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*Review*

# Comprehensive Analysis of Temporal–Spatial Fusion from 1991 to 2023 Using Bibliometric Tools

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**Abstract:** Due to budget and sensor technology constraints, a single sensor cannot simultaneously provide observational images with both a high spatial and temporal resolution. To solve the above problem, the spatiotemporal fusion (STF) method was proposed and proved to be an indispensable tool for monitoring land surface dynamics. There are relatively few systematic reviews of the STF method. Bibliometrics is a valuable method for analyzing the scientific literature, but it has not yet been applied to the comprehensive analysis of the STF method. Therefore, in this paper, we use bibliometrics and scientific mapping to analyze the 2967 citation data from the Web of Science from 1991 to 2023 in a metrological manner, covering the themes of STF, data fusion, multi-temporal analysis, and spatial analysis. The results of the literature analysis reveal that the number of articles displays a slow to rapid increase during the study period, but decreases significantly in 2023. Research institutions in China (1059 papers) and the United States (432 papers) are the top two contributors in the field. The keywords "Sentinel", "deep learning" (DL), and "LSTM" (Long Short-Term Memory) appeared most frequently in the past three years. In the future, remote sensing spatiotemporal fusion research can address more of the limitations of heterogeneous landscapes and climatic conditions to improve fused images' accuracy.

**Keywords:** bibliometrics; spatiotemporal fusion; remote sensing; multi-temporal synthesis; network analysis; Web of Science

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## 1. Introduction

With the development of aerospace technology, more and more remote sensing satellites have been successfully launched and are widely used in resource and environment monitoring, disaster prevention and reduction, sustainable development monitoring, and other fields [1–3]. It is challenging for one satellite sensor to have high spatial and temporal resolution, even with the growing number of remote sensing satellites in operation [4]. Sentinel-2, WorldView-3, and Landsat 9 are a few examples of high-spatial-resolution but poor-temporal-resolution satellites that produce amazing surface photos at resolutions of 0.3 to 1 m. On the other hand, satellites such as GOES, the Terra and Aqua satellites on board Moderate Resolution Imaging Spectroradiometer (MODIS), and the National Oceanic and Atmospheric Administration (NOAA) series, although lower in spatial resolution (usually in the range of a few hundred meters to one kilometer), can provide almost real-time data updates [5]. Over the last twenty years, the field of remote sensing has seen significant advancements, with the development of over 100 spatiotemporal fusion (STF) models [6]. These innovations now allow for the generation of images that boast a high resolution across both the spatial and temporal dimensions.

Although the remote sensing STF technique has been widely studied and applied, there is no bibliometric approach to analyze research trends in relation to it in detail. This paper aims to fill this research gap by providing a comprehensive view of the development history of the STF technique in remote sensing and pointing out possible future research directions in this field. The concept of bibliometrics was initially introduced by Pritchard in 1969 [7], who defined it as “the application of mathematical and statistical methods to books and other means of communication of knowledge”. As such, bibliometrics is unique as a powerful instrument for examining the development of science research. It measures data extracted from Internet academic reference sources related to a specific research topic, including author distribution, publication volume, and the active participation of research institutes in the sector. According to Ellegaard and Wallin [8], bibliometrics can be used to find important research within a field of study, offering a knowledge map with keywords, institution affiliations, national connections, and distribution characteristics. Additionally, it provides a quantitative assessment of the present state and prospective trends within research topics. In general, a deeper understanding of a research field is achieved with an increased number of references included in bibliometric analysis [9]. While the general approach to bibliometrics in remote sensing studies has been similar, the specific research topics have varied significantly [10–17]. This work is the first bibliometric examination of the literature on STF in remote sensing.

## 2. Purpose and Scope of the Study

### *2.1. Purpose of the Study*

The primary aim of this review is to thoroughly investigate the history, current status, and future trends of remote sensing STF through bibliometric analysis methods. The focus is on three areas:

a. Technological advances: identifying and analyzing critical advances in the field of technology, including theories, methodologies, and use cases.
b. Academic contributions and leadership: analyzing critical scholars, research institutions, and publications that have significantly impacted the field.
c. Research hotspots and trends: using bibliometric tools to reveal significant research themes and trends and predict possible future research directions.

Three questions are raised in light of the above objectives:

1. What is the global trend in the scientific literature on temporal and spatial integration of remote sensing?
2. What insights can be derived from this trend?
3. What emerging research trends can be anticipated in the field of remote sensing STF?

### *2.2. Scope of the Study*

a. Period: we focus on the literature within the last 30 years (1991–2023), reflecting the latest research developments.
b. Data source: we mainly analyze the literature from Web of Science.
c. Keywords and themes: we focus on relevant themes such as “spatiotemporal fusion”, “data fusion”, “remote sensing”, “spatial analysis”, and other related topics.

## 3. Bibliometric Methods and Framework

### *3.1. Literature Search Methodology*

We chose the “Web of Science Core Collection SCI Expanded” database as the data source for our study and focused on STF in remote sensing. To this end, we used advanced search techniques to construct a search formula containing multiple keywords: TS = (“Data Fusion” or “Temporal–Spatial Fusion” or “Spatiotemporal Fusion” or “Multitemporal Analysis” or “Spatial Analysis”). Within the foundational collection “Science Citation Index Expanded (SCI-

EXPANDED)—1945–present", our initial search resulted in 30,820 documents. Subsequently, we performed a more refined screening of this literature, explicitly restricting the scope to the field of remote sensing. This process resulted in 2967 relevant documents, with data updated to 19 December 2023. These bibliographic records were exported to a plain text file format, including the entire record and cited references.

### 3.2. In-Depth Bibliometric Analysis

In their study, Aria and Cuccurullo meticulously delineated the methodology for bibliometric analysis, encompassing five meticulous steps, namely, study design, data collection, data analysis, data visualization, and interpretation of results, which are covered in their studies [10,12–17]. Figure 1 demonstrates the flow of this complete methodology. In the research design phase, remote sensing STF was first identified as the research theme, and three research questions were defined for this theme. Subsequently, we decided to use the Web of Science (WOS) Science Citation Index (SCI) Expanded database as our main source of data. During the data collection phase, we acquired 2967 documents from the database through a comprehensive literature search. Considering the importance of peer review, during the literature screening process, we specifically utilized a document type filter to ensure the quality of the literature by selecting only the papers included in the WOS database. Ultimately, 2967 papers published between 1991 and 2023 were screened. The entire set of bibliographic records was smoothly imported into the Biblioshiny web program, facilitating a thorough analysis. These records were also converted into the bibliometric data format used in R (RData) format for use in subsequent stages of data analysis. Through this meticulous series of steps, this study ensured the accuracy and reliability of the data obtained.

