



# Review on the Possibilities of Mapping Old-Growth Temperate Forests by Remote Sensing in Europe

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## Abstract

Old-growth forests (OGF) provide valuable ecosystem services such as habitat provision, carbon sequestration or recreation maintaining biodiversity, carbon storage, or human well-being. Long-term human pressure caused OGFs in Europe to be rare and scattered. Their detailed extent and current status are largely unknown. This review aims to identify potential methods to map temperate old-growth forests (tOGF) by remote sensing (RS) technology, highlights the potentials and benefits, and identifies main knowledge gaps requesting further research. RS offers a wide range of data and methods to map forests and their properties, applicable from local to continental scale. We structured existing mapping approaches in three main groups. First, parameter-based approaches, which are based on forest parameters and usually applied on local to regional scale using detailed data, often from airborne laser scanning (ALS). Second, direct approaches, usually employing machine learning algorithms to generate information from RS data, with high potential for large-area mapping but so far lacking operational applications and related sound accuracy assessment. Finally, indirect approaches integrating various existing data sets to predict OGF existence. These approaches have also been used for large area mapping with a main drawback of missing physical evidence of the identified areas to really hold OGFs as compared to the likelihood of OGF existence. In conclusion, studies dealing with the mapping of OGF using remote sensing are quite limited, but there is a huge amount of knowledge from other forestry-related applications that is yet to be leveraged for OGF identification. We discuss two scenarios, where different data and approaches are suitable, recognizing that one single system cannot serve all potential needs. These may be hot spot identification, detailed area delineation, or status assessment. Further, we pledge for a combined method to overcome the identified limitations of the individual approaches.

**Keywords** Forest conservation · Old-growth forest · Remote sensing · Mapping

## 1 Introduction

For a very long time, human activities have had a vast impact on the European forest landscape. Since the mid-Holocene, forests have been cleared for agriculture, grazed by domestic

cattle, and intensively managed and altered for wood production [1, 2]. As a result, forests with little or no traces of human intervention—often referred to as “primary forests”—have become extremely rare. According to some studies [3,

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4], the extent of primary forests in Europe covers approximately 1.4 million ha, or 0.13% of the total forest area.

The Food and Agriculture Organization has developed a global definition of the term “primary forest” published in 2020: “Primary forests are naturally regenerated forests of native tree species, where there are no clearly visible indications of human activities and ecological processes are not significantly disturbed” [5]. However, due to the scarcity of primary forests in Europe, a wider concept is needed to identify forests with a high degree of naturalness and conservation value. In this context, the concept of old-growth forests is gaining attention, also of policy makers [6].

This concept of old-growth forests (OGF) has been developed for the Pacific Northwest of the USA by Franklin [7] and Spies [8]. It has been implemented in the rest of North America in the 1990s [9, 10], and, since the early 2000s, it has started to appear also more and more in Europe [11–22]. A wide range of definitions and descriptions exist, but the common denominator is that it refers to forest ecosystems containing advanced structural stages of natural forest development such as the presence of more large old trees, higher structural complexity, and larger amounts of deadwood in advanced decay stage in comparison to communities of the same forest type.

According to the Convention on Biological Diversity (CBD), “Old growth forest stands are stands in primary or secondary forests that have developed the structures and species normally associated with old primary forest of that type have sufficiently accumulated to act as a forest ecosystem distinct from any younger age class” [23]. Old growth is thus not necessarily “virgin” or “primeval,” but can also re-develop following human disturbances [10]. These may have developed through deliberate or unintentional non-intervention over shorter or longer time. When applying the above definition of OGF, the total area may reach around 3% of the total forest area in Europe [24]. A definition and description for old-growth forests is currently under development for Europe, describing them as formerly managed forests that have redeveloped structural features that are typically associated with primary forests after a period of non-intervention.

Though rather small in extent and highly fragmented, primary and OGF habitats in Europe are essential for ecosystem conservation and they are highly valuable for Europe’s biodiversity [1, 4, 25]. Moreover, the forests internal microclimate characterized by a cooling effect and the forests potential to capture significant amounts of carbon dioxide make a valuable contribution to climate regulation [26–29] and may provide better ecosystem services than managed forests [30]. Although their values have been known for a long time and many areas have been largely protected, other areas were and are still under threat in different countries [31, 32]. Within the frame of the Biodiversity strategy to 2030, the European Union (EU) demands to put all remaining primary and

old-growth forest of Europe under strict protection [6]. In order to enforce protective measures, the extent of primary and old-growth forests needs to be known and the status of the forests must be monitored to detect deterioration or monitor restoration progresses. This is also the aim of the EU-funded LIFE project PROGNOSSES, which has a focus on ancient and primeval beech forests of the Carpathians and other regions of Europe. This study is a part of the project’s efforts to improve mapping and monitoring of such temperate OGFs in Europe.

Old-growth forests are not defined or identified by a single attribute [33], but a combination of several factors may serve as important indicators. This is even more critical, if forests from different ecosystems are considered (Mediterranean, temperate, boreal). To cope with the complexity, we focus our review on temperate OGFs (tOGFs) in Europe, nonetheless integrating studies from other areas, as long as they refer to characteristics that are relevant to or easily transferable to temperate European forests. In Sect. 4, we discuss some aspects on transferability, links, and limitations with regard to other OGFs. There is a wide variability and combination of features exhibited in OGFs, and the features do not simply “add-up” as the sum of a series of rigid criteria [34]. The extreme complexity of ecological processes that shapes natural forests’ dynamics [35], especially late-successional ones, demonstrated to converge to stand structural complexity [12], and more variably to biomass-related attributes. OGFs may therefore be described or delineated based on a set of multiple criteria that may or may not be simultaneously present. Furthermore, instead of applying strict dichotomous decisions on determining old growth, there is also a strong tendency to apply a gradual scale (index of “old-growthness” or OGI) to indicate the extent to which a forest meets specific criteria or approximates certain reference values [36–38]. Although there is no common definition of OGF, a review of literature on OGF criteria and indicators revealed strong commonalities between the studies. Table 1 summarizes the most commonly used OGF criteria, the related references, and also highlights, which remote sensing (RS) derived forest parameter(s) could be used to generate the respective OGF criterion. Although not all of the references cited in the table strictly relate to OGF, but could be used for OGF mapping due to similar or even the same criteria.

A review on OGF definitions [39] identifies three broad groups of criteria: (i) structural and compositional features, (ii) successional processes, and (ii) biogeochemical processes. Structural and compositional features comprise the existence of large old trees, numerous large logs and snags, diverse tree community, multi-layered canopy, structural complexity, and/or canopy gaps. Successional processes are related to external disturbances, either man-made (harvesting) or nature-made (wind-throw, forest fires, or climate

**Table 1** OGF criteria identified in the literature and related parameters from remote sensing (data)

| OGF criterion  | Details  | References (for OGF criteria)                                    | RS forest parameters to generate the criteria   |
|--|--|--|---|
| <b>Large and old trees</b>                                 | <b>Tree height and age</b><br>Presence of large trees (LT) and very large trees (VLT)  | [11, 12, 16, 17, 21, 39, 40, 42, 57]                             | <i>Individual tree detection</i><br><i>Individual tree height</i><br><i>Tree crown delineation</i>  |
| <b>Deadwood</b>  | <b>Dominance of VLT and LT [%]</b><br><b>Presence of coarse woody debris (CWD)</b><br><b>Diversity of CWD</b>                          | [11, 12, 17, 21, 39, 40, 42, 43, 57–60]                          | <i>Lying deadwood</i><br><i>Standing deadwood</i>   |
| <b>Structural complexity and diversity of living stand</b> | <b>Above ground biomass (AGB)</b><br><b>Diameter size distribution of living trees</b><br><b>Spatial distribution pattern of trees</b> | [11, 37, 42, 61]<br>[12, 13, 17, 37, 42, 58, 61, 62]<br>[39, 40] | <i>Canopy cover</i><br><i>Stand Height</i><br><i>Height distribution, AGB</i><br>DBH as a function of <i>individual tree height</i> and/or crown size ( <i>tree crown delineation</i> )<br><br><i>Canopy cover</i><br><i>Individual tree detection</i><br><i>Canopy cover</i><br><i>Gap detection</i> |
| <b>Tree species composition</b>                            | <b>Dominance of native late-successional tree species</b><br><b>Presence of non-native species</b>                                     | [58]<br>[39, 40]   | Derived indicator from <i>canopy cover</i> and <i>tree/stand height</i><br><i>Vertical structure</i> based on ALS point distribution or <i>individual tree distribution</i><br><i>Tree species classification</i>   |
| <b>Existence of specific biota</b>                         | <b>Presence of invertebrate, lichens, or moss species</b>  | [25, 28, 57, 59]   | Not possible  |

