remote sensing

Review

Bibliometric Analysis of Global NDVI Research Trends from 1985 to 2021

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Abstract: As one of the earliest remote sensing indices, the Normalized Difference Vegetation Index (NDVI) has been employed extensively for vegetation research. However, despite an abundance of NDVI review articles, these studies are predominantly limited to either one subject area or one area, with systematic NDVI reviews being relatively rare. Bibliometrics is a useful method of analyzing scientific literature that has been widely used in many disciplines; however, it has not yet been applied to comprehensively analyze NDVI research. Therefore, we used bibliometrics and scientific mapping methods to analyze citation data retrieved from the Web of Science during 1985–2021 with NDVI as the topic. According to the analysis results, the amount of NDVI research increased exponentially during the study period, and the related research fields became increasingly varied. Moreover, a greater number of satellite and aerial remote sensing platforms resulted in more diverse NDVI data sources. In future, machine learning methods and cloud computing platforms led by Google Earth Engine will substantially improve the accuracy and production efficiency of NDVI data products for more effective global research.

Keywords: bibliometrix; NDVI; remote sensing; network analysis; visualization; Web of Science

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1. Introduction

As one of the most important components of terrestrial ecosystems, vegetation connects ecological elements such as hydrology, soil, and atmosphere, and provides a strong guarantee for natural ecosystems and human wellbeing [1,2]. Changes in vegetation cover have an important impact on global warming and biodiversity; however, prior to the development of remote sensing technology, the availability of vegetation information on large temporal and spatial scales was limited [3]. Indeed, vegetation indices based on remote sensing are crucial for analyzing large-scale vegetation changes. Notably, the Normalized Difference Vegetation Index (NDVI) has been widely used to monitor vegetation since its proposal in 1969 [4]. Almost all earth observation satellites are equipped with sensors that can generate this index at different spatiotemporal resolutions. The NDVI has since become the dominant index for vegetation research because of its long-term data series, simplicity, and ease of use [5,6].

After decades of development, several NDVI time-series datasets have been generated with various temporal and spatial resolutions. Sources of free satellite remote sensing data typically include the Advanced Very High-Resolution Radiometer (AVHRR), SPOT/VEGETATION, Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), Landsat, Sentinel, and GaoFen. Commercial remote sensing satellites such as WorldView, Planet, and JILIN provide more flexible, higher resolution, and higher revisit-time data. In recent years, the rapid development of unmanned aerial vehicle (UAV) technology has also driven the application of UAV remote sensing. NDVI mapping is an important application of UAV remote sensing, with a spatial resolution reaching the centimeter level [7].

NDVI has been applied to multiple disciplines [8–11] through the use of multi-platform, multi-sensor [12,13], multi-phase satellite [12,14,15] and aerial [16] remote sensing data sources, providing important parameters related to productivity [17,18], evapotranspiration [19,20], phenology [21–23], land cover [9], and other research. Existing NDVI review articles tend to focus on the assessment of environmental changes and ecosystem responses [3,24–28]. As the most important factor affecting terrestrial water budgets after precipitation, evapotranspiration is also often calculated using vegetation indices [29,30]. Other researchers have used the NDVI in the following ways: to determine the relationship between carbon dioxide flux and the NDVI [31,32] by calibrating the remote sensing inversion results of CO_2 flux [33,34]; to monitor fire areas and assess the impact of fire on ecosystems [35,36]; to assess drought conditions and related impacts on the ecological environment and agricultural production [37–40]; as an evaluation index of land degradation, which is related to vegetation productivity and biophysical variables such as land and atmospheric flux [41–43]; and to estimate crop yield [44] and ensure sustainable agricultural management [45]. Many review articles have focused on the NDVI, summarizing NDVI research progress, research areas, and key issues in its application (e.g., atmospheric effects, saturation phenomena, and sensor effects) [46]. For example, Li et al. systematically summarized the reconstruction methods of NDVI, analyzed the advantages and disadvantages of each reconstruction method, and evaluated the quality of NDVI reconstruction data, as well as discussing future development trends of NDVI reconstruction technology [47].

“Bibliometrics” was first proposed by Pritchard in 1969 [48], and is defined as “the application of mathematical and statistical methods to books and other knowledge dissemination media”. Thus, bibliometrics is a powerful tool for analyzing the progress of scientific research as it can quantify information derived from online scientific citation databases related to a specific research topic, including the authors in the field, the number of publications, and the distribution of research institutions. Bibliometrics can also identify important literature in the research field, provide keywords, institutions, country linkages, and distribution characteristics in the form of a knowledge map, and quantify the current status and future trends of the research topic [49]. In general, the more references a bibliometric method incorporates, the more able we are to understand the research field [50]. Table 1 lists previous remote sensing studies that have employed the bibliometrics approach. Despite the similar method, the exact research topic differs significantly among these studies. To the best of our knowledge, this is the first study to conduct a bibliometric analysis of NDVI literature [51].

Table 1. List of previous studies using the bibliometric method.

Reference	Fields
(Zhang et al., 2017, pp. 2010–2015)	Remote Sensing
(Zhang and Chen, 2020, pp. 1991–2018)	Chinese Loess Plateau
(Tamiminia et al., 2020)	Google Earth Engine
(Li et al., 2021)	Grassland Remote Sensing
(Zhao et al., 2022)	Earth Observation Satellite Data
This paper	NDVI

To achieve our research aim, we pose the following research questions [52]:

Q1. What is the global trend of scientific literature on NDVI?

Q2. What information can be found from this trend?

Q3. What are the future research trends of NDVI?

The specific objectives of this study are as follows:

(1) Provide bibliometric information on 17,755 scientific studies extracted from the Web of Science (WOS) Scientific Citation Indexing (SCI) Expanded database;
(2) Use the bibliometrix R-package and biblioshiny web app to convert and analyze quantitative data of the selected articles;
(3) Use the total citations or H index to identify the leading authors, countries, and institutions in NDVI research;
(4) Use the keywords to analyze the research history and current research hotspots.

The paper is organized as follows. Section 2 presents the data and methods used in the bibliometric analysis. Section 3 presents and discusses the results of the bibliometric analysis. Section 4 summarizes the research status of NDVI and discusses future development trends according to the analysis results.