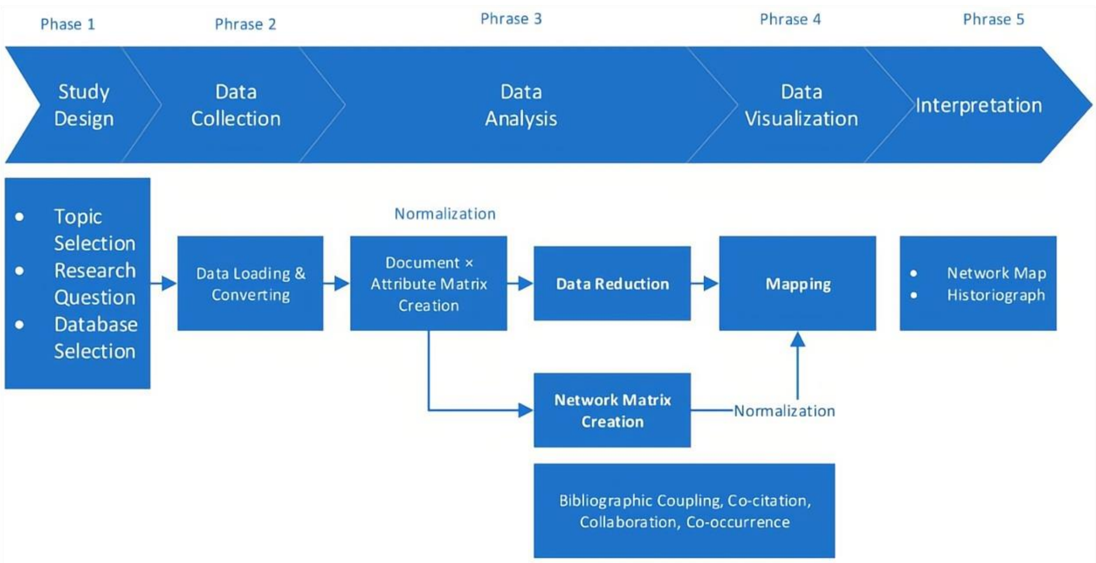



**Figure 1.** Illustrative depiction of the bibliometric analysis methodology [18].

Using R programs, we performed a descriptive bibliometric assessment and created a matrix of information that included each of the documents in the third step of our data analysis procedure. Next, in phase four, we employed a variety of tools to analyze and visualize the data further. These tools included Biblioshiny version 4.0, Tidyverse version 2.0.0 (specifically ggplot2), VOSviewer version 1.6.20, and Python version 3.12.3, with the help of which we generated concept maps, co-citation networks, and a variety of other diagrams that helped to provide a more visual and in-depth understanding of the data. In addition, we applied Bradford's law to analyze journal distribution, which allowed us to identify sources that have a significant influence in the field. This way, we could more accurately locate those journals and publications that contributed most to remote sensing STF. Section 4 of this study will ultimately detail our data analysis and visualization results interpretation. The interpretation includes an essential reading of the data and an in-depth understanding of the research area. Such analysis and interpretation help to better reveal current and future remote sensing STF trends.

## 4. Findings and Discussion

The initial findings from the bibliometric analysis encapsulate the bibliographic statistics. In this section, we offer an in-depth analysis of indicators, information, and hot keywords in the relevant literature in the field of study, the country of origin and institution of the first author, the journal from which the study originated, the top ten authors globally, and the most influential papers.

### *4.1. Extensive Bibliometric Evaluation*

Figure 2 illustrates the scientific output throughout the study period. Only five articles were published in 1991, and the number of documents gradually increased. Especially after 2016, the number of papers related to STF increased rapidly, reaching a peak of 471 documents in 2022 and then decreasing in 2023 with 347 papers. The average annual growth rate reached 14.17%. As shown in Section 4.3, the main contributor to the total number of articles was China. The decline in 2023 corresponds to a decrease in the number of papers from China. Table 1 details the essential information of 2967 papers published in the WOS SCI Extended database during the period of 1991–2023. The average number of citations per paper over the last 33 years is 34.22. These papers involved 9017 authors, including 97 independent authors. On average, there were five authors per paper (precisely 4.63). The Collaboration Index, which is the total number of authors of multi-authored articles divided by the total number of multi-authored articles, is 3.11 [19]. In total, 7989 author keywords were covered by these publications.

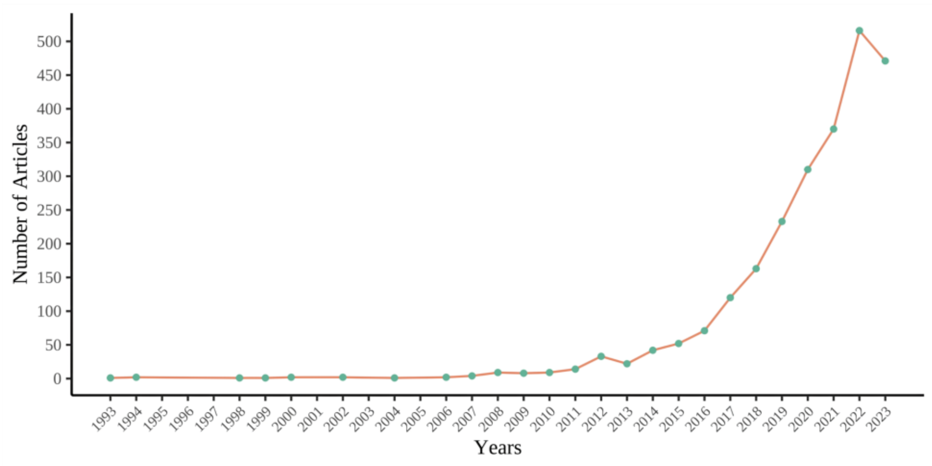



**Figure 2.** The scientific literature on STF in remote sensing produced from 1991 to 2023.

**Table 1.** Key information on remote sensing for STF.

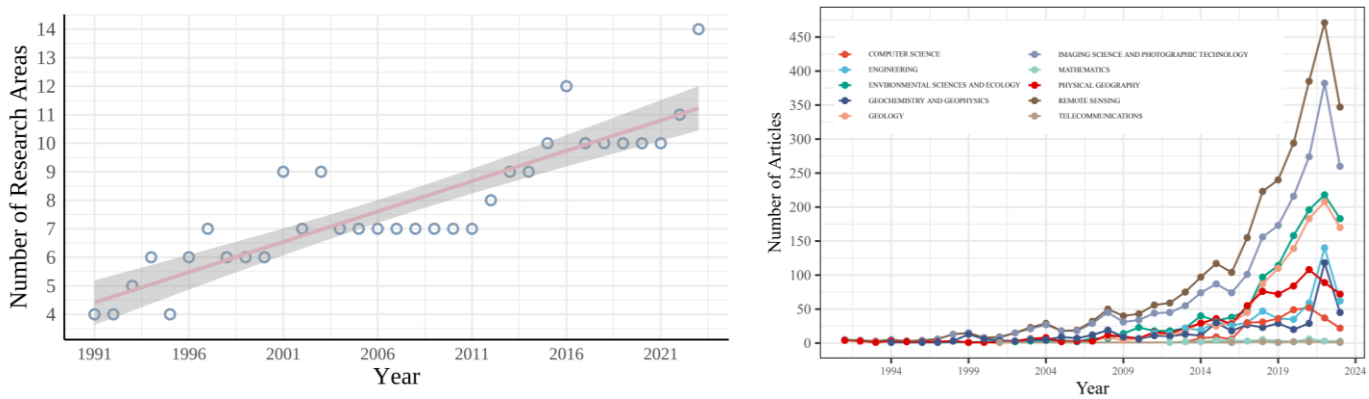
| Main Details | Synopsis | Worth |
|---|---|---|
| Documents | Total number of papers | 2967 |
| Sources | The distribution of frequency of sources, including books and periodicals | 41 |
| Timespan | Years of release | 1991–2023 |
| References | Total number of citations, total number of keywords used by authors | 101,780 |
| Author's Keywords (DE) | Total number of phrases that frequently appear in the title of an article | 7989 |
| Keywords Plus (ID) | References | 4473 |
| Authors | Total number of writers | 9017 |

**Table 1.** *Cont.*

| Main Details | Synopsis | Worth |
|---|---|---|
| Authors of single-authored documents | The number of lone writers for each piece | 97 |
| Authors of multi-authored documents | The number of writers for publications with multiple authors | 8920 |
| Authors per document | The average number of writers for every document | 3.04 |
| Co-authors per document | The mean quantity of co-authors for every document | 4.63 |
| Average citations per document | The mean quantity of citations found in every document | 34.22 |
| Collaboration Index | A measure of the level of collaboration in academic research | 3.11 |
| International co-authorships % | Researchers and academics from different countries working together | 33.7 |

### 4.2. WOS Research Domains

Clarivate Analytics's WOS research domains are used to categorize research publications [15]. Each document in the WOS database is categorizable into a minimum of one particular subject of study. This analysis shows that the literature on remote sensing STF covers an increased number of research subjects in 2023, 14, compared to 4 in 1991 (Figure 3a). The top 10 research fields with the highest production include remote sensing, computer science, mathematics, environmental science and ecology, geology, physical geography, engineering, geochemistry and geophysics, imaging science and photographic technology, geology, and telecommunications. Figure 3b illustrates the annual progression of the ten most prolific areas in STF research, delineating the shift in focus areas over time. Preceding 2009, geochemistry and geophysics, computer and imaging science, and photographic science and photographic technology were the main fields of study, after which each area garnered increasing attention. By 2022, remote sensing became the dominant area, with a large output of STF literature. However, all fields show a clear downward trend by 2023. The three scientific fields with the highest number of closely linked citations are remote sensing, imaging science and photographic technology, and environmental science with ecology.