change). Biogeochemical processes include decay stages, closed nutrient cycles, and increased understory vegetation. The authors of [40] defined six criteria to differentiate old-growth forests from other forests: (i) existence of large trees per species and site; (ii) wide variation in tree sizes and tree spacing; (iii) accumulations of large-size (in relation to the living trees) dead standing and fallen trees; (iv) decadence in the form of broken or deformed tops or bole and root decay; (v) multiple canopy layers; and (vi) canopy gaps and understory patchiness.

In their publication, the authors [41] identified (i) the absence of signs of human activity like artificial structures, stumps, cattle grazing alongside with (ii) a natural forest composition, (iii) presence of veteran trees, and (iv) standing and lying dead wood as the main criteria to differentiate primary forest from other forests. Again, there is the difference between primary forests and OGF, but a significant overlap in criteria used to distinguish either of them from other (NOGF, non-primary) forests. In a global meta-study [12], the most important criteria to differentiate old-growth forests from other forests were identified separately for all continents. For Europe, (i) age of the trees, (ii) presence of large and very large trees, and (iii) the amount of coarse woody debris (CWD) were identified as the most decisive parameters. Other authors [42] also found the most significant differences between managed and old-growth forests in (i) the presence of large trees (mean diameter), (ii) presence of CWD, and (iii) volume of living trees (similar to biomass). The authors of [37] defined (i) the successional status, (ii) development stage, (iii) tree species diversity, (iv) proportion of native species, (v) variability of tree dimensions and density, (vi) density of regeneration layer, (vii) amount of dead wood, (viii) decay stage, and (ix) the existence of microhabitats as important criteria in the definition of OGF. Several studies reported on the strict dependence of living and dead biomass attributes on site conditions, and established minimum or range values for biomass attributes within the same bioclimatic zone, and found that maximum tree age and stand structural complexity converged to naturalness-related ecological processes [12, 16]. A summary of the identified OGF criteria is given in Table 1.

For proper mapping and monitoring of forests, traditional terrestrial assessments have been performed using sample plots. Such plots are usually a circle or a square with 0.03–0.15 ha of size. Manual in situ methods are used to map and monitor forest properties at these plots, which is often difficult and time consuming [43]. In addition, a comparison of existing in situ survey methods for forest biodiversity assessment highlighted that no common methodology is used in Europe [44]. This applies even more to old-growth forests due to often remote and not easily accessible locations of these forests, which is in many cases the reason for their very existence. Alternative approaches using remote sensing (RS)

and geo-information technology may help in this endeavor [45]. Already in 2012, a study [46] stated that Earth Observation (EO) has a role to play in monitoring biodiversity in general. Further, another source [24] stated that “while the identification of undocumented primary and old-growth forests in the field remains crucial, inventorying and monitoring applications might benefit from using state-of-art remote sensing technology.” However, already in 1998, Norheim [47] found strong differences in OGF extent depending on RS data and methods used. Most authors [3, 48, 49] agree that remote sensing-based classification or indirect habitat modeling with geo-information technology is means to identify “potential” old-growth forests, which can consecutively be evaluated in more detail by targeted field surveys.

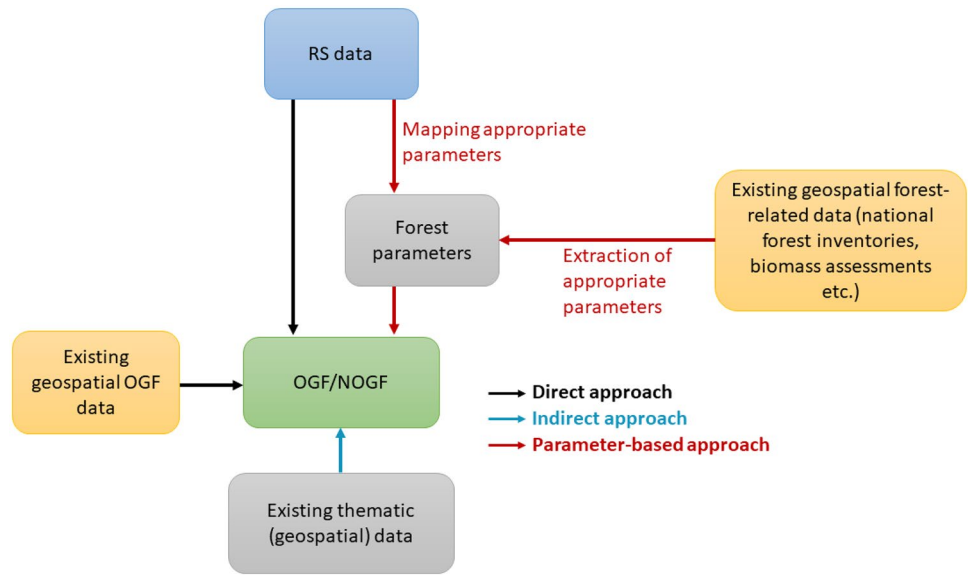
The initial premise for this review was the structuring of OGF mapping approaches from a RS point of view in three groups: the **parameter-based approaches**, the **indirect approaches**, and the **direct approaches**. They are schematically outlined in Fig. 1. First, parameter-based approaches are based on (several) individual forest parameters as listed in Table 1. Studies either use individual forest parameters derived from RS data within the study itself or from existing forest-related data (such as national forest inventories or biomass assessments). Second, indirect approaches employ existing thematic geospatial data as proxies to model the potential existence or absence of OGF. Such proxy data are for example: roads, settlements, specific land use categories, socio-economic indicators such as population density, and climate data. They sometimes also use occurrence or absence of specific indicator biota like insects or fungi. Third, the direct approaches use RS data to directly classify OGF without any intermediate step. This third group has gained increased interest with the development of more efficient machine learning methods in recent years. In addition to these three groups, also several combinations of the three approaches are possible. In the following subchapters, we review the data and methods used for each of the three approaches.

Based on this premise, the aim of this study was to analyze and review each approach regarding previously used RS data and methods. This is to provide a comprehensive picture on common agreements, the status of research (i.e., what is already well known), and the main knowledge gaps in the identification and mapping of OGF. Further, we highlight the main conceptual differences between the three approaches. Finally, we give an outlook to the next steps and future trends in OGF mapping and monitoring.