2. Related Literature

The input data for the bibliometric method are derived from online scientific citation databases, which are used to comprehensively and quantitatively analyze the current status and future trends of the research topic [52]. Table 1 lists the remote sensing studies that have employed a similar approach to this review. However, despite the similar method, the exact research topic differs significantly among these studies. For example, Zhang et al. (2017) performed a scientometrics analysis of the Web of Science Category "Remote Sensing" to study the research status and development trend of global remote sensing from 2010 to 2015 [48]; Zhang and Chen (2020) provided a comprehensive overview of research on the Chinese Loess Plateau [53]; Tamiminia et al. (2020) conducted a bibliometric and meta-analysis of the Google Earth Engine [54]; Li et al. (2021) quantified the research trends and areas in grassland remote sensing [55]; and Zhao et al. (2022) presented an overview of the applications of earth observation satellite data [56]. To the best of our knowledge, this is the first study to conduct a bibliometric analysis of NDVI literature.

3. Materials and Methods

3.1. Literature Search Strategy

The WOS Core Collection SCI Expanded database was selected as the data source. The search formula for the advanced method selected according to NDVI research was as follows: TS = (NDVI or Normalized Difference Vegetation Index or Normalised Difference Vegetation Index). The search results returned 17,998 documents on WOS (updated to 16 March 2022). All records were exported to plain text files with the record content "full record and cited references."

3.2. Bibliometric Analysis

The bibliometric analysis method is described in Aria and Cuccurullo [57]. The analysis comprised five rigorous steps: study design, data collection, data analysis, data visualization, and interpretation [51,58]. Figure 1 presents a schematic of the full methodology. First, in the study design phase, the NDVI was selected as the study topic and three research questions were defined. The WOS SCI Expanded database was selected as the research data resource. Second, in the data collection phase, literature retrieval returned 17,998 documents. As the peer review process facilitates reliable scientific communication, stimulates meaningful research questions, and ensures accurate conclusions [58], we used the document type filter on WOS and included articles and data papers. The final sample comprised 17,755 papers published between 1985 and 2021. All records were imported into the biblioshiny web program and converted to bibliometrix RData for subsequent analysis. In the third phrase, we used R software to perform a descriptive bibliometric analysis and create a matrix comprising all documents. In the fourth stage, biblioshiny, tidyverse (ggplot2), and VOSviewer were used to create conceptual maps, co-citation networks, and other charts. Bradford's Law can reveal the journal distribution, which was used to identify the influential sources. Section 3 presents our interpretation of the data analysis and visualization results.

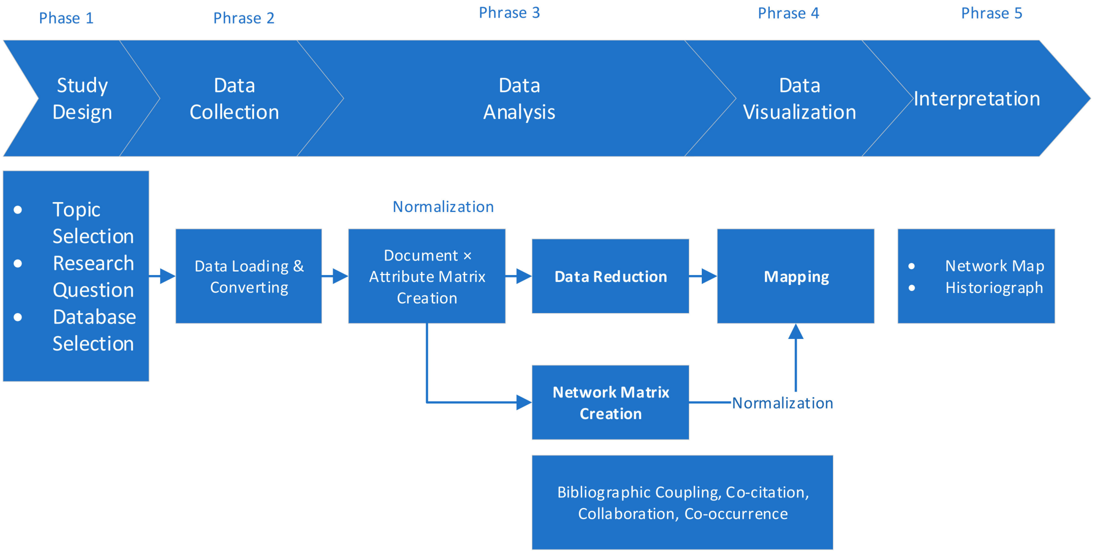


Figure 1. Schematic of the bibliometric analysis methodology adapted with permission from Refs. [57,58]. Copyright 2017, Aria and Cuccurullo, and copyright 2020, Silvana et al.

4. Results and Discussion

The initial results of the bibliometric analysis provide a summary of bibliometric statistics. Subsequently, we analyzed the authors, indicators, information, keywords, and countries of the relevant literature.

4.1. Descriptive Bibliometric Analysis

Figure 2 shows the scientific production throughout the study period. The first paper with NDVI as the topic was published (in the WOS SCI Expanded database) in 1985, entitled "Multitemporal Dimensionality of Images of Normalized Difference Vegetation Index at Continental Scales" [59]. From only one paper published that year, the number of papers began to gradually increase. After 2010, the number of NDVI-related papers increased rapidly, reaching 2389 in 2021, corresponding to an annual growth rate of 24.89%. Table 2 shows key information on the 17,755 papers published between 1985 and 2021 in the WOS SCI Expanded database. Over the past 36 years, an average of 493 NDVI research papers were published per year, with average of 32.29 citations per paper. These papers involved 39,838 authors and 455 single-author papers. On average, each article involved two authors (2.33). The Collaboration Index, which gives the total number of authors of multi-authored articles divided by the total number of multi-authored articles, was 2.38 [60]. Moreover, the papers generated a total of 27,664 author keywords.

