remote sensing

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Review

Potential of Earth Observation to Assess the Impact of Climate Change and Extreme Weather Events in Temperate Forests—A Review

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Abstract: Temperate forests are particularly exposed to climate change and the associated increase in weather extremes. Droughts, storms, late frosts, floods, heavy snowfalls, or changing climatic conditions such as rising temperatures or more erratic precipitation are having an increasing impact on forests. There is an urgent need to better assess the impacts of climate change and extreme weather events (EWEs) on temperate forests. Remote sensing can be used to map forests at multiple spatial, temporal, and spectral resolutions at low cost. Different approaches to forest change assessment offer promising methods for a broad analysis of the impacts of climate change and EWEs. In this review, we examine the potential of Earth observation for assessing the impacts of climate change and EWEs in temperate forests by reviewing 126 scientific papers published between 1 January 2014 and 31 January 2024. This study provides a comprehensive overview of the sensors utilized, the spatial and temporal resolution of the studies, their spatial distribution, and their thematic focus on the various abiotic drivers and the resulting forest responses. The analysis indicates that multispectral, non-high-resolution timeseries were employed most frequently. A predominant proportion of the studies examine the impact of droughts. In all instances of EWEs, dieback is the most prevailing response, whereas in studies on changing trends, phenology shifts account for the largest share of forest response categories. The detailed analysis of in-depth forest differentiation implies that area-wide studies have so far barely distinguished the effects of different abiotic drivers at the species level.

Keywords: forest; temperate forest; climate change; extreme weather events; drought; storm; late frost; remote sensing; earth observation; review

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1. Introduction

1.1. Climate Change and Extreme Weather Events in Temperate Forests

Approximately one-third of the world's land area is forested [1,2], which provides a variety of ecological, economic, and social benefits to people, the environment, and health [3]. In addition to their socio-ecological services, forests are large-scale carbon dioxide sinks [4], as they contain 80–90% of the global plant biomass [5] and continuously offer a high natural carbon storage potential [6,7]. Due to these two aspects, forests are of particular importance for both climate change adaptation and climate change mitigation. However, forests are increasingly under pressure from human impact [8,9]. Forest disturbance is steadily increasing due to a growing number of threats, such as deforestation, fragmentation, invasion, and especially the negative effects of climate change [10–13].

As early as 1967, the results of a computer model that included the essential elements of the Earth's climate for the first time showed the extent to which the doubling of carbon dioxide would affect the Earth's global temperature [14]. The greenhouse effect is a radiative process in which atmospheric gases, such as carbon dioxide, absorb and re-emit thermal infrared radiation, trapping heat and causing the surface temperature of the planet to rise [15]. The strong increase in the concentration of carbon dioxide in the atmosphere was first observed almost ten years later, in 1976 [16]. In 1990, the first IPCC (Intergovernmental Panel on Climate Change) report [17] demonstrated the anthropogenic influence on climate change. A few years later, Cox et al. [18] described how global warming was further accelerated by feedback effects in the carbon cycle. Today, the consequences of climate change are widely known and described. They are ubiquitous in both social [19] and scientific [20] discourse. The rise in global surface temperature [21,22] and the increase in Extreme Weather Events (EWEs) [23,24] have had an evident impact on global ecosystems, especially forest biomes [25]. For example, species are increasingly migrating towards the poles [26], and forests are becoming more vulnerable to drought and heatwave-induced tree mortality [12,27,28]. Due to their location in the most densely populated regions of the world, temperate forests have been the most affected by change, fragmentation, or degradation in the past [29]. While these direct anthropogenic disturbances are now mainly confined to tropical forests [30], temperate forests are now increasingly exposed to the effects of climate change and the associated EWEs [31,32]. Olson et al. [33] divided the world into 14 biomes and 8 biogeographic regions, based on the distribution of a wide range of flora and fauna across the planet, to enhance their utility in conservation planning at both global and regional scales. Two of these biomes are temperate forests: temperate mixed deciduous forests, and temperate coniferous forests. These forests cover about 5.3 million km^2, and account for 16% of the world's forest area [11]. With their location in the temperate zone, which is characterized by seasonal extremes [34], the two biomes together cover large parts of Europe, the west coast of the USA, and Canada, as well as their east coast, parts of East Asia, sections of the southern Andes, and small areas of Oceania [33].

Rising global surface temperatures are disrupting atmospheric and oceanic patterns, leading to the intensification and increased frequency of EWEs such as droughts, storms, late frosts, heavy snowfall, and floods [24,35,36]. These symptoms of climate change are also occurring in temperate forests, and are having a major impact on them. Fast adaptation of different tree species to rapidly changing conditions is only partially possible [32,37]. This is demonstrated by extreme events such as the droughts of 2003 and 2018, with massive impacts on European forests [38–43]. In parallel to the increase in intensity and the duration of droughts, the number and intensity of storms are also increasing as a result of climate change [35]. The effects on temperate forests are illustrated by the example of the storm Vaia in autumn 2018 in northern Italy [44–46]. Storm winds of up to 200 km/h, combined with heavy rainfall, caused widespread damage in almost 500 municipalities [47]. Another increasingly frequent extreme event is spring frost [36,48]. In temperate forests, especially for the dominant native tree species in Europe, the European beech [49], sub-zero temperatures immediately after the buds burst are particularly critical [50]. As a result of changing climate conditions, the phenology, as well as the productivity, of forests are shifting [51]. The faster warming in spring and the longer-lasting warmth in autumn lead to an extension of the growing season and disparity between the green and thermal seasons [52]. The combination of the different EWEs and the changing climatic conditions thus lead to profound changes in temperate forests.

1.2. Remote Sensing Perspective

It is crucial to improve our understanding of how climate change and EWEs affect temperate forests. Remote sensing allows for efficient forest health assessment of large areas [53], the monitoring of otherwise inaccessible areas [54], and offers the possibility of repeated measurements [55], which means that changes due to climate change or EWEs can be tracked particularly effectively. This makes remote sensing an indispensable tool for environmental monitoring. A number of large open data archives, such as those of the AVHRR (Advanced Very High Resolution Radiometer), MODIS (Moderate Resolution

Imaging Spectroradiometer), or Landsat missions, have expanded the possibilities of forest research from the local to the global level in high temporal and spatial resolution [56,57].

For forestry research, this allows for the possibility to investigate the causes of forest damage and to analyze the dynamics of forest recovery [53,58]. The high temporal availability enables timely monitoring of forest damage, and thus the rapid adaptation of forest management [59]. The use of remote sensing technologies to evaluate forest information is not a new phenomenon [55]. Since the 1980s, AVHRR has allowed for the monitoring of forests on a global scale with a repeat rate of one to two days [60–62]. MODIS provides the same frequency with increased spectral and spatial resolution [63]. Based on the MODIS timeseries, a large number of forest products have been produced since the turn of the millennium, such as the MODIS Fire Products [64,65], the Vegetation Continuous Fields product [66], or the MODIS Land Cover Dynamics product [67,68]. Even longer timeseries with higher spatial resolution are provided with Landsat, a satellite series that has offered comprehensive information on forest condition, cover, and structure since 1972 [69,70]. Optical data with higher spatial, spectral, and temporal resolution is the Sentinel-2 observation satellite pair, which has a wide range of applications in the context of forest disturbances [71–74] or environmental monitoring in general [75,76]. By harmonizing several sensors, such as Sentinel-2 and Landsat 8, changes in the environment can be detected more effectively [77,78]. The latest generations of satellites, such as PlanetScope and Worldview (both commercial), allow for the monitoring of trees at the individual/species level [79,80], as well as the near real-time detection of forest changes [71], and their potential benefits are just beginning to be realized.

In addition to the optical sensors mentioned above, other types of sensors offer a wide range of possibilities to monitor the effects of climate change and associated EWEs on temperate forests. For example, satellite or airborne LiDAR images can serve as important indicators of forest disturbances [81,82]. Also, UAVs with different sensors are increasingly being used for very high-resolution studies, such as health and species classification of individual trees [83,84]. Weather-independent SAR data, and thus uninterrupted timeseries, such as those from Sentinel-1, are valuable in the context of forest monitoring and disturbance mapping [85–87]. Overall, remote sensing offers great potential for research on the effects of climate change and EWEs. The development of increasingly advanced spatial, temporal, and spectral sensor systems, coupled with the growth of open-access data archives, is enabling a better understanding of forest ecosystem functioning and its response to changing environmental influences.

1.3. Structure and Objectives of This Review

In this review, we examine the potential of Earth observation for assessing the impacts of climate change and EWEs in temperate forests by reviewing 126 scientific papers published between 1 January 2014 and 31 January 2024. Due to the increasing impact of climate change and EWEs on temperate forests over the past decade [35,38,41] and the launch of high-potential Earth system observers, the Sentinel satellites [75], 2014 was identified as an appropriate starting year. The overall structure of the review is outlined below:

- The introduction in Section 1 presents the relevance of the potential of remote sensing to monitor temperate forests in the context of a changing climate and an increasing number and intensity of EWEs.
- The literature selection process is explained in Section 2 by providing an overview of the literature databases used and the filters applied. By focusing on the primary abiotic disturbances caused by climate change and EWEs, these filters include the distinction from biotic forest disturbances such as bark beetle infestations.
- Section 3 presents the results of the review process. It aims to identify the potential of Earth observation to determine the impacts of climate change and EWEs on temperate forests. First, the evolution of the research field over time is described. This is followed by the identification of hotspots of study areas and author affiliations. The sensors used and the temporal and spatial scales are presented in the next subsection. The Section 3

concludes with a detailed analysis of the research foci. The studies are classified according to climate change or different EWEs and their remotely sensed impacts on temperate forests, as well as an in-depth analysis of the forest differentiations used in the studies to identify relevant research gaps.

- The discussion of the results, the limitations of the review, and the urgent need for dense forest monitoring is presented in Section 4.
- Section 5 highlights the main findings, and concludes with the potential of remote sensing to detect the impacts of climate change and EWEs on temperate forests.

2. Materials and Methods

For the literature review, we used the Web of Science platform. This platform allows for an in-depth literature search with the utilization of search strings and additional filtering. This enables the exclusion of certain languages, disciplines, publication years, or topics that should not be included in the publications. We employed conditional statements, shown in Table 1, to ensure the inclusion of certain criteria. We filtered the publications based on three terms: 'Topic' (TS) returns search results based on title, abstract, and keywords; 'title' (TI) returns results based on only the title; and 'author keyword' (AK) returns only results which match the keywords specified by the author.

Table 1. Criteria entered in the WoS search string. The complete list of criterion geographic scale is included in Table S1. The asterisk (*) represents any group of characters, including the absence of characters.

Criteria	Conditions
Forest	TI = (forest* OR tree* OR conifer* OR needleless OR spruce OR pine OR fir OR larch OR broadleaf OR deciduous OR beech OR oak OR maple OR birch OR chestnut OR aspen OR elm OR linde* OR woodland* OR canop*) OR AK = (forest* OR tree* OR conifer* OR needleless OR spruce OR pine OR fir OR larch OR broadleaf OR deciduous OR beech OR oak OR maple OR birch OR chestnut OR aspen OR elm OR linde OR woodland* OR canop*)
Geographical Scale	List of countries and continents with temperate forests (see Table S1)
Weather Extreme OR Climate Change	(TI = (drought OR storm OR cold spell OR coldspell OR heatwave OR heat wave OR climate induced OR climate change OR water deficit OR abiotic disturbance OR snow breakage OR snow damage) OR TI = ((extreme OR heavy OR severe OR intense OR strong OR high OR late OR early) AND (weather OR climate OR wind OR rain OR precipitation OR temperature OR frost OR meteorology OR stress OR freeze))) OR AK = (drought OR storm OR cold spell OR coldspell OR heatwave OR heat wave OR climate induced OR climate change OR water deficit OR abiotic disturbance OR snow breakage OR snow damage)
Remote Sensing	TS = (remote sensing OR remotely sensed OR earth observation OR satellite OR spaceborne OR multispectral OR hyperspectral OR imaging spectroscopy OR SAR OR radar OR thermal OR Sentinel OR Landsat OR MODIS OR AVHRR OR Envisat OR SPOT OR RapidEye OR WorldView OR IKONOS OR Quickbird OR Pleiades OR Planet OR skycat OR denis OR PRISMA OR enmap OR Hyperion OR COSMO OR ALOS OR TerraSAR OR TanDEM OR RADARSAT OR ASTER OR SRTM OR ICESat OR GEDI OR ecostress OR Copernicus OR Suomi NPP)
Type	Article
Language	English
Date	1 January 2014, 31 January 2024
Excluding Factors	NOT (TI = (beetle* OR insect* OR urban* OR fire*) OR AK = (beetle* OR insect* OR urban* OR fire*) OR TS = (boreal* OR tropical* OR subtropical* OR mangrove* OR bamboo* OR crop* OR grassland* OR wheat* OR tundra OR marine* OR kelp OR bird))

The TS filter was applied for the category of forests, and includes terms such as "wood", "tree", "deciduous", "conifer", and more. We also included the most common tree species, for example, "spruce", "fir", "larch", "pine", "beech", "oak", "maple", "chestnut", "aspen", "elm", or "linde*". In the case of geographical scale, all countries and continents with temperate forests are included, as well as the terms "temperate" and "mid-latitude". The terms "temperate" and "mid-latitude" must be represented in TS to fulfill the search requirements. The criteria for climate change and weather extremes had a more complex conditional statement Publications were filtered that directly name such a phenomenon in the title or as an author's keyword, such as "drought" or "flood". In addition, we sought publications that used a descriptive adjective to describe an "extreme" phenomenon in combination with a "normal" phenomenon in the title, such as "extreme" or "severe" in combination with "weather" or "precipitation". The context of remote sensing was established through a topic search using a list of commonly used sensors and remote sensing terms. The language used is English and the type of publication is set to "article". The selected timeframe includes all publications from 1 January 2014 to 31 January 2024. Based on this combination of conditional statements, we derived 937 publications.

