forests

Review

Evaluating the Research Status of the Remote Sensing-Mediated Monitoring of Forest Biomass: A Bibliometric Analysis of WOS

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Abstract: Forests serve as the largest carbon reservoir in terrestrial ecosystems, playing a crucial role in mitigating global warming and achieving the goal of "carbon neutrality". Forest biomass is intrinsically related to carbon sinks and sources in forest ecosystems, and thus, the accurate monitoring of forest biomass is of great significance in ensuring ecological security and maintaining the global carbon balance. Significantly, remote sensing is not only able to estimate forest biomass at a large spatial scale but does so quickly, accurately, and without loss. Moreover, it can obtain forest biomass in areas inaccessible to human beings, which have become the main data source for forest biomass estimation at present. For this reason, this study analyzes the current research status, research hotspots, and future research trends in the field of remote sensing monitoring of forest biomass based on 1678 forest biomass remote sensing monitoring results from 1985 to 2023 obtained from the Web of Science Core Collection database. The results showed that the following: (1) The number of publications showed an exponential upward trend from 1985 to 2023, with an average annual growth rate of 2.64%. The top ten journals contributed to 53.76% of the total number of publications and 52.89% of the total number of citations in the field. (2) In particular, *Remote Sensing of Environment* has maintained a leading position in the field for an extended period, boasting the highest impact factor. Additionally, the author Saatchi S. stands out with the highest total number of citations for articles. (3) Keyword clustering analysis revealed that the main research topics in the remote sensing monitoring of forest biomass can be categorized into the following: optical remote sensing, LiDAR remote sensing, SAR remote sensing, and carbon stock. The explosion of keywords in the last six years indicates that an increasing number of researchers are focusing on carbon, airborne LiDAR data, biomass mapping, and constructing optimal biomass models.

Keywords: bibliometric analysis; forests; biomass; remote sensing; Web of Science

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1. Introduction

Forests are the largest carbon reservoirs in terrestrial ecosystems, storing more than 70% of the carbon in these systems [1]. Remarkably, it has been reported that forests globally can offset more than 25% of anthropogenic carbon emissions annually, establishing themselves as an important guarantee for mitigating atmospheric CO_2 concentrations and achieving the goal of "carbon neutrality" [2]. Additionally, forest biomass serves as a source of nutrients for the entire forest ecosystem and is closely related to the carbon sinks and sources within it [3,4]. Therefore, the accurate monitoring of forest biomass is crucial for ensuring ecological security, maintaining the global carbon balance, and preparing for future climate change [5,6].

Traditional forest biomass estimation primarily utilizes methods such as the clearcut method, standard timber method, and regression method [7]. While these traditional methods boast higher accuracy, they are plagued by drawbacks: they are time-consuming and labor-intensive, cannot facilitate continuous, large-scale monitoring, and are notably destructive to the ecological environment [8]. In contrast, remote sensing emerges as a superior alternative, offering quick, accurate, non-destructive large-scale forest biomass estimation. Moreover, it can access forest biomass in areas otherwise unreachable by humans, thus becoming the main data source for forest biomass estimation. Remote sensing technology varies according to the type of sensor used, and can be classified into optical remote sensing [1], radar remote sensing (SAR) [9], and light detection and ranging (LiDAR) remote sensing [10]. Each type of remote sensing datum presents unique strengths and limitations in forest biomass estimation [11]. Optical remote sensing, the most widely used type, is susceptible to weather influences and prone to the "saturation" phenomenon in high-biomass areas [10]. Conversely, SAR remote sensing overcomes weather-related limitations, providing insights into the forest canopy level and vertical structure, making it a promising data source for biomass inversion [12]. However, SAR's effectiveness varies with different wavelengths, each having its own saturation points [10]. Meanwhile, SAR is sensitive to moisture. In comparison, LiDAR, unlike optical images and SAR backscattering coefficients, avoids the saturation effect in high-biomass and structurally complex forest areas [13]. Yet, the limitations of LiDAR lie in its limited scope and higher cost of data acquisition.

Forest biomass is not only a key indicator for assessing forest health, carbon sequestration capacity, and productivity, but also an important variable for quantifying forest structure and function [14]. It encompasses aboveground biomass (branches and leaves) and belowground biomass (roots), representing the accumulation of annual net primary production over the plants' life cycle in a forest [15]. Typically, the longer a forest exists, the more biomass it tends to accumulate. Due to the challenge of obtaining below-ground biomass in the field, previous remote sensing forest biomass monitoring primarily focused on above-ground biomass, with below-ground biomass mostly estimated using the ratio coefficient of above-ground to below-ground biomass. To estimate forest biomass based on remote sensing data, regression models or machine learning methods are often employed to construct forest biomass models. These models are then synergized with remote sensing data to quantitatively invert forest biomass [16–18]. As a field of significant research value and potential, the application of remote sensing technology in studying forest biomass has emerged as a prevalent approach. Consequently, the results of related studies have garnered considerable attention from researchers.

