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Review

Knowledge Domain and Emerging Trends in Monitoring of Forest Fires Using Remote Sensing: A Scientometric Review Based on CiteSpace Analysis

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Abstract: With global warming, the incidence of forest fires has risen significantly, negatively affecting the ecological balance and the environment. This paper is aimed at summarizing the current state of research and global development trends regarding monitoring of forest fires with remote sensing. In the present study, a total of 8841 documents from 2009 to 2024 were extracted with the goal of gaining insights into the progress and dynamics of forest fire monitoring based on remote sensing and the core library of the Web of Science (WoS) and visualized and analyzed with CiteSpace bibliometric software. Results show that research on remote sensing to monitor forest fires has mainly gained momentum in the last 16 years and has shown a significant increase after 2018. The United States, as a major research center, leads the global scientific community in terms of national and institutional collaborations. Forests, with 382 publications, was ranked first as the leading published journal in the field. Dr. Sun of the University of Northeast Forestry University, China, became the most prolific author, ranking first with 16 citations. The influence of driving factors on forest fires imposed on properties of soil drivers is revealed through the analysis of trends in research areas. Forest fire spread, index, fire trend will be the next focus of research. By combining biblio-metric methods and systematic reviews, these findings provide forest fire managers and researchers with a deeper comprehension of the development of monitoring forest fires using remote sensing.

Keywords: forest fire; remote sensing; monitoring; CiteSpace; bibliometric analysis; Web of Science; co-authorship analysis; co-citation analysis; research trend

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1. Introduction

Forest fires often occur in forested ecosystems worldwide and rank first among the three major natural disasters occurring in forests (Xiang et al., 2023). Global warming has led to a rise in both frequency and area impacted by forest fires, not only damaging the environment and jeopardizing ecological security but also endangering human lives and property (Babu et al., 2023; Jiao et al., 2023). For example, fires in the Amazon rainforest and Australia that occurred in 2019 and 2020 burned large areas of forests and wildlife habitats (de Santana et al., 2023; B. Wang et al., 2022). In 2023, the western provinces of Canada, namely British Columbia and Alberta, were afflicted by severe forest fires. These fires engulfed an area exceeding 121,000 square kilometers, rendering it one of the most catastrophic wildfire events in the country's history (Jain et al., 2024). Subsequently, in 2024, deadly fast-moving fires in Hawaii and Chile, as well as widespread fires in northwestern South America had a significant impact on the global environment (Jones et al., 2024). With an advantageous speed and the ability to monitor large areas and document the forest dynamics of a target at any time, remote sensing serves as a crucial means to detect and monitor forest fires in many countries (Xie et al., 2022b). In the early 1980s, with the development of Geographic Information Systems (GISs), the USA, Canada, and other nations began to carry out monitoring of forest fires through remote sensing, such as the United States used the system, Forest

Fire Advanced Technology, to detect and monitor forest fires. Meanwhile, the USA uses earth observation satellites for monitoring forest fires (Dasgupta et al., 2007; Sulla-Menashe et al., 2014; J. Wang & Zhang, 2020), surface temperatures, and humidity, as well as for forecasting levels of forest fire danger. In 1968, Canada established the Canadian Forest Fire Danger Ranking System (Wotton, 2009), which severs as one of the most well-developed and widely used system in the world at present. Exceptionally, Canada uses satellite tower infrared equipment to monitor forest fires much faster and more efficiently than aerial-based equipment. Poland uses remote sensing combined with GIS tools to monitor forest fires for national forest fire risk zoning and monitoring, fire damage surveys and assessments, and monitoring of trail restoration (Niklasson et al., 2010; Hościło & Turleg, 2014). The present study visualizes and analyzes literature related to monitoring forest fires using remote sensing, which provides a clear picture of the status quo and tendency of the remote sensing usage for forest fire monitoring. Researchers concerning this field have made some progress, and the relevant studies review this theme from different angles, like the early forest fire detection using a radio acoustic detection system (Hefeeda & Bagheri, 2009; Sahin & Ince, 2009; Tsiourlis et al., 2009). In recent years, scholars used deep learning and machine learning (ML) methods to conduct research related to forest fire modeling, mapping (Milanović et al., 2023; Y. Zheng et al., 2023), occurrence assessment, and smoke detection model construction (Qian et al., 2023; Shao et al., 2023), burn area detection, and so on while using multi-source remote sensing imagery (da Silva et al., 2023; Xu et al., 2022). Few researches have used knowledge mapping to quantitatively analyze amounts of previous researches using metrics, as most rely on expert opinion such as analyzing publications, word frequencies, citations, and co-citations. Although many nearly accessible online knowledge bases, books, and articles exist, their overall structure is unknown. To overcome the subjectivity of research, knowledge mapping as a new multidisciplinary research field provides scientific research studies with a visual analysis of the knowledge structure of a relevant field (Minaei-Bidgoli et al., 2004). CiteSpace version 6.2.R6 (64-bit) is a tool that measures the literature and presents the structure and trends of the research in a given subject area visually, providing various analytical approaches, like keyword, co-occurrence, as well as collaborative network types of analysis. Therefore, the present study used CiteSpace to visualize the research literature on monitoring forest fires using remote sensing and explored knowledge structure and future development trends concerning the number of issued papers, research collaboration (individual, institutional, and national collaboration), frequently cited literature, keywords, and research frontiers. In terms of the organization of this paper, (1) Section 2 presents the data sources, methods for analysis, and software parameter design, (2) Section 3 analyzes publication sources, research areas, annual trends, collaborative networks of literature, countries, authors, and institutions to show the knowledge structure of the focal topic. In conjunction with the keyword co-occurrence network, emerging trends in the focus topic are analyzed, the main findings are summarized, and new directions for future research of remote-sensing-based forest fire monitoring are suggested.

2. Materials and Methods

2.1. Data Sources, Search Strategy, and Data Processing

The statistics applied for the bibliometrics analysis came from the Thomson Reuters Web of Science (WoS) Core Collection, which consists primarily of SCI-Expanded databases. All of the searches were carried out within one day to prevent any bias owing to daily updates of the database. The strategy used during the search was Topic search #1 = ("forest fire" OR "forest-fire") AND Topic search #2 = ("Remote sensing") AND Topic search #3 = ("monitoring"), and then the results were refined by [Document Types = (Articles and Review) Timespan: 2009–01–01 to 2024–12–31]. Based on the WoS categorization tags, a total of 8841 articles were selected after eliminating unpublished or incomplete studies, like conference papers and abstracts. Furthermore, the authors, titles, abstracts, keywords, and references were imported into CiteSpace 6.2.R6. CiteSpace, a visualization information software, is often used in academic research and shows a visual type of keyword cluster maps, co-authored networks, dynamic knowledge, distribution maps of time zones, and co-cited networks (Xue et al., 2020). We used CiteSpace to combine cluster and correlation analysis, explore the main content, research hotspots, evolution trends, and research areas, analyze internal links of study hotspots in different phases, and discuss the tendencies of future research.

2.2. Setting of Algorithms and Parameters in Econometric Analysis

After the data was processed, the dataset was imported into CiteSpace. Here are the specific parameters in it. Time Slicing consists of "Year Per Slice" and "Time," which is the time frame for published literature. 1 January 2009 to 31 December 2024 was the set time interval; one year was the set time slice. The map produced by CiteSpace was on the basis of the initial collinear matrix and normalized; the new type of matrix was used to visualize the network. These parameters include Jaccard indices, cosine similarity measures, dice coefficients, and pointwise interaction information. The notion of density portrays the tightness or strength of the associations between nodes, and by dividing the "actual number of relationships," the "theoretical maximum number of relationships" was figured up. The value range of density was 0 to 1. Judging from the clustering clarity and the network structure, two indicators, namely, silhouette (S) and modularity (Q) were provided by CiteSpace to assess the mapping impact. Generally, Q remains within the scope of 0–1. A Q value > 0.3 indicates the structure of clustering is pronounced and clustering with S exceeding 0.5 is usually taken as reasonable. Clustering with S over 0.7 is a high confidence level (C. Chen et al., 2014). Mediation centrality, indicating the importance of a node, is on the basis of the quantity of the shortest paths through a node. This metric is applied by CiteSpace to explore and evaluate the influence of studies on the network, and as a node with intermediary centrality greater than 0.1 is called a critical node, it is usually highlighted with a purple circle (C. Chen et al., 2012). Node size in the authors' collaboration graph means the number of published papers by an author, institution, or country, and connections reflect partnership strength. In the network graph of topics, keywords, and scientific categories, node size represents the occurrence frequency, and the connection represents co-occurrence intensity. In addition, data clustering, another important method, is used to facilitate the analysis of knowledge networks in CiteSpace. More specifically, terms are categorized based on their similarity and scored by a specific algorithm, where the highest-scoring term in each cluster is selected as the label for the cluster (Yuan et al., 2021).

2.3. Other Statistical Analysis Tools

This paper used Microsoft Excel software for data analysis.

3. Results

3.1. Analysis of Publication Sources, Research Area, and Annual Trends

The yearly amounts of publications on the research theme can be divided into three time periods: 2009–2012, 2013–2017, and 2018–2024 as discussed in detail below (Figure 1). *Environmental Sciences* had the most publications regarding the monitoring of forest fires using remote sensing during the study period, followed by *Environmental Sciences*; other fields of research had over three hundred publications in total, including those in *Agricultural and Biological Sciences*, *Remote Sensing*, and *Forestry*.

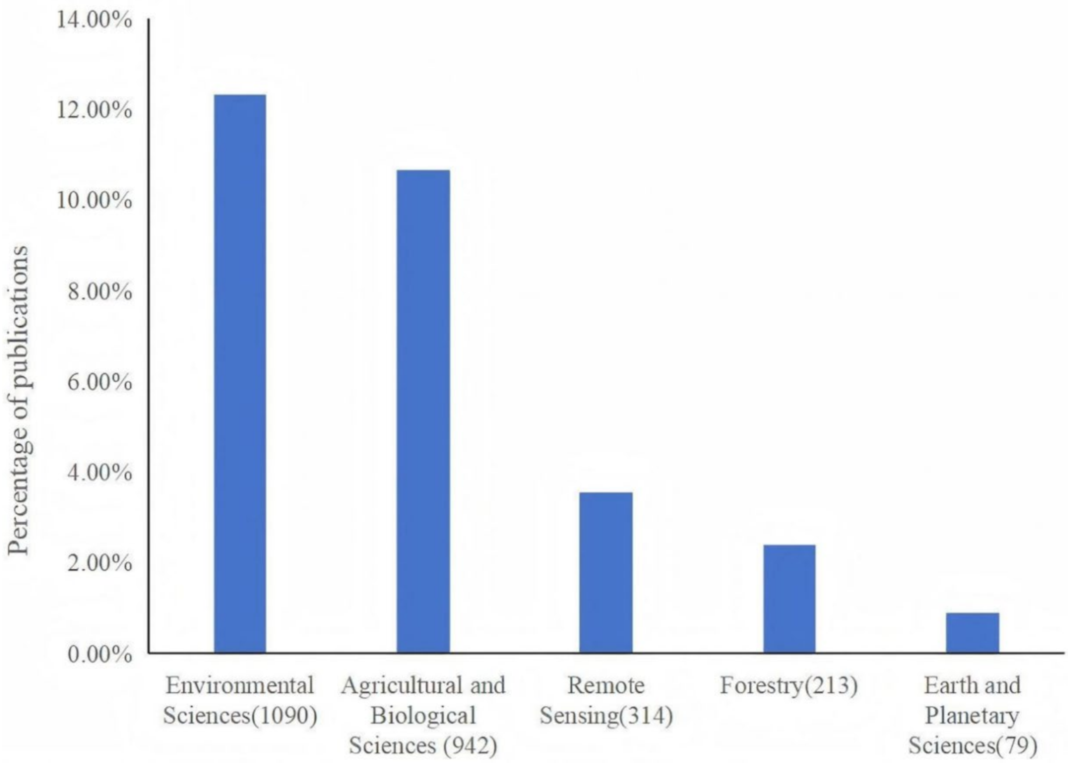

Figure 1. The top five most frequently appearing research areas involving the monitoring of forest fires with remote sensing.