Figure 1 depicts the workflow utilized, which involves two stages of filtering: an automated filter (shown in the last row of Table 1), and a subsequent manual filter. Automated filtering can be achieved through the use of specific 'NOT' statements. To ensure the inclusion of only temperate forests, the sub-tropical, tropical, boreal, tundra, mangrove, and bamboo forests located in the USA, China, Russia, and Canada were excluded. Additionally, terms such as 'crop', 'grassland', 'wheat', 'marine', 'kelp', or 'bird' are excluded from the literature search due to their divergent focus. The filtering process excluded terms such as 'beetle' or 'insect' in TI or AK to establish a clear distinction from biotic disturbances. Additionally, publications with 'fire' or 'urban' in TI or AK were excluded, resulting in a total of 447 publications. Manual filtering was then applied to exclude publications that lacked a remote sensing context, had incorrect study areas, did not focus on forests, or only addressed seedlings or tree-line shifts. As a result of these criteria, 126 relevant articles were identified (Table S2).

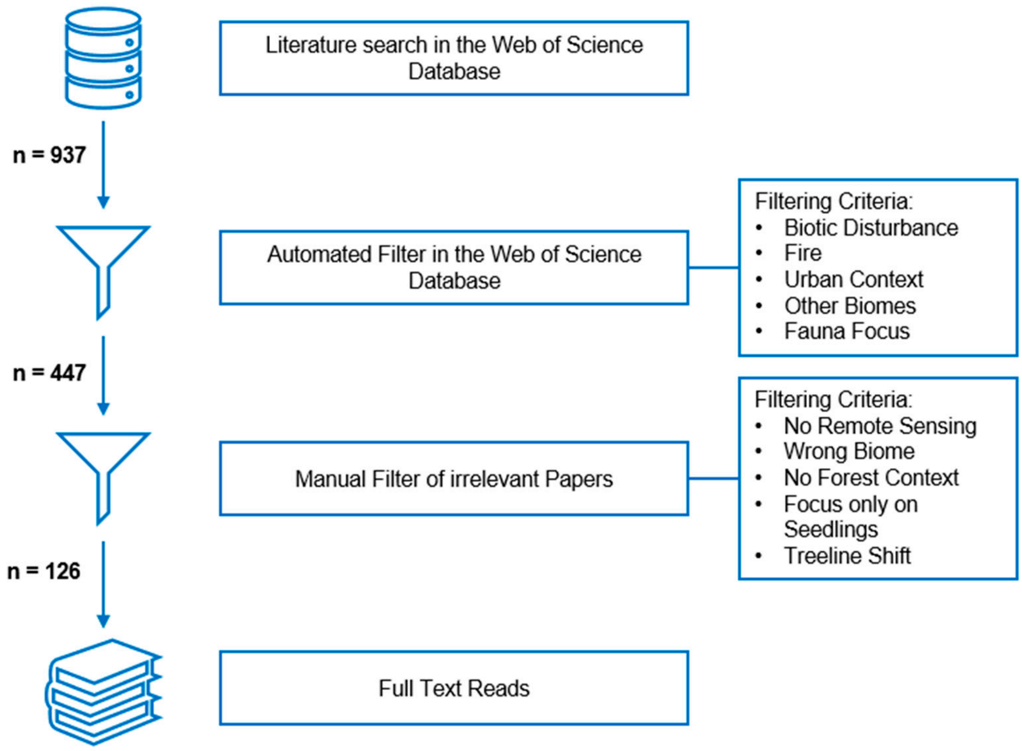


Figure 1. Workflow chart outlining the literature search process used to identify relevant scientific articles about remote-sensed forest responses to weather extremes and climate change.

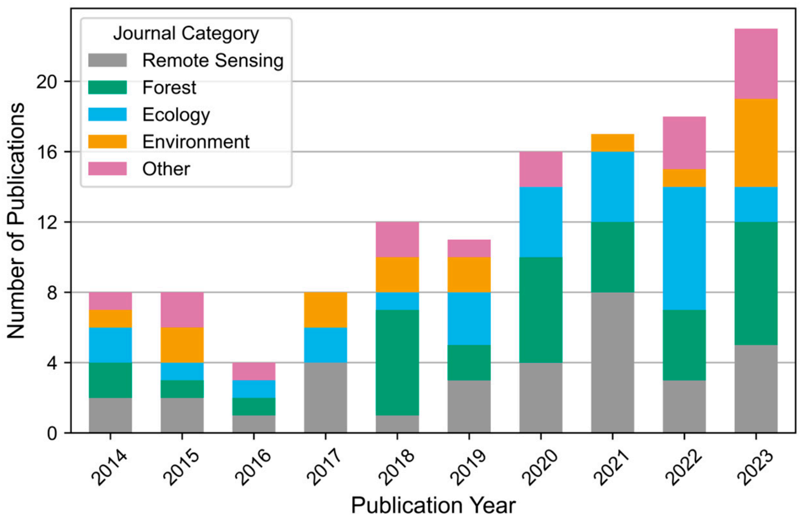
3. Results

The following section presents the main findings of the reviewed articles on the potential of Earth observation to assess the impacts of climate change and EWEs in temperate forests:

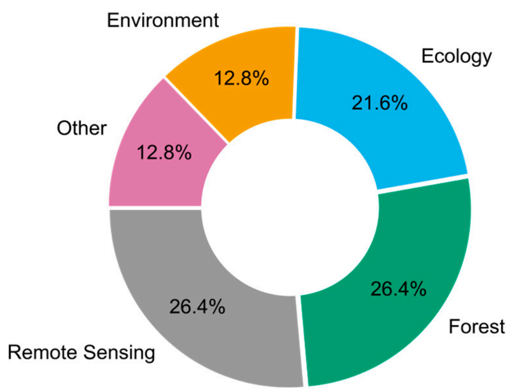
- First, the distribution of publications in different journal categories is shown in Section 3.1.
- In Section 3.2., the publications are subdivided spatially, both with regard to the affiliation of the first author and with regard to the study area.
- The analysis of the sensor name and sensor type, as well as their carrier system, is presented in Section 3.3.
- In Sections 3.4 and 3.5, the spatial and temporal resolutions, as well as the different study periods, are analyzed in detail.
- This is followed by an in-depth examination of the thematic foci in Section 3.6, including the differentiation of various EWEs and trend analyses.
- Subsequently, in Section 3.7, an in-depth analysis of the detailed forest differentiation of the respective studies is presented in order to identify conclusive research gaps.

3.1. Development of Research Interest over Time

The development of a field of research can be analyzed by the number of publications over the years. The composite Figure 2 includes a bar chart and a donut chart, providing a comprehensive visualization of the number of publications within each journal category per year and an overall distribution. We have created five categories of journals in order to assign each publication to a specific class: "Remote Sensing", "Forest", "Ecology", "Environment", and "Other". The category "Other" includes all journals that do not fit into one of the four categories, such as "Journal of Mountain Science", "Journal of Agricultural Meteorology", or "Theoretical and applied Climatology".



(**a**)



(**b**)

Figure 2. Distribution of publications subdivided into different journal categories: temporal (**a**), and overall (**b**).

In the bar chart on the left side of Figure 2, the year 2024 is excluded due to the limited number of publications until the end of January. By that date, only one paper had been published in the category "Remote Sensing". The period starting in 2014 shows a steady increase in the number of publications in all categories except 2016 and 2019. The year 2023 has the highest number of publications with 23, and with almost 60% having been published in the last four years, the increase becomes particularly clear. There is no clear shift in any of the categories. Nevertheless, the graph shows that the categories “Remote Sensing” and “Ecology” were represented in every year, in contrast to “Forest” and “Environment”. In the overall distribution of the 126 publications, slightly more than a quarter of each can be assigned to the categories “Remote Sensing” (26.4%) and “Forest” (26.4%). About 21.6% of the publications belong to the “Ecology” category, and 12.8% belong to the “Environment” category. Sixteen publications could not be assigned to any of these categories, corresponding to 12.8% of the total number of articles reviewed.

3.2. Spatial Analysis on Affiliations and Study Areas

With the exception of Africa and Antarctica, every continent has major temperate forests [33], which is mostly reflected in the affiliations of the first authors and in the spatial distribution of the study areas. Figure 3 shows the number of first author affiliations for each country. On a continental scale, Europe has the highest number of publications with first author affiliations (n = 57). The temperate forest layer in the map suggests that large areas in Europe are covered by temperate forest. Asia has less partial temperate forest cover. One third of all first authors have their affiliation in Asia (n = 42). North America has 27 publications with first author affiliations.

The differences between countries are more distinct. In total, 37 first authors have their affiliation in China, followed by the United States with 24 and Germany with 19. Spain and Italy have more than five each, and all other countries listed have between one and three first author affiliations. Figure 3 illustrates that all countries with first author affiliations have temperate forests within their nations. On the contrary, the observation is not transferable. Not all countries with temperate forests have affiliations within that country. No publications with first author affiliations were found for Chile, Argentina, Australia, or New Zealand.

Figure 4 shows the same pattern. This comprehensive representation of the number of publications with study areas within the country shows that Chile, Argentina, Australia, and New Zealand have temperate forest. However, there are no analyses of the effects of climate change or EWEs on temperate forests. The other observations in the previous figure are reflected in Figure 4. A quantitative comparison of the affiliation of the first authors with the study sites shows a strong correlation (Cramer’s V: 0.79). The deviation from a perfect correlation can be explained with the two subgraphs. Nearly half of study sites are in Europe (n = 58), followed by publications with sites in Asia (n = 41), 32 of which are in China and North America (n = 26). The study by Bórnez et al. [88] examined the responses of deciduous forest phenology to climatic anomalies in the Northern Hemisphere over a period of just under 20 years by using Copernicus Global Land Service LAI 1 km version 2, derived from SPOT VEGETATION and PROBA-V data. Therefore, no single continent can be attributed to this study. In addition, the perfect correlation mentioned above is affected by studies that show transboundary study areas. For example, there are seven studies with study areas covering Europe and one covering all of North America. There are five studies in Europe, three in Asia, and one in North America that do not cover continents, but include several nations. The high Cramer’s V value suggests that foreign research involvement in this research topic is not very common due to the predominantly national interest in the state of forests.

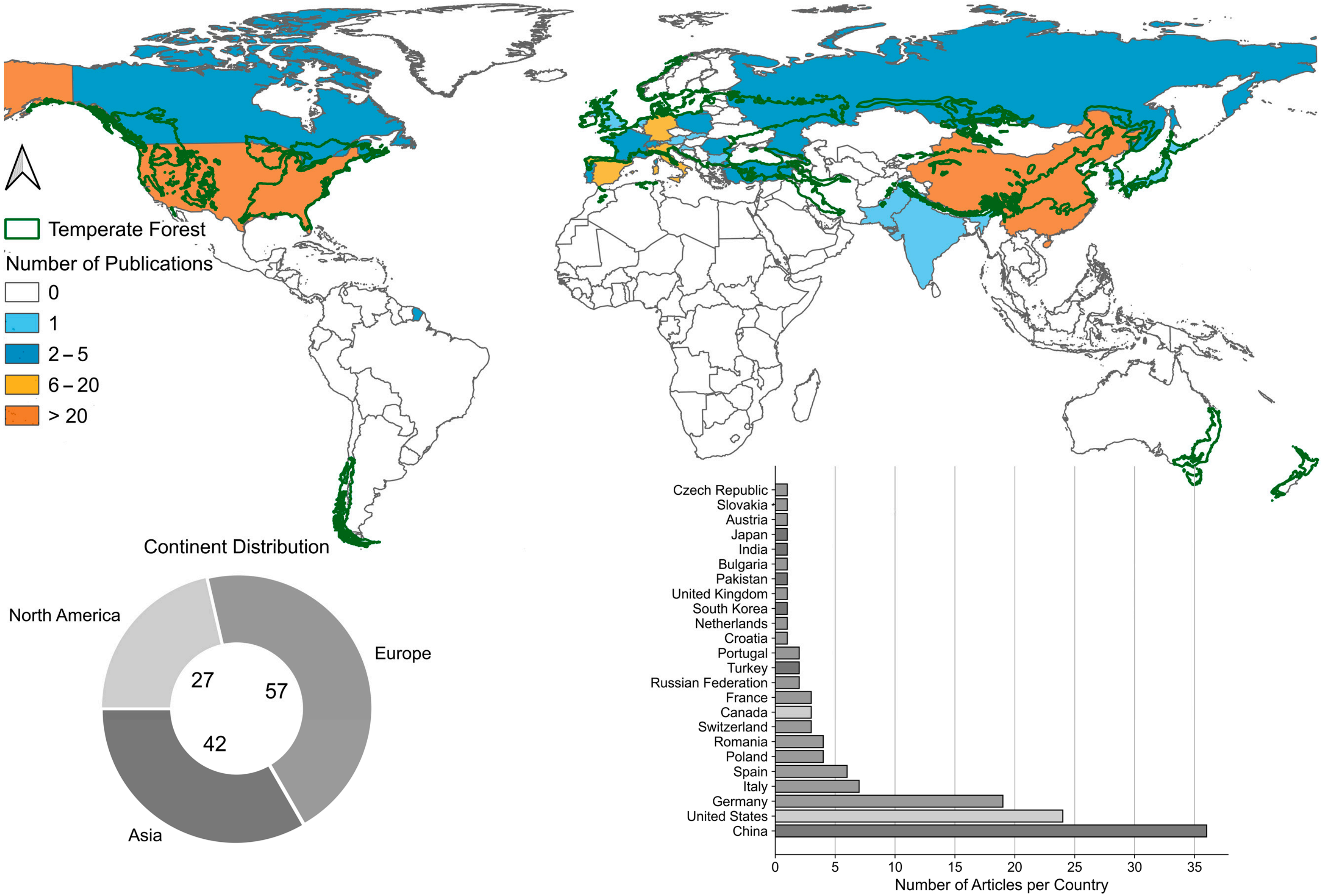


Figure 3. Map and bar chart of the spatial distribution of first author affiliations by country and in the donut chart by continent. The distribution of the temperate forest according to Olson et al. [33] is marked with a green outline.