Although a significant volume of studies on the remote sensing monitoring of forest biomass have been published, a comprehensive analysis of research hotspots and future development trends in this area remains insufficiently explored. Bibliometric analysis can effectively review research hotspots, trends, and even predict future directions in a research field [19]. This approach enables researchers to both quantitatively and qualitatively analyze the published literature, exploring underlying structures and deep mechanisms [20]. Given the continuous development of bibliometric analysis software such as CiteSpace [21], Bibliometrix R-package [22], and VOSviewer [23], bibliometrics has become increasingly popular among researchers. Concerning the analyzed tools, Bibliometrix contains a more extensive set of techniques and is suitable for practitioners due to Biblioshiny [24,25]. VOSviewer has fantastic visualization and is capable of loading and exporting information from many sources [25,26]. CiteSpace is a freely available software tool for analyzing, detecting, and visualizing trends and patterns in the scientific literature [27,28]. In this context, this study's metrological visualization and analysis of literature related to the remote sensing monitoring of forest biomass aims to shed light on the current research status and emerging trends in this domain. Furthermore, it aspires to provide a robust scientific reference for future research on the remote sensing monitoring of forest biomass.

2. Materials and Methods

2.1. Data Sources

The data used in this study were obtained from the Web of Science (WOS) Core Collection database. The literature search was conducted on 8 January 2024, and the following parameters were set for the topic search to ensure that an accurate dataset was obtained: TS = ("forest biomass*" or "tree biomass*" or "forest aboveground biomass*" or "plantation* biomass*") and TS = ("remote sensing*" or "RS" or "LiDAR" or "SAR" or "optical"). The language was set to English. The publication type was set to "articles" and "review articles". In total, 1678 publications were retrieved, including 1623 articles and 55 review articles, and the selected publications were exported in text format, containing the title, year, author, keywords, abstract, country, citation, and other details of each publication.

2.2. Methods

Bibliometric analysis can scientifically map trends in the evolution of topics in the field, identify emerging topics, and predict future research directions via searching and analyzing publications, literature sources, and references. In this study, 1678 works from the literature related to the remote sensing monitoring of forest biomass were visualized, analyzed, and data-mined using Citespace 5.7.R 5, Bibliometrix 4.1.4 R-package, VOSviewer 1.6.20, and Microsoft Excel 365. Among them, Bibliometrix 4.1.4 R-package is a web-based online open-source tool written in R, which developed by Massimo Aria from the University of Naples Federico II in the Italy. VOSviewer 1.6.20 is a freely available text mining software developed by Van Eck and Waltman (Leiden University) in the Netherlands. Citespace 5.7.R 5 is a powerful document visualization analysis software invented by Chaomei Chen in the United States of America.

The obtained publication information was imported into the Bibliometrix 4.1.4 interface in order to facilitate the analysis of the number of publications, citations, journals, and authors, and of the institutional information, per year. Performance analysis can be utilized to assess the contribution of authors, institutions, countries, and journals to the volume of publications in the field. In this study, the growth of publications from 1985 to 2023 was revealed by counting the number of published articles annually using Excel 365. CiteSpace 5.7.R 5 was used to draw a knowledge graph of the remote sensing monitoring of forest biomass and obtain the co-occurrence network, intellectual base, and research hotspots related to it, so as to provide reference for objectively understanding the research conducted in this field. Keywords are the core vocabulary of a publication and can reflect the topic of the paper. Co-occurrence was defined as the number of times that two terms emerged in the same paper. Keyword co-occurrence analysis involved calculating the occurrences of the author keywords extracted from the collected 1678 papers using VOSviewer 1.6.20. Keyword theme evolution can be used to show the research hotspots in different periods; in this study, Bibliometrix 4.1.4 software was used to clearly explore the past research shifts and future trends of keywords by dividing the time slices into four periods (1985–2000, 2001–2008, 2009–2016, and 2017–2023). Keyword outbreak can be used to reveal the more popular topics in recent years, based on Citespace 5.7.R 5 software, to obtain the top 20 keywords; from this, important keywords that have exploded in the last 6 years were analyzed.

3. Results

3.1. Basic Characteristics of the Publication

3.1.1. Quantity of Publication and Citations

The number of published papers reflects, to some extent, the year-to-year changes and future trends of research topics. The year-to-year trend of the number of publications related to the remote sensing monitoring of forest biomass obtained from WOS is shown in Figure 1. The horizontal axis indicates the year, and the vertical axis indicates the number of publications and the number of citations [28]. With the launch of the first civilian SAR satellite (Seasat) in 1978, the application of SAR for monitoring in various fields was promoted. Schreier et al. (1984) [29] determined, in a terrain mapping study in Canada, that airborne LiDAR data would be useful for vegetation canopy height determination. This discovery propelled the future application of airborne LiDAR in forest biomass monitoring. The purpose of the Copernicus program is to achieve global, continuous, high-quality, large-scale Earth observation capabilities, providing accurate, timely, and easily accessible information to understand and mitigate climate change. With the implementation of the Copernicus program in 2011, it has spurred a wave of interest in forest biomass monitoring. With the publication of the first relevant article on the topic in 1985 ('Remote sensing forest biomass: an evaluation using high resolution remote sensor data and loblolly pine plots'), the curtain was raised on the remote sensing monitoring of forest biomass. An exponential fit (Figure 1, R^2 = 0.9152) to the number of publications indicated an exponential upward trend in the number of publications from 1985 to 2023. In addition, in terms of the number of publications, there were two inflection points in the publication of forest biomass remote sensing monitoring studies; the first inflection point was in 2010, when the number of annual publications exceeded 30 for the first time. This may have been related to the Copernicus program. The second inflection point was in 2015, when the number of publications exceeded 100 for the first time. This may have been related to the convening of the United Nations Climate Change Conference in 2015. From 2015 to 2023, the average annual number of publications was 129.33, with an average annual growth rate of 4.75%. In addition, after 2021, the number of studies in the literature again had an increasing trend, which may have been related to the Chinese government's dual-carbon target in 2021. In terms of the average number of citations per article, 1992 had the highest average number of citations per article (526), which may have been related to the fact that both articles published in that year received high citations (487 and 567 citations, respectively) [30,31].