The top seven nations concerning the number of articles in this field are Switzerland, Netherlands, Australia, England, the United States, and Germany. The top 15 journals publishing the largest amount of papers regarding remote-sensing-based forest fire monitoring from 2009 to 2024 are listed in Table 1, with the number two being *Forests* and *Remote Sensing*, followed by *International Journal of Wildland Fire*, *Forest Ecology and Management*, and *Fire Ecology*.

Table 1. The top 15 journals publishing papers on studies using remote sensing to monitor forest fires.

Rank	Research direction	Country	Count	Percentage (%)	IF* 2024	Research Area
1	Forests	Switzerland	382	4.32	2.237	Agricultural and Biological Sciences (Q1)
2	Remote Sensing	Switzerland	314	3.55	3.668	Remote Sensing (Q1)
3	International Journal of Wildland Fire	Australia	313	3.54	2.636	Agricultural and Biological Sciences (Q1)
4	Forest Ecology and Management	Netherlands	247	2.79	3.48	Agricultural and Biological Sciences (Q1)
5	Fire Ecology	United States	232	2.62	3.6	Forestry (Q1)
6	Fire Switzerland	Switzerland	213	2.41	3	Forestry (Q1)
7	Atmospheric Chemistry and Physics	Germany	210	2.37	4.739	Environmental Sciences (Q1)
8	Science of the Total Environment	Netherlands	201	2.27	7.503	Environmental Sciences (Q1)
9	Atmospheric Environment	England	133	1.50	3.301	Environmental Sciences (Q1)
10	Sustainability	Switzerland	112	1.27	2.937	Environmental Sciences (Q2)
11	Journal of Environmental Management	England	92	1.04	7.635	Environmental Sciences (Q2)
12	Natural Hazards	United States	89	1.01	3.359	Environmental Sciences (Q2)
13	Environmental Research Letters	England	87	0.98	5.029	Environmental Sciences (Q1)
14	Remote Sensing of Environment	United States	87	0.98	10.611	Environmental Sciences (Q1)
15	Atmosphere	Switzerland	79	0.89	2.9	Environmental Sciences (Q3)

Note: IF*, impact factor.

The distribution of annual publication outputs related to the topic of this paper from 2009 to 2024 is depicted in Figure 2 and is on the basis of the statistical analysis results of 8841 documents exported from WoS. Obviously, the quantity of publications as a whole shows an upward trend, which implies that research related to remote sensing monitoring forest fires has received a considerable amount of attention; great progress has been made over the past 16 years. Between 2009 and 2012, the number of publications fluctuated sharply. In 2010, the number of documents fell by about 10%, but in 2011 increased by nearly 25% over the numbers in 2010, although the number fell again in 2012 (Figure 2). Several reasons are responsible for this phenomenon; most likely the time required for the design and establishment of a system of forest fire risk rating and a modeling system varied widely in different countries (Laneve et al., 2012), making this type of research exhibit a state of steady growth with some fluctuations (J. H. Zhang et al., 2012). The optimization of methods and systems has resulted in the fast advancement of forest fire monitoring based on remote sensing (Aydin et al., 2019; Freitas et al., 2020; Kotel'nikov et al., 2020; Partheepan et al., 2023; Wang et al., 2018). From 2018 to 2024, the number of publications began to rise steadily, nearly doubling from the average 2009 to 2012 with the average number of documents published annually at this later stage reaching 608.

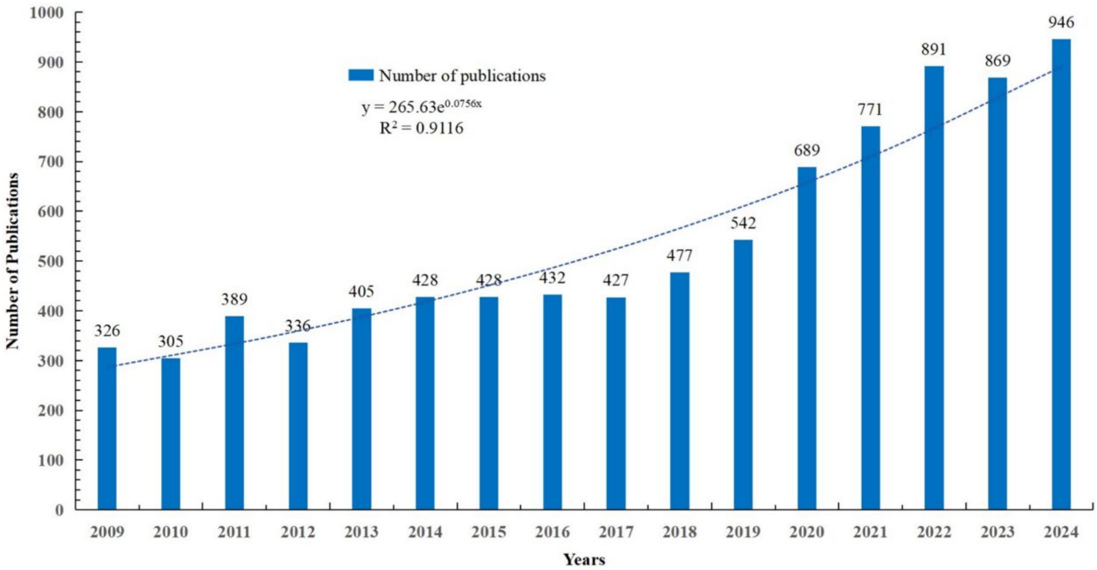

Figure 2. Annual trend chart of publications using remote sensing to monitor forest fires from 2009 to December 31, 2023.

3.2. Document Co-citation Analysis

The relationship between two papers that are cited in the same subsequent work is known as co-citation. A network of document co-citation is made up of co-citation relationships among many documents. A network like this is helpful for analyzing documents, which is more accurate than a straightforward study of citation links and can offer insights into the evolution of literature. As shown in Figure 3, using one year per slice, the top 134 levels of the most frequently cited works from every slice were found with Pathfinder software used to filter the data; then, a document with a co-citation network with clusters was obtained.

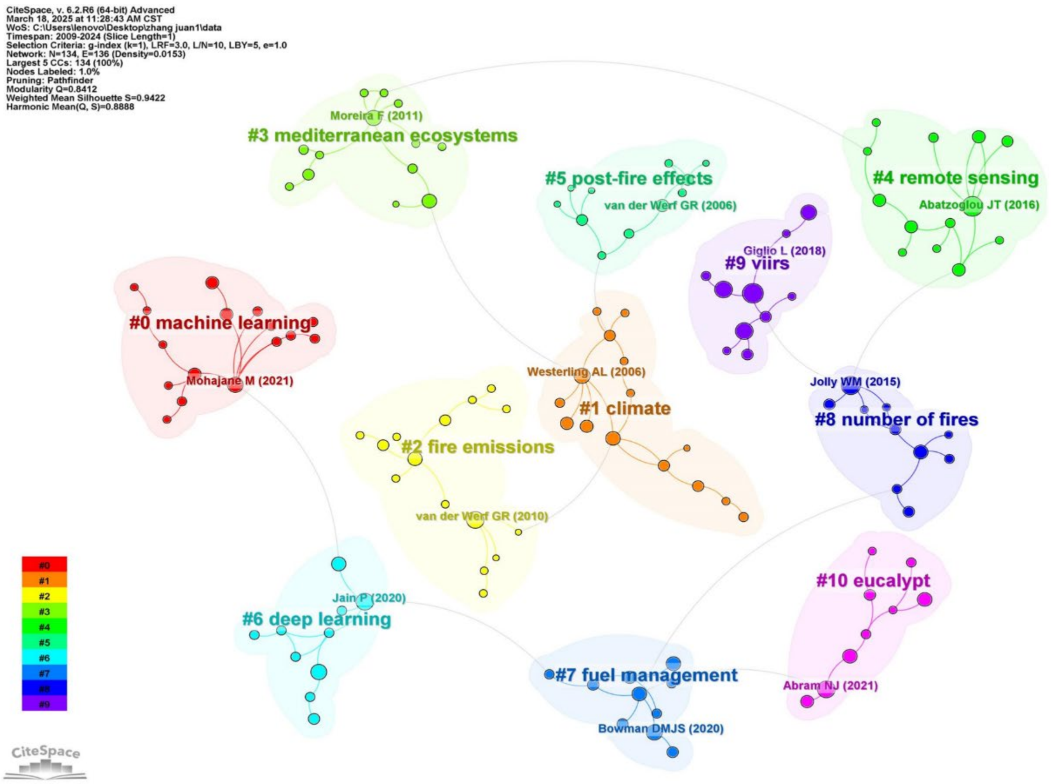

Figure 3. Network of document co-citation with the following clusters: (1) climate, (2) fire emissions, (3) mediterranean, (4) remote sensing, (5) post-fire effects, (6) deep learning, (7) fuel management, (8) number of fires, (9) viirs, (10) eucalypt.

Table 2 presents the top 10 documents, which are the most frequently cited works connected with the major topic. The most commonly used is the publication by Abatzoglou and Williams (2016), which predicts the growing influence of Anthropogenic Climate Change (ACC) on fuel aridity, which is projected to increasingly promote the potential for wildfires across the western USA; fuel aridity is predicted to become important for managing and studying wildfire in the coming decades. Giglio et al. (2016) improved the performance of the active fire detection algorithm known as Collection 6, addressing the false alarms of the previously used Collection 5 product data in small forest fire detection, and the omission of large scales of fires masked by thick smoke. Van der Werf et al. (2010, 2017) quantified global fire emission patterns, providing an international evaluation of the contribution of various sources to the overall international fire emissions. Jain et al. (2020) presented a scoping evaluation of ML methods application in managing and studying wildfire and raised wildfire researchers' awareness of various ML methods. Jolly et al. (2015) created a map of the spatio-temporal tendencies of forest fires from 1979 to 2013 and a basic yearly measure of the duration of the fire weather season using 3 data sets of daily global climate and 3 indices of fire danger. Their study results serve as an indicator for global forest fire management. These papers have been mentioned alongside a wide range of other papers that have established themselves as the foundational works in the area. Chuvieco et al. (2019) summarized and evaluated forest fire burned area mapping methods and burned area products, based on historical trends in satellite sensor-based burned area monitoring, thereby identifying new potential opportunities for enhancing future fire burn area detection techniques. Abram et al. (2021) used climate models to predict the future impact of climate change on bushfires in southeastern Australia, providing optimal fire prevention strategies to limit projected increase in fire risk.

Table 2. Top ten references related to using remote sensing to monitor forest fires based on citation frequency.