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

**Figure 3.** (**a**) Countless WOS research topics about remote sensing STF are covered in the literature. (**b**) The temporal dynamics of the top ten WOS research areas with the highest productivity in the literature on remote sensing STF.

### 4.3. Exploration of Research Countries

The results show that authors from 50 countries have researched STF in remote sensing. The five countries with the most research outputs are China (1059 papers), the United States (432 papers), Italy (215 papers), Germany (169 papers), and Spain (101 papers). Since 2015, the number of publications from China has increased, surpassing that of the United States (Figure 4a). China's share of remote sensing STF scientific output has grown yearly, reaching 61.38% by 2023 (Figure 4b). Apart from the quantity of scientific outputs, the map of national collaborations can also serve as an indicator of a country's research strength.

Figure 5 illustrates global collaborations, showing that the United States (64 collaborative connections) has the most national collaborations, followed by China (52), Germany (51), Italy (45), France (42), the United Kingdom (39), Spain (29), the Netherlands (27), India (24), Canada (23), and Japan (23). Cooperation in remote sensing STF research is more limited in other countries. China cooperates mainly with the United States, Germany, the United Kingdom, France, Australia, Canada, and Italy. In contrast, the United States cooperates mainly with Germany, France, Italy, Canada, Spain, and the United Kingdom.

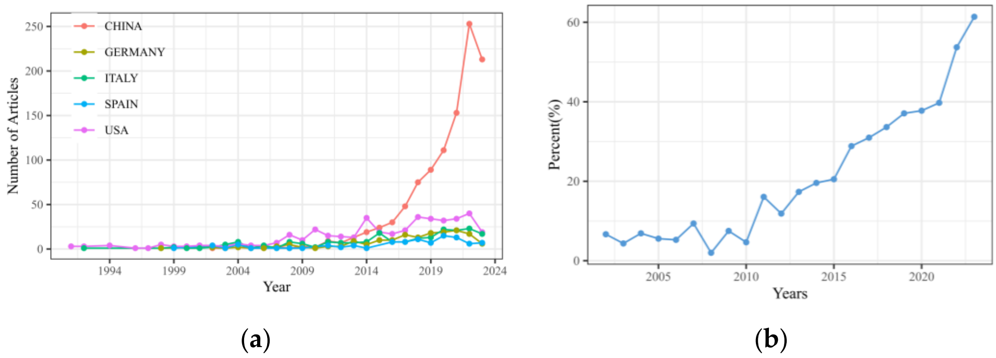



**Figure 4.** (**a**) Top five countries by annual scientific output; (**b**) annual proportion of scientific production in China.

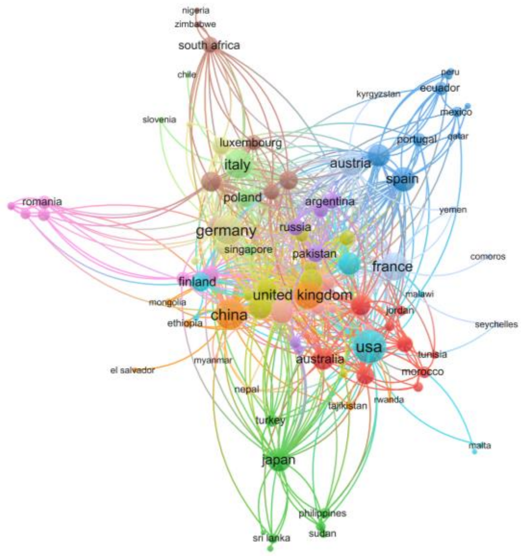



**Figure 5.** Map of research cooperation between countries.

## 4.4. Global Research Institutions

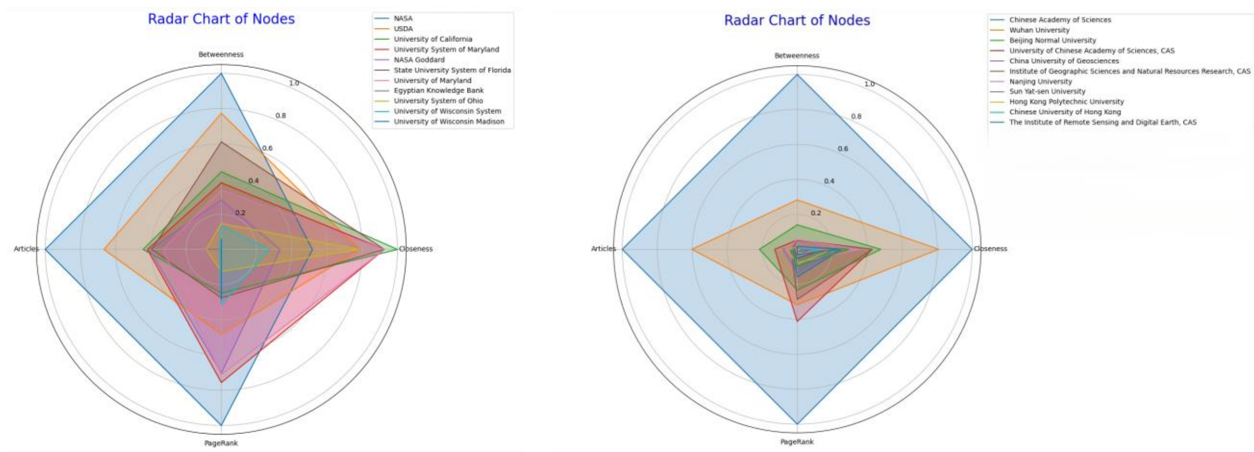
Research on STF in remote sensing has been conducted at 1624 institutions worldwide. Each research institution's influence was evaluated by counting the citations that its publications received. The ten most influential research institutions were determined by tallying all of the citations received by their publications, which included 180 articles and each institution's first-author accomplishments. The impact of the papers varied greatly from institution to institution, with Wuhan University in China (2203 citations) and the University of Florence in Italy (2011) having the highest total number of citations, followed by Beijing Normal University (2006), the Goddard Space Flight Center (1753), the German Aerospace Center (DLR), the Remote Sensing Technology Institute (1678), Texas A&M University (1493), the Instituto Superior Técnico (1359), the University of Tokyo (1330), Earth Resources Technology, Inc. (1316), and the Aerospace Information Research Institute, Chinese Academy of Sciences (1116) (Table 2).

**Table 2.** The top ten organizations in total citations for remote sensing spatial and temporal integration research.

| Institution | Country | TC | TA |
|---|---|---|---|
| Wuhan University | China | 2203 | 75 |
| University of Florence | Italy | 2011 | 8 |
| Bejing Normal University | China | 2006 | 35 |
| Goddard Space Flight Center | USA | 1753 | 11 |
| German Aerosp Center DLR; Remote Sensing Technol Institute | Germany | 1678 | 1 |
| Texas A&M University | USA | 1493 | 8 |
| Instituto Superior Técnico | Portugal | 1359 | 1 |
| University of Tokyo | Japan | 1330 | 12 |
| Earth Resources Technology, Inc. | USA | 1316 | 2 |
| Aerospace Information Research Institute | China | 1116 | 27 |

For analyzing international research networks in STF of remote sensing, we used cluster analysis to classify research institutions. This analysis was performed on the program Biblioshiny, and the results are presented in the form of a radar chart drawn in Python. The radar chart reveals institutions' trends and relative positions in remote sensing STF in different countries. In each radargram, different colors represent different institutions, and their shapes and sizes reflect each institution's performance in other metrics. The primary metrics used to assess these clusters include betweenness, closeness, PageRank, and the number of articles published (Articles).