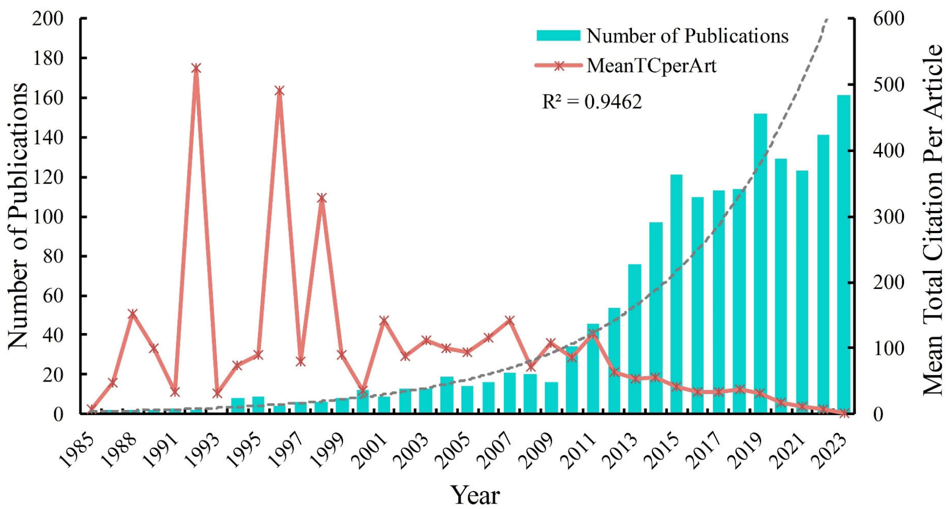

Figure 1. Trends in the quantity of publications and citations identified via WOS that are related to forest biomass using remote sensing from 1985 to 2023.

3.1.2. Subject Category Analysis

The analysis of the disciplinary categories of publications shows that the remote sensing monitoring of forest biomass is associated with 66 disciplines, indicating that this theme is a multidisciplinary research topic. In addition, the top 10 disciplinary categories in terms of number of publications are shown in Table 1, from which it can be seen that remote sensing (892 publications, 53.16%) is the most relevant discipline to the theme, followed by Imaging Science photographic technology (761 publications, 45.35%), and environmental sciences (705 publications, 42.01%).

Table 1. Top 10 subject categories sorted by the number of articles.

Subject	TP	Ration%
Remote sensing	892	53.16
Imaging Science Photographic Technology	761	45.35
Environmental sciences	705	42.01
Geosciences multidisciplinary	384	22.88
Forestry	299	17.82
Engineering electrical electronic	155	9.24
Geography physical	131	7.81
Ecology	124	7.39
Geochemistry geophysics	108	6.44
Meteorology atmospheric sciences	62	3.69

Note: TP: total publications between 2001 and 2023.

Discipline correlation analysis can be used to explain the intrinsic connections between different disciplines. The covariance mapping of discipline categories generated based on Citespace is shown in Figure 2, which contains 42 nodes and 141 connections. Each node represents a discipline category. The amount of subject category publications is positively correlated with the node size, while the color of the rings and links corresponds to the year; the thicker the annual ring is, the more publications are published in that period of time, and the thickness of the connecting line between the nodes is positively correlated with the strength of the subject category co-occurrence [32]. The remote sensing monitoring of forest biomass involves multiple disciplines, as can be seen in Figure 2; remote sensing exists as a mediator connecting different disciplines, and the links include environmental sciences and ecology, imaging science photographic technology, environmental sciences, geosciences multidisciplinary, forestry, geology, and other disciplines. The above results indicate that the remote sensing monitoring of forest biomass requires the intersection of different fields and multiple disciplines.

