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REMOTE SENSING (J SUAREZ, SECTION EDITOR)

A Review of Dendrochronology and Remote Sensing Integration for Forest Growth and Disturbance Monitoring

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Abstract

Purpose of Review Understanding forest growth and its response to climate variability and disturbance is critical for monitoring carbon dynamics and managing forest ecosystems under global change. Tree-ring width (TRW) data from dendrochronology and vegetation indices (VIs) derived from remote sensing offer complementary perspectives on forest growth—one reflecting carbon accumulation in wood, the other photosynthetic activity by foliage and changes in canopy cover. Their complementary spatial and temporal scales also enable upscaling measurements through time and space. The review synthesizes 78 multidisciplinary studies that integrate these two disciplines to evaluate their combined potential in assessing forest growth.

Recent Findings The review revealed growing interest in combining dendrochronology and remote sensing, with diverse applications and methodological approaches, which we have grouped in three dominant areas of research: (1) examining relationships between TRW, VIs, and climate; (2) assessing long-term growth and productivity trends; and (3) evaluating responses to disturbance and extreme climatic events. We showcase a subset of relevant studies and highlight some key results, with many reporting strong interannual TRW-VIs positive relationships during growing season months. Research on growth trends shows more mixed outcomes, as the growth recorded by TRW and VIs is often decoupled over longer timescales. In disturbance-related studies, TRW generally reflects stronger and more prolonged growth reductions than VIs, suggesting it is more sensitive to stress-induced source and sink limitations. Despite methodological advances, challenges remain, including scale mismatches between ground and satellite data, limited use of high-resolution imagery, and underrepresentation of ecological metadata.

Summary Integrating dendrochronology and remote sensing enhances the spatial and temporal scope of forest growth monitoring. In this review, we summarize interdisciplinary studies, examining their methodological approaches, including sampling strategies, growth proxies, and statistical analyses. We then outline persistent challenges, including spatial biases in tree-ring datasets, scale mismatches between ground plots and satellite data, and the physiological distinctions underlying foliage activity and radial growth. Ultimately, we identify key opportunities for further development in this interdisciplinary field, such as expanding ecological metadata collection, adopting higher resolution satellite imagery, and improving our understanding of the complex physiological processes underlying forest growth.

Keywords Dendrochronology · Remote sensing · Tree-rings · Vegetation indices · Tree growth · Forest productivity

Introduction

Forests worldwide are a major carbon sink, storing 1.4 Pg of carbon and offsetting 15% of fossil-fuel emissions in the 2010 s [1]. A major driver of this sink is the growth of trees, which accumulate biomass and sequester carbon in their wood structures [2]. Measuring forest growth is thus essential to track carbon pools and to understand the global carbon cycle, allowing better predictions of the carbon-climate system [3]. In addition, tree growth measurements

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are critical for sustainable forest management at national and regional levels, providing yield estimates and guiding adaptive management strategies [4]. Growth also provides insights into forest health and is linked to ecosystem services such as water and air purification, climate regulation, and protection from natural disturbances [5]. Consequently, it is becoming increasingly critical to efficiently and accurately measure tree growth across space and time.

Tree growth is a complex process, beginning with carbon uptake by the foliage, and ending with its storage in wood structures, involving trade-offs in allocation to the different organs and their functions at every step [6, 7]. The foliage of trees absorbs atmospheric carbon dioxide and converts it into carbohydrates through the process of photosynthesis, which is powered by solar energy captured in chlorophyll [8]. The assimilated carbon is then partitioned into the tree's biomass, including its trunk, branches, leaves, and roots [9], and resource allocation is optimized to maximize competitive fitness, reproduction, defense and growth [10]. Competition is among the strongest determinants of tree growth, while numerous exogenous factors—including climate, stand dynamics, and disturbances—also play important roles [11]. The interactions between intrinsic and environmental drivers of growth contribute to substantial variability in the process, the mechanisms of which remain only partially understood [12].

The measurement of tree growth is a critical topic in terrestrial ecology, and represents a central objective in several disciplines, notably dendrochronology. Dendrochronology is the science which studies annually resolved growth increments of woody plants (annual rings), using proxies such as tree-ring width (TRW), density, isotopes, and wood anatomy [13]. Remote sensing is defined as the use of satellite, aerial, or drone-based sensors to monitor the physical characteristics of an area [14]. Within the context of forest research, sensors capture spectral information on foliage, from which vegetation indices (VIs) are derived [15] that represent foliar chemical and pigment constituents such as chlorophyll [16]. These spectral indices have been corelated to attributes such as phenological timing, foliar stress and overall plant health, and can in turn be used to predict tree growth [17]. Dendrochronology deals with direct measurements of radial stem growth of individual trees, whilst remote sensing deals with estimations of foliage cover and photosynthetic activity. Consequently, these proxies correspond to two aspects of carbon exchange: uptake (carbon sources) by the foliage (VIs) and use and accumulation (carbon sinks) in the woody tissues, mainly in the stem (TRW).

Global change is affecting forests worldwide, with increasing growth trends observed in wet boreal and temperate regions, while decreasing trends are observed in many moisture-limited forests [18–20]. Extensive research is being conducted on the spatial and temporal variability of forest productivity globally, using various datasets and methods from both remote sensing and dendrochronology [21]. Canadian boreal forested ecosystems are a good example, where remote sensing studies generally agree on the presence of a browning trend, particularly in densely forested areas, contrasting with a prominent greening trend towards the tundra, although the location and magnitude of the observed trends vary [22–25]. These results also agree with dendrochronology studies detecting a negative response of black spruce (*Picea mariana* Mill.) to temperature increases, particularly in the southern part of its range [26–28]. And yet, despite the abundant literature generated by the dendrochronology and remote sensing fields, the confidence in the observed trends is generally low because the different datasets and methods employed all have multiple sources of uncertainty [29–31], and results are often contrasting. For example, using Canada's national forest inventory's tree-ring network, Hember et al. [32] report prevalent growth increases between 1901 and 2001. In contrast, using satellite data, Goetz et al. [24] found almost no greening in the North American boreal forest, and report browning in 7% of the total area.

What is apparent however is that while dendrochronology and remote sensing can both provide insights into forest growth and productivity, studies often use these approaches individually. The need to understand ecosystem responses to global change has led to a growing interest in interdisciplinary research [33], with many recent studies pairing remote sensing and dendrochronology data and techniques. However, various approaches and methods have been used, making it difficult to compare and interpret results. Consequently, there is a need to summarize the methodologies employed to combine the two disciplines, which follow different principles and assumptions for measuring growth and productivity. Although two reviews have already examined publications combining dendrochronology and remote sensing, these were not systematic reviews of the literature, and their aims were to provide an overview of the relationship found between TRW and VIs, with a focus on NDVI reconstruction [34], and on the vulnerability to drought stress specifically in the Mediterranean [35].

In this review, we synthesize the multidisciplinary studies that paired dendrochronology and remote sensing. In doing so we highlight their complementarity while also recognizing the role each discipline can play in monitoring tree growth and forest productivity. Our specific objectives are to (1) review the principal approaches used in both fields with a particular focus on the methods used for linking tree-ring and remote sensing data, (2) demonstrate current applications and the potential for combining these disciplines, and (3) identify the limits of existing multidisciplinary studies and propose opportunities for future research.

Article Selection

We conducted a systematic literature search using Google Scholar to identify relevant publications linking remote sensing and dendrochronological data. We searched all combinations of the keywords "remote sensing", "satellite imagery" or "vegetation index" paired with (AND) "dendrochronology" or "tree-rings" and filtered to obtain recent articles published in the period 2015–2025. The titles and abstracts were first manually assessed to filter relevant studies. We only included peer-reviewed literature written in English and excluded papers dealing exclusively with shrubs, retaining 56 publications following this step. Next, we added supplementary publications by scanning the references section of the previously identified papers for relevant articles, enabling us to include earlier studies that were missed in the initial search. We obtained 78 interdisciplinary papers which were classified by location of study area, year of publication (Fig. 1), and various methodological aspects (Supplementary Information).

The remainder of this paper will be structured as follows. We first describe the key principles in dendrochronology and remote sensing supporting their individual use for measuring growth, as well as the main approaches used in both disciplines separately. We then build a case for how these two disciplines are complementary in various aspects and describe how the similarities between their productivity and growth proxies allow for their integration. Further, we detail the approaches and the methods employed in the reviewed publications, particularly regarding objectives, sampling schemes, growth proxies, and statistical analyses. Finally, we conclude by highlighting critical limits of current studies and opportunities for future research.

Dendrochronology

Dendrochronology relies on precise annual measurements of radial growth increment of individual trees, which can be scaled up to estimate stand or forest biomass increment (e.g [36]). It is typically used to study the interannual variability of growth in response to climate (climate-growth relationships), as trees subject to similar climate conditions exhibit synchronized growth patterns [13]. A fundamental principle

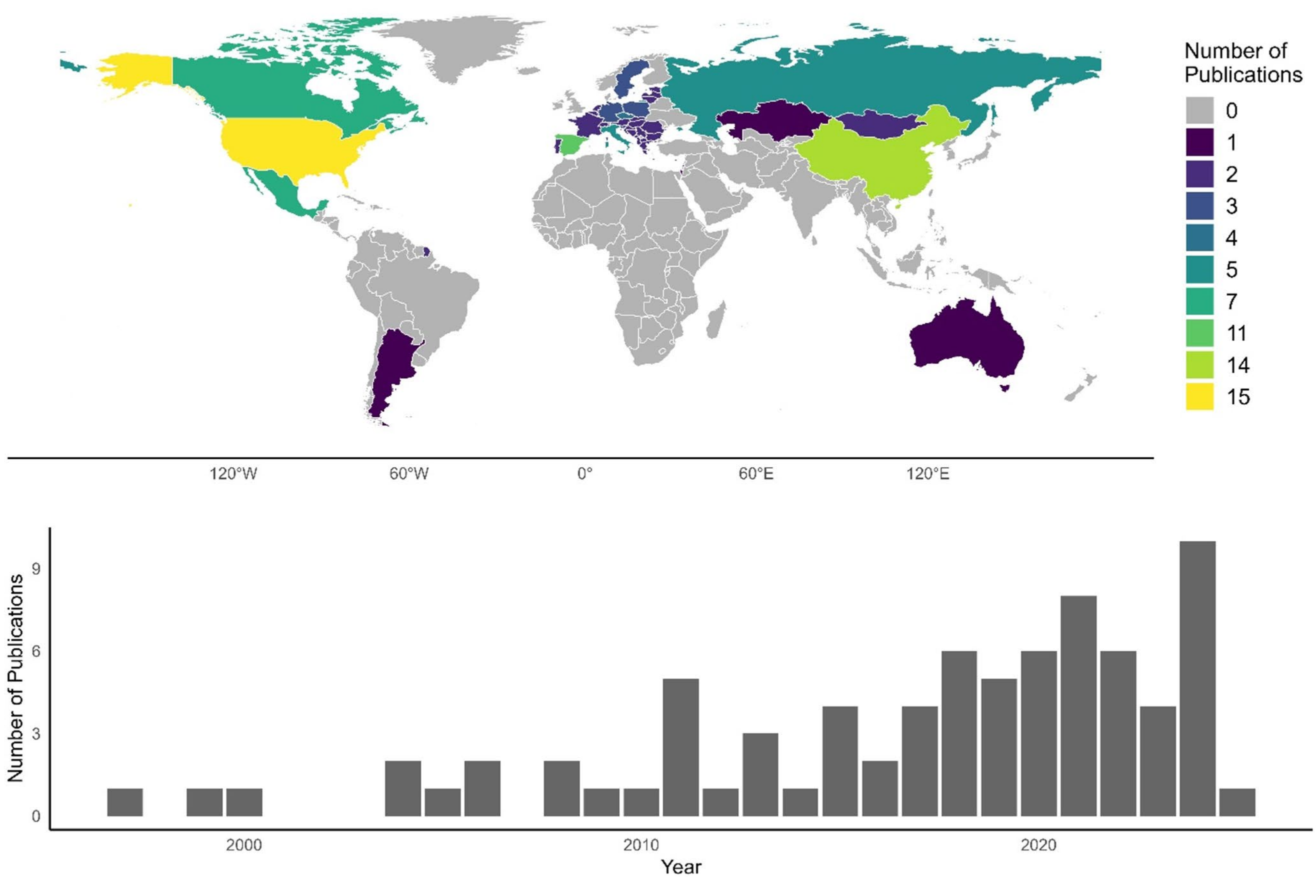


Fig. 1 Geographical location of studies and the number of published articles per year

of dendrochronology is that tree growth is driven by the most limiting climatic factor, making TRW a good proxy for past climate [37]. For example, growth typically responds positively (negatively) to precipitation in dry (humid) regions, while it responds positively (negatively) to temperature in cold (warm) regions (but see [158, 159]). However, according to the principle of aggregate tree growth, growth is not only driven by climate and varies according to tree age-size as well as competition and disturbances [13]. In addition, there is significant autocorrelation in tree-ring time series [40], as a portion of annually sequestered carbon is allocated to non-structural carbohydrate reserves, which can be mobilized in subsequent years when photosynthetic activity is limited [41]. Growth measurements obtained from dendrochronology therefore contain a wealth of information and can help answer a large array of ecological questions. These include not only forest productivity and its relationship with climate, but also the occurrence and impacts of disturbances such as fire, insect outbreaks, and drought, as well as longer-term processes of forest dynamics, competition, and ecosystem resilience. For a complete understanding of dendrochronology and dendroecology, see Fritts & Swetnam [38].