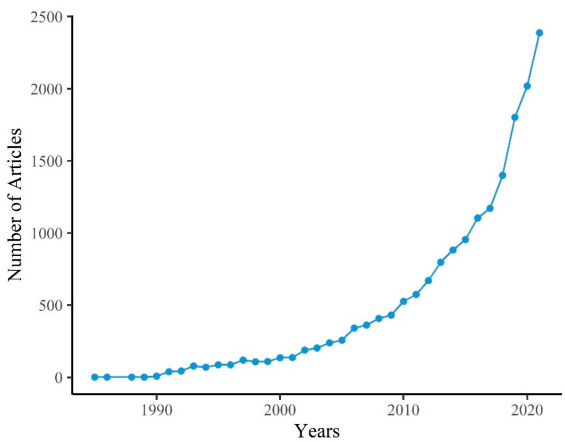


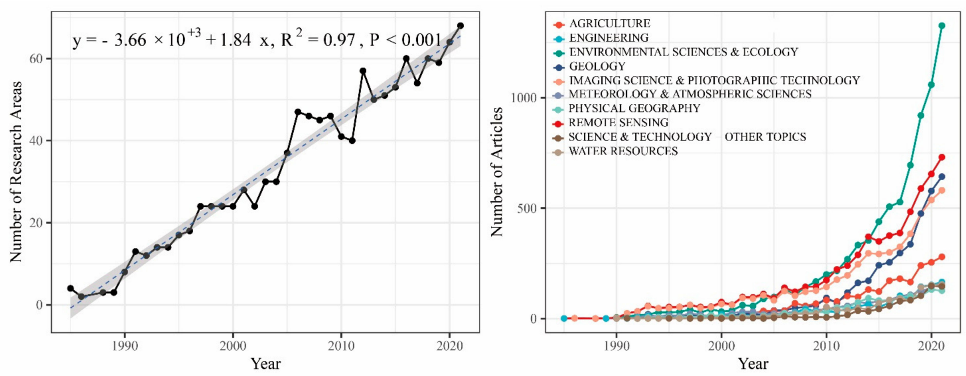
Figure 2. Scientific production of NDVI-related literature from 1985 to 2021.

Table 2. Key information of NDVI-related literature identified by the bibliometric analysis.

Main Information	Description	Value
Documents	Total number of documents	17,755
Sources	The frequency distribution of sources as journals, books, etc.	1258
Timespan	Years of publication	1985–2021
References	Total number of references	369,335
Author's keywords (DE)	Total number of author's keywords	27,664
Keywords Plus (ID)	Total number of phrases that frequently appear in the title of an article's references	15,425
Authors	Total number of authors	39,838
Authors Appearances	The authors' frequency distribution	85,789
Authors of single-authored documents	The number of single authors per articles	455
Authors of multi-authored documents	The number of authors of multi-authored articles	39,383
Authors per document	Average number of authors in each document	2.24
Co-Authors per Documents	Average number of co-authors in each document	4.83
Average citations per documents	Average number of citations in each document	32.29
Collaboration Index		2.29

4.2. WOS Research Areas

WOS research areas, assigned by Clarivate Analytics, were used to classify the research papers [53]. Each paper can be classified into at least one research area in the WOS database. In this study, the number of research areas covered by the NDVI literature increased from four in 1985 to 68 in 2021 (Figure 3a). The top ten most productive research areas were Environmental Sciences and Ecology, Remote Sensing, Imaging Science and Photographic Technology, Geology, Agriculture, Meteorology and Atmospheric Sciences, Engineering, Physical Geography, Water Resources, and Science and Technology—Other Topics, which represented 15,997 of the 17,755 publications, accounting for approximately 90.10% of the total. The annual evolution of the ten most productive areas of NDVI research is shown in Figure 3b, which illustrates changes in the focus areas of NDVI research. Before 2010, the dominant research areas were Imaging Science and Photographic Technology and Remote Sensing, with Environmental Sciences and Ecology increasing rapidly in popularity in later years, becoming the dominant NDVI literature output field by 2015. Following implementation of the United Nations global Sustainable Development Goals in 2015 [61], researchers have paid increasing attention to changes in the environment and ecology, explaining the explosive growth in the number of publications in this field. According to the total number of citations in each research area, in the fields of Environmental Sciences and Ecology, Imaging Science and Photographic Technology, and Remote Sensing, the radiological and biophysical properties of the vegetation index received the most citations [62]. Some remote sensing indices related to NDVI, such as the normalized difference water index (NDWI) [63], leaf area index (LAI) [8,64,65], soil-adjusted vegetation index (SAVI) [66,67], and physiological reflectance index (PRI) [68], were also widely cited.

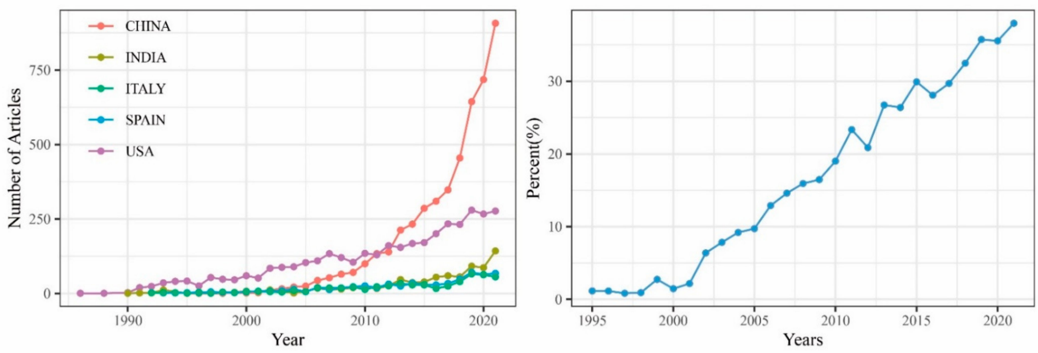


(**a**) (**b**)

Figure 3. (**a**) Number of WOS research areas covered in NDVI-related literature. (**b**) Temporal evolution of the top ten most productive WOS research areas in NDVI-related literature.

4.3. Research Countries and Institutions

According to the results, 114 countries have engaged in NDVI research. The top five research countries with the largest number of scientific productions were China (4808), the USA (3702), India (819), Spain (634), and Italy (569). Since 2013, the number of Chinese publications grew rapidly and surpassed that of the USA (Figure 4a). The proportion of China's NDVI scientific production increased each year, to 37.97% in 2021 (Figure 4b). In addition to the number of scientific productions, the country collaboration map can be used to measure a country's research strength. Figure 5 depicts the global collaborations, and shows that the USA (97) had the largest number of country connections, followed by Germany (86), China (84), Australia (76), France (74), and Italy (73). Other countries showed less cooperation in NDVI research, with less than 70 connections. Countries with more than 100 instances of cooperation between countries were identified as the main cooperation countries. The USA mainly cooperated with China, Canada, the United Kingdom, Germany, Spain, Australia, France, Brazil, and Italy, whereas China mainly cooperated with the USA, Australia, Canada, the United Kingdom, Japan, and Germany.



(**a**) (**b**)

Figure 4. (**a**) Top five countries according to annual scientific production; (**b**) annual proportion of China's scientific production.