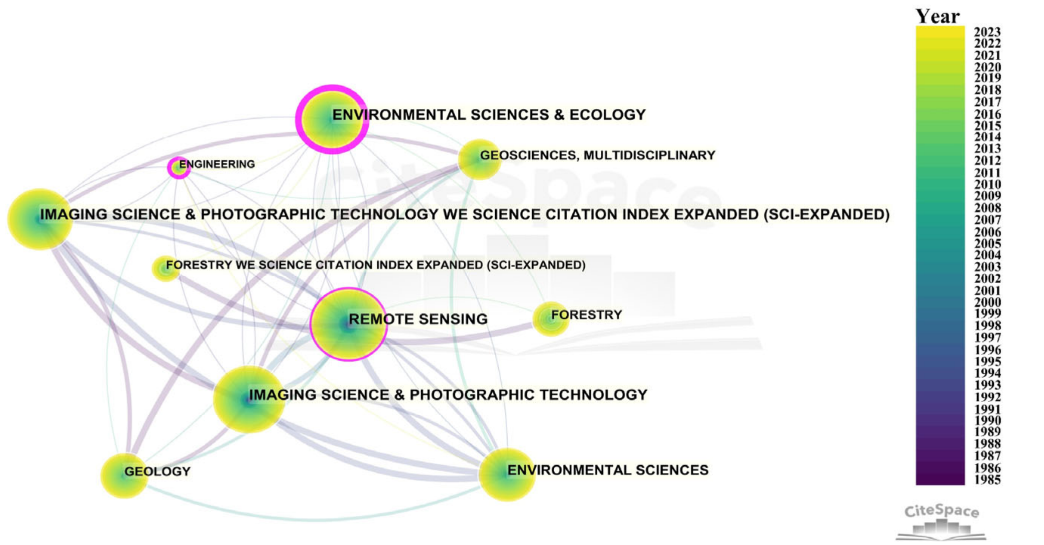

Figure 2. A visualization of the co-occurring subject category network.

3.2. Journal and Author Analysis

The 1678 publications related to the remote sensing monitoring of forest biomass analyzed in this paper were published in 261 journals. Table 2 shows the top 10 journals in terms of the number of publications. In general, the average number of citations per paper (TC/NP) of a journal is a relatively good indicator of a journal's impact in that research area [28]. In addition, the journal impact factor (IF) and H Index are also important factors to with which to measure its value. As can be seen in Table 2, the journals *Remote Sensing* and *Remote Sensing of Environment* published more than 100 articles on the remote sensing monitoring of forest biomass. *Remote Sensing of Environment* has been a longtime leader in the field with the highest IF (14.2) and H Index (77). The top ten journals involve remote sensing, forestry, ecology, geochemistry geophysics, and other research fields, indicating the cross-disciplinary nature of the remote sensing monitoring of forest biomass. It can also be seen that the top ten journals cumulatively published 890 papers related to the topic, accounting for 53.04% of the total number of publications, and received 44,277 citations, accounting for 43.09% of the total number of citations. *IEEE Transactions on Geoscience and Remote Sensing* has the highest TC/TP (102.52), followed by *Remote Sensing of Environment* (86.97) and *ISPRS Journal of Photogrammetry and Remote Sensing* (81.91). From this, it can also be seen that on the subject of the remote sensing monitoring of forest biomass, MDPI (333) published the most articles, followed by ELSEVIER (286) and IEEE-INST (164), while SPIE (27) published the least.

Table 2. Top 10 journal sorted by the number of articles.

Sources	TP	TC	TC/TP	IF	H Index
Remote Sensing	247	6162	24.95	5.6	42
Remote Sensing of Environment	194	16872	86.97	14.2	77
Forests	86	1180	13.72	3.0	20
IEEE Transactions on Geoscience and Remote Sensing	81	8304	102.52	3.6	32
International Journal of Remote Sensing	80	3692	46.15	3.8	29
Forest Ecology and Management	57	2424	42.53	8.8	39
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	42	1003	23.88	5.5	17
International Journal of Applied Earth Observation and Geoinformation	41	1349	32.90	7.2	24
ISPRS Journal of Photogrammetry and Remote Sensing	35	2867	81.91	12.4	27
Journal of Applied Remote Sensing	27	424	15.70	1.7	10

Note: IF: five-year impact factor from the 2022 edition of Journal Citation Reports® in WOS. TC: the total citations for a journal. TC/TP: average number of citations per paper for a journal.

The year-to-year variation in the top ten journals in terms of the number of forest biomass remotely sensed and monitored is shown in Figure 3. The journals *Remote Sensing* and *Remote Sensing of Environment* are highly favored by researchers; 247 and 194 articles were published, respectively. This is followed by the *Forests* and *IEEE Transactions on Geoscience and Remote Sensing* journals. In addition, most of the journals experienced rapid growth after 2012. MDPI (*Remote Sensing* and *Forests*) journals have shown exponential growth with a faster growth rate. The *Remote Sensing of Environment* journal showed exponential growth though to 2019, but the growth rate slowed down after 2019.

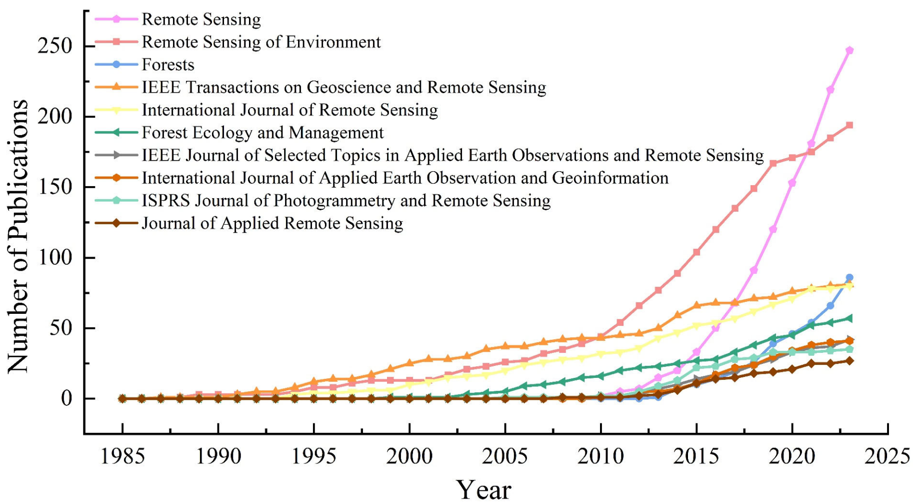

Figure 3. Time series change of journals.