In terms of research applications, dendrochronology largely focuses on climate-growth relationships, which allow reconstructing past climate (e.g [37]). and assessing the climate sensitivity of tree growth (e.g [26]). Dendrochronology research also focuses on growth trends in response to climate warming (e.g [39]). or CO_2 fertilization (e.g [160]). Growth trends are defined as long-term or low-frequency variations in growth, as opposed to interannual variations or high-frequency variations. However, assessing trends using tree-ring data is a major challenge, as it is difficult to distinguish endogenous (e.g. tree age-size, competition) from exogenous influence such as climate warming, both of which occur at low frequencies [43]. Also, research focusing on trends is challenging, as tree-ring datasets are often inadequate due to their biased spatial coverage and poorly replicated population sampling [44]. Other research topics include disturbance and extreme climatic events impacts (e.g [42, 45]). However, dendrochronology is mainly used to study non-stand replacing disturbances, as trees need to remain mostly intact (but not necessarily alive) to allow tree cores and disks to be collected.

Remote Sensing

Remote sensing relies on frequent (annual or intra-annual) measurements of forest biophysical attributes, which can in turn be used to estimate forest productivity via three approaches: physiology, dimension analysis, or foliar concentration [17]. First, physiological estimations involve calculating how much biomass can be produced from light absorbed by the foliage [46]. The Normalized Difference Vegetation Index (NDVI) is the most widely used surrogate for photosynthetic activity and is derived from red and near-infrared reflectance values, exploiting the fact that chlorophyll strongly absorbs red light while reflecting near-infrared radiation [47]. Second, dimension analyses involve developing relationships between field measurements of tree weight or size and remotely sensed forest attributes, which are used subsequently to predict productivity across landscapes [48]. Third, foliar concentration estimations of growth involve measuring biochemical compounds in leaves (e.g. chlorophyll and nitrogen) or measuring the amount of foliage (leaf area index; LAI). These foliage traits can then be estimated from VIs across broad scales based on statistical relationships with field data. For a complete description of how forest growth and productivity is characterized using remote sensing, see Coops [17].

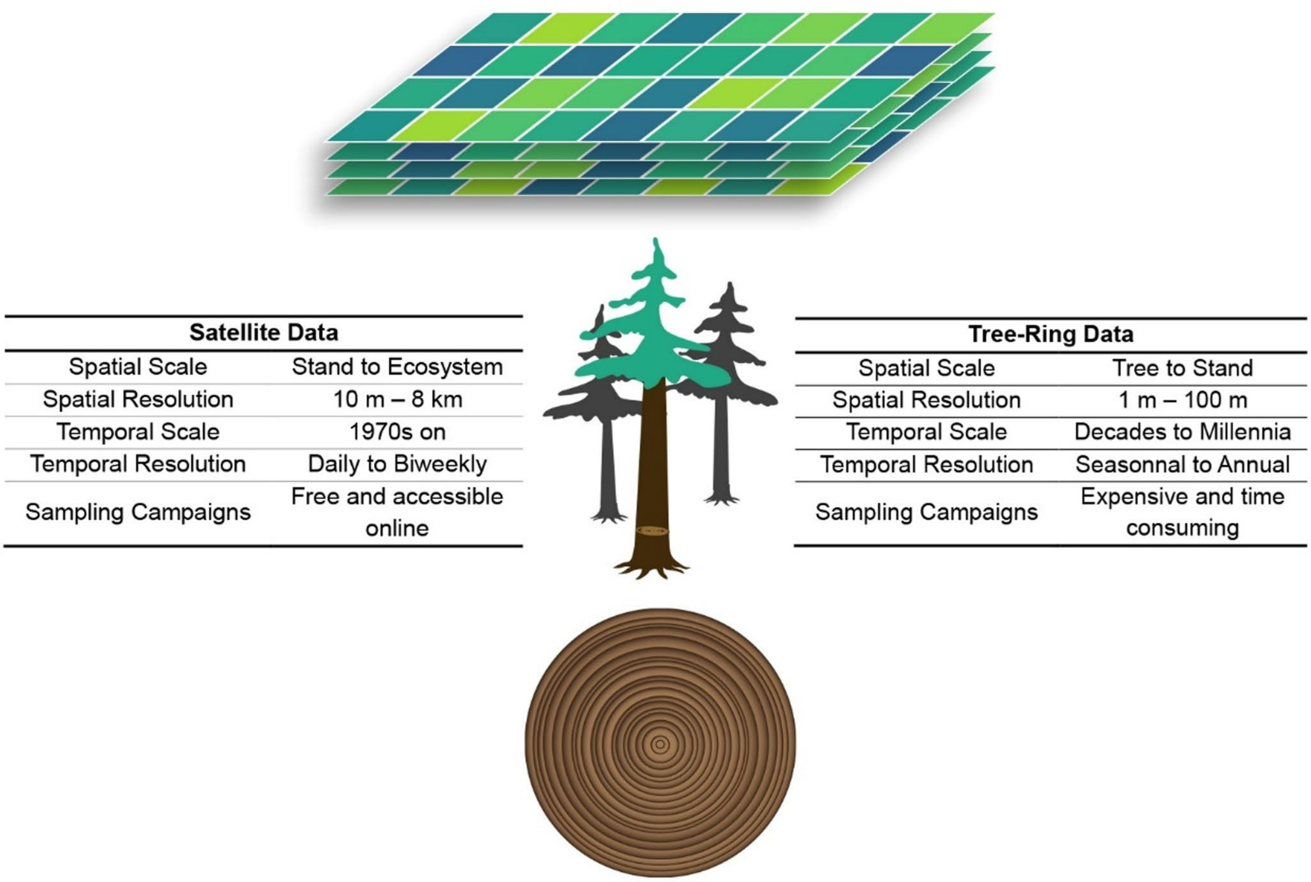
Spatial variations in photosynthetic activity are driven by limiting climatic factors: boreal regions are primarily constrained by temperature and semi-arid and arid regions by precipitation, while temperate zones face a mix of limiting factors that change over the growing season [49]. Interannual variations in photosynthetic activity are also driven by climate [50, 51]. However, unlike dendrochronology research, the climate sensitivity of photosynthetic activity is seldom the object of remote sensing research, and growth-limiting climatic factors are instead presumed based on geographical location, which allows for mapping forest productivity worldwide [46, 52]. In addition, extensive research focuses on canopy activity trends (greening and browning) in response to global change (e.g [53])., but it remains a challenge to attribute a cause to such trends detected from remote sensing as many environmental factors can influence greenness, especially when the spatial resolution of imagery is coarse [54]. Another large body of literature focuses on disturbance (e.g [55, 56])., although generally centered on stand-replacing disturbances because detecting subtle canopy changes can be challenging. Nevertheless, recent studies have been successful in using moderate resolution satellite time series data to detect and characterize non-stand replacing disturbances such as insect defoliation (e.g [57]). and there is growing interest in drought impacts assessment and monitoring [58].

Complementarity of Dendrochronology and Remote Sensing Data

Dendrochronology and remote sensing are complementary disciplines: while their similar temporal resolution allows for direct comparison of measurements at least annually, their differing temporal and spatial scales enable upscaling measurements through time and space (Fig. 2). Consistent satellite imagery is available only since the 1970 s, and tree-ring time series can span decades to millennia, allowing to extend the VI records back in time [34]. While dendrochronology provides exceptional information at the tree and stand levels, extending these growth estimates more broadly across space is problematic because plot networks are sparsely distributed over the landscape, as sampling is expensive and time consuming. Dendrochronology and remote sensing also offer complementary views into tree growth processes: VIs quantify canopy photosynthetic capacity (source activity), while TRW record the carbon invested in stem wood (sink activity). The distinction between these two physiological processes is critical for modelling forest carbon pools, as source and sink activities both constrain biomass accumulation differently [59, 60], which greatly influences carbon pools calculations [61].

Research Objectives and Main Findings

We began our systematic review by categorizing the 78 selected publications based on their primary research focus and related objectives. We identified three dominant axes of research: (1) examining relationships between TRW, VIs and climate; (2) assessing long-term growth trends; and (3) investigating growth responses to disturbance and extreme climatic events (e.g. drought, frost). As multiple objectives are formulated and explored in most studies, some publications are included in more than one of these dominant axes of research (Supplementary Information). The following subsections summarize the studies conducted in each research axis, highlighting their main research objectives and some key findings. We also showcase a subset of studies that demonstrate current applications and the potential for combining dendrochronology and remote sensing.



Satellite Data	
Spatial Scale	Stand to Ecosystem
Spatial Resolution	10 m – 8 km
Temporal Scale	1970s on
Temporal Resolution	Daily to Biweekly
Sampling Campaigns	Free and accessible online

Tree-Ring Data	
Spatial Scale	Tree to Stand
Spatial Resolution	1 m – 100 m
Temporal Scale	Decades to Millennia
Temporal Resolution	Seasonnal to Annual
Sampling Campaigns	Expensive and time consuming

Fig. 2 Complementarity of dendrochronology and remote sensing data

Relationships Between TRW, VIs and Climate

Annual measurements of TRW and VIs are often well correlated as both radial growth and photosynthetic activity are sensitive to climate across space and time (e.g [62–64])., albeit cambium activity is more sensitive to water limitation than photosynthesis [59]. The relationship between TRW and VIs is the focus of 21% of the reviewed publications, and an additional 47% also assess the relationships between one or both proxies and climate variables (climate-growth relationships). Generally, the objectives of these publications were to determine whether TRW and VIs are correlated with each other and with climate and, if so, to identify the timing and interval of the strongest correlations. In some cases, studies also explore the environmental conditions that favour strong relationships. Among the publications studying these relationships, some also have the specific objective of reconstructing VIs before their period of availability from satellite imagery (10% of all publications).

Several studies investigate the timing of the relationships, using fine temporal scale data from satellites with frequent returns, with results varying globally, depending on species and geographic location [65]. Nonetheless, most studies find the strongest correlations during the growing season months (e.g [62–64])., sometimes with a lag (e.g [66, 67])., while in some cases correlations are weak or inexistent (e.g [68]). The correlations between TRW and climate are generally stronger than the correlations between VIs and climate (e.g [69–72])., but not always [73, 74]. Although the relationship between TRW and VIs is mainly explained by their climate sensitivity, the timing of strongest correlations between TRW and NDVI does not necessarily correspond to the timing of the strongest climate-growth relationships [75]. Also, the temporal stability of the relationships between TRW and VIs has not yet been assessed but still deserves attention [76].

Regarding geographic location, relationships between TRW, VIs and climate are found in a variety of forest types and environmental conditions. Studies have been conducted in marginal conditions such as latitudinal tree lines (e.g [77, 78]). and altitudinal tree lines (e.g [73])., while some are located in arid regions (e.g [79, 80])., but also in temperate regions (e.g [81]). We did not notice any relationship between locations of the studies and the strength of the reported relationships (see [65]).

Furthermore, some studies went beyond traditional tree-ring measurements and incorporated tree productivity or stand volume to establish links with VIs. For example, strong relationships were found when total tree productivity (i.e. TRW, tree height, litterfall and seed production) was considered, although litterfall was the least correlated with NDVI [82]. Additionally, stand volume monitoring based on TRW measurements upscaled with allometric equations has yielded promising results in plantations [83], likely because volume measurements reflect more accurately crown sizes or leaf area, tree vigour, and in turn canopy greenness. Also, the regular forest structure and homogeneous composition of plantations may reduce noise in the remote sensing data, resulting in synchronized crown and volume growth rates.