References	Citation counts	Betweenness Centrality	Year	Source
Abatzoglou J. T. (Abatzoglou & Williams, 2016)	124	0.09	2016	Proceedings of the National Academy of Sciences
Giglio L. (Giglio et al., 2016)	121	0.12	2016	Remote Sensing of Environment
Jolly W. M. (Jolly et al., 2015)	101	1.14	2015	Nature Communications
van der Werf G. R. (van der Werf et al., 2017)	96	0.06	2017	Earth System Science Data
Jain P. (Jain et al., 2020)	92	0.64	2020	Environmental Reviews
van der Werf G. R. (van der Werf et al., 2010)	87	0.36	2010	Atmospheric Chemistry and Physics
Abram N. J. (Abram et al., 2021)	82	0.23	2021	Communications Earth & Environment
Chuvieco E. (Chuvieco, 2019)	82	0.03	2019	Remote Sensing of Environment
Mohajane M. (Mohajane et al., 2021)	75	0.41	2021	Ecological Indicators
Westerling A. L. (Westerling et al., 2006)	72	0.92	2006	Science

3.3. Country Co-authorship Analysis

Knowledge maps can offer messages concerning nations and productive workteams that contribute significantly to the focus topic highlighting relevant forestry researchers; these maps can contribute to their future collaboration (Liang et al., 2017). Table 3 shows the United States of America (USA) ranked first in the publication to the total number of articles; China ranked second but was closely followed by Canada and Spain leading the top 10. Besides, the overall number of publications in China has been increasing yearly, which tends to place China among the world's top countries studying forest fire. For more information, refer to Figure 4 and Table 3.

Table 3. Top ten countries in the number of published articles related to using remote sensing to monitor forest fires.

Rank	Count	Betweenness Centrality	Country	Mean (Year)
1	2004	0.06	United States	2009
2	1314	0	People's Republic of China	2009
3	866	0	Canada	2009
4	853	0.06	Spain	2009
5	553	0	Australia	2009
6	464	0.24	India	2009
7	462	0.17	Germany	2009
8	438	0	Portugal	2009
9	427	0.55	England	2009
10	407	0	Italy	2009

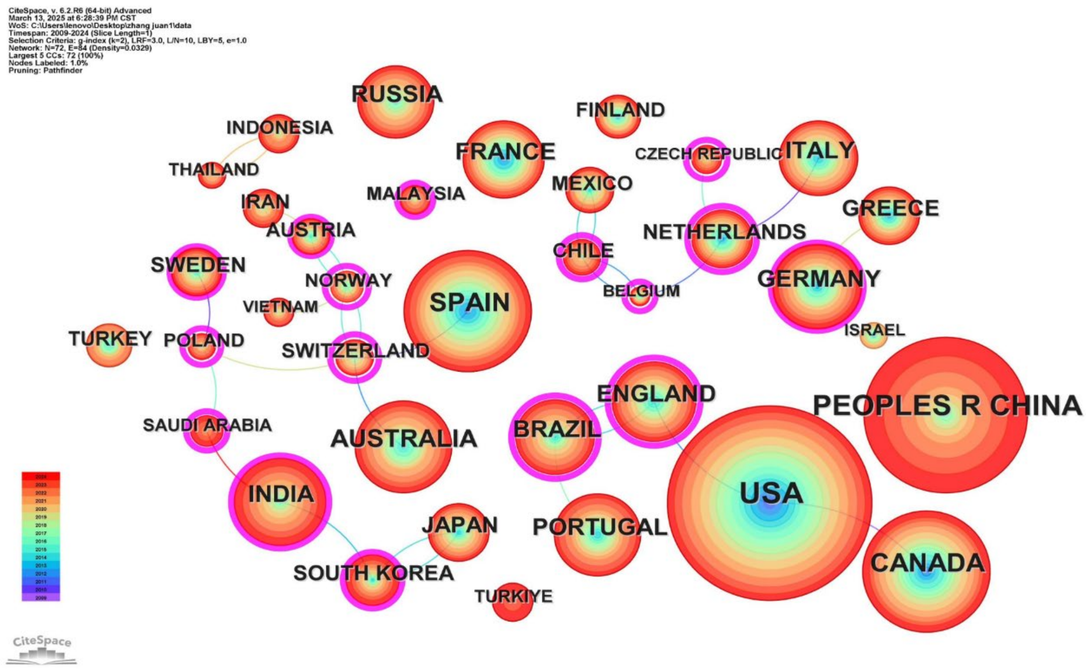

Figure 4. Graphic network of the use of collaborative analysis between countries publishing research related to using remote sensing to monitor forest fires.

Figure 4 presents an analysis of collaboration among countries conducting forest fire monitoring research that is based on remote sensing. Of these, England had the most collaborative efforts and had developed close ties with other countries, such as the USA, Brazil, Portugal, and Canada, with a Betweenness Centrality (BC) of 0.55. India ranks second in terms of cooperation intensity and has established close ties with South Korea, Saudi Arabia, and Japan, with a Betweenness centrality (BC) of 0.24. In addition, Switzerland shows a tendency to cooperate with different countries, including Australia, Spain, Norway, and Poland. The USA, with the largest number of publications, only cooperates closely with Canada and England. China, which has the second-largest number of publications, maintains cooperative relations with several countries, such as Bulgaria, Ethiopia, and Iceland. Although no direct positive connection was found between national partnerships and the number of publications, it looks like firm partnerships appear to facilitate advancements in research, as demonstrated by the top countries' partnerships concerning the number of journal publications. Hence, countries other than England can benefit from strengthening cooperation and exchange.

3.4. Author Co-authorship Analysis

Several researchers have worked with collaborators to publish on the focus topic in several countries as follows (Table 4). For example, Sun Long, a professor at Northeast Forestry University, carried out an investigation on behavior concerning forest fire, forest fire monitoring, and warning systems, along with studying the influences of forest fire imposed on forest ecology (H. Hu et al., 2016; T. Hu et al., 2017a; T. Hu et al., 2017b), which provided an empirical benchmark for exploring the effects of fire disturbance on the carbon balance of soil in boreal forests and estimation of soil carbon flux (Sun et al., 2014). Additionally, Sun and his research team assessed fire risk in temperate forests, analyzed burn severity models in subtropical forests (Guo et al., 2022; Masinda et al., 2022), and conducted satellite-based spatiotemporal wildfire analysis on the Mongolian Plateau (Bao et al., 2023). The results significantly improve the accuracy and efficiency of fire monitoring, prediction, and evaluation. Guo Futao, a professor at Fujian Agriculture and Forestry University, and his team utilized remote sensing, GIS, and machine learning models, they systematically investigated the deposition of nitrogen and other pollutants from wildfire smoke on soil properties, plant physiology, and ecosystem nitrogen cycling (Z. Huang et al., 2024; H. Lin et al., 2023). Additionally, they developed fire risk zoning methods based on fuzzy logic and analytical network processes, and revealed the spatiotemporal dynamics of water-soluble ions and particulate matter emissions from wildfires (Zhan et al., 2023). The research explored the effects of fires on tree ring growth, elemental concentrations, and post-fire forest succession trajectories (Wei et al., 2023; Zhong et al., 2023). Flannigan M., a fire scientist at the University of Alberta, Canada, studies forest fire in North America and Eurasia, including the impact of a shifting climate on wildland fire conditions worldwide (Flannigan et al., 2009), as well as the evolution of fire in Eurasia, and the sensitivity of fuel moisture to changes in precipitation and temperature in relation to wildland fire (Flannigan, 2015). Lin H., a professor at Nanjing Forestry University, developed fuzzy reasoning and big data analysis algorithms used for fire risk assessment and quantification (H. Lin et al., 2018), constructed a small-target model for forest fire detection and a model for forest fire risk for China's national forest parks through computer network technology (J. Lin et al., 2022), drew a fire risk map (P. Zhao et al., 2021), and obtained high precision of forest fire monitoring and prediction results.

Table 4. Data concerning the top twenty authors publishing research related to using remote sensing to monitor forest fires.

Rank	Author	Country	Count	Year of first article
1	Sun, Long	China	16	2022
2	Guo, Futao	China	16	2016
3	Flannigan, Mike D.	Canada	13	2009
4	Pourghasemi, Hamid Reza	Iran	8	2020
5	Zhang, Gui	China	8	2024
6	Yang, Guang	China	7	2023
7	Lin, Haifeng	China	7	2023
8	Feng, Zhongke	China	7	2022
9	Nolan, Rachael H.	Australia	7	2013
10	Palmer, P. I.	UK	6	2022
11	Jin, Huijun	China	6	2022
12	Li, Xiaoying	China	6	2018
13	Parisien, Marc-Andre	Canada	6	2013
14	Camia, Andrea	Italy	6	2014
15	Bergeron, Yves	Canada	6	2020
16	Tiefenbacher, John P.	United States	5	2024
17	Ning, Jibin	China	5	2013
18	Parrington, M.	UK	5	2013
19	San-miguel-ayanz, Jesus	Spain	5	2013
20	Bai, Di	China	5	2023

However, as shown in Figure 5, the connections between the nodes denoting nations tend to be more fragmented than the links between the nodes indicating authors. Forest fire researchers showed less team cohesion, team cooperation among paper authors was less obvious, and academic communication was less obvious, with only four studies showing team cooperation. In 2011, to understand the emission and plume evolution of boreal forest fires, a research team comprising Diskin G. S., Blake D. R., and Fuelberg H. E., utilized a United States National Aeronautics & Space Administration (NASA) DC-8 and other aircraft to monitor the biomass emission factors from northern Canadian forest fires, employing gas chromatography to analyze 79 non-methane volatile organic compounds (Simpson et al., 2011). They also assessed the influence of aerosols from boreal forest fires imposed on the climate of the Arctic (Kondo et al., 2011). Since 2013, a research team, led by Palmer P. I., Parrington M., Oram D. E., and Bauguitte S. J.-B., has used the Aircraft and Satellites experiment (also known as the BORTAS experiment) to assess the effect of boreal forest fires on tropospheric oxidants across the Atlantic, acquiring a complete chemical snapshot of pyrogenic plumes from wildfires (O'Shea et al., 2013) to determine impact extent of the dissemination of volcanic emissions on the atmosphere (Palmer et al., 2013; Parrington et al., 2013). After 2020, Eskandari et al. (2020) used data-mining approaches to construct a fire danger model based on messages about topography, climate, land cover, and other factors influencing fire risk in natural regions of Iran. In subsequent research, the team applied ML models to accurately predict wildfires and map areas susceptible to wildfire (Eskandari et al., 2021; Yousefi et al., 2020). The team consisting of Li X., Jin H., and Sun L. explored the influences of wildfires imposed on Northeast China's permafrost regions, including the effects of wildfire on vegetation succession and on the storage of nitrogen and carbon in soil (X. Li et al., 2023), the characteristics of permafrost after fire and the effects of climate warming (X. Li et al., 2022).

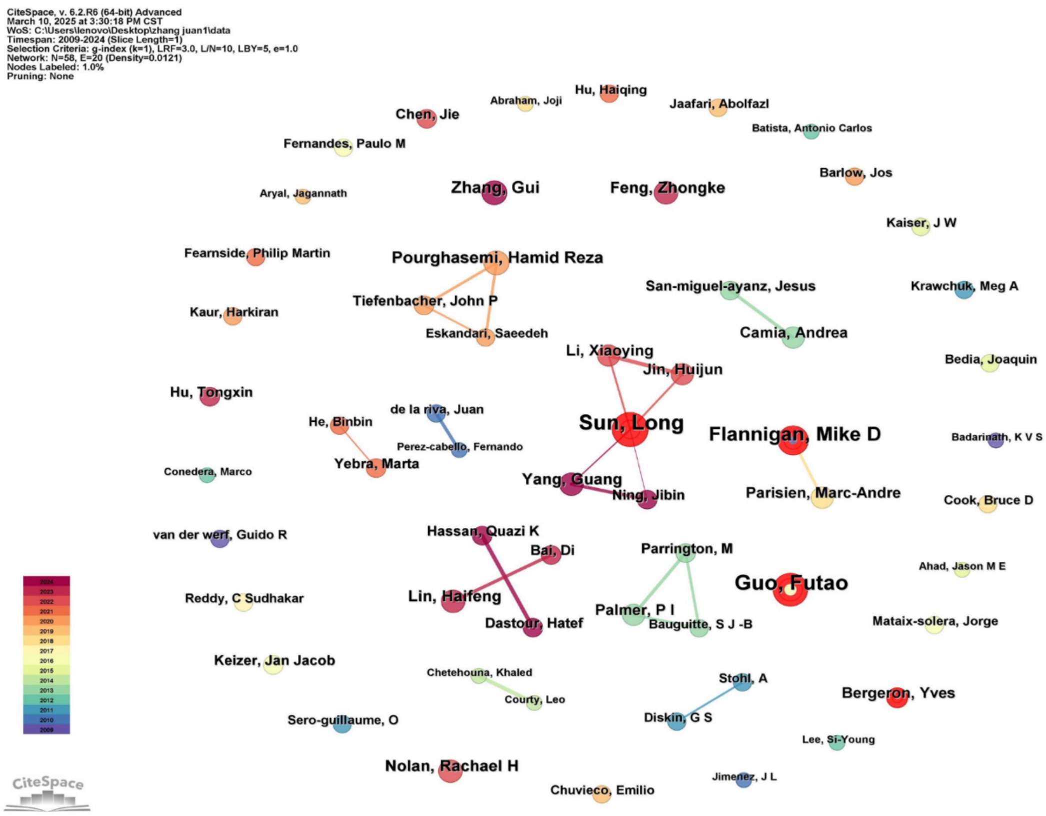

Figure 5. Author collaboration network for published research related to applying remote sensing to forest fire monitoring.