As depicted in Figure 6a, the National Aeronautics and Space Administration (NASA) and the Chinese Academy of Sciences (CAS) exhibit robust profiles across all four measured indicators. Their prominence in metrics like betweenness, closeness, PageRank, and publication volume highlights their significant roles in the field of spatiotemporal fusion (STF) within remote sensing. Most of the first clusters are U.S. institutions, with NASA, the United States Department of Agriculture (USDA), the University of California (U.C.) system, and the University of Maryland system playing critical roles in spatial and temporal fusion of remote sensing. The USDA has a significant impact in the field of agricultural sciences, and the U.C. system and the University of Maryland system demonstrate extensive collaboration and theoretical contributions to multidisciplinary research. The second cluster contains mainly Chinese research organizations (Figure 6b). Wuhan University, Beijing Normal University, China University of Geosciences, and Tsinghua University also show importance in the research network and extensive academic connections.




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

**Figure 6.** (**a**) Geographic distribution of research institutions across the United States; (**b**) overview of research institutions in China.

### 4.5. Pivotal Source Journals

STF remote sensing investigations were published in 420 main journals; in 2023, there were 14 publication sources, up from 4 in 1991. We also looked at how widely renowned sources distributed research publications on remote sensing in the field of STF. The top 5 journals published 1855 papers (62.52% of the total), while 31 journals (7.32% of the total) published only 1 remote sensing time–space fusion paper. Out of all the journals, 104 (41.46%) produced a maximum of 10 publications. The top five scientific journals by total number of published articles are displayed in Figure 7: Remote Sensing (849), IEEE Transactions on Geoscience and Remote Sensing (321), ISPRS International Journal of Geo-Information (281), IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (203), and Remote Sensing of Environment (201). Table 3 shows that the Journal of Remote Sensing had the largest annual growth rate, while the Journal of Remote Sensing of the Environment had the highest total number of citations. Following Bradford's law, the source journals for remote sensing STF research papers exhibit a high degree of dispersion. The number of regional references was used to choose the top ten most influential journals (Table 3). In the field of remote sensing STF studies, the journals indicated by asterisks are regarded as primary source journals, including the journals IEEE Transactions on Geoscience and Remote Sensing and Remote Sensing. Therefore, these journals were crucial in STF research during the study period.

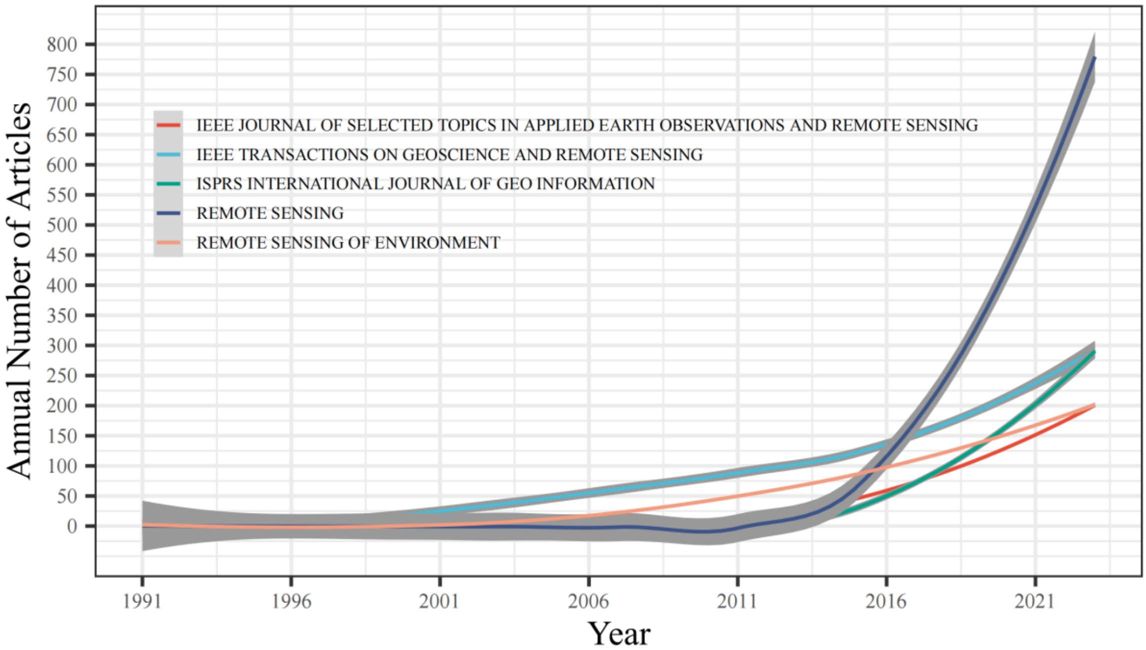



**Figure 7.** Temporal analysis of published sources of remote sensing STF studies.

**Table 3.** Top ten locally cited journals in remote sensing STF research.

| Sources | N.LC | ND | JCI (2022) | H Index |
|---|---|---|---|---|
| Remote Sensing of the Environment | 14,494 | 201 | 2.45 | 238 |
| IEEE Transactions on Geoscience and Remote Sensing * | 10,306 | 321 | 1.89 | 216 |
| Remote sensing * | 8772 | 849 | 1.02 | 81 |
| International Journal of Remote Sensing | 5145 | 186 | 0.66 | 151 |
| ISPRS Journal of Photogrammetry and Remote Sensing | 3798 | 118 | 2.58 | 110 |
| IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing | 2745 | 203 | 1.12 | 64 |
| IEEE Geoscience and Remote Sensing Letters | 2400 | 103 | 1.13 | 89 |

**Table 3.** *Cont.*

| Sources | N.LC | ND | JCI (2022) | H Index |
|---|---|---|---|---|
| Photogrammetric Engineering and Remote Sensing | 2366 | 57 | 0.28 | 114 |
| International Journal of Applied Earth Observation and Geoinformation | 1885 | 106 | 1.46 | 76 |
| International Journal of Geosciences and Remote Sensing | 1361 | 120 | | |

Abbreviations: N.LC, the total number of local citations; X *, the journal, which is a fundamental resource within the STF domain study based on Bradford's law.

### *4.6. Influential Authors*

One common metric used to assess academic achievement is the H-index, which measures the frequency with which a scientist's works have been cited [20]. In remote sensing STF, we found the ten most prominent researchers. Among them, the STARFM algorithm based on the weight function model proposed by Gao, F. (from Earth Resources Technology, Inc., with an H-index of 27) is one of the most cited articles, with 1268 citations [5]. Other notable researchers include Chanussot, J. (from the University of Savoy, with an H-index of 24) and Zhu, X.X. (from DLR, the German national space agency, with an H-index of 20), both of whom have made notable academic contributions to the field (Table 4). Three of these ten most influential researchers are from China, two are from the United States, and one each are from Germany, France, Portugal, Japan, and Iceland, respectively, demonstrating international collaboration. A total of 2967 papers enlisted the contributions of 9017 authors, with 97 independent authors responsible for 102 single-author papers. The collaboration index was 3.11, and the average quantity of co-authors for each manuscript was 4.63, highlighting remote sensing STF research as a typical field of multi-author collaboration.