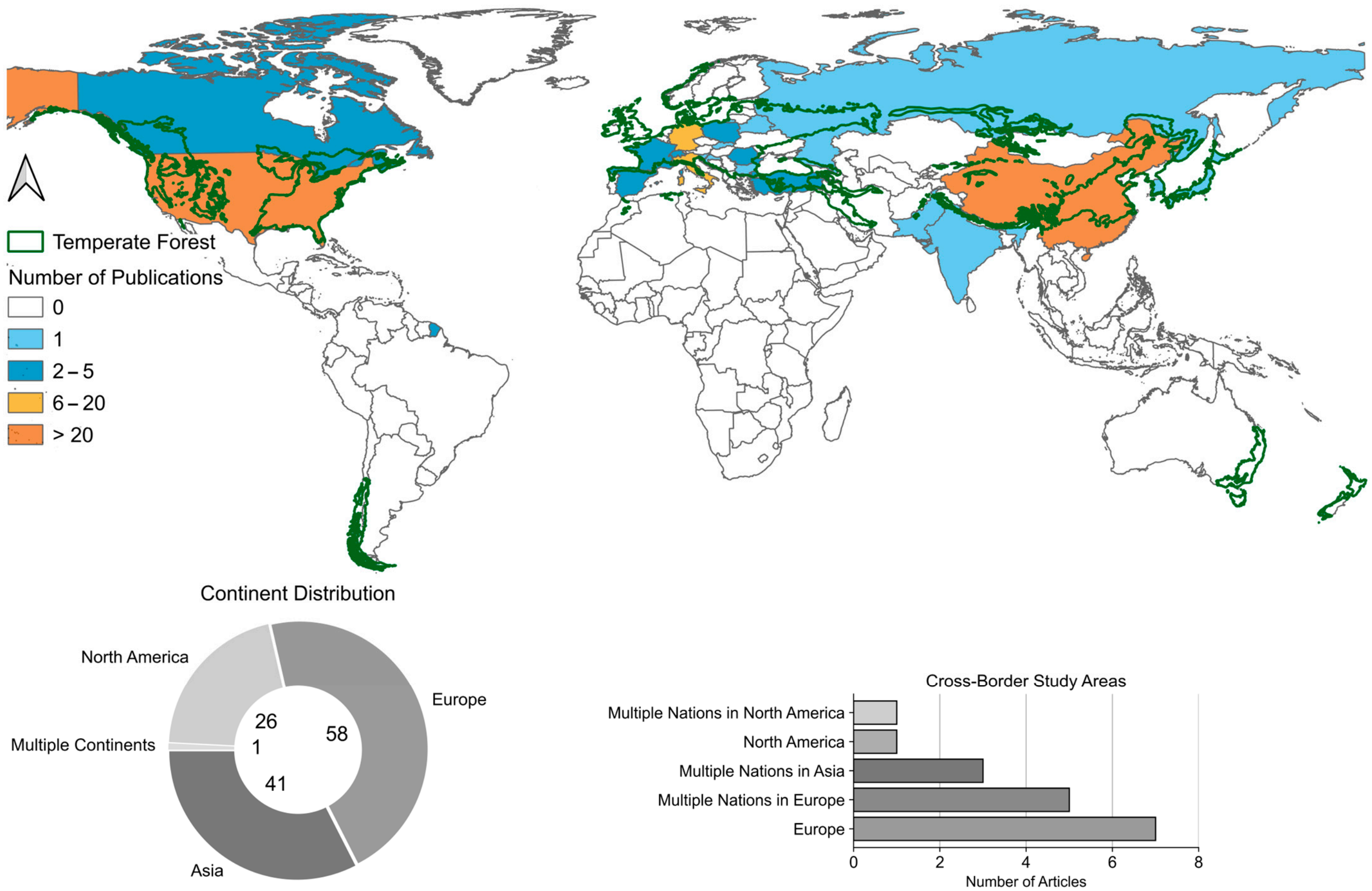


Figure 4. Map of the spatial distribution of study areas by country and in the donut chart by continent. The bar chart illustrates the distribution of cross-border study areas. The distribution of the temperate forest according to Olson et al. [33] is marked with a green outline.

3.3. Sensors and Sensor Type

The selection of sensors is primarily influenced by the focus of the study. Different sensor types are differently suited for the detection of the impact on forest of individual EWEs or climate change. In addition, the study area size is decisive for the choice of sensor. In recent decades, the number of available data have increased distinctly [57,58,75,76,78,89–94]. In general, several sensor types are available to detect the impacts of climate change or EWEs in temperate forests [90,91,94].

Basically, remote sensing sensors can be divided into two categories: active sensors, and passive sensors. Active sensors actively emit a signal and measure its reflection from the ground [95]. Passive sensors measure the electromagnetic radiation reflected from the surface. The radiation detected is typically measured over a range from visible light (VIS) to short-wave infrared (SWIR), and is particularly sensitive to atmospheric disturbances such as clouds, fog, and similar phenomena [95]. Passive sensors are further subdivided into multispectral, hyperspectral, thermal, and passive microwave sensors. Multispectral sensors have several bands in addition to the optically VIS RGB bands. These often include near-infrared (NIR), SWIR, and red-edge. Hyperspectral sensors often have more than one hundred bands with narrow bandwidths [96]. SAR and LiDAR are active sensors, but SAR (synthetic aperture radar) is unaffected by cloud cover, while LiDAR scans can acquire data only under cloudless conditions [95]. Figure 5 shows the different sensors, sensor types, and platforms used.

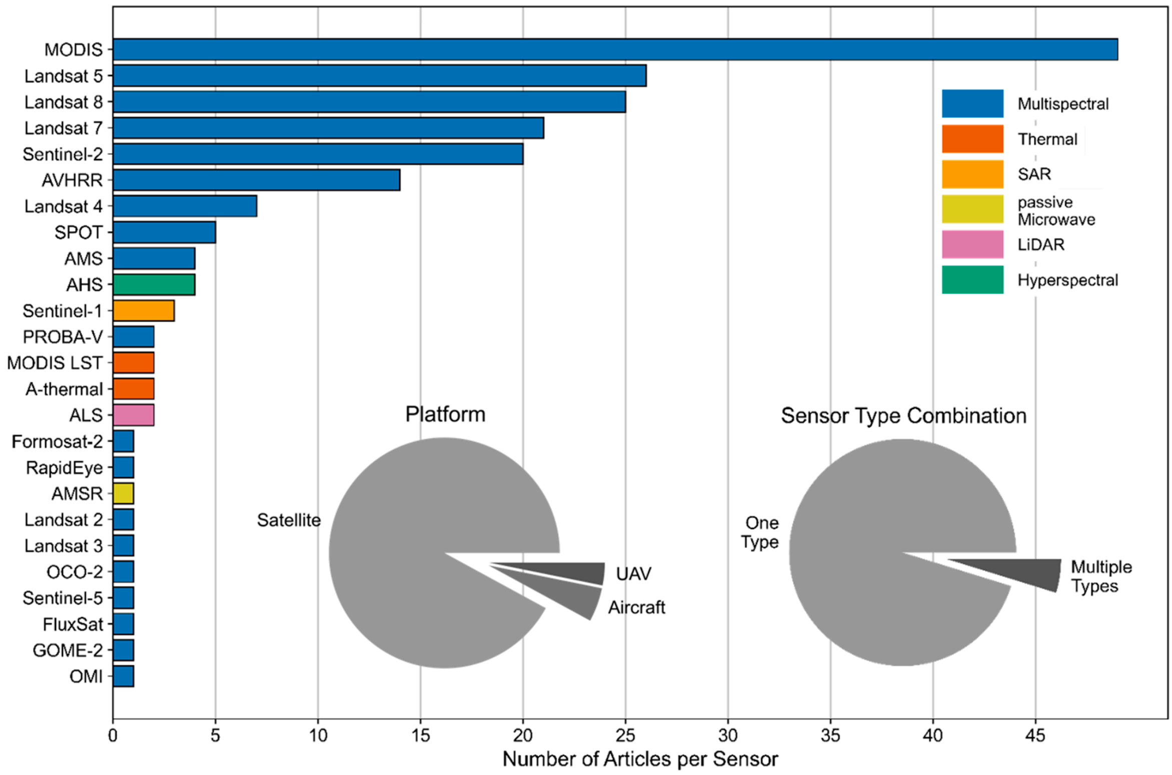


Figure 5. Overview of the different remote sensing sensors, their platform, and the sensor type combination used in the reviewed articles. Abbreviations: A-thermal—Airborne thermal, AHS—Airborne Hyperspectral Sensor, ALS—Airborne Laser Scanning, AMS—Airborne Multispectral Sensor, AMSR—Advanced Microwave Scanning Radiometer, AVHRR—Advanced Very High Resolution Radiometer, GLAS—Geoscience Laser Altimeter System, MODIS—Moderate Resolution Imaging Spectroradiometer, MODIS LST—Moderate Resolution Imaging Spectroradiometer Land Surface Temperature, OCO-2—Orbiting Carbon Observatory-2, PROBA-V—Project for On-Board Autonomy—Vegetation, SPOT—Satellite Pour l'Observation de la Terre.

The use of multispectral sensors clearly predominates in the reviewed articles. Multispectral sensors were used in 118 studies. Four studies each used thermal and hyperspectral sensors. Three studies used Sentinel-1 data, which belongs to the group of SAR sensors. Two studies used ALS data, and one study used passive microwaves. Among the multispectral sensors, the familiar ones clearly dominate. MODIS is by far the most frequently used sensor, with a total of 48 studies. Most MODIS data and products are available from the year 2000 onwards [64,66,67]. The spatial resolution ranges from 231 m to 1000 m, depending on the band. A major advantage over other sun-synchronous satellite platforms is the daily repeat rate north of 30° latitude [63]. The temporal resolution of the Landsat archive is less; the individual satellite systems have a repeat rate of about 16 days. However, the spatial resolution is distinctly better. The current versions Landsat 8 and Landsat 9 have a resolution of 30 m in the VIS, NIR, and SWIR. The Landsat archive additionally provides the longest timeseries available, with the first images dating back to 1972 [97]. A total of 30 studies have used the Landsat archive, mostly combining multiple sensors. The most commonly used sensors within that group were Landsat 5 and Landsat 8.

Altogether, 20 studies were conducted with Sentinel-2. The multispectral satellite pair has been providing composites with a 5-day repeat rate since 2015. With a resolution of 10 m in the VIS and NIR, the sensor can be used for wide range of applications to provide multidisciplinary routine measurements for operational purposes [75]. AVHRR is one of the most widely used sensors, with 14 studies. The multiband data archive of AVHRR starts in 1981. Different products offer spatial resolution between 1.1 and 8 km, with up to daily revisit cycles [98–100]. When all studies employing optical sensors are aggregated, the proportion is 96%. Of these studies, over 80% utilize the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI).

The donut chart on the left in Figure 5 shows the distribution of the platforms. The employed sensors revealed that a large proportion of the data are spaceborne. A total of six studies used aircrafts as carrier systems, and four used UAV. Different sensor types were rarely combined (4.7% of all studies). Thermal data were combined with multispectral data three times. Each Sentinel-1 was combined with Sentinel-2, MODIS was combined with AMSR, and ALS was combined with AHS, represented by the donut chart on the right.

3.4. Temporal and Spatial Resolution

The section below examines the spatial resolution and temporal periods of remote sensing data in the reviewed articles. Figure 6 illustrates the time period covered by the remote sensing data in comparison to the publication dates of the reviewed articles. Each study was categorized, based on the best spatial resolution of the sensors. The categories are as follows: very high spatial resolution (below 10 m), high resolution (10 to 30 m), medium resolution (above 30 to 1000 m), and coarse resolution (more than 1000 m). The remote sensing data time periods are grouped into four categories: mono-temporal (with only one time-step), multi-temporal (with multiple observations in one year), multi-temporal (multiple years with single observations), and timeseries (with at least ten timesteps and multiple recordings over several years). Figure 6 shows that the majority of the reviewed articles used timeseries to detect extreme weather impacts or long-term trends on midlatitude forests. Forest impacts can be measured with their changes. Therefore, the collection of repetitive data is a great advantage. Satellite-based timeseries analysis profits from this feature, and is therefore the most commonly used temporal resolution group. These systems typically have a medium-to-coarse resolution. The MODIS and AVHRR missions have been ongoing for a long time, resulting in a wealth of data. These two sensors are clearly identified in the Figure. The light-blue lines starting in 1982 are associated with studies using AVHRR, and the dark-blue lines starting around 2000 are associated with studies using MODIS. The light-orange lines with long-time periods represent Landsat, which has a long data archive. For example, Katrandzhiev et al. [101] used the Landsat database to create a complete 42-year timeseries to study the effects of climate change on high mountain ecosystems in Bulgaria.