## 2 Methodology

The review methodology used in this study is twofold: first (Sect. 2.1), existing publications are reviewed to compile the state-of-the-art for the three approaches. The search was

**Fig. 1** Schematic illustration of the three main approaches to map OGF based on remote sensing and other geospatial data



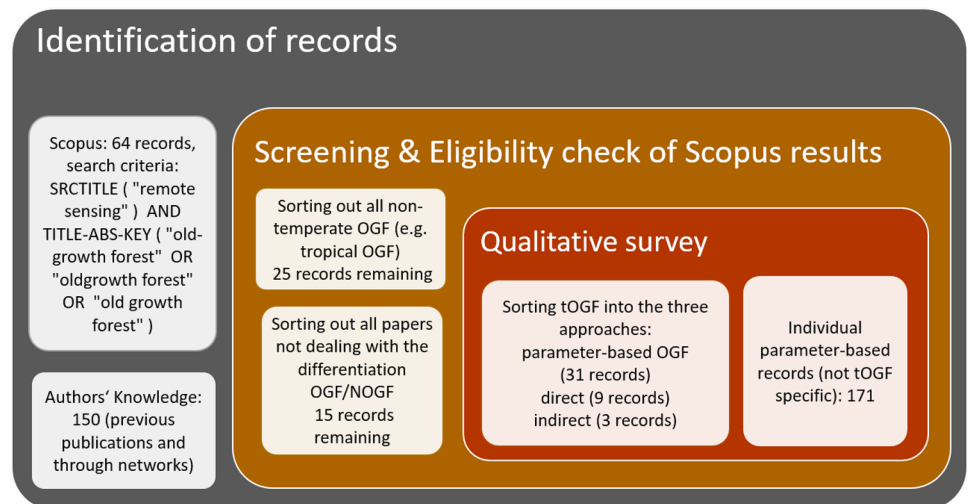
following the PRISMA approach [50] performed in two stages: first, we searched in journals with “remote sensing” in the title for all publications including the term “old-growth forest” (and similar terms, see Fig. 2) in the Elsevier SCOPUS database. This search was followed by a screening and eligibility check eliminating records with a focus on non-temporal OGFs and studies merely taking place on an OGF site but not targeting the differentiation of OGF/NOGF. In addition to this structured search, we also included studies based on the knowledge of the authors and their networks. Due to the common project (LIFE project PROGNOSSES) dealing with the mapping of old-growth beech forests in Europe, there is a clear focus/bias in this part of the literature selection. Finally, in a qualitative survey, we first sorted the resulting OGF records into the three approaches. Second, we grouped the parameter-based approaches according to RS input data type. For each of the approaches, examples are shown in the respective results sections.

The second part of the review (Sect. 2.2) is a quantitative assessment of classification methods used within all three approaches. These classification methods are of cross-cutting nature, as a specific classification method, e.g., Random Forest, can be used either to classify a specific parameter within the parameter-based approach or to classify OGF directly. For this assessment, a separate literature search was performed, as this part of the search is not restricted to the classification of OGF. More details on that methodology are given in Sect. 2.2.

**2.1 Review of Mapping Approaches**

Concerning the parameter-based approach, the first step was to relate the OGF criteria identified in the introduction to forest parameters that can be generated from RS data, see Table 1 for the result. Next, an extensive search was conducted for publications targeting these forest parameters. It

**Fig. 2** Literature review for mapping approaches (2.1) following the PRISMA guidelines





has to be mentioned that many of these forest parameters are used for other applications than OGF classification; thus, the publications reviewed do not necessarily have a focus on tOGF. This is also represented in the number of studies given in Fig. 2: 171 parameter-based records without tOGF focus compared to 31 parameter-based records with tOGF focus. The second step sorted identified publications per forest parameter by input RS data type to get an overview on which parameters can be gathered from which data sources. The data types reviewed in this publication are: Airborne Laser Scanning (ALS), optical very high-resolution (VHR) data, optical high-resolution (HR) data, and Synthetic Aperture Radar (SAR) data. Each type is briefly explained below.

ALS is an active remote sensing technology able to provide 3D characteristics because it penetrates the forest canopy and, therefore, delivers information on forest vertical structure, with point densities typically between 1 and 100 points/m<sup>2</sup>. Accordingly, the level of accuracy and the capability to map a certain forest parameter vary with the point density. The emitted laser pulses can either be recorded as discrete returns (single or multiple return system) or as one continuous return (full-waveform system) [51]. Generally, wall-to-wall mapping is possible, but usually rather costly in terms of acquisition as well as processing time and computational capacity.

For this study, all optical imagery with a pixel size smaller or equal to 5 m is considered to be VHR data. Usually, these are orthophotos from aerial surveys or from VHR satellite data (e.g., Pleiades, World View) and contain four bands (visible and near infrared). Wall-to-wall assessment is possible and the acquisition costs depend on the sensor used. Several VHR sensors also allow stereo-processing, which can be used to deduce 3D information of the canopy [52–55]. However, in contrast to ALS, there is no penetration of the crown and thus no information below the upper canopy.

Optical HR data has a spatial resolution between 5 and 30 m. The most frequently used imagery is from the European Space Agency's Sentinel-2 and NASA's Landsat mission since they are available free of charge. They have multispectral bands ranging from visible and near to shortwave infrared, allow for wall-to-wall assessment, and have a high repeat rate (frequent images) which enables to incorporate temporal characteristics of spectral reflection in the analysis. The high repeat rates result in dense image time series which enable time series analyses that also take into account the change in spectral reflectance. Moreover, the Landsat mission has been providing continuous Earth observation data since 1972 which allows historical analysis for the last five decades [56].

Finally, SAR is an active sensing system of different wavelengths (X, L, C, S, P with X being the shortest and P being the longest wavelength). Longer wavelengths can

penetrate the vegetation and give information on the forest structure and biomass. Wall-to-wall assessment is possible and repeat rate is similar to HR data. The costs depend on band and sensor; there are no acquisition costs for C band Sentinel-1 data.

Aside from the parameter-based approach, we also used all available sources to generate a comprehensive review of existing studies for direct and indirect approaches to map OGF in temperate forests of Europe. In full awareness that this review does not cover all studies ever done in this field, we are however confident to show the broad picture.

## 2.2 Quantitative Assessment of Classification Methods

For the second part of the review, we searched the SCOPUS database in Journals with “remote sensing” in the journal title and “forest” or “tree” in the title, abstract, or keywords (search string: SRCTITLE (“remote sensing”) AND TITLE-ABS-KEY (“forest” OR “tree”)). This led to 1242 publications. Instead of dealing with each publication individually, we categorized the methods into algorithm groups. The following eleven algorithms/algorithm groups were identified:

1. Thresholding, local maximum or local minimum approaches
2. Regions growing and watershed approaches
3. Spectral mixture analysis
4. Template matching
5. (Multiple) linear and non-linear regression
6. Bayesian approaches
7. Support Vector Machine (SVM)
8. Clustering algorithms
9. Dimensionality reduction algorithms
10. Random forest (RF) and ensemble learning approaches
11. Artificial neural (ANN) network and deep learning (DL) approaches

Exemplarily, the search string for the first category would be: SRCTITLE (“remote sensing”) AND TITLE-ABS-KEY (“forest” OR “tree”) AND (“thresholding” OR “local maximum” OR “local minimum”). In order to see the temporal development of the different algorithms, we sorted the publications by publication date into 5-year intervals starting from 1997 until the end of 2021.

## 3 Results

The results of the first review are given in Sects. 3.1, 3.2, and 3.3 per approach. Section 3.4 summarizes the results of the methods review.

### 3.1 Parameter-Based Approach

For the parameter-based approach, the first step is to link OGF criteria to remote sensing-based parameters. Table 1 reviews the literature regarding this connection. Each potential OGF criterion is shown in the first column, the respective identified RS parameters in the last. Details and references for the OGF criteria are given in the middle.

The second part reviews the RS data types which can be used to map the above-mentioned forest parameters. The type of input remote sensing data is of high relevance, since it determines not only the achievable forest parameters and extent of study area, but also relates to costs and accuracies.

The result of the conducted literature analysis (202 records) is a matrix (Table 2) with the columns representing different input remote sensing data types and the rows representing the target forest parameters. The aim of this matrix is to provide an overview of the data types that have been used to map the target forest parameters. Thus, also not OGF-related studies are included as long as they aim to generate the same forest parameters. Although this matrix will never be complete, we are confident that the main studies are captured and that knowledge gaps are correctly depicted. This matrix is also meant to serve as a quick reference work to allow scientists to easily find the relevant study they may

be interested in. Gray color marks those cells in the matrix, where a derivation of the respective forest parameter from this data type is not (yet) possible due to physical restrictions, e.g., deriving individual tree crowns from optical HR data. All papers, which specifically aim at mapping forest parameters to distinguish OGF from NOGF, are printed bold. If authors combined different data sets to generate a single forest parameter, they are mentioned in the same row repeatedly in different columns, as for example [65]. Similarly, if authors used the same data set to derive multiple forest parameters, they are mentioned in the same column repeatedly.