Growth Trends Assessment

From a forest growth perspective, besides understanding the climate sensitivity of growth, it is also important to monitor long-term productivity trends and determine whether they are modified by global change. The longitudinal nature of both data sources enables temporal trends to be assessed. This is another approach frequently used in the reviewed literature, with 23% of the publications assessing the long-term evolution of growth. The objectives of these publications were to determine whether growth is accelerating or slowing down, to quantify the magnitude of trends, to compare the trends in tree-ring proxies and VIs and, in some cases, to map the spatial variability of the identified trends. Detrended TRW, basal area increment (BAI) and TRW without detrending are used to measure growth trends in 50%, 33% and 17% of reviewed publications assessing trends, respectively.

There is an overall disagreement between trends in tree-ring proxies and VIs [62, 81, 84–86], with generally more increasing trends found in VIs than in tree-ring proxies (e.g [66, 87]). These discrepancies may be explained by various physiological or methodological aspects, which will be discussed later (see Limits and Opportunities). However, consistent decreasing temporal trends in TRW and VIs were found for white spruce (*Picea glauca* Moench) and black spruce at the northern limit of their range, in the boreal forest of interior Alaska, where tree growth is increasingly limited by water availability [88]. In contrast, consistent increasing temporal trends were found for Qinghai spruce (*Picea crassifolia* Kom.) in high elevation stands of the Tibetan plateau, where tree growth is mainly limited by minimum temperatures, and where both temperatures and precipitation are increasing [89].

Disturbance and Extreme Climatic Events

Results from the literature suggest that TRW and VIs growth signals are complementary as they show different responses following disturbance events. Accordingly, the study of disturbance impacts can benefit from combining dendrochronology's precision with remote sensing's powerful wall-to-wall monitoring capacity, leveraging their complementary spatial scales. Among reviewed publications, 21% focus on disturbance and extreme climatic events, namely forest decline (6 publications), drought (5 publications), insect outbreaks (4 publications) and late spring frost (1 publication). These publications usually focus on specific events rather than analysing the whole length of the time series. Their objectives are to assess and compare the response of VIs and TRW following disturbance events and, in some cases, to examine their spatial extent over the landscape using remote sensing. A variety of approaches have been used in studies of disturbance and extreme climatic events, making it difficult to summarize publications. For this reason, we highlight here some key examples of methodologies used for each type of event, as well as some key findings.

Drought

For publications assessing drought impacts, recurring approaches are the calculation of resistance, resilience and recovery indices [90, 91], following Lloret et al. [92] or the calculation of drought and legacy effects (i.e. growth decrease during the drought year relative to previous growth, and relative to expected growth following drought) [93]. In some studies, radial growth was found to be more sensitive to drought than foliage greenness as it displays a more pronounced decline [91] and a longer recovery period [93, 94]. However, when drought occurs towards the end of the growing season, leaf browning can be detected by satellite imagery, while the current year's growth ring is usually not impacted [90], highlighting the importance of considering drought timing in these analyses [94].

Insect Outbreaks

The detection and assessment of insect outbreaks is the subject of only four publications and change detection approaches are used in two of them [95, 96]. For example, Babst et al. [95] compared Landsat images from autumnal moth (*Epirrita autumnata*) outbreaks with a reference image (no outbreak) to identify areas of NDVI change and to quantify the severity of defoliation. They used this same approach for TRW data, comparing mean series of TRW (chronologies) from stands showing growth reductions during outbreak years with reference chronologies from species or stands unaffected by the moth, allowing them to date past outbreaks and to quantify the growth reductions. The direct comparison of TRW and NDVI change in years of outbreak suggested a non-linear relationship between both proxies, with greater reductions in radial growth beyond a certain level of defoliation.

Forest Decline

Forest decline can be defined as the consequence of particularly severe or sequential disturbance events, and dieback from drought in the Mediterranean region is a recurring topic studied by four out of six publications [97–100]. Since declining stands are characterized by leaf browning, defoliation, and/or mortality, they are generally easily detected by remote sensing (e.g [97, 98]). However, some publications did not find significant relationships between TRW and VIs in declining stands [99, 100], suggesting a decoupling of stem and foliage growth. Additionally, the climatic sensitivity of declining stands may differ from that of healthy stands, as pointed out by [98] who found that the growth of the former was mainly driven by spring moisture availability, whereas the growth of healthy stands was more sensitive to summer temperatures. Finally, the spatially continuous nature of satellite imagery data also allows relating the spatial patterns of decline to potential underlying drivers. Several publications were interested in topographical and ecological variables that increase the probability of decline, such as elevation [101, 102], aspect [99, 102], age [99], tree diameter, stand density, and basal area [100].

Methods Used for Combining Tree-Ring and Remote Sensing Data

The 78 reviewed publications exhibited a wide variety of approaches and methods used to collect and process tree-ring and remote sensing data. This section reviews the sampling strategies, growth proxies, detrending techniques, and statistical approaches employed across all studies.

Sampling Strategies

Dendrochronological Sampling

Dendrochronological studies often occur in locations where understanding climate-growth relationships and reconstructing past climate is the principal research objective [13], although this is becoming less common [103]. As a result, methods were adapted to isolate the climate signal in the time series; sites are usually selected in marginal conditions with a specific climatic factor limiting growth, such as in ecosystem transition zones (ecotones). Dominant trees are also preferably selected to reduce noise attributable to stand-level dynamics and competition, and a site chronology is calculated by averaging growth of multiple trees to reduce noise attributable to tree-level processes [104]. Such practices result in key biases within the compiled data [44], which must be recognised and understood prior to their analysis. Due to changing research needs, dendrochronological methods are evolving to enable understanding growth patterns across various sites and climate conditions [103], and dendroecological datasets representative of forest ecosystems are being assembled (e.g [105, 106]). which in turn enable meaningful conclusions to be drawn at large spatial scales.

Since remote sensing data is available globally, the spatial extent of publications depends primarily on the tree-ring datasets used. As the collection and processing of tree cores is costly and time consuming, the sampling schemes of the reviewed publications often rely on previously available tree-ring data, which limits the questions that can be addressed and the conclusions that can be drawn from the data. Numerous tree-ring datasets are publicly available through the International Tree-Ring Data Bank (ITRDB; [107, 108]), although they are spatially biased towards forests in climatically marginal sites, and many of them overlap only briefly with the period during which satellite imagery is available [109]. In addition, most of these datasets were collected for traditional dendrochronology purposes following the biased (albeit justifiably when initially collected) sampling methods described above, making them less suitable for broad spatial scale assessments of forest productivity.

For this reason, most reviewed publications cover small spatial scales, with 82% of studies conducted at the regional scale, while only 10% and 8% were conducted at the national and global scales, respectively. Research at the global scale [65, 66, 75, 78, 110, 111] makes use of all available ITRDB data with certain quality criteria. Research at the national scale generally uses more fit-for-purpose sampling schemes, with denser plot networks uniformly distributed or representatively sampled across landscapes (e.g [85, 112, 113]). In fact, national-scale studies tended to include more dendrochronology sample plots than global-scale studies, with an average of 428 plots compared with 362 (Fig. 3a). In contrast, regional-scale studies used tree-ring data from an average of 12 plots and were in some cases able to upscale the results to large spatial scales (e.g [114]).,

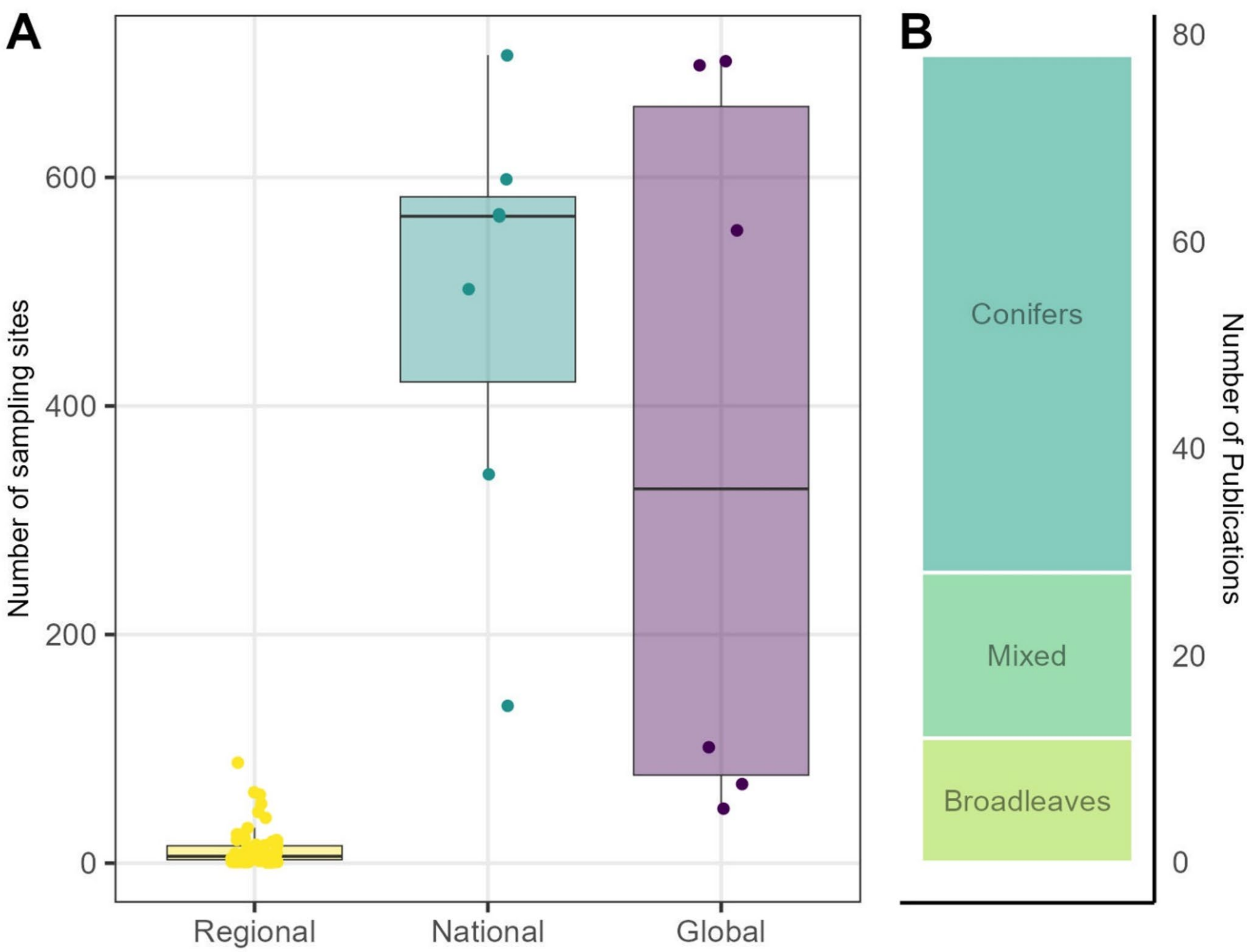


Fig. 3 Number of sampling sites for each spatial scale of study (**a**) and species group (**b**) used in the reviewed publications