3.5. Analysis of Institution Co-authorship

Figure 6 shows the network of cooperation between institutions related to applying remote sensing to forest fire monitoring. Nodes represent institutions, and the node sizes indicate the number of articles published by each institution. The distance between the nodes indicates the extent to which 2 institutions collaborate. As the distance becomes closer, the cooperation becomes more frequent.

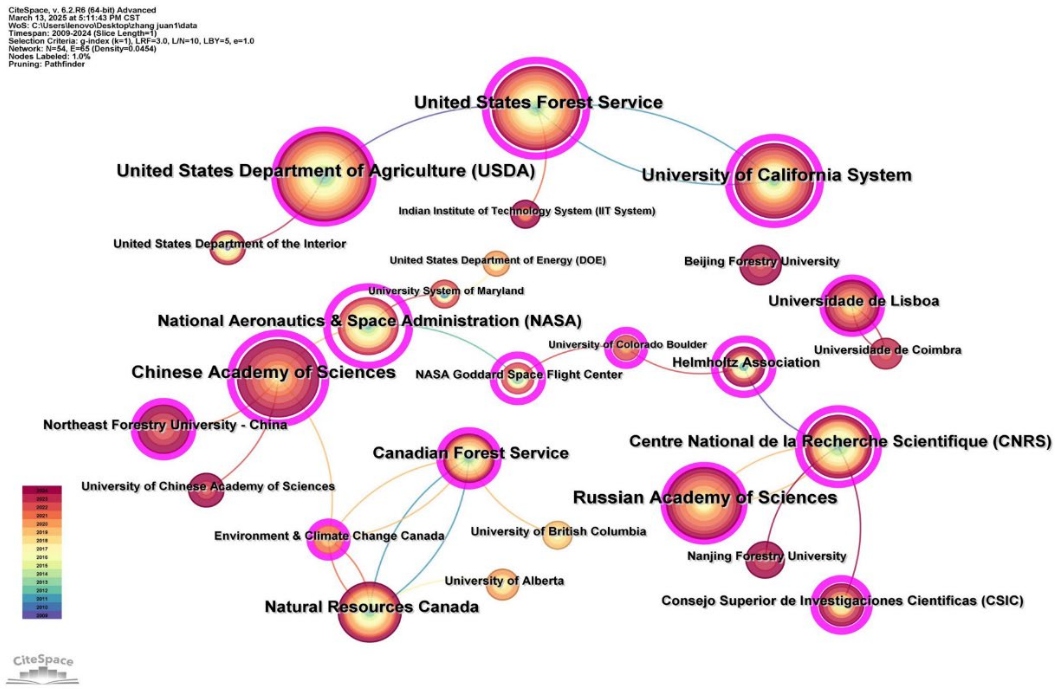

Figure 6. Institutional collaboration network for published research related to applying remote sensing to forest fire monitoring.

The United States Department of Agriculture (USDA) came to first place in the number of articles published, and the next were the United States Forest Service (USFS), the University of California System, and the Chinese Academy of Sciences (Table 5). Almost half of the top twenty institutions came from the USA, accounting for 13.87% of all publications, which shows that United States research dominates this area. In terms of the betweenness centrality, NASA had the largest value, implying that it exerts a greater impact in the area of monitoring forest fires using remote sensing. In addition, China ranks second in the value of betweenness centrality, with the Chinese Academy of Sciences (CAS) as the center in close cooperation with Northeast Forestry University, University of Chinese Academy of Sciences, NASA, and Environment & Climate Change Canada. Institutions all have cooperative relationships with each other, especially the USFS, Canadian Forest Service, Centre National de la Recherche Scientifique (CNRS), and the CAS, which form the key strength of scientific study and actively cooperate closely with many institutions.

Table 5. Statistics of the top 20 authors publishing research related to applying remote sensing to forest fire monitoring.

Rank	Institution	Count	Betweenness Centrality	Year of the first publication
1	United States Department of Agriculture (USDA)	349	0.15	2009
2	United States Forest Service	331	0.61	2009
3	Chinese Academy of Sciences	295	0.64	2010
4	University of California System	284	0.72	2009
5	Russian Academy of Sciences	250	0.15	2011
6	Centre National de la Recherche Scientifique (CNRS)	235	0.79	2009
7	Natural Resources Canada	212	0.07	2009
8	National Aeronautics & Space Administration (NASA)	178	1.22	2009
9	Canadian Forest Service	165	0.22	2009
10	Universidade de Lisboa	121	0.15	2010
11	Consejo Superior de Investigaciones Cientificas (CSIC)	87	0.54	2012
12	Northeast Forestry University - China	86	0.21	2021
13	Helmholtz Association	62	0.88	2009
14	Nanjing Forestry University	54	0	2022
15	Beijing Forestry University	51	0.07	2022
16	University of Chinese Academy of Sciences	45	0	2022
17	United States Department of the Interior	44	0.07	2009
18	NASA Goddard Space Flight Center	41	0.96	2012
19	Environment & Climate Change Canada	39	0.25	2011
20	University of British Columbia	38	0	2016

3.6. Mapping and Analysis of Keywords

3.6.1. High-frequency Keywords

Keywords summarize the content of literature, so evaluating keyword frequency and centrality can help analyze the research frontiers (Luo et al., 2021). This research used CiteSpace to analyze the keywords in the literature that address forest fire monitoring research based on remote sensing. The type of node was set to keyword, with a T = 30 threshold, and the rest were set to the default. A group of similar keywords were combined and invalid ones were eliminated; at last, a knowledge map of the study hotspot was prepared (Figure 7) and the top 20 keywords were obtained (Table 6), which shows the centrality ranking of the top 20 keywords. Nine nodes were found with intermediation centrality greater than 0.1, and the three keywords with the highest intermediation centrality were wildfire, climate, and fire. Other mediation-centric keywords were risk, boreal forest, emissions, management, dynamics, and vegetation, with the highest listed first (Table 6).

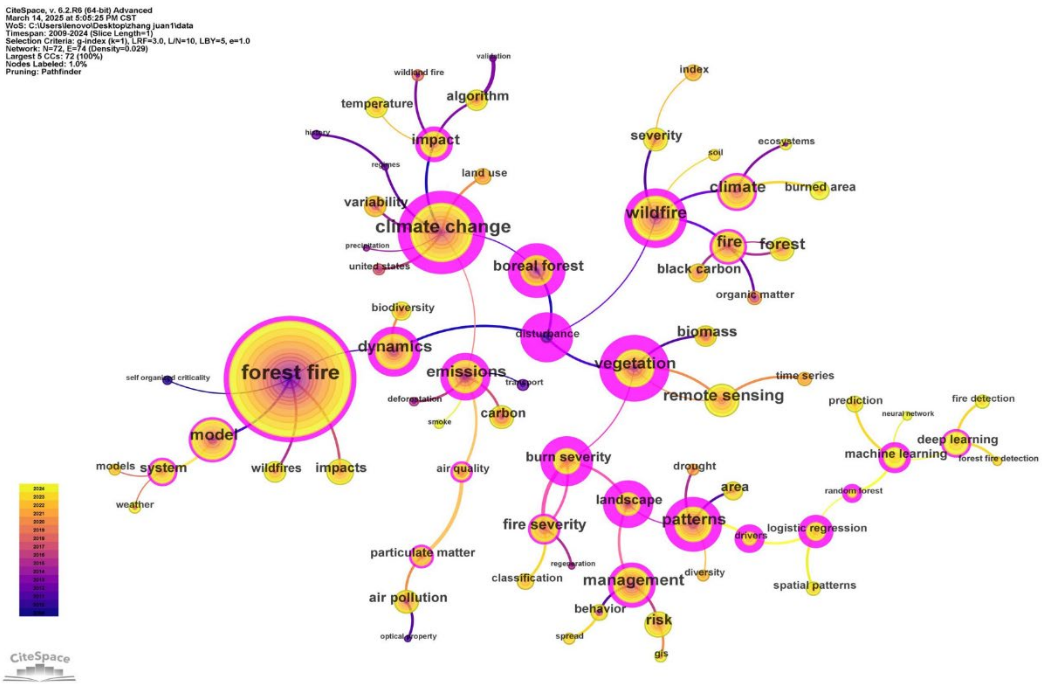

Figure 7. Keyword network for published research related to applying remote sensing to forest fire monitoring.

Table 6. Statistics of the top 20 keywords in published research related to applying remote sensing to forest fire monitoring.

Bank	Keyword	Frequency	Betweenness Centrality	Year of first appearance
1	forest fire	3183	0.37	2009
2	climate change	1149	0.94	2009
3	wildfire	702	0.52	2009
4	model	581	0.16	2009
5	vegetation	568	1.02	2009
6	management	531	0.22	2009
7	climate	531	0.11	2009
8	dynamics	496	0.46	2009
9	fire	495	0.17	2009
10	patterns	460	0.63	2010
11	remote sensing	445	0.06	2010
12	emissions	418	0.42	2009
13	forest	404	0	2009
14	impact	381	0.22	2009
15	boreal forest	351	0.85	2009
16	risk	312	0.06	2014
17	biomass	277	0	2009
18	fire severity	251	0.11	2010
19	landscape	240	0.85	2012
20	carbon	240	0	2009

3.6.2. Keyword Cluster Graph Analysis

Next, the ClusterView module in CiteSpace software was used to carry out cluster investigation on the knowledge map of keywords; this software clustered those keywords into nine clusters (Figure 8). Classes of clusters are represented with the same color nodes and were named subsequent to the key keyword node (Table 7). These included impact of biomass combustion and carbon emissions from forest fires on airborne particulate matter and human health risks (#0 particulate matter, #4 organic matter, #5 Black carbon), forest fire algorithm research using machine learning and deep learning (#2 deep learning, #9 machine learning), effects of forest fires with different severity degrees on vegetation (#fire severity), remote sensing for forest fire risk assessment, biodiversity monitoring and forest management (#3 remote sensing, #6 forest fire), impact of forest fires patterns under climate change across regions (#7 patterns, #8 climate change).