Depending on the data used and forest parameter to be mapped, assessment on two different levels can be conducted (mentioned in brackets in Table 2): individual tree detection (ITD) or area-based assessments (ABA). The area to be looked at can be a forest stand, a moving window, or a raster. ITD assessment relies on detailed input data such as ALS [66] or optical VHR data [67]. ABA and ITD can also be combined, as shown in Fig. 3. Many forest parameters are generated per stand (e.g., canopy cover), while single tree detection based on ALS data is also included as stem numbers per ha. A comprehensive review of methods for individual tree assessments with a focus on LiDAR data, but also including studies based on optical and SAR data, was published in 2016 [68]. Similarly, an international

**Table 2** Matrix of RS parameters and RS datasources

| RS Parameter/<br>Data →                                  | ALS                                     | Optical VHR                           | Optical HR                         | SAR  |
|--|---|---------------------------------------|------------------------------------|--|
| Individual tree detection / tree crown delineation (ITD) | [76–78]<br>[68,69,76,79–99]             | [78,100]<br>[99,101–106]              |                                    | [107–111]  |
| Individual Tree Height (ITD)                             |   | [96,112,113]                          |                                    | [109,114,115]                                    |
| Stand Height (ABA)                                       | [27,116–119]<br>[65,94,120–125]         | [53,54,121,123–130]                   | [65,70,124,131,132]                | [133,134]<br>[65,115,121,124,125,131,135–143]    |
| Height distribution (ABA)                                | [116,119]<br>[123,141,144,145]          | [54,123]                              |                                    | [115]  |
| Standing deadwood (ITD, ABA)                             | [146,147]<br>[60,85,147–155]            | [85,106,154,156–160]                  | [161]<br>[162]                     |  |
| Lying deadwood (ITD, ABA)                                | [146,147,163]<br>[60,146–148,163–167]   | [43]<br>[157,159,160]                 |                                    |  |
| Canopy cover (ABA)                                       | [116,117]<br>[168–170]                  | [171]<br>[172–177]                    | [178]<br>[168,170,172,176,179–182] | [183,184]  |
| Canopy gaps (fraction/distribution) (ABA)                | [116,119]<br>[185–194]                  | [171,195–197]<br>[54,188,193,198–202] | [203]<br>[200,204,205]             | [206]  |
| AGB or timber volume (ITD/ABA)                           | [27,207]<br>[27,65,120,124,125,208–211] | [212]<br>[124,125,208,212–214]        | [65,124,127,132,210,215,216]       | [65,107,108,124,125,136,137,215,217–219,219–225] |
| (Standwise) Vertical structure (ABA)                     | [27,116,117]<br>[64,82,226–234]         | [228]                                 | [235–238]<br>[64,239–241]          | [115,240,242–247]                                |
| Tree species (ITD or ABA)                                | [87,90,150,248–253]                     | [212,254,255]<br>[256–264]            | [49]<br>[263,265–270]              | [133]<br>[271]                                   |

OGF specific papers indicated in bold

comparison of tree detection approaches based on optical and LiDAR data was performed in the early 2010ers [69].

There are also several research activities using point-wise data, i.e., terrestrial laser scanning (TLS) or, more recently, space-borne laser scanning (SLS) to map forest parameters, with some of them specifically related to OGF [70–74]. However, for brevity reasons, we will not go into further detail on TLS and SLS in this paper. For more information on forest parameter retrieving with TLS, the reader is referred to a related review article [75].

For the identification of individual trees (tree position, tree height, and/or tree crown), two broad categories of methods can be distinguished: raster-based methods and point cloud-based methods. Raster-based methods use one or more images with an arbitrary number of bands as input. The information the pixel values represent can either be optical [101, 103, 104] or SAR backscatter information [76, 101], or they represent height (e.g., mean, maximum, dominant height at pixel area) or pulse intensities derived from 3D point clouds that are projected into 2D [69, 81, 270, 271]. Assessment approaches based on point clouds, e.g., 3D data, derived from LiDAR, photogrammetric/radargrammetric processing, or from interferometric SAR [109], are targeting at the 3-dimensional shape of certain features, e.g., cone- or dome-shaped features representing tree crowns or cylinders assumed to represent tree stems [81, 99]. The majority of all studies using height information (either raster based or point cloud based) to delineate tree crowns or tree objects used clustering [82, 85, 87, 91, 111, 272] or region growing algorithms [69, 76, 80, 81, 84, 87, 89, 95, 103, 104]. More recently, deep learning has also been used for this purpose [99, 102]. For area-based height assessments (stand height and height distribution), regression-based methods are predominantly used [116, 122, 123, 125, 128–131, 138, 211], but also RF [122, 124, 138, 140], SVM [138, 140], or ANN [240] is applied.

Methods to assess canopy cover are manifold and range from thresholding of height metrics [117, 168] and regression algorithms [116, 167, 178, 181] to regression and decision trees and various other well-established machine learning algorithms such as Gradient Boost, SVM, or ANN [169, 171, 173, 179, 180, 182, 240]. It has been successfully demonstrated that object-based approaches applying a comprehensive, empirically defined set of rules based on spectral and/textural image characteristics are particularly suitable when optical VHR imagery is available [170, 172, 176]. Canopy gaps are mostly detected by applying empirically defined thresholds for height metrics or spectral values [170, 185, 187, 191, 192, 196, 200, 201], but also RF and SVM as well as spectral mixture analysis have been used [198, 204]. Instead of providing absolute information, e.g., gap or no gap, some studies provide canopy cover percentages or gap probabilities for a certain analysis unit which can be a single

image pixel or an analysis grid of certain extent [184, 186, 199]. In some way related to canopy cover is the assessment of the history of forest cover using RS data. Several papers returned from the SCOPUS search dealt with this assessment in Asia [181, 273, 274].

To classify tree species based on RS data (either ITD or ABA), RF and SVM algorithms are the classifier of choice in many studies [49, 211, 249, 252, 256, 263–265, 268, 269, 275–277]. In addition, the linear discriminant analysis method [87, 246], regression [149], and, more recently, also deep learning algorithms have been employed to map tree species [90, 260].

Various studies dealing with the differentiation between dead and living trees use regression-based methods [85, 149, 150, 152, 153, 159, 159, 161], but also SVM [106], RF [158], or deep learning [156] has been used for this purpose. In addition, for the detection of lying deadwood also template matching algorithms were employed [164].

For the determination of the vertical structure of a forest, e.g., number of tree layers, mostly height information acquired by ALS is used because laser pulses can penetrate the canopy. Depending on the wavelengths, this is also true for some SAR sensors. The used methods range from straightforward thresholding operations [115, 228, 231], regression models [227], clustering algorithms [82] to newer ensemble learning and instance-based algorithms such as RF or SVM [230], and deep learning [229]. More recently, attempts have been made to investigate the use of optical data and the combination of optical and SAR data in a classification approach building on neural networks to derive forest vertical structure [226, 237, 238]. Figure 3 shows an example of several forest parameters being mapped for the same area; the input data sets are ALS and Sentinel-2 optical HR images.

### 3.2 Indirect Approach

Instead of mapping the physical existence of OGF, the indirect approach aims at identifying areas of possible existence of OGF. This information can be a valuable element in OGF mapping. All indirect approaches are based on other existing (geospatial) data sets, sometimes combined with other data sets, such as questionnaires and literature review [4]. This study compiled a database of primary forests of Europe (including OGF) by using a boosted regression tree algorithm to model the current distribution of primary forests using different biophysical, socio-economic, and forest-related predictor variables. Based on the calculated model, a comprehensive 1 km × 1 km resolution map representing the likelihood of the occurrence of primary forest in Europe was produced. Figure 4 (left) shows the final map of the likelihood of the occurrence of primary forests in the Carpathians.