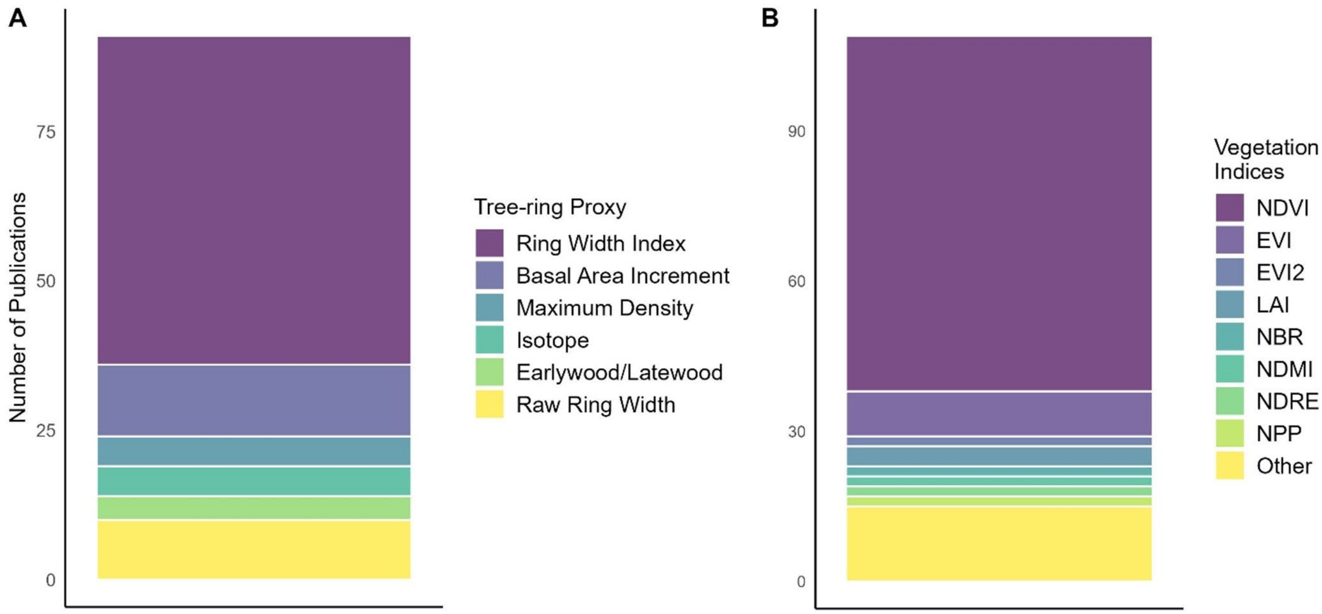


Fig. 4 Tree-ring proxies (**a**) and Vegetation indices (**b**) used in the reviewed publications

most often in grasslands [71, 79, 80, 115, 116]. In addition, considerable tree-ring research has focused on conifer species at high-latitude and high-altitude sites, which is also reflected in the publications selected for this review as 65% of studies dealt exclusively with conifers, while only 14% dealt exclusively with broadleaves, and 21% mixed (Fig. 3b). The number of trees cored per plot varied between 4 and 131, with a median of 16 and an average of 24 trees. The sampled trees were generally dominant in the canopy, which is justified by the fact that sensors mainly capture the foliage of dominant trees, and that they account for most of the biomass in a stand [117].

Remote Sensing Derived Sampling

While satellites offer a global perspective, they have different sensors, revisit intervals, archive lengths and spatial resolutions, providing data whose suitability may vary depending on specific research objectives. Most reviewed studies utilised coarse and moderate spatial resolution data, principally the Advanced Very High Resolution Radiometer (AVHRR; 45% of publications), the Moderate-Resolution Imaging Spectroradiometer (MODIS; 29% of publications), and Landsat (26% of publications). The AVHRR sensor has a spatial resolution of 1 km and of 8 km (Global Area Coverage) for older data [118], the MODIS sensor has spatial resolutions of 250 m, 500 m, or 1 km depending on spectral bands, while Landsat has a 30 m spatial resolution. Satellites such as Sentinel-1 (1% of publications) and Sentinel-2 (4% of publications) with finer spatial resolution of down to 5 m and 10 m respectively, were less commonly employed. This may partly be attributed to the length and availability of the imagery archive, with Landsat data being collected since 1972 (although only available free and open since 2008), AVHRR since 1978, MODIS since 2000, Sentinel-1 since 2014, and Sentinel-2 since 2015.

Besides spatial resolution and archive length, the revisit frequency of the satellites is also important, as annual or intra-annual observations are needed to allow direct comparison with dendrochronological records. The AVHRR, MODIS and Sentinel sensors offer products of high temporal resolution (i.e. at least biweekly, depending on data quality) which enables a detailed assessment of the climate influence on photosynthetic activity, as climate data is often also available at this resolution. However, even if 74% of publications use AVHRR or MODIS data with an initially biweekly temporal resolution, many of them aggregate the values by calculating their average or sum, or by using the maximum value. As a result, the temporal resolution of the spectral imagery used in the reviewed publications is either biweekly (13% of publications), monthly (36% of publications), seasonal (29% of publications) or annual (22% of publications).

Growth Proxies

Tree-Ring Proxies

Ring width indices (RWI), which represent detrended TRW, is the most frequently used tree-ring proxy, with 70% of publications reviewed (Fig. 4a). Other proxies include basal area increment (BAI; 16% of publications), TRW without detrending (17% of publications), maximum latewood density (6% of publications), carbon or oxygen isotopes (6% of publications), and earlywood and latewood measurements (5% of publications) –note that some publications use more than one proxy. These different proxies capture various components of radial growth, with each being potentially linked to different climate factors at varying temporal scales [119]. BAI measures the ring surface area, as calculated with a simple geometrical equation, and reflects total tree growth (i.e. biomass increment) much better than TRW [120]. Maximum latewood density represents the wood density of the latewood cells, which have thick cell walls and small lumens and are formed at the end of the growing season. It usually carries a strong common signal among trees and sites related to summer maximum temperatures, and it is less influenced by previous season climate than TRW. Isotope proxies represent the relative abundances of different stable isotopes found in each annual growth ring. Common measurements include the ratio of ^{13}C to ^{12}C ($\delta^{13}C$) and of ^{18}O to ^{16}O ($\delta^{18}O$). Because stable isotope ratios are determined by physiological processes in trees such as photosynthetic assimilation rates and stomatal conductance, they can be used as indicators of tree intrinsic water-use efficiency, stomatal conductance rates, and water stress [121]. Earlywood and latewood width measurements capture growth at a finer time scale than TRW, as they are produced at the beginning and end of the growing season, respectively. However, earlywood width is not exclusively linked to the climatic conditions of the current growing season because its formation largely depends on the remobilization of stored carbon [122].

Vegetation Indices

Among vegetation indices, NDVI is the most used by far, accounting for 91% of publications (Fig. 4b). The Enhanced Vegetation Indices (EVI and EVI2) are used in 14% of publications, while all other VIs appear in less than 5% of publications–note that some publications use more than one VI. The NDVI and EVI both measure vegetation greenness using red and near-infrared bands, as the absorption of red light and the reflection of near-infrared radiation are leaf traits associated with abundant chlorophyll and efficient light absorption for photosynthesis [47]. The NDVI's widespread use is partly explained by its compatibility with early sensors such as the AVHRR, which only provides red and NIR bands. However, NDVI tends to saturate in areas with high biomass, limiting its sensitivity in dense vegetation. To address this, EVI was developed for the MODIS sensor, incorporating a blue band and correction coefficients to account for atmospheric and background noise [15]. EVI2, a two-band version, was later introduced to preserve the benefits of EVI while remaining compatible with sensors lacking a blue band [123].

In addition to these widely used indices, several other VIs provide complementary information on forest structure and function. The Leaf Area Index (LAI) quantifies canopy density by estimating the amount of leaf surface area per unit ground area, a key determinant of light interception and photosynthetic capacity, evapotranspiration, and net primary production [124]. The Normalized Difference Moisture Index (NDMI) uses shortwave infrared and near infrared reflectance to track moisture content in vegetation, while the Normalized Difference Red Edge Index (NDRE) uses red-edge bands to capture subtle variations in chlorophyll content [125, 126]. Additionally, the Tasseled Cap transformation generates composite indices (brightness, greenness, and wetness) from weighted linear combinations of spectral bands. The Tasseled Cap greenness (TCG) index is conceptually similar to NDVI and is often used for the same purposes [127]. For a complete description of key vegetation indices, see Xue & Su [128].

Detrending of Proxies

A common practice in dendrochronology is to detrend time series with mathematical functions [129], with the goal of isolating the signal of interest from the time series by removing what is considered noise [43]. This practice is highly subjective, as the selected method influences the information preserved in the time series [43]. Because of this, there is no consensus on the most appropriate standardization method, which always depends on the specific research objective and on the growth patterns observed in the time series. The most popular detrending methods applied to TRW data in the reviewed publications is smoothing splines (31% of publications) and negative exponential curves (30% of publications). Some studies also opted to omit detrending (17% of publications) as time series were often short relative to tree age, thus minimizing the age-size trend, which is why the use of raw TRW or BAI is considered adequate (e.g [22]). In 9% of cases, authors did not specify their detrending method, and the other detrending methods were all used in less than 5% of publications. Publications assessing climate-growth relationships mostly used smoothing splines because they are more flexible and efficient in removing the low and medium frequencies from the signal, thus highlighting the climate signal, which is mostly expressed at high frequencies, i.e. 1–10 years [37]. The publications assessing growth trends mostly used negative exponential functions, no detrending, or the regional curve standardization method (RCS; [130]). These conservative forms of detrending are generally preferred when the objective is to assess trends because they specifically target the removal of the age-size trend from the time series and retain more of low frequency signal [131].

Some publications also calculate residuals or anomalies of VIs by detrending (e.g [72, 111, 113, 132–134]). or standardizing (e.g [73, 110, 116, 135]). time series measurement. However, studies often provide little methodological detail and use inconsistent terminology, making it difficult to understand the precise calculations that are involved. Detrending is mainly done by fitting linear functions and subtracting or dividing each data point from the value predicted by the functions. Standardization (or z-score normalization) is done by calculating the deviation of each datapoint from the average (difference from mean divided by standard deviation), which rescales data to a mean of 0 and a standard deviation of 1. The calculation of residuals or anomalies enhances the interannual variations in VIs, which might strengthen TRW-VI correlations.

Statistical Analyses

The statistical analyses carried out in the studies depend on the specific objectives of the publications (relationship between growth proxies and their link to climate, growth trends assessment, disturbance and extreme climatic events). The interannual relationships between VIs, TRW and climate are calculated with Pearson correlations (80% of publications), linear (mixed) models (12% of publications), or Spearman and Kendall rank correlations (8% of publications). The magnitude and signs of growth trends are determined by fitting linear (mixed) models (66% of publications) segmented linear models (17% of publications) and by using the Mann-Kendall test (17% of publications). General additive mixed models [85] and Spearman correlations were also used [64], each in one publication. In 17% of cases, different statistical models were used for each proxy, and some studies assessed trends only in VIs (33% of publications) or in TRW (11% of publications). The publications assessing disturbance and extreme climatic events (21% of publications) employ a diverse array of methodological approaches and statistical analyses, so we can't comprehensively summarize them, see Disturbance and Extreme Climatic Events for key examples.

Limits and Opportunities

Spatial Representativeness of Tree-Ring Data

As tree-ring datasets are not necessarily sampled with requirements of spatial representativeness, they are often spatially biased [44]. In contrast, satellite-based remote sensing typically provides wall-to-wall data coverage of any area of interest. To ensure the spatial representativeness of tree-ring datasets used in conjunction with remote sensing data, ground plots should be established to fit the extent of the study area, especially when the study aims at generating spatially continuous predictions of forest growth. Plots should be located a priori and tailored to the specific research question, the heterogeneity of the landscape and the spatial scale of interest, as is the norm in the field of ecology [136]. To match the broad spatial scale of remote sensing data and allow generation of spatially explicit predictions of growth over landscapes, tree cores should be collected from numerous and diverse sites as opposed to a few sites with high sample replication [137]. A global effort toward systematic sampling is needed to enable a more comprehensive study of tree-rings and remote sensing. A good example are national forest inventory programs, which are based on either systematic or stratified randomized sampling designs and in some cases include tree core sampling, thus resulting in extensive tree-ring networks (e.g [105, 106]). These datasets must include precise geographic coordinates, which are essential for combining national forest inventory cores with remote sensing data.

In cases where tree cores are sampled specifically for interdisciplinary studies combining dendrochronology and remote sensing, we suggest stratifying the study area into forest types, targeting stands larger than a single pixel, setting a minimum distance from roads or water, and collecting a precise GPS point at plot center. Tree selection criteria should be determined based on stand structure and composition. In even-aged stands, targeting dominant trees with large crowns may increase the TRW-VI correlations, but also overestimates stand-level growth measurements [44], so these should be considered specifically as estimates of dominant layer growth. In irregular stands, coring trees of all age classes is crucial, as the establishment of young cohorts may have an impact on canopy greenness. In mixed forests, all species should be sampled, and the number of samples should be representative of their proportion in the stand.