**Table 4.** Top ten authors with the highest H-index.

| Author | H Index | TC | Country | UN |
|---|---|---|---|---|
| Gao, F. | 27 | 5873 | USA | Earth Resources Technology, Inc. |
| Chanussot, J. | 24 | 6123 | France | University of Savoy Mont Blanc—Chambery |
| Zhu, X.X. | 20 | 3526 | Germany | Remote Sensing Technology Institute IMF |
| Yang, Y. | 19 | 1319 | USA | University of Maryland; Hydrol and Remote Sensing Lab |
| Yokoya, N. | 17 | 2821 | Japan | University of Tokyo |
| Huang, B. | 16 | 1143 | China | Chinese University of Hong Kong |
| Zhu, X.L. | 16 | 2289 | China | Beijing Normal University |
| Benediktsson, J.A. | 15 | 2295 | Iceland | University of Iceland |
| Du, Q. | 15 | 1960 | USA | Mississippi State University |
| Chen, J. | 14 | 1898 | China | National Geomatics Center of China |

### *4.7. Influential Papers*

For identifying the most impactful papers from 1991 to 2023, we utilized citation counts as a primary metric, following methodologies proposed in previous studies [21]. Our analysis distinguishes between the global reference factor (GRF), which accounts for all citations recorded in Web of Science, and the local reference factor (LRF), which reflects citations within the specific field (see Tables 5 and 6 for detailed metrics). Table 7 presents a detailed overview of the models used in the top ten local papers, along with their respective contributions. One standout paper in our analysis is the Spatio-Temporal Adaptive Reflectance Fusion Model (STARFM) proposed by Dr. Gao Feng from the USDA. This influential work pioneered a weight function-based approach for surface reflectance fusion, effectively integrating the high-resolution spatial capabilities of Landsat with the high-frequency temporal data from MODIS. The STARFM algorithm has demonstrated its ability to predict surface reflectance with an accuracy comparable to that of the Landsat Enhanced Thematic Mapper Plus (ETM+). Its effectiveness was substantiated through both simulated and actual Landsat/MODIS datasets [5]. This seminal paper has garnered widespread recognition, significantly influencing the development of spatiotemporal fusion (STF) research. The continuous increase in its citation numbers serves as a testament to its enduring relevance and foundational role in the field. The success of the STARFM method has provided robust support for ongoing advancements in the remote sensing STF domain, illustrating the practical and theoretical value of integrating spatial and temporal data to enhance remote sensing capabilities.

**Table 5.** Top ten papers based on local reference factor.

| Document | DOI | LRF | GRF | Contribution |
|---|---|---|---|---|
| On the blending of the Landsat and MODIS surface reflectance: predicting daily Landsat surface reflectance | 10.1109/TGRS.2006.872081 | 359 | 1268 | Introduced a weight function-based approach for surface reflectance fusion. |
| An enhanced spatial and temporal adaptive reflectance fusion model for complex heterogeneous regions | 10.1016/j.rse.2010.05.032 | 300 | 800 | Improved accuracy of fine-resolution reflectance predictions, particularly in heterogeneous landscapes. |
| A flexible spatiotemporal method for fusing satellite images with different resolutions | 10.1016/j.rse.2015.11.016 | 204 | 413 | Combines a demixing-based approach with weighting functions and spatial interpolation techniques. |
| A new data fusion model for high spatial- and temporal-resolution mapping of forest disturbance based on Landsat and MODIS | 10.1016/j.rse.2009.03.007 | 191 | 525 | Improves detection of land cover changes and disturbances with enhanced spatial and temporal resolution. |
| Spatiotemporal Fusion of Multisource Remote Sensing Data: Literature Survey, Taxonomy, Principles, Applications, and Future Directions | 10.3390/rs10040527 | 131 | 267 | Categorizes existing spatiotemporal data fusion methods and outlines future research directions. |
| A comparison of STARFM and an unmixing-based algorithm for Landsat and MODIS data fusion | 10.1016/j.rse.2014.09.012 | 129 | 259 | Combines Bayesian theory and the STARFM moving window concept to estimate changes in fine-resolution elements. |
| Spatiotemporal Satellite Image Fusion Using Deep Convolutional Neural Networks | 10.1109/JSTARS.2018.2797894 | 108 | 199 | Leverages machine learning to model the correlation across observed coarse–fine image pairs. |
| Spatiotemporal Satellite Image Fusion Through One-Pair Image Learning | 10.1109/TGRS.2012.2213095 | 100 | 178 | Establishes correspondence between LSHT and HSLT data through super-resolution techniques. |
| Use of MODIS and Landsat time series data to generate high-resolution temporal synthetic Landsat data using a spatial and temporal reflectance fusion model | 10.1117/1.JRS.6.063507 | 96 | 186 | Leverages unmixing to enhance image resolution before applying spatiotemporal fusion. |
| Generating daily land surface temperature at Landsat resolution by fusing Landsat and MODIS data | 10.1016/j.rse.2014.02.003 | 95 | 363 | Modifies STARFM to refine surface temperature data by considering the annual temperature cycle and urban thermal landscape heterogeneity. |

**Table 6.** Top ten papers based on global reference factor.

| Document | DOI | LRF | GRF | Contribution |
|---|---|---|---|---|
| Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources | 10.1109/MGRS.2017.2762307 | 62 | 1678 | Leverages deep learning to advance remote sensing, improve analysis tasks, and gain new insights into processing remote sensing data. |

**Table 6.** *Cont.*

| Document | DOI | LRF | GRF | Contribution |
|---|---|---|---|---|
| Hyperspectral Remote Sensing Data Analysis and Future Challenges | 10.1109/MGRS.2013.2244672 | 13 | 1359 | Offers a thorough examination of hyperspectral data analysis methods, delineates cutting-edge techniques, and outlines future research directions. |
| On the blending of the Landsat and MODIS surface reflectance: predicting daily Landsat surface reflectance | 10.1109/TGRS.2006.872081 | 359 | 1268 | Introduced a weight function-based approach for surface reflectance fusion. |
| Geographic Object-Based Image Analysis—Towards a new paradigm | 10.1016/j.isprsjprs.2013.09.014 | 20 | 1043 | Investigates per-pixel method limitations and concludes GEOBIA is a fresh, evolving paradigm. |
| Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data | 10.1109/LGRS.2017.2681128 | 23 | 921 | Introduces a multilevel deep learning architecture for classifying land cover and crop types. |
| Remote sensing of the urban heat island effect across biomes in the continental USA | 10.1016/j.rse.2009.10.008 | 13 | 906 | Examines and contrasts the urban heat island (UHI) response in various biomes across the continental USA, emphasizing the impact of ecological factors on UHI intensity. |
| Multiresolution-based image fusion with additive wavelet decomposition | 10.1109/36.763274 | 56 | 889 | Discusses a technique that uses multiresolution wavelet decomposition to merge high-resolution panchromatic and low-resolution multispectral images. |
| Spectral and Spatial Classification of Hyperspectral Data Using SVMs and Morphological Profiles | 10.1109/TGRS.2008.922034 | 16 | 856 | Explores using morphological transformations for processing hyperspectral imagery in urban areas. |
| An enhanced spatial and temporal adaptive reflectance fusion model for complex heterogeneous regions | 10.1016/j.rse.2010.05.032 | 300 | 800 | Improved accuracy of fine-resolution reflectance predictions, particularly in heterogeneous landscapes. |
| Coupled Nonnegative Matrix Factorization Unmixing for Hyperspectral and Multispectral Data Fusion | 10.1109/TGRS.2011.2161320 | 55 | 696 | Presents a coupled non-negative matrix factorization (CNMF) algorithm designed to fuse low-spatial-resolution hyperspectral and high-spatial-resolution multispectral data. |

The advancements in spatiotemporal data fusion are well documented through several high-impact papers. The Enhanced Spatio-Temporal Adaptive Reflectance Fusion Model (ESTARFM) algorithm, ranked second by LRF and ninth by GRF, represents a significant improvement over the well-known STARFM algorithm. This enhanced model addresses the limitations of STARFM by improving the accuracy of fine-resolution reflectance predictions, particularly in heterogeneous landscapes. It introduces a conversion factor that refines weight calculations based on the spectral similarity between fine- and coarse-resolution image elements, facilitating more precise studies of global landscape changes on seasonal and interannual scales [22]. Following this, the Flexible Spatio-Temporal Data Fusion (FSDAF) method, ranked third in LRF, combines a demixing-based approach with weighting functions and spatial interpolation techniques. This hybrid algorithm effectively merges frequent coarse spatial resolution data from MODIS with infrequent high-resolution data from Landsat, generating consistently high-resolution synthetic images. The FSDAF method's superiority in producing accurate images, particularly in capturing reflectance changes due to land cover transitions, highlights its potential to enhance the availability of high-resolution time series data for rapid surface dynamics studies [23]. Moreover, the Spatio-Temporal Adaptive Algorithm for mapping Reflectance Change (STAARCH) method, which ranks fourth in LRF, introduces a novel approach to mapping reflectance changes using a weight function to identify change spots dynamically. By blending data from Landsat TM/ETM+ and MODIS, STAARCH improves the detection of land cover changes and disturbances with enhanced spatial and temporal resolution. Validation using a disturbance dataset confirmed its ability to accurately date disturbances over multiple years, showcasing improvements over previous data fusion techniques [24].