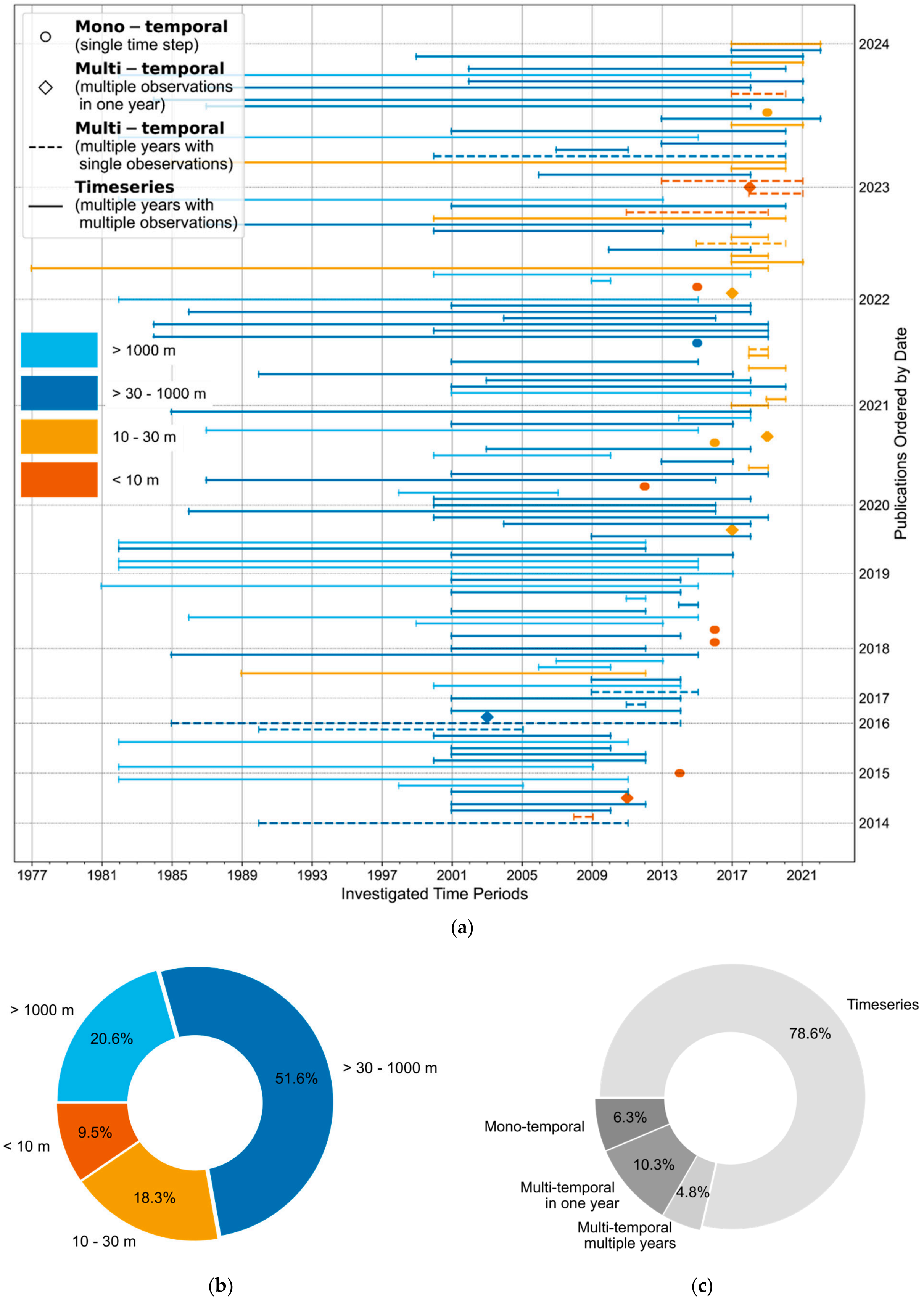


Figure 6. Overview of investigated timeframes in reviewed publications. The temporal resolution is depicted using different point and line styles, while colors indicate the spatial resolution (**a**). Summary of the spatial resolution (**b**) and temporal resolution (**c**).

Overall, coarse (20.6%) and medium resolution (51.6%) studies predominate. This is especially the case in the first years of the publication year timeframe. Almost one fifth (18.3%) of the publications used high resolution data, which increased in 2017 and can be traced back to the start of the Copernicus program. With around one tenth (9.5%) of all publications, the use of very high-resolution data is low, especially in older study periods. Overall, only two of the papers reviewed used high-resolution spaceborne data to assess the impacts of climate change and EWEs in temperate forests. Chehata et al. [102] used an already available high resolution sensor (Formosat-2) to study storm damage in forests after a January 2009 storm event in southwestern France, and Elatawneh et al. [103] used multi-seasonal RapidEye data to update the forest cover database of the Bavarian Forest National Park.

Only 6.3% of all studies use mono-temporal data, and 10.3% use multi-temporal data, with observations in one year. Compared to satellite systems with regular repeat cycles, high-resolution sensors mostly use UAVs or aircraft as carrier systems, and therefore have mostly single-date data acquisitions. Consequently, only satellite systems were used to study the impacts of climate or EWEs change on a timeseries basis (78.6% of all) or multi-temporal over several years (4.8% of all).

3.5. Spatial Resolution (Pixel Size and Study Areas)

To assess the impact of climate change or various EWEs, research has been conducted at different spatial extents and resolutions. Figure 7 shows the relationship between spatial extent and its spatial mapping resolution. Due to the wide range of pixel sizes and study area sizes, the axes are logarithmic. In around 13.5% of the studies, the size of the study area was not stated or could be found out retrospectively; these publications are not included in Figure 7.

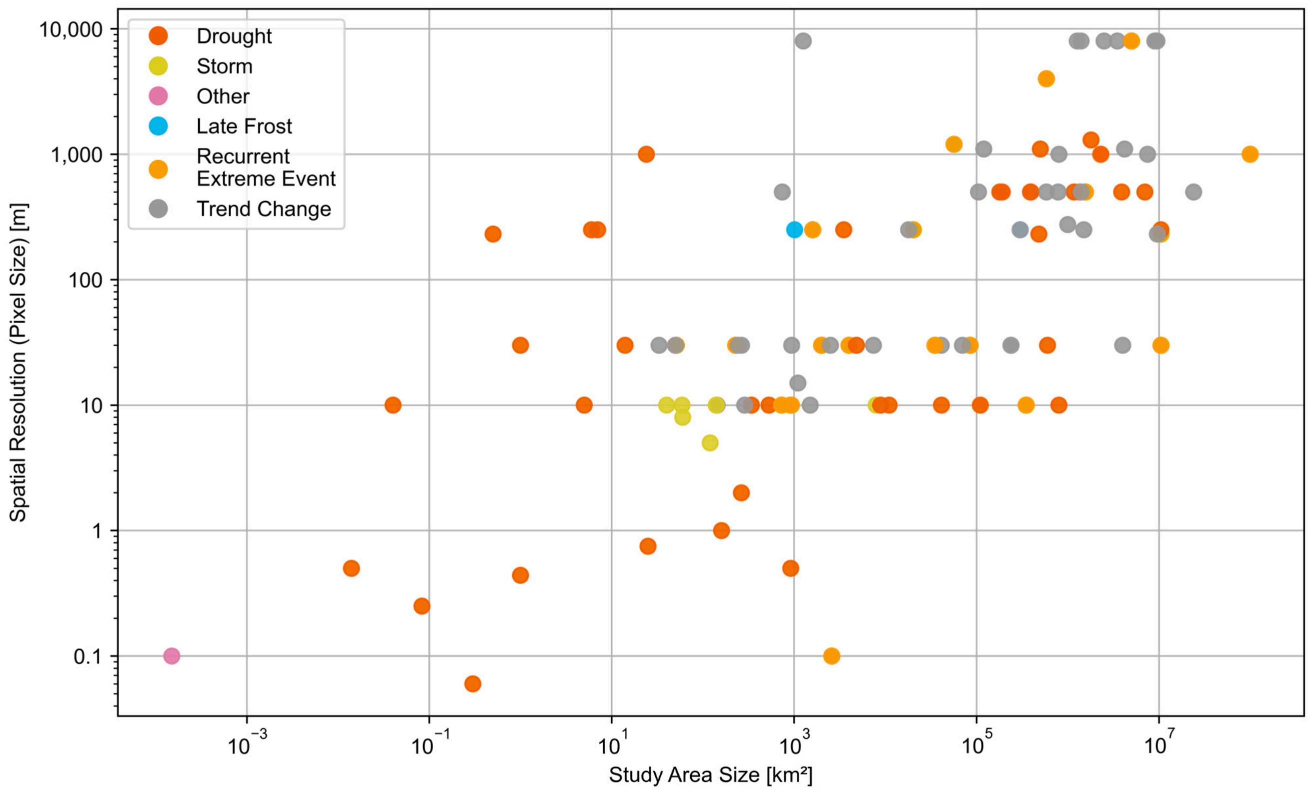


Figure 7. The relationship between the spatial extent and mapping resolution among the reviewed articles. The color code represents the observed extreme weather events or trend changes.

The spatial extent varies greatly, from local studies with 0.15 ha [104] to multi-continent extent up to the entire northern hemisphere [88], while the pixel size ranged from 0.07 m [105] to 8000 m [106–112]. The average study area size is above 3.7 million km^2, while the median lies at approximately 35,000 km^2. This is due to a number of large-scale study areas. The distribution of scatter points shows a correlation between pixel size and the size of the study area (Figure 7). Studies with high-resolution sensors tend to examine small areas, while studies with coarse-resolution sensors tend to examine large areas. The Spearman correlation, useful to quantify nonlinear relationships between two variables [113], is 0.64. About 27 studies have a study area size of more than about 1,000,000 km^2, with only one study using a sensor with a resolution of less than 250 m. Eleven studies have a study area size of 10 km^2 or less, with a predominance of high-resolution sensors and a pixel size of up to 10 m. Parallel to the x-axis, the most frequently used sensors are clearly visible: Sentinel-2 with 10 m, Landsat with 30 m, MODIS between 231 and 1000 m, and AVHRR with 8000 m pixel size.

While drought studies have been conducted at all study area sizes and spatial resolution levels, other extreme weather or climate change phenomena can be clustered more distinctly. For example, trend analyses can only be found at a certain resolution and study area size, which is due to the longer time period available for the coarser resolution sensors. The same applies to studies of recurring extreme events. In contrast, the effects of storms in temperate forests are only investigated in smaller studies with higher resolution sensors. Five of the eight storm event studies have a study area size of 40–140 km^2. The clustering effect is even more pronounced in terms of resolution, with seven of the eight studies using sensors with a pixel size of 10 m or less. The studies investigating the effects of late frost used only the MODIS sensor, and therefore did not use pixel resolutions smaller than 250 m.

3.6. Review of Thematic Foci on Extreme Weather Events and Climate Change

Following the initial examination of the technical aspects of the studies, the subsequent sections address the thematic foci, categorized according to the different EWEs, and climate change, summarized as abiotic drivers. The first part examines the differentiation of EWEs, recurrent EWEs, and long-term trend changes due to climate change, as well as forest responses. Section 3.7 focuses on the detailed forest differentiation of the reviewed articles.

Forest changes can be triggered by a variety of factors. The objective of this review was to examine all publications that can explain remotely sensed forest changes caused by EWEs or climate change. Anthropogenic and biotic influences, as well as fire, were explicitly excluded. After reviewing all 126 publications, six categories with at least three mentions could be formed, which in turn can be divided into three subcategories: first, publications dealing with a single EWE, such as “Drought”, “Storm”, “Late Frost”, or “Other” EWEs; second, extreme events that recur several times over long periods of time; and third, studies dealing with changing long-term trends due to the influence of climate change. As a study may deal with more than one extreme event, it may be assigned to more than one group. The total number of articles reviewed does not reflect the sum of all mentions in the thematic focus categories. Figure 8 illustrates that a total of 71 studies, or more than half of the studies, address the effects of drought on temperate forests. Long-term trend studies represent the second most frequently mentioned category, with approximately one third of the studies (n = 44). A total of 23 studies were conducted to investigate the effects of recurrent climate extremes. Of these, more than three quarters focused on recurrent drought events. A total of eleven studies investigated the effects of remotely sensed storms, four studies examined the impact of late frosts, and three studies focused on all climate extremes not mentioned more than twice. The “Other” category encompasses two studies on the influence of floods, and one study encompasses the consequences of heavy snowfall in forests.