Innovations in Satellite Sensors and Remote Sensing Products

So far, most research combining remote sensing and dendrochronology has used sensors providing data at a coarse spatial resolution such as the AVHRR and MODIS. These coarse resolution products often feature mixed pixels, with multiple land cover types occurring in different proportions, hampering the ability to monitor forest growth in fragmented landscapes [138]. Also, when the objective is to upscale forest productivity at the landscape level, coarse resolution products are known to consistently over-estimate net primary productivity in fragmented landscapes [139]. We suggest that more studies make use of moderate spatial resolution sensors such as Landsat and Sentinel-2. Also, the combination of Landsat and Sentinel-2 imagery, known as Harmonized Landsat Sentinel (HLS; [140]), provides moderate spatial resolution data at a higher temporal resolution than individual sensors can supply, enabling sub-annual change detection and monitoring (e.g [141]). Yet, high temporal resolution data is often unnecessary, as seasonally averaged climate variables are good predictors of wood and foliage dynamics. The best available pixel (BAP) approach can be used to minimize the phenological variation of spectral indices within the growing season ([142]). There is also an opportunity for supplementing data collection with even finer spatial scale data, including airborne laser scanning, digital aerial photogrammetry, and commercial satellites such as the PlanetScope constellation. Such fine spatial resolution data can enable the understanding of growth processes at the tree level, rather than at the pixel level. For example, georeferencing the sample trees allows the assessment of their local environment within the stand and its impact on their growth [143]. In addition, measuring spectral indices with radiometers mounted directly on the sample trees allows for daily monitoring of reflectance, enabling the assessment of phenology's impact on photosynthetic activity and radial growth [144]. Despite the great potential of these technologies to address questions at both the stand and tree scales, our review of the literature indicates that these techniques are, for now, very rarely used in conjunction with dendrochronology.

Beyond spatial resolution, advances in satellite technology offer new opportunities to better capture forest growth processes. One promising development is the growing use of Synthetic Aperture Radar (SAR), an active form of remote sensing which emits microwave signals and is thus unaffected by cloud cover and can operate day and night, unlike optical sensors [145]. SAR from Sentinel-1 has been widely adopted due to its global coverage, frequent revisit time, high spatial resolution (5–20 m) and free availability. SAR is sensitive to surface roughness, LAI, and forest structure attributes, and its complementarity with optical data suggests potential for integration with tree-ring data [112]. Another opportunity emerges from global LiDAR data aquired by spaceborne platforms including the Global Ecosystem Dynamics Investigation (GEDI; [146]) and the Advanced Topographic Laser Altimeter System (ATLAS) onboard the Ice, Cloud, and land Elevation Satellite 2 (ICESat-2; [147]). The increasing availability of bi- and multitemporal LiDAR datasets enables measuring height growth increment, which presents a marked opportunity to improve forest growth analysis [148].

Ecological Factors Influencing TRW-VI Relationships and Growth Responses to Climate

The variable—and in some cases inexistent—nature of the relationships between TRW and VIs may be explained by ecological drivers not yet considered in the reviewed analyses. Although it is widely recognized that growth patterns are influenced by a variety of ecological factors [11], tree-ring data are rarely supplemented with ecological tree- or plot-level metadata. The correlation between VIs and TRW appears to be strongly (yet, non-exclusively) determined by their climatic dependencies in specific periods of the year [75]. While considerable effort has gone into identifying the timing and duration of the strongest correlations between VIs, TRW and climate, fewer publications have investigated the role of environmental factors that can impact the TRW-VI relationships, as well as their response to climate. The covariates that have been included in such research efforts so far are aspect and elevation (e.g [149])., soil moisture (e.g [132])., species composition (e.g [112])., forest cover (e.g [84])., stand age (e.g [73]). and stand density (e.g [99]).

To better understand the dynamics between VIs, TRW and climate, and to identify the circumstances under which the correlations are strongest, we suggest that future studies collect additional ecological data in ground plots and from individual trees or using complementary sources of data (e.g. topographic wetness, LiDAR structural metrics, soil maps, etc.). Combining these ecological variables with VI and TRW data in multivariate or mixed modeling frameworks would enable the identification of factors influencing the link between growth proxies, as well as their climate sensitivity. Such variables may also explain spatial patterns in the strength of TRW-VI relationships, allowing the mapping of areas where integrated monitoring is effective, and supporting the development of more accurate models of forest growth and climate response.

NDVI Reconstructions

NDVI reconstructions cannot always be reliably expanded spatially, particularly in heterogenous landscapes subject to disturbance. Indeed, the assumption that tree growth in a few undisturbed sites can predict NDVI over large forested areas (e.g [150]). is debatable given the complexity of forest structures and dynamics. As a result, one limitation of NDVI reconstructions is that they should only be applicable to homogenous and undisturbed landscapes, which are rare cases in nature. Also, it is essential to validate the temporal stability of TRW-VI relationships, which might change over time, just as the sensitivity of tree growth to climate is temporally variable [76]. Despite such limitations, reconstructing VI records using TRW data remains a valuable opportunity to explore long-term vegetation dynamics, enabling retrospective analysis of greening and browning trends in response to historical climatic and anthropogenic influences [34].

Physiological Factors Influencing TRW-VI Relationships

One key limitation of combining dendrochronology and remote sensing data is that they measure the growth and condition of two different tree organs (i.e. stem and foliage), which are regulated by physiological processes subject to environmental influence. Therefore, decoupling between TRW and VIs may result from (1) the trade-offs involved in resource allocation to foliage and stem, (2) the different growth curves for stem and crown resulting from the geometry of trees, (3) the capacity of trees to store carbon as reserves to use in subsequent years when needed, or (4) the asynchrony of phenology and carbon uptake in the foliage and wood formation in the stem.

First, there are trade-offs in allocation to primary (height) and secondary (radial) growth. Trees subjected to strong competition within a stand (often in early developmental stages) maximize their competitive fitness by prioritizing light foraging, resulting in increased height and crown growth [151], and in turn enhanced greenness. Because such allocation priority occurs at the expense of other sinks and notably the stem's secondary growth, this may result in the decoupling of VIs and TRW. Additionally, stress events limit carbon inputs, also resulting in the prioritization of foliage restoration, which is essential to maintain metabolism [152]. In fact, the overall low variability in photosynthetic activity and greenness may be explained by the conservative nature of carbon allocation to foliage, which tends to remain stable even under varying resource availability, whereas stem growth is a good indicator of total tree carbon balance as it is sensitive to changes in resources and environment [153].

Second, the various possible measurements of tree organs (i.e. diameter, height, basal area, crown area, stem volume) have different dimensional measures (i.e. length; 1-dimensional, area; 2-dimensional, and volume; 3-dimensional) and thus increase at different rates (i.e. linearly, quadratically and cubically), following allometric equations. Consequently, stem and crown growth don't follow the same curves, and crown growth culminates later than stem diameter growth [154]. This likely results in photosynthetic capacity continuing to increase well after the peak in TRW, which might explain the frequently observed decoupling of TRW and VIs trends. However, stem volume increases continuously with crown area [154], suggesting that total biomass production may be better related to VIs than TRW.

Third, the storage of non-structural carbon following its uptake by the foliage may result in radial growth not being representative of the current season's photosynthetic activity. This is the main reason for the often observed one-year lag in the response of radial growth to climate [40], but non-structural carbon reserves can even be accessed multiple years after their storage and are used when resources are limited, for example following stress events [41].

Fourth, the processes of photosynthesis and stem growth are not necessarily synchronized, although non-structural carbon travels from foliage to stem typically in a few days [6]. This asynchrony between foliage and radial growth peaks can be explained by phenology mismatches [93, 97]. However, it should not significantly impact the interannual relationships between VIs and TRW (see [144]) because TRW represents total growth over the growing season, regardless of the time it took for the carbon to effectively be used for growth. Thus, the maximum value of VIs—or any aggregate value representative of the growing season conditions—should be able to capture this signal. Lags of a few months or more between carbon uptake and accumulation (e.g [67]). are due to non-structural carbon storage, not to the duration of carbon transport [122].

The limited understanding of resource allocation, storage of non-structural carbon, and timing of growth processes provides several research opportunities in the field of tree physiology [10], which are beyond the scope of this review. Regarding the integration of dendrochronology and remote sensing, a research opportunity lies in integrating phenological and radial growth data at the finest possible temporal and spatial scale (i.e. daily measurements of individual trees) using radiometers and point dendrometers mounted on individual trees [144]. This integration would provide a better understanding of how short-term environmental fluctuations influence tree growth, providing an essential link between small-scale physiological processes and larger-scale remote sensing observations.

Most importantly, there is an opportunity to improve forest productivity assessments by integrating the complementary growth processes (i.e. carbon uptake and accumulation) that remote sensing and dendrochronology provide: VIs measure canopy photosynthetic (source) activity and TRW measure meristematic (sink) activity. Recent physiological studies reveal that annual biomass accumulation is often more limited by sink activity than by source activity [59, 155]. Yet most large-scale forest productivity assessments remain built around source-driven models, which can lead to significant overestimation of growth (e.g [61]). Pairing co-located sink and source observations is thus an opportunity for refining models and accurately measuring forest growth and productivity.

Research on Disturbance and Extreme Climatic Events

Linking TRW and VI time series can be challenging in disturbed landscapes. Firstly, subtle impacts on foliage can prevent detection of these events [57]. Secondly, post-disturbance radial growth and spectral trajectories are highly variable, as TRW and VIs often show different patterns following disturbance events. While this can be seen as an issue, it provides a valuable opportunity to better understand the relationships between carbon uptake and accumulation, and the underlying resource allocation mechanisms in the context of disturbance. The complementary TRW and VI time series each capture distinct environmental signals and are subject to different sources of biases. For example, tree-ring data may overestimate forest productivity losses from drought, as cores are often preferentially sampled in marginal site conditions where trees are more vulnerable to climatic stress [156]. In contrast, forest productivity models based on spectral indices may underestimate drought impacts because their inputs for moisture availability are limited to vapor-pressure deficit from climate rasters and do not take soil moisture into account [157]. Such complementarity could be leveraged to refine forest productivity models by integrating both data sources, thereby reducing the bias associated with disturbance impacts on growth.

In addition, the lack of studies focusing on disturbance is a notable problem, as this topic is important in each discipline separately, but accounts for only a small proportion of the interdisciplinary publications reviewed, highlighting a gap in the literature. There is a need for more interdisciplinary studies combining the wall-to-wall monitoring capacity of remote sensing with the precision and sensitivity of tree-rings in the context of forest disturbance. VIs and tree-ring time series can both be used retroactively to study past events, opening a wealth of research potential. This retrospective nature of the data is an opportunity to increase our understanding of the complex ecological processes underlying disturbance and extreme climatic events, and to identify early diagnostic spectral patterns characteristic of vulnerable stands. This would enable the vulnerability of forest stands to be predicted over the landscape using spatially explicit spectral and ecological data (e.g [101])., which is crucial as the frequency and severity of disturbance and climatic events is increasing with global change.

Conclusion

In this review, we demonstrated that dendrochronology and remote sensing offer distinct yet complementary perspectives on forest growth and its response to environmental change. By integrating these two disciplines, the precision and accuracy of forest productivity measurements can be improved by leveraging the duality of growth processes represented by VIs (carbon uptake through photosynthesis) and TRW (carbon accumulation in stem wood). Additionally, their complementary spatial scales allow for upscaling precise measurements across landscapes, and their retrospective nature offers vast research potential. Despite these opportunities, substantial challenges remain; biases in data acquisition, the lack of ecological metadata, and the poor understanding of the physiological mechanisms involved in modulating VIs and TRW relationships. Future work should address these issues in order to produce reliable forest productivity assessments. Ultimately, coupling dendrochronology and remote sensing holds significant promise for advancing our understanding of forest growth under global change. As forests face increasing pressures from climate variability and intensifying disturbance regimes, this interdisciplinary approach will be key to building a more comprehensive forest growth monitoring framework.

Key References

- Vicente-Serrano SM, Camarero JJ, Olano JM, et al. Diverse relationships between forest growth and the Normalized Difference Vegetation Index at a global scale. Remote Sens Environ. 2016; 187:14–29. https://doi.org/10.1016/j.rse.2016.10.001.

  This paper analyzes the global relationship between TRW and NDVI, using a large dataset spanning diverse biomes and species. The study finds that the relationships are highly variable, depending on factors such as climate zone, species, and temporal scale.

- Jevšenak J, Klisz M, Mašek J, et al. Incorporating high-resolution climate, remote sensing and topographic data to map annual forest growth in central and eastern Europe. Science of the Total Environment. 2024; 913:1–14. https://doi.org/10.1016/j.scitotenv.2023.169692.

  This study develops random forest models for predicting growth with climate variables, VIs and topographic data. The species-specific models can explain up to 52% of model variance. This highlights the potential of integrated data sources for mapping annual tree growth.

- Gazol A, Camarero JJ, Vicente-Serrano SM, et al. Forest resilience to drought varies across biomes. Glob Chang

Biol. 2018; 24:2143–2158. https://doi.org/10.1111/gcb.14082.

