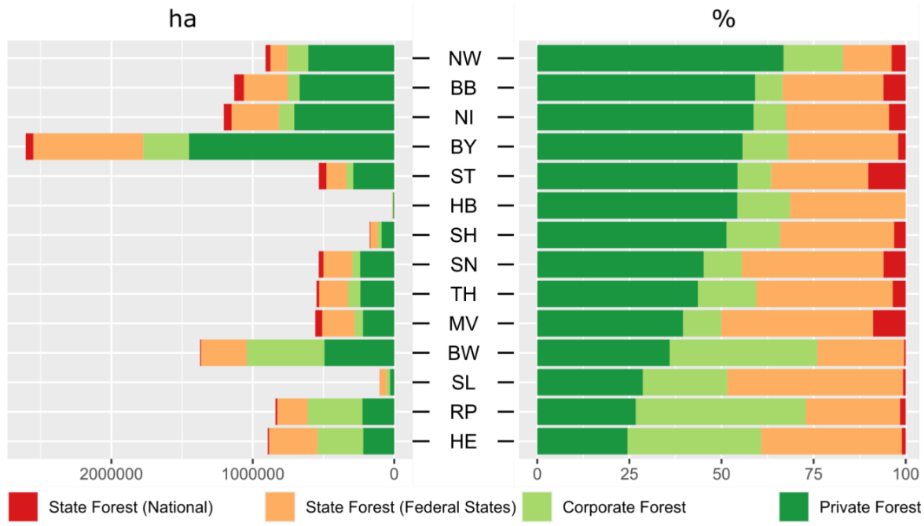

Figure 6. Forest ownership in Germany per federal state in terms of area in hectares and in percentages of the forested area [22].

2.2. Current Forest Monitoring and Reporting Practice in Germany

EO is not yet implemented in operational forest monitoring in Germany [23,26]. BMEL is responsible for forest monitoring in Germany. According to the German forest act (*Bundeswaldgesetz*), the federal states are responsible for the assessment of German forests, which is to be conducted on a decadal basis (German forest act, *Bundeswaldgesetz*). Forest research institutes of the federal states conduct and finance the assessments and prepare regional reporting, whereas the Johann Heinrich von Thünen Institute, Federal Research Institute for Rural Areas, Forestry and Fisheries, Institute for Forest Ecosystems manages the data and coordinates the method harmonization, analyses, and reporting at a national and international level on behalf of the BMEL [26].

There are four different branches contributing to the German forest monitoring activities: 1. national forest inventory (NFI) (*Bundeswaldinventur*), 2. national forest soil inventory (NFSI) (*Bodenzustandserhebung*), 3. crown condition survey (CCS) (*Waldzustandserhebung*), and 4. intensive monitoring. The NFSI (level I, based on a systematic sampling grid), the CCS (also level I), and the intensive monitoring (level II, based on 68 measurements plots) are embedded in the Europe-wide forest monitoring system of the International Cooperative Programme on Forests (ICP Forest): The points of the systematic random sampling network in the 16 × 16 km^2 grid are part of the larger European network. Additionally, the measurements of the level II areas in Germany are submitted to the European forest monitoring of ICP Forests [27]. Level II monitoring was introduced as an integrated part of the ICP Forests under the umbrella of the Geneva Convention on Long-range Transboundary Air Pollution (CLRTAP) as an important complement to Level I monitoring (CCS, NFSI) in order to investigate ecosystem-based cause-effect relationships in forest ecosystems [26]. NFSI, CCS, and intensive forest monitoring at level II are, therefore, important parts of the German national forest monitoring programme [28] (see Table 1).

The accounting of forest properties as demanded by German law is based on a fixed sampling scheme and conducted by means of visual assessment of plots and individual trees in the field as well as additional field measurements. The specific legislation defines the following parameters to be monitored: 1. crown condition, 2. tree growth, 3. needle and leaf analyses, 4. ground vegetation, 5. atmospheric fluxes, 6. litter, 7. soil water abundance and content, 8. soil condition, 9. meteorological parameters, 10. phenology, and 11. air quality (§1 ForUmV).

The first NFSI was based on a fixed 16 × 16 km Europe-wide grid corresponding to 420 plots where the grid coincides with the forest. Since the second, there are about 1859 NFSI plots distributed over Germany based on an 8 × 8 km grid. They were established from 1987 to 1992 and resampled after approximately 15 years from 2006 to 2008. A total of 68 level II plots are defined for continuous measurements, which are under responsibility of the Federal States. However, soil analyses at level II plots are conducted only every 10 years whereas most parameters are recorded continuously.

Complementary to the long-term soil assessment and the continuous intensive monitoring at level II, each German federal state provides annual reports of crown condition. The most common sampling design is a cross cluster with four satellites in which each comprises six trees, indicating a total of 24 trees per plot based on the national 16 × 16 km^2 sampling grid. However, some federal states densify the common grid in order to fulfill reporting requirements on a federal state level. The monitored parameters focus on defoliation, but discolouration, insect infestation, fructification, and others are recorded as well [26].

German federal states provide annual reports about forest condition following fixed sampling protocols specific for each federal state. The assessment focuses on the crown condition of the four major tree species in Germany, pine, spruce, beech, and oak. These annual reports supplement the decadal inventories. The reports document fluctuations in crown condition and, hence, forest condition over time [10].

Extensive monitoring takes place on a decadal basis [26]. The decadal forest inventory program (*Bundeswaldinventur*) aims at assessing large-scale forest properties and forest production potential. Parameters related to forest condition are not assessed with this program. Responsibility for the data collection is with the federal states. Data collection in the field is conducted by specialists, mostly freelancers, who are specifically trained and contracted by the federal states. The parameters required to be recorded comprise operating mode, type of ownership, forest structure, tree species, age, tree diameter, tree height on selected sample trees, terrain features, special tree characteristics, dead wood, and land use before or after forest growth [29]. The sampling design differs among the different federal states. Based on a common 4 × 4 km^2 grid, some federal states use double (2.83 × 2.83 km^2) or four-fold (2 × 2 km^2) sample density [21,22,30]. The nodes of the grid are the inventory plots with 150 m × 150 m sections. There were three inventories conducted in the past, the first 1986–1989 in Western Germany, the second 2001–2003 and the third in 2011/2012. The next inventory is scheduled for 2021/2022. During the third inventory in 2012, about 60,000 plots were sampled and about 150 parameters (terrain, stand, and tree characteristics) of approximately 420,000 trees were recorded.

Table 1. Current forest monitoring and reporting practice in Germany (References [26,28,31,32]).

Title	Repetition Interval	Grid	Purpose	Recorded Properties	Executing Institution
national forest inventory, NFI (*Bundeswaldinventur*)	decadal the next NFI is scheduled for 2021/2022	base: 4×4 km^2 grid; double density: 2.83×2.83 km^2; quadruple density: 2×2 km^2	large-scale inventory and wood production potential, i.e. an economically motivated initiative	approx. 150 parameters (e.g. tree species, tree height, diameter, age, amount of deadwood)	data collection by individual forest specialists, reporting and analyses by Federal Research Institute for Rural Areas, Forestry and Fisheries (*Thünen Institut*)
national forest soil inventory, NFSI (*Bodenzustandserhebung*)	approx. 15 years the last survey was conducted 2006–2008	16×16 km^2 grid corresponding to 420 plots intersecting with forests in Germany during the first inventory; 8×8 km^2 corresponding to 1859 plots	generatation of reliable data on the current state and changes in forest soils and selected features of the forests	soil hemistry, soil reaction, aqua regia, C, N, S, P, 1:2 extraction nitrogen, cation exchange capacity, soil water, tree growth, ground vegetation, tree nutrition (leave/needle chemistry)	individual data collection of the 16 federal states— reporting and analyses by the Federal Research Institute for Rural Areas, Forestry and Fisheries (*Thünen Institut*)
crown condition survey, CCS (*Waldzustandserhebung*)	annual	16×16 km^2 grid corresponding to 420 plots at national level; some federal states perform the assessment on denser grids and assess additional points for the monitoring at federal state level (e.g. 4×4 km^2 or 2×2 km^2)	assessment of spatial and temporal variation of tree vitality; detection of drivers and effects of plant stress	crown condition, impact factors (e.g. insects)	
intensive monitoring	continuous some parameters are assessed periodically (e.g. soil assessment on decadal basis)	case studies at 68 sites	understanding cause-effect relationships in forest ecosystems	crown condition, impacts factors, soil chemistry, soil reaction, aqua regia, C, N, S, P, cation exchange capacity, soil solution, tree growth, ground vegetation, tree nutrition, litterfall, deposition, meteorology, air quality	

3. Major Challenges for Forests in Germany

Today, at the intersection of climate change adaptation and mitigation, the insurance of raw material and energy supply, as well as the preservation of nature and biodiversity, Germany's forests face major challenges.

3.1. Forest Disturbances in Germany

Disturbances are relevant drivers of change in forest ecosystems [33]. They alter forest structures and functioning, enhancing the heterogeneity of individual forest stands to landscape scales [34,35]. So far, there is steady evidence of fluctuating disturbance regimes with climate change, demanding forest managers to focus on the resilience of forest ecosystems for these disturbances [36,37].

Currently, the main pressures affecting German forests are primarily related to climate change [38,39]. The increase of extreme and fluctuating weather conditions will likely affect the frequency and severity of abiotic disturbances (e.g., drought stress, forest fires' occurrence, and windthrow) and biotic disturbances (forest pests and disease outbreaks), resulting in modified ecosystems, and, thus, decreasing their function and their provision of products and services [40].

With some regional differences, there is an overall trend of a decline in healthy forests in Germany. At the national level, forests without crown defoliation currently cover only 22% of the area with 42% being slightly damaged and 36% being seriously damaged [10]. About 36% and 26% of the two dominant coniferous tree species, which are spruce and pine, and about 47% and 50% of the two dominating deciduous tree species, including beech and oak, are classified as seriously damaged in the latest annual report [10]. The main reasons for short-term deteriorating forest conditions are repeated periods of drought and warm conditions, favouring insect infestation [25]. Extreme weather events increasingly cause physical damage, e.g., through windthrow, hail, or heavy snow [41]. Between 2018 and 2019, damages related to natural hazard disturbances were estimated at 2.5 billion EUR [42]. Between January 2018 and March 2018 only, around 1% (114.000 hectares [ha]) of Germany's forested areas were affected by wind storms and bark beetle outbreaks with one-third of tree damages attributed to wind storms and two-thirds linked to bark beetle attacks, respectively [42,43].

Forest management, however, has had a serious impact on long-term conditions and their provision of ecosystem services [44]. Despite intensive management to enhance forest resilience and reduce natural hazard impacts, forests are susceptible to natural disturbances (anthropological and natural) [45–47], which are closely related to changes in climate and human land use.