On global scale, the authors of [278] mapped forest management by downscaling of existing data from national and



**Parameters per segment:**

Dominant height &amp; std [m] 26 m &amp; 3.1 m

Canopy cover (shown) [%] 86 %

Main species [codes] 2 (larch)

Vertical structure [classes] 3

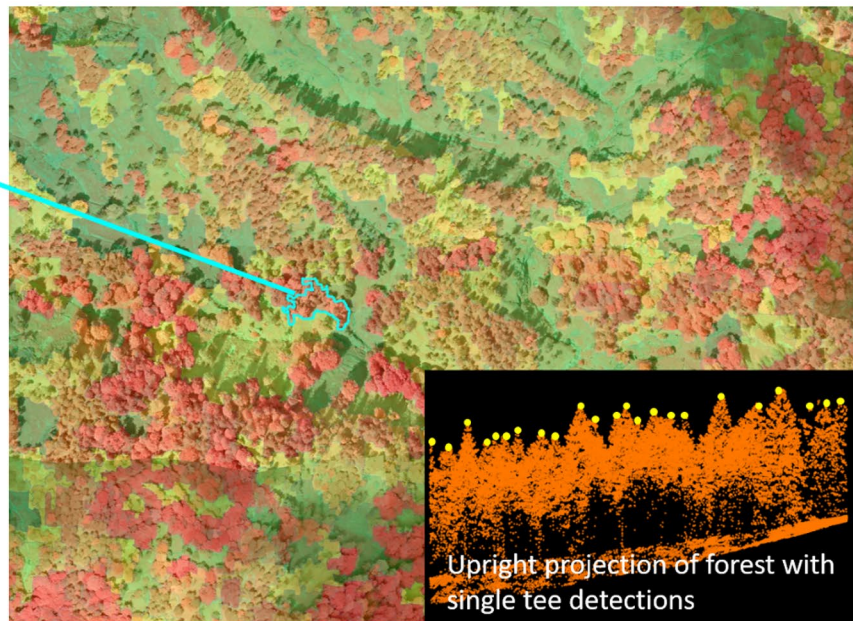
Mean height &amp; std. [m] 18.1 m &amp; 5.2 m

Height a.s.l. [m] 900 m

Exposition [8 classes] south-east

Tree density [no./ha] 365/ha

(based on single tree detections)



**Fig. 3** Generation of several forest parameters from ALS and Sentinel-2 satellite data, wall-to-wall mapping, one segment shown as example

subnational forest management of 2000 collected in the Forest Resource Assessment of the Food and Agricultural Organization of the United Nations and enhanced by subnational statistics for some countries. The classification was performed on two levels, each having three categories. Level 1 (forest classes) includes primary, naturally regrown and planted forest, while Level 2 distinguishes between forest uses. The authors calculated a multinomial logit fit model using a set of 21 predictor variables representing the categories accessibility, governance, soil, climate and terrain conditions, and forest properties to generate global likelihood maps of 1 km × 1 km spatial resolution. The predictor variables are based on the PREDICTS database (Projecting Responses of Ecological Diversity in Changing Terrestrial Ecosystems [279]).

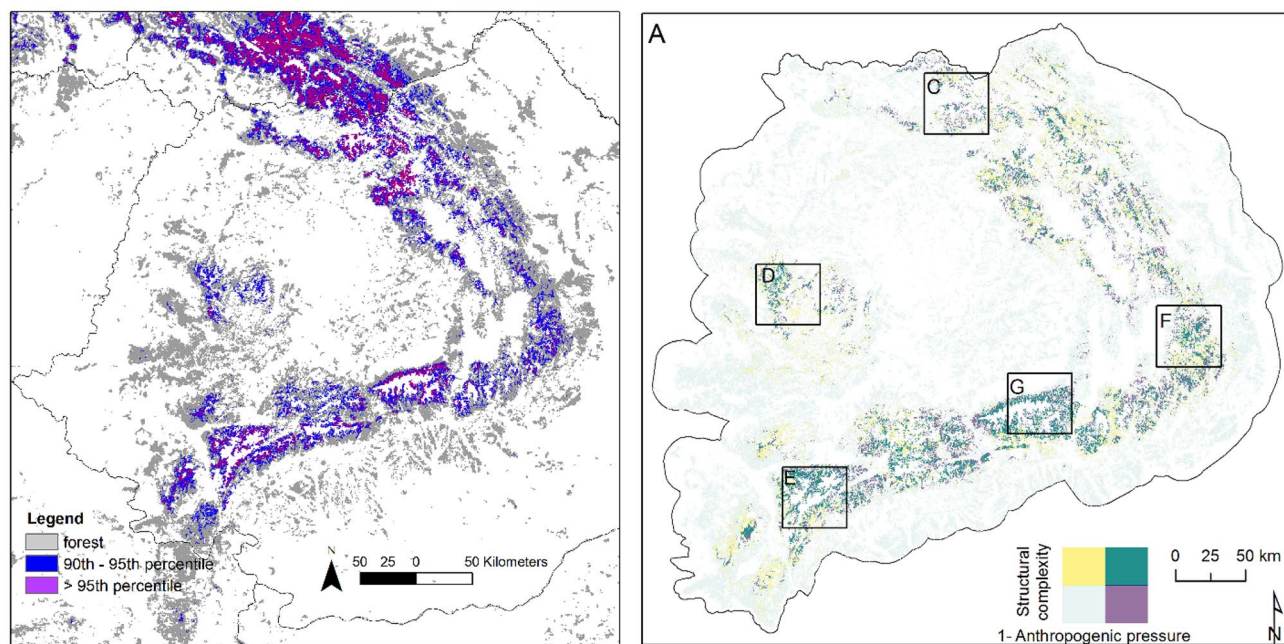
The Romanian Carpathians were in the focus of an approach to map high conservation value forest (HCVF), which includes OGF [280]. The work of this study is based on three different data sources: forest loss data from Romania from 1955 to 1965 derived from historical Corona spy satellite data [281], digitized historical military topographic maps between 1968 and 1978, and maps of forest disturbance regimes across Europe from 1986 until 2016 derived from Landsat satellite image data [282]. The third data set was further used to assess the canopy's structural complexity based on different spectral-temporal metrics from Landsat and ALOS-2 PALSAR-2 imagery. Additionally, they evaluated anthropogenic pressure by calculating a human pressure index based on additional data on transportation network,

population density, and local reliance on firewood. Combining the structural complexity and anthropogenic pressure, they generated a comprehensive forest map of the Romanian Carpathians with four classes (primary HCVF, HCVF at risk, managed forest, and restoration forest). Figure 3 (right) shows the result of their modeling.

As a summary, Table 3 lists all predictor variables used in the three reviewed studies. There are 5 predictor variables that were used in all of them (highlighted in bold in the table): tree cover or forest maps, topographic information on elevation and slope, population density, and travel time to the nearest city.

### 3.3 Direct Approach

In accordance with the geographic origin of the term “old-growth forest” laid out in the introduction, the first studies employing direct assessment approaches of OGF by means of remote sensing data focus on temperate coniferous forests of the western US [234, 284, 285]. Although not directly in the focus of our review due to a different geographic area, we briefly review some main US studies below. To differentiate between young forests, mature forests, and OGF within a coniferous forest stand, the authors of [234] employed Landsat 5 and regression analysis and obtained 75% accuracy for the OGF class. By making use of Landsat 7 Enhanced Thematic Mapper imagery and an unsupervised classification approach, the authors of [285] successfully classified old and mature coniferous forest in eight different ecoregions in



**Fig. 4** The result of two mapping exercises using indirect approaches to map likelihood of primary forest in the Carpathians. Left: Map of highest likelihood of primary forest occurrence in Europe based on [4] with data from [283]. Right: Presence of High Conservation Value

Forests in Romania from [280]. Green indicates prime HCVF, light blue indicates managed forests, and purple indicates forests with restoration potential towards HCVF

the Pacific Northwest, USA. The achieved overall classification accuracies vary between 89 and 94% for the different ecoregion.