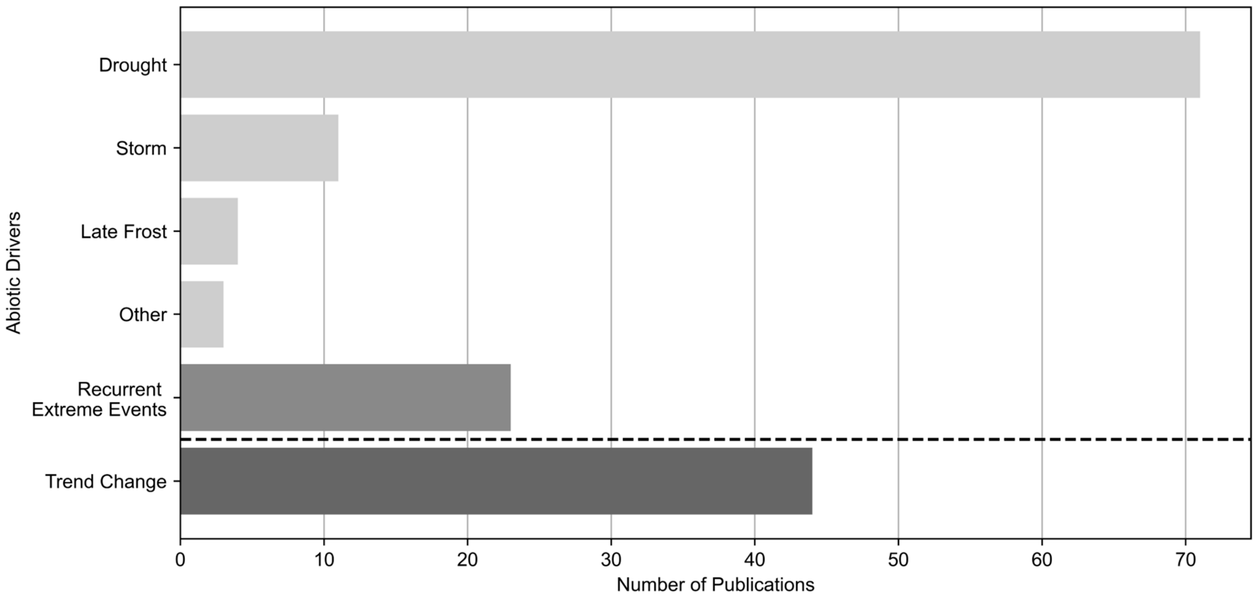


Figure 8. Number of publications dealing with the respective abiotic driver subdivided into Extreme Weather Event (light gray), Recurrent Extreme Events (darker gray), or long-term Trend Changes (below dashed line) due to climate change. Studies may cover more than one extreme event.

In addition to examining the impact of extreme events on forests, we also investigated the response of forests to climate change. Figure 9a illustrates that more than three quarters (79%) of all publications that link a specific forest response to one or more EWEs or long-term trend changes. The responses were divided into three categories (Figure 9b): tree, stand, or forest dieback; changes in phenology; and variations in productivity. In most cases, mortality was associated with climate change or EWEs (54.5%), followed by changes in phenology (25.3%) and productivity (20.2%). The category of phenology encompasses long-term shifts in the start of the season, end of the season, or growing phase, as well as single events, such as drought or late frost-induced early wilting phenomena.

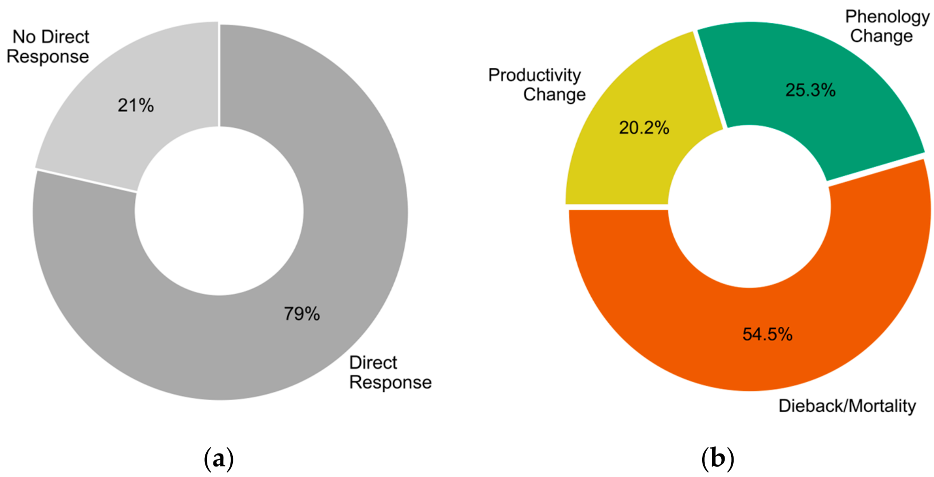


Figure 9. The distribution of whether the study analyzed a direct forest response to climate change or extreme weather event with remote sensing or not (**a**). The distribution of the different associated forest response categories (**b**).

Figure 10 shows a breakdown of the described responses according to the different abiotic drivers. The respective abiotic drivers are presented in relative terms, with the absolute values visualized in Figure 8. The relative representation enables a direct comparison between the abiotic drivers in relation to the forest response categories, i.e., the impact of the abiotic drivers on the temperate forest. It is notable that drought was primarily associated with dieback (55%), yet a considerable proportion of studies did not indicate a forest response (22%) or imply productivity changes (17%). Only 6% of drought studies are associated with a shifting phenology. Storm events are exclusively associated with tree or forest mortality. Two publications have been identified that associate mortality with late frost-affected forests. One publication associated productivity change with the same phenomenon, while another was linked to early wilting. These publications were therefore included in the phenology category. In the "Other" group, the two studies on flood extremes [114,115] and the study on heavy snowfall [104] attributed forest damage and forest dieback to the respective extreme events. In the case of recurring EWEs, the majority of extreme events were associated with forest dieback (60%). Approximately 14% of the studies analyzed the impact of extreme events on productivity, and two studies examined changes in phenology in relation to recurring extreme events. Around 28% of the studies dealing with long-term trend changes did not directly associate the remotely sensed signal with changes in the forest. Frequently, without a clear link to forest effects, only changes in the vegetation index were documented. Nevertheless, phenological changes represent the most prevalent category of associated impacts, with 46% of trend studies attributing them. This is followed by productivity changes (18%) and mortality occurrences (8%).

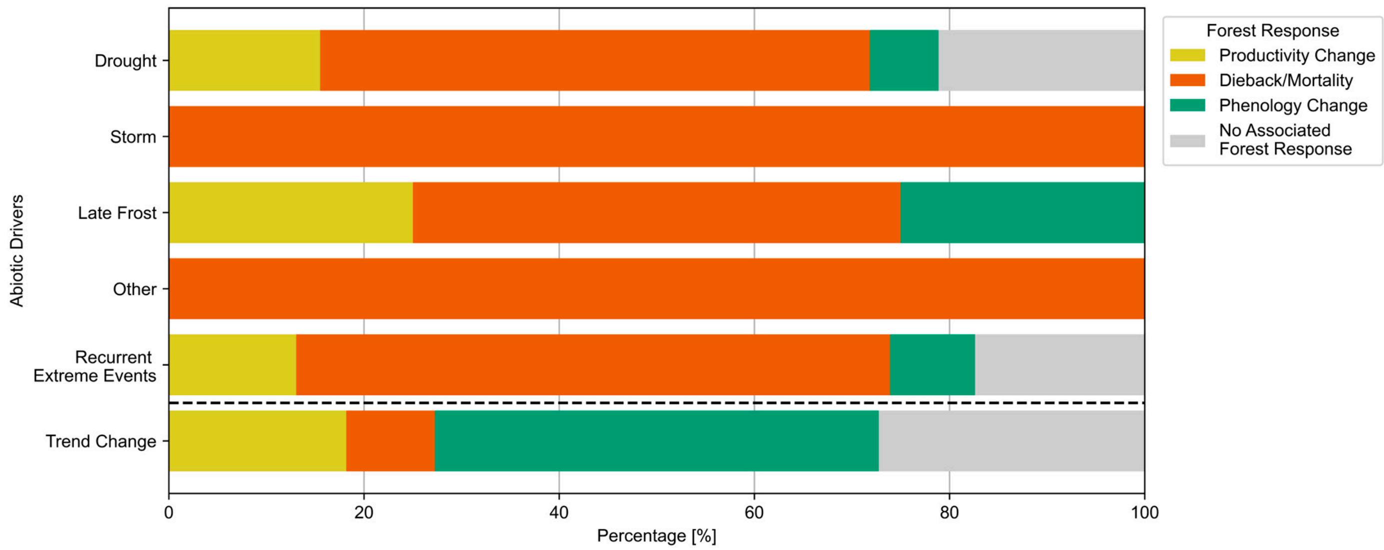


Figure 10. The relative values of the associated forest response categories differentiated by extreme weather events, recurrent extreme events, or climate change-induced trend changes, whereby the absolute figures fluctuate greatly.

3.6.1. Drought

A total of 49 studies dealt exclusively with the extreme event of drought. The distribution of associated forest responses varies widely, as shown in Figure 10.

Drought is most rarely associated with phenological changes. Three studies investigated the extent to which drought events induced early wilting. Using multispectral timeseries from MODIS and Sentinel-2, changes in the NDVI or EVI signal could be attributed to early leaf shedding [38,116,117]. Both Descals et al. [116] and Brun et al. [38] demonstrated the impact of the severe 2018 drought in Central Europe on temperate forests and the resulting early leaf shedding. While Descals et al. [116] confirmed that early leaf shedding occurred during the entire study period (2017–2021), increased in extent with increasing drought intensity, and was linked to anomalously high temperatures and arid conditions, Brun et al. [38] focused exclusively on the effects of the 2018 drought. Additionally, both studies demonstrated that early leaf shedding can have an impact into the next year. Xie et al. [117] also reached the same conclusion for the North American temperate deciduous forest, additionally noting that moderate heat waves and drought stress resulted in delayed leaf fall.

Eight of the drought studies dealt with the impact of drought on forest productivity. Common to all these studies is the use of spatially coarse resolution sensors to calculate forest productivity or biomass production [118–125]. Zhao et al. [123] discovered that soil moisture controls productivity. They were able to show a strong correlation between soil moisture and a severe drought in China in 2022. According to this, there is a threshold for soil moisture. Below this point, forest productivity decreases distinctly. The methods and data that can be used to measure changes in forest productivity related to drought have been analyzed several times [119,122,125]. Zheng et al. [119] used signals measured using GOME-2 and OMI, as well as the flux tower, to analyze the effects of drought on photosynthesis, isoprene emissions, and atmospheric formaldehyde in mid-latitude U.S. forests, and showed that both flux-derived Gross Primary Production (GPP) and remotely sensed measurements show a reduction during drought. Using solar induced flux (SIF) measurements, Zhang et al. [122] were able to show that, in Europe, the effects of drought are reflected by a relatively moderate reduction in SIF. By comparing remotely sensed data with in situ data, these studies underline the potential of remote sensing to detect productivity changes. Another focus of productivity studies was the comparison of different ecosystems [120,122]. Gazol et al. [120], for example determined the resilience of Spanish forests based on their productivity. It was shown that Mediterranean forests in particular have lower resilience but higher recovery compared to temperate forests in the north. Resilience, as used in this publication, refers to the framework proposed by Lloret et al. [126]. The term is defined as the capacity to reach pre-episode growth levels. The original methodology employed the use of tree ring data for the calculation. Gazol et al. [120] adapted this approach to remotely sensed data, quantifying the difference in NDVI before and after the dry year (i.e., the capacity of trees to recover NDVI values similar to those observed prior to the drought).

However, the largest group ($n = 27$) of studies with an exclusive focus on droughts refer to the mortality of a tree, stand, or forest. The focus of the studies on Germany [87,105,127–131] and the USA [132–138] is noticeable. With seven study areas in each country, this proportion is distinctly higher than the overall distribution. The focus of the research with plots in Germany was on the influence of several other forest variables on the effects of drought in the forest. The extent to which a forest is damaged by drought does not depend solely on the characteristics of the drought. For example, in pine forests, the outer areas of the forest are more affected [105]. Soil type, soil texture, stoniness, effective rooting depth, and available water capacity (AWC) also determine the effects of drought. The proportion of dead spruce correlates with AWC [131]. Tree species play a role, e.g., beech is more sensitive to drought than oak. According to Meyer et al. [129], this can be measured using spaceborne NDVI during severe droughts, as was the case in Germany in 2003. Beloiu et al. [127] compared different NDVI values of four years before, during, and after a drought, and analyzed their relationship with forest structure type, soil moisture, and climate variables. They showed that different years show different relationships between the RS signal and other variables. Hajek et al. [128] came also to an unexpected conclusion when they compared the influence of drought in forests with different tree species densities. By employing airborne hyperspectral sensors, they discovered that plots with greater species richness were not less affected by drought-induced NDVI decreases. Klisz et al. [139] came to a comparable assumption, emphasizing that the location of the forest, rather than the tree species composition, is the critical factor influencing drought-induced forest damage.

Studies in the USA have focused on the Sierra Nevada region [133–135,137]. Again, several variables were shown to influence vulnerability to drought. The comprehensive study by Hemming-Schroeder et al. [135] used AHS and ALS data to show that mortality risk increases with tree height, forest density, and distance to the nearest river. The US studies also showed that tree species are particularly important. By accounting for tree species, Das et al. [133] were able to improve their mortality risk models. A method rarely used in this context is that of Brewer et al. [132], who implemented a spectral unmixing method to assess partial cover of piñon and juniper, as well as dead piñon. Using Landsat multispectral imagery from 2009 to 2016, they found increasing areas of dead piñon, especially during severe 2011–2014 drought.