3.1.1. Drought and Heat Stress

According to the International Panel on Climate Change (IPCC), increased heat events and water restrictions present key risks for Europe, which will further intensify in the next few decades [48].

In 2003, Central Europe experienced the most severe periods of droughts recorded until then. The extreme heat wave led to an almost total reduction of water reserves in forest soils, affecting the condition of forest stands. The 2003 drought was considered to be the exemplification of a "hotter drought" and characterized as the most severe event occurring in Europe during the last 500 years [25]. Nevertheless, following the events of 2003, an even larger heat wave impacted Central Europe in 2018. Analyses have confirmed that the extreme drought that occurred in 2018 was climatically more extreme than the one in 2003 with a greater impact on forest ecosystems in Austria, Germany, and Switzerland [25]. In 2018, the mean growing season's (April to October) air temperature was more than 3.3 °C above the long-term average, and 1.2 °C higher than in 2003. The extreme droughts and heat waves of 2018 (preceded by less severe droughts in 2017) caused considerable forest damage in several parts of Germany. This was observed in young trees with the highest mortality rates reported for the Norway spruce and European beech [25,49]. Tree species almost equally compromised were Scotch pine, silver fir, and oak. However, the higher rates of mortality on spruce trees were projected from reports about previous drought events [50–55]. As a consequence of the 2018 heat stress, the extent of forest fires was exceptionally high in some parts of Germany [49]. The BMEL estimated that an area of more than 2.450 km^2 must be afforested to restore the affected forest stands [56]. A press release by the Association of German Foresters [57] estimated an economic loss up to 3.5 billion EUR since the year 2018. These losses have been estimated based on the accumulation of 160 million cubic meters of dead wood [56].

3.1.2. Vulnerability Due to Pests and Pathogens

Insect infestations are recognized as a severe threat with devastating consequences for timber markets [58,59]. At the same time—similar to non-biotic disturbances such as wildfires or wind storms—insect outbreaks (e.g., European bark beetle, *Ips typographus* L.) can be considered essential for natural ecosystems [60]. Bark beetle infestations have spread across more than 10 million hectares in Europe [61,62]. Damage related to bark beetle attacks is expected to increase in the coming years as a result of climate change [63–66]. Extended periods of drought and an increased presence of dead wood in forest gaps create favourable conditions for bark beetle propagation to rise [64,67–69]. Drought enables bark beetle infestations to progress by stressing trees and, thus, enhancing the occurrence and severity of these attacks [66,70–73]. In Reference [73], tree damage and dieback by bark beetles have been well documented.

Bark Beetle infestation starts when the temperature rises above 16°C. In Germany, bark beetle attacks begin earlier each year when compared to previous infestations, which is a result of warmer summers due to climate change. In addition, extended periods of droughts have largely increased the spread of insects. The majority of the bark beetle outbreaks took place in North Rhine-Westphalia, Hesse, Rhineland-Palatinate, Bavaria, Baden-Wuerttemberg, Saxony, and Thuringia where the spruce population is relatively high [43]. Solely in North Rhine-Westphalia, 12 million m^3 of forest were lost due to bark beetle attacks in 2019. However, Norway spruce has been the most affected tree species. Due to its economic relevance for the forest sector, this has led to rising concerns. In addition to bark beetle attacks in spruce stands, pines have been weakened by Nun Moths and Pine Moths, oaks have been disturbed by Oak Moths, and several mycosis infections have led to damages in forest stands [7].

3.1.3. Wind Storms and Snow Break Vulnerability

With increasing frequency and intensity of extreme weather events, heavy storms have become more common in Germany. In recent years, forests were affected by storms like “Vivian” and “Wiebke” (1990), “Lothar” (1999), “Kyrill” (2007), “Xavier” and “Herwart” (October 2017), and “Friederike” (January 2018). As a consequence of the storms of 2017 and 2018, 18.5 Mio. m^3 of destroyed trees had to be harvested in Germany in 2018, which is almost four times more than in 2017 [74]. Even higher forest losses were caused in 2007 by hurricane “Kyrill” with wind speeds of 180 km/h, which led to 31.3 Mio. m^3 of dead wood [75]. The risk of windbreak is, by far, higher for conifers than for broadleaf trees. Norway spruce is the most prone species, followed by Scots pine, European beech, and oak, as well as other deciduous species [76]. Moreover, 22% of the wood, which needed to be harvested in 2018 (due to storm damage) included pine and larch, and all remaining conifer species, such as spruce, fir, and Douglas fir - amounting to 69%, while broadleaf trees constituted only 9% of storm-damaged timber [74]. Furthermore, windthrow risk seems to be related to tree height and exposure, and can be higher in thinned and mixed stands with large fractions of broadleaf trees [76–78]. Forest injuries due to snow are more seldom compared to wind-related, insect-related, and drought-related damages. In Germany, the federal state of Bavaria—where snow is more frequent than other parts of Germany [79]—usually shows the highest annual snow-related forest damage [74,80,81].

3.2. Climate Change Adaptation Strategies

Increasing dry periods and weather extremes impact Germany’s forests. As long as such weather extremes occur in a relatively seldom manner, i.e., or as isolated events, the stability of forests is not generally impaired, but climate change and its long-term changes in the frequency or intensity of extreme events could lead to large-scale hazards for forests [82]. At the same time, sustainably managed forests can have a positive effect on climate change since they function as a carbon sink. Therefore, climate protection and adaptation to climate change is one of the major fields mentioned in the German Forest Strategy 2020 [82], and adaptation of forests and forestry is a critical topic in the German Adaptation Strategy to Climate Change [83]. German forests will be transferred to climate-adaptable, near-natural, and sustainably managed mixed forests, which reduce the risk of large-scale forest damage, and continue to sequester carbon in the future [49]. In general, research on regional climate change forecasts and the impact of climate change on forests will increase for improved adaptation planning [82,83]. However, it is already known that one major aspect of climate change adaptation of German forests is the conversion to mixed stands and tree species, which are more resistant to direct and indirect effects of climate change (particularly spruce, which is, currently, the most common and economically the most relevant tree species in Germany). From this vantage point, it is not well adapted to the observed and projected changing climatic conditions.

4. Institutional Landscape in the Forest Sector

Forestry policy in the EU remains primarily a national competence, even though some European measures have an impact on the forests of the Union. As forest inventories are compiled on a national level based on the legislation of the respective country, we concentrate on the institutional landscape of the forestry sector in Germany. Overall, it is very complex and comprises forest research, forest management, forest administration, and forestry itself.

Above all, federal and state authorities have sovereign tasks and superordinate functions to fulfil with regard to the German forest. BMEL is the institution responsible for developing legislations such as the law on the conservation of forests and the promotion of forestry (*Bundeswaldgesetz*) [84] and for writing strategy papers such as the Forest Strategy 2020 [82]. Furthermore, the BMEL is committed to combating progressive deforestation, illegal logging, and unsustainable forest management, and coordinates the international forest policy of the German Federal Government [85]. BMU is a Supreme Federal Agency like BMEL and is responsible for legislation development, e.g., law on nature conservation and landscape management (*Bundesnaturschutzgesetz*) and strategies of the federal government (e.g., national biodiversity strategy) [86]. BMU is the highest national authority in national forest protection policy, and is involved in international forest protection [87]. All ministries have subordinate authorities (*Nachgeordnete Bundesbehörden*) such as the Federal Agency for Agriculture and Food, BLE—who e.g., on behalf of BMU and BMEL provide and manage the funding tool "Forest Climate Fund" (*Waldklimafonds*). The funding programs are generally based on the research programs of the institutions mentioned here. With its decision to establish the Forest Climate Fund, the federal government underlines the importance of German forest ecosystems and the positive effects of sustainable forest management and wood use for climate adaptation [88]. Furthermore, the German Environment Agency (*Umweltbundesamt*—UBA) under BMU is the federal agency responsible for enforcement of various laws and regulations, e.g., on sustainable forest management [89]. One of the main tasks of the German Federal Agency for Nature Conservation (*Bundesamt für Naturschutz*—BfN) under BMU is the provision of a central interface for the transfer of scientific findings into the political decision-making process, and for implementation in practice, for example, on forest management under climate change [90,91].

Implementation of laws and forest management of federal forest stands are the main tasks of the authorities on the federal level. For each of the 16 German federal states, the state forest administrations comprise the upper and lower forest authorities. The administrative tasks can be summarized to the sovereign tasks such as forest supervision, regional development and planning, and the consultation of private and corporate forest owners.

The forest administrations of the federal states are organized in three levels—Ministry of the State, and two further levels of state offices (*Landesanstalt* and *Landesamt*). In detail, however, the tasks of the authorities vary. As an example, for Bavaria [92], the highest forestry authority is the Bavarian State Ministry of Food, Agriculture and Forestry. State Offices of Food, Agriculture and Forestry with the forestry divisions are the lower authorities.

Two federal research institutes conduct national and international forest research—the Federal Research Institute for Rural Areas, Forestry and Fisheries under the auspices of BMEL (*Thünen-Institut)*, which carries out the Federal Forest Inventory *(Bundeswaldinventur)* [30,93] and, second, the Federal Research Centre for Cultivated Plants, Department Forestry under BMEL (*Julius-Kühn-Institut*), which studies forest damage factors, such as pests [94]. Federal states such as Baden-Württemberg operate research facilities, which are subordinate to the Forest Research Institute Baden-Wuerttemberg (*Forstliche Versuchs- und Forschungsanstalt*—FVA). FVA works in various fields, such as biodiversity and protection of forests, effects of climate change on forests, and measurements and mapping of tree parameters to support and advise the forest management authority of the State of Baden-Württemberg (*ForstBW)*. In Bavaria, the special authority (*Sonderbehörde*) is the Bavarian State Institute of Forestry (*Bayerische Landesanstalt für Wald und Forstwirtschaft—LWF*). Their research topics involve, among others, ecosystem service assessment, pest infestations of trees, sustainable forest management, and the effect of climate change on the forests.

Forest-related research institutions at the German universities include faculties, departments, research chairs, and forest research institutes. Several universities in Germany own the forest for research purposes. German universities and universities of applied sciences offer numerous courses in forestry and forest management and combine the programs with environmental and ecological research.

The forest of the University of Wuerzburg, to name only one, was a church donation when the university was founded in the 16th century. The production of valuable wood, normal wood use, student excursions, and scientific experimental areas are the main uses. Another example is the Technical University of Dresden, where the lectures and practical courses take place directly in the Tharandt Forest Botanical Garden, where the faculty is located. It was founded in 1811 for research purposes and is one of the oldest scientific collections of woody plants in the world.