The H index is used to assess the number of citations of papers published by a particular researcher in a particular field and is an important indicator of the impact of papers published in a particular field. The top ten authors with the highest H index are Naesset E. (21), Gobakken T. (21), Saatchi S. (20), Herold M. (19), Nelson R. (19), Sun G. Q. (18), Phillips O. L. (15), Dubayah R. (15), Asner G. P. (15), Avitabile V. (15), and Wang C. (15) (Table 3). The top ten most influential authors were Nelson R., who was the first to start researching the field and also had the highest TC/TP for his article, Saatchi S., whose article had the highest total number of citations (1967), and Naesset E., whose article had the highest H index (21) and TP (34). The 1678 papers analyzed involved 6698 authors, with an average of 3.40 authors per paper and 0.29 contributions per author. According to the published papers in the last five years, Herold M. has been more active in recent years.

Table 3. Top 10 influential authors sorted by H index.

Authors	H Index	TP	TC	TC/TP	PY_Start	TP (2019–2023)
Naesset E.	21	34	1471	43.26	2010	7
Gobakken T.	21	32	1361	42.53	2010	4
Saatchi S.	20	27	1967	72.85	1995	11
Herold M.	19	25	1144	45.76	2014	17
Nelson R.	19	20	2154	107.70	1988	0
Sun G. Q.	18	27	1378	51.04	1994	5
Phillips O. L.	15	19	1773	93.32	2013	13
Dubayah R.	15	20	1017	50.85	2003	11
Asner G. P.	15	19	898	47.26	2002	5
Avitabile V.	15	16	879	54.94	2012	8
Wang C.	15	22	762	34.64	2008	9

3.3. Country and Institution Analysis

The corresponding authors of the 1678 publications analyzed in this analysis were from 66 countries. Figure 4 shows the top 10 most influential countries. In order of the number of publications, USA (380), China (355), India (86), Germany (85), United Kingdom (77), Brazil (71), Finland (55), Italy (55), Canada (54), and France (48 articles) were the most influential. It is also possible to rank the top ten countries in terms of the average number of citations of their papers; the country with the highest average number of citations is France (111.4), which is the result of multiple highly cited articles [31–33]. This is followed by USA (74.8 citations) and United Kingdom (57.1 citations). China (21.7) and India (19.7) have a relatively low average number of citations.

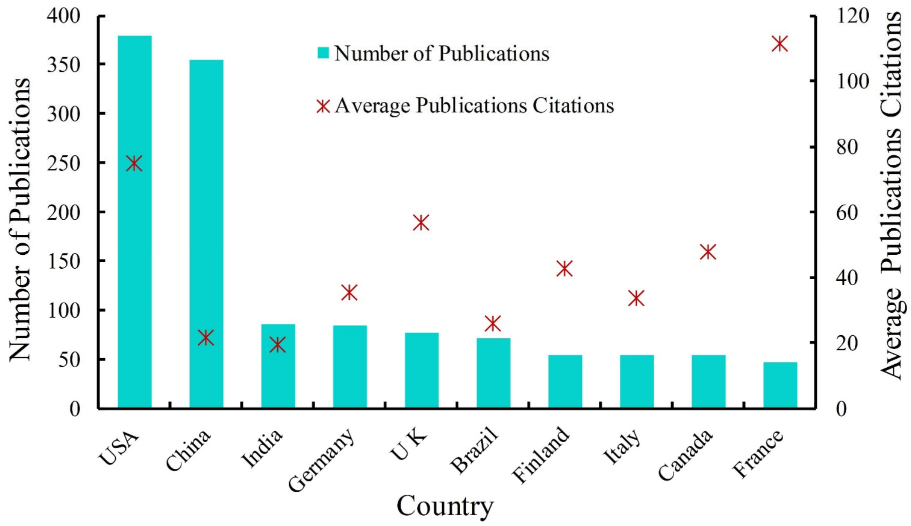

Figure 4. The publications and average publications citations of countries.

The 10 most influential issuing organizations are listed in Table 4. Chinese Academy of Sciences ranked first with 139 articles issued, followed by the University of Maryland College Park (97 articles) and the United States Forest Service (88 articles). In total, 4 of the top 10 institutions (1st, 6th, 9th, and 10th) belong to China, and in terms of affiliation, the University of Chinese Academy of Sciences is part of the Chinese Academy of Sciences. Four institutions belong to the United States (the second, third, fourth, and fifth, respectively). The remaining two are located in Northern Europe. California Institute of Technology has the highest TC/TP (112.99), which may be related to the high number of citations received by four articles published by this institution [32,34–36], whereas National Aeronautics and Space Administration's high TC/TP of 84.47 may be attributed to Saatchi's publication in the journal *Proceedings of The National Academy of Sciences of The United States of America* [34].

Table 4. Top 10 most productive institutions between 2001 and 2023.