**Table 7.** Review of key models of spatiotemporal data fusion and their influence.

| Rank by LRF | Model/Method | DOI | Key Contribution |
| --- | --- | --- | --- |
| 1 | STARFM | 10.1109/TGRS.2006.872081 | Pioneer of the STARFM algorithm, a weight function-based approach for surface reflectance fusion. |
| 2 | ESTARFM | 10.1016/j.rse.2010.05.032 | Significant contributions to remote sensing data fusion methodologies. |
| 3 | FSDAF | 10.1016/j.rse.2015.11.016 | Advanced developments in data fusion applications. |
| 4 | STAARCH | 10.1016/j.rse.2009.03.007 | Developed improved methods for assessing environmental changes using data fusion. |
| 5 | Comprehensive review article | 10.3390/rs10040527 | Further enhancements in the field of spatiotemporal data fusion. |
| 6 | STRUM | 10.1016/j.rse.2014.09.012 | Introduced new techniques in urban landscape monitoring through data fusion. |
| 7 | CNN-based STF method | 10.1109/JSTARS.2018.2797894 | Development of novel spatiotemporal fusion algorithms for enhanced accuracy. |
| 8 | Dictionary pair learning-based STF | 10.1109/TGRS.2012.2213095 | Improved methodologies for spatial data fusion, impacting environmental studies. |
| 9 | New data fusion model | 10.1117/1.JRS.6.063507 | Contributions to temporal data analysis and fusion. |
| 10 | SADFAT | 10.1016/j.rse.2014.02.003 | Advanced the understanding of spatial dynamics through innovative fusion techniques. |

The fifth most impactful paper in the LRF is a comprehensive review article that categorizes existing spatiotemporal data fusion methods, discusses the underlying principles, and outlines future research directions. This paper is instrumental in summarizing application prospects and synthesizing knowledge across various studies published in remote sensing journals. Notably, it utilizes a literature citation map based on X. Zhu et al. [4] to identify highly cited works, enhancing the understanding of field dynamics. Following this, the sixth-ranked paper by LRF introduces the Spatiotemporal Reflectance Unmixing Model (STRUM). STRUM innovatively combines Bayesian theory and the STARFM moving window concept to estimate changes in fine-resolution elements directly from coarse image elements. Demonstrated using analog, Landsat, and MODIS imagery, and assessing temporal Normalized Difference Vegetation Index (NDVI) profiles, STRUM effectively captures phenological changes, showcasing the utility of hybrid data fusion approaches [25].

The seventh-ranked paper proposes a novel deep convolutional neural network (CNN)-based method for spatiotemporal fusion (STF) tailored for remote sensing data. This approach leverages machine learning (ML) to model the correlation across observed coarse–fine image pairs, addressing the complex correspondence and significant spatial resolution gaps between MODIS and Landsat images. The dual five-layer CNN architecture not only extracts valid image features effectively but also learns the end-to-end mapping, yielding superior fusion results compared to sparse representation-based methods [26]. The eighth most influential paper, by Song and Huang, develops a dictionary-pair learning-based STF method that utilizes a unique two-stage fusion model. This method establishes a correspondence between low-spatial-resolution, high-temporal-resolution (LSHT) data, and high-spatial-resolution, low-temporal-resolution (HSLT) data through super-resolution techniques and high-pass modulation. The fusion model effectively captures surface reflectance changes associated with climate and land cover type changes, outperforming other well-known STF algorithms in accuracy and detail [27].

Notably, the ninth and tenth most influential papers ranked by LRF, which focus on specific advancements in data fusion models, do not appear in the top ten papers ranked by GRF. The ninth LRF paper introduces a new data fusion model that leverages unmixing to enhance image resolution before applying STF, utilizing classification maps from high-resolution imagery of the T1 temporal phase to reverse decompose the low-resolution imagery [28]. The tenth LRF paper presents the Spatio-Temporal Adaptive Data Fusion Algorithm for Temperature Mapping (SADFAT), which modifies STARFM by integrating considerations of the annual temperature cycle and urban thermal landscape heterogeneity to refine surface temperature data [29].

Among the GRF's most influential papers, only the third- and ninth-ranked papers overlap with the LRF's top ten, highlighting a divergence in citation impact and local relevance. The highest-ranked GRF paper explores the application of deep learning in remote sensing, with a focus on image recognition, target detection, and semantic segmentation, underscoring the growing importance of artificial intelligence (AI) technologies in this field [30]. The second place GRF paper provides an overview of six significant themes in hyperspectral data analysis, including fusion, unmixing, and classification, reflecting key trends and challenges in remote sensing [31]. Subsequent GRF papers address a variety of topics: the fourth-ranked paper critiques the limitations of pixel-by-pixel analysis in high-resolution imagery, advocating for the Geographic Object-Based Image Analysis (GEOBIA) paradigm in geographic information science [32], while the fifth delves into deep learning for land cover and crop classification using multi-temporal, multi-source satellite imagery [33]. The remaining papers explore methods related to the urban heat island effect, the fusion of high-resolution panchromatic with low-resolution multispectral images, and the integration of low-spatial-resolution hyperspectral and high-spatial-resolution multispectral data [34–37].

### *4.8. History and Frontier Applications*

This study detected 7989 author keywords from 2967 papers published in STF studies from 1991 to 2023. Figure 8 depicts the trend of author keywords over time, with the $x$-axis representing the year and the $y$-axis denoting the keywords. Each "dumbbell" or dot represents a keyword's relative importance or popularity in a given year. At the same time, the length of the horizontal line indicates the duration of or attention received by the keyword between years. The yellow dot represents the first quartile of the publication year associated with the keyword, while the purple dot indicates the third quartile of the publication year. The red dot marks the median of the publication year, signifying the concentrated period when the paper was published. The size of the dots reflects the number of documents. The size of the central red dot mirrors the frequency of keywords; the larger the dot, the more often a keyword appears. "Data fusion", "remote sensing", "spatial analysis", "deep learning", "MODIS", "Landsat", "lidar", "spatial resolution", "spatiotemporal fusion", and "machine learning" are the top ten keywords in terms of frequency. Landsat, MODIS, WorldView-2, and Sentinel are the most widely used remote sensing space–time fusion sensors. These remote sensing satellites provide a rich spatial and temporal data source for environmental monitoring and surface characterization. Six hundred and fifty-six papers were published in 2012–2023, accounting for 22.4% of the total papers. Landsat provides medium-to-high-spatial-resolution imagery for monitoring surface changes such as urban sprawl, deforestation, etc. Landsat provides a rich spatial and temporal data source for environmental monitoring and characterization in spatial and temporal fusion. In STF, Landsat data are often used to provide finer spatial details in combination with other data with a higher temporal resolution but a lower spatial resolution (e.g., MODIS). One of the prerequisites for the fusion of Landsat and MODIS is the similarity of orbital parameters. It is also possible to combine dual generative adversarial network (GAN) models with Cubesat constellation images for the super-resolution of historical Landsat images for spatially enhanced long-term vegetation monitoring [38]. MODIS data are often combined with other data sources to improve spatial resolution or long-term temporal tracking. The latest MODIS data can be used for data fusion to estimate urban heat wave temperatures [39], combined with deep neural networks for progressive spatiotemporal image fusion [40] and the STF of surface temperatures based on convolutional neural networks [41].