An even more heterogeneous picture also emerges for national parks (NPs), whose administrations have different official responsibilities that depend, among other things, on the federal state. For example, the administration of the NP Bavarian Forest has the status of a lower forestry and hunting authority, while the administration of the NP Harz has the status of a lower nature conservation authority. The Harz NP has the largest forest NP area in Germany with 24,750 ha. The Bavarian Forest NP has the second largest forest area with 24,250 ha, but, with 98%, it has the largest proportion of forest within the NP when compared to all national parks in Germany [95,96].

In summary, the forestry sector in Germany is very diverse, as is the landscape of federal foundations, associations, and NGOs, which have not been addressed here, as this is not within the scope of this paper.

5. Methodology of the Review

For this review, we collected all available research articles investigating forest-related topics by means of remote sensing in Germany. The literature search has been conducted based on the bibliography database of the Web of Science platform with no restriction on the date of publication. We only considered research articles published in peer-reviewed journals. In addition to English articles, German citation indexed publications have also been included. We set up the literature database for this review in the first quarter of 2020. Therefore, the cut-off date for including new publications was 1 April 2020.

During the literature search, we used the following keywords: forest OR forestry AND remote sensing OR earth observation AND Germany. Alterations in the keywords helped to refine the search, e.g., replacing Germany with the different federal states 'Bavaria'/'Thuringia'/'Saxony'/etc., or using 'satellite'/'airborne'/'UAV (Unmanned Aerial Vehicle)', 'hyperspectral'/'lidar (Light Detecting and Ranging)'/'radar'/etc., 'Landsat'/'Sentinel'/'Worldview'/etc. instead of remote sensing. The search query resulted in a very large number of research articles (n > 200), but still included some irrelevant research articles, e.g., studies using only terrestrial-based systems such as terrestrial lidar (TLS). Those were excluded.

The remaining 166 identified research articles [33,60,97–260] were analysed to extract relevant information for this review using the following parameters.

- General information:
    - Publication year
    - 1st author's institution, institution category (e.g., federal state research institution), and research background (EO, forestry)
    - Publishing journal and journal category (e.g., ecology)
    - Affiliated project and funding / financing (e.g., BMEL)
    - Potential users of results (e.g., timber industry)
- Site specific information:
    - Name and location of study area including federal state (e.g., Black Forest, Baden-Wuerttemberg)
    - Spatial coverage of study area (in hectares)
    - Predominant forest type (deciduous, coniferous, mixed)
    - Information on forest management (e.g., protected area)
- Information about remote sensing data:
    - Platform (satellite, aircraft, UAV)
    - Sensor type (e.g., multispectral) and instrument name (e.g., Sentinel-2)
    - Geometric resolution of EO data (ground sampling distance)
    - Temporal resolution of EO data (mono-temporal or multi-temporal, subdivided in mono-annual or multi-annual)
    - Time period observed (e.g., March-October 2007)
- Information on research:
    - Research topic considered (e.g., forest disturbance)
    - Parameters examined within the study (e.g., tree species)
    - Examined object scale (leave, tree, stand, forest, landscape)
    - Applied methodology (e.g., linear regression)
    - Information about validation and accuracy of results

The results of this comprehensive literature review will be presented below. Section 6.1 presents an overview of the temporal development of the review articles and additional information about the first author's affiliation and funding of the studies. Section 6.2 focuses on the spatial coverage of the different studies including the spatial extent and the investigated forest types. The employed remote sensing instruments and techniques (Section 6.3) and the temporal resolution of the data sets (Section 6.4) are followed by Section 6.5, which highlights the addressed research topics and methods applied. Finally, additional auxiliary data are presented in Section 6.5.

6. Results: Present Remote Sensing-Based Forest Research

6.1. Temporal Development of Publications, Author Affiliation, and Funding of Studies

The temporal development of the 166 investigated research articles is illustrated in Figure 7. The graphic shows very clearly that the number of studies has constantly increased over the last

23 years. The majority of the studies have been released within the last decade. Only two articles were published in the 20th century. The growth in number is also related to the increased availability of remote sensing data (e.g., first Sentinel satellite in 2014). This fact is also reflected in the presentation of the journal category with an increasing number of studies published in remote sensing-related journals within recent years. The use of EO for various forest-related issues is increasingly being investigated by remote sensing specialists.

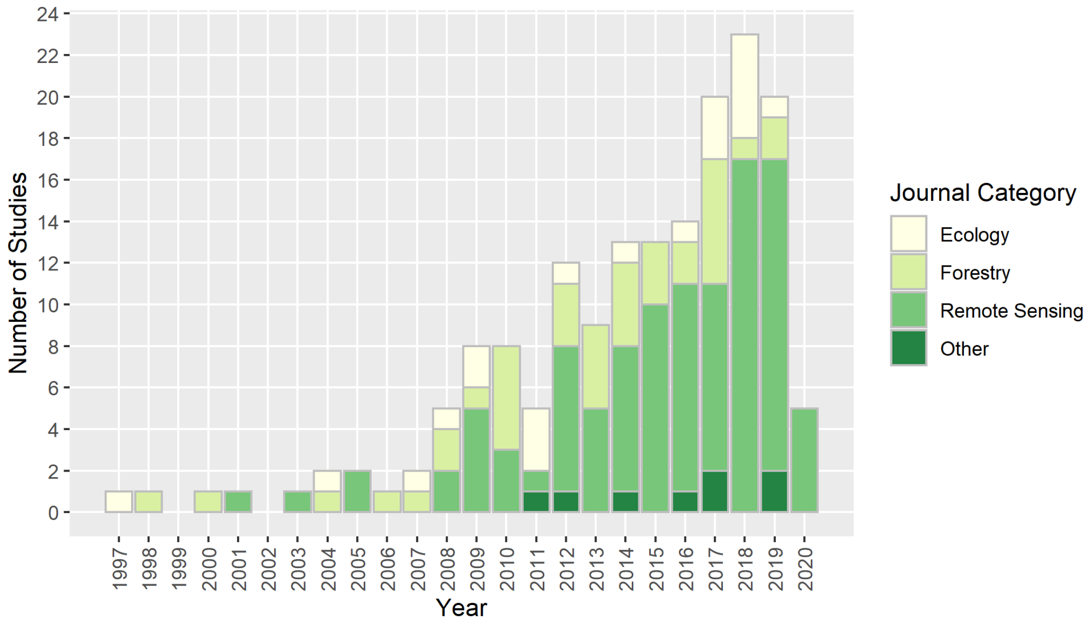

Figure 7. Studies ordered by year of publication.

Since we are only looking at studies within Germany, the majority of first authors are mainly scientists who are employed at German universities or German research institutions (Figure 8). Studies were mainly conducted at universities with the majority of authors having a remote sensing background. The federal research institutions in Germany shown in Figure 8 are the Bavarian Forest National Park, the Forest Research Institute Baden-Wuerttemberg (FVA), and the Bavarian State Institute of Forestry (LWF). The term "German state research institutions" stands for, to give one example, research centres within the Helmholtz Association.

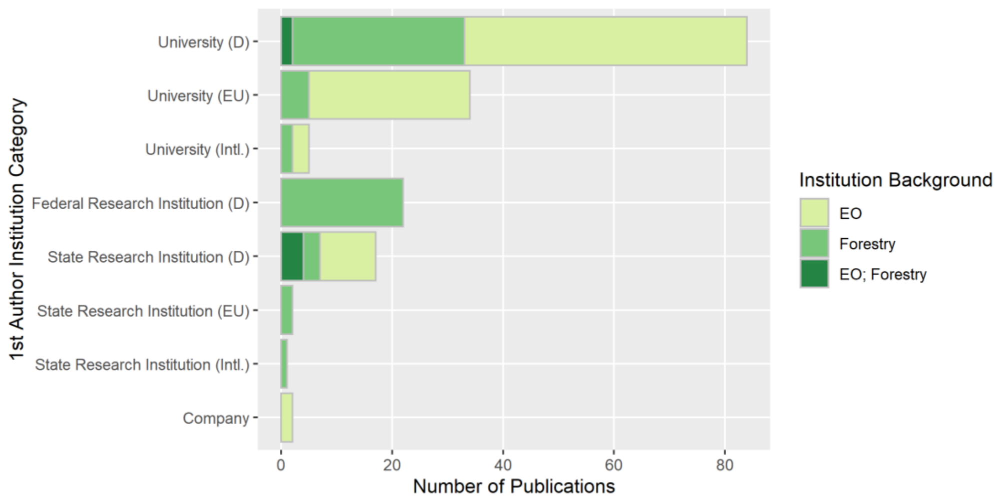

Figure 8. Number of studies by research institution.

Considering the funding of the 166 research studies, 11% were financed by federal state ministries (mainly Bavaria). Furthermore, 18% of the studies received funding from federal ministries (mainly Federal Ministry for Economic Affairs and Energy, BMWi). The German Federal Environmental Foundation (DBU) and the German Research Foundation (DFG) funded 9% of the published studies. In total, 38% of the research studies have received financial support from various German institutions.

6.2. Spatial Coverage, Spatial Extent, and Investigated Forest Types

With respect to spatial coverage, the majority (i.e., 89%) of the investigated studies focused on a local to regional scale. Only six out of 166 research papers were covering the German forest area as a whole (11.4 million ha), using mainly multispectral data of medium spatial resolution (MODIS and AVHRR) to generate information on phenology, vegetation condition (drought, frost damage), or biomass.

Twelve studies were dealing with the total forest area of one or two federal states. Rhineland-Palatinate, with its 840,000 ha forest area was covered most often (five papers), followed by the city state of Berlin (three papers, 29,000 ha forest area), and Baden-Wuerttemberg (two papers, 1.4 million ha forest area). We found one paper each for the total forest areas of Bavaria (2.6 million ha), Schleswig-Holstein (1700 ha), and Saarland (103,000 ha). Studies on federal scale very often use space-borne multispectral sensors with a higher spatial resolution as a data source (mainly of the Landsat and SPOT families), but also supplementary information based on airborne data. Especially information on forest types, tree species and timber volume seem to be of interest on this spatial scale.

The number of studies per federal state is shown in Figure 9. Most studies were carried out in one of the two federal states with the largest forest areas (Bavaria and Baden-Wuerttemberg). Bavarian forests were subject to research in 89 out of 166 reviewed articles and 47 papers were dealing with one or several forests in Baden-Wuerttemberg. The federal state with the highest percentage of forest cover, Rhineland-Palatinate, came out in third place, with its forests mentioned in 23 studies. Forests in the city states of Bremen and Hamburg were not investigated at all (apart from nationwide studies), forests in Hesse, North Rhine-Westphalia, Saarland, and Schleswig-Holstein once each.

Figure 9 also shows the location of the most frequently observed forest areas. By far, the most studied forest was the Bavarian Forest National Park with its 24,250 ha. It was the only subject of research in 57 of the reviewed journal papers (34%) and one of several study areas in two other papers, reflecting not only the strong research interest of the national park administration, but also its close link to national, European, and international universities.