This paper examines forest resilience to drought across Spain by analyzing tree-ring data from over 500 sites using standardized metrics of resistance, recovery, and resilience. The study finds that forest responses to drought vary significantly across biomes, and that TRW is generally more sensitive to drought than NDVI.

- Levesque M, Andreu-Hayles L, Smith WK, et al. Tree-ring isotopes capture interannual vegetation productivity dynamics at the biome scale. Nat Commun. 2019; 10:742. https://doi.org/10.1038/s41467-019-08634-y.

  This paper compares tree-ring isotope records with NDVI and gross primary productivity (GPP) data across Northeastern America, and shows strong correlations, particularly in moisture-limited environments. This study demonstrates that tree-ring stable isotopes can effectively capture interannual variations in vegetation productivity across broad spatial scales.

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Data Availability Data is provided within the supplementary information file.

Declarations

Competing interests The authors declare no competing interests.

References

1. Pan Y, Birdsey RA, Phillips OL, et al. The enduring world forest carbon sink. Nature. 2024;631:563–9. https://doi.org/10.1038/s41586-024-07602-x.
2. Myneni RB, Dong J, Tucker CJ, et al. A large carbon sink in the Woody biomass of Northern forests. PNAS. 2001;98:14784–9.
3. Piao S, Wang X, Wang K, et al. Interannual variation of terrestrial carbon cycle: issues and perspectives. Glob Chang Biol. 2020;26:300–18. https://doi.org/10.1111/gcb.14884.
4. Achim A, Moreau G, Coops NC, et al. The changing culture of silviculture. Forestry. 2022;95:143–52. https://doi.org/10.1093/forestry/cpab047.
5. Hernández-Blanco M, Costanza R, Chen H, et al. Ecosystem health, ecosystem services, and the well-being of humans and the rest of nature. Glob Chang Biol. 2022;28:5027–40. https://doi.org/10.1111/gcb.16281.
6. Dietze MC, Sala A, Carbone MS, et al. Nonstructural carbon in woody plants. Annu Rev Plant Biol. 2014;65:667–87. https://doi.org/10.1146/annurev-arplant-050213-040054.
7. Lambers H, Chapin FS, Pons TL. Growth and Allocation. Plant Physiological Ecology. 2008; In: Plant Physiological Ecology, 2nd edition. Springer New York, pp 237–246.
8. Hall DO, Rao K, Photosynthesis. Sixth edition. 1999; Cambridge University Press.
9. Farrar JF, Jones DL. The control of carbon acquisition by roots. New Phytol. 2000;147:43–53. https://doi.org/10.1046/j.1469-8137.2000.00688.x.
10. Poorter H, Niklas KJ, Reich PB, et al. Biomass allocation to leaves, stems and roots: Meta-analyses of interspecific variation and environmental control. New Phytol. 2012;193:30–50. https://doi.org/10.1111/j.1469-8137.2011.03952.x.
11. Itter MS, Finley AO, D'Amato AW, et al. Variable effects of climate on forest growth in relation to climate extremes, disturbance, and forest dynamics. Ecol Appl. 2017;27:1082–95. https://doi.org/10.1002/eap.1518.
12. Le Roux X, Lacointe A, Escobar-Gutiérrez A, Le Dizès S. Carbon-based models of individual tree growth: a critical appraisal. Ann Sci. 2001;58:469–506.
13. Fritts H. Tree rings and climate. London: Academic; 1976.
14. Schowengerdt RA. Remote Sensing: models and methods for image processing, Third Edition. 2006; Elsevier.
15. Huete A. Vegetation Indices. Encyclopedia of Remote Sensing. 2014; In: Encyclopedia of Remote Sensing. Springer, New York, NY.
16. Curran PJ. Remote sensing of foliar chemistry. Remote Sens Environ. 1989;30:271–8.
17. Coops NC. Characterizing forest growth and productivity using remotely sensed data. Curr Forestry Rep. 2015;1:195–205. https://doi.org/10.1007/s40725-015-0020-x.
18. Hember RA, Kurz WA, Coops NC. Increasing net ecosystem biomass production of Canada's boreal and temperate forests despite decline in dry climates. Glob Biogeochem Cycles. 2017;31(1):134–58. https://doi.org/10.1002/2016GB005459.
19. Nemani RR, Keeling CD, Hashimoto H, et al. Climate-driven increases in global terrestrial net primary production from 1982

to 1999. Science. 2003;300:1560–3. https://doi.org/10.1126/science.1082750.
20. Sulla-Menashe D, Woodcock CE, Friedl MA. Canadian boreal forest greening and browning trends: an analysis of biogeographic patterns and the relative roles of disturbance versus climate drivers. Environ Res Lett. 2018;13:014007. https://doi.org/10.1088/1748-9326/aa9b88.
21. Boisvenue C, Running SW. Impacts of climate change on natural forest productivity – evidence since the middle of the 20th century. Glob Chang Biol. 2006;12:862–82. https://doi.org/10.1111/j.1365-2486.2006.01134.x.
22. Beck PSA, Goetz SJ. Satellite observations of high Northern latitude vegetation productivity changes between 1982 and 2008: ecological variability and regional differences. Environ Res Lett. 2011;6:045501. https://doi.org/10.1088/1748-9326/7/2/029501.
23. Berner LT, Goetz SJ. Satellite observations document trends consistent with a boreal forest biome shift. Glob Chang Biol. 2022;28:3275–92. https://doi.org/10.1111/gcb.16121.
24. Goetz SJ, Bunn AG, Fiske GJ, Houghton RA. Satellite-observed photosynthetic trends across boreal North America associated with climate and fire disturbance. Proc Natl Acad Sci U S A. 2005;102:13521–5. https://doi.org/10.1073/pnas.0506179102.
25. Guay KC, Beck PSA, Berner LT, et al. Vegetation productivity patterns at high Northern latitudes: a multi-sensor satellite data assessment. Glob Chang Biol. 2014;20:3147–58. https://doi.org/10.1111/gcb.12647.
26. Chagnon C, Wotherspoon AR, Achim A. Deciphering the black Spruce response to climate variation across Eastern Canada using a meta-analysis approach. Ecol Manage. 2022;520:1–9. https://doi.org/10.1016/j.foreco.2022.120375.
27. D'Orangeville L, Duchesne L, Houle D et al. Northeastern North America as a potential refugium for boreal forests in a warming climate. Science (1979). 2016; 352:1452–1456. https://doi.org/10.1126/science.aaf4951
28. Girardin MP, Hogg EH, Bernier PY, et al. Negative impacts of high temperatures on growth of black spruce forests intensify with the anticipated climate warming. Glob Chang Biol. 2016;22:627–43. https://doi.org/10.1111/gcb.13072.
29. Alcaraz-Segura D, Chuvieco E, Epstein HE, et al. Debating the greening vs. browning of the North American boreal forest: differences between satellite datasets. Glob Chang Biol. 2010;16:760–70. https://doi.org/10.1111/j.1365-2486.2009.01956.x.
30. Duchesne L, Houle D, Ouimet R, et al. Large apparent growth increases in boreal forests inferred from tree-rings are an artefact of sampling biases. Sci Rep. 2019;9:6832. https://doi.org/10.1038/s41598-019-43243-1.
31. Marchand W, Girardin MP, Gauthier S, et al. Untangling methodological and scale considerations in growth and productivity trend estimates of Canada's forests. Environ Res Lett. 2018;13:093001. https://doi.org/10.1088/1748-9326/aad82a.
32. Hember RA, Kurz WA, Girardin MP. Tree ring reconstructions of stemwood biomass indicate increases in the growth rate of black spruce trees across boreal forests of Canada. J Geophys Res Biogeosciences. 2019;124:2460–80. https://doi.org/10.1029/2018JG004573.
33. Pearl JK, Keck JR, Tintor W, et al. New frontiers in tree-ring research. Holocene. 2020;30:923–41. https://doi.org/10.1177/0959683620902230.
34. Zhang T, Song J, Fan Y, et al. Vegetation index research on the basis of Tree-Ring data: current status and prospects. Forests. 2023;14:1–17. https://doi.org/10.3390/f14102016.
35. Italiano SSP, Camarero JJ, Colangelo M, et al. Assessing forest vulnerability to climate change combining remote sensing and tree-ring data: issues, needs and avenues. Forests. 2023;14:1–13. https://doi.org/10.3390/f14061138.
36. Bouriaud O, Bréda N, Dupouey JL, Granier A. Is ring width a reliable proxy for stem-biomass increment? A case study in European beech. Can J for Res. 2005;35:2920–33. https://doi.org/10.1139/x05-202.
37. Briffa K, Jones P, Bartholin T, et al. Fennoscandian summers from AD 500: temperature changes on short and long timescales. Clim Dyn. 1992;7:111–9.
38. Fritts HC, Swetnam TW, Dendroecology. A Tool for Evaluating Variations in Past and Present Forest Environments. Adv Ecol Res. 1989; In: Advances in Ecological Research. pp 111–188.
39. Girardin MP, Guo XJ, Bernier PY, et al. Changes in growth of pristine boreal North American forests from 1950 to 2005 driven by landscape demographics and species traits. Biogeosciences. 2012;9:2523–36. https://doi.org/10.5194/bg-9-2523-2012.
40. Monserud RA. Time-series analyses of tree-ring chronologies. For Sci. 1986;32:349–72.
41. Richardson AD, Carbone MS, Keenan TF, et al. Seasonal dynamics and age of stemwood nonstructural carbohydrates in temperate forest trees. New Phytol. 2013;197:850–61. https://doi.org/10.1111/nph.12042.
42. Moreau G, Achim A, Pothier D. An accumulation of Climatic stress events has led to years of reduced growth for sugar maple in Southern Quebec, Canada. Ecosphere. 2020;11:1–15. https://doi.org/10.1002/ecs2.3183.
43. Cook ER. The decomposition of tree-ring series for environmental studies. Tree-Ring Bull. 1987;47:37–59.
44. Nehrbass-ahles C, Babst F, Klesse S. The influence of sampling design on tree-ring-based quantification of forest growth. Glob Chang Biol. 2014;20:2867–85. https://doi.org/10.1111/gcb.12599.
45. Bergeron Y, Denneler B, Charron D, Girardin M-P. Using dendrochronology to reconstruct disturbance and forest dynamics around lake Duparquet, Northwestern Quebec. Dendrochronologia. 2002;20:175–89.
46. Running SW, Nemani RR, Heinsch FA et al. A continuous satellite-derived measure of global terrestrial primary production. Bioscience 2004;54:547–60.
47. Tucker CJ. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens Environ. 1979;8:127–50.
48. Cook EA, Iverson LR, Graham RL. Estimating forest productivity with thematic mapper and biogeographical data. Remote Sens Environ. 1989;28:131–41.
49. Churkina G, Running SW. Contrasting climatic controls on the estimated productivity of global terrestrial biomes. Ecosystems. 1998;1:206–15.
50. Richard Y, Poccard I. A statistical study of NDVI sensitivity to seasonal and interannual rainfall variations in Southern Africa. Int J Remote Sens. 1998;19:2907–20.
51. Zhou L, Kaufmann RK, Tian Y, et al. Relation between interannual variations in satellite measures of Northern forest greenness and climate between 1982 and 1999. J Geophys Res Atmos. 2003;108:4004. https://doi.org/10.1029/2002jd002510.
52. Monteith JL. Climate and the efficiency of crop production in Britain. Phil Trans R Soc Lond B. 1977;281:277–94.
53. de Jong R, Verbesselt J, Schaepman ME, de Bruin S. Trend changes in global greening and browning: contribution of short-term trends to longer-term change. Glob Chang Biol. 2012;18:642–55. https://doi.org/10.1111/j.1365-2486.2011.02578.x.
54. Stow D, Petersen A, Hope A, et al. Greenness trends of Arctic tundra vegetation in the 1990s: comparison of two NDVI data sets from NOAA AVHRR systems. Int J Remote Sens. 2007;28:4807–22. https://doi.org/10.1080/01431160701264284.
55. Cohen WB, Yang Z, Healey SP, et al. A landtrendr multispectral ensemble for forest disturbance detection. Remote Sens Environ. 2018;205:131–40. https://doi.org/10.1016/j.rse.2017.11.015.