Affiliation	Country	TP	TC	TC/TP
Chinese Academy of Sciences	China	139	4267	30.70
University of Maryland College Park	USA	97	4106	42.33
United States Forest Service	USA	88	4992	56.73
National Aeronautics and Space Administration	USA	75	6410	85.47
California Institute of Technology	USA	71	8022	112.99
Chinese Academy of Forestry	China	45	1053	23.40
Norwegian University of Life Sciences	Norway	44	1678	38.14
Swedish University of Agricultural Sciences	Sweden	38	1808	47.58
University of Chinese Academy of Sciences	China	37	1235	33.38
Nanjing forestry University	China	34	824	24.24

3.4. Keywords Analysis

Keywords can express the topic of the paper [37], reflect the research progress and predict the future development trend in this research area [38,39]. In addition, based on keywords it is also possible to identify emerging terms that have not yet received widespread attention, revealing emerging directions in remote sensing monitoring of forest biomass. In this study, we used Citespace 5.7.R 5 to analyze the co-occurrence of author's keywords, and found that there were terms with the same meaning in the generated keyword maps (e.g., biomass maps and biomass mapping, allometric models and allometric model, etc.). Therefore, this study merged the keywords before keyword analysis.

Undoubtedly, forest biomass, as the keyword of this study, appeared the most times (419 times) and had the highest mediational centrality (Figure 5). forest biomass was closely related to aboveground biomass (402), LiDAR (391), biomass (391), and vegetation (330), model (183), carbon (180), etc. The above keywords all appeared a high number of times and became important nodes in the network.

In order to better explore the research themes presented by the keywords, this study was based on VOSviewer 1.6.20 software for keyword clustering analysis, and the keyword threshold in this study was set to 9 times to construct the co-occurrence network. Figure 6 depicts the author keyword co-occurrence graph. The size of the nodes in the graph indicates the frequency of occurrence of author keywords, and the width of the link lines represents the frequency of co-occurrence between different author keywords [40,41]. It can be seen that the co-occurrence classes out four clusters, each containing 12–32 author keywords.

The yellow cluster is related to optical remote sensing, including the keywords above-ground, Landsat, and leaf area index. Optical remote sensing is currently the most widely used data source for biomass estimation [42,43]. Optical remote sensing has an early start and long continuity, and it has been applied to biomass estimation research since as early as the 1980s [44]. With the continuous development of optical remote sensing sensors, more and more high-temporal- and -spatial-resolution sensors have been gradually used to estimate forest biomass [45], and the more widely used sensors at home and abroad include Landsat, Sentinel-2, Wordview, GF-2, etc. [46–49]. To use optical remote sensing data for biomass estimation, a statistical model between remote sensing features (e.g., vegetation index; texture features) and measured data is usually established first, and then the constructed biomass model is used for biomass inversion at the regional scale [18,50]. However, traditional regression models (e.g., linear, exponential, logarithmic, and polynomial) sometimes fail to accurately describe the complex nonlinear relationships between biomass and remote sensing features [51]. In recent years, with the not-so-considerable development of artificial intelligence algorithms (e.g., machine learning), machine learning algorithms, such as SVM and RF, have been widely used for forest biomass estimation [18].

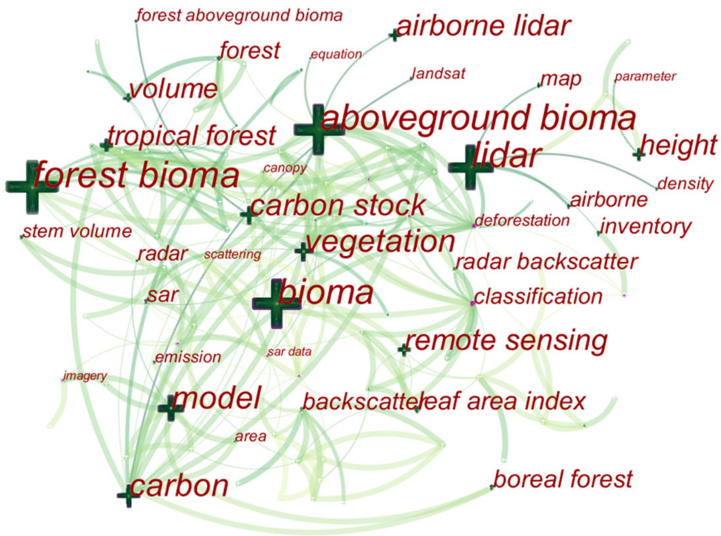

Figure 5. A visualization of the keyword co-occurring network.