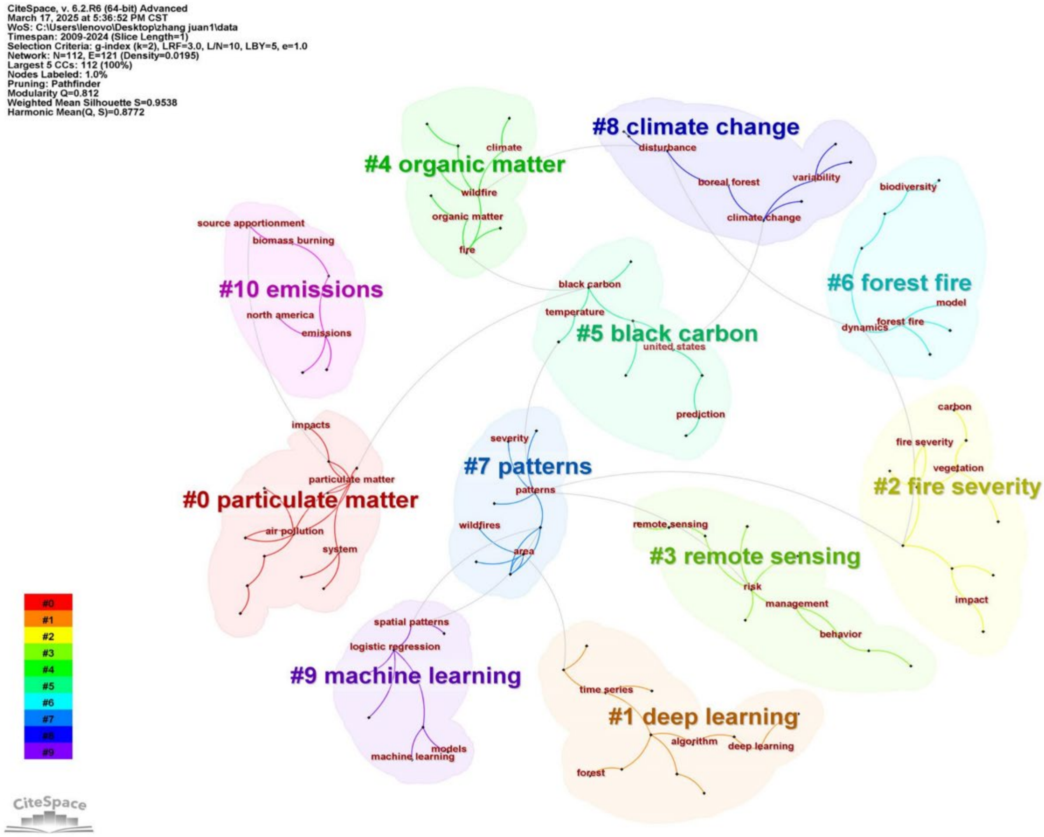

Figure 8. Keyword clustering for research related to using remote sensing to monitor forest fires: (0) particulate matter, (1) deep learning, (2) fire severity, (3) remote sensing, (4) organic matter, (5) black carbon, (6) forest fire, (7) patterns, (8) climate change, (9) machine learning.

Table 7. Statistics of the different clusters of keywords for research related to using remote sensing to monitor forest fires.

Cluster-ID	Cluster	Labels
#0	particulate matter	air pollution; impacts; system; particulate matter; air quality; transport; smoke; fire management; polycyclic aromatic hydrocarbons; exposure; mortality; aerosol; susceptibility; pollution
#1	deep learning	forest; algorithm; deep learning; time series; index; land-use; deforestation; MODIS; fire detection; forest fire detection; validation; Landsat; ndvi
#2	fire severity	vegetation; impact; fire severity; biomass; carbon; landscape; burn severity; regimes; wildland fire; spread; history; California
#3	remote sensing	management; remote sensing; risk; behavior; burned area; gis; self-organized criticality; performance; risk assessment; cover; forest fire model
#4	organic matter	water; fire; soil; forests; organic matter; climate; wildfire; water repellency; prescribed fire; ecosystems
#5	black carbon	black carbon; temperature; prediction; united states; optimization; biomass burning emissions; optical property; probability; Europe; carbon monoxide
#6	forest fire	forest fire; model; dynamics; biodiversity; conservation; diversity; community; ozone; fire history
#7	patterns	patterns; severity; area; wildfires; weather; drought; trends; drivers; regeneration
#8	climate change	climate change; boreal forest; variability; disturbance; classification; growth; precipitation; tree mortality; responses
#9	machine learning	machine learning; logistic regression; spatial patterns; models; random forest; neural network; ignition; regression

The largest cluster was Cluster-ID #0 with the tag particulate matter. The related keywords mainly included air pollution, impacts, system, particulate matter, air quality, transport, smoke, fire management, polycyclic aromatic hydrocarbons, exposure, mortality, aerosol, susceptibility; pollution. During the burning process of forest fires, a large number of inhalable particles will be produced, which will be suspended in the air and form smoke, causing serious impacts on air quality and human health. Remote sensing monitoring of particulate matter after forest fires can provide scientific basis for formulating effective forest management and fire prevention policies (Nurlatifah et al., 2025; Yuchi et al., 2016). The topic, Cluster-ID #0, discusses the use of remote sensing data to monitor and assess the impact of inhalable particulate matter on urban air quality and human health. For example, Sofowote and Dempsey (2015) applied the source term modeling technique of simplified Quantitative Transport Bias Analysis (sQTBA) integrated with meteorological analyses, to determine and identify air quality source locations that influence forest fires in Ontario. Dreessen et al. (2016) employed Surface in situ, balloon-borne, and remote sensing observations to monitor the impact of the Canadian wildfire smoke on air quality across the northern Mid-Atlantic (MA) of the United States. Yao et al. (2018b) utilized the CALIPSO satellite combined with a random forests model to predict and estimate the smoke state of forest fires in Canada. Attiya and Jones (2022) employed MODIS (Moderate Resolution Imaging Spectroradiometer) and CALIPSO satellite data, combined with NAAPS and HYSPLIT models to simulate the forest fires of characteristics of smoke aerosols and air quality levels obtained in Australia. D. Chen et al. (2023) established a methodological framework based on the Wildland Fire Emissions Inventory System (WFEIS), the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model, and the Arctic-Boreal Vulnerability Experiment (ABoVE) Wildfire Date of Burning (WDoB) dataset, an Arctic-oriented fire product, and studied changes in Alaska's air quality under the long-term effects of wildfires, providing key data for strategies to improve air quality. Nurlatifah et al. (2025) utilized satellite instruments such as MODIS, VIIRS (Visible Infrared Imaging Radiometer Suite), and the GEMS (Geostationary Environment Monitoring Spectrometer), and employed the WRF-HYSPLIT (Weather Research and Forecasting model coupled with the Hybrid Single Particle Lagrangian Integrated Trajectory model), to identify and analyze the spatial distribution of $PM_{2.5}$ from forest fires in central Kalimantan in October 2023. At present, single satellite data such as MODIS, VIRR, and CALIPSO are insufficient for precise forest fire monitoring, and multi-source data fusion enables long-term fire and smoke monitoring (Yin et al., 2023). Additionally, Sentinel-5P/Tropomi offers high-resolution aerosol, ozone, and nitrogen dioxide data, which supports smoke monitoring (Wang et al., 2020). Combining random forest or deep learning can effectively simulate the impact of forest fire smoke on air quality (L. Li et al., 2020).

The second largest cluster was Cluster-ID #1, with a deep learning tag; the related keywords mainly included forest, algorithm, deep learning, time series, index, land-use, deforestation, MODIS, fire detection, forest fire detection, validation, Landsat, ndvi. This cluster mainly integrates the high spatial resolution of Landsat and the high temporal resolution of MODIS, combined with deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), which has shown significant potential in land-use classification, deforestation monitoring, fire detection, time series analysis, and NDVI calculation. For example, L. Zhao et al. (2022) developed a lightweight Convolutional Neural Network (CNN) model to detect fire smoke from Landsat imagery, significantly improving the accuracy and efficiency of early-stage smoke detection. X. Hu et al. (2024) proposed AF-Net, an active fire detection model based on enhanced Object-Contextual Representations (OCR), addressing the accuracy limitations in UAV image-based fire detection caused by data imbalance, such as insufficient fire samples. Seydi et al. (2022) proposed a deep learning-based fire detection framework capable of capturing multi-scale features of fire regions, significantly enhancing the model's ability to identify complex terrains and fire boundaries. Verbesselt et al. (2010) employed time series analysis and NDVI to monitor post-fire vegetation recovery dynamics mapping. Hansen et al. (2013) integrated Landsat data with machine learning methods to achieve high-accuracy global deforestation mapping, though limitations persisted in data resolution, temporal scale, and classification precision. F. Zhao et al. (2022) introduced a method utilizing dense time-series Sentinel-1 SAR imagery and deep learning, addressing the limitations of optical remote sensing under cloud cover and seasonal variability, and enabling high-precision, high-frequency monthly mapping of forest harvesting. Fodor and Conde (2023) integrated Landsat, Sentinel-2, and MODIS data into a deep multimodal learning framework to rapidly detect deforestation and burned areas in satellite imagery, overcoming the inefficiency and accuracy limitations of traditional methods. The studies provide critical technical support for precise forest fire monitoring and management, and future research could further explore multi-source data fusion and the development of real-time fire early warning systems.

The third largest cluster was Cluster-ID #2, with a fire severity tag; the related keywords mainly included vegetation, impact, fire severity, biomass, carbon, landscape, burn severity, regimes, wildland fire, spread, history, and California. In recent years, remote sensing technology has significantly advanced in forest fire research, particularly in assessing fire severity and its impacts on vegetation, biomass, carbon cycling, and landscape dynamics. Many researchers suggest that fire severity is closely linked to vegetation recovery, carbon emissions, and ecosystem functionality. For example, X. Chen et al. (2011) employed Landsat and MODIS satellite data to derive the Normalized Difference Vegetation Index (NDVI) and the Normalized Burn Ratio (NBR), integrating field-based Composite Burn Index (CBI) measurements to evaluate post-fire burn severity and vegetation recovery in forest ecosystems. Miller et al. (2009) utilized Landsat data to develop the delta Normalized Burn Ratio (dNBR) method for evaluating fire severity and vegetation recovery potential. Liu et al. (2020) utilized ICESat-2 photon-counting data, integrated with Landsat and Sentinel-2 optical remote sensing data, to map burned areas. Compared to traditional optical remote sensing methods such as dNBR, ICESat-2 data demonstrated superior performance in detecting burned areas in complex terrains and low-intensity fire scenarios (Liu et al., 2020). Von Nonn et al. (2024) developed an open-source workflow to spatially align and integrate high-resolution drone imagery with Landsat and Sentinel-2 satellite data, significantly improving the accuracy and spatial resolution of burn severity assessments. Lutz et al. (2010) employed remote sensing data to analyze the effects of high-severity fires on biomass and carbon stocks, highlighting significant carbon release due to wildfires. Herbert (2022) utilized time series analysis and high-resolution remote sensing data to validate forest growth models and quantify tradeoffs between forest growth, carbon storage, and fire risk, offering a scientific foundation for forest management in fire-prone ecosystems. Additionally, Steel et al. (2015) used MODIS and Landsat data to study the relationship between wildfire spread, climate, and topography in California, revealing spatial patterns of fire severity. More recently, Y. Zhao et al. (2023) developed an integrated predictive model combining remote sensing data, climate models, and ecosystem models. Through time series analysis, the model assessed fire frequency, severity, and spatial distribution in California and other global regions, providing an effective tool for evaluating future fire risks (Y. Zhao, 2023). The results provide a scientific foundation for fire management and ecosystem restoration strategies.