Also set in the USA, the authors of [286] used ALS data to map forest successional stages across a structurally diverse, mixed-species forest in Northern Idaho. They

**Table 3** Publications reviewed for the indirect approach and used predictor variables. Predictor variables used in all three studies are marked in bold

| Publications        | [278]  | [280]  | [4]  |
|---------------------|--|--|--|
| Study area          | Global   | Romanian Carpathians   | Europe   |
| Predictor variables | <ul style="list-style-type: none"> <li>- Net primary production</li> <li>- <b>Percentage tree cover</b></li> <li>- Forest gain between 2000 and 2014</li> <li>- Forest loss between 2000 and 2014</li> <li>- <b>Elevation; - slope</b></li> <li>- Sand content in soil; - clay content in soil</li> <li>- Soil depth; - depth of topsoil; - carbon content in subsoil, in top 50 cm soil layer and in topsoil; - soil drainage</li> <li>- Aridity Index</li> <li>- Market access</li> <li>- <b>Travel time to major cities</b></li> <li>- Distance to roads; - distance to rivers</li> <li>- <b>Population density</b></li> <li>- Aggregated governance index</li> </ul> | <ul style="list-style-type: none"> <li>- <b>Historical forest data (historical forest map 1955–1965 [281], military topographic maps 1968–1978, forest disturbance 1986 until 2016 [282])</b></li> <li>- Tasseled cap wetness,</li> <li>- brightness, - greenness (based on Landsat); - start of season; - peak of season; - end of season</li> <li>- Annual mosaics of L-band backscatter in HH/HV orientation (2)</li> <li>- <b>Elevation; - slope</b></li> <li>- <b>Population density 2015</b></li> <li>- Distance to the nearest road</li> <li>- <b>Travel time to major cities</b></li> <li>- Density of houses using firewood for heat</li> </ul> | <ul style="list-style-type: none"> <li>- Growing degree day</li> <li>- Mean annual temperature</li> <li>- Water availability)</li> <li>- Soil (Crop suitability)</li> <li>- <b>Elevation; - slope; - aspect</b></li> <li>- Ruggedness; - solar radiation</li> <li>- <b>Forest cover; - forest core area</b></li> <li>- Growing stock net annual increment</li> <li>- Biogeographical region</li> <li>- <b>Population density</b></li> <li>- <b>Travel time to the nearest city</b></li> <li>- Harvesting intensity 2000–2015 averaged</li> <li>- Forest cover 1850;</li> <li>- Wood demand 1828</li> </ul> |
| Algorithm           | Multinomial logit regression   | Maximum entropy  | Boosted regression trees   |



calculated different ALS metrics describing the forest height and canopy cover. The RF algorithm was used to model six different classes of successional stages with an overall accuracy of about 95%. In their study which was also based on ALS data, the authors of [287] tested whether young secondary forests have distinct canopy structural characteristics compared to primary forest and if forests located in higher altitude have a lower complex structure than forests in lower altitudes. Their results were not significantly indicating that structural complexity is linearly related to forest age or elevation range. Instead, they found that structure varies within and among forest age groups, leading to the conclusion that forest development is not sequential but can follow multiple pathways.

Coming back to Europe, a more recent study [288] produced a map of potential primary forest in the Romanian Carpathians. The authors employed optical Sentinel-2 data and developed an object-based classification approach. Forest segments are generated using the Sentinel-2 data and refined by manual revision. Based on existing field measurements, they developed a classification approach based on empirical thresholds for the leaf area index (LAI) and the

LAI (leaf water content) to distinguish young forest stands from primary and OGF. Based on the results produced by [288] and further existing and verified OGF inventories in combination with additional information gathered during field surveys and other mapping projects, OGF in Romania was mapped by visual assessment of historic and current VHR data [48]. They used historical CORONA satellite images as well as aerial and VHR satellite image time series provided by Google Earth and other optical data providers to identify potential further OGF areas not yet included in existing inventories. The results of this mapping exercise are depicted in Fig. 5.

By employing a machine learning algorithm, the authors of [49] mapped OGF directly developing an object-based approach using mean and standard deviation values of optical Sentinel-2 10 and 20 m bands as well as six vegetation indices and Grey Level Co-occurrence Matrix textural features. Existing OGF reference plots provided by WWF Ukraine and additionally acquired NOGF plots served as segments for the object-based classification. By using a random forest classifier, the authors identified OGF with an overall accuracy of about 85%.

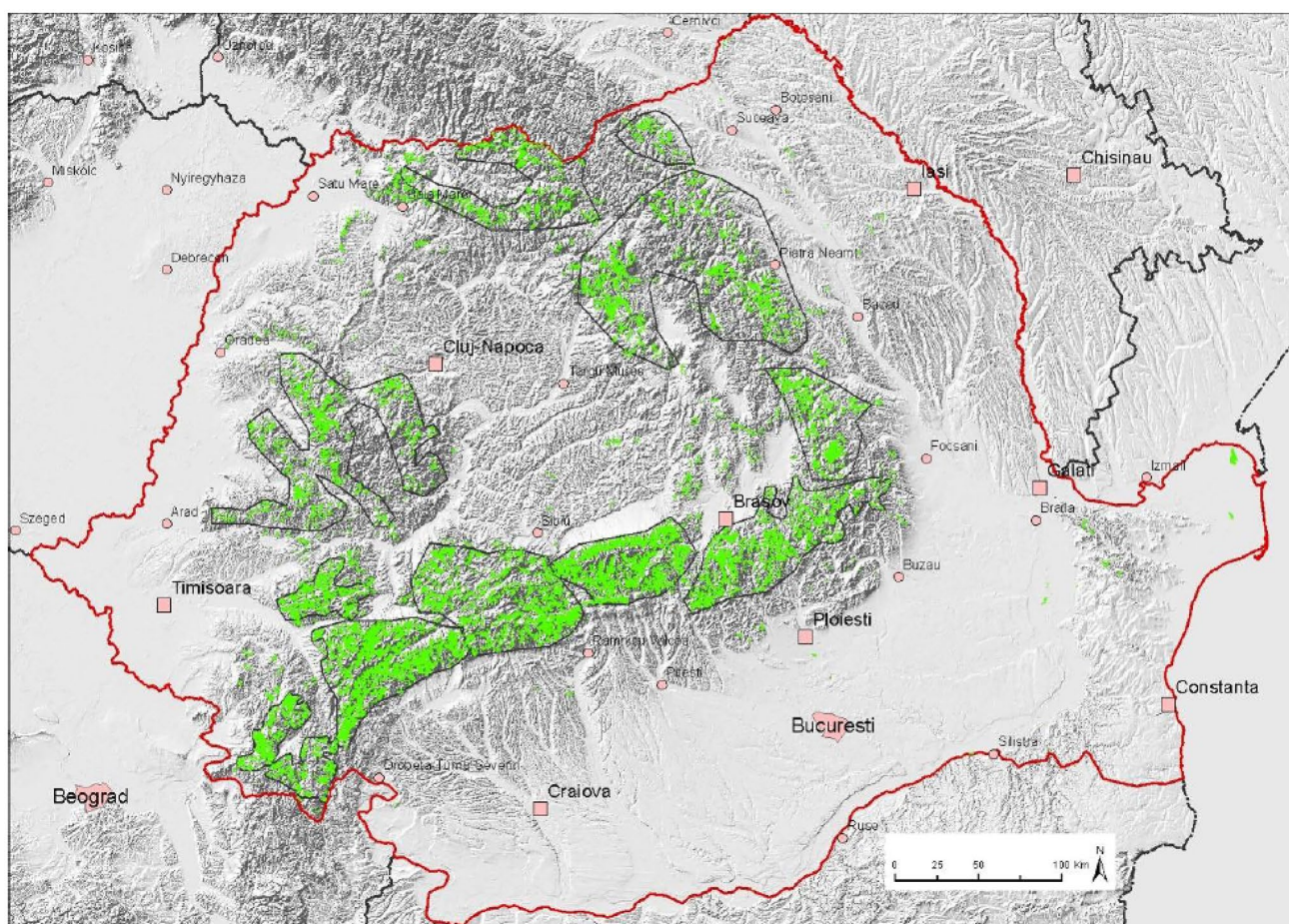


Fig. 5 Map of primary forests in Romania from [48]

Table 4 provides a summary of the data, metrics, and algorithms used in reviewed publications. In studies using optical satellite imagery, either from Landsat or Sentinel-2 sensors, spectral band and the Normalized Difference Vegetation Index (NDVI) are used. Landsat based studies also employed the Tasseled Cap (TC) Brightness (TCB), Greenness (TCG), and Wetness (TCW).