Karlsruhe was the second most frequently mentioned test area with 15 contributions, followed by the Hainich National Park, Traunstein, Schorfheide-Chorin, Steigerwald, and Black Forest with 12, 9, 8, 7, and 6 contributions. Swabian Jura, Idarwald, and Freiburg were each listed four times. The Hainich National Park was the only subject of research in two studies, but mentioned 10 times as one of several study sites, often in the so-called "Biodiversity Exploratories." The Biodiversity Exploratories (Hainich with 130,600 ha, Schorfheide-Chorin with 129,200 ha and Swabian Jura with 42,200 ha) belong to an infrastructure program financed by the German Research Foundation and serve as an open research platform for scientists from all over Germany.

Figure 10 shows the extent of all study sites (sometimes several per reviewed papers) in six spatial categories. The majority of the study sites (50%) had a spatial extent of between 1000 and 100,000 ha. Larger study areas mostly refer to studies at federal state (>100,000–10,000,000 ha) or at the national level (>10,000,000 ha). Furthermore, 15% of the study areas looked at study sites of >100-1000 ha, 8% of the study areas had a rather small spatial extension of 20-100 ha, and 10% less than 20 ha. Concerning the latter, most of the studies belonging to this class were dealing with airborne and UAV data. Only three out of 19 of these used spaceborne information.

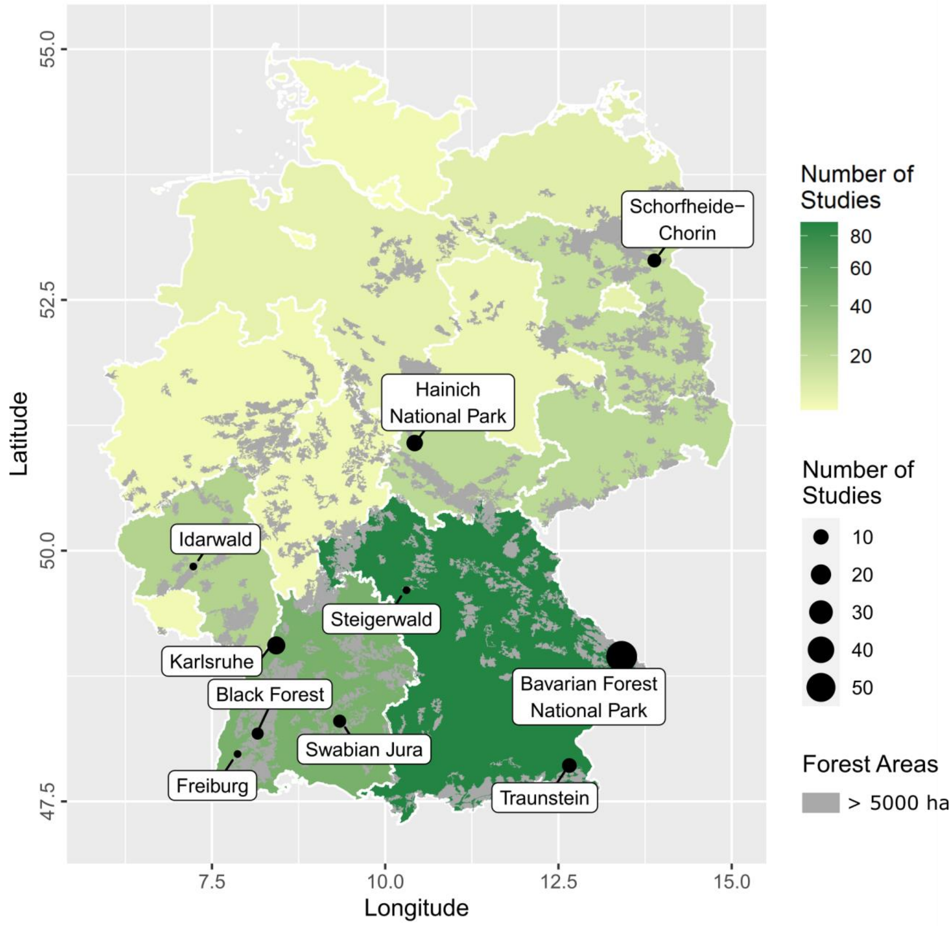

Figure 9. Number of studies per federal state (greenish colours, multiple entries possible), location of top study sites (black dots), and largest continuous forest areas in Germany (grey areas).

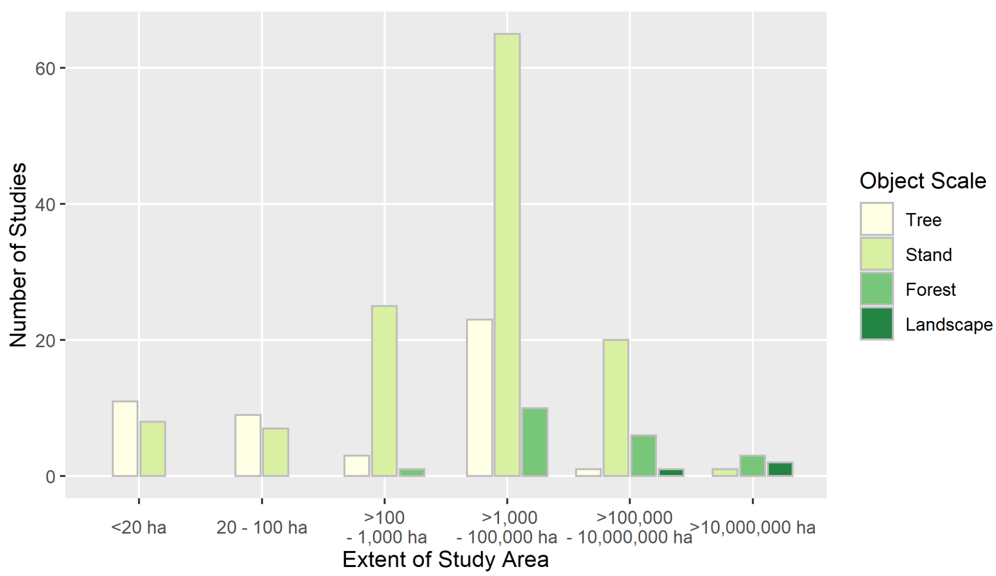

Figure 10. Size of study areas in relation to the observed object scale. Note that some studies have compared several study sites, which may result in multiple entries per reviewed publication.

Furthermore, we also considered the investigated object scale in relation to the size of the study areas (Figure 10). For our review, we used the four categories “tree,” “stand,” “forest,” and “landscape.” Studies that focused on the detection of single trees [103,140,142,209] were assigned to the “tree” class, whereas studies that concentrated on larger contiguous groups of trees such as those in conjunction with a disturbance assessment due to windthrow or bark beetle infestation, the monitoring of succession, or biomass estimation, were classified as “stand” scale (e.g., [60,98,123,167,183], among many others). The class “forest” was assigned to studies that looked at entire forest areas, to identify forest types such as Reference [195]. Last but not least, studies were put into the class “landscape” if they examined not only forest areas, but also other land cover classes with respect to phenological parameters (as green-up) or the vegetation condition in general [105,116,121].

With regard to the object scale, the majority of the studies (64%) derived forest parameters at a stand level. However, studies with a relatively small spatial extension of up to 100 ha focused mainly on the tree level. In contrast, forest and landscape scale were of greater importance when larger study areas at the national level were involved.

With respect to the investigated forest types, almost half of the studies dealt with mixed forests, even though this forest type is not yet very common in Germany (see Section 2). This overrepresentation has to do with the fact that a disproportionately high number of studies were carried out in the Bavarian Forest National Park, where the three major forest types are all mixed forests [142]. Coniferous and deciduous forests were subject to research in one quarter of the studies each, leading to an underrepresentation of needle-leaf forests compared to the occurrence of this forest type in Germany.

6.3. Employed Remote Sensing Sensors

Figure 11 shows the distribution of employed remote sensing platforms and sensor types with respect to the investigated object scale of the examined forest parameter. Within the three categories of remote sensing platforms (spaceborne, airborne, and UAV), multispectral, panchromatic, hyperspectral, thermal, lidar, SAR, stereo, and aerial (RGB, CIR) sensors are distinguished. Airborne platforms are the most frequently used and provide the input for 57% of all considered EO-based forest studies in Germany. Spaceborne platforms are also used with a comparable frequency of 41%. In contrast, UAV platforms with only 2% are hardly used for forestry studies in the publication period under consideration, which can also be ascribed to the novelty of this sensor type. In particular, airborne lidar and spaceborne multispectral sensors play an important role in the investigation of forest-relevant topics. While data from spaceborne platforms is used for all observation scales, airborne and UAV platforms are primarily used at the tree and stand level.

Regarding the relationship between the remote sensing platform, the spatial resolution of the input data, the size of the study area, and investigated object scale, a direct correlation between these parameters becomes apparent, as shown in Figure 12. The higher spatial resolution of data provided by UAVs and airborne platforms explains the more frequent use at tree level compared to spaceborne platforms. In contrast, spaceborne platforms are more often deployed in larger study areas since they can cover large areas cost-efficiently, whereas airborne and especially UAV platforms require a much higher effort to obtain information for large areas. Spaceborne platforms providing data with a spatial resolution of 1 m up to 1 km are mainly used to investigate forest-related topics at stand or forest level for large study areas. Data from airborne platforms with spatial resolution between 0.1 and 10 m serve as a base for investigations at a tree level and stand level in most cases with study areas in the order of 0.1 to 1000 km^2. Data from UAV platforms, which offer the highest spatial resolution, are mostly used for local studies with single trees as an observation level in study areas smaller than 0.1 km^2.