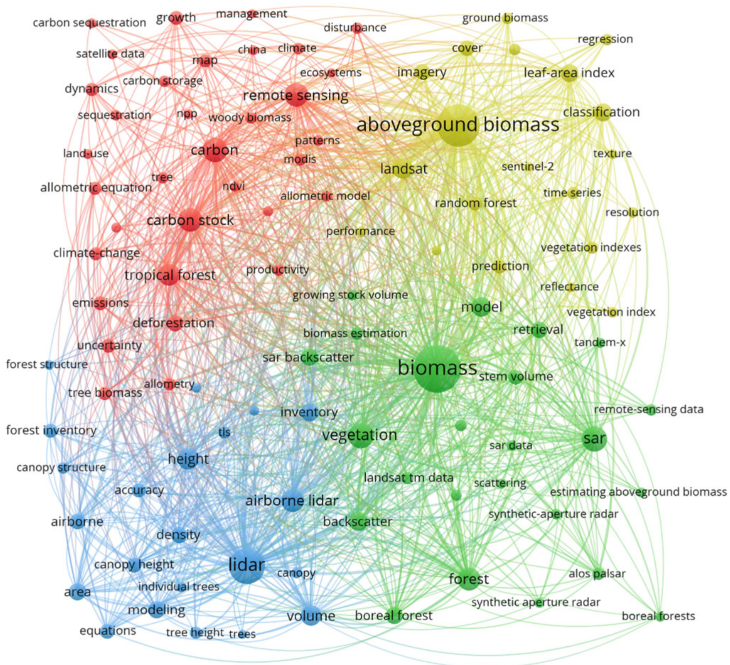

Figure 6. Co-occurrence network based on author keywords.

The green cluster is related to SAR remote sensing, including the keywords biomass, forest, and radar. Unlike traditional optical remote sensing, SAR overcomes the limitations of weather effects (e.g., cloudy, foggy, etc.) and has the ability to obtain features such as forest canopy level shape and vertical structure, which has greater potential in forest biomass inversion [52]. Numerous scholars have linked different bands (the I-band, P-band, etc.), polarization modes, and radar backscattering intensities of SAR with forest biomass to study the relationship between it and biomass [53], and a study showed that the radar backscattering coefficient and forest biomass were positively correlated. In addition, the sensitivity of backscattering coefficients of different bands to forest biomass was different, while the L-band and P-band had high robustness with forest structural parameters (tree age, tree height, biomass, etc.) in previous studies, and were often used for tree height and biomass inversion [54,55].

The blue cluster is related to LiDAR remote sensing, including the keywords LiDAR, airborne LiDAR, and height. LiDAR technology is able to obtain three-dimensional structural information of forest trees, realizing the leap from the two-dimensional to three-dimensional study of forest trees [13], and it is one of the most effective and accurate techniques for estimating forest biomass [56,57]; LiDAR data overcome the saturation of vegetation indices and SAR in inverted biomass in high-density forest areas [58]. Based on LiDAR data, forest biomass is usually inverted using either direct or indirect methods; the direct method is to establish a regression model with forest biomass by using the characteristic factors such as density, intensity, and height extracted from the point cloud data, and the indirect method is to firstly obtain the structural parameters of the forest, and then to establish the relationship between the forest parameters and the forest biomass [59]. Although the structural parameters acquired using ground-based LiDAR combined with anisotropic growth equations or structural quantitative modeling combined with single-tree density can obtain single-tree or sample-plot scale biomass with high accuracy, the data acquisition range is limited and cannot satisfy regional-scale biomass monitoring [60]. With the development of UAVs, UAV-mounted LiDAR can acquire large-scale forest structural information, but due to the limited density of the point cloud, it is not possible to acquire the structural parameters of the breast diameter, which is closely related to biomass. Therefore, the single-tree biomass from ground-based LiDAR inversion is usually used as the true value to obtain forest biomass by modeling with the characteristic factors (tree height, crown spread, height percentile, etc.) extracted from UAV LiDAR data [61]. However, UAVs are limited by flight time and magnetic field, and the range of data acquisition is still limited and is often used for typical forest or specific tree species studies [62].

The red clusters in our analysis are closely associated with carbon stocks, prominently featuring keywords like 'carbon', 'carbon stock', and 'remote sensing'. Forests, as the cornerstone of terrestrial ecosystems, play a pivotal role in maintaining the terrestrial carbon cycle and stabilizing global climate conditions. Significantly, forest carbon stock is not only a crucial indicator of forest ecosystem structure and function but also forms the foundation for studying carbon sinks and their potential. This can be inferred from forest biomass using the carbon content coefficient [63,64]. Typically, research on forest carbon stock primarily focuses on typical forest areas, with forest type data usually derived from land use remote sensing interpretation. Previous studies have identified tree age as a key determinant of forest structure and function, influencing biomass accumulation [65], net primary productivity [66], and other aspects. However, predicting tree age is fraught with uncertainties and does not increase uniformly over time. Furthermore, environmental factors like climate, soil, and stand conditions also impact forest growth and variations in carbon density [65]. In a related development, the Chinese government's 2020 strategic decision to aim for a carbon peak by 2030 and carbon neutrality by 2060 has spurred increasing interest among Chinese scholars in monitoring forest carbon stock changes [67–69].

Keyword bursts, as indicated in Table 5, provide insights into the areas garnering greater interest over specific periods [70]. The red lines in the table represent cycles of keyword bursts [71]. It is evident that in the past six years, keywords such as 'Carbon', 'Map', 'Model', and 'Airborne LiDAR' have been particularly active. The Paris Agreement in 2016, with its commitment to carbon neutrality, has catalyzed research in carbon sequestration. Concurrently, advancements in UAVs and the miniaturization of LiDAR equipment have made UAV Airborne LiDAR a leading data source for forest biomass monitoring. Mostly, remotely sensed data are employed to construct inverse forest biomass models, each with its own limitations, making the pursuit of an optimal model a hot research area. Additionally, forest biomass mapping analysis, aimed at assessing biomass status on global or regional scales, has emerged as another significant research focus in recent years.