Studies with Chinese study areas are also well represented. The three studies by first author Xu Peipei [140–142] on the importance of canopy height showed that taller trees had the highest damage rate, that shorter trees were more likely to recover after drought than taller trees, and that the resilience of taller trees decreased more during particularly severe drought. Age is closely related to size, which, according to Liu et al. [143], is positively correlated with mortality in the southern taiga. In addition to tree size, forest type also plays a role in drought resilience. Using MODIS timeseries, Li et al. [144] showed that deciduous broadleaf forests were better adapted during the 2002 drought in China.

A total of 11 drought studies were not assigned to a forest response category [145–155]. Most of these studies used MODIS timeseries and compared them with climate timeseries, in particular with the Standardized Precipitation Evapotranspiration Index (SPEI), which is often used in the context of drought. Studies on all continents with temperate forests were able to demonstrate the relationship between SPEI and MODIS timeseries.

In summary, it can be concluded that relationships between drought events and forest dieback can be identified using various methods of relationship analysis between the remote sensing signal and one or more weather/climate variables. The methods used to test the relationship ranged from simple linear regression models to more complex generalized additive mixed models. Drought-related studies that did not directly investigate the relationship with climate variables examined, e.g., the relationship between soil [123,131], tree species [129,133,156], species richness [128], forest types [43,144], forest structure [127,140,141,143], dendrochronology data [129,139], or drought-related mortality [105,136,157,158] with remote sensing signals or remote sensing-driven products. The focus on these relationships is mainly explained by the fact that these variables determine the effects of drought in temperate forests, although their strength of influence varies from site to site. In order to delve deeper into the influencing variables, we have created a sub-section (Section 3.7) on in-depth forest differentiation.

3.6.2. Storm

A total of 11 studies dealing with the effects of storms in temperate forests were found in all the articles reviewed. Common to all of them is that the authors tried to detect damaged or completely destroyed forest patches and are therefore categorized within "dieback/mortality". Seven of these studies focused on windthrow. The scope of the studies was limited to smaller areas (<8000 km^2) compared to drought or trend studies, which cover areas up to the entire northern hemisphere. Also noteworthy was the exclusive use of high-resolution sensors to measure windthrow. The most frequently used sensor was Sentinel-2. Multispectral sensors allow for the calculation of vegetation indices. Since the values of the VIs change [44,71] or the variance of the VIs increases after a storm event [45], this type of sensor is particularly suitable for detecting possible damage. In the study of Garamszegi et al. [159], the potential of Sentinel-2 to predict storm areas and intensities at a small scale in Germany was investigated. Using logistic regression and random forest (RF) machine learning models, texture measures such as roughness were shown to be the best predictors. Also, Piragnolo et al. [45] used RF with Sentinel-2 scenes to detect wind damage after the Vaia EWE in northern Italy. The results showed a strong negative correlation between the decrease in NDMI (Normalized Difference Moisture Index) or NDVI and the severity of the damage. The authors suggest the use of multiple VIs together to improve RF accuracy.

The Vaia storm event was the focus of two additional studies. For Olmo et al. [44], the NDWI8A (Normalized Difference Wetness Index 8A) and NDWI (Normalized Difference Wetness Index) indices derived from the Sentinel-2 tiles proved to be the most suitable for monitoring windthrow after the Vaia event. The third study on forest damage caused by the Vaia storm event was carried out by Vaglio Laurin et al. [46]. The main focus was the comparison between Sentinel-2 and Sentinel-1. A higher accuracy was achieved with Sentinel-2, although Sentinel-1 offers many advantages for various applications due to its weather independence. These investigations provide examples of how severe storm events can have environmental and economic consequences for temperate forests.

Sentinel-1 SAR data were used for storm damage detection in another study. Rüetschi et al. [86] used a simple and direct method of change detection, "image differencing", by calculating the difference between pre-storm and post-storm Sentinel-1 composites. The validation of their method at an independent test site showed that the method worked better for areal windthrow than for scattered windthrow.

Sub 10 m high resolution sensors have been used by Elatawneh et al. [103] and Chehata et al. [102]. The high resolution of the Formosat-2 satellite enabled the object-based detection of changes in storm-damaged forests in the publication of Chehata et al. [102], although the small-scale study was limited to homogeneous stands only. The authors achieved higher overall accuracies (87.8%) for the object-based approach compared to the pixel-based approach, and highlighted the positive correlation between tree age and wind sensitivity. Elatawneh et al. [103] showed that high-resolution satellite data (RapidEye) can be used to determine storm damage very accurately in comparison to methods based on aerial imagery shortly after an event.

In summary, both optical and SAR data are highly suitable for the detection of windthrow areas. Windthrow is detected with greater accuracy over larger areas, and the age of the trees affects their sensitivity to wind. Furthermore, it was established that storm events are exclusively associated with dieback, with a regional focus on Europe. Four other studies [71,114,160,161] did not deal exclusively with storms, and are described in more detail elsewhere.

3.6.3. Late Frost

Four of the reviewed publications dealt with the impact of late frost events on temperate forests. Two studies focused exclusively on the extreme event of late frost [48,162]. Two other studies focused on other extreme events in addition to late frost [160,161]. Olano et al. [162] used the MODIS NDVI timeseries in a support vector machine to distinguish late frost from non-late frost pixels in Spanish beech forests. Dendrochronology and photo interpretation were used to iteratively improve the model. The study showed that the defoliation events caused by late frosts are a phenomenon with a low recurrence rate and are located at high altitudes where precipitation is lower than average. In Italian beech forests, Bascietto et al. [48] investigated the influence of late frost events on growth anomalies using MODIS data. This publication is one of two studies using thermal bands, in this case to detect late frost events together with multispectral bands to quantify the anomalies. It was evident that the two late frost events were very different in their spatial patterns and effects. Both studies investigated late frost events in southern Europe, which is only partially covered by the extent of temperate forests. This is because Mediterranean forests are not dominated by evergreen coniferous species, which are likely to be less affected by late frost than deciduous species. Apart from the geographical focus, it is notable that late frost events are usually examined in connection with specific tree species, in this case, exclusively beech. The reason for this is the respective vulnerability of the tree species, which depends on the specific budburst and defense mechanisms [160,163]. Decuyper et al. [161] also investigated the consequences of extreme events in beech forests, but did not focus only on late frost events. The focus of this study was on the comparison of dendrology data and remote sensing data, which showed that an ice storm is more evident in both types of data than other extreme events.

The paper by Buras et al. [160] had a much broader scope. This publication presented the European Forest Condition Monitor, which used the MODIS timeseries to record various changes throughout the European forest. In addition to different EWEs, the effects of late frost were presented. This comprehensive study confirms the stronger impact on beech forests compared to others, and shows that the effects of late frost events extend far into the year.

3.6.4. Other

Studies dealing with extreme events that do not yet fit into any of the above categories and that do not investigate trend changes in climatic conditions fall into the "Other" category. Only three studies dealing with two other extreme events, namely floods and heavy snowfall, could not be classified. In the study by Fagherazzi et al. [114], the authors described how remote sensing data can be used to quantify flood damage in coastal forests. Rising sea levels and more intense storms are flooding the forest and salinizing the soil. This damages the forest and changes the remotely sensed reflection signal from the vegetation. The authors found that the Normalized Difference Wetness Index (NDWI), calculated from the Landsat timeseries, was best suited to capture the effects of storms on coastal forests.

Samec et al. [115] examined the impact of floods and droughts on the temperate forest in the Hrubý Jeseník Mountains (Czech Republic) between 2004 and 2013. The study assessed the influence of various environmental factors, including drought and management, on forest damage. In addition to in situ data, MODIS data were employed for timeseries analysis. The results indicated that strong winters or droughts exert a more pronounced influence on the NDVI than flood events, thereby demonstrating a stronger association with forest decline. The third publication under "Other" addressed the issue of forest damage caused by heavy snowfall. Nagai et al. [104] described the potential of multispectral UAV imagery to detect damage to individual trees or completely destroyed trees. The use of structure from motion point clouds (photogrammetry) resulted in an overall accuracy of 0.9 for the detection of trees damaged by wet and heavy snow.

3.6.5. Recurrent Extreme Events

The category of recurring extreme events can be divided into two subcategories. Of the 23 publications in this category, 5 dealt with various recurring extreme events [114,115,160,161,164] and 18 dealt with recurring drought events [74,88,165–180].

Of these eighteen studies, three studies focused on changes in the productivity of forests: two in China, and one on the Iberian Peninsula. Zhong et al. [180] employed a 12-year MODIS timeseries to demonstrate that planted forests exhibited heightened sensitivity to recurrent drought events relative to natural forests in China. Shi et al. [178] utilized AVHRR data spanning 30 years to investigate the growth variability along the drought gradient in China. Both studies revealed a negative correlation between tree growth and water deficit. The same sensor and the same timeframe were used in a study by Peña-Gallardo et al. [175] to analyze productivity changes in a different study area (the Iberian Peninsula). Here, the focus was on the relationship between remote sensing or tree-ring data and various drought indices. It was found that tree-ring growth appears to be a more reliable indicator of the response of forests to drought.

As with single drought events, mortality was the most frequently associated forest response category for recurring droughts/events. The research by Bento et al. [171] on dieback in forest ecosystems and spatial variability of drought impact focused on the Iberian Peninsula. They found that the eastern forests of Spain and Portugal were more affected by droughts than forests in other regions of the peninsula. This research utilized a commonly used method for assessing the impact of recurrent droughts on temperate forests, namely, relationship analysis. The correlation between climate variables and remote sensing signals in the context of forest dieback has been studied on several occasions [172,174,179]. These studies demonstrated a correlation between forest decline and summer temperatures or the severity of drought or water stress. Tao et al. [179] reached the same conclusion as the previously mentioned study by Zhong et al. [180], namely, that planted compared to natural forests in China react more strongly to the effects of drought. In contrast, Bórnez et al. [88] employed a relationship analysis approach to ascertain and justify changes in phenology. The study of the entire Northern Hemisphere has demonstrated that an earlier start of the season is more dependent on temperature, while the later end of the season is influenced by both temperature and precipitation. The occurrence of extreme droughts, such as those experienced in Western Europe in 2003 and the USA in 2012, have resulted in a shift of more than 20 days in the timing of the start and end of the season in a predominant portion of these regions.

The effects of recurring severe droughts and the associated forest dieback have been widely studied in Europe [74,167–170]. Senf et al. [168] have quantified the forest mortality caused by droughts with the help of Landsat timeseries and correlation analyses. According to this, 500,000 ha of forest were destroyed by droughts alone between 1987 and 2016. This does not even include the most severe droughts of the recent past. A noteworthy aspect of studies on recurring droughts in Europe is the year 2018, which demonstrated a clear correlation with widespread canopy loss in Central Europe. Thonfeld et al. [74] calculated the loss across Germany using the saturation line-based Disturbance Index. Schwarz et al. [169] were able to use aerial photographs to show how canopy mortality increased during droughts in Luxembourg. West et al. [170] demonstrated that the drought signal in the canopy of German beech forests is only detectable with a delay to the meteorological drought peak. Li et al. [167] used MODIS timeseries combined with tree heights for Europe to show that shorter forests are less resilient to drought due to the deeper tree roots.

The studies that did not deal exclusively with recurrent droughts primarily employed the MODIS sensor to determine the induced alterations in the forest. These include the already mentioned drought monitor by Buras et al. [160], the study by Samec et al. [115] on the consequences of alternating droughts and floods in temperate mountain forests, and the general analysis of the effects of extreme events in the Slovenian beech forest by Decuyper et al. [161]. In the context of other extreme events, the study by Fagherazzi et al. [114] was mentioned earlier, which investigated recurrent storm-induced flooding in coastal forests using the Landsat timeseries. The fifth study dealing with different extreme events is the publication by Pilaš et al. [164]. The study investigated the consequences of recurrent climatic anomalies in a Croatian forest. The study employed the Fraction of Absorbed Photosynthetic Active Radiation (FAPAR), as measured using SPOT and PROBA-V, to examine the effects on various forest types and tree species. Similarly, Bórnez et al. [88] demonstrated that elevated temperatures at the beginning of the year, as a consequence of global warming, resulted in an earlier start to the season, with Pilaš et al. [164] emphasizing the earlier start of the season in beech forests.

In conclusion, it can be stated that recurring extreme events, particularly recurring droughts, result in temperate forest dieback, shifting defoliation forward in the year, and lowering productivity, regardless of the location on Earth. This is evidenced by the correlations between climate variables and remote sensing signals. As longer time periods are required to capture the short- and longer-term effects of multiple droughts, the studies in this thematic focus area used sensors or sensor combinations that already have a long measurement time background.