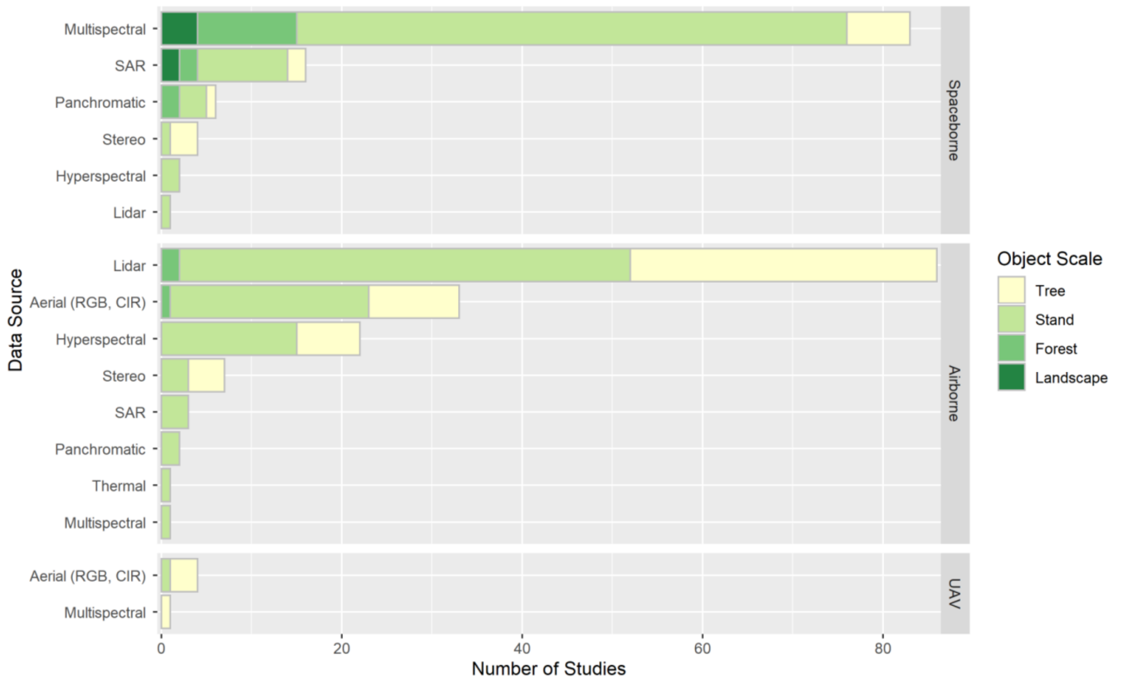

Figure 11. Number of studies in relation to the platform and sensor type by the object scale investigated. Note that studies investigating multiple object scales were counted multiple times.

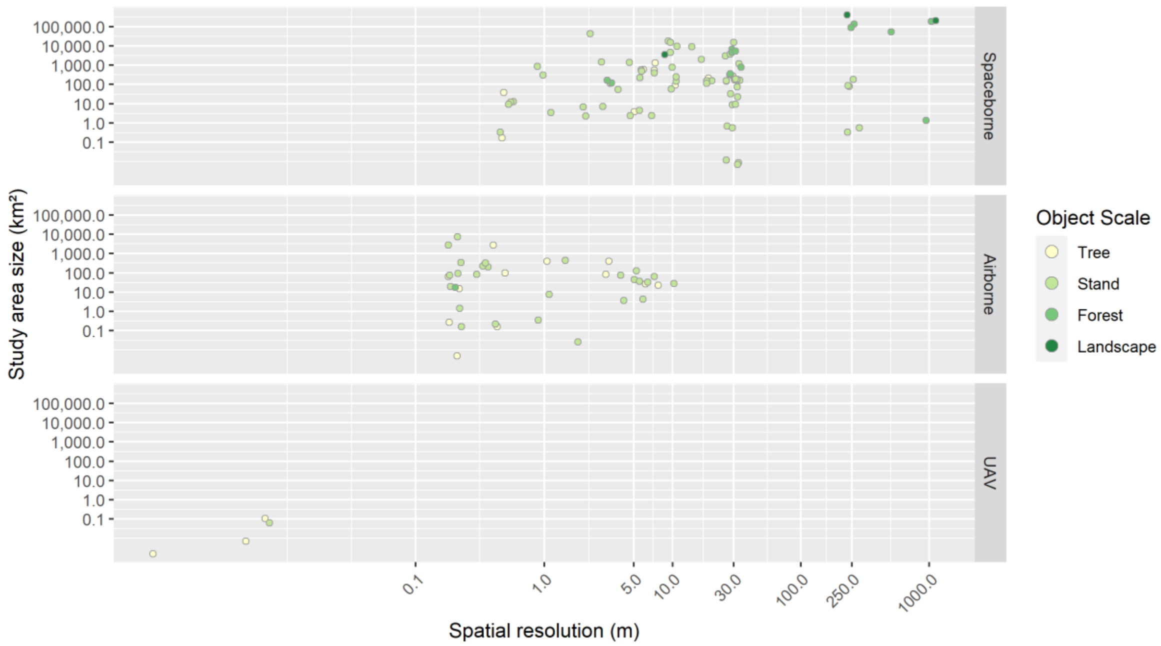

Figure 12. Spatial resolution in relation to platform type and size of study area by object scale investigated. Note that, for improved interpretability of the graphic, a jitter effect has been applied to separate overlapping points from each other, i.e., x-coordinates and y-coordinates are only approximate. Note that studies could be displayed multiple times, if they investigated multiple object scales or utilized multiple sensors.

Under additional consideration of the research topic investigated (Figure 13), it becomes apparent that spaceborne platforms and, in particular, multispectral and SAR sensors are used, especially in the context of forest disturbance as well as biomass and productivity. Other important research topics where spaceborne sensors, in particular multispectral and SAR sensors, are frequently applied, encompass the determination of forest cover and type as well as forest structure classification. In contrast, topics like biodiversity and habitats, phenology, or plant traits were covered less often (<10 studies). Regarding airborne sensors, research on biomass and productivity as well as forest structure were most frequently investigated based on lidar sensors as well as aerial cameras. The topic "Biodiversity and habitats" was the third most frequent research topic, followed by studies on forest disturbance. Less covered topics within the category of airborne sensors are plant traits, forest cover and type, or forest phenology. From the literature review, only five studies were based on UAV data, implementing research on forest structure, biomass, and productivity, as well as biodiversity and habitats.

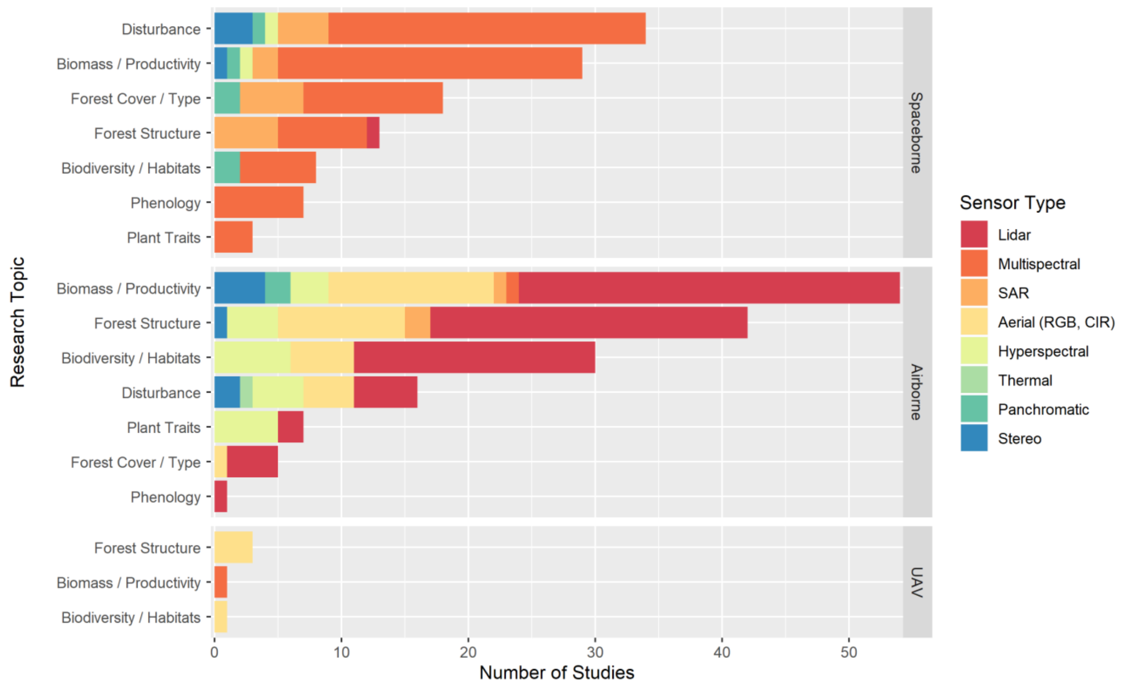

Figure 13. Number of times a given sensor type was used in relation to platform type and research topic by sensor type employed. Note that studies could be counted multiple times if they investigated multiple research topics or utilized multiple platforms or sensor types.

6.4. *Temporal Resolution*

Looking at the temporal resolution of the EO datasets used, we distinguished between mono-temporal analyses, those based on data acquired at a single point in time, and multi-temporal analyses with further partitioning into mono-annual and multi-annual studies to separate short intra-annual time-series from long-term time-series. As discussed in Section 6.3, a sizeable number of studies utilized multi-source data sets such as lidar and aerial imagery or data from non-contiguous test regions, often originating from different acquisition dates. Given that, conceptually, those data could have been acquired at the same point in time. Such studies were categorized as mono-temporal.

Overall, the majority of studies (59%) relied on mono-temporal input data plus another 8% which were effectively performing mono-temporal analysis, albeit in multiple years. Additionally, 15% of studies were based on multi-temporal inputs within a single year, while 18% reported long-term, multi-annual analyses. That mono-temporal analysis plays such a dominant role that may be attributed to the fact that forests, for the most part, are "slow" ecosystems, where changes from year to year are incremental. Noteworthy exceptions are questions of disturbance or externally driven developments such as phenology. Split-up by application domain (Figure 14), multi-temporal analyses are mainly found in studies investigating disturbance, biomass/productivity, forest structure, and, by definition, phenology.

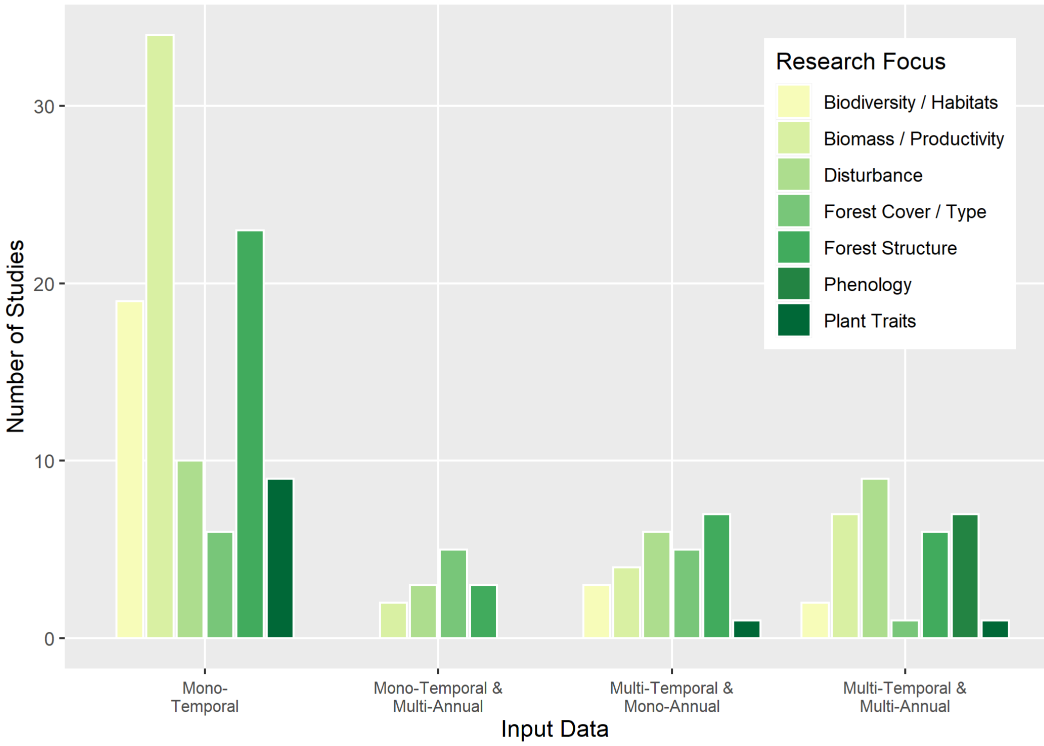

Figure 14. Temporal resolution of input data-sources and output products for seven application domains.