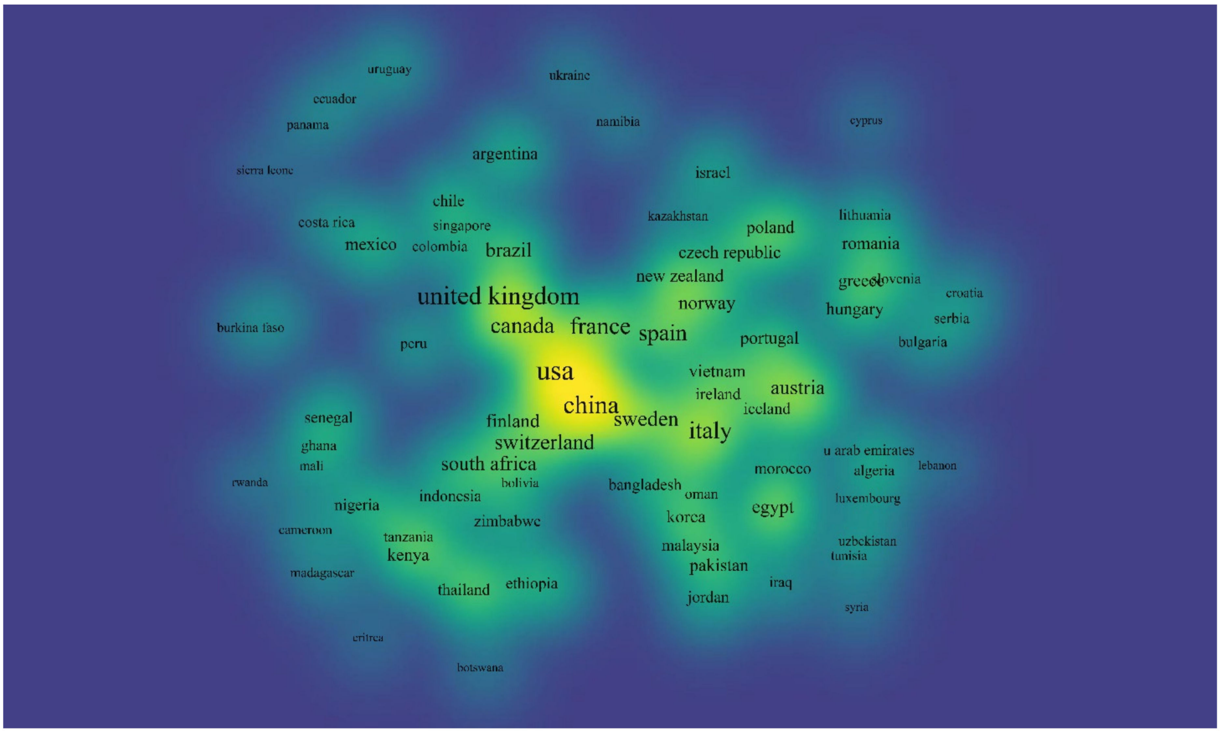


Figure 5. Map showing research collaboration between countries.

We then calculated the total citations for papers published in each country, extracted the top ten countries, and calculated the total number of articles, average number of citations in these countries (Figure 6). The United States had by far the most total citations of all countries (198,934), followed by China (100,116), Spain (29,048), Canada (20,910), Germany (18,370), Italy (16,299), the United Kingdom (16,210), France (15,931), Australia (15,812), and The Netherlands (12,100). In terms of average article citations, there were smaller differences between the top ten countries. The United States showed the highest average number of citations (53.74), followed by The Netherlands (50.42), Spain (45.82), the United Kingdom (41.04), Canada (39.83), France (39.34), Germany (38.59), Australia (33.22), Italy (28.64), and China (20.82). Although China had more total citations, the average number of citations was significantly lower than that of other countries because of the large number of papers and the low quality of many of these papers. Thus, the United States revealed a leading position in the field of NDVI-related research.

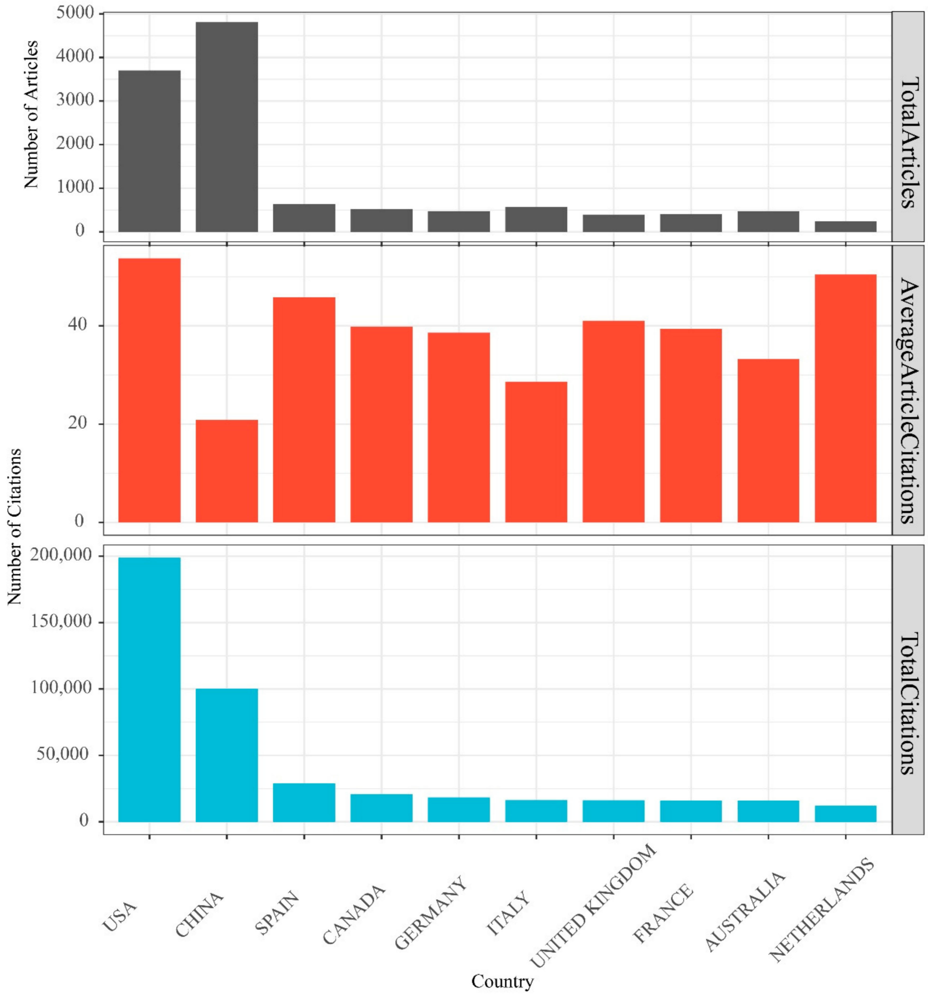


Figure 6. Total Articles, total and average number of citations in the top ten most highly cited countries.