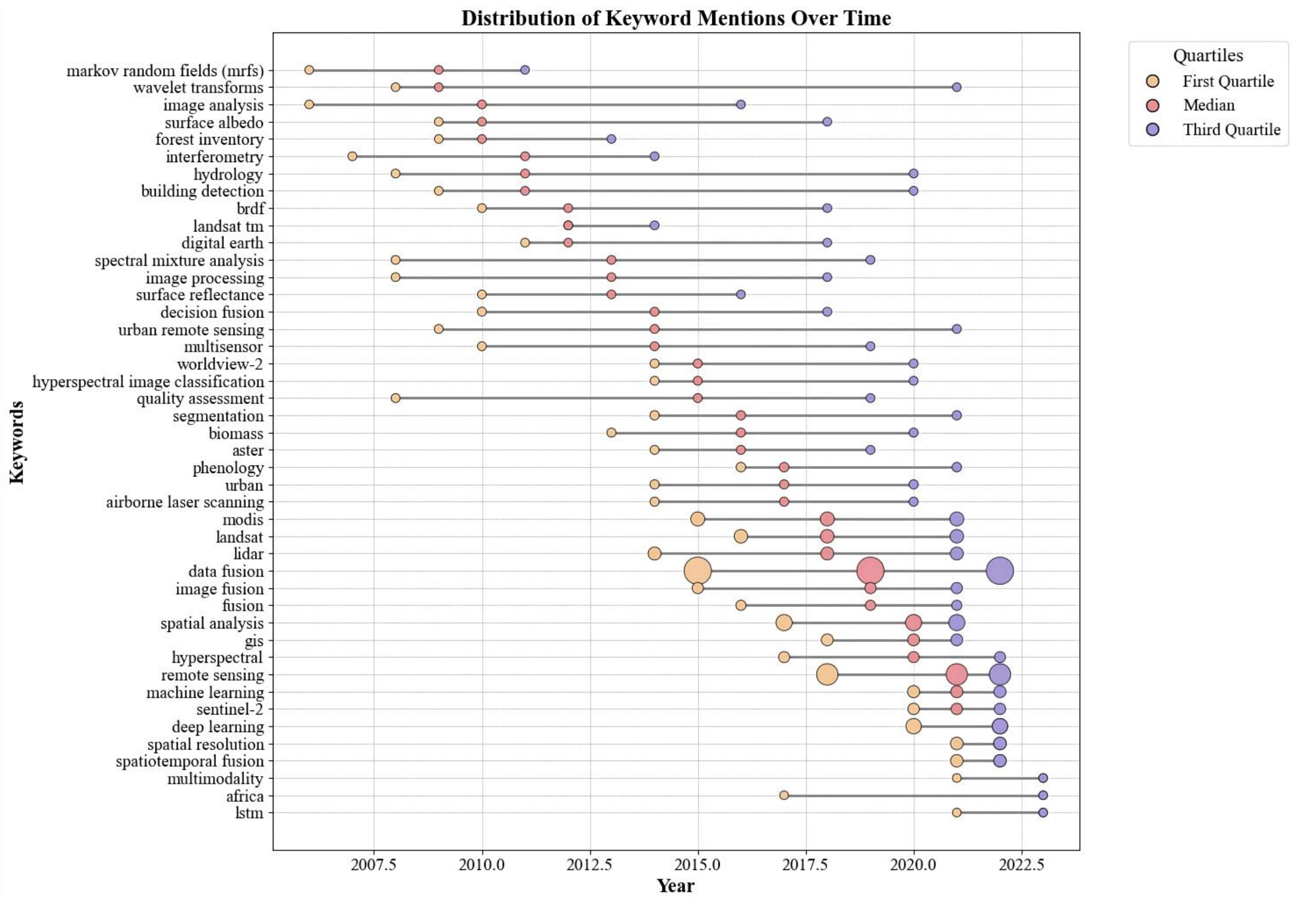



**Figure 8.** Author keyword temporal trends.

The amount of research on Sentinel data has grown the fastest in recent years. There is an increasing demand for hyperspectral data; conversely, the fusion of Landsat and MODIS images has been widely studied and provides a reasonable basis for developing fusion workflows for Sentinel-2 and Sentinel-3 data [42]. Recent studies show more applications of Sentinel data in ecological environments, such as the near-real-time monitoring of tropical forest disturbances fused with Landsat data [43], the monitoring of maize nitrogen concentration merged with radar (C-Sar), optical and sensor satellite data [44], and the fusion of multimodal satellite-borne Lidar data with visual images to estimate forest canopy height [45]. Light Detection and Ranging (LiDAR) and hyperspectral imagery (207 articles for 2014–2023) are two basic types of data used in remote sensing applications. High-resolution topographic data can be obtained using LiDAR data, which makes it easier to combine and understand different remote sensing datasets [46]. The electromagnetic spectrum that an object reflects or emits is captured by hyperspectral imaging, enabling various materials to be identified and analyzed based on their unique spectral characteristics. Hyperspectral imaging (10 articles for 2013–2022) is a more advanced technique than multispectral imaging [47], which collects information across the entire spectrum of waves at a very high resolution. A thorough and in-depth examination of the Earth's surface, atmosphere, and environment is made possible by data from a variety of sensors, such as LiDAR, multispectral or hyperspectral imaging, and radar [48].

It is also evident from the figure that the keywords “machine learning”, “deep learning”, and “LSTM” appearing behind the timeline were the hotspots of STF research in recent years, and there were 318 articles in 2017–2023. ML- and DL-based STF models do not rely on assumptions but on establishing complex relationships between input and output images. According to a survey of existing STF models, there are ten times more DL STF models than ML STF models. The first DL artificial neural network (ANN) STF model was proposed in 2015 [49], followed by convolutional neural networks in STF models, which led to a rapid increase in STF models based on DL. Deep convolutional networks are the most commonly used CNN method among STF methods, followed by GAN, AutoEncoder, LSTM, and Transformer. Different convolutional neural networks have been developed in STF models at other times (see Table 8). There are seven commonly used DL strategies for existing STF methods: residual learning, attention mechanism, super-resolution, multi-stream, composite loss function, multi-scale mechanism, and migration learning. The main applications of DL techniques in STF are land cover classification [33,50–59], change detection [60–69], and multi-sensor data fusion [70–74]. “Spatial analysis” and “GIS” had a total of 443 publications in 2017–2023, and the synergy between STF, spatial analysis, and the Geographic Information System (GIS) provides more integrated and fine-grained tools and methods.

**Table 8.** Overview of application of ML and DL in spatiotemporal fusion technology.

| Category | Description |
|---|---|
| ML Models | Utilizes models like random forests, regression trees, and decision trees to establish relationships between input and output images, focusing on direct mappings, but may struggle with the high-dimensional nature of RS images. |
| DL Models | Predominantly uses CNNs which handle complex, non-linear mappings effectively, automatically learning and extracting high-level features for reconstructing or predicting finer-resolution images. |
| CNN Variants | - Deep Convolutional Networks: stack multiple layers to learn spatial features.<br>- GANs and AutoEncoders: for sophisticated image synthesis and feature representation.<br>- LSTMs and Transformers: address temporal dynamics in STF, less commonly used. |
| Specific CNN Models in STF | - STFDCNN, VDCNSTF: focus on non-linear mapping and super-resolution.<br>- ESRCNN, DSTFN: predict specific bands of satellite images with techniques like self-adoption and multi-temporal fusion. |
| Advancements and Innovations | - Advanced Models: direct processing of fine–coarse image pairs, use of 3D CNNs for depth in feature extraction.<br>- Innovations like BiaSTF and HDLSFM: combine different CNN models or integrate with other algorithms like linear regression for enhanced prediction accuracy and application relevance. |

## 5. Current Challenges and Future Research Projections

### *5.1. Numerous STF Studies, More Limited Practical Applications*

This study’s research patterns suggest that STF research is presently going through a growth phase. Despite the growing presence of STF models in this field of research, their applications are still relatively limited, especially in practical Earth observation applications. Taking agricultural scenarios oriented toward asynchronous phenological changes as an example, although STF has been recognized as an effective tool for predicting missing high-spatial-resolution images, most of the STF methods are based on the assumption that there is a consistent albedo relationship for the same land cover type between the base date and the prediction date. However, this assumption does not always hold in agricultural scenarios, as climatic changes can vary significantly across crop types or the same crop at different growth stages [75]. Expanding the scope of studies to include asynchronous phenological changes is crucial to advancing the practical application of STF techniques. Such studies focus on temporal variability, spatial variability, and spatial–temporal interactions and are typical examples of in-depth investigations of the spatial–temporal variability of natural phenomena. In agricultural applications, images of critical phenological periods are vital because they capture the unique spectral characteristics of crops. The diversity of phenological changes, especially in the context of current climate change and environmental change, has become an essential area of research. It provides critical information on ecosystem health, species migration patterns, agricultural production, and biodiversity. Critical phenological periods usually last for a short amount of time and are synchronized with the rainy season. However, obtaining high-spatial-resolution imagery of critical phenological periods is still challenging, relying only on a single satellite platform. This challenge further emphasizes the importance of developing more advanced STF models and methods to better capture and understand the dynamics of these critical periods.