The fourth largest cluster was Cluster-ID #3, with a remote sensing tag. The related keywords mainly included management, remote sensing, risk, behavior, burned area, gis, self-organized criticality, performance, risk assessment, cover, and forest fire model. The application of remote sensing technology in forest fire monitoring and management has further advanced, achieving significant progress in fire risk assessment, behavior modeling, and burned area mapping. For example, Adab et al. (2013) employed remote sensing and GIS techniques to model forest fire risk in northeast Iran, achieving high accuracy in identifying fire-prone areas and providing a scientific basis for fire prevention and resource management. Van Le et al. (2021) propose a deep neural computing (DNC) approach combining CNN and LSTM for spatial wildfire danger prediction in tropical climates, achieving 92.5% accuracy and outperforming traditional methods by 20–25%, providing a robust tool for wildfire prevention and ecological management in tropical regions. Maffei et al. (2021) employed multi-spectral and thermal remote sensing data to predict forest fire characteristics, integrating spatial and thermal information for improved fire detection and severity assessment. Ikhsan et al. (2023) used the Information Value Method (IVM) with GIS and remote sensing data to model forest and land fire susceptibility in Kotawaringin Barat Regency, Indonesia, achieving high prediction accuracy for effective fire risk management. Demir and Dursun (2024) utilized the RUSLE model integrated with Google Earth Engine to assess pre- and post-fire erosion in the Manavgat River Basin, providing insights into the impact of forest fires on soil erosion dynamics. González et al. (2024) employed remote sensing and GIS to assess forest fire severity in Vilcabamba, Ecuador, developing a management conceptual model that improved fire severity mapping accuracy in previous studies by integrating multi-source data. Singh and Srivastava (2025) utilized a GIS-based multicriteria technique to identify fire-prone regions in Lamington National Park, validated by field and Sentinel-2 data, achieving high accuracy and providing a reliable tool for fire risk management and conservation planning. The studies provide critical technical support for forest fire management, risk mitigation, and ecosystem restoration.

The fifth largest cluster was Cluster-ID #4, with the organic matter tag. The related keywords mainly included water, fire, soil, forests, organic matter, climate, wildfire, water repellency, prescribed fire, and ecosystems. Remote sensing technology has significantly advanced in monitoring forest fires and their impacts on water, soil, and ecosystems. For example, Van Eck et al. (2016) used physically-based modeling combined with field and remote sensing data to analyze post-fire runoff in a Portuguese forest catchment, improving vegetation recovery estimates by integrating high-resolution spatial and temporal data. Rust et al. (2019) integrated field data, remote sensing, and hydrological modeling to analyze post-fire water quality in western US forests, addressing spatial and temporal monitoring limitations through multi-source data fusion to evaluate fire impacts on watershed dynamics and water quality. Mastrolonardo et al. (2024) employed field measurements and remote sensing to assess post-fire erosion and sediment yield in a Mediterranean forest catchment in Italy, revealing significant increases in sediment transport and providing insights for post-fire land management and erosion control. Ross et al. (2024) utilized LiDAR-derived forest structure data to analyze the impact of fire frequency on forest ecosystems, providing high-resolution 3D insights into post-fire recovery and overcoming limitations of traditional 2D remote sensing methods for fire impact assessment. Busby et al. (2023) employed remote sensing and field inventory to analyze fire effects of wind-driven megafires in the western Cascades, linking fire severity to weather conditions and pre-fire forest structure, providing critical insights for fire management and forest resilience strategies. Beltrán-Marcos et al. (2023) integrated UAV and Sentinel-2 data to estimate post-fire topsoil organic carbon, showing that combining high-resolution and multispectral data enhances soil carbon assessment accuracy and supports ecosystem recovery monitoring. Fernández-García et al. (2023) reviewed wildfire severity impacts on forest soils and outlined post-fire restoration strategies, highlighting soil recovery as critical for climate change mitigation and ecosystem resilience enhancement. These advancements have elucidated fire's role in soil properties, water cycles, and carbon dynamics, aiding climate change mitigation and post-fire restoration. By integrating field data with high-resolution remote sensing, researchers have overcome traditional limitations, providing robust tools for fire management and ecosystem recovery amid rising wildfire risks. The results show the effects of forest fires on soil properties, water cycling, and carbon dynamics, supporting climate change mitigation and post-fire recovery. By integrating field data with high-resolution remote sensing, researchers overcome traditional limitations, offering robust tools for fire management and ecosystem restoration amid increasing wildfire risks.

3.7. Analysis of Research Frontiers and Emerging Trends

In the form of time evolution, the Time Zone View module of CiteSpace was applied to build a Time Zone distribution map of keywords to investigate the thematic shifts in remote sensing monitoring forest fires in the past 16 years. The time slices in CiteSpace were set to one slice per year, the top 50 keywords that were cited with high frequency were extracted from the corresponding slices of each year, and the network was pruned using the pathfinder model to get the network of keyword covariance.

As shown in Figure 9, most of the frequently used keywords are concentrated in the early stage of the study, such as the keywords "forest fire" and "remote sensing" Among them, climate change is the earliest high-frequency word, followed by words related to the research background, how to monitor and manage forest fires including wildfires, and post-disaster vegetation by remote sensing under climate change. In recent years, new keywords have appeared less frequently, with "soil," "fire detection," "spread," and "diversity" being frequently used keywords; their emergence has led to an increasing depth and breadth of research in this field.

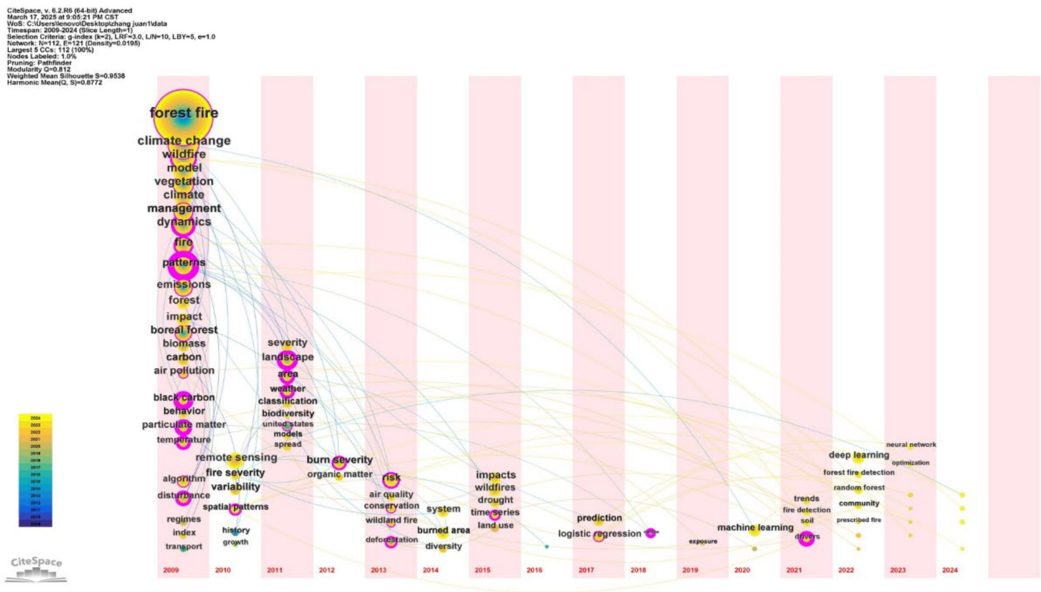

Figure 9. Keyword time zone diagram for published research related to using remote sensing to monitor forest fires.

Subject terms or keywords in the relevant previous studies were explored for emergent terms to decide the ongoing advancement of fire research and new research perspectives. The time-zone function of CiteSpace was used to explore emergent terms and to identify cutting-edge topics in the field. As shown in Figure 10, the top 15 emergent terms over the past 15 years were identified. The first, second, and third were history (from 2010 to 2016), transport (from 2009 to 2012), and the

United States (from 2016 to 2018), respectively. The following less frequently used terms are drivers (from 2021 to 2024), growth (from 2010 to 2014), spread from (2021 to 2024), land use (from 2019 to 2022), and others. Keywords were classified based on the first year of their appearance; the position and length of the red blocks in Figure 10 represent the time interval of keyword highlighting. According to the frequency and time length of the most frequently cited keywords, the research hotspot of monitoring forest fires using remote sensing was divided into three time periods (stages) as discussed below.

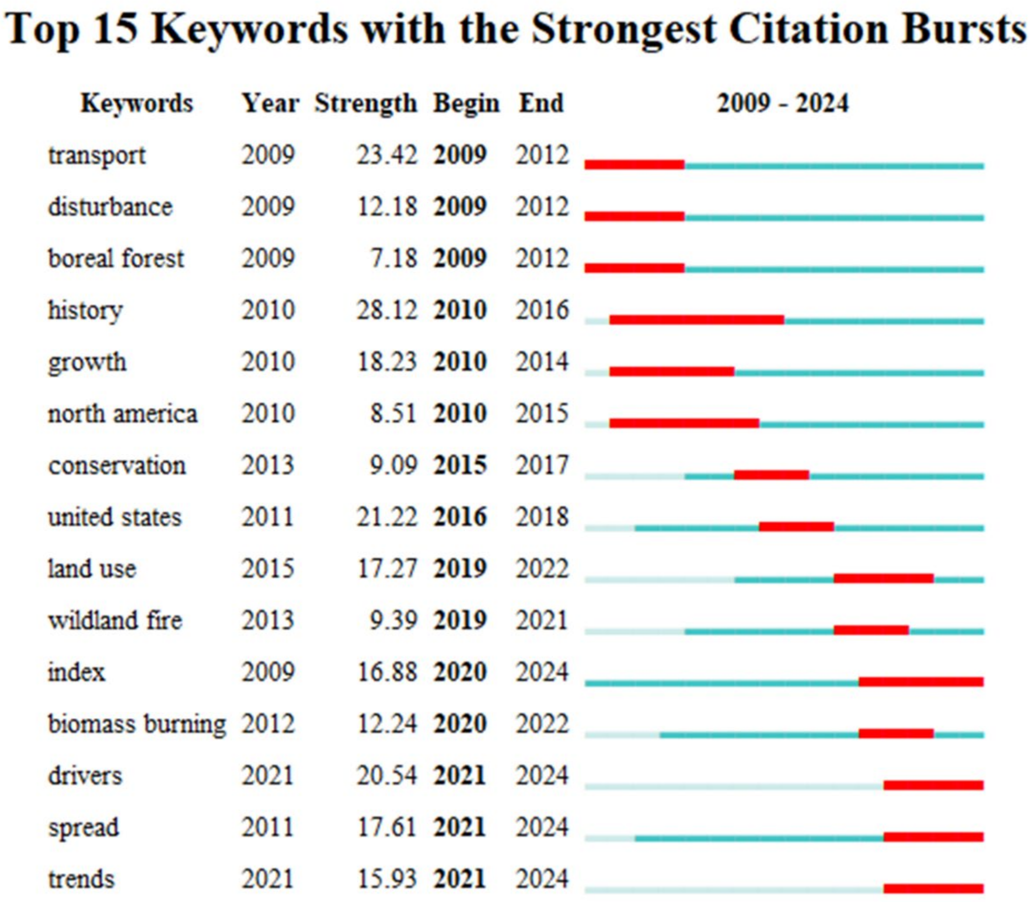

Figure 10. Top fifteen words in emerging frequency in research related to using remote sensing to monitor forest fires.