Figure 15 shows the investigated time periods and the corresponding temporal resolution of the input data-sets. The time-line of EO-based forest studies in Germany begins in 1972 with Landsat 1 MSS [104]. Beginning in 1985, that is, the launch of Landsat 5 MSS/TM, until the year 2000, German forests were investigated or analysed on average in seven studies per year. This period is followed by a significant increase in studies in the period 2001 to 2013 with 27 studies per year on average. For the following observation period, 2014-2020, there is a slight decrease in the number of studies, which is likely an artefact due to yet unpublished, ongoing research activity.

While mono-temporal analysis remained the most frequent strategy, a notable increase in the total number of multi-temporal studies was found since 2017, which was, for the largest part, driven by multispectral sensors. Most notably, these were Landsat 5 TM and Landsat 8 OLI, MODIS, RapidEye, and Sentinel-2 MSI. Yet multi-temporal lidar and SAR-based studies were also reported. Clearly, for Germany's temperate forest ecosystems, there is significant discriminatory information in intra-seasonal variation, such as leaf-off vs. leaf-on conditions, which is exploited by studies of the multi-temporal, mono-annual category. Leiterer [175], for example, report significant improvements in forest type structure classification by combining leaf-on and leaf-off lidar data, as opposed to using a single acquisition. Thirteen publications make use of multi-temporal time series from at least 10 years. Six studies deal with either forest disturbances [33,139,208] or phenology [116,121,184], which are both subject areas where long time series are necessary to statistically back up statements on trends and changes.

Overall, there is some evidence of EO-based studies moving to more timely analysis, which is to be expected with the increasingly densified acquisition schedules and improved data accessibility. On average, the time-gap between the acquisition date of the last used data-source and the publication year is shrinking by 38 days per year.

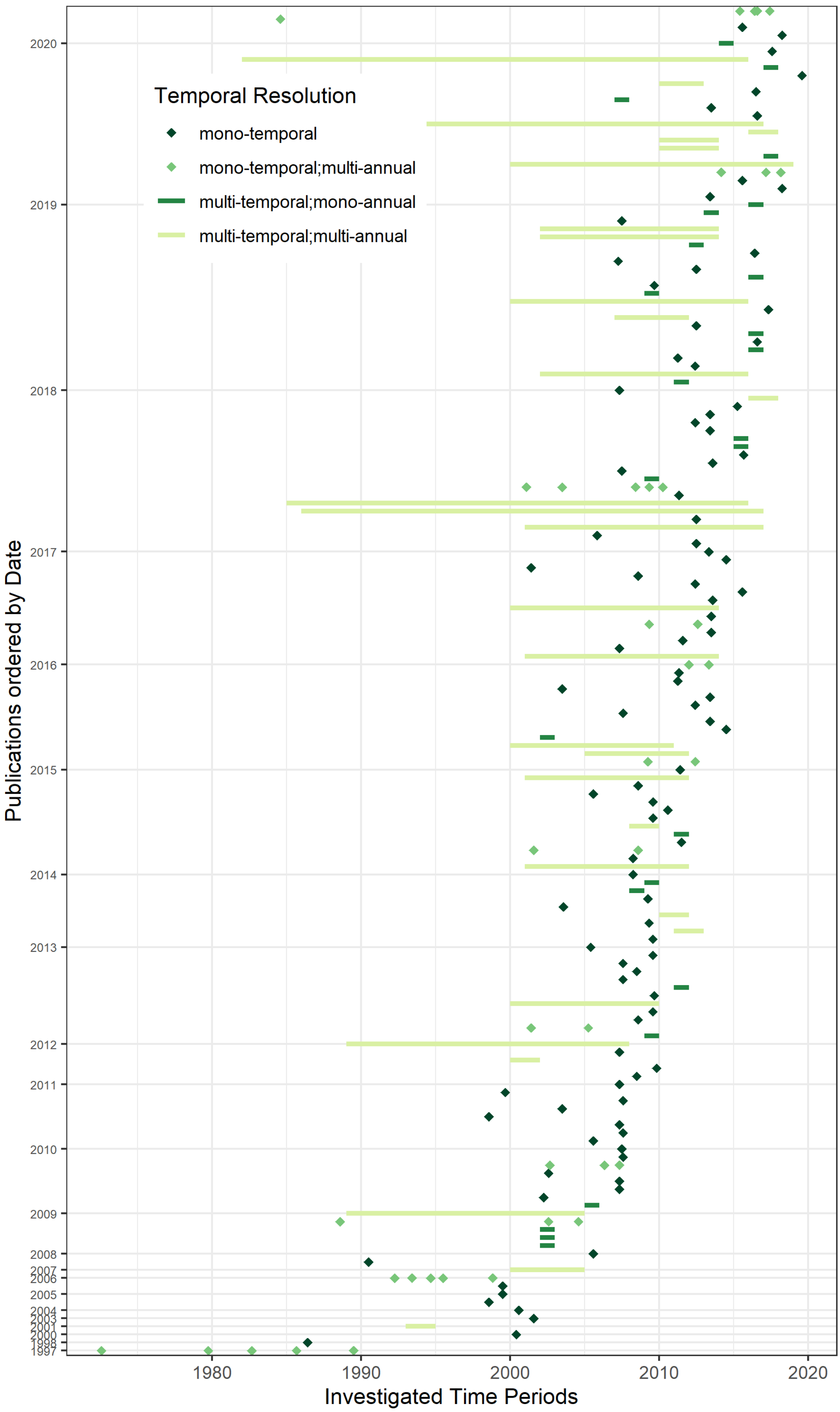

Figure 15. Investigated time periods (x-axis) for every publication (y-axis). The dates on the y-axis show publication years.

6.5. Research Topics

We have divided the large number of research topics into different categories suitable to cover the diversity of studied parameters. The seven categories and the number of studies belonging to each of them are shown in Figure 16.

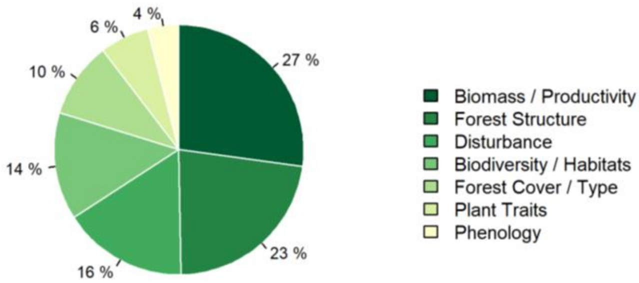

Figure 16. Examined research topic categories. Note that some studies cover different topics, which may result in multiple entries.

6.5.1. Biomass/Productivity

The majority of publications (47 studies) cover the topic "Biomass/Productivity." Forest productivity includes the estimation of timber volume [236], which is of high economic interest to forest management and timber industry, and, thus, strongly demanded information. In addition to the economic value, forest growth is also related to the new biomass generated [154] and, therefore, to changes in the carbon stock [238]. This information is relevant for assessments of atmospheric carbon sequestration and is, thus, needed for further climate action planning.

Looking at the methods used, it can be seen that most of the studies employ some sort of regression analysis between in-situ data and EO data [98,120,165,174,179,228]. A diverse set of different algorithms is employed with the most popular algorithms including linear and generalized linear models, support vector machines, and Random Forests. Like others, Latifi et al. [170], for example, report Random Forest to be the best method for predicting timber volume and biomass.

In 2014, Fassnacht et al. [128] analysed the importance of sample size, data type, and prediction method for remote sensing-based estimations of aboveground forest biomass. They confirmed previous findings that the most important factor for the accuracy of biomass estimates is the sensor type with lidar yielding the highest accuracies. They also found that the prediction method was generally more important than the sample size, but it should be noted that they only considered airborne data. Tum et al. [247] used MODIS data to model the forest biomass in Germany and concluded that the sample size of 1 km^2 resolution is insufficient to describe the heterogeneous small-scale structure of mid-European forests.

Many of the studies have the use of digital surface models (DSM) in common, and use digital terrain models (DTM) to derive canopy height models (CHM) [154,217,233]. Maack et al. [179] found CHM to be the most important predictor for biomass regression. The parameter stem diameter at breast height (DBH) is also often used, especially when it comes to studies targeting stem volume [128,171,222,243].

One of the latest publications in 2019 by Schumacher et al. [217] uses a combination of multi-temporal Sentinel 2 images and 3D photogrammetric point clouds to enhance the accuracy of timber volume models. Their method resulted in up to 50% smaller standard errors compared to using only inventory plots.

Analyses of biomass and productivity have been mainly conducted in managed forests (e.g., Traunstein, Black Forest, and surroundings) (Figure 17).