Globally, 11,025 institutions have engaged in NDVI research. The influence of each institution was evaluated according to the number of citations of papers published by that research institution, with the top ten institutions according to the total number of citations considered to be the top ten most influential research institutions, which accounted for 591 articles (including first author achievements for each institution). The impact of papers from different institutions varied substantially, with Goddard Space Flight Center, USA, showing the highest number of total citations (18,493), followed by IGSNRR, CAS (5771), University of Arizona (5285), IRSDE, CAS (3651), University of Copenhagen (3024), Peaking University (2915), Beijing Normal University (2698), EROS Data Center (2584), University of Nebraska (2579), and Ben-Gurion University of the Negev (2525) (Table 3). Although Denmark and Israel were not ranked highly according to the number of papers published, these countries had an important impact on NDVI research because of their large number of citations.

Table 3. Top ten institutions according to total number of citations in NDVI-related research.

Institution	Country	TC	TA
Goddard Space Flight Center	USA	18,493	102
IGSNRR, CAS	China	5771	240
University Arizona	USA	5285	4
IRSDE, CAS	China	3651	161
University Copenhagen	Denmark	3024	21
Peaking University	China	2915	19
Beijing Normal University	China	2698	25
EROS Data Center	USA	2584	12
University of Nebraska	USA	2579	1
Ben-Gurion University of the Negev	Israel	2525	6

Abbreviations: TA, total number of articles; TC, total number of citations; IGSNRR, Institute of Geographic Sciences and Natural Resources Research; CAS, Chinese Academy of Sciences; IRSDE, Institute of Remote Sensing and Digital Earth; EROS, Earth Resources Observation and Science.

4.4. Most Influential Source Journals

NDVI studies have appeared in 1258 journals, with the annual number of publication sources increasing from 1 in 1985 to 456 in 2021. We also examined the distribution of NDVI research papers within major sources. The top five journals published 4854 (27.34%) of the total number of papers, whereas 466 journals (37.04%) published only one paper on NDVI. A total of 1047 journals (83.23%) published no more than 10 papers. As shown in Figure 7, the top five journals with the largest number of papers published were Remote Sensing (1843), International Journal of Remote Sensing (1289), Remote Sensing of Environment (1063), International Journal of Applied Earth Observation and Geoinformation (378), and Ecological Indicators (281). The journal Remote Sensing had a highest growth rate of the annual number of published papers, whereas Remote Sensing of Environment had the largest number of total local citations (Table 4). According to Bradford's Law, the source journals of NDVI research papers were highly scattered; the top ten most influential journals were selected according to the number of local citations, as shown in Table 4. Journals marked with an asterisk were the core source journals in the field of NDVI research according by Bradford's Law and included Remote Sensing of Environment, International Journal of Remote Sensing, Remote Sensing, Agricultural and Forest Meteorology, International Journal of Applied Earth Observation, and Geoinformation. Thus, these journals played an essential role in NDVI research during the study period.

Table 4. Top ten journals ranked by the number of local citations in NDVI-related research.

Sources	N. LC	ND	IF	H Index
Remote Sensing of Environment *	94,096	1063	10.164	238
International Journal of Remote Sensing *	45,760	1289	3.151	151
Remote Sensing *	23,047	1843	4.848	81
IEEE Transactions on Geoscience and Remote Sensing	15,488	180	5.600	216
Agricultural And Forest Meteorology *	12,776	226	5.734	144
Global Change Biology	12,649	131	10.86	217
Journal of Geophysical Research-Atmospheres	10,363	117	4.261	-
Science	9463	1	47.728	1058
International Journal of Applied Earth Observation and Geoinformation *	8623	378	5.933	76
Nature	8547	3	49.962	1096

Abbreviations: X *, the journal is the core resource (classified by Bradford Law) of NDVI research; N. LC, number of the total local citation; IF, impact factor in 2020.

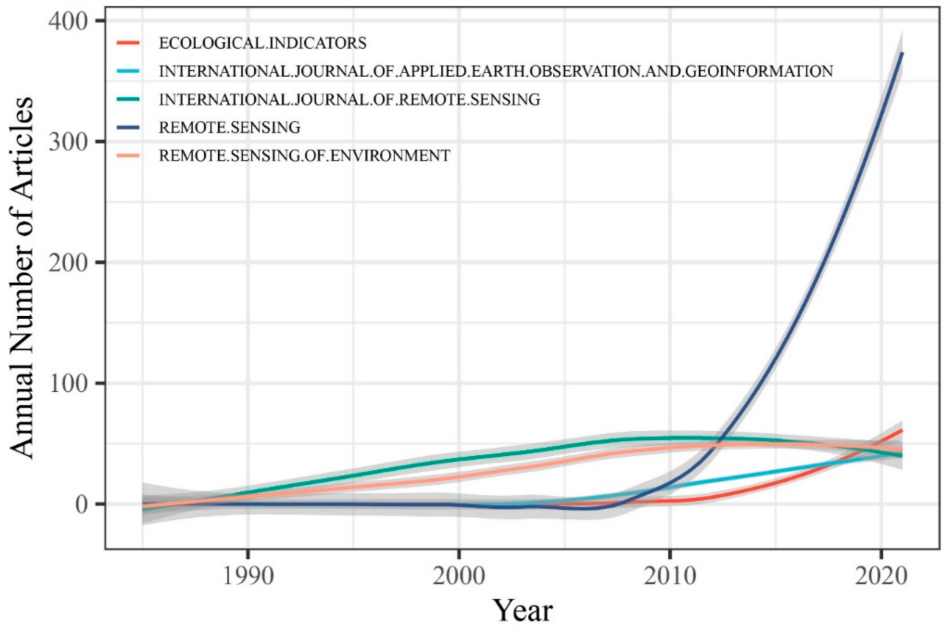


Figure 7. Temporal analysis of the publication source of NDVI-related research.

4.5. Most Influential Authors

The H index, which is based on the number of times the papers written by a particular scientist is cited, is a widely accepted measure of scientific performance [69]. The top ten authors with the largest H index were Tucker C.J. (57), Myneni R.B. (46), Piao S.L. (40), Chen W. (35), Pradhan B. (35), Fensholt R. (34), Paruelo J.M. (33), Xiao X.M. (32), Huete A.R. (31), and Eklundh L. (29) (Table 5). Tucker C.J. was the earliest NDVI study author recorded in WOS database, as well as the most influential researcher with the highest number of citations. Among the top ten most influential researchers, six were from the USA and one was from each of the following countries: China, Germany, Denmark, and Sweden. Liu Y. and Wang L. published the largest number of articles (86 each) but did not appear in Table 5 because of a low number of citations. The 17,755 papers involved 39,838 authors. A total of 455 independent authors published 566 single-authored documents. The average number of co-authors per paper was 4.83 and the Collaboration Index was 2.29. Overall, each author contributed an average of 0.446 papers. There were 2.24 authors per paper and 4.83 co-authors per paper. These results also indicate that NDVI research is typically a multi-author cooperative field.