56. Hermosilla T, Wulder MA, White JC, et al. An integrated Landsat time series protocol for change detection and generation of annual gap-free surface reflectance composites. Remote Sens Environ. 2015;158:220–34. https://doi.org/10.1016/j.rse.2014.11.005.
57. Brown MS, Coops NC, Mulverhill C, Achim A. Detection of non-stand replacing disturbances (NSR) using harmonized Landsat-Sentinel-2 time series. ISPRS J Photogramm Remote Sens. 2025;220:264–76. https://doi.org/10.1016/j.isprsjprs.2024.12.014.
58. West H, Quinn N, Horswell M. Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. Remote Sens Environ. 2019;232:111291. https://doi.org/10.1016/j.rse.2019.111291.
59. Fatichi S, Leuzinger S, Körner C. Moving beyond photosynthesis: from carbon source to sink-driven vegetation modeling. New Phytol. 2014;201:1086–95. https://doi.org/10.1111/nph.12614.
60. Wiley E, Helliker B. A re-evaluation of carbon storage in trees lends greater support for carbon limitation to growth. New Phytol. 2012;195:285–9. https://doi.org/10.1111/j.1469-8137.2012.04180.x.
61. Leuzinger S, Manusch C, Bugmann H, Wolf A. A sink-limited growth model improves biomass estimation along boreal and alpine tree lines. Glob Ecol Biogeogr. 2013;22:924–32. https://doi.org/10.1111/geb.12047.
62. Berner LT, Beck PSA, Bunn AG, et al. High-latitude tree growth and satellite vegetation indices: correlations and trends in Russia and Canada (1982–2008). J Geophys Res. 2011;116(G1):1–13. https://doi.org/10.1029/2010JG001475.
63. Leavitt SW, Chase TN, Rajagopalan B, et al. Southwestern U.S. tree-ring carbon isotope indices as a possible proxy for reconstruction of greenness of vegetation. Geophys Res Lett. 2008;35:1–5. https://doi.org/10.1029/2008GL033894.
64. Lopatin E, Kolström T, Spiecker H. Determination of forest growth trends in Komi Republic (northwestern Russia): combination of tree-ring analysis and remote sensing data. Boreal Environ Res. 2006;11:341–53.
65. Vicente-Serrano SM, Camarero JJ, Olano JM, et al. Diverse relationships between forest growth and the normalized difference vegetation index at a global scale. Remote Sens Environ. 2016;187:14–29. https://doi.org/10.1016/j.rse.2016.10.001.
66. Tei S, Sugimoto A. Time lag and negative responses of forest greenness and tree growth to warming over circumboreal forests. Glob Chang Biol. 2018;24:4225–37. https://doi.org/10.1111/gcb.14135.
67. Wong CYS, Young DJN, Latimer AM, et al. Importance of the legacy effect for assessing Spatiotemporal correspondence between interannual tree-ring width and remote sensing products in the Sierra Nevada. Remote Sens Environ. 2021;265:1–12. https://doi.org/10.1016/j.rse.2021.112635.
68. Beck PSA, Andreu-Hayles L, D'Arrigo R, et al. A large-scale coherent signal of canopy status in maximum latewood density of tree rings at Arctic treeline in North America. Glob Planet Change. 2013;100:109–18. https://doi.org/10.1016/j.gloplacha.2012.10.005.
69. del Castillo J, Voltas J, Ferrio JP. Carbon isotope discrimination, radial growth, and NDVI share spatiotemporal responses to precipitation in Aleppo pine. Trees. 2015;29:223–33. https://doi.org/10.1007/s00468-014-1106-y.
70. Liang E, Eckstein D, Liu H. Assessing the recent grassland greening trend in a long-term context based on tree-ring analysis: a case study in North China. Ecol Indic. 2009;9:1280–3. https://doi.org/10.1016/j.ecolind.2009.02.007.
71. Coulthard BL, Touchan R, Anchukaitis KJ, et al. Tree growth and vegetation activity at the ecosystem-scale in the Eastern Mediterranean. Environ Res Lett. 2017;12:084008. https://doi.org/10.1088/1748-9326/aa7b26.
72. Peña-Gallardo M, Vicente-Serrano SM, Camarero JJ, et al. Drought sensitiveness on forest growth in Peninsular Spain and the Balearic Islands. Forests. 2018;9:524. https://doi.org/10.3390/f9090524.
73. Correa-Díaz A, Silva LCR, Horwath WR, et al. Linking remote sensing and dendrochronology to quantify climate-induced shifts in high-elevation forests over space and time. J Geophys Res Biogeosciences. 2019;124:166–83. https://doi.org/10.1029/2018JG004687.
74. Pasho E, Alla AQ. Climate impacts on radial growth and vegetation activity of two co-existing mediterranean pine species. Can J for Res. 2015;45:1748–56. https://doi.org/10.1139/cjfr-2015-0146.
75. Kaufmann RK, D'Arrigo RD, Paletta LF, et al. Identifying climatic controls on ring width: the timing of correlations between tree rings and NDVI. Earth Interact. 2008;12(14):1–14. https://doi.org/10.1175/2008EI263.1.
76. Peltier D, Ogle K. Tree growth sensitivity to climate is temporally variable. Ecol Lett. 2020;23:1561–72. https://doi.org/10.1111/ele.13575.
77. Andreu-Hayles L, D'Arrigo R, Anchukaitis KJ, et al. Varying boreal forest response to Arctic environmental change at the Firth River, Alaska. Environ Res Lett. 2011;045503. https://doi.org/10.1088/1748-9326/6/4/045503.
78. Kaufmann RK, D'Arrigo RD, Laskowski C, et al. The effect of growing season and summer greenness on Northern forests. Geophys Res Lett. 2004;31:1–4. https://doi.org/10.1029/2004GL019608.
79. Liang EY, Shao XM, He JC. Relationships between tree growth and NDVI of grassland in the semi-arid grassland of North China. Int J Remote Sens. 2005;26:2901–8. https://doi.org/10.1080/01431160500056931.
80. He J, Shao X. Relationships between tree-ring width index and NDVI of grassland in Delingha. Chin Sci Bull. 2006;51:1106–14. https://doi.org/10.1007/s11434-006-1106-4.
81. Bonney MT, He Y. Temporal connections between long-term Landsat time-series and tree-rings in an urban–rural temperate forest. Int J Appl Earth Obs Geoinf. 2021;103:1. https://doi.org/10.1016/j.jag.2021.102523.
82. Wang J, Rich PM, Price KP, Kettle WD. Relations between NDVI and tree productivity in the central Great Plains. Int J Remote Sens. 2004;25:3127–38. https://doi.org/10.1080/0143116032000160499.
83. Coops N, Bi H, Barnett P, Ryan P. Estimating mean and current annual increments of stand volume in a regrowth eucalypt forest using historical Landsat multi spectral scanner imagery. J Sustain For. 1999;9:149–68. https://doi.org/10.1300/J091v09n03_07.
84. Brehaut L, Danby RK. Inconsistent relationships between annual tree ring-widths and satellite-measured NDVI in a mountainous subarctic environment. Ecol Indic. 2018;91:698–711. https://doi.org/10.1016/j.ecolind.2018.04.052.
85. Girardin MP, Bouriaud O, Hogg EH, et al. No growth stimulation of Canada's boreal forest under half-century of combined warming and CO2 fertilization. Proc Natl Acad Sci U S A. 2016;113:8406–14. https://doi.org/10.1073/pnas.1610156113.
86. Wen Y, Jiang Y, Jiao L, et al. Inconsistent relationships between tree ring width and normalized difference vegetation index in montane evergreen coniferous forests in arid regions. Trees. 2022;36:379–91. https://doi.org/10.1007/s00468-021-02211-x.
87. Correa-Díaz A, Romero-Sánchez ME, Villanueva-Díaz J. The greening effect characterized by the normalized difference vegetation index was not coupled with phenological trends and tree growth rates in eight protected mountains of central Mexico. Ecol Manage. 2021;496:1–12. https://doi.org/10.1016/j.foreco.2021.119402.

88. Beck PSA, Juday GP, Alix C, et al. Changes in forest productivity across Alaska consistent with biome shift. Ecol Lett. 2011;14:373–9. https://doi.org/10.1111/j.1461-0248.2011.01598.x.
89. Wei M, Jiao L, Zhang P, et al. Spatio-Temporal diversity in the link between tree radial growth and remote sensing vegetation index of Qinghai Spruce on the Northeastern margin of the Tibetan plateau. Forests. 2023;14:1–19. https://doi.org/10.3390/f14020260.
90. Meyer BF, Buras A, Rammig A, Zang CS. Higher susceptibility of Beech to drought in comparison to oak. Dendrochronologia (Verona). 2020;64:1–10. https://doi.org/10.1016/j.dendro.2020.125780.
91. Gazol A, Camarero JJ, Vicente-Serrano SM, et al. Forest resilience to drought varies across biomes. Glob Chang Biol. 2018;24:2143–58. https://doi.org/10.1111/gcb.14082.
92. Lloret F, Keeling EG, Sala A. Components of tree resilience: effects of successive low-growth episodes in old Ponderosa pine forests. Oikos. 2011;120:1909–20. https://doi.org/10.1111/j.1600-0706.2011.19372.x.
93. Kannenberg SA, Novick KA, Alexander MR, et al. Linking drought legacy effects across scales: from leaves to tree rings to ecosystems. Glob Chang Biol. 2019;25:2978–92. https://doi.org/10.1111/gcb.14710.
94. Camarero JJ, Franquesa M, Sangüesa-Barreda G. Timing of drought triggers distinct growth responses in Holm oak: implications to predict warming-induced forest defoliation and growth decline. Forests. 2015;6:1576–97. https://doi.org/10.3390/f6051576.
95. Babst F, Esper J, Parlow E. Landsat TM/ETM+and tree-ring based assessment of spatiotemporal patterns of the autumnal moth (*Epirrita autumnata*) in northernmost Fennoscandia. Remote Sens Environ. 2010;114:637–46. https://doi.org/10.1016/j.rse.2009.11.005.
96. DeRose RJ, Long JN, Ramsey RD. Combining dendrochronological data and the disturbance index to assess Engelmann spruce mortality caused by a spruce beetle outbreak in Southern Utah, USA. Remote Sens Environ. 2011;115:2342–9. https://doi.org/10.1016/j.rse.2011.04.034.
97. Castellaneta M, Rita A, Camarero JJ, et al. Declines in canopy greenness and tree growth are caused by combined climate extremes during drought-induced dieback. Sci Total Environ. 2022;813:1–12. https://doi.org/10.1016/j.scitotenv.2021.152666.
98. Crespo-Antia JP, Gazol A, Pizarro M, et al. Matching vegetation indices and tree Vigor in pyrenean silver Fir stands. Remote Sens (Basel). 2024;16:1–16. https://doi.org/10.3390/rs16234564.
99. Dorman M, Svoray T, Perevolotsky A, et al. What determines tree mortality in dry environments? A multi-perspective approach. Ecol Appl. 2015;25:1054–71. https://doi.org/10.1890/14-0698.1.
100. Moreno-Fernández D, Julio Camarero J, García M, et al. The interplay of the tree and Stand-Level processes mediate Drought-Induced forest dieback: evidence from complementary remote sensing and tree-Ring approaches. Ecosystems. 2022;25:1738–53. https://doi.org/10.1007/s10021-022-0079.
101. Morin-Bernard A, Achim A, Coops NC, White JC. Integration of tree-ring data, Landsat time series, and ALS-derived topographic variables to quantify growth declines in black Spruce. Ecol Manage. 2024;557:1–18. https://doi.org/10.1016/j.foreco.2024.121765.
102. Wang Z, Lyu L, Liu W, et al. Topographic patterns of forest decline as detected from tree rings and NDVI. Catena (Amst). 2021;198:1–9. https://doi.org/10.1016/j.catena.2020.105011.
103. Babst F, Bodesheim P, Charney N, et al. When tree rings go global: challenges and opportunities for retro- and prospective insight. Quat Sci Rev. 2018;197:1–20. https://doi.org/10.1016/j.quascirev.2018.07.009.
104. Stokes MA, Smiley TL. An introduction to tree-ring dating. 1996; University of Arizona.
105. DeRose RJ, Shaw JD, Long JN. Building the forest inventory and analysis tree-ring data set. J Forest. 2017;115:283–91. https://doi.org/10.5849/jof.15-097.
106. Duchesne L, D'Orangeville L, Ouimet R, et al. Extracting coherent tree-ring Climatic signals across Spatial scales from extensive forest inventory data. PLoS ONE. 2017;12:1–20. https://doi.org/10.1371/journal.pone.0189444.
107. Grissino-Mayer HD, Fritts HC. The international tree-ring data bank: an enhanced global database serving the global scientific community. Holocene. 1997;7:235–8.
108. Zhao S, Pederson N, D'Orangeville L, et al. The International Tree-Ring Data Bank (ITRDB) revisited: Data availability and global ecological representativity. J Biogeogr. 2019;46:355–68. https://doi.org/10.1111/jbi.13488
109. Larson ER, Allen S, Flinner NL, et al. The need and means to update chronologies in a dynamic environment. Tree-Ring Research. 2013;69:21–7. https://doi.org/10.3959/1536-1098-69.1.21.
110. Bhuyan U, Zang C, Vicente-Serrano SM, Menzel A. Exploring relationships among tree-ring growth, climate variability, and seasonal leaf activity on varying timescales and Spatial resolutions. Remote Sens (Basel). 2017;9:1–13. https://doi.org/10.3390/rs9060526.
111. Seftigen K, Frank DC, Björklund J, et al. The climatic drivers of normalized difference vegetation index and tree-ring-based estimates of forest productivity are spatially coherent but temporally decoupled in Northern hemispheric forests. Glob Ecol Biogeogr. 2018;27:1352–65. https://doi.org/10.1111/geb.12802.
112. Jevšenak J, Klisz M, Mašek J, et al. Incorporating high-resolution climate, remote sensing and topographic data to map annual forest growth in central and Eastern Europe. Sci Total Environ. 2024;913:1–14. https://doi.org/10.1016/j.scitotenv.2023.169692.
113. Vicente-Serrano SM, Martín-Hernández N, Camarero JJ, et al. Linking tree-ring growth and satellite-derived gross primary growth in multiple forest biomes. Temporal-scale matters. Ecol Indic. 2020;108:1–12. https://doi.org/10.1016/j.ecolind.2019.105753.
114. Levesque M, Andreu-Hayles L, Smith WK, et al. Tree-ring isotopes capture interannual vegetation productivity dynamics at the biome scale. Nat Commun. 2019;10:742. https://doi.org/10.1038/s41467-019-08634-y.
115. Bumann E, Awada T, Wardlow B, et al. Assessing responses of *Betula papyrifera* to climate variability in a remnant population along the Niobrara River Valley in Nebraska, U.S.A., through dendroecological and remote-sensing techniques. Can J for Res. 2019;49:423–33. https://doi.org/10.1139/cjfr-2018-0206.
116. Erasmi S, Klinge M, Dulamsuren C, et al. Modelling the productivity of Siberian larch forests from Landsat NDVI time series in fragmented forest stands of the Mongolian forest-steppe. Environ Monit Assess. 2021;193:200. https://doi.org/10.1007/s10661-021-08996-1.
117. Xu K, Wang X, Liang P, et al. Tree-ring widths are good proxies of annual variation in forest productivity in temperate forests. Sci Rep. 2017;7:1945. https://doi.org/10.1038/s41598-017-02022-6.
118. Cracknell AP. Advanced very high resolution radiometer AVHRR. 1st ed. London: CRC; 1997.
119. D'Arrigo R, Jacoby GC, Free RM. Tree-ring width and maximum latewood density at the North American tree line: parameters of Climatic change. Can J for Res. 1992;22:1290–6.
120. Leblanc D. Relationships between breast-height and whole-stem growth indices for red Spruce on whiteface Mountain, new York. Can J for Res. 1990;20:1399–407.