Table 5. Keywords with bursts in the last six years.

Key Words	Strength	Begin	End	2001–2023
carbon	6.37	2018	2021	
map	10.61	2019	2021	
airborne LiDAR	15.73	2018	2022	
model	12.85	2021	2023	

Figure 7 illustrates the evolution of authors' keywords in the field of forest biomass monitoring, where the size of the keywords corresponds to their frequency of occurrence [28]. The analysis reveals distinct phases in the technological and thematic focus over the years.

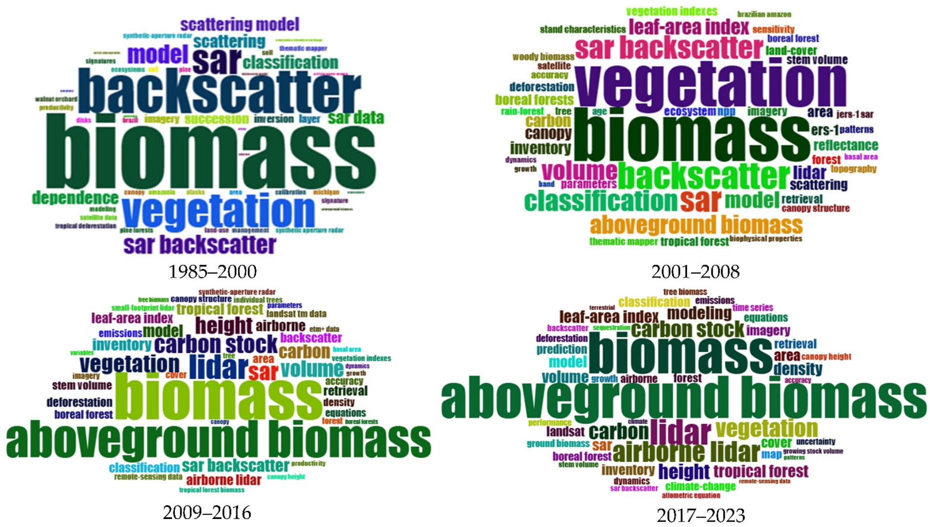

Figure 7. The evolution of the "word cloud", 1985–2023.

Before 2000, the predominant keywords were 'biomass', 'SAR', and 'backscatter', indicating an initial focus on forest biomass monitoring using SAR technology. The period 2001–2008 marked the gradual introduction of LiDAR technology in forest biomass monitoring. The emphasis began to shift towards aboveground biomass monitoring, reflecting the emerging role of LiDAR as a novel tool. In 2009–2016, LiDAR technology increasingly replaced SAR as the primary method for forest biomass monitoring. This era also saw rapid advancements in extracting forest structural parameters (like tree height and volume) and a nascent interest in carbon stock monitoring. In 2017–2023, LiDAR continued to dominate the technological landscape for forest biomass monitoring. Meanwhile, optical remote sensing (e.g., Landsat, Sentinel-2) witnessed extensive application. Research focusing on typical forests surged, and the use of UAV LiDAR for biomass monitoring began to rise. Concurrently, in response to global warming and to track forest carbon sequestration capacity, there was a growing focus on 'carbon', 'carbon stock', and 'density'.

4. Conclusions

This paper employs a bibliometric methodology to analyze research in the field of the remote sensing monitoring of forest biomass, utilizing the Web of Science core dataset as its primary data source. Our analysis reveals that the number of publications has experienced an exponential upward trend from 1985 to 2023, with an impressive average annual growth rate of 4.75%. Significantly, the top ten journals have contributed to 53.04% of the total publications and 43.09% of the total citations in this field. In terms of disciplinary impact, *Remote Sensing*, *Imaging Science and Photographic Technology*, and *Environmental Sciences* emerge as the three most influential disciplines in this research area. Notably, the journal *Remote Sensing of Environment* has consistently led the field, boasting the highest IF and H-index. Furthermore, *IEEE Transactions on Geoscience and Remote Sensing* stands out as the journal with the highest average number of citations. Among individual contributors, Saatchi S. is distinguished as the author with the highest total number of citations for their articles.

Based on the keyword clustering analysis, the principal research topics in forest biomass remote sensing monitoring can be categorized into four key areas: optical remote sensing, LiDAR remote sensing, SAR remote sensing, and carbon stock analysis. Notably, the keyword explosion over the past six years indicates an increasing focus among researchers on carbon, airborne LiDAR data, along with efforts in biomass mapping and the construction of optimal biomass models. Furthermore, there is a discernible shift in the methodology of forest biomass monitoring, evolving from single-datum biomass estimation to a synergistic approach utilizing multiple data sources.

However, this study is not without its limitations. First, our analysis relied solely on the Web of Science core dataset for literature collection, excluding other potential datasets. Additionally, while research hotspots and topic evolution were identified, a detailed analysis of each hotspot was not conducted. Lastly, in the keyword burst analysis, both CiteSpace 5.7.R 5 and Bibliometrix 4.1.4 software were employed, yet neither tool can analyze author keywords. This limitation may have affected the comprehensiveness of the final generated keywords.

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