3.6.6. Trend Change

With a total of 44 studies on the effects of trend changes due to climate change on temperate forests, this topic is the second largest. The distribution of the study areas is noteworthy. Overall, more than half of the study areas are in Asia (n = 25), 20 of which are in China. There are clear trends in the breakdown of forest response categories. In contrast to the other drivers, the most common forest response in the trend change category is a shift in phenology. Studies from Asia are overrepresented in this category, and their approach is very similar. A longer timeseries of multispectral sensors were used to measure the changes caused by climate change and the influence of other variables on the start or end of the season or the length of the growing season [111,112,181–186]. Common to all studies is that they show how changing climatic conditions affected the development of the seasons. Accordingly, the start of season (SOS) is shifting earlier in the year, and the end of season (EOS) is being delayed in the course of the year. This extends the length of the growing season. These studies also examined the influence of various independent climate variables on phenology. The results overlap. Du et al. [181] showed that minimum temperatures in particular control the dynamics of SOS and EOS in semi-arid mountainous regions of China, which was also confirmed by Wang et al. [185], who emphasized night temperature as the most important driver of phenology changes. Zhang et al. [112] and Qiao et al. [184] showed how spring temperature evidently influences the start of the season. These studies demonstrate that precipitation has less influence on phenology in northern China. In addition, the influence of topography and exposure was proven [182,186]. Also the study by Park et al. [187] on phenological changes in subalpine forests on Jeju Island, South Korea, confirmed that rising temperatures affect SOS. Similarly, the study by Şenel et al. [188] was on climate change-induced phenological changes in Turkish beech forests, in which chilling hours and growing degree days explicitly showed the highest correlations with SOS.

Seven studies analyzed phenological changes as a result of climate change in North America. What they all have in common is the use of multispectral timeseries [106,189–194], while the time periods examined ranged from 10 [194] to well over 30 years [192]. These studies focused on the influence of hydrologic cycles on phenology, which is influenced by precipitation and temperature. For example, O'Leary et al. [193] showed that earlier mean annual snowmelt was significantly correlated (Spearman rank correlation, p val = 0.046, p = 0.594) with earlier onset of green-up at the landscape scale. Similar results to the Asian studies were found in North America. Friedl et al. [189] identified thermal forcing as the main driver of spring phenology, while Li et al. [191] found that the phenology of deciduous forests in North America has shown an advanced SOS and delayed EOS over the last two decades, driven by climate variability.

The proportion of studies with European study sites is below average. Only three studies address the effects of changing climatic conditions on phenology in Europe. Senf et al. [195] focused on the development of a Bayesian hierarchical model for estimating spatial and temporal variation in vegetation phenology from the Landsat timeseries. Uphus et al. [196] investigated the effects of climate change on beech phenology and found that the overstory SOS increased with higher mean April canopy temperature, although the understory was not affected by the temperature change. Pilaš et al. [164] confirmed the already known phenomenon that beech forest types have a very high capacity to shift their phenology towards an earlier spring as a consequence of global warming.

Changing climatic conditions also affect forest productivity. Five studies looked at the impact of climate change on the productivity of Asian forests [107,197–200]. Xi et al. [199] and Du et al. [107] used NDVI timeseries to investigate the impact of climate change on net primary productivity. Du et al. [107] found that, in general, the Net Primary Production (NPP) of Chinese forests is increasing steadily, although there are spatial patterns. Xi et al. [199] mainly mentioned the variability of precipitation as a conditional variable. In contrast, Khan et al. [197] and Lv et al. [198] used only mono-temporal multispectral data to investigate the influence of different climatic conditions on productivity. Lv et al. [198] were able to prove that temperature and soil moisture have the greatest influence on productivity. They are the only two studies that fall into the "trend change" category and only use mono-temporal data. Their assignment to this category was based on the authors' assumption that the various climatic conditions studied in the study areas will change in the future, and that the trend can therefore be studied in advance by using sites that are already drier. The influence of trend changes on productivity has also been investigated for European forests. The two studies by the first author Remus et al. [201,202] modelled net primary productivity in Romania using the Landsat archive and machine learning methods. Both studies were able to show that above-ground biomass (AGB) in Romania has increased since 1987, and that Romanian forests have recently experienced a large-scale improvement in carbon fluxes and stocks. Han et al. [203] took a different approach by incorporating phenological shifts due to changing climatic conditions into a process-based ecosystem simulation model. The results showed that, in European forests, phenological variation reduces net ecosystem exchange. As a possible reason, the authors pointed to the opposite effect of increased heterotrophic respiration directly induced by the extension of the growing season. This result is in contrast to other studies.

Only four studies, all located in Asia, focused on forest and tree mortality as a result of changing climate conditions using only multispectral timeseries [108,174,204,205]. For example, it has been shown that forest cover in northeastern China is more dependent on active disturbance (e.g., logging) than on climate trends [108], and that NDVI and Normalized Difference Infrared Index (NDII) are negatively correlated with mortality in birch forests in northern China [205].

Several trend studies did not include a precise description of the effects at the forest level (phenological changes, mortality, or productivity changes). However, these studies commonly described changes in vegetation indices and associated changes in vegetation as a result of changing climatic conditions [101,109,110,206–214].

In summary, the studies dealing with trend changes focus mainly on changes in phenology. Here, the results are mostly in agreement in saying that higher spring temperatures in particular lead to an earlier start of the season, regardless of the location of the study site. It has been shown that, in most cases, forest productivity increased in the long-term, and that forest decline was usually caused by active disturbances such as logging.

3.7. Review of In-Depth Forest Differentiation

In addition to the thematic focus on weather differences, extremes, and long-term climate change, the differentiation of the forest was examined, particularly with regard to the identification of research gaps. The differentiation criteria chosen by the authors in relation to forests are therefore presented below.

One way of distinguishing forests is by forest type. Three forest types can be differentiated in temperate forests: coniferous forests, deciduous forests, and mixed forests. Sixty studies investigated only one forest type, in nine studies the forest type was not specified. The remaining 57 studies investigated the effects of climate change or EWEs in two or more forest types. Figure 11 shows the distribution of the investigated forest types according to the proportion of mentions. Coniferous and deciduous forests were mentioned equally frequently in 66% of the studies. The effects in mixed forests, on the other hand, were only examined in 44% publications. The mention of the different forest types does not yet indicate whether the authors differentiated the forest according to the different impacts of EWEs and climate change.

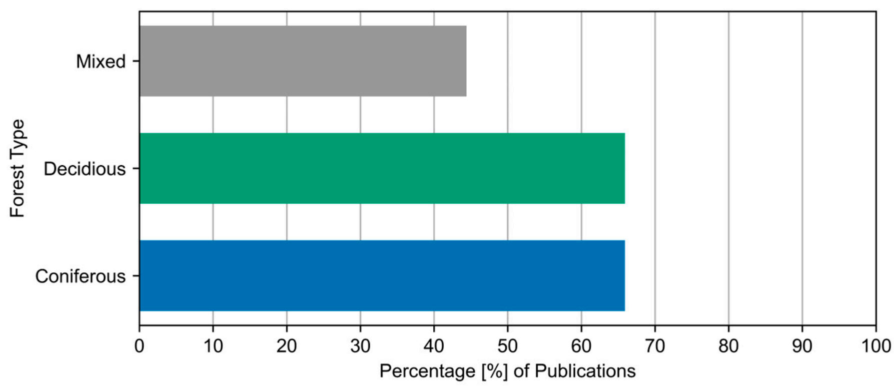


Figure 11. Percentage of forest types investigated. At least two forest types were mentioned in 57 studies.

The effects of EWEs and climate change may vary depending on forest characteristics. For example, the impact of drought on the forest depends on species composition, forest structure, forest type, stand location, or management type. Based on this, we built five forest differentiation types named "Tree Species", "Forest Structure", "Forest Type", "Stand Location", and "Management Type". The left donut chart in Figure 12 shows whether the studied forest was classified according to one of these criteria. According to this, 60.3% of the publications distinguish between the impacts of climate change and EWEs according to at least one forest characteristic. The donut chart on the right shows the distribution of area coverage. The bar chart combines these two points and shows the number of publications that differentiate the effects of EWEs or climate change according to the forest characteristics (x-axis), and additionally indicates the territorial extent via the color.

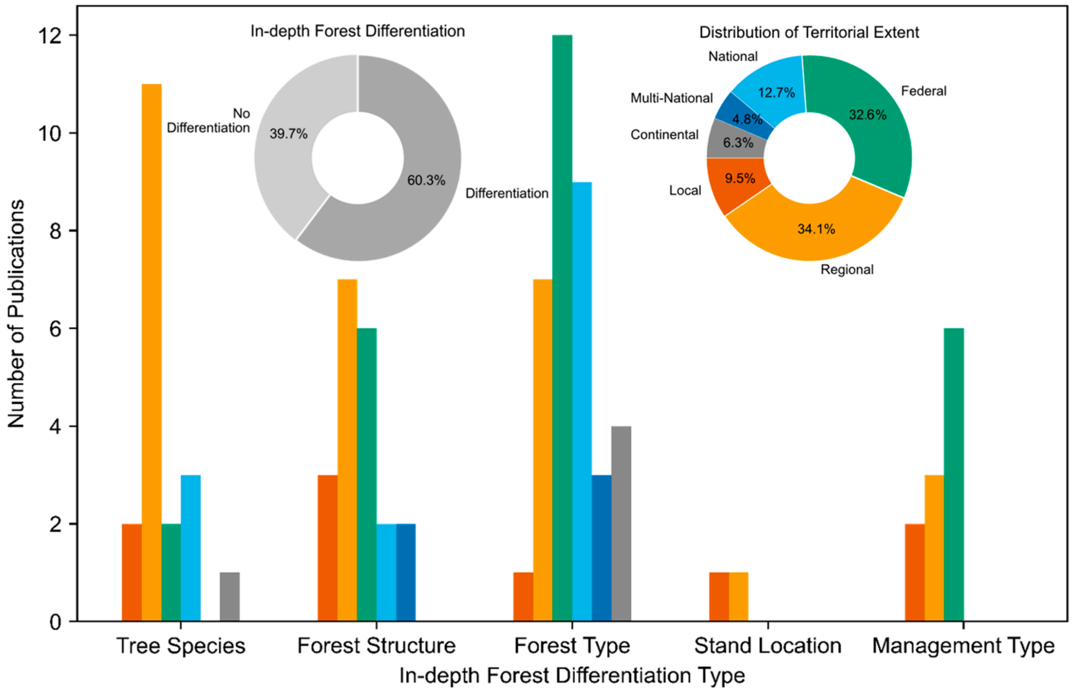


Figure 12. The utilization of in-depth forest differentiation is illustrated in the left donut chart. In-depth forest differentiation describes whether or not the analyzed forest is subdivided by different forest characteristics. These characteristics are displayed on the x-axis, and are categorized according to the scale of the study area. An overview of the general distribution of territorial extents is presented in the right donut chart, which also represents the color code for the bar chart.

The authors most frequently differentiate the forest by forest type at all scales. The location of the stand is only considered in two studies. Buras et al. [105] investigated whether pine trees at the edge of the forest are affected by higher mortality rates during drought. Using a combination of dendroecology and remote sensing, it was shown that proximity to the forest edge is negatively related to mortality and positively related to growth. Hemming-Schroeder et al. [135] used ALS and AHS data in their study of conifer mortality in the Sierra Nevada to show, among other things, that mortality increases with distance from a river.

Relatively little distinction was made between different types of forest management. A commonly used distinction of forest management is that between natural and planted forest. For example, Luo et al. [150] investigated the intensity of drought impacts in planted and natural forests using the MODIS timeseries. Other studies followed similar approaches to distinguish the different responses of planted and natural forests in China [180,213]. Luo et al. [150] and Zhong et al. [180] demonstrated that natural forests are more vulnerable to drought, while Yu et al. [213] focused on carbon sequestration and showed lower values for planted forests.

In turn, Sankey and Tatum [154] examined the effects of forest thinning on drought resilience using airborne thermal data. They demonstrated that the benefits of forest restoration thinning are enhanced during periods of unprecedented drought.

In general, studies using this forest differentiation have only been conducted at smaller scales. When differentiating between the effects of climate change and EWEs on forest structure, there are at least two publications at each territorial scale. In most cases, a distinction was made according to tree height, sometimes with a direct research focus on the importance of tree height in the context of drought events [140,141,143,158,167]. However, studies conducted in Asia by Peipei [140,141] showed lower drought resistance in taller trees, and furthermore, the study by Li et al. [167] about central European forests showed higher resistance.

A clear trend of territorial scales can be seen in the differentiation of effects of climate change and EWEs in relation to different tree species. More than two thirds (n = 13) of the nineteen studies that made this subdivision examined the different impacts at a regional or smaller scale, two studies made it at a federal scale, three at a national scale, and one at a continental scale. However, the national and continental studies are not area-wide studies, but rather are widely distributed sample points with different tree species. In the study of Gazol et al. [120], AVHRR images were analyzed in combination with tree-ring data from 502 forests in Spain with eleven different tree species to investigate forest resilience to drought events. Nevertheless, they did not differentiate between tree species across the whole area. A very similar approach with 402 forest stands was used by Peña-Gallardo et al. [175] to investigate the sensitivity of forest growth to drought events. Contrary to punctual studies, Pilaš et al. [164] used detailed forest type maps (with one to eight different tree species) from the Forest Ecosystem Inventory to differentiate tree species in Croatia on an area-wide basis and to investigate the effects of different climate anomalies on different biomes. They showed differences in the ability of some tree species to better utilize rainfall during very wet periodic episodes, and recommended more research to draw conclusions about the overall resilience of forests under future climate change.