121. Farquhar GD, Ehleringer IJR, Hubick KT. Carbon isotope discrimination and photosynthesis. Annu Rev Plant Physiol Plant Mol Biol. 1989;40:503–37.
122. Michelot A, Simard S, Rathgeber C, et al. Comparing the intra-annual wood formation of three European species (*Fagus sylvatica*, *Quercus petraea* and *Pinus sylvestris*) as related to leaf phenology and non-structural carbohydrate dynamics. Tree Physiol. 2012;32:1033–45. https://doi.org/10.1093/treephys/tps052.
123. Jiang Z, Huete AR, Didan K, Miura T. Development of a two-band enhanced vegetation index without a blue band. Remote Sens Environ. 2008;112:3833–45. https://doi.org/10.1016/j.rse.2008.06.006.
124. Asner GP, Scurlock JMO, Hicke JA. Global synthesis of leaf area index observations: implications for ecological and remote sensing studies. Glob Ecol Biogeogr. 2003;12:191–205. https://doi.org/10.1046/j.1466-822X.2003.00026.x.
125. Horler DNH, Dockray M, Barber J. The red edge of plant leaf reflectance. Int J Remote Sens. 1983;4:273–88. https://doi.org/10.1080/01431168308948546.
126. Madonsela S, Cho MA, Naidoo L, et al. Exploring the utility of Sentinel-2 for estimating maize chlorophyll content and leaf area index across different growth stages. J Spatial Sci. 2021;68:339–51. https://doi.org/10.1080/14498596.2021.2000898.
127. Crist EP, Cicone RC. The utility of the tasseled cap concept to simulated thematic mapper data. Photogramm Eng Remote Sens. 1984;50:343–52.
128. Xue J, Su B. Significant remote sensing vegetation indices: a review of developments and applications. J Sens. 2017;2017:1–17. https://doi.org/10.1155/2017/1353691.
129. Cook ER, Kairiukstis LA. Methods of dendrochronology: applications in environmental sciences.1990; Springer Science & Business Media
130. Helama S, Melvin TM, Briffa KR. Regional curve standardization: state of the art. Holocene. 2017;27:172–7. https://doi.org/10.1177/0959683616652709.
131. Peters RL, Groenendijk P, Vlam M, Zuidema PA. Detecting long-term growth trends using tree rings: a critical evaluation of methods. Glob Chang Biol. 2015;21:2040–54. https://doi.org/10.1111/gcb.12826.
132. Mašek J, Tumajer J, Lange J, et al. Variability in Tree-ring width and NDVI responses to climate at a landscape level. Ecosystems. 2023;26:1144–57. https://doi.org/10.1007/s10021-023-0082.
133. Montoya-Jiménez LR, Gómez-Guerrero A, Pedraza-Oropeza FJA, et al. Short-term tree-ring series of *Pinus hartwegii* Lindl. taken at ground level correlate to normalized difference vegetation index series. Forests. 2024;15:324. https://doi.org/10.3390/f15020324.
134. Shi H, Peng X, Zhou YJ, et al. Resilience and response: unveiling the impacts of extreme droughts on forests through integrated dendrochronological and remote sensing analyses. Forest Ecosystems. 2024;11:100209. https://doi.org/10.1016/j.fecs.2024.100209.
135. Decuyper M, Chávez RO, Čufar K, et al. Spatio-temporal assessment of Beech growth in relation to climate extremes in Slovenia – an integrated approach using remote sensing and tree-ring data. Agric For Meteorol. 2020;287:107925. https://doi.org/10.1016/j.agrformet.2020.107925.
136. Scholes RJ. Taking the mumbo out of the jumbo: progress towards a robust basis for ecological scaling. Ecosystems. 2017;20:4–13. https://doi.org/10.1007/s10021-016-0047-2.
137. Mérian P, Lebourgeois F. Consequences of decreasing the number of cored trees per plot on chronology statistics and climate-growth relationships: a multispecies analysis in a temperate climate. Can J for Res. 2011;41:2413–22. https://doi.org/10.1139/X11-149.
138. D'arrigo RD, Malmstrom CM, Jacoby GC, et al. Correlation between maximum latewood density of annual tree rings and NDVI based estimates of forest productivity. Int J Remote Sens. 2000;21:2329–36.
139. Coops NC, White JD, Scott NA. Estimating fragmentation effects on simulated forest net primary productivity derived from satellite imagery. Int J Remote Sens. 2004;25:819–38. https://doi.org/10.1080/0143116031000115094.
140. Claverie M, Ju J, Masek JG, et al. The harmonized Landsat and Sentinel-2 surface reflectance data set. Remote Sens Environ. 2018;219:145–61. https://doi.org/10.1016/j.rse.2018.09.002.
141. Mulverhill C, Coops NC, White JC, et al. Evaluating the potential for continuous update of enhanced forest inventory attributes using optical satellite data. Forestry. 2024;98:253–65. https://doi.org/10.1093/forestry/cpae029.
142. White JC, Wulder MA, Hobart GW, et al. Pixel-based image compositing for large-area dense time series applications and science. Can J Remote Sens. 2014;40:192–212. https://doi.org/10.1080/07038992.2014.945827.
143. Irwin LAK, Coops NC, Riofrío J, et al. Prioritizing commercial thinning: quantification of growth and competition with high-density drone laser scanning. Forestry. 2025;98:293–307. https://doi.org/10.1093/forestry/cpae030.
144. Eitel JUH, Griffin KL, Boelman NT, et al. Remote sensing tracks daily radial wood growth of evergreen needleleaf trees. Glob Chang Biol. 2020;26:4068–78. https://doi.org/10.1111/gcb.15112.
145. Moreira A, Prats-Iraola P, Younis M, et al. A tutorial on synthetic aperture radar. IEEE Geosci Remote Sens Mag. 2013;1:6–43. https://doi.org/10.1109/MGRS.2013.2248301.
146. Dubayah R, Blair JB, Goetz S, et al. The global ecosystem dynamics investigation: high-resolution laser ranging of the earth's forests and topography. Sci Remote Sens. 2020;1:100002. https://doi.org/10.1016/j.srs.2020.100002.
147. Neumann TA, Martino AJ, Markus T, et al. The Ice, Cloud, and land elevation Satellite – 2 mission: A global geolocated photon product derived from the aadvanced Ttopographic Llaser Aaltimeter ssystem. Remote Sens Environ. 2019;233:111325. https://doi.org/10.1016/j.rse.2019.111325.
148. Tompalski P, Coops NC, White JC et al. Estimating changes in forest attributes and enhancing growth projections: a review of existing approaches and future directions using airborne 3D point cloud data. Curr Forestry Rep. 2021;7: 25-30 .
149. Correa-Díaz A, Gómez-Guerrero A, Vargas-Hernández JJ, et al. Long-term wood micro-density variation in alpine forests at central Mexico and their spatial links with remotely sensed information. Forests. 2020;11:452. https://doi.org/10.3390/F11040452.
150. Wang H, Chen F, Zhang R, Qin L. Seasonal dynamics of vegetation of the central Loess Plateau (China) based on tree rings and their relationship to climatic warming. Environ Dev Sustain. 2017;19:2535–46. https://doi.org/10.1007/s10668-016-9870-z.
151. Weiner J. Allocation, plasticity and allometry in plants. Perspect Plant Ecol Evol Syst. 2004;6:207–15.
152. Nakajima H. Refoliation of deciduous canopy trees following severe insect defoliation: comparison of *Fagus crenata* and *Quercus crispula*. Plant Ecol. 2018;219:665–75. https://doi.org/10.1007/s11258-018-0825-3.
153. Litton CM, Raich JW, Ryan MG. Carbon allocation in forest ecosystems. Glob Chang Biol. 2007;13:2089–109. https://doi.org/10.1111/j.1365-2486.2007.01420.x.
154. Pretzsch H. The course of tree growth. Theory and reality. Ecol Manage. 2020;478:118508. https://doi.org/10.1016/j.foreco.2020.118508.
155. Körner C. Paradigm shift in plant growth control. Curr Opin Plant Biol 2015;25:107–14.

156. Klesse S, DeRose RJ, Guiterman CH, et al. Sampling bias overestimates climate change impacts on forest growth in the Southwestern United States. Nat Commun. 2018;9:5336. https://doi.org/10.1038/s41467-018-07800-y.
157. Stocker BD, Zscheischler J, Keenan TF, et al. Drought impacts on terrestrial primary production underestimated by satellite monitoring. Nat Geosci. 2019;12(4):264–70. https://doi.org/10.1038/s41561-019-0318-6.
158. Charney ND, Babst F, Poulter B, et al. Observed forest sensitivity to climate implies large changes in 21st century North American forest growth. Ecol Lett. 2016;19:1119–28. https://doi.org/10.1111/ele.12650.
159. Babst F, Bouriaud O, Poulter B, et al. Twentieth century redistribution in Climatic drivers of global tree growth. Sci Adv. 2019;5:1–9. https://doi.org/10.1126/sciadv.aat4313.
160. Huang JG, Bergeron Y, Denneler B, et al. Response of forest trees to increased atmospheric CO2. Crit Rev Plant Sci. 2007;26:265–83. https://doi.org/10.1080/07352680701626978.