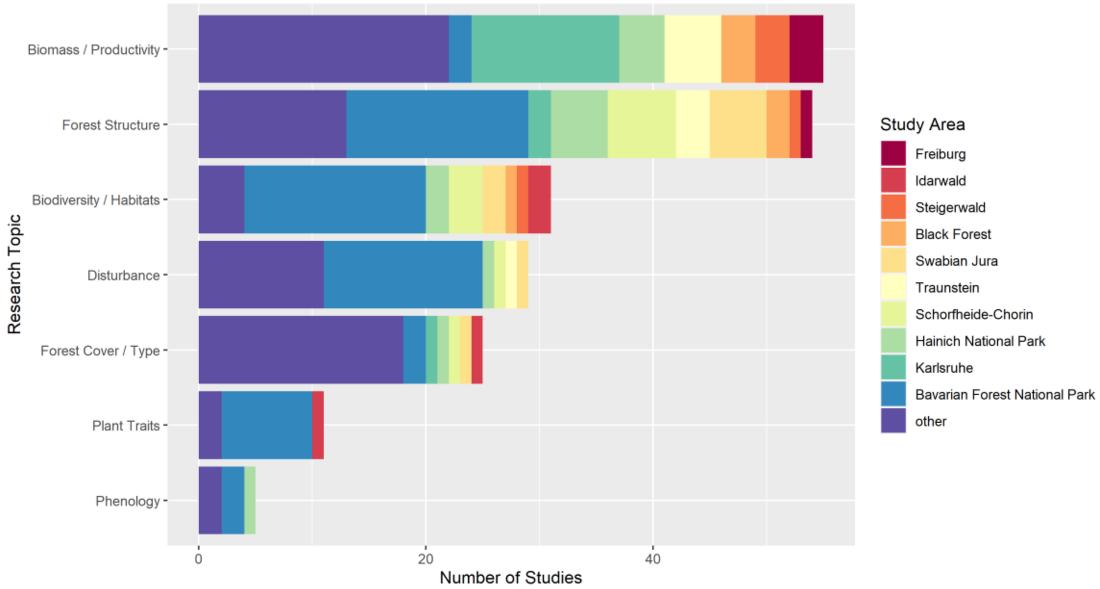

Figure 17. Research topics by study areas. Note that the order of the mentioned topics has changed when compared to Figure 16 since some studies were conducted in several research areas.

6.5.2. Forest Structure

The second most frequent topic dealt with is "Forest Structure" with 39 publications. Forest structure comprises stand structure [126], canopy gaps [137], stand density [248], and vertical forest structure (e.g., tree height and tree crown diameter) [240]. Some of the publications are also assigned to the topic "Biomass/Productivity" [132], which discusses the relevance of forest structure for biomass and productivity. The forest structure is also a very important parameter when it comes to biodiversity mapping or the evaluation of habitat suitability. This is why some research studies cover both topics [106,153], forest structure, and biodiversity.

Forest structure can be specified according to canopy closure and vertical layering. Abdullahi et al. [99] classified nine classes of forest structure based on X-band InSAR data. For the most part, either lidar or radar data was used to derive the forest structure [99,144,175,216]. Tello et al. [240] compared forest structure maps estimated by means of radar and lidar and found them to be of similar quality. Latifi et al. [168] explored the potential of lidar metrics for describing vegetation cover. They showed that the mean height of lidar reflections to be a robust predictor for modelling canopy cover of the highest forest layer. When it comes to undergrowth vegetation density mapping, Leiterer et al. [175] highlighted the necessity to use leaf-on and leaf-off full-waveform lidar.

The methods applied in the 39 publications are diverse. Amiri et al. [103] used a top-down segmentation in conjunction with lidar data. Different regression analysis methods were applied by References [126,142,168,196]. Fischer et al. [132] utilized the forest model FORMIND, (an individual-based vegetation model that simulates the growth of forests on the hectare scale [261]) to simulate the field forest structure and, subsequently, simulate the lidar measurements for correlation analysis to find the best remote sensing predictors for the forest structure. One of the few studies relying on optical data is using spectral unmixing of forest crown components [118].

Concerning the accuracy, Schlund et al. [215] achieved a mean error of less than 1m with a TanDEM-X-based canopy height model.

The forest structure is an essential parameter for many forestry-related aspects and plays a key role in sustainable forest management. This importance is mirrored in the fact that the forest structure is a research topic addressed throughout Germany in different sites, for different forest management regimes and different forest types (Figure 17).

6.5.3. Disturbance

Twenty-eight papers deal with disturbances. Among the different disturbance agents, bark beetle damage was the most prominent one [60,97,167]. Other disturbances comprise windthrow [123,141,239], droughts [105,122,208], frost [160], and fire [199].

Bark beetle damage detection often aims at early detection [97,200]. The sensors used to detect bark beetle infested areas differ widely including [60,129,173] using hyperspectral airborne data. Some studies explored multispectral and thermal spaceborne data [97,163] or a combination of multispectral spaceborne data and airborne orthophotos [167,172]. There are also two publications that used SAR data ([200], X-band, and [239], L-band). However, early-stage detection was not feasible with either L-band [239] or X-band SAR alone but proved to be reasonable in combination with optical data [200]. The detection of heavily infested stands also works with only SAR data [239].

Windthrow has pronounced effects on forest structure and is, therefore, often explored with active systems such as lidar [204,205] and SAR [211,239]. Most studies rely on high spatial resolution data [123,125,141], but even Sentinel-1 C-band with 10-m spatial resolution and ALOS PALSAR-2 with 30-m spatial resolution are useful in the windthrow detection. In terms of methods, bi-temporal change detection is a common technique, which is sometimes applied within an object-based framework [123,125]. Hamdi et al. [141] used a CNN deep learning approach to detect storm damage with pixelwise classification of multispectral aerial images. Whereas most of the mentioned studies addressing windthrow applied a kind of before-and-after comparison, there are a few studies based on time series data where storm damage is recorded as one of multiple disturbance agents to reconstruct forest disturbance history and recovery [33,221].

Forest droughts were assessed with MODIS at a larger scale [105,208]. Dotzler et al. [122] explored the potential of EnMAP and Sentinel-2 data for drought detection with higher spatial resolution using images simulated from hyperspectral airborne data. All studies used spectral indices. The two MODIS-based studies take advantage of the temporal information. Bachmair et al. [105] derived vegetation condition index (VCI) and vegetation health index (VHI) [262] from NDVI (normalized difference vegetation index) and LST (land surface temperature) time series. Reinermann et al. [208] used EVI (enhanced vegetation index) time series. Dotzler et al. [122] used spectral indices specifically sensitive to water stress.

Depending on the disturbance type, sensor and data, timing, and methods, the accuracies vary widely. Polewski et al. [204] detected fallen trees in ALS (airborne laserscanning) point clouds with 97% correctness and 71% completeness. Senf et al. [221] created maps to assess forest disturbance dynamics based on Landsat data and achieved overall accuracies ranging from 81% to 93%. Latifi et al. [167] mapped bark beetle damages with an overall accuracy of 67%-95%.

6.5.4. Biodiversity/Habitats

Twenty-four of the reviewed publications dealt with research questions in the context of forest biodiversity. Almost half of the respective papers looked at animal species and habitat suitability (e.g., [153] for bats, [186–188] for beetles, [189,190] for birds, and [249] for spiders), while others examined plant species diversity in the tree [102] or herb layer [139]. Four studies [102,186,188,218] dealt with the identification of dead wood, as it is a biotope for numerous animal and plant species. It also functions as a carbon sink, contributing to climate protection until the carbon is released again by decomposition processes.

Forest biodiversity is often linked to structural canopy parameters. Airborne laser scanning has proven to be particularly successful in describing a complex three-dimensional vegetation structure and, hence, was used by all but one study to derive parameters such as canopy height, gap depth, crown area, or canopy surface roughness. Zielewska-Buttner et al. [259] combined structural and spectral data to identify and characterize deadwood in order to model habitat requirements of species highly specialized on particular types of standing deadwood (e.g., the three-toed woodpecker). Six of the studies used spaceborne EO data (Sentinel-1, Landsat 4-7, QuickBird, and RapidEye), airborne hyperspectral sensors were employed three times, and airborne and UAV RGB(-CIR) imagery five times. With respect to biodiversity in general, several studies support silviculture strategies that result in a higher variety of canopy densities and vertical variabilities across forest stands [107]. Bae et al. [106] demonstrated the potential of area-wide biodiversity monitoring by remote sensing using Sentinel-1 data. In order to do so, they stress the necessity of stratified and standardized collected local species data.

The employed methodologies included decision tree algorithms (e.g., boosted regression trees [108] and Random Forest [153,176]), statistical analysis [135,218], and classification techniques (e.g., support vector machines [114,245]).

Concerning the derived quality, Gonzales et al. retrieved an overall accuracy of 86.6% [138] for the object-based mapping of forest habitats with lidar and high resolution colour infrared imagery in the Bavarian Forest National Park.

All studies in the context of forest biodiversity covered only local to regional scales.

6.5.5. Forest Cover/Type

Forest cover/type comprises the generation of forest/non-forest masks [109], forest type differentiation like the discrimination between deciduous and coniferous forests [124,195,201], and tree species classification [131,152,255]. A total of 17 publications could be assigned to this topic area.

Some of the publications related to forest cover/type mapping used spaceborne SAR data (X-band, C-band, and L-band). Their thematic detail is restricted to rather coarse classes such as forest/non-forest [109,112,241] or deciduous/coniferous forest types [201]. On the other hand, tree species mapping was often done with multi-spectral or hyperspectral data [131,152,230] or with lidar data [138,157]. In particular, Sentinel-2 proved to be promising in tree species mapping [152,255]. Reference [152] achieved 67% overall accuracy for seven tree species based on a single Sentinel-2 image subjected to a machine learning classifier. Wessel et al. [255] achieved 88% overall accuracy for four tree species/types using multi-temporal Sentinel-2 data. All studies on tree species mapping rely on high quality reference data. Immitzer et al. [150] found that very high resolution reference data should cover roughly 1% of the total area in order to achieve 10%–15% error (RMSE) for mapping spruce and pine in Bavaria.

Among the publications related to forest cover/type and tree species mapping, there is a preference for machine learning algorithms such as support vector machines and Random Forest [60,109,138,152,219,255]. Even though most of the publications generated hard classifications, there are also some papers producing fractional cover estimates, such as deciduous/coniferous fractions [219] or pine/spruce fractional cover [150].

The work by Stoffels et al. [229] generated forest maps with different levels of detail. They achieved high overall accuracies of 93% for a forest/non-forest mask, 91% for a forest type discrimination, 84% for the classification of five dominant tree species, and 55% for the species development stage estimation, respectively. Their results demonstrated that satellite data can be used for the derivation of high-resolution forest information layers for operational forest management.

6.5.6. Plant Traits

Eleven papers dealt with different plant characteristics, known as plant functional traits. These include leaf chlorophyll content [119], chlorophyll and nitrogen concentration [214,253], leaf water content [257], leaf area index (LAI) [191,206,213], and specific leaf area [100,101]. The spatial and temporal information on plant traits helps to understand how forest ecosystems are changing.

Airborne hyperspectral data (HySpex, HyMap) or spaceborne multispectral data (Landsat 7-8, Sentinel-2) were the preferred input data basis with vegetation indices often being calculated as an intermediate step. Neinavaz et al. [191] combined thermal data with reflectance spectral data of Landsat-8 for the prediction of LAI and found out that this combination can increase the estimation accuracy of the LAI in a forest ecosystem. In most of the eleven studies, in situ data served as an input for validation.

The employed methodologies include the use of regression analysis [213,214], but also—especially when the papers were published in the last five years—radiative transfer models and inversion techniques [100,101,206,223,257], Random Forest algorithms [136], and artificial neural networks [191].