### *5.2. Deep Learning-Based Uncertainty in STF Data*

Further exploration is needed. Significant progress has been made in deep learning remote sensing STF in the last three years, and most STF models have adopted deep learning techniques. A substantial amount of labeled data are required for efficient model training to direct algorithms in identifying and deciphering particular features and patterns in data collected via remote sensing. On the other hand, creating labeled datasets takes a lot of work. The precision, reliability, and completeness of training data play a pivotal role in shaping the model's performance and generalization capabilities [76]. Variations in temporal patterns, spectral features, or spatial sub-resolution may result from different sources, sensors, or acquisition times [77]. The atmospheric conditions, sensor constraints, data gathering methods, and natural variability brought on by clouds, haze, or aerosols are some of the factors that might introduce uncertainty into remotely sensed data [78]. Furthermore, the spatial and temporal variability of natural phenomena contributes to the heightened uncertainty of remote sensing-based AI models [79]. The training process becomes more difficult and biased as a result of these irregularities. Missing observations or irregular temporal sampling intervals might make it more difficult for the model to effectively represent temporal trends in time series analysis. Addressing these challenges is crucial for enhancing the robustness and reliability of remote sensing AI models in the face of real-world complexities [80]. In remote sensing STF applications, deep learning models focus on learning and understanding the heterogeneity between coarse-resolution (low-spatial-resolution) and acceptable-resolution (high-spatial-resolution) images rather than the subtle variations in the time series. This results in models that do not perform as well in dealing with $\Delta C$ (the change in coarse pixels between t1 and t2) as they do with spatial heterogeneity. Therefore, training $\Delta C$ algorithms is missing in deep learning-based STF models. Deep learning models that are complex frequently serve as "black boxes", posing challenges for individuals to comprehend and elucidate their internal mechanisms and decision-making processes [81]. The $\Delta C$ algorithm in STF involves complex spatiotemporal data processing, which may be difficult to simulate and reproduce in deep learning model training. Although deep learning is very effective in spatial feature recognition, it still has room for improvement in handling complex STF tasks, especially in understanding and learning the amount of temporal change ($\Delta C$).

### *5.3. STF Application Accuracy Is Less Evaluated*

To comprehensively assess the performance of different models, we need a benchmark dataset covering the diversity of the Earth's surface and containing images from various sensors. Obtaining a high-quality and high-resolution benchmark dataset covering a wide range of regions and a long time series is challenging. There is a relative lack of publicly available benchmark datasets in this area. The STF model involves complex algorithms that deal with data that include both spatial and temporal dimensions, which adds to the difficulty of implementation and evaluation. Since STF models are relatively new applications in remote sensing, widely recognized evaluation standards or methodologies have not yet been established, making comparing different studies difficult. In practical applications, STF models need to cope with various challenges, such as the performance of different surface cover types, different climatic conditions, and the fusion of data from other sensors, which may affect the accuracy assessment of the models. Developing and evaluating STF models requires specialized knowledge and resources, limiting the number of institutions or teams that can conduct such evaluations. STF models may still be in the early stages of development at this time, but more assessments of their accuracy are expected to emerge as the technology matures and the range of applications expands.

### *5.4. Forecast of Future Research Directions*

#### 5.4.1. STF Benchmark Dataset

Future research in STF will promote the application of STF models in dealing with various time-varying homogeneous or heterogeneous landscapes. Additional benchmark datasets from multiple sensors and landscapes are needed to train and test STF models. In addition, applying data enhancement techniques to simulate different time-varying scenarios will help to enhance these models' generalization ability. Future STF models will be able to handle data fusion tasks in complex environments more systematically and robustly with such datasets.

#### 5.4.2. Deep Learning STF Based on Time Series Analysis

Deep learning has demonstrated strong potential in dealing with the spatiotemporal heterogeneity of remote sensing data. To properly handle spatial heterogeneity, spatiotemporal data fusion algorithms need to be able to recognize and adapt to the complexity and diversity of the data in the spatial dimension while maintaining accurate tracking of the amount of change in the temporal dimension. In terms of training strategy optimization, designing a loss function specifically for $\Delta C$ characteristics will enable the model to pay more attention to temporal changes. Meanwhile, improving the model's interpretability will help us to better understand and improve the model's handling of temporal variations and reveal the logic behind the model's predictions.

#### 5.4.3. An Applied Study of STF in Asynchronous Physical Climate Change

Regularly evaluating the effectiveness of models in handling time variation and optimizing them based on feedback are also critical components of future research. Extensive testing and empirical studies are conducted to validate the model's performance in real-world applications. With the continuous advancement of deep learning technology, more innovations and breakthroughs are expected to be realized in this field. In particular, in the direction of research on asynchronous phenological changes, combining remote sensing data from different times and spatial resolutions can provide a more comprehensive view of phenological changes. This may include using advanced algorithms and models for processing and interpreting large amounts of remotely sensed data to identify and predict climatic changes. The potential applications of this line of research are wide-ranging and include improving climate change models, guiding agricultural practices, conserving biodiversity, and managing natural resources.

## 6. Conclusions

Over the past several decades, there has been a sustained increase in the volume of publications, encompassing an ever-broadening array of research domains. This review presents a comprehensive bibliometric analysis of STF research in remote sensing from 1991 to 2023. Over 33 years, the field has experienced exponential growth in published articles, rising from 5 papers in 1991 to 18 papers by 2005, culminating in 347 documents by 2023. Predominant contributing nations include China, the United States, Italy, Germany, and Spain; the Chinese Academy of Sciences and Wuhan University in China are leading research institutions. The most influential journals in this field have been identified as

Remote Sensing, IEEE Transactions on Geoscience and Remote Sensing, and the ISPRS Journal of Photogrammetry and Remote Sensing. The most prominent authors contributing to this work are Gao, F., Chanussot, J., and Zhu, X.X.

Many other efficient bibliometric tools are available: CiteSpace handles visualizing complex data, and HistCite and BibExcel manage and organize large amounts of data. Publish or Perish and SciMAT provide a more profound analysis. Pajek provides large-scale network analysis, handling and analyzing large-scale datasets. In addition, there are EndNote, Mendeley, and Zotero reference management tools. Scopus, Incites, ESI, and Altmetric provide detailed data analysis. In this article, Biblioshiny delivers a user-friendly interface that makes complex analyses easy for researchers unfamiliar with programming. However, when using the bibliometrix participle algorithm, there is still room for improvement in its intelligence and keyword extraction accuracy. Therefore, we need to enhance the semantic understanding of citation data and combine multiple bibliometric approaches in our subsequent research to enhance the accuracy of the specific statistics and ensure greater precision, intelligence, and comprehensive knowledge extraction. Future research could also explore knowledge graph-based approaches to construct a literature knowledge graph to mine interdocument associations and patterns. This can better parse the semantic relationships within literature data, provide rich and in-depth semantic information for the lexical algorithm, and further improve the accuracy and intelligence of knowledge extraction.

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