Table 5. Top ten most influential authors ranked by the H index.

Author	H Index	G Index	TC	NP	PY_Start	Country
Tucker C.J.	57	83	15385	83	1985	USA
Myneni R.B.	46	68	10160	68	1992	USA
Piao S.L.	40	54	7408	54	2003	China
Chen W.	35	62	3939	67	2010	USA
Pradhan B.	35	55	5385	55	2010	Germany
Fensholt R.	34	67	4963	67	2003	Denmark
Paruelo J.M.	33	54	3155	54	1993	USA
Xiao X.M.	32	56	4353	56	2001	USA
Huete A.R.	31	44	6835	44	1992	USA
Eklundh L.	29	43	5798	43	1993	Sweden

Abbreviations: TC: Web of Science Core Collection times cited count; NP: number of scientific productions; PY_start: First year published.

4.6. Most Influential Papers

This subsection identifies the most influential papers (according to their number of citations [70]) from 1985 to 2021. The difference between the Local Citation Score (LCS = number of citations within the field) and the Global Citation Score (GCS = total number of citations in WOS) (Tables 6 and 7) is worth noting. The most influential paper according to both LCS and GCS is an evaluation of the MODIS vegetation index product. The results of this paper showed that, in semi-arid, grassland/shrub, savanna, and tropical forest areas, MODIS products and aerial survey vegetation index products have a strong correspondence. This paper also evaluated the sensitivity of MODIS to distinguish vegetation differences in sparse and dense vegetation areas, finding that MODIS NDVI is close to saturation in high biomass areas (such as Amazon rainforest areas), whereas MODIS EVI is still sensitive to canopy changes [62].

Table 6. Top ten papers according to the local citation score.

Paper	DOI	Year	LCS	GCS
HUETE A, 2002, REMOTE SENS ENVIRON	10.1016/S0034-4257(02)00096-2	2002	1725	4784
PETTORELLI N, 2005, TRENDS ECOL EVOL	10.1016/j.tree.2005.05.011	2005	898	1690
TUCKER CJ, 2005, INT J REMOTE SENS	10.1080/01431160500168686	2005	865	1566
GAO BC, 1996, REMOTE SENS ENVIRON	10.1016/S0034-4257(96)00067-3	1996	773	2819
CARLSON TN, 1997, REMOTE SENS ENVIRON	10.1016/S0034-4257(97)00104-1	1997	749	1626
CHEN J, 2004, REMOTE SENS ENVIRON	10.1016/j.rse.2004.03.014	2004	599	1174
ZHOU LM, 2001, J GEOPHYS RES-ATMOS	10.1029/2000JD000115	2001	563	1068
JONSSON P, 2004, COMPUT GEOSCI-UK	10.1016/j.cageo.2004.05.006	2004	539	1172
REED BC, 1994, J VEG SCI	10.2307/3235884	1994	529	987
QI J, 1994, REMOTE SENS ENVIRON	10.1016/0034-4257(94)90134-1	1994	458	1442

Abbreviations: DOI: Digital Object Identifier; LCS: Local Citation Score; GCS: Global Citation Score.

Table 7. Top ten papers according to the global citation score.

Paper	DOI	Year	LCS	GCS
HUETE A, 2002, REMOTE SENS ENVIRON	10.1016/S0034-4257(02)00096-2	2002	1725	4784
GAO BC, 1996, REMOTE SENS ENVIRON	10.1016/S0034-4257(96)00067-3	1996	773	2819
MCFEETERS SK, 1996, INT J REMOTE SENS	10.1080/01431169608948714	1996	324	2579
XU HQ, 2006, INT J REMOTE SENS	10.1080/01431160600589179	2006	256	1877
PETTORELLI N, 2005, TRENDS ECOL EVOL	10.1016/j.tree.2005.05.011	2005	898	1690
LOVELAND TR, 2000, INT J REMOTE SENS	10.1080/014311600210191	2000	169	1671
HANSEN MC, 2000, INT J REMOTE SENS	10.1080/014311600210209	2000	180	1656
CARLSON TN, 1997, REMOTE SENS ENVIRON	10.1016/S0034-4257(97)00104-1	1997	749	1626
TUCKER CJ, 2005, INT J REMOTE SENS	10.1080/01431160500168686	2005	865	1566
QI J, 1994, REMOTE SENS ENVIRON	10.1016/0034-4257(94)90134-1	1994	458	1442

The second most influential paper according to LCS (ranked 5 for GCS) is a review article that summarizes the characteristics of various NDVI data such as AVHRR, MODIS, Landsat, and SPOT for the first time. It also summarizes NDVI data synthesis and smoothing algorithms such as maximum value compositing, curve-fitting, step-wise logistic regression, best index slope extraction (BISE), and weighted least-squares linear regression, and discusses the noise in NDVI data. They also discuss the application scope of NDVI time-series data at different time scales in ecology and in response to ecological environment change [3]. The third most influential paper according to LCS (ranked 9 for GCS) described a set of AVHRR-based sensors that are compatible with MODIS and SPOT data for NDVI long-term series products [71], that is, the widely used GIMMS NDVI products. The fourth most influential paper according to LCS (ranked 2 for GCS) used NDWI for remote sensing of vegetation liquid water from space. NDWI is defined as $(\rho(0.86\ \mu m) - \rho(1.24\ \mu m))(\rho(0.86\ \mu m) + \rho(1.24\ \mu m))$, where ρ represents the radiance in reflectance units. They reported that NDWI is sensitive to changes in the liquid water content of vegetation canopies [63]. The fifth most influential paper according to LCS (ranked 8 for GCS) discusses the correlations between the NDVI, LAI, and fractional vegetation cover using a simple radiative transfer model incorporating vegetation, soil, and atmospheric components [8]. The sixth most influential paper according to LCS does not appear in the top ten list according to GCS. This article introduces a method based on the Savitzky–Golay filter to remove noise (especially cloud pollution and atmosphere) from NDVI time series, which was applied to the 10 day maximum. The results showed that this method is more suitable for the reconstruction of high-quality NDVI time series than the BISE algorithm or Fourier fitting method [72].