Stage 1 (2009–2014): Affected by many factors such as global warming, previously rare large-scale forest fires with increasing frequency occurred in the USA, Canada, Spain, and other nations since 2009, causing serious losses and grave consequences. Forest fires discharge air contaminants like PM_{10}, $PM_{2.5}$, black carbon as well as organic aerosols. Specifically, $PM_{2.5}$ is transported over long distances and across administrative borders under the action of weather and weather dynamics, which creates serious influences on the environment and damages the health of human beings. During Stage 1, many researchers began to pay attention to the evaluation and forecasts of the effects of wildfires imposed on air quality, using techniques like Satellite-based (CALIPSO) light detection and ranging (McKendry et al., 2011), MODIS imagery combined with the Chemistry Transport Model (Ito, 2011), and the GEOS-Chem chemical transport model (Y. Chen et al., 2009) to build a meteorological analysis and forecast method, improving the accuracy of analyzing and predicting the influence of forest fires imposed on quality of air. Forest fires serve as a crucial type of disturbance that occurs in various forested ecosystems and can affect the structure and function of forests. Monitoring vegetation responses to fire disturbance is significant. Some researchers began to use MODIS imagery to conduct long-term monitoring of vegetation after fires (van Leeuwen et al., 2010). Radar-based remote sensing combined with multi-temporal spatial synthetic aperture radar data has been applied to analyze vegetation structure, regeneration characteristics, and recovery of fire-burned areas (Goetz et al., 2010). Landsat thematic mapper and reinforced thematic mapper time series statistics (He et al., 2011) and hyperspectral Earth Observation-1 satellite statistics have been applied to monitor and analyze the physiological features and spatial patterns of fire-disturbed vegetation (Numata et al., 2011). Therefore, remote sensing imagery has excellent potential for monitoring the growth and recovery of vegetation after fires.

Stage 2 (2015–2018): Since the beginning of the 20th century, average temperatures have increased by about 1.1 °C in California and Oregon and by about 0.8 °C in Washington state. As higher temperatures caused by climate change dry out vegetation, wildfires burn more intensely and spread quickly from suburban to urban areas. Severe heat and drought during that period led to frequent fires in California, Arizona, Oregon, and Washington. California is a major forest fire-prone area in the world, with multiple wildfires raging and causing significant damage during a long fire season that is becoming even longer. During this stage, remote sensing imagery was mainly used to monitor and analyze historical forest fires in the USA with the aim of realizing forest fire prevention and management. Since 2016, Landsat imagery has been used to accurately detect many fires in the USA and to distinguish between burning and non-burning areas (Meddens et al., 2016). By 2017, tree mortality caused by fires in various states of the United States was quantified using Above-Ground Carbon stocks and disturbance data from remote sensing, suggesting the need for continuous observing and describing of tree mortality rates in the coming decades to inform management of forest and greenhouse gas (Berner et al., 2017). Based on light detection and ranging and Landsat imagery, fuel loading was monitored and mapped through ML models such as random forest, so that fire behavior modeling at the landscape scale was realized (Bright et al., 2017). In the last decades, the United States has been able to restore pre-European settlement frequent fire regimes in many landscapes and improve forest resilience through various fuel treatments designed to reduce fuel loads as a part of forest management. Since 2018, researchers proposed a new fire burn index that allows low- and mixed-severity fires to be detected and described more accurately (McCarley et al., 2018). At the same time, with multi-temporal remote sensing statistics and cloud computing, the extent of burns from the 2013 Creek Fire was assessed and changes in land surface characteristics were tracked; as a result, fire treatments such as planned burning, commercial logging, forest thinning and resource-efficient burning, i.e. managed wildfires were found to be the most effective methods used in reducing the likelihood of dangerous fires and increasing post-fire recovery (Petrakis et al., 2018).

Stage 3 (2019–2024): Climate change has further exacerbated the threat of forest fires to biodiversity. All of the world will face longer fire seasons and more severe forest fires, and even areas that previously had few forest fires may become high-risk areas. In addition, population growth and irrational land use have made it more difficult to control forest fires. Monitoring the effects of fires, their onset, and recovery processes after fires is critical to recommending actions designed to mitigate the risks and impacts of these catastrophic events. Researchers have used land-use data combined with topography, climate, and human drivers to develop fire susceptibility maps, verifying the accuracy of fires detected by remote sensing to delineate fire danger areas and mitigate forest fires (Razavi-Termeh et al., 2020; Venkatesh et al., 2020). Meanwhile, to make up for the limitations of a single remote sensing satellite in monitoring fires, the researchers proposed the synergistic inversion and forest fire observation with multi-source remote sensing data (Tian et al., 2022b; Xie et al., 2022a). Moreover, deep learning, such as Convolutional Neural Network (CNN; McCarthy et al., 2021) and ML methods (Dahan et al., 2023; Deng et al., 2023), is used in conjunction with satellite imagery and spatial analyses to guarantee the forest fire detection at the early stage and facilitate response management. In addition, it becomes possible to monitor and model wildfires in a variety of terrestrial ecosystems because of the increasing remote sensing data availability. Important research began to use the spectral characteristics of remote sensing statistics from multiple sources to calculate land surface temperature, the normalized differential vegetation index, forest vegetation type, and temperature vegetation dryness index to construct a composite fire danger index (C. Chen et al., 2023). Burned area estimation products can be obtained using remote sensing statistics from multiple sources, which can quickly interpret and analyze the driving factors of the success of fire suppression and spread control (Crowley et al., 2019; Y. Zhao et al., 2023). Drivers are the key variables in building fire prediction models, and analyzing fire-driving factors can improve the accuracy of different fire monitoring systems (Chang et al., 2023). As wildfire activity continues to increase in frequency and severity, ecological resilience after fires decreases; ecosystems are at risk of collapse if they fail to recover after fires, so more research has begun to focus on the evaluation of the forests' recovery capacity from wildfire disasters. For example, Sentinel-2 satellite remote sensing imagery can be used to calculate greening, humidity, and fire severity indices, which can then be used to assess forest resilience after fire (Avetisyan et al., 2022); the use of satellite image monitoring can be used to develop new post-fire recovery-post-fire stability indices, methods, and so on (Gibson et al., 2022). The richness and diversity of vegetation can be used as one of the best indicators to estimate vegetation recovery after forest fires (Serra-Burriel et al., 2021). Using aperture radar backscatter (Sentinel-1) and multispectral emissivity fusion to estimate the vertical structural diversity of plant communities, vertical structural diversity monitoring has acted a crucial part in maintaining the restoration of ecosystem functions in fire-prone landscapes compared with post-fire vegetation restoration (Aydin-Kandemir & Demir, 2023). At the same time, extreme wildfires lead to a loss of wildlife habitat. Remote sensing data can be extracted from burned areas combined with pre-fire data such as species richness with fire data, which can then be analyzed and assessed for wildlife resilience and fire impacts on ecosystems (Fernández-Guisuraga et al., 2023). Research in this period of time provides important information related to monitoring wildfires with remote sensing and related risk research. Future research on forest fires will focus on four key areas: forest fire drivers, fire spread, fire index, and fire trends, aiming to enhance understanding and management through advanced technologies and interdisciplinary approaches.

Forest fire drivers primarily include natural factors (e.g., climate change, vegetation type, and topography, and anthropogenic factors (e.g., agricultural burning and urbanization). Existing studies have utilized remote sensing technologies with multi-source data (e.g., optical, thermal infrared, and radar) to quantify the spatial distribution and dynamics of these factors, coupled with machine learning algorithms to develop fire prediction models. However, challenges remain, such as inconsistencies in spatial, temporal, and spectral resolutions among different remote sensing data sources, which hinder data fusion. While current models perform well in specific regions, their accuracy diminishes when applied to other areas. Additionally, the spatial heterogeneity and dynamic nature of human activities (e.g., land-use changes) are difficult to precisely capture. To address these issues, future research should focus on developing unified data preprocessing frameworks to integrate multi-resolution remote sensing data, enhancing data consistency. Leveraging transfer learning and region-specific training methods can improve model generalizability while combining high-resolution satellite imagery (e.g., WorldView, Gaofen) and social media data can enable more accurate quantification of anthropogenic influences.

Fire spread is influenced by a combination of fuel, topography, and meteorological conditions. Remote sensing technologies, utilizing high spatiotemporal resolution data (e.g., UAV imagery and thermal infrared data), enable real-time monitoring of fire boundaries and intensity. When integrated with physical models (e.g., fluid dynamics) and numerical simulations, these technologies can reveal fire spread patterns. However, challenges remain, including the limited revisit cycles of current remote sensing systems, which hinder real-time monitoring, and the significant uncertainties in fuel, meteorological, and topographic parameters within fire spread models. Additionally, simulation accuracy is often low in complex terrains and vegetation conditions. To address these issues, UAVs and near-real-time satellite data (e.g., GOES, Himawari) can enhance monitoring frequency. Future efforts should focus on optimizing model parameters using ground-based measurements and machine learning algorithms, as well as integrating LiDAR and high-resolution DEM data to improve simulation accuracy in complex environments.

Fire indices (e.g., NDVI, NBR, FWI) are derived from remote sensing data to assess fire risk by evaluating vegetation status, meteorological conditions, and surface temperature (Z. Wang et al., 2024). However, most existing indices rely on static data, limiting their ability to reflect dynamic fire risks and their applicability across diverse ecosystems and climatic conditions. Future research will focus on developing region-specific fire indices tailored to different ecosystems and integrating real-time remote sensing and meteorological data to build robust, dynamic fire risk assessment models.

At present, Fire trend analysis primarily relies on long-term remote sensing data (e.g., MODIS, AVHRR) to reveal spatiotemporal patterns in fire frequency, intensity, and extent, combined with climate models to predict future trends. However, challenges such as sensor discrepancies, data gaps, and the complex relationship between climate change and fire trends persist. Quantifying the impacts of fires on carbon cycling, biodiversity, and ecosystem services faces issues like data insufficiency, model uncertainties, and interdisciplinary barriers. To address these challenges, future efforts will focus on developing data correction algorithms, leveraging multi-source data integration, and establishing long-term databases to enhance data quality and consistency. Additionally, comprehensive model development, multi-source data fusion, parameter optimization, quantification of human activities, and long-term monitoring and experiments will help reduce uncertainties, providing more reliable scientific insights into the climate-fire relationship. Building multi-source data integration systems, long-term monitoring networks, interdisciplinary collaborations, and data-sharing platforms will support holistic assessments and management of fire-related ecological impacts

4. Limitations

As for the limitations, this research only analyzed articles from the database WoS, which is a major weakness of CiteSpace, resulting in an incomplete literature search for this study and potentially biased results. Currently, most of the visualization work has been created according to WoS, which is the representative and most extensively used database in this area and therefore often adopted. Other data sources such as Scopus or Microsoft Academic Search are easily overlooked, while more data sources would provide a wider range of research for analysis. Second, due to the constraints of the project, the intervals between studies were not very long, with extracted articles published between 2009 and 2024. In addition, some of the potential publications were published recently, which made it difficult to retrieve and cite these research papers. Future research should be conducted using additional databases and different tools.

5. Discussion

This paper describes in detail the theoretical framework and new developments in the field of remote sensing monitoring of forest fires. We analyze countries, institutions, individuals, and the key themes in the relevant field, and predict new directions for future development in this field.