The derived accuracy varied according to the considered parameter. Ali et al. [100] retrieved leaf dry matter content and specific leaf area with an RMSE of 4.39% (R^2 = 0.59) and 4.90% (R^2 = 0.85), respectively, from HySpex data. Gara et al. [136] found Sentinel-2 data to be suitable to estimate leaf mass per area (R^2 = 0.67, RMSE = 65.9 g/cm^2), and chlorophyll (r^2 = 0.55, RMSE = 0.38 g/cm^2), nitrogen (r^2 = 0.53, RMSE = 1.13 g/cm^2) and carbon content (r^2 = 0.68, RMSE = 31.9 g/cm^2).

Furthermore, 8 out of the 11 studies related to plant functional traits were undertaken in the Bavarian Forest National Park (see Figure 17).

6.5.7. Phenology

Strongly linked to plant traits, but putting more emphasis on the seasonal variation, seven out of 166 papers looked at phenological parameters. The latter describe the seasonal rhythms of plant development, such as the start of the growing season (green-up date) [121], end of the season, and length of the season [184]. If recorded over a sufficiently-long time period, phenology can be a sensitive indicator of climatological changes.

With respect to remote sensing data, the availability of long time series and a frequent revisit time (preferably daily) is required for phenological investigations. The reviewed studies mainly used AVHRR [116,121] or MODIS data [162,184,185,206], often in the form of derived vegetation indices such as NDVI or EVI. Curve-fitting [162,184,185] and wavelet analysis [116] have proven to be well-suited to extract the desired information from space-borne time-series. For broadleaved species and late occurring understory vegetation, Misra et al. [184] found significant correlations between ground and EO-derived observations of the start of the season, but also revealed the limitations of a different start of season estimation methods and data inherent uncertainties.

Looking at the achieved accuracies of EO-derived phenological parameters, Senf et al. [220] showed an overall strong agreement of Landsat-based estimates of the start of the season with ground-based observations of bud-break variability (r = 0.82).

7. Discussion

With respect to our review methodology, we should mention that a few papers might not have been included, which could potentially hold additional information. With our geographical focus put only on papers dealing with study sites in Germany or all of Germany, we might have missed some information provided in European or global studies that include Germany. However, at that scale, we do not expect to find much additional detail or more precise findings when compared to the national or federal studies. As there were only six studies covering the whole country area, it can be expected that studies covering Europe (and Germany then being only a small area within the image analyses) would not supply in-depth bio-geophysical parameters allowing for differentiated products with respect to the country. We have, furthermore, only analysed studies published in peer-reviewed journals, which, in turn, explains the high number of publications from universities. The administrative sector mainly publishes results in white paper reports, which are not covered within our review, as is usually the case with many other scientific literature reviews.

There is also an interesting, non-uniform spatial distribution of studied forest sites. For example, only one study was conducted on forests in the “Harz,” which is known for the extensive damage this region has suffered due to the recent drought years. The literature found in this review is biased toward national parks and mixed forests, as a large share of studies was undertaken in the Bavarian Forest NP, which also seems to result in a disproportionately strong focus on certain disturbances, such as the bark beetle. Nevertheless, such hot spot areas, with their enormous amount of data and in-situ information, serve as a laboratory for the further development of ideas and methods (e.g., Data Pool Initiative for the Bohemian Forest Ecosystem [263]).

With respect to the strengths and weaknesses of EO in the forest sector, we underline that forests, for the most part, are "slow" reacting ecosystems, where changes from year-to-year are incremental. This is why classical field inventories every five years are, in many cases, sufficient for the need of local foresters. The "near real-time" promise of EO is of particular interest in the area of forest disturbances (e.g., windthrow, avalanches, forest fires, and bark beetle infestations). On the other side, longer time-series of EO data allow for monitoring purposes in the fields of forest development, regeneration, and changes in phenology. Time-series analysis also plays a major role in the detection of drought impacts on forest systems, even though there has been hardly any scientific study published.

The current scientific literature on remote sensing-based forest research in Germany suggests a steady increase in the use of EO-based data for different forest-related analyses. This is very likely due to an increasing number and suitability (with respect to spatial, temporal, and spectral resolution) of available EO sensors and data. Furthermore, it is becoming progressively easier to freely access EO data. Data processing literacy is increasing as well.

The recent increase in the availability of high spatial - high temporal resolution EO data sources parallels an observed increase in multi-temporal analyses. Coming with the increased data volume are new challenges in terms of storing and processing such data. A number of technical solutions including many of which are open-source software, are available, facilitating big EO data analyses such as dedicated array data base systems (e.g., SciDB, RasDaMan, OpenDataCube) or distributed processing frameworks (e.g., Hadoop map-reduce) and many others. While larger research institutes often have in-house expertise and computing infrastructures, the barrier for smaller entities has been significantly lowered in recent years through the public availability of cloud-based storage and processing services such as Google Earth Engine, Amazon Web Services (AWS), EU Copernicus Data, and Information Access Services (DIAS) or the System for Earth Observation Data Access, Processing, and Analysis for Land Monitoring (SEPAL). This paradigm shift in EO data analyses toward multi-source, high-resolution, time-series analyses is expected to also transform EO applications in forestry in Germany in the coming years.

A finding that stands out from our analyses is the fact that there are only very few studies at the national level. Although new sensor types and improved data availability (free of charge, sufficiently high spatial resolution, and frequent and complete coverage) would allow a continuous monitoring of all forests in Germany, it seems that the potential of EO for wall-to-wall monitoring is not yet fully exploited. The rather complex institutional landscape in the forest sector can be an explanation for this, since actual forest management is usually carried out at a local, regional, or federal state level. Another reason may be the fact that the necessary processing infrastructure or knowledge thereof to analyse a large amount of data has only recently been established at the research institutes, universities, and public authorities. In addition, numerous limitations of EO derived information compared to in-situ data still exist. When it comes to the identification of certain tree species (not to name understory vegetation or even animal species), EO can either not provide this information at all, or not with the same accuracy as in situ data. On the other hand, a complete and regular mapping of forest cover in Germany (and also of other parameters such as forest types, biomass estimation, forest disturbance such as windthrow, fires, or drought effects, etc.) could already be delivered with sufficiently high accuracy. This could then be supplemented with further detailed studies (based on higher-resolution EO data or in-situ inventories). Still, a gap exists between the needs and demands of forest managers, who usually operate at stand level and are interested in in-depth information on species variety, biodiversity, chemical properties of leaves, and understory temperature, and EO scientists working with spaceborne data, which usually has its advantages for large scale mapping and monitoring endeavors in a cost-efficient manner. Only one paper did explicitly define and list the data and mapping requirements of the federal forest service (of Rhineland-Palatinate) in order to provide high-resolution forest information layers derived from satellite data for operational forest management [229]. The pilot project confirmed that the operational requirements for mapping accuracies can be fulfilled. According to our experience, common language and mutual understanding must still be established and improved further.

In America, for example, remote sensing is an important source of information to support forest management [264]. Even though field visits are tedious, labor intensive, and costly, they are the basis of the forest inventories especially in large countries such as the United States. EO is used in these countries to support sampling-based inventorying activities to a larger extent than in Germany. Therefore, remote sensing, especially with time series of freely available satellite data, plays a crucial role in complementing ground surveys in these countries [265]. Our results show that the forest-related scientific output in Germany is, so far, not yet strongly linked and integrated into forest inventory programs. However, there is also sufficient evidence that remote sensing is capable of providing operational forest information at a national, federal, and local level [229].

Furthermore, we expect that novel opportunities will arise when the archives of higher resolution satellite data of sensors such as Ikonos, Quickbird, Worldview, or Planet become freely available in the future. Data with a spatial resolution of around one meter or better—when combined with data of higher spectral resolution (e.g., Sentinel-2)—holds the potential for additional information on crown size and shape, species, disturbances, or other forest parameters that might even be relevant at the stand level. A large potential lies in the synergistic analyses of all available EO data for a specific site—be it optical, multispectral, thermal, or radar data. The analyses of all EO data using novel deep learning algorithms on image cubes of complex data—all with their specific advantages—will lead to an increased in-depth understanding of the correlation and also causalities between signatures and patterns in imagery data and geo-physical and chemical properties within our forest stands.

8. Conclusions

In conclusion, the review of published research in the field of remote sensing-based monitoring of forests in Germany provided an extensive overview of the EO data currently in use, their temporal and spatial resolution, and the associated fields of application. In order to relate the findings of the review to the observed ecosystem, we described the forest in Germany in detail regarding its historic development and current status, the forest management and monitoring practices, the institutional landscape in the forest sector, and the present challenges and foreseen climate adaption strategies. The main results considering the objectives of this review defined in Section 1.2 are summarized hereafter.

- We reviewed 166 research articles published since 1997 mainly in journals associated with remote sensing, ecology, or forestry. The publications could be subdivided into seven main research topics. In summary, ~27% of all studies focused on parameters related to biomass and productivity, ~23% on forest structure, 16% on forest disturbances, ~14% on biodiversity and habitats, ~10% on forest cover and forest type, ~6% on plant traits, and ~4% on phenology.
- Considering the spatial extent and coverage of the studies, we found that the majority focused on a local to regional scale (~90%) observing parameters mainly at the stand level. The review pointed out the existence of several "hot spots" when it comes to the surveyed forest areas in Germany. One example is the Bavarian Forest National Park serving as a study area in 34% of the reviewed articles.
- Regarding the employed remote sensing platforms and sensor types, airborne platforms are the most frequently used (57%), but they are increasingly being replaced or supplemented by spaceborne platforms (41%). Airborne lidar data and spaceborne multispectral data were mostly employed data types for forest studies in Germany. We found a direct correlation between the remote sensing platform, spatial resolution of the input data, size of the study area, and the investigated object scale (tree, stand, forest, and landscape).

- Throughout the different research topics, the majority of studies relied on mono-temporal input data (67%). Multi-temporal analysis is mainly found in studies investigating forest disturbances and phenology. Since 2017, there is a notable increase in multi-temporal studies.
- Looking at the different research topics, the forest structure is an essential parameter to most of the forestry related aspects, such as linking canopy closure with habitat characterisation. Horizontal and vertical structure information is, therefore, often used as an additional input parameter to most of the reviewed studies.

Overall, the use of remote sensing for forest monitoring has gained more interest during the last few years. However, there is still a lack of nationwide studies and forest parameter assessments. In order to support forest management and authorities with information from EO, it is necessary to further develop robust monitoring methods and implement them at the state or federal level. Furthermore, we expect an increased in-depth understanding of the correlation and causalities between signatures and patterns in EO data and geo-physical and chemical properties within forest stands using novel deep learning algorithms on image cubes combining different types of EO data.

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