The seventh and eighth most influential papers according to LCS also do not appear in the top ten list according to GCS. The former paper explores the response between NDVI and climate change in different regions of the Northern Hemisphere from 1981 to 1999. Changes in NDVI and temperature were found to be highly correlated with precipitation [73]. The latter paper presents a satellite sensor time-series analysis program called TIMESAT. This program integrates three different least-squares algorithms to process remote sensing time-series images. The first algorithm is classified as a Savitzky–Golay filter and the other two are least-squares methods. NOAA AVHRR NDVI data for the African region were then processed using the TIMESAT program, resulting in spatially coherent images of seasonal parameters such as the beginnings and ends of growing seasons, seasonally integrated NDVI, and seasonal amplitudes [74]. The ninth most influential paper according to LCS does not appear in the top ten list according to GCS. This paper proposes a method to effectively and objectively evaluate the phenological characteristics of large-scale vegetation based on AVHRR NDVI data. These measures include the onset of greenness, time of peak NDVI, maximum NDVI, rate of greenup, rate of senescence, and integrated NDVI. The results showed a strong correlation between satellite-derived metrics and predicted phenological characteristics [75]. Finally, the tenth most influential paper according to both LCS and GCS proposes a SAVI to reduce the effect of soil on the canopy spectrum. MSAVI, which has a modified factor L, introduces a SAVI function with a variable L function and has been shown to increase the dynamic range of the signal, thereby further reducing the influence of the soil background and improving the sensitivity of the vegetation signal to the soil noise ratio [66].

As for the remaining most influential papers according to GCS, the paper ranked third, which does not appear in the LCS top ten list, used the NDWI to delineate open water features. NDWI is defined as (GREEN − NIR)/(GREEN + NIR), where GREEN is a band that encompasses the reflected green light and NIR represents the reflected near-infrared radiation [76]. The paper ranked fourth, which does not appear in the LCS top ten list, presents a modified NDWI (MNDWI) to enhance and extract water information for a water region with a background dominated by built-up land areas [77]. The papers ranked sixth and seventh, which do not appear in the LCS top ten list, both employ AVHRR data for land-cover classification [9,78].

Except for the fourth most influential paper according to LCS, which applies the NDWI to water research [63], all other papers focus on the vegetation index; specifically, the development of the vegetation index, time-series products, and methods [8,62,66,71,72,74], or research into the response of the vegetation index to phenology, climate change, and the environment [3,73,75]. Six of the most influential papers according to GCS are consistent with those in the LCS top ten, with the rest focusing on NDWI [76,77] or land-cover research [9,78].

4.7. Analysis of Historical and Current Research Hotspots

In this study, we detected 27,664 author keywords in the 17,755 papers published on NDVI research during 1985–2021. Figure 8 shows the trends of author keywords over time, where the X-axis shows the year and the Y-axis shows the keyword. The position of the green dot is the first quantile of the publication year corresponding to the keyword, the position of the red dot is the third quantile of the publication year, the position of the blue dot is the median of the publication year, and the size of the dot reflects the number of papers. The terms that received the longest continuous attention were NOAA and AVHRR, which are both key sensors [79–81], net primary production [82–84] and grassland [17,85–87], which are both key research topics, and Siberia [88–90], which is a key study area. The size of the blue dot in the middle reflects the frequency of the keyword; the larger the dot, the higher the frequency of the keyword. The top ten keywords according to frequency were NDVI, remote sensing, MODIS, vegetation index, climate change, Landsat, phenology, LST, GIS, and LAI. Among these keywords, "NDVI" appeared most frequently. "Remote sensing" was one of the most important NDVI research fields, which verifies our previous results. "MODIS" and "Landsat" are two important satellite data resources; "MODIS" is the most widely used sensor in NDVI-related research, with a total of 1442 papers from 1997 to 2021 [91–94], whereas "Landsat" was a keyword for 1115 papers from 1992 to 2021. From the perspective of the research content, Landsat can be applied to research on urban heat islands [95–98], land-cover changes [99–102], farmland monitoring, and crop yield estimation [103–107]. "Vegetation Index", "Climate Change", "Phenology", "LST", and "LAI" were also important research directions. "GIS" was the most widely used research method.

The farther the red dot is to the right of Figure 8 and the larger the blue dot, the more recent the publication and the greater the number of papers published for the corresponding keyword, respectively, which can reflect the research trends. Regarding the sensors related to NDVI research, "Sentinel-2" and "UAV" were hotspots of NDVI research in recent years. The high temporal and spatial resolution and the unique red-edge band of Sentinel-2 make it widely applicable for the calculation of vegetation biophysical parameters [108–110], the more detailed analysis of phenological changes [111–114], the identification of crop species, and the estimation of crop yield [115–119]. The number of publications for the keyword "UAV" increased rapidly in the past three years, with 165 publications during 2019–2021, accounting for 77% of the total number (214 during 2008–2021). UAVs have higher spatial resolution and flexibility than satellite remote sensing platforms; however, the sensor quality varies widely [46]. Regarding the applications of NDVI research, UAVs are mainly used for small-scale precision agriculture [45,120,121], agricultural yield estimation [122–125], and disaster assessment [126–128]. "Random Forest", "Machine Learning", and "Deep Learning" were the most frequent keywords related to methods in recent years, with 640 papers. "Google Earth Engine" is an online remote sensing platform that has emerged in recent years, allowing users to deploy algorithms online, use supercomputers to perform calculations on massive data, produce global vegetation index reconstruction products [129–131], and automatically map land cover [132–134].

We observed that some keywords with the same meaning caused statistical errors because of inconsistent spelling. Therefore, the author keywords were sorted, any keyword synonyms or different spellings were combined, and quantitative analysis was performed. For example, NOAA-AVHRR, NOAA/AVHRR, NOAA AVHRR, National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), Advanced Very High Resolution Radiometer (AVHRR), Advanced Very High Resolution Radiometer, and other spellings were combined as AVHRR. The specific combination of keywords is shown in Table S1. This step was performed to compensate for the lack of reference to professional knowledge in the Porter's stemming algorithm of the bibliometrix package, used to extract the proper nouns [57], which can lead to an unsatisfactory segmentation effect of some proper nouns.