Sun Long, Guo Futao, and Mike D. Flannigan have great influence in the field of remote sensing monitoring of forest fires, which deserves the attention of researchers in related research fields. Sun Long and Guo Futao have studied the effects of forest fires on carbon and nitrogen cycles in larch forests in the Greater Khingan Mountains and their response mechanisms, focusing on soil cycles and vegetation recovery in burned areas. They led a team to develop key technologies for fire risk warnings and spread simulations, established a national forest and grassland fire warning system, and implemented it across most regions in China (H. Hu et al., 2016; T. Hu et al., 2017a). Mike D. Flannigan's research through future climate simulation has shown increased fire activity in many northern and temperate forests around the world. Climate change has a greater impact on forest fire activity in northern Canada and Russia, as well as grassland fire activity in Australia. Consequently, many researchers have begun to use Landsat, MODIS, lidar, multispectral and other remote sensing data to monitor fire activity and vegetation restoration in the region, which is used to scientifically guide forest resource management and reduce fire risk (Caccamo et al., 2015; S. Huang et al., 2019; Levin et al., 2021; Meng et al., 2018; Petrakis et al., 2018; Sever et al., 2012; Shah et al., 2023). After 2000, with the development of remote sensing technology and the increase in the amount of data, R language was used to process and analyze remote sensing data, including the monitoring and assessment of forest fires (Deng et al., 2023; Donager et al., 2018; Nisa et al., 2014). Since 2017, countries such as China, the United States, the European Union, the United Kingdom, and Japan have elevated AI to a national strategy and plan (Attard-Frost et al., 2024).With the development of remote sensing technology and the advancement of machine learning algorithms, researchers have begun to explore the application of machine learning technology to the monitoring and evaluation of forest fires. From the early days of traditional machine learning algorithms, such as support vector machines (SVMs; Anggraeni & Lin, 2011; Koetz et al., 2008) and random forests (Random Forest; Bright et al., 2017; João et al., 2018; Schroeder et al., 2017; Yao et al., 2018a), they are often used to identify fire signatures in remote sensing images. With the development of deep learning technology, deep learning models, such as convolutional neural networks (CNNs; J. Huang et al., 2022; Kang et al., 2022; McCarthy et al., 2021; Radman et al., 2023; Zikiou et al., 2024), long short-term memory networks (LSTMs; Bahadori et al., 2023), and long short-term memory networks (LSTMs; Bahadori et al., 2023; Duangsuwan & Klubsuwan, 2023; Fan et al., 2022; Hong et al., 2024; Muthukumar et al., 2022), are better able to process complex data to accurately identify fire signs and assess fire risks. More and more scientists have shifted their attention to how to better use machine learning and deep learning to improve the efficiency and accuracy of forest fire monitoring, a trend that reflects the significant increase in academic publications on the topic since 2020. On August 9, 2021, the United Nations Intergovernmental Panel on Climate Change (IPCC) released an updated scientific assessment report on climate change in Geneva, Switzerland, noting that drought is becoming more common in the future as world temperatures continue to rise. Extreme weather conditions have led to unprecedented temperatures and forest fires around the world, such as the wildfires in Australia and the Amazon, and habitat loss has led to the extinction of a large number of wild animals, which has had a huge impact on global ecosystems and species diversity. Since 2021, most researchers have begun to focus on the use of remote sensing data to monitor post-fire spatial changes, migration monitoring, and species activities (Aydin-Kandemir & Demir, 2023) and to analyze the spatial and temporal distribution drivers of forest fires, which is conducive to the formulation of fire prevention measures and decision-making (Rotich & Ojwang, 2021; Sikuzani et al., 2023; Tian et al., 2022a). At the same time, the use of remote sensing satellite data to monitor carbon emissions from forest fires has become a research hotspot (Liu et al., 2023). According to research statistics, the frequency of extreme fire events increased by 2.2 times from 2003 to 2023, and the last 7 years included the most extreme 6 years (Cunningham et al., 2024). In 2021, boreal forest burning in Eurasia and North America released a record 480 million tons of carbon dioxide, accounting for 23% of total global carbon dioxide emissions from fires (B. Zheng et al., 2023). In the future, we should focus on the risk of wildfires in the boreal forests, and establish remote sensing monitoring, forecasting, and evaluation systems for wildfire carbon emissions, to provide support for the formulation of scientific and effective wildfire management and regulation policies.

The United States Department of Agriculture (USDA), a federal government agency responsible for protecting agriculture, forestry, and pastoralism, has a large position in the number of publications and the level of cooperation between relevant research institutions. The USDA's affiliate, the United States Forest Service (USFS), established the Missoula Fire Science

Laboratory, and in 1998 began the Joint Fire Science Program with the Department of Agriculture's Forest Service, systematically developing fire prediction and analysis software, such as BehavePlus fire scenario prediction software and the National Fire Risk Rating System (NFDRS), whose laboratories are well-known in the field of remote sensing monitoring of forest fires (Andrews, 2014; Finney, 2005). As a world-class educational and scientific institution, the University of California system actively cooperates with the Center for Remote Sensing (CSTARS), the United States Forest Service, and the United States California Forest and Fire Protection Agency, such as the early fire detection system of the Geosynchronous Environmental Satellite (GOES), to the project to develop “Alert California AI” using artificial intelligence (AI) technology to monitor and prevent forest fires, and improve the forest fire prevention and extinguishing capabilities in United States California region. Forest fire losses are minimized. The Chinese Academy of Sciences is the highest academic institution of natural sciences in China, which has built a complete natural science system, including chemistry, materials science, physics, mathematics, environment and ecology, earth science and other disciplines are the world's most advanced projects, and has long been committed to the application of satellite remote sensing technology in forest fire prevention technology research. In the 80s of the 20th century, the research institute carried out forest fire monitoring, mainly involving the identification of smoke areas, the detection of ignition points, and the dynamic monitoring of forest fire combustion (Jiao et al., 2023; X. Li et al., 2015; X. Li et al., 2014; Qu et al., 2009; Z. Zhang et al., 2010; Y. Zhao et al., 2023).

Our analysis of publications and international cooperation networks shows that the United States is a major force in remote sensing monitoring of forest fires. The United States is in a typically Eastern Mediterranean climate, often exposed to heat, drought, and strong winds, especially in United States California, where forest fires occur every year. It has been concerned and studied by most researchers. Beginning in 1960, the United States National Aeronautics and Space Administration (NASA) launched TIROS and ERTS satellites, which began to be used for fire monitoring and disaster response. The subsequent launch of a series of Landsat satellites, MODIS and OLI has provided researchers around the world with high-resolution images to extract forest fire hotspots and monitor fire spread. NASA actively cooperates with other countries and international organizations to share forest fire remote sensing data and research results, which provides important support for promoting global forest fire monitoring, early warning, and response. With the advancement of remote sensing technology, a new generation of remote sensing sensors and platforms will be developed and deployed, these advanced sensors can provide higher quality data, including higher spatial resolution and wider spectral range, and more accurate forest fire monitoring methods will be studied in the future, focusing on the development of machine learning technology combined with traditional forest fires, and the development of efficient fire prevention, monitoring, early warning and response technologies and ecological restoration management planning.

Keywords that appear suddenly or change significantly at a specific time represent an emerging field of research or trend. Analyzing the trend of keywords over time can provide insight into the evolution of the field of study. The keywords of citation burst detection and its topic development point to the key research topics of remote sensing monitoring of forest fires, such as “history,” “transport,” “United States,” “drivers,” “growth,” “spread” and so on. Among them, the word “history” is the most prominent, with an outbreak intensity of 28.12. From 2009 to 2017, researchers paid more attention to the impact of forest fires on human health and the environment, emphasizing the use of remote sensing to monitor forest fire disturbance factors, spatial patterns, and post-disaster vegetation detection and air quality assessment in the early stage. Research hotspots include “soil,” “fire detection,” “spread,” and “diversity”. Keywords such as “vegetation,” “climate change,” "boreal forest,” “landscape,” “patterns,” and “wildfire” have become the main research topics of forest fire management. The shift in research hotspots from 2009–2019 to 2020－2024 reflects evolving challenges driven by climate change, technological advancements, and the need for integrated ecosystem management strategies in forest fire monitoring and mitigation. Monitoring post-fire soil health using remote sensing is critical for achieving global climate goals such as carbon neutrality and land degradation neutrality. Post-fire changes in soil properties, including organic matter content, water repellency, and nutrient cycling, directly influence vegetation regrowth, carbon sequestration, and hydrological processes. The increasing frequency and intensity of wildfires necessitate a deeper understanding of soil’s role in ecosystem resilience and carbon storage. High-resolution remote sensing (e.g., UAVs, Sentinel-2) and machine learning enable detailed monitoring of soil characteristics and recovery dynamics. The integration of UAVs, thermal sensors, and AI (e.g., deep learning models) has revolutionized fire detection capabilities, enabling real-time monitoring and early warning systems. Understanding fire propagation is essential for effective firefighting, evacuation planning, and risk mitigation, reducing response times and resource allocation costs for fire management agencies. Furthermore, fire regimes significantly impact species composition, habitat availability, and ecosystem services. Research on fire-biodiversity relationships supports the development of conservation strategies and adaptive management practices, enhancing ecosystem resilience amid increasing wildfire risks. Researchers monitor land-use change through remote sensing, identify high-fire risk areas and the speed and direction of fire spread by understanding information such as forest density, vegetation type, and soil moisture, and develop new remote sensing indices to monitor the fire spread process and provide key information for decision-makers. Remote sensing can help researchers assess the impact of fires on the structure and function of forest ecosystems, as well as the recovery after fires. Under global climate change, the increasing frequency of wildfires worldwide requires enhanced monitoring and evaluation. Forest fire management agencies should strengthen interdisciplinary cooperation by integrating remote sensing, meteorological, and geographic information data to develop risk-based prevention strategies. Promote the construction of fire early warning systems and simulation models, optimize resource allocation, improve emergency response efficiency, strengthen international cooperation, and effectively respond to cross-border fire challenges.

6. Conclusions

To know the progress of forest fire monitoring using remote sensing, an analysis of document co-citation, author, country, and institution co-authorship, and keyword analysis was used to conduct a comprehensive econometric analysis. In this study, CiteSpace, a commonly used bibliometric software, was used as the research object for papers included in WoS from 2009 to 2024. The results show the yearly number of publications is increasing, though a slight decrease has been found recently. At the national level, the five nations with the largest volume of papers published on the focus topic were the USA, China, Canada, Spain, and Australia. The USA collaborated with most countries such as Brazil, Portugal, and Canada has made an outstanding contribution to international collaborative research. On the institutional scale, the NASA-centered network had the highest collaboration intensity, forming close partnerships with other institutions. At the researcher level, ten research groups were identified, with the highest intensity in groups including Oram D. E., Bauguitte S. J.-B., Palmer P. I., and Parrington M. as members, along with Flannigan M. D. and. Parisien M.-A as another group. In addition, the three most productive authors were Sun L. from Northeast Forestry University, China, Guo F. T. from Fujian Agriculture and Forestry University, China, and Flannigan M. D. from the University of Alberta, Canada. At the journal level, Forests ranked first with 382 publications followed by Remote Sensing and the International Journal of Wildland Fire with 314 and 313 publications, respectively. At the research field level, Environmental Sciences, Agricultural and Biological Sciences, and Remote sensing ranked highest with 1090, 942, and 314 publications.

Besides, the analysis of co-citation contained both previous studies and individual levels. In terms of the previous studies, the cluster literature co-citation analysis showed 10 research directions in the area of forest fire monitoring based on climate, fire emissions, mediterranean, remote sensing, post-fire effects, deep learning, fuel management, number of fires, viirs, and eucalypt. For example, the large wildfires' spatial dynamics can be explored with satellite-based active fire statistics, which is an efficient means to systematically obtain information on a global scale. Fire monitoring and modeling can be improved based on fire activity data, thus providing decisive data support for the vast majority of fire analysts. Based on the keyword cluster graph analysis, it was found that the years 2009–2024 could be categorized into ten main themes: particulate matter, deep learning, fire severity, remote sensing, organic matter, black carbon, forest fire, patterns, climate change, and machine learning. From 2003 to 2014, the main themes were transport, disturbance, boreal forest, history, and growth. From 2015 to 2018, the main themes were the United States and conservation as hot topics of research. From 2019 to 2024, the main themes were, index, biomass burning, drivers, spread, and trends as the hotspots that had the most frequent appearance over the past 6 years. Finally, an exploration of the research tendencies through the keyword time zone map was conducted to determine the influences of forest fires imposed on properties of soil, fire point detection, forest fire spread, and biodiversity are expected to be the next focus of this type of research. China occupied ten of the top twenty individual rankings, with L. Sun from the University of Northeast Forestry, China, ranking first with 16 citations in total.

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