### 3.4 Results of Classification Methods Review

This part of the review is to assess which classification methods have been used previously and how this has developed over the past 25 years. Table 5 shows the number of publications in Elsevier's SCOPUS database over time. Visualized

in Fig. 6, it can clearly be seen that the use of random forest or (other) ensemble learning approaches has increased significantly in the past 10 years. Artificial neural networks and deep learning have become widely used only in the last five years.

## 4 Discussion

With the new EU Biodiversity strategy to 2030 calling to protect remaining primary and old-growth forests in Europe, the scientific community has also increased efforts on identifying and monitoring of primary and OGFs. One remaining challenge lies in the absence of a common definition

**Table 4** Publications reviewed for the direct approach including metrics used

| Publication | Study Area            | Data                   | Metrics   | Algorithm  |
|-------------|-----------------------|------------------------|---|--|
| [234]       | Pacific Northwest USA | Landsat 5              | Tasseled cap wetness (TCW), brightness (TWB), greenness (TCG)   | Regression analysis  |
| [284]       | Pacific Northwest USA | Landsat 5<br>SRTM DEM  | Spectral bands,<br>NDVI,<br>Ratio TM 4/3I,<br>Ratio TM 4/5,<br>Ratio TM 4/7,<br>Relative sun incidence,<br>TCW, TWB, TCG  | ISODATA  |
| [285]       | Pacific Northwest USA | Landsat 7              | Spectral bands  | ISODATA  |
| [286]*      | Inland Northwest USA  | ALS                    | Maximum Height<br>Range of Heights<br>Mean Height<br>Median Height<br>Modal Height<br>Heights 25th Percentile<br>Canopy Cover (Vegetation Returns/Total Returns <sub>s</sub> 100)<br>Percentage of Vegetation ReturnsN1 m and b=2.5 m<br>Percentage of Vegetation ReturnsN10 m and b=20 m<br>Percentage of Vegetation ReturnsN20 m and b=30 m | Random forest  |
| [287]       | Pacific Northwest USA | ALS                    | 95th percentile height<br>Rumple index<br>Canopy density  | Hierarchical clustering  |
| [193]       | Pacific Northwest USA | ALS                    | 95th percentile height<br>Rumple index<br>Canopy density  | Random forest  |
| [48]        | Romanian Carpathians  | Google Earth,          | RGB VHR images, existing OGF data   | Visual analysis  |
| [49]        | Ukraine Carpathians   | Sentinel-2<br>SRTM DEM | Spectral bands (mean + standard deviation);<br>Mean of NDVI, EVI, AVI, SI, NDII,<br>RENDVI, GLCM contrast, entropy and mean for B3, B8 and B12, elevation, slope  | Random forest  |
| [288]       | Romanian Carpathians  | Sentinel-2             | Spectral bands, NDVI, LAI, LAI CW (leaf water content), NDVI slope  | Multi-level analysis: image segmentation, nearest neighbor classification, threshold-based classification, visual analysis |

\*Only those metrics are listed which turned out to be important for the analysis

**Table 5** Number of publications in Elsevier's SCOPUS database

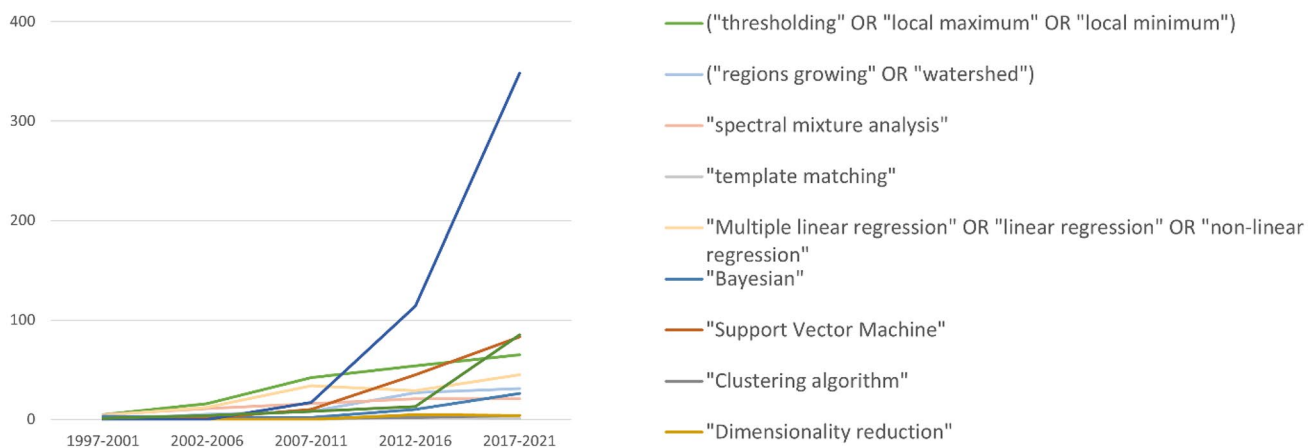
| Algorithm or algorithm group   | 1997–2001 | 2002–2006 | 2007–2011 | 2012–2016 | 2017–2021 |
|--|-----------|-----------|-----------|-----------|-----------|
| Thresholding OR local maximum OR local minimum                           | 5         | 16        | 42        | 54        | 65        |
| Regions growing OR watershed   | 0         | 5         | 8         | 27        | 31        |
| Spectral mixture analysis  | 5         | 11        | 16        | 21        | 21        |
| Template matching  | 0         | 0         | 0         | 2         | 1         |
| Multiple linear regression OR linear regression OR non-linear regression | 4         | 12        | 34        | 29        | 45        |
| Bayesian   | 3         | 2         | 2         | 10        | 26        |
| Support Vector Machine (SVM)   | 0         | 1         | 10        | 45        | 83        |
| Clustering algorithm   | 0         | 0         | 1         | 2         | 4         |
| Dimensionality reduction   | 0         | 0         | 0         | 5         | 4         |
| Random forest (RF) OR ensemble learning                                  | 0         | 0         | 17        | 114       | 348       |
| Artificial neural (ANN) network OR deep learning (DL)                    | 1         | 4         | 8         | 13        | 85        |

and related criteria and thresholds, which are now being worked on at a European level. Nonetheless, there are certain criteria indicating OGF which can be related to forest parameters that, in turn, can be derived by means of remote sensing. Since remote sensing technology has proven to be of valuable support for forestry applications, such as forest inventories, it offers a unique opportunity to support mapping and monitoring of OGFs.

This study provides a review on existing literature with a set of certain limitations. These limitations may present a notable bias in the subject matter covered and therefore need to be addressed to provide the readership with the clear picture to put the results of this review in perspective. First, since the systematic search did not return the expected number of studies, pre-existing knowledge of the authors has been included. Therefore, also the results are to a large extent based on pre-existing knowledge of the authors. Second, due to the focus on European temperate OGF, the review is based mainly on European literature, with a low coverage of articles dealing with tOGFs elsewhere. Third,

articles dealing with “old-growth” forests but qualified with other terms (e.g., “primeval,” “primary,” “overmature”) have not been considered. Fourth, journals of forest ecology and management were not considered if the articles were not previously known by the authors, as the search was limited to journals with “remote sensing” in the title.