Rita et al. [153] carried out a further area-wide study of drought on forests and on different tree species. The tree species map of Europe used here, which is now almost 15 years old, is based on a combination of compositional kriging and multinomial multiple logistic regression modeling of National Forest Inventory and ICP forest data [215]. Rita demonstrated that species classified as "miscellanea"—broad-leaved and oak—from mesic sites exhibited the most pronounced decline in NDVI values. Consequently, the effects of extreme events and climate change on different tree species, using high resolution tree species maps covering large areas, have not yet been carried out in any of the reviewed articles.

4. Discussion

4.1. Findings in Comparison to Previous Reviews

In recent years, a large number of reviews have been published on the topic of forests and climate change. Some of them are limited to remote sensing methods, and others deal with other data sources and methods in the context of forests and climate change. In the following section, the main findings of this review are summarized and, where possible, discussed in relation to the findings of other reviews.

The focus of this review was on temperate forests. We were able to show that research on this ecosystem is only carried out by countries that cover temperate forests. It was noticeable that, with the applied method, we could not identify any publication from or about Australia, New Zealand, Chile, or Argentina.

Many recent reviews discuss the possibilities of monitoring tropical forests with RS, focusing more on direct anthropogenic impacts and degradation [216–219]. In contrast, research on temperate forests has been investigating the effects of EWEs using remote sensing data for some time. Fifteen years ago, Frolking et al. [220] summarized the potential of spatial data for research on forest degradation and regeneration. The very recent review by Fassnacht et al. [58] summarizes the current challenges, considerations, and directions of remote sensing in forestry. Even more detailed evaluations of the remote sensing data used can be found in Holzwarth et al. [221,222]. The authors examined the development of remote sensing research on German forests. In principle, the two reviews are much more spatially limited and have a broader focus. They revealed an increasing interest on studies of disturbances, most of which are directly or indirectly caused by climate change and its consequences. The shift towards disturbance studies is accompanied by a shift towards timeseries analysis. In fact, in our review, timeseries account for more than three quarters of all studies, because climate changes and EWEs tend to occur over longer periods of time and their effects evolve over several years. Since, with the exception of Landsat, long-term series are only available from satellite systems with low spatial resolution, systems with pixel sizes more than 30 m predominate in our review, accounting for more than two thirds of the sensors used.

The proportion of publications not using satellite data is less than 8% in our review, and is distinctly higher in reviews with limited spatial scope [221,222]. The wide range of multispectral satellite systems available offer the opportunity that observation gaps can be filled more and more effectively. Therefore, optical data were used in more than 96% of the studies in our review. This is also reflected in the general distribution of the use of Earth observation satellite data in publications worldwide, where, e.g., optical data clearly outnumber radar data [94].

Similarly, there is already a large collection of reviews from recent years that address the increasing pressure on forests due to climate change without focusing on remote sensing data and methods. Kleinman et al. [223], for example, focus on the ecological consequences of combined disturbances in forest ecosystems, Zhang et al. [224] examine studies on the effects of drought on biodiversity, Vacek et al. [225] analyze publications on the effects of climate change on tree growth as well as on crises and management strategies for European forests, Keenan [226] also deals with the adaptation of forest management to climate change, and Park et al. [227] asks the general question whether forest management can adapt to the uncertainties of climate change in the 21st century. All of these reviews and studies emphasize the problem of water scarcity, mostly caused by droughts. This is reflected in the above-average attention given to the issue. More than 70 of the 126 publications used deal with the effects of droughts on forests. The focus on drought is not surprising. Compared to other EWEs, water scarcity has the strongest negative impact on forests and the highest risk for large-scale changes, which can be monitored by remote sensing techniques [38,224,228,229]. Research into this influence is therefore particularly important, especially as drought events are already causing increasing monetary damage [41,230] and are expected to increase in frequency and severity over large parts of the world [231–233]. With only four studies on the effects of late frost events, this extreme is underrepresented compared to other weather extremes. So far, frost damage has been a regular phenomenon, especially in southern Europe. Combined with the results of studies on phenological changes with earlier SOS, the likelihood of damage in temperate forests becomes much higher, and the issue more relevant.

The analysis of the results of the studies on the various abiotic drivers has revealed clear trends. While the effects of storms and late frosts are studied almost exclusively in Europe, the focus of trend changes is in Asia. There is no regional focus in studies on the effects of droughts, but it has been shown that a large number of variables determine the severity of the impact. In addition to temperature and precipitation, tree species, forest type, location, management, and soil properties have an important impact on forest response.

4.2. A Need for Dense High-Resolution Forest Monitoring, and Future Research Trends

Given the increasing frequency of disturbances in forests [13], the decreasing resilience of forests [229], or the rising tree mortality due to changing climate conditions and more frequent EWEs [27,234], comprehensive, temporally, and spatially high-resolution forest monitoring is crucial. However, methodological problems or missing data could be solved in the near future. In the field of remote sensing, there are trade-offs between the spatial and temporal resolution of the sensor [235]. The future of satellite remote sensing data includes smaller and more cost-effective platforms, so-called CubeSats, which operate as a unified system or constellation. CubeSats can provide data with higher spatial resolutions well below 10 m, with a daily revisit time [235,236]. This allows for the detection of small-scale successional events in forests and the timely detection of damage caused by EWEs. Very high-resolution systems offer the possibility of object-based detection, for example, of forest damage at the individual tree level [102].

In addition to new satellite systems, forest monitoring can be improved by combining [77,78] and making better use of existing satellite data. As the evaluation of the studies has shown, almost exclusively multispectral data have been used so far, which has the disadvantage of being weather dependent. The SAR sensor of Sentinel-1 can therefore be used as an independent data source for the detection of forest response to extreme events or as a supplement to multispectral timeseries [45,46]. The positive development in improving forest monitoring is also due to the increasing number of publicly available data archives such as Landsat [57] or the Sentinel series [75,76]. Regardless of the improving satellite database, the problem of missing in situ data remains [176,205,237]. In particular, in situ data can be used to improve the interpretation of remote sensing signals to help verify quality [237,238] and to gain a better understanding of the forest system.

In addition to data improvements and accessibility, methodological options are evolving rapidly. In most of the studies reviewed, correlations between climate extremes and remote sensing signals were measured using simple correlation indicators such as Spearman and Pearson. In contrast, Wu et al. [110] used convergent cross-mapping as a novel technique to uncover non-linear causalities between timeseries data. Zimmermann et al. [239] additionally recommend the use of individual extreme values instead of the commonly used mean values, e.g., to better understand spatial patterns of tree species. The use of artificial intelligence and advanced machine learning offers great potential for climate impact research in forests with remote sensing [224,240]. Random forest or support vector machines have already been used in many of the studies, often reaching overall accuracies above 0.85 [46,138,157,179]. To reduce the problems of opacity and inexplicability, understanding the processes behind artificial intelligence must not be neglected in the future [241].

The evaluation of the different studies has shown that investigations have already been carried out at all spatial scales. However, there is a direct negative correlation between the depth of the studies and the size of the study area. For example, the effects of extreme events on specific tree species or the effects of different management practices on forest response have only been investigated in very localized study areas. Large-scale studies have been limited to changes in phenology [88,191], biomass production [107], or forest damage [13], with no differentiation by tree species, stand location, or management type.

Finally, there is a need to better understand the response of forests to variables such as soil conditions, management practices, forest structure, tree species distribution, or stand location. Whether tall or short trees and natural or planted forests are more affected by drought depends on different site conditions, and does not follow a general rule. The increasing challenges posed by climate change require rapidly adaptable forest management strategies which take into account forest disturbance interactions at the landscape scale in order to maintain resilience, resistance, enhance biodiversity, and enable sustainability. Many scientific findings from remotely sensed forest formations are already being used for forest management strategies [58,149], which, in the case of satellite-based observations, can offer the possibility of near real-time monitoring [59,103].

The accelerating development of methods, especially in the field of artificial intelligence, and the increasing availability of high-resolution spaceborne data will noticeably influence the trends of future research in satellite-based forest science, enabling continuous detailed forest monitoring.

4.3. Limitations

Considering the scope and depth of this review, there are several limitations that may affect the completeness and applicability of the results. Limitations in the literature reviews can arise in the pre-selection of papers due to restrictions in the search string. Web of Science is one of the most widely used principle search systems [242], and makes the literature searches reproducible and, if the complexity remains at a reasonable level, transparent [243].

However, Boolean expressions like "AND" make the search very sensitive [244] and depend on clear formulation by authors. At the same time, Boolean strategies allow for clear delineations [243,244].

For example, the timeframe from January 2014 to January 2024 excludes studies published before and after this date. However, as remote sensing is developing rapidly [55,89,90], especially in forestry applications [58], and this review is intended to represent the current state of research rather than historical development, our timeframe was considered to be appropriate, especially since important milestones in remote sensing took place after or around the beginning of the timeframe, such as the launch of the Copernicus program [91], the commissioning of Landsat 8 [93], or the launch of commercial high-resolution satellite fleets such as Planet [235].

The non-use of the term "disturbance" in the search string and the exclusion of terms such as "beetle" or "insects", which describe biotic disturbances, had a major influence on the selection of studies examined. Avoiding the term "disturbance" was intended to circumvent a one-sided focus on disturbances in the forest and not necessarily on forest responses to changing climate conditions or EWEs. Examples of this would be the changes in phenology or the effects on productivity as described in the results. Consequences, such as bark beetle infestations or forest fires, are closely related to weather extremes in the forest, especially drought. Excluding "fire", "beetle", and "insect" resulted in a reduction in over 70 papers that were selected as relevant before the manual filter.

However, by excluding these terms from the TI and AK, it was ensured that papers in which the bark beetle occurs were not generally excluded, but that papers dealing centrally with this biotic disturbance were excluded. Again, this restriction was important in order to be able to make statements about the influence of extreme events that are as independent as possible.

The final evaluation of the individual papers is influenced by the categorization of the contents, which can lead to a loss of information. In order to provide an overall picture of the current state of science, these supplements are important. They enable a straightforward comparison of the databases, methods, and results of different studies.

5. Conclusions

This review provides a comprehensive overview of the potential of remote sensing to detect the impacts of climate change and EWEs in temperate forests. By constructing a search string of relevant terms using automated and manual filtering methods, we obtained 126 relevant studies published between 1 January 2014 and 31 January 2024. From these studies, information was collected on the study areas, the origins of the authors, the sensors used, their temporal and spatial resolution, and the time period studied. In addition, we analyzed which extreme events or trend analyses were examined, what the associated consequences in the forest were, and to what extent the studies differentiated the forest. The main findings are summarized below:

- The increasing relevance of research on the impacts of climate change and EWEs on temperate forests is underlined by the increasing number of publications, with almost 60% of all studies published in the last four years.
- Only countries with temperate forests conducted research on these biomes. Europe dominates both the number of first author affiliations (n = 57) and the number of study areas (n = 58) within the continent. However, when looking at individual countries, China stands out, with 36 first author affiliations and 32 study area assignments.
- Optical data are used in 96% of the studies, more than 92% of the studies use satellites as a carrier system, and only about 5% of the studies combine different sensor types.
- Studies utilizing timeseries data predominate, accounting for more than three quarters of all studies (78.6%). With the exception of Landsat, long-term series are only available from satellite systems with medium-to-coarse spatial resolution.
- Sensors with spatial resolutions higher than 30 m predominate in this review, accounting for more than two thirds (69.9%) of the sensors used.

- Study sizes range from very small studies (0.15 ha) to multi-continental studies, with large studies focusing more on long-term trend changes or drought events, and smaller studies focusing more on storms or other weather extremes.
- In total, 71 of the 126 studies dealt with drought, followed by studies on trend changes (n = 44). Recurrent extreme events were examined in 23 studies, and the effects of storms were examined in 11 studies. Four studies examined the effects of late frost, two studies examined the effects of floods on temperate forests, and one study examined the effects of heavy snowfall.
- When attributing different impacts to forests, extreme events such as drought, storms, floods, heavy snowfall, and recurrent extreme events were most often associated with forest mortality (50–100%). In the case of changes in climatic conditions, most studies associated the forest change with a shifting phenology (46%). Different EWEs are regionally focused, and so the effects of storms and late frosts are studied almost exclusively in Europe and the effects of changing trends are studied primarily in temperate forests of Asia.
- The intensity of EWEs together with soil conditions, tree species, forest type, structure, management, and stand location influence the response of the forest. These factors vary from site to site, and a better understanding is needed.
- In more than 60% of the studies, the forest is further differentiated. In most cases, however, only forest types or forest structures are distinguished. Only in a few cases are impacts differentiated by tree species, and then only for very small or non-comprehensive areas.
- The predominant focus on droughts (56.3% of all studies) is confirmed by other reviews, and is explained by the fact that water limitation, usually triggered by droughts, has the greatest area-wide impact on forests, in contrast to other extreme events.

With this review, we present a comprehensive analysis of the current state of remote sensing capabilities to detect the impacts of climate change and weather extremes on temperate forests. Future studies should combine as many of the following aspects as possible to enable rapid, comprehensive, and high-resolution monitoring: multispectral dense and long time series, high temporal and spatial resolution, national-to-continental study areas, and detailed forest differentiation. In addition, the potential for artificial intelligence and the need for in situ data to enable a better understanding of forest systems should not be underestimated.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16122224/s1, Table S1: Criteria entered in the WoS search string. The asterisk (*) represents any group of characters, including the absence of characters; Table S2: Overview of the 126 relevant articles, including title, authors, sensor, resolution in meters, period, region, extreme weather events (EWEs), and forest response. Abbreviations: Res—Resolution, AS—Asia, NA—North America, EU—Europe.

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