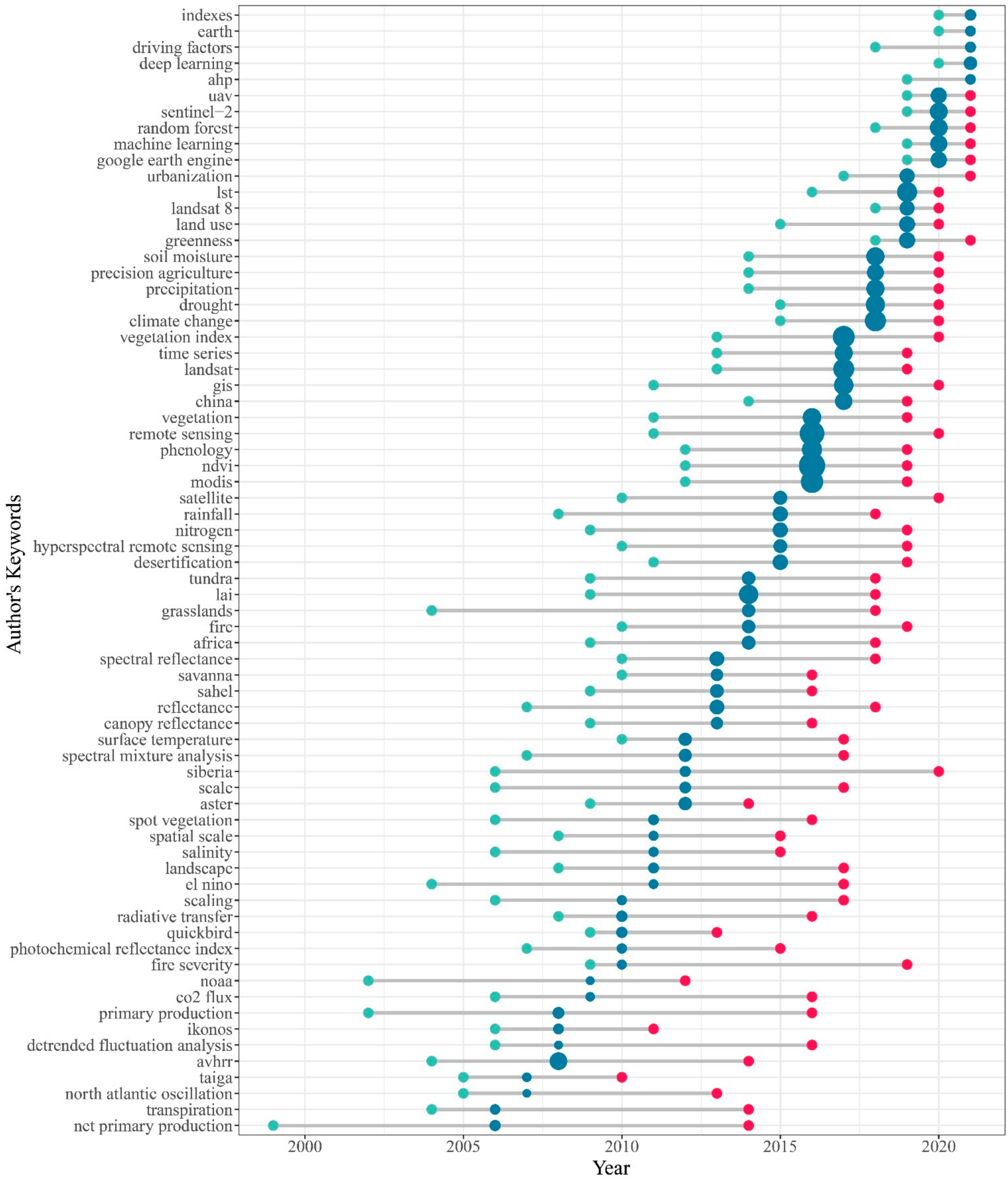


Figure 8. Temporal trends in author keywords.

5. Conclusions and Future Directions

Regarding the global trend of scientific literature on NDVI, the number of publications has grown exponentially in recent decades to cover a wider range of research fields. In this review, we present a comprehensive overview of the NDVI research field from 1985 to 2021 using bibliometric analysis. In the past 36 years, NDVI research has experienced exponential growth in the number of articles published, from one article in 1985 to 2389 articles in 2021. The United States, China, India, Spain, and Italy were the main research countries; the Goddard Space Flight Center and the Chinese Academy of Sciences were the main research institutions; the most influential journals included Remote Sensing, International Journal of Remote Sensing, and Remote Sensing of Environment; and Tucker C.J., Myneni R.B., and Piao S.L. were the main authors.

The research trends determined in this study indicate that NDVI research data sources are becoming more abundant, the areas of application are increasing, and research methods are becoming increasingly diverse. Early NDVI research was predominantly based on NOAA and AVHRR sensors. Later, with the addition of IKONOS, QuickBird, SPOT, MODIS, Landsat, Sentinel, UAV, etc., the data sources became increasingly abundant, and the spatial resolution developed from 8 km (GIMMS NDVI) to 1 km (SPOT NDVI and MODIS NDVI; also 500 m and 250 m), 30 m (Landsat NDVI), 10 m (Sentinel-2 NDVI), and even centimeter-level spatial resolution (UAV NDVI). Moreover, time series data are becoming longer, to more than 40 years. The number of research areas has also increased each year, from an initial focus on remote sensing to a wider range encompassing dozens of fields such as ecology, remote sensing, geology, agriculture, and public health. Furthermore, original research methods were based on early index calculation and time series analysis. With the addition of novel data sources and the development of cloud computing, new research methods such as machine learning, deep learning, random forest, and Google Earth Engine have since been added.

As for the future of NDVI research, the intersection and integration of multiple disciplines will likely become a key trend, and the application of the NDVI to ecology will become more extensive. As people increasingly focus on health, the environment and public health will become more popular applications of NDVI research. An increasing abundance of sensors and data sources and the development of multi-source data fusion and reconstruction technology will lead to more multi-source NDVI products that can provide higher spatiotemporal resolution and longer time series. The widespread popularity of UAVs will make it possible to study the NDVI of the sky and the ground. Machine learning and cloud computing platforms led by Google Earth Engine will greatly improve the accuracy and production efficiency of NDVI data products. In particular, the cloud computing platform can provide super computing power that traditional desktop computers and servers cannot match, which will greatly improve the efficiency of NDVI data processing and make it possible to conduct more precise and longer-term global-scale research.

However, the current bibliometrix word segmentation algorithm is not sufficiently intelligent, and the extraction of some keywords lacks accuracy. Therefore, subsequent bibliometric research should strengthen the semantic understanding of citation data to increase the accuracy of word segmentation statistics and ensure the more accurate and intelligent extraction of bibliometric knowledge. Although this paper found a trend of exponential growth in NDVI research, and there is positive feedback in the development of this scientific direction, the mechanism of feedback is still unclear and needs further exploration.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/rs14163967/s1, Table S1: list of the combined keywords.

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