Three approaches has been identified in this review: the parameter-based, the indirect, and the direct approach. From the review, we see that the direct approach has been developed and mostly been used in North America and only recently was applied in the Carpathians in Europe [48, 49, 287]. One reason might be the availability of higher resolution data, which is more important for small-structured forest patches in Europe as compared to larger and more homogeneous areas in the USA and Canada. Another reason for the higher popularity of the parameter-based approach in Europe might also be the availability of data and information for other purposes (forest monitoring, management, habitat mapping), that could easily be re-used for OGF mapping.

**Fig. 6** Number of publications per period using the identified methods/method groups



There is a big potential to apply direct approaches more widely in Europe, as examples from the Carpathians already show. Certainly, adaptations might be needed, especially, if the approaches should be applied to other ecoregions like the Mediterranean or the boreal forest zones of Europe. This is however even more true for the transfer of parameter-based approaches.

Finally, indirect approaches are not easily transferable from one region to another, as existing frame conditions, available data, and OGF definitions strongly differ. Especially the distance to roads or settlements is not as important in Europe as it might be on other areas, e.g., if an OGF is under protection. There are several tOGF assigned as UNESCO Natural World Heritage, which are very close to or even surrounded by settlements and streets. Thus, the indirect approach has clear limitations for applicability in Europe and should rather be used in combination with other approaches or with regionally adapted thresholds (see scenario 1).

A broad spectrum of methods and approaches have already been developed to identify and map OGF, often on specific case studies. This makes it impossible to compare achieved accuracies due to different procedures of accuracy assessment, including sampling design and accuracy measures calculated, reference data, and site conditions. In order to allow for a thorough comparison of methods and achievable results, we urge for a systematic international comparison of methods for OGF classification on a homogenized data set and a common evaluation approach (similar to the comparison of tree detection algorithms from [69]). A further complication resides in the multi-parameter nature of OGF classification. While one forest parameter might be very accurately mapped, this does not necessarily result in accurate OGF mapping. It may well be that moderate accuracies for several forest parameters may be more important for correct OGF classification due to the trade-off and complementarity between parameters. Keeping this and also the costs of different data sets in mind, there is not one solution for all. As a result, it is impossible to draw any general conclusions which of the three approaches (parameter-based, indirect or direct) is to be preferred.

Based on this literature study, therefore, we propose two scale-dependent optimal scenarios to be tested in practice.

(a) Scenario 1: Regional to continental-wide evaluation of tOGF

The aim of this scenario is to identify so far unknown tOGF stands on a broader geographical scale, e.g., regional, country-wide, or continental-wide. Generally, the larger the assessment area, the more important it is to use highly automated assessment approaches based on freely available RS data and existing reference data. Therefore, direct approaches using free and open RS data, like the Copernicus optical and SAR data sets, in combination with other meaningful geospatial

data sets in an automatic machine learning procedure seem to be the most suitable and efficient approach, which has been shown in examples mainly from North America. The main obstacle of a scenario using the direct approach is the availability of sufficient, reliable, representative, and consistent reference data covering all types of OGF occurring in the area of investigation. In ideal circumstances, enough reference data is available to perform training of the selected algorithm and validation of results with an independent data set. However, since the number of conducted studies using direct approaches based on up-to-date machine learning methods is rather small (see Sect. 3.3), future research is crucial to exploit the full mapping potential. The second option for such an assessment would be an indirect approach using a wide variety of existing geospatial data to “predict” the presence of potential tOGFs with mathematical models, as done for example in [280] or in [4] with the related aim to detect “potential” primary and tOGF in Europe. Ideally, both the direct and the indirect approach should be jointly applied in a combinatory method. The fact that there is not one single, binary denominator of tOGF might also be a major challenge in applying one approach on continental scale. Therefore, it will probably be necessary to geographically split the mapping area in contained strata in order to account for different dominant criteria and threshold values, often related to growth conditions and forest composition.

(b) Scenario 2: Detailed mapping for quantifiable monitoring and/or decision support

The general assumption for this scenario is that detailed ground-truth data is already available, quantifying specific old-growth indicators for (potential) tOGF stands and their surroundings. In this case, a parameter-based approach using ALS data in combination with additional satellite or airborne data would be most suitable. The applications for this more local scenario can be twofold. A first application is the more detailed delineation of the borders of known tOGF areas and the characteristics of their surroundings. This mapping can provide valuable information and recommendations for policy makers for the definition of new or expanding of existing protection zones or it may serve as a basis for setting up an in situ field assessment network. The second application is the monitoring of known tOGFs over time in order to assess their conservation and quality. A parameter-based approach can objectively assess the different RS forest parameters listed in Table 1 to support the assessment of the respective tOGF criteria. However, since ALS data and/or very high-resolution optical data is needed to provide detailed information on

local scale, developing and maintaining such a monitoring system are always associated with additional costs for acquisition of RS data.

## 5 Summary and Knowledge Gaps

In conclusion, the number of publications dealing with tOGF mapping as main focus found in this study is rather limited. However, there is a lot of knowledge from other forestry-related applications that map forest parameters using RS currently underexploited for its use to assess OGF. This is a chance to leverage the full potential of remote sensing technology independent of the primary application focus. In terms of methods, we identified three groups: parameter-based approaches, direct approaches, and indirect approaches. The first type of approach is mostly suitable for local assessments with a clear focus on ALS data, due to its ability to penetrate the canopy and deliver information on the vertical and horizontal structure of the forest. A second reason is the high resolution, which allows to detect individual trees and gather their specific properties such as size and position. In combination with optical data to derive tree species information, this data currently returns highest accuracy values and largest level of detail. However, using ALS data and optical VHR data is usually rather cost-intensive. Therefore, its use for large-area assessment, e.g., country and continental-wide, is usually not feasible. For such large-area assessments, both the direct and indirect approaches have been used, typically employing HR optical and SAR data as well as other geospatial data sets. The applied algorithms to map different forest parameters or OGF directly range from regression algorithms to region growing, ensemble learning (especially RF), SVM, and newer ANN and deep learning architectures with a clear recent focus on RF, SVM, and ANN including deep learning algorithms.

We could identify five main knowledge and research gaps. The first issue is the absence of commonly accepted definitions, indicators, and threshold values to define and assess OGF, even when restricted to temperate forests (tOGF). Both, an acknowledged definition for OGF itself and also for indicators of “old-growth-ness,” are lacking. A second challenge relates to one specifically important OGF criterion, dead wood amounts. Data on dead wood are often lacking from traditional forest inventories and RS assessments of forest stands in Europe. In the parameter-based approach, the most important need is to develop more accurate and more efficient dead wood assessment methods. Third, for the direct approach, large comparative studies on accuracy assessments are needed. Fourth, a combination of direct and indirect approaches should be tested, as it could provide important data combinations that can improve the accuracy

of assessments, as it may reduce the errors of the individual methods. And fifth and finally, the absence of reference values for primary temperate forests in Europe are lacking. Such reference values are essential to assess the level of old-growth-ness of a forest. This is not only problematic for dendrometric parameters, but also for species composition, where we are to rely on hypothetical extrapolation of natural forest types and their species composition.

Nevertheless, the increasing spatial and temporal resolution of area-wide RS data, especially from satellite data across large areas, provides a large potential for forest classifications and assessments, that no longer should rely on statistical data from ground-based sample grids (like NFIs). The further development of RS methodology in forest classification and its application will be beneficial not only for the mapping of OGF, but also as inputs for national restoration plans and to monitor the spatial trends in the degradation or restoration status [289] of forest ecosystems in Europe and elsewhere.

**Author Contribution** C.S. and M.H. wrote the main manuscript text. C.S. prepared Fig. 1; M.H. prepared Fig. 2. The tables were produced jointly by C.S., M.H., A.D., V.B., H.K., and K.V. Further, K.V. wrote large parts of the introduction. K.V., H.K., and V.B. wrote main parts of Sect. 4. All authors reviewed the manuscript several times. The authors would like to appreciate the anonymous reviewers’ comments, which helped to improve the manuscript.

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## Declarations

**Ethics Approval** Not applicable.

**Consent to Participate** Not applicable.

**Consent for Publication** Not applicable.

**Conflict of Interest** The authors declare no